Planning level sizing of heat pumps and hot water tanks incorporating model predictive control and future electricity tariffs

Abstract

Heat pumps and hot water tanks in local energy systems require sizing to enable load shifting; increase on-site renewables self-consumption; decrease costs through variable electricity pricing; and utilise low-cost wind power. Existing planning level tools were found to have limitations. Here an open-source planning-level modelling tool, PyLESA, is presented and applied to a sizing study for a district heating network. The aims of the study were to investigate: (i) model predictive control vs. fixed order control, (ii) existing and future wind-influenced electricity tariffs, and (iii) optimal cost size combinations of heat pump and hot water tank. Results indicate that for this case model predictive control offers savings over fixed order control for all investigated electricity tariffs. The lowest levelized cost of heat for the existing tariffs was for a time-of-use tariff, 750kW heat pump and 500m^3 hot water tank combination. For the future wind-influenced tariff a 1000kW heat pump and 2000m^3 hot water tank was cost optimal and showed model predictive control benefits over fixed order control with levelized heat costs reducing 41%, and heat demand met by renewables increasing 18%. These results illustrate the advantage of combining flexible tariffs with model predictive control and optimally sized heat pumps and thermal storage; and demonstrate PyLESA in the design of local energy systems.

Keywords

Heat pump; thermal storage; model predictive control (MPC); local energy systems; energy system modelling; load shifting

1. Introduction

Heat pumps and thermal storage together with smart controls to harmonise with local and global renewable generation in new electricity markets with flexibility tariffs has been proposed as a potentially promising solution [1–3]. A number of load shifting mechanisms are possible via such systems and are explored in this paper such as: increasing on-site PV self-consumption; decreasing costs through variable electricity tariffs; and utilising low cost wind power.

1.1. Load Shifting with Heat Pumps and Thermal Storage

Heat pumps are a decentralised technology which can combine the electrical and thermal sectors. They can efficiently use electricity and low-grade heat sources to provide useful heat, most commonly for small-scale households purposes but increasingly for district heating and industrial applications [4]. Previous studies have identified large-scale heat pumps for district heating as providing 25-30% of heat in future roadmaps for Europe [5], and conclude the technology is mature [6]. 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. The intermittency inherent in renewable generation from wind and on-site PV will provide value for the use of heat pumps in

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flexible systems which can be appropriately controlled [3]. Flexible heat pumps offer the possibility to shift the electrical consumption of the heat pump to match with intermittent renewable generation, such as to increase on-site PV self-consumption [7].

Thermal storage provides flexibility to a heat pump-based system by decoupling heat demand from electrical consumption. Applications include hot water tanks in domestic buildings with smart control [8], phase change materials (PCM) [9], inherent thermal storage in buildings [10], etc. Hot water tanks are important in 4th generation district heating systems [11]. The low incremental costs and reduced losses give economic advantages for larger scale storage systems such as in district heating, providing district level systems with the flexibility required to gain benefits from embedded renewable generation and emerging electricity market arrangements such as time-of-use tariffs, power purchase agreements, and balancing service payments [12].

1.2. Existing and Future Electricity Tariffs

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 which are issued a day ahead. They 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 [13].

Time-of-use pricing at the moment is largely driven by electricity demand profiles and only require simple time-based controls to gain the majority of the benefits of flexibility. However, as the proportion of renewable generation increases tariffs will change to reflect this; resulting in less predictable profiles and greater price differentials. In order to benefit from these highly variable tariffs, improved communications and control technologies will be required.

Future commercial arrangements through aggregators and others will potentially further reward flexibility from heat pumps that can contribute to local network and wider grid electricity services such as local power purchase agreements avoiding curtailment, frequency response and other longer-term balancing requirements [14,15], engagement in these services will also require communication and control solutions [16].

1.3. 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 [17,18] at commercial and also community cooperative scales [19–22]. Communications services available to these platforms include weather forecasts, day-ahead time-of-use tariffs, and shorter term calls for response.

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. Many control approaches have been investigated. The control strategies referred to here are the supervisory controls for the flexible system, each sub-component will have its own lower level controls e.g. PID or PLC etc. [23,24].

Hard and Soft classifications of supervisory control were identified in literature [25]. Soft controls include neural networks, fuzzy logic, and reinforcement learning based controls. These have been successfully applied to various renewables, heat pump and storage problems [26,27]. Reinforcement learning has been applied to demand response aggregation of electrical water heaters using a 40-45 day learning period [28]. Hard controls use physical models to determine control signals which optimise a system performance parameter. Adaptive control is a hard approach which accounts for changing dynamics of a system and requires less detail in the physical system model, it has been applied to micro-grid operation to evaluate flexibility benefits [29]**.** Model predictive control (MPC) captures the dynamics of an energy systems in a model which can be based on combination of physical models with statistical and machine learning techniques. MPC and a range of non-predictive controls have been studied extensively for thermal storage [25,30], and a comparison of rule based control and MPC suggested MPC has significant advantages [31].

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

1.4. Energy System Modelling Tools

It is clear renewables, heat pumps, thermal storage, time-of-use tariffs, electricity services markets and optimal control strategies can play an important role in aiding the transition to a low-carbon energy system. However, it is important that these systems are modelled sufficiently such that the associated benefits from enabling various load shifting mechanisms can be quantified at the planning level of design, so systems are correctly specified.

Numerous software tools with capability for modelling such local energy systems exist [32] and have previously been reviewed [33–35]. A tool selection process [36] was proposed and used to identify COMPOSE [37], DER-CAM [38], EnergyPLAN [39], EnergyPRO [40], and MARKAL/TIMES [41] tools as passing 'essential capability' criteria for modelling systems with heat pumps, thermal storage, wind turbines, PV, and a grid-connection. However, limitations were also identified in modelling of controls, thermal characteristics, and electricity network interactions which could potentially result in designs that do not fully consider the potential benefits of 'smart' controls and systems without sufficient flexibility for participation in future electricity markets.

Østergaard & Andersen [42] used EnergyPRO to model a generic district heating system to investigate the impact of electricity taxes on the flexible operation of heat pumps. The research sized the heat pump and thermal storage to show an electricity tax equal to the hourly spot market electricity price incentivises 20% more thermal storage capacity. However, EnergyPRO does have limitations. EnergyPRO does not track temperature in hot water tanks, requires users to input electricity prices, and uses either an analytical or linear programming method for control which use perfect foresight of variables over the entire simulation period. Practical controls do not use foresight over very long periods (e.g., a year), as forecasts on these timescales of weather and electricity prices are very uncertain.

A range of detailed simulation tools have been used for detailed design studies [44–48] such as TRNSYS [49], Energy+ [50], IDA-ICE [51], ESP-r [52], Modelica libraries [53] however the use of these tools for planning-level design is problematic due to multiple factors associated with level of expertise, complexity, detailed input data requirements and availability at early design stage, model calibration requirements, etc. While some of these tools allow open-source adaptation and development there is a high knowledge barrier associated with these very detailed and multi-functional tools.

PyLESA (Python for Local Energy Systems Analysis) [54] is an open-source tool capable of modelling local energy systems containing both electrical and thermal sector technologies in hourly timesteps. It was developed by the authors 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 to address the issues found with existing tools. The design of future local energy systems which incorporate heat pumps, thermal storage, future electricity markets, and predictive control strategies requires sufficiently accurate planning-level modelling tools to correctly capture the performance of these systems.

1.5. Aims

The aims of this paper are to present an open-source planning-level modelling tool, PyLESA, and describe its application to a sizing study for district heating network. Presenting and applying PyLESA forms a novel contribution because existing planning-level tools do not capture hot water tanks, heat pumps, MPC, and future electricity tariffs in the level of detail captured with PyLESA. PyLESA allows the role of control strategies, and existing and future electricity tariffs to be captured at the planning stage and supports sizing of components within local energy systems so potential benefits of flexibility can be realised.

An overview of PyLESA's functionality is provided, and then the control strategy and electricity tariff functionality are described in detail. More details on the other functionality of PyLESA can be found in [54].

The aim of the sizing study was to design and size a low-cost and highly renewable local energy system for the case study. The proposed design to be modelled consists of an air-source heat pump and hot water tank (plus back-up electric heat) heating system with a connection to on-site PV generation, participation in variable electricity tariffs, and operation by a model predictive control strategy.

The heat pump and hot water tank components of the proposed design require sizing 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 specific aims were developed in order to investigate the various load shifting mechanisms and aid design and sizing decisions for the heat pump and hot water tank components of the proposed design. These aims use KPIs to allow comparisons between control strategies and electricity tariffs, and sizing decisions to be made. Specific aims are to:

- Investigate the performance of the 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, day and night, 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 Levelized Cost of Heat (LCOH) heat pump and hot water tank size combination for the different control strategies with both the existing tariffs and the future wind-based tariff.

The control strategies are described in Section 4.2. Three existing (flat rates, day and night, and time-of-use) electricity tariffs, and a future wind-based electricity tariff are described in Section 4.3.

2. Sizing Methodology and Key Performance Indicators (KPIs)

The methodology of the sizing study is framed to ensure that the specific aims are achieved. This methodology reflects the structure of the rest of this paper and consists of the following steps:

1) Outline the proposed design of the local energy system.
2) Description of PyLESA the modelling tool for planning-level design of local energy systems applied in this sizing study.
3) Set out the input requirements for modelling the proposed design using PyLESA by (i) presenting the input data, and (ii) outlining the parametric ranges for multiple runs for different size combinations of heat pump and hot water tank, and reruns for all combinations of control strategy and electricity tariffs.
4) Carry out a qualitative inspection of the operational results to verify modelling and control strategies, and to compare and explore the control strategies and electricity tariffs.
5) Explore the sizing results by (i) tabulating the KPIs of the optimal heat pump and hot water tank sizing results for each control strategy and electricity tariff combination, and (ii) evaluation of the output 3D plots of the KPIs for the time-of-use and wind tariffs with model predictive control.

