

Energy Efficiency Improvements in a Microbrewery in South Africa

By

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DECLARATION

I, Joseph Eminsang Conduah, student number _____, hereby declare that this research project, which is submitted to the Central University of Technology, Free State, for the degree Doctor of Engineering in Electrical Engineering, is my own independent work and complies with the Code of Academic Integrity, as well as other relevant policies, procedures, rules, and regulations of the Central University of Technology, Free State.

This project has not been submitted before by any person in fulfilment (or partial fulfilment) of the requirements for the attainment of any qualification.

J.E. Conduah

Date

DEDICATION

This thesis is dedicated to the heavenly Father, God Almighty, my source of inspiration,
and to my blessed family and friends, for all their support and love.

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ABSTRACT

The brewing industry constitutes a significant portion of energy demand in the food and beverage sector, with microbreweries consuming approximately 0.65 kWh of electrical energy to produce 1 L of beer, which is almost 50% more than large-scale breweries. This equates to around 5.2% of total production costs, which highlights the critical need for energy efficiency improvements. Despite this substantial consumption, the implementation of optimised energy management strategies remains limited, particularly for thermal processes in craft beer production, which account for 8% of operational costs. More studies are needed to explore effective energy management schemes for breweries, with a particular focus on heating and cooling loads during critical production phases.

This study shows that demand-side management, coupled with time-of-use (ToU) tariff optimisation, presents opportunities for significant cost savings in brewery operations. The research aimed to address key challenges in energy-intensive brewing processes, particularly in South Africa, where craft beer production has grown substantially in recent years. This work emphasises predictive modelling of brewery energy performance using machine learning, optimal control strategies, and comprehensive economic analysis to minimise energy costs while maintaining production quality. The study proposes an integrated approach that combines process optimisation, a hybrid thermal–electrical energy system incorporating solar thermal collectors, a heat pump, and TES, and an optimisation-based control methodology designed to leverage ToU tariff structures and reduce peak-period grid dependence.

The investigation employed the Performance, Operation, Equipment, and Technology (POET) framework to systematically analyse energy usage patterns in brewery operations. A real-time monitoring system using a Power Quality Analyzer (PEL103) was installed in a Bloemfontein microbrewery to collect detailed load profile data. Subsequently, an artificial neural network (ANN) model was developed using shallow neural net fitting (nftool) to predict energy requirements across various production stages, including mashing, boiling, fermentation, and cold storage. The ANN model processed input variables such as process temperatures, flow rates, and equipment states, which achieved regression values between 0.90 and 0.98, with mean squared errors below 15%.

The study also implemented optimisation strategies using model predictive control methods to evaluate hybrid energy system configurations that incorporated renewable sources and thermal energy storage (TES). Simulations demonstrated that shifting energy-intensive processes to off-peak periods could yield 33% cost savings, while the integration of photovoltaic systems with battery storage reduced grid dependence by 10% to 15%. The POET framework analysis projected potential energy savings ranging from 10% to 70%, depending on the level of implementation: conceptual improvements (50% to 60%), active controls (25% to 35%), technical upgrades (60% to 70%), and further engineering optimisations (10% to 20%).

The results indicate that TES systems can achieve up to 69% energy savings compared to conventional grid-powered operations, with a breakeven point within 1.5 years for a system that costs approximately USD 50 000.

The ANN model proved particularly effective in optimising batch scheduling to align with ToU tariff periods while maintaining product quality standards. Furthermore, the study found that comprehensive implementation of energy efficiency measures could reduce long-term energy costs by 35% over a 20-year period, assuming 5% annual inflation and 10% electricity price increases.

The study demonstrates that the synergistic integration of ANN-based predictive modelling, an optimisation-based control strategy, and a hybrid thermal-electrical energy system significantly enhances energy efficiency in microbrewery operations. These integrated methods also improve operational costs by optimising thermal supply, reducing dependence on grid electricity, and increasing the effective use of renewable energy. The developed methodologies provide a replicable framework for energy management in food and beverage production, with particular relevance for small to medium enterprises in emerging markets. The findings underscore the importance of integrated energy solutions that combine technological improvements with operational optimisation to achieve both economic and environmental sustainability goals in industrial processes.

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LIST OF ABBREVIATIONS

AI	Artificial intelligence
ANN	Artificial neural network
BEMS	Brewery energy management software
BEP	Breakeven point
CO ₂	Carbon dioxide
CO _{2e}	Carbon dioxide equivalent
COP	Coefficient of performance
CSIR	Council for Scientific and Industrial Research
DHI	Diffuse horizontal irradiance
DNI	Diffuse normal irradiance
DSM	Demand-side management
EMMS	Energy monitoring and management system
ERP	Enterprise resource planning
ETC	Evacuated tube collector
GHI	Global horizontal irradiance
HPWH	Heat pump water heating/heater
HVAC	Heating, ventilation, and air conditioning
IoT	Internet of Things
ITES	Ice thermal energy storage
LCC	Life-cycle cost
LM	Levenberg-Marquardt
MPC	Model predictive control
MSE	Mean squared error
NAR	Non-linear autoregressive [model]
NARX	Non-linear autoregressive with exogenous inputs [model]
NLA	National Liquor Authority
PEL	Power and Energy Logger
POET	Performance, Operation, Equipment, and Technology
PV	Photovoltaic
R	Correlation coefficient
ROI	Return on Investment
SAURAN	Southern African Universities Radiometric Network

SCADA	Supervisory Control and Data Acquisition
SCIP	Solving constraint integer programs
SO ₂	Sulphur dioxide
STES	Solar thermal energy system
TES	Thermal energy storage
ToU	Time-of-use
UPS	Uninterruptible power supply
USA	United States of America
USD	United States dollar
VFD	Variable frequency drive
ZAR	South African rand

LIST OF UNITS

°C	Degree(s) Celsius
g	Gram(s)
hL	Hectolitre(s)
J/g.°C	Joules per gram per degree Celsius
J/kg	Joules per kilogram
kg	Kilogram(s)
kW	Kilowatt
kWh	Kilowatt-hour
L	Litre(s)
m	Metre(s)
m ²	Square metre(s)
V	Volt
W	Watt
ZAR/kWh	South African rand(s) per kilowatt-hour

CHAPTER 1: INTRODUCTION

1.1 BACKGROUND

South Africa currently faces a severe power crisis, with experts predicting that the prospects for recovery remain bleak. This crisis continues to pose a significant threat to the country's economic outlook in the coming years [1]. At present, the national energy supplier, Eskom, is unable to meet the increasing demand for electricity. The importance of sustainable energy management across all major sectors cannot be overstated [1,2]. To implement energy management activities effectively, it is essential to first identify the energy-intensive processes. Once these processes have been recognised, targeted initiatives can be proposed to reduce energy consumption. The effective implementation of these initiatives is crucial for maximising energy savings, which may, in turn, alleviate the strain on the national grid and mitigate load shedding or curtailment [3].

Several studies have investigated energy management practices applied to residential, commercial, and industrial energy consumers [4-6]. In this context, the beer production industry, which falls within the industrial sector, warrants closer examination regarding energy consumption [7]. Various energy audits conducted on breweries worldwide have demonstrated potential for improvements in energy efficiency. However, the literature pertaining to energy management activities in South African breweries is limited. Moreover, existing studies have primarily focused on reducing energy consumption in large and medium-scale breweries. Larger breweries often have access to advanced energy-efficient technologies that aid in minimising energy consumption [8]. Although energy-efficient equipment may entail high initial costs, these costs are generally offset over time by the energy savings achieved. This approach, often referred to as deep retrofits, involves replacing inefficient or obsolete equipment with more efficient technologies that incorporate smart control functionalities. Conversely, in the case of small-scale breweries, or microbreweries, the implementation of low-cost, less efficient equipment for beer production is sometimes unavoidable [9].

The beer production process in most breweries is fundamentally similar, although the techniques employed may vary slightly based on factors such as brewery size (production

volume) and the type of beer brewed. The key stages in brewing include milling, mashing, separation, boiling, cooling, fermentation, pasteurisation, maturation, and packaging [10].

Approximately 43 kWh is required to produce 1 hL of beer in medium- to large-scale breweries [11]. In microbreweries, producing the same quantity of beer may necessitate more energy due to economies of scale and less efficient equipment. According to Nassary and Nasolwa [8], roughly 80% of the energy used by breweries is allocated to thermal processes. These thermal processes involve heating and cooling systems that regulate the temperature of water and beer mixtures. Specifically, the processes that require heating and cooling include mashing, wort boiling, cooling, fermentation, maturation, and pasteurisation. Typically, heating is achieved through electric resistive elements, while refrigeration systems are employed for cooling. Both processes are energy-intensive and essential for beer production.

In addition to retrofitting costly equipment, energy management can also be applied by optimising the operation of existing equipment. Retrospective demand-side management (DSM) applied to energy-intensive equipment has been observed to be highly effective in reducing energy costs and, in some instances, overall energy usage [5].

Eskom has implemented the time-of-use (ToU) tariff to encourage load shifting among consumers. This approach involves increasing the cost of electricity during peak energy usage periods, while a standard tariff applies during moderate demand periods. During off-peak periods, the cost of energy is significantly lower. This DSM incentive presents an opportunity for some industries to reduce their energy costs 43kWh [12]. However, in the beer production industry, certain processes may not be easily adjusted without compromising the quality of the final product [13]. Consequently, each process must be scheduled and controlled with precision to maintain product quality. Control techniques can be applied to govern multiple processes, which can ensure optimal scheduling based on the energy consumption and duration of each process.

Following a walkthrough energy assessment of a microbrewery conducted in May 2019, several processes such as water heating, mashing, wort boiling, cooling, fermentation, and cold storage were identified as targets for energy conservation measures. The literature suggests that research focused on the energy management of these processes has yielded promising results. The primary challenges identified include high energy consumption and inefficient scheduling, which contribute to the elevated cost of beer production due to the

energy-intensive nature of the processes and a lack of effective energy management. The aim of this research was to develop an energy management model that reduces the current pattern of thermal and electrical energy consumption in the main brewing processes and to identify areas of energy wastage in order to ultimately achieve a substantial reduction in total energy consumption and associated costs.

1.2 PROBLEM STATEMENT

The production of beer is an energy-intensive process, with small-scale breweries consuming significantly more energy per unit of production than large-scale facilities [11]. An energy audit conducted on a microbrewery in Bloemfontein revealed that approximately 0.65 kWh of electrical energy is required to produce 1 L of beer, with nearly 97% of this energy allocated to heating and cooling processes [11,14]. These processes are time-sensitive and must follow a strict sequential order to maintain beer quality, which makes energy management particularly challenging. Furthermore, the brewery operates under a ToU tariff, whereby the majority of energy-intensive processes occur during peak-cost periods, which substantially increases operational costs [15]. While the integration of renewable energy sources, such as solar photovoltaic (PV) systems, has been explored, variability in solar resources and the absence of effective energy storage solutions limit their effectiveness [16].

Despite the growing need for energy efficiency in the brewing industry, existing studies primarily focus on large-scale breweries, neglecting the operational and economic constraints that are unique to small-scale breweries. Current energy optimisation strategies, such as DSM and predictive load balancing, are often designed for large-scale industrial applications and do not address the intermittent and batch-processing nature of microbrewery operations. The lack of tailored energy management frameworks leaves small-scale brewers vulnerable to excessive energy costs and sub-optimal operational efficiency. Several key sub-problems contribute to this inefficiency:

1. The absence of structured energy management strategies designed specifically for small-scale breweries limits the potential for cost reduction and efficiency improvements [17].
2. The lack of exergy recovery systems to capture and reuse waste heat leads to unnecessary energy losses [18].

3. Inadequate insulation increases standby energy losses due to thermal conduction [19].
4. Sub-optimal maintenance schedules cause inefficiencies in heating, cooling, and overall process control [20].
5. Non-continuous operations and batch processing, as compared to optimised continuous flow systems, impact energy efficiency [21].

1.3 OBJECTIVES

This research aimed to develop a predictive energy optimisation framework specifically for microbreweries, employing artificial neural networks (ANNs) and machine learning forecasting techniques to enhance load scheduling and reduce energy costs. In contrast to traditional DSM methods, the framework incorporates real-time operational constraints, ToU tariffs, and the batch-processing nature of microbrewery operations in order to provide a practical and scalable solution for small-scale breweries.

The primary objective of this research was to establish an optimal control and energy management framework for a microbrewery in Bloemfontein, South Africa, with the goal of minimising operational costs while maintaining the quality of beer production. This entailed the development of a mathematical model and an advanced scheduling algorithm to optimise the operation of major energy-intensive processes while adhering to system constraints. These constraints encompass the physical characteristics of equipment, process time, temperature requirements, and other operational limitations. The proposed framework also integrated DSM strategies and renewable energy sources to enhance efficiency and sustainability. Furthermore, an economic feasibility analysis was conducted to evaluate the financial viability of the proposed scheduling system in comparison to existing baseline operations.

The specific objectives of the project were as follows:

- Conduct a comprehensive literature review on beer production processes and energy reduction strategies, with a focus on the POET (Performance, Operation, Equipment, and Technology) framework as a tool for maximising energy savings.

- Analyse the energy consumption profile of the microbrewery through an energy audit to identify key energy-intensive processes and evaluate potential DSM opportunities, such as load shifting and process optimisation.
- Investigate the feasibility of renewable energy systems and energy storage for improving energy efficiency, with emphasis on solar thermal energy for water heating and its integration into the brewing process.
- Develop a mathematical model of the power flow and energy usage across the beer production line using MATLAB to incorporate the major thermal and electrical loads of the system.
- Design and implement an optimal energy management algorithm for the microbrewery, considering time-based pricing and renewable energy integration to reduce energy costs while ensuring that production constraints are met.
- Simulate the optimal scheduling and operation of the proposed system using case study data and compare its performance against the existing system as a baseline.
- Perform a techno-economic analysis to evaluate the cost-effectiveness and return on investment (ROI) of the proposed optimised brewing process, including quantifying potential energy and cost savings over time. This must be compared to the existing system (baseline) located at the case study.

1.4 RESEARCH METHODOLOGY

To achieve the objectives of this study, the following stepwise approach (see Figure 1.1) was employed to optimise the energy utilisation and performance of the hybrid renewable/grid system applied to beer production processes in the microbrewery:

- Background and energy survey: The methodology began with a comprehensive energy survey of the microbrewery, forming the foundation for identifying all major thermal and electrical energy demands within the beer production line. This survey included a walkthrough audit, direct measurements, and an assessment of energy consumption patterns across key processes such as water heating, mashing, wort boiling, cooling, fermentation, and cold storage. As part of this assessment, critical energy infrastructure including boilers, heating elements, refrigeration units, chillers, heat exchangers, tanks, and associated distribution systems was documented and

analysed. This baseline evaluation provided the necessary operational insight for subsequent model development, system variable identification, and optimisation studies.

- System variables identification: The initial model employed was predicated on ANNs to predict performance variables associated with the heating and cooling processes in the microbrewery. This was accomplished through the application of mathematical and thermophysical energy balance models. Key input and target variables for the ANN model were identified, including energy consumption data for heating and cooling, water and beer mixture temperatures, as well as other critical operational parameters. The subsequent model entailed the integration of a hybrid energy system, comprising both renewable energy sources (PV and solar thermal) and grid electricity. A comprehensive energy management strategy was formulated to optimise the operation of these systems and to minimise energy costs. The model further identified independent, control, and state variables that are essential for effective energy management and optimisation. Additionally, an economic analysis was conducted to evaluate the feasibility of the proposed hybrid system.
- Data collection (input variables) and case study:
 - Real-time input data were collected from power quality analysers and data loggers at Stellar Brewery in Bloemfontein, South Africa. These datasets included energy consumption associated with heating and cooling processes; in addition to information regarding the temperature of the water supplied to the heating systems, outlet water and beer mixture temperatures, and ambient air temperature. Solar irradiance data were sourced from a local weather station.
 - A baseline system configuration was documented, in which power was supplied to the heating and cooling processes from the grid, supplemented by additional load management strategies aimed at optimising energy consumption. These data were utilised to simulate the baseline operation and to establish a comparative framework for the proposed hybrid system.
- Proposed hybrid renewable/grid system and solar collector sizing:

- Static optimisation techniques were employed to ascertain the sizing of the proposed hybrid energy system. The selection of system components was predicated on the availability of renewable energy sources, the load demand profiles of the heating and cooling processes, and the initial investment costs. Optimisation was conducted utilising tools such as MATLAB.
- The sizing of the solar water heating system was determined based on hot water consumption data collected during comprehensive energy audits of the microbrewery. Furthermore, thermal energy storage (TES) systems, such as ice storage units, were evaluated to optimise energy usage by minimising the consumption of cold storage systems during peak pricing periods under the ToU tariff.
- Mathematical modelling of the power flow through the system was executed to facilitate comparison with the baseline system. This approach enabled detailed performance and economic analyses of the proposed system's potential energy savings.
- Model development:
 - The optimal energy management model was developed and implemented with the objective of minimising operational costs while ensuring that the quality of beer production is maintained. This model was specifically designed to integrate both electrical and thermal storage systems and to regulate energy flow in accordance with ToU tariff schedules.
 - Simulations of the proposed hybrid energy system were conducted using MATLAB, utilising optimisation toolboxes and algorithms to address challenges associated with mixed-integer programming. The simulations incorporated the dynamic behaviour of both energy generation and consumption components, optimising for minimal energy expenditure and maximal production efficiency.
- Simulation results and discussion:
 - The performance of the proposed hybrid system was evaluated under various operating conditions. Key parameters such as energy consumption, heating load, and storage system behaviour were assessed. The simulation results were compared to the baseline system to quantify energy savings and cost reductions.

- Several scenarios were modelled to examine the impact of different energy supply configurations. These included a baseline scenario in which all energy was supplied by the grid; an optimised scenario where energy was sourced from the grid, renewable energy, and storage systems; and a scenario involving the hybrid system under optimal control strategies.
- The economic analysis concentrated on the total cost savings over a 20-year period, which compared the proposed hybrid system with the baseline system. Average monthly savings were calculated, and a life-cycle cost (LCC) analysis was conducted to determine the breakeven point and long-term financial benefits of the proposed system.

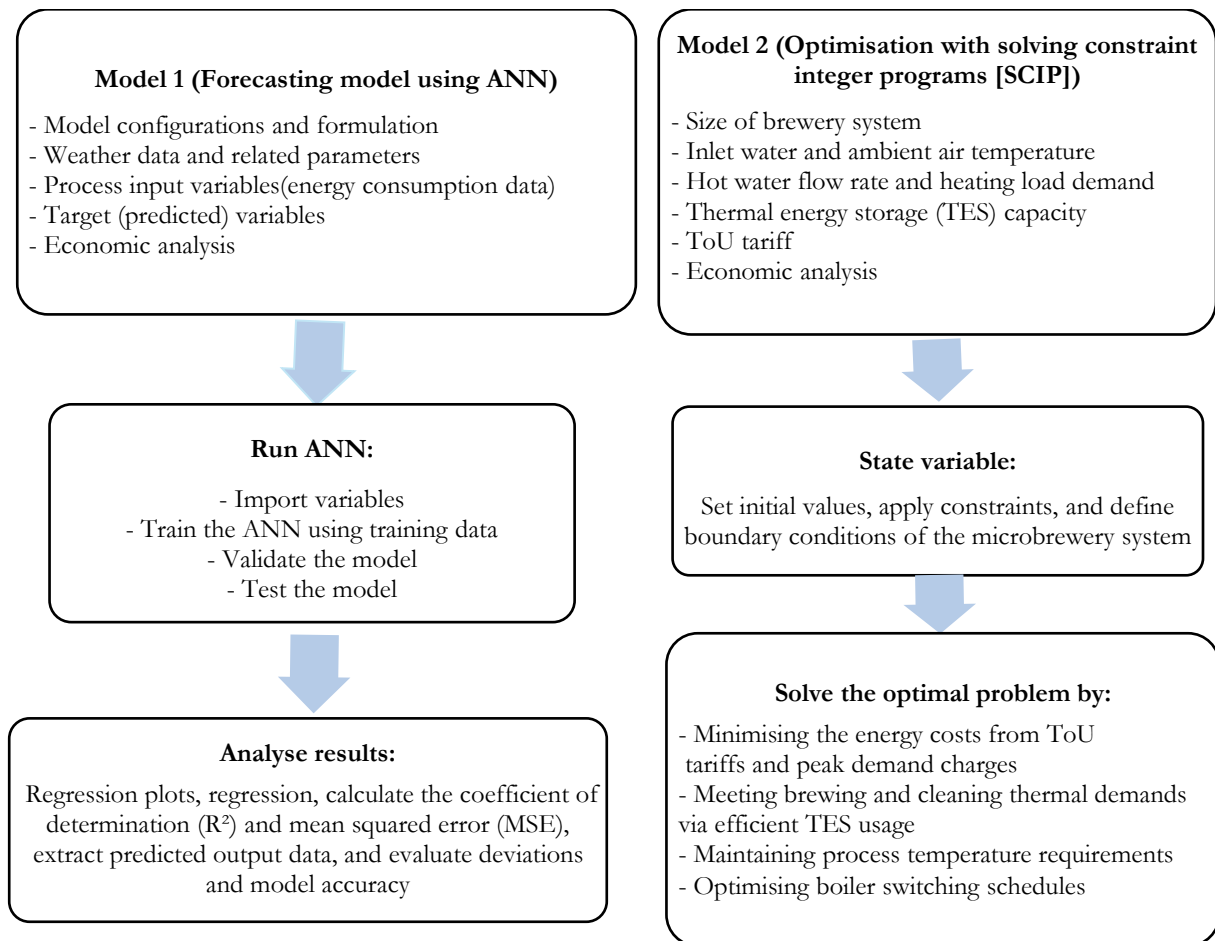


Figure 1.1: Flowchart methodology and research design

1.5 CONTRIBUTIONS TO KNOWLEDGE

The contributions of the study to the existing body of knowledge are delineated as follows:

Model 1: Forecasting energy consumption and enhancing sustainability in microbreweries: Integrating ANN-based models with thermal storage solutions (Chapter 3):

1. A brewery-specific ANN forecasting model was developed and validated, capable of predicting thermal and electrical energy consumption in microbreweries with high level of predictive accuracy regression values ranging from 0.85705 to 0.99856 and MSE values that were low (normalized to <15% of maximum variability).. This is a novel contribution, as it provides a customised prediction tool calibrated using real brewery operational data rather than generic industrial models.
2. A novel integration of ANN forecasting with thermal energy storage (TES) was established, enabling proactive prediction of heating and cooling loads and demonstrating how TES can synergistically reduce peak demand and smooth thermal loads in microbrewery operations.
3. The research contributes to knowledge by demonstrating the practical integration of artificial intelligence into sustainable brewery operations. The use of NAR and NARX ANN architectures show how AI-driven forecasting can improve resource efficiency, support intelligent process scheduling, and enhance low-carbon operational planning in process-intensive industries.
4. A new methodological framework for forecasting brewery process energy behavior using non-linear, non-deterministic data was developed. This provides a replicable approach that may be applicable to similar small-scale brewery operations
5. The study quantified the sustainability gains achieved through forecasting-driven improvements in prediction accuracy. These gains include enhanced thermal load management, more efficient energy planning, and expanded opportunities for renewable energy integration.
6. The developed ANN forecasting framework is compatible with emerging smart-grid and microgrid environments. Its short-term predictive capability supports

tariff-responsive control and interaction with distributed energy resources (DERs), potentially contributing to long-term adaptability within future intelligent energy systems.

Model 2: Optimal energy management of hybrid renewable energy systems for brewer

1. A hybrid energy management solution was developed, combining solar thermal collectors, a heat pump water heating system (HPWH), thermal energy storage, and grid electricity in a coordinated optimisation model. This integrated design is an original contribution, demonstrating a unified approach to brewery thermal–electrical energy management.
2. Studies related to brewery energy systems have typically relied on optimisation algorithms, such as genetic algorithms, simulated annealing, fuzzy logic, and model predictive control (MPC) methods. However, the model in this study utilises the SCIP optimisation technique within the OPTI-master solver, enabling deterministic non-linear optimisation of system operations in real time to minimise energy costs while efficiently managing complex energy flows and dynamic brewery demands. This approach constitutes a novel methodological contribution.
3. The research demonstrated significant efficiency improvements, including a 74% reduction in thermal energy use, over 72-75% reduction in seasonal energy costs, and a 73.53% annual cost reduction, achieving a 1.25-year break-even period. These results establish new performance benchmarks for hybrid energy optimisation in microbreweries.
4. A techno-economic model specifically tailored for microbrewery hybrid systems was developed, enabling breweries to evaluate life-cycle cost, payback, and tariff-driven cost reduction strategies. This tool forms part of the study's distinct contribution to knowledge.
5. The application of the POET framework was extended and contextualised for South African breweries, identifying the energy-intensive stages (responsible for approximately 85% of energy consumption) and providing actionable optimisation insights. This adapts POET theory for real brewery thermal process management, forming a contextual knowledge contribution.

6. A key contribution is the demonstration that hybrid thermal-renewable energy systems can be effectively aligned with emerging smart-grid and microgrid technologies. The optimisation framework developed in this study supports decentralised control, renewable-energy integration, and dynamic tariff interaction, positioning breweries for future grid-interactive operation.
7. The study contributes to sustainable energy-systems engineering by presenting an integrated optimisation architecture that may enhance brewery energy efficiency, reduce operational costs, and support improved resilience under changing energy-market conditions. It also offers a potential pathway toward scalable clean-energy transitions in small- to medium-scale process industries.

Application of the POET framework and contextual contributions:

1. The study systematically applied the POET framework to optimise energy management in major beer production processes. It addressed a significant gap in the South African industry, where water heating, mashing, wort boiling, cooling, and cold storage account for approximately 85% of total energy consumption.
2. Furthermore, it offers valuable region-specific insights into energy consumption patterns, potential savings, and sustainability challenges, thereby tailoring solutions to the operational realities of South African breweries.
3. The research presents solutions aimed at reducing energy demand and operational costs associated with heating and cooling loads in microbreweries. This, in turn, may contribute to more stable product pricing for consumers and bolster the economic sustainability of small-scale brewers.
4. A decrease in energy costs may facilitate reinvestment in cleaner technologies, enhanced production efficiency, and the creation of local employment opportunities. Such developments may foster community development, mitigate environmental pollution, and improve social and economic outcomes for the surrounding region.
5. By equipping brewery managers, engineers, and policymakers with actionable tools and recommendations, the research promotes improved energy efficiency, operational performance, and sustainability practices across the sector.

In summary, the study contributes original forecasting and optimisation models, advances the application of the POET framework in the brewery context, and demonstrates significant social and economic benefits, thereby enhancing both academic knowledge and practical approaches to sustainable energy management in beer production.

1.6 HYPOTHESES

The study's hypotheses are as follows:

- The ANN model may forecast power consumption patterns in the microbrewery setting. In addition, targeted energy-saving interventions may be identified.
- The baseline operational and energy cost can be valued by the implementation of optimal energy management model for a hybrid RES with TES.
- Optimal control strategies applied to microbrewery systems will enhance the economic feasibility of implementing the proposed energy-efficient equipment.

1.7 LIMITATIONS

The study was conducted with the following limitations:

- This research focused on a small-scale brewery (microbrewery) due to its unique operational and energy demand characteristics. Nevertheless, the proposed energy management strategies may be adapted for comparable small-scale food and beverage processing facilities.
- The case study is centred on a microbrewery located in South Africa, selected due to the availability and quality of relevant operational data. However, the methodologies and findings presented in this research may be applicable to similar facilities in other regions, contingent upon appropriate adjustments.
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1.8 PUBLICATIONS FROM THE STUDY

Conference papers:

- Conduah, J. Kusakana, K., & Hohne, P. A. (2019). Energy efficiency improvements in a microbrewery in South Africa. In *Proceedings of the 2019 Open Innovations Conference (OI)*, pp. 132–137. doi:10.1109/OI.2019.8908193

- Conduah, J. E., Kusakana, K., & Hohne, P. A. (2020). Energy monitoring for potential cost saving in electricity bills in a microbrewery in South Africa. In *Proceedings of the 18th Industrial and Commercial Use of Energy Conf. (ICUE)*. https://www.researchgate.net/publication/346648077_ENERGY_MONITORING_FOR_POTENTIAL_COST_SAVING_IN_ELECTRICITY_BILLS_IN_A_MICROBREWERY_IN_SOUTH_AFRICA

Journal articles:

- Conduah, J. E., Kusakana, K., Odufuwa, O. Y., Hohne, P. A., & Ma, T. (2025). Forecasting energy consumption and enhancing sustainability in microbreweries: Integrating ANN-based models with thermal storage solutions. *Journal of Energy Storage*, 112, 115508. <https://doi.org/10.1016/j.est.2025.115508>
- Conduah, J. E., Kusakana, K., & Hohne, P. A. (2025). Energy management of the major energy-intensive processes in beer production – A systematic review within the POET framework. *Submitted*.

1.9 THESIS LAYOUT

This thesis comprises five chapters, with the main research results presented in Chapters 3 and 4. The structure of the thesis is as follows:

Chapter 1 provides an overview of the study, including the background, motivation, problem statement and research objectives, research methodology and contributions, as well as the limitations of the study.

Chapter 2 offers a comprehensive literature review on energy management in the brewing sector, the optimisation of hybrid energy systems, and the integration of renewable technologies such as PV panels, solar thermal collectors, and energy storage systems. The review also examines control strategies and energy efficiency standards pertinent to microbrewery operations. Additionally, it includes an in-depth analysis of beer production processes and associated energy reduction strategies. Special emphasis is placed on the POET framework as a structured approach to maximise energy savings and enhance overall system performance in microbrewery environments.

Chapter 3 discusses the prediction and validation of energy consumption data in the case study microbrewery, employing an ANN model. Operational and environmental data specific to the brewery's context are analysed to enhance predictive accuracy.

Chapter 4 outlines the development of optimal energy control models for the brewery's hybrid energy system using the SCIP solver in MATLAB. It presents simulation results comparing baseline and optimised configurations and highlights reductions in energy consumption and peak demand. This chapter also provides a techno-economic analysis of the proposed hybrid energy system in the microbrewery, assessing LCCs, breakeven points (BEP), and payback periods. It underscores cost savings arising from reduced energy use and demand charges, thereby supporting the financial viability of renewable technologies and control strategies.

Chapter 5 concludes the study and offers recommendations for future research in the domain of sustainable energy management in small-scale brewing operations.

CHAPTER 2:

ENERGY MANAGEMENT OF THE MAJOR ENERGY-INTENSIVE PROCESSES IN BEER PRODUCTION – A SYSTEMATIC REVIEW USING THE POET FRAMEWORK

2.1 INTRODUCTION

This chapter examines the existing energy management strategies employed in major energy-intensive processes in beer production with the aim of identifying optimal solutions that ensure efficient and sustainable operations. The anticipated outcomes are intended to establish a structured approach for managing energy consumption while preserving the quality and consistency of beer production processes.

The POET framework is utilised to assess, analyse, and explore enhancements in energy efficiency in the beer production industry, particularly in South Africa, where energy costs and consumption present significant challenges. This framework facilitates a comprehensive evaluation of energy usage trends, optimisation techniques, and their implications for overall operational costs and sustainability.

The chapter is structured as follows: Section 2.2 provides an overview of sustainable energy efficiency implementation using the POET framework. Section 2.3 presents a detailed description of the methodology employed, clarifies the aim of the study, and highlights the specific contributions it makes to the field. Section 2.4 summarises the relevant literature on energy management initiatives in breweries, categorised by the levels of the POET hierarchy. Section 2.5 discusses the key findings obtained from the literature review. Section 2.6 summarises the main insights and implications. Section 2.7 presents valuable recommendations for future research and highlights potential areas for further investigation.

2.2 GENERAL OVERVIEW

The brewing sector in South Africa significantly contributes to national energy consumption in the food and beverage industry, accounting for approximately 30% of total energy use [22]. Industries are categorised based on energy consumption to address their specific needs, distinguishing between energy-intensive and non-energy-intensive sectors

[23,24]. In energy-intensive industries, energy costs account for 5% or more of production budgets, whereas non-energy-intensive sectors incur costs ranging from 1% to 3% [25,26]. In particular, thermal processes in microbreweries represent around 8% of total production costs, which makes them a primary focus for energy optimisation strategies [27]. Large-scale breweries have been reported to consume approximately 0.43 kWh per litre of beer produced, while microbreweries typically exhibit higher energy demands due to less efficient equipment and a lack of economies of scale [11].

Previous research has explored various energy-saving interventions in breweries, including insulation enhancement, heat recovery systems, and the integration of renewable energy sources [28]. Studies emphasise the importance of energy efficiency and recommend measures such as proper insulation for tanks and pipelines [29], automation of boiler systems [30], conservation of compressed air and steam [31], optimisation of refrigeration loads [32], and utilisation of waste biogas [33]. Implementing these measures can enhance energy efficiency, reduce costs, and promote environmental sustainability by minimising waste and lowering greenhouse gas emissions [26]. Additionally, the adoption of ice thermal energy storage (ITES) systems has been shown to significantly reduce cooling-related electricity usage, which can provide breweries with a means to better manage energy costs [1,34]. Moreover, the integration of solar and hybrid renewable systems has enhanced energy performance by reducing reliance on traditional energy sources [5,35].

Improving energy efficiency is essential not only for operational cost reduction but also for minimising environmental impacts. Various studies have demonstrated that deploying hybrid energy systems and advanced control strategies, such as MPC and machine learning, can enhance system performance. For instance, upgrades to refrigeration systems have resulted in efficiency improvements of 15% and a 25% reduction in peak demand [36].

The POET framework offers a systematic approach to implementing such upgrades, which can enable focused improvements across targeted areas of energy usage [37]. Research outcomes have indicated that initiatives guided by the POET framework can yield energy savings ranging from 10% to 70%, depending on the scale and depth of intervention [11].

Microbreweries, in particular, stand to gain significantly from these efficiency enhancements. The combination of solar thermal systems with TES has demonstrated the potential to reduce annual energy costs by up to 50%. Additionally, hybrid PV systems with

battery storage have shown seasonal energy savings ranging from 42% to 66% in South African brewery operations [14]. These findings highlight the dual benefit of energy cost reduction and alignment with broader global sustainability commitments, such as those outlined under the Kyoto Protocol [38].

Internationally, breweries have implemented innovative energy-saving approaches, including waste heat recovery, biogas systems, and DSM techniques to improve their energy efficiency [39,40]. Comparative case studies from Europe and North America have demonstrated that integrated energy management systems can result in energy savings of 20% to 30% [41]. However, South African breweries have lagged in adopting such solutions, largely due to limited sector-specific research, financial constraints, and regulatory challenges [42].

One major issue that confronts South African breweries is the steady escalation of electricity prices. The increasing cost of industrial tariffs over the past decade has further emphasised the need for effective and tailored energy management strategies [43]. In South Africa, the industrial sector consumes 51% of the country's total energy, which is significantly higher than the global average of 37% [44,45]. Addressing this challenge requires a combined approach that incorporates technological upgrades, process optimisation, and supportive regulatory frameworks [46,47].

Furthermore, traditional brewing operations, such as mashing and fermentation, also present considerable potential for energy savings. Enhancing the efficiency of these processes supports broader sustainability goals by reducing emissions and overall resource usage. As electricity prices continue to rise and environmental regulations become more stringent, the need for robust energy management strategies becomes increasingly critical.

To bridge the identified gaps and seize emerging opportunities, this study investigated optimal energy management techniques for the beer production process by applying the POET framework. The following sections review current initiatives, evaluate their applicability in the South African brewing context, and propose actionable solutions for sustainable energy practices in the industry.

2.2.1 Beer production processes

The fundamental process of beer production remains largely consistent across breweries, with variations influenced by factors such as the size of the brewery and the

specific type of beer being brewed [40,48]. Crucial stages in the brewing process include milling, mashing, filtration/lautering, boiling, cooling, fermentation, and packaging [49].

Beer production, a centuries-old craft, involves the combination of four essential natural ingredients: hops, malted cereal grain, yeast, and water [50,51]. Approximately 10 L of water are required to produce 1 L of beer, primarily for brewing, rinsing, and cooling [52].

Craft beer manufacturing encompasses pre-fermentation, fermentation, and post-fermentation processes, which include milling, mashing, lautering, wort boiling, fermentation, and packaging [53]. The brewery typically comprises a hot block, where high thermal energy operations occur that use saturated steam, and a cold block, which houses fermentation, maturation, filtration, carbonation, and packaging processes [26,50]. Tank temperatures in the cold block are regulated using glycol solutions and control systems, with refrigeration serving as the primary source of energy consumption. Figure 2.1 illustrates the key stages of beer production, including milling, mashing, lautering, boiling, fermentation, and packaging. It highlights energy-intensive processes such as wort boiling and cooling, which are essential for optimising energy management in breweries. Understanding these stages ensures consistent quality in craft beer production and enables targeted energy-saving interventions to enhance efficiency and reduce costs. Further details are provided in the subsequent sections.

2.2.1.1 Stage 1: Milling

The first stage in the brewing process, milling, involves crushing the malted barley to break apart the grain kernels. The objective is to achieve a consistent grind that exposes the starchy endosperm without shredding the husk, which acts as a natural filter bed during the subsequent lautering stage [54]. This process is typically performed using a roller mill and is a relatively low-energy step compared to the thermal processes that follow. However, the quality of the grind has significant implications for extraction efficiency in the mashing stage, as it indirectly influences overall energy and resource use.

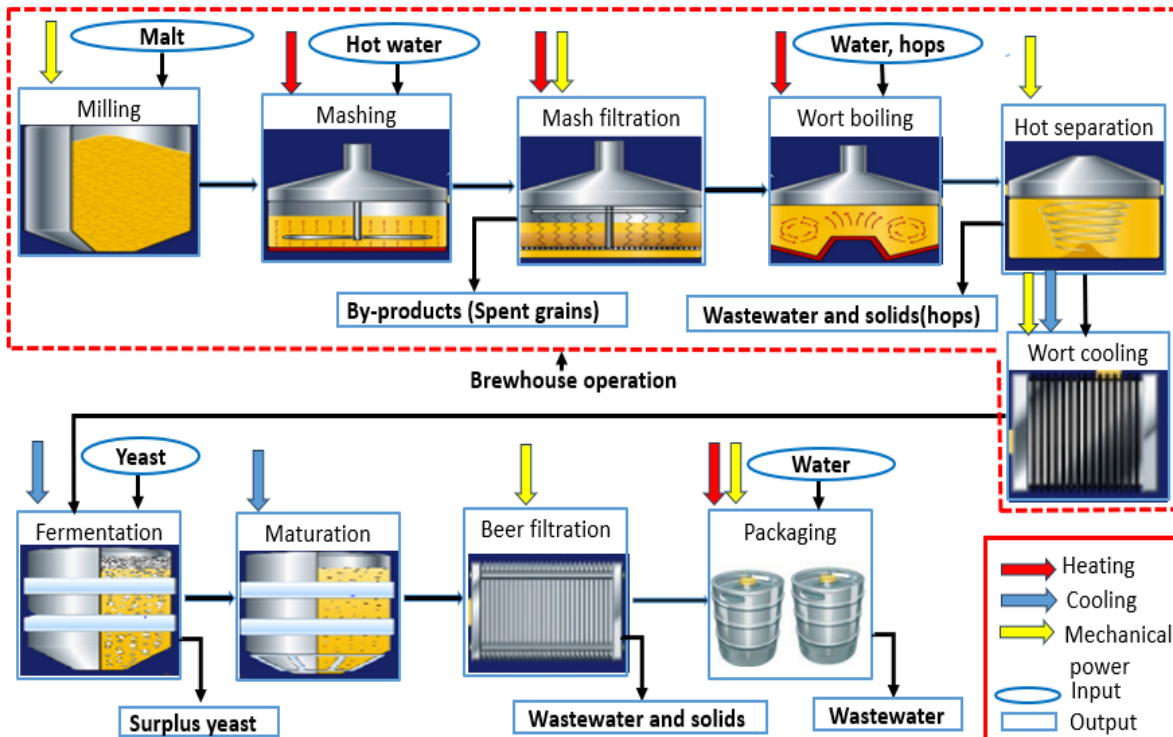


Figure 2.1: System layout of beer production processes

Adapted from Conduah et al. [11]

2.2.1.2 Stage 2: Mashing

During mashing, crushed malt (grist) and hot water are combined in a mash tun and typically maintained at temperatures between 65 °C and 75 °C for 60 to 90 minutes to extract fermentable sugars. This process results in sugar-saturated water or wort explosions [26]. Various temperature rests in the mashing process are crucial: a protein rest (50 °C to 55 °C for 10 to 20 minutes) aids in protein breakdown, followed by a saccharification rest (63 °C to 67 °C for 45 to 60 minutes) during which complex starches are converted into fermentable sugars, and, finally, the mash-out phase (75 °C to 78 °C for 10 to 15 minutes) halts enzymatic activity, reduces wort viscosity, and ensures optimal brewing conditions [26]. Sugar, occasionally added to reduce malt usage and impart different flavours, alters beer characteristics [54]. However, some countries, such as Germany, strictly utilise only water, malt, hops, and yeast in beer production [55], which ensures quality [50]. The mashing process consumes significant energy and fuel, with spent grain from the mash tun serving as animal feed or fertiliser [26,55].

2.2.1.3 Stage 3: Mash filtration/lautering

Following the mashing process, the wort is transferred to a lauter tun, which is a large vessel equipped with a sieve-like bottom for filtration and separation from the grain [26]. In the lauter tun, the mash settles on the slotted deck or false bottom. This creates a filter bed that allows the wort to pass through into the kettle [26]. Water is sprayed over the grain during the sparging process to improve sugar extraction [56].

Craft brewers often opt for manual lauter tuns due to cost considerations, although automated options are also available [55]. The operational functions of the lauter tun include warming the vessel and filling the under-deck space with water at approximately 75 °C to 78 °C. The mash is then transferred into the lauter tun, where three distinct layers form: large and thick solids, settled grains, and fine particles [57]. The wort is continuously recirculated until it reaches a clear state, at which point it is diverted away from the lauter tun and directed to the kettle for further processing.

2.2.1.4 Stage 4: Wort boiling

During the wort boiling phase of brewing, the temperature of the wort is raised significantly from around 70 °C to 100 °C. This stage involves vigorous boiling to facilitate water evaporation, which is the most thermally intensive step in brewing. Typically, 4% to 12% of the total wort volume is evaporated during this stage [58].

In this process, the clear, sweet wort is heated and sterilised in a brewing kettle, with hops added for flavour complexity and density throughout the boil. This process, lasting 60 to 90 minutes at boiling temperature (~100 °C), removes volatile compounds and ensures sterilisation [59]. The first hops serve as preservatives and bittering agents, boiled for approximately 60 minutes, while second hops contribute flavouring, typically added 15 to 30 minutes before the end of the boil. A final set of aroma hops may be included during the last five minutes to improve lost oil properties [54]. Additional flavours and colouring can also be introduced during this stage [26,41]. Adjuncts such as sucrose syrup, honey, or sugar may be added to increase alcohol levels, with the boiling process lasting one to two hours and consuming nearly half of the brewing energy [54]. Spent hops and impure solids settle to the bottom, which allows the clear wort to be drained off [54].

2.2.1.5 Stage 5: Wort cooling

The wort cooling stage is crucial in beer brewing and involves the rapid reduction of boiled wort temperature from approximately 100 °C to an optimal range of 18 °C to 20 °C prior to yeast fermentation. Rapid cooling is essential to prevent contamination and preserve delicate flavours [60]. This process is typically facilitated by a heat exchanger with two stages in series, wherein cold water circulates to absorb heat from the wort, which ensures efficient cooling [61]. The first stage employs mains water as a cooling fluid, while the second utilises chilled water at a temperature between -2 °C and 0 °C for effective cooling [26].

2.2.1.6 Stage 6: Fermentation

After cooling in a heat exchanger, the wort is conveyed to the fermentation tank at a suitable temperature between 18 °C and 24 °C, where yeast is added to metabolise or ferment the sugars that are present [26]. Fermentation typically lasts around five days but can extend to multiple weeks or even months, depending on the type of beer. As yeast generates heat during this process, brewers must carefully control the temperature [62]. Post-fermentation, the beer may undergo conditioning and ageing in the fermentation tank or be transferred to the bright tank for further processing. Some of the yeast can be reused, while the surplus may find applications in yeast tablets, animal feed, or distillation; however, some breweries opt to dispose of it [63].

2.2.1.7 Stage 7: Packaging

Packaging in beer production involves cleaning, sanitising, filling, and sealing containers to maintain quality and prevent contamination [64]. Techniques are tailored to meet market demands and ensure beer freshness until consumption, which makes it the most labour-intensive part of brewing. Machinery complexity increases to reduce costs and preserve quality [65]. Efficient packaging is critical for profitability and demands high capital investment and influencing product attractiveness, particularly in beer filling, which carries a risk of secondary contamination [65].

2.2.2 Energy-intensive processes in microbreweries

The fundamental beer production process remains largely consistent across breweries.

As described above, the processes involved in beer production remain fundamentally similar [8]. The stepwise process layout involved in beer production is illustrated in Figure 2.2. This figure may be evaluated in terms of energy usage.

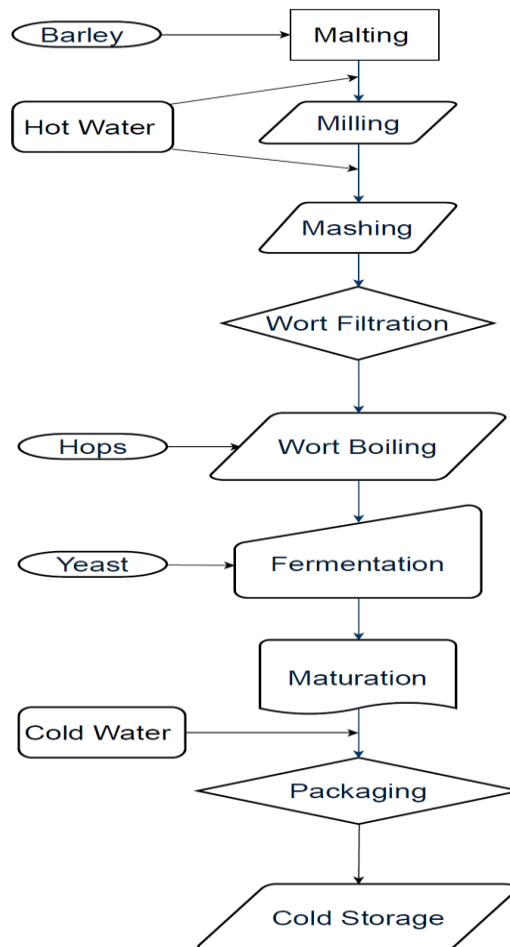


Figure 2.2: Typical beer production processes [8]

A walkthrough energy audit was conducted at a microbrewery in the city of Bloemfontein in South Africa to obtain preliminary data on energy consumption associated with its processes.

In Figure 2.2, it can be observed that water is introduced both prior to and subsequent to the milling process. The added water must attain a temperature of no less than 85 °C before milling and mashing can commence. This temperature is achieved by employing a boiler, as illustrated in Figure 2.3.



Figure 2.3: Water boiler

The brewery analysed in the case study raises the thermal level of 1 100 L of water through the utilisation of a 12 kW resistive element system to achieve the desired temperature. The duration required to heat this volume of water is approximately seven hours. However, it has been observed that the heating elements, regulated by a thermostat set to 85 °C, do not operate continuously for the entire seven-hour period. This is primarily attributable to the thermostat switching the resistive elements off once the desired temperature is attained. The thermostat alternates between on and off states to accommodate standby losses throughout the seven-hour duration. The energy required to heat this volume of water can be calculated using Equation 2.1 [67]:

$$Q = m \cdot C \cdot \Delta t \quad (2.1)$$

Where:

Q is the energy required to raise the temperature of the water;

m is the mass of the water in grams (g);

C is the specific heat capacity of water (4.186 J/g.°C); and

Δt is the change in temperature required (°C).

Using the equation, it can be deduced that approximately 83 kWh of energy is required to increase the temperature of water to the desired level of 85 °C. This figure is an approximation and does not account for standby losses. Consequently, a minimum of 83 kWh per day is necessary for water heating purposes. The energy requirements for other processes are detailed in Table 2.1. The energy consumption was calculated in terms of energy utilised per batch of 800 L of beer. The first three processes listed in the table primarily involve heating (the addition of heat to the beer mixture), while the remaining three processes represent the extraction of heat.



Figure 2.4: Mashing (mixer)



Figure 2.5: Wort boiler

A preliminary walkthrough energy audit was conducted on a microbrewery in the Bloemfontein region of South Africa to obtain initial energy consumption data for the processes involved. The estimated energy requirements for the key processes are summarised in Table 2.1.

Table 2.1: Microbrewery energy audit results

Process	Process duration (hours)	Energy consumption (kWh)
Water heating (85 °C)	7	83
Mashing (65 °C to 78 °C)	3	25.65
Wort boiling (97 °C)	1.67	60
Cooling (to 18 °C)	1.3	1.8
Fermentation (18 °C)	336	31.87
Packaging (0 °C to 18 °C)	4	11.12
Cold storage (0 °C)	Up to 4 360	304.65

The estimated energy consumption was approximately 518.09 kWh per batch of 800 L of beer, which translates to an energy requirement of 0.65 kWh per litre of beer produced. Furthermore, it was observed that approximately 97% of the total energy consumed may be attributed to heating and cooling processes. Additionally, the peak demand during the day is 77 kW, which occurs at midday.

In comparison to traditional medium- to large-scale breweries, an excess of approximately 0.22 kWh is necessary to produce the equivalent volume of beer. This excess consumption accounts for approximately 8% of the total production cost of the beer. Consequently, it is evident that energy management initiatives are essential to reduce energy consumption and, as a result, enhance the competitiveness of microbreweries in order to maintain profitability in the beer market.

2.2.3 Energy management in microbreweries

To evaluate the energy usage of energy-intensive processes in beer production, it is necessary to consult the relevant fundamentals of energy management, which include [34]:

- energy efficiency;
- mechanical energy basics;
- electric motors, power factor, and lighting;
- thermal energy transfer, energy balance, and insulation;
- water and brew mixture heating systems, and steam;

- HPWHs and refrigeration;
- energy management auditing;
- measurement and verification; and
- identification of energy management and energy-saving potentials.

It is essential to comprehend the processes involved in the beer production process in its entirety to identify potential energy-saving initiatives. Incorporating the fundamentals of energy management into any energy system may provide invaluable insight into determining opportunities for energy savings [68,69].

The energy efficiency of the beer production system serves as an indicator of how effectively energy is converted into usable energy rather than wasted as heat or other forms of unwanted energy [70].

Mechanical systems such as motors, pumps, and fans may influence the power factor of the system, which could result in inefficient energy utilisation.

Lighting systems, particularly incandescent lighting technology, are known for their poor energy efficiency. However, in the context of a beer production facility, lighting systems may only account for a small fraction of the overall energy consumption [71].

The transfer of thermal energy may be regarded as one of the most important processes involved in beer production, while the associated energy balance of energy transfer plays an integral role in identifying and quantifying energy losses in the system [72]. The energy balance of the system may similarly indicate the effectiveness of the existing insulation against energy losses.

The equipment used to heat water and beer mixtures often employs electric resistive elements; these systems consume substantial amounts of energy and may be perceived as one of the most energy-intensive processes [72]. An alternative technology capable of converting electrical energy into thermal energy at higher efficiencies could be employed to reduce energy consumption. This may include the utilisation of a heat pump system [72]. However, this technology may at times be ineffective in raising the temperature of the water or mixtures to the desired level within the short timeframe required for the next step in the beer production schedule [73]. The heat pump system operates on the same principle as refrigeration; however, in this case, the process is reversed to extract heat rather than

transferring it to a specific medium [36]. The refrigeration process may similarly be regarded as one of the primary energy-intensive processes, as it consumes energy over extended periods during the production of beer [7].

In order to propose adequate energy management initiatives, a thorough energy audit is required to ascertain the amount of energy consumed by each process [7]. Additionally, this will enhance the accuracy of data when formulating the energy balance equation for the system as a whole [74]. As part of the energy auditing procedure, adequate measurement and verification are necessary to ensure data accuracy. This is achieved by employing reliable data-logging systems or power quality analysers [75].

Upon completing a successful energy audit, the system may be mathematically modelled using appropriate computer hardware and software to provide a simulation of the operation of all processes involved in the brewery [76]. This will enable technicians, engineers, and energy managers to design energy management initiatives based on a computer-based model. Consequently, valuable data may be obtained regarding how the system would respond to various energy efficiency initiatives [77]. Moreover, employing mathematical modelling may prove to be highly cost-effective, as it requires minimal capital resources compared to implementing the system in the real world while measuring the resulting savings [7].

Energy management initiatives may encompass the application of control techniques, equipment retrofits, or the implementation of alternative renewable energy systems [78]. The aim is therefore to reduce the energy requirements of a given process while maintaining load requirements.

The application of control techniques may involve DSM based on the ToU tariff structure. This effectively means that energy-intensive loads are shifted to periods with lower energy pricing.

Equipment retrofits involve upgrading or replacing existing equipment with higher efficiency alternatives capable of meeting the same load requirements.

The implementation of renewable energy systems requires careful consideration, as these systems are often subject to high initial implementation costs and, as a result, extended payback periods, typically within the range of six to eight years.

Furthermore, the energy yield of these systems may also depend on the availability of renewable energy in the specific location of the brewery.

In summary, various energy management solutions exist for reducing energy consumption and associated costs in breweries. All available solutions may be evaluated in terms of feasibility through mathematical modelling and computer-based simulations, which may ultimately provide solutions for maximum energy savings.

2.3 SUSTAINABLE ENERGY EFFICIENCY IMPLEMENTATION VIA THE POET FRAMEWORK: GENERAL OVERVIEW

This study employed the POET framework to evaluate energy efficiency in the beer brewing industry and to examine prospective advancements and the potential for hybrid energy systems in South African microbreweries [11]. It highlights the significant role of beer production, noting that modifications to processes can affect quality and result in increased electricity costs during peak demand periods, particularly in light of escalating tariffs in South Africa [79].

2.3.1 Scalability of the POET framework across industries

The applicability of the POET framework extends beyond the realm of beer production, which demonstrates considerable potential for scalability across various industries, including food processing, textile manufacturing, and chemical production [64]. Each sector presents unique energy consumption patterns and challenges that could benefit from the systematic approach offered by the POET methodology. Nevertheless, the implementation of the framework in diverse sectors is accompanied by several challenges, which include:

- Socio-economic factors: Economic disparities between larger corporations and smaller enterprises can significantly influence the ability and willingness of smaller businesses to invest in energy-efficient technologies. Many small enterprises operate with constrained budgets, which limits their capacity to implement energy-saving practices [17,80].
- Regulatory variability: Variations in regulatory environments across regions or countries can create barriers to the adoption of best practices as defined by the POET framework. In some regions, strict environmental regulations may encourage the implementation of energy-saving measures, whereas in others, weaker regulations may fail to incentivise such changes [81].

- Technological readiness: The availability of advanced energy management technologies and the quality of infrastructure differ by industry. Some sectors may lack access to the necessary tools to implement state-of-the-art energy efficiency measures, which can impede progress [82].
- Cultural resistance: Industries with long-established energy practices may encounter cultural resistance to change. In such sectors, entrenched practices and a reluctance to adopt new methods aligned with the POET framework can hinder the transition to more energy-efficient strategies [83].

2.3.2 Applications and benefits of the POET framework

Despite these challenges, successful implementations of the POET framework across various sectors have demonstrated significant energy savings and improved operational efficiency. Energy-intensive industries, including manufacturing and utilities, have benefitted from the adoption of structured energy management practices [84]. To further promote the adoption of the POET framework, future research should address the socio-economic, regulatory, and technological barriers that hinder the widespread implementation of energy efficiency measures, which will enhance sustainability across industries.

The sustainability of energy management programmes is crucial in addressing the challenges of energy efficiency and environmental conservation [85]. A well-designed organisational structure is essential for sustainability because it provides a framework for effective implementation, coordination, and monitoring of energy initiatives [86]. Additionally, energy policies can offer external mechanisms that support sustainability efforts by establishing guidelines and regulations [87].

Effective engineering support is vital for evaluating the technical feasibility of a system [88]. This involves activities such as energy analysis, system modelling, and the implementation of optimisation techniques. By providing reliable engineering support, the dependability of energy solutions is enhanced, which makes a significant contribution to sustainability [89].

The POET framework, delineated as Performance (P), Operation (O), Equipment (E), and Technology (T) efficiency, conceptualised and presented by Xia and Zhang in 2010 [90], offers a comprehensive structure for energy audits, energy-saving identification, and

strategies for improving energy efficiency. Numerous studies across various sectors have highlighted the effectiveness of the POET framework, including healthcare institutions [91], cruise control of heavy haul trains [90], wastewater treatment processes [92], mineral processing [93], cooling systems [94], pumping systems operation [95], commercial buildings [37], and conveyor belt systems [96], which demonstrates its effectiveness in achieving average electrical energy savings of approximately 40% [37,90–96]. Effective energy management hinges on optimising the efficiency of electrical equipment in both buildings and industrial processes. However, fully capitalising on the potential cost savings in these structures can be challenging. To address this issue, it is crucial to structure an energy management programme into four distinct levels.

While this study focused on beer production, the principles of the POET framework can be applied broadly across various industries. In food and beverage production, optimising heating, cooling, and refrigeration can yield significant savings [97]. Textile manufacturing benefits from waste heat recovery and efficient boiler systems [98]. Chemical and pharmaceutical industries can enhance distillation and cooling processes with energy-efficient equipment and renewable energy sources [99]. Automotive manufacturing can reduce energy consumption through audits and efficient lighting [100].

The pulp and paper industry achieves substantial energy savings through cogeneration and process integration [101]. Applying the POET framework across these sectors can improve energy efficiency and support sustainability, which warrants further research into these broader applications [102].

2.4 METHODOLOGY: SYSTEMATIC REVIEW USING THE POET FRAMEWORK

Energy efficiency plays a crucial role in brewery operations by reducing energy consumption and associated costs. Several studies have examined the potential energy and cost savings achieved through energy-efficient initiatives in breweries [103].

The methodology of this study was grounded in the POET framework, which categorises energy efficiency into four dimensions: performance, operation, equipment, and technology efficiency.

The primary objective of this research was to establish an optimal control and energy management framework for a microbrewery in Bloemfontein, South Africa, with the goal of minimising operational costs while maintaining the quality of beer production.

To achieve this, a systematic review approach was adopted to synthesise current research findings and address predefined research questions. This study therefore sought to answer the following research questions:

- Research Question 1: What evidence is available in the literature concerning the potential energy and cost savings that can be achieved through the implementation of energy management strategies in breweries?
- Research Question 2: Can breweries effectively implement energy-efficient initiatives to meet energy targets set by organisations such as the Council for Scientific and Industrial Research (CSIR) and the National Liquor Authority (NLA)?
- Research Question 3: What is the economic feasibility of implementing energy efficiency initiatives in breweries to meet energy targets with respect to the preceding questions?

The study employed the POET framework to thoroughly review energy efficiency in breweries, covering performance, operation, equipment, and technology efficiency [104].

To address the research questions, an extensive review of energy efficiency measures applicable to the beer production industry using the POET framework was conducted.

To identify relevant studies on energy efficiency in brewery operations, a systematic search strategy was implemented using well-established research databases such as Google Scholar, ScienceDirect, IEEE Xplore, and industry-specific platforms. Keywords such as “energy efficiency”, “beer production”, “microbreweries”, “POET framework”, “hybrid energy systems”, “energy-intensive processes”, and “model predictive control” guided the search, which allowed the researcher to compile a broad selection of high-quality, peer-reviewed articles, conference papers, and reports [104,105] that focused on enhancing energy efficiency in breweries.

Breweries are recognised for their high energy consumption, which is primarily driven by thermal processes. As detailed in Section 2.5.1.1, the research focus on these processes

is justified because they represent the most energy-intensive aspects of brewery operations [25]. The specified search strategy, combined with the POET perspective, ensured a comprehensive exploration of energy efficiency avenues during the literature review. Articles were required to be in English, available in full text, recent in publication, and directly addressing energy-intensive processes in beer production. The researcher prioritised recent publications to incorporate the latest advancements while also including select older studies for foundational insights.

Furthermore, the study incorporated insights from global industrial initiatives aimed at enhancing energy efficiency in breweries. By synthesising data from these initiatives, this research offers a comprehensive overview of successful strategies, innovative approaches, and best practices in energy management in the brewing sector [105].

International programmes were benchmarked to identify cutting-edge practices and emerging trends in brewery energy efficiency [107], which facilitated a comparative analysis that highlighted opportunities for improvement, innovation, and optimisation on a global scale.

Additionally, the research included case studies and success stories from leading breweries worldwide. These real-world examples illustrate effective energy efficiency initiatives and their outcomes, which provide actionable insights and inspiration for brewery managers, industry practitioners, and policymakers that are striving to enhance energy management practices and achieve sustainability goals [108].

This research on beer production energy management prioritised data security and research integrity by emphasising robust cryptographic standards and strong security protocols, as highlighted by Canto et al. [109,110]. These measures safeguard sensitive data and ensure reliable findings while supporting efficient data management through:

- the implementation of secure cryptographic standards [110]; and
- the mitigation of threats such as poisoning attacks [111].

By integrating insights from global industrial literature, conducting rigorous systematic reviews, benchmarking global initiatives, and analysing case studies, this study aimed to enhance its impact, relevance, and practical utility within the context of energy efficiency in breweries [26,112]. This comprehensive approach enriched the findings and provides valuable guidance for stakeholders who are seeking to implement sustainable energy

management practices in the brewing industry through ensuring a thorough examination of all critical areas [113].

Consequently, this study makes a significant contribution by thoroughly evaluating energy efficiency strategies in breweries. It utilised the POET framework to explore dimensions such as performance, operational practices, equipment upgrades, and technological advancements. Through a systematic review of global literature and industrial initiatives, it offers insight into effective strategies, innovative approaches, and best practices for managing energy in breweries. The study also examined the potential energy and cost savings achievable through sustainable measures, which provided valuable data on economic feasibility and average payback periods. By offering practical guidance for brewery managers during the planning phase of energy efficiency projects, including information on average payback periods and economic feasibility, this research supports stakeholders in enhancing energy efficiency and advancing sustainability goals in brewery operations.

However, the limitations of the POET framework become evident when assessing energy efficiency initiatives within its hierarchy [90]. Precisely quantifying the “effort” versus potential “profits”, as outlined by the Pareto principle, is challenging due to variations in technology, operations, and brewery contexts. Consequently, presenting data on energy savings and payback periods as averaged ranges rather than exact values is more practical. This approach acknowledges variability and aids stakeholders in decision making. It is thus essential to represent quantitative data from the literature as averaged ranges for energy savings and associated payback periods across all levels of the hierarchy [114].

2.4.1 Research studies validating hybrid energy integration in microbreweries

To substantiate the findings, the researcher presents two research studies that corroborate both the quantitative data derived from the systematic review and the results reported by Conduah et al. [27] and Kusakana [14]. These studies validate the significant financial, operational, and environmental advantages associated with the integration of hybrid solar thermal systems in microbreweries.

2.4.1.1 Case Study 1: Hybrid solar thermal systems enhanced by machine learning

In the study titled “Forecasting energy consumption and enhancing sustainability in microbreweries: Integrating ANN-based models with thermal storage solutions”, Conduah et al. [27] investigated the integration of hybrid solar thermal systems enhanced by machine learning in the microbrewery sector. This research utilised ANN-based models in conjunction with thermal storage solutions to optimise energy consumption, reduce operational costs, and enhance sustainability within the brewing industry.

The key findings from this study were as follows:

(a) Annual energy cost savings

The integration of a hybrid solar thermal system in the study generated an annual energy cost saving of approximately USD 95 372.05, based on the following factors:

- Optimised energy consumption patterns facilitated by predictive ANN modelling.
- Strategic use of ToU pricing, which involved shifting high-energy tasks to off-peak periods.
- A reduction in reliance on grid energy, with solar thermal energy supplementing traditional power sources.

These savings are consistent with the projected 50% reduction in total energy costs highlighted in the systematic review, which underscored the cost-effectiveness of integrating HPWHs and TES systems into brewery operations.

(b) Reduction in energy consumption

The adoption of solar thermal energy systems (STESs) was anticipated to decrease overall energy consumption by 25% to 30%, to be accomplished through:

- the replacement of approximately 69% of grid-sourced energy with solar-generated thermal energy; and
- enhanced load balancing and TES, which would diminish reliance on peak demand.

