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Method Article

Identification of a dynamic system model for a building and heating system including heat pump and thermal energy storage

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ABSTRACT

Controllers employing optimal control strategies will path the way to enable flexible operations in future power grids. As buildings will increasingly act as prosumers in future power grids, optimal control of buildings' energy consumption will play a major role in providing flexible operations. Optimal controllers such as model predictive controller are able to manage buildings' operations and to optimise their energy consumption. For online optimisation, model predictive controller requires a model of the energy system. The more accurate the system model represents the system dynamics, the more accurate the model predictive controller predicts the future states of the energy system while optimising its energy consumption. In this article, we present a system model that can be used in online MPC, including dynamic programming as optimisation strategy. The system model is validated using a building and heating system, including heat pump and thermal energy storage.

The following bullet points summarise the main requirements for the configuration of the system model:

- The system model performs fast with low computational effort in less than 1 s;
- The system model can be implemented in online MPC;
- The system model accurately represents the dynamic behaviour.

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### Specifications Table

| Subject Area | Energy |
|--------------|--------|
| More specific subject area | Control of building energy systems |
| Method name | Dynamic system model of a building and heating system for online optimisation |
| Name and reference of original method | n/a |
| Resource availability | n/a |

### Method details

To implement large amounts of renewable energy sources, power systems are required to change towards flexible operations. One possible source of flexible operations is the energy consumption of buildings, as buildings account for a large proportion of total energy consumption [1]. To adapt the energy consumption of buildings to fluctuations in supply, we need innovative control strategies that enable flexible operations and optimally manage the energy consumption.

Controllers employing optimal control strategies are for example model predictive controller (MPC) [2]. To optimise the energy consumption, the MPC integrates a model of the building energy system. This system model implements disturbances (for example the weather forecasting) and predicts the future states of the building energy system [3,4]. So far, simplified system models such as resistance-capacitance (RC) network models have been predominantly used to study MPC in buildings. The RC models represent the building and heating system and are often validated offline. For online MPC, models of the building and heating system are converted to continuous-time state-space models via model linearisation [4,5]. The use of linear modelling for online optimisation is due to their ease of implementation and their low computational effort [4,5]. Linear models, however, have shown a low performance in predicting the energy consumption of buildings because they are not able to represent the complex and dynamic interactions within building energy systems [4,6].

To make a step towards application of MPC in building energy systems, we need to develop models of building energy systems for online optimisation that, (1) can accurately predict the energy consumption, (2) can perform fast with low computational effort, (3) can fit into online optimisation schemes. Furthermore, if the same system model can be used in both, offline validation and online optimisation, then model reduction (state-space linearisation of the model) for MPC is obsolete.

In this article, we present a detailed system model that can be used in online MPC [7]. For the MPC, the system model is configured to fit into a dynamic programming scheme as optimisation strategy. The MPC modelling approach, thus, does not require any model reduction for online optimisation because the developed system model can be used for both offline validation and online optimisation.

For offline validation, the datasets of non-time-series data were randomly divided into three datasets (training, validation, and testing). For time-series black-box modelling, the identification – including training (70%), validation (15%), and testing (15%) – was done in a so-called series-parallel architecture using standard backpropagation. After identification, the nonlinear autoregressive with external (exogenous) input (NARX) model was transformed into a multi-step-ahead prediction network. The performance of all models of the system components was tested using a dataset of unseen data. For each of the models, the procedure was repeated more than 100 times to obtain the best performance.

For offline and online validation, model performance of the system and the system components was calculated using root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), coefficient of determination (R²), and goodness of fit (G) [2,8–13]. The mathematical descriptions of the performance metrics can be found in Appendix A.

For online implementation, additionally, the system model is configured to perform fast with low computational effort and to accurately predict the dynamics of the system components. We note that the developed system model provides a plug-and-play solution to integrate models of the system components.

As we aim to identify a dynamic system model of the building and heating system, we firstly present the system model and the experimental set up, including data acquisition and processing.
Then we describe the modelling of the system components and their validation, and finally we discuss the application of the system model for online optimisation.

