Development of an Adaptable Load Management System for Different Household Categories in South Africa

Rebaone Goodwill Magagane

Dissertation submitted in fulfilment of the requirements for the degree

Master of Engineering in Electrical Engineering

in the

Department of Electrical, Electronic and Computer Engineering
Faculty of Engineering, Built Environment and Information Technology

at the

Central University of Technology, Free State

Supervisor: Dr. BT Mangara, PhD

Co-supervisor: Dr. TG Bihi, D. Eng

Bloemfontein, South Africa

September 2025

DECLARATION

I, Rebaone Goodwill Magagane, student number: ________, hereby declare that this dissertation, titled “Development of an Adaptable Load Management System for Different Household Categories in South Africa” submitted in partial fulfilment for the degree Master of Engineering in Electrical Engineering at the Central University of Technology, Free State, is my own original work. All the sources that I have used or quoted have been acknowledged by means of complete references.

I further confirm that this dissertation has not been previously submitted, in whole or in part, for the award of any other qualification or examination at this or any other institution. I also affirm that I have not allowed and will not allow anyone to copy or use my work with the intention of passing it off as their own.

Signed: ______________________

Name: Rebaone Goodwill Magagane

Date: 2025/09/15

ABSTRACT

South African residential electricity demand is rising, requiring efficient load management to optimise energy consumption and prevent grid instability. Traditional household load management methods are often inflexible. They fail to adapt to different household income levels and energy consumption patterns. This results in uneven energy savings and potential grid instability. To address this, the study developed a MATLAB model to control appliance usage and manage peak demand. The model uses a prioritised, staggered switch-off mechanism of appliances for household types classified as low-, middle-, and high-income when predefined load limit thresholds are exceeded.

If total power consumption exceeds these limits, the model switches off appliances in a prioritised and staggered manner, starting with the geyser, HVAC, stove, and plugs, while keeping lights on for safety. The MATLAB model integrated load profiles for each household category from literature on South African household consumption.

The findings demonstrate a maximum reduction for the three household groups over 24-hour duration. This study contributes an adaptable load management model that incorporates both household income and appliance usage patterns. Unlike traditional methods that assume a uniform load reduction or shedding strategy, the staggered switch-off mechanism provides reliable control and ensures equitable energy savings across income levels.

Keywords: Adaptable, Energy Consumption Patterns, Household Income Levels, Household Load Management, Load Management System, Load Profile,

MATLAB model, Peak Demand Reduction, Socioeconomic, Staggered Switch-Off Mechanism.

Central University of Technology, Free State

ACKNOWLEDGMENTS

I am expressing my gratitude to God Almighty for giving me the strength, courage, wisdom and perseverance to undertake and complete this research journey.

I extend my sincere appreciation to my supervisor Dr BT Mangara and co-supervisor Dr TG Bihi for their support, encouragement, and mentorship insights throughout the duration of this study. Their teachings, critical insights, and guidance were instrumental in helping shape the direction and depth of this research study.

I am grateful to the National Research Foundation's business units, the South African Radio Astronomy Observatory, and Ithemba Labs for their support with tuition fees and conference registration.

To my wife, I extend heartfelt thanks for her patience, unwavering support during late nights, periods of frustration, and moments of self-doubt, which sustained me throughout this journey. I also thank my family and friends for their prayers, moral support, and belief in my abilities.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACRONYMS

BAU	Business as Usual
CNN	Convolution Neural Network
DG	Distributed Power Generation
DSP	Digital Signal Processing
DSC	Design Science Research
E	Energy
EMC	Electromagnetic Compatibility
ESA	Energy Saving Awareness
GA	Genetic Algorithm
GWO	Grey Wolf Optimization
HESS	Home Energy Storage System
HEMS	Home Energy Management System
HTT	Hilbert-Huang Transform
HVAC	Heating, Ventilation and Air Conditioning
IoT	Internet of Things
IT	Information Technology
k	Kilo
LSTM	Long Short-Term Memory
LEAP	Long Range Energy Alternatives Planning
MAPE	Mean Absolute Percentage Error
MEPS	Minimum Energy Performance Standard
NERSA	National Energy Regulator of South Africa
P	Power
RMSE	Root Mean Square Error
REC	Residential Electricity Consumption
SABS	South African Bureau of Standards
S&L	Standard and Labelling
SPEER	Single Phase Electrical Energy Router
TAM	Technology Acceptance Model
TOU	Time of Use
UNDP	United Nations Development Programme
V2H	Vehicle to Home
Wh	Watt-hour
Wi-Fi	Wireless Fidelity

1 CHAPTER 1: INTRODUCTION

South Africa’s energy demand is rising due to industrialisation and population growth [1], [2]. This exerts a strain on the aging electricity grid that grapples with operational inefficiencies and maintenance issues [1], [2]. The diverse socioeconomic landscape further adds to the issue by influencing a wide range of consumer behaviours and energy consumption patterns [1], [2].

In South Africa, as well as in many other developing countries where electricity supply output is less than the demand, shedding the load has been a common approach to manage the power grid during peak periods and to avoid imbalances between supply and demand [3], [4]. Although load shedding offers a quick fix to prevent system collapse during peak periods, it also causes significant inconvenience and economic losses for consumers [2], [3].

Household electricity usage constitutes a considerable portion of overall electricity consumption, especially in the times of peak demand situations [1]- [4]. This highlights the importance of incorporating load management techniques aimed at efficient utilisation and distribution of electricity supply.

There are distinct patterns of energy consumption across different economic strata in South Africa. This highlights the need for adaptable, data-driven energy management systems that can take into consideration variables such as income, availability of resources, and consumer patterns.

The energy sector in South Africa requires residential energy management systems to ensure reliable grid system performance and security. Furthermore, effective load management is essential for regulating electricity supply and consumption, reducing tariff costs for consumers, and enhancing overall grid reliability.

1.1 Problem Statement

South Africa lacks an adaptable and effective load management system for diverse households, resulting in energy inefficiencies and increased stress on the electricity grid. Existing systems do not adequately account for the distinct economic constraints and energy consumption patterns of different household groups. Therefore, developing flexible load management system is essential for optimizing energy use across diverse households.

1.2 Research Aims and Objectives

The aim of this research is to develop an adaptable load management system for different household categories in South Africa, reflecting diverse socioeconomic circumstances, including low-, middle-, and high-income levels.

The system will be designed to minimise electricity costs for households and reduce consumer demand during peak and off-peak hours when demand exceeds supply. This strategy seeks to alleviate grid stress caused by planned maintenance or unforeseen challenges, such as unit failures, coal supply or handling issues, demand prediction errors, and fuel shortages for open gas turbines.

To achieve the research aim, the following objectives are set:

- Data collection: Gather primary data on electricity usage and preferences among low-, middle-, and high-income households in South Africa through a comprehensive literature review.
- Load profiling: Generate load consumption profiles for household appliances and devices across various income levels using the collected data.
- Model development: Develop an optimised load consumption model that ensures energy usage remains below or near a specified threshold while still satisfying user needs.
- System design: Design an adaptable load management system integrated with the optimised load consumption model, capable of:
  - Encouraging consumers to shift the operation of their appliances or devices to off-peak hours via real-time monitoring, or manual and remote-control.
  - Implementing an enforced staggered switch-off mechanism for appliances based on priority levels during grid stress periods:
    - Priority 1: lights
    - Priority 2: plugs
    - Priority 3: stove
    - Priority 4: HVAC (heating, ventilation, and air-conditioning)
    - Priority 5: water heater (geyser).
  - Excluding lighting fixtures from the switch off mechanism to prevent misuse of darkness for criminal activity.
- Prototype development: Constructing a prototype to evaluate the system's functionality, usability, and adaptability.
- Experimental testing: Assess efficacy of the system in decreasing consumer tariff costs, mitigating demand during peak hours, and satisfying user preferences.

1.3 Dissertation Structure and Outline

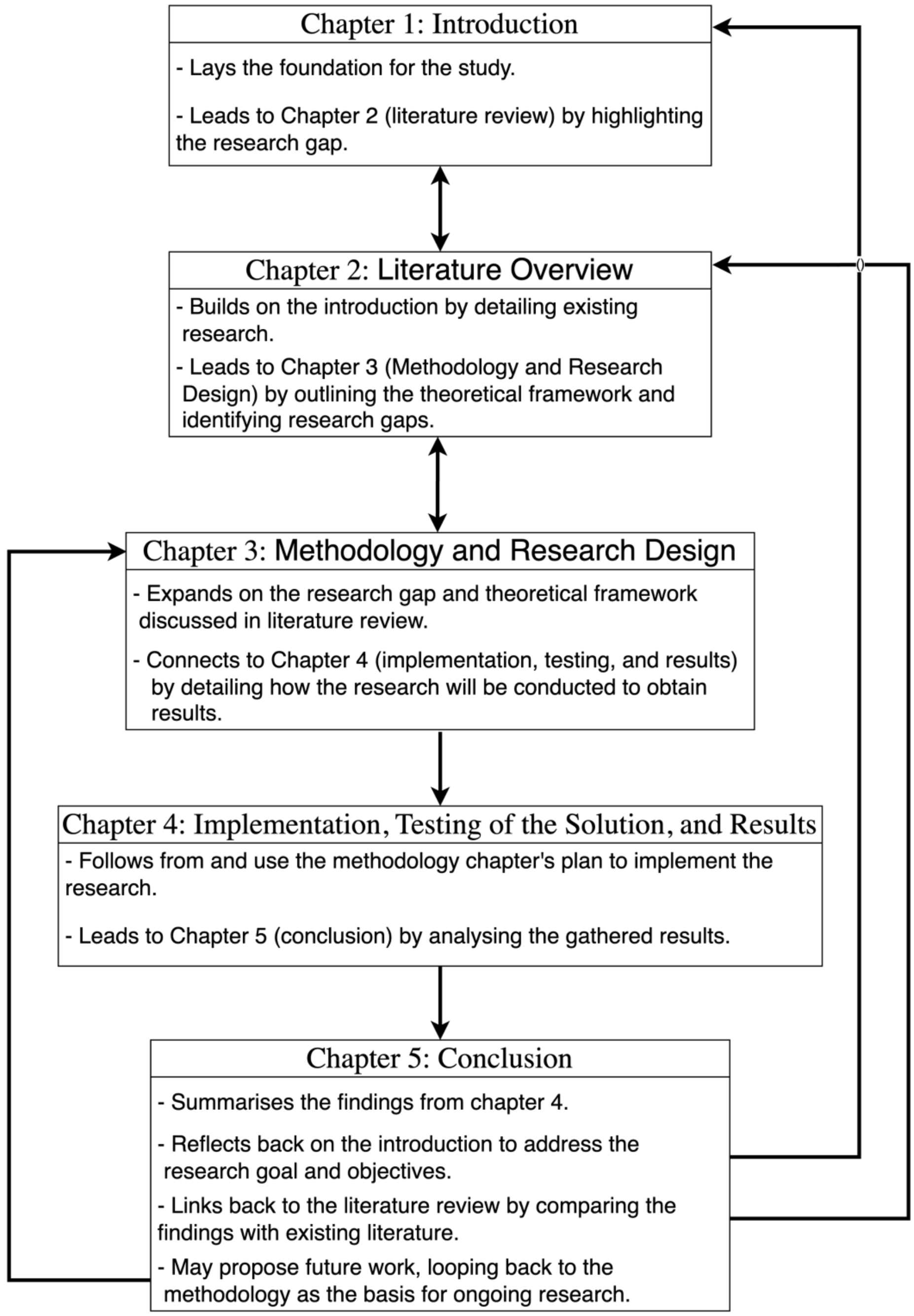

Figure 1: Dissertation flow and chapter linkage

This Dissertation is structured as follows with the following chapters:

i. Chapter 1: Introduction

This chapter provides an overview of the research topic background, summary of existing literature, problem statement, aims and objectives, and the overall structure of the dissertation.

ii. Chapter 2: Literature Review

This chapter reviews existing research on household load management systems, with a focus on their adaptability across income groups. It identifies knowledge gaps, outlines the theoretical framework, and presents the research questions guiding the study.

iii. Chapter 3: Methodology and Research Design

This chapter introduces the methodology used in the research. It describes the data collection methods used, explains the approach for selecting households with different income levels, and outlines the methods used for data analysis.

iv. Chapter 4: Implementation, Testing of Solution and Results

This chapter examines the development and evaluation of the adaptable load management system, its validation across different income levels, the effective presentation of data, and the results pertaining to load management and system adaptability.

v. Chapter 5: Conclusion

The final chapter summarises the key findings, including the performance of adaptable load management system for different for households across different income groups in South Africa. It identifies the study's limitations, suggesting areas for future research, concluding with the potential impact of the research on adaptable energy management.

2 CHAPTER 2: LITERATURE REVIEW

Chapter 2 presents a review of existing research on household load management systems, with a particular focus on how these systems adapt to household needs. The review evaluates household energy management strategies, emphasising their effectiveness and limitations in meeting energy control and efficiency requirements.

The chapter then identifies and articulates the research gap by examining the limitations of existing load management techniques, particularly regarding their adaptability to diverse socio-economic contexts. This discussion sets the stage for the development of an adaptable household load management system.

Subsequently, the chapter introduces the theoretical frameworks fundamental to the study. These frameworks provide an academic perspective for analysing the problem, highlighting the intersection of load management systems and the socioeconomic dynamics that influence their efficacy. Applying these frameworks assist in understanding household energy management systems in South Africa, considering both technical and societal factors.

The chapter concludes by providing an overview of the research questions guiding the study. These questions are designed to investigate how load management can be made adaptable and efficient for low-, middle-, and high-income households in South Africa.

2.1 Literature Overview

The literature overview summarises the current body of research on household energy management systems, evaluating aspects such as innovation, cost, and infrastructure alignment. It aims to inform the development of an adaptable load management system for South African households, promoting cost effective strategies, reduced consumption, and improved electrical stability by identifying gaps and potential enhancements. To structure this overview, the subsequent sub-sections examine key focus areas identified in the literature as central to modern household energy management systems.

2.1.1 Machine learning for household energy forecasting and management

Several studies have explored machine learning techniques for household load management. Rambabu et al. [5], utilised tree-based models, particularly Random Forest and XGBoost, to forecast household energy usage, demonstrating strong performance in short-term energy prediction. Lin et al. [6], developed a non-intrusive household load management system employing neuro-computing for load forecasting, employing energy decomposition without intrusive monitoring.

Ma et al. [7], applied deep learning and probabilistic forecasting to enhance short-term load forecasting accuracy at the household level, addressing the variability and personalisation of household power consumption. Bakiri and Mbebati [8] combined nonlinear regression with an adaptive splines technique, achieving a 14,73% improvement in load forecasting accuracy.

2.1.2 Optimisation algorithms for energy management

Ristic et al. [9], reviewed the use of the Grey Wolf Optimisation (GWO) algorithm for household energy management. The authors assessed how GWO could optimise electrical energy regulation, achieve cost reduction, and facilitate renewable energy integration. Mota et al. [10], employed a genetic algorithm for load shifting in photovoltaic energy-sharing communities, examining cost reduction under dynamic pricing and local generation, and demonstrating cost reduction at both individual and community levels.

Zhao et al. [11] developed an energy optimisation algorithm using digital signal processing (DSP) for a single-phase electric energy router. The algorithm optimises battery charge and discharge cycles, as well as energy exchange with the grid, based on historical and real-time data analysis.

2.1.3 IoT-based household energy management

Ulloa-Vásquez et al. [12], developed a high-resolution Internet of Things (IoT)-based Smart Socket ILM system for detailed monitoring of household appliance energy use, enhancing device recognition, reducing computational demands, and enabling effective household energy management.

Ogidan et al. [13] proposed a web-based load-shedding control system using IoT technologies to improve real-time awareness of energy consumption, demonstrating minimal measurement inaccuracies and potential integration with smart metering systems.

2.1.4 Smart home energy management systems (HEMS)

Balavignesh et al. [14], developed an optimisation-driven energy management system for smart homes within a smart grid, employing advanced algorithms to balance energy expenses, usage, and user satisfaction. Their findings indicated that integrating renewable energy sources with real-time pricing significantly enhanced home energy management. Abdalla et al. [15] examined the integration of electric vehicles and home energy storage in smart homes, demonstrating cost reduction and load curve levelling through Vehicle to Home (V2H) and Home Energy Storage Systems (HESS) methods.

2.1.5 Smart metering infrastructure

Sanabria-Villamizar et al. [16] used smart meter data and Hilbert-Huang Transform (HHT) to analyse household energy consumption. They proposed a methodology to address the limitations of traditional time-series approaches and improve the accuracy of load profiles, underlining the importance of the optimal data sampling frequency.

2.1.6 Socioeconomic factors in energy consumption

Qiao and Lin [17] studied household energy management, focusing on the relationship between income and energy-saving awareness (ESA). They employed regression models, revealing an inverted U-shaped pattern between income and energy usage. The results indicated that high-income households, moderated by ESA, are more likely to adopt environmentally friendly practices.

2.1.6.1 Tariff Structures and Behavioral Motivation in South Africa

South Africa's electricity pricing framework incorporates time-of-use (TOU) and inclining block tariffs, which create strong financial incentives for households to shift consumption away from peak periods. Under TOU tariffs, evening peak rates (17:00–20:00) can exceed off-peak rates by more than 200%, making demand-side management strategies economically attractive for consumers [46], [47].

Behavioral economics theories, such as Nudge Theory and the Technology Acceptance Model (TAM), indicate that consumers are more likely to adopt load-shifting behaviors when tangible cost savings are evident [22]-[24]. Studies by Kiianchuk and Makhotilo [19] demonstrate that tariff-based incentives significantly improve participation in demand response programs, while Qiao and Lin [17] highlight the role of energy-saving awareness in moderating consumption patterns.

The proposed system leverages these behavioral drivers by prioritizing load reduction during high-tariff periods, thereby aligning technical control strategies with economic motivation. This synergy between tariff structure and consumer readiness enhances the real-world feasibility of adaptive load management solutions in South Africa.

2.1.7 Community energy management

Mo et al. [18] applied deep reinforcement learning for energy allocation in dynamic community systems. The authors developed a user-responsive model to address uncertainties in renewable energy supply and demand, demonstrating effective low-carbon dispatch.

2.1.8 Demand-side management

Kiianchuk and Makhotilo [19], investigated household energy consumption by evaluating the effectiveness of smart and naïve demand response methods. Their findings showed that the smart method effectively reduced energy consumption and peak demand by adjusting washing times and utilising smart appliances.

2.1.9 Main findings from the literature overview

The overview indicates that South Africa requires an adaptable load management system to optimise household electricity use. Existing literature highlights the application of smart technologies in household energy management systems, including the IoT, advanced data analytics, and algorithmic approaches, which offer potential solutions. However, these technologies face challenges related to complexity, computational requirements, and limited validation, including assumptions underlying the models. Furthermore, the literature emphasises the integration of renewable energy sources into household energy management systems to achieve a sustainable mix of energy.

In South Africa, this integration is constrained by cost, compatibility with existing infrastructure, and regulatory considerations. These limitations underscore the need for further research into household electricity consumption patterns across different socioeconomic groups to inform the development of a tailored household load management system.

The preceding section provided a thematic overview of existing research on household energy management, highlighting key approaches such as machine learning, optimisation algorithms, IoT integration, and socioeconomic modelling. To build on these findings, the following section revisits and expands upon selected studies in greater technical detail. This deeper analysis focuses on the design, functionality, and performance of household load management systems.

2.2 Detailed Review of Load Management Systems

Building upon the literature overview discussed in Section 2.1, this section examines prior studies that specifically address household load management systems and their practical implementations. Whereas the previous overview presented a summary of related, this section provides a more detailed examination of how these systems are designed, configured, and applied across different household contexts.

2.2.1 Overview of household load management systems

Household load management systems are a specialised subset of energy management systems, designed to shape and shift household electricity demand patterns. These systems apply a variety of techniques to monitor, control, and optimise energy usage, regulating the operation of devices such as HVAC units, water heaters, and appliances either at the individual device level or across the entire household.

Their primary function is to strategically redirect energy consumption from peak demand periods, when the grid faces maximum strain and electricity rates are typically higher. By reducing demand during these periods, load management systems deliver dual benefits: lowering household energy costs while simultaneously supporting overall grid stability.

Historically, early household management systems relied on manual control of appliances, often involving direct control by utilities during peak demand periods. The introduction of smart grid technologies, advanced metering infrastructure, artificial intelligence, and machine learning algorithms has enabled the implementation of dynamic and responsive household load management systems.

2.2.2 Household load management techniques

Previous and current studies employed a range of techniques on load management systems for households. For this study, these techniques are categorised into Home Energy Management Systems (HEMS), Smart Metering Infrastructure, Smart appliances and Devices and Load Management Algorithms, which are discussed in detail below.

2.2.2.1 Home Energy Management Systems (HEMS)

Recent advancements in HEMS have leveraged artificial intelligence and optimisation algorithms to forecast energy consumption and improve efficiency in residential settings.

Ma et al. [7] conducted a comparative review of the current state of short-term load forecasting for individual households, with a specific emphasis on its implementation within HEMS. Their study found that models such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) were particularly effective in capturing complex, non-linear consumption patterns.

Additionally, the authors highlighted the value of probabilistic forecasting methods, which offer a range of potential consumption outcomes, thereby allowing HEMS to better accommodate uncertainty in household behaviours. While promising, their findings noted challenges with data quality, such as noise and missing variables like weather conditions and appliance use, which can limit model precision. The authors concluded that improved data preprocessing and enhanced model interpretability are necessary for practical implementation. The comparison is illustrated in Table 1 below.

Table 1: Comparison of forecast models. Source: Adapted from [7]

Model	Advantage	Shortcomings	Application Situation
Classical time series model	Simple to understand, modelling time is short	Poor performance on complex time series prediction problems	Simple time series data prediction
LSTM	Able to learn long-term dependencies	Risk of overfitting the model	Process non-linear and non-stationary time series
CNN	Features can be learned automatically	Not good for non-linear time series data	Lack of historical data, short forecast time

Abdalla et al. [15] investigated a home energy management strategy that leverages Vehicle-to-Home (V2H) and Home Energy Storage System (HESS) to optimise energy consumption and minimise electricity costs. The authors employed a control algorithm to manage the charging and discharging of the electric vehicle (EV) battery based on variables such as time-of-use electricity pricing, household load demand, EV, and HESS operational characteristics.

Using simulation-based validation, they tested four configurations: no energy system (baseline- scenario A), V2H only-scenario B, HESS only- scenario C, and a combined V2H-HESS setup-scenario D. Results demonstrated that the combined system (Scenario D) achieved the greatest cost reduction and load flattening, with Scenario B (V2H only) performing better than HESS alone (Scenario C). These outcomes are illustrated in Figure 2, which compares daily electricity costs across scenarios.

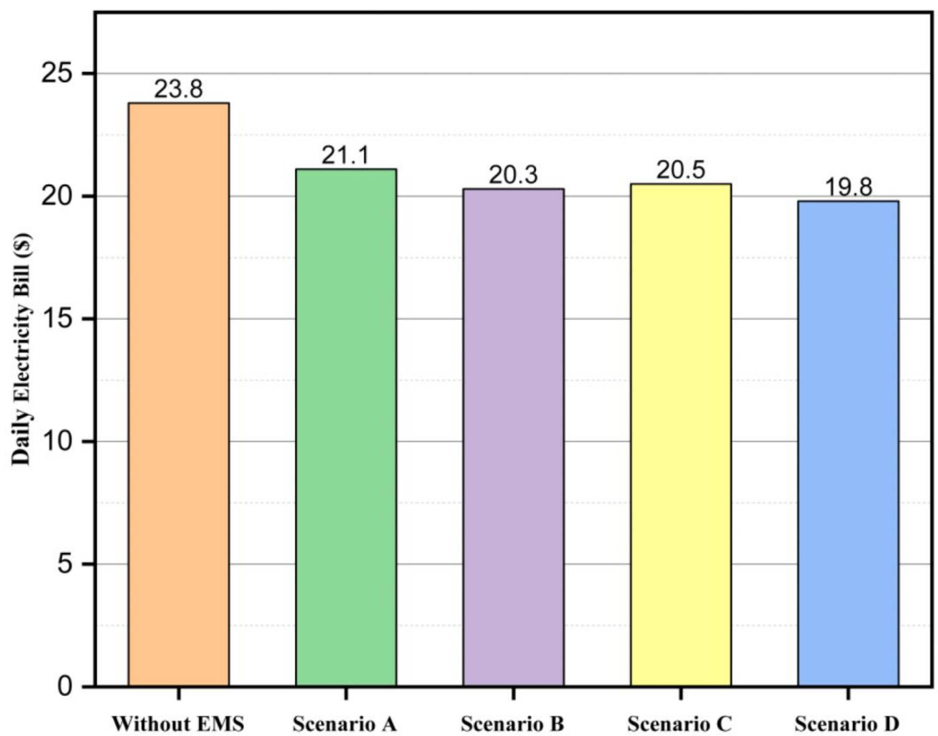

Figure 2: Daily electricity bill comparison. Source: Adapted from [15]

While effective in simulation, the study acknowledged the need for real-world validation and greater transparency in algorithm design to support implementation feasibility.

Ristic et al. [9] conducted a review to explore the potential of Grey Wolf Optimisation (GWO) Algorithm in optimising Household HEMS. GWO is a metaheuristic optimisation technique inspired by the hunting behaviour and social hierarchy of grey wolves; it simulates their social hierarchy and cooperative strategy to address complex optimisation challenges. The authors analysed the application of GWO algorithm in HEMS, focusing on the optimisation of appliance scheduling to align with electricity tariffs and user preferences.

The algorithm supports dynamic scheduling of flexible vs. inflexible appliances and integrates effectively with renewable sources like solar and wind. However, the study noted that GWO's performance depends heavily on parameter tuning and may face scalability limitations in larger or more diverse residential setups.

2.2.2.2 Smart Metering Infrastructure

Sanabria-Villamizar et al. [16] presented an approach to analysing household energy consumption patterns using smart meter data and the Hilbert-Huang Transform (HHT) signal processing method. Their methodology, illustrated in Figure 3, employed HHT to decompose complex consumption signals into simpler intrinsic mode functions through empirical mode decomposition, addressing the limitations of traditional time-series methods.

The HHT was used to evaluate each intrinsic mode function, enabling the identification of its instantaneous frequency and amplitude. This approach allowed for a representation of energy usage in the time-frequency domain. The authors also examined the impact of different data sampling frequencies on the precision of load profile characterisation.