A microbrewery with an initial annual consumption of 1 000 000 kWh signifies a yearly reduction of 250 000 kWh to 300 000 kWh. The systematic review further substantiated this by indicating that breweries can realise energy savings ranging from 10% to 70%, depending on the level of intervention.

(c) Carbon emissions reduction

The projected energy savings were expected to result in a reduction in carbon emissions of approximately 125 000 kg to 150 000 kg carbon dioxide (CO₂) annually, based on:

- the standard grid electricity emissions factor of 0.5 kg CO₂/kWh; and
- the expected energy savings of 250 000 kWh to 300 000 kWh per year.

These findings are consistent with the 15% to 50% reduction in CO₂ emissions documented in the systematic review, which illustrates the significant environmental benefits associated with the integration of hybrid renewable energy systems in microbreweries.

(d) Economic viability and investment analysis

The financial assessment suggests that the proposed hybrid system offers strong economic viability with the following:

- An initial investment of USD 50 000 for solar thermal system integration.
- A breakeven period of 1.5 years, after which energy savings fully offset capital costs.

This finding is consistent with the economic analysis detailed in the systematic review, which demonstrated that the LCC comparison indicated that hybrid renewable systems can reduce energy expenditures by 50% over a 20-year period, with a BEP occurring within 1.5 years.

(e) Validation through case studies and literature

The case study of a microbrewery in Bloemfontein, South Africa, included in the systematic review, provided real-world validation of the proposed strategies. The key findings included:

- 25% reduction in peak electricity demand due to the integration of solar thermal energy and ITES.
- 15% improvement in refrigeration efficiency, achieved through predictive control strategies.
- 30% total annual energy savings, aligning with our projected consumption reductions.

Furthermore, ANN-based predictive models have demonstrated efficacy in optimising energy efficiency in the brewery sector. Conduah et al. [27] identified that breweries that

employ machine learning techniques for predictive energy management realised substantial cost savings and improvements in operational efficiency.

Table 2.2 outlines the anticipated financial and environmental advantages associated with the implementation of a hybrid solar thermal system in a microbrewery, with emphasis on significant cost reductions, energy savings, and sustainability impacts.

Table 2.2: Summary of projected financial and environmental benefits of hybrid solar thermal systems in a microbrewery

Metric	Project value	Supporting evidence
Annual energy cost savings	USD 95 372.05	Derived from systematic review and ANN modelling [27]
Projected energy consumption reduction	25% to 30%	Based on POET framework analysis and solar thermal integration estimates
Estimated annual carbon emissions reduction	125 000 to 150 000 kg CO ₂ ; 15% to 50% CO ₂ emissions	Calculated using standard emissions factor and energy savings
BEP	1.5 years	Time to recover initial investment through energy savings
Validation through case studies	25% reduction in peak electricity demand 30% total annual energy savings	Observed from a case study of a South African microbrewery

In summary, the data presented above provide clear, quantifiable evidence that supports claims regarding the efficiency of the proposed hybrid STES in microbreweries. These projections, corroborated by both Conduah et al. [27] and this study’s systematic review, demonstrate the significant financial, operational, and environmental incentives for breweries to adopt machine learning-driven energy optimisation strategies.

2.4.1.2 Case study 2: Grid-connected dual-tracking photovoltaic (PV) system with battery storage

Kusakana’s study [14], titled “Optimal energy management of a grid-connected dual-tracking photovoltaic system with battery storage: Case of a microbrewery under demand response”, investigated the integration of a grid-connected PV system with battery storage at a microbrewery in Bloemfontein, South Africa. The research employed demand response strategies to optimise energy management and minimise operational costs.

The key findings of this study included:

- Annual energy cost savings of ZAR 603 490.49 (approximately USD 34 206.44) over a 20-year period.
- Daily savings of up to 66.27% on non-brewing days, with seasonal savings of 57.7% in summer and 42.9% in winter.
- A BEP achieved in 9.5 years (ZAR 398 583.18 or USD 22 592.09), with full investment recovery in 13.8 years.

While the study did not directly quantify reductions in carbon emissions, it highlighted significant ecological benefits, such as decreased reliance on conventional electricity and fossil fuels, which resulted in a reduced environmental footprint. Furthermore, the study underscored the importance of time-varying pricing structures and demand response in optimising energy consumption and enhancing financial sustainability in facilities with fluctuating energy demands.

In conclusion, both case studies demonstrated substantial economic and environmental benefits arising from advanced energy optimisation in microbreweries. Conduah et al. [27] illustrated the advantages of hybrid solar thermal systems enhanced by machine learning, while Kusakana [14] confirmed the effectiveness of PV-battery storage in conjunction with demand response strategies. Collectively, these studies advocate for the adoption of hybrid renewable solutions to achieve long-term cost savings, sustainability, and improved operational efficiency, thereby validating the utilisation of such systems as a sustainable energy solution for the brewing industry.

2.5 ENERGY MANAGEMENT STRATEGIES UTILISING THE POET ENERGY MANAGEMENT FRAMEWORK

The energy efficiency improvement guidelines provide a framework for enhancing the energy efficiency of breweries. These guidelines may encompass conceptual, active, technical, and engineering dimensions. Each dimension can be categorised to reflect the performance, operation, equipment, and technological efficiency of critical brewing systems, including wort production, fermentation, and refrigeration. The energy efficiency levels and subcategories are examined in the following subsections [115].

2.5.1 Conceptual level

At the conceptual level, the emphasis is on identifying cost-saving activities that necessitate lower-level skills and reduced expertise. This involves the management of energy through the analysis of components and utility consumption data. In the context of beer production, this entails an examination of consumption data, the identification of critical production components, and the implementation of straightforward cost-saving measures.

2.5.1.1 Technology efficiency at the conceptual level

Figure 2.6 illustrates the energy consumption of the different stages of the brewing process in breweries across South Africa.

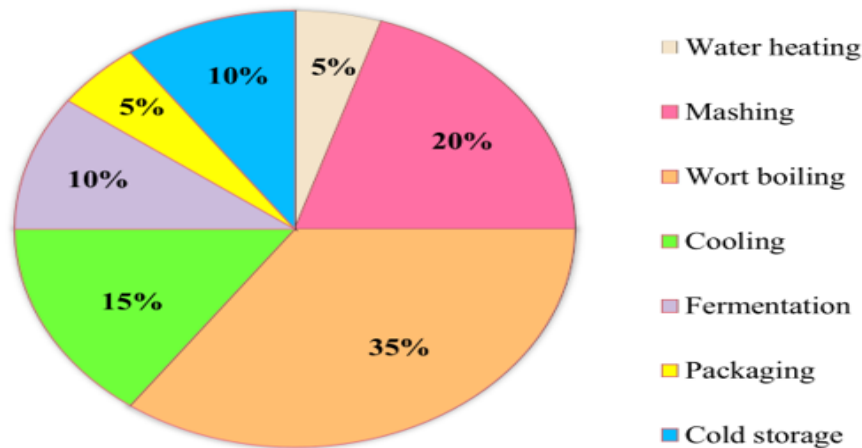


Figure 2.6: Energy consumption of breweries across South Africa [120]

Technological efficiency in beer brewing processes and equipment is crucial for identifying electricity consumption inefficiencies and establishing a foundation for improvements. Research into eco-friendly brewing technologies aims to enhance sustainability and resilience [116,117], while various models assess and improve energy efficiency [118].

Energy efficiency in brewing directly impacts total energy use [26] and is particularly important amid fluctuating energy prices. Furthermore, an evaluation of energy-use intensity across various sectors indicates that the food service sector ranks the highest in most developed countries, contributing to 67% of greenhouse gas emissions [119]. Technological advancements have increased brewing efficiency [26]. Despite these advancements, high water and energy consumption persist as challenges. Minimising water

usage and implementing efficient water management practices are essential to mitigate environmental impact. These challenges stem from the intrinsic nature of the brewing process, which necessitates substantial amounts of both water and energy resources.

To gain a comprehensive understanding of the typical energy usage spectrum in breweries, it is essential to analyse energy consumption data. Figure 2.6 presents the average percentages of energy consumed by various processes in South African breweries [120]. The chart indicates that wort boiling is the most energy-intensive process, accounting for 35% of overall energy consumption. The second-largest consumer is the refrigeration and cold storage process, which utilises up to 25% of the total energy. The cooling process, although requiring relatively less energy, still contributes significantly to overall energy consumption. The mashing process, a critical element in the brewing cycle, is another notable contributor, accounting for approximately 20% of energy usage. Fermentation follows, constituting 10% of overall energy consumption, while both water heating and the packaging department individually represent 5% of the total energy spectrum.

This detailed breakdown reveals the intricate energy spectrum in breweries and illuminates key processes that warrant attention for potential efficiency improvements.

In retrospect, four major thermal energy-intensive processes are identified: wort boiling, mashing, cold storage/refrigeration, and water heating systems. Collectively, these processes constitute approximately 85% of total energy consumption, which renders them pivotal areas for potential enhancements in energy efficiency. Conversely, fermentation and packaging account for around 15% of the total energy consumed. This classification facilitates a targeted approach to address energy-intensive aspects in brewery operations.

2.5.1.2 Equipment efficiency at the conceptual level

To enhance equipment efficiency and reduce energy consumption in beer production, breweries should prioritise the upgrading of energy-intensive processes such as cold storage, mashing, wort boiling, and water heating systems. This entails replacing or retrofitting existing equipment with more energy-efficient alternatives to optimise operational performance and minimise energy usage [17,124].

Modernising brewery systems is imperative due to ageing infrastructure, which frequently lacks advanced technology that results in diminished performance and increased operational costs. Achieving this modernisation necessitates the acquisition and installation

of cutting-edge components available in the market to enhance overall equipment efficiency in beer production systems. The typical system layout of a beer brewing process was depicted in Figure 2.1, where each component serves specific roles [118].

Hot water systems are integral to brewery hygiene and production processes. In brewery water heating systems, energy consumption is predominantly concentrated on the heating element (70% to 90%), followed by thermostats and controls (5% to 10%), insulation (5% to 15%), pumps (approximately 5% or less), storage tanks (10% to 20%), heat exchangers (5% to 15%), and safety features (about 1% or less) [126,127]. The precise percentages depend on system specifics and efficiency factors. Replacing conventional components with advanced technologies, such as XTEND, could potentially yield up to 25% savings on hot water costs and a reduction in electricity bills.

The selection of a water heating device necessitates careful evaluation. For instance, a highly efficient heat pump could be employed in water heating, mashing, wort boiling, and cleaning by extracting heat from low-temperature sources. While HPWHs offer energy savings of up to 65% compared to traditional electric storage tank water heaters, they are also associated with challenges, such as higher failure rates and initial investment costs, which may influence replacement decisions [120]. Figure 2.7 presents a schematic diagram of a typical HPWH [127], which illustrates the continuous heat transfer process in a closed-loop system.

These strategies not only enhance energy efficiency but also contribute to sustainable brewery operations by reducing environmental impact and improving cost-effectiveness.

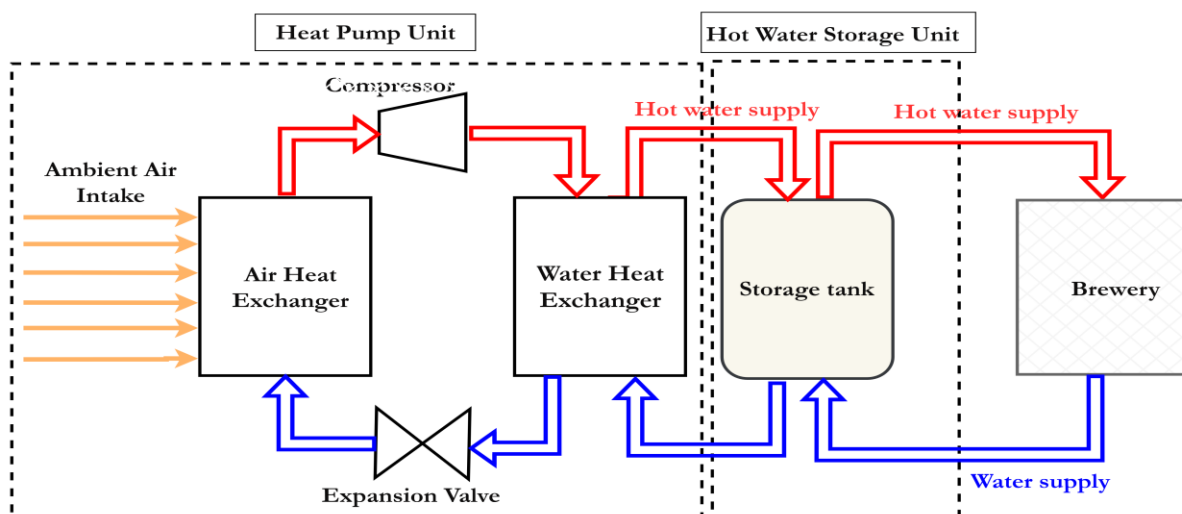


Figure 2.7: Heat pump water heater (HPWH) schematic diagram [127]

Table 2.3: Options to improve brewery systems at the conceptual level

Source	Activity	Description	Remarks
[85,86]	Process upgrading	Replace or retrofit energy-intensive processes (cold storage, mashing, wort boiling, water heating) equipment with more efficient equipment.	Energy savings depend on the process; typically reduces energy consumption by 10% to 30%.
[90,131]	Replace ageing brewery infrastructure with advanced technology components.	Upgrade the entire brewing system with a more efficient system. System modernisation.	Boosts equipment efficiency; potential operational cost savings of 15% to 25%.
[64,155]	Hot water system improvement	Upgrade components of brewery hot water systems: heating element (70% to 90% of energy use), thermostats (5% to 10%), insulation (5% to 15%), pumps (~5%), tanks (10% to 20%), heat exchangers (5% to 15%), and safety features (~1%).	Up to 25% savings on hot water costs; improves system energy efficiency significantly.
[132]	Monitoring refrigerant level	Engage in optimal monitoring of the refrigerant level in the chillers according to the manufacturer's specifications. Reducing excess refrigerant charge leads to average energy efficiency reduction and capacity degradation.	Save ~20% energy costs due to decreased efficiency reduction and degradation.

2.5.1.3 Operational efficiency at the conceptual level

Operational efficiency at the conceptual level concentrates on specific processes involved in beer production, including water heating, wort boiling, mashing, and refrigeration. The objective is to identify a range of cost-saving activities that, when applied strategically, can lead to substantial improvements in energy efficiency. This level entails the adoption of practical and straightforward measures that can be effectively managed, often by personnel who possess basic skills.

A significant aspect of enhancing operational efficiency in beer production is the optimisation of water heating systems, which are critical for various brewing processes [123]. Key improvements encompass upgrading components such as heating elements, storage tanks, and heat exchangers to more efficient alternatives, such as XTEND elements, which can yield savings of up to 25% in hot water costs [120]. Likewise, optimising the wort boiling and mashing processes through the analysis of burners, kettles, and heat exchangers aids in conserving energy and enhancing beer quality [128]. Refrigeration systems, which are vital for preserving beer, can also benefit from advanced

compressors, evaporators, and control systems, which will result in reduced energy consumption and operational expenses.

Simple yet impactful actions, such as turning off systems when not in use and optimising operational parameters, can lead to considerable cost savings and diminished energy bills [129]. Ensuring smooth brewery operations necessitates routine maintenance tasks, including cleaning [130], purging [131], and the removal of blockages and sediments [26]. Furthermore, monitoring refrigerant levels [132], replacing ageing components [112], and contemplating system upgrades or replacements [133] are crucial. Additionally, the integration of supplementary components can further enhance brewery efficiency [14].

To implement these improvements effectively at the conceptual level, breweries must comprehend their energy consumption patterns and utility usage data. Regular monitoring and tracking of energy use during beer production are essential for identifying patterns and trends, which will enable breweries to make informed decisions regarding areas in need of enhancement.

In conclusion, operational efficiency at the conceptual level in beer production encompasses various domains, including water heating, wort boiling, mashing, and refrigeration. It centres on identifying practical, cost-effective measures for improving energy efficiency, which can be managed by personnel with basic skills. By optimising these processes through component analysis and data-driven decision making, breweries can realise significant energy savings and enhance their overall sustainability.

2.5.1.4 Performance efficiency at the conceptual level

At the conceptual level of performance efficiency in beer brewing processes, a comprehensive approach is essential. This approach addresses technological security, quantifies benefits, and mitigates negative impacts. By adopting backup systems, tracking performance metrics, and reducing energy consumption, breweries can enhance operational and energy efficiency, reduce costs, and support environmental sustainability. These strategies are crucial for the long-term success of the brewing industry [134].

In breweries, the Energy Performance Index serves as a tailored benchmark that evaluates parameters such as energy security, consumption, costs, and carbon emissions per beer batch [135]. This index assists in assessing and improving overall performance efficiency [136]. Technological assessment involves identifying outdated or malfunctioning

equipment through regular maintenance and inspections, thereby ensuring process efficiency and reliability. Establishing performance metrics and collecting data enable breweries to quantify savings and benefits, which allows them to monitor improvements in energy consumption and ingredient wastage. LCC analysis and technological advancements can further enhance brewing efficiency [26]. Despite these advancements, high water and energy consumption continue to pose challenges, as they extend beyond acquisition costs and inform efficient investment decisions. ROI analysis is employed to determine whether efficiency upgrades justify their initial investments.

Energy security is a critical consideration, supported by uninterruptible power supplies (UPSs) and generators to prevent disruptions caused by power interruptions [137]. UPS systems provide short-term power while generators start to ensure continuous brewing operations and consistent product quality. Monthly energy consumption profiles are utilised to establish baseline usage, which guides the implementation of energy-saving initiatives and the setting of efficiency targets [120]. Monitoring energy consumption trends aids breweries in reducing energy costs and carbon emissions, which aligns with sustainability goals and enhances operational efficiency.

Improving energy security and reducing energy consumption in a brewery enhances performance efficiency and overall energy efficiency, which aligns with sustainability objectives and drives operational cost reductions.

2.5.2 Active level

Beer production systems, at this stage of enhancing energy efficiency, prioritise the verification of the accuracy of data collected at the conceptual level. Concurrently, efforts are directed towards investigating additional equipment and strategies aimed at improving energy efficiency and achieving savings in the existing energy-intensive system [136]. Active-level management at this stage may encompass the validation of data through the utilisation of equipment, software, and online monitoring tools. This may involve the assessment of technologies such as energy monitoring and management systems (EMMSs), variable frequency drives (VFDs), and brewery energy management software (BEMS). Consequently, further efforts are required to augment overall efficiency at this level.

2.5.2.1 *Technology efficiency at the active level*

Breweries employ technology, data analysis, and automation to ensure consistent product quality, reduce production costs, and enhance sustainability. By utilising contemporary equipment and software, breweries can optimise processes, minimise waste, and implement energy-efficient practices. This approach emphasises the importance of continuous process improvement, quality control, and adherence to regulatory standards.

Furthermore, breweries are increasingly adopting cost-effective energy monitoring technologies to measure and track energy usage, which enables real-time data transmission and alerts regarding abnormal consumption or system faults [137]. For example, breweries in Germany have integrated advanced energy monitoring systems with Internet of Things (IoT) and machine learning algorithms, which resulted in a 10% to 15% reduction in energy consumption [138]. In contrast, breweries in South Africa remain in the early phases of adopting such technologies, which presents opportunities for substantial enhancement. To further improve efficiency, breweries can implement advanced technologies such as smart controls, variable speed controls, and integrated technical energy systems. These advancements play a crucial role in enhancing operational efficiency while supporting sustainability initiatives in the brewing industry [127,137–139].

Table 2.4: Brewery technologies to improve cost and efficiency

Technology	Description	Remarks/challenges
EMMSs [137,138]	These systems employ IoT and machine learning algorithms to monitor energy consumption in real time.	High initial setup costs and complexity in integrating with existing systems may pose challenges. Breweries using these systems may achieve a 10% to 15% reduction in energy use.
Smart controls [89,137]	Automated control systems that adjust according to environmental variables, occupancy, and production stages.	The accuracy of sensors may be affected by thermal interference, obstructions, or incorrect placement in the conditioned space.
VFDs	Adjust the compressor speeds and equipment operations based on real-time demand to optimise energy use.	Optimal performance relies on correct system sizing and effective integration with existing infrastructure.
BEMS	Integrate software to analyse and optimise energy usage, thus improving operational efficiency.	Requires skilled personnel for both setup and continuous monitoring to ensure optimal operation at all times.
Heat recovery systems [137,140]	Recapture and reuse waste heat from the brewing processes to reduce energy loss.	Integration with existing systems, particularly older infrastructure, can present significant challenges.

Technology	Description	Remarks/challenges
Energy storage solutions [137,140]	Store energy during low demand periods for use during peak periods to balance loads and reduce costs.	Significant investment is required in energy storage infrastructure, which may present financial barriers.
Solar thermal systems [14,27]	Use solar energy to preheat water or power heating systems, thus reducing reliance on traditional energy sources.	Efficiency is influenced by geographic location and climate and requires specific integration strategies for optimal operation.
Integrated technical energy systems [89,127,137–139]	A system that integrates various energy sources, such as solar and geothermal, to maximise energy efficiency.	High upfront costs and the need for a detailed compatibility analysis between various system components.

2.5.2.2 Equipment efficiency at the active level

At this level, equipment efficiency in a comprehensive beer production system focuses on the upgrading and integration of advanced technology throughout the brewing process. This involves the systematic replacement of outdated equipment with more efficient alternatives. Simultaneously, advanced sensors and controllers are strategically implemented to facilitate real-time adjustments and optimise operational parameters. The sensors employed include CO₂ sensors, temperature sensors, pressure sensors, and others, which were selected for their affordability, ease of installation, and reliable performance.

Efforts to enhance energy management in beer production concentrate on fundamental strategies for improving overall efficiency [17]. This encompasses the installation of additional sensors to achieve precise control over water heating, mashing, wort boiling, cooling, and refrigeration processes [41]. Effective maintenance planning necessitates a choice between corrective maintenance and preventive maintenance, supported by energy dashboards that adjust schedules based on historical equipment performance [120]. Maintenance schedules take into account environmental factors and equipment ageing to sustain operations, reduce energy consumption, and prevent disruptions. Specific maintenance tasks include inspecting hot water conduits, replacing sacrificial anodes, and maintaining mash tuns and wort grant outlets. Optimising heating elements and steam traps during the wort boiling stage enhances energy transfer and minimises heat loss. The integration of advanced equipment, sensors, and proactive strategies aims to achieve comprehensive energy and cost savings, thereby supporting sustainable and cost-effective brewing processes [139].

2.5.2.3 Operational efficiency at the active level

Achieving operational efficiency in beer production necessitates a comprehensive strategy that integrates computer programming, specialised software, and extensive staff training.

This integration facilitates dynamic responses to varying conditions that impact the brewing process and enables real-time adjustments that enhance both efficiency and adaptability.

In the contemporary market, software solutions such as BrewMasters and brewery enterprise resource planning (ERP) systems function as dedicated workstations for monitoring and managing energy consumption, encompassing tasks such as recipe formulation, production scheduling, and quality control. These systems assist in optimising equipment start times, streamlining operations, and improving overall efficiency and quality. Furthermore, staff training is crucial to ensure the effective operation of these programmes in response to conditional variations in order to maximise the advantages of these technologies and support sustained improvements over time.

2.5.2.4 Performance efficiency at the active level

Improving active-level performance efficiency in beer production necessitates the enhancement of energy security through the establishment of reliable backup systems, supported by the implementation of a comprehensive database and monitoring devices. This meticulous approach facilitates the collection of vital information regarding generator systems, including load specifications and maintenance records, which are essential for assessing reliability in the beer production process [100].

The systematic evaluation of these data ensures sustained energy security and optimised performance efficiency, which underscores the importance of a tailored and reliable energy framework for the brewing industry.

2.5.3 Technical level

Further energy improvements, beyond the conceptual and active levels, are examined at this stage [119]. A comprehensive approach is employed, which integrates technology, engineering, and operational practices to minimise energy consumption and enhance sustainability in the brewing process [119]. The technological focus is refined to encompass

advanced energy technologies, such as HPWHs, ITES, and renewable energy for heating and cooling applications.

Additional initiatives at this level aim to validate the energy savings asserted from the preceding stages and may involve further retrofitting, process optimisation, automation control, and the integration of cyber-physical systems to enhance energy efficiency. ToU tariffs incentivise breweries to reduce energy consumption during peak demand periods, which impacts processes such as water heating, mashing, wort boiling, and refrigeration [141].

The implementation of efficient DSM systems enables breweries to capitalise on these tariffs, which allows them to achieve significant energy savings while enhancing overall efficiency and sustainability [120,142]. A technical-level approach is crucial for ensuring optimised energy usage without compromising product quality, which will yield long-term cost reductions and environmental benefits.

2.5.3.1 Technology efficiency at the technical level

Technological advancements in the production of beer at a technical level have significantly enhanced critical stages of brewing, which resulted in improved efficiency and precision. Breweries in the United States of America (USA), for instance, have integrated solar thermal systems with heat pumps, which achieved energy savings of up to 30% [145]. Conversely, breweries in South Africa are in the early stages of adopting hybrid renewable energy systems, which possess the potential to deliver similar energy-saving benefits.

Innovations such as energy-efficient heat exchangers have improved water heating systems that allow for precise temperature control, which is essential during the mashing process. The integration of automated brewing systems equipped with sophisticated sensors ensures consistent temperature profiles during mashing, which minimises errors and allows for greater flexibility in recipe adjustments.

Technology plays a crucial role in optimising efficiency during wort boiling by regulating temperature and pressure to ensure a uniform wort that attains the desired flavour profiles [49]. Energy-efficient refrigeration systems, equipped with VFDs, contribute to sustainability during the fermentation stage. Additionally, Supervisory Control and Data Acquisition (SCADA) software and IoT technologies enable real-time analysis of brewing operations, which ensures quality control throughout the process [143].

Radio frequency identification, blockchain, and IoT-based smart packaging technologies further optimise supply chain management, which reduces waste and maintains beer quality during transport [144].

2.5.3.2 Equipment efficiency at the technical level

Enhancing equipment efficiency at the technical level is crucial for advancing sustainability in the beer production industry. Breweries are increasingly recognising the significance of implementing advanced technologies and operational strategies to improve equipment performance [120]. The integration of renewable energy systems and appropriate energy storage solutions is vital for achieving substantial efficiency improvements and reducing reliance on the electric grid [145]. Systems that operate without storage can achieve electrical energy savings of up to 33%, while hybrid renewable energy systems aim for savings between 33% and 100%, focusing on minimising grid dependence through ToU tariff optimisation [146]. Despite economic challenges, breweries prioritise optimal design strategies to ensure minimal payback periods [26,146].

The adoption of solar water heaters can lead to grid energy savings of up to 70%, while hybrid water heating systems also offer significant savings [147]. DSM combined with TES or electrical energy storage systems during refrigeration phases can result in energy savings of 25% to 50%, and waste heat recovery initiatives can enhance overall system efficiency by 20% to 35% [148]. An accurate assessment of hot water demand is essential for selecting the most suitable heating system [2]. ITES systems in microbreweries can contribute to approximately 5% energy savings [149]. Effective energy management requires precise control of equipment operation using DSM technologies. While DSM offers significant opportunities for microbreweries to optimise energy use, challenges such as pricing structures based on ToU tariffs may arise, which necessitate careful scheduling and control to ensure that product quality is maintained [150].

2.5.3.3 Operational efficiency at the technical level

Operational efficiency in beer production can be significantly enhanced at the technical level by incorporating sustainable practices, such as the integration of renewable energy systems with energy storage. These strategic measures offer substantial potential for energy

and cost savings across critical stages of production. They not only enhance environmental sustainability but also contribute to operational effectiveness and financial benefits.

Optimising energy and cost savings in breweries involves several key strategies. Advanced heaters equipped with controls can provide up to 15% savings [7], while efficient heat recovery systems may achieve approximately 20% savings [151]. Timed heating schedules during off-peak hours further enhance cost efficiency, which can offer an additional 10% reduction [14]. Integrating renewable energy sources, such as solar or wind, along with energy storage solutions, can significantly lower energy expenses by up to 20% [152,153]. HPWH systems contribute substantial savings of around 25% [70].

Efficient mashing techniques, including precise temperature control and automated mixing systems, support energy savings of up to 12% and an additional 8%, respectively. Flexible brewing schedules aligned with energy demand patterns can yield a further 5% in savings. High-efficiency wort boiling systems, such as steam boilers, can save approximately 18% in energy costs [134]. Adapting to real-time energy demand through variable boil intensities and scheduling boiling during off-peak hours can collectively reduce energy expenses by up to 25% [134]. Integrating smart cooling systems with real-time monitoring and thermal storage solutions can achieve additional savings of up to 15% and 12%, respectively [154].

Regular energy audits, data analytics for consumption patterns, continuous employee training in energy-efficient practices, and optimal maintenance protocols ensure ongoing operational efficiencies and maximise savings [90].

2.5.3.4 Performance efficiency at the technical level

Enhancing the technical performance efficiency of a brewery's beer production system necessitates a multifaceted approach. The process commences with a comprehensive cost analysis, which includes an inventory of brewing equipment, the solicitation of quotations for energy-efficient upgrades, and a detailed breakdown of operational expenses. This financial groundwork establishes a foundation for informed decision making in subsequent stages.

The approach further entails a meticulous evaluation of production metrics aimed at optimising brewing equipment, automating processes, managing resources efficiently, and minimising environmental impact. It encompasses benchmarking against industry

standards, simulation modelling for validation purposes, real-time monitoring for continuous improvement, and thorough documentation to effectively track and report progress.

2.5.4 Engineering level and prospective improvement

At the engineering level, also referred to as the further improvement stage, specialised energy efficiency initiatives are implemented in beer brewing systems. These initiatives focus on optimising specific areas of the brewing process using techniques that are aligned with the POET framework, including maintenance plans, energy monitoring dashboards, and precise operational controls. The goal of these measures is to maximise energy efficiency in the brewery and achieve predefined energy-saving targets [50,155].

The scalability and applicability of the POET framework extend beyond the brewing industry. For example, energy-intensive processes such as pasteurisation, refrigeration, and packaging in the food and beverage sector can also benefit from the framework. Research in the dairy industry indicates that adopting energy-efficient technologies and operational optimisations can reduce energy consumption by 20% to 30% [123,156].

Similarly, in the textile industry, the implementation of waste heat recovery systems and the optimisation of boiler operations have demonstrated significant energy savings [157]. These examples illustrate the potential for the cross-sectoral application of the POET framework.

However, implementing these measures in other regions or sectors poses challenges, including high initial investment costs, a lack of technical expertise, and regulatory barriers. For instance, limited access to financing and inconsistent energy policies in developing countries can obstruct the adoption of advanced energy-efficient technologies [158,159].

While the POET framework provides a structured approach to energy management, its successful implementation requires overcoming these socio-economic and regulatory obstacles.

2.5.4.1 Technological efficiency at the engineering level

Technological efficiency at the engineering level in beer production integrates automation, artificial intelligence (AI), and advanced technologies to optimise processes and enhance energy savings in energy-intensive operations, such as water heating, mashing, wort boiling, refrigeration, and cooling [50]. By employing sophisticated real-time

monitoring, predictive maintenance, economic analysis, and dynamic optimisation strategies, breweries can acquire valuable insight into achieving significant energy savings and accurately evaluating payback periods [134,160,161].

2.5.4.2 Equipment efficiency at the engineering level

Equipment efficiency at the engineering level in beer production systems can be achieved through the application of advanced energy system optimisation techniques. Incorporating maintenance schedules, occupancy levels, ambient temperature, and real-time forecasting into a system's operational timetable enhances overall performance. The use of control techniques such as on-off control, proportional-integral-derivative control, robust control, adaptive control, and intelligent control further contributes to streamlining and optimising the beer production process [164,165].

2.5.4.3 Operational efficiency at the engineering level

Efficiency in engineering processes remains crucial for achieving sustainability and cost-effectiveness. Techniques such as MPC and machine learning have demonstrated energy savings ranging from 4% to 51.23% and cost reductions between 12% and 70.74% [142]. In brewing processes, dynamic optimisation using MPC and machine learning fine-tunes temperature control and leverages time-based pricing mechanisms to enhance energy efficiency. In refrigeration, MPC adapts to varying load demands and dynamic tariffs to ensure maximised efficiency under changing conditions [78].

A comprehensive approach at the engineering level, involving a deep understanding of process intricacies, supports the successful implementation of these strategies. Real-time simulation tools are essential for validating and optimising predictive models. Additionally, integrating hybrid systems that combine traditional and renewable energy sources further enhances system efficiency. The adoption of advanced control strategies offers considerable potential for significant energy and cost savings across industrial processes, as exemplified in applications such as water heating, brewing, and refrigeration systems [22].

2.5.4.4 Performance efficiency at the engineering level

Performance efficiency at the engineering level is crucial for optimising beer production processes with the aim to achieve higher productivity, quality, and sustainability. One effective strategy involves expanding the information scope in the existing energy console. This expansion incorporates critical indicators such as energy costs, energy waste, carbon emissions, staff knowledge, skill level, LCCs, and ROI. With an enriched console serving as a centralised hub, breweries can continuously monitor, analyse, and optimise key elements in the brewing process.

Real-time optimisation in brewing achieves significant energy savings, exceeding 50%, while maintaining beer quality by adjusting variables such as CO₂ effects, temperature, pressure, humidity, and occupancy [165]. Advanced modelling enhances energy management [166] by integrating performance indicators and optimising processes in real time [167].

Considerations of financial constraints, payback periods, and incentives ensure accurate feasibility assessments [168]. Expanded energy dashboards facilitate comparisons and improvements across breweries. Real-time simulation tools validate system models, mitigate risks, and support evidence-based policymaking [169], which improve overall energy efficiency [53].

2.6 DISCUSSION AND KEY FINDINGS

Energy management strategies in breweries are typically structured around the POET framework, which classifies actions into conceptual, active, technical, and continuous improvement stages. These strategies largely rely on established energy-saving measures intended to reduce operational costs, enhance process efficiency, and ensure compliance with regulatory standards, while also supporting broader sustainability objectives.

Conventional brewery energy management practices primarily focus on process optimisations, including improved heat recovery during wort boiling, optimisation of refrigeration cycles, and the adoption of energy-efficient technologies such as VFDs and high-efficiency boilers.

At present, energy management initiatives in breweries are often carried out as isolated projects rather than through integrated real-time control systems. As a result, energy

savings and efficiency gains tend to be fully realised only under favourable conditions, such as when production schedules, operational demands, and ambient temperatures align optimally. Although there is considerable potential for reducing energy use and costs, the highest possible savings are only intermittently achieved.

Since electricity pricing, production loads, and environmental conditions are dynamic and variable, conventional energy management practices are not consistently effective across all operating scenarios. Currently, optimal strategies that could lower energy expenses while maintaining stable production performance have not been broadly implemented to predict or adapt to disturbances caused by fluctuating production levels, dynamic electricity tariffs (including ToU rates), and changing environmental factors. One key reason for this limitation is the lack of simulation-based tools used to inform the optimal control and management of energy use in breweries. Additionally, the absence of comprehensive evaluations and validations of results by incorporating predictive analytics and optimisation tools – such as fuzzy logic, ANNs, closed-loop control, and other advanced techniques – limits the ability to fully exploit off-peak electricity tariffs and varying production demands in line with ToU and maximum demand frameworks.

An approach to achieving optimal energy management in breweries is highlighted as follows:

- The information derived from the systematic review may be used to develop models that simulate the performance of various energy management strategies under differing operational conditions.
- The exploration of real-time control systems and predictive analytics tools is essential to facilitate dynamic responses to fluctuations in production schedules, energy pricing structures (including ToU tariffs), and environmental variables.
- The integration of optimisation methods, such as ANNs, fuzzy logic systems, and other advanced monitoring tools, may contribute to achieving consistent and enhanced energy savings across a range of operational scenarios.

- Further research is required to validate these models under actual brewery conditions to ensure their reliability, adaptability, and effectiveness in achieving sustainable energy management objectives.

Building upon these observations, a structured analysis based on the POET energy management framework was conducted to systematically evaluate energy-saving opportunities and their feasibility across breweries.

Following the investigation and review of literature on hybrid energy systems integrated with TES in a microbrewery setting, Table 2.5 presents a general summary and comparison of the key findings.

Table 2.5: Overview of energy management strategies utilising the POET energy management framework

Source	Case study	System type	Control strategy type	Outcome
Conceptual level	Identifies cost-saving activities through component analysis and utility consumption data [134,161,162]	Evaluates electricity consumption and adopts environmentally friendly technologies [22,23,24]	Replaces or retrofits equipment to improve operational performance and reduce energy consumption [14,36,112]	Optimises brewing processes such as water heating and refrigeration for energy savings [120,134]
Technology used	Component analysis tools, utility consumption analysis tools	Energy-efficient lighting, motors	High-efficiency boilers, advanced heating, ventilation, and air conditioning (HVAC) systems	Energy performance monitoring systems, process optimisation software
Remarks	Up to 60% energy cost savings (approximately 15% of total energy consumption)	Up to 25% savings on hot water costs (approximately 10% of total energy consumption)	Significant energy savings (approximately 20% of total energy consumption)	Improved operational efficiency (approximately 5% of total energy consumption)
Active level	Uses data analysis and automation for product quality, cost reduction, and sustainability [161,137,139]	Upgrades and integrates cutting-edge technology with real-time adjustments [139]	BrewMasters software, brewery ERP systems, real-time monitoring systems	Enhances energy security with backup systems and comprehensive monitoring [120]
Technology used	Data analysis tools, automation systems, smart controls, VFDs, EMMSs, BEMS	CO ₂ , temperature, pressure sensors, smart controls, ITES, TES, energy dashboards	High-efficiency boilers, advanced HVAC systems	Backup energy systems, database systems, energy monitoring devices
Remarks	Improved operational efficiency through data analysis and automation	Enhanced control and optimisation with advanced sensors	Streamlined operations and optimised equipment utilisation	Improved operational efficiency (approximately 5% of total energy consumption), sustained energy security and optimised performance efficiency
Technical level	Integrates advanced energy technologies, optimises processes, and retrofits equipment [138,146]	Implements energy-efficient practices in brewing stages [83,134,150]	Integrates software and training for dynamic responses to brewing	Uses simulation modelling, real-time analytics, and validation against benchmarks [26,132,145–149]

Source	Case study	System type	Control strategy type	Outcome
Technology used	HPWHs, ITES renewable energy systems, cyber-physical systems, SCADA, IoT	Renewable energy systems (solar, wind), energy storage, smart controls, advanced refrigeration systems, waste heat recovery systems	Advanced heating systems, heat recovery systems, automated mixing systems, high-efficiency boilers, smart cooling systems	Simulation modelling tools, real-time data analytics platforms, supervisory control system
Remarks	Improved operational efficiency through data analysis and automation	Enhanced control and optimisation with advanced sensors	Streamlined operations and optimised equipment utilisation	Improved operational efficiency (approximately 5% of total energy consumption)
Engineering level	Automation, AI, and supply chain optimisation for energy-intensive processes [120]	Sophisticated maintenance plans, smart sensors for predictive maintenance, automated self-diagnostics, and advanced control algorithms for adaptive cooling [93,134]	Advanced system optimisation integrating maintenance schedules, occupancy levels, and real-time forecasting [49,93,134]	Expanded energy console with critical indicators, real-time optimisation for >50% energy cost savings [26,169]
Technology used	Automation, AI, HPWHs, ITES, renewable energy	Smart sensors, automated self-diagnostics, self-optimising algorithms, predictive analytics, and variable speed compressors	MPC, machine learning, dynamic optimisation, time-based pricing, load shifting	High computing, advanced modelling, real-time optimisation tools, renewable energy
Remarks	Moderate percentage savings of total energy consumption (payback: one to two years)	Water heating: 15% to 20% energy savings; refrigeration and cooling: 10% to 15% energy savings, 25% to 30% energy cost reduction	Energy savings 4% to 51.23%, cost reductions 12% to 70.74%	>50% potential energy cost savings

TES systems present a significant opportunity for breweries to enhance energy management by shifting both cooling and heating loads from peak to off-peak periods. In brewing operations, TES is typically employed to store chilled water or ice for fermentation cooling, as well as hot water or steam for cleaning and brewing processes. By decoupling energy generation from immediate demand, TES facilitates the reduction of peak electricity consumption, enables the utilisation of lower off-peak electricity tariffs, and enhances overall system efficiency. However, despite the evident operational benefits of TES technologies, their adoption in breweries remains limited. Recent findings indicate that TES systems may exhibit a lower coefficient of performance (COP) compared to conventional direct-use systems, primarily due to storage and transfer losses. Consequently, the economic justification for TES in breweries is most compelling when dynamic pricing structures, such as ToU tariffs, are implemented and when TES operation is optimised in real time. A review from the perspective of the POET energy management framework suggests that the estimated efficiency improvements and potential percentage energy cost savings for TES applications in breweries can be categorised across the conceptual, active, technical, and continuous improvement levels, as illustrated in Figure 2.8.

Building upon these insights, a comprehensive evaluation of energy management strategies in the brewery sector can be framed using the POET energy management framework.

2.6.1 Analysis from the POET framework perspective

The POET energy management framework offers a systematic approach to optimise energy efficiency across four levels: conceptual, active, technical, and further improvement. This framework is instrumental in evaluating energy management in sectors such as beer production, where energy efficiency can markedly influence both operational costs and sustainability initiatives [170].

The systematic review presented in this paper sought to address three pivotal research questions from a POET perspective, as outlined in the methodology section:

1. What evidence is available in the literature concerning the potential energy and cost savings that can be achieved through the implementation of energy management strategies in breweries?

2. Can breweries effectively implement energy-efficient initiatives to meet energy targets set by organisations such as the CSIR and the NLA?
3. What is the economic feasibility of implementing energy efficiency initiatives in breweries to meet energy targets with respect to the preceding questions?

To answer these questions, the literature review identified a substantial body of scholarly work concerning energy efficiency initiatives, with a predominant focus on critical industrial processes involved in beer production, including water heating systems, mashing, wort boiling, refrigeration, and cooling. Despite the availability of research pertaining to these processes, there exists a notable lack of studies specifically targeting the brewery sector. As a result, data from similar industrial processes were utilised to estimate average energy savings associated with each efficiency initiative.

In light of the absence of brewery-specific studies, projections of potential energy savings were derived from findings related to analogous industrial processes. These estimates are elaborated upon throughout the thesis, with average savings illustrated at each level of the POET framework.

Figure 2.8 depicts the maximum potential energy savings across the conceptual, active, technical, and further improvement levels for each efficiency initiative.

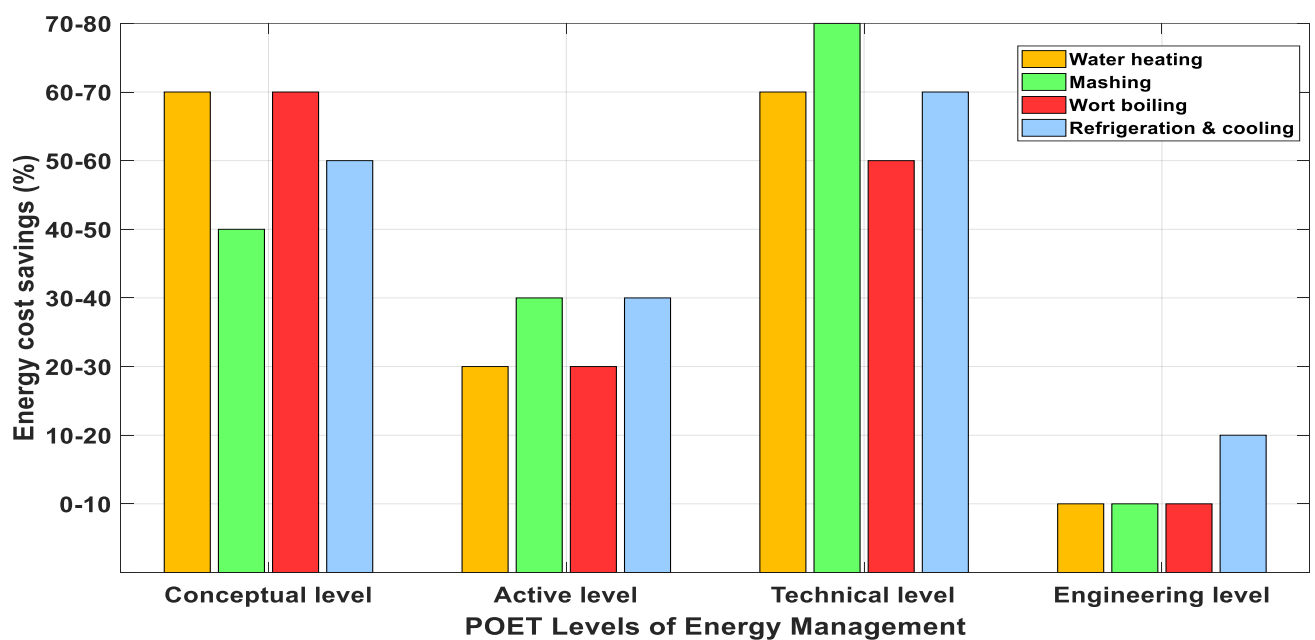


Figure 2.8: Maximum potential energy savings achievable for each POET energy management level in beer production systems

Figure 2.8 presents the estimated energy savings achievable at different POET levels:

- Conceptual level: Emphasises straightforward, cost-effective efficiency measures.
- Active level: Necessitates a moderate investment in process optimisation and control.
- Technical level: Integrates external energy sources, including renewable energy and high-efficiency equipment.
- Engineering level: Executes advanced technological upgrades that necessitate a higher investment but provide significant long-term efficiency benefits.

The estimates are derived from industry data and literature. They indicate that higher POET levels necessitate increased investment but yield substantial long-term savings through the implementation of energy efficiency measures and the adoption of advanced technologies.

The second research question investigated whether breweries can successfully implement energy-efficient initiatives to fulfil regulatory targets established by organisations such as the CSIR and the NLA. The review concluded that breweries could attain these energy targets if technical-level measures were implemented. However, the feasibility of implementing these measures largely depends on the initial investment required and the availability of external incentives, including government subsidies or favourable policies.

The third research question examined the economic feasibility of implementing energy efficiency measures at each corresponding POET level. According to the Pareto principle, 80% of energy savings can be realised with 20% of the effort at the conceptual level. However, advancing through subsequent levels necessitates greater effort and investment to achieve additional savings. This trend is reflected in the following approximate ratios:

- 60/40 at the active level;
- 40/60 at the technical level; and
- 20/80 for further improvements, focusing on fine-tuning systems for modest additional savings.

These findings are substantiated by a comparative analysis of energy savings and payback periods across each POET level, as illustrated in Figures 2.8 and 2.9.

Figure 2.8 depicts the maximum potential energy savings achievable at each POET energy management level, with a focus on electrical energy supplied by the national grid. The estimates are based on extrapolations from existing research to represent a best-case scenario.

It is important to note that savings derived from renewable energy sources and technologies, such as HPWHs, were excluded from this analysis.

Figure 2.9 highlights the estimated payback periods for the implementation of energy efficiency measures at various POET levels, as analysed in prior studies. Initiatives at the conceptual and active levels typically offer shorter payback periods, thereby providing rapid returns with minimal investment. Conversely, measures at the technical and engineering levels necessitate higher initial costs but ultimately yield long-term efficiency benefits. The data presented were derived from industry studies and real-world implementation examples.

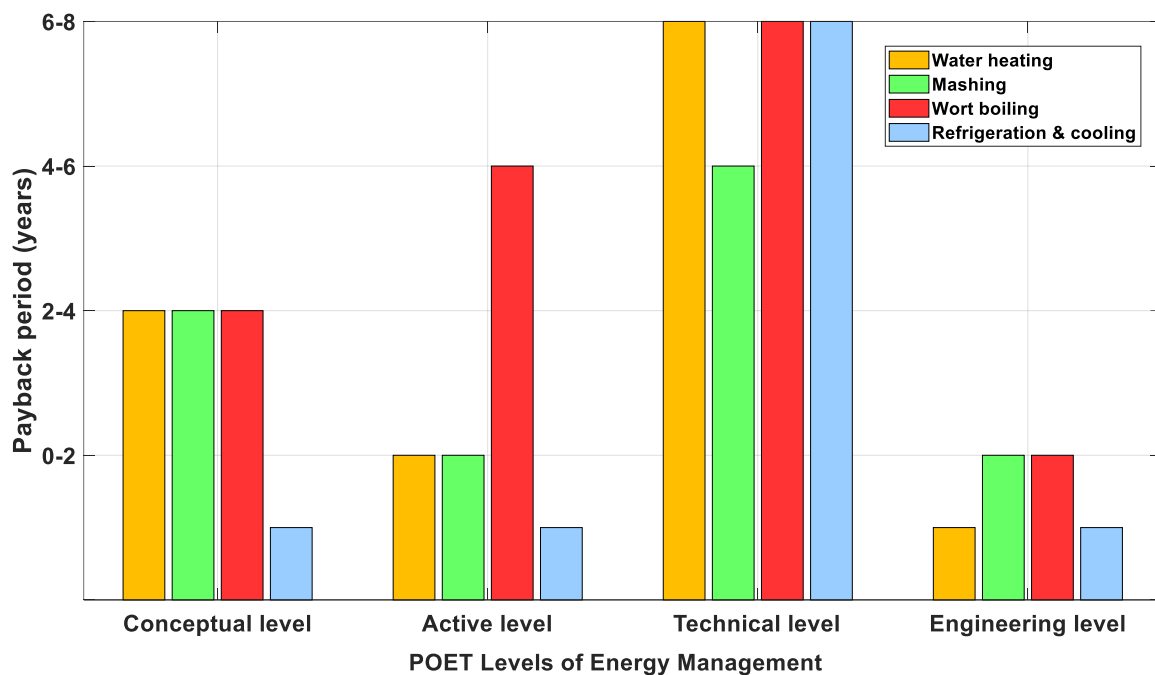


Figure 2.9: Expected payback period for each POET energy management level in beer production systems

Figure 2.9 illustrates the estimated time necessary to recuperate the investment costs associated with the implementation of energy efficiency measures at various POET levels.

- Initiatives at the conceptual and active levels typically offer shorter payback periods with minimal investment, which renders them financially advantageous.
- In contrast, technical and engineering-level measures, although necessitating higher initial expenditures, deliver enduring efficiency benefits, which makes them appropriate for long-term energy savings.

It is evident from Figures 2.8 and 2.9 that the active level necessitates a greater investment of effort compared to the conceptual level, which results in diminished energy savings. However, a notable increase in savings is observed at the technical level, which is likely attributable to the incorporation of external energy sources, such as renewable energy supplies and HPWHs, which enhance overall efficiency.

Figure 2.9 further illustrates that initiatives at the conceptual level generally provide short payback periods accompanied by substantial returns. Conversely, as energy savings diminish at the active level (as depicted in Figure 2.8), the payback periods correspondingly extend (as shown in Figure 2.9). Attaining significant energy savings at the technical level necessitates higher costs and greater effort in comparison to the lower levels.

Industry standards stipulate that a process is considered economically feasible if the payback period falls within the range of two to four years [171]. However, the integration of renewable energy systems and HPWHs typically results in extended payback periods, which vary as follows:

- Six to 12 years for renewable energy systems; and
- Three to 10 years for HPWHs [2].

Additional energy efficiency measures can be implemented to reduce payback periods and enhance feasibility. These measures, as discussed in Section 2.5.4, focus on optimal operation and maintenance. Although the potential for additional energy efficiency improvements is lower than that of technical solutions, an average saving of approximately 10% can still be realised with relatively low effort, which will result in shorter payback periods.

Emphasising efficiency measures at the engineering level provides significant incentives. Implementing the proposed initiatives at this stage can yield the highest ROI:

- Optimal operation and maintenance strategies are emphasised, which typically result in payback periods of one to two years and significantly enhance the feasibility of more advanced initiatives.
- While these measures offer moderate energy savings, they maximise overall returns and improve long-term energy efficiency.

By progressively implementing energy efficiency measures across the POET levels, breweries can achieve continuous improvements in energy efficiency that will lead to long-term cost reductions and sustainability gains.

2.6.2 Comparative analysis of global trends

The findings of this review indicate that while South African breweries have made significant progress, their energy consumption patterns are consistent with global trends. The integration of advanced energy management systems has effectively reduced energy costs across various industries, including brewing. This suggests that South African breweries could achieve similar advantages by adopting tailored efficiency strategies.

To provide a global perspective, this review examines case studies from European, North American, and Asian breweries that have successfully implemented energy-saving initiatives. German breweries have optimised energy use through waste heat recovery and process automation [134,151,172]. North American breweries, such as Anheuser-Busch, have leveraged AI-driven energy management and renewable energy adoption [173]. Additionally, Asian breweries, particularly in Japan and China, have integrated solar and biomass energy solutions to reduce dependence on fossil fuels [174]. These comparisons contextualise the challenges and opportunities faced by South African breweries within a broader international framework.

Microbreweries that are committed to sustainability are at the forefront of adopting renewable energy. In New Zealand, Garage Project, a craft brewery in Wellington, installed a solar PV system that cut its energy costs by 20% [175].

The global shift towards sustainability is evident in various regions. For example, the United States Craft Brew Alliance aims to source 100% of its electricity from renewable energy by 2030, with some of its members already achieving this goal [176]. In Germany, the Bavarian State Brewery Weihenstephan has reduced its energy costs by 30% through biogas combined heat and power systems [172]. However, in South Africa, breweries still rely heavily on conventional grid electricity, which indicates a gap in policies that support energy efficiency. This presents an opportunity for the country to adopt similar sustainable practices, supported by policy-driven incentives and investments.

To further substantiate these findings, Table 2.6 presents a comparative analysis of global energy efficiency initiatives, summarising capital investments, cost savings, projected energy reductions, and estimated carbon emission reductions. These case studies serve as valuable benchmarks and offer practical insights for breweries that are seeking to enhance sustainability and operational efficiency.



Table 2.6: Summary of global brewery energy efficiency investments and savings

Brewery name	Capital investment for efficiency measures (USD million)	Total annual energy cost & annual energy cost savings (USD million)	Percentage energy cost savings (%) & BEP (years)	Projected energy consumption reduction (%)	Estimated annual carbon emissions reduction (kg CO ₂)	Key efficiency measures implemented
Anheuser- Busch, St. Louis, USA	100	166.7 50	30 (1-3)	10-30	20 000-40 000	Advanced monitoring systems, heat recovery, boiler optimisation, and energy management systems [26,36, 151,164]
Labatt Brewing Company, London, Canada	40	80 20	25 (2-3)	15-25	8 000-12 000	Monitoring and tracking programmes, upgraded boiler systems, enhanced insulation [26,36,120]
Carlsberg-Tetley Brewery, London, United Kingdom	5	46.7 7	15 (0.5-1)	15-30	3 000-6 000	Refrigeration fault diagnostics system [26,93,120,169]
Asahi Breweries, Tokyo, Japan	25	60 12	20 (1-3)	15-20	4 000-8 000	Enhanced insulation and water-saving equipment [37,40, 60,148]
Miller Brewing Company, Milwaukee, USA	75	120 30	25 (2-4)	15-25	15 000-30 000	High-efficiency refrigeration units, compressed air optimisation, lighting upgrades [37,17,149]
Coors Brewing Company, Golden, USA	60	125 25	20 (2-3)	10-20	10 000-25 000	Steam system improvements, energy-efficient motors, process automation [37,58,60]
Pyramid Breweries, Portland, USA	30	50 15	30 (1-2)	20-30	5 000-15 000	Installation of VFDs, water heating efficiency measures, process optimisation technologies [1,37, 57,89]
New Belgium Brewing Company, Fort Collins, USA	20	66.7 25	15 (1-3)	10-15	3 000-10 000	Insulation improvements, energy-efficient lighting, and programmable control systems [36,134]
El Aguila Heineken Brewery, New Mexico, USA	10	50 5	10 (1-2)	5-10	2 000-4 000	Monitoring and control systems for cooling installations [36,134]

The POET framework illustrates how strategic energy investments can lead to significant energy cost savings, financial benefits, and reductions in carbon emissions in the brewing industry. As a pivotal global sector, breweries encounter the persistent challenge of balancing efficiency, costs, and sustainability. The POET framework offers a structured methodology for achieving these objectives [177].

Anheuser-Busch exemplifies the technical application of the POET framework by investing USD 100 million in advanced brewing equipment and energy-efficient processes. This investment yielded USD 50 million in annual energy cost savings, a 30% reduction in energy expenses, and a carbon reduction of 20 000 to 40 000 kg CO₂ [26,134,178].

At the operational and engineering levels, Miller Brewing and Coors Brewing invested USD 75 million and USD 60 million, respectively, and generated annual energy cost savings of USD 30 million and USD 25 million while achieving reductions in carbon emissions of 10 000 to 30 000 kg CO₂ through process optimisation and equipment upgrades [36,134,179].

Labatt Brewing Company, aligning with operational efficiency at the active level of the POET framework, reduced its energy costs by 25% through a USD 40 million investment that focused on improvements in brewing and cooling processes [38,180].

Smaller-scale investments further underscore the effectiveness of the POET framework in promoting energy efficiency. Carlsberg-Tetley Brewery invested USD 5 million and achieved 15% energy cost savings and USD 7 million in annual financial savings [36,142,169].

Similarly, Pyramid Breweries allocated USD 30 million to a combination of engineering and operational enhancements that resulted in a 30% reduction in energy consumption [26,36,134]. Operating at the engineering level, Asahi Breweries optimised its production processes with a USD 25 million investment, which led to securing 20% energy cost savings and USD 12 million in cost reductions [134,182]. This highlights an opportunity for South African breweries to adopt similar retrofitting strategies.

New Belgium Brewing and El Aguila Heineken Brewery adopted a conceptual approach with an emphasis on innovation-driven operational changes and sustainable brewing techniques.

These case studies confirm that investments in energy efficiency yield substantial financial and environmental benefits, with a BEP ranging from one to four years. By adopting similar strategies, breweries in South Africa can achieve up to 50% energy cost savings and 15% to

50% reductions in CO₂ emissions through hybrid energy systems and predictive analytics. The POET framework provides a structured approach to cost-effective sustainability, operational efficiency, and industry leadership. It harmonises technical innovation, engineering advancements, and sustainability initiatives that enable breweries to reduce costs, enhance financial sustainability, and minimise their environmental footprint.

2.6.3 Comparative analysis of ANN-Based hybrid energy optimisation approaches using the POET Framework

Recent developments in brewery energy optimisation show a clear move from conventional rule-based and single-source thermal systems toward data-driven, multi-energy frameworks. Within the Performance dimension of the POET framework, traditional systems typically reliant on thermostats, fixed schedules, and resistive electric heating struggle to maintain consistent thermal efficiency under varying load conditions [11,27]. From an Operation perspective, these systems lack predictive capability and cannot adjust dynamically to fluctuations in demand, tariffs, or solar availability, resulting in only modest efficiency improvements [28-33]. As a result, such approaches address isolated operational needs rather than supporting the holistic optimisation required by the POET framework.

In contrast, Artificial Neural Networks (ANNs), which are computational models inspired by biological neural structures and widely used for nonlinear pattern recognition and time-series forecasting, offer substantial advantages across the Performance and Operation dimensions of the POET framework. Nonlinear autoregressive (NAR) and nonlinear autoregressive with exogenous inputs (NARX) ANN models commonly used for forecasting nonlinear time-series data effectively capture the thermal and electrical behaviour of brewery processes such as water heating, mashing, and fermentation cooling [190]. Through iterative learning, these models refine prediction accuracy and consistently achieve forecasting performances above 90% [73,193-196]. This improved accuracy supports more reliable batch scheduling, enhanced pre-heating cycles, and better load shifting under ToU tariffs. These capabilities strengthen tariff-responsive operational control and contribute directly to POET's performance-driven optimisation goals.

The integration of ANN forecasting with hybrid energy systems including heat pumps, solar thermal collectors, and thermal energy storage (TES) further reinforces the Equipment and Technology components of POET. Conventional hybrid configurations often rely on

fixed-rule or PID controllers, which do not fully utilise TES storage capacity or accommodate variable heat-pump performance under changing conditions. In contrast, ANN-informed optimisation improves coordination between TES, renewable inputs, and heat-pump operation, yielding reductions in peak electrical demand and more effective use of low-cost thermal energy [192,197-199]. These outcomes highlight the value of advanced control technologies in improving system-wide resource efficiency.

Comparatively, the ANN-based hybrid optimisation method developed in this study demonstrates a more comprehensive application of the POET framework than conventional approaches. It integrates ANN-driven forecasting (Performance), optimisation-based scheduling (Operation), coordinated use of TES, heat pumps, and solar collectors (Equipment), and advanced optimisation algorithms (Technology) within a unified energy-management architecture. While traditional systems treat heating processes, storage vessels, and renewable inputs separately, the proposed method dynamically allocates thermal and electrical resources based on real-time loads, ToU tariffs, and operational constraints. This synergy results in improved thermal stability, reduced grid reliance during peak-tariff periods, and greater utilisation of renewable and stored energy [73,192]. Collectively, these improvements reflect strong advancement across all four POET dimensions and establish a more integrated and effective pathway for brewery energy optimisation.

2.6.4 Improvements in Predictive Accuracy, Energy Savings, Cost-Effectiveness, and Operational Flexibility

The predictive accuracy achieved by ANN-based models represents a notable improvement over conventional forecasting methods used in brewery energy management. Traditional linear and rule-based models often struggle to capture the nonlinear interactions between thermal loads, production schedules, and environmental conditions [11,27]. In contrast, the ANN architecture developed in this study featuring NAR and NARX configurations achieved forecasting accuracies ranging from approximately 86% to 99.8%, depending on the dataset and model type [73,193-196], outperforming the typical 60–75% accuracy range reported for linear or autoregressive models in industrial thermal systems [28-33]. This enhanced accuracy provides a stronger foundation for real-time decision-making,

enabling more precise scheduling of heating and cooling operations and improving the reliability of peak-demand forecasting.

Substantial improvements in energy savings were also observed relative to existing methods documented in the literature. Conventional energy-management approaches commonly rely on thermostatic heating, fixed-time control, or limited load-shifting strategies, which are unable to dynamically respond to tariff variations or process fluctuations [28-33]. By integrating ANN-driven forecasting with hybrid thermal-energy systems including TES, solar thermal collectors, and a heat pump the proposed method enables optimal allocation of thermal resources. As demonstrated in this study, this approach reduces thermal energy consumption by up to 69% and peak electricity demand by up to 33% [192], exceeding the modest efficiency gains typically reported for isolated interventions such as thermostat optimisation or simple load-shifting [11,27].

The proposed method also demonstrates marked improvements in cost-effectiveness. Traditional heating systems relying on resistive elements and grid electricity incur higher operational costs, particularly under time-of-use (ToU) tariff structures [28]. By combining predictive modelling with optimisation-based scheduling, the hybrid system prioritises stored thermal energy and renewable heat during high-tariff periods, thereby reducing peak-period grid dependence. This strategy lowers annual operational costs by up to 33% and results in a payback period of approximately 1.5 years [192]. These results indicate that predictive hybrid-energy optimisation offers both technical and financial advantages, outperforming conventional renewable-only or TES-only interventions documented in earlier studies [11,27].

Operational flexibility is another area in which the proposed method surpasses traditional approaches. Conventional brewery operations treat heating, storage, and renewable inputs as separate subsystems, limiting the ability to adapt to production variability or real-time tariff signals [28-33]. The ANN-optimised hybrid configuration developed in this study actively coordinates heat-pump operation, TES charge discharge cycles, and solar thermal utilisation in response to real-time load conditions. This coordinated control framework enhances system responsiveness, supports consistent process temperatures, and maintains production reliability even under fluctuating demand or environmental conditions [192]. Such flexibility is rarely achieved in conventional systems and constitutes a meaningful advancement in brewery energy-management practice.

2.7 ADDRESSING SHORTCOMINGS IN CURRENT RESEARCH

Quantifying energy savings prior to implementation presents a significant challenge, particularly in the South African brewery sector. Although existing research extensively addresses energy efficiency strategies for individual processes such as water heating and cooling, a critical gap persists in the integration of coordinated optimisation and predictive control strategies across the entire production chain, including mashing, wort boiling, and refrigeration. The absence of holistic energy management frameworks restricts the realisation of potential system-wide savings.

Research into renewable energy integration, particularly solar thermal and hybrid renewable configurations that are tailored to the South African context, demonstrates considerable promise. However, many studies overlook advanced systems, such as integrated solar thermal technologies combined with TES and MPC, which could provide substantial energy and cost savings, particularly during peak demand periods and under fluctuating energy tariffs.

