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Optimal control of demand flexibility under real-time pricing for heating systems in buildings: A real-life demonstration

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HIGHLIGHTS

• EMPC is applied to a house, and the prediction performance is determined.
• Determination of demand flexibility is demonstrated in an EMPC framework.
• A method is introduced to enable the control of demand flexibility using real-time pricing.
• KPIs are quantified according to energy and power, energy efficiency, and energy costs.
• KPIs for energy efficiency are developed which refer to the effective utilization of HP and TES.

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ABSTRACT

The identification, quantification, and control of demand flexibility is the major challenge for future grid operations and requires innovative methods and new control strategies. Optimal control strategies such as economic model predictive control have gained attention in building energy management systems. The present experimental case study demonstrates the application of an economic model predictive controller under real-time pricing, including day-ahead prices and imbalance prices. For real-time prices in balancing and spot markets, we introduce a method that presents a flexibility service to provide demand flexibility for a notification time of 1 h < t < t day_end in advance. The flexibility service can be used as an ancillary service for innovative flexibility markets. The flexibility service includes a dynamic modification of the day-ahead prices to enable the adaption of energy consumption to errors in forecasting of renewable energy generation. The developed method was tested under real-life conditions, which also included the stochastic behaviour of occupants and the dynamic behaviour of the building and heating system. During the test periods, the controller managed the total operational costs of the heat pump’s electricity consumption and achieved a prediction performance of Root Mean Square Error between 0.17 and 0.22 kWh. To show the provision of demand flexibility, key performance indicators were quantified according to the categories 1) energy and power, 2) energy efficiency, and 3) energy costs. We introduce this categorization to present the benefits of using flexibility indicators along with conventional performance indicators in real-life applications.

1. Introduction

The transformation of the world’s energy systems is driven by the rapid growth of renewable energy sources such as wind and solar. In 2017, renewable sources increased to 14.3% of the primary energy supply among European regions, according to the Organisation for Economic Cooperation and Development [1]. However, the integration of renewable energy into power grids creates challenges in balancing fluctuations and ensuring reliable grid operations. A radical change of power systems towards flexible operations on both supply and demand sides can satisfy the needs for reliable and robust energy networks [2]. As buildings account for a large proportion of energy consumption, demand flexibility of buildings represents a major potential source of flexibility [3]. In 2015, Annex 67 was initiated under the International Energy Agency’s Energy in Buildings and Communities program to characterize building flexibility and to identify potential flexibility of single buildings and building clusters. Annex 67 also aims to provide building flexibility metrics by defining performance indicators for use...
in comparing buildings, including various energy systems [3]. Annex 67 has investigated the flexibility of multiple applications – for example, residential and non-residential buildings with energy systems including heat pumps (HPs), electric heating, structural storage, and thermal energy storage (TES) tanks.

One of the earliest Annex 67 studies presented the potential flexibility of the structural thermal mass of residential building stock using rule-based control [4]. The authors showed that structural storage capacity contributes to heating flexibility. They also emphasized that larger power shifting can result in a decrease in storage efficiency. The performance indicators from [4] were adopted in a study using a residential building with an HP, electric heating, and TES [5]. The authors in [5] optimized the charging and discharging of TES tanks using model predictive control (MPC) and day-ahead electricity prices. The main conclusion of that study was that TES tanks with water, phase-change materials, or thermochemical materials can be designed to provide short-term flexibility (up to 24 h) in an MPC framework. In [6], an MPC framework was investigated for heating and cooling using an HP and the structural storage of a residential building. The authors concluded that MPC controllers have great potential to increase flexibility by using time-varying electricity prices and carbon intensity. In [7], economic MPC (EMPC) was successfully applied in a residential building with an HP and structural storage. The experimental case study showed that demand flexibility can be optimized by associating operational electricity costs with performance indicators for demand flexibility. These examples from Annex 67 demonstrate that MPC strategies can enable the full potential of demand flexibility. However, only one of these studies was an experimental investigation of optimal control for demand flexibility [7]. This may be because of the lack of common metrics for demand flexibility to track control performance indicators and control signals.

1.1. Literature review of flexibility indicators for control of energy systems in buildings

Claub et al. [8] classify performance indicators for the control of building energy systems into flexibility indicators and conventional indicators. The latter represent, for example, energy consumption, costs of energy consumption, and CO₂ emissions. In examining flexibility indicators, early studies quantified demand flexibility in the framework of rule-based control (RBC) (Table 1). Recently, flexibility indicators have gained more attention in optimal control (OC) of residential and office buildings that include energy systems with electrical batteries.
electric heating, and TES tanks (Table 1).

Table 1 shows that flexibility indicators in OC and RBC can be classified in terms of size (energy) and time (power), energy efficiency, and energy costs. Likewise, conventional performance indicators can be allocated to their respective categories: for example, energy consumption (energy), coefficient of performance (energy efficiency), and costs of energy consumption (energy costs). The categorization can help in identifying adequate key performance indicators (KPIs) for control. However, a question from this brief review remains: How can real-life applications benefit from the quantification of flexibility indicators for control?

1.2. Literature review of control signals to enable demand flexibility in buildings

System operators and aggregators provide incentive-based and price-based control signals to enable flexible operations of building energy management systems [20,21]. Incentive-based signals support direct load management in which the central actor regulates the load. To ensure reliable grid management, direct load control for frequency and voltage control is likely to be required as a short-term flexibility service, which regulates the electricity system from seconds to several minutes in advance. For longer notification times, balancing markets (up to 1 h) and spot markets (up to 48 h) have been established, which can include both incentive-based and price-based signals. When electricity prices are used, the building energy management system receives time-varying price signals and adapts electricity consumption accordingly. One variable pricing scheme, for example, is real-time pricing (RTP), which typically consists of day-ahead prices and intra-day prices [21]. Day-ahead prices aim to schedule the energy consumption for the next day. To compensate for imbalances from the day-ahead market, intra-day prices are traded during the day of operation. In spot markets, electricity prices are being traded and disseminated up to 5 min in advance [22]. However, power imbalances are caused by differences between commercial trade schedules and measurements of electrical power injected into and taken from the electricity grid. In the Netherlands, therefore, the Transmission-System-Operator (TSO) provides imbalance prices, which act as a competitive product in the balancing market [23].

To date, only a few studies have used RTP signals to determine demand flexibility in building energy systems. Those studies mainly incorporate day-ahead electricity prices from power spot markets [5–7,13–17]. Based on these time-varying prices, the studies quantified flexibility indicators that represent demand flexibility as shown in Table 1.