**Experimental setup and system modelling**

We tested and modelled a low energy house, which was located in the Netherlands. Between November 2017 and April 2018, measurement data were recorded for the building and heating system, including occupants’ domestic hot water profile and the heating demand. The heating system of the building consisted of a heat pump (HP), a photovoltaic thermal solar collector (PVT), a space heating (SH) tank, and a domestic hot water (DHW) tank. **Table 1** lists the properties of the building and heating system. For the system model, additionally, we modelled the SH demand that was supplied by an integrated floor heating system throughout the entire building. We also implemented a stochastic modelling approach for the DHW demand that was retrieved from the stochastic behaviour of occupants. **Fig. 1** shows the system model of the building and the heating system that is illustrated as process flow diagram. **Fig. 2** illustrates the system model that is implemented in an MPC framework.

We, therefore, defined the models of the weather forecasting, the HP, the SH tank, the SH demand, the DHW tank, and the DHW demand as the system components.

For acquisition of measurement data, the HP was equipped with sensors that measured temperatures in the upper third of each tank. The HP also had sensors for the ambient temperature and the supply and return temperatures of the evaporator and condenser circuits. A DT80-dataTaker data logger was installed for this project to capture all DHW and SH tank supply and return temperatures along with measurements at two heights in the DHW tank and three heights in the SH tank. Temperature sensors for the data logger and the heat pump were Negative-Temperature-

**Table 1** Properties of the building and heating system.

| Building and heating system | Properties                                                                 |
|-----------------------------|---------------------------------------------------------------------------|
| Detached house              | Total floor area = 345 m² ;                                               |
|                             | Annual heating energy consumption = 55.6 kWh/m²                             |
| HP                          | NIBE F1155-16 ;                                                           |
|                             | Nominal heating output = 16 kW                                            |
| PVT                         | TripleSolar with a total area = 30 m²                                     |
| SH tank                     | Volume = 1000 L ;                                                        |
|                             | Insulation thickness = 0.2 m ;                                           |
|                             | Insulation thermal conductivity = 0.07 W/(mK)                              |
| DHW tank                    | Volume = 300 L ;                                                         |
|                             | Insulation thickness = 0.05 m ;                                          |
|                             | Insulation thermal conductivity = 0.07 W/(mK)                              |

**Fig. 1.** Flow diagram of the building heating system.
Fig. 2. Methodological framework of the system model implemented in online MPC.
Coefficient thermistors with a tolerance of 5% (accuracy of 0.1 °C at 20 °C). Flow meters were also installed to provide information on fluid flow rates in the HP evaporator and condenser circuits and the floor heating circuit and to measure tap water demand. The Huba-Control flow meters measured in a range between 0.5 and 150 L/min with +/- 2% accuracy. The experimental setup also included an electricity meter from Imbema-Controls to measure energy consumption by the HP. Electricity consumption values were issued via pulse outputs of 1000 imp/kWh to the data logger. The electricity that was generated by the PVT was not measured because the current system directly fed electricity into the power grid.

Measurement data were recorded with a 1-min time step and submitted to a MATLAB controller (Fig. 3). MATLAB 2017a was used for the processing of data. To exchange information with the heat pump, a Modbus Remote-Terminal-Unit was installed, which enabled the use of Modbus as a communication protocol. Modbus is widely used in building management systems because this message structure is reliable for bi-directional communication of data.

Weather forecasting model

Short-term weather forecasting included forecasting of global and horizontal solar radiation and ambient temperature. The local ambient temperature was obtained from professional online forecasting [14]. An application programming interface between the forecasting service and the MATLAB controller was created to retrieve real-time forecasting of the ambient temperature. Forecasting of the global and horizontal solar radiation was implemented by designing a feedforward artificial neural network (ANN) that had been successfully applied in a previous case study [2]. The ANN integrated the input signals including year, month, day, hour of day, sunshine hours, ambient temperature, dew point temperature, relative humidity, cloud cover factor, air pressure, precipitation, and direct and diffuse beam irradiance [2]. To obtain the direct and diffuse beam irradiance, a simplified clear sky model was used, which was developed by Bird and Hulstrom [15]. For weather forecasting, the ANN was trained, validated, and tested using a weather data set of 7 years (2011–2017) of hourly data [16]. For the hourly forecasting of solar radiation $Q_{gss}^{pred}$ (W/m²), the best configuration was found with 50 hidden layers, resulting in an RMSE of 22, MAE of 12, MAPE of 0.19, R² of 0.99, and G of 0.88, which were in good agreement with results from other studies [2,17–19].

