Evaluating the accuracy of the Beta Probability Density Function for a Changed Socio-Economic Electrification Load Profile in the Free State

by

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Declaration

I, **Renier Johannes Oosthuizen** (Identity Number: ____________, Student Number: _________), hereby declare that this research project, submitted to the Central University of Technology for the degree of Master of Engineering in Electrical Engineering, is my original work. This research complies with the Code of Academic Integrity and all other relevant policies, procedures, rules, and regulations of the Central University of Technology. I further declare that this work has not been submitted previously, in whole or in part, by me or any other individual, to obtain any academic qualification.

Acknowledgments

The song “Gaudeamus Igitur” has always held deep personal significance for me. In the spirit of its lyrics, I would like to extend my heartfelt gratitude to the following:

I rejoice in the life I have been blessed with by God Almighty, from my birth to my eventual death.

For those who have shaped my journey, I express my deepest thanks to my late father, Deon Johannes Oosthuizen, whose life has been an enduring source of inspiration and example.

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My dearest mother, Reinette Oosthuizen, is a guiding source of wisdom.

My brother, Gerrit Oosthuizen, who exemplifies the pursuit of a higher calling.

My wife, Estienne Oosthuizen, the love of my life and the mother of our children, whose presence is the indescribable reason for who I am and who I have become.

To those who will one day share fully in this rejoicing:

My children, George and Stienna Oosthuizen: may this serve as an inspiration for you to pursue the God-given purpose you were created for tirelessly. Amen!

Forever, all glory be to God Almighty!

Abstract

Accurate estimation of After Diversity Maximum Demand (ADMD) is essential for the reliable and cost-effective planning of low-voltage distribution networks in areas undergoing rapid socio-economic change. When ADMD values are misestimated, planners risk either under-built infrastructure that leads to operational constraints or over-designed systems that incur unnecessary capital expenditure. South Africa's widely used standard, SANS 507-1:2019, derives residential ADMD values from a Beta probability density function calibrated on historical datasets. Whether these values still reflect present-day consumption patterns in electrifying Free State communities remains uncertain, and addressing this uncertainty is vital to maintaining sound planning practice.

This study evaluates the applicability and reliability of the SANS 507-1:2019 ADMD values, and their underlying Beta-PDF model, within socio-economically diverse electrification settings across the Free State. The aim is to determine whether the standard continues to provide dependable design guidance or whether contextual adjustment is warranted as community load profiles evolve.

Historical transformer-zone load data were processed using documented quality controls, including the exclusion of implausibly low loads, to derive observed ADMD values defined as the 99.5th-percentile load for each consumer class and supply category. These were compared with the standard's theoretical ADMDs, and deviations were evaluated against a ±12% planning-tolerance threshold.

The analysis shows that only 6 of 52 class-by-case comparisons fall within this tolerance, indicating that standard ADMD values often diverge from observed demand. Larger deviations align with regional distinctions recognised in SANS 507-1:2019, demonstrating that geographic and socio-economic context materially influence demand behaviour. The evidence therefore shows that, in several Free State settings, the Beta-PDF-based standard no longer consistently reflects actual ADMD.

The study contributes an auditable and reproducible procedure for deriving and validating ADMD in changing socio-economic electrification environments. It further recommends targeted refinement of standard ADMD parameters and supports future recalibration efforts grounded in empirical, region-specific load data to improve the accuracy and relevance of national planning frameworks.

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Chapter 1 — Introduction

South Africa's electricity demand has shifted markedly with continued urbanisation, industrial growth, and large-scale electrification of previously underserved areas [1], [2], [3], [4]. These socio-economic changes complicate demand forecasting, particularly in provinces such as the Free State, where diverse living standards and consumption behaviours co-exist. In such contexts, accurate demand estimation is essential for efficient infrastructure planning, equitable access, and reliable supply [5], [6], [7].

Within national planning practice, the SA standard ADMD (SANS 507-1:2019), parameterised using a Beta probability density function is widely used as a proxy for residential demand [7]. However, rapid changes in household energy use raise questions about whether the standard parameters still reflect current load characteristics in socio-economically diverse settings [8].

Accordingly, this dissertation examines the applicability of the standard ADMD values in the Free State and outlines the conditions under which they may need context-specific adjustment. The detailed aims and objectives are presented in Section 1.3.

1.1 Background of the Study

South Africa's demand landscape is shaped by historical inequality, ongoing socio-economic transitions, and the expansion of electrification to communities previously lacking grid access. Programmes such as the Integrated National Electrification Programme (INEP) have connected millions of households [4], [7], [9]. Yet, outcomes vary by locality: urban centres often benefit from robust legacy infrastructure, while rural, peri-urban, and informal settlements may face supply constraints and uneven development [7].

As access expands, household consumption evolves from basic end-uses (lighting, cooking, heating) toward more diverse, appliance-rich profiles as income and access improve. These shifts are heterogeneous: demand varies by income, housing type, household size, appliance penetration, and infrastructure quality [5], [10], [11]. Time-of-use (ToU) patterns also differ (e.g., sharper peaks in lower-income contexts; broader sustained demand in higher-income areas), such heterogeneity challenges uniform planning assumptions .

In practice, planners often rely on statistical models to summarise residential demand. The Beta PDF, used in SANS 507-1:2019 to parameterise standard ADMD values, was derived from historical datasets during earlier electrification phases [12], [13]. As conditions evolve, however, parameters calibrated to past patterns may no longer capture present-day demand in all contexts.

This study is situated within that reality. It focuses on the Free State, a province that combines urban areas, developing townships, peri-urban settlements, and rural communities, to examine whether standard ADMD values remain representative across contrasting local conditions. The specific aims and research questions are set out in Section 1.3, with methodological details in — Methodology.

1.2 Problem Statement

Forecasting residential electricity demand in South Africa is becoming increasingly complex due to rapid socio-economic transitions, uneven electrification progress, and shifting consumption behaviours. National planning tools such as SANS 507-1:2019 rely on statistical models, specifically the Beta probability density function (PDF), to derive After Diversity Maximum Demand (ADMD) values used in low-voltage network design [14], [15], [16]. Although the Beta PDF is valued for flexibility and theoretical robustness, its parameters were calibrated on legacy datasets that may no longer reflect the diversity and variability of present-day demand in the Free State [7].

The Free State Province illustrates this challenge. Spanning rural villages to formal urban suburbs, it exhibits complex and heterogeneous demand patterns. These realities call into question the assumption that a single set of ADMD values can adequately represent such diversity. If the Beta PDF parameters, as currently applied in SANS 507-1:2019, do not capture these variations, the risk is twofold: under-designed infrastructure may lead to voltage instability or load shedding, while over-designed systems result in unnecessary capital expenditure and inefficient asset use.

Despite widespread use of the Beta PDF, there has been limited empirical assessment of its parameter validity in contemporary, real-world Free State settings. This gap has implications not only for engineering design but also for equitable service delivery and long-term infrastructure investment.

This study, therefore, critically evaluates the validity of the Beta PDF parameters used in SANS 507-1:2019 by comparing the standard ADMD values with observed demand across socio-economically diverse case studies in the Free State, South Africa. The findings will indicate whether context-specific adjustment or recalibration is necessary to maintain the relevance and effectiveness of current planning standards.

1.3 Research Aim and Objectives

Aim

Evaluate whether the SA standard ADMD (SANS 507-1:2019), parameterised via a Beta probability density function, remains representative of observed residential demand in the Free State and identify where context-specific adjustment may be warranted.

To support this aim, the specific objectives of the study are to:

- Compare standard ADMD values with observed ADMD (operationalised as the 99.5th-percentile load) across socio-economically diverse Free State case studies.
- Quantify deviations between standard and observed values using percentage error and appropriate summary statistics.
- Assess the applicability of the Beta-PDF parameterisation (as used by SANS 507-1:2019) under present-day demand characteristics without re-estimating parameters.
- Identify contexts (e.g., supply class, breaker-size strata, settlement type) in which the standard meets a practical planning tolerance (±12%) and contexts in which it does not.
- Inform planning practice by indicating where context-specific adjustments should be considered in future work.

1.4 Research Questions

Primary Research Questions

Does the SA standard ADMD (SANS 507-1:2019), parameterised via a Beta probability density function, remain representative of observed residential demand in the Free State?

Secondary questions

- How do standard ADMD values compare with observed demand across socio-economically diverse residential contexts in the Free State?
- What factors are associated with discrepancies between predicted and observed ADMD (e.g., socio-economic profile, housing formality, breaker size, connection age, historical load characteristics)?
- Does the evidence indicate that context-specific adjustment or recalibration is warranted in particular settings?

1.5 Contribution of the Study

Scientific

- Provides an auditable, data-driven procedure to derive observed ADMD (operationalised as the 99.5th-percentile load) and to compare it with the SA standard ADMD (SANS 507-1:2019) across diverse Free State contexts; evaluates the present-day applicability of the Beta-PDF parameterisation without re-estimating parameters.

Practical (planning)

- Identifies where standard values appear representative versus non-representative, clarifying design risk (under-/over-sizing) and supporting evidence-informed planning decisions.

Policy/standards

- Highlights conditions under which context-specific adjustment of standard ADMD values may be warranted, informing targeted refinement of parameters in future standards work.

1.6 Study Scope and Delimitations

Geographic scope

- Free State Province, South Africa. Case studies span a mix of urban areas, developing townships, peri-urban settlements, and rural communities. Results are interpreted for the Free State and are not claimed to be nationally representative.

System/asset scope

- Low-voltage residential demand relevant to distribution network planning. Non-residential customers were excluded unless explicitly classified as residential in the utility database.

Temporal scope

- Historical load records available for the study period (as detailed in Chapter 3). Findings reflect conditions during this window; prospective forecasting beyond the dataset horizon is out of scope.

Data sources and references

- Utility customer/billing and transformer-zone load records (aggregated for analysis).
- Geographic context from GIS layers used to relate zones and settlements (see Chapter 3).
- SANS 507-1:2019 as the reference for SA standard ADMD values and Beta-PDF parameterisation.

Operational definitions

- Observed ADMD is operationalised as the 99.5th-percentile load for the relevant analysis unit (e.g., zone/class/stratum).
- A ±12% planning-tolerance is used to interpret alignment between standard and observed values.
- Standard ADMD values and Beta-PDF parameters are taken as published in SANS 507-1:2019; parameters are not re-estimated in this study.

Analysis granularity

- Comparisons performed across case studies and strata such as supply class, breaker-size (NMD, A), connection type, and other context variables where available.
- Temporal aggregations (e.g., annual/monthly and 24-hour profiles by month) were applied as specified in Chapter 3.

Inclusion/exclusion & data quality

- Active residential connections only. Records with missing/invalid key fields were excluded where required by the analysis.
- Implausibly low loads (< 1 kVA) are rejected during cleaning.
- Handling of missing intervals/outliers and any interpolation choices are documented in Chapter 3.
- Data are analysed in aggregated form without personally identifiable information.

Delimitations

- The study evaluates the present-day applicability of the Beta-PDF parameterisation used by SANS 507-1:2019; it does not re-estimate Beta parameters or propose new standard values.
- The study does not quantify class- or region-specific recalibration magnitudes; recommendations for context-specific adjustment are qualitative and left for future work.
- Detailed techno-economic analysis, voltage-drop/protection simulations, and operational reliability studies are out of scope.
- Findings are scoped to the Free State case studies and should not be generalised to other provinces without additional evidence.

1.7 Methodology Overview

This study employs a quantitative research approach to evaluate the accuracy and reliability of the Beta Probability Density Function (PDF) in predicting After Diversity Maximum Demand (ADMD) values, as outlined in SANS 507-1:2019 [15], [16], [17]. The analysis focuses on residential electricity consumption patterns across multiple case studies in the Free State Province, selected to reflect a range of socio-economic contexts and electrification maturity levels.

Historical load data from these case studies form the empirical foundation for analysis. Using tools such as Microsoft Power BI and relevant statistical techniques, the study compares Beta PDF-derived ADMD values to measured peak demand values [18], [19], [20]. Key evaluation metrics include the 99.5th percentile load, deviation between predicted and observed values, and the influence of variables such as connection age and historical load profiles.

This methodology is intended to assess whether the Beta PDF remains a valid and effective tool for infrastructure planning in today's dynamic socio-economic landscape, or whether contextual adjustments are required to enhance its predictive performance in South Africa's residential environments.

1.8 Structure of the Dissertation

This dissertation is structured into five chapters.

Chapter 1 introduces the background, problem statement, objectives, research questions, and scope of the study.

Chapter 2 presents a review of relevant literature, including theoretical frameworks, the Beta PDF model, and existing load forecasting standards.

Chapter 3 outlines the research methodology, including data collection methods, case study selection, and analytical tools.

Chapter 4 presents the results of the case study analyses, including comparisons between measured and predicted ADMD values.

Chapter 5 discusses the findings, highlights implications for infrastructure planning and policy, and concludes with recommendations for future research.

1.9 Definitions and Key Terms

This section provides a preliminary list of key definitions and terms used throughout the dissertation. These definitions are essential for ensuring a clear and consistent understanding of the concepts discussed in the study.

After Diversity Maximum Demand (ADMD): The maximum electrical load expected at a particular point in time, averaged over a group of consumers, accounting for the fact that not all consumers will use their maximum load simultaneously. ADMD is a critical metric for planning electrical infrastructure.

Beta Probability Density Function (Beta PDF): A flexible statistical model used to describe the distribution of random variables that are bounded between two specified values. In the context of this study, the Beta PDF is used to predict electricity load profiles.

Living Standards Measure (LSM): A classification system used in South Africa to segment the population based on their living standards. LSM is often used in market research and social studies to understand consumption patterns, including electricity usage.

Load Profile: A representation of the variation in electrical demand over time for a specific consumer or group of consumers. Load profiles are used to understand patterns of electricity consumption.

99.5th Percentile Load: A statistical measure indicating the load level that is exceeded only 0.5% of the time. It is used in this study to assess the peak demand that must be accounted for in network planning.

Standard Deviation: A measure of the dispersion or spread of a set of values. In the context of this study, it indicates the variability in electricity consumption within a specific group of consumers.

SANS 507-1:2019: The South African National Standard that provides guidelines for the estimation of ADMD values and other parameters for the design of electrical networks.

Socio-Economic Context: The social and economic environment in which individuals or groups live. This includes factors such as income, education, employment, and access to services, which influence consumption patterns, including electricity use.

Network Planning: The process of designing and developing electrical infrastructure to meet the current and future demand for electricity. It involves estimating load profiles, determining the capacity of electrical networks, and planning for expansions or upgrades.

Load Forecasting: The practice of predicting future electricity demand based on historical data, consumption patterns, and other relevant factors. Accurate load forecasting is essential for ensuring that electrical networks are appropriately sized and that resources are efficiently allocated.

Geographic Information System (GIS): A system designed to capture, store, manipulate, analyse, manage, and present spatial or geographic data. GIS is often used in network planning to map out the distribution of electrical networks and identify areas of demand.

Electrification: The process of extending access to electricity to households, businesses, and other entities that previously lacked it. In South Africa, electrification is a key component of development policies aimed at improving living standards and economic opportunities.

Temporal Scope: The period over which the study is conducted, or the data is analysed. Temporal scope is essential for understanding trends and patterns over time in load forecasting.

Deviation: The difference between the predicted value and the actual value. In this study, deviation is used to measure the accuracy of ADMD predictions.

Data Analysis: The process of systematically applying statistical and logical techniques to describe and evaluate data. Data analysis is a key component of this study's methodology.

Comparative Analysis: A method used to compare different sets of data or models to identify similarities, differences, and trends. In this study, comparative analysis is used to evaluate the performance of the Beta PDF against traditional ADMD estimation methods.

Infrastructure Development: The construction and improvement of foundational services and facilities, such as electrical networks, that are necessary for economic development and societal well-being.

Utility Companies: Organisations that provide essential services such as electricity, water, and natural gas to consumers. Utility companies are key stakeholders in the planning and operation of electrical networks.

Policymaking: The process by which governments and other authoritative bodies create rules, regulations, and guidelines to manage and govern public services, including electricity supply.

Chapter 2 — Literature Review

Chapter 1 established the importance of accurate electricity demand forecasting in South Africa, with specific focus on the Free State Province, where diverse socio-economic conditions significantly influence consumption patterns [21], [22], [23]. It outlined the research problem of evaluating the accuracy and reliability of the After Diversity Maximum Demand (ADMD) values proposed by SANS 507-1:2019 [24], [25], [26]. It introduced the Beta Probability Density Function (PDF) as a potentially effective tool for refining these predictions in a region characterised by varied load profiles and unique distribution challenges [27], [28], [29], [30].

Building upon this foundation, the purpose of Chapter 2 is to systematically review existing literature relevant to electricity demand forecasting, load profiling, and distribution network planning, with particular emphasis on the Free State context [13], [31], [32], [33], [34], [35]. This chapter examines key theories, empirical studies, and standards that address the estimation of ADMD values, especially in regions characterised by socio-economic diversity and varying geographic conditions [36], [37], [38]. By critically analysing the strengths and limitations of current approaches, this review highlights shortcomings in the existing knowledge base. It underscores the need for locally tailored methods, such as the Beta PDF, to enhance forecasting accuracy and reliability [39], [40], [41]. The reader will gain a deeper understanding of the theoretical underpinnings and practical considerations involved in applying these models to the Free State's unique electricity distribution landscape.

2.1 Introduction to the literature review

This chapter provides a comprehensive overview of the literature that underpins the research objectives of this study, with a specific focus on the Free State Province in South Africa. The literature review is structured to address key themes relevant to the design and planning of residential electricity distribution networks, focusing on the following areas:

1. **Socio-Economic Electrification Programmes** – The impact of socio-economic electrification programmes on distribution network design, particularly concerning After Diversity Maximum Demand (ADMD) values and transformer loading in residential areas [42]. This section explores existing studies that highlight the influence of electrification policies and demographic factors on load diversity and demand patterns [43].
2. **Statistical Modelling and Probability Density Functions (PDFs)** – The application of statistical models, including the Beta Probability Density Function (PDF), in predicting load profiles and transformer loading [3], [4]. This section reviews literature assessing the effectiveness of these models in forecasting electricity demand within diverse socio-economic contexts, with an emphasis on their application in the Free State Province [5].
3. **Load Profiles and Residential Distribution Networks** – A detailed examination of existing literature on load profiles for residential distribution networks, focusing on the importance of accurate load estimation and forecasting models [5]. This section also considers how load profiles inform capacity planning, demand response programmes, and energy efficiency initiatives [6].

By systematically reviewing these areas, this chapter aims to identify shortcomings in the current knowledge base, justify the selected research methodology, and establish a theoretical foundation for the analysis presented in subsequent chapters.

2.2 Theoretical Framework

This section outlines the key concepts, models, and theories relevant to load profiling and electricity demand forecasting within South Africa's evolving electrification landscape, with a focus on the Free State Province. It first summarises the socio-economic and historical context shaping electricity consumption patterns in South Africa, including the influence of the Integrated National Electrification Programme (INEP) [42], [43], [44]. It then reviews theoretical principles underlying load profiling and the calculation of After Diversity Maximum Demand (ADMD), which remain critical to distribution network design and planning [45], [46], [47]. Finally, it considers statistical models for bounded residential demand, emphasising the Beta probability density function (PDF) as a commonly used tool and assessing its applicability in the Free State context [33], [48]. This theoretical framing sets up the empirical analysis that follows.

2.2.1 History and Context of Electrification in South Africa

Electrification in South Africa has a complex and transformative history tied to socio-economic development and political change. Before 1994, apartheid-era policies produced significant disparities in electricity access; a substantial share of black South Africans, particularly in rural and peri-urban areas, lacked reliable electricity services [42], [44]. At that time, the national electrification rate was about 36% of households.

The transition to democracy in 1994 marked a turning point [29], [43], [44], [45]. Recognising electricity's role in socio-economic development, quality of life, and equity, the government launched ambitious programmes to expand access, prioritising rural and underserved communities to redress historical imbalances [45].

2.2.1.1 The Integrated National Electrification Programme (INEP)

Launched in 1994, INEP is a cornerstone of South Africa's drive to expand electricity access nationwide. It aims to provide affordable, safe, and sustainable energy solutions, with implementation by Eskom, municipalities, and non-grid service providers [9] [49].

By March 2016, the programme had connected over 6.7 million households to the grid, increasing the national electrification rate from 36% (1994) to 88% (2016) [9]. These gains have supported improvements in education, healthcare, and economic opportunity in previously underserved areas [12], [45].

Alongside grid roll-outs, INEP's Non-Grid Electrification Programme exceeded targets with 25,076+ connections; since inception, over 123,379 non-grid systems, primarily solar powered, have been installed across provinces, including the Eastern Cape, KwaZulu-Natal, Northern Cape, and Limpopo [9]. Such systems are also being considered for urban informal settlements to extend basic services [50], [51]. In parallel, microgrids, localised grids capable of islanded operation, are increasingly deployed in rural and urban settings to enhance reliability and resilience [6], [31], [51], [52].

INEP's commitment to universal access by 2025/26 led to the Electrification Master Plan (EMP) [53], which seeks stronger coordination among implementing entities, strategic integration of technologies (including microgrids), and aligned grid/non-grid roll-outs in unserved areas. The EMP provides a roadmap to connect remaining households, bridge the energy divide, and support sustainable development [9], [54], [55].

2.2.1.2 Economic Benefits for Residential Communities

Electrification programmes stimulate local economies through job creation and business activity linked to the construction, operation, and maintenance of electricity infrastructure, benefits that are particularly significant in underdeveloped areas [31], [44], [53]. Reliable supply enables the formation and growth of small enterprises (including home-based businesses), longer operating hours, and productivity gains, with resulting increases in household income and living standards [49]. More dependable power also attracts small-scale investment, e.g., grocery stores, repair workshops, and internet cafés - reinforcing local economic growth and poverty reduction [56]. These effects are documented alongside broader development initiatives [9], [53].

2.2.1.3 Social Benefits for Residential Communities

Social benefits are substantial. Electrified homes and schools provide improved learning environments through adequate lighting, enabling study after dark and access to information and communication technologies (ICT) that support teaching and learning [9], [53], [56].

Healthcare services benefit from powered clinical equipment, secure cold chains for vaccines and medicines, and extended operating hours, contributing to improved health outcomes [42], [56]. In households, access to appliances improves comfort and living conditions.

Electrification also enhances safety and security: well-lit streets and homes reduce accidents and crime; electric lighting replaces hazardous alternatives such as kerosene lamps, mitigating fire and respiratory risks [3], [13]. Greater connectivity through modern communication devices improves social inclusion and access to emergency services [13].

In combination, electrification programmes support economic participation, strengthen education and healthcare, and improve safety and quality of life. They provide a platform for sustainable development and contribute to long-term socio-economic resilience in disadvantaged communities [12]. [53].

2.2.2 Socio-Economic Factors and Their Impact on Electricity Consumption

In South Africa, the development of After Diversity Maximum Demand (ADMD) parameters has increasingly been shaped by regional socio-economic characteristics that influence electricity consumption patterns [38], [57], [58], [59], [60]. This shift moves from generic assumptions toward more refined, data-driven models that incorporate local context [16], [61].

ADMD values can vary significantly across regions due to several key factors:

Socio-Economic Factors: Income levels, household size, and lifestyle habits influence consumption. Regions with higher incomes and larger households typically exhibit higher ADMD values due to greater appliance ownership and more frequent peak-demand periods [42], [45], [46].

Climate: Temperature extremes affect usage through heating and cooling needs. Regions with harsh winters or hot summers may show higher seasonal ADMD due to increased use of heaters, air conditioners, and other temperature-regulating appliances [48], [62], [63].

Infrastructure Development: The age, efficiency, and type of infrastructure affect ADMD. Urban areas with newer, energy-efficient buildings and modern networks may display different profiles from rural areas, where older infrastructure can contribute to higher demand [46], [56], [64].

Cultural and Behavioural Norms: Peak-usage times and appliance-use patterns vary across regions and demographic groups. Cultural practices (e.g., traditional cooking methods or social activities) can also influence ADMD estimates [28], [39], [44].

2.2.3 Introduction to Load Profile Modelling

Load profile modelling analyses and forecasts electricity consumption patterns over time. It plays a central role in the design and operation of distribution networks by helping utilities predict peak demand, characterise variability, and allocate resources efficiently [65], [66]. These insights support infrastructure planning decisions, improve operational stability, and enhance overall supply reliability [42], [43], [45], [67].

A key outcome of load profile modelling is the estimation of After Diversity Maximum Demand (ADMD). ADMD reflects the expected diversified peak demand per connection for a group of consumers, adjusted by a diversity factor to account for non-simultaneous usage patterns [68], [69]. It is a critical parameter for sizing network components such as transformers and feeders, helping to avoid both over-sizing and under-sizing [45], [67].

Historically, utilities derived load profiles from limited data and simplifying assumptions. With the advent of smart meters, advanced data analytics, and improved monitoring, load modelling has become increasingly granular and context-specific [17], [46], [70]. These advances enable planners to tailor infrastructure more closely to real-world consumption behaviours [64].

Effective load modelling also supports broader objectives such as demand-side management, tariff structuring, and the integration of distributed energy resources [17], [64], [68], [71]. By capturing variations across household types, socio-economic conditions, seasons, and time-of-use (TOU) periods, it allows utilities and policymakers to design more adaptive and resilient energy systems [6], [11].

The following section reviews the statistical techniques used in load profiling, with particular focus on the Beta probability density function (PDF) that underpins ADMD estimation in SANS 507-1:2019 [7].

Statistical distributions used in residential load profiling, including the Beta PDF and alternatives, are reviewed in Section 2.2.4. Percentile-based demand thresholds referenced later (e.g., the 99.5th percentile) are introduced in Section 2.2.5 and defined formally in — Methodology.

2.2.4 The Beta Probability Density Function and Alternatives

Accurate modelling of residential electricity demand requires statistical techniques capable of capturing variability, skewness, and diversity in consumer load patterns [14], [15], [72]. Among these, the Beta probability density function (PDF) has gained prominence for representing bounded, non-normal distributions common in residential consumption data. In South Africa, the Beta PDF underpins After Diversity Maximum Demand (ADMD) estimation in SANS 507-1:2019, which guides network component sizing and infrastructure design [12], [73], [74].

The Beta PDF is defined on the interval [0, 1] and shaped by two parameters, α (alpha) and β (beta), which determine the skewness and concentration of the distribution [15]. This flexibility makes it well-suited to modelling normalised load data, where values represent proportions of maximum demand [13], [75]. The distribution accommodates asymmetric consumption behaviours observed in residential environments, especially in communities with diverse appliance ownership and usage habits [76], [77].

In general applications, observed load values are first normalised, and the shape parameters are estimated using techniques such as the method of moments or maximum likelihood estimation (MLE) [15], [54], [78]. The fitted distribution then supports identification of high-percentile demand thresholds (e.g., 95th or 99.5th percentiles) that inform conservative yet realistic design. In this study, however, Beta-PDF parameters are taken as published in SANS 507-1:2019 and are not re-estimated; the evaluation focuses on the representativeness of the standard values [7], [40].

Several studies report that the Beta PDF effectively models residential load variability, particularly in South African contexts where socio-economic heterogeneity and electrification maturity vary widely [36], [45], [46]. Its performance, however, depends on the quality and representativeness of the underlying data and on periodic validation as consumption patterns shift over time [79], [80], [81].

Alternative Load Modelling Techniques

- **Monte Carlo simulations:** Captures stochastic variability by generating synthetic demand scenarios based on probabilistic rules [45], [67].
- **Time-of-Use (ToU) analysis:** Classifies consumption by temporal pattern to support demand-side management through tariff structures [47].
- **Gaussian and log-normal models:** Useful in some contexts but less flexible for bounded or markedly skewed demand data [44].
- **Machine learning methods:** Emerging tools such as artificial neural networks (ANNs), support vector machines (SVMs), and decision trees use multi-variable inputs for load prediction [50], [51].
- **Hybrid models:** Combine deterministic and probabilistic elements to address uncertainty in load prediction, including the influence of renewable generation or informal supply connections [49], [70] [5].

Each technique has strengths and limitations depending on data quality, load characteristics, and application context. The Beta PDF remains a strong candidate due to its simplicity and adaptability [15], [82]. Still, it must be continuously validated against real-world load data, especially in socio-economically dynamic regions such as the Free State [48], [83], [84].

The following section outlines the implementation and evaluation approach used in this study for assessing the Beta PDF within the stated framework. Percentile-based thresholds used in this study (e.g., 99.5th percentile) are outlined in Section 2.2.5; computational details appear in — Methodology.

2.2.5 The Beta Probability Density Function in Load Forecasting

The Beta Probability Density Function (PDF) is a valuable statistical tool in electricity load forecasting, offering flexibility in modelling demand variability within a fixed range [15], [16]. Unlike traditional probability distributions such as the normal or log-normal, the Beta PDF is bounded on [0, 1], making it well-suited to normalised electricity-demand data where consumption is inherently limited by connection or infrastructure capacity [7], [85]. This characteristic, together with the ability to assume a variety of shapes via the shape parameters α (alpha) and β (beta), makes the Beta PDF effective in diverse and dynamic consumption contexts [85], [86].

One of the key advantages of the Beta PDF is its adaptability [38], [41], [47]. The parameters α and β control skewness and concentration, allowing both symmetrical and asymmetrical consumption profiles to be represented [15], [16]. This is particularly useful in residential environments where usage varies with socio-economic factors, appliance ownership, and behavioural patterns. In general applications, identifying upper-tail quantiles (e.g., the 95th or 99.5th percentiles) from the fitted distribution supports conservative yet realistic decisions for infrastructure sizing and reliability planning [72].

Methodological note. In standard practice, historical load data are first normalised to [0, 1], then α and β are estimated (e.g., by the method of moments or maximum likelihood estimation (MLE)). The fitted distribution is validated and, where appropriate, recalibrated as patterns evolve. In this study, however, the Beta-PDF parameters are taken as published in SANS 507-1:2019 and are not re-estimated; we evaluate the representativeness of the standard values by comparing them with observed ADMD operationalised as the 99.5th-percentile load [60], [72].

Empirical applications in South Africa have demonstrated the Beta PDF's effectiveness. For example, Bekker and Gaunt (2006) applied it to estimate After Diversity Maximum Demand (ADMD) in rural electrification projects where incomplete data hindered traditional approaches [36]. The Beta PDF's capacity to represent bounded, skewed distributions supported more appropriate transformer and feeder sizing in underdeveloped areas. Related work also explores hybrid approaches that combine the Beta PDF with behavioural or machine-learning models to improve forecasting accuracy when demographic and temporal variability are material [48].

The Beta PDF also underpins the ADMD estimation method in SANS 507-1:2019, South Africa's standard for low-voltage network design [63]. The standard parameterises residential demand curves using the Beta distribution, providing utilities with a consistent basis for distribution planning across a range of settlement types and economic conditions [85], [87].

Given its mathematical flexibility, empirical validation, and institutional adoption, the Beta PDF remains a robust and practical model for electricity-demand analysis . In this study, the published Beta-PDF–based standard values serve as the reference; we assess their representativeness against observed Free State loads to evaluate predictive relevance in contemporary electrification planning [33], [38], [57].

2.3 Review of Empirical Studies
This section provides a comprehensive review of empirical studies that explore various methodologies and models for electricity load forecasting and distribution network planning. The focus is on examining how different approaches, including probabilistic models, machine learning techniques, and hybrid frameworks, have been applied in real-world scenarios to address the challenges of demand variability, uncertainty, and grid reliability. By analysing these studies, this review aims to identify key insights, gaps in the existing knowledge base, and best practices that can inform future research and enhance the accuracy and efficiency of load forecasting and network design, particularly in the context of diverse socio-economic and geographic environments like those found in South Africa.

2.3.1 Electrification and Load Profiling in the South African Context
This section examines the unique challenges and considerations of electrification and load profiling within the South African context, where diverse socio-economic conditions and historical disparities shape electricity consumption patterns. The review will explore how different electrification programmes, such as the Integrated National Electrification Programme (INEP), have impacted electricity access and demand across various regions [9]. Additionally, the section will analyse the application of load profiling techniques, including probabilistic models like the Beta PDF, to capture the variability in electricity demand influenced by factors such as income levels, household size, and regional climate differences [36], [45]. By examining these empirical studies, the review aims to highlight best practices and challenges in demand forecasting and distribution network planning, providing insights into optimising electricity supply in South Africa's diverse landscape.

2.3.1.1 Case Studies in the Free State Province and Similar Regions
In South Africa, the SANS 507-1:2019 guidelines play a crucial role in establishing standards for planning and designing electricity distribution networks in residential areas [63]. These guidelines include parameters such as the After Diversity Maximum Demand (ADMD) values, which are outlined in Table 2 of the standard and classify domestic consumers based on typical design load characteristics [63]. The application of SANS 507-1:2019 is particularly relevant in township electrification initiatives, where it helps standardise and optimise the deployment of electricity infrastructure to address the unique consumption patterns and needs of diverse consumer groups [28], [42]

Several case studies, as part of the NRS Load Research Project, in the Free State Province and similar regions have demonstrated the effectiveness of these guidelines in improving electricity distribution efficiency and reliability [7]. For example, empirical studies have shown that implementing SANS 507-1:2019 standards in township areas helps to appropriately size transformers and feeders, reducing the risk of overloading and minimising technical losses [36], [45]. The standardisation provided by SANS 507-1:2019 also facilitates better planning and resource allocation by allowing for the application of probabilistic models, such as the Beta PDF, to predict peak demand and optimise load profiles across varying socio-economic contexts [47], [49].

These case studies underscore the importance of applying reliable standardised guidelines like SANS 507-1:2019 in rural and peri-urban electrification projects [7], [88]. By using these guidelines to inform network planning, utilities can enhance the efficiency and sustainability of electricity supply, addressing the unique needs of diverse communities while optimising infrastructure investments [49], [51].

2.3.1.2 Current Standards and Guidelines
The SANS 507-1:2019 standard serves as a fundamental guideline for the planning and design of electricity distribution networks in South Africa, particularly in residential areas [35], [40], [88], [89]. It establishes criteria for classifying domestic consumers based on their typical electricity consumption patterns [86]. It provides methods for calculating After Diversity Maximum Demand (ADMD), which is crucial for the effective sizing and design of electrical infrastructure. The standard is closely aligned with the Guidelines for Human Settlement

Planning and Design (Red Book), which aims to promote sustainable and inclusive development by ensuring equitable access to essential services like electricity [9], [63].

1. **Scope and Applicability of SANS 507-1:**
The SANS 507-1:2019 standard applies to a wide range of residential settlement types, from rural and informal areas to urban estates and high-rise buildings. By providing a framework for classifying consumers based on their energy usage, it enables planners and utilities to develop tailored solutions that meet the specific needs of different community types. For instance, the standard defines multiple consumer classes, including rural settlements, informal settlements, township areas, and various kinds of urban residences, each with unique load profiles and ADMD values [7], [90].

2. **Development and Classification of After Diversity Maximum Demand (ADMD):**
The ADMD values outlined in SANS 507-1:2019 provide a standardised approach to determining the peak electrical load that can be expected from a group of consumers under normal conditions. These values are essential for infrastructure planning, allowing utilities to size transformers, feeders, and other network components efficiently without overbuilding or underbuilding the system. ADMD calculations consider the diversity of consumer behaviour, ensuring that not all consumers are expected to demand maximum power simultaneously. This results in more accurate load forecasts and optimised infrastructure investment [28], [45].

3. **Consumer Classification and Load Parameters:**
Table 1 presents the classification of domestic consumers as per SANS 507-1:2019, which is essential for understanding the varying load requirements across different consumer groups [63]. The table illustrates the diverse range of ADMD values and monthly energy consumption (in kWh) for each class, reflecting the varying demand patterns that must be considered in network design and planning:

Table 1: SANS 507-1:2019 (Table 2) Classification of domestic consumers

Class ID	Consumer Class	Units / Month (kWh) 7	ADMD 7	a 7	b 7	c 7	u 7	o 7	Units / Month (kWh) 15	ADMD 15	a 15	b 15	c 15	u 15	o 15
1	Rural settlement, Non-urban, scattered	91	0.43	0.18	1.73	20	1.88	3.42	107	0.49	0.19	1.58	20	2.15	3.72
2	Rural villages	91	0.43	0.18	1.73	20	1.88	3.42	107	0.49	0.19	1.58	20	2.15	3.72
3	Informal settlement	217	0.91	0.25	1.01	20	3.94	5.29	266	1.09	0.52	6.09	60	4.74	5.87
4	Township area	391	1.56	0.69	5.44	60	6.77	7.11	472	1.86	0.79	5.09	60	8.1	7.82
5	Urban residential I	575	2.25	0.91	4.69	60	9.77	8.62	657	2.55	1	4.39	60	11.1	9.21
6	Urban residential II	788	3.04	1.12	3.96	60	13.23	10.09	846	3.26	1.17	3.77	60	14.19	10.46
7	Urban townhouse complex or duplex	704	2.73	1.04	4.23	60	11.87	9.54	762	2.95	1.1	4.04	60	12.81	9.92
8	Urban Townhouse II	1 374.00	5.24	1.43	2.34	60	22.77	13.33	1 482.00	5.64	1.45	2.92	60	24.54	13.85
9	Urban Estate								2 550.00	9.64	2.01	1.83	80	41.93	18.16
10	High-rise (small)	363	1.45	0.66	5.57	60	6.31	6.85	441	1.75	0.76	5.22	60	7.59	7.56

11	High rise (medium)	474	1.87	0.8	5.08	60	8.13	7.83	561	2.19	0.9	4.74	60	9.54	8.52
12	Hostel	278	1.13	0.54	6.02	60	4.93	5.99	342	1.37	0.63	5.67	60	5.97	6.65

4. **Implications for Network Design and Planning:**
The diverse ADMD values in the SANS 507-1:2019 standard demonstrate the variation in electricity demand among different residential consumer classes, from rural settlements to urban high-rise buildings. This diversity highlights the need for a tailored approach to network design and capacity planning, ensuring that infrastructure investments are optimised to meet specific demand patterns. Probabilistic models, such as those using the Beta PDF, are instrumental in capturing this variability and uncertainty, supporting more accurate demand forecasts and efficient resource allocation [28], [42].

By providing a standardised framework for calculating ADMD values, the SANS 507-1:2019 standard plays a pivotal role in promoting consistency and efficiency in the design of electricity distribution networks. It helps utilities and planners ensure that networks are neither overbuilt nor underbuilt, reducing costs while maintaining reliability and safety standards [45], [90].

2.3.1.3 Scope and Applicability of SANS 507-1

SANS 507-1:2019 provides comprehensive and regularly updated guidelines for the provision of electricity distribution networks in residential areas across South Africa. Managed and administered by the NRS Project Management Agency (PMA) on behalf of the Electricity Supply Industry, the standard is periodically revised to incorporate the latest findings from load research and reflect evolving consumption patterns and technological advancements [63].

The classification of domestic consumers, as outlined in Table 2 of SANS 507-1, is based on parameters such as After Diversity Maximum Demand (ADMD), household size, income levels, appliance usage, and regional climatic conditions. This classification is derived from rigorous analysis of monitored load data collected from diverse case studies conducted across South Africa between 1993 and 2012, which included at least 60 consumers per study to capture a wide range of consumption behaviours [28], [90].

ADMD, defined by SANS 507-1, represents the highest annual simultaneous load per site over a specified 5-minute interval, excluding short-term overload conditions. These parameters are normalised for the interior climate of South Africa, characterised by cold winters and low rainfall, with variations also considered for regions with differing climatic conditions, such as the Cape Peninsula's colder and wetter climate or Durban's warmer coastal conditions [42], [45].

2.3.1.4 Concept of Load Maturity

Load maturity refers to the evolution of electricity consumption patterns in an area over time. Within the framework of SANS 507-1, it acknowledges that ADMD values may change as infrastructure ages and consumer behaviours adapt [63]. For newly electrified areas, initial ADMD values are typically lower due to limited appliance ownership and usage. However, as these areas mature, ADMD values are expected to increase due to the growth in consumer demand and gradual changes in lifestyle and consumption habits [28], [42].

This dynamic perspective is essential for long-term planning and infrastructure development, allowing utilities to forecast future demand more accurately and optimise network design accordingly [38], [63]. Figure 1, illustrates the typical S-curve growth pattern for a system, showing the initial phase of electrification, the subsequent period of rapid growth as more consumers are connected, and finally, the maturity phase where growth stabilises [13], [63], [91].

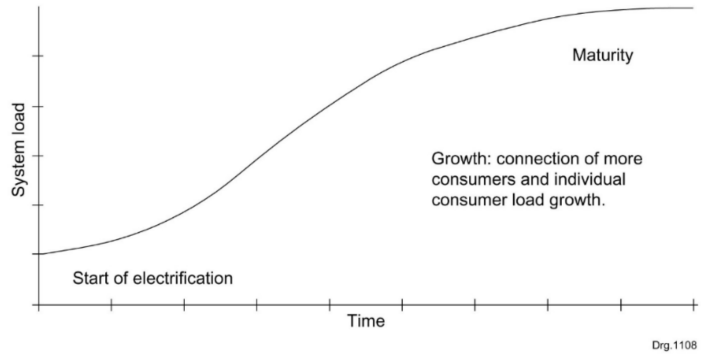


Figure 1: S-Curve Showing System Load Growth from Electrification to Maturity

Figure 1 *Reproduced/Adapted from SANS 507-1:2019, Drawing 1108. Axes are qualitative as in the source: the x-axis shows conceptual time progression, and the y-axis indicates relative demand (no numeric scaling). The curve is illustrative of typical electrification adoption [63].*

2.3.1.5 Potential Impacts on the Accuracy of SANS 507-1:2019 and Future Revisions

The effectiveness of SANS 507-1:2019, particularly its After Diversity Maximum Demand (ADMD) guidelines, depends on its ability to reflect changing consumption patterns and planning requirements [7]. While the standard has served as a foundational tool for electricity distribution design, several dynamic factors challenge its long-term accuracy and underscore the need for ongoing revision [34].

Technological advancements, including smart metering, IoT appliances, and home energy management systems, are reshaping the way electricity is consumed and monitored [64], [92], [93]. These tools generate high-resolution data that can better capture peak demand variations, enabling more granular and real-time ADMD estimations than those based on legacy assumptions [64].

Socio-economic and demographic shifts also impact consumption patterns [73], [94], [95]. Household income levels, urbanisation rates, and appliance ownership profiles influence peak demand differently across regions [6], [31], [53]. As these socio-economic conditions evolve, so too must the input assumptions underpinning ADMD values to ensure infrastructure sizing remains appropriate [88], [96].

Environmental factors such as climate change are further influencing load profiles, primarily through changing heating and cooling loads [48], [54]. As temperature extremes become more frequent, seasonal load forecasting models must adapt, potentially requiring regional adjustments to ADMD [62], [86], [97].

Policy developments, such as subsidies for rooftop solar, electrification of transport, or energy efficiency incentives, add another layer of variability [78]. These policies can flatten or shift load curves, calling for ADMD models that are more responsive to regulatory changes and integrated energy planning [98], [99]. Lastly, improved data availability opens opportunities for more adaptive modelling [38], [74], [75], [100]. However, this also introduces the need for standardised methodologies, data privacy protocols, and consistent calibration mechanisms across utilities [101].

In light of these evolving conditions, periodic revision of SANS 507-1:2019 is essential [6], [7], [12], [102]. The Beta Probability Density Function, while still applicable, must be recalibrated regularly using updated load data to retain its predictive value [12], [75], [102]. Incorporating regional socio-economic indicators, consumption trends, and real-time analytics can enhance the robustness of the standard, ensuring its continued relevance in a dynamic planning environment [12], [13], [34], [75], [102].

2.3.2 Application of the Beta PDF in Load Forecasting

The Beta Probability Density Function (PDF) is utilised in load forecasting to model the variability and uncertainty in electricity demand, providing a probabilistic approach to predict peak loads and manage diverse consumer behaviours. Its flexibility in representing different load profiles makes it a valuable tool for electricity distribution planning in South Africa, particularly when dealing with heterogeneous residential areas [28], [47].

2.3.2.1 Integration of the Beta PDF in SANS 507-1:2019

Within SANS 507-1:2019, the Beta PDF to refine the estimation of After Diversity Maximum Demand (ADMD) values, accounting for diverse consumer load patterns and regional climatic differences. This approach enhances the accuracy of load forecasts by considering the probabilistic distribution of demand across different consumer classes, thus optimising infrastructure design and capacity planning [28], [42], [89], [103]. The use of the Beta PDF aligns with the standard's objective to provide a robust framework for electricity distribution that adapts to dynamic consumption patterns and future uncertainties [9].

2.3.3 Role and Application of the Beta PDF in SANS 507-1:2019

SANS 507-1:2019 employs the Beta Probability Density Function (PDF) to improve the accuracy of load forecasting and planning for electricity distribution networks [6], [13], [104]. The Beta PDF's flexibility allows it to effectively model diverse consumption patterns across different residential areas, including both formal urban zones and townships [6], [52]. This approach provides a probabilistic framework that captures the variability and uncertainty inherent in electricity demand, enabling more precise ADMD calculations and infrastructure planning [63] Gaunt (1999); [28] Herman and Gaunt (2008). By accounting for diverse consumer behaviours and regional differences, the Beta PDF helps create adaptable load profiles that better reflect actual consumption trends, ultimately supporting more resilient and efficient network design SABS Standards Division (2019) [45].

2.3.3.1 Relationship Between the Beta PDF and the SANS 507-1:2019 ADMD Tables

SANS 507-1:2019 applies the Beta probability distribution as the underlying statistical model for diversified residential demand [105], [106]. During the development of the standard, parameters of the Beta distribution were calibrated using large-sample national load research datasets to represent the statistical spread of normalised household demand within low-voltage networks [42], [107]. Instead of requiring designers to evaluate the Beta PDF directly, the standard consolidates the outputs of the fitted distribution into tabulated ADMD values for practical field use [63].

The ADMD values published in SANS 507-1:2019 therefore represent pre-computed percentile outcomes obtained from the Beta-distribution-based modelling process [42], [107]. In other words, the tables do not constitute a separate or alternative estimation method but rather provide simplified access to the diversified peak values generated by the underlying Beta PDF model [63].

Comparing observed ADMD values obtained from measured LV infrastructure with the SANS tabulated ADMD values is consequently equivalent to evaluating the accuracy of the Beta-distribution assumptions embedded in the standard [63]. The empirical analysis undertaken in this study therefore serves as a direct assessment of whether the Beta-PDF-derived demand predictions remain representative across different socio-economic groups, breaker-size categories and settlement types under contemporary load conditions [69], [73], [108].

2.3.4 Practical Construction of Load Profiles Using Beta PDF

Constructing load profiles using the Beta PDF involves collecting granular data on electricity consumption patterns and normalising these to fit within a 0 to 1 range, reflecting minimum and maximum demand. The shape parameters (α and β) of the Beta distribution are estimated using methods such as maximum likelihood estimation or the method of moments, enabling the accurate representation of load variability across different consumer classes [43], [45]. This method allows utilities to forecast peak demands more accurately, optimise resource allocation, and enhance the reliability of distribution networks by accommodating diverse consumption behaviours and potential future growth.

2.3.5 Future Revisions and Innovations in SANS 507-1:2019

Future revisions of SANS 507-1:2019 will need to adapt to emerging factors influencing electricity demand. These include socio-economic changes, technological advancements, climate variability, and economic fluctuations. The integration of advanced technologies such as smart meters, real-time data analytics, and smart grid systems could further refine the application of the Beta PDF by providing more precise, dynamic inputs for load forecasting models [9], [17], [49] . Additionally, incorporating machine learning and artificial intelligence into Beta PDF-based models could enhance forecasting accuracy and adaptability, enabling continuous updates to load profiles based on evolving consumption patterns and environmental conditions [28], [36].

2.4 Applications in Distribution Network Planning

The use of advanced data analytics tools, such as Microsoft Power BI, plays a crucial role in optimising distribution network planning by enabling the analysis of large datasets collected from various sources like smart meters and Current Voltage Monitors (CVMs) [29]. These tools support the development of detailed load profiles, enhance predictive modelling, and facilitate scenario analysis to anticipate future demand patterns and infrastructure needs [18], [19], [109]. By leveraging the capabilities of Power BI, utilities can identify potential bottlenecks, assess the impact of new technologies like distributed generation, and design resilient networks that meet the evolving demands of consumers [19], [110]. This section explores the specific applications of these data-driven approaches in enhancing the efficiency, reliability, and sustainability of electricity distribution networks.

2.4.1 Capacity Planning

Effective capacity planning is crucial for maintaining a reliable electricity distribution network. Analysing load profiles, particularly peak load data, supports decisions on network expansion, transformer sizing, and infrastructure upgrades, ensuring that the network can handle maximum demand without risking outages or disruptions [111], [112]. By leveraging tools such as Microsoft Power BI, utilities can visualise and model these load patterns to make informed choices that optimise resource allocation and infrastructure investments [19], [112].

2.4.2 Demand Response Programmes

Designing demand response programmes relies heavily on accurate load profiling to identify periods of peak demand and opportunities for load shifting or reduction. These programmes play a vital role in enhancing grid stability by managing consumption during high-demand periods, thereby reducing operational costs, and minimising the need for additional capacity [19], [47], [110]. Power BI's capabilities in scenario analysis and dynamic data visualisation aid in developing these strategies by providing a clearer picture of consumption behaviours and potential response measures [18].

2.5 Current Shortfalls in Residential Load Forecasting

The field of residential load forecasting is currently faced with several critical challenges that hinder its effectiveness in accurately predicting electricity demand across diverse socio-economic contexts. Existing techniques often rely on historical data and simplified modelling assumptions that fail to capture the complexities of modern consumption patterns, particularly in areas undergoing rapid socio-economic change. Furthermore, there are notable gaps in the current standards and guidelines, such as those in SANS 507-1, which do not adequately reflect the evolving dynamics of electricity usage in residential sectors [63]. Additionally, significant data and methodological challenges, including issues with data accuracy, integration, and consistency, further complicate load forecasting efforts. While emerging technologies like IoT and smart grids offer promising solutions, their integration into existing frameworks remains limited [113], [114]. This section explores these shortfalls, highlighting the limitations of current forecasting techniques, gaps in existing standards, data-related challenges, and potential future directions for advancing residential load forecasting.

2.5.1 Limitations of Existing Load Forecasting Techniques

Current load forecasting techniques face several significant limitations that impact their effectiveness in accurately predicting residential electricity demand. One significant shortfall is the reliance on historical consumption data, which may not accurately reflect current or future patterns due to socio-economic changes, shifts in consumer behaviour, and the increasing penetration of distributed energy resources [111]. Traditional methods, such as regression analysis, while applicable in some contexts, often fail to capture the complexity and variability inherent in modern residential load profiles, particularly in diverse socio-economic environments like South Africa [42].

Additionally, the deterministic nature of many existing forecasting models does not account for uncertainties in load demand, such as those arising from weather variations, economic fluctuations, and technological adoption. This often leads to over- or underestimation of demand, resulting in inefficient resource allocation and potential grid reliability issues [89]. For instance, models like the Beta Probability Density Function (PDF) have shown promise in accounting for load variability but require further refinement to enhance their predictive accuracy under diverse conditions [115].

Furthermore, the integration of emerging technologies such as smart meters and advanced metering infrastructure, which offer more granular data, poses new challenges related to data handling, privacy, and interoperability. While these technologies present opportunities for more dynamic and real-time forecasting, the lack of standardised methods for incorporating this data into existing models remains a significant barrier [42], [49]. To address these limitations, future research must focus on developing hybrid models that leverage machine learning, real-time analytics, and probabilistic approaches to improve forecast accuracy and reliability.

2.5.2 Shortcomings in Current Standards and Guidelines

Current standards and guidelines for electricity distribution, such as SANS 507-1, play a critical role in shaping load forecasting methodologies and infrastructure planning. However, several gaps in these standards limit their effectiveness in the context of dynamic and evolving residential electricity consumption patterns. One significant shortfall is their reliance on static models and assumptions that do not account for the diverse socio-economic factors influencing consumption in different regions. For instance, SANS 507-1:2019 relies on generalised After Diversity Maximum Demand (ADMD) values that may not adequately capture the variability in consumption across urban, peri-urban, and rural areas, leading to potential over- or under-design of network infrastructure [42], [50], [63].

Another gap is the limited integration of new technological advancements, such as smart grids and IoT-enabled devices, within these standards. While these technologies offer more granular and real-time data that could significantly enhance load forecasting accuracy, current guidelines do not provide frameworks for effectively incorporating this data into planning models [5]. Additionally, existing standards often lack provisions for incorporating emerging energy sources, such as decentralised renewable energy systems, into traditional grid management practices. This gap limits the ability of utilities to optimise grid resilience and reliability in the face of increased penetration of distributed generation [50].

Furthermore, the guidelines fail to account for the growing importance of probabilistic and machine learning-based forecasting methods. Traditional approaches emphasised in standards like SANS 507-1, which rely on deterministic models, do not adequately address the inherent uncertainties in electricity demand, such as those arising from climate change or economic fluctuations [115]. This limitation calls for a revision of current standards to incorporate probabilistic models, like the Beta Probability Density Function (PDF), which have shown promise in better modelling the variability and uncertainty of load profiles [112], [116].

In conclusion, there is a pressing need to update existing standards and guidelines to reflect contemporary consumption patterns, integrate advanced technologies, and adopt more robust statistical methods [14], [15], [16], [54]. Addressing these gaps will help enhance the accuracy and reliability of load forecasting and improve the overall planning and management of electricity distribution networks.

2.5.3 Data and Methodological Challenges

Data and methodological challenges present significant barriers to effective load forecasting and distribution network planning. One of the primary issues is data accuracy, which is often compromised due to inconsistencies in data collection methods and the limitations of existing data sources. Current Voltage Monitors (CVMs) and smart meters, while helpful, frequently suffer from calibration errors, data loss, and communication failures, which can introduce inaccuracies into load profile models [9], [67]. These challenges are compounded by the diverse socio-economic contexts within South Africa, where data from different regions may vary significantly in quality and completeness [42], [89].

The integration of heterogeneous datasets from various devices and systems poses another significant challenge. Disparate data formats, communication protocols, and storage standards make it difficult to achieve seamless data integration and interoperability, which are crucial for accurate load forecasting [46], [49]. Moreover, there are concerns related to data privacy and security, particularly when leveraging real-time data from smart grids and IoT devices [54]. Ensuring compliance with data protection regulations while maintaining the integrity and availability of data is a delicate balance that utilities must navigate [47].

Methodologically, traditional load forecasting models, such as those based on deterministic approaches, fail to adequately capture the stochastic nature of electricity demand, particularly in areas with high variability in consumption patterns. Probabilistic models, like the Beta Probability Density Function (PDF), offer a more robust approach by accounting for uncertainties and variations in load profiles; however, these models require high-quality, high-resolution data that is often not available [43], [112], [115]. Additionally, advanced methodologies such as machine learning and artificial intelligence, which could potentially enhance predictive accuracy, require large amounts of clean and well-structured data, which is not always feasible given the current state of data management in many utilities [49].

Furthermore, there are significant challenges related to the use of existing data for long-term forecasting. The socio-economic landscape, consumer behaviour, and technological adoption rates are all evolving rapidly, making historical data less reliable for future predictions. This requires continuous updating of models and recalibration of parameters, which can be resource-intensive and complex to implement [63], [89].

To address these data and methodological challenges, future research must focus on developing standardised data collection protocols, improving data integration and interoperability, and adopting more sophisticated statistical and machine learning models that can handle the complexity and uncertainty of modern electricity demand.

2.6 Summary

The literature shows that residential ADMD is context-sensitive to socio-economic profile, settlement formality, and infrastructure condition. The Beta probability density function (PDF) as used in SANS 507-1:2019 remains a practical model for bounded residential demand but requires periodic validation against observed data. Studies commonly use upper-tail percentiles (e.g., 95th–99.5th) as proxies for diversified peak, conditional on transparent handling of data quality (plausibility filters, outliers, gaps) and awareness of seasonality/TOU effects. Consistent with this evidence, the present study adopts observed 99.5th-percentile loads as the empirical comparator to standard ADMD values and evaluates representativeness in the Free State. The methodological specifics (filters, percentile estimator, aggregations, and quality assurance (QA)) are set out in — Methodology.

The literature also confirms that the diversified demand tables published in SANS 507-1:2019 originate from a Beta-distribution modelling process applied to historical residential datasets, which positions empirical ADMD comparison as a practical test of the continued suitability of the Beta-based assumptions in contemporary contexts.

2.7 Chapter 2 Conclusion

Chapter 2 reviewed the key concepts, modelling approaches and standards relevant to diversified residential demand estimation. The discussion highlighted the role of diversity, empirical ADMD analysis and the Beta-distribution-based modelling framework applied in SANS 507-1:2019. The chapter also emphasised how contemporary consumption trends and socio-economic variability influence the suitability of standardised demand parameters. This review established the theoretical foundation for the empirical investigation by clarifying the mechanisms through which diversified demand may be evaluated and compared across differing residential contexts.

Chapter 3 — Methodology

This chapter outlines a systematic and replicable approach for obtaining research results necessary for evaluating the accuracy of the Beta Probability Density Function (PDF) as a statistical model for predicting residential loads in the Free State Province of South Africa. Different distribution transformer zones were used as case studies, representing a variety of socio-economic scenarios across the region. Load values are derived from both proposed (theoretical) and measured (actual) data. Proposed values serve as benchmark-based recommendations contained in standards, such as those provided by the South African Bureau of Standards (SABS). In contrast, measured values reflect real-world electricity consumption patterns in the Free State Province.

The ultimate goal is to assess the reliability of the Beta PDF model by comparing its predicted load profiles with observed data. This comparison quantifies the model's accuracy and provides insights for policymakers, utility companies, and researchers focused on energy planning and distribution. In summary, this chapter establishes a rigorous foundation for evaluating statistical models within the context of South African residential electrification.

3.1 Introduction

This methodology chapter forms the backbone of the dissertation, outlining the systematic approach adopted to evaluate the accuracy and reliability of the Beta Probability Density Function (PDF) in predicting After Diversity Maximum Demand (ADMD) values within the diverse socio-economic landscape of the Free State Province, South Africa. This section provides a comprehensive overview of the research design, data collection methods, and analytical techniques employed in the study. By detailing the processes used to gather and analyse empirical data, this chapter establishes a foundation for assessing the alignment between the proposed ADMD values and actual electricity consumption patterns. The methodologies discussed here are essential for ensuring that the research objectives are achieved with rigour and precision, thereby contributing meaningfully to the ongoing discourse on electrical infrastructure planning in varied socio-economic contexts.

3.1.1 Methodology Overview

This chapter outlined the systematic approach employed to evaluate the reliability of the After Diversity Maximum Demand (ADMD) values proposed by SANS 507-1:2019. The research relies on data collected from utility connection databases and Current Voltage Monitors (CVMs) installed in residential transformer zones across the Free State Province, South Africa. The chapter details the processes used to transform raw data into meaningful insights through Microsoft Power BI, which served as the primary tool for data processing, statistical analysis, and visualisation.

Key methodologies include the analysis of load profiles using the 99.5th percentile to derive ADMD values that accurately reflect typical high-demand scenarios. These derived values are then compared against the theoretical ADMD values proposed by SANS 507-1:2019, enabling a critical assessment of their accuracy and reliability. The chapter also discusses the significance of considering seasonal variations, daily load patterns, and the aggregation of data over different time frames to ensure comprehensive and robust findings.

Throughout the chapter, ethical considerations, such as data privacy, informed consent, and responsible data handling, were addressed, alongside limitations related to data quality, assumptions, and the generalizability of the findings. This methodological framework provides a solid foundation for the subsequent analysis and evaluation of ADMD values in the context of residential electrification in the Free State Province.

3.2 Methodology Objectives

The objective of this methodology chapter was to provide a comprehensive and transparent account of the research processes undertaken to achieve the study's objectives. This chapter aimed to ensure that the research steps are articulated and replicable, thereby enabling other researchers to reproduce the study. The methodology includes detailed descriptions of data collection procedures, analytical techniques, and validation methods to ensure the reliability, accuracy, and robustness of the findings.

3.2.1 Methodology Structure

The methodology chapter was structured to guide the reader through the systematic processes employed in this research, starting with the data collection methods and progressing to the critical evaluation of the proposed After Diversity Maximum Demand (ADMD) values.

1. **Data Collection Methods and Processing:** This section details the primary sources of data, including utility connection databases and Current Voltage Monitors (CVMs), and explains how these sources were utilised. It describes the use of Microsoft Power BI as the primary tool for data processing and analysis, highlighting its role in transforming raw data into actionable insights.
2. **Connections Analysis:** This part explores the methods used to analyse connection trends over time, categorise connections by type, and assess their impact on load profiles. It emphasises the importance of understanding how connection growth influences the reliability of the ADMD values.
3. **Load Profiles:** This section discusses the methodology for deriving and analysing historical load profiles, focusing on the use of the 99.5th percentile to identify realistic ADMD values. It also covers the analysis of load profiles by year, month, and daily demand, providing a comprehensive understanding of load patterns.
4. **Evaluating the Proposed ADMD Accuracy:** The final section outlined the retrospective analysis used to compare the theoretical ADMD values proposed by SANS 507-1:2019 with the observed values derived from empirical data. It discusses the criteria for assessing accuracy and the implications of any deviations found.
5. **Ethical Considerations and Limitations:** This concluding part addresses the ethical aspects of data use, such as privacy and confidentiality, and highlights the study's limitations, including data quality, assumptions made, and the scope of generalizability.

3.3 Selection of Case Studies

The selection of case studies is a critical component of this research, ensuring that the analysis accurately reflects the diverse socio-economic and geographic conditions present in the Free State Province, South Africa. This section outlines the criteria and rationale for choosing specific residential areas for detailed analysis. By focusing on well-established electrified zones with a sufficient number of connections, the study aims to evaluate the reliability of the proposed After Diversity Maximum Demand (ADMD) values across a representative sample of the region's population. The selected case studies are designed to provide a robust foundation for analysing real-world electricity consumption patterns and assessing the applicability of the Beta Probability Density Function (PDF) in load forecasting.

3.3.1 Criteria

Several key criteria guided the selection of case studies for this research to ensure that the analysis accurately reflects the long-term reliability of the SANS 507-1:2019 standards in well-established residential areas. The study focuses exclusively on areas with established electrification, as these provide a stable environment for assessing the applicability and effectiveness of the proposed After Diversity Maximum Demand (ADMD) values over time.

To maintain the study’s relevance to residential networks, areas with significant business activity were deliberately excluded. While small businesses may be present within residential zones, their impact is considered negligible for this research, allowing the focus to remain on typical residential consumption patterns.

Another critical criterion is the number of connections within each case study. By the requirements of SANS 507-1:2019, only case studies with more than 30 connections were selected. This ensures that the analysis is relevant to networks of sufficient size, as the standard is not suited for application in small connection groups. By adhering to these criteria, the selected case studies are representative of typical residential networks, providing a robust basis for evaluating the reliability of the proposed ADMD values.

The analysis commences with Case Study C because Cases A and B did not meet the minimum connection-count requirements defined in earlier, and were therefore excluded from the final dataset.

3.3.2 Case Study Description

Each case study is situated in a well-established residential area within the Free State Province, South Africa, with a focus on locations where electrification infrastructure has been in place for an extended period. These areas are characterised by stable residential populations, ensuring that the load profiles represent long-term consumption patterns rather than transient or newly developing trends. The number of connections in each case study exceeds 30, in line with the applicability requirements of SANS 507-1:2019.

3.3.3 Socio-Economic Characteristics

The socio-economic characteristics of the selected case studies are representative of typical residential areas, focusing on factors such as household income levels, population density, and housing types. Small businesses, where present, are limited in number and have a negligible impact on overall load profiles, allowing the study to focus on residential demand, the primary concern of the SANS 507-1:2019 standard. The selected areas do not include significant commercial or industrial activity, ensuring that residential consumption patterns primarily influence the load profiles.

3.3.4 Electrification Status

The selected case studies have a well-established electrification status, with infrastructure that has been in place for several years. This provides a solid foundation for assessing the reliability of the SANS 507-1:2019 ADMD values over time, as the load profiles reflect mature, stable residential areas rather than newly electrified zones. The infrastructure in these areas is fully developed, providing consistent access to electricity, with no significant ongoing electrification projects.

3.3.5 Case Study Requirements

The case studies meet all necessary data requirements, including comprehensive connection records and detailed load profiles. Each area has more than 30 connections, ensuring that the analysis is applicable under SANS 507-1:2019. The selected cases are consistent in terms of data availability and quality, providing a reliable basis for comparison and analysis. By focusing on established residential areas, the study ensures that its findings are relevant to the long-term application of the SANS standard in similar contexts.

3.4 Data Collection Methods and Processing

The data collection process for this research relies on two primary sources, which are essential for obtaining accurate and reliable inputs for the analysis. These sources have been carefully chosen to ensure a comprehensive and robust dataset that aligns with the research objectives. By leveraging these key data sources, the study aims to gather detailed and precise information to serve as the foundation for evaluating the reliability of the Beta Probability Density Function (PDF) in predicting residential electricity loads across the selected transformer zones.

3.4.1 Data Processing Structure

The data processing structure used in this study is designed to efficiently manage, analyse, and visualise the datasets required to evaluate After Diversity Maximum Demand (ADMD) values. Power BI is the primary tool for data processing, chosen for its robust data modelling capabilities, which allow for seamless integration, transformation, and analysis of diverse datasets. The structure involves creating several interconnected data tables that represent various aspects of the study, such as connection details, measured load data, geographic information, and theoretical ADMD values.

The data processing begins with importing raw datasets from multiple sources, including utility connection databases, Current Voltage Monitors (CVMs), and geographic mapping tools. These datasets are then cleaned and transformed into structured tables to ensure they are ready for analysis. The structured data is subsequently loaded into Power BI, where relationships between the tables are established to enable dynamic data interaction and facilitate complex analyses.

3.4.1.1 Data Tables and Relationship

To effectively analyse After Diversity Maximum Demand (ADMD) values, several data tables were created in Power BI, each serving a specific function. The key tables in the data processing structure include:

Connections Table:
Contains detailed information on each connected supply within the transformer zones under study, including fields such as:

- Connection Date
- Breaker Size NMD (A)
- Installed Load (kVA)
- Connection Type (e.g., SPU or PPU)
- Geographic coordinates (Latitude, Longitude)
- Case Study ID

This table served as the foundation for analysing the relationship between the number of connections, their characteristics, and the corresponding load demand.

Measured Load Table:
Includes historical load data collected from Current Voltage Monitors (CVMs), with key fields such as:

- Log Time (timestamp of each load measurement)
- S Load (kVA) (instantaneous load recorded)
- GPS Location (for spatial analysis)
- Case Study ID

This table is critical for calculating the 99.5th percentile load values and analysing daily, monthly, and yearly load profiles.

Theoretical ADMD Values Table:
Contains the theoretical ADMD values based on SANS 507-1:2019, structured by Class ID and connection type. Key fields include:

- Class ID
- Listed ADMD values (per connection type)
- Number of connections (for calculating proposed ADMD)

This table provides the basis for comparing proposed ADMD values against observed values.

3.4.1.2 Geographic Information Table:

Provides geographic and demographic data relevant to each case study, including:

- Transformer Zone ID
- Municipality
- Climate Zone
- Socio-economic indicators

This table supports spatial analysis, enabling the study to consider geographic and environmental factors that may impact load demand.

3.4.1.3 Relationship Between Tables:

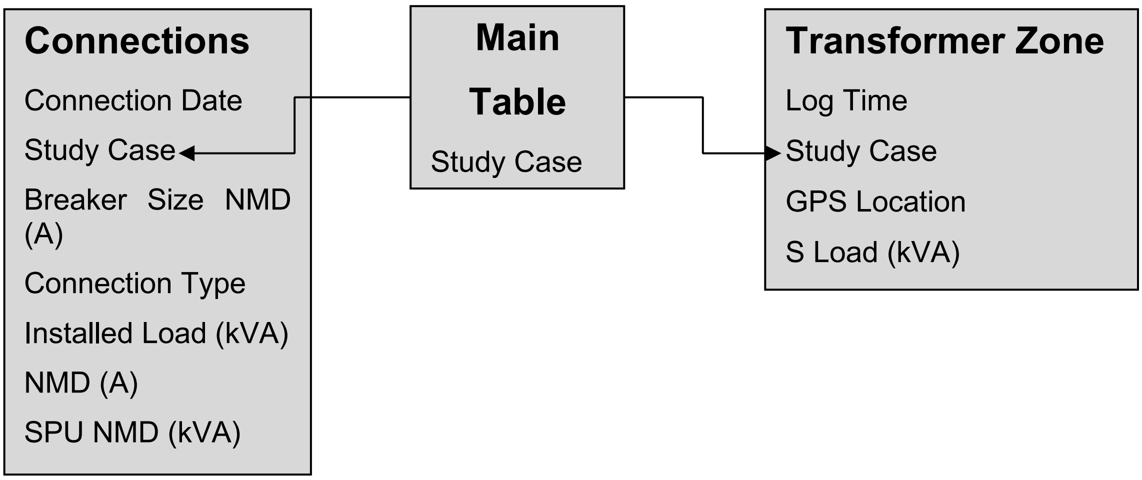
Power BI's data modelling features allow these tables to be linked through key fields, establishing relationships that enable dynamic data analysis:

- The Connections Table is related to the Measured Load Table by the Case Study ID, allowing for a direct correlation between the number and type of connections and the measured load data.

- The Measured Load Table is linked to the Theoretical ADMD Values Table via the Case Study ID and Class ID fields, which facilitate a comparison between observed load profiles and the theoretical ADMD values.

- The Geographic Information Table is connected to both the Connections Table and the Measured Load Table using the Transformer Zone ID, supporting a spatial analysis of load demand based on geographic and socio-economic factors.

By leveraging these relationships, Power BI enables a comprehensive analysis of how different variables, such as connection types, geographic characteristics, and time-based load variations, affect the reliability and applicability of the proposed ADMD values. This structured data processing approach ensures that all relevant factors are considered, providing a robust basis for evaluating ADMD values according to SANS 507-1:2019 standards.



3.4.2 Current Voltage Monitors

Current Voltage Monitors (CVMs) are electronic devices installed at transformer zones or structures, specifically designed to monitor and record various technical parameters in real-time. These devices are equipped with current transformers to measure secondary current flow and potential meters to measure voltage, among other parameters that, while important, are not the focus of this research. CVMs can communicate with a central database via a mobile radio network. When there is a significant change (delta) in any of the monitored parameters, the CVM triggers a write procedure, creating a new record in the database. This record includes all relevant information at the specific timestamp, such as GPS location, log timestamp, per-phase current, and per-phase voltage.

The data collected by CVMs provides raw inputs essential for the measured load aspect of this research. Since the data is already collected in real-time and formatted for immediate use, no additional data collection methods are required. The processing of this raw data, received in CVM format, was discussed in detail in this chapter. Additionally, ethical considerations related to data protection and the safeguarding of intellectual property were addressed to ensure the responsible handling of all collected data.

3.4.3 Utility Connection Databases

All case studies included in this research fell under the supply area of the national electricity utility. The utility's internal connection database was used to extract information related to active customer connections and historical load data. The data included variables such as customer type (e.g., prepaid or post-paid), metering configuration, circuit breaker rating (commonly referred to as the "c value"), and Supply Group Codes (SGCs). These fields formed the basis for grouping connections into standardised residential categories, which enabled consistent comparisons across case studies.

To maintain data integrity and analytical relevance, only active residential connections were considered in this analysis. Records containing missing or inconsistent SGCs, undefined c-values, or inactive statuses were excluded to mitigate the risk of distortion in the aggregation process. The refined dataset allowed for the identification of temporal and spatial trends in electrification uptake, infrastructure evolution, and connection demographics across the different case study zones.

This database served as a foundational input for calculating After Diversity Maximum Demand (ADMD) values by classifying load behaviour according to measurable field characteristics rather than relying solely on assumed or generalised parameters. By using this structured dataset, the study ensured a statistically grounded approach to evaluating the accuracy of the Beta Probability Density Function (PDF) in predicting ADMD within socio-economically diverse regions.

3.4.4 Microsoft Power BI as a Data Processing Tool

Microsoft Power BI was a central tool in the data processing and analysis methodology of this research. As a powerful analytics platform, Power BI offers extensive capabilities for handling large datasets, applying complex algorithms, and generating interactive visualisations. Its ease of use and robust functionality make it an ideal choice for processing the raw data collected from various sources and transforming it into meaningful insights.

In this study, Power BI was employed to perform data cleaning, filtering, aggregation, and transformation. By leveraging Power BI's built-in algorithms, complex statistical analyses (such as the calculation of the 99.5th percentile and the aggregation of daily load profiles) are conducted efficiently and accurately. This approach allows the research to bypass the need for manually detailing complex mathematical formulas, as Power BI automates these processes, ensuring both accuracy and consistency.

The 99.5th percentile $P_{99.5}$ was calculated in Power BI using the `PERCENTILEX.INC()` DAX function, which applies the empirical quantile formula $P_{99.5} = L_{[0.995 \times n]}$ to the sorted and filtered dataset, which returns the 99.5th-percentile threshold (with inclusive rank); so only the top 0.5% of values lie above it.

Moreover, Power BI's visualisation capabilities play a crucial role in this methodology. The tool enables the creation of clear and intuitive visual representations of the data, such as charts, graphs, and distribution curves, which are essential for interpreting the results and effectively communicating them. In this study, these visualisations facilitated the comparison of observed ADMD values with Beta PDF predictions, highlighted deviations in high-demand periods, and supported evidence-based recommendations for network design adjustments. By integrating Power BI into the research workflow, the study achieves a streamlined and consistent approach to data analysis, ensuring that the findings are both reliable and easily understandable.

In summary, the use of Power BI is pivotal in simplifying the explanation of the methodology, allowing the focus to remain on the insights derived from the data rather than the technicalities of the calculations. This section underscores the importance of Power BI in achieving the research objectives, providing a foundation for the subsequent analyses and interpretations presented in this chapter.

3.5 Geographic Overview

The Geographic Overview is a crucial component of this study, providing essential context to understand how each case study is influenced by surrounding climate, socio-economic factors, and proximity within municipal districts. This contextual information is derived using the GPS locations of the transformer zones selected for each case study, which are plotted using Geographic Information Systems (GIS) tools to create a comprehensive spatial overview. By identifying precise GPS coordinates, the transformer zones can be accurately located within specific municipal districts, ensuring that the study areas are clearly defined within their respective boundaries.

To enhance the geographic analysis, Power BI's advanced mapping capabilities were utilised to generate detailed visual representations of the spatial distribution of the selected case studies within the Free State Province, South Africa. Using the "Map" visualisation feature, which integrates Bing Maps web services and Embedded Maps, geographic data points corresponding to each case study were plotted. This integration allowed for an interactive exploration of the socio-economic and infrastructural characteristics surrounding each transformer zone, providing a visual framework to understand the geographic factors influencing electricity consumption patterns across different regions.

Once the geographic locations are established, further research is conducted to gather detailed information about the surrounding areas. This includes examining socio-economic changes and activities within the vicinity, which can significantly impact electricity consumption patterns. Factors such as local economic activities, population demographics, and infrastructure development are analysed to understand their influence on the load profiles. Additionally, the proximity of transformer zones to formally established towns is considered, as this can affect access to services, economic opportunities, and overall electricity demand.

By integrating these various elements, the Geographic Overview provides a nuanced understanding of the environmental and socio-economic context of each case study. The maps generated through Power BI not only facilitate a better understanding of the spatial relationships between study areas but also support the identification of geographic trends that might impact the reliability of the proposed After Diversity Maximum Demand (ADMD) values. This comprehensive approach allows for a more accurate evaluation of the ADMD values and the reliability of the Beta Probability Density Function (PDF) model in predicting residential loads. Understanding these contextual factors is essential for interpreting the results and making informed recommendations for electricity infrastructure planning and policy development.

3.6 Connections

This section describes how the customer/connection dataset was prepared and analysed to contextualise measured load behaviour per transformer zone and case study. Records were restricted to active residential service groups and joined to the measured-load table via Transformer Zone ID and Case Study (see 3.4.1 for model relationships). The key fields used were Connection Type (PPU/SPU), Breaker Size NMD, `c` (A), Installed Load (kVA), where available, Connection Date, POS UID/Meter ID, and Transformer Zone ID. Duplicates were dropped on `Meter/Connection ID`, `Connection Date`, and rows with missing or invalid `c` or `Installed Load` were excluded for the specific computations that required them. Aggregations were implemented as DAX measures that evaluate in the report context; figures presented these measures with units indicated in captions. Where data completeness affected interpretation (e.g., missing Installed Load in legacy records), brief notes were provided in-text and cross-referenced in 3.10 (Limitations).

3.6.1 Proportion of Installed Load by Connection Type

This analysis quantified how the installed-load base was split between PPU and SPU connections within each transformer zone and case study, to avoid confounding later ADMD comparisons with connection-mix effects.

Method

Connection Type grouped active residential rows; Installed Load (kVA) was summed per group and divided by the all-type total.

Arithmetic

$$Proportion_{(type)} = \frac{\Sigma\, Installed\ Load_{type}}{\Sigma\, Installed\ Load_{(Total)}} \times 100 \qquad (1)$$

DAX

```
Installed Load (kVA) :=
    SUM ( 'Connections'[Installed Load (kVA)] )


Proportion by Type (%) :=
    DIVIDE (
        [Installed Load (kVA)],
        CALCULATE ( [Installed Load (kVA)], ALL('Connections'[Connection Type]) )
    ) * 100
```

Note. Rows lacking the Installed Load were excluded from both the numerator and denominator for this computation.

3.6.2 Distribution of Connections by Circuit Breaker Size

This analysis described how connections were distributed across breaker sizes c (A), overall and by connection type, because breaker size composition is a known driver of peak-demand behaviour and aligns with SANS class characteristics.

Method

Within PPU strata, records were counted per breaker size c after removing missing/invalid c. The corresponding stratum total normalised counts are obtained to obtain shares that are comparable across zones of different sizes.

Arithmetic

$$Share_c = \frac{\#\{Connections\ with\ NMD = C\}}{\#\{all\ active\ connections\ in\ stratum\}} \times 100 \qquad (2)$$

DAX

```
Conn Count (in context) :=
   COUNTROWS ( 'Connections' )
Conn Total (stratum) :=
   CALCULATE (
      COUNTROWS('Connections'),
      REMOVEFILTERS('Connections'[Breaker Size NMD (A)])
   )
```

3.6.3 Connection Trends

This view tracked new connections over time at an annual cadence to contextualise growth across case studies and zones.

Method

Each record was assigned to the calendar year of its Connection Date using a calendar table related to that column. Yearly new connections and the cumulative total up to the current year were computed.

Arithmetic

$$NewConn(Y) = \#\{ConnectionDate\ in\ calendar\ year\ Y\}\,, CumConn(Y) = \sum_{t \leq Y} NewConn(t) \tag{3}$$

DAX

```
-- Calendar table is related to 'Connections'[Connection Date]
-- Visuals place Calendar[Year] on the axis


New Connections (Year) :=
   COUNTROWS ( 'Connections' )


Cumulative Connections (to Year) :=
VAR MaxYear =
   MAX ( 'Calendar'[Year] )
RETURN
   CALCULATE (
      [New Connections (Year)],
      FILTER ( ALL ( 'Calendar'[Year] ), 'Calendar'[Year] <= MaxYear )
   )
```

Reporting

Figures present annual counts and cumulative totals by zone/case study using Calendar[Year] on the axis; no additional per-visual configuration is required beyond standard labels and units.

3.6.4 Connection Age Analysis by Breaker Size

This analysis summarised the connection age by breaker size to indicate the maturity of the customer base and its relation to demand characteristics.

Method

For each connection i, age in years was computed relative to the study cut-off date (the maximum Log Time in the measured-load table). Summaries per c reported the median (P50), upper decile (P90), and banded shares where relevant (e.g., <7 years; <15 years) to align with typical planning horizons; thresholds were discussed in the text rather than encoded as chart artefacts.

Arithmetic

$$Age_i(years) = \frac{(Cut - off\ Date) - (Connection\ Date_i)}{365.25} \tag{4}$$

DAX

```
Study Cutoff :=
    MAX ( 'Measured Load'[Log Time] )


Conn Age (Years) :=
    DATEDIFF ( 'Connections'[Connection Date], [Study Cutoff], YEAR )
```

Reporting

Age distributions and summary statistics were presented per breaker size c; where banded shares were shown, the denominator was the count within the group being reported (zone, case study, or connection type).

3.7 Load Profiles

This section examines the load profiles of the study areas to provide a detailed understanding of electricity consumption patterns and their implications for infrastructure planning and demand forecasting. The methodology for deriving these historical load profiles from Current Voltage Monitor (CVM) data involves several key steps to ensure that the analysis is both accurate and relevant to the research objectives.

The CVM data, which includes recorded values of current and voltage, is processed to calculate the instantaneous load experienced by each transformer at the associated timestamp. This approach provides a direct measure of the load on the transformer, assuming a balanced system and a power factor of one for simplicity and practical reasons. This simplification avoids the complexity of incorporating load factor variations, streamlining the analysis while maintaining its relevance to typical operating conditions.

To ensure that the data reflects everyday operating scenarios, specific filters were applied to exclude instances of outages or load shedding. Data points with load values below one kVA are removed to avoid skewing the results, as these could represent atypical conditions like outages that do not reflect the infrastructure's typical performance. By filtering out these outliers, the analysis focuses on representative data of the normal load experienced by the transformer zones.

The data also undergoes a rigorous validation process to ensure its cleanliness and usability. While the details of this process are proprietary, it guarantees that the final dataset is reliable and free from errors that could distort the outcomes. The study specifically focuses on 13 residential transformer zones across various townships in the Free State Province, South Africa, labelled alphabetically from C to O. CVM data is grouped according to these case studies, allowing for a deeper understanding of the historical load profiles specific to each zone.

Analysing the data within the context of a normal distribution allows for a clearer understanding of how the load is distributed over time, which is crucial for identifying patterns and trends in electricity consumption. It is important to note that, in this study, the normal distribution was applied solely to characterise the measured diversified load profiles of the collective transformer zone. The Beta Probability Density Function (PDF) referenced in SANS 507-1:2019 is not generated here but rather forms the basis of the proposed ADMD values in the standard, which are evaluated against the empirical results obtained from the normal distribution analysis.

By breaking down the data into various modes of analysis, including temporal load profiling, statistical distribution fitting, percentile-based demand assessment, and socio-technical correlation analysis. This approach enables a thorough understanding of the factors influencing the After Diversity Maximum Demand (ADMD) characteristics of residential transformer zones. The insights gained from this analysis form a critical foundation for evaluating the effectiveness of the proposed ADMD values, assessing their alignment with real-world usage, and identifying discrepancies that could impact their reliability in various scenarios.

The findings presented in this section were explored further in subsequent sections of this chapter, where the ADMD values are compared and evaluated in greater detail. This analysis aims to validate the ADMD calculations and optimise future electrical infrastructure development in accordance with SANS 507-1:2019 standards.

3.7.1 Mathematical definitions used in this study

This subsection consolidates the mathematical definitions and notational conventions referenced in 3.7. We define the Beta probability density function and its parameter estimation approach, the inclusive sample quantile used to obtain the 99.5th-percentile ADMD, the percentage-deviation accuracy metric, and the load normalisation applied before fitting. Stating these items up front clarifies notation and separates universal mathematics from the implementation details described in the following subsections.

Beta distribution

The Beta PDF on $x \in [0,1]$ is

$$f(x;\alpha,\beta) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha,\beta)}, \qquad B(\alpha,\beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)} \tag{5}$$

With mean $\mu = \frac{\alpha}{\alpha+\beta}$ and variance $\sigma^2 = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$.

For normalised load samples $x_1, \dots, x_n \in [0,1]$ with the sample mean m and variance s^2, method-of-moments estimates are

$$\hat{\alpha} = m\left(\frac{m(1-m)}{s^2} - 1\right), \hat{\beta} = (1-m)\left(\frac{m(1-m)}{s^2} - 1\right), \tag{6}$$

Provided $0 < s^2 < m(1-m)$ Otherwise, parameters are obtained via constrained MLE.

Empirical ADMD (99.5th percentile) definition

Let $S = \{s_1, \dots, s_n\}$ be cleaned transformer loads (kVA), sorted in ascending order to $s_1 \le \dots \le s_n$. The inclusive sample quantile at probability $p = 0.995$ is

$$h = (n-1)p + 1, k = \lfloor h \rfloor, \delta = h - k, Q_{0.995} = s_{(k)} + \delta\left[s_{k+1} - s_{(k)}\right] \tag{7}$$

Which interpolation rule is used by `PERCENTILEX.INC`. $Q_{0.995}$ is taken as the observed ADMD for the active grouping (year/month/day).

Accuracy metric used in comparisons
For proposed $ADMD$, $ADMD_{prop}$ and observed $ADMD_{obs}$, the deviation is

$$Deviation(\%) = \frac{ADMD_{prop} - ADMD_{obs}}{ADMD_{obs}} \times 100, \tag{8}$$

With $\pm 12\%$ considered acceptable (per SANS Table 2 footnote).

Normalisation is used when fitting the Beta

To relate real loads $S(t)$, the unit interval for Beta fitting, values are scaled as $x(t) = \frac{S(t)}{S_{max}}$ where S_{max} where S_{max} is a fixed engineering bound (e.g., nameplate rating or study-wide high percentile). Parameter estimation is then performed on $x(t)$.

Notation

$\Gamma(\cdot)$ denotes the Gamma function;
$\mathrm{B}(\cdot,\cdot)$ the Beta function;
α, β are Beta parameters;
$\mathrm{p} = 0.995$;
$ADMD_{obs}$ and $ADMD_{prop}$ denote observed and proposed ADMD;
And $S(t)$ is transformer apparent load (kVA).

3.7.2 Historical Load Profile Analysis

The analysis of historical load profiles is a critical step in deriving a rational After Diversity Maximum Demand (ADMD) value, which served as one of the two key comparator values in this research, alongside the real measured value. To gain an accurate understanding of historical load conditions, data collected from Current Voltage Monitors (CVMs) is utilised. This real-time data provides a measurable outcome that can be directly compared to theoretical ADMD values proposed by SANS 507-1:2019.

The raw data obtained from CVMs requires processing through various algorithms, including data cleaning routines, time-series aggregation functions, percentile ranking calculations, moving average smoothing, and statistical distribution fitting, to transform it into actionable insights. These algorithms help identify trends, patterns, and statistical characteristics within the historical load profiles. The methodology outlined in this section describes the processes used to convert raw data into usable information that contributes to the research outcomes.

To facilitate the analysis of historical load profiles, Power BI was employed to perform arithmetic calculations and produce visual outputs that offer a clear representation of the data. The following steps outline the methodology:

1. **Data Preparation and Visualisation Using a Line Chart:**
   The historical load data from CVMs was imported into Power BI, focusing on key fields: [Log Time] and [S Load (kVA)].

   A line chart was created to represent the load profile over time visually. The X-Axis was set to Measured Load'[Log Time] to display the time series data, and the Y-Axis was set to Measured Load'[S Load (kVA)] to show the corresponding load values.

   Several additional lines were included on the chart to provide context and support the analysis:

   Maximum Line: Represents the highest observed load value within the dataset, which helps to identify peak demand periods.

Average Line (Mean Load): Calculated using the DAX formula:

$$Mean\ Load\ (S) = CALCULATE(AVERAGE('Measured\ Load'[S\ Load\ (kVA)]),$$
$$FILTER('Measured\ Load','Measured\ Load'[Case\ Study]))$$

This line indicates the average load across the study period, highlighting general consumption trends.

Load P99.5 Line (99.5th Percentile): Represents the 99.5th percentile of the load distribution, calculated using:

$$Load\ P99.5 = PERCENTILEX.INC('Measured\ Load','Measured\ Load'[S\ Load\ (kVA)], 0.995)$$

This line reflects the typical peak load conditions, excluding extreme outliers and providing a more realistic basis for the ADMD value.

2. **Calculation of Key Metrics:**
   Earliest Date and Last Date: The time range of the dataset is established using:

$$Earliest\ Date = FIRSTDATE('Measured\ Load'[Log\ Time].[Date])$$

$$Last\ Date = LASTDATE('Measured\ Load'[Log\ Time].[Date])$$

These metrics help define the analysis period and ensure the time series data is accurately represented.

Standard Deviation and Median Calculations: Additional metrics such as the median load and standard deviation are calculated to understand the distribution characteristics:

$$Median\ Load\ (S) = CALCULATE(MEDIAN('Measured\ Load'[S\ Load\ (kVA)]),$$
$$FILTER('Measured\ Load','Measured\ Load'[Case\ Study]))$$

$$Standard\ Deviation\ Load\ (S) = CALCULATE(STDEV.S('Measured\ Load'[S\ Load\ (kVA)]),$$
$$FILTER('Measured\ Load','Measured\ Load'[Case\ Study]))$$

These statistics provide insight into the variability and central tendency of the load data.

Normal Distribution Line Chart:

To complement the line chart, a Normal Distribution line chart was created to analyse how the load data conforms to a normal distribution. This chart uses the following DAX formula:

$$Normal\ Dist\ Load\ (S) = NORM.DIST('Measured\ Load'[S\ Load\ (kVA)], Mean, StanDev, FALSE())$$

This function calculates the normal distribution values for the load data using the mean and standard deviation, allowing for a comparison of the actual load distribution against the expected normal distribution.

By representing the data in this manner, it becomes easier to identify deviations from normality, which could indicate unusual patterns or behaviours in load consumption.

3. **Interpretation of Visual Outputs:**
   The visual outputs, particularly the line chart and the normal distribution line chart, provide a comprehensive view of the historical load profiles. The Load P99.5 line served as a key indicator for determining a rational ADMD value, focusing on the typical peak load conditions rather than extreme values.

The inclusion of the maximum, mean, and 99.5th percentile lines provides a robust framework for evaluating the variability in load demand and understanding the range of typical and peak conditions. This approach ensures a balanced perspective between conservative and realistic load forecasting.

3.7.3 99.5th Percentile Load Analysis

The 99.5th Percentile Load Analysis was employed in this study to estimate upper load values while excluding extreme outliers, providing a realistic measure of peak demand under typical operating conditions. By focusing on the 99.5th percentile, the analysis captures high-demand scenarios that occur frequently enough to impact infrastructure planning, without being distorted by rare or exceptional events. This approach ensures a balanced estimation of After Diversity Maximum Demand (ADMD), essential for designing resilient and efficient electrical networks.

This analysis is conducted across different time frames (yearly, monthly, and daily) to capture both long-term trends and short-term variations in load demand. Yearly and monthly analyses identify trends and seasonal fluctuations, while daily intervals provide insights into specific peak periods. This multi-dimensional approach enhances understanding of load behaviour, supporting more accurate ADMD calculations and better infrastructure planning.

The subsequent sections will detail how the 99.5th percentile load is calculated and interpreted for each time frame, illustrating its implications for the reliability and applicability of the proposed ADMD values in line with SANS 507-1:2019 standards.

3.7.3.1 How the 99.5th percentile is aggregated and calculated

Data basis & filters

Instantaneous transformer-load values S_{Load}, kVA from CVMs, records were cleaned to represent normal operation: records < 1 kVA (outage/load-shedding artefacts) were excluded before any aggregation. Case-study filters were applied per transformer zone. Duplicate timestamps and rows with missing/invalid key fields were removed.

Time base

Percentiles were evaluated on the native metering interval (e.g., 30- or 60-minute) with timestamps aligned to local time.

Why the 99.5th percentile

The 99.5th percentile was used as a robust proxy for typical peak demand, capturing frequently recurring high-load conditions while suppressing rare extremes.

Computation engine

All percentiles were computed in Power BI using `PERCENTILEX.INC` over the filtered rows in the current evaluation context (inclusive definition; Hyndman–Fan Type 7 with linear interpolation between bracketing order statistics). The generic measure is:

```
Load_P99_5 :=
VAR CleanRows =
    FILTER(
        'Measured Load',
        NOT ISBLANK('Measured Load'[S Load (kVA)]) &&
        'Measured Load'[S Load (kVA)] >= 1 &&
        (ISBLANK('Measured Load'[IsOutage]) || 'Measured Load'[IsOutage]
= FALSE)
    )
RETURN
PERCENTILEX.INC(CleanRows, 'Measured Load'[S Load (kVA)], 0.995)
```

This returns the 99.5th percentile of S_{Load}, for whatever grouping is active (year, month, day/time-of-day, case study).

Aggregation levels used

- **Yearly**
  Group by Log Time → Year and evaluate Load P99_5 per case study per year (Figures/plots in 3.7).

- **Monthly (two views)**
  (i) Year-on-year: group by Year × Month to see seasonal patterns across years;

  (ii) Aggregated month: group by Month across all years to obtain a single 12-month profile. Both views evaluate `Load P99_5` within their filter contexts.

- **Diurnal (24-hour) profiles:** Create a Time-of-Day key from Log Time (e.g., HH:MM or native interval). For each interval bin, evaluate `Load P99_5` over all days; where required, repeat per month to obtain monthly diurnal profiles.

Completeness rule.
A percentile for any grouping (year/month/interval bin) was reported only if ≥ 90% of expected intervals were present for that unit; units below threshold were flagged and omitted (or footnoted where shown).

Implementation notes.
The cleaning step precedes percentile evaluation (so the iterator table excludes < 1 kVA rows). Groupings are created with the date hierarchy and/or a derived Time-of-Day column; the measure respects the active context, so no explicit `SUMMARIZE` is required for the visuals used in this study.

Downstream use
For each grouping, the resulting value was stored as $ADMD_{obs}\,(kVA)$ and joined to the corresponding SA standard ADMD (SANS 507-1:2019). Deviation metrics and the ± 12% planning-tolerance rule are defined in Section 3.8.3.

3.7.3.2 99.5th Percentile load analysis by year

The 99.5th percentile load for each year was calculated by aggregating all available load records within the specified study timeframe. This aggregation enables a comprehensive view of the ADMD trends, capturing the highest, yet typical, load values experienced each year without being skewed by extreme outliers.

To perform this analysis, Power BI was utilised for its robust data processing and visualisation capabilities. Power BI facilitated the efficient calculation of the 99.5th percentile load using the DAX function:

```
Load P99_5 = PERCENTILEX.INC('Measured Load', 'Measured Load'[S Load
(kVA)], 0.995)
```

This formula calculates the 99.5th percentile of the load values, ensuring that only the most relevant upper load data points are considered for each year.

1. **Data Preparation and Calculation:**
   The load data was imported into Power BI, with the `[Log Time]` field representing the timestamp of each load measurement. The data was grouped by year using the `[Log Time]` (by Year) on the X-axis, enabling a precise, chronological analysis of load values.

   Power BI's DAX language was used to compute the Load P99.5 for each year. The function `PERCENTILEX.INC` was applied to the dataset to calculate the 99.5th percentile of the [S Load (kVA)] for each year, thereby isolating the high-demand values that occur under typical conditions.

2. **Visualisation with Line Chart:**
   A line chart was generated in Power BI to visualise the aggregated 99.5th percentile loads across different years. The X-axis was set to `Measured Load'[Log Time]` (by Year), and the Y-axis was set to the calculated Load P99.5. This graphical representation allowed for an intuitive comparison of load demands over time, highlighting trends and fluctuations in the ADMD.

   An overall 99.5th Percentile line was included in the chart to provide a reference point, showing the aggregated percentile value across all years. This reference line helps to contextualise yearly variations against the overall trend.

3. **Trend Line Inclusion:**
   A trend line was added to the line chart to illustrate the overall direction of the 99.5th percentile load values over the study period. The trend line was generated using Power BI’s built-in analytics tools, providing a visual indication of whether load demands have generally increased, decreased, or remained stable over the years. This trend analysis is critical for understanding long-term changes in load behaviour, which can influence future infrastructure planning and ADMD considerations.

By leveraging Power BI for both arithmetic calculations and visual outputs, this study was able to analyse and compare ADMD trends year-on-year systematically. This analysis provides a clear depiction of how load demands have evolved within the transformer zones under study. Understanding these trends is crucial for assessing the long-term reliability and applicability of ADMD values proposed for infrastructure planning and design.

The subsequent sections will further explore these findings, focusing on the implications of observed trends and their alignment with the proposed ADMD values by SANS 507-1:2019 standards.

3.7.3.3 99.5th Percentile load analysis by month

Analysing the 99.5th percentile load on a monthly interval is a critical component of this research, as it provides valuable insights into the seasonality of load profiles and how After Diversity Maximum Demand (ADMD) values fluctuate throughout the year. This analysis is critical in the context of South Africa's interior Free State Province, where climatic variations between cooler and hotter months can significantly impact electricity demand.

The monthly analysis was conducted using two complementary approaches:

1. **Year-on-Year Breakdown:**
   This approach involved calculating the 99.5th percentile load for each month across different years to observe how ADMD values change within the same month from one year to the next. This method highlights any seasonal patterns or trends that may emerge over time, providing a detailed view of how load demands respond to seasonal shifts.

2. **Aggregated Monthly Profile:**
   In this approach, all available records were combined into a single annual profile, which aggregates the 99.5th percentile load values for each month across all years in the study period. This provides a comprehensive overview of the typical seasonal load distribution, allowing for the identification of consistent patterns in ADMD values throughout the year.

Power BI was utilised for this analysis due to its robust data processing and visualisation capabilities. The following steps outline the methodology employed using Power BI:

1. **Data Preparation and Calculation:**
   The load data from the Current Voltage Monitors (CVMs) was imported into Power BI, with the [Log Time] field used to capture the timestamp of each load measurement.

   For the year-on-year breakdown, the [Log Time] was categorised by year and month, allowing for a detailed temporal analysis of the load data. Power BI's DAX function was used to calculate the 99.5th percentile load for each month:

   $$Load\ P99.5 = PERCENTILEX.INC('Measured\ Load', 'Measured\ Load'[S\ Load\ (kVA)], 0.995)$$

   This calculation was applied separately for each month within each year, resulting in a series of 99.5th percentile values that reflect the highest typical load values for each month across different years.

