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Comparison of control approaches for variable speed air source heat pumps considering time variable electricity prices and PV

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HIGHLIGHTS

- Study of complexity vs. performance of controllers for a variable speed heat pump.
- Rule based, predictive and model predictive controls (MPC) tested.
- Results show importance to consider different KPIs for controller testing.
- MPC outperforms other control approaches, even with forecast error.
- Larger storage only beneficial with MPC.

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ABSTRACT

The influence of different control strategies and boundary conditions on heat pump system performance are investigated in this study and the trade-off between complexity and performance of different controllers is addressed. For this purpose five different control approaches for a variable speed air source heat pump in a multi family house are compared for three different use-cases. The used controls differ in complexity and the use of external input data like price and weather forecasts. The use-cases are: Constant electricity prices, time variable electricity prices and PV self-consumption. Four different rule-based controllers are compared to a convex MPC approach, presented in this work.

Results show that the MPC approach reduces annual operating cost by 6–11% for constant electricity prices and 6–16% in the case of variable electricity prices. Rule-based approaches lead to cost reductions of 2–4%. MPC could increases PV self-consumption from 56% to 58% up to 64–71%. The rule base approaches are found computationally less demanding and easier to design. However fine-tuning has been considerable work and with changing boundary conditions rules had to be readjusted. It showed that increasing thermal storage without MPC is not beneficial and optimised controls are a prerequisite to benefit from increased storage sizes.

1. Changing boundary conditions and new opportunities for heat pump controls

Three developments will change the way heat pumps (HP) will be operated. First, the integration of heat pumps into smart grids [1]. In this context managing the demand side will be increasingly important to balance an increased electricity generation from fluctuating renewable sources. It has been shown that heat pumps, connected to thermal storage or actively using the building's thermal mass, can provide flexibility in operation, which can be used for tasks in the power system. In this context time variable electricity prices can be used as a way to align heat pump operation with the needs of the power system, which influences the boundary conditions for HP operation.

The second development is an increase of on-site photovoltaic (PV) electricity generation and the motivation to self-consume an optimal share of the generated electricity. This will influence the choice of control strategy and the boundary conditions for HP operation.

The third development is the availability of forecasts and cheap computation capacity on a controller level, which led to an extension of existing control approaches by:

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1. The use of forecasts for loads, PV electricity and prices to derive a control trajectory.
2. The use of heuristics or optimisation methods to derive a control trajectory.

Those approaches now compete with existing rule-based non-predictive approaches.

A central question is to which extend additional information and additional complexity improves controller performance, and to what extend new control approaches are needed to successfully integrate heat pumps into a smarter and increasingly renewable electric system? Furthermore the question is how the different control strategies and smart grid boundary conditions will impact heat pump system operation?

1.1. Previous work

Advanced controls for heat pump systems have been studied in the past mostly with a focus on model predictive controls (MPC). First studies on MPC with heat pumps for space heating under time variable electricity tariffs have already been presented in 1988 [2]. The maximum principle of optimal control is applied to derive control trajectories which are reported to be optimal. The solution has bang-bang characteristics and the control task is reduced towards finding an optimal switching point for the heat pump. [3] uses a linear optimal control formulation for MPC to control heat pumps used for heating residential buildings with a floor heating system. Thermal capacity of the building is used to shift electricity consumption to periods with low electricity prices. For the given case, cost savings of 25–35% are reported. In [4] linear MPC is used to control a multi energy system comprising of a heat pump, slab cooling, an electric water heater, lead-acid battery storage, and photovoltaic panels. The building energy system is operated with respect to day-ahead and real-time prices. [5] presents MPC of domestic heat pump directly connected to a Danish single-family house. Using a constant COP, a linearised building model and a convex cost function, the optimal control problem is solved using a convex solver. For the given case the resulting savings on an example winter day are within the range of 7–12% compared to a conventional control approach. [6] presented a set of model predictive control approaches using a time dependent COP formulation and a linearised building model. This was done for the case of On-Off heat pumps with pulse width modulation used for space heating in single family houses. The objective was tracking a building reference temperature while minimising electricity costs, which was achieved by solving a quadratic optimisation problem. A cost reduction of up to 13% was reported. [7] extended the approach towards adaptive controls, highlighting the importance of parameter identification schemes and predictions. [8–10] extends the MPC approach accounting for uncertainties in weather predictions further. Stochastic MPC is used to satisfy temperature constraints of different buildings at minimum costs. For the presented cases it was shown that the stochastic approach outperforms a conventional MPC approach. Iterative linearisation is used to estimate a system model used for solving a convex optimal control problem at each receding horizon step.

In [11] a comparison of convex and non-convex problem formulation is presented for an On-Off heat pump, showing that the non-convex formulation results in 4–6% less costs. This is extended in [12] towards a variable speed heat pump. The focus of both papers is on using building thermal mass and floor heating's thermal inertia as storage. ACADO direct multiple shooting is used to solve the optimal control problem.

[13] compares a rule-based and a model predictive controller for an energy management system including batteries, a ground source heat pump, PV, shiftable appliances and thermal storage. Dynamic programming is used to solve the resulting non-linear control problem. Here the non-linearities in the heat pump are respected. Stratification of the thermal storage is neglected. Different scenarios for batteries and thermal storages size are investigated. It is shown that the dynamic programming approach significantly outperforms the rule-based approaches with respect to annual operation costs, however with respect to self-consumption the benefit of the dynamic programming approach are not as dominant.

1.2. Contribution of this work

The previous studies highlight the potential of improved controls with a focus on MPC. The considered performance criteria are mostly annual operating cost or PV self-consumption rates. Whereas a detailed analyses of the operation of the heat pump, the storage and the back-up heater with respect to a more comprehensive set of key performance indicators (KPI) is missing. Frequently this is not possible as the used models in the presented studies do not cover non-linearities of the heat pump, stratification of the thermal storage (also criticised in [14]) or are directly based on the results of the optimal control problem.

By the use of appropriate models, controllers and a broad range of key performance indicators this work provides a comprehensive picture about the different controls options and important control design parameters. Each controller is tested for different boundary conditions and storage sizes.

In most studies MPC approaches are compared to one single and often poorly designed controller for benchmark. This might lead to an overestimation of MPC. This is why a considerable amount of research time was spent to fine-tune the benchmark controllers. Four different rule-base controllers, including a predictive controller are compared to MPC to provide a differentiated picture of the trade-off between complexity and performance. Furthermore the MPC is assessed in the presence of forecast errors, with an interesting result (see Section 4).

Some of the MPC approaches presented in literature are based on non-linear programming methods, which can be computationally intensive and might hinder deployment in the field. The presented MPC approach based on quadratic programming and is lean enough to be implemented on real devices, as done in the GreenHP project [15].

The depth of analyses and the discussion of results as shown in this paper are more detailed than in any of the previous work, thereby providing a more comprehensive picture of important operational aspects and the trade-offs between the different controllers and control goals, which are discussed in Section 5.

2. Models used

The different controllers are tested for a multi family house with six living units, each with two residents, located in Potsdam, Germany. The house is equipped with a variable speed air source heat pump connected to a stratified thermal energy storage tank for domestic hot water (DHW) and space heating (SH). DHW is prepared using an external heat exchanger (fresh water station FWS). A 10 kWp PV plant is mounted on the roof, southward oriented and 35° inclined. The modelled system is shown in Fig. 1 and explained in the following.

2.1. Electricity and DHW demand profiles using synPRO

Electricity demand for appliances is modelled using the stochastic bottom-up model synPRO. The approach is introduced and validated in [16]. It is based on the Harmonized European

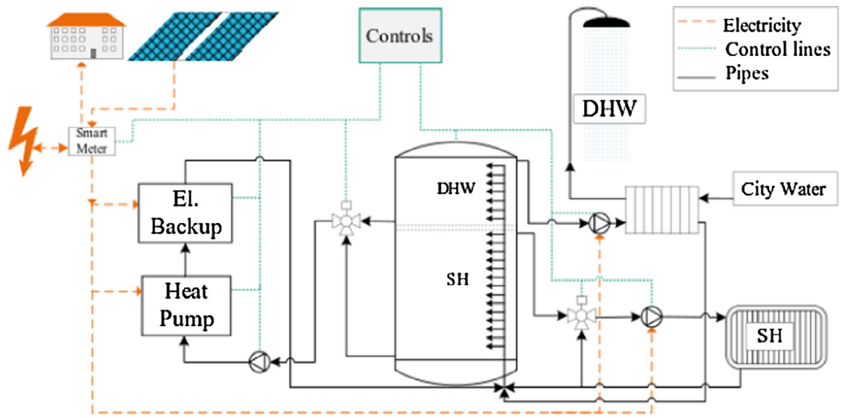


Fig. 1. Modelled parts of the building energy system.