Recent work on demand flexibility has considered alternative control signals such as the grid carbon intensity [6,24,25], which is defined as the proportion of CO2 emitted per unit of energy consumption [25]. Carbon intensity as a control signal can serve to minimize CO2 emissions of buildings. The authors in [25] argued that the usage of carbon-based signals and price-based signals can lead to conflicting control objectives; for example, cost-optimal control using price-based signals does not reduce the yearly CO2 footprint of buildings compared with optimization of CO2 emissions. We must emphasize that the authors in [25] focused on a yearly evaluation of buildings’ flexibility rather than concentrating on short-term balancing and spot markets. As for these short-term markets for demand flexibility, a question remains: Can building energy systems provide short-term demand flexibility in balancing and spot markets?

1.3. Main contributions and outline

To increase integration of renewables into power systems, we need to create a common metric for demand flexibility. A review of relevant literature reveals that the determination of demand flexibility of buildings strongly depends on the chosen control strategy, control signals, and KPIs. Optimal control – or more precisely MPC and EMPC – were found to be the most advanced control strategies that can provide various control objectives and can include a multitude of control signals. However, only a few studies have implemented MPC and EMPC in buildings as part of experimental investigations.

This study demonstrates the use of EMPC in regulating demand flexibility of a building. We use the building heating system, including HP and TES, to provide demand flexibility in relation to the power grid. The contributions of this experimental case study are summarized as follows:

- An EMPC strategy is applied to a heating system of a residential building. A variety of techniques are used to model the components of the heating system. We introduce a method to determine the prediction performance of different models within an EMPC framework.
- Conventional KPIs and KPIs for demand flexibility are classified in terms of size (energy) and time (power), energy efficiency, and energy costs. For KPIs of energy efficiency, additionally, we introduced KPIs that refer to the effective utilization of available sources such as HP and TES. The KPIs are presented for use in EMPC validation.
- We introduce a method that enables the control of demand flexibility in balancing and spot markets using day-ahead prices and imbalance prices. Day-ahead prices are modified during the day of operation to provide a flexibility service. The flexibility service can be used as an ancillary service for flexibility markets (for example provided by EPEX SPOT) and enables dynamic optimization of demand flexibility.

The main advantage of this flexibility service is the implementation of a simple one-way trading mechanism, which enables the use of more detailed MPC approaches with moderate computational effort of solving the optimal control problem (OCP). In this study, the EMPC optimization algorithm is solved once per hour of operation.

The outline of this paper is as follows. Section 2 presents the methodological framework of the experimental case study. In 2.1, the experimental setup in a detached house is described. In 2.2, a method is introduced to control demand flexibility using day-ahead and imbalance prices. The developed method requires an EMPC formulation (2.4), which is validated (2.5) and compared with conventional RBC (2.3). The performance evaluations of RBC and EMPC are described in section 2.6, including determination of conventional KPIs and KPIs for demand flexibility. The results of the experimental case study, including performance evaluation of RBC and EMPC, are presented in section 3. Finally, section 4 discusses the main contributions of this case study, and section 5 provides concluding remarks and recommendations for future research.

2. Methodology

For the experimental case study of demand flexibility in real-time power markets, a detached house was used that was located in Amstelveen, the Netherlands. During the test period, a family of four lived in the house. Occupants’ domestic hot water profile and the heating demand were measured between November 2017 and April 2018 under real-life conditions. Measurement data were also recorded for the building heating system, including the HP and TES tanks. During this period, three different controllers were analysed: one standard RBC and two EMPC strategies (EMPC1 and EMPC2). The RBC utilized constant temperature set points for the TES tanks. The EMPC strategies determined the optimal trajectory of temperature set points of TES tanks by scheduling the electricity consumption of the HP based on optimized operational electricity costs. Real-time electricity prices were included in the optimization. The OC was designed to meet occupant comfort requirements and to enable demand-oriented flexibility. The
order of magnitude of demand flexibility was quantified by KPIs that contained information about energy and power, energy efficiency, and energy costs.

2.1. Experimental setup

Experiments were performed in a detached house that had been built in 2017 (Fig. 1). The low-energy house had a total floor area of 345 m$^2$ on four levels and was designed to achieve an annual heating energy consumption of 55.6 kWh/m$^2$.

The heating system of the test building was equipped with a water-to-water HP that charged the TES tanks for domestic hot water (DHW) and space heating (SH) (Fig. 2). Control of the HP $\beta$ had three modes: charging DHW tank $g_{\text{DHW}}$, charging SH tank $g_{\text{SH}}$, and idle mode. The HP was of type F1155-16 from NIBE with an inverter-controlled compressor [26]. The HP had a nominal heating output of 16 kW (according to EN 14825) and a maximal supply temperature of 70 °C. Low-temperature heat on the evaporator side of the HP was generated by a highly efficient photovoltaic thermal solar collector (PVT) from Triple Solar [27]. A total 20 m$^2$ of PVT panels were installed on the roof facing south, and an additional 10 m$^2$ of PVT panels were placed on the property of the house. The 300-L DHW tank had insulation that was 0.05 m thick with a thermal conductivity of 0.07 W/(mK). A thermo-static three-way valve regulated the temperature of the tap water, with a maximum setting of 60 °C. Space heating was supplied by an integrated floor heating system throughout the entire building. Thermostats regulated the indoor temperature on each level. When space heating was demanded, the SH tank was discharged, and a thermostatic three-way valve regulated the temperature of floor heating to a maximum of 35 °C. The 1,000-L SH tank was insulated using a material 0.2 m thick with thermal conductivity of 0.07 W/(mK). This tank was designed to provide efficient charging and discharging by establishing thermal stratification [28–30]. Thermal stratification could be disrupted, however, because during operation colder water entered the upper part of the tank, resulting in downward fluid motion with convective mixing [28,30]. To maintain a vertical temperature gradient, pipe connections were configured as can be seen in Fig. 2. Cold tap water entered the bottom of the SH tank, passed through an immersed heat exchanger coil, and left from the middle of the SH tank to the DHW tank. From the SH tank, low-temperature heat was provided to the floor heating loop.

We created a MATLAB controller (MATLAB 2017) that retrieved real-time measurement data from the heating system and regulated the energy consumption of the HP. A more detailed description of the MATLAB controller, including acquisition and processing of measurement data, can be found in the MethodsX article [31] that is published alongside this research article.

2.2. Real-time pricing

To manage power supply and demand, system operators have established power spot markets in which suppliers and consumers trade electricity. Current power spot markets offer RTP, including day-ahead and intra-day prices. In the Netherlands, the TSO also provides imbalance prices, which act as a competitive product in the balancing market. We used a one-way pattern, including hourly day-ahead prices, to optimize the energy consumption for the next day and hourly imbalance prices to optimize the energy consumption for the next hour (one hour of notification time before real-time). The hourly day-ahead prices $c_{\text{day-ahead}}$ were retrieved from the Amsterdam-Power-exchange spot market, and imbalance prices $c_{\text{imb}}$ were used from Tennet, a Dutch electricity TSO.

