Modelling and Design of Local Energy Systems Incorporating Heat Pumps, Thermal Storage, Future Tariffs, and Model Predictive Control

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Declaration

This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

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Abstract

The planning-level design of local energy systems requires sufficiently capable modelling tools which incorporate heat pumps, thermal storage, future electricity markets, and predictive control strategies. Gaps were identified in a review of existing local energy system tools: (i) ability to adapt and access source code; (ii) temperature dependence for heat pump models; (iii) stratification model for thermal storage models; (iv) modelling of evolving electricity markets; and (v) ability to explore predictive controls.

A novel modelling tool, PyLESA, has been developed to tackle these gaps and to explore predictive and non-predictive controls, and existing and future electricity tariffs. PyLESA possesses the following modelling capabilities: resources, and electrical and heat demands; electricity production; heat pump; hot water tank; electricity tariffs; fixed order control (FOC); model predictive control (MPC); and KPIs.

A sizing study for a proposed design of a district heating network was devised to showcase an application of PyLESA. Aims were to compare control strategies and electricity tariffs, and to identify an optimal size combination of heat pump and hot water tank. Comparisons between control strategies found that MPC offers savings over FOC. The lowest levelized cost of heat for the existing electricity tariffs was for the time-of-use tariff with MPC, 750kW heat pump and 500m^3 hot water tank.

A wind tariff, with a 1000kW heat pump and 2000m^3 hot water tank, benefits from using MPC over the FOC: levelized heat costs reduce by 41.1%, and heat demand met by RES increases from 52.8% to 70.2%. It is shown that the proposed design can be sized using existing electricity tariffs, and additional hot water tank capacity added later to benefit from future tariffs.

The results convey the advantage of combining flexible tariffs with optimally sized thermal storage and showcase PyLESA as capable of usefully aiding the design of local energy systems.

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Useful Abbreviations

ASHP – Air Source Heat Pump

CAES – Compressed Air Energy Storage

CHP – Combined Heat and Power

CIBSE – Chartered Institution of Building Services Engineers

COP – Coefficient of Performance

DSM – Demand Side Management

EMPC – Economic Model Predictive Control

ES – Electrical Storage

FOC – Fixed Order Control

GSHP – Ground Source Heat Pump

HP – Heat Pump

KPI – Key Performance Indicator

LCOE – Levelized Cost Of Energy

LCOH – Levelized Cost Of Heat

LZCT – Low or Zero Carbon Technology

MPC – Model Predictive Control

NPC – Net Present Cost

OO – Operational Optimisation

PCM – Phase Change Material

PID – Proportional-Integral-Derivative

PLC – Programmable Logic Controller

PV – Photovoltaics

PyLESA – Python for Local Energy Systems Analysis

RES – Renewable Energy Sources

SSM – Simple Storage Model

WSHP – Water Source Heat Pump

WWHC – West Whitlawburn Housing Cooperative

Source code for PyLESA

PyLESA stands for Python for Local Energy Systems Analysis and is pronounced "pai-lee-suh". It is an open source tool capable of modelling local energy systems containing both electrical and thermal sector technologies modelled in hourly timesteps. It was developed by the author as part of the work of this thesis with the aim of aiding the planning-level design of local energy systems, and the focus is on modelling systems with heat pumps and thermal storage alongside time-of-use electricity tariffs and model predictive control. Additionally, it is anticipated that the tool provides a framework for future development including electrical battery studies and participation in grid balancing mechanisms.

The source code of PyLESA can be accessed from the following GitHub repository: https://github.com/andrewlyden/PyLESA.

1. Introduction

This chapter introduces the general context and background underpinning the motivation for the work carried out in this thesis. It begins with a discussion of the current transition of the energy system in Scotland and the UK. Local energy systems are clearly defined to help contextualise the scale and scope of this work. Heat pumps, thermal storage, electricity markets, and control strategies are then explored and discussed with a view to motivating the vital role they can play in flexible, low-carbon, low-cost, and local energy systems. Finally, an overview of widely used energy modelling tools, and reviews of modelling tools, is provided to give a flavour of the current status and future challenges of local energy system modelling.

1.1. General Context

The usage and sourcing of energy is currently undergoing a fundamental transition as society aims to tackle climate change, improve urban environments, and progress energy equity. Reducing energy use across all sectors including buildings, industry, and transport, and increasing sourcing energy from sustainable sources are both required to meet these aims. This transition mandates a paradigm shift in how energy systems at all scales are designed. Supply of energy using renewable energy sources such as wind and solar are low-grade and stochastic and cannot easily be matched to inflexible demand. This contrasts with the high energy density and abundant nature of fossil fuels which when burned in power plants provide a means of meeting demand. This problem necessitates new methods for introducing flexibility in future energy systems to match supply and demand.

Various storage technologies can introduce the required flexibility at different timescales (sub-second, day, seasonal). However, there are significant future uncertainties and differences in the efficiencies and costs of these storage technologies. Future systems need to be designed carefully to ensure optimal solutions for different applications are implemented.

Another consequence of a renewable energy-based system is the localisation of energy production. While fossil fuels are used to produce electricity in large-scale and centralised power plants, renewable energy can be produced regionally, across the country in smaller scale installations. This has given rise to the increased importance of local energy systems which are formed of a variety of co-located demand, supply, and storage technologies which can be integrated within the wider national energy system.

Heat pumps can play a vital role in local energy systems as they can utilise low-carbon power generation and sources of low-grade heat to meet space heating and hot water demands. They can be employed in single dwellings or be scaled up to supply district heating networks. Importantly they can be used with hot water tanks which are one of the cheapest forms of storage technology currently available. Heat pumps and thermal storage together have the potential capability to add flexibility to local energy systems in a cost and carbon effective way.

A low-carbon, local energy system is complex and needs to be modelled to be understood and properly designed. These systems need suitable control strategies to be able to optimise the use of time-of-use electricity tariff structures and local energy production via renewable energy sources.

1.2. Transitioning Energy System

Future energy system pathways to aid in tackling climate change in the UK have emerged which involve interactions between a centralised power grid with large amounts of fluctuating renewable power and decentralised local systems including generation and storage [1–3]. Technologies already exist which can contribute to this potential pathway: rooftop PV on domestic households with bi-directional grid flows [4], community-owned distributed wind farms [5], micro-hydro schemes [6], smart grids [7], district heating utilising waste heat [8] or combined heat and power (CHP) [9], hydrogen from renewable energy sources [10], etc.

Scotland is undergoing a transition to a low-carbon energy system, underpinned by the introduction of renewable energy sources into the electricity grid network. Renewable sources accounted for 74.6% of gross electricity consumption in 2018 [11]. However, electricity is only 23.5% of final energy consumption of which heat constituted 52.0% and transport 24.4% in 2016 [11]. Efforts are necessary to decarbonise the heat sector where non-electrical, renewable sources contributed 5.9% to heat demand in 2017 [11].

Traditionally Scotland has developed a gas grid in urban areas and used oil and electricity to heat homes in rural areas. Little district heating has been developed with approximately only 30,000 buildings connected to district heating as of 2018 [11]. District heating can potentially increase the use of renewable heat. This has led to interest in micro-district heating in rural towns and villages with low heat demand density, as well as larger scale district heating projects such as housing schemes. Many of these rely on expensive electrical heating due to restrictions on gas infrastructure in high-rise dwellings. This, coupled with government incentives and grants, has made district heating an economically favourable alternative with the added benefit of the perceived low-carbon aspect.

There has been a significant uptake of biomass boilers in Scotland. These installations are typically set-up to provide heat for large public buildings and are often built by local councils to meet their sustainability targets. However, it is unclear that these systems have been built to best practice and there is concern around sustainability and air pollution issues related to the burning of wood for domestic heating [12]. Additionally, biomass may have a pivotal role to play in the wider energy system in decarbonising difficult sectors such as high-temperature industry and heavy transportation [13].

Electrification of heat could prove to be an effective method of decarbonising heat due to the transition of the electrical grid to higher penetrations of renewable energy sources. As this transition is occurring, electrical heat options such as heat pumps will become increasingly low-carbon as seen from the falling grid carbon intensity factors in Figure 1.1 [11]. From a holistic view of the wider energy system it is worthwhile exploring design options incorporating heat pumps as the primary heat source.

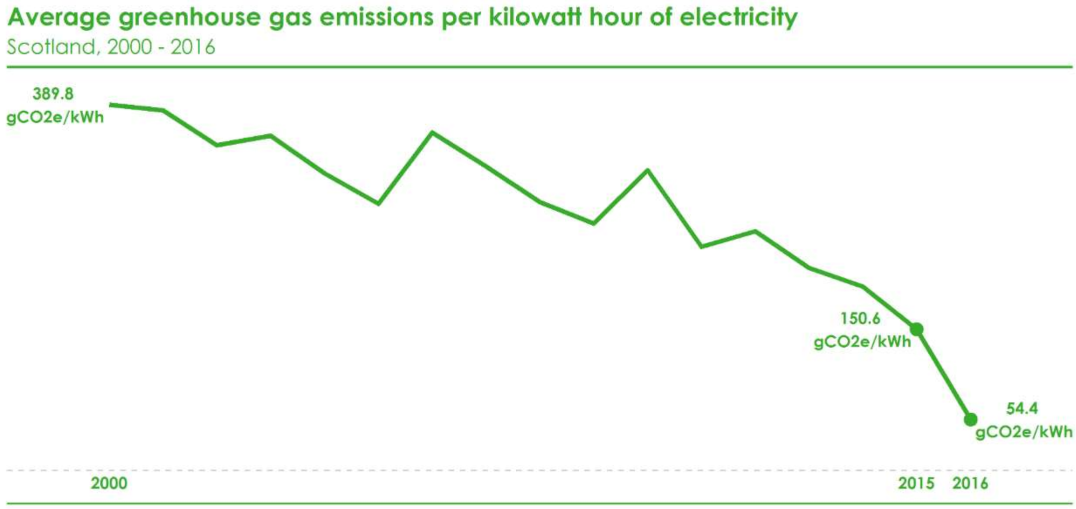


Figure 1.1: Average carbon intensity factor for electricity consumed in Scotland [11]

1.3. Local Energy Systems

Local energy systems consist of energy production units and demand side management (DSM) enabling technologies co-located with demands [14]. There are many terms used to describe similar energy systems such as community, district, decentralised, etc. Each have their own specific definitions and different interpretations in technical, social, and economic contexts. The term local energy system is used here in a technical context and defined on the co-location of technologies and the scale, ranging from a cluster of buildings to an entire region of a country.

An example of a local energy system may contain locally owned wind turbines and/or PV which provide electricity to local customers, and heat generation units utilising local resources (e.g. biomass, local renewable generation) serving district heating networks.

The implementation of these has been motivated by reducing imported energy costs, increasing self-reliance, reducing carbon footprints, and providing revenue streams via government subsidies and exported electricity. The development of such systems in the UK marks a shift from the historical means of delivering electricity from centralised fossil fuel power production plants and providing heating from gas via large-scale piping infrastructure.

Local energy systems also open opportunities for sector integration possibilities. Energy sectors which have been historically considered in silo can be designed holistically. This could be designing a heat pump with a thermal store controlled to turn on when there is local excess generation of wind power. These require connected systems to facilitate logic decisions based on external signals.

Local energy systems should also be designed to be integrated within the wider national energy system. Only considering on-site renewable power production could lead to very large capacities of expensive storage technologies being installed, but often local energy systems are connected to a wider national grid network. This grid in the future could heavily rely on wind power from across the country and have periods of large excess production. A local energy system should be designed to take advantage of this. Additionally, grid services which provide response to stress events to ensure grid stability could in the future be aided by local energy systems.

1.4. Heat Pumps

Heat pumps are a decentralised technology which couple the electrical and thermal sectors. They efficiently use electricity and low-grade heat sources to provide heat at useful temperatures, commonly for small-scale household purposes of hot water and space heating although district heating and industrial applications do exist [15]. Previous studies have identified large-scale heat pumps for district heating as providing 25-30% of heat in future roadmaps for Europe [16], and concluded the technology is mature for deployment [17].

CHP provide competition to heat pumps as a low-carbon form of district heating supply, however it is possible a combination of both could be employed to optimise energy balancing in larger schemes [18]. CHP can increase overall primary energy efficiency in comparison to traditional power generators by making use of waste heat. They are usually located close to heat demands and are categorised as a decentralised form of electricity and heat production. Natural gas is currently the most commonly used fuel in CHP plants. Biomass is potentially a cleaner fuel [19], however due to limited availability and sustainability concerns, it is likely to be more useful in other sectors [13]. Synthetic fuels, such as hydrogen, produced from renewable power could be used and these have been identified as important for 100% renewable energy systems [20].

Viability of each of the competing technologies is dependent on local conditions and grid dynamics such as power prices and carbon intensities. A local system may have existing renewable generation or heat infrastructure, e.g. gas grid, available to utilise which influences technology choices. When the grid power price and carbon intensity is high, CHP electricity production is favourable, however, when these are low and lots of renewable power production is on the grid (or there is low demand), electrical consumption with heat pumps can provide low-cost and low-carbon heat. This simple example illustrates the importance of using control strategies which account for grid dynamics and local power generation in design. As power grids become increasingly low-carbon it is possible heat pumps could become the dominant source of low-carbon heat for district heating networks.

1.5. Thermal and Electrical Storage

A flexible energy system consists of generation, demand, and storage components which can respond to stochastic weather conditions and the dynamic carbon intensity and pricing of a renewable-dependent electrical grid. The control of shifting demand and production is commonly known as Demand Side Management (DSM) and is enabled by storage technologies such as electrochemical batteries, hot water tanks, hydrogen electrolysers, etc., and non-technology methods such as encouraging behavioural change. Flexibility technologies have been analysed and compared in previous studies in the electrical network [21] and across sectors [22].

Thermal storage can provide flexibility to an energy system when paired with heat pumps by decoupling the heat demand and electrical consumption. Applications of thermal storage include hot water tanks and heat pumps in domestic buildings with smart control [23], phase change materials (PCM) for solar water heating [24], thermal mass of residential buildings [25], etc. Hot water tanks can be used in district heating and have been identified as an important component of 4th generation district heating systems [26]. The economic savings due to scale for hot water tanks at the district-level provides motivation for encouraging their usage [27].

There are a number of potential applications of electrical storage technologies and these range from large scale generation and transmission network systems, to smaller-scale generation and distribution network systems, to individual consumers and end-users [28]. These applications have been categorised in literature [29]: (i) *Generation* – arbitrage, power reserve, area control, frequency regulation, and black-start; (ii) *Transmission and distribution* – system stability, voltage regulation, and asset deferral; (iii) *Energy service* –

Energy management, power quality, and power reliability; (iv) *Renewables* – Transmission curtailment, load-shifting, grid frequency support, and fluctuation suppression.

1.6. Electricity Markets

Electricity markets are changing to reflect the transition from dispatchable power generation to stochastic, renewable power generation. Traditional tariffs such as flat rate or day/night periods are being challenged by emerging half hourly time-of-use tariffs issued a day ahead. These incentivise users with reduced prices during periods of surplus zero marginal cost renewable generation, and correspondingly dis-incentivise with increased prices during periods of peak demand and low renewable generation. This reflects pricing already being seen in wholesale markets with negative pricing in high wind and low demand periods [30]. The time-of-use pricing is currently largely driven by electricity demand profiles which only require simple time-based controls to gain most of the benefits of flexibility. However, as the proportion of renewable generation increases the tariffs will become more variable and motivate deploying improved communications and control technologies.

Future commercial arrangements through aggregators, and others, could further reward flexibility which can contribute to local network and wider grid electricity services such as frequency response and other longer-term balancing requirements. Engagement in these services will also require communication and control solutions.

1.7. Control Strategies

Communication and control are essential in enabling flexibility to deliver value in future energy systems. Secure communications, monitoring and control software and hardware platforms are being standardised, developed and deployed at commercial [31,32] and community cooperative scales [33–36]. Communications services available to these platforms include weather forecasts and next 24-hour time-of-use tariffs.

These platforms allow controls to be developed that optimise the operation of the system to meet the customer needs while maximising financial parameters or meeting other objectives such as maximising local or global renewable (self) consumption etc.

Predictive controls and non-predictive controls have been studied with extensive literature on control methods with building integrated thermal energy storage [37,38]. A rule-based controller has been compared to an MPC control finding that MPC control is vital when sizing thermal storage [39].

Classical local-loop control is typically PID (Proportional-Integral-Derivative) and PLC (Programmable Logic Controller). These use predetermined setpoints and instructions instead of predictions of load and supply which allow improved optimisation. A PID control for drying temperature has been designed for a heat pump for drying [40], and a PLC control has been designed to provide commercial demand side management to shed load during peak hours [41]. PID and PLC control offer the local control which implements the control decisions from supervisory controllers.

Two classifications of supervisory control have been identified in literature [38]: hard and soft control. Soft controls have the capability to learn complex relationships between system input and output variables, e.g. neural network control, fuzzy logic control, and reinforcement learning control. Neural network control has been applied to optimise control of batteries in a household [42] and fuzzy logic control used to optimise the performance of a PV, solar thermal and heat pump hybrid system [43]. Reinforcement learning control uses machine learning to determine how to take actions in order to maximize a long-term objective over a sequence of decisions. It has been applied to a demand response aggregator of electrical water heaters using a 40-45 day learning period [44].

Hard control uses physical models to determine control signals which optimise a system performance parameter. Model predictive control (MPC) captures the dynamics of an energy system, and this can be based upon building and system simulation models or artificial intelligent techniques. An MPC controller consists of several key components:

- Objective function which an optimiser minimises/maximises.
- Prediction horizon which is the period over which the optimisation is performed.
- Decision timestep which is the interval between solving optimisation problem.
- Manipulated variables can be varied by the controller.
- Optimisation solver which is chosen based upon optimisation type and required speed.
- Feedback signal which provides updated system variables for next optimisation step.

Adaptive control is another hard control approach which accounts for the changing dynamics of a system and requires less accuracy of the physical system model. It consists of three main components: the optimal control models which contain the objective functions and constraints; the identification of the time-varying control parameters which are adjusted; and optimal algorithms which make decisions and determine the values for the control variables. Downsides include overcomplication and large computational time requirements meaning that this control has been rarely applied. However, it has been applied to microgrid operation to evaluate flexibility benefits [45].

Combinations of control methods have also been applied with a typical approach using two stages. Firstly, a preliminary learning stage where a simple dynamic model is developed in order to train the controller. Secondly, a refined learning phase where the controller is applied to an actual system and continues to learn and further improves its performance via feedback from actual performance.

A key challenge is how to capture these controls together with appropriate system characteristics in early stage modelling to appropriately inform design.

1.8. Modelling Local Energy Systems

Given the importance of local energy systems and wide variation in possible supply, storage control options, and variation in contexts such as climates and user expectations, there have been many efforts to provide modelling support for the planning process from a range of different perspectives. A general method for community energy planning is described in [46] and a key element identified is the use of modelling tools. This thesis focusses on the planning-level stage of design where often there is a limited set of data available. Many planning-level energy system tools have been developed and applied to a range of situations, and a sample of the most popular ones are discussed below.

EnergyPLAN [47] is a national and regional planning tool which has been used to model a 100% renewable energy future for Denmark [48] and for many other studies [49]. It is applicable at community scale, and was used to model the island of Mljet in Croatia [50] in a comparative study with H_2RES, an alternative tool designed for simulating the integration of renewables and hydrogen storage into island systems [51]. In this study, it was shown that both tools gave very similar results; H_2RES focus is technical while EnergyPLAN supports technical and economic analyses. Both tools are deterministic and use an hourly energy balance over a year to calculate energy generated, stored, rejected, consumed, exported, lost, and produced in excess, as well as percentage of energy consumed from renewable sources.

HOMER [52] is a community scale tool, originally developed to support design of off-grid electrical energy systems but expanded to model grid connected and thermal systems [53]. One example is modelling a hybrid solar-biomass system for a remote area in Pakistan [54]. This study used electricity demand, available solar and biomass resource, and costs to analyse the techno-economic viability of such a system. HOMER was used to optimise system size using an hourly energy balance and with minimum net present cost (NPC) as objective function.

Merit [55] is another community scale tool which has been used to model a hybrid wind/solar system for a care home in Scotland [56]. Merit models demand, supply and storage using an hourly energy balance and provides results showing demand/supply match and renewable and non-renewable supply. Multiple systems were modelled, and those shown to satisfy demand all year round analysed. The tool provides technical analysis only with cost calculations being done outside of the tool.

TRNSYS [57] has a user-defined timestep as small as 1 second. A comprehensive library of components is available. Systems are described in detail and the solver is dynamic which means that TRNSYS is usually a building-level simulation tool [58]. The number of components and parameters required for a community scale system could be complex requiring expert level of technical systems knowledge. These complex calculations take considerable time. It has been used to model hybrid solar PV/thermal systems with thermal and electrical storage [59] etc. TRNSYS and similar building-level simulation tools can be scaled up for use at community scale.

The tools described above are a sample of those available and serve to illustrate different approaches. There is general agreement that hourly modelling timesteps (or less) are required to adequately model such systems [60]. Tools are often first developed from a specific perspective e.g. hydrogen for H_2RES, off-grid for HOMER, building systems for TRNSYS, and then adapted to support broader planning of community scale systems. How to choose between the plethora of different tools, particularly for planning of renewable energy systems where storage and DSM are to be considered is a key challenge.

A number of reviewers have previously provided an overview of modelling tool capabilities specific to the effective integration of renewable energy. In general it was found that the prior work, although a useful foundation for tackling the aims of this thesis, did not fully: (i) address all storage and DSM options, (ii) provide a sufficiently detailed categorisation of the models used to represent storage and DSM, and (iii) provide a structured tool selection process. The most relevant of these previous works are briefly described below.

[61] reviewed 37 tools (narrowed down from 68) regarding their suitability for the integration of renewable energy into energy systems; the details on the storage technologies used in the tools are high level i.e. stating whether a tool is capable of modelling pumped hydroelectric, battery, compressed air and hydrogen storage. Thermal storage and DSM are not included in the provided tables; 'thermal storage' is mentioned for 3 of the tools in textual descriptions. The underlying models for electrical and thermal storages are not discussed in detail; such information can be useful to inform tool selection as some models can be more accurate than others [62,63]. The authors provide the review to inform tool selection and the provided information is indeed useful in this regard, but a formal selection process is not specified.

[64] considered 72 tools to find those capable at city scale of modelling multi energy systems considering all relevant energy carriers (electricity, heating, cooling, transport etc.). They considered in detail 13 of the tools which were open source. Information regarding the tools was usefully tabulated including: available RES components, storage options, economic parameters, scale, availability, objective, modelling approach, timestep, evaluation criteria, user friendliness and training requirement. The paper identified the different storage technologies included in the energy tools but did not give detail on the underlying models. While it was highlighted that grid balancing is essential in districts utilising stochastic energy sources the DSM and grid support modelling capability of the tools was not captured. No tool selection process was specified.

[65] reviewed 20 tools chosen based on their ability to "simulate and analyse urban energy systems". Storage discussion was limited to seasonal thermal storage modelling, with building level storage capability documented within the tables but not in detail, DSM also is not covered in detail.

Several further reviews of energy system tools have been undertaken. [66] reviewed 219 studies, examining areas of urban energy systems (technology design, building design, urban climate, systems design, policy assessment, land use and transportation modelling) to evaluate their potential for integrated urban design. [67] reviewed 6 bottom-up tools which focus on optimisation of community energy systems, finding DER-CAM and MARKAL/TIMES to be the most appropriate. [68] documented the capabilities and inputs/outputs of 11 energy tools, a short paragraph on each was provided in terms of their energy, economic and environmental analysis capabilities. [69] undertook a review of 12 tools to consider the methods available for integrated energy analysis for cities and territories.

1.9. Uncertainty in Energy System Modelling

Energy system modelling tools are being used to provide decision support, and therefore it is important to consider the types of uncertainties and the methods which exist for incorporating uncertainty into the design process.

Typologies of uncertainty have been developed for different purposes [70], and Mirakyan and De Guio [71] developed an overall framework of uncertainty specific to modelling and decision support in the context of energy planning. The sources of uncertainty which form this particular framework are described here:

- **Linguistic uncertainty:** has been defined "as uncertainty that arises because our natural language is vague, ambiguous, and because the precise meaning of words can change over time" [72]. It has an influence at all stages of modelling because the information used in energy planning and modelling is in linguistic terms.
- **Variability uncertainty:** is due to inherent variability of human and natural systems (e.g. wind and temperature changes).
- **Decision uncertainty**: can occur where there is ambiguity over how to define modelling objectives.
- **Planning procedural uncertainty:** can occur because of available resources or time.
- **Knowledge uncertainty:** occurs due to the limitation of our knowledge. It may be reduced by additional research and empirical efforts. There are different subcategories of this uncertainty and these are described below.
    - **Context and framing uncertainty:** occurs when setting out of the context and boundary conditions of the modelling and is influenced by the modellers/stakeholders perception of the scope of the planning exercise.

- **Model inputs and parameters:** Input data can describe external conditions (i.e. weather data), or model system data which defines characteristics of the system. Uncertainty of the input data and parameters may occur due to: measurement errors, data reading, user-error, and biases in data retrieval.
- **Model structure uncertainty:** occurs due to incomplete understanding of the system processes (e.g. performance of components), when approximating a real, complex system to a mathematical model. The complexity of the model is dependent on the context of the modelling exercise, the available data input to the model, and the required outputs from the model (reliant on the requirements for validation and interpretation of the results).
- **Model technical uncertainties:** occur due to errors/bugs in the software and/or hardware.
- **Model output uncertainty:** defined as the accumulation of all the other described uncertainties.

Methods exist for incorporating uncertainty analysis into the decision making of energy system planning. A number of these methods have been reviewed in literature in relation to their application in energy system planning and feasibility [73]. A sample of these are explored below:

- **Stochastic optimisation techniques:** Stochastic optimisation studies introduce uncertainty to input parameters which exhibit stochastic behaviour using a range of different modelling approaches such as fuzzy, dynamic, and interval mathematical programming [74]. One study used interval parameter fuzzy linear programming and multistage stochastic programming which were integrated with a mixed-integer linear programming framework in order to aid planning of energy and environmental systems management under multiple uncertainties [75]. Examples of stochastic input parameters are electricity prices, fuel prices, production costs of power plants, CO2 emission policy, energy demand, and technological efficiency.
- **Monte Carlo simulation:** Monte Carlo simulation performs uncertainty analysis by modelling possible outputs using a range of values (in the form of a probability function) for an input parameter which has inherent uncertainty. It repeatedly calculates results, each time using a different set of random values from the

probability functions. For example, this method has been applied to optimal sizing of cogeneration systems under long-term uncertainty in energy demand [76].

- **Scenario analysis:** Uncertainty can be incorporated by evaluating various scenarios which incorporate the dynamics and the drivers resulting in a specific future scenario. Scenarios utilised often represent situations that are likely to occur or extreme cases (worst-case or best-case scenarios). For example, in a study modelling Egyptian office buildings, to capture the inherent variability in operation and behaviour a set of 'best and worst case parameter sets' were used to investigate their impacts on performance [77].

Other methods for incorporating uncertainty analysis include mean-variance portfolio analysis [78], real-options analysis [79], and multi-criteria decision analysis (MCDA) [80].

This section provides a discussion of the types of uncertainty related to energy system modelling and identified that knowledge uncertainty can be reduced through research and empirical efforts. It also explored methods for incorporating uncertainty analysis into energy system decision making. The approach taken in this thesis is to develop a modelling framework which can be integrated into these methods.

1.10. Related Projects

The work undertaken in this thesis builds on the experiences and outputs from related previous and ongoing projects, as well as the literature explored in this chapter.

The ORIGIN project (Orchestration of Renewable Integrated Generation In Neighbourhoods) aimed to develop and implement load shifting mechanisms in order to both maximise the usage of local renewable generation and minimise the import of energy [81]. The project developed algorithms which were capable of (i) encouraging occupant behavioural change, and (ii) remote control of systems. An ecovillage, Findhorn, was used to trial the developed algorithms and different types of system were tested on-site. One of these system types consisted of a close to Passivhaus standard dwelling with space heating and hot water delivered by an air-source heat pump, with auxiliary electric boost, coupled with solar thermal. MPC was implemented on this system type and was shown to reduce use of the auxiliary electric boost by 44% in summer and increase the match of the boost heat with renewable generation by 22%. This highlights the potential benefits of employing MPC along with heat pumps, thermal storage, and local renewable generation (i.e. solar thermal in this example). These systems require planning-level modelling in order to capture these benefits at the early stage of design.

The author of this thesis was involved in Annex 31 of the IEA Technology Collaboration Programs (TCPs), Energy Conservation through Energy Storage, "Energy storage with energy efficient buildings and districts: Optimization and automation" [82]. The aim of this annex was to address challenges in integrating thermal energy storage systems in buildings/districts from the perspective of design, development of simplified modelling tools, and optimization techniques. The work undertaken in this annex identified the need for simplified design modelling tools at the district-level which capture heat pumps, thermal storage, electrical storage, and optimal control strategies.

These projects, along with the literature reviewed in this chapter, point towards the need for design modelling tools which can incorporate heat pumps, thermal storage, local renewable generation, and MPC.

1.11. Problem Statement

Overall, it is clear that there is a need to transition the energy system from the current paradigm of centralisation, and reliance on fossil fuels for flexibility to using zero-carbon technologies across all energy sectors aided by decentralisation and measures to incentivise and enable renewable-led flexibility.

The design of future local energy systems which incorporate heat pumps, thermal storage, future electricity markets, and predictive control strategies is complex and requires sufficiently accurate planning-level modelling tools to help aid in understanding the performance of these systems. This is vital in comprehending the role that properly designed low-carbon, integrated, local energy systems will have in the transition to a 100% renewable energy system.

2. Research Question, Aims, and Methodology

2.1. Research Question

The research question to be addressed in this thesis is:

Can a modelling methodology and supporting modelling tool be developed that usefully aids the planning-level design of local energy systems incorporating heat pumps, thermal storage, local renewable electricity production, time-of-use electricity tariffs, and predictive controls?

2.2. Research Aims

The following aims are set out to help answer the research question:

- Identify gaps in existing planning-level modelling tools.
- Develop a modelling methodology capable of aiding design of local energy systems incorporating heat pumps, thermal storage, local renewable electricity production, time-of-use electricity tariffs, and predictive controls.
- Develop a supporting modelling tool with the capabilities to address the identified gaps.
    - Open source to enable accessibility and build upon previous work.
    - Heat pump model with explicit temperature-dependent performance.
    - Hot water tank model with explicit thermal characteristics.
    - Future electricity markets.
    - Set of supervisory control strategies including model predictive control.
- Explore developed control strategies and existing and future electricity tariffs through demonstration of application of the modelling methodology by undertaking a sizing study.
    - Demonstrate application of the developed modelling tool and position it in the context of the state of the art.

- Compare the performance of predictive and non-predictive control strategies.
- Compare the use of existing electricity tariffs.
- Investigate the use of a future wind-based renewable electricity tariff.

The scope of the work undertaken in this thesis is limited to the planning-level design of local energy systems where it is desirable to use modelling tools with hourly or sub-hourly timesteps, low-carbon technology models, and storage and DSM capabilities. This type of tool would preferably provide useful outputs with minimal computational time or input requirements. More detailed building and system design tools which require high user expertise, are computationally heavy, and have detailed input demands, have been considered outside of the scope of this paper.

2.3. Research Methodology

The research methodology sets out the work undertaken in order to tackle the stated research question and aims. The thesis chapters follow the structure outlined below.

Chapter 3

1. Identification of gaps in existing tools through a review of existing modelling tools, categorisation of capabilities, selection process to identify appropriate tools, and application to a case study.

Chapter 4

2. Introduction of the novel modelling tool including modelling methodology, capabilities, framework and applications with the ability to address the identified gaps.

Chapter 5

3. Description and validation of new modelling tool capabilities: resources and demands; electricity production technologies; heat pumps; hot water tanks; electricity tariffs; fixed order controls; model predictive controls; and key performance indicators.

Chapter 6

4. Carry out a sizing study for a proposed design of a residential district heating system aided by an application of the developed modelling methodology to

explore and inform design decisions regarding control strategies and electricity tariffs.

   a. Carry out operational analysis.
   b. Size heat pump and thermal storage capacities.

Chapter 7

5. Discussion and conclusions of the contributions and strengths in relation to addressing both the identified modelling tool capability gaps and the exploration of the control strategies and electricity tariffs; limitations and future developments of the novel modelling tool; and potential future applications.

3. Review of Existing Modelling Tools

This chapter reviews existing modelling tools with the aim of identifying gaps to be addressed in the proposed modelling tool. The focus is on the tool capabilities regarding storage technologies and demand side management (DSM), but the categorisation section covers a wide range of capabilities and forms a thorough review of the overall ability of the identified tools to perform according to user requirements. This work appears in a peer-reviewed journal paper co-authored by the author [83].

The review consists of the following steps:

- Initial screening process to identify 13 applicable local energy system modelling tools from an initial list of 51.
- Categorisation and tabulation of the modelling capabilities overall with focus on heat pumps, storage, and DSM capabilities.
- Development of a tool selection process using the tables and demonstration for a case study.
- Discussion of the tool selection process and modelling tool capabilities.
- Identification of the gaps to be addressed in this research.

The scope of the review has been limited, in line with the thesis scope, to tools designed for hourly or sub-hourly timestep modelling of local energy systems containing low-carbon technology, storage and DSM, for use at the planning stage. More detailed building and system design tools have been considered outside of the scope of this thesis.

There is an increasing trend towards using modelling tools in conjunction with other modelling tools or external software such as MATLAB [84], GEN-OPT [85], EnergyTRADE [86] etc. particularly to support mathematical optimisations or realistic controls. These multi-tool processes are also outside the focus of this review.

It is recognised that tools are continuously being developed and that the screening analysis and the tool classification exercise will need to be refreshed periodically. The work of this review, in addition to providing a current snapshot, provides a useful framework for this refresh within the context of the proposed tool selection process.

3.1. Initial Screening Process

An initial list of 51 tools with some ability to model an energy system was derived from: literature including review papers and papers describing the development and application of tools; tool user manuals and websites; and communications with tool providers. Tools captured in previous reviews but clearly not capable of modelling local energy systems were discounted. For example, Envi-met is a microclimate and landscaping tool [87], and Radiance is used in daylight prediction [88].

A set of criteria were applied to the 51 tools in order to determine in more detail their potential suitability. A tool passed the criteria if it could be used at local energy system scale (i.e. was defined as such or had a case study demonstrating this capability), was appropriate to the planning stage, incorporated renewable and low-carbon technology and storage and DSM, had hourly or sub-hourly timestep and could cover either thermal or electrical energy supply. The screening process is captured in Table 3.1 along with relevant references. Additionally, the dark shading indicates fail and light shading indicates potential fail.

This process resulted in the identification of 15 tools suitable for modelling community scale energy systems incorporating renewable energy sources, storage and DSM, for use at planning design stages. Two of the 15, MODEST and Mesup/PlaNET were discounted due to lack of accessible information required for more detailed analysis. This left 13 tools to be carried forward into the categorisation of capabilities and tool selection processs.

Table 3.1: Screening process for 51 tools using a set of criteria

Tools	Criteria Met?	Local energy system scale	Case study	Planning -level design	LZCT	Storage/ DSM	Time step	Electrical	Thermal	References
AEOLIUS	No	National/ regional	No	Yes	Yes	Yes	Minutes	Yes	No	[61]
Balmorel	No	No	No	Yes	Yes	Yes	Hourly	Yes	Yes	[89]
BCHP Screening Tool	No	No	No	Yes	No	Yes	Hourly	Yes	Yes	[61,90]
Biomass decision support tool	Yes	Yes	-	Yes	Yes	Yes	Hourly	No	Yes	[91]
CitySim	No	Yes	-	No	Yes	Yes	Hourly	Yes	Yes	[65,92,93]
COMPOSE	Yes	Yes	-	Yes	Yes	Yes	Hourly	Yes	Yes	[61,94]
DECC 2050 Calculator	No	No	No	Yes	Yes	Yes	Yearly	Yes	Yes	[95]
DER-CAM	Yes	Yes	-	Yes	Yes	Yes	5 mins	Yes	Yes	[96,97]
E4Cast	No	No	No	Yes	Yes	Yes	Yearly	Yes	Yes	[61]
EMPS	No	No	No	Yes	Yes	Yes	Weekly	Yes	No	[61,98]
EnergyPlan	Yes	National/ regional	Yes	Yes	Yes	Yes	Hourly	Yes	Yes	[47,50]
EnergyPRO	Yes	Yes	-	Yes	Yes	Yes	Minutes	Yes	Yes	[99,100]
ENPEP-BALANCE	No	National/ regional	No	Yes	Yes	No	Yearly	Yes	Yes	[61,69,94]
ESP-r	No	Yes	-	No	Yes	Yes	Seconds	Yes	Yes	[58,101]

ETEM/Markal-lite	No	Yes	-	Yes	Yes	Yes	Yearly	Yes	Yes	[69,102,103]
eTransport	Yes	Yes	-	Yes	Yes	Yes	Hourly	Yes	Yes	[104,105]
GTMax	No	No	No	Yes	Yes	Yes	Hourly	Yes	Yes	[61,106]
H2RES	Yes	Yes	-	Yes	Yes	Yes	Hourly	Yes	Yes	[50,107,108]
HOMER	Yes	Yes	-	Yes	Yes	Yes	Minutes	Yes	Yes	[52,109,110]
Hybrid2	Yes	Yes	-	Yes	Yes	Yes	Minutes	Yes	No	[111,112]
HYDROGEMS	No	Yes	-	No	Yes	Yes	Minutes	Yes	No	[61,113]
IDA-ICE	No	No	No	No	Yes	Yes	Minutes	No	Yes	[65]
iHOGA	Yes	Yes	-	Yes	Yes	Yes	Minutes	Yes	No	[114–116]
IKARUS	No	No	No	Yes	Yes	Yes	5 years	Yes	Yes	[61,69]
INFORSE	No	No	No	Yes	Yes	Yes	Yearly	Yes	Yes	[61]
Invert	No	National/ regional	Yes	Yes	Yes	No	Yearly	Yes	Yes	[61,117]
KULeuven OpenIDEAS framework	No	Yes	-	No	Yes	Yes	Minutes	Yes	Yes	[61,118,119]
LEAP	No	No	No	Yes	Yes	Yes	Yearly	Yes	Yes	[69,120,121]
MARKAL/TIMES	Yes	Yes	-	Yes	Yes	Yes	Hourly	Yes	Yes	[122,123]
MERIT	Yes	Yes	-	Yes	Yes	Yes	Minutes	Yes	Yes	[124]
Mesap/PlaNet	Yes	Yes	-	Yes	Yes	Yes	Minutes	Yes	Yes	[61,69,125]
MESSAGE	No	No	No	Yes	Yes	Yes	5 Years	Yes	Yes	[61,69,105,126]

MiniCAM	No	National/ regional	No	Yes	Yes	Yes	15 years	Yes	Yes	[61]
MODEST	Yes	Yes	Yes	Yes	Yes	Yes	Hourly	Yes	Yes	[61,127,128]
NEMS	No	No	No	Yes	No	Yes	Yearly	Yes	Yes	[61]
Neplan	No	Yes	-	No	Yes	Yes	Minutes	Yes	Yes	[129]
NetSim	No	Yes	-	No	Yes	No	Hourly	No	Yes	[130,131]
ORCED	No	No	No	Yes	Yes	Yes	Hourly	Yes	No	[125,132]
PERSEUS	No	No	No	Yes	Yes	Yes	36-72/year	Yes	Yes	[61]
Polysun	No	No	No	Yes	Yes	Yes	15 minutes	Yes	Yes	[84,133]
PRIMES	No	No	No	Yes	Yes	Yes	Yearly	Yes	Yes	[130,134]
ProdRisk	No	Yes	-	Yes	Yes	Yes	Hourly	Yes	No	[61,135]
RAMSES	No	No	No	Yes	Yes	Yes	Hourly	Yes	Yes	[61,136]
RETScreen	No	Yes	-	Yes	Yes	Yes	Monthly	Yes	Yes	[61,69,137,138]
SimREN	Yes	Yes	-	Yes	Yes	Yes	Minutes	Yes	Yes	[61,120,139]
STREAM	No	National/ regional	No	Yes	Yes	Yes	Hourly	Yes	Yes	[140]
Termis	No	Yes	-	No	Yes	No	Minutes	No	Yes	[141,142]
TRNSYS	No	Yes	-	No	Yes	Yes	Seconds	Yes	Yes	[57,59,61,65,94,116]
UniSyD3.0	No	No	No	Yes	Yes	Yes	Bi-weekly	Yes	Yes	[61]
WASP	No	Yes	-	Yes	Yes	Yes	12/year	Yes	Yes	[61]
WILMAR Planning Tool	No	No	No	Yes	Yes	Yes	Hourly	Yes	Yes	[61]

3.2. Categorisation of Modelling Tool Capabilities

Tool capabilities tables were generated for the 13 modelling tools that document:

- Input data requirements and input support capabilities.
- Electrical and thermal supply technology modelling capabilities including district heating.
- Design optimisation, outputs capabilities, controls and DSM modelling capabilities.
- Storage modelling capabilities and underlying storage models.
- Practical considerations.

These tables are intended to be useful in the tool selection process (described later in Section 3.3) by providing information on the capability of tools to be assessed against requirements for a local energy system analysis task.

3.2.1. Input Data Requirements and Input Support Capabilities

Tools have different levels of input data requirements; some tools require the energy demand profiles, local climate, system characteristics, or generation profiles to be explicitly input as time series directly by the user. Other tools have embedded functions and libraries that provide support in generating detailed datasets from simple inputs, and/or support a mix of both directly entered and tool generated calculation inputs. This functionality could be essential, desirable, or not applicable depending on availability of data or expertise.

The key characteristics related to data input requirements for the various tools are captured in Table 3.2 and described below.

Demand profile generator

Tools were deemed to contain a demand profile generator ('Yes' in Table 3.2) if functionality exists to support synthesis of electrical, thermal or fuel demand profiles in hourly or sub-hourly timesteps from simple inputs such as monthly or annual bill data or descriptions of building numbers and types, demographics, etc. Others which take the approach that either explicit half-hourly or hourly metered data needs to be obtained, or potentially generated using a secondary modelling process (e.g. using building performance simulation tools), were categorised as 'No' for this category.

Resource assessor

A resource assessor gives access to weather and other resources (e.g. solar radiation, wind, water, biogas and biomass) in a suitable data input format (e.g. from national or international datasets) based on simple inputs (e.g. location). The resources covered were identified for each tool.

Supply profile generator

A supply profile generator provides electric, thermal or fuel-producing system outputs for use in the modelling. 'Modeller' describes a tool which generates the supply profile from the resource input (e.g. climate) and the device specifications. For example, in HOMER, local wind speeds (the resource input) and a specific wind turbine specification (a power curve and other details) are used to calculate the wind turbine supply profile. 'Database and input' describes a tool where the hourly or sub-hourly supply profiles are input directly requiring the user to do some outside tool calculations or source such datasets.

Table 3.2: Input data support capabilities

Tools	Demand profile generator	Resource assessor	Supply profile generator
Biomass decision support tool	Yes	No	Modeller
COMPOSE	No	No	Database and input
DER-CAM	No	S, T, Wi	Modeller
EnergyPLAN	No	No	Database and input
EnergyPRO	Yes	B, H, S, T, Wi	Modeller
eTransport	Yes	Yes*	Modeller
H2RES	No	B, H, S, Wi	Modeller
HOMER	Yes	B, H, S, T, Wi	Modeller
Hybrid2	Yes	S, Wi	Modeller
iHOGA	Yes	H, S, Wi	Modeller
MARKAL/TIMES	No	B, H, S, T, Wi	Modeller
Merit	Yes	S, T, Wi	Modeller
SimREN	Yes	Yes*	Modeller

Resource Assessor Key: Biomass (B); Hydro (H); Solar radiation (S); Temperature (T); Wind (Wi)

***indicates that a resource assessor exists but the specifics were unable to be determined.**

3.2.2. Electrical and Thermal Supply Technology Modelling Capabilities

Tools vary with respect to the range of supply technologies that can be directly modelled. This section captures information about available supply technologies within the different tools and more detailed description is given in Table 3.3.

A wide range of electrical supply systems can be modelled, most tools support modelling of connection to the external electricity grid. Two categories have been assigned for modelling of the grid connection: 'Grid simple' allows for limitless import and export, with static pricing; more complex 'Grid' models include features such as connection limits and charges, complex time-based import and export tariffs etc. In general, the tools lack the ability to model the evolving electricity markets and tariffs.

The modelling of district heating systems, if available in the tools, is only as an estimated heat loss. This is a continuous heat loss as a percentage of peak load in the Biomass decision support tool, or a percentage of real-time load as in EnergyPRO. The heat demand density, distribution temperature and other factors such as controls which have a large effect on ancillary energy use and losses in district systems are not directly considered and are required to be captured by the user in inputting thermal demand profiles.

District heating is becoming more popular in the UK [143,144], and is ubiquitous in Scandinavia and Eastern and Central Europe [145]. It has potential to increase energy system overall efficiency and provide flexibility for more effective use of waste heat and renewables using thermal storage which is much cheaper at district scale than for individual buildings, and much cheaper than an equivalent capacity of electrical storage [146]. It is therefore important to consider district heating while it will not necessarily be appropriate in all circumstances.

Heat pumps are commonly modelled using simple energetic models which do not account for temperature dependent COP. Additionally, available data for specific heat pumps is often limited such as a COP provided under one set of conditions. This leads to an overestimation of seasonal performance.

Table 3.3: Electrical and thermal supply technologies and district heating

Tools	**Electrical supply**	**Thermal supply**	**District heating**
Biomass decision support tool	No	FBo	Yes
COMPOSE	B, C, CHP, G, Gr, PV, Wi	CHP, EBo, FBo, HP, ST	No
DER-CAM	CHP, D, G, Gr, PV, Wi	CHP, EBo, FBo, Geo, HP, ST	No
EnergyPLAN	B, C, CHP, D, G, Geo, Gr, GrS, H, N, PP, PV, T, Wa, Wi	CHP, EBo, FBo, Geo, HP, I, ST, Was	Yes
EnergyPRO	B, C, CHP, D, G, Gr, H, PV, Wi	CHP, EBo, FBo, HP, ST	Yes
eTransport	CHP, Gr, PP	CHP, FBo, HP	Yes
H2RES	B, C, D, G, GrS, H, PV, Wa, Wi,	EBo, FBo	No
HOMER	B, C, CHP, D, G, Gr, H, PV, Wi	CHP, FBo	No
Hybrid2	D, PV, Wi	None	No
iHOGA	D, G, Gr, H, PV, Wi	None	No
MARKAL/TIMES	B, C, CHP, D, G, Geo, Gr, GrS, H, N, PP, PV, T, Wa, Wi	CHP, EBo, FBo, Geo, HP, I, ST, Was	No
Merit	C, CHP, G, GrS, PV, Wi,	CHP, HP, ST	No
SimREN	Geo, H, PP PV, Wi	CHP	No

Key:

Electrical: Biomass power plant (B); Coal power plant (C); Combined heat and power plant (CHP); Diesel plant (D); Gas plant (G); Geothermal plant (Geo); Grid (Gr); Grid simple (GrS); Hydro (H); Nuclear (N); Generic power plant (PP), Photovoltaic (PV); Tidal (T); Wave (Wa); Wind (Wi)

Thermal: Combined heat and power (CHP); Electric boiler (EBo); Fuel boiler (FBo); Geothermal (Geo); Heat pump (HP); Industrial surplus (I); Solar thermal (ST); Waste incineration (Was)

3.2.3. Design Optimisation and Output Capabilities

Two attributes important in supporting design tasks are: the capability of the tool to aid the identification of optimum design solutions, and the ability of the tool to directly provide outputs required to support decision making. Key capabilities of the 13 tools in these areas are captured in the first two columns of Table 3.4 and further discussed below.

Design optimisation

Optimisation tools find the minima, or maxima, for a defined objective function by systematically searching a defined modelling space according to a mathematical algorithm. Design optimisation involves a search for the optimal system w.r.t. combination and sizing of components. Most of the reviewed tools, where they support optimisation, use a full factorial deterministic approach based on user defined inputs to solve the optimisation problem and use a simple financial and/or carbon emissions objective. HOMER historically has executed a grid search based on user defined inputs specifying the system options to be included but recently provided an update allowing users to only input upper and lower limits to the grid search. iHOGA was the only identified tool with multi-objective function capability, it includes a choice of available objective functions and embedded genetic algorithms [147]. The Biomass decision support tool supports the optimisation of thermal storage size. A number of reviews have covered the mathematical optimisation methods that could potentially be employed [148,149]. Tools which do not directly support mathematical optimisation could be used within an external mathematical optimisation process by an iterative approach, but this can be logistically complex or require advanced software skills to automate.

Outputs

The outputs are key in assessing system performance. Different tools focus on different aspects of the system performance; most tools provide financial analysis such as cost/kWh of energy produced or information on energy market interactions, some are purely technical and focus on the energy production, system analysis, demand/supply match, or fuel consumption, others assess emission and renewable penetration, and others consider social factors such as job creation and the human development index. Specific tool outputs can be used in external calculations to generate a wider range of analysis outputs but only the in-tool capabilities are documented here.

Table 3.4: Design optimisation, outputs, controls and DSM controls capabilities

Tools	Design optimisation	Outputs	Controls	DSM control
Biomass Decision Support Tool	S	E, EP, FA, FC, RP, SA	FO, NO	FO
COMPOSE	E, F	E, EP, FA, FC, SA	MO, OO (F)	OO (F)
DER-CAM	E, F	A, E, EP, FA, FC, SA	DC, EV, LS, MO, OO (F, E)	DC, EV, LS, OO (F, E)
EnergyPLAN	No	E, EP, FA, FC, SA, RP	FO, LS, MO, OO (F)	FO, LS, OO (F)
EnergyPRO	No	E, EMI, EP, FA, FC, SA	EV, MO, NO, OO (F), UO	EV, OO (F)
eTransport	F	E, EMI, EP, FA, FC, SA	MO, OO (F)	OO (F)
H2RES	No	EP, FC, RP, SA	FO, MO	FO
HOMER	F	A, E, EP, FA, FC, RP, SA	AC, LS, MO, NO, OO (F), UO	LS, OO (F)
Hybrid2	No	EP, FA, SA	FO, LS, MO, NO	FO, LS
iHOGA	F, A, E, F, HDI, JC, NPC	A, E, EP, FA, FC, HDI, JC, RP, SA	FO, MO, NO, OO (F)	FO, OO (F)
MARKAL/TIMES	F	E, EMI, EP, FA, FC, RP, SA,	MO, NO, OO (F)	OO (F)
Merit	No	EP, FC, M, SA	FO, LS, MO	FO, LS
SimREN	No	EMI, EP, SA	-	-

Key for Table 3.4:

Design Optimisation: Autonomy (A); Emissions (E); Financial (F); Human development index (HDI); Job creation (JC); System (S)

Outputs: Autonomy (A); Emissions (E); Energy market interaction (EMI); Energy production (EP); Financial analysis (FA); Fuel consumption (FC); Human development index (HDI); Job creation (JC); Demands/supply match (M); Renewable penetration (RP); System analysis (SA)

Controls/DSM Controls: Advanced control (AC); Demand curtailment (DC); Electric vehicles (EV); Fixed order (FO); Load shifting (LS); Modulating output (MO); Non-modulating output (NO); Operational optimisation (OO) with objective function in brackets; User-defined order (UO)

3.2.4. Control Modelling Capabilities including DSM

The ability to correctly capture controls is important in assessing the performance of local energy systems. Particularly when assessing the impacts of storage and DSM. Modelling tools often have in-built control logic intended to mimic real or idealised controls, it is important to comprehend and assess the control regime underpinning each of the models. Control capabilities of the 13 tools are captured previously in Table 3.4 and are further discussed below.

3.2.4.1. General Control Capabilities

Controls regulate how supply, storage and DSM technologies meet loads by determining the control logic and constraints applied. A simple local energy system control strategy can include: (i) an order of dispatch for the different resources, and (ii) a set of constraints.

Operational Optimisation

Operational Optimisation (OO) control is where the tool optimises, at each timestep, the order of dispatch of supply, storage, and DSM technologies to satisfy an objective function which may relate to cost, emissions, etc. There are differences in detailed logical implementation between tools; a general description is given here.

Most tools use the OO control chronologically i.e. calculations are performed at each individual timestep to establish an optimum based on prevailing conditions at that timestep only, before the next timestep is then considered. Storage is generally charged and discharged when it is deemed favourable to do so according to the specific logical implementation and objective function. Typically charging will occur when there is excess energy from renewable or non-modulating supply where storage is deemed to have benefit over export or curtailment, or where grid parameters, e.g. tariff, make charging from grid advantageous. Discharge from available storage is generally treated as a dispatchable supply option. The value attached to storage charge and discharge takes account of characteristics of the storage system, e.g. efficiencies and costs, plus parameters such as tariffs and carbon contents. For example, in HOMER the discharge energy cost includes average charge energy cost, efficiencies, and battery wear, lifetime and replacement costs.

OO control is applied non-chronologically in some tools e.g. in EnergyPRO the whole calculation period is scanned for energy supply costs and an optimised supply schedule determined, with excess low-cost generation charging storage and discharge occurring to meet demand in subsequent favourable high cost periods. These OO control functionalities may replicate real control systems for situations where local renewable consumption is prioritised or where a set tariff structure is established for energy import and export; the non-chronological OO implementation may in some circumstances provide an optimistic view of system performance as perfect foresight is implied.

Fixed Order Control

Fixed Order Control (FOC) is where there is an available set of functions with pre-defined order of dispatch of supply, and fixed conditions for the use of storage and DSM technologies. Dispatchable supply is dispatched in a fixed order in periods where non-dispatchable, typically renewable, supply is below demand. EnergyPLAN, H2RES, and Merit charge electrical storage in periods of excess renewable production and prioritise discharge from electrical storage over generators and power plants. In Merit thermal storage discharge is prioritised over other thermal supply options. In EnergyPLAN thermal storage charging is prioritised to absorb excess electricity or heat production and discharged to avoid non-renewable generation. In iHOGA batteries can charge/discharge at fixed, user input tariff values. In the Biomass decision support tool excess heat from the biomass boiler is stored in a thermal storage and discharged when demand exceeds supply. EnergyPLAN includes several selectable functions for dealing with excess electricity production. Hybrid2 contains embedded functionality for 13 pre-defined fixed order controls relating to the practical performance of electric systems [150].

User-defined Order

User-defined Order (UO) control is where the order of dispatch, for at least some part of the supply, is defined by the user. For example, UO in EnergyPRO requires all supply options to be given an order of preference, which can also include separate priorities for production to satisfy different (peak, high, low) loads; storage priority setting is not an option and in this tool storage operation always follows the OO control strategy.

Modulating Output

Modulating Output (MO) control applied to a dispatchable supply allows modulation of output to match load above some minimum supply output level. In all tools the grid connection, if enabled, can modulate output to follow electrical load with a minimum supply level of zero. HOMER can only designate grid or generator supplies to this control while in EnergyPRO, DER-CAM, and eTransport any dispatchable supply can be assigned.

Non-modulating Output

Non-modulating Output (NO) control sets the constraint that a designated supply must run at a fixed output whenever it is running. In the Biomass decision support tool, the designated supply is the biomass boiler. In EnergyPRO the user selects supplies. In iHOGA and HOMER the designated supplies are the generators. In these two tools a set state of charge can be specified, and the designated supply will continue operating, regardless of availability of renewable generation, until the set point is reached. This mimics a common feature in real systems used to maximise battery life but which reduces the potential for renewable inputs to the store.

Advanced Control

HOMER offers the capability to use Advanced Control (AC) strategies where users can define more complex control operating regimes than those previously outlined by interfacing with externally written code in MATLAB [151].

3.2.4.2. DSM-related Control Capabilities

The general control modelling capabilities described in the previous section, such as OO and FOC, can be used where there is storage in the system to capture DSM functionality associated with storage charging and discharging. Several tools have further DSM specific functionality to represent 'Load Shifting', 'Demand Curtailment' and 'Electrical Vehicles' in the system. All DSM related control capabilities are captured in the 'DSM control' column of Table 3.4, further DSM specific functionalities are described below.

Load Shifting

Load Shifting (LS) is where a flexible load is defined which can be met or deferred to a later timestep within a limited deferrable time period, while incurring no loss. The flexible load can be input as a specific energy quantity over the deferrable period in EnergyPLAN which uses 1 day, 1 week, or 4 weeks deferrable periods, and in Hybrid2 which allows users to input the deferrable period. In DER-CAM the flexible load is sized as a percentage of the main load over a 1-day deferrable period. The flexible loads in these tools are actuated when lowest cost or surplus energy is available within the flexibility period. HOMER and Hybrid2 can accommodate more detailed model parameters such as: average deferrable load (kWh/day), capacity (kWh), peak load (kW), and minimum load ratio, flexible load in these tools is treated as secondary to the main load but prioritised over charging storage.

Demand Curtailment

Demand Curtailment (DC) is where demand can be curtailed under certain conditions, and, unlike load shifting, is not shifted but reduced. DER-CAM is the only reviewed tool capable of modelling DC and curtails demand when tariff prices exceed a user defined curtailment cost (£/kWh) within an annual maximum number of curtailment hours. There is also additional functionality to allow for up to 5 daily hourly profiles capturing the proportions of the main load which can be curtailed at each timestep.

Electric vehicles

Electric vehicles are going to play a vital role in the future of energy systems [152,153], and there has been research into the system flexibility they can provide [154,155]. Only two of the identified tools include models for an electric vehicle to grid interaction. EnergyPRO has a model based on the energetic capacity of the batteries in the cars, and limits on the charging and discharging along with associated efficiencies. The demand for the vehicles is input as a time series and there are options accounting for availability. Charging/discharging can be set to on/off with charging allowed at zero demand, it can be set to proportional to the driving demand time series, or it can be set its own time series. EnergyPLAN contains a similar model. The inputs are for maximum discharge/charge, capacity of batteries in vehicles, efficiencies, and a time series for demand. Simpler assumptions are made on the availability, with the fraction of cars driving at peak demand and, of cars parked used to calculate the connection of cars to grid.

3.2.5. Storage Modelling Capabilities and Underlying Models

This section looks at relevant capabilities of the 13 screened tools and underlying models with respect to storage functionality. Such functionality enables DSM and, in the reviewed tools, is used with the operational optimisation and fixed order controls (see Section 3.2.4.1).

Storage capabilities are captured in two look-up tables for use in tool selection. Table 3.5 describes the range of storage modelling capabilities available in each tool, with more detailed descriptions of these capabilities in the sub-sections below. Table 3.6 gives a summary of the more advanced models i.e. more detailed models than the simple storage model (SSM) for each storage technology; SSM can be used to model all storage types and is not included in Table 3.6 for this reason. A brief summary of each capability and underlying model is given below, further details including model equations can be found in the relevant references.

Table 3.5: Storage modelling capabilities and underlying models

Tools	Electrical storage	Thermal storage	Fuel synthesis	Fuel storage
Biomass decision support tool	No	MB	No	B
COMPOSE	KiBaM	CS, SSM	No	No
DER-CAM	FB, SSM	MB	No	No
EnergyPLAN	CAES, PH, SSM	SSM, STS	BF, BG, EF, GtL, H	G, O, M
EnergyPRO	PH, SSM	CS, MB	BF, BG, EF, GtL, H	G, O, M
eTransport	Yes	Yes	Yes	Yes
H2RES	Yes	Yes	No	Yes
HOMER	FB, KiBAM, MkiBaM, PH, SSM	No	H	H
Hybrid2	EKiBaM	No	No	No
iHOGA	KiBAM, MKiBaM, SSM	No	H	H
MARKAL/TIMES	Yes	Yes	Yes	Yes
Merit	EKiBaM	SSM	No	No
SimREN	Yes	No	No	No

Key:

Electrical: Compressed air energy storage model (CAES); Extended kinetic battery model (EKiBaM); Flow battery model (FB); Kinetic battery model (KiBaM); Modified kinetic battery model (MKiBaM); Pumped hydro model (PH); Simple storage model (SSM)

Thermal: Cold storage model (CS); Moving boundary model (MB); Seasonal thermal storage model (STS); Simple storage model (SSM)

Fuel synthesis: Biofuel (BF); Biogas (BG); Electrofuel (EF); Gas to liquid (GtL); Hydrogen (H)

Fuel storage: Biomass (B); Gas (G); Hydrogen (H); Methanol (M); Oil (O)

*"Yes" indicates that the tool has a certain capability but specific models used were not able to be confirmed; these tools were assumed to have SSM as minimum electrical and thermal storage models

Table 3.6: Electrical and thermal storage technologies and advanced models (beyond SSM)

Electrical storage (ES) type	**Advanced ES models used**	**Thermal storage (TS) type**	**Advanced TS models used**
Lead-acid battery	EKiBaM, KiBaM, MKiBaM	Hot water tank	MB
Li-ion battery	EKiBaM, KiBaM, MKiBaM	Cold storage	CS
Flow battery	FB	Seasonal thermal storage	STS
Pumped hydro	PH		
CAES	CAES		

Key:

Electrical: Compressed air energy storage model (CAES); Extended kinetic battery model (EKiBaM); Flow battery model (FB); Kinetic battery model (KiBaM); Modified kinetic battery model (MKiBaM); Pumped hydro model (PH); Simple storage model (SSM)

Thermal: Cold storage model (CS); Moving boundary model (MB); Seasonal thermal storage model (STS); Simple storage model (SSM)

Note: SSM can be used to model all storage types and is not included

3.2.5.1. Electrical Storage Modelling Capabilities and Underlying Models

Electrical storage is a general term used here to include electrochemical (li-ion, flow, lead-acid batteries), electromagnetic (supercapacitors), and mechanical (CAES, hydro, flywheels) forms. Electrical storage can be represented using a number of different mathematical models, the different models used in the tools are categorised and described below. The level of detail required at the planning stage depends on the specifics of the system being modelled and the outputs to be derived from the modelling.