The scalability of energy-efficient systems across various regions is highly dependent on factors such as local energy policies, renewable resource availability, and broader economic conditions. In Europe and North America, policy-driven incentives, including subsidies and tax credits, have effectively supported the adoption of sustainable practices in breweries. Similar initiatives in South Africa could significantly accelerate the transition to energy-efficient brewing, particularly in areas with high solar irradiance. Nevertheless, challenges persist in regions with inconsistent renewable energy resources or limited policy support. Furthermore, socio-economic factors, including access to financing and technical expertise, represent critical barriers. Small and medium-sized enterprises, in particular, often encounter difficulties in securing the necessary capital for energy efficiency investments, despite the considerable long-term operational savings that these technologies can deliver.

Addressing these shortcomings necessitates future research that rigorously applies structured frameworks, such as the POET methodology, to optimise energy management across all stages of beer production. International case studies, particularly from breweries in Canada and Denmark, have demonstrated that the integration of predictive analytics and automated process control within structured optimisation frameworks can yield energy

efficiency improvements of up to 30%, which indicates significant potential benefits for South African breweries.

This study applied a structured optimisation framework and examined energy-intensive processes to provide quantitative evidence in supporting energy-efficient practices in South African breweries.

2.8 CONCLUSION

The beer production industry in South Africa plays a crucial role in the energy consumption of the food and beverage sector and accounts for approximately 30% of total energy usage. Microbreweries, in particular, face unique energy challenges, with thermal processes contributing around 8% of their production costs. While large breweries typically consume 0.43 kWh per litre of beer, microbreweries often encounter significantly greater energy demands for equivalent production volumes. This study advances the field of industrial energy management by exploring energy efficiency practices in South African breweries, building upon prior research, and providing valuable insights.

Major energy-intensive processes (water heating, mashing, wort boiling, cooling, and cold storage) consume 85% of brewery energy and can be optimised using the POET framework. The framework identified the following potential savings: 50% to 60% at the conceptual level, 25% to 40% actively, 60% to 70% technically, and 10% to 20% through engineering improvements, which demonstrates its efficacy. The comparative analysis also shows that ANN-based predictive modelling and hybrid energy optimisation approaches offer additional performance gains by improving forecasting accuracy, reducing energy consumption, lowering operational costs, and enhancing system flexibility, further reinforcing the relevance of advanced methods within the POET framework.

While the potential for energy savings is substantial, economic challenges, such as high upfront costs and extended payback periods for technical upgrades and renewable energy installations, may hinder the realisation of maximum savings. In addition, government support is essential to meet ambitious energy reduction goals. The adoption of MPC is proposed as an effective solution to optimise energy consumption in brewery systems, which aligns with sustainability objectives and improves system performance. MPC can potentially reduce energy costs by up to 50%, which makes it a promising tool for enhancing energy efficiency in breweries.

This study contributes to a more sustainable brewing industry and offers a practical roadmap for improving energy efficiency across various sectors. The POET framework and proposed energy efficiency measures can be applied beyond the brewing industry to sectors such as dairy, textiles, and chemical manufacturing, where similar energy-saving opportunities exist. For instance, energy-efficient refrigeration and heat recovery in the dairy industry and waste heat recovery in textiles have demonstrated significant energy savings. Moreover, integrating ANN-based models with thermal storage solutions for forecasting energy consumption presents a promising avenue for optimisation. However, challenges such as high initial costs, lack of technical expertise, and regulatory barriers remain.

Finally, this study emphasises the need to integrate global best practices, as demonstrated in countries such as Australia and Canada, where breweries have successfully reduced greenhouse gas emissions by combining renewable energy sources and energy recovery technologies. By learning from these international examples and adopting integrated energy efficiency strategies, South Africa's brewing industry can progress towards more sustainable, energy-efficient production practices.

CHAPTER 3:

FORECASTING ENERGY CONSUMPTION AND ENHANCING SUSTAINABILITY IN MICROBREWERIES: INTEGRATING ANN-BASED MODELS WITH THERMAL STORAGE SOLUTIONS

3.1 INTRODUCTION

This chapter focuses on the development of an ANN model that employs a neural network fitting tool (nftool) to forecast energy requirements and to enhance the operational efficiency of microbrewery processes with non-linear input variables. A comprehensive dataset was generated and utilised to construct and validate the model. It incorporated variables such as production volumes, ambient conditions, cooling load requirements, and batch processing durations across various production phases. The model predicts power consumption across brewing stages, estimates heat requirements for processes such as water heating, mashing, and wort boiling, and integrates energy storage systems.

The selection of input variables such as ambient temperature, batch load, production volume, cooling-load demand, and time-of-use (ToU) electricity tariffs is theoretically justified by their influence on the nonlinear thermal and electrical behaviour of microbrewery processes, and operationally supported by their strong correlation with real-world energy consumption patterns. Ambient temperature affects heat-pump performance, refrigeration loads, and heat losses; batch and production load determine the thermal intensity required across brewing stages; and cooling-load variations reflect the demands of fermentation, cold storage, and process-temperature stability. Incorporating ToU tariffs enables the ANN to learn cost-sensitive consumption patterns, supporting tariff-responsive scheduling of heating systems and thermal energy storage (TES). Collectively, these variables capture the dominant drivers of brewery energy demand, ensuring that the ANN accurately reflects both the theoretical dynamics of the system and the operational conditions influencing daily brewery performance.

The study demonstrates the application of machine learning to microbrewery energy systems in serving as a benchmark for evaluating ANN methodologies in energy prediction while providing insight into the impact of parameter variation on brewing operations. The

findings highlight the accuracy of neural networks in forecasting energy parameters associated with microbrewery production systems.

In addition to saving time and costs on energy feasibility studies, these technologies support the development of more efficient strategies for optimising energy consumption, particularly in consideration of ToU tariff pricing based on production schedules. Moreover, the integration of machine learning, thermal storage, and economic analysis offers significant opportunities to reduce operational costs and environmental impact.

These findings underscore the pivotal role of predictive models in optimising resource allocation, minimising expenses, and promoting sustainable brewing practices. This approach encourages the adoption of renewable energy and advanced storage solutions, which can further enhance the sustainability of microbrewery operations.

Predictive modelling combined with hybrid energy systems is more suitable for microbrewery energy management than traditional techniques because it enables proactive, data-driven coordination of heating, cooling, and storage processes that fluctuate due to batch-based production. Conventional thermostatic and rule-based controls respond only to instantaneous conditions and cannot anticipate peak loads, time-of-use tariff variations, or changes in renewable-thermal availability, often resulting in inefficient energy use and higher operational costs. In contrast, predictive models such as NAR and NARX provide accurate short-term forecasts of thermal and electrical demand, allowing hybrid systems incorporating heat pumps, solar thermal collectors, and thermal energy storage (TES) to be optimally scheduled. This integration enhances renewable-energy utilisation, improves TES charge–discharge planning, and reduces grid dependence during high-tariff periods, delivering a more flexible, efficient, and cost-effective energy-management strategy tailored to the dynamic operating environment of microbreweries.

The selection of ANN architectures specifically the Nonlinear Autoregressive (NAR) and Nonlinear Autoregressive with Exogenous Inputs (NARX) models was motivated by the nonlinear, dynamic, and time-dependent behaviour of heating and cooling processes in microbrewery operations. Brewing systems exhibit batch-driven variability, fluctuating process loads, strong thermal–electrical interactions, and sensitivity to ambient conditions. These characteristics make the underlying energy patterns highly complex and unsuitable for representation using traditional linear models.

Linear regression, autoregressive methods, and rule-based estimation techniques are unable to capture these nonlinear dependencies. In contrast, NAR models learn complex

temporal structures within energy-consumption time series, while NARX models incorporate exogenous variables such as ambient temperature, production volume, and cooling demand. These capabilities make NAR and NARX the most appropriate ANN architectures for achieving high forecasting accuracy, supporting predictive control, and enabling proactive energy management.

In addition, the adoption of an optimisation-based hybrid energy-control strategy is essential because conventional thermostatic and fixed-rule approaches cannot effectively coordinate heat pumps, thermal energy storage (TES), and solar thermal inputs. These traditional controllers respond only to immediate conditions and lack the predictive capability required to manage fluctuating thermal loads or variations in time-of-use tariffs.

Integrating ANN-generated forecasts with optimisation-based scheduling provides a forward-looking control framework that enhances system intelligence and responsiveness. This combined ANN-optimisation approach enables optimal TES charge-discharge planning, improves utilisation of renewable thermal energy, reduces reliance on grid electricity during high-tariff periods, and overcomes key limitations of previous forecasting and control methods. As a result, it offers a more flexible, efficient, and cost-effective energy-management pathway for microbrewery operations.

The layout of this chapter is as follows: Section 3.2 outlines the development of the ANN model, Section 3.3 presents the results and discusses case studies using parameters from a microbrewery operation, Section 3.4 evaluates the performance of the NAR and NARX models, Section 3.5 reports the results of the economic analysis, and Section 3.6 concludes the chapter.

3.2 ANN MODEL DEVELOPMENT

3.2.1 System data description

The selected case study was Stellar Brewery, situated in Bloemfontein, South Africa. This microbrewery utilises a brewing process that is characterised by specific temperature control stages, including mashing and wort boiling (see Figure 3.1). The detailed schematic illustrates the precise regulation of material and energy flows at each stage, which is essential for understanding variations in energy consumption throughout the production process.

Figure 3.2 presents three critical pieces of equipment involved in the initial stages of brewing. The process commences with the water boiler, which is responsible for heating

water for mashing. This heated water is subsequently transferred to the mashing tun, where it is combined with crushed malted grains to produce wort. The wort is then processed in the wort boiler, where it is heated to the appropriate temperature during the boiling phase to facilitate the addition of hops and the preparation for fermentation.

Furthermore, Figure 3.3 illustrates the configuration of the Power and Energy Logger (PEL3), which monitors energy consumption throughout the brewing process. The PEL3 records voltage, current, power, and energy consumption across multiple phases and provides real-time data that are crucial for energy audits, power quality analysis, and optimising energy management strategies.

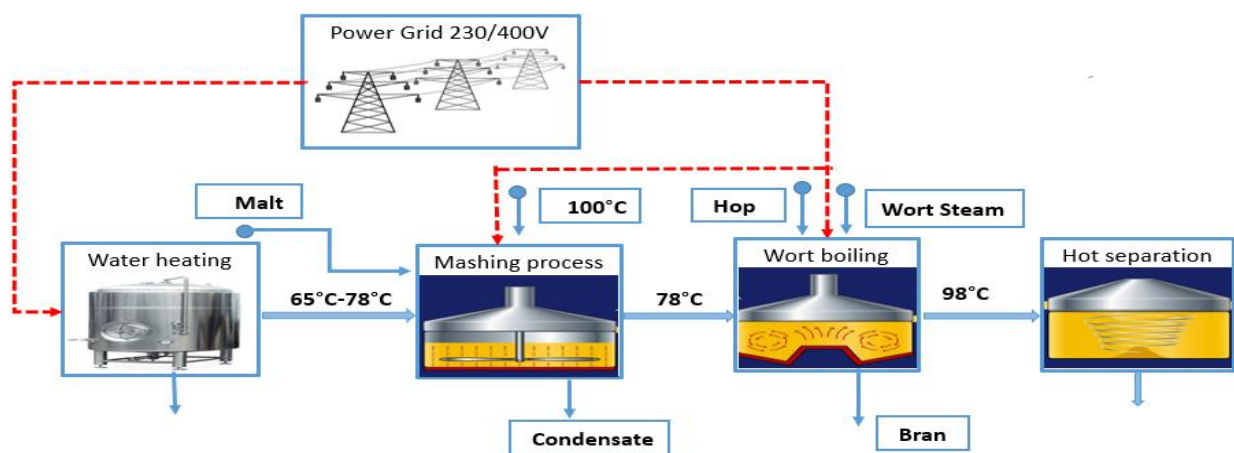


Figure 3.1: Schematic layout of the microbrewery beer production process, illustrating key stages and energy flow



Figure 3.2: Key brewhouse equipment: Water boiler (left), mashing (mixer) (middle), and the wort boiler (right)

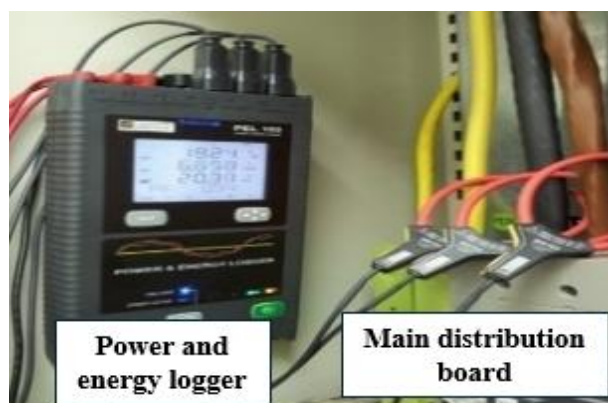


Figure 3.3: Setup of the Power and Energy Logger (PEL3), which monitors energy consumption in the microbrewery

The beer production process commences with heating the water using grid electricity (230/400 V) to a precise temperature of 65 °C. This step typically requires approximately six to seven hours for 1 100 L of water, depending on the efficiency of the heating system. Proper and controlled heating is essential for achieving the optimal temperature necessary for the subsequent mashing stage, which directly influences the consistency and quality of the final beer. The reliability of the electrical supply plays a critical role in ensuring the success of this phase.

Subsequent to the heating phase, the water is blended with malt during the mashing stage at a temperature of 78 °C. This critical phase, lasting between 60 and 90 minutes, facilitates enzymatic reactions wherein malt enzymes convert starches into fermentable sugars, which results in a mixture of condensate and bran. Accurate control of both temperature and duration during mashing is fundamental for achieving the desired sugar profile and flavour complexity of the final product. The quality of the mash directly impacts the efficiency and outcomes of the subsequent brewing stages.

The mash is then transferred to the wort boiling stage, where it is heated to 97 °C. This boiling process, typically lasting about 60 to 90 minutes, serves to sterilise the wort and enables the extraction of essential flavours and bitterness from the hops, which are introduced at a higher temperature of approximately 150 °C. The generation of wort steam during this phase is integral for developing the beer's bitterness and aroma. Precise management of temperature and time during boiling is essential for proper flavour development and the elimination of undesirable compounds that significantly affect the final quality of the beer.

Following the boiling stage, the wort undergoes hot separation, which generally lasts between 20 and 30 minutes. This process removes solid residues such as spent hops and trub accumulated during boiling. Effective hot separation clarifies the wort and ensures a clean medium prior to fermentation. The efficiency of this process is crucial for the stability and quality of the final beer product. This sequence of processes underscores the importance of meticulous temperature and material flow control throughout the brewing operation.

The dataset utilised in this study comprised a blend of empirical and simulated data, which integrated real-world measurements from brewery operations, including fermentation temperatures, ingredient quantities, process flow rates, equipment performance, and meteorological variables such as ambient temperature and humidity. The combination of operational and environmental data provided a robust foundation for predictive modelling efforts.

The dataset was structured to accurately reflect brewery conditions and to ensure that input variables were sourced from operational records and direct measurements. This comprehensive approach enhanced the relevance and applicability of the predictive models developed.

... Operational data were collected in real time from the microbrewery from March 2022 to September 2023, encompassing energy consumption, production metrics, and meteorological conditions. A total of 100 samples were selected to capture a diverse range of operational scenarios. Prior to training the predictive models, the dataset underwent preprocessing, which included interpolation for handling missing values, normalisation of input features, and the removal of outliers to ensure data integrity.

Input variables were meticulously derived from operational records, field measurements, and meteorological sources, which ensured high fidelity to actual brewery operations. This enriched dataset enabled the development of models that were capable of capturing key operational metrics such as power consumption, production yields, energy efficiency, and overall performance.

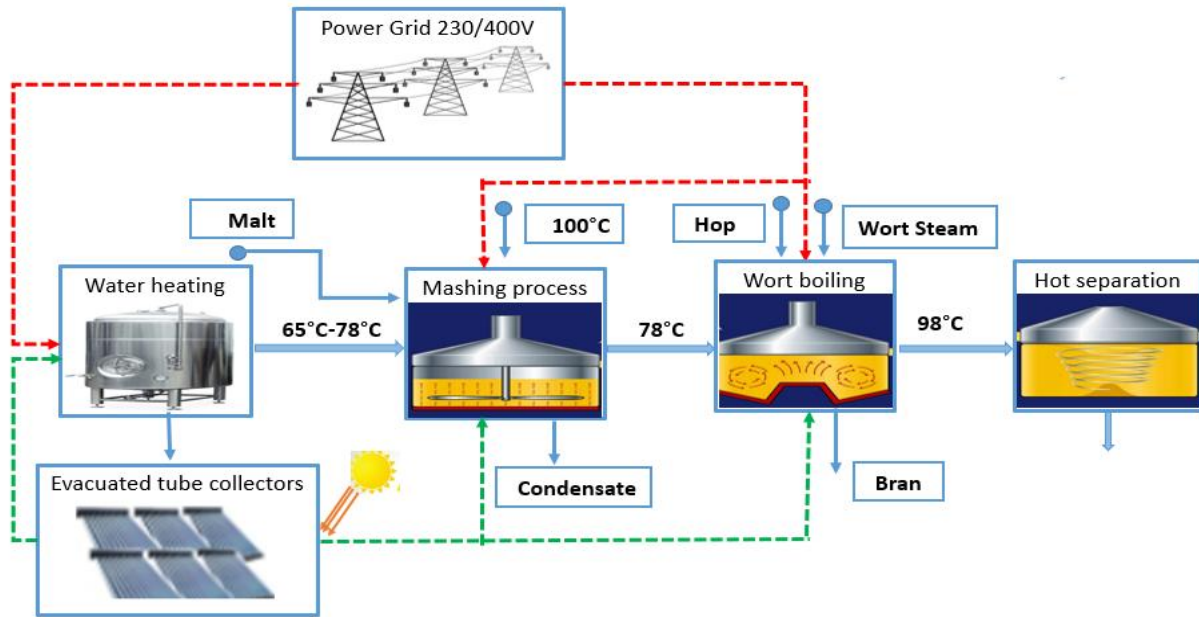


Figure 3.4: Schematic layout of microbrewery energy-efficient beer production process

Figure 3.4 illustrates the comprehensive setup of the microbrewery. It highlights key stages such as water heating, mashing, wort boiling, hot separation, and steam and condensate management. The schematic also anticipates potential future upgrades, which indicate the possible integration of evacuated tube solar thermal systems to enhance energy efficiency and supplement the grid power supply. Although the solar thermal storage system is not currently installed, its depiction reflects ongoing initiatives aimed at incorporating renewable energy solutions. The flowchart underscores the emphasis on resource efficiency and showcases the critical equipment involved in the beer production process. While the hot separation stage is included for the completeness of the process flow, it is excluded from the energy consumption analysis, as it is not considered an energy-intensive stage in comparison to the other thermal processes.

3.2.2 Solar collector model

The energy balance for the brewing system, which integrates both grid-supply and solar thermal energy sources, is articulated in Equation 3.1. This balance encompasses the heat energy provided and the energy utilised by diverse processes in the brewing system, as illustrated in Figure 3.1.

Equation 3.1 delineates the thermal energy balance for the brewing system, incorporating heat supplied from both grid and solar thermal sources, as represented in Figure 3.1.

$$Q_{grid}(t) + Q_{coll}(t) = Q_w(t) + Q_{mash}(t) + Q_{wort}(t) + Q_{other_{losses}}(t) \quad (3.1)$$

This equation encapsulates the principle that the total energy provided by the grid and solar thermal sources is equivalent to the sum of the energy consumed by the various processes in the brewing system.

The instantaneous heat gain from the solar collector, as delineated in Equation 3.2, is determined by the collector's area, solar irradiance, and heat transfer efficiency, which are pivotal for enhancing energy efficiency in the brewing process [5]. Equation 3.3 employs the isotropic diffuse model to assess the total hourly solar irradiance absorbed by the collector, taking into account both direct and diffuse irradiance, as well as ground reflectance to optimise solar energy capture for heating [182,183]. The absorbed heat, \dot{Q}_{coll} , represents the usable thermal energy available to the system, which ensures energy balance and effective conversion. Finally, Equation 3.5 imposes operational limits on \dot{Q}_{coll} , to prevent overloading, which is essential for maintaining safety and system efficiency [184]. The system can achieve reliable performance by adhering to these parameters while maximising energy utilisation.

In summary, these equations collectively elucidate the energy dynamics in the brewing system and emphasise the critical role of solar thermal energy in optimising energy efficiency and ensuring sustainable brewing practices.

Equation 3.2 defines the solar heat gain $\dot{Q}_{coll}(t)$ based on collector area, solar irradiance, and efficiency [5]:

$$\dot{Q}_{coll}(t) = A_c \cdot G(t) \left[\frac{(F_R(\tau\alpha)t_{(h)})\dot{m}_c(t)C_{p,c}}{\dot{m}_c(t)C_{p,c} + A_c F_R U_L} \right] \quad (3.2)$$

Equation 3.3 calculates the total solar irradiance $G(t)$, using the isotropic diffuse model, accounting for direct, diffuse, and ground-reflected radiation [182,183]:

$$G(t) = G_{DNI} \cos \theta_\beta + G_{DHI} \left[\frac{1 + \cos \beta_{coll}}{2} \right] + \rho_g G_{GHI} \left[\frac{1 - \cos \beta_{coll}}{2} \right] \quad (3.3)$$

The heat gain from the collector $\dot{Q}_{coll}(t)$, as defined in Equation 3.2, is considered the usable thermal energy available for process heating in the system.

Finally, Equation 3.4 imposes operational limits on the heat gain from \dot{Q}_{coll} to prevent overloading and ensuring system safety and efficiency [184]:

$$0 \leq \dot{Q}_{coll} \leq \dot{Q}_{coll}^{max} \quad (3.4)$$

Where:

A_c is the collector area in square metres (m^2);

$G(t)$ is the variable global solar irradiance absorbed by the collector in (w/m^2);

F_R is the collector heat removal factor;

$\tau\alpha$ is the transmittance-absorptance product;

$t_{(h)}$ is the time in seconds (3 600 s);

$\dot{m}_c(t)$ is the mass flow rate of water inside the collector (kg/h);

$C_{p,c}$ is the heat capacity of water, valued at 4 184 J/kg·°C;

U_L is the overall heat transfer coefficient of the collector;

$T_a(t)$ is the variable ambient temperature in degrees Celsius (°C);

$\dot{m}_c(t)$ is the mass flow rate of water inside the collector (kg/h);

$C_{p,c}$ is the heat capacity of water, valued at 4 184 J/kg·°C;

U_L is the overall heat transfer coefficient of the collector;

G_{DNI} is direct normal irradiance (w/m^2), representing solar radiation received perpendicularly to the sun's rays;

G_{DHI} is diffuse horizontal irradiance (w/m^2), representing scattered solar radiation incident on a horizontal surface;

G_{GHI} is global horizontal irradiance respectively (w/m^2), representing the sum of direct and diffuse radiation on a horizontal surface;

θ_β is the incidence angle on a tilted surface (degrees);

β_{coll} is the slope of the collector array (degrees);

ρ_g is the instantaneous heat gain from the STES (W);

$Q_{coll}(t)$ is the instantaneous heat gain from the STES (degrees); and

Q_{coll}^{max} is the maximum possible heat gain from the collector (W).

This equation encapsulates the principle that the total energy supplied by the electrical grid and solar thermal sources is equivalent to the sum of the energy consumed by the various processes in the brewing system.

As illustrated in Figure 3.1, the energy balance between the electrical grid, solar thermal energy, and the brewing processes is delineated by Equation 3.1. The instantaneous heat gain from the solar collector, $\dot{Q}_{coll}(t)$, is determined by the collector area A_c , the incident solar irradiance $G(t)$, and the collector's thermal efficiency, as outlined in Equation 3.2. These factors are essential for enhancing energy efficiency in the brewing operation [5].

Equation 3.3 utilises the isotropic diffuse model to calculate the total hourly solar irradiance $G(t)$ absorbed by the collector, considering contributions from direct and diffuse irradiance and ground reflectance to optimise the capture of solar energy [182,183].

The heat gain from the collector $\dot{Q}_{coll}(t)$, as expressed in Equation 3.2, is regarded as the usable thermal energy delivered to the system, thereby upholding the principle of energy conservation throughout the process.

Finally, Equation 3.4 establishes operational limits on $\dot{Q}_{coll}(t)$ to prevent system overloading, which maintains both safety and efficiency [184]. Adhering to these operational limits ensures reliable system performance while maximising the utilisation of available solar energy.

In summary, these formulations collectively form a comprehensive framework that describes the dynamic energy interactions in the brewing process. They highlight the significant role of solar thermal energy in improving energy efficiency and promoting sustainable brewing practices.

3.2.3 Model architecture

3.2.3.1 Ablation study and hyperparameter selection

A comprehensive evaluation of multiple ANN configurations was conducted to ascertain the optimal architecture for the predictive model. This involved an ablation study that explored combinations of one to three hidden layers, each containing between five and 20 neurons. Various activation functions, including Log-Sigmoid and Tan-Sigmoid, were assessed in conjunction with different training algorithms such as Levenberg-Marquardt

(LM), Scaled Conjugate Gradient, and Bayesian Regularisation [185]. This methodology ensured a thorough examination of potential architectural configurations.

The final model was selected based on the minimisation of MSE, the maximisation of the R^2 for model fit, and the optimisation of training efficiency [186]. The selected architecture comprised a single hidden layer containing 10 neurons and utilised the tanh activation function and the LM training algorithm [187]. This configuration provided an effective trade-off between predictive accuracy and computational efficiency.

The chosen model achieved an MSE of 0.0018 and an R-value of 0.998, outperforming more complex models, which exhibited MSEs ranging from 0.005 to 0.02 and R-values between 0.85 and 0.95. The introduction of deeper architectures yielded minimal gains in prediction accuracy while increasing training time and elevating the risk of overfitting [188].

These results demonstrate that augmenting complexity through additional hidden layers and neurons did not significantly enhance accuracy but instead resulted in longer training durations and an increased potential for overfitting.

3.2.3.2 Variable selection for the model

In this study, the operational parameters of breweries served as the foundation for predictive modelling, with ANN employed to enhance the understanding and optimisation of production efficiency. This subsection elucidates the selection of input and target variables for the ANN model and emphasises the correlation analysis between input variables (e.g., energy consumption, ambient conditions, and production rates) and target metrics (e.g., power consumption and product yield).

Effective prediction in microbrewery operations necessitates the identification of critical variables such as energy inputs, process flow rates, ambient conditions, equipment efficiency, and system configurations. The analysis of these variables facilitated the optimisation of performance indicators, including fermentation quality, product yield, and energy efficiency. The selection of variables is justified based on their relevance and correlation with target metrics, which ensured a robust data foundation for the model.

ANNs are particularly well-suited to capture the inherent complexity of brewing processes and to detect non-linear patterns in large datasets, which enable the prediction of how operational changes influence energy consumption and efficiency. In this study, the

application of ANN enhanced production efficiency by leveraging relevant and impactful operational data.

3.2.3.3 Mathematical foundations of ANNs

The structure and functioning of ANNs are pivotal for optimising energy consumption in microbreweries. The mathematical representation of neuron outputs is central to understanding this process. The output (y) of a neuron, as expressed in Equation 3.5, is computed as the weighted sum of its inputs, adjusted by an activation function [149]. This process captures complex relationships in the data that enable the model to learn intricate patterns that influence energy usage and production efficiency in brewing operations.

Equation 3.5 defines the output (y) of a single neuron based on the weighted sum of its inputs x_i , bias term b and activation function f [149].

$$y = \left(f \sum_{i=1}^n w_i x_i + b \right), \quad (3.5)$$

Equation 3.6 calculates the final output (y) of a multi-layer ANN, where inputs are processed through L layers and an activation function f_L at the output layer.

$$y = \left(f_L \sum_{i=1}^{n_L} w_{iL} x_{iL} + b^L \right), \quad (3.6)$$

Equation 3.7 defines the MSE as the average squared difference between predicted outputs y_i and actual target $y_{target,i}$ [149]:

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - y_{target,i})^2, \quad (3.7)$$

Equation 3.8 presents the weight update rule for backpropagation, adjusting ω_i by the MSE gradient scaled by the learning rate η [189]:

$$\omega_i = \omega_i - \eta \frac{\partial MSE}{\partial \omega_i}. \quad (3.8)$$

Equation 3.5 defines the output (y) of a single neuron in an ANN as the weighted sum of its inputs x_i , the bias term b and an activation function f [149]. This equation captures the fundamental operation of a neuron, where the inputs are scaled by their respective weights

and the bias is added to introduce a shift, before being passed through the activation function. The output (y) is the transformed result that enables the model to represent complex, non-linear relationships between the input data and energy consumption in the microbrewery context.

Equation 3.6 extends this principle to a network that comprises multiple layers. The final output (y) is derived by propagating the inputs through L layers, with each layer applying distinct weights, biases, and activation functions. In the final layer, the activation function converts the computed result into the network's predicted output. This layered structure enables hierarchical feature learning, which allows the ANN to capture progressively more abstract representations of the input data, thereby enhancing the model's ability to predict patterns that influence energy use in brewing operations.

Equation 3.7 introduces the MSE, a standard loss function for evaluating ANN performance. It computes the average squared difference between the predicted outputs y_i and the corresponding target values $y_{target,i}$. By quantifying the prediction errors, the MSE provides a metric for assessing model accuracy. In the context of energy optimisation in microbreweries, minimising the MSE leads to improved predictive capabilities that support more efficient energy management practices.

Finally, Equation 3.8 presents the weight adjustment rule utilised during the backpropagation process. Each weight ω_i is updated by subtracting a fraction of the gradient of the MSE with respect to that weight, scaled by the learning rate η [189]. This iterative updating mechanism systematically reduces prediction error across the network. In microbrewery energy optimisation, backpropagation is essential for enabling the ANN to learn the optimal set of weights for precise energy consumption forecasting.

Where (Equations 3.5 to 3.8):

- y is the output of the neuron (unit depends on the application, e.g., power consumption in kW);
- f is the activation function (e.g., tanh);
- w_i represents the weight associated with the i -th connection to the neuron (dimensionless);
- x_i is the value of the i -th input to the neuron (e.g., temperature in °C, power in kW);
- b is the bias term (same units as y);

n is the number of inputs to the neuron;

L is the final output layer;

f_L is the activation function applied in the final layer;

n_L is the number of neurons in the output layer;

w_{iL} is the weight of the i -th connection in the output layer;

x_{iL} are the inputs to the output layer;

MSE is the mean squared error;

b^L is the bias term in the output layer;

N is the total number of samples;

y_i is the predicted output for the i -th sample;

$y_{\text{target},i}$ is the actual target value for the i -th sample (unit: same as y);

η is the learning rate that determines the size of the weight updates, controlling the step size during optimisation (dimensionless);

ω_i represents the weight associated with the i -th connection; and

$\frac{\partial \text{MSE}}{\partial \omega_i}$ is the gradient of the MSE with respect to ω_i , which indicates the direction and magnitude of change needed to reduce the error.

The equations and methodology outlined encapsulate the operational dynamics of ANNs in predicting energy consumption in microbreweries. Through systematic training, comprehensive error evaluation, and meticulous parameter optimisation, ANNs facilitate the implementation of effective energy management strategies in microbreweries. This, in turn, contributes to a reduction in operational costs and an enhancement of environmental sustainability.

3.2.3.4 Data processing and importing data into MATLAB

Ensuring the accuracy of predictive models necessitates effective data preprocessing. This study implemented a comprehensive data-cleaning process to address outliers, missing values, and inaccuracies. Data alignment techniques were also employed to rectify inconsistencies and minimise potential errors that could adversely affect prediction outcomes. The cleaned dataset was subsequently imported into MATLAB's neural network toolbox (nftool), which facilitated the efficient organisation of data structures essential for

training neural networks. The data were categorised into distinct variable sets, classifying inputs such as energy consumption metrics and operational parameters, alongside targets such as power consumption and product yield. This meticulous organisation ensured that the ANN model could effectively learn from and generalise within the dataset.

3.2.3.5 Training and testing the ANN model

The dataset utilised for training the ANN model was obtained from Stellar Brewery in Bloemfontein, South Africa. It comprised historical energy consumption data collected over a two-year period, encompassing approximately 10 000 data points. The dataset included a variety of operational parameters, such as energy consumption for heating, cooling, and fermentation processes. Prior to training, the dataset underwent preprocessing, which included normalisation to ensure that all input features were on a comparable scale, as well as the removal of outliers to enhance model accuracy.

The structure of the ANN model consisted of 10 hidden layers, each containing 50 neurons. The hidden layers employed suitable activation functions, while the output layer utilised a linear activation function to predict energy consumption values. The data were partitioned into subsets for training (70%), validation (15%), and testing (15%). Performance evaluation metrics, including MSE and R^2 , were monitored during the validation phase to mitigate overfitting and ensure robust predictive accuracy.

3.2.4 Input and targets of the ANN model

For the ANN model, the inclusion of a diverse set of input variables was essential for enhancing prediction accuracy. These variables encompassed input power consumption values related to heating, cooling, and fermentation processes, production rates measured as the volume of beer, ambient conditions such as temperature and humidity, equipment performance parameters, and other relevant operational variables.

Furthermore, certain constant parameters, such as surface area and thermal conductivity, were incorporated as reference values to provide context for the operational environment. Although these constants were not utilised directly as input variables, they were instrumental in defining baseline conditions that influenced model performance.

High-impact input variables were prioritised through correlation analysis with the target outputs. A correlation matrix was constructed to quantify the relationships between input

and target variables, presenting correlation values for each pair (e.g., energy consumption, ambient temperature, flow rate, and corresponding targets such as total energy consumption and product yield).

A cut-off threshold for selecting significant variables was established at a correlation coefficient (R) of 0.7. Only variables with a correlation exceeding this threshold were included in the final model, while those with lower correlations were excluded, as they were deemed to have minimal impact on predictions of energy consumption.

Based on this analysis, the following variables were identified as the most impactful for predicting the energy consumption: heating system power input, control valve position, ambient temperature, and flow rate of the heating medium. These variables exhibited the highest

R-values with the target outputs, which confirmed their significance in determining energy usage patterns.

The target outputs comprised overall energy consumption, operational efficiency, and product yield. Table 3.1 provides a detailed summary of the selected inputs and targets, including their respective units and operational ranges. Examples of the inputs include control valve position, ambient temperature, initial heating medium temperature, and flow rates.

The analysis also focused on evaluating the NAR and NARX models for predictive performance. For the NAR model, critical input parameters included lagged energy consumption values from previous time steps (t-1, t-2, and t-3), which achieved R-values between 0.9975 and 0.9986. The NARX model incorporated these lagged values alongside exogenous inputs such as ambient temperature (varying between 15 °C and 25 °C \pm 5 °C), production rates (ranging from 1 000 L to 1 100 L \pm 10%), and flow rates of the heating medium (ranging from 50 L to 60 L per minute \pm 20%).

The NARX model demonstrated R-values between 0.9545 and 0.9743, which highlighted its strong predictive capability. These parameters were essential for assessing the models' ability to accurately predict energy consumption patterns in microbrewery operations.

Table 3.1: Pearson correlation matrix showing the strength and direction of relationships among the variables

Variable	Energy consumption	Operational efficiency	Ambient temperature	Humidity	Power consumption	Cooling load
Energy consumption	1.00	0.75	0.55	0.45	0.82	0.88
Operational efficiency	0.75	1.00	0.35	0.40	0.65	0.72
Ambient temperature	0.55	0.35	1.00	0.70	0.50	0.60
Humidity	0.45	0.40	0.70	1.00	0.40	0.50
Power consumption	0.82	0.65	0.50	0.40	1.00	0.90
Cooling load	0.88	0.72	0.60	0.50	0.90	1.00

Table 3.2: Summary of input variables and target variables for the ANN mode

Type	Variable	Description	Unit	Range	Correlation with target
Inputs	Heating system power input	Power input to the heating system	kW	5–50	0.82
	Control valve position	Valve position controlling heating medium	(%)	10–100	0.75
	Ambient temperature	Ambient temperature in the brewery	°C	15–30	0.79
	Flow rate of heating medium	The flow rate of the heating medium	L./min	10–100	0.85
	Fermentation temperature	Temperature during the fermentation process	°C	18–22	0.65
	Cooling load demand	Demand for cooling during production	kW	5–30	0.77
	Production volume	The volume of beer produced (batch size)	Litres	50–500	0.8
	Ambient humidity	Relative humidity in the brewery	%	40–70	0.72
	Water heating temperature	Temperature during the water heating process	°C	50–80	0.85
	Mashing temperature	Temperature during the mashing process	°C	62–68	0.76
	Wort boiling temperature	The boiling point of wort during brewing	°C	90–105	0.88
	Heat exchange efficiency	Efficiency of the heat exchanger		70–90	0.69
	Targets	Total energy consumption	Total energy consumed during production	kWh	10–150
Operational efficiency		The ratio of useful energy used in production	%	40–90	
Product yield		Amount of beer produced per unit of energy	Litres/kWh	0.5–10	
Temperature consistency		Temperature consistency across the brewing process	°C		

3.2.5 Structure and description of ANN model input-output fitting, regression, and curve fitting (nftool)

This section outlines the implementation of MATLAB's nftool for input-output fitting, regression, and curve fitting in the ANN model. The LM algorithm was specifically selected due to its superior performance in training neural networks, particularly in dynamic systems where feedback is present [190]. This algorithm integrates the advantages of gradient descent and the Gauss-Newton method to facilitate rapid convergence and enhanced accuracy.

The LM algorithm improves both convergence speed and predictive accuracy by synthesising gradient descent and Gauss-Newton techniques. The nftool application is employed to define the network architecture, establish input-output mappings, and optimise model parameters. This methodology ensures robust predictive capabilities, which are essential for accurate energy management and process optimisation in microbreweries, thus supporting improved operational efficiency and cost control.

The ANN model consists of 10 hidden neurons organised in a single hidden layer, as illustrated in Figure 3.5. The network was developed using MATLAB's Neural Network Toolbox, which was also utilised to generate the network diagram. This configuration was chosen to balance model complexity and performance to ensure accurate predictions while minimising computational load.

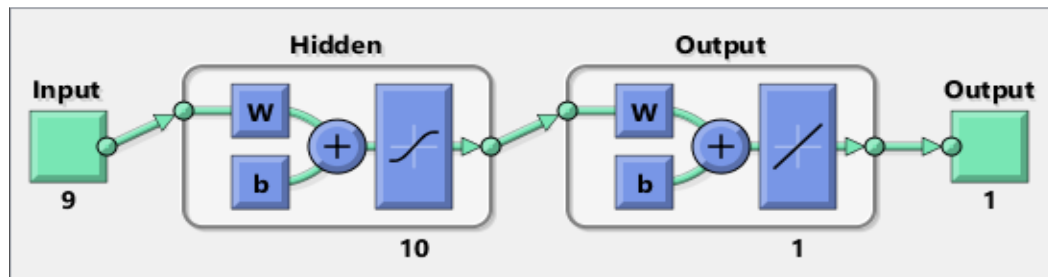


Figure 3.5: Network diagram for input-output fitting, regression, and curve fitting using MATLAB's nftool for predicting energy consumption in microbrewery operations

3.2.6 Configuration to predict the performance indicators

This section examines the application of ANNs that are specifically designed to predict critical performance indicators in beer production, including heating energy demands and total power consumption. The ANN model aims to provide actionable insights that optimise energy management in the brewing process by leveraging historical data in conjunction with real-time inputs.

Key performance indicators encompass heating energy, which quantifies the energy required for processes such as mashing and wort boiling to facilitate efficient heating and energy cost management. Cooling efficiency represents another crucial metric, which monitors factors such as cooling load and the COP to ensure effective temperature control during fermentation. Total power consumption reflects the energy usage across various brewery operations, which enables comprehensive energy management. Finally, the energy-to-production ratio evaluates the correlation between energy inputs and production rates in order to enhance operational efficiency and product quality. Through these predictions, ANNs empower breweries to make data-driven decisions that optimise energy consumption, reduce costs, and promote sustainable operations.

3.2.7 Economic analysis for ANN

A comprehensive economic analysis is crucial for assessing the viability of implementing a proposed hybrid grid-connected solar energy storage system with thermal storage, as opposed to a conventional grid-connected system for a microbrewery. Establishing a baseline scenario that utilises the power grid to meet the microbrewery's energy demands facilitates a clear comparison of the benefits and savings associated with the proposed solar thermal solution.

To evaluate the project's economic feasibility and the investment's present value, it is essential to acknowledge that the installation of a solar thermal storage system can result in substantial long-term savings on energy costs and related expenses. Consequently, a thorough assessment of the economic feasibility of this initiative is critical.

The financial viability of a solar TES system is assessed using key financial metrics including Present Value (PV), Net Present Value (NPV), and Payback Period (PBP). Present Value (PV), as outlined in Equation 3.9 [14], estimates the current worth of future cash flows based on a discount rate, which provides insight into the system's long-term economic benefits. Net present value (NPV), defined in Equation 3.10 [149], determines the profitability of the investment by calculating the difference between the present value of cash inflows and the initial capital cost. This parameter is critical for evaluating the project's overall financial return.

The payback period (PBP), detailed in Equation 3.11 [14], estimates the time required to recover the initial investment, accounting for variations in cash flow and discount rates. This metric aids stakeholders in assessing how swiftly the project can generate a ROI.

Equation 3.12 introduces the LCC analysis, which encompasses all costs associated with the system, including operational, maintenance, energy, and salvage costs, to provide a comprehensive view of the financial impact over the system's life cycle [149].

Together, these equations form a robust framework for evaluating the financial and economic feasibility of the solar TES system in order to ensure sustainable and cost-effective energy solutions for stakeholders.

According to Equation 3.9, the present value of future cash flows is calculated as [14]:

$$PV_E = CF(n) \cdot (1 + r)^{-n}, \quad (3.9)$$

Equation 3.10 defines the expression for the net present value [149]:

$$NPV_{n=1}^m = \sum_{n=1}^m PV_E(n) - CC, \quad (3.10)$$

Equation 3.11 presents the expression for the repayment period [5]:

$$Payback\ Period = m_y + (-NPV_{n=1}^m) \cdot [PV_E(m_y + 1)]^{-1}, \quad (3.11)$$

Where:

$PV_E(n)$ is the present value of cash flow in the n-th year;

$CF(n)$ is the cash flow in the n-th year;

r denotes the discount rate;

m is the number of years;

N is the total number of years in the analysis;

NPV refers to the net present value of the investment;

CC is the capital cost of the project; and

m_y is the final year with a negative cumulative cash flow.

Finally, Equation 3.12 estimates the total LCC of the system [14]:

$$LCC = C_{IC(i)} + C_{RC(i)} + C_{OMC(i)} + C_{EC(i)} - C_{SC(i)}, \quad (3.12)$$

Where:

$C_{IC(i)}$ is the initial cost;

$C_{RC(i)}$ is the replacement cost;

$C_{OMC(i)}$ is the operational and maintenance costs;

$C_{EC(i)}$ is the energy cost; and

$C_{SC(i)}$ is the salvage cost associated with the system components.

Table 3.3 presents the investment costs associated with solar TES systems. As discussed in Section 3.2.7, the simulation results provide a comparative analysis of the energy costs for both the baseline and proposed systems. The estimated investment cost for an STES is USD 11 100, with an additional USD 3 100 required for the integration of thermal storage [5,191].

Table 3.3: Cost to invest in a solar thermal energy storage (TES) system

Initial capital investment	Cost (USD)	Cost (USD)
4kW 24VDC solar collector panel cost		
12 units	475*12	5 700
Controller cost	1 100	1 100
Inverters and accessories cost	3 300	3 300
Thermal storage cost		3 100
Installation cost	1 000	1 000
Total investment	11 100	14 200

Table 3.4: Seasonal time-of-use (ToU) tariff rates for electricity consumption

Season	Months	Period	Time	Rate (ZAR/kWh)	Rate (USD/kWh)
High demand (winter)	June to August	Peak	06:00–09:00, 17:00–19:00	4.896	0.272
		standard	09:00–17:00, 19:00–22:00	2.99	0.166
	Off-peak	00:00–06:00, 22:00–24:00	2.196	0.122	
Low demand (summer)	September to May	Peak	07:00–10:00, 18:00–20:00	3.16	0.176
		standard	06:00–07:00, 10:00–18:00, 20:00–22:00	1.764	0.098
	Off-peak	00:00–06:00, 22:00–24:00	1.638	0.091	

3.2.8 Annual energy cost saving

Table 3.5 analyses the annual energy costs associated with various supply options and pricing periods for a microbrewery. It compares the baseline energy costs with those of a proposed hybrid system that incorporates TES and highlights the potential for substantial cost savings through optimised energy management.

Table 3.5: Annual energy cost savings analysis

Supply option and pricing periods	Energy cost per season (USD)		Cost USD/year
	Winter (days)	Summer (days)	
Off-peak	8*92*17.1319 = 12609.0972	8*270*23.8101 = 51429.7778	64038.875
Standard	11*92*13.3204 = 13480.229	11*270*18.6608 = 55422.4778	68902.7068
Peak	5*92*52.5108 = 24154.9665	5*270*73.5633 = 99310.4891	123465.4556
Total baseline	50144.2924	206162.7447	256307.0371
Off-peak	8*92*6.9516 = 5116.3438	8*270*16.218 = 35030.827	40147.1708
Standard	11*92*5.4482 = 5513.5461	11*270*12.711 = 37750.411	43263.9571
Peak	5*92*21.4774 = 9879.6189	5*270*50.107 = 67644.2472	77523.8661
Total proposed system	20509.5088	140425.4857	160934.9945
Total savings (USD)	29634.7836	65737.259	95372.0426
Total savings (ZAR)	533426.10	1183270.66	1716696.8

Energy costs are categorised into three distinct pricing periods: off-peak, standard, and peak. These categories reflect the varying rates charged by suppliers based on the time of day and seasonal demand, which are crucial for understanding overall expenses.

The proposed hybrid energy system, incorporating TES, is designed to enhance cost savings despite necessitating a greater initial capital investment. The performance and economic benefits of this system are directly influenced by the prevailing ToU tariff structure, as indicated in Table 3.6. The analysis encompasses both service and capacity charges, which facilitate strategic operational adjustments in response to tariff variations.

Energy costs are evaluated separately for the winter and summer seasons to account for differing consumption behaviours. The total annual energy expenditure is computed from daily energy usage across the three pricing categories, with the high-demand season spanning 92 days and the low-demand season covering 273 days. For instance, the off-peak energy cost during winter is determined as follows:

$$\text{Off-peak cost} = 8 \text{ hours} \times 92 \text{ days} \times 17.1319 \text{ USD/hour} = \text{USD } 12\,609.10$$

Equivalent computations were undertaken for the standard and peak pricing periods to produce a comprehensive depiction of seasonal energy expenses.

Table 3.6 presents the annual energy cost breakdown for the proposed hybrid system equipped with TES in the microbrewery. The analysis indicates anticipated annual savings of approximately USD 95 372.045, which are attributable to optimised load management and the strategic utilisation of off-peak electricity tariffs.

Through the implementation of this hybrid configuration, the microbrewery is able to regulate its energy demand effectively by reallocating energy-intensive operations to periods of reduced electricity rates. This results in immediate financial benefits while promoting a sustainable mode of operation, which enables more efficient resource utilisation and investment in product quality enhancement.

These savings underscore the critical role of sustainable energy strategies in the brewing sector. As energy prices continue to escalate, the adoption of innovative energy management techniques will bolster the microbrewery's position as a model of economic and environmental responsibility.

In conclusion, the proposed hybrid energy system with TES effectively addresses fluctuating energy demand and tariff schedules and results in substantial reductions in energy

costs. This evaluation highlights the combined advantages of increased profitability and ecological sustainability that can place the microbrewery at the forefront of sustainable brewing innovation and contribute to a more efficient, environmentally conscious future.

3.2.9 Renewable energy integration

3.2.9.1 Solar thermal energy system (STES)

The proposed STES is designed to harness solar energy for heating purposes in the brewery in order to significantly reduce reliance on conventional energy sources. This system represents a sustainable solution that aims to meet the brewery's energy demands in an environmentally friendly manner. Below is a detailed description of the TES system, which is central to the storage and efficient distribution of thermal energy throughout the brewing process.

- **System components:** This system comprises 12 evacuated tube collectors (ETCs), each with an aperture area of 1.57 m², totalling 18.84 m². These collectors effectively capture solar energy, even under low-light conditions. The thermal energy is stored in a 1 200-L stainless steel TES tank, which is insulated to minimise heat loss. Stainless steel (Grade 441) is employed due to its high thermal conductivity, durability, and resistance to corrosion. Water, with a specific heat capacity of 4 184 J/kg·°C, is utilised as the heat transfer fluid. It provides efficient thermal energy transfer and represents a safe, cost-effective choice for the brewery.
- **Operational mechanism:** During periods of sunlight, the ETCs absorb solar radiation and convert it into thermal energy that heats the circulating water. This heated water is stored in the TES tank, with a charging rate of 12 kW. A pump circulates the heat transfer fluid from the collectors to the tank. When hot water is required, the system discharges thermal energy at a rate of 3.5 kW and delivers hot water to brewing processes via a secondary pump.
- **Benefits of the STES:** By utilising solar energy, the brewery can significantly reduce electricity consumption, which will lead to substantial cost savings. The use of solar thermal energy lessens reliance on fossil

fuels, which decreases greenhouse gas emissions and lowers the carbon footprint. Furthermore, the system enhances energy independence and protects the brewery from fluctuations in energy prices and potential supply disruptions.

- Future enhancements: Future plans include the addition of solar collectors, the integration of advanced control systems, and the development of enhanced storage solutions to improve system efficiency and support the brewery's sustainability objectives.

3.3 RESULTS AND DISCUSSION OF THE PREDICTIONS

3.3.1 Non-linear autoregressive (NAR) neural network output for predicting five-day power consumption in the summer, September 2023

This study employed an ANN model, specifically the NAR model, to predict power consumption in beer production processes. The dataset was partitioned into 70% for training, 15% for validation, and 15% for testing. By leveraging historical data, the model effectively captures complex non-linear relationships and accounts for temporal dependencies, which renders it suitable for predicting power consumption in the dynamic environment of brewing operations.

Figure 3.6 depicts a simple neural network architecture featuring a single hidden layer and an output layer, where the input value of “1” is processed by a hidden neuron, producing an intermediate value of “10” through a transformation involving its weight (W) and bias (b). The output layer subsequently takes this transformed value and generates the final output of “1”, utilising its weight and bias parameters.

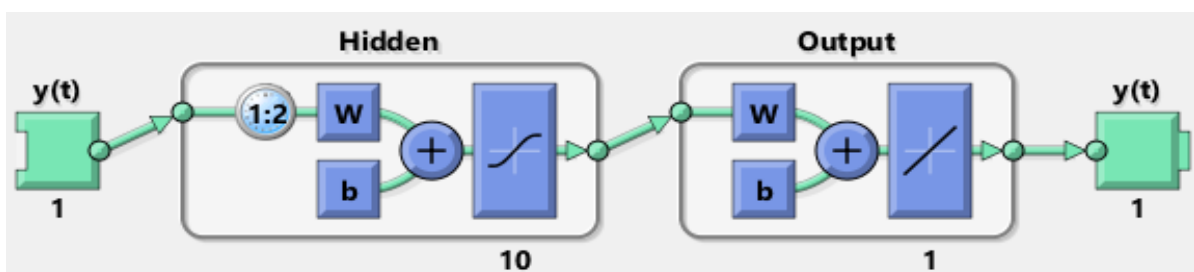


Figure 3.6: NAR neural network architecture for predicting five-day power consumption in a microbrewery (summer, September 2023)

The energy profile for September 2023, as illustrated in Figure 3.7, provides significant insight into the operational efficiency of the microbrewery. Daily energy consumption exhibits fluctuations, with low-demand periods averaging approximately 50 kWh and peak periods reaching 200 kWh, which are associated with essential brewing processes such as mashing, boiling, and packaging. High-demand days recorded energy consumption ranging from 800 to 1 200 kWh, with an average daily consumption of around 900 kWh, while non-brewing days recorded consumption levels between 400 and 500 kWh. Notable peaks in energy consumption occur during the mashing process (08:00 to 10:00), boiling (10:00 to 12:00), and cooling/packaging in the afternoon. A comprehensive understanding of these patterns is essential for enhancing operational efficiency, minimising costs during peak pricing periods, and informing sustainability initiatives, including investments in energy-efficient equipment and heat recovery systems.

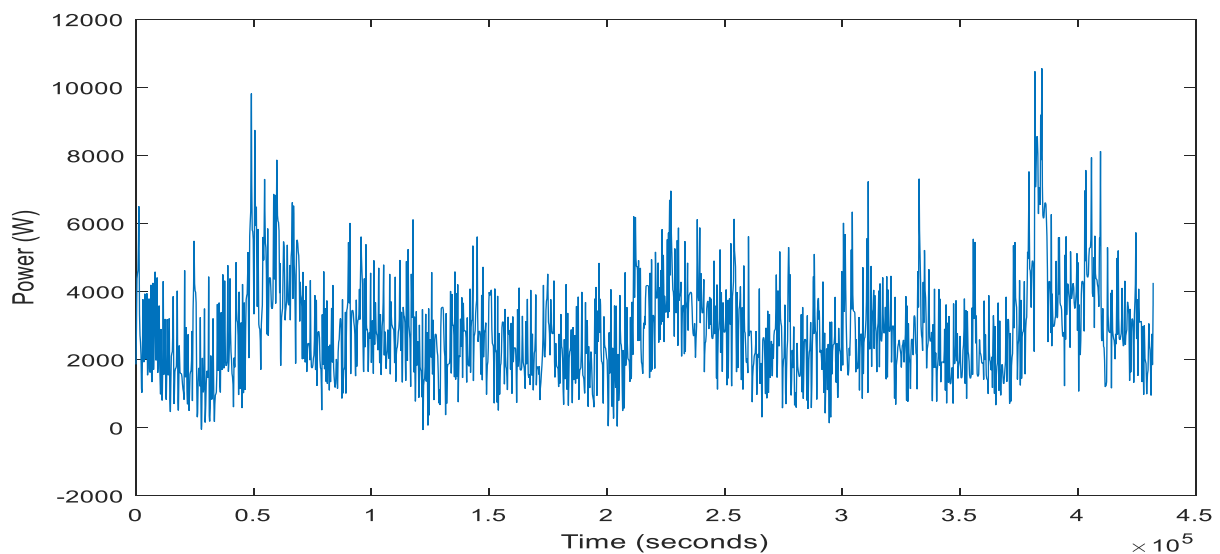


Figure 3.7: Load profile of the microbrewery analysed using the NAR model (September 2023)

Figure 3.8 presents regression plots that illustrate the performance of the neural network model in predicting power consumption. The training dataset achieved an R-value of 0.9961, which indicated a high degree of fit to the training data.

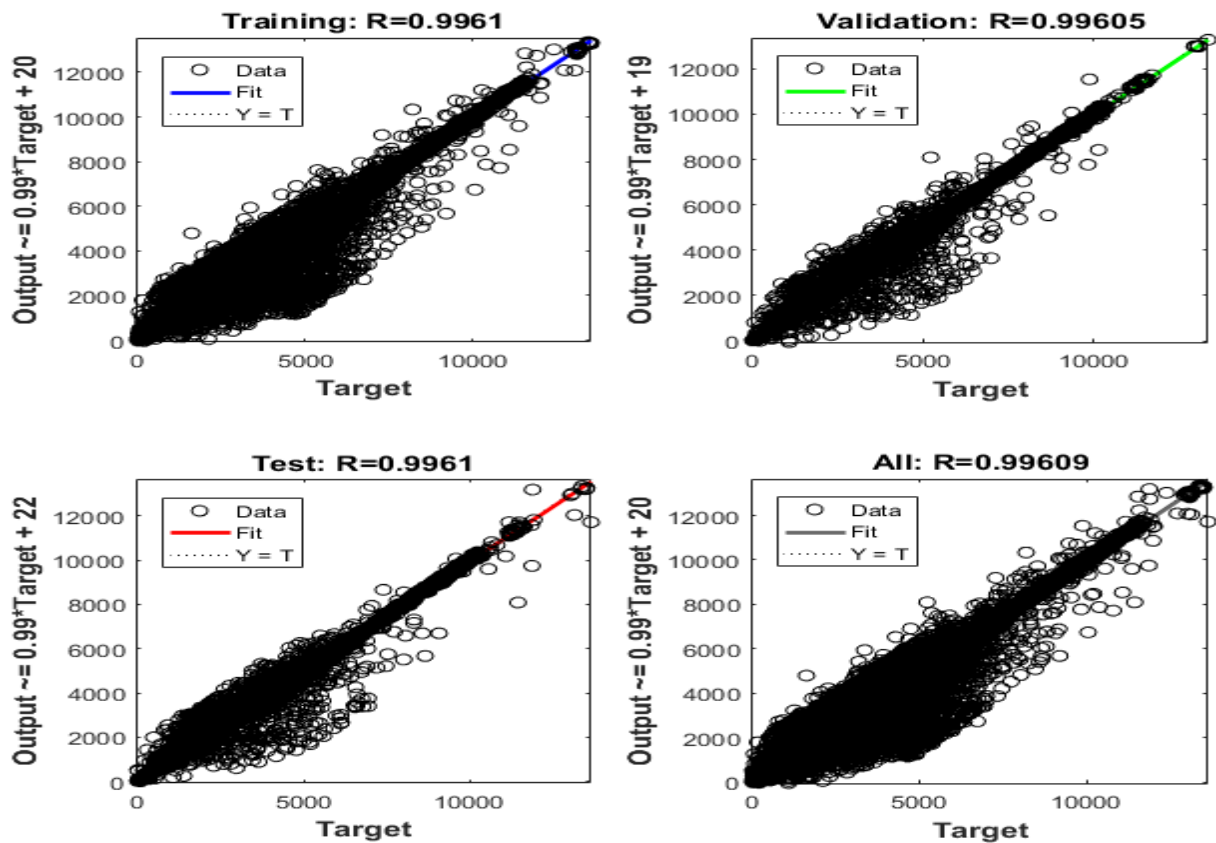


Figure 3.8: Regression plot of training, validation, testing, and all predictions for the power consumption of the microbrewery, analysed using the NAR model (September 2023)

The validation dataset exhibited an R-value of 0.99605, which indicated a strong capacity for generalisation to novel data. The test dataset recorded an R-value of 0.9961, which demonstrated consistent performance on previously unseen data. The overall R-value was 0.99609, which further substantiated the model’s robustness across all datasets. These plots illustrate a clear linear relationship between predictions and actual values and highlight the model’s effectiveness and appropriateness for predicting power consumption in microbreweries.

3.3.2 Non-linear autoregressive with exogenous inputs (NARX) network output for predicting five-day power consumption in the summer, September 2023

The prediction of the five-day power consumption values for September 2023 was conducted using the NARX neural network model. The architecture of the NARX network, illustrated in Figure 3.9, comprised an input layer, a hidden layer, and an output layer. In this configuration, the input layer transmits a value of 1 to the hidden layer’s neuron, which

concurrently receives a bias term of 1 000 to adjust the neuron's output. The incorporation of the bias term enhances the model's flexibility during the learning process. The hidden neuron calculates a weighted sum of the inputs, applying specific weights (denoted as W) alongside a bias term (b). Following processing through an activation function, the resultant value is forwarded to the output layer to produce a final output value of 1.

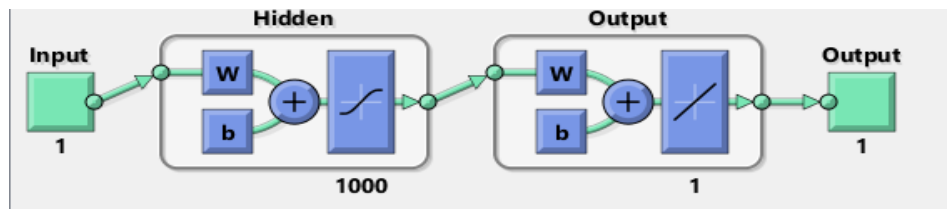


Figure 3.9: NARX neural network architecture for predicting five-day power consumption in a microbrewery (summer, September 2023)

The NARX model is characterised by the incorporation of recurrent connections, whereby the output from the previous timestep is reintroduced into the network as part of the current input, in contrast to a standard feedforward network.

Figure 3.10 displays regression plots that compare the predictions of the neural network model with the actual target values across various datasets. The training dataset achieved an R-value of 0.85705, which indicated a strong fit to the training data. The validation dataset exhibited an R-value of 0.85638, which reflected a consistent ability to generalise to unseen data. The test dataset maintained an R-value of 0.85606, while the overall R-value across all datasets was 0.8568. These results not only demonstrate effective learning but also highlight areas for potential enhancement in the model's predictive capabilities.

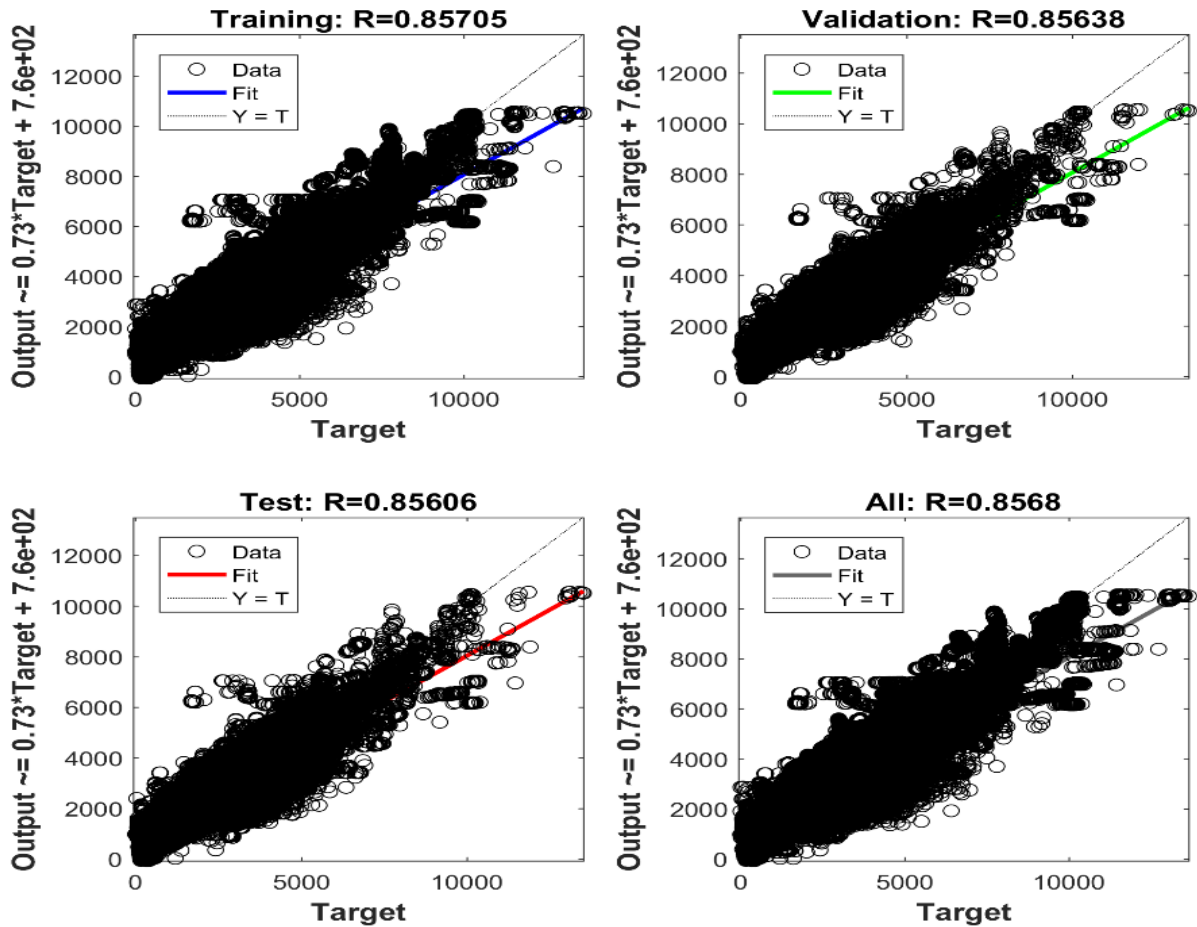


Figure 3.10: Regression plot of training, validation, testing, and all predictions for the power consumption of the microbrewery, analysed using the NARX model (September 2023)

Figure 3.11 illustrates the ANN predictions in relation to the target power consumption parameters, accompanied by percentage deviations. The graph encompasses the predicted power values (represented by blue dots), the actual target values (indicated by green dots), and the corresponding percentage deviations (displayed as an orange line).