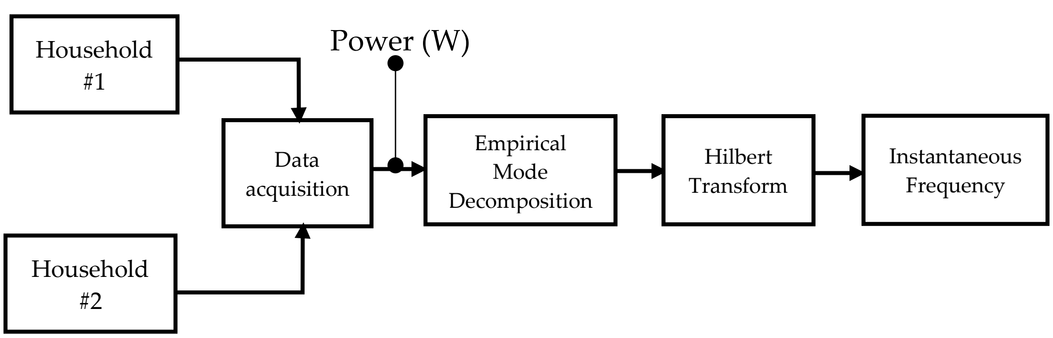

Figure 3: Process block diagram. Source: Adapted from [16]

The results demonstrate signal reconstruction with errors below 25% for data resolution of up to 10 minutes. Lower errors of value 0.71% for 30-second resolution were also observed. While the methodology improved the characterisation of non-linear, non-stationary energy data, it also posed computational challenges that may limit scalability.

Balavignesh et al. [14] proposed an optimisation-based energy management system for smart homes within a smart grid network. Their system, illustrated in Figure 4, optimised appliance operation based on real-time pricing (RTP) and critical peak pricing (CPP) schemes, achieving improved cost efficiency across multiple simulation scenarios.

RTP is a dynamic a dynamic pricing mechanism in which electricity tariffs vary continuosly according to real-time market conditions or grid demand, encouraging consumers to shift usage to off-peak periods. CPP, on the other hand, applies substantially higher tariffs during predefined critical peak periods to reduce demand when the grid is under stress. These approaches provide a practical means of incentivising load reduction and cost optimisation within residential energy management frameworks.

Table 2 and Table 3 summarise cost reductions under different tariff configurations, highlighting the framework's adaptability.

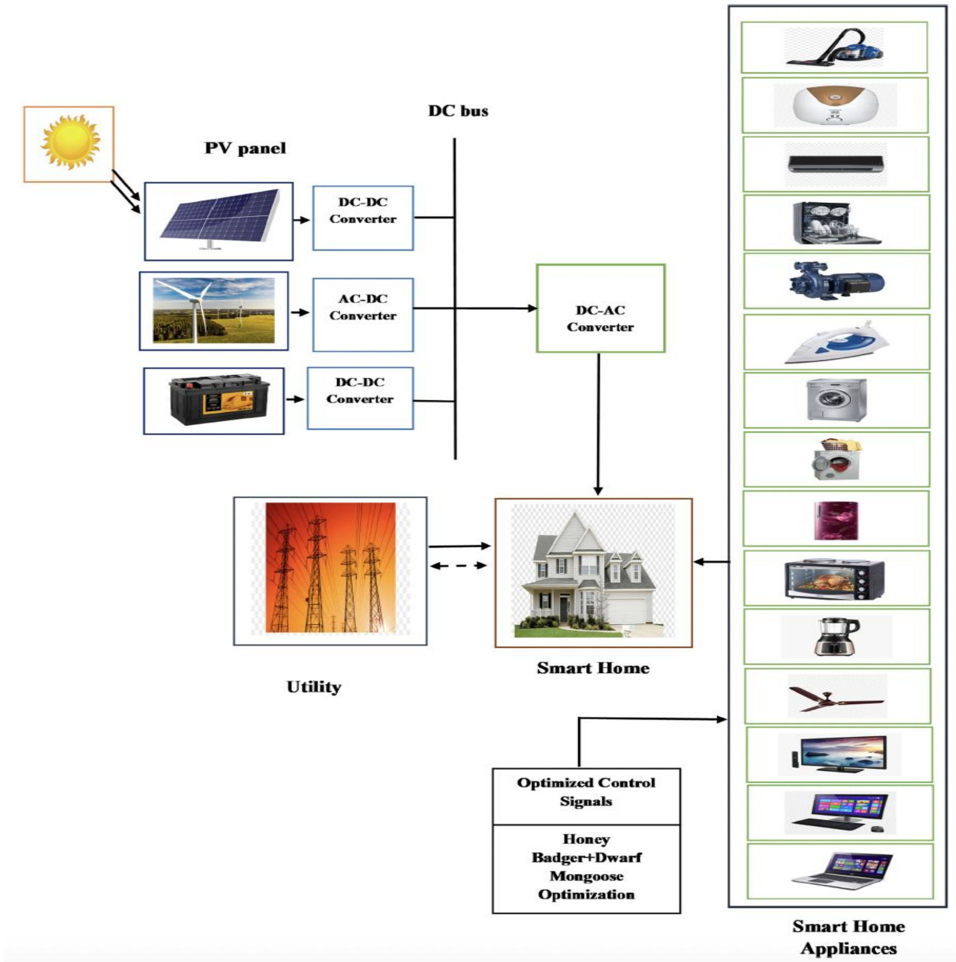

Figure 4: System architecture diagram. Source: Adapted from [14]

Table 2: Total electricity cost for RTP and CPP at instance 1. Source: Adapted from [14]

RTP Techniques	**Total Electricity Cost (cent)**
Unscheduled	146.86
HEMS Model	171.75
RUO Algorithm	170.19
Harris Hawks Algorithm	126.7
Adaptive Coati Algorithm	112.98
Proposed Hybrid HBA+DMO	104.03
CPP Techniques	**Total Electricity Cost (cent)**
Unscheduled	2596.87
HEMS Model	2524.52
RUO Algorithm	1800.41
Harris Hawks Algorithm	1511.84
Adaptive Coati Algorithm	1320.47
Proposed Hybrid HBA+DMO	1039.65

Table 3: Total electricity cost for RTP and CPP at instance 2. Source: Adapted from [14]

RTP Techniques	**Total Electricity Cost (cent)**
Unscheduled	1722.44
HEMS Model	1560.86
RUO Algorithm	1337.30
Harris Hawks Algorithm	1483.84
Adaptive Coati Algorithm	1374.91
Proposed Hybrid HBA+DMO	1153.79
CPP Techniques	**Total Electricity Cost (cent)**
Unscheduled	4965.36
HEMS Model	3690.15
RUO Algorithm	3659.44
Harris Hawks Algorithm	3469.05
Adaptive Coati Algorithm	3241.26
Proposed Hybrid HBA+DMO	2808.10

Despite its effectiveness in simulations, the study acknowledged the need for further evaluation of system scalability, communication infrastructure, and real-world applicability.

Mo et al. [18] investigated the use of a deep reinforcement learning algorithm to achieve low-carbon economic dispatch in a community integrated energy system. The authors employed a Deterministic Policy Gradient agent to optimise energy dispatch, incorporating uncertainty modelling techniques such as Latin Hypercube Sampling.

The simulation results demonstrated that the reinforcement learning approach achieved low-carbon dispatch under varying uncertainty levels (5%, 10%, and 15%), accounting for renewable energy fluctuations, load variations, temperature changes, and uncertainties associated with the number of trips, time periods, and mileage of electric vehicles.

While the study confirmed the potential of deep reinforcement learning for low-carbon dispatch, it also underscored the limitations, particularly computational complexity and reliance on the precise uncertainty modelling. The authors emphasised that the computational demands of deep reinforcement learning pose challenges for real-time implementation in large-scale community-integrated energy systems.

Zhao et al. [11] investigated a digital signal processor (DSP)-based household energy management system designed to optimise energy consumption through integration with a single-phase electrical energy router (SPEER), as illustrated in Figure 5.

Their methodology employed a particle swarm intelligence algorithm that leveraged historical energy consumption data and real-time grid pricing to inform decisions on battery charging and discharging and energy exchange between the household and the grid. Real-time optimisation was enabled by the DSP, which allowed the system to adapt dynamically to fluctuating energy prices and consumption patterns.

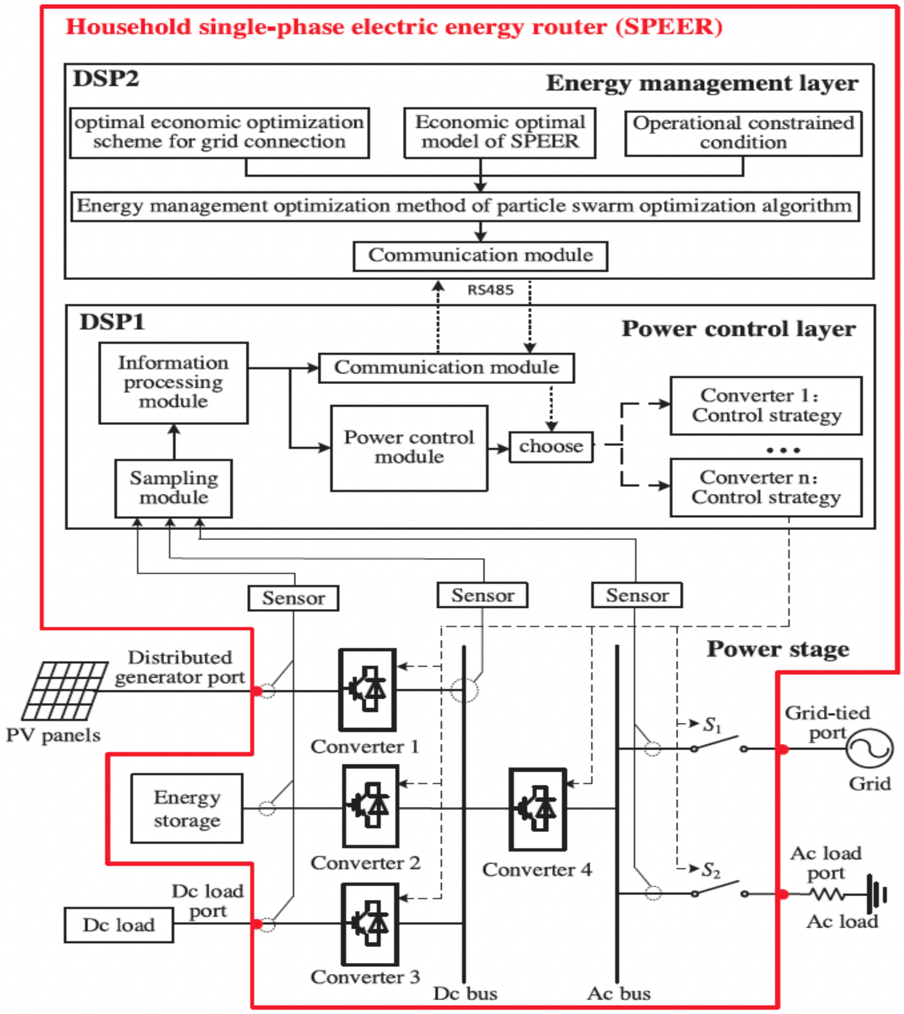

Figure 5: DSP-based system architecture. Source: Adapted from [11]

The study findings demonstrated both cost savings and improved efficiency of the system. Simulation and hardwire-in-the-loop experiments confirmed reductions in energy costs and overall consumption. The optimised energy consumption is illustrated in Figure 6, showing the dynamic interchange between power generation from distributed energy sources, household load demand, and the battery charging and discharging over a 10-minute period.

The system successfully performed peak saving and shifting. At time t1, during peak distributed power generation (DG), the battery charged at maximum capacity (Pbat) effectively storing surplus energy. Near t2, when household demand (Pload) peaked and DG output declined, the battery discharged at maximum power to supplement supply, thereby shifting energy usage and maintaining load stability.

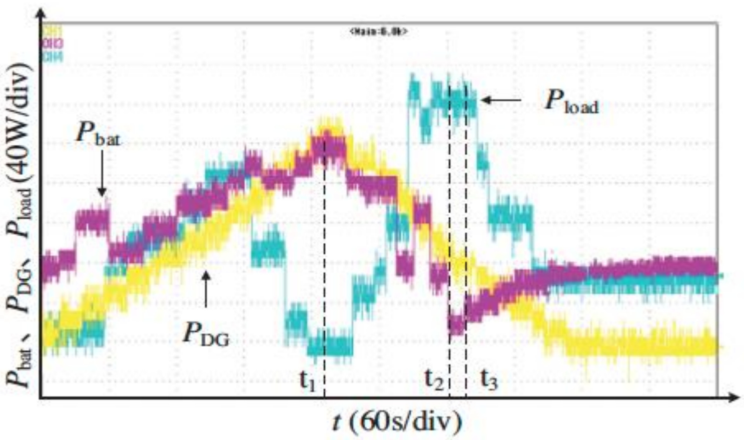

Figure 6: Power curves of DG, load and optimised battery charge/discharge power. Source: Adapted from [11]

The study acknowledged several limitations, particularly the scalability of the single-phase household energy router to manage larger energy systems with diverse sources and loads. The authors also outlined that the system's dependence on simulation data necessitates further research into its performance in real-world applications.

2.2.2.3 Smart Appliances and Devices

Smart appliances and monitoring tools are increasingly central to residential load management by enabling real-time control and user feedback. Several studies have explored their effectiveness in improving energy efficiency and supporting demand-side strategies, as discussed below.

Ulloa-Vásquez et al. [12] evaluated the use of smart sockets devices that plug into outlets and track individual appliance usage via current and voltage sensors. These sockets enabled detailed monitoring by capturing energy data at high frequency and transmitting it via Wi-Fi using secure messaging protocols.

Their results showed a 91.7% average accuracy in identifying six different household appliances, as illustrated in Table 4. This was achieved by training machine learning algorithms on the appliance energy usage profiles that were collected. The system, although promising, was restricted to plug-in appliances and depended on consistent user behaviour for precision and comprehensiveness.

Table 4: Appliance Prediction Matrix. Source: Adapted from [12]

	Kettle	**Fridge**	**Electric Oven**	**Microwave**	**Heater**	**Washer**
Kettle	86.6%	1.6%	0%	4.2%	8.5%	0%
Fridge	0%	98.4%	1.9%	1.4%	0%	0%
Electric Oven	6.7%	0%	94.4%	5.6%	0%	0%
Microwave	0%	0%	0%	83.3%	0%	3.3%
Heater	6.7%	0%	3.7%	1.4%	91.5%	0%
Washer	0%	0%	0%	4.1%	0%	96.7%
Accuracy	86.6%	98.4%	94.4%	83.3%	91.5%	96.7%
Error	13.4%	1.6%	5.6%	16.7%	8.5%	3.3%

Kiianchuk and Makhotilo [19] simulated demand response strategies to compare two types of household behaviours: a “naïve” strategy that involved minimal user engagement and a “smart” strategy focused on shifting high-load appliance use to off-peak hours. Their findings revealed that the smart strategy led to a 40% reduction in peak demand, compared to only 11% under the naïve strategy.

The resulting household load profiles under both conditions are presented in Figure 7, which highlights the effectiveness of load shifting in flattening peak consumption curves.

The curves labelled as “Usual” represent profiles for unlimited power consumption, while the other curves represent profiles when a family participates in Demand Response Program (DRP) under “Naïve” (Figure 7a) and “Smart” (Figure 7b) strategies.

In Figure 7, the family begins their evening washing routine at a convenient hour of 18:30. A "Naive" consumer simply turns off the appliances in the living room to engage in DRP, whereas a "Smart" consumer adjusts the timing of laundry washing to the night time, starting from 21:30.

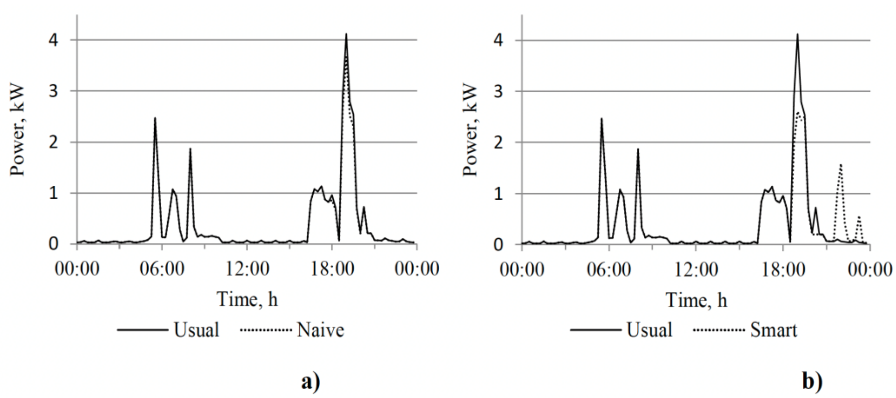

Figure 7: Load profiles of a consumer household on working day with laundry in the evening. Source: Adapted from [19]

Although effective in simulation, the model's applicability depends on consumer awareness and voluntary participation, and it has not been validated against real-world usage data.

Ogidan et al. [13] proposed a web-based system for remote appliance control, enabling households to monitor and shed loads in real time. The system used a Wi-Fi-enabled microcontroller to transmit appliance data to a web application. However, its performance was limited by communication losses and inconsistencies in measuring inductive loads. The authors also noted the system's dependence on stable internet connectivity, which may hinder its use in underserved areas.

Together, these studies highlight the value of smart device integration in household energy management. However, challenges such as user behaviour variability, communication reliability, and cost remain critical barriers, especially in low- and middle-income settings.

2.2.2.4 Load Management Optimisation Algorithms and Advanced Methods

Recent studies have applied advanced computational techniques to optimise household energy consumption. These approaches fall into two main categories: machine learning-based forecasting and algorithmic optimisation.

a. Machine Learning and Forecasting Techniques

Rambabu et al. [5] conducted a study to investigate the effectiveness of machine learning algorithms in predicting household energy consumption. The authors compared various regression models, including Random Forest, XGBoost, and Lasso Regression using environmental predictors such as temperature and humidity.

Their results, illustrated in Figure 8, indicate that tree-based models (especially Random Forest and XGBoost) achieve the highest prediction accuracy based on R-squared scores.

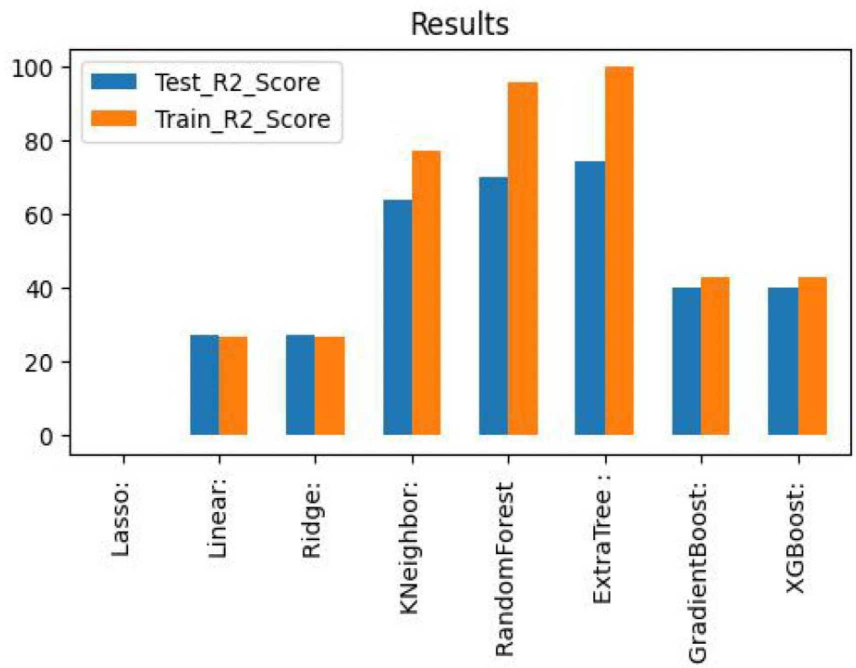

Figure 8: R-squared scores for training and test sets. Source: Adapted from [5]

Similarly, Lin et al. [6] employed a neurocomputing-based method that used artificial intelligence and machine learning to predict households' energy use. Their approach combined energy decomposition with AI to achieve high accuracy without the need for physical sensors.

As shown in Table 5, two out of five tested appliances demonstrated a mean absolute percentage error below 10%, indicating a highly accurate estimate. The remaining appliances were within the 10–20% and 20–50% ranges, which are considered well and reasonably estimated. The model, illustrated in Figure 9, also demonstrated GPU-accelerated real-time forecasting.

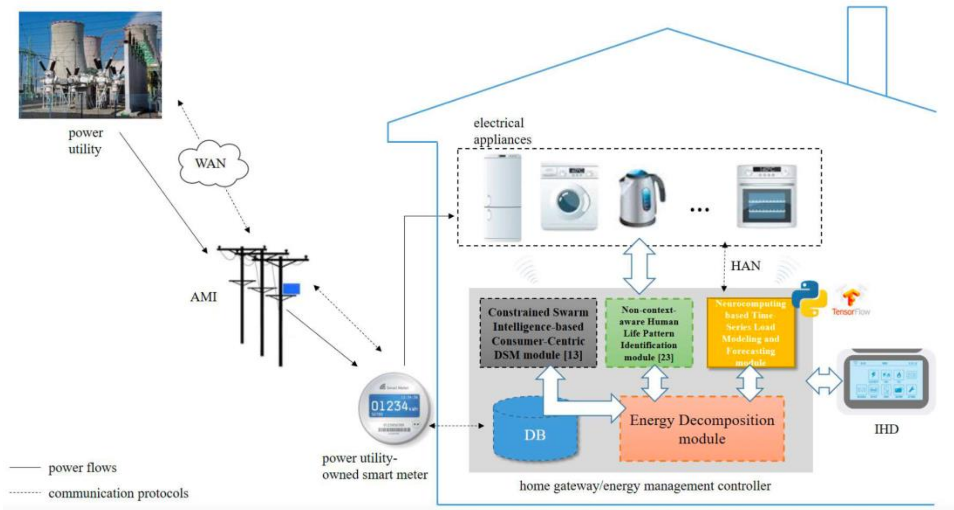

Figure 9: Neuro-computing and energy decomposition-based time-series load forecasting model diagram (figure appears truncated as presented in the original source). Source: Adapted from [6]

Table 5 below demonstrates that the electricity demand estimates were precisely forecasted. Five appliances were tested and monitored in the period of five days of which four of the appliances showed mean absolute percentage error of less than 10%, demonstrating a highly accurate estimate.

Table 5: Five-day electricity demand, in kWh for five individual monitored appliances. Source: Adapted from [6]

Estimated electricity demand (kWh)	Electric water boiler	Steamer	TV	Range Hood	PC
actual	1.53	5.07	9.36	0.73	18.23
forecasted	1.03	4.35	9.35	0.60	18.24
Mean absolute percentage error (MAPE) (%)*	32.68	14.21	0.11	17.81	0.06

*Less than 10%: highly accurately estimated; 10-20%: well estimated; 20-50% reasonably estimated; and greater than 50%: inaccurately estimated.

While promising, these studies were based on single-household data and lacked validation in real-world environments, which limits scalability.

Bakiri and Mbebati [8], extended forecasting models to the context of developing countries using adaptive spline regression. Their study identified income, appliance ownership, and household size as key determinants of electricity usage. Their study identified income, appliance ownership, and household size as key determinants of electricity usage. Among the univariate models, the income variable achieved the lowest forecasting error (RMSE = 0.8244 kWh), followed by appliance ownership (0.9868 kWh) and household size (1.2314 kWh).

When all three predictors were incorporated into a multivariate model, the RMSE value decreased to 0.7031 kWh, representing a 14.73 % reduction in forecasting error compared to the average of the univariate models. This improvement, as reported in the original study, demonstrates that combining socioeconomic and household parameters substantially enhances prediction accuracy in developing-country contexts.

Figure 10 below provides a visual summary of these results, illustrating the comparative forecasting errors (RMSE) for each model configuration. It should be noted that the percentage reduction originates from the cited study and is not recalculated in this dissertation but presented to highlight the model's relative performance improvement.

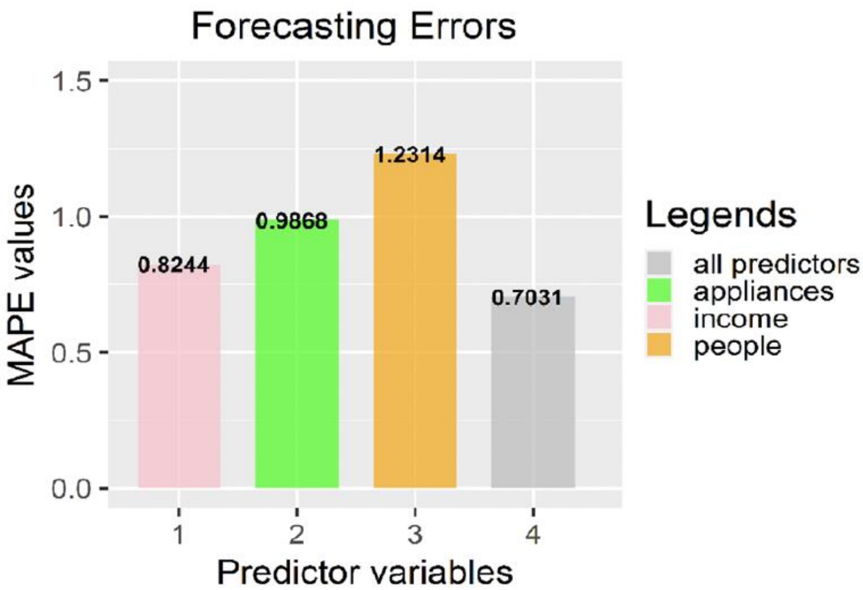

Figure 10: Forecasting errors. Source: Adapted from [8]

The authors acknowledged that while income, household size, and appliance count are significant determinants, there were some limitations with the study. It required the incorporation of additional factors such as occupancy patterns to improve the model's accuracy.

b. Optimisation Algorithms

Optimisation-based approaches aim to reduce energy costs by scheduling or shifting appliance usage. Mota et al. [10], presented a Genetic Algorithm (GA) to optimise energy usage in individual households as well as within a photovoltaic energy-sharing community.

The study findings demonstrated that the GA achieved a cost reduction of 24.3% for individual households, illustrated in Figure 11, and 11.8% for an energy sharing community that was compared to the baseline scenario illustrated in Table 6 and Figure 12.

The baseline scenario is referred to a business as usual (BaU) where energy consumption is simulated without any optimisation or intervention from the

GA. The primary significance of the work was to demonstrate the practicality and benefits of employing a GA for energy management in smart households and communities.