2. **Visualisation with Line Chart:**
   A line chart was generated in Power BI to visualise the aggregated 99.5th percentile loads for each month. The X-axis was set to Measured Load'[Log Time] (by Year and Month), enabling a chronological view of the data, while the Y-axis was set to the calculated Load P99.5 values.

   The line chart displayed the 99.5th percentile load values across all months, allowing for an easy comparison of seasonal peaks and trends over time.

3. **Aggregated Monthly Profile Visualisation:**
   To visualise the aggregated monthly profile, Power BI combined all available load records across the study period into a single chart. This aggregation provided an overall view of how the 99.5th percentile load values typically vary across the months of the year.

The line chart for the aggregated profile helped identify consistent seasonal patterns in the ADMD values, such as recurring peaks during certain months due to climatic factors. This visual output was crucial for understanding the impact of seasonality on load demands and for validating the applicability of the proposed ADMD values under different seasonal conditions.

By leveraging Power BI for both arithmetic calculations and visual outputs, this study was able to generate clear and actionable insights into the seasonal dynamics of load profiles. The combination of year-on-year and aggregated monthly analysis provided a nuanced understanding of how ADMD values vary with climatic conditions, ensuring that the proposed ADMD values are reliable and applicable across different seasonal contexts. This analysis is crucial for informing infrastructure planning and design, ensuring that the electrical networks are adequately prepared to handle seasonal fluctuations in demand.

3.7.4 99.5th Percentile Load Analysis: Daily Demand Profiles

Analysing daily demand profiles is essential for gaining a comprehensive understanding of the After Diversity Maximum Demand (ADMD) within residential transformer zones, particularly in the context of Free State Province townships. Daily load profiles reveal the behavioural characteristics of electricity consumption across 24 hours, highlighting the specific peak periods and the duration of these peaks. This insight is crucial for infrastructure planning and design, as it directly impacts decisions regarding the sizing and rating of electrical distribution networks.

The application of the 99.5th percentile in analysing daily demand profiles ensures a high level of reliability and accuracy in the results, allowing for the identification of typical peak loads without being skewed by extreme outliers. This method provides a realistic representation of the daily load that transformers experience, which is vital for making informed decisions about network infrastructure.

From a planning perspective, understanding the daily load profile helps in assessing the specific peak periods experienced by transformers, as well as the duration of these peaks. This information is crucial because infrastructure with higher ratings is required to accommodate higher peak loads, which, in turn, increases the cost of the infrastructure. However, electrical distribution systems are typically designed to accommodate overload conditions for short durations, meaning that not every peak load demands an increase in infrastructure rating. By illustrating the daily peaks and their associated durations, this analysis enables more precise and cost-effective infrastructure planning, helping to avoid the financial losses associated with either overdesigning or underdesigning the network.

Concerning the SANS standards and the proposed ADMD values, having unreliable ADMD values could lead to significant financial losses, whether due to overinvestment in unnecessary infrastructure or the risks associated with insufficient infrastructure. Therefore, accurate daily load profile analysis is critical to ensuring that the network infrastructure is appropriately sized and rated.

Given the distinct climatic conditions in the Free State Province, it is essential to differentiate between daily load profiles during hotter and colder months. Colder months generally exhibit longer and higher peak durations compared to hotter summer months, reflecting the increased demand for heating. The methodology employed in this research involves a twofold approach: first, demonstrating the daily load profile for each month, aggregated into an annual profile, and second, presenting a fully aggregated daily load profile that encapsulates the entire year. This comprehensive analysis provides a detailed and accurate representation of daily load patterns, informing both the reliability of the ADMD values and the subsequent infrastructure design decisions.

3.7.4.1 Aggregated 99.5th Percentile load by 24-h day by Month

The methodology for deriving a daily After Diversity Maximum Demand (ADMD) profile, represented as a typical profile for each associated month, is a critical component of this research. This approach allows for a granular understanding of how climatic variations throughout the year impact load profiles in residential areas within the Free State Province. By analysing these daily profiles on a monthly intervals, the study provides valuable insights into the behavioural patterns of electricity consumption as influenced by seasonal changes.

Using Power BI as the primary data analysis tool, the daily load profiles are calculated by aggregating the 99.5th percentile load values for each hour of the day across the entire month. This aggregation method ensures that the profile reflects the typical high-demand scenarios experienced during each hour, without being distorted by extreme outliers that may only occur sporadically.

The process begins by collecting the load data for each 24 hours within the month across all available years in the study timeframe. For each hour, the 99.5th percentile load value is determined, capturing the most representative peak load for that hour while excluding anomalous spikes. These hourly 99.5th percentile values are then compiled to form a complete daily ADMD profile for the month.

The resulting profile is an aggregation of these hourly values, creating a typical daily load profile that represents the residential area's demand pattern for that specific month. This methodology provides a detailed view of how load demand fluctuates throughout the day and across different months, offering critical insights for infrastructure planning and design.

By using this approach, the research ensures that the ADMD profiles are both accurate and reflective of real-world conditions, enabling more precise decision-making regarding the sizing and rating of electrical distribution networks. The typical daily profiles derived from this analysis serve as a foundational tool for understanding how seasonality affects load demands and ensuring that the network infrastructure is capable of handling these variations efficiently.

3.7.4.2 Aggregated 99.5th Percentile load by 24-h day

Analysing daily demand profiles is essential for gaining a comprehensive understanding of the After Diversity Maximum Demand (ADMD) within residential transformer zones, particularly in the context of Free State Province townships. Daily load profiles reveal the behavioural characteristics of electricity consumption across 24 hours, highlighting specific peak periods and their duration. This insight is crucial for infrastructure planning and design, as it directly impacts decisions regarding the sizing and rating of electrical distribution networks.

To achieve this, Power BI was employed to generate two key visualisations for daily demand profiles using the 99.5th percentile metric:

1. **Aggregated Daily Profile by Month:**
   Power BI was used to create a line chart that represents the 99.5th percentile aggregated daily load profile, broken down by each month. The X-axis was set to represent the hours of a 24-hour day, while the Y-axis displayed the calculated 99.5th percentile load values.

   This approach allows for the identification of typical daily peak loads for each month, offering insights into how electricity demand varies over different periods of the year. The use of the 99.5th percentile ensures that the load values considered are representative of typical high-demand scenarios, avoiding distortion by extreme outliers.

2. **Fully Aggregated 24-Hour Daily Load Profile:**
   Power BI was also utilised to generate a combined aggregation, representing a single load profile for a typical 24-hour day across the entire study period. This visualisation provided an overall view of daily demand patterns, capturing the most common peak periods and their duration throughout the year.

   By creating a fully aggregated daily profile, the study identified general trends in load behaviour, such as standard peak times and the extent of load variation within a day. This profile is crucial for understanding the consistent patterns that impact network infrastructure planning, ensuring that the network can reliably handle typical daily demand variations.

Utilisation of Power BI for Analysis:
The application of Power BI in this analysis enabled efficient data processing and visualisation, providing clear insights into daily load profiles:

1. **Data Calculation:**

   The 99.5th percentile load was calculated using Power BI's DAX function:

$$Load\ P99.5 = PERCENTILEX.INC('Measured\ Load', 'Measured\ Load'[S\ Load\ (kVA)], 0.995)$$

This function was applied to calculate the 99.5th percentile load for each hour of the day, aggregated by month, and then further combined to form a single annual profile. The calculations ensured that only the most relevant upper load data points were considered for the daily analysis.

2. **Visual Output Generation:**

   Power BI's line chart capabilities allowed for a visual representation of both the monthly aggregated and the fully aggregated daily profiles. The charts highlighted peak periods and durations, which are critical for understanding the load demand behaviour over a typical 24-hour day.

   The inclusion of these visual outputs helped illustrate how daily load patterns differ between colder and hotter months, reflecting seasonal variations in demand due to factors like heating in colder months and cooling in warmer months.

By using Power BI to perform these calculations and generate visual outputs, this study was able to provide a detailed and accurate representation of daily load patterns, which is vital for assessing the reliability of ADMD values and guiding infrastructure design decisions. Accurate daily load profile analysis helps ensure that the network is appropriately sized and rated, avoiding the costs associated with overdesign or the risks of insufficient infrastructure.

The differentiation of daily load profiles by month and the aggregation into a single annual profile, supported by Power BI, enables a nuanced understanding of how load demands fluctuate seasonally and daily. This approach ensures that the proposed ADMD values are robust and applicable under various conditions, providing a reliable foundation for future infrastructure planning by SANS standards.

3.8 Evaluating the Proposed ADMD Accuracy

This section evaluates the accuracy of the proposed After Diversity Maximum Demand (ADMD) values presented in SANS 507-1:2019 by comparing them to the observed ADMD values derived from the case study data. The objective is to assess how closely the standard's recommended values align with the real-world load behaviour observed in the residential transformer zones under study.

In this analysis, each case study is compared against the proposed ADMD values for all relevant Consumer Class IDs, rather than selecting a single "best-suited" class. This approach recognises that within a given transformer zone, the connected load base may be at different stages of the infrastructure growth curve, with some connections representing early-stage consumption patterns while others are more mature. As a result, no single class designation may holistically capture the profile of the entire case study. Comparing across multiple classes provides a more comprehensive evaluation of the SANS 507-1:2019 ADMD proposals against the measured load behaviour, ensuring that partial maturity effects and mixed socio-economic conditions are fully considered.

The subsections that follow describe the process for deriving the theoretical ADMD values (Section 3.8.1) and the observed ADMD values (Section 3.8.2), as well as the comparison framework applied to assess the alignment between them.

3.8.1 Deriving Theoretical ADMD Values

The theoretical ADMD values for comparison are sourced directly from the SANS 507-1:2019 standard. These values are specified according to Consumer Class ID, which classifies the size and type of the electrical network based on the number of connections supplied by a transformer. Each class is associated with a set of proposed ADMD values derived through statistical modelling; specifically, the application of the Beta probability density function to historical electrification data during the development of the standard.

For each relevant Consumer Class ID, the proposed ADMD value corresponding to the number of active connections in the case study is extracted from the SANS 507-1:2019 tables. These extracted values form the baseline theoretical benchmarks for subsequent comparison with the observed ADMD figures calculated from the measured load profiles.

3.8.2 Deriving Observed ADMD Values

The observed ADMD values are derived from the analysis of historical load profiles, as outlined in Section 3.6, Load Profiles. Specifically, the 99.5th percentile load values are used as the empirical benchmark against which the theoretical ADMD values are evaluated.

Power BI is utilised to compute these observed ADMD values by leveraging its data processing capabilities to aggregate and analyse the historical load data effectively. This process involves importing cleaned time-series load data, grouping records by transformer zone and analysis period, summing and averaging demand values over defined intervals, and then applying DAX functions (such as `PERCENTILEX.INC` for percentile extraction and SUMX for aggregated demand totals) to generate the observed ADMD figures.

These steps ensure that the calculations reflect the full dataset while isolating the 99.5th percentile loads for precise comparison with the theoretical values. By applying consistent statistical and computational procedures across all case studies, the observed ADMD values provide a robust empirical counterpart to the theoretical figures from SANS 507-1:2019, enabling a fair and reliable assessment of their accuracy.

3.8.3 Comparative Accuracy Analysis and Scope of Class ID Evaluation

In line with the rationale outlined at the start of Section 3.8, this comparative analysis evaluates each case study against the proposed ADMD values for all relevant Consumer Class IDs, rather than a single "best-suited" class. This approach ensures that the comparison accounts for the mixed stages of infrastructure maturity and socio-economic diversity present within the transformer zones, providing a more holistic evaluation of the SANS 507-1:2019 recommendations.

This research does not aim to identify the most appropriate or "actual" Class ID for each case study. Instead, the objective is to assess the reliability of the proposed ADMD values across a broad range of scenarios. By evaluating all applicable Class IDs, the analysis avoids bias toward a single classification. Instead, it provides insights into how the Beta Probability Density Function (PDF)–derived values perform under varied conditions. This approach also highlights which Class IDs perform best in specific contexts, without pre-emptively assuming that one classification universally applies to the entire case study.

The comparative process involves aligning the theoretical ADMD values for each Consumer Class ID with the observed ADMD values calculated in Section 3.8.2. For each pairing, percentage differences, error margins, and absolute deviations are calculated using the formula:

$$Deviation\ (\%) = \frac{Proposed\ ADMD - Observed\ ADMD}{Observed\ ADMD} \times 100 \qquad (9)$$

A deviation of 0% indicates perfect alignment between proposed and observed values. Negative deviations suggest that the proposed ADMD values underestimate demand (observed values are higher), while positive deviations indicate overestimation. Following the guidance in the footnotes of Table 2 of SANS 507-1:2019, a deviation within ±12% is considered acceptable for practical planning purposes.

Power BI plays a pivotal role in executing this comparative analysis - the platform's DAX functions, including `PERCENTILEX.INC` for percentile calculations and SUMX for aggregated demand totals, enable efficient computation of deviations and facilitate automated visualisation through bar charts, scatter plots, and other formats. These visual outputs make it possible to identify trends, patterns, or anomalies in ADMD accuracy across different Class IDs and case studies at a glance.

By integrating the evaluation of accuracy with the scope of Class ID coverage, this section ensures that the analysis is both technically rigorous and broad enough to capture the variability inherent in real-world load growth and infrastructure maturity stages.

3.8.4 Detailed Comparison and Presentation

The results of the accuracy analysis are systematically presented in Power BI using tables and graphical outputs. Power BI’s dynamic, interactive dashboards enable a clear comparison of the proposed ADMD values against the observed ADMD values for each Class ID. The detailed comparison highlights any significant deviations that could impact the reliability of the ADMD values proposed by SANS 507-1:2019.

Power BI’s visualisations, such as heat maps or conditional formatting in tables, help to identify which scenarios fall within the acceptable deviation range quickly. This approach ensures that the findings are easily interpretable and actionable, supporting decision-making regarding the reliability and applicability of the proposed ADMD values.

The core of this research lies in assessing whether the proposed ADMD values can be considered reliable. Power BI's analytical and visualisation tools enhance this evaluation by providing clear, data-driven insights into the accuracy of these values. Suppose the results show that even the best-case outcome of Class ID selection fails to predict the observed ADMD values accurately. In that case, it will indicate a fundamental lack of reliability in the standard’s proposed values. Conversely, demonstrated accuracy for any Class IDs would support the reliability of the SANS 507-1:2019 ADMD values.

In either case, the risk of selecting an incorrect Class ID underscores a critical shortfall in the standard's practical application, necessitating further scrutiny and potential revision of the guidelines.

3.9 Ethical Considerations

In conducting this research, several ethical considerations have been carefully addressed to ensure the responsible use of data and the protection of individual and community interests. All data used in this study have been anonymised to protect the privacy of residents in the Free State Province townships. No personally identifiable information (PII) is included in the datasets, and all sensitive operational data from Eskom Holdings Limited has been handled with strict confidentiality.

Informed consent was obtained from any individuals involved in the data collection process, and appropriate data use agreements were secured from Eskom to ensure compliance with their policies and guidelines. The data has been stored securely, with measures such as encryption and access controls in place to prevent unauthorised access.

Additionally, this research has been conducted with a commitment to beneficence, aiming to improve infrastructure planning and reliability in a way that ultimately benefits the communities involved. The findings are reported transparently, with an explicit acknowledgement of any limitations in the data or methodology that could affect the reliability of the conclusions drawn.

These ethical considerations are integral to the integrity of the research, ensuring that it is conducted responsibly and with respect for the rights and interests of all stakeholders involved.

3.10 Limitations

While this research provides valuable insights into the accuracy and reliability of the SANS 507-1:2019 proposed ADMD values, several limitations should be considered when interpreting the results.

First, the availability and quality of the data used in this study present potential constraints. Incomplete or inconsistent data from utility connection databases and CVM records may affect the accuracy of the derived ADMD values. Additionally, the reliance on historical load profiles introduces a dependency on the quality and completeness of past data, which may not always be optimal.

Assumptions made in the analysis, such as assuming a balanced load and a constant load factor, are necessary for simplifying the methodology but may not fully reflect real-world conditions. The exclusion of minor NMDs also limits the scope of the analysis, potentially omitting relevant data that could influence the results.

Geographically, this study focuses on the Free State Province region, and the findings may not be directly applicable to other areas with different climatic conditions or infrastructure. The regional specificity, combined with the broad scope of Class ID analysis, means that while the research offers a comprehensive evaluation, it does not address the specific applicability of any single Class ID to a particular area.

Methodologically, the use of Power BI for data processing introduces its own set of constraints. While it simplifies complex calculations, it may limit the transparency and reproducibility of the research. Additionally, the generalizability of the findings beyond the Free State Province region is limited, as the study's results are closely tied to the specific characteristics of the data and infrastructure in the area studied.

By acknowledging these limitations, the research maintains transparency and provides a clear context within which the findings should be understood. This ensures that the conclusions drawn are robust and reflective of the study's constraints.

3.11 Summary of research methodology

This chapter outlines the comprehensive methodology employed to evaluate the reliability of the SANS 507-1:2019 proposed ADMD values in well-established residential areas within the Free State Province, South Africa. The research relies on data collected from utility connection databases and Current Voltage Monitors (CVMs), which is processed and analysed using Microsoft Power BI. The study focuses on residential transformer zones with more than 30 connections to ensure relevance to the SANS standard.

Key methodologies include the analysis of historical load profiles using the 99.5th percentile to derive ADMD values, which are then compared against theoretical values proposed by the SANS standard. This approach was applied across various time frames (annual, monthly, and daily), to capture both long-term trends and seasonal variations.

Ethical considerations, such as data privacy and the responsible use of sensitive information, were addressed throughout the chapter, alongside limitations related to data quality and the scope of the study. These considerations ensure that the research is conducted responsibly and ethically.

Overall, the methodology is designed to provide a robust and accurate assessment of the ADMD values, ensuring that the research findings are both reliable and applicable to the planning and design of residential electrical networks.

3.12 Alignment with Research Objectives

The methodological framework applied in this study aligns with the research objectives by providing a structured process for analysing diversified residential demand. The preparation of normalised datasets, calculation of ADMD values and comparative assessments directly support the objectives related to evaluating contemporary diversified demand behaviour and its relationship to the SANS 507-1:2019 reference values.

The methodological design also facilitates comparative analysis across socio-economic groups and breaker-size categories, thereby addressing the objective of assessing the representativeness of standardised diversified demand parameters within diverse residential contexts.

3.13 Chapter 3 Conclusion

Chapter 3 outlined the methodological approach used to evaluate diversified demand within the selected study areas. The process included data preparation, ADMD determination, case study selection and comparative analysis against the SANS 507-1:2019 reference values. The methodology was structured to ensure alignment with the broader research objectives by applying consistent analytical procedures across socio-economic and breaker-size categories. This chapter therefore provides the operational framework for the empirical analyses presented in Chapter 4.

Chapter 4 — Results and Discussion

This chapter reports the empirical comparison between observed ADMD (99.5th-percentile load, $Q_{0.995}$) and the SA standard ADMD (SANS 507-1:2019) across the Free State case studies. The data sources, cleaning rules, aggregation levels, and quantile estimator are described in Chapter 3. This chapter presents results only. For each case, we report:

- connection composition and breaker-size mix,
- historical and percentile load profiles, and
- deviations and coverage within the ±12% planning tolerance.

We then identify a best-fit consumer class per case using a rules-based approach: classes are first constrained by the case's eligibility (connection type/size), then ranked by absolute deviation from $Q_{0.995}$; where ties or near-ties occur, we reference observed connection characteristics, load maturity, and seasonal/diurnal patterns. Figures and tables are organised within the case-study subsections for traceability to the underlying data and calculations.

This chapter keeps all per-case evidence in line to preserve context. A summary appears at the end (Section 4.14). Each case section starts with Key findings for quick scanning, followed by the supporting figures and tables. Methods are not repeated here (see Chapter 3).

Class-selection rule: A class is deemed eligible only if its connection type or size aligns with the case profile; from among eligible classes, the one with the least absolute deviation from Q0.995 is selected, with ties broken using connection characteristics, load maturity, and seasonal or diurnal patterns.

The ADMD values published in SANS 507-1:2019 originate from a Beta-distribution-based modelling process. As a result, comparing observed ADMD values from the study areas with the tabulated SANS values is effectively a comparison between field-measured diversified demand behaviour and the Beta-distribution assumptions embedded in the standard. The differences observed in the subsequent sections therefore provide practical insight into how contemporary residential consumption aligns with, or departs from, the diversified demand representation inherent to the Beta PDF model. This interpretation positions the empirical analysis in this chapter as a direct assessment of the continued applicability of the Beta-distribution-derived ADMD parameters under modern operating conditions.

4.1 Case Study C

Case Study C explores load profiles and ADMD values in the Tshepiso and Mbeki neighbourhoods near Deneysville, examining factors affecting electricity demand.

4.1.1 Geographic Overview

Case Study C is geographically located at GPS coordinates 28.083302, -26.89443, as illustrated in Figure 2. This area includes the neighbourhoods of Tshepiso and Mbeki, near Deneysville.

Figure 2: Geographic location for Case Study C

The transformer zone for Case Study C is situated within the local municipal boundaries of Deneysville, which falls under the Metsimaholo Local Municipality in the Fezile Dabi District Municipality, Free State Province of South Africa. The local municipal authorities are responsible for providing public services, maintaining infrastructure, and promoting community development within this area.

The economy of Case Study C is diverse, with key activities including agriculture, manufacturing, and services. Deneysville serves as an important agricultural hub due to its proximity to the Vaal Dam, which supports irrigation and various water-related activities. Additionally, the town benefits from tourism, particularly related to the Vaal Dam's recreational offerings, contributing to local economic activities. Small-scale manufacturing and retail businesses also provide employment opportunities and support the local economy.

The climate in this region is generally temperate, characterised by cold winters and warm summers. Winter months (June to August) often experience significant temperature drops, increasing heating requirements. Conversely, summer months (November to February) may see a rise in temperatures, leading to higher demand for cooling. The region receives moderate rainfall, primarily during the summer months, which influences agricultural activities and impacts electricity consumption patterns.

The socioeconomic factors within Case Study C's area play a critical role in shaping electricity demand patterns. The community is diverse with low to middle-income households, with varying access to economic opportunities and public services. Education and healthcare facilities in the area contribute to the overall quality of life, with schools and clinics relying on a stable electricity supply to function effectively.

Economic disparities and employment rates affect consumption patterns, with higher electricity usage typically observed in more affluent areas due to the presence of more electrical appliances and higher energy consumption per household. In contrast, lower-income areas might exhibit reduced demand but can still present peaks during specific times, such as evening hours when residential activities are at their peak.

In summary, the geographic and socioeconomic context of Case Study C provides a comprehensive backdrop for analysing electricity consumption patterns. The combination of diverse economic activities, temperate climate, and varying socioeconomic factors offers a rich dataset for evaluating the accuracy of proposed ADMD values and understanding their implications for local electricity infrastructure planning.

4.1.2 Connections

4.1.2.1 Proportion of Installed Load by Connection Type

Figure 3 illustrates the proportion of the total installed load (measured in kilovolt-amperes, kVA) attributed to Prepaid Units (PPU) and Single-Phase Units (SPU) for Case Study C. This visual representation provides a clear comparison between the two connection types in terms of their contribution to the total installed load.

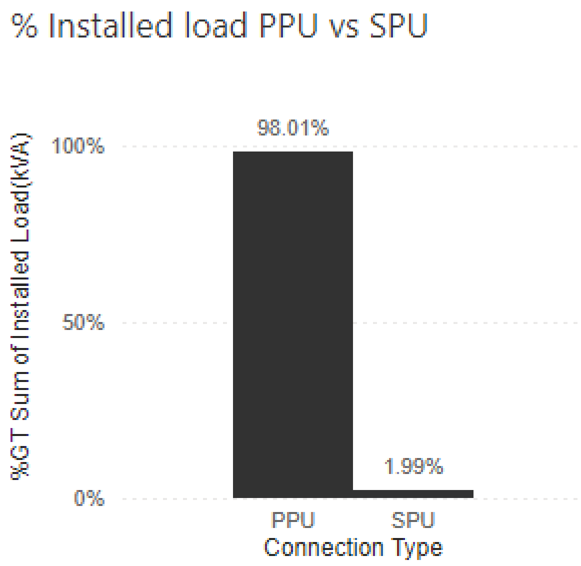


Figure 3: % Installed load by type PPU vs SPU for Case Study C

The graph illustrated in Figure 3 indicates that a significant majority (98.01%) of the total installed load is attributed to PPU connections. In contrast, SPU connections constitute a small portion (1.99%) of the total installed load. The difference highlights the predominance of PPU connections in this case study. The overwhelming majority of the installed load being attributed to PPU connections suggests a dominance of pre-paid units in this area. Typical of township areas in the Free State Province, which benefited from government electrification programmes, prepaid connections are installed at inception. Due to the low representation of SPU connections, their influence may be largely ignored for this research.

4.1.2.2 Distribution of PPU Connections by Circuit Breaker Size

Figure 4 illustrates the total Prepaid Users (PPU) connections by circuit breaker size (measured in amperes, A) for Case Study C. This visual representation provides a clear comparison of the distribution of PPU connections between two circuit breaker sizes: 20A and 60A. It highlights the dominance of each PPU Notified Maximum Demand (NMD) in terms of their contribution to the overall connections, graphically represented in Figure 4 as a pie chart.

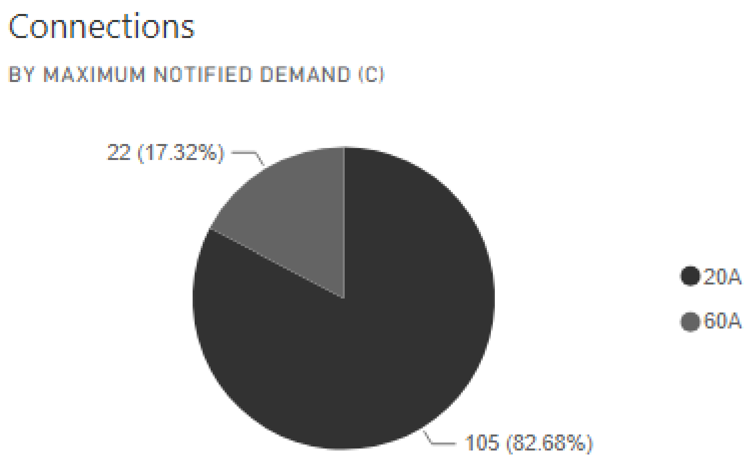


Figure 4: Total PPU connections by Circuit Breaker Size (c) for Case Study C

Figure 4 shows that a significant majority (82.68%) of the total PPU connections are fitted with 20A circuit breakers, which is typical for subsidised basic grid-access connections. In contrast, 60A circuit breakers constitute a smaller portion (17.32%) of the total PPU connections, representing connections upgraded as part of paid NMD upgrades. This notable difference highlights the prevalence of 20A circuit breakers in this case study, suggesting that most PPU connections are designed for basic access and lower power consumption levels.

4.1.2.3 Connection Trends

Figure 5 illustrates the total connections contribution by year for Case Study C. This graph provides a historical perspective on the number of established connections. This representation aims to provide insights into the load growth in terms of age.

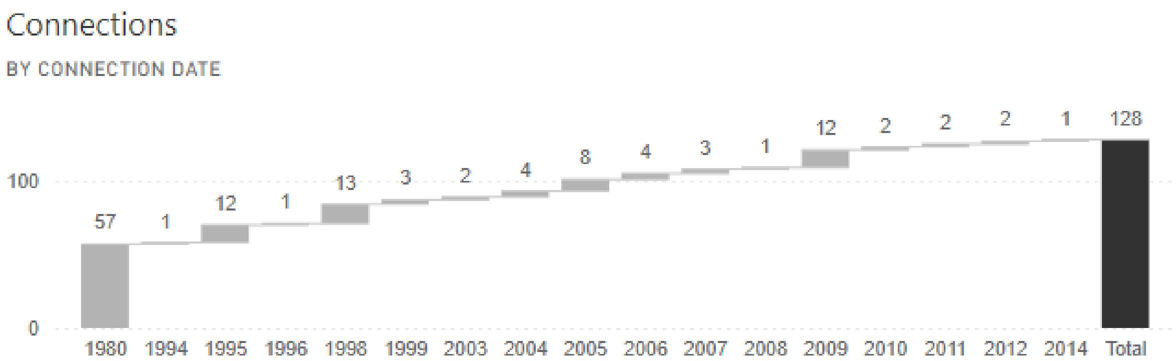


Figure 5: Total connections over time for Case Study C

The graph shown in Figure 5 indicates that a significant number of connections were established in 1980, with 57 connections. Thereafter, there was a noticeable decline in new connections until 1995. From 1995 onwards, there has been a gradual increase in the number of connections each year, with notable spikes in 1998 and 2009. This pattern suggests periods of concentrated development and expansion of the electrical distribution network, particularly in the late 1990s and early 2000s.

4.1.2.4 Connection Age Analysis by Breaker Size

The diverging bar chart in Figure 6 illustrates the average age of connections categorised by each circuit breaker size for Case Study C.

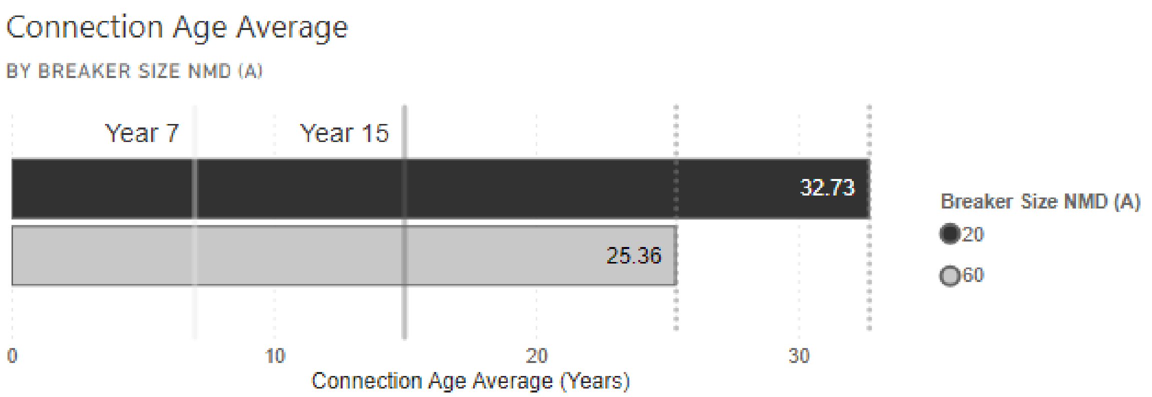


Figure 6: Connection Age Analysis for Case Study C

From Figure 6, it is observed that the average age of connections with 20A circuit breakers is 32.73 years, while the average age of connections with 60A circuit breakers is 25.36 years. The difference in average ages, with the 20A connections being older by approximately 7.37 years compared to the 60A connections, suggests a significant variance in the installation or upgrade times for these breaker sizes.

Given that both categories of circuit breaker size have connection ages significantly higher than 15 years, it is appropriate to use the 15-year parameters according to SANS 507-1:2019 – Table 2. Additionally, it should be noted that the 'c' values for 20A, 15-year parameters are limited to Class ID 1 and 2, whereas the 60A Class IDs, according to the 15-year 'c' values, are from Class ID 3 and higher.

The following conclusions can be drawn from the above analysis. Firstly, the presence of both 20A and 60A connections suggests a heterogeneous consumer group. Secondly, the significant difference in the average ages of the two categories indicates a pattern of load growth and upgrading. The younger average age for 60A connections could imply that these connections have been installed more recently, possibly as upgrades from 20A connections to accommodate increased demand.

This pattern aligns with typical practices where electrical infrastructure is upgraded to meet higher demand, resulting in newer, larger-capacity connections replacing older, smaller ones. The data thus reflects the evolving nature of electrical connections in residential areas, highlighting how infrastructure adapts to changing demands over time. The older average age of the 20A connections suggests that these have been in place longer, potentially awaiting upgrades as demand increases. The substantial difference in ages indicates that upgrades from 20A to 60A connections have been more frequent or recent, leading to a younger average age for the higher capacity connections.

4.1.3 Load Profiles

4.1.3.1 Historical Load Profile Analysis

The historical load profile for Case Study C, as depicted in Figure 7, represents a dense sampling of instantaneous load data collected from January 1, 2019, to August 26, 2021. This profile provides a comprehensive overview of the electrical consumption patterns over the given period. Key metrics, such as the mean load, maximum recorded demand, and the 99.5th percentile, are prominently highlighted to indicate typical and peak usage levels. The mean value, represented by the "Mean: 54.70" line, serves as an average indicator of the load during the study timeframe. The maximum demand, indicated by the "Maximum: 153.04" line, marks the highest observed load, reflecting peak consumption. The 99.5th percentile line, considered the measured After Diversity Maximum Demand (ADMD) value, at "99.5th Percentile: 115.13," is crucial for infrastructure planning and assessing the adequacy of existing electrical systems to meet peak demands.

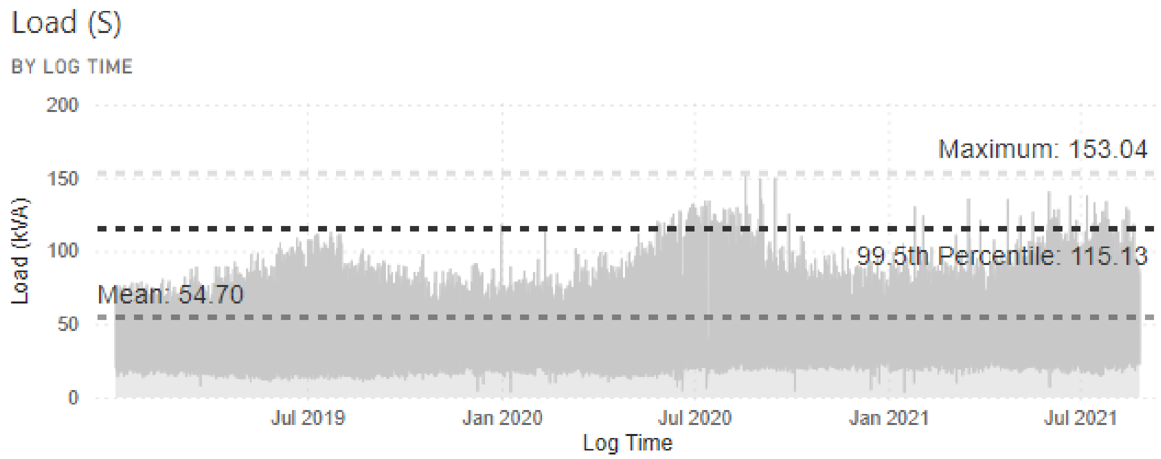


Figure 7: Historical load profile for Case Study C

Figure 7 Illustrates several essential characteristics of electrical consumption within Case Study C. The mean load, represented by a horizontal line labelled "Mean: 54.70," indicates a consistent average usage throughout the study period. The profile exhibits fluctuations, with some seasonal and daily variations, reflecting changes in consumption patterns. The maximum demand, indicated by the "Maximum: 153.04" line, was significantly higher than the mean, suggesting occasional peaks in usage. The 99.5th percentile value, marked at "99.5th Percentile: 115.13," represents a conservative estimate of the ADMD, indicating that the system must be capable of handling loads up to this value most of the time.

The normal distribution of the historical load profile data for Case Study C, shown in Figure 8The distribution of the load data is illustrated as a bell curve, providing a statistical representation. This graphical depiction allows for an understanding of the central tendency, variability, and skewness of the data, offering insights into typical and extreme load values.

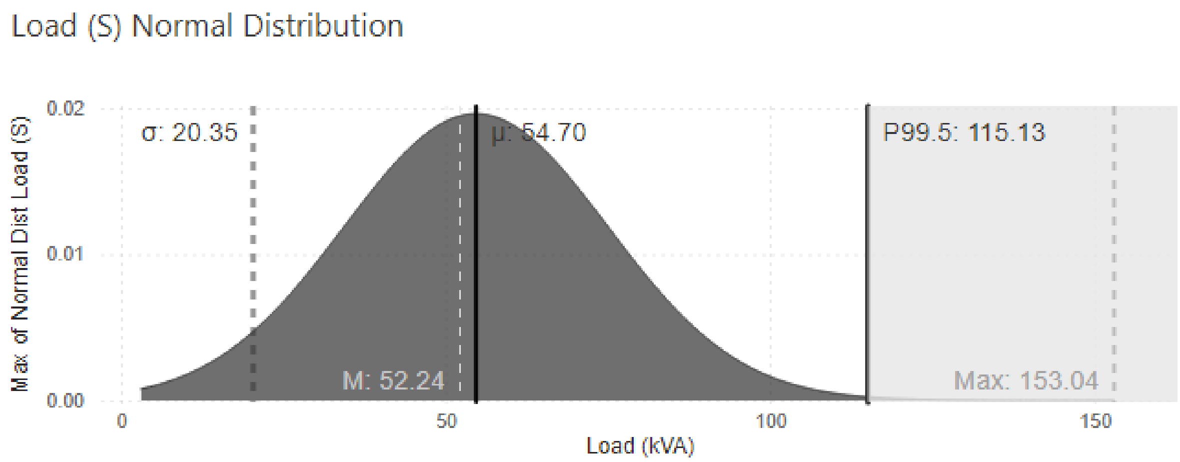


Figure 8: Normal distribution of Historical Load Profile data for Case Study C

The bell curve in Figure 8 reveals a normal distribution centred around the mean (μ) of 54.70 kVA, with a standard deviation (σ) of 20.35 kVA. The peak of the curve, or the mode (M), is close to "M: 52.24," suggesting that most data points cluster around this value. The 99.5th percentile, marked at "P99.5: 115.13," indicates the point beyond which only 0.5% of the data points lie, highlighting the upper tail of the distribution. The maximum recorded load indicated at "Max: 153.04" underscores the presence of occasional extreme values. The bell curve's shape and spread provide a clear picture of the data's overall distribution, with the majority of load values falling within a predictable range around the mean, reflecting a relatively stable consumption pattern with occasional peaks.

4.1.3.2 99.5th Percentile Load Analysis

In evaluating the 99.5th percentile across various aggregations for Case Study C, a comprehensive analysis is conducted to understand the After Diversity Maximum Demand (ADMD), with the 99.5th percentile being considered as the observed ADMD. This evaluation finds data illustrated in Figure 9, Figure 10, and Figure 11, which provide insights into annual, monthly, and overall trends, respectively.

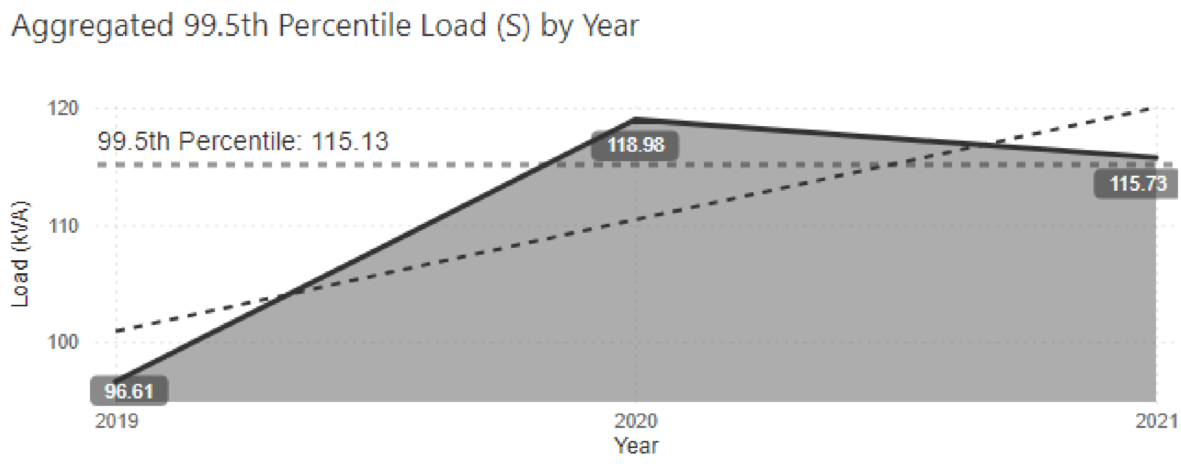


Figure 9: 99.5th Percentile load by year for Case Study C

Figure 9 presents the 99.5th percentile load by year for Case Study C, covering the period from January 2019 to August 2021. This graph highlights the peak loads aggregated annually, providing a clear view of demand trends over time. The 99.5th percentile line, set at 115.13 kVA, serves as a benchmark for these values. Notably, the minimum value recorded was 96.61 kVA in 2019, while the maximum reached 118.98 kVA in 2020, with a slight decrease to 115.73 kVA in 2021. This indicates an overall upward trend from 2019 to 2020, followed by stabilisation. The data for 2020And 2021 exceed the 99.5th percentile line, while 2019 falls below, indicating periods of increased demand in recent years.

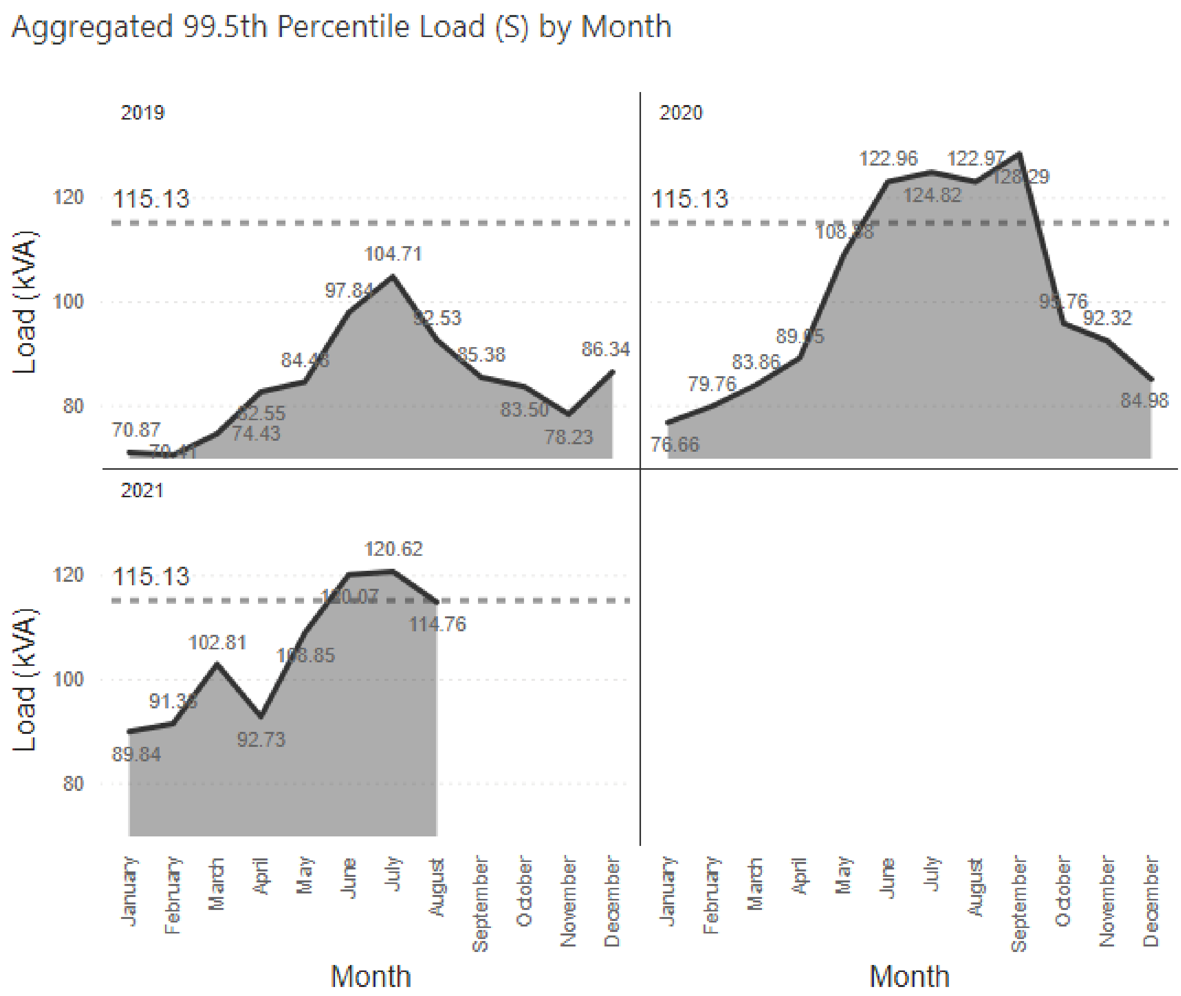


Figure 10: 99.5th Percentile load by each year for Case Study C

Figure 10 further breaks down the 99.5th percentile load by each year, offering a more granular view of monthly variations within each year. The graph shows that in 2019, the peak load occurred in June at 104.71 kVA, while 2020 saw a peak in September at 128.92 kVA. In 2021, the highest load was recorded in August at 120.62 kVA. The analysis shows that monthly values fluctuate, with certain months significantly exceeding the 99.5th percentile threshold, particularly in 2020And 2021, reflecting heightened demand during these periods.

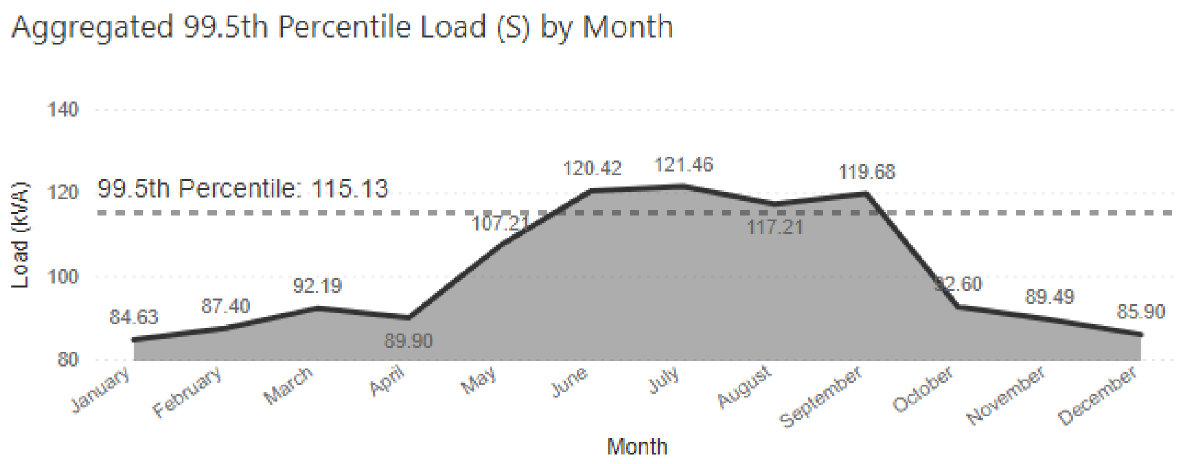


Figure 11: Aggregated 99.5th Percentile load by Month for Case Study C

Figure 11 provides a comprehensive view of the aggregated 99.5th percentile load by month across all years. It highlights a peak in June and July, with the highest value reaching 121.46 kVA in July. The monthly trend shows a rise in demand starting in May, peaking mid-year, and then gradually decreasing towards December, where the load drops to 85.90 kVA. This trend suggests seasonal variations in demand, with mid-year experiencing higher consumption.

The 99.5th percentile load analysis for Case Study C reveals significant insights into the ADMD patterns. The data indicate an overall increasing trend in peak demand, with notable variations by year and month. The highest loads often exceed the 99.5th percentile threshold, particularly in the mid-year months. This analysis underscores the importance of accurate load forecasting and infrastructure planning to accommodate these peaks. The findings suggest a need for further investigation into the factors driving these fluctuations, such as seasonal effects, economic conditions, and changes in consumer behaviour, to ensure a reliable and efficient electricity supply.

4.1.3.3 99.5th Percentile Load Analysis: Daily Demand Profiles

The 99.5th percentile load analysis provides insights into the highest electricity demand scenarios, representing the load that is only exceeded by 0.5% of occurrences. This analysis helps identify peak demand periods and assess infrastructure needs. The following figures illustrate the daily demand profiles aggregated by month and then combined into a single 24-hour period for Case Study C.

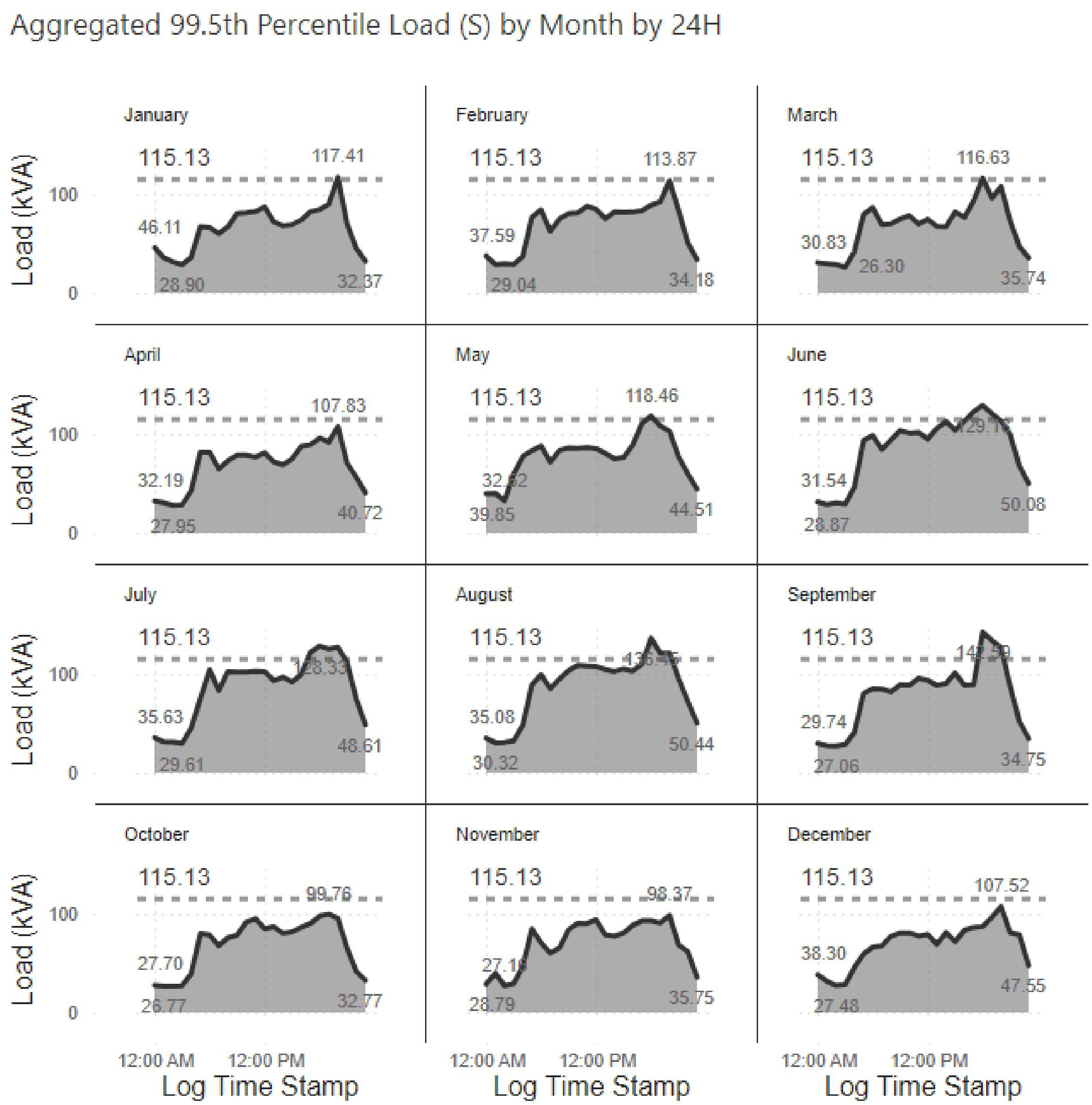


Figure 12: Aggregated 99.5th Percentile load by 24-h day by Month for Case Study C

Figure 12 presents the monthly aggregated 99.5th percentile load profiles, highlighting variations in demand throughout the year. Each panel shows the daily load profile, with the 99.5th percentile load line marked at 115.13 kVA. Notable seasonal variations can be observed:

> **Winter Months (June - August)**: The daily peaks consistently exceed the 99.5th percentile line, indicating higher demand. In June, the peak load reaches approximately 129.71 kVA, while July and August see peaks around 136.33 kVA and 137.56 kVA, respectively.
>
> **Summer Months (December - February)**: The daily peaks generally remain below the 99.5th percentile line, with February showing a peak of 113.87 kVA. The demand is lower during this period, reflecting decreased heating needs.

Transitional Months (March, September): These months show peaks near the 99.5th percentile line. March has a peak of 116.63 kVA, while September has a higher peak at 149.52 kVA, potentially due to heating and cooling overlap.

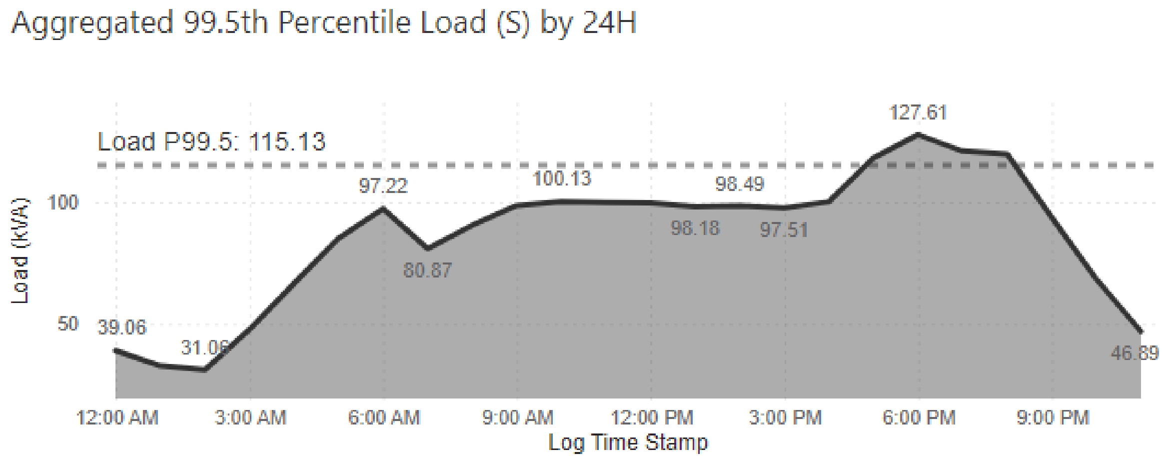


Figure 13: Aggregated 99.5th Percentile load by 24-h day for Case Study C

Figure 13 consolidates the daily demand profiles into a single 24-hour period, providing an overview of the typical daily demand pattern. The 99.5th percentile load line remains at 115.13 kVA. Key observations include:

Morning and Evening Peaks: There is a sharp increase in demand during early morning hours (around 6:00 AM), reaching a load of approximately 97.22 kVA. The evening peak, occurring around 6:00 PM, surpasses the 99.5th percentile line with a load of 127.61 kVA, indicating a significant increase in residential activities such as cooking and heating.

Off-Peak Periods: The lowest demand occurs during late night and early morning hours, with the load dropping below 50 kVA, well below the 99.5th percentile line.

The 99.5th Percentile Load Analysis for Case Study C highlights significant seasonal and daily variations in electricity demand. The data reveal that peak demands are more pronounced during winter months, often exceeding the 99.5th percentile threshold, indicating higher heating requirements. Conversely, summer months show lower peaks, reflecting reduced energy consumption. The analysis underscores the importance of understanding these patterns for effective energy infrastructure planning and resource allocation.

4.1.4 Proposed ADMD vs Measured ADMD

This section aims to compare the proposed After Diversity Maximum Demand (ADMD) values suggested by SANS 507-1:2019 Year-15 parameters with the observed ADMD values for Case Study C. This comparison is crucial for assessing the accuracy and reliability of the proposed standards in predicting real-world electricity demand. By analysing the discrepancies between these values, we can determine the applicability of the SANS guidelines and identify any necessary adjustments for improved planning and infrastructure design.

- Total Connections: 128
- Average Age: 31.31 years (greater than 15 years; therefore, Year-15 parameters are used)
- Installed Load: 802.60 kVA (6.27 kVA per connection)
- P99.5 Load: 115.13 kVA (0.90 kVA per stand)
- Resultant P99.5 Diversity Factor (DF): 0.14

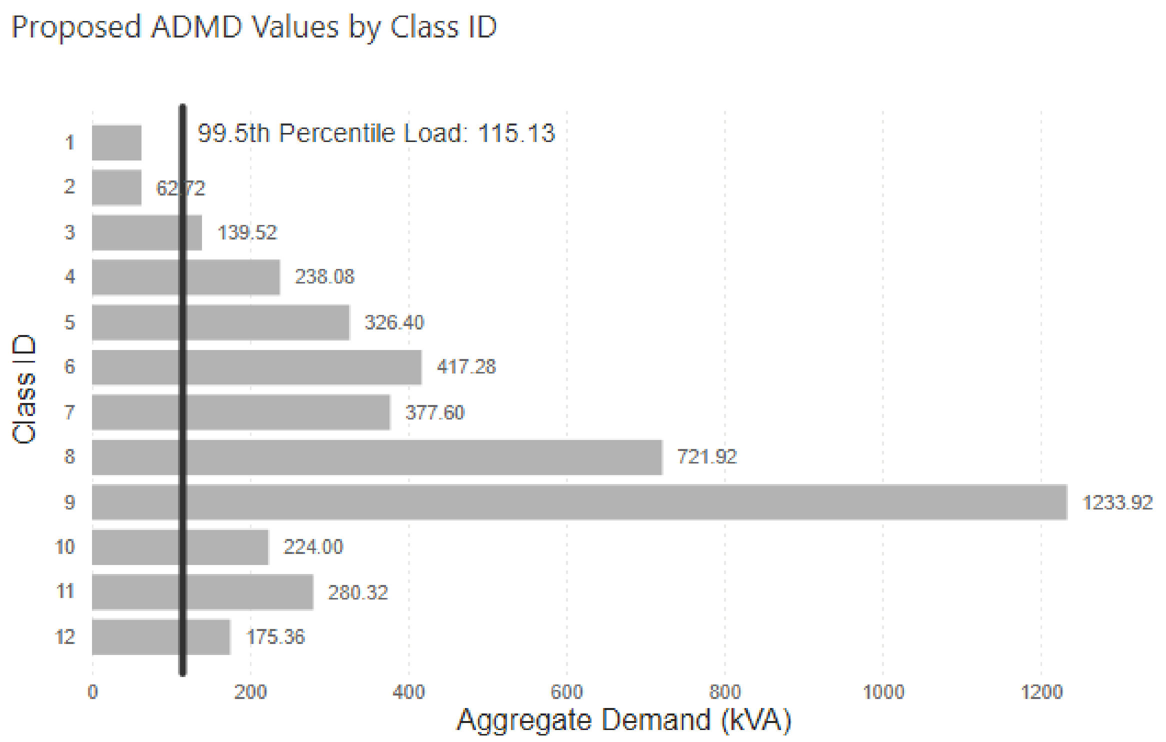


Figure 14: Proposed Year-15 ADMDs result by Class ID for Case Study C

The data from Figure 14 reveals that the proposed ADMD values for most consumer classes significantly exceed the measured 99.5th percentile load. Notably, Class ID 9 (Urban Estate) has a proposed ADMD value that is more than ten times the measured load, indicating a possible overestimation. On the other hand, lower class IDs such as 1 and 2 show a proposed ADMD that is closer to the measured load, although still higher. This suggests that the SANS guidelines may need revision to reflect actual consumption patterns better.

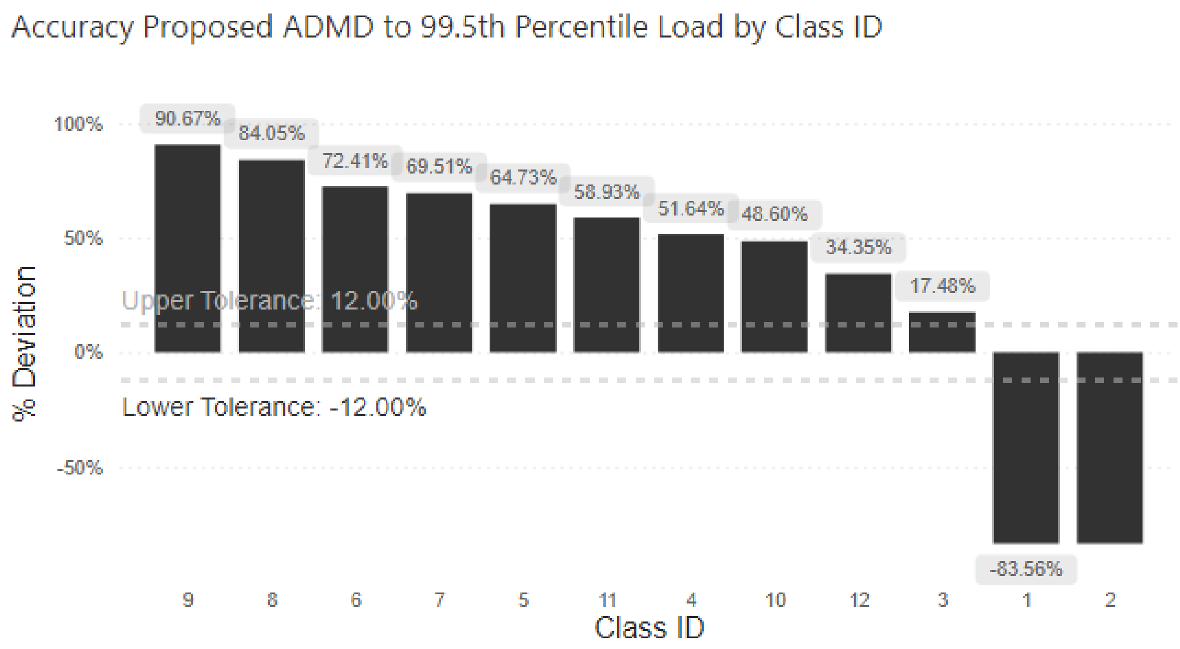


Figure 15: Deviation of SANS 507-1:2019 Year-15 ADMD by Class ID vs. 99.5th Percentile Load for Case Study C

Figure 15 presents the percentage deviation of the proposed ADMD values from the measured 99.5th percentile load for each class ID. The deviation is significant across most classes, with Class ID 9 showing the highest positive deviation at 90.67%. In contrast, Class IDs 1 and 2 show negative deviations, indicating that the proposed values are lower than the measured loads for these classes.

The deviations highlighted in Figure 15 indicate a substantial overestimation of the ADMD values for most consumer classes according to the SANS 507-1:2019 Year-15 parameters. The high positive deviations, particularly for Class ID 9, suggest that the current proposed values do not accurately capture the actual demand patterns. The negative deviations for Class IDs 1 and 2 indicate that the proposed values for these classes may be overly conservative, yet still not entirely accurate. This discrepancy underscores the need for a more nuanced approach in setting ADMD standards that consider the specific characteristics and consumption behaviours of different consumer classes.

Table 2: Detailed Comparison of Proposed ADMD vs observed ADMD for Case Study C

ID	Consumer Class	SANS 15 Year ADMD (kVA)	Case SANS 15 Year ADMD (kVA)	Accuracy	Deviation
1	Rural settlement, Non-urban, scattered	0.49	62.72	183.56%	-83.56%
2	Rural villages	0.49	62.72	183.56%	-83.56%
3	Informal settlement	1.09	139.52	82.52%	17.48%
4	Township area	1.86	238.08	48.36%	51.64%
5	Urban residential I	2.55	326.4	35.27%	64.73%
6	Urban residential II	3.25	417.28	27.59%	72.41%
7	Urban townhouse complex or duplex	2.95	377.6	30.49%	69.51%
8	Urban Townhouse II	5.64	721.92	15.95%	84.05%
9	Urban Estate	9.64	1233.92	9.33%	90.67%
10	High-rise (small)	1.75	224	51.40%	48.60%

11	High rise (medium)	2.19	280.32	41.07%	58.93%
12	Hostel	1.37	175.36	65.65%	34.35%

Table 2 provides a detailed comparison of the proposed and observed ADMD values for each consumer class. The accuracy and deviation columns highlight the discrepancies between the proposed values and the actual measured loads. Notably, Classes 1 and 2 show the highest negative deviation, suggesting that the proposed ADMD values significantly underestimate the actual load for rural settlements and villages. Conversely, Classes 8 and 9 show the highest positive deviations, indicating an overestimation for urban estates and high-end residential areas. These observations reinforce the need for revising the proposed ADMD values to better align with real-world consumption patterns.

The comparison between the proposed ADMD values and the observed ADMD values for Case Study C reveals significant discrepancies, particularly for higher consumer classes. The proposed values tend to overestimate the actual demand for urban estates and high-end residential areas, while underestimating the load for rural settlements and villages. These findings suggest that the current SANS 507-1:2019 Year-15 parameters may not accurately reflect the diverse consumption patterns observed in different consumer classes. Therefore, it is crucial to re-evaluate these standards and consider more tailored approaches to ensure reliable and efficient electricity infrastructure planning.

Interpretive Note: Case Study C

- Installed base is PPU-dominant. PPU carries ~98.01% of the installed load (SPU 1.99%). Within PPU, breaker sizes are 20A = 82.68% and 60A = 17.32%.
- Average connection age is 31.31 years. By breaker size: 32.73 years (20A) and 25.36 years (60A), so Year-15 parameters were appropriate.
- Observed ADMD (P99.5) is 115.13 kVA total (0.90 kVA/stand).
- Best fit (exact class ID): Class 3 (Informal settlement) with 1.09 kVA/stand → 139.52 kVA case total, +17.48% vs observed. Classes 1–2 are below the empirical level (≈0.49 kVA/stand; −45.6% vs 0.90), while classes above 3 propose higher per-stand values than 1.09 and therefore overshoot by larger margins.

20A supplies dominate the breaker mix, and the connections are mature, which empirically aligns with a lower-to-mid ADMD regime. Among the SANS options, Class 3 produces the lowest absolute deviation from the measured 99.5th-percentile ADMD and matches the observed connection composition better than the lower or higher classes.

4.2 Case Study D

Case Study D explores load profiles and ADMD values in Tumahole and parts of Parys, examining factors affecting electricity demand.

4.2.1 Geographic Overview

Case Study D is geographically located at GPS coordinates 28.065296, -26.894026, as illustrated in Figure 16. This area includes the neighbourhoods of Tshepiso township and parts of Mbeki, near Deneysville, within the Fezile Dabi District Municipality.

GPS Location 28.065296;-26.894026

Figure 16: Geographic location for Case Study D

The transformer zone for Case Study D is situated within the local municipal boundaries of the Metsimaholo Local Municipality, which falls under the Fezile Dabi District Municipality in the Free State Province of South Africa. The local municipal authorities are tasked with infrastructure development, service delivery, and community welfare within this region.

The economy of the surrounding area is diverse, with key activities including agriculture, manufacturing, and services. Deneysville serves as a significant agricultural hub due to its proximity to the Vaal Dam, which supports irrigation and various water-related activities. The town also benefits from tourism, particularly related to the Vaal Dam's recreational offerings, contributing to local economic activities. Additionally, small-scale manufacturing and retail businesses provide employment opportunities and support the local economy.

The climate in this region is generally temperate, characterised by cold winters and moderate to warm summers. Winter months (June to August) often experience significant temperature drops, increasing heating requirements. Conversely, summer months (November to February) may see a rise in temperatures, leading to higher demand for cooling. The region receives moderate rainfall, primarily during the summer months, which influences agricultural activities and impacts electricity consumption patterns.

The socioeconomic factors in Case Study D's area play a critical role in shaping electricity demand patterns. The community is socioeconomically diverse, comprising low to middle-income households, with varying access to economic opportunities and public services. Education and healthcare facilities in the area contribute to the overall quality of life, with schools and clinics relying on a stable electricity supply to function effectively.

Economic disparities and employment rates affect consumption patterns, with higher electricity usage typically observed in more affluent areas due to the presence of more electrical appliances and higher energy consumption per household. In contrast, lower-income areas might exhibit reduced demand but can still present peaks during specific times, such as evening hours when residential activities are at their peak.

In summary, the geographic and socioeconomic context of Case Study D provides a comprehensive backdrop for analysing electricity consumption patterns. The combination of diverse economic activities, temperate climate, and varying socioeconomic factors offers a rich dataset for evaluating the accuracy of proposed ADMD values and understanding their implications for local electricity infrastructure planning.

4.2.2 Connections

4.2.2.1 Proportion of Installed Load by Connection Type

Figure 17 illustrates the proportion of the total installed load (measured in kilovolt-amperes, kVA) attributed to Prepaid Units (PPU) and Single-Phase Units (SPU) for Case Study D. It provides a clear comparison between the two connection types in terms of their contribution to the total installed load.

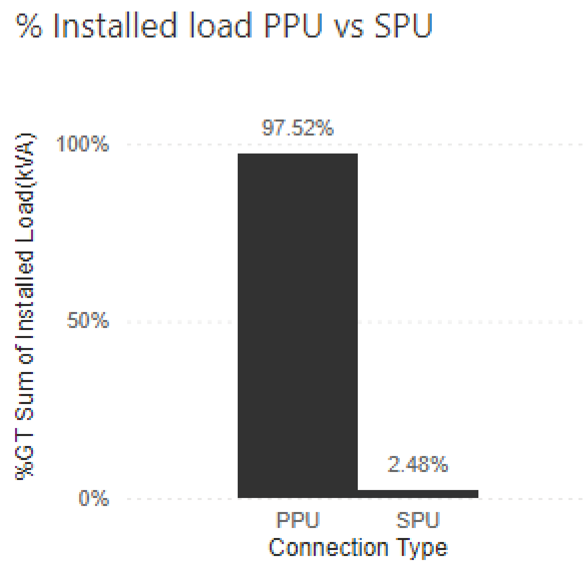


Figure 17: % Installed load by type PPU vs SPU for Case Study D

The graph illustrated in Figure 17 indicates that a significant majority (97.52%) of the total installed load is attributed to PPU connections. In contrast, SPU connections constitute a small portion (2.48%) of the total installed load. This difference highlights the dominance of PPU connections in this case study. The predominance of the installed load being attributed to PPU connections suggests these connections are part of connections delivered by government electrification programmes, as highlighted in — Literature Review.

4.2.2.2 Distribution of PPU Connections by Circuit Breaker Size

Figure 18 illustrates the total Prepaid Unit (PPU) connections by circuit breaker size (measured in amperes, A) for Case Study D. This visual representation provides a clear comparison of the ratio and distribution that makes up PPU connections between two notified maximum demand (NMD) sizes: 20A and 60A, highlighting the predominance of each in terms of their contribution to the overall connections.

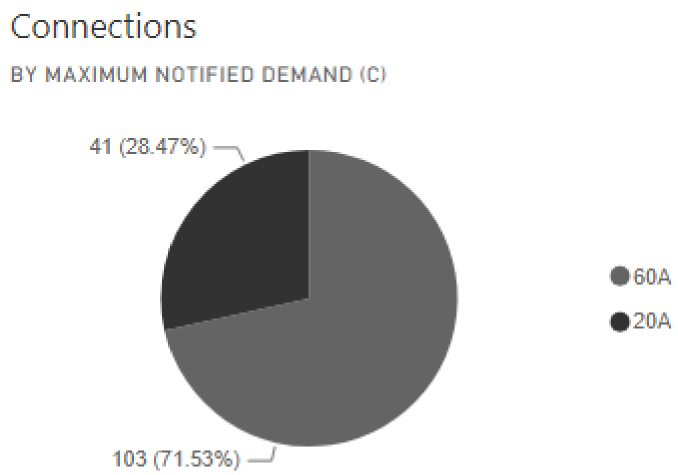


Figure 18: Total PPU connections by Circuit Breaker Size (c) for Case Study D

The graph illustrated in Figure 18, indicates that a significant majority (71.53%) of the total PPU connections utilise 60A circuit breakers as their notified maximum demand. In contrast, 20A circuit breakers constitute a smaller portion (28.47%) of the total PPU connections. This difference highlights the prevalence of 60A circuit breakers in this case study. This is indicative that the majority of connections are at the higher end of individual peak demands. In terms of the LSM and the associated “c” values indicated in Table 2 of SANS 507-1:2019, 60A connections are at the higher end of the expressed Class IDs. On the other hand, the presence of 20A connections indicates some connections have been established long ago, and are likely at the tail end of the load growth curve. 20A to 60A upgrades are not typically funded or subsidised by government entities, as seen with initial 20A connections.

4.2.2.3 Connection Trends

Figure 19 This visual representation illustrates the total number of connections over time for Case Study D, providing a historical overview of the growth and development of connections in the area and highlighting notable increases and trends over the years.

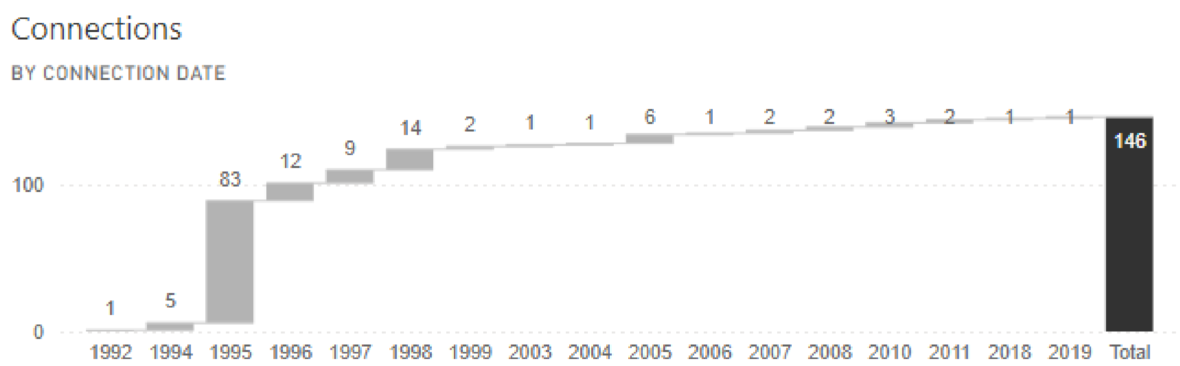


Figure 19: Total connections over time for Case Study D

The graph illustrated in Figure 19 shows a significant growth in connections from 1995 onwards. The most notable increase occurred in 1995, with a total of 83 connections being established in that year alone. Subsequent years saw a more gradual increase, with smaller increments of connections being added annually. This trend indicates a period of rapid development in the mid-1990s, followed by steady growth in the subsequent years, reflecting the expansion and infrastructure development within the area.

4.2.2.4 Connection Age Analysis by Breaker Size

The diverging bar chart in Figure 20 illustrates the average age of connections categorised by each circuit breaker size for Case Study D.

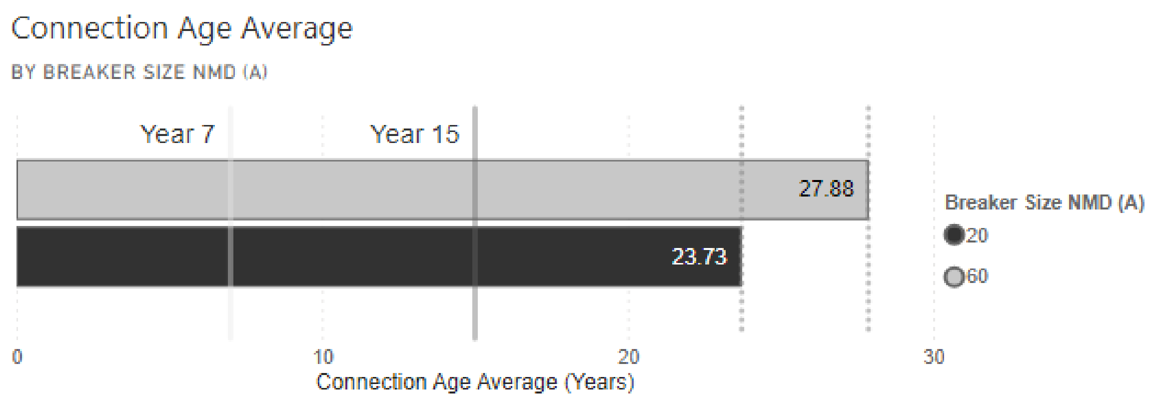


Figure 20: Connection Age Analysis for Case Study D

From Figure 20, it is observed that the average age of connections with 20A circuit breakers is 23.73 years, while the average age of connections with 60A circuit breakers is 27.88 years. The difference in average ages, with the 60A connections being older by approximately 4.15 years compared to the 20A connections, suggests a potential variance in the installation or upgrade times for these breaker sizes.

Given that both categories of circuit breaker size have connection ages significantly higher than 15 years, it is appropriate to use the 15-year parameters according to SANS 507-1:2019 – Table 2. Additionally, it should be noted that the 'c' values for 20A, 15-year parameters are limited to Class ID 1 and 2, whereas the 60A Class IDs, according to the 15-year 'c' values, are from Class ID 3 and higher.

The following conclusions can be drawn from the above analysis. Firstly, the presence of both 20A and 60A connections suggests a heterogeneous consumer group. Secondly, the difference in the average ages of the two categories indicates a pattern of load growth and upgrading. The older average age for 60A connections could imply that these connections have been in place longer, possibly initially installed for higher demand consumers or upgraded over time from 20A to 60A as demand increased.

This pattern aligns with typical practices where electrical infrastructure is upgraded to meet higher demand, resulting in newer, larger-capacity connections replacing older, smaller ones. The data thus reflects the evolving nature of electrical connections in residential areas, highlighting how infrastructure adapts to changing demands over time. The noticeable difference in ages suggests that while upgrades from 20A to 60A connections have occurred over time, the older average age of 60A connections indicates these upgrades were made earlier in the development of the electrical infrastructure in the study area.

4.2.3 Load Profiles

4.2.3.1 Historical Load Profile Analysis

The historical load profile for Case Study D, as presented in Figure 21, represents a comprehensive collection of instantaneous load data spanning from February 11, 2019, to December 31, 2023. This dataset captures the variations in electrical consumption over an extended period, providing valuable insights into daily and seasonal patterns. Key indicators, such as the mean load, maximum demand, and the 99.5th percentile, are marked to highlight the typical and peak load conditions. The mean value, indicated by the "Mean: 61.21" line, offers an average load measurement throughout the study period. The maximum demand, represented by the "Maximum: 210.85" line, identifies the peak load observed, while the 99.5th percentile line, labelled "99.5th Percentile: 142.96," signifies the measured After Diversity Maximum Demand (ADMD) value, critical for evaluating infrastructure capacity and planning.

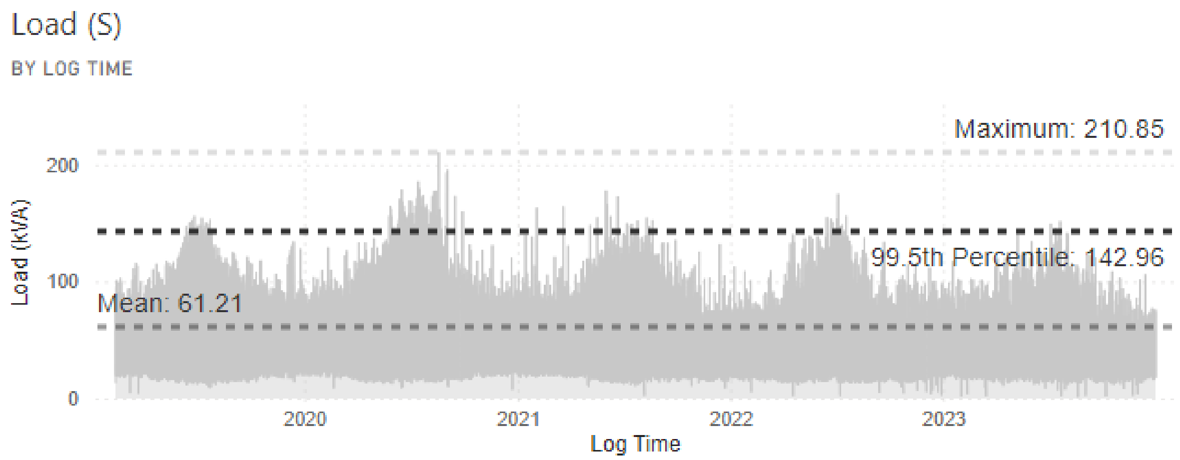


Figure 21: Historical load profile for Case Study D

As depicted in Figure 21, the historical load profile for Case Study D illustrates various significant features of the electrical load data. The mean load, represented by the "Mean: 61.21" line, suggests a moderate average consumption level. The profile demonstrates notable fluctuations, with distinct peaks, particularly noticeable during specific periods, reflecting increased demand. The maximum recorded demand, shown by the "Maximum: 210.85" line, indicates significant peaks, likely corresponding to specific high-consumption events or seasons. The 99.5th percentile, represented by the "99.5th Percentile: 142.96" line, provides a conservative estimate of the ADMD, ensuring that infrastructure can support loads up to this threshold under typical peak conditions.

The normal distribution of the historical load profile data for Case Study D, illustrated in Figure 22, provides a statistical representation of the data's distribution, shaped as a bell curve. This graphical depiction is essential for understanding the central tendency, variability, and the presence of outliers in the load data, offering a deeper statistical insight into the overall consumption patterns.

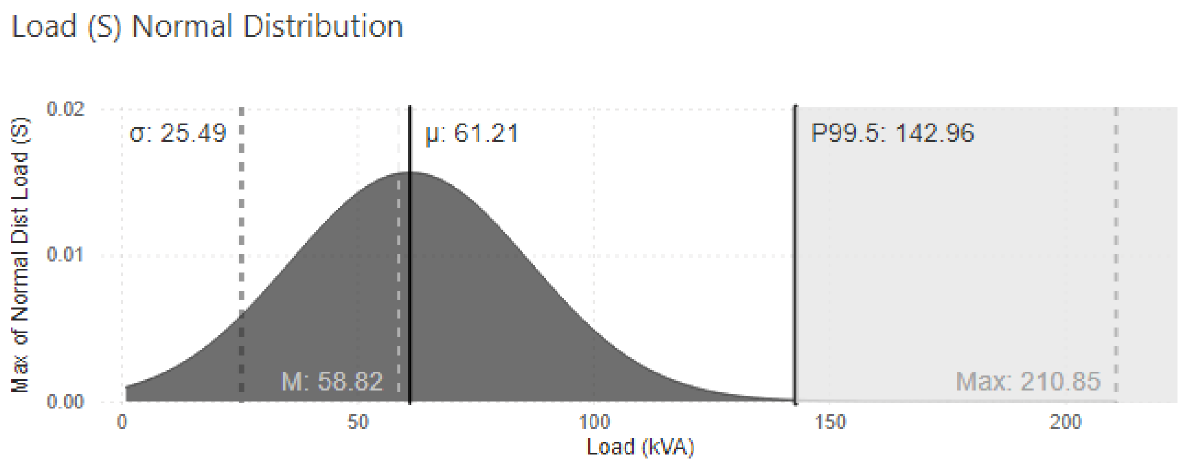


Figure 22: Normal distribution of Historical Load Profile data for Case Study D

The bell curve in Figure 22 portrays the historical load profile data as a normal distribution centred around the mean (μ) of 61.21 kVA, with a standard deviation (σ) of 25.49 kVA. The mode (M), indicated near "M: 58.82," aligns closely with the mean, suggesting a symmetrical distribution with most data points concentrated around these values. The 99.5th percentile, denoted as "P99.5: 142.96," marks the point beyond which only a small fraction of data points lie, highlighting the tail end of the distribution. The maximum observed load, "Max: 210.85," lies significantly higher than the 99.5th percentile, indicating the presence of occasional extreme values. Statistically, the bell curve's shape suggests a relatively normal distribution with a slight skewness, as noted in the occasional extreme values. This skewness reflects the instances of higher-than-usual loads, which are captured by the extended tail on the right side of the distribution.

4.2.3.2 99.5th Percentile Load Analysis

In the comprehensive evaluation of the After Diversity Maximum Demand (ADMD) for Case Study D, the 99.5th percentile load is analysed across various aggregations to understand the demand patterns. This analysis includes an examination of the data presented in Figure 23, Figure 24, and Figure 25, which illustrates the 99.5th percentile load by year, by each year, and by month, respectively.

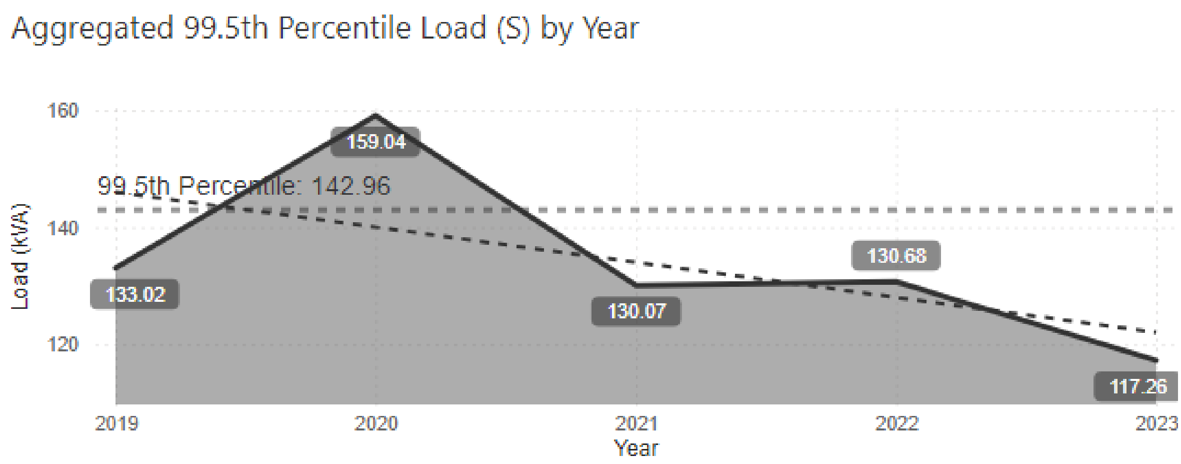


Figure 23: 99.5th Percentile load by year for Case Study D

Figure 23 shows the 99.5th percentile load aggregated by year for Case Study D, covering the period from February 2019 to December 2023. This graph provides an overview of the peak loads each year, with the 99.5th percentile line set at 142.96 kVA, indicating the observed ADMD. The data reveals a minimum load of 117.26 kVA in 2023 and a maximum load of 159.04 kVA in 2020. The trend suggests a peak in 2020, followed by a gradual decline in subsequent years. Notably, the loads in 2019 and 2021 also exceeded the 99.5th percentile line, while 2022 and 2023 fell below it, suggesting variability in demand over the years.

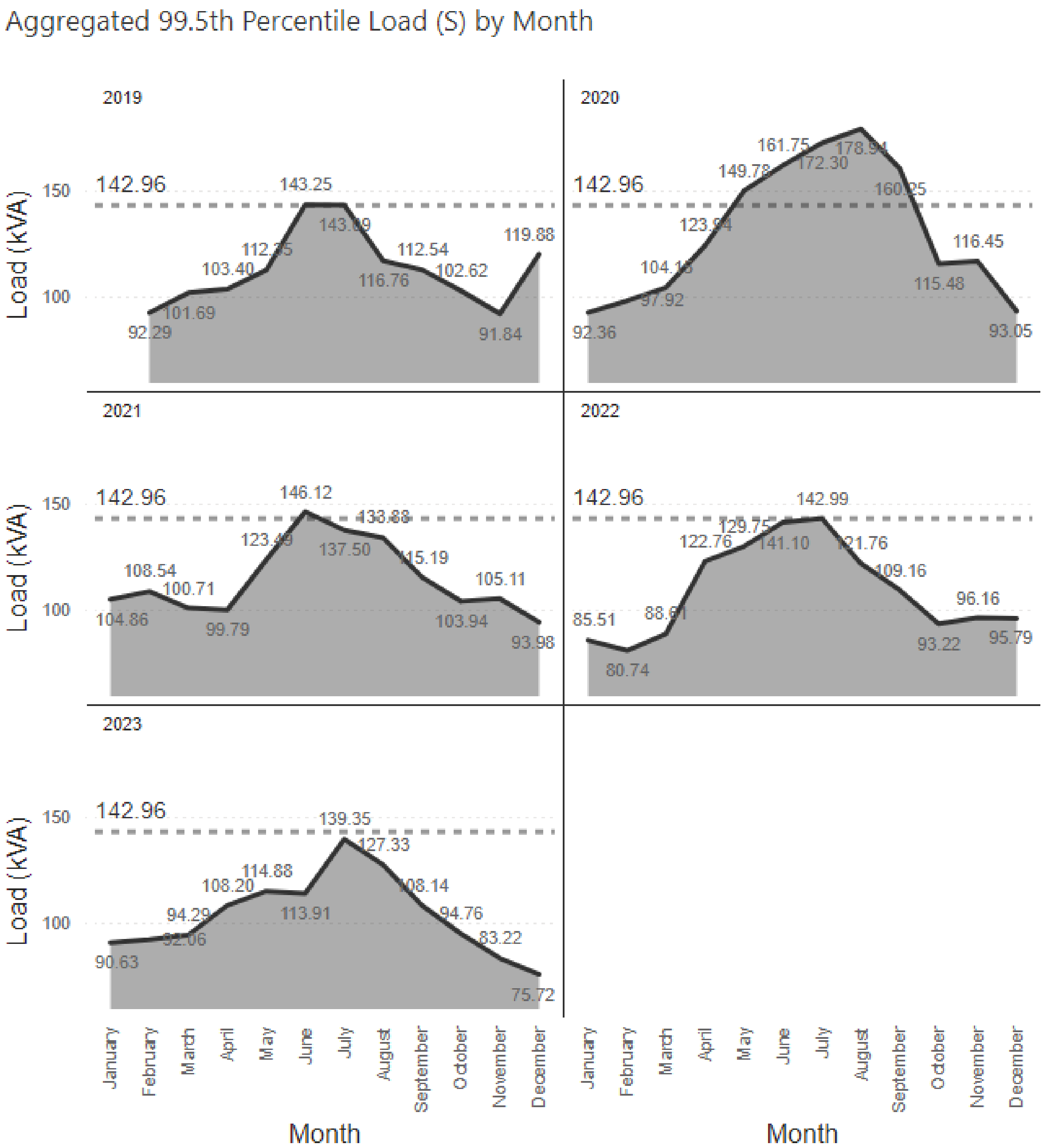


Figure 24: 99.5th Percentile load by each year for Case Study D

Figure 24 provides a detailed view of the 99.5th percentile load by each year, further breaking down the data into monthly values. In 2019, the peak was observed in August at 143.25 kVA, while 2020 had its highest load in July at 178.94 kVA. For 2021, the peak occurred in May at 146.12 kVA, and in 2022, July reached 142.99 kVA, closely aligning with the 99.5th percentile line. The year 2023 displayed a more modest peak in June at 139.35 kVA. The monthly analysis shows fluctuations, with significant peaks often surpassing the observed ADMD threshold, particularly in mid-year months, indicating periods of high demand.

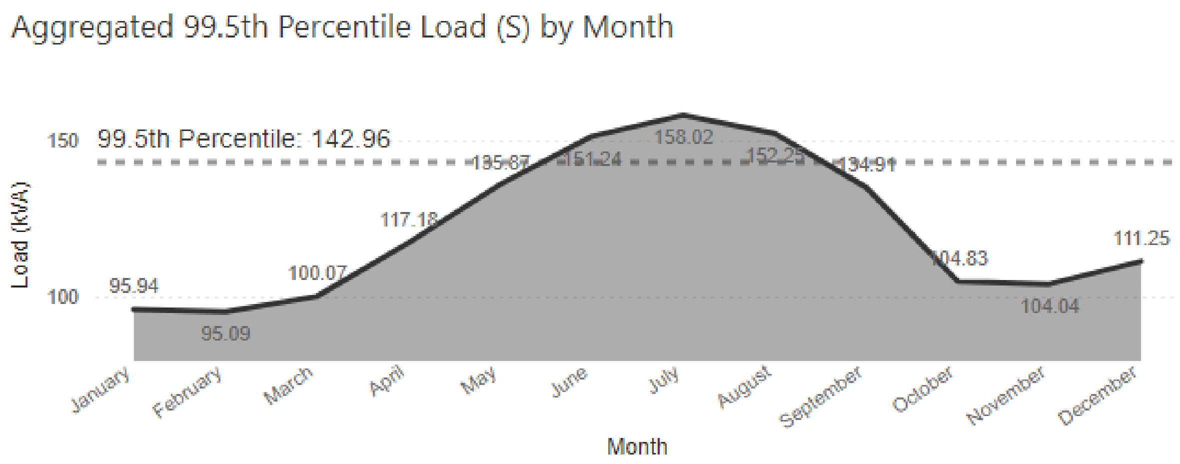


Figure 25: Aggregated 99.5th Percentile load by Month for Case Study D

Figure 25 aggregates the 99.5th percentile load by month across all years, providing a comprehensive monthly trend. The data reveals that June and July consistently experienced the highest loads, with a peak of 158.02 kVA in July. The load generally increases from February, peaking mid-year, and then declines towards December, where the load drops to 111.25 kVA. This pattern suggests a seasonal effect, with mid-year months consistently exhibiting higher electricity consumption.

The 99.5th percentile load analysis for Case Study D offers crucial insights into the ADMD patterns, with the 99.5th percentile serving as the observed ADMD. The analysis reveals a noticeable peak in demand around 2020, followed by a declining trend in subsequent years. Monthly data indicate that mid-year periods typically experience the highest demand, often exceeding the 99.5th percentile threshold. This analysis underscores the importance of accounting for these variations in planning and infrastructure development, ensuring the capacity to meet peak demand periods. Further investigation into the factors influencing these trends, such as weather patterns, economic activities, and consumer behaviour, is essential for accurate forecasting and resource management.

4.2.3.3 99.5th Percentile Load Analysis: Daily Demand Profiles

This analysis delves into the 99.5th percentile load profiles for Case Study D, focusing on the highest demand periods that are exceeded only 0.5% of the time. The 99.5th percentile load is a critical indicator for understanding extreme usage scenarios, which are essential for planning and managing electrical infrastructure. By examining these profiles, we can identify both seasonal and daily patterns in electricity consumption, providing insights into how demand fluctuates throughout the year. This analysis not only aids in assessing peak load requirements but also helps in determining the reliability and adequacy of current energy systems to handle extreme demand scenarios. The figures below offer a detailed view of these load profiles, illustrating how electricity demand varies across different months and within a typical 24-hour period.

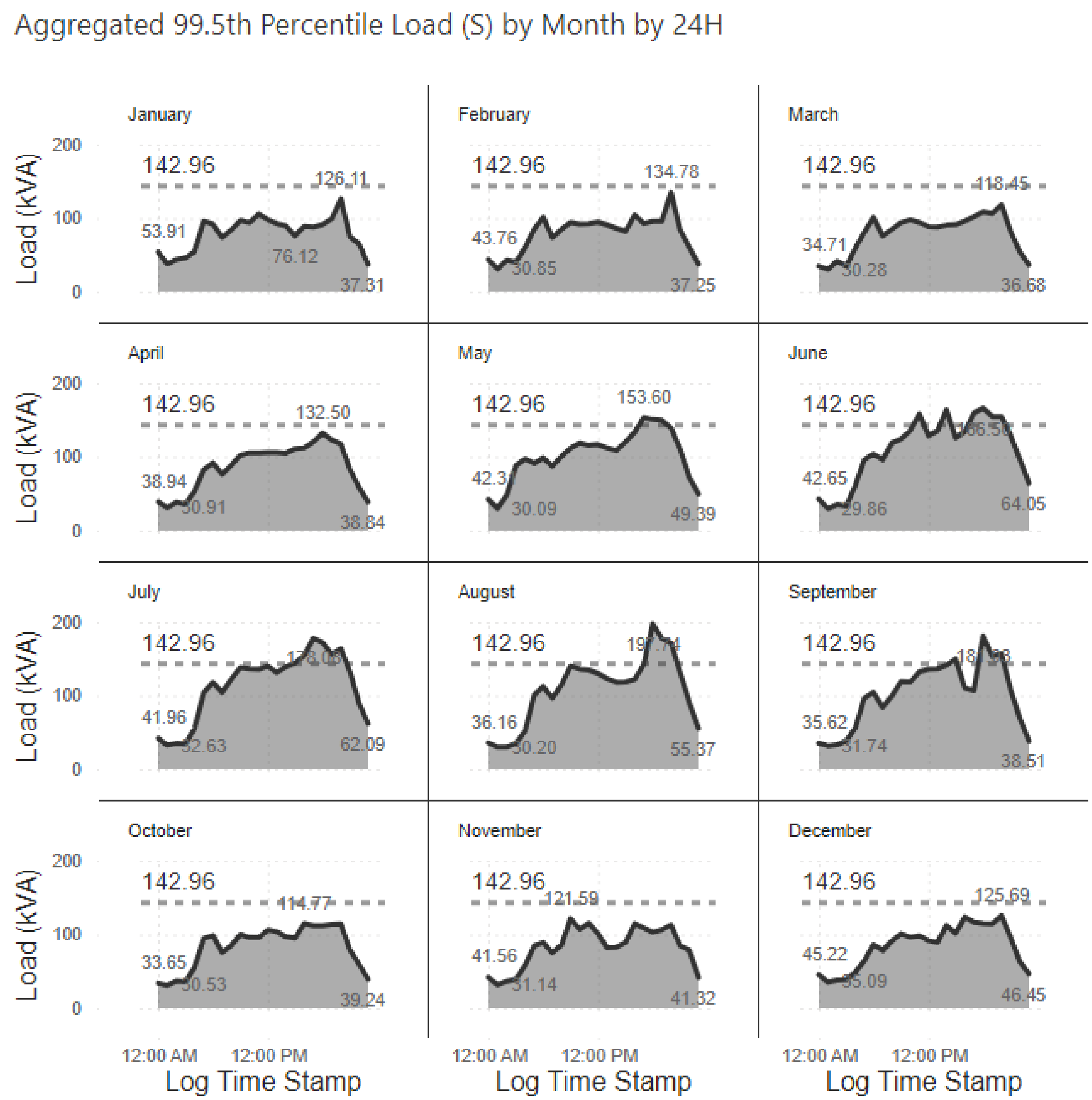


Figure 26: Aggregated 99.5th Percentile load by 24-h day by Month for Case Study D

Figure 26 illustrates the monthly variations in the 99.5th percentile load, depicting how demand fluctuates throughout the year. The dashed line at 142.96 kVA marks the 99.5th percentile load threshold, with each month's daily peaks represented.