SH tank model

For the SH tank, grey-box and black-box models are typically applied to online optimisation. For optimal control, grey-box models are one-node capacity models [20–24] or one-dimensional multi-node models [20,25–27]. Black-box models include, for example, ANN [10,28], transfer function, state-space (SS) or autoregressive exogenous [8] models. However, because of the lack of experimental MPC implementations, none of the grey-box or black-box SH tank models have shown superior performance. In the present study, we first developed four SH tank models, then tested the prediction performance of these models using measurement data, and finally chose the best performing model to
be integrated into the system model for online MPC. The developed SH tank models were a one-node (capacity), a multi-node (multi-layer), a time-series ANN (recurrent dynamic network), and a discrete-time SS model. The SH tank models were designed to predict supply temperatures (SH demand, HP, and DHW tank) (Fig. 1) and internal SH tank temperatures. The latter was used to calculate degree minutes (°m) (dimensionless quantity to regulate SH tank charging). Table 2 shows the results of the prediction performance (supply temperatures in °C) of the different SH tank models.

The best performing SH tank model was the multi-node model (Table 2), which was thus chosen to be integrated into the system model for online MPC. The reason for the variability in prediction performances may be the presence of three inlet and outlet ports, which leads to high model complexity. In the multi-node model, the complexity is represented by 30 layers, which is the best configuration that was found. This multi-layer configuration was based on the one-dimensional convection-diffusion-reaction equation [26,27,29,30] (Eq. (1)). Heat transfer through convection and conduction was simulated according to

\[
\frac{\partial T_{SH}}{\partial t} = \frac{\alpha}{\rho c_p} \frac{\partial^2 T_{SH}}{\partial z^2} - v_{SH} \frac{\partial T_{SH}}{\partial z} + \gamma (Q_{HX SH} - Q_{loss SH}), \quad 0 \leq z \leq z_{max}, \quad t \geq 0. \tag{1}
\]

\[
\alpha = \frac{\lambda}{\rho c_p}, \tag{1a}
\]

\[
\gamma = \frac{1}{\rho c_p}, \tag{1b}
\]

where \(\partial T_{SH}/\partial z\) is the vertical temperature distribution, \(z\) is the spatial vertical coordinate, and \(z_{max}\) is the height of the SH tank. The speed of water flow \(v_{SH}\) was calculated as flow rate divided by the cross-sectional area perpendicular to the water flow. The flow rate depended on the operating mode, which included charging and discharging. For Eq. (1), inlet temperatures during charging (HP circuit) and discharging (floor heating circuit) were implemented as Dirichlet boundary conditions. According to inflow and outflow positions of the HP and floor heating circuits, the vertical temperature array \(z\) was divided into multiple sections. For each section of \(z\), a virtual layer was added at both ends to represent inlet and outlet temperatures for charging and discharging the SH tank.

The SH tank was also used for preheating tap water through an immersed heat exchanger coil. The heat exchange \(Q_{HX SH}\) between the SH tank and tap water (to the DHW tank) was implemented as a source term in Eq. (1) according to

\[
Q_{HX SH} = \frac{c_p \rho A_{HX SH} V_{DHW}}{V_{SH}} (T_{HX SH \ out} - T_{HX SH \ in})
\]

\[
= \frac{c_p \rho A_{HX SH} V_{DHW}}{V_{SH}} (T_{SH} - T_{HX SH \ in}) \left[ 1 - e^{-\frac{h_{HX SH} S L \ c_{DHW}}{c_p \rho A_{HX SH} V_{DHW}}}. \tag{2} \right]
\]

where \(A_{HX SH}, L, \) and \(S\) are the cross-sectional area, the length, and the circumference of the heat exchanger, respectively. \(h_{HX SH}\) is the heat exchange coefficient, which depends on the speed of the heat exchanger fluid \(v_{DHW}\) [29,31]. Eq. (1) also included the heat loss of the SH tank \(Q_{loss SH}\) to the ambient environment \(T_{amb}\) according to

\[
Q_{loss SH} = \frac{h_{amb SH} A_{amb SH} (T_{SH} - T_{amb})}{V_{SH}}, \tag{3}
\]
where $A_{\text{amb},SH}$ is the surface area of the SH tank, and $h_{\text{amb},SH}$ is the heat exchange coefficient between SH tank and ambient environment. Eq. (1) was solved numerically using the combination of a Crank–Nicolson scheme [26,29,30,32] for the diffusion problem and an upwind scheme [33] for the convection problem. Additionally, the upwind scheme was used to solve mixing effects that resulted from temperature inversion in the SH tank. The combination of the Crank–Nicolson scheme and the upwind scheme successfully established the simulation of thermal stratification, charging, and discharging.