A set of KPIs (Table 1) are used in this sizing study to quantify the ability of the proposed design to enable 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 those output by PyLESA and the renewable-related KPIs were adapted to suit this sizing study and provide clarity on the specific Renewable Energy Source (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. 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 1: Set of KPIs for sizing study

KPI	Comment	Equation
Levelized cost of heat (**LCOH**)	Economic metric to size the heat pump and hot water tank components	$\frac{CAPEX + 20 * HEATOPEX}{(HEAT\ DEM) * 20}$
On-site RES used (**ORESpv**)	RES is the on-site PV generation	$1 - \frac{SUM\ EXPORT}{SUM\ PV\ GENERATION}$
Heat met from RES (**HRESpv**)	Used for the existing electricity tariffs where on-site PV is only source of RES	$\frac{SUM\ HEAT\ FROM\ PV}{SUM\ HP + SUM\ AUX}$
Heat met from RES (**HRESpv+windtariff**)	Used for the wind electricity tariff where both on-site PV and electrical imports during high wind periods are classed as RES	$\frac{SUM\ HEAT\ FROM\ WIND + SUM\ HEAT\ FROM\ PV}{SUM\ HP + SUM\ AUX}$

3. Proposed Design of Local Energy System

The sizing study is applied to a residential district heating scheme operated by West Whitlawburn Housing Co-operative (WWHC) [55]. 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. As an alternative to the current design at WWHC it is proposed that a centralised 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 model predictive control strategy, can offer a solution for low-carbon and low-cost provision of heat. The model of this system assumes the end-user heat demand is not influenced by the proposed design.

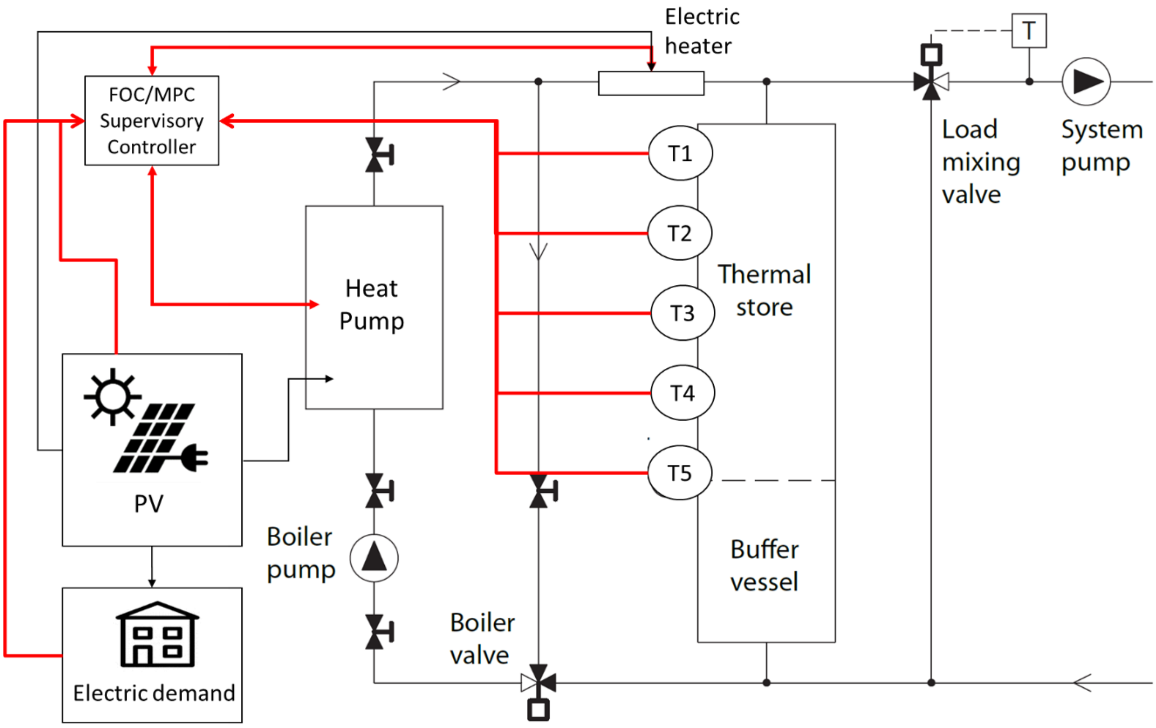

Figure 1: Schematic of proposed design of new low-carbon and low-cost energy system

Figure 1 illustrates the proposed setup, combining all the components discussed above. The relative position of the temperature sensors on the thermal store are illustrated by T1, T2, T3, T4, and T5. 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.

4. PyLESA Description

PyLESA is described here generally in terms of its modelling capabilities, details on the underlying models can be found in [54,56]. Details are provided here on the pertinent capabilities for the sizing study performed in this paper – the control strategies (fixed order control and model predictive control), and synthesis of existing and future electricity tariffs.

4.1. Introducing PyLESA

PyLESA is an open-source tool capable of modelling local energy systems containing both electrical and thermal sector technologies modelled in hourly timesteps. While the tool is configured for hourly timesteps, consistent with data commonly available at the planning stage of design, the open-source code is available to be adapted by others to shorter timesteps if desired, shorter timesteps may of course require mitigations to manage increased computational loads. The tool is flexible in accepting exogenous demand and RES generation inputs. The capabilities of PyLESA are tabulated: Table 2 shows the high-level capabilities and Table 3 shows the modelling and assessment capabilities under the categorisation developed in [36]. Figure 2 displays the models and energy flows of PyLESA.

Table 2: High-level capabilities of PyLESA

High-level capability	Comment
Scale	Developed specifically for local energy systems
Detail of design	Developed specifically for planning-level design
Low and/or zero carbon technologies	Wind turbine, PV, heat pump
Storage/Demand Side Management (DSM) technologies	Storage: Electrical storage, hot water tank DSM: Fixed order control, MPC
Timestep	Hourly timestep chosen for easier data collection and lower computational run time
Electrical technologies	Electrical demand, electrical RES production, electrical storage, and grid
Thermal technologies	Heat demand, heat pumps, auxiliary heat, and hot water tanks

Table 3: Categorisation of PyLESA tool capabilities

Input data requirements and input support	
Demand profile generator	Yes
Resource assessor	Yes
Supply profile generator	Models supply technologies explicitly
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	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 in an object-orientated way, many existing tools do not require any programming proficiency

Key – Outputs: Energy market interaction (EMI); Energy production (EP); Financial analysis (FA); Fuel consumption (FC); Demands/supply match (M); Renewable penetration (RP); System analysis (SA)

Controls/DSM Controls: Fixed order (FO); Model predictive control (MPC)

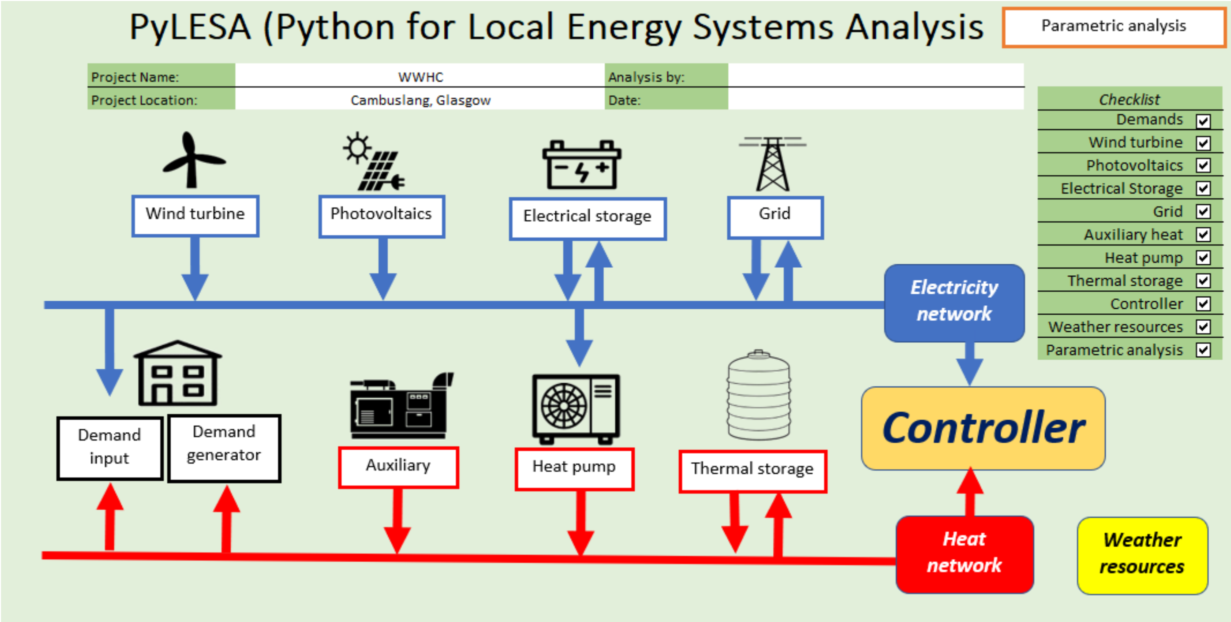

Figure 2: Models and energy flows of PyLESA

4.2. Control Strategies

4.2.1. 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.