To be able to participate in spot markets for a notification time of $1h < t < l_{\text{day-end}}$, a flexibility service was developed that can be used as an ancillary service. The idea of the flexibility service was to compensate for variations in renewable energy generation for a notification time of $1h < t < l_{\text{day-end}}$. The flexibility service makes it possible to adapt to errors in the forecasting of renewable energy generation. For example, weather forecasting estimates peak solar power at a certain moment within the day of operation. For this moment, optimal planning of control actions is required to provide demand flexibility. A flexibility service, therefore, is offered towards this moment of peak solar power. In this study, hourly forecasting of global and horizontal solar radiation was used to estimate the peak hour during the day. For this peak hour, it was assumed that $c_{\text{day-ahead}} = 0$. Based on this assumption, $c_{\text{day-ahead}}$ was modified to create a dynamic pricing plan $c_{\text{mod-day-ahead}}$ and enable a dynamic optimization of demand flexibility. Fig. 3 shows the results of an example test day, including standard day-ahead price $c_{\text{day-ahead}}$ and the modification of the day-ahead price $c_{\text{mod-day-ahead}}$.

The different control strategies incorporated the following assumptions and steps:

- In RBC, day-ahead and imbalance prices were not used.
- EMPC1 included $c_{\text{imb}}$ and $c_{\text{mod-day-ahead}}$. First, EMPC1 determined a unique energy consumption profile (24-h plan) for the next day. Second, during the EMPC1 test day, hourly $c_{\text{imb}}$ were implemented to optimize the energy consumption for the next hour.
- EMPC2 included $c_{\text{imb}}$ and $c_{\text{mod-day-ahead}}$. First, EMPC2 determined an energy consumption profile for the next day. Second, during the test day, hourly intra-day prices were used to optimize the energy consumption for the next hour. Third, day-ahead prices were modified to optimize the energy consumption profile and to enable dynamic optimization of demand flexibility for a notification time of $1h < t < l_{\text{day-end}}$. 

**Fig. 1.** Test building near Amstelveen, the Netherlands, during the construction phase in summer 2017 (left); photovoltaic thermal solar collector (PVT) from Triple Solar on the roof of the building (right).
2.3. RBC

Rules-based control was used for the heat pump and regulated the temperature of the SH and DHW tanks using temperature set points. The RBC retrieved measurements from one sensor located in the upper third of each tank. Charging of the DHW tank took priority over charging of the SH tank. When the measured DHW tank temperature fell below the lower bound of 42 °C, charging was requested from the HP. The charging process was stopped at the upper bound temperature of 52 °C. Regulation of the SH tank charging was based on degree minutes ($°\,m$). According to the HP manufacturer, $°\,m$ is a dimensionless quantity calculated using

$$
°\,m = \frac{T_{SH} - T_{SH\,set}}{100},
$$

with

$$
°\,m \leq 100,
$$

where $T_{SH}$ is the measured SH tank temperature, and $T_{SH\,set}$ is the default temperature set point of 34 °C. The charging process of the SH tank started when $°\,m$ fell below a value of −60. The HP compressor stopped the charging process at $°\,m = 0$.

2.4. EMPC

The EMPC framework enabled optimal control of the building heating system with hourly optimization time steps [5,32,33]. During each control time step, real-time measurements served as the starting point for online optimization. The EMPC framework exploited a receding horizon of a full day (24-h period). In EMPC, OC decisions were implemented as diagrammed in Fig. 4.

An optimal control problem was formulated to minimize the total costs of electricity usage of the HP $J_{HP}(x)$. The state variables $x$ integrated temperatures and fluid flow within the building heating system referring to the HP, DHW tank, DHW demand, SH tank, and SH demand. The control variables $u$ included temperature set points of the DHW tank and SH tank. As with the RBC, charging of the DHW tank had priority over charging of the SH tank. The charging decision for the DHW tank was either ON or OFF. The OCP decision variable included the temperature set point $T_{SH\,set}$ of the SH tank. To reduce the computational effort of solving the OCP, a two-step approximation method was applied to the decision state of $T_{SH\,set}$. The optimal control trajectory of $T_{SH\,set}$ was generated in less than 20 min of computational time.

The first approximation step determined the state space with $T_{SH\,set}(t) \in [34, 36, 38, \ldots, 50]$, which included a temperature step of 2 °C.
This temperature step was chosen in accordance with early measurements where hourly temperature variations of the SH tank of ≥2 °C were observed. The minimum \( T_{SH \text{ set }} \) of 34 °C was identical to the reference control to meet occupant comfort requirements. Due to the safety requirements of the test set-up, a maximum \( T_{SH \text{ set }} \) of 50 °C was chosen. The second approximation step was the reduction of the number of possible decision states at each optimization time step as shown in Algorithm 1.

**Algorithm 1 (Procedure to perform the 2nd step of the approximation of control decision states.)**

```matlab
for each decision \( u(t) \)
    \( T_{SH \text{ set }}(t - 1) \) to \( T_{SH \text{ set }}(t) \)
    if \( t = [1, 2] \)
        \( T_{SH \text{ set min}} \leq T_{SH \text{ set}}(t) \leq T_{SH \text{ set max}} \)
    elseif \( c_{\text{day ahead}}(t) \neq c_{\text{day ahead}}(t - 1) \)
        \( c_{\text{day ahead}}(t - 1) \neq c_{\text{day ahead}}(t - 1) \)
    else
        \( \Delta T_{SH \text{ set}} = T_{SH \text{ set}}(t) - T_{SH \text{ set}}(t - 1) \)
        \(-4 \leq \Delta T_{SH \text{ set}} \leq 4 \)
    end
end
```

During EMPC1 and EMPC2 optimization, when \( c_{\text{imb}} \) was used, the optimal set point \( T_{SH \text{ set}}(t) \) could change between 34 °C and 50 °C at \( t = [1, 2] \). For EMPC2, the optimal set point \( T_{SH \text{ set}}(t) \) could also change between \( T_{SH \text{ set min}} \) and \( T_{SH \text{ set max}} \) for modified day-ahead prices. To investigate the effect of day-ahead prices on the variations of the optimal temperature set point, we used the day-ahead prices between January and March 2018 to calculate the optimal temperature set points. It was observed that the set point varied by maximally +/- 4 °C. For EMPC1 and EMPC2, therefore, in decision states in which no modified day-ahead prices were assumed, hourly set point changes were limited to a maximum change of 4 °C.