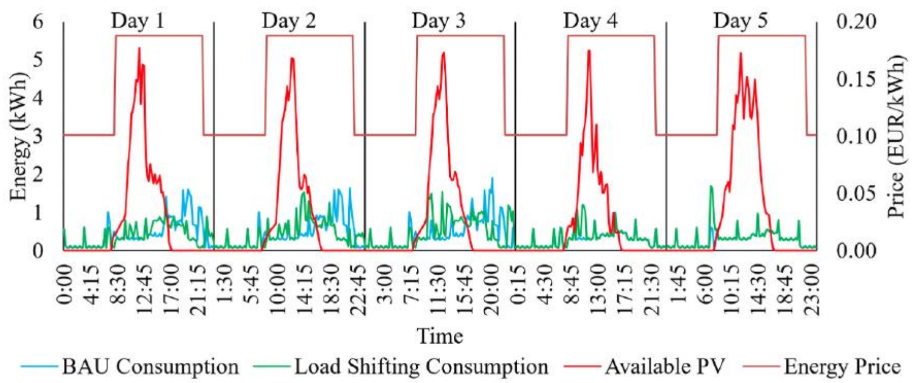

Figure 11: Individual household energy consumption, available PV and energy price case study. Source: Adapted from [8]

Table 6: Household community energy cost saving. Source: Adapted from [8]

Placement	House	BAU Cost in EUR	Load Shifting in EUR	Cost Difference between BAU and Load Shifting (change in %)
1st	1	16.74	12.25	4.49 (-26.8%)
2nd	10	14.07	11.22	2.85 (-20.3%)
3rd	11	15.00	12.30	2.70 (-18.0%)
…	…	…	…	…
18th	6	9.96	9.34	0.62 (-6.2%)
19th	17	15.75	15.18	0.57 (-3.6%)
20th	12	7.54	7.43	0.11 (-1.5%)

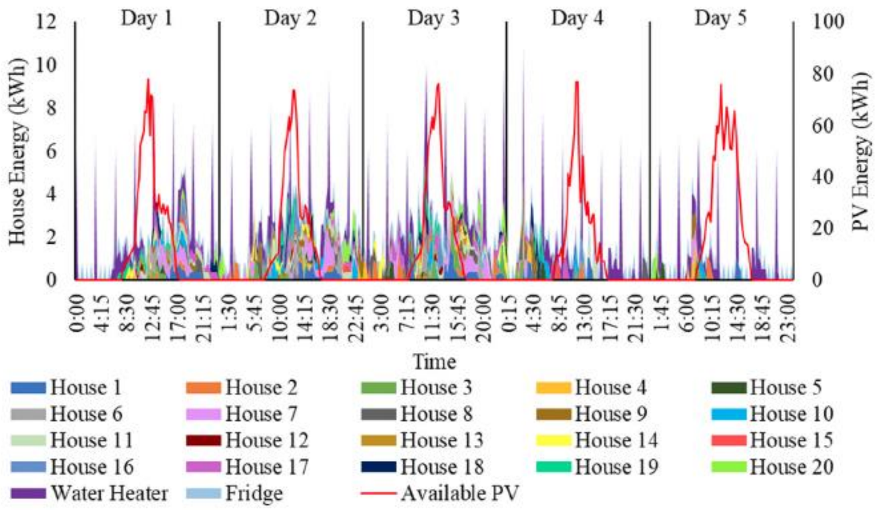

Figure 12: Energy consumption per household community case study. Source: Adapted from [8]

The study acknowledged that despite effectiveness of the GA in a simulated environment, further investigation is required to assess its robustness in a real-world uncertainty such as appliance usage fluctuations. In addition, the requirement for computation complexity of GAs can pose a challenge for real-time applications. The study's dependence on simulated data may also create limitations in accuracy.

c. Socio-economic Influences on Load Behaviour

Qiao and Lin [17], explored the correlation between household income, energy-saving awareness, and electricity consumption patterns. The study employed a quantitative method, which is the regression model to analyse the correlation.

The study revealed a direct relationship between income and power use. Indicating that higher income households tend to consume large amounts of energy. Further investigation revealed a point of stability in consumption after reaching a specific income level, which suggested a link that followed an inverted U-shaped pattern. This observation implied that income had an impact on energy usage up to a specific level.

The study acknowledged the limitations with the results extending beyond the straightforward correlation, emphasising the moderate function of Energy Saving Awareness (ESA). Households with higher levels of ESA demonstrated a limited growth in consumption, even when income increased. This suggests that enhancing energy consciousness might mitigate the inclination for energy use to rise because of economic prosperity.

2.3 Research Gap Identification

A review of current literature on household load management systems, including HEMS, load control algorithms, smart metering, and appliance integration reveals significant advances. However, several key research gaps were revealed, particularly when applied to the South African context. Below are the identified gaps in literature:

- Lack of Income-Level Differentiation:
  Most studies assume homogenous energy consumption patterns, overlooking the diverse affordability, appliance ownership, and usage behaviours across low-, middle-, and high-income households in South Africa.
- Limited Real-World Validation:
  Numerous studies predominantly depend on simulation data without validating models across varied household environments, thereby diminishing practical applicability.
- Computational and Data Constraints:
  Advanced algorithms, such as deep reinforcement learning and genetic algorithms, demand high-quality, granular consumption data and face limitations related to computational complexity and deployment costs.

- Narrow Focus on Developed Contexts:
  Existing HEMS studies are predominantly based in developed countries, with assumptions on infrastructure, digital literacy, and appliance ownership that do not align with South African realities.
- Inadequate Algorithm Metrics:
  Some algorithms demonstrate strong forecasting accuracy, for example, deep learning methods in [6], but fail to report cost savings or load-shifting impacts under real-world peak demand scenarios.
- Scalability and Infrastructure Barriers:
  Challenges in the widespread deployment of smart meters and HEMS are infrequently discussed in low-resource settings, particularly concerning installation expenses, technical upkeep, and insufficient policy backing.
- Smart Appliance Limitations:
  Current systems often ignore hardwired appliances and rely on user-driven behaviour recognition, reducing reliability and limiting broader implementation.
- Communication and Data Loss Challenges:
  Studies highlight vulnerability to data inaccuracies caused by communication breakdowns (for example, Wi-Fi outages) and emphasise the need for a more robust communication infrastructure.

This research aims to address the identified gaps by developing an adaptable household load management system tailored to South Africa’s distinct socio-economic landscape. By differentiating energy consumption patterns across the three income household groups and implementing control based on realistic appliance ownership, the system aims to:

- Maximise energy efficiency across diverse households.
- Enable equitable load management.
- Improve cost savings and grid stability across socio-economic groups.

2.4 Theoretical Framework

This section discusses the conceptual foundation of this study, utilising the insights gained from the literature review's previous sections and guiding the development of load management system tailored for South African households with different income levels.

The key concepts to load management include energy consumption behaviour, socio-economic differences in access and usage, and load control. These concepts are interrelated and support the development of a system that aligns with the financial and technical realities of the three household income groups.

This framework also guides how variables such as household income, appliance ownership, usage patterns, and threshold-based control interact to influence the design of an optimised load management solution tailored to diverse South African contexts.

2.4.1 Theoretical background, guiding concepts, and variables

The theoretical foundation of this study on developing a load control system for different household categories in South Africa draws on interconnected theoretical and conceptual frameworks from electrical engineering, energy management, and behavioural economics. These frameworks establish a systematic foundation for comprehending the relationships among household energy consumption, load management, and socio-economic factors, particularly household income. Presented below are the theories, concepts, and factors that direct the study:

a. Household Energy Consumption

   The energy consumption theory is selected to assist in understanding household energy consumption. It underpins the factors that influence household energy, such as socio-economic status and household size, and it also outlines how these factors interact.

The key energy consumption driver concepts central to study are illustrated below:

i. Household income level: The concept assumes that higher income households have greater access to and ownership of energy-intensive appliances, which result in higher levels of energy consumption [20], [21]. It also outlines that this type of household may own larger residences that require more energy for heating, cooling, and lighting. In comparison, low-income households may have reduced energy consumption due to smaller living areas and a small number of appliances [20], [21].

ii. Household size: The concept assumes that larger households tend to consume more energy due to higher number of occupants and associated activities, such as cooking, heating, and entertainment [20], [21].

iii. Behavioural patterns: The concept relates to daily routines, habits, and preferences of all family members. In general, it refers to those families whose members are more likely to stay at home and have a higher energy consumption than other families whose members leave for work or school [20], [21]. The level of income also contributes to modifying these behaviours. High-income households often exhibit lifestyles that demand greater energy consumption, such as frequent use of high-capacity entertainment systems or maintaining home offices [20], [21].

Household energy consumption can be mathematically formulated using electrical energy formula as the total energy consumption (E) over a period (T) expressed by equation 1 below:

$$E_{total} = \sum_{i=1}^{n} P_i \times t_i \quad (1)$$

Where E_{total} is the total household energy consumption, P_i is the power consumption of appliance *i*, t_i is the time duration for which appliance *i* is used, and *n* is the total number of appliances.

b. Behavioural Economics Theory:

The behavioural economics theory combines insights from psychological human behaviour with economic models to help understand how individuals make decisions [22]-[24]. The theory is crucial for this study to assist in explaining decision-making processes of households regarding energy consumption influenced by socio-economic factors such as household income and household size. The key behavioural economics selected concepts applicable to the study are described below:

i. Bounded rationality: The concept states that consumers often make decisions based on limited information, cognitive bias, and time constraints rather than optimal calculations [22]- [24].

ii. Nudge theory: The theory states that small interventions or subtle changes in the environment can influence consumer behaviour without restricting choices. For instance, real-time feedback on energy consumption can result in and promote reduced energy consumption [22]- [24].

iii. Value-Belief-Norm Theory: The theory posits that values shape beliefs about the environment, which in turn, affect personal norms and pro-environmental actions. Young et al. [25] examined consumer behaviour and sustainable consumption, warranting additional exploration through this perspective.

iv. Technology Acceptance Model (TAM): TAM is a model that is applied to understand user adaptation to new energy technologies or management systems. The adoption is influenced by key factors such as perceived usefulness and perceived ease of use. Chulmo et al. [26] investigated the adoption of smart green information technology (IT) by providing insights on the applicability of the technology acceptance model. Peiffer et al. [27] discussed modelling the adoption of clean energy technologies, which could also benefit from the integration of the TAM.

v. Energy Justice Frameworks: These frameworks pertain to energy equity and fairness in energy accessibility and management. These frameworks can assist in analysing the distributional impacts of energy policies and technologies on different household groups. Qiao and Lin [17] investigated the impact of individual characteristics and external factors on energy-saving behaviour. Klein et al. [28] discussed energy citizenship and digitisation, which are linked to energy justice concepts. The authors outlined that further research is required to examine the effects of energy management solutions on different social groups and to guarantee equal access.

Socio-economic factors include household income H_i and household size H_s variables. The variables can be mathematically formulated to represent their relationship with energy consumption (E) as:

$$E = f(H_i, H_s, other\ socioeconomic\ variables) \qquad (2)$$

Where *f* is the function representing the relationship between the socio-economic variables and energy consumption.

The relationship between socioeconomic factors (independent variable – that is., income level and household size) and household energy consumption (dependent variable) can also be utilised as a statical method of linear regression analysis. The general form of linear regression for energy consumption can be mathematically formulated as:

$$E_{behavior} = \beta_0 + \beta_1 \times H_i + \beta_2 \times H_s + \epsilon + \cdots + \beta_n \times X_n \qquad (3)$$

Where $E_{behavior}$ is the energy consumption considering behavioural factors, H_i is household income, H_s represents household size, X_n represents other behavioural factors, $\beta_0, \beta_1, \beta_2, \beta_n$ are coefficients representing the sensitivity to energy consumption based on the socio-economic behavioural factors, and ϵ is the error value or unobserved factors.

2.4.2 Conceptual model

The conceptual model is discussed in Chapter 1, section 3.2 and illustrated in Figure 13 and Figure 14. The framework consists of interconnected modules that will address the gaps identified in literature.

2.5 Research Questions and Hypothesis

Building upon and guided by the theoretical framework and the identified gaps in the literature review, this research aims to address the following questions:

- Research question 1: How well does existing literature capture the distinct energy consumption behaviours and appliance usage patterns across different socio-economic groups in South Africa?
  Hypothesis 1: The studies focusing on the South African context or similar developing countries will highlight factors and variables such as income levels, household size, appliance ownership, and usage patterns as the determinants of energy consumption variations.

- Research question 2: What method can be used to create a tailored load profile for different household income categories in South Africa, considering their distinct appliance ownership patterns and energy usage behaviours?
  Hypothesis 2: The development of adaptive, threshold-based load profiles derived from income-linked appliance usage data will enable accurate

simulation of household electricity demand across low-, middle-, and high-income categories.

- Research question 3: How effectively can an optimised load-management model regulate energy consumption to remain at or below the defined threshold level while minimising disruption to user activity?
  Hypothesis 3: Implementation of an adaptive, threshold-based load-management model incorporating staggered appliance switch-off logic will effectively reduce peak-hour energy demand while maintaining essential household functions.

- Research question 4: To what degree will the development of a prototype demonstrate its functionality, usability, and adaptability in a simulated environment?
  Hypothesis 4: The prototype, when implemented in a simulated environment, will effectively demonstrate its core functions (load monitoring and control, threshold-based optimisation, and response to grid simulated signals).

- Research question 5: To what extent can the MATLAB-based prototype demonstrate system functionality and validate performance under simulated operating conditions?
- Hypothesis 5: Simulation results will demonstrate that the proposed load-management system achieves a measurable shift in energy consumption away from peak hours while maintaining user-safety constraints and threshold compliance.

2.6 Chapter Summary

This chapter outlined the theoretical foundation and reviewed relevant literature on household energy management. It identified key research gaps, particularly the absence of solutions tailored to South Africa's diverse socio-economic groups, and underscored the need for an adaptable load management system. The discussion of gaps, the conceptual framework, and the research questions together provide the basis for the study's methodology, system development, and validation presented in the subsequent chapters.

3 CHAPTER 3: METHODOLOGY AND RESEARCH DESIGN

3.1 Introduction

This chapter presents the methodology and research design for the development of an adaptable load management system tailored for low-, medium-, and high-income households in South Africa. It outlines the research approach, data collection methods, system development techniques, and analysis framework.

3.2 Methodology and Research Design Overview

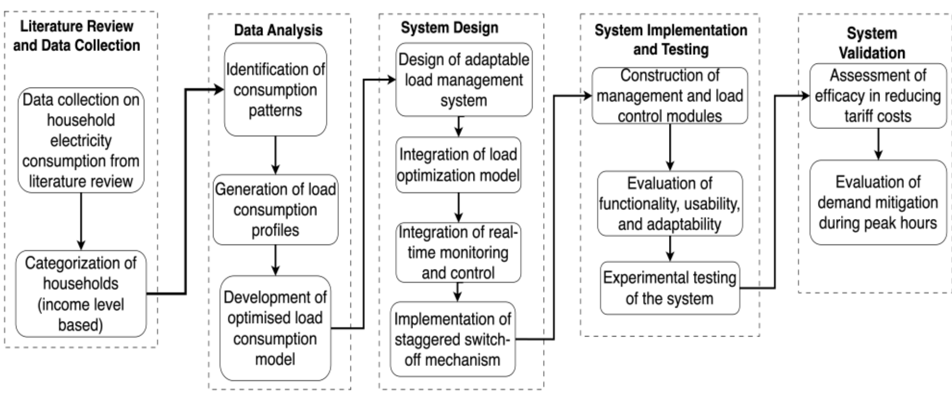

Figure 13: Research design flowchart

To achieve the aims and objectives, the following methodology and research design will be implemented:

a. User requirements identification and data collection:

To determine the need for the household load management system, primary data on South African low-, middle-, and high-income household's electricity consumption, preferences (cost saving, flexibility, and control) and challenges (safety and reliability) be collected through literature from journals, conference proceedings, and industry reports.

b. Load consumption profile creation:

The data collected from literature sources will be analysed and synthesised to generate load consumption profiles for household appliances and devices. This process involves examining data for each household category (low-, middle-, and high-income) to capture appliance and device electricity consumption patterns during peak and off-peak demand periods across different intervals.

c. Optimal load consumption model generation:

- Following the creation of load consumption profiles, an optimised load consumption model will be generated using statistical analysis to determine the average consumption threshold for each household category.
- This threshold will serve as the optimal target, aiming to maintain energy usage below or close to the threshold while meeting user requirements.

d. System design:

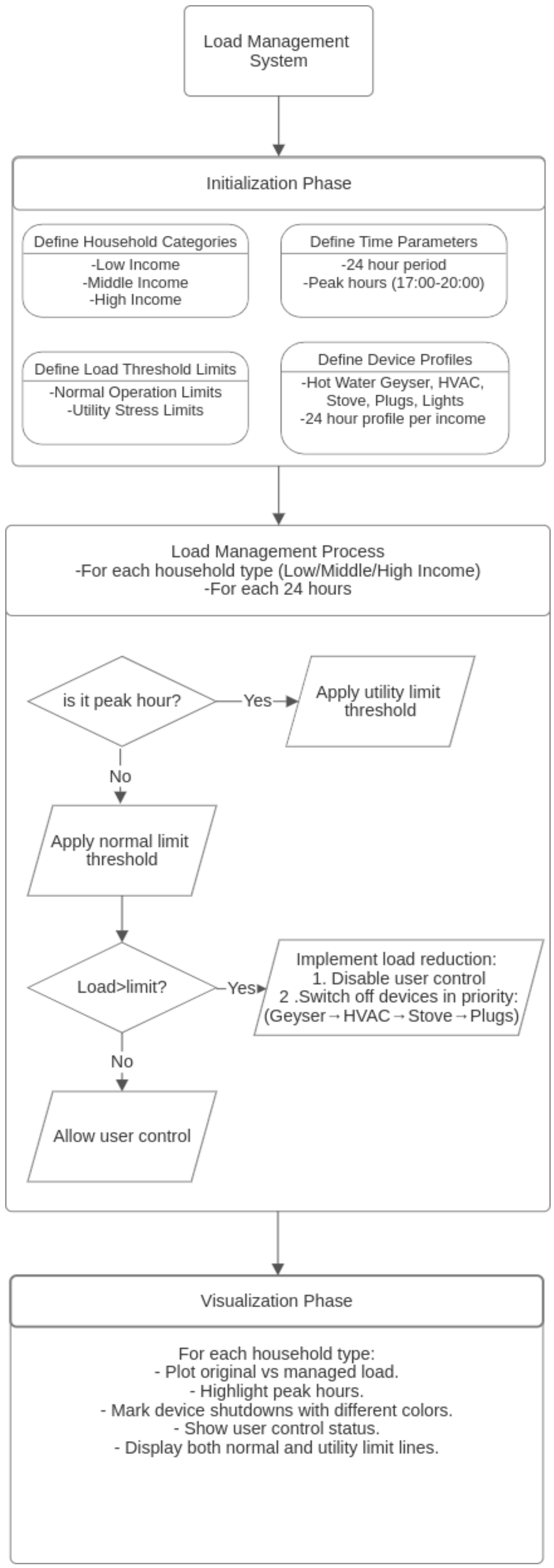

Figure 14: Adaptable load management system architecture

Following the generation of an optimal load consumption model, an adaptable load management system incorporating this model will be designed. The system will consist of two sub-systems:

i. Load management sub-system:

This sub-system will monitor and manage household consumption and generate load management controls based on the optimised model threshold and simulated grid conditions through user (manual, remote) and automatic control.

- User control: Allows consumers to manage their loads when the household consumption is within the optimised model threshold and under normal grid conditions.
- Automatic control: Prioritises loads during peak periods when household consumption exceeds the optimised threshold and the grid is under stress conditions, overriding user control during this period.

ii. Load control sub-system:

- Measurement simulation: The subsystem will use profile data to represent current and voltage conditions. Appliance usage per hour will be modelled using binary vectors (1=ON, 0=OFF) and energy consumption is calculated based on known appliance power ratings.
- Load switching logic: Each appliance will be associated with a control state which is switched ON or OFF based on decisions received from the Load Management System. These state changes simulate the role of relays or solid-state switches in a real-world system.
- Feedback mechanism: The Load Control Subsystem will transmit simulated appliance states and the total load values

back to Load Management at each time step. This feedback loop ensures continuous evaluation and closed-loop control.

e. Prototype development:

Upon completing the system design, the next phase involves developing a functional prototype. This prototype will serve as a platform test to evaluate the system's functionality and adaptability. Testing will be conducted in a simulated environment that reflects real-world household categories and the grid conditions. A simulated setup environment is used to mitigate the regulatory constraints (South African bureau of standards, the national energy regulator of South Africa, and electromagnetic compatibility compliance) that could limit the study time.

f. Experimental testing and evaluation:

Following prototype development, the testing and evaluation phase will commence. This phase will focus on assessing functionality, usability, and adaptability. Performance will be evaluated using measurable metrics, including:

- Energy savings (%): Comparing managed vs. unmanaged consumption.
- Load reduction (%): Quantifying the decrease in household peak demand.
- Tariff cost savings: Evaluating reductions in electricity expenditure under applicable South African tariff structures.

These tests aim to verify and validate the system's effectiveness in reducing household electricity costs, mitigating peak demand, and alleviating grid stress.

3.3 Research Design

The study employs a design-based and prototype-driven research design that integrates both qualitative and quantitative approaches to develop and evaluate an adaptable household load management system for different income levels in South Africa. The research framework follows the engineering systems development lifecycle, comprising problem identification, data acquisition, model development, system design, prototyping, and evaluation.

3.3.1 Design orientation

The research is solution-oriented, aiming to create a practical application that addresses electricity load optimisation at the household level. A quasi-experimental methodology is employed, utilising a simulated household environment to validate system performance while ensuring compliance with regulatory standards [29], [30]. This approach enables iterative fine-tuning and controlled testing.

3.3.2 Mixed-methods approach

This study adopts a mixed-method research approach, combining qualitative and quantitative methods to ensure both a comprehensive understanding of the problem and a robust evaluation of the solution. Mixed-methods approaches are particularly effective in engineering research, where human-centred requirements and data-driven modelling are both crucial for successful system development and validation [29], [31]. These methods collectively support the system development and validation processes outlined below:

a. Qualitative component:

   The qualitative component focuses on contextual understanding, specifically the social, behavioural, and experiential aspects of household electricity consumption. It examines user preferences (e.g., flexibility, control, and affordability), load usage habits, and systemic challenges across the three income groups.

Data was synthesised from existing literature, national surveys, and policy reports [32], [33] that describe how different income groups in South Africa experience and respond to energy availability, pricing structures, and demand-side management initiatives. The insights guided the system design, particularly concerning appliance prioritisation, user control functionalities, and load sensitivity to peak-hour limitations.

This approach aligns with Creswell et al.'s [29] view that qualitative research helps uncover the "how" and "why" behind user needs and behaviours.

b. Quantitative component:

The quantitative component focuses on numerical modelling and statistical evaluation. Appliance-level and hourly household energy consumption data were extracted from secondary sources, including the 2021 Residential Electricity Consumption in South Africa Survey published by the Department of Mineral Resources and Energy [32].

The data are used to:

- Construct 24-hour appliance-specific load profiles for different household income levels.
- Define energy consumption thresholds based on national usage averages for the three income groups.
- Develop and evaluate control algorithms, specifically a staggered switch-off mechanism.
- Measure system performance using indicators such as peak demand reduction, compliance rate, and switching frequency.

This component aligns with the principle that quantitative research allows for an objective assessment of the efficacy and scalability of technical interventions [34].

3.3.3 Simulation-based validation

The system is assessed in a simulated environment due to regulatory compliance requirements (SABS, NERSA, and EMC regulations), [35], [36]. The simulations replicate household electricity consumption patterns and grid stress scenarios to assess the effectiveness of the system's adaptability and performance in managing electrical loads.

3.3.4 Research Design Phases

The research design adopts a simulation-based experimental approach to develop and evaluate an adaptable household load management system tailored to the energy consumption behaviours of low-, middle-, and high-income households in South Africa. In this study, 'experimental' refers exclusively to MATLAB-based simulations rather than physical prototype testing. This approach enables controlled evaluation of system logic and adaptability before future hardware implementation. The methodology is divided into the following key phases:

a. User Requirements Identification and Analysis

   An initial review and assessment of national household electricity consumption data and socio-economic studies were performed, focusing on trends specific to the three household income groups in South Africa. Key user requirements, which include flexibility, affordability, and control, are identified and derived from the literature.

b. Load Consumption Profile Creation:

   Household appliance-level consumption data from the literature were synthesised to construct load profiles for each household income category. The analysis captures usage trends and identifies key appliances contributing to both peak and off-peak demand periods.

c. Optimal Load Consumption Model Generation:

A statical analysis of the load profiles was conducted to derive average consumption thresholds for each household type. These thresholds form the basis of an optimised model that guides energy usage and maintains consumption below predefined limits without compromising lighting as a priority.

d. System Conceptualisation and Design

The system architecture was developed, comprising two integrated sub-systems:

- Load Management Sub-system: Responsible for interpreting load profile data, comparing the total load against income specific thresholds, and implementing control logic to activate the staggered switch-off mechanism.
- Load Control Sub-system: Utilises logical structures and state variables in MATLAB to model appliance switching, priority ranking, and feedback on system actions.

A staggered switch-off mechanism is incorporated to prioritise appliance loads and improve grid stability. The system design was implemented in MATLAB using control structures, vector operations, and graphical user interface elements to replicate system behaviour in a real-world context.

e. System Integration

All components were integrated within MATLAB to model real-time system behaviour in response to dynamic load conditions. Appliance states are represented using binary vectors, and switching logic was implemented according to priority rankings. Simulation parameters include grid stress scenarios, user input toggles, and varying load curves for different income groups. Communication and data interchange among sub-systems are represented as function calls and shared data structures.

f. Experimental Testing and Performance Evaluation
The system was tested within a simulated residential environment reflecting the operational characteristics of different income households. Evaluation metrics included threshold compliance rate, peak demand reduction, control action frequency, and responsiveness. Results are presented through plots that compare original and managed load profiles, including logs of appliance switching behaviour.

3.4 Research Approach

The study adopts the Design Science Research (DSR) methodology as its guiding framework. The DSR emphasises the iterative development of artefacts or solutions to address real-world challenges and validates them through analysis [37]. The following core activities define the study approach:

a. Constructing load profiles: Usage of secondary data to generate representative household energy consumption profiles segmented by income level.
b. Designing the artefact: Developing a MATLAB model implementing prioritised appliance control and a staggered switch-off mechanism.
c. Demonstrating utility: Simulating the load profiles under various conditions.
d. Evaluate effectiveness: Assessing the model's ability to maintain household loads below defined thresholds while preserving critical services, such as lighting.

This approach ensures that the developed model is contextually relevant, technically feasible, and responsive to the socioeconomic realities of electricity use in South Africa.

3.5 Data Collection Methods

This study employs a secondary data approach to model household electricity consumption profiles and supports the development of an adaptable load management system. Data were sourced from prior academic literature to ensure representative, income-specific load behaviour across South African households. Historical energy consumption data provide an empirical foundation for developing realistic household load profiles, which are subsequently used to guide the experimental phases of design, development, and verification.

3.5.1 Data source selection

The data collection strategy for this study is based on secondary data selected for its reliability, national representativeness, and relevance to the simulation environment. The following three data categories were utilised:

- Energy access and usage behaviour by income level.
- Appliance-specific energy consumption estimates; and
- Socio-economic contextual indicators.

The principal source of data is the Residential Electricity Consumption (REC) survey from the study 2021 Residential Electricity Consumption in South Africa research project report conducted by SANEDI, the Department of Mineral Resources and Energy, and the University of Cape Town [32]. The REC was a national data collection effort designed to analyse household electricity consumption patterns, appliance ownership, and energy expenditures among low-, middle-, and high-income households.

To support the accuracy of appliance-level estimates, the study consulted the Existing Minimum Energy Performance Standards (MEPS) Status Quo Integrated Report (2019) [38], developed by the South African Department of Energy in collaboration with the United Nations Development Programme (UNDP). The MEPS report, while lacking time-series data, provides validated appliance power ratings efficiency metrics that support the development of load profiles.