Winter Months (June - August): Notable increases in daily peaks are observed, with loads often exceeding the 99.5th percentile line. For example, June peaks at 165.65 kVA and August reaches 199.14 kVA, indicating substantial demand likely due to heating requirements.

Summer Months (December - February): The demand generally stays below the 99.5th percentile line. However, December shows a high peak of 125.69 kVA, which might be due to increased cooling or holiday activities.

Transitional Months (March, September): Peaks during these months, such as 158.45 kVA in March and 189.95 kVA in September, also surpass the 99.5th percentile threshold, indicating fluctuating energy needs during changing weather conditions.

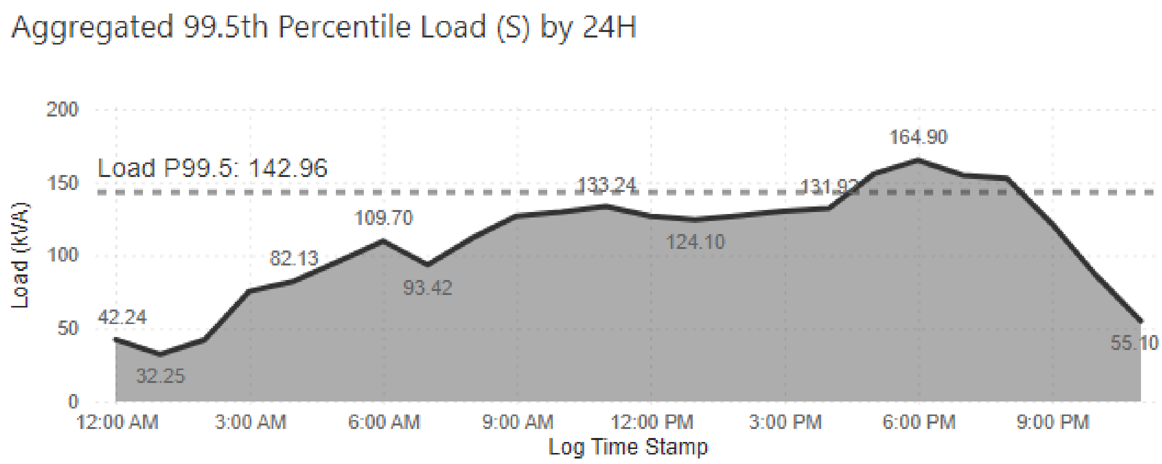


Figure 27: Aggregated 99.5th Percentile load by 24-h day for Case Study D

Figure 27 provides an aggregated view of daily demand patterns, highlighting the general trends over a typical 24-hour period. The 99.5th percentile line is set at 142.96 kVA, and key daily peaks are noted:

Morning Peak: The demand rises sharply starting around 3:00 AM, reaching 109.70 kVA by 6:00 AM. This increase correlates with morning activities.

Evening Peak: The highest demand occurs around 6:00 PM, with a significant peak at 164.90 kVA, reflecting typical residential evening usage such as cooking and heating.

Off-Peak Periods: The lowest demand is observed in the early morning hours, with a minimum load of 32.25 kVA.

The 99.5th Percentile Load Analysis for Case Study D demonstrates significant seasonal and daily variations in electricity demand. The data indicate that peak demands are most pronounced during the winter months, often exceeding the 99.5th percentile threshold due to increased heating needs. The analysis also reveals critical daily peaks in the morning and evening, essential for planning infrastructure and resource allocation to meet these demands.

4.2.4 Proposed ADMD vs Observed ADMD

This section aims to compare the proposed After Diversity Maximum Demand (ADMD) values suggested by SANS 507-1:2019 Year-15 parameters with the observed ADMD values for Case Study D. This comparison is crucial for assessing the accuracy and reliability of the proposed standards in predicting real-world electricity demand. By analysing the discrepancies between these values, we can determine the applicability of the SANS guidelines and identify any necessary adjustments for improved planning and infrastructure design.

Summary of Key Metrics

- Total Connections: 146
- Average Age: 26.71 years (greater than 15 years; therefore, Year-15 parameters are used)
- Installed Load: 1,651.00 kVA (11.31 kVA per connection)
- P99.5 Load: 142.96 kVA (0.98 kVA per stand)
- Resultant P99.5 Diversity Factor (DF): 0.09

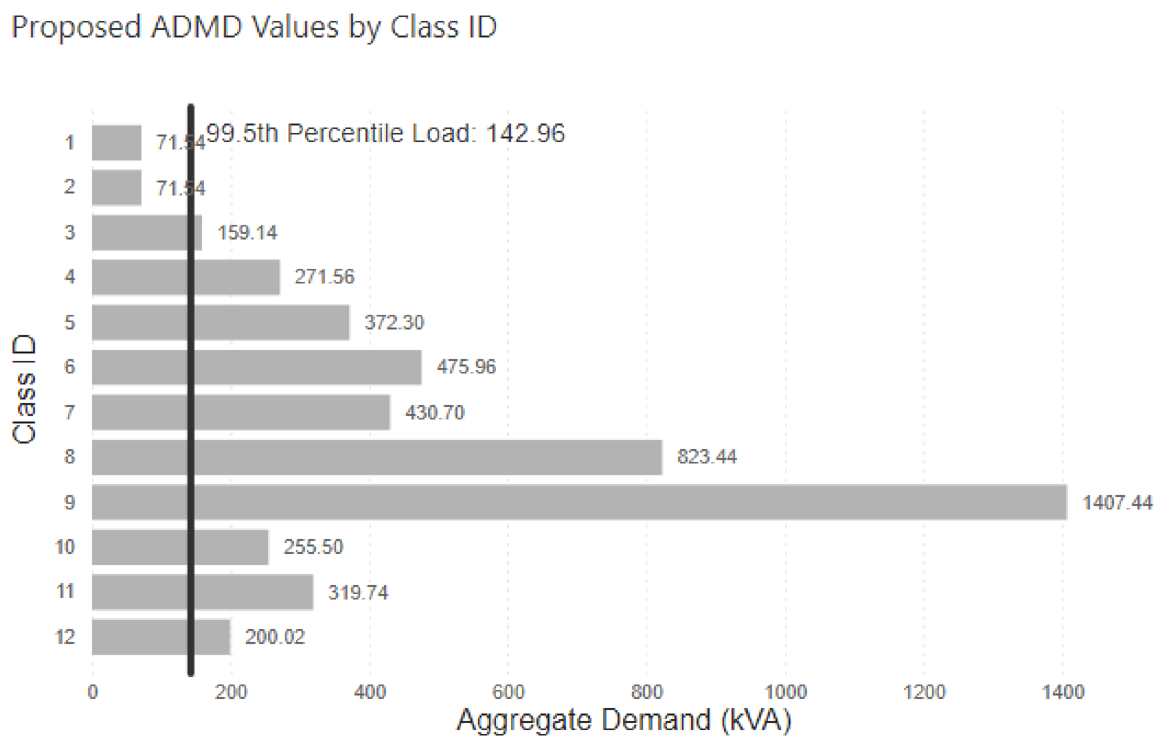


Figure 28: Proposed Year-15 ADMDs result by Class ID for Case Study D

Figure 28 illustrates the proposed ADMD values for different consumer classes as per SANS 507-1:2019 Year-15 parameters, compared against the measured 99.5th percentile load (142.96 kVA). The proposed ADMD values show significant variation across different classes, with Class ID 9 and 8 exhibiting the highest proposed values at 1407.44 kVA and 823.44 kVA, respectively. The vertical line at 142.96 kVA indicates the 99.5th percentile load, serving as a benchmark for comparison.

The data from Figure 28 reveals that the proposed ADMD values for most consumer classes significantly exceed the measured 99.5th percentile load. Notably, Class ID 9 (Urban Estate) has a proposed ADMD value that is nearly ten times the measured load, indicating a possible overestimation. On the other hand, lower class IDs such as 1 and 2 show a proposed ADMD that is closer to the measured load, although still higher. This suggests that the SANS guidelines may need revision to reflect better actual consumption patterns, particularly for higher consumer classes.

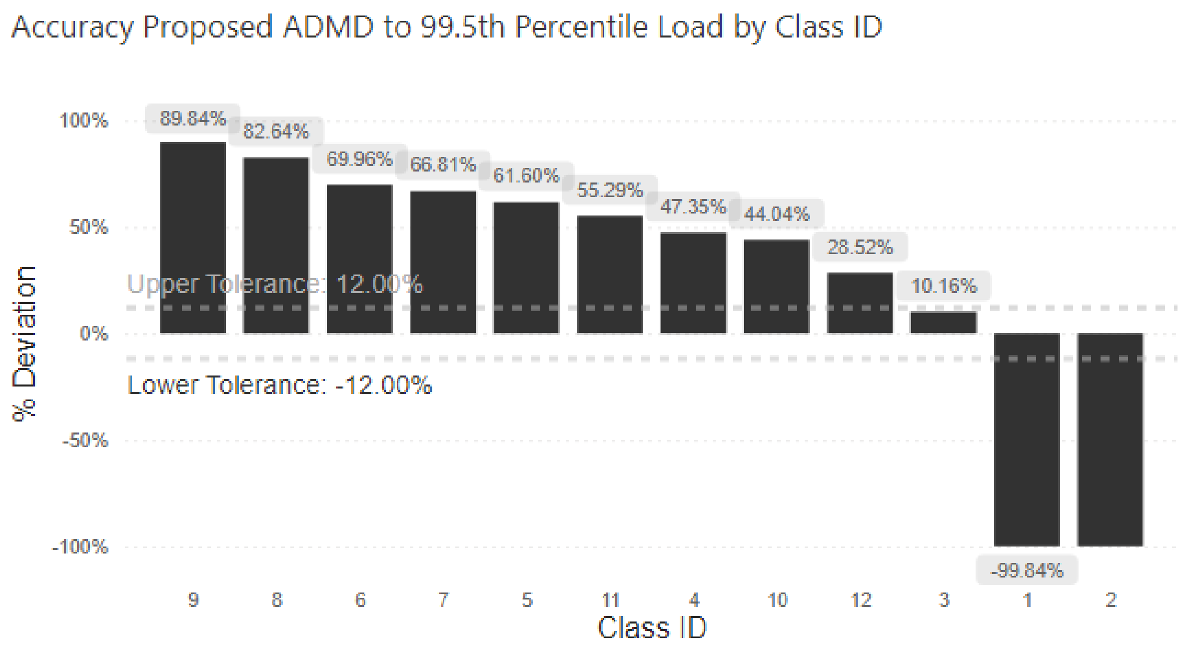


Figure 29: Deviation of SANS 507-1:2019 Year-15 ADMD by Class ID vs. 99.5th Percentile Load for Case Study D

Figure 29 presents the percentage deviation of the proposed ADMD values from the measured 99.5th percentile load for each class ID. The deviation is significant across most classes, with Class ID 9 showing the highest positive deviation at 89.84%. In contrast, Class IDs 1 and 2 show negative deviations, indicating that the proposed values are lower than the measured loads for these classes.

The deviations highlighted in Figure 29 indicate a substantial overestimation of the ADMD values for most consumer classes according to the SANS 507-1:2019 Year-15 parameters. The high positive deviations, particularly for Class ID 9, suggest that the current proposed values do not accurately capture the actual demand patterns. The negative deviations for Class IDs 1 and 2 indicate that the proposed values for these classes may be overly conservative, yet still not entirely accurate. This discrepancy underscores the need for a more nuanced approach in setting ADMD standards that consider the specific characteristics and consumption behaviours of different consumer classes.

Table 3: Detailed Comparison of Proposed ADMD vs Measured ADMD for Case Study D

ID	Consumer Class	SANS 15 Year ADMD (kVA)	Case SANS 15 Year ADMD (kVA)	Accuracy	Deviation
1	Rural settlement, Non-urban, scattered	0.49	71.54	199.84%	-99.84%
2	Rural villages	0.49	71.54	199.84%	-99.84%
3	Informal settlement	1.09	159.14	89.84%	10.16%
4	Township area	1.86	271.56	52.65%	47.35%
5	Urban residential I	2.55	372.30	38.40%	61.60%
6	Urban residential II	3.26	475.96	30.04%	69.96%
7	Urban townhouse complex or duplex	2.95	430.70	33.19%	66.81%
8	Urban Townhouse II	5.64	823.44	17.36%	82.64%
9	Urban Estate	9.64	1407.44	10.16%	89.84%
10	High rise (small)	1.75	255.50	55.96%	44.04%

11	High rise (medium)	2.19	319.74	44.71%	55.29%
12	Hostel	1.37	200.02	71.48%	28.52%

Table 3 provides a detailed comparison of the proposed and observed ADMD values for each consumer class. The accuracy and deviation columns highlight the discrepancies between the proposed values and the actual measured loads. Notably, Classes 1 and 2 show the highest negative deviation, suggesting that the proposed ADMD values significantly underestimate the actual load for rural settlements and villages. Conversely, Classes 8 and 9 show the highest positive deviations, indicating an overestimation for urban estates and high-end residential areas. These observations reinforce the need for revising the proposed ADMD values to better align with real-world consumption patterns.

Interpretive Note: Case Study D

- Installed base is PPU-dominant. PPU carries 97.52% of the installed load; within PPU, breaker sizes are 60A = 71.53% and 20A = 28.47%.
- Average connection age is 26.71 years, which supports the use of Year-15 parameters.
- Observed ADMD (P99.5) is 142.96 kVA total (0.98 kVA/stand).
- Best fit (exact class ID): Class 3 (Informal settlement) with 1.09 kVA/stand → 159.14 kVA case total, +10.16% vs observed. Higher classes propose larger per-stand values and therefore over-estimate by wider margins; Classes 1–2 are materially below the empirical level (≈0.49–0.62 kVA/stand) and under-estimate.

The breaker mix is skewed to 60A, and the connections' age is beyond 15 years, which places the zone in a mid-demand regime; among the SANS options, Class 3 yields the least absolute deviation from the measured 99.5th-percentile ADMD and aligns with the observed connection composition.

4.3 Case Study E

Case Study E explores load profiles and ADMD values in the Matwabeng Suburbs and Extensions 5 and 6 in Senekal, examining factors affecting electricity demand.

4.3.1 Geographic Overview

Case Study E is geographically located at GPS coordinates 27.638313, -28.3369, as illustrated in Figure 30. This area includes the neighbourhoods of Matwabeng Suburbs, Matwabeng Extension 5, and Matwabeng Extension 6.

GPS Location 27.638313;-28.3369

Figure 30: Geographic location for Case Study E

The transformer zone for Case Study E is situated within the Senekal town, part of the Setsoto Local Municipality, which falls under the Thabo Mofutsanyana District Municipality in the Free State Province of South Africa. The local municipal authorities are responsible for providing public services, maintaining infrastructure, and promoting community development within this area.

The economy in and around Case Study E is predominantly driven by agriculture, with the region being known for its production of crops such as maize, wheat, and sunflowers. Livestock farming is also a significant activity. Additionally, the local economy is supported by small-scale retail businesses and service industries that cater to the needs of the community. The presence of these economic activities influences the electricity demand, particularly during peak agricultural seasons when the usage of electrical equipment and irrigation systems increases.

The climate in this region is seasonal, characterised by cold winters and warm summers. Winter months (June to August) often experience low temperatures, leading to higher electricity consumption for heating purposes. During the summer months (November to February), the electricity demand may rise due to the increased use of cooling systems. The region receives moderate rainfall, mainly during the summer, which impacts agricultural activities and subsequently affects electricity consumption patterns.

The socioeconomic factors in the Matwabeng area significantly impact electricity consumption patterns. The community is socioeconomically diverse, comprising low to middle-income households, with varying levels of access to economic opportunities and public services. Educational institutions and healthcare facilities within the area rely on a stable electricity supply to operate efficiently.

Economic disparities within the community influence energy consumption, with more affluent households typically using more electrical appliances and therefore having higher electricity demand. In contrast, lower-income households might have lower overall electricity consumption but still exhibit significant usage during peak times, such as in the evenings when residential activities are at their highest.

In summary, the geographic and socioeconomic context of Case Study E provides a comprehensive understanding of the area's electricity consumption patterns. The combination of agricultural activities, seasonal climate, and diverse socioeconomic factors offers valuable data for evaluating the accuracy of proposed ADMD values and their implications for local electricity infrastructure planning.

4.3.2 Connections

4.3.2.1 Proportion of Installed Load by Connection Type

Figure 31 illustrates the proportion of the total installed load (measured in kilovolt-amperes, kVA) attributed to Prepaid Units (PPU) and Small Power Users (SPU) for Case Study E. This visual representation provides a clear comparison between the two connection types in terms of their contribution to the total installed load.

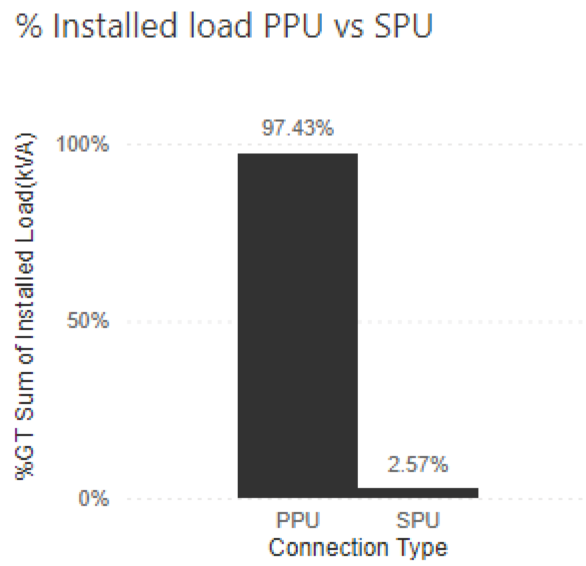


Figure 31: % Installed load by type PPU vs SPU for Case Study E

The graph illustrated in Figure 31 indicates that a majority (97.43%) of the total installed load is attributed to PPU connections. In contrast, SPU connections constitute a small portion (2.57%) of the total installed load. Concerning — Literature Review, this indicates the connections being delivered as part of government-funded electrification programmes, which are typical of township areas in the Free State Province.

4.3.2.2 Distribution of PPU Connections by Circuit Breaker Size

Shown in Figure 32 is an illustration of the distribution of Prepaid Unit (PPU) connections according to circuit breaker size (measured in amperes, A) for Case Study E. The comparison of the distribution of PPU connections between two notified maximum demand sizes, 20A and 60A, highlights the prevalence of each size, enabling conclusions to be drawn regarding their significance in influencing load characteristics.

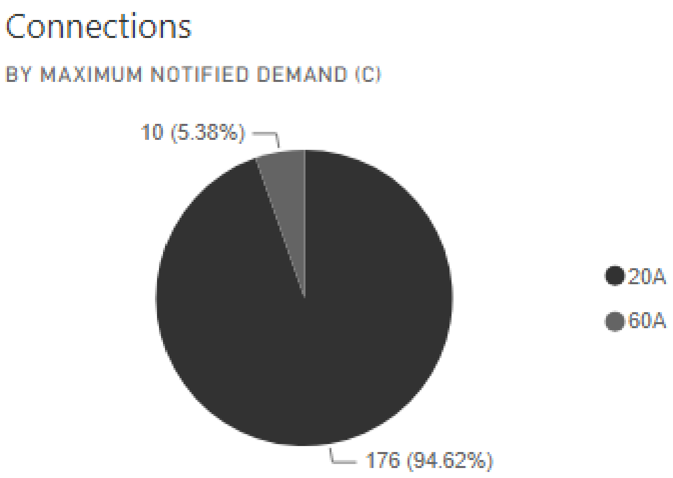


Figure 32: Total PPU connections by Circuit Breaker Size (c) for Case Study E

The graph illustrated in Figure 32 shows that a significant majority (94.62%) of the total PPU connections utilise 20A circuit breakers. In contrast, 60A circuit breakers make up a smaller portion (5.38%) of the total PPU connections. This difference highlights the prevalence of 20A circuit breakers in this case study. This is indicative of the majority of connections being at the lower end of individual peak demands.

In terms of the LSM and the associated “c” values indicated in Table 2 of SANS 507-1:2019, 20A connections are at the lower end of the expressed Class IDs. On the other hand, the presence of 60A connections indicates some connections have either been established long ago or have been increased from 20A to 60A. These upgrades are funded by individuals, unlike 20A connections, which are typically subsidised by state funding. Notably, 20A connections are initially installed through electrification programmes.

4.3.2.3 Connection Trends

Figure 33 shows the total connections over time for Case Study E. This graph provides insight into the growth and development of connections within the study area, illustrating the annual changes in the number of connections from 2001 to 2017.

Figure 33: Total connections over time for Case Study E

In Figure 33, the year 2002 marks the highest increase in connections, with 87 new connections. This significant growth period reflects a substantial development in electrification efforts within the area. The following year, 2003, saw a continuation of this trend, albeit at a slightly reduced pace, with 31 new connections. Another notable increase occurred in 2004, with 24 new connections. Subsequent years show smaller, yet consistent growth, showing ongoing but more modest expansion. The overall trend illustrates a steady increase in connections, culminating in 187 by 2017. This pattern of growth underscores the evolving infrastructure and increasing demand for electricity within the study area over the specified period.

4.3.2.4 Connection Age Analysis by Breaker Size

The diverging bar chart in Figure 34 illustrates the average age of connections categorised by each circuit breaker size for Case Study E.

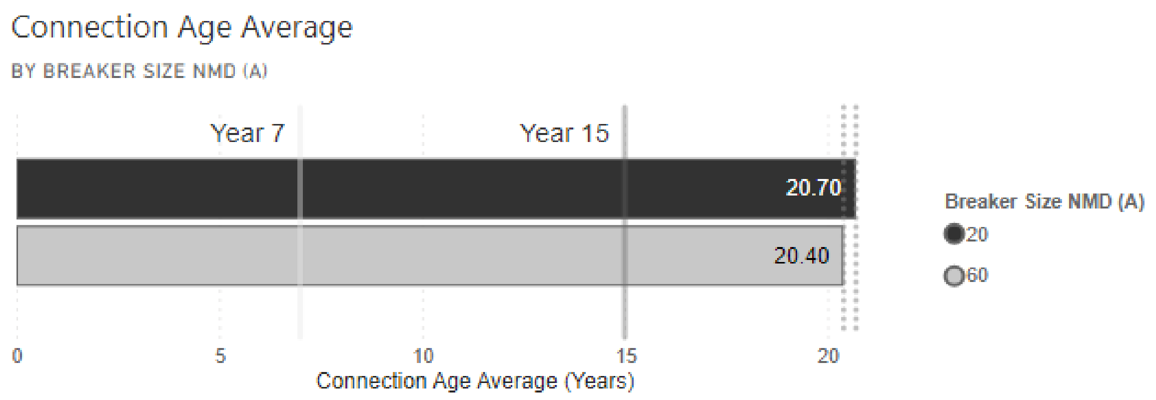


Figure 34: Connection Age Analysis for Case Study E

From Figure 34, it is observed that the average age of connections with 20A circuit breakers is 20.70 years, while the average age of connections with 60A circuit breakers is 20.40 years. The minimal difference in average ages, with the 20A connections being older by approximately 0.30 years compared to the 60A connections, suggests that both types of connections were likely established around the same time.

Given that both categories of circuit breaker size have connection ages significantly higher than 15 years, it is appropriate to use the 15-year parameters according to SANS 507-1:2019 – Table 2. Additionally, it should be noted that the 'c' values for 20A, 15-year parameters are limited to Class ID 1 and 2, whereas the 60A Class IDs, according to the 15-year 'c' values, are from Class ID 3 and higher.

The following conclusions can be drawn from the above analysis. Firstly, the presence of both 20A and 60A connections suggests a heterogeneous consumer group. Secondly, the similarity in the average ages of the two categories indicates that there has not been significant load growth necessitating upgrades from 20A to 60A connections. If significant individual load growth were present, we would expect the average age of 60A connections to be noticeably lower due to older 20A connections being upgraded over time.

This pattern reflects a stable demand for electricity within the study area, with the existing infrastructure sufficiently meeting the needs of the consumers without necessitating widespread upgrades. The data thus highlights a consistent and stable electrical demand in the residential area covered by Case Study E. The slight difference in ages also suggests that while upgrades may have occurred, they have not been so frequent or recent as to alter the average age difference between the breaker sizes significantly.

4.3.3 Load Profiles

4.3.3.1 Historical Load Profile Analysis

The historical load profile for Case Study E, as shown in Figure 35, provides a detailed view of instantaneous electrical load data from January 1, 2019, to December 31, 2023. This dataset captures fluctuations in electricity consumption over an extended period, allowing for the identification of trends and patterns. Key metrics, such as the mean load, maximum demand, and the 99.5th percentile, are indicated. The mean value, marked as "Mean: 64.28," represents the average load over the study period. The maximum demand, shown by the "Maximum: 240.13" line, represents the highest recorded load, while the 99.5th percentile, indicated as "99.5th Percentile: 139.74," serves as the measured After Diversity Maximum Demand (ADMD) value, crucial for evaluating the capacity of the electrical infrastructure.

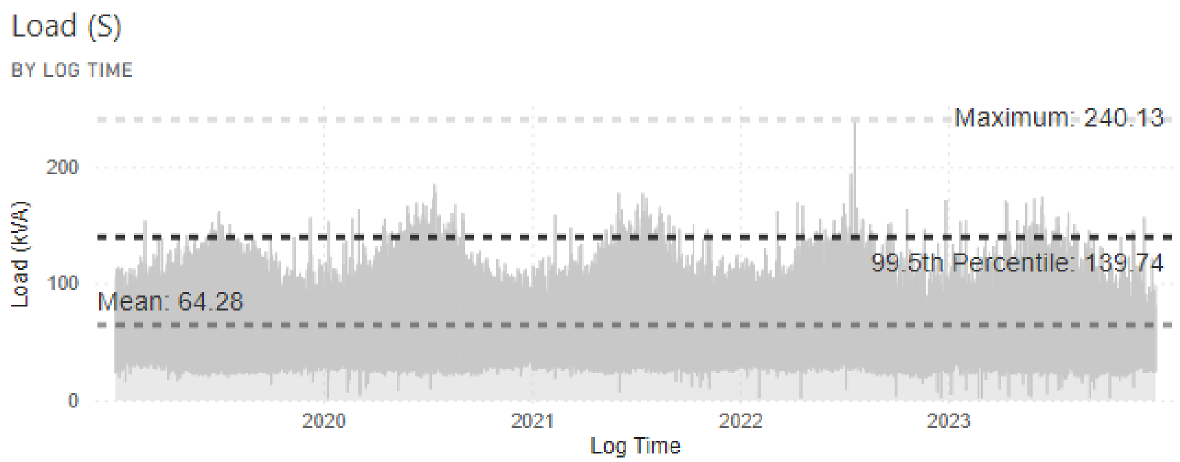


Figure 35: Historical load profile for Case Study E

As depicted in Figure 35, the historical load profile for Case Study E highlights several essential characteristics. The mean load, represented by the "Mean: 64.28" line, suggests a steady average consumption level throughout the period. The profile displays considerable variability, with noticeable peaks and troughs reflecting changes in demand. The maximum demand, indicated by the "Maximum: 240.13" line, shows significant peak usage, which could correspond to specific high-consumption periods. The 99.5th percentile, marked at "99.5th Percentile: 139.74," provides a conservative estimate of the ADMD, ensuring that the infrastructure can handle typical peak loads.

The normal distribution of the historical load profile data for Case Study E, illustrated in Figure 36, presents the data as a bell curve. This statistical representation helps to understand the distribution of load values, indicating central tendency, variability, and the presence of outliers.

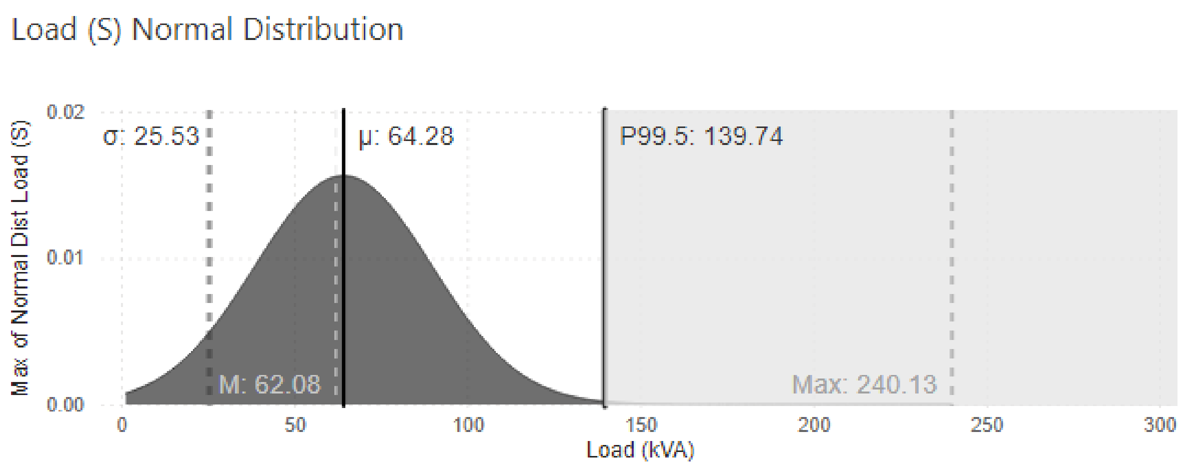


Figure 36: Normal distribution of Historical Load Profile data for Case Study E

In Figure 36, the bell curve portrays the historical load profile data as a normal distribution centred around the mean (μ) of 64.28 kVA, with a standard deviation (σ) of 25.53 kVA. The mode (M), shown near "M: 62.08," aligns closely with the mean, suggesting that most of the data points cluster around this central value. The 99.5th percentile, labelled "P99.5: 139.74," marks the upper limit for most of the data points, indicating that only a small portion exceeds this value. The maximum recorded load, "Max: 240.13," is considerably higher than the 99.5th percentile, highlighting the presence of significant outliers. Statistically, the bell curve shape suggests a relatively normal distribution with a slight rightward skew, indicating occasional higher-than-usual loads. The presence of extreme values is captured by the extended tail on the right side of the distribution, reflecting infrequent but substantial peaks in consumption.

4.3.3.2 99.5th Percentile Load Analysis

In the analysis of the After Diversity Maximum Demand (ADMD) for Case Study E, the 99.5th percentile load is considered a critical measure to understand demand patterns. This section evaluates the data across various aggregations as presented in Figure 37, Figure 38, and Figure 39, offering a comprehensive insight into the ADMD trends from January 2019 to December 2023.

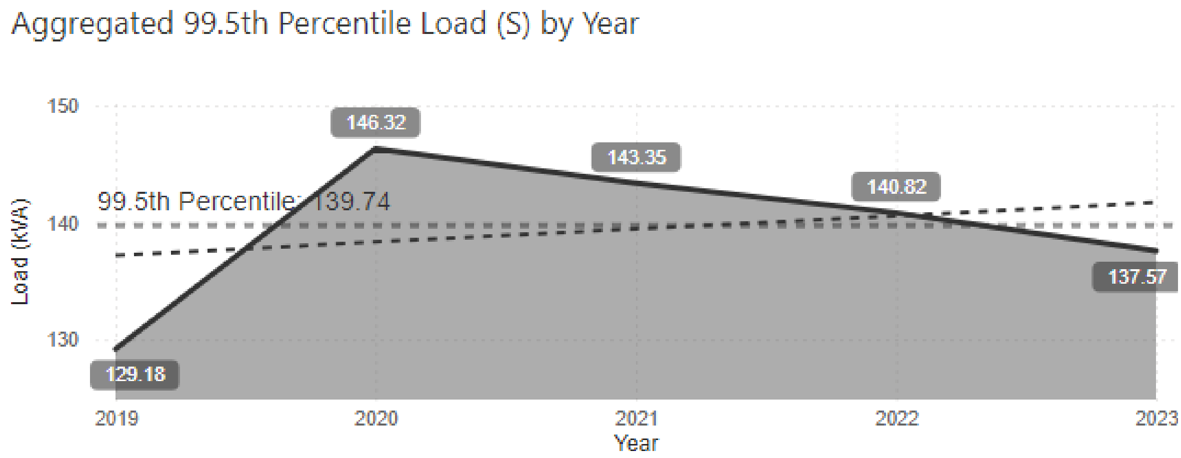


Figure 37: 99.5th Percentile load by year for Case Study E

Figure 37 displays the 99.5th percentile load by year for Case Study E, illustrating annual peak loads over the period. The graph identifies the 99.5th percentile line at 139.74 kVA, representing the observed ADMD. The lowest recorded load was 129.18 kVA in 2019, while the highest was 146.32 kVA in 2020. The trendline indicates a peak in 2020, followed by a slight decline in 2021 and a gradual decrease through to 2023, with the value for 2023 being 137.57 kVA. Notably, the years 2020And 2021 recorded values above the 99.5th percentile line, while 2019 and 2023 fell below it, reflecting fluctuating demand across these years.

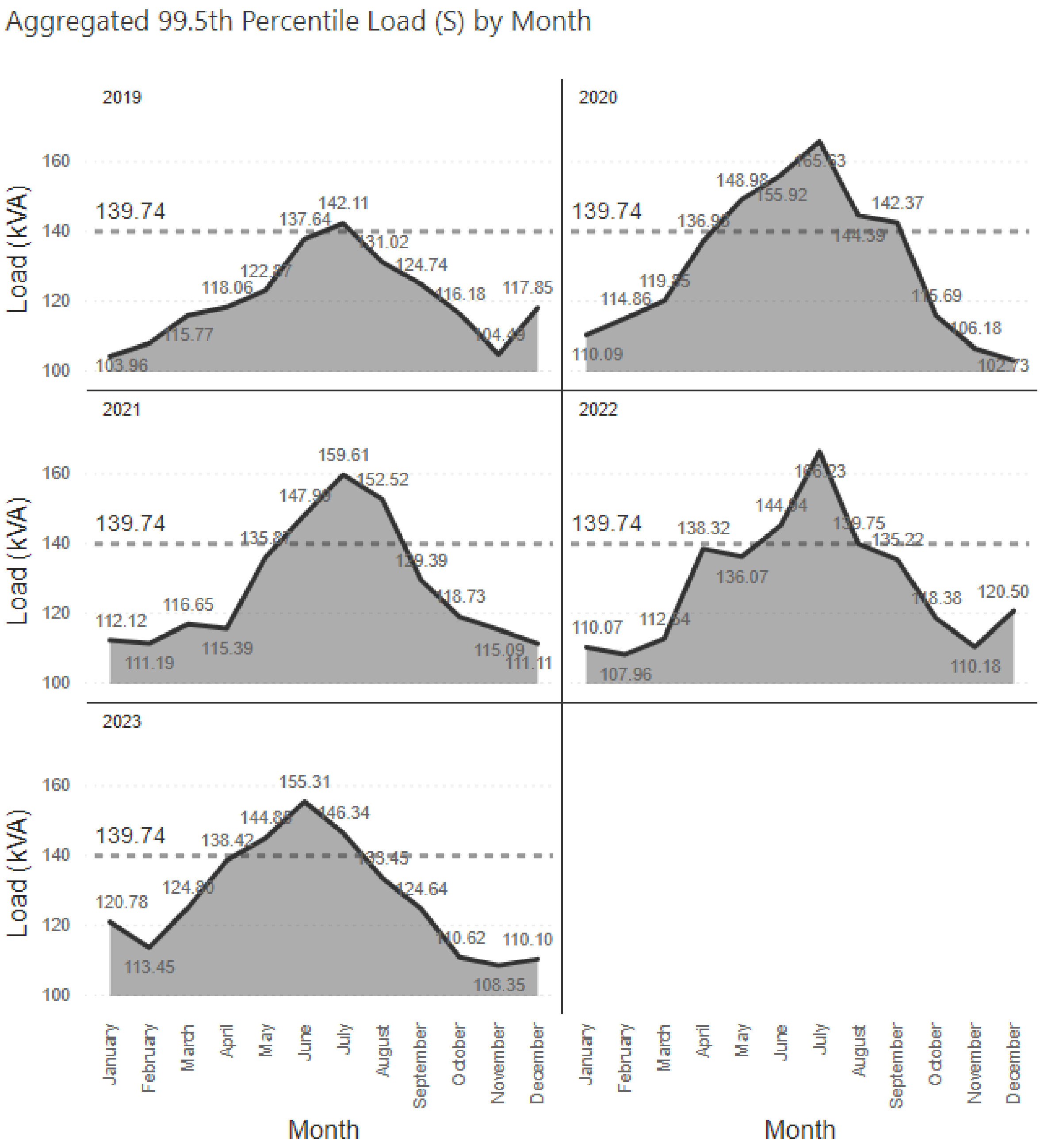


Figure 38: 99.5th Percentile load by each year for Case Study E

Figure 38 provides a more detailed breakdown of the 99.5th percentile load by each year, focusing on monthly variations. In 2019, the peak load was observed in June at 142.11 kVA, while in 2020, it reached a maximum in July at 163.53 kVA. For 2021, the highest load was recorded in July at 159.61 kVA, indicating a notable peak. The year 2022 showed a peak in August at 166.23 kVA, and 2023 had its highest load in June at 155.31 kVA. The monthly data indicate significant fluctuations, with many months, particularly in mid-year, exceeding the observed ADMD threshold.

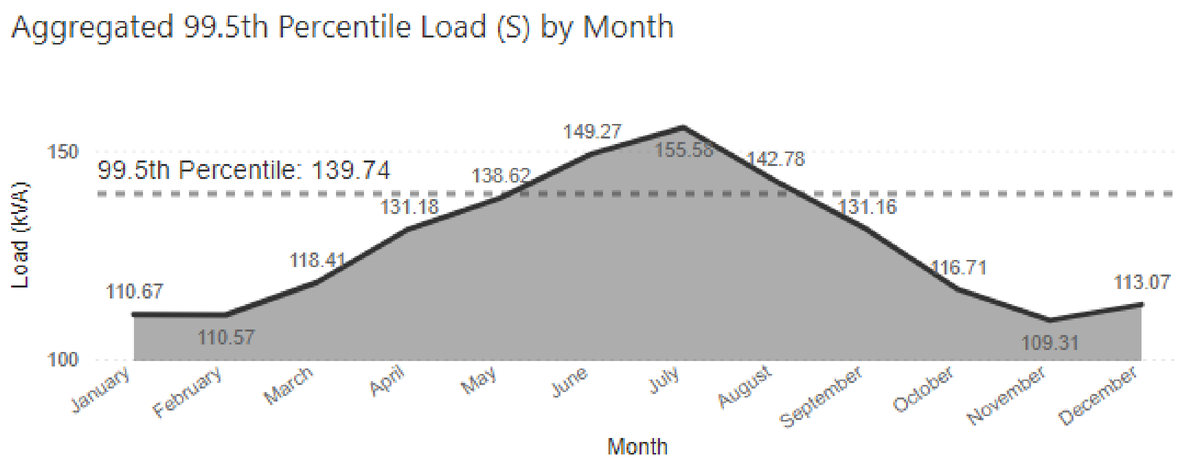


Figure 39: Aggregated 99.5th Percentile load by Month for Case Study E

Figure 39 aggregates the 99.5th percentile load by month across all years, providing a comprehensive view of the seasonal demand trends. The data shows that loads typically increase from February, peaking in June and July, before gradually declining towards the end of the year. The highest load observed was 155.55 kVA in July, while the lowest was 110.57 kVA in February. This pattern suggests a strong seasonal influence on demand, with mid-year months consistently experiencing higher loads.

The analysis of the 99.5th percentile load for Case Study E highlights significant variations in peak demand, with the 99.5th percentile serving as the observed ADMD. The data shows a general peak in demand around 2020And 2021, followed by a decline. The monthly breakdown further reveals a consistent pattern of increased loads during the middle of the year, often surpassing the 99.5th percentile threshold. This analysis underscores the importance of considering these variations in infrastructure planning and load forecasting, ensuring the system's capability to accommodate peak demands. The findings call for a closer examination of the factors driving these trends, such as seasonal weather patterns, economic activities, and consumer behaviours, to optimise electricity supply and demand management.

4.3.3.3 99.5th Percentile Load Analysis: Daily Demand Profiles

This analysis examines the 99.5th percentile load profiles for Case Study E, providing insight into the highest demand periods that occur only 0.5% of the time. This metric is crucial for understanding extreme usage scenarios, which are key to effective infrastructure planning and management. By analysing these profiles, we can identify both seasonal and daily patterns in electricity consumption, offering a comprehensive view of how demand fluctuates throughout the year and within a typical day.

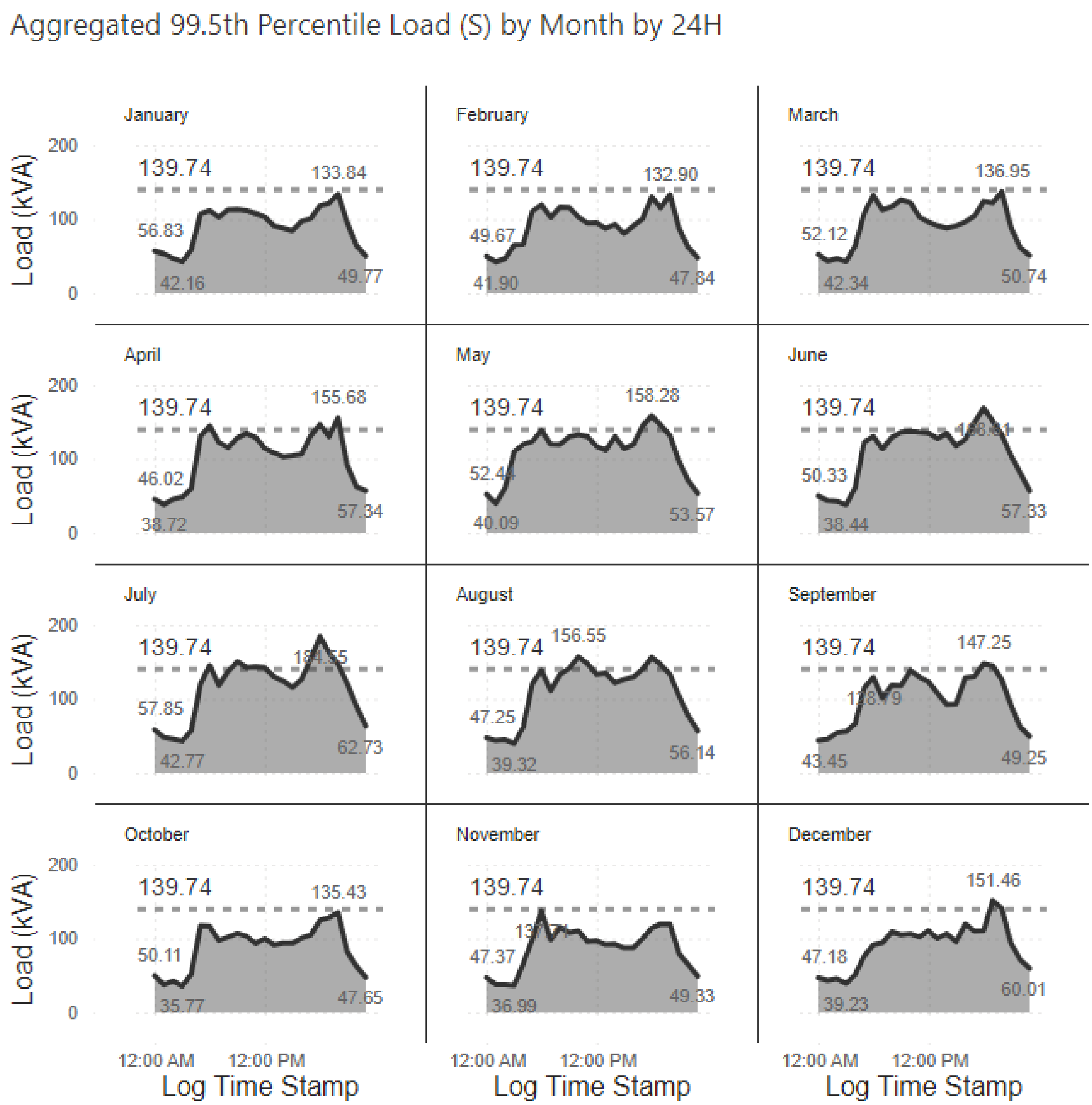


Figure 40: Aggregated 99.5th Percentile load by 24-h day by Month for Case Study E

Figure 40 illustrates the monthly variations in the 99.5th percentile load, showing how daily demand peaks vary throughout the year. The dashed line represents the 99.5th percentile load threshold set at 139.74 kVA. The graph highlights several key observations:

Winter Months (June - August): There are notable increases in daily peaks, often exceeding the 99.5th percentile line. For example, June peaks at 159.74 kVA, and August reaches 156.55 kVA, indicating higher energy consumption likely due to heating requirements.

Summer Months (December - February): The demand generally remains below the 99.5th percentile line, with December showing a peak of 151.46 kVA, potentially due to cooling or holiday activities.

Transitional Months (March, September): March shows a peak of 136.95 kVA, while September reaches 147.25 kVA, indicating fluctuations as the seasons change.

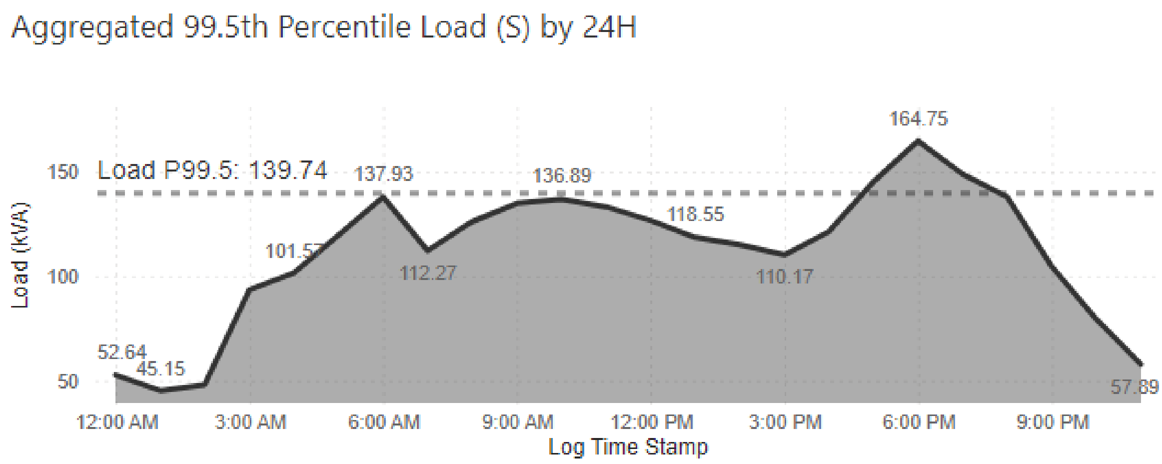


Figure 41: Aggregated 99.5th Percentile load by 24-h day for Case Study E

Figure 41 provides a consolidated view of the 99.5th percentile load data over a typical 24-hour period. The 99.5th percentile load line at 139.74 kVA helps to highlight the general patterns of daily demand:

Morning and Evening Peaks: A significant increase in load is observed starting around 3:00 AM, reaching a notable peak of 137.93 kVA by 6:00 AM. The highest demand occurs in the evening around 6:00 PM, with a peak load of 164.75 kVA, indicating typical residential activities such as cooking and heating.

Off-Peak Periods: The lowest demand is recorded during the early morning hours, with a load of 32.25 kVA, well below the 99.5th percentile threshold.

The 99.5th Percentile Load Analysis for Case Study E highlights significant seasonal and daily variations in electricity demand. The data indicate that peak demands are particularly high during the winter months, often exceeding the 99.5th percentile threshold due to increased heating needs. The analysis also underscores the importance of morning and evening peaks in residential electricity consumption patterns. These insights are essential for effective planning and management of energy infrastructure to ensure reliable service during periods of maximum demand.

4.3.4 Proposed ADMD vs Observed ADMD

This section aims to compare the proposed After Diversity Maximum Demand (ADMD) values suggested by SANS 507-1:2019 Year-15 parameters with the observed ADMD values for Case Study E. This comparison is crucial for assessing the accuracy and reliability of the proposed standards in predicting real-world electricity demand. By analysing the discrepancies between these values, we can determine the applicability of the SANS guidelines and identify any necessary adjustments for improved planning and infrastructure design.

Summary of Key Metrics

- Total Connections: 187
- Average Age: 20.66 years (greater than 15 years; therefore, Year-15 parameters are used)
- Installed Load: 972.60 kVA (5.20 kVA per connection)
- P99.5 Load: 139.74 kVA (0.75 kVA per stand)
- Resultant P99.5 Diversity Factor (DF): 0.14

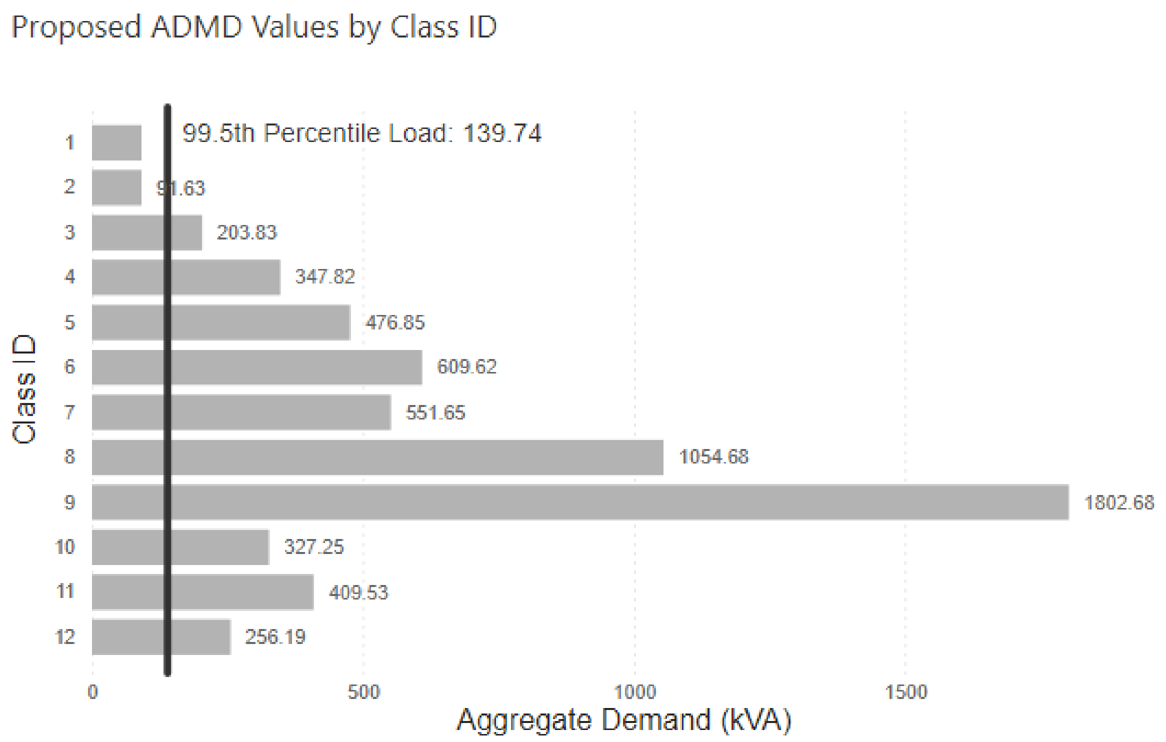


Figure 42: Proposed Year-15 ADMDs result by Class ID for Case Study E

Figure 42 illustrates the proposed ADMD values for different consumer classes as per SANS 507-1:2019 Year-15 parameters, compared against the measured 99.5th percentile load (139.74 kVA). The proposed ADMD values show significant variation across different classes, with Class ID 9 and 8 exhibiting the highest proposed values at 1802.68 kVA and 1054.68 kVA, respectively. The vertical line at 139.74 kVA indicates the 99.5th percentile load, serving as a benchmark for comparison.

The data from Figure 42 reveals that the proposed ADMD values for most consumer classes significantly exceed the measured 99.5th percentile load. Notably, Class ID 9 (Urban Estate) has a proposed ADMD value that is nearly thirteen times the measured load, indicating a possible overestimation. On the other hand, lower class IDs such as 1 and 2 show a proposed ADMD that is closer to the measured load, although still higher. This suggests that the SANS guidelines may need revision to reflect better actual consumption patterns, particularly for higher consumer classes.

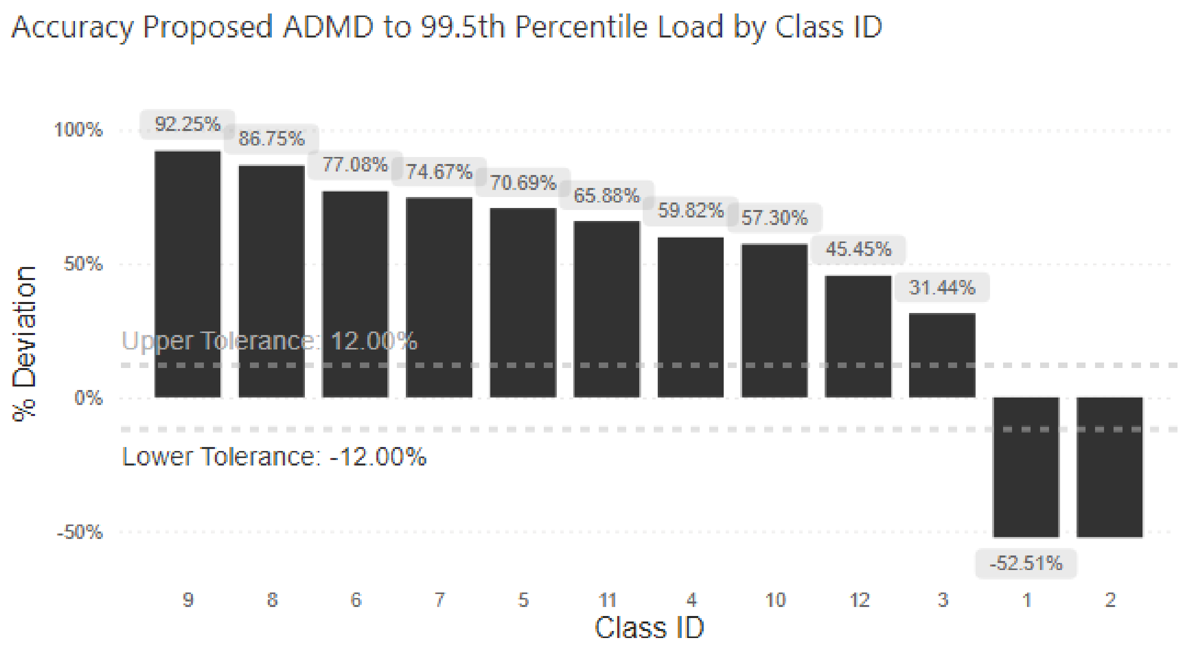


Figure 43: Deviation of SANS 507-1:2019 Year-15 ADMD by Class ID vs. 99.5th Percentile Load for Case Study E

Figure 43 presents the percentage deviation of the proposed ADMD values from the measured 99.5th percentile load for each class ID. The deviation is significant across most classes, with Class ID 9 showing the highest positive deviation at 92.25%. In contrast, Class IDs 1 and 2 show negative deviations, indicating that the proposed values are lower than the measured loads for these classes.

The deviations highlighted in Figure 43 indicate a substantial overestimation of the ADMD values for most consumer classes according to the SANS 507-1:2019 Year-15 parameters. The high positive deviations, particularly for Class ID 9, suggest that the current proposed values do not accurately capture the actual demand patterns. The negative deviations for Class IDs 1 and 2 indicate that the proposed values for these classes may be overly conservative, yet still not entirely accurate. This discrepancy underscores the need for a more nuanced approach in setting ADMD standards that consider the specific characteristics and consumption behaviours of different consumer classes.

Table 4: Detailed Comparison of Proposed ADMD vs Observed ADMD for Case Study E

ID	Consumer Class	SANS 15 Year ADMD (kVA)	Case SANS 15 Year ADMD (kVA)	Accuracy	Deviation
1	Rural settlement, Non-urban, scattered	0.49	91.63	152.51%	-52.51%
2	Rural villages	0.49	91.63	152.51%	-52.51%
3	Informal settlement	1.09	203.83	68.56%	31.44%
4	Township area	1.86	347.82	40.18%	59.82%
5	Urban residential I	2.55	476.85	29.31%	70.69%
6	Urban residential II	3.26	609.62	22.92%	77.08%
7	Urban townhouse complex or duplex	2.95	551.65	25.33%	74.67%
8	Urban Townhouse II	5.64	1054.68	13.25%	86.75%
9	Urban Estate	9.64	1802.68	7.75%	92.25%
10	High rise (small)	1.75	327.25	42.70%	57.30%

11	High rise (medium)	2.19	409.53	34.12%	65.88%
12	Hostel	1.37	256.19	54.55%	45.45%

Table 4 provides a detailed comparison of the proposed and observed ADMD values for each consumer class. The accuracy and deviation columns highlight the discrepancies between the proposed values and the actual measured loads. Notably, Classes 1 and 2 show the highest negative deviation, suggesting that the proposed ADMD values significantly underestimate the actual load for rural settlements and villages. Conversely, Classes 8 and 9 show the highest positive deviations, indicating an overestimation for urban estates and high-end residential areas. These observations reinforce the need for revising the proposed ADMD values to better align with real-world consumption patterns.

The comparison between the proposed ADMD values and the observed ADMD values for Case Study E reveals significant discrepancies, particularly for higher consumer classes. The proposed values tend to overestimate the actual demand for urban estates and high-end residential areas, while underestimating the load for rural settlements and villages. These findings suggest that the current SANS 507-1:2019 Year-15 parameters may not accurately reflect the diverse consumption patterns observed in different consumer classes. Therefore, it is crucial to re-evaluate these standards and consider more tailored approaches to ensure reliable and efficient electricity infrastructure planning.

Interpretive Note: Case Study E

- Installed base is PPU-dominant (177/187; 94.65% PPU vs 10/187; 5.35% SPU). Within PPU, breaker sizes are 20A = 94.62% and 60A = 5.38%; PPUs carry ~97.43% of the installed connected load.
- Average connection age is 20.66 years. Since this exceeds 15 years, Year-15 parameters were appropriate.
- Observed ADMD (P99.5) is 139.74 kVA total (0.75 kVA/stand).
- Best fit (exact class ID): Class 3 (Informal settlement) with 1.09 kVA/stand → 203.83 kVA case total, +31.44% vs observed. Classes 1–2 are below the empirical level (≈0.49–0.62 kVA/stand) and underestimate; classes above 3 propose higher per-stand values than 1.09 and overshoot by larger margins.

The 20A-heavy breaker mix and mid-age stock indicate a lower-to-mid demand profile; among the SANS options, Class 3 yields the least absolute deviation from the measured 99.5th-percentile ADMD and aligns better with the observed connection composition than the lower or higher classes. However, the difference from observation remains material.

4.4 Case Study F

Case Study F explores load profiles and ADMD values in the Harrismith area, examining factors affecting electricity demand.

4.4.1 Geographic Overview

Case Study F is geographically located at GPS coordinates 29.099197, -28.244131, as illustrated in Figure 44. This area encompasses the neighbourhood of 42nd Hill within the administrative boundaries of Intabazwe and Lotusville.

GPS Location ● 29.099197;-28.244131

Figure 44: Geographic location for Case Study F

The transformer zone for Case Study F is situated within the local municipal boundaries of Harrismith, part of the Maluti-a-Phofung Local Municipality, which falls under the Thabo Mofutsanyana District Municipality in the Free State Province of South Africa. This area is governed by local municipal authorities responsible for infrastructure development, public services, and community welfare.

The economy of the surrounding area is diverse, with key activities including agriculture, manufacturing, and services. Harrismith serves as a necessary logistics and transport hub due to its strategic location on the N3 highway, which connects Johannesburg and Durban. This strategic position supports a robust transport and logistics sector, contributing significantly to the local economy. Additionally, the presence of various manufacturing industries, particularly in textiles and automotive components, provides employment opportunities for residents.

The climate in this region is generally temperate, characterised by cold winters and moderate to warm summers. Winter months (June to August) often experience significant temperature drops, necessitating increased heating requirements. Conversely, summer months (November to February) may see a rise in temperatures, leading to higher demand for cooling. The region receives moderate rainfall, primarily during the summer months, which influences agricultural activities and impacts electricity consumption patterns.

The socioeconomic factors in Case Study F's area play a critical role in shaping electricity demand patterns. The community is socioeconomically diverse, comprising low to middle-income households, with varying access to economic opportunities and public services. Education and healthcare facilities in the area contribute to the overall quality of life, with schools and clinics relying on a stable electricity supply to function effectively.

Economic disparities and employment rates affect consumption patterns, with higher electricity usage typically observed in more affluent areas due to the presence of more electrical appliances and higher energy consumption per household. In contrast, lower-income areas might exhibit reduced demand but can still present peaks during specific times, such as evening hours when residential activities are at their peak.

In summary, the geographic and socioeconomic context of Case Study F provides a comprehensive backdrop for analysing electricity consumption patterns. The combination of diverse economic activities, temperate climate, and varying socioeconomic factors offers a rich dataset for evaluating the accuracy of proposed ADMD values and understanding their implications for local electricity infrastructure planning.

4.4.2 Connections

4.4.2.1 Proportion of Installed Load by Connection Type

The graph shown in Figure 45 visually represents the ratio of installed load by quantifying the PPU vs the SPU installed load that constitutes the case study.

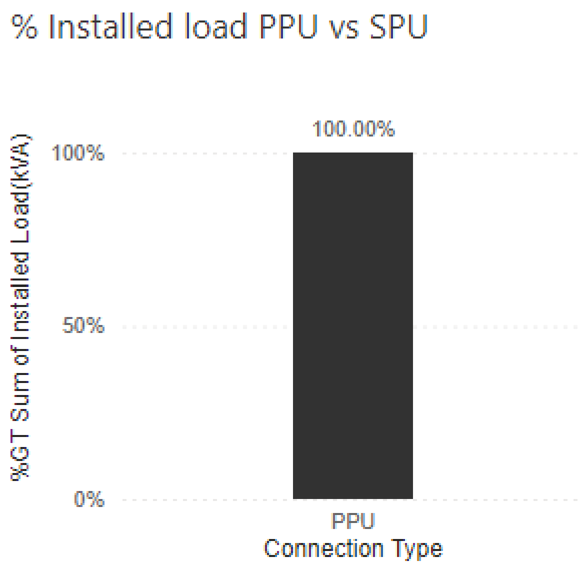


Figure 45: % Installed load by type PPU vs SPU for Case Study F

From Figure 45, a clear inference can be drawn: the PPU connections make up 100% of the installed load. Thus, this gives a strong indication that the connections are purely residential-type loads, which were connected as part of electrification programmes in this specific township. The following section, however, will look at the ratio between the various NMDs that make up the PPU connections for this case study.

4.4.2.2 Distribution of PPU Connections by Circuit Breaker Size

Figure 46 presents an illustration of the distribution of Prepaid Unit (PPU) connections by circuit breaker size (measured in amperes, A) for Case Study F. This visual comparison between two notified maximum demand sizes, 20A and 60A, highlights the prevalence of each size and its impact on load characteristics.

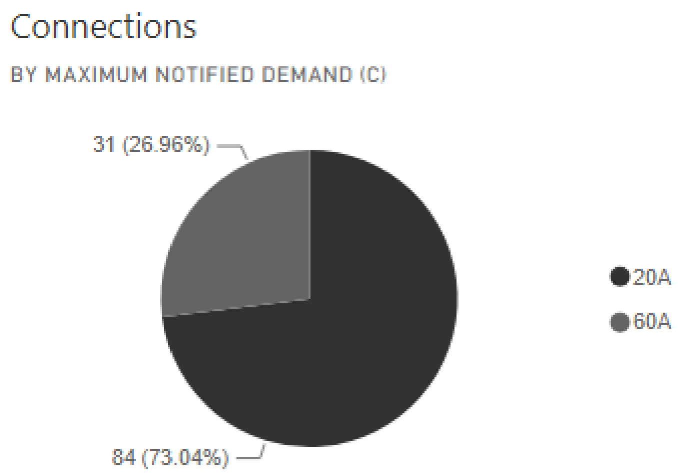


Figure 46: Total PPU connections by Circuit Breaker Size (c) for Case Study F

The graph in Figure 46 indicates that a substantial majority (73.04%) of the total PPU connections utilise 20A circuit breakers. In contrast, 60A circuit breakers represent a smaller portion (26.96%) of the total PPU connections. This difference underscores the dominance of 20A circuit breakers in this case study, indicating that most connections are at the lower end of individual peak demands.

Referring to the LSM and the associated “c” values in Table 2 of SANS 507-1:2019, 20A connections fall within the lower Class IDs. Conversely, the presence of 60A connections signifies that some connections have either been established for a long time or have been upgraded from 20A to 60A. These upgrades are typically funded by the individuals, unlike the 20A connections, which are generally subsidised by government programmes. The 20A connections are commonly installed as part of universal electrification initiatives.

4.4.2.3 Connection Trends

The connection trends for Case Study F are illustrated in Figure 47, presenting an insightful overview of the historical load growth in terms of total connections.

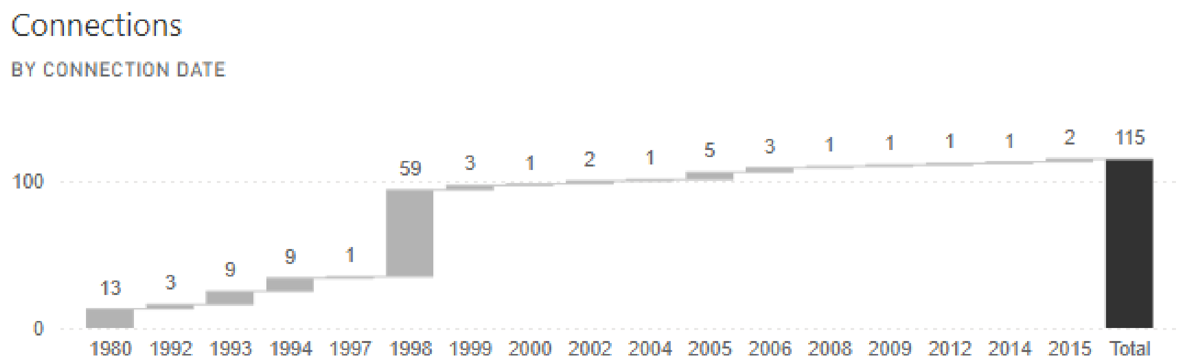


Figure 47: Total connections over time for Case Study F

Figure 47 demonstrates that the initial connections were recorded in 1980, with subsequent additions continuing up to 2015. The most significant surge in connections occurred in 1998, with 59 new connections added, which is the highest annual growth observed in this dataset. Before this peak, there were moderate increases in 1993 and 1994, with nine new connections each year.

Following the substantial growth in 1998, the number of new connections per year was relatively low, with annual additions ranging from one to five connections between 1999 and 2015. Notably, there were smaller peaks in 2005 and 2006, where five and three new connections were added, respectively.

By the end of the period, the total number of connections reached 115. The observed data indicate that the growth rate experienced a notable peak in the late 1990s, followed by a prolonged period of reduced growth. This deceleration in the growth rate suggests a possible saturation in the geographic area, which is a crucial consideration for the design and planning of transformer zones.

The historical connection data for Case Study F highlights the dynamic nature of network expansion and the impact of spatial constraints on growth. Understanding these trends is essential for effective infrastructure planning and ensuring the sustainability of future expansions.

4.4.2.4 Connection Age Analysis by Breaker Size

The diverging bar chart illustrates the average age of connections categorised by each circuit breaker size for Case Study F.

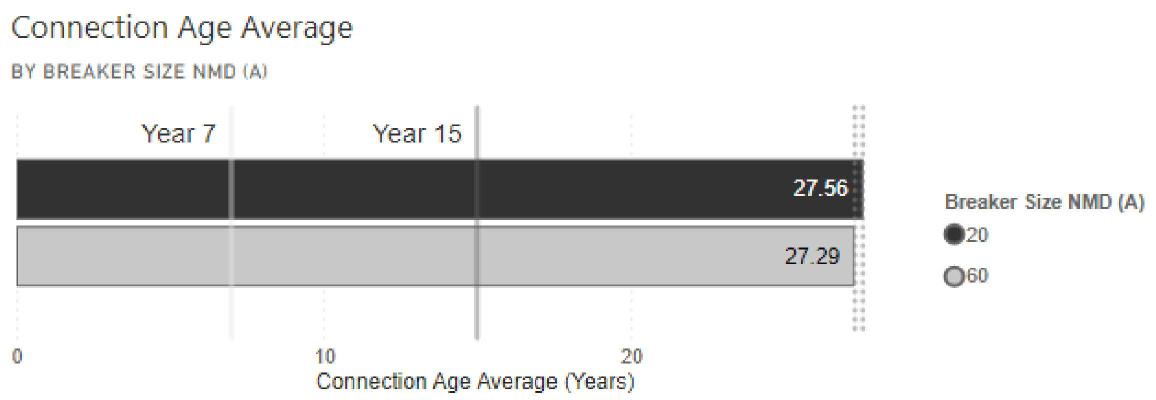


Figure 48: Connection Age Analysis for Case Study F

From Figure 48, it is observed that the average age of connections with 20A circuit breakers is 27.56 years, while the average age of connections with 60A circuit breakers is 27.29 years. The minimal difference in average ages, with the 20A connections being older by approximately 0.27 years compared to the 60A connections, suggests that both types of connections were likely established around the same time.

Given that both categories of circuit breaker size have connection ages significantly higher than 15 years, it is appropriate to use the 15-year parameters according to SANS 507-1:2019 – Table 2. Additionally, it should be noted that the 'c' values for 20A, 15-year parameters are limited to Class ID 1 and 2, whereas the 60A Class IDs, according to the 15-year 'c' values, are from Class ID 3 and higher.

The following conclusions can be drawn from the above analysis. Firstly, the presence of both 20A and 60A connections suggests a heterogeneous consumer group. Secondly, the similarity in the average ages of the two categories indicates that there has not been significant load growth necessitating upgrades from 20A to 60A connections. If significant individual load growth were present, we would expect the average age of 60A connections to be noticeably lower due to older 20A connections being upgraded over time.

This pattern reflects a stable demand for electricity within the study area, with the existing infrastructure sufficiently meeting the needs of the consumers without necessitating widespread upgrades. The data thus highlights a consistent and stable electrical demand in the residential area covered by Case Study F. The slight difference in ages also suggests that while upgrades may have occurred, they have not been so frequent or recent as to alter the average age difference between the breaker sizes significantly.

4.4.3 Load Profiles

4.4.3.1 Historical Load Profile Analysis

The historical load profile for Case Study F, as illustrated in Figure 49, captures a detailed sample of instantaneous load data from August 28, 2020, to December 31, 2023. This profile provides an in-depth view of the variations in electrical consumption over this period. Key indicators, such as the mean load, maximum demand, and the 99.5th percentile, are prominently marked to illustrate typical and peak load conditions. The mean load, shown as "Mean: 36.76," represents the average electrical load throughout the study timeframe. The maximum demand, indicated by the "Maximum: 107.02" line, highlights the peak load recorded, while the 99.5th percentile, marked as "99.5th Percentile: 79.74," is considered the measured After Diversity Maximum Demand (ADMD) value, providing a critical reference for infrastructure adequacy assessments.

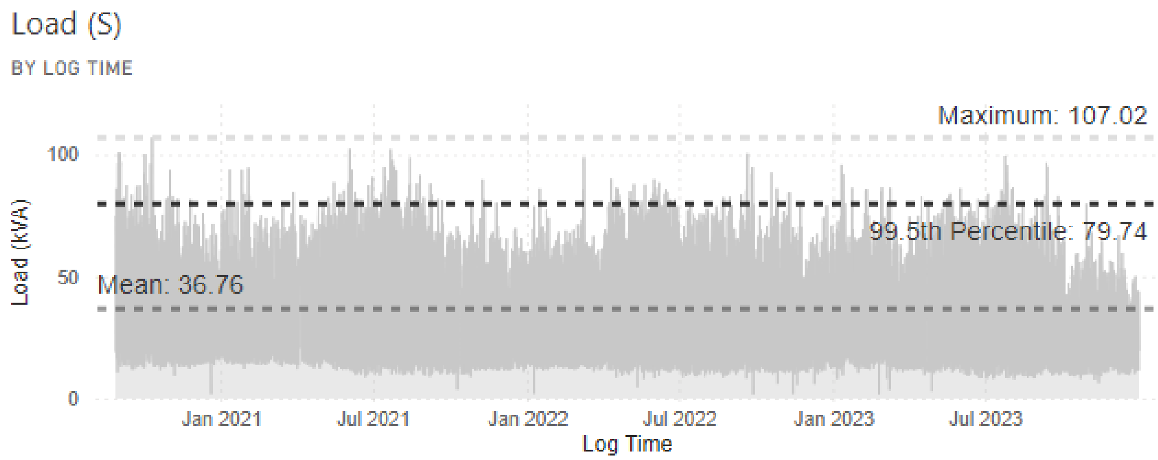


Figure 49: Historical load profile for Case Study F

In Figure 49, the historical load profile for Case Study F demonstrates several notable characteristics. The mean load, represented by the "Mean: 36.76" line, suggests a relatively low average consumption level. The profile exhibits some variability, with discernible peaks and troughs, indicating fluctuations in demand over time. The maximum demand, shown by the "Maximum: 107.02" line, represents occasional high consumption periods. The 99.5th percentile, indicated at "99.5th Percentile: 79.74," provides a threshold below which 99.5% of the load data falls, offering a reliable estimate for planning infrastructure to accommodate typical peak loads.

The normal distribution of the historical load profile data for Case Study F, as depicted in Figure 50, offers a statistical representation of the load data, modelled as a bell curve. This visualisation helps in understanding the central tendency, dispersion, and the presence of outliers within the dataset.

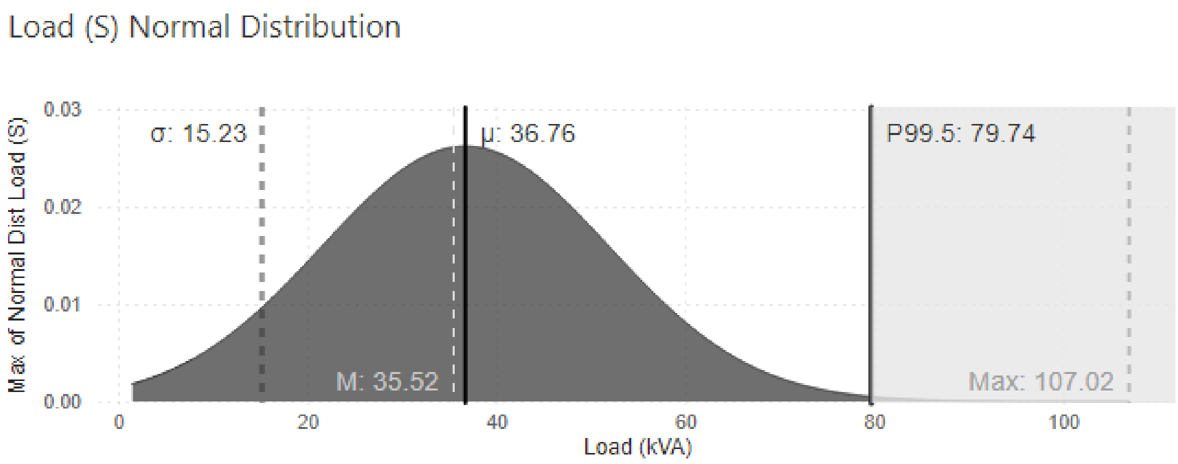


Figure 50: Normal distribution of Historical Load Profile data for Case Study F

Figure 50 illustrates the normal distribution of the load data, with the curve centred around the mean (μ) of 36.76 kVA and a standard deviation (σ) of 15.23 kVA. The mode (M), indicated near "M: 35.52," closely aligns with the mean, showing a concentration of data points around these central values. The 99.5th percentile, labelled "P99.5: 79.74," marks the upper limit for most data points, suggesting that only a small fraction of the data exceeds this value. The maximum load, "Max: 107.02," indicates the highest recorded value, far exceeding the 99.5th percentile, highlighting the presence of extreme outliers. The shape of the bell curve suggests a relatively normal distribution with slight skewness, as indicated by the extended tail on the right side, which captures the occasional high loads beyond the typical range. This distribution suggests a stable consumption pattern with occasional peaks, essential for designing and managing electrical infrastructure.

4.4.3.2 99.5th Percentile Load Analysis

In evaluating the After Diversity Maximum Demand (ADMD) for Case Study F, the 99.5th percentile load is a key metric for understanding peak demand patterns. This section analyses the data presented in Figure 51, Figure 52, and Figure 53, providing a comprehensive overview of the load trends from August 2020 to December 2023.

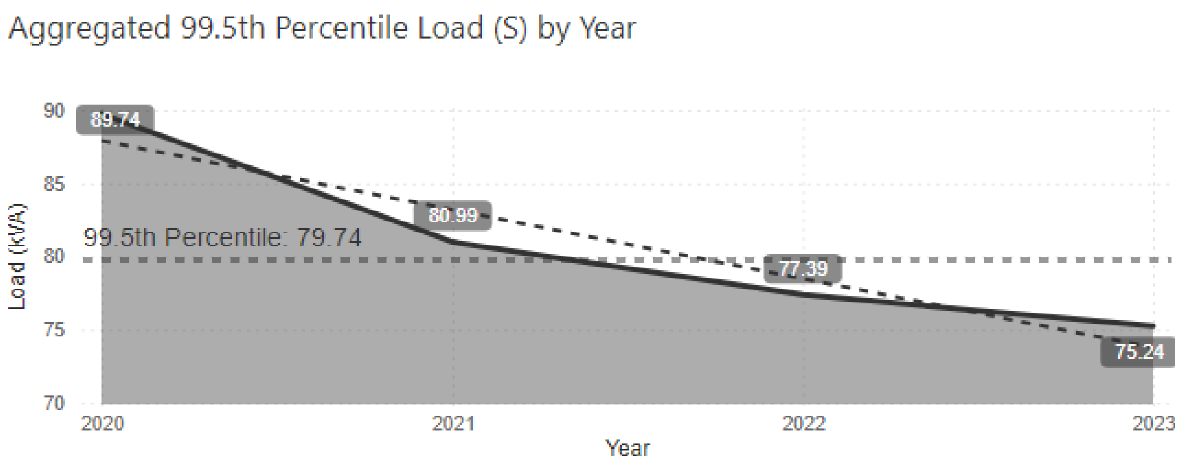


Figure 51: 99.5th Percentile load by year for Case Study F

Figure 51 illustrates the 99.5th percentile load by year for Case Study F, showing the aggregated annual values. The 99.5th percentile line, set at 79.74 kVA, represents the observed ADMD. The highest load was recorded in 2020At 89.74 kVA, while the lowest was 75.24 kVA in 2023. The trendline shows a consistent decline over the years, indicating a gradual reduction in peak load values. The data points for 2020And 2021 are above the 99.5th percentile line, whereas 2022 and 2023 fall below it, reflecting a downward trend in demand.

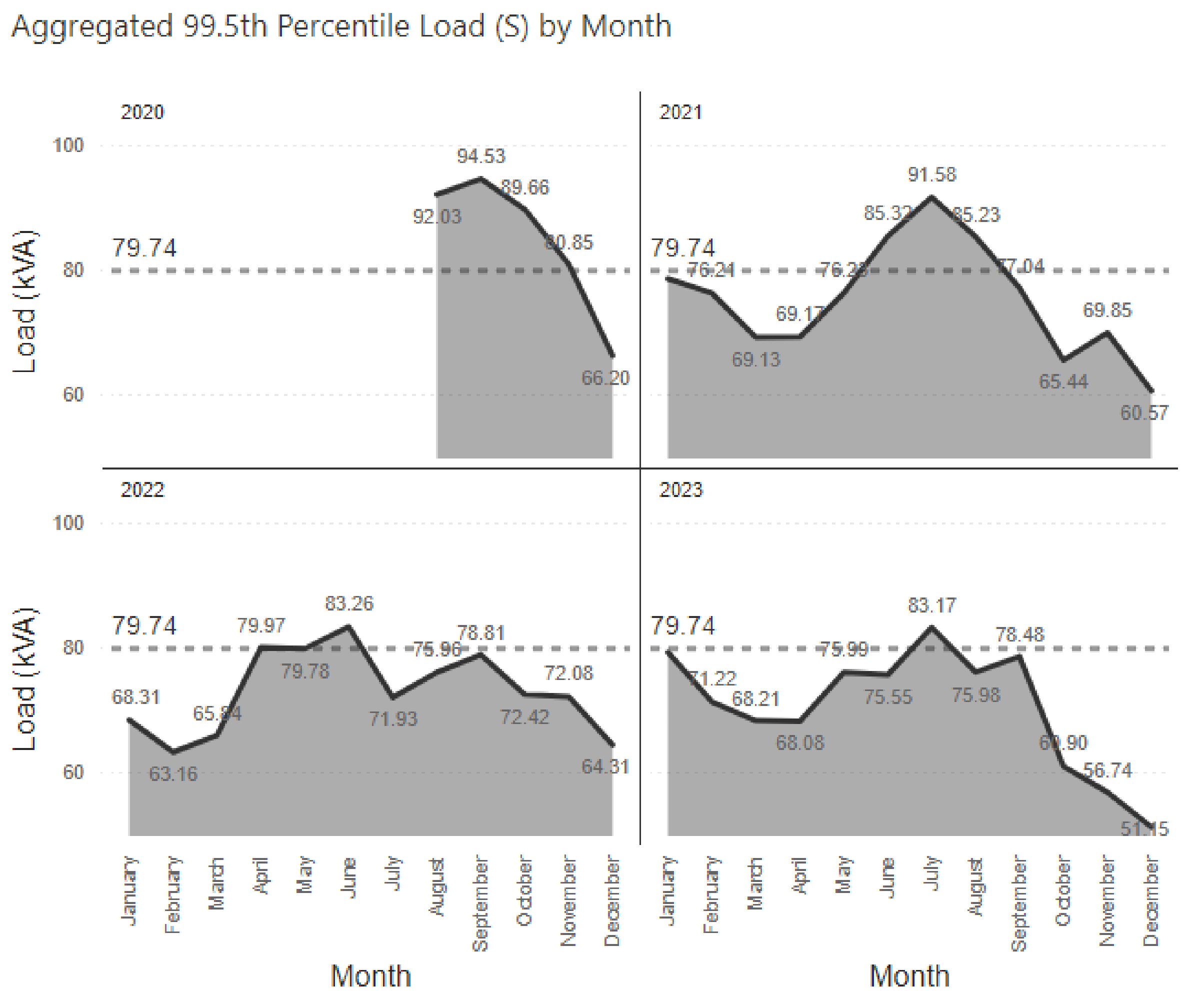


Figure 52: 99.5th Percentile load by each year for Case Study F

Figure 52 offers a breakdown of the 99.5th percentile load by each year, focusing on monthly variations. In 2020, the peak occurred in September at 94.53 kVA, while 2021 saw its highest load in July at 91.58 kVA. For 2022, the peak was in June at 83.26 kVA, and in 2023, it occurred in July at 83.17 kVA. The analysis highlights that monthly values frequently fluctuate, with some months, especially mid-year, exceeding the observed ADMD threshold, indicating periods of higher demand.

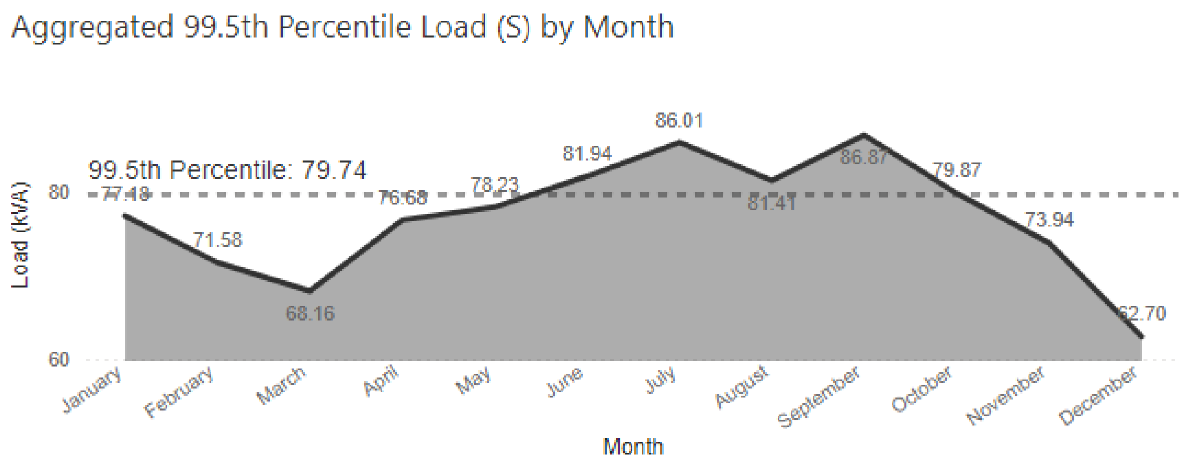


Figure 53: Aggregated 99.5th Percentile load by Month for Case Study F

Figure 53 aggregates the 99.5th percentile load by month across all the years, providing a comprehensive view of monthly demand patterns. The data shows that the highest load was in July, reaching 86.01 kVA, while the lowest was 68.16 kVA in March. The trend suggests that loads typically rise from April, peak around July, and then decrease towards December, indicating a seasonal variation in demand.

The 99.5th percentile load analysis for Case Study F highlights significant variations in ADMD, with the 99.5th percentile serving as the observed ADMD. The overall trend shows a decrease in peak loads over the years, with notable peaks occurring in mid-year months. This decline in peak load values suggests a reduction in maximum demand, which may influence infrastructure planning and load management strategies. The findings highlight the importance of monitoring and adapting to these changes to ensure an efficient and reliable electricity supply, taking into account factors such as seasonal effects, economic conditions, and consumer behaviours.

4.4.3.3 99.5th Percentile Load Analysis: Daily Demand Profiles

This analysis focuses on the 99.5th percentile load profiles for Case Study F, providing an understanding of the peak demand periods that are exceeded only 0.5% of the time. The 99.5th percentile load is a crucial metric for identifying extreme usage scenarios, which are vital for infrastructure planning and energy management. By examining these profiles, we can discern both seasonal and daily patterns in electricity consumption, offering insights into the variations in demand throughout the year and within a typical day.

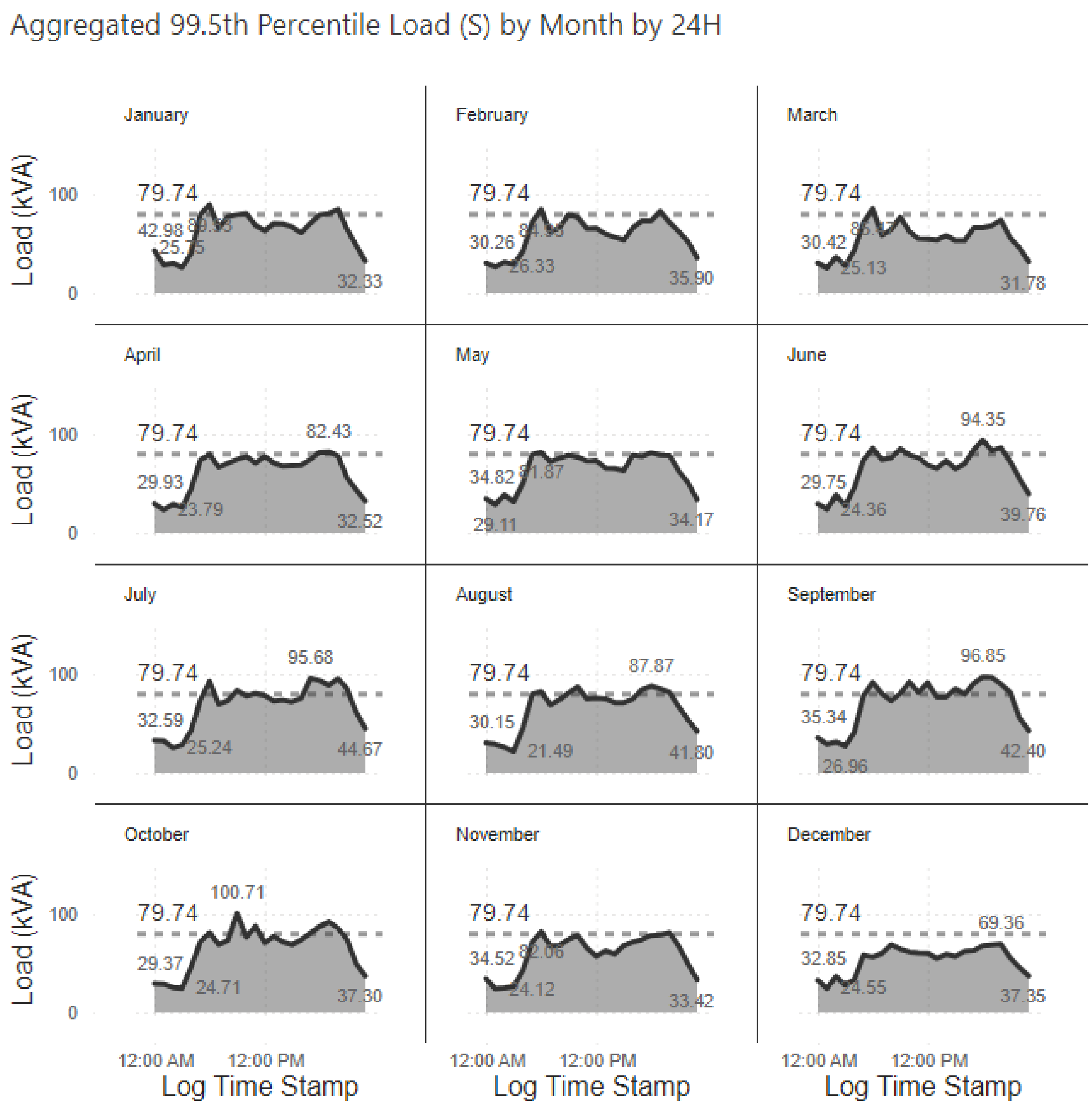


Figure 54: Aggregated 99.5th Percentile load by 24-h day by Month for Case Study F

Figure 54 presents the monthly variations in the 99.5th percentile load, illustrating how daily peaks vary throughout the year. The dashed line at 79.74 kVA represents the 99.5th percentile load threshold. Key observations include:

Winter Months (June - August): The daily peaks show notable increases, with loads occasionally surpassing the 99.5th percentile line. June reaches a peak of 94.35 kVA, while July and August reach 95.68 kVA and 87.87 kVA, respectively. These peaks suggest higher energy usage, likely due to heating requirements.

Summer Months (December - February): Demand generally remains below the 99.5th percentile line, with the highest peak in December reaching 69.36 kVA, indicating moderate energy usage during this period.

Transitional Months (March, September): These months exhibit fluctuations in demand, with March reaching a peak of 96.85 kVA and September showing similar levels. This variation may reflect the transition between seasonal energy needs.

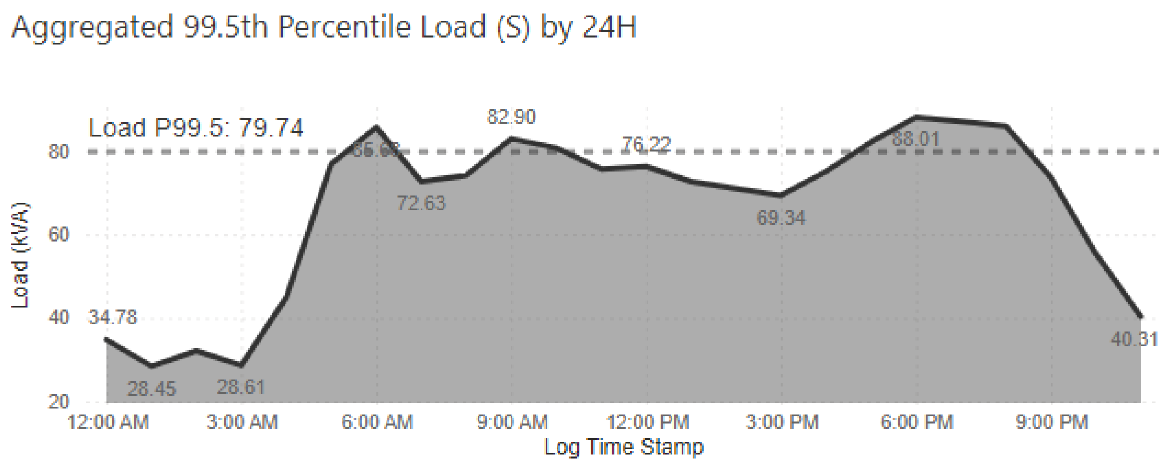


Figure 55: Aggregated 99.5th Percentile load by 24-h day for Case Study F

Figure 55 consolidates the daily demand data into a single 24-hour profile, providing an overview of the typical daily load pattern. The 99.5th percentile load line at 79.74 kVA marks the threshold for identifying extreme demand levels:

> Morning and Evening Peaks: There is a noticeable increase in load starting around 3:00 AM, with a peak of 82.90 kVA by 6:00 AM. The highest demand occurs in the evening around 6:00 PM, reaching a peak of 88.01 kVA, indicating typical residential activities such as cooking and heating.
>
> Off-Peak Periods: The lowest demand occurs in the early morning hours, with the load dropping to around 28.45 kVA, well below the 99.5th percentile threshold.

The 99.5th Percentile Load Analysis for Case Study F reveals significant seasonal and daily variations in electricity demand. The data indicate that peak demands are more pronounced during the winter months, with the occasional exceedance of the 99.5th percentile threshold due to increased heating requirements. The analysis also highlights the importance of morning and evening peaks in shaping residential electricity consumption patterns. Understanding these variations is essential for effective planning and management of energy infrastructure, ensuring reliable service during periods of maximum demand.

4.4.4 Proposed ADMD vs Observed ADMD

This section aims to compare the proposed After Diversity Maximum Demand (ADMD) values suggested by SANS 507-1:2019 Year-15 parameters with the observed ADMD values for Case Study F. This comparison is crucial for assessing the accuracy and reliability of the proposed standards in predicting real-world electricity demand. By analysing the discrepancies between these values, we can determine the applicability of the SANS guidelines and identify any necessary adjustments for improved planning and infrastructure design.

Summary of Key Metrics

- Total Connections: 115
- Average Age: 27.49 years (greater than 15 years; therefore, Year-15 parameters are used)
- Installed Load: 814.20 kVA (7.08 kVA per connection)
- P99.5 Load: 79.74 kVA (0.69 kVA per stand)
- Resultant P99.5 Diversity Factor (DF): 0.10

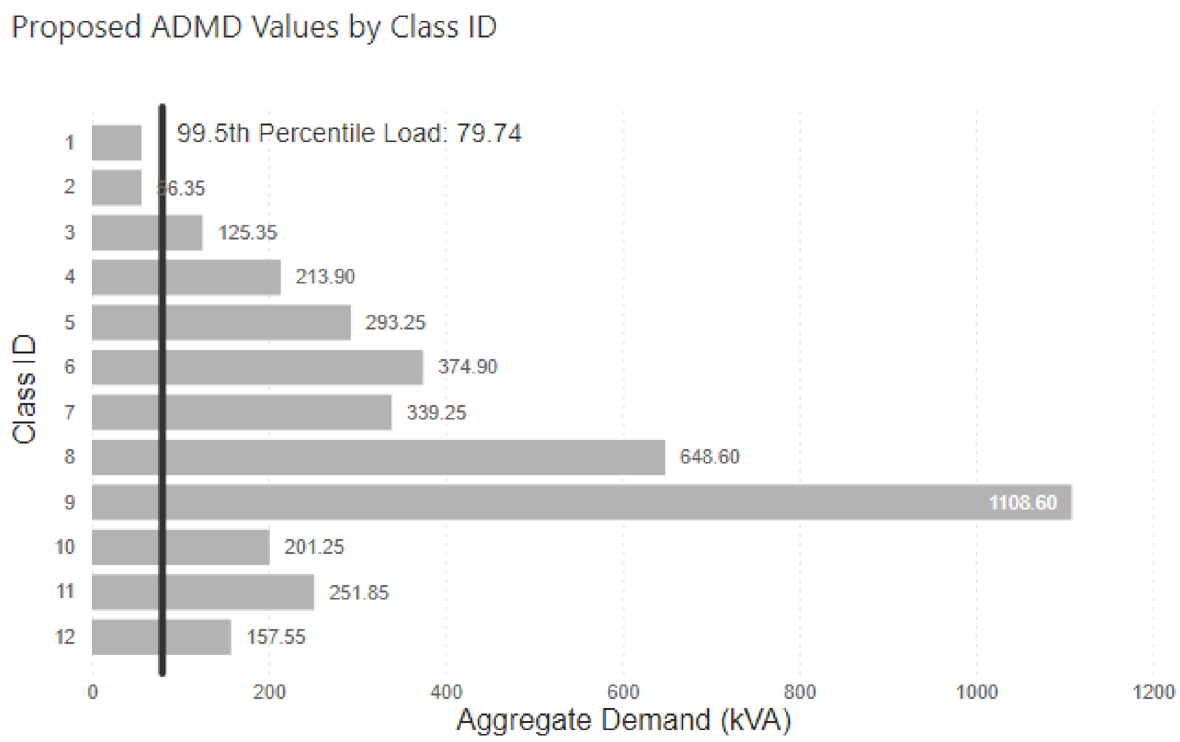


Figure 56: Proposed Year-15 ADMDs result by Class ID for Case Study F

Figure 56 illustrates the proposed ADMD values for different consumer classes as per SANS 507-1:2019 Year-15 parameters, compared against the measured 99.5th percentile load (79.74 kVA). The proposed ADMD values show significant variation across different classes, with Class ID 9 and 8 exhibiting the highest proposed values at 1108.60 kVA and 648.60 kVA, respectively. The vertical line at 79.74 kVA indicates the 99.5th percentile load, serving as a benchmark for comparison.