Time-of-Use Survey [17], where 14,000 people noted their daily time usage for three days. This information is used to build the model.

Based on probability distributions for number of starts, start times and durations of different activities an activity schedule for each person in the building is generated. Individual activities are then linked to their specific electric and DHW consumption footprint. The electricity consumption for household appliances is based on measured data. The energy demand for each tapping is calculated based on the volume flow rates as well as the hot and cold water temperatures taken from VDI 2067 [18]. Further explanation and validation of the electric and DHW load profiles are given in [16,19] respectively.

2.2. Building heat load

The space heating load is calculated using a 5R1C building model. The model is based on the simplified hourly method according to DIN EN 13790 [20] for calculating heating and cooling demands. The heat load model is presented and validated in [19]. Inputs to the model are irradiation, building physics and internal gains. Internal gains are calculated based on building occupancy and the use of electric devices, obtained from the synPRO behavioural model [16].

2.3. Heat distribution system

For heat distribution in the building a radiator system is used. The needed supply water temperature for space heating T_{supply} is calculated via an ambient temperature $T_{amb,t}$ dependent heating curve:

$$T_{supply} = a_0 + a_1 T_{amb,t} + a_2 T^2_{amb,t} \qquad [^\circ C] \qquad \forall T_{amb,t} \leqslant 15\,^\circ C \tag{1}$$

The coefficients a_i vary depending on the type of heat distribution system. Here radiators, which require a supply temperature of 56.5 °C at −10 °C are used. The coefficients are: 46.316, −1.12, and −0.0106 respectively.

2.4. Storage and hydraulic layout

The stratified storage is modelled using the plug-flow principle presented in [21]. The storage is discretised into N nodes. For each node the equation for mass- and energy transfer is solved. All flows coming into the storage are stratified to the layer with the closest temperature to the incoming streams.

The top third of the storage is used for DHW and the bottom part is used as buffer for space heating. The water for DHW is supplied to a heat exchanger (fresh water station) where the heat is transferred to the incoming city water. A heat exchanger efficiency of 0.95 is assumed.

The heat pump is supplied from two levels of the storage. In DHW operation the heat pump is supplied from the top level of the storage. In space heating mode water from the bottom of the storage is supplied to the heat pump.

2.5. Heat pump

The model scheme of the used variable speed air source heat pump is depicted in Fig. 2. Different control decisions directly or indirectly influence efficiency and thermal output of the heat pump unit. Those are changes in water mass flow, changes in compressor and fan speed, and changes in water inlet temperature. Furthermore changes in ambient air temperature influence the conditions on the evaporator side of the heat pump and thus heat pump efficiency and thermal capacity. To account for those effects a semi-empirical heat pump model comprising the main components of the heat pump is used. The component submodels are briefly described in Table 1. Thermal inertia is represented by thermal mass nodes located in the condenser and the evaporator. The model is based on a simple refrigerant cycle. A moving surface approach is taken to iteratively determine the areas for desuperheating and condensing in the condenser unit. The thermodynamic library *CoolProp* is used to determine the fluid properties at different temperature and pressure conditions. The evaporator and condenser are modelled using semi-empirical models for heat transfer,

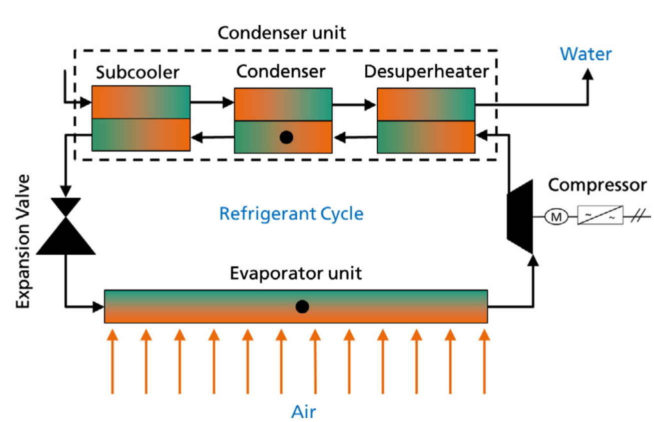


Fig. 2. Schematic drawing of the modelled heat pump components.

Table 1
Components and submodels used for the heat pump model.

Component	Model	Refs.
Inverter and drive	Efficiency correlation depending on part load ratio	[24,25]
Compressor	Isentropic efficiency dependent on pressure ratio and built in pressure ratio	[22]
Desuperheater	Moving surface, assuming dew-point conditions at outlet	
Desuperheater refrigerant side	Dittus Boelter	[26]
Desuperheater water side	Dittus Boelter	[26]
Condenser	Moving surface, e, NTU, dynamic energy balance	[27,28]
Condenser refrigerant side	Nusselt theory	[22]
Condenser water side	Modified Dittus Boelter	[29]
Subcooler refrigerant side	Constant heat exchanger efficiency	
Expansion valve	Isenthalp expansion	[30]
Evaporator	e, NTU, dynamic energy balance	[27,28]
Evaporator refrigerant side	Pierres correlation	[31, p. 8:25]
Evaporator air side	Heat transfer – mass flow correlation	[31]
Refrigerant	Thermodynamic library Coolprop	[32]

a dynamic energy balance equation and thermophysical properties of the refrigerant. The compressor is modelled using a variable isentropic efficiency dependent on compression ratio [22]. Inverter efficiency and drive losses are accounted using a characteristic curve. Please refer to the supplementary material [23] for more details.

2.6. Electric back-up heater

An electric back-up heater is installed at the outlet of the heat pump to supply heat in the case when heat pump thermal capacity is not sufficient. The conversion efficiency from power to heat η is set to 0.98. The power of the electric back-up can be modulated continuously between 0% and 100%.

2.6.1. Heat pump and back-up heater sizing

The heat pump is sized for mono energetic operation at the norm ambient air temperature $T_{\mathrm{air,norm}} = -14\,^{\circ}\mathrm{C}$, where a heating load of $\dot{Q}_{\mathrm{SH,norm}} = 16\,\mathrm{kW}$ has to be covered. To cover the domestic hot water load a capacity 0.2 kW/occupant [33] is added in total 2.4 kW. The total HP thermal capacity at A-14/W55 is 18.4 kW. To cover colder days a back-up heater of 8 kW is added.

3. Controls

The target of controls is to satisfy the thermal demand at lowest possible cost. This means keeping the temperatures at the top layer of the DHW and at the space heating part of the storage at the set-points so that the heat required from the building is provided at the needed temperature level. Furthermore the heat pump's minimum on- and off-times have to be respected. Different types of controls with different level of complexity and ICT requirements are implemented To make use of on-site PV or time variable prices.

3.1. Rule-based controllers (RBC)

Rule-based controllers use expert rules for determining the control signals. Those rules are based on available information and measurements. Temperature sensors, smart metre data, a clock and predictions are used to design four different rule-based controllers explained in the following.

3.1.1. Thermal controller (RBC-T)

The thermal controller (baseline) uses the temperature difference between the top layer storage sensor T_{s} and the set-point $T_{\mathrm{s,set}}$ to adjust the speed υ_{comp} of the compressor using a P controller.

$$\upsilon_{\mathrm{comp}} = \upsilon_{\mathrm{comp,min}} + K_{\mathrm{P}} \cdot (T_{\mathrm{s,set}} - T_{\mathrm{s}}) \tag{2}$$

The RBC-T controller does not use any information except the temperature readings. The controller operates within a temperature band (hysteresis) of 10 K. After being switched on the heat pump is operated for 10 min at optimum compressor speed $\upsilon_{\mathrm{comp,opt}}$ before the P controller is activated. DHW operation is favoured over space heating as the building itself provides some thermal inertia to allow for small violations of the space heating supply temperature. To avoid frequent HP starts, a minimum run-time of 10 min and a minimum pause-time of 20 min are implemented.