At lower power levels, approximately 1 kW, the predicted and actual values exhibited a close correspondence, with deviations around $\pm 5\%$. However, as power levels increased to approximately 6 kW, the deviation escalated to about +10%. Beyond 6 kW, the deviation increased markedly to approximately +15%, which signified a decline in prediction accuracy at elevated power consumption levels.

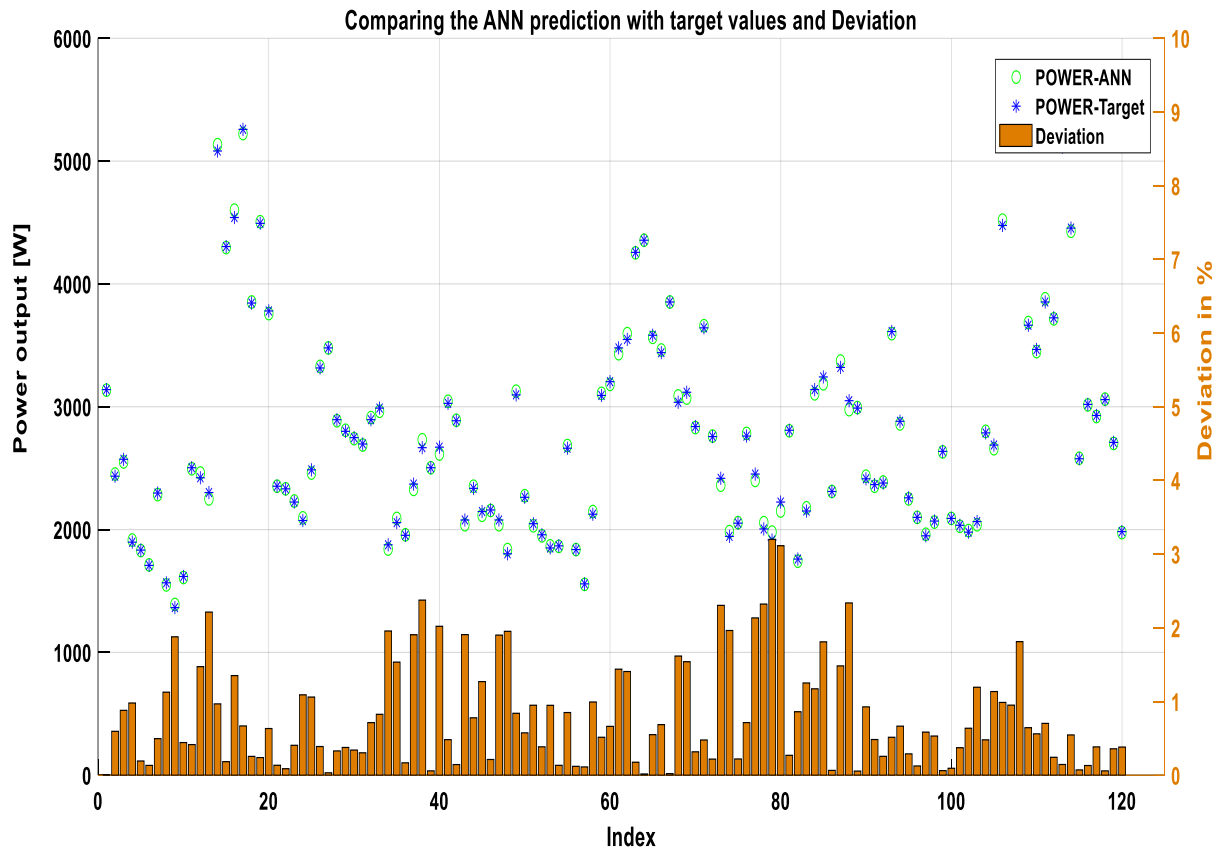


Figure 3.11: ANN prediction versus target power consumption parameters with percentage deviation (September 2023)

Overall, although the ANN model demonstrated reasonable predictive accuracy at lower power levels, there remains considerable potential for improvement at higher consumption ranges. The deviation across the dataset typically ranged from -5% to +15%, which highlights the need for further optimisation of the model, particularly to enhance forecasting accuracy at elevated power levels.

3.3.3 Prediction of input power to the microbrewery (March 2022)

The prediction of input power for March 2022 was conducted using an NAR neural network model. Figure 3.12 illustrates the regression plots that compare the model's predictions with the actual target values across the training, validation, and testing datasets. The model attained remarkably high R-values of 0.99752 for the training set, 0.99835 for the validation set, and 0.99856 for the test set, which demonstrated exceptional fit and robust generalisation capability.

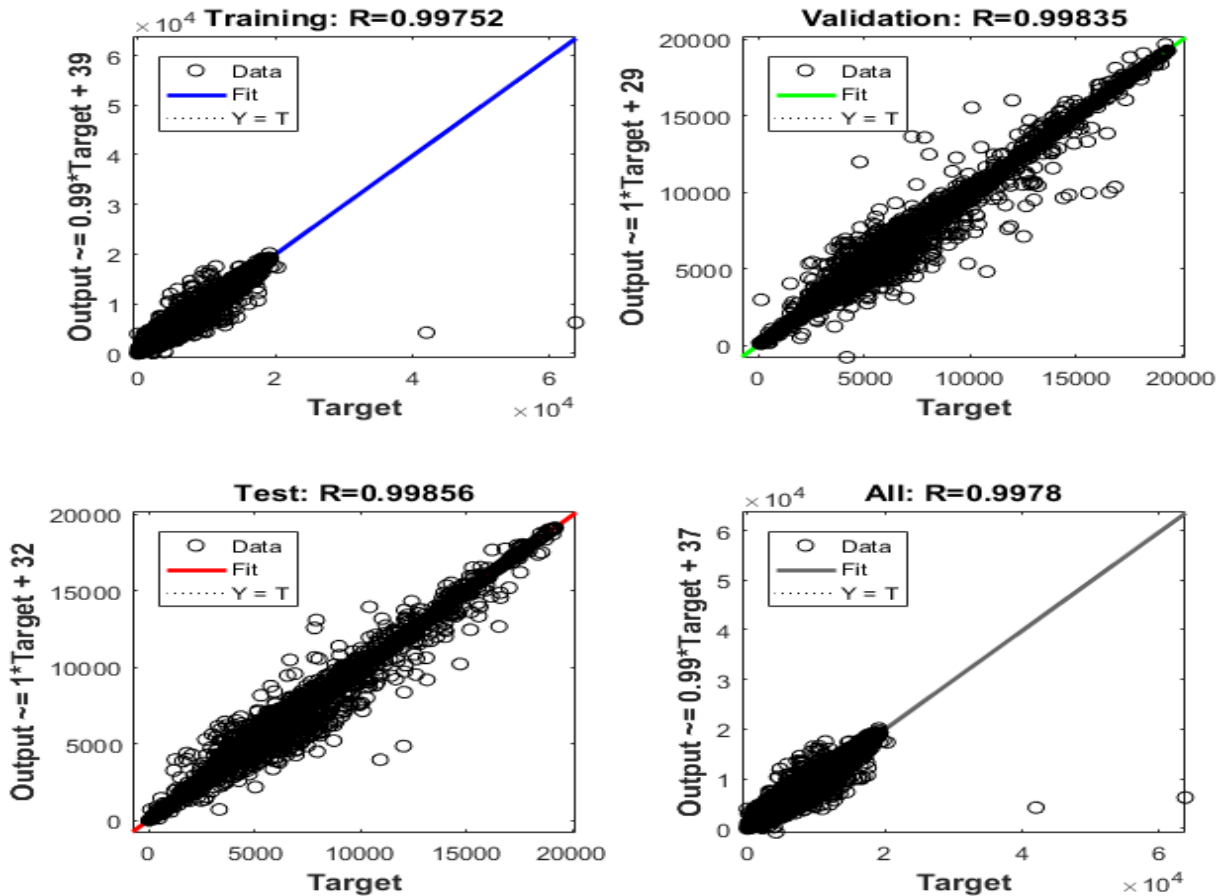


Figure 3.12: Regression plot of training, validation, testing, and all predictions for the power consumption of the microbrewery, analysed using the NAR model (March 2022)

The overall R-value was 0.9978, which further confirmed the robust performance across all datasets. These plots illustrate a clear linear relationship between the predicted and actual values and reflect the model's effective learning process and accurate mapping of input-output relationships. The consistently high R-values suggest that the model is highly accurate and suitable for predicting power consumption targets.

Figure 3.13 illustrates the performance of the NARX model for the same dataset, with four scatter plots that depict the relationship between predicted and actual target values. The top-left plot exhibits a strong linear relationship with an R-value of 0.95453, which indicates that the model effectively captured the data patterns. The top-right plot shows an even higher R-value of 0.97428, which suggests robust generalisation on the validation data.

The bottom-left plot yields an R-value of 0.97003, which is slightly lower and indicates some deviations in prediction. The bottom-right plot, with an R-value of 0.9559, reveals a more scattered distribution, which suggests reduced consistency in performance.

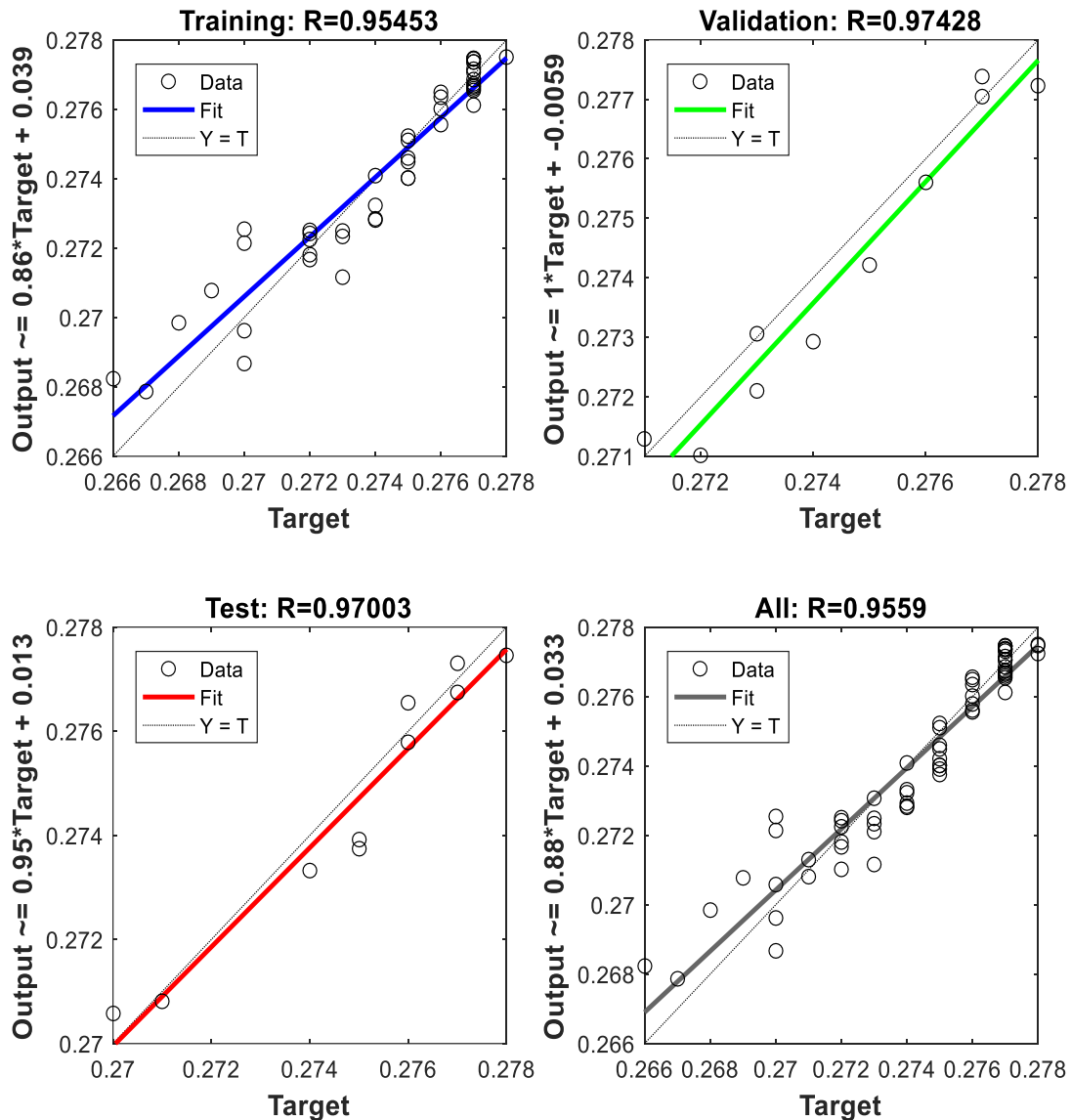


Figure 3.13: Regression plot of training, validation, testing, and all predictions for the power consumption of the microbrewery, analysed using the NARX model (March 2022)

Overall, while the model exhibited high predictive accuracy, the increased variability observed in the lower plots highlights potential areas for further refinement and enhancement of the model.

Figure 3.14 illustrates the energy profiles of two critical power variables in the microbrewery, namely the measured input power (P_{in} Summer 1) and the ANN-predicted power output (ANN P_{out} Summer 1), over a period of 120 hours. The vertical axis represents power in kW, while the horizontal axis denotes time in hours. The blue line (P_{in} Summer 1) and the orange line (ANN P_{out} Summer 1) depict the energy consumption profiles of the respective components. Initially, P_{in} Summer 1 consumed approximately

5 kW, whereas ANN Pout Summer 1 consumed around 2 kW. Both values increased over the first 50 hours, with Pin Summer 1 peaking at approximately 16 kW near the 50th hour, and ANN Pout Summer 1 reaching approximately 14 kW near the 30th hour. Following these peaks, both profiles gradually declined, with Pin Summer 1 decreasing to approximately 3 kW and ANN Pout Summer 1 decreasing to around 1.5 kW by the conclusion of the 120-hour period.

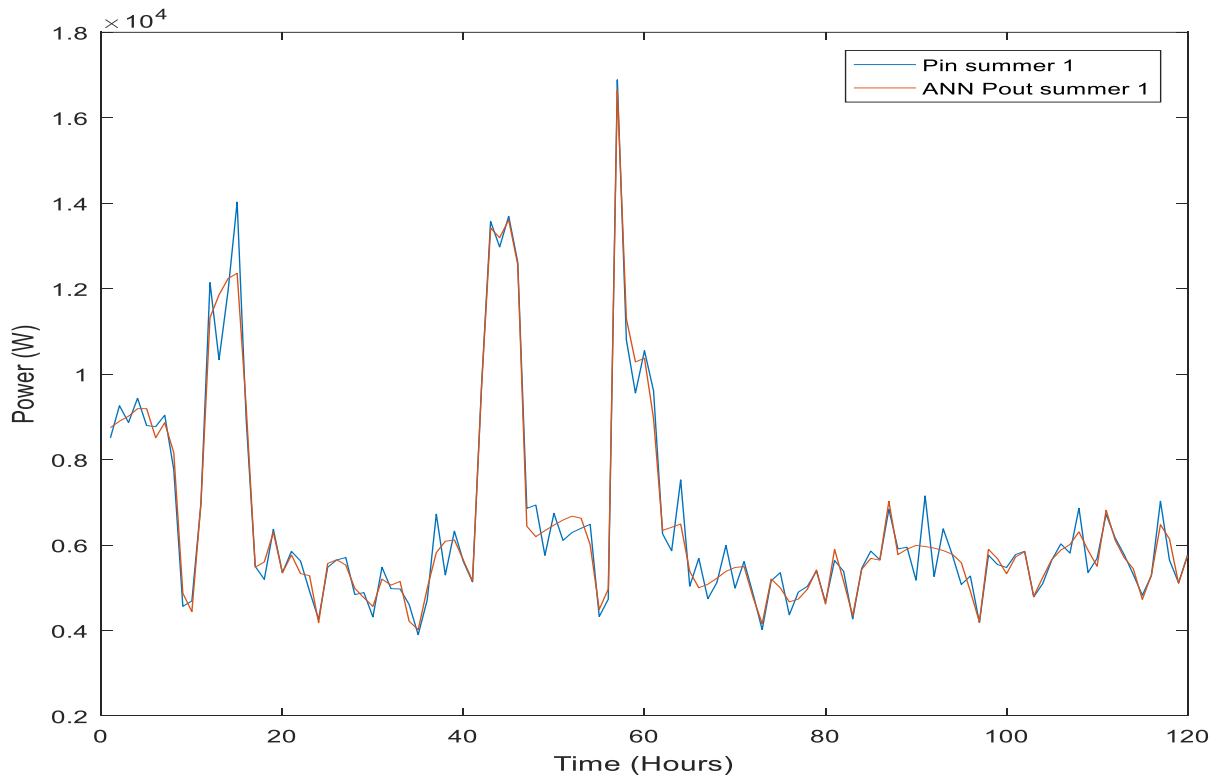


Figure 3.14: Energy profile of Pin and PANN of the microbrewery (March 2022)

These dynamic energy consumption patterns reflect the influence of operational factors and indicate opportunities for optimising equipment operation, adjusting production schedules, and implementing energy-saving strategies to enhance overall efficiency and sustainability.

Figure 3.15 illustrates the ANN predictions compared to the target power consumption parameters, accompanied by the corresponding percentage deviation. The plot includes predicted values (blue dots), actual values (green dots), and the percentage deviation (orange line).

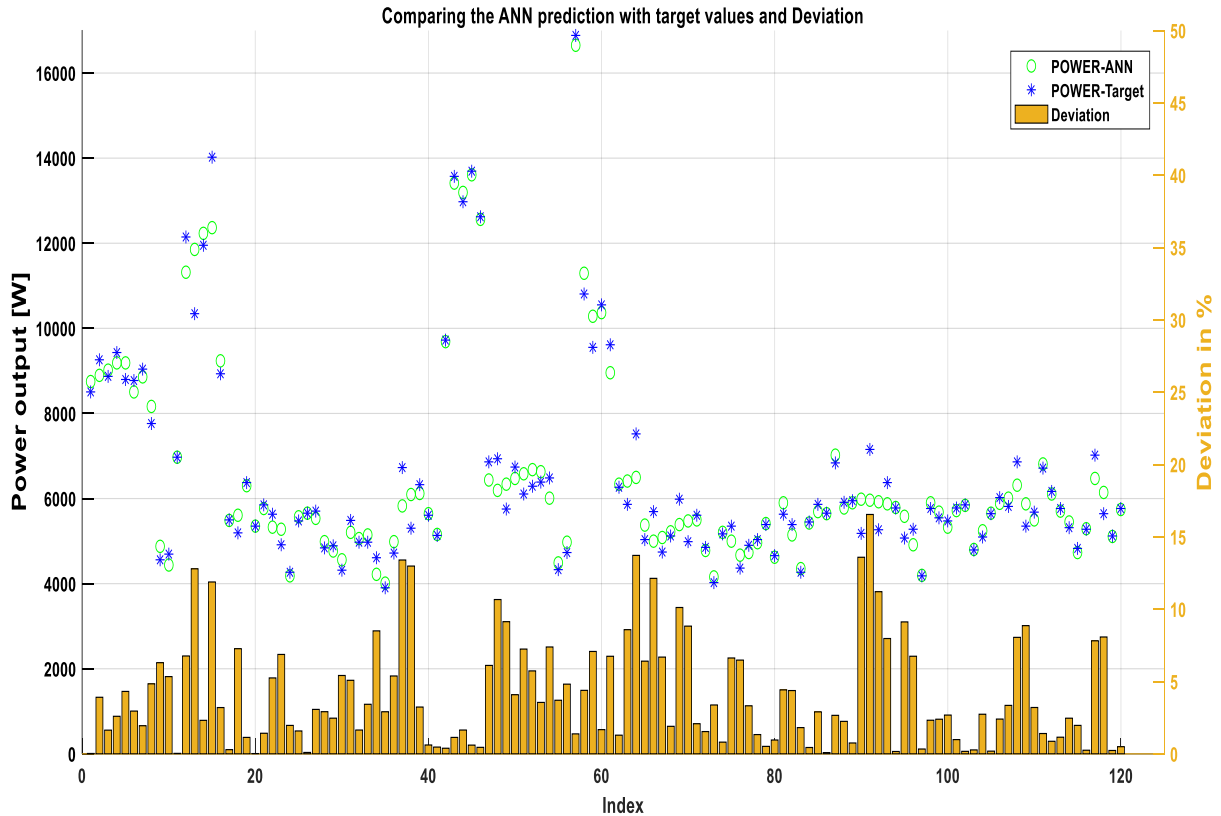


Figure 3.15: ANN prediction versus target power (March 2022) parameters with percentage deviation

At lower power levels (10 W to 20 W), the predictions generated by the ANN closely aligned with the target values, exhibiting deviations within $\pm 5\%$. However, as power levels increased to the range of 40 W to 60 W, these deviations expanded to approximately $+10\%$. At power levels exceeding 60 W, the percentage deviation escalated significantly to around 45%, which suggests that the ANN model encountered difficulties in maintaining accurate predictions at these elevated levels. While the model demonstrated commendable performance for lower to mid-range power levels, it exhibited substantial error at higher levels. This analysis from March 2022 underscores the necessity of continuous optimisation to improve the model's accuracy, particularly within the higher power ranges.

3.3.4 Prediction of the cooling load (August 2023)

As previously discussed in this chapter, accurately estimating the cooling load for the primary objective is crucial. The ANN prediction procedure was conducted repeatedly,

maintaining a distribution of the data for training, validation, and testing at 70%, 15%, and 15%, respectively. The number of hidden layers was fixed at 10.

Figure 3.16 illustrates the regression plots of the neural network model's predictions compared to the actual values across various datasets. The model attained an R-value of 0.9982 for the training set, 0.99819 for the validation set, and 0.99812 for the test set.

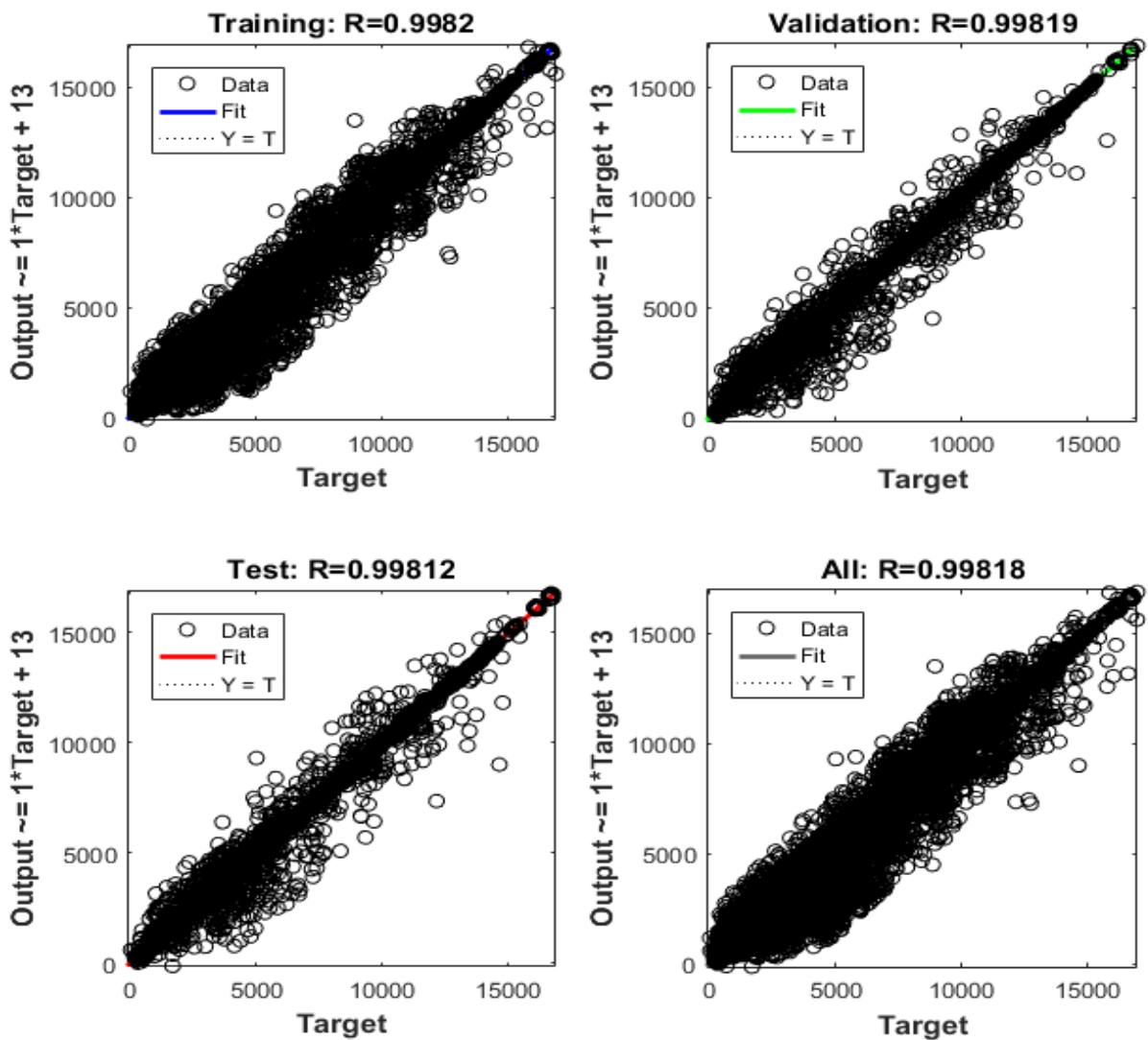


Figure 3.16: Regression plot of training, validation, testing, and all predictions for cooling load, analysed using the NAR model (August 2023)

The overall R-value was 0.99818. The plots illustrate a strong linear relationship, with data points closely aligning with the fitted line. This demonstrates the model's high accuracy and effective generalisation of new data.

Figure 3.17 displays regression plots comparing the neural network model's predictions to the actual target values across different datasets. The model showed an R-value of 0.86057 for training data, which indicated a good fit. On validation and test data, it scored 0.86159 and 0.86439, respectively, which demonstrated effective generalisation and consistent performance.

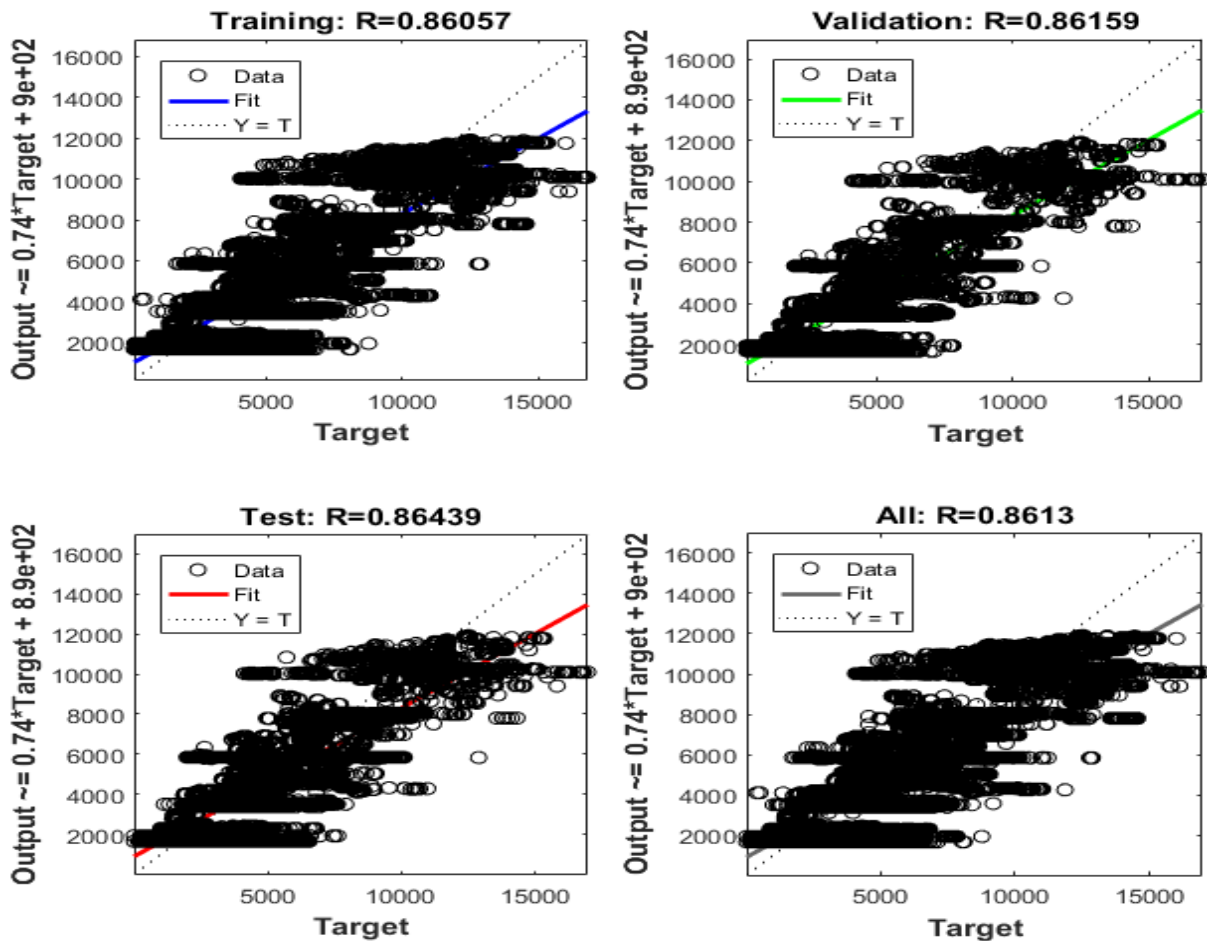


Figure 3.17: Regression plot of training, validation, testing, and all predictions for the power consumption of the microbrewery, analysed using the NARX model (August 2023)

The overall R-value was 0.86613, which confirmed robust performance across all datasets. The plots illustrate a linear relationship between the predictions and actual values, with data points closely adhering to the fitted line. Although the R-values were approximately 0.86, suggesting reasonable model performance, potential for further enhancement remains.

Figure 3.18 presents the ANN predictions in relation to target cooling load parameters, accompanied by percentage deviation, which demonstrates the efficacy of the ANN model

in predicting cooling loads. The plot includes predicted values (blue dots in the scatter plots), actual values (green dots in the scatter plots), and percentage deviation (orange line).

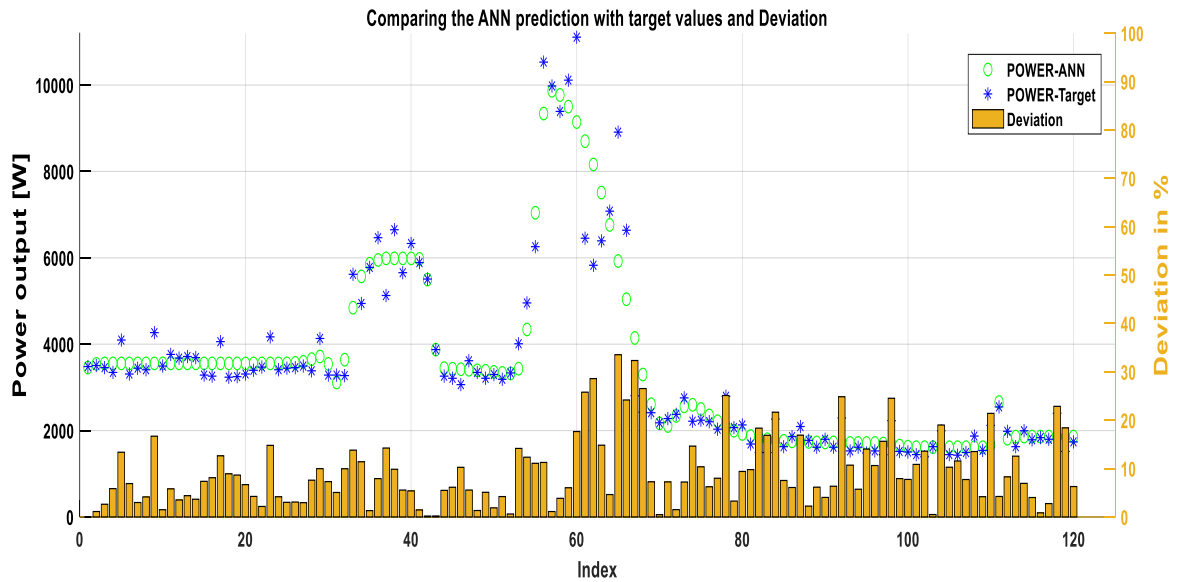


Figure 3.18: ANN prediction versus target cooling load parameters with percentage deviation (August 2023)

At lower cooling loads (20 W to 40 W), the predictions generated by the ANN closely aligned with the target values, exhibiting deviations within $\pm 5\%$. As cooling loads increased to the range of 60 W to 80 W, these deviations expanded to approximately $+10\%$. For higher cooling loads that exceeded 80 W, the percentage deviation remained within the $+10\%$ range, which indicated a reasonable level of performance by the ANN model. Overall, the model demonstrated consistent efficacy across the entire cooling load spectrum, with deviations predominantly around $\pm 10\%$. This analysis underscores the model's accuracy and suggests that ongoing monitoring and optimisation are critical for sustaining reliability.

3.4 PERFORMANCE EVALUATION OF NAR AND NARX MODELS

Table 3.6 summarises the R and MSE performance metrics for both the NAR and NARX models across various periods (March 2022, August 2023, and September 2023). This facilitates a clearer and more effective comparison of model performance and highlights the strengths of both approaches. Table 3.6 is a revised table that summarises the key performance metrics for both the NAR and NARX models.

Table 3.6: Key performance metrics for power consumption prediction

Date	Model	Correlation (R) Training	Correlation (R) Validation	Correlation (R) Testing	MSE Training	MSE Validation	MSE Testing
March 2022	NAR	0.99752	0.9978	0.99856	0.00496	0.00488	0.00288
March 2022	NARX	0.95453	0.97428	0.97428	0.08988	0.05128	0.05128
August 2023	NAR	0.9982	0.99819	0.99812	0.00360	0.00362	0.00375
August 2023	NARX	0.86057	0.86159	0.86439	0.25984	0.25686	0.26567
September 2023	NAR	0.9961	0.99605	0.9961	0.00780	0.0079	0.00780
September 2023	NARX	0.85705	0.85638	0.88606	0.26546	0.26690	0.21650

The data distribution for training, validation, and testing comprised 70% for training, 15% for validation, and 15% for testing, which ensured consistent model evaluation throughout the experiments.

Table 3.6 provides a clear, side-by-side comparison of the performance of the NAR and NARX models. It demonstrates the superior predictive accuracy and robustness of both models across the three datasets.

The NAR algorithm consistently attained high R-values ranging from 0.9975 to 0.9986 across the training, validation, and testing sets, accompanied by low MSE values between 0.0029 and 0.0049, which indicated a high level of predictive accuracy.

The NARX model, while still performing satisfactorily, exhibited a broader range of performance across different datasets, with R-values spanning from 0.9545 to 0.9743 and MSE values from 0.0513 to 0.0899. This variability reflects its potential for enhancement, particularly in scenarios where temporal dependencies are more complex.

The percentage deviations between the predicted and actual values were predominantly minimal, ranging from -5% to +10%, which affirmed the model's precision and reliability.

In conclusion, when comparing the NAR and NARX models, both exhibited high correlation values and low deviations. However, the NAR algorithm consistently recorded higher correlation values, which rendered it more effective for accurately predicting power usage in brewery operations.

3.5 RESULTS OF THE ECONOMIC ANALYSIS

Figure 3.19 presents a comparison of the LCC between the baseline system and the proposed STES, emphasising its financial benefits over time.

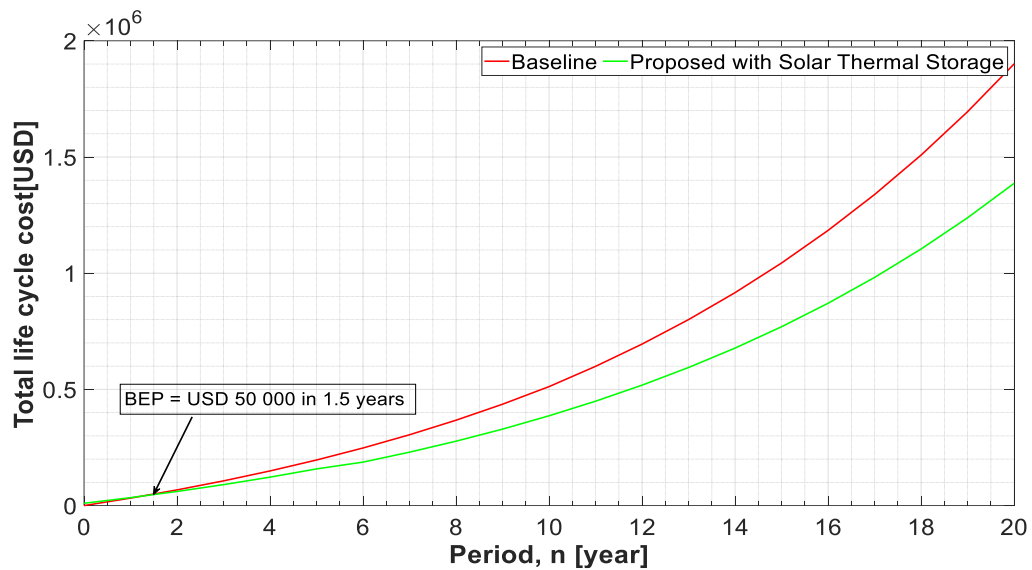


Figure 3.19: Life-cycle cost (LCC) analysis for the baseline and optimal system with a solar TES system

The analysis included two key input parameters: an average inflation rate of 5% and an annual electricity price increase of 10%. The term “average inflation cost” signifies the anticipated rise in overall prices for equipment and services, while the “annual electricity price increase rate” reflects the expected 10% annual growth in electricity expenses.

The graph illustrates the total LCC in USD for both the baseline and proposed systems over a 20-year period. The red line represents the baseline system, which demonstrates a consistent increase in costs due to its reliance on traditional energy sources, approaching USD 1.9 million by Year 20. In contrast, the green line representing the proposed system exhibits lower initial costs and a slower rate of increase, reaching approximately USD 1.4 million by the end of the observation period.

The BEP occurs when the overall costs of both systems intersect, as indicated by their respective cost curves, which account for initial investments and total annual expenses over 20 years. This intersection reveals that the proposed system reaches the BEP after 18 months of operation, with total costs of around USD 50 000.

The LCC analysis indicates that the implementation of the predictive model in conjunction with STES can result in 69% energy savings compared to solely relying on grid electricity.

This analysis highlights the long-term financial advantages of the proposed system, which enhances efficiency and reduces dependence on conventional energy sources. It also

highlights the economic sustainability of employing advanced forecasting techniques in brewery heating processes, particularly in the context of rising energy costs.

Furthermore, Figure 3.19 illustrates the variation in LCC for the proposed solar TES system, utilising the same financial parameters. The inflation rate indicates anticipated increases in equipment and service prices, while the increase in electricity prices suggests substantial annual growth in energy expenses.

3.6 CONCLUSION

This study successfully applied an ANN model to predict key performance metrics in microbrewery operations, focusing on power consumption. The ANN model can facilitate operational cost reductions of up to 20%, with projected annual savings of approximately USD 95 372.045, while simultaneously improving product quality and resource management. A dataset comprising 100 samples was compiled, which incorporated real-time operational data, meteorological information, and energy consumption metrics.

The ANN model exhibited high accuracy, with R-values for training datasets (0.99752, 0.99835, 0.99856, 0.99678, 0.85705), validation datasets (0.99680, 0.99790, 0.99560, 0.98845, 0.85638), and testing datasets (0.99012, 0.99670, 0.98234, 0.97560, 0.85606). The percentage deviations between the predicted and actual values were minimal, ranging from -5% to +10%, which affirmed the model's precision.

A sensitivity analysis was conducted to determine the influence of key input variables on the ANN forecasting model. The updated results indicate that variations in process temperature have a measurable and consistent impact on predicted power consumption, with higher temperature deviations associated with increased energy demand. The analysis also confirms that ingredient composition and thermal load profiles contribute significantly to fluctuations in model accuracy, reinforcing the importance of maintaining stable brewing and thermal operating conditions for optimal forecasting performance. Furthermore, the NAR model outperformed the NARX model in predictive accuracy, with strong R-values indicating its capability to model complex brewing relationships. The minimal deviations between predicted and actual energy consumption further confirmed the reliability of these models, which rendered them essential for optimising energy management strategies.

Additionally, the LCC analysis demonstrated that utilising the predictive model alongside solar TES can achieve energy cost savings of 69% relative to grid electricity. The solar

thermal solution can reach its BEP within 1.5 years of an initial investment of approximately USD 50 000, which indicates a strong ROI.

In conclusion, this study illustrated that the integration of a predictive model with renewable energy systems can assist breweries in reducing operational costs, enhancing sustainability, and realising significant financial benefits. By leveraging advanced predictive technologies, microbreweries can optimise energy consumption and contribute to a more sustainable brewing industry.

The key findings include the following:

- The ANN model demonstrated robust capability to predict power consumption, as evidenced by R-values that reflected a strong aptitude for modelling complex relationships. The MSE values remained low, normalised to less than 15% of maximum variability.
- The deviations between predicted and actual values produced by the model were minimal, typically ranging from 5% to 10%. This low level of discrepancy is critical for microbreweries that are seeking to enhance operational efficiency and effectively manage energy consumption.
- The insights derived from the ANN model can facilitate the optimisation of energy usage and process control, with the potential to reduce operational costs by 10% to 20% while simultaneously improving product quality.
- The predictions generated by the model provide valuable guidance for improved resource management and energy utilisation, thereby supporting sustainable practices and potentially decreasing energy consumption by 15% to 25%.

The forecasting framework developed in this chapter is also well suited for integration with emerging smart-grid and microgrid technologies. The NAR and NARX models' ability to provide short-term, high-accuracy predictions enables dynamic participation in demand-response programmes, tariff-responsive scheduling, and real-time coordination with distributed energy resources such as rooftop PV and thermal storage. As microbreweries increasingly adopt decentralised energy solutions, the adaptability of the proposed ANN approach and while the NARX model achieved regression values its capacity to update with

new data and respond to evolving load characteristics ensures long-term compatibility with advanced energy-management architectures. This positions the predictive-control system as a scalable, future-oriented tool capable of enhancing operational flexibility and resilience in modern industrial energy networks.

While the ANN-based hybrid energy-management method is robust, its broader applicability may vary across different microbrewery settings. System performance is influenced by local geographical and climatic conditions, including solar-irradiance levels, ambient temperatures, and seasonal patterns. These factors affect solar-thermal collector output, heat-pump efficiency, and cooling-load behaviour. Regional electricity-tariff structures, especially differences in ToU pricing and demand-charge policies, also shape the level of achievable cost savings. Brewery-specific factors such as production scale, scheduling routines, equipment configuration, TES capacity, and the reliability of local energy infrastructure further affect optimisation outcomes. Therefore, although the methodology is adaptable to many contexts, site-specific calibration that accounts for climate, tariff conditions, and infrastructure is essential to ensure accurate forecasting and meaningful energy and economic benefits.

Furthermore, this research addressed a significant gap in the application of ANNs in the brewing industry by providing practical solutions to enhance efficiency, reduce costs, and support sustainable practices. The findings underscored the potential of ANNs as valuable tools for improving the operational capabilities of microbreweries that can contribute to energy-efficient beer production. The successful implementation of this model promotes a more sustainable brewing industry, aligning with broader environmental goals and enhancing the competitiveness of microbreweries.

In terms of future research, these advancements in predictive modelling present opportunities for further enhancing energy optimisation strategies in the brewing industry. Future investigations should concentrate on integrating additional operational variables and real-time data to refine prediction accuracy. Exploring the utilisation of tailored ANN models in conjunction with external factors, such as ambient conditions and market trends, could yield more effective strategies for optimising production processes. This approach aimed to maximise resource utilisation and achieve significant cost savings, which specifically address the unique challenges and requirements of microbrewery operations.

CHAPTER 4:

OPTIMAL ENERGY MANAGEMENT OF HYBRID RENEWABLE ENERGY SYSTEMS FOR BREWERY THERMAL PROCESSES: ALGORITHM FORMULATION

4.1 INTRODUCTION

This chapter presents the development of an optimisation-based control model aimed at enhancing thermal energy efficiency in microbrewery operations.. The model coordinates the operation of a hybrid energy system comprising solar thermal collectors, a heat pump water-heating system, and a thermal energy storage (TES) unit, ensuring that these components function synergistically to meet process heat demands. Its primary objective is to minimise total energy costs by reducing electricity consumption, optimising TES charging and discharging cycles, and limiting reliance on grid-supplied power during high-tariff peak periods. The control strategy was implemented using the SCIP solver, which effectively handles non-linear equations and binary variables. The model operated under a ToU electricity tariff to enable cost-efficient energy distribution across key brewing processes.

The chapter is structured as follows: Section 4.2 presents the mathematical formulation, Section 4.3 outlines model implementation, Section 4.4 discusses simulation and economic results, Section 4.5 analyses the results, Section 4.6 summarises the key findings, and Section 4.7 concludes the chapter.

4.2 MATHEMATICAL MODEL DEVELOPMENT

4.2.1 Description of the system

In microbreweries, a significant portion of energy demand is associated with hot water used in processes such as mashing, sparging, fermentation vessel cleaning, and sanitation. To improve energy efficiency and reduce electricity costs, a hybrid system comprising solar thermal collectors, a heat pump, and a TES tank was proposed. The TES unit enables hot water to be stored during periods of low demand or high solar availability and used later during peak brewing operations. The heat pump consumes approximately one-third of the electrical energy compared to conventional electric water heaters [192]. Previous studies

energy balance is accurately captured and explicitly represented within the optimisation model.

- The heat pump operated at a constant power rating and functioned at full capacity when switched..

Small commercial brewery heat pumps typically use ON/OFF control rather than variable-speed modulation. Modelling full-load operation reflects actual equipment behavior and avoids the need for complex part-load performance equations in the optimisation routine.

- The COP of the heat pump was regarded as variable during operation.

COP depends on inlet-water temperature and ambient air conditions. This temperature-dependent behaviour was incorporated into the optimisation model to ensure that changes in heat-pump efficiency under different operating conditions were represented accurately.

- Heat losses from the solar collectors, heat pump unit, and water circulation system were deemed negligible.

These losses are small relative to the major process-heating demands in brewery operation. Excluding them simplifies the model structure and reduces computational burden without significantly affecting thermal-energy accuracy.

- Fluid flow throughout the system was assumed to be steady-state.

Only standby heat losses $Q_L(t)$ and hot-water draw-off $Q_D(t)$ were included. Transient flow behaviour was neglected because microbrewery demand patterns are stable and predictable, making steady-state representation sufficient for the optimisation constraints.

- Solar-irradiation data were sourced from the SANRAL meteorological database.

Hourly Global Horizontal Irradiance (GHI), Direct Normal Irradiance (DNI), and Diffuse Horizontal Irradiance (DHI) data for Bloemfontein were used as solar inputs. Linear interpolation was applied to fill minor gaps, ensuring consistency with the hourly optimisation time step and accurate representation of seasonal variation. consistency with the hourly optimisation time step and ensure accurate modelling of seasonal solar variation.

- The SCIP solver was configured with defined feasibility and optimality tolerances and a maximum runtime limit.

The SCIP solver applied specified feasibility and optimality thresholds to maintain numerical stability. A solver timeout ensured computational efficiency; if full convergence was not achieved within the allotted time, the best available feasible solution was accepted. Precision levels between 10^{-3} and 10^{-4} were used to support reliable simulation of the thermal-energy system.

The thermal performance of the ETC in microbrewery operations was analysed using Equation 4.1. ETCs provide hot water for various thermal processes, including water heating, mashing, wort boiling, lautering, cleaning-in-place, and sanitation. The total absorbed solar radiation can be estimated by multiplying each term by the appropriate transmittance-absorptance product [197]. It was assumed that the transmittance-absorptance product remained consistent across all radiation types. This simplification is reasonable because evacuated-tube collectors exhibit minimal variation in optical efficiency between beam, diffuse, and ground-reflected radiation, making a single $(\tau\alpha)$ value appropriate for modelling purposes. The proposed model simulated the thermal and electrical energy interactions in the system, which allowed for a comparative assessment of the performance between the baseline and hybrid configurations. Key parameters encompassed solar energy input, TES dynamics, heat pump operation, and electricity consumption from the grid, all evaluated under a ToU tariff structure.

Using the isotropic diffuse model, Equation 4.1 can be used to determine the total solar radiation incident on a tilted collector surface, derived from the components of solar irradiance [197–199]:

$$G(t) = (\tau\alpha) \left(G_{DNI}(t) \cos \theta_{\beta} + G_{DHI}(t) \left[\frac{1 + \cos \beta_{coll}}{2} \right] + G_{GHI}(t) \rho_g \left[\frac{1 - \cos \beta_{coll}}{2} \right] \right) \quad (4.1)$$

Where:

$G(t)$ is the variable total hourly solar radiation on a tilted collector (W/m^2);

G_{DNI} , G_{DHI} , and G_{GHI} are the direct normal irradiance, diffuse horizontal irradiance, and global horizontal irradiance respectively in (W/m^2);

τ is the transmittance of the glass;

α is the absorptance of the glass;

θ_{β} is the incidence angle of beam radiation ($^{\circ}$);

β_{coll} is the tilt angle ($^{\circ}$);

ρ_g is the foreground's albedo; and

A_{ap} is the aperture area of a collector (m^2).

To assess the thermal performance of the evacuated tube solar collector utilised in the beer brewing process, Equation 4.1 was integrated over the entire absorber surface area of the collector system. It was assumed that the aperture area remained constant across the collector surface. This simplification is appropriate, as evacuated-tube collectors are manufactured with uniform aperture geometry, ensuring consistent incident-radiation capture along the length of each tube. The thermal performance correlations are delineated in Equations 4.2 and 4.4, as adapted from Giglmayr et al. [197].

The total incident solar radiation intercepted by the collector tubes in the microbrewery system is expressed as:

$$I_B(t)A_{abs} = (A_{ap}) \left(G_{DNI}(t) \cos \theta_{\beta} + G_{DHI}(t) \left[\frac{1 + \cos \beta_{coll}}{2} \right] + G_{GHI}(t) \rho_g \left[\frac{1 - \cos \beta_{coll}}{2} \right] \right) \quad (4.2)$$

Where:

A_{ap} is the aperture area of a collector.

The performance equation for the total absorbed radiation by the solar collector tubes is as follows:

$$G(t)A_{abs} = (\tau\alpha)A_{ap}G(t) \quad (4.3)$$

Hence:

$$G(t) = (\tau\alpha) \left(G_{DNI}(t) \cos \theta_{\beta} + G_{DHI}(t) \left[\frac{1 + \cos \beta_{coll}}{2} \right] + G_{GHI}(t) \rho_g \left[\frac{1 - \cos \beta_{coll}}{2} \right] \right) \quad (4.4)$$

Equation 4.5 represents the useful heat transferred by the solar collector, ($Q_{coll}(t)$), during beer production. It quantifies the thermal energy gained by evaluating the increase in the temperature of the heat transfer fluid as it flows through the collector. This heat gain reflects the energy available to support critical brewing operations such as mashing or water heating, as given below [198]:

$$\dot{Q}_{coll}(t) = \dot{m}_c(t)C_{p,c}\Delta T_{cf}(t) = \dot{m}_c(t)C_{p,c}(T_{c,o}(t) - T_{c,i}(t)) \quad (4.5)$$

Where:

$\dot{m}_c(t)$ is the mass flow of the of the refrigerant solution (kg/s);
 $C_{p,c}$ is the specific heat capacity of refrigerant solution (J/kg °C);
 $T_{c,o}(t)$ is the outlet temperature of the refrigerant solution (°C); and
 $T_{c,i}(t)$ is inlet temperature of the refrigerant solution (°C).

Equation 4.6 expresses the energy balance of the solar collector employed in the brewery system, which represents the net thermal power output derived from the total incident solar irradiation. This equation encompasses both the energy input obtained from solar radiation and the losses sustained during operation, as follows [197]:

$$\dot{Q}_{coll}(t) = G(t)A_{abs} - \dot{Q}_{Loss_man}(t) \quad (4.6)$$

Equation 4.7 quantifies the heat loss from the manifold to the surrounding environment. This loss, denoted as $Q_{Loss_man}(t)$, is influenced by the temperature difference between the manifold and ambient air and is expressed as follows [200]:

$$Q_{Loss_man} = U_{Loss_man}A_{man}(T_{mean}(t) - T_{amb}(t)) \quad (4.7)$$

Furthermore, Equation 4.8 defines the mean temperature $T_{mean}(t)$ of the heat transfer fluid circulating through the solar collector system in the brewery, calculated as:

$$T_{mean}(t) = \left(\frac{T_{c,o}(t) + T_{c,i}(t)}{2} \right) \quad (4.8)$$

Therefore, Equation 4.9 is the net useful thermal output of the solar collector used in the brewery heating process, as follows:

$$\dot{Q}_{coll}(t) = G(t)A_{abs} - U_{Loss_man}A_{man} \left(\frac{T_{c,o}(t) + T_{c,i}(t)}{2} - T_{amb}(t) \right) \quad (4.9)$$

Where:

$G(t)$ is the variable total absorbed hourly solar radiation on a tilted collector (W/m²);

A_{abs} is the effective energy absorption area of the collector (m²);

U_{Loss_man} is the manifold heat loss coefficient as specified by the manufacturer data (W/m² °C);

A_{man} is the internal surface area of the manifold where heat losses occur (m²); and

$T_{amb}(t)$ is the ambient temperature at time t (°C).

In brewery heating systems, the inlet temperature of the refrigerant solution is typically assumed to be close to the ambient temperature. This assumption is reasonable as refrigerant loops in small brewery heat-pump systems are typically exposed to ambient air, causing the inlet temperature to align closely with outdoor conditions. This provides a practical and sufficiently accurate basis for modelling heat-pump inlet behaviour. The mass flow rate and outlet temperature are unknown and are estimated using the collector efficiency (η), which is defined as the ratio of useful heat output to incident solar energy in Equation 4.10 [197]:

$$\eta = \frac{G(t)A_{abs} - \dot{Q}_{Loss_man}(t)}{A_{abs} I_{\beta}(t)} \quad (4.10)$$

Where:

η is the tube efficiency of the collector, and substituting Equation 4.9 into Equation 4.10 gives the following expression:

$$\eta = \frac{1}{A_{abs} I_{\beta}(t)} \left(G(t)A_{abs} - U_{Loss_man} A_{man} \left[\frac{T_{c,o}(t) + T_{c,i}(t)}{2} - T_{amb}(t) \right] \right) \quad (4.11)$$

Firstly, to determine the outlet temperature of the refrigerant solution, Equation 4.11 is re-arranged and simplified to yield Equation 4.12:

$$T_{c,o}(t) = 2 \left(\frac{G(t)A_{abs} - \eta A_{abs} I_{\beta}(t)}{U_{Loss_man} A_{man}} + T_{amb}(t) \right) - T_{c,i}(t) \quad (4.12)$$

The rated power input of the heat pump at the compressor unit is given as:

$$\dot{W}_{comp} = P_{hp} t_{(h)} \quad (4.13)$$

The required electric power to the heat pump is controlled by the switch ($S_{hp}(t)$) and is given as [155]:

$$\dot{Q}_{hp} = P_{hp} t_{(h)} S_{hp}(t) \times COP \quad (4.14)$$

Where:

$P_{hp}(t)$ is the input power to the heat pump (kW); and

$S_{hp}(t)$ is the control switch of the heat pump.

4.2.2 Brewery process

In brewery operations, the electric resistive element integrated into each storage tank functions as an auxiliary heat source that ensures the availability of hot water and maintains the desired temperatures for processes such as water heating, mashing, and wort production. As shown in Figure 4.1, the secondary heat gain, denoted by $\dot{Q}_{EL,p}(t)$ (where p represents the specific process – water heating, mash, or wort), is supplied by the electric resistive element. This element operates under the control of a switch $S_{e,p}(t)$, which activates it to provide full-rated power as necessary in order to ensure consistent temperature regulation throughout each process. The heat gain from the electric resistive element for process p can be represented by Equation 4.15, based on [201]:

$$\dot{Q}_{EL,p}(t) = P_{EL,p} t_{(h)} S_{e,p}(t) \quad (4.15)$$

Where:

$\dot{Q}_{EL,p}(t)$ is the variable heat gain from the electric resistive element for process p (J);

$P_{EL,p}$ is the full-rated power supplied to the electric resistive element of the boiler process p (kW);

$S_{e,p}(t)$ is the control switch of the electric resistive element of the storage tank for process p (on/off status);

$t_{(h)}$ is the duration of time in hours (3 600s) when the element is active; and

p denotes the process type, where $p = w$ for water heating, $p = M$ for mashing, and $p = wort$ for wort storage.

Equation 4.16 represents the standby heat losses, $Q_{L,w}(t)$, through the casing of storage tanks used in brewery processes such as water heating, mashing, and wort boiling. These losses occur due to the thermal energy dissipated as a result of the temperature gradient between the contents of the tank and the surrounding ambient air. As illustrated in Figure 4.1, the standby loss for each process p (where p represents water, mash, or wort) depends on the heat loss coefficient of the tank, its surface area, and the temperature differential between the stored fluid and the external environment. This relationship is quantitatively expressed as follows [5]:

$$\dot{Q}_{L,p}(t) = U_{s,p}t_{(h)}A_{s,p}(T_{s,p}(t) - T_{amb}(t)) \quad (4.16)$$

Where:

$\dot{Q}_{L,p}(t)$ is the standby thermal loss through the tank casing for process p in J;

$U_{s,p}$ is the heat loss coefficient of the storage tank for process p in $\text{W}/\text{m}^2 \text{ } ^\circ\text{C}$;

$A_{s,p}$ is the surface area of the storage tank for process p in m^2 ;

$T_{s,p}(t)$ is the variable temperature of the water or solution inside the tank for process p ($^\circ\text{C}$);

$T_{amb}(t)$ is the variable ambient temperature of the surrounding air in $^\circ\text{C}$;

$t_{(h)}$ is the duration of time in hours (3 600 seconds) over which the loss is considered; and

p denotes the process type, where $p = w$ for water heating, $p = M$ for mashing, and $p = wort$ for wort boiling.

Equation 4.17 represents the thermal losses $Q_{D,p}(t)$ caused by hot water demand in brewery processes. Each time hot water is needed, the demand flow rate is activated, which causes the temperature $T_{s,p}(t)$ to drop as cold water enters the tank. The cold water flows in to maintain a constant volume in the tank. These losses are calculated as follows [5]:

$$\dot{Q}_{D,p}(t) = C_{p,p}\dot{W}_{D,p}(t)(T_{s,p}(t) - T_{m,p}(t)) \quad (4.17)$$

Where:

$\dot{Q}_{D,p}(t)$ is the heat loss due to hot water demand for process p in J;

$C_{p,p}$ is the specific heat capacity of the fluid for process p in $\text{J}/\text{kg } ^\circ\text{C}$;

$c_{p,w}$ is the specific heat capacity of the water ($4\,184 \text{ J}/\text{kg } ^\circ\text{C}$);

$c_{p,M}$ is the specific heat capacity of the mash mixture ($3\,730 \text{ J}/\text{kg } ^\circ\text{C}$);

$c_{p,wort}$ is the specific heat capacity of the wort mixture ($4\,100 \text{ J}/\text{kg } ^\circ\text{C}$);

$\dot{W}_{D,p}(t)$ is the hot water demand flow rate for process p in kg/h ;

$T_{s,p}(t)$ is the variable tank temperature for process p in $^\circ\text{C}$; and

$T_{m,p}(t)$ is the temperature of the inlet (municipal) water for process p in $^\circ\text{C}$.

Equation 4.18 expresses the energy balance $\dot{Q}_{s,p}(t)$, for each process p , formulated as a first-order differential equation that represents the rate of thermal energy change in the respective storage tank or boiler.

$$\dot{Q}_{s,p}(t) = M_p c_{p,p} \dot{T}_{s,p} \quad (4.18)$$

Where:

$\dot{Q}_{s,p}(t)$ is the rate of thermal energy change for process p in W;

M_p is the mass of the medium or fluid in the tank for process p in kg;

$c_{p,p}$ is the specific heat capacity of the medium for process p in J/kg·°C; and

$\dot{T}_{s,p}$ is the time derivative of the fluid temperature inside the tank in °C.

4.2.2.1 Water heating

Equation 4.19 expresses the energy balance $\dot{Q}_{s,w}(t)$ for the water heating process w , which accounts for both heat gains and losses in the system. The energy gains from the system included contributions from the collector energy, $\dot{Q}_{coll}(t)$, the energy supplied by the heat pump, $\dot{Q}_{HP}(t)$, and the energy supplied by the electric resistive element, $\dot{Q}_{EL,w}(t)$, for the heating process of the water. The energy losses in the system are due to the hot water demand, $\dot{Q}_{D,w}$, and standby losses, $\dot{Q}_{L,w}(t)$, which represent power losses through the casing material. The resulting energy balance for the water heating process is given by Equation 4.19:

$$\dot{Q}_{s,w}(t) = M_w c_{p,w} \dot{T}_{s,w} = \dot{Q}_{coll}(t) + \dot{Q}_{HP}(t) + \dot{Q}_{EL,w}(t) - \dot{Q}_{L,w}(t) - \dot{Q}_{D,w}(t) \quad (4.19)$$

Where:

$\dot{Q}_{s,w}(t)$ is the rate of thermal energy change for water heating (W);

M_w is the water mass inside the water storage tank (kg);

$c_{p,w}$ is the heat capacity of water (4 184 J/kg/°C);

$\dot{T}_{s,w}$ is the derivative of the temperature variation of the water in the storage tank (°C);

$\dot{Q}_{coll}(t)$ is the energy collected from external sources;

$\dot{Q}_{HP}(t)$ is the energy supplied by the heat pump;

$\dot{Q}_{EL,w}(t)$ is the energy supplied by the electric resistive element for water heating;

$\dot{Q}_{L,w}(t)$ is the standby losses through the casing of the water storage tank; and

$\dot{Q}_{D,w}(t)$ is the hot water demand.