Simple Storage Model

A tool possessing a Simple Storage Model (SSM), which can interact with supply and load, can model any storage technology. EnergyPLAN and EnergyPRO use the SSM to define all types of storage, including all electrical storage types. iHOGA, DER-CAM and HOMER support the use of the SSM, e.g. for high-performance batteries [136]. HOMER also recommends its use for simple pumped hydro storage systems. The SSM consists of a simple energy in/out balance via an energy store. Energy can enter the store below a threshold maximum charging rate up to a maximum store capacity. There can be self-discharge from the store e.g. a percentage or other function at each timestep. Energy can leave the store below a threshold maximum discharging rate. For charging and discharging there are associated efficiencies, which combine with self-discharge to give a round-trip efficiency. Charge and discharge efficiencies are both generally fixed values. The SSM has fixed maximum charge and discharge rates independent of the state of the system, this approximation may be sufficient for some analyses, but may not be realistic in other cases, more detailed models are available. Storage lifecycle analysis is included in some tools with the SSM, e.g. in HOMER lifetime is modelled as both an energy throughput and time, however performance degradation effects are only included in the MKiBaM model described later.

Kinetic Battery Model

The Kinetic Battery Model (KiBaM) was first developed for modelling lead-acid batteries in hybrid energy systems [156]. It is described as a two tank model [157], where one tank holds the available energy to directly support charge and discharge and the other holds the bound energy which transfers energy to and from the available tank according to a defined exchange function representing the chemical process. The model supports charge/discharge rates as functions of stored energy in the two tanks. The underpinning electronic mechanisms are still simplified with voltage modelled only as a linear function of energetic state etc. iHOGA and HOMER both possess this model and have libraries of electrochemical batteries with parameters established from test data.

Extended kinetic battery model

Work was done to improve the KiBaM in terms of modelling voltage behaviour [158]. These models are denoted here as Extended Kinetic Battery Models (EKiBaM). Hybrid2 includes such an improved model [159], with voltage, charging and discharging efficiencies and current as non-linear functions of the state of charge. Merit also contains a different but similar model with improved voltage modelling [124].

Modified Kinetic Battery Model

A further Modified Kinetic Battery Model (MKiBaM) is used by HOMER and iHOGA to give deeper insights. This includes a thermal model component whereby the resistive properties of the battery produce heat which affects temperature, capacity and lifetime. Secondly, it involves cycle-by-cycle degradation of the battery as a function of depth of discharge; this is accounted for using the Rainflow counting algorithm [160], which iHOGA also utilises to account for corrosion effects over time. iHOGA offers customised models for lead-acid batteries [161,162] and Li-ion batteries [163–165].

Flow battery model

Flow batteries can also be modelled explicitly with models which account for the independence between capacity and charge/discharge and other flow cell characteristics. Flow battery specific models based on manufacturers data are included in DER-CAM [166] and HOMER [157].

Pumped hydro model

Pumped hydro is often modelled using the SSM by factoring in the capacity and efficiency of the pump and generator as well as the capacity of the reservoir. EnergyPLAN and HOMER include pumped hydro as a technology using the SSM. Only EnergyPRO includes an explicit pumped hydro model and includes inputs such as reservoir volume, friction factors and head difference.

Compressed air energy storage model

A simple compressed air energy specific storage model (CAES) is included in EnergyPLAN, with a focus on the economic trading possible [167].

3.2.5.2. Thermal Storage Modelling Capabilities and Underlying Models

Thermal storage allows for sensible or latent heat to be kept for meeting a demand later. It can include hot water tanks, brick radiator stores, phase change materials (PCM), and cold storages. It can also be designed for buildings or community/district scales. A summary of different thermal storage models including underlying equations is given by [63]. The tools that are the focus of this paper use only the least complex models, some of the limitations associated with this are discussed later. The categorisation of thermal storage models found in the tools is captured in Table 3.5 and Table 3.6, and described below.

Simple storage model

The SSM model does not consider temperatures but only accounts for energy and was described earlier. EnergyPLAN uses the SSM to model all thermal storage technologies.

Moving boundary model

The most common model for thermal storage in the examined tools is the moving boundary model (MB), where the additional inputs over the SSM are top and bottom tank temperatures. It assumes that there is no mixing between the upper hot zone and the lower cold zone and the thermocline boundary layer is infinitesimally small. This is again an energy balance model with inflows and outflows of energy moving the boundary layer up and down the store and stored energy calculated based on the thermocline position. The model does not explicitly capture temperature variation due to losses and destratification. This model is incorporated in the Biomass decision support tool, DER-CAM, EnergyPRO, and Merit. The model can be adjusted in EnergyPRO using a utilisation factor which reduces the useful energy which can be used for supply. DER-CAM allows for different high temperature and low temperature stores within the system to allow for different heat generation devices [168]. EnergyPRO also uses the MB model for cold storage (CS) and was the only tool identified to have electrical, heat, and cold storage modelling capability.

Seasonal thermal storage model

A seasonal thermal storage model is included in EnergyPLAN. It is simplified and only two inputs are required: capacity, and 'days of optimising storage' which allows for the model to identify inter-seasonal variations in demand. [65] set out the state of art in modelling seasonal thermal storage in building-scale simulation tools, but in general this functionality is not supported in the tools analysed here apart from EnergyPLAN.

Other thermal storage models

Temperature variations, and therefore entropy considerations, are vital in real thermal storage analysis [169]. There may appear to be enough energy in a tank to meet the energy demand, but if the temperature does not meet the supply requirement it is not useful energy. The MB model does not account for changes in the temperature zones; there are no entropic considerations. A summary of modelling approaches for sensible thermal storage tanks [63] includes the MB model and highlights the models which would be used to include entropy, with increasing detail at the expense of computational and data input complexities.

3.2.5.3. Modelling of Fuel Synthesis and Storage

Fuel synthesis is the production of fuels within a system creating a new energy vector which can be used across a range of energy sectors, and acts as storage to be used later [170]. EnergyPLAN, iHOGA and HOMER can model the synthesis of hydrogen. This is produced using electricity with an electrolyser to form hydrogen, stored in a hydrogen tank, and then converted to meet transport, heat, or electricity demands. All three technical components can be modelled within the three tools. EnergyPRO contains a simple model for the synthesis of any fuel. EnergyPLAN allows for synthesis of different types of fuel: biofuel, biogas, hydrogen from electrolysis, electrofuel, and gasification to liquid transport fuel. These fuels are used to form interactions between energy sectors and ensure high-value energy is used for high-value processes.

These fuels must then be kept in storage. The Biomass decision support tool can size biomass fuel storage, while iHOGA and HOMER can model hydrogen storage tanks. EnergyPLAN can model gas, oil and methanol storages, and EnergyPRO can model any fuel storage as a generic model.

3.2.6. Practical Considerations

Table 3.7 sets out the practical considerations associated with selecting a tool: cost, access, support, whether it is academic or commercial, user-friendliness, and whether there is existing available expertise.

Cost may be a vital factor in choosing an energy system tool and depends on the resources available to a user. A student is likely to choose a free tool which there is abundance of: Biomass decision support tool, COMPOSE, DER-CAM, EnergyPLAN, iHOGA, Hybrid2, Merit and MODEST. Often tools are available at discounted prices for students. A government agency or an engineering consultancy may have the resources available to afford the cost for a tool such as 3,000+ EUR for EnergyPRO, 500-1,500 USD for HOMER, or 1,275-3,130 EUR to manipulate the code for MARKAL/TIMES.

Accessibility is defined in terms of availability, purchase requirement, and if the tool was downloadable or browser based. Available support as indicated by tool websites and verified by the authors is listed. These include user manual, available contact details, videos, training, and an online forum. The tools are classed as academic or commercial based on the development and ownership of the tools through either a university/research group, or a private company, respectively.

User friendliness was judged on the provision of an intuitive model-building pathway which was subjectively graded by the authors at a low, medium, or high level. This required first-hand knowledge of the tools so where the tool was not available to the authors, the grade by [94] was referenced.

Most modelling tools require a significant investment in time to develop expertise in order to be used correctly and proficiently so there will be a strong practical driver to use a modelling tool which has established available expertise if this exists. If there is no established expertise available and the aim is to develop such an expertise, then this driver will be less strong or zero.

Table 3.7: Practical considerations

Tools	Cost	Access	Support	Academic / Commercial	User friendly
Biomass decision support tool	Free	Download	User manual, videos, online course	Commercial	High
COMPOSE	Free	Download	Videos, forum	Academic	Med
DER-CAM	Free	Browser	User manual, videos, forum	Academic	Med
EnergyPLAN	Free	Download	User manual, contact, videos, training, online course	Academic	High
EnergyPRO	3,000+ EUR for all modules	Purchase	User manual, contact, training	Commercial	High
eTransport	Not available	Not available	Not available	Academic	High[1]
H2RES	Not available	Not available	NA	Academic	Not available
HOMER	Free 2-week trial, 500 - 1500 USD	Purchase	User manual, contact, videos, forum	Commercial/ Academic	High
Hybrid2	Free	Download	User manual, contact	Academic	Not available

iHOGA	Educational Free, 500 EU for 1 year	Purchase	User manual, forum, contact	Academic	Med
MARKAL/TIMES	Costs 1275-3130 EUR to manipulate source code	Download	User manual, paid support, forum	Academic	Low[1]
Merit	Free	Download	Training	Academic	Med
SimREN	Not available	Not available	Not available	Commercial	Not available

[1]From [94], [2] User to self-assess

3.2.7. Discussion

Through the categorisation and documentation of tool capabilities it is apparent that there are many differences between tools. Some tools, such as EnergyPLAN, combine all energy sectors based on the view that holistic consideration across sectors leads to optimal solutions. Other tools are primarily single domain focussed, e.g. iHOGA has strong capabilities for electrical analysis with a wide range of storage models but no thermal capability.

Design optimisation capabilities in the tools generally optimise for financial or technical considerations. Only iHOGA optimises for human considerations (human development index, job creation) and two tools optimise for environmental considerations. Much work has been done on external optimisation used in a two-step process. This may influence the lack of embedded optimisation options in the tools, another factor is the preference for the simplicity and transparency available in full factorial parametric analysis.

The review identified a lack of detailed district heating modelling capability in any of the local energy system tools, with only a heat loss parameter as input, factors such as the heat demand density, distribution temperatures, network layouts and controls which have a large effect on ancillary energy use and losses in district systems are not directly addressed.

Analysis of controls modelling capabilities in the tools showed a wide range including operational optimisation, fixed order, and user-defined orders, for dispatch of supply and storage. Operational optimisation control is usually used with a cost based objective function, other possible objective functions such as maximising local use of renewable generation, minimising grid imports or minimising emissions are not generally directly supported, with DER-CAM a notable exception. More advanced predictive controls based on weather forecast and demand prediction are not supported, although the non-chronological operational optimisation in EnergyPRO and the deferrable load functionality in HOMER etc. can represent this type of control but with significant simplifications. The option to run tools in combination with external control algorithms in separate software packages is one way round this limitation.

The tools, with the exception of DER-CAM, focus on load shifting and use of storage where there is grid connection to optimise value based on cost (arbitrage) while it is widely accepted that other grid services (such as frequency stabilisation, peak reduction, avoidance of capital investments etc.) may also be very important.

The review of storage functionality and modelling revealed frequent use of the simple storage model. More complex models for electrochemical storage exist particularly for use with lead-acid, li-ion and flow batteries.

Thermal storage and heat pumps are generally limited to simple energetic models which do not directly take account of temperature variations other than in assessing capacity. These may be suitable for initial planning design stages but have limitations. For thermal storage, to take account of temperatures, heat transfer rates, stratification, and phase change in thermal stores necessitates more complex models. These will be required in the future to support realistic modelling of the hybrid systems and advanced controls for which these parameters have critical importance.

There were few tools found to be directly capable of analysing fuel synthesis technologies, such technology, however, is currently unlikely to be at a local energy system scale in the short term. For this reason, tools developed for regional scale have most capability.

The wide range of tools available and their differing capabilities makes a capability categorisation of value to the end user of such tools, and of use to inform those looking to expend effort or resources in modelling of such systems. The abundance of available tools and rapidly developing field dictated that it was impossible to include them all. The author believes the selection is however reasonably representative of the state of the art in tools for planning-level design at local energy system scale.

A gap in this review is the exclusion of open source modelling tools written in programming languages such as Python, GAMS, Java, Fortran, C++, Julia, etc. An overview of these tools is available on the opendmod website [171].

An element not considered here is the validation of the modelling tools. So far in available literature case studies are largely based on design and do not include monitored data on completed schemes that include DSM and storage. Experience in the buildings industry has found that performance gaps are common [172] and identified that industry process needs to evolve to address these gaps [173]. It is critical that similar issues are addressed to avoid performance gaps in future local energy systems.

3.3. Tool Selection Process

A stepwise tool selection process was developed in order to compare different tools in the context of a specific modelling problem. The methodology is based on a software selection method from Sandia National Laboratories [174] in order to aid in the identification of an appropriate tool for a particular analysis. This analysis was for the planning-level design of a local energy system incorporating storage and DSM.

3.3.1. Determination of Requirements

The first process step is to establish which of the modelling tool capabilities (documented in the previous tables) are 'essential', 'desirable' or 'not applicable' and to assign values of 2, 1, and 0 respectively to each of these tool capabilities. This process requires that each of the capabilities described in the column headings and associated keys of the tables are individually considered against the requirements for the intended analysis.

For example, if we look at Table 3.2 then the three tool capabilities captured are 'demand profile generator', 'resource assessor', and 'supply profile generator'. If the user requires the tool to provide demand profiles, weather data and renewable generation supply profiles from simple input data, such as location and demographics, then these capabilities would be considered essential and each of these capabilities would be assigned a value of 2. Alternatively, if the user has available data for demand, weather and renewable generation and supply (e.g. from monitored data) then these capabilities are not applicable so would be assigned a value of 0 and can be eliminated from further consideration. If the user can source information and generate the demand, weather and renewable generation input data, but with significant effort, then this capability could be ranked as desirable and allocated a value of 1.

Similarly, if we consider Table 3.3 it may be that it is essential that there is capability to model electrical generation with both PV and wind so each of these capabilities would be allocated a 2, while if there is no potential for hydro then this capability would be allocated a 0.

When this process is complete the essential and desirable capability requirements have been established. The first 4 rows of Table 3.8 illustrate this process for a simple case study example which will be described in more detail in Section 3.3.3.

3.3.2. Scoring of Tools Against Requirements

Once the requirements have been established then each of the tools can be scored against them. The first consideration is whether all the essential capabilities are available, if a given modelling tool has all the essential capabilities it can be considered further, those which do not pass this check can be discounted. For the tools which pass, their scores for the essential plus desirable capabilities are summed into an overall score and ranked with the most suitable tools having the highest scores. Again, Table 3.8 illustrates this process for the simple case study which is described in more detail in the following section.

3.3.3. Example Application of the Modelling Tool Selection Process

Findhorn is an ecovillage in the north-east of Scotland with an ambition to transition to a local, low-carbon energy system. It consists of around 75 buildings, with a private wire electrical network, wind and solar generation, a grid connection, micro-district heating from biomass, and individual household heat pumps and solar thermal systems. The community could be said to be net zero carbon but has large electricity surpluses and shortfalls due to stochastic demands and renewable production. They have an interest in the use of thermal and electrical storage with advanced controls as a potential route to achieving their aims. They had also previously been monitored as a research and demonstration site for advanced DSM [81].

The community overall objective is to increase their energy autonomy and use of local renewable energy resources; they have some concerns over the sustainability of biomass. To help achieve their objective they enlisted support from a University and after an initial scoping process identified two future illustrative scenarios to be investigated: 1) increased electrical generation plus battery storage, and 2) increased electrical generation plus heat pumps and large hot water tanks replacing the micro-district biomass heat source. The modelling tool selection process was then applied in order to identify suitable software to use for the investigation.

The first step was to review the tool capability requirements: demand profile generator, resource assessor, and supply profile modeller capabilities (Table 3.2) were all deemed to have zero value (i.e. not applicable) since multi-year sub-hourly data was readily available from monitoring.

Electrical supply technologies wind, grid, and solar PV were deemed to be essential (Table 3.3). Thermal supply modelling of fuel boiler (biomass fuel in this case) and heat pumps were deemed essential. Capability to model solar thermal and district heating in detail were scored desirable. These were not considered essential at this stage as the primary focus was on the electrical supply system and the available monitoring data which includes heat delivery from existing heat production units, solar inputs, and distribution losses.

Design optimisation capability (Table 3.4) was deemed desirable but not essential as the view was taken that the relatively simple range of options to be investigated could be covered through a full factorial deterministic investigation and modelling outputs analysed outside of the tool to establish potential optima. The output of hourly data allowing either: autonomy, emissions, or renewable penetration to be established was deemed essential. This level of system performance parameter output would then allow the other required outputs to be calculated outside of the tool.

For control capabilities (Table 3.4), either FOC or OO control was deemed essential to support the required ordering of dispatch of supply and storage, in addition to the MO control inherent in all the tools for representing the grid. DSM-specific control functionality was not required in this example.

Storage modelling capability was deemed essential for both electrical and thermal storage (Table 3.5 and Table 3.6). It was deemed that the simple storage model was sufficient but that it would be desirable for more complex models to be available. Fuel synthesis and fuel storage are not required in this simple illustrative study.

These technical requirements are captured in the top 4 rows of Table 3.8 and then each of the tools are assessed against these requirements. Where a tool has an essential or desirable capability then it scores 2 or 1 respectively against that capability, otherwise it scores 0. Once all the potentially capable tools have been assessed they are ranked: (i) the tools which do not have all the essential capabilities are deemed 'FAIL' to meet the essential requirements, and only those that 'PASS' this test considered further, (ii) the remaining tools are then ranked based on their cumulative score. This process is illustrated in Table 3.8, with the result in this case that 6 tools are capable with similar scores of either 20 or 21.

Table 3.8: Output from application of tool selection process

	Essential Capabilities	Overall Score	Design optimisation	Outputs	Controls and DSM	Supply technologies							Storage			
	Pass	**Score**	**Yes**	**A, E, or RES**	**FO or OO**	**WT**	**PV**	**Fuel boiler**	**Grid**	**District Heating**	**Solar Thermal**	**Heat Pump**	**Battery SSM**	**Battery >SSM**	**TS SSM**	**Hot water tank >SSM**
D=Desirable E=Essential			**D**	**E**	**E**	**E**	**E**	**E**	**E**	**D**	**D**	**E**	**E**	**D**	**E**	**D**
Value			**1**	**2**	**2**	**2**	**2**	**2**	**2**	**1**	**1**	**2**	**2**	**1**	**2**	**1**
COMPOSE	Pass	21	1	2	2	2	2	2	2	0	1	2	2	1	2	0
DER-CAM	Pass	21	1	2	2	2	2	2	2	0	1	2	2	0	2	1
EnergyPRO	Pass	21	0	2	2	2	2	2	2	1	1	2	2	0	2	1
EnergyPLAN	Pass	20	0	2	2	2	2	2	2	1	1	2	2	0	2	0
MERIT	Pass	20	0	2	2	2	2	2	2	0	1	2	2	1	2	0
MARKAL/ TIMES	Pass	20	1	2	2	2	2	2	2	0	1	2	2	0	2	0
eTransport	F	16	1	2	2	0	0	2	2	1	0	2	2	0	2	0
H2RES	F	16	0	2	2	2	2	2	2	0	0	0	2	0	2	0
HOMER	F	16	1	2	2	2	2	2	2	0	0	0	2	1	0	0
iHOGA	F	14	1	2	2	2	2	0	2	0	0	0	2	1	0	0
Biomass support tool	F	11	1	2	2	0	0	2	0	1	0	0	0	0	2	1
Hybrid2	F	9	0	0	2	2	2	0	0	0	0	0	2	1	0	0
SimREN	F	6	0	0	0	2	2	0	0	0	0	0	2	0	0	0

3.3.4. Discussion

The categorisation and selection process presented is not limited to the tools identified here but is intended to provide a framework which can be used in future to refresh the capabilities categorisation or be applied to further tools. The review of required capabilities as the first part of the selection process can also form a guide for modellers to ensure relevant factors are considered. More detailed scoring systems in the selection process would be possible, the pair-wise comparison suggested by [175] remains to be investigated.

The tool selection process does not take into account the potential for multiple tools to be used together to analyse the system under consideration, such work is recommended for future studies. The more detailed simulation modelling tools currently used in buildings and systems domains have potential to be developed for community scale energy systems in future. These would allow more physical detail to be captured in planning level design studies. Their capabilities could also be assessed using the same tool selection process.

One observation from carrying out the review has been that the source code is generally hidden in the tools. There is generally an inflexible software environment, limiting the ability to adapt or evolve the tools or incorporate functionality from elsewhere independent of the tool supplier.

The developed selection process will be used in the sizing study, Chapter 6 where the modelling methodology is applied, to consider the position the novel tool to be developed in this thesis sits within the state of the art of the existing identified modelling tools.

3.4. Gaps to be Addressed

The identified tools were reviewed against their ability to model local energy systems incorporating heat pumps, thermal storage, local renewable electricity production, time-of-use electricity tariffs, and predictive controls. The gaps identified, and to be addressed in this thesis are:

- Ability to adapt source code and import or exploit functionality from elsewhere.
- Temperature dependence for the heat pump models.
- Detailed model with temperature characteristics for the thermal storage models.
- Ability to model the evolving electricity markets and tariffs.
- Ability to explore predictive controls.

This chapter has achieved the first stated research aim from Chapter 2: Identify gaps in existing planning-level modelling tools.

These gaps will be addressed by developing a modelling framework and appropriate models addressing the required functionality. This work expands on the growing energy system modelling capabilities previously built in the open source programming language Python. The proposed modelling framework will be elaborated in the next chapter, and the subsequent chapter will detail the underlying models and their validation.

4. Introducing PyLESA: Modelling Methodology, Capabilities, Framework, and Applications

This chapter describes: (i) a modelling methodology capable of aiding planning-level design of local energy systems and, (ii) the capabilities and framework of the novel modelling tool PyLESA which was developed in this thesis. The methodology sets out the steps for applying PyLESA which can model local energy systems incorporating heat pumps, thermal storage, local renewable electricity production, future electricity tariffs, and predictive controls. This chapter also explores potential types of design studies which can be aided by application of the modelling methodology. The underlying models used in PyLESA address the gaps identified in the review of existing modelling tools.

4.1. Brief Introduction to PyLESA

PyLESA stands for Python for Local Energy Systems Analysis and is pronounced "pai-lee-suh". It is an open source tool capable of modelling local energy systems containing both electrical and thermal sector technologies modelled in hourly timesteps. It was developed by the author as part of the work of this thesis with the aim of aiding the planning-level design of local energy systems. The focus is on modelling systems with heat pumps and thermal storage alongside time-of-use electricity tariffs and model predictive control. Additionally, it is anticipated that the tool provides a framework for future development including electrical battery studies and participation in grid balancing mechanisms.

The source code of PyLESA can be accessed from the following GitHub repository: https://github.com/andrewlyden/PyLESA.

4.2. Modelling Methodology

The modelling methodology developed in this work sets out the steps for applying the new modelling tool PyLESA to carry out a specified design/scoping/parametric/scenario analysis and is outlined below:

1. Define and gather data on the local energy system to be modelled including resources, demands, supply, storage, grid connection, and control strategy.
2. Optionally run the demand and resource assessment methods to generate hourly or sub-hourly profiles depending on available data from step 1.
3. Input gathered the relevant input data from steps 1 and 2 on the local energy system into the input Excel workbook.
4. Input the increments and ranges to be modelled within the required parametric design into the input Excel workbook.
5. Run PyLESA for the specified analysis.
   - 5.1. Using a terminal (e.g. PowerShell) navigate to the relevant directory, i.e. "…/PyLESA/PyLESA".
   - 5.2. Enter "python run.py".
   - 5.3. When prompted enter the input Excel workbook filename (excluding the file extension ".xlsx").
6. Analyse the outputs saved in the "outputs" folder, particularly the KPIs, to inform the specified analysis.

These steps will be explored further in Chapter 6 where the methodology will be applied to a sizing study for a residential district heating scheme.

Steps 1, 2, and 3 relate to the required data input to PyLESA and this highlights the importance of the quality of the data to perform useful modelling. Step 4 defines the specific analysis to be carried out, step 5 executes the analysis, and step 6 post processes the analysis outputs.

Since the modelling methodology centres around the use of PyLESA, the rest of this chapter describes the capabilities and framework of this tool. Firstly, a discussion of the motivation behind choosing Python as the programming language is given. Then, a summary of the capabilities of the tool is provided with the contributions which have been made towards identified gaps in existing modelling tools, highlighted in Chapter 3.

Finally, the framework of the modelling tool and potential design studies are described. For further modelling details see Chapter 5 which provides a detailed description of the models and assessments used in the modelling tool.

4.3. Motivation for Choosing Python

Open source was identified as an important requirement when choosing a programming language. This is because open source software can be easily accessed, studied, and, built upon. The Open Energy Modelling (openmod) Initiative have highlighted that openness "… allows the community to advance the research frontier and gain the highest benefit from energy modelling for society" [176]. For the tool developed as part of this thesis to make a larger impact it should be open source as this allows the energy modelling community the ability to learn from and improve the developed modelling methodology.

A gap in the review of modelling tools from Chapter 3 is the exclusion of open source modelling tools written in programming languages such as Python, GAMS, Java, Fortran, C++, Julia, etc. An overview of these tools is available on the opendmod website [171]. A significant proportion of these tools use Python as either the sole language, or partly contributing to the modelling or processing parts of the software.

Python is an interpreted, high-level, general-purpose programming language with a design philosophy which emphasises the readability of the code. Its object-oriented approach allows for programmers to write clear, logical code which can be understood by others in the energy modelling community. Potential advantages of using Python include transparency, adaptability and re-usability of utilities developed across a range of applications including mathematics, optimisation, machine learning as well as energy systems [177–179]. This is, in addition to the rising popularity of Python across all scientists and engineers, where it has been dubbed "…the de facto standard for exploratory, interactive, and computation-driven scientific research" [180].

A particular advantage of using Python for energy modelling, as well as the ability to effectively disseminate the modelling code, is building on existing models. pvlib [181] is a Python package for modelling photovoltaic systems and windpowerlib [182] is a Python package for modelling wind turbines. Instead of developing the code for models of these technologies from scratch, using Python as the programming language means that it is easy to directly use these packages.

Python energy system models exist which could have research synergy with the topics tackled in this thesis. PyPSA (Python for Power Systems Analysis) [183] and pandapower [184] are tools which model and optimise electrical power systems. These have been applied to perform analysis of power systems, e.g. a study involving the sectoral interactions of a highly-renewable European energy system [185] which utilises PyPSA. oemof (Open Energy Modelling Framework) uses a novel approach of providing a toolbox for the representation, analysis and modelling of renewable energy and sector integrated systems [186], and OSeMOSYS (Open Source Energy Modelling System) is intended for national and regional policy development and provides a framework for the analysis of energy systems over the medium (10–15 years) and long term (50–100 years) using linear optimization or mixed integer programming [187].

These frameworks and models could have provided the basis for a starting point for the modelling developed in this thesis. However, this would have required a high-level of Python competence and instead a modelling tool was built primarily from scratch to aid the author in gaining proficiency in Python programming. Additionally, it would be an insightful future exercise for the review of modelling tools in Chapter 3 to include those identified through the openmod initiative as well as the developed tool.

Based on the potential to build directly on the state of the art, and pass forward to others through open source, Python appears an apposite choice of a programming platform for developing new energy system modelling utilities to address the shortcomings of the existing tools.

4.4. Tool Capabilities

The capabilities of PyLESA are tabulated using the structure of the review of modelling tools from Chapter 3. Table 4.1 shows the screening requirements applied with comments detailing the result; the tool passes all the defined criteria. Table 4.2 shows the modelling and assessment capabilities following the categorisation and highlights, with red bold text, the capabilities which address the gaps in existing modelling tools. Figure 4.1 displays the models and energy flows of PyLESA.

PyLESA has been developed with the aim to address the gaps identified in the review of existing modelling tools and therefore to advance the state of the art.

Table 4.1: Screening requirements applied to PyLESA

Criteria	Result	Comment
Scale	Yes	Developed specifically for local energy systems
Case study	Yes	Application of tool to residential district heating scheme, see Chapter 6
Planning-level design	Yes	Developed specifically for planning-level design
Low and/or zero carbon tech	Yes	Wind turbine, PV, heat pump
Storage/DSM	Yes	Storage: Electrical storage, hot water tank DSM: Fixed order control, MPC
Timestep	Hour	Hourly timestep chosen for easier data collection and lower computational run time
Electrical	Yes	Electrical demand, electrical RES production, electrical storage, and grid
Thermal	Yes	Heat demand, heat pumps, auxiliary heat, and hot water tanks

Table 4.2: Categorisation of PyLESA tool capabilities

Input data requirements and input support	
Demand profile generator	Yes
Resource assessor	Yes
Supply profile generator	Modeller
Electrical and thermal supply technology modelling capabilities	
Electrical supply	Grid, PV, Wind turbine
Thermal supply	Auxiliary electric heat, Fuel boiler, **Heat pump**
District heating	Yes
Design optimisation and output capabilities	
Design optimisation	Parametric analysis
Outputs	EMI, EP, FA, FC, M, RP, SA
Controls/DSM controls	AC, OO, FO, **MPC**
Storage modelling capabilities and underlying models	
Electrical storage	Simple storage model
Thermal storage	**Multi-node model**
Fuel synthesis	No
Fuel storage	No
Practical considerations	
Cost	Free (open source)
Access	Download (open source)
Support	Author and ESRU
Academic/commercial	Academic
User friendly	Medium. Chosen because while Python is very popular, and the code is commented and structured, many existing tools do not require any programming proficiency
Available expertise	Yes/No

Red bold text indicates the capabilities which address the gaps in existing modelling tools

Key – Outputs: Autonomy (A); Emissions (E); Energy market interaction (EMI); Energy production (EP); Financial analysis (FA); Fuel consumption (FC); Human development index (HDI); Job creation (JC); Demands/supply match (M); Renewable penetration (RP); System analysis (SA)

Controls/DSM Controls: Advanced control (AC); Demand curtailment (DC); Electric vehicles (EV); Fixed order (FO); Load shifting (LS); Modulating output (MO); Model predictive control (MPC); Non-modulating output (NO); Operational optimisation (OO) with objective function in brackets; User-defined order (UO)

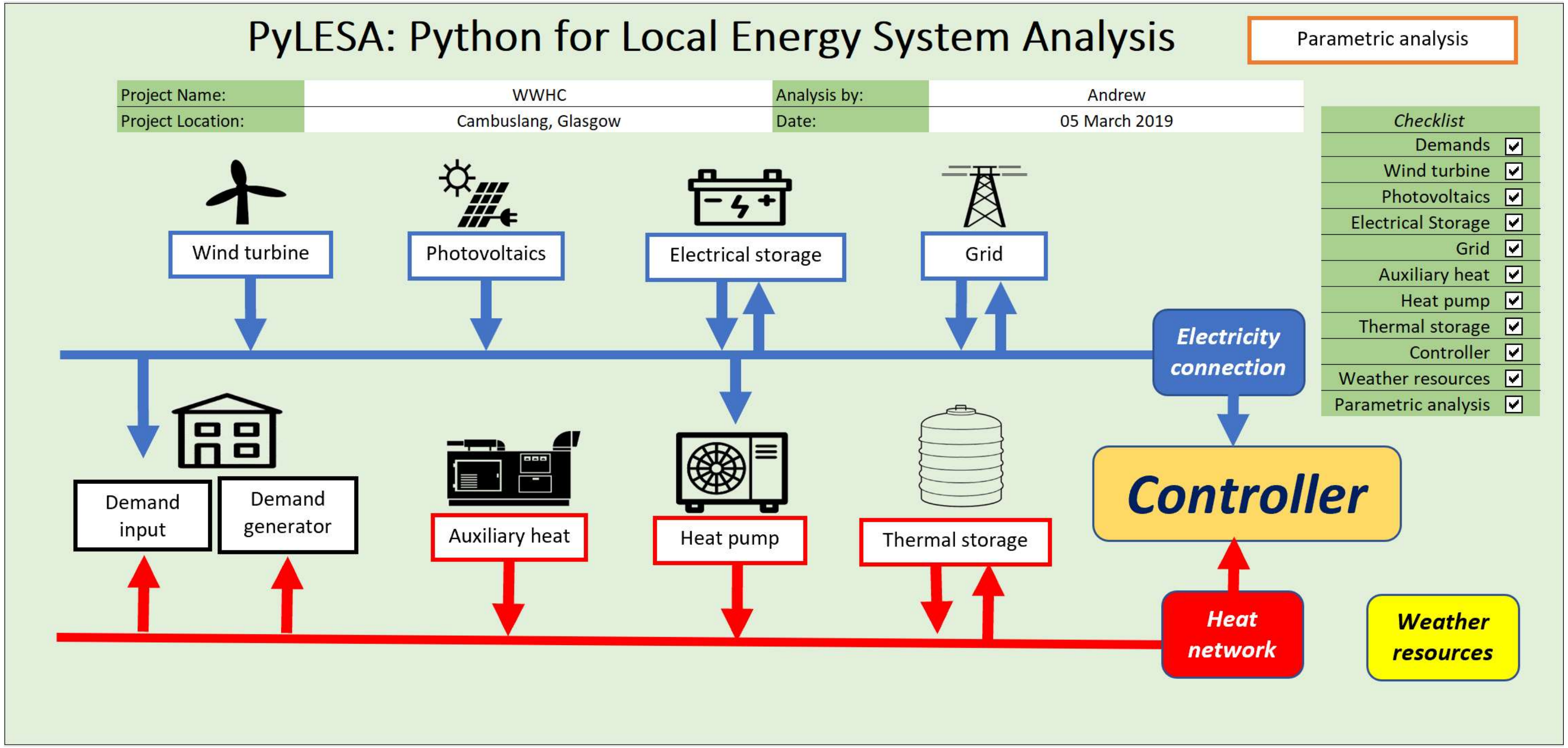


Figure 4.1: Models and energy flows of PyLESA

4.5. Tool Framework

The framework of PyLESA is described in this section which explores the interaction of the different models and assessment methods employed to model a local energy system. In brief, an Excel workbook is used for inputting data; the modelling is performed in hourly timesteps and models for the technologies and assessment methods are written in Python scripts; and outputs are in the form of an array of numerical outputs and graphical 3D plots of Key Performance Indicators (KPIs). Figure 4.2 is a graphical representation of the framework of the modelling tool and is described and shown below.

The modelling tool follows an object orientated class structure throughout and typically technology models and assessment methods are calculated by initialising the appropriate class object and executing a method. Models are run using hourly timesteps with the input data of first timestep and number of timesteps used to calculate the modelling period.

Data is input via an Excel workbook where a cover sheet, Figure 4.1 from earlier, displays the models and energy flows of PyLESA. Through this sheet the worksheets relating to the inputs for each of the models and assessment methods can be accessed and the necessary data input. Then a Python script is run which reads, processes and locally saves the input data from the Excel workbook. Demand assessment scripts can be run to synthesise heat and electricity demands which can inform the data input to the Excel input workbook. Additionally, parametric analysis inputs are also input into the Excel workbook.

The *fixed_order.py* or *mpc.py* Python scripts contain control classes and methods which determine how the assessment and technology models are run. The first step for both is to run the renewable generation models and obtain renewable electricity production over the modelling period. Each timestep in the modelling period is taken sequentially and algorithms applied to determine the order of dispatch and magnitude of supply of the various input supply technologies in order to meet supply (further details in Chapter 5). Class objects for each of the technologies and the assessment methods feed into the control class to set constraints and calculate potential actions.

Using the *run.py* script automates the process of running all of the iterations of the model defined in the parametric analysis step.

Results over the modelling period relating to a wide range of data are appended to a dictionary object and manipulated using the *outputs.py* script. The resulting output from running this script are a CSV file containing an array of numerical outputs and *.png* graphical 3D plots of KPIs.

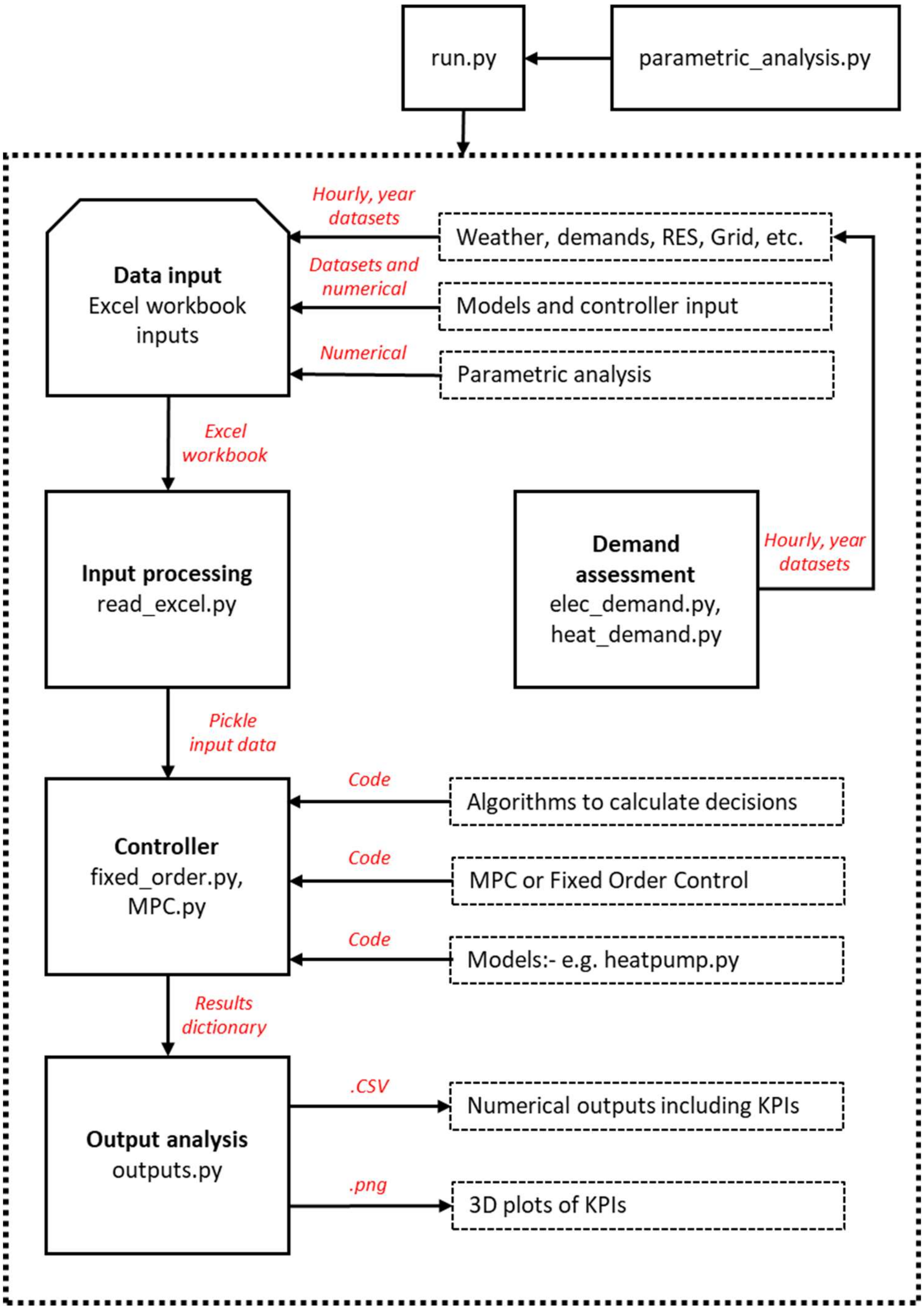


Figure 4.2: Framework of PyLESA showing workflow of a run

4.6. Tool Applications: Potential Design Studies

Three types of design studies which can benefit from applying PyLESA are discussed in this section: a feasibility study, an operation study, and a sizing study. General information regarding the type of design study is given, before an example study is described to illustrate the benefits of applying PyLESA.

4.6.1. Feasibility Study

A feasibility study is an evaluation of the practicality of a proposed plan. For a local energy system this could aim to investigate the practicalities of the installation of a variety of sustainable energy options [188]. Several different steps can be taken to achieve this aim. An example feasibility study template is outlined to illustrate the role of PyLESA:

1. Review a full range of energy supply and efficiency options and narrow down options based on their applicability to the local energy system.
2. Technical appraisal of the potential performance of the narrowed down options.
3. Economic assessment of the costs and benefits relating to the capital and operational costs as well as sources of funding and external financial benefits.
4. Assessment of the environmental and social impacts of options.

The first step is highly dependent on the specifics of the local energy system, including the geographical location, the weather resources, and availability of skills. An assessment of the local energy system, without the need for modelling, would allow the designer to rule out a number of options. This results in a narrowed down list of options which have practical potential.

The second and third step require sufficiently detailed modelling such that the potential benefits of the narrowed down list of options are captured. Modelling the system using PyLESA results in technical and economic output KPIs which can be used to inform the technical appraisal and economic assessments required. In its current form PyLESA is limited in the technologies it can model. Therefore, where the narrowed down list contains technologies beyond PyLESA's capabilities, either alternative modelling tools can be used, or new methods can be developed to further the capabilities of PyLESA.

The fourth step involves an assessment of the environmental impacts, some of which can be calculated from the technical outputs from modelling along with additional environmental information of the technologies, i.e. emissions from CO_2, NO_x and SO_x, etc. Expert knowledge of the geographical area and population are required to perform a full environmental impact assessment (EIA) [189]. Assessment of the social impacts are out of the scope of this thesis.

In conclusion, application of the PyLESA to a local energy system can inform the technical and economic aspects of the example feasibility study provided, which aims to investigate the practicalities of the installation of a variety of sustainable energy options.

4.6.2. Operation Study

An operation study examines the operation of an existing local energy system and aims to investigate avenues for improving performance. Often the controls on existing heating systems with low-carbon technologies are poorly designed or installed and analysis is required to identify opportunities for improvement.

An example operation study could be to analyse an underperforming existing heat pump and hot water tank heating system. The study could use the following steps:

1. Monitor the major components of the existing heating system, e.g. heat output and electrical usage of heat pump, hot water tank temperatures at different levels, demand flow rates and temperatures, etc.
2. Model the heating system according to design to determine expected performance.
3. Compare to identify differences between design and actual performance, and subsequently the components which are causing the performance gap.
4. Model the heating system with alternative control strategies to identify potential improvements to the control design.

The first step requires an energy monitoring kit capable of collecting all the relevant data, see [36] for an example open source monitoring kit. Description of this step is outside the scope of the work in this thesis.

The modelling required in the second and fourth steps can be performed using PyLESA as long as the control to be modelled is the fixed order or model predictive control strategies. However, given the flexible and open source nature of PyLESA, bespoke control strategies can be developed and incorporated into the tool. In future a substantial catalogue of control strategies could be contained within PyLESA which would mean that operational studies, such as the example outlined here, would be able to compare several control strategies easily.

4.6.3. Sizing Study

A number of methods have been used for carrying out sizing studies for energy systems and have been classified in literature [190] into three categories: probabilistic, analytical, and iterative.

Probabilistic methods combine models for generation and load to create a risk model using a variety of optimisation indicators and design constraints. A number of studies have used this type of method to size solar, wind, and/or battery storage hybrid systems [191–193].

Analytical methods typically use computational tools to model energy systems and assess performance (the tools reviewed in Chapter 3 are often used in analytical methods). Different system configurations and component sizes are modelled using the computational tools and the outputs relating to system performance compared. Often tools have design optimisation algorithms which use a single or multiple objective function(s) to automate this process. HOMER [194] is an example of a computational tool which has been designed to carry this type of sizing study.

Iterative methods use a recursive process which runs until a configuration is modelled which meets design specifications. Genetic algorithms are an optimisation method which are used to find global optimal solutions from a population of candidate solutions which are evolved towards better solutions [195]. A study developed a genetic algorithm to optimize the capacity and operation strategy for a CHP and ground source heat pump coupled heating system [196].

The data used in methods for sizing studies is also important. Methods which use average values such as monthly weather data and worst-case scenarios such as coldest day over 20 years to size different energy system components can lead to oversizing because of large variability in sub-monthly weather data and the low probability of worst-case scenarios.

In the UK buildings industry, sizing methods rely on estimating peak demands for a design day (i.e. coldest day) and sizing the primary unit to match this peak [91]. For hybrid systems, typically the heat pump is sized to match base load and the auxiliary units are oversized to provide back-up and peaking capability. When including thermal storage another approach is to size the primary unit such that continuous output matches the demand for the design day, with the thermal storage sized to meet peaks. This approach may enable the thermal storage benefits of plant optimisation and enhancing service and resilience but do not enable the other benefits: grid services, shifting electricity consumption according to tariffs, and increasing on-site generation self-consumption.

The modelling methodology developed in this thesis uses an analytical approach coupled with a parametric analysis step to perform sizing studies. The capacities of the heat pump and hot water tank can be input as a range and the tool will automatically run multiple simulations. These are then graphically output as 3D plots where KPIs of the various size combinations can be readily compared. Extension of this method could be integration of an optimisation algorithm such as that employed in the analytical method used by HOMER, or an iterative approach using genetic algorithms. Additionally, a simpler future step is to extend the parametric analysis to other technologies such as capacity of battery storage, number of PV, and number of wind turbines.

PyLESA will be showcased in Chapter 6 by carrying out a sizing study for an existing residential district heating scheme looking to incorporate heat pumps, thermal storage, time-of-use electricity tariffs, and predictive controls.

4.7. Summary and Next Steps

This chapter provides the context and outlines a high-level specification of the development and potential applications of the proposed modelling tool, PyLESA.

The next steps are to delve into the details of the underlying models which underpin PyLESA and tackle the identified gaps in existing modelling tools. Then, in order to further validate and demonstrate the use of PyLESA, an application of the modelling methodology will be made. This will aid design decisions for a sizing study focussing on the optimal sizing combinations for heat pump and hot water tank capacities; comparison of the developed control strategies; and comparison of a range of existing and future electricity tariffs.

5. Detailing PyLESA: Underlying Models and Assessment Methods

This chapter covers the input requirements, detailed description and validation of the underlying models and assessment methods used in PyLESA (Python for Local Energy Systems Analysis). A published peer-reviewed, conference paper by the author introduces aspects of the underlying models [197], but this chapter provides greater detail and contains a more complete description.

Validation consists of discussion of previous applications of adopted methods, comparison to real data, or inspection and explanation of the outputs. Validation of the control strategies is undertaken as part of the application in Chapter 6, as a well-defined specific local energy system is required to discuss the operation of controls in detail. The following models and assessment methods are described:

- Resource and demand assessment
- Electricity production technologies
- Heat pump and auxiliary heat units
- Electrical storage
- Hot water tank
- Electricity tariffs
- Fixed order control
- Model predictive control
- Modelling outputs including KPIs

Contributions to the state of the art are made in the development of the following models to address previously identified gaps:

Section 4.3

- Open source development to enable accessibility and build upon previous work by writing the majority of the code in Python.

Section 5.3

- Heat pump model which uses standard test data to generate performance maps using multiple variable linear regression analysis with explicit temperature dependence.

Section 5.5

- Hot water tank modelled using a multi-node approach to represent thermal characteristics through state of charge dependence on node temperatures.

Section 5.6

- Future wind-based electricity tariff generator.

Section 5.8

- Model predictive control strategy to optimise system operation.

All of Sections 4 and 5 describe the contribution below

- Novel tool for modelling local energy systems incorporating heat pumps, thermal storage, future electricity tariffs, and model predictive controls.

5.1. Resource and Demand Assessment and Input Methods

Methods have been developed that support the user to input the required resource and demand information that allows an energy system analysis to be placed in the correct context. The user may have direct access to the required input data at the correct timestep, or the user may need support in assessing these inputs indirectly, e.g. from available data sources or datasets.

Resources is the term used here to describe weather and climate related parameters such as wind speed, direct and indirect solar insolation, and ground or water temperatures. These parameters influence the output of the models. For example, wind turbine and PV where wind speed and solar radiation data drives the power output, or a hot water tank located outside where air temperature is a factor in calculating heat loss. Resource assessment methods are included which provide access to available international and national datasets.

A range of energy demands are considered, e.g. electrical power, heat, and transport energy demands across the range of entities that make up the district to be analysed.

Demand assessment methods are included which provide a means for synthesising hourly electrical and heat demand profiles from simple inputs, which are often all that is available at the planning-level stage.

The PyLESA tool has been configured to be flexible and support multiple direct and indirect data entry methods. Data can be input into PyLESA using an Excel workbook template that has been created for this purpose as illustrated in Figure 5.1, Figure 5.2 and Figure 5.3. Methods that can be used to indirectly establish the required resource and demand inputs are described in more detail in the following subsections.

Demand and district heat profile input

hour	heat demand	electrical demand	temp_flow	temp_source
1	368.605	56.0575	60	65
2	308.365	54.1513	60	65
3	282.41	79.7317	60	65
4	316.8125	98.1754	60	65
5	438.5275	98.5837	60	65
6	399.3	142.5824	60	65
7	394.5425	175.8237	60	65
8	449.83	236.5069	60	65
9	445.49	271.2651	60	65
10	486.15	314.5437	60	65
11	474.1425	256.177	60	65
12	583.6225	332.1888	60	65
13	622.8875	318.7942	60	65
14	549.775	297.6658	60	65
15	574.6875	271.5148	60	65
16	636.3025	166.3686	60	65
17	688.7025	320.7977	60	65
18	620.07	280.7625	60	65
19	664.285	411.2014	60	65
20	598.815	435.9547	60	65
21	663.75	471.2565	60	65
22	644.22	493.9438	60	65
23	540.9525	267.944	60	65
24	483.23	162.8849	60	65
25	474.15	70.38	60	65

temp_return
40
ΔT across source
10

Figure 5.1: Electrical and heat demand input requirements

Demand profile generator

Back to Cover

	Type	Age	Bedrooms	Number of type
House Type 1	detached	pre-1983	1	0
House Type 2	semi-detached	1983-2002	2	0
House Type 3	mid-terrace	2003-2007	3	0
House Type 4	detached-bungalow	post-2007	4	0
House Type 5	semi-detached-bungalow	pre-1983	3	0
House Type 6	ground-floor-flat	post-2007	2	96
House Type 7	mid-floor-flat	post-2007	2	352
House Type 8	top-floor-flat	post-2007	2	96
House Type 9	detached	pre-1983	4	0
House Type 10	detached	pre-1983	4	0
			Total dwellings	**544**
Average Daily DHW	4	kwh/person/day		

Figure 5.2: Heat demand profile generator input requirements

Weather resource inputs

	Solar			Wind				Air		Water (for HP)
Hour	DHI	GHI	DNI	wind_speed_10	wind_speed_50	roughness_length	pressure	air_temperature	air_density	water_temperature
1	0	0	0	6.998		0.01	1	3.026		
2	0	0	0	7.174		0.01	1	2.296		
3	0	0	0	7.417		0.01	1	1.695		
4	0	0	0	7.418		0.01	1	1.223		
5	0	0	0	7.528		0.01	1	0.901		
6	0	0	0	7.842		0.01	1	0.701		
7	0	0	0	8.069		0.01	1	0.472		
8	0	0	0	7.986		0.01	1	0.063		
9	0	0.347	0	7.798		0.01	1	-0.406		
10	25	36.021	58	7.748		0.01	1	-0.016		
11	56	93.129	130	7.518		0.01	1	1.176		
12	73	124.514	151	7.587		0.01	1	2.115		
13	78	124.782	128	8.695		0.01	1	2.871		
14	68	101.961	93	9.674		0.01	1	3.253		
15	42	56.609	44	10.346		0.01	1	3.069		
16	8	10.007	10	10.546		0.01	1	2.381		
17	0	0	0	10.294		0.01	1	1.651		
18	0	0	0	9.811		0.01	1	1.006		
19	0	0	0	9.312		0.01	1	0.453		
20	0	0	0	8.44		0.01	1	-0.125		
21	0	0	0	8.045		0.01	1	-0.618		
22	0	0	0	8.103		0.01	1	-0.782		
23	0	0	0	7.948		0.01	1	-0.96		
24	0	0	0	7.656		0.01	1	-1.155		
25	0	0	0	7.261		0.01	1	-1.339		
26	0	0	0	6.773		0.01	1	-1.478		
27	0	0	0	6.444		0.01	1	-1.459		
28	0	0	0	6.32		0.01	1	-1.265		

Figure 5.3: Weather resource input requirements

5.1.1. Local Resources

Accessing available data on local resources requires access to the necessary databases containing hourly datasets. For weather resources, local stations and reanalysis climate databases can be used to obtain datasets over several years. Typically, it is easier to access a greater number of year datasets from reanalysis databases than from weather stations (as these often require payment to access, e.g. Met Office in the UK [198]). Reanalysis datasets allow access to data which enables energy system modellers to characterise the variability of renewable energy resources across days and months. They have emerged as a popular tool to the energy modelling community and have been applied to both national/global scale [199] and small-scale energy systems [200].

The website renewables.ninja [201] provides free and easy access to hourly data from the NASA MERRA reanalysis [202] dataset. The website offers a simple interface where a point on Google Maps can be clicked and the weather datasets for that point can be downloaded, see Figure 5.4 for a screenshot. MERRA has many advantages over other reanalysis datasets. It provides hourly data (other datasets use 3 or 6-hourly intervals), global coverage, has a high spatial resolution across Europe (1/2° latitude and 2/3° longitude, 50 × 50 km), and is stable over long-timescales [203]. MERRA includes direct and diffuse solar radiation, windspeed, air temperature, etc. for the past 37 years (from 1987). The MERRA dataset is widely used in energy system modelling and has advantages, however studies have shown that it has systematic errors and needs to be corrected in order to reduce error.

MERRA solar data was used as input to the Global Solar Energy Estimator (GSEE) to model PV power output for plants in different European countries and this was compared to measured data from individual and aggregated PV plants [199]. The use of MERRA input data was found to cause an overestimation of output when simulating individual sites. The study found that, for aggregated sites, that applying a simple linear correction to the MERRA solar data to adjust for the overestimation improved the fit of the simulated to measured power output. The authors concluded that it was likely that the corrected data was suitable for the type of energy modelling studies, such as planning-level design, where the resultant PV power output uncertainty will be similar to other input data and model uncertainties. However, this study did not investigate applying this correction method when modelling individual PV sites. Therefore, while it the functionality to use MERRA input solar data after applying a simple linear correction factor is included in PyLESA, this approach has not been validated and it is better to input validated data.

MERRA wind data was used to model wind turbine power output across Europe and it was found that it causes errors and suffers spatial bias when uncorrected, overestimating wind output by 50% in northwest Europe and underestimating by 30% in the Mediterranean [203]. The study describes a method of correcting the systematic error in the MERRA dataset of the wind speed by using correction factors (both a multiplicative factor and a linear offset). The study developed a set of correction factors for countries across Europe, based on the ratio of observed to simulated wind capacity factor for each country. The study did not investigate the suitability for this correction method for modelling individual sites. Therefore, while correction factors can be used in PyLESA to account for over-estimation of the MERRA wind speed data, this method is not validated for individual wind turbines and it is recommended that validated data sources are used when available.

PyLESA can accept any source of local resource input, and it is recommended that any data input is validated in order to reduce uncertainties and errors. However, at the planning-level stage there is often no validated and stable hourly data available and a corrected MERRA reanalysis dataset can be used to carry out concept design studies with the caveat that it introduces significant uncertainty into the output.

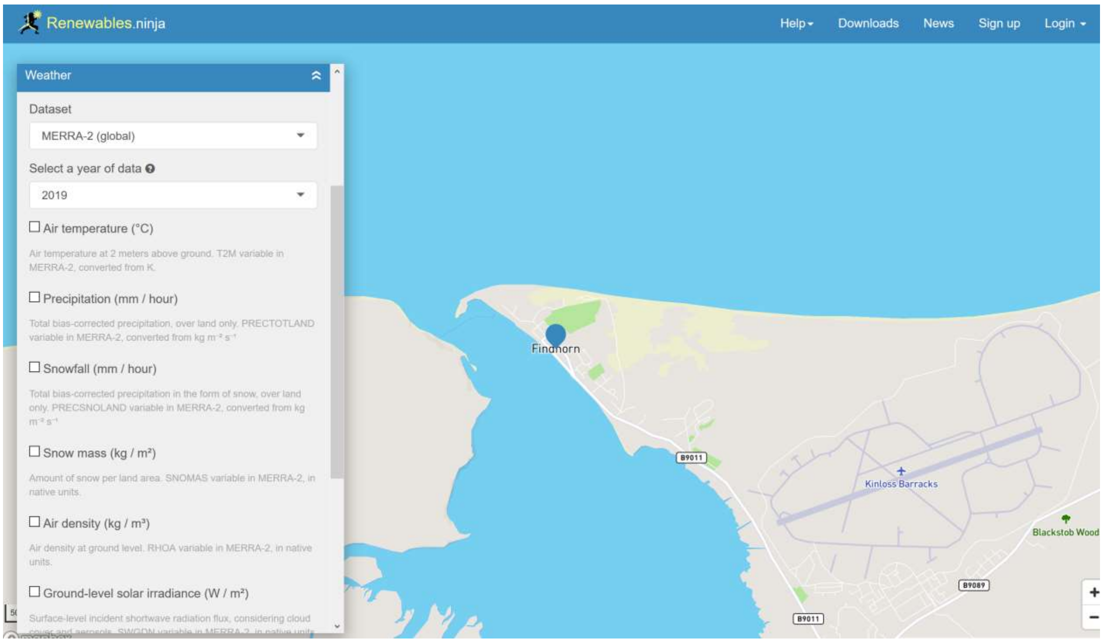


Figure 5.4: Screenshot of renewables.ninja website for obtaining weather resource data from the MEERA dataset with the example of Findhorn, Scotland

5.1.2. Electrical Demand

PyLESA can support data input for non-heating electrical demand from a range of sources. For the UK context of the applications in this thesis, it has been configured to use electrical demand profiles on an hourly timestep such as those generated using HOMER software [194]. HOMER contains a module which allows the user to generate a profile based upon building types: residential, commercial, industrial and community.

Choice of peak demand month accounts for seasonal variability, and a random variability parameter is used to include hourly and daily variability. For additional accuracy, the resultant hourly profile over a year can be scaled to match the building mix to be modelled e.g. by using CIBSE benchmarks [204] for different building types. HOMER has been used to synthesise community (or local) electrical loads and validated in previous studies by comparing modelled output to real data [205,206]. An agreement suitable for planning-level design was found. The resultant profile using HOMER is not a function of local weather conditions and therefore is fixed for any weather year. It could be adjusted to include an ambient temperature dependence to improve prediction.

PyLESA can accept hourly electrical demand profiles from any source, and the method described here can be used where the user has access to and knowledge of the HOMER software.

5.1.3. District Heating Demand

Predicting heat demand is necessary to generate an hourly profile over a year and for use in a predictive control using lookahead periods. A review of existing, similar methods can be found in [207] which highlights the need for a simplified approach.

A method for generating hourly profiles for the district heating demand of a residential scheme was developed in PyLESA using regression analysis of pre-simulated housing standard profiles, scaling based on floor area, and applying diversity using a moving average method. This method builds on work done in the development of the demand assessment method used in the Biomass decision support tool [91] which generates a design day demand profile and an annual energy estimation. The described method uses simple inputs typically available at the planning-level design stage and is included as a functionality of PyLESA. The Biomass decision support tool method that was adapted in PyLESA also covers non-domestic building types, in future this functionality could be easily incorporated in PyLESA.

The flow diagram, Figure 5.5, shows flow of the PyLESA hourly heat demand profile generating method and the steps below describe the method in more detail:

1. Buildings to be modelled are split into archetypes based upon the following ages and types. It is assumed that the age of the building indicates the building regulations applied during construction.
    1.1. Ages: pre-1983, 1983-2002, 2003-2007, and post 2007.

1.2. Building types: detached, semi-detached, mid-terrace, detached bungalow, semi-detached bungalow, ground floor flat, mid floor flat, and top floor flat.

2. Detailed building simulation models provide standard profiles for each age and type and are a function of average day temperature and hour of day (see [91] for floor areas, U-values, ventilation rates, and controls used in the detailed simulation). Regression models are applied to the standard profiles to predict demand as a function of hour of day and outdoor temperature.
3. The standard profiles are linearly scaled according to floor area which is calculated from the user input number of bedrooms and then each of the building types are multiplied by the total number of each type.
4. Diversity is applied by smoothing the demand in each hour across multiple hours by applying a moving average algorithm. This calculation is based on flattening of the peak heat demand by a factor of 0.63 and is applicable for groups of dwellings above 10. This is in accordance with diversity factors used by district heat pipe manufacturers Isoplus [208].
5. Underground piping heat losses are calculated using industry standard pipe sizing software [208] which take the types, lengths and diameters of the different piping sections of the network, the design flow and return temperatures, and a design ambient temperature to calculate day heat loss. Using average ambient temperatures for each day of the design year, the tool is used to calculate the heat loss every day of a year. This is uniformly distributed across each hour of that day and added to the diversified heat demand.
6. Hot water demand is added by either (i) a constant baseload by specifying the demand in kWh/person/day, or (ii) scaling standard profiles obtained from measurements in the EST 107-household survey from 2008 [209]. Further hourly specification of hot water demand has been investigated in literature [210].

This results in a method for predicting demand for any hour of the design year as a function of outdoor temperature for use in the control strategies.