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 4 illustrates how two separate rules can be defined to be applied depending on if the electricity import tariff price at the modelled timestep is above or below a user-defined “electricity import price setpoint". This allows for a different set of rules according to electricity tariff, e.g., for a day/night tariff to load shift from higher prices during the day to lower prices during the night.

Table 4: Rules for fixed order control strategy, split into condition based on an electricity import price setpoint (ES – Electrical storage, HP – Heat pump, E-AUX – Electrical auxiliary, TS – Thermal storage, AUX – Auxiliary)

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 3 shows the flow of results and checks when running the fixed order controller in PyLESA. The validation of this controller will be explored in Section 6 where the operational results are described, it is easier to analyse the operational decisions made using a well-defined example.

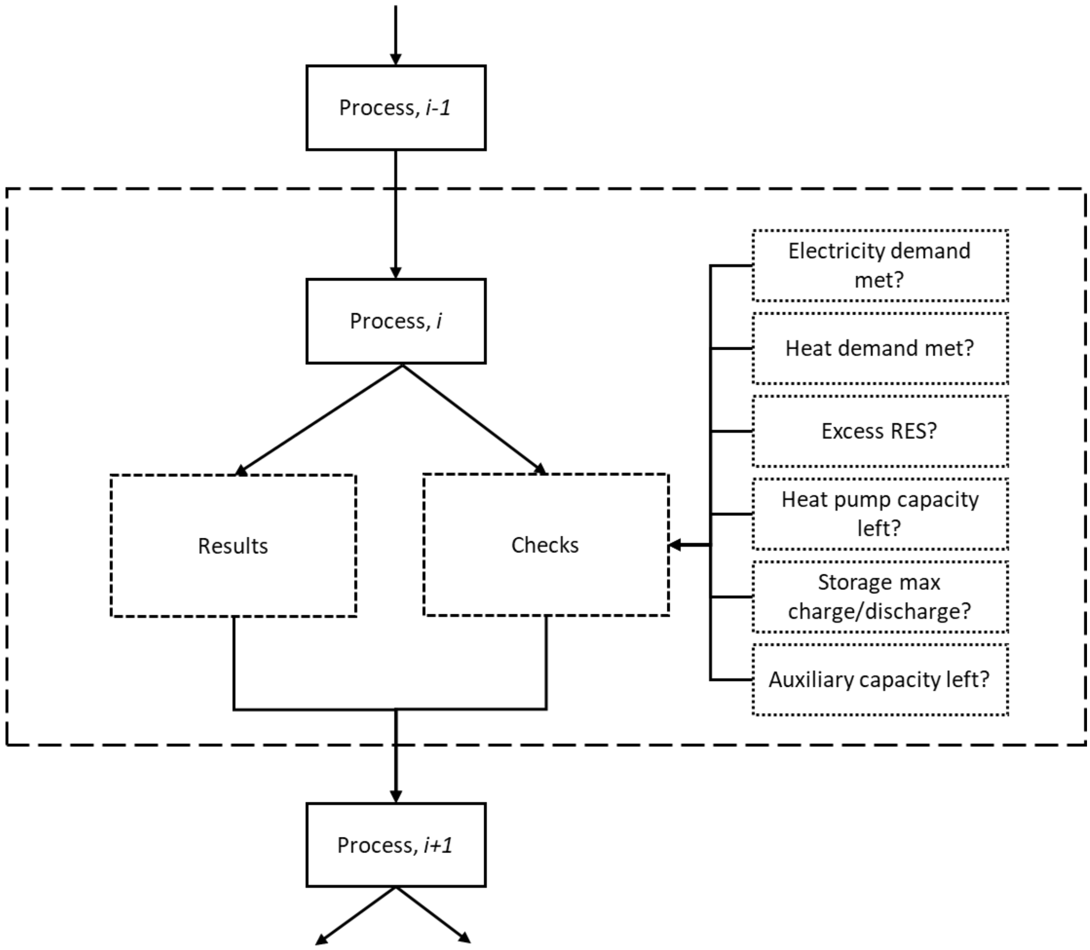

Figure 3: Flow diagram showing process i as a chunk of the flow of results and checks when running the fixed order controller

4.2.2. 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.

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.

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 (1), thermal storage state of charge (2), heat pump thermal output (3), electric auxiliary thermal output (4), and storage charging (5), use of surplus on-site renewable generation (6).

$$HD = HP_{trd} + HP_{tid} + AUX_d + AUX_{rd} + TS_d \tag{1}$$

$$\frac{d\,\mathrm{SOC}}{dt} = TS_c - TS_d - losses \tag{2}$$

$$HP_{on/off}.HP_{t\_var} = HP_{trs} + HP_{trd} + HP_{tid} + HP_{tis} \tag{3}$$

$$AUX = AUX_d + AUX_s + AUX_{rd} + AUX_{rs} \tag{4}$$

$$TS_c = HP_{trs} + HP_{tis} + AUX_{rs} + AUX_s \tag{5}$$

$$RES_{\mathrm{surplus}} = (HP_{trs} + HP_{trd})/COP + AUX_{rd} + AUX_{rs} + export \tag{6}$$

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 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 (7), state equations (1-6) lumped into a generic state equation (8), inequality constraints (9-13), and allowed values for the heat pump status where integer on/off operation is allowed (14).

$$\min_{x,u} \ \phi = \sum_{\mathrm{k}\in\mathcal{M}}[\mathrm{I_{c,k}}(\mathrm{HP_{I,k}} + \mathrm{ED_{I,k}}) + \mathrm{A_{c,k}}\mathrm{AUX_{I,k}} \ - \mathrm{E_{c,k}}\mathrm{EX_{e,k}}] \tag{7}$$

s.t.

$$x_{k+1} = A_d x_k + B_d u_k + E_d d_k \tag{8}$$

$$HP_{duty,k} \geq HP_{\mathrm{t\,var,k}} \geq HP_{min,k} \tag{9}$$

$$SOC_k \leq TS_{capacity} \tag{10}$$

$$TS_{c,k} \leq TS_{\max charge} \tag{11}$$

$$TS_{d,k} \leq SOC_k \tag{12}$$

$$AUX_k \leq AUX_{capacity} \tag{13}$$

$$HP_{status} \in \{0, 1\} \tag{14}$$

$\mathcal{M} \in \{0, 1, \ldots, N\}$ and N is the prediction horizon and a sampling time of 1 hour is used. In the lumped generic state equation (8) x represents the state variables which are the temperatures of the node of the thermal storage, and u represents the control variables which are the responses of the heat pump, thermal storage, and auxiliary boiler. The forecast variables, d, are the electricity tariff prices, the weather forecast parameters, the user dependent demands, and the renewable generation outputs. Several of the state variables are functions of these forecast variables. These are factored by the variables A, B, and E which are the matrix forms of the state equations described earlier.

The forecast variables (e.g., representing weather forecast over a 24- or 48-hour future time horizon) are refreshed with new values read into the control dataset at each new calculation timestep. 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 generated. Forecast variables are updated in the next iteration of the optimisation problem, and this is repeated for the entire simulation period.

The binary ON/OFF status of the heat pump is required due the minimum thermal output of the heat pump. This requires the problem to be solved using a mixed integer linear programming (MILP) approach. Within PyLESA the minimum thermal output of the heat pump can be set to zero and a liner programming (LP) approach can be used which decreases computational time.

It is assumed here that forecast variables 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 benefits from MPC will potentially be overestimated. Using realistic future time horizons over which predictions of forecast variables with relatively low uncertainty helps reduce this overestimation. In practical systems the error in forecasts is mitigated with measures including hourly re-optimisations and 'safety margins' applied to forecasts. Stochastic MPC approaches have been developed which incorporate the uncertainty in forecast variables [57]. Alternative approaches for incorporating uncertainty of prediction variables have used the future value of the reference signal [58], and historical value of the control signal [59]. PyLESA provides a platform for incorporating such methods in future.

The presented MILP is solved using GEKKO, a Python package for machine learning and optimisation [60]. 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 [61]. 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 [62] and optimization of a hybrid solar thermal and fossil fuel system [63].

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. Currently the developed MPC can incorporate all the developed models except the electrical storage model, and inclusion of this can be easily done as future tool development.

4.3. Electricity tariffs

Existing and future tariffs can be generated and modelled in PyLESA, 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.