The data from Figure 56 reveals that the proposed ADMD values for most consumer classes significantly exceed the measured 99.5th percentile load. Notably, Class ID 9 (Urban Estate) has a proposed ADMD value that is over fourteen times the measured load, indicating a possible overestimation. On the other hand, lower class IDs such as 1 and 2 show a proposed ADMD that is closer to the measured load, although still higher. This suggests that the SANS guidelines may need revision to reflect better actual consumption patterns, particularly for higher consumer classes.

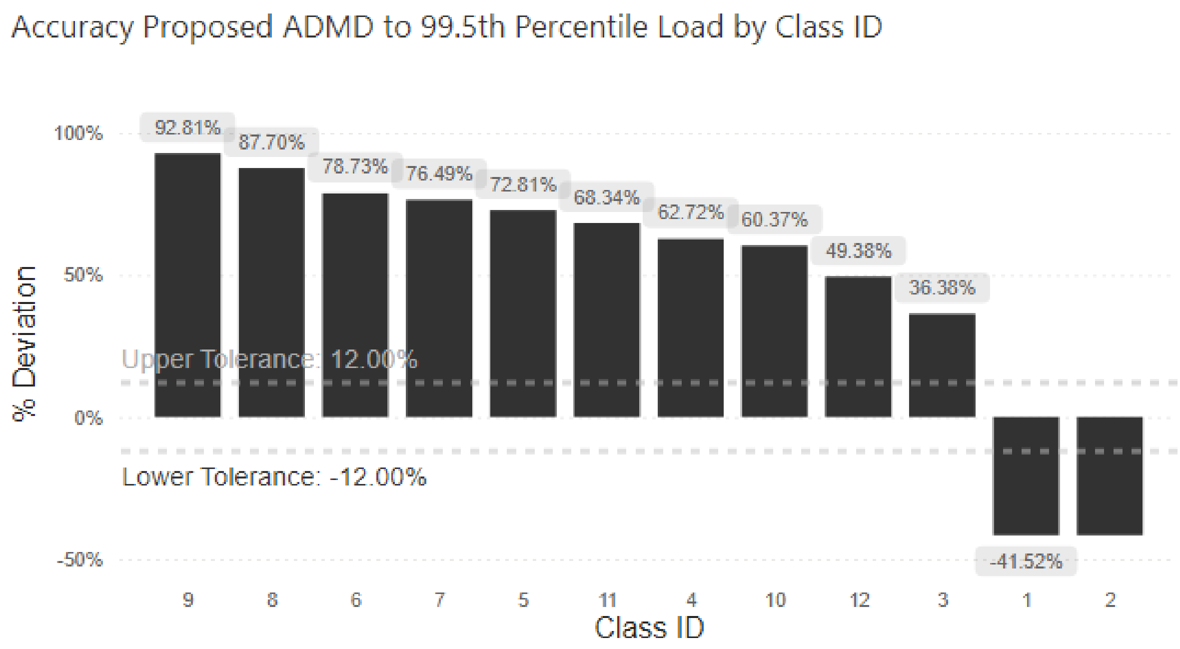


Figure 57: Deviation of SANS 507-1:2019 Year-15 ADMD by Class ID vs. 99.5th Percentile Load for Case Study F

Figure 57 presents the percentage deviation of the proposed ADMD values from the measured 99.5th percentile load for each class ID. The deviation is significant across most classes, with Class ID 9 showing the highest positive deviation at 92.81%. In contrast, Class IDs 1 and 2 show negative deviations, indicating that the proposed values are lower than the measured loads for these classes.

The deviations highlighted in Figure 57 indicate a substantial overestimation of the ADMD values for most consumer classes according to the SANS 507-1:2019 Year-15 parameters. The high positive deviations, particularly for Class ID 9, suggest that the current proposed values do not accurately capture the actual demand patterns. The negative deviations for Class IDs 1 and 2 indicate that the proposed values for these classes might be more conservative, yet still not entirely accurate. This discrepancy underscores the need for a more nuanced approach in setting ADMD standards that consider the specific characteristics and consumption behaviours of different consumer classes.

Table 5: Detailed Comparison of Proposed ADMD vs Observed ADMD for Case Study F

ID	Consumer Class	SANS 15 Year ADMD (kVA)	Case SANS 15 Year ADMD (kVA)	Accuracy	Deviation
1	Rural settlement, Non-urban, scattered	0.49	56.35	141.52%	-41.52%
2	Rural villages	0.49	56.35	141.52%	-41.52%
3	Informal settlement	1.09	125.35	63.62%	36.38%
4	Township area	1.86	213.90	37.28%	62.72%
5	Urban residential I	2.55	293.25	27.19%	72.81%
6	Urban residential II	3.26	374.90	21.27%	78.73%
7	Urban townhouse complex or duplex	2.95	339.25	25.31%	74.69%
8	Urban Townhouse II	5.64	648.60	12.30%	87.70%
9	Urban Estate	9.64	1108.60	7.19%	92.81%
10	High rise (small)	1.75	201.25	39.63%	60.37%

11	High rise (medium)	2.19	251.85	31.66%	68.34%
12	Hostel	1.37	157.55	50.62%	49.38%

Table 5 provides a detailed comparison of the proposed and observed ADMD values for each consumer class. The accuracy and deviation columns highlight the discrepancies between the proposed values and the actual measured loads. Notably, Classes 1 and 2 show the highest negative deviation, suggesting that the proposed ADMD values significantly underestimate the actual load for rural settlements and villages. Conversely, Classes 8 and 9 show the highest positive deviations, indicating an overestimation for urban estates and high-end residential areas. These observations reinforce the need for revising the proposed ADMD values to better align with real-world consumption patterns.

The comparison between the proposed ADMD values and the observed ADMD values for Case Study F reveals significant discrepancies, particularly for higher consumer classes. The proposed values tend to overestimate the actual demand for urban estates and high-end residential areas, while underestimating the load for rural settlements and villages. These findings suggest that the current SANS 507-1:2019 Year-15 parameters may not accurately reflect the diverse consumption patterns observed in different consumer classes. Therefore, it is crucial to re-evaluate these standards and consider more tailored approaches to ensure reliable and efficient electricity infrastructure planning.

Interpretive Note: Case Study F

- Installed base is PPU-dominant. Within PPU, breaker sizes are 20A = 73.04% and 60A = 26.96%.
- Average connection age is about 27 years. By breaker size: 27.56 years (20A) and 27.29 years (60A), so Year-15 parameters were appropriate.
- Observed ADMD (P99.5) is 79.74 kVA total (0.69 kVA/stand).
- Best fit (exact class ID): Class 3 (Informal settlement) with 1.09 kVA/stand → 125.35 kVA case total, +36.38% vs observed. Classes 1–2 are below the empirical level, while classes above 3 propose higher per-stand values than 1.09 and overshoot by larger margins.

The breaker mix is dominated by 20A with a meaningful 60A minority, and the stock is mature; empirically, this aligns with a lower-to-mid ADMD regime. Among the SANS options, Class 3 yields the lowest absolute deviation from the measured 99.5th-percentile ADMD, although it remains above the observed value.

4.5 Case Study G

Case Study G explores load profiles and ADMD values in the Reitz area, examining factors affecting electricity demand.

4.5.1 Geographic Overview

Case Study G is geographically located at GPS coordinates 28.455894, -27.79947, as illustrated in Figure 58. This area includes the neighbourhoods of Itshokolele, Petsana Extension 2, Petsana, and Cremona Outlying.

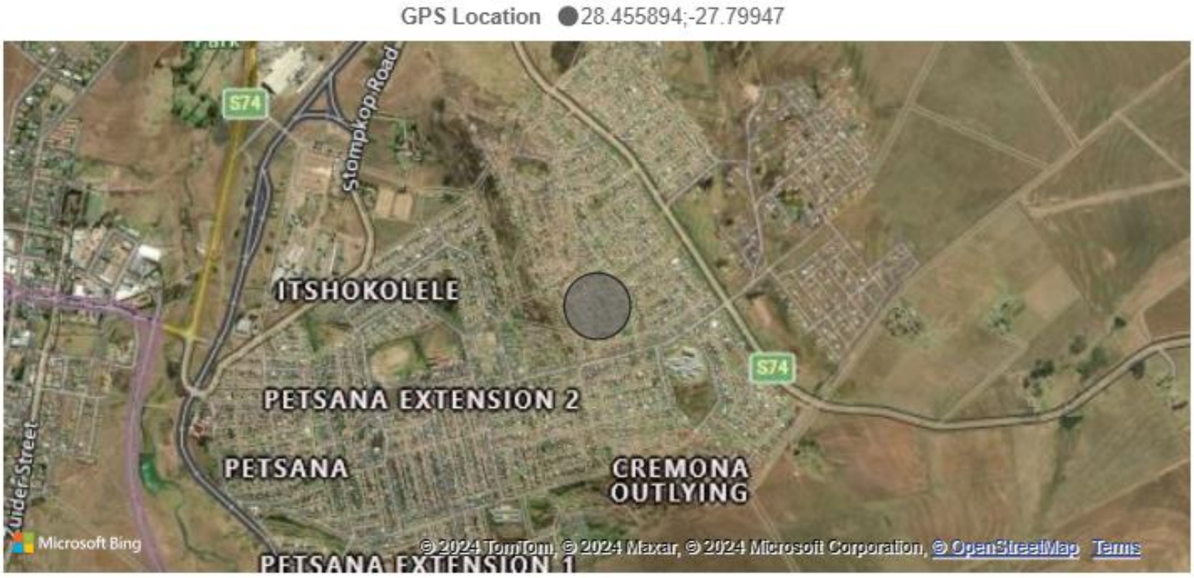


Figure 58: Geographic location for Case Study G

The transformer zone for Case Study G is situated within the local municipal boundaries of Reitz, which falls under the Nketoana Local Municipality in the Thabo Mofutsanyana District Municipality, Free State Province of South Africa. The local municipal authorities are responsible for providing public services, maintaining infrastructure, and promoting community development within this area.

The economy surrounding Case Study G is predominantly driven by agriculture, with the region being known for its production of crops such as maize, wheat, and sunflowers. Livestock farming also plays a significant role. Reitz serves as an agricultural hub, supporting various agro-processing activities that add value to the primary agricultural products. Additionally, small-scale retail businesses and service industries cater to the local population's needs, influencing the electricity demand.

The climate in this region is generally temperate, characterised by cold winters and warm summers. Winter months (June to August) often experience low temperatures, leading to higher electricity consumption for heating purposes. During the summer months (November to February), the electricity demand may rise due to the increased use of cooling systems. The region receives moderate rainfall, mainly during the summer, which impacts agricultural activities and subsequently affects electricity consumption patterns.

The socioeconomic factors in Case Study G's area significantly impact electricity consumption patterns. The community is socioeconomically diverse, comprising low to middle-income households, with varying levels of access to economic opportunities and public services. Educational institutions and healthcare facilities within the area rely on a stable electricity supply to operate efficiently.

Economic disparities within the community influence energy consumption, with more affluent households typically using more electrical appliances and therefore having higher electricity demand. In contrast, lower-income households might have lower overall electricity consumption but still exhibit significant usage during peak times, such as in the evenings when residential activities are at their highest.

In summary, the geographic and socioeconomic context of Case Study G provides a comprehensive understanding of the area's electricity consumption patterns. The combination of agricultural activities, temperate climate, and diverse socioeconomic factors offers valuable data for evaluating the accuracy of proposed ADMD values and their implications for local electricity infrastructure planning.

4.5.2 Connections

4.5.2.1 Proportion of Installed Load by Connection Type

Figure 59 represents the ratio of installed load by comparing the presence of PPU and SPU, each as a percentage of the installed load for the transformer zone.

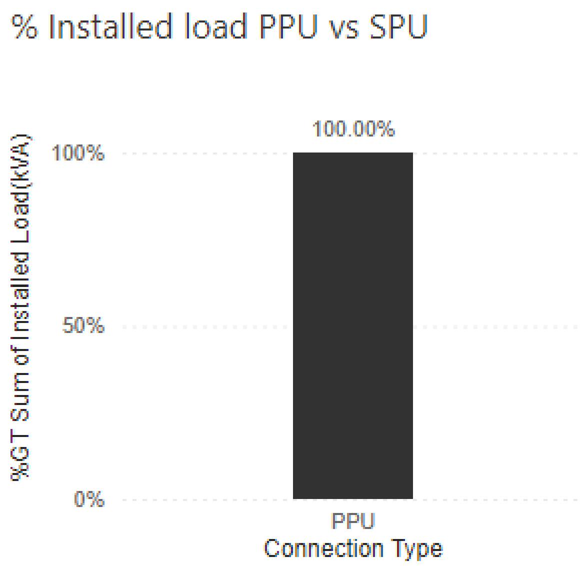


Figure 59: Installed load by type PPU vs SPU for Case Study G

As was seen in 4.5.2, Figure 59 shows that 100% of the installed load is attributed to residential-type PPU connections. This is in line with the overall research focus area to investigate residential loads prediction accuracy. Also, the indication of 100% of the load being attributed to PPU suggests that these connections are also part of an electrification programme at one stage.

4.5.2.2 Distribution of PPU Connections by Circuit Breaker Size

Represented in Figure 60 is a pie chart that represents the ratio of 20A vs 60A connections according to the “c” value as referred to in SANS 507-1:2019, table 2. This illustration aims to highlight the base load that influences the load characteristics and aids in contextualising Case Study G’s Class ID contributions.

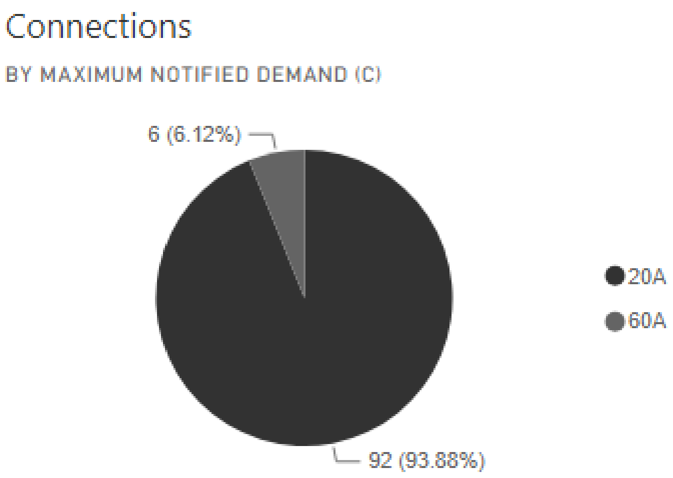


Figure 60: Total PPU connections by Circuit Breaker Size (c) for Case Study G

The inferences that can be drawn from Figure 60 is, most (93.88%) of the connections are 20A connections according to the installed breaker size. Alternatively referred to as the connection's NMD. There are some individual connections (6.12%) that have a 60A current limit. Overall, the ratio indicates that this specific case study falls at the lower end of the Class ID described in Table 2 of SANS 507-1:2019.

4.5.2.3 Connection Trends

The connection trends for Case Study G are depicted in Figure 61, offering a detailed view of the historical load growth in terms of total connections.

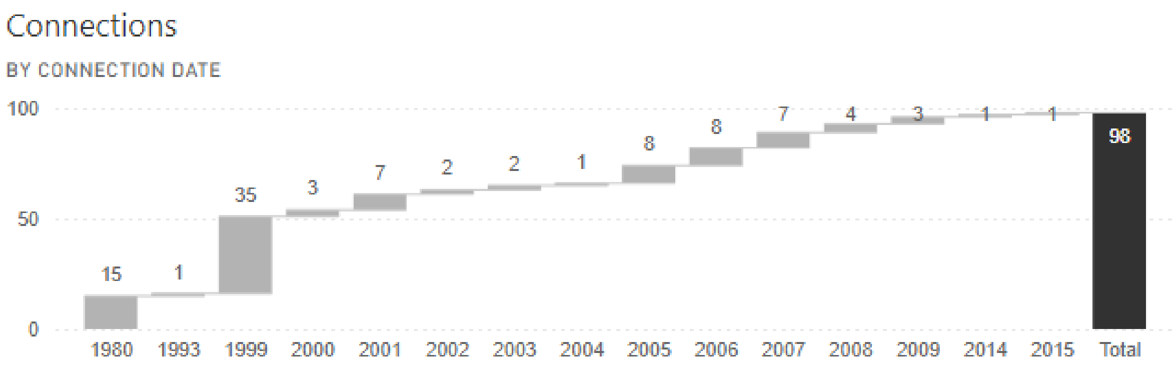


Figure 61: Total connections over time for Case Study G

As shown in Figure 61 the first connections were recorded as early as 1980, with the latest connections occurring in 2015. Notably, in 1999, there was a significant increase with 35 connections added, marking the highest annual growth within the observed period. From 2000 to 2015, the remaining connections were accumulated, contributing to the total of 98 connections. During this interval, the number of new connections ranged from one to eight annually.

The visualised data reveal distinct phases of growth: a period of rapid increase in the late 1990s, followed by an extended period of lower growth levels. This deceleration in the connection growth rate may suggest a geo-spatial saturation effect, a critical parameter considered in the design of transformer zones.

By analysing connection trends, it is evident that the growth dynamics have evolved, likely influenced by the spatial limitations and the increasing maturity of the network. Understanding these patterns is crucial for planning future expansions and optimising the existing infrastructure.

4.5.2.4 Connection Age Analysis by Breaker Size

The diverging bar chart in Figure 62 illustrates the average age of connections categorised by each circuit breaker size for Case Study G.

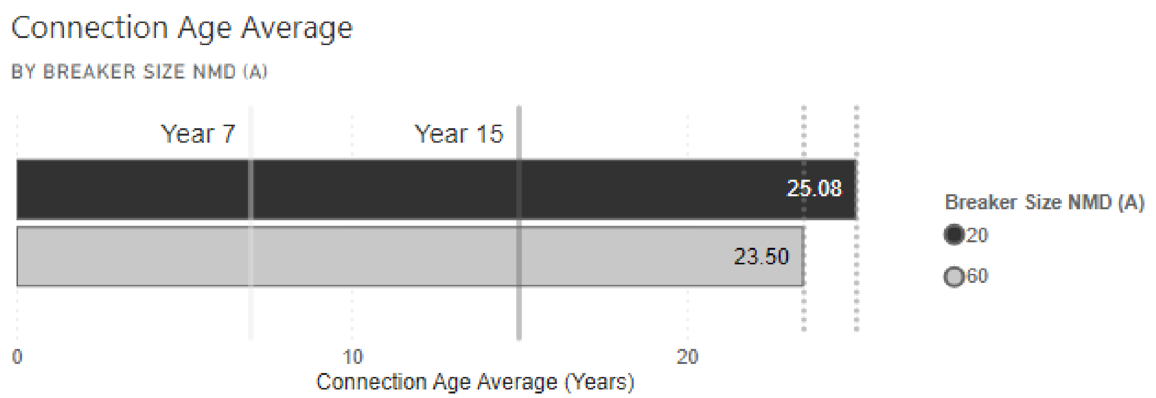


Figure 62: Connection Age Analysis for Case Study G

From Figure 62, it is observed that the average age of connections with 20A circuit breakers is 25.08 years, while the average age of connections with 60A circuit breakers is 23.50 years. The difference in average ages, with the 20A connections being older by approximately 1.58 years compared to the 60A connections, suggests a potential variance in the installation or upgrade times for these breaker sizes.

Given that both categories of circuit breaker size have connection ages significantly higher than 15 years, it is appropriate to use the 15-year parameters according to SANS 507-1:2019 – Table 2. Additionally, it should be noted that the 'c' values for 20A, 15-year parameters are limited to Class ID 1 and 2, whereas the 60A Class IDs, according to the 15-year 'c' values, are from Class ID 3 and higher.

The following conclusions can be drawn from the above analysis. Firstly, the presence of both 20A and 60A connections again suggests a heterogeneous consumer group. Secondly, the difference in the average ages of the two categories indicates a pattern of load growth and upgrading. The younger average age for 60A connections could imply that these connections have been installed more recently, possibly as upgrades from 20A connections to accommodate increased demand.

This pattern aligns with typical practices where electrical infrastructure is upgraded to meet higher demand, resulting in newer, larger capacity connections replacing older, smaller ones. The data thus reflects the evolving nature of electrical connections in residential areas, highlighting how infrastructure adapts to changing demands over time. The difference in ages also suggests that while upgrades have occurred, they have not been so frequent or recent as to alter the average age difference between the breaker sizes significantly. The older average age of the 20A connections indicates that these have been in place longer, potentially awaiting upgrades as demand increases.

4.5.3 Load Profiles

4.5.3.1 Historical Load Profile Analysis

The historical load profile for Case Study G, depicted in Figure 63, offers a detailed analysis of instantaneous load data collected from January 1, 2019, to December 31, 2023. This dataset provides a comprehensive view of electricity consumption patterns over this period, highlighting the variability and consistency of electrical loads. Key metrics, such as the mean load, maximum demand, and the 99.5th percentile, are prominently indicated. The mean load, shown as "Mean: 47.95," represents the average consumption level. The maximum demand, represented by the "Maximum: 129.29" line, reflects the highest observed load, while the 99.5th percentile line, indicated as "99.5th Percentile: 100.30," is considered the measured After Diversity Maximum Demand (ADMD) value, critical for assessing the capacity of the electrical infrastructure.

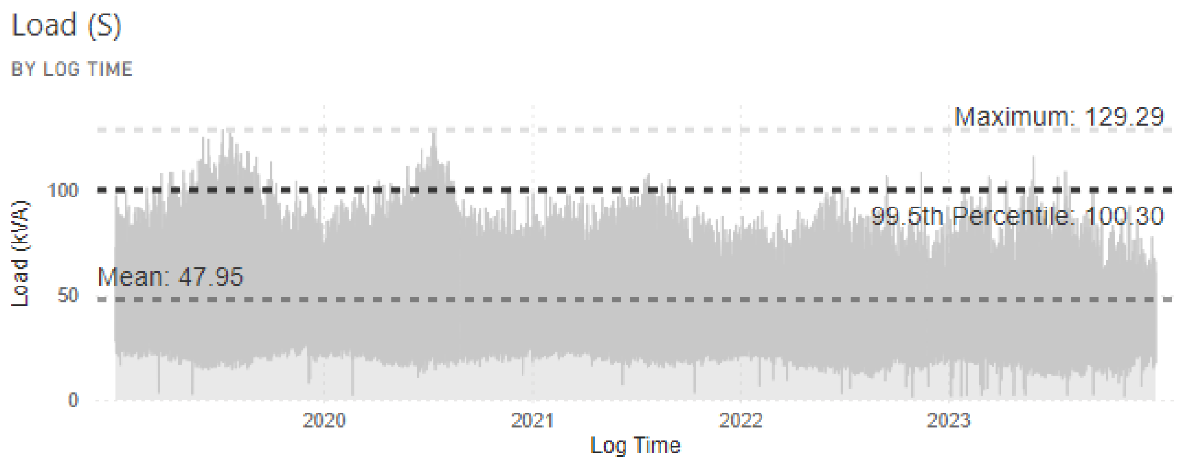


Figure 63: Historical load profile for Case Study G

Figure 63 illustrates the historical load profile for Case Study G, highlighting several key characteristics. The mean load, indicated by the "Mean: 47.95" line, suggests a moderate average consumption level. The profile shows notable fluctuations, with seasonal and daily variations reflecting changes in consumption patterns. The maximum recorded demand, demonstrated by the "Maximum: 129.29" line, indicates significant peak periods, potentially due to specific events or higher consumption periods. The 99.5th percentile, marked at "99.5th Percentile: 100.30," offers a conservative estimate of the ADMD, ensuring that the infrastructure can handle typical peak loads.

The normal distribution of the historical load profile data for Case Study G, as shown in Figure 64, provides a statistical representation of the data, illustrating it as a bell curve. This visual representation helps to understand the central tendency, spread, and presence of outliers in the load data.

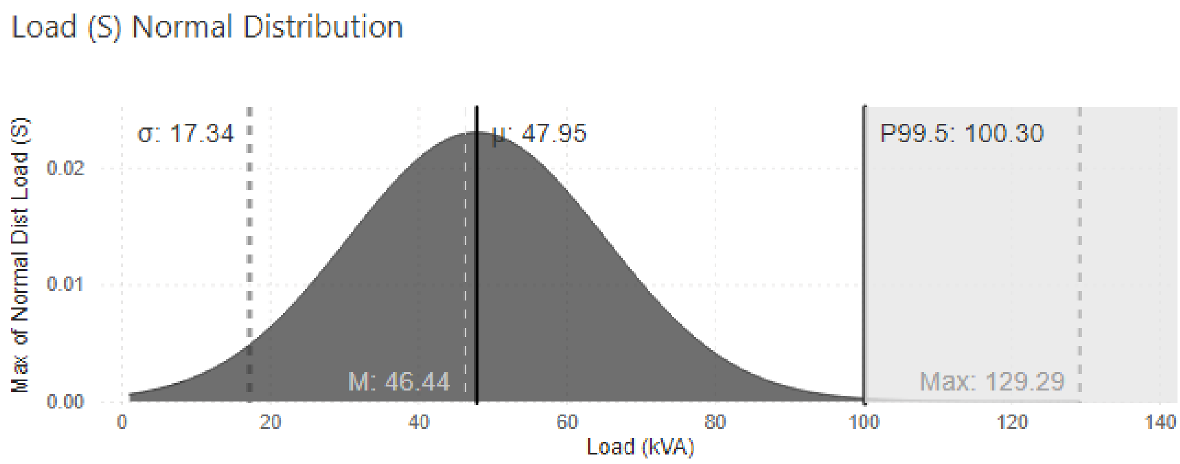


Figure 64: Normal distribution of Historical Load Profile data for Case Study G

In Figure 64, the bell curve represents the normal distribution of the load data, centred around the mean (μ) of 47.95 kVA, with a standard deviation (σ) of 17.34 kVA. The mode (M), indicated near "M: 46.44," is closely aligned with the mean, indicating a concentration of data points around these central values. The 99.5th percentile, labelled "P99.5: 100.30," marks the point below which 99.5% of the data lies, with the maximum value at "Max: 129.29," indicating the extreme values in the dataset. The bell curve's shape, typical of a normal distribution, suggests a slight skewness, as evidenced by the extended tail on the right side. This skewness indicates occasional instances of higher-than-typical loads, which are significant for planning and managing electrical infrastructure to accommodate potential peaks in demand.

4.5.3.2 99.5th Percentile Load Analysis

To gain a comprehensive understanding of the After Diversity Maximum Demand (ADMD) for Case Study G, this section evaluates the 99.5th percentile load across various aggregations. The analysis considers data presented in Figure 65, Figure 66, and Figure 67, providing insights into the load patterns from January 2019 to December 2023.

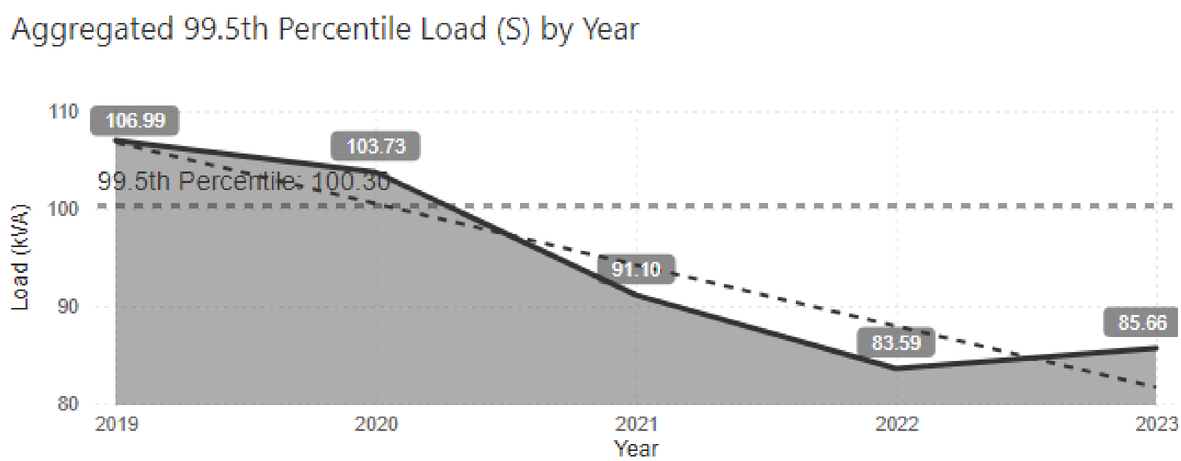


Figure 65: 99.5th Percentile load by year for Case Study G

Figure 65 illustrates the 99.5th percentile load by year for Case Study G. This figure provides an overview of the peak loads aggregated annually, with the 99.5th percentile line set at 100.30 kVA, representing the observed ADMD. The maximum load was recorded in 2019 at 106.99 kVA, while the minimum was 85.66 kVA in 2023. The trendline shows a downward trajectory, indicating a gradual decline in peak loads over the years. Notably, 2019 and 2020 loads exceeded the 99.5th percentile line, whereas 2021, 2022, and 2023 recorded values below it, reflecting a consistent decrease in demand.

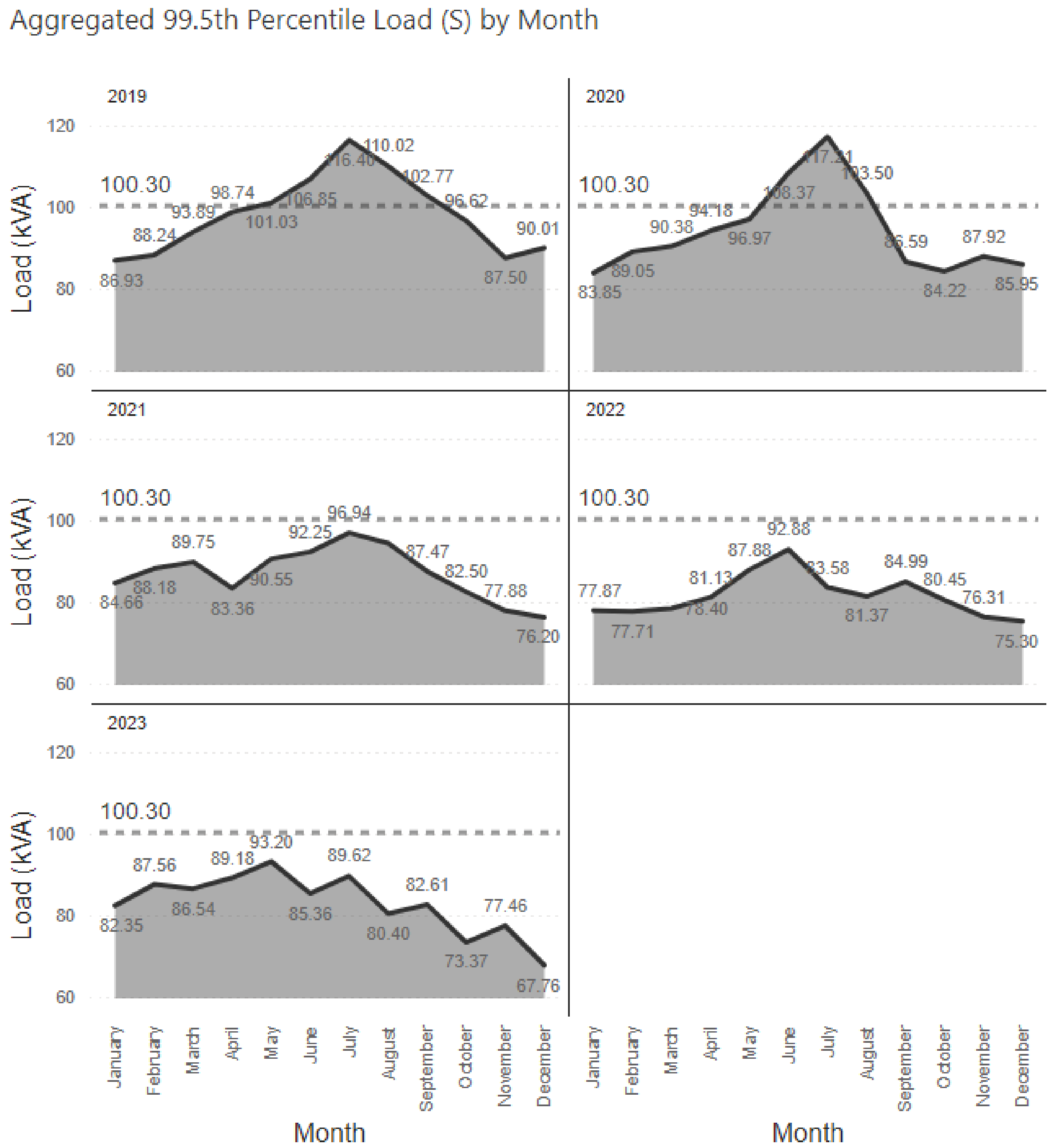


Figure 66: 99.5th Percentile load by each year for Case Study G

Figure 66 provides a detailed breakdown of the 99.5th percentile load by each year, highlighting monthly variations. In 2019, the peak occurred in June at 110.02 kVA, and in 2020, the highest load was observed in July at 113.50 kVA. For 2021, the peak was in May at 96.94 kVA, while 2022 saw its highest load in June at 92.88 kVA. In 2023, the peak load occurred in June at 93.53 kVA. This data shows that the monthly peak values have been consistently decreasing, with fewer months exceeding the 99.5th percentile threshold, indicating a reduction in high-demand periods.

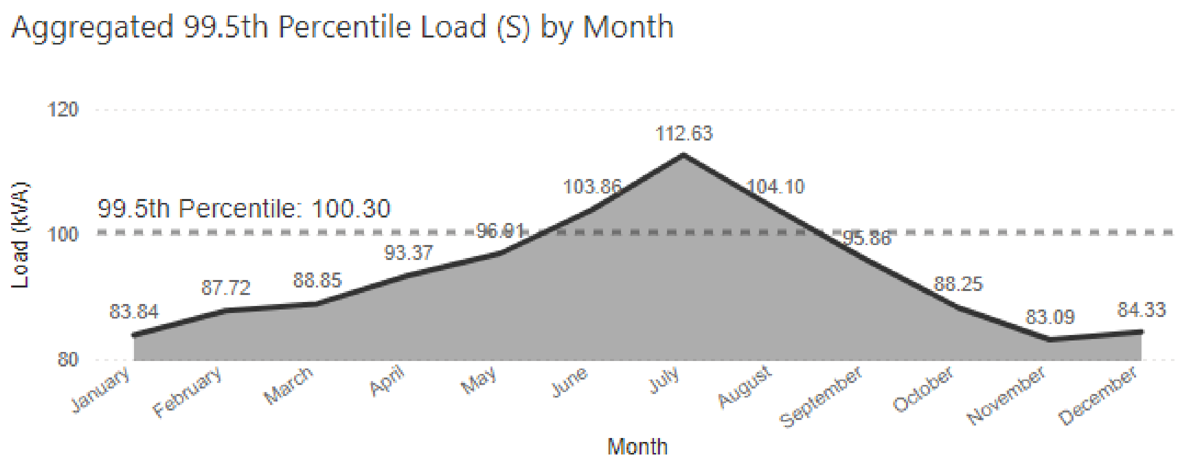


Figure 67: Aggregated 99.5th Percentile load by Month for Case Study G

Figure 67 aggregates the 99.5th percentile load by month across all years, offering a comprehensive view of seasonal demand variations. The data reveals that July consistently experienced the highest loads, with the peak reaching 112.63 kVA. In contrast, February typically saw the lowest demand, with a value of 87.72 kVA. The trend shows an increase in loads from February, peaking in July, and then a steady decline towards December. This seasonal pattern suggests higher electricity consumption in mid-year months.

The 99.5th percentile load analysis for Case Study G indicates significant variations in ADMD, with the 99.5th percentile serving as the observed ADMD. The overall trend reveals a decline in peak load values from 2019 to 2023, with notable decreases in monthly peaks, particularly in recent years. This demand reduction suggests changes in consumption patterns or efficiency improvements. The analysis highlights the need for continued monitoring and adaptation in planning and infrastructure management, ensuring the system's capability to handle peak demands efficiently. Understanding these trends, including seasonal fluctuations, is crucial for effective load forecasting and resource allocation.

4.5.3.3 99.5th Percentile Load Analysis: Daily Demand Profiles

This analysis investigates the 99.5th percentile load profiles for Case Study G, which highlights the periods of maximum electricity demand that are exceeded only 0.5% of the time. The 99.5th percentile load is a critical measure for understanding the highest usage scenarios, vital for designing and managing electrical infrastructure. By analysing these profiles, we can observe both seasonal and daily variations in energy consumption, providing a comprehensive view of how demand changes throughout the year and within a typical day.

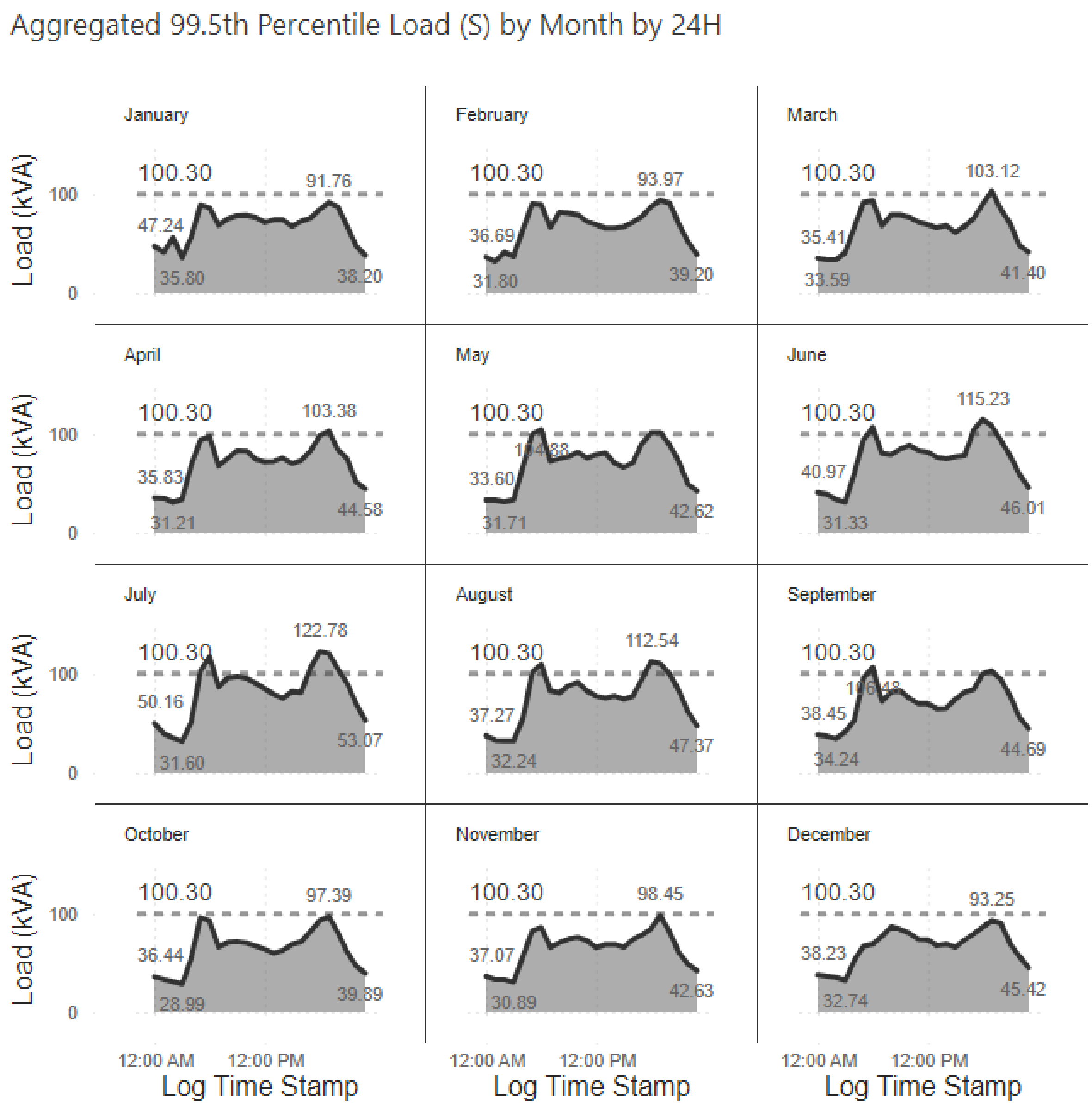


Figure 68: Aggregated 99.5th Percentile load by 24-h day by Month for Case Study G

Figure 68 illustrates the monthly 99.5th percentile load profiles, showcasing how daily demand peaks vary across different months. The dashed line at 100.30 kVA marks the 99.5th percentile load threshold. Key observations include:

Winter Months (June - August): The data shows a notable increase in daily peaks, often surpassing the 99.5th percentile threshold. For example, June reaches a peak of 115.23 kVA, while July and August show peaks of 122.78 kVA and 112.54 kVA, respectively. These peaks indicate higher energy usage, likely due to heating requirements.

Summer Months (December - February): During these months, the demand generally remains below the 99.5th percentile line, with the highest peak in February at 93.97 kVA. This reflects moderate energy consumption, possibly due to cooling needs.

Transitional Months (March, September): The transitional months show peaks near or slightly above the 99.5th percentile threshold, with March reaching 103.12 kVA and September at 101.69 kVA, indicating variability in energy demand as seasons change.

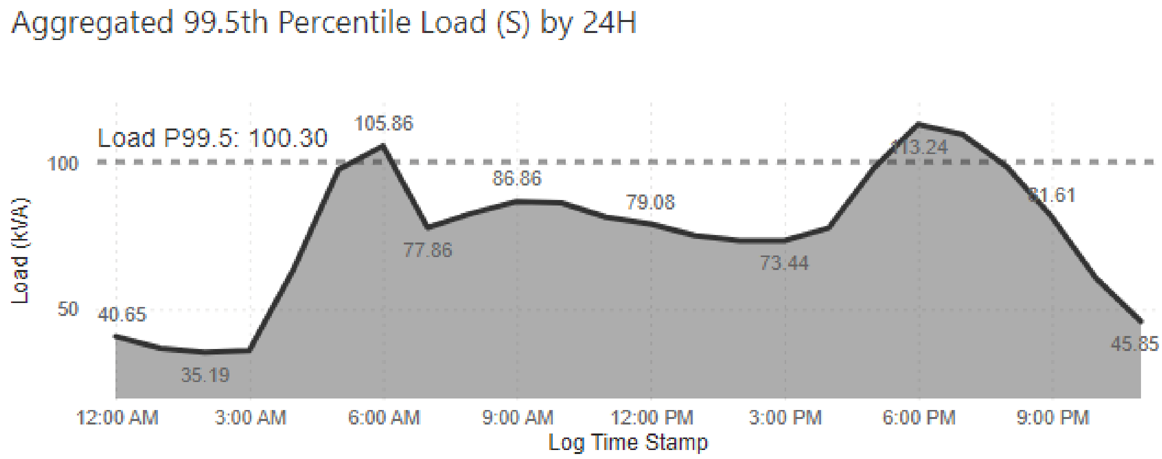


Figure 69: Aggregated 99.5th Percentile load by 24-h day for Case Study G

Figure 69 presents an aggregated view of the daily demand profile over a typical 24-hour period. The 99.5th percentile load line at 100.30 kVA helps to identify critical demand periods:

Morning Peak: A significant increase in load is observed starting around 3:00 AM, with a peak of 105.86 kVA at 6:00 AM. This rise correlates with morning activities as residents begin their day.

Evening Peak: The highest demand occurs around 6:00 PM, with a peak load of 113.24 kVA, indicating typical residential activities such as cooking and heating.

Off-Peak Periods: The lowest demand occurs late at night and early morning, with the load dropping to around 35.19 kVA, significantly below the 99.5th percentile threshold.

The 99.5th Percentile Daily Load Analysis for Case Study G reveals notable seasonal and daily variations in electricity demand. The data indicate that peak demands are more pronounced during winter months, with frequent exceedances of the 99.5th percentile threshold, reflecting increased heating needs. The analysis also highlights significant daily peaks in the morning and evening, essential for understanding residential electricity consumption patterns. These insights are crucial for effective planning and management of energy infrastructure to ensure reliable service during periods of maximum demand.

4.5.4 Proposed ADMD vs Observed ADMD

This section aims to compare the proposed After Diversity Maximum Demand (ADMD) values suggested by SANS 507-1:2019 Year-15 parameters with the observed ADMD values for Case Study G. This comparison is crucial for assessing the accuracy and reliability of the proposed standards in predicting real-world electricity demand. By analysing the discrepancies between these values, we can determine the applicability of the SANS guidelines and identify any necessary adjustments for improved planning and infrastructure design.

Summary of Key Metrics

- Total Connections: 98
- Average Age: 24.98 years (greater than 15 years; therefore, Year-15 parameters are used)
- Installed Load: 506.00 kVA (5.16 kVA per connection)

- P99.5 Load: 100.30 kVA (1.02 kVA per stand)
- Resultant P99.5 Diversity Factor (DF): 0.20

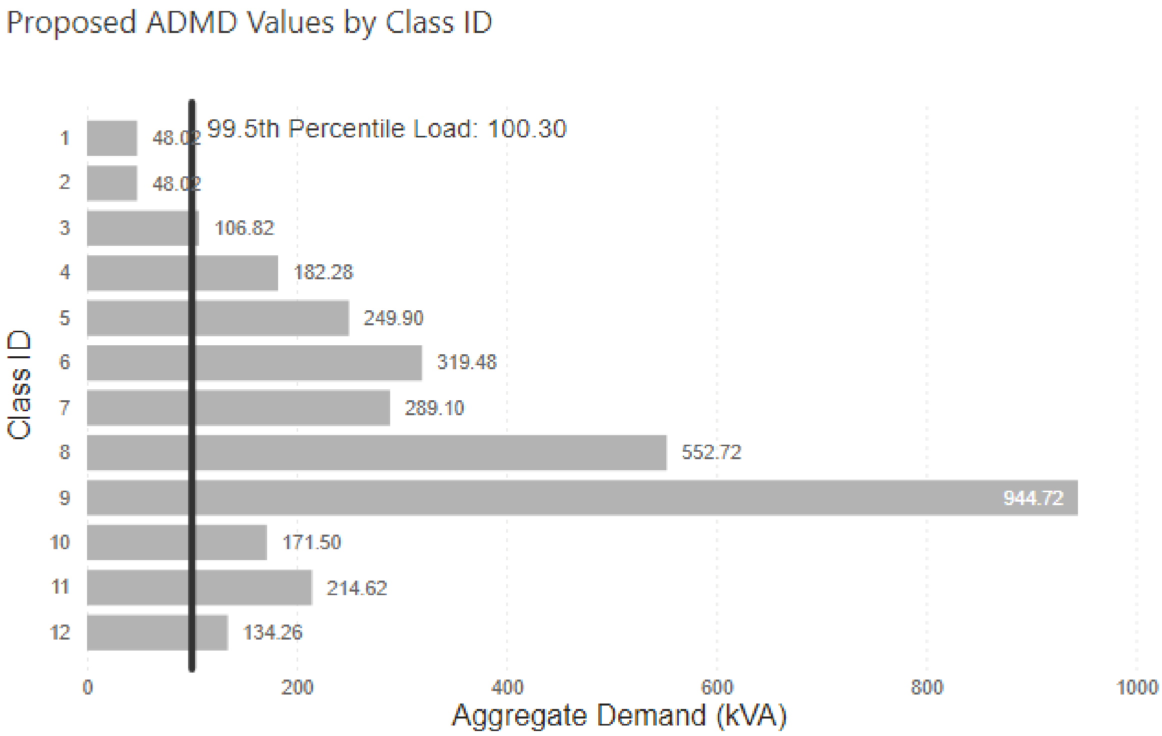


Figure 70: Proposed Year-15 ADMDs result by Class ID for Case Study G

Figure 70 illustrates the proposed ADMD values for different consumer classes as per SANS 507-1:2019 Year-15 parameters, compared against the measured 99.5th percentile load (100.30 kVA). The proposed ADMD values show significant variation across different classes, with Class ID 9 and 8 exhibiting the highest proposed values at 944.72 kVA and 552.72 kVA, respectively. The vertical line at 100.30 kVA indicates the 99.5th percentile load, serving as a benchmark for comparison.

The data from Figure 70 reveals that the proposed ADMD values for most consumer classes significantly exceed the measured 99.5th percentile load. Notably, Class ID 9 (Urban Estate) has a proposed ADMD value that is nearly ten times the measured load, indicating a possible overestimation. On the other hand, lower class IDs such as 1 and 2 show a proposed ADMD that is closer to the measured load, although still higher. This suggests that the SANS guidelines may need revision to reflect better actual consumption patterns, particularly for higher consumer classes.

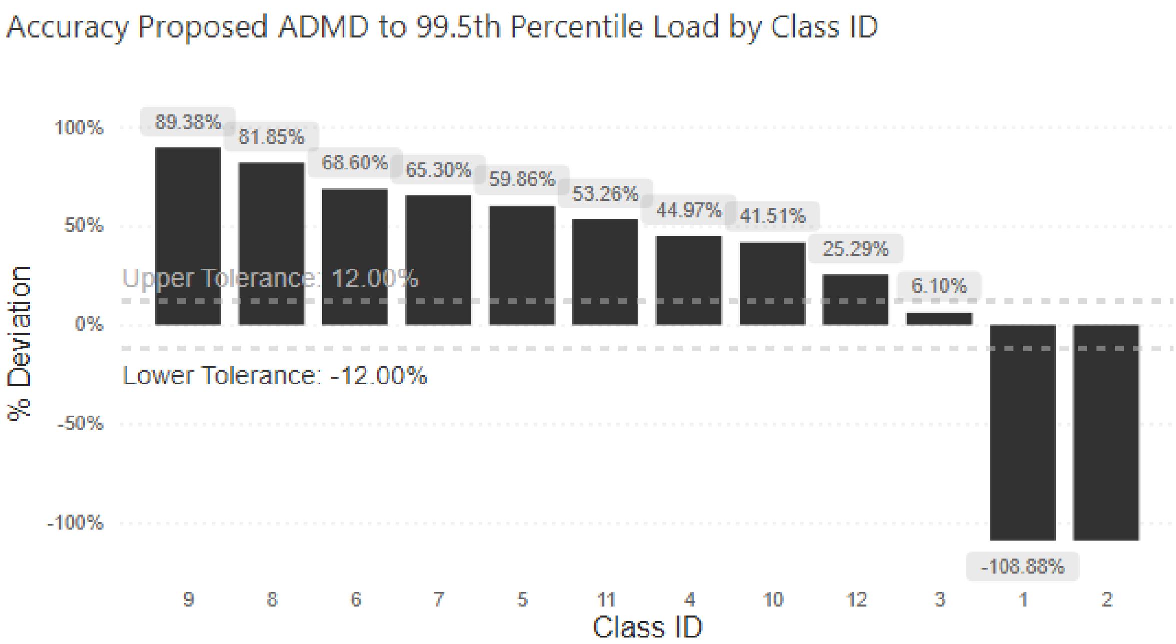


Figure 71: Deviation of SANS 507-1:2019 Year-15 ADMD by Class ID vs. 99.5th Percentile Load for Case Study G

Figure 71 presents the percentage deviation of the proposed ADMD values from the measured 99.5th percentile load for each class ID. The deviation is significant across most classes, with Class ID 9 showing the highest positive deviation at 89.38%. In contrast, Class IDs 1 and 2 show negative deviations, indicating that the proposed values are lower than the measured loads for these classes.

The deviations highlighted in Figure 71 indicate a substantial overestimation of the ADMD values for most consumer classes according to the SANS 507-1:2019 Year-15 parameters. The high positive deviations, particularly for Class ID 9, suggest that the current proposed values do not accurately capture the actual demand patterns. The negative deviations for Class IDs 1 and 2 indicate that the proposed values for these classes may be overly conservative, yet still not entirely accurate. This discrepancy underscores the need for a more nuanced approach in setting ADMD standards that consider the specific characteristics and consumption behaviours of different consumer classes.

Table 6: Detailed Comparison of Proposed ADMD vs Observed ADMD for Case Study G

ID	Consumer Class	SANS 15 Year ADMD (kVA)	Case SANS 15 Year ADMD (kVA)	Accuracy	Deviation
1	Rural settlement, Non-urban, scattered	0.49	48.02	208.88%	-108.88%
2	Rural villages	0.49	48.02	208.88%	-108.88%
3	Informal settlement	1.09	106.82	93.90%	6.10%
4	Township area	1.86	182.28	55.03%	44.97%
5	Urban residential I	2.55	249.90	40.14%	59.86%
6	Urban residential II	3.26	319.48	31.40%	68.60%
7	Urban townhouse complex or duplex	2.95	289.10	34.70%	65.30%
8	Urban Townhouse II	5.64	552.72	18.15%	81.85%
9	Urban Estate	9.64	944.72	10.62%	89.38%

10	High rise (small)	1.75	171.50	58.49%	41.51%
11	High rise (medium)	2.19	214.62	46.74%	53.26%
12	Hostel	1.37	134.26	74.71%	25.29%

Table 6 provides a detailed comparison of the proposed and observed ADMD values for each consumer class. The accuracy and deviation columns highlight the discrepancies between the proposed values and the actual measured loads. Notably, Classes 1 and 2 show the highest negative deviation, suggesting that the proposed ADMD values significantly underestimate the actual load for rural settlements and villages. Conversely, Classes 8 and 9 show the highest positive deviations, indicating an overestimation for urban estates and high-end residential areas. These observations reinforce the need for revising the proposed ADMD values to better align with real-world consumption patterns.

The comparison between the proposed ADMD values and the observed ADMD values for Case Study G reveals significant discrepancies, particularly for higher consumer classes. The proposed values tend to overestimate the actual demand for urban estates and high-end residential areas, while underestimating the load for rural settlements and villages. These findings suggest that the current SANS 507-1:2019 Year-15 parameters may not accurately reflect the diverse consumption patterns observed in different consumer classes. Therefore, it is crucial to re-evaluate these standards and consider more tailored approaches to ensure reliable and efficient electricity infrastructure planning.

Interpretive Note: Case Study G

- Installed base is PPU-only. Within PPU, breaker sizes are 20A = 93.88% and 60A = 6.12%.
- Average connection age is 24.98 years. By breaker size: about 25.08 years (20A) and 23.50 years (60A), so Year-15 parameters were appropriate.
- Observed ADMD (P99.5) is 100.30 kVA total (≈1.02 kVA/stand).
- Best fit (exact class ID): Class 3 (Informal settlement) with 1.09 kVA/stand → 106.82 kVA case total, +6.10% vs observed. Classes 1–2 are below the empirical level, while classes above 3 propose higher per-stand values than 1.09 and overshoot by larger margins.

The PPU-only base and the strong 20A dominance indicate a lower-to-mid demand profile; among the SANS options, Class 3 produces the least absolute deviation from the measured 99.5th-percentile ADMD and aligns best with the observed connection composition.

4.6 Case Study H

Case Study H explores load profiles and ADMD values in Thandanani and Riemland within the Nketoana Local Municipality, examining factors affecting electricity demand.

4.6.1 Geographic Overview

Case Study H is geographically located at GPS coordinates 28.459128, -27.679349, as illustrated in Figure 72. This area includes the neighbourhoods of Thandanani, Riemland, and parts of Petrus Steyn.

GPS Location 28.450716;-27.802288

Figure 72: Geographic location for Case Study H

The transformer zone for Case Study H is situated within the local municipal boundaries of Nketoana Local Municipality, which falls under the Thabo Mofutsanyana District Municipality in the Free State Province of South Africa. The local municipal authorities are responsible for providing public services, infrastructure maintenance, and promoting community welfare within this region.

The economy surrounding Case Study H is primarily driven by agriculture, with a focus on the production of crops such as maize, wheat, and sunflowers. Livestock farming also contributes significantly to the local economy. Petrus Steyn serves as an agricultural hub, supporting various agro-processing activities that add value to primary agricultural products. Additionally, the presence of small-scale retail businesses and service industries caters to the local community's needs, impacting the overall electricity demand.

The climate in this region is generally temperate, characterised by cold winters and warm summers. Winter months (June to August) often experience low temperatures, leading to increased electricity consumption for heating purposes. During the summer months (November to February), the electricity demand may rise due to the increased use of cooling systems. The region receives moderate rainfall, mainly during the summer, which influences agricultural activities and affects electricity consumption patterns.

The socioeconomic factors in Case Study H's area play a critical role in shaping electricity demand patterns. The community is socioeconomically diverse, comprising low to middle-income households, with varying levels of access to economic opportunities and public services. Educational institutions and healthcare facilities within the area rely on a stable electricity supply to operate efficiently.

Economic disparities within the community influence energy consumption, with more affluent households typically using more electrical appliances and thus having higher electricity demand. In contrast, lower-income households might have lower overall electricity consumption but still exhibit significant usage during peak times, such as in the evenings when residential activities are at their peak.

In summary, the geographic and socioeconomic context of Case Study H provides a comprehensive backdrop for analysing electricity consumption patterns. The combination of diverse economic activities, temperate climate, and varying socioeconomic factors offers a rich dataset for evaluating the accuracy of proposed ADMD values and understanding their implications for local electricity infrastructure planning.

4.6.2 Connections

4.6.2.1 Proportion of Installed Load by Connection Type

Figure 73 is a visual representation of the installed load by type (PPU vs SPU) in a percentage form. It aims to indicate the presence or absence of each load type.

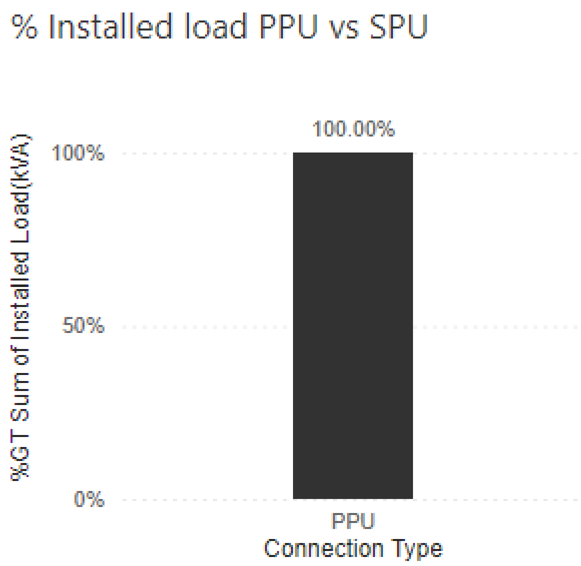


Figure 73: % Installed load by type PPU vs SPU for Case Study H

As was seen with previous case studies, when compared with the exact graphical representation of the installed load, Figure 73 This indicates that the installed load for Case Study H is purely PPU in type. The homogeneity of load type being PPU shows that these connections are part of universal grid access programmes, as highlighted in the literature review.

4.6.2.2 Distribution of PPU Connections by Circuit Breaker Size

Figure 74 shows a pie chart representing the various connection upper demand limits, as set by the connection's circuit breaker size. Also referred to as the "c" value in SANS 507-1:2019. The inference that Figure 74 allows for the drawing of how the installed load proportionally contributes to the load characteristics.

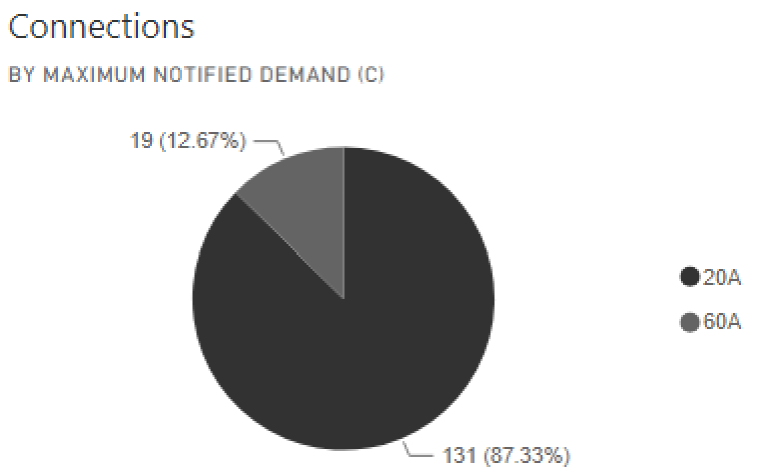


Figure 74: Total PPU connections by Circuit Breaker Size (c) for Case Study H

From Figure 74, it can be seen that 87.33% of the connections are limited to 20A, and 12.69% of the total number of connections are limited to 60A. With 20A being the predominant circuit breaker size installed, it can be understood that these connections are overall at lower peak demands. This also shows that Case Study H falls at the lower end of Class IDs as described by Table 2, SANS 507-1:2019. With that being stated, it would also be reasonable to conclude the potential for load growth beyond the current Class IDs.

4.6.2.3 Connection Trends

The connection trends for Case Study H are depicted in Figure 75, providing a detailed view of the historical load growth in terms of total connections.

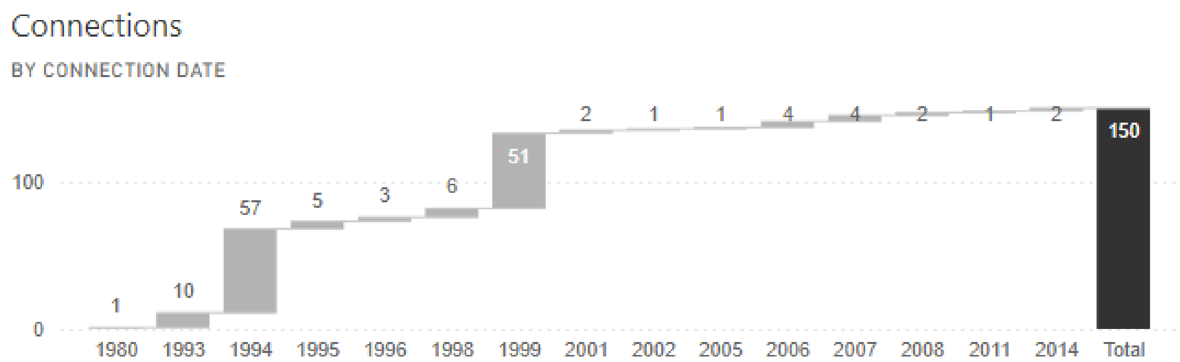


Figure 75: Total connections over time for Case Study H

As shown in Figure 75, the first connections for Case Study H were recorded in 1980, with the most recent connections occurring in 2014. A notable increase in connections occurred in 1994, where 57 new connections were added. This was followed by another significant increase in 1999 with 51 connections, marking the two most significant annual growth periods in the dataset.

Before these peaks, there were smaller increases in 1993 (10 connections) and 1995 (five connections). Following the 1999 peak, the number of new connections per year generally remained low, ranging from one to six connections annually between 2000 and 2014. Small peaks were observed in 2006 and 2007, each with four new connections.

By the end of the observed period, the total number of connections reached 150. The data illustrate a pattern of early rapid growth followed by an extended period of slower growth. This deceleration likely indicates geo-spatial saturation, which is an important factor in the design and planning of transformer zones.

Analysing these trends reveals the evolving dynamics of network expansion and the potential constraints imposed by geographic saturation. Such insights are essential for future infrastructure planning and for maintaining the balance between network growth and sustainability.

4.6.2.4 Connection Age Analysis by Breaker Size

The diverging bar chart in Figure 76 illustrates the average age of connections categorised by each circuit breaker size for Case Study H.

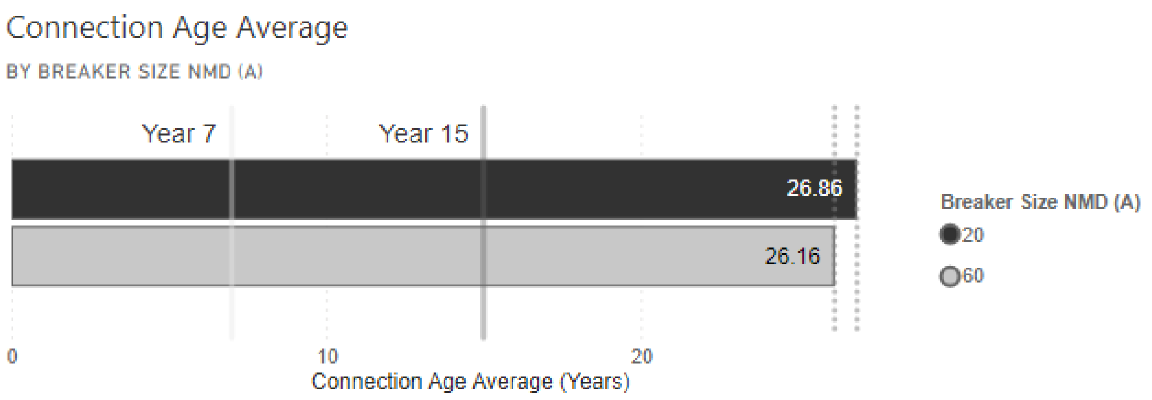


Figure 76: Connection Age Analysis for Case Study H

From Figure 76, it is observed that the average age of connections with 20A circuit breakers is 26.86 years, while the average age of connections with 60A circuit breakers is 26.16 years. The slight difference in average ages, with the 20A connections being older by approximately 0.70 years compared to the 60A connections, suggests that both types of connections were likely established around the same time.

Given that both categories of circuit breaker size have connection ages significantly higher than 15 years, it is appropriate to use the 15-year parameters according to SANS 507-1:2019 – Table 2. Additionally, it should be noted that the 'c' values for 20A, 15-year parameters are limited to Class ID 1 and 2, whereas the 60A Class IDs, according to the 15-year 'c' values, are from Class ID 3 and higher.

The following conclusions can be drawn from the above analysis. Firstly, the presence of both 20A and 60A connections suggests a heterogeneous consumer group. Secondly, the similarity in the average ages of the two categories indicates that there has not been significant load growth necessitating upgrades from 20A to 60A connections. If significant individual load growth were present, we would expect the average age of 60A connections to be noticeably lower due to older 20A connections being upgraded over time.

This pattern reflects a stable demand for electricity within the study area, with the existing infrastructure sufficiently meeting the needs of the consumers without necessitating widespread upgrades. The data thus highlights a consistent and stable electrical demand in the residential area covered by Case Study H. The slight difference in ages also suggests that while upgrades may have occurred, they have not been so frequent or recent as to significantly alter the average age difference between the breaker sizes.

4.6.3 Load Profiles

4.6.3.1 Historical Load Profile Analysis

The historical load profile for Case Study H, depicted in Figure 77, provides a comprehensive overview of the electrical load data collected from January 1, 2019, to December 31, 2023. This dataset captures the variations in load demand over a significant period, offering insights into daily and seasonal consumption patterns. Key indicators, such as the mean load, maximum demand, and the 99.5th percentile, are highlighted to illustrate typical and peak usage levels. The mean load, represented by the "Mean: 54.52" line, indicates the average load throughout the study timeframe. The maximum demand, shown as the "Maximum: 149.56" line, represents the highest recorded load, while the 99.5th percentile, marked as "99.5th Percentile: 119.91," is considered the measured After Diversity Maximum Demand (ADMD) value, essential for infrastructure planning and reliability assessments.

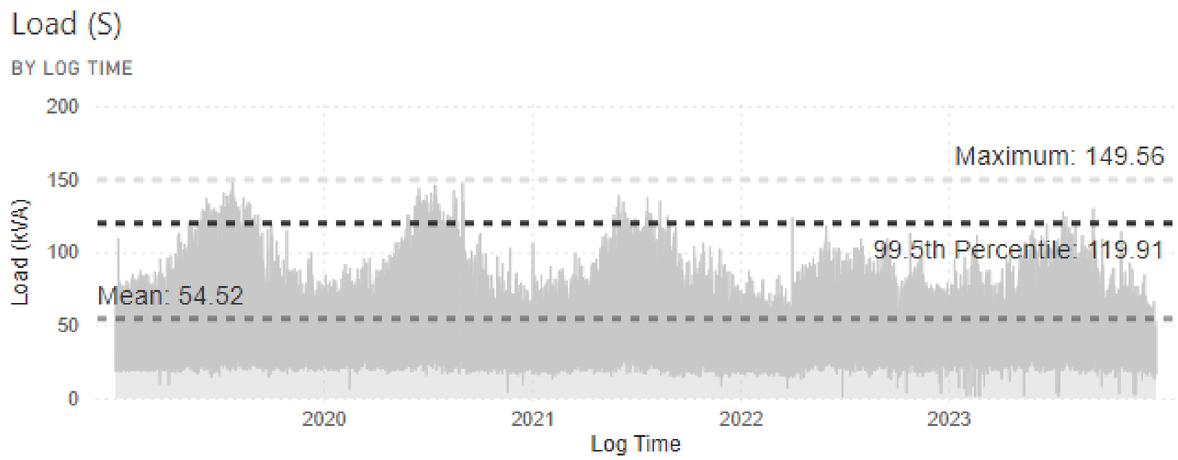


Figure 77: Historical load profile for Case Study H

As illustrated in Figure 77, the historical load profile for Case Study H reveals several critical characteristics. The mean load, indicated by the "Mean: 54.52" line, suggests a stable average consumption level across the period. The profile shows notable variability, with significant peaks and troughs, reflecting changes in load demand due to various factors such as seasonal effects or specific high-demand events. The maximum recorded demand, marked by the "Maximum: 149.56" line, indicates occasional high usage periods, which are essential for understanding the system's capacity limits. The 99.5th percentile, represented by the "99.5th Percentile: 119.91" line, offers a conservative estimate of the ADMD, crucial for ensuring that the infrastructure can handle most peak loads.

The normal distribution of the historical load profile data for Case Study H, shown in Figure 78, provides a statistical depiction of the load data, modelled as a bell curve. This visualisation aids in understanding the central tendency, spread, and presence of outliers within the dataset.

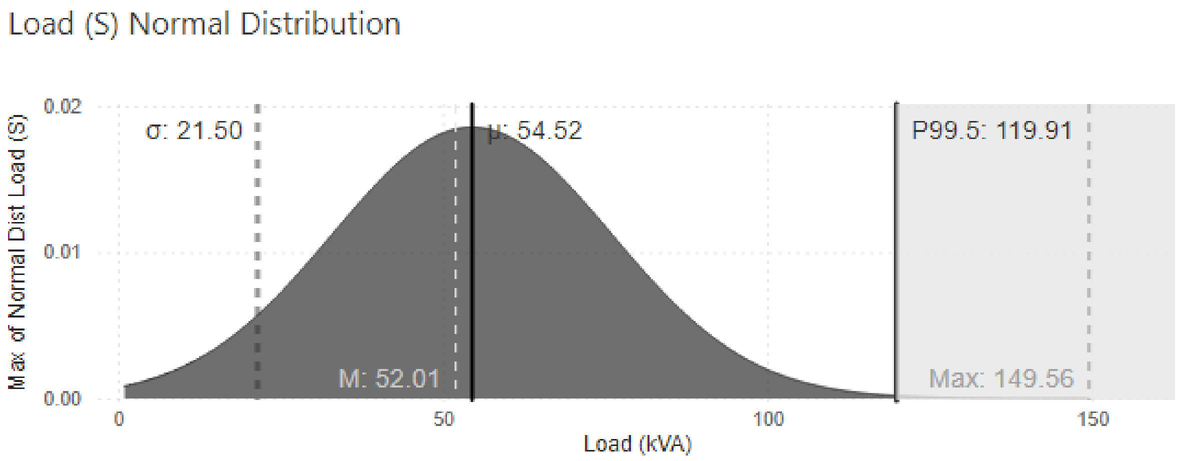


Figure 78: Normal distribution of Historical Load Profile data for Case Study H

Figure 78 illustrates the normal distribution of the load data, centred around the mean (μ) of 54.52 kVA, with a standard deviation (σ) of 21.50 kVA. The mode (M), noted near "M: 52.01," is close to the mean, indicating a typical central clustering of data points. The 99.5th percentile, labelled "P99.5: 119.91," indicates the point below which 99.5% of the load values fall, highlighting the typical peak demand levels. The maximum recorded load, "Max: 149.56," lies beyond the 99.5th percentile, capturing the extreme values in the dataset. The bell curve shape suggests a reasonably normal distribution with slight skewness towards the right, reflecting occasional instances of higher-than-usual loads. This skewness indicates the presence of significant outliers that may impact the planning and management of electrical infrastructure, ensuring it can accommodate these peaks.

4.6.3.2 99.5th Percentile Load Analysis

In assessing the After Diversity Maximum Demand (ADMD) for Case Study H, the 99.5th percentile load provides a critical measure of peak demand patterns. This analysis examines data presented in Figure 79, Figure 80, and Figure 81, covering the period from January 2019 to December 2023. These figures offer a comprehensive view of the 99.5th percentile load, helping to understand the variations in electricity demand.

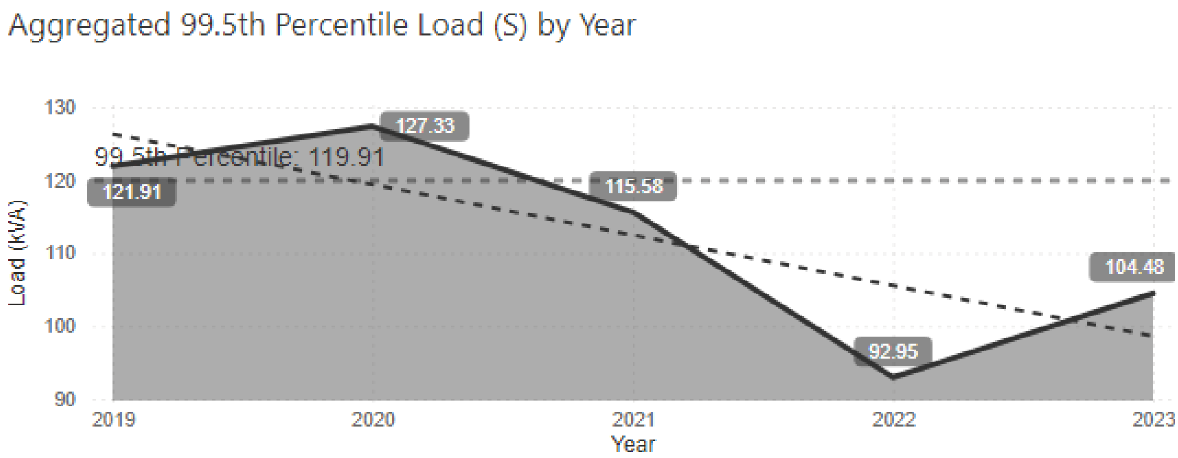


Figure 79: 99.5th Percentile load by year for Case Study H

Figure 79 illustrates the 99.5th percentile load by year for Case Study H. The figure highlights annual peak loads with the 99.5th percentile line set at 119.91 kVA, representing the observed

ADMD. The maximum load recorded was 127.33 kVA in 2020, while the minimum was 92.95 kVA in 2022. The trendline indicates a decrease from 2020, followed by a slight rise in 2023 to 104.48 kVA, suggesting a partial recovery in demand. Notably, the years 2019, 2020, and 2021 exceeded the 99.5th percentile line, whereas 2022 and 2023 were below it, reflecting fluctuations in peak load values over the study period.

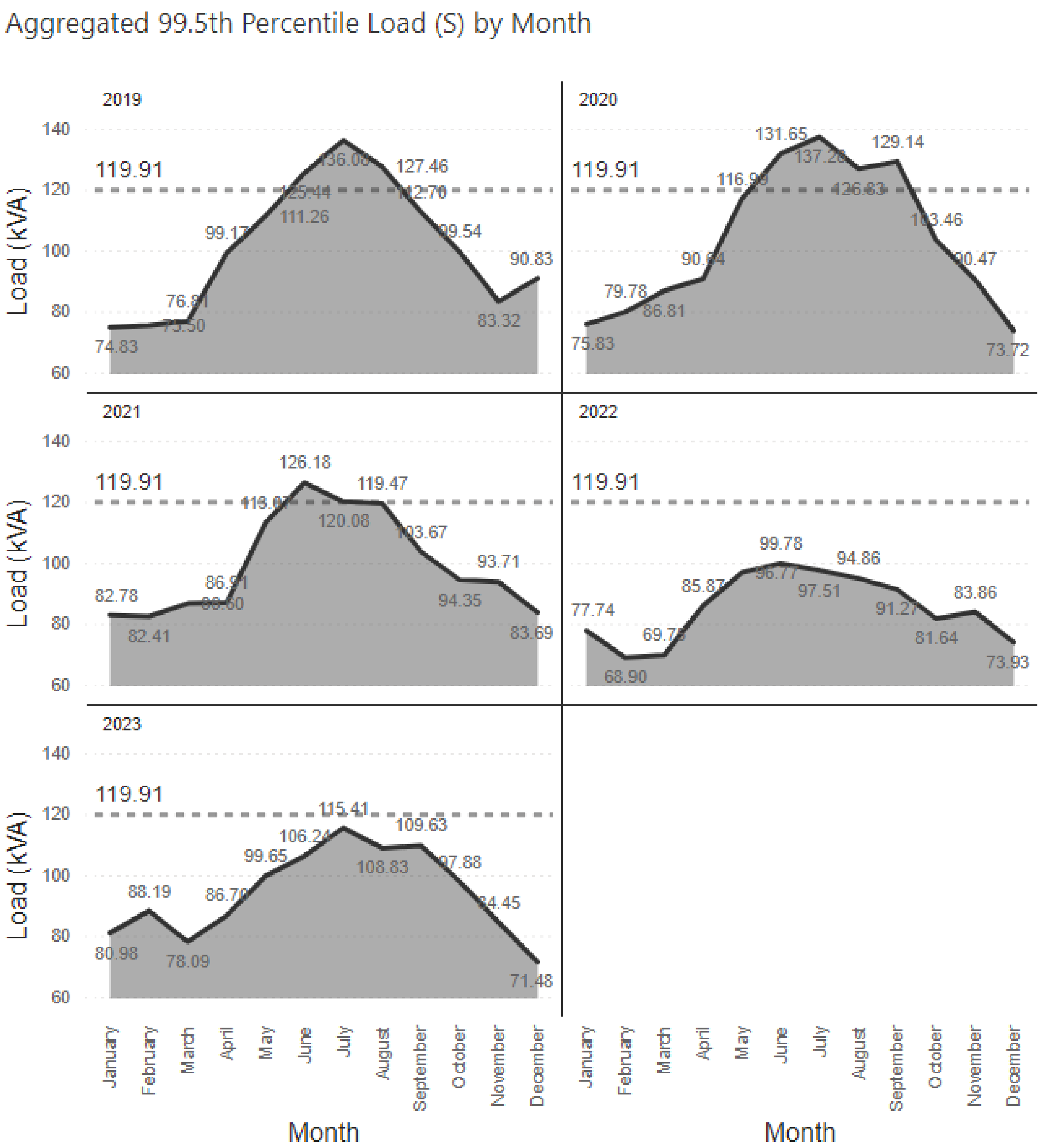


Figure 80: 99.5th Percentile load by each year for Case Study H

Figure 80 provides a more granular analysis of the 99.5th percentile load by each year, detailing monthly variations. In 2019, the peak occurred in July at 127.46 kVA, and in 2020, the highest load was observed in July at 137.26 kVA. For 2021, the peak was recorded in June at 126.18 kVA, while 2022 saw its highest load in August at 99.78 kVA. The year 2023 had a peak load in July at 115.41 kVA. The data indicate that monthly peaks often occurred in the mid-year months, with a notable decline in overall peak values observed in 2022.

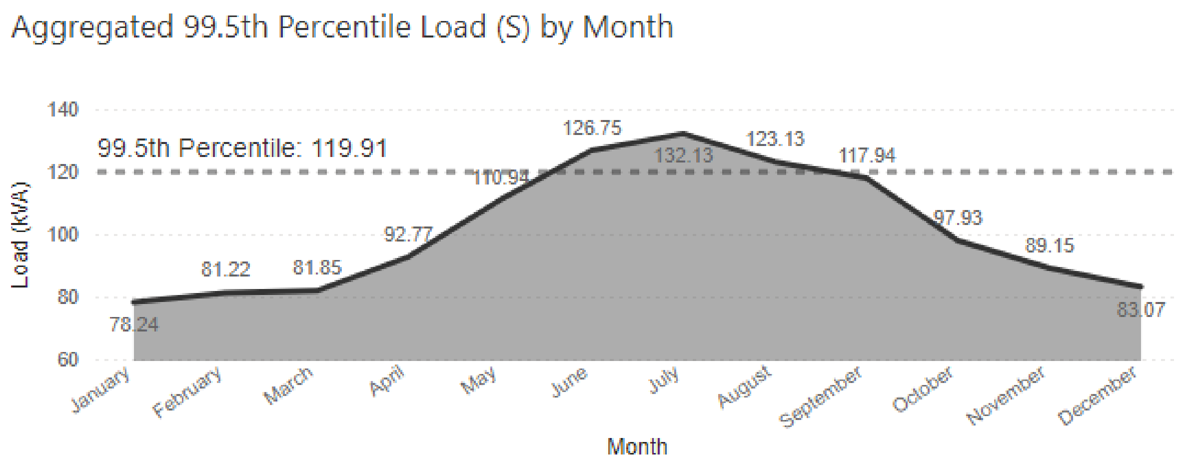


Figure 81: Aggregated 99.5th Percentile load by Month for Case Study H

Figure 81 aggregates the 99.5th percentile load by month across all years, providing a comprehensive view of seasonal demand patterns. The data shows a consistent peak in July, reaching 132.13 kVA, while the lowest load was in January at 78.24 kVA. The trend suggests increasing loads from February, peaking in mid-year, and then declining towards December. This seasonal variation highlights the higher electricity consumption during the middle of the year.

The 99.5th percentile load analysis for Case Study H reveals significant variations in ADMD, with the 99.5th percentile serving as the observed ADMD. The data demonstrates a peak in demand around 2020, followed by a notable decline in 2022, and a partial recovery in 2023. Monthly analysis shows that mid-year periods consistently experience the highest loads, often surpassing the 99.5th percentile threshold. This fluctuation indicates changes in consumption patterns, potentially influenced by various factors such as weather conditions, economic activities, and consumer behaviour. The analysis underscores the importance of adaptive planning and infrastructure management to handle peak demands, ensuring a reliable electricity supply efficiently.

4.6.3.3 99.5th Percentile Load Analysis: Daily Demand Profiles

This analysis explores the 99.5th percentile load profiles for Case Study H, providing insights into the maximum demand periods that occur only 0.5% of the time. The 99.5th percentile load is an essential metric for identifying peak usage scenarios, which are crucial for infrastructure planning and energy management. By examining these profiles, we can understand both seasonal and daily variations in electricity consumption, offering a detailed view of demand patterns throughout the year and within a typical day.

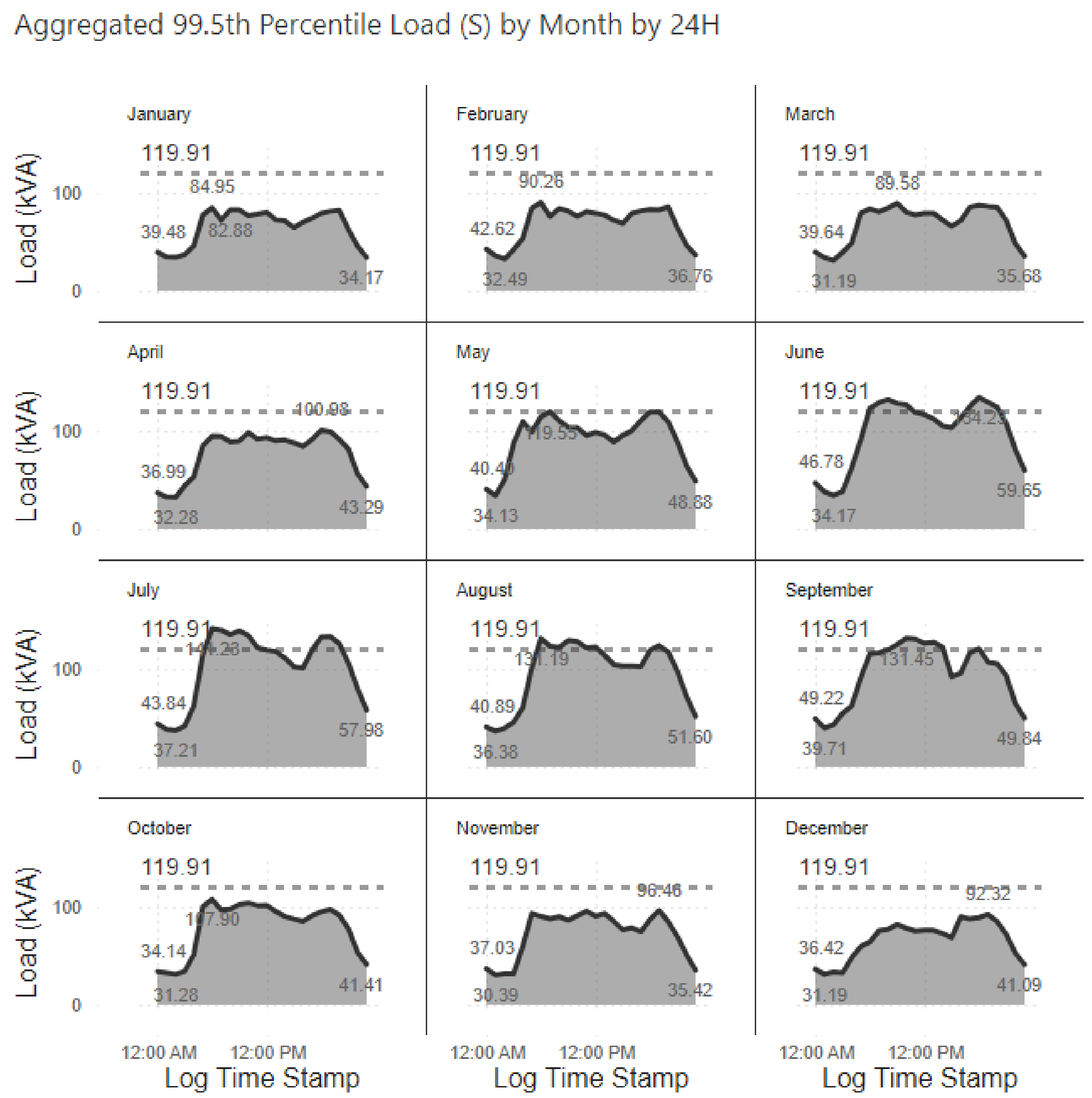


Figure 82: Aggregated 99.5th Percentile load by 24-h day by Month for Case Study H

Figure 82 displays the monthly 99.5th percentile load profiles, illustrating how daily demand peaks fluctuate across the year. The dashed line at 119.91 kVA represents the 99.5th percentile load threshold. Key observations include:

Winter Months (June - August): These months exhibit higher daily peaks, often exceeding the 99.5th percentile line. For instance, June shows a peak of 134.23 kVA, while July and August reach 127.28 kVA and 119.19 kVA, respectively. These peaks indicate increased energy consumption, likely due to heating needs.

Summer Months (December - February): The demand during these months generally stays below the 99.5th percentile line, with the highest peak in February at 90.26 kVA. This suggests a lower overall energy demand, possibly due to milder temperatures and reduced heating requirements.

Transitional Months (March, September): March and September show peaks near the 99.5th percentile threshold, with peaks of 89.58 kVA and 131.45 kVA, respectively. This indicates fluctuations in energy use during seasonal transitions.

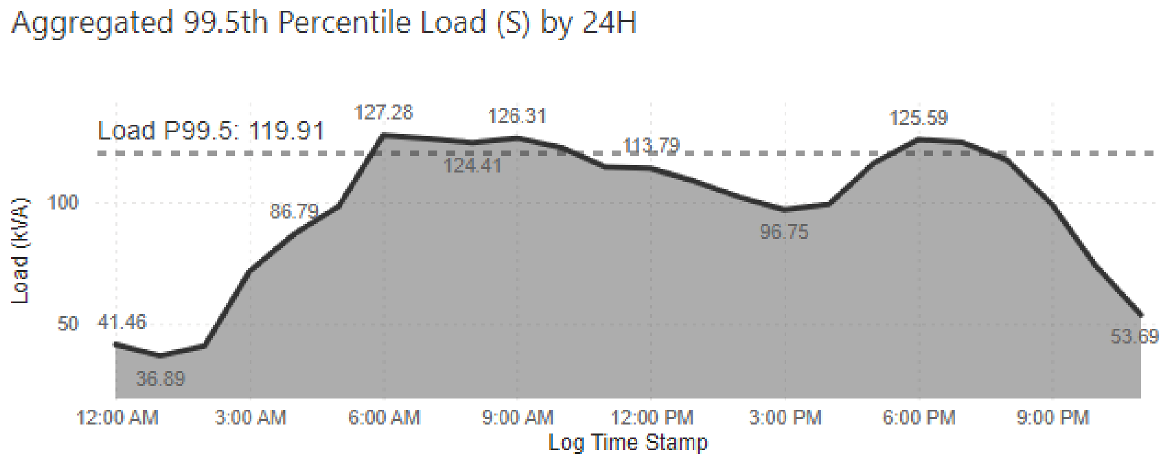


Figure 83: Aggregated 99.5th Percentile load by 24-h day for Case Study H

Figure 83 provides a consolidated view of the daily demand profile over a typical 24-hour period. The 99.5th percentile load line at 119.91 kVA marks the critical demand periods:

Morning Peak: A significant increase in load is observed around 3:00 AM, with a peak of 127.28 kVA at 6:00 AM. This rise correlates with early morning activities as households begin their day.

Evening Peak: The highest demand occurs around 6:00 PM, reaching a peak load of 125.59 kVA, reflecting common residential activities such as cooking and heating.

Off-Peak Periods: The lowest demand occurs during late night and early morning hours, with the load dropping to around 36.89 kVA, well below the 99.5th percentile threshold.

The 99.5th Percentile Load Analysis for Case Study H highlights significant seasonal and daily variations in electricity demand. The data shows that peak demands are more pronounced during the winter months, often exceeding the 99.5th percentile threshold, due to increased heating requirements. The analysis also underscores the importance of morning and evening peaks in shaping daily electricity consumption patterns. Understanding these variations is essential for adequate energy infrastructure planning and management, ensuring reliable service during periods of maximum demand.

4.6.4 Proposed ADMD vs Observed ADMD

This section aims to compare the proposed After Diversity Maximum Demand (ADMD) values suggested by SANS 507-1:2019 Year-15 parameters with the observed ADMD values for Case Study H. This comparison is crucial for assessing the accuracy and reliability of the proposed standards in predicting real-world electricity demand. By analysing the discrepancies between these values, we can determine the applicability of the SANS guidelines and identify any necessary adjustments for improved planning and infrastructure design.

Summary of Key Metrics

- Total Connections: 150
- Average Age: 26.77 years (greater than 15 years; therefore, Year-15 parameters are used)

- Installed Load: 864.80 kVA (5.77 kVA per connection)
- P99.5 Load: 119.91 kVA (0.80 kVA per stand)
- Resultant P99.5 Diversity Factor (DF): 0.14

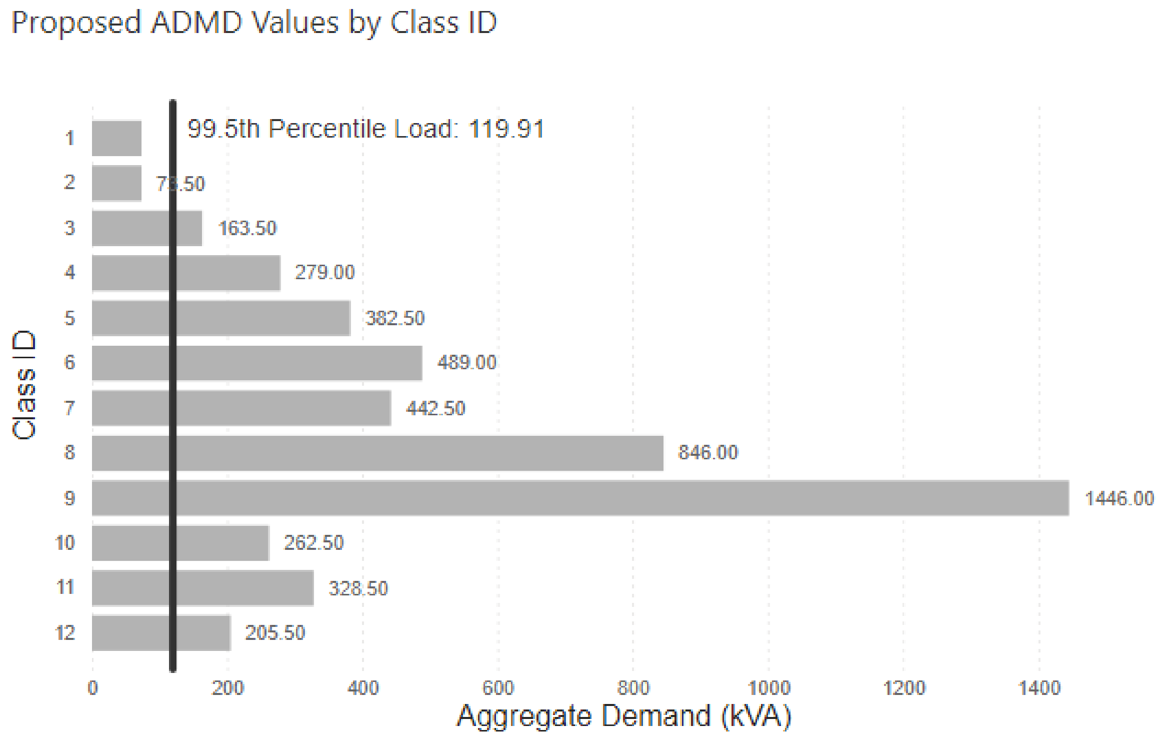


Figure 84: Proposed Year-15 ADMDs result by Class ID for Case Study H

Figure 84 illustrates the proposed ADMD values for different consumer classes as per SANS 507-1:2019 Year-15 parameters, compared against the measured 99.5th percentile load (119.91 kVA). The proposed ADMD values show significant variation across different classes, with Class ID 9 and 8 exhibiting the highest proposed values at 1446.00 kVA and 846.00 kVA, respectively. The vertical line at 119.91 kVA indicates the 99.5th percentile load, serving as a benchmark for comparison.

The data from Figure 84 reveals that the proposed ADMD values for most consumer classes significantly exceed the measured 99.5th percentile load. Notably, Class ID 9 (Urban Estate) has a proposed ADMD value that is over twelve times the measured load, indicating a possible overestimation. On the other hand, lower class IDs such as 1 and 2 show a proposed ADMD that is closer to the measured load, although still higher. This suggests that the SANS guidelines may need revision to reflect better actual consumption patterns, particularly for higher consumer classes.

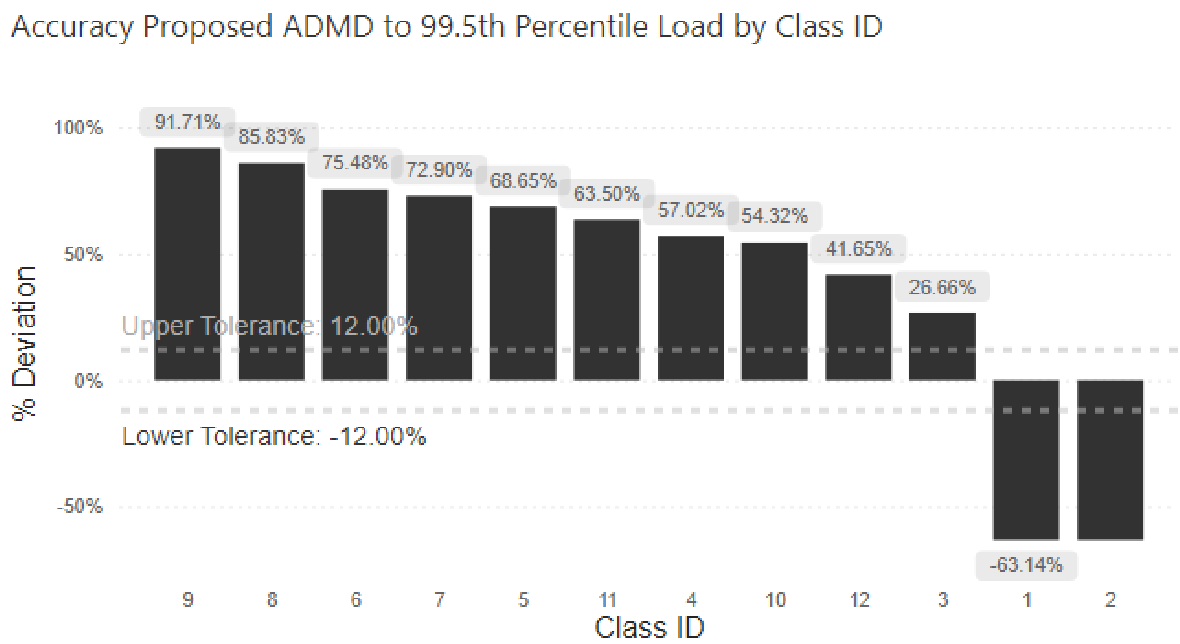


Figure 85: Deviation of SANS 507-1:2019 Year-15 ADMD by Class ID vs. 99.5th Percentile Load for Case Study H

Figure 85 presents the percentage deviation of the proposed ADMD values from the measured 99.5th percentile load for each class ID. The deviation is significant across most classes, with Class ID 9 showing the highest positive deviation at 91.71%. In contrast, Class IDs 1 and 2 show negative deviations, indicating that the proposed values are lower than the measured loads for these classes.