This method was applied to a 544 flat district heating scheme at West Whitlawburn in order to compare to an existing method which can predict annual heating demand (this is used as the case study for an application of PyLESA in Chapter 6). The scheme consists of a mix of ground, mid and top floor flats, and delivers both space heating and domestic hot water (assumed 2kWh/person/day). Each flat has a floor area of 70m^2 and, due to recent retrofit improvements to the building fabric, was modelled as post-2007. Annual underground piping losses were calculated to be 837MWh. Local monitoring data of air temperature from 2017 was also used. The developed method predicted an annual heat demand of 4017MWh.

BREDEM (BRE Domestic Energy Model) [211] is a monthly calculation tool which can be used to predict space heating and hot water demand of properties connected to district heating networks. It predicts that post-2000 flats will have a combined space heating and hot water demand of 6218kWh [212]. The piping losses calculated in the previous method were then added as these were not included in this calculation. This method predicts an annual demand of 4220MWh. This is 5.1% higher than the prediction from the developed method and indicates that the developed district heating demand method predicts reasonable values. Further work and data are required to validate the hourly output of the method.

Monitoring data was collected for the heat demand at WWHC over the year 2017 and the annual demand for this year was measured to be 3301MWh. This is lower than the demand modelled in both the developed model and in BREDEM. It was not investigated whether 2017 was a typical weather year, or if it was particularly mild or warm, which would have an impact on the heat demand for this year. Other factors causing this include the social demographics of the residents, many are in fuel poverty, and under-occupancy, with the housing scheme not always operating at full occupancy. This highlights the uncertainty in heat demand due to the variable behaviour of different occupants. Work has previously captured this behaviour when predicting heat demands [213], and this could be incorporated within PyLESA in future.

PyLESA can accept a heating demand profile from any source. The demand method presented here is a useful means of generating an hourly profile based on simple inputs, which may be all that is available at the planning stage.

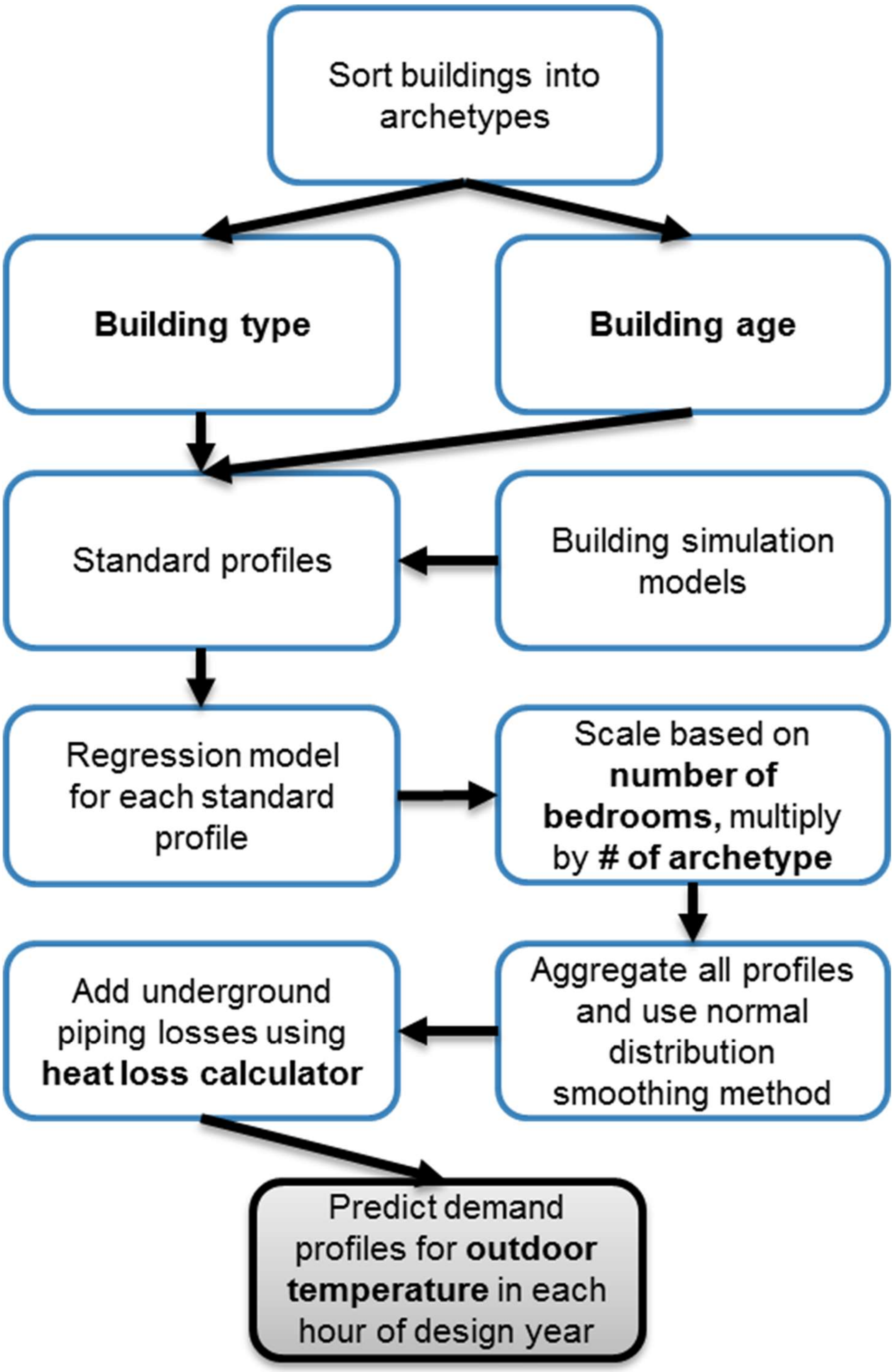


Figure 5.5. Flow diagram of district heating demand prediction method with user inputs in text bold

5.2. Electrical Production Technologies

The electrical production technologies modelled in PyLESA are wind turbines and PV. It is assumed that these are situated on-site and can directly meet the local electrical demand via a local network which allows self-consumption. A grid connection is also included in PyLESA which provides the option to configure limitless import and export electricity tariffs, described in detail in Section 5.6.

The renewable electricity production technology models enable assessment of their generation against local demands along with the opportunities for sector coupling and load shifting through storage and controls to increase the utilisation of on-site renewable generation. For example, heat pumps controlled to utilise renewable generation including load shifting using thermal stores.

Both the wind turbine and PV models in PyLESA are existing Python modules which have been independently validated [214,215]. Figure 5.6 and Figure 5.7 show the input requirements for the wind turbine and PV models respectively.

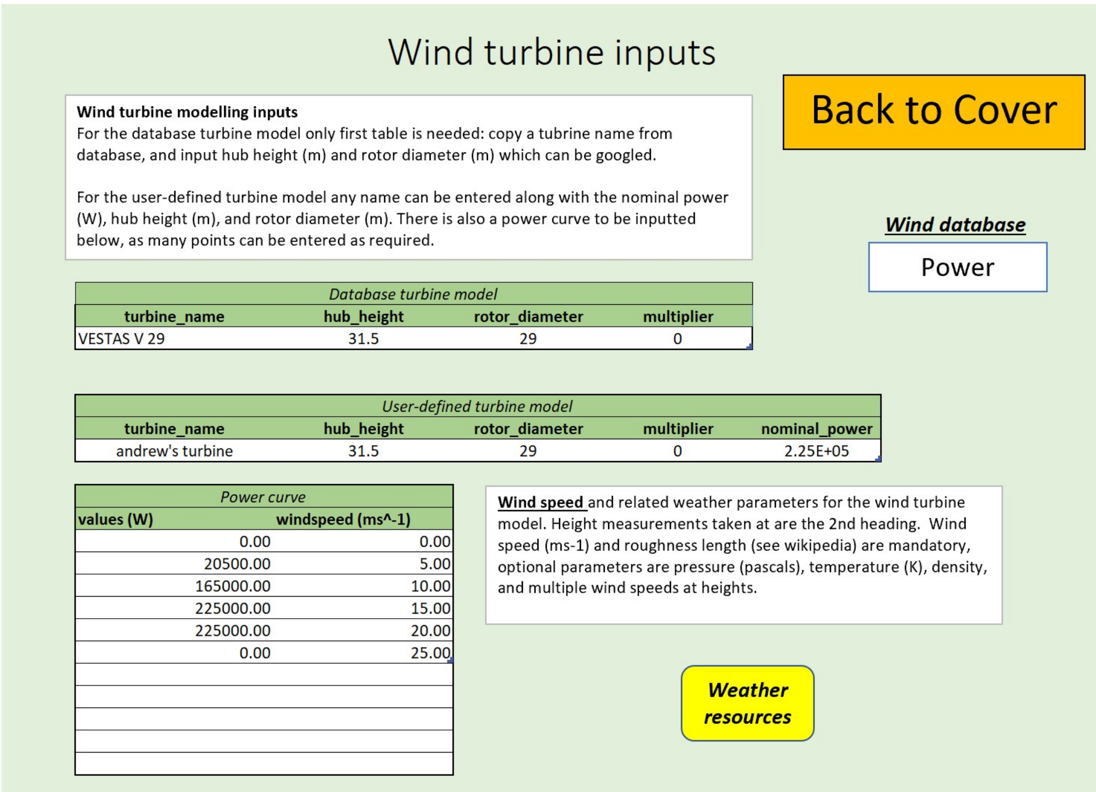


Figure 5.6: Wind turbine input requirements

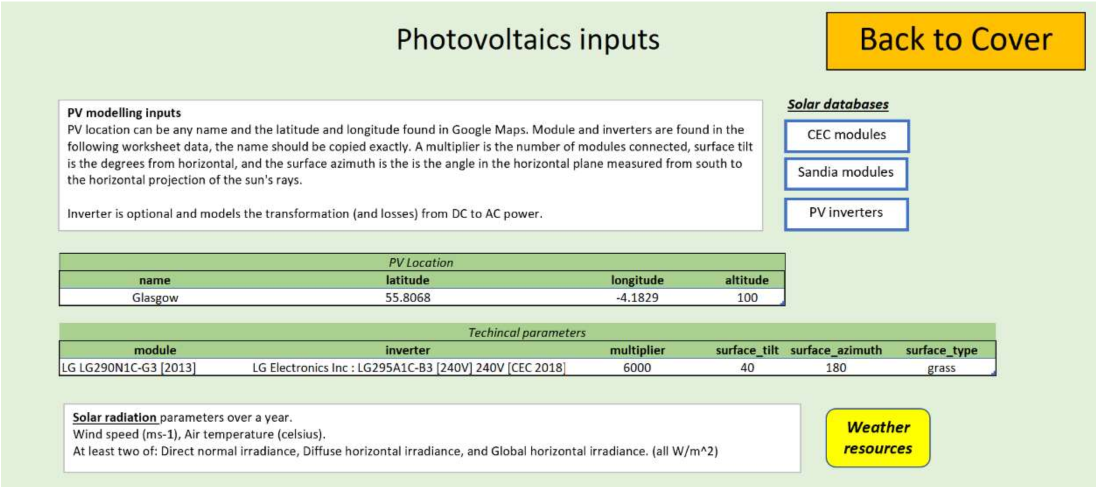


Figure 5.7: PV input requirements

5.2.1. Wind Turbine Model and Validation

Windpowerlib [182] is an existing Python library which contains functions and classes for calculating the power output from wind turbines and is used in this methodology. A choice between a user input wind curve and selecting from a database of power curves from different manufacturers is provided to simplify the input requirements of the user. Hub height and rotor diameter are the additional technical inputs. Local condition inputs are wind speed (including measurement height) and roughness length as mandatory, and pressure, air density, air temperature, and wind speeds at different heights as optional. The power is output in hourly timesteps.

A first step validation of the Windpowerlib method is through examination of the previous applications [186]. In this work a further validation was carried out using an example of the modelling output for the power output from 5x Vestas V27 wind turbines located at Whitelee, Scotland, for weather data from the year 2017. These wind turbines individually have a rated power of 225kW, 27.0m diameters, and cut-in and cut-out wind speeds of 3.0m/s and 25m/s respectively [216]. The modelled output is shown in Figure 5.8 and Figure 5.9. The modelled capacity factor is 20% compared to a reported actual 2017 capacity factor of 18% [217] which shows sufficient agreement for the Scottish context, which in conjunction with the prior validations confirms it is suitable for planning-level design.

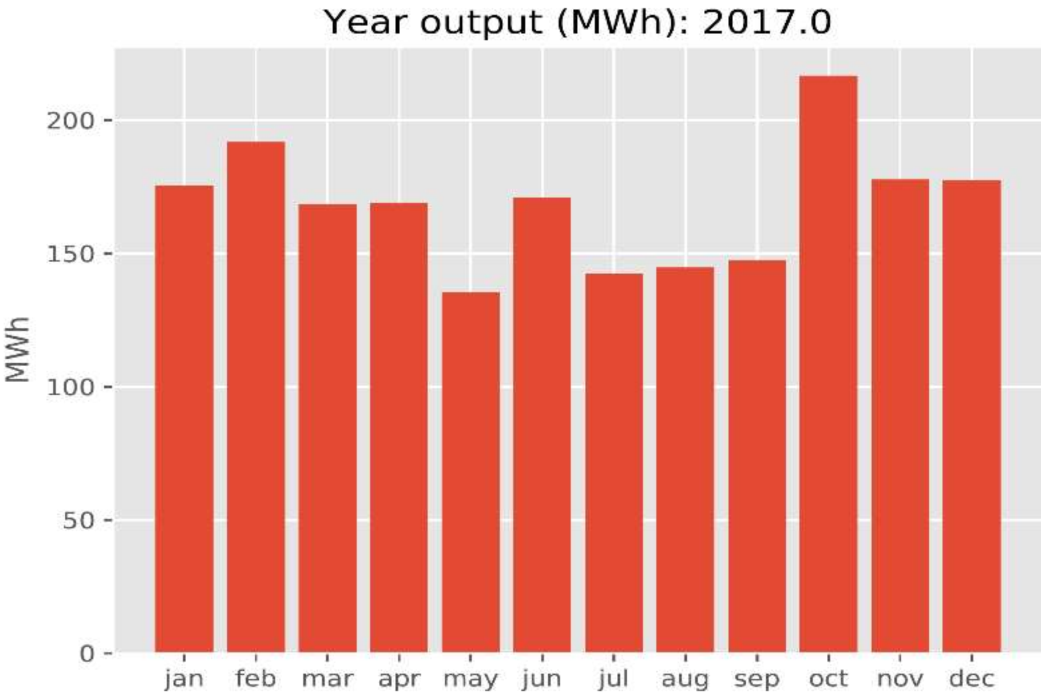


Figure 5.8: Monthly wind power output for each month and output for year

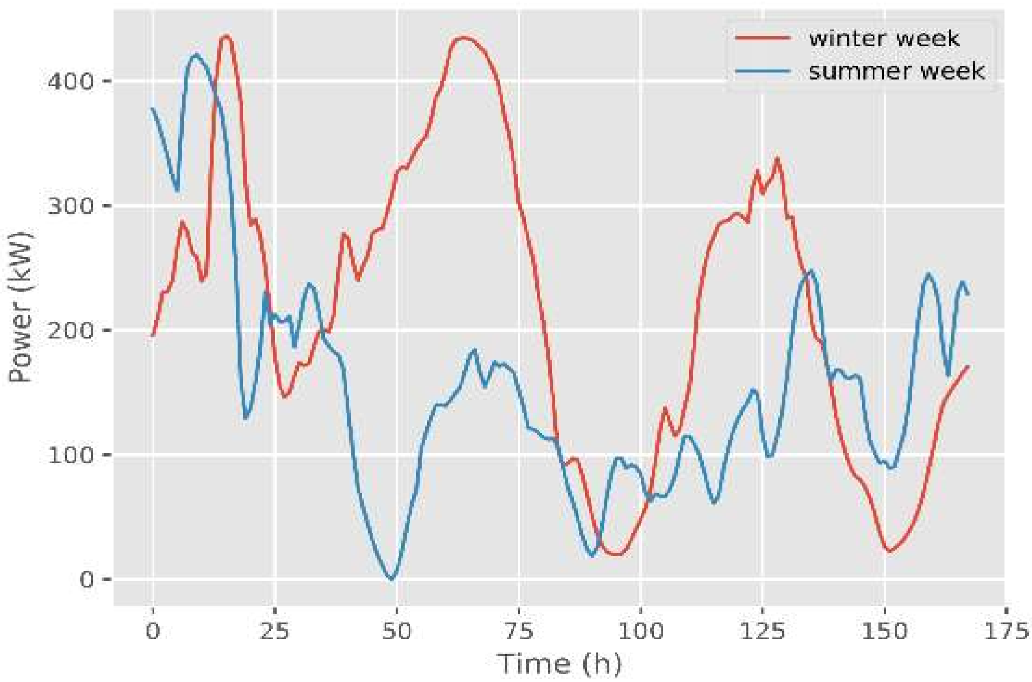


Figure 5.9: Hourly wind power output for example winter and summer weeks

5.2.2. Photovoltaics (PV) Model and Validation

PV is modelled using the PVLIB Python library [181]. The model consists of a module and an optional inverter, and the power output is dependent on the technical model and the location. A database for the module and inverter is used to input measured performance characteristics based on PVUSA test conditions [218]. The surface azimuth, surface tilt, surrounding surface type, and a multiplier are also used to complete the technical model. PV location is defined by latitude, longitude, and altitude and local conditions by wind speed, air temperature and at least two of direct normal irradiance, diffuse normal irradiance, and global horizontal irradiance. The power is output in hourly timesteps.

Validation of the PVLIB method is through previous applications [219] and using an example of the modelling output for the power output from 6x residential PV panels located at Findhorn, Scotland for weather data from the year 2017 as shown in Figure 5.10. The modelling gives an 1660kWh annual output. Two existing modelling tools and a field monitoring trial were used to independently calculate annual output:

- PVGIS [220]: 1540 ± 73.5kWh
- Renewables.ninja [201]: 1719kWh
- BRE field trial [221]: 1500kWh (results for this latitude suggest 800kWh/kWp)
- PVLIB: 1660kWh

The PVLIB shows a sufficiently good correspondence with these monitoring studies and models to allow it to be used for the planning-level stage that PyLESA has been developed to support.

Windpowerlib and PVLIB have been demonstrated to be useful Python modules and are particularly useful because they are open source and can be easily accessed and the source code inspected. They form the models utilised to model on-site renewable power technologies within PyLESA.

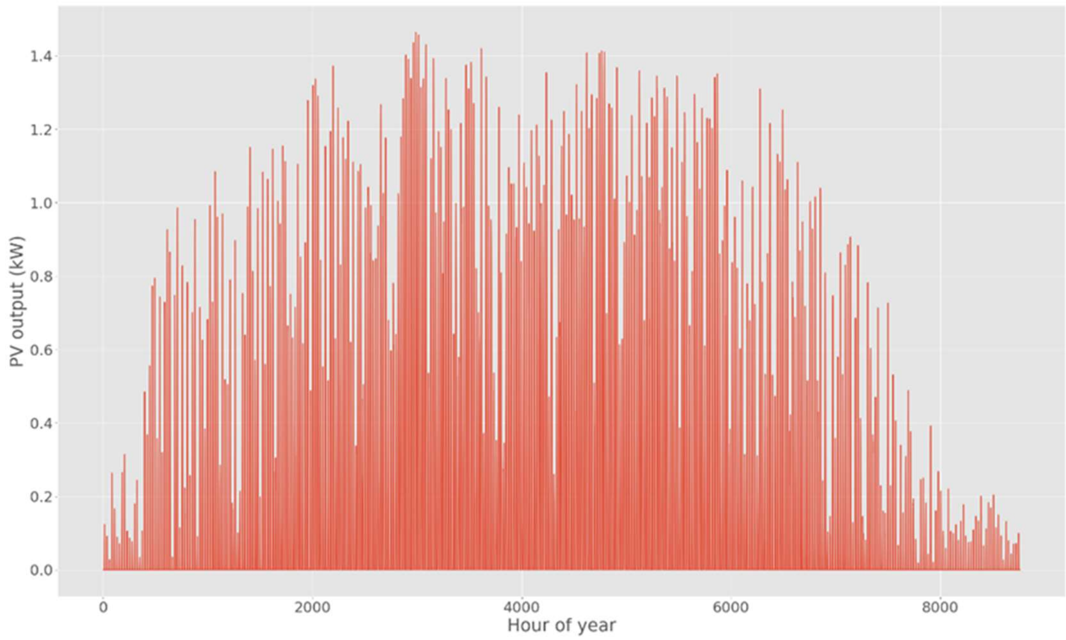


Figure 5.10: Hourly PV output for year at Findhorn

5.3. Heat Pumps and Auxiliary Heat Units

The focus of this work, as established earlier, is to investigate the role of heat pumps in conjunction with thermal storage and controls in converting renewable electricity into heat energy that usefully meets heating demands. Heat pumps are often not implemented as stand-alone heat generation but rather they are commonly integrated with direct electric 'boost heaters' and back-up heating such as gas boilers. In this work these integrated systems have been modelled to be used to provide hot water for use in district heating. However, the underlying models can be directly used for mini-districts, single residential buildings, etc., with only minor modification of PyLESA. An example of this would be modifying the code to model a mini-district energy centre delivering heat to a few flats with separate hot water tank and heat pump operation for space heating and domestic hot water provision (this has been done but is not reported in this thesis).

Heat pumps are commonly modelled at the planning stage using simple energetic models which do not account for temperature dependent COP. Additionally, available data for specific heat pumps is often limited and COP under one set of conditions is provided. This leads to an overestimation of seasonal performance.

Here, a more detailed heat pump modelling approach is developed going beyond the current state of the art in available modelling tools highlighted in Chapter 3. This approach requires standard test data to generate performance maps using multiple variable linear regression analysis with explicit temperature dependence.

The thermal production technologies modelled in PyLESA include large and smaller scale heat pumps as primary units, back up and boost direct electric heaters, and fuel boilers as auxiliary units.

There are several key characteristics which influence the performance of heat pumps. There is variation in the steady state thermal output and power consumption across the operating range of heat source and heating system water temperatures and flow rates. Transient behaviour including during start-up, shut-down and setpoint variations are largely influenced by the thermal inertia of the heat pump, i.e. the energy absorbed by the different components (primarily the condenser). A study [222] concluded that for an ASHP the transient induced reduction in COP is less than 2% for correctly designed systems with continuous run times above 15 minutes. Fixed output heat pumps can run the compressor in two modes: on or off. Their performance can be significantly reduced by excessive cycling caused by oversizing, with a study suggesting a seasonal efficiency reduction up to 25% under stated circumstances [223]. Variable speed heat pumps can vary thermal output by controlling the speed of the compressor which is typically achieved through an inverter-based variable speed drive or a stepwise compressor speed controller.

ASHP evaporators can grow frost which requires defrost mechanisms. Studies have reviewed defrosting techniques and show COP can be reduced by around 15% in some circumstances [224,225]. ASHPs therefore require additional modelling consideration with respect to the defrost cycles which effect performance in temperature regions where freezing conditions are possible. Water source heat pumps (WSHP) are assumed to have a constant flow or limitless supply of ambient water, meaning that there is no degradation of the source temperature. Ground source heat pump (GSHP) models have been developed throughout literature [226] but an explicit ground model is not included in this work.

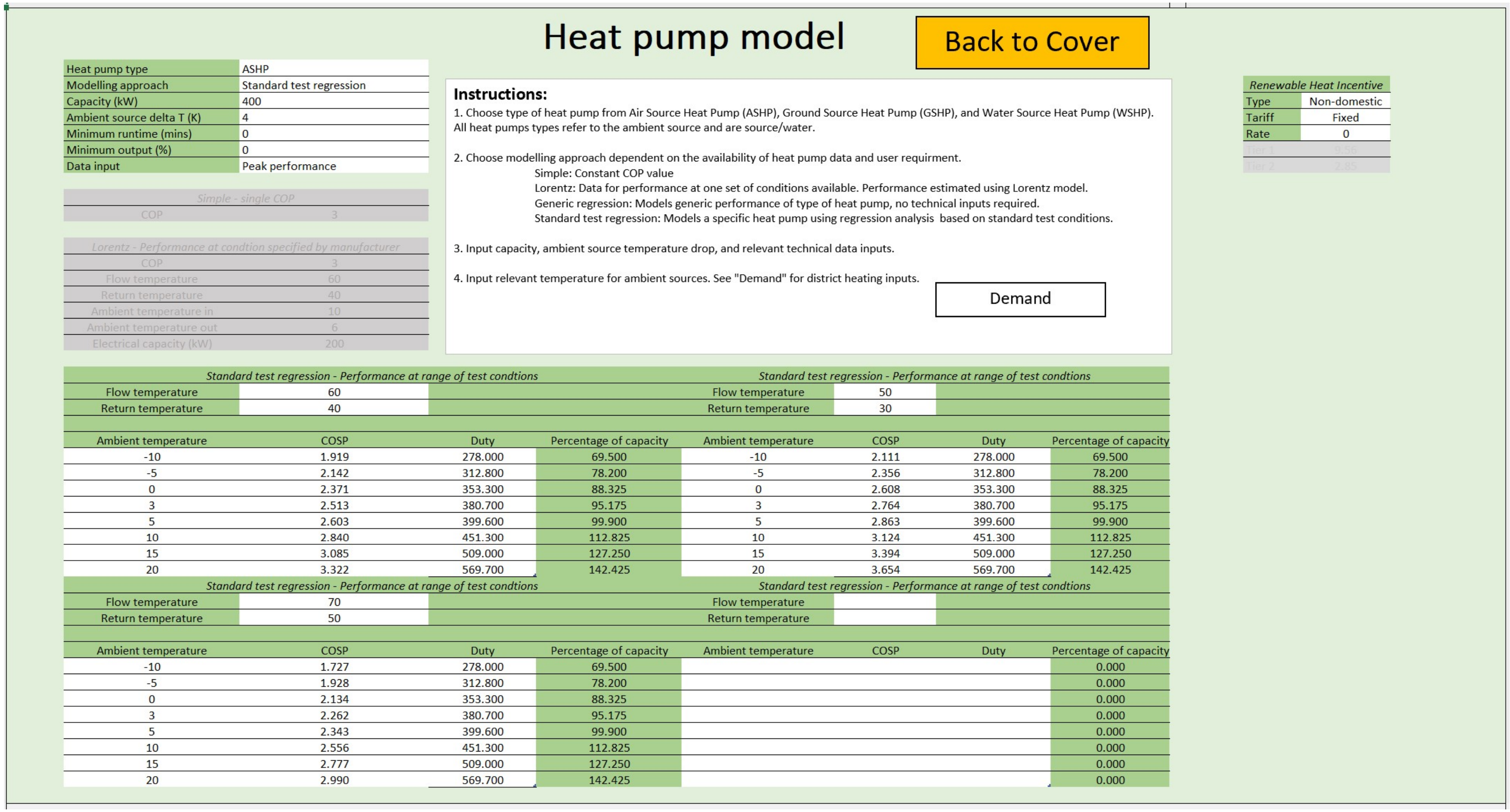
Approaches for modelling heat pumps can be categorised into black box, grey box, and white box. Black box models do not factor in the physical system but consist of look-up tables or equation fit models. Grey box models can include aspects of the physical system such as refrigeration cycle equations, fundamental system characteristics such as defrost cycles, and empirical-based equation fit models. White box models use explicit models to represent each of the major components of the heat pump thermodynamic cycle.

Three separate grey box approaches for modelling ASHP and WSHP, with different modelling detail input requirements, have been developed in PyLESA and can each be used in the methodology depending on the available input data and desired level of detail in the available outputs. The three approaches are:

- The Generic Regression Model
- The Lorentz Model
- The Standard Test Regression Model

The Generic and Standard Test regression models use performance maps based upon empirical data while including an algorithm to incorporate defrosting for ASHPs. The Lorentz model uses one empirical data point along with the idealised Carnot cycle performance to calculate an estimation of heat pump performance. The Generic Regression Model and The Standard Test Regression Model approaches are grey box quasi-steady state as they include a reduction in performance to account for the dynamic effects and defrosting without fully capturing the associated physical details of evaporator design, the system defrosting cycle, and associated controls. The Lorentz Model is grey box steady state as it does not account for dynamic effects and defrosting, rather being based on a simple equation.

General inputs required for the heat pump modelling in PyLESA are heat pump type (ASHP or WSHP/GSHP), modelling approach, rated thermal capacity of the heat pump, the difference between the source in and out temperatures, operation mode (variable or fixed speed), auxiliary heat requirement (monovalent or bivalent), and data input type (peak performance if data does not include defrost cycling). Figure 5.11 shows the heat pump modelling input Excel worksheet with the standard test regression model activated. The three methods are set out in the following sections.



Heat pump model

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Heat pump type	ASHP
Modelling approach	Standard test regression
Capacity (kW)	400
Ambient source delta T (K)	4
Minimum runtime (mins)	0
Minimum output (%)	0
Data input	Peak performance

Simple - single COP	
COP	3

Lorentz - Performance at condtion specified by manufacturer	
COP	3
Flow temperature	60
Return temperature	40
Ambient temperature in	10
Ambient temperature out	6
Electrical capacity (kW)	200

Instructions:

1. Choose type of heat pump from Air Source Heat Pump (ASHP), Ground Source Heat Pump (GSHP), and Water Source Heat Pump (WSHP). All heat pumps types refer to the ambient source and are source/water.

2. Choose modelling approach dependent on the availability of heat pump data and user requirment.
   Simple: Constant COP value
   Lorentz: Data for performance at one set of conditions available. Performance estimated using Lorentz model.
   Generic regression: Models generic performance of type of heat pump, no technical inputs required.
   Standard test regression: Models a specific heat pump using regression analysis based on standard test conditions.

3. Input capacity, ambient source temperature drop, and relevant technical data inputs.

4. Input relevant temperature for ambient sources. See "Demand" for district heating inputs.

Demand

Renewable Heat Incentive	
Type	Non-domestic
Tariff	Fixed
Rate	0

Standard test regression - Performance at range of test condtions

Flow temperature: 60; Return temperature: 40

Ambient temperature	COSP	Duty	Percentage of capacity
-10	1.919	278.000	69.500
-5	2.142	312.800	78.200
0	2.371	353.300	88.325
3	2.513	380.700	95.175
5	2.603	399.600	99.900
10	2.840	451.300	112.825
15	3.085	509.000	127.250
20	3.322	569.700	142.425

Standard test regression - Performance at range of test condtions

Flow temperature: 50; Return temperature: 30

Ambient temperature	COSP	Duty	Percentage of capacity
-10	2.111	278.000	69.500
-5	2.356	312.800	78.200
0	2.608	353.300	88.325
3	2.764	380.700	95.175
5	2.863	399.600	99.900
10	3.124	451.300	112.825
15	3.394	509.000	127.250
20	3.654	569.700	142.425

Standard test regression - Performance at range of test condtions

Flow temperature: 70; Return temperature: 50

Ambient temperature	COSP	Duty	Percentage of capacity
-10	1.727	278.000	69.500
-5	1.928	312.800	78.200
0	2.134	353.300	88.325
3	2.262	380.700	95.175
5	2.343	399.600	99.900
10	2.556	451.300	112.825
15	2.777	509.000	127.250
20	2.990	569.700	142.425

Standard test regression - Performance at range of test condtions

Flow temperature: ; Return temperature:

Ambient temperature	COSP	Duty	Percentage of capacity
			0.000
			0.000
			0.000
			0.000
			0.000
			0.000
			0.000
			0.000

Figure 5.11: Heat pump modelling input sheet with standard test regression model activated

5.3.1. Generic Regression Model

This approach uses a generic regression performance map to calculate the COP as a function of flow temperature and ambient temperature. The following regression relations were obtained from [227] and are based upon surveys of manufacturer datasheets and field trials. While they were obtained for household-scale heat pumps, the assumption is made that they are also applicable to large-scale heat pumps. Ideally, a dataset of performance data for large-scale heat pumps would be used, however, this was not readily available, but this can be done as future work. Additionally, for ASHPs a 15% reduction in COP is assumed below 5°C. For the COP of an ASHP, where ΔT is the difference between flow temperature and ambient temperature:

$$COP_{ASHP} = 6.81 - 0.121\Delta T + 0.000630\Delta T^2 \qquad for\ 15 \leq \Delta T \leq 60$$

The same paper includes a regression function for a generic ground source heat pump (GSHP) and is included here as also representative of a water source heat pump (WSHP) due to similar dynamics of the ambient sources:

$$COP_{WSHP} = 8.77 - 0.150\Delta T + 0.000734\Delta T^2 \qquad for\ 20 \leq \Delta T \leq 60$$

This approach is useful when quickly appraising heat pumps without data for a specific heat pump. Figure 5.12 shows the application of the generic regression model to a 14kW ASHP by displaying the COP variation with flow and ambient temperature.

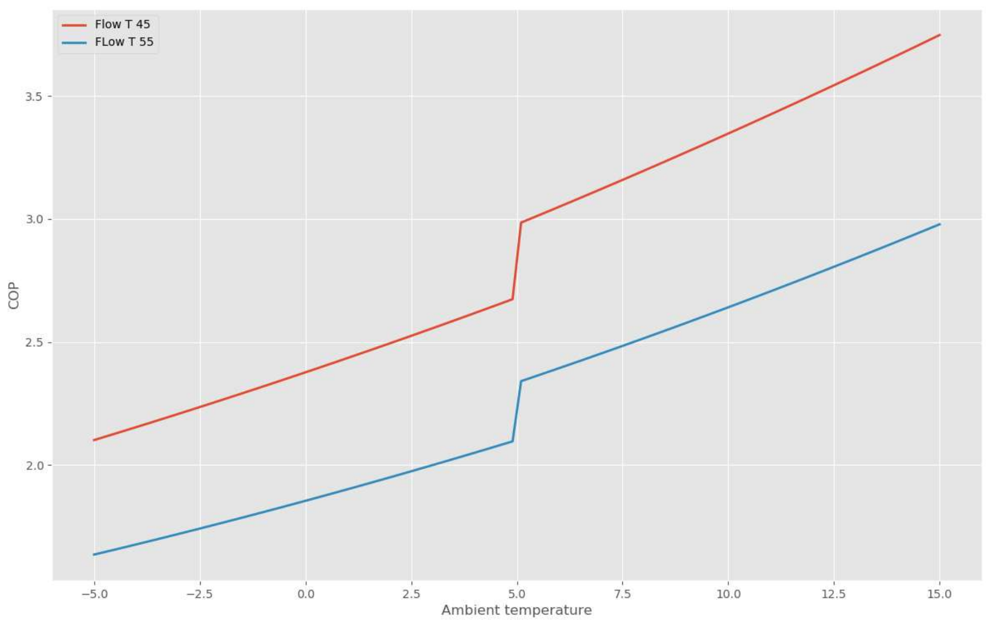


Figure 5.12: Generic ASHP regression model COP variation for a 14kW heat pump

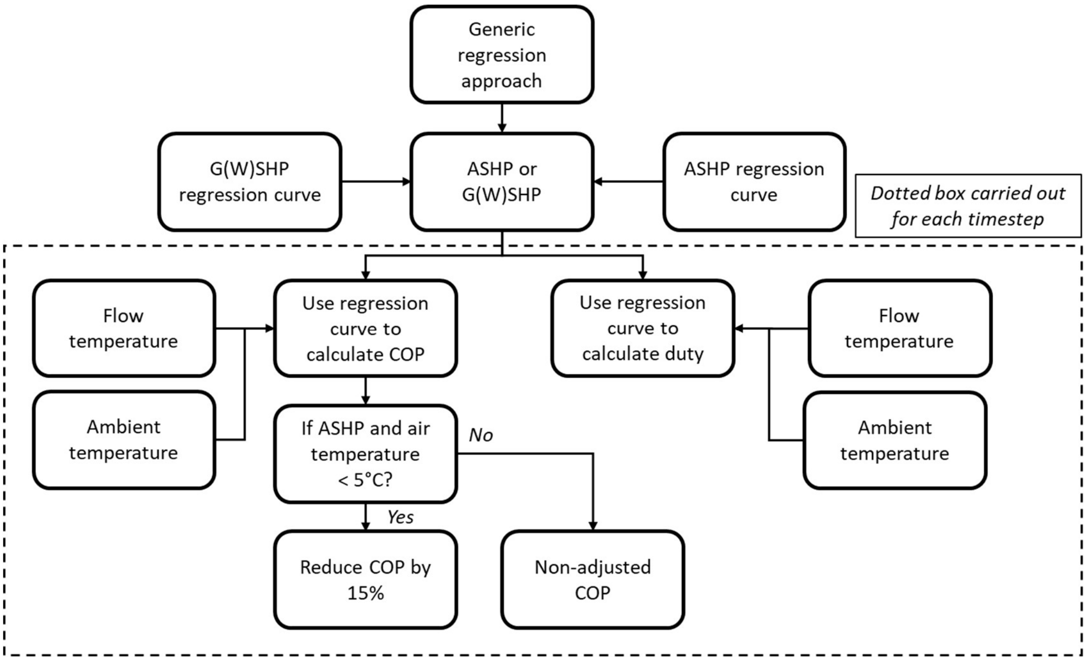


Figure 5.13: Flow diagram of generic regression model

5.3.2. Lorentz Model

The Lorentz approach involves calculating a real COP based upon one set of operating conditions and then calculating the maximum COP, the Lorentz efficiency, under the same operating conditions. The real COP divided by the Lorentz efficiency gives the heat pump efficiency. For each timestep the Lorentz efficiency for the conditions is calculated and then multiplied by the heat pump efficiency to give the modelled COP. The maximum thermal output in a timestep is given by the input maximum electrical capacity multiplied by the modelled COP. This follows the same modelling approach as used in a standard industry modelling tool EnergyPRO (Figure 5.15) and detailed equations can be found in the user manual [228]. This approach is useful with limited data, i.e. COP under a single operating condition, but likely leads to overestimation of COP in other operating conditions.

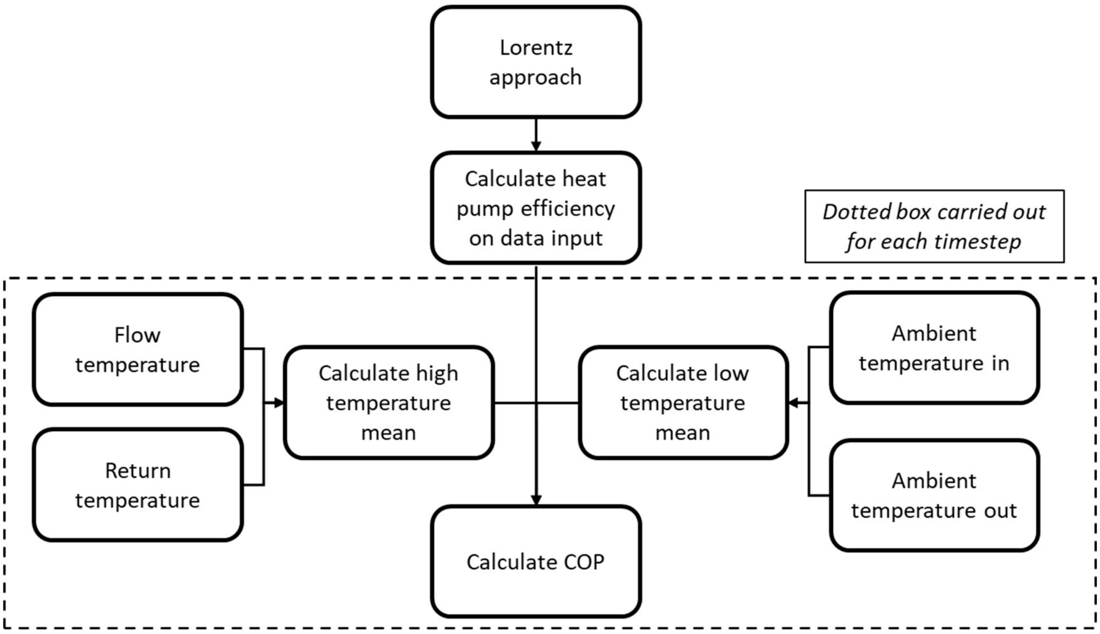


Figure 5.14: Flow diagram of Lorentz model

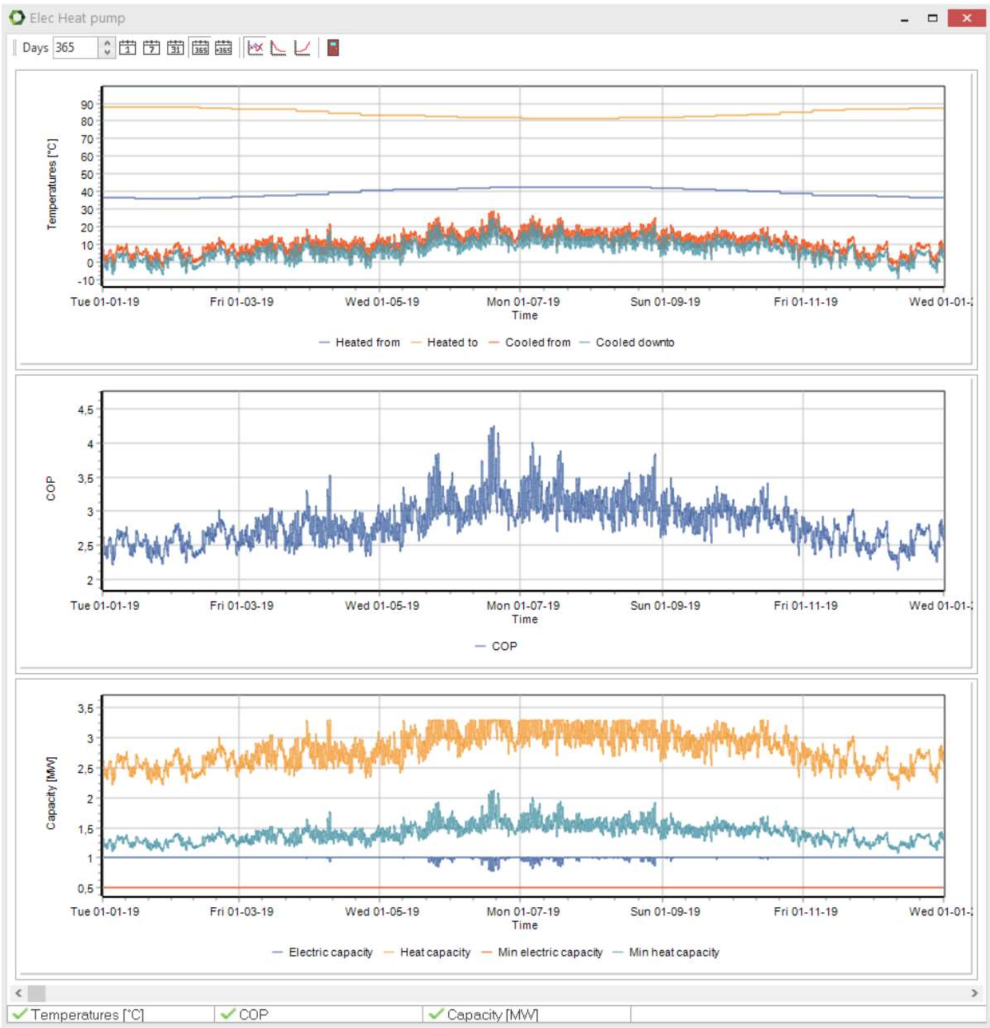


Figure 5.15: Lorentz model output from EnergyPRO [218]

5.3.3. Standard Test Regression Model

The Standard Test Regression Model is based on multiple variable linear regression analysis using measured COP and duty (maximum thermal output) at a range of test conditions. Ambient temperature (T_a) and flow temperature (T_f) are used as the two independent variables. Coefficients for the following 2nd degree polynomial functions for COP and duty are calculated automatically based on the input data. Predictions are made in each of the timesteps using these equations and the flow and ambient temperatures.

$$COP = \alpha_0 + \alpha_1 T_a + \alpha_2 T_f + \alpha_{11} T_a^2 + \alpha_{22} T_f^2 + \alpha_{12} T_a T_f$$

$$duty = \beta_0 + \beta_1 T_a + \beta_2 T_f + \beta_{11} T_a^2 + \beta_{22} T_f^2 + \beta_{12} T_a T_f$$

If the data input is at peak performance, defrost cycling and dynamic effects, such as start up and shut down, are not included in the data. Thus, for ASHPs a 15% reduction in COP to account for defrosting is assumed below 5°C but not included for WSHPs. If the data input is at integrated performance, then cycling behaviour and dynamic effects are included in the testing. This should be the case if measurements are taken under standard test conditions according to EN14511 [229].

This method is the most detailed of the three approaches and should yield realistic heat pump performance across a wider operational range. While the necessary data is not always readily available, using standard test conditions means that manufacturers should possess the necessary data and correspondence could be sought to obtain this data. Part load effects on COP for variable speed heat pumps are neglected in all three modelling approaches. Inclusion of this would be a useful future development.

Validation of the heat pump models is difficult because the models are generated based upon the input data. Therefore, it is up to the user to ensure that the input data is validated and accurately reflects the performance of the heat pump to be modelled. In Chapter 6 the modelling methodology is applied to the case study using the Standard Test Regression Model and the performance of the heat pump will be explored.

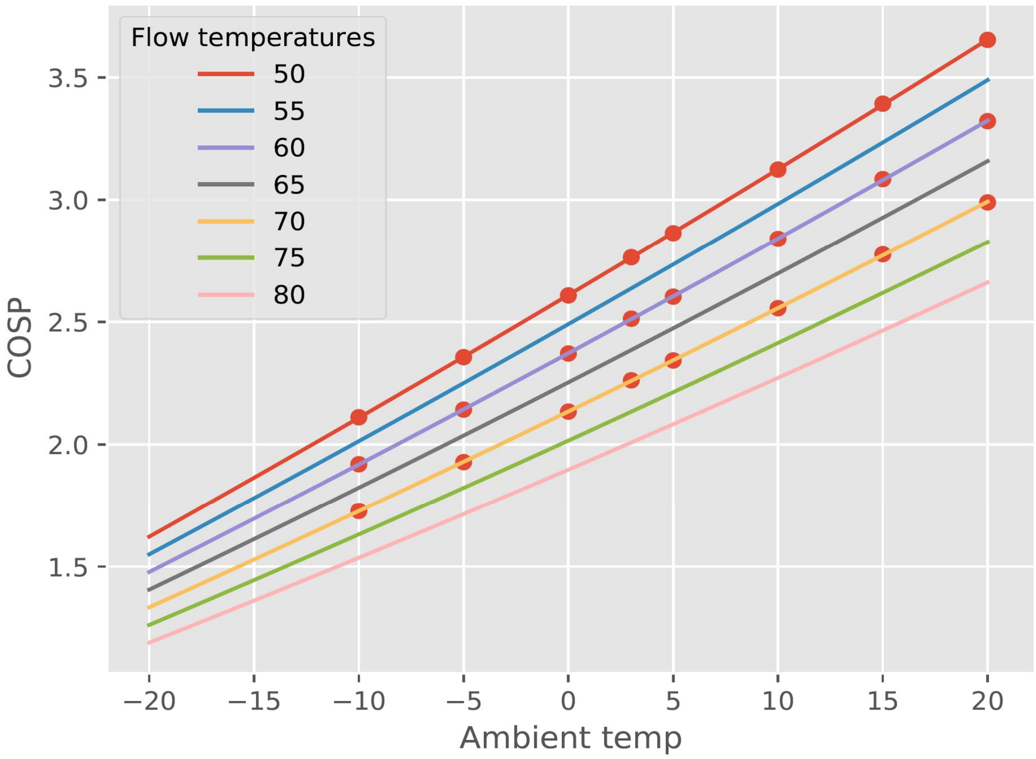


Figure 5.16: Standard test regression model variation of COP

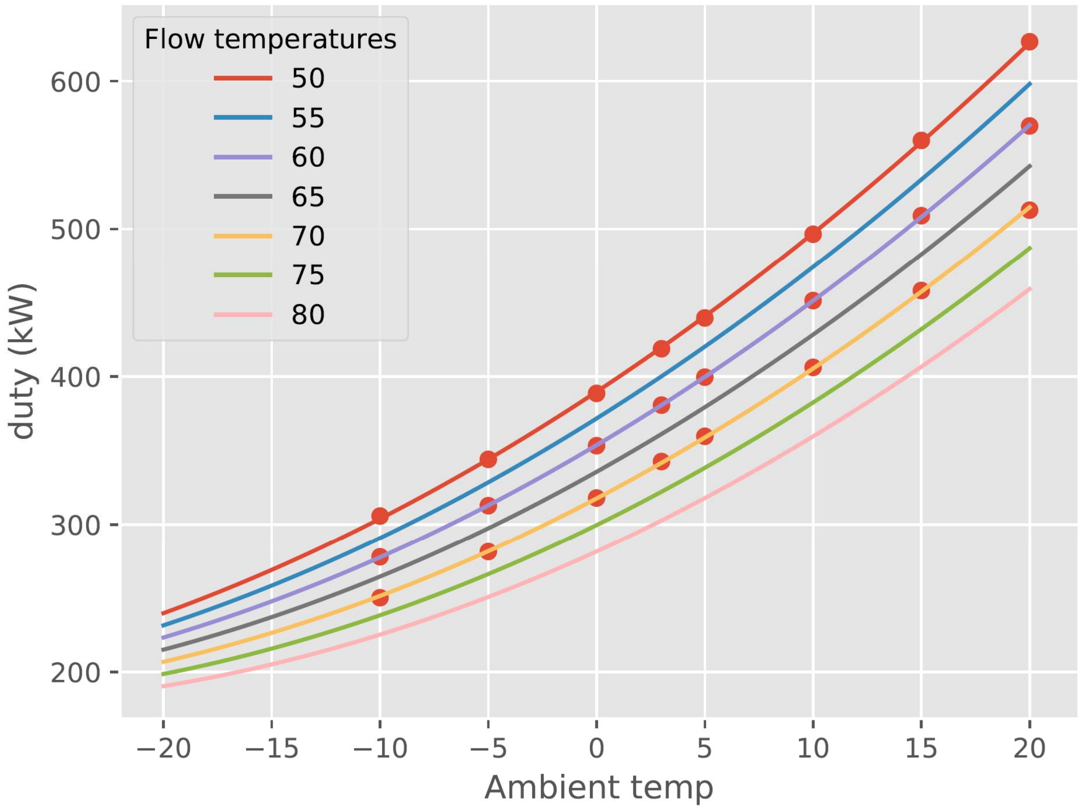


Figure 5.17: Standard test regression model variation of duty (maximum output)

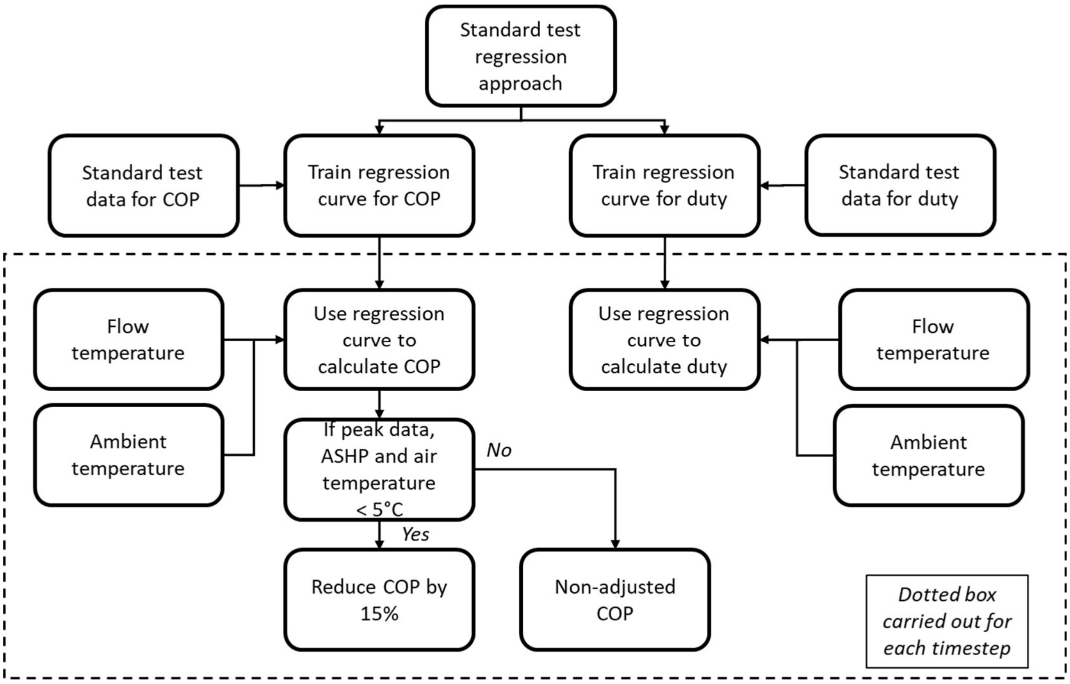


Figure 5.18: Flow diagram of standard test regression model

5.3.4. Auxiliary Heat Units and Schematic of Setup

Heat pumps are not generally used as the sole heating unit and are typically installed alongside auxiliary heat units such as gas boilers and direct electric heaters. In these systems the heat pump is a priority unit and the auxiliary units allow under sizing of the heat pump to reduce capital costs. Additionally, they provide resilience to the heat supply for periods of breakdown or planned maintenance.

Figure 5.19 is a schematic of the connections between the heat pump, electric heater, and thermal store, all connecting to a district heating network.

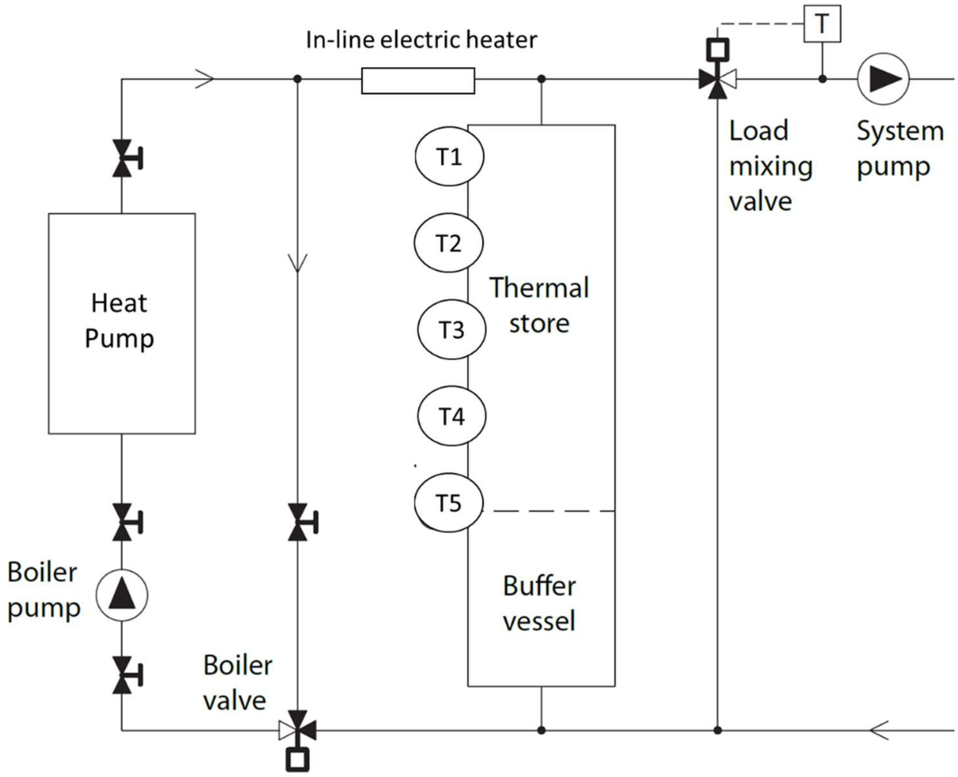


Figure 5.19. Heat pump, thermal store, electric heater, and heat network using a 2-port connection

5.4. Electrical Storage

Storage models for battery storage and hot water tanks are employed to investigate DSM strategies. Electrical storage models have been developed in detail in previous studies and utilised in different tools [83]. The input requirements for the electrical storage model are shown in Figure 5.20.

Electrical storage inputs

capacity	initial state	charge max	discharge max	charge eff	discharge eff	self discharge
0	0	250	250	0.9	0.9	0.01

Figure 5.20: Electrical storage input requirements

In PyLESA a simple battery model is used which captures the essential technical parameters: capacity, initial state, max charging/discharging, efficiency charging/discharging, min/max state of charge, and self-discharge. A schematic of the energy flows is displayed in Figure 5.21.

Given the generic nature of the model, any electrical storage technology, e.g. flow batteries, lithium-ion batteries, lead-acid batteries, which operates on the appropriate timestep can be modelled in a low-detail manner by using simplifying assumptions.

This simplistic model has been included as a starting point for future work on incorporating a more advanced electrical storage model for technologies such as batteries, pumped hydro, flywheels, etc. Therefore, this model has not been validated but given its widespread usage in existing modelling tools, see Section 3.2.5, it is widely accepted within current practice as a model capable for planning-level modelling and is included in PyLESA.

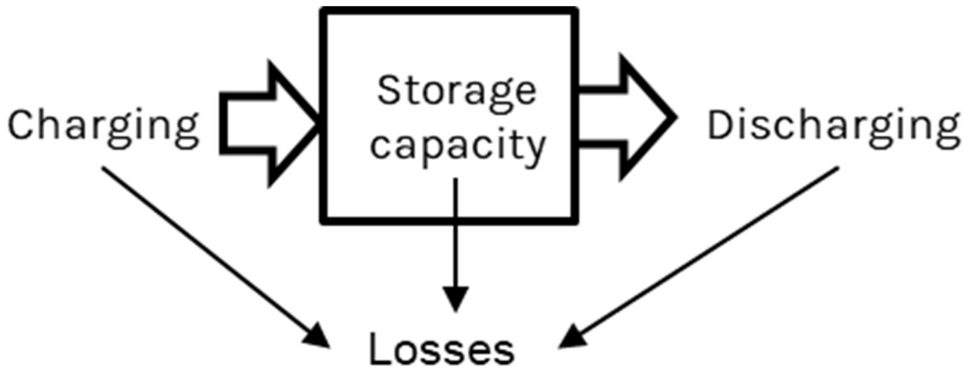


Figure 5.21. Simple battery model schematic

$$Q(t+\Delta t) = \begin{cases} Q(t) + \eta_c Q_c(\Delta T) - Q_s(\Delta T) \; if \; Q_{cm} \geq Q_c \; and \; Q_d = 0 \\ Q(t) - \eta_d Q_d(\Delta T) - Q_s(\Delta T) \; if \; Q_{dm} \geq Q_d \; and \; Q_c = 0 \\ C \; if \; Q(t) + \eta_c Q_c(\Delta T) - Q_s(\Delta T) \geq C \; and \; Q_d = 0 \\ M \; if \; Q(t) - \eta_d Q_d(\Delta T) - Q_s(\Delta T) \leq M \; and \; Q_c = 0 \end{cases}$$

The stored energy Q at the time $t + \Delta t$ can be expressed in the above equation where ΔT is the timestep, η_c is the charging efficiency, η_d is the discharging efficiency, $Q_c(\Delta T)$ is the charging energy, $Q_d(\Delta T)$ is the discharging energy, $Q_s(\Delta T)$ is the self-discharge, Q_{cm} is the max charging rate, Q_{dm} is the max discharging rate, C is the capacity, and M is the minimum state of charge.

5.5. Hot Water Tank

Hot water tanks provide a cheap form of mid-term (from days to minutes) thermal storage, particularly when used at scale for district heating, and in comparison, to battery storage. A contribution is described in this section of the use of a multi-node approach in PyLESA to represent the stratification and to incorporate thermal characteristics through state of charge dependence on node temperatures.

The contributions of this work consist of (i) an extension of the Duffie and Beckman model [230] by the development of an ambient heat loss method, and (ii) Python code implementing the multi-node model which can be utilised in PyLESA and in other planning-level tools.

The approach taken is similar to those implemented in detailed building design simulation such as TRNSYS [231]. This addresses the gap which has been identified in planning-level modelling tools in representing the temperature dependence of hot water tanks. Figure 5.22 shows the PyLESA input requirements for modelling the hot water tank.

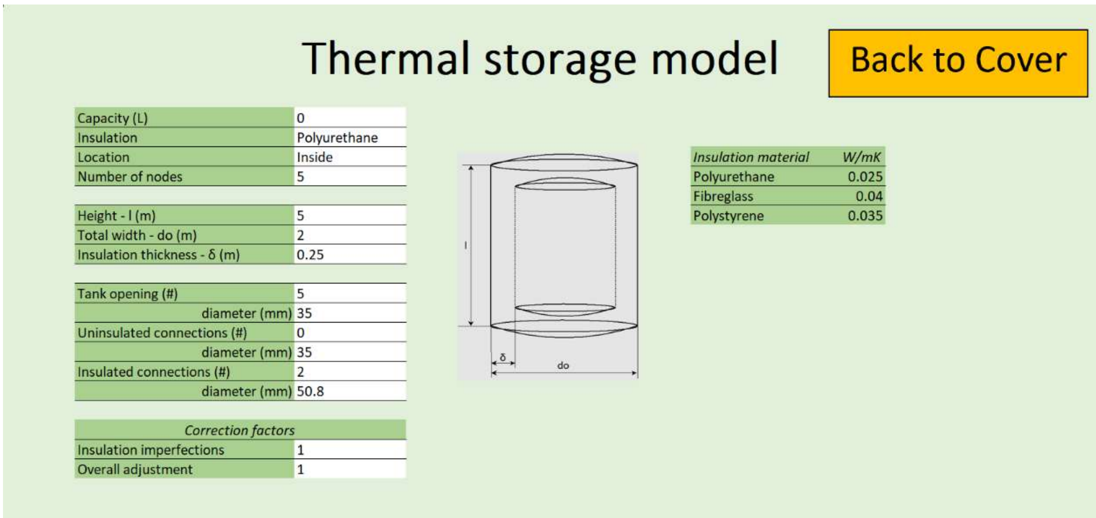


Figure 5.22: Hot water tank modelling input requirements

The hot water tank is modelled as a cylinder which is vertically orientated with an outside shell of insulation. The tank is configured using a 2-port connection and the use of 5 temperature sensors, in accordance with CIBSE guidance [232] for district heating design, see Figure 5.19 for a schematic showing this configuration.