If the HP is not able to supply the demand an electric back-up heater supports the HP. The electric back-up heater is activated if the heat pump is in operation longer than 15 min. and the storage is 10°C below the set-point.

3.1.2. Timer controls (RBC-Timer)

A timer is used to overrule the temperature set-points of the thermal controller to increase or avoid heat pump operation at certain times. In times where heat pump operation is favourable the upper hysteresis for the storage temperature is increased by 5 K and in times where operation should be avoided it is reduced by 5 K. The time slots are tailored to the use-cases.

The allowed temperature hysteresis in the storage is reduced before 9:00 and increased from 11:00 to 14:00 in order to increase PV self-consumption. The controls are activated if the ambient temperature exceeds 10 °C to avoid PV friendly operation at days with little irradiation.

In case of time variable electricity prices the day is divided into high, medium and low price time slots. At high price the controller hysteresis is reduced and at low price it is increased. The time slots are based on an analyses of the electric price profile shown in Fig. 6 (b) and are static during the whole year. High price time slots are 7:00–12:00 and 17:00–21:00 and the low price time slot is from 2:00 to 6:00.

3.1.3. Rule-based PV optimised controller (RBC-PV)

To maximise self-consumption from on-site generated PV the thermal controller is extended to reduce grid feed-in. A smart metre is used for information about current net electricity consumption. If excess PV electricity is available and exceeds the minimum required power for the heat pump to operate, the heat pump is switched on. A PID controller is used to adjust compressor speed to minimise electricity feed-into the grid. During this operation the maximum allowed storage temperature is set to 60 °C. The controller is presented, tested and explained in more detail in [34].

3.1.4. Predictive rule-based controller (PRBC)

This controller uses a prediction of thermal load, electricity price and PV generation. Ambient temperature, thermal load, PV generation and electricity prices are predicted for the next 24 h. Depending on the use-case the controller has two modes:

PV mode: Heat pump operation is scheduled to fulfil the predicted thermal demand, whilst maximising PV self-consumption. If PV generation is available three cases can occur:

1. PV generation is sufficient to satisfy the thermal demand running the HP at optimum compressor speed: HP operates at optimum compressor speed when a threshold PV generation is exceeded.
2. PV generation sufficient to satisfy the thermal demand running the HP with increased compressor speed: PV is used by adjusting compressor speed.
3. PV generation is not sufficient to satisfy the thermal demand: The HP will run at a the needed compressor speed to fulfil the thermal demand during times when PV generation is available.

Variable price mode: The storage should be charged at times of minimum cost. For that purpose the thermal output and the expected COP of the HP are calculated for different compressor speeds. Depending on the chosen compressor speed the needed operational hours to fulfil the thermal demand are calculated. For each set of compressor speed and operation hours, the heat pump operation scheduled along the price signal using a greedy heuristic. The solution for the compressor speed which yields the minimum total costs is selected and applied. The maximum allowed storage temperature is set to 60 °C for both operation modes.

3.2. Model predictive controller (MPC)

In model predictive controls (MPC) a simplified system model is used to predict the effects of the controls (inputs) on the system state in each time step. Prediction of external influences (e.g. the thermal loads) on the system can be included to find an optimal control signal. To obtain the control signal an optimisation (optimal control) problem is solved in each time step covering the complete prediction horizon. The problem is dependent on the current system state, a prediction of external influences and the underlying system model. The first element of the optimised control sequence is applied to the system. In the next time step the procedure is repeated. Fig. 3 shows a schematic overview of the MPC set-up, detailed explanation is provided in the supplementary material [23]. There are three states that are considered in the optimisation model. Two states represent the storage temperatures of the DHW part and the space heating section respectively. The controls are the heat pump heat flow to the DHW or to the space heating zone

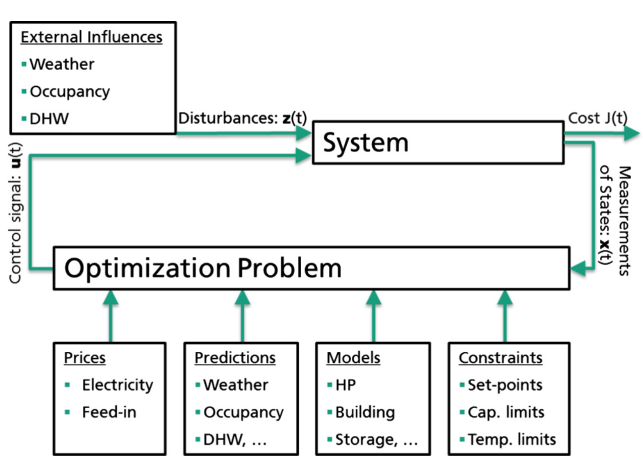


Fig. 3. Description of the MPC procedure.

of the storage and the heat from the electric back-up heater to the two zones.

3.2.1. Formulation of optimisation problem

The objective of the optimal control problem that is solved at each time step, is to find a control trajectory $\mathbf{u}^*$ that minimizes the cost-function J. The total cost is the sum of the stage cost l at each time-step over the prediction horizon N. l represents the time-varying cost which is a function of the state variables ($\mathbf{x}$), inputs ($\mathbf{u}$), known disturbances ($\mathbf{z}$), and the cost vector ($\mathbf{c}$) for electricity prices.

$$\arg\min_{U_t} \sum_{k=0}^{N-1} l(\mathbf{c}_{t+k|t}, \mathbf{u}_{t+k|t}, \mathbf{x}_{t+k|t}, \mathbf{z}_{t+k}) \tag{3a}$$

$$\text{s.t.}$$

$$\mathbf{u}_{t+k|t} \in \mathcal{U}(t+k), \quad \forall k = 0, 1, \ldots, N-1 \tag{3b}$$

$$\mathbf{x}_{t+k|t} \in \mathcal{X}(t+k), \quad \forall k = 1, 2, \ldots, N \tag{3c}$$

The subscript '$t+k|t$' assigned to these variables represents value of the variable at time step $t+k$ as predicted at time step t. The system is modelled as linear time invariant system:

$$\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{E}\mathbf{z}(t) \tag{4}$$

$\mathbf{A}$ represents the influence of the system on itself that is the losses in the heat storage, $\mathbf{B}$ represents the influence of the controls on the system that is it accounts for the amount of heat produced by the heat pump relative to the storage and $\mathbf{E}$ represents the influence of external disturbances, such as SH and DHW demand and cellar temperature, on the system. Eq. (4) discretised and added to the optimal control problem in the condensed form. Further all the controls and states have to be within the allowed range $\mathcal{U}, \mathcal{X}$, adding the above constraints to the optimal control problem.

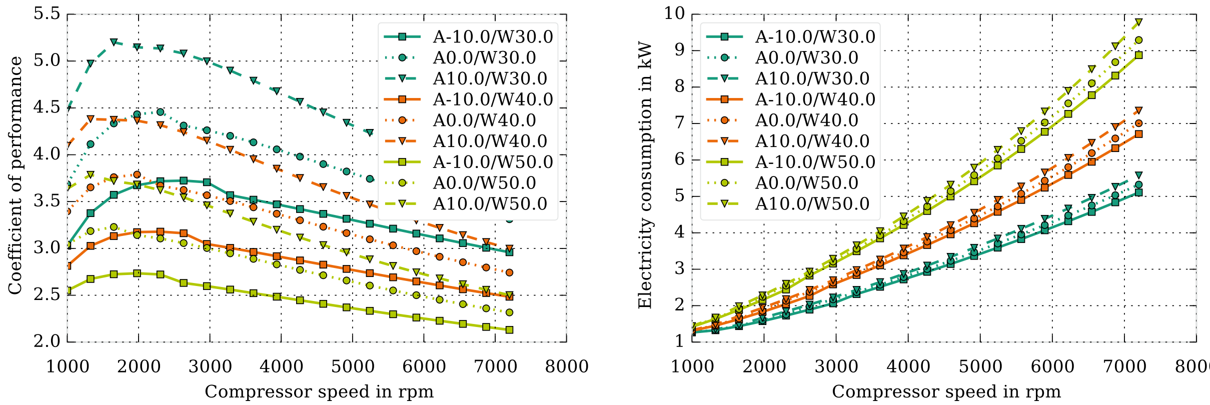
3.2.2. Objective function and constraints

The relationship between compressor speed and COP is nonlinear as shown in Fig. 4. Increasing compressor speed increases COP up to a certain point, due to reduced losses in the compression process. From that point onwards heat pump efficiency decreases with increased compressor speed due to a decreasing specific heat exchanger surface and increasing losses in the compression process. COP in the optimal control problem formulation is separated in two regions: one above and one below the optimal point. For these regions COP is approximated using Taylor linearisation. Furthermore the separate operation modes are considered. Those are DHW, SH, PV. Each operation mode is considered by introducing a virtual heat pump unit. Each virtual unit has individual costs depending on price and the corresponding Taylor coefficients for the individual operation points. The virtual units are linked via the constraints.