It is important to note that, in contrast to RBC, EMPC implemented the possibility of stopping the charging of the SH tank when \( T_{SH \text{ set}}(t) \) changed. In particular, if \( T_{SH \text{ set}}(t) \leq T_{SH \text{ set}}(t - 1) \) & \& \( T_{SH \text{ set}}(t - 1) < T_{SH}(t - 1) \), the SH tank was set to zero. For example, when \( T_{SH \text{ set}}(t) \) changed from 50 °C to 34 °C, while \( T_{SH \text{ set}}(t - 1) \) was required, charging was disabled by setting the \( \Delta m \) equal to 0.

EMPC1 and EMPC2 applied the minimization of operational costs \( J_{IP} \) in a rolling horizon control framework with \( t \in \{1, 2, \ldots, N\} \) and \( N = 24 \). For each control time step, the cost function \( J_{IP}(t) \) was calculated according to Algorithm 2.

**Algorithm 2 (Procedure to calculate the cost function \( J_{IP}(t) \).)**

```matlab
for each decision \( u(t) \)
    \( T_{SH \text{ set}}(t - 1) \) to \( T_{SH \text{ set}}(t) \)
    if \( t = 1 \)
        \( J_{IP}(t) = (c_{\text{day ahead}}(t)P(t)\Delta t + c_{\text{imb}}(P(t) - P_{IP 24\text{h plan}}(t))\Delta t) \)
    else
        \( J_{IP}(t) = (c_{\text{day ahead}}(t)P(t)\Delta t) \)
    end
end
```

In Algorithm 2, \( P_{IP} \) is the electricity consumption of the HP (kWh), and \( P_{IP 24\text{h plan}} \) is the scheduled electricity consumption for the next day (24-h plan) based on day-ahead prices. For both forms of EMPC, during each control time step, \( c_{\text{imb}} \) was used to calculate a control decision, which could result in a deviation from the scheduled power plan \( P_{IP 24\text{h plan}} \) at \( t = 1 \). For EMPC1, \( P_{IP 24\text{h plan}} \) was determined on the day before using \( c_{\text{day ahead}} \). For EMPC2, \( P_{IP 24\text{h plan}} \) was calculated a day ahead and could change at each control time step \( P_{IP mod 24\text{h plan}} \) due to the consideration of flexibility assuming \( c_{\text{day ahead}} \).

The EMPC framework integrated a system model of the building and heating system, which consisted of the models of system components (weather forecasting, SH tank, SH demand, DHW tank, DHW demand, and HP) [31]. The PVT system as the heat source of the HP was considered in the HP model. Table 2 shows the models of the system components that were implemented as system model in the EMPC framework. All models of the system components were identified offline. A detailed description of the identification procedure can be found in the MethodsX article [31] that is published alongside this research article.

### 2.5. EMPC validation

The EMPC performance was obtained in three validation steps: (1) RBC, (2) EMPC1, and (3) EMPC2. In (1), the standard RBC regulated the electricity consumption of the HP, while the EMPC predicted the dynamic behaviour of the controlled system without interaction between EMPC and HP. In (2) and (3), EMPC1 and EMPC2 solved the optimal control problem of \( T_{SH \text{ set}} \) and regulated on/off control of charging of the DHW tank. To determine the performance of the EMPC, the predictions of the electricity consumption of the HP (\( P_{IP} \)) were compared using the performance metrics root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), coefficient of determination (\( R^2 \)), and goodness of fit (G) [73,43-39]. The mathematical descriptions of the performance metrics can be found in Appendix 1.

The EMPC performance and the overall EMPC prediction error were the result of the prediction performance of the models of the system components (weather forecasting, SH tank, SH demand, DHW tank, DHW demand, and HP). To identify EMPC’s modelling performance, the EMPC was recalculated using the experimental results from (1) RBC, (2) EMPC1, and (3) EMPC2. For example, to retrieve the performance of the HP model, the EMPC was simulated using experimental results of the HP’s input parameters, which are SH tank output, DHW tank output, and weather forecasting. In a second example, to determine the prediction performance of the SH tank model, experimental results of SH tank input parameters and experimental results of HPs input parameters from the DHW tank and weather forecasting were used. In this case, the performance of the EMPC was evaluated using the performance metrics root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), coefficient of determination (\( R^2 \)), and goodness of fit (G) [73,43-39]. The mathematical descriptions of the performance metrics can be found in Appendix 1.
second example, an overall prediction error was first calculated, which included the SH tank model and the HP model. Then, to determine the individual prediction error of the SH tank model, the fractional error was calculated according to

\[ \Delta e = \sqrt{\left( \frac{\Delta s_1}{s_1} \right)^2 + \cdots + \left( \frac{\Delta s_n}{s_n} \right)^2}, \]

(2)

where \( \Delta e \) is the absolute error, and \( \Delta s_1, \ldots, \Delta s_n \) are the fractional errors that result from the different models of the system components \( s_1, \ldots, s_n \).

In the present study, the fractional errors of the models for weather forecasting, SH tank, SH demand, DHW tank, DHW demand, and HP were taken from the RMSE.

2.6. Evaluation of control strategies

The three different control strategies, RBC, EMPC1, and EMPC2, were tested on a daily basis, and the results were analysed. To correctly assess the test results of these control strategies, environmental conditions such as ambient temperature \( T_{\text{amb}} \) and global and horizontal solar radiation \( Q_{\text{gsr, hsr}} \) were summarized on a daily basis. Furthermore, for the test days, the running mean ambient temperature \( T_{\text{rm, amb}} \) was calculated according to

\[ T_{\text{rm, amb}} = \frac{T_1 + T_2 + T_3}{3}, \]

(3)

which is a weighted running mean of the series of previous days that is simplified according to

\[ T_{\text{rm, amb}} = (1 - \alpha_m)T_{\text{amb, m-1}} + \alpha_m T_{\text{amb, m}}, \]

(4)

where \( T_{\text{rm, amb}} \) is the daily running mean ambient temperature of the previous days with \( m = 1 \) for the day before and so on, and \( \alpha_m \) is a constant between 0 and 1, recommended to be 0.8 [41]. \( T_{\text{rm, amb}} \) was used to identify the normalized electricity consumption of the HP \( P_{\text{HP, norm}} \) according to

\[ P_{\text{HP, norm}} = f(T_{\text{rm, amb}}, Q_{\text{gsr, hsr}}). \]

Identification of \( P_{\text{HP, norm}} \) was retrieved in MATLAB from a regression function, which was obtained from RBC test days. Likewise, the normalized operational electricity costs \( J_{\text{HP, norm}} \) was identified with a regression function according to

\[ J_{\text{HP, norm}} = f(P_{\text{HP, norm}}, T_{\text{rm, amb}}, Q_{\text{gsr, hsr}}). \]

To compare the performance of the three control strategies (RBC,

Table 2

<table>
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<tr>
<th>Dataset</th>
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</tr>
</thead>
<tbody>
<tr>
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<td>Black-box model</td>
<td>Feedforward artificial neural network (ANN)</td>
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<td>SH tank</td>
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<td>HP including PVT</td>
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<td>Electricity consumption of the HP</td>
</tr>
</tbody>
</table>
EMPC1, and EMPC2), conventional KPIs and KPIs for demand flexibility were defined. The KPIs were categorized into three domains – energy and power, energy efficiency, and energy costs – and are shown in Table 3.