The main characteristics [230] which require capturing in the modelling are:

- Capacity per unit volume

- Temperature range of operation
- Means and power requirements of charging and discharging
- Structural elements of tank
- Control
- Degree of stratification

Physical processes of hot water tanks include: (i) heat losses through tank due to a difference in internal temperature and external ambient temperature, (ii) conduction heat transfer in the water due to temperature differences at different layers, (iii) convective flows due to cooling of water at edge of tank resulting in density differences, (iv) buoyancy induced flows due to load temperature being lower than temperature of layer it is entering at, (v) entering fluid mixing with lower temperature water due to high flow rate (carrying kinetic energy), and (vi) recirculation of water from connections.

A selection process [233] was used to select a model to represent the stratification in the tank, see Figure 5.23. The main selection decisions were to select a suitable model for simulating without data and a balance between accuracy and computational time. The multi-node model was chosen as it fits these criteria. In addition, due to the use of 5 temperature sensors a 5-node model was selected as a default, however, the number of nodes can be changed by the user.

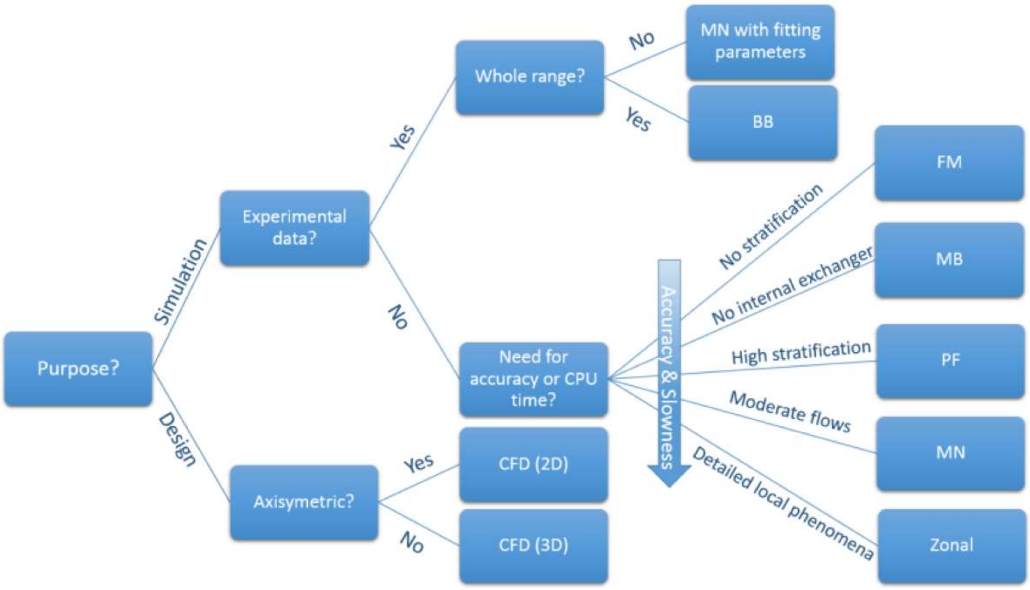


Figure 5.23: Decision tree for modelling stratification of hot water tank

In the multi-node model, the hot water tank is divided into N nodes which are disks of fixed volumes. Each node has energy and mass balance equations which can be used to determine the changes in temperature due to input and output flow. This results in N differential equations which are solved simultaneously to calculate the final node temperatures for each node. Duffie and Beckman's description of a multi-node model provides the basis for the model developed here [230].

Figure 5.24 shows the energy balance for node *i*, including the top and bottom nodes and above and below nodes. The final energy balance equation for each node, denoted *i,* contains four terms which each have an explicit node temperature dependence:

- Ambient heat loss between inside and outside of the tank.
- Charging and discharging.
- Mixing between nodes.

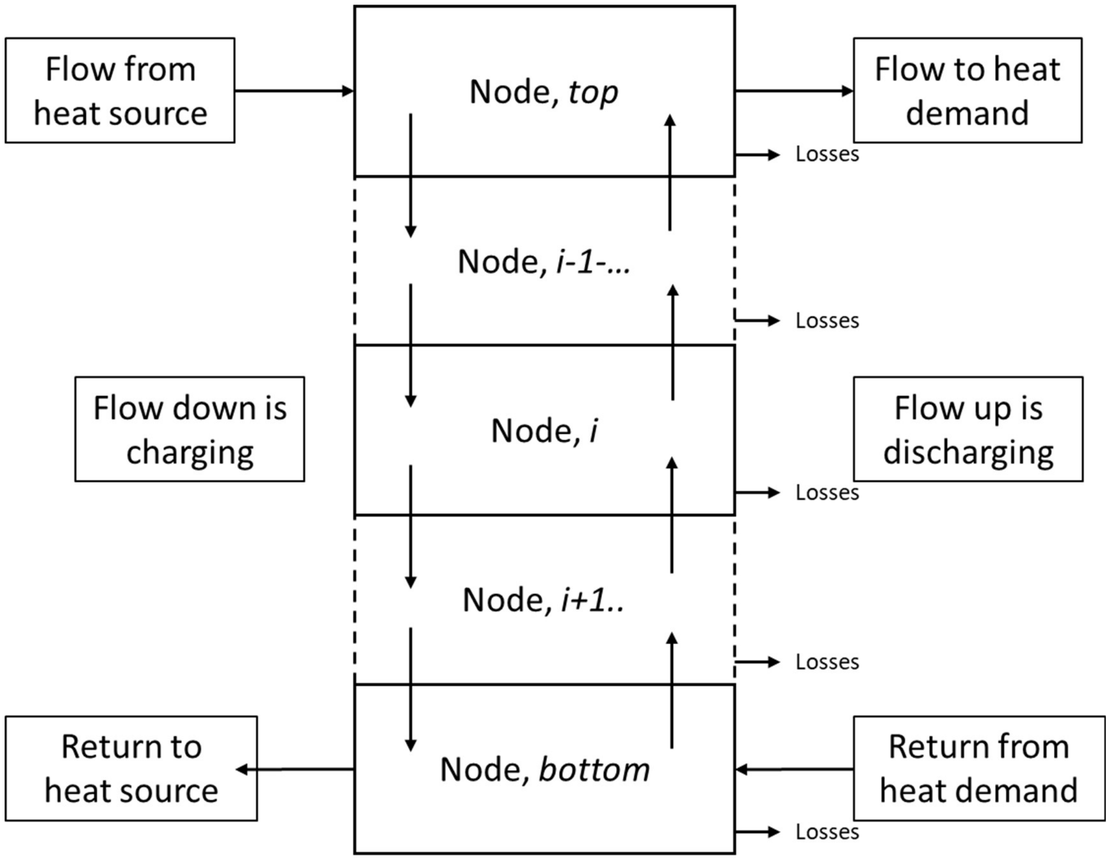


Figure 5.24: Energy balance for node i, including the top, bottom, above, and below nodes

5.5.1. Ambient Heat Loss

The ambient heat loss is applied to each node in the multi-node model, with additional heat loss for the top and bottom nodes. The calculation uses the following steps:

- Calculate ideal conduction losses through the cylinder at the side and the top/bottom, including a correction factor to account for insulation imperfections.
- Estimate losses from openings in insulation, e.g. pipe connections.
- Factor by a user input empirical sensitivity parameter.

Heat losses from a hot water storage tank occurs through the insulation material due to the temperature difference between the water medium inside the tank and the temperature outside the tank. If the tank is located indoors then a 15°C constant room temperature is assumed, and if it is located outside then outdoor air temperature is assumed. Figure 5.25 shows a schematic of the hot water tank to be modelled; a vertical cylinder with an outside shell of insulation. The curvature of the top and bottom surfaces is assumed to be negligible and modelled as flat.

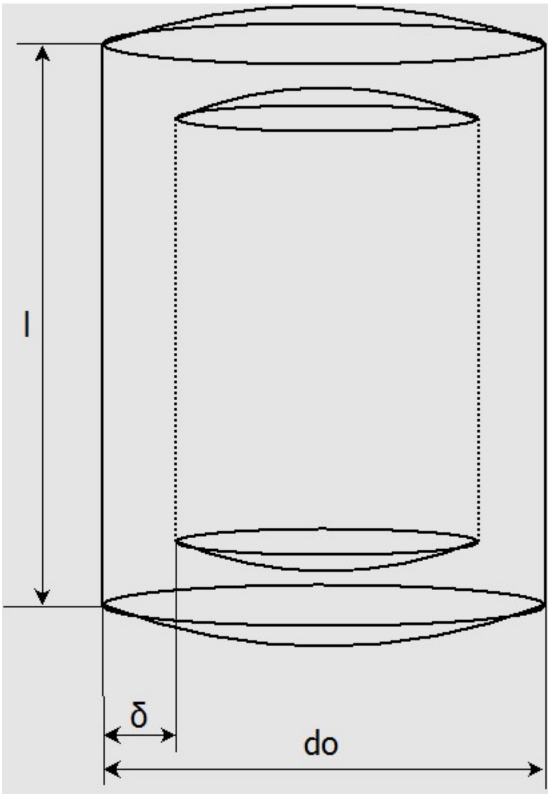


Figure 5.25. Hot water tank schematic to be modelled

The heat loss from the tank can be estimated by assuming the insulation material provides the only significant resistance to heat flow, i.e. neglecting the relatively small convective resistances on the inside and outside tank surface, and the minor conductive resistances provided by the tank wall and the tank cladding. This calculation also assumes the tank is at steady state conditions. The heat losses through the horizontal section and the top and bottom plane wall sections are included in the calculation. The losses at the corners are neglected.

For the horizontal losses, Fourier's law of conduction (the only heat transfer considered) is used to calculate the heat transfer between inside the tank and outside the tank (for cylindrical tank):

$$Q_{cond,cyl} = -kA\frac{dT}{dr}$$

where $A = 2\pi \Delta r L$

integrating both sides…

$$\int_{r_1}^{r_2} \frac{Q_{cond,cyl}}{A} dr = \int_{T_0}^{T_i} kdT$$

$$Q_{cond,cyl} = 2\pi kL \frac{T_i - T_0}{\ln{(r_2/r_1)}}$$

Taylor expansion of the natural log, assuming small $r_2 - r_1$…

$$\ln(r_2/r_1) = \frac{2\Delta r}{r_2 + r_1}$$

$$Q_{cond,cyl} = \pi Lk(r2 + r1)\left[\frac{T_i - T_o}{r2 - r1}\right]$$

where $Q_{cond,cyl}$ is the horizontal heat transfer, k is the thermal conductivity, A is the surface area, L is the height of the cylinder, T_i is the temperature of node i, T_0 is the ambient temperature, r_2 is the total cylinder radius, and r_1 is the internal cylinder radius.

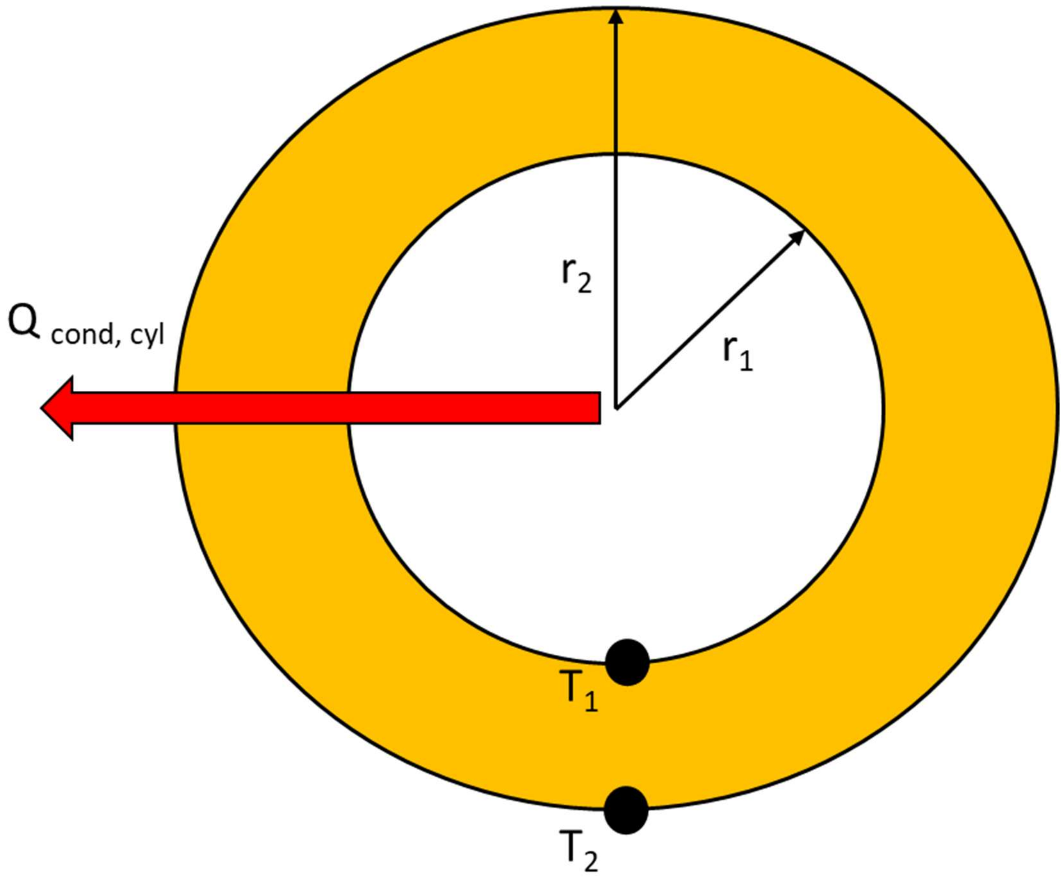


Figure 5.26: Schematic showing horizontal conduction loss from hot water tank through the insulation layer

For the vertical losses from the top and bottom plane walls:

$$Q_{top/bottom} = -kA\frac{dT}{dx}$$

$$Q_{top/bottom} = k\pi {r_1}^2\left[\frac{T_i - T_o}{r2 - r1}\right]$$

Combining the horizontal and vertical heat losses:

$$Q_{cond,cyl} + Q_{top/bottom} = k\pi {r_1}^2 L\left[\frac{T_i - T_o}{r2 - r1}\right](r_2 + r_1)$$

The calculation for this first step then includes a correction factor, F_c, to account for insulation imperfections, such as voids and thermal bridges between the inner tank shell and outer casing (e.g. a stainless-steel ring supporting the inner tank shell on the ground).

$$Q_{Step\ 1} = F_c\ (Q_{cond,cyl} + Q_{top/bottom})$$

Table 5.1: Thermal conductivity of insulation materials

Insulation Material	Thermal conductivity [W/m.K]
Polyurethane	0.025
Fibreglass	0.040
Polystyrene	0.035

Further corrections are made by considering the openings in the insulation such as for pipe connections, valves, thermostats and electric elements.

Table 5.2: Empirical approximations of heat loss due to tank insulation openings

Tank insulation opening	Heat loss increase [kWh/24 h @ ΔT = 55 K]
Tank opening (e.g. thermostat pocket)	$A_{opening}\ \times\ 27$
Uninsulated pipe or fitting (e.g. PTR valve)	$d_{pipe}\ \times\ 5$
Insulated pipe or fitting	$d_{pipe}\ \times 3.5$

Losses from these are added to the previously calculated heat losses to give a final heat loss (divide by 0.024 to convert from kWh/day to W). PTR valve is a pressure relief valve, thermostat pocket is for thermostats (i.e. temperature sensors), and insulated pipe or fitting is where water is taken in and out of the tank.

$$Q_{losses} = Q_{Step\ 1} + connection\ losses$$

The final step is to add an empirical factor, F_e, which can be input by the user who has data on heat loss from the hot water tank to be modelled. This is introduced as hot water tanks have been monitored to have higher heat losses than theoretical models suggest.

$$Q_{losses\ empircal} = Q_{los} \quad * F_e$$

An alternative approach would have been to determine a regression equation based on existing hot water tank data and to determine a lumped heat loss coefficient which encompasses all the theoretical considerations included here. However, this approach would require monitored data. Therefore, it was decided, since the work here focusses on design, that this data may not be available and that a theoretical approach with correction factors was more suitable.

5.5.2. Charging and Discharging

The hot water tank can be in a state of charging, discharging, or standby. These states dictate which of the flows and returns are active to and from the heat source and demand. Flow from the heat source to the tank and flow from the tank to the heat demand are only to or from the top node. Return from the heat demand to the tank and return from the tank to the heat source are only to or from the bottom node. This means that in each modelling timestep the maximum charge/discharge is limited to the volume of one node. To get around this an internal hot water tank timestep is used based on the number of nodes. For example, take a hot water tank with 5 nodes and a volume of 1000L. The maximum charge/discharge in one timestep is a total flow of 200L but there may be situations where the charge/discharge is larger than this. Therefore, for each model timestep (1 hour) the number of internal hot water tank simulation timesteps is the same as the number of nodes. In this example there are 5 nodes, so 5 hot water tank internal timesteps are run for each model timestep in order for the tank to be able to charge/discharge fully in each simulation timestep.

The state of the hot water tank is calculated using the following charging and discharging functions.

$$F_i^c = \begin{cases} 1 & \text{if } i = 1 \text{ and } T_{c,o} > T_{s,1} \\ 1 & \text{if } T_{s,i-1} \geq T_{c,o} > T_{s,i} \\ 0 & \text{if } i = 0 \text{ or if } i = N+1 \\ 0 & \text{otherwise} \end{cases}$$

If the charging function is 1 then the node is charging, and the following charging term is non-zero.

$$Q_{charging} = F_c \dot{m_{in}} c_p T_{in}$$

where F_c is the charging function, m_{in} is the mass flow of charging water into the node *i*, c_p is the specific heat of water, and T_{in} is the temperature of charging water.

Similar equations are used for the discharging term.

$$F_i^L = \begin{cases} 1 & \text{if } i = N \text{ and } T_{L,r} < T_{s,N} \\ 1 & \text{if } T_{s,i-1} \geq T_{L,r} > T_{s,i} \\ 0 & \text{if } i = 0 \text{ or if } i = N+1 \\ 0 & \text{otherwise} \end{cases}$$

$$Q_{dischargin} = -F_d \dot{m_{out}} c_p T_i$$

where F_d is the discharging function, m_{out} is the mass flow of discharging water out of the node *i*, c_p is the specific heat of water, and T_i is the node temperature.

5.5.3. Mixing Between Nodes

The mixing between nodes is dependent on the state of the hot water tank, and therefore the charging and discharging functions from above. The following equations, along with the state of the tank, are used to determine the mixing term.

If the hot water tank is in a state of charging, the direction of mixing between node *i* and the node above is downwards:

$$Q_{mix} = F_c \dot{m_{down}} * c_p * T_{i-1}$$

If the hot water tank is in a state of discharging, the direction of mixing between node *i* and the node above is upwards:

$$Q_{mix} = F_d * -1 * \dot{m}_{up} * c_p * T_i$$

In these equations a negative sign is representative of flow leaving the node *i*.

If the hot water tank is in a state of charging, the direction of mixing between node i and the node below is downwards:

$$Q_{mix} = F_c * -1 * \dot{m_{down}} * c_p * T_i$$

If the hot water tank is in a state of discharging, the direction of mixing between node i and the node below is upwards:

$$Q_{mix} = F_d \dot{m}_{up} * c_p * T_{i+1}$$

5.5.4. Final Energy Balance Equation

The final energy balance equation for a node, denoted i, contains the four terms which are described above and can be written as:

$$\left(m_i c_p\right)\frac{dT_i}{dt} = F_c \dot{m}_{in} c_p T_{in} - F_d \dot{m}_{out} c_p T_i + \dot{m}_{down} c_p T_{i-1} - \dot{m}_{up} c_p T_i - \dot{m}_{down} c_p T_i$$
$$+ \dot{m}_{up} c_p T_{i+1} - F_e \left[F_c k \left[\frac{T_i - T_o}{r_2 - r_1}\right] \pi[{r_1}^2 + h(r_2 + r_1)] + c.l.\right] \left(m_i c_p\right)$$

This equation can be written in a simpler format using coefficients:

$$\frac{dT_i}{dt} = AT_i + BT_{i-1} + CT_{i+1} + D$$

where the coefficients are:

$$A * \left(m_i c_p\right) = -F_d \dot{m}_{out} c_p - \dot{m}_{up} c_p - \dot{m}_{down} c_p$$
$$- F_e\, F_c k \left[\frac{T_i}{r_2 - r_1}\right] \pi[{r_1}^2 + h * (r_2 + r_1)] \left(m_i c_p\right)$$

$$B * \left(m_i c_p\right) = \dot{m}_{down} c_p$$

$$C * \left(m_i c_p\right) = \dot{m}_{up} c_p$$

$$D * \left(m_i c_p\right) = F_c \dot{m}_{in} c_p T_{in} + F_e F_c k \left[\frac{T_o}{r_2 - r_1}\right] \pi[{r_1}^2 + h(r_2 + r_1)]\left(m_i c_p\right)$$
$$+ F_e c.l.\left(m_i c_p\right)$$

Each node can be written in this form which together are a set of N first-order ordinary differential equations. These are solved simultaneously using the *odeint* function from the SciPy software package which is commonly used to solve a system of ordinary differential equations [234].

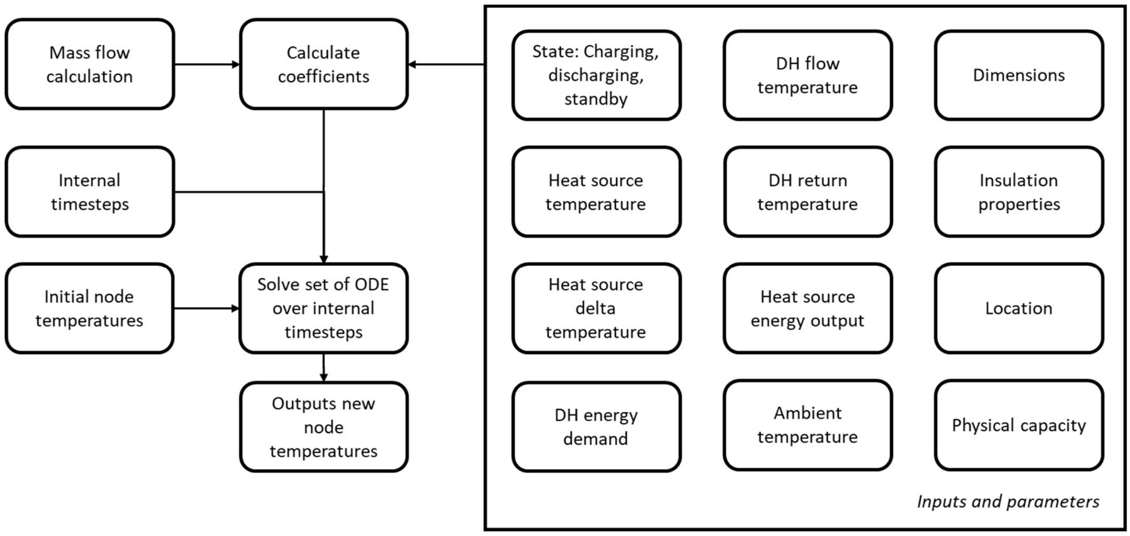


Figure 5.27: Flow diagram for hot water tank model

5.5.5. Validation

The developed multi-node model was validated by comparison between modelled output and monitored data collected from a biomass and hot water tank district heating system at West Whitlawburn (see description in Section 6.2). A 10-hour charging period, a 3-hour discharging period, and a two-day period of operation are analysed by interpreting the difference in node temperature evolutions between the model output and the data. 6 nodes were used in the model to directly compare to the 6 temperature points available from the monitored data, and 15-minute timesteps were used in both the modelling output and monitored data. The analysis is undertaken both graphically, with explanation of differences, and statistically, through calculation of the absolute error and the mean absolute percentage error. While graphically the evolution of the node temperatures looks different for the modelled output and the monitored data, the statistical analysis shows that there is a small absolute percentage error for each node and on average across all nodes. This validation section ends with a comparison of the outputs from the multi-node model and a simple energetic model.

5.5.5.1. Charging Period (10-hour)

Figure 5.28 shows the evolution of the node temperatures over a 10-hour charging period for the modelled output and monitored data. The model output shows in the first timestep the top node charging, along with increases in the temperatures of the nodes below the top node, due to mixing from the nodes above. In subsequent timesteps all nodes are

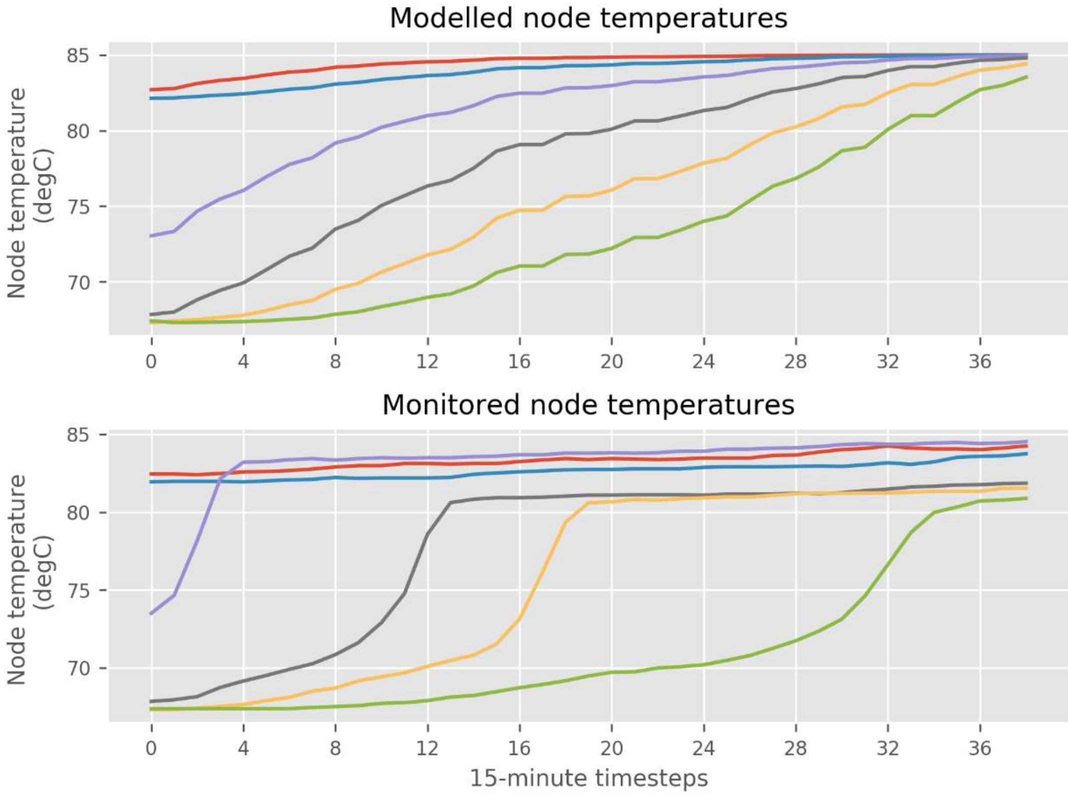


Figure 5.28: 10-hour charging period showing modelled and monitored node temperatures. Four 15-minute timesteps is one hour.

charged and, additionally, increase in temperature due to mixing from the nodes above. The monitored data displays a node temperature evolution with short periods of each node increasing in temperature from low to high.

Comparison of the two shows that the time taken to charge the hot water tank is similar in both the data and model. It also indicates the thermocline is smaller for the real tank than is modelled, meaning there is greater stratification in the real tank. This is caused by the mixing between the nodes in the model, an effect which is increased with low flow relative to node volume. The use of the internal timesteps for the hot water tank reduces the flow in each computational step and further increases the mixing between the fixed volume nodes. It is possible to capture greater stratification by using a larger number of nodes relative to flow rates. However, this results in slower computational time. Alternatively, a moving boundary model, which uses two variable mass nodes, could be a more computationally efficient approach for modelling perfect stratification.

The absolute error on the node temperatures for the modelled hot water tank is shown over the charging period in Figure 5.29. The absolute error briefly exceeds 6°C for the 3rd and 6th nodes (purple and green on graphs), and these nodes are discussed below.

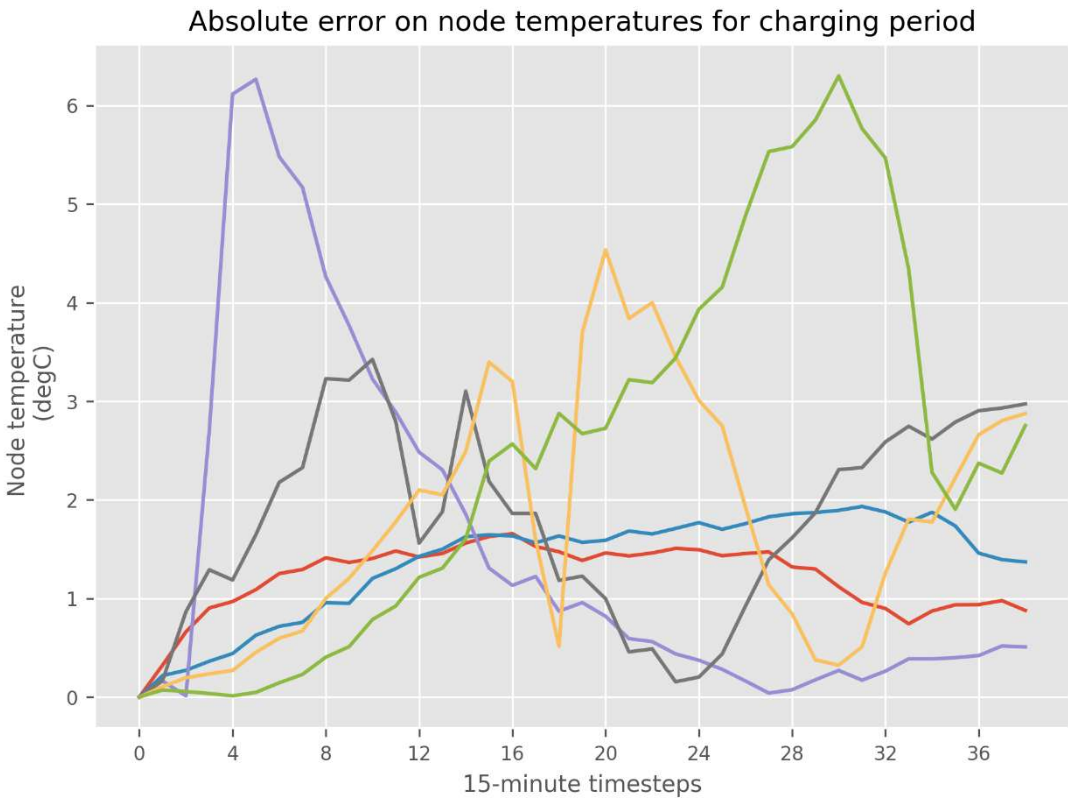


Figure 5.29: Absolute error on node temperatures for 10-hour charging period. Four 15-minute timesteps is one hour.

For the 3rd node the monitored data shows the thermocline pass at the 4th timestep, and after this the temperature exceeds the nodes above. This could be due to uncertainty around the exact position of the inlet, which in the real tank could be closer to the third node than the top node. There could also be dynamic turbulent effects near the top of the tank which cause this temperature inversion. The multi-node model assumes that the inlet is to the top node and does not include turbulent effects.

For the 6th node the real tank shows slight increase in temperature until a sharper gradient around the 30th timestep. This indicates low mixing from the nodes charging above, and the movement of the thermocline through the node around the sharp temperature gradient. The model shows a more consistent temperature gradient slope and does not capture the sharp temperature gradient caused by the thermocline. As discussed earlier, this is due to the low flow and number of nodes modelled causing greater mixing between the nodes over the charging period.

The mean absolute error and mean absolute percentage error were calculated for each node over the charging period. The average of the mean absolute percentage error across the nodes is 2.2% and this is in agreement with a similar multi-node tank model which was validated against experimental data [235]. Additionally, due to the reasons discussed above relating to greater node mixing in the model output, the bottom node has the largest margin of error. An average across the nodes of a mean absolute percentage error of 2.2% indicates that the model is suitable to represent the charging period of a hot water tank.

Table 5.3: Statistical analysis of example charging period

Statistical Measure	1	2	3	4	5	6	Average
Mean absolute error (°C)	1.2	1.4	1.5	1.8	1.8	2.5	1.7
Mean absolute percentage error (%)	1.5	1.6	1.8	2.3	2.3	3.4	2.2

5.5.5.2. *Discharging Period (3-hour)*

Figure 5.30 shows the evolution of the node temperatures over the discharging period for the modelled output and monitored data. The model output shows the node temperatures decreasing as the hot water tank meets a heat demand. The lower nodes decrease temperature first, while the above nodes decrease in temperature due to mixing from the nodes below. The hot water tank stops discharging when the top node drops below the service temperature of the district heating network.

The monitored data displays a node temperature evolution where each node consistently reduces in temperature, and short periods where there is a more rapid decrease in temperature from low to high as the thermocline moves within the tank. The tank is emptied when the top node decreases to the service temperature (in this example this is 72°C).

Comparison between the model and data shows that the time taken to charge the hot water tank is similar in both the data and model. However, it shows the thermocline is smaller for the real tank than is modelled, meaning there is greater stratification in the real tank. This effect appears to be less pronounced for the discharging period compared to the charging period analysed above.

The end of the discharging scenario has ending node temperatures in a range between the return temperature and the service temperature. There will be scenarios where nodes are charged above the return temperature but below the service temperature. In these scenarios the charging is not wasted because in subsequent periods less charging is required from the heat source to charge the hot water tank to a stage where some nodes are above the service temperature.

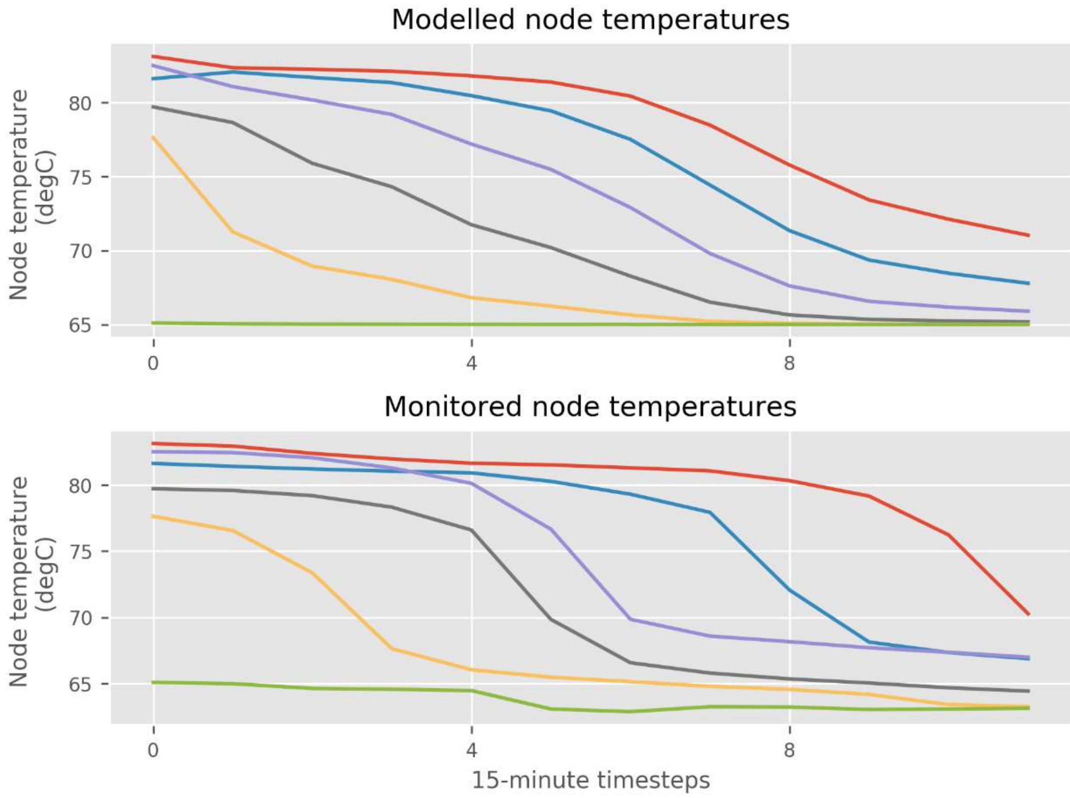


Figure 5.30: Discharging period showing modelled and monitored node temperatures. Four 15-minute timesteps is one hour.

The absolute error on the node temperatures for the modelled hot water tank is shown over the charging period in Figure 5.31. The absolute error briefly exceeds 5°C for the 1st and 4th nodes (red and yellow on graphs). The 1st node mixes with other nodes earlier in the multi-node model than the real tank data, and as a result towards the end of the discharging period is below the real tank node temperature. The 4th node discharges more quickly in the model than in the real tank.

The mean absolute error and mean absolute percentage error were calculated for each node over the discharging period. The average of the mean absolute error across the nodes is 1.4°C and this is, as with the charging period, in broad agreement with a similar multi-node tank model which was validated against experimental data [235]. An average across the nodes of a mean absolute percentage error of 1.9% indicates that the model is suitable to represent the discharging period of a hot water tank.

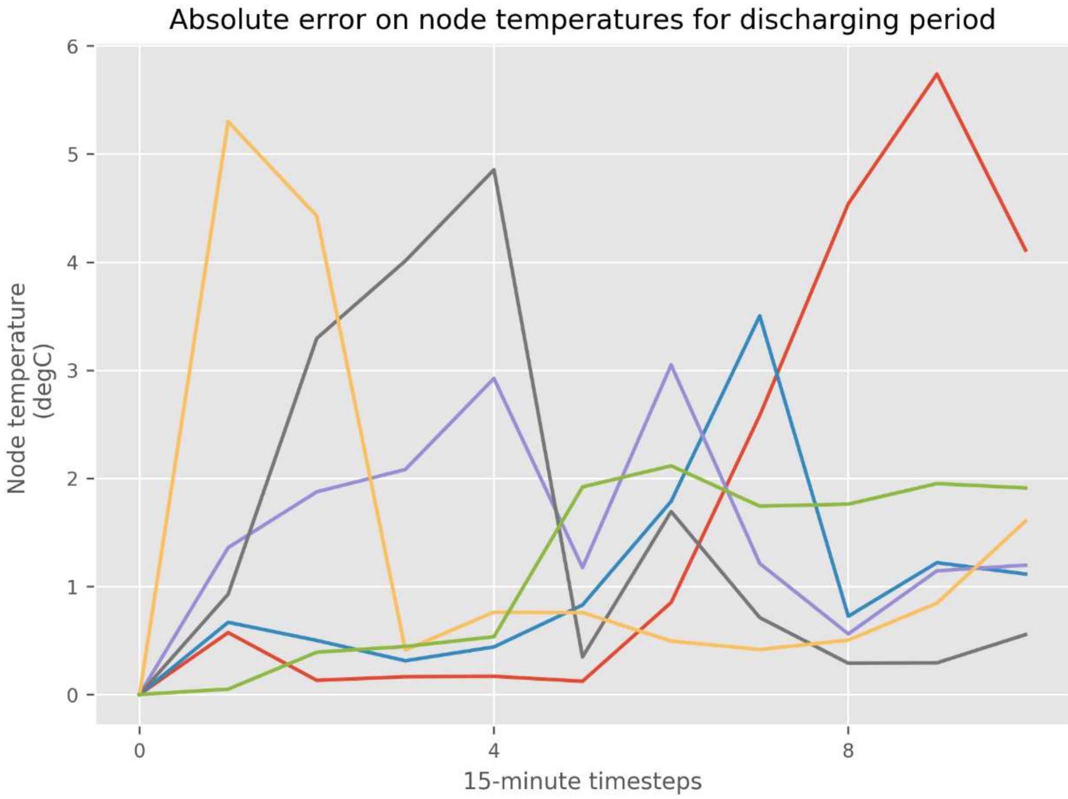


Figure 5.31: Absolute error on node temperatures for discharging period. Four 15-minute timesteps is one hour.

Table 5.4: Statistical analysis of example discharging period

Statistical Measure	1	2	3	4	5	6	Average
Mean absolute error (°C)	1.6	1.0	1.5	1.5	1.4	1.2	1.4
Mean absolute percentage error (%)	2.1	1.3	2.0	2.0	2.1	2.0	1.9

5.5.5.3. *Two-Day Period*

An example two-day period is analysed in order to investigate the ability of the model to respond to both charging and discharging period, and to carry out statistical analysis over a longer time period.

Figure 5.32 shows the evolution of the node temperatures over the two-day period for the modelled output and monitored data. The model output shows the node temperatures increasing and decreasing over the period as the hot water tank is charged and discharged, and the monitored data shows similar patterns.

Figure 5.33 shows the absolute error, and there are periods with an absolute error higher than that identified in the charging and discharging periods. This can be due to

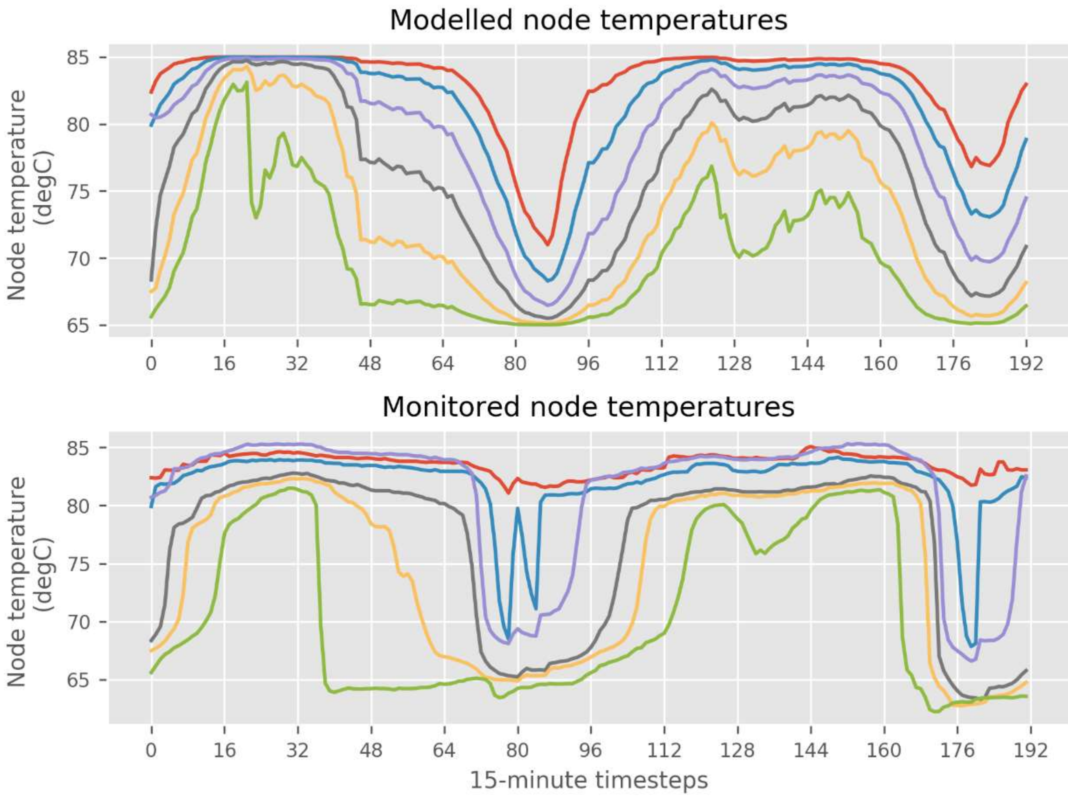


Figure 5.32: Two-day period with charging and discharging periods showing modelled and monitored node temperatures. Sixteen 15-minute timesteps is four hours.

reliability of the data. For example, the 2nd node shows the highest absolute error over the period, and this is due to a charging event which occurs in the real tank data, as seen by the increase of temperature of the 2nd node. However, this does not correlate with the data on the output from the heat source and the demand of the district heating network, which indicates that there is missing or wrong data, or that there are dynamics between the measured points which is not captured. Additionally, the error is also due to not fully capturing the stratification, as was identified in analysis of the charging and discharging periods earlier.

The mean absolute error and mean absolute percentage error were calculated for each node over the charging period. The average of the mean absolute error across the nodes is 2.5°C, and an average across the nodes of a mean absolute percentage error of 3.2%. The maximum absolute values over the 2-day period exceed 12°C which indicates that the model is not suitable for precise tracking of the node temperatures. However, the average error over the period is still low which indicates that while the model does not provide accurate snapshots of the tank node temperature it is capturing the consecutive charging and discharging events over this two-day period. The statistical analysis for the charging, discharging, and two-day period indicates that the model is suitable to represent the consecutive charging and discharging events, over multi-day periods, characteristic of a hot water tank in a district heating system.

Table 5.5: Statistical analysis of example 2-day period

Statistical Measure	1	2	3	4	5	6	Average
Mean absolute error (°C)	1.6	2.2	2.7	2.4	2.8	3.4	2.5
Mean absolute percentage error (%)	1.9	2.7	3.3	3.2	3.7	4.6	3.2

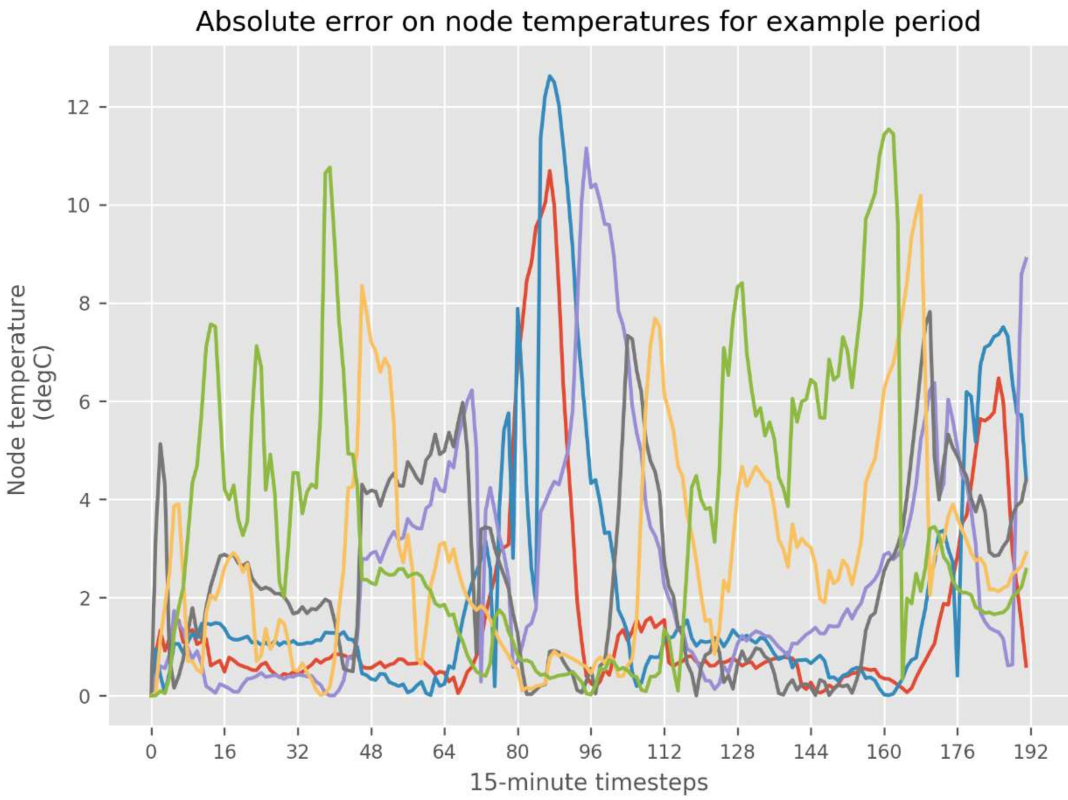


Figure 5.33: Absolute error on node temperatures for two-day period. Sixteen 15-minute timesteps is four hours.

5.5.5.4. Comparison to Energetic Model

The developed multi-node model was also compared to a simple energetic model which is typically used by planning-level energy system tools similar to PyLESA.

Figure 5.34 shows the calculated available discharging capacity output by both the multi-node model and energetic model over the same two-day period examined in the previous sub-section. The available discharging capacity is calculated using the multi-node model based upon node temperatures in each timestep, while the energetic model either adds or subtracts the charging or discharging energy below a maximum capacity. The available discharging capacity calculated using the multi-node model at the beginning of the evaluated period is used as the starting value for the energetic model.

The energetic model predicts both higher charging and discharging compared to the multi-node model. This can be seen by an increase in the difference between the available discharging capacity over the two-day period. At the end of this period the energetic model predicts the available discharging capacity is 277kWh (+35%) greater than the multi-node model.

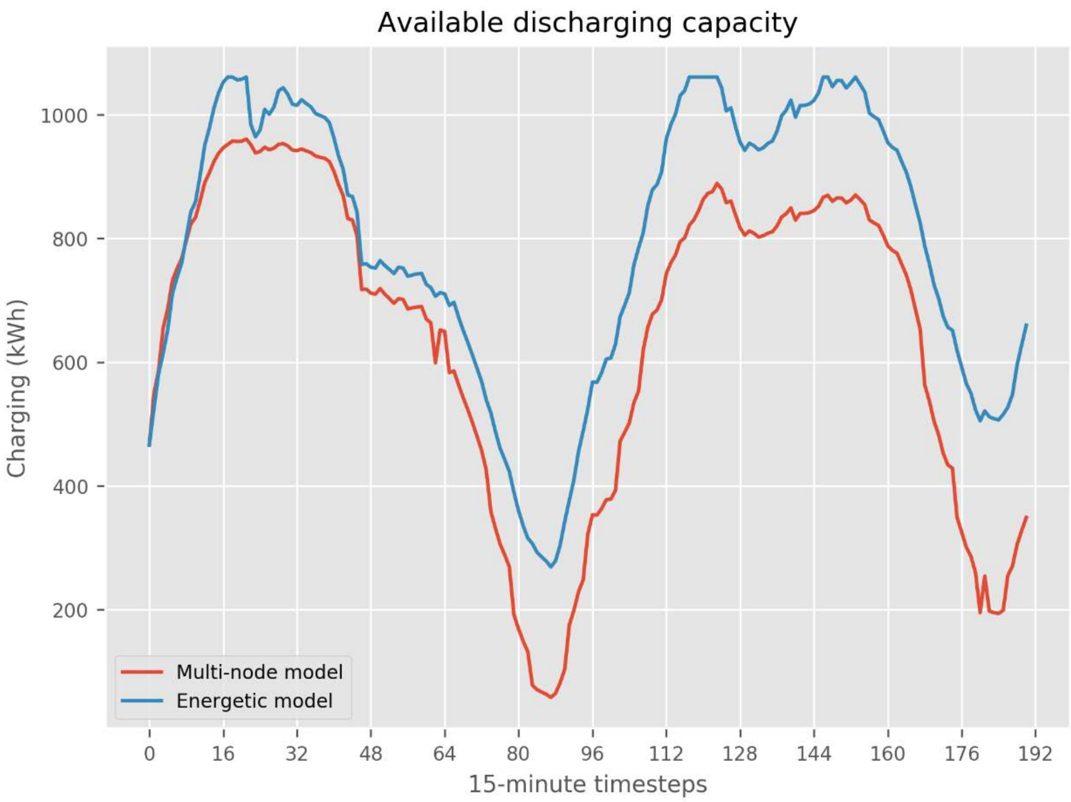


Figure 5.34: Comparison of output from multi-node model and energetic model. Sixteen 15-minute timesteps is four hours.

In conclusion, this work shows the strengths and weaknesses of a multi-node model and its importance in planning-level modelling tools in order to justify its inclusion in PyLESA. The multi-node model is an approach which attempts to capture the thermal characteristics of a hot water tank in order to capture the available state of charge more realistically than the commonly used energetic model. Other models of hot water tank may be included in PyLESA and these may more accurately capture the evolution of node temperatures. However, it is key that balance is struck between accuracy and the need for simple inputs along with low computational times. In future work and outside the scope of this thesis, thermal storage modelling may benefit from standardised system performance testing across a range of thermal storage technologies and their applications which would enable standard modelling methods to be established.

5.6. Electricity Tariffs

Existing and future tariffs can be generated and modelled in PyLESA. A contribution to the state of the art is made by including a future wind-based electricity tariff generator in PyLESA. This allows PyLESA to perform analysis of future energy system scenarios which may include electricity pricing structures which are highly differential and based on renewable power generation. This differs to existing tariffs which are priced according to demand and inflexible baseload generation, amongst other complex factors.

The input requirements for these are in Figure 5.35, Figure 5.36, and Figure 5.37, and the modelling details are described below. Figure 5.38 is an example of the inputs required for future work to be done by including the balancing mechanism and grid services.

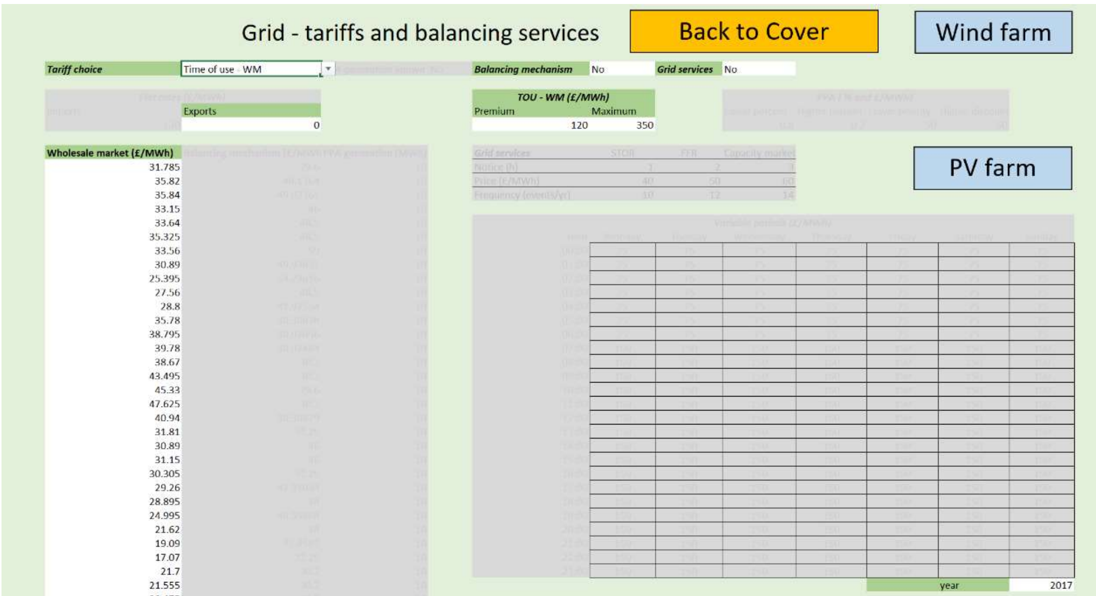
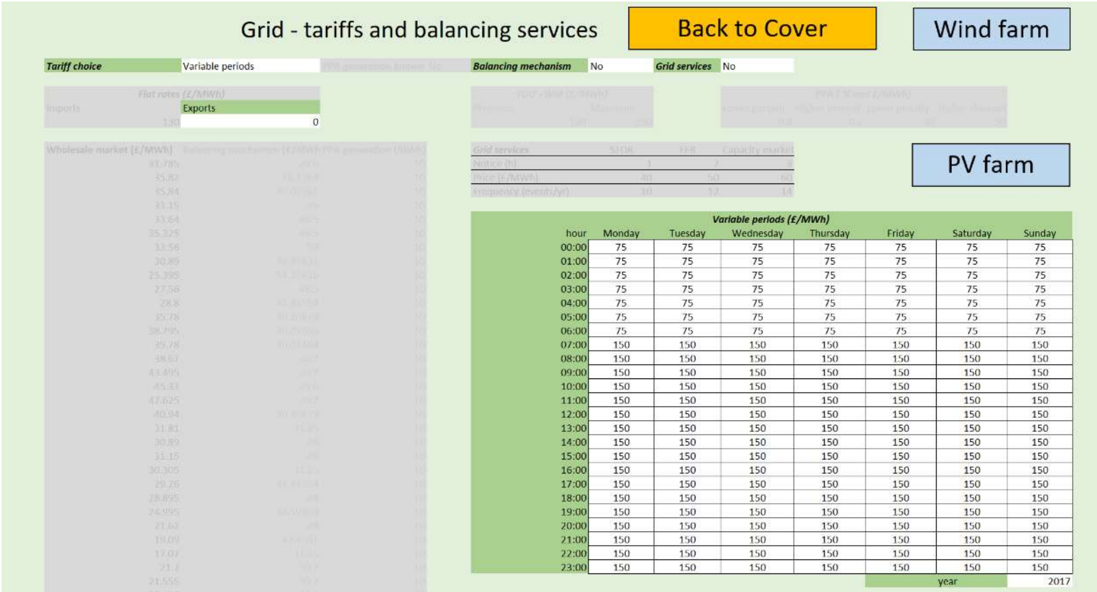


Figure 5.35: Input requirements for time-of-use tariff linked to wholesale market



hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
00:00	75	75	75	75	75	75	75
01:00	75	75	75	75	75	75	75
02:00	75	75	75	75	75	75	75
03:00	75	75	75	75	75	75	75
04:00	75	75	75	75	75	75	75
05:00	75	75	75	75	75	75	75
06:00	75	75	75	75	75	75	75
07:00	150	150	150	150	150	150	150
08:00	150	150	150	150	150	150	150
09:00	150	150	150	150	150	150	150
10:00	150	150	150	150	150	150	150
11:00	150	150	150	150	150	150	150
12:00	150	150	150	150	150	150	150
13:00	150	150	150	150	150	150	150
14:00	150	150	150	150	150	150	150
15:00	150	150	150	150	150	150	150
16:00	150	150	150	150	150	150	150
17:00	150	150	150	150	150	150	150
18:00	150	150	150	150	150	150	150
19:00	150	150	150	150	150	150	150
20:00	150	150	150	150	150	150	150
21:00	150	150	150	150	150	150	150
22:00	150	150	150	150	150	150	150
23:00	150	150	150	150	150	150	150

Figure 5.36: Input requirements for variable periods tariff

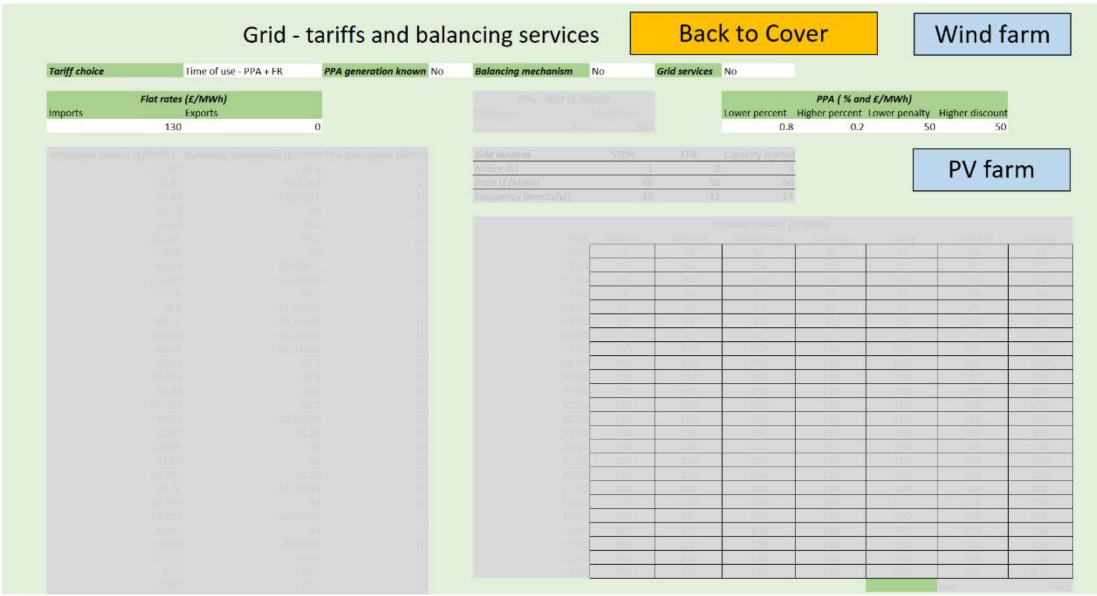


Figure 5.37: Input requirements for a future wind-based tariff coupled with a flat rate base

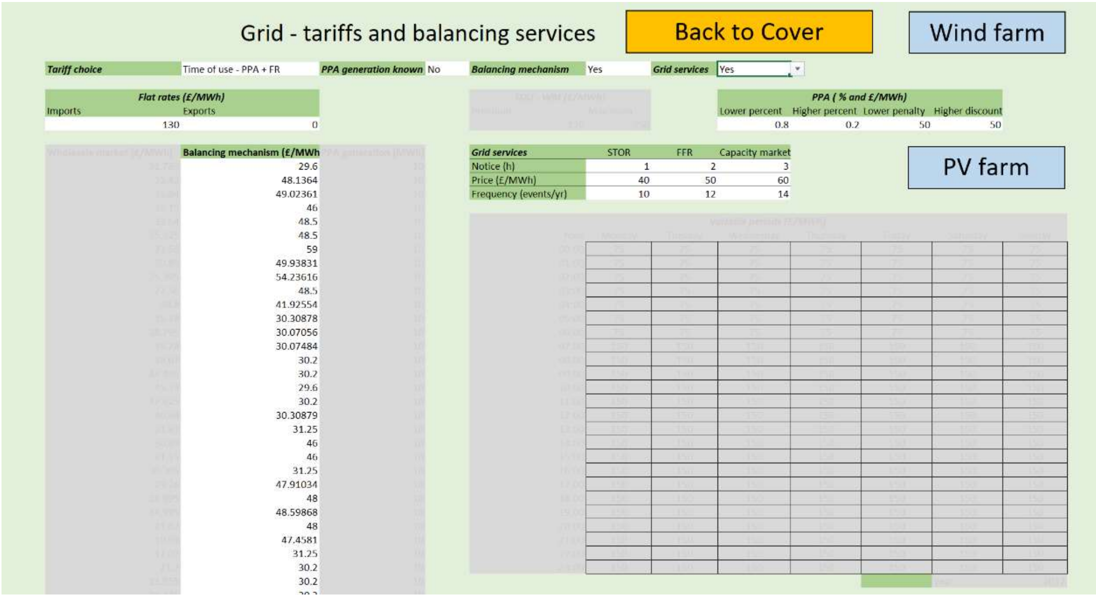


Figure 5.38: Example of future work to be done by including balancing mechanism and grid services

5.6.1. Existing

Traditionally, domestic electricity tariffs available from energy suppliers in the UK have been flat rate tariffs where a price is agreed which is static regardless of when electricity is used or variable periods tariffs, such as economy 7 where a cheaper electricity price is available for 7 hours during the night. A newer form of tariff is time-of-use where electricity prices fluctuate hourly (or sub-hourly) and are linked to the wholesale market. This encourages users to shift demand from peak periods.