The transformation of the continuous optimisation result to the individual operation times is done via duty cycle, splitting the operation times of the heat pump into DHW and SH operation. As the compressor requires a minimum speed to operate, the possible control signal is semi continuous. This is solved by post-processing the optimisation results rejecting too low compressor speeds. Hence the mixed-integer characteristics of the problem are omitted by post-processing the solution.

Minimum required and maximum allowed temperature in the storage and the temperature dependent available heat pump capacity are used as constraints. An estimation of the available heat that can be produced using PV electricity is used as constraints for the PV case.

The resulting optimisation problem is convex quadratic in the objective function and linear in the constraints. It is solved using *cvxopt* [35].



(a) COP (b) Electricity demand

Fig. 4. Electricity demand and COP of the HP model for different compressor speed, ambient temperature and HP input temperatures with $\dot{m}_{\text{water}} = 0.8$ kg/s, $\dot{m}_{\text{air}} = 0.942$ kg/s.

For more details on the formulation and implementation of the MPC approach please read the supplementary material [23].

3.2.3. Coupling MPC to system model

The MPC is coupled to the detailed model. The MPC sends the requested heat and the operation mode (DHW or SH) and receives the temperature of the DHW and SH storage. As the storage is stratified there is no single temperature representing the state of the storage. The storage tank is equipped with 4 sensors, one at the top and bottom of each zone. The top sensors in each zone are used for the MPC, as they were found to deliver the best results in terms of cost reduction and temperature violations, which is discussed in Section 5.

3.3. Use-cases for controller comparison

To test the performance of the controllers under different conditions, three use-cases are simulated for each controller. The different cases are shown in Fig. 5. Those cases are:

1. Thermal: In this case a constant electricity price of 19 ct/kWh is applied and no PV is considered.
2. PV self-consumption: In this case a 10 kWp plant southwards oriented and 35 ° inclination is installed on the building. A feed-in tariff of 12.3 ct/kWh is paid and the electricity price is constant.
3. Variable el. prices: In this case the time variable electricity price based on the day-ahead spot price and no PV plant is applied. The price c is constituted of a fixed share of 10.5 ct/kWh and a variable share based on the day-ahead spot price for electricity at EEX, which is multiplied by two to increase the variability of the pricing structure, leading to:

$$c_{\text{el}} = 10.5 + 2 \cdot c_{\text{EEX}} \quad [\text{ct/kWh}] \tag{5}$$

Each use-case is simulated with four different storage sizes to evaluate the impact of design on controller performance. Additionally a sensitivity analyses towards forecast errors is performed for the MPC.

4. Results

This section presents the simulation results for the different use-cases and control approaches. General operational aspects are highlighted in the first part and the controller performance is assessed in the second part. The investigated system is a multi-family house, where an air-source heat pump is connected to a stratified storage tank and used for space heating and the preparation of domestic hot water. Climate and price data is used for Potsdam, Germany, year 2012. Fig. 6(a) shows the average daily demand profiles for space heating and domestic hot water as well as the PV production. Fig. 6(b) shows the average daily electricity prices for the variable price scenario. The simulations are done with a 10 s time-resolution for one year using the simulation framework COLSIM [21].

4.1. Operational characteristics

The way the heat pump and thermal storage are operated is depending on the control approach and the use-case. To investigate and demonstrate how the controls effect the main operational characteristics, HP electricity consumption over time and storage temperature over time are used. The presented results are simulated using a 3000 l thermal storage.

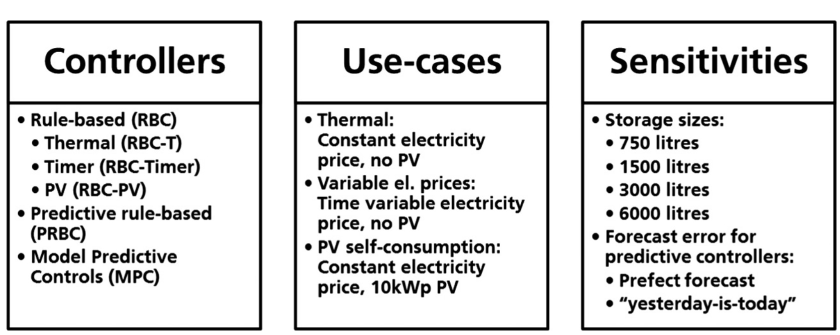
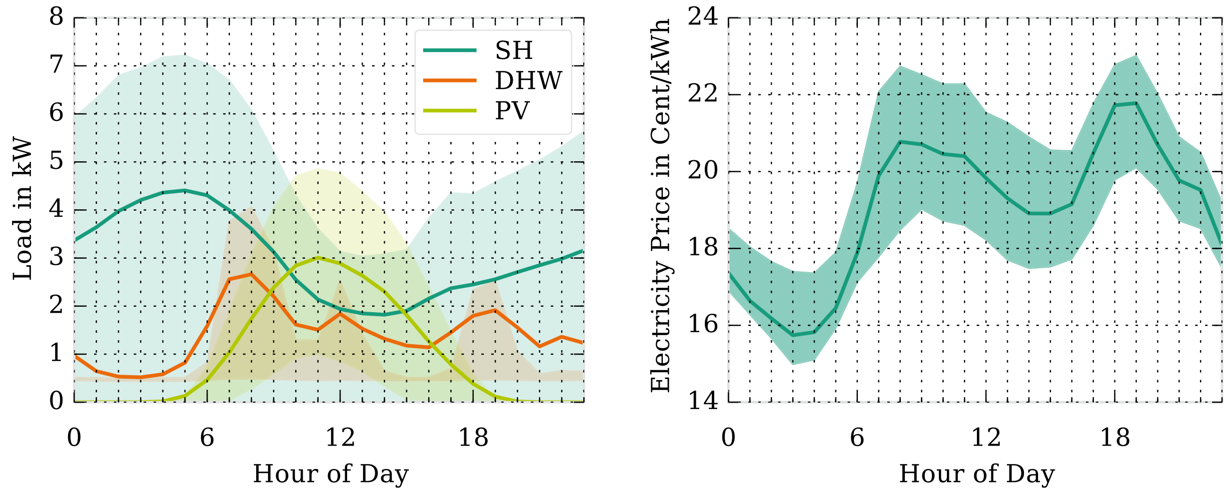


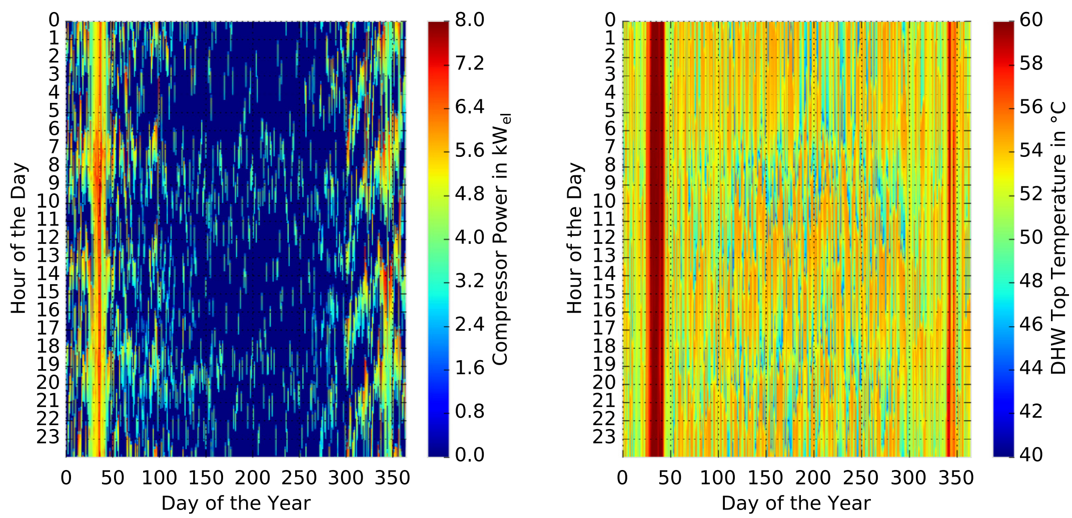
Fig. 5. Implemented controllers, use-cases representing different boundary conditions, and sensitivities.