The deviations highlighted in Figure 85 indicate a substantial overestimation of the ADMD values for most consumer classes according to the SANS 507-1:2019 Year-15 parameters. The high positive deviations, particularly for Class ID 9, suggest that the current proposed values do not accurately capture the actual demand patterns. The negative deviations for Class IDs 1 and 2 indicate that the proposed values for these classes may be overly conservative, yet still not entirely accurate. This discrepancy underscores the need for a more nuanced approach in setting ADMD standards that consider the specific characteristics and consumption behaviours of different consumer classes.

Table 7: Detailed Comparison of Proposed ADMD vs Observed ADMD for Case Study H

ID	Consumer Class	SANS 15 Year ADMD (kVA)	Case SANS 15 Year ADMD (kVA)	Accuracy	Deviation
1	Rural settlement, Non-urban, scattered	0.49	73.50	163.14%	-63.14%
2	Rural villages	0.49	73.50	163.14%	-63.14%
3	Informal settlement	1.09	163.50	73.34%	26.66%
4	Township area	1.86	279.00	42.98%	57.02%
5	Urban residential I	2.55	382.50	31.35%	68.65%
6	Urban residential II	3.26	489.00	24.52%	75.48%
7	Urban townhouse complex or duplex	2.95	442.50	27.10%	72.90%
8	Urban Townhouse II	5.64	846.00	14.17%	85.83%
9	Urban Estate	9.64	1446.00	8.29%	91.71%
10	High-rise (small)	1.75	262.50	45.68%	54.32%

11	High rise (medium)	2.19	328.50	36.50%	63.50%
12	Hostel	1.37	205.50	58.35%	41.65%

Table 7 provides a detailed comparison of the proposed and observed ADMD values for each consumer class. The accuracy and deviation columns highlight the discrepancies between the proposed values and the actual measured loads. Notably, Classes 1 and 2 show the highest negative deviation, suggesting that the proposed ADMD values significantly underestimate the actual load for rural settlements and villages. Conversely, Classes 8 and 9 show the highest positive deviations, indicating an overestimation for urban estates and high-end residential areas. These observations reinforce the need for revising the proposed ADMD values to better align with real-world consumption patterns.

The comparison between the proposed ADMD values and the observed ADMD values for Case Study H reveals significant discrepancies, particularly for higher consumer classes. The proposed values tend to overestimate the actual demand for urban estates and high-end residential areas, while underestimating the load for rural settlements and villages. These findings suggest that the current SANS 507-1:2019 Year-15 parameters may not accurately reflect the diverse consumption patterns observed in different consumer classes. Therefore, it is crucial to re-evaluate these standards and consider more tailored approaches to ensure reliable and efficient electricity infrastructure planning.

Interpretive Note: Case Study H

- Installed base is PPU-dominant. Within PPU, breaker sizes are 20A = 87.33% and 60A = 12.67%.
- Average connection age is about 26.8 years. By breaker size: 26.86 years (20A) and 26.16 years (60A), so Year-15 parameters were appropriate.
- Observed ADMD (P99.5) is 119.91 kVA total (≈0.80 kVA/stand).
- Best fit (exact class ID): Class 3 (Informal settlement) with 1.09 kVA/stand gives a +26.66% deviation versus the observed value; Classes 1–2 are below the empirical level (≈0.49–0.62 kVA/stand), while classes above 3 propose higher per-stand values than 1.09 and overshoot by larger margins.

The breaker mix is predominantly 20A, and the stock is beyond 15 years, which places the zone in a lower-to-mid demand regime; among the SANS options, Class 3 yields the least absolute deviation from the measured 99.5th-percentile ADMD and aligns best with the observed connection composition.

4.7 Case Study I

Case Study I explores load profiles and ADMD values in Itshokolele, Petsana Extension 2, Petsana, and parts of Reitz, examining factors affecting electricity demand.

4.7.1 Geographic Overview

Case Study I is geographically located at GPS coordinates 28.446457, -27.798777, as illustrated in Figure 86. This area includes the neighbourhoods of Itshokolele, Petsana Extension 2, Petsana, and parts of Reitz.

GPS Location 28.446457;-27.798777

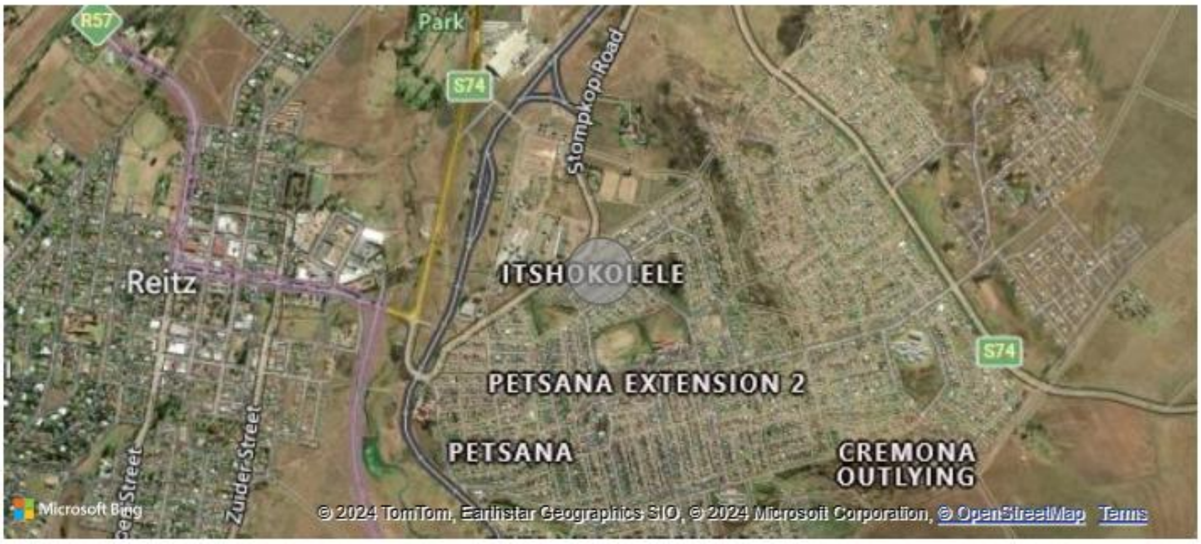


Figure 86: Geographic location for Case Study I

The transformer zone for Case Study I is situated within the local municipal boundaries of Reitz, which falls under the Nketoana Local Municipality in the Thabo Mofutsanyana District Municipality, Free State Province of South Africa. The local municipal authorities are responsible for providing public services, maintaining infrastructure, and promoting community development within this area.

The economy in and around Case Study I is predominantly driven by agriculture, with the region being known for its production of crops such as maize, wheat, and sunflowers. Livestock farming also plays a significant role. Reitz serves as an agricultural hub, supporting various agro-processing activities that add value to the primary agricultural products. Additionally, small-scale retail businesses and service industries cater to the local population's needs, influencing the electricity demand.

The climate in this region is generally temperate, characterised by cold winters and warm summers. Winter months (June to August) often experience low temperatures, leading to higher electricity consumption for heating purposes. During the summer months (November to February), the electricity demand may rise due to the increased use of cooling systems. The region receives moderate rainfall, mainly during the summer, which impacts agricultural activities and subsequently affects electricity consumption patterns.

The socioeconomic factors in Case Study I's area significantly impact electricity consumption patterns. The community is socioeconomically diverse, comprising low to middle-income households, with varying levels of access to economic opportunities and public services. Educational institutions and healthcare facilities within the area rely on a stable electricity supply to operate efficiently.

Economic disparities within the community influence energy consumption, with more affluent households typically using more electrical appliances and therefore having higher electricity demand. In contrast, lower-income households might have lower overall electricity consumption but still exhibit significant usage during peak times, such as in the evenings when residential activities are at their highest.

In summary, the geographic and socioeconomic context of Case Study I provides a comprehensive understanding of the area's electricity consumption patterns. The combination of agricultural activities, temperate climate, and diverse socioeconomic factors offers valuable data for evaluating the accuracy of proposed ADMD values and their implications for local electricity infrastructure planning.

4.7.2 Connections

4.7.2.1 Proportion of Installed Load by Connection Type

Figure 87 is a graphical representation of the installed load for Case Study I by type (PPU vs SPU) in a percentage value.

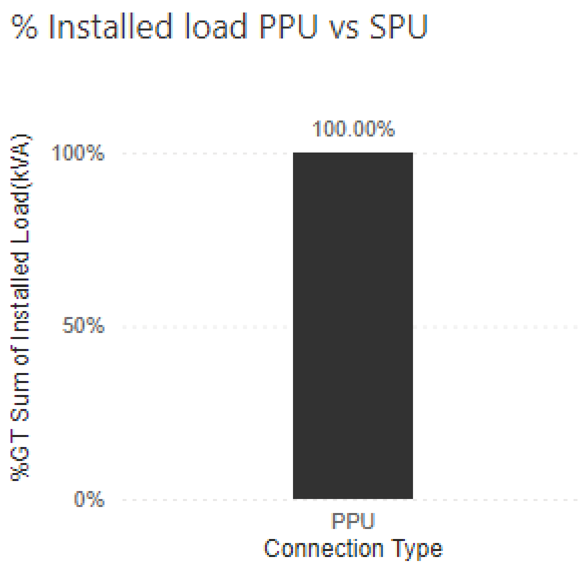


Figure 87: % Installed load by type PPU vs SPU for Case Study I

From Figure 87, the installed load is entirely composed of PPU type connections. As described in Chapter 2, this is a result of the prescriptive requirements as set out by subsidised connections as part of electrification programmes. The following section will highlight the various breaker sizes of the PPU connections and how different NMDs may have come about.

4.7.2.2 Distribution of PPU Connections by Circuit Breaker Size

As shown in Figure 87 the case study is made up of PPU connection types only. Figure 88 breaks down the proportions of the PPU maximum allowable demands for the connections. This provides insight into understanding the installed load and how each contributes to the load characteristics.

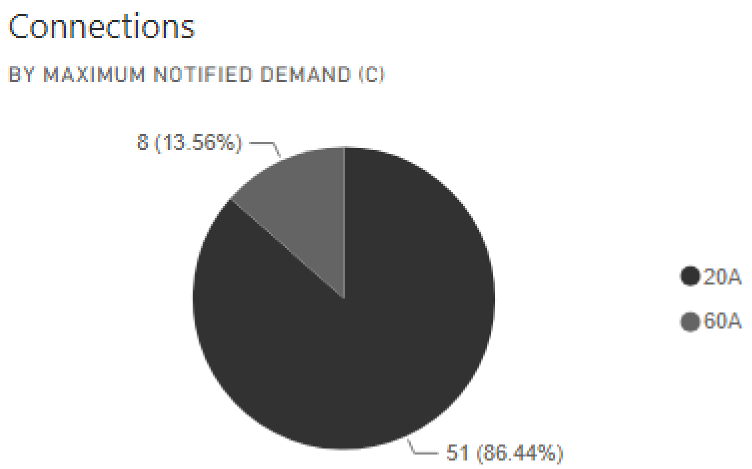


Figure 88: Total PPU connections by Circuit Breaker Size (c) for Case Study I

Figure 88 Indicates 86.44% of the total connections are made up of 20A connections. On the other hand, only 8 of the 51 (13.56%) connections are rated at 60A maximum demand. It is thus possible to conclude that the current base load is at a lower Class ID, and potential growth may still be seen as time goes on.

4.7.2.3 Connection Trends

The connection trends for Case Study I are illustrated in Figure 89, providing a comprehensive overview of the historical load growth in terms of total connections.

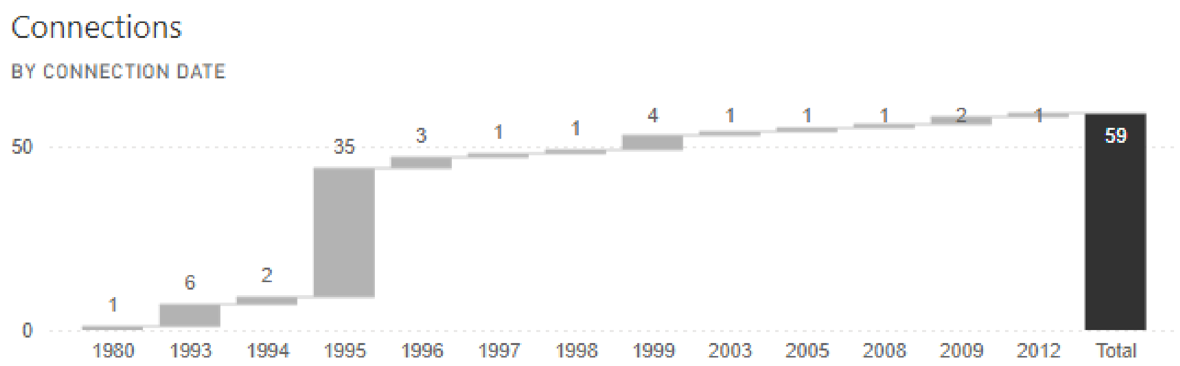


Figure 89: Total connections over time for Case Study I

As shown in Figure 89, the initial connections for Case Study I were recorded in 1980, with the latest connections occurring in 2012. The most significant increase in connections occurred in 1995, with 35 new connections added, marking the highest annual growth observed in this dataset. Before this peak, there were moderate increases in 1993 and 1994, with six and two new connections, respectively.

Following the substantial growth in 1995, the number of new connections per year was relatively low, with annual additions ranging from one to four connections between 1996 and 2012. Notably smaller peaks were observed in 1999 (four connections) and 2005 (four connections).

By the end of the period, the total number of connections reached 59. The data indicate a pattern of early rapid growth followed by a prolonged period of reduced growth. This deceleration in the growth rate may suggest a geo-spatial saturation effect, which is a critical parameter in the design and planning of transformer zones. The historical connection data for Case Study I highlights the evolving nature of connection growth and the impact of spatial constraints on growth.

4.7.2.4 Connection Age Analysis by Breaker Size

The diverging bar chart in Figure 90 illustrates the average age of connections categorised by each circuit breaker size for Case Study I.

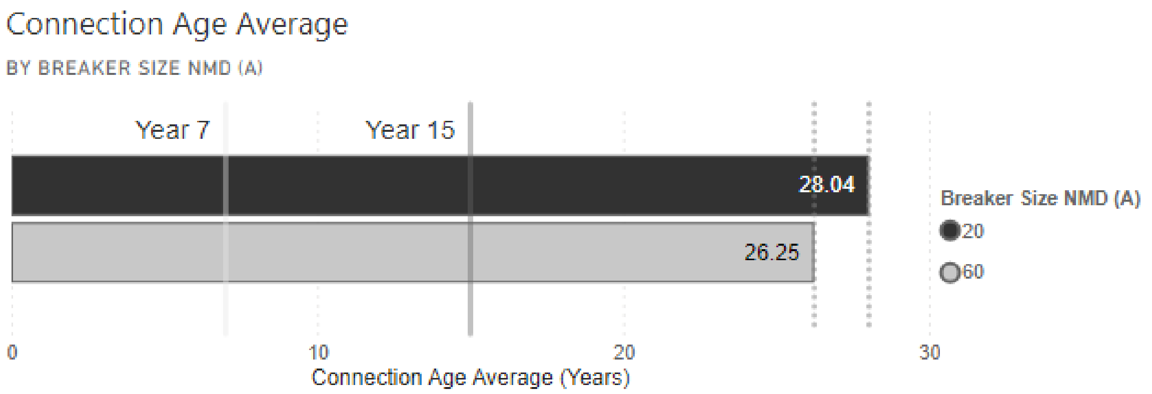


Figure 90: Connection Age Analysis for Case Study I

From Figure 90, it is observed that the average age of connections with 20A circuit breakers is 28.04 years, while the average age of connections with 60A circuit breakers is 26.25 years. The difference in average ages, with the 20A connections being older by approximately 1.79 years compared to the 60A connections, suggests a potential variance in the installation or upgrade times for these breaker sizes.

Given that both categories of circuit breaker size have connection ages significantly higher than 15 years, it is appropriate to use the 15-year parameters according to SANS 507-1:2019 – Table 2. Additionally, it should be noted that the 'c' values for 20A, 15-year parameters are limited to Class ID 1 and 2, whereas the 60A Class IDs, according to the 15-year 'c' values, are from Class ID 3 and higher.

The following conclusions can be drawn from the above analysis. Firstly, the presence of both 20A and 60A connections suggests a heterogeneous consumer group. Secondly, the difference in the average ages of the two categories indicates a pattern of load growth and upgrading. The younger average age for 60A connections could imply that these connections have been installed more recently, possibly as upgrades from 20A connections to accommodate increased demand.

This pattern aligns with typical practices where electrical infrastructure is upgraded to meet higher demand, resulting in newer, larger-capacity connections replacing older, smaller ones. The data thus reflects the evolving nature of electrical connections in residential areas, highlighting how infrastructure adapts to changing demands over time. The difference in ages suggests that while upgrades have occurred, they have not been so frequent or recent as to alter the average age difference between the breaker sizes significantly. The older average age of the 20A connections indicates that these have been in place longer, potentially awaiting upgrades as demand increases.

4.7.3 Load Profiles

4.7.3.1 Historical Load Profile Analysis

The historical load profile for Case Study I, as presented in Figure 91, provides a detailed analysis of instantaneous electrical load data from January 1, 2019, to December 31, 2023. This profile captures the variability and trends in electricity consumption over this period. Key indicators, such as the mean load, maximum demand, and the 99.5th percentile, are highlighted to showcase typical and peak usage levels. The mean load, indicated by the "Mean: 50.79" line, reflects the average electrical load over the study period. The maximum demand, represented by the "Maximum: 161.40" line, denotes the highest recorded load, while the 99.5th percentile, shown as "99.5th Percentile: 126.69," serves as the measured After Diversity Maximum Demand (ADMD) value, which is essential for evaluating the capacity and reliability of the electrical infrastructure.

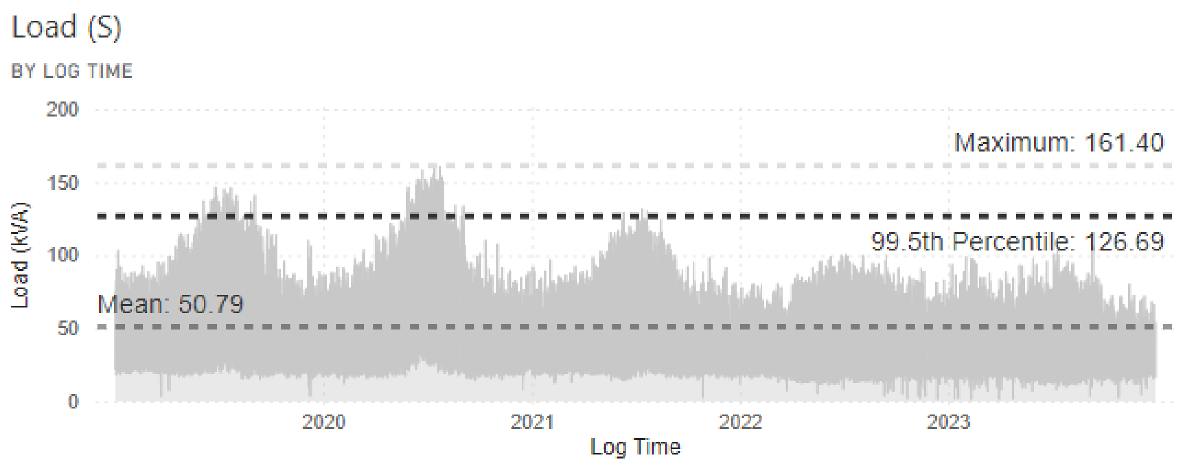


Figure 91: Historical load profile for Case Study I

Figure 91 Illustrates the historical load profile for Case Study I, revealing several essential characteristics. The mean load, marked by the "Mean: 50.79" line, suggests a moderate consumption level. The profile shows considerable fluctuations, with significant peaks and troughs, indicating varying demand patterns influenced by factors such as seasonal changes or specific high-demand events. The maximum demand, marked by the "Maximum: 161.40" line, highlights periods of exceptionally high usage. The 99.5th percentile, represented by the "99.5th Percentile: 126.69" line, provides a conservative estimate of the ADMD, crucial for ensuring that the system can accommodate typical peak loads.

The normal distribution of the historical load profile data for Case Study I, depicted in Figure 92, provides a statistical representation of the load data, modelled as a bell curve. This graph helps in understanding the central tendency, dispersion, and the presence of outliers in the dataset.

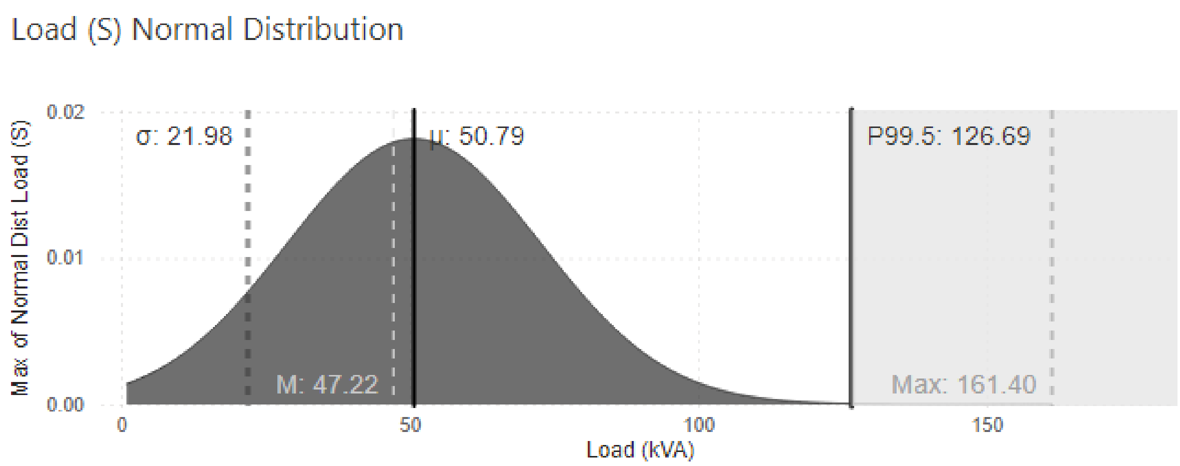


Figure 92: Normal distribution of Historical Load Profile data for Case Study I

Figure 92 shows the bell curve of the normal distribution of the load data, centred around the mean (μ) of 50.79 kVA, with a standard deviation (σ) of 21.98 kVA. The mode (M), noted near "M: 47.22," aligns closely with the mean, suggesting a typical clustering of data points around these central values. The 99.5th percentile, labelled "P99.5: 126.69," indicates the threshold below which 99.5% of the data falls, with the maximum recorded value at "Max: 161.40," representing the extreme data points. The shape of the bell curve, characteristic of a normal distribution, shows a slight rightward skew, indicating the presence of higher-than-usual loads occasionally. This skewness reflects significant outliers that can impact planning and resource allocation, ensuring the infrastructure can handle potential peak loads.

4.7.3.2 99.5th Percentile Load Analysis

To gain comprehensive insights into the After Diversity Maximum Demand (ADMD) for Case Study I, this section evaluates the 99.5th percentile load across various aggregations. The analysis includes data from Figure 93, Figure 94, and Figure 95, covering the period from January 2019 to December 2023. These figures provide a detailed understanding of the load patterns and variations.

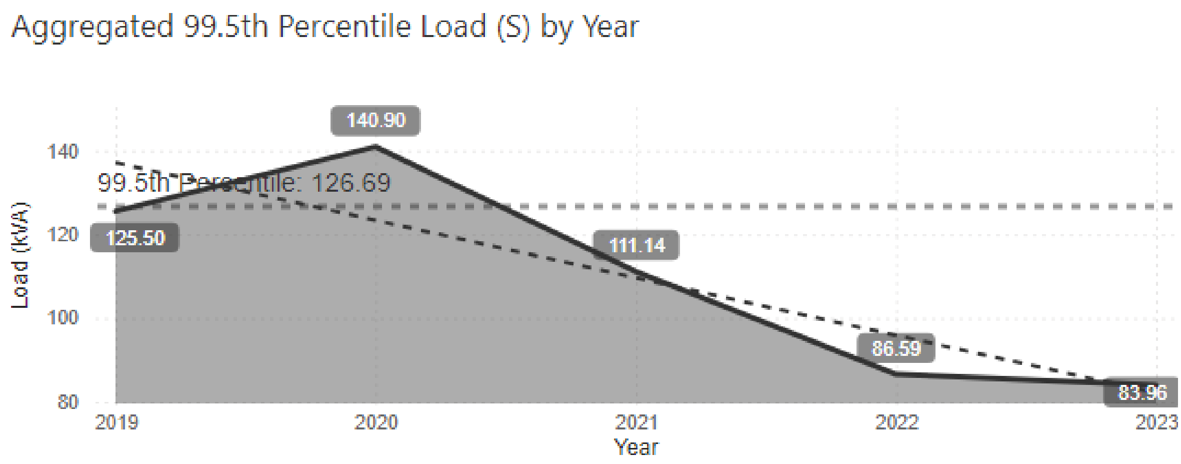


Figure 93: 99.5th Percentile load by year for Case Study I

Figure 93 illustrates the 99.5th percentile load by year for Case Study I. This figure showcases the annual peak loads, with the 99.5th percentile line established at 126.69 kVA, representing the observed ADMD. The maximum load recorded was 140.90 kVA in 2020, while the minimum was 83.96 kVA in 2023. The trendline indicates a peak in 2020, followed by a steady decline through subsequent years, reflecting a consistent decrease in peak load values. Notably, the years 2019, 2020, and 2021 exceeded the 99.5th percentile line, while 2022 and 2023 fell below it, highlighting a downward trend in demand.

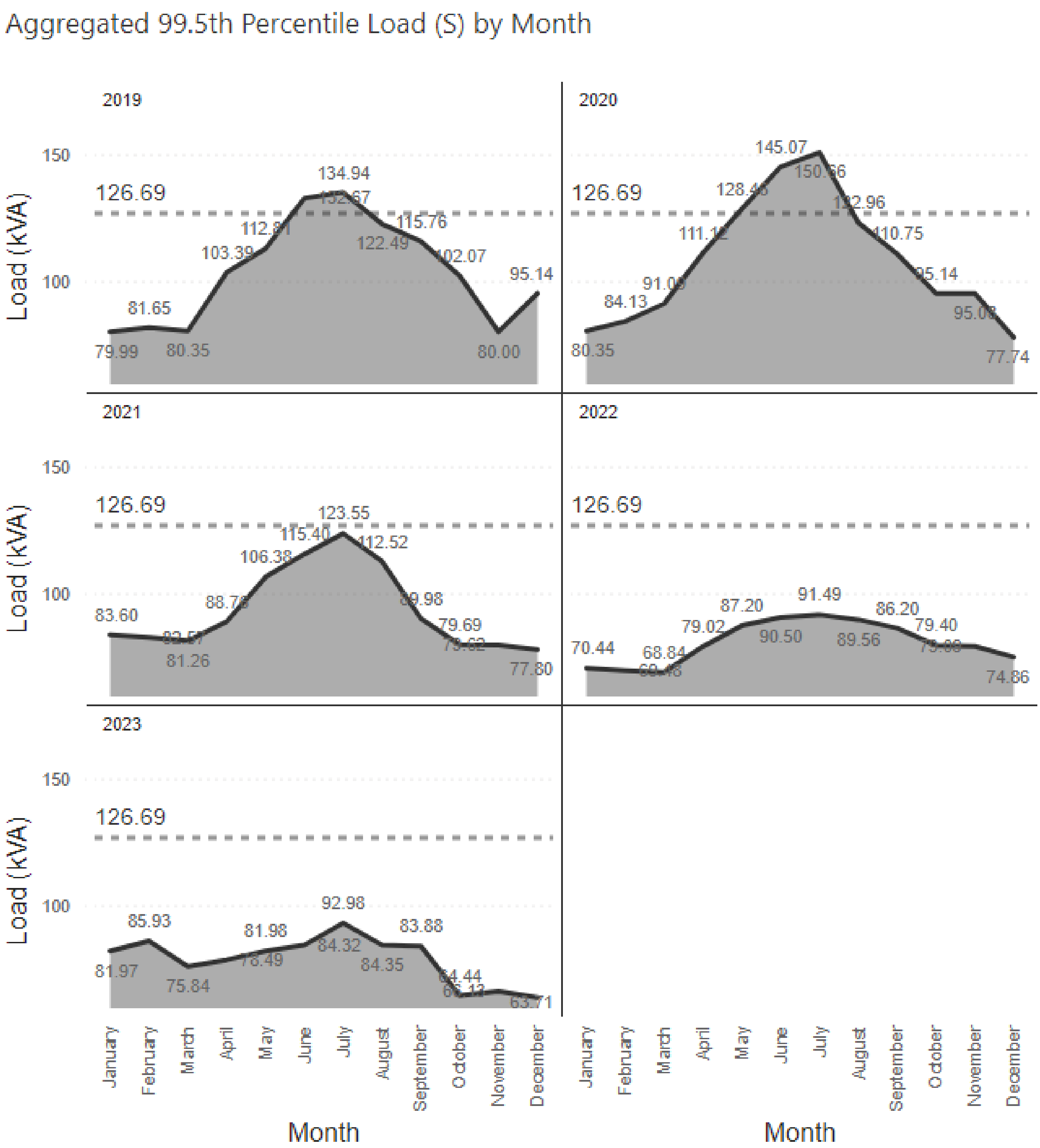


Figure 94: 99.5th Percentile load by each year for Case Study I

Figure 94 provides a breakdown of the 99.5th percentile load by each year, highlighting monthly variations. In 2019, the peak occurred in June at 134.94 kVA, and in 2020, the highest load was recorded in July at 145.07 kVA. For 2021, the peak was in June at 123.55 kVA, while 2022 saw its highest load in July at 91.49 kVA. The year 2023 had a peak load in July at 92.98 kVA. This data reveals that the highest monthly peaks have been progressively decreasing, particularly in recent years, with fewer months surpassing the observed ADMD threshold.

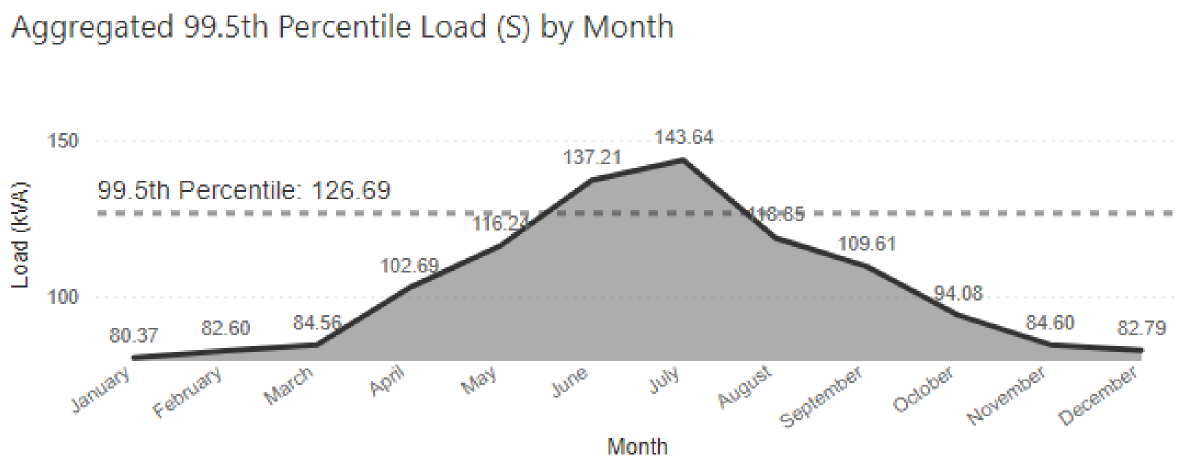


Figure 95: Aggregated 99.5th Percentile load by Month for Case Study I

Figure 95 aggregates the 99.5th percentile load by month across all years, providing a comprehensive view of seasonal demand patterns. The data indicates that loads generally increase from April, peaking in July at 143.64 kVA, and then decline towards December. The lowest load was observed in December at 82.79 kVA. This seasonal trend suggests higher electricity consumption in mid-year months, potentially due to seasonal factors.

The 99.5th percentile load analysis for Case Study I indicates significant variations in ADMD, with the 99.5th percentile line serving as the observed ADMD. The analysis shows a clear peak in demand in 2020, followed by a notable decline through 2023. The data highlights that monthly peaks generally occur mid-year, with a consistent reduction in peak loads over the years. These trends suggest a shift in consumption patterns, possibly influenced by efficiency measures, changes in population behaviour, or other factors. The analysis underscores the importance of adapting planning and infrastructure management strategies to accommodate these changes, ensuring the reliability and efficiency of the electricity supply system.

4.7.3.3 99.5th Percentile Load Analysis: Daily Demand Profiles

The 99.5th percentile load analysis for Case Study I provides a detailed examination of the highest demand periods that occur only 0.5% of the time. This analysis is crucial for identifying peak usage scenarios, which are essential for effective infrastructure planning and energy management. By studying these profiles, we can observe both seasonal and daily variations in electricity consumption, offering insights into how demand fluctuates throughout the year and within a typical day.

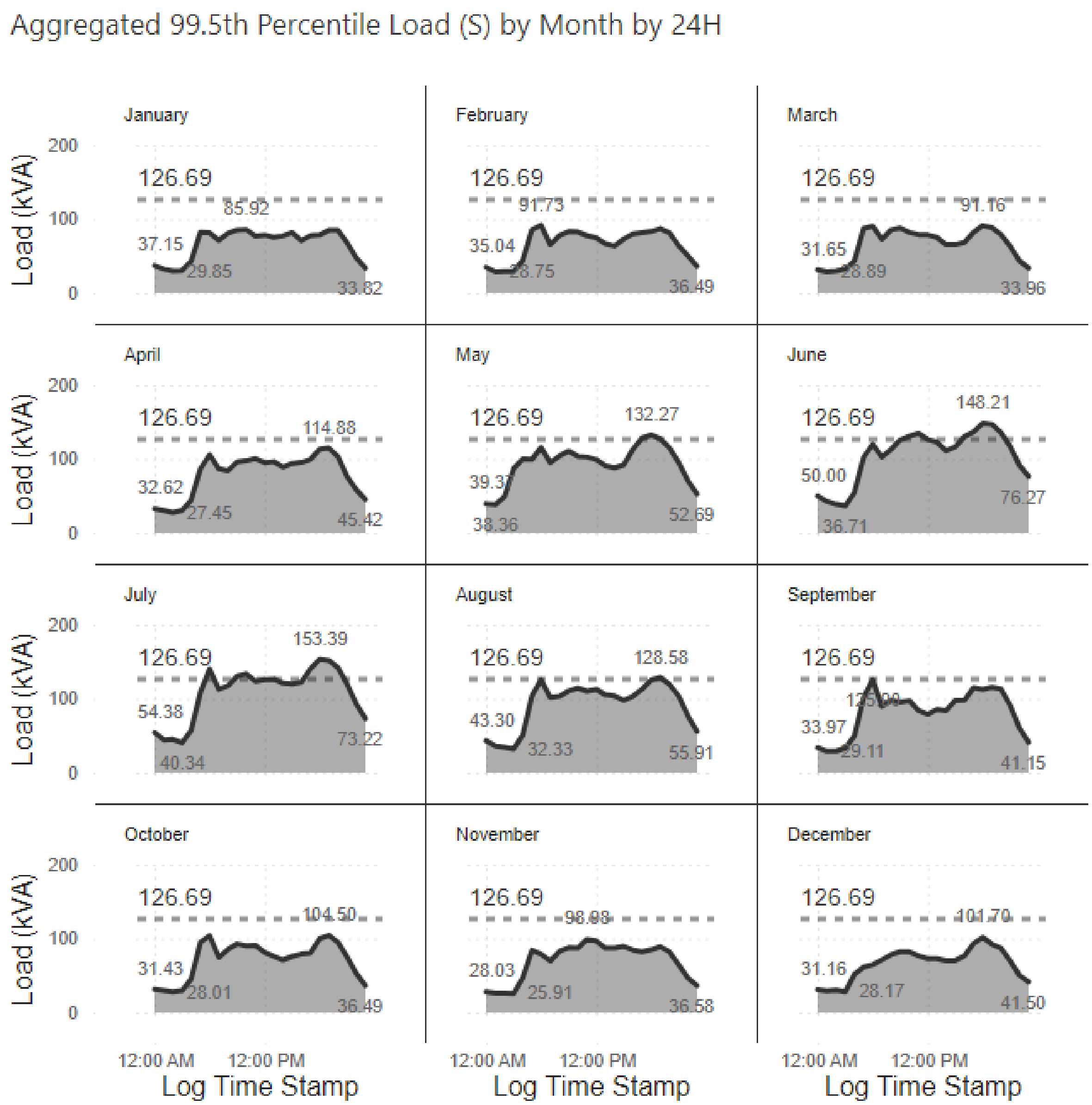


Figure 96: Aggregated 99.5th Percentile load by 24-h day by Month for Case Study I

Figure 96 illustrates the monthly variations in the 99.5th percentile load, showing how daily demand peaks vary throughout the year. The dashed line at 126.69 kVA marks the 99.5th percentile load threshold. Key observations include:

Winter Months (June - August): These months display significant increases in daily peaks, often exceeding the 99.5th percentile line. June, for example, reaches a peak of 148.21 kVA, while July and August have peaks of 153.39 kVA and 128.58 kVA, respectively. These high values indicate increased energy consumption, likely due to heating needs.

Summer Months (December - February): Demand generally remains below the 99.5th percentile threshold, with the highest peak in February at 91.73 kVA. This lower demand suggests moderate energy usage, possibly due to milder temperatures.

Transitional Months (March, September): These months show peaks near the 99.5th percentile line, with March reaching 91.16 kVA and September showing a peak of 135.04 kVA, reflecting the variability in energy use during changing seasons.

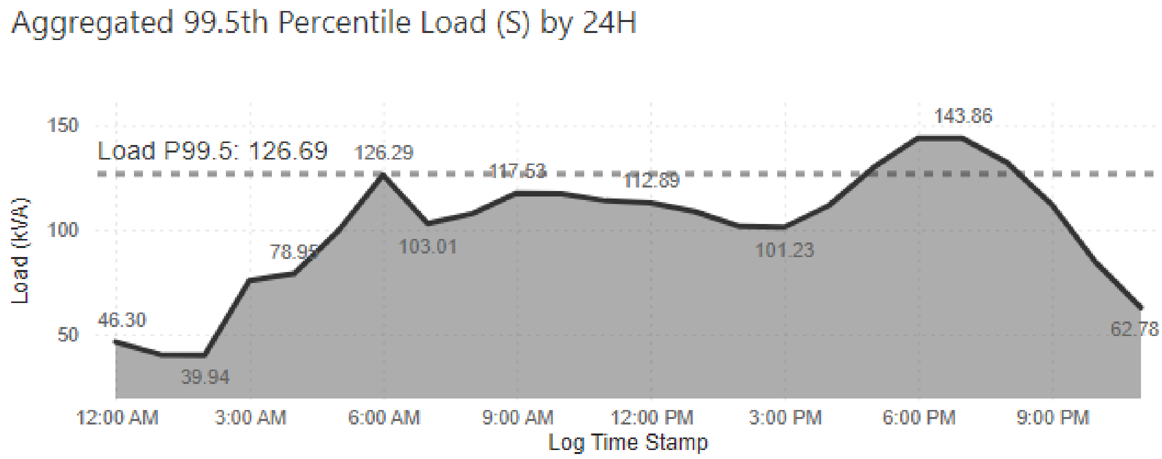


Figure 97: Aggregated 99.5th Percentile load by 24-h day for Case Study I

Figure 97 consolidates the daily demand data into a single 24-hour profile, providing an overview of the typical daily load pattern. The 99.5th percentile load line at 126.69 kVA indicates critical demand periods:

Morning Peak: A sharp increase in load begins around 3:00 AM, with a peak of 126.29 kVA at 6:00 AM. This rise is associated with morning activities as residents start their day.

Evening Peak: The highest demand is observed around 6:00 PM, reaching a peak of 143.86 kVA, indicative of typical residential activities such as cooking and heating.

Off-Peak Periods: The lowest demand occurs during the late night and early morning hours, with the load dropping to around 39.94 kVA, well below the 99.5th percentile threshold.

The 99.5th Percentile Load Analysis for Case Study I reveals distinct seasonal and daily variations in electricity demand. The data indicate that peak demands are more pronounced during the winter months, with frequent exceedances of the 99.5th percentile threshold due to increased heating needs. The analysis also highlights significant daily peaks in the morning and evening, which are crucial for understanding residential electricity consumption patterns. These insights are vital for planning and managing energy infrastructure to ensure reliable service during periods of maximum demand.

4.7.4 Proposed ADMD vs Observed ADMD

This section aims to compare the proposed After Diversity Maximum Demand (ADMD) values suggested by SANS 507-1:2019 Year-15 parameters with the observed ADMD values for Case Study I. This comparison is crucial for assessing the accuracy and reliability of the proposed standards in predicting real-world electricity demand. By analysing the discrepancies between these values, we can determine the applicability of the SANS guidelines and identify any necessary adjustments for improved planning and infrastructure design.

Summary of Key Metrics

- Total Connections: 59

- Average Age: 27.80 years (greater than 15 years; therefore, Year-15 parameters are used)
- Installed Load: 345.00 kVA (5.85 kVA per connection)
- P99.5 Load: 126.69 kVA (2.15 kVA per stand)
- Resultant P99.5 Diversity Factor (DF): 0.37

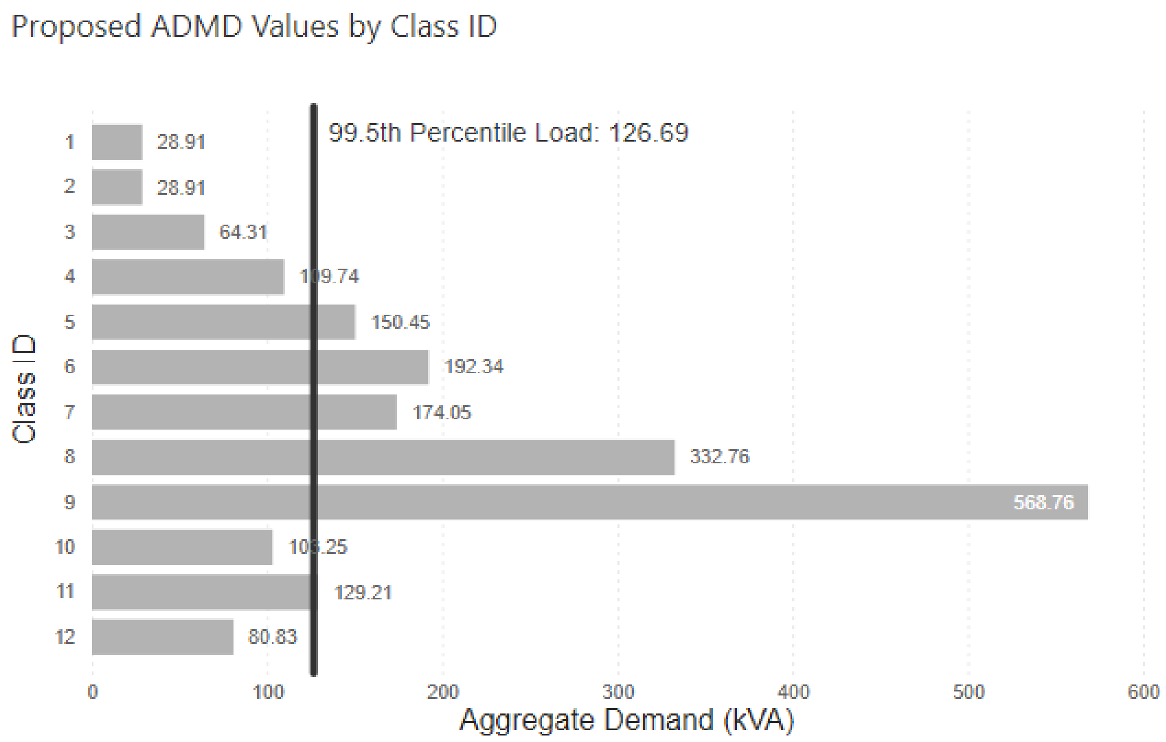


Figure 98: Proposed Year-15 ADMDs result by Class ID for Case Study I

Figure 98 illustrates the proposed ADMD values for different consumer classes as per SANS 507-1:2019 Year-15 parameters, compared against the measured 99.5th percentile load (126.69 kVA). The proposed ADMD values show significant variation across different classes, with Class ID 9 and 8 exhibiting the highest proposed values at 568.76 kVA and 332.76 kVA, respectively. The vertical line at 126.69 kVA indicates the 99.5th percentile load, serving as a benchmark for comparison.

The data from Figure 98 reveals that the proposed ADMD values for most consumer classes significantly exceed the measured 99.5th percentile load. Notably, Class ID 9 (Urban Estate) has a proposed ADMD value that is over four times the measured load, indicating a possible overestimation. On the other hand, lower class IDs such as 1 and 2 show a proposed ADMD that is closer to the measured load, although still higher. This suggests that the SANS guidelines may need revision to reflect better actual consumption patterns, particularly for higher consumer classes.

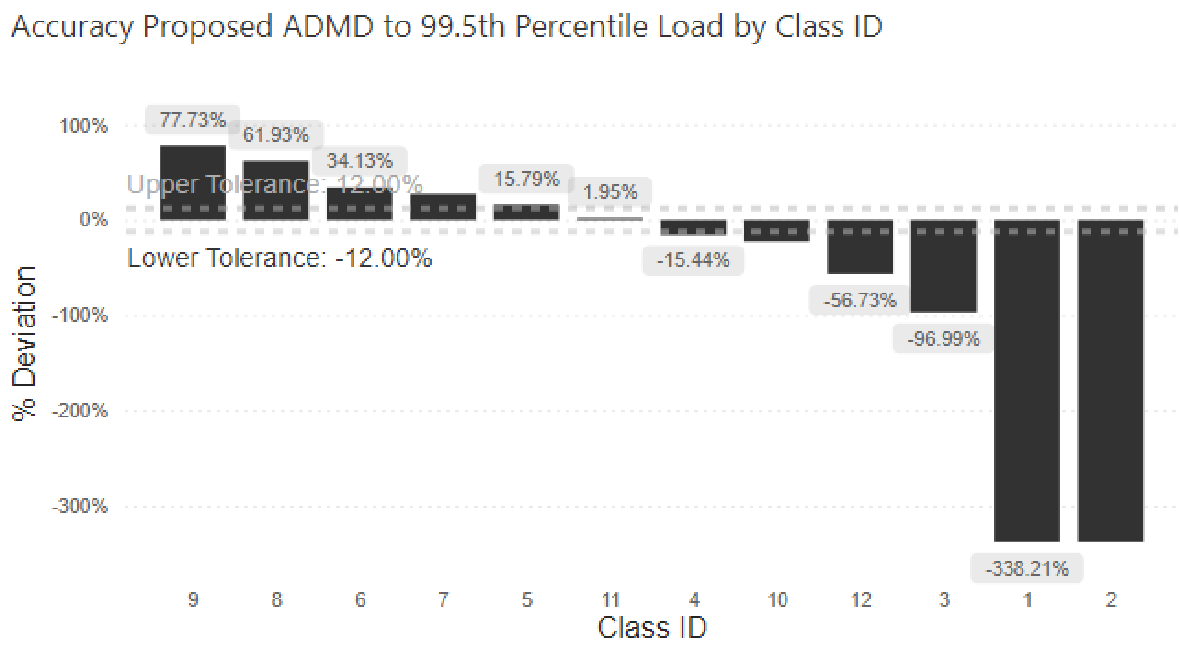


Figure 99: Deviation of SANS 507-1:2019 Year-15 ADMD by Class ID vs. 99.5th Percentile Load for Case Study I

Figure 99 presents the percentage deviation of the proposed ADMD values from the measured 99.5th percentile load for each class ID. The deviation is significant across most classes, with Class ID 9 showing the highest positive deviation at 77.73%. In contrast, Class IDs 1 and 2 show negative deviations, indicating that the proposed values are lower than the measured loads for these classes.

The deviations highlighted in Figure 99 indicate a substantial overestimation of the ADMD values for most consumer classes according to the SANS 507-1:2019 Year-15 parameters. The high positive deviations, particularly for Class ID 9, suggest that the current proposed values do not accurately capture the actual demand patterns. The negative deviations for Class IDs 1 and 2 indicate that the proposed values for these classes may be overly conservative, yet still not entirely accurate. This discrepancy underscores the need for a more nuanced approach in setting ADMD standards that consider the specific characteristics and consumption behaviours of different consumer classes.

Table 8: Detailed Comparison of Proposed ADMD vs Observed ADMD for Case Study I

ID	Consumer Class	SANS 15 Year ADMD (kVA)	Case SANS 15 Year ADMD (kVA)	Accuracy	Deviation
1	Rural settlement, Non-urban, scattered	0.49	28.91	438.21%	-338.21%
2	Rural villages	0.49	28.91	438.21%	-338.21%
3	Informal settlement	1.09	64.31	196.99%	-96.99%
4	Township area	1.86	109.74	115.44%	-15.44%
5	Urban residential I	2.55	150.45	84.21%	15.79%
6	Urban residential II	3.26	192.34	65.87%	34.13%
7	Urban townhouse complex or duplex	2.95	174.05	72.79%	27.21%
8	Urban Townhouse II	5.64	332.76	39.07%	61.93%
9	Urban Estate	9.64	568.76	22.27%	77.73%
10	High-rise (small)	1.75	108.25	122.70%	-22.70%

11	High rise (medium)	2.19	129.21	98.05%	1.95%
12	Hostel	1.37	80.83	156.73%	-56.73%

Table 8 provides a detailed comparison of the proposed and observed ADMD values for each consumer class. The accuracy and deviation columns highlight the discrepancies between the proposed values and the actual measured loads. Notably, Classes 1 and 2 show the highest negative deviation, suggesting that the proposed ADMD values significantly underestimate the actual load for rural settlements and villages. Conversely, Classes 8 and 9 show the highest positive deviations, indicating an overestimation for urban estates and high-end residential areas. These observations reinforce the need for revising the proposed ADMD values to better align with real-world consumption patterns.

The comparison between the proposed ADMD values and the observed ADMD values for Case Study I reveals significant discrepancies, particularly for higher consumer classes. The proposed values tend to overestimate the actual demand for urban estates and high-end residential areas, while underestimating the load for rural settlements and villages. These findings suggest that the current SANS 507-1:2019 Year-15 parameters may not accurately reflect the diverse consumption patterns observed in different consumer classes. Therefore, it is crucial to re-evaluate these standards and consider more tailored approaches to ensure reliable and efficient electricity infrastructure planning.

Interpretive Note: Case Study I

- Installed base is PPU-only. Within PPU, breaker sizes are 20A = 86.44% and 60A = 13.56%.
- Average connection age is 30.26 years. By breaker size: 29.92 years (20A) and 31.94 years (60A), so Year-15 parameters were appropriate.
- Observed ADMD (P99.5) is 126.69 kVA total.
- Best fit (exact class ID): Class 11 with a +1.95% deviation versus the observed value, which is within a ±12% acceptance band. Classes 1–3 are below the empirical level, while several higher suburban classes propose larger per-stand values and overshoot by wider margins.

The presence of a non-trivial 60A share and a mature connection base aligns with a mid-range demand profile; among the SANS options, Class 11 produces the least absolute deviation from the measured 99.5th-percentile ADMD and matches the observed composition most closely.

4.8 Case Study J

Case Study J explores load profiles and ADMD values in Tumahole and parts of Parys, examining factors affecting electricity demand.

4.8.1 Geographic Overview

Case Study J is geographically located at GPS coordinates 28.227524, -26.838212, as illustrated in Figure 100. This area includes the neighbourhoods of Tumahole and parts of Parys.

Figure 100: Geographic location for Case Study J

The transformer zone for Case Study J is situated within the local municipal boundaries of Parys, which falls under the Ngwathe Local Municipality in the Fezile Dabi District Municipality, Free State Province of South Africa. The local municipal authorities are responsible for providing public services, maintaining infrastructure, and promoting community development within this area.

The economy surrounding Case Study J is diverse, with key activities including agriculture, tourism, and small-scale manufacturing. Parys is known for its agricultural production, particularly of maize and sunflower crops. Additionally, the town's proximity to the Vaal River makes it a popular destination for tourism, contributing significantly to the local economy. The presence of small-scale retail businesses and service industries also plays a role in supporting the local population and influencing electricity demand.

4.8.2 Connections

4.8.2.1 Proportion of Installed Load by Connection Type

Figure 101 is a graphical representation of the installed load by percentage of PPU and SPU connection types. The proportions are shown in percentages, where omission of one or the other will indicate homogeneity.

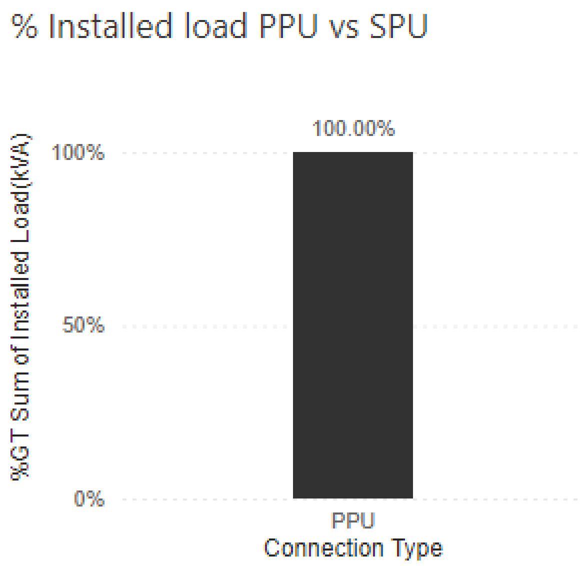


Figure 101: % Installed load by type PPU vs SPU for Case Study J

From Figure 101 100% of the connections are comprised of PPU, forming part of the total installed load in Case Study J. This further confirms that these connection types are typical of those observed in electrified township areas within the Free State Province.

4.8.2.2 Distribution of PPU Connections by Circuit Breaker Size

Figure 102 shows the ratio of connections by circuit breaker size for Case Study J. Representing the number and percentage of connections by 20A and 60A, respectively.

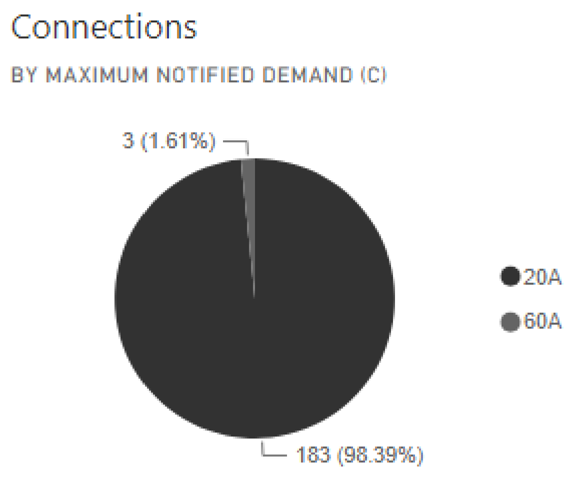


Figure 102: Total PPU connections by Circuit Breaker Size (c) for Case Study J

From Figure 102 it can be seen that of the 186 connections, (98.39%) are limited to 20A maximum allowable current. In contrast, a mere 1.61% of the connections are at the higher 60A current limit. Clearly, Figure 102 Demonstrates that Case Study J is at the extreme lower end of the Class IDs. Also showing that plenty of load growth may still be potentially induced as time goes on.

4.8.2.3 Connection Trends

The connection trends for Case Study J are depicted in Figure 103, providing an insightful overview of the historical load growth in terms of total connections.

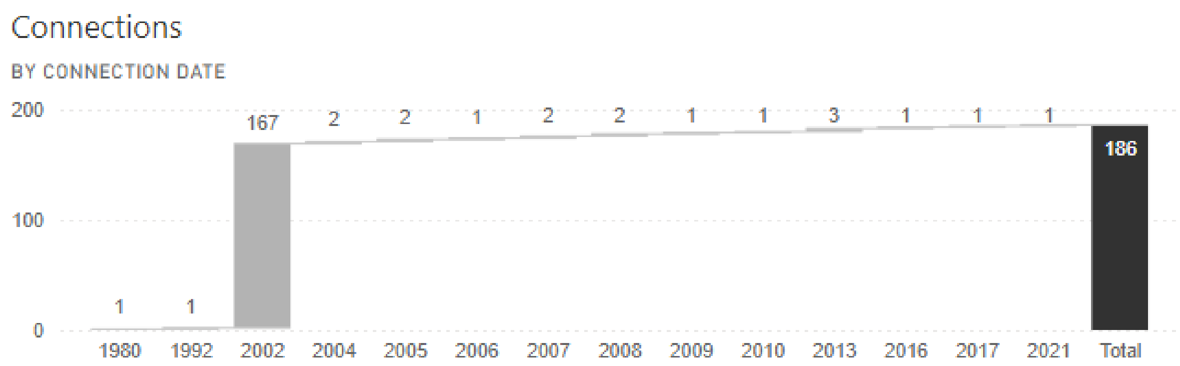


Figure 103: Total connections over time for Case Study J

Figure 103 shows that the initial connections for Case Study J were recorded in 1980 and 1992, with the most recent connections occurring in 2021. The most significant surge in connections happened in 2002, with 167 new connections added, marking the highest annual growth within the observed period. This surge is particularly notable compared to the other years.

Following the substantial increase in 2002, the number of new connections per year was relatively low, ranging from one to three connections annually between 2003 and 2021. There were small peaks in 2004, 2005, 2007, 2013, and 2021, where two or three new connections were added in those respective years.

By the end of the period, the total number of connections reached 186. The data illustrate a pattern of an initial rapid growth period, mainly concentrated in 2002, followed by an extended period of much lower growth rates. This deceleration likely points to geo-spatial saturation, an essential consideration for transformer zone design and planning.

4.8.2.4 Connection Age Analysis by Breaker Size

The diverging bar chart in Figure 104 illustrates the average age of connections categorised by each circuit breaker size for Case Study J.

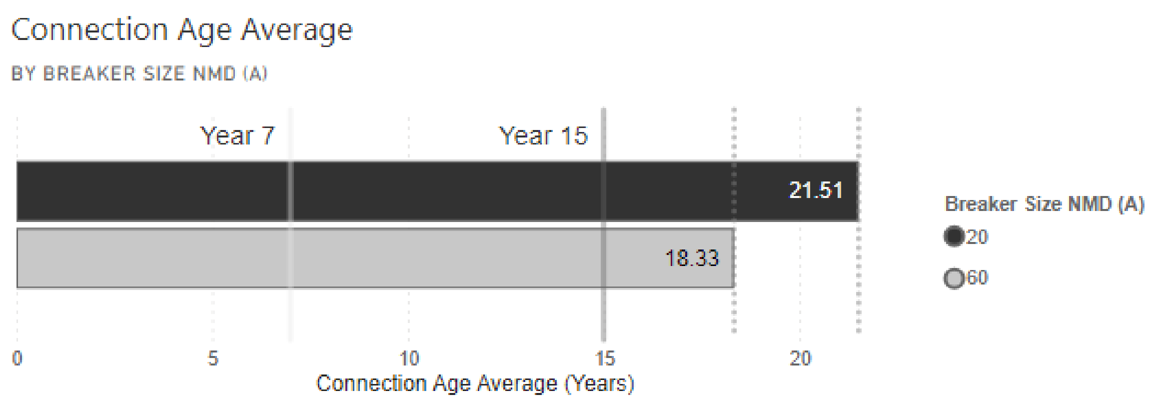


Figure 104: Connection Age Analysis for Case Study J

From Figure 104, it is observed that the average age of connections with 20A circuit breakers is 21.51 years, while the average age of connections with 60A circuit breakers is 18.33 years. The difference in average ages, with the 20A connections being older by approximately 3.18 years compared to the 60A connections, suggests a potential variance in the installation or upgrade times for these breaker sizes.

Given that both categories of circuit breaker size have connection ages significantly higher than 15 years, it is appropriate to use the 15-year parameters according to SANS 507-1:2019 – Table 2. Additionally, it should be noted that the 'c' values for 20A, 15-year parameters are limited to Class ID 1 and 2, whereas the 60A Class IDs, according to the 15-year 'c' values, are from Class ID 3 and higher.

The following conclusions can be drawn from the above analysis. Firstly, the presence of both 20A and 60A connections suggests a heterogeneous consumer group. Secondly, the difference in the average ages of the two categories indicates a pattern of load growth and upgrading. The younger average age for 60A connections could imply that these connections have been installed more recently, possibly as upgrades from 20A connections to accommodate increased demand.

This pattern aligns with typical practices where electrical infrastructure is upgraded to meet higher demand, resulting in newer, larger capacity connections replacing older, smaller ones. The data thus reflects the evolving nature of electrical connections in residential areas, highlighting how infrastructure adapts to changing demands over time. The noticeable difference in ages suggests that upgrades from 20A to 60A connections have occurred over time, leading to a younger average age for the higher capacity connections.

4.8.3 Load Profiles

4.8.3.1 Historical Load Profile Analysis

The historical load profile for Case Study J, illustrated in Figure 105, captures a detailed record of instantaneous electrical load data from July 8, 2019, to December 31, 2023. This profile provides valuable insights into the consumption patterns over time, highlighting typical and peak load levels. The mean load, indicated by the "Mean: 65.43" line, represents the average electrical consumption throughout the study period. The maximum demand, shown by the "Maximum: 195.49" line, identifies the highest recorded load, while the 99.5th percentile, marked as "99.5th Percentile: 144.84," serves as the measured After Diversity Maximum Demand (ADMD) value. This value is critical for assessing the infrastructure's capacity to handle peak loads.

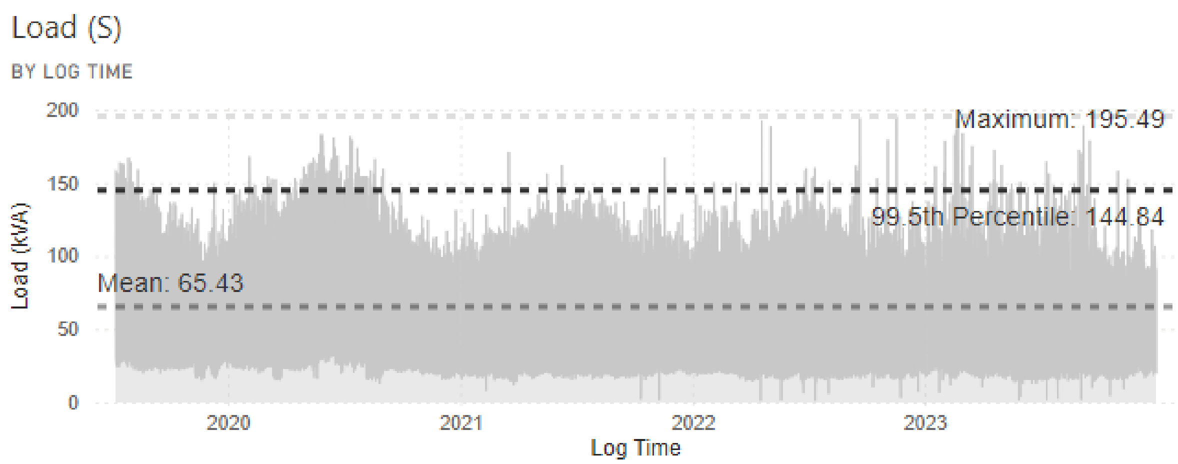


Figure 105: Historical load profile for Case Study J

Figure 105 showcases several key characteristics of the load profile for Case Study J. The mean load, denoted by the "Mean: 65.43" line, suggests a moderate average consumption level over the study period. The profile exhibits significant variability, with noticeable peaks and troughs reflecting changes in demand. The maximum demand, indicated by the "Maximum: 195.49" line, shows substantial peaks, possibly due to specific high-consumption events or periods. The 99.5th percentile, represented by the "99.5th Percentile: 144.84" line, provides a reliable estimate for the ADMD, ensuring the electrical infrastructure can accommodate typical peak demands.

The normal distribution of the historical load profile data for Case Study J, depicted in Figure 106, presents the data as a bell curve. This statistical representation helps in understanding the central tendency, variability, and the presence of outliers in the load data.

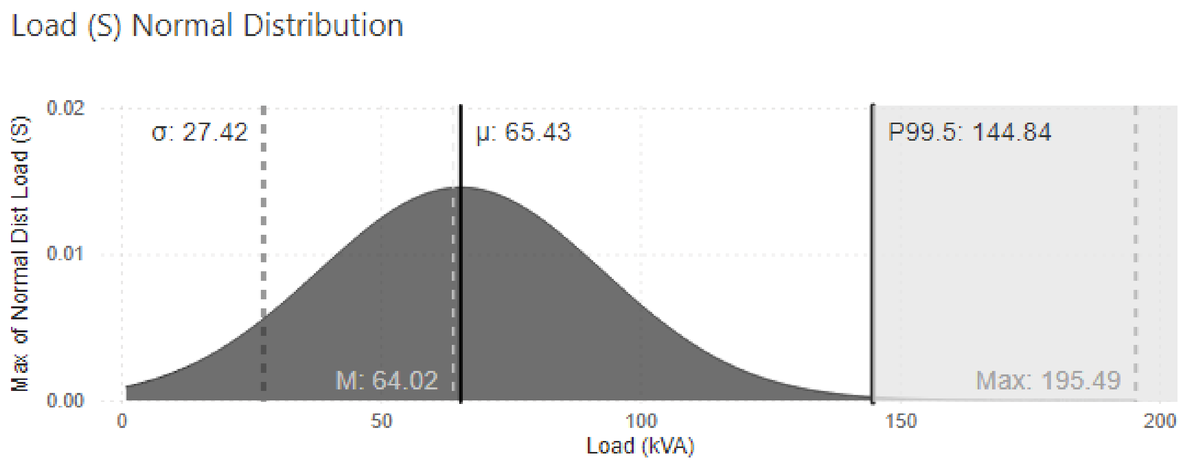


Figure 106: Normal distribution of Historical Load Profile data for Case Study J

Figure 106 illustrates the bell curve of the normal distribution for the load data, centred around the mean (μ) of 65.43 kVA, with a standard deviation (σ) of 27.42 kVA. The mode (M), noted near "M: 64.02," closely aligns with the mean, indicating a typical clustering of data points around these central values. The 99.5th percentile, labelled "P99.5: 144.84," signifies the point below which 99.5% of the data points lie, highlighting the typical upper range of load values. The maximum recorded load, "Max: 195.49," lies well beyond the 99.5th percentile, showcasing the presence of extreme values. The shape of the bell curve, typical of a normal distribution, shows a slight skew to the right, reflecting occasional instances of higher-than-average loads. This skewness indicates that while most data points cluster around the mean, there are significant instances of higher consumption, which are essential considerations for infrastructure planning and resource allocation.

4.8.3.2 99.5th Percentile Load Analysis

In this section, we evaluate the After Diversity Maximum Demand (ADMD) for Case Study J by analysing the 99.5th percentile load across various aggregations. The analysis utilises data from Figure 107, Figure 108, and Figure 109, spanning from July 2019 to December 2023. These figures provide a detailed view of the load patterns, highlighting the variations in peak electricity demand.

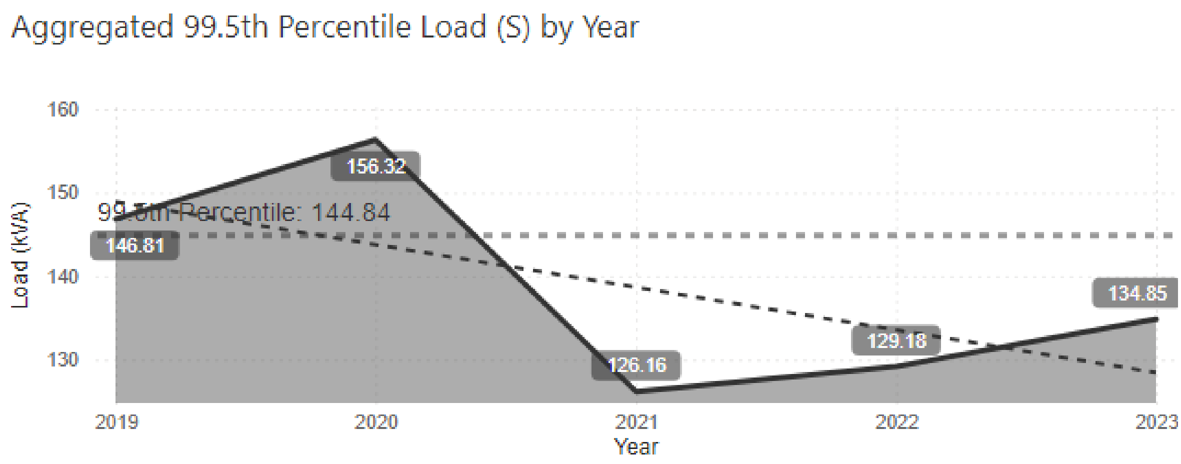


Figure 107: 99.5th Percentile load by year for Case Study J

Figure 107 presents the 99.5th percentile load by year for Case Study J. The graph illustrates the annual peak loads, with the 99.5th percentile line established at 144.84 kVA, representing the observed ADMD. The maximum load recorded was 156.32 kVA in 2020, while the minimum was 126.16 kVA in 2021. The trendline indicates an initial increase in demand, peaking in 2020, followed by a notable decline, and then a slight recovery in 2023 to 134.85 kVA. The years 2019 and 2020 had loads exceeding the 99.5th percentile line, while 2021, 2022, and 2023 remained below it, reflecting fluctuations in peak demand.

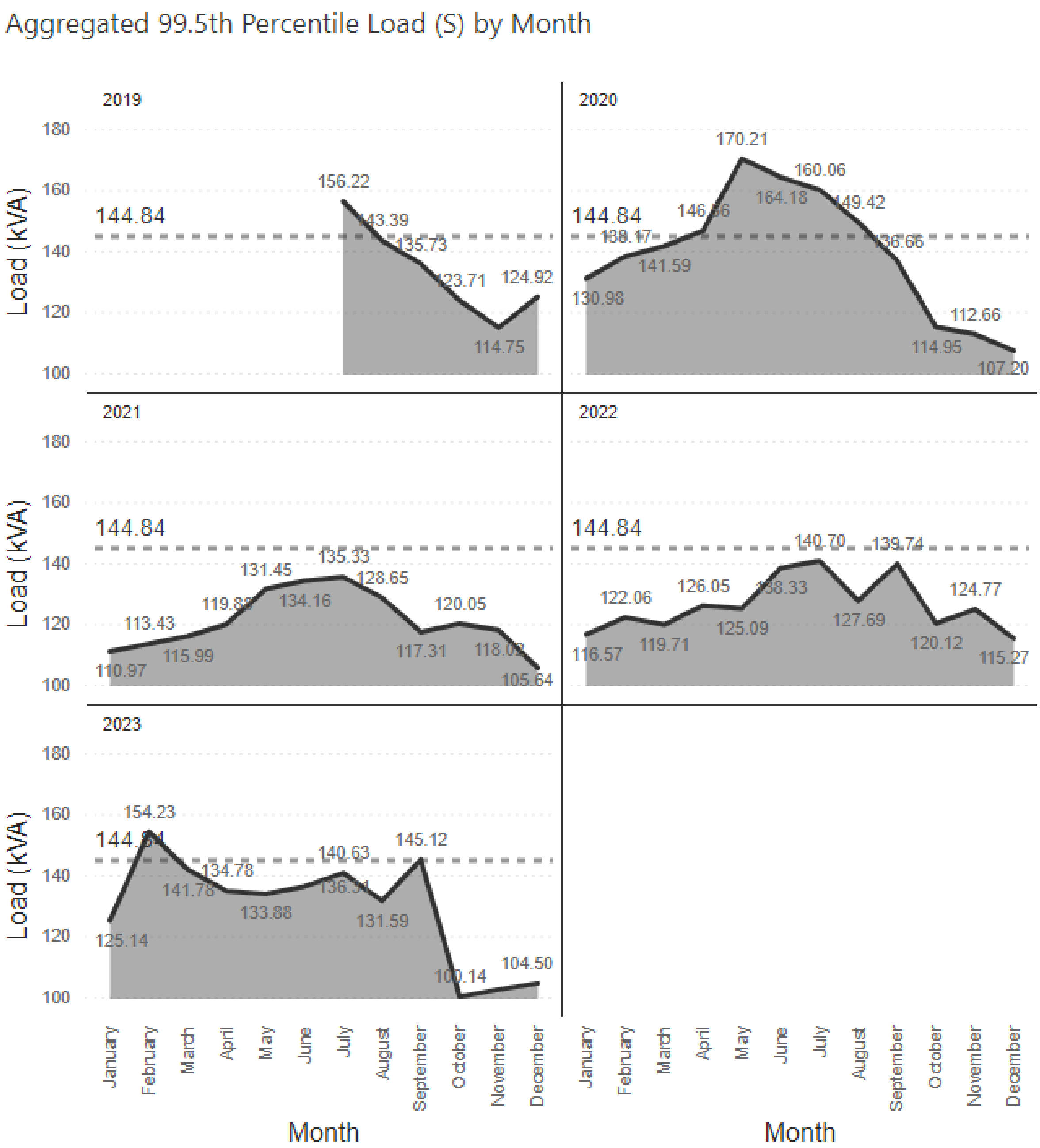


Figure 108: 99.5th Percentile load by each year for Case Study J

Figure 108 provides a detailed breakdown of the 99.5th percentile load by each year, focusing on monthly variations. In 2019, the peak occurred in June at 156.22 kVA, and in 2020, the highest load was observed in May at 170.21 kVA. For 2021, the peak was in June at 128.65 kVA, while 2022 saw its highest load in May at 140.70 kVA. The year 2023 experienced a peak load in February at 154.23 kVA. This analysis reveals that monthly peaks have been declining since 2020, with fewer instances exceeding the 99.5th percentile threshold, indicating a reduction in high-demand periods.

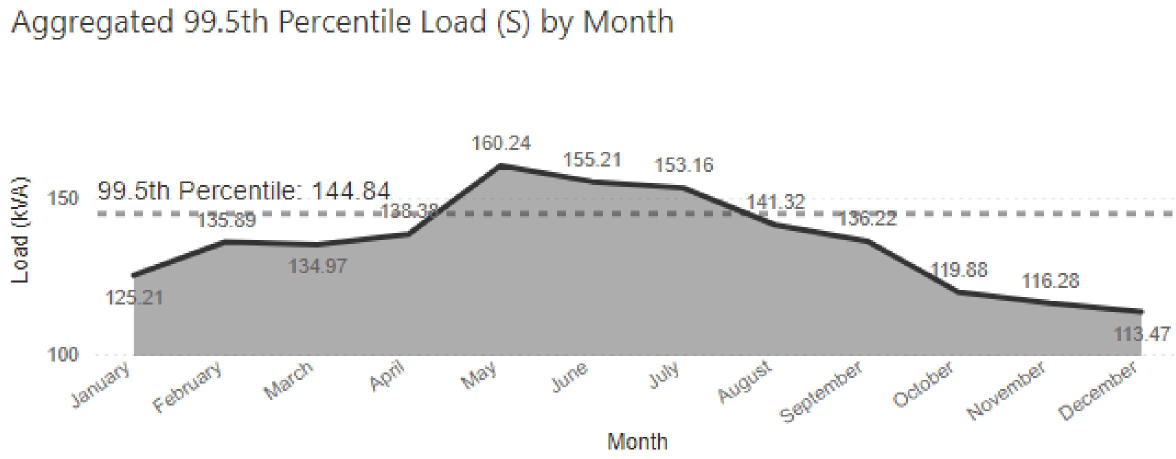


Figure 109: Aggregated 99.5th Percentile load by Month for Case Study J

Figure 109 aggregates the 99.5th percentile load by month across all years, providing a comprehensive view of seasonal demand patterns. The data shows that loads generally increase from February, peaking in May at 160.24 kVA, and then gradually decrease towards December. The lowest load recorded was in December at 113.47 kVA. The consistent peak during the mid-year months suggests higher electricity consumption, possibly due to seasonal factors.

The 99.5th percentile load analysis for Case Study J provides significant insights into the ADMD patterns, with the 99.5th percentile serving as the observed ADMD. The data indicates a peak in demand around 2020, followed by a general decline, with some recovery observed in 2023. The monthly analysis demonstrates that the highest loads typically occur in the first half of the year, particularly around May, with a noticeable reduction in demand in subsequent months. These trends highlight the need for careful planning and management to accommodate peak loads and ensure a reliable electricity supply. Understanding these variations is crucial for optimising infrastructure and resource allocation, particularly in response to changing demand patterns.

4.8.3.3 99.5th Percentile Load Analysis: Daily Demand Profiles

The 99.5th percentile load analysis for Case Study J provides a detailed examination of the maximum demand periods, representing the highest levels of electricity consumption that occur only 0.5% of the time. This metric is crucial for identifying peak usage scenarios, which are vital for infrastructure planning and energy management. By analysing these profiles, we can observe both seasonal and daily variations in electricity consumption, offering insights into how demand fluctuates throughout the year and within a typical day.

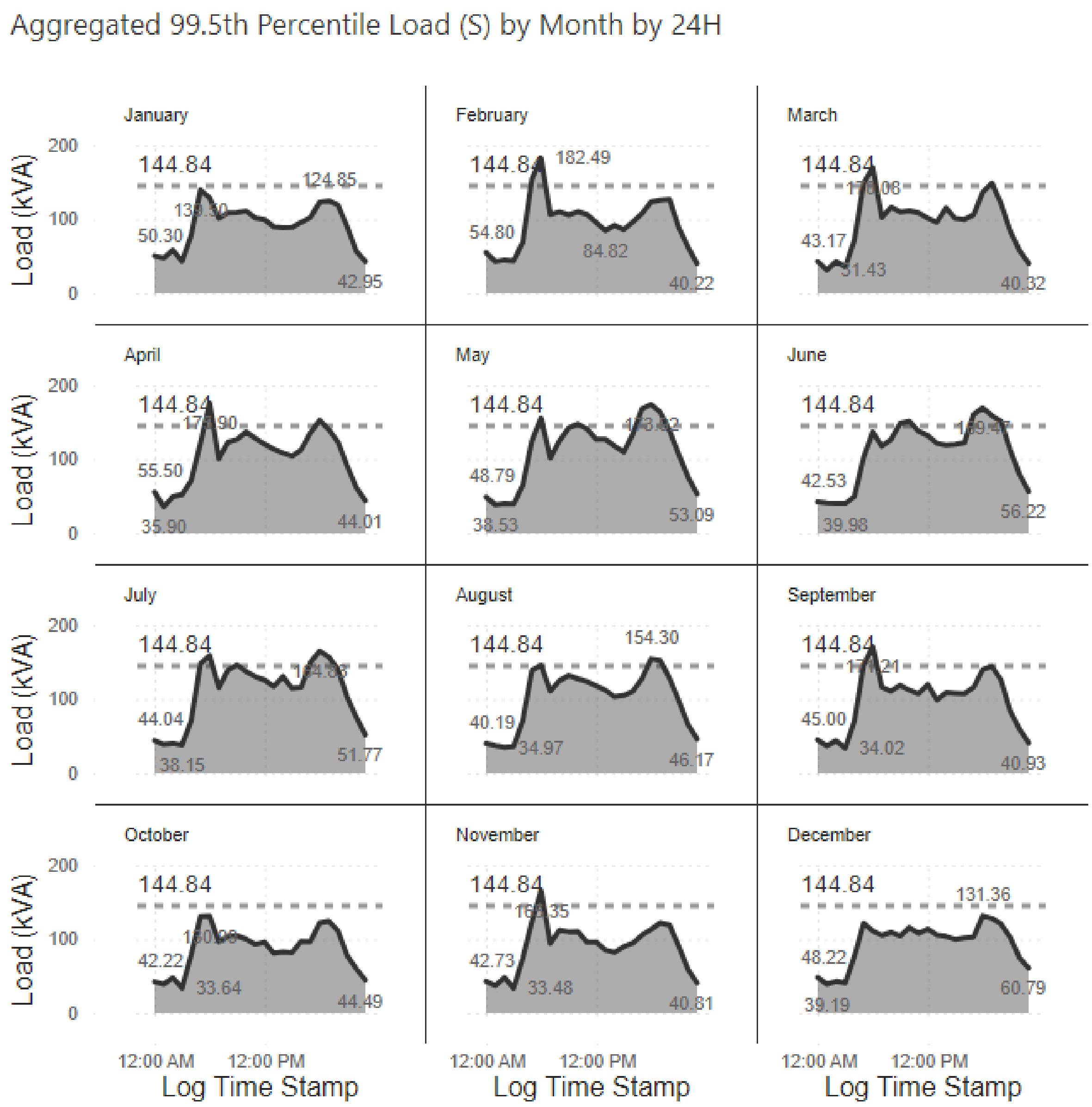


Figure 110: Aggregated 99.5th Percentile load by 24-h day by Month for Case Study J

Figure 110 shows the monthly variations in the 99.5th percentile load, illustrating how daily demand peaks change throughout the year. The dashed line at 144.84 kVA marks the 99.5th percentile load threshold. Key observations include:

> **Winter Months (June - August)**: These months show significant increases in daily peaks, often exceeding the 99.5th percentile line. For instance, June reaches a peak of 149.97 kVA, while July and August have peaks of 142.07 kVA and 154.30 kVA, respectively. These high values indicate increased energy consumption, likely due to heating needs.
>
> **Summer Months (December - February)**: During these months, demand generally remains below the 99.5th percentile threshold, with the highest peak in February at 182.49 kVA. This suggests a mixed demand pattern, possibly influenced by both heating and cooling needs.

Transitional Months (March, September): These months exhibit peaks near or above the 99.5th percentile threshold, with March reaching 171.08 kVA and September showing a peak of 135.04 kVA, reflecting variability in energy use during seasonal transitions.

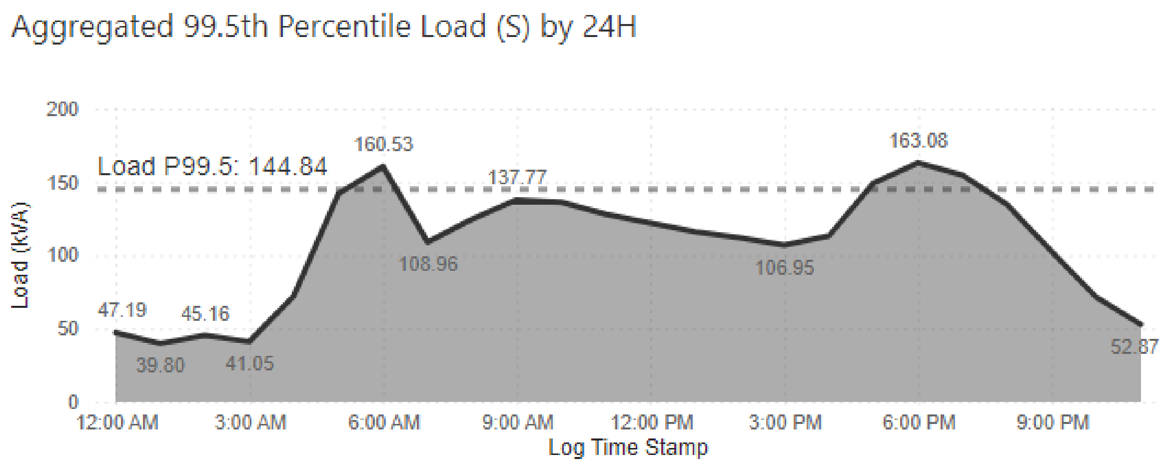


Figure 111: Aggregated 99.5th Percentile load by 24-h day for Case Study J

Figure 111 consolidates the daily demand data into a single 24-hour profile, providing an overview of the typical daily load pattern. The 99.5th percentile load line at 144.84 kVA helps identify critical demand periods:

Morning Peak: A sharp increase in load begins around 3:00 AM, with a peak of 160.53 kVA at 6:00 AM. This rise correlates with morning activities as households start their day.

Evening Peak: The highest demand occurs around 6:00 PM, reaching a peak of 163.08 kVA, indicative of typical residential activities such as cooking and heating.

Off-Peak Periods: The lowest demand occurs during the late night and early morning hours, with the load dropping to around 39.80 kVA, well below the 99.5th percentile threshold.

The 99.5th Percentile Load Analysis for Case Study J highlights significant seasonal and daily variations in electricity demand. The data indicate that peak demands are more pronounced during the winter months, with frequent exceedances of the 99.5th percentile threshold due to increased heating needs. The analysis also underscores the importance of morning and evening peaks in shaping residential electricity consumption patterns. Understanding these variations is essential for adequate energy infrastructure planning and management, ensuring reliable service during periods of maximum demand.

4.8.4 Proposed ADMD vs Observed ADMD

This section aims to compare the proposed After Diversity Maximum Demand (ADMD) values suggested by SANS 507-1:2019 Year-15 parameters with the observed ADMD values for Case Study J. This comparison is crucial for assessing the accuracy and reliability of the proposed standards in predicting real-world electricity demand. By analysing the discrepancies between these values, we can determine the applicability of the SANS guidelines and identify any necessary adjustments for improved planning and infrastructure design.

Summary of Key Metrics

- Total Connections: 186

- Average Age: 21.46 years (greater than 15 years; therefore, Year-15 parameters are used)
- Installed Load: 883.20 kVA (4.75 kVA per connection)
- P99.5 Load: 144.84 kVA (0.78 kVA per stand)
- Resultant P99.5 Diversity Factor (DF): 0.16

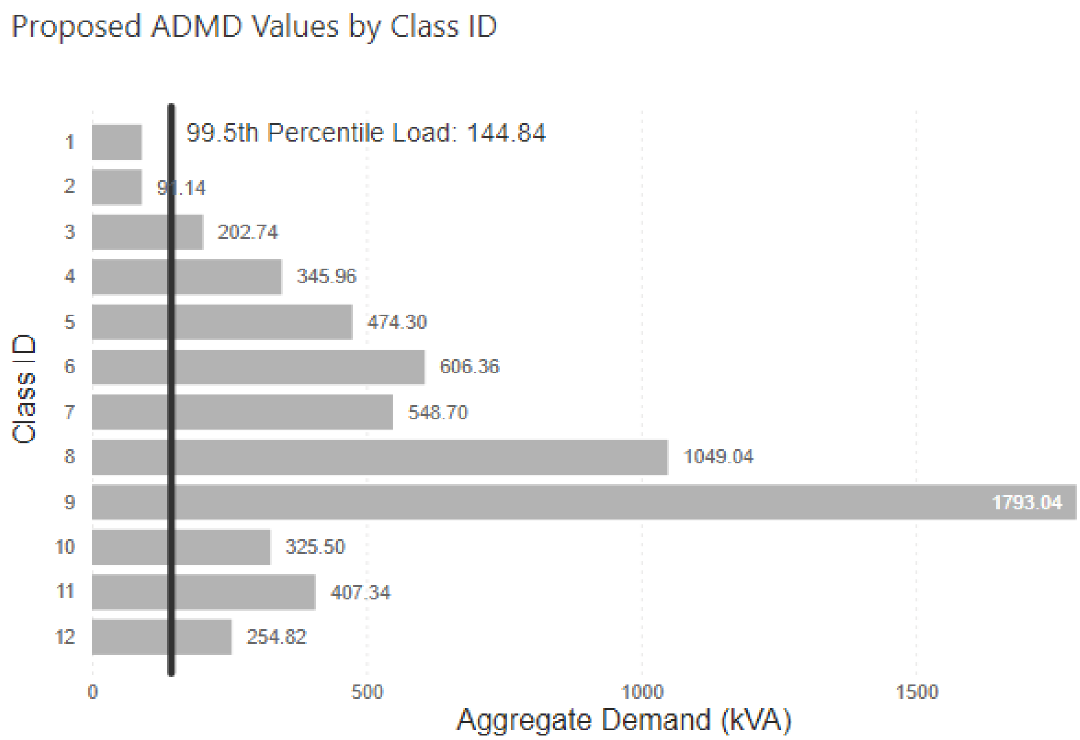


Figure 112: Proposed Year-15 ADMDs result by Class ID for Case Study J

Figure 112 illustrates the proposed ADMD values for different consumer classes as per SANS 507-1:2019 Year-15 parameters, compared against the measured 99.5th percentile load (144.84 kVA). The proposed ADMD values show significant variation across different classes, with Class ID 9 and 8 exhibiting the highest proposed values at 1793.04 kVA and 1049.04 kVA, respectively. The vertical line at 144.84 kVA indicates the 99.5th percentile load, serving as a benchmark for comparison.

The data from Figure 112 reveals that the proposed ADMD values for most consumer classes significantly exceed the measured 99.5th percentile load. Notably, Class ID 9 (Urban Estate) has a proposed ADMD value that is over twelve times the measured load, indicating a possible overestimation. On the other hand, lower class IDs such as 1 and 2 show a proposed ADMD that is closer to the measured load, although still higher. This suggests that the SANS guidelines may need revision to reflect better actual consumption patterns, particularly for higher consumer classes.

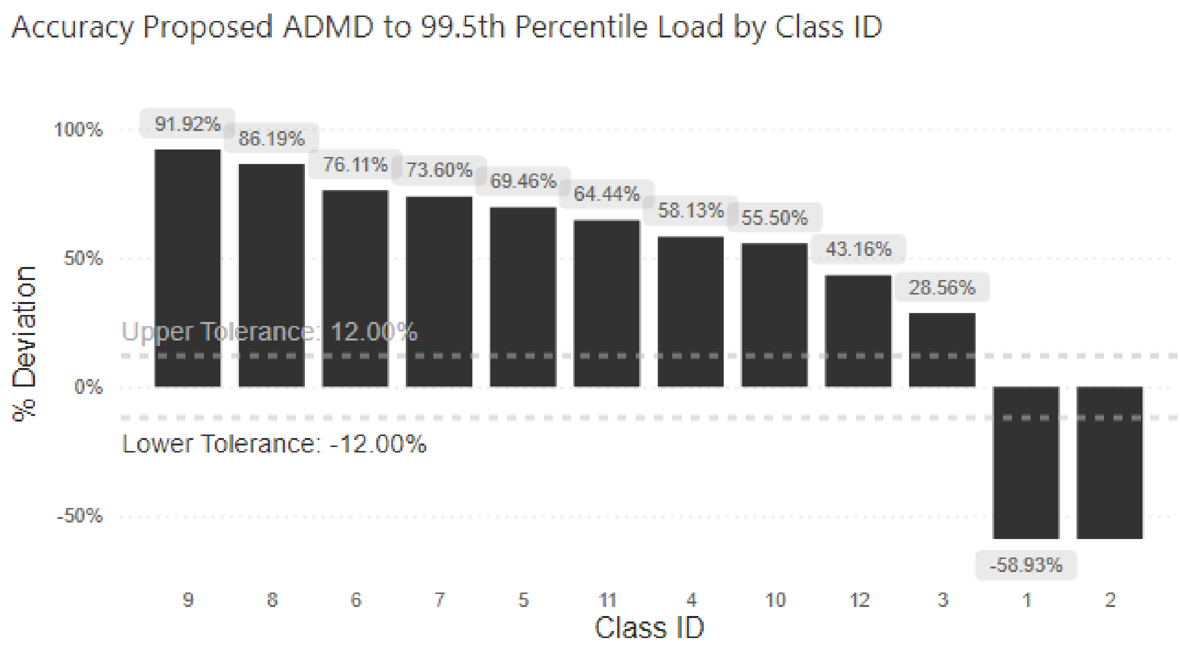


Figure 113: Deviation of SANS 507-1:2019 Year-15 ADMD by Class ID vs. 99.5th Percentile Load for Case Study J

Figure 113 presents the percentage deviation of the proposed ADMD values from the measured 99.5th percentile load for each class ID. The deviation is significant across most classes, with Class ID 9 showing the highest positive deviation at 91.92%. In contrast, Class IDs 1 and 2 show negative deviations, indicating that the proposed values are lower than the measured loads for these classes.

The deviations highlighted in Figure 113 indicate a substantial overestimation of the ADMD values for most consumer classes according to the SANS 507-1:2019 Year-15 parameters. The high positive deviations, particularly for Class ID 9, suggest that the current proposed values do not accurately capture the actual demand patterns. The negative deviations for Class IDs 1 and 2 indicate that the proposed values for these classes may be overly conservative, yet still not entirely accurate. This discrepancy underscores the need for a more nuanced approach in setting ADMD standards that consider the specific characteristics and consumption behaviours of different consumer classes.

Table 9: Deviation of SANS 507-1:2019 Year-15 ADMD by Class ID vs. 99.5th Percentile Load for Case Study J

ID	Consumer Class	SANS 15 Year ADMD (kVA)	Case SANS 15 Year ADMD (kVA)	Accuracy	Deviation
1	Rural settlement, Non-urban, scattered	0.49	91.14	158.93%	-58.93%
2	Rural villages	0.49	91.14	158.93%	-58.93%
3	Informal settlement	1.09	202.74	71.44%	28.56%
4	Township area	1.86	345.96	41.87%	58.13%
5	Urban residential I	2.55	474.30	30.54%	69.46%
6	Urban residential II	3.26	606.36	23.89%	76.11%
7	Urban townhouse complex or duplex	2.95	548.70	26.40%	73.60%
8	Urban Townhouse II	5.64	1049.04	13.81%	86.19%
9	Urban Estate	9.64	1793.04	8.08%	91.92%
10	High rise (small)	1.75	325.50	44.50%	55.50%

11	High rise (medium)	2.19	407.34	35.56%	64.44%
12	Hostel	1.37	254.82	56.84%	43.16%

Table 9 provides a detailed comparison of the proposed and observed ADMD values for each consumer class. The accuracy and deviation columns highlight the discrepancies between the proposed values and the actual measured loads. Notably, Classes 1 and 2 show the highest negative deviation, suggesting that the proposed ADMD values significantly underestimate the actual load for rural settlements and villages. Conversely, Classes 8 and 9 show the highest positive deviations, indicating an overestimation for urban estates and high-end residential areas. These observations reinforce the need for revising the proposed ADMD values to better align with real-world consumption patterns.

The comparison between the proposed ADMD values and the observed ADMD values for Case Study J reveals significant discrepancies, particularly for higher consumer classes. The proposed values tend to overestimate the actual demand for urban estates and high-end residential areas, while underestimating the load for rural settlements and villages. These findings suggest that the current SANS 507-1:2019 Year-15 parameters may not accurately reflect the diverse consumption patterns observed in different consumer classes. Therefore, it is crucial to re-evaluate these standards and consider more tailored approaches to ensure reliable and efficient electricity infrastructure planning.

Interpretive Note: Case Study J

- Installed base is PPU-only. Within PPU, breaker sizes are 20A = 98.39% and 60A = 1.61%.
- Average connection age is 21.46 years. By breaker size: 21.51 years (20A) and 18.33 years (60A), so Year-15 parameters were appropriate.
- Observed ADMD (P99.5) is 144.84 kVA total (0.78 kVA/stand).
- Best fit (exact class ID): Class 2 at 0.62 kVA/stand, which is −20.5% relative to the empirical 0.78 kVA/stand. Class 1 at about 0.49 kVA/stand underestimates by roughly −37%, while Class 3 at 1.09 kVA/stand overshoots by about +39.7%.

The extreme 20A dominance and relatively young stock align with a low-demand regime; among the available SANS options, Class 2 has the least absolute deviation from the measured 99.5th-percentile ADMD, although it still differs materially from the empirical value.

4.9 Case Study K

Case Study K explores load profiles and ADMD values in the neighbourhoods of Meqheleng and parts of Ficksburg within the Setsoto Local Municipality, examining factors affecting electricity demand.

4.9.1 Geographic Overview

Case Study K is geographically located at GPS coordinates 27.862938, -28.903648, as illustrated in Figure 114. This area includes the neighbourhoods of Meqheleng and parts of Ficksburg.

Figure 114: Geographic location for Case Study K

The transformer zone for Case Study K is situated within the local municipal boundaries of Ficksburg, which falls under the Setsoto Local Municipality in the Thabo Mofutsanyana District Municipality, Free State Province of South Africa. The local municipal authorities are responsible for providing public services, maintaining infrastructure, and promoting community development within this area.

The economy in and around Case Study K is diverse, with key activities including agriculture, tourism, and small-scale manufacturing. Ficksburg is known as the "Cherry Capital of the World" and hosts an annual cherry festival, which attracts tourists and boosts the local economy. Agriculture is prominent, with significant production of cherries, asparagus, and other crops. Additionally, small-scale manufacturing and retail businesses support the local economy and provide employment opportunities.

The climate in this region is generally temperate, characterised by cold winters and warm summers. Winter months (June to August) often experience low temperatures, leading to higher electricity consumption for heating purposes. During the summer months (November to February), the electricity demand may rise due to the increased use of cooling systems. The region receives moderate rainfall, mainly during the summer, which impacts agricultural activities and affects electricity consumption patterns.

The socioeconomic factors in Case Study K's area significantly impact electricity consumption patterns. The community is socioeconomically diverse, comprising low to middle-income households, with varying levels of access to economic opportunities and public services. Educational institutions and healthcare facilities within the area rely on a stable electricity supply to operate efficiently.

Economic disparities within the community influence energy consumption, with more affluent households typically using more electrical appliances and therefore having higher electricity demand. In contrast, lower-income households might have lower overall electricity consumption but still exhibit significant usage during peak times, such as in the evenings when residential activities are at their highest.