Additional socio-economic context was drawn from the General Household Survey 2021 conducted by Statistics South Africa [39]. Although it lacks hourly consumption data, it offers significant insights into household electricity access, preferred energy sources, and regional disparities.

Lastly, to improve the precision of appliance-level usage modelling, supplementary indicative estimates were obtained from publicly available online resources to cross-reference appliance power ratings and usage durations, including:

- SRS Solar's Household Appliances Electricity Consumption Guide [40].
- Justin Bonello's Eco-Audit on typical home appliance consumption [41].

While these supplementary sources are not peer-reviewed, they provide usable baseline values for appliance power ratings and usage durations. All values are cross-referenced with the principal data source, serving as supplementary inputs to refine the South African household energy behaviour.

3.5.2 Data extraction from the Residential Electricity Consumption in South Africa Research Project Report

This study utilises residential electricity consumption data from the survey conducted in [32] as part of its methodology to generate household load profiles. Hughes et al. [32] examined residential electricity consumption in South Africa using three main components. First, they conducted a national Residential Electricity Consumption Survey (REC) to gather data from 2,075 households through online panels, municipal e-surveys, and a limited door-to-door survey. This data provided insights into demographics, appliance ownership, usage behaviours, and electricity consumption across income groups.

Second, the study employed the South African residential sector calibrated model (LEAP Model) to estimate appliance ownership trends and annual electricity usage. Finally, it assessed the impact of the appliance Standards and Labelling (S&L) program from 2015 to 2020, projecting its potential influence through 2040. The analysis included estimates of energy savings driven by behavioural interventions, solar water heater adoption, and improvements in energy efficiency. This national survey collected data on:

- Household appliance ownership by income level.
- Annual electricity consumption estimates per appliance; and
- Time-of-use behaviours and seasonal demand trends.

The data collected was processed to develop 24-hour load profiles for the three income groups using the following procedure:

1. Annual-to-Daily Conversion: Appliance energy usage (in kWh/year) is divided by 365 to estimate daily usage.
2. Time-of-Use Allocation: Daily energy consumption is distributed across 24 hours using probabilistic time-of-use models aligned with typical household activity patterns.
3. Households are grouped into three income segments, each with a threshold derived from average consumption.
4. Load segmentation: Appliances are grouped into categories and priority levels of water heater, HVAC, cooking, plugs, and lighting.

This method allows for the development of realistic household energy demand across income groups. This dataset was selected due to its contextual relevance and coverage of socio-economic factors influencing energy usage in the residential sector in South Africa. The selection of this study is justified by the limited availability of research that explicitly examines household income as a determinant of electricity consumption in South Africa.

Existing literature primarily focuses on international case studies, which may not adequately address the unique socioeconomic and energy consumption patterns of South African households. The study therefore provides a contextually relevant foundation for deriving household load profiles of different household income groups to ensure an accurate representation of real-world usage.

3.6 Load Consumption Profile Creation

The development of household load consumption profiles is a critical component of the methodology, forming the basis for simulation, control logic, and performance evaluation of the adaptable load management system. These profiles represent the distributed electricity demand across the three household income groups and are constructed using a data-driven approach informed by the national survey data in [32]. This section begins with the theoretical and foundational framework of load profiles, followed by the derivation of load profiles of South African households categorised by income.

3.6.1 Original load profile

The original load profile represents the household's natural energy consumption without the application of load management [42], [43]. The original load exhibit peaks during periods of high activity of appliance usage in the household. The original load can be expressed by the equation below as:

$$L_o(t) = \sum_{i=1}^{n} P_i(t) \qquad \forall t \qquad (4)$$

Where $L_o(t)$ is the instantaneous original load measured in kilowatts (kW) at time, t, $P_i(t)$ represents the original power consumption in kilowatts (kW) of appliance *i* at time *t*, and *n* is the total number of appliances managed. ∀*t* indicates that the condition always applies *t* within the specified range, in this case a 24-hour period [44].

3.6.2 Managed load profile

The managed load profile reflects household energy consumption after the application of a load management strategy. The applied strategy includes switching off or reducing the power of certain appliances, with the objective of reducing the peaks in the original load profile and encouraging the shift of energy use to off-peak periods. The managed load profile is expressed using the equation below:

$$L_m(t) = \sum_{i=1}^{n} P'(t) \quad (5)$$

Where $L_m(t)$ is the instantaneous managed load in kilowatts (kW) at time t, $P'(t)$ represents the adjusted power consumption in kilowatts (kW) of appliance *i* at time *t* when load management is applied, and *n* is the total number of appliances managed.

3.6.3 South African household load profile development

The development process begins by identifying relevant data from the study Residential Electricity Consumption in South Africa [32] to identify key parameters such as appliance penetration rates, usage times, and power ratings to formulate load profiles for 24-hour usage across the three household categories: low-, medium-, and high-income households.

3.6.3.1 Load Profile Development for Low-Income Households

a. Monthly Electricity Expenditure:

The research [32] revealed considerable variability in electricity expenses among low-income households. The mean monthly spending on electricity was estimated at 452 South African rand, while the median monthly spending is 300 South African rand. These figures highlighted the financial constraints faced by low-income households.

b. Appliance Ownership and Usage Patterns:

- Lighting: Low-income households use an average of 4.4 lamps, operating approximately six hours per day.
- Cooking: The most common cooking appliances are electric stovetops and ovens, with kettles being used extensively for water heating.
- Refrigeration: 94.2% of households own at least one refrigerator, while 15.4% possess more than one.
- Washing machines: 51.7% of households own washing machines, with top-loading models being more common.
- Tumble dryers: 10.6% own tumble dryers.
- Television: 83.9% of households own at least one television, which indicates widespread media consumption.
- Air conditioning: Only 5.8% of households have air conditioning units, signifying limited reliance on active cooling systems.

c. Conversion of Annual Appliance Consumption to Daily Load Profiles (Low-Income Households)

Study [32] demonstrated annual electricity consumption per appliance for low-income households, which is converted to daily consumption in Table 7 to estimate hourly electricity consumption provided in Table 8 and appendix B.1. The daily consumption is determined as follows:

$$E_{daily} = \frac{E_{annual}}{365} \tag{6}$$

Each appliance's daily consumption is calculated by dividing its annual energy use by 365 days, then allocating its energy consumption over 24 hours using the time-of-use probability distribution.

Table 7: Annual to Daily Consumption Appliance Conversion for Low-Income Household.

Category	Appliance	Annual Consumption (kWh/year)	Daily Consumption (kWh/day)
Geyser	Water heater (geyser)	0 kWh (if not electric)	0 kWh
HVAC	Air Conditioning	735 kWh	2.01 kWh
Stove	Cooking (Stove + Oven)	450 kWh	1.23 kWh
Plugs	Microwave	45 kWh	0.12 kWh
	Kettle	192 kWh	0.53 kWh
	Fridge/Freezer	487 kWh	1.33 kWh
	Washing Machine	179 kWh	0.49 kWh
	Tumble Dryer	795 kWh	2.18 kWh
	Television	168 kWh	0.46 kWh
	Total Plugs	1866 kWh	5.11 kWh
Lights	Lighting	229 kWh	0.63 kWh

d. Estimated Hourly Electricity Consumption for Low-Income Households

Using the consumption data in Table 7 extracted from [32], the hourly electricity consumption for low-income households is estimated by distributing the total daily energy use across 24 hours based on typical time-of-use patterns and grouping the appliances.

Hourly load fluctuations are derived from daily electricity consumption projections utilising time-of-use distribution.

Table 8 below provides an estimated hourly load distribution based on the typical appliance usage patterns and time of use throughout the day. A corresponding representation is provided in appendix B.1.

Table 8: Distributed 24-Hour Low-Income Household Load Profile.

Hour	Geyser (kW)	HVAC (kW)	Stove (kW)	Plugs (kW)	Lights (kW)
00:00	0	0	0	0.12	0
01:00	0	0	0	0.12	0
02:00	0	0	0	0.12	0
03:00	0	0	0	0.12	0
04:00	0	0	0	0.12	0.02
05:00	0	0.07	0.08	0.22	0.09
06:00	0	0.11	0.14	0.32	0.1
07:00	0	0.09	0.08	0.22	0.05
08:00	0	0.09	0.08	0.22	0.04
09:00	0	0.13	0	0.12	0
10:00	0	0.13	0	0.12	0
11:00	0	0.14	0.08	0.22	0
12:00	0	0.14	0.13	0.32	0
13:00	0	0.14	0.08	0.22	0
14:00	0	0.19	0	0.22	0
15:00	0	0.19	0	0.22	0
16:00	0	0.14	0	0.22	0
17:00	0	0.09	0.09	0.32	0.04
18:00	0	0.09	0.24	0.42	0.1
19:00	0	0.09	0.14	0.32	0.1
20:00	0	0.09	0.09	0.32	0.04
21:00	0	0.09	0	0.25	0.04
22:00	0	0	0	0.12	0.01
23:00	0	0	0	0.12	0
SUM	0	2.01	1.23	5.11	0.63

e. Key Observations

The following are the key observations made from the hourly load profile. The analysis indicates notable fluctuations in electricity consumption during the day, marked by peak and off-peak intervals:

1. Morning peak (6:00-9:00): Increased electricity consumption due to increased demand for lighting, cooking appliances, and electric kettles as households prepare for the day's work and school activities.
2. Evening peak (17:00-21:00): The highest energy consumption occurs in the evening, driven primarily by cooking activities, household lighting, and entertainment devices such as televisions.
3. Overnight Consumption (00:00-5:00): Energy demand remains low during the night with electricity attributed to appliances such as refrigerators operating continuously.

The load profile indicates that low-income households have a daily energy consumption of 8.98 kWh/day, which is the total estimated level of energy consumption.

3.6.3.2 Electricity Consumption for Middle-Income Households

a. Monthly Electricity Expenditure

The research showed that households with middle incomes had a significant amount of variation in their consumption of electricity. The mean monthly expenditure on electricity was estimated to be 797 South African rand, while the median monthly expenditure was estimated at 525 South African rand.

b. Conversion of Annual Appliance Consumption to Daily Load Profiles (Middle-Income Households)

Table 9 shows middle-income households' annual electricity consumption per appliance category converted to daily consumption using equation (6). Hourly load variations are then calculated from time-of-use distribution estimates of daily electricity consumption.

Table 9: Annual to Daily Consumption Conversion for Middle-Income Household.

Category	Appliance	Annual Consumption (kWh/year)	Daily Consumption (kWh/day)
Geyser	Water heater (geyser)	2804 kWh	7.68 kWh
HVAC	Air Conditioning	709 kWh	1.94 kWh
Stove	Cooking (Stove + Oven)	457 kWh	1.25 kWh
Plugs	Microwave	54 kWh	0.15 kWh
	Kettle	210 kWh	0.58 kWh
	Fridge/Freezer	499 kWh	1.37 kWh
	Washing Machine	192 kWh	0.53 kWh
	Tumble Dryer	573 kWh	1.57 kWh
	Television	235 kWh	0.64 kWh
	Total Plugs	1763 kWh	4.84 kWh
Lights	Lighting	287 kWh	0.79 kWh

c. Estimated Hourly Electricity Consumption for Middle-Income Households

Table 10 provides an estimated hourly load distribution based on the typical appliance usage patterns and time of use throughout the day.

Table 10: Distributed 24-Hour Middle-Income Household Load Profile.

Hour	Geyser (kW)	HVAC (kW)	Stove (kW)	Plugs (kW)	Lights (kW)
00:00	0.14	0.03	0	0.12	0
01:00	0.14	0.03	0	0.12	0
02:00	0.14	0.03	0	0.12	0
03:00	0.14	0.03	0	0.12	0
04:00	0.14	0.03	0	0.12	0
05:00	0.75	0.08	0.07	0.17	0.04
06:00	0.75	0.08	0.17	0.27	0.14
07:00	0.75	0.08	0.07	0.22	0.14
08:00	0.4	0.08	0.07	0.22	0.03
09:00	0.2	0.12	0	0.17	0.03
10:00	0	0.12	0	0.17	0
11:00	0	0.12	0.07	0.22	0
12:00	0	0.12	0.15	0.32	0
13:00	0	0.12	0.07	0.22	0
14:00	0	0.18	0	0.22	0
15:00	0	0.18	0	0.22	0
16:00	0	0.13	0	0.22	0
17:00	0.75	0.08	0.07	0.27	0.04
18:00	0.75	0.08	0.27	0.37	0.14
19:00	0.75	0.08	0.17	0.32	0.14
20:00	0.75	0.08	0.07	0.27	0.03
21:00	0.75	0.02	0	0.17	0.03
22:00	0.38	0.02	0	0.1	0.03
23:00	0	0.02	0	0.1	0
SUM	7.68	1.94	1.25	4.84	0.79

d. Key Observations

The following are the key observations made from the hourly load profile for middle-income households. The analysis indicates notable fluctuations in electricity consumption during the day, marked by peak and off-peak intervals:

1. Morning peak (5:00-8:00): Increased electricity consumption due to geyser operation, cooking appliances, and lighting as households prepare for work and school. The geyser alone contributes significantly to the morning peak.
2. Evening peak (17:00-21:00): The highest energy consumption occurs in the evening, primarily driven by geyser usage, cooking activities, HVAC operation, household lighting, and entertainment devices such as televisions.
3. Overnight Consumption (00:00-5:00): Energy demand remains low during the night with electricity attributed to appliances such as refrigerators operating continuously and standby appliances.
4. Midday Consumption (10:00-16:00): Moderate electricity consumption occurs due to HVAC usage and intermittent appliance loads such as microwaves and washing machines, while the geyser remains inactive.

The load profile indicates that middle-income households have an average daily energy consumption of 16.50 kWh/day, which is the total level of energy consumption.

3.6.3.3 Electricity Consumption of High-Income Households

a. Monthly Electricity Expenditure

Following the same methodology that was used for households with low and middle incomes, the research [32] showed that households with high incomes had a significant amount of variation in their consumption of electricity. The mean monthly expenditure on electricity was estimated to be 1,338 South African rand, while the median monthly expenditure was found to be approximately 1,000 South African rand.

b. Conversion of Annual Appliance Consumption to Daily Load Profiles (High-Income Households)

The study [32] generated an annual electricity consumption per appliance category. The consumption data from Table 11 serves as the basis for estimating daily electricity demand in high-income households using equation (6).

Table 11: Annual to daily consumption conversion for high-income household.

Category	Appliance	Annual Consumption (kWh/year)	Daily Consumption (kWh/day)
Geyser	Water heater (geyser)	3923 kWh	10.75 kWh
HVAC	Air Conditioning	682 kWh	1.87 kWh
Stove	Cooking (Stove + Oven)	580 kWh	1.59 kWh
Plugs	Microwave	59 kWh	0.16 kWh
	Kettle	225 kWh	0.62 kWh
	Fridge/Freezer	543 kWh	1.49 kWh
	Washing Machine	237 kWh	0.65 kWh
	Tumble Dryer	573 kWh	1.57 kWh
	Television	342 kWh	0.94 kWh
	Total Plugs	1866 kWh	5.11 kWh
Lights	Lighting	438 kWh	1.2 kWh

c. Estimated Hourly Electricity Consumption for High-Income Households

Hourly load variations are derived from daily electricity consumption estimates using time-of-use distribution.

Table 12 provides an estimated hourly load distribution based on the typical appliance usage patterns and time of use throughout the day.

Table 12: Distributed 24-Hour High-Income Household Load Profile.

Hour	Geyser (kW)	HVAC (kW)	Stove (kW)	Plugs (kW)	Lights (kW)
00:00	0.22	0.02	0	0.09	0
01:00	0.22	0.02	0	0.09	0
02:00	0.22	0.02	0	0.09	0
03:00	0.22	0.02	0	0.09	0
04:00	0.22	0.02	0	0.09	0.03
05:00	1.08	0.08	0.1	0.19	0.09
06:00	1.08	0.08	0.2	0.29	0.14
07:00	1.08	0.08	0.1	0.24	0.14
08:00	0.68	0.08	0.1	0.24	0.09
09:00	0.37	0.12	0	0.14	0.03
10:00	0	0.12	0	0.14	0
11:00	0	0.12	0.1	0.22	0
12:00	0	0.12	0.19	0.31	0
13:00	0	0.12	0.1	0.24	0
14:00	0	0.17	0	0.24	0
15:00	0	0.17	0	0.24	0
16:00	0	0.12	0	0.24	0
17:00	1.08	0.08	0.1	0.34	0.09
18:00	1.08	0.08	0.3	0.44	0.19
19:00	1.08	0.08	0.2	0.39	0.19
20:00	1.08	0.08	0.1	0.34	0.09
21:00	0.67	0.03	0	0.19	0.09
22:00	0.37	0.02	0	0.14	0.03
23:00	0	0.02	0	0.09	0
SUM	10.75	1.87	1.59	5.11	1.2

d. Key Observations

The following key observations were made from the hourly load profile. The analysis indicates notable fluctuations in electricity consumption during the day, marked by peak and off-peak intervals:

1. Morning peak (5:00-8:00): Increased electricity consumption due to high demand for hot water from the geyser, cooking appliances and kettle, and lighting as households prepare for work and school. The geyser alone contributes significantly to the morning peak.
2. Evening peak (17:00-21:00): The highest energy consumption occurs in the evening, primarily driven by geyser usage, cooking activities, HVAC operation, household lighting, and entertainment devices such as televisions.
3. Overnight Consumption (00:00-5:00): Energy demand remains low during the night with electricity attributed to appliances such as refrigerators operating continuously and standby appliances.
4. Midday Consumption (10:00-16:00): Moderate electricity consumption occurs due to continuous operation of HVAC and refrigerator, with occasional cooking and laundry washing.

The load profile indicates that high-income households have an average daily energy consumption of 20.52 kWh/day, which is the total level of energy consumption.

3.7 Optimal Load Consumption Threshold Generation

3.7.1 Income-based load thresholds

Thresholds were determined based on the maximum observed hourly loads for each income group, as shown in Tables 8, 10, and 12. To ensure practical feasibility, normal thresholds were set at approximately 70% of the maximum observed load, while peak thresholds (applied during 17:00–20:00) were set at 50% of the maximum load. This approach balances grid stability with household functionality and reflects realistic appliance usage patterns. The approach was selected based on following:

- Grid Stability During Peak Hours

Applying stricter limits during the evening peak period helps reduce strain on the grid when demand is highest, while allowing more flexibility during off-peak hours.

- Functional Household Operation
  Setting thresholds as a percentage of the maximum observed load ensures that essential appliances can operate under normal conditions. This prevents complete disconnection of high-power devices and maintains usability for households.

The thresholds applied in the system are:

- Low-income households: Normal = 0.60 kW; Utility Control Peak = 0.43 kW
- Middle-income households: Normal = 1.13 kW; Utility Control Peak = 0.81 kW
- High-income households: Normal = 1.46 kW; Utility Control Peak = 1.05 kW

These values allow essential appliances to operate under normal conditions while enforcing stricter limits only during peak hours. This time-dependent strategy improves technical feasibility and consumer acceptability compared to static limits.

3.7.2 Staggered switch-off control logic

The central feature of the load management system is the staggered switch-off mechanism, which introduces an adaptable and prioritised load reduction strategy. Unlike most of the conventional methods discussed in chapter 2 that initiate a complete shutdown when consumption reaches a limit threshold, the staggered mechanism approach applies a hierarchical control logic that sequentially deactivates non-essential appliances based on the predefined levels.

The priority levels are classified as follows:

- Low-priority appliances: Water heater (geyser), HVAC, Stove
- Medium-priority appliances: Plug loads
- High-priority appliances: Lighting (exempted from disconnection)

This prioritisation guarantees the reduction of discretionary loads to keep consumption within acceptable limits while ensuring that essential household functions, such as lighting, remain uninterrupted.

The control logic and algorithm functions at each time step according to the following sequence:

1. Evaluate the total household consumption $L_o(t)$.
2. If $L_o(t)$ > threshold, identify all currently active appliances and sort them by ascending priority.
3. Iteratively deactivate the lowest-priority active appliance.
4. Recalculate the total power $L_o(t)$ and repeat the process until $L_o(t) \leq Threshold$.

This logic is implemented in MATLAB using nested and iterative control structures.

3.8 System Design

The system design of the Adaptable Household Load Management is informed by the energy consumption behaviour across income levels in South Africa, including the requirements derived from the analysis of appliance usage patterns in section 3.6. The system is implemented and evaluated entirely as a MATLAB-based software model. The system block and flow diagram is illustrated in Figure 14.

The architecture comprises the following two core sub-systems:

- Load Management System
- Load Control Subsystem

The subsystems function in correlation to monitor electricity consumption, compare it with load threshold limits described in section 3.7, and execute a control strategy that prioritises essential appliances while shedding non-critical loads. The system is designed to support the following two modes of operation:

- User-Controlled Mode: In this mode, users are allowed to interact with the system manually or remotely to appliance states, provided that the total load remains within the assigned threshold. This mode supports user preferences providing flexibility and customisability during normal grid and household load conditions.
- Automated Priority Control Mode: This mode engages when domestic electricity usage surpasses the established threshold or when the grid encounters stress conditions. The system automatically overrides manual controls and applies staggered switch-off mechanisms to reduce the load. Appliances are deactivated in order of priority: water heater (geyser), HVAC, stove, and plugs, until total consumption decreases below the threshold limit.

3.8.1 Load management subsystem

The Load Management Subsystem is implemented in MATLAB and functions as the central processing and the decision-making unit. The unit is primarily responsible for:

- Load Profile Integration: Hourly appliance level load profiles are imported into MATLAB based on the national survey [32]. Each profile is organised as a 24-hour matrix depicting energy consumption in kW across various appliance categories, including water heater (geyser)s, HVAC systems, stoves, plugs, and lighting.
- Threshold Evaluation: Compares the total household consumption to the optimised load threshold for each of the household categories. If

the threshold is exceeded, the subsystem applies corrective control actions.

- Control Logic Module: The subsystem activates a staggered switch-off mechanism when the load exceeds the threshold. Appliances are ranked by control priority with non-essential loads deactivated first until the load returns to within acceptable limits.
- User Control Module: The user control module monitors household energy use and allows appliance operation and control if usage is within the threshold, otherwise it restricts the user from having control of appliance operation.
- Utility Grid stress Module: It monitors household consumption during the grid stress period (17:00-20:00). If consumption exceeds the stricter utility threshold, appliances are further switched off to help stabilise the overall power system.
- Automatic Override Mechanism: Suspends user control when simulated system grid constraints are active or consumption exceeds the threshold.

3.8.2 Load control subsystem

The load control subsystem is responsible for simulating the behaviour of the real-world electrical components, including measurement, load regulation, and feedback. The functional operation is implemented using MATLAB logic and state variables. The core functions include:

- Measurement Simulation: The subsystem uses profile data to represent current and voltage conditions. Appliance usage per hour is modelled using binary vectors (1=ON, 0=OFF) and energy consumption is calculated based on known appliance power ratings.

- Load Switching Logic: Each appliance is associated with a control state, which is switched ON or OFF based on decisions received from the Load Management System. These state changes simulate the role of relays or solid-state switches in a real-world system.

- Feedback Mechanism: The Load Control Subsystem transmits simulated appliance states and the total load values back to the Load Management System at each time step. This feedback loop ensures continuous evaluation and closed-loop control.

3.9 Prototype Development

A prototype was developed in a MATLAB-based environment to validate the design and operation of the Adaptable Household Load Management System. The prototype includes modular implementation of the Load Management Sub-system and the Load Control Sub-system discussed in section 3.8. It simulates key functionalities including threshold monitoring, appliance prioritisation, staggered switch-off mechanism, and autonomous vs user-controlled modes. The interactions between the subsystems are executed through software modules enabling closed-loop behaviour without the need for physical sensors or switching devices.

The choice to simulate the prototype rather than deploying a physical hardware implementation was primarily motivated by the need to bypass regulatory and compliance constraints that could otherwise delay or complicate the research timeline. Simulation-based prototype development allows for controlled testing while avoiding regulatory constraints related to electromagnetic compatibility (EMC), electrical safety, and embedded systems certification under South African standards. Physical implementations involving alternating current (AC) switching and power regulation in South Africa are subject to stringent national standards including:

- SANS 10142-1: The South African Wiring Code for Low-Voltage Installations enforced by the South African Bureau of Standards (SABS) for safety and wiring compliance [35].

- NERSA Grid Codes: The National Energy Regulator of South Africa (NERSA) mandates compliance with national grid codes for systems interfacing with or simulating utility supply behaviour [45].
- Electromagnetic Compatibility Compliance (EMC): Hardware-based electronic systems must adhere to limits on electromagnetic interference as outlined in SABS EMC standards aligned with Comité International Spécial des Perturbations Radioélectriques (CISPR), which is an international organisation that develops standards for electromagnetic compatibility [36].

Adopting a simulation-based prototype ensures the study remains and complies with electrical safety and research boundaries while still offering a functional and analytical system for testing and evaluation. The simulated environment allows for fast iteration, reproducibility, and control over variable household scenarios and simulated grid signals.

While the preceding section outlined the justification and simulation-based rationale for prototype development, the following subsection provides a detailed account of the additional components, control algorithms, and MATLAB modules that distinguish the implemented prototype from the conceptual system design. The intention is to demonstrate how the system architecture of Section 3.7 was operationalised into an executable and verifiable simulation model within MATLAB.

3.9.1 Enhanced MATLAB-Based Prototype Implementation

The MATLAB-based prototype extends the conceptual system design described in Section 3.7 into a fully functional and executable simulation environment. While the system design establishes the structural and algorithmic framework of the Adaptable Household Load Management System, the prototype operationalises this framework through the integration of simulation modules and the interaction between the Load Management and Load Control Subsystems. The implementation provides a dynamic testing platform capable of representing user-controlled and autonomous operation modes under both normal and constrained grid conditions.

The enhanced MATLAB prototype comprises the following functional components:

- Dual-threshold Control Logic:
  Two hierarchical load limits are implemented, (i) a household-specific operating threshold that regulates consumption under normal conditions, and (ii) a utility-enforced constraint that activates automatically during simulated grid stress periods (17:00–20:00). This dual-threshold approach allows the system to model both consumer-side management and utility-imposed demand response.
- Grid-Stress Detection and Automatic Override:
  The prototype identifies peak-hour intervals using a pre-defined time vector and enforces a stricter operating limit. During these periods, the system disables user control and initiates automated load shedding according to the established priority sequence (geyser → HVAC → stove → plugs).
- User-Controlled and Autonomous Operating Modes:
  Under normal operating conditions, users retain the ability to manually control appliance states provided that the total load remains within the allowable threshold. When either the household limit or the utility constraint is exceeded, the system automatically transitions into autonomous mode, temporarily overriding user control to stabilise load demand.
- Event-Driven Control Functions:
  The prototype executes control decisions at each hourly time step using iterative logic implemented in the manageLoadWithGridStress function. This function evaluates instantaneous household consumption, applies

switch-off actions, and records device states for subsequent performance analysis.