4.3.1. 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: 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

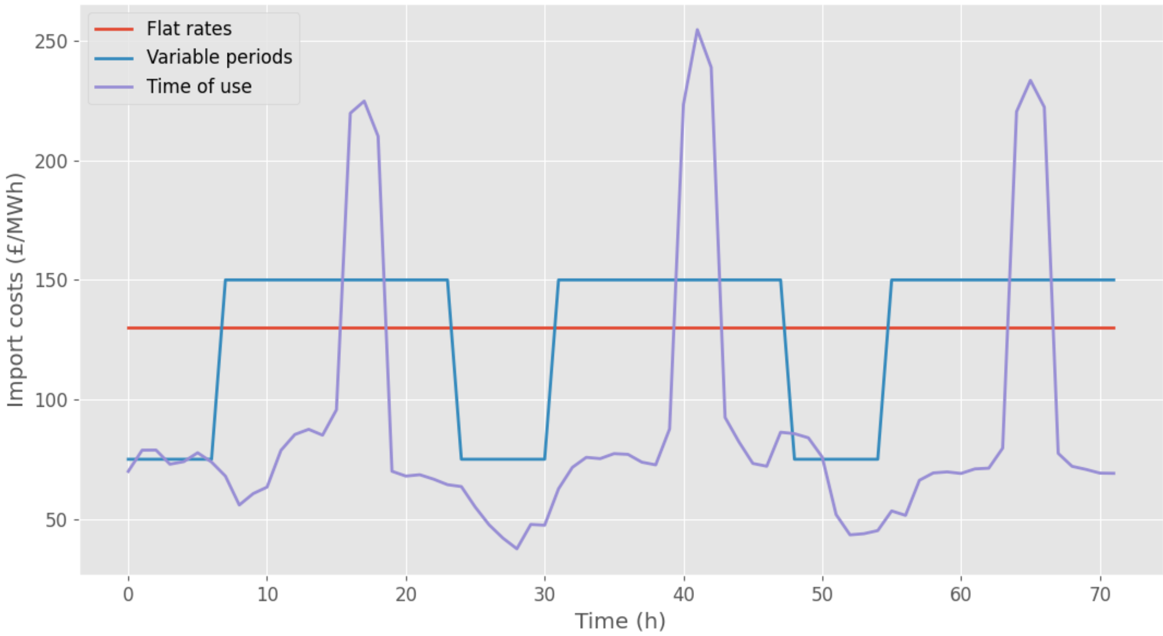

Figure 4: Existing electricity tariffs over 72 hours

4.3.2. Future

Possible future renewable tariff synthesis can be supported in PyLESA. This future wind-based tariff mimics the low-cost electricity that might be available to avoid curtailment and the high cost electricity resulting from the least optimal backup generation being used on low wind days.

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, the discount, and premium to be applied to the base tariff are defined by the user. Figure 5 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, e.g. capturing grid service market opportunities.

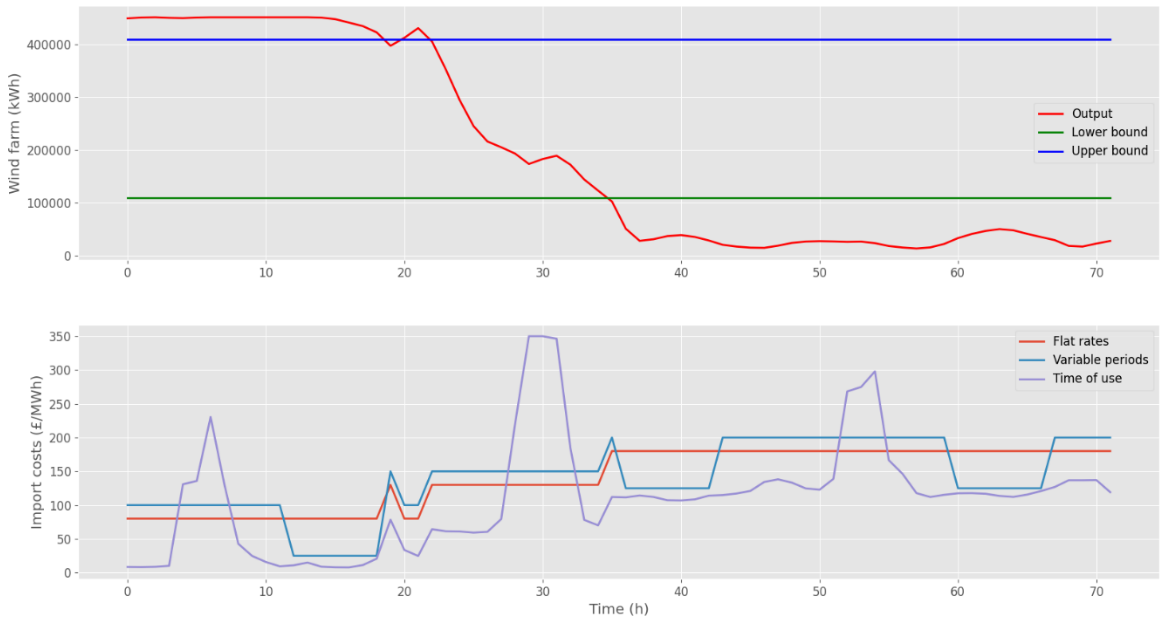

Figure 5: Top graph: wind farm modelled output including upper band and lower band over 72 hours; Bottom graph: renewable electricity tariff with discounts and premiums applied over the same 72 hours.

5. PyLESA Modelling Inputs

This section sets out the modelling of the proposed design using PyLESA by (i) presenting input data, and (ii) outlining the parametric ranges for multiple runs for different size combinations of heat pump and hot water tank, and reruns for all combinations of control strategy and electricity tariffs.

5.1. Input Data

This section details each component of the proposed setup outlining the required, and available, input data.

Resource and Demand Assessment and Input Methods

Local resources: MERRA reanalysis hourly dataset [64] for 2017 for wind speed (at 10m height). Air temperature was collected using local sensors for 2017 for air temperature.

Electrical Demand: Generic community electrical demand profile synthesised in HOMER [65].

District Heating Demand: Hourly monitored data from WWHC for the year 2017.

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. Incentives for PV are not to be included in this modelling exercise.

Heat Pumps and Auxiliary Heat Units

Heat pump: Star Refrigeration ASHP Neatpump [66] with variable speed compressor and 65/55 flow/return temperatures feeding a district heating network at 60/40 flow/return temperatures, with backup electric heater with 100% efficiency sized to peak heat demand. Heat pump performance curves available. Capital cost assumed linear at £600/kW [67] and no economy of scale was assumed in this illustrative example. Incentives for the heat pump are not to be included in this modelling exercise.

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 [67].

Electricity Tariffs

Four different electricity import tariffs are modelled in the sizing study using the following inputs. For clarity in this example, exports to the grid from the on-site PV have been set to zero value, and other on-site uses of PV generation are not considered.

Flat rate: £130/MWh.

Day and night: 12am to 7am - £75/MWh, 7am to 12am - £150/MWh.

Time-of-use: Tracks wholesale market with £120/MWh premium from 4pm to 7pm and £350/MWh maximum.

Wind: Combination of day and night base tariff adjusted by wind pricing structures. 12am to 7am - £75/MWh, 7am to 12am - £150/MWh; and a £50/MWh discount applied during top 20% of wind output and a £50/MWh premium applied during bottom 20% of wind output. Wind output is based upon Whitelee Wind Farm, which consists of 215x Siemens SWT-2.3MW.

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 day and night 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.

Model Predictive Control

MPC requires the prediction horizon as an input. For the existing electricity tariffs a 24-hour period was used to capture day and night pricing etc. and for the wind tariff a 168-hour (1 week) prediction horizon was used to capture periods longer than a day with high or low wind generation affected prices.

5.2. Parametric Ranges

The following parametric ranges are modelled using PyLESA for the control strategies and electricity tariffs:

- 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.

6. Operational Analysis

To illustrate the modelling of the PV, heat pump and thermal storage system with both FOC and MPC for different tariff arrangements two scenarios are examined in this section: (i) FOC with a daily tariff with low-cost imports at night, and (ii) MPC with a wind-based tariff where there are variable periods with high import costs. A summer week is shown for a day and night tariff with fixed order control using an example 1000kW heat pump and 500m^3 hot water tank size combination. A windless winter week is shown for the wind-based tariff with MPC using an example 3000kW heat pump and 3000m^3 hot water tank size combination. 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. These scenarios were selected to provide an insight into the operation of the underlying models, analysis for a wider range of system sizes and combinations of control strategies and electricity tariffs, and modelling validations, can be found in [42]. Modelling results have been compared to an EnergyPLAN model of the same case study showing similar overall results for comparable scenarios, while PyLESA offered improved level of detail, e.g., in hot water tank and controls including MPC [54].

6.1. Day and Night Tariff and Fixed Order Control

The operation of the fixed order control with the day and night tariff is displayed for a summer week in Figure 6. 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).

During the low-cost period, when the hot water tank is full, the heat pump modulates its output to match demand and charge the hot water tank. 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. Surplus PV generation is the total PV generation minus the PV generation used to meet electrical demand, while export is the PV