(a) Demand and PV generation

(b) Electricity price

Fig. 6. Yearly average daily profiles for space heating (SH) and domestic hot water (DHW) demand, PV generation and the variable electricity price (right). Shaded areas show the 0.25/0.75 percentiles.



(a) HP electricity demand

(b) DHW top layer temp.

Fig. 7. Heat pump power and storage top layer temperatures using RBC-T.

4.1.1. Thermal (RBC-T)

Fig. 7 shows the heat pump compressor power and the temperature in the top level of the storage applying the rule-based thermal controller. The link between HP operation and thermal demand is visible, particularly during cold winter days. In Fig. 7 (b) it can be seen, that the top level temperature of the thermal storage stays within the bounds of 45 °C and 55 °C. During hours of high DHW loads, storage temperature decreases. During the coldest time of the year (around day 30) the space heating setpoint temperature is close to 60 °C and the DHW part of the storage has also to be heated up to this temperature. Besides that no systematic use of the storage can be observed.

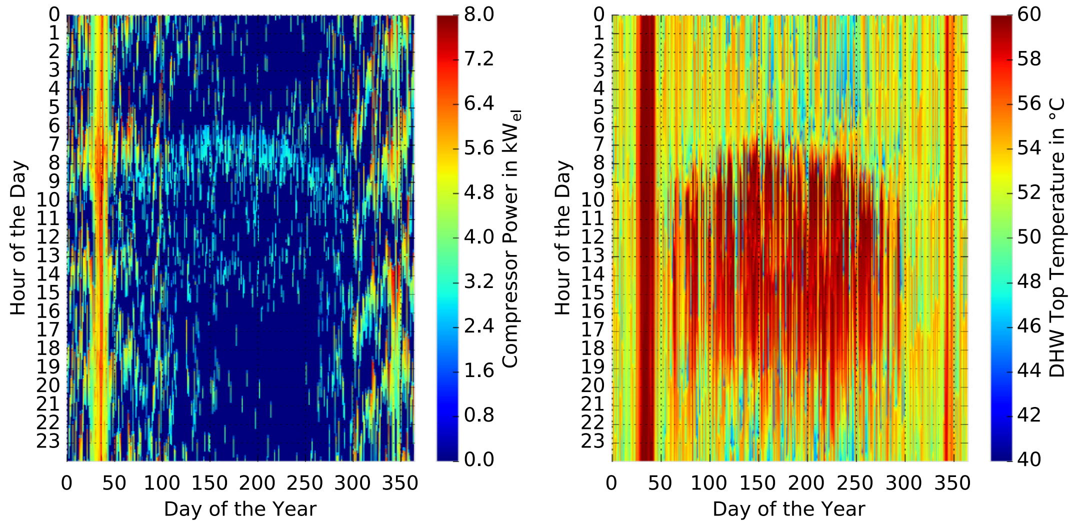
4.1.2. PV-Follow (RBC-PV)

HP operation and top layer storage temperature using the rule-based PV adjusted controller are shown in Fig. 8 for the PV use-case. During summer times and changing season at times with sufficient PV the heat pump is operated for PV self-consumption. Leading to heat pump operation mostly during morning hours. This has the disadvantage that the storage is heated already early in the day and kept at around 60 °C during the afternoon, which leads to losses. Furthermore the ambient temperature during that time of the day is comparably low. Operating the heat pump during the afternoon could improve COP. It shows that the heat pump is only operated for 1–2 h to charge the storage. Storage capacity and low thermal demand during that time of year are the limiting factors to longer HP operation.

During winter times the HP is operated as in the thermal case and space heating demand determines operation.

4.1.3. Timer controls (RBC-Timer)

HP operation and top layer storage temperature using the timer control are shown in Fig. 9 for the PV and the variable price use-case. The time intervals with changed hysteresis can be clearly recognised. Optimising towards PV self-consumption leads to two short operation intervals of the heat pump. During this time



(a) HP electricity demand (b) DHW top layer temp.

Fig. 8. Heat pump power and storage top layer temperatures using the RBC-PV.

storage temperature is increased stepwise. Compared to the PV-follow controller the HP is operated at higher compressor speed during those intervals and the storage reaches its maximum temperature later in the day. Optimising towards time variable electricity prices leads to increase operation during late night and avoided operation during evening hours. A clear pattern of heating and cooling down of the DHW storage part can be observed.

4.1.4. Predictive rule-based controller (PRBC)

HP operation and top layer storage temperature using the predictive rule-based control are shown in Fig. 10 for the PV and the variable price use-case. For the PV case a shift of heat pump operation towards times with excess PV can be observed. During this time the controller overheats the storage to increase PV self-consumption. Compared to the RBC-PV storage is heated later in the day and operation is distributed more evenly. Furthermore the storage reaches its maximum temperature comparably later during the day.

In the case of time variable electricity prices the PRBC leads to HP operation at high PLR during the night, when electricity prices are low. This operation is not favourable for COP. The storage is charged only once per day at high temperature. This is due to using a greedy heuristic that tries to operate the HP at the lowest price time slots.

4.1.5. Model predictive controller (MPC)

HP operation and top layer storage temperature using model predictive controls are shown in Fig. 11 for the PV and the variable price use-case.

For the PV case, using the presented MPC leads to HP operation during the afternoon at comparably low compressor speed. The MPC uses the PV electricity as late as possible in the afternoon and stores sufficient heat to cover the DHW demand during the following morning.

For the variable price case two main operation windows of the heat pump can be recognised, leading to two charging cycles for the storage. The first one ranges from 2 am to 5 am and the second operation window ranges from 1 pm to 4 pm. Furthermore the use of the prediction and optimisation allows the MPC to keep the storage temperatures low during most times of the year only heating it up when directly needed. Which leads to high COP and reduced losses.

4.2. Performance characteristics

Evaluating heat pump operation and the performance of controller has many aspects that should be considered. For this purpose the following indicators are suggested:

- Annual operation cost: The annual electricity cost for the heat pump and the back-up heater are used to quantify the monetary performance. The feed-in tariff is used for the cost of self-consumed electricity from the PV plant.
- Energy demand: Total electricity demand of the heat pump and the back-up heater
- Self-consumption rate: Self-consumption of the PV electricity by the building and its heating system is used to quantify the use of renewable electricity.
- Seasonal performance factor: The seasonal performance factor defined as the ratio of the annual heat demand for space heating Q_{sh} and DHW Q_{DHW} over the used electricity W_{el} for heat pump and the back-up heater is used.