Equation 4.20 is obtained by substituting Equation 4.9 for the solar thermal gain $\dot{Q}_{coll}(t)$,

Equation 4.14 for the heat pump power input \dot{Q}_{hp} , and Equations 4.15 to 4.17 for the auxiliary electric heating $\dot{Q}_{EL,p}(t)$, standby losses $\dot{Q}_{L,p}(t)$, and demand losses $\dot{Q}_{D,p}(t)$. The process-specific subscripts p are replaced with w for the water heating process. Substituting these into the general energy balance (Equation 4.19) results in the net rate of heat change in the water storage tank, $\dot{Q}_{s,w}(t)$.

$$\begin{aligned} \dot{Q}_{s,w}(t) = M_w C_{p,w} \dot{T}_{s,w} = & G(t)A_{abs} - U_{Loss_{man}} A_{man} \left(\frac{T_{c,o}(t) + T_{c,i}(t)}{2} - T_{amb}(t) \right) \\ & + P_{hp} t_{(h)} S_{hp}(t) \times COP + P_{EL,w} t_{(h)} S_{e,w}(t) - U_{s,w} t_{(h)} A_{s,w} (T_{s,w}(t) - T_{amb}(t)) \\ & - C_{p,w} \dot{W}_{D,w}(t) (T_{s,w}(t) - T_{amb}(t)) \end{aligned} \quad (4.20)$$

$$\text{Let } Y_w(t) = G(t)A_{abs} - U_{man_Loss} A_{man} \left(\frac{T_{c,o}(t) + T_{c,i}(t)}{2} - T_{amb}(t) \right) \quad (4.21)$$

Substituting Equation 4.21 into Equation 4.20 and simplifying further yields Equation 4.22:

$$\begin{aligned} M_w C_{p,w} \dot{T}_{s,w} = & Y_w(t) + P_{hp} t_{(h)} S_{hp}(t) \times COP + P_{EL,w} t_{(h)} S_{e,w}(t) \\ & - U_{s,w} t_{(h)} A_{s,w} (T_{s,w}(t) - T_{amb}(t)) - C_{p,w} \dot{W}_{D,w}(t) (T_{s,w}(t) - T_w(t)) \end{aligned} \quad (4.22)$$

Equation 4.23 expresses the temperature of the water inside the storage tank, $\dot{T}_{s,w}$, as the key state variable that governs the thermal dynamics of the system. Applying the energy balance and re-arranging Equation 4.22 to make $\dot{T}_{s,w}$ the subject gives the following expression:

$$\begin{aligned} \dot{T}_{s,w} = & \frac{Y_w(t)}{M_w C_{p,w}} + \frac{P_{hp} t_{(h)} S_{hp}(t) \times COP}{M_w C_{p,w}} + \frac{P_{EL,w} t_{(h)} S_{e,w}(t)}{M_w C_{p,w}} \\ & - \frac{U_{s,w} t_{(h)} A_{s,w} (T_{s,w}(t) - T_{amb}(t))}{M_w C_{p,w}} \\ & - \frac{C_{p,w} \dot{W}_{D,w}(t) (T_{s,w}(t) - T_{m,w}(t))}{M_w C_{p,w}} \end{aligned} \quad (4.23)$$

Equation 4.23 is further simplified to obtain Equation 4.24:

$$\begin{aligned} \dot{T}_{s,w}(t) = & - \left(\frac{U_{s,w}t(h)A_{s,w} + C_{p,w}\dot{W}_{D,w}(t)}{M_w C_{p,w}} \right) T_{s,w}(t) + \frac{P_{hp}t(h) \times COP}{M_w C_{p,w}} S_{hp}(t) + \frac{P_{EL,w}t(h)}{M_w C_{p,w}} S_{e,w}(t) \\ & + \left(\frac{Y_w(t)}{M_w C_{p,w}} + \frac{U_{s,w}t(h)A_{s,w}T_a(t) + C_{p,w}W_{D,w}(t)T_m(t)}{M_w C_{p,w}} \right) \end{aligned} \quad (4.24)$$

The energy balance equation (Equation 4.24) is separated into components in Equations 4.25 to 4.28, forming the state, control, and constraint equations for the state-space formulation [5]:

$$\alpha(t) = \frac{U_{s,w}t(h)A_{s,w} + C_{p,w}\dot{W}_{D,w}(t)}{M_w C_{p,w}} \quad (4.25)$$

$$\beta_1 = \frac{P_{hp}t(h) \times COP}{M_w C_{p,w}} \quad (4.26)$$

$$\beta_2 = \frac{P_{EL,w}t(h)}{M_w C_{p,w}} \quad (4.27)$$

$$\gamma(t) = \frac{Y_w(t)}{M_w C_{p,w}} + \frac{U_{s,w}t(h)A_{s,w}T_a(t) + C_{p,w}W_{D,w}(t)T_m(t)}{M_w C_{p,w}} \quad (4.28)$$

In the state-space representation (Equation 4.29), the state variable is $\dot{T}_{s,w}(t)$, the control or decision variables are $S_{hp}(t)$ and $S_{e,w}(t)$, and the disturbance variable in the system is γ [5]:

$$\dot{T}_{s,w} = -\alpha(t)T_{s,w}(t) + \beta_1 S_{hp}(t) + \beta_2 S_{e,w}(t) + \gamma(t) \quad (4.29)$$

Where:

α represents the terms of initial variables of the system;

β_1 and β_2 define the terms of the control variable of the system;

γ describes the terms of disturbance of the system;

$S_{h,p}$ describes the control input related to the heat pump operation; and

$S_{e,w}$ describes the binary switching control input.

4.2.2.2 Mashing process

Equation 4.30 describes the energy balance $\dot{Q}_{s,M}(t)$, for the mashing process, accounting for all relevant heat gains and losses in the mash boiler:

$$\dot{Q}_{s,M}(t) = M_M c_{p,M} \dot{T}_{s,M} = \dot{Q}_{coll}(t) + \dot{Q}_{D,W}(t) + \dot{Q}_{EL,M}(t) - \dot{Q}_{L,M}(t) - \dot{Q}_{D,M}(t) \quad (4.30)$$

Where:

$\dot{Q}_{s,M}(t)$ is the rate of thermal energy change in the mash boiler (W);

M_M is the mash mass inside the storage tank (kg);

$c_{p,M}$ is the heat capacity of the mash mixture (4 184 J/kg/°C);

$\dot{T}_{s,M}$ is the derivative of the temperature variation of the mash inside the tank (°C);

$\dot{Q}_{coll}(t)$ is the energy collected from external sources (e.g., solar thermal);

$\dot{Q}_{D,W}(t)$ is the energy required to meet the mash mixture demand from the water heating system (W);

$\dot{Q}_{EL,M}(t)$ is the energy supplied by the electric resistive tank for the mashing process (W);

$\dot{Q}_{L,M}(t)$ is the standby heat losses through the mash boiler casing (W); and

$\dot{Q}_{D,M}(t)$ is the energy demand due to hot water use in the mashing process (W).

Equation 4.31 is obtained by substituting Equation 4.9 for the solar thermal gain $\dot{Q}_{coll}(t)$, and Equations 4.15 to 4.17 for the auxiliary electric heating $\dot{Q}_{EL,p}(t)$, standby losses $\dot{Q}_{L,p}(t)$, and demand losses $\dot{Q}_{D,p}(t)$, respectively. The process-specific subscripts p are replaced with M for the mashing process in Equations 4.15 to 4.17. Substituting these into the general energy balance (Equation 4.30) results in the net rate of heat change in the water storage tank, $\dot{Q}_{s,M}(t)$.

$$\begin{aligned} \dot{Q}_{s,M}(t) = M_M c_{p,M} \dot{T}_{s,M} = & G(t) A_{abs} - U_{Loss_man} A_{man} \left(\frac{T_{c,o}(t) + T_{c,i}(t)}{2} - T_{amb}(t) \right) \\ & + c_{p,w} \dot{W}_{D,w}(t) (T_{s,w}(t) - T_{m,w}(t)) + P_{EL,M} t_{(h)} S_{e,M}(t) - U_{s,M} t_{(h)} A_{s,M} (T_{s,M}(t) - \\ & T_{amb}(t)) - c_{p,M} \dot{W}_{D,M}(t) (T_{s,M}(t) - T_{amb}(t)) \end{aligned} \quad (4.31)$$

$$\text{Let } Y_M(t) = G(t)A_{abs} - U_{Loss_man}A_{man} \left(\frac{T_{c,o}(t)+T_{c,i}(t)}{2} - T_{amb}(t) \right) \quad (4.32)$$

Substituting Equation 4.32 into Equation 4.31 and simplifying further yields Equation 4.33:

$$\begin{aligned} M_M C_{p,M} \dot{T}_{s,M} = & Y_M(t) + C_{p,w} \dot{W}_{D,w}(t) (T_{s,w}(t) - T_{m,w}(t)) + P_{EL,M} t_{(h)} S_{e,M}(t) \\ & - U_{s,M} t_{(h)} A_{s,M} (T_{s,M}(t) - T_{amb}(t)) - C_{p,M} \dot{W}_{D,M}(t) (T_{s,M}(t) - T_{m,M}(t)) \end{aligned} \quad (4.33)$$

Equation 4.34 expresses the temperature of the water in the storage tank, $\dot{T}_{s,M}$, as the key state variable that governs the thermal dynamics of the system. Applying the energy balance and re-arranging Equation 4.33 to make $\dot{T}_{s,M}$ the subject gives the following expression:

$$\begin{aligned} \dot{T}_{s,M} = & \frac{Y_M(t)}{M_M C_{p,M}} + \frac{C_{p,w} \dot{W}_{D,w}(t) (T_{s,w}(t) - T_{m,w}(t))}{M_M C_{p,M}} + \frac{P_{EL,M} t_{(h)} S_{e,M}(t)}{M_M C_{p,M}} \\ & - \frac{U_{s,M} t_{(h)} A_{s,M} (T_{s,M}(t) - T_{amb}(t))}{M_M C_{p,M}} - \frac{C_{p,M} \dot{W}_{D,M}(t) (T_{s,M}(t) - T_{m,M}(t))}{M_M C_{p,M}} \end{aligned} \quad (4.34)$$

Simplified once more yields Equation 4.35:

$$\begin{aligned} \dot{T}_{s,M}(t) = & - \left(\frac{U_{s,M} t_{(h)} A_{s,M} + C_{p,M} \dot{W}_{D,M}(t)}{M_M C_{p,M}} \right) T_{s,M}(t) + \frac{P_{EL,M} t_{(h)} S_{e,M}(t)}{M_M C_{p,M}} + \\ & \left(\frac{Y_w(t)}{M_M C_{p,M}} + \frac{C_{p,w} \dot{W}_{D,w}(t)}{M_M C_{p,M}} T_{s,w}(t) - \frac{C_{p,w} \dot{W}_{D,w}(t)}{M_M C_{p,M}} T_{m,w}(t) + \frac{U_{s,M} t_{(h)} A_{s,M}}{M_M C_{p,M}} T_{amb}(t) \right) \\ & + \frac{C_{p,M} \dot{W}_{D,M}(t)}{M_M C_{p,M}} T_{m,M}(t) \end{aligned} \quad (4.35)$$

The energy balance equation (Equation 4.35) is separated into components in Equations 4.36 to 4.38 to form the state, control, and constraint equations for the state-space formulation [5]:

$$\alpha(t) = \frac{U_{s,M} t_{(h)} A_{s,M} + C_{p,M} \dot{W}_{D,M}(t)}{M_M C_{p,M}} \quad (4.36)$$

$$\beta_2 = \frac{P_{EL,M} t_{(h)}}{M_M C_{p,M}} \quad (4.37)$$

$$\gamma(t) = \frac{Y_M(t)}{M_M C_{p,M}} + \frac{C_{p,w} \dot{W}_{D,w}(t) T_{s,w}(t) - C_{p,w} \dot{W}_{D,w}(t) T_{m,w}(t)}{M_M C_{p,M}} + \frac{U_{s,M} t_{(h)} A_{s,M} T_{amb}(t) + C_{p,M} \dot{W}_{D,M}(t) T_{m,M}(t)}{M_M C_{p,M}} \quad (4.38)$$

In the state-space representation (Equation 4.39), the state variable is $\dot{T}_{s,M}(t)$, the control or decision variables are $S_{e,M}(t)$ and the disturbance variable in the system is γ [5]:

$$\dot{T}_{s,M} = -\alpha(t) T_{s,M}(t) + \beta_2 S_{e,M}(t) + \gamma(t) \quad (4.39)$$

Where:

α represents the terms of initial variables of the system;

β_2 defines the terms of the control variable of the system;

γ describes the terms of disturbance of the system;

$S_{h,p}$ describes the control input related to the heat pump operation; and

$S_{e,M}$ describes the binary switching control input.

4.2.2.3 Wort boiling process

Equation 4.40 describes the energy balance $\dot{Q}_{s,wort}(t)$, for the mashing process, which accounts for all relevant heat gains and losses in the mash boiler:

$$\dot{Q}_{s,wort}(t) = M_{wort} c_{p,wort} \dot{T}_{s,wort} = \dot{Q}_{coll}(t) + \dot{Q}_{D,M}(t) + \dot{Q}_{EL,wort}(t) - \dot{Q}_{L,wort}(t) - \dot{Q}_{D,wort}(t) \quad (4.40)$$

Where:

$\dot{Q}_{s,wort}(t)$ is the rate of thermal energy change in the wort boiler (W);

M_{wort} is the wort mass inside the storage tank (kg);

$c_{p,wort}$ is the heat capacity of the wort mixture (4 184 J/kg/°C);

$\dot{T}_{s,wort}$ is the derivative of the temperature variation of the mash inside the tank (°C);

$\dot{Q}_{coll}(t)$ is the energy collected from external sources (e.g., solar thermal);

$\dot{Q}_{D,M}(t)$ is the energy required to meet the wort mixture demand from the water heating system (W);

$\dot{Q}_{EL,wort}(t)$ is the energy supplied by the electric resistive tank for the wort boiling process (W);

$\dot{Q}_{L,wort}(t)$ is the standby heat losses through the wort boiler casing (W); and

$\dot{Q}_{D,wort}(t)$ is the energy demand due to hot water used in the wort boiling process (W).

Equation 4.41 is obtained by substituting Equation 4.9 for the solar thermal gain $\dot{Q}_{coll}(t)$, and Equations 4.15 to 4.17 for the auxiliary electric heating $\dot{Q}_{EL,p}(t)$, standby losses $\dot{Q}_{L,p}(t)$, and demand losses $\dot{Q}_{D,p}(t)$ respectively. The process-specific subscripts p are replaced with M for the mashing process in Equations 4.15 to 4.17. Substituting these into the general energy balance (Equation 4.40) results in the net rate of heat change in the water storage tank, $\dot{Q}_{s,M}(t)$.

$$\begin{aligned} \dot{Q}_{s,wort}(t) = M_{wort}C_{p,wort}\dot{T}_{s,wort} = & G(t)A_{abs} - U_{Loss_{man}}A_{man}\left(\frac{T_{c,o}(t) + T_{c,i}(t)}{2} - T_{amb}(t)\right) \\ & + C_{p,M}\dot{W}_{D,M}(t)\left(T_{s,M}(t) - T_{m,M}(t)\right) + P_{EL,wort}t_{(h)}S_{e,wort}(t) - \\ & U_{s,wort}t_{(h)}A_{s,wort}\left(T_{s,wort}(t) - T_{amb}(t)\right) - C_{p,wort}\dot{W}_{D,wort}(t)\left(T_{s,wort}(t) - T_{amb}(t)\right) \end{aligned} \quad (4.41)$$

$$\text{Let } Y_{wort}(t) = G(t)A_{abs} - U_{Loss_{man}}A_{man}\left(\frac{T_{c,o}(t)+T_{c,i}(t)}{2} - T_{amb}(t)\right) \quad (4.42)$$

Substituting Equation 4.42 into Equation 4.41 and simplifying further yields Equation 4.43:

$$\begin{aligned} M_{wort}C_{p,wort}\dot{T}_{s,wort} = & Y_{wort}(t) + C_{p,M}\dot{W}_{D,M}(t)\left(T_{s,M}(t) - T_{m,M}(t)\right) + P_{EL,wort}t_{(h)}S_{e,wort}(t) \\ & - U_{s,wort}t_{(h)}A_{s,wort}\left(T_{s,wort}(t) - T_{amb}(t)\right) - C_{p,wort}\dot{W}_{D,wort}(t)\left(T_{s,wort}(t) - T_{m,wort}(t)\right) \end{aligned} \quad (4.43)$$

Equation 4.44 expresses the temperature of the water inside the storage tank, $\dot{T}_{s,M}$, as the key state variable that governs the thermal dynamics of the system. Applying the energy balance and re-arranging Equation 4.43 to make $\dot{T}_{s,M}$ the subject yields the following equation:

$$\begin{aligned} \dot{T}_{s,wort} = & \frac{Y_{wort}(t)}{M_{wort}C_{p,wort}} + \frac{C_{p,M}\dot{W}_{D,M}(t)\left(T_{s,M}(t) - T_{m,M}(t)\right)}{M_{wort}C_{p,wort}} \\ & + \frac{P_{EL,wort}t_{(h)}S_{e,wort}(t)}{M_{wort}C_{p,wort}} - \frac{U_{s,wort}t_{(h)}A_{s,wort}\left(T_{s,wort}(t) - T_{amb}(t)\right)}{M_{wort}C_{p,wort}} \\ & - \frac{C_{p,wort}\dot{W}_{D,wort}(t)\left(T_{s,wort}(t) - T_{m,wort}(t)\right)}{M_{wort}C_{p,wort}} \end{aligned} \quad (4.44)$$

Simplified once more gives Equation 4.45:

$$\begin{aligned}
\dot{T}_{s,wort}(t) = & - \left(\frac{U_{s,wort} t^{(h)} A_{s,wort} + C_{p,wort} \dot{W}_{D,wort}(t)}{M_{wort} C_{p,wort}} \right) T_{s,wort}(t) \\
& + \frac{P_{EL,wort} t^{(h)}}{M_{wort} C_{p,wort}} S_{e,wort}(t) \\
& + \left(\frac{Y_{wort}(t)}{M_{wort} C_{p,wort}} + \frac{C_{p,M} \dot{W}_{D,M}(t)}{M_{wort} C_{p,wort}} T_{s,M}(t) - \frac{C_{p,M} \dot{W}_{D,M}(t)}{M_{wort} C_{p,wort}} T_{m,M}(t) \right. \\
& \left. + \frac{U_{s,wort} t^{(h)} A_{s,wort}}{M_{wort} C_{p,wort}} T_{amb}(t) + \frac{C_{p,wort} \dot{W}_{D,wort}(t)}{M_{wort} C_{p,wort}} T_{m,wort}(t) \right)
\end{aligned} \tag{4.45}$$

The energy balance equation (Equation 4.45) is separated into components in Equations 4.46 to 4.48 to form the state, control, and constraint equations for the state-space formulation [5]:

$$\alpha(t) = \frac{U_{s,wort} t^{(h)} A_{s,wort} + C_{p,wort} \dot{W}_{D,wort}(t)}{M_{wort} C_{p,wort}} \tag{4.46}$$

$$\beta = \frac{P_{EL,wort} t^{(h)}}{M_{wort} C_{p,wort}} \tag{4.47}$$

$$\begin{aligned}
\gamma(t) = & \frac{Y_{wort}(t)}{M_{wort} C_{p,wort}} + \frac{C_{p,M} \dot{W}_{D,M}(t) T_{s,M}(t) - C_{p,M} \dot{W}_{D,M}(t) T_{m,M}(t)}{M_{wort} C_{p,wort}} \\
& + \frac{U_{s,wort} t^{(h)} A_{s,wort} T_{amb}(t) + C_{p,wort} \dot{W}_{D,wort}(t) T_{m,wort}(t)}{M_{wort} C_{p,wort}}
\end{aligned} \tag{4.48}$$

In the state-space representation (Equation 4.49), the state variable is $\dot{T}_{s,wort}(t)$, the control or decision variables are $S_{e,wort}(t)$, and the disturbance variable in the system is γ [14]:

$$\dot{T}_{s,wort} = -\alpha(t) T_{s,wort}(t) + \beta_2 S_{e,wort}(t) + \gamma(t) \tag{4.49}$$

Where:

α represents the terms of the initial variables of the system;

β defines the terms of the control variable of the system;

γ describes the terms of disturbance of the system;

$S_{h,p}$ describes the control input related to the heat pump operation; and

$S_{e,M}$ describes the binary switching control input.

4.2.3 Discretising the brewery hot water temperature

4.2.3.1 Water heating

Equation 4.49 represents a continuous model of hot water temperature characterised by an infinite number of degrees of freedom. To facilitate time-dependent simulations, the equation is discretised into successive time intervals, denoted by the k-th time step. This discretisation simplifies the complexity of the continuous formulation, which enhances computational feasibility. By transitioning to a discrete function space, a finite set of basis functions is employed to achieve accurate temperature approximations under specified initial and boundary conditions. Subsequently, the forward Euler method is applied, and the spatial equation is articulated in Equation 4.50 to model temperature at each time step:

$$T_{k+1} = T_k(1 - t_{s,w}\alpha_k) + t_{s,w}\beta_1 S_{hp_k} + t_{s,w}\beta_2 S_{e,w_k} + t_{s,w}\gamma_k \quad (4.50)$$

Equation 4.50 defines the first computed temperature value T_{k+1} following the initial value T_k , evaluated at the sampling time $t_{s,w}$. When the temperature is expressed as T_1 at $k=0$, the initial value becomes T_0 . The associated control variable and disturbance term are denoted by S_{hp_0} , S_{e,w_0} , and γ_0 respectively. Incorporating these terms, the discrete-time temperature model is as shown in Equation 4.51:

$$T_1 = T_0(1 - t_{s,w}\alpha_0) + t_{s,w}\beta_1 S_{hp_0} + t_{s,w}\beta_2 S_{e,w_0} + t_{s,w}\gamma_0 \quad (4.51)$$

Equation 4.52 is similarly expressed for the next interval, $k=1$, as follows: then T_2 is

$$T_2 = T_1(1 - t_{s,w}\alpha_1) + t_{s,w}\beta_1 S_{hp_1} + t_{s,w}\beta_2 S_{e,w_1} + t_{s,w}\gamma_1 \quad (4.52)$$

Considering the substitution of T_1 in Equation 4.51, Equation 4.50 was substituted into Equation 4.52, which resulted in Equation 4.53. After factorising, the expanded form of T_2 is shown in Equation 4.54 as:

$$T_2 = [T_0(1 - t_{s,w}\alpha_0) + t_{s,w}\beta_1 S_{hp_0} + t_{s,w}\beta_2 S_{e,w_1} + t_{s,w}\gamma_0](1 - t_{s,w}\alpha_1) + t_{s,w}\beta_1 S_{hp_1} + t_{s,w}\beta_2 S_{e,w_1} + t_{s,w}\gamma_1, \quad (4.53)$$

$$T_2 = T_0[(1 - t_{s,w}\alpha_0)(1 - t_{s,w}\alpha_1)] + t_{s,w}[(1 - t_{s,w}\alpha_1)S_{hp_0} + S_{hp_1}]\beta_1 + t_{s,w}[(1 - t_{s,w}\alpha_1)S_{e,w_0} + S_{e,w_1}]\beta_2 + t_{s,w}[(1 - t_{s,w}\alpha_1)\gamma_0 + \gamma_1] \quad (4.54)$$

Furthermore, applying the same steps used from Equation 4.51 to Equation 4.54 for the case where $k=2$, the expression for T_3 is given in Equation 4.55:

$$\begin{aligned}
T_3 = & T_0[(1 - t_{s,w}\alpha_0)(1 - t_{s,w}\alpha_1)(1 - t_{s,w}\alpha_2)] \\
& + t_{s,w}[(1 - t_{s,w}\alpha_1)(1 - t_{s,w}\alpha_2)S_{hp_0} + (1 - t_{s,w}\alpha_2)S_{hp_1} + S_{hp_2}]\beta_1 + \\
& t_{s,w}[(1 - t_{s,w}\alpha_1)(1 - t_{s,w}\alpha_2)S_{e,w_0} + (1 - t_{s,w}\alpha_2)S_{e,w_1} + S_{e,w_2}]\beta_2 \\
& + t_{s,w} [(1 - t_{s,w}\alpha_1)(1 - t_{s,w}\alpha_2)\gamma_0 + (1 - t_{s,w}\alpha_2)\gamma_1 + \gamma_2]
\end{aligned} \tag{4.55}$$

Equations for subsequent expressions can be obtained by repeating the previous steps. The resulting general expression of the discretisation relationship is shown in Equation 4.56:

$$\begin{aligned}
T_{k+1} = & T_0 \left[\prod_{j=0}^k (1 - t_{s,w}\alpha_j) \right] + \left[t_{s,w} \sum_{j=0}^k S_{hp,w_j} \prod_{i=j+1}^k (1 - t_{s,w}\alpha_i) \right] \beta_1 + \left[t_{s,w} \sum_{j=0}^k S_{e,w_j} \prod_{i=j+1}^k (1 - t_{s,w}\alpha_i) \right] \beta_2 \\
& + t_{s,w} \sum_{j=0}^k \gamma_j \prod_{i=j+1}^k (1 - t_{s,w}\alpha_i)
\end{aligned} \tag{4.56}$$

Additionally, Equation 4.56 enables the visualisation of temperature changes at each sampling time $t_{s,w}$ at an interval of k , starting from the initial temperature T_0 of the water in the storage tank. It also incorporates the binary control signal (1 for ON, 0 for OFF) for S_{e,w_j} S_{hp,w_j} and accounts for disturbance factors that affect the system.

4.2.3.2 Mashing process

Equation 4.39 represented a continuous model of hot water temperature during the mashing process, featuring infinite degrees of freedom. To render it suitable for time-dependent simulations, the equation is discretised into successive time intervals, denoted by the k -th time step. This discretisation reduces the complexity of the continuous formulation, thereby enhancing its computational feasibility. By transitioning to a discrete function space, a finite set of basis functions is employed to achieve accurate temperature approximations under specified initial and boundary conditions.

Subsequently, the forward Euler method is applied, and the spatial equation is articulated in Equation 4.57 to model temperature at each time step:

$$T_{k+1} = T_k(1 - t_{s,M}\alpha_k) + t_{s,M}\beta S_{e,M_k} + t_{s,M}\gamma_k \tag{4.57}$$

Equation 4.57 defines the first computed temperature value T_{k+1} following the initial value T_k , evaluated at the sampling time $t_{s,M}$. When the temperature is expressed as T_1 at $k=0$, the initial value becomes T_0 . The associated control variable and disturbance term are denoted as S_{e,M_0} and γ_0 . Incorporating these terms, the discrete-time temperature model is as shown in Equation 4.58:

$$T_1 = T_0(1 - t_{s,M}\alpha_0) + t_{s,M}\beta S_{e,M_0} + t_{s,M}\gamma_0 \quad (4.58)$$

Equation 4.59 is similarly expressed for the next interval, $k=1$, as follows: then T_2 is

$$T_2 = T_1(1 - t_{s,M}\alpha_1) + t_{s,M}\beta S_{e,M_1} + t_{s,M}\gamma_1 \quad (4.59)$$

Considering the substitution of T_1 in Equation 4.58, Equation 4.57 was substituted into Equation 4.59, which resulted in Equation 4.60. After factorising, the expanded form of T_2 is shown in Equation 4.61 as:

$$T_2 = [T_0(1 - t_{s,M}\alpha_0) + t_{s,M}\beta S_{e,M_0} + t_{s,M}\gamma_0](1 - t_{s,M}\alpha_1) + t_{s,M}\beta S_{e,M_1} + t_{s,M}\gamma_1 \quad (4.60)$$

$$T_2 = T_0[(1 - t_{s,M}\alpha_0)(1 - t_{s,M}\alpha_1)] + t_{s,M}[(1 - t_{s,M}\alpha_1)S_{e,M_0} + S_{e,M_1}]\beta + t_{s,M}[(1 - t_{s,M}\alpha_1)\gamma_0 + \gamma_1] \quad (4.61)$$

Furthermore, applying the same steps used from Equation 4.58 to Equation 4.61 for the case where $k=2$, the expression for T_3 is given in Equation 4.62:

$$T_3 = T_0[(1 - t_{s,M}\alpha_0)(1 - t_{s,M}\alpha_1)(1 - t_{s,M}\alpha_2)] + t_{s,M}[(1 - t_{s,M}\alpha_1)(1 - t_{s,M}\alpha_2)S_{e,M_0} + (1 - t_{s,M}\alpha_2)S_{e,M_1} + S_{e,M_2}]\beta + t_{s,M}[(1 - t_{s,M}\alpha_1)(1 - t_{s,M}\alpha_2)\gamma_0 + (1 - t_{s,M}\alpha_2)\gamma_1 + \gamma_2] \quad (4.62)$$

Equations for subsequent expressions can be obtained by repeating the previous steps. The resulting general expression of the discretisation relationship is shown in Equation 4.63:

$$T_{k+1} = T_0 \left[\prod_{j=0}^k (1 - t_{s,M}\alpha_j) \right] + \left[t_{s,M} \sum_{j=0}^k S_{e,M_j} \prod_{i=j+1}^k (1 - t_{s,M}\alpha_i) \right] \beta_2 + \quad (4.63)$$

$$t_{s,M} \sum_{j=0}^k \gamma_j \prod_{i=j+1}^k (1 - t_{s,M} \alpha_i).$$

Additionally, Equation 4.63 enables the visualisation of temperature changes at each sampling time $t_{s,M}$ at an interval of k , starting from the initial temperature T_0 of the brewery's thermal storage tank. It also incorporates the binary control signal (1 for on, 0 for off) for S_{e,M_j} and accounts for disturbance factors that affect the system.

4.2.3.3 Wort boiling process

Equation 4.49 modelled the dynamic evolution of hot water temperature during wort boiling. To enable time-dependent simulation, the continuous equation is approximated over discrete time steps k .

Subsequently, the forward Euler method is utilised, and the spatial equation is articulated in Equation 4.64 to model the temperature at each time step:

$$T_{k+1} = T_k(1 - t_{s,wort} \alpha_k) + t_{s,wort} \beta S_{e,M_k} + t_{s,wort} \gamma_k \quad (4.64)$$

Equation 4.64 defines the first computed temperature value T_{k+1} following the initial value T_k , evaluated at the sampling time $t_{s,w}$. When the temperature is expressed as T_1 at $k=0$, the initial value becomes T_0 . The associated control variable and disturbance term are denoted $S_{e,wort_0}$ and γ_0 . Incorporating these terms, the discrete-time temperature model is as shown in Equation 4.65:

$$T_1 = T_0(1 - t_{s,wort} \alpha_0) + t_{s,wort} \beta S_{e,wort_0} + t_{s,wort} \gamma_0 \quad (4.65)$$

Equation 4.66 is similarly expressed for the next interval, $k=1$, as follows: then T_2 is

$$T_2 = T_1(1 - t_{s,wort} \alpha_1) + t_{s,wort} \beta S_{e,wort_1} + t_{s,wort} \gamma_1 \quad (4.66)$$

Considering the substitution of T_1 in Equation 4.65, Equation 4.64 was substituted into Equation 4.66, which results in Equation 4.67. After factorising, the expanded form of T_2 is shown in Equation 4.68 as:

$$T_2 = [T_0(1 - t_{s,wort}\alpha_0) + t_{s,wort}\beta S_{e,wort_0} + t_{s,wort}\gamma_0](1 - t_{s,wort}\alpha_1) + t_{s,wort}\beta S_{e,wort_1} + t_{s,wort}\gamma_1 \quad (4.67)$$

$$T_2 = T_0[(1 - t_{s,wort}\alpha_0)(1 - t_{s,wort}\alpha_1)] + t_{s,wort}[(1 - t_{s,wort}\alpha_1)S_{e,wort_0} + S_{e,wort_1}]\beta + t_{s,wort}[(1 - t_{s,wort}\alpha_1)\gamma_0 + \gamma_1] \quad (4.68)$$

Furthermore, applying the same steps used from Equation 4.65 to Equation 4.68 for the case where $k=2$, the expression for T_3 is given in Equation 4.69:

$$T_3 = T_0[(1 - t_{s,wort}\alpha_0)(1 - t_{s,wort}\alpha_1)(1 - t_{s,wort}\alpha_2)] + t_{s,wort}[(1 - t_{s,wort}\alpha_1)(1 - t_{s,wort}\alpha_2)S_{e,wort_0} + (1 - t_{s,wort}\alpha_2)S_{e,wort_1} + S_{e,wort_2}]\beta + t_{s,wort}[(1 - t_{s,wort}\alpha_1)(1 - t_{s,wort}\alpha_2)\gamma_0 + (1 - t_{s,wort}\alpha_2)\gamma_1 + \gamma_2] \quad (4.69)$$

Equations for subsequent expressions can be obtained by repeating the previous steps. The resulting general expression of the discretisation relationship is shown in Equation 4.70:

$$T_{k+1} = T_0 \left[\prod_{j=0}^k (1 - t_{s,wort}\alpha_j) \right] + \left[t_{s,wort} \sum_{j=0}^k S_{e,wort_j} \prod_{i=j+1}^k (1 - t_{s,wort}\alpha_i) \right] \beta_2 + t_{s,wort} \sum_{j=0}^k \gamma_j \prod_{i=j+1}^k (1 - t_{s,wort}\alpha_i). \quad (4.70)$$

Additionally, Equation 4.70 enables the visualisation of temperature changes at each sampling time $t_{s,wort}$ at an interval of k , starting from the initial temperature T_0 of the brewery's thermal storage tank. It also incorporates the binary control signal (1 for ON, 0 for OFF) for $S_{e,wort_j}$ and accounts for disturbance factors that affect the system.

4.2.4 Objective function, boundaries, and constraints

The primary objective was to minimise the energy costs associated with heating operations in the microbrewery while maximising the contribution from the PV power source. This cost reduction is governed by the ToU electricity tariff. The control algorithm is designed to identify optimal switching strategies that prioritise energy consumption during off-peak low-cost periods and to avoid usage during peak pricing intervals. At the same time,

PV power, which is typically the highest during sunny and warm conditions, is fully utilised in the heating system. The corresponding objective function was presented in Equation 4.28.

4.2.5 Control optimisation problem

4.2.5.1 Objective function formulation

To minimise the energy costs associated with the compressor and electric resistive element, the ToU tariff structure plays a central role in formulating the objective function. As illustrated in Figure 4.2 and defined in Equations 4.71 and 4.72, the ToU structure distinguishes between low demand (summer) and high demand (winter).

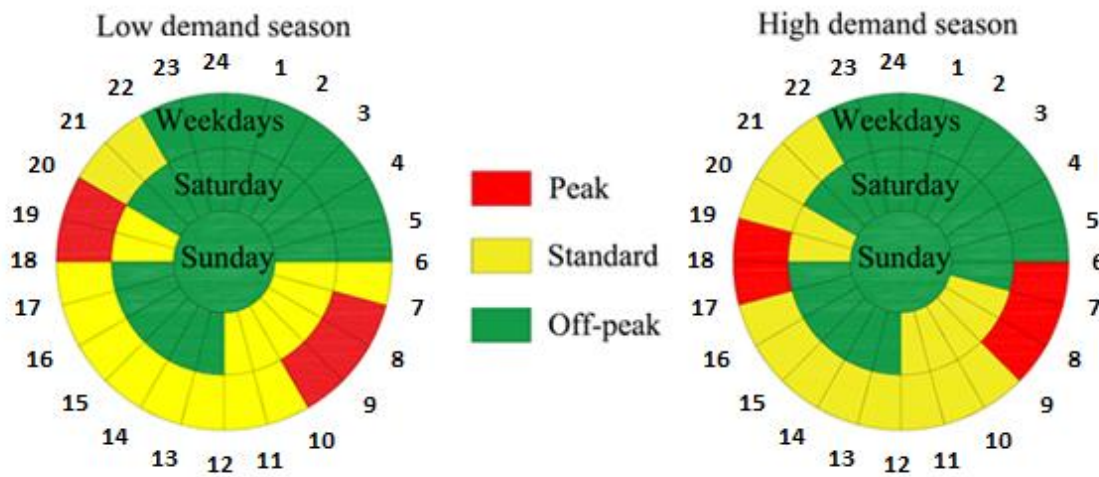


Figure 4.2: Electricity pricing periods under the ToU tariff

The control strategy adjusts the operational states of key components to prioritise energy use during the lowest-cost intervals, which effectively avoids high-tariff periods. This is achieved through the switching functions S_{hp,w_k} and S_{e,w_k} , which schedule operations in line with the prevailing electricity rates.

The parameters ψ_{LD} and ψ_{HD} represent the cost of electrical energy during low-demand (summer) and high-demand (winter) seasons (ZAR/kWh), respectively. The peak ψ_p , off-peak ψ_0 , and standard pricing periods ψ_s are calculated based on these rates, as defined in Equations 4.71 and 4.72. Each is further segmented into peak ψ_p , off-peak ψ_0 , and standard pricing periods ψ_s .

$$\psi_{LD}(t) = \begin{cases} \psi_p; t \in T_k, T_k = [7,10) \cup [18,20); \\ \psi_o; t \in T_k, T_k = [0,6) \cup [22,24); \\ \psi_s; t \in T_k, T_k = [6,7) \cup [10,18) \cup [20,22). \end{cases} \quad (4.71)$$

$$\psi_{HD}(t) = \begin{cases} \psi_p; t \in T_k, T_k = [6,9) \cup [17,19); \\ \psi_o; t \in T_k, T_k = [0,6) \cup [22,24); \\ \psi_s; t \in T_k, T_k = [9,17) \cup [19,22). \end{cases} \quad (4.72)$$

These values form the electricity price signal used in the optimisation model in Equations 4.72 and 4.73, which also aims to maximise the use of available PV power during high solar irradiance periods. The control model uses a 15-minute sampling time, with the sampling interval $k = 1 \dots, N$, where $N = 24$.

4.2.6 Process-specific objective functions

Each process is associated with a specific energy consumption profile and equipment usage pattern. To accommodate this, distinct objective functions are defined for each process. These functions aim to minimise energy costs while incorporating the PV offset.

4.2.6.1 Water heating objective function

The cost minimisation function may be seen as the primary objective function [5]:

$$\min J_w = t_s \sum_{k=1}^N \left(\left(P_{hp_k} S_{hp_k} + P_{EL,w_k} S_{e,w_k} \right) \psi_k - P_{PV_k} \right) \quad (4.73)$$

This function minimises the net cost of energy utilised by the electric heating element for water, while being adjusted for the available PV power at each time step, and simultaneously maximises the utilisation of PV power.

4.2.6.2 Mashing objective function

$$\min J_M = t_s \sum_{k=1}^N \left(\left(P_{EL,M_k} S_{e,M_k} \right) \psi_k - P_{PV_k} \right) \quad (4.74)$$

This function targets the energy cost minimisation for the mash tun heater, which is used primarily during standard tariff periods.

4.2.6.3 Wort boiling objective function

Equation 4.75 governs the energy cost of maintaining boiling conditions for the wort and is critical for ensuring product quality.

$$\min J_{wort} = t_s \sum_{k=1}^N \left((P_{hp_k} S_{hp_k} + P_{EL, wort_k} S_{e, wort_k}) \psi_k - P_{PV_k} \right) \quad (4.75)$$

Where: (Equations 4.73 to 4.75):

J_w , J_M , and J_{wort} represent the total cost function for water heater, mash mixture, and wort respectively, measured in ZAR;

t_s is the sampling time (hours);

P_{hp_k} is power of the heat pump compressor (kW);

P_{EL, w_k} , P_{EL, M_k} , and $P_{EL, wort_k}$ are the rated power of the electric resistive elements for the water heater, mash mixture, and wort respectively at time step k (kW);

S_{e, w_k} , S_{e, M_k} , and $S_{e, wort_k}$ are the binary switching statuses (1 = on, 0 = off) of the electric resistive element for the water heater, mash mixture, and wort respectively at time step k;

ψ_k represents the ToU hourly pricing period (ZAR/kWh), as described in Equation 4.72 for the low-demand (summer) season and Equation 4.73 for the high-demand (winter) season; and

PV_k is available PV power at time step k.

4.2.7 Thermal requirements of brewing processes

Brewing processes, specifically water heating, mashing, and wort boiling, require precise thermal control to ensure both energy efficiency and product quality. Although these processes operate within distinct temperature ranges and time constraints, their optimisation structures exhibit significant similarities. Consequently, a generalised thermal control framework is employed to minimise redundancy and facilitate modular optimisation.

4.2.7.1 General thermal tracking objective

For each process $p \in \{\text{water, mash, wort}\}$, the control objective is to minimise the squared deviation between the actual process temperature $T_{s,p}(t)$ and the desired temperature profile $F_p(t)$. This ensures that the heating profile closely follows brewing requirements.

The secondary objective function $J_{s,p}$ to minimise thermal deviation from the desired temperature profile is shown in Equation 4.76:

$$\min J_{s,p} = \int_{t_0}^{t_f} (T_{s,p}(t) - F_p(t))^2 dt \quad (4.76)$$

Where:

$J_{s,p}$ represents the fixed final temperature state function, measured in °C;

t_0 is the initial sampling interval at $T_{s,p}(t) = T_{s,p}(t_0)$ (initial temperature for process p at time t); and

t_f is the final sampling interval at $T_{s,p}(t) = T_{s,p}(t_f)$ (final temperature).

This objective facilitates accurate temperature regulation and enhances energy efficiency during each stage of the brewing process.

4.2.8 Fixed final state condition for brewing processes

To ensure continuous and stable operation of the optimal energy control scheme across the water heating, mashing, and wort boiling processes, it is imperative that the thermal energy at the final time step of each process's storage or mixing tank corresponds to the initial thermal energy at the commencement of the control horizon. This condition ensures that the net thermal energy gained and lost during the control period is balanced, which maintains process consistency and prevents thermal drift.

Moreover the final temperature, ($T_s(t_f)$), should closely match the initial temperature, ($T_s(t_0)$), in the storage tank to maintain consistency in the system's operation. This principle is expressed in the generalised form of Equation 4.77:

$$\sum_{k+1}^N (Q_{s_k}) = 0 \quad (4.77)$$

Where Q_{s_k} is the thermal energy change at time step k .

This objective is attained by minimising the temperature difference between the initial and final stages of the brewing process to ensure that it remains within the optimal range for each phase. By implementing a strategy that mitigates operational inefficiencies, the system

is able to maintain precise temperature control throughout. Consequently, Equation 4.78 delineates the tertiary objective function, which minimises the squared difference between the final and initial temperatures, which promotes thermal stability, process efficiency, and product consistency.

$$\min J_t = \int_{t_0}^{t_f} (T_{s,p}(t_f) - T_{s,p}(t_0))^2 dt \quad (4.78)$$

Where:

$T_{s,p}(t_0)$ and $T_{s,p}(t_f)$ represent the initial and final temperatures for process p , where $p \in \{\text{water heating, mashing, wort boiling}\}$.

4.2.8.1 Water heating process

The objective function for water heating incorporates both the heat pump and the electric element. Consequently, the overall objective function is represented by the expression provided in Equation 4.79:

$$\begin{aligned} \min J_W = w_1 & \left(t_s \sum_{k=1}^N \left((P_{hp_k} S_{hp_k} + P_{EL,w_k} S_{e,w_k}) \psi_k - P_{PV_k} \right) \right) \\ & + w_2 \left(t_s \sum_{k=1}^N (T_{w,k} - F_{w,k})^2 + t_s \sum_{k=1}^N (T_{w,N} - T_{w,0})^2 \right) \end{aligned} \quad (4.79)$$

4.2.8.2 Mashing process

The mashing process is heated solely by an electric resistive element:

$$\begin{aligned} \min J_M = w_1 & \left(t_s \sum_{k=1}^N \left((P_{EL,M_k} S_{e,M_k}) \psi_k - P_{PV_k} \right) \right) \\ & + w_2 \left(t_s \sum_{k=1}^N (T_{M,k} - F_{M,k})^2 + t_s \sum_{k=1}^N (T_{M,N} - T_{M,0})^2 \right) \end{aligned} \quad (4.80)$$

4.2.8.3 Wort boiling process

Similarly, the wort boiling process relies on electric heating. Equation 4.81 governs the energy cost of maintaining boiling conditions for wort and is critical for ensuring product quality:

$$\begin{aligned} \min J_{wort} = & w_1 \left(t_s \sum_{k=1}^N \left((P_{EL,wort,k} S_{e,wort,k}) \psi_k - P_{PV,k} \right) \right) \\ & + w_2 \left(t_s \sum_{k=1}^N (T_{wort,k} - F_{wort,k})^2 + t_s \sum_{k=1}^N (T_{wort,N} - T_{wort,0})^2 \right) \end{aligned} \quad (4.81)$$

Where (Equations 4.79 to 4.81):

J_w , J_M , and J_{wort} are the aggregate objective functions that must be minimised for water heating, mash mixture, and wort respectively;

w_1 is the weighting factor to adjust the priority given to energy cost minimisation;

w_2 is the weighting factor to adjust the priority given to thermal requirement level minimisation;

t_s is the sampling time (hours);

T_k represents the temperature of the water at each time step k ;

$P_{PV,k}$ is the PV power available at time step k ;

$F_{w,k}$, $F_{M,k}$, and $F_{wort,k}$ are the reference or target temperatures for the water at time step k ;

$T_{w,N}$, $T_{M,N}$, and $T_{wort,N}$ are the final temperature of the water, mash, and wort at the last time step, N ; and

$T_{w,0}$, $T_{M,0}$, and $T_{wort,0}$ are the initial temperature of the water, mash, and wort at the beginning of the time steps.

The aggregate objective function presented in Equation 4.81 is formulated as a non-linear mixed-integer function that incorporates a binary control variable. This function must be optimally resolved to ascertain the most efficient switching schedule for the heat pump

compressor and the electric resistive heater employed in the thermal energy system of the microbrewery [5].

Each expression balances cost optimisation with process efficiency:

- The first term minimises net power cost after PV offset.
- The second term ensures accurate temperature tracking and thermal stability over the control horizon.
- Weight factors allow prioritisation between economic and thermal objectives based on operational goals.

4.2.9 Constraints on the state of the temperature in the storage tank in brewing processes

Efficient thermal management in brewery operations is essential for maintaining product quality, optimising energy use, and reducing operating costs. The brewing process encompasses several thermally dependent stages, including hot water preparation, mashing, and wort boiling, which are all governed by time-varying thermal and operational constraints. These constraints are aligned with ToU electricity tariffs and thermal demand schedules. The specific constraints on the state of the temperature are detailed below for each stage.

4.2.9.1 Water heating system constraints

For the water heating system in brewing, temperature control is constrained to ensure process efficiency and preparation for subsequent stages. The water in the hot liquor tank is heated from 22 °C (summer) or 15 °C (winter) to a target of 85 °C during off-peak hours (23:00 to 06:00) to minimise energy costs while preparing for mashing. Heating is deactivated between 06:00 and 08:00 to avoid high electricity tariffs. The energy management system optimises schedules using low-cost energy sources while maintaining process quality through precise temperature control.

The temperature function is constrained as shown in Equation 4.82:

$$F(t) = \begin{cases} T_{s,w}(t), t \in [00h00,06h00) \cup [23h00,24h00) \\ 85, t \in [06h30] \\ T_0(t_0), t \in [24h00] \end{cases} \quad (4.82)$$

Where $F(t)$ is the desired temperature function based on the heating schedule and water demand profile:

$$\begin{aligned}
T_{k+1} = T_0 & \left[\prod_{j=0}^k (1 - t_{s,w} \alpha_j) \right] + \left[t_{s,w} \sum_{j=0}^k S_{hp,w_j} \prod_{i=j+1}^k (1 - t_{s,w} \alpha_i) \right] \beta_1 \\
& + \left[t_{s,w} \sum_{j=0}^k S_{e,w_j} \prod_{i=j+1}^k (1 - t_{s,w} \alpha_i) \right] \beta_2 + t_{s,w} \sum_{j=0}^k \gamma_j \prod_{i=j+1}^k (1 - t_{s,w} \alpha_i)
\end{aligned} \tag{4.83}$$

4.2.9.2 Mashing process constraints

In the mashing process, energy utilisation is constrained to maintain the requisite temperature and mixing parameters. During standard pricing periods, which commence at 08:00, hot water is discharged from the hot liquor tank into the insulated mash tank, where the temperature is maintained between 65 °C and 78 °C. The 4 kW x 3 heating element operates for a duration of two hours during standard pricing, followed by the operation of a 0.75 kW stirrer for one hour. Water is added incrementally over the course of one hour, while sugars are concurrently transferred to the boiler. The energy management system optimises operational timing to balance energy savings with thermal consistency, which ensures proper sugar extraction.

$$F(t) = \begin{cases} T_{s,M}(t), & t \in [08h00,13h00] \\ 78, & t \in [13h00] \\ T_0(t_0), & t \in [20h00] \end{cases} \tag{4.84}$$

The corresponding temperature dynamics for mashing stage is expressed in Equation 4.85:

$$\begin{aligned}
T_{k+1} = T_0 & \left[\prod_{j=0}^k (1 - t_{s,M} \alpha_j) \right] + \left[t_{s,M} \sum_{j=0}^k S_{e,M_j} \prod_{i=j+1}^k (1 - t_{s,M} \alpha_i) \right] \beta + \\
& t_{s,M} \sum_{j=0}^k \gamma_j \prod_{i=j+1}^k (1 - t_{s,M} \alpha_i)
\end{aligned} \tag{4.85}$$

4.2.9.3 Wort boiling process constraints

In the wort boiling process, meticulous energy management is essential for maintaining optimal temperatures that re conducive to critical biochemical reactions. The wort is heated using a 7 kW resistive heating system until it reaches a temperature of 97 °C for a duration of 30 minutes, commencing at 15:00. Hops are introduced during the period from 15:00 to 17:00, followed by a subsequent boiling phase of two hours to facilitate the coagulation of

proteins and the separation of suspended particles. The energy management algorithm is designed to schedule operations in a manner that mitigates peak tariff costs while maximising energy efficiency and preserving process integrity and ensuring the quality of the final product. The wort temperature function is constrained as shown in Equation 4.86:

$$F(t) = \begin{cases} T_{s,wort}(t), t \in [15h00,17h00) \\ 98, t \in [17h00) \\ T_0(t_0), t \in [24h00) \end{cases} \quad (4.86)$$

Where $F(t)$ is the desired temperature function; and,

$$T_{k+1} = T_0 \left[\prod_{j=0}^k (1 - t_{s,wort} \alpha_j) \right] + \left[t_{s,wort} \sum_{j=0}^k S_{e,wort_j} \prod_{i=j+1}^k (1 - t_{s,wort} \alpha_i) \right] \beta \quad (4.87)$$

$$+ t_{s,wort} \sum_{j=0}^k \gamma_j \prod_{i=j+1}^k (1 - t_{s,wort} \alpha_i)$$

The switching status of a function is represented by a singular binary value that indicates whether the system is switched on or off, thereby delivering either full-rated power or no power, respectively, to the electrical unit as needed. The switching functions of the heat pump and the storage tanks are delineated in Equation 4.88 [5].

$$\begin{aligned} S_{hp_k} &\in \{0,1\} \\ S_{e,w_k} &\in \{0,1\} \\ S_{e,m_k} &\in \{0,1\} \\ S_{e,wort_k} &\in \{0,1\} \end{aligned} \quad (4.88)$$

Where:

S_{hp_k} , S_{e,w_k} , S_{e,m_k} , and $S_{e,wort_k}$ are the binary states of the heat pump, which correspond to the electric heating elements for water heating, mashing, and wort boiling respectively at each time step k . A value of 1 indicates that the unit is active, whereas 0 denotes that it is inactive.

Equation 4.89 represents the actual temperature profile during critical beer brewing processes such as water heating, mashing, and wort boiling. T_k^{min} denotes the minimum

allowable temperature required to initiate and sustain each process effectively. T_k^{max} is the upper limit that must not be exceeded to maintain process stability and product quality.

$$T_k^{min} \leq T_k \leq T_k^{max} \quad (4.89)$$

4.2.9.4 Assumptions in the model analysis

The mathematical model of the microbrewery thermal-energy system was developed under the following assumptions, each adopted to simplify computation while preserving physical accuracy:

- The heating load cycles for the processes of water heating, mashing, and wort boiling were modelled separately.

Each brewing stage has distinct temperature set-points and batch durations; modelling them individually reflects actual process behaviour and avoids incorrectly coupling unrelated heating demands.

- Multiple heating elements in each process were represented as a single equivalent heating unit.

Brewery heating elements typically operate in parallel and provide additive thermal output. Consolidating them reduces optimisation complexity without affecting total heating capacity.

- The thermal storage and processing vessels associated with each brewing stage were treated as independent but simplified subsystems, allowing their thermal behaviour to be modelled explicitly and enabling tractable incorporation into the optimisation framework.

A lumped-parameter approach captures dominant heat-transfer behaviour while avoiding the computational burden of detailed transient modelling, which is unnecessary for optimisation.

- The electrical energy consumption of auxiliary equipment, such as circulation pumps, agitators, and control valves, was not included in the simulation.

These loads contribute a small fraction of total energy use compared with major thermal processes. Excluding them improves model efficiency and focuses the optimisation on the primary energy drivers.

4.2.10 Implementation of a MATLAB-based optimisation model for brewing processes

The input parameters, system constants, and process functions were implemented in MATLAB, with optimisation conducted using the SCIP solver via the OPTI Toolbox. SCIP was specifically chosen due to its suitability for addressing the complexities of energy management in brewing systems. The selection was based on the following key considerations:

Firstly, SCIP's mixed-integer programming capabilities are well-equipped to handle the combined discrete and continuous decision variables typical of brewing processes, such as equipment activation schedules and temperature control set-points. Its robust performance across various industrial applications reinforces its reliability for brewing process optimisation.

Secondly, SCIP offers high computational efficiency, which is made possible by advanced algorithmic features such as adaptive branching rules, conflict analysis, and cutting-plane techniques [132]. These methods facilitate fast and effective exploration of the solution space while ensuring strict adherence to the operational constraints of the brewing system.

The MATLAB-based implementation incorporated several core components that are essential for accurately modelling and optimising the brewing process. Input variables were extracted from screened brewing datasets in Microsoft Excel, capturing detailed recipe specifications and system equipment parameters. These were complemented by hard-coded constants representing the physical characteristics of the brewing system, including vessel thermal properties and heat transfer coefficients. In parallel, M-file formulations were developed to represent the fundamental brewing process equations, specifically those that govern thermal dynamics and energy balances.

Following the implementation phase, the model was executed and refined through iterative debugging. The resulting outputs were then validated against historical brewing data to ensure accuracy and alignment with real-world operating conditions. This validation step was critical for establishing the model's reliability and for confirming that the optimisation framework accurately represented actual brewing performance.

. The definition of the objective function constructed using a weighted multi-objective formulation and the integration of brewing-process constraints such as temperature limits,

ramp-rate restrictions, and required phase durations are explicitly presented in Sections 4.2.4 to 4.2.8, where the objective function, boundary conditions, and process-specific constraints are developed in detail. The configuration settings necessary for interfacing with the SCIP solver were also established. This solver was employed due to its ability to handle mixed-integer programming problems effectively, particularly those involving complex combinations of discrete and continuous decision variables.

The optimisation framework employed a weighted sum approach to consolidate multiple performance goals into a single aggregate objective function. Specifically, the optimisation targeted the minimisation of energy costs ($W_1 = 0.4$), the maximisation of process consistency or thermal requirement ($W_2 = 0.3$), and the maximisation of PV utilisation ($W_3 = 0.3$). These weights were carefully selected to reflect the brewery's operational priorities while ensuring consistency with the study's methodological structure. The composite function was then solved using the SCIP solver to derive optimal process schedules and control strategies.

The complete logic of the optimisation framework, including the interdependencies among process variables and control decisions, is presented in Figure 4.3 through a brewery-specific flowchart.

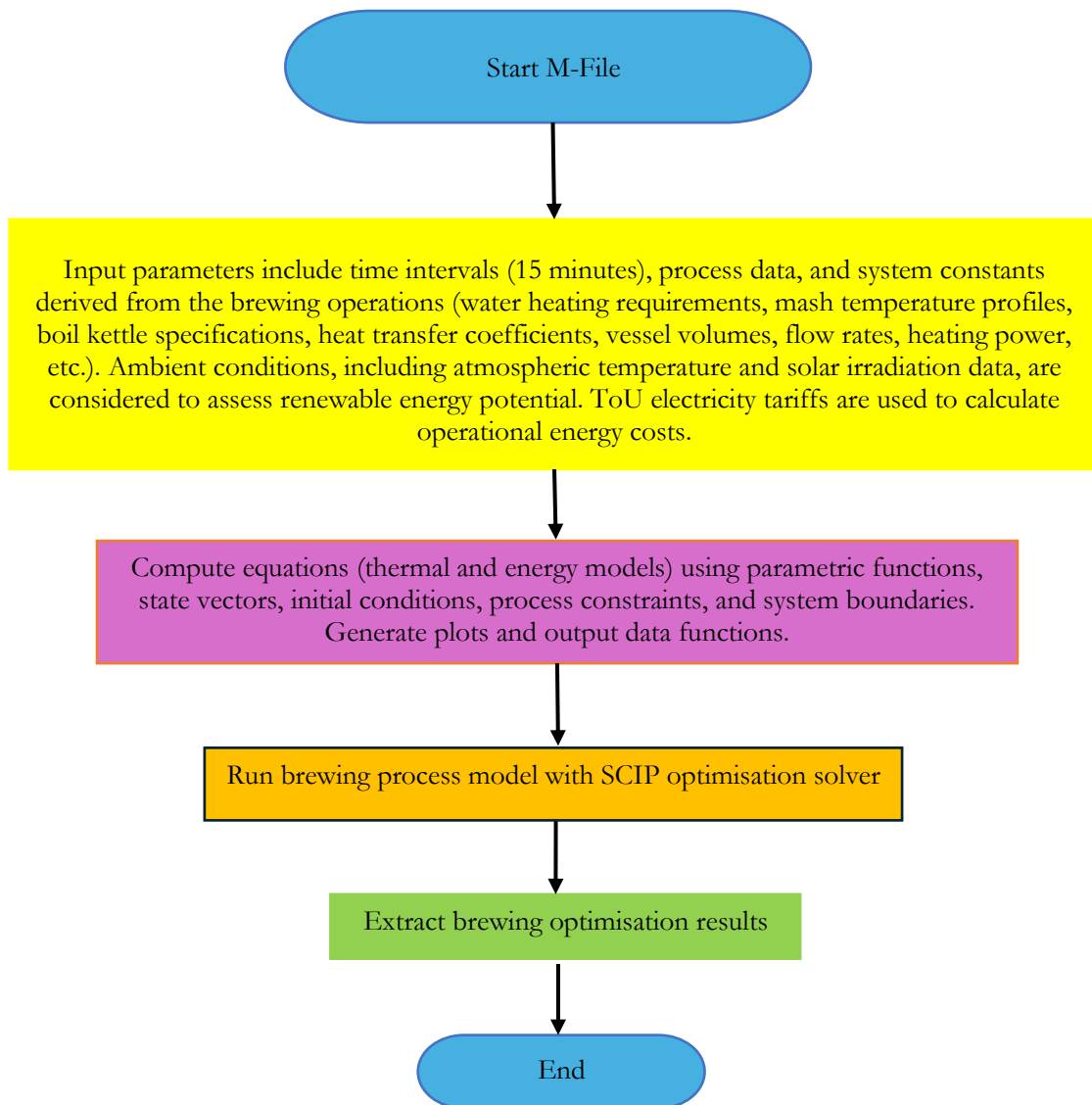


Figure 4.3: Brewing energy optimisation model flowchart

The SCIP solver requires that the microbrewery thermal energy model be formulated in a mixed-integer non-linear programming structure. This standard form was presented in Equation 4.90. The objective function is minimised by default and is subject to the constraints defined in the equation. The mathematical model for the brewery's heating processes must be appropriately reformulated to comply with SCIP's input requirements.

The primary output of the optimisation is the control variable that governs heating activation across the various brewing stages [5]:

$$\begin{aligned}
 & \min_x f(x) \\
 & \text{Subject to: } Ax \leq b \\
 & A_{eq}x = b_{eq} \\
 & lb \leq x \leq ub \\
 & c(x) \leq d \\
 & c_{eq}(x) = d_{eq} \\
 & x_i \in \mathbb{Z} \\
 & x_j \in \{0,1\}
 \end{aligned} \tag{4.90}$$

Where:

- $f(x)$ is the objective function;
- $Ax \leq b$ is the linear inequality constraint;
- $A_{eq}x = b_{eq}$ is the linear equality constraint;
- $lb \leq x \leq ub$ is the decision variable bounds;
- $c(x) \leq d$ is the non-linear inequality constraint;
- $c_{eq}(x) = d_{eq}$ is the non-linear equality constraint;
- x_i is an integer number decision variable; and
- x_j is a binary number decision variable.

The objective function is consequently replaced with $f(x)$; no linear inequality or equality constraints are present. The decision variable, as shown in Equation 4.90, is a binary value, which means that only a value of 1 or 0 may be obtained as the switching status. The lower and upper boundaries are therefore shown in Equations 4.91 and 4.92 respectively [5]:

$$lb^T = [0 \dots 0_N] \tag{4.91}$$

$$ub^T = [1 \dots 1_N] \tag{4.92}$$

The control variable that should be optimised is therefore constrained, as shown in Equation 4.93:

$$lb \leq x \leq ub \tag{4.93}$$

4.3 SIMULATION RESULTS AND DISCUSSION

This section presents simulation results that compare the baseline system with a proposed optimal hybrid energy system for brewery process heating. Simulations were conducted using the SCIP solver in MATLAB's OPTI Toolbox environment. The hybrid configuration integrates evacuated tube solar thermal collectors, a heat pump unit, and a high-capacity hot water storage tank. These components supply heat for water heating (80 °C to 85 °C), mashing (65 °C to 79 °C), and wort boiling (98 °C), leveraging seasonal solar availability and ToU electricity pricing.

The baseline system operates based on conventional set-point temperature control. In contrast, the proposed hybrid energy system employs optimal control strategies to maintain the required process temperatures while reducing grid energy consumption and associated costs, which reflects the core objective of this research.

Relevant data inputs, including seasonal load profiles, ToU electricity tariffs, weather data, and other key operational parameters, were collected for both summer and winter periods. The component specifications, system configurations, and simulation settings are also detailed in this section.

4.3.1 Data description

This section presents the case study used to model the thermal energy system of a microbrewery. It includes the environmental data, hot water usage profile, and component sizing for the proposed system. These data inputs form the basis for developing both the baseline system and the optimal control strategy, which are later evaluated and compared.

4.3.2 Case study and data acquisition

The case study focused on the heating processes of the Stellar Brewery system (Bloemfontein, South Africa), which was selected to evaluate the performance of a hybrid thermal energy system under real-world operating conditions. Environmental and solar irradiance data were collected from the Southern African Universities Radiometric Network (SAURAN), with measurements obtained from the monitoring station located at the Central University of Technology, Free State (CUT) in Bloemfontein (Latitude: -29.121337; Longitude: 26.215909; Elevation: 1 397 m).

The dataset included ambient air temperature, inlet water temperature, and various forms of solar irradiance (global horizontal irradiance [GHI], diffuse horizontal irradiance [DHI], and diffuse normal irradiance [DNI]). These profiles are shown in Figures 4.4 and 4.5 for two representative seasonal extremes: a typical winter day in August and a typical summer day in March. This selection helps to illustrate daily variations across different seasons.

The microbrewery operates in a Köppen BSk cold semi-arid climate (29.0852°S, 26.1596°E; 1 395 m elevation) with marked seasonal variation ($\Delta T=15.6$ °C between January's 23.9 °C and June's 8.3 °C). These conditions create unique brewing constraints that require specialised process adaptations.

Key irradiance values for the winter and summer periods are presented in Figures 4.2 and 4.3. The data were extracted directly from SAURAN in Microsoft Excel format and used to inform the simulation of the proposed thermal system.

4.4 MATHEMATICAL MODEL DEVELOPMENT

4.4.1 Description of the system

This section presents comprehensive simulation results of both the baseline and the optimal operation of the proposed hybrid energy system for brewery process heating. The simulations were performed using the mixed-integer nonlinear programming (MINLP) formulation in the MATLAB OPTI Toolbox. The objective was to evaluate the performance of the optimal control strategy applied to the hybrid energy system, which aims to minimise energy costs while ensuring a reliable thermal energy supply for mashing and wort boiling processes. The system consists of evacuated tube solar thermal collectors, a heat pump unit, and a high-capacity hot water storage tank.

Process heat demand profiles for mashing (65 °C to 78 °C) and wort boiling (98 °C) were analysed, along with seasonal variations in solar irradiance. Key system parameters, including component sizing, ToU tariff structures, and simulation settings, are provided to establish the framework for the optimisation study.

Figures 4.4 and 4.5 present the recorded measurements of DHI, DNI, and GHI for representative summer and winter days, respectively. The data were obtained using SAURAN instruments installed as part of the microbrewery's hybrid thermal energy system.