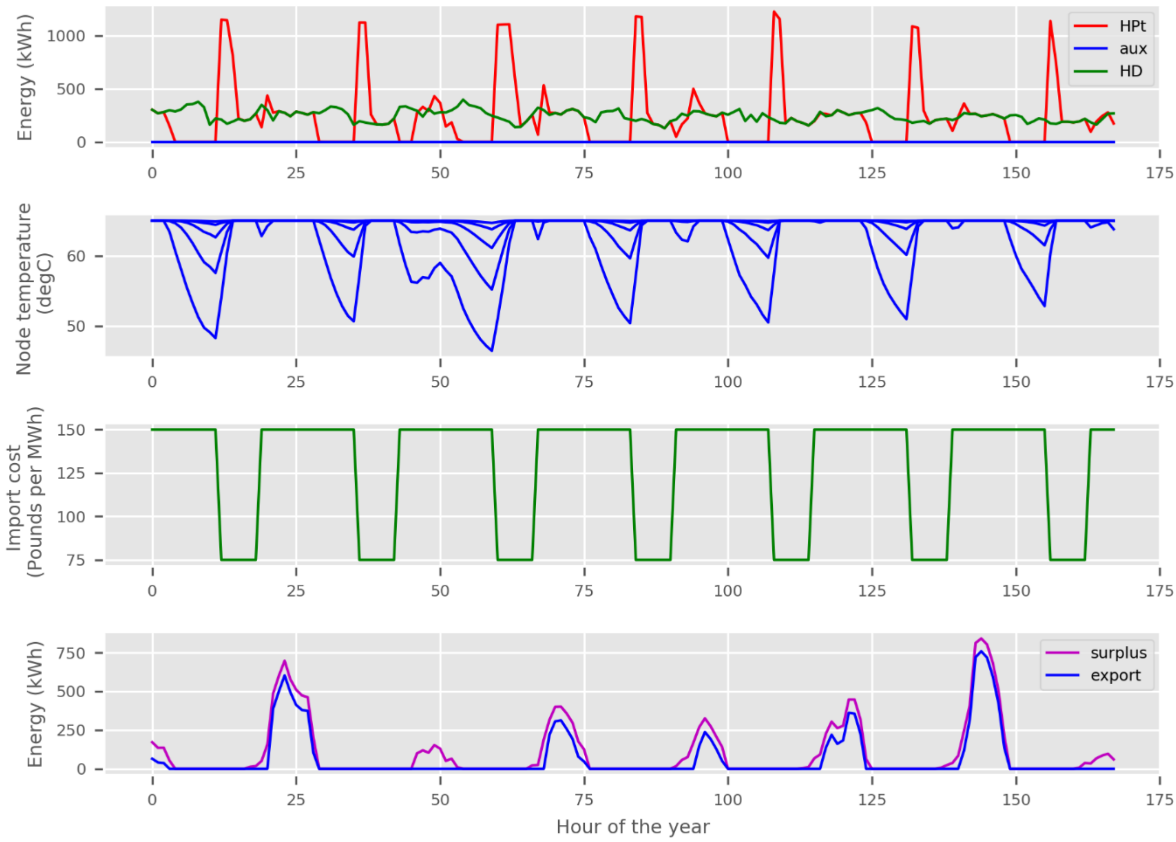

Figure 6: Operational graphs with FOC and variable periods tariff over a summer week. HPt = heat pump heat output, aux = auxiliary heat output, and HD = heat demand.

generation which is not used locally to meet demand or charge storage but is exported to the grid. However, often the hot water tank has only briefly been discharging after fully charging from the low-cost overnight period, and there is little spare capacity to utilise the surplus PV generation.

6.2. Wind Tariff and MPC

The operation of the MPC with the wind tariff is displayed for a winter 10-day period with an 8-day windless spell from the end of day 2. 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. In the displayed operation period, the 4th graph shows there is little surplus PV generation left after PV generation has been used to meet electrical demand, and no PV export.

In the first two days (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 8-day 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 occurs during the highest heat pump performance periods which are when the air temperature is highest.

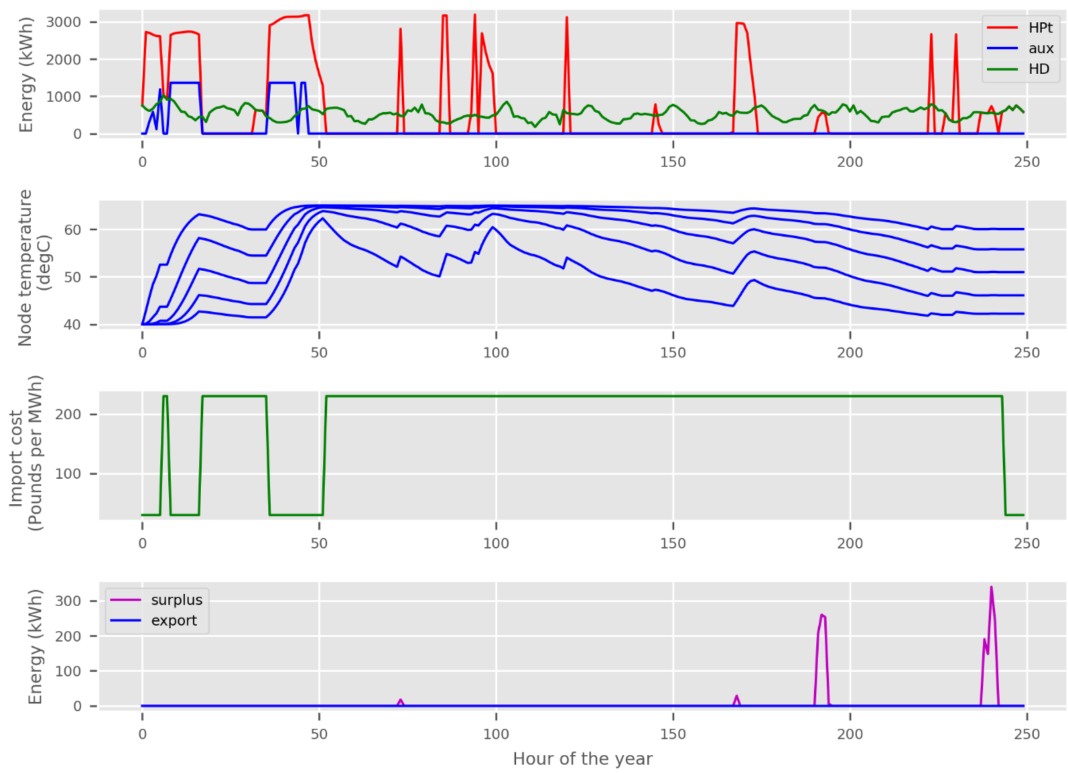

Figure 7: Operational graphs with MPC and wind tariff over a windless winter 10-day period. HPt = heat pump heat output, aux = auxiliary heat output, and HD = heat demand.

7. Sizing Study

The heat pump and hot water tank sizes are now investigated for three existing electricity tariffs (flat rate, variable day and night periods, and time-of-use) and the future wind-based electricity tariff, for each of the two control strategies (FOC and MPC).

Results for the optimum LCOH size combinations of heat pump and hot water tank are shown in Table 6 for the existing electricity tariffs and control strategies, and in Table 7 for the wind electricity tariff and control strategies.

The remainder of this section describes 3D plots of the KPIs (LCOH, ORESpv, HRESpv, and HRESpv+windtariff) for MPC with the time-of-use tariff and wind tariff. Further 3D plots for all combinations of control strategies and electricity tariffs can be found in [42].

Table 6: 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%)
Day and night	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 7: 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%)

7.1. Time-of-use Tariff and MPC

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 (Figure 8). 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, the MPC optimises the usage of the excess PV generation.

The MPC enables almost all of the surplus PV generation to be self-consumed above a hot water tank capacity of 300m^3 (Figure 9). 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. 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 10).

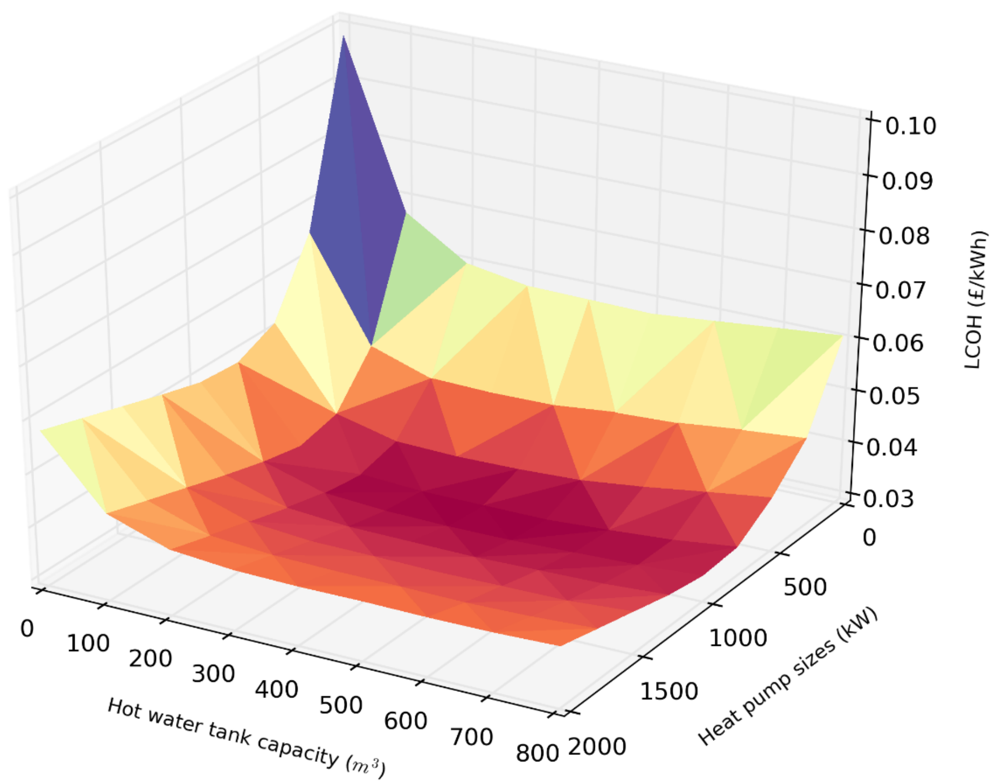

Figure 8: 3D plot of LCOH (levelized cost of heat) for MPC with time-of-use tariff