In summary, the geographic and socioeconomic context of Case Study K provides a comprehensive understanding of the area's electricity consumption patterns. The combination of agricultural activities, tourism, temperate climate, and diverse socioeconomic factors offers valuable data for evaluating the accuracy of proposed ADMD values and their implications for local electricity infrastructure planning.

4.9.2 Connections

4.9.2.1 Proportion of Installed Load by Connection Type

Figure 115 represents the percentage of installed load PPU vs SPU in terms of their contribution to the total load installed as part of Case Study K.

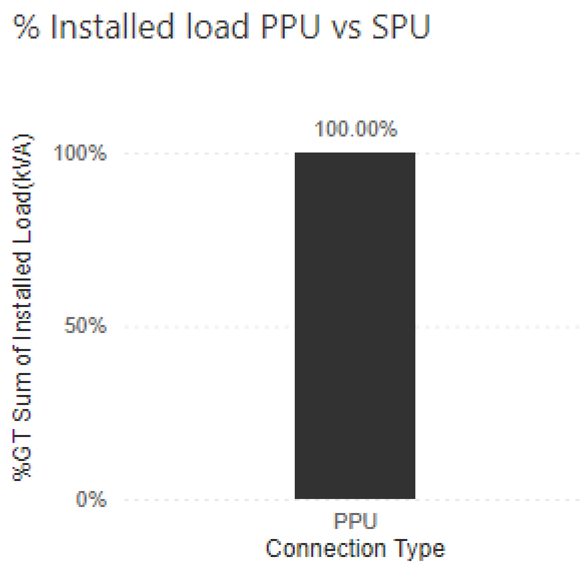


Figure 115: % Installed load by type PPU vs SPU for Case Study K

The same as most of the previous Case Studies Figure 115 shows the homogeneity of the installed load being attributed to PPU connections. Thus, showing the influence of electrification programmes on the installed load types in township areas of the Free State Province.

4.9.2.2 Distribution of PPU Connections by Circuit Breaker Size

Figure 116 is a pie chart that graphically represents how the connections that make up Case Study K are made up according to breaker sizes.

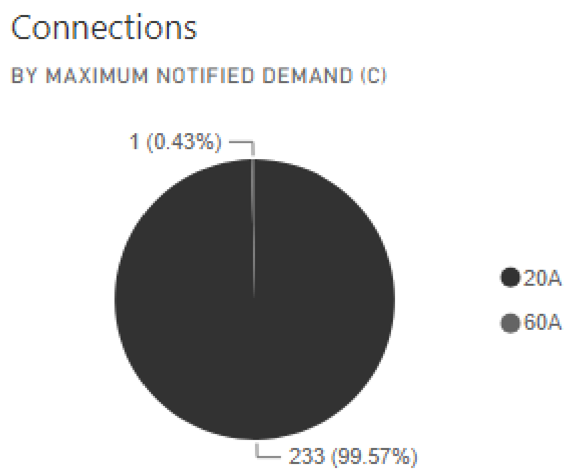


Figure 116: Total PPU connections by Circuit Breaker Size (c) for Case Study K

Case Study K is made up of 99.57% of 20A connections, as shown in Figure 116, totalling 233 connections. In stark contrast, there is only a single 60A connection, constituting less than 1% of the total connections. Interestingly, Case Study K provides fascinating insights as the load and connection types can be considered homogeneous. Thus, Case Study K should offer the ideal benchmark for the accuracy of the SANS 507-1:2019.

4.9.2.3 Connection Trends

The connection trends for Case Study K are illustrated in Figure 117, providing a comprehensive overview of the historical load growth in terms of total connections.

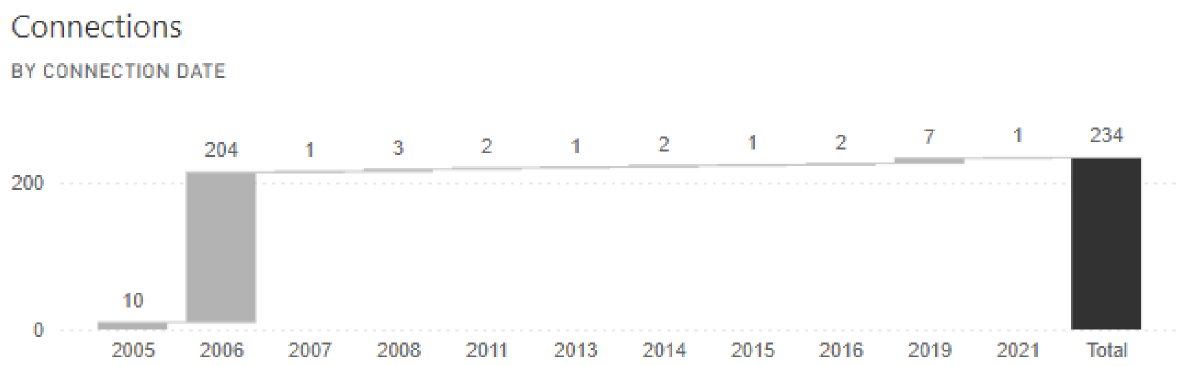


Figure 117: Total connections over time for Case Study K

As shown in Figure 117, the initial connections for Case Study K were recorded in 2005, with the latest connections occurring in 2021. The most significant increase in connections occurred in 2006, just following the initial connections, with 204 new connections added, marking the highest annual growth observed in this dataset. This surge represents a substantial portion of the total connections.

Following the substantial growth in 2006, the number of new connections per year was relatively low, ranging from one to seven connections between 2007 and 2021. Less significant peaks were observed in 2008 (three connections) and 2019 (seven connections).

By the end of the period, the total number of connections reached 234. The data indicate a pattern of an initial rapid growth period, primarily concentrated in 2006, followed by an extended period of significantly lower growth rates. This deceleration indicates a likely saturation in the geographic area. The significance of deceleration and saturation plays a crucial part during the planning and design phase when transformer zones are being designed.

4.9.2.4 Connection Age Analysis by Breaker Size

The diverging bar chart in Figure 118 illustrates the average age of connections categorised by each circuit breaker size for Case Study K.

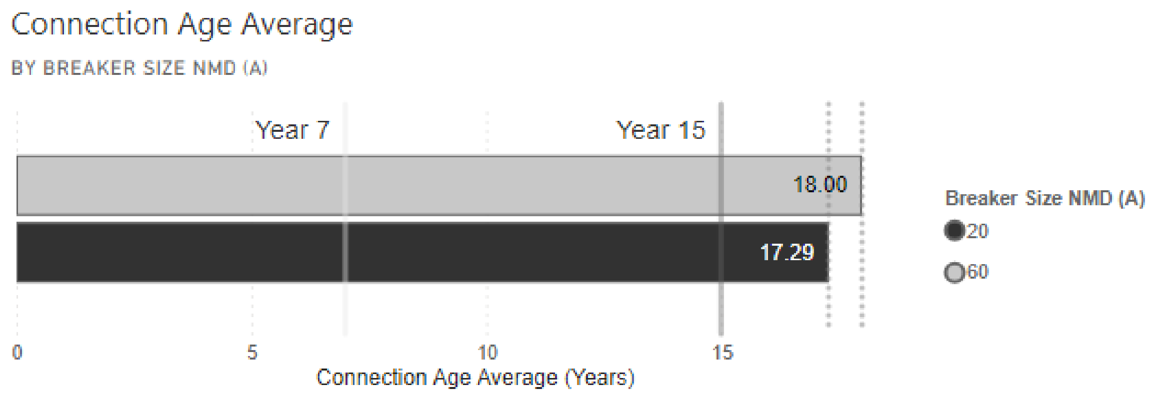


Figure 118: Connection Age Analysis for Case Study K

From Figure 118, it is observed that the average age of connections with 20A circuit breakers is 17.29 years, while the average age of connections with 60A circuit breakers is 18.00 years. The slight difference in average ages, with the 60A connections being older by approximately 0.71 years compared to the 20A connections, suggests that both types of connections were likely established around the same time.

Given that both categories of circuit breaker size have connection ages higher than 15 years, it is appropriate to use the 15-year parameters according to SANS 507-1:2019 – Table 2. Additionally, it should be noted that the 'c' values for 20A, 15-year parameters are limited to Class ID 1 and 2, whereas the 60A Class IDs, according to the 15-year 'c' values, are from Class ID 3 and higher.

The following conclusions can be drawn from the above analysis. Firstly, the presence of both 20A and 60A connections suggests a heterogeneous consumer group. Secondly, the similarity in the average ages of the two categories indicates that there has not been significant load growth necessitating upgrades from 20A to 60A connections. If significant individual load growth were present, we would expect the average age of 60A connections to be noticeably lower due to older 20A connections being upgraded over time.

This pattern reflects a stable demand for electricity within the study area, with the existing infrastructure sufficiently meeting the needs of the consumers without necessitating widespread upgrades. The data thus highlights a consistent and stable electrical demand in the residential area covered by Case Study K. The slight difference in ages also suggests that while upgrades may have occurred, they have not been so frequent or recent as to alter the average age difference between the breaker sizes significantly.

4.9.3 Load Profiles

4.9.3.1 Historical Load Profile Analysis

The historical load profile for Case Study K, depicted in Figure 119, provides an in-depth analysis of instantaneous electrical load data collected from January 3, 2019, to December 31, 2023. This profile captures the variability and trends in electrical consumption over time. Key metrics, such as the mean load, maximum demand, and the 99.5th percentile, are highlighted to indicate typical and peak load conditions. The mean load, shown by the "Mean: 62.31" line, represents the average consumption level throughout the study period. The maximum demand, represented by the "Maximum: 177.97" line, denotes the highest recorded load, while the 99.5th percentile, shown as "99.5th Percentile: 118.68," serves as the measured After Diversity Maximum Demand (ADMD) value. This value is critical for infrastructure planning and ensuring adequate system capacity to handle peak loads.

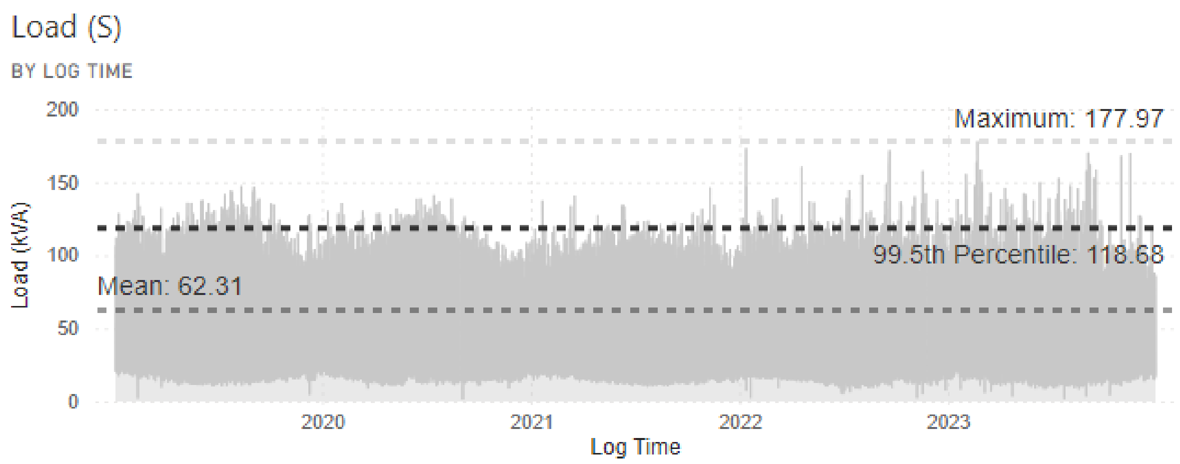


Figure 119: Historical load profile for Case Study K

Figure 119 illustrates several notable features of the historical load profile for Case Study K. The mean load, marked by the "Mean: 62.31" line, suggests a moderate average consumption level. The profile displays significant variability, with marked peaks and troughs reflecting fluctuations in demand. The maximum demand, indicated by the "Maximum: 177.97" line, highlights periods of exceptionally high usage, potentially due to specific high-demand events or seasonal factors. The 99.5th percentile, represented by the "99.5th Percentile: 118.68" line, offers a conservative estimate of the ADMD, ensuring that the infrastructure can accommodate typical peak loads without exceeding capacity.

The normal distribution of the historical load profile data for Case Study K, shown in Figure 120, provides a statistical representation of the data as a bell curve. This visualisation helps to understand the central tendency, variability, and the presence of outliers in the dataset.

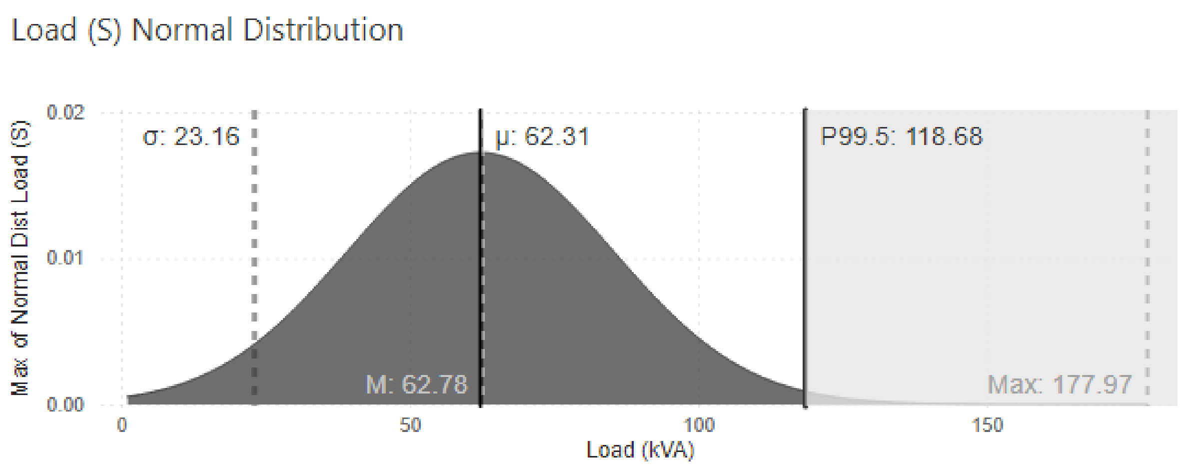


Figure 120: Normal distribution of Historical Load Profile data for Case Study K

Figure 120 depicts the normal distribution of the load data, with the curve centred around the mean (μ) of 62.31 kVA and a standard deviation (σ) of 23.16 kVA. The mode (M), indicated near "M: 62.78," aligns closely with the mean, suggesting a clustering of data points around these values. The 99.5th percentile, labelled "P99.5: 118.68," indicates the value below which 99.5% of the data points fall, reflecting the typical upper range of load values. The maximum recorded load, "Max: 177.97," lies beyond the 99.5th percentile, highlighting the presence of extreme values in the dataset. The bell curve's shape, characteristic of a normal distribution, shows a slight rightward skew, indicating occasional higher-than-average loads. This skewness suggests that while most consumption falls within a predictable range, there are instances of significant peaks, which are crucial for infrastructure and resource planning.

4.9.3.2 99.5th Percentile Load Analysis

This section evaluates the After Diversity Maximum Demand (ADMD) for Case Study K by analysing the 99.5th percentile load across various aggregations. The analysis is based on data presented in Figure 121, Figure 122, and Figure 123, covering the period from January 2019 to December 2023. These figures provide detailed insights into the variations in electricity demand and peak loads.

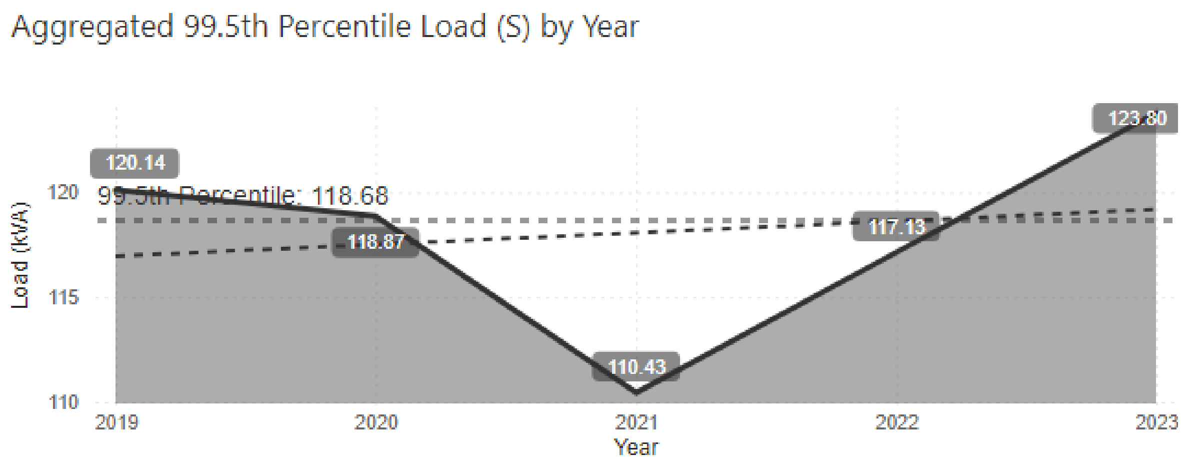


Figure 121: 99.5th Percentile load by year for Case Study K

Figure 121 illustrates the 99.5th percentile load by year for Case Study K. The graph highlights the annual peak loads, with the 99.5th percentile line established at 118.68 kVA, representing the observed ADMD. The maximum load recorded was 123.80 kVA in 2023, while the minimum was 110.43 kVA in 2021. The trendline indicates a dip in demand around 2021, followed by a significant rise in 2023, suggesting a recovery in demand. Notably, the years 2019, 2022, and 2023 had loads exceeding the 99.5th percentile line, while 2020And 2021 fell below it, reflecting fluctuating demand patterns.

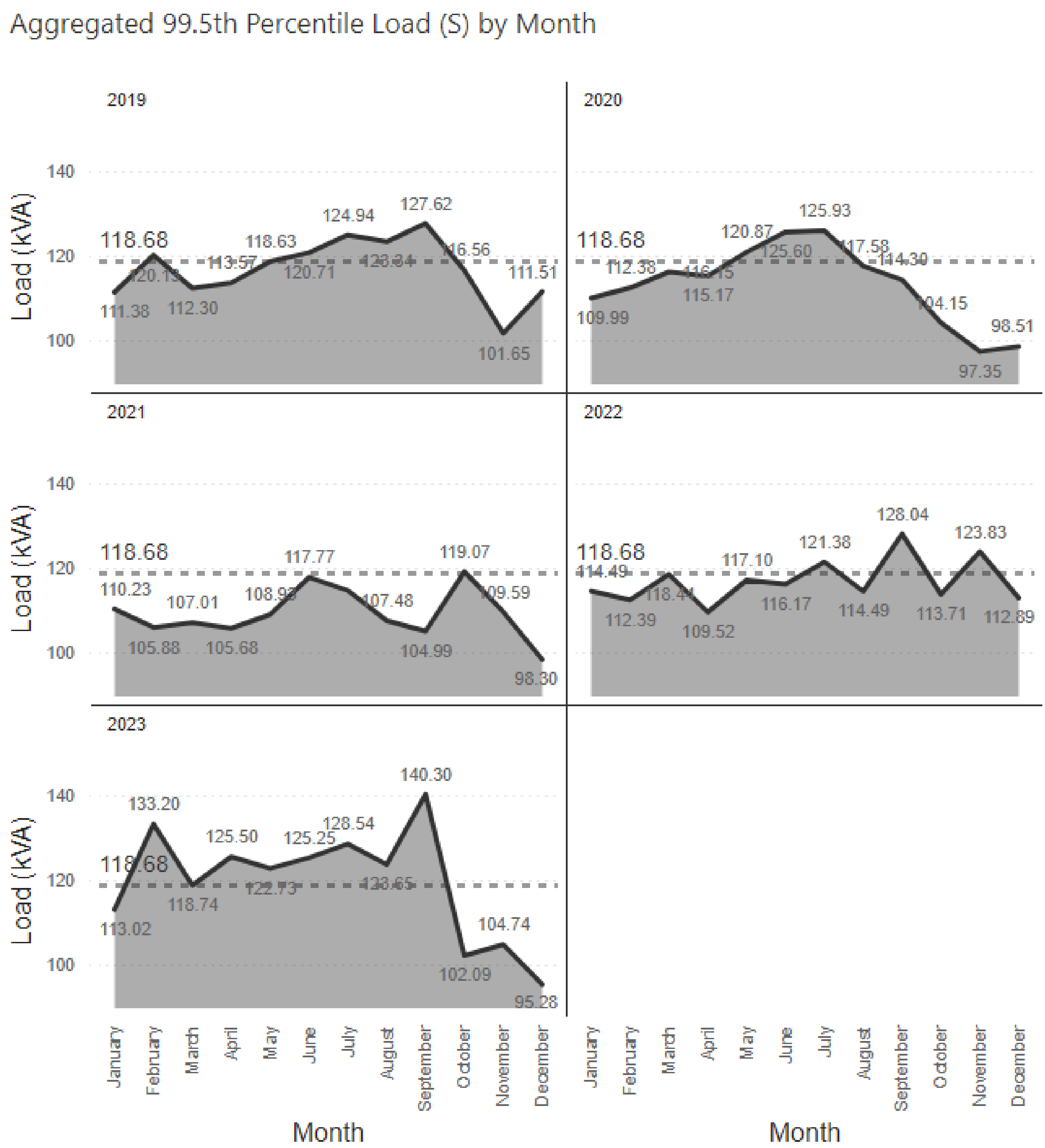


Figure 122: 99.5th Percentile load by each year for Case Study K

Figure 122 provides a detailed breakdown of the 99.5th percentile load by each year, focusing on monthly variations. In 2019, the peak occurred in September at 127.62 kVA, and in 2020, the highest load was observed in August at 125.93 kVA. For 2021, the peak was in May at 119.07 kVA, while 2022 saw its highest load in December at 123.83 kVA. The year 2023 experienced a peak load in September at 140.30 kVA. This data shows a pattern of increasing peaks, particularly in the latter months of each year, suggesting rising demand.

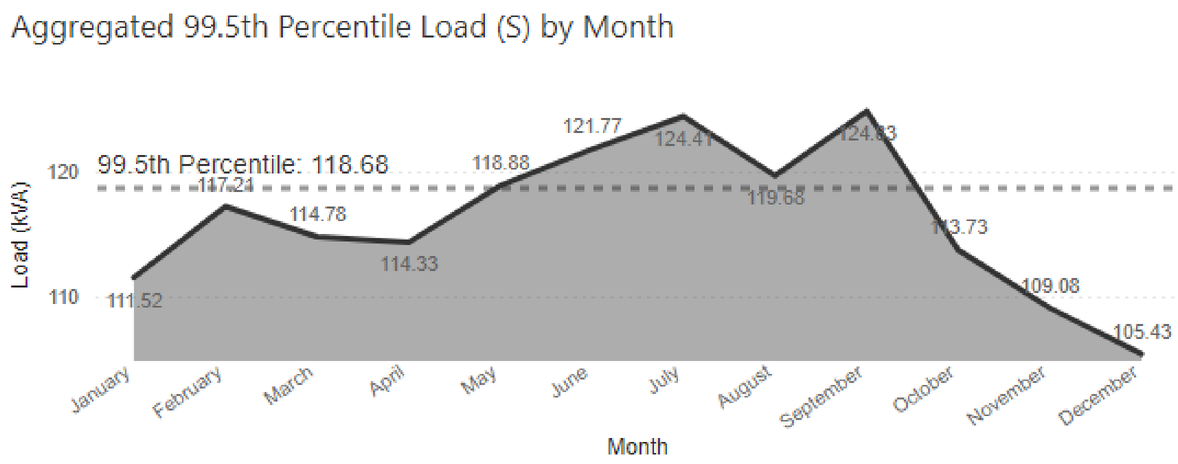


Figure 123: Aggregated 99.5th Percentile load by Month for Case Study K

Figure 123 aggregates the 99.5th percentile load by month across all years, providing a comprehensive view of seasonal demand patterns. The data indicates that loads typically increase from February, peaking in September at 140.30 kVA, and then declining towards December, with the lowest recorded load in December at 105.43 kVA. This trend highlights higher electricity consumption in mid to late-year months, possibly due to seasonal influences.

The 99.5th percentile load analysis for Case Study K reveals significant variations in ADMD, with the 99.5th percentile line serving as the observed ADMD. The analysis shows a dip in demand around 2021, followed by a notable recovery in 2023. The monthly analysis highlights that peak loads typically occur towards the end of the year, particularly around September, with a noticeable increase in demand compared to earlier years. These trends underscore the importance of understanding and planning for these variations to ensure a reliable electricity supply and efficient infrastructure management. Adapting to these changing demand patterns is crucial for optimising resource allocation and meeting peak electricity needs.

4.9.3.3 99.5th Percentile Load Analysis: Daily Demand Profiles

The 99.5th percentile load analysis for Case Study K focuses on identifying the maximum demand periods that are exceeded only 0.5% of the time. This metric is crucial for understanding peak usage scenarios, which are essential for infrastructure planning and energy management. By examining these profiles, we gain insights into the seasonal and daily variations in electricity consumption, providing a comprehensive view of how demand changes throughout the year and within a typical day.

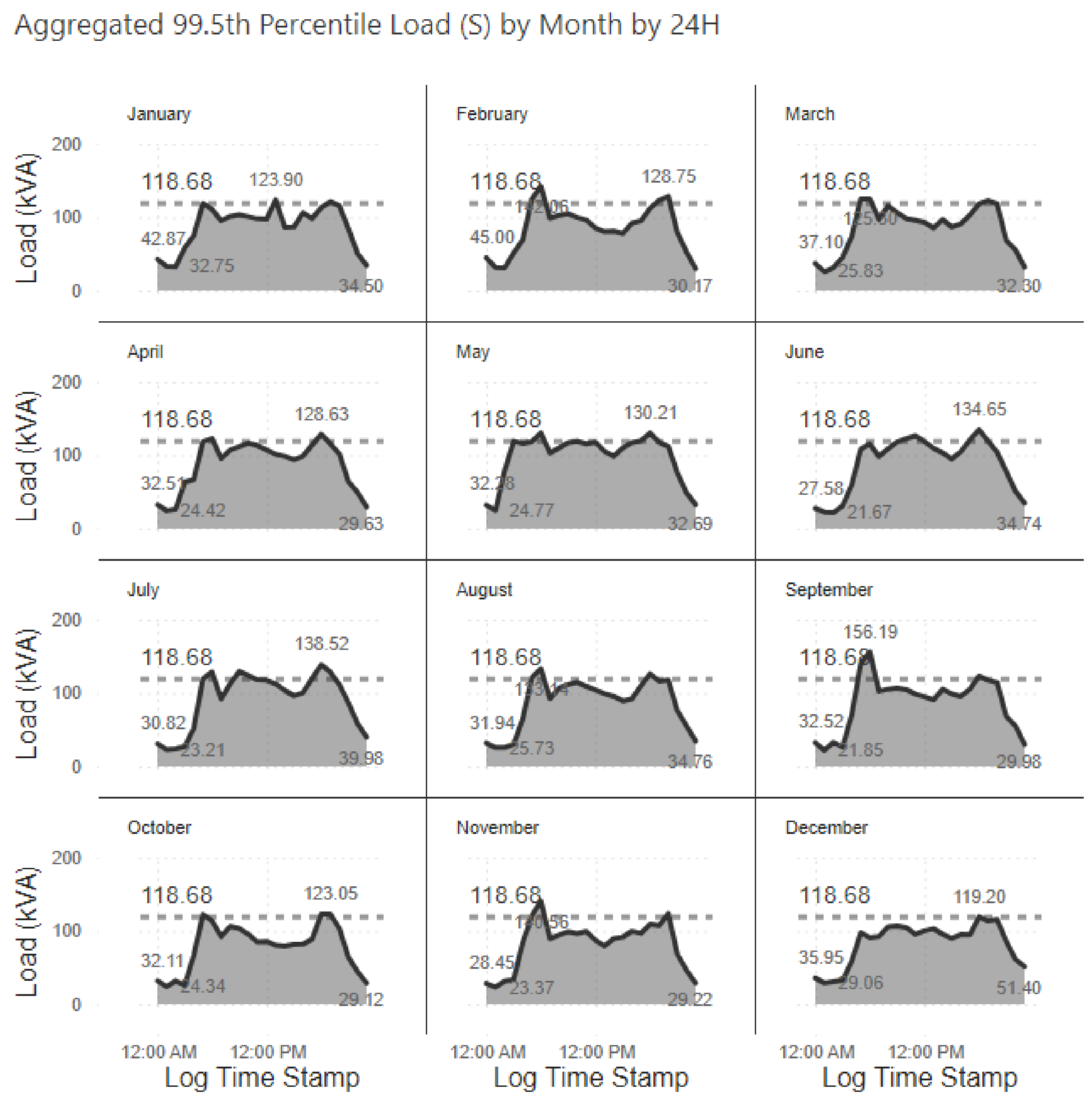


Figure 124: Aggregated 99.5th Percentile load by 24-h day by Month for Case Study K

Figure 124 displays the monthly variations in the 99.5th percentile load, illustrating how daily demand peaks fluctuate across different months. The dashed line at 118.68 kVA represents the 99.5th percentile load threshold. Key observations include:

Winter Months (June - August): These months generally exhibit higher daily peaks, often surpassing the 99.5th percentile line. June, for example, reaches a peak of 134.65 kVA, while July and August show peaks of 138.52 kVA and 156.19 kVA, respectively. These high values indicate increased energy consumption, likely due to heating requirements.

Summer Months (December - February): The demand during these months is lower, with the peaks typically below the 99.5th percentile line. For instance, January's peak is at 123.90 kVA, and February's peak reaches 128.75 kVA, indicating a relatively stable energy demand.

Transitional Months (March, September): March and September show peaks near the 99.5th percentile line, with March reaching 115.00 kVA and September showing a peak of 156.19 kVA. These values suggest fluctuations in energy use during changing weather conditions.

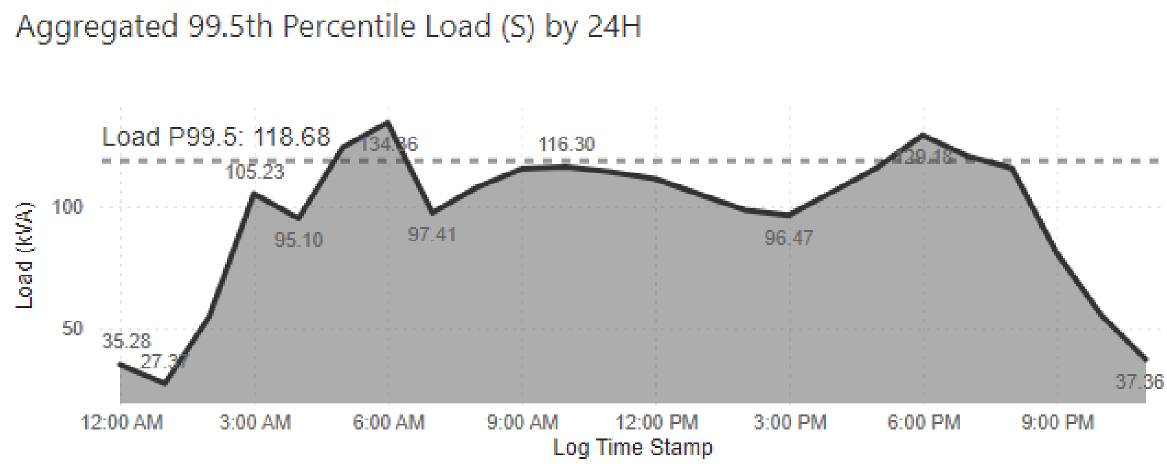


Figure 125: Aggregated 99.5th Percentile load by 24-h day for Case Study K

Figure 125 consolidates the daily demand data into a single 24-hour profile, providing an overview of the typical daily load pattern. The 99.5th percentile load line at 118.68 kVA helps identify critical demand periods:

Morning Peak: A noticeable increase in load begins around 3:00 AM, reaching a peak of 134.86 kVA at 6:00 AM. This rise correlates with early morning activities as residents start their day.

Evening Peak: The highest demand occurs around 6:00 PM, with a peak load of 119.24 kVA, reflecting typical residential activities such as cooking and heating.

Off-Peak Periods: The lowest demand occurs late at night and early morning, with the load dropping to around 35.28 kVA, well below the 99.5th percentile threshold.

The 99.5th Percentile Load Analysis for Case Study K highlights significant seasonal and daily variations in electricity demand. The data indicate that peak demands are more pronounced during the winter months, often exceeding the 99.5th percentile threshold due to increased heating needs. The analysis also underscores the importance of morning and evening peaks in shaping residential electricity consumption patterns. Understanding these variations is crucial for effective energy infrastructure planning and management, ensuring reliable service during periods of maximum demand.

4.9.4 Proposed ADMD vs Observed ADMD

This section aims to compare the proposed After Diversity Maximum Demand (ADMD) values suggested by SANS 507-1:2019 Year-15 parameters with the observed ADMD values for Case Study K. This comparison is crucial for assessing the accuracy and reliability of the proposed standards in predicting real-world electricity demand. By analysing the discrepancies between these values, we can determine the applicability of the SANS guidelines and identify any necessary adjustments for improved planning and infrastructure design.

Summary of Key Metrics

- Total Connections: 234

- Average Age: 17.29 years (greater than 15 years; therefore, Year-15 parameters are used)
- Installed Load: 1,085.60 kVA (4.64 kVA per connection)
- P99.5 Load: 118.68 kVA (0.51 kVA per stand)
- Resultant P99.5 Diversity Factor (DF): 0.11

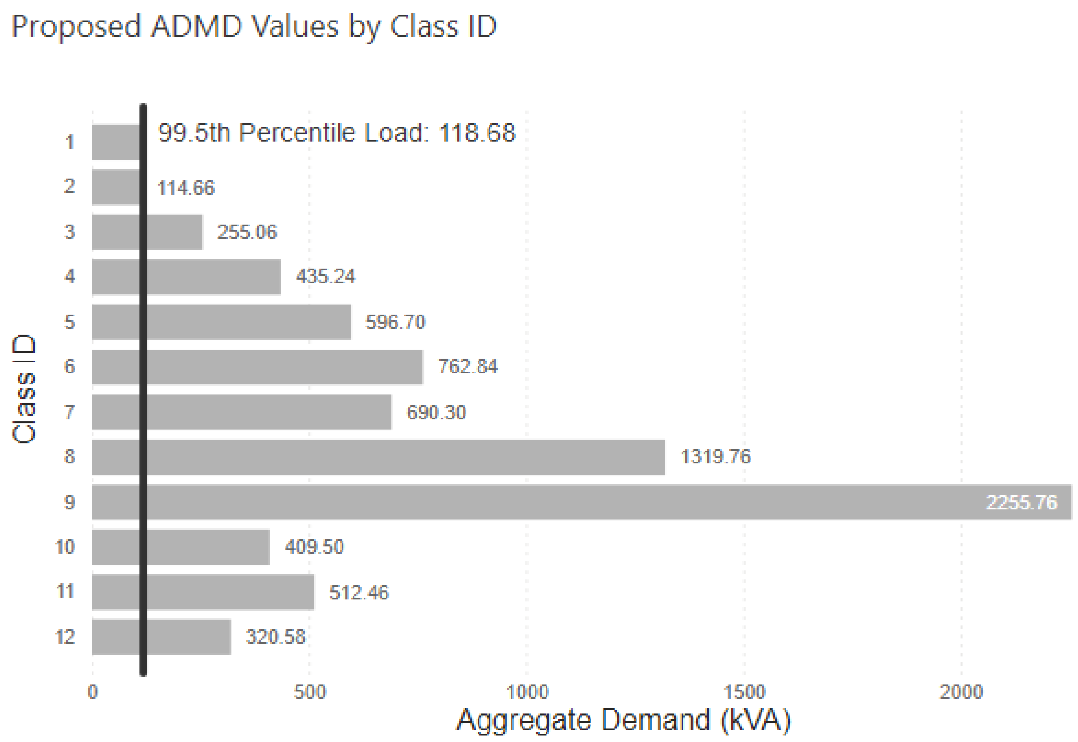


Figure 126: Proposed Year-15 ADMDs result by Class ID for Case Study K

Figure 126 illustrates the proposed ADMD values for different consumer classes as per SANS 507-1:2019 Year-15 parameters, compared against the measured 99.5th percentile load (118.68 kVA). The proposed ADMD values show significant variation across different classes, with Class ID 9 and 8 exhibiting the highest proposed values at 2,255.76 kVA and 1,319.76 kVA, respectively. The vertical line at 118.68 kVA indicates the 99.5th percentile load, serving as a benchmark for comparison.

The data from Figure 126 reveals that the proposed ADMD values for most consumer classes significantly exceed the measured 99.5th percentile load. Notably, Class ID 9 (Urban Estate) has a proposed ADMD value that is over nineteen times the measured load, indicating a possible overestimation. On the other hand, lower class IDs such as 1 and 2 show a proposed ADMD that is closer to the measured load, although still higher. This suggests that the SANS guidelines may need revision to reflect better actual consumption patterns, particularly for higher consumer classes.

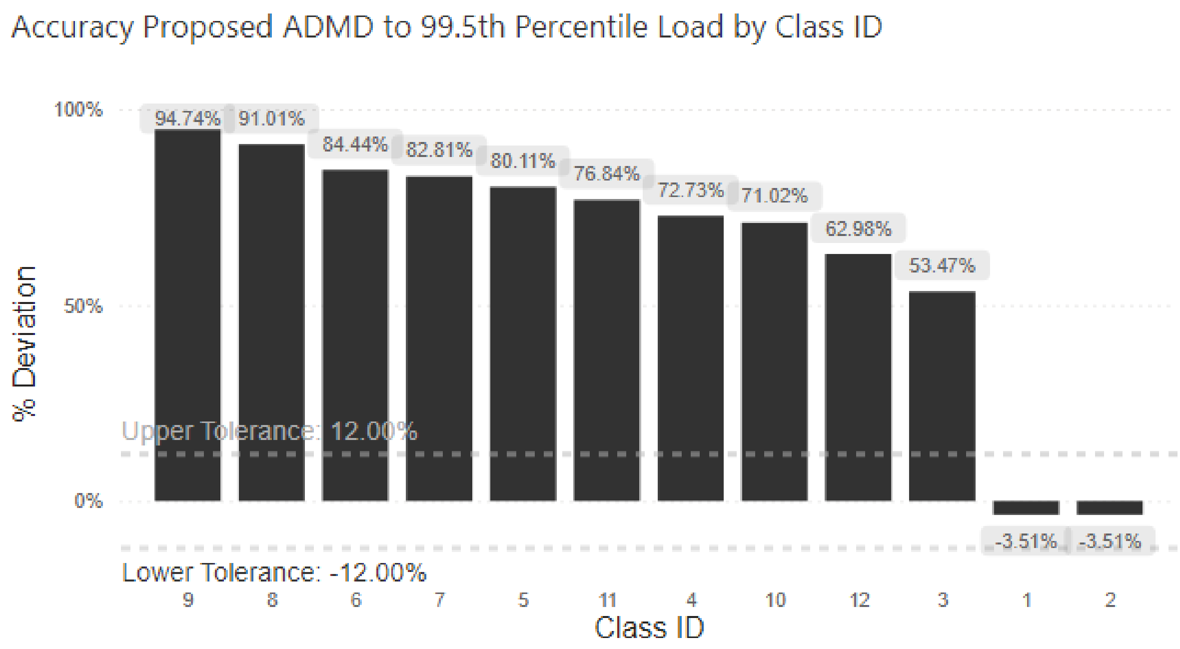


Figure 127: Deviation of SANS 507-1:2019 Year-15 ADMD by Class ID vs. 99.5th Percentile Load for Case Study K

Figure 127 presents the percentage deviation of the proposed ADMD values from the measured 99.5th percentile load for each class ID. The deviation is significant across most classes, with Class ID 9 showing the highest positive deviation at 94.74%. In contrast, Class IDs 1 and 2 show minimal deviation, indicating that the proposed values are relatively close to the measured loads for these classes.

The deviations highlighted in Figure 127 indicate a substantial overestimation of the ADMD values for most consumer classes according to the SANS 507-1:2019 Year-15 parameters. The high positive deviations, particularly for Class ID 9, suggest that the current proposed values do not accurately capture the actual demand patterns. The minimal deviations for Class IDs 1 and 2 indicate that the proposed values for these classes are relatively accurate, but still exhibit slight overestimation. This discrepancy underscores the need for a more nuanced approach in setting ADMD standards that consider the specific characteristics and consumption behaviours of different consumer classes.

Table 10: Detailed Comparison of Proposed ADMD vs Observed ADMD for Case Study K

ID	Consumer Class	SANS 15 Year ADMD (kVA)	Case SANS 15 Year ADMD (kVA)	Accuracy	Deviation
1	Rural settlement, Non-urban, scattered	0.49	114.66	103.51%	-3.51%
2	Rural villages	0.49	114.66	103.51%	-3.51%
3	Informal settlement	1.09	255.06	46.53%	53.47%
4	Township area	1.86	435.24	27.27%	72.73%
5	Urban residential I	2.55	596.70	19.89%	80.11%
6	Urban residential II	3.26	762.84	15.56%	84.44%
7	Urban townhouse complex or duplex	2.95	690.30	17.19%	82.81%
8	Urban Townhouse II	5.64	1,319.76	8.99%	91.01%
9	Urban Estate	9.64	2,255.76	5.26%	94.74%
10	High rise (small)	1.75	409.50	28.98%	71.02%

11	High rise (medium)	2.19	512.46	23.16%	76.84%
12	Hostel	1.37	320.58	37.02%	62.98%

Table 10 provides a detailed comparison of the proposed and observed ADMD values for each consumer class. The accuracy and deviation columns highlight the discrepancies between the proposed values and the actual measured loads. Notably, Classes 1 and 2 show minimal deviation, suggesting that the proposed ADMD values closely align with the actual load for rural settlements and villages. Conversely, Classes 8 and 9 show the highest positive deviations, indicating an overestimation for urban estates and high-end residential areas. These observations reinforce the need for revising the proposed ADMD values to better align with real-world consumption patterns.

The comparison between the proposed ADMD values and the observed ADMD values for Case Study K reveals significant discrepancies, particularly for higher consumer classes. The proposed values tend to overestimate the actual demand for urban estates and high-end residential areas, while closely matching the load for rural settlements and villages. These findings suggest that the current SANS 507-1:2019 Year-15 parameters may not accurately reflect the diverse consumption patterns observed in different consumer classes. Therefore, it is crucial to re-evaluate these standards and consider more tailored approaches to ensure reliable and efficient electricity infrastructure planning.

Interpretive Note: Case Study K

- Installed base is PPU-dominant. Within PPU, breaker sizes are 20A = 99.57% with a single 60A connection, indicating a highly uniform lower-capacity mix.
- Average connection age is 17.29 years (20A) and 18.00 years (60A), so Year-15 parameters were appropriate.
- Observed ADMD (P99.5) is 118.68 kVA total (0.51 kVA/stand) across 234 connections.
- Best fit (exact class ID): Class 1 or Class 2 (tie). Both specify 0.49 kVA/stand → 114.66 kVA case total, −3.51% vs observed. Classes above 2 propose larger per-stand values and overestimate by wider margins.

The near-total 20A dominance and late-teen average ages correspond to a low-demand regime; the 0.49 kVA/stand planning value in Classes 1–2 is closest to the empirical 0.51 kVA/stand, which explains the least absolute deviation.

4.10 Case Study L

Case Study L explores load profiles and ADMD values in the neighbourhoods of Meqheleng Zone 6, Meqheleng Zone 7, and parts of Ficksburg, examining factors affecting electricity demand.

4.10.1 Geographic Overview

Case Study L is geographically located at GPS coordinates 27.86757, -28.906116, as illustrated in Figure 128. This area includes the neighbourhoods of Meqheleng Zone 6, Meqheleng Zone 7, and parts of Ficksburg.

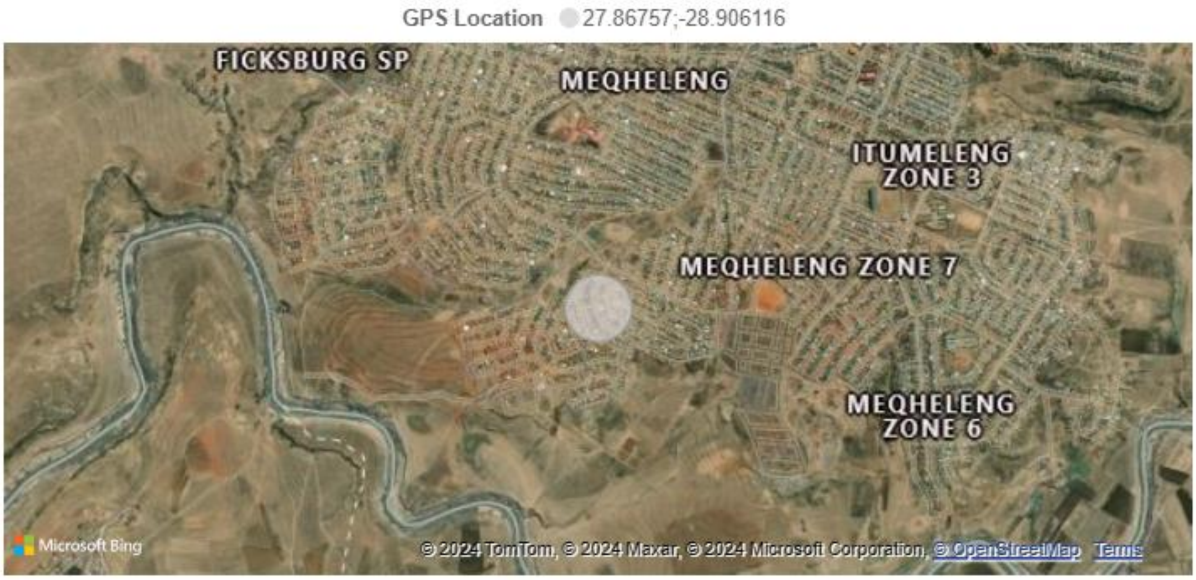


Figure 128: Geographic location for Case Study L

The climate in this region is generally temperate, characterised by cold winters and warm summers. Winter months (June to August) often experience low temperatures, leading to higher electricity consumption for heating purposes. During the summer months (November to February), the electricity demand may rise due to the increased use of cooling systems. The region receives moderate rainfall, mainly during the summer, which impacts agricultural activities and affects electricity consumption patterns.

The socioeconomic factors in Case Study L's area significantly impact electricity consumption patterns. The community is socioeconomically diverse, comprising low to middle-income households, with varying levels of access to economic opportunities and public services. Educational institutions and healthcare facilities within the area rely on a stable electricity supply to operate efficiently.

Economic disparities within the community influence energy consumption, with more affluent households typically using more electrical appliances and therefore having higher electricity demand. In contrast, lower-income households might have lower overall electricity consumption but still exhibit significant usage during peak times, such as in the evenings when residential activities are at their highest.

In summary, the geographic and socioeconomic context of Case Study L provides a comprehensive understanding of the area's electricity consumption patterns. The combination of agricultural activities, tourism, temperate climate, and diverse socioeconomic factors offers valuable data for evaluating the accuracy of proposed ADMD values and their implications for local electricity infrastructure planning.

4.10.2 Connections

4.10.2.1 Proportion of Installed Load by Connection Type

Figure 129 is a percentage graphic representation of the installed load for Case Study L. The graph illustrates the presence and ratio of PPU vs SPU connection types.

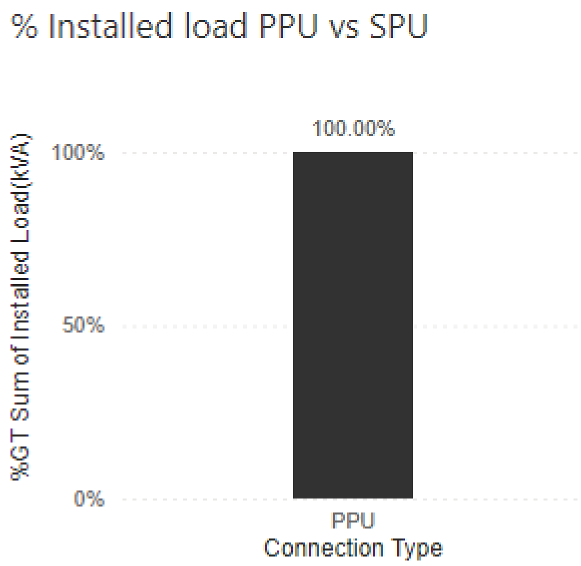


Figure 129: % Installed load by type PPU vs SPU for Case Study L

Figure 129 proves, like the majority of the preceding case studies, that the installed load exclusively consists of PPU connections. As was previously established, this is a typical phenomenon seen in Free State Province townships that government electrician programmes have electrified.

4.10.2.2 Distribution of PPU Connections by Circuit Breaker Size

Figure 130 illustrates a pie chart that represents the ratio of PPU connections, *see* Figure 129, that makes up the total connections of Case Study L.

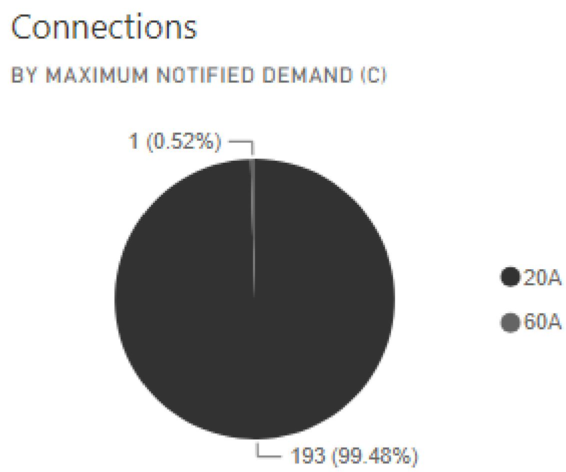


Figure 130: Total PPU connections by Circuit Breaker Size (c) for Case Study L

Like with Case Study K, Figure 130, shows that 99.48% of the connections are made up by 20A connections to a total of 193. On the other hand, 60A connections amount to less than 1% (0.52%) of the total connections in Case Study L. Case Study L therefore provides an almost ideal case study to investigate the accuracy of the proposed ADMD values as proposed in SANS 507-1:2019, as this case study could be treated as a homogeneous case.

4.10.2.3 Connection Trends

The connection trends for Case Study L are illustrated in Figure 131, providing a comprehensive overview of the historical load growth in terms of total connections.

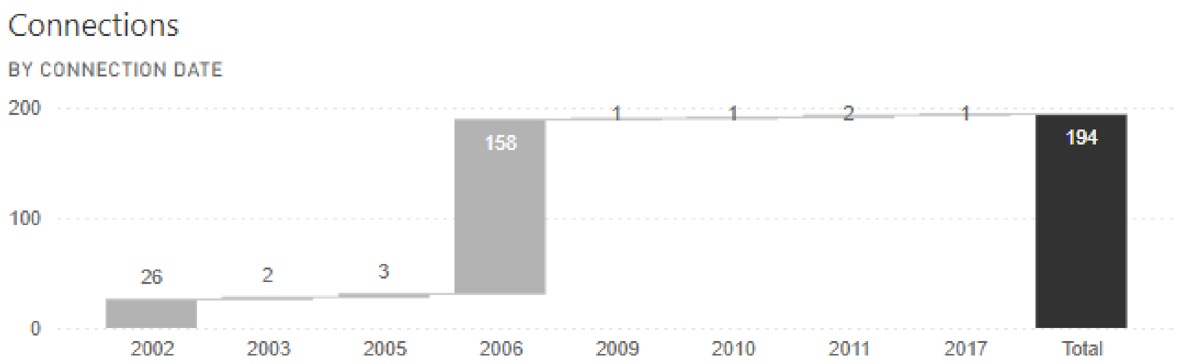


Figure 131: Total connections over time for Case Study L

As shown in Figure 131, the initial connections for Case Study L were recorded in 2002, with the latest connections occurring in 2017. The most significant increase in connections occurred in 2006, with 158 new connections added, marking the highest annual growth observed in this dataset. Before this peak, there was a notable increase in 2002 with 26 new connections, followed by smaller increments in 2004 (two connections) and 2005 (three connections).

Following the substantial growth in 2006, the number of new connections per year was minimal, with annual additions ranging from 1 to 2 connections between 2009 and 2017. This includes small peaks in 2009, 2011, and 2017, each with one to two new connections.

By the end of the period, the total number of connections reached 194. The data illustrate a pattern of initial rapid growth, mainly concentrated in 2006, followed by an extended period of significantly lower growth rates. This deceleration suggests a possible saturation in the geographic area, which is a crucial consideration for the design and planning of transformer zones.

The historical connection data for Case Study L highlights the evolving nature of network expansion and the impact of spatial constraints on growth. Effective infrastructure planning must consider these trends to maintain sustainability and efficiency in future expansions.

4.10.2.4 Connection Age Analysis by Breaker Size

The diverging bar chart in Figure 132 illustrates the average age of connections categorised by each circuit breaker size for Case Study L.

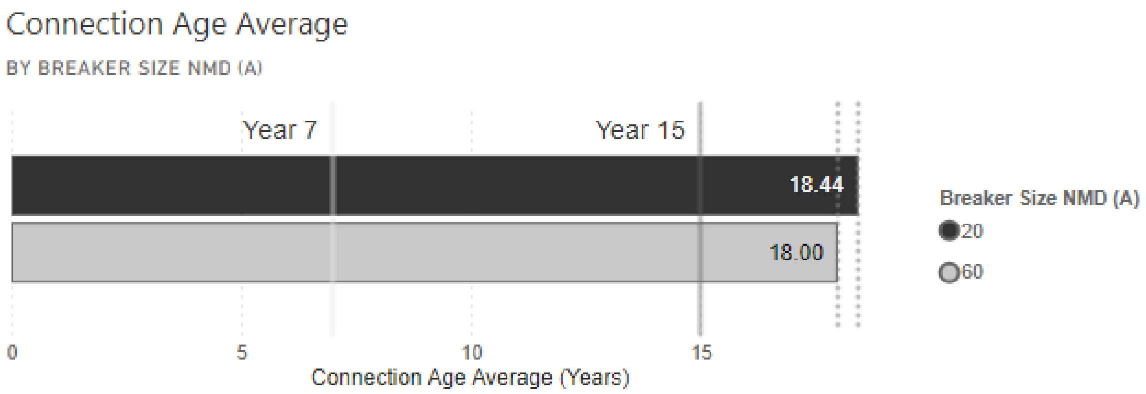


Figure 132: Connection Age Analysis for Case Study L

From Figure 132, it is observed that the average age of connections with 20A circuit breakers is 18.44 years, while the average age of connections with 60A circuit breakers is 18.00 years. The slight difference in average ages, with the 20A connections being older by approximately 0.44 years compared to the 60A connections, suggests that both types of connections were likely established around the same time.

Given that both categories of circuit breaker size have connection ages around or slightly higher than 15 years, it is appropriate to use the 15-year parameters according to SANS 507-1:2019 – Table 2. Additionally, it should be noted that the 'c' values for 20A, 15-year parameters are limited to Class ID 1 and 2, whereas the 60A Class IDs, according to the 15-year 'c' values, are from Class ID 3 and higher.

The following conclusions can be drawn from the above analysis. Firstly, the presence of both 20A and 60A connections suggests a heterogeneous consumer group. Secondly, the similarity in the average ages of the two categories indicates that there has not been significant load growth necessitating upgrades from 20A to 60A connections. If significant individual load growth were present, we would expect the average age of 60A connections to be noticeably lower due to older 20A connections being upgraded over time.

This pattern reflects a stable demand for electricity within the study area, with the existing infrastructure sufficiently meeting the needs of the consumers without necessitating widespread upgrades. The data thus highlights a consistent and stable electrical demand in the residential area covered by Case Study L. The slight difference in ages also suggests that while upgrades may have occurred, they have not been so frequent or recent as to alter the average age difference between the breaker sizes significantly.

4.10.3 Load Profiles

4.10.3.1 Historical Load Profile Analysis

The historical load profile for Case Study L, shown in Figure 133, provides a comprehensive view of instantaneous electrical load data from June 12, 2019, to December 31, 2023. This profile captures the variability and trends in electricity consumption over this period. Key metrics, such as the mean load, maximum demand, and the 99.5th percentile, are prominently indicated. The mean load, represented by the "Mean: 41.15" line, signifies the average load throughout the study period. The maximum demand, marked by the "Maximum: 123.00" line, denotes the highest recorded load, while the 99.5th percentile, indicated as "99.5th Percentile: 89.26," is considered the measured After Diversity Maximum Demand (ADMD) value. This ADMD value is crucial for assessing the infrastructure's capacity to accommodate typical peak loads.

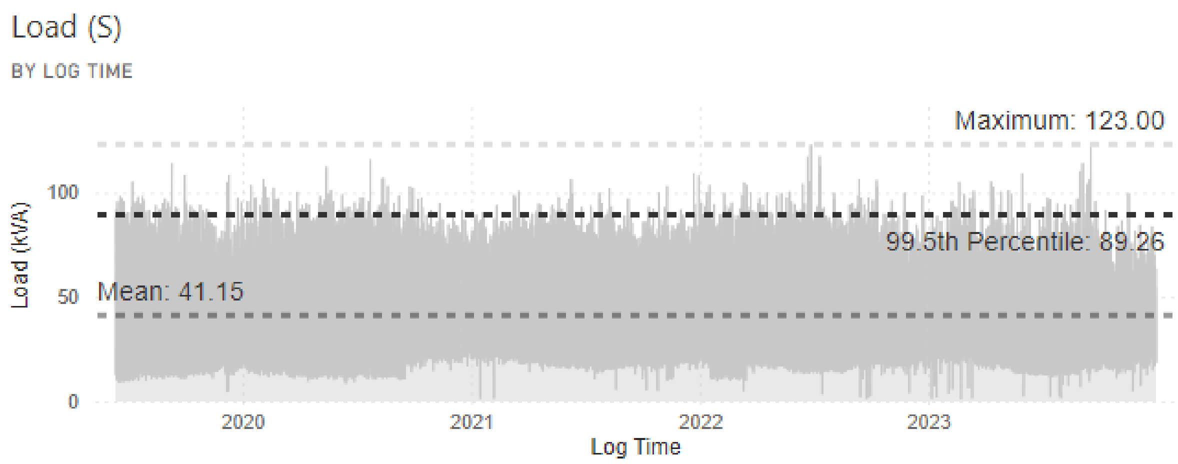


Figure 133: Historical load profile for Case Study L

As depicted in Figure 133, the historical load profile for Case Study L highlights several significant characteristics. The mean load, indicated by the "Mean: 41.15" line, suggests a moderate consumption level over the study period. The profile shows moderate variability, with distinct peaks and troughs reflecting changes in demand. The maximum demand, represented by the "Maximum: 123.00" line, points to periods of higher consumption, which specific high-demand events may influence. The 99.5th percentile, marked at "99.5th Percentile: 89.26," provides a reliable estimate of the ADMD, ensuring that the infrastructure can handle typical peak demands.

The normal distribution of the historical load profile data for Case Study L, as illustrated in Figure 134, presents the data in the form of a bell curve. This statistical representation helps to understand the central tendency, spread, and presence of outliers within the dataset.

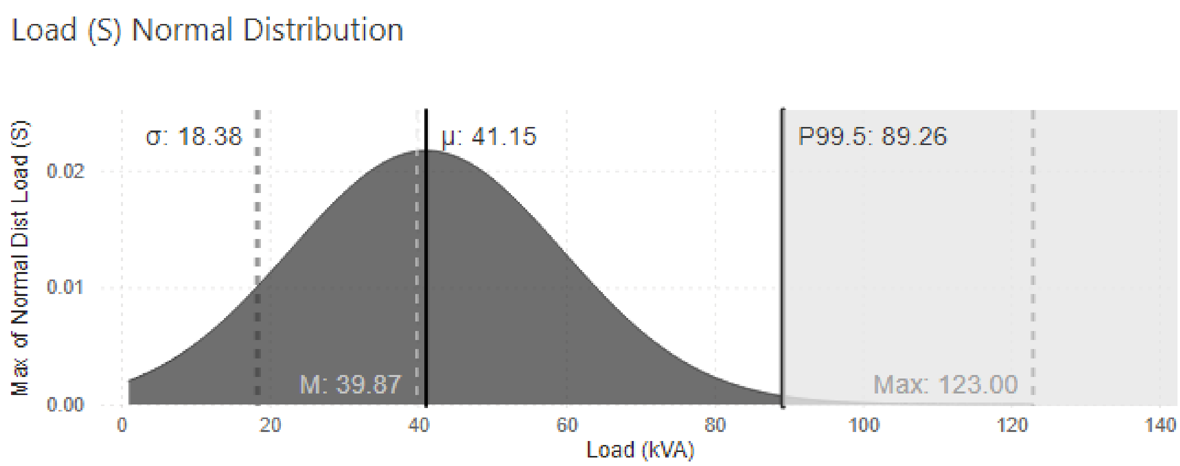


Figure 134: Normal distribution of Historical Load Profile data for Case Study L

Figure 134 displays the bell curve of the normal distribution for the load data, centred around the mean (μ) of 41.15 kVA, with a standard deviation (σ) of 18.38 kVA. The mode (M), shown near "M: 39.87," aligns closely with the mean, indicating a typical concentration of data points around these values. The 99.5th percentile, labelled "P99.5: 89.26," marks the threshold below which 99.5% of the data points lie, highlighting the typical upper range of load values. The maximum recorded load, "Max: 123.00," lies beyond the 99.5th percentile, indicating the presence of extreme values in the dataset. The shape of the bell curve, characteristic of a normal distribution, suggests a slight rightward skew, reflecting occasional higher-than-average loads. This skewness indicates that while most data points cluster around the mean, there are instances of significant peaks, which are essential for planning and managing the electrical infrastructure.

4.10.3.2 99.5th Percentile Load Analysis

This section evaluates the After Diversity Maximum Demand (ADMD) for Case Study L by analysing the 99.5th percentile load across various aggregations. The analysis is based on data presented in Figure 135, Figure 136, and Figure 137, spanning from June 2019 to December 2023. These figures provide detailed insights into the variations in electricity demand and peak loads over time.

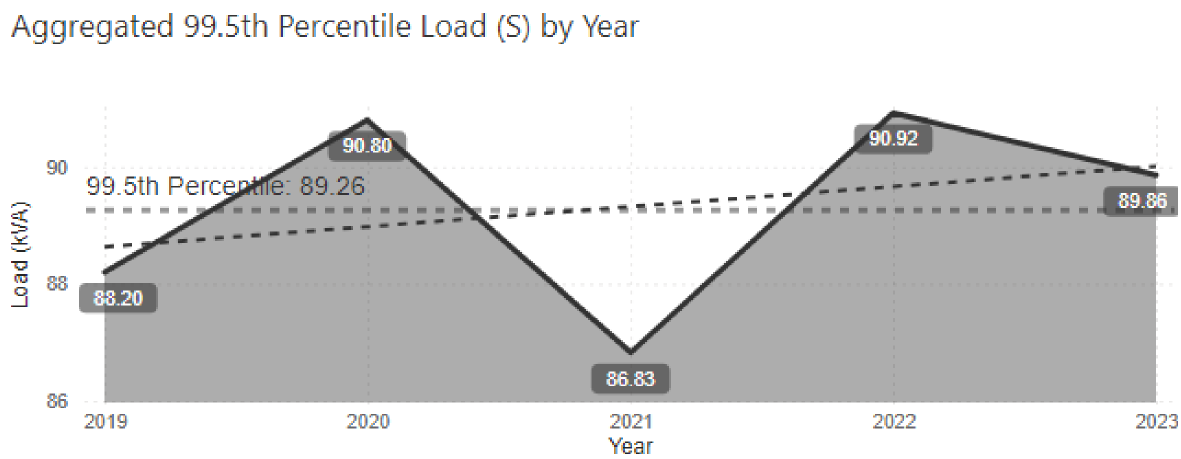


Figure 135: 99.5th Percentile load by year for Case Study L

Figure 135 illustrates the 99.5th percentile load by year for Case Study L. The graph displays annual peak loads, with the 99.5th percentile line established at 89.26 kVA, representing the observed ADMD. The maximum load recorded was 90.92 kVA in 2022, while the minimum was 86.83 kVA in 2021. The trendline indicates a slight increase in demand, peaking in 2020, followed by a decline in 2021, and a subsequent rise in 2022 and 2023, reaching 89.86 kVA. Notably, the years 2019, 2020, and 2022 had loads exceeding the 99.5th percentile line, while 2021 and 2023 were closer to this threshold, reflecting a stable demand pattern.

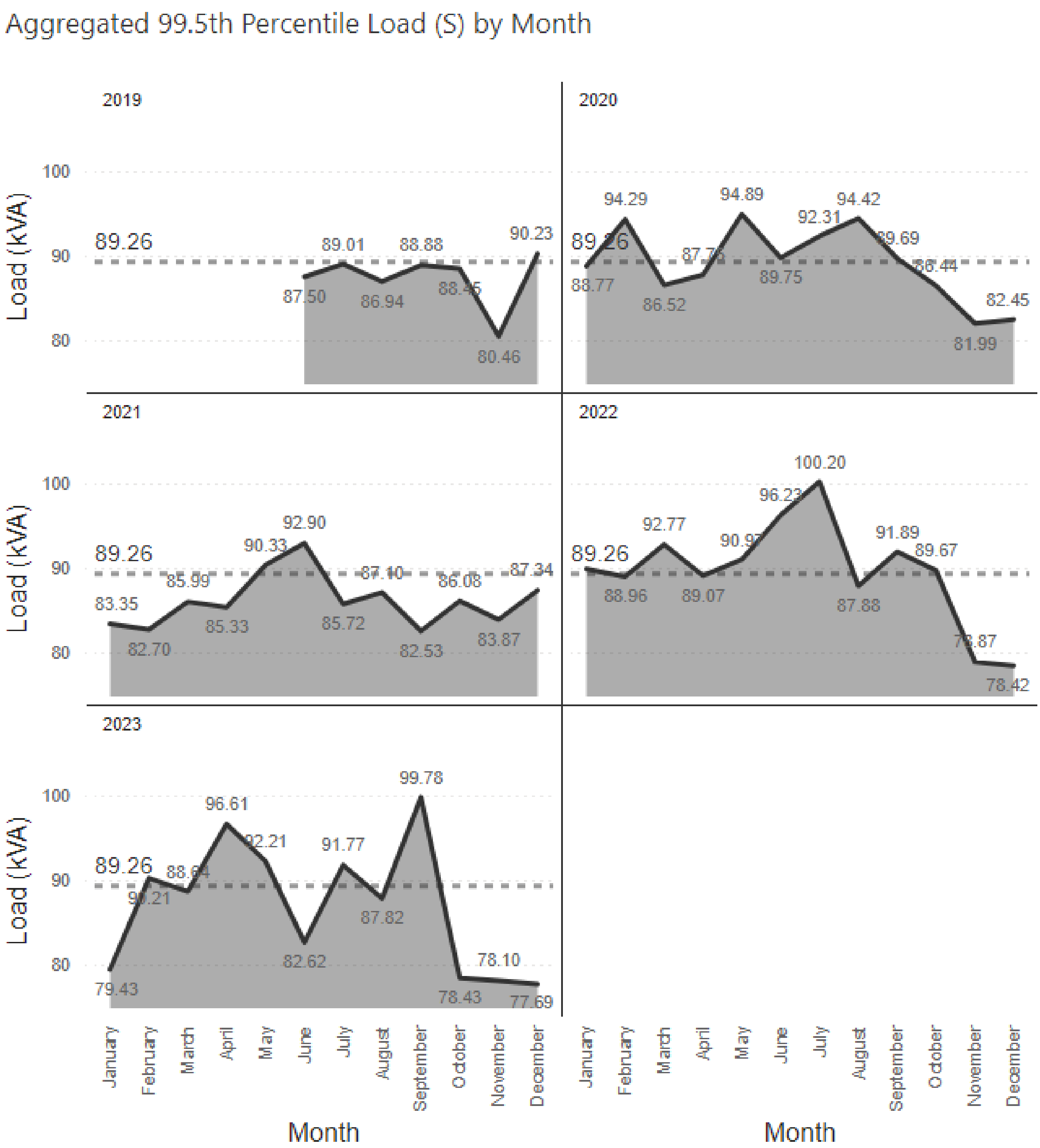


Figure 136: 99.5th Percentile load by each year for Case Study L

Figure 136 provides a detailed breakdown of the 99.5th percentile load by each year, focusing on monthly variations. In 2019, the peak occurred in April at 90.23 kVA, while in 2020, the highest load was observed in July at 94.89 kVA. For 2021, the peak was in June at 92.90 kVA, and in 2022, the highest load was recorded in July at 100.20 kVA. The year 2023 had a peak load in September at 99.78 kVA. This data indicates that monthly peaks generally occur mid-year, with a trend of slightly increasing peak values over the years.

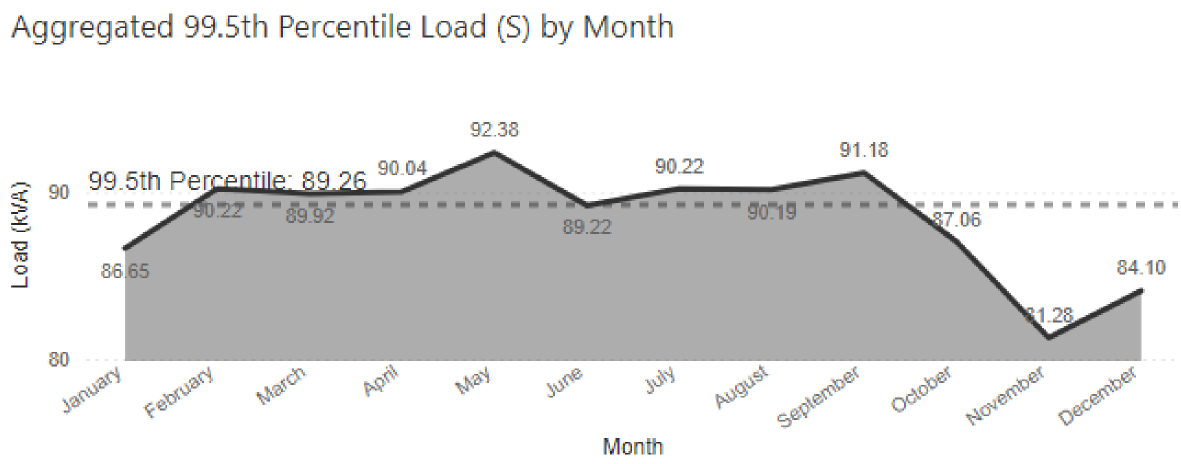


Figure 137: Aggregated 99.5th Percentile load by Month for Case Study L

Figure 137 aggregates the 99.5th percentile load by month across all years, providing a comprehensive view of seasonal demand patterns. The data shows that loads generally peak around May, with the highest recorded in 2022 at 92.38 kVA, and then decline towards December, with the lowest load in December at 84.10 kVA. This trend suggests a pattern of higher electricity consumption during mid-year months.

The 99.5th percentile load analysis for Case Study L provides significant insights into the ADMD patterns, with the 99.5th percentile line serving as the observed ADMD. The data indicates a stable yet slightly increasing trend in peak demand, particularly evident in mid-year months. The analysis shows that peak loads have been relatively consistent, with a slight upward trend in 2022. These observations underscore the importance of monitoring and planning for potential increases in demand, ensuring a reliable electricity supply and efficient infrastructure management. Understanding these variations is crucial for optimising resource allocation and meeting peak electricity needs effectively.

4.10.3.3 99.5th Percentile Load Analysis: Daily Demand Profiles

The 99.5th percentile load analysis for Case Study L provides a comprehensive study of the peak electricity demand periods, representing the highest usage levels that occur only 0.5% of the time. This analysis is vital for understanding extreme consumption scenarios, which are critical for infrastructure planning and energy management. By analysing these profiles, we can identify both seasonal and daily variations in electricity consumption, offering valuable insights into how demand fluctuates throughout the year and within a typical day.

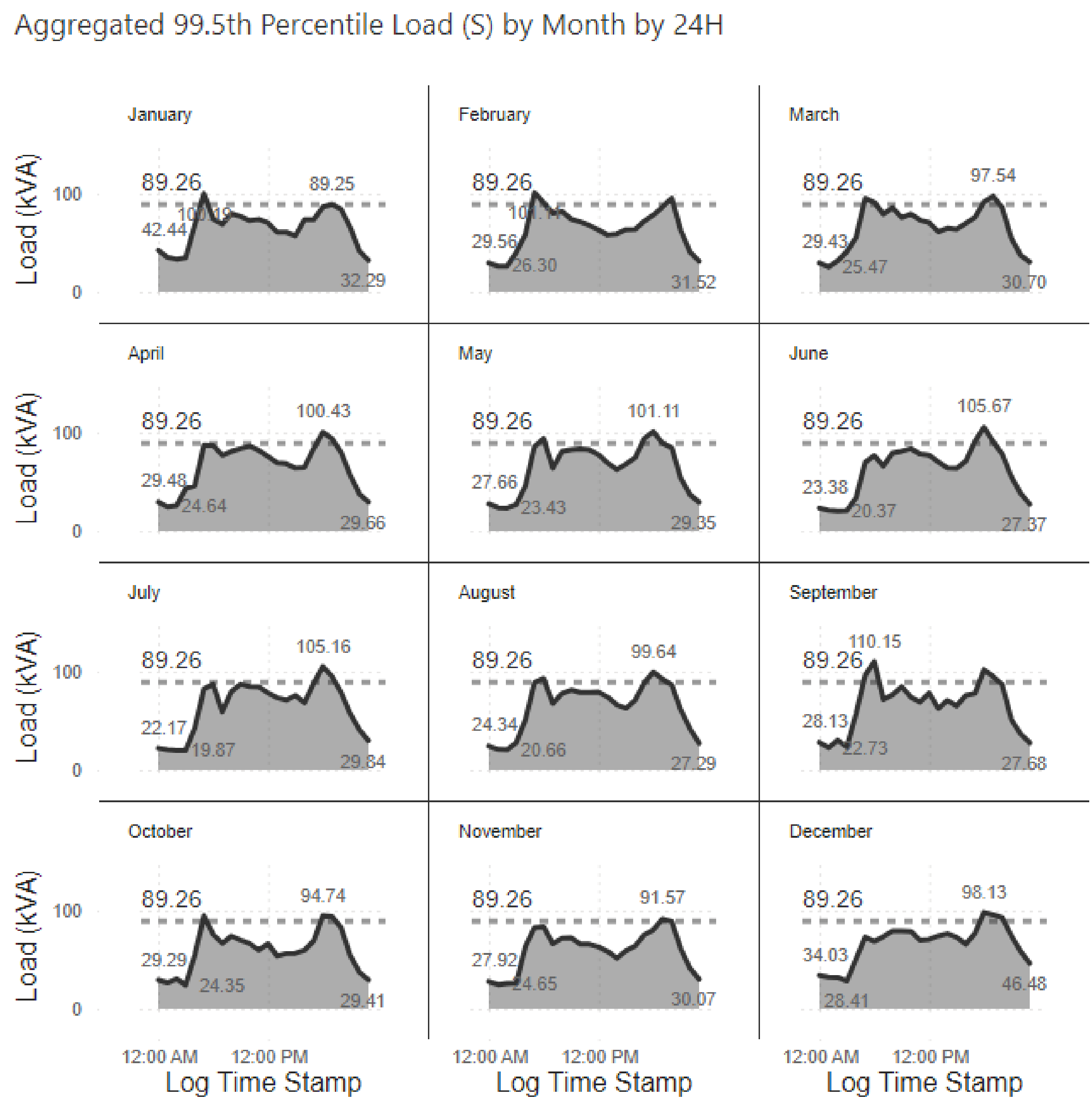


Figure 138: Aggregated 99.5th Percentile load by 24-h day by Month for Case Study L

Figure 138 illustrates the monthly variations in the 99.5th percentile load, highlighting the changes in daily demand peaks throughout the year. The dashed line at 89.26 kVA marks the 99.5th percentile load threshold. Key observations include:

Winter Months (June - August): These months exhibit higher daily peaks, often exceeding the 99.5th percentile line. For instance, June reaches a peak of 105.67 kVA, while July and August have peaks of 105.16 kVA and 99.64 kVA, respectively. These peaks suggest increased energy consumption, likely due to heating requirements.

Summer Months (December - February): The demand during these months generally remains below the 99.5th percentile threshold, with the highest peak in January at 89.25 kVA and February at 106.06 kVA, indicating relatively lower energy usage.

Transitional Months (March, September): These months show peaks near or above the 99.5th percentile line, with March reaching 97.54 kVA and September showing a peak of 110.15 kVA, reflecting variability in energy use during changing weather conditions.

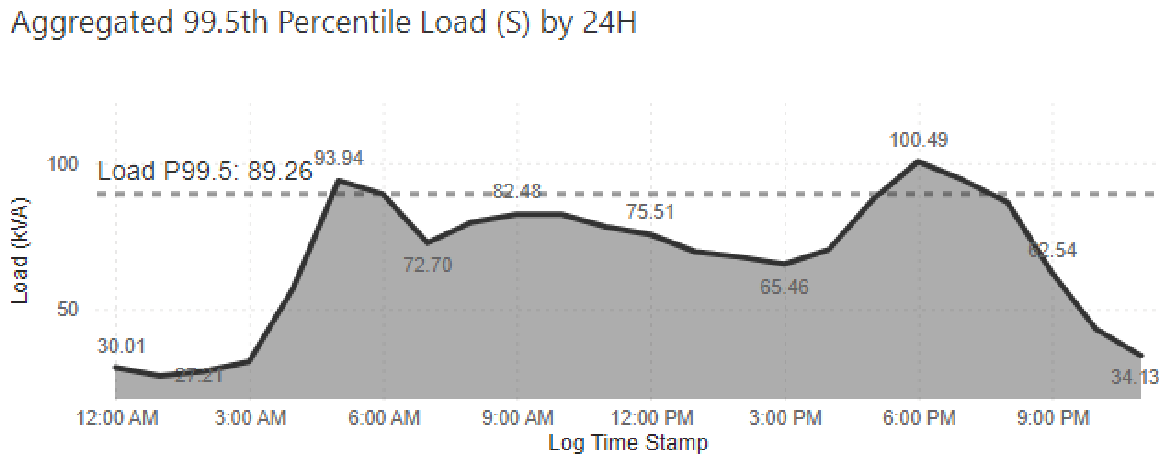


Figure 139: Aggregated 99.5th Percentile load by 24-h day for Case Study L

Figure 139 consolidates the daily demand data into a single 24-hour profile, providing an overview of the typical daily load pattern. The 99.5th percentile load line at 89.26 kVA highlights the critical demand periods:

Morning Peak: A significant increase in load begins around 3:00 AM, with a peak of 93.94 kVA at 6:00 AM. This rise correlates with early morning activities as residents start their day.

Evening Peak: The highest demand occurs around 6:00 PM, reaching a peak load of 100.49 kVA, reflecting typical residential activities such as cooking and heating.

Off-Peak Periods: The lowest demand occurs late at night and early morning, with the load dropping to around 30.01 kVA, well below the 99.5th percentile threshold.

The 99.5th Percentile Load Analysis for Case Study L reveals notable seasonal and daily variations in electricity demand. The data indicate that peak demands are more pronounced during the winter months, with frequent exceedances of the 99.5th percentile threshold due to increased heating needs. The analysis also emphasises the importance of morning and evening peaks in shaping residential electricity consumption patterns. Understanding these variations is crucial for effective energy infrastructure planning and management, ensuring reliable service during periods of maximum demand.

4.10.4 Proposed ADMD vs Observed ADMD

This section aims to compare the proposed After Diversity Maximum Demand (ADMD) values suggested by SANS 507-1:2019 Year-15 parameters with the observed ADMD values for Case Study L. This comparison is crucial for assessing the accuracy and reliability of the proposed standards in predicting real-world electricity demand. By analysing the discrepancies between these values, we can determine the applicability of the SANS guidelines and identify any necessary adjustments for improved planning and infrastructure design.

Summary of Key Metrics

- Total Connections: 194
- Average Age: 18.44 years (greater than 15 years; therefore, Year-15 parameters are used)
- Installed Load: 901.60 kVA (4.65 kVA per connection)

- P99.5 Load: 89.26 kVA (0.46 kVA per stand)
- Resultant P99.5 Diversity Factor (DF): 0.10

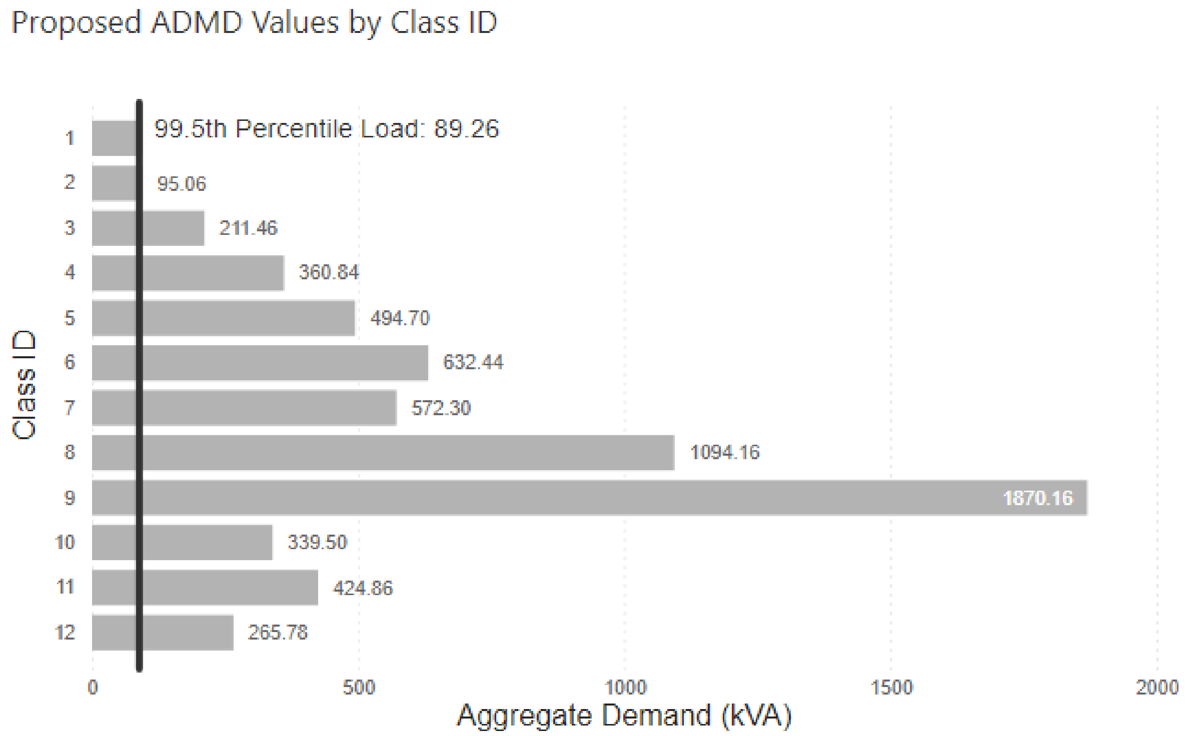


Figure 140: Proposed Year-15 ADMDs result by Class ID for Case Study L

Figure 140 illustrates the proposed ADMD values for different consumer classes as per SANS 507-1:2019 Year-15 parameters, compared against the measured 99.5th percentile load (89.26 kVA). The proposed ADMD values show significant variation across different classes, with Class ID 9 and 8 exhibiting the highest proposed values at 1,870.16 kVA and 1,094.16 kVA, respectively. The vertical line at 89.26 kVA indicates the 99.5th percentile load, serving as a benchmark for comparison.

The data from Figure 140 reveals that the proposed ADMD values for most consumer classes significantly exceed the measured 99.5th percentile load. Notably, Class ID 9 (Urban Estate) has a proposed ADMD value that is over twenty times the measured load, indicating a possible overestimation. On the other hand, lower class IDs such as 1 and 2 show a proposed ADMD that is closer to the measured load, although still higher. This suggests that the SANS guidelines may need revision to reflect better actual consumption patterns, particularly for higher consumer classes.

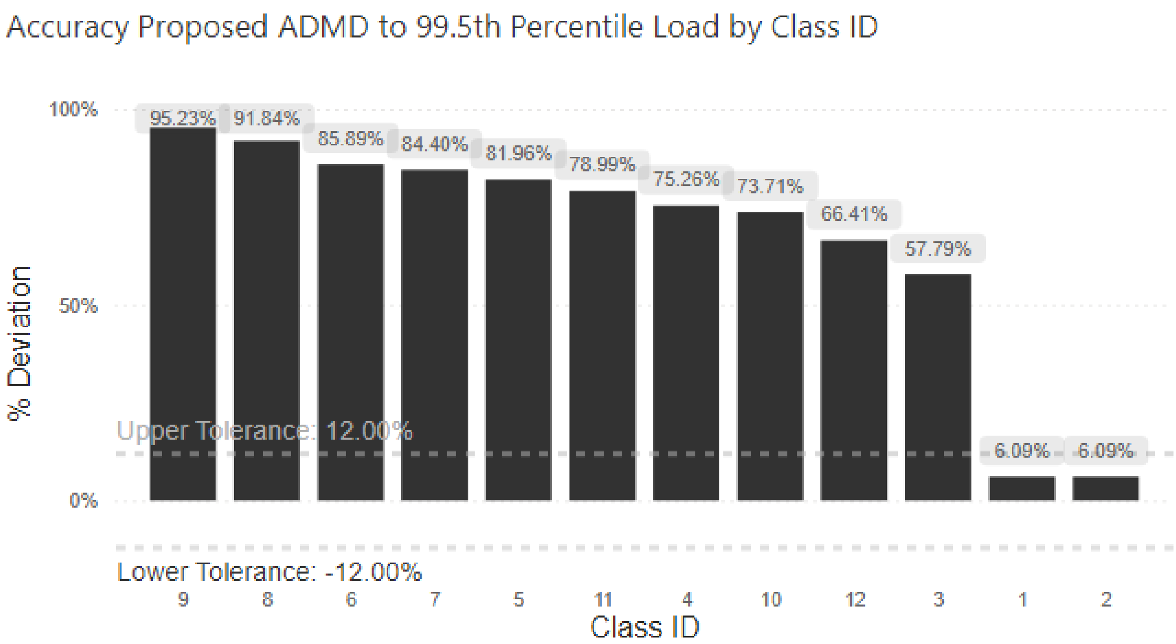


Figure 141: Deviation of SANS 507-1:2019 Year-15 ADMD by Class ID vs. 99.5th Percentile Load for Case Study L

Figure 141 presents the percentage deviation of the proposed ADMD values from the measured 99.5th percentile load for each class ID. The deviation is significant across most classes, with Class ID 9 showing the highest positive deviation at 95.23%. In contrast, Class IDs 1 and 2 show minimal deviation, indicating that the proposed values are relatively close to the measured loads for these classes.

The deviations highlighted in Figure 141 indicate a substantial overestimation of the ADMD values for most consumer classes according to the SANS 507-1:2019 Year-15 parameters. The high positive deviations, particularly for Class ID 9, suggest that the current proposed values do not accurately capture the actual demand patterns. The minimal deviations for Class IDs 1 and 2 indicate that the proposed values for these classes are relatively accurate, but still exhibit slight overestimation. This discrepancy underscores the need for a more nuanced approach in setting ADMD standards that consider the specific characteristics and consumption behaviours of different consumer classes.

Table 11: Detailed Comparison of Proposed ADMD vs Observed ADMD for Case Study L

ID	Consumer Class	SANS 15 Year ADMD (kVA)	Case SANS 15 Year ADMD (kVA)	Accuracy	Deviation
1	Rural settlement, Non-urban, scattered	0.49	95.06	93.91%	6.09%
2	Rural villages	0.49	95.06	93.91%	6.09%
3	Informal settlement	1.09	211.46	42.21%	57.79%
4	Township area	1.86	360.84	24.74%	75.26%
5	Urban residential I	2.55	494.70	18.04%	81.96%
6	Urban residential II	3.26	632.44	14.15%	85.89%
7	Urban townhouse complex or duplex	2.95	572.30	15.60%	84.40%
8	Urban Townhouse II	5.64	1,094.16	8.16%	91.84%
9	Urban Estate	9.64	1,870.16	4.77%	95.23%
10	High rise (small)	1.75	339.50	26.29%	73.71%

11	High rise (medium)	2.19	424.86	21.01%	78.99%
12	Hostel	1.37	265.78	33.59%	66.41%

Table 11 provides a detailed comparison of the proposed and observed ADMD values for each consumer class. The accuracy and deviation columns highlight the discrepancies between the proposed values and the actual measured loads. Notably, Classes 1 and 2 show minimal deviation, suggesting that the proposed ADMD values closely align with the actual load for rural settlements and villages. Conversely, Classes 8 and 9 show the highest positive deviations, indicating an overestimation for urban estates and high-end residential areas. These observations reinforce the need for revising the proposed ADMD values to better align with real-world consumption patterns.

The comparison between the proposed ADMD values and the observed ADMD values for Case Study L reveals significant discrepancies, particularly for higher consumer classes. The proposed values tend to overestimate the actual demand for urban estates and high-end residential areas, while closely matching the load for rural settlements and villages. These findings suggest that the current SANS 507-1:2019 Year-15 parameters may not accurately reflect the diverse consumption patterns observed in different consumer classes. Therefore, it is crucial to re-evaluate these standards and consider more tailored approaches to ensure reliable and efficient electricity infrastructure planning.

Interpretive Note: Case Study L

- Installed base is PPU-dominant. Within PPU, breaker sizes are 20A = 83.62% and 60A = 16.38%.
- Average connection age is 30.40 years. By breaker size: 31.21 years (20A) and 29.29 years (60A), so Year-15 parameters were appropriate.
- Observed ADMD (P99.5) is 216.23 kVA total (1.07 kVA/stand).
- Best fit (exact class ID): Class 3 (Informal settlement) with 1.09 kVA/stand → ≈220.18 kVA case total, +1.83% vs observed. Classes 1–2 are well below the empirical level (≈0.49–0.62 kVA/stand), while higher classes propose larger per-stand values and overshoot by wider margins.

The strong 20A dominance and mature stock align with a lower-to-mid demand profile near one kVA/stand; among the SANS options, Class 3 yields the least absolute deviation from the measured 99.5th-percentile ADMD and corresponds best to the observed connection composition.

4.11 Case Study M

Case Study M explores load profiles and ADMD values in the neighbourhoods of Ratau and parts of Moroka Extension in Thaba Nchu, examining factors affecting electricity demand.

4.11.1 Geographic Overview

Case Study M is geographically located at GPS coordinates 26.820549, -29.23259, as illustrated in Figure 142. This area includes the neighbourhood of Ratau and parts of Moroka Extension.

GPS Location 26.820549;-29.23259

Figure 142: Geographic location for Case Study M

The transformer zone for Case Study M is situated within the local municipal boundaries of Thaba Nchu, which falls under the Mangaung Metropolitan Municipality in the Free State Province of South Africa. The local municipal authorities are responsible for providing public services, maintaining infrastructure, and promoting community development within this area.

The economy in and around Case Study M is diverse, with key activities including agriculture, retail, and services. Thaba Nchu is known for its agricultural activities, with significant production of crops such as maize, sorghum, and sunflowers. Livestock farming is also prominent in the region. Additionally, small-scale retail businesses and service industries cater to the needs of the local population, influencing the electricity demand.

The climate in this region is generally temperate, characterised by cold winters and warm summers. Winter months (June to August) often experience low temperatures, leading to higher electricity consumption for heating purposes. During the summer months (November to February), the electricity demand may rise due to the increased use of cooling systems. The region receives moderate rainfall, mainly during the summer, which impacts agricultural activities and affects electricity consumption patterns.

The socioeconomic factors in Case Study M's area significantly impact electricity consumption patterns. The community is socioeconomically diverse, comprising low to middle-income households, with varying levels of access to economic opportunities and public services. Educational institutions and healthcare facilities within the area rely on a stable electricity supply to operate efficiently.

Economic disparities within the community influence energy consumption, with more affluent households typically using more electrical appliances and therefore having higher electricity demand. In contrast, lower-income households might have lower overall electricity consumption but still exhibit significant usage during peak times, such as in the evenings when residential activities are at their highest.

In summary, the geographic and socioeconomic context of Case Study M provides a comprehensive understanding of the area's electricity consumption patterns. The combination of agricultural activities, temperate climate, and diverse socioeconomic factors offers valuable data for evaluating the accuracy of proposed ADMD values and their implications for local electricity infrastructure planning.

4.11.2 Connections

4.11.2.1 Proportion of Installed Load by Connection Type

Figure 143 shows the graphical percentage ratio of the installed load by comparing PPU to SPU connection types.

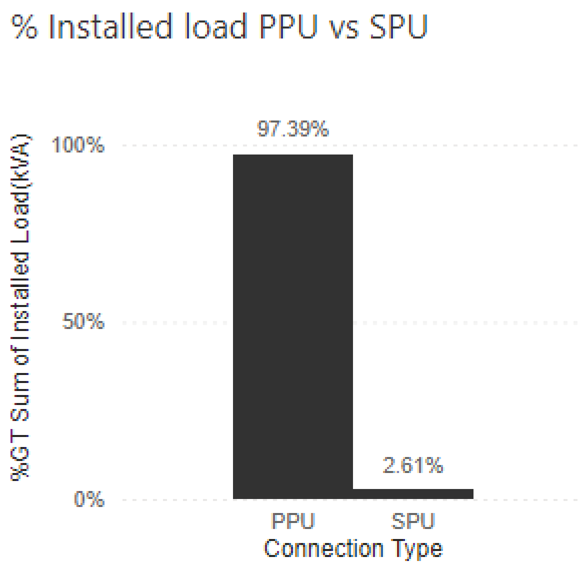


Figure 143: % Installed load by type PPU vs SPU for Case Study M

As seen with earlier representations of similar graphs (Figure 143), the presence of SPU installed load is evident, making up 2.61% of the total installed load. The remaining portion of the installed load is seen to be 97.39%. Given the low proportional representation of SPU load, it is rational to consider SPU load as a negligible factor in achieving the research aim.

4.11.2.2 Distribution of PPU Connections by Circuit Breaker Size

The pie chart in Figure 144 shows the makeup of connections by different circuit breaker sizes, as referred to in SANS 507-1:2019, Table 2, as the "c" value. Primarily, the "c" values represent either a 20A or a 60A circuit breaker size.

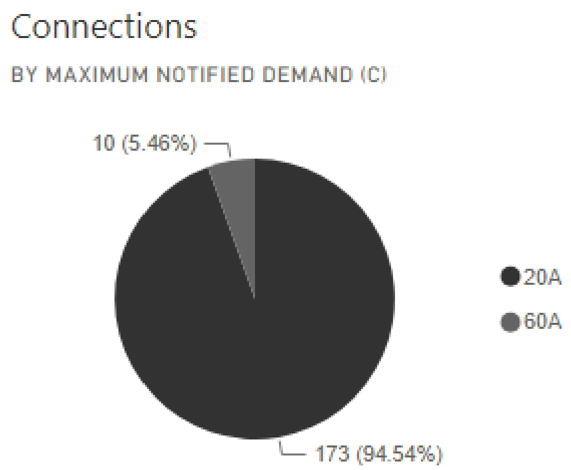


Figure 144: Total PPU connections by Circuit Breaker Size (c) for Case Study M

Illustrated in Figure 144 The majority of connections are 20A, totalling 173 (94.54%). A significantly smaller number of 60A connections are present in this case, totalling no more than ten connections, which amounts to 5.46% of the total number of connections. With 20A being the predominant circuit breaker size, it follows the typical phenomenon of townships in the Free State Province, which have seen electrification projects benefit from access to the grid. It should also be noted that with the majority of connections still being on 20A, real growth potential is still present.

4.11.2.3 Connection Trends

The connection trends for Case Study M are illustrated in Figure 145, providing a comprehensive overview of the historical load growth in terms of total connections.

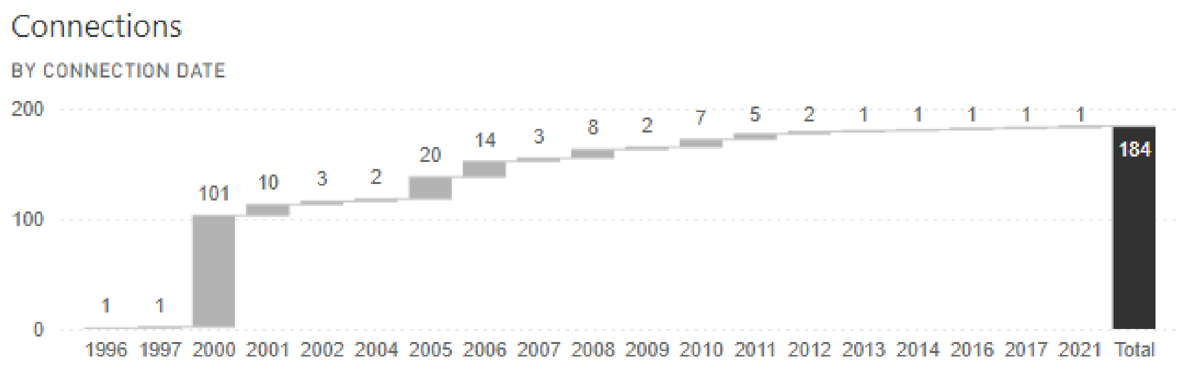


Figure 145: Total connections over time for Case Study M

As shown in Figure 145, the initial connections for Case Study M were recorded in 1996, with the latest connections occurring in 2021. The most significant increase in connections occurred in 2000, with 101 new connections added, marking the highest annual growth observed in this dataset. Before this peak, there was a smaller increment in 1997 with one connection.

Following the substantial growth in 2000, the number of new connections per year varied, with notable increases in 2005 (20 connections) and smaller increments spread over the following years. Between 2001 and 2021, annual additions ranged from 1 to 14 connections. Significant growth years included 2001 (10 connections), 2005 (20 connections), 2006 (14 connections), and 2007 (8 connections).