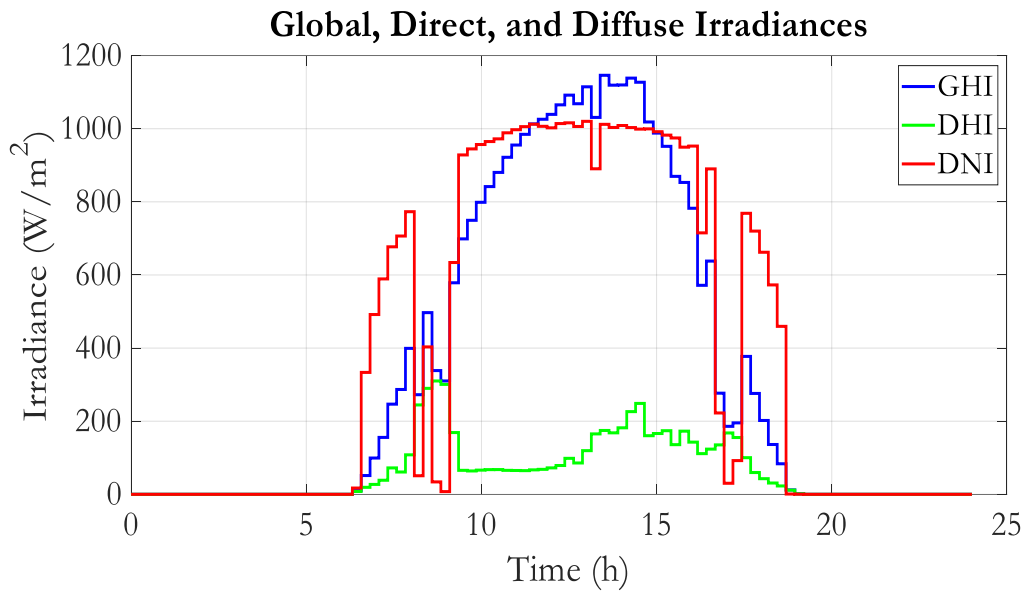


Figure 4.4: Solar irradiance during the summer (March 2022)

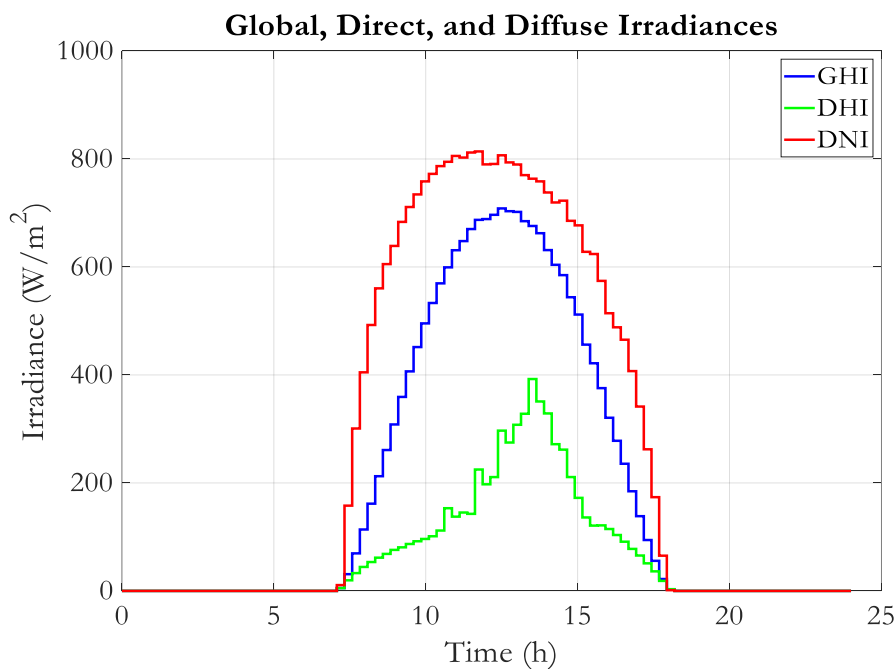


Figure 4.5: Solar irradiance during the winter (August 2023)

Figures 4.6 to 4.11 depict the ambient air and corresponding inlet temperatures for water, mash, and wort during the summer and winter seasons, respectively. These temperature profiles are crucial for assessing the thermal performance of the water heating system, as well as the mashing and wort boiling processes. The ambient air temperature data, obtained

directly from the SAURAN measurement network, facilitate precise simulation and underpin the optimisation of energy consumption across these essential brewing operations.

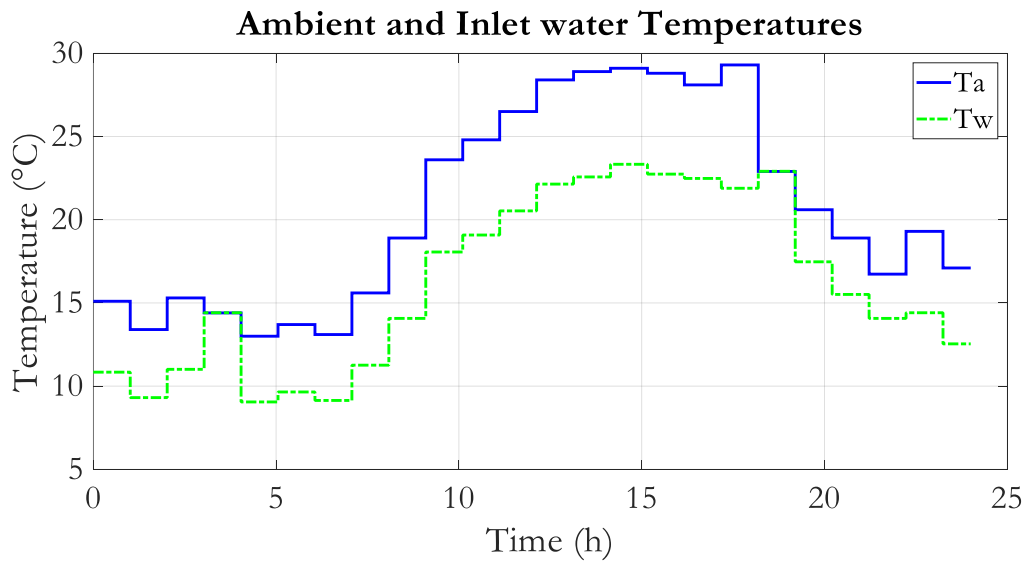


Figure 4.6: Ambient air and inlet water temperature during the summer (March 2022)

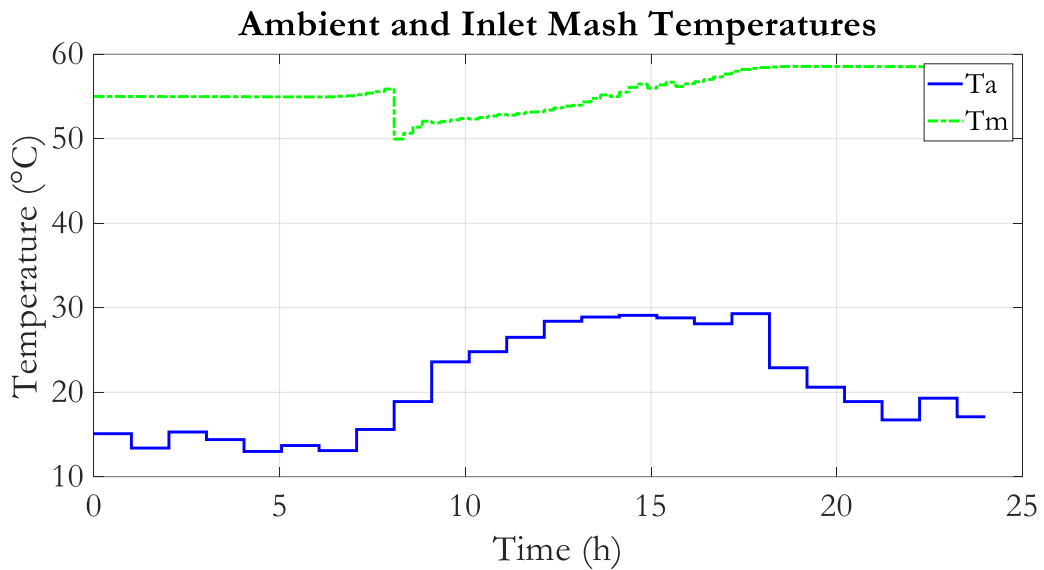


Figure 4.7: Ambient air and inlet mash temperature during the summer (March 2022)

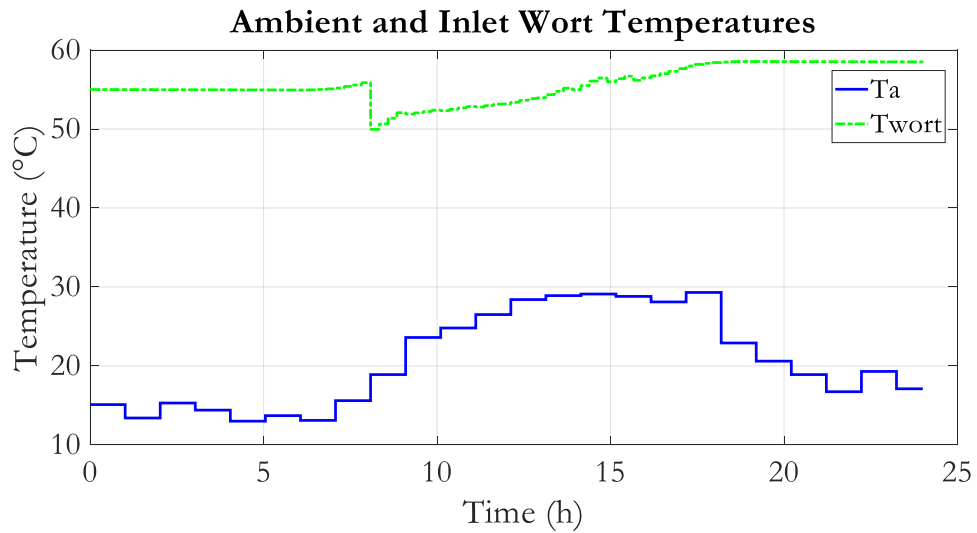


Figure 4.8: Ambient air and inlet wort temperature during the summer (March 2022)

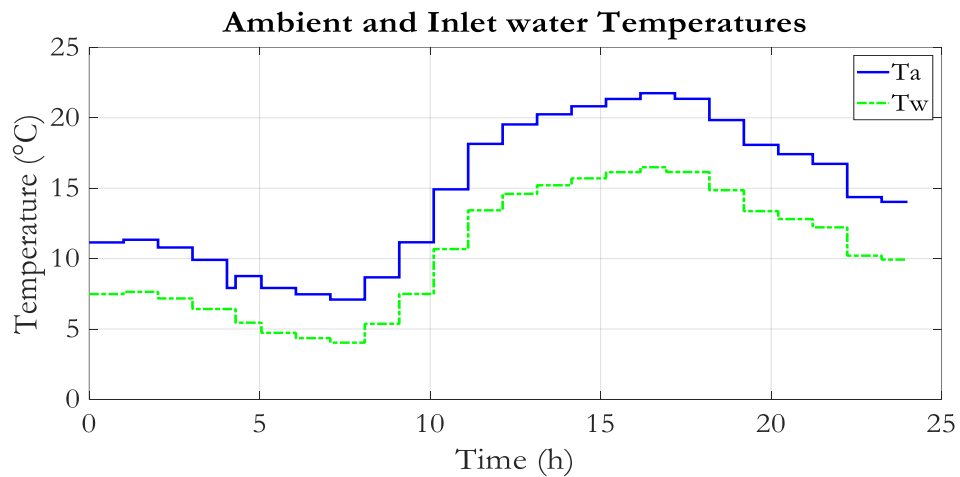


Figure 4.9: Ambient air and inlet water temperature during the winter (August 2022)

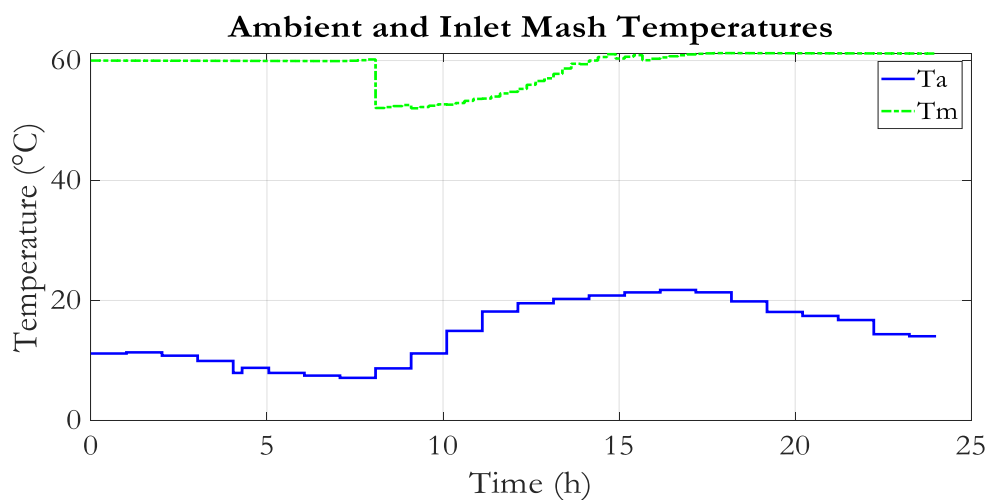


Figure 4.10: Ambient air and inlet mash temperature during the winter (August 2022)

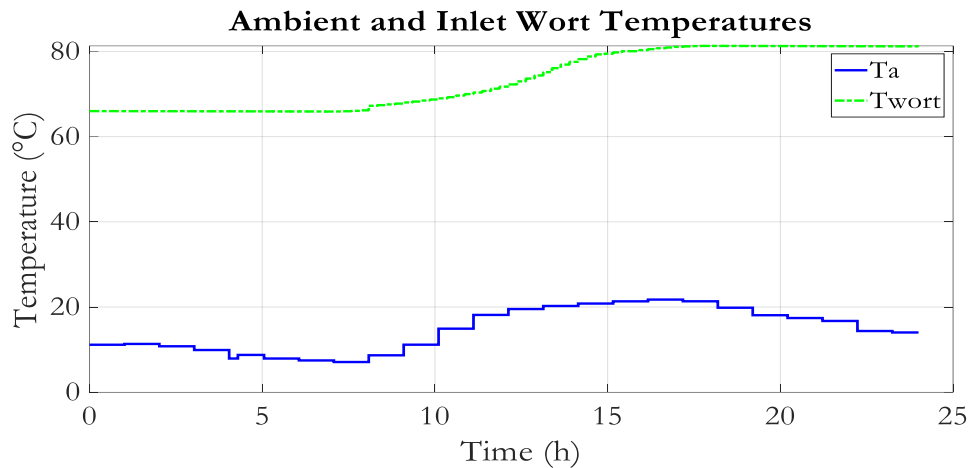


Figure 4.11: Ambient air and inlet wort temperature during the winter (August 2022)

The microbrewery sources its process water from a local supply; however, no recorded measurements were available for the inlet water temperature. Consequently, seasonal median inlet temperatures were therefore assumed as 11 °C in winter and 21 °C in summer. These values reflect typical regional groundwater conditions, which vary far less than ambient air temperatures, resulting in minimal seasonal fluctuation in inlet water temperature [196,5].

Water consumption for key thermal processes, including water heating, mashing, and wort boiling, was estimated using standard brewing ratios and published references [197]. These values were adjusted according to the brewery’s average daily production. Thermal energy requirements were extrapolated from existing energy usage profiles and adapted from relevant case studies [197].

Seasonal consumption patterns were incorporated using data from Bukhari et al. [198], which reflect variations in utility demand throughout the year. A process-specific consumption factor was calculated by integrating water usage ratios, energy requirements, seasonal adjustments, and the number of production batches.

Hot water demand was distributed over a 24-hour brewing schedule, calculated at 15-minute intervals for each process stage. The resulting summer and winter consumption profiles are presented in Figures 4.12 and 4.13.

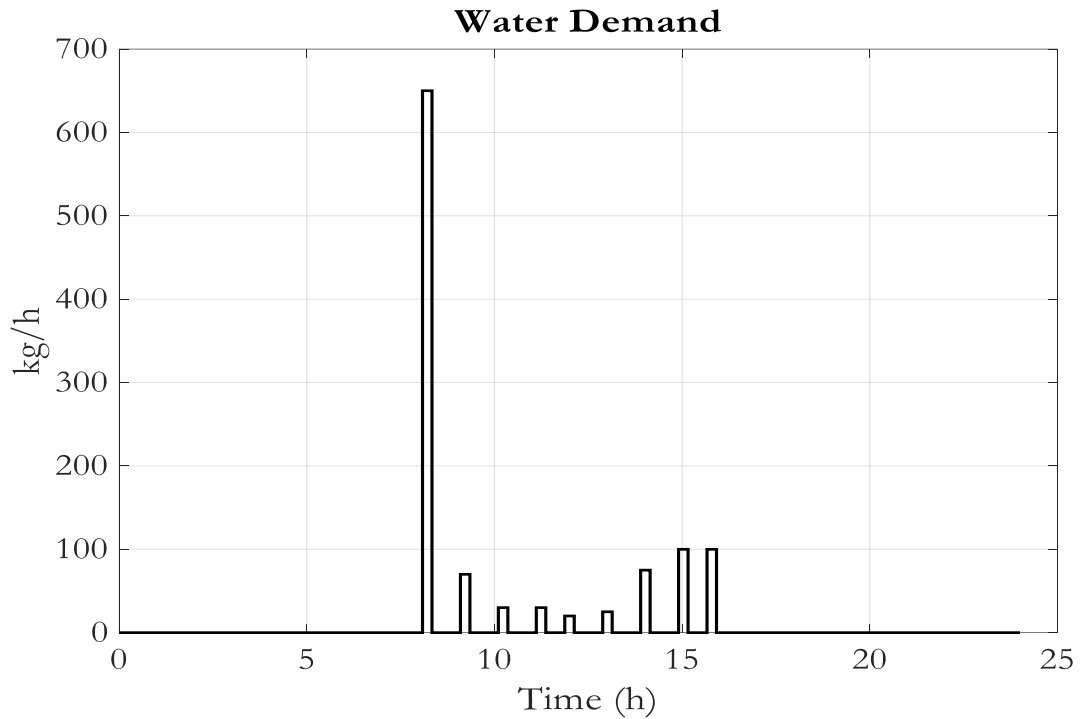


Figure 4.12: Hot water demand (flow rate) during the summer (March 2022)

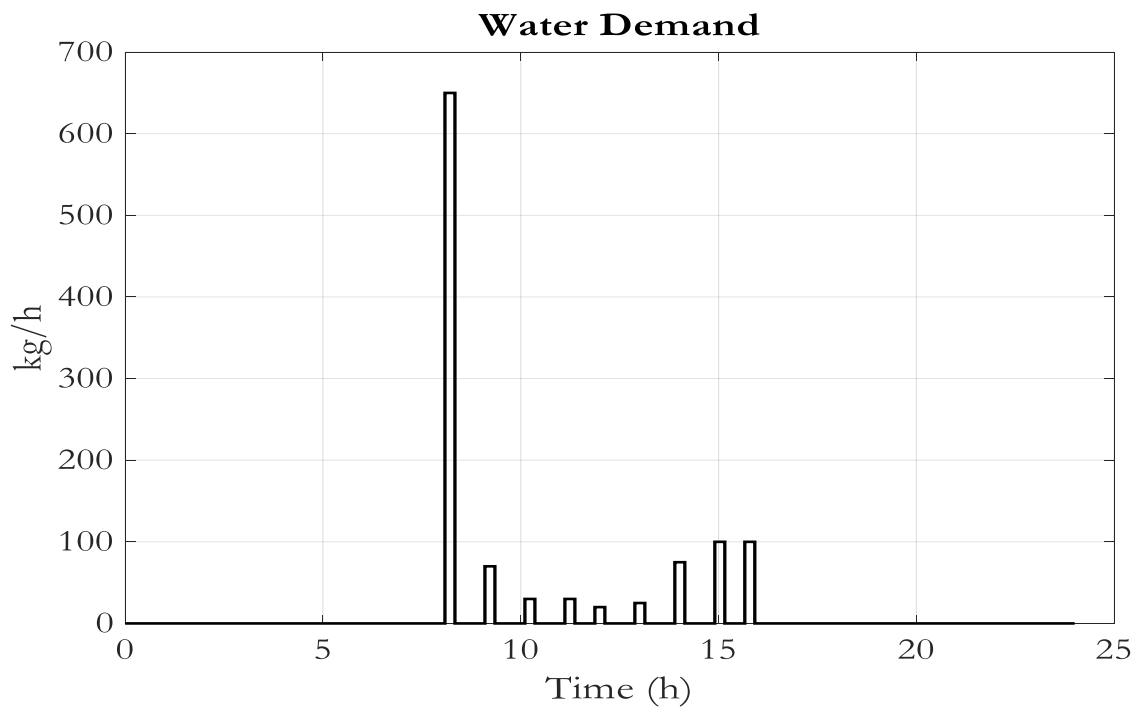


Figure 4.13: Hot water demand (flow rate) during the winter (August 2023)

To capture the daily seasonal variations, the microbrewery's hot water consumption was adjusted by applying a seasonal factor in order to create distinct hot water demand profiles for both winter and summer.

The calculations indicated that the mashing process consumed more hot water compared to water heating and wort boiling; the mashing profile was therefore utilised as the reference. According to the generated profiles, a significant amount of hot water is drawn during the early morning and late afternoon periods, which coincide with Eskom's peak electricity tariffs. This reflects the brewery's operational pattern, wherein initial brewing activities commence early in the day and cleaning or final processing occurs later in the afternoon.

4.4.2 Component sizes and simulation parameters

This section outlines the component specifications and simulation parameters employed to evaluate an optimal energy management strategy for a hybrid water heating system that is designed to meet the thermal demands of a microbrewery. The system serves critical brewing processes, including water heating, mashing, and wort boiling.

The baseline system is modelled as a conventional thermostat-controlled setup, where all thermal energy is supplied via a 24 kW electric resistive element. This system heats water in a 1 200 L insulated storage tank to support brewing activities, such as heating hot liquor, mashing (typically 65 °C to 70 °C), and wort boiling (98 °C).

In contrast, the proposed hybrid system integrates three energy sources: solar thermal collectors, a heat pump unit, and a backup electric heater. The solar subsystem comprises an ETC featuring 12 borosilicate glass tubes and internal copper heat pipes. A water-glycol solution is employed as the heat transfer fluid. This type of collector was selected based on local supplier specifications and existing literature due to its superior performance in colder climates, where it outperforms flat plate collectors. The collector tilt is fixed at 30°, which is near-optimal for annual solar gain in Bloemfontein [5].

Due to limited available data on liquid-source heat pumps for brewery applications, the heat pump parameters are based on typical air-source heat pumps commonly utilised in South African commercial systems. A COP of 4.23 and an input power of 11 kW are assumed. These values represent average performance characteristics of commercially available units reported in the literature, making them suitable reference parameters for modelling purposes [211,122]. These values represent average performance characteristics of commercially available units reported in the literature, making them suitable reference parameters for modelling purposes [211,122].

For consistency, both the baseline and hybrid models employ the same storage tank volume (1 200 L). However, in the hybrid configuration, the electric resistive element is downrated to 12 kW and used solely as an auxiliary heat source during periods of low solar availability or peak demand. This sizing is reflective of the microbrewery's production scale and batch frequency to ensure a reliable supply while enhancing energy efficiency.

Thermal demand profiles are derived from batch brewing operations, which determine the timing and intensity of heating requirements for each process stage. This setup facilitates a direct performance comparison between the conventional and hybrid systems under realistic operating conditions.

The specific heat capacity values utilised in the model are based on standard brewing literature. For the mash mixture, a value of 3 700 J/kg·°C was employed to account for the presence of grain solids. For wort during boiling, a slightly higher value of 4 100 J/kg·°C was applied, reflecting typical extract concentrations in the range of 10 °C to 15 °C [334,335]. These values are consistent with those used in similar energy modelling studies and were applied across both system configurations.

Table 4.1 summarises the component sizes and simulation parameters for both configurations, adapted to the microbrewery context and supported by sources [204].

Table 4.1: Component specifications and operating parameters of the proposed microbrewery hybrid energy system

Parameter	Value	Unit	Description
Collector			
$C_{p,c}$	3 550	(J/kg °C)	Specific heat capacity of the transfer fluid
η	0.8	(–)	Collector tube efficiency factor
A_{man}	0.00038	(m ²)	Manifold cross-sectional area [diameter = 22 mm]
A_{ap}	1.57	(m ²)	Aperture area of the collector, capturing solar energy
A_{abs}	1.47	(m ²)	Effective absorbance area of the collector
$U_{coll,Loss}$	≤ 0.55	(Wm ² /°C)	Heat loss coefficient
β_{coll}	30	(°)	Tilt angle of the collector array for optimal solar exposure
θ_w	0	(°)	Angle of incidence for winter season
θ_s	0	(°)	Angle of incidence for summer season
τ	0.94	(–)	Absorptivity coefficient of the collector material
α	0.92	(–)	Transmittance coefficient of the collector material
ρ_g	0.2	(–)	Foreground's albedo
	12		Total number of collectors installed
Heat pump			
P_{hp}	11	(kW)	Input power required by the heat pump
COP	4.23	(–)	COP (–)
Water heating process			
A_s	0.9583	(m ²)	Area of the storage tank [diameter = 610 mm]
M_w	1 100	(kg)	Mass of water in the storage tank

Parameter	Value	Unit	Description
$c_{p,w}$	4 184	($J/kg\ ^\circ C$)	Specific heat capacity of water
U_s	0.3	($Wm^2/^\circ C$)	Overall heat loss capacity of the storage tank
F_R	0.6646	(–)	Heat removal factor
$P_{EL,R}$	12	(kW)	Rated power of water heating element (baseline)
$P_{EL,R}$	6	(kW)	Rated power of water heating element (proposed)
$\dot{T}_{s,w}$	85	($^\circ C$)	Desired water temperature of the storage tank
$T_{s,min}$	22	($^\circ C$)	Minimum temperature of the storage tank
$T_{s,max}$	85	($^\circ C$)	Maximum temperature of the storage tank
Mashing process parameters			
A_s	0.9583	(m^2)	Area of the storage tank [diameter = 610 mm]
M_M	1 245	(kg)	Mass of the mash mixture in the storage tank
$c_{p,M}$	3 700	($J/kg\ ^\circ C$)	Specific heat capacity of the mash mixture
U_s	0.3	($Wm^2/^\circ C$)	Overall heat loss capacity of the storage tank
F_R	0.6646	(–)	Heat removal factor
$P_{EL,M}$	24	(kW)	Rated power of mash heating element (baseline)
$P_{EL,Mp}$	12	(kW)	Rated power of mash boiling element (proposed)
$\dot{T}_{s,M}$	78	($^\circ C$)	Storage tank desired mashing temperature
$T_{s,min}$	65	($^\circ C$)	Storage tank minimum temperature
$T_{s,max}$	78	($^\circ C$)	Storage tank maximum temperature
Wort boiling process			
A_s	0.9583	(m^2)	Area of the storage tank [diameter = 610 mm]
M_{wort}	800	(kg)	Mass of the wort mixture in the storage tank
$c_{p,wort}$	4100	($J/kg\ ^\circ C$)	Specific heat capacity of wort mixture
U_s	0.3	($Wm^2/^\circ C$)	Overall heat loss capacity of the storage tank
F_R	0.6646	(–)	Heat removal factor
$P_{EL,wort}$	48	(kW)	Rated power of wort heating element (baseline)
$P_{EL,wort,p}$	24	(kW)	Rated power of wort boiling element (proposed)
$\dot{T}_{s,wort}$	78	($^\circ C$)	Storage tank desired wort boiling temperature
$T_{s,min}$	22	($^\circ C$)	Storage tank minimum temperature
$T_{s,max}$	98	($^\circ C$)	Storage tank maximum temperature

4.5 SYSTEM SIMULATIONS

To evaluate the performance of the proposed optimally controlled hybrid thermal system, simulations were conducted and compared with a conventional baseline system. The analysis concentrated on typical high-demand days during the winter and summer seasons, specifically targeting the microbrewery's core thermal processes of water heating, mashing, and wort boiling. Seasonal thermal demand profiles were utilised as inputs, as illustrated in Figures 4.5 and 4.10 and discussed in Section 4.4.1.

The system input data from Table 4.1 were applied to model both configurations. Each system incorporates three dedicated thermal storage tanks, one for each brewing process. The baseline system relies solely on electric resistive heating controlled by thermostats to maintain process temperatures, while the hybrid system incorporates solar thermal collectors

and a heat pump whose operation is coordinated through an optimisation-based control strategy designed to minimise energy consumption and reduce operational costs.

Energy costs were calculated using the ToU tariff structure presented in Table 4.2, which reflects seasonal variations, with higher peak rates in winter and lower off-peak prices in summer. Equipment switching and temperature control adhered to the parameters detailed in Table 4.3, with sampling intervals and control horizons selected to align with the slow thermal dynamics of brewing.

In the baseline system, the electric resistive element in each storage tank is switched on when the temperature falls below the process-specific lower set-point and is switched off once the upper set-point is reached. This ensures a continuous thermal energy supply throughout the brewing process. As only one process operates at a time, the respective tank is replenished with cold water during hot liquid draw-offs to maintain constant volume and uninterrupted operation. The temperature set-points are 60 °C to 70 °C for water heating, approximately 65 °C for mashing, and 98 °C for wort boiling.

The simulation results for both the baseline system and the optimised hybrid energy system are presented in Sections 4.5.1 and 4.5.2. Section 4.5.3 conducts a detailed comparison between these systems and assesses their relative energy efficiency and economic performance specific to brewery operations.

4.5.1 Baseline system (without optimal scheduling)

The baseline system simulates the thermal energy requirements for three critical brewing processes (water heating, mashing, and wort boiling) using three separate electric storage tanks, each equipped with a conventional electric resistive heating element. The configuration is based on the components and parameters outlined in Table 4.1.

Each tank operates independently and is regulated by a dedicated thermostat controller, which governs the heating element based on fixed temperature set-points:

- The water heating tank operates with a default set-point temperature of 60 °C, encompassing a typical control range of ± 5 °C. Mains cold water enters the tank during hot water draw-offs to supply both process and cleaning water as required.

- The mash tun (mashing tank) is maintained at a set-point temperature of 65 °C, which is optimal for enzymatic starch conversion during the mash rest phase. The heating element cycles as necessary to sustain this temperature throughout the mashing duration.
- The wort boiling tank (kettle) is regulated at a set-point temperature of 98 °C to provide continuous heat for the duration of the boiling phase, which typically lasts between 60 and 90 minutes, to ensure effective sterilisation and hop isomerisation.

This baseline configuration employs simple thermostatic control without the incorporation of real-time optimisation or load scheduling. The baseline system is simulated independently for the summer and winter seasons, with the results delineated in the respective seasonal case sections below.

Figures 4.14 to 4.19 depict the switching behaviour of the thermostats and the resultant temperature fluctuations observed in each of the three tanks during a typical brewing cycle.

4.5.1.1 Baseline system operation: Summer case

(a) Switching profile and tank temperature during the off-peak period (00:00 to 06:00)

During the summer brewing schedule, the off-peak period (00:00 to 06:00) is utilised to mitigate energy costs by preheating 1 100 L of water in the storage tank. Energy monitoring data from PEL103 indicate that the water temperature rises from 22 °C to 85 °C over the course of six hours, employing a 12 kW electric resistive heating element, as illustrated in Figure 4.15.

The heating element remains on during this interval, with no switching cycles recorded by the thermostat controller (see Figure 4.14). This continuous operation leads to the consistent temperature increase depicted in Figure 4.15. No hot water is extracted during this timeframe; instead, the heated liquor is retained for mashing, which commences after 08:00.

Throughout the off-peak period, both the mashing tank and the wort boiling vessel remain inactive, with no heating or switching activity occurring.

The switching status of the heating element is represented as a binary signal (0 = off, 1 = on). Background colour bands in the figures denote the ToU tariff schedule across the 24-hour day. The element is on during off-peak hours (00:00 to 06:00) and is switched off

during standard (09:00 to 17:00, 20:00 to 24:00) and peak periods (06:00 to 09:00, 17:00 to 20:00). A constant base load, resulting from fermentation and cold storage, runs continuously and constitutes part of the system's critical load.

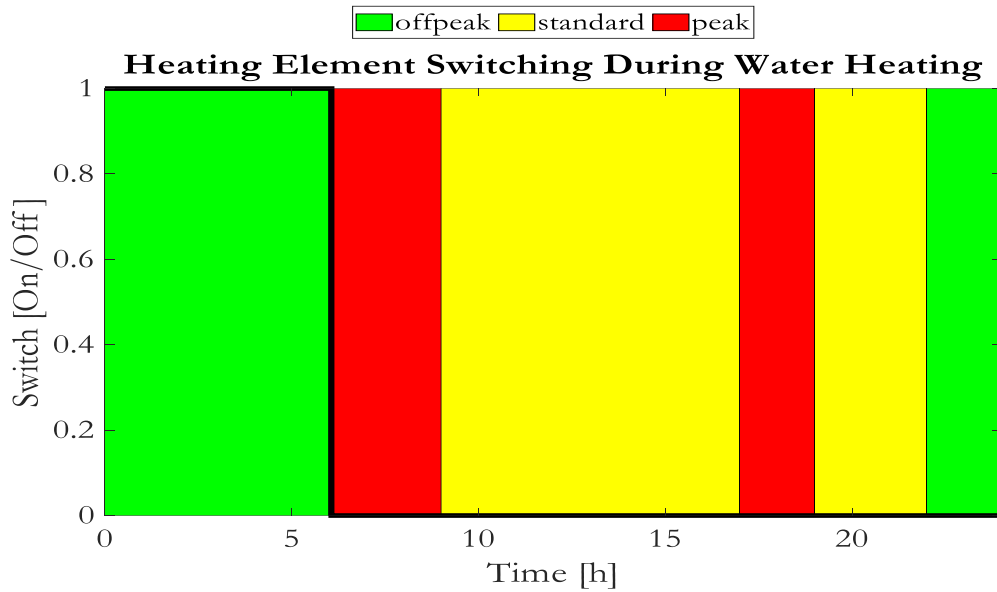


Figure 4.14: Switching function of the water heating element during the summer

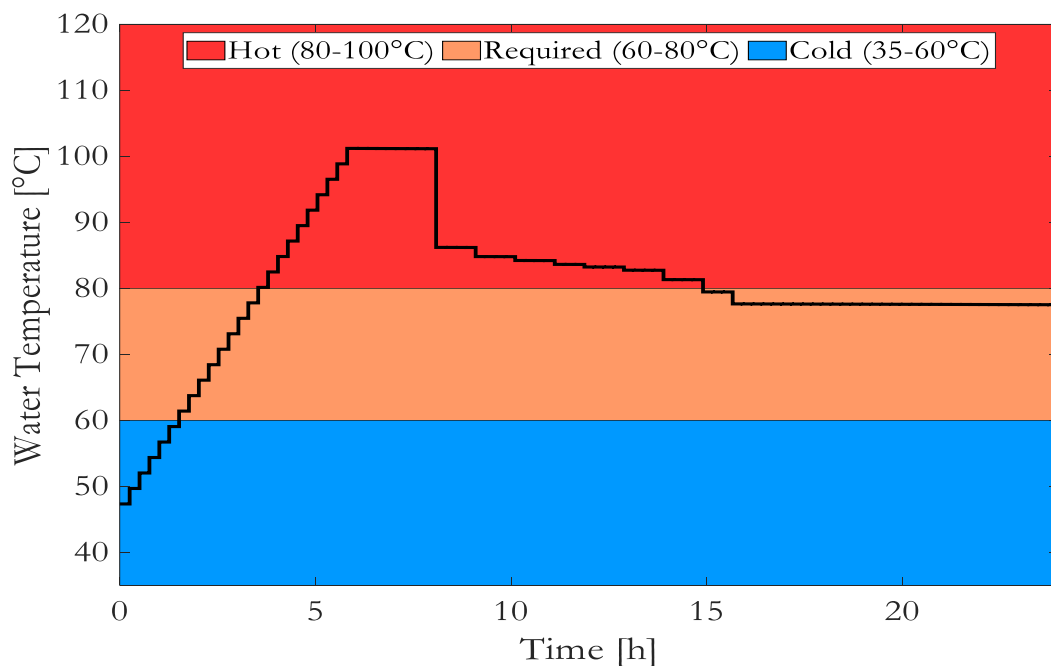


Figure 4.15: Storage tank water temperature of the proposed hybrid system for the summer

(b) *Switching profile and temperature behaviour during the standard period (06:00 to 07:00)*

As illustrated in Figure 4.14 no switching of the three heating elements takes place during this period. Furthermore, there is no demand for hot water from brewing processes, which

leads to a complete absence of energy consumption. Nevertheless, a consistent decline in the temperature of the storage tank is observed, which is attributable to standby thermal losses, as demonstrated in Figure 4.15.

(c) Switching profile and temperature behaviour during the standard period (07:00 to 09:00)

To mitigate energy costs during the peak tariff period, the resistive heating element in the hot water storage tank is switched off from 08:00 to 09:00, in accordance with a demand response strategy. In the absence of active heating, the temperature of the tank gradually decreases due to standby losses and anticipated demand.

At 08:00, 650 L of hot water – the largest draw in the brewing cycle – are transferred to the insulated mash tun over an approximate duration of 15 minutes, initiating the mashing process at 65 °C (see Figure 4.16). In response, the mash tun’s heating element switches on to raise and maintain the mash temperature, operating for one hour (see Figure 4.17). An additional 70 L are drawn at 09:00 to facilitate the next stage, during which malted barley and specialty grains are introduced. Heating continues beyond this period to sustain optimal mashing conditions.

Throughout this time, the wort boiling vessel remains inactive, with no operation of its 12 kW heating element. A steady base load of 2.2 kW from fermentation and cold storage systems persists (see Figure 4.16). Although summer peak rates are applicable, energy costs remain lower than those incurred during the winter peak period.

To further reduce energy costs during the peak tariff period, the resistive heating element in the hot water storage tank is switched off at 06:00, which coincides with the commencement of the morning peak period. It remains off until approximately 08:00, as part of a comprehensive demand response strategy. During this interval, the tank temperature gradually declines due to standby losses and anticipated hot water demand.

At 08:00, 650 L of hot water – the largest draw in the brewing cycle – are transferred to the insulated mash tun over a duration of roughly 15 minutes. The mashing process commences at 65 °C (see Figure 4.16). In response, the mash tun’s electric heating element switches on at 08:00 and remains operational for approximately one hour to raise and maintain the mash temperature (see Figure 4.18). The heater is subsequently switched off briefly around 09:00, followed by intermittent on/off cycling at 10:00, 12:00, and 14:00,

which reflects pulse heating to sustain the desired mash temperature while minimising energy consumption during the standard tariff period.

At 09:00, an additional 70 L of hot water are drawn to support the subsequent stage of the brewing process, during which malted barley and specialty grains are incorporated into the mash. The heating element remains intermittently active until approximately 15:00, at which point the mashing process concludes.

Throughout this duration, the wort boiling vessel remains inactive, with no operation of its 12 kW heating element. A constant base load is maintained from fermentation and cold storage systems (see Figure 4.17). Although summer peak rates apply during the early morning and late afternoon, energy costs remain lower than those associated with the winter peak period due to the control strategy and ToU alignment.

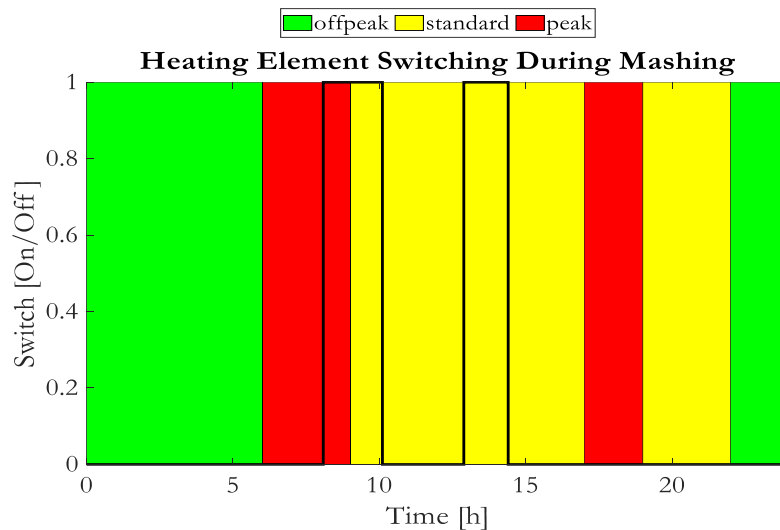


Figure 4.16: Switching function of mash during the summer season

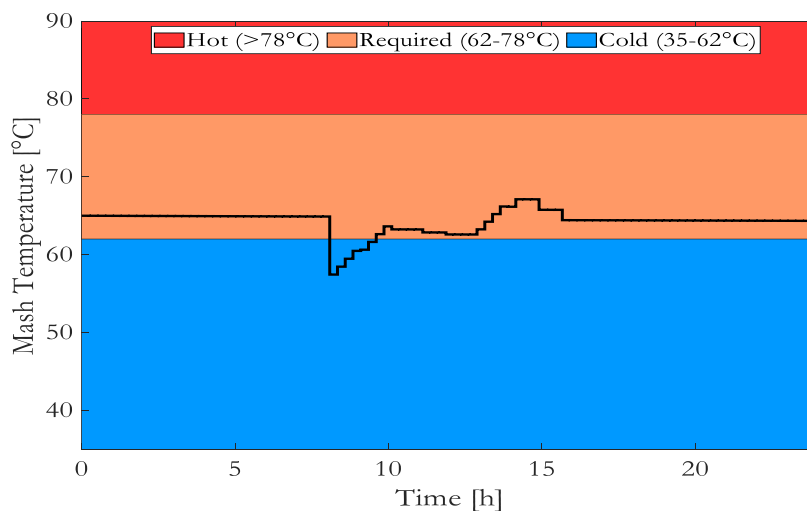


Figure 4.17: Storage tank mash temperature for the summer season

(d) *Switching profile and power demand during the standard period (10:00 to 18:00)*

Water heating initially remains inactive, as the tank was preheated prior to this stage. However, intermittent withdrawals for brewing, primarily during mashing and sparging, gradually decrease the temperature of the tank. Withdrawals occur at 10:00 (30 L), 13:00 (30 L), 15:00 (25 L), and 17:00 (100 L) (see Figure 4.7), which result in a consistent decline in temperature (see Figure 4.16).

The mashing phase occurs from 10:00 to 13:00, during which the 12 kW heating element is activated (see Figure 4.17) to increase the mash temperature from 65 °C to 75 °C to optimise enzymatic activity and to facilitate starch conversion. Additional hot water is added intermittently for temperature regulation and during sparging to maintain consistent wort quality. When the temperature of the hot water tank reaches the lower set-point, the electric resistive heater switches on at 13:40 for one hour to reheat to the upper set-point, in alignment with the standard tariff period to minimise energy costs.

Wort boiling commences at 15:00 and proceeds until 17:00, utilising the 7 kW element to heat the wort to 97 °C, thereby promoting hop isomerisation, sterilisation, and the removal of volatile compounds. This process is conducted during the moderate tariff period to further reduce costs. After 17:00, heating ceases as the processes of cooling and fermentation begin.

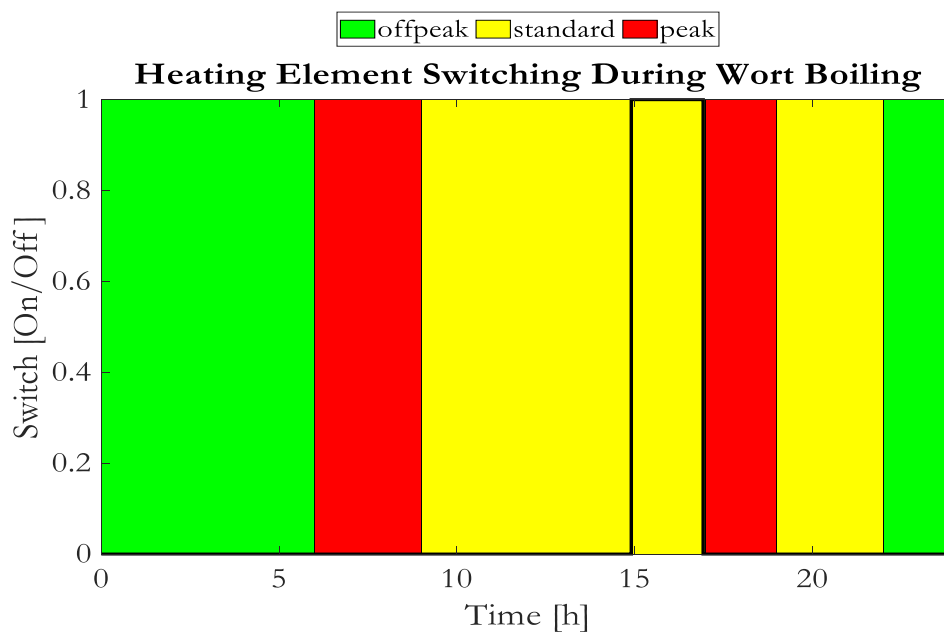


Figure 4.18: Switching function of wort during the summer season

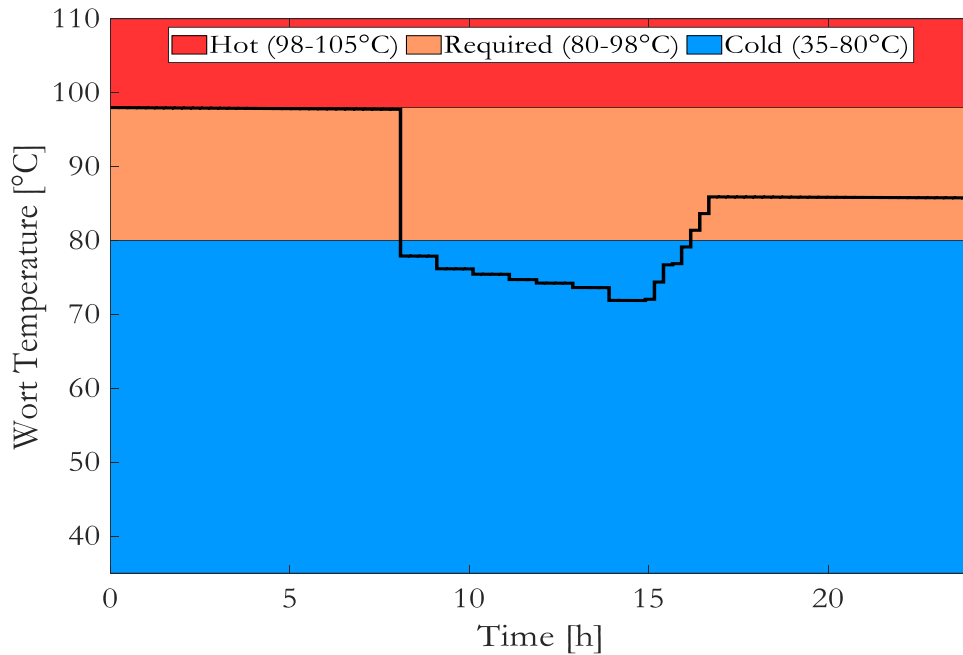


Figure 4.19: Storage tank wort temperature during the summer brewing season

4.5.1.2 Baseline system operation: Winter case

(a) Switching profile and water temperature during the off-peak period (00:00 to 06:00)

The winter brewing scenario employs the same off-peak preheating strategy as that utilised in summer, with water heating scheduled from 00:00 to 06:00 to minimise energy costs. Due to lower ambient temperatures, the initial water temperature is approximately 15 °C lower than the typical 22 °C observed in summer, which results in a steeper heating curve (see Figure 4.21). Nevertheless, the 1 100 L storage tank achieves the target temperature of 85 °C within the six-hour timeframe using a 12 kW resistive heating element (see Figure 4.21).

The heating element operates continuously without thermostat intervention (see Figure 4.20). No hot water is drawn during this period, and both the mashing and wort boiling vessels remain inactive. A constant base load from fermentation and cold storage persists throughout this duration, as indicated by the red line in Figure 4.20.

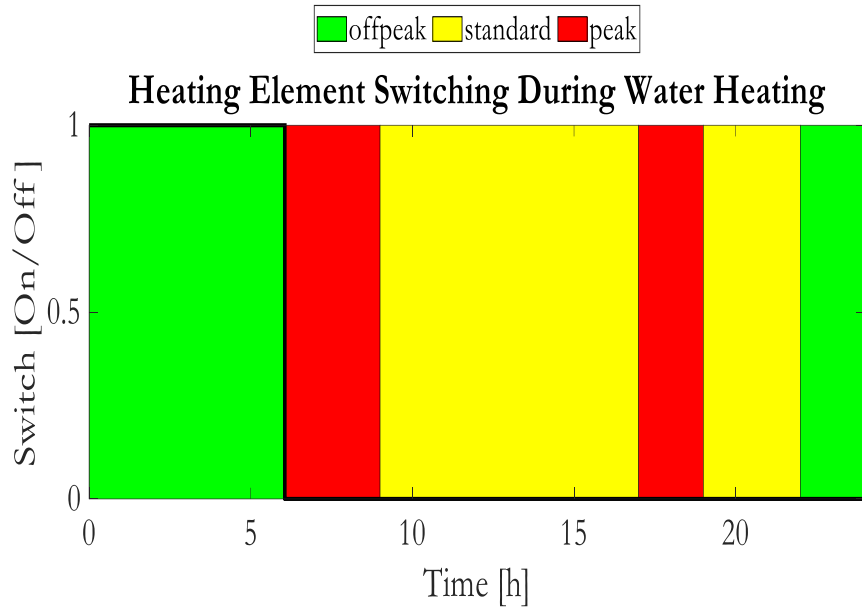


Figure 4.20: Heating resistive element switching during the winter season

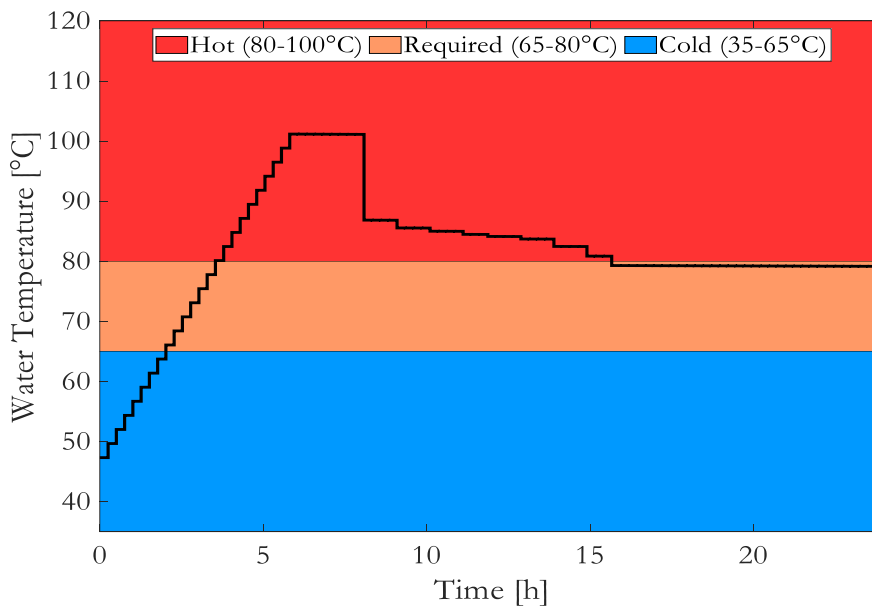


Figure 4.21: Storage tank water temperature during the winter season

(b) *Switching profile and water temperature during the peak period (06:00 to 09:00)*

During the winter peak electricity pricing period (06:00 to 09:00), the resistive heating element in the hot water storage tank is deactivated as part of a demand response strategy aimed at reducing operational costs. In the absence of active heating, the storage temperature steadily declines due to thermal standby losses and process demand.

At 08:00, 650 L of hot water – the maximum single withdrawal during the brewing cycle – are transferred into the mash tun over a period of 15 minutes, which initiates the mashing process at 65 °C. This demand spike, illustrated in Figure 4.22, accelerates the temperature drop in the tank. To stabilise mash conditions, the mash tun’s 12 kW heating element switches on and operates for one hour, maintaining the required mash temperature, as shown in Figure 4.23.

The wort boiling vessel remains offline during this interval, with no activation of its 12 kW resistive element. Meanwhile, a constant 2.2 kW base load from the cold storage and fermentation chamber persists and contributes to the facility’s critical demand, as indicated by the red line in Figure 4.25. Compared to summer, electricity prices during the winter peak are significantly higher, which underscores the importance of thermal scheduling and energy efficiency during this period.

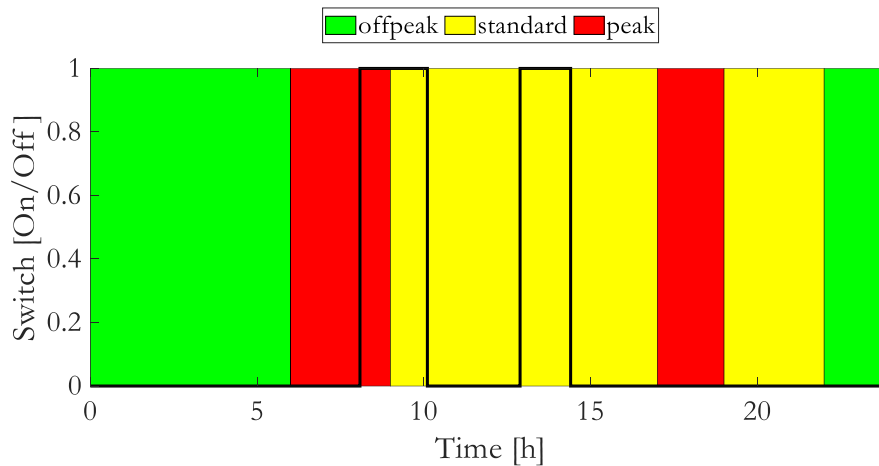


Figure 4.22: Switching function of the mashing process during the winter season

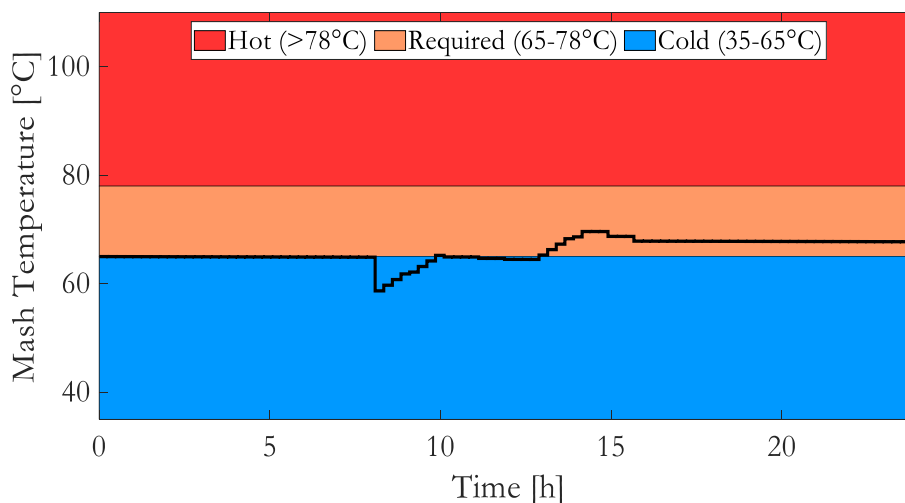


Figure 4.23: Storage tank mash temperature during the winter season

(c) *Switching profile and water temperature during the standard period (09:00 to 17:00)*

Water heating remains inactive at the commencement of the standard period (09:00 to 17:00), as the storage tank was preheated during the off-peak hours. A gradual decline in temperature occurs due to intermittent hot water draws for mashing and sparging – 30 L at 10:00, 30 L at 13:00, and 60 L at 15:00 (see Figure 4.23). At 10:30, the water tank temperature reaches the lower set-point, prompting the electric resistive heating element to switch on. It operates for one hour to restore the upper temperature limit (see Figure 4.10), with energy consumption occurring within the standard tariff window.

The mashing process is conducted from 10:00 to 13:00, during which the 12 kW mash tun heating element is switched on for two hours to raise the temperature from 65 °C to 75 °C (see Figure 4.25). Additional hot water is introduced as necessary for sparging and temperature control to facilitate efficient sugar extraction.

Wort boiling commences at 15:00, with the heating element switching on to maintain the boil at 97 °C until 17:00. This stage facilitates hop isomerisation, sterilisation, and the removal of volatiles. At 17:00, the element is switched off, which marks the transition to cooling and fermentation.

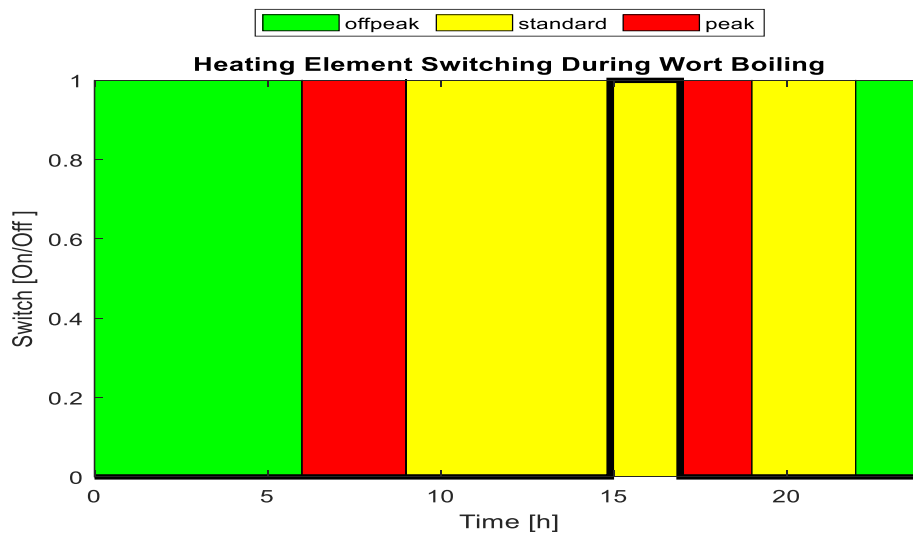


Figure 4.24: Switching function of the wort boiling process during the winter season

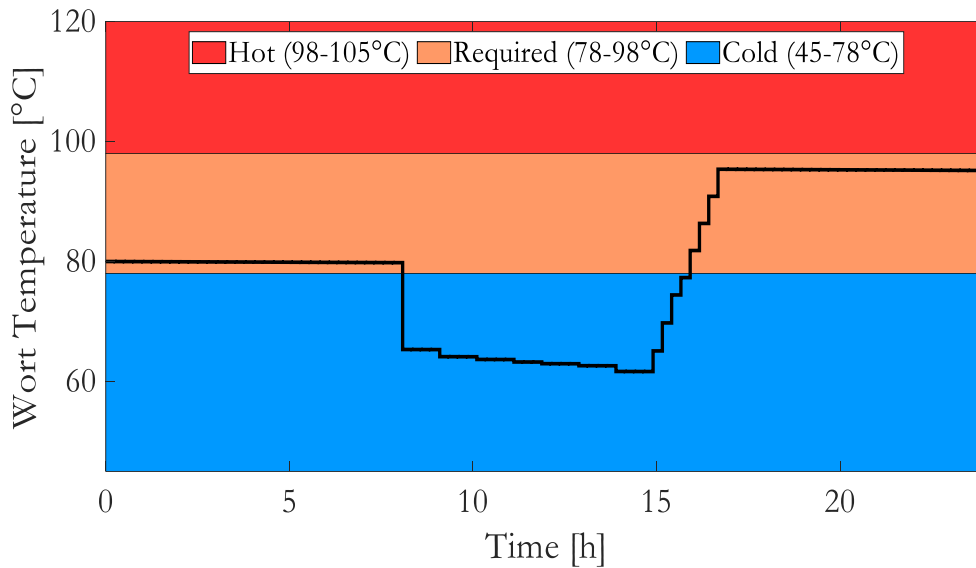


Figure 4.25: Storage tank wort temperature during the winter season

4.5.2 Optimal control of the hybrid renewable energy system with TES

4.5.2.1 Summer case

(a) Switching profile and water temperature during the off-peak period (00:00 to 06:00)

In the summer brewing schedule, the off-peak period (00:00 to 06:00) is strategically employed to minimise operational costs by selectively heating water using the hybrid energy system. In contrast to the baseline configuration, which continuously heats the storage tank using a resistive element, the proposed optimal control strategy intermittently activates the heat pump in response to forecasted hot water demand.

Figure 4.26 illustrates the system's switching profile in relation to the ToU tariff structure – off-peak (green), standard (yellow), and peak (red). During the off-peak period, the heat pump remains inactive, and no switching occurs for the electric resistive element throughout the control horizon (see Figure 4.27), thereby minimising reliance on high-cost electricity.

As depicted in Figure 4.28, the 1 100 L storage tank is preheated to approximately 66 °C. No hot water is drawn during this period; the heated water is stored for use in mashing, which commences after 08:00. Thermal processes such as mashing and wort boiling remain inactive overnight. A constant 2.2 kW base load, primarily from refrigeration and fermentation systems, persists during this time and contributes to the microbrewery's critical load profile, as represented by the red baseline in Figure 4.29.

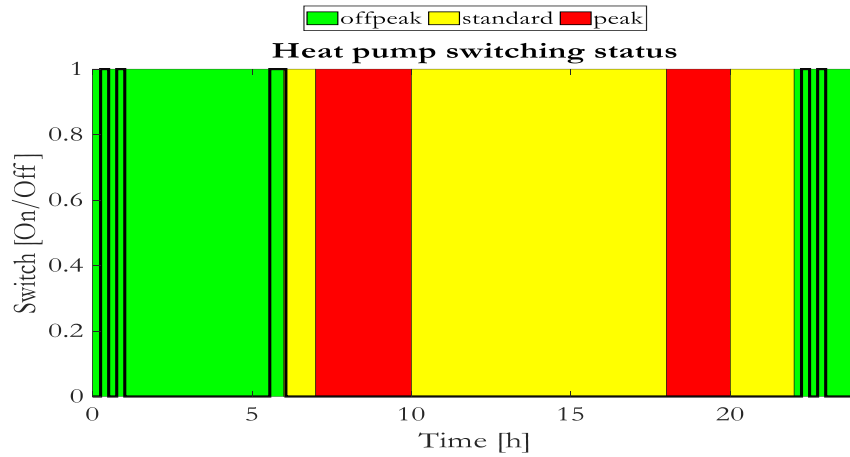


Figure 4.26: Heat pump switching function during the summer

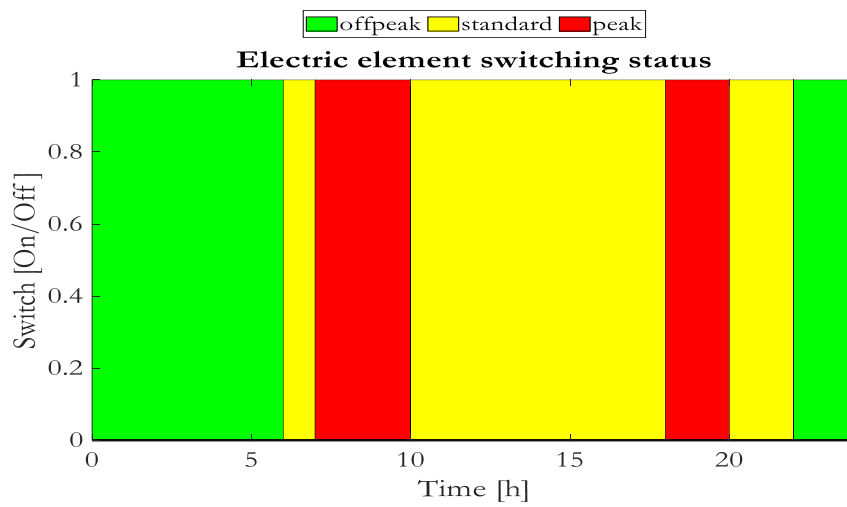


Figure 4.27: Electric resistive element switching status during the summer (March 2022)

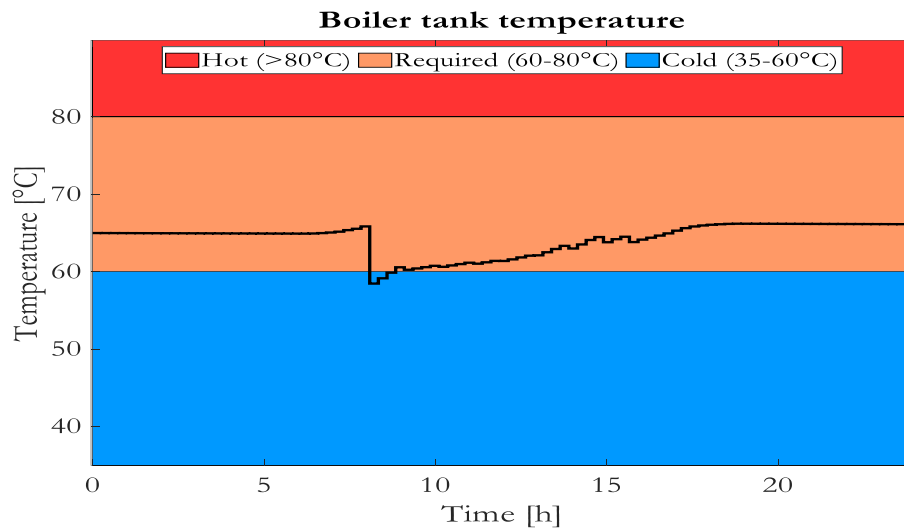


Figure 4.28: Water storage tank temperature of the proposed hybrid system during the summer

(b) Switching profile and water temperature during the standard period (06:00 to 07:00)

During the standard period, there is no demand for hot water in the microbrewery (see Figure 4.29), and the temperature in the insulated storage tank gradually decreases due to standby thermal losses (see Figure 4.30). There is no switching activity for either the heat pump or the electric resistive element (see Figures 4.26 and 4.27), which results in zero electricity consumption during this interval. Additionally, thermal processes such as mashing and wort boiling have not yet commenced.