- Dynamic Data Exchange and Feedback:
  Continuous feedback between subsystems is maintained throughout the simulation. The Load Management Subsystem communicates threshold exceedances and switching commands, while the Load Control Subsystem returns updated appliance states and total load values. This closed-loop operation enables adaptive system behaviour across varying load scenarios.
- Visualisation and Analytical Interface:
  A graphical output module, implemented in the plotLoadManagementWithGridStress function, visualises hourly load patterns, threshold compliance, appliance switch-off events, and grid-stress periods using MATLAB's plotting environment. Shaded overlays highlight grid stress intervals, while data markers differentiate user-controlled and autonomous operation phases. This visualisation supports system validation and comparative analysis across low-, medium-, and high-income household configurations.

The inclusion of these executable modules transforms the conceptual MATLAB system design into a simulation prototype that demonstrates closed-loop control, user-system interaction, and grid-responsive adaptability. The prototype provides quantitative and visual validation of system behaviour, enabling repeatable experiments under diverse household and grid-stress scenarios without the need for physical hardware deployment.

3.10 Testing and Evaluation Framework

The testing and evaluation phase assesses the performance, adaptability, and responsiveness of the Adaptable Load Management System under simulated operating conditions. The evaluation framework utilises a simulation-based testing methodology to validate functionality, adherence to load thresholds, and control logic behaviour across various household income configurations within the MATLAB environment.

3.10.1 Evaluation objectives

The key objectives of the evaluation framework are as follows:

- To validate the correct execution of the staggered switch-off control logic.
- To assess the system's ability to maintain household load within predefined thresholds across each income group category.
- To examine the system responsiveness to the simulated overload grid conditions.

3.10.2 Simulation environment

All tests are conducted using MATLAB leveraging both scripts and graphic user interfaces built with MATLAB App Designer. The system is evaluated using real-world load profiles in Table 8, Table 10, and Table 12 derived from the national residential electricity consumption data, including the corresponding representations in appendix B.1, B.2, and B.3. These profiles are represented as 24-hour time-series vectors separated by appliance and income level.

The following components are simulated for each test case:

- Appliance-level hourly power consumption (kW).
- Control thresholds for low-, middle-, and high-income households.
- Hourly evaluation of system load vs threshold.
- Execution of control actions (appliance switch-off).

3.10.3 Test scenarios

The system was tested under multiple scenarios to simulate household energy demand conditions:

- Scenario A- Normal Load: Household load remains below the threshold throughout the day.
- Scenario B- Moderate Load: Load exceeds the threshold during morning and evening peaks.
- Scenario C- Sustained Load: Load remains above the threshold for consecutive hours.
- Scenario D: Grid stress Condition: Simulated grid signal overrides user control and activates automatic priority mode.
- Scenario E: Manual Control Mode: User interacts with the system to manually switch appliance states during normal conditions.

Each scenario is applied to the three household income profiles to test adaptability across socio-economic contexts.

3.10.4 Evaluation metrics

The following performance metrics were used to evaluate the system:

- Threshold Compliance Rate: Percentage of time steps during which the total household loads remained at or below the income specific threshold.
- Load Reduction Effectiveness: Difference in peak demand before and after control intervention.
- Control Action Count: Total number of switch-off events triggered per scenario.
- Logical Correctness: Verifying whether the control logic preserved the priority order of appliances and prevented the deactivation of high-priority appliances such as lighting.

3.10.5 Data logging and analysis

The system logs hourly load values, control actions, appliance states, and mode transitions (user vs autonomous). These logs are used to generate plots comparing original and managed load profiles, appliance switch-off patterns, and threshold compliance trends. The data is further analysed to quantify energy savings and deduce potential tariff cost reduction in real-world deployment.

3.11 Ethical consideration

This study is based entirely on simulation and does not involve direct interaction with human and animal participants. Ethical considerations are observed to ensure the responsible use of data, software tools, and research outcomes. The following principles are observed throughout the project:

3.11.1 Use of secondary data

The household load profiles, and appliance usage data utilised in this study were derived from a publicly available national household consumption report [32]. The dataset on Residential Electricity Consumption in South Africa from 2021 was utilised to develop load profiles. No personal, identifiable, or confidential information was accessed or used during the research. The dataset was utilised exclusively for academic and research purposes, with all analyses performed in accordance with fair use and data citation standards.

3.11.2 Regulatory compliance in system design

Implementation in a simulated environment avoids the need for regulatory clearance associated with physical systems. Real-world compliance with SABS wiring codes, NERSA grid codes, and EMC standards applies only to hardware-based deployments. By using MATLAB-based simulation, this study eliminates risks and delays linked to certification requirements while still enabling rigorous evaluation of control logic and system adaptability

3.11.3 Risk avoidance

Conducting the study in a simulated environment inherently eliminates physical risks such as electrical hazards and equipment damage. This is a standard characteristic of simulation-based research and is noted here for completeness.

3.11.4 Transparency and reproducibility

The software code, assumptions, and input parameters utilised in the simulation were documented to guarantee transparency and reproducibility. MATLAB simulation files were structured to support academic verification and reuse by future researchers.

3.11.5 Institutional ethical compliance

Formal ethical clearance was not required as the research did not involve human subjects or animal testing and did not include direct experiments involving private households. However, ethical standards concerning academic integrity, intellectual property, and responsible data utilisation were maintained consistently.

3.12 Chapter Summary

This chapter outlined the research design and methodology framework adopted in the development of the Adaptable Load Management System for different household categories in South Africa. The study followed a design science approach that incorporates simulation-based modelling to represent real-world electricity consumption behaviour across specific household income categories. Key processes included the creation of load consumption profiles, the formulation of income-based consumption thresholds, the design of a staggered switch-off control logic, and the implementation of the system in MATLAB for functionality and performance testing.

The chapter also detailed the system architecture comprising load management and load control subsystems. This included the rationale for employing a simulation prototype to address regulatory, time constraints, and safety. A systematic testing and evaluation framework was created to evaluate threshold compliance, load reduction, and system adaptability across diverse operational scenarios. Ethical considerations concerning data utilisation, software integrity, and simulation safety were also examined.

The next chapter presents the results and analysis derived from the simulation experiments. It evaluates the system’s effectiveness in reducing peak demand, enforcing control logic, and responding to household demands, while providing insights into its potential for real-world deployment.

4 CHAPTER 4: IMPLEMENTATION, TESTING OF SOLUTION, AND RESULTS

4.1 Introduction

This chapter presents the implementation and performance evaluation of the Adaptable Household Load Management System. The implementation is a MATLAB-based simulation focusing on the integration of income specific load profiles, control algorithms, and system performance under different test scenarios. The chapter outlines how the system is developed, configured, and evaluated to meet the objectives outlined in Chapter 1 and is based on the design discussed in Chapter 3. This chapter includes a detailed description of the MATLAB-based prototype, simulation parameters, load control methodology, and the results derived from different operational scenarios.

4.2 Prototype Implementation

4.2.1 Software platform setup

The MATLAB R2025a is the selected environment due to its advanced capabilities in numeric computing and control system design. MATLAB's ease of matrix manipulation ensures suitability for simulating household energy consumption profiles and executing control.

Key elements of the setup include:

- Appliance Load Profiles
- Consumption Threshold Limits
- Utility Threshold Limits

- Staggered Switch-Off Control Logic
- Time of the Day Control Loop
- Data Visualisation and Logging

This platform enables the development and simulation of the Adaptable Household Load Management System forming the basis for performance evaluation under variable consumption and control conditions.

4.2.2 Data acquisition and load profile structuring

The input dataset comprises 24-hour appliance level electricity consumption profiles developed in Chapter 3 for the three household income groups in South Africa. Profiles were categorised based on reported ownership and usage of key household appliances that are water heater, HVAC, stove, plug loads, and lighting.

These profiles are static in nature, representing electricity consumption for different household income groups. Static profiles do not change dynamically during the simulation but serve as true reflective and representative baselines for evaluating the performance of the adaptive load management system.

Data is structured in Comma-Separated Values (CSV) files reflecting low-income load profiles in Table 8, Table 10 for middle-income and Table 12 for high-income, with corresponding representations in appendix B.1, B.2, and B.3. Data is structured with time-series resolution at hourly intervals resulting in 24 steps per day.

Pseudocode implementation is as follows:

```
% Pseudocode: Load Household Load Profiles Based on Income Level
% Load load profile data for low-income households
tablelow=readtable('LowIncomeProfile.csv')
```

% Load load profile data for middle-income households
tablemiddle=readtable('MiddleIncomeProfile.csv')

% Load load profile data for high-income households
tablehigh=readtable('HighIncomeProfile.csv')

The module uses a MATLAB function that reads data from a file and stores it as a table. The function is essential for handling tabular data in a spreadsheet or CSV file.

4.2.3 Control logic implementation

The control logic follows a staggered switch-off mechanism where non-essential appliances are switched off sequentially when the total instantaneous load exceeds the predefined limit threshold.

The device prioritisation scheme ranked from most essential to least is as follows:

1. Lights (excluded, most essential)
2. Plugs
3. Stove
4. HVAC
5. Water heater (geyser)

This non-binary shedding mechanism ensures minimal disruptions to essential household functions such as lighting while achieving a notable load reduction. The priority control logic structure is defined as a cell array named priorities that store the order in which the appliances should be switched off and it is implemented in MATLAB as follows:

Priorities={`Plugs',`Stove',`HVAC',`Water Heater'}.

4.2.4 Optimised load threshold implementation

Load thresholds for the income groups are configured based on the average consumption derived from Table 8, Table 10, and Table 12 and in appendices B.1 - B.3. These thresholds represent the maximum allowable average hourly power demand for each household income group. Table 13 presents the defined threshold values for income groups:

Table 13: Assigned Load Threshold by Income Group

Income Category	Assigned Threshold
Low-Income	0.60 kW
Middle-Income	1.13 kW
High-Income	1.46 kW

The thresholds are implemented in MATLAB using a vector array structure. The MATLAB code snippet is as follows:

Limit thresholds = [0.60,1.13,1.46].

Each step evaluates the total household power consumption against the corresponding income-based threshold. If consumption exceeds the allowable limit, the system automatically activates the staggered switch-off control logic to reduce the load in a hierarchical manner.

4.2.5 Staggered switch-off mechanism implementation

A staggered switch-off control mechanism is implemented to enforce consumption limits while preserving critical loads. The switching logic preserves essential services such as lighting while shedding noncritical loads defined in section 4.2.3. The control mechanism operates iteratively over each income category (hh) and time step (t) as illustrated in the following MATLAB pseudocode:

```
for hh = 1 to 3        % Loop through 3 household income groups
   for t = 1 to N      % Loop through each time step (for example, 24 hours)
```

```
    if rawprofile{hh}(t) > thresholds(hh)
       % If the household load exceeds its allowed threshold at hour t

       % Step 1: Begin staggered switch-off control logic

       % Step 2: Identify the list of appliance loads at time t for household hh

       % Step 3: Sort appliances by priority (from lowest to highest priority)

       % Step 4: Iteratively switch off the lowest priority appliance
       %         Recompute the total load after each deactivation

       % Step 5: Stop once total load ≤ threshold(hh)
    end
  end
end
```

From the pseudocode:

- hh represents household income category (1: low-income, 2: middle-income, 3: high-income).
- t represents the hourly time step (from 1 to 24)
- rawprofile{hh}(t) denotes the aggregate load at time t for household type hh.
- Threshold(hh) denotes the maximum allowable load consumption for household hh.

The model initiates a staggered switch-off mechanism when it detects overload, removing appliances in a priority manner until the total load complies with the threshold for the specific income category. The staggered switch-off mechanism ensures that energy consumption remains within the limits while maintaining the system's adaptability and equity.

Once the total load returns to within the allowable threshold in a subsequent hourly evaluation cycle, the system automatically restores the previously deactivated appliances in reverse order of their switch-off priority. The control logic therefore operates on discrete hourly intervals corresponding to the time-series resolution of the input load profiles. At each time step, the total load is reassessed, and if sufficient capacity becomes available, the control system re-enables appliances sequentially while preserving essential loads such as lighting. This cyclical evaluation and restoration process ensures that load regulation remains dynamic and responsive to changing household demand conditions throughout the 24-hour simulation period.

This restoration mechanism complements the user-control function described in the following section, allowing households to regain manual control once automated restrictions are lifted.

4.2.6 User control function

The Adaptable Household Load Management System incorporates a user control function in addition to automated load regulation. The user control function forms part of the system's adaptability, allowing the household to interact with the load management interface under normal operating conditions.

This function allows for manual or remote control, including scheduled control over appliances when household consumption remains within the allowable defined threshold for each income group category. It involves switching the appliance on or off manually or remotely or setting preferences for future operation given that the total household load remains within the designated income specific threshold.

The control mechanism is structured such that the user input is conditionally allowed only when the increasing load at a given time step is less than or equal to the predefined threshold. The system enters automated mode once the total load exceeds the threshold during which the user control is completely disabled.

The logic is implemented in a MATLAB simulation using conditional structures as illustrated in the pseudocode below:

```
FOR each household hh from 1 to 3
   FOR each time t from 1 to N
    IF rawProfile at time t for household hh ≤ threshold for    household hh
    THEN Set user control enabled to TRUE
         % Users may operate appliances within allowed limit
      ELSE
         Set user_control_enabled to FALSE
         % Users may NOT operate appliances beyond allowed limit
      END IF
   END FOR
END FOR
```

This dual mode of operation ensures a balance between automated demand side management and user autonomy. It reflects real world scenarios where customers or end users prefer control over appliance usage but still require protection from exceeding capacity constraints. The function also lays the foundation for the integration of user interfaces such as the graphic user interface (GUI) application or web dashboard.

4.2.7 Utility response function (grid stress condition)

The system incorporates a secondary stringent utility-imposed threshold in addition to the income-specific household load thresholds. The mechanism simulates grid stress conditions by enforcing stricter thresholds which temporarily override the defined household limit thresholds for each income category.

This control layer is activated during peak hours and declared grid stress conditions, simulating demand side directives issued by the utility operator to maintain grid stability. The system switches from household defined thresholds to utility-imposed limits based on the hour of the day.

The implementation logic in MATLAB denotes household Threshold(hh) denoted as the normal threshold for income group hh and the utilityThreshold(hh) is the stricter threshold applied during peak hours. A binary condition checks whether the current hour t belongs to the peak demand interval the following is the representation of the MATLAB code representation:

```
Define peakHours as [17, 18, 19, 20]

For each household hh from 1 to 3 do
   For each hour t from 1 to 24 do

      If t is in peakHours then
         Set appliedThreshold ← utilityThreshold[hh]
      Else
         Set appliedThreshold ← householdThreshold[hh]
      End If

      If totalLoad[hh][t] > appliedThreshold then
         Initiate staged appliance switch-off
         using predefined appliance priority logic
      End If

   End For
End For
```

4.3 Simulation Scenarios and Parameters

This section details the key parameters and scenarios employed in development to evaluate the effectiveness of the load management system.

4.3.1 Time resolution

Each load profile for household income is segmented and discretised into 24 hourly intervals covering a full day's consumption. The resolution is sufficient to capture a day's load characteristics, such as morning and evening peaks. The hourly intervals enable the model to assess when and how load interventions should occur based on household consumption patterns.

4.3.2 Grid-strain period classification

The 24-hour profile is segmented into operational periods that represent varying levels of grid demand and cost sensitivity. This is to reflect real-world conditions and time-of-use tariff structure. The periods are defined as follows:

- Morning Peak (06:00-9:00)
  This period is associated with increased residential demand that is due to the user requirements for water heating, cooking and lighting before the users leave for work or school activities, often on a mid-week basis.
- Evening Peak (17:00-20:00)
  This peak is the most critical period characterised by grid stress and load-shedding risk. It is also a period of high demand and the highest TOU applied tariff rates.
- Moderate Load Window (12:00-14:00)
  A mid-day window is where demand is at moderate level and tariffs are higher than off-peak but lower than peak-level tariffs.
- Off-Peak Periods

The remaining hours outside peak and moderate periods are classified as off-peak hours. These periods are associated with lower tariffs and reduced grid congestion.

These windows enable the load management system to apply appliance control that maximises both grid support and economic efficiency.

4.3.3 Performance metrics

The following static performance metrics are defined and applied across the three household profiles to assess the effectiveness of the load management system interventions:

- Peak Demand Reduction (kW):
  Peak demand reduction is illustrated by the equation below to quantify the effectiveness of the load management system in mitigating the peak electricity consumption:

  $$\Delta Peak = \max(originalProfile) - \max(managedLoad) \quad (7)$$

  This metric quantifies the reduction in the maximum hourly load observed in the profile after the application of staggered switch-off mechanism for appliances. It reflects the ability of the model to flatten the demand curve and reduce peak stress on the grid.
- Tariff-Based Cost Savings (ZAR):
  The economic benefits of the load management system are assessed through a tariff-based cost savings metric which is defined as:

  $$\sum_{t=1}^{24}[originalProfile(t) - managedLoad(t)] \times tariff(t) \quad (8)$$

  Where $originalProfile(t)$ represents the original hourly load at time interval *t,* managedLoad(*t*) is the load after control interventions are applied and tariff(*t*) represents the time-off-use electricity tariff applied at hour *t*.

The expression quantifies the accumulative monetary savings for the households expressed in South African rand (ZAR) which result from the temporal reduction of loads during high-cost tariff periods. The metric reflects the cost efficiency of the staggered switch-off mechanism. By applying the calculation over 24-hour period, the load management system offers a cost-benefit comparison between unmanaged and managed household consumption patterns.

The peak demand reduction and tariff-based cost savings metrics provide a quantitative basis for comparing the original unmanaged and managed load profiles in terms of both grid impact and household cost efficiency.

4.4 Results and Plots

This section presents the quantitative outcome of the load management system for the managed and unmanaged load profiles across the three household income groups of low-, middle-, and high- income. The performance is assessed based on each household's ability to maintain consumption below its defined threshold after applying the load management staggered switch-off mechanism. The results are reported both visually through graphical representation and numerically to demonstrate peak demand reduction and system effectiveness.

4.4.1 Low-income household original vs managed load profiles

Figure 15 illustrates the original and managed load profiles for low-income households. The graph displays the following key elements, dashed blue lines indicate original load profile, red solid lines indicate managed load profile, black dashed lines indicate threshold (0.60 kW), as established in section 3.7.1, and appliance markers indicate the state of appliance switch-off.

The appliance-coloured markers on the graph indicate which appliance was last switched off to reduce energy consumption to below or at threshold, thereby achieving a managed load. The shutdown sequence follows a staggered appliance switch-off mechanism defined in section 3.7.2: the water heater (geyser) is switched off first, followed by HVAC (green marker), stove (navy blue marker), and lastly plugs (purple marker).

Low-income households in this study often do not have water heaters (geyser), therefore, only three appliances are controlled. The plot shows the effect of applying the control to deactivate non-critical appliances in a priority-order when consumption exceeds the threshold.

Figure 15: Low-income household load profile pattern before and after management interventions.

a. Original Load Profile (blue dashed line)
   The original load profile for low-income households represented by the blue dashed line in Figure 15 demonstrates low power consumption compared to middle- and high-income groups, attributed to the ownership

of fewer and low energy-intensive appliances. However, the intermittent power consumption peaks occur throughout the 24-hour period as follows:

- Morning peak (05:00-08:00):
  - Hour 5: 0.46 kW
  - Hour 6: 0.67 kW
  - Hour 7: 0.44 kW
  - Hour 8: 0.43 kW
- Evening peak (17:00-20:00):
  - Hour 17: 0.54 kW
  - Hour 18: 0.85 kW (highest peak)
  - Hour 19: 0.65 kW
  - Hour 20: 0.54 kW

These intermittent peaks highlight increased usage of appliances by low-income households during active periods such as cooking and heating.

b. Managed Load Profile (red solid line)

The managed load indicated by a red solid line in Figure 15 shows the results of a staggered appliance switch-off control for load reduction to ensure demand remains below the set threshold (black dashed horizontal line) of 0.60 kW. For every hour where the original load exceeds the threshold, appliances were switched off until the load was equal to or less than 0.60 kW. As observed in Figure 15 for low-income load management, the following adjustments in Table 14 were applied:

Table 14: Low-income applied load reduction interventions and outcomes across peak hours.

Hour	Original Load (kW)	Applied Switch-off (in priority order)	Reduction (kW)	Resulting Managed Load (kW)
6:00	0.67	HVAC off	0.11	0.56
18:00	0.85	HVAC off+Stove off	0.33	0.52
19:00	0.65	HVAC off	0.09	0.56

During all other hours, the original load remained equal or less than 0.6 kW, therefore, no appliance was switched off and the managed load equals the original load. The peaks are successfully managed, reducing electricity consumption during high-demand periods and ensuring a stable load profile. This indicates the effective application of a load management strategy aimed at reducing peak consumption while maintaining household energy needs within acceptable levels.

4.4.2 Middle-income household original vs managed load profiles

Figure 16 illustrates the original and managed load profiles for middle-income households. The graph displays three key elements:

- Dashed blue line indicates original load profile, red solid line indicates managed load profile.
- Black dashed line indicates threshold (1.13 kW) as established in section 3.7.1.
- Appliance markers indicate the state of appliance switch-off.

The coloured appliance markers on the graph indicate which appliance was last switched off to bring the original load below or equal to threshold therefore achieving managed load. The shutdown sequence follows a staggered appliance switch-off mechanism defined in section 3.7.2 of water heater (geyser) (red marker) switched off first, if the load is still above threshold, the HVAC (green marker), stove (navy blue marker), and lastly plugs (purple marker) are switched off.

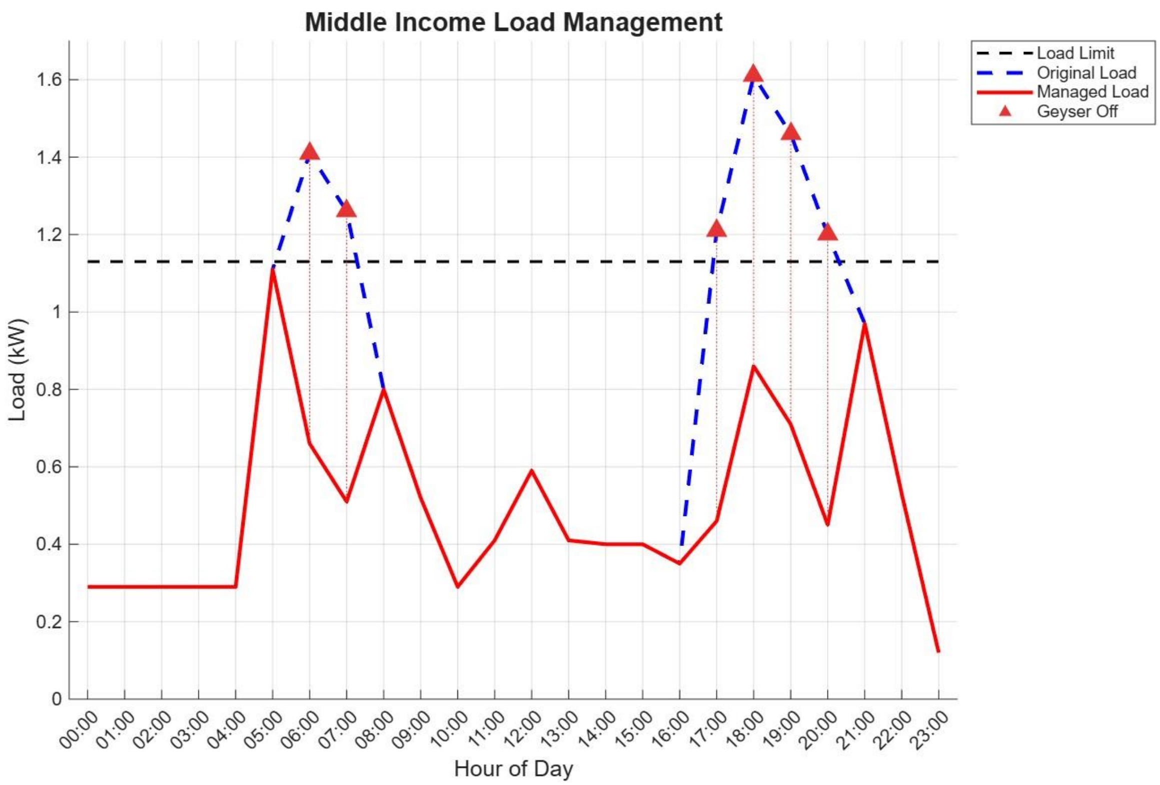

Figure 16: Middle-income household load profile pattern before and after management interventions.

a. Original Load Profile

Middle-income households exhibit a more varied and higher energy consumption profile compared to low-income households. This is due to the presence of additional energy-intensive appliances, including larger refrigerators, air-conditioning units, multiple entertainment systems, and electric water heaters. Compared to low-income households, the power consumption peaks for middle-income households occur in the morning, and evening periods as follows:

- Morning peak (05:00-08:00):
  - Hour 5: 1.11 kW
  - Hour 6: 1.41 kW
  - Hour 7: 1.26 kW
  - Hour 8: 0.8 kW
- Evening peak (17:00-20:00):
  - Hour 17: 1.21 kW
  - Hour 18: 1.61 kW (highest peak)
  - Hour 19: 1.46 kW
  - Hour 20: 1.2 kW

This analysis identifies evening demand surges exceeding morning peaks. The surges highlight increased usage of high-power appliances by middle income households during active periods such as cooking and heating.

b. Managed Load Profile

The managed load shows a significant reduction compared to the original load, ensuring electricity demand remains within the 1.13 kW set limit threshold.

The managed load indicated by the red solid line in Figure 16 shows the results of a staggered appliance switch-off control for load reduction to ensure demand remains below the set threshold (black dashed horizontal line) of 1.13 kW.

For every hour where the original load exceeds the threshold, appliances were switched off in a staggered manner until the load was equal to or less than 1.13 kW. As observed in Figure 16 or middle-income load management, the following adjustments in Table 15 were applied:

Table 15: Middle-income applied load reduction interventions and outcomes across peak hours.

Hour	Original Load (kW)	Applied Switch-off (in priority order)	Reduction (kW)	Resulting Managed Load (kW)
6:00	1.41	Geyser off	0.75	0.66
7:00	1.26	Geyser off	0.75	0.51
17:00	1.21	Geyser off	0.75	0.46
18:00	1.61	Geyser off	0.75	0.86
19:00	1.46	Geyser off	0.75	0.71
20:00	1.2	Geyser off	0.75	0.45

During all other hours, the original load remained equal or less than 1.13 kW, therefore no appliance was switched off and the managed load equals the original load. The results in Table 15 demonstrate that geyser alone resolved significant peak violations for middle-income households. The peaks are successfully managed, reducing electricity consumption during high-demand periods and ensuring a stable load profile.

4.4.3 High-income household original vs managed load profiles

Figure 17 illustrates the original and managed load profiles for high-income households. The graph displays three key elements:

- Dashed blue line indicates original load profile, red solid line indicates managed load profile.
- Black dashed line indicates threshold (1.46 kW) as established in section 3.7.1.
- Appliance markers indicate the state of appliance switch-off.