Table 5.6: Existing electricity tariff descriptors and examples

Tariff	Description	Pricing structure example
Flat rates	Fixed price	£130/MWh – All times
Variable periods	Variable hourly with a fixed structure, e.g. day/night, weekday/weekend	£150/MWh – Day £75/MWh - Night
Time-of-use	Variable hourly, or sub-hourly, e.g. linked to wholesale market	Linked to wholesale market, premium pricing period between 4pm and 7pm, maximum set to £350/MWh

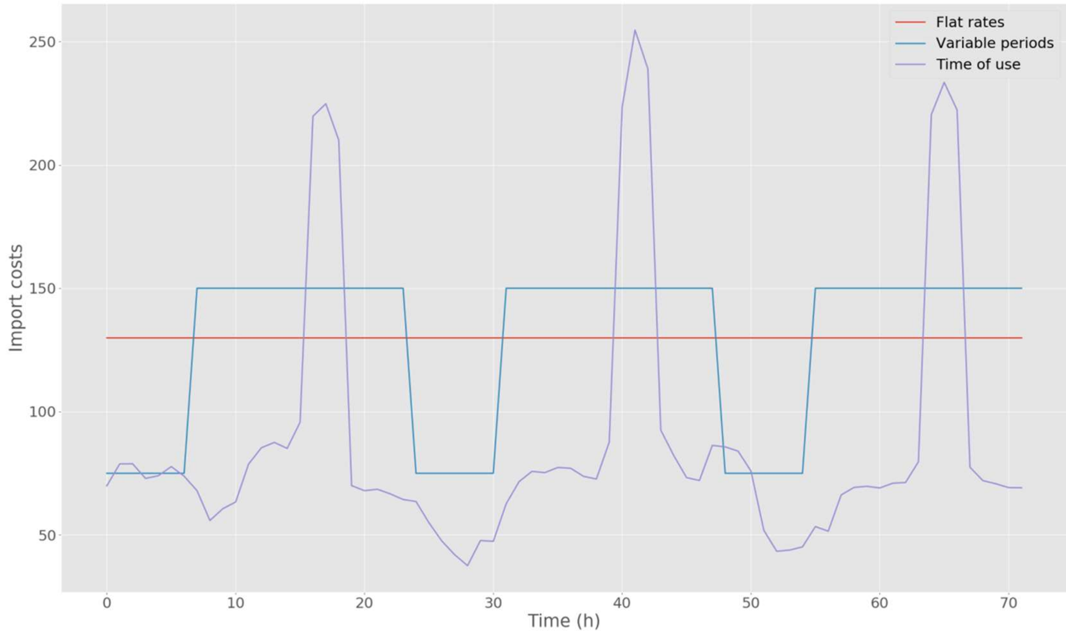


Figure 5.39: Existing electricity tariffs over 72 hours

5.6.2. Future

In the future electricity grids are expected to be highly dependent on stochastic renewable energy sources. Electricity prices could be affected by this with decreases during periods where there are abundant zero-marginal cost renewable electricity and increases during periods of low renewable electricity and there is increased reliance on power from dispatchable sources.

Possible future renewable tariff synthesis can be supported in PyLESA. For example, a future tariff could be synthesised in PyLESA using the following method. Firstly, an existing tariff is chosen as a base: (i) a continuously fixed tariff, (ii) low demand coupled with inflexible generation (such as nuclear) causing low price periods during the night, or (iii) a flexible tariff based on avoidance of peak late afternoon demands. Then, a wind farm output is modelled using the same method for the on-site wind power generation described previously, and the resultant hourly power output is separated into top and bottom bands of production. A discount is applied to the base tariff where wind power output is in the top band of production and a premium applied where it is in the bottom band. The wind bands, and the discount, and premium to be applied to the base tariff are defined by the user. Figure 5.40 shows PyLESA synthesised tariffs with the wind generation discount and premium applied to each of the three base cases. The functionality in PyLESA allows other future tariff scenarios to be generated and investigated in the modelling of future scenarios.

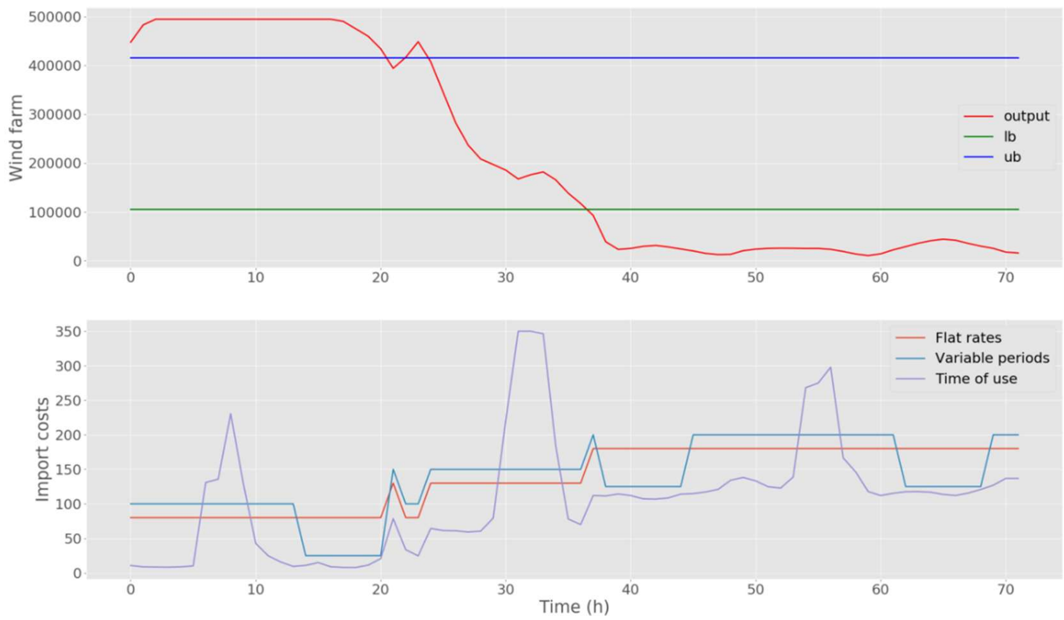


Figure 5.40: Top graph: wind farm modelled output including upper band and lower band over 72 hours; Bottom graph: renewable electricity tariff with discounts and premiums applied over the same 72 hours

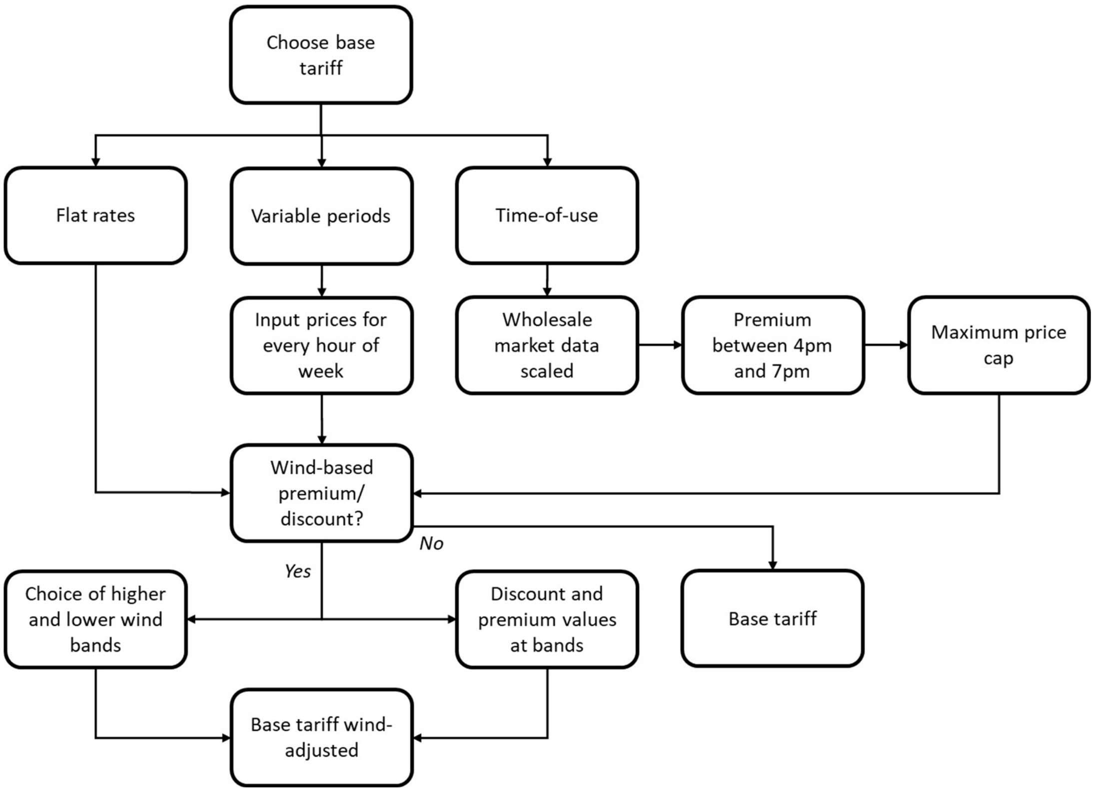


Figure 5.41: Flow diagram for electricity tariff generator

5.7. Fixed Order Control

The fixed order control implementation in PyLESA uses a pre-defined set of rules to order the dispatch of supply and determine the usage of storage. The user can rearrange the set of rules at the start of the simulation but cannot change the order according to dynamic system variables during the simulation period. This functionality is intended as a representation of a commonly employed control when introducing load shifting mechanisms. It will be compared to more advanced model predictive control which is described in the next section. Figure 5.42 shows the input requirements for the fixed order controller.

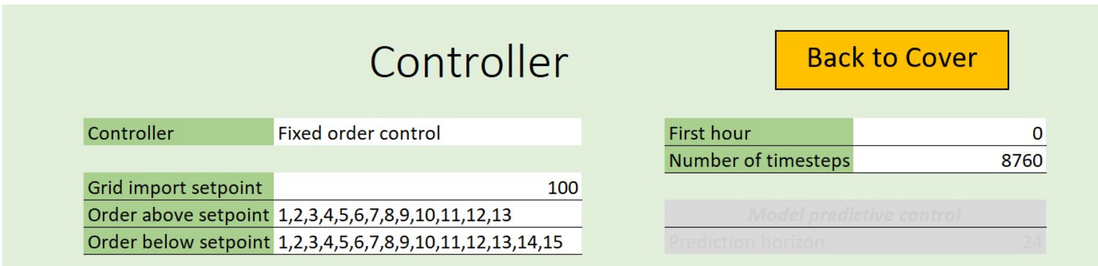


Figure 5.42: Fixed order control input requirements

This control is used to represent a classical controller which uses fixed setpoints for components (e.g. thermal storage temperature setpoint) to provide on/off and PID output responses. Table 5.7 splits the set of processes between above/below an import setpoint. This split allows for a different set of rules for day and night to take load shift from higher prices during the day to lower prices during the night.

Table 5.7: Rules for fixed order control strategy, split into condition based on an import setpoint

Above import setpoint	
Electricity demand	
1	RES to demand
2	ES to demand
3	Import to demand
Heat demand	
4	HP RES to demand
5	E-AUX RES to demand
6	TS to demand
7	ES to HP to demand
8	HP import to demand
9	AUX to demand
Thermal storage	
10	HP RES to TS
11	E-AUX RES to TS
Electricity storage	
12	RES to ES
Export	
13	RES to export

Below import setpoint	
Electricity demand	
1	RES to demand
2	Import to demand
3	ES to demand
Heat demand	
4	HP RES to demand
5	E-AUX RES to demand
6	HP import to demand
7	TS to demand
8	ES to HP to demand
9	AUX to demand
Thermal storage	
10	HP RES to TS
11	E-AUX RES to TS
12	HP import to TS
Electricity storage	
13	RES to ES
14	Import to ES
Export	
15	RES to export

The processes are run sequentially with the output from each process producing a set of results and checks. Figure 5.43 shows the flow of results and checks when running the fixed order controller in PyLESA. The validation of this controller can be found in Chapter 6, where the methodology is applied to a case study. This is because it is easier to analyse the operational decisions made using a well-defined example.

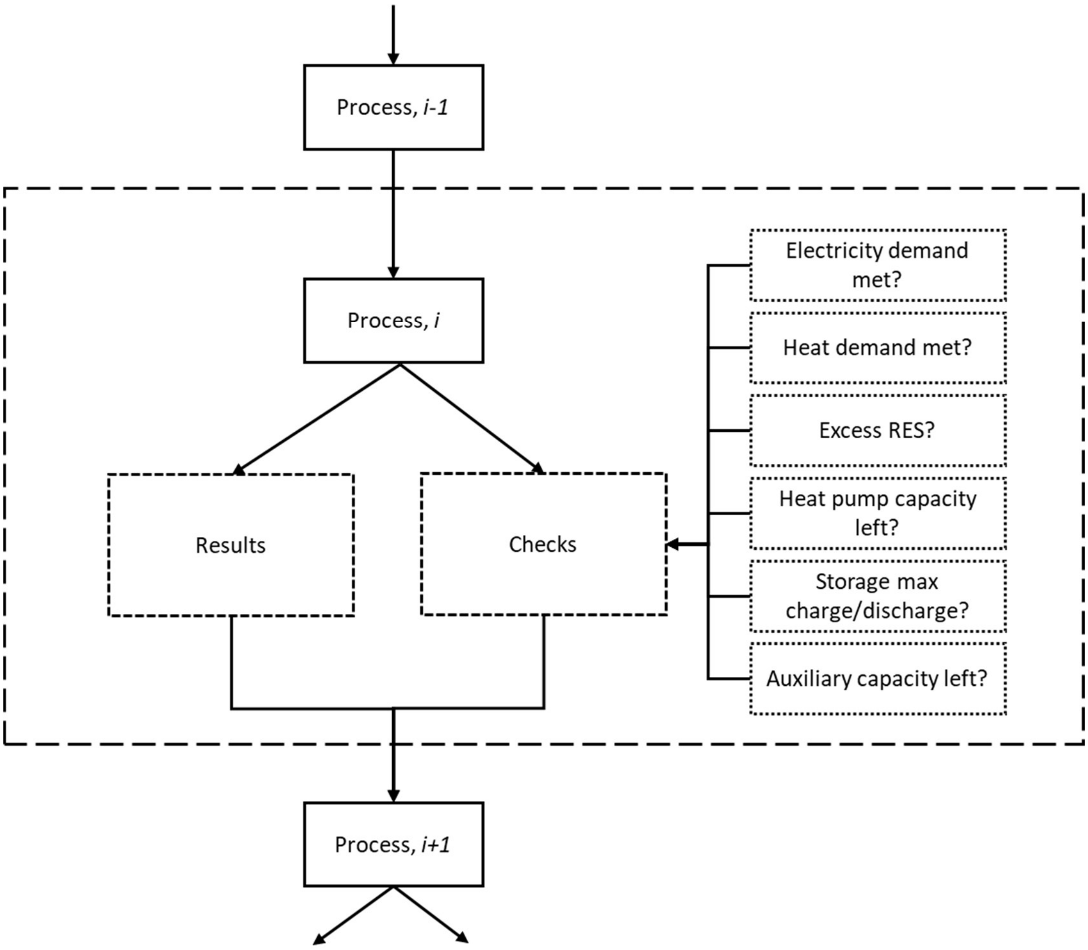


Figure 5.43: Flow diagram showing process i as a chunk of the flow of results and checks when running the fixed order controller

5.8. Model Predictive Control

Model Predictive Control (MPC) captures the dynamic influences of energy systems and optimises the performance of the components as a supervisory control strategy. MPC can be based upon models from building and system simulation models or artificial intelligent techniques. Contributions to the state of the art are made by including MPC in PyLESA as the review identified a gap in the ability of existing planning-level energy tools to model a model predictive control strategy.

An MPC controller consists of several key components:

- Objective function which an optimiser minimises/maximises.
- Prediction horizon which is the period over which the optimisation is performed.
- Decision timestep which is the interval between solving optimisation problem.
- Manipulated variables can be varied by the controller.
- Optimisation solver which is chosen based upon optimisation type and required speed.
- Feedback signal which provides updated system variables for next optimisation step.

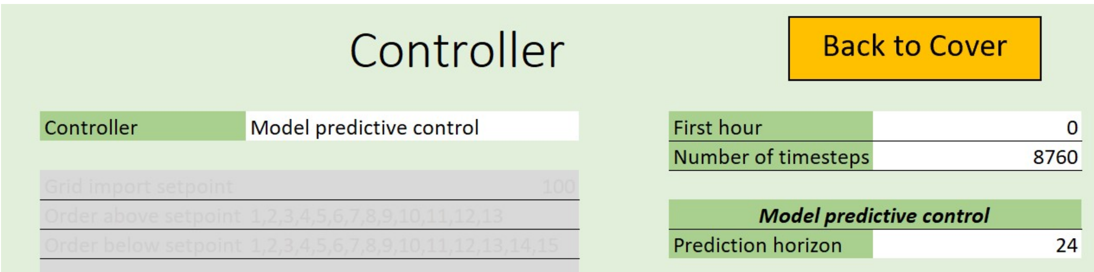


Figure 5.44: Model predictive control input requirements

PyLESA uses Economic Model Predictive Control (EMPC) which aims to maximise the economic performance of a system by varying control variables to minimise costs over a receding prediction horizon. It is useful for complex local energy systems which consist of multiple supply options, stochastic renewable power generation, storage, and fluctuating electricity prices. Traditional controllers are not suited to optimise the operation of these types of systems. PyLESA allows the range of optimisation algorithms available in Python to be accessed.

State equations are used to predict changes in state variables and are shown here for the heat balance, thermal storage state of charge, storage charging, heat pump thermal output, electric auxiliary thermal output, and use of surplus on-site renewable generation.

$$HD = HP_{trd} + HP_{tid} + AUX_{d} + AUX_{rd} + TS_{d}$$

$$\frac{d\,\mathrm{SOC}}{dt} = TS_{c} - TS_{d} - losses$$

$$HP_{on/off}.HP_{t\_var} = HP_{trs} + HP_{trd} + HP_{tid} + HP_{tis}$$

$$AUX = AUX_{d} + AUX_{s} + AUX_{rd} + AUX_{rs}$$

$$TS_{c} = HP_{trs} + HP_{tis} + AUX_{rs} + AUX_{s}$$

$$RES_{\mathrm{surplus}} = (HP_{trs} + HP_{trd})/COP + AUX_{rd} + AUX_{rs} + export$$

where HD is the heat demand, HP_{trd} is the heat pump thermal output from renewables to demand, HP_{tid} is the heat pump thermal output from imports to demand, AUX_{d} is the auxiliary thermal output to demand, AUX_{rd} is the auxiliary thermal output from renewables to demand, TS_{d} is the thermal storage discharging, SOC is the state of charge of the thermal storage, TS_{c} is the thermal storage charging, *losses* is the losses from the thermal storage, $HP_{on/off}$ is the binary on/off state of the heat pump, HP_{t_var} is the total thermal output of the heat pump, HP_{trs} is the heat pump thermal output from renewables to storage, HP_{tis} is the heat pump thermal output from imports to storage, AUX is the total auxiliary thermal output, AUX_{s} is the auxiliary thermal output from imports to storage, AUX_{rs} is the auxiliary thermal output from renewables to storage, $RES_{surplus}$ is the surplus electricity after electrical demand electrical demand has been met, COP is the coefficient of performance of the heat pump in that timestep, and *export* is the surplus electricity exported from the local energy system.

A mixed integer linear programming problem can then be formulated which minimises electricity costs by controlling the heat pump and thermal storage. The formulation contains: the objective function, state equations lumped into a generic state equation, inequality constraints, and allowed values for the heat pump status (integer on/off operation is allowed).

$$\min_{x,u,y} \phi = \sum\nolimits_{k \in \mathcal{M}} [\mathrm{I_{c,k}}(\mathrm{HP_{i,k}} + \mathrm{ED_{i,k}}) + \mathrm{A_{c,k}}\mathrm{AUX_{i,k}} - \mathrm{E_{c,k}}\mathrm{EX_{e,k}}]$$

s.t.

$$x_{k+1} = A_d x_k + B_d u_k + E_d d_k$$

$$HP_{duty,k} \geq HP_{\mathrm{t\,var,k}} \geq HP_{min,k}$$

$$SOC_k \leq TS_{capacity}$$

$$TS_{c,k} \leq TS_{\max charge}$$

$$TS_{d,k} \leq SOC_k$$

$$AUX_k \leq AUX_{capacity}$$

$$HP_{status} \in \{0, 1\}$$

$\mathcal{M} \in \{0, 1, \ldots, N\}$ and N is the prediction horizon and a sampling time of 1 hour is used. At each timestep the optimisation problem is solved, and a set of control variables is obtained. The first control variable is implemented and new state variables and forecast variables are updated in the next iteration of the optimisation problem.

It is assumed in this formulation that forecast variables and cost coefficients are known with perfect foresight. However, an MPC running in real-time is dependent on the accuracy of the predictions of the forecast variables. Therefore, the perfect foresight MPC approach results in an idealised operational schedule; the potential benefits from MPC will be overestimated. Stochastic MPC approaches have been developed which incorporate the uncertainty in forecast variables [236]. Alternative approaches for incorporating uncertainty of prediction variables have used the future value of the reference signal [237], and historical value of the control signal [238]. In future PyLESA can be developed to incorporate methods for representing prediction error.

The presented mixed integer linear programming problem is solved using GEKKO, a Python package for machine learning and optimisation [239]. It uses large-scale solvers for linear, quadratic, nonlinear, and mixed integer programming and in the MPC developed for PyLESA the APOPT solver is used [240]. GEKKO has previously been used in energy system analysis to optimise the performance of thermal storage to minimise cost operation of a district energy system in a time-of-use electricity market [241] and optimization of a hybrid solar thermal and fossil fuel system [242].

The developed MPC strategy uses a simplified energetic model for the thermal storage in the optimisation problem. This may lead to overestimation of the ability of the thermal store to meet demand in a later period, and an increase in the electrical import costs due to sub-optimal deployment of the heat sources.

The validation of this controller is undertaken in Chapter 6, where PyLESA is applied to a case study. This is because it is easier to analyse the operational decisions made using a well-defined example.

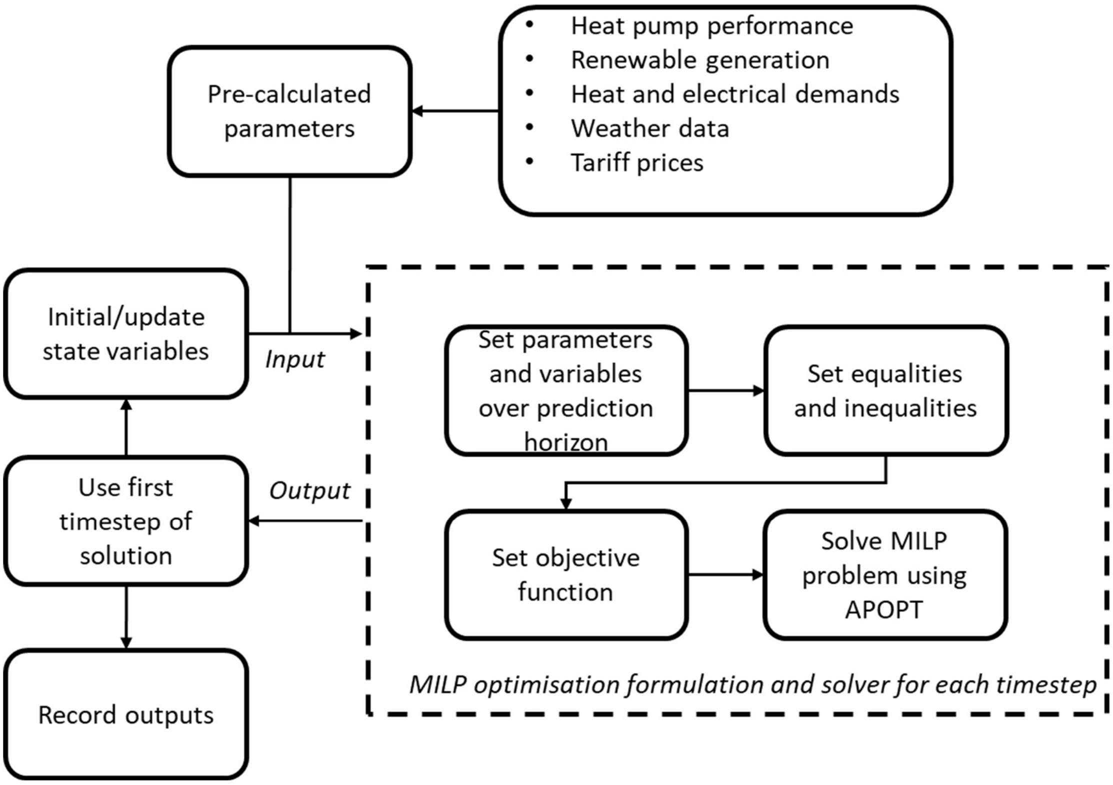


Figure 5.45: Flow diagram for model predictive control

5.9. Modelling Outputs (KPIs)

A set of Key Performance Indicators (KPIs) are included as outputs from PyLESA in order to compare different system configurations and component sizes.

Economic KPIs are useful for design studies such as sizing studies, as larger heat pumps and thermal storage will generally decrease operating cost, but this needs to be balanced against the increase in capital cost. Levelized cost of heat and energy can be used as a metric to explore this relationship. Larger thermal storage can mean that a smaller heat pump is required which is economically advantageous because thermal storage has a smaller capital cost compared to heat pumps.

The economic KPIs are simplified because they are designed to allow for comparisons between system configurations and component sizes, as opposed to being used to make final financial decisions. For example, the levelized cost of heat does not include a discount factor or maintenance costs. However, raw outputs from the tool, along with additional financial parameters, can be used to calculate more advanced economic KPIs, and/or the tool developed to incorporate these directly.

Technical KPIs are useful as economics are not always the sole driver of a project. Additionally, future electricity tariff prices are uncertain [243,244] particularly when calculating KPIs over 20-year system lifetimes.

The full set of KPIs output from PyLESA are listed in Table 5.8 and the equations used are described in the following sub-sections.

Table 5.8: Set of key performance indicators which are outputs of the modelling methodology

Economic KPIs	Technical KPIs
Capital cost (£)	On-site RES used (%)
Operating cost (£)	On-site RES used (kWh)
Cost of heat (£)	Grid RES used (kWh)
Cost of electricity (£)	Total RES used (kWh)
Lifetime total cost (£)	Demand met by RES (%)
Levelized cost of heat (£/kWh)	Heat met by RES (%)
Levelized cost of energy (£/kWh)	Peak HP to demand ratio
	Heat pump utilisation (%)
	Days of storage content

5.9.1. Levelized Cost of Energy

Levelized Cost of Energy (LCOE) is defined here as a measure of the average cost of meeting electrical and heat demands over a 20-year project lifetime and has units of £/kWh.

$$LCOE = \frac{CAPEX + 20 * OPEX - INCENTIVE}{(HEAT\ DEM + ELEC\ DEM) * 20}$$

5.9.2. Levelized Cost of Heat

Levelized Cost of Heat (LCOH) is defined as a measure of the average cost of meeting the heat demand over a 20-year project lifetime and has units of £/kWh.

$$LCOH = \frac{CAPEX + 20 * HEATOPEX - INCENTIVE}{(HEAT\ DEM) * 20}$$

5.9.3. On-Site RES Used

On-site RES used (ORES) is a metric which quantifies the percentage of self-consumption of on-site renewable power generation. It can be adapted to specify the source of on-site renewable power generation, i.e. ORESpv for on-site PV in the sizing study in Chapter 6.

$$ORES = 1 - \frac{SUM\ EXPORT}{SUM\ RES\ GENERATION}$$

5.9.4. Grid RES Used

Grid RES used (GRES) is a metric which quantifies the percentage of the grid imports which are classed as generated from RES. In this work it is only applicable for the wind tariff. During periods where a discount is applied there is a high penetration of wind on the grid and imports during these periods are classed as from renewable energy sources.

$$GRES = \frac{SUM\ RES\ IMPORTS}{SUM\ IMPORTS}$$

5.9.5. Demand Met by RES

Demand met by RES (DRES) is the percentage of the total electrical and heat demand which is met from both Grid RES and On-site RES. As a reminder, the electrical demand here refers to non-heat electricity. It can be adapted to specify the source of RES, i.e. on-site PV and electrical imports during high wind periods in the sizing study in Chapter 6.

$$DRES = \frac{SUM\ GRID\ RES + SUM\ ONSITE\ RES}{SUM\ HP + SUM\ AUX + SUM\ ELECTRIC\ DEMAND}$$

5.9.6. Heat Met by RES

Heat met by RES (HRES) is the percentage of the total heat demand which is met by Grid RES and On-site RES. It can be adapted to specify the source of RES, i.e. HRESpv and/or HRESpv+windtariff as used for on-site PV and/or electrical imports during high wind periods in the sizing study in Chapter 6.

$$HRES = \frac{SUM\ GRID\ RES\ HEAT + SUM\ ONSITE\ RES\ HEAT}{SUM\ HP + SUM\ AUX}$$

5.9.7. Peak HP to Demand Ratio

Peak Heat Pump to Demand ratio (PHPD) is the peak output of the heat pump and peak demand over the simulation period. This is a measure of the utilisation of the heat pump capacity. If a heat pump is oversized this ratio will be low.

$$PHPD = \frac{PEAK\ HEAT\ PUMP\ OUTPUT}{PEAK\ HEAT\ DEMAND}$$

5.9.8. Heat Pump Utilisation

Heat Pump Utilisation (HPU) is defined as the percentage of heat demand which is met by the heat pump. It does not incorporate losses from the heat pump, so may result in a higher than 100% percentage.

$$HPU = \frac{SUM\ HEAT\ PUMP\ OUTPUT}{SUM\ HEAT\ DEMAND}$$

5.9.9. Days of Storage Content

Days of Storage Content (DOSC) is a measure for quickly comparing the energetic capacity of a hot water tank in the context of the heat demand to be met and has units of days. The average day demand takes the annual demand and divides it by the number of days in a year, 365. The equation below contains the following parameters with units: capacity in kg, C_p in kJ/(kg °C), T in °C, and average day demand in kWh.

$$DOSC = \frac{CAPACITY * C_p * \Delta T}{3600 * AVERAGE\ DAY\ DEMAND}$$

5.10. Discussion

The underlying models of PyLESA detailed in this chapter have been developed to address the identified gaps from the review of existing modelling tools, and the contributions to the state of the art are discussed below:

- **Open source:** PyLESA is written primarily in Python and incorporates previous tools for modelling wind turbines and PV. The inputs are via an Excel workbook which is not open source software. However, building a GUI in Python for inputting data and viewing modelling outputs would complete PyLESA as a fully open source modelling tool. A distinct advantage of using open source software is the ability to build upon the work done in the developed modelling tool. Several avenues of further work are identified in this discussion (and in Chapter 7) and PyLESA provides a useful framework for undertaking it.

- **Heat pump:** A few heat pump modelling approaches have been detailed, and the choice is dependent on the available data. The standard test regression approach includes explicit temperature dependence and is an advance on the existing models utilised by planning-level modelling tools. Dynamic effects and part load conditions are largely neglected, and for timesteps ≤10 minutes a dynamic model is needed to capture start-up characteristics. To fully capture these a future advanced model could be developed which uses a white-box model where each of the major components of the heat pump is modelled [245]. However, this approach could increase the input data requirements beyond that available at the planning-level.
- **Hot water tank:** The multi-node modelling approach advances on the simple energetic models utilised by other tools, as it means that thermal characteristics can be represented while maintaining low input requirements. This modelling approach means that the state of charge and heat loss of the hot water tank is dependent on the node temperatures. The developed model increases computational time significantly and the code could be optimised to decrease this. The model does not allow for multiple heat sources to charge the tank, nor does it allow the heat source to inject at any other node but the top node. This would form a useful future development as technology such as solar thermal could be incorporated to provide complimentary heat to a heat pump and hot water tank system. The developed model exaggerates the mixing between nodes which is likely to occur for a hot water tank designed to be highly stratified, as is desirable for the load shifting mechanisms investigated. Therefore, while the energetic models used in existing models likely result in underestimations of the capacity required to perform load shifting, the model developed within PyLESA is likely to overestimate the capacity required.
- **Future electricity markets:** A wind-based electricity tariff generator has been presented as a way of including a tariff which could exist in the UK in the future. This is because of the high resource of onshore and offshore wind power that exists, and a future 100% renewable energy system would likely have wind power as one of the main producers of energy. Electricity markets which incentivise

flexibility will become more prevalent as the grid decarbonises. This will likely involve higher rewards from participating in ancillary markets such as those existing, e.g. balancing mechanism, frequency response, and new markets, e.g. European wide balancing energy market TERRE [246].

- **Predictive control:** PyLESA incorporating a model predictive control strategy allows analysis including optimal system operation. Particular advantages from this are where dynamic time-of-use tariffs are connected in which case simple rule-based controls would need to be constantly updated by an expert to minimise import costs. Additionally, where on-site renewable production competes with the electricity tariff, it is non-trivial to identify the low-cost periods. MPC enables an optimal operation which ensures that current and future on-site generation and electricity prices are included in the control decisions. An important aspect of future work on the MPC strategy presented here is the inclusion of uncertainties in the future predictions as currently these are modelled with perfect foresight [247,248]. This overestimates the benefits of the MPC as in its present form it always makes the right decision.

Further methods and assessments, and future developments are also discussed:

- **Resource assessment methods:** Resource data can be obtained via the MERRA reanalysis dataset which provides a free, hourly dataset for a number of years. The method provides a means of obtaining data easily, but it does not consider analysis such as developing a typical meteorological year [249], or investigating resilience to extreme [250], or worst case, weather conditions. This type of analysis would typically be performed at the detailed design level but inclusion at the planning stage would improve robustness.
- **Electrical demand:** This method relies on the use of a commercial software which is not open source. While this ensures that the method is user-friendly and reliable, it means that there is a cost and the underlying code is not accessible. Implementing a similar solution with open source software would contribute towards a fully open source software solution. However, demand profile generation is not within the scope of the aims of this thesis, and it was decided to use an existing method.

- **Heat demand:** The method used to simulate heat demand is built upon the method used in the Biomass decision support tool [91] which produced a design day demand profile. The new method used the same underlying pre-simulated building models to produce an hourly heat demand over the year. Importantly, this only requires simple inputs so is suitable at the planning stage.

  The focus was on residential district heating schemes, therefore similar methods could be developed for other building types, e.g. industry, commercial. When applying diversity the moving average algorithm used could be modified to reflect real data from monitored UK district heating schemes. Additionally, more detailed modelling of the district heating network losses would allow better comparison of the effect on system performance of changes in flow and return temperature.

  Only one heat demand can be input into the current model. Allowing input of separate space heating and hot water demand profiles would allow for the modelling of systems where there are separate hot water tanks and heat pump modes (high/low temperature outputs). This is commonly the case for single buildings.

  Stochastic demand profile generators exist which can be used to account for unpredictable influences on demand such as occupancy behaviour and could be incorporated into this tool [213,251].

- **Energy production technologies:** Adding an electrical generator which produces power from a fuel would allow for off-grid energy systems to be simulated [252–254]. A number of additional renewable energy technologies could also be added, e.g. tidal, wave, pumped hydro, solar thermal.
- **Electrical storage:** This method used a simple energetic model which is the most often employed by other modelling tools. This can give an idea of how a generic electrical storage technology may perform. However, more detailed models which are technology specific could be included as future work.
- **Thermal storage:** The developed hot water tank model is a contribution to the state of the art and is discussed above. Additional thermal storage technologies could be included in future work such as Phase Change Materials (PCM)

[255,256], next generation smart hot water tanks [257], building thermal mass [258], etc.

- **Control strategies:** The model predictive control strategy is a contribution to the state of the art and is discussed above. The fixed order control strategy developed is similar to the control algorithms used in existing modelling tools and is a useful basis as a comparator to explore the performance benefits of the MPC. This will be explored further in Chapter 6 where the two will be compared for a case study. PyLESA has been written in an object-orientated manner which should allow for future work to build upon it as a framework. This means that further control strategies can be developed within the tool. These could be simple, rule-based controllers which have special conditions, e.g. forced opportunistic charging from on-site renewable power production, and it could be heuristic controls which are data driven and adapt operation according to analysis of performance data [259].
- **Modelling outputs:** The set of KPIs developed allow for analysis of the economic and technical performance of the modelled energy system. When the tool is run an output file is saved which contains all the hourly output data of a full range of parameters. This allows users to inspect the data and develop their own KPIs which can be specific to their analysis.
- **Uncertainty:** PyLESA does not explicitly account for sources of uncertainty, however it can be integrated within existing design methodologies which include uncertainty analysis (see Section 1.9.). Integrating PyLESA with an uncertainty analysis method such as Monte Carlo simulation would account for the inherent uncertainty of input parameters, such as demand, and output design solutions which are robust to these uncertainties. Scenario analysis is another approach which, for example, could use worst-case (coldest) weather years, to ensure robust solutions for uncertainties in weather. PyLESA can also be used in conjunction with design optimisation methods which are used to search for an optimum design solution for a given objective function and often incorporate uncertainty [260].

The modelling methodology which describes the application of the developed modelling tool PyLESA will be applied and validated further in the next chapter using a case study of a housing cooperative. The case study currently consists of a biomass district heating network and are looking to investigate the potential benefits from installing heat pumps and thermal storage with predictive controls and alternative electricity tariffs.

6. Applying PyLESA: Proposed Design and Sizing Study

This chapter explores the application of the developed modelling tool, PyLESA, for a sizing study undertaken for a proposed design of a specific local energy system. The primary aim from the perspective of the case study was to identify a low-cost and highly renewable size combination of heat pump and hot water tank for three existing electricity tariffs, a future wind-based tariff, and the developed control strategies. Additional aims of the application were to showcase PyLESA as a useful tool to aid planning-level design; and provide validation of the developed control strategies and workflow of the steps of the tool.

In a peer-reviewed, conference paper the author performed a simple application of PyLESA to inform a sizing study for a proposed design of a district heating scheme with the fixed order controller and a time-of-use electricity tariff [261]. This chapter expands on this work to compare the fixed order control and model predictive control as well as four electricity tariffs.

The chapter is structured as follows:

- The aims, KPIs, and methodology of the sizing study are outlined.
- The existing system and proposed design are described.
- The steps of applying the modelling methodology are set out including the required input data requirements.
- The modelling input requirements for the sizing study are provided.
- The results from PyLESA are presented for the performance of the model predictive control and the fixed order control for all the modelled electricity tariffs, along with a comparison of outputs to EnergyPLAN.
- Sizing results for the existing electricity tariffs and a future electricity tariff with both controllers are discussed and graphically represented using 3D KPI plots.

The chapter concludes with a discussion which considers the results and the performance differences for the range of electricity tariffs and control strategies, as well as the overall applicability and usefulness of PyLESA in aiding the sizing study.

6.1. Study Aims, KPIs, and Methodology

The sizing study aims are split between two perspectives: informing design decisions for the case study, and assessing the contribution of the developed modelling capabilities of PyLESA to the state of the art.

From the case study perspective, the aim of the application of the developed methodology was to aid the design and sizing of a low-cost and highly renewable local energy system. A design consisting of an air-source heat pump and hot water tank system, plus back-up electric heat, with a connection to on-site PV generation, participation in a variable electricity tariff, and operation by a predictive control strategy, was proposed as a solution to meet this aim.

The heat pump and hot water tank components of the proposed design require sizing in order to enable the following load shifting mechanisms: increase on-site PV self-consumption; take advantage of varying electricity costs under existing electricity tariffs; and utilise low cost wind power under a future wind-based electricity tariff.

A set of KPIs (Table 6.1) are used in this sizing study to quantify the ability of the proposed design to enable these load shifting mechanisms and allow for comparisons of the technical and economic performance under the different control strategies and electricity tariffs. The KPIs were chosen from Section 5.9. and the renewable-related KPIs were adapted to suit this sizing study and provide clarity on the specific source of RES.

The LCOH was used as the KPI for choosing the optimal heat pump and hot water tank size combination. LCOH acts as a cost metric and as a proxy for quantifying the ability of the proposed design to enable the various load shifting mechanisms. Technical renewable-related KPIs were also used to further explore the performance of the proposed design with the different control strategies and electricity tariffs.

ORES has been adapted to ORESpv to clarify that the on-site PV generation is the only form of on-site RES generation included in this study. HRES has been divided into two adapted KPIs. HRESpv is defined to clarify that the on-site PV generation is the only contributing RES generation source to this KPI and is used for the existing electricity tariffs. HRESpv+windtariff is defined to clarify that both the on-site PV generation and the electrical imports during high wind periods (as defined in the wind tariff, Section 6.4.5.) contribute to the RES in this KPI and is used solely for the wind electricity tariff. These KPIs were chosen to illustrate the framework application and PyLESA tool capabilities, other choices could be made in applications that best suit the situation.

Table 6.1: Set of KPIs for sizing study

KPI	Comment	Section
Levelized cost of heat (LCOH)	Same as in previous chapter	5.9.2.
On-site RES used – PV (ORESpv)	Adapted ORES to represent the on-site PV generation	5.9.3.
Heat met from RES – PV (HRESpv)	Adapted HRES for the existing electricity tariffs where on-site PV is only source of RES	5.9.6.
Heat met from RES – PV+Windtariff (HRESpv+windtariff)	Adapted HRES for the wind electricity tariff where both on-site PV and electrical imports during high wind periods are classed as RES	5.9.6.

A set of specific aims were developed in order to illustrate the use of the tool to investigate various load shifting mechanisms and aid sizing decisions for the proposed heat pump and thermal store design. These aims use the above KPIs as metrics to allow comparisons and sizing decisions to be made. Specific aims are to:

- Investigate the performance of the developed control strategies, fixed order control and model predictive control, with respect to their ability to enable the various load shifting mechanisms.
- Investigate the use of existing electricity tariffs (flat rate, variable periods, and time-of-use), particularly in relation to the proposed systems ability to take advantage of variable electricity import costs.
- Explore the ability of the proposed system to utilise low cost wind power with the use of a future wind-based electricity tariff.
- Identify an optimal LCOH heat pump and hot water tank size combination for the different control strategies with both the existing tariffs and the wind tariff.

From the perspective of assessing the contributions of PyLESA to the state of the art the following aims were set out:

- Review the position of the developed modelling tool in the context of the state of the art of existing modelling tools.
- Validation of the developed control strategies.
- Demonstrate the function of the developed tool.

The methodology of the sizing study is framed to ensure that the above aims are achieved. It is based around the concept of an existing local energy system investigating the possibility of converting to a new proposed design. This methodology can be easily adapted for designing from scratch.

The sizing study methodology reflects the structure of the rest of this chapter and consists of the following steps:

1) Describe the case study and set out the existing local energy system.
2) Outline the design of the proposed local energy system.
3) Identify input data availability and output requirements.
4) Model the proposed local energy system with PyLESA using the modelling methodology, including multiple runs for different size combinations of heat pump and hot water tank. Rerun for all combinations of control strategy and electricity tariffs.
5) Carry out a qualitative inspection of the operation to verify modelling and control strategies, including a comparison to EnergyPLAN, and to compare and explore the control strategies and electricity tariffs.
6) Tabulate the KPIs of the optimal heat pump and hot water tank sizing results for each control strategy and electricity tariff combination.
7) Evaluate the output 3D plots of the KPIs for each control strategy and electricity tariff combination.

The scope of this application is to illustrate the deterministic modelling capabilities of PyLESA for heat pump and hot water tank sizing. It does not consider other system component sizing and uncertainties in a wider optimisation and robustness analysis, although PyLESA could be adapted to support such analysis in future.

6.2. Case Study Description

The sizing study is applied to a residential district heating scheme operated by West Whitlawburn Housing Co-operative (WWHC) [262]. The scheme connects to 544 flats and is supplied by a biomass boiler and backup gas boilers. WWHC are interested in investigating the potential of transforming their existing assets into a low-cost and highly renewable local energy system incorporating on-site PV, a heat pump, a hot water tank, time-of-use electricity tariffs representing potential future power purchase arrangements with local large scale wind generation (WWHC is adjacent to Whitelee wind farm, one of the biggest in Europe), and predictive controls.

WWHC is a fully mutual, tenant owned and controlled Housing Co-operative with charitable status, located in the south of Glasgow in Cambuslang, South Lanarkshire. It is in an area of multiple deprivations and they hold an overarching aim to provide affordable, sustainable, and community energy to the households. Previously, heat was supplied via electric storage and panel heaters in the individual flats as gas heating could not be installed due to regulations which apply to the multi-storey and low-rise tenement buildings. A demand reduction initiative has seen these properties have fabric upgrades to the buildings, windows, and roofs, in addition to the substantial external cladding installed onto the multi-storey flats.

To tackle the problem of fuel poverty in the community alternatives to the inefficient electric heaters were sought. Therefore, a biomass district heating system was installed with a centralised energy centre supplying domestic instantaneous heat and hot water to 544 of the flats via a district heating network. A 740kW Viessman Pyrotec biomass boiler operates as the primary heat source and is connected in parallel to a 50m^3 hot water tank. 3x 1.2MW gas boilers are included to contribute to large peaks in demand during winter and provide back up in the event of a breakdown or maintenance of the biomass boiler. See Figure 6.3: Schematic of existing setup of the WWHC energy centre for a schematic of the existing setup of the WWHC energy centre.

There are concerns around sustainability and air pollution issues related to the burning of wood for domestic heating [12]. Additionally, biomass may have a pivotal role to play in the wider energy system in decarbonising difficult sectors such as high-temperature industry and heavy transportation [13]. From this holistic view of the wider energy system it is worthwhile exploring alternative design options.

Figure 6.1: Panoramic view of WWHC with the 6 high rise towers and 5 low rise blocks

Figure 6.2: WWHC hot water tank and flue chimney in foreground, and boiler house in background

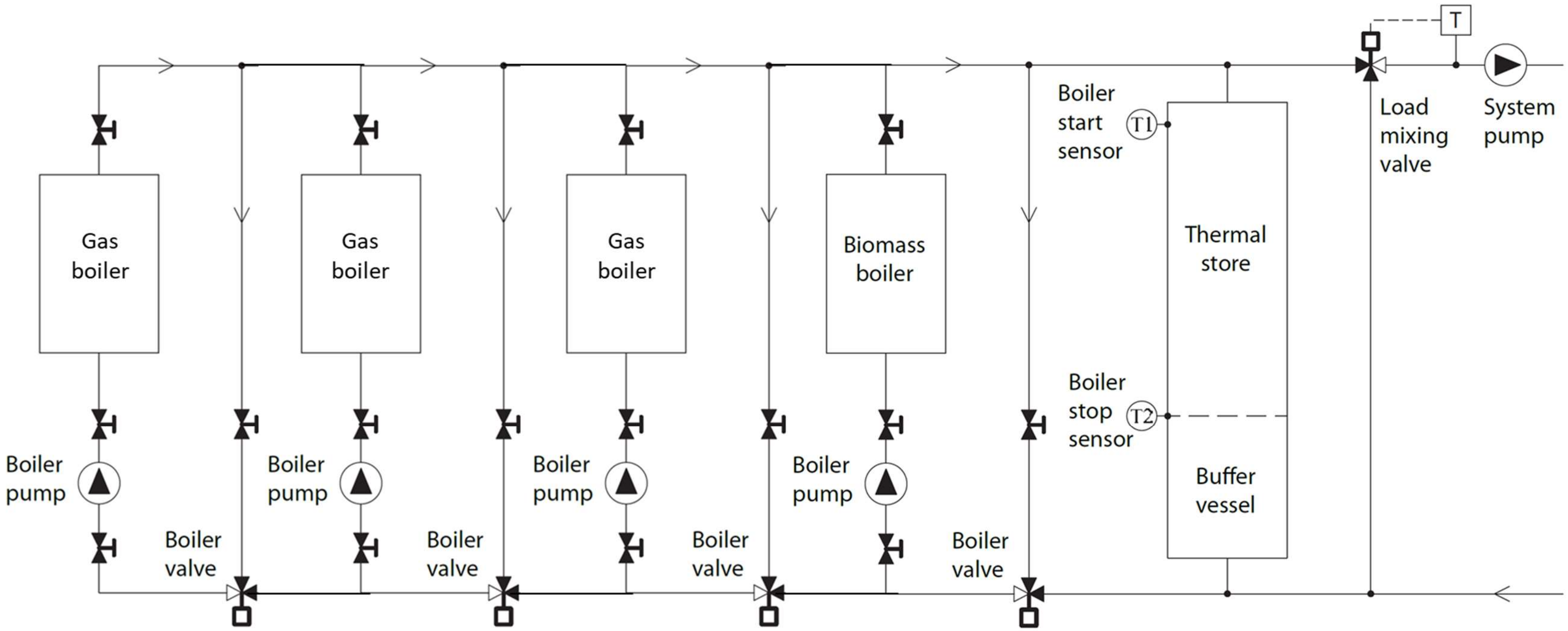


Figure 6.3: Schematic of existing setup of the WWHC energy centre

6.3. Proposed Design

As an alternative to the current design at WWHC it is proposed that an air-source heat pump and hot water tank system, plus back-up electric heat, with a connection to on-site PV generation, participation in a time-of-use electricity tariff, and operation by a predictive control strategy, can offer a solution for low-carbon and low-cost provision of heat. This section discusses the motivation behind the choice of the various components and ends with a schematic illustrating the proposed setup of the design.

The choice of heat source for a heat pump influences performance and installation cost. Generally, ground source heat pumps have a high initial capital cost but offer lower running costs because of improved COP due to the on average higher and more stable temperature of the ground. Air source heat pumps (ASHP) have lower capital costs but typically perform with a lower seasonal COP due to on average lower air temperatures. A 400kW ASHP, using R134a as the refrigerant, is capable of providing hot water at 62°C and has been installed along with a district heating network at Hillpark, Glasgow. This connects to 351 homes which are similar to the residential scheme of WWHC [263]. Performance data for the COP and the maximum thermal output (duty) was readily available thanks to links to the heat pump manufacturer, Star Refrigeration [264]. For these reasons it seems apt to investigate the potential of installing a similar heat pump at WWHC and modelling it using the available performance data. A back-up electric heater is included as it fits with an all-electric design and simplifies the local energy system by removing gas as an energy vector.

Thermal storage generally either stores sensible or latent heat. The primary technology utilising latent heat are Phase Change Materials (PCM), and these can be expensive, are primarily installed at a small-scale in homes, and they have the complication of being associated with a fixed phase change temperature [256]. Hot water tanks are a widely used, inexpensive example of a sensible storage technology [265]. Hot water tanks were chosen as the investigated thermal storage for inclusion in the proposed design because it is cheap, technically simple, allows temperature flexibility, and can be built in a wide range of capacities. Additionally, WWHC already has a hot water tank to aid in the operation of the biomass boiler so it is assumed that there is community acceptance and knowledge regarding this technology.

On-site renewable generation possibilities are dependent on the resources available in the local energy system. PV is a renewable power generation technology which is cheap and widely installed in the UK. PV can connect to local electrical loads, such as the residential electrical demand from the flats, to meet the electrical consumption needs of the heat pump and auxiliary heater, and to the national grid to be exported. Therefore, PV is chosen to be included on-site as part of the proposed system because it is cheap, widely used, can contribute to both local electrical and heat demands, and can be exported when not locally needed. PV has the limitation that while it supplies electricity in the summer, its winter performance is limited. Hence, PV on its own is not an obvious fit with winter space heating demand.

Renewable electrical power can also be sourced from at a range of scales through the renewables connected to the local distribution network and through transmission via the national grid, not solely from the on-site renewable power generation discussed above. Wind is the predominant renewable electrical generation source on the Scottish networks and transmission grid with excess capacity available being exported or curtailed [266] (wind farm constraint payments in the UK have risen from £174,00 in 2010 to £139 million in 2019, with Scottish onshore wind farms receiving 94% of the 2019 payment [267]). With further offshore and onshore capacity expansion planned there are expected to be greater incentives to increase demand on high wind days. The use of this renewable grid power will be explored in the proposed design indirectly through a representative local wind influenced tariff rather than directly through on-site wind generation. In this sizing study the primary KPI used to measure the ability of the proposed design to utilise low cost wind power is HRESpv+windtariff. This KPI is the percentage of the heat demand met by both the on-site PV generation and the electrical imports during high wind periods.

Several electricity tariffs currently exist which incentivise shifting demand. Flat rate tariffs are the most common domestic electricity tariff and do not change electricity prices according to time of use. Variable periods tariffs such as day/night and weekday/weekend tariffs incentivise users to shift to low-cost periods. Time-of-use pricing structures vary prices in hourly, or sub-hourly, timesteps and can include facets such as dependence on the wholesale market, premium price periods, etc. Future tariffs may emerge which are based on inflexible, stochastic renewable generation and incentivise shifting electricity consumption to periods of high renewable generation. An example is the wind tariff discussed above. It is proposed that all these types of electricity tariff are included as options in the proposed design so that modelling can differentiate which is the most appropriate in terms of cost and integration with renewable generation.

Both a traditional fixed order controller and a model predictive controller would be useful to include in the proposed design to compare the performance of each. Benefits from simple tariffs may be maximised using only simple controls, while more complex designs may require the optimisation element from model predictive control. These controls are modelled with a view to maximising the use of on-site renewable generation and minimising overall electricity import costs.

Figure 6.4 is a schematic which illustrates the proposed setup, combining all the components discussed above. The system provides both space heating and hot water through a district heating network. Note that the design study carried out here does not size the buffer section of the hot water tank which is required for safe operation of the heat source but instead focuses solely on sizing the thermal store section which enables load shifting. On the diagram, red lines indicate communication between component and controller, and not shown is the grid connection which allows import and export priced by the electricity tariffs.

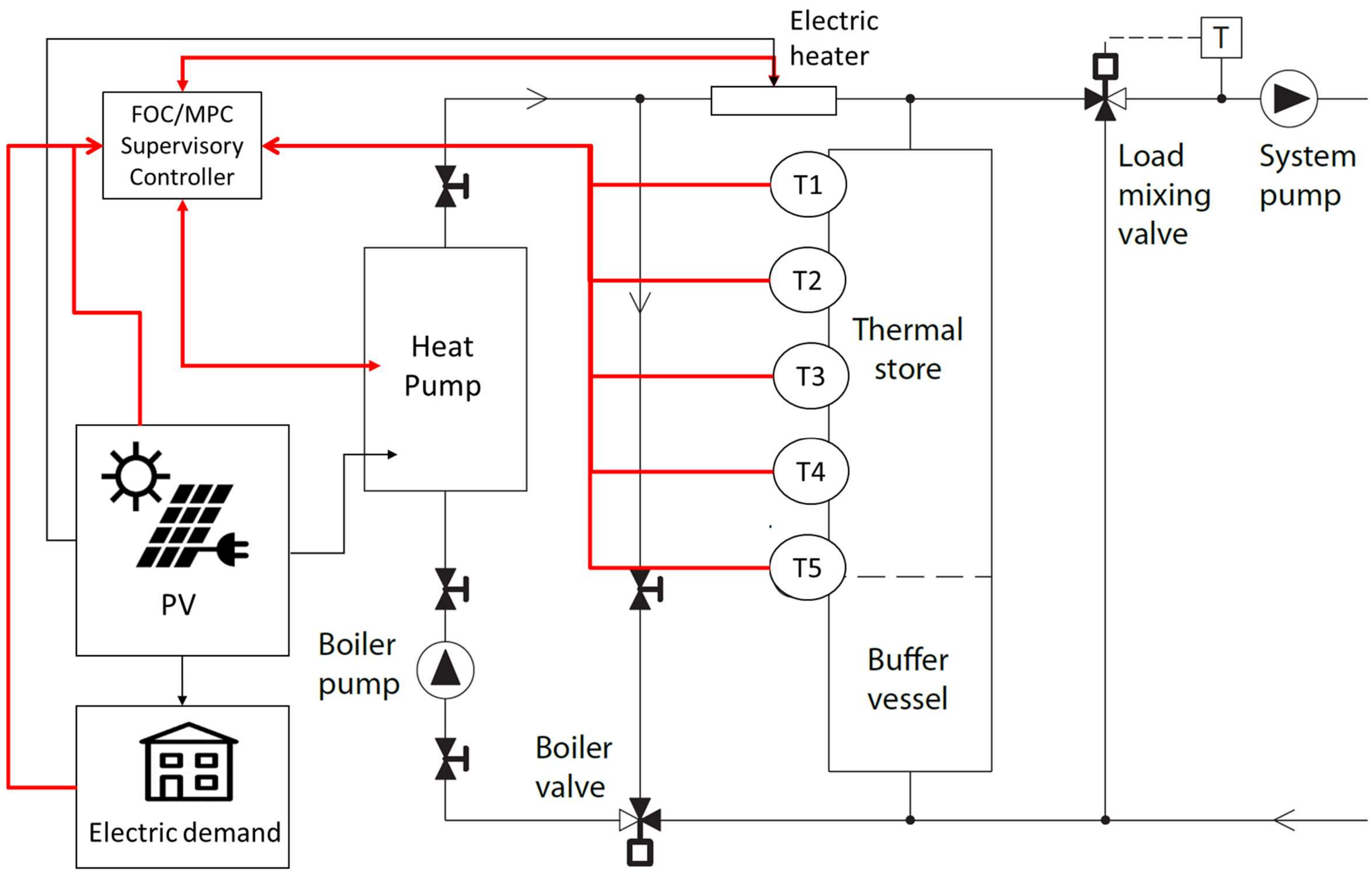


Figure 6.4: Schematic of proposed design

6.4. Input Data and Output Requirements

This section details each component of the proposed setup outlining the required and available input data, and ending with the modelling output requirements. The structure follows the description of the underlying models in Chapter 5.

The year 2017 is used as the reference year and subsequently the collected data is applicable to this year.

6.4.1. Resource and Demand Assessment and Input Methods

- **Local resources:** The only available local resource data was air temperature, which was collected on-site using local sensors with 2017 data available. Wind speed data was collected from the MERRA reanalysis hourly dataset for 2017 for wind speed (at 10m height) due to the lack of available on-site data. A simple multiplication correction factor of 0.67 is applied to this data, in accordance with a study which shows a 50% overestimation of the MERRA wind speed for northwest European countries [203]. The uncertainty introduced by using the MERRA could be further reduced by using the correction factors as calculated specifically for the UK [203] or by using more reliable data, such as from a weather station.
- **Electrical Demand:** Due to a lack of monitoring data a generic community electrical demand profile was synthesised in HOMER.
- **District Heating Demand:** Hourly monitored data was available for the district heating demand for WWHC including for the year 2017.

6.4.2. Electrical Production Technologies

- **PV:** 1.74MW rated capacity, 6000 x 290W LG LG290N1C-G3 [2013] panels, south-facing, with 40° surface tilt and LG295A1C-B3 [240V] 240V [CEC 2018] inverters. This capacity was chosen to ensure that there is a large opportunity for utilising excess PV generation with the heat pump and hot water tank. There will be periods where the 1.74MW PV generation exceeds electrical demand, which has a peak of 650kW. Additionally, there will be periods where the excess PV generation can be used to meet heat demand, which has a peak of 1.36MW. Due to uncertainties in the future of government incentives for PV, these are not to be included in this modelling exercise.

6.4.3. Heat Pumps and Auxiliary Heat Units

- **Heat pump:** Star Refrigeration ASHP Neatpump [264] with variable speed compressor and 65/55 flow/return temperatures feeding a district heating network at 60/40 flow/return temperatures. The heat pump and district heating temperatures are the same as used for an existing ASHP and district heating scheme in Scotland, with similar building characteristics as WWHC. It is assumed that the heat exchangers in the flats at WWHC can be adapted to work at these temperatures. This type of ASHP was chosen because it is state of the art and the performance curves were available. Capital costs were assumed linear at £600/kW as given by the Danish Energy Agency [268]. Due to uncertainties in the future of government incentives for heat pumps, these are not to be included in this modelling exercise.
- **Electric heater:** Backup electric heater with 100% efficiency sized to peak heat demand. This capacity was chosen to ensure that the electric heater can act as a back up to the heat pump and always meet heat demand.

6.4.4. Hot Water Tank

- **Hot water tank:** Modelled using the following inputs: 5 nodes, polyurethane insulation, located outside, 5 thermostat tank openings with diameter 35mm, and 2 insulated connections for the flow and return with diameter 50.8mm. Capital cost is presumed to follow an exponential decay function for £/m^3 [268], Figure 6.5. This configuration is typical of hot water tanks used in current district heating schemes. 5 nodes were chosen to balance the accuracy in modelling tank stratification and computational time.