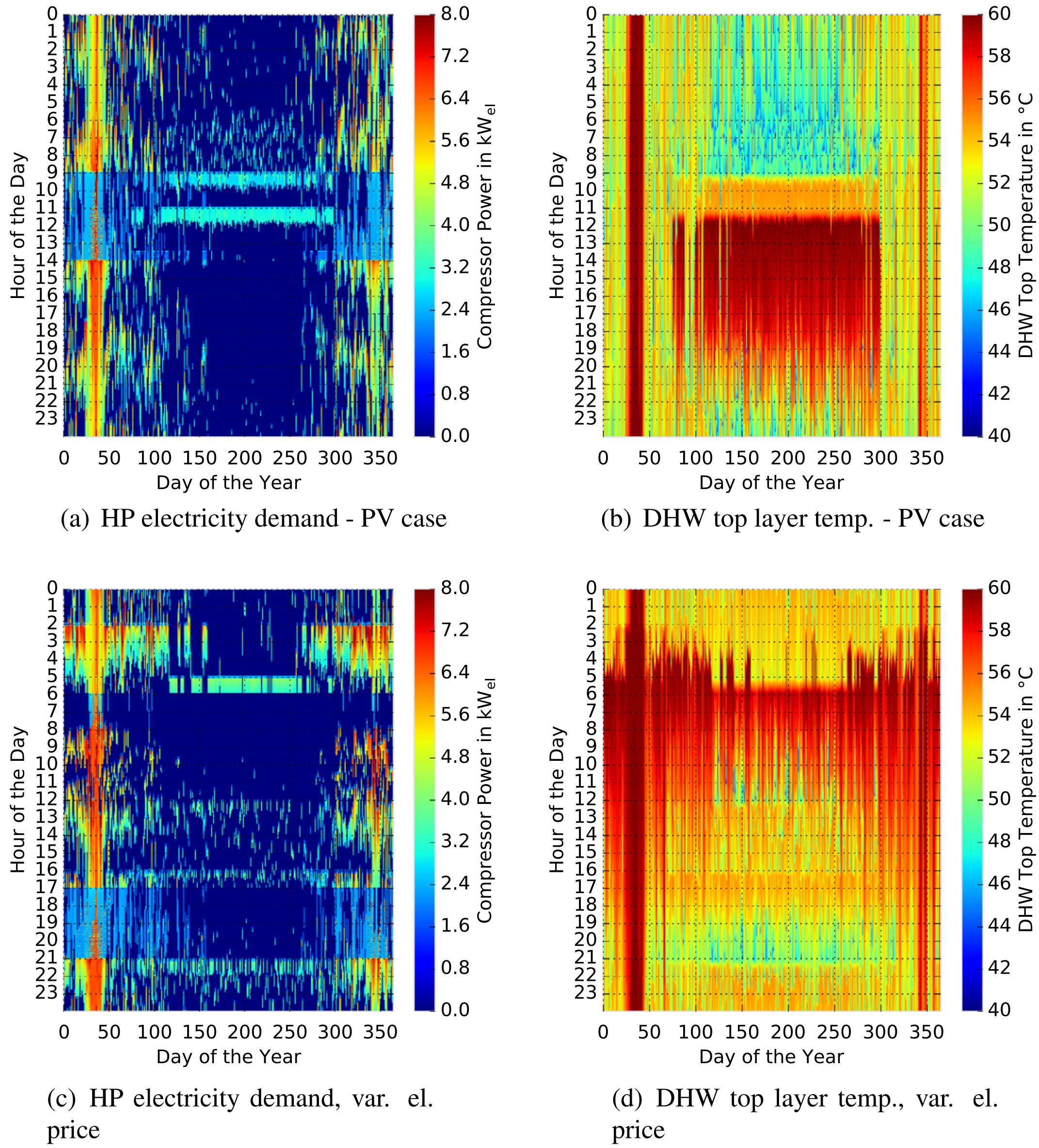
$$SPF = \frac{Q_{SH} + Q_{DHW}}{W_{el}} \qquad [-] \tag{6}$$

- Temperature violations: The total time of violations of the minimum allowed temperature at the outlet storage layers for DHW and SH are used as criteria for comfort, which in this case is similar to the tracking performance of the controls.
- Back-up heater usage: Total operating hours of the back-up heater are used to investigate the quality of controls and for better interpretation of the energetic parameters.
- Heat pump usage: Part load ratio (PLR) of the HP and the total number of HP starts gives indication of how the heat pump is used.

4.2.1. Comparison of control approaches

Fig. 12 shows the key results of the one year simulation for the different use-cases (big columns), controllers (small columns) and storage sizes (colour of dots).

The results show that the potential savings in annual electricity cost using adjusted controls is between 2% and 16%. In the case of constant electricity prices (thermal case) using the MPC leads to cost savings of 6–11%. The number of comfort violations could be reduced almost to zero for DHW and SH at the cost of increasing



(a) HP electricity demand - PV case

(b) DHW top layer temp. - PV case

(c) HP electricity demand, var. el. price

(d) DHW top layer temp., var. el. price

Fig. 9. Heat pump power and DHW storage top layer temperatures using the Timer.

annual operation hours of back-up heater up to 50–150 h. This is done mainly to keep the heating curve set-points at all times. Nevertheless SPF could be increased by 3–12% mainly due to heat pump operation at lower compressor speed.

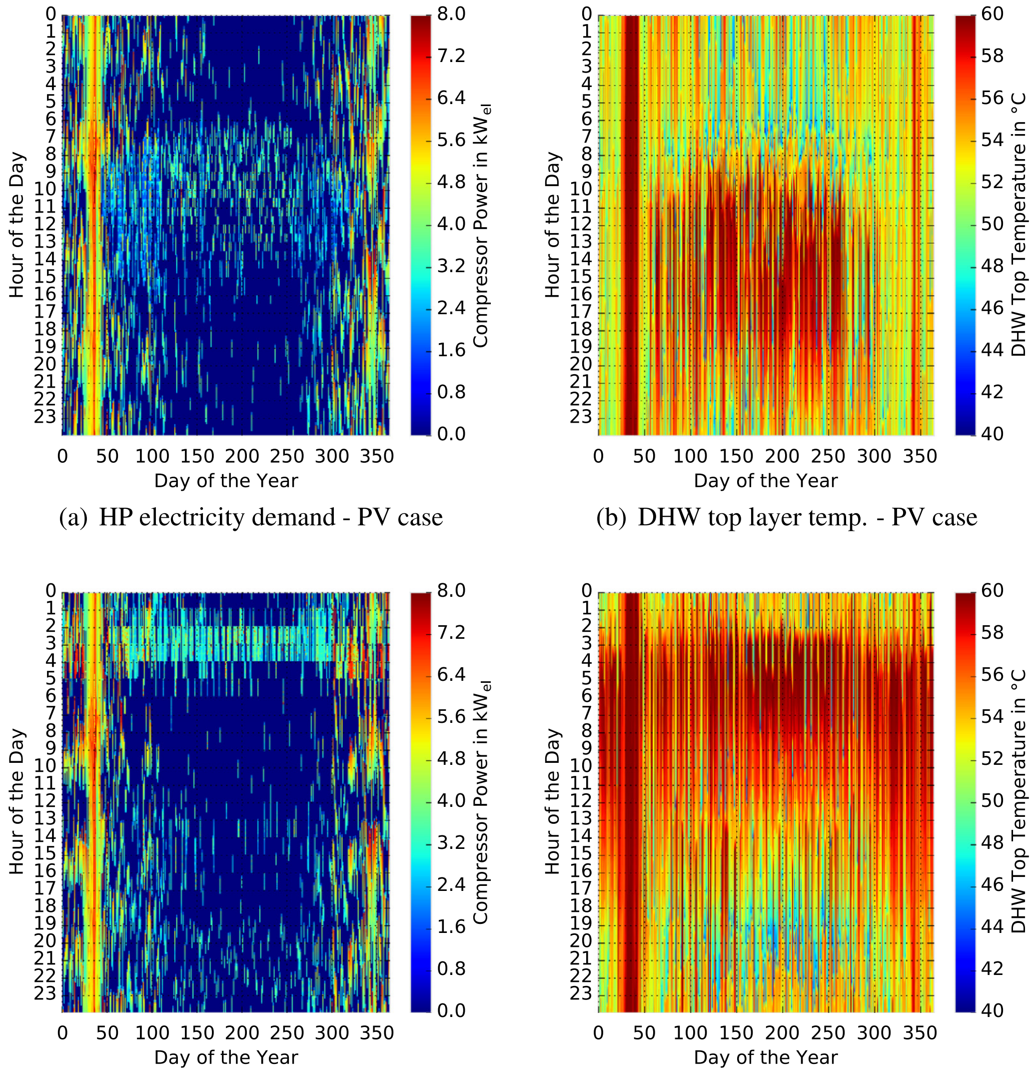
In the case of variable electricity prices the results show that the annual electricity cost could be reduced by 6–16% for the MPC, 2–4% for the Timer. The PRBC reduces costs by 2% for the 6000 l storage but increases the cost for all other storage sizes by 1%, due to increased electricity consumption. Introducing time variable electricity prices led to increased electricity consumption for all controllers. Reasons for this are operation at higher compressor speeds, operation during night time where outdoor temperatures are lower and operation at higher water temperatures to charge the storage. This can be seen in Figs. 7–11. Increased compressor speed and increased storage temperatures lead to lower COPs of the heat pump and storage losses. Those losses can overcompensate the potential gains obtained by a "smart", price oriented, operation (see PRBC). However as storage is operated at higher temperatures the hours of comfort violation are reduced.