The appliance-coloured markers on the graph indicate which appliance was last switched off to bring the original load below or equal to threshold and achieve managed load. The shutdown sequence follows a staggered appliance switch-off mechanism order defined in section 3.7.2 of water heater (geyser) (red marker) switched off first, if the load is still above threshold, then followed by HVAC (green marker), stove (navy blue marker), and lastly plugs (purple marker).

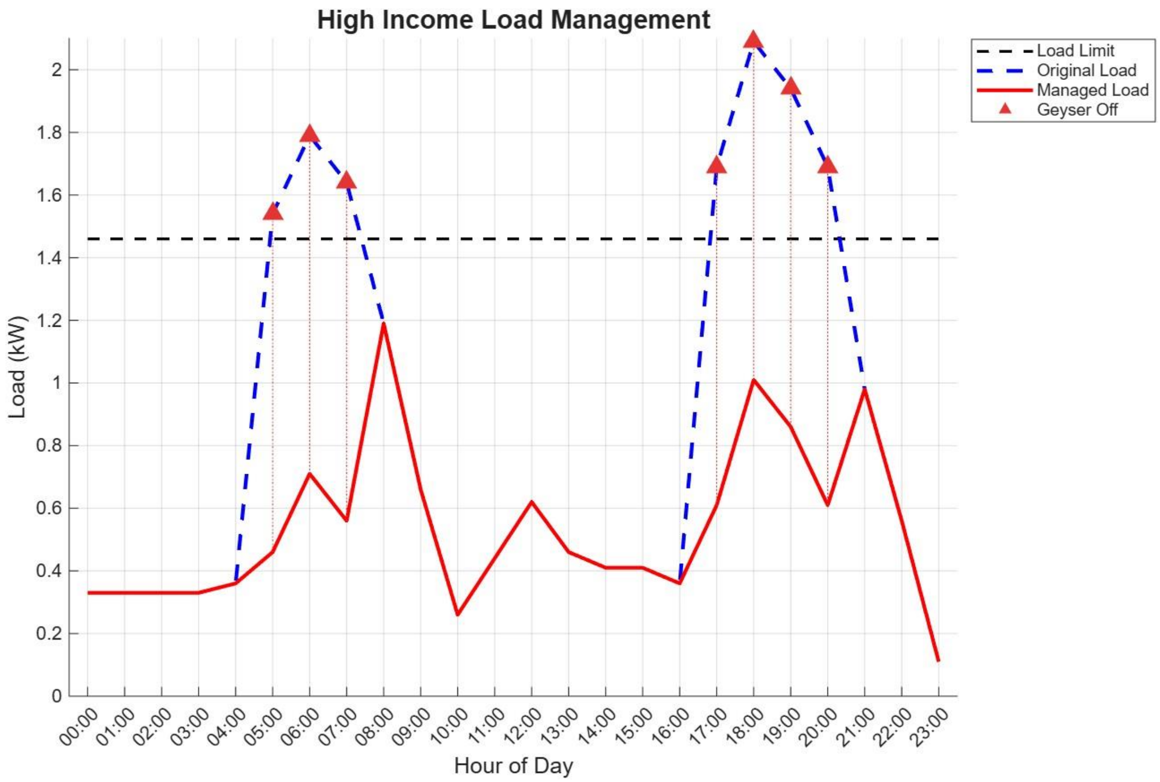

Figure 17: High-income household load profile pattern before and after management interventions.

a. Original Load Profile

High-income households present the highest power consumption profile due to extensive usage of energy-intensive appliances when compared to low- and middle-income households. These households are typically larger with living spaces that require more energy for cooking, heating, and cooling.

In addition, high-income households tend to own a vast number of appliances such as large refrigerators, dishwashers, laundry washing machines, dryers, kitchen appliances, entertainment systems, and pool pumps contributing significantly to energy consumption. This includes HVAC systems that are required to run continuously for comfort. The 24-hour peaks are illustrated below:

- Morning peak (05:00-08:00):
  - Hour 5: 1.54 kW
  - Hour 6: 1.79 kW
  - Hour 7: 1.64 kW
  - Hour 8: 1.19 kW
- Evening peak (17:00-20:00):
  - Hour 17: 1.69 kW
  - Hour 18: 2.09 kW (highest peak)
  - Hour 19: 1.94 kW
  - Hour 20: 1.69 kW

Overall, this results in a varied load profile with peaks occurring during the morning, evening, and night. As illustrated in Figure 17, the original profile peak reaches the highest 2.09 kW consumption.

b. Managed Load Profile

The managed load profile indicates that substantial reductions occurred during peak hours. The most significant reduction was 1.90kW at 18:00, primarily due to switching off major appliances. Lesser reductions were applied throughout the day where necessary, ensuring optimal load distribution. Table 16 below demonstrates the applied load switching-off action and resulting outcomes.

Table 16: High-income applied load reduction interventions and outcomes across peak hours.

Hour	Original Load (kW)	Applied Switch-off (in priority order)	Reduction (kW)	Resulting Managed Load (kW)
5:00	1.54	Geyser off	1.08	0.46
6:00	1.79	Geyser off	1.08	0.71
7:00	1.64	Geyser off	1.08	0.56
17:00	1.69	Geyser off	1.08	0.61
18:00	2.09	Geyser off	1.08	1.01
19:00	1.94	Geyser off	1.08	0.86
20:00	1.69	Geyser off	1.08	0.61

The adjusted load profile shows that power demand was successfully limited to 1.46 kW for most high-load periods, preventing excessive strain on the power system while maintaining essential household functions.

4.4.4 Clarification on Energy vs Power Reduction

Figures 16–18 illustrate significant reductions in peak power demand, rather than overall energy conservation. The total daily energy consumption remains nearly constant, indicating that the system shifts appliance operation to off-peak hours rather than eliminating usage. Quantitatively, the area under the power-time curve (representing total daily energy consumption) differs by less than 1% between original and managed profiles:

- Low-income: 8.98 kWh original vs 8.90 kWh managed (0.9% difference)
- Middle-income: 16.50 kWh original vs 16.40 kWh managed (0.6% difference)
- High-income: 20.52 kWh original vs 20.40 kWh managed (0.6% difference)

In contrast, peak demand reductions are substantial: 34%, 47%, and 52% respectively. This confirms that the intervention is a load-shifting strategy, not an energy-saving measure.

4.4.5 User control analysis across income groups

This section presents a comparative analysis of user control action and activity implemented on the system across the three income groups based on their consumption patterns and system responses. The functionality of user control forms a critical component in the evaluation of the Adaptable Load Management System. The control mechanism illustrated in section 3.8 System Design and 4.2.6 Implementation enables or restricts user autonomy in appliance usage based on a comparison between the original load and the threshold specific to each income group.

When the original load exceeds threshold, the system automatically disables user control and applies staggered switch-off of appliances. This is visually represented on the load management plots for each income group discussed in the following sub-sections by green asterisk markers (user control enable) and red cross marker (user control disabled).

a. Low-Income Household

As illustrated in Figure 18, the load profile for low-income households reflects low consumption with threshold of 0.60 kW. User control was maintained for most of the day, enabled for 21 out of 24 hours. The system only intervened for 3 hours, primarily within the morning peak (5:00-8:00), and evening peak (17:00-20:00) when the original load exceeded the threshold.

Figure 18: Low-income household load management with user control status.

b. Middle-Income Household

User control for middle-income was enabled for 18 hours out of 24 as demonstrated in Figure 19. The system intervened for 6 hours to disable user control mostly during morning peak (5:00-8:00), and evening (17:00-20:00).

Compared to low-income households, the middle-income show reduced activity during midday, likely due to occupants being at school or work. However, the morning and evening peaks demonstrate higher appliance usage than low-income.

Figure 19: Middle-income household load management with user control status.

c. High-Income Household

The high-income user control function is demonstrated in Figure 20. User control was enabled for 17 of 24 hours and disabled by the system for 7 hours mostly during the morning (5:00-08:00), and evening peak (17:00-20:00).

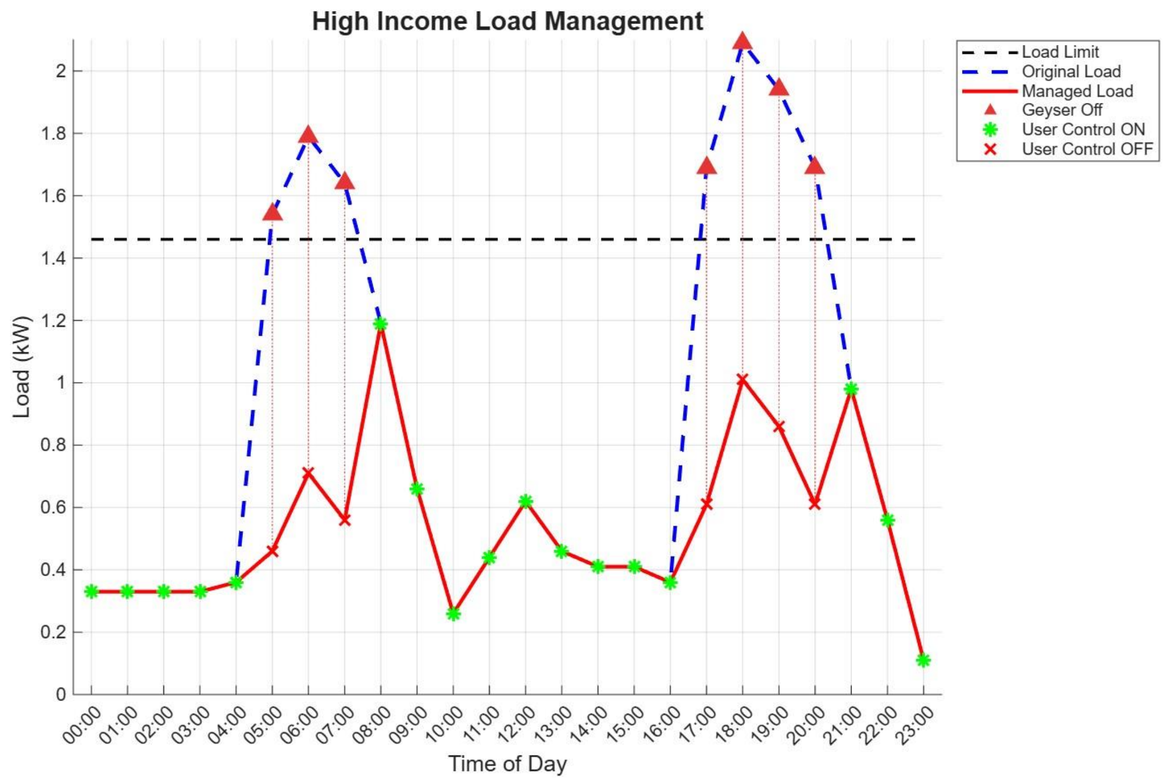

Figure 20: High-income household load management with user control status.

4.5 Grid Stress Period Analysis (17:00-20:00)

This section evaluates the performance of the adaptable load management system in mitigating peak demand conditions during grid stress periods across the three income household groups. The evening peak period recorded the highest consumption of all the income categories, and it is recognised as the most critical interval for grid stress.

During this period, concurrent activities such as cooking, water heating, lighting, and climate control produce a spike in electricity demand. The system introduces a second threshold for grid stress for a period of 17:00-20:00 (highlighted in pink), which is the utility threshold (indicated by red dashed line).

The threshold manages the managed load during 17:00-20:00 to switch off appliances further in a staggered manner until the managed load is equal to or less than the utility threshold. The utility threshold is only applied during grid stress peak evening periods from 17:00 to 20:00, while the normal threshold (black dashed line) governs load management during all other hours.

The utility threshold is set at approximately 20% below the normal threshold (indicated black dashed line). The technical justification for selecting a 20% selection lies in its ability to still maintain the exclusion of essential lighting load from the switch-off mechanism, while enforcing staggered switch off heating and cooking activities. Overall, this preserves the quality of life while achieving 5-10% grid relief during the evening peak period. The grid stress period results analysis is discussed in the following sections for each household category.

a. Low-Income Household

Figure 21 shows the performance of grid stress management for low-income households. The utility threshold is set at 0.43 kW (red dashed line), which is below the normal set threshold of 0.60 kW (black dashed line).

The utility threshold is only applied during grid stress peak evening periods from 17:00 to 20:00, while the normal threshold (black dashed line) governs load management during all other hours. The graph shows that the grid stress period was active between 17:00-20:00 (shaded pink region).

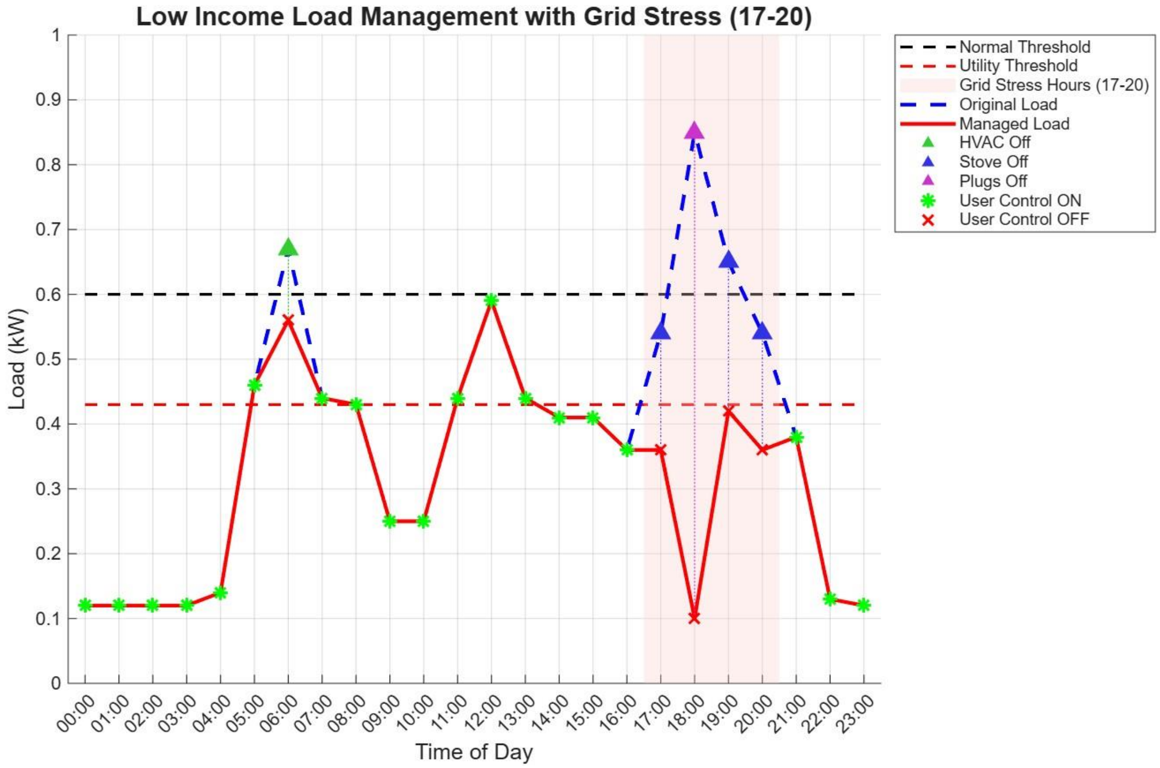

Figure 21: Load management during grid stress period for low-income households.

After applying the first normal threshold (0.60 kW) illustrated in Figure 15, two demand peaks occurred between 17:00 and 20:00, during which the managed load (red solid line) exceeded the utility threshold (0.43 kW), reaching 0.52 kW at both 18:00 and 0.56 kW 19:00. In response, the control mechanism activated further staggered switch-offs. In addition to the HVAC and stove, which had already been deactivated, the plug load (indicated by purple marker) was also reduced at 18:00 peak to bring the load within the stricter utility limit. Stove was deactivated in addition to the HVAC at 19:00 peak.

User control was disabled during this period as indicated by the red crosses on the graph reflecting the system's full automated control during the critical grid stress window. The performance period is demonstrated in Table 17 below:

Table 17: Low-income load management performance during grid stress period.

Time (hour)	Original Load (kW)	Normal threshold Managed Load (kW)	Utility Threshold Managed load (kW)	Appliances switched off
18:00	0.85	0.52	0.1	HVAC, Stove, Plugs
19:00	0.65	0.56	0.42	HVAC, Stove

b. Middle-Income Household

Figure 22 shows the performance of grid stress management for middle-income households. The utility threshold is set at 0.81 kW (red dashed line), which is below the normal set threshold of 1.13 kW (black dashed line).

The utility threshold is only applied during grid stress peak evening periods from 17:00 to 20:00, while the normal threshold (black dashed line) governs load management during all other hours. The graph shows that the grid stress period was active between 17:00-20:00 (shaded pink region).

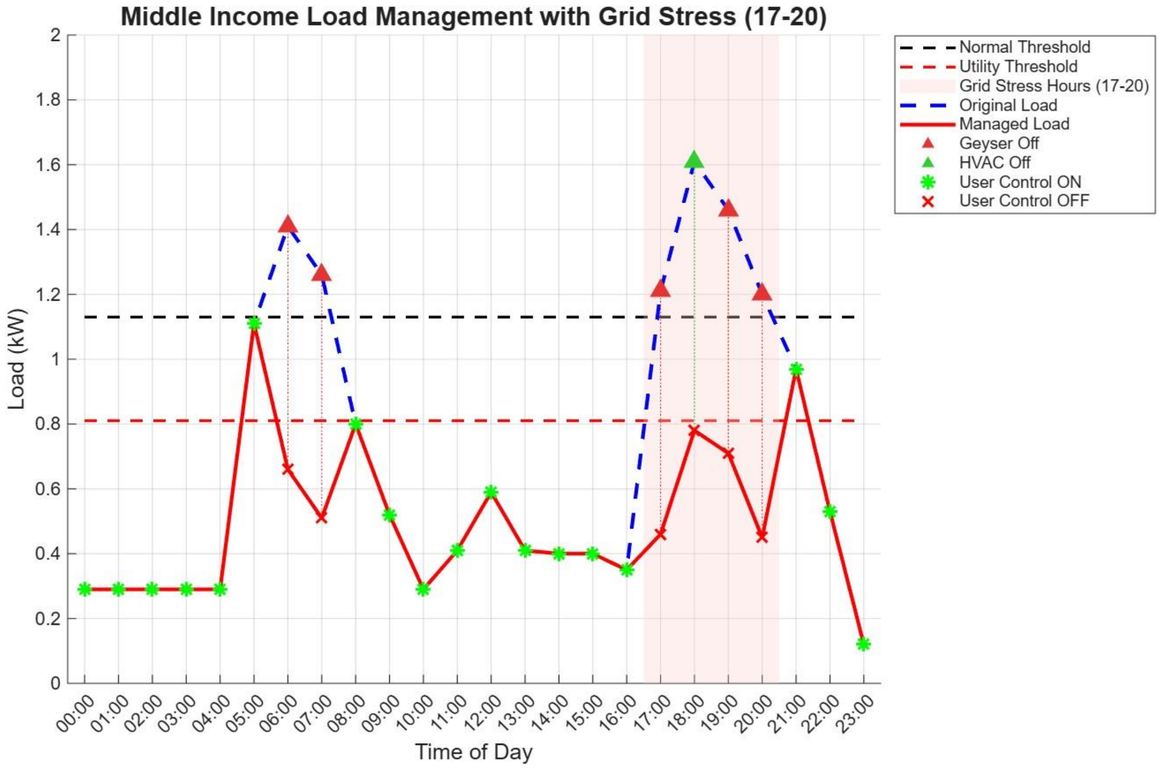

Figure 22: Load management during grid stress period for middle-income households.

After applying the first normal threshold (1.13 kW) demonstrated in Figure 16, one demand peak occurred at 18:00, during which the managed load (red solid line) exceeded the utility threshold (0.81 kW), reaching 0.86 kW. In response, the control mechanism activated further staggered switch-offs. In addition to the water heater (geyser) which was already deactivated, the HVAC load (indicated by green marker) was also deactivated to bring the load within the stricter utility limit.

User control was disabled during this period as indicated by the red crosses on the graph reflecting the system's full automated control during the critical grid stress window. The grid stress period performance is demonstrated in Table 18 below:

Table 18: Middle-income load management performance during grid stress period.

Time (hour)	Original Load (kW)	Normal Threshold Managed Load (kW)	Utility Threshold Managed Load (kW)	Appliances switched off
18:00	1.61	0.86	0.78	Geyser, HVAC

c. High-Income Household

Figure 23 shows the performance of grid stress management for high-income households. The utility threshold is set at 1.05 kW (red dashed line), which is below the normal set threshold of 1.46 kW (black dashed line).

The utility threshold is only applied during grid stress peak evening periods from 17:00 to 20:00, while the normal threshold (black dashed line) governs load management during all other hours. The graph shows that the grid stress period was active between 17:00-20:00 (shaded pink region).

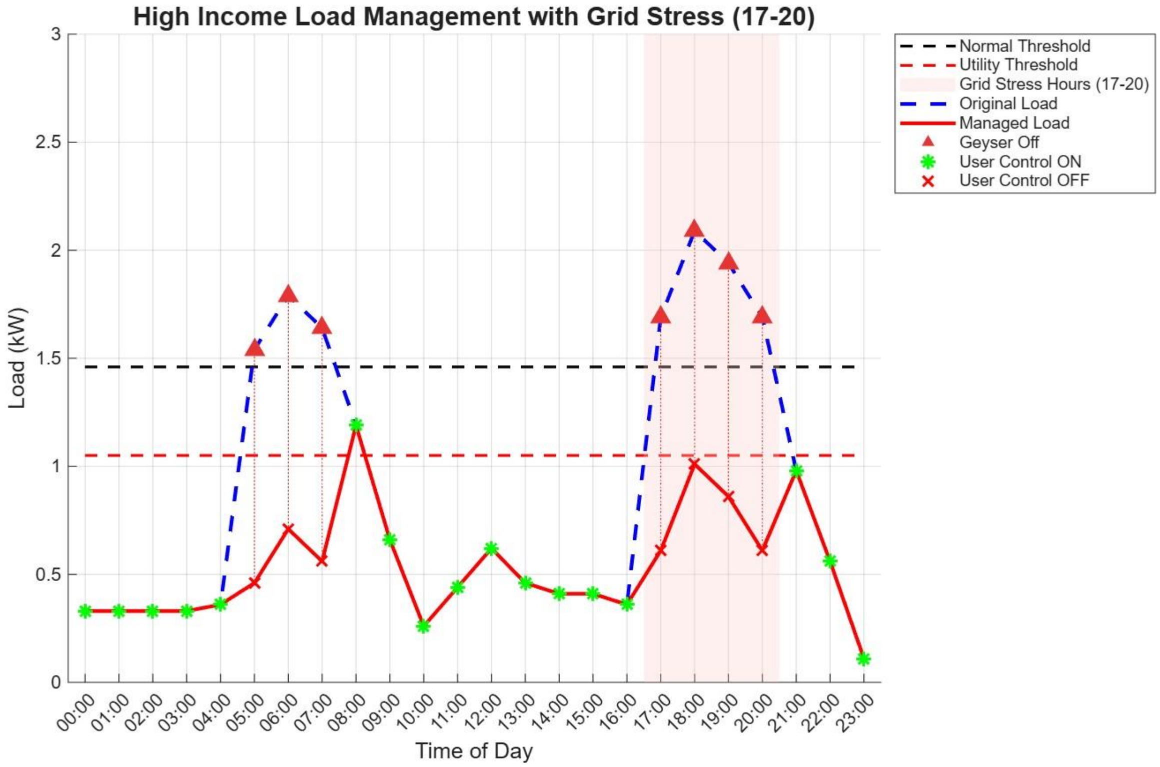

Figure 23: Load management during grid stress period for high-income households.

After applying the first normal threshold of 1.46 kW, as illustrated in Figure 17, no additional utility threshold was required for the high-income household, since its demand remained below the stricter limit of 1.05 kW.

User control was disabled during this period as indicated by the red crosses on the graph reflecting the system's full automated control during the critical grid stress window.

4.6 Peak Reduction and Energy Savings Summary

This section quantifies the effectiveness of the adaptable load management system in reducing peak electricity demand across income groups. Two scenarios are evaluated from the previously obtained results:

- Scenario 1: Peak reduction without applying the stricter utility threshold during grid stress period, only normal household thresholds defined in section 4.2.4 are applied across the full 24-hour period.
- Scenario 2: Peak reduction with the utility threshold defined in section 4.5 applied between 17:00 and 20:00.

4.6.1 Scenario 1: Without grid stress window utility threshold applied

Table 19 presents the peak demand reduction achieved when only the normal threshold was applied across the full 24-hour period. The managed load in this case was limited to the normal thresholds specific per income group defined in section 4.2.4. The table also includes the absolute percentage reductions for each income group.

Table 19: Peak demand reduction across income groups without grid stress period application (normal threshold only).

Income Group	Peak Original (kW)	Peak Managed (kW)	Reduction (%)	Peak Savings(kW)
Low	0.85 (max)	0.56 (max)	34	0.29
Middle	1.61 (max)	0.86 (max)	47	0.75
High	2.09 (max)	1.01 (max)	52	1.08

The system achieved peak demand reduction ranging from 34% to 52% with high-income households benefiting the most due to its larger baseline consumption.

4.6.2 With grid stress window utility threshold applied

This section evaluates the influence of applying a more stringent threshold during the grid stress window (17:00-20:00). Unlike the normal threshold, the utility threshold introduced deeper appliance control within the evening peak periods to reduce stress on the national grid.

Table 20 presents updated peak demand values based on the maximum observed load across 24-hour profile, which now reflects the impact of the grid stress utility threshold. The maximum peaks across the 24-hour period remain unchanged for three income groups when utility threshold is applied.

Table 20: Peak demand reduction with grid stress utility threshold applied.Table 19

Income Group	Peak Original (kW)	Applied Utility Threshold Peak Managed (kW)	Reduction (%)	Peak Savings(kW)
Low	0.85 (max)	0.42 (max)	51	0.43
Middle	1.61 (max)	0.78 (max)	52	0.83
High	2.09 (max)	1.01 (max)	52	1.08

4.7 Interpretation of Results

The results reveal the following trend regarding the Adaptable Load Management System control strategy's effectiveness across the three household income categories:

- High-income households
  Consume more than low and middle-income households, but a load management strategy is applied to reduce non-essential appliances, ensuring the managed load remains within the set limit despite higher baseline consumption. It showed the most peak reduction with a 52% decrease in peak demand at 1.08 kW absolute reduction.
- Medium-income households
  Experienced noticeable load reduction, but less than high-income households, achieving a significant peak saving with a 47% reduction at 0.75 kW.
- Low-income households
  Demonstrated minimal load reduction due to their consistently low and stable energy consumption, achieving a peak reduction of 34%, reflective of comparative lower baseline consumption.

The results demonstrate that the Adaptive Load Management System is successful in flattening peak demand curves, preserving critical appliance usage and promoting equitable energy access across the socio-economic groups.