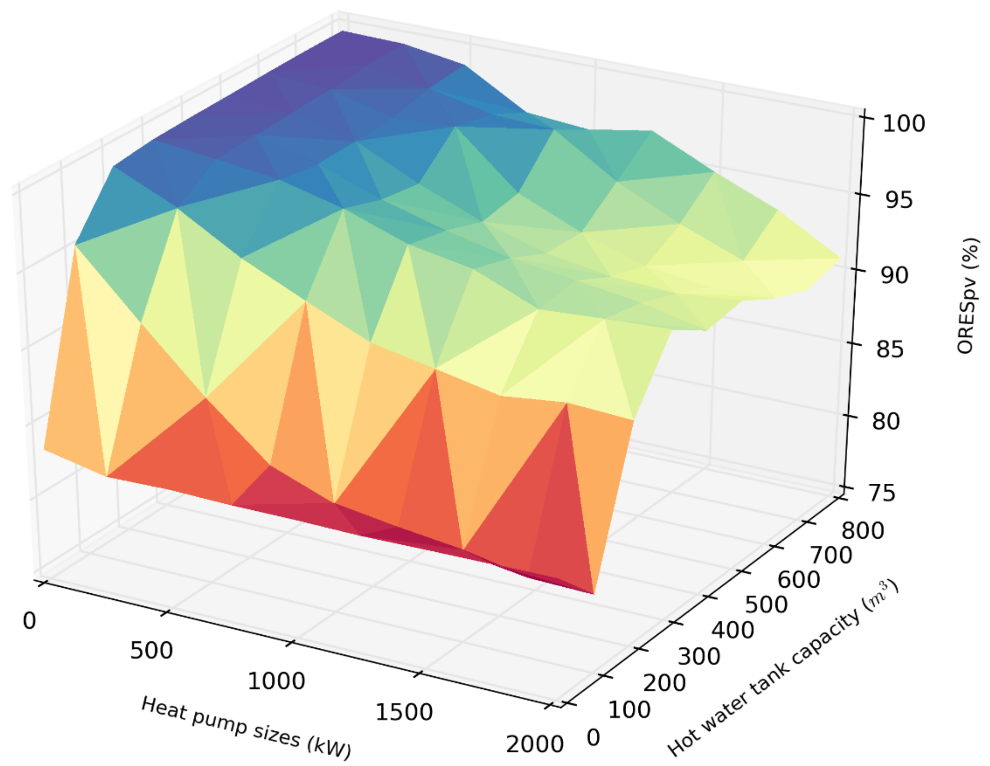

Figure 9: 3D plot of ORESpv (on-site PV self-consumption) for MPC with time-of-use tariff

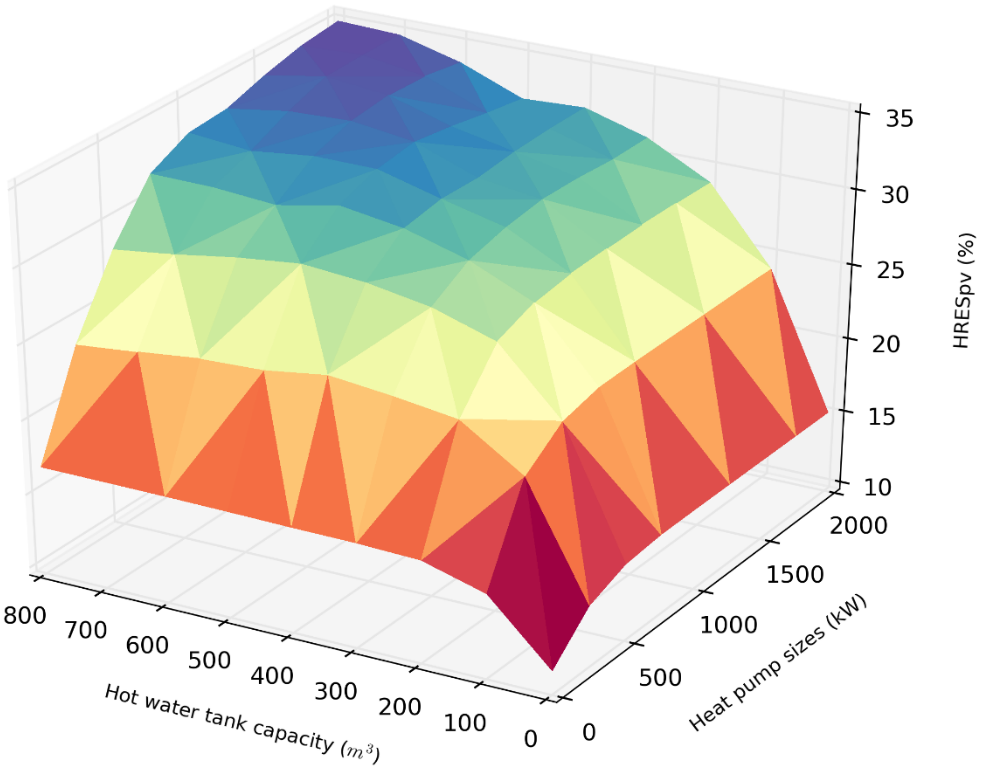

Figure 10: 3D plot of HRESpv (heat demand from on-site PV) for MPC with time-of-use tariff

7.2. Wind Tariff and MPC

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.

Using MPC over the fixed order control decreases LCOH by 44.1%, which clearly shows that using MPC is beneficial (Figure 11). 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.

As with the existing electricity tariffs, the MPC enables almost all of the surplus PV generation to be self-consumed (Figure 12). 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. Figure 13 shows the percentage of heat demand met from on-site PV and high wind grid import increasing 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. In this case over 70% of the heat was generated from on site PV and low cost wind grid import.

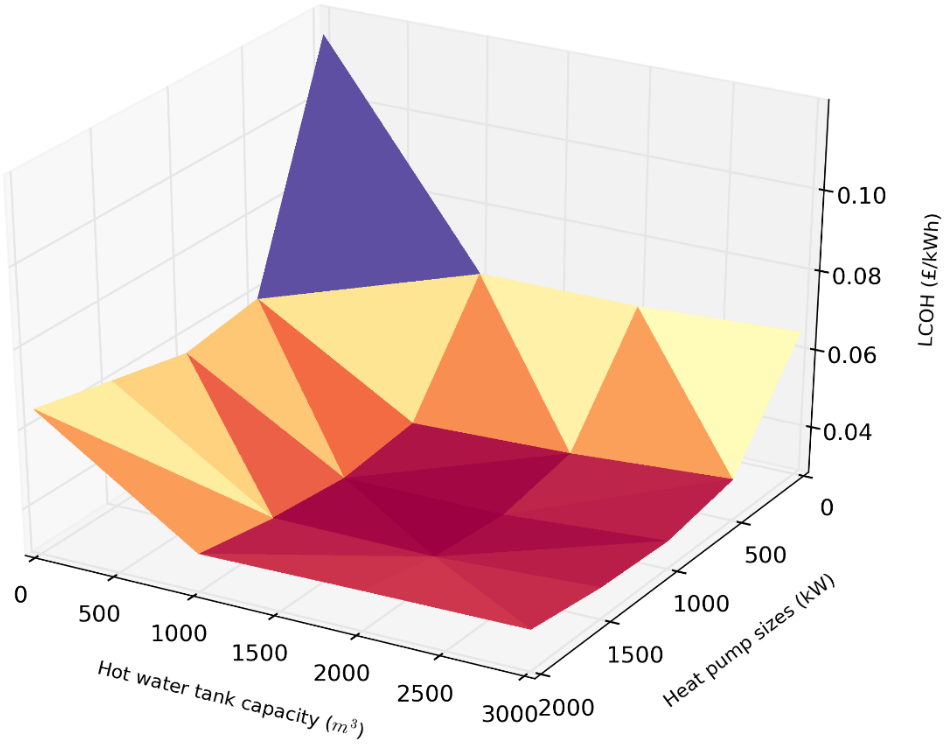

Figure 11: 3D plot of LCOH (levelized cost of heat) for MPC with wind tariff

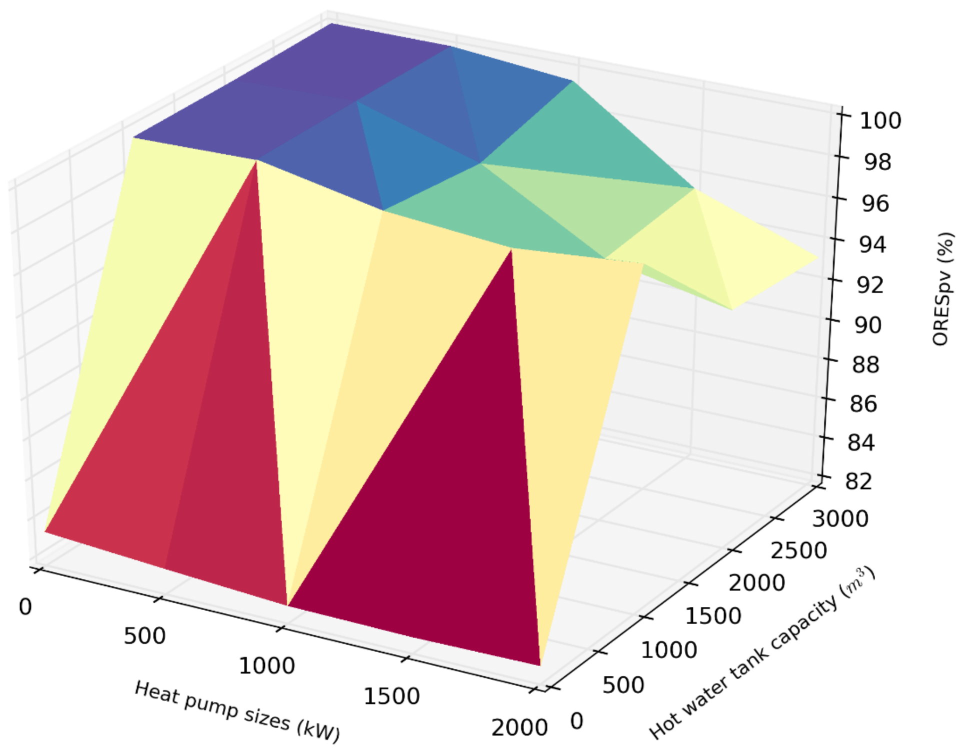

Figure 12: 3D plot of ORESpv (on-site PV self-consumption) for MPC with wind tariff