In the PV self-consumption use-case, adjusting controls leads to reduced annual electricity costs and increased PV self-consumption, compared to the RBC-T. The possible increase in self-consumption is between 4 %pt and 15 %pt. The strongest improvements are found for the MPC controller followed by RBC-PV controller. For the MPC controller all indicators are improved for storage sizes up to 3000 l. Up to a storage volume of 3000 l SPF and self-consumption are increased simultaneously in the MPC case, which is not the case for RBC-PV controller, where increased self-consumption is mainly achieved by overheating the storage during hours of PV availability. The PRBC controller leads to an increase of self-consumption of approximately 2–4%. Generally the PRBC approach leads to similar results to the non-predictive rule-based controllers.

4.2.2. *Influence of forecast error*

To test the MPC under realistic conditions, forecast errors have been introduced. Those are indicated by *err* in Fig. 12. A persistence forecast ("yesterday-is-today") is used for price, ambient temperature, space heating and DHW demand.

It is found that the negative influence of forecast errors on annual operation cost is marginal. Cost reduction in all cases could still be achieved with predictive controls. A reason for this is a high



(a) HP electricity demand - PV case
(b) DHW top layer temp. - PV case
(c) HP electricity demand, var. el. price
(d) DHW top layer temp., var. el. price

Fig. 10. Heat pump power and DHW storage top layer temperatures using the PRBC.

day to day auto correlation in the demand, price and PV data. The structure of the electricity price, the heat load and the PV generation is similar from day to day.

Introducing imperfect forecasts in all cases led to a more frequent violation of storage temperatures and thus comfort. However those violations led to lower storage temperatures, which can result in energy savings at the expense of comfort violations.

4.2.3. Influence of storage size

The influence of storage size in the different scenarios is clearly visible. For all use-cases increasing storage size leads to reduced comfort violations and reduced switching of the heat pump.

For constant electricity prices and the RBC-T controller, increasing storage size leads to increased electricity consumption and increased annual operation costs, due to increased storage losses with increased size. Using an MPC in this use-case leads decreasing electricity costs with increasing storage size. However the cost benefits having a storage larger than 1500 l seem negligible, even with improved controls.

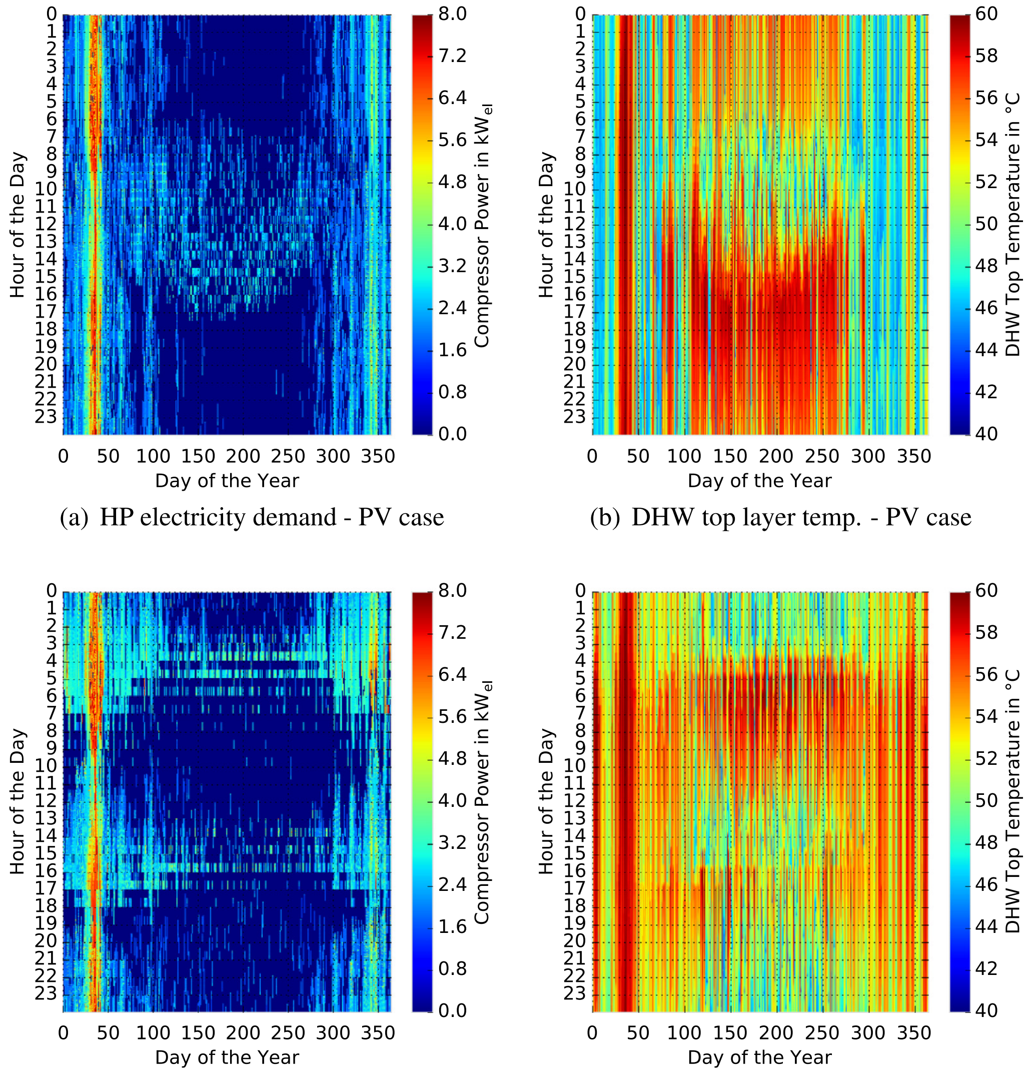
In the case of time variable electricity prices a similar trend can be observed. Increasing storage size leads to lower SPF for all rule-based approaches. Annual operation costs are lowest for the 6000 l case but the cost benefits having a storage larger than 1500 l seem negligible. Using an MPC leads to the lowest costs with the 6000 l storage, here the benefit of increasing the storage is more pronounced than in the constant price case. However when considering investment costs, space requirements and effort using a 6000 l storage questionable.

In the case of PV increasing the storage volume leads to increased self-consumption rates for the tailored control approaches. From an annual electricity cost perspective there seems little justification for increasing the storage volume for the rule-based controllers. For the MPC controller the annual operation cost benefits of increasing storage volume decreases from 3000 l onwards.

For all use-cases the reduction in annual operation costs achieved by increasing storage are marginal or even negative for the rule-base approaches. Hence it can be concluded that to profit from larger storage volumes advanced controls are a must.

5. Discussion and recommendations for HP controller design

The control strategies currently used for most of the heat pumps installed have a great potential to be improved. The results



(a) HP electricity demand - PV case

(b) DHW top layer temp. - PV case

(c) HP electricity demand, var. el. price

(d) DHW top layer temp., var. el. price

Fig. 11. Heat pump power (left) and DHW tank temperatures (right) for MPC.

show that the improvement by using improved rule-based controls is between 2% and 4% and can be further improved by using predictive control and MPC leading up to 16% operating cost reduction.

The reduction in operating costs when combining large storage and MPC has to be seen with respect to the needed investment cost and space requirements for storage as well as the cost for additional hardware for computation and the needed communication infrastructure for advanced controls. The achieved cost reductions should also be seen with respect to the selected pricing structure and might change in absolute numbers if a different electricity price and feed-in tariff is chosen and the chosen PV (see citeFischer2015f).