4.8 Chapter Summary

This chapter presented the implementation and performance evaluation of the Adaptable Load Management System tailored for different household incomes in South Africa. The model was applied to 24-hour load profiles representing low-, middle- and high-income South African households, each constructed using realistic appliance-level consumption data obtained from literature.

The chapter began by outlining the simulation parameters which included hourly time resolution, grid-strain window classification, and performance metrics such as peak demand reduction and tariff-based cost savings. The control logic was implemented to prioritise device-level switching action when the consumption exceeds the threshold ensuring that the household loads for each income category remained within the threshold limits.

The results demonstrate that the system successfully reduces peak consumption across the three income groups with the most significant reduction achieved for middle- and high-income households. The quantitative metrics confirmed the following:

- Low-income households achieve a 34% peak reduction.
- Medium-income households achieved a 47% peak reduction.
- High-income households achieve a 52% peak reduction.

These outcomes highlighted the system's adaptability and effectiveness across the different household types. The practical benefits of the model were further validated by its ability to achieve peak savings while reducing stress on the grid.

5 CHAPTER 5: DISCUSSION AND ANALYSIS OF FINDINGS

5.1 Introduction

This chapter discusses the results from Chapter 4. It focuses on evaluating the system's performance in managing peak demand and realizing cost savings under a time-of-use (TOU) tariff structure. The chapter compares the findings of this study with benchmarked studies in the literature review to contextualise the performance and effectiveness of the Adaptive Load Management System.

The contributions of this research study are highlighted, its limitations acknowledged, and suggests future research work. This chapter presents a quantitative analysis of peak demand reduction and cost savings. The analysis presents the achievement of demand-side management with a focus on balancing grid stability, household consumption patterns, and economic beneficiation.

Following quantitative analysis, a benchmark comparison is made with demand-side management strategies presented in the literature review to provide context and demonstrate relative advantages of the Adaptable Load Management System.

The chapter concludes by discussing the limitations encountered during the study and outlining the key lessons learned in the process. These insights are essential for refining the model and considering future real-world applications. Finally, the chapter highlights the potential implications for the broader adoption of the system and provides recommendations for future scalability and integration into existing energy infrastructure.

5.2 Quantitative Analysis

This section presents an evaluation of the numerical results obtained from Chapter 4. The analysis focuses on the two key performance indicators, peak reduction and time-of-use (TOU) tariff cost savings. The findings inform the validation of the research objectives and hypothesis outlined in Chapter 1.

5.2.1 Peak demand reduction (%)

The staggered switch-off mechanism achieved a notable load reduction for all the household income categories. The following is a summary of the findings:

- Low-income households:
  Peak demand was reduced by 34%, from 0.85 kW (max) to 0.56 kW (max).
- Middle-income households:
- Peak demand was reduced by 47%, from 1.61 kW (max) to 0.86 kW (max).
- High-income households:
  Peak demand was reduced by 52%, from 2.09 kW (max) to 1.01 kW (max).

These findings support Hypothesis 3, which proposed that applying income-based load thresholds and a staggered appliance switch-off mechanism would effectively limit peak demand within acceptable and practical bounds. In this context, acceptable limits refer to threshold values that balance grid stability with essential household needs ensuring that critical loads such as lighting and basic plug circuits remain active while non-essential, high-consumption devices (for example, water heater (geyser) and HVAC systems) are selectively curtailed.

Furthermore, the defined thresholds were determined based on daily consumption data derived from typical South African households within each income group (as presented in Chapter 3). This ensures that the applied limits remain realistic and reflective of actual household consumption capacity rather than arbitrary technical constraints.

It is acknowledged, however, that sustained consumer participation would depend on behavioural and economic motivation. Under South Africa's time-of-use (TOU) and inclining block tariff structures, households stand to gain measurable cost savings when consumption is shifted away from high-tariff peak hours. Studies such as Kiianchuk and Makhotilo [19] and Eskom tariff guidelines [46]-[47] confirm that such financial incentives play a decisive role in consumer willingness to adopt demand-side management systems. Therefore, while the grid benefits from peak reduction, the feasibility of system adoption is strengthened by aligning control strategies with existing tariff-based financial motivators.

5.2.2 Estimated cost savings (time-of-use tariff basis)

A representative time-of-Use (TOU) tariff structure was used to evaluate the financial benefits of reducing peak demand. In accordance with the revised Eskom and municipal tariff structures for the year 2025/2026 approved by National Energy Regulator of South Africa (NERSA), the evening peak period was extended to three hours (17:00-20:00) [46].

Eskom provides a range of residential tariffs categorised according to their power demand, as demonstrated in the Tariffs and Charged Booklet 2025/2026 [47]. For this study, home power 4 category is selected, which is a single-phase 16kVA (80 A per phase). Energy charge for the category is 268.78 cents/kWh, which is equivalent to R2.69. A peak tariff rate of R2.69 per kWh is applied for the evening peak window (17:00-20:00). The following estimated savings were obtained using the hourly peak reductions for each household category:

- Low-income households:
  - Peak reduction (savings): 0.29 kW
  - Energy saved per day: 0.29 kW× 3hours = 0.87 kWh
  - Daily cost savings: 0.87 kWh × R2.69= R2.34
  - Annual saving: R2.34 × 365 days = R854.10
- Middle-income households:
  - Peak reduction (savings): 0.75 kW
  - Energy saved per day: 0.75 kW × 3h= 2.25 kWh
  - Daily cost savings: 2.25kWh × R2.69 = R6.05
  - Annual saving: R6.05× 365 = R2 208.25
- High-income households:
  - Peak reduction (savings): 1.08 kW
  - Energy saved per day: 1.53 kW × 3h = 3.24 kWh
  - Daily cost saving: 3.24 kWh × R2.69 = R8.72
  - Annual saving: R8.72 × R365 = R3 182.80

These savings highlight the economic potential of the Load Management System, particularly for middle-income and high-income households that use more energy. The monetary benefit for low-income households is less, but the relative savings are significant in terms of their consumption and contribute to greater affordability and energy equity.

The inclusion of low-income households in the control framework ensures that all income groups benefit from the improved load stability, less strain on the grid, and lower costs. This aligns with South Africa’s broader goals of demand-side management and equitable energy access.

5.3 Benchmark Comparison

To put the results of this study into context, it is essential to compare the performance of the Adaptable Load Management System against the existing approaches reported in literature.

Kiianchuk and Makhotilo [19] demonstrated approximately 40% savings during peak times in a residential setup using a smart demand-response strategy that relied on hardware and consumer engagement platforms. This study achieves higher reductions, 47% for medium-income households and 52% for high income households. This improvement demonstrates the efficacy of the appliance staggered switch-off mechanism, which capitalises on existing South African consumption patterns derived from literature and appliance priorities.

Ulloa-Vásquez et al. [12] reported 91.7% of appliance detection accuracy using machine learning for load disaggregation. Although such detection capabilities are essential for real-time monitoring and autonomous decision making, this study isolates the performance of the control logic itself by assuming perfect knowledge of appliance states as a baseline condition. The results demonstrate that priority-based appliance shedding can result in substantial overall savings.

The methodology presented in this dissertation offers a cost-effective, high-impact solution that achieves peak reductions and tariff cost savings. However, doing so comes with a trade-off of temporarily interrupting user access to non-essential appliances, underscoring the significance of striking a balance between technical gains with consumer comfort and behaviour.

5.4 Limitations and Lessons Learned

Despite the promising results of the Adaptable Household Load Management framework, there are several limitations that need to be acknowledged to ensure a balanced evaluation of its real-world applicability. These observations discussed below also inform and suggest possible directions for future work.

a. Simulation Environment vs Real-World Deployment

   The MATLAB-based prototype developed for this study operates under perfect conditions, assuming instant communication and perfect appliance or device responsiveness. In the real-world, smart grid context factors such as communication latency, packet loss, and device actuation delays can significantly impact system reliability and timing accuracy.

   Noted network unreliability and hardware-induced delays can reduce the effectiveness of the demand response scheme. Therefore, this suggests that future implementation must incorporate robust communication protocols and account for retry mechanisms to mitigate the effects of these real-world limitations.

b. Scalability and Performance

   The current prototype functions well for the three household profiles (low-, middle-, and high-income), but its computational design is not optimised for large scale deployment. A centralised MATLAB script may become computationally unresponsive or expensive when scaled to hundreds or thousands of households.

   Real-time implementation would necessitate optimised algorithms such as vectorised operations and reduced computational overhead, or the system would need to be moved to a distributed edge computing architecture. These kinds of improvements would ensure responsiveness, fault tolerance, and scalability.

5.5 Chapter Summary

This chapter provided an evaluation of the Adaptable Load Management System developed as part of this research, focusing on its comparative performance to the previous work and its real-world limitations. The results of a series of benchmarks showed that the staggered switch-off mechanism can reduce peak demand significantly for middle- and high-income households without the need for complex algorithms.

Furthermore, the limitations of the simulation-based prototype were examined. Key constraints or limitations included the lack of real-world communication modelling and the absence of scalability testing beyond a few representative profiles. These limitations suggest the need for network and computational factors into future versions. Lessons learned from this study suggest the need for robust control architectures and scalable deployment strategies to translate the model into a practical and sustainable solution.

Chapter 5 established that the system is effective in a controlled simulation, but further research and testing in the real world is required to fully validate its practical viability and social impact.

6 CONCLUSIONS AND RECOMMENDATIONS

6.1 Introduction

This chapter summarises how the study met each objective outlined in the LS262a form (attached in appendix A), which is the application for approval of a master's research project proposal. The study aimed to develop an Adaptive Household Load Management System that is sensitive to income using a staggered switch-off mechanism to address the energy consumption difficulties in South Africa.

The research was guided by the six primary objectives, each of which has been addressed through stages of analysis, modelling, implementation, and evaluation. This chapter outlines how each objective was met, highlights the original contributions of the work, and proposes potential directions for future improvements and deployment.

6.2 Summary of Key Findings

This section provides the synthesis of the major findings from the study directly mapped to the objectives outlined in the LS262a form. The research aimed to develop and evaluate an adaptive income-based household load management system for South African household contexts with emphasis on adaptability.

a. Objective 1-4: Conceptual Development and Modelling (Met)

- Conducted a literature review on South African household electricity consumption to gather and analyse data on electricity and appliance usage across household income groups.
- Created three distinct household load profiles for low-, middle-, and high-income households based on appliance level usage, time-of-use estimates, and probability distributions.
- Designed an optimised threshold-based, income adaptive load consumption model with staggered switch-off mechanism management architecture. The algorithm reduces consumption by assigning switch-off priorities to appliances.
- Developed a complete MATLAB implementation including load profiles data ingestion, computation of loads, staggered switch mechanism logic, and graphical visualisations. The model distinguished between essential and non-essential load and adjusted consumption accordingly.

b. Objective 5: System Implementation (Prototype Demonstrated)

- A MATLAB-based prototype was developed that ingests household income load profile, computes hourly total demand, and applies income specific thresholds.
- The control logic executed staggered switch-off appliances in a priority order.
- Generated visualisation of original unmanaged and managed load curves per income group, which enabled performance comparison, adaptability and usability evaluation, and system validation.

c. Objective 6: Experimental Validation (Results and Impact)

Experimental simulation tests demonstrated the following peak demand reductions:

- Low-income household: Peak demand was reduced by 34%, from 0.85 kW to 0.56 kW. Annual saving yielded an annual potential saving R854.10 during peak billing periods.
- Middle-income household: peak demand was reduced by 47%, from 1.61 kW to 0.86 kW. Annual saving yielded an annual potential saving of R2 208.25 during peak billing periods.
- High-income household: peak demand was reduced by 52%, from 2.09 kW to 1.01 kW. Annual saving yielded an annual potential saving of R3 182.80 during peak billing periods.

6.3 Contributions

This work contributes the following elements to the field of residential demand-side energy management in South Africa:

a. Income-Adaptive Threshold

   The study introduces a novel approach to demand side-management through income adaptive median based load thresholds, where consumption limits are set according to the median (50^{th} percentile) of each group's load profile.

b. Hierarchical Switch Off Logic

   A novel non-binary appliance prioritised shedding algorithm mechanism was implemented differentiating between essential and non-essential appliances. This logic ensured that a basic need such as lighting is preserved while non-essential appliances such as water heater (geyser), HVAC, stove, and plugs are shed first in a staggered order until consumption meets the threshold.

c. Prototype Software Framework

The MATLAB-based implementation provides a code base that covers data ingestion, control logic, threshold development, and time-series visualisation.

Together, these contributions offer a contextually appropriate solution: a tailored intervention that accounts for specific technical, social, economic, or environmental conditions of a problem. The solution is tailored to residential load management challenges in South Africa and emerging economies. It also lays the groundwork for practical deployment and policy integration.

6.4 Future Extensions

The promising results and modular design of the model open several avenues for further research, improvements, and real-world implementation:

a. Field Trials and Smart Meter Integration:
   Pilot deployment of the system on a set of smart meters in low-income communities to validate the algorithm's performance and measure key metrics, including communication latency, user control behaviours, and demand control features.

b. Edge Device and Internet of Things (IoT) Deployment:
   Porting the prototype to microcontrollers such as ESP32, Raspberry Pi, or Arduino to enable distributed control via smart plugs or in-line switches. This will enable plug and play demand management and eliminate software dependencies.

c. Adaptive Forecasting:
   Integration of predictive models such as Long Short-Term Memory (LSTM) neural networks to allow next-day forecasting. This can improve the

responsiveness of threshold adjustment and minimise reactive shedding of appliances.

d. Behavioural Feedback and Incentives:
   Developing a user dashboard or mobile application to notify users of upcoming or possible switch offs and provides consumption insights. Tariff-based incentives can also be introduced to encourage acceptance and compliance.

e. Robustness and Scalability:
   System robustness can be improved by adopting reliable communication protocols such as Message Queuing Telemetry Transport (MQTT) to address communication latency and loss. The code base can also be optimised to support large scale deployment through vectorisation or deployment on cloud platforms.

f. Policy Simulation:
   Evaluation of system performance through simulation of regulatory frameworks such as NERSA demand-based pricing to help quantify the socio-economic and grid level impacts of deploying the system at scale.

6.5 Concluding Remarks

This work demonstrates that a tailored income-based demand management approach can deliver significant peak reductions and cost savings across different household profiles. The next step is ensuring that energy futures are resilient, just, and socially adaptable by integrating the prototype into real-world use through hardware integration, behavioural alignment, and policy simulation.

REFERENCES

[1] N. W. Hlongwane and O. D. Daw, “Electricity Consumption and Population Growth in South africa,” *IJEEP,* vol. 13, no. 3, May. 2023.

[2] T. Mabugu and R. Inglesi-Lotz, “The effect of mismatched supply and demand of electricity on economic growth in South Africa,” *Energy Sources, Part B: Economics, Planning, and Policy,* vol. 17, no. 1, p. 3556, Feb. 2022.

[3] J. Doe, “Efficient Energy Management for the South African Grid,” *Journal of Sustainable Energy,* vol. 45, no. 3, Jul.2023.

[4] S. Słupik, K.-Ł. J. al and J. Trzęsiok, “An Innovative Approach to Energy Consumer Segmentation—A Behavioural Perspective. The Case of the Eco-Bot Project,” *Energies,* vol. 14, no. 12, p. 3556, Jun. 2021.

[5] M. Rambabu, N. S. Ramakrishna and P. K. Polama, “Prediction and Analysis of Household Energy Consumption by Machine Learning Algorithms in Energy Management,” *E3S Web of Conferences,* vol. 350, p. 02002, 2022.

[6] Y. -H. Lin, H. -S. Tang, T. -Y. Shen and C. -H. Hsia, “A Smart Home Energy Management System Utilizing Neurocomputing-Based Time-Series Load Modelling and Forecasting Facilitated by Energy Decomposition for Smart Home Automation,” *IEEE Access,* vol. 10, pp. 116747-116765, 2022.

[7] P. Ma, S. Cui, M. Chen, S. Zhou and K. Wang, “Review of Family-Level Short-Term Load Forecasting and Its Application in Household Energy Management System,” *Energies,* vol. 16, no. 15, p. 5809, Aug. 2023.

[8] H. Bakiri and H. Mbembati , “The Effect of Electricity Consumption Determinants in Household Load Forecasting Models,” *Journal of Electrical Systems and Information Technology,* vol. 10, no. 52, pp. 1-15, 2023.

[9] O. Ristic, M. Veskovic, S. Milunovic Koprivica, S. Nogo and L. Paunovic,

"Optimization household energy management system using GWO algorithm: A review," in *in Proc. XII International Conference on Social and Technological Development*, Trebinje, Republic of Srpska, Bosnia and Herzegovina, June 15-18, 2023.

[10] B. Mota, P. Faria and Z. Vale, "Energy cost optimization through load shifting in a photovoltaic energy-sharing household community," *Renewable Energy,* vol. 221, p. 119812, Feb. 2024.

[11] G. Zhao, P. Zha and J. Liu, "DSP-based energy optimization management of household single-phase electric energy router with historical and real-time data," *IET Power Electronics,* vol. 17, no. 2, pp. 326-336, Dec. 2023.

[12] F. Ulloa-Vásquez, V. Heredia-Figueroa, C. Espiroza-Iriarte, J. Tobar-Rios and F. Aguayo-Reyes, "Characterization of the Electrical Consumption Pattern of Household Appliances for Home Energy Management Using High-Resolution Measurement Techniques in," in *Integrative Approaches in Urban Sustainability - Architectural Design, Technological Innovations and Social Dynamics in Global Contexts*, Vols. 2023, pp. , United Kingdom, IntechOpen, Apr. 10, 2024, pp. 1-21.

[13] O. Ogidan and Y. Shobowale, "Development of load shedding web-based monitoring and control system," *Journal of Engineering, Technology and Innovation,* vol. 2, no. 2, pp. 01-07, May 2023.

[14] S. Balavignesh, C. Kumar, S. Ueda and T. Senjyu, "Optimization-based optimal energy management system for smart home in smart grid," *Energy Reports,* vol. 10, p. 3733–3756, Nov. 2023.

[15] M. A. A. Abdalla et al., "Optimizing Energy Usage and Smoothing Load Profile via a Home Energy Management Strategy with Vehicle-to-Home and Energy Storage System," *Sustainability,* vol. 15, no. 20, p. 15046, Oct. 2023.

[16] M. Sanabria-Villamizar, M. Bueno-López and J. C. Hern, "Characterization of household-consumption load profiles in the time and frequency domain," *International Journal of Electrical Power & Energy*

Systems , vol. 137, p. 107756, May 2022.

[17] Q. Qiao and B. Lin, "Management of Household Energy Saving and Its Green Alternatives," *Journal of Global Information Management,* vol. 32, no. 1, pp. 1-22, Feb. 2024.

[18] M. Mo et al., "Deep-Reinforcement-Learning-Based Low-Carbon Economic Dispatch for Community-Integrated Energy System under Multiple Uncertainties," *Energies,* vol. 16, no. 7669, 2023.

[19] V. Kiianchuk and K. Makhotilo, "Analysing household consumers' demand response through behavioural load profiles," in *Proc. Technical Scientific Conference of Undergraduate,Master, PhD students, Technical University of Moldova*, Chisinau, Republic of Moldova, Apr. 5-7, 2023.

[20] U. Mutumbi , G. Thondhlana and S. Ruwanza, "The Status of Household Electricity Use Behaviour Research in South Africa between 2000 and 2022," *Energies,* vol. 15, no. 23, p. 9018, Oct. 2022.

[21] K. Zhou and S. Yang, "Understanding household energy consumption behavior: The contribution of energy big data analytics," *Renewable and Sustainable Energy Reviews,* vol. 56, no. , p. 810–819, April 2016.

[22] E. R. Frederiks, K. Stenner and E. V. Hobman, "Household energy use: Applying behavioural economics to understand consumer decision-making and behaviour," *Renewable and Sustainable Energy Reviews,* vol. 41, p. 1385–1394, October 2015.

[23] N. Norouzi, M. Fani, E. H. Bahramani, M. H. Hemmati and Z. B. Jafarabadi, "Behavioral Economics and Energy consumption: Investigating the Role of Attitudes and Beliefs on Household Electricity Consumption in Iran," *Journal of Artificial Intelligence and Big Data,* vol. 1, no. 1, July 2021.

[24] L. C. Siebert, A. Sbicca, A. R. Aoki and G. Lambert-Torres, "A Behavioral Economics Approach to Residential Electricity Consumption," *Energies,* vol. 10, no. 6, p. 768, June 2017.

[25] C. W. Young, K. Hwang, S. McDonald and C. Oates, "Sustainable

Consumption: Green Consumer Behaviour when Purchasing Products," *Sustainable Development,* vol. 18, no. 1, pp. 20-31, 2009.

[26] K. Chulmo and C. Namho, "Examining the eco-technological knowledge of Smart Green IT adoption behavior: A self-determination perspective," *Technological Forecasting and Social Change,* vol. 88, pp. 140-155, October 2014.

[27] E. Peiffer and N. MacCarty, "How Modeling the Adoption of Household Clean Energy Technologies can Inform Stakeholder Decisions," in *2020 IEEE Global Humanitarian Technology Conference (GHTC)*, Seattle, WA, USA, 2020.

[28] L. Klein, A. Kumar, A. Wolff and Naqvi, "Understanding the role of digitalization and social media on energy citizenship," *Open Res Europe,* vol. 3, no. 6, 2023.

[29] J. W. Creswell and V. L. Plano Clark, Designing and Conducting Mixed Methods Research, California: Sage, 2018.

[30] D. Benyon, Designing User Experience: A Guide to HCI, UX and Interaction Design, London: Pearson, 2014.

[31] M. Tashakkori and C. Teddlie, Mixed Methodology: Combining Qualitative and Quantitative Approaches, Thousand Oaks, California: Sage, 1998.

[32] A. Hughes and R. Larmour, "Residential Electricity Consumption in South Africa," University of Cape Town, Department of Mineral Resources and Energy, South African National Energy Development Institute, Pretoria, 2021.

[33] Statistics South Africa, "General Household Survey 2021," Pretoria, 2022.

[34] B. Cohen, L. Manion and K. Morrison, "Research Methods in Education, 8th ed.," Routledge, London, 2018.

[35] SABS, *SANS 10142-1: Wiring of Premises,* Pretoria, South Africa: South African Bureau of Standards, 2021.

[36] SABS, *SANS CISPR 22: Electromagnetic compatibility (EMC) – Requirements,* Pretoria, South Africa: South African Bureau of Standards, 2006.

[37] A. R. Hevner, S. T. March, J. Park and S. Ram, "Design science in information systems research," *MIS Quarterly,* vol. 28, no. 1, pp. 75-105, 2004.

[38] Department of Energy and UNDP, "Existing Minimum Energy Performance Standards (MEPS) Status Quo Integrated Report," South Africa, 2019.

[39] Statistics South Africa (Stats SA), "General Household Survey 2021," Pretoria, South Africa, 2022.

[40] SRS Solar, "Household Appliances Electricity Consumption Guide," srssolar.co.za, [Online]. Available: https://srssolar.co.za/home-solar/household-appliances-electricity-consumption/. [Accessed June 2025].

[41] J. Bonello, "Eco-Audit: How much electricity do your appliances really use?," [Online]. Available: https://justinbonello.com/uncategorized/eco-audit/. [Accessed June 2025].

[42] O. Mohammed and A. Mohamed , "Real-Time Energy Management Algorithm for Smart Home with Integrated Renewable Energy and Storage Resources," *IEEE Trans. Smart Grid,* vol. 9, no. 5, p. 4949–4959, Sep. 2018.

[43] S. K. Panda and G. N. Tiwari, "Load management strategies for smart grids: A review," *IEEE Transactions on Smart Grid, vol. 10,* vol. 10, no. 2, pp. 2452-2461, 2019.

[44] B. Gao, X. Liu and Z. Zhu, "A Bottom-Up Model for Household Load Profile Based on the Consumption Behaviour of Residents," *Energies,* vol. 11, no. 8, p. 2112, 2018.

[45] NERSA, *South African Grid Code: Network Code,* Pretoria, South Africa: National Energy Regulator of South Africa, 2016.

[46] ESKOM, "2025/2026 Price Increase," Eskom Holdings SOC Ltd, 19

March 2025. [Online]. Available: https://www.eskom.co.za/distribution/2025-2026-price-increase/. [Accessed 15 July 2025].

[47] ESKOM, "Schedule of Standard Prices: 2025/2026," Eskom Holdings SOC Ltd, South Africa, Jul.2025.

[48] R. Usman, P. Mirzania, S. W. Alnaser, P. Hart and C. Long, "Systematic Review of Demand-Side Management Strategies in Power Systems of Developed and Developing Countries," *Energies,* vol. 15, no. 21, p. 7858, Oct. 2022.

[49] I. Laicane, D. Blumberga, A. Blumberga and M. Rosa, "Reducing Household Electricity Consumption through Demand Side Management: The Role of Home Appliance Scheduling and Peak Load Reduction," *in Energy Procedia,* vol. 72, p. 222–229, June 2015.

[50] H. Cai, S. Shen, Q. Lin, X. Li and H. Xiao, "Predicting the Energy Consumption of Residential Buildings for Regional Electricity Supply-Side and Demand-Side Management," *IEEE Access,* vol. 7, p. 30386–30397, Feb. 2019.

[51] CSIR Energy Centre, "Statistics of utility-scale power generation in South Africa:2021," Council for Scientific and Industrial Research, Pretoria, 2022.

Central University of Technology, Free State

APPENDIX A APPLICATION FOR APPROVAL OF MASTER

Central University of Technology, Free State

LS 262a

APPLICATION FOR APPROVAL OF MASTER, DOCTORAL, POST-DOCTORAL, OR STAFF RESEARCH PROJECTS

This form should be completed electronically. Please add relevant supportive documents as appendices.

SECTION 1: GENERAL INFORMATION

This section is compulsory.