### 2.6.1. KPIs – energy and power

The electricity consumption of the HP ($P_{\text{HP}}$) is a classical KPI. For the current experimental setup, the HP’s electricity consumption was measured for charging the SH tank ($P_{\text{HP SH}}$) and charging the DHW tank ($P_{\text{HP DHW}}$). The calculation of the ratio ($P_{\text{HP}}/P_{\text{HP norm}}$) compared the HP’s electricity consumption under EMPC and RBC. The instantaneous power flexibility was simulated to identify the demand flexibility of the HP ($P_{\text{inst HP SH}}$) and the SH tank ($Q_{\text{inst SH}}$). When using the instantaneous power flexibility as a KPI, it is possible to completely identify the demand flexibility. The instantaneous power flexibility is defined as the evolution of electrical power and heating power during a flexibility event [5]. For example, during low price periods of $c_{\text{day-ahead}}$, an increase of demand flexibility is requested. In the present study, for EMPC2, which included $c_{\text{mod day-ahead}}$, the evolution of electrical power of the HP with the SH tank ($P_{\text{out HP SH}}$) and the evolution of the charging power of the SH tank ($Q_{\text{out SH}}$) were simulated. In the results, we illustrated the instantaneous power flexibility $F_{\text{inst HP SH}}$ and $Q_{\text{inst SH}}$ to show the major importance of this flexibility indicator.

### 2.6.2. KPIs – energy efficiency

Conventional KPIs are primarily used to identify energy efficiency issues such as the coefficient of performance (COP) of the HP, which was determined for the charging of the SH tank (COP$_{\text{HP SH}}$) and the DHW tank (COP$_{\text{HP DHW}}$). Additionally, we developed energy efficiency indicators for demand flexibility, which refer to the effective utilization of available sources such as the HP and the SH tank. We introduce the effective utilization of the capacity of the SH tank ($\epsilon_{\text{SH tank}}$) according to

$$\epsilon_{\text{SH tank}} = \frac{\max Q_{\text{SH}}(t)}{Q_{\text{SH max}}},$$

where $Q_{\text{SH max}}$ is the maximum storage capacity, which refers to the amount of heat stored in the SH tank at $T_{\text{SH max}}$ of 50 °C. The effective utilization of the capacity of the HP ($\epsilon_{\text{HP}}$) is introduced according to

$$\epsilon_{\text{HP}} = \frac{\max P_{\text{HP}}(t)}{P_{\text{HP max}}},$$

where $P_{\text{HP max}}$ is the maximum capacity, which refers to the maximum power of the HP, which is retrieved from experimental data as shown in Appendix II.

### 2.6.3. KPIs – energy costs

Conventional KPIs and KPIs for demand flexibility integrate operational costs of electricity consumption of the HP. The total operational cost of the HP’s electricity consumption ($J_{\text{HP}}$) is a classical KPI. The calculation of the ratio ($J_{\text{HP}}/J_{\text{HP norm}}$) gave a comparison of the HP’s operational costs under EMPC and RBC. It should be emphasized that $J_{\text{HP norm}}$ was calculated based on $c_{\text{day-ahead}}$.

The flexibility factor ($FF$) was calculated to identify demand flexibility. The flexibility factor presented the potential shift in energy consumption for heating from high-price to low-price periods [5,7,16]. In the present study, the flexibility factor was simulated for the energy consumption of the HP to compensate for the heating demand of the SH tank according to

$$FF = \left(\frac{\int_{t_{\text{start}}^{\text{end}}} \text{inst HP SH} P_{\text{HP SH}} dt + \int_{t_{\text{start}}^{\text{end}}} \text{inst SH} P_{\text{SH}} dt}{\int_{t_{\text{start}}^{\text{end}}} \text{inst HP SH} P_{\text{HP SH}} dt}\right)^{1/2},$$

with $-1 \leq FF \leq 1$.

### 3. Results

During the measurement period between November 2017 and April 2018, experiments were carried out to test the performance of the applied EMPC framework. The EMPC performance was obtained from three validation steps, (1) RBC, (2) EMPC1, and (3) EMPC2, which are shown in sections 3.1.1 (1), 3.1.2 (2), and 3.1.3 (3). Performance data of EMPC validation were broken down by different models of the EMPC framework, as illustrated in section 3.1.4. In section 3.2, the three control strategies are compared according to the performance indicators of energy and power (3.2.1), energy efficiency (3.2.2), and energy costs (3.2.3). For all test cases, identical imbalance prices ($c_{\text{imb}}$) and day-ahead prices ($c_{\text{day-ahead}}$) were assumed (Fig. 5). For EMPC2, $c_{\text{day-ahead}}$ was modified to create a dynamic pricing plan including $c_{\text{mod day-ahead}}$.

#### 3.1. EMPC validation

##### 3.1.1. RBC

The first step in validating the EMPC was performed on 26 March 2018. The conventional RBC was applied to regulate the heating system with a constant SH tank temperature set point ($T_{\text{SH set}}$) of 34 °C (Fig. 6a), which resulted in a low number of on/off cycles of the HP: three cycles for charging the SH tank ($c_{\text{imb}}$) (Fig. 6b) and two cycles for charging the DHW tank ($c_{\text{ding}}$) (Fig. 6c). Fig. 6 also shows the results of the predicted and the measured electricity consumption of the HP ($P_{\text{HP}}$). The prediction performance was calculated for $P_{\text{HP}}$ (kWh) with RMSE = 0.17,

![Fig. 5. Real-time pricing including a) day-ahead prices ($c_{\text{day-ahead}}$) and b) imbalance prices ($c_{\text{imb}}$) used for validation steps (1) RBC, (2) EMPC1, and (3) EMPC2.](image-url)
MAE = 0.13, MAPE = 0.28, R² = 0.91, and G = 0.71.