(c) Switching profile and water temperature during the peak period (07:00 to 10:00)

To minimise electricity costs during the peak tariff period, both the heat pump and the resistive element remain off between 07:00 and 08:00 (see Figures 4.30 and 4.31), which results in zero energy consumption. In the absence of active heating, the temperature of the hot water storage tank decreases due to standby losses and increasing process demand.

At 08:00, 650 L of hot water are transferred to the mash tun to initiate mashing at 65 °C, followed by a further 70 L at 09:00 for grain infusion. The mash tun heater operates for one hour to maintain the set-point temperature while the wort boiler remains inactive.

Consequently, the temperature of the storage tank drops sharply, falling below 60 °C and continuing to decline due to draw-off and ambient heat loss (see Figure 4.30).

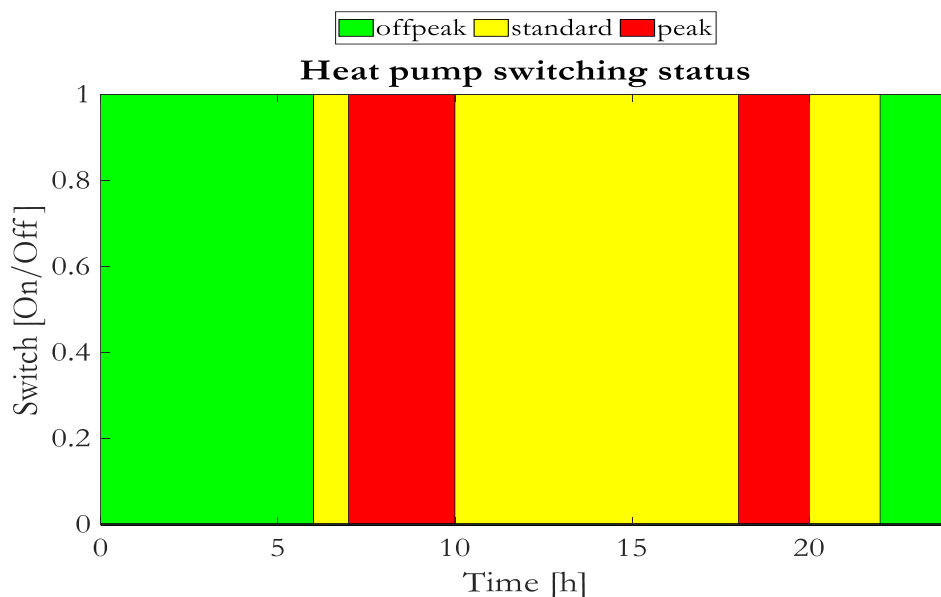


Figure 4.29: Heat pump switching for the summer season

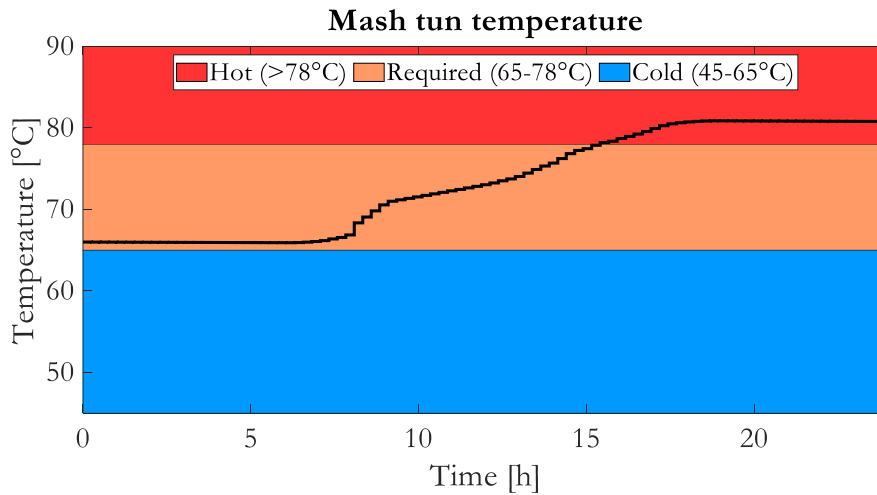


Figure 4.30: Storage tank mash temperature of the proposed hybrid system during the summer

During the standard electricity pricing period of 10:00 to 18:00 in the summer, there is no switching occurring for either the heat pump (see Figure 4.31) or the electric resistive element (see Figure 4.32). This phenomenon can be attributed to the adequate storage of thermal energy and stable temperature conditions in the system. The mashing process is conducted from 10:00 to 15:00, followed by wort boiling from 15:00 to 17:00, both of which depend on heat that was stored earlier during the off-peak period. The storage tank successfully maintains target temperatures without necessitating additional energy input, which indicates effective energy preloading and minimal heat loss. Given that electricity prices remain moderate during this period, and thermal demand is satisfied without the activation of heating devices, energy costs are optimised while ensuring process continuity.

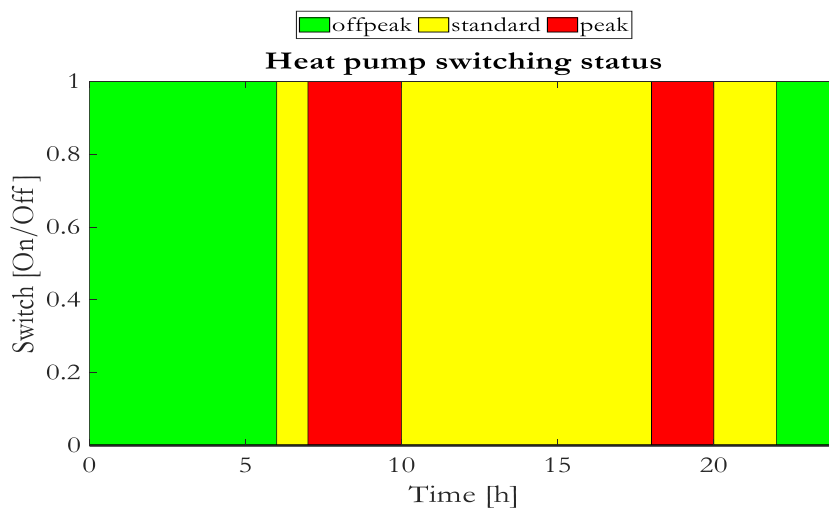


Figure 4.31: Heat pump switching for the summer season

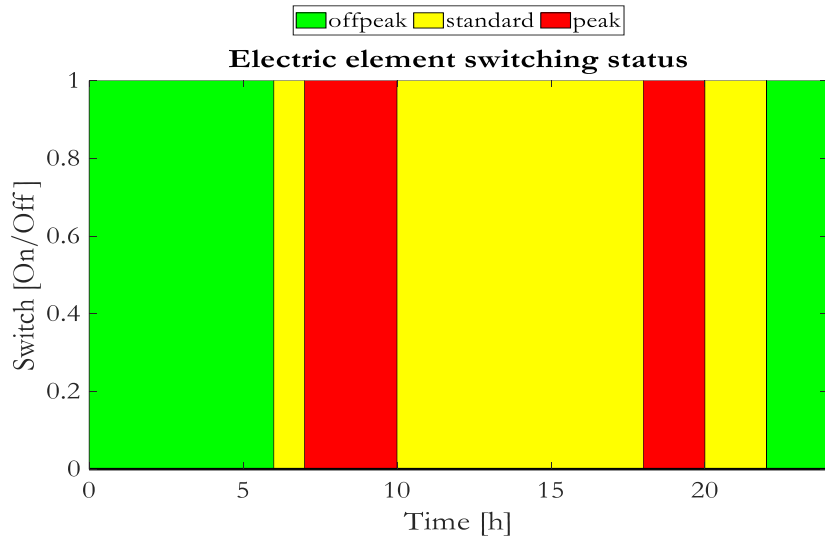


Figure 4.32: Electric resistive element switching for the summer season

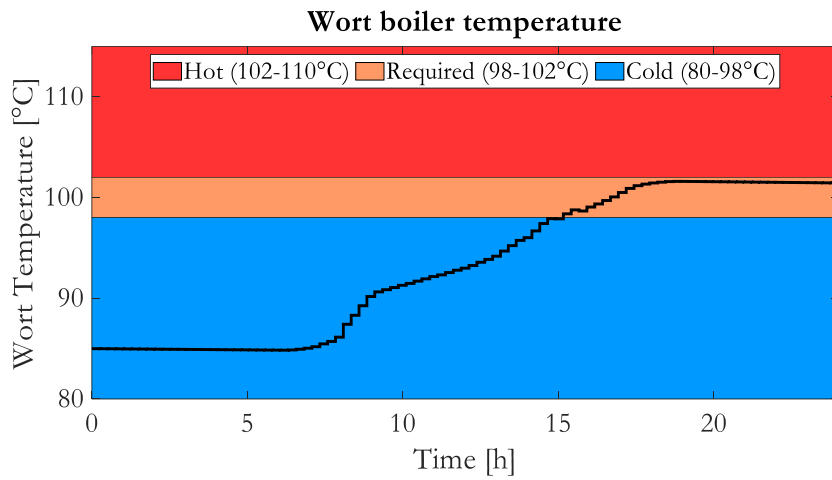


Figure 4.33: Storage tank wort temperature of the proposed hybrid system for the summer season

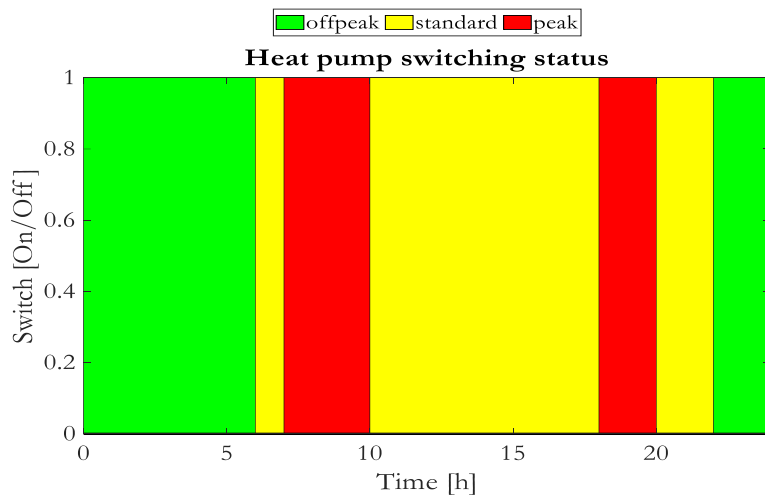


Figure 4.34: Heat pump switching for water heating processes during the summer season

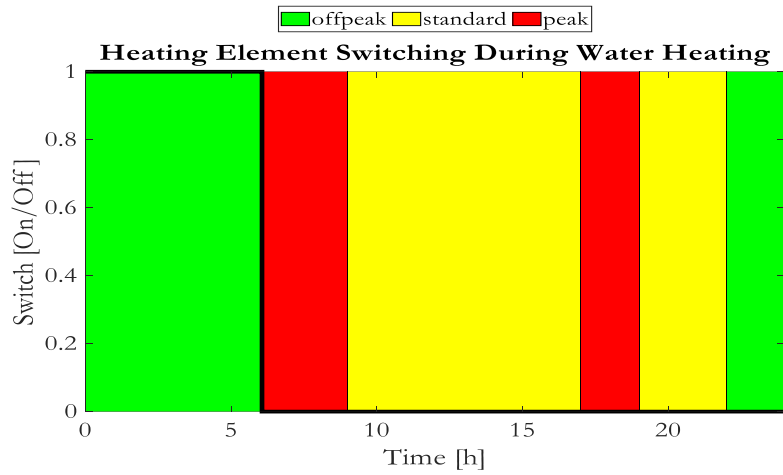


Figure 4.35: Electric resistive element water heating process of switching for the summer

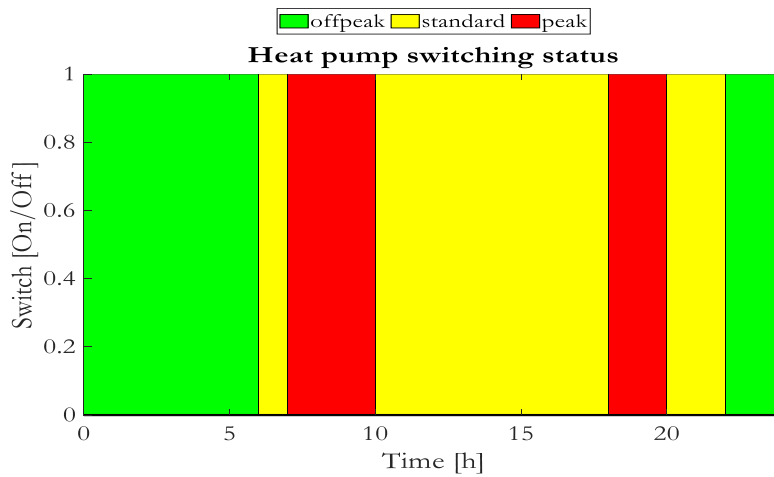


Figure 4.36: Heat pump switching for the wort boiling process for the summer

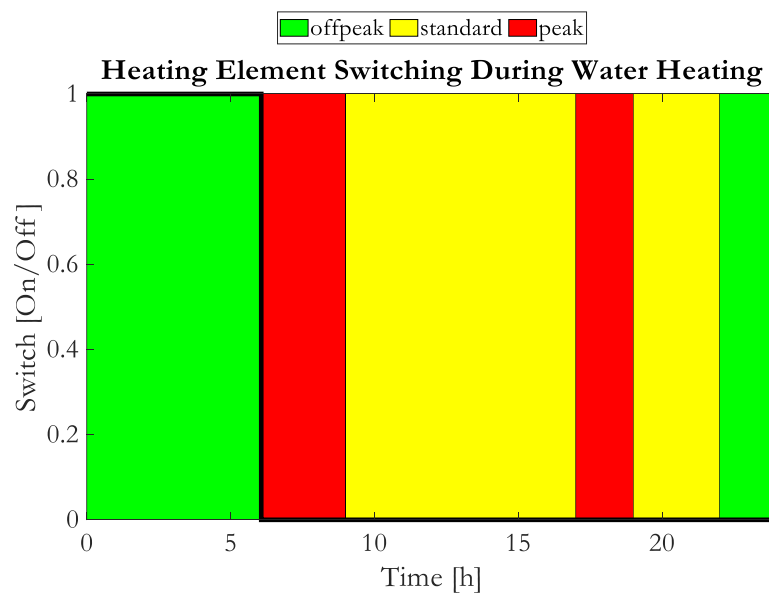


Figure 4.37: Electric resistive element switching for wort boiling during the summer

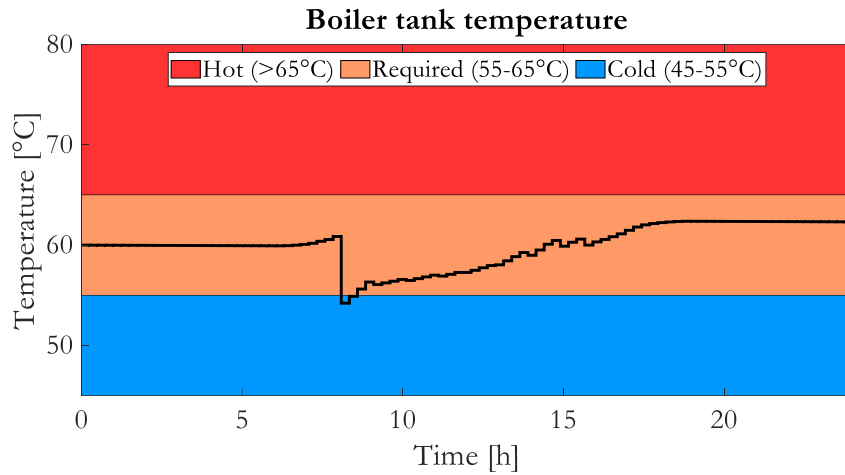


Figure 4.38: Water storage tank temperature during the summer

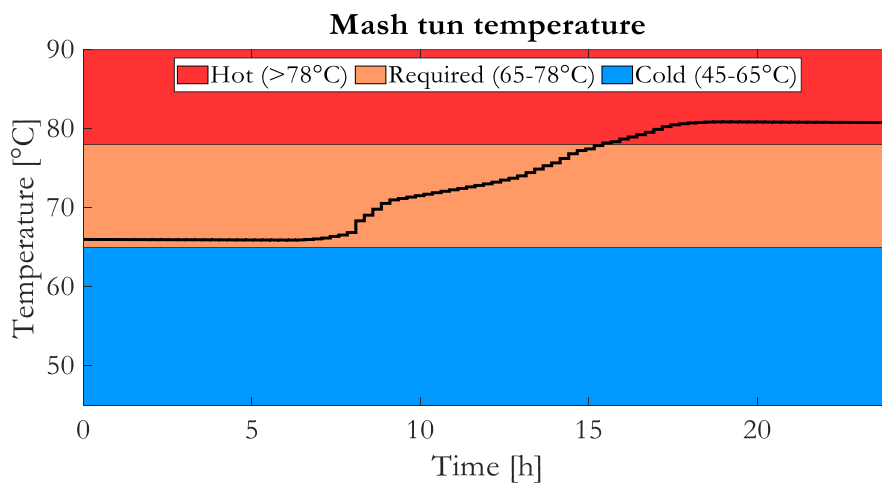


Figure 4.39: Mash storage tank temperature during the summer

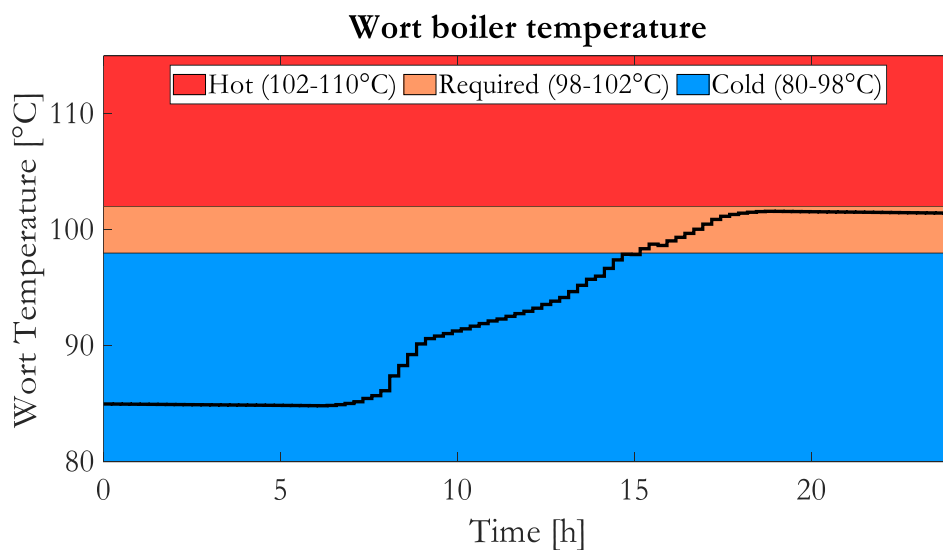


Figure 4.40: Wort storage tank temperature during the summer

4.5.2.2 Optimal control of the proposed hybrid energy system: Winter case

(a) Switching profile and water temperature during the off-peak period (00:00 to 06:00)

In the winter brewing schedule, the off-peak period (00:00 to 06:00) is strategically employed to minimise operational costs. However, owing to lower ambient temperatures and increased heat losses, the heating strategy of the system is adjusted accordingly. At the commencement of the control horizon, the temperature of the hot water in the storage tank (see Figure 4.41) is recorded to be below 63 °C.

No switching occurs for either the heat pump unit (see Figure 4.42) or the electric resistive element (see Figure 4.43) during this period, as confirmed by Figure 4.16, which results in zero electricity consumption. Despite the absence of active heating, post 06:00, the insulated 1 100 L water storage tank retains sufficient thermal energy from prior operation, which maintains temperatures close to the desired level (see Figure 4.44).

During this timeframe, no hot water is drawn, and all mashing and wort boiling processes have yet to commence. A consistent base load from fermentation and refrigeration continues to operate in the background, which contributes to the system's critical demand profile.

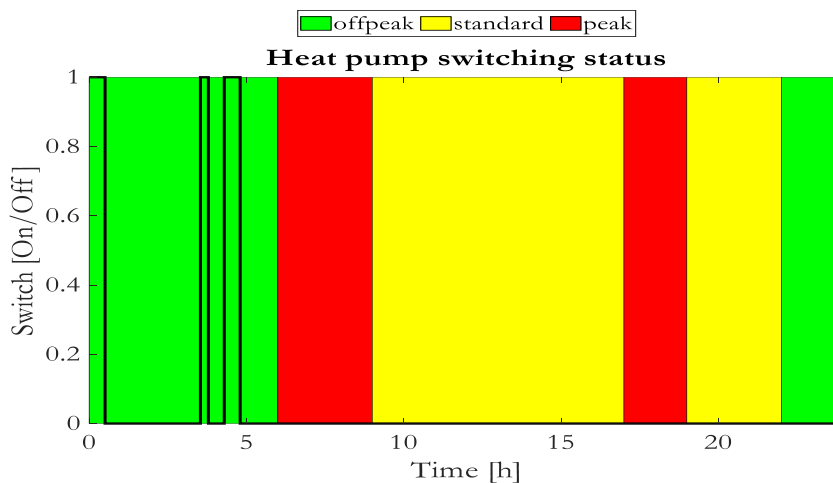


Figure 4.41: Heat pump switching for the winter season

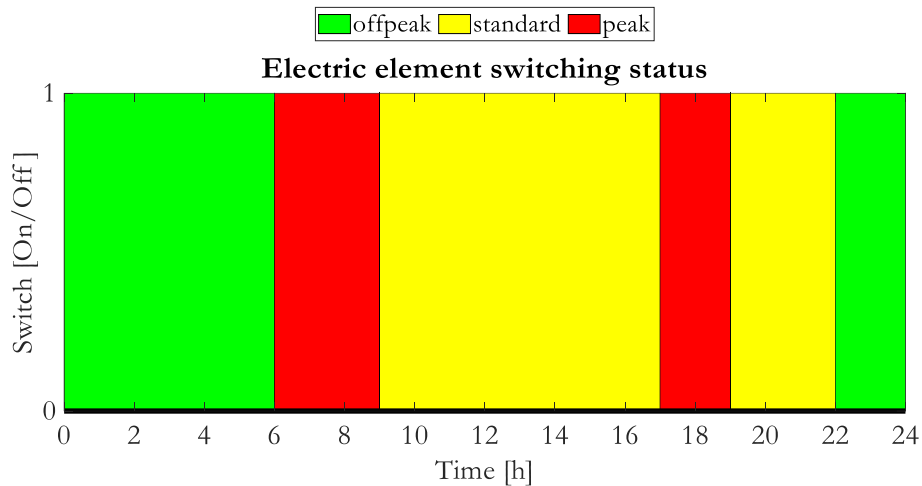


Figure 4.42: Electric resistive element switching for the winter season

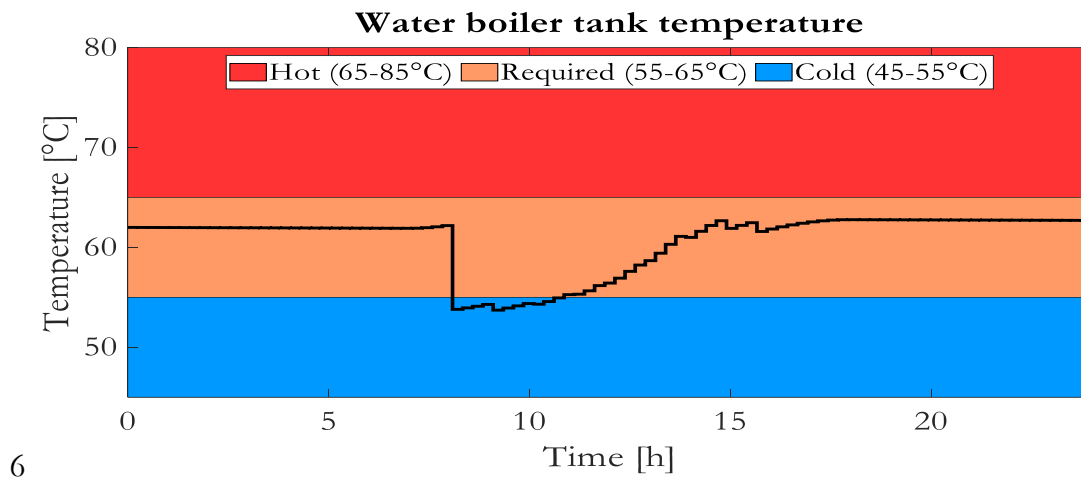


Figure 4.43: Water storage tank temperature during the winter

(b) *Switching profile and water temperature during the peak period (06:00 to 09:00)*

To mitigate elevated electricity costs during the winter peak tariff period, both the heat pump and the electric resistive element remain inactive (see Figures 4.44 and 4.45). In the absence of active heating, the temperature of the storage tank experiences a steady decline due to ambient losses and increasing process demand, particularly between 06:00 and 07:00 (see Figure 4.46).

At 08:00, 650 L of hot water are transferred to the mash tun to commence mashing at 65 °C, followed by an additional 70 L at 09:00 for grain infusion. The mash tun heater operates for one hour to sustain the designated temperature (see Figure 4.10), while both the wort boiler and the water storage tank remain inactive. No switching is recorded for either

control system during this period (see Figures 4.15 and 4.16), which results in zero electricity consumption.

(c) Switching profile and water temperature during the standard period (09:00 to 17:00)

During this period, no switching occurs for either the heat pump unit (see Figure 4.12) or the electric resistive element (see Figure 4.14). The electricity price remains moderate for consumption during this timeframe. The hot water demand fluctuates throughout this period, while the hot water temperature (see Figure 4.14) continues to gradually decrease to below 60 °C.

(d) Switching profile and water temperature during the peak period (17:00 to 19:00)

Similarly, no switching occurs for either the heat pump unit (see Figure 4.44) or the electric resistive element (see Figure 4.45) during this period. The hot water demand (see Figure 4.6) continues to fluctuate, and the hot water temperature gradually decreases to below 60 °C, while remaining above 50 °C.

During the standard tariff period, no switching occurs for either the heat pump or the electric resistive element (see Figures 4.44 and 4.45), as the system strategically avoids energy use despite moderate electricity prices. Hot water is drawn intermittently throughout this period (see Figure 4.6), which contributes to a gradual decline in the storage tank temperature, which falls below 60 °C by the end of the period (see Figures 4.46 and 4.47).

Mashing continues until approximately 15:00, with the mash tun heater operating to maintain the target temperature (see Figure 4.10). From 15:00 to 17:00, the wort boiling process commences, which draws additional thermal energy and causes the wort temperature to rise sharply. Despite these active brewing operations, no switching is triggered in the water heating system, which results in continued thermal depletion of the storage tank.

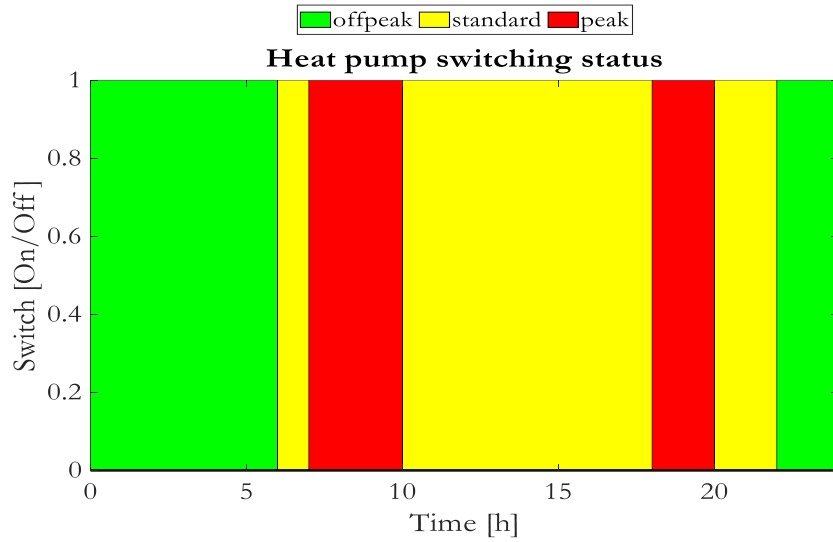


Figure 4.44: Heat pump switching for wort boiling during the winter season

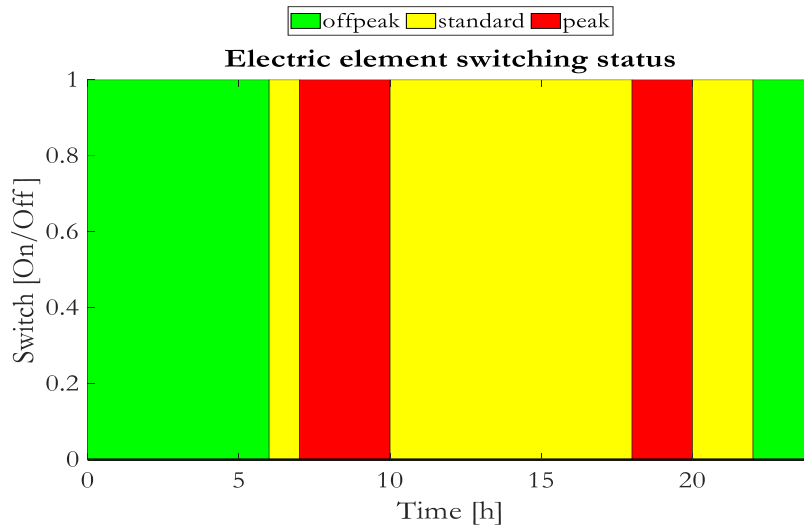


Figure 4.45: Electric resistive element switching for wort boiling during the winter season

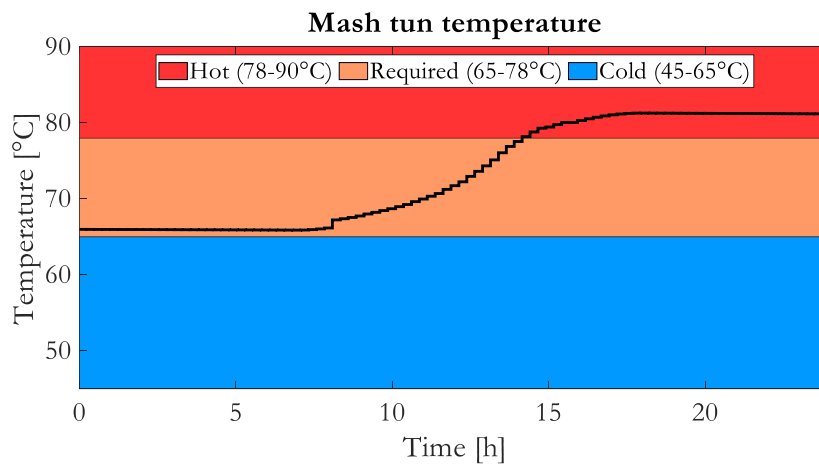


Figure 4.46: Storage mash tank temperature of the hybrid system for the winter season

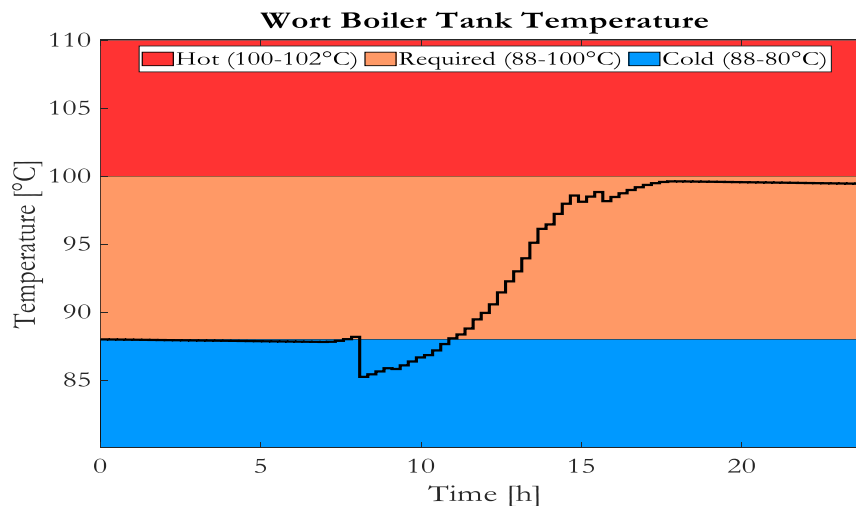


Figure 4.47: Storage wort tank temperature of the hybrid system for the winter season

4.5.3 Comparison between the baseline and optimal control of the hybrid renewable energy system in a microbrewery

Both the baseline and hybrid renewable energy systems elevate the thermal level of the process water to 60 °C and above, which ensures compliance with sanitation standards in the brewing process, including the effective elimination of *Legionella* bacteria. The operation of the thermostat in both systems was simulated within a 3 °C control band, which confirmed precise temperature regulation throughout the brewing cycle. These systems successfully maintained the thermal requirements necessary for mashing, wort boiling, and equipment cleaning, which supported uninterrupted brewery operations.

In the baseline system, thermal energy is provided exclusively by an electric resistive element, which switches on whenever the process water temperature falls to or below the defined set-point. This includes activation during peak ToU tariff periods, irrespective of electricity pricing, which leads to significant energy consumption and elevated operational costs. The absence of intelligent control results in frequent heating cycles, particularly during high-demand brewing periods, which increases the brewery's total energy expenditure.

The hybrid renewable energy system, governed by an optimal control strategy, strategically selects low-tariff time blocks within the ToU pricing schedule to perform the majority of water heating. The system prioritises solar thermal and heat pump technologies as the primary heat sources, while the electric resistive element is employed only as a supplementary energy source when renewable energy supply is insufficient. Based on the switching profile results, the heat pump is activated during early morning off-peak hours to

preheat the storage tank, while the resistive element remains inactive throughout this period. This ensures that water is already at the required temperature before thermal demand peaks during brewing activities. As a result, the brewery benefits from reduced reliance on high-cost grid electricity, lower energy bills, and improved sustainability, all while maintaining strict process temperature requirements.

4.6 SUMMARY

In this chapter, the optimal operational control model of a hybrid renewable energy system for a microbrewery was simulated using the SCIP solver in the MATLAB OPTI Toolbox. Seasonal extremes for winter and summer were derived from historical weather data specific to Bloemfontein, while water inlet and ambient temperature values were approximated based on existing literature relevant to brewing operations. These data formed the basis for developing two system models: a baseline configuration using conventional control and a proposed system that incorporates optimal control strategies. The simulation examined the daily non-linear thermal loads typical of brewing processes, the variability of renewable energy resources, and the dynamic behaviour of the storage tank temperature, all in relation to the resulting daily operational costs. A comparative analysis of switching profiles between the baseline and the optimally controlled systems was also conducted.

The optimal energy management model was further utilised to:

- Minimise operational costs through the implementation of the proposed optimally controlled hybrid system during critical brewing phases, including mashing, wort boiling, and cleaning.
- Evaluate the influence of solar irradiance on thermal performance when the solar thermal system operates in conjunction with the heat pump, with particular emphasis on its impact on storage tank temperature dynamics under the ToU electricity pricing structure.
- Highlight the significance of accounting for seasonal variations in thermal load, renewable energy availability, inlet water temperature, and ambient conditions when assessing the daily and annual operational costs of the hybrid energy system.

The simulation results indicate that the proposed system primarily heats water using the HPWH, particularly during off-peak tariff periods in the early morning and evening. This operational strategy leads to significant cost savings, as the HPWH requires approximately one-third of the energy consumed by an electric resistive heater. Furthermore, electricity tariffs during off-peak periods are significantly lower than those during standard and peak periods. In contrast, the baseline system relies on electric resistive heating, with switching primarily occurring during standard and peak periods, which results in elevated energy costs.

Given the differences in system configuration between the proposed and baseline setups, a further techno-economic evaluation was warranted. This is discussed in the following chapter, where cumulative energy usage and LCCs are assessed over a 20-year operational horizon for the microbrewery application.

4.6.1 Solar irradiation potential and thermal output from solar collectors

Evaluating solar irradiation at the microbrewery site is essential for appropriately sizing the solar thermal collector system and estimating its thermal energy output. The system provides heat for key brewing processes such as hot water production, mashing, and wort boiling. Solar energy is captured and stored in a TES unit, which reduces reliance on grid electricity and enhances sustainability. Figures 4.48 and 4.49 illustrate the site's solar radiation levels and expected thermal output per square metre, which are critical for optimising the system's performance and energy management throughout the day in both the summer and winter seasons.

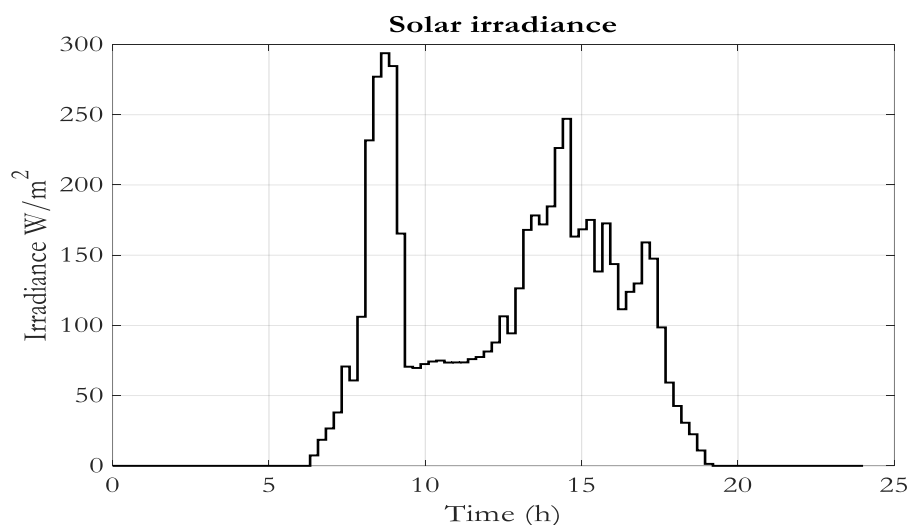


Figure 4.48: Hourly solar power generation profile in the summer (March 2022)

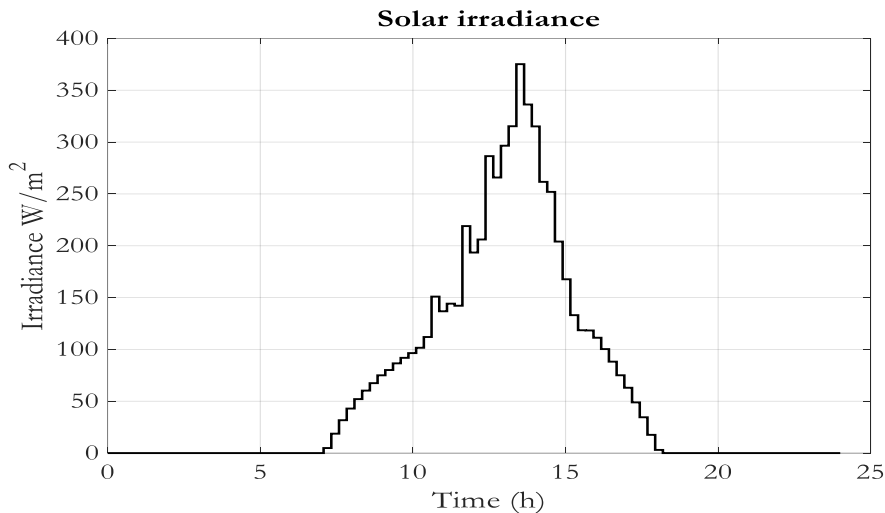


Figure 4.49: Hourly solar power generation profile in the winter (August 2023)

4.6.2 Environmental impact analysis

In addition to the economic advantages, the implementation of the proposed energy-saving system contributes significantly to environmental sustainability. An annual electricity saving of 233 922.65 kWh has been recorded, which results directly in a reduction of greenhouse gas and pollutant emissions, given the reliance on fossil fuel-based electricity generation in South Africa.

4.6.2.1 Reduction in carbon dioxide equivalent (CO_{2e}) emissions

To evaluate the environmental impact, the electricity savings were converted into avoided CO_{2e} emissions. Based on an emission factor range of 0.95 to 1.03 kg CO_{2e}/kWh, which is typical for South Africa's grid, the annual CO_{2e} reduction was calculated as follows:

- Lower bound: $233\,922.65 \text{ kWh} \times 0.95 \text{ kg CO}_2\text{e/kWh} = 222\,226.52 \text{ kg CO}_2\text{e}$
- Upper bound: $233\,922.65 \text{ kWh} \times 1.03 \text{ kg CO}_2\text{e/kWh} = 240\,940.33 \text{ kg CO}_2\text{e}$

This equates to an estimated annual carbon emissions reduction of 222.23 to 240.94 tonnes of CO_{2e}.

4.6.2.2 Sulphur dioxide (SO₂) emissions reduction

SO₂ emissions are another major concern associated with coal-based electricity generation. Using an emission factor of 5.39 g SO₂/kWh, the SO₂ emissions savings were

estimated as $233\,922.65 \text{ kWh} \times 5.39 \text{ g SO}_2/\text{kWh} = 1\,260\,814.09 \text{ g SO}_2$. This is equivalent to approximately 1.26 tonnes of SO_2 emissions avoided annually.

In summary, these results demonstrate that the proposed system not only achieves significant cost savings but also aligns with environmental sustainability goals. The reduction of over 220 tonnes of CO_2e and over one tonne of SO_2 per year underscores the potential for this solution to contribute meaningfully to emission mitigation targets in the microbrewery sector and similar energy-intensive industries. The following section presents a detailed economic analysis of these energy savings.

4.6.3 Economic analysis

A comprehensive economic evaluation was conducted to assess the feasibility of an energy management system implemented in a microbrewery and to estimate the investment's present value over time. In the long term, integrating a hybrid solar TES system connected to the grid is anticipated to reduce energy consumption and associated costs. It was therefore essential to perform a detailed assessment of the economic feasibility of this solution. The analysis included an estimate of the simple payback period based on the net present value to provide insight into when the investment is likely to be recovered. Key financial factors such as inflation, depreciation, operational expenses, and maintenance costs were considered to determine the overall economic performance. The mathematical formulations used to calculate the present value, net present value, and simple payback period were presented in Equations 4.11 to 4.13, as detailed in Section 4.2 [182]. These equations estimated the present value of future cash flows, net present value, and the payback period, respectively. In addition, the LCC was evaluated using Equation 4.57, which incorporated all major cost components, including initial investment, salvage value, replacement, operation, maintenance, and energy costs for each system element.

Section 4.2 outlines the simulation outcomes and compares the energy expenditures of the baseline and proposed configurations for the microbrewery. According to Table 4.2, the capital investment for the STES is estimated at USD 10 100. Incorporating TES adds approximately USD 3 300, while the installation of a heat pump contributes an additional USD 2 700 to the overall system cost [5,191].

Table 4.2: Cost to invest in a solar TES system and heat pump

Initial capital investment	Cost (USD)	Cost (USD)
4 kW 24VDC solar collector panel cost (USD)		
12 units	475*12	5 700
Controller cost (USD)	100	100
Inverters and accessories cost (USD)	3 300	3 300
Thermal storage cost		3 100
11 kW commercial heat pump		2 200
Installation cost (USD)	1 000	1 700
Total investment	10 100	16 100

The electricity tariff applicable to the microbrewery adheres to a ToU structure, which employs an exchange rate of USD 1 = ZAR 18 for cost conversions [33]. This section assesses the utility electricity costs associated with both the baseline and proposed control strategies within the context of typical brewing operations. As outlined in Section 4.3, the baseline system, which utilises conventional thermostat-based electric heating and cooling, exhibited an energy consumption of approximately 222 413.10 kWh during the summer period and 89 942.82 kWh during the winter. These consumption figures form the foundation for estimating daily and annual electricity costs, as detailed in Table 4.3.

Table 4.3: Seasonal ToU tariff structure applied in the model

Season	Months	Period	Time	Rate (ZAR)	Rate (USD)
High demand (winter)	June - August	Off-peak	00:00–06:00, 22:00–24:00	70.27	3.904
		Standard	09:00–17:00, 19:00–22:00	131.56	7.309
		Peak	06:00–09:00, 17:00–19:00	429.9	23.833
Low demand (summer)	September - May	Off-peak	00:00–06:00, 22:00–24:00	52.42	2.912
		Standard	06:00–07:00, 10:00–18:00, 20:00–22:00	77.62	4.312
		Peak	07:00–10:00, 18:00–20:00	187.1	10.394
Parameter	Description			Value	
ts	Sampling time (min.)			15	
N	Control horizon (-)			96	
Hours	Total hours in control horizon (hour)			24	

4.6.4 Daily energy consumption and savings

Table 4.2 presented the typical daily energy consumption and associated costs for both the conventional and proposed hybrid systems under standard summer and winter conditions. A comparative analysis of the two systems facilitates the derivation of monthly daily savings based on their performance variations across each season.

Table 4.4: Daily energy usage and associated savings

Season	Baseline system		Optimally controlled system		Annual savings	
	Energy (kWh)	Cost (ZAR/USD)	Energy (kWh)	Cost (ZAR/USD)	Energy (%)	Cost (%)
Summer	814.70	3 774.20	241.79	1 027.60	70.32	72.78
		209.68		57.09		
Winter	977.64	5 059.00	135.04	1 254.10	86.19	75.21
		281.06		69.67		

To estimate the annual energy consumption, associated costs, and total savings, the calculated daily values are extrapolated based on the number of days in each season – 92 days for winter and 273 days for summer. Table 4.5 presents the computed annual savings for the microbrewery, which are derived from a comparative analysis between the baseline and optimised systems. Table 4.5 compares the total yearly electricity expenses for the baseline system and the proposed optimal control model. The latter integrates TES and intelligent load scheduling, which significantly reduce electricity costs by shifting consumption to lower tariff periods.

Table 4.5: Seasonal energy consumption and savings

Season	Baseline system		Optimally controlled		Annual savings	Annual savings	
	Energy (kWh)	Cost (ZAR/USD)	Energy (kWh)	Cost (ZAR/USD)	Cost (ZAR/USD)	Energy (%)	Cost (%)
Summer	219 969	1 030 356.60	66 008.67	280 534.80	749 821.80	70.32	72.78
		57 242.03		15 585.27	41 656.77		
Winter	89 942.88	46 5428.00	12 423.68	115 377.20	350 050.80	86.19	75.21
		25 857.11		6 409.84	19 447.27		
Total	312 355.98	1 495 748.60	78 432.35	395 912.20	1 099 872.60	74.89	73.53
		83099.40		21 995.11	61 104.04		

4.6.5 Energy and cost optimisation in microbrewery operations

The integration of the optimised hybrid energy system in the microbrewery's thermal process yielded considerable improvements in both energy efficiency and cost performance. Unlike the baseline configuration, which operates without regard to tariff fluctuations, the optimised system strategically aligns energy usage with low-cost periods defined by the ToU tariff structure. This demand-shifting capability results in substantial operational savings.

During the summer season, the optimised system achieved a cost reduction of approximately ZAR 749 821.00 (USD 41 656.77), while in winter, savings reached ZAR 350 050.80 (USD 19 447.27). These figures represent cost reductions of 72.78% and 75.21% respectively, relative to the baseline scenario. In addition to financial savings, a marked decrease in energy consumption during peak pricing hours was observed, which contributed to a more sustainable and efficient use of electrical energy.

Over a full operational year, the system demonstrated a total cost saving of ZAR 1 099 872.60 (USD 61 104.03), which equated to a 73.53% reduction in electricity-related expenditure. These results underscore the effectiveness of intelligent energy scheduling and highlight the economic and environmental advantages of ToU-responsive control strategies in microbrewery applications.

4.6.6 Results of the economic analysis

Figure 4.50 presents a comparison of the total LCC between the baseline electric water heating system and the proposed optimally controlled hybrid system over a 20-year project lifetime. This section provides a detailed LCC analysis that incorporated both economic and energy performance metrics to evaluate the long-term feasibility of each system.

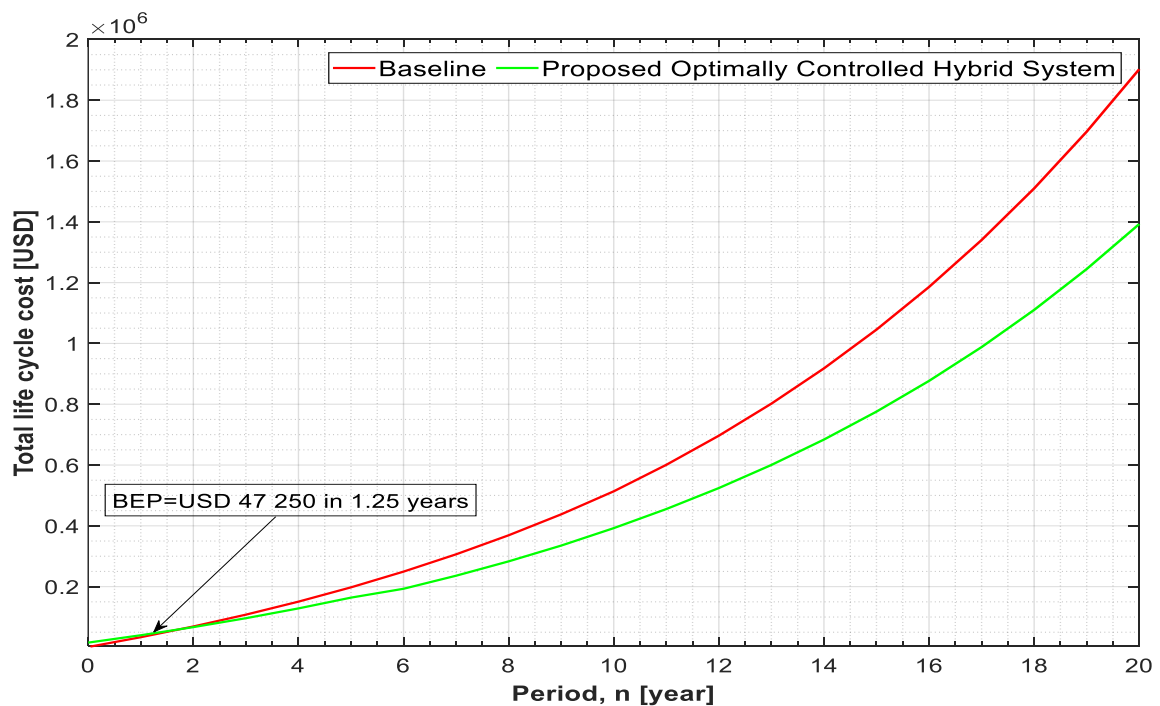


Figure 4.50: LCC analysis for the baseline system and optimal system with solar TES system and heat pump

The economic assessment is based on two key financial parameters: an average inflation rate of 5% per annum and an annual electricity price escalation rate of 10% per annum. These values serve as input parameters in the simulation and reflect realistic cost projections for equipment, services, and energy over the analysis period. The inflation rate accounts for the anticipated increase in equipment and component replacement costs, while the electricity price increase encapsulates the growing burden of energy expenses on operational costs.

In the comparison, the red curve represents the baseline system, which relies entirely on conventional electric resistive heating. The green curve corresponds to the proposed optimal hybrid system, which integrates a solar TES system and a heat pump with control strategies to enhance efficiency and reduce reliance on grid electricity. The analysis encompasses all major cost elements, such as the initial capital investment, annual operational and maintenance costs, and inflation-adjusted component replacement expenses.

Although the baseline system appears more cost-effective in the initial stages due to its lower upfront cost, its total expenditure increases sharply over time, which is primarily driven by the compounded effect of escalating electricity tariffs and frequent equipment replacements. In contrast, the proposed hybrid system, despite a moderately higher initial investment, exhibits a significantly slower rise in cumulative cost. This is attributed to improved energy efficiency, reduced dependency on grid-supplied electricity, and the ability to shift heating loads away from high-tariff periods through predictive control.

The financial BEP between the two systems is attained after approximately 1.25 years, when both systems reach a cumulative cost of USD 47 250 (ZAR 850 500). Beyond this point, the proposed optimal hybrid system maintains a consistent cost advantage over the baseline.

By the conclusion of the 20-year project life, the baseline system accumulates a total cost of approximately USD 1.93 million, while the proposed hybrid system concludes at just USD 1.387 million. This results in a substantial lifetime saving of USD 3.65 million, which equates to a 74.3% reduction in total expenditure. These findings underscore the clear economic advantage of the proposed system, which offers not only long-term cost savings but also enhances resilience to rising electricity prices.

Furthermore, the integration of solar thermal energy and predictive control strategies significantly enhances operational efficiency, which renders the system particularly well-suited to energy-intensive industrial applications such as microbreweries. Overall, the

proposed hybrid configuration demonstrates strong potential for delivering both economic and energy performance benefits, which reinforces its suitability as a sustainable solution for industrial energy management.

This analysis accentuates the long-term financial advantages of the proposed system, which improves efficiency and decreases reliance on conventional energy sources. It also illustrates the economic sustainability of employing advanced forecasting techniques in brewery heating processes, particularly in light of rising energy costs.

Furthermore, Figure 4.50 reflects the variation in LCC for the proposed solar TES system, utilising the same financial parameters. The inflation rate indicates anticipated increases in equipment and service prices, while the increase in electricity prices suggests significant annual growth in energy expenses.

4.7 CONCLUSION

This chapter presented the development and evaluation of an optimisation-based energy-efficiency control strategy for a hybrid thermal energy system implemented in a microbrewery located in Bloemfontein, South Africa. The system configuration incorporated electric heat pumps, solar-thermal collectors, and a thermal energy storage (TES) unit that were integrated to support key brewing processes, including hot-water generation, mashing, and wort boiling. The proposed optimal-control strategy aimed to minimise operational energy costs through intelligent scheduling informed by process heat-demand profiles and a time-of-use (ToU) electricity-tariff structure. The control model was implemented using the SCIP solver, which effectively addresses the nonlinear and mixed-integer characteristics of the optimisation problem.

The baseline configuration represented a traditional system employing thermostat-controlled electric heating without solar integration or optimisation. In contrast, the proposed hybrid system introduced solar-thermal energy and a mixed-integer optimisation framework capable of shifting energy-intensive processes to lower-tariff periods and improving the utilisation of stored thermal energy. Although battery storage was not included in the present study, its integration in future work may enhance demand flexibility and further reduce grid reliance.

The simulation results revealed that the proposed optimal control model significantly reduced grid electricity usage and system energy costs by 72.78% in summer, saving

ZAR 749 821.80 (USD 41 656.77), and by 75.21% in winter, saving ZAR 350 050.80 (USD 19 447.77). Annual savings total ZAR 1 099 872.60 (USD 61 104.04), which represented a reduction of 73.53%. Environmentally, the system minimised 222 to 241 tonnes of carbon emissions annually. Economically, the BEP is reached within 1.25 years, with projected savings over a 20-year lifespan amounting to ZAR 65.75 million (USD 3.65 million), which reduces LCCs by 74.31%. These benefits were achieved without compromising process efficiency or product quality.

Although the proposed hybrid-optimisation approach performs strongly in this case study, its applicability in other microbreweries may vary due to differences in climate, tariffs, and operational conditions. Solar irradiance levels, seasonal temperatures, and local weather patterns influence solar-thermal collector output and heat-pump performance. These factors directly affect thermal availability and seasonal energy savings. Brewery-specific factors such as production scale, scheduling patterns, equipment configuration, TES capacity, and local energy-infrastructure reliability also impact system performance. Therefore, site-specific calibration that accounts for local climate, tariff conditions, and infrastructure is essential to ensure accurate optimisation and meaningful economic and environmental benefits.

Furthermore, the proposed optimisation framework is highly adaptable to emerging smart-grid and microgrid environments. As energy systems shift toward decentralised architectures with greater renewable generation, storage, and real-time pricing, the hybrid thermal system developed in this study can integrate seamlessly with advanced energy-management platforms. Its supervisory control enables demand-response participation, dynamic tariff optimisation, and grid-interactive operation with distributed energy resources. This adaptability strengthens system resilience, increases renewable-energy utilisation, and positions microbreweries to incorporate future technologies such as battery storage, dynamic pricing signals, and microgrid controllers.

Overall, the findings highlight the substantial value of integrating solar-thermal energy with optimal-control strategies for industrial thermal applications. For microbreweries, such approaches offer significant environmental and financial advantages, support resilience against increasing energy costs, and promote sustainable production practices. The outcomes of this study establish a foundation for broader adoption of renewable-integrated optimisation models within the food and beverage manufacturing sector and provide a pathway toward more efficient, cost-effective, and sustainable industrial energy systems.

CHAPTER 5:

GENERAL CONCLUSION AND FUTURE WORK

5.1 SUMMARY

This chapter concludes the investigation into energy efficiency improvements for a microbrewery in South Africa through the integration of predictive modelling, hybrid renewable energy systems, and optimal control strategies.

An energy audit conducted at a microbrewery in Bloemfontein revealed that producing 800 L of beer consumed approximately 518.09 kWh, which is equivalent to 0.65 kWh per litre and nearly 50% above industry norms. The majority of this energy consumption was attributed to thermal processes, including water heating (83 kWh per batch), wort boiling (60 kWh), and cold storage (over 300 kWh per cycle). These high demands were further exacerbated by reliance on inefficient grid-powered heaters and the lack of process scheduling aligned with ToU electricity tariffs. The study addressed this challenge and highlighted that thermal operations account for over 85% of total energy consumption in microbreweries, which is substantially more than in large-scale brewing.

Chapter 2 provided a global review of energy management practices in the brewing industry and emphasised the potential of hybrid systems and advanced control methods. The POET framework was employed to identify energy-saving opportunities at four levels: conceptual, operational, technical, and engineering, with projected savings ranging from 10% to 70%, depending on the depth of implementation. Operational changes, such as scheduling adjustments, technical upgrades including insulation and heat pump installation, and system-level interventions with solar thermal integration were assessed as part of the structured roadmap.

Chapter 3 focused on the development and application of ANNs for predicting energy demand at various brewing stages. Utilising real-time data from 100 samples, two ANN architectures were developed: the NAR model and the NARX model. The models forecasted four performance indicators: input power, cooling load, thermal storage temperature, and heat pump output. Regression values reached 0.9978 for input power, 0.9982 for cooling load, and 0.9961 for storage-temperature forecasting, while the NAR model achieved MSE values between 0.0029 and 0.0049. These results indicate strong predictive capability and

suggest that ANN-based forecasting may support more precise scheduling to align energy consumption with low-tariff periods and help reduce peak demand.

ANNs also identified recurring consumption patterns linked to batch sizes and brewing frequency, which provided critical insights for process optimisation. This enabled scenario testing and virtual experimentation, which reduced reliance on physical trials. The models' adaptability to non-linear, time-dependent load behaviours rendered them suitable for ongoing energy management improvements in microbreweries.

Additionally, a comprehensive economic analysis was conducted to assess the feasibility of the proposed system. The LCC evaluation indicated that with an initial investment of approximately USD 50 000, the hybrid energy system achieved a BEP within 1.5 years. The system also demonstrated resilience under fluctuating economic conditions, including inflation and ToU electricity tariffs. Over a 20-year period, projected cost savings exceeded USD 700 000, which underscores the long-term financial viability and sustainability of the solution.

Chapter 3 explored the application of ANNs to model and forecast energy consumption in a microbrewery by focusing on improving predictive accuracy for thermal and electrical demands. The ANN approach was implemented to support intelligent decision making in scheduling energy-intensive brewing processes and aligning them with cost-effective energy supply periods.

To develop the forecasting model, a dataset comprising 100 samples was generated through real-time monitoring of the brewery's operational parameters. The inputs included ambient temperature, time of day, batch load, and energy price signals under a ToU tariff structure. These variables were selected for their influence on power consumption and cooling demand during brewing, fermentation, and cold storage stages.

The ANN was trained to predict four key performance indicators: input power consumption, cooling load, thermal storage temperature, and heat pump output. These metrics were chosen due to their critical role in determining the system's energy behaviour and the potential for optimisation in hybrid energy configurations.

Two ANN architectures were utilised: the NAR model and the NARX model. The NAR model yielded R^2 values of up to 0.9982 for cooling load and 0.9978 for input power prediction, while the NARX model achieved regression values ranging from 0.857 to 0.9756 across training, validation, and testing datasets, as reflected in Table 3.6.. The MSE values

ranged between 0.0513 and 0.0899, with most predictions deviating by only $\pm 5\%$, and in extreme cases, up to $\pm 15\%$ at higher load levels, which demonstrated strong predictive capability for the NAR configurations, while the NARX architecture provided moderate performance consistent with its reliance on exogenous inputs.

The minimal deviation between actual and predicted values confirmed the consistency and reliability of the ANN framework. Furthermore, the models successfully captured the non-linear and time-dependent characteristics of the brewery's energy use, especially during peak and off-peak tariff transitions. These predictions enabled more effective scheduling of heating and cooling loads to coincide with low-tariff periods, which significantly reduced operational costs.

The ANN model was also capable of identifying recurring consumption patterns linked to batch sizes and brewing frequency, which provided valuable insight for future system planning and control. This capability allowed for virtual experimentation that enabled scenario testing without disrupting ongoing production.

The proposed ANN-based forecasting framework demonstrated strong potential for real-world application in small to medium-scale breweries. By integrating high-accuracy predictive tools into energy management systems, brewery operators can make informed decisions that reduce energy expenses and improve overall efficiency. Additionally, the method supports the broader transition towards smart manufacturing practices by enabling adaptive control strategies based on data-driven forecasts.

The results confirmed that ANN models offer a powerful and cost-effective means of enhancing energy predictability in microbreweries. The successful application in this case underscores the value of machine learning in process industries, particularly when used alongside hybrid energy systems and optimisation-based control methods.

Chapter 4 focused on the optimisation of a hybrid thermal energy system implemented in a microbrewery located in Bloemfontein, South Africa. The system was developed to address the high thermal energy demand associated with brewing operations, particularly in processes such as water heating, mashing, wort boiling, and cold storage. The integrated system comprised a heat pump, solar thermal collectors, and a TES unit, which were managed through an optimisation-based control strategy aimed at reducing grid electricity dependence and lowering energy costs. The integration of solar thermal collectors, TES, and a heat pump achieved energy savings of up to 74.31% compared to the baseline system.

The TES unit was designed to accumulate thermal energy during off-peak electricity tariff periods, which could be utilised during peak hours to supply heat to the brewery's process units. A glycol-based circulation system was employed to distribute stored thermal energy to various points of use, such as hot water tanks and brewing vessels. The solar thermal system operated during daylight hours, which contributed to the thermal load and reduced the burden on the grid-connected heat pump.

To assess the effectiveness of the proposed solution, simulations were carried out to compare the performance of the existing system (reliant solely on grid electricity and conventional electric heating) with the optimised hybrid system under a cost-minimising control regime. The control model was implemented in MATLAB using the SCIP solver and was structured to prioritise thermal energy dispatch based on ToU tariffs, predicted load demand, and renewable energy availability.

Given the variability in brewing schedules and process demands, the control model incorporated a dynamic switch that allowed energy supply to be directed from either the solar thermal collectors, TES, or heat pump, based on cost and system constraints. The logic also controlled auxiliary components such as pumps and mixing valves, which enabled the system to align thermal output with real-time requirements while minimising peak-hour consumption.

Over a projected operational lifespan of 20 years, and accounting for an average inflation rate of 5% and 10% annual electricity price increases, the model forecasted total cost savings of around 35% compared to the baseline. These results highlight the financial benefits of transitioning to a smart, renewable-supported thermal energy system in energy-intensive production environments.

An LCC analysis confirmed the economic viability of the system, with a total upfront investment of approximately USD 47 250. The BEP was achieved within one year and three months, which highlights the short-term return potential of the investment. Beyond financial savings, the system also offered operational benefits, including improved process control, reduced reliance on grid electricity during load-shedding events, and increased utilisation of renewable thermal energy.

These findings reinforce the potential of combining renewable energy technologies with intelligent control to optimise energy use in microbreweries. The system not only lowered

electricity consumption and operating costs but also contributed to broader sustainability goals by decreasing greenhouse gas emissions and improving energy resilience.