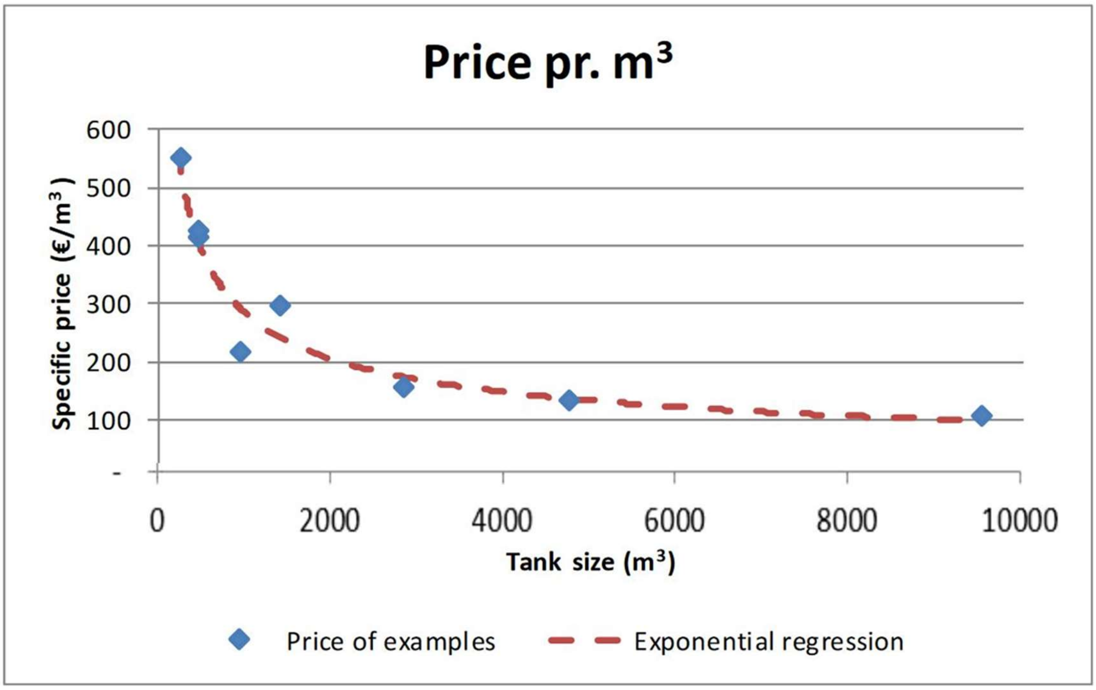


Figure 6.5: Exponential function of hot water tank volume and specific price

6.4.5. Electricity Tariffs

4 different electricity tariffs are modelled in the sizing study using the following inputs. The prices used for the different tariffs are representative of typical prices available from domestic energy suppliers in 2017. Exports have been set to zero value in order to increase the incentive for the system to self-consume. Additionally, while currently export prices can be agreed and sold to an energy supplier, there is uncertainty as to the future value of exports from on-site generation such as PV.

- **Flat rate:** £130/MWh.
- **Variable periods:** 12am to 7am - £75/MWh, 7am to 12am - £150/MWh.
- **Time-of-use:** Tracks wholesale market (2017 prices) with £120/MWh premium from 4pm to 7pm and £350/MWh maximum. This mimics the currently available Octopus Agile tariff [30].
- **Wind:** Combination of variable periods and wind pricing structures. 12am to 7am - £75/MWh, 7am to 12am - £150/MWh and a £50/MWh discount during top 20% of wind output and a £50/MWh premium during bottom 20% of wind output. Wind output is based upon Whitelee Wind Farm, which consists of 215x Siemens SWT-2.3MW.

6.4.6. Fixed Order Control

The fixed order controller requires an import setpoint. For the flat rate electricity tariff the import setpoint was set below the import cost to avoid unnecessary charging and discharging of the hot water tank using high-cost grid imports. For the variable periods electricity tariff the import setpoint was set between the day and night import costs to enable load shifting from day to night. For the time-of-use and wind electricity tariff the import setpoint was set to £100/MWh.

6.4.7. Model Predictive Control

MPC only requires the prediction horizon as an input. For the existing electricity tariffs a 24-hour period was used and for the wind tariff a 168-hour (1 week) prediction horizon was used. The existing tariffs used follow a 24-hour pattern because they generally follow demand, therefore a prediction horizon of 24 hours captures general price fluctuations. The wind tariff is variable over a longer timescale as it is dependent on periods of high or low wind, therefore a 1 week prediction horizon to take advantage of longer term variations.

6.4.8. Output Requirements

Economic and technical outputs are required to inform comparisons of the control strategy and electricity tariff combinations. Additionally, sizing the heat pump and hot water tank components require outputs which can quantify the ability of the proposed design to perform the following load shifting mechanisms: increase on-site PV self-consumption; take advantage of varying electricity costs under various existing electricity tariffs; and utilise low cost wind power under a future wind-based electricity tariff.

A set of KPIs to be used in this sizing study was described in Section 6.1. and displayed in Table 6.1. LCOH was the economic metric chosen as it can act as a proxy for quantifying the ability of the proposed design to enable the various load shifting mechanisms. Technical renewable-related KPIs (ORESpv, HRESpv, and HRESpv+windtariff) were also used to further explore the performance of the proposed design with the different control strategies and electricity tariffs. These KPIs can be calculated from economic and renewable-related outputs, and are directly calculated with PyLESA.

6.5. Application of PyLESA Modelling Methodology

This section describes applying the developed modelling methodology, from Chapter 4, which sets out the steps for running PyLESA, for the proposed design of WWHC. The aim is to size a heat pump and a hot water tank as part of a low-cost and highly renewable local energy system. The following are the methodology steps including the details relating to this specific application.

1. **Define the local energy system to be modelled:**

   The proposed design for WWHC was defined in Section 6.3, and the input data available outlined in Section 6.4.

2. **Optionally run the demand and resource assessment methods:**

   Resource method and electrical demand methods were run as monitored data was not available. However, not needed for the heat demand as monitored data was available.

3. **Input gathered data to PyLESA:**

   Take data from first two steps and input to PyLESA using the Excel workbook.

4. **Input ranges to be modelled for parametric analysis:**

   - Fixed Order Control and Model Predictive Control with existing tariffs:
     - Hot water tank capacity range: 0 -> 800m^3 in 100m^3 steps.
     - Heat pump thermal output capacity: 0 -> 2000kW in 250kW steps.
   - Fixed Order Control with wind tariff:
     - Hot water tank capacity range: 0 -> 3000m^3 in 250m^3 steps.
     - Heat pump thermal output capacity: 0 -> 3000kW in 500kW steps.
   - Model Predictive Control with wind tariff:
     - Hot water tank capacity range: 0 -> 3000m^3 in 1000m^3 steps.
     - Heat pump thermal output capacity: 0 -> 3000kW in 500kW steps.

5. **Run PyLESA:**

   - Use the *run.py* script inputting the appropriate input Excel workbook name.
   - Rerun the tool for all combinations of control strategy (fixed order and model predictive control) and electrical tariffs (flat rate, variable periods, time-of-use, and wind).

6. **Analyse the outputs:**
   - In order to illustrate (and further validate) the system operation in detail, an operation analysis snapshot is provided allowing inspection of four example week operational graphs consisting of (i) heat pump thermal output, auxiliary electric heat output, and heat demand, (ii) hot water tank node temperatures, (iii) import costs, and (iv) surplus and exports.
   - To showcase how PyLESA can support component sizing and compare control strategies and electricity tariffs, KPIs for the optimal LCOH heat pump and hot water tank size combinations with the range of control and tariffs are tabulated. These KPIs are LCOH, ORESpv, HRESpv, and HRESpv+windtariff. See Section 6.1. for further details on these.
   - To explore the ability of the proposed design in enabling the various load shifting mechanisms, the same set of KPIs are presented for the modelled ranges of heat pump and hot water tank sizes using 3D graphs.

6.6. Outputs from PyLESA

Running PyLESA produces several graphical and numerical outputs which can inform planning-level design decisions such as those encountered in this sizing study. This section gives a brief overview of example of outputs from PyLESA to inform the reader the type of analysis which is readily available after running the tool. The next two sections will then present the operational analysis results and sizing results for the sizing study.

To provide an illustrative example of PyLESA outputs, the results for a possible WWHC design option is presented here, with a 1000kW heat pump and 500m^3 hot water tank size combination, a variable periods tariff and MPC.

Raw data containing the hourly, sub-data of the underlying outputs is made available in the *outputs.pkl* file. This is saved at the end of running the tool and can be used to perform external analysis. This is the file which the *outputs.py* script uses to perform the output analysis included in PyLESA to produce numerical and graphical outputs.

The output graphical plots are a mixture of bar charts, 2D plots, and 3D plots. The 2D plots are generated for a summer week, winter week, and the year in hourly timesteps. If the user has defined a modelling period shorter than a year then the plots are generated for the user-defined period.

Key performance indicators (KPIs) have been developed within PyLESA and are described in Section 5.9. LCOH was the economic metric chosen as it can act as a proxy for quantifying the ability of the proposed design to enable the various load shifting mechanisms. Technical renewable-related KPIs (ORESpv, HRESpv, and HRESpv+windtariff) were also used to further explore the performance of the proposed design with the different control strategies and electricity tariffs. These KPIs are used in Section 6.8. where 3D plots illustrate the sizing decisions and performance of the electricity tariffs and control strategies investigated.

The total PV, wind turbines and combined renewable power production (Figure 6.6) are output as bar charts which display the gross power production for each month, along with a heading which contains the annual power production for the modelled year. This example does not include on-site wind power production and hence the wind power production is zero, this is included here because the outputs described in this section follow a generic template and are designed to be useful for a wide variety of modelling exercises.

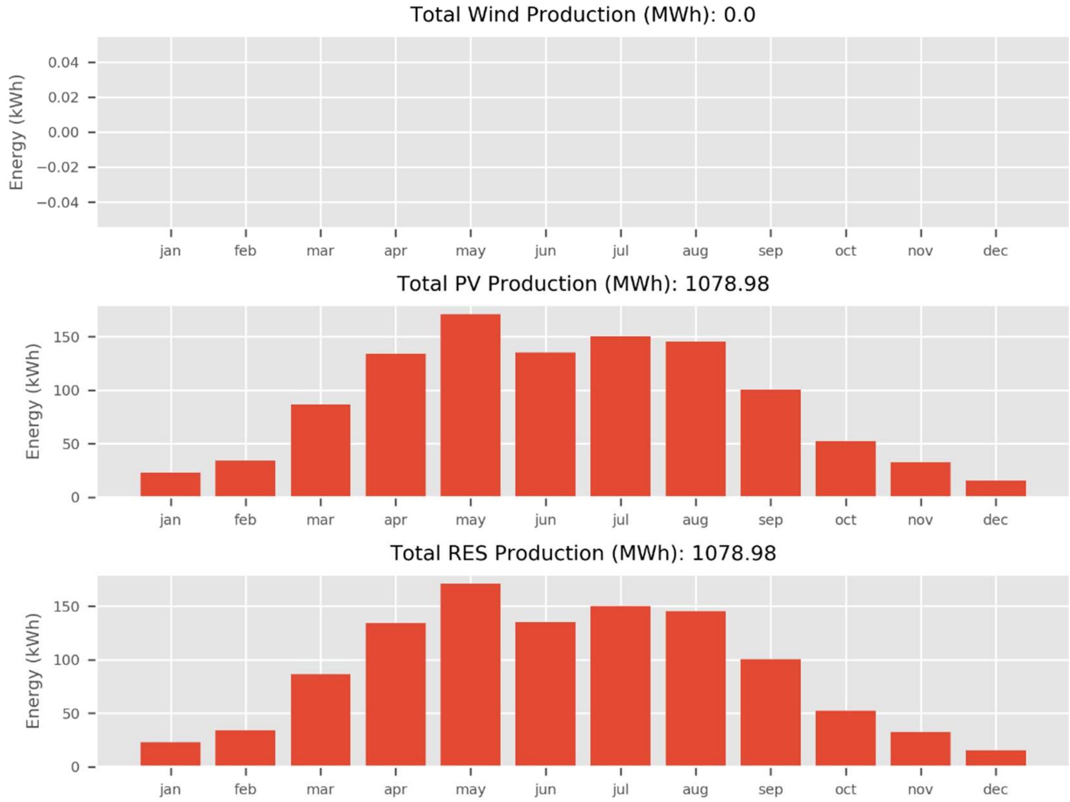


Figure 6.6: Total PV, wind turbines and combined renewable power production in bar charts

Electrical demand, renewable generation, and renewable generation usage plots are included together in Figure 6.7 for a summer week as this season has the highest PV production. The electrical demand plot allows the modeller to quickly assess which supply options are meeting electrical demand from imports, renewable generation (RES), and/or electrical storage (ES). The renewable generation plot displays, on an hourly scale, the wind and PV power generation and is included to compliment the above bar charts. The renewable generation usage plot shows how the PV and wind power generation is being used within the local energy system. In the example figure the electrical demand uses a baseload proportion of the generation, while the heat pump and auxiliary electric heater consume most of the remainder. Little of the power is exported showing that, for this week, the system has enough flexibility built in to self-consume almost all of the on-site renewable power generation.

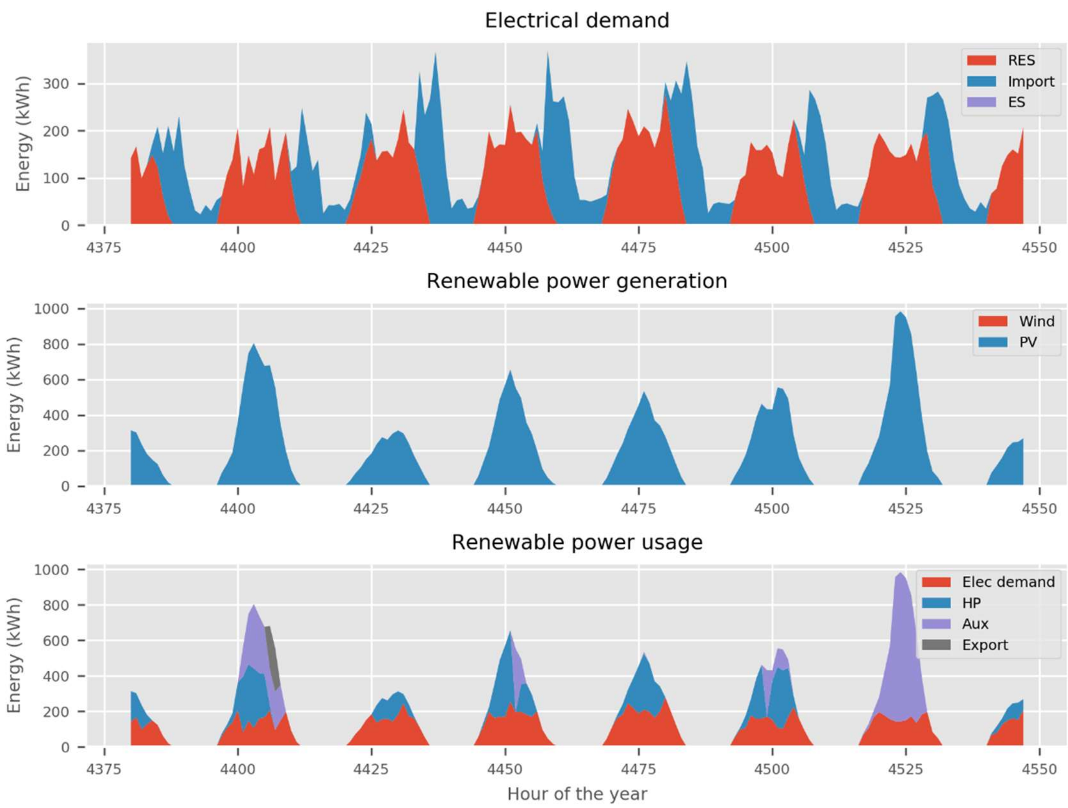


Figure 6.7: Electrical demand, renewable generation, and renewable generation usage plots for summer week

The grid interaction plots, Figure 6.8, shows the flow of imports and exports along with the financials of the import cost and cashflow for a summer week. As was seen from the renewable power usage plot, little power is exported from the local energy system for the example summer week. The variable periods pricing structure can be readily viewed, along with the cashflow which is useful as a proxy metric of viewing the combined import and export interaction. In this example exports have no value which explains why the short period of export does not result in a positive cashflow.

Two figures are output to explore the modelling results of the heat pump. Figure 6.9 shows the heat demand, heat pump output, and heat pump electrical usage. Additionally, Figure 6.10 displays the variation in heat pump performance in terms of the COP and maximum thermal output. The heat demand plot shows when the heat demand is met by the heat pump, the hot water tank discharging, and the auxiliary heat. It can be seen by viewing the heat demand and heat pump thermal output plots together that, in this example, load shifting is occurring as there are distinct periods where the heat pump thermal output is charging the hot water tank, the heat pump turns off, and then the hot

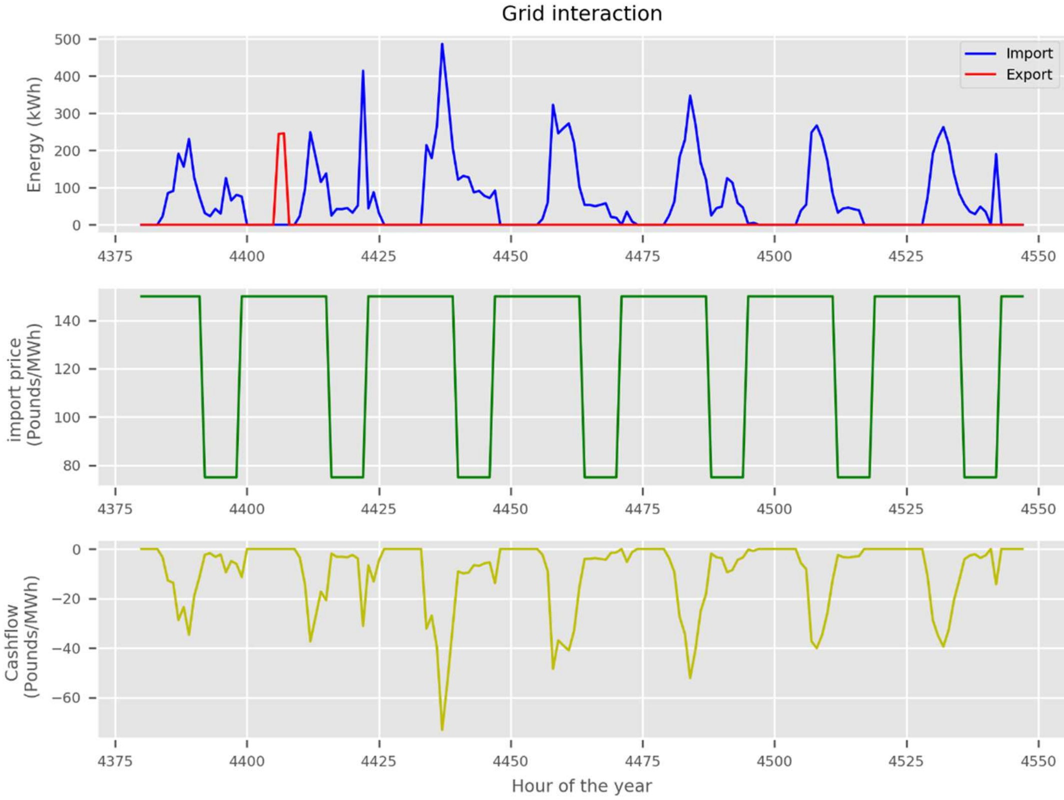


Figure 6.8: Grid interaction plot for summer week

water tank meets the heat demand. The heat pump is utilising excess power generation from the PV to charge the hot water tank to meet the heat demand in a later period, where the PV is not producing.

In this analysis the usage of excess PV generation is assigned a zero-marginal cost and exports zero value. In this case the MPC makes no distinction in the electrical cost between running the heat pump or auxiliary electric heater. The MPC does include the advantage that using the heat pump is a more efficient conversion of the surplus electricity into heat than using the auxiliary electric heat. However, there are periods where there is no advantage from the more efficient use of the surplus, such as where the hot water tank can be filled, or the hot water tank charged sufficiently to cover the heat demand until the next PV surplus, by either the heat pump or auxiliary electric heat. This is seen in the periods where the heat pump turns off and the electric heater meets demand and charges storage using surplus PV generation, and discharging the hot water tank is then capable of meeting the heat demand until the next PV surplus. See Section 6.8.2.2. for further discussion of the operation of this example.

The hot water tank plots combine the calculated energy flow of charging and discharging along with the modelled node temperature variations, Figure 6.11. The top and middle plots show the charging and discharging over a summer week, and these coincide with the heat pump and auxiliary electric heater utilising the hot water tank to shift load in order to maximise use of on-site PV power generation. The bottom plot shows the fluctuation of the temperature of the nodes, which matches the periods of charging and discharging. In the summer the heat demand is substantially lower than in the winter, and this leads to an underutilisation of the hot water tank in the summer. This is seen in this plot as the temperatures of the lower nodes are consistently at lower temperatures than the maximum, which means that effectively only a fraction of the hot water tank capacity is being used.

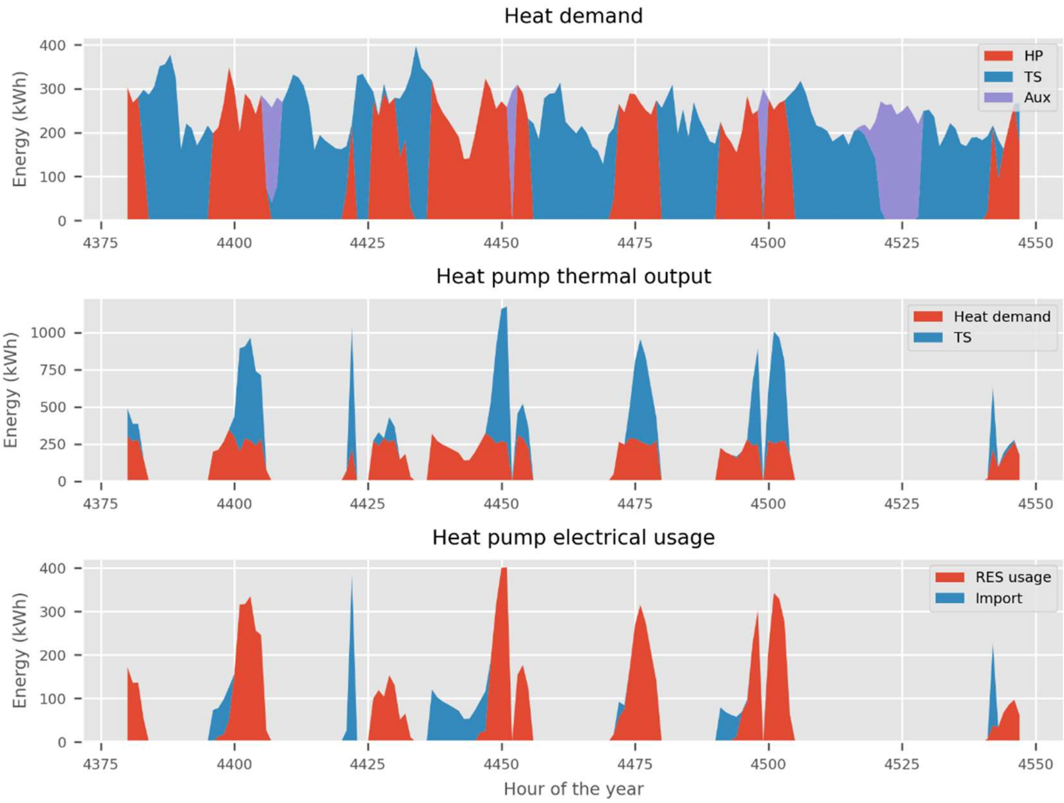


Figure 6.9: Heat demand, heat pump output, and heat pump electrical usage plots for summer week

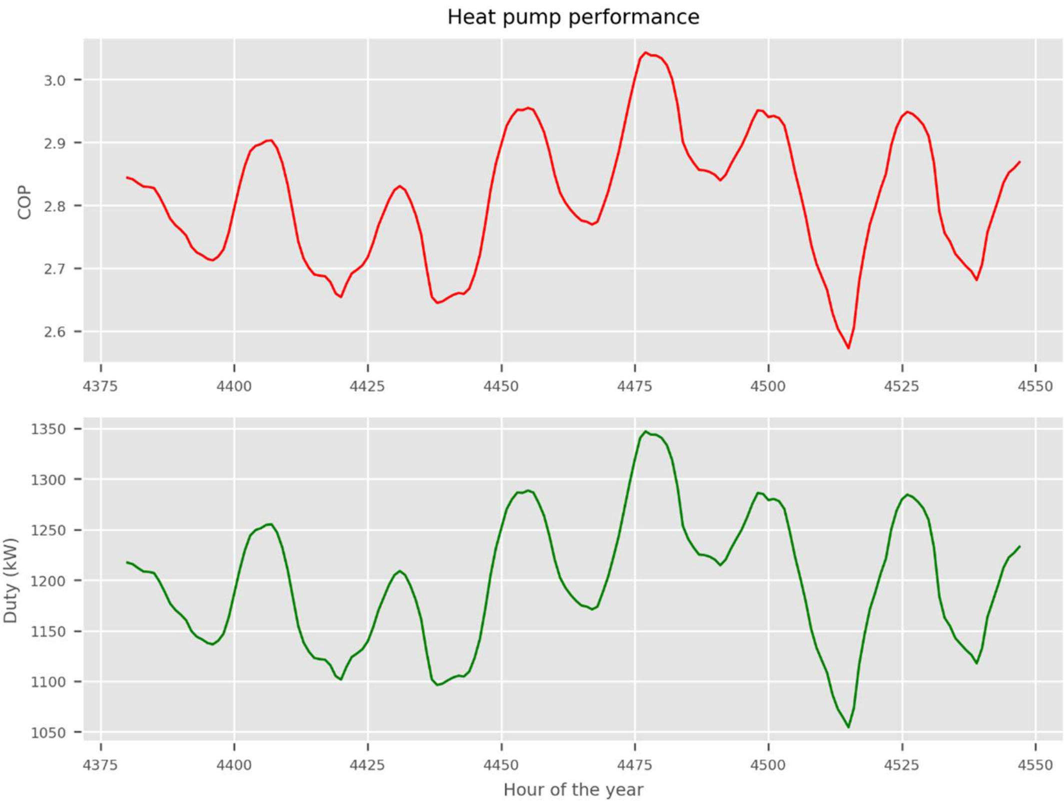


Figure 6.10: Heat pump performance with COP and duty

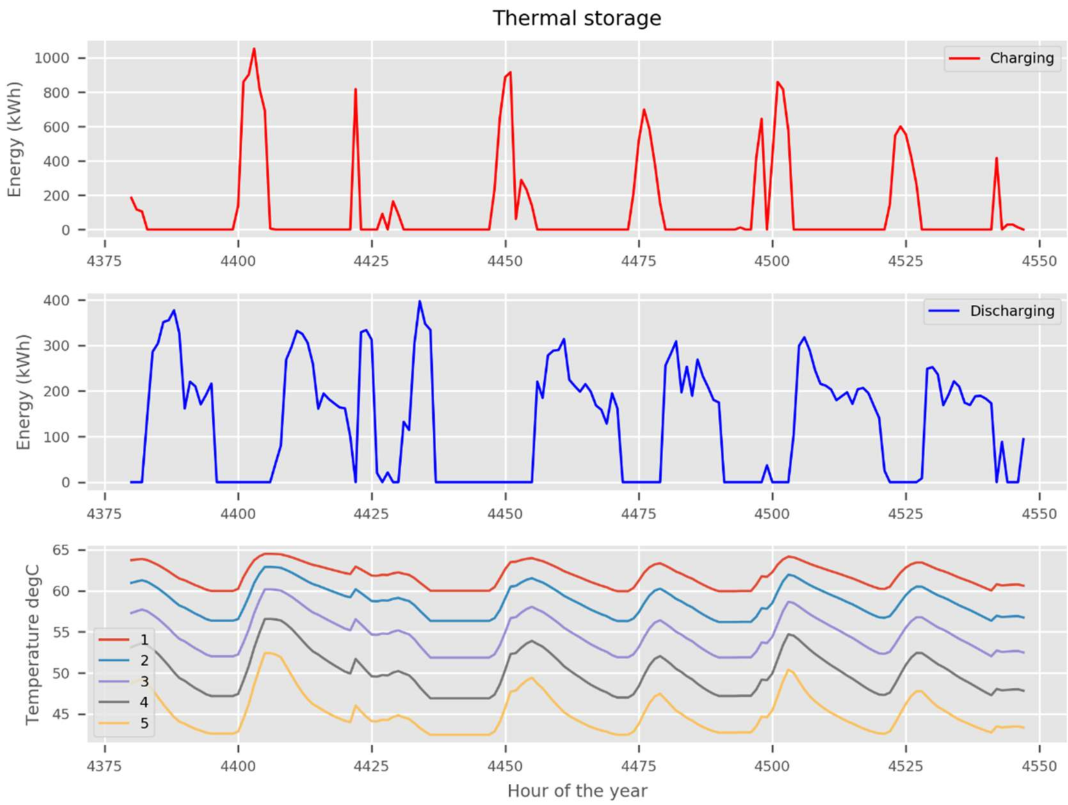


Figure 6.11: Thermal storage charging and discharging as energy, and node temperatures for summer week

Thus far, the graphical outputs described have generally focussed on individual components of the local energy system. However, to understand the complex interactions between the supply, demand, and storage components it is useful to view these plots side by side in a figure. Operational graphs are output to help understand the relationships between the system components, and consist of four plots: heat pump output, auxiliary, and heat demand; hot water tank node temperatures; import cost; and, surplus and export. These are explored fully for the different control strategies and electricity tariffs in the Section 6.7.

6.6.1. Comparison to EnergyPLAN

The aim of this section is to compare the outputs from a widely used planning-level modelling tool, EnergyPLAN, to PyLESA, to help build confidence in the modelling capabilities of PyLESA. This was done by comparing a sample of outputs from both tools and explaining differences in the output due to the different hot water tank modelling and control approaches. EnergyPLAN was chosen because it is widely used, can model all the required components, is free to download and use, and the author has user expertise. The scope of this section is not a detailed analysis of EnergyPLAN, which is one of the tools reviewed in detail in Chapter 3, or PyLESA, where the outputs are explored in detail elsewhere in this chapter. The purpose of this section is to check if the outputs from both tools are similar, and that any differences can be explained by the different functionality. Given the widespread usage of EnergyPLAN, it is assumed that if PyLESA can produce similar outputs then it is producing reasonable outputs. This can then help build confidence in the modelling capabilities of PyLESA.

Both tools were used to model the proposed design of WWHC (described in Section 6.3.), with a 1000kW heat pump and 500m^3 hot water tank size combination, a variable periods tariff and MPC. This size combination was chosen as it has large enough capacities to use the heat pump and hot water tank to load shift to both utilise excess PV generation and to take advantage of the day/night electrical import cost timings of the variable periods tariff.

The inputs to EnergyPLAN are described here:

- The electricity and heat demands are input using the annual demand and distributions of the hourly variation. For the heat demand monitored data was input, and for the electricity demand the synthesised profile from HOMER was input.
- PV generation is input as a capacity and a distribution profile. The solar radiation global horizontal incident from the MERRA reanalysis dataset was input as the distribution profile, while the capacity was adjusted to match the annual power production as modelled using PVLIB.
- The heat pump is input as a fixed electrical capacity and COP. This was input as 417kW to obtain a 1000kW heat output capacity using a COP of 2.4. This is the seasonal COP over the year as calculated by PyLESA, and is used because

EnergyPLAN can only accept a fixed COP. A 1000kW auxiliary electric boiler is also added for backup and peak demand periods.

- For the hot water tank, the energetic capacity is calculated using the specific heat formula, where the mass is 500,000kg and the delta T is 25°C (from 65°C heat pump flow and 40°C district heating return temperatures). The energetic capacity is calculated and input as 14.5MWh.
- The variable periods tariff is input as a timeseries distribution, with day prices of £150/MWh and night prices of £75/MWh.
- The technical control strategy selected balances heat and electrical demands, while maximising self-consumption of excess electrical generation. A sample of the available control strategies were tested, and this one was found to minimise operational costs.

Table 6.2 shows the imports, percentage of PV exported, import costs, and LCOE are similar for both tools. This suggests that the outputs from PyLESA are in broad agreement with the outputs from the widely used planning-level tool, EnergyPLAN, and therefore, producing outputs which are reasonable. However, the outputs are not exactly the same, and this is due to the differences in the way PyLESA and EnergyPLAN models and controls the hot water tank. These differences are discussed in the rest of this section.

Table 6.2: Outputs from application of PyLESA and EnergyPLAN

Output (over a year)	PyLESA	EnergyPLAN
Imports (MWh)	2011	2000
Percentage of PV generation exported (%)	4.5	9.3
Import costs (£k)	247	273
LCOE (p/kWh)	5.8	6.3

The tools use different approaches for modelling the hot water tank. PyLESA uses the multi-node model which accounts for the evolution of temperature throughout the tank, and for losses to both the environment and mixing. EnergyPLAN uses an energetic model which does not account for any losses and does not incorporate temperatures of the tank. This contributes to the higher imports and lower percentage of PV generation exported (increased PV self-consumption) as output by PyLESA compared to

EnergyPLAN, as there is a greater energy requirement for meeting demands plus the losses.

There are also differences in the approaches of the tools to the control of the hot water tank. In this example, PyLESA has been applied with MPC which optimises the operation of the hot water tank over a 24-hour period in order to minimise electricity costs. This means that the hot water tank is used to flexibly operate the heat pump and auxiliary electric heater in order to meet demand by using excess PV generation and avoiding the high-cost periods of the variable tariff. EnergyPLAN controls the hot water tank using a technical strategy which stores excess PV generation whenever possible and is independent of fluctuations of prices of the variable tariff.

The control logic used by EnergyPLAN results in periods where the storage reaches capacity and forces excess PV generation to be exported. PyLESA operates to maximise the use of the excess PV generation, as it is considered zero marginal cost electricity. Additionally, it also occasionally uses the auxiliary electric heater to use or store excess PV generation. This is because operation is minimised for cost and does not distinguish between the greater energy utilisation possible by using the heat pump over the auxiliary electric heater. The optimisation strategy, use of the auxiliary electric heater, and losses from the hot water tank all contribute to a lower percentage of the PV generation which is exported in the outputs from PyLESA compared to EnergyPLAN.

EnergyPLAN does not attempt to shift electricity imports to low-cost periods, in contrast to PyLESA which accounts for both PV generation and the variability of the electricity tariff when operating the heat pump and hot water tank. This contributes to lower import costs and LCOE from PyLESA compared to EnergyPLAN. This is despite the higher energy demand for PyLESA due to incorporating hot water tank losses, which will contribute to increasing import costs and LCOE for PyLESA.

This analysis does not explore the extent to which the different approaches change the outputs, and this can be done as future work to complete a more detailed comparison of the two tools. However, the above discussion of the effects of the different approaches to control and modelling of the hot water tank explains the reasons for the differences between the outputs.

PyLESA could be configured to imitate the control logic of EnergyPLAN by setting losses to zero and utilising a significantly longer prediction horizon. However, this approach is not realistic as keeping the hot water tank hot over periods of days, as

EnergyPLAN does in periods of high PV generation, will result in higher heat losses. Not modelling these heat losses results in a lower overall energy demand than would be expected with a system containing a hot water tank. This highlights the advantage of using PyLESA with its more realistic hot water tank modelling and control. Additionally, EnergyPLAN cannot be configured to imitate the more realistic control used by PyLESA. This highlights the greater user flexibility of PyLESA over EnergyPLAN.

In conclusion, the similar outputs show that PyLESA produces reasonable outputs, while the differences in the outputs can be explained by the more realistic approach taken to the modelling and control of hot water tanks in PyLESA than in EnergyPLAN.

6.7. Operational Analysis Results

This section contains the results and discussion of the operational analysis for all the modelled combinations of control strategies and electricity tariffs. The algorithms and decision making behind the controllers will be discussed by examination of the behaviour of the supply and storage components as they meet demand. This contributes to two aims of the sizing study, (i) to compare the performance of the control strategies and, (ii) to compare the performance of the electricity tariffs.

This section also contributes to another aim of the sizing study which was to validate the control strategies by inspection. This is crucial as the development of these constitute a contribution made to the state of the art. Additionally, the analysis in this section helps validate the workflow of PyLESA; ensuring that the underlying models work together and can produce outputs which are logical and realistic.

The operational graphs presented here consist of four plots: heat pump output, auxiliary, and heat demand; hot water tank node temperatures; import cost; and, surplus and export. A summer week and winter week are shown for most tariff and control combinations, with a windless winter week shown for the wind tariff with MPC.

The following key applies to all the operational graphs: HPt – heat pump heat output, aux – auxiliary heat output, and HD – heat demand.

The case study for the control strategy and electricity tariff combinations use a 1000kW heat pump and 500m^3 hot water tank size combination as the illustrative example to carry out the analysis, except those with the wind tariff where a 3000kW heat pump and 3000m^3 hot water tank combination was used. A different size combination is chosen for the wind tariff to explore the ability of a larger sized system to take advantage of the larger price differentials on a longer timescale.

6.7.1. Fixed Order Control

6.7.1.1. *Flat Rate Tariff*

The operation of the fixed order control with the flat rate tariff is displayed for a summer week in Figure 6.12 and a winter week in Figure 6.13. The main load shifting mechanism on display is shifting heat pump electricity consumption to match excess PV generation which charges the hot water tank to meet heat demand during periods of little or no PV generation. Since the flat rate tariff does not vary with time (3rd plot) there is no cost benefit for shifting heat pump operation according to import cost.

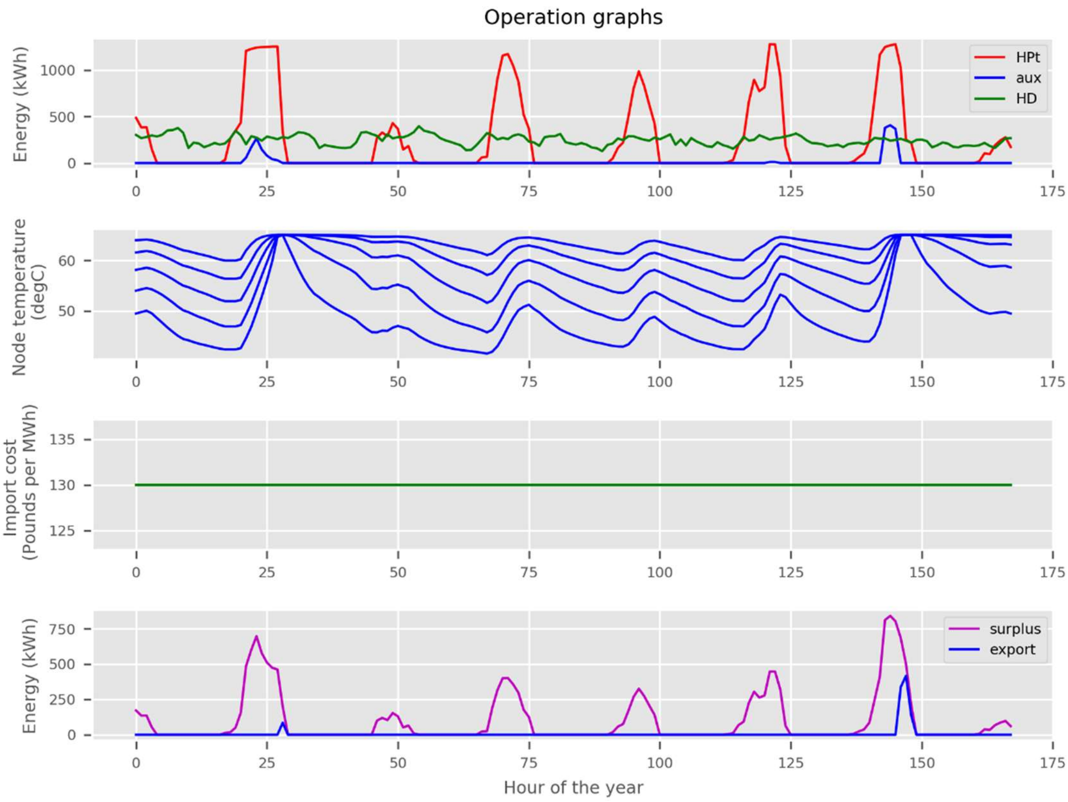


Figure 6.12: Operational graphs with FOC and flat rate tariff over a summer week

The heat pump capacity, stated as 1000kW, is the rated capacity under rated operating conditions. The heat pump output exceeds 1000kW in the 1st plot because it is operating in summer conditions which are warmer than the rated conditions which results in a high heat pump maximum output.

In the first few hours of the plotted period, the heat pump is meeting demand (1st plot) from surplus PV generation (4th plot) and charging the storage (2nd plot). When there is no longer surplus PV generation the heat pump turns off and the hot water tank discharges to meet demand. Then, the hot water tank becomes depleted, the top node drops below the required flow temperature of the district heating network, and the heat pump modulates output to meet heat demand. Surplus PV generation is available again and the heat pump operates at maximum output to meet demand and charge storage. The controller also chooses to turn on the auxiliary electric heater to aid charging of the hot water tank in the periods where relying on the heat pump using surplus PV is insufficient to cover the heat demand. After the PV is no longer producing a surplus, the hot water tank discharges to meet the heat demand. Over the remainder of the plotted week a similar pattern as described is repeated. Excess PV generation is utilised by the heat pump and electrical heater to meet demand and charge the hot water tank. This then discharges to meet demand where there is no excess PV generation.

During the winter there is little surplus PV generation and therefore, few opportunities to shift load using the hot water tank. Figure 6.13 shows the heat pump modulating output to meet heat demand (1st plot), negligible hot water tank charging/discharging (2nd plot), and small peaks of surplus generation (4th plot) which will be used by the heat pump to directly meet the heat demand.

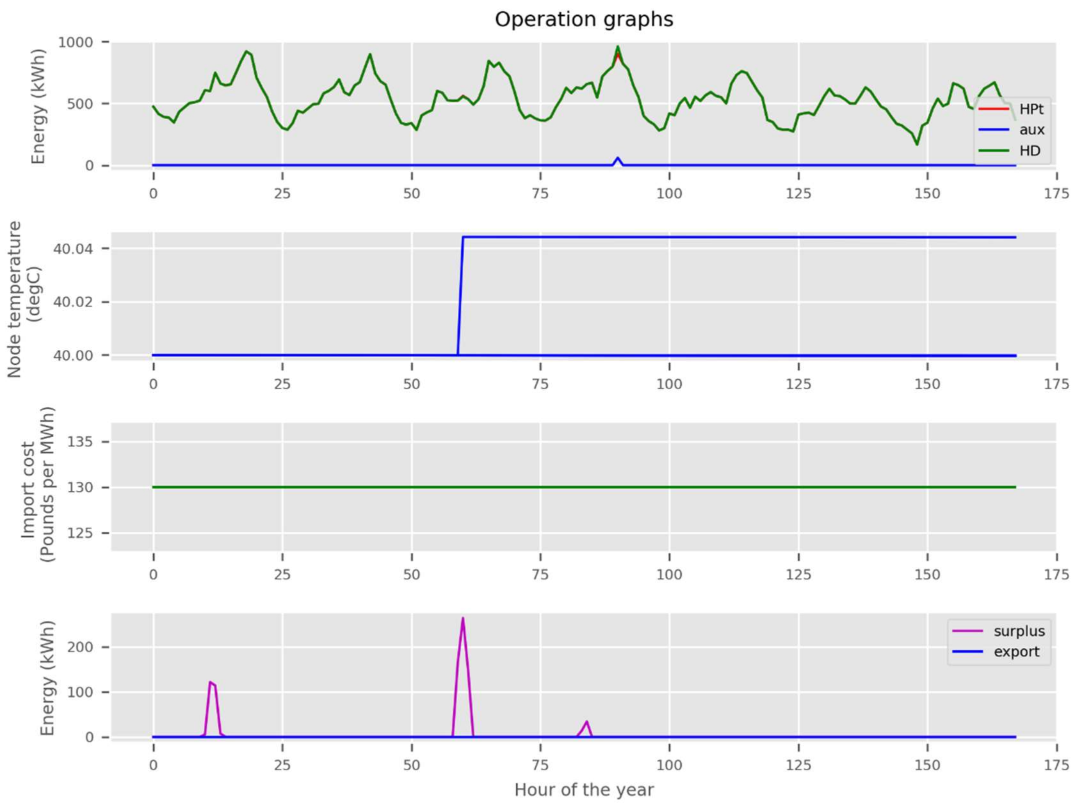


Figure 6.13: Operational graphs with FOC and flat rate tariff over a winter week

6.7.1.2. *Variable Periods Tariff*

The operation of the fixed order control with the variable periods tariff is displayed for a summer week in Figure 6.14 and a winter week in Figure 6.15. Load shifting occurs in this example for both utilising excess PV generation and avoiding importing during high-cost electricity tariff periods during the day (3rd plot).

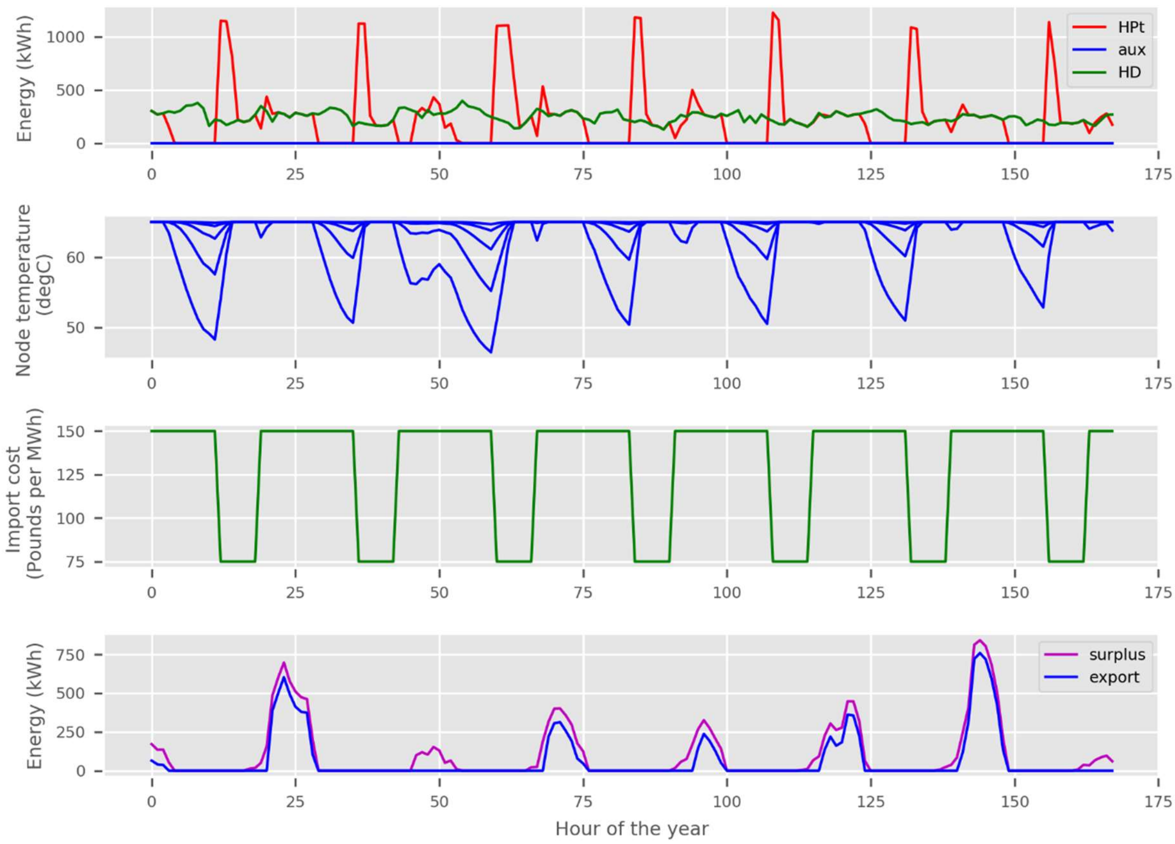


Figure 6.14: Operational graphs with FOC and variable periods tariff over a summer week

At the start of the displayed summer week, the heat pump is meeting demand from surplus PV generation (4th plot). When there is no longer surplus PV generation the heat pump turns off and the hot water tank discharges to meet demand (2nd plot). When the import cost drops from £150/MWh to £75/MWh (3rd plot) the heat pump output is turned up to the maximum output and simultaneously meets the heat demand and charges the hot water tank. During the low-cost period, when the hot water tank is full, the heat pump modulates its output to match demand. During the high-cost period the hot water tank discharges and the heat pump turns off unless there is surplus PV generation, in which case the heat pump meets demand and charges the hot water tank. However, because the hot water tank has only briefly been discharging after fully charging from the low-cost overnight period, there is little spare capacity to utilise the surplus PV generation.

During the winter, there is little surplus PV generation and the primary load shifting mechanism is moving demand from day to night. The higher demand in the winter means that the heat pump operates at maximum output during the low-cost period to meet demand and charge the hot water tank. In the displayed example, at the start of the high-cost period, the hot water tank discharges to meet demand but there is not enough stored heat to meet the entire demand during the high-cost period. When the hot water tank is empty the heat pump modulates its output to meet heat demand.

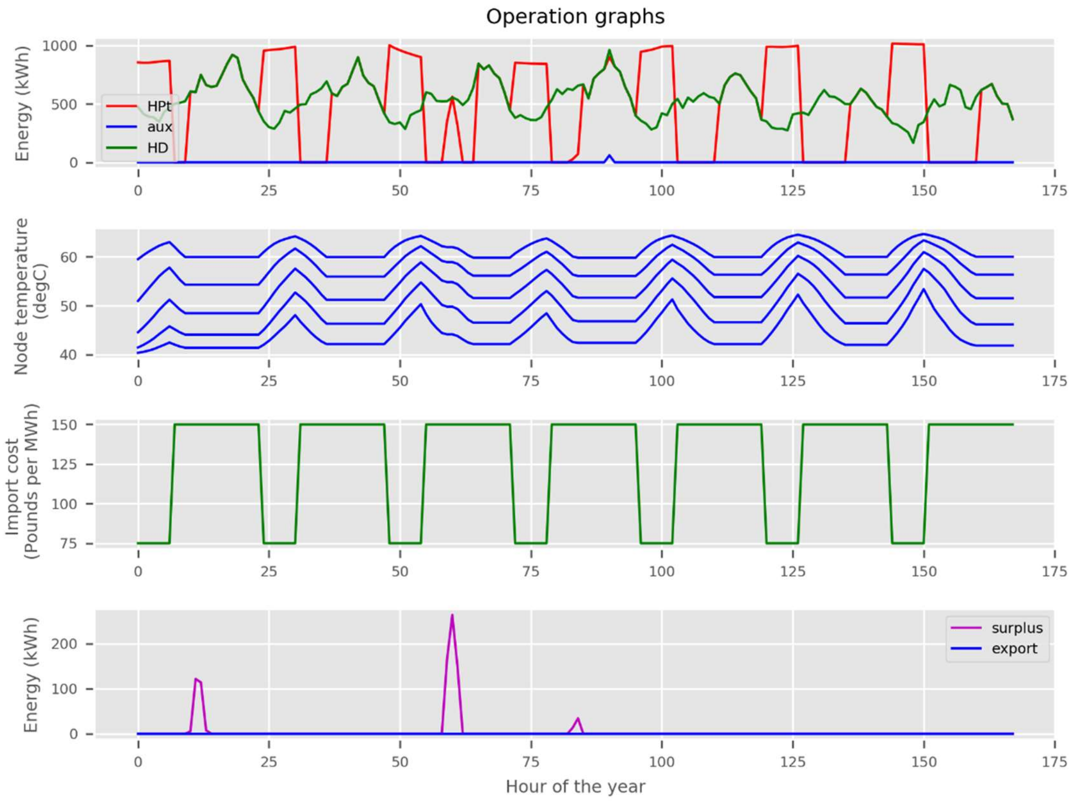


Figure 6.15: Operational graphs with FOC and variable periods tariff over a winter week

6.7.1.3. *Time-of-use Tariff*

The operation of the fixed order control with the time-of-use tariff is displayed for a summer week in Figure 6.16 and a winter week in Figure 6.17. Load shifting occurs mainly to avoid importing during the premium period which occurs each day between 4pm and 7pm (3rd plot), and due to the lack of sophistication of the fixed order control the surplus PV generation is largely exported.

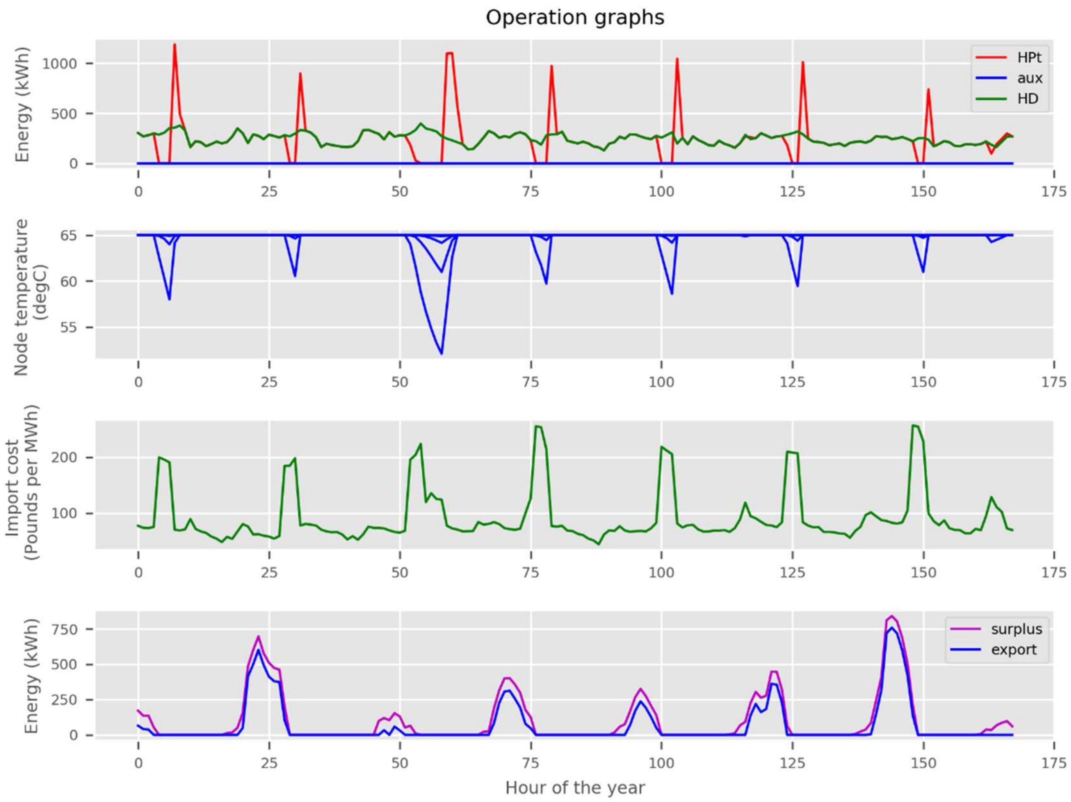


Figure 6.16: Operational graphs with FOC and time-of-use tariff over a summer week

The heat pump operation (1st plot) generally follows the heat demand but spikes to charge the hot water tank immediately after the premium price period. The hot water (2nd plot) stays fully charged for long periods and discharges to meet heat demand during the premium price period. While there are periods of surplus PV generation, this is largely exported because of the lengthy periods where the hot water tank is fully charged.

The size of the hot water tank is also sufficient in the winter week to cover the larger heat demand during the premium period.

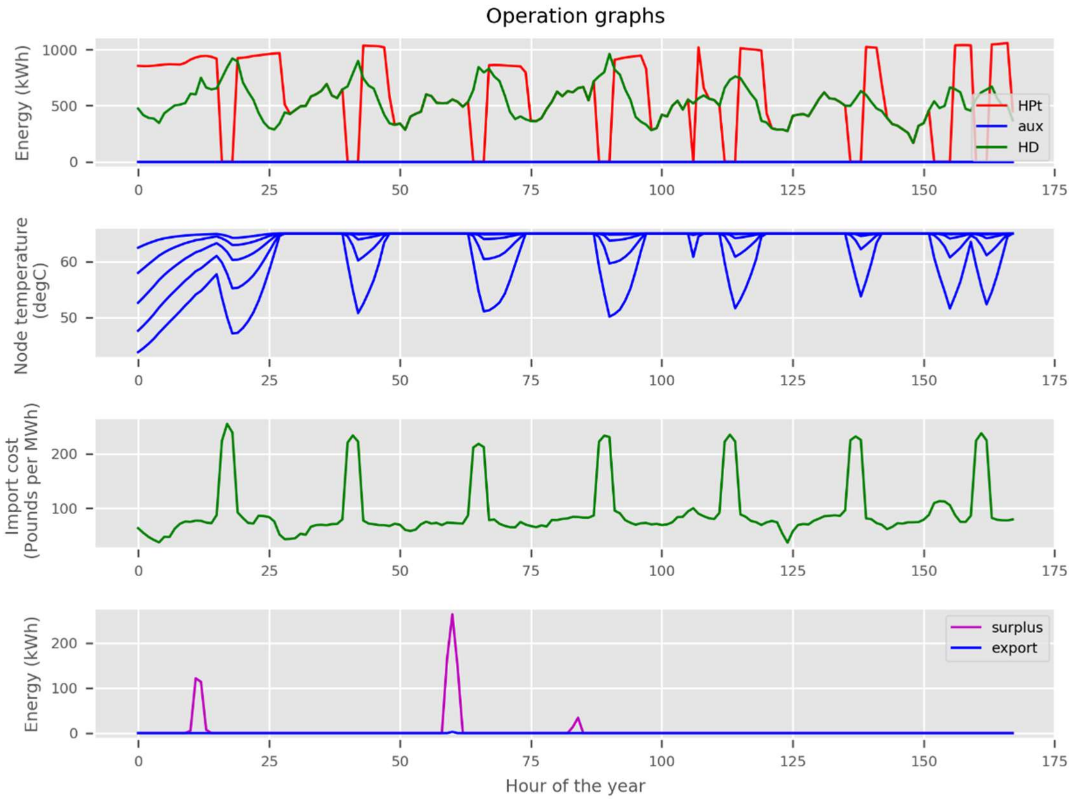


Figure 6.17: Operational graphs with FOC and time-of-use tariff over a winter week

6.7.1.4. Wind Tariff

The operation of the fixed order control with the wind tariff is displayed for a summer week in Figure 6.18 and for a winter week in Figure 6.19.

The larger size of heat pump allows the demand to be met during the low-cost periods where there is a large amount of wind on the grid. The large hot water tank meets the low summer demand for long periods using surplus PV generation and cheap wind tariff imports.

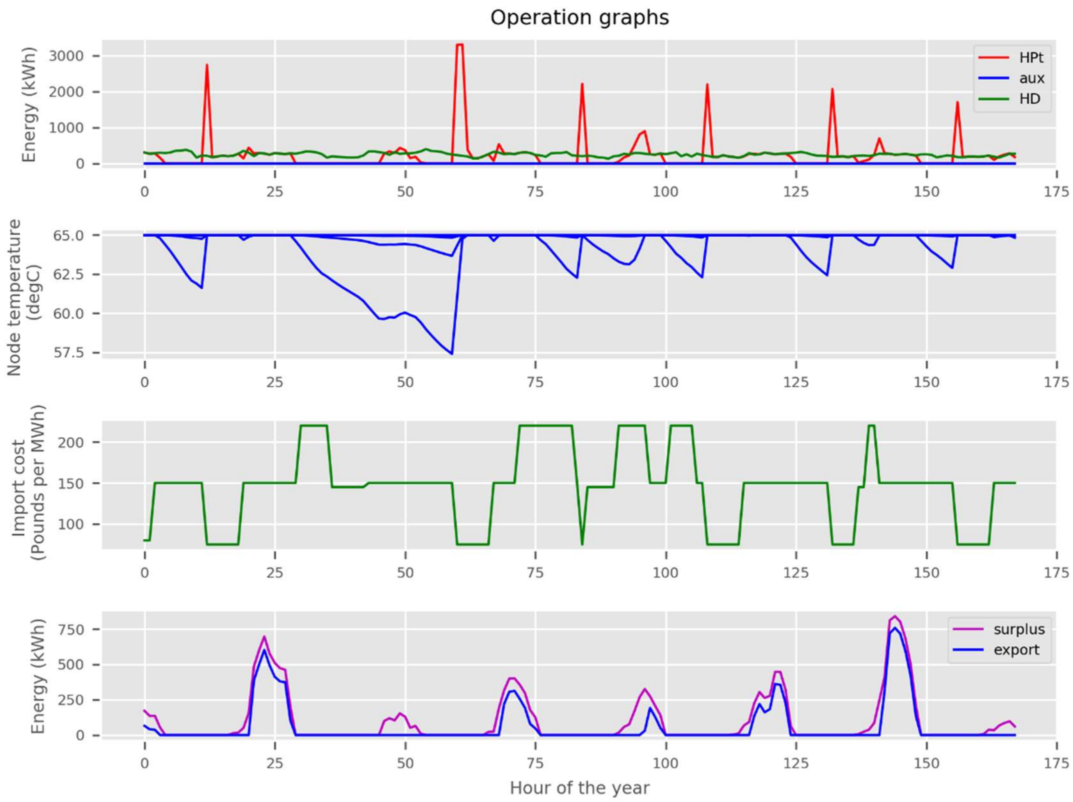


Figure 6.18: Operational graphs with FOC and wind tariff over a summer week

Load shifting occurs mainly to avoid importing during the premium period which occurs each day between 4pm and 7pm (3rd plot), and due to the lack of sophistication of the fixed order control the surplus PV generation is largely exported.