By the end of the period, the total number of connections reached 184. The data illustrate a pattern of initial rapid growth, primarily concentrated in 2000, followed by fluctuating growth rates in the subsequent years. This fluctuation suggests varying rates of network expansion and potential periods of geo-spatial saturation, a critical consideration for the design and planning of transformer zones.

The historical connection data for Case Study M highlights the evolving nature of network expansion and the impact of spatial constraints on growth. Effective infrastructure planning must consider these trends to maintain sustainability and efficiency in future expansions.

4.11.2.4 Connection Age Analysis by Breaker Size

The diverging bar chart in Figure 146 illustrates the average age of connections categorised by each circuit breaker size for Case Study M.

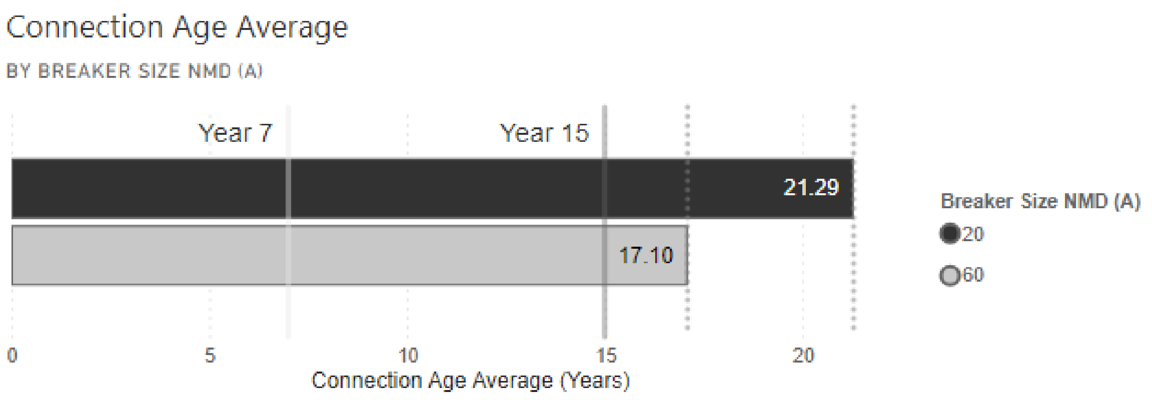


Figure 146: Connection Age Analysis for Case Study M

From Figure 146, it is observed that the average age of connections with 20A circuit breakers is 21.29 years, while the average age of connections with 60A circuit breakers is 17.10 years. The difference in average ages, with the 20A connections being older by approximately 4.19 years compared to the 60A connections, suggests a significant variance in the installation or upgrade times for these breaker sizes.

Given that both categories of circuit breaker size have connection ages significantly higher than 15 years, it is appropriate to use the 15-year parameters according to SANS 507-1:2019 – Table 2. Additionally, it should be noted that the "c" values for 20A, 15-year parameters are limited to Class ID 1 and 2, whereas the 60A Class IDs, according to the 15-year "c" values, are from Class ID 3 and higher.

The following conclusions can be drawn from the above analysis. Firstly, the presence of both 20A and 60A connections suggests a heterogeneous consumer group. Secondly, the significant difference in the average ages of the two categories indicates a pattern of load growth and upgrading. The younger average age for 60A connections could imply that these connections have been installed more recently, possibly as upgrades from 20A connections to accommodate increased demand.

This pattern aligns with typical practices where electrical infrastructure is upgraded to meet higher demand, resulting in newer, larger capacity connections replacing older, smaller ones. The data thus reflects the evolving nature of electrical connections in residential areas, highlighting how infrastructure adapts to changing demands over time. The older average age of the 20A connections suggests that these have been in place longer, potentially awaiting upgrades as demand increases. The substantial difference in ages indicates that upgrades from 20A to 60A connections have been more frequent or recent, leading to a younger average age for the higher capacity connections.

4.11.3 Load Profiles

4.11.3.1 Historical Load Profile Analysis

The historical load profile for Case Study M, shown in Figure 147, provides an overview of instantaneous electrical load data from March 3, 2021, to December 31, 2023. This profile illustrates the variability in electricity consumption over time, capturing significant data points such as the mean load, maximum demand, and the 99.5th percentile. The mean load, represented by the "Mean: 51.82" line, indicates the average consumption throughout the study period. The maximum demand, marked as "Maximum: 146.03," represents the highest observed load. The 99.5th percentile, indicated by the "99.5th Percentile: 109.16" line, serves as the measured After Diversity Maximum Demand (ADMD) value, which is crucial for infrastructure capacity planning and reliability assessments.

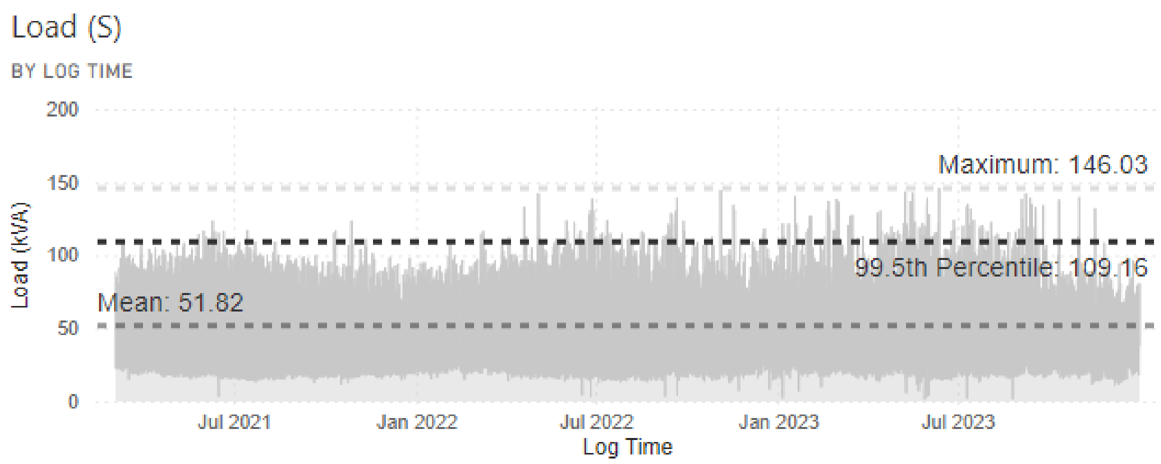


Figure 147: Historical load profile for Case Study M

Figure 147 highlights several essential characteristics of the load profile for Case Study M. The mean load, shown by the "Mean: 51.82" line, suggests a stable average consumption level. The profile exhibits variations with noticeable peaks and troughs, reflecting fluctuations in demand over time. The maximum demand, represented by the "Maximum: 146.03" line, points to specific periods of high usage, possibly related to seasonal factors or special events. The 99.5th percentile, marked at "99.5th Percentile: 109.16," provides a conservative estimate of the ADMD, ensuring the infrastructure can handle typical peak loads without exceeding capacity.

The normal distribution of the historical load profile data for Case Study M, as depicted in Figure 148, presents the data as a bell curve. This statistical representation provides insights into the central tendency, variability, and presence of outliers in the dataset.

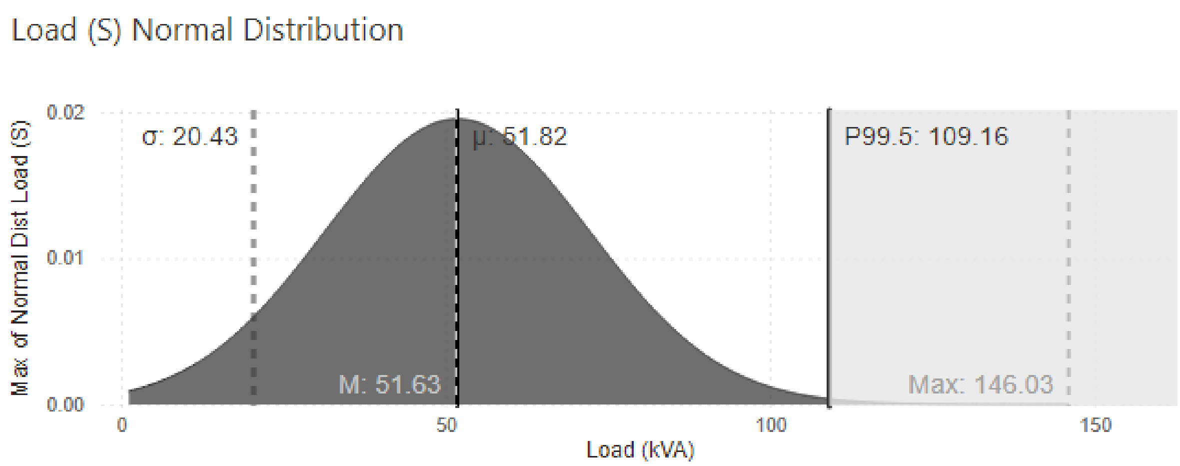


Figure 148: Normal distribution of Historical Load Profile data for Case Study M

Figure 148 illustrates the bell curve of the normal distribution for the load data, centred around the mean (μ) of 51.82 kVA and a standard deviation (σ) of 20.43 kVA. The mode (M), indicated near "M: 51.63," aligns closely with the mean, suggesting a typical clustering of data points around these values. The 99.5th percentile, labelled "P99.5: 109.16," marks the threshold below which 99.5% of the data points lie, representing the upper limit of typical consumption. The maximum recorded load, "Max: 146.03," lies beyond the 99.5th percentile, indicating the presence of extreme values. The bell curve shape, characteristic of a normal distribution, shows a slight rightward skew, reflecting occasional instances of higher-than-average loads. This skewness suggests that while most consumption falls within a predictable range, there are instances of significant peaks, which are critical for ensuring the system's capacity to manage high-demand periods.

4.11.3.2 99.5th Percentile Load Analysis

To gain a comprehensive understanding of the After Diversity Maximum Demand (ADMD) for Case Study M, this section evaluates the 99.5th percentile load across various aggregations. The analysis considers data from Figure 149, Figure 150, and Figure 151, covering the period from March 2021 to December 2023. These figures provide insights into the variations in electricity demand and peak loads.

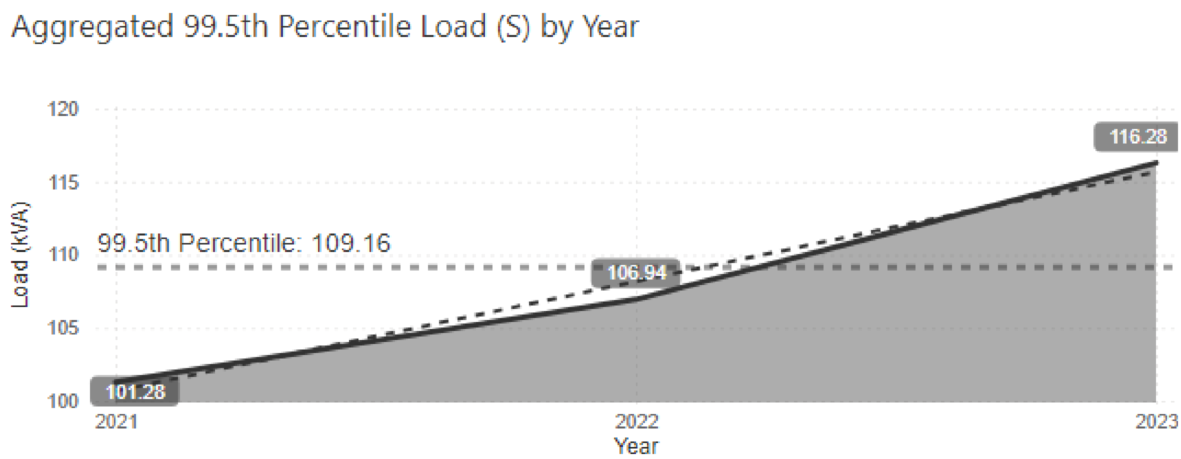


Figure 149: 99.5th Percentile load by year for Case Study M

Figure 149 illustrates the 99.5th percentile load by year for Case Study M. The graph displays annual peak loads, with the 99.5th percentile line set at 109.16 kVA, representing the measured ADMD. The maximum load recorded was 116.28 kVA in 2023, while the minimum was 101.28 kVA in 2021. The trendline indicates a consistent increase in demand over the years, showing a steady upward trajectory. Notably, all years, except 2021, had loads exceeding the 99.5th percentile line, indicating an upward trend in peak demand.

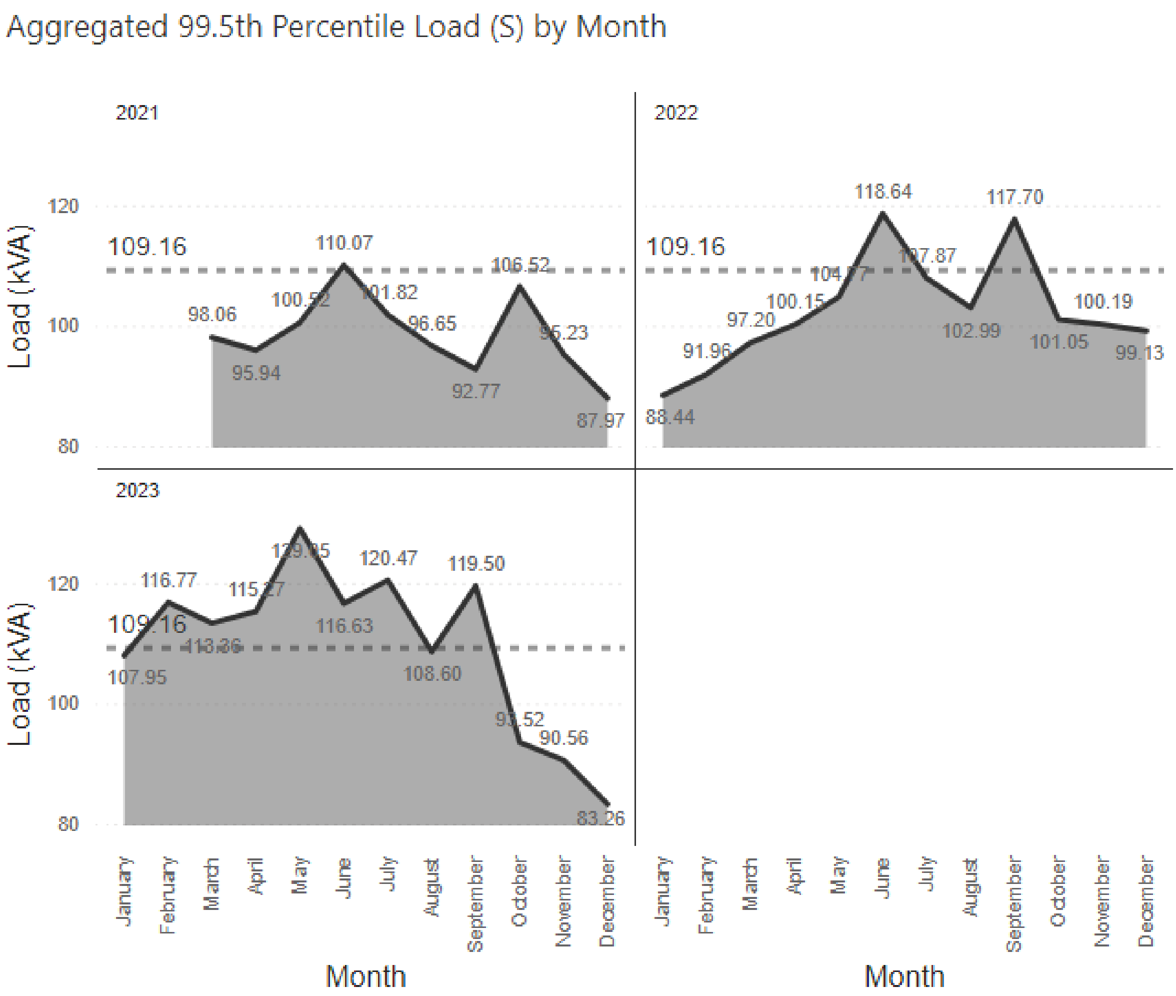


Figure 150: 99.5th Percentile load by each year for Case Study M

Figure 150 provides a detailed breakdown of the 99.5th percentile load by each year, focusing on monthly variations. In 2021, the peak occurred in June at 110.07 kVA, while in 2022, the highest load was observed in July at 118.64 kVA. For 2023, the peak load occurred in July at 120.47 kVA. The analysis highlights an upward trend in monthly peak values, with significant increases observed from 2021 to 2023. The data also shows a consistent pattern of higher loads in mid-year months, especially in June and July.

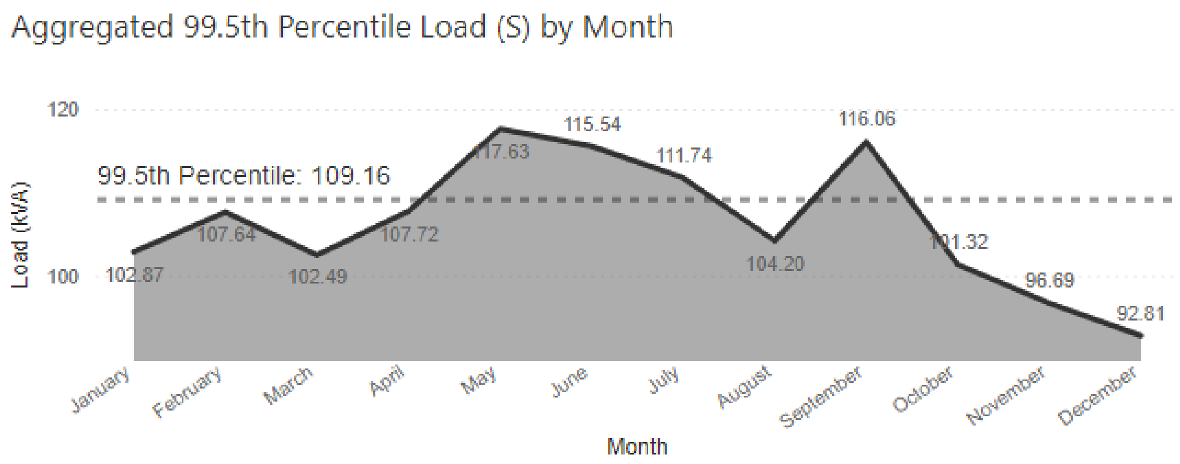


Figure 151: Aggregated 99.5th Percentile load by Month for Case Study M

Figure 151 aggregates the 99.5th percentile load by month across all years, providing a comprehensive view of seasonal demand patterns. The data indicates that loads generally rise from February, peaking in July at 115.54 kVA, and then decline towards December, with the lowest recorded in December at 92.81 kVA. This seasonal trend suggests higher electricity consumption during the middle of the year.

The 99.5th percentile load analysis for Case Study M reveals significant insights into ADMD patterns, with the 99.5th percentile serving as the observed ADMD. The data shows a clear upward trend in peak demand, particularly noticeable in mid-year months, with significant peaks occurring in June and July. The consistent increase in demand highlights the importance of planning for higher peak loads and ensuring the capacity to meet these demands. This analysis emphasises the need for efficient resource allocation and infrastructure planning to accommodate the growing demand and maintain a reliable electricity supply.

4.11.3.3 99.5th Percentile Load Analysis: Daily Demand Profiles

The 99.5th percentile load analysis for Case Study M provides a detailed examination of peak electricity demand periods, focusing on the highest consumption levels that occur only 0.5% of the time. This metric is essential for identifying peak usage scenarios, which are crucial for infrastructure planning and energy management. By analysing these profiles, we can gain insights into the seasonal and daily variations in electricity consumption, offering a comprehensive understanding of how demand fluctuates throughout the year and within a typical day.

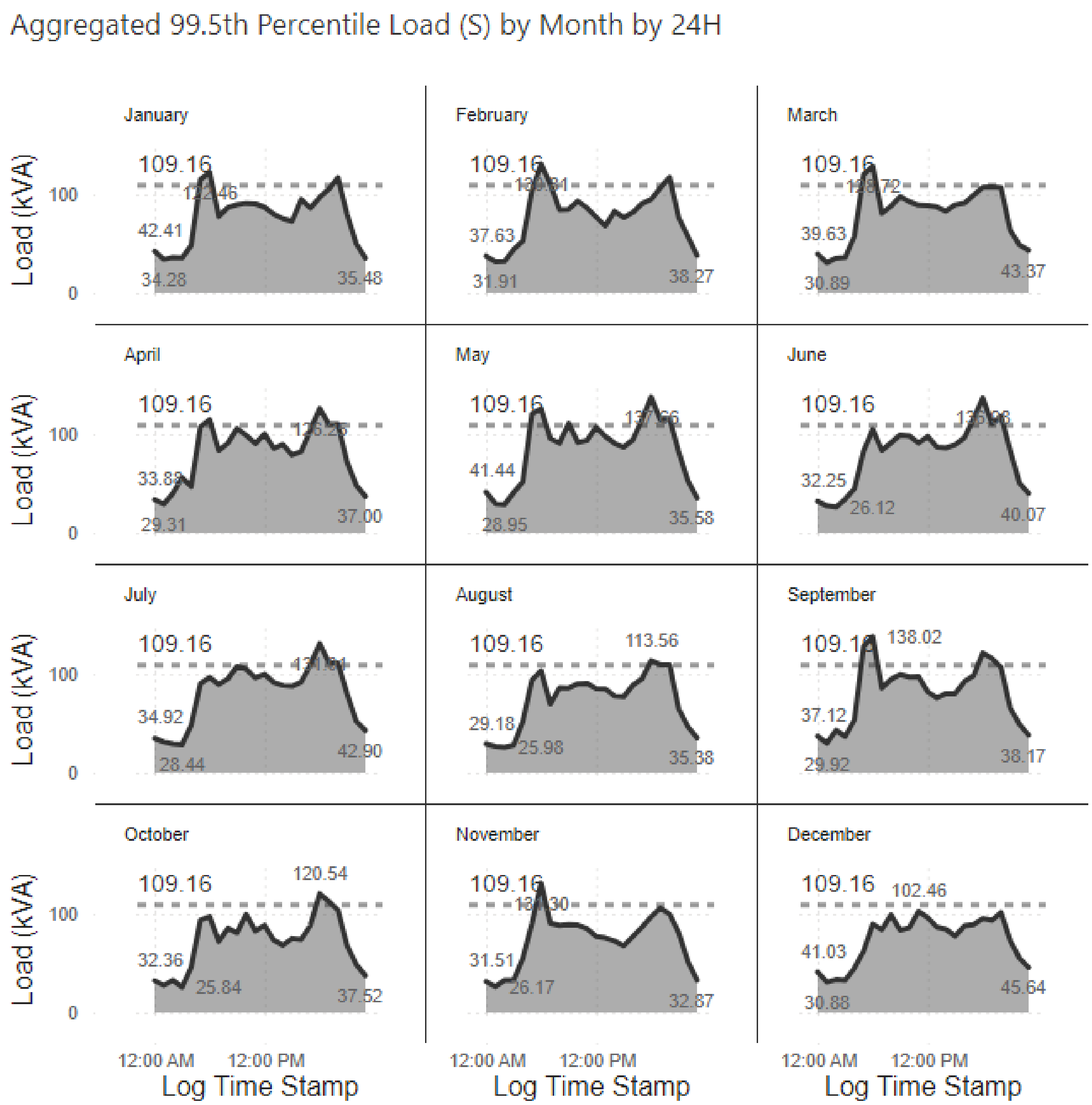


Figure 152: Aggregated 99.5th Percentile load by 24-h day by Month for Case Study M

Figure 152 illustrates the monthly variations in the 99.5th percentile load, showing how daily demand peaks change across different months. The dashed line at 109.16 kVA represents the 99.5th percentile load threshold. Key observations include:

Winter Months (June - August): These months generally exhibit higher daily peaks, often surpassing the 99.5th percentile line. For example, June shows a peak of 113.99 kVA, and July and August reach peaks of 113.56 kVA and 125.67 kVA, respectively. These high values indicate increased energy consumption, likely due to heating needs.

Summer Months (December - February): During these months, demand generally remains below the 99.5th percentile threshold. The highest peak is in February at 112.74 kVA, indicating moderate energy usage.

Transitional Months (March, September): March and September show peaks near or above the 99.5th percentile line, with March reaching 119.72 kVA and September showing a peak of 138.02 kVA, reflecting variability in energy use during changing seasons.

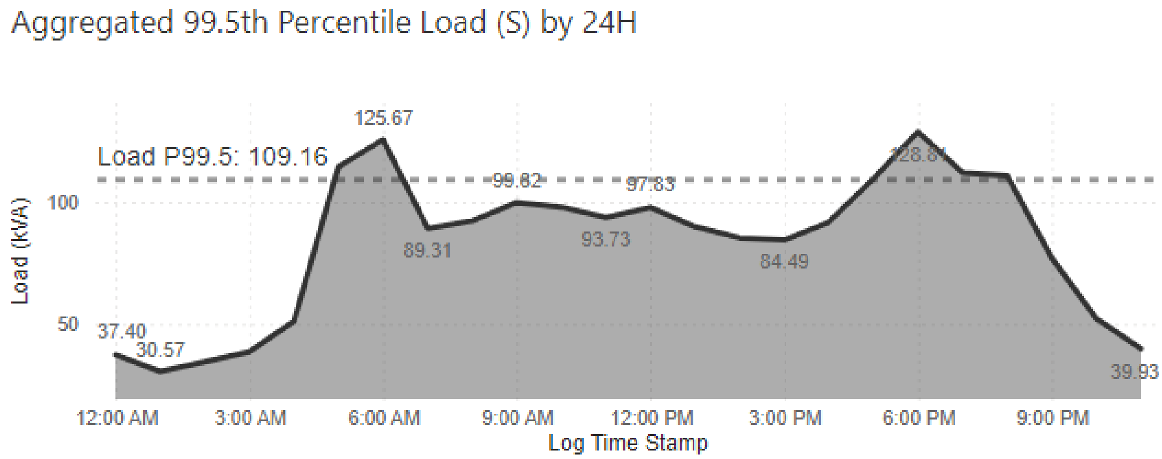


Figure 153: Aggregated 99.5th Percentile load by 24-h day for Case Study M

Figure 153 consolidates the daily demand data into a single 24-hour profile, providing an overview of the typical daily load pattern. The 99.5th percentile load line at 109.16 kVA helps identify critical demand periods:

Morning Peak: A sharp increase in load begins around 3:00 AM, reaching a peak of 125.67 kVA at 6:00 AM. This rise correlates with morning activities as residents start their day.

Evening Peak: The highest demand occurs around 6:00 PM, with a peak load of 128.61 kVA, indicative of typical residential activities such as cooking and heating.

Off-Peak Periods: The lowest demand occurs late at night and early morning, with the load dropping to around 30.57 kVA, well below the 99.5th percentile threshold.

The 99.5th Percentile Load Analysis for Case Study M reveals significant seasonal and daily variations in electricity demand. The data indicate that peak demands are more pronounced during the winter months, with frequent exceedances of the 99.5th percentile threshold due to increased heating needs. The analysis also emphasises the importance of morning and evening peaks in shaping residential electricity consumption patterns. Understanding these variations is crucial for effective energy infrastructure planning and management, ensuring reliable service during periods of maximum demand.

4.11.4 Proposed ADMD vs Observed ADMD

This section aims to compare the proposed After Diversity Maximum Demand (ADMD) values suggested by SANS 507-1:2019 Year-15 parameters with the observed ADMD values for Case Study M. This comparison is crucial for assessing the accuracy and reliability of the proposed standards in predicting real-world electricity demand. By analysing the discrepancies between these values, we can determine the applicability of the SANS guidelines and identify any necessary adjustments for improved planning and infrastructure design.

Summary of Key Metrics

- Total Connections: 184
- Average Age: 21.10 years (greater than 15 years; therefore, Year-15 parameters are used)
- Installed Load: 958.80 kVA (5.21 kVA per connection)

- P99.5 Load: 109.16 kVA (0.59 kVA per stand)
- Resultant P99.5 Diversity Factor (DF): 0.11

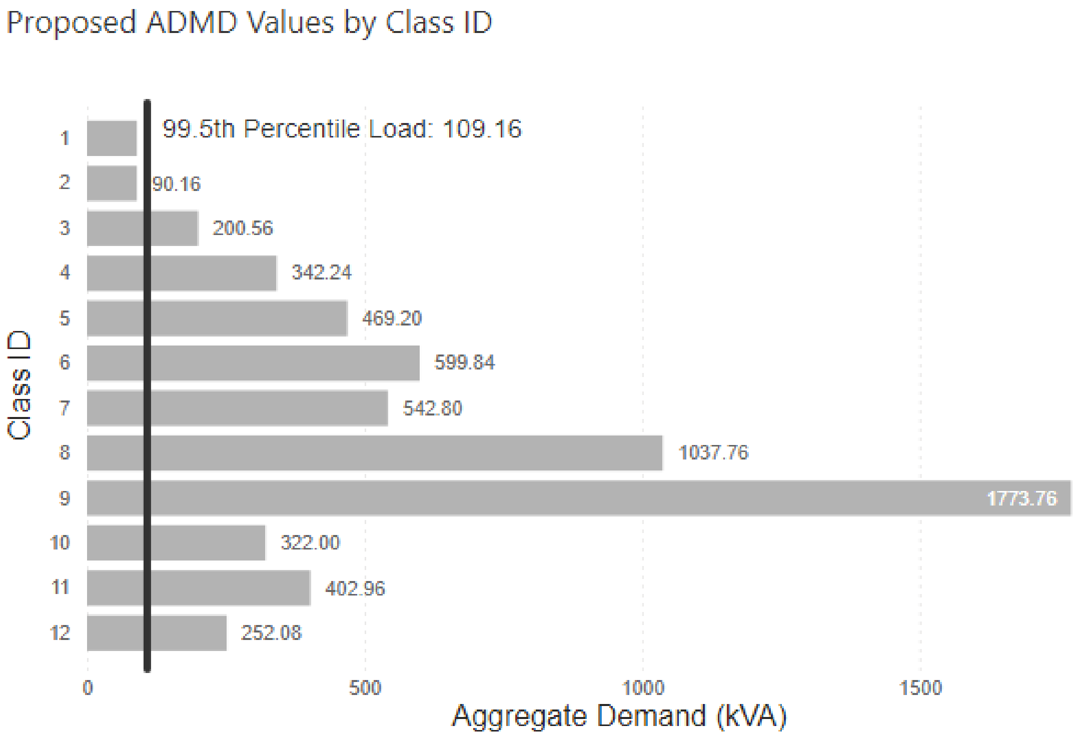


Figure 154: Proposed Year-15 ADMDs result by Class ID for Case Study M

Figure 154 illustrates the proposed ADMD values for different consumer classes as per SANS 507-1:2019 Year-15 parameters, compared against the measured 99.5th percentile load (109.16 kVA). The proposed ADMD values show significant variation across different classes, with Class ID 9 and 8 exhibiting the highest proposed values at 1,773.76 kVA and 1,037.76 kVA, respectively. The vertical line at 109.16 kVA indicates the 99.5th percentile load, serving as a benchmark for comparison.

The data from Figure 154 reveals that the proposed ADMD values for most consumer classes significantly exceed the measured 99.5th percentile load. Notably, Class ID 9 (Urban Estate) has a proposed ADMD value that is over sixteen times the measured load, indicating a possible overestimation. On the other hand, lower class IDs such as 1 and 2 show a proposed ADMD that is closer to the measured load, although still higher. This suggests that the SANS guidelines may need revision to reflect better actual consumption patterns, particularly for higher consumer classes.

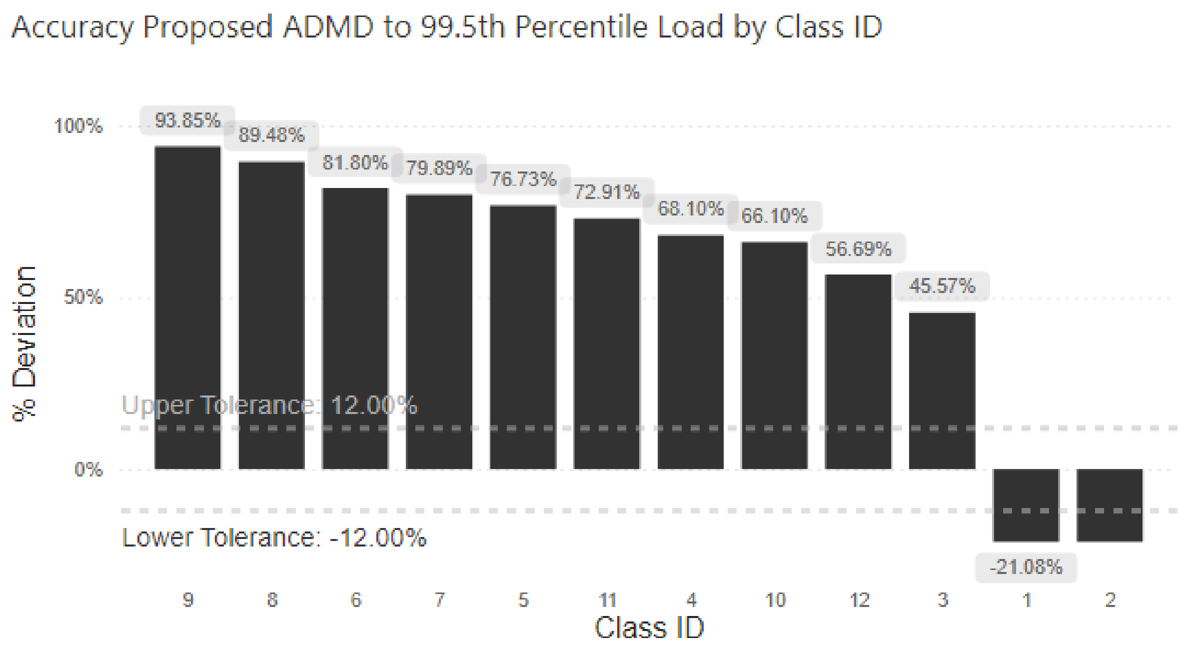


Figure 155: Deviation of SANS 507-1:2019 Year-15 ADMD by Class ID vs. 99.5th Percentile Load for Case Study M

Figure 155 presents the percentage deviation of the proposed ADMD values from the measured 99.5th percentile load for each class ID. The deviation is significant across most classes, with Class ID 9 showing the highest positive deviation at 93.85%. In contrast, Class IDs 1 and 2 show minimal deviation, indicating that the proposed values are relatively close to the measured loads for these classes.

The deviations highlighted in Figure 155 indicate a substantial overestimation of the ADMD values for most consumer classes according to the SANS 507-1:2019 Year-15 parameters. The high positive deviations, particularly for Class ID 9, suggest that the current proposed values do not accurately capture the actual demand patterns. The minimal deviations for Class IDs 1 and 2 indicate that the proposed values for these classes are relatively accurate, but still exhibit slight overestimation. This discrepancy underscores the need for a more nuanced approach in setting ADMD standards that consider the specific characteristics and consumption behaviours of different consumer classes.

Table 12: Detailed Comparison of Proposed ADMD vs Observed ADMD for Case Study M

ID	Consumer Class	SANS 15 Year ADMD (kVA)	Case SANS 15 Year ADMD (kVA)	Accuracy	Deviation
1	Rural settlement, Non-urban, scattered	0.49	90.16	121.08%	-21.08%
2	Rural villages	0.49	90.16	121.08%	-21.08%
3	Informal settlement	1.09	200.56	54.43%	45.57%
4	Township area	1.86	342.24	31.90%	68.10%
5	Urban residential I	2.55	469.20	23.27%	76.73%
6	Urban residential II	3.26	599.84	18.20%	81.80%
7	Urban townhouse complex or duplex	2.95	542.80	20.11%	79.89%
8	Urban Townhouse II	5.64	1,037.76	10.52%	89.48%
9	Urban Estate	9.64	1,773.76	6.15%	93.85%
10	High-rise (small)	1.75	322.00	33.90%	66.10%

11	High rise (medium)	2.19	402.96	27.09%	72.91%
12	Hostel	1.37	252.08	43.31%	56.69%

Table 12 provides a detailed comparison of the proposed and observed ADMD values for each consumer class. The accuracy and deviation columns highlight the discrepancies between the proposed values and the actual measured loads. Notably, Classes 1 and 2 show minimal deviation, suggesting that the proposed ADMD values closely align with the actual load for rural settlements and villages. Conversely, Classes 8 and 9 show the highest positive deviations, indicating an overestimation for urban estates and high-end residential areas. These observations reinforce the need for revising the proposed ADMD values to better align with real-world consumption patterns.

The comparison between the proposed ADMD values and the observed ADMD values for Case Study M reveals significant discrepancies, particularly for higher consumer classes. The proposed values tend to overestimate the actual demand for urban estates and high-end residential areas, while closely matching the load for rural settlements and villages. These findings suggest that the current SANS 507-1:2019 Year-15 parameters may not accurately reflect the diverse consumption patterns observed in different consumer classes. Therefore, it is crucial to re-evaluate these standards and consider more tailored approaches to ensure reliable and efficient electricity infrastructure planning.

Interpretive Note: Case Study M

- Installed base is PPU-dominant. Within PPU, breaker sizes are 20A = 94.54% and 60A = 5.46%.
- Average connection age is about 33.4 years. By breaker size: 33.52 years (20A) and 33.21 years (60A), so Year-15 parameters were appropriate.
- Observed ADMD (P99.5) is 109.16 kVA total.
- Best fit (exact class ID): Class 1 or Class 2 at 0.49 kVA/stand, which is −21.08% relative to the empirical level; higher classes propose larger per-stand values and overshoot by wider margins.

The extreme 20A dominance and mature stock point to a low-demand regime, which explains why Classes 1–2 are closest in absolute deviation, although they still differ materially from the measured 99.5th-percentile ADMD.

4.12 Case Study N

Case Study N explores load profiles and ADMD values in the neighbourhoods of Bultfontein Settlement and parts of Bultfontein Extension 2 and Extension 4, examining factors affecting electricity demand.

4.12.1 Geographic Overview

Case Study N is geographically located at GPS coordinates 26.81697, -29.174314, as illustrated in Figure 156. This area includes the neighbourhood of Bultfontein Settlement and parts of Bultfontein Extension 2 and Extension 4.

GPS Location 26.81697;-29.174314

Figure 156: Geographic location for Case Study N

The transformer zone for Case Study N is situated within the local municipal boundaries of Thaba Nchu, which falls under the Mangaung Metropolitan Municipality in the Free State Province of South Africa. The local municipal authorities are responsible for providing public services, maintaining infrastructure, and promoting community development within this area.

The economy in and around Case Study N is diverse, with key activities including agriculture, retail, and services. Thaba Nchu is known for its agricultural activities, with significant production of crops such as maize, sorghum, and sunflowers. Livestock farming is also prominent in the region. Additionally, small-scale retail businesses and service industries cater to the needs of the local population, influencing the electricity demand.

The climate in this region is generally temperate, characterised by cold winters and warm summers. Winter months (June to August) often experience low temperatures, leading to higher electricity consumption for heating purposes. During the summer months (November to February), the electricity demand may rise due to the increased use of cooling systems. The region receives moderate rainfall, mainly during the summer, which impacts agricultural activities and affects electricity consumption patterns.

The socioeconomic factors in Case Study N's area significantly impact electricity consumption patterns. The community is socioeconomically diverse, comprising low to middle-income households, with varying levels of access to economic opportunities and public services. Educational institutions and healthcare facilities within the area rely on a stable electricity supply to operate efficiently.

Economic disparities within the community influence energy consumption, with more affluent households typically using more electrical appliances and therefore having higher electricity demand. In contrast, lower-income households might have lower overall electricity consumption but still exhibit significant usage during peak times, such as in the evenings when residential activities are at their highest.

In summary, the geographic and socioeconomic context of Case Study N provides a comprehensive understanding of the area's electricity consumption patterns. The combination of agricultural activities, temperate climate, and diverse socioeconomic factors offers valuable data for evaluating the accuracy of proposed ADMD values and their implications for local electricity infrastructure planning.

4.12.2 Connections

4.12.2.1 Proportion of Installed Load by Connection Type

Figure 157 shows a bar graph, comparing the ratio of SPU vs PPU proportions installed as percentages.

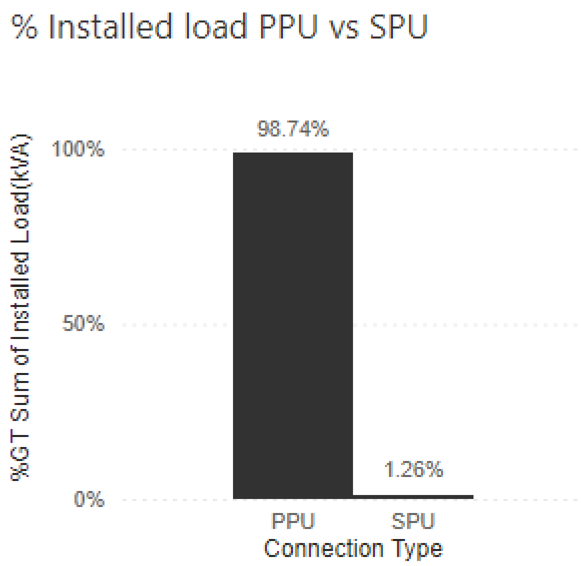


Figure 157: % Installed load by type PPU vs SPU for Case Study N

The installed load type in Case Study N, as shown in Figure 157, indicates that PPU connections make up 98.74% of the total installed load. In comparison, the SPU proportion of the load is only made up by 1.26% of the installed load. Therefore, the negligible presence of SPU installations suggests that SPU loads will have a minimal impact on overall load profile characteristics.

4.12.2.2 Distribution of PPU Connections by Circuit Breaker Size

The pie chart in Figure 158 illustrates the ratio of 20A vs 60A connections that forms part of Case Study N.

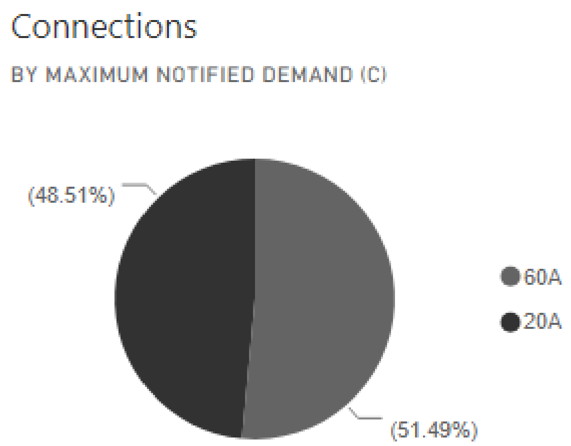


Figure 158: Total PPU connections by Circuit Breaker Size (c) for Case Study N

Clearly shown in Figure 158 is the almost equally divided ratio of 20A and 60A connections at 51.49% and 48.51% respectively. The balanced ratio in some sense is unique compared to most of the case studies. This potentially provides insights into heterogeneity in connection circuit breaker size.

4.12.2.3 Connection Trends

The connection trends for Case Study N are illustrated in Figure 159, providing a comprehensive overview of the historical load growth in terms of total connections.

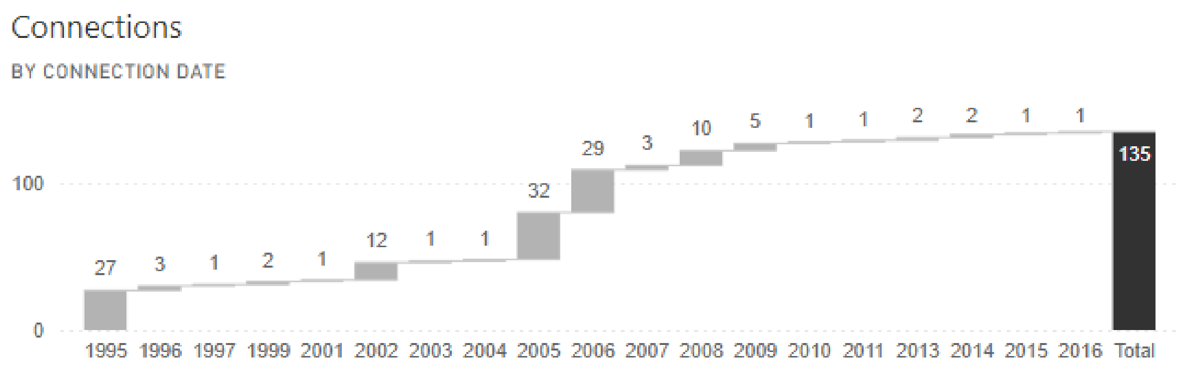


Figure 159: Total connections over time for Case Study N

As shown in Figure 159, the initial connections for Case Study N were recorded in 1995, with the latest connections occurring in 2016. The most significant increase in connections occurred in 2005, with 32 new connections added, marking the highest annual growth observed in this dataset. This was preceded by a lower increase in 2002 with 12 connections.

Following the substantial growth in 2005, there was another notable increase in 2006 with 29 new connections, and subsequent growth was observed in 2007 with 10 connections. Between 1996 and 2016, annual additions ranged from one to five connections, with peaks in 2004 (one connection), 2008 (five connections), and smaller increments spread over the other years.

By the end of the period, the total number of connections reached 135. The data illustrates a pattern of initial moderate growth followed by significant increases in the mid-2000s, and then a period of reduced growth rates in subsequent years. This deceleration suggests a possible saturation in the geographic area, which is a crucial consideration for the design and planning of transformer zones.

The historical connection data for Case Study N highlights the evolving nature of network expansion and the impact of spatial constraints on growth. Effective infrastructure planning must consider these trends to maintain sustainability and efficiency in future expansions.

4.12.2.4 Connection Age Analysis by Breaker Size

The diverging bar chart in Figure 160 illustrates the average age of connections categorised by each circuit breaker size for Case Study N.

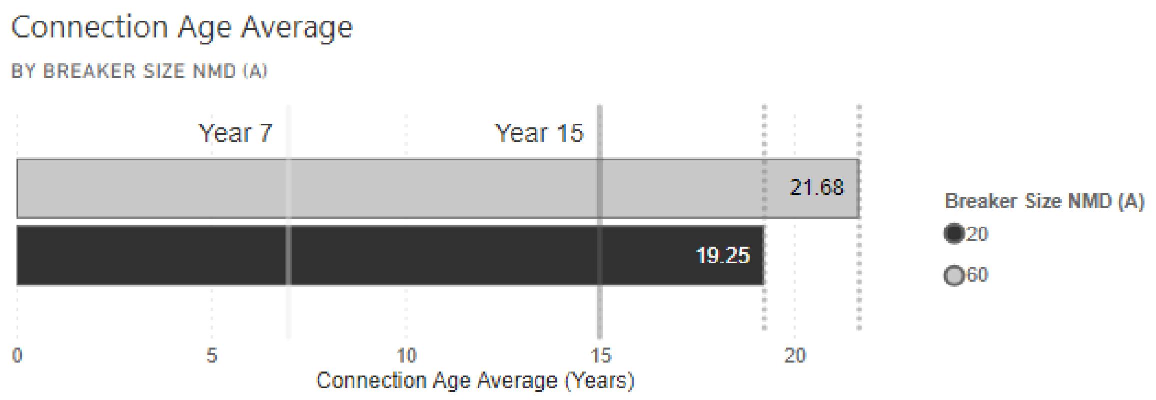


Figure 160: Connection Age Analysis for Case Study N

From Figure 160, it is observed that the average age of connections with 20A circuit breakers is 21.68 years, while the average age of connections with 60A circuit breakers is 19.25 years. The difference in average ages, with the 20A connections being older by approximately 2.43 years compared to the 60A connections, suggests a significant variance in the installation or upgrade times for these breaker sizes.

Given that both categories of circuit breaker size have connection ages significantly higher than 15 years, it is appropriate to use the 15-year parameters according to SANS 507-1:2019 – Table 2. Additionally, it should be noted that the “c” values for 20A, 15-year parameters are limited to Class ID 1 and 2, whereas the 60A Class IDs, according to the 15-year “c” values, are from Class ID 3 and higher.

The following conclusions can be drawn from the above analysis. Firstly, the presence of both 20A and 60A connections suggests a heterogeneous consumer group. Secondly, the significant difference in the average ages of the two categories indicates a pattern of load growth and upgrading. The younger average age for 60A connections could imply that these connections have been installed more recently, possibly as upgrades from 20A connections to accommodate increased demand.

This pattern aligns with typical practices where electrical infrastructure is upgraded to meet higher demand, resulting in newer, larger capacity connections replacing older, smaller ones. The data thus reflects the evolving nature of electrical connections in residential areas, highlighting how infrastructure adapts to changing demands over time. The older average age of the 20A connections suggests that these have been in place longer, potentially awaiting upgrades as demand increases. The substantial difference in ages indicates that upgrades from 20A to 60A connections have been more frequent or recent, leading to a younger average age for the higher capacity connections.

4.12.3 Load Profiles

4.12.3.1 Historical Load Profile Analysis

The historical load profile for Case Study N, depicted in Figure 161, provides a detailed analysis of instantaneous electrical load data from November 2, 2020, to December 31, 2023. This profile captures the variability and trends in electricity consumption over the specified period. Key metrics such as the mean load, maximum demand, and the 99.5th percentile are highlighted to indicate typical and peak load conditions. The mean load, represented by the "Mean: 44.29" line, reflects the average consumption throughout the study timeframe. The maximum demand, marked by the "Maximum: 146.28" line, identifies the highest recorded load, while the 99.5th percentile, indicated as "99.5th Percentile: 95.67," serves as the measured After Diversity Maximum Demand (ADMD) value. This ADMD value is crucial for infrastructure planning and ensuring adequate capacity for handling peak loads.

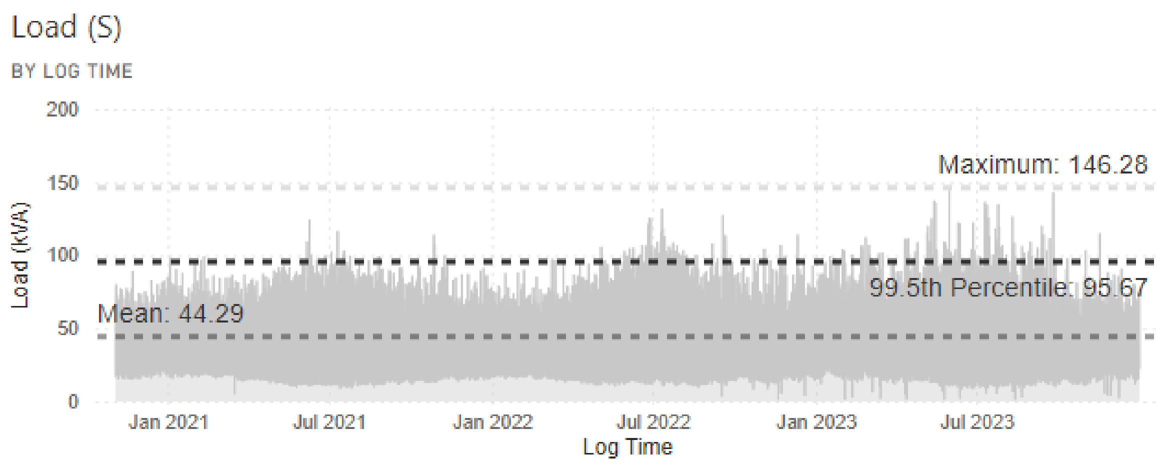


Figure 161: Historical load profile for Case Study N

Figure 161 illustrates several notable characteristics of the load profile for Case Study N. The mean load, shown by the "Mean: 44.29" line, suggests an average consumption level over the study period. The profile shows notable variability, with distinct peaks and troughs reflecting fluctuations in demand. The maximum demand, indicated by the "Maximum: 146.28" line, points to specific periods of high consumption, potentially driven by seasonal factors or special events. The 99.5th percentile, represented by the "99.5th Percentile: 95.67" line, offers a reliable estimate of the ADMD, ensuring that the infrastructure can accommodate typical peak loads without exceeding capacity.

The normal distribution of the historical load profile data for Case Study N, as presented in Figure 162, displays the data as a bell curve. This statistical representation helps to understand the central tendency, spread, and presence of outliers within the dataset.

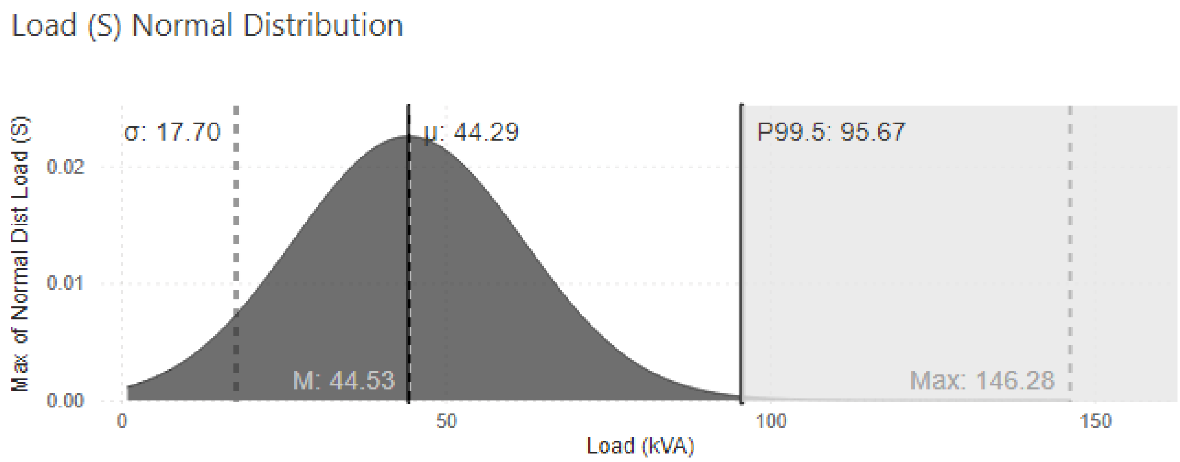


Figure 162: Normal distribution of Historical Load Profile data for Case Study N

Figure 162 shows the bell curve of the normal distribution for the load data, centred around the mean (μ) of 44.29 kVA, with a standard deviation (σ) of 17.70 kVA. The mode (M), noted near "M: 44.53," aligns closely with the mean, indicating a typical concentration of data points around these values. The 99.5th percentile, labelled "P99.5: 95.67," marks the threshold below which 99.5% of the data points lie, indicating the upper limit of typical consumption. The maximum recorded load, "Max: 146.28," lies beyond the 99.5th percentile, highlighting the presence of extreme values in the dataset. The bell curve's shape, characteristic of a normal distribution, shows a slight rightward skew, suggesting occasional instances of higher-than-average loads. This skewness indicates that while most consumption is within a predictable range, there are significant peaks, which are essential for planning and managing the electrical infrastructure to ensure it can handle high demand periods.

4.12.3.2 99.5th Percentile Load Analysis

This section evaluates the After Diversity Maximum Demand (ADMD) for Case Study N by analysing the 99.5th percentile load across various aggregations. The analysis draws on data from Figure 163, Figure 164, and Figure 165, covering the period from November 2020 to December 2023. These figures provide insights into the variations in electricity demand and peak loads.

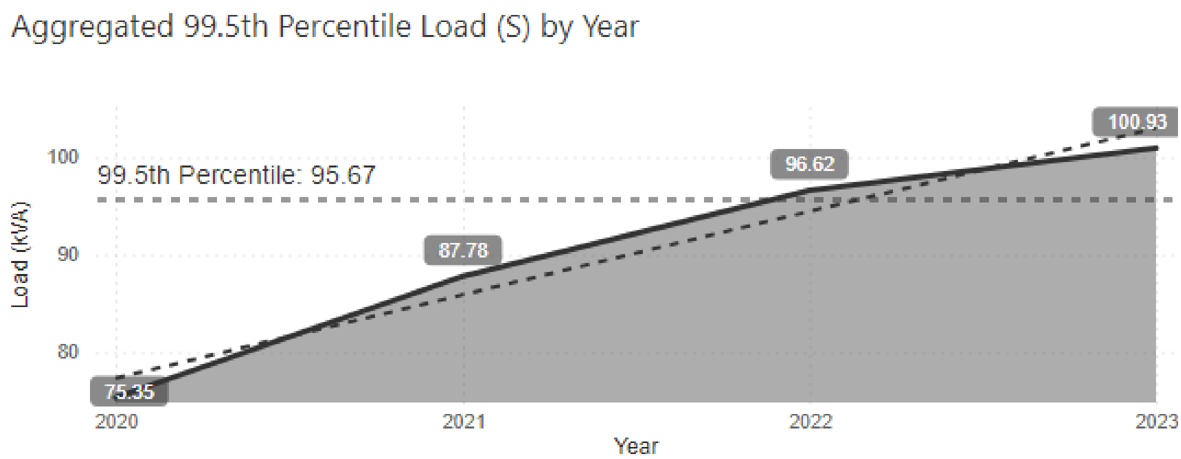


Figure 163: 99.5th Percentile load by year for Case Study N

Figure 163 illustrates the 99.5th percentile load by year for Case Study N. The graph displays annual peak loads, with the 99.5th percentile line established at 95.67 kVA, representing the observed ADMD. The maximum load recorded was 100.93 kVA in 2023, while the minimum was 75.35 kVA in 2020. The trendline shows a steady increase in demand over the years, indicating a rising trend in peak load values. The years 2022 and 2023 had loads exceeding the 99.5th percentile line, suggesting an upward trend in electricity consumption.

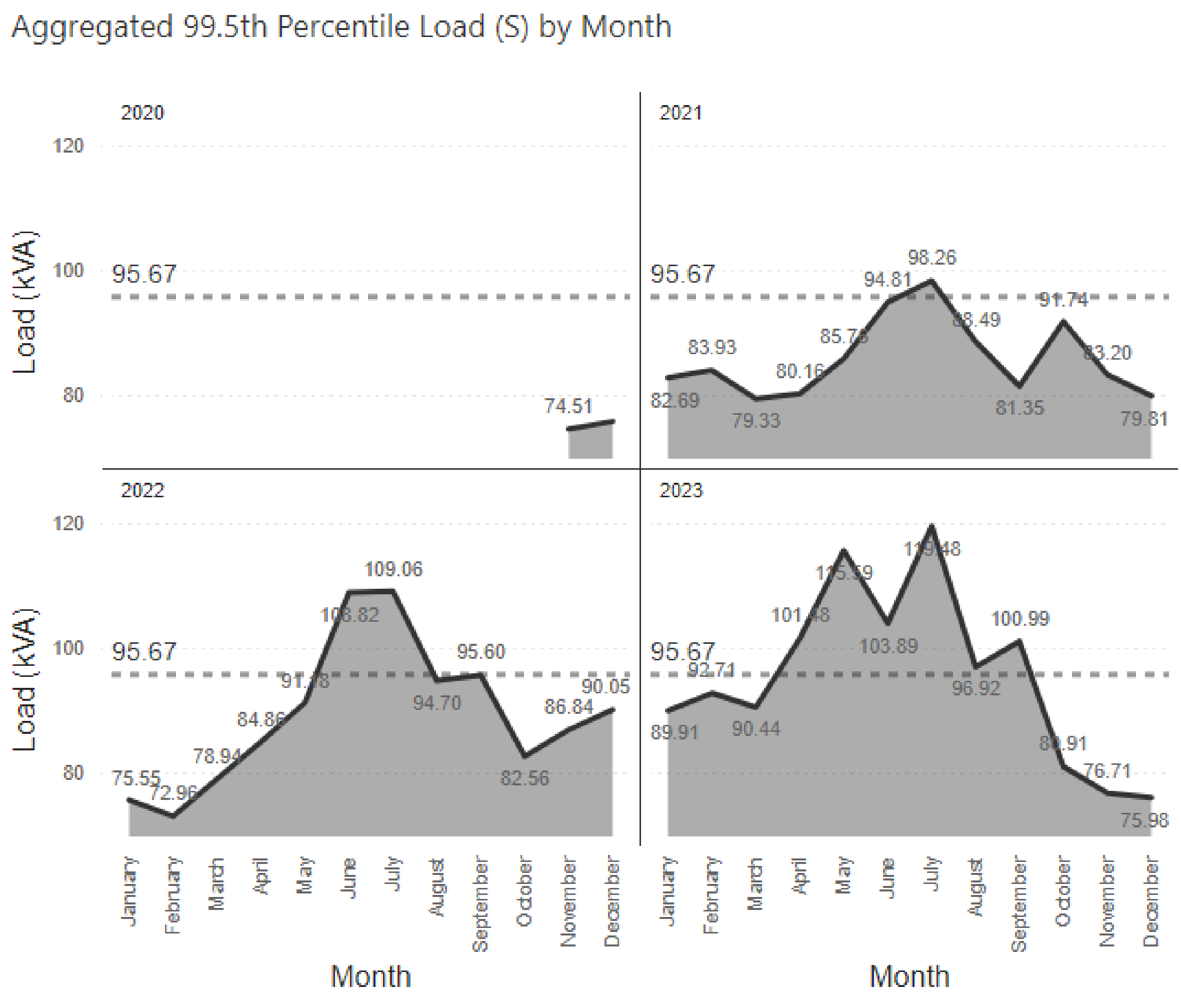


Figure 164: 99.5th Percentile load by each year for Case Study N

Figure 164 provides a detailed breakdown of the 99.5th percentile load by each year, focusing on monthly variations. In 2020, the available data shows a low peak due to limited months recorded, with the load reaching 74.51 kVA in December. In 2021, the peak occurred in June at 98.26 kVA, while in 2022, the highest load was observed in June at 109.06 kVA. For 2023, the peak load was recorded in June at 119.48 kVA. The analysis indicates that monthly peaks generally occur around mid-year, with significant increases observed, particularly from 2021 onwards.

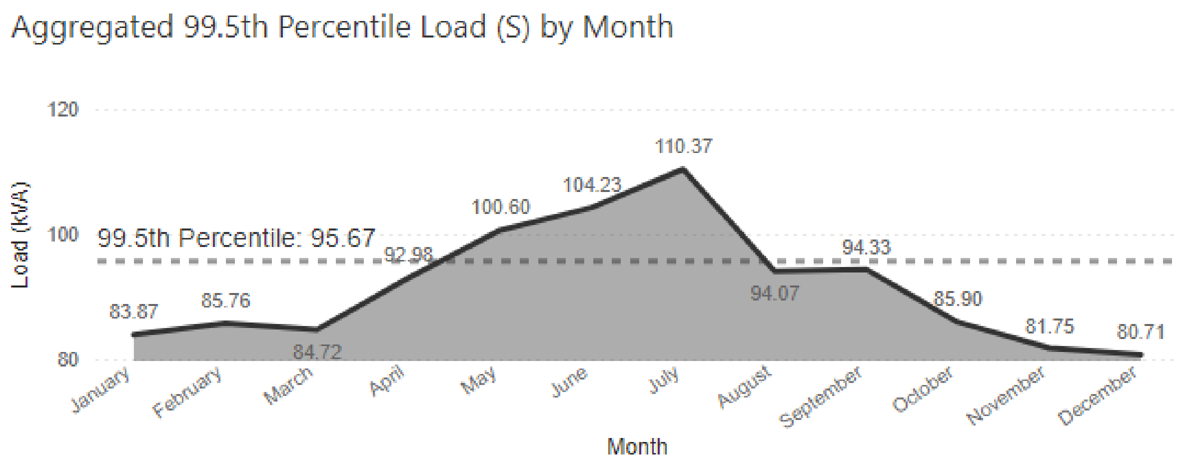


Figure 165: Aggregated 99.5th Percentile load by Month for Case Study N

Figure 165 aggregates the 99.5th percentile load by month across all years, providing a comprehensive view of seasonal demand patterns. The data indicates that loads typically increase from April, peaking in July at 110.37 kVA, and then decline towards December, with the lowest recorded in December at 80.71 kVA. This seasonal trend suggests higher electricity consumption during mid-year months.

The 99.5th percentile load analysis for Case Study N reveals a significant upward trend in ADMD patterns, with the 99.5th percentile serving as the observed ADMD. The data shows a consistent increase in peak demand, particularly noticeable in mid-year months, with significant peaks occurring around June and July. The analysis highlights the importance of monitoring these trends to ensure a reliable electricity supply and efficient infrastructure management. As demand continues to rise, optimising resource allocation and planning for peak loads becomes increasingly critical for maintaining system stability and meeting consumer needs.

4.12.3.3 99.5th Percentile Load Analysis: Daily Demand Profiles

The 99.5th percentile load analysis for Case Study N offers an in-depth study of peak electricity demand periods, highlighting the highest consumption levels that occur only 0.5% of the time. This metric is essential for understanding extreme usage scenarios, which are critical for infrastructure planning and energy management. By analysing these profiles, we gain valuable insights into the seasonal and daily variations in electricity consumption, providing a detailed understanding of how demand fluctuates throughout the year and within a typical day.

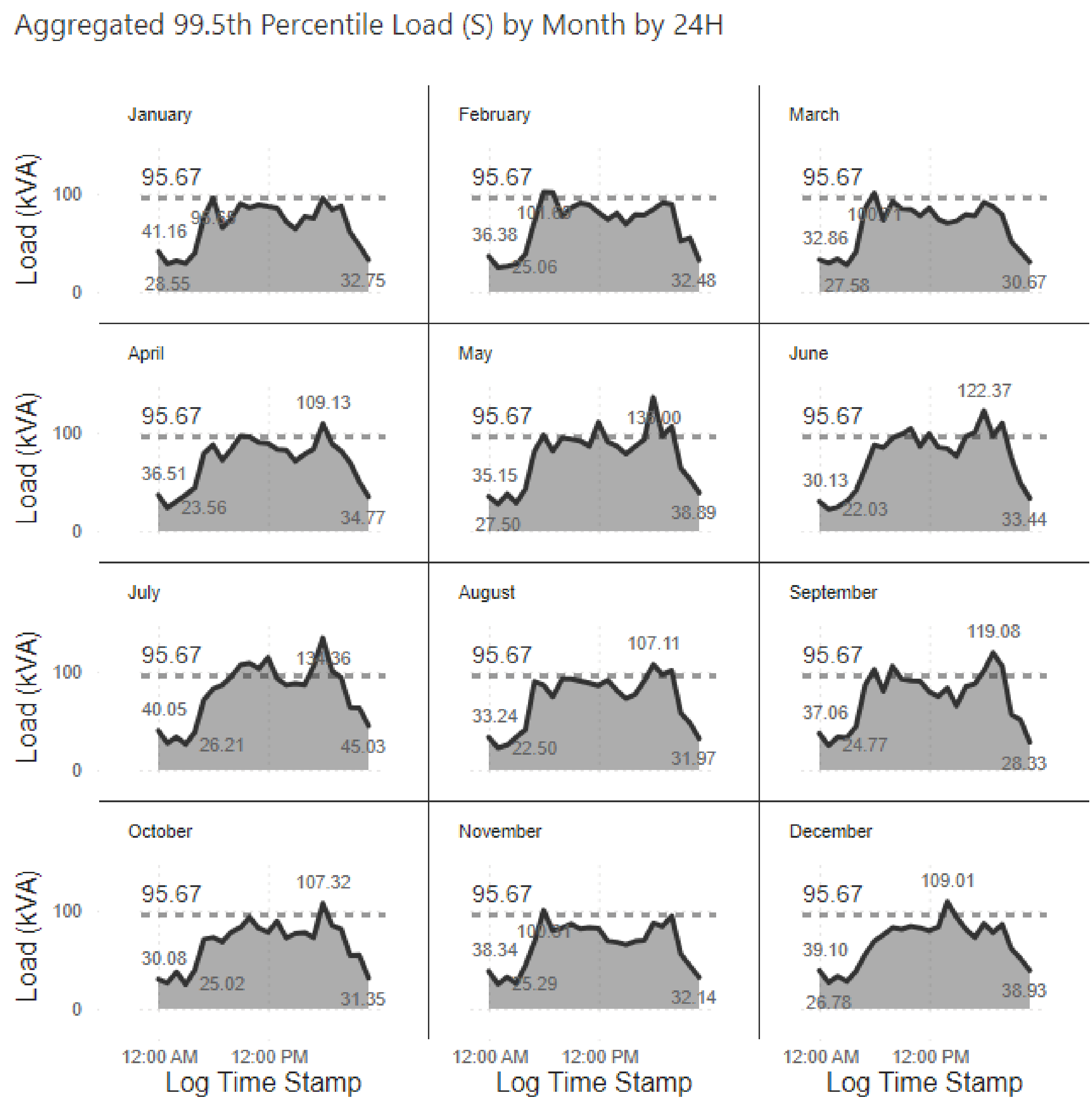


Figure 166: Aggregated 99.5th Percentile load by 24-h day by Month for Case Study N

Figure 166 displays the monthly variations in the 99.5th percentile load, illustrating how daily demand peaks change throughout the year. The dashed line at 95.67 kVA represents the 99.5th percentile load threshold. Key observations include:

Winter Months (June - August): These months generally show higher daily peaks, often exceeding the 99.5th percentile line. For example, June reaches a peak of 122.37 kVA, while July and August have peaks of 113.36 kVA and 107.11 kVA, respectively. These peaks indicate increased energy consumption, likely due to heating needs.

Summer Months (December - February): The demand during these months generally remains below the 99.5th percentile threshold. January shows a peak of 95.27 kVA, and February reaches 105.06 kVA, suggesting moderate energy usage.

Transitional Months (March, September): These months exhibit peaks near or above the 99.5th percentile line, with March reaching 109.78 kVA and September showing a peak of 119.08 kVA, reflecting variability in energy use during seasonal changes.

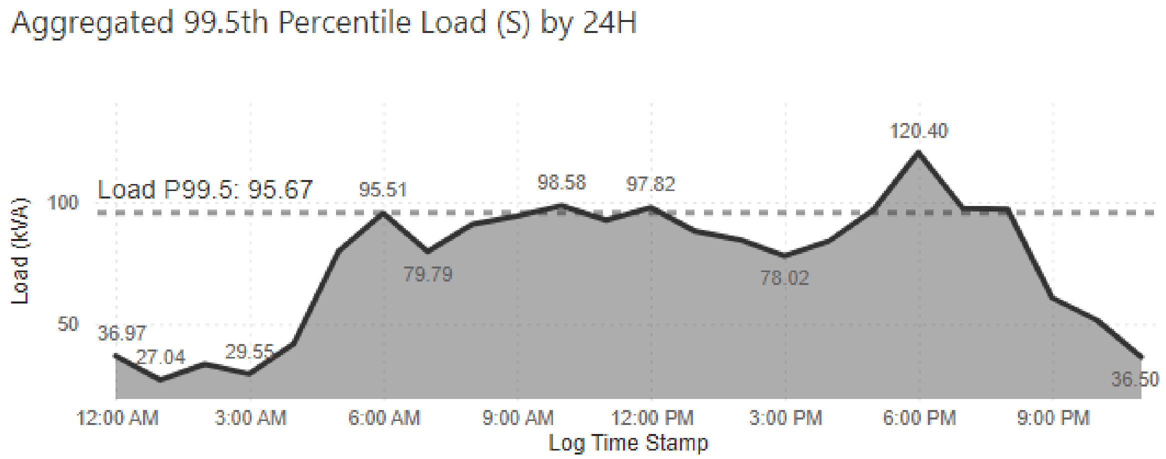


Figure 167: Aggregated 99.5th Percentile load by 24-h day for Case Study N

Figure 167 consolidates the daily demand data into a single 24-hour profile, providing an overview of the typical daily load pattern. The 99.5th percentile load line at 95.67 kVA helps identify critical demand periods:

Morning Peak: A significant increase in load begins around 3:00 AM, reaching a peak of 95.51 kVA at 6:00 AM. This rise correlates with morning activities as residents start their day.

Evening Peak: The highest demand occurs around 6:00 PM, with a peak load of 120.40 kVA, indicating typical residential activities such as cooking and heating.

Off-Peak Periods: The lowest demand occurs late at night and early morning, with the load dropping to around 27.04 kVA, well below the 99.5th percentile threshold.

The 99.5th Percentile Load Analysis for Case Study N highlights significant seasonal and daily variations in electricity demand. The data shows that peak demands are more pronounced during the winter months, with frequent exceedances of the 99.5th percentile threshold due to increased heating requirements. The analysis also underscores the importance of morning and evening peaks in shaping residential electricity consumption patterns. Understanding these variations is crucial for effective energy infrastructure planning and management, ensuring reliable service during periods of maximum demand.

4.12.4 Proposed ADMD vs Observed ADMD

This section aims to compare the proposed After Diversity Maximum Demand (ADMD) values suggested by SANS 507-1:2019 Year-15 parameters with the observed ADMD values for Case Study N. This comparison is crucial for assessing the accuracy and reliability of the proposed standards in predicting real-world electricity demand. By analysing the discrepancies between these values, we can determine the applicability of the SANS guidelines and identify any necessary adjustments for improved planning and infrastructure design.

Summary of Key Metrics

- Total Connections: 135
- Average Age: 20.55 years (greater than 15 years; therefore, Year-15 parameters are used)
- Installed Load: 1,267.20 kVA (9.39 kVA per connection)

- P99.5 Load: 95.67 kVA (0.71 kVA per stand)
- Resultant P99.5 Diversity Factor (DF): 0.08

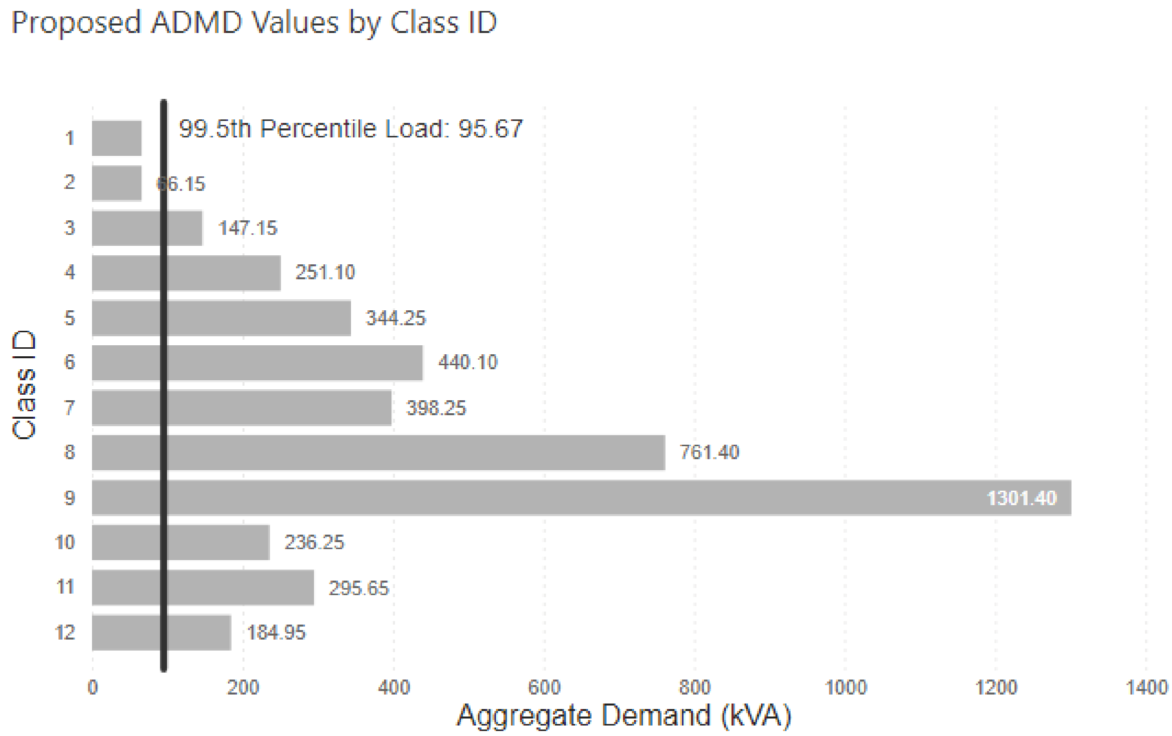


Figure 168: Proposed Year-15 ADMDs result by Class ID for Case Study N

Figure 168 illustrates the proposed ADMD values for different consumer classes as per SANS 507-1:2019 Year-15 parameters, compared against the measured 99.5th percentile load (95.67 kVA). The proposed ADMD values show significant variation across different classes, with Class ID 9 and 8 exhibiting the highest proposed values at 1,301.40 kVA and 761.40 kVA, respectively. The vertical line at 95.67 kVA indicates the 99.5th percentile load, serving as a benchmark for comparison.

The data from Figure 168 reveals that the proposed ADMD values for most consumer classes significantly exceed the measured 99.5th percentile load. Notably, Class ID 9 (Urban Estate) has a proposed ADMD value that is over thirteen times the measured load, indicating a possible overestimation. On the other hand, lower class IDs such as 1 and 2 show a proposed ADMD that is closer to the measured load, although still higher. This suggests that the SANS guidelines may need revision to reflect better actual consumption patterns, particularly for higher consumer classes.

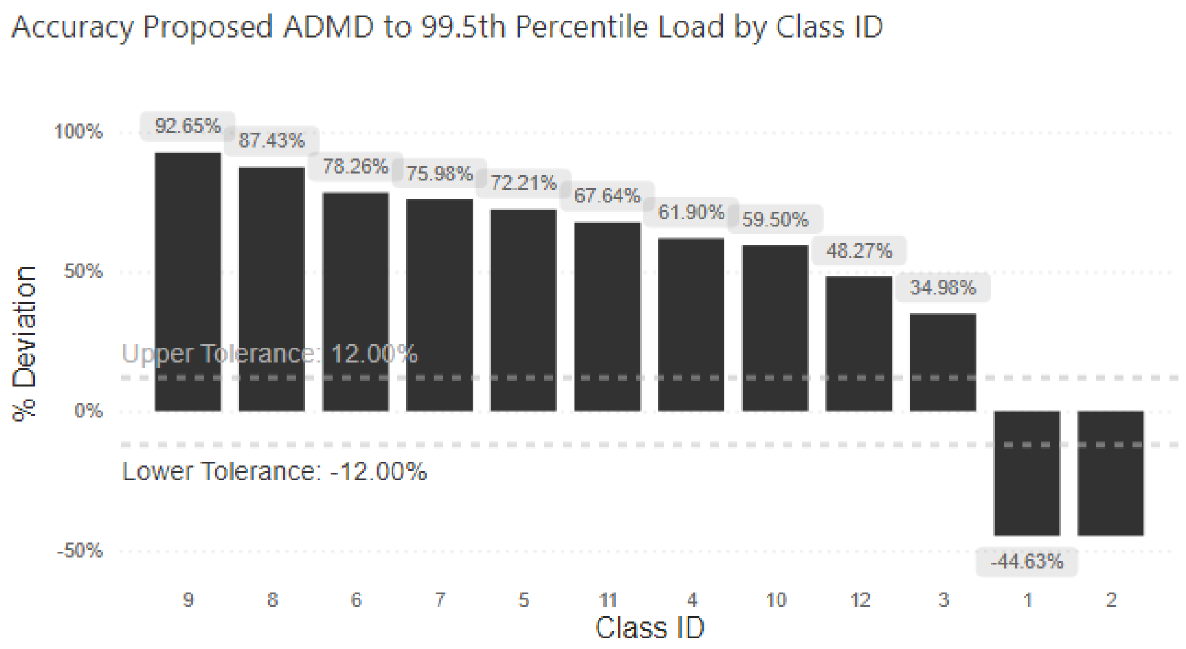


Figure 169: Deviation of SANS 507-1:2019 Year-15 ADMD by Class ID vs. 99.5th Percentile Load for Case Study N

Figure 169 presents the percentage deviation of the proposed ADMD values from the measured 99.5th percentile load for each class ID. The deviation is significant across most classes, with Class ID 9 showing the highest positive deviation at 92.65%. In contrast, Class IDs 1 and 2 show minimal deviation, indicating that the proposed values are relatively close to the measured loads for these classes.

The deviations highlighted in Figure 169 indicate a substantial overestimation of the ADMD values for most consumer classes according to the SANS 507-1:2019 Year-15 parameters. The high positive deviations, particularly for Class ID 9, suggest that the current proposed values do not accurately capture the actual demand patterns. The minimal deviations for Class IDs 1 and 2 indicate that the proposed values for these classes are relatively accurate, but still exhibit slight overestimation. This discrepancy underscores the need for a more nuanced approach in setting ADMD standards that consider the specific characteristics and consumption behaviours of different consumer classes.

Table 13: Detailed Comparison of Proposed ADMD vs Observed ADMD for Case Study N

ID	Consumer Class	SANS 15 Year ADMD (kVA)	Case SANS 15 Year ADMD (kVA)	Accuracy	Deviation
1	Rural settlement, Non-urban, scattered	0.49	66.15	144.63%	-44.63%
2	Rural villages	0.49	66.15	144.63%	-44.63%
3	Informal settlement	1.09	147.15	65.02%	34.98%
4	Township area	1.86	251.10	38.10%	61.90%
5	Urban residential I	2.55	344.25	27.79%	72.21%
6	Urban residential II	3.26	440.10	21.74%	78.26%
7	Urban townhouse complex or duplex	2.95	398.25	24.02%	75.98%
8	Urban Townhouse II	5.64	761.40	12.75%	87.43%
9	Urban Estate	9.64	1,301.40	7.35%	92.65%
10	High-rise (small)	1.75	236.25	40.50%	59.50%

11	High rise (medium)	2.19	295.65	32.36%	67.64%
12	Hostel	1.37	184.95	51.73%	48.27%

Table 13 provides a detailed comparison of the proposed and observed ADMD values for each consumer class. The accuracy and deviation columns highlight the discrepancies between the proposed values and the actual measured loads. Notably, Classes 1 and 2 show minimal deviation, suggesting that the proposed ADMD values closely align with the actual load for rural settlements and villages. Conversely, Classes 8 and 9 show the highest positive deviations, indicating an overestimation for urban estates and high-end residential areas. These observations reinforce the need for revising the proposed ADMD values to better align with real-world consumption patterns.

The comparison between the proposed ADMD values and the observed ADMD values for Case Study N reveals significant discrepancies, particularly for higher consumer classes. The proposed values tend to overestimate the actual demand for urban estates and high-end residential areas, while closely matching the load for rural settlements and villages. These findings suggest that the current SANS 507-1:2019 Year-15 parameters may not accurately reflect the diverse consumption patterns observed in different consumer classes. Therefore, it is crucial to re-evaluate these standards and consider more tailored approaches to ensure reliable and efficient electricity infrastructure planning.

Interpretive Note: Case Study N

- Installed base is PPU-dominant. Within PPU, breaker sizes are 60A = 62.09% and 20A = 37.91%.
- Average connection age is 27.32 years. By breaker size: 26.96 years (20A) and 27.78 years (60A), so Year-15 parameters were appropriate.
- Observed ADMD (P99.5) is 118.21 kVA total.
- Best fit (exact class ID): Class 3 (Informal settlement) at 1.09 kVA/stand, giving a +34.98% deviation versus the empirical ADMD. Classes above 3 propose larger per-stand values and overshoot by wider margins, while Classes 1–2 are below the empirical level.

The 60A majority suggests a higher-capacity consumer base, yet the observed ADMD sits in a mid-range band; among the SANS options, Class 3 produces the least absolute deviation from the observed 99.5th-percentile ADMD and aligns better with the empirical breaker composition than lower or higher classes.

4.13 Case Study O

Case Study O explores load profiles and ADMD values in the neighbourhoods of Malebogo and parts of Hertzogville within the Tokologo Local Municipality, examining factors affecting electricity demand.

4.13.1 Geographic Overview

Case Study O is geographically located at GPS coordinates 25.494314, -28.12434, as illustrated in Figure 170. This area includes the neighbourhoods of Malebogo and parts of Hertzogville.

Figure 170: Geographic location for Case Study O

The transformer zone for Case Study O is situated within the local municipal boundaries of Hertzogville, which falls under the Tokologo Local Municipality in the Lejweleputswa District Municipality, Free State Province of South Africa. The local municipal authorities are responsible for providing public services, maintaining infrastructure, and promoting community development within this area.

The economy in and around Case Study O is predominantly driven by agriculture, with significant production of crops such as maize, sunflower, and sorghum. Livestock farming also plays an essential role in the local economy. The presence of small-scale retail businesses and service industries supports the local population and influences the electricity demand.

The climate in this region is generally temperate, characterised by cold winters and warm summers. Winter months (June to August) often experience low temperatures, leading to higher electricity consumption for heating purposes. During the summer months (November to February), the electricity demand may rise due to the increased use of cooling systems. The region receives moderate rainfall, mainly during the summer, which impacts agricultural activities and affects electricity consumption patterns.

The socioeconomic factors in Case Study O's area significantly impact electricity consumption patterns. The community is socioeconomically diverse, comprising low to middle-income households, with varying levels of access to economic opportunities and public services. Educational institutions and healthcare facilities within the area rely on a stable electricity supply to operate efficiently.

Economic disparities within the community influence energy consumption, with more affluent households typically using more electrical appliances and therefore having higher electricity demand. In contrast, lower-income households might have lower overall electricity consumption but still exhibit significant usage during peak times, such as in the evenings when residential activities are at their highest.

In summary, the geographic and socioeconomic context of Case Study O provides a comprehensive understanding of the area's electricity consumption patterns. The combination of agricultural activities, temperate climate, and diverse socioeconomic factors offers valuable data for evaluating the accuracy of proposed ADMD values and their implications for local electricity infrastructure planning.

4.13.2 Connections

4.13.2.1 Proportion of Installed Load by Connection Type

Figure 171 represents the percentage ratio of SPU and PPU load proportions that represents the load that forms part of Case Study O.

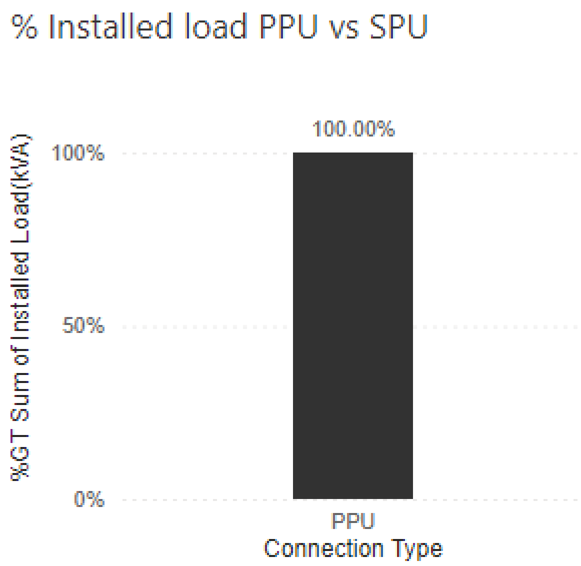


Figure 171: Installed load by type PPU vs SPU for Case Study O

As is seen with the majority of case studies that make up these research subjects, Figure 171 shows 100% of the installed load is of PPU type. Thus, indicating the absence of any SPU installed loads.

4.13.2.2 Distribution of PPU Connections by Circuit Breaker Size

In Figure 172 a pie chart is presented to illustrate the connections that form part of Case Study O by the total connections according to individual breaker sizes. Thus, highlighting the contribution of various maximum demands on the impact of load characteristics for Case Study O.

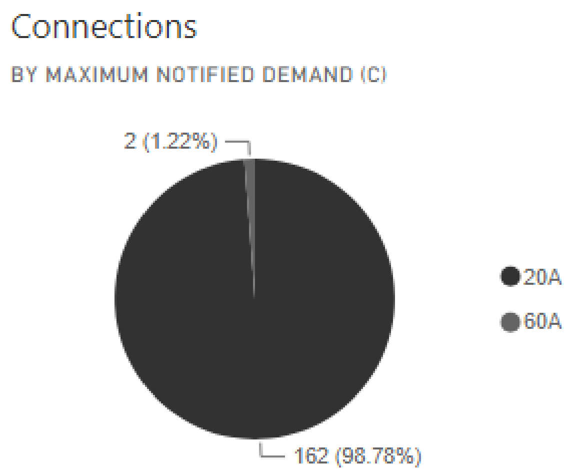


Figure 172: Total PPU connections by Circuit Breaker Size (c) for Case Study O

Figure 172 clearly shows that the overwhelming majority of connections are limited to 20A maximum supply currents at 98.78% of the total connections. It can further be seen that there is a stark representation of the higher 60A connections, making up 1.22% of the total connections. From the data, it can be concluded that this case study falls closer to the low end of Class IDs as described in SANS 507-1:20719, Table 2. Suggesting that this load in this case study has possibly not yet reached load maturity, or the load growth has settled at a lower final demand.

4.13.2.3 Connection Trends

The connection trends for Case Study O are illustrated in Figure 173, providing a comprehensive overview of the historical load growth in terms of total connections.

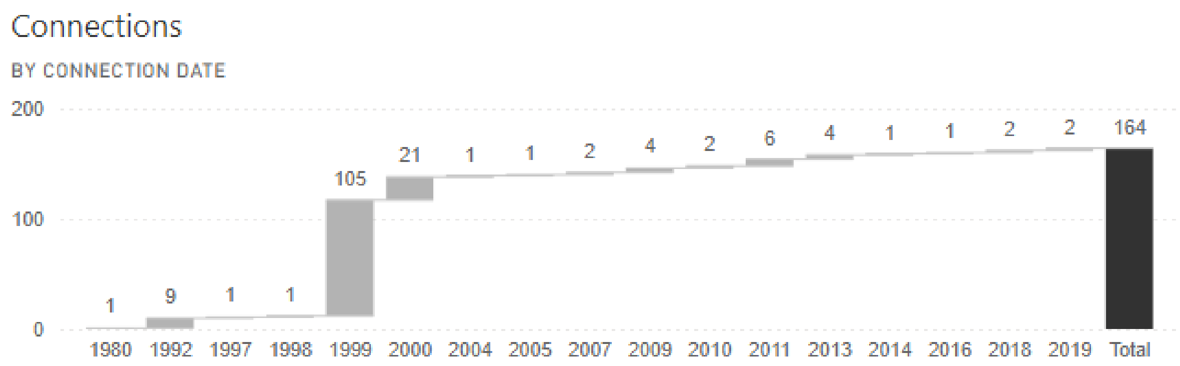


Figure 173: Total connections over time for Case Study O

As shown in Figure 173, the initial connections for Case Study O were recorded in 1980, with the latest connections occurring in 2019. The most significant increase in connections occurred in 1999, with 105 new connections added, marking the highest annual growth observed in this dataset. This was followed by a reduced increase rate in 2000 with 21 connections.

Following the substantial growth in 1999 and 2000, the number of new connections per year varied, with notable additions in subsequent years. Between 2001 and 2019, annual additions ranged from one to six connections, with peaks in 2009 (four connections), 2010 (six connections), and 2011 (four connections).

By the end of the period, the total number of connections reached 164. The data illustrates a pattern of initial moderate growth, followed by significant increases at the turn of the millennium, and then a period of steadier, lower growth rates in subsequent years. This deceleration suggests a possible saturation in the geographic area, which is a crucial consideration for the design and planning of transformer zones.

The historical connection data for Case Study O highlights the evolving nature of network expansion and the impact of spatial constraints on growth. Effective infrastructure planning must consider these trends to maintain sustainability and efficiency in future expansions.

4.13.2.4 Connection Age Analysis by Breaker Size

The diverging bar chart in Figure 174 illustrates the average age of connections categorised by each circuit breaker size for Case Study O.

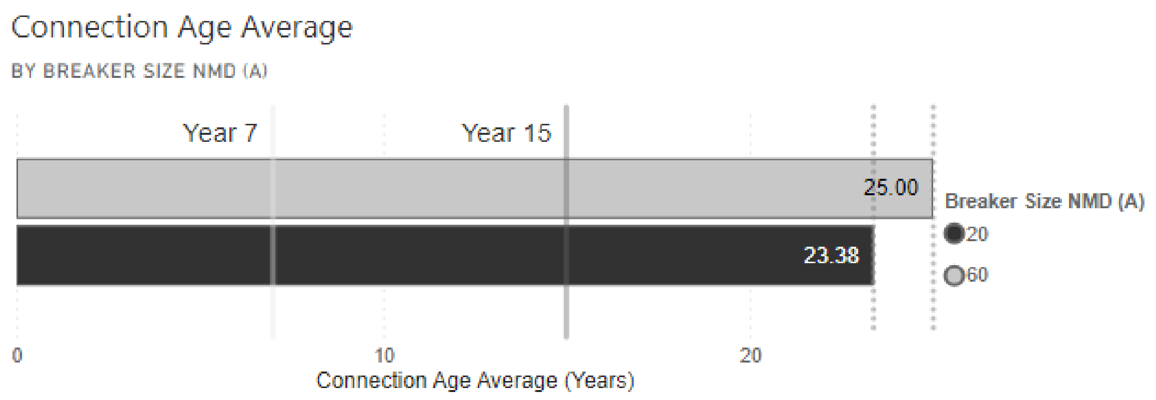


Figure 174: Connection Age Analysis for Case Study O

From Figure 174, it is observed that the average age of connections with 20A circuit breakers is 23.38 years, while the average age of connections with 60A circuit breakers is 25.00 years. The difference in average ages, with the 60A connections being older by approximately 1.62 years compared to the 20A connections, suggests a potential variance in the installation or upgrade times for these breaker sizes.

Given that both categories of circuit breaker size have connection ages significantly higher than 15 years, it is appropriate to use the 15-year parameters according to SANS 507-1:2019 – Table 2. Additionally, it should be noted that the “c” values for 20A, 15-year parameters are limited to Class ID 1 and 2, whereas the 60A Class IDs, according to the 15-year “c” values, are from Class ID 3 and higher.

The following conclusions can be drawn from the above analysis. Firstly, the presence of both 20A and 60A connections suggests a heterogeneous consumer group. Secondly, the difference in the average ages of the two categories indicates a pattern of load growth and upgrading. The older average age for 60A connections could imply that these connections have been in place longer, possibly initially installed for higher demand consumers or upgraded over time from 20A to 60A as demand increased.

This pattern aligns with typical practices where electrical infrastructure is upgraded to meet higher demand, resulting in newer, larger capacity connections replacing older, smaller ones. The data thus reflects the evolving nature of electrical connections in residential areas, highlighting how infrastructure adapts to changing demands over time. The noticeable difference in ages suggests that while upgrades from 20A to 60A connections have occurred over time, the older average age of 60A connections indicates these upgrades were made earlier in the development of the electrical infrastructure in the study area.

4.13.3 Load Profiles

4.13.3.1 Historical Load Profile Analysis

The historical load profile for Case Study N, depicted in Figure 175, provides an overview of instantaneous electrical load data collected from November 2, 2020, to December 31, 2023. This profile captures the variations in electricity consumption over the given period, offering insights into daily and seasonal patterns. Key indicators such as the mean load, maximum demand, and the 99.5th percentile are prominently displayed to indicate typical and peak load levels. The mean load, marked by the "Mean: 43.18" line, represents the average load throughout the study timeframe. The maximum demand, shown as the "Maximum: 117.63" line, reflects the highest recorded load, while the 99.5th percentile, marked as "99.5th Percentile: 85.55," serves as the measured After Diversity Maximum Demand (ADMD) value. This ADMD value is crucial for infrastructure planning, ensuring that the system can handle peak demands.

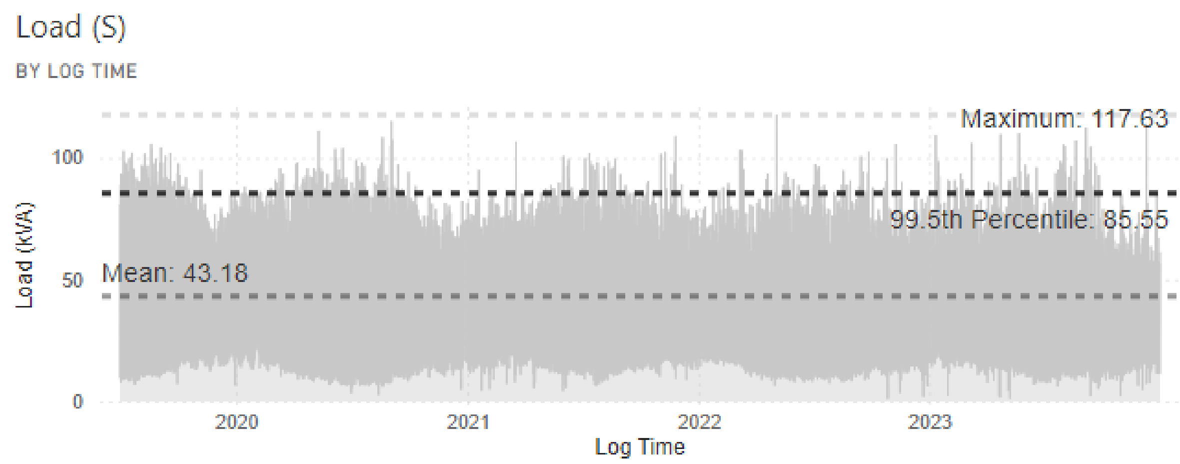


Figure 175: Historical load profile for Case Study O

Figure 175 illustrates several notable features of the historical load profile for Case Study N. The mean load, represented by the "Mean: 43.18" line, indicates a moderate consumption level over the study period. The profile shows fluctuations with distinct peaks and troughs, suggesting variability in demand influenced by various factors. The maximum demand, indicated by the "Maximum: 117.63" line, highlights periods of high consumption. The 99.5th percentile, shown as "99.5th Percentile: 85.55," provides a conservative estimate of the ADMD, ensuring that the infrastructure is designed to accommodate typical peak loads without exceeding capacity.

The normal distribution of the historical load profile data for Case Study N, presented in Figure 176, displays the data in a bell curve format. This statistical representation helps in understanding the central tendency, variability, and the presence of outliers within the dataset.