The simulation study provided a strong foundation for implementing cost-effective and scalable energy solutions in small-scale brewing facilities. By understanding the interaction between energy supply, production scheduling, and economic constraints, microbreweries can adopt energy systems that align with both operational and environmental objectives.

5.2 RECOMMENDATIONS FOR FUTURE RESEARCH

Future research should investigate how optimal control strategies in microbrewery energy systems can be integrated with emerging smart grid technologies. This includes exploring the interaction between hybrid thermal systems such as solar thermal collectors, heat pumps, and TES and intelligent grids to enable demand-side response, bi-directional energy flow, and real-time load balancing. Such integration could improve operational flexibility and support broader sustainability and grid stability goals.

The long-term impact of climate variability on the performance of solar-assisted heating and cooling systems also warrants attention. As extreme weather events become more common, evaluating their effect on system efficiency can inform adaptive strategies to enhance resilience under changing conditions.

Incorporating behavioural aspects, such as batch scheduling, staff routines, and seasonal production cycles, into predictive control models offers further potential. Embedding these patterns in energy optimisation algorithms can improve alignment between operations and energy use. Feedback-enabled systems that merge human input with machine learning could enhance responsiveness and efficiency.

Research into microgrid integration is another promising direction. Localised microgrids could allow small-scale breweries to independently generate, store, and distribute energy. Assessing the technical and economic feasibility of brewery clusters that function as microgrids may support decentralised, community-based energy models.

AI also has potential in monitoring and fault detection. Real-time AI diagnostics could identify issues such as heat transfer inefficiencies, storage losses, or solar underperformance, which can reduce downtime and improve system performance.

LCC assessments of hybrid energy technologies are needed to evaluate environmental and economic impacts from installation to decommissioning. Similarly, building-integrated

solutions, such as rooftop solar collectors and passive thermal storage, should be examined to understand how architecture and insulation influence energy performance.

Hybrid storage systems that combine TES with electrical batteries could help to manage both thermal and electrical loads, which will enhance reliability during grid outages or load shedding.

Future work should also incorporate more detailed life-cycle cost (LCC) assessments that account for maintenance requirements, component degradation, replacement intervals, and end-of-life considerations for solar-thermal collectors, heat pumps, and TES units. Comprehensive environmental-impact evaluations covering embodied energy, full life-cycle greenhouse-gas emissions, and waste-management implications would provide a more holistic assessment of long-term sustainability and financial performance.

Further research should evaluate system resilience under real grid disturbances such as cable faults, voltage instability, and load shedding. The proposed hybrid system offers reliability advantages over electric-only heating because it can continue operating using solar-thermal input, heat-pump output, and TES discharge during supply interruptions. Quantifying this benefit, together with assessing integration with smart-grid and microgrid technologies including demand-response capability, tariff-adaptive operation, and partial-islanding would strengthen understanding of the system's long-term robustness.

Future studies may also extend the hybrid framework to include real-time fault detection and predictive maintenance using AI-based diagnostics. This would enable early identification of heat-loss issues, collector underperformance, or TES degradation, improving system uptime and reliability. Additional work should examine the integration of complementary technologies such as photovoltaic generation, biomass heating, phase-change storage, and battery systems to optimise both thermal and electrical loads and enhance overall system autonomy.

Finally, exploring community-based energy models, such as shared infrastructure, cooperative storage, and peer-to-peer trading, may offer pathways to more sustainable local energy economies. Socio-economic impacts, including job creation and cost savings, should also be assessed to support policy and investment decisions.

These directions aim to guide innovation in sustainable energy management across the microbrewery sector.

These future research directions aim to deepen our understanding of sustainable energy management in microbreweries and provide a foundation for innovations that enhance efficiency, resilience, and environmental stewardship across the industry.

REFERENCES

- [1] Ateba, B. B., & Prinsloo, J. (2019). Strategic management for electricity supply sustainability in South Africa. *Utilities Policy*, 56, 92–103. <https://doi.org/10.1016/j.jup.2018.10.010>
- [2] Hohne, P. A., Kusakana, K., & Numbi, B. P. (2019). A review of water heating technologies: An application to the South African context. *Energy Reports*, 5, 1–19. <https://doi.org/10.1016/j.egy.2018.10.013>
- [3] Raphoolo, I. V., & de Kock, J. A. (2019). Dynamic load-shedding for enhancement of power system stability for the Lesotho 132 kV transmission network. In *2019 Southern African Universities Power Engineering Conference/ Robotics and Mechatronics/ Pattern Recognition Association of South Africa (SAUPEC/RobMech/PRASA)*, pp. 376–382. <https://doi.org/10.1109/robomech.2019.8704813>
- [4] Kusakana, K. (2019). Impact of time of use tariff and demand profiles on prosumers in peer-to-peer energy sharing scheme. In *2019 Advances in Science and Engineering Technology International Conferences (ASET)*, pp. 1–7. <https://doi.org/10.1109/icaset.2019.8714235>
- [5] Hohne, P. A., Kusakana, K., & Numbi, B. P. (2019). Optimal energy management and economic analysis of a grid-connected hybrid solar water heating system: A case of Bloemfontein, South Africa. *Sustainable Energy Technologies and Assessments*, 31, 273–291. <https://doi.org/10.1016/j.seta.2018.12.027>
- [6] Yong, C., Desen, J., Wen, L., Yunlong, C., & Li, C. (2019). Research on the cost of distributed photovoltaic plant of China based on whole life cycle perspective. *IEEE Access*, 7, 89379–89389. <https://doi.org/10.1109/access.2019.2924318>
- [7] Bär, R. M., & Voigt, T. (2019). Analysis and prediction methods for energy efficiency and media demand in the beverage industry. *Food Engineering Reviews*, 11(3), 200–217. <https://doi.org/10.1007/s12393-019-09195-y>

- [8] Nassary, E. K., & Nasolwa, E. R. (2019). Unravelling disposal benefits derived from underutilized brewing spent products in Tanzania. *Journal of Environmental Management*, 242, 430–439. <https://doi.org/10.1016/j.jenvman.2019.04.068>
- [9] Hargrave, A., & Koponen, B. (2019). *To beer or not to beer: Investigating Swedish microbrewing through an integrated resource-based and institutional capital view* (Bachelor's thesis). Jönköping University.
- [10] Kok, Y. J., Ye, L., Muller, J., Ow, D. S. W., & Bi, X. (2018). Brewing with malted barley or raw barley: What makes the difference in the processes? *Applied Microbiology and Biotechnology*, 103(3), 1059–1067. <https://doi.org/10.1007/s00253-018-9537-9>
- [11] Conduah, J., Kusakana, K., & Hohne, P. A. (2019). Energy efficiency improvements in a microbrewery in South Africa. In *2019 Open Innovations (OI)* (pp. 132–137). IEEE.
- [12] Kusakana, K. (2016). Optimal scheduling for distributed hybrid system with pumped hydro storage. *Energy Conversion and Management*, 111, 253–260. <https://doi.org/10.1016/j.enconman.2015.12.081>
- [13] Miles, R. E., Snow, C. C., Meyer, A. D., & Coleman, H. J. (1978). Organizational strategy, structure, and process. *Academy of Management Review*, 3(3), 546–562. <https://doi.org/10.5465/amr.1978.4305755>
- [14] Kusakana, K. (2020). Optimal energy management of a grid-connected dual-tracking photovoltaic system with battery storage: Case of a microbrewery under demand response. *Energy*, 212, 118782.
- [15] United States Environmental Protection Agency. (2009). *Customer incentives for energy efficiency through electric and natural gas rate design: A resource of the National Action Plan for Energy Efficiency*. https://www.epa.gov/sites/default/files/2015-08/documents/rate_design.pdf
- [16] Hassan, Q., Algburi, S., Sameen, A. Z., Salman, H. M., & Jaszczur, M. (2023). A review of hybrid renewable energy systems: Solar and wind-powered solutions: Challenges, opportunities, and policy implications. *Results in Engineering*, 20, 101621. <https://doi.org/10.1016/j.rineng.2023.101621>
- [17] Gennitsaris, S., Oliveira, C. O., Vris, G., Bofilios, A., Ntinou, T., Frutuoso, A. R., Queiroga, C., Giannatsis, J., Sofianopoulou, S., & Dedoussis, V. (2023). Energy efficiency management in small and medium-sized enterprises: Current situation,

- case studies and best practices. *Sustainability*, 15(4), 3727. <https://doi.org/10.3390/su15043727>
- [18] Al-Sayyab, A. K. S., Mota-Babiloni, A., & Navarro-Esbri, J. (2023). Renewable and waste heat applications for heating, cooling, and power generation based on advanced configurations. *Energy Conversion and Management*, 291, 117253. <https://doi.org/10.1016/j.enconman.2023.117253>
- [19] Rodrigues, F. A., & de Lemos, M. J. S. (2021). Stratification and energy losses in a standby cycle of a thermal energy storage system. *International Journal of Energy for a Clean Environment*, 22(5), 1–32.
- [20] Chew, K. H., Klemes, J. J., Wan Alwi, S. R., & Manan, Z. A. (2013). Industrial implementation issues of total site heat integration. *Applied Thermal Engineering*, 61(1), 17–25.
- [21] Silva, D., Brányik, T., Dragone, G., Vicente, A., Teixeira, J., & Almeida e Silva, J. (2008). High gravity batch and continuous processes for beer production: Evaluation of fermentation performance and beer quality. *Chemical Papers*, 62(1), 34–41.
- [22] Corigliano, O., & Algieri, A. (2024). A comprehensive investigation on energy consumptions, impacts, and challenges of the food industry. *Energy Conversion and Management*, X(23), 100661. <https://doi.org/10.1016/j.ecmx.2024.100661>
- [23] Borge-Diez, D., Rosales-Asensio, E., Açikkalp, E., & Alonso-Martinez, D. (2023). Analysis of power to gas technologies for energy intensive industries in European Union. *Energies*, 16(1), 538.
- [24] Lakkanawanti, W., Dungtripop, M., Suttipun, M., & Madi, H. (2022). Energy conservation and firm performance in Thailand: Comparison between energy-intensive and non-energy-intensive industries. *Energies*, 15(20), 7532. <https://doi.org/10.3390/en15207532>
- [25] Rohdin, P., & Thollander, P. (2006). Barriers to and driving forces for energy efficiency in the non-energy intensive manufacturing industry in Sweden. *Energy*, 31, 1836–1844. <https://doi.org/10.1016/j.energy.2005.10.010>
- [26] Olajire, A. A. (2020). The brewing industry and environmental challenges. *Journal of Cleaner Production*, 256, 102817. <https://doi.org/10.1016/j.jclepro.2012>

- [27] Conduah, J. E., Kusakana, K., Odufuwa, O. Y., Hohne, P. A., & Ma, T. (2025). Forecasting energy consumption and enhancing sustainability in microbreweries: Integrating ANN-based models with thermal storage solutions. *Journal of Energy Storage*, 112, 115508. <https://doi.org/10.1016/j.est.2025.115508>
- [28] Mainardis, M., Hickey, M., & Dereli, R. K. (2024). Lifting craft breweries' sustainability through spent grain valorisation and renewable energy integration: A critical review in the circular economy framework. *Journal of Cleaner Production*, 447, 141527. <https://doi.org/10.1016/j.jclepro.2024.141527>
- [29] Velasco, D. C. R., Gonçalves, V. P. D., Oliveira, M. P., Simonassi, N. T., Lopes, F. P. D., & Vieira, C. M. F. (2025). Industrial piping system: Design and corrosion protection. *Surfaces*, 8(1), 18.
- [30] Varganova, A. V., Khramshin, V. R., & Radionov, A. A. (2023). Operating modes optimization for the boiler units of industrial steam plants. *Energies*, 16(6), 2596.
- [31] Shi, X., He, Q., Liu, Y., An, X., Zhang, Q., & Du, D., 2024. Thermodynamic and techno-economic analysis of a novel compressed air energy storage system coupled with coal-fired power unit. *Energy*, 292, 130591.
- [32] Daixin, T., Hongwei, X., Huijuan, Y., Hao, Y., & Wen, H. (2022). Optimization of group control strategy and analysis of energy saving in refrigeration plant. *Energy and Built Environment*, 3(4), 525–535.
- [33] Saboohi, Z., & Hosseini, S. E. (2025). Advancements in biogas production: Process optimization and innovative plant operations. *Clean Energy*, 9(2), 52–65.
- [34] Odufuwa, O. Y., Kusakana, K., & Numbi, B. P. (2018). *Review of optimal energy management applied on ice thermal energy storage for an air conditioning system in commercial buildings*. <https://tinyurl.com/34zcb2pr>
- [35] Giedraityte, A., Rimkevicius, S., Marciukaitis, M., Radziukynas, V., & Bakas, R. (2025). Hybrid renewable energy systems – A review of optimization approaches and future challenges. *Applied Sciences*, 15(4), 1–30.
- [36] Dong, Y., Coleman, M., & Miller, S. A. (2021). Greenhouse gas emissions from air conditioning and refrigeration service expansion in developing countries. *Annual Review of Environment and Resources*, 46(1), 59–83.

- [37] Xia, X., Zhang, J., & Cass, W. (2012). Energy management of commercial buildings—a case study from a POET perspective of energy efficiency. *Journal of Energy in Southern Africa*, 23(1), 23–31.
- [38] Scarrow, R. M., & Crenshaw, E. M. (2015). The ecology of energy use: Using the POET model to analyze consumption and intensity across nations 1970–2000. *Population and Environment*, 36(3), 311–330.
- [39] Elkhatat, A., & Al-Muhtaseb, S. (2024). Climate change and energy security: A comparative analysis of the role of energy policies in advancing environmental sustainability. *Energies*, 17(13), 3179.
- [40] Baiano, A. (2021). Craft beer: An overview. *Comprehensive Reviews in Food Science and Food Safety*, 20(2), 1829–1856.
- [41] Li, Y., Qiu, Q., He, X., & Li, J. (2011). *Energy use project and conversion efficiency analysis on biogas produced in breweries*. Paper presented at the World Renewable Energy Congress, Sweden, 8–13 May. https://ep.liu.se/en/conference-article.aspx?series=eecp&issue=57&volume=7&Article_No=2
- [42] Rozon, F. (2024). *An outlook on the energy mix at South African beverage manufacturers and opportunities for greater adoption of renewable energy solutions* (Doctoral dissertation). Stellenbosch University.
- [43] Saleem, M. U., Shakir, M., Usman, M. R., Bajwa, M. H. T., Shabbir, N., Shams Ghahfarokhi, P., & Daniel, K. (2023). Integrating smart energy management system with Internet of Things and cloud computing for efficient demand side management in smart grids. *Energies*, 16(12), 4835.
- [44] Koko, S. P., Kusakana, K., & Vermaak, H. J. (2018). Optimal sizing of a micro-hydrokinetic pumped hydro storage hybrid system for different demand sectors. In W. Rivera (Ed.), *Sustainable cloud and energy services: Principles and practice* (pp. 219–242). Springer.
- [45] Ukoba, K., Jen, T., & Yusuf, A. A. (2025). Transformation of South Africa’s energy landscape: Policy implications, opportunities, and technological innovations in the Fourth Industrial Revolution. *Energy Strategy Reviews*, 59, 101752. <https://doi.org/10.1016/j.esr.2025.101752>
- [46] Maliat, A., Kotian, S., & Ghahremanlou, D. (2024). Assessment of a hybrid renewable energy system incorporating wind, solar, and storage technologies in

- Makkovik, Newfoundland and Labrador. *Journal of Sustainability for Energy*, 3(2), 87–104. <https://doi.org/10.56578/jse030203>
- [47] Chowdhury, J. I., Hu, Y., Haltas, I., Balta-Ozkan, N., & Varga, L. (2018). Reducing industrial energy demand in the UK: A review of energy efficiency technologies and energy saving potential in selected sectors. *Renewable and Sustainable Energy Reviews*, 94, 1153–1178.
- [48] Sturm, B., Hugenschmidt, S., Joyce, S., Hofacker, W., & Roskilly, A. P. (2013). Opportunities and barriers for efficient energy use in a medium-sized brewery. *Applied Thermal Engineering*, 53(2), 397–404. <https://doi.org/10.1016/j.applthermaleng.2012.05.006>
- [49] Carvalho, G., Leite, A. C., Leal, R., & Pereira, R. (2023). The role of emergent processing technologies in beer production. *Beverages*, 9(1), 7.
- [50] Kubule, A., Zogla, L., Ikaunieks, J., & Rosa, M. (2016). Highlights on energy efficiency improvements: A case of a small brewery. *Journal of Cleaner Production*, 138, 275–286. <https://doi.org/10.1016/j.jclepro.2016.02.131>
- [51] Guido, L. F. (2019). Brewing and craft beer. *Beverages*, 5(3), 51.
- [52] Simate, G. S., Cluett, J., Iyuke, S. E., Musapatika, E. T., Ndlovu, S., Walubita, L. F., & Alvarez, A. E. (2011). The treatment of brewery wastewater for reuse: State of the art. *Desalination*, 273(2–3), 235–247.
- [53] Salanja, L. C., Coldea, T. E., Ignat, M. V., Pop, C. R., Tofana, M., Mudura, E., Borsa, A., Pasqualone, A., & Zhao, H. (2020). Non-alcoholic and craft beer production and challenges. *Processes*, 8(11), 1382.
- [54] Villacreces, S., Blanco, C. A., & Caballero, I. (2022). Developments and characteristics of craft beer production processes. *Food Bioscience*, 45, 101495.
- [55] Nehra, M., Gahlawat, S. K., & Grover, N. (2023). *Craft beers: Fortification, processing, and production*. CRC Press.
- [56] Rojas-Pérez, L. C., Narváez-Rincón, P. C., & Ballesteros, I. (2022). Improving sugar extraction from brewers' spent grain using sequential deproteinization and acid-catalyzed steam explosion in a biorefinery context. *Biomass and Bioenergy*, 159, 106389.
- [57] Skendi, A., Harasym, J., & Galanakis, C. M. (2018). Recovery of high added-value compounds from brewing and distillate processing by-products. In C. M. Galanakis

- (Ed.), *Sustainable recovery and reutilization of cereal processing by-products* (pp. 189–225). Woodhead Publishing.
- [58] Holbrook, C. J. (2020). Brewhouse operations. In C. Smart (Ed.), *The craft brewing handbook: A practical guide to running a successful craft brewery* (pp. 65–109). Woodhead Publishing.
- [59] Palmer, J. (2017). *How to brew: Everything you need to know to brew great beer every time*. Brewers Publications.
- [60] Sridhar, A., Ponnuchamy, M., Kumar, P. S., & Kapoor, A. (2021). Food preservation techniques and nanotechnology for increased shelf life of fruits, vegetables, beverages and spices: a review. *Environmental Chemistry Letters*, *19*(2), 1715–1735.
- [61] Osintsev, K., Aliukov, S., Kuskarbekova, S., Tarasova, T., Karelin, A., Konchakov, V., & Kornyakova, O. (2023). Increasing thermal efficiency: Methods, case studies, and integration of heat exchangers with renewable energy sources and heat pumps for desalination. *Energies*, *16*(13), 4930.
- [62] Liszkowska, W., & Berlowska, J. (2021). Yeast fermentation at low temperatures: Adaptation to changing environmental conditions and formation of volatile compounds. *Molecules*, *26*(4), 1035.
- [63] Rachwał, K., Waśko, A., Gustaw, K., & Polak-Berecka, M. (2020). Utilization of brewery wastes in food industry. *PeerJ*, *8*, e9427.
- [64] Ciont, C., Epuran, A., Kerezsi, A. D., Coldea, T. E., Mudura, E., Pasqualone, A., Zhao, H., Suharoschi, R., Vriesekoop, F., & Pop, O. L. (2022). Beer safety: New challenges and future trends within craft and large-scale production. *Foods*, *11*(17), 2693.
- [65] Chukwunweike, J., Anang, A. N., Adeniran, A. A., & Dike, J. (2024). Enhancing manufacturing efficiency and quality through automation and deep learning: Addressing redundancy, defects, vibration analysis, and material strength optimization. *World Journal of Advanced Research and Reviews*, *23*(3), 1271–1295.
- [66] Hofmann, R., & Fischer, J. (2015). Beer packaging: Microbiological hazards and considerations. In A. E. Hill (Ed.), *Brewing microbiology: Managing microbes, ensuring quality and valorising waste* (pp. 319–334). Woodhead Publishing.
- [67] Faghri, A., Zhang, Y., & Howell, J. R. (2010). *Advanced heat and mass transfer*. Global Digital Press.

- [68] Linder, C. (2019). Customer orientation and operations: The role of manufacturing capabilities in small-and medium-sized enterprises. *International Journal of Production Economics*, 216, 105–117. <https://doi.org/10.1016/j.ijpe.2019.04.029>
- [69] Vooradi, R., Anne, S. B., Tula, A. K., Eden, M. R., & Gani, R. (2019). Energy and CO₂ management for chemical and related industries: issues, opportunities and challenges. *BMC Chemical Engineering*, 1(1), 7. <https://doi.org/10.1186/s42480-019-0007-7>
- [70] Duflou, J. R., Sutherland, J. W., Dornfeld, D., Herrmann, C., Jeswiet, J., Kara, S., Hauschild, M., & Kellens, K. (2012). Towards energy and resource efficient manufacturing: A processes and systems approach. *CIRP Annals*, 61(2), 587–609. <https://doi.org/10.1016/j.cirp.2012.05.002>
- [71] Wang, G., Wang, Z., Han, Z., & Rodriguez, R. D. (2019). Investigation of efficiency models in EnergyPlus and AMCA Standard 207 for induction motors powered by variable frequency drives. *Energy and Buildings*, 196, 94–102. <https://doi.org/10.1016/j.enbuild.2019.05.043>
- [72] Liyu, A. K., Modu, B., & Tan, C. W. (2018). A review of renewable energy development in Africa: A focus in South Africa, Egypt and Nigeria. *Renewable and Sustainable Energy Reviews*, 81, 2502–2518. <https://doi.org/10.1016/j.rser.2017.06.055>
- [73] Chua, K. J., Chou, S. K., & Yang, W. M. (2010). Advances in heat pump systems: A review. *Applied Energy*, 87(12), 3611–3624. <https://doi.org/10.1016/j.apenergy.2010.06.014>
- [74] Harish, V. S. K. V., & Kumar, A. (2016). A review on modeling and simulation of building energy systems. *Renewable and Sustainable Energy Reviews*, 56, 1272–1292. <https://doi.org/10.1016/j.rser.2015.12.040>
- [75] Tangwe, S., & Simona, M. (2018). Evaluation of performance of air-source heat pump water heaters using the surface fitting models: 3D mesh plots and 2D multi contour plots simulation. *Thermal Science and Engineering Progress*, 5, 516–523. <https://doi.org/10.1016/j.tsep.2018.02.007>
- [76] Petek, J., Glavič, P., & Kostevšek, A. (2016). Comprehensive approach to increase energy efficiency based on versatile industrial practices. *Journal of Cleaner Production*, 112, 2813–2821. <https://doi.org/10.1016/j.jclepro.2015.10.011>

- [77] Zhou, K., Fu, C., & Yang, S. (2016). Big data driven smart energy management: From big data to big insights. *Renewable and Sustainable Energy Reviews*, 56, 215–225. <https://doi.org/10.1016/j.rser.2015.11.050>
- [78] Serale, G., Fiorentini, M., Capozzoli, A., Bernardini, D., & Bemporad, A. (2018). Model predictive control (MPC) for enhancing building and HVAC system energy efficiency: Problem formulation, applications and opportunities. *Energies*, 11(3), 631. <https://doi.org/10.3390/en11030631>
- [79] Collins, K. J., Rogerson, C. M., & Rogerson, J. (2023). The evolution of the craft beer industry in the Global South: The experience of South Africa. *Studia Periegetica*, 44(4), 49–72.
- [80] Herce, C., Martini, C., Toro, C., Biele, E., & Salvio, M. (2024). Energy efficiency policies for small and medium-sized enterprises: A review. *Sustainability*, 16(3), 1023.
- [81] García-Quevedo, J., & Jové-Llopis, E. (2021). Environmental policies and energy efficiency investments. An industry-level analysis. *Energy Policy*, 156, 112461. <https://doi.org/10.1016/j.enpol.2021.112461>
- [82] Pandey, V., Sircar, A., Bist, N., Solanki, K., & Yadav, K. (2023). Accelerating the renewable energy sector through Industry 4.0: Optimization opportunities in the digital revolution. *International Journal of Innovation Studies*, 7(2), 171–188.
- [83] Chowdhury, S., Budhwar, P., Dey, P. K., Joel-Edgar, S., & Abadie, A. (2022). AI-employee collaboration and business performance: Integrating knowledge-based view, socio-technical systems and organisational socialisation framework. *Journal of Business Research*, 144, 31–49. <https://doi.org/10.1016/j.jbusres.2022.01.069>
- [84] Sa, A., Thollander, P., & Cagno, E. (2017). Assessing the driving factors for energy management program adoption. *Renewable and Sustainable Energy Reviews*, 74, 538–547. <https://doi.org/10.1016/j.rser.2017.02.061>
- [85] Andrei, M. (2023). *The role of industrial energy management in the transition toward sustainable energy systems: Exploring practices, knowledge dynamics and policy evaluation* (Doctoral dissertation). Linköping University.
- [86] Agupugo, C. P., Ajayi, A. O., Nwanevu, C., & Oladipo, S. S. (2022). Policy and regulatory framework supporting renewable energy microgrids and energy storage systems. *Engineering Science and Technology Journal*, 5, 2589–2615.

- [87] Ahmed, S., Ali, A., & D'Angola, A. (2024). A review of renewable energy communities: Concepts, scope, progress, challenges, and recommendations. *Sustainability*, 16(5), 1749.
- [88] Du, X., & Chen, W. (2000). Towards a better understanding of modelling feasibility robustness in engineering design. *Journal of Mechanical Design*, 122(4), 385–394.
- [89] Chu, S., & Majumdar, A. (2012). Opportunities and challenges for a sustainable energy future. *Nature*, 488(7411), 294–303.
- [90] Xia, X., & Zhang, J. (2010). Energy efficiency and control systems – From a POET perspective. *IFAC Proceedings Volumes*, 43(1), 255–260. <https://doi.org/10.3182/20100329-3-PT-3006.00047>
- [91] Hohne, P. A., Kusakana, K., & Numbi, B. P. (2020). Improving energy efficiency of thermal processes in healthcare institutions: A review on the latest sustainable energy management strategies. *Energies*, 13(3), 569. <https://doi.org/10.3390/en13030569>
- [92] Zhang, S., & Tang, Y. (2018). A POET based energy audit methodology for WWTPs. In *Proceedings of the 2018 37th Chinese Control Conference (CCC)* (pp. 7399–7404). IEEE.
- [93] Xia, X., & Zhang, J. (2015). Operation efficiency optimisation modelling and application of model predictive control. *IEEE/CAA Journal of Automatica Sinica*, 2(2), 166–172. <https://ieeexplore.ieee.org/document/7081656>
- [94] Odufuwa, O. Y., Kusakana, K., & Numbi, B. P. (2020). Optimal energy management of ice thermal energy storage based air conditioning system for commercial buildings in real-time – A review based on POET framework. *Journal of Physics: Conference Series*, 1577(1), 012049.
- [95] Zhang, H., Xia, X., & Zhang, J. (2012). Optimal sizing and operation of pumping systems to achieve energy efficiency and load shifting. *Electric Power Systems Research*, 86, 41–50.
- [96] Energy efficiency and control systems – From a POET perspective. *IFAC Proceedings Volumes*, 43(1), 255–260. <https://doi.org/10.3182/20100329-3-PT-3006.00047>
- [97] Tokos, H., Pintarič, Z. N., & Glavič, P. (2010). Energy saving opportunities in heat integrated beverage plant retrofit. *Applied Thermal Engineering*, 30(1), 36–44.
- [98] Lim, J., Lee, H., Cho, H., Shim, J. Y., Lee, H., & Kim, J. (2022). Novel waste heat and oil recovery system in the finishing treatment of the textile process for cleaner

- production with economic improvement. *International Journal of Energy Research*, 46(14), 20480–20493.
- [99] Kiss, A. A., & Smith, R. (2020). Rethinking energy use in distillation processes for a more sustainable chemical industry. *Energy*, 203, 117788. <https://doi.org/10.1016/j.energy.2020.117788>
- [100] Kluczek, A., & Olszewski, P. (2017). Energy audits in industrial processes. *Journal of Cleaner Production*, 142, 3437–3453.
- [101] Ali, R. H., Samee, A. A. A., & Maghrabie, H. M. (2023). Thermodynamic analysis of a cogeneration system in pulp and paper industry under singular and hybrid operating modes. *Energy*, 263, 125964.
- [102] Schuler, A., & Kotsis, G. (2023). A systematic review on techniques and approaches to estimate mobile software energy consumption. *Sustainable Computing: Informatics and Systems*, 41, 100919.
- [103] Malinauskaite, J., Jouhara, H., Ahmad, L., Milani, M., Montorsi, L., & Venturelli, M. (2019). Energy efficiency in industry: EU and national policies in Italy and the UK. *Energy*, 172, 255–269.
- [104] Stevens, E. R., & Laynor, G. (2024). Enhancing the quality and efficiency of regulatory science literature reviews through innovation and collaboration with library and information science experts. *Frontiers in Medicine*, 11, 1434427.
- [105] Heath, A., Levay, P., & Tuvey, D. (2022). Literature searching methods or guidance and their application to public health topics: A narrative review. *Health Information & Libraries Journal*, 39(1), 6–21.
- [106] Bonato, S. V., De Jesus Pacheco, D. A., Schwengber ten Caten, C., & Caro, D. (2022). The missing link of circularity in small breweries' value chains: Unveiling strategies for waste management and biomass valorization. *Journal of Cleaner Production*, 336, 130275.
- [107] Borowski, P. F. (2021). Innovative processes in managing an enterprise from the energy and food sector in the era of industry 4.0. *Processes*, 9(2), 381.
- [108] Oke, A. E., Aliu, J., Ebekozi, A., Akinpelu, T. M., Olatunde, T. S., & Ogunsanya, O. A. (2024). Strategic drivers for the deployment of energy economics principles in the developing construction industry: A Nigerian perspective. *Environmental Progress & Sustainable Energy*, 43(3), e14351. <https://doi.org/10.1002/ep.14351>

- [109] Cintas-Canto, A., Kaur, J., Mozaffari-Kermani, M., & Azarderakhsh, R. (2023). ChatGPT vs. lightweight security: First work implementing the NIST cryptographic standard ASCON. *arXiv preprint*, arXiv:2306.08178.
- [110] Cintas-Canto, A., Kaur, J., Mozaffari-Kermani, M., & Azarderakhsh, R. (2023). Algorithmic security is insufficient: A comprehensive survey on implementation attacks haunting post-quantum security. *arXiv preprint*, arXiv:2305.13544.
- [111] Mozaffari-Kermani, M., Sur-Kolay, S., Raghunathan, A., & Jha, N. K. (2014). Systematic poisoning attacks on and defenses for machine learning in healthcare. *IEEE Journal of Biomedical and Health Informatics*, 19(6), 1893–1905.
- [112] Nia, A. M., Mozaffari-Kermani, M., Sur-Kolay, S., Raghunathan, A., & Jha, N. K. (2015). Energy-efficient long-term continuous personal health monitoring. *IEEE Transactions on Multi-Scale Computing Systems*, 1(2), 85–98.
- [113] Sehnem, S., Lopes de Sousa Jabbour, A. B., Amarildo da Conceicao, D., Weber, D., & Julkovski, D. J. (2021). The role of ecological modernization principles in advancing circular economy practices: Lessons from the brewery sector. *Benchmarking: An International Journal*, 28(9), 2786–2807.
- [114] Balezentis, T., Siksnylyte-Butkiene, I., & Streimikiene, D. (2021). Stakeholder involvement for sustainable energy development based on uncertain group decision making: Prioritizing the renewable energy heating technologies and the BWM-WASPAS-IN approach. *Sustainable Cities and Society*, 73, 103114.
- [115] Nwankwo, A. A. (2022). Green business strategies and performance of breweries in South-East Nigeria. *International Journal of Innovative Social Sciences & Humanities Research*, 10(1), 127–138.
- [116] Amui, L. B. L., Jabbour, C. J. C., Lopes de Sousa Jabbour, A. B., & Kannan, D. (2017). Sustainability as a dynamic organizational capability: A systematic review and a future agenda toward a sustainable transition. *IEEE Transactions on Engineering Management*, 64(4), 492–503.
- [117] Blundel, R., Monaghan, A., & Thomas, C. (2013). SMEs and environmental responsibility: A policy perspective. *Business Ethics: A European Review*, 22(3), 246–262.
- [118] Withers, D. P. (2021). Brewing green beer: Building a regulatory scheme robust to changes in brewing technologies. *Texas A&M Law Review*, 8(1), 9–26.

- [119] Li, Y., Chiu, Y. H., Wu, M., Li, Y., & Lin, T. Y. (2021). Chinese liquor company management efficiency from a social responsibility perspective: A two-stage dynamic directional distance function. *Economic Research*, 34(1), 2085–2114.
- [120] Yong, J. Y., Klemes, J. J., Varbanov, P. S., & Huisingh, D. (2016). Cleaner energy for cleaner production: Modelling, simulation, optimisation and waste management. *Journal of Cleaner Production*, 111, 1–16.
- [121] Prabakaran, R., Lal, D. M., & Devotta, S. (2021). Effect of thermostatic expansion valve tuning on the performance enhancement and environmental impact of a mobile air conditioning system. *Journal of Thermal Analysis and Calorimetry*, 143, 335–350.
- [122] Al-Ghaili, A. M., Kasim, H., Al-Hada, N. A., Jørgensen, B. N., Othman, M., & Jihua, W. (2021). Energy management systems and strategies in buildings sector: A scoping review. *IEEE Access*, 9, 63790–63813.
- [123] Brush, A., Masanet, E., & Worrell, E. (2011). *Energy efficiency improvement and cost saving opportunities for the dairy processing industry: An ENERGY STAR® guide for energy and plant managers*. <https://www.osti.gov/servlets/purl/1171534>
- [124] Department of Mineral Resources and Energy. (2021). *South African energy sector report*. <https://www.energy.gov.za/files/media/explained/2021-South-African-Energy-Sector-Report.pdf>
- [125] Conduah, J. E., Kusakana, K., & Hohne, P. A. (2020). Energy monitoring for potential cost saving in electricity bills in a microbrewery in South Africa. In *Proceedings of the 18th Industrial and Commercial Use of Energy Conference (AIUE)*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3741160
- [126] Herrando, M., Wang, K., Huang, G., Otanicar, T., Mousa, O. B., Agathokleous, R. A., Ding, Y., Kalogirou, S., Ekins-Daukes, N., Taylor, R. A., & Markides, C. N. (2023). A review of solar hybrid photovoltaic-thermal (PV-T) collectors and systems. *Progress in Energy and Combustion Science*, 97, 101072.
- [127] Tan, W. Y., Li, M., Devkota, L., Attenborough, E., & Dhital, S. (2023). Mashing performance as a function of malt particle size in beer production. *Critical Reviews in Food Science and Nutrition*, 63(21), 5372–5387.
- [128] Cai, W., Wang, L., Li, L., Xie, J., Jia, S., Zhang, X., Jiang, Z., & Lai, K. (2022). A review on methods of energy performance improvement towards sustainable

- manufacturing from perspectives of energy monitoring, evaluation, optimization and benchmarking. *Renewable and Sustainable Energy Reviews*, 159, 112227.
- [129] Georgiadis, G. P., Elekidis, A. P., & Georgiadis, M. C. (2021). Optimal production planning and scheduling in breweries. *Food and Bioproducts Processing*, 125, 204–221.
- [130] Bokulich, N. A., & Bamforth, C. W. (2013). The microbiology of malting and brewing. *Microbiology and Molecular Biology Reviews*, 77(2), 157–172.
- [131] Durkee, J. (2006). *Management of industrial cleaning technology and processes*. Elsevier.
- [132] Majumder, S., Istalingamurthy, D., Sadashiva Murthy, B. M., & Prakash, B. M. (2023). Impact of different electrodes, mediators, and microbial cultures on wastewater treatment and power generation in the microbial desalination cell (MDC). *Water Science & Technology*, 88(12), 3194–3225.
- [133] Kuznar, D., Piltaver, R., Gradišek, A., Gams, M., & Luktrek, M. (2017). An intelligent system to monitor refrigeration devices. *Expert Systems*, 34(5), e12199.
- [134] Galitsky, C., Martin, N., Worrell, E., & Lehman, B. (2019). *Energy efficiency improvement and cost saving opportunities for breweries: An ENERGY STAR (R) guide for energy and plant managers*. Lawrence Berkeley National Laboratory.
- [135] Energy efficiency and control systems – From a POET perspective. *IFAC Proceedings Volumes*, 43(1), 255–260. <https://doi.org/10.3182/20100329-3-PT-3006.00047>
- [136] Ali, H. M., Rehman, T., Arici, M., Said, Z., Durakovic, B., Mohammed, H. I., Kumar, R., Rathod, M. K., Buyukdagli, O., & Teggat, M. (2024). Advances in thermal energy storage: Fundamentals and applications. *Progress in Energy and Combustion Science*, 100, 101109.
- [137] Otles, S., & Sakalli, A. (2019). Industry 4.0: The smart factory of the future in beverage industry. In A. M. Grumezescu & A. M. Holban (Eds.), *Production and management of beverages: Volume 1: The science of beverages* (pp. 439–469). Woodhead Publishing.
- [138] Sturm, B., Hugenschmidt, S., Joyce, S., Hofacker, W., & Roskilly, A. P. (2013). Opportunities and barriers for efficient energy use in a medium-sized brewery. *Applied Thermal Engineering*, 53(2), 397–404. <https://doi.org/10.1016/j.applthermaleng.2012.05.006>.

- [139] Pandiyan, P., Saravanan, S., Usha, K., Kannadasan, R., Alsharif, M. H., & Kim, M. K. (2023). Technological advancements toward smart energy management in smart cities. *Energy Reports*, *10*, 648–677.
- [140] Moloto, H. M., Pretorius, L., & Pretorius, J. H. C. (2023). Using linear programming to improve productivity and profitability with six-sigma in the fast-moving consumer goods industry. In *Proceedings of the Portland International Conference on Management of Engineering and Technology (PICMET)* (pp. 1–7). IEEE.
- [141] Storgårds, E. (2000). *Process hygiene control in beer production and dispensing* (Doctoral dissertation). Helsingin Yliopisto.
- [142] Rübmann, M., Lorenz, M., Gerbert, P., Waldner, M., Justus, J., Engel, P., & Harnisch, M. (2015). Industry 4.0: The future of productivity and growth in manufacturing industries. *Digital Transformation*, *9*(1), 54–89.
- [143] Antunes, P., Carreira, P., & da Silva, M. M. (2014). Towards an energy management maturity model. *Energy Policy*, *73*, 803–814.
- [144] Jagtap, S., Duong, L. N. K., Trollman, H., Bader, F., Garcia-Garcia, G., Skouteris, G., Li, J., Pathara, P. B., Martindale, W., Swainson, M., & Rahimifard, S. (2021). IoT technologies in the food supply chain. In C. M. Galanakis (Ed.), *Food technology disruptions* (pp. 175–211). Academic Press.
- [145] McIlwaine, A. M., Foley, A. M., Morrow, D. J., Al Kez, D., Zhang, C., Lu, X., & Best, R. J. (2021). A state-of-the-art techno-economic review of distributed and embedded energy storage for energy systems. *Energy*, *229*, 120461.
- [146] Gur, T. M. (2018). Review of electrical energy storage technologies, materials and systems: Challenges and prospects for large-scale grid storage. *Energy & Environmental Science*, *11*(10), 2696–2767.
- [147] Dehghan, M., Pfeiffer, C. F., Rakhshani, E., & Bakhshi-Jafarabadi, R. (2021). A review on techno-economic assessment of solar water heating systems in the middle east. *Energies*, *14*(16), 4944.
- [148] Arteconi, A., Ciarrocchi, E., Pan, Q., Carducci, F., Comodi, G., Polonara, F., & Wang, R. (2016). Thermal energy storage coupled with PV panels for demand side management of industrial building cooling loads. *Applied Energy*, *185*, 1984–1993. <https://doi.org/10.1016/j.apenergy.2016.01.025>

- [149] Odufuwa, O., Tartibu, L., Kusakana, K., Hohne, P., & Numbi, B. (2024). Application of artificial neural networks in predicting the performance of ice thermal energy storage systems. *Journal of Energy Storage*, *95*, 112547. <https://doi.org/10.1016/j.est.2024.112547>
- [150] Stanelyte, D., Radziukyniene, N., & Radziukynas, V. (2022). Overview of demand-response services: A review. *Energies*, *15*(5), 1659.
- [151] Beck, A., Knottner, S., Unterluggauer, J., Halmschlager, D., & Hofmann, R. (2022). An integrated optimization model for industrial energy system retrofit with process scheduling, heat recovery, and energy supply system synthesis. *Processes*, *10*(3), 572. <https://doi.org/10.3390/pr10030572>
- [152] Nekrasov, S. A. (2021). Reducing costs for integration of renewable energy sources: A way to making renewable energy more accessible. *Thermal Engineering*, *68*(8), 593–603.
- [153] Tan, K. M., Babu, T. S., Ramachandaramurthy, V. K., Kasinathan, P., Solanki, S. G., & Raveendran, S. K. (2021). Empowering smart grid: A comprehensive review of energy storage technology and application with renewable energy integration. *Journal of Energy Storage*, *39*, 102591. <https://doi.org/10.1016/j.est.2021.102591>
- [154] Andrae, A. S., & Edler, T. (2015). On global electricity usage of communication technology: Trends to 2030. *Challenges*, *6*(1), 117–157. <https://doi.org/10.3390/challe6010117>.
- [155] Gaonwe, T. P., Kusakana, K., & Hohne, P. A. (2022). A review of solar and air-source renewable water heating systems, under the energy management scheme. *Energy Reports*, *8*, 1–10.
- [156] Shine, P., Upton, J., Sefeedpari, P., & Murphy, M. D. (2020). Energy consumption on dairy farms: A review of monitoring, prediction modelling, and analyses. *Energies*, *13*(5), 1288.
- [157] Rakib, M. I., Saidur, R., Mohamad, E. N., & Afifi, A. M. (2017). Waste-heat utilization – The sustainable technologies to minimize energy consumption in Bangladesh textile sector. *Journal of Cleaner Production*, *142*, 1867–1876. <https://doi.org/10.1016/j.jclepro.2016.11.098>
- [158] Falcone, P. M. (2023). Sustainable energy policies in developing countries: A review of challenges and opportunities. *Energies*, *16*(18), 6682.

- [159] Oyewole, O. J., Al-Faryan, M. A. S., Adekoya, O. B., & Oliyide, J. A. (2024). Energy efficiency, financial inclusion, and socio-economic outcomes: Evidence across advanced, emerging, and developing countries. *Energy*, *289*, 130062. <https://doi.org/10.1016/j.energy.2023.130062>
- [160] Obioha-Val, O., Olaniyi, O. O., Selesi-Aina, O., Gbadebo, M. O., & Kolade, T. M. (2024). Machine learning-enabled smart sensors for real-time industrial monitoring: Revolutionizing predictive analytics and decision-making in diverse sector. *Asian Journal of Research in Computer Science*, *17*(11), 10–9734.
- [161] Koulouris, A., Misailidis, N., & Petrides, D. (2021). Applications of process and digital twin models for production simulation and scheduling in the manufacturing of food ingredients and products. *Food and Bioproducts Processing*, *126*, 317–333.
- [162] Han, M., Zhang, X., Xu, L., May, R., Pan, S., & Wu, J. (2018). *A review of reinforcement learning methodologies on control systems for building energy*. <https://www.diva-portal.org/smash/get/diva2:1221058/FULLTEXT01.pdf>
- [163] Kong, L. X., Perebikovskiy, A., Moebius, J., Kulinsky, L., & Madou, M. (2016). Lab-on-a-CD: A fully integrated molecular diagnostic system. *SLAS Technology*, *21*(3), 323–355. <https://doi.org/10.1177/2211068215588456>
- [164] Boakye-Yiadom, K. A., Ilari, A., & Duca, D. (2022). Greenhouse gas emissions and life cycle assessment on the black soldier fly (*Hermetia illucens* L.). *Sustainability*, *14*(16), 10456.
- [165] Tahmasebinia, F., Lin, L., Wu, S., Kang, Y., & Sepesgozar, S. (2024). Advanced energy performance modelling: Case study of an engineering and technology precinct. *Buildings*, *14*(6), 1774. <https://doi.org/10.3390/buildings14061774>
- [166] Odufuwa, O. Y., Tartibu, L. K., & Kusakana, K. (2025). Artificial neural network modelling for predicting efficiency and emissions in mini-diesel engines: Key performance indicators and environmental impact analysis. *Fuel*, *387*, 134294.
- [167] Qadir, S. A., Al-Motairi, H., Tahir, F., & Al-Fagih, L. (2021). Incentives and strategies for financing the renewable energy transition: A review. *Energy Reports*, *7*, 3590–3606. <https://doi.org/10.1016/j.egy.2021.06.041>
- [168] Olufemi-Phillips, A. Q., Ofodile, O. C., Toromade, A. S., Igwe, A. N., & Adewale, T. T. (2024). Strategies for adapting food supply chains to climate change using simulation models. *Strategies*, *20*(11), 1021–1040.

- [169] Clairand, J. M., Briceno-Leon, M., Escriva-Escriva, G., & Pantaleo, A. M. (2020). Review of energy efficiency technologies in the food industry: Trends, barriers, and opportunities. *IEEE Access*, *8*, 48015–48029.
- [170] Moya, J. A., & Pardo, N. (2013). The potential for improvements in energy efficiency and CO₂ emissions in the EU27 iron and steel industry under different payback periods. *Journal of Cleaner Production*, *52*, 71–83. <https://doi.org/10.1016/j.jclepro.2013.02.028>
- [171] Muster-Slawitsch, B., Weiss, W., Schnitzer, H., & Brunner, C. (2011). The green brewery concept – Energy efficiency and the use of renewable energy sources in breweries. *Applied Thermal Engineering*, *31*(13), 2123–2134.
- [172] Chen, W., Men, Y., Fuster, N., Osorio, C., & Juan, A. A. (2024). Artificial intelligence in logistics optimization with sustainable criteria: A review. *Sustainability*, *16*(21), 9145.
- [173] Kang, S., Selosse, S., & Maïzi, N. (2015). Strategy of bioenergy development in the largest energy consumers of Asia (China, India, Japan and South Korea). *Energy Strategy Reviews*, *8*, 56–65.
- [174] Saxena, D., Dhall, N., & Malik, R. (2021). Sustainable banking: A roadmap to sustainable development. *Corporate Governance and Sustainability Review*, *5*(3), 42–56.
- [175] Ball, P., & MacBryde, J. (2022). Developing a framework for adopting environmental manufacturing practices: Learning from breweries. *Production Planning & Control*, *33*(8), 758–773.
- [176] Selim, O. M., Abousabae, M., Hasan, A., & Amano, R. S. (2021). Analysis of energy savings and CO₂ emission reduction contribution for industrial facilities in USA. *Journal of Energy Resources Technology*, *143*(8), 082303.
- [177] Yan, R., Chen, M., Xiang, X., Feng, W., & Ma, M. (2023). Heterogeneity or illusion? Track the carbon Kuznets curve of global residential building operations. *Applied Energy*, *347*(10.1016).
- [178] Wikipedia. (n.d.). *Miller Brewing Company*. https://en.wikipedia.org/wiki/Miller_Brewing_Company
- [179] Bhuyan, S., & McCafferty, M. (2013). US brewing industry profitability: A simultaneous determination of structure, conduct, and performance. *Journal of Agricultural & Food Industrial Organization*, *11*(1), 139–150.

- [180] Gammelgaard, J. (2015). Case study I: Internationalization of brewery companies: The case of Carlsberg. In P. J. Buckley & P. N. Ghauri (Eds.), *International business strategy* (pp. 108-114). Routledge.
- [181] Tsuji, M., Shigeno, H., Ueki, Y., Idota, H., & Bunno, T. (2017). Characterizing R&D and HRD in the innovation process of Japanese SMEs: Analysis based on field study. *Asian Journal of Technology Innovation*, 25(2), 367–385.
- [182] Gaonwe, T., Hohne, P., & Kusakana, K. (2022). Optimal energy management of a solar-assisted heat pump water heating system with a storage system. *Journal of Energy Storage*, 56, 105885. <https://doi.org/10.1016/j.est.2022.105885>
- [183] Roberts, N. V., & Henneking, S. (2021). Time-stepping DPG formulations for the heat equation. *Computers & Mathematics With Applications*, 95, 242–255. <https://doi.org/10.1016/j.camwa.2020.05.024>
- [184] Odufuwa, O., Kusakana, K., Numbi, B., & Tartibu, L. (2024). Optimal energy management of grid-connected PV for HVAC cooling with ice thermal storage system. *Journal of Energy Storage*, 77, 109844. <https://doi.org/10.1016/j.est.2023.109844>
- [185] Yanis, M., Budiman, A. Y., Mohruni, A. S., Sharif, S., Suhaimi, M. A., & Dwipayana, H. (2023). Levenberg-Marquardt, Bayesian-regularization, and scaled conjugate gradient algorithms for predicting surface roughness accuracy on side milling *AIP Conference Proceedings*, 2544(1), 020013. <https://doi.org/10.1063/5.0117323>
- [186] Taoufik, N., Boumya, W., Achak, M., Chennouk, H., Dewil, R., & Barka, N. (2022). The state of art on the prediction of efficiency and modeling of the processes of pollutants removal based on machine learning. *Science of the Total Environment*, 807, 150554.
- [187] Yan, Z., Zhong, S., Lin, L., & Cui, Z. (2021). Adaptive Levenberg–Marquardt algorithm: A new optimisation strategy for Levenberg–Marquardt neural networks. *Mathematics*, 9(17), 2176. doi:10.3390/math9172176
- [188] Santos, C. F. G. D., & Papa, J. P. (2022). Avoiding overfitting: A survey on regularization methods for convolutional neural networks. *ACM Computing Surveys (Csur)*, 54(10s), 1–25.

- [189] Bukhari, M. M., Alkhamees, B. F., Hussain, S., Gumaei, A., Assiri, A., & Ullah, S. S. (2021). An improved artificial neural network model for effective diabetes prediction. *Complexity*, 2021(1), 1–10. doi:10.1155/2021/5525271
- [190] Hakim, G. P., Hadi Habaebi, M., Elsheikh, E. A., Suliman, F. M., Islam, M. R., Yusoff, S. H. B., & Anzum, R. (2024). Levenberg Marquardt artificial neural network model for self-organising networks implementation in wireless sensor network. *IET Wireless Sensor Systems*, 14(5), 195–208.
- [191] Shabir, I., Dash, K. K., Dar, A. H., Pandey, V. K., Fayaz, U., & Srivastava, S. (2023). Carbon footprints evaluation for sustainable food processing system development: A comprehensive review. *Future Foods*, 7, 100215.
- [192] Zhang, M., & Huan, Z. (2013). Study on performance of heat pump water heaters in South Africa. In *2013 Proceedings of the 21st Domestic Use of Energy Conference* (pp. 1–6). IEEE.
- [193] Yongoua, J., Tangwe, S., & Simon, M. (2016, March). A review on the performance assessment and optimization techniques of air source heat pump water heaters used in South Africa. In *2016 International Conference on the Domestic Use of Energy (DUE)* (pp. 1–8). IEEE. doi: 10.1109/DUE.2016.7466725.
- [194] Willem, H., Lin, Y., & Lekov, A. (2017). Review of energy efficiency and system performance of residential heat pump water heaters. *Energy and Buildings*, 143, 191–201. <https://doi.org/10.1016/j.enbuild.2017.02.023>
- [195] Çakır, U., Çomaklı, K., Çomaklı, Ö., & Karlı, S. (2013). An experimental exergetic comparison of four different heat pump systems working at same conditions: As air to air, air to water, water to water and water to air. *Energy*, 58, 210–219. <https://doi.org/10.1016/j.energy.2013.06.014>.
- [196] Guo, X., & Goumba, A. P. (2018). Air source heat pump for domestic hot water supply: Performance comparison between individual and building scale installations. *Energy*, 164, 794–802. doi:10.1016/j.energy.2018.09.065
- [197] Gigmayr, S., Brent, A. C., Gauché, P., & Fechner, H. (2015). Utility-scale PV power and energy supply outlook for South Africa in 2015. *Renewable Energy*, 83, 779–785.
- [198] Sezen, K., & Gungor, A. (2022). Comparison of solar assisted heat pump systems for heating residences: A review. *Solar Energy*, 249, 424–445. <https://doi.org/10.1016/j.solener.2022.11.051>

- [199] Dai, L., Li, S., DuanMu, L., Li, X., Shang, Y., & Dong, M. (2015). Experimental performance analysis of a solar assisted ground source heat pump system under different heating operation modes. *Applied Thermal Engineering*, 75, 325–333. <https://doi.org/10.1016/j.applthermaleng.2014.09.061>
- [200] Elsheniti, M. B., Kotb, A., & Elsamni, O. (2019). Thermal performance of a heat-pipe evacuated-tube solar collector at high inlet temperatures. *Applied Thermal Engineering*, 154, 315–325. doi:10.1016/j.applthermaleng.2019.03.106.
- [201] Leonzio, G., Fennell, P. S., & Shah, N. (2022). Air-source heat pumps for water heating at a high temperature: State of the art. *Sustainable Energy Technologies and Assessments*, 54, 102866. <https://doi.org/10.1016/j.seta.2022.102866>
- [202] Bodzin, S. (1997). Air-to-water heat pumps for the home. *Home Energy*, 14(4). <https://www.osti.gov/biblio/569264>
- [203] Morrison, G. L., Anderson, T., & Behnia, M. (2004). Seasonal performance rating of heat pump water heaters. *Solar Energy*, 76(1–3), 147–152.
- [204] Nkwetta, D. N., & Smyth, M. (2012). Performance analysis and comparison of concentrated evacuated tube heat pipe solar collectors. *Applied Energy*, 98, 22–32.
- [205] Tangwe, S., & Kusakana, K. (2021). Evaluation of the coefficient of performance of an air source heat pump unit and an air to water heat pump. *Journal of Energy in Southern Africa*, 32(1), 27–40.
- [206] Bugaje, I. (2006). Renewable energy for sustainable development in Africa: A review. *Renewable and Sustainable Energy Reviews*, 10(6), 603–612. <https://doi.org/10.1016/j.rser.2004.11.002>

APPENDIX A: SUMMARY OF ARTIFICIAL NEURAL NETWORK (ANN) FORECASTING MODEL PERFORMANCE FOR CHAPTER 3

Performance Metric	Result	Comment
Dataset size	100 samples	Real-time data including production, thermal loads, and meteorological variables.
ANN architectures evaluated	NAR, NARX	Both capture nonlinear time-dependent behaviour; NAR performed best overall.
Training R-value	NAR: 0.99678 – 0.99856 NARX: 0.85705	Indicates excellent correlation between predicted and actual values.
Validation R-value	NAR: 0.98845 – 0.99790 NARX: 0.85638	Confirms robustness and generalisation capability
Testing R-value	NAR: 0.97560 – 0.99670 NARX: 0.85606	Demonstrates strong predictive accuracy on unseen data.
Mean Squared Error (MSE)	< 0.015	Well below acceptable thresholds for industrial energy forecasting.
Prediction deviation	–5% to +10%	The thermal discharge rate of the system.
Best-performing model	NAR	Outperformed NARX in capturing process dynamics.
Energy cost reduction (ANN only)	10–20%	Improved scheduling reduces peak usage and inefficient heating cycles.
Economic benefit	~USD 95 372 annual savings	Based on predictive optimisation of thermal loads.
TES-enabled cost reduction (ANN + Solar TES)	69% vs grid-only	From life-cycle cost analysis (LCCA).

APPENDIX B: SUMMARY OF OPTIMISATION MODEL RESULTS FOR CHAPTER 4

Performance Metric	Result	Comment
System configuration	Solar collectors + HPWH + TES + Grid	Hybrid thermal–electrical system.
Optimisation platform	MATLAB + OPTI/SCIP	Deterministic nonlinear, mixed-integer control.
Thermal energy reduction	74.31%	Relative to grid-only baseline.
Seasonal cost reduction	72.78% (Summer), 75.21% (Winter)	Achieved through load shifting and TES utilisation.
Annual cost reduction	73.53%	Compared with resistive-baseline heating.
Life-Cycle Cost (LCC) savings	~35%	Over 20 years with 5% inflation and 10% tariff growth.
Break-even period (BEP)	1.25 years	Very favourable investment return
Upfront system cost	USD 47 250	.Includes HPWH, TES, and solar-thermal installation.
Environmental benefit	222–241 tCO ₂ e avoided annually	Due to renewable substitution and reduced grid use.
Total lifetime economic benefit	65.75 million (USD 3.65 million)	Over the 20-year lifespan.
Operational advantage	Reduced peak demand; improved renewable penetration	TES improves thermal autonomy.

APPENDIX C: COMPARATIVE SUMMARY OF ANN FORECASTING VS OPTIMIZATION OUTCOMES FOR CHAPTERS 3 AND 4

Category	ANN Model (Chapter 3)	Optimisation Model (Chapter 4)
Purpose	Predict short-term energy demand	Minimise total energy cost through optimal control
Technique	AI-based forecasting (NAR/NARX)	Mixed-integer deterministic optimization
Data used	Historical/dynamic brewery data	Forecasts, tariffs, scheduling, constraints
Accuracy	0.85705 (NARX) to 0.99856 (NAR).	Not applicable (control, not prediction)
Energy savings	10–20% (forecast-driven)	74% thermal reduction; 73% annual cost reduction
Economic savings	USD ~95 000/year	ZAR 1.1 million/year (USD ~61 000)
Environmental impact	Indirect improvements	222–241 tonnes CO _{2e} avoided annually
Strengths	Accurate load prediction; supports scheduling	Real-time energy optimisation and tariff adaptation
Best application	Forecasting, planning, proactive control	System-wide optimisation and renewable utilisation
Integration potential	Smart grids, microgrids, TES optimisation	DER coordination, demand response, tariff shifting

APPENDIX D: TARGET ANN PREDICTED POWER OUTPUT VALUES AND DEVIATION FOR CHAPTER 3

Index	Pin Target	Poutput ANN	Deviation (%)	Index	Pin Target	Poutput ANN	Deviation (%)
1	3486.1967	3462.9860	0.0514	51	3192.4153	3332.9420	0.3113
2	3505.2456	3545.1509	0.0884	52	3338.7997	3318.2933	0.0454
3	3457.1769	3550.5241	0.2068	53	4005.5669	3438.0407	1.2570
4	3342.8931	3550.8744	0.4607	54	4956.7711	4344.4585	1.3562
5	4099.4517	3550.8972	1.2150	55	6257.0572	7037.7559	1.7292
6	3305.8425	3550.8986	0.5428	56	10526.2608	9339.9026	2.6276
7	3444.8228	3550.8987	0.2350	57	9979.3786	9867.3667	0.2481
8	3403.9906	3550.8986	0.3254	58	9388.7169	9765.1133	0.8337
9	4262.5042	3550.8985	1.5762	59	10112.0611	9501.5559	1.3522
10	3497.7578	3550.8983	0.1177	60	11109.1397	9147.1583	4.3455
11	3770.0425	3550.8982	0.4854	61	6456.6064	8701.2661	4.9716
12	3680.3086	3550.8979	0.2866	62	5823.1908	8155.3326	5.1654
13	3714.3158	3550.8975	0.3620	63	6391.4839	7505.0202	2.4663
14	3686.0425	3550.8971	0.2993	64	7083.1061	6754.9371	0.7268
15	3289.4586	3550.8964	0.5791	65	8910.0908	5921.7880	6.6187
16	3262.9336	3550.8956	0.6428	66	6642.2492	5036.0436	3.5575
17	4064.8053	3550.8947	1.1472	67	2802.7658	4142.5254	2.9674
18	3233.9344	3550.8940	0.7075	68	2426.0358	3302.7851	1.9419
19	3243.2750	3550.8947	0.6867	69	2414.9097	2604.3166	0.4195
20	3313.7756	3550.9016	0.5293	70	2180.6986	2170.4460	0.0227
21	3400.1944	3550.9309	0.3365	71	2274.7633	2109.8080	0.3654
22	3473.8822	3551.0366	0.1722	72	2375.2086	2339.2978	0.0795
23	4168.3244	3551.3942	1.3665	73	2760.3022	2560.8797	0.4417
24	3404.1983	3552.5535	0.3286	74	2217.2250	2597.7061	0.8427
25	3448.5347	3556.1581	0.2384	75	2238.3436	2497.2904	0.5735
26	3456.7314	3566.7431	0.2437	76	2204.7272	2351.4232	0.3249
27	3488.7333	3594.9381	0.2352	77	2033.7850	2210.7721	0.3920
28	3377.6925	3655.6720	0.6157	78	2794.1883	2092.6065	1.5539
29	4130.0883	3717.6833	0.9134	79	2066.9550	1999.0836	0.1503
30	3283.2408	3542.1216	0.5734	80	2127.2836	1927.1683	0.4432
31	3278.9961	3112.9118	0.3679	81	1689.3950	1872.6890	0.4060
32	3275.0444	3637.5658	0.8030	82	1495.4406	1831.7552	0.7449
33	5615.1258	4839.6338	1.7177	83	1497.1975	1801.1439	0.6732
34	4938.2308	5574.4293	1.4091	84	2269.8819	1778.3173	1.0887
35	5782.9206	5859.7820	0.1702	85	1628.4514	1761.3262	0.2943
36	6466.1533	5953.8719	1.1347	86	1862.1378	1748.6937	0.2513
37	5130.2789	5982.7607	1.8882	87	2093.2606	1739.3092	0.7839

Index	Pin Target	Poutput ANN	Deviation (%)	Index	Pin Target	Poutput ANN	Deviation (%)
38	6646.3700	5990.9935	1.4516	88	1772.1075	1732.3413	0.0881
39	5659.7786	5992.7630	0.7375	89	1620.7989	1727.1698	0.2356
40	6333.3811	5991.8841	0.7564	90	1795.8728	1723.3324	0.1607
41	5884.8775	5971.6391	0.1922	91	1611.1742	1720.4850	0.2421
42	5503.2561	5492.7348	0.0233	92	2286.5183	1718.3696	1.2583
43	3870.1378	3877.9861	0.0174	93	1532.9344	1716.7858	0.4072
44	3258.1847	3447.7100	0.4198	94	1617.2144	1715.5441	0.2178
45	3216.0136	3426.4747	0.4661	95	1473.8611	1714.3246	0.5326
46	3068.3350	3419.2250	0.7772	96	1530.1197	1712.1174	0.4031
47	3610.8503	3410.0365	0.4448	97	1438.5222	1705.2816	0.5908
48	3352.3586	3397.6890	0.1004	98	2232.9656	1685.1336	1.2133
49	3208.6936	3381.1352	0.3819	99	1520.5547	1651.5077	0.2900
50	3295.7636	3359.3015	0.1407	100	1500.7864	1627.0223	0.2796

APPENDIX E: SUMMARY OF OPTIMISATION VARIABLES VALUES FOR CHAPTER 4

Variable name	Definition	Baseline value	Optimised value	Units
Pel	Power supplied by electric element to water storage tank	24	12	kW
Qel	Energy gain in storage tank from electric element	43 200 000	36 000 000	W
Qhp	Energy gain in storage tank from heat pump	-	77 760 000	W
Alpha	Coefficient related to water and tank thermal dynamics	0.000223	0.00025	-
Beta1	Coefficient related to the heating-effect control variable from the heat pump	-	16.8955	-
Beta2	Coefficient related to the heating-effect control variable from the electric heater.	9.3864	0.7822	-
Gamma	Coefficient related to solar gain of the system	0.0038	0.0038	-
Peak	ToU tariff during peak hours	3.16	3.16	(ZAR/kWh)
Standard	ToU tariff during standard hours	1.764	1.764	(ZAR/kWh)
Off-peak	ToU tariff during peak hours	1.638	1.638	(ZAR/kWh)
W1	Weighting factor for cost minimisation priority	0.4	0.4	-
W2	Weighting factor for maintaining brewing optimal temperature	0.3	0.3	-
W3	Weighting factor for PV usage maximisation	0.3	0.3	-
To	Initial or setpoint temperature	60	60	°C
Tdesired	Desired temperature	80	80	°C
x	Switching variable	-	-	Binary
fval	Objective function value	516 262	837 400	ZAR
exitflag	Optimisation exit status	-	1	-
info	Optimisation information	-	SCIP	-