Again, in the winter week the large heat pump and hot water tank are operated to take advantage of the low-cost periods. This shows the potential of coupling large hot water tanks with this type of future electricity tariff which has large price differentials over long periods.

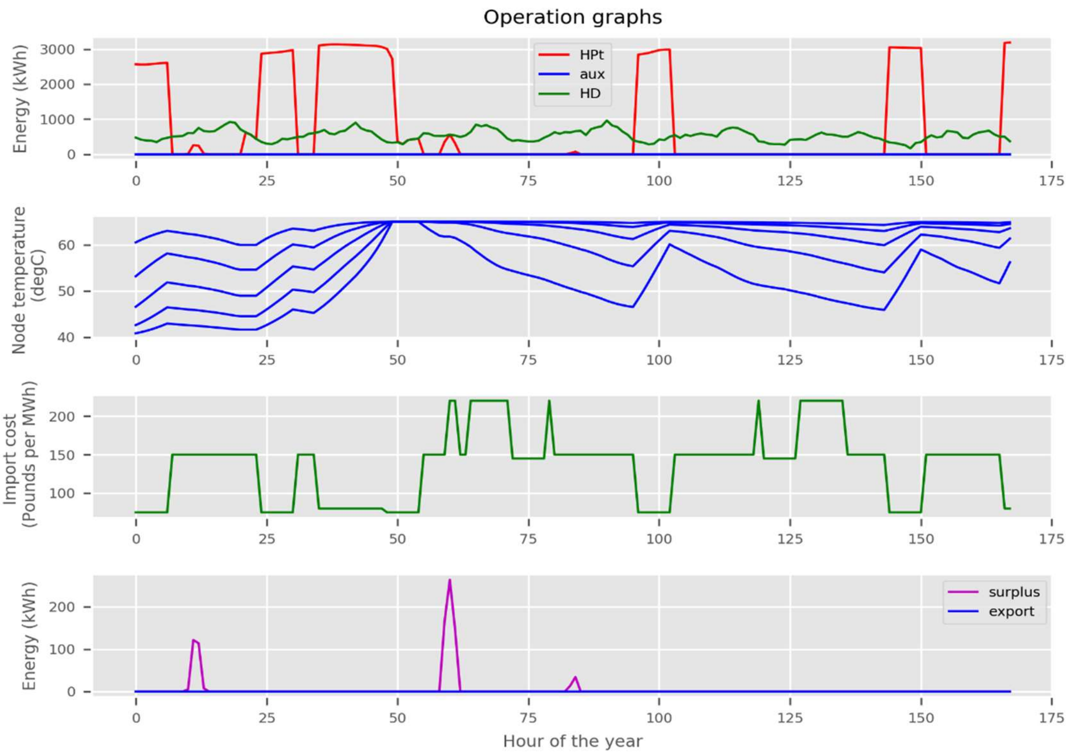


Figure 6.19: Operational graphs with FOC and wind tariff over a winter week

6.7.2. Model Predictive Control

6.7.2.1. *Flat Rate Tariff*

The operation of the MPC with the flat rate tariff is displayed for a summer week in Figure 6.20 and a winter week in Figure 6.21. The main load shifting mechanism is moving heat pump electricity consumption to match excess PV generation which charges the hot water tank to meet heat demand during periods of little or no PV generation. Since the flat rate tariff is constant (3rd plot), shifting heat pump operation according to import cost does not happen.

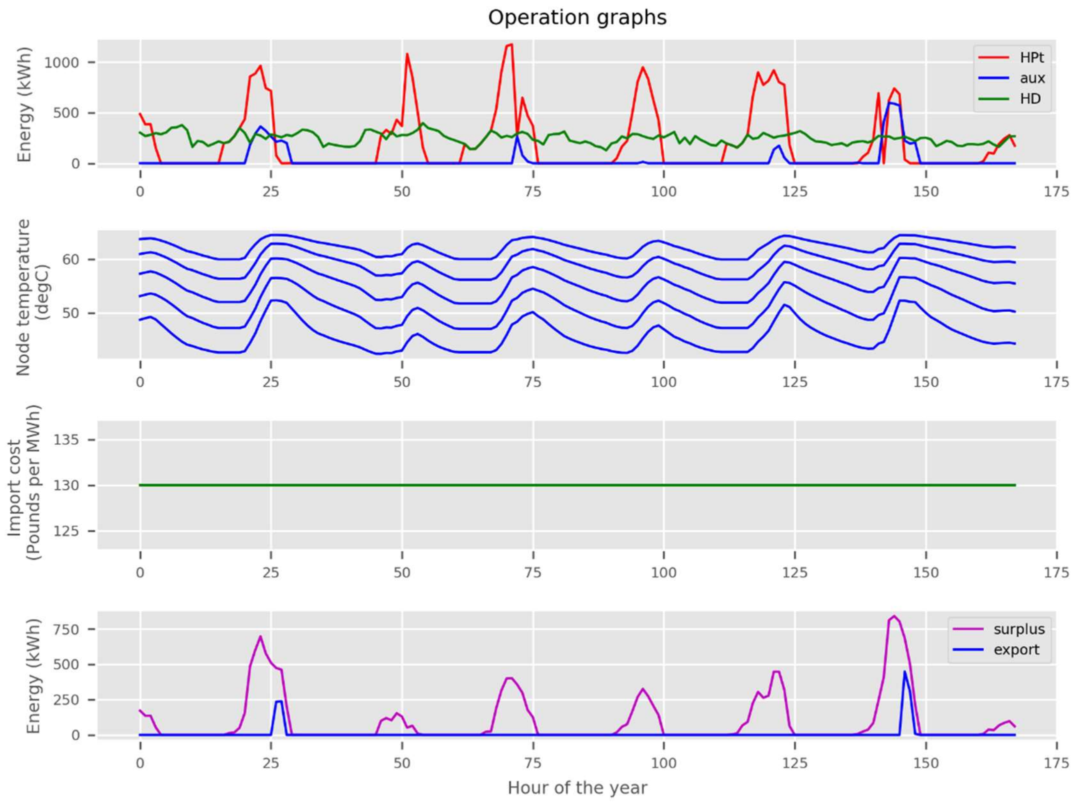


Figure 6.20: Operational graphs with MPC and flat rate tariff over a summer week

In the first hours of the plotted period, the heat pump is running on surplus PV generation, charging the hot water tank and meeting the heat demand. Then the surplus PV generation goes to zero and the hot water tank is discharged to meet demand, until it is fully discharged, and the heat pump turns back on to meet demand. When surplus PV generation later returns, it is used by both the heat pump and electric heater to meet demand and charge storage.

The heat pump only operates in the plotted period when there is surplus PV generation. The MPC optimises the operation based on minimising operational costs.

Since the usage of excess PV generation is assigned a zero-marginal cost, the algorithm makes no distinction in cost between running the heat pump or auxiliary electric heater. This is seen in periods where the heat pump turns off and the electric heater meets demand.

In the winter period, where there excess PV generation is negligible, the heat pump is primarily controlled to meet demand and charge storage in periods where the COP is highest. This results in a high number of heat pump cycling as the controller optimises the performance.

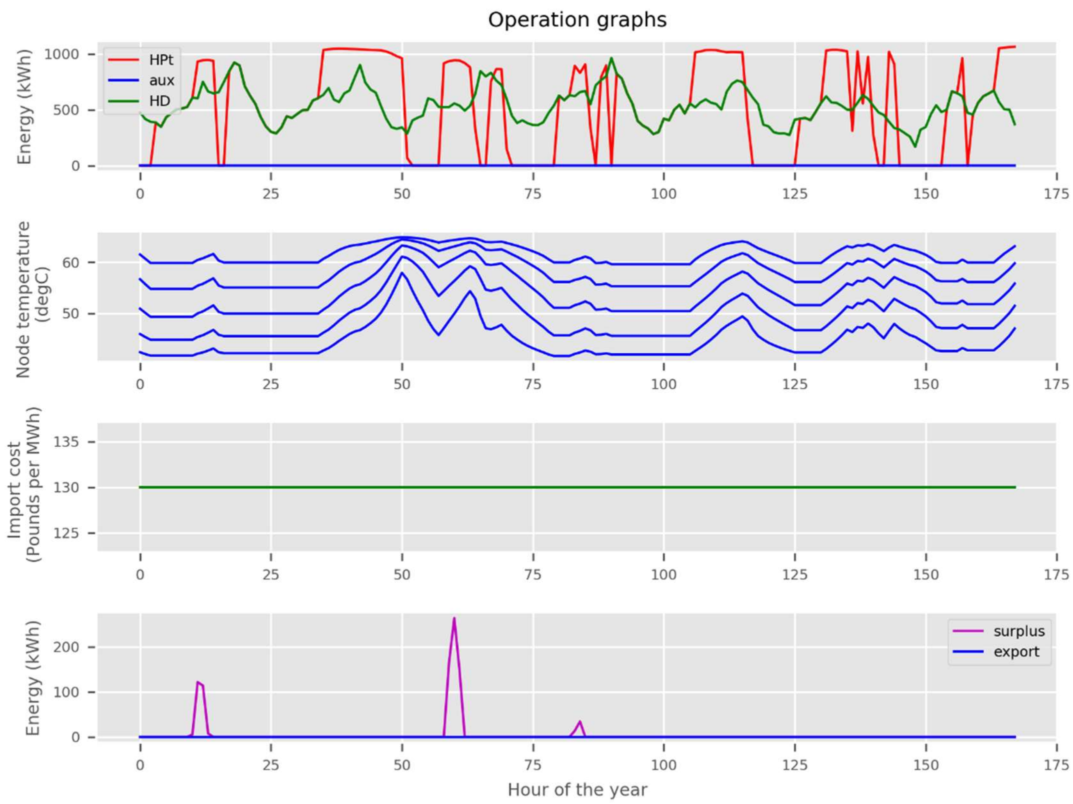


Figure 6.21: Operational graphs with MPC and flat rate tariff over a winter week

6.7.2.2. *Variable Periods Tariff*

The operation of the MPC with the variable periods tariff is displayed for a summer week in Figure 6.22 and a winter week in Figure 6.23.

In the summer week, the system shifts heat pump and electrical heater usage to match the surplus PV generation. The operation manages to cover most of the heat demand using the surplus. This means that in the summer week shown, there is little interaction with the variable periods tariff. Between the 25th and 50th hour of the summer week the heat pump is turned on at the end of the low-cost period and charges the hot water tank to avoid a proportion of the consumption during the high-cost period, despite the excess of PV generation and spare hot water tank capacity in the 26th hour. The implemented MPC uses a simplified energetic model in the optimisation problem, which leads to an overestimation of the use of the hot water tank. In the illustrated period, the hot water tanks ability to meet demand from the 26th hour is overestimated, and this shortfall met at the end of the low-cost period. This shows a limitation of the implemented MPC in PyLESA.

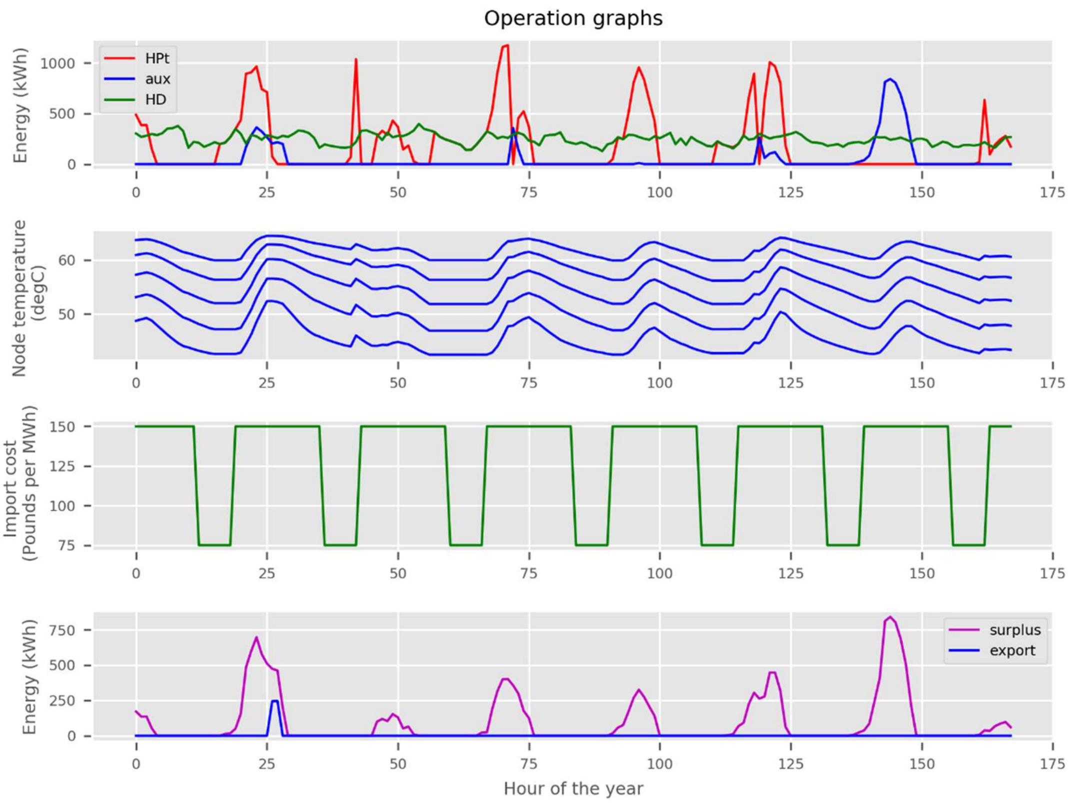


Figure 6.22: Operational graphs with MPC and variable periods tariff over a summer week

In the winter period the surplus PV generation is negligible and the MPC instead maximises the heat pump output during the night to shift as much load as possible from the high-cost period to the low-cost period. There is insufficient heat pump capacity to charge the hot water tank to cover the entire high-cost period. During the day, the heat pump charges the hot water tank during higher COP periods to improve overall performance, and ultimately minimise the operational cost.

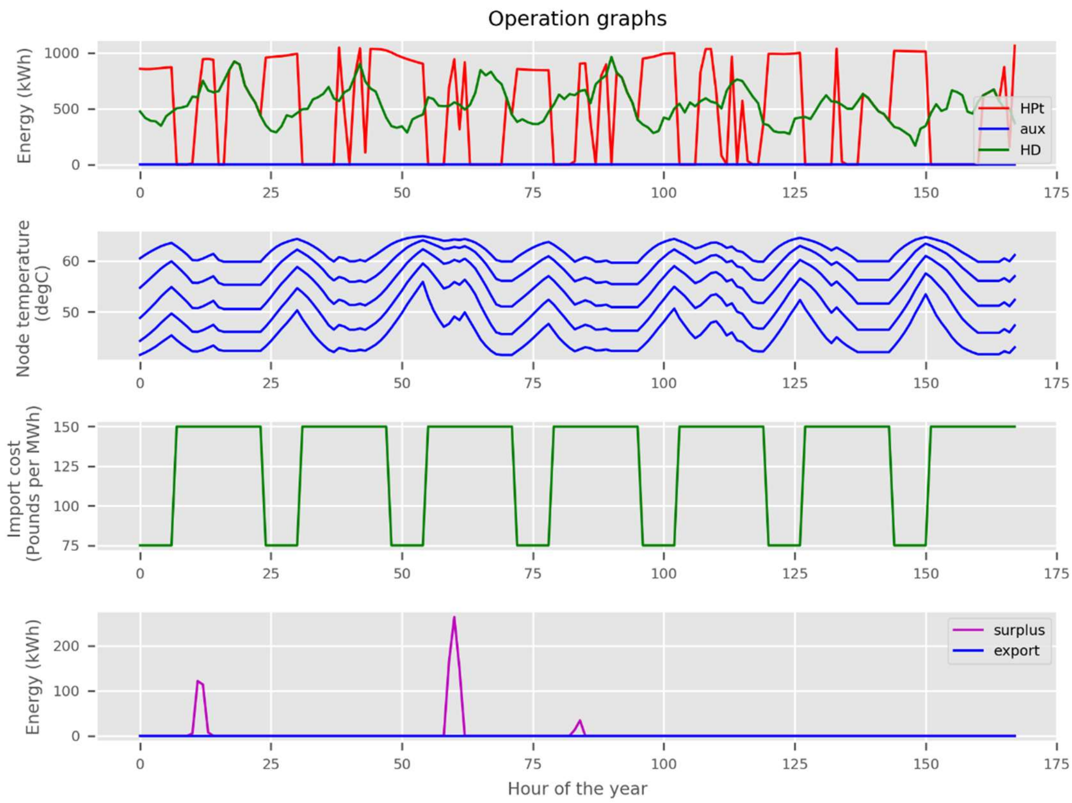


Figure 6.23: Operational graphs with MPC and variable periods tariff over a winter week

6.7.2.3. *Time-of-use Tariff*

The operation of the MPC with the time-of-use tariff is displayed for a summer week in Figure 6.24 and a winter week in Figure 6.25. The time-of-use tariff is variable hourly throughout the day and the MPC should be adept at ensuring that electrical consumption coincides with the lowest cost periods.

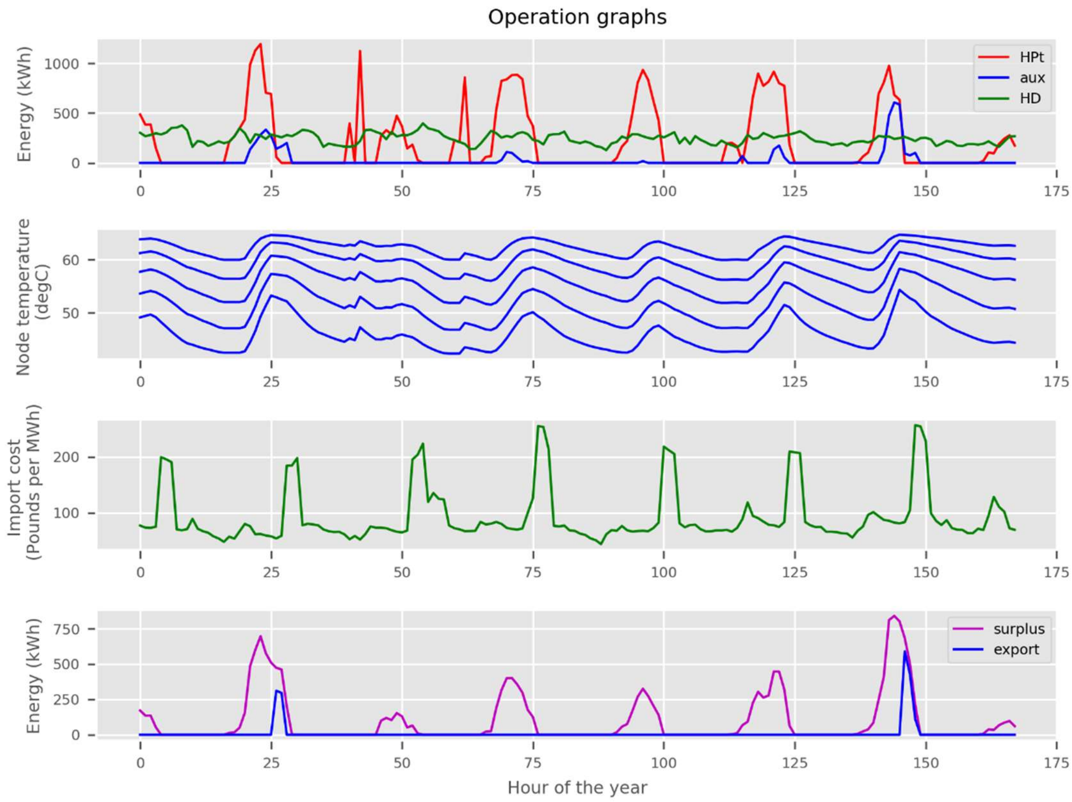


Figure 6.24: Operational graphs with MPC and time-of-use tariff over a summer week

In the summer week, operation is similar to the MPC and variable periods combination. The MPC successfully shifts most of the electrical consumption to match the surplus PV generation, while utilising the lowest cost periods of the time-of-use tariff to meet the remaining heat demand.

In the winter period, the surplus PV generation is negligible and the MPC instead optimises the heat pump output to match the lowest cost periods of the time-of-use tariffs, as well as incorporating the effect of outdoor temperature on the COP. This results in a complex operation of the heat pump cycling on and off throughout the day, responding to fluctuations in electricity prices and ambient temperature.

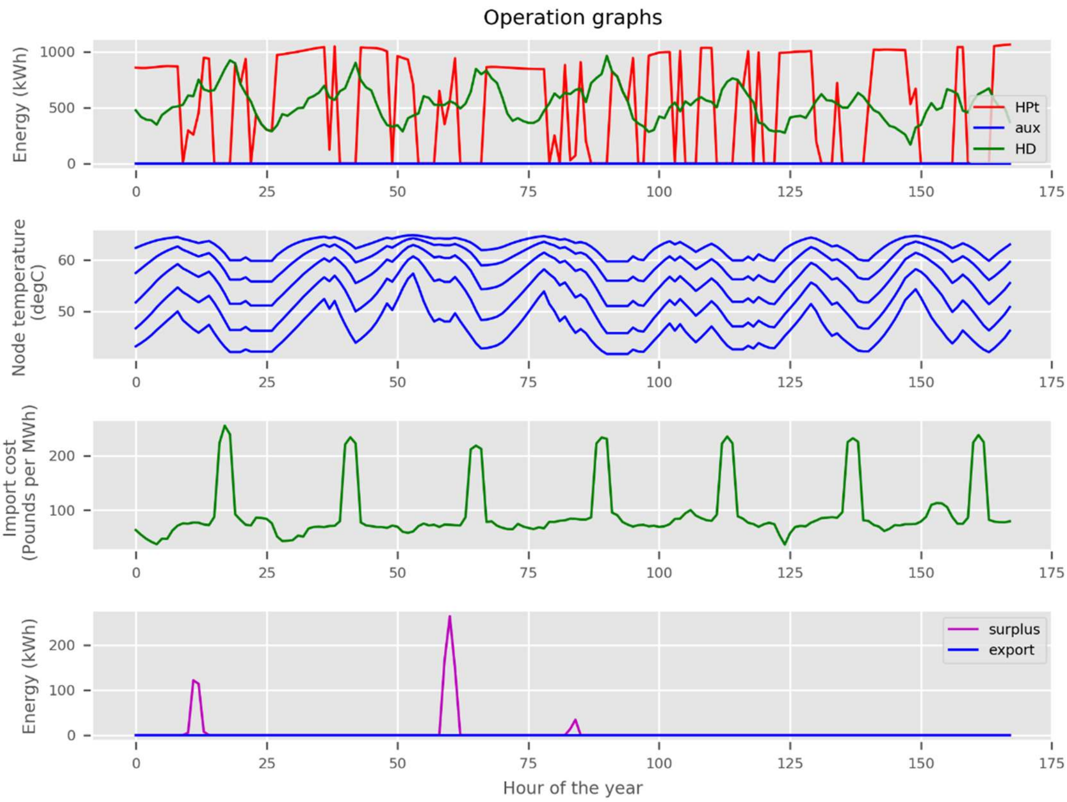


Figure 6.25: Operational graphs with MPC and time-of-use tariff over a winter week

6.7.2.4. Wind Tariff

The operation of the MPC with the wind tariff is displayed for a windless, winter 10-day period. The MPC is modified to a 168-hour prediction horizon when modelling using the wind-based tariff with a 3000kW heat pump and 3000m^3 hot water tank. The increase in prediction horizon increases computational time but allows for operation to be optimised during windless periods.

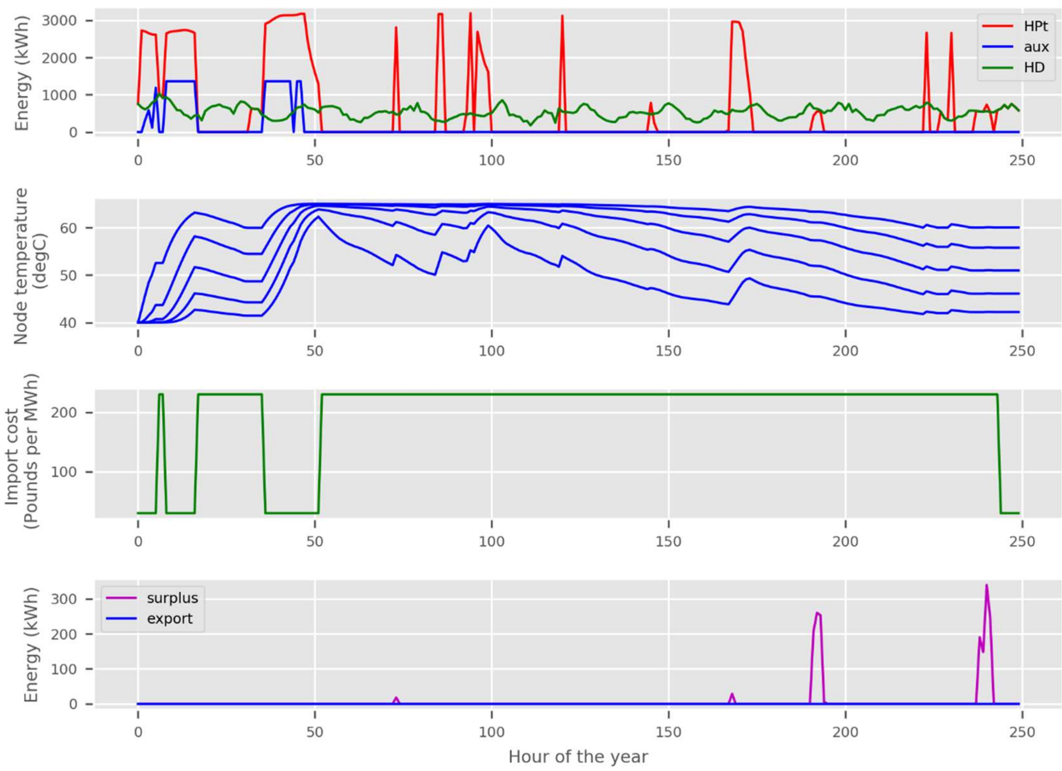


Figure 6.26: Operational graphs with MPC and wind tariff over a windless winter 10-day period

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In the first 50 hours there are periods of high wind resulting in low cost, and it is during these periods the heat pump operates at maximum output to fill storage and meet demand. Additionally, the auxiliary electric heat turns on because the direct electric heat is cheaper in these periods than operating the heat pump in the high-cost periods. The hot water tank is then used to cover a large proportion of the high-cost period, as can be seen by the trend of reducing node temperatures. However, there is not enough capacity to cover this entire period and the heat pump occasionally operates to charge the hot water tank. This will occur during the highest heat pump performance periods which are when the air temperature is highest.

6.7.3. Discussion

The operational analysis results allow discussions on the performance of the developed control strategies and the existing electricity tariffs, as well as exploring the use of a future wind-based electricity tariff. Additionally, this close examination of the operation ensures that the control strategies are operating as expected and that the workflow connecting the underlying models of PyLESA can produce logical and useful outputs.

Flat rate tariff:

- The fixed order control enables load shifting to increase the self-consumption from on-site PV generation. This is because load shifting heat pump and electric heater power consumption for surplus PV generation is the only avenue of reducing costs. The flat rate tariff offers no incentive for shifting load.
- Consequently, qualitative analysis of the operation does not reveal an advantage of using MPC as it performs the same function – increasing utilisation of surplus PV generation.

Variable periods tariff:

- The fixed order control attempts to load shift for both increasing use of surplus PV generation and avoiding high-cost tariff periods. However, the hot water tank is often fully charged at the end of the low-cost period and just before there are surpluses of PV generation. This results in a significant portion of PV generation being exported, despite this having zero value to the local energy system in this case study. Additionally, keeping the hot water tank at a high temperature for long periods will incur higher tank losses.
- MPC allows the operation to optimise for both avoiding high-cost periods and utilising PV with the variable periods tariff. This results in a much higher utilisation of surplus PV generation, and lower import costs as a result of only charging the hot water tank at low-cost periods in order to cover the remaining heat demand.

Time-of-use tariff:

- This is a highly variable tariff outside the premium period meaning that using the fixed order control is limited to avoiding imports during the premium period. The fixed order control is not suited to avoid the premium period and load shift based on price variations outside of the premium.

- MPC makes it possible to avoid premium prices and take advantage of the other variable prices. Additionally, similar to the variable periods tariff, the PV utilisation can be maximised and imports limited to the lowest cost periods and restricted to only meeting the remainder of the demand in the calculation period.

Wind tariff:

- Using the fixed order control with the wind tariff shows great potential for the use of large hot water tanks and heat pumps with this type of tariff. The heat pump only runs in the low-cost and renewable periods which should lead to low operating costs and a high percentage of heat met by renewables.
- MPC requires a longer prediction horizon than that used for the existing electricity tariffs to account for the large windows of fluctuations, over periods closer to a week. It can be seen that the electric heater is still needed to see the system through long periods of high cost. However, the sizing results should show employing the MPC resulting in a higher proportion of renewables meeting demand.

6.8. Sizing Results

The heat pump and hot water tank are sized for the proposed design using three existing electricity tariffs: flat rate, variable periods, and time-of-use; and a future wind-based electricity tariff. Price data for the existing tariffs is from 2017 and taken to be representative of the types of price differentials available and allow this sizing study to investigate and compare system performance using the different tariff structures.

The KPI levelized cost of heat (LCOH) was used to select the optimum size combination in this study. The LCOH metric does not reflect the total cost of the system, as only the heat pump and hot water tank capital expenditures are included, but it does provide a helpful insight into trade-offs between the larger capital cost and the smaller operating cost associated with increasing capacities of heat pump and hot water tank. The capital cost plot is shown in Figure 6.27 and the shape of this plot shows the relative expensive cost of increasing heat pump capacity as compared to hot water tank capacity.

Cost may not be the sole driver of a project, as environmental, e.g. CO_2 emissions, or wider societal benefits may be more important. Therefore, 3D plots are included for the existing electricity tariffs of the following KPIs: LCOH, ORESpv, and HRESpv. For the wind tariff 3D plots of the following KPIs are displayed: LCOH, ORESpv, and HRESpv+windtariff. ORESpv is the percentage of on-site PV generation which is self-consumed. HRESpv is the percentage of the heat demand which is met through usage of the on-site PV generation. HRESpv+wind is the percentage of the heat demand which is met through both the usage of the on-site PV generation and the usage of electrical imports during high wind periods. See Section 6.1. for further details on these.

Results for the optimum LCOH size combinations of heat pump and hot water tank are in Table 6.3 for the existing electricity tariffs and developed control strategies, and in Table 6.4 for the wind electricity tariff and developed control strategies.

Table 6.3: Optimum LCOH results for the existing electricity tariffs and control strategies including KPIs (brackets is the relative change from FOC to MPC)

Tariff	Control	HP (kW)	TS (m^3)	HRESpv (%)	ORESpv (%)	LCOH (p/kWh)
Fixed Rate	FOC	750	400	33.8	92.7	4.75
	MPC	750	500	32.7	96.7	4.62 (-2.7%)
Variable Periods	FOC	1000	400	18.7	70.2	4.49
	MPC	1000	500	33.6	95.5	4.13 (-8.0%)
Time-of-use	FOC	750	300	15.8	67.0	3.86
	MPC	750	500	32.1	95.9	3.11 (-19.4%)

Table 6.4: : Optimum LCOH results for the wind electricity tariff and control strategies including KPIs (brackets is the relative change from FOC to MPC)

Tariff	Control	HP (kW)	TS (m^3)	HRESpv+windtariff (%)	ORESpv (%)	LCOH (p/kWh)
Wind	FOC	1000	1500	52.8	73.8	5.81
	MPC	1000	2000	70.2	98.1	3.25 (-44.1%)

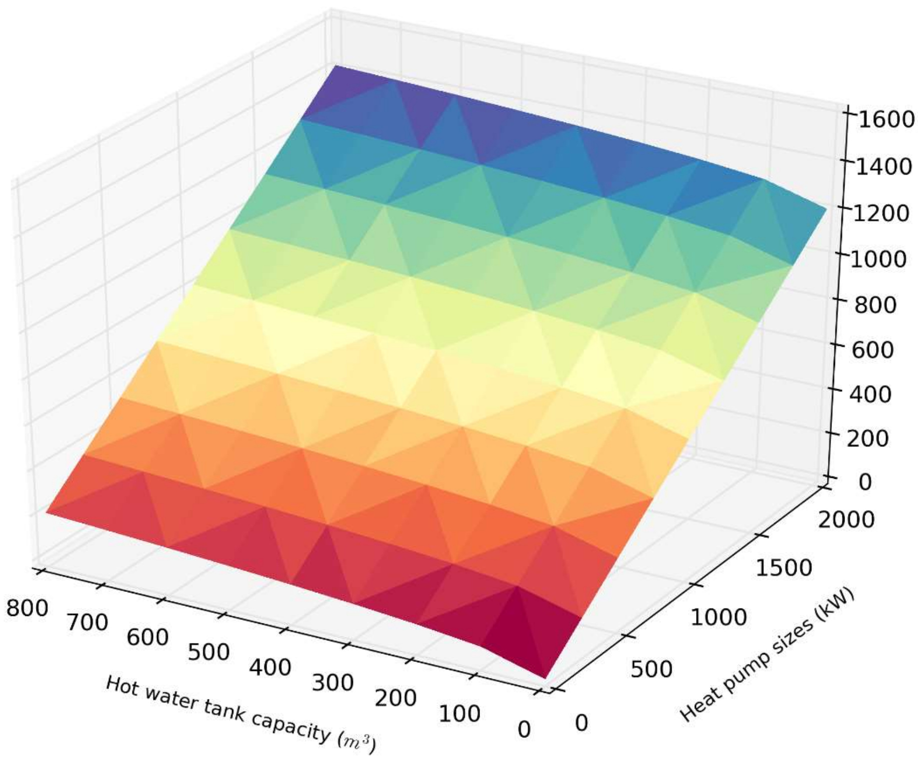

Figure 6.27: 3D plot of capital cost for a range of size combinations

6.8.1. Fixed Order Control

6.8.1.1. Flat Rate Tariff

The main load shifting mechanism for fixed order control with the flat rate tariff is shifting heat pump electricity consumption to match excess PV generation. The LCOH optimum size combination is a 750kW heat pump and a 400m^3 hot water tank.

The LCOH is reduced by increasing hot water tank capacity before levelling off above capacities of 400m^3 (Figure 6.28), and by increasing heat pump capacity to 750kW after which the LCOH increases. The main driver for the reduction in LCOH is increasing the heat pump capacity, as the higher usage of the heat pump over the auxiliary electric heat meets the heat demand more efficiently. Another driver is a larger hot water tank which allows higher on-site PV self-consumption (Figure 6.29). Both graphs show the same levelling off point with increasing hot water tank capacity.

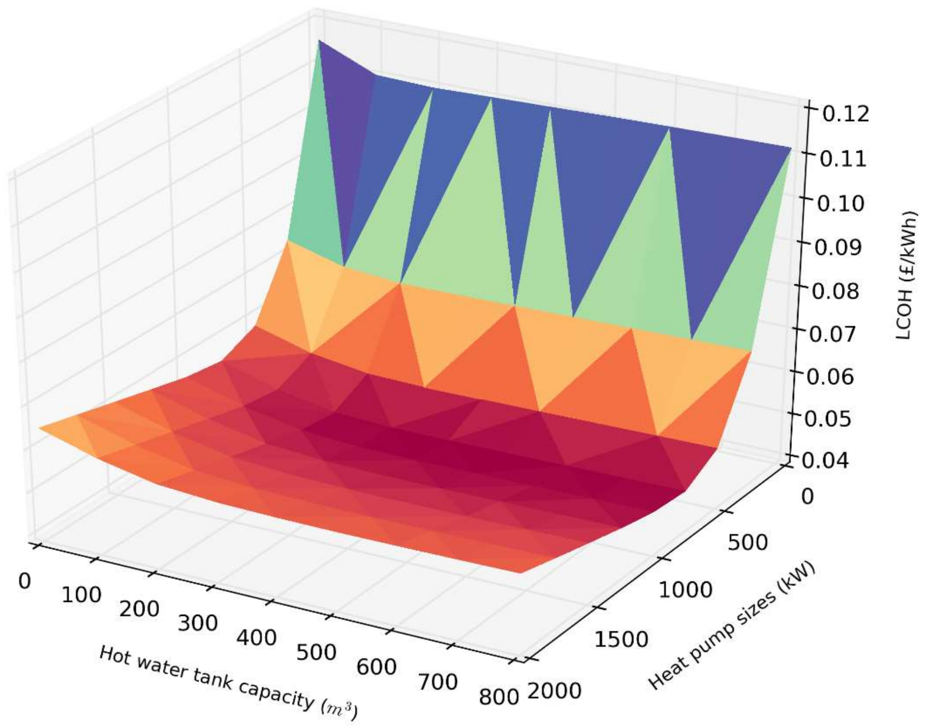

Figure 6.28: 3D plot of LCOH (levelized cost of heat) for FOC with flat rate tariff

The on-site PV self-consumption increases with a larger hot water tank, and then levels off above hot water tank capacities of 400m^3. The decrease in on-site PV self-consumption as heat pump size increases is due to the more efficient conversion of electricity to heat using the heat pump as opposed to the auxiliary electric heater.

This is clarified in Figure 6.30 which shows that increasing the heat pump and hot water tank capacities also increases the percentage of the heat demand met by on-site PV. Therefore, while the on-site PV self-consumption decreases with greater heat pump usage, the increase in efficient use of the produced electricity results in a higher percentage of heat demand met by on-site PV.

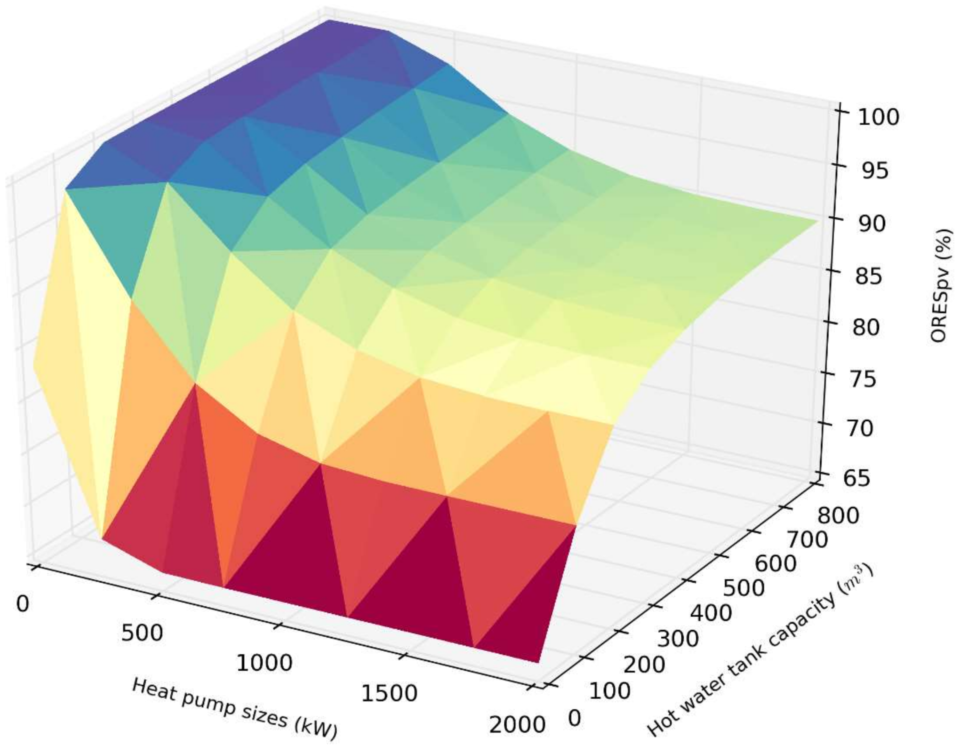

Figure 6.29: 3D plot of ORESpv (on-site PV self-consumption) for FOC with flat rate tariff

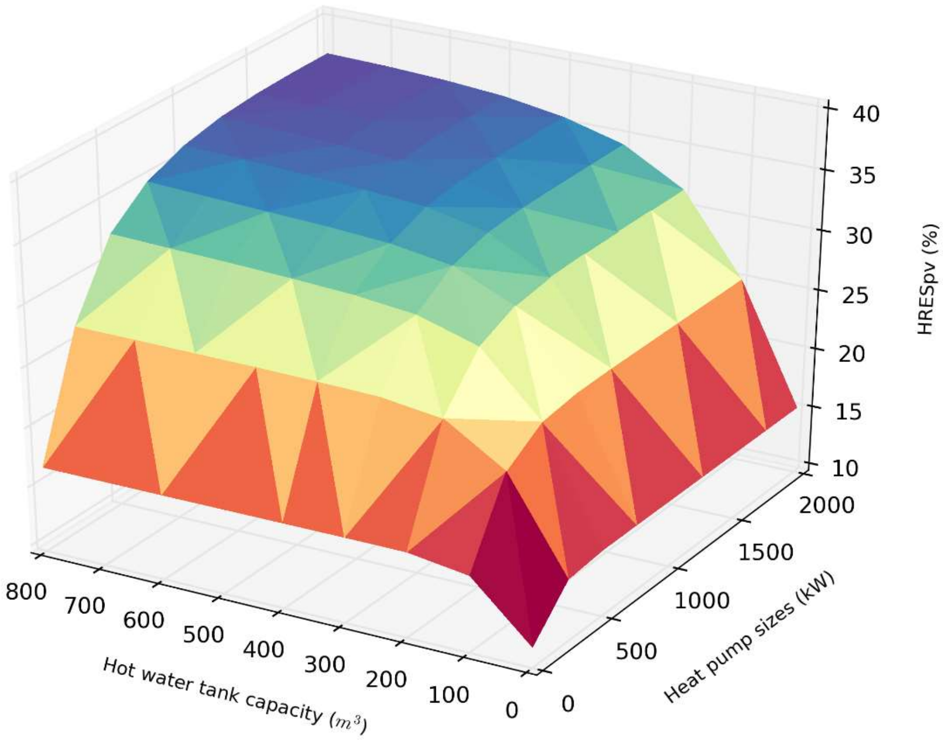

Figure 6.30: 3D plot of HRESpv (heat demand from on-site PV) for FOC with flat rate tariff

6.8.1.2. *Variable Periods Tariff*

The fixed order control with the variable periods tariff shifts load to move electricity consumption from the high-cost period during the day to the low-cost period at night, and to utilise excess PV generation. The LCOH optimum size combination is a 1000kW heat pump and a 400m^3 hot water tank. This is a larger heat pump capacity but the same hot water tank capacity as compared to the optimum found for the flat rate tariff (750kW heat pump and 400m^3 hot water tank).

The size of the hot water tank is limited to the heat pump running at full output for the duration of the low-cost period, as seen in the levelling of LCOH (Figure 6.31) for additional hot water tank capacity larger than 500m^3.

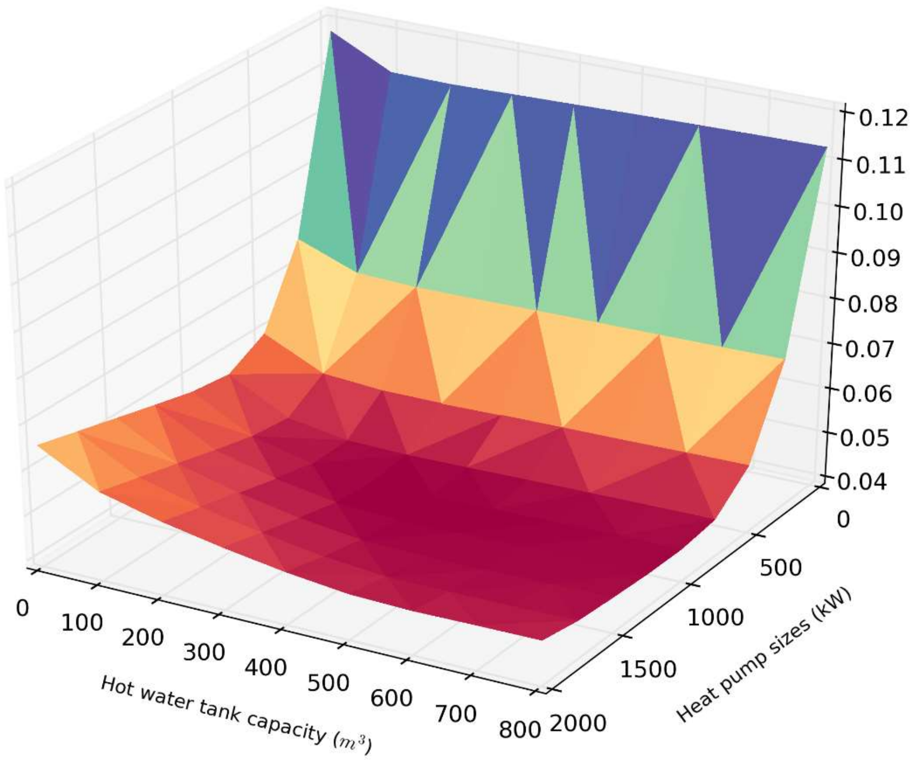

Figure 6.31: 3D plot of LCOH (levelized cost of heat) for FOC with variable periods tariff

An interesting phenomenon occurs when increasing the size of heat pump beyond 250kW. The percentage of heat demand from on-site PV decreases, and this is because the increased charging of the hot water tank during the night, decreases the potential for charging using the surplus PV generation further (Figure 6.33). While increasing heat pump capacity decreases the LCOH by shifting additional load from day to night, the renewable fraction lowers because of the hot water tank having less available charging during the day where there is surplus of generation. This disadvantage of the controller can be seen as additional storage has little effect on increasing the usage of on-site PV above 100m^3 (Figure 6.32).

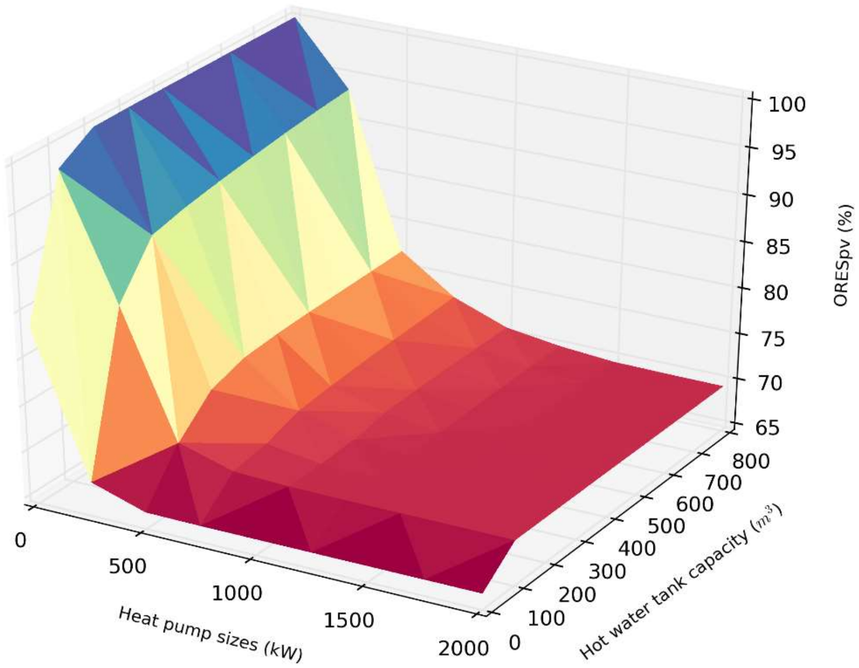

Figure 6.32: 3D plot of ORESpv (on-site PV self-consumption) for FOC with variable periods tariff

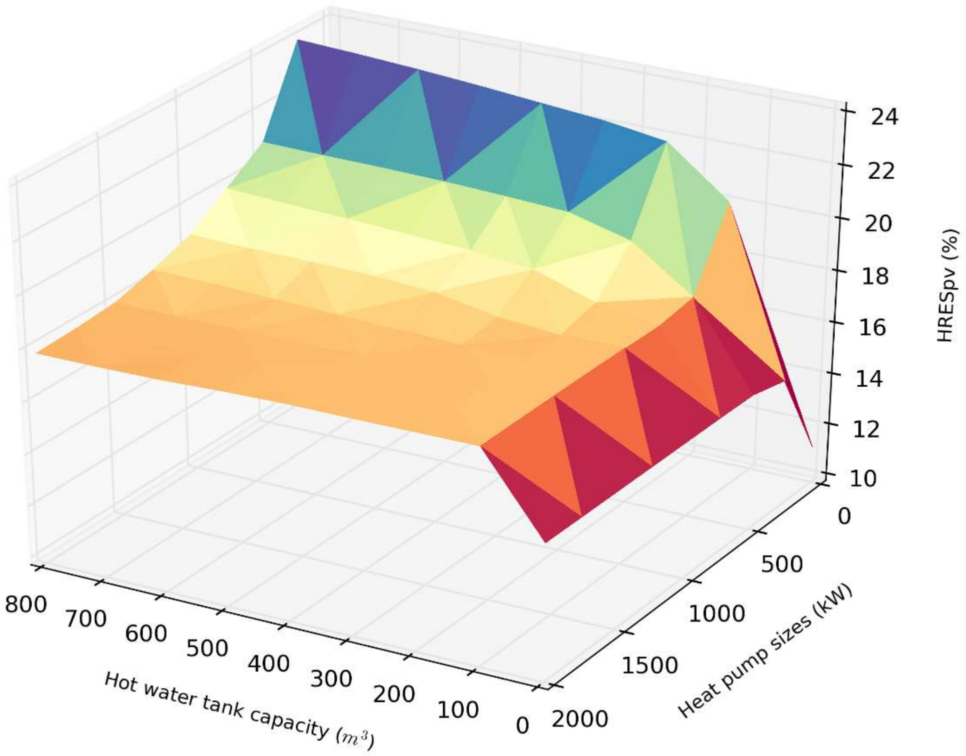

Figure 6.33: 3D plot of HRESpv (heat demand from on-site PV) for FOC with variable periods tariff

6.8.1.3. Time-of-use Tariff

The fixed order control with the time-of-use tariff shifts load mainly to avoid importing during the premium period which occurs each day between 4pm and 7pm, and due to the lack of sophistication of this control strategy the surplus PV generation is largely exported. The LCOH optimum size combination is a 750kW heat pump and a 300m^3 hot water tank.

The tariff varies through all periods of the day making it difficult to choose a setpoint for the fixed order controller. The setpoint in this example is below the premium period cost to ensure that the controller is attempting to use the hot water tank and avoid heat pump usage in this period. A sensitivity analysis would be required to fine tune the setpoint. With this primary objective of avoiding the premium period, the optimum hot water tank for minimising LCOH is smaller than for the other tariffs as there is only a three-hour period for which the hot water tank is used to shift load.

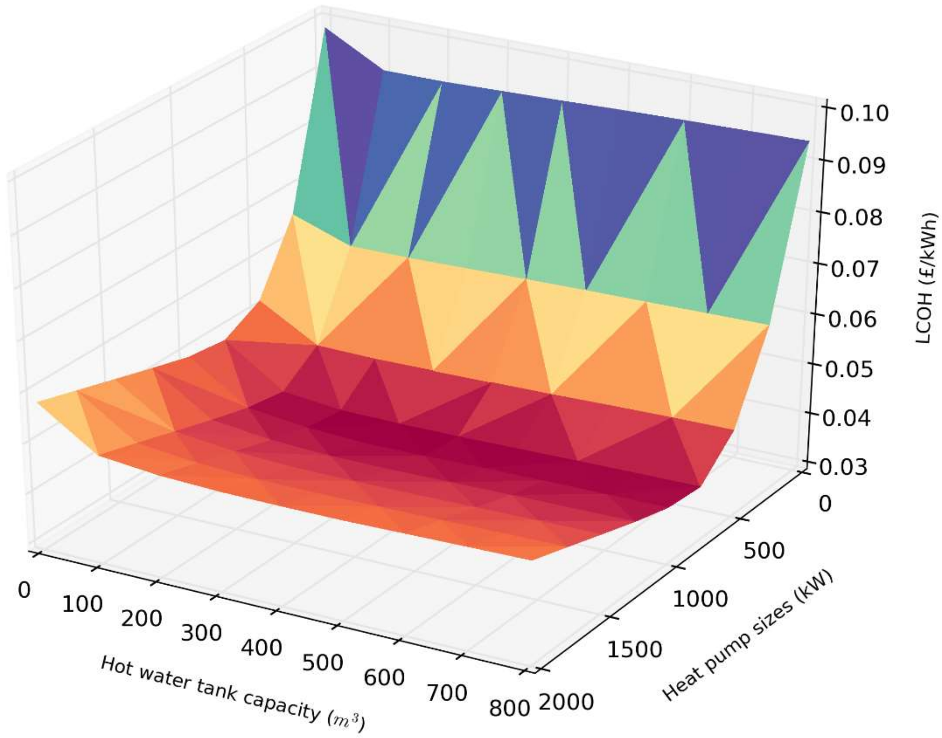

Figure 6.34: 3D plot of LCOH (levelized cost of heat) for FOC with time-of-use tariff

Similar to the variable periods, the on-site PV self-consumption and percentage of heat demand met by on-site PV is limited due to insufficient hot water tank capacity during PV generation which is due to limitations with the fixed order control strategy.

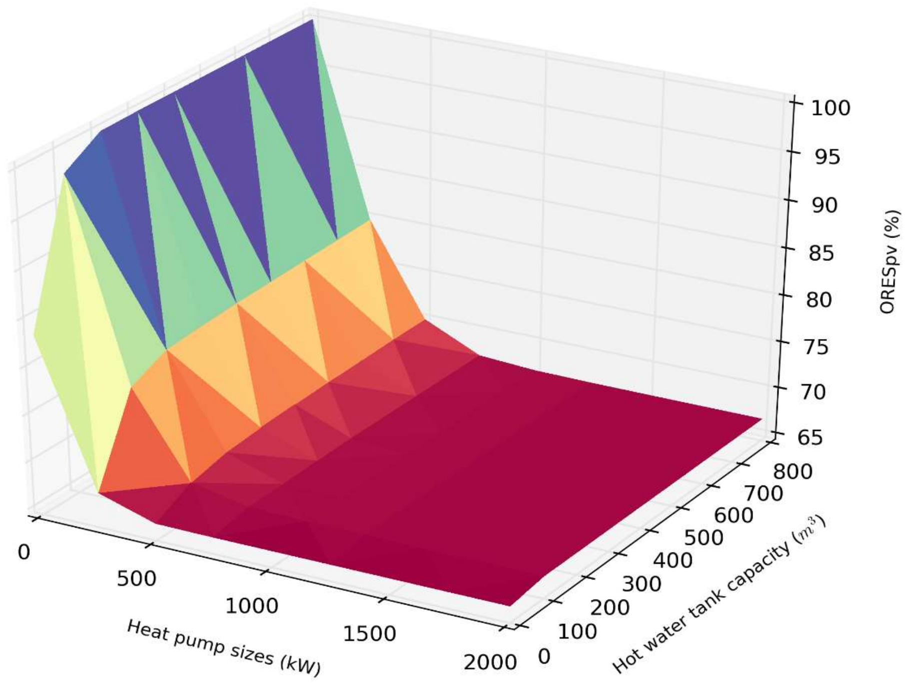

Figure 6.35: 3D plot of ORESpv (on-site PV self-consumption) for FOC with time-of-use tariff

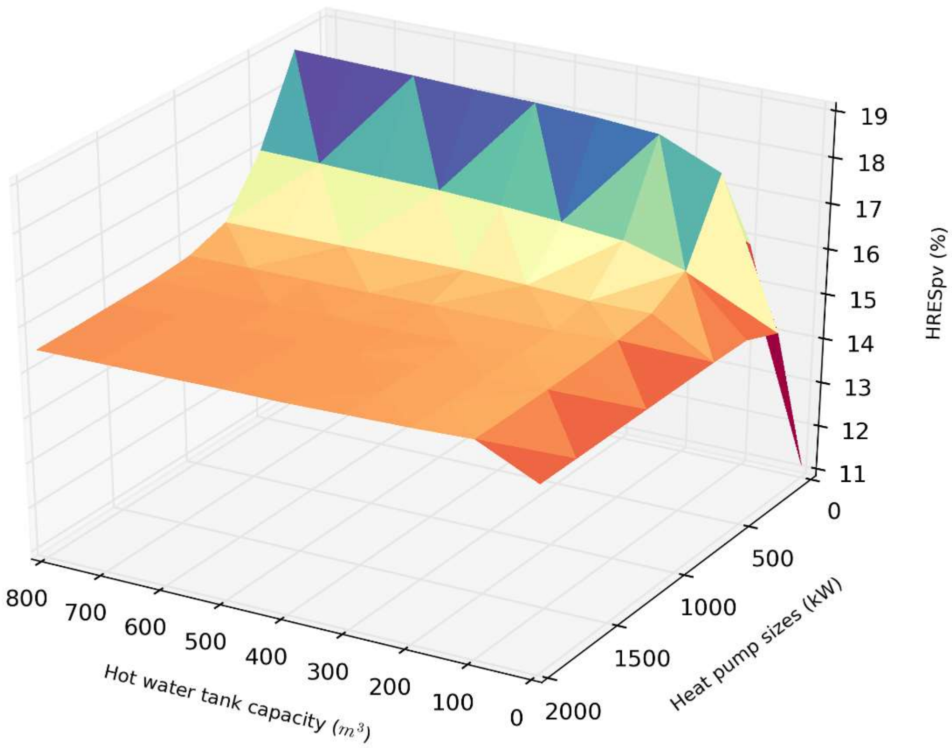

Figure 6.36: 3D plot of HRESpv (heat demand from on-site PV) for FOC with time-of-use tariff

6.8.1.4. *Wind Tariff*

The wind tariff incentivises load shifting by offering high price differentials between windy and non-windy periods, in addition to the day/night differential. As with the time-of-use tariff the fixed order control is difficult to setup due to the importance of defining the setpoint. The LCOH optimum size combination is a 1000kW heat pump and a 1500m^3 hot water tank.

The fixed order control does not successfully take advantage of the price differentials available with the wind tariff. The modelling results show a higher LCOH than the existing tariffs. This is because the control is not shifting enough load from the high cost periods, which are substantially higher than the existing tariffs, to the low-cost periods, which are substantially lower than the existing tariffs.

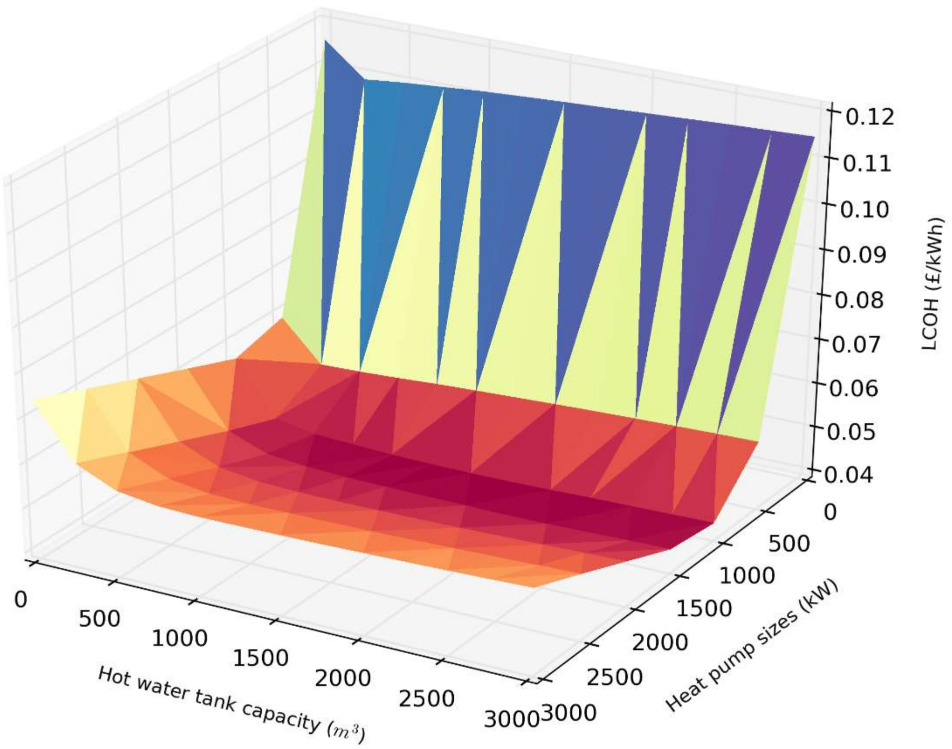

Figure 6.37: 3D plot of LCOH (levelized cost of heat) for FOC with wind tariff

Similar to the variable periods and time-of-use tariffs, the on-site PV self-consumption and percentage of heat demand met by on-site PV and high wind grid import is limited due to insufficient hot water tank capacity during PV generation which is due to charging the storage according to the import price and only charging from the surplus PV generation opportunistically. However, unlike the existing tariffs, importing using the wind tariff during periods of high-wind can be classed as from RES. Therefore, the percentage of heat demand met from on-site PV and high wind grid import increases with additional heat pump capacity up to 1500kW and for any additional hot water tank capacity.