With respect to the performance of the individual controllers the presented results represent a status, where each controller had been fine-tuned and a set of choices was made that influences the performance of each controller.

5.1. Recommendations

During the process of modelling and simulation the following lessons have been learned and are recommended to be considered when developing heat pump controllers:

- Be clear about your priorities! It shows that different control objectives are conflicting and a trade-off has to be made. E.g. in the MPC case the back-up heater is used intensely to always keep the storage temperature within the limits at the cost of efficiency. The results for the variable price case and the PV case show that changed operation leads to lower annual operation costs and higher self-consumption at the cost of increased electricity demand.
- Be clear about the needed level of complexity! It is shown that well tuned rule-based approaches can yield improvements that are only 2–5% points lower than those of the MPC approach. From a computational point of view those approaches were highly favourable and also the time designing the rules was shorter than the time used to design the MPC. However fine-tuning of the rules was non trivial and rules had to be adjusted for each minor change in the system or the boundary conditions.
- Be clear about the needed level of robustness against changing boundary conditions! It showed that the results in this study were very sensitive towards tuning of the different controllers. Changes in temperature settings, sensors used for temperature tracking, preferred compressor speed and back-up heater oper-

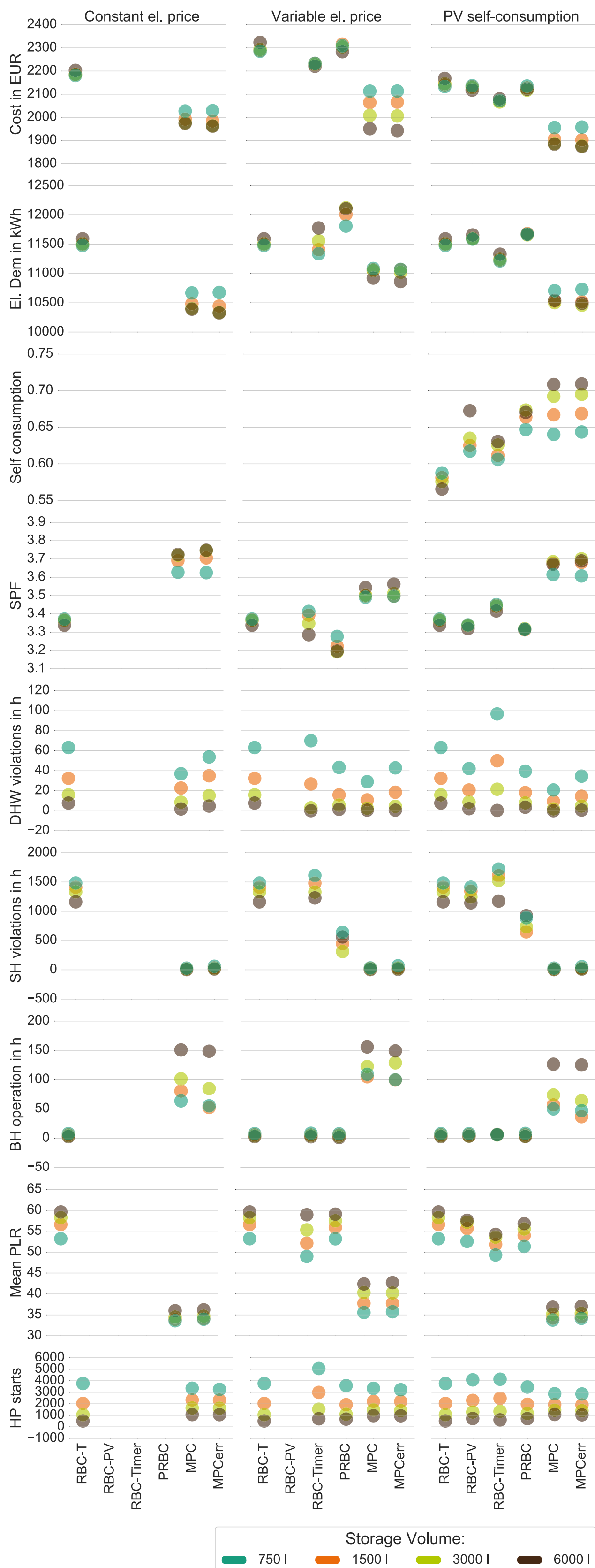


Fig. 12. Key results (annual values for the simulated year) for the different controllers and the use-cases.

ation strategy could change the results. In the work leading to the presented results, MPC showed the most robust behaviour against changes in the model, controls parameters and changes in the load profiles. However setting up the MPC and coupling it to forecasts and connecting it to the system showed to be a challenging task.

- Optimise your temperature settings! It turned out that temperature settings in the storage, in terms of dead-band and maximum allowed temperature had a significant impact on the results. Increasing the allowed overheating temperature for the "smart" controls led to results where no improvement could be found. As a consequence we strongly suggest for further MPC formulations to take storage temperature into consideration directly. This makes the model most likely non-linear but might be worth the complexity (see also [11,12]).
- Choose the right sensors! The way the sensors in the storage were used strongly influenced the results in the MPC case. The storage is equipped with 4 sensors one at the top and bottom of each zone, resulting in three options for the MPC:
  1. Using the top temperatures $T_{s,top}$.
  2. Using the bottom temperatures $T_{s,bot}$.
  3. Using an estimated temperature between top and bottom $\hat{T}_s$.

  It was found that only relying on the top level sensors, led to good tracking performance but relatively low temperatures in the bottom of the tank. This leads to energy savings but large parts of the storage remained unused.
  Using the bottom sensor resulted in high temperatures in large parts of the storage for a long time. Here the energy losses outweigh the advantage of using the whole tank.
  Using an estimated temperature in the storage is suggested in [36]. The authors stated that assuming a linear profile between two sensor values, leads to a robust initial profile estimate. The storage temperature estimate $\hat{T}_{s,i}$ for each part i sent to the MPC is:

$$\hat{T}_{s,i}(t) = \frac{T_{s,top,i}(t) - T_{s,bot,i}(t)}{2} + \Delta T_i \quad [K] \tag{7}$$

  An offset ΔT_i is used as a tuning parameter to adjust the temperature constraints of the MPC controller. This led to results, with moderate use of the storage without overheating the storage too frequently.
  In the presented case the best results where achieved using only the top level sensors. It was found that choosing, positioning and using the different storage temperature sensors is a non-trivial task and strongly depends on the control approach and the stratification quality of the storage.
- Consider use-case, storage size and designated controls! Interestingly it showed that no single storage size was superior for all use-cases. Far more the findings of this study show that the optimal storage size depends on the use-case and the implemented controllers. This should be considered when designing heat pump systems and controls. Further when including investment costs as done in [37] the optimum size will most likely be even smaller.

6. Conclusion

In this study five different approaches to control a variable speed heat pump in a multi family house have been compared for three different use-cases. The used controls differ in complexity and the use of external input data like price and weather forecasts. The use-cases are: Constant electricity prices, time variable electricity prices and PV self-consumption. Four different rule-based controllers are compared to a convex MPC approach, presented in this work.

It showed that MPC outperforms the other control approaches in all three cases in terms of annual operation cost, efficiency and comfort. However the effort of modelling and adjusting controls to the case should be considered. The less complex rule-based approaches have been found to yield about 2–4% decreased costs compared to 6–16% for the MPC approach. The rule-based approaches are found computationally less demanding and easier to design. However fine-tuning rule-based controllers demands considerable effort and rules need to be continuously adapted to the varying boundary conditions.

The negative cost impact of prediction errors, using a "yesterd ay-is-today" forecast have been found almost negligible, which is good as it could reduce the complexity for MPC forecasting. However this finding should be investigated in more detail. Temperature settings and allowed temperature ranges are found a decisive parameter in design of controllers and should be included in the MPC formulation. It has shown that optimising heat pump operation under variable boundary conditions such as variable electricity prices or self-consumption on-site PV potentially leads to lower seasonal efficiency on heat pump system level.

An investigation of different storage sizes showed that use-case, control strategy and storage sizing are strongly inter-connected and any change in one can have an immense effect on the best choice of the others. Consequently, an integrated solution including the designated use-case, dimensioning and controls should be introduced at the early design phase of the system.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.apenergy.2017.06.110.

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