1.1 Type of Application

(Mark with an X the applicable category)

- ☐ Postdoc Fellowship Programme Track 1 (Full time postdocs) *
- ☐ Postdoc Fellowship Programme Track 2 (Part time postdocs who completed studies at the CUT but not working at CUT) *
- ☐ Postdoc Fellowship Programme Track 3 (Staff members who completed their doctorates at any university)
- ☐ Postdoc Fellowship Programme Track 4 (Part time postdocs) *
- ☐ Full Time Doctoral Student*
- ☐ Part Time Doctoral Student*
- ☐ Full Time Master's Student*
- ☐ Part Time Master's Student*
- ☐ Staff project for non-qualification purposes

**Any person enrolled as a student at CUT, while also holding a position at a place of work in terms of the Labour Relations Act (Act 66 of 1995), is considered to be a part time student or postdoc while any other status is considered to be full time.*

1.2 Biographical Information

Title:	Mr.
First names:	Rebaone Goodwill
Surname:	Magagane
Faculty/Academic Development Support/ Academic Planning/Research & Innovation	Engineering, Built Environment, and Information Technology
Department:	Electrical, Electronic and Computer Engineering
Postal Address:(to receive mail via postal services)	5 Lara Close, Mandalay, Cape Town, 7785
Mobile Number:	0833524423
E-mail:	rebamagagane@gmail.com
ID number / Passport number:	9310255580080
Nationality:	South African
Student number: (if applicable)	212077171
Staff number: (if applicable)	
Highest Qualification Obtained:	Baccalaureus Technologiae: Electrical Engineering
Date qualification was obtained:	01-01-2017
University at which qualification was obtained from:	Central University of Technology, Free State

See Endnote[i]

Page **1** of **9**

Central University of Technology, Free State

SECTION 2: MASTER *OR* DOCTORAL RESEARCH PROJECT PROPOSAL

2.1 Full details of qualification (ACCORDING TO CUT Calendar)

Master of Engineering in Electrical Engineering (M_ENGE)

2.2 Supervision

Internal	**Title and Name**	**Highest qualification**
Main Supervisor:	Dr Bernard Tonderayi Mangara	PhD
Co-Supervisor 1:	Dr Thabo Bihi	D.Eng.
Co-Supervisor 2:		
External		
Main Supervisor:	Title and Name: Postal Address: (to receive mail via postal services) Contact Mobile Number: EMAIL: ☐ Please attach CV:	
Co-Supervisor 1:	Title and Name: Postal Address: (to receive mail via postal services) Contact Mobile Number: EMAIL: ☐ Please attach CV:	
Co-Supervisor 2:	Title and Name: Postal Address: (to receive mail via postal services) Contact Mobile Number: EMAIL ☐ Please attach CV:	

See endnote[ii]

2.3 The Protocol

Title:
Development of an adaptable load management system for different household categories in South Africa

Summary: (no more than 200 words)
The energy management sector in South Africa is experiencing inefficiencies, particularly in relation to the reliability of the power grid and the utilization of energy by different household income brackets. These inefficiencies contribute to the higher energy costs, grid strain, and restricted ability to manage energy consumption, affecting both household consumers and the overall reliability of the power grid. This research is centred around the development of a comprehensive and adaptive load management system to address the challenge of effectively managing energy usage across various household categories in South Africa. This study aims to address the various challenges encountered by households with various income levels in minimizing electricity consumption and alleviating grid burden when the electricity demand exceeds the supply. The anticipated outcomes will consist of benefits such as energy conservation, cost reduction, and improved grid stability, which will have a positive impact on households across the economic spectrum of South Africa.

Literature review including references: (Recommended as 1000 words, excluding references)

The literature review evaluates household energy management systems, focusing on innovation, costs, and infrastructure alignment. It aims to create an adaptable load management system in South African households, promoting cost, reduced consumption, and electricity stability by identifying gaps and potential improvements.

Rambabu et al. [1],conducted an analysis using machine learning to forecast home energy usage, with a focus on environmental characteristics obtained from sensor networks. The study tested a variety of algorithms and the results showed that tree-based models, particularly Random Forest and XGBoost, performed well in predicting short-term energy usage.

Lin et al. [2], developed an energy management system for smart homes that employs neurocomputing for load forecasting, utilizing energy decomposition without intrusive monitoring. This method facilitated smart home automation by forecasting appliance consumption patterns, potentially improving energy management without the need for additional hardware.

Sanabria-Villamizar et al. [3], explored household energy consumption behaviour using smart meter data and the Hilbert-Huang transform for detailed analysis. The study utilized a novel methodology to address the constraints of traditional time-series methodologies, contributing to improved load profile accuracy and underlining the importance of optimum data sampling frequency.

Ulloa-Vásquez et al. [4], developed a high-resolution Internet of Things (IoT)-based Smart Socket ILM System. This system allows for thorough monitoring of energy usage in domestic appliances, improves device recognition, reducing computational demands and enables effective management of household energy.

Kiianchuk and Makhotilo [5], the study analysed energy consumption patterns in households and evaluated the effectiveness of Smart and Naive demand response methods. The Smart method effectively reduced energy consumption and peak load by adjusting washing times and usage of smart appliances.

Ogidan et al. [6], created a web-based monitoring and control system for load shedding, utilizing IoT technologies to provide real-time awareness of energy use at the appliance level. Multiple load types were examined, revealing minimal measurement inaccuracies. This enables the process of making well-informed decisions on energy management and has the potential to be integrated with smart metering systems to improve load management.

Ma et al. [7], conducted an analysis of deep learning techniques and probabilistic forecasting to enhance the precision of short-term load forecasting at the household level. This analysis aimed to address the variability and personalization of household power consumption patterns in home energy management systems.

Abdalla et al. [8], examined a smart home energy management approach that integrates electric vehicles and home energy storage systems to enhance energy efficiency and optimize load profiles. They showcased cost reductions and load curve levelling by modelling several situations, providing valuable insights on how to integrate V2H (Vehicle to Home) alongside HESS (Home Energy Storage System) to improve efficiency and sustainability in smart homes.

Balavignesh et al. [9], investigated an optimization-driven energy management system for smart homes within a smart grid, utilizing advanced algorithms to harmonize energy expenses, usage, and user satisfaction. Through the integration of renewable sources and the implementation of real-time pricing, the study successfully attained notable efficiencies in the management of home energy, thus potentially transforming energy use within residential sectors.

Bakiri and Mbebati [10], conducted an evaluation of home energy usage in Tanzania, whereby they identified income, household size, and appliance count as significant factors influencing this behaviour. Their application of nonlinear regression analysis and adaptive splines technique demonstrated that the combined use of these predictors improves load forecasting accuracy by 14.73%, indicating a strong model for predicting residential energy consumption.

Mo et al. [11], utilized deep reinforcement learning to enhance the efficiency of energy allocation in dynamic community systems. The authors presented a user-responsive model that effectively addresses uncertainties in renewable energy sources and demand. This model demonstrates efficient low-carbon dispatch capabilities and exhibits potential adaptability to real-world variability.

Ristic et al. [12], conducted a review on the optimization of household energy management systems using the Grey Wolf Optimization (GWO) algorithm. The research examined the potential of the GWO in effectively regulating electrical energy consumption, leading to a decrease in energy expenses and the facilitation of renewable energy integration.

Zhao et al. [13], developed an energy optimization algorithm for a single-phase electric energy router utilizing digital signal processing (DSP) techniques, incorporating the analysis of both historical and real-time data. By enhancing the efficiency of battery charge/discharge cycles and grid energy exchanges, the research demonstrates notable advancements in household economic advantages and energy conservation.

Mota et al. [14], examined the process of reducing costs in photovoltaic energy-sharing communities. The researchers presented a study that introduced a Genetic Algorithm-based methodology for load shifting to decrease energy costs, considering dynamic pricing and local generation. They demonstrated cost reductions in both individual and community case studies, confirming the efficacy of sharing energy resources at the community level.

Qiao and Lin [15], conducted a study on household energy management, examining the relationship between income and Energy-Saving Awareness (ESA). Regression models were employed to evaluate power consumption, thereby uncovering a correlation characterized by an inverted U-shaped pattern between income and usage. The research findings illustrate the moderating influence of ESA, indicating that high-income households have the capacity to take the lead in adopting environmentally friendly options.

Main findings from the review

The literature suggests that South Africa needs a comprehensive and adaptable load management system to optimize household electricity usage. Smart technologies such as the Internet of Things and advanced data analytics are increasingly crucial, but they require complex computational resources and lack validation and modelling assumptions. Moreover, integrating renewable energy sources into households can create a sustainable energy mix, but it faces challenges in terms of costs and infrastructure compatibility. Financial constraints include the costs associated with renewable energy adoption and the implementation of advanced analytics systems. Aligning new load management strategies with existing South African regulations and infrastructure is another challenge. Gathering extensive data from various socioeconomic groups is also necessary to customize the load management system to meet the specific needs of different households. These limitations underscore the need for further research to establish a comprehensive and adaptable load management system in South Africa.

References

[1] M. Rambabu, N. S. S. Ramakrishna, and P. K. Polamarasetty, "Prediction and Analysis of Household Energy Consumption by Machine Learning Algorithms in Energy Management," *E3S Web of Conferences*, vol. 350, p. 02002, 2022.

[2] Y.-H. Lin, H.-S. Tang, T.-Y. Shen, and C.-H. Hsia, "A Smart Home Energy Management System Utilizing Neurocomputing-Based Time-Series Load Modeling and Forecasting Facilitated by Energy Decomposition for Smart Home Automation," *IEEE Access*, vol. 10, pp. 116747–116765, 2022.

[3] M. Sanabria-Villamizar, M. Bueno-López, J. C. Hernández, and D. Vera, "Characterization of household-consumption load profiles in the time and frequency domain," *International Journal of Electrical Power & Energy Systems*, vol. 137, p. 107756, May 2022.

[4] F. Ulloa-Vásquez, V. Heredia-Figueroa, C. Espinoza-Iriarte, J. Tobar-Ríos, and F. Aguayo-Reyes, "Characterization of the Electrical Consumption Pattern of Household Appliances for Home Energy Management Using High-Resolution Measurement Techniques in IoT Environments", in *Sustainable Built Enviroment,* United Kingdom: IntechOpen, 2023, pp. 1-21.

[5] V. Kiianchuk,K. Makhotilo, "Analysing household consumers' demand response through behavioural load profiles," in Proc. Technical Scientific Conference of Undergraduate, Master, PhD students, Technical University of Moldova, Chisinau, Republic of Moldova, vol. I, Apr. 5-7, 2023.

[6] O. Ogidan,Y. Shobowale, "Development of load shedding web-based monitoring and control system," *Journal of Engineering, Technology and Innovation*, vol. 2, no. 2, pp. 01-07, May 2023.

[7] P. Ma, S. Cui, M. Chen, S. Zhou, and K. Wang, "Review of Family-Level Short-Term Load Forecasting and Its Application in Household Energy Management System," *Energies*, vol. 16, no. 15, p. 5809, Aug. 2023.

[8] M. A. A. Abdalla *et al.*, "Optimizing Energy Usage and Smoothing Load Profile via a Home Energy Management Strategy with Vehicle-to-Home and Energy Storage System," *Sustainability*, vol. 15, no. 20, p. 15046, Oct. 2023.

[9] S. Balavignesh, C. Kumar, S. Ueda, and T. Senjyu, "Optimization-based optimal energy management system for smart home in smart grid," *Energy Reports*, vol. 10, pp. 3733–3756, Nov. 2023.

[10] H. Bakiri and H. Mbembati, "The Effect of Electricity Consumption Determinants in Household Load Forecasting Models," *Journal of Electrical Systems and Information Technology*, vol. 10, no. 52, pp. 1-15, 2023.

[11] M. Mo, X. Xiong, Y. Wu, et al., "Deep-Reinforcement-Learning-Based Low-Carbon Economic Dispatch for Community-Integrated Energy System under Multiple Uncertainties," *Energies*, vol. 16, no. 7669, 2023.

[12] O. Ristic, M. Veskovic, S. Milunovic Koprivica, S. Nogo, and L. Paunovic, "Optimization household energy management system using GWO algorithm: A review," in Proc. XII International Conference on Social and Technological Development, Trebinje, Republic of Srpska, , Bosnia and Herzegovina, June 15-18, 2023.

[13] G. Zhao, P. Zha, and J. Liu, "DSP-based energy optimization management of household single-phase electric energy router with historical and real-time data," *IET Power Electronics*, vol. 17, no. 2, pp. 326–336, Dec. 2023.

[14] B. Mota, P. Faria, and Z. Vale, "Energy cost optimization through load shifting in a photovoltaic energy-sharing household community," *Renewable Energy*, vol. 221, p. 119812, Feb. 2024.

[15] Q. Qiao and B. Lin, "Management of Household Energy Saving and Its Green Alternatives," *Journal of Global Information Management*, vol. 32, no. 1, pp. 1–22, Feb. 2024.

Problem Statement: (no more than 500 words)

In South Africa, there is a significant absence of an optimal, efficient, and tailored load management strategy that seeks to accommodate the needs of different households, including diverse energy consumption patterns, appliance preferences, daily routines, family sizes and economic constraints. This problem contributes to energy inefficiency, strain on the power grid, and hinders efforts towards sustainable energy practices. As a result, there is a critical need to develop a comprehensive adaptable load management system that can address these difficulties and optimize energy usage in households of different sizes and income levels.

Research Aim and Objectives: (no more than 500 words)

The aim of this research is to develop a Comprehensive and Adaptable Load Management System for different Household Categories in South Africa with diverse socioeconomic circumstances, encompassing low-, middle- and high-income levels. The system will be designed with the aim of minimizing tariff costs on the different household consumers and lower consumer demand during peak and off-peak hours when the demand exceeds supply, this strategy aims to alleviate grid strain that may occur due planned maintenance or to unforeseen challenges such as unit failures, coal supply/handling issues, demand prediction errors and shortage/depletion of fuel for open gas turbines. To achieve the research aim, the following objectives are set:

1. To gather primary data on electricity usage and preferences among low, middle, and high-income households in South Africa by conducting a comprehensive literature review.
2. To generate load consumption profiles for household appliances and devices across various income levels using the collected data.
3. To develop an optimized load consumption model that ensures energy usage remains below or near a specified threshold, while still satisfying user needs.
4. To design a system for load management that is adaptable and integrated with an optimum load consumption model. The system will be capable of the following:
   a. Encourage consumers to shift the operation of their appliances or devices to off peak hours, through real-time monitoring, manual and remote-control capabilities.
   b. Implement an enforced staggered switch-off mechanism for appliances based on their priority levels and criticality described below during grid strain periods when demand exceeds supply.
      - Priority 1: lights, priority 2: plugs, priority 3: stove, priority 4: HVAC (heating, ventilation, and air conditioning), priority 5: geyser.
   c. Exclude the lighting fixture from the switch off mechanism, to prevent misuse of darkness by criminals.
5. To construct a prototype of the system with the purpose of evaluating its functionality, usability, and adaptability.
6. To conduct experimental testing to assess the efficacy of the system in decreasing tariff costs for consumers, mitigating demand during peak hours, and satisfying user preferences.

Methodology & Research Design:(no more than 1000 words)

To achieve the aims and objectives, the following methodology and research design will be implemented:

1. User Requirements Identification and Data Collection:
   To determine the need for the household load management system, primary data on South African low-, middle- and high-income household's electricity consumption, preferences (cost saving, flexibility, and control) and challenges (safety and reliability) specific to household categories will be collected through literature from journals, conference proceedings and industry reports.
2. Load Consumption Profile Creation:
   The collected data from literature sources will be analysed and synthesized to generate a load consumption profile on household appliances/devices. The method will involve examining the data on each household category (low-, middle- and high-income) capturing appliance/device electricity consumption patterns for peak and off-peak demand periods over different time intervals.
3. Optimal load consumption model Generation:
   Generating an optimised load consumption model derived from a load consumption profile using statistical analysis to determine average consumption threshold, the threshold will be defined as an optimal target with the aim to maintain energy usage below or close to the threshold while meeting user requirements.
4. System Design:
   Developing a preliminary and detailed design of the Adaptable Load Management System incorporated with the optimised load consumption model based on the identified user requirements gathered from literature. The system will consist of two sub-systems:
   a. Load Management Sub-system: the module will collect real-time load consumption data from the load control module, generate load management control based on the optimised model and simulated grid conditions through user (manual, remote) and automatic control. The user control will allow customers to manage their loads when the consumption is within the optimised model threshold and under normal grid conditions, while automatic control will prioritize the loads during periods of high demand and grid strain conditions, overriding user controls during this period.
   b. Load Control Sub-system: The load control module will be responsible for measuring and conditioning of alternating current and voltage of load appliances, as well as in the regulation of power supply to the appliances. The system will evaluate and implement load control instructions received from the load management module, offer immediate feedback on control operations, and transmit measured electrical parameters to the load management module for post-processing.
5. Prototype development:

A prototype based on the system design will be developed to test its functionality, usability and adaptability in a simulated laboratory setup that resembles the real-world household categories and the grid conditions. A simulated environment is picked to mitigate the regulatory constraints (South African Bureau of Standards, the National Energy Regulator of South Africa, and Electromagnetic Compatibility Compliance) that might hinder the study time.

6. Experimental Testing and Evaluation Conduction:
   Functionality, usability, and adaptability tests will be conducted to evaluate the system's effectiveness and validate its performance in terms of its ability to minimise tariff costs on the customer and to reduce demand during peak hours to avoid stress on the grid.

Limitations and Delimitations:

- Geographical delimitation:
  The study's focus on South Africa may restrict the applicability of the results to other nations or areas characterized by distinct energy consumption patterns, regulatory structures, or socio-economic circumstances.
- Sample size and scope limitation:
  The study will be limited in terms of sample size and scope, as it will concentrate on distinct household types (low, middle, and high-income) within the context of South Africa.
- Data collection limitation:
  The scope of the research will be limited to collecting data on household electricity usage through a review of relevant literature sources.

Ethical Considerations/Identify Ethical Challenges:

Not Applicable

Expected Outcomes: Research publications and presentations.

a) Scientific outcomes:	• A functional Comprehensive Adaptable Load Management System for different Household Categories in South Africa. • An MEng Dissertation. • Publications (At least one conference paper and one journal article).
b) Social impact:	This study has the potential to enhance public awareness regarding energy efficiency, reduce household electricity tariff costs, promote sustainability, and stimulate technological advancements within the energy sector. As a result, these outcomes can lead to positive societal impacts, such as energy conservation, economic savings, and environmental benefits.
c) Innovations / patents:	Not Applicable

Study time frame:

Activity	Target Dates	
	Start Date	**End Date**
Research Proposal Planning, Writing and Approval.	September 2023	May 2024
Registration (first year)	May 2024	
Chapter 2: Literature Review Completion.	June 2024	August 2024
Data collection on household consumption to create load profile.	September 2024	October 2025
Conference Paper Draft compilation based on literature review and data collection and analysis.	November 2024	December 2025
Conference Paper submission to an academic conference.	January 2025	
Registration (second year)	February 2025	
Chapter 3: Methodology and Research Design.	January 2025	March 2025
Chapter 4: Implementation, Testing of Solutions and Results.	April 2025	May 2025
AGU notification for dissertation submission.	April 2025	
Journal Article Draft Compilation.	June 2025	July 2025
Journal Article Submission to a Peer Reviewed Journal for Publication.	August 2025	

Central University of Technology, Free State

Chapter 5: Conclusions	August 2025	September 2025
Dissertation submission.	September 2025	

See Endnote[iii]

2.4 Innovation & Intellectual Property

Any Innovation possibilities within the project? N/A
Any possible Intellectual Property (IP) that can come from project? N/A
Any cooperation with other parties that can have influence on IP ownership? N/A
Any possible patents that can come from project? N/A at this stage
Do you need assistance with IP and/or Patents? (If yes indicate what assistance is needed) N/A

See Endnote[iv]

SECTION 3: POST DOCTORAL FELLOWSHIP PROGRAMMES

3.1 Postdoctoral Mentor

Internal	Title and Name	Highest qualification
Postdoctoral Mentor:		

3.2 Research Project Proposal

Project Description: (no more than 3000 words)	
Ethical Considerations/Identify Ethical Challenges:	
Expected Outcomes:	
a) Scientific outcomes:	
b) Social impact:	
c) Innovations / patents:	
Timelines:	
Financial support required from CUT: a) Living expenses: b) Project expenses: (attach a budget breakdown)	
Other financial support available:	

SECTION 4: RESEARCH PROJECT FOR NON-QUALIFICATION PURPOSES

4.1 Project Proposal

Project Description: (no more than 2000 words)

Page 7 of 9

Central University of Technology, Free State

Timelines:
Financial support required from CUT: c) Living expenses: d) Project expenses: (attach a budget breakdown)
Ethical Considerations/Identify Ethical Challenges:
Expected Outcomes:

a) Scientific outcomes:	
b) Social impact:	
c) Innovations / patents:	

SECTION 5: APPROVAL OF RESEARCH PROJECT

Signature of Applicant: **(**I confirm that this is my own work, and I will execute my research in line with CUT policy and procedures**)**	R. Mugongera	**Date:**	09/04/2024
Signature of Main Supervisor / Mentor **(**I commit to supervise the student/post doctorate**)**	BTM 2024/04/09	**Date:**	09/04/2024
Signature of Co-supervisor (1) **(**I commit to co-supervise the student**)**	[signature]	**Date:**	09/04/2024
Signature of Co-supervisor (2) **(**I commit to co-supervise the student**)**			
Signature of Head of Department: **(**I approve the study/project and will avail the required resources**)**	[signature]	**Date:**	26/04/2024

Central University of Technology, Free State

Ethical Approval

- ☐ Approval by the Faculty Research and Innovation Committee (FRIC)
- ☐ Approval number: ---

Note: The approval number must be indicated as: [Name of Faculty e.g.: EIT] + year [e.g. 2017] + number [0+]

Where applicable, approval by accredited ethics committees:

- ○ Approval by an accredited Ethics Committee (including biomedical, clinical, radiology and somatology)
- ○ Approval by Animal Ethics Committee (also including agricultural and environmental ethics)

Note: Proved of the ethical clearance must be added to this application.

Approval by FACULTY RESEARCH AND INNOVATION COMMITTEE (FRIC)

Signature of FRIC Chair:	[signature]	**Date:**	16-04-2024

Ratification by FACULTY BOARD

Signature of FACULTY DEAN:	[signature]	Digitally signed by Prof M Masinde Date: 2024.05.16 09:48:32 +02'00'

Endnotes:

[i] Attach the applicant CV including additional information: a list of research outputs such as supervision, Publications, conference attendances, patents, etc.

[ii] The appointment of a supervisor and/or co-supervisor should already be in place by the time of application. For a master studies the supervisor must have a doctorate, and if not, a co-supervisor must have a doctorate. For a doctorate studies, postdoc fellowship all supervisors/mentors must have doctorates.

[iii] Please consult the annual *CUT CALENDAR* and annual *CUT ASSESSMENT MANUAL* for regulations and procedures regarding enrolment, registration, and maximum residency periods. LS262a must be used for funding applications.

[iv] Please complete the form "Appendix to FEIT LS262a" if you did answer "Yes" to any of the questions.

APPENDIX B THREE INCOME GROUPS HOUSEHOLD LOAD PROFILES

B.1 Low Income Household Load Profile

Low Income Hosehold Load Profile

Hour	Geyser (kW)	HVAC (kW)	Stove (kW)	Plugs (kW)	Lights (kW)	Total(kW)
00:00	0	0	0	0.12	0	0.12
01:00	0	0	0	0.12	0	0.12
02:00	0	0	0	0.12	0	0.12
03:00	0	0	0	0.12	0	0.12
04:00	0	0	0	0.12	0.02	0.14
05:00	0	0.07	0.08	0.22	0.09	0.46
06:00	0	0.11	0.14	0.32	0.1	0.67
07:00	0	0.09	0.08	0.22	0.05	0.44
08:00	0	0.09	0.08	0.22	0.04	0.43
09:00	0	0.13	0	0.12	0	0.25
10:00	0	0.13	0	0.12	0	0.25
11:00	0	0.14	0.08	0.22	0	0.44
12:00	0	0.14	0.13	0.32	0	0.59
13:00	0	0.14	0.08	0.22	0	0.44
14:00	0	0.19	0	0.22	0	0.41
15:00	0	0.19	0	0.22	0	0.41
16:00	0	0.14	0	0.22	0	0.36
17:00	0	0.09	0.09	0.32	0.04	0.54
18:00	0	0.09	0.24	0.42	0.1	0.85
19:00	0	0.09	0.14	0.32	0.1	0.65
20:00	0	0.09	0.09	0.32	0.04	0.54
21:00	0	0.09	0	0.25	0.04	0.38
22:00	0	0	0	0.12	0.01	0.13
23:00	0	0	0	0.12	0	0.12
Sum (kW)	0	2.01	1.23	5.11	0.63	8.98

B.2 Middle Income Household Load Profile

Middle Income Hosehold Load Profile

Hour	Geyser (kW)	HVAC (kW)	Stove (kW)	Plugs (kW)	Lights (kW)	Total(kW)
00:00	0.14	0.03	0	0.12	0	0.29
01:00	0.14	0.03	0	0.12	0	0.29
02:00	0.14	0.03	0	0.12	0	0.29
03:00	0.14	0.03	0	0.12	0	0.29
04:00	0.14	0.03	0	0.12	0	0.29
05:00	0.75	0.08	0.07	0.17	0.04	1.11
06:00	0.75	0.08	0.17	0.27	0.14	1.41
07:00	0.75	0.08	0.07	0.22	0.14	1.26
08:00	0.4	0.08	0.07	0.22	0.03	0.8
09:00	0.2	0.12	0	0.17	0.03	0.52
10:00	0	0.12	0	0.17	0	0.29
11:00	0	0.12	0.07	0.22	0	0.41
12:00	0	0.12	0.15	0.32	0	0.59
13:00	0	0.12	0.07	0.22	0	0.41
14:00	0	0.18	0	0.22	0	0.4
15:00	0	0.18	0	0.22	0	0.4
16:00	0	0.13	0	0.22	0	0.35
17:00	0.75	0.08	0.07	0.27	0.04	1.21
18:00	0.75	0.08	0.27	0.37	0.14	1.61
19:00	0.75	0.08	0.17	0.32	0.14	1.46
20:00	0.75	0.08	0.07	0.27	0.03	1.2
21:00	0.75	0.02	0	0.17	0.03	0.97
22:00	0.38	0.02	0	0.1	0.03	0.53
23:00	0	0.02	0	0.1	0	0.12
Sum (kW)	7.68	1.94	1.25	4.84	0.79	16.5

B.3 High Income Household Load Profile

High Income Hosehold Load Profile

Hour	Geyser (kW)	HVAC (kW)	Stove (kW)	Plugs (kW)	Lights (kW)	Total(kW)
00:00	0.22	0.02	0	0.09	0	0.33
01:00	0.22	0.02	0	0.09	0	0.33
02:00	0.22	0.02	0	0.09	0	0.33
03:00	0.22	0.02	0	0.09	0	0.33
04:00	0.22	0.02	0	0.09	0.03	0.36
05:00	1.08	0.08	0.1	0.19	0.09	1.54
06:00	1.08	0.08	0.2	0.29	0.14	1.79
07:00	1.08	0.08	0.1	0.24	0.14	1.64
08:00	0.68	0.08	0.1	0.24	0.09	1.19
09:00	0.37	0.12	0	0.14	0.03	0.66
10:00	0	0.12	0	0.14	0	0.26
11:00	0	0.12	0.1	0.22	0	0.44
12:00	0	0.12	0.19	0.31	0	0.62
13:00	0	0.12	0.1	0.24	0	0.46
14:00	0	0.17	0	0.24	0	0.41
15:00	0	0.17	0	0.24	0	0.41
16:00	0	0.12	0	0.24	0	0.36
17:00	1.08	0.08	0.1	0.34	0.09	1.69
18:00	1.08	0.08	0.3	0.44	0.19	2.09
19:00	1.08	0.08	0.2	0.39	0.19	1.94
20:00	1.08	0.08	0.1	0.34	0.09	1.69
21:00	0.67	0.03	0	0.19	0.09	0.98
22:00	0.37	0.02	0	0.14	0.03	0.56
23:00	0	0.02	0	0.09	0	0.11
Sum (kW)	10.75	1.87	1.59	5.11	1.2	20.52