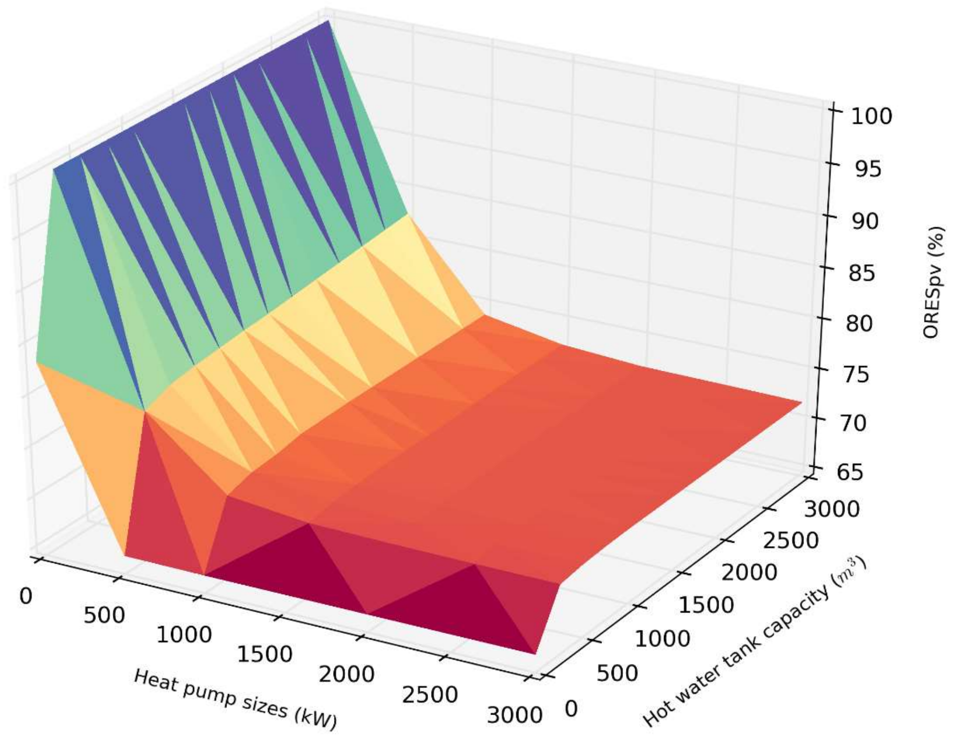

Figure 6.38: 3D plot of ORESpv (on-site PV self-consumption) for FOC with wind tariff

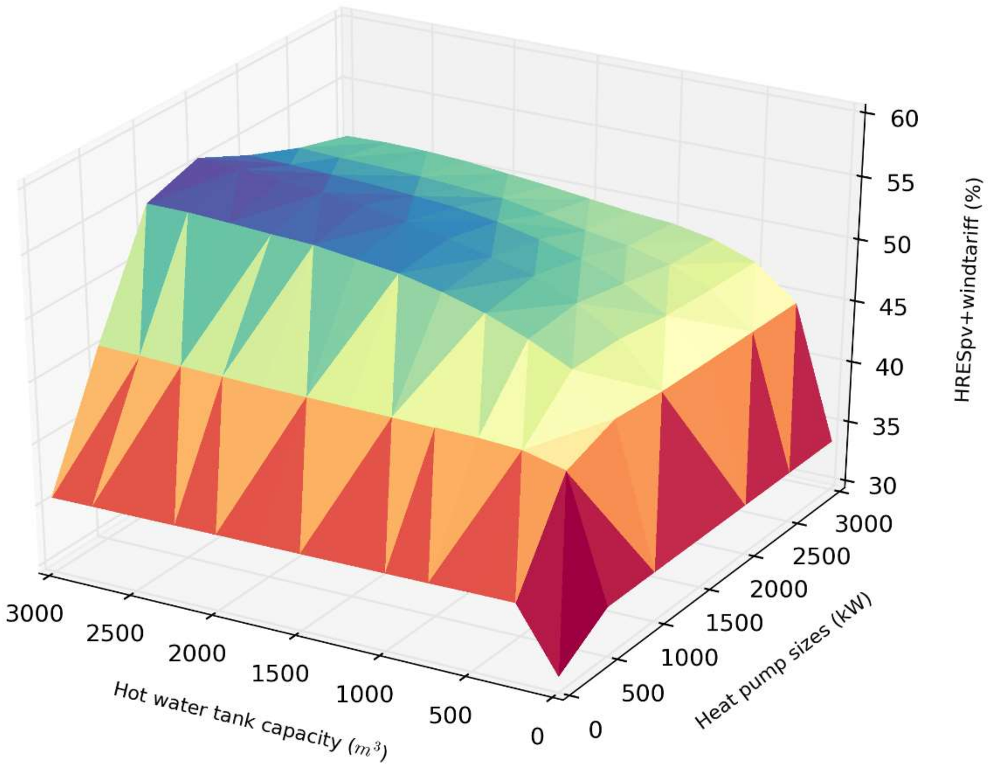

Figure 6.39: 3D plot of HRESpv+windtariff (heat demand from on-site PV and electrical imports during high wind periods) for FOC with wind tariff

6.8.2. Model Predictive Control

6.8.2.1. Flat Rate Tariff

The only load shifting opportunity for MPC with the flat rate tariff is shifting heat pump electricity consumption to match excess PV generation. The LCOH optimum size combination is a 750kW heat pump and a 500m^3 hot water tank.

Compared to the fixed order control, use of the MPC reduces the LCOH by 2.7%. This is small because the fixed order control is only storing heat generated via excess PV generation and discharging the hot water tank when no excess is available. As this is the only form of load shifting available, the MPC performs a similar process.

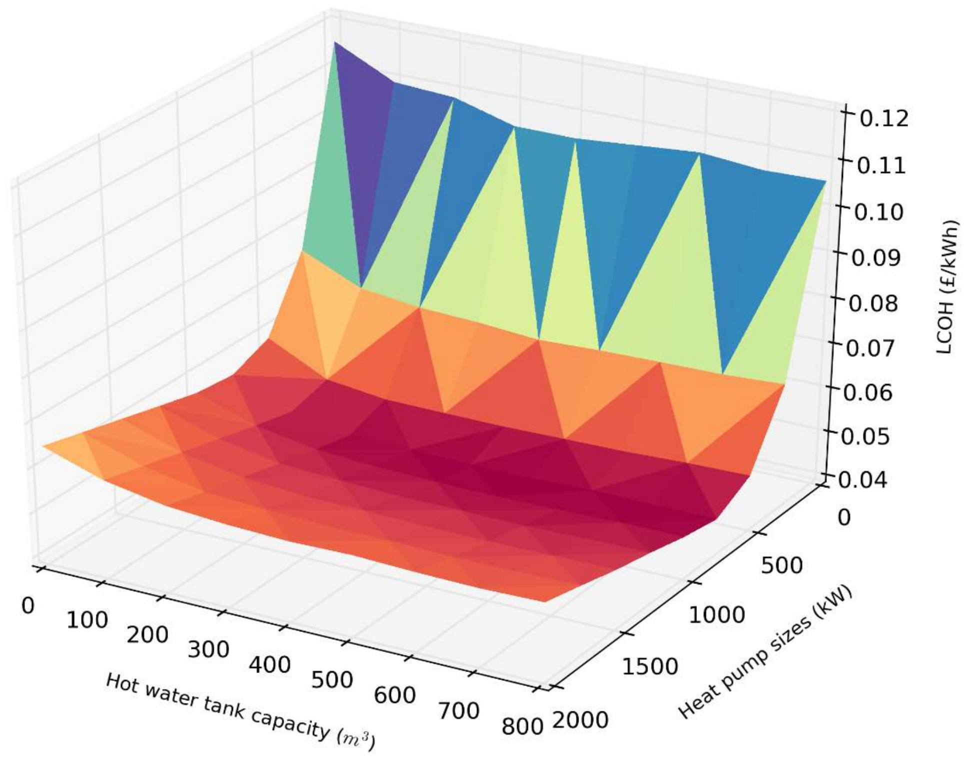

Figure 6.40: 3D plot of LCOH (levelized cost of heat) for MPC with flat rate tariff

The MPC control strategy is slightly better at utilising the surplus PV generation. This is because the MPC optimisation is cost-driven and PV generated electricity is modelled with zero marginal cost which means that use of the heat pump and auxiliary electric heat are equal in priority of dispatch. Meanwhile, the fixed order control always prioritises the heat pump. This means that when employing MPC there will be more periods where the auxiliary electric heat uses the surplus generation.

As with the fixed order control, while the on-site PV self-consumption decreases with greater heat pump usage, the increase in efficient use of the produced electricity results in a higher percentage of heat demand met by on-site PV.

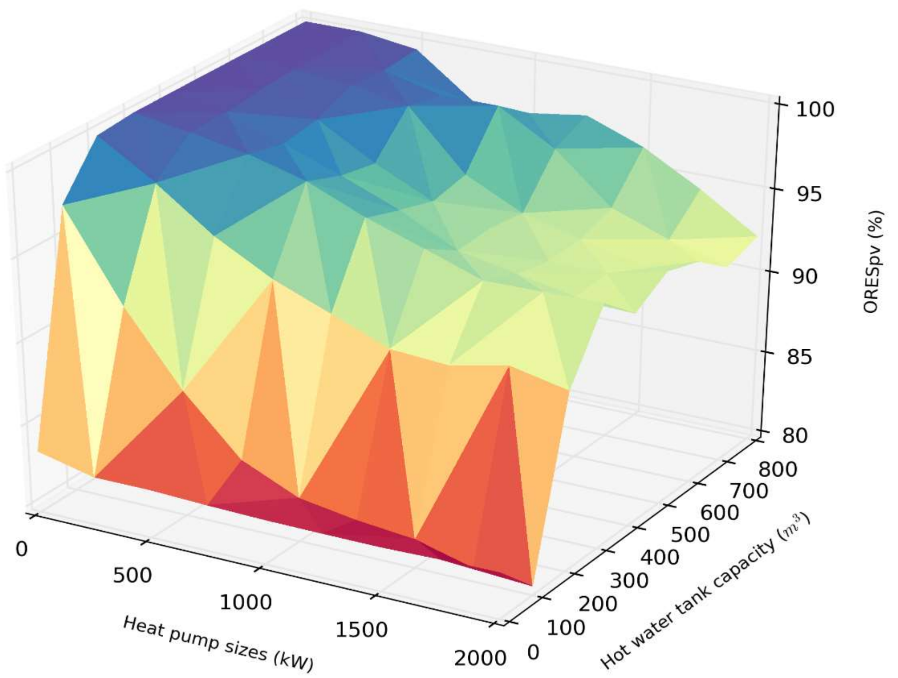

Figure 6.41: 3D plot of ORESpv (on-site PV self-consumption) for MPC with flat rate tariff

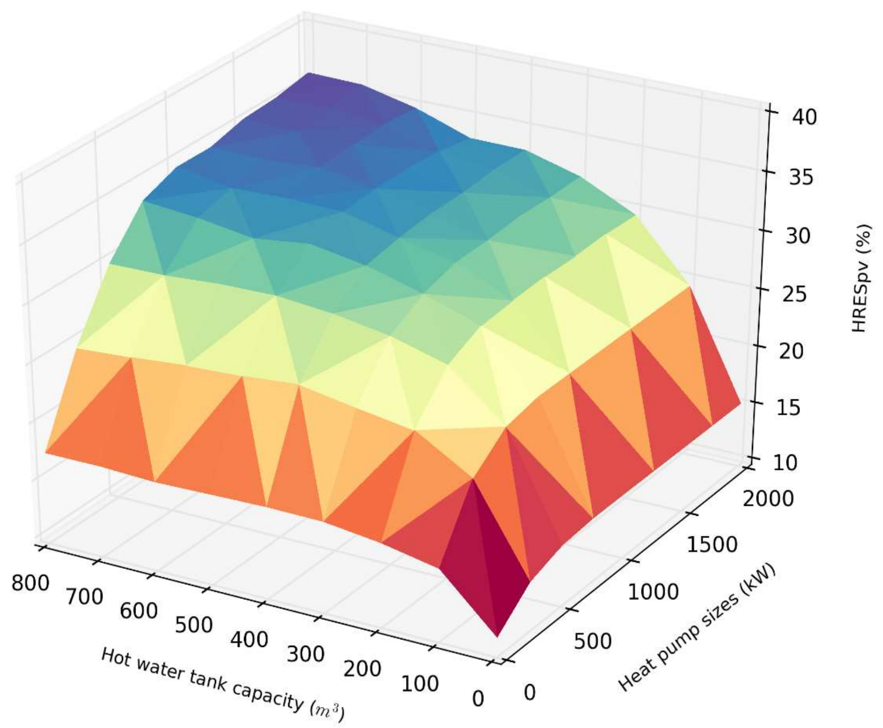

Figure 6.42: 3D plot of HRESpv (heat demand from on-site PV) for MPC with flat rate tariff

6.8.2.2. *Variable Periods Tariff*

The MPC with the variable periods tariff aims to optimise operation in order to shift load to move electricity consumption from the high-cost period during the day to the low-cost period at night, and to utilise excess PV generation. The LCOH optimum size combination is a 1000kW heat pump and a 500m^3 hot water tank.

Using MPC with the variable periods tariff decreases the LCOH by 8.0%. This saving is made because the MPC allows greater usage of the on-site excess PV generation. This is achieved by limiting the charging of the hot water tank during the cheaper night-time periods such that there is sufficient capacity during the day to increase the storing of heat from excess PV generation.

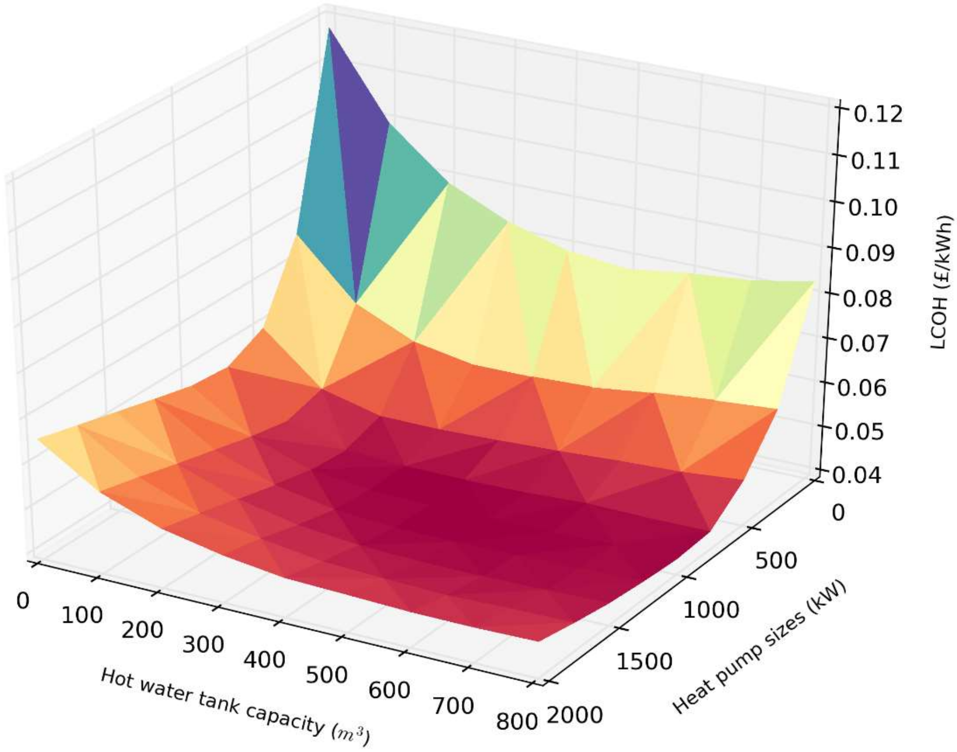

Figure 6.43: 3D plot of LCOH (levelized cost of heat) for MPC with variable periods tariff

The MPC enables almost all of the surplus PV generation to be self-consumed above a hot water tank capacity of 300m^3 (Figure 6.44). Increasing the heat pump capacity reduces the self-consumption of the PV, and this is because of a greater use of the heat pump which is more efficient than the auxiliary electric heat. This is again, similar to previous tariffs, seen in the increase in percentage of heat demand met from on-site PV by increasing either heat pump or hot water tank capacities.

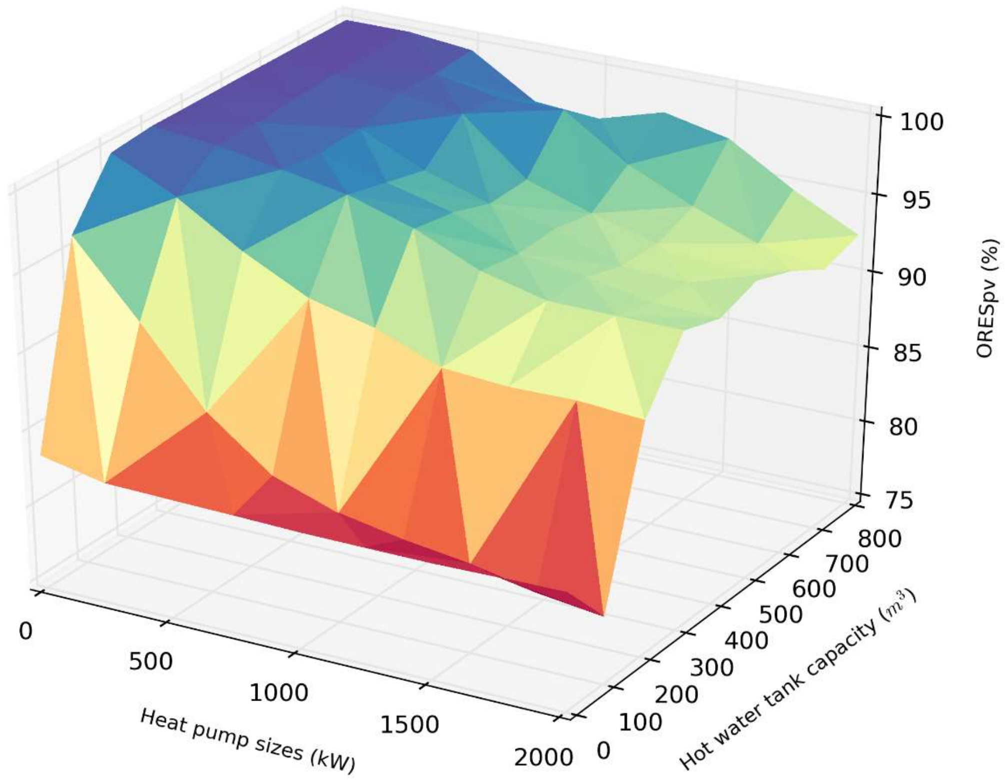

Figure 6.44: 3D plot of ORESpv (on-site PV self-consumption) for MPC with variable periods tariff

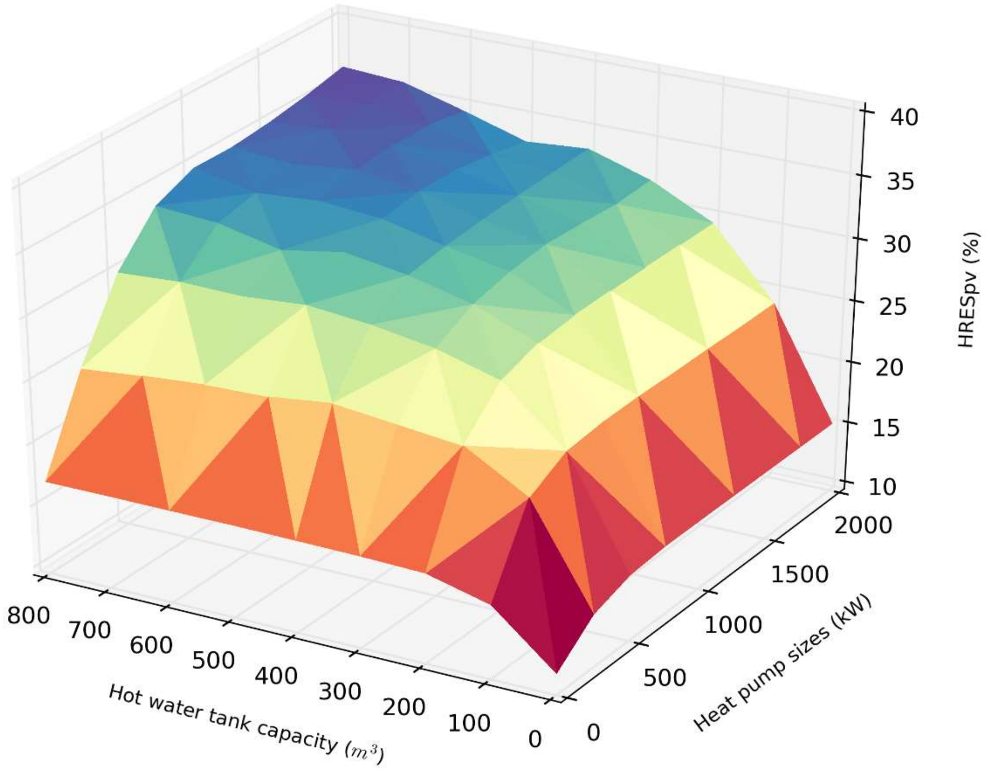

Figure 6.45: 3D plot of HRESpv (heat demand from on-site PV) for MPC with variable periods tariff

6.8.2.3. *Time-of-use Tariff*

The time-of-use tariff is variable hourly throughout the day and the MPC should be adept at ensuring that electrical consumption coincides with the lowest cost periods, including utilising surplus PV generation. The LCOH optimum size combination is a 750kW heat pump and a 500m^3 hot water tank.

Using MPC over the fixed order control decreases LCOH by 19.4%, making it the lowest LCOH tariff for this control strategy. The savings come about because the fixed order controller is limited to avoiding the premium period and does not use the storage to shift load in the other price-varying periods. The MPC has the advantage of not requiring a setpoint and can therefore utilise all the storage to shift load outside the premium period to minimise operating cost across all periods. Additionally, as was seen with the variable periods tariff, the MPC optimises the usage of the excess PV generation.

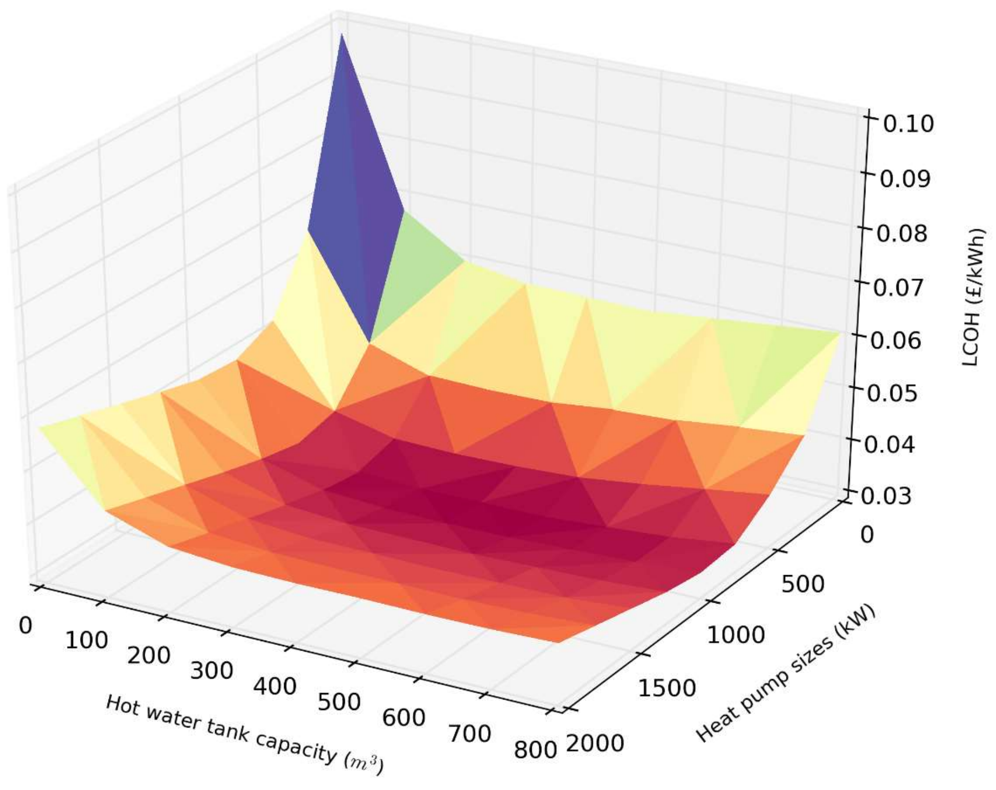

Figure 6.46: 3D plot of LCOH (levelized cost of heat) for MPC with time-of-use tariff

As with the variable periods tariff, the MPC enables almost all of the surplus PV generation to be self-consumed above a hot water tank capacity of 300m^3 (Figure 6.47). A drop in the self-consumption for large heat pump and hot water tank combinations is due to the greater proportion of heat demand being met by the heat pump which is more efficient than the auxiliary electric heat. Again, similarly to previous tariffs, an increase in percentage of heat demand met from on-site PV is achieved by increasing either heat pump or hot water tank capacities.

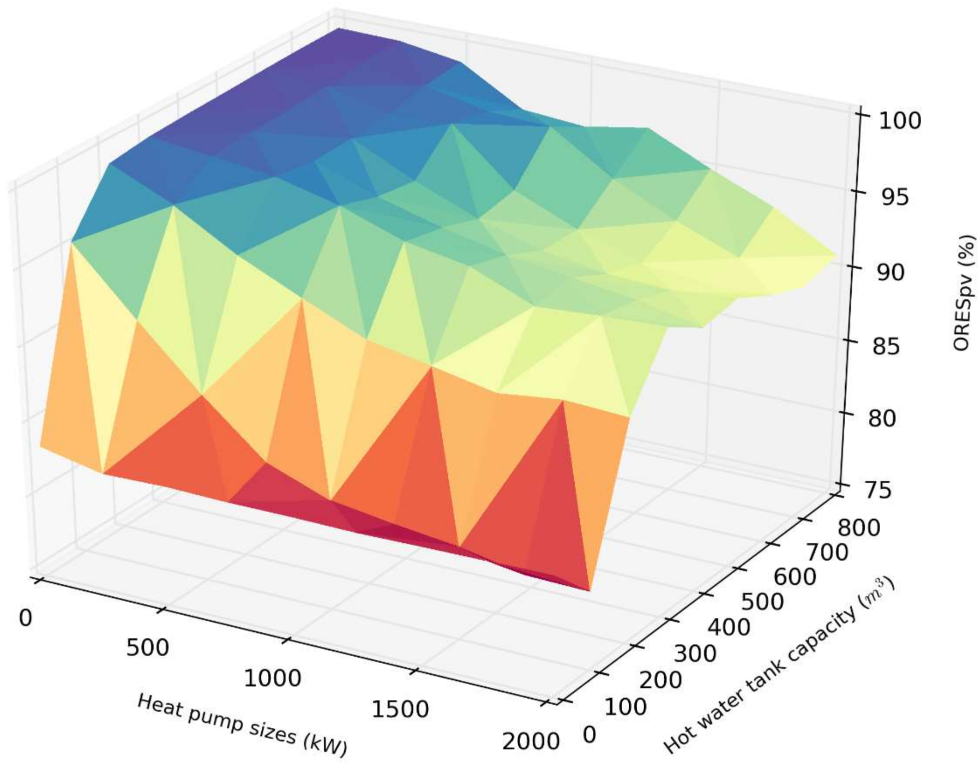

Figure 6.47: 3D plot of ORESpv (on-site PV self-consumption) for MPC with time-of-use tariff

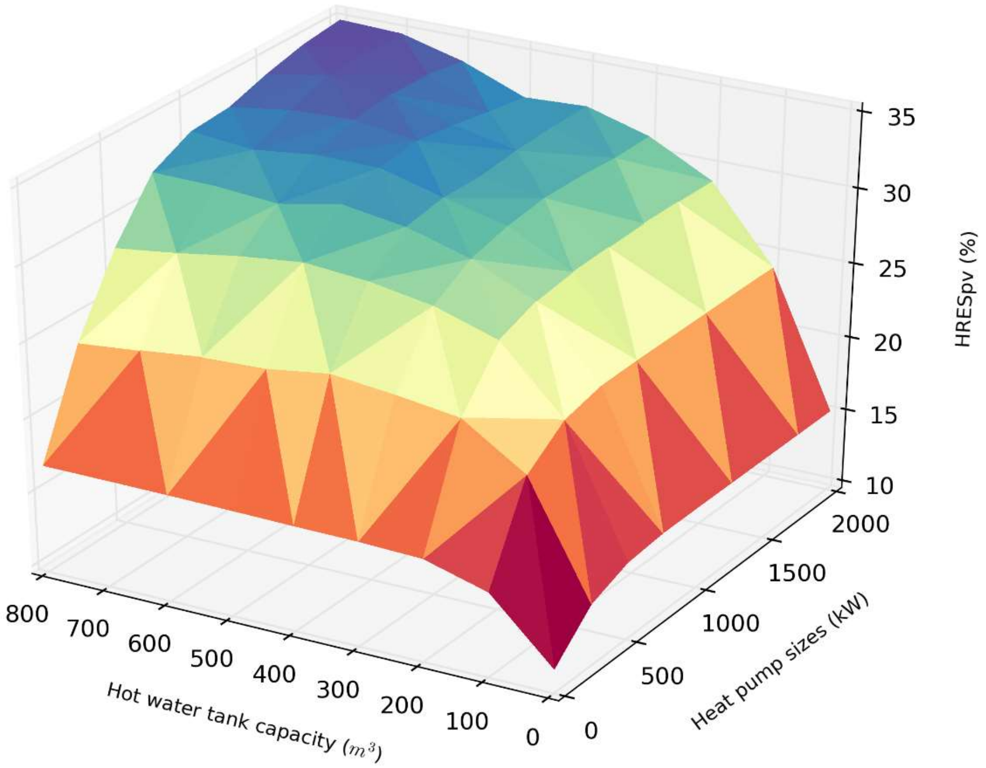

Figure 6.48: 3D plot of HRESpv (heat demand from on-site PV) for MPC with time-of-use tariff

6.8.2.4. *Wind Tariff*

The wind tariff incentivises load shifting by offering high price differentials between windy and non-windy periods, in addition to the day/night differential. The MPC with the wind tariff uses a 168-hour prediction horizon which allows the operation to account for long periods of lots of wind or no wind. The LCOH optimum size combination is a 1000kW heat pump and a 2000m^3 hot water tank, marking a significant increase in optimal hot water tank size and similar optimal heat pump size compared to the existing tariffs. Due to the larger parametric steps used for the hot water tank sizes, two additional simulations were undertaken for a 1000kW heat pump with both 1500m^3 and 2500m^3 hot water tank capacities. These both result in an increase in LCOH, therefore a 2000m^3 hot water tank remains the optimal size.

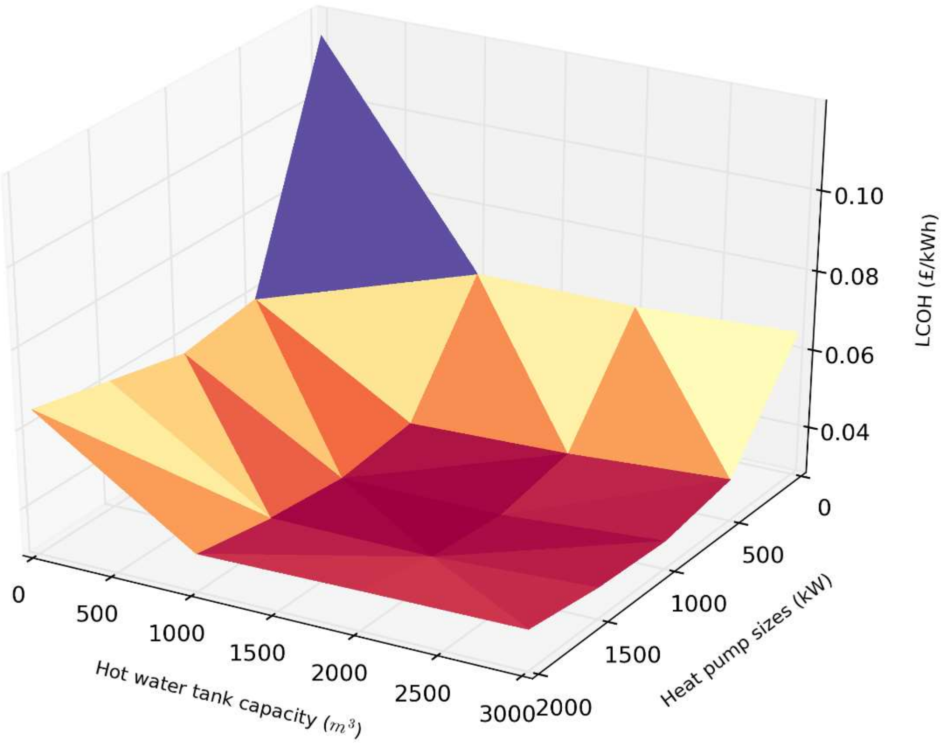

Figure 6.49: 3D plot of LCOH (levelized cost of heat) for MPC with wind tariff

Using MPC over the fixed order control decreases LCOH by 44.1%, which clearly shows that using MPC is beneficial. These substantial savings are possible due to the ability of the MPC, with the week-long prediction horizon, to optimally shift the heat pump electrical consumption to the periods of low-cost. The wind tariff is highly variable with a large differential between low-wind and high-wind periods, and this heavily incentivises the load shifting mechanism which is enabled by a large hot water tank and use of MPC.

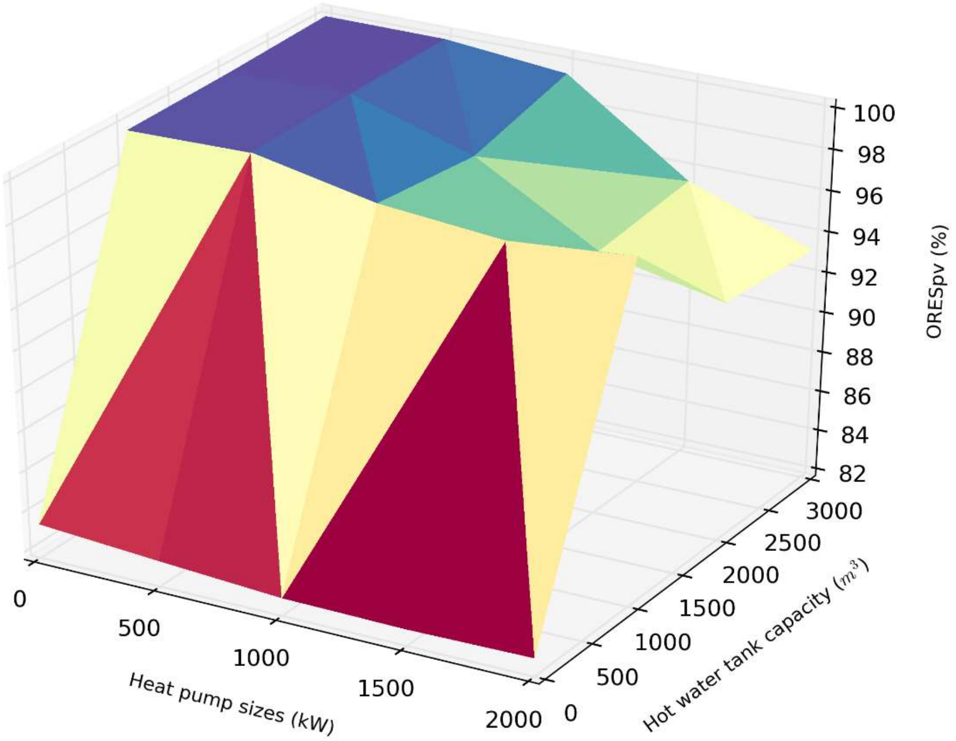

Figure 6.50: 3D plot of ORESpv (on-site PV self-consumption) for MPC with wind tariff

As with the existing electricity tariffs, the MPC enables almost all of the surplus PV generation to be self-consumed. A drop in the self-consumption for larger heat pump and hot water tank combinations is due to the greater proportion of heat demand being met by the heat pump which is more efficient than the auxiliary electric heat.

Unlike the existing tariffs, importing using the wind tariff during periods of high-wind can be classed as from RES. In Figure 6.51 it can be seen that the percentage of heat demand met from on-site PV and high wind grid import increases with additional heat pump capacity and hot water tank capacity. With the wind tariff and MPC, along with a large hot water tank, the percentage of heat demand met from on-site PV and high wind grid import is greater than any of the other tariff and control combinations. This illustrates the importance of combining MPC with a large hot water tank in future highly renewable energy systems in order to maximise the local energy system renewable usage.

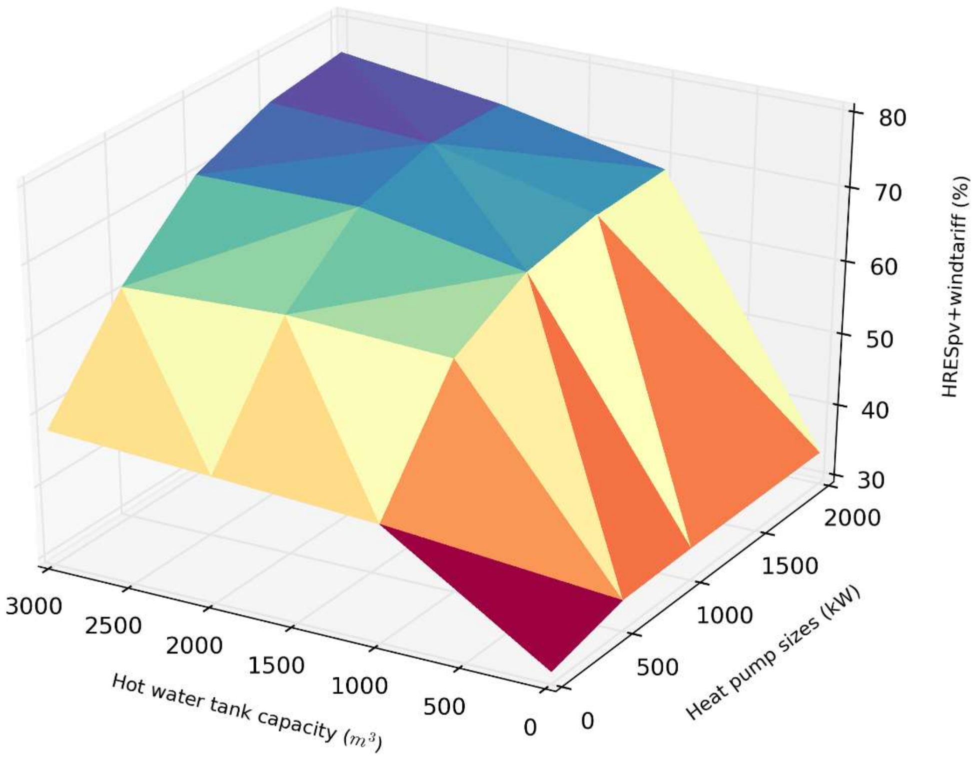

Figure 6.51: 3D plot of HRESpv+windtariff (heat demand from on-site PV and electrical imports during high wind periods) for MPC with wind tariff

6.8.3. Discussion

Tariffs with greater variability provide more incentive to use the hot water tank to load shift demand, as can be seen with lower LCOH for variable periods and time-of-use tariffs over the flat rate tariff (using the given cost assumptions).

When using the fixed order controller, the flat rate and time-of-use tariffs both have an optimal heat pump capacity of 750kW. This similarity is linked to the comparable, short duration of the surplus PV generation and the premium period. The flat rate tariff utilising surplus PV generation is the main load shifting mechanism, while with the time-of-use tariff avoiding heat pump usage during the three-hour premium period is the primary objective. Additionally, the variable periods tariff has a higher optimal heat pump capacity of 1000kW which reflects the longer duration of the low-cost period. For the variable periods tariff, shifting heat pump electrical consumption from day to night is the main utility of the hot water tank.

When using the fixed order controller, the flat rate and variable periods tariffs both have an optimal hot water tank capacity of 400m^3. Increasing hot water tank capacity for the variable periods tariff does not reduce operating cost with the fixed order controller because the controller is not predictive and cannot increase the usage of surplus PV generation and is limited in shifting load from day to night. The time-of-use tariff with the fixed order controller has the lowest optimum hot water tank capacity because it is only avoiding heat pump usage in a three-hour window.

Using MPC does not affect the optimal size of heat pump but increases the optimal hot water tank size. With MPC, the hot water tank can load shift for multiple objectives such as day to night shifting, optimising heat pump COP by shifting operating times, and utilising excess PV generation.

Comparisons between the control strategies found that MPC offers savings over the fixed order control for all the existing electricity tariffs, but particularly for a time-of-use tariff where savings of 19.4% were obtained. Comparisons between the existing electricity tariffs found that the time-of-use tariff delivered the lowest levelized cost of heat. This conveys the advantage of combining tariffs which promote flexibility through load shifting with optimally sized hot water tank.

MPC has the largest reduction in LCOH when paired with the wind tariff. Using MPC over the fixed order control decreases LCOH by 44.1%. This shows how when using a tariff which heavily incentivises the load shifting mechanism, a larger hot water tank and use of MPC is advantageous. Additionally, the percentage of heat demand met by on-site PV and high wind grid import increases from 52.8% to 70.2% for the fixed order control and MPC.

The wind tariff optimal heat pump and hot water tank combination, 1000kW heat pump and 2000m^3 hot water tank, has the same heat pump capacity as the existing tariff optimal sizes but has a larger hot water tank capacity. This means that systems which are sized for the existing electricity tariffs can be modified later by adding hot water tank capacity to take advantage of future tariffs, such as the wind tariff used in this sizing study.

6.9. Results Summary

Application of this methodology to a sizing study for a residential district heating scheme has showcased the ability of PyLESA as a useful aid to investigate the benefits of model predictive control (MPC) and different electricity tariffs including a novel future wind tariff. PyLESA has proved to be a useful addition to the current set of existing modelling tools to model the proposed design for WWHC including heat pumps, hot water tank, variable electricity tariffs, and MPC. Close examination of the operational analysis provided a validation of the underlying algorithms of the control strategies and showed that running PyLESA can produce logical and useful outputs.

The operational analysis results provided a qualitative discussion of the comparisons of the developed control strategies and the electricity tariffs. It identified limitations with the fixed order controller when attempting to shift load beyond simple situations, i.e. when attempting to utilise on-site renewable generation as well as avoiding high-cost periods of a tariff. The operation of the MPC was explored and this illustrated the advantages of the MPC which can optimise the operation of the heat pump and hot water tank, for a number of objectives, in order to lower operating costs. The operational analysis also revealed the potential for the use of large hot water tanks and heat pumps with the future wind tariff.

A 750kW heat pump and 500m^3 hot water tank using MPC and a time-of-use electricity tariff were found to deliver the lowest LCOH in comparison with the existing electricity tariff structures and control strategies. This marks a significant 10x expansion of the existing hot water tank at WWHC which is used to aid peaks in demand for the existing biomass boiler. This signifies a shift in the methods which are used to size hot water tank; sizing to enable load shifting and not only for flattening peak demands during design periods.

An optimal size combination of a 1000kW heat pump and a 2000m^3 hot water tank was found with MPC and the wind tariff. For the wind tariff performance improvements were found by using MPC over the fixed order control: LCOH reducing from 5.81p/kWh to 3.25p/kWh (44.1% reduction); and heat demand met by on-site PV and high wind grid import increasing from 52.8% to 70.2%. The optimal heat pump size for the wind tariff was found to be similar, or the same, as for the existing tariffs. The optimal hot water tank capacity is significantly larger. Therefore, the proposed design could be sized for an existing electricity tariff and later additional hot water tank capacity can be added to take advantage of future tariffs.

7. Conclusions

The previous chapters have described the development of the local energy system modelling tool, PyLESA, and the application of it to inform a sizing study of a proposed design for a district heating network.

This chapter discusses the strengths and limitations of the research undertaken. This will consist of discussion on the contributions to the state of the art in terms of the modelling capabilities of PyLESA; exploration of the performance of the control strategies and electricity tariffs; the limitations of PyLESA and potential future tool developments; and potential applications of PyLESA. The chapter ends with a final summary.

7.1. Contributions

Several contributions have been made in this work. They were achieved in order to answer the central research question, which was introduced in Chapter 2 and is restated below:

Can a modelling methodology and supporting modelling tool be developed that usefully aids the planning-level design of local energy systems incorporating heat pumps, thermal storage, local renewable electricity production, time-of-use electricity tariffs, and predictive controls?

Specific aims were set in order to answer this research question and a research methodology was developed to organise the work required to achieve these aims. These aims are discussed below and are split between those which address the gaps in existing modelling tools, and those which explore the developed control strategies and electricity tariffs in the context of the proposed district heating system design. The contributions made are highlighted in this discussion.

7.1.1. Addressing Modelling Capability Gaps

The first research aim which was to identify gaps in existing planning-level modelling tools. This was achieved by categorising the capabilities of the identified tools and developing a modelling tool selection process. By analysis of these capabilities against the local energy system specified in the research question, a set of modelling gaps were identified.

The second and third research aims were to develop a modelling methodology and supporting modelling tool which would address the identified gaps and aid design decisions at a planning level by modelling local energy systems incorporating heat pumps, thermal storage, local renewable electricity production, time-of-use electricity tariffs, and predictive controls. This was achieved by the development of a modelling methodology which consists of the steps for applying the novel modelling tool, PyLESA. The modelling capabilities of PyLESA was then described, including details of the models which contributed to identified gaps.

The discussion below concerns how the specific gaps were addressed, and the strengths of the contributions made. The limitations and future developments of PyLESA and its underlying models will be discussed in Section 7.2.

Ability to adapt source code and import or exploit functionality from elsewhere.

PyLESA was written in the programming language Python which was chosen because it is open source and widely used across science and engineering fields. This meant that PyLESA could build on the state of the art, utilising energy system models previously built, as well as providing a platform from which the developed models can be shared with other researchers in the energy system modelling community. As compared to the reviewed tools which were primarily written in programming languages which require expert software development skills, or are completely closed source, PyLESA offers the explicit ability for others to adapt the source code or to easily couple PyLESA with other energy system models developed in Python.

Temperature dependence for the heat pump models.

It was identified that in the reviewed tools that heat pumps were being modelled using simple energetic models and are based upon a limited set of performance data. This leads to an overestimation of performance across the operating conditions. In PyLESA a more detailed heat pump modelling approach is developed which uses standard test data to generate performance maps using multiple variable linear regression analysis with explicit temperature dependence. This extends the current state of the art of approaches employed by energy system planning tools.

Detailed stratification model for the thermal storage models.

Similar to the approach of the reviewed tools for modelling heat pumps, when modelling thermal storage simple energetic models are utilised which do not capture the thermal characteristics associated with stratified hot water tanks. The multi-node modelling approach advances on these simple energetic models with thermal characteristics modelled in more detail. The state of charge and heat loss of the hot water tank is dependent on the node temperatures. This approach means that a hot water tank can be represented with more detail while maintaining low input requirements which is helpful at the planning stage.

Ability to model the evolving electricity markets and tariffs.

Existing modelling tools either have in-built simple tariffs which used fixed prices and unlimited import and export or allow the user to input unique tariffs. As an advancement on this, PyLESA can generate a range of electricity tariffs. Some of which reflect existing and emerging tariffs such as the flat rates, variable periods, and time-of-use tariffs. Additionally, a wind-based electricity tariff generator has been presented as an example of a tariff which could exist in the UK in the future. A future UK 100% renewable energy system would likely have wind power as one of the main producers of energy, and therefore, a tariff pricing structure which is linked to wind power production is likely to be similar to a future electricity tariff.

Ability to explore predictive controls.

A distinct disadvantage of the existing modelling tools was the lack of options for control strategies with a notable gap for utilising predictive controls. These typically use simple rule-based controls which need to be adjusted by an expert in order to minimise import costs. There are also cases where on-site renewable production competes with a variable electricity tariff which makes it difficult to identify a low-cost operation schedule. Modelling local energy systems including a model predictive control strategy allows the performance to be optimised. MPC enables the operation to minimise cost, even when multiple competing dynamics influences are active, such as heat pump performance, variable tariffs, and on-site renewable power generation. In PyLESA an economic MPC strategy was developed and incorporated. These aspects were further explored in the sizing study where the performance of the MPC was compared to the fixed order control, with both using a range of electricity tariffs.

7.1.2. Exploration of Developed Control Strategies and Electricity Tariffs

The fourth research aim was to demonstrate the application of PyLESA by undertaking a sizing study and explore the control strategies and electricity tariffs. This aim was achieved by carrying out a sizing study for a proposed design of a residential district heating system which incorporates a heat pump, a hot water tank, on-site PV electricity production, variable electricity tariffs, and MPC. The sizing study allowed for the developed control strategies and the use of existing electricity tariffs to be compared. These were compared by operational analysis which was used to qualitatively describe the control strategies and the influence of the different electricity tariffs, and also compared by sizing of the heat pump and hot water tank capacities for the different control strategies and electricity tariffs. Additionally, these included an exploration of a future wind-based renewable electricity tariff.

The discussion below concerns the findings on the comparisons of the developed control strategies and existing electricity tariffs. It also discusses the exploration of the use of a future wind-based renewable electricity tariff which is useful for studies of future energy systems with large renewable penetrations. Finally, a discussion of the results from the sizing study of the proposed design for WWHC for the optimal heat pump and hot water tank size combination with control strategy and electricity tariff conclude this section.

Compare the performance of the developed control strategies for existing tariffs.

The fixed order control and MPC perform differently for each of the electricity tariffs. There is little advantage of using MPC over the fixed order control when the only load shifting mechanism available is utilisation of surplus PV generation. The fixed order control enables as much load shifting as the MPC to increase the self-consumption from on-site PV generation. The advantages of the MPC are illuminated when there are multiple load shifting mechanisms available, e.g. surplus generation, low-cost tariff periods, heat pump performance. The MPC can optimise the operation of the heat pump and hot water tank for all of these objectives simultaneously, resulting in lower operating costs.

Comparisons between the control strategies found that MPC offers savings over the fixed order control for all the existing electricity tariffs, but particularly for a time-of-use tariff where savings of 19.4% were obtained.

Compare the use of existing electricity tariffs.

Load shifting with the flat rates tariff is only incentivised by attempting to increase the self-consumption from on-site PV generation. This is because load shifting heat pump and electric heater power consumption for surplus PV generation is the only avenue of reducing costs.

With the variable periods tariff load shifting is useful for both increasing use of surplus PV generation and avoiding high-cost tariff periods. However, the hot water tank is often fully charged at the end of the low-cost period and just before there are surpluses of PV generation. This results in a significant portion of PV generation being exported, despite this having zero value to the local energy system in this case study. Employing MPC results in a much higher utilisation of surplus PV generation, and lower import costs as a result of only charging the hot water tank at low-cost periods in order to cover the remaining heat demand.

The time-of-use tariff is highly variable, while the fixed order control does not take advantage of this variability. The MPC makes it possible to avoid premium prices and take advantage of all the periods of variability. Additionally, similar to the variable periods tariff, the PV utilisation can be maximised, and imports limited to the lowest cost periods and restricted to only meeting the remainder of the demand in the calculation period.

Comparisons between the existing electricity tariffs found that the time-of-use tariff delivered the lowest levelized cost of heat. This conveys the advantage of combining tariffs which promote flexibility through load shifting with optimally sized hot water tank capacity.

Explore the use of a future wind-based renewable electricity tariff.

From the operational analysis, it is apparent that using the fixed order control with the wind tariff shows great potential for the use of large hot water tanks and heat pumps for this type of tariff. The heat pump generally runs in the low-cost and renewable periods which should lead to low operating costs and a high percentage of heat met by renewables. MPC requires a longer prediction horizon than that used for the existing electricity tariffs to account for the large windows of fluctuations, over periods closer to a week. It can be seen in the operational graphs that the electric heater is still needed to see systems through long periods of high cost.

The sizing results show that using MPC over the fixed order control decreases LCOH by 44.1%. This shows that using the wind tariff, which heavily incentivises the load shifting mechanism, a larger hot water tank and use of MPC, is advantageous. Additionally, the percentage of heat demand met by on-site PV and high wind grid import increases from 52.8% to 70.2% for the fixed order control and MPC.

Identify optimal heat pump and hot water tank size combination.

A 750kW heat pump and 500m^3 hot water tank using MPC and a time-of-use electricity tariff were found to deliver the lowest LCOH in comparison with the existing electricity tariff structures and control strategies. This marks a significant 10x expansion of the existing hot water tank at WWHC, which is used to aid peaks in demand for the existing biomass boiler. This signifies a shift in the methods which are used to size hot water tanks; sizing to enable load shifting and not only for flattening peak demands during design periods.

The wind tariff optimal heat pump and hot water tank combination is a 1000kW heat pump and 2000m^3 hot water tank, this has the same heat pump capacity as the existing tariff optimal sizes but has a larger hot water tank capacity. This means that systems which are sized for the existing electricity tariffs can be modified later by adding hot water tank capacity to take advantage of future tariffs, such as the wind tariff used in this sizing study.

7.2. Future Tool Development

In this section the limitations of the framework and underlying models of PyLESA are explored along with potential future tool developments. PyLESA has the potential to incorporate a significant number of models for an assortment of technologies, and the discussion presented is limited to the particularly pertinent models.

7.2.1. Tool Framework

Several existing frameworks could have provided the basis as a starting point for developing the models which addressed the identified gaps. Instead, PyLESA was built primarily from scratch to aid the author in gaining proficiency in Python programming. Given the nature of Python and the accessibility of the code of PyLESA, it is possible for others to take individual models/class objects and implement them within existing/developing frameworks. Ultimately, PyLESA itself now offers a useful framework for modelling local energy systems which can be expanded by incorporating new models or developing the existing models, but alternative research directions were available.

The modelling framework uses an Excel workbook as the method for the user to input the necessary data, and outputs several images and .csv files. A more pythonic method would be to develop an open source GUI written in Python where data can be input, the tool can be run, and outputs explored.

For certain types of analysis, it would be useful to be able to model systems on smaller timescales. An hourly timestep is used in PyLESA due to the typical data availability at the planning stage and the modelling assumptions used. For example, the heat pump regression model does not explicitly account for dynamic effects associated with actions such as startup/shutdown. Therefore, using a timestep below 15 minutes would result in inaccurate outputs for these short periods.

The current framework limits the number of technologies and demands which can be modelled. For example, it may be useful to be able to model a system with a heat pump connected to two hot water tanks for providing hot water and space heating separately. PyLESA could be modified to include the option to model two hot water tanks and two heat demands.

The capital costs which are used to calculate financial KPIs such as levelized cost of energy/heat, currently only include the heat pump and hot water tank capital costs. In order to perform sizing and feasibility studies looking at other components of the local energy system, it would be useful to incorporate the full range of capital cost expenditures, e.g. wind turbine costs and district heat network piping installation costs.

7.2.2. Demand Modelling

Simplified, deterministic assessment methods have been presented as a means of generating electrical and heat demands at the required timestep and detail for inputting into PyLESA. These methods only produce demands for a single year and do not account for year-to-year variability and extreme demand events. Weather has a significant impact on peak demand and energy use, and varies across years [269,270]. Therefore, an improvement to the methods developed as part of PyLESA would be to generate demand profiles based on weather data over multiple years. Additionally, sub-hourly, high-resolution models which use stochastic techniques could be incorporated to account for a range of occupancy behaviours, and other complex factors [213]. District heating network piping models could also be incorporated to facilitate aiding design decisions, and computationally inexpensive methods for modelling these have been reviewed in literature [271].

7.2.3. Heat Pump and Auxiliary Units

The most advanced model for heat pumps in PyLESA is the standard test regression model. This approach uses a relatively substantial amount of data input regarding the performance of the heat pump under the standard test range of operating conditions, and this is not always readily available at the planning-stage. This is the reason simpler models, similar to those utilised in existing modelling tools, have been included as alternative approaches. Despite this, a more detailed approach, requiring greater input requirements, could fully capture the major components such as the physical details of evaporator design, the system defrosting cycle, and associated controls [39,272]. This more detailed approach could include important factors such as COP as a function of the variation of the compressor speed. It would also allow for simulations at a high time resolution as the dynamic effects below 15-minutes could be fully captured.

PyLESA does not incorporate solar thermal and this technology has the potential to be an auxiliary, renewable heat generation unit which could assist a heat pump in meeting heat demands. Models have been developed previously for solar thermal hot-water heating systems [273], and photovoltaic thermal flat plate collectors [274].

7.2.4. Thermal Storage

PyLESA uses a multi-node modelling approach for hot water tanks and this was justified as a suitable balance between accuracy and computational time. The developed model exaggerates the mixing between nodes which is likely to occur for a hot water tank designed to be highly stratified, as is desirable for the load shifting mechanisms investigated. Therefore, while the energetic models used in existing models likely result in underestimations of the capacity required to perform load shifting, the model developed within PyLESA is likely to overestimate the capacity required.

To increase the user flexibility of PyLESA, hot water tank models with both increased and decreased accuracy could be included. Fully mixed or moving boundary models, similar to those used by existing modelling tools, provides a computationally efficient approach, but fails to capture stratification. More complex approaches include 2D or 3D CFD simulations [275], zonal approach [276], etc. PyLESA could also be developed to include more thermal storage technologies such as phase change materials [255,256], next generation smart hot water tanks [257], and building thermal mass [258].

A potential development of this approach would be to allow for multiple heat sources to charge the tanks at different points of the tank. This would enable the integration of solar thermal as a complimentary renewable source of heat along with a heat pump.

7.2.5. Electrical Storage and Fuel Synthesis

PyLESA uses a simple storage model for electrical storage, and this only captures generic energetic technical characteristics of different types of storage. More detailed models which are technology specific could be included, e.g. HOMER and iHOGA models for battery types reviewed earlier [277–279], pumped hydro [280], CAES [281].

PyLESA is not capable of analysing fuel synthesis technologies as they are currently unlikely to be applicable at a local energy system scale in the short term. However, this capability could be included in the future, using models such as those developed for hydrogen [282–284].

7.2.6. Electricity Tariffs and Balancing Markets

In PyLESA existing and future wind electricity tariffs can be modelled. Balancing markets could provide a greater incentive for flexibility and may become more prevalent as the grid decarbonises e.g. balancing mechanism, frequency response, and new markets such as the European wide balancing energy market TERRE [48]. Including these would be a useful future tool development. This would require a smaller simulation timestep to be used, which requires developing the underlying models and assessment methods, in particular the demand assessment and heat pump model.

The future tariff developed is based upon wind power production which may be suitable in the UK context, but for other countries it may be apt to include a future tariff which is dependent on PV. A future tariff could also be developed based upon an energy systems model of the UK using a national-scale energy modelling tool such as EnergyPLAN [285]. Additionally, PyLESA currently uses a flat rate for the export tariff, however variable export tariffs are also emerging [286].

7.2.7. Model Predictive Control

PyLESA includes model predictive control and this formed an important contribution to the state of the art of planning-level local energy system modelling. An important aspect of future work on the developed MPC is the inclusion of uncertainties in the future predictions as currently these are modelled with perfect foresight [49,50]. This overestimates the benefits of the MPC which will always makes the perfect decisions, even when using a long prediction horizon. Further research is required to include uncertainties with weather forecasts and electricity prices at the design stage, although a large number of studies have developed controllers suitable for real-time control of various energy systems, e.g. thermal storage [287,288], HVAC applications [289], building cooling [290], community battery storage [291], community micro-grid [292], stochastic MPC [248,293].

7.3. Future Tool Applications

PyLESA has been applied to a sizing study for a proposed design of an existing district heating network as is described in Chapter 6. Potential applications of using PyLESA to inform feasibility studies and operation studies have already been discussed in Section 4.5.

The applicability of PyLESA to different scales of energy system is another potential tool development. For example, developing the tool to enable separate thermal stores and multiple heat pump operation modes in order to model configurations commonly used at the building or mini-district scale. It would also be useful to add to the set of control strategies in order to be able to easily model the assortment of controls which are used at the different scales, which would in turn increase the number of situations PyLESA is applicable to.

PyLESA could also be utilised as the first step towards the development of the software and hardware necessary to build a real-time model predictive controller. This could be possible through the open-source communications and control software and hardware available from the OpenEnergyMonitor project [36].

7.4. Final Summary

In this thesis a modelling methodology and a supporting modelling tool, PyLESA, have been developed which can usefully aid the planning-level design of local energy systems incorporating heat pumps, thermal storage, local renewable electricity production, time-of-use electricity tariffs, and predictive controls.

Several gaps were identified in a review of the modelling capabilities of existing energy system tools: (i) ability to adapt source code and import or exploit functionality from elsewhere; (ii) temperature dependence for the heat pump models; (iii) detailed stratification model for the thermal storage models; (iv) ability to model the evolving electricity markets and tariffs; and (v) ability to explore predictive controls.

These gaps motivated the development of the novel modelling tool PyLESA which can aid design studies at the planning stage and includes appropriate technology and control models to tackle the identified gaps. The following tool capabilities of PyLESA were described and validated: resources and demands; electricity production technologies; heat pumps; hot water tanks; electricity tariffs; fixed order controls; model predictive controls; and key performance indicators.

A sizing study was then devised to showcase the application of PyLESA and to explore the developed control strategies, and existing and future electricity tariffs. Comparisons between the control strategies found that MPC offers savings over the fixed order control for all the existing electricity tariffs, but particularly for a time-of-use tariff where savings of 19.4% were obtained. Comparisons between the existing electricity tariffs found that the time-of-use tariff delivered the lowest levelized cost of heat. This conveys the advantage of combining tariffs which promote flexibility through load shifting with optimally sized hot water tank.

A 750kW heat pump and 500m^3 hot water tank using MPC and a time-of-use electricity tariff were found to deliver the lowest LCOH in comparison with the existing electricity tariff structures and control strategies. This signifies a shift in the methods which are used to size hot water tank; sizing to enable load shifting and not only for flattening peak demands during design periods.

An optimal size combination of a 1000kW heat pump and a 2000m^3 hot water tank was found for MPC and the wind tariff. With the wind tariff, performance improvements were obtained by using MPC over the fixed order control: LCOH reducing from

5.81p/kWh to 3.25p/kWh (44.1% reduction); and heat demand met by on-site PV and high wind grid import increasing from 52.8% to 70.2%. The optimal heat pump size was similar for the existing tariffs and future tariff. Therefore, the proposed design could be sized for an existing electricity tariff and later, additional hot water tank capacity added to take advantage of future tariffs.

The research has highlighted the advantage of combining flexible tariffs with optimally sized thermal storage and showcased PyLESA as capable of usefully aiding the design of local energy systems.

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