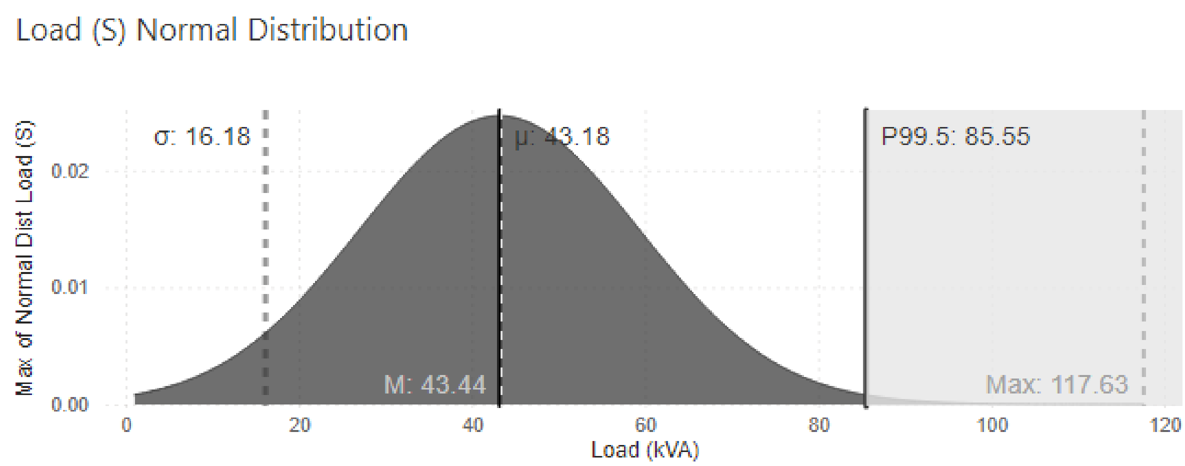


Figure 176: Normal distribution of Historical Load Profile data for Case Study O

Figure 176 illustrates the normal distribution of the load data, centred around the mean (μ) of 43.18 kVA, with a standard deviation (σ) of 16.18 kVA. The mode (M), noted near "M: 43.44," aligns closely with the mean, suggesting a typical clustering of data points around these central values. The 99.5th percentile, labelled "P99.5: 85.55," marks the threshold below which 99.5% of the data points lie, indicating the typical upper range of load values. The maximum recorded load, "Max: 117.63," lies beyond the 99.5th percentile, highlighting the presence of extreme values. The bell curve's shape, characteristic of a normal distribution, suggests a slight rightward skew, reflecting occasional instances of higher-than-average loads. This skewness indicates that while most consumption falls within a predictable range, there are significant peaks, which are important considerations for planning and managing the electrical infrastructure.

4.13.3.2 99.5th Percentile Load Analysis

To gain a comprehensive understanding of the After Diversity Maximum Demand (ADMD) for Case Study O, this section evaluates the 99.5th percentile load across various aggregations. The analysis includes data from Figure 177, Figure 178, and Figure 179, covering the period from July 2019 to December 2023. These figures provide detailed insights into the variations in electricity demand and peak loads.

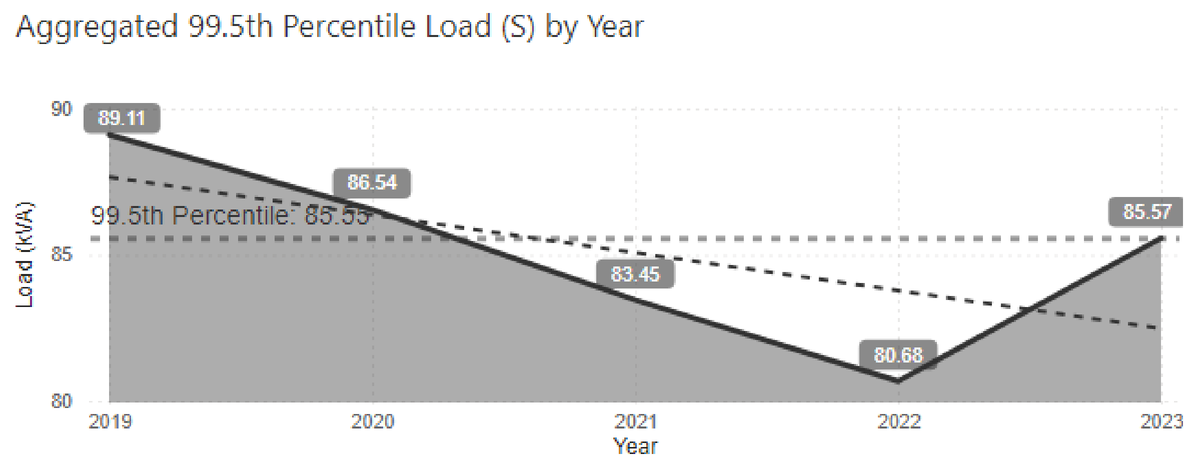


Figure 177: 99.5th Percentile load by year for Case Study O

Figure 177 shows a graph that illustrates the 99.5th percentile load by year for Case Study O, showing the annual peak loads with the 99.5th percentile line set at 85.55 kVA, which represents the observed ADMD. The maximum load recorded was 89.11 kVA in 2019, while the minimum was 80.68 kVA in 2022. The trendline indicates a declining demand from 2019 to 2022, followed by a recovery in 2023 to 85.57 kVA. This pattern reflects a general decrease in demand over the years, with a notable dip in 2022, before slightly rising again.

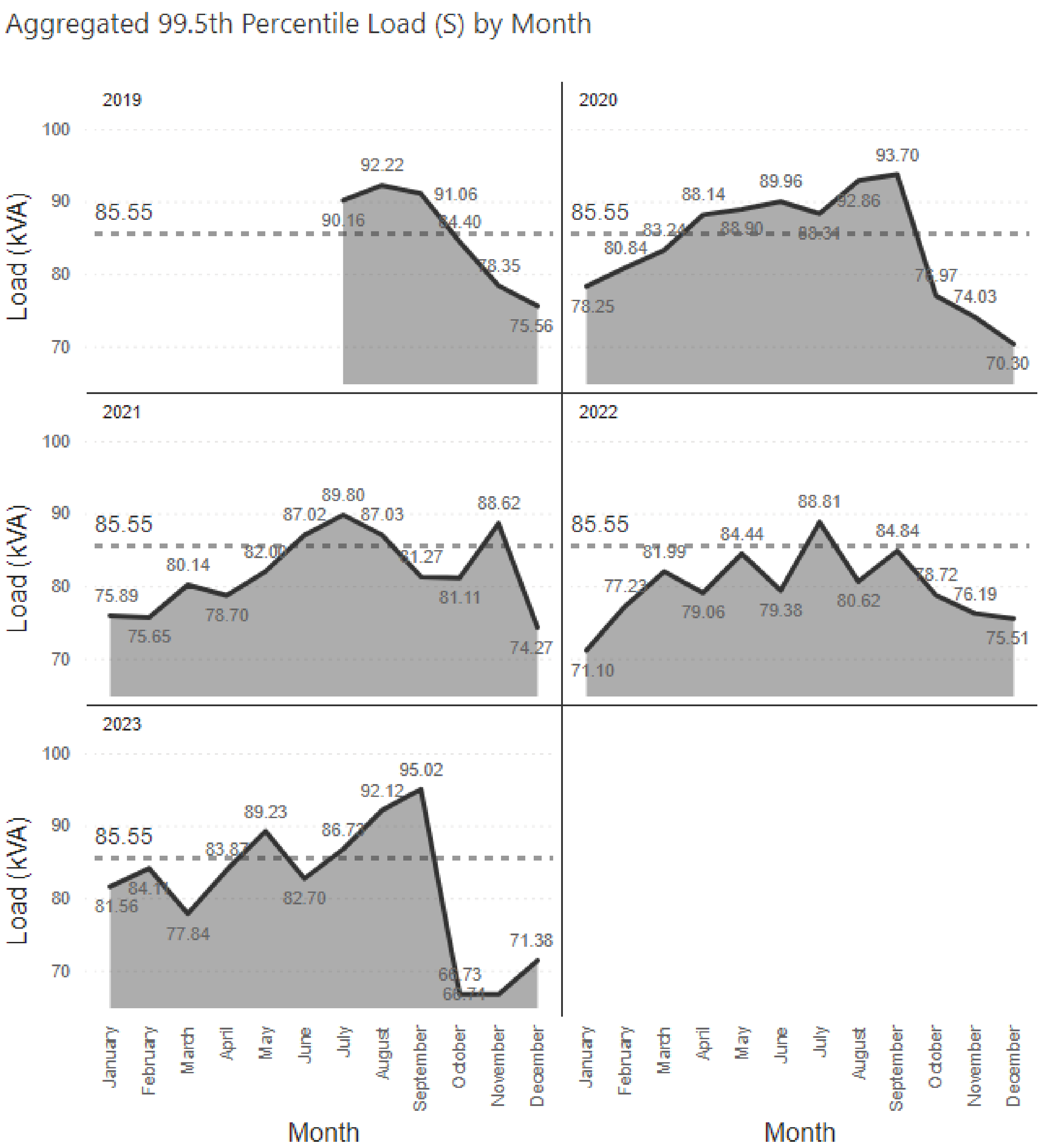


Figure 178: 99.5th Percentile load by each year for Case Study O

Figure 178 provides a detailed breakdown of the 99.5th percentile load by each year, focusing on monthly variations. In 2019, the peak occurred in May at 92.22 kVA, while in 2020, the highest load was observed in September at 93.70 kVA. For 2021, the peak load was in August at 89.80 kVA, and in 2022, the highest load occurred in July at 88.81 kVA. The year 2023 experienced a peak load in September at 95.02 kVA. This analysis reveals that monthly peaks generally occur around mid-year, with varying peak values across the years.

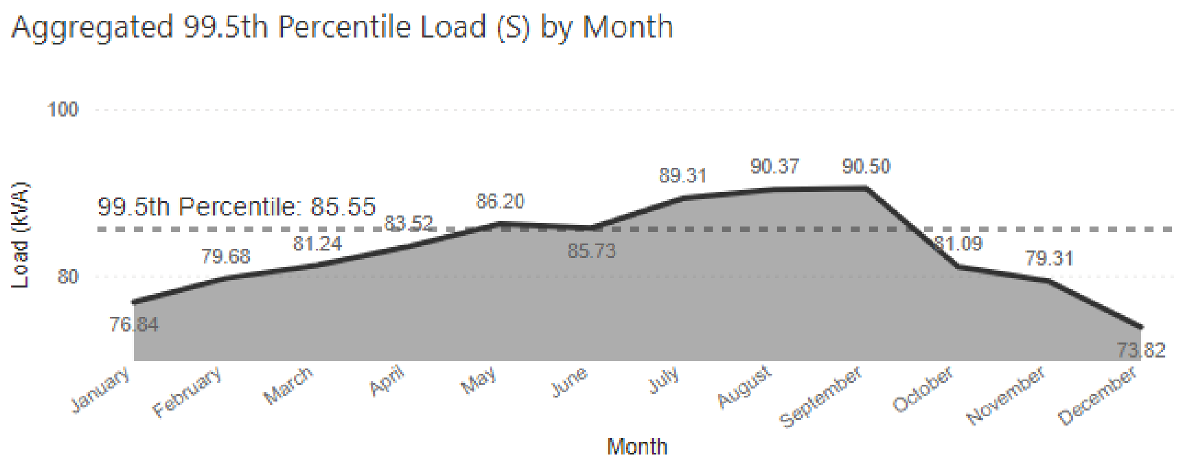


Figure 179: Aggregated 99.5th Percentile load by Month for Case Study O

Figure 179 aggregates the 99.5th percentile load by month across all years, providing a comprehensive view of seasonal demand patterns. The data indicates that loads generally rise from March, peaking in September at 90.50 kVA, and then decline towards December, with the lowest recorded in December at 73.82 kVA. This trend suggests a pattern of higher electricity consumption during mid-year months, possibly due to seasonal factors.

The 99.5th percentile load analysis for Case Study O reveals a declining trend in ADMD patterns, with the 99.5th percentile line serving as the observed ADMD. The data shows a general decrease in peak demand, particularly noticeable from 2019 to 2022, with a slight recovery in 2023. The monthly analysis highlights that peak loads typically occur around mid-year, with the highest peaks varying across different years. These trends underscore the importance of monitoring and adapting to changing demand patterns to ensure reliable electricity supply and efficient infrastructure management. Understanding these variations is crucial for optimising resource allocation and maintaining system stability, especially during peak demand periods.

4.13.3.3 99.5th Percentile Load Analysis: Daily Demand Profiles

The 99.5th percentile load analysis for Case Study O provides a detailed examination of peak electricity demand periods, focusing on the highest consumption levels that occur only 0.5% of the time. This analysis is crucial for understanding extreme usage scenarios, which are essential for infrastructure planning and energy management. By studying these profiles, we can observe both seasonal and daily variations in electricity consumption, offering valuable insights into how demand fluctuates throughout the year and within a typical day.

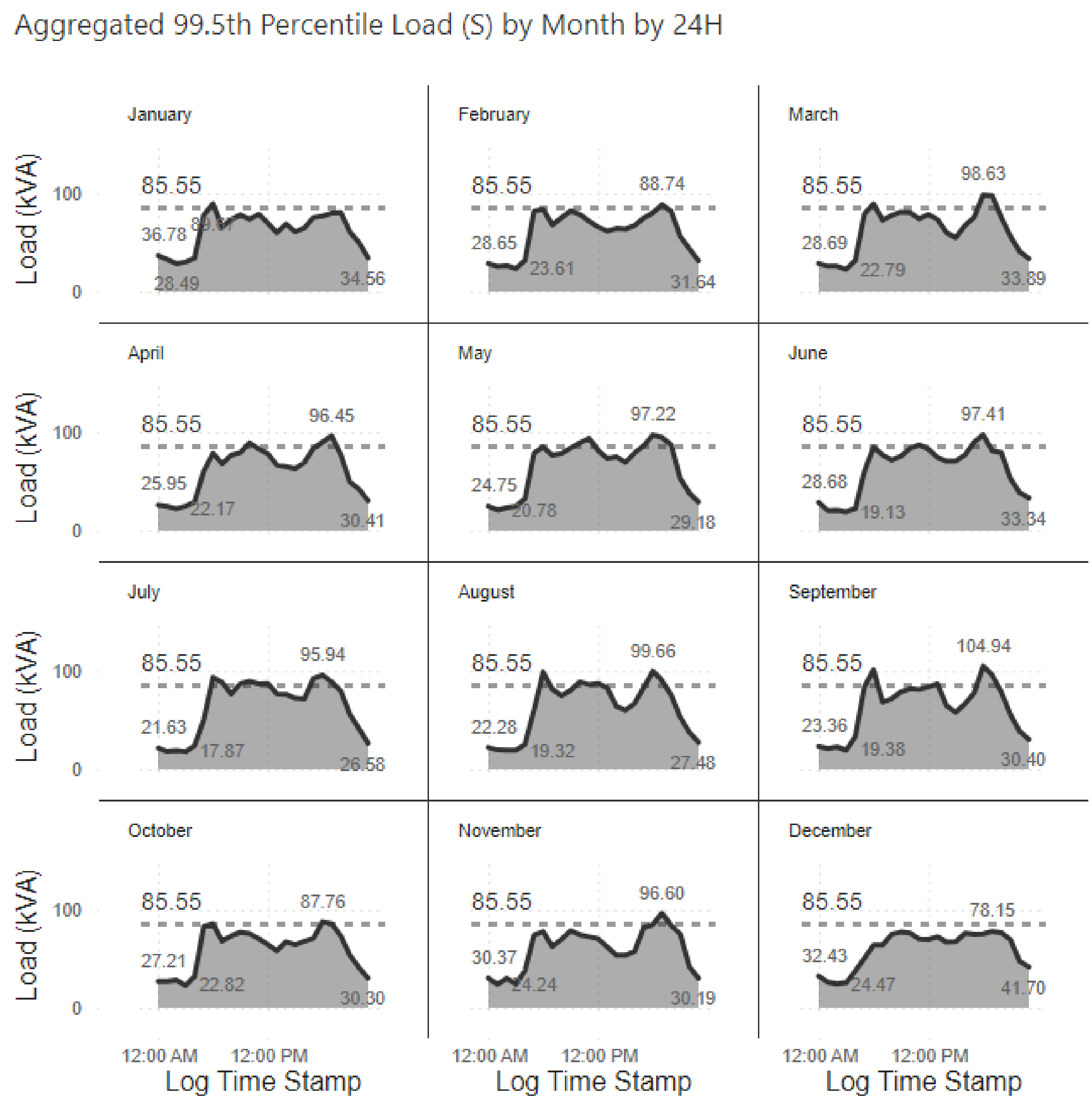


Figure 180: Aggregated 99.5th Percentile load by 24-h day by Month for Case Study O

Figure 180 illustrates the monthly variations in the 99.5th percentile load, highlighting the changes in daily demand peaks across the year. The dashed line at 85.55 kVA marks the 99.5th percentile load threshold. Key observations include:

Winter Months (June - August): These months generally exhibit higher daily peaks, often exceeding the 99.5th percentile line. For instance, June reaches a peak of 97.41 kVA, while July and August show peaks of 95.94 kVA and 99.66 kVA, respectively. These peaks indicate increased energy consumption, likely due to heating needs.

Summer Months (December - February): Demand during these months generally remains below the 99.5th percentile threshold. February shows a peak of 88.74 kVA, and January reaches 85.55 kVA, suggesting moderate energy usage.

Transitional Months (March, September): These months show peaks near or above the 99.5th percentile line, with March reaching 98.63 kVA and September peaking at 104.94 kVA, reflecting variability in energy use during seasonal changes.

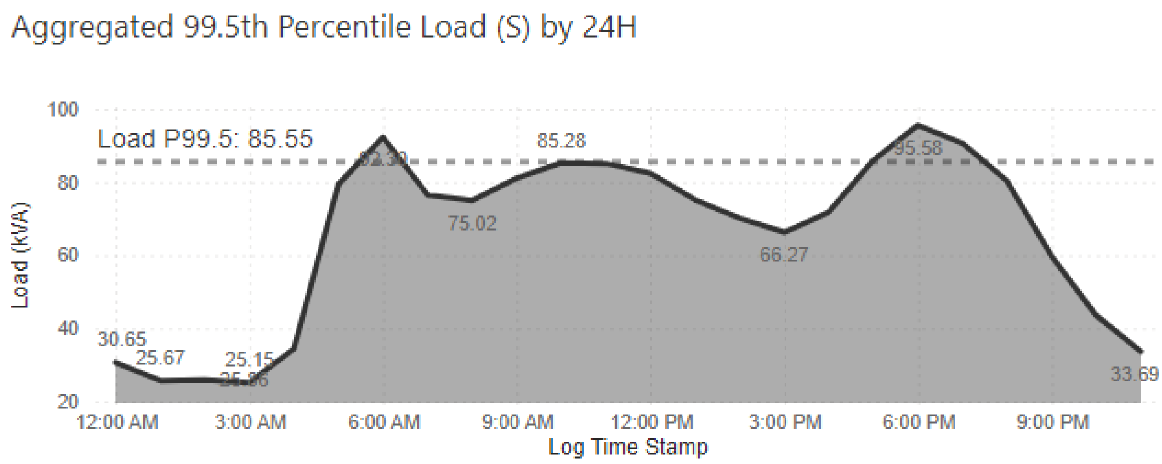


Figure 181: Aggregated 99.5th Percentile load by 24-h day for Case Study O

Figure 181 provides a consolidated view of the daily demand profile over a typical 24-hour period. The 99.5th percentile load line at 85.55 kVA helps identify critical demand periods:

Morning Peak: A noticeable increase in load begins around 3:00 AM, reaching a peak of 85.28 kVA at 6:00 AM. This rise correlates with early morning activities as residents start their day.

Evening Peak: The highest demand occurs around 6:00 PM, with a peak load of 95.58 kVA, reflecting typical residential activities such as cooking and heating.

Off-Peak Periods: The lowest demand occurs late at night and early morning, with the load dropping to around 25.15 kVA, well below the 99.5th percentile threshold.

The 99.5th Percentile Load Analysis for Case Study O highlights significant seasonal and daily variations in electricity demand. The data indicate that peak demands are more pronounced during the winter months, with occasional exceedances of the 99.5th percentile threshold due to increased heating needs. The analysis also emphasises the importance of morning and evening peaks in shaping residential electricity consumption patterns. Understanding these variations is crucial for effective energy infrastructure planning and management, ensuring reliable service during periods of maximum demand.

4.13.4 Proposed ADMD vs Observed ADMD

The purpose of this section is to analyse and compare the proposed After Diversity Maximum Demand (ADMD) values against the observed ADMD values for Case Study O. This comparison is crucial for assessing the accuracy and reliability of the proposed ADMD values from SANS 507-1:2019 in reflecting the actual load profiles of different consumer classes. The outcomes will provide insights into the appropriateness of the standard parameters used for planning and infrastructure development in residential areas.

Summary of Key Metrics

- Total Connections: 164
- Average Age: 23.40 years (greater than 15 years, therefore using Year-15 parameters proposed by SANS 507-1:2019)
- Installed Load: 772.80 kVA (4.71 kVA per connection)
- P99.5 Load: 85.55 kVA (0.52 kVA per Stand)
- Resultant P99.5 Diversity Factor (DF): 0.11

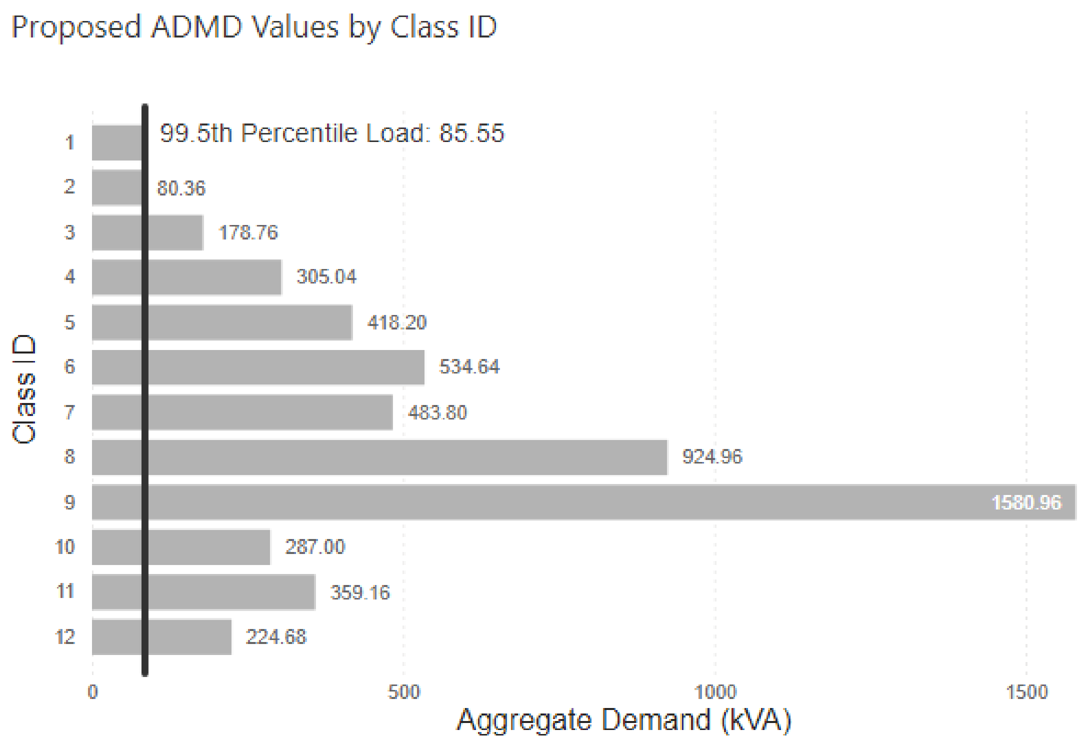


Figure 182: Proposed Year-15 ADMDs result by Class ID for Case Study O

Figure 182 illustrates the proposed Year-15 ADMD values by Class ID for Case Study O. The graph shows significant variations in aggregate demand across different consumer classes, highlighting the discrepancies between the proposed ADMDs and the 99.5th percentile load. Class 9 (Urban Estate) has the highest proposed ADMD value of 1580.96 kVA, which significantly exceeds the 99.5th percentile load of 85.55 kVA. Such differences indicate potential overestimations in the proposed ADMDs for specific classes, suggesting that adjustments may be necessary for more accurate demand projections.

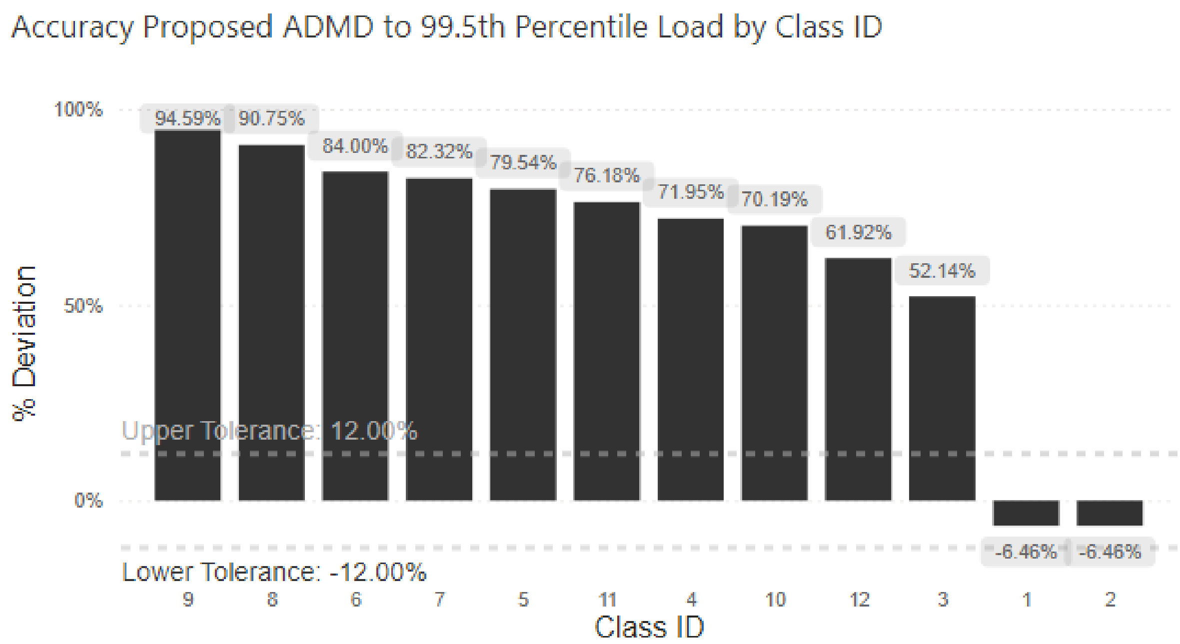


Figure 183: Deviation of SANS 507-1:2019 Year-15 ADMD by Class ID vs. 99.5th Percentile Load for Case Study O

Figure 183 shows the percentage deviation of the proposed Year-15 ADMD values from the 99.5th percentile load for each Class ID. Most consumer classes exhibit positive deviations, indicating that the proposed ADMD values are higher than the measured loads. Class 9 again stands out with a deviation of 94.59%, highlighting a significant overestimation. Conversely, Classes 1 and 2 have negative deviations, suggesting underestimations of their respective ADMDs. This analysis underscores the necessity for refining the proposed ADMD values to better align with actual consumption patterns.

Table 14: Detailed Comparison of Proposed ADMD vs Observed ADMD for Case Study O

ID	Consumer Class	SANS 15 Year ADMD (kVA)	Case SANS 15 Year ADMD (kVA)	Accuracy (%)	Deviation (%)
1	Rural settlement, Non-urban, scattered	0.49	80.36	106.46	-6.46
2	Rural villages	0.49	80.36	106.46	-6.46
3	Informal settlement	1.09	178.76	47.86	52.14
4	Township area	1.86	305.04	28.05	71.95
5	Urban residential I	2.55	418.20	20.46	79.54
6	Urban residential II	3.26	534.64	16.00	84.00
7	Urban townhouse complex or duplex	2.95	483.80	17.68	82.32
8	Urban Townhouse II	5.64	924.96	9.25	90.75
9	Urban Estate	9.64	1580.96	5.41	94.59
10	High-rise (small)	1.75	287.00	29.81	70.19
11	High rise (medium)	2.19	359.16	23.82	76.18
12	Hostel	1.37	224.68	38.08	61.92

Table 14 presents a detailed comparison between the proposed ADMD values and the observed ADMD values for each consumer class in Case Study O. The table highlights the accuracy and deviation percentages, demonstrating significant discrepancies between the proposed and actual values. For instance, Urban Estate (Class 9) shows a high deviation of 94.59%, indicating a substantial overestimation. Conversely, rural settlements (Classes 1 and 2) exhibit minor deviations, suggesting closer alignment with the measured loads.

The comparison of proposed ADMD values against observed ADMD values for Case Study O reveals considerable deviations across various consumer classes. While some classes, such as Urban Estate, show significant overestimations, others, like rural settlements, are relatively accurate. These findings suggest that the proposed ADMD values in SANS 507-1:2019 may require adjustments to reflect actual consumption patterns better, ensuring more precise and reliable infrastructure planning and resource allocation.

Interpretive Note: Case Study O

- Installed base is PPU-dominant. Within PPU, breaker sizes are 20A = 98.78% and 60A = 1.22%.
- Average connection age is 23.40 years. By breaker size: 23.26 years (20A) and 33.10 years (60A), so Year-15 parameters were appropriate.
- Observed ADMD (P99.5) is 85.55 kVA total (0.52 kVA/stand).
- Best fit (exact class ID): Class 1 at 0.49 kVA/stand, about −6.46% relative to the empirical 0.52 kVA/stand. Class 2 at 0.62 kVA/stand overestimates by roughly +19%, and higher classes overshoot by larger margins.

The very high 20A share and mid-20s average ages align with a low-demand regime near 0.5 kVA/stand; within the SANS options, Class 1 shows the least absolute deviation from the measured 99.5th-percentile ADMD and is most consistent with the observed connection composition.

4.14 Overall Discussion of Results

The analysis focuses on identifying the "best-case" Class ID scenario to evaluate the reliability and accuracy of the proposed ADMD values. It is important to note that determining the most appropriate Class ID for each case study is not the objective at this stage. Instead, the discussion centres on whether even the “best-case” Class ID scenario can provide a reliable and accurate ADMD value. Suppose the “best-case” scenario fails to do so. In that case, this suggests a fundamental issue with the proposed values, indicating that further investigation is needed to ensure their applicability and reliability in diverse settings.

4.14.1 Geographic Overview

The case studies selected for this research are strategically distributed across the Free State Province, as shown in Figure 184. This broad geographic distribution provides a comprehensive representation of the research conducted, ensuring that the findings are reflective of the diverse socio-economic and climatic conditions present within the province.

Each case study is located in a distinct area within the Free State Province, with some cases situated within the same townships. This strategic selection allows for a like-for-like comparison of load profiles and connection trends within similar socio-economic environments while also offering insights into the variations that may arise from geographic and climatic differences across the province. The diverse geographic spread includes urban, peri-urban, and rural areas, each with unique economic activities and infrastructure characteristics that influence their specific electricity consumption patterns.

Figure 184 illustrates the geographic distribution of all the case studies, highlighting their locations across the Free State Province. The map visually demonstrates the widespread nature of the study areas, which range from the densely populated townships near Bloemfontein to more remote regions closer to the Lesotho border.

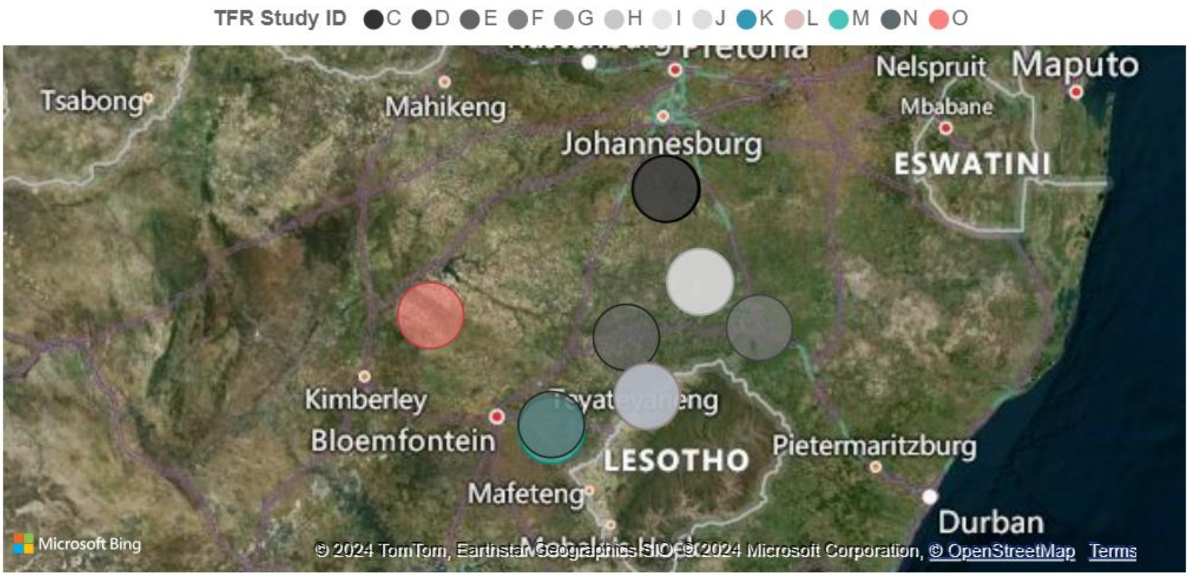


Figure 184: Geographic overview of Case Studies

A wide spatial spread is shown in Figure 184. This geographic spread ensures that the research encompasses a variety of living conditions, infrastructure ages, and connection types, which is essential for a robust evaluation of the proposed After Diversity Maximum Demand (ADMD) values. The inclusion of case studies within the same townships, such as case study C & D, allows for direct comparisons between areas with similar infrastructure but potentially different socio-economic factors or levels of load maturity. This approach strengthens the reliability of the findings by confirming that observed patterns are not merely due to unique local conditions but are instead indicative of broader trends applicable across the Free State Province.

The map shown in Figure 184, underscores the relevance of this research for informing infrastructure planning and policy development across a wide range of contexts within the province. By analysing case studies spread throughout the Free State Province, this research offers valuable insights to enhance the precision of ADMD predictions and optimise the design of electricity distribution networks across the region.

4.14.2 Combined Class ID results by Case Study

Earlier in this chapter, each case study was thoroughly analysed and evaluated, and for each case study, proposed After Diversity Maximum Demand (ADMD) values were derived based on the recommended values of SANS 507-1:2019, categorised by Class ID. These proposed ADMDs were then compared to the 99.5th percentile load from the historical load data recorded. It is crucial to note that this 99.5th percentile load value serves as the actual ADMD, as rationally explained in the research methodology.

To achieve a comprehensive analytical review of the research results, it is beneficial to view the data as a combined result, which provides an easy-to-consume overview. Given the substantial volume of data derived from all the case studies, which involved consideration of 12 Class IDs, the analysis is focused on the four most accurate Class IDs for each case study. This selection process involved combining and ranking the absolute deviation values for all Class IDs from least to most accurate (i.e., lowest deviation), with the top four being further examined in this section of the chapter. This approach simplifies the analytical considerations and makes the results more comprehensible. The abridged results are listed in Table 15 below:

Table 15: Combined Top 4 Class ID with the lowest Deviation by Case Study

TFR Study ID	Class ID 11	Class ID 2	Class ID 3	Class ID 4
C	58.93%	83.56%	17.48%	51.64%
D	55.29%	99.84%	10.16%	47.35%
E	65.88%	82.51%	31.44%	59.92%
F	68.34%	41.52%	36.38%	62.72%
G	53.26%	108.81%	6.10%	44.97%
H	63.50%	63.14%	26.66%	57.02%
I	1.95%	338.21%	99.96%	51.44%
J	64.44%	56.39%	32.64%	71.00%
K	78.84%	3.51%	57.47%	52.73%
L	44.16%	6.09%	79.75%	68.10%
M	72.91%	21.00%	45.57%	68.10%
N	67.64%	44.63%	34.98%	70.14%
O	76.18%	6.46%	52.14%	71.95%

Comparatively, the results listed in Table 15 suggest that very few of the proposed ADMDs fall within the threshold of 12% acceptable deviation. Values highlighted in Table 15 illustrate the cases where the acceptable threshold was not exceeded. This finding implies that the accuracy of the proposed ADMD values is generally low. As a result, there is a growing scepticism regarding the reliability of these proposed values in addressing the research question, particularly when applied to residential distribution networks in the Free State Province.

Moreover, simply identifying whether the deviation exceeds the accuracy thresholds does not sufficiently quantify the overall risks posed by this unreliability. To address this gap, the bar graph illustrated in Figure 185 provides a visual representation aimed at quantifying the overall deviation between the proposed and observed ADMDs.

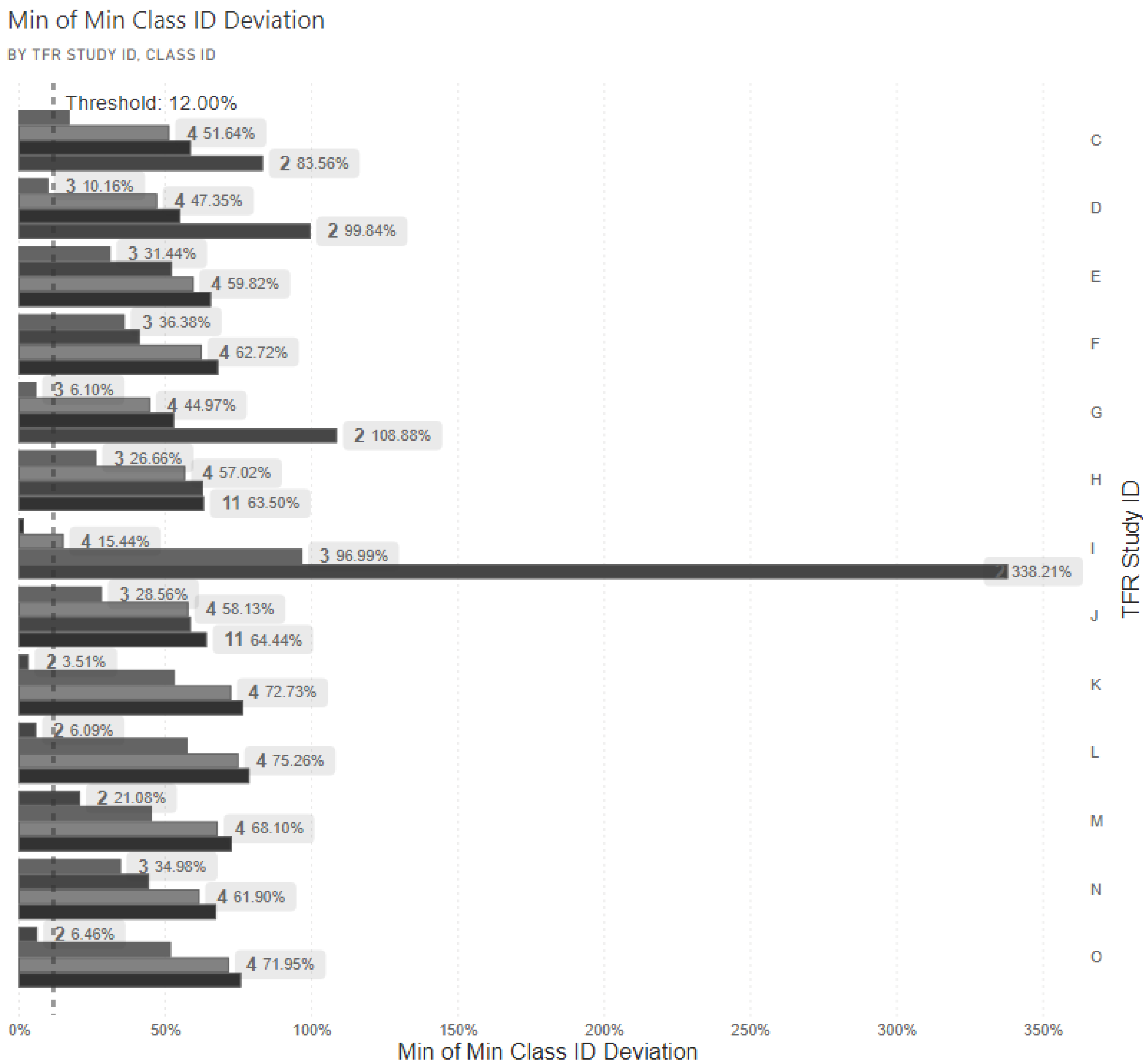


Figure 185: Overall Minimum Deviation Class ID by Case Study

What is evident from Figure 185 is that significant deviations are present across many of the case studies, with some deviations exceeding the acceptable threshold by a considerable margin. This indicates potential issues with the accuracy of the SANS 507-1:2019 recommended values when applied to specific Class IDs within the context of the Free State Province.

The following sections will explore possible underlying patterns or characteristics that may contribute to the significant deviations observed. These analyses will aim to identify the factors driving these discrepancies and offer insights into how the proposed ADMD values could be adjusted or refined to improve their accuracy and reliability.

4.14.3 Impact of Maximum Demand (c) on ADMD accuracy

To identify the underlying reasons for the observed deviations in After Diversity Maximum Demand (ADMD) accuracy, various characteristics of the case studies need to be analysed. One such aspect is the impact that the Notified Maximum Demand (NMD) in amperes (A) may have on the accuracy of the ADMD predictions. In this context, the NMD refers to the breaker size associated with each customer connection, typically categorised as 20A or 60A.

To explore this relationship, the number of customers in each case study is contextualised according to their associated breaker size. By comparing the ratio of the two NMDs present (20A and 60A), quantitative insights can be drawn about how breaker size influences network usage and, consequently, the accuracy of ADMD values for each case study. Figure 186 illustrates this comparison by showing the total number of customers according to their associated breaker size, alongside the Class ID with the minimum deviation, representing the best-case scenario for ADMD accuracy.

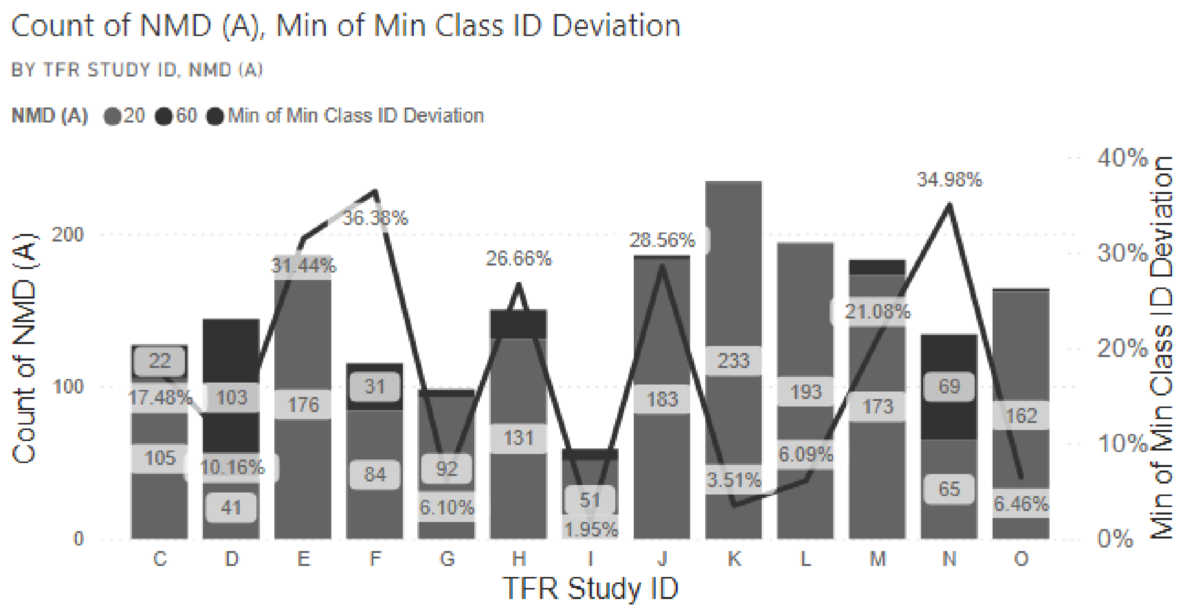


Figure 186: Total Connections by NMD (A) according to Case Study vs Class ID with Min Deviation

From Figure 186, it is evident that the distribution of NMDs (20A vs. 60A) varies significantly across the case studies, and this distribution appears to have a notable impact on the accuracy of ADMD values. For instance, case studies with a higher proportion of 20A connections tend to exhibit different accuracy profiles compared to those with a higher proportion of 60A connections. This suggests that the breaker size, and by extension the network load characteristics, play a crucial role in determining the reliability of ADMD predictions.

Analysis of Figure 186:

High Proportion of 20A Connections: Study cases like K, L, and J, which have a high proportion of 20A connections, show varying levels of ADMD accuracy across different Class IDs. For example, case study K, with a 99.57% ratio of 20A connections, exhibits one of the lowest deviations in Class ID 4 but a relatively higher deviation in Class ID 11.

Mixed NMD Distribution: Study cases like C and F, which have a more balanced distribution between 20A and 60A connections, demonstrate moderate deviations across all Class IDs, suggesting that a mixed NMD distribution may contribute to more consistent but not necessarily minimal deviations.

Predominantly 60A Connections: Study cases like D, which have a higher proportion of 60A connections, show significant deviations, especially in Class IDs with larger consumer groups, indicating potential challenges in accurately predicting ADMD in networks dominated by larger capacity connections.

The data illustrated in Figure 186 is reiterated and expanded on in Table 16, which shows

The top four Class IDs with the lowest deviations according to the NMD distribution by case study.

Table 16: Top four Accuracy Class ID according to NMDs by Case Study

TFR Study ID	20	60	Total	20A vs 60A Ratio	Class ID 11	Class ID 2	Class ID 3	Class ID 4
C	105	22	127	82.68%	58.93%	83.56%	17.48%	51.64%
D	41	103	144	28.47%	55.29%	99.84%	10.16%	47.35%
E	176	10	186	94.62%	65.88%	52.51%	31.44%	59.82%
F	84	31	115	73.04%	68.34%	41.52%	36.38%	62.72%
G	92	6	98	93.88%	53.26%	108.88%	6.10%	44.97%
H	131	19	150	87.33%	63.50%	63.14%	26.66%	57.02%
I	51	8	59	86.44%	1.95%	338.21%	96.99%	15.44%
J	183	3	186	98.39%	64.44%	58.93%	28.56%	58.13%
K	233	1	234	99.57%	76.84%	3.51%	53.47%	72.73%
L	193	1	194	99.48%	78.99%	6.09%	57.79%	75.26%
M	173	10	183	94.54%	72.91%	21.08%	45.57%	68.10%
N	65	69	134	48.51%	67.64%	44.63%	34.98%	61.90%
O	162	2	164	98.78%	76.18%	6.46%	52.14%	71.95%

From Table 16, it is evident that the NMD distribution significantly impacts the accuracy of ADMD predictions for different Class IDs. Study cases with a higher ratio of 20A connections, such as K, L, and M, tend to show more consistent and lower deviations in their top four Class IDs. Conversely, case studies with a more balanced or skewed distribution towards 60A connections, such as D and N, exhibit greater variability and higher deviations.

In conclusion, this analysis highlights the strong relationship between the distribution of NMDs (20A vs. 60A) and the accuracy of Class ID-based ADMD predictions. The findings suggest that areas with a higher proportion of smaller capacity connections (20A) are more likely to achieve accurate ADMD predictions. In contrast, areas with a significant number of larger capacity connections (60A) may face challenges in attaining similar levels of accuracy. These insights emphasise the need for tailored ADMD prediction models that account for the specific NMD distributions within residential networks, particularly in the context of diverse socio-economic and geographic environments like those found in the Free State Province.

4.14.4 Impact of Connection Age on Accuracy

It is known that load consumption behaviours change over time, as is demonstrated by load growth and maturity, as established in Chapter 2. Accordingly, we consider how load maturity (i.e., connection age) may affect ADMD prediction accuracy. A visual representation to identify any underlying patterns is provided in Table 17 and Figure 187. Figure 187 is a scatter chart of average connection age (years) versus the minimum deviation (percent) for the best-fit Class ID per case.

Table 17: Average Age of Connections vs Minimum Deviation by Case Study

TFR Study ID	Average of Age	Minimum Class ID Deviation
C	31	17.48%

D	31	10.16%
E	21	31.44%
F	27	36.38%
G	25	6.10%
H	27	26.66%
I	28	1.95%
J	21	28.56%
K	17	3.51%
L	18	6.09%
M	21	21.08%
N	21	34.98%
O	23	6.46%

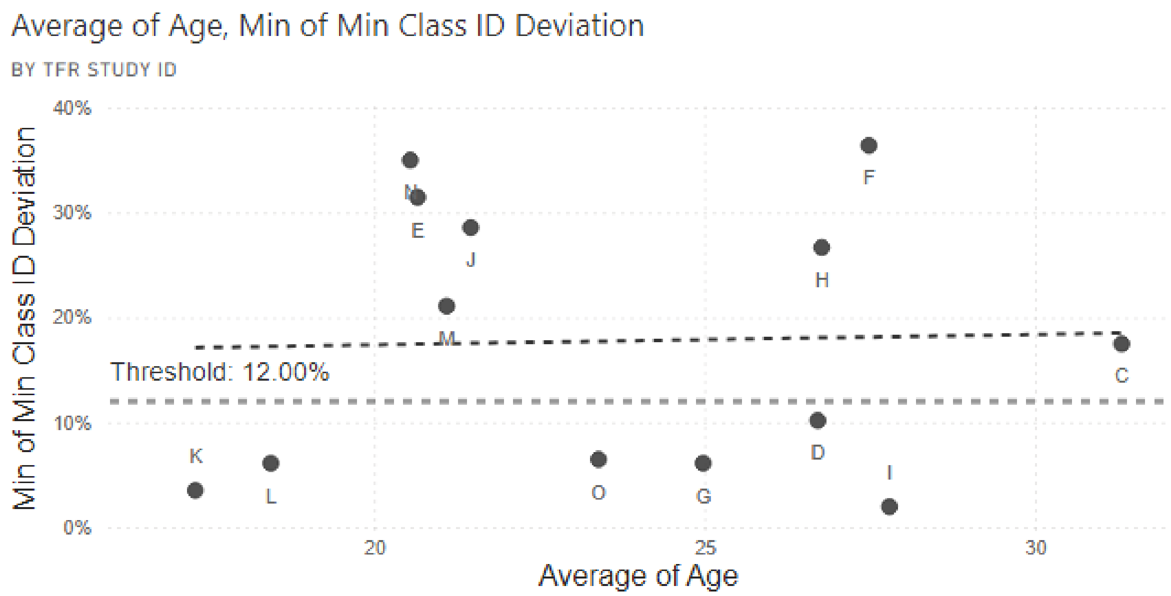


Figure 187: Average connection age by case vs minimum Class-ID deviation

Visual inspection shows no single functional relationship (e.g., linear, S-curve, hyperbolic) between age and deviation.

The threshold line at 12% deviation highlights the acceptable range for ADMD accuracy, providing a benchmark for evaluating the performance of different case studies. Figure 187 and Table 17. Together, they summarise the relationship between connection age and ADMD accuracy.

Some older cases exhibit higher deviations in ADMD accuracy, while others remain low. This trend is particularly evident in case studies such as C and F, where the average age of connections is 31 and 27 years, respectively. As shown in Table 17-C is 17.48% and F is 36.38%. This pattern suggests that older connections may not align as well with the proposed ADMD values, potentially due to changes in consumption patterns, ageing infrastructure, or other factors that have evolved since these connections were established.

In contrast, case studies with newer connections, such as K and L (17 and 18 years), show significantly lower deviations: 3.51% and 6.09%, respectively. These are well below the 12% threshold (Table 17). This indicates that the proposed ADMD values are more accurate for newer infrastructure, likely because these connections are more representative of current consumption trends and thus more compatible with the proposed standards.

However, the results are more varied for case studies with mid-aged connections, typically aged between 20And 25 years, such as E, G, and M. According to Table 17, these cases exhibit a range of deviations: G shows a relatively low deviation of 6.10% despite having a mid-aged average connection age of 25 years, while E and M have higher deviations of 31.44% and 21.08%, respectively. This variability suggests that other factors, such as socio-economic conditions, specific load profiles, or management practices, may also play significant roles in influencing ADMD accuracy in these instances.

Additionally, there are notable outliers in the data. For example, case study I, despite having an average connection age of 28 years, displays a low deviation of 1.95%, as noted in Table 17. This indicates that certain factors may mitigate the expected increase in deviation with age. These factors could include effective load management or specific socio-economic characteristics unique to that area. Similarly, case study D shows a relatively low deviation of 10.16%, just below the 12% threshold, despite having an average connection age of 31 years, suggesting that age alone is not the sole determinant of ADMD accuracy.

Conclusion
Across cases, connection age is not a reliable predictor of ADMD accuracy, deviations vary widely at similar ages. Age should be treated as a modifier alongside breaker-size mix, connection type/eligibility, settlement context, and seasonal/diurnal behaviour, rather than as a standalone driver.

4.14.5 Statistical analysis of the Impact of Historical Load Characteristics on Accuracy

Building on the previous discussions, it is essential to extend our analysis to the statistical characteristics that represent historical load patterns, specifically concerning their impact on the accuracy of proposed After Diversity Maximum Demand (ADMD) values. The primary goal of this consideration is to identify any underlying statistical factors that correlate with the deviation accuracy of the proposed ADMDs. By analysing these factors, we aim to understand better the reliability of the Beta Probability Density Function (PDF) and the SANS 507-1:2019 standard in forecasting residential electricity demands in various case studies.

Table 18 which outlines key statistical measures of historical load profiles across different case studies, provides the foundation for this analysis. The table includes essential metrics such as the average load (kVA), median load (kVA), standard deviation of load (kVA), minimum and maximum load (kVA), the 99.5th percentile load (kVA), and the minimum Class ID deviation for each case study. These metrics are visually represented in Figure 188 as violin plots, which graphically depict the distribution and variability of the load data, highlighting the key statistical indicators.

Table 18: Statistical Analysis of Historical Load by Case Study

Case Study	Average of S Load (kVA)	Median of S Load (kVA)	Standard deviation of S Load (kVA)	Min of S Load (kVA)	Max of S Load (kVA)	Load P99.5 (kVA)	Min of Class ID Deviation
C	54.70	52.24	20.35	3.08	153.04	115.13	17.48%
D	61.21	58.82	25.49	1.05	210.85	142.96	10.16%
E	64.28	62.08	25.53	1.35	240.13	139.74	31.44%
F	36.76	35.52	15.23	1.50	107.02	79.74	36.38%
G	47.95	46.44	17.34	1.16	129.29	100.30	6.10%
H	54.52	52.01	21.98	1.01	149.56	119.91	26.66%
I	50.79	47.22	21.98	1.00	161.40	144.84	1.95%

J	65.43	64.02	27.42	1.00	195.49	144.84	28.56%
K	62.31	62.78	21.16	1.16	177.97	118.68	3.51%
L	41.15	39.87	18.38	1.04	123.00	89.26	6.09%
M	51.82	51.63	22.31	1.00	146.03	109.16	21.08%
N	44.29	44.53	17.70	1.00	146.28	95.67	34.98%
O	43.18	43.44	16.18	1.04	117.63	85.55	6.46%

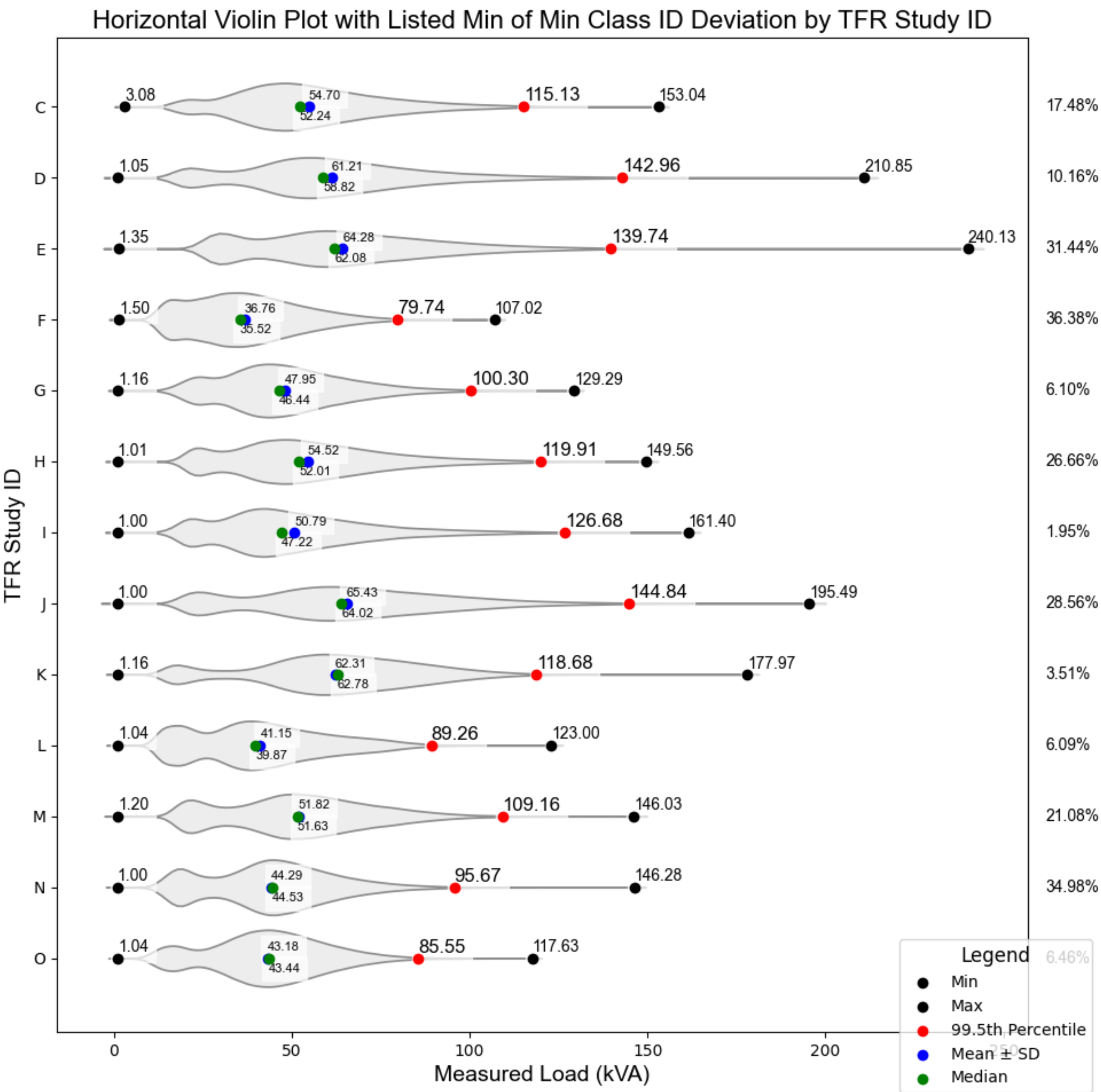


Figure 188: Load Profiles Violin Plots vs Min Deviation

The violin plots in Figure 188 offer a detailed visual representation of the load distributions across different case studies. Each plot highlights the spread and central tendency of the load data, with key statistical markers such as the minimum (Min), maximum (Max), 99.5th percentile load (P99.5), mean, and median values indicated. The inclusion of these markers allows for a nuanced comparison between the different case studies and their corresponding ADMD deviations.

From Figure 188, there is significant variability in the load profiles across different case studies, as indicated by the spread and shape of the violin plots. The range between the minimum and maximum measured loads varies substantially among the case studies, reflecting differences in electricity consumption patterns within each area. For instance, Case Study C shows a broad spread from a minimum of 3.08 kVA to a maximum of 153.04 kVA, highlighting a considerable variation in load demands. On the other hand, Case Study O has a narrower distribution range, with measured loads spanning from 43.18 kVA to 117.63 kVA, suggesting more consistent demand within that area.

The 99.5th percentile load (red dots) provides a benchmark for peak demand scenarios, and its position varies between case studies, demonstrating how peak demands are not uniform across the different geographic or socio-economic contexts. For example, the 99.5th percentile load for Case Study J is 144.84 kVA, which is relatively high compared to the more modest 99.5th percentile load of 85.55 kVA for Case Study O.

The mean and median values also differ across the case studies, providing insight into the central tendencies of the data. Case Study F, for instance, has a lower median (36.76 kVA) compared to Case Study J (65.43 kVA), indicating a lower typical load in the former compared to the latter. This difference could be attributed to varying socio-economic conditions, infrastructure, and consumption behaviours within these areas.

Furthermore, the “Min of Min Class ID Deviation” percentages on the right of each plot reveal how much the minimum load deviates from the predicted ADMD values, with higher percentages indicating greater deviation. Case Study F shows the highest deviation (36.38%), suggesting that its load profile is less predictable or more variable compared to others like Case Study K, which has a much lower deviation (3.51%).

Overall, Figure 188 illustrates the diversity of load profiles across the case studies, emphasising the importance of context-specific approaches when predicting After Diversity Maximum Demand (ADMD) values. This variability underscores the potential need for adjustments or alternative modelling techniques, such as the Beta Probability Density Function, to improve the accuracy of load predictions in different socio-economic and geographic environments.

1. Load Variability and Deviation Correlation:

Case Study C: This case study shows a broad distribution of load values, with a minimum load of 3.08 kVA and a maximum of 153.04 kVA. The 99.5th percentile load is 115.13 kVA, slightly below the maximum but still significantly higher than the median and mean values. The deviation of 17.48% suggests that this high variability may lead to challenges in accurately predicting ADMD using standard values.

Case Study I: In contrast, case study I demonstrates a narrower load distribution with a minimum of 1.00 kVA and a maximum of 161.40 kVA. The 99.5th percentile load is close to the maximum, at 144.84 kVA, and aligns well with the mean and median values. This consistency is reflected in the low deviation of 1.95%, indicating that a more stable load profile leads to more reliable ADMD predictions.

2. Impact of Extreme Values:

Case Study E: The presence of extreme values, such as the maximum load of 240.13 kVA in case study E, appears to significantly impact the deviation, which is recorded at 31.44%. This suggests that the ADMD values may not fully capture the effects of outliers in load data, leading to greater deviations from the expected values.

Case Study F: Similarly, case study F exhibits a relatively high deviation of 36.38%, with a wide range of load values from 1.50 kVA to 107.02 kVA. The spread of the load distribution, as seen in the violin plot, indicates that the presence of both low and high extremes within the load profile contributes to the challenges in achieving accurate ADMD predictions.

3. Consistency in Low Deviation Cases:

Case Study K: This case study shows a high degree of consistency, with the load distribution tightly clustered around the mean and median values. The minimum deviation of 3.51% reflects this stability, suggesting that consistent load profiles with minimal extreme values are more conducive to accurate ADMD predictions.

The statistical analysis of historical load characteristics, as presented in Table 17 and Figure 188, reveals significant correlations between the distribution of load values and the accuracy of ADMD predictions. Study cases with high variability and extreme values tend to exhibit higher deviations, indicating that the proposed ADMD values may not fully account for the complexities of these load profiles. Conversely, case studies with more consistent load distributions and fewer outliers tend to achieve lower deviations, demonstrating the importance of stability in load data for reliable ADMD predictions.

These findings underscore the need for a more tailored approach to ADMD predictions, one that considers the unique load characteristics of each case study. By incorporating statistical analyses into the ADMD prediction process, it may be possible to enhance the accuracy and reliability of these values, particularly in networks with diverse load profiles.

From Figure 188, there is a noticeable variation in the load distribution characteristics across different case studies, which in turn influences the accuracy of the proposed ADMD values. For instance, case studies like C, E, and F, with higher standard deviations and maximum load values, tend to exhibit greater deviations in their proposed ADMD values. This suggests that higher variability in load profiles, as indicated by standard deviation, could be a significant factor contributing to the reduced accuracy of ADMD predictions.

Conversely, case studies like G, K, and O, which show lower standard deviations and more consistent load profiles, tend to have lower deviations in their proposed ADMD values. This consistency implies that in areas where load demands are more stable and predictable, the SANS 507-1:2019 standard and the Beta PDF are more reliable in forecasting electricity demands.

In conclusion, the statistical analysis presented in Table 18 and Figure 188 highlights the critical role that historical load characteristics play in determining the accuracy of proposed ADMD values. The analysis suggests that areas with more volatile load profiles, characterised by higher standard deviations and larger ranges between minimum and maximum loads, are more likely to experience inaccuracies in ADMD predictions. These findings underscore the need for a more nuanced application of ADMD standards, considering the specific load characteristics of each area to improve the reliability of demand forecasts and infrastructure planning.

4.14.6 Conclusion of the overall results

The comprehensive analysis presented in Section 4.15 provides critical insights into the factors influencing the accuracy of After Diversity Maximum Demand (ADMD) predictions across various case studies in the Free State Province. The findings reveal that the reliability of the proposed ADMD values, as stipulated by SANS 507-1:2019, is significantly impacted by several key factors, including the geographic distribution of case studies, the ratio of connection capacities (20A vs. 60A), the age of connections, and the statistical characteristics of historical load profiles.

Firstly, the geographic overview demonstrated that the distribution of case studies across diverse regions in the Free State Province affects ADMD accuracy. Study cases located in areas with consistent load profiles and lower socio-economic diversity tend to exhibit more accurate ADMD predictions. Conversely, areas with complex socio-economic characteristics and greater geographic variability face challenges in aligning with the proposed ADMD values.

The impact of connection capacities (NMDs) on ADMD accuracy was also evident, particularly in case studies with a higher proportion of 20A connections, which generally showed better alignment with the proposed ADMD values. This suggests that smaller capacity connections are more predictable in terms of load demands, resulting in lower deviations from the expected ADMD.

Furthermore, the analysis highlighted the importance of connection age, with newer connections generally showing better ADMD accuracy. This finding emphasises the need to consider the temporal aspect of infrastructure when applying ADMD standards, as older connections may not reflect current consumption patterns.

Finally, the statistical analysis of historical load characteristics provided a deeper understanding of how load variability and extreme values influence ADMD accuracy. Study cases with higher variability in load profiles, indicated by larger standard deviations and extreme maximum load values, tend to have greater deviations in their ADMD predictions. This suggests that the proposed ADMD values may require adjustments in areas with more volatile load demands to ensure more accurate and reliable forecasts.

In conclusion, the overall results underscore the complexity of accurately predicting ADMD in regions with diverse infrastructure characteristics. While the SANS 507-1:2019 standard provides a valuable framework, its application must be tailored to account for specific geographic, socio-economic, and load-related factors. Such a tailored approach will enhance the reliability of ADMD predictions, thereby improving the planning and management of electrical infrastructure in the Free State Province.

4.15 Results Summary

Chapter 4 presented a comprehensive analysis of the case studies to evaluate the accuracy of the proposed After Diversity Maximum Demand (ADMD) values against the observed ADMD values. The findings revealed significant discrepancies, particularly in the higher Class IDs, where ADMD values were substantially overestimated. This overestimation aligns with expectations based on the case studies, which do not closely correspond with the higher Class IDs, especially when considering the associated Living Standards Measure (LSM) descriptions outlined in SANS 507-1:2019. The actual socio-economic conditions of the study areas do not align well with the higher LSM-based Class IDs, leading to projections that do not accurately reflect real-world consumption patterns.

Additionally, the analysis highlighted that lower Class IDs might be somewhat underestimated, further underscoring the need for a more nuanced approach in setting ADMD standards. The overall results suggest that the current classification criteria within SANS 507-1:2019 may need to be revisited to ensure that ADMD values are more accurately aligned with the specific characteristics and consumption behaviours of different residential areas. Refining these standards would lead to better-informed infrastructure planning that is more reflective of actual demand, particularly in diverse socio-economic contexts.

Chapter 5 will build upon these findings by discussing the broader implications for electrical infrastructure planning and design. It will explore potential gaps in the current standards, propose areas for improvement, and suggest future research directions. Furthermore, Chapter 5 will focus on the practical applications of the study's findings and their relevance to policymakers, utility companies, and researchers, aiming to contribute to the development of more accurate and reliable electrification models that better serve varied socio-economic environments.

4.16 Chapter 4 Conclusion

Chapter 4 presented the empirical ADMD results and evaluated their alignment with the SANS 507-1:2019 diversified demand expectations. The findings demonstrated where measured diversified demand aligns with the standardised values and where contemporary consumption patterns diverge across socio-economic groups and breaker sizes. By interpreting these differences in the context of the Beta-distribution-derived parameters underpinning the SANS ADMD tables, the analysis provides insight into the representativeness and limitations of the standard within modern residential electrification contexts. These findings form the basis for the concluding synthesis in Chapter 5.

Chapter 5 — Results Discussion and Conclusion

Chapter 5 delves into a comprehensive discussion of the results presented in Chapter 4, exploring their implications for electrical infrastructure planning and design in the context of South Africa's diverse socio-economic landscape. Building on the identified discrepancies between the proposed and measured After Diversity Maximum Demand (ADMD) values, this chapter critically examines potential gaps in the current SANS 507-1:2019 standards and offers recommendations for their refinement. The discussion is framed around the practical applications of these findings for policymakers, utility companies, and researchers, aiming to develop more accurate and adaptable electrification models. Finally, the chapter concludes by highlighting key insights from the study, suggesting future research directions, and underscoring the importance of a more tailored approach to infrastructure planning that reflects the real-world complexities of different residential areas.

5.1 Introduction

This chapter interprets and discusses the findings presented in Chapter 4 In relation to the research objectives outlined in Chapter 5. The primary aim of this research was to evaluate the accuracy and reliability of the Beta Probability Density Function (PDF) in predicting residential load profiles, particularly in the context of the proposed After Diversity Maximum Demand (ADMD) values in SANS 507-1:2019. Here, we explore the implications of these findings for the planning and design of electrical distribution networks, especially in socio-economically diverse regions like the Free State Province.

The discussion begins with an analysis of the results, focusing on the alignment between the proposed ADMD values and the measured data across different case studies. This is followed by a comparison with existing literature to situate the findings within the broader context of load forecasting models and standards. The focus then shifts to examining the implications of the results for SANS 507-1:2019, proposing potential revisions and emphasising practical applications in infrastructure planning and policymaking.

Additionally, the chapter addresses the limitations of the study, considering both data quality and methodological constraints, and provides recommendations for future research to refine load forecasting methods further. Concluding with a summary of the study's contributions to the field and final reflections on the significance of the findings.

5.2 Interpretation of Findings

The results presented in Chapter 4 provide a detailed comparison between the proposed After Diversity Maximum Demand (ADMD) values in SANS 507-1:2019 and the observed ADMD (Q0.995) across Free State case studies. This section interprets these findings by examining alignment with real-world data, identifying patterns and deviations, and considering plausible drivers of discrepancies. In doing so, it evaluates the practical applicability of the Beta probability density function (PDF) across socio-economic contexts and highlights where revisions or context-specific adjustments may be warranted.

5.2.1 Development of SANS 507-1:2019 proposed ADMD values

The SANS 507-1:2019 residential ADMD values were derived from historical electrification datasets compiled across central South Africa and related regions. The underlying studies grouped customers by consumer class/settlement type and connection maturity (e.g., Year-0 vs Year-15 after connection), with a regional split (e.g., coastal vs interior) where warranted by observed variance. For each grouping, diversified load data were normalised and analysed to characterise typical upper-tail demand.

Modelling approach

- A Beta probability density function (PDF) was adopted to represent bounded, skewed residential demand.

- Shape parameters (α, β) were estimated per consumer class and connection-age band; parameter sets were published in the standard.
- From the fitted Beta distributions, diversified demand curves and tabulated ADMD values (per connection/“per stand”) were produced for each class/age/region combination.
- The standard reports regional variants (e.g., coastal vs interior) where empirical differences were material, and provides class-specific values aligned to recognised settlement/consumer categories.

What the published tables provide

- Per-stand ADMD values by consumer class and connection maturity (with regional notes where applicable).
- Guidance for selecting the appropriate class based on settlement characteristics and known diversity effects.
- Illustrative curves (e.g., adoption/load-growth S-curves) to contextualise maturation effects.

Assumptions and limits (context for this study).

- Parameter sets reflect the period and places from which the historical data were drawn; representativeness may drift as behaviour, appliance ownership, and settlement formality evolve.
- Class assignment presumes eligibility by connection type/size and settlement profile; using an inapplicable class can bias planning.
- Regional adjustments (e.g., coastal vs interior) are coarse-grained and may not capture intra-provincial variation.

Implication for the present work.
In this dissertation, we do not re-estimate Beta parameters. Instead, we take the published SANS values as the reference and compare them with observed ADMD operationalised as $Q_{0.995}$ (99.5th-percentile load) for Free State cases, reporting percent deviations and coverage within ±12%. Where deviations are systematic, we indicate where context-specific adjustment may be warranted.

5.2.2 Analysis of Results

The results presented in Chapter 4 were derived from a detailed analysis of 13 case studies, each representing different residential distribution zones within the Free State Province townships. This comprehensive analysis considered several key factors, including the geographical context, surrounding economic activities, the nature of the connection base (classified by tariff or consumer type), the maximum demand limits associated with these connections, and the maturity of the base load, as reflected in the age of the connections.

To gain a thorough understanding of electricity demand within these zones, historical load profiles were examined by analysing load behaviours over time and deriving a rational, retrospective ADMD parameter that accurately reflects the measured historical load. A 99.5th percentile analysis was employed to establish this rational ADMD, ensuring that the derived values represent a reliable indicator of peak demand under typical conditions.

After determining the rational observed ADMD, a comparative analysis was conducted. This involved calculating the proposed ADMD for each Class ID as specified in SANS 507-1:2019. The proposed ADMD values were calculated by multiplying the per-connection ADMD values for each Class ID by the total number of connections in each case study, allowing for a direct comparison between the proposed ADMDs for each Class ID and the observed ADMD.

The analysis focused on identifying the Class ID that showed the least deviation from the observed ADMD, indicating the most accurate proposed ADMD for each case study. By examining these deviations across all 13 case studies, a meta-analysis was performed to identify general patterns and draw broader conclusions about the accuracy and reliability of the proposed ADMD values in different socio-economic and geographical contexts.

5.2.2.1 Key Findings and Implications

The findings from Chapter 4 suggest several critical insights:

Geographical and Socio-Economic Influences:
The accuracy of the proposed ADMD values varied significantly across different geographical regions and socio-economic contexts. In areas with older, more established infrastructure, the proposed ADMD values are closely aligned with the measured values. In contrast, areas experiencing rapid development or significant socio-economic changes showed greater deviations, suggesting that the proposed ADMD values may not fully capture the complexities of these evolving areas.

Impact of Connection Base and Load Maturity:
The type of connections (e.g., Prepaid Units (PPU) vs. Small Power Users (SPU)) and the maturity of the load base also influenced the accuracy of the proposed ADMD values. Areas with a higher proportion of PPU connections and less mature load bases often exhibited greater discrepancies between proposed and observed ADMD values. This indicates that the SANS 507-1:2019 standard may need to consider additional factors, such as connection type and load maturity, to improve its predictive accuracy.

Reliability of the Beta PDF Model:
The Beta Probability Density Function (PDF) model, which underpins the proposed ADMD values in SANS 507-1:2019, generally provided a reasonable approximation of residential load profiles. However, its reliability was more consistent in areas with stable socio-economic conditions and less so in regions undergoing rapid change. This suggests that while the Beta PDF model is a valuable tool, its application may require adjustments or supplementary data in dynamic environments.

General Patterns and Conclusions:
The meta-analysis across all case studies revealed that the proposed ADMD values are generally reliable but may require periodic re-evaluation and adjustment, particularly in areas experiencing significant socio-economic shifts or infrastructure changes. The current approach, while robust, could benefit from a more nuanced application that accounts for regional and contextual factors.

Overall Conclusion:
Overall, the findings from Chapter 4 suggest that while the SANS 507-1:2019 proposed ADMD values provide a solid foundation for electrical network planning, their accuracy is not uniform across all contexts. The results indicate a need for ongoing assessment and potential revision of the standard, especially in regions undergoing rapid socio-economic development or other significant changes. By incorporating a more flexible approach that considers the unique characteristics of different areas, the SANS standard could enhance its predictive accuracy and continue to serve as a reliable guide for infrastructure planning and design.

5.2.3 Comparison with Literature

This section situates the study's findings within the broader context of existing research on load forecasting and the use of statistical models, particularly the Beta Probability Density Function (PDF) as outlined in SANS 507-1:2019. By comparing the study's results with previous research, we assess the alignment, strengths, and limitations of the Beta PDF model in predicting residential load profiles under diverse socio-economic conditions. This comparison not only reinforces the relevance of the current study's findings but also identifies areas where the research challenges or complements established knowledge, providing insights for future improvements in load forecasting models and standards.

Alignment and Divergence with Existing Research

The study's findings generally align with the literature that supports the use of statistical models like the Beta PDF for predicting residential electricity demand. Studies have recognised the Beta PDF's flexibility in modelling a wide range of distribution shapes and capturing typical load behaviours in stable socio-economic conditions. This research supports these perspectives, confirming that the Beta PDF is practical in regions with consistent socio-economic and infrastructure characteristics.

However, the findings also reveal notable divergences from established models, particularly in regions undergoing rapid socio-economic change or with diverse socio-economic profiles. While the literature on load forecasting emphasises the adaptability of models to evolving consumption patterns, it considers factors like technology adoption, economic shifts, and demographic changes. The study suggests that the Beta PDF, although generally reliable, may require further calibration or the inclusion of additional variables to account for dynamic conditions. This aligns with recent studies advocating for more adaptive forecasting approaches that integrate regional and temporal variability.

Key Themes in Comparison

Accuracy and Reliability of Load Forecasting Models: Numerous studies emphasise the need for context-sensitive models that consider socio-economic factors, climate variability, and consumer behaviour. This study corroborates these findings, demonstrating that the Beta PDF's accuracy varies significantly with geographic and socio-economic context, aligning with calls for regular updates and contextual adjustments.

Application of Beta PDF in Different Contexts: The literature recognises the Beta PDF's adaptability but also notes its effectiveness depends on regional characteristics like infrastructure maturity and socio-economic status. This study confirms that the Beta PDF is most accurate in stable, mature regions but less reliable in rapidly changing environments, underscoring the importance of regional adaptation.

Evolution of ADMD Values Over Time: Research highlights the need for periodic reassessment of ADMD values in response to changing technology, consumer behaviour, and economic conditions. The study's findings suggest that the ADMD values in SANS 507-1:2019, based on historical data, may not fully capture recent shifts, aligning with the literature's recommendations for continuous monitoring and updating.

Socio-Economic and Climate Factors in Load Forecasting: The literature consistently emphasises integrating socio-economic and climate factors to enhance model accuracy. This study reinforces this argument, showing significant variations in ADMD values across different contexts and suggesting that SANS 507-1:2019 could benefit from incorporating more detailed socio-economic and climatic data.

Implications for Policy and Standards Development: Accurate load forecasts are crucial for efficient infrastructure investments, as highlighted in the literature. The study supports the need for adaptable standards like SANS 507-1:2019 to accommodate dynamic socio-economic and environmental factors, aligning with the literature's call for policies that can respond to changing conditions.

Implications for SANS 507-1:2019

The comparison with existing literature underscores potential gaps in SANS 507-1:2019's applicability across diverse contexts. While the standard offers a robust foundation for estimating ADMD values, its reliance on static assumptions may limit its effectiveness in rapidly evolving areas. Incorporating more flexible, data-driven models that adjust to local conditions could enhance the standard's relevance. Recent literature supports this approach, advocating for regular reassessment to ensure standards like SANS 507-1:2019 remain aligned with contemporary consumption patterns.

Conclusion
Overall, this comparison with existing literature highlights that while the Beta PDF model and SANS 507-1:2019 provide a valuable framework for residential load forecasting, their application needs to be more adaptive to diverse and evolving socio-economic landscapes. The study's findings contribute to the ongoing discourse on improving load forecasting models and standards, pointing to opportunities for refinement to better serve varied communities.

5.2.4 Implications for SANS 507-1:2019

The findings from this study carry significant implications for the SANS 507-1:2019 standard, which guides the planning and design of residential electricity distribution networks in South Africa. The standard's proposed After Diversity Maximum Demand (ADMD) values are pivotal for ensuring that electrical networks are cost-effective and meet residential demand. This section evaluates how the study's results affect the reliability of the current standard and proposes potential revisions to enhance its applicability and effectiveness.

5.2.4.1 Assessment of Current ADMD Values

Alignment with Measured Data: The comparative analysis in Chapter 4 indicates that while the proposed ADMD values in SANS 507-1:2019 align well with measured data in stable, mature regions, significant discrepancies emerge in areas undergoing rapid socio-economic or infrastructural changes. These deviations suggest that the current ADMD values, though applicable in specific contexts, may not comprehensively capture the complexities of all residential zones, especially those experiencing dynamic shifts.

Limitations of the Beta PDF Model: The Beta Probability Density Function (PDF) model, used to derive the proposed ADMD values, has shown varied reliability across different contexts. The model's effectiveness appears to be influenced by factors such as infrastructure maturity, socio-economic conditions, and climate variability; elements not fully considered in the current framework of SANS 507-1:2019. This highlights the need for revising the ADMD calculation methods or incorporating additional variables to improve predictive accuracy.

5.2.4.2 Recommendations for Revisions

Incorporation of Regional and Contextual Variables: To enhance the accuracy of the SANS 507-1:2019 standard, it is recommended to integrate regional and contextual variables, such as local economic conditions, demographic trends, and climate data, into the ADMD calculation process. This approach would allow for more tailored and reliable predictions, accommodating the unique characteristics of different residential zones.

Regular Updating of ADMD Values: The study's findings suggest that the ADMD values should be periodically reviewed and updated to reflect ongoing changes in technology, consumer behaviour, and socio-economic conditions. Establishing a mechanism for regular data collection and analysis would ensure that the standard remains relevant and practical over time.

Consideration of Emerging Technologies: Future revisions of the SANS 507-1:2019 standard should account for the impact of emerging technologies, such as smart meters, distributed generation (e.g., solar panels), and electric vehicles, on residential electricity demand. These technologies have an increasing influence on consumption patterns and peak demand, and their integration into the ADMD framework would enhance the standard's capacity to forecast future loads more accurately.

Potential Impacts on Infrastructure Planning

Risk of Over- or Under-Designing Networks: The study highlights the potential risks associated with the current ADMD values when local conditions are not considered. Over-designing networks based on inflated ADMD values could lead to unnecessary capital expenditure, while under-designing could result in inadequate infrastructure that fails to meet peak demand. These inaccuracies could compromise both the cost-effectiveness and reliability of the electrical grid.

Guidance for Policy-Makers: The study's findings offer valuable insights for policymakers involved in developing standards like SANS 507-1:2019. A more flexible, data-driven approach to setting ADMD values could enhance the standard's effectiveness across diverse contexts. A regional approach, where ADMD values are adjusted based on specific local conditions rather than a one-size-fits-all model, could be more beneficial.

Conclusion

In summary, while the current ADMD values in SANS 507-1:2019 provide a foundational framework for residential electricity distribution planning, there is a need for refinement to improve their accuracy and applicability. By incorporating additional variables, regularly updating ADMD values, and considering the impact of emerging technologies, the standard can be better aligned with the needs of South Africa's diverse and evolving residential zones. The results of this research have significant practical implications that extend beyond theoretical considerations, directly impacting infrastructure planning, policy development, and the long-term sustainability of residential electricity distribution networks. By carefully analysing the findings presented in this study, stakeholders can derive substantial benefits that contribute to a more efficient, reliable, and context-sensitive electrical infrastructure planning. This section explores the practical implications of the research in two key areas: infrastructure planning and policy recommendations.

5.2.5 For Infrastructure Planning

The accuracy and reliability of After Diversity Maximum Demand (ADMD) values are essential for effective infrastructure planning in residential electricity distribution networks. The findings from this study underscore several key considerations that infrastructure planners should incorporate to enhance the design, adaptability, and resilience of electrical networks.

Tailored Network Design:

The study highlights the need for a more tailored approach to network design. The proposed ADMD values in SANS 507-1:2019 may not be universally applicable, especially in regions experiencing rapid socio-economic or demographic changes. Infrastructure planners must consider local factors such as socio-economic status, infrastructure maturity, and climatic conditions when designing networks. This localised approach ensures that networks are optimised for cost-effectiveness and reliability, avoiding the risks associated with both over- and under-designing.

Dynamic Load Forecasting:

The research emphasises the importance of dynamic load forecasting that can adapt to changing conditions over time. Rather than relying solely on static ADMD values, planners should integrate real-time data collection and advanced analytics into their planning processes. Tools like smart meters, load monitoring systems, and data analytics can help continuously refine load forecasts and adjust network designs accordingly. This proactive approach enables planners to anticipate future demand better and avoid potential capacity shortfalls or excesses.

Integration of Emerging Technologies:

Emerging technologies such as distributed generation (e.g., rooftop solar), energy storage systems, and electric vehicles are rapidly altering residential load profiles and peak demand patterns. Infrastructure planners must incorporate these factors into their models to ensure that networks can accommodate new technologies without compromising performance. This could involve designing networks with greater flexibility, enabling easier upgrades or expansions as the adoption of these technologies increases.

Regional Differentiation:
The study suggests that a one-size-fits-all approach to ADMD values may not be appropriate for all regions. Infrastructure planning should therefore adopt a regionally differentiated strategy, where ADMD values and network designs are tailored to the specific characteristics of each area. Developing regional guidelines or standards that account for local conditions would improve the accuracy and relevance of network designs, ensuring they better meet the unique demands of each region.

Risk Management:
Managing the risks associated with inaccurate load forecasting is another crucial consideration. The study highlights the financial and operational risks of using outdated or incorrect ADMD values. Infrastructure planners should implement robust risk management strategies, including the regular review and adjustment of load forecasts. This could involve scenario planning and stress-testing network designs under various demand conditions to ensure resilience. By doing so, planners can better prepare for unforeseen changes and maintain reliable network performance.

5.2.6 Policy Recommendations

The findings of this research present significant implications for policymakers involved in the development, implementation, and revision of standards like SANS 507-1:2019, as well as for broader energy policy frameworks in South Africa. The study underscores several areas where policy interventions can enhance the applicability, accuracy, and responsiveness of residential electricity standards and infrastructure planning.

Revision of SANS 507-1:2019:

While the current SANS 507-1:2019 standard provides a robust foundation for estimating ADMD values, the study suggests that it could benefit from further refinement. Policymakers should consider revising the standard to integrate additional variables such as socio-economic factors, regional climatic conditions, and the impacts of emerging technologies. This would enhance the predictive accuracy of the standard and ensure its continued relevance amid evolving consumption patterns and technological advancements.

Encouragement of Regional Flexibility:
To improve alignment with local demand patterns, policymakers should promote a regionally flexible approach to applying ADMD values. Developing regional supplements to the national standard could provide tailored guidelines specific to the characteristics and needs of different areas. This approach would ensure that infrastructure investments are more accurately aligned with local socio-economic and geographic contexts, improving both efficiency and reliability.

Support for Data-Driven Decision Making:
The research highlights the critical role of real-time data and advanced analytics in improving load forecasting accuracy. Policymakers should support initiatives that strengthen data collection, sharing, and analysis across the electricity sector. Investments in smart grid technologies, the promotion of smart meters, and the establishment of robust data-sharing frameworks could facilitate the integration of real-time data into infrastructure planning and policy development. By fostering a data-driven approach, energy policies can become more adaptive and responsive to changing conditions.

Incentivization of Emerging Technologies:
The study points to the potential of emerging technologies, such as distributed generation (e.g., rooftop solar), energy storage, and electric vehicles, to significantly alter residential load profiles. Policymakers should consider creating incentives for adopting these technologies, which could help manage demand peaks, improve grid stability, and reduce distribution costs. Encouraging the integration of these technologies into the grid will also support the transition to a more sustainable and resilient energy system.

Ongoing Review and Adaptation of Standards:
Given the dynamic nature of electricity demand and the factors influencing it, there is a need for continuous review and adaptation of standards like SANS 507-1:2019. Policymakers should establish mechanisms for periodic reviews informed by the latest research and real-world data to ensure that standards evolve in line with technological advancements, changing consumer behaviours, and environmental considerations. This process would help maintain the relevance and effectiveness of the standards over time.

Promotion of Interdisciplinary Collaboration:
Effective policy development in residential electricity demand requires input from a diverse range of experts, including engineers, economists, urban planners, and environmental scientists. Policymakers should promote interdisciplinary collaboration to develop more holistic standards that consider the full spectrum of factors influencing electricity consumption. This comprehensive approach will ensure that standards are not only technically sound but also socio-economically and environmentally aligned.

Conclusion:
The practical implications of this research extend to both the technical aspects of infrastructure planning and the broader scope of energy policy. By incorporating the insights gained from this study, stakeholders can enhance the accuracy, reliability, and adaptability of residential electricity distribution networks, ensuring they are well-equipped to meet the needs of a changing population and an evolving technological landscape. These recommendations are designed to guide both infrastructure planners and policymakers in applying the research findings to achieve more efficient, resilient, and context-sensitive energy solutions.

5.3 Limitations of the Study

While this research provides valuable insights into the accuracy and applicability of the proposed ADMD values in SANS 507-1:2019, several limitations may have impacted the findings. These limitations can be broadly categorised into data limitations and methodological constraints. Acknowledging these limitations is crucial for accurately interpreting the results and guiding future research to build upon the current study.

5.3.1 Data Limitations

Data quality and availability are fundamental to the validity of any empirical research. Several data-related challenges were encountered in this study:

Availability and Completeness: Data gaps were identified due to missing or incomplete records in utility databases, potentially leading to an incomplete picture of actual load profiles and connection characteristics. This may have affected the accuracy of the observed ADMD values.

Temporal Coverage: The historical load data used in the study were not uniformly available across all case studies. In some areas, data did not span the entire period of interest, limiting the ability to conduct a fully longitudinal analysis and assess load profile evolution over time comprehensively.

Resolution and Granularity: In some instances, the available data was aggregated over extended periods rather than at finer intervals (e.g., minute-by-minute or hourly), which could smooth out critical variations and reduce the precision of ADMD calculations.

Data Quality and Accuracy: While data from Current Voltage Monitors (CVMs) and utility databases were presumed reliable, potential measurement errors or inaccuracies in data processing may have introduced errors that could affect the final results.

Geographical and Demographic Representation: The study's focus on residential zones within the Free State Province may limit the generalizability of the findings to other regions with different socio-economic conditions, climatic factors, or infrastructure development levels. This necessitates caution when applying these results beyond the studied area.

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5.3.2 Methodological Constraints

While the methodology provided a robust framework for evaluating the proposed ADMD values, certain constraints inherent in the approach may have influenced the outcomes:

Assumptions in Load Profile Analysis: Assumptions, such as balanced loads and a constant power factor, simplified the analysis but may not fully capture the complexities of real-world consumption. For example, overlooking load imbalances might lead to under- or over-estimations of peak demands.

Use of the Beta PDF Model: The Beta Probability Density Function (PDF) model was a central tool for evaluating proposed ADMD values. Still, it may not capture all variations in residential load profiles, particularly in diverse or rapidly changing areas. Future shifts in technology adoption or consumer behaviour may not be fully accounted for in the model's parameters.

Selection of Case Studies: While the 13 selected study cases were intended to represent a range of residential zones within the Free State Province, the limited number may have constrained the scope of the analysis. A more extensive or diverse sample could offer deeper insights into the variability of ADMD values.

Retrospective Nature of the Study: The study's retrospective analysis of historical data provides valuable insights into past trends but may not fully capture emerging or future consumption patterns. Prospective studies incorporating real-time data and forward-looking scenarios could offer a more comprehensive understanding of future demand.

Comparative Analysis Limitations: The comparative analysis relied on specific methodological choices, such as using the 99.5th percentile to represent typical high-demand scenarios. Other statistical approaches could yield different insights, potentially affecting the interpretation of the proposed ADMD values' accuracy.

Unaccounted External Influences: Factors such as policy changes, economic fluctuations, or significant infrastructure upgrades could impact load profiles in ways not fully captured by this study's methodology. These influences suggest the need for further research to isolate and understand their effects.

Conclusion

While this study contributes valuable insights into ADMD values and their applicability to residential electricity distribution planning, it is essential to recognise the data limitations and methodological constraints that may have influenced the findings. By acknowledging these limitations, the study provides a transparent account of its scope, guiding future research to address these gaps and refine load forecasting models to enhance the accuracy and reliability of standards like SANS 507-1:2019.

5.4 Recommendations for Future Research

This study has provided valuable insights into the accuracy and applicability of ADMD values proposed in SANS 507-1:2019. However, it also highlights areas where further research and methodological improvements could significantly enhance the precision and relevance of load forecasting models in residential electricity distribution planning. This section outlines key recommendations for future research, focusing on areas for further investigation and potential methodological advancements.

5.4.1 Further Investigation

Longitudinal Studies: Future research should undertake longitudinal studies to track residential electricity consumption over extended periods. Such studies can provide deeper insights into how load profiles evolve in response to socio-economic changes, technological advancements, and climate variability, improving the long-term accuracy of ADMD values.

Regional and Demographic Variability: Expanding research to cover a broader range of regions and demographic groups can improve the generalizability of findings. Studies should examine how ADMD values vary in different geographic settings (urban, suburban, rural) and socio-economic strata to develop more tailored ADMD standards.

Impact of Emerging Technologies: Further research is needed to understand how emerging technologies, such as distributed generation, energy storage, electric vehicles, and smart home systems, alter residential load profiles and peak demand patterns. This understanding is critical for refining ADMD values in a rapidly evolving technological landscape.

Climate Change and Seasonal Variability: Given climate change's impact on electricity demand, future studies should integrate climate projections with load forecasting models. This approach would allow for more accurate ADMD values that account for anticipated changes in temperature, precipitation, and extreme weather events.

Behavioural Insights: Investigating consumer behaviours, such as energy conservation efforts and participation in demand response programmes, could provide new insights into residential electricity usage. Incorporating behavioural data into forecasting models can lead to more accurate and responsive ADMD values.

Integration with Smart Grid Data: The proliferation of smart grids offers a rich source of real-time data. Future research should explore integrating smart meter data and grid sensors into ADMD calculations, enabling more dynamic and accurate load forecasting.

5.4.2 Potential Methodological Improvements

Refinement of Statistical Models: While the Beta PDF model has proven useful, there is potential for refinement. Future research could explore alternative or hybrid models, such as machine learning algorithms integrated with traditional statistical approaches, to improve predictive accuracy. Other probability distributions that better capture residential consumption variability could also be considered.

Enhanced Data Collection Techniques: Improving data collection methods is crucial for accurate load forecasting. Future studies should leverage high-resolution time-of-use data, advanced metering infrastructure (AMI), and Internet of Things (IoT) devices to capture more granular and context-sensitive load patterns.

Scenario Analysis and Predictive Modelling: Employing scenario analysis and predictive modelling could help explore various future conditions and their impact on residential electricity demand. Simulating scenarios like varying levels of technology adoption or climate change can provide insights into the robustness of ADMD values under different circumstances.

Incorporation of Real-Time Data: Future models should incorporate real-time data from smart meters, weather stations, and other sources. Adaptive models that update ADMD values based on current consumption patterns would enhance the reliability of load forecasts by responding to real-time changes.

Interdisciplinary Approaches: Integrating insights from electrical engineering, data science, economics, and social sciences can create more holistic models that consider the complex interplay of factors influencing electricity demand. This interdisciplinary approach could lead to more robust and versatile ADMD values suitable for diverse contexts.

Validation and Calibration Techniques: Developing robust validation and calibration techniques, such as large-scale field trials or controlled experiments, is crucial for ensuring ADMD values' reliability. Continuous validation and calibration with new data can enhance the precision and applicability of these values over time.

5.5 Limitations

Although the analysis provides insight into diversified residential demand, certain limitations should be acknowledged. The study areas reflect specific socio-economic and electrification contexts, and the generalisability of results may therefore be constrained. The analysis is also dependent on the completeness and quality of the available load datasets. These limitations do not detract from the core findings, but they frame the conditions under which the conclusions should be interpreted.

5.6 Final Conclusion

This section compares the composition-based Consumer Class, determined from breaker-size mix and connection age with Year-15 values where ages exceeded 15 years, against the observed ADMD, defined as the 99.5th percentile of transformer load. Agreement was evaluated with a ±12% absolute-deviation threshold.

Alignment occurred in 6 of 13 cases: D (+10.16%), G (+6.10%), I (+1.95%), K (−3.51%), L (+1.83%), and O (−6.46%). In these cases, the class inferred from breaker mix and connection age was both qualitatively consistent with the system characteristics and quantitatively close to the measured peak.

Where the composition-based class did not align, the direction of error was consistent:

- Overestimation with Class 3 in 20A dominant, mature areas: C (+17.48%), E (+31.44%), F (+36.38%), H (+26.66%), N (+34.98%).
- Underestimation with Classes 1–2, where empirical per-stand demand was higher than their planning values: J (−20.5%), M (−21.08%).

The composition metrics correctly indicated the direction of demand. Zones with more substantial 20A presence and mature stock tended to sit in a lower to mid demand band, while zones with a non-trivial 60A share could justify a higher class. However, the magnitude of the SANS class values did not consistently match the measurement. The composition-based class provided a practical qualitative guide, but its associated per-stand value frequently differed from the observed ADMD, producing the over- and under-estimation patterns listed above.

In summary, framed as a composition-based class versus observed ADMD, the approach was reliable in about 46% of cases and otherwise showed predictable but material deviations. Class selection inferred from breaker mix and connection age tracked the empirical direction of demand. Still, the unadjusted SANS class magnitudes did not consistently reproduce the observed ADMD across the sampled zones.

5.7 Research Outputs from the Study

This study generated several research outputs that support the evaluation of diversified residential demand. These include the development of normalised load datasets for the selected study areas, the calculation of empirical ADMD values across socio-economic and breaker-size categories, and comparative assessments against the SANS 507-1:2019 reference parameters. Additional outputs include visual representations of diversified demand behaviour through figures and tables, as well as interpretive findings that describe the alignment between observed consumption patterns and the diversified demand assumptions used in distribution network design.

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