### 3.1.2. EMPC1

The EMPC1 strategy was applied on 05 April 2018 and incorporated real-time pricing \((c_{d\text{ay-ahead}})\) and \((c_{imb})\) as illustrated in Fig. 5. For EMPC1, we assumed static day-ahead prices \(c_{d\text{ay-ahead}}\). The results of the control decisions of EMPC1 are shown in Fig. 7a. Between 9:00 and 10:00, when \(c_{imb}\) reached negative values, \(T_{\text{SH set}}\) was changed to the maximum setting of 50 °C to enable high power to the HP, which charged the SH tank. As can be seen in Fig. 7b, applying EMPC1 resulted in an increase in the number of on/off cycles for charging the SH tank, which are almost twice the number of cycles with RBC. This was because \(m\) were set to zero at \(T_{\text{SH set}}(t) \leq T_{\text{SH set}}(t - 1) \&\& T_{\text{SH set}}(t) < T_{\text{SH set}}(t - 1)\). The results of the predicted and measured \(P_{\text{HP}}\) are shown in Fig. 7d–f. The prediction performance was calculated for \(P_{\text{HP}}\) (kWh) with RMSE = 0.22, MAE = 0.13, MAPE = 0.27, R² = 0.85, and G = 0.62.
3.1.3. EMPC2

Real-time pricing, including cday ahead and cimb, was implemented in EMPC2 and tested on 01 April 2018. A modified day-ahead price cmod day ahead was used, which related to the forecasting of one daily peak of global and horizontal solar radiation (Fig. 8). As shown in Fig. 8, between 14:00 and 15:00, the daily hourly peak of solar radiation was observed, and cmod day ahead was set to zero. The results of the control decisions of EMPC2 are shown in Fig. 9a. Between 9:00 and 10:00, when cimb reached a daily minimum, the HP provided maximum power for charging the SH tank with TSH set = 50°C. It was also observed that during the daily peak of solar radiation with cmod day ahead = 0, the HP charged the SH tank with TSH set = 46°C. It can be noticed that 2 h before the peak of solar radiation, TSH set was changed to 38 °C. EMPC2 changed this set point to provide the best charging conditions for the peak hour (2 h later), during which maximum charging was requested. The results of the predicted and measured PHP are shown in Fig. 9d–f. The prediction performance was calculated for (kWh) with RMSE = 0.22, MAE = 0.16, MAPE = 0.31, R² = 0.87, and G = 0.64.

3.1.4. EMPC’s modelling performance

Previous sections showed the results of the prediction performance of PHP during test days for RBC, EMPC1, and EMPC2. The overall prediction performance of PHP was a result of the performance of the different models implemented in the EMPC framework. The fractional prediction error for each of these models was calculated according to Equation (2) and is shown in Fig. 10 as the percentage of the absolute error (RMSE) of the testing days for RBC, EMPC1, and EMPC2.

In Fig. 10, the two models responsible for the largest fraction of the prediction error for each test day are highlighted (exploded view). During RBC and EMPC2 testing days, the largest fractional errors were calculated for the HP model and the SH tank model, whereas during the EMPC1 test day, the largest fractional prediction errors were obtained for the HP model and the SH demand model.

3.2. Evaluation of control strategies

From the test results of the different control strategies (RBC, EMPC1, and EMPC2), KPIs were calculated for energy and power, energy efficiency, and energy costs. The environmental conditions for the three testing days are summarized in Table 4.

Experimental results of environmental conditions and KPIs of control established a benchmark for comparing performances of the different control strategies, as detailed in the following sections.

3.2.1. KPIs – energy and power

The HP charged the SH and DHW tanks. The HP’s electricity consumption of the HP (PH) was measured and e) predicted and f) the difference between predicted and measured.

![Fig. 8. EMPC2 experimental results for 01.04.2018: a) measured Qgsr hsr, b) cmod day ahead c) cimb. cmod day ahead was set to zero during predicted and measured peak of Qgsr hsr.](image)

![Fig. 9. EMPC2 experimental results for 01.04.2018: a) temperature set point for the SH tank TSH set, b) control output charging the SH tank (βSH), and c) control output charging the DHW tank (βDHW). Electricity consumption of the HP (PHP) d) measured and e) predicted and f) the difference between predicted and measured.](image)
consumption ($P_{HP}$) for charging the SH ($P_{HP \ SH}$) and DHW tanks ($P_{HP \ DHW}$) for the three testing days was measured, and the ratio of $P_{HP}/P_{HP \ norm}$ was calculated (Table 5). For EMPC1, $P_{HP}$ increased by 4%. We could not conclude, however, that EMPC1 resulted in greater energy consumption than RBC, because the 4% $P_{HP}$ increase was within the regression error of 5%. In contrast, the HP’s electricity consumption under EMPC2 increased by 9%.

In EMPC2, real-time pricing, including $c_{mod \ day \ ahead}$, was introduced to offer a dynamic pricing plan for the next 24 h so as to be able to continuously adapt the energy consumption profile. Additionally, the $c_{mod \ day \ ahead}$ was set to zero according to the daily peak of solar radiation, which occurred between 14:00 and 15:00 (Fig. 8). During this period, EMPC2 forced the HP to provide maximum charging power to the SH tank. The instantaneous power flexibility was calculated to illustrate the provision of maximum charging power during a flexibility time step $\Delta t_{flex}$ of 60 min (Fig. 11). It can be seen in Fig. 11 that during the flexibility event ($c_{mod \ day \ ahead}=0$), between 14:00 and 15:00, the HP provided high charging power to the SH tank ($Q_{inst \ SH}$) of up to 13.8 kW (Fig. 11a) driven by great electricity consumption by the HP ($P_{inst \ HP \ SH}$) of up to 2.5 kW (Fig. 11b). It was observed that between 14:00 and 15:00 it took about 50 min of $\Delta t_{flex}$ to increase $P_{inst \ HP \ SH}$ to above 2 kW. This was due to the primary control of the HP’s compressor, which was regulated based on $\theta_m$: as the $\theta_m$ value decreased, the $P_{inst \ HP \ SH}$ value increased.

### 3.2.2. KPIs – energy efficiency

The HP electricity consumption and the heating power provided to the SH and DHW tanks were measured. Accordingly, the HP’s efficiency was calculated for charging the SH tank ($COP_{HP \ SH}$) and the DHW tank ($COP_{HP \ DHW}$) (Table 6). Experimental results showed that this heating system worked efficiently, with a $COP_{HP \ SH}$ between 5.9 and 6.4 and a $COP_{HP \ DHW}$ between 3.3 and 4.0, which were in accordance with theoretical assumptions from manufacturer’s data. An overview of experimental data on the HP’s efficiency is shown in Appendix II. For all control strategies, $COP_{HP \ SH}$ was higher than $COP_{HP \ DHW}$, which was due to higher charging temperatures for the DHW tank than for the SH tank. Table 6 also lists effective utilization of capacity of the SH tank ($cap \ SH \ tank$) and effective utilization of capacity of the HP ($cap \ HP$). It can

### Table 4

Experimental results – environmental conditions.