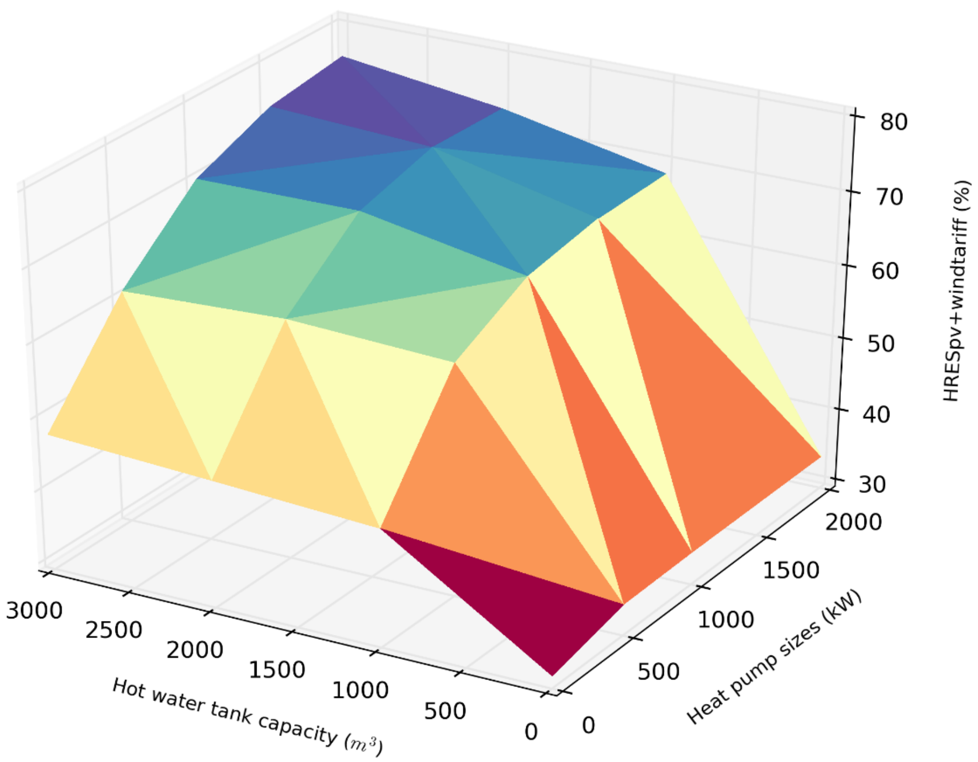

Figure 13: 3D plot of HRESpv+windtariff (heat demand from on-site PV and electrical imports during high wind periods) for MPC with wind tariff

8. Discussion

PyLESA has been presented and applied to a sizing study for a residential district heating scheme. This has showcased the ability of PyLESA as a useful aid to investigate the benefits of model predictive control and different electricity tariffs including a novel future wind tariff. 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.

In terms of future PyLESA tool development inclusion of emerging balancing markets could provide a greater incentive for flexibility e.g. balancing mechanism, frequency response, and new ancillary markets such as the European wide balancing energy market TERRE [68]. Another important aspect of future work could be the inclusion of uncertainties in the MPC formulation as these are currently modelled with perfect foresight [69,70].

The operational analysis results provided a qualitative discussion of the comparisons of the developed control strategies and the electricity tariffs. The time-of-use tariff is highly variable 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, the self-consumption of PV 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.

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. The wind tariff with 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. The auxiliary 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.

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 the case study site. This signifies a shift in the methods which are used to size hot water tanks in district heating systems; sizing to enable load shifting and not only for flattening peak demands.

An optimal size combination of a 1000kW heat pump and a 2000m^3 hot water tank was found with MPC and the future wind-based 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.

9. Conclusions

In conclusion, the open-source tool PyLESA has proven capable of usefully aiding the design of local energy systems while advancing the state-of-the-art modelling capability at the planning-level stage of design. It can be used to support further research and development in the modelling of local energy systems. In the case study MPC has been demonstrated to reduce costs and increase the usage of renewable energy; and sizing hot water tanks larger than is currently common has been shown to be beneficial with future highly variable wind tariffs. This paper has highlighted benefits from combining flexible tariffs with MPC and optimally sized heat pumps and thermal storage.

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References

[1] Kim YJ, Fuentes E, Norford LK. Experimental Study of Grid Frequency Regulation Ancillary Service of a Variable Speed Heat Pump. IEEE Trans Power Syst 2016;31:3090–9. https://doi.org/10.1109/TPWRS.2015.2472497.

[2] Papaefthymiou G, Hasche B, Nabe C. Potential of heat pumps for demand side management and wind power integration in the German electricity market. IEEE Trans Sustain Energy 2012;3:636–42. https://doi.org/10.1109/TSTE.2012.2202132.

[3] Fischer D, Madani H. On heat pumps in smart grids: A review. Renew Sustain Energy Rev 2017;70:342–57. https://doi.org/10.1016/j.rser.2016.11.182.

[4] EHPA. Large scale heat pumps in Europe. Eur Heat Pump Assoc 2017.

[5] Connolly D, Lund H, Mathiesen BV, Werner S, Möller B, Persson U, et al. Heat Roadmap Europe: Combining district heating with heat savings to decarbonise the EU energy system. Energy Policy 2014;65:475–89. https://doi.org/10.1016/j.enpol.2013.10.035.

[6] David A, Mathiesen BV, Averfalk H, Werner S, Lund H. Heat Roadmap Europe: Large-scale electric heat pumps in district heating systems. Energies 2017;10:578. https://doi.org/10.3390/en10040578.

[7] Fischer D, Lindberg KB, Madani H, Wittwer C. Impact of PV and variable prices on optimal system sizing for heat pumps and thermal storage. Energy Build 2016;128:723–33. https://doi.org/10.1016/j.enbuild.2016.07.008.

[8] Alimohammadisagvand B, Jokisalo J, Kilpeläinen S, Ali M, Sirén K. Cost-optimal thermal energy storage system for a residential building with heat pump heating and demand response control. Appl Energy 2016;174:275–87. https://doi.org/10.1016/j.apenergy.2016.04.013.

[9] Mahfuz MH, Anisur MR, Kibria MA, Saidur R, Metselaar IHSC. Performance investigation of thermal energy storage system with Phase Change Material (PCM) for solar water heating application. Int Commun Heat Mass Transf 2014;57:132–9. https://doi.org/10.1016/j.icheatmasstransfer.2014.07.022.

[10] Le Dréau J, Heiselberg P. Energy flexibility of residential buildings using short term heat storage in the thermal mass. Energy 2016;111:991–1002. https://doi.org/10.1016/j.energy.2016.05.076.

[11] Lund H, Werner S, Wiltshire R, Svendsen S, Thorsen JE, Hvelplund F, et al. 4th Generation District Heating (4GDH). Energy 2014;68:1–11. https://doi.org/10.1016/j.energy.2014.02.089.

[12] Lund H, Østergaard PA, Connolly D, Ridjan I, Mathiesen BV, Hvelplund F, et al. Energy Storage and Smart Energy Systems. Int J Sustain Energy Plan Manag 2016;11:3–14.

https://doi.org/10.5278/ijsepm.2016.11.2.

[13] Steele P. Agile pricing explained | Octopus Energy 2019. https://octopus.energy/blog/agile-pricing-explained/ (accessed April 10, 2020).

[14] Lee ZE, Sun Q, Ma Z, Wang J, MacDonald JS, Max Zhang K. Providing Grid Services With Heat Pumps: A Review. ASME J Eng Sustain Build Cities 2020;1. https://doi.org/10.1115/1.4045819.

[15] Meesenburg W, Markussen WB, Ommen T, Elmegaard B. Optimizing control of two-stage ammonia heat pump for fast regulation of power uptake. Appl Energy 2020;271:115126. https://doi.org/10.1016/j.apenergy.2020.115126.

[16] Zajc M, Kolenc M, Suljanović N. Virtual power plant communication system architecture. Smart Power Distrib. Syst. Control. Commun. Optim., Elsevier; 2018, p. 231–50. https://doi.org/10.1016/B978-0-12-812154-2.00011-0.

[17] Usef Energy – Universal Smart Energy Framework n.d. https://www.usef.energy/ (accessed April 10, 2020).

[18] VHPready Services GmbH. Home - VHPready Services GmbH 2018. https://www.vhpready.de/en/home/ (accessed April 10, 2020).

[19] REScoop.eu project proposals - News n.d. https://www.rescoop.eu/blog/rescoop-eu-project-proposals (accessed April 10, 2020).

[20] FLEXcoop Project n.d. http://www.flexcoop.eu/ (accessed April 10, 2020).

[21] WiseGRID · WiseGRID n.d. https://www.wisegrid.eu/ (accessed April 10, 2020).

[22] OpenEnergyMonitor. Home | OpenEnergyMonitor 2016. https://openenergymonitor.org/ (accessed April 10, 2020).

[23] Gürel AE, Ceylan I. Thermodynamic analysis of PID temperature controlled heat pump system. Case Stud Therm Eng 2014;2:42–9. https://doi.org/10.1016/j.csite.2013.11.002.

[24] Roman R, Wilson R. Commercial Demand Side Management Using a Programmable Logic Controller. IEEE Trans Power Syst 1995;10:376–9. https://doi.org/10.1109/59.373959.

[25] Thieblemont H, Haghighat F, Ooka R, Moreau A. Predictive control strategies based on weather forecast in buildings with energy storage system: A review of the state-of-the art. Energy Build 2017;153:485–500. https://doi.org/10.1016/j.enbuild.2017.08.010.