<table>
<thead>
<tr>
<th>Control strategy</th>
<th>$T_{ambi}$ (°C)</th>
<th>$T_{rem \ ami}$ (°C)</th>
<th>$Q_{gsr \ hsr}$ (kWh/m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RBC</td>
<td>4.8</td>
<td>4.9</td>
<td>1.4</td>
</tr>
<tr>
<td>EMPC1</td>
<td>6.5</td>
<td>6.5</td>
<td>1.2</td>
</tr>
<tr>
<td>EMPC2</td>
<td>5.1</td>
<td>5.3</td>
<td>0.6</td>
</tr>
</tbody>
</table>

### Table 5

KPIs for control strategies - energy and power.

<table>
<thead>
<tr>
<th>Control strategy</th>
<th>$P_{HP \ SH}$ (kWh)</th>
<th>$P_{HP \ DHW}$ (kWh)</th>
<th>\left(\frac{P_{HP}}{P_{HP \ norm}} - 1\right)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RBC</td>
<td>10.6</td>
<td>1.4</td>
<td>–</td>
</tr>
<tr>
<td>EMPC1</td>
<td>8.9</td>
<td>1.2</td>
<td>+ 4%</td>
</tr>
<tr>
<td>EMPC2</td>
<td>13.9</td>
<td>0.4</td>
<td>+ 9%</td>
</tr>
</tbody>
</table>

### Table 6

KPIs for control strategies – energy efficiency.

<table>
<thead>
<tr>
<th>Control strategy</th>
<th>$COP_{HP \ SH}$</th>
<th>$COP_{HP \ DHW}$</th>
<th>$cap \ HP$</th>
<th>$cap \ SH \ tank$</th>
</tr>
</thead>
<tbody>
<tr>
<td>RBC</td>
<td>5.9</td>
<td>3.9</td>
<td>0.78</td>
<td>0.49</td>
</tr>
<tr>
<td>EMPC1</td>
<td>6.4</td>
<td>4.0</td>
<td>0.91</td>
<td>0.60</td>
</tr>
<tr>
<td>EMPC2</td>
<td>6.1</td>
<td>3.3</td>
<td>0.96</td>
<td>0.56</td>
</tr>
</tbody>
</table>

### Table 7

KPIs for control strategies – costs.

<table>
<thead>
<tr>
<th>Control strategy</th>
<th>$J_{HP}$ (€)</th>
<th>\left(\frac{J_{HP}}{J_{HP \ norm}} - 1\right)</th>
<th>$FF$</th>
</tr>
</thead>
<tbody>
<tr>
<td>RBC</td>
<td>0.58</td>
<td>−2%</td>
<td>0.07</td>
</tr>
<tr>
<td>EMPC1</td>
<td>0.42</td>
<td>−15%</td>
<td>0.27</td>
</tr>
<tr>
<td>EMPC2</td>
<td>0.61</td>
<td>−12%</td>
<td>0.37</td>
</tr>
</tbody>
</table>

Fig. 10. EMPC’s modelling performance under RBC, EMPC1, and EMPC2. The fractional prediction error of each model (weather forecasting, SH tank, SH demand, DHW tank, DHW demand, and HP) is shown as the percentage of the absolute error (RMSE) for RBC, EMPC1, and EMPC2.
be seen from Table 6 that EMPC increases effective utilization of the capacity of both the HP and the SH tank.

3.2.3. KPIs – energy costs

For the control strategies EMPC1 and EMPC2, the total costs of electricity usage (J_{HP}) were calculated according to Algorithm 2. In the same way it was for EMPC1, the total cost for RBC was retrieved using $c_{day-ahead}$ and $c_{imb}$. Table 7 lists $J_{HP}$ and shows the ratio $J_{HP}/J_{HP\ norm}$, which indicates that the use of EMPC reduces the total operational costs of electricity consumption. For RBC, a decrease of $J_{HP}$ compared to $J_{HP\ norm}$ was due to the consideration of $c_{imb}$ and $c_{day-ahead}$. To create $J_{HP\ norm}$ only $c_{day-ahead}$ was used. The application of EMPC also improved demand flexibility in terms of costs, as can be seen in an increase of the flexibility factor (FF) compared to RBC.

4. Discussion

The experimental results showed an energy-efficient operation of the heating system, including HP and TES. It was observed that the performance of the heating system was in good agreement with the results from other studies, which used heating systems in office buildings and residential buildings, including HP combined with PCM and TCM tanks [5], HP and fan coils, radiators, and air-handling units [18], HP in combination with CHP [42], and CHP combined with TES [20].

During the test days, the overall performance in predicting HP electricity consumption was between 0.17 and 0.22 kWh as measured by RMSE; this is an improvement over results in other studies [43]. For performance in predicting $V_{HP}$, the largest fractional prediction errors were determined for the HP model (20–23%) and the SH tank model (18–23%). The HP was modelled as an ANN – more precisely, a recurrent dynamic network with feedback connections – using $T_{amb}$ and $Q_{HP\ out}$ as input variables for modelling the evaporator side. A detailed approach to modelling the evaporator circuit could increase the prediction performance but also would require an additional model of the PVT system.

For the SH tank, the presence of three inlet and outlet ports meant a more complex model was required. A multi-node grey-box model was configured, which outperformed ANN and state-space black-box models. In the case of the black-box models, this was because the measurement data did not sufficiently reflect all possible cases of different states of the SH tank. The use of a fast, high performing multi-node grey-box model in an EMPC/MPC framework is recommended for the SH tank.

For modelling SH demand, ANN black-box models have already shown good prediction performance [7,43]. In the present study, SH demand was predicted by applying a recurrent dynamic network, which resulted in a fractional prediction error of 15–24%. To improve the prediction performance of heating, cooling or energy load profiles for buildings, black-box modelling approaches such as support vector machines, deep neural networks, or combined models including ensemble and improved models [44] could be further investigated.

The use of a one-node grey-box model (capacity model) of the SH tank resulted in a fractional prediction error of 12–15%, indicating that there is still room for improvement. We recommend that future applications use multi-node grey-box models even for well-mixed DHW tanks.

To identify DHW demand, Markov chains were applied, showing a fractional prediction error of 9–19%. To improve performance in predicting DHW demand profiles, black-box modelling approaches such as support vector machines [45] could be further investigated.

For the weather forecasting model, online forecasting was combined with a feedforward network (an ANN) to forecast solar radiation. A fractional prediction error of 10–11% showed that this model performs well and can be recommended for the use in an EMPC/MPC framework. For a possible performance improvement, a shorter time step for predictions could be used [7,46], however, this would lead to a larger state space regarding OCP formulation of EMPC.

We compared the performances of EMPC and RBC using conventional indicators and indicators for demand flexibility. These performance indicators were categorized into three domains: energy and power, energy efficiency, and energy costs. This categorization emphasizes the necessity of quantifying demand flexibility indicators according to the following benefits:

1. Performance indicators in the category of energy costs can be included in the formulation of OCP [7]. This makes it possible to optimize demand flexibility by creating a cost function, which incorporates operational costs of energy usage that are associated with demand flexibility [7].
2. Performance indicators in the category of energy and power can provide detailed information about energy consumption in relation to the power grid. For example, the flexibility indicator instantaneous power flexibility presents the evolution of electrical power and heating power during a requested flexibility event [5].
3. Performance indicators in the category of energy efficiency can be used to identify performance issues of the current energy system. For example, in the present study, we introduced a measure of the effective utilization of SH tank capacity. We determined a maximum value of 0.6 across all control strategies, which implies that the current SH tank is oversized for the request of demand flexibility under RTP. We note that for the retrofitting of the current system or the design of new systems, a comprehensive overview is required of all efficiency indicators, such as the COP of the HP.

We used a one-way trading pattern, including dynamic day-ahead prices and imbalance prices. In contrast to complex trading mechanisms using intra-day pricing, this one-way trading mechanism can be simply implemented in an EMPC framework and enables dynamic optimization of demand flexibility. Recent studies have investigated complex trading and simple one-way trading mechanisms for demand flexibility. In [47], a simulation study served to investigate intra-day trading of transient building load. The study concluded that one-hour intra-day trading can bring economic benefits. The authors in [47] suggested a simple one-way trading pattern that could also be adapted to longer trading horizons. Integrating flexible demand into current trading markets was also investigated by [48]. This simulation study [48] showed that above a certain ratio of flexible consumers, the current trading mechanism can hinder correct predictions of energy consumption. The authors in [48] suggested more direct control of flexible demand. In [21], authors argued that direct control of flexible demand can increase the reliability of demand-side actions caused by fluctuating prices in trading markets. These authors [21] suggest direct control for flexibility provision of 1 to 30 min before real-time and the use of pricing markets and/or trading markets for longer notification times. In a simulation study [49], hourly RTP and CO2 intensity were integrated as weighted sums into an MPC's cost function. The study [49] found that optimal control can integrate a trade-off between cost optimization and CO2 emissions, which can be directly linked to renewable energy sources. To facilitate renewable integration, there are several approaches to control demand flexibility. However, these control approaches have to fit into existing electricity markets or have to lead to innovative flexibility markets [50] such as local flexibility markets [51].

5. Conclusion

We developed and demonstrated an economic model predictive controller to optimally manage the total operational costs of electricity consumption of a heat pump in a house. The experiments were performed in a residential building with a hydraulic heating system, an HP, and TES tanks. During the test periods, the stochastic behaviour of occupants was implemented in the EMPC. The EMPC also included different modelling techniques of the system components (weather
forecasting, the SH tank, the SH demand, the DHW tank, the DHW demand, and the HP). We introduced a methodology to determine the fractional prediction error of all models applied in the EMPC framework. We recommend measuring the fractional prediction error to assess the impact of modelling techniques on EMPC prediction performance. The overall performance in predicting the HPs electricity consumption was a result of the prediction errors of the different models. The study realized good performance at predicting HP energy consumption.

The performance of EMPC and RBC were compared by quantifying conventional indicators and flexibility indicators. We introduced a categorization of indicators according to 1) energy and power, 2) energy efficiency, and 3) energy costs. This categorization helps to make clear the benefits of using flexibility indicators in real-life applications. Those benefits include 1) detailed information on demand flexibility in relation to the power grid, 2) demand flexibility for retrofitting and design of new energy systems, and 3) optimal control of demand flexibility. We also introduced KPIs in the category of energy efficiency to measure the effective utilization of available sources such as HP and TES.

A building heating system, including HP and TES, was used to demonstrate the provision of demand flexibility for real-time power markets. We introduced a flexibility service that can be used as an ancillary service for flexibility markets. The flexibility service is based on a dynamic modification of day-ahead prices. This modification was used to adapt energy consumption to errors in the forecasting of renewable energy generation. To facilitate renewable integration and control demand flexibility, the introduced methodology is one possible solution that fits into flexibility markets. However, demand flexibility was dynamically optimized using a notification time of $1h < t < t_{dayend}$. For shorter-term provision of demand flexibility where $t < 1h$, we suggest investigating direct control of demand flexibility to ensure reliable grid operations. Eventually, a combination of direct control (incentive-based) and price-based control of demand flexibility will create robust energy networks, which are of vital importance for the integration of renewable sources.

CRediT authorship contribution statement

Christian Finck: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing - original draft, Visualization, Data curation. Rongling Li: Writing - review & editing, Supervision. Wim Zeiler: Supervision, Funding acquisition.

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Appendix I. – Performance metrics

\[ i \] is the sample number, \( n \) is the total number of samples, \( e \) is the estimated data point, \( o \) is the output, and \( \bar{o} \) is the mean output.

\[ \text{Root Mean Square Error} \]
\[ \text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (e_i - o_i)^2} \]

\[ \text{Mean Absolute Error} \]
\[ \text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |e_i - o_i| \]

\[ \text{Mean Absolute Percentage Error} \]
\[ \text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{e_i - o_i}{o_i} \right| \]

\[ \text{Coefficient of Determination} \]
\[ R^2 = 1 - \frac{\sum_{i=1}^{n} (o_i - e)^2}{\sum_{i=1}^{n} (o_i - \bar{o})^2} \]

\[ \text{Goodness of Fit} \]
\[ G = 1 - \frac{\left( \sum_{i=1}^{n} (e_i - o_i)^2 \right)^{\frac{1}{2}}}{\left( \sqrt{\sum_{i=1}^{n} (o_i - \frac{1}{n} \sum_{i=1}^{n} o_i)^2} \right)^{\frac{1}{2}}} \]
Appendix II. – Experimental data for heat pump

Experimental data for heat pump COP_{HP} = f (T_{supply heating}, T_{return brine}); curve fitting of experimental data using a polynomial fitting curve ($R^2 = 0.89$, RMSE = 0.36).

Experimental data for heat pump COP_{HP} vs. $P_{HP}$; the heat pump regulates the electricity consumption of the compressor according to $P_{HP,min} = 0.42$ kW, $P_{HP,max} = 2.7$ kW, and $P_{HP} = 0.06$ kW; box plots for $P_{HP,min}$, $P_{HP}$, and $P_{HP,max}$.

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