[26] Huang T, Liu D. A self-learning scheme for residential energy system control and management. Neural Comput Appl 2013;22:259–69. https://doi.org/10.1007/s00521-011-0711-6.

[27] Andrew Putrayudha S, Kang EC, Evgueniy E, Libing Y, Lee EJ. A study of photovoltaic/thermal (PVT)-ground source heat pump hybrid system by using fuzzy logic control. Appl Therm Eng 2015;89:578–86. https://doi.org/10.1016/j.applthermaleng.2015.06.019.

[28] Ruelens F, Claessens BJ, Vandael S, Iacovella S, Vingerhoets P, Belmans R. Demand response of a heterogeneous cluster of electric water heaters using batch reinforcement learning. Proc. - 2014 Power Syst. Comput. Conf. PSCC 2014, Institute of Electrical and Electronics Engineers Inc.; 2014. https://doi.org/10.1109/PSCC.2014.7038106.

[29] Holjevac N, Capuder T, Kuzle I. Adaptive control for evaluation of flexibility benefits in microgrid systems. Energy 2015;92:487–504. https://doi.org/10.1016/j.energy.2015.04.031.

[30] Yu Z, Huang G, Haghighat F, Li H, Zhang G. Control strategies for integration of thermal energy storage into buildings: State-of-the-art review. Energy Build 2015;106:203–15. https://doi.org/10.1016/j.enbuild.2015.05.038.

[31] Fischer D, Bernhardt J, Madani H, Wittwer C. Comparison of control approaches for variable speed air source heat pumps considering time variable electricity prices and PV. Appl Energy 2017;204:93–105. https://doi.org/10.1016/j.apenergy.2017.06.110.

[32] OEP n.d. https://openenergy-platform.org/factsheets/models/ (accessed June 17, 2020).

[33] Connolly D, Lund H, Mathiesen B V., Leahy M. A review of computer tools for analysing the integration of renewable energy into various energy systems. Appl Energy 2010;87:1059–82. https://doi.org/10.1016/j.apenergy.2009.09.026.

[34] Allegrini J, Orehounig K, Mavromatidis G, Ruesch F, Dorer V, Evins R. A review of modelling approaches and tools for the simulation of district-scale energy systems. Renew Sustain Energy Rev 2015;52:1391–404. https://doi.org/10.1016/j.rser.2015.07.123.

[35] Olsthoorn D, Haghighat F, Mirzaei PA. Integration of storage and renewable energy into district heating systems: A review of modelling and optimization. Sol Energy 2016;136:49–64. https://doi.org/10.1016/j.solener.2016.06.054.

[36] Lyden A, Pepper R, Tuohy PG. A modelling tool selection process for planning of community scale energy systems including storage and demand side management. Sustain Cities Soc 2018;39:674–88. https://doi.org/10.1016/j.scs.2018.02.003.

[37] ENERGIANALYSE.DK - SOFTWARE n.d. http://www.energianalyse.dk/index.php/software (accessed February 15, 2021).

[38] Stadler M, Groissböck M, Cardoso G, Marnay C. Optimizing Distributed Energy Resources and building retrofits with the strategic DER-CAModel. Appl Energy 2014;132:557–67. https://doi.org/10.1016/j.apenergy.2014.07.041.

[39] Lund H. EnergyPLAN Advanced Energy Systems Analysis Computer Model 2015.

[40] EMD International. energyPRO - User Guide 2001. https://doi.org/10.2307/2234838.

[41] Seebregts AJ, Goldstein GA, Smekens K. Energy/Environmental Modeling with the MARKAL Family of Models. Oper. Res. Proc. 2001, Springer Berlin Heidelberg; 2002, p. 75–82. https://doi.org/10.1007/978-3-642-50282-8_10.

[42] Østergaard PA, Andersen AN. Variable taxes promoting district heating heat pump flexibility. Energy 2021;221:119839. https://doi.org/10.1016/j.energy.2021.119839.

[43] Kolhe M, Ranaweera KMIU, Gunawardana AGBS. Techno-economic optimum sizing of hybrid renewable energy system. IECON Proc. (Industrial Electron. Conf., 2013, p. 1898–903. https://doi.org/10.1109/IECON.2013.6699421.

[44] Kalogirou SA. Use a TRNSYS for modelling and simulation of a hybrid pv-thermal solar system for Cyprus. Renew Energy 2001;23:247–60. https://doi.org/10.1016/S0960-1481(00)00176-2.

[45] Kelly NJ, Cockroft J. Analysis of retrofit air source heat pump performance: Results from detailed simulations and comparison to field trial data. Energy Build 2011;43:239–45. https://doi.org/10.1016/j.enbuild.2010.09.018.

[46] Priarone A, Silenzi F, Fossa M. Modelling Heat Pumps with Variable EER and COP in EnergyPlus: A Case Study Applied to Ground Source and Heat Recovery Heat Pump Systems. Energies 2020;13:794. https://doi.org/10.3390/en13040794.

[47] Chargui R, Sammouda H. Modeling of a residential house coupled with a dual source heat pump using TRNSYS software. Energy Convers Manag 2014;81:384–99. https://doi.org/10.1016/j.enconman.2014.02.040.

[48] Lohani SP, Schmidt D. Comparison of energy and exergy analysis of fossil plant, ground and air source heat pump building heating system. Renew Energy 2010;35:1275–82. https://doi.org/10.1016/j.renene.2009.10.002.

[49] Beckman WA, Broman L, Fiksel A, Klein SA, Lindberg E, Schuler M, et al. TRNSYS The most complete solar energy system modeling and simulation software. Renew Energy 1994;5:486–8. https://doi.org/10.1016/0960-1481(94)90420-0.

[50] Crawley DB, Lawrie LK, Winkelmann FC, Buhl WF, Huang YJ, Pedersen CO, et al. EnergyPlus: Creating a new-generation building energy simulation program. Energy Build 2001;33:319–31. https://doi.org/10.1016/S0378-7788(00)00114-6.

[51] IDA ICE - Simulation Software | EQUA 2019. https://www.equa.se/en/ida-ice (accessed April 16, 2021).

[52] Energy Systems Research Unit (ESRU) University of Strathclyde. ESP-r n.d.

[53] Wetter M. Modelica-based modelling and simulation to support research and development in building energy and control systems. J Build Perform Simul 2009;2:143–61. https://doi.org/10.1080/19401490902818259.

[54] Lyden A. Modelling and Design of Local Energy Systems Incorporating Heat Pumps, Thermal Storage, Future Tariffs, and Model Predictive Control. University of Strathclyde, 2020.

[55] District Heating | West Whitlawburn Housing Co-operative Ltd n.d. http://www.wwhc.org.uk/our-properties/district-heating/ (accessed April 28, 2020).

[56] Lyden A, Tuohy P. A methodology for designing decentralised energy systems with predictive control for heat pumps and thermal storage. E3S Web Conf 2019;111:06014. https://doi.org/10.1051/e3sconf/201911106014.

[57] Oldewurtel F, Parisio A, Jones CN, Gyalistras D, Gwerder M, Stauch V, et al. Use of model predictive control and weather forecasts for energy efficient building climate control. Energy Build 2012;45:15–27. https://doi.org/10.1016/j.enbuild.2011.09.022.

[58] Rehrl J, Horn M. Temperature control for HVAC systems based on exact linearization and model predictive control. Proc. IEEE Int. Conf. Control Appl., 2011, p. 1119–24. https://doi.org/10.1109/CCA.2011.6044437.

[59] Karlsson H, Hagentoft CE. Application of model based predictive control for water-based floor heating in low energy residential buildings. Build Environ 2011;46:556–69. https://doi.org/10.1016/j.buildenv.2010.08.014.

[60] Beal LDR, Hill DC, Abraham Martin R, Hedengren JD. GEKKO optimization suite. Processes 2018;6:106. https://doi.org/10.3390/pr6080106.

[61] APOPT Solutions n.d. https://apopt.com/index.php (accessed April 22, 2020).

[62] Powell KM, Edgar TF. An adaptive-grid model for dynamic simulation of thermocline thermal energy storage systems. Energy Convers Manag 2013;76:865–73. https://doi.org/10.1016/j.enconman.2013.08.043.

[63] Powell KM, Hedengren JD, Edgar TF. Dynamic optimization of a hybrid solar thermal and fossil fuel system. Sol Energy 2014;108:210–8. https://doi.org/10.1016/j.solener.2014.07.004.

[64] Staffell I, Pfenninger S. Using bias-corrected reanalysis to simulate current and future wind power output. Energy 2016;114:1224–39. https://doi.org/10.1016/j.energy.2016.08.068.

[65] HOMER Energy. HOMER Pro 2014:2017.

[66] Neatpump | Star Refrigeration Products n.d. https://www.star-ref.co.uk/our-products/neatpump.aspx (accessed January 25, 2020).

[67] Danish Energy Agency. Technology Data 2018. https://ens.dk/en/our-services/projections-and-models/technology-data (accessed March 12, 2019).

[68] TERRE n.d. https://www.entsoe.eu/network_codes/eb/terre/ (accessed April 23, 2020).

[69] Parisio A, Glielmo L. Stochastic Model Predictive Control for economic/environmental operation management of microgrids. 2013 Eur. Control Conf. ECC 2013, 2013, p. 2014–9. https://doi.org/10.23919/ecc.2013.6669807.

[70] Maasoumy M, Razmara M, Shahbakhti M, Vincentelli AS. Handling model uncertainty in model predictive control for energy efficient buildings. Energy Build 2014;77:377–92. https://doi.org/10.1016/j.enbuild.2014.03.057.