**SH demand model**

The space heating demand comes from the floor heating system that extracts heat from the SH tank. The SH demand model was a black-box model that was developed using the Neural Network Toolbox in MATLAB. Previous case studies successfully applied ANNs for prediction of space heating demand [34]. Amasyali and El-Gohary [34] provided a comprehensive review of ANNs to forecast the energy consumption of residential and non-residential buildings, concluding that there was a lack of studies of residential buildings that considered hourly prediction of energy demand. In one of the few studies, Chou and Bui [35] reported that in addition to support vector regression, ANN can play a major role in predicting hourly heating and cooling loads.

In the present study, we created an ANN to solve a time-series problem which was a NARX problem. A NARX model is a recurrent dynamic network using feedback connections according to

$$i(t) = f(i(t-1), i(t-2), \ldots, i(t-n_i), w(t-1), w(t-2), \ldots, w(t-n_w)), \quad (4)$$

where $i(t)$ is the output signal, and $w(t)$ represents the exogenous input variables [36]. The ANN simulated the heating demand based on the input variables: ambient temperature, global and horizontal solar radiation, supply temperature to floor heating, and time of day. The room temperature set points were excluded as ANN input signals because set points were kept at a constant value of 21.5 °C. The best configuration for the heating demand (kWh) was found with three input delays, three feedback delays, and a hidden layer size of 20, resulting in an hourly performance with an RMSE of 2.2, MAE of 1.3, MAPE of 0.18, R2 of 0.94, and G of 0.77.

**DHW tank model**

The model of the DHW buffer tank was conceived as a grey-box capacity model which represented a fully-mixed one-node model [21,37–39]. The purpose of the DHW tank model was to predict future average temperatures. The evolution of the average temperature $T_{\text{DHW}}$ (°C) was represented according to

$$\rho V_{\text{DHW}} \frac{dT_{\text{DHW}}}{dt} = Q_{\text{HP, DHW}} - Q_{\text{tapwater, DHW}} - Q_{\text{loss, DHW}}. \quad (5)$$

where $Q_{\text{HP, DHW}}$ is the heat delivered by the heat pump, $Q_{\text{tapwater, DHW}}$ is the heat extracted by tap water usage, and $Q_{\text{loss, DHW}}$ is the heat loss to the ambient environment. The DHW tank model was identified ($T_{\text{DHW}}$ in °C) as showing a good prediction performance with an RMSE of 0.90, MAE of 0.74, MAPE of 0.01, R2 of 0.83, and G of 0.60, which were comparable to results of other studies [40,41].

**DHW demand model**

The DHW demand model was a discrete-time Markov chain model for tap water demand. Markov chains represent random processes and are used to predict stochastic behaviour, such as tap water demand [42,43], wind power generation [44], and occupancy presence [45,46]. In this study, the stochastic behaviour of tap water is represented by a time-homogeneous Markov chain $\{Y_t\}$ for $t > 0$ and the states $a_b \in S_{ab}$ with

$$P(Y_{t+1} = b \mid Y_t = a, Y_{t-1} = a_{t-1}, \ldots, Y_0 = a_0) = P(Y_{t+1} = b \mid Y_t = a) = P_{ab}. \quad (6)$$
The Markov chain was associated with a probability transition matrix $P$ in which $P_{ab}$ denoted the probability of moving from state $a$ to state $b$ with $P_{ab} = P(y_t = b \mid y_{t-1} = a)$ [47]. The DHW demand model used a row vector of probabilities of tap water usage $p[t]$ with $p_b[t] = P(Y_t = b)$, which evolved according to

$$p[t] = p[t - 1]P.$$  

Real-time measurements were used to determine $p[0]$ at each control time step. Furthermore, continuous measurements of tap water usage served to create the transition probability $P$. Tap water flow measurement data were averaged over a time step of 15 min and implemented in the online optimisation. A distinction was made between tap water demand on weekdays and weekends [43]. For example, during the week, at 8:30 the probability of changing from state $a$ to $b$ was

$$P = \begin{bmatrix}
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
\end{bmatrix},$$

where $a, b \in \{0, 1, 2, \ldots, 7\}$ represents the minimum and maximum water flow in L/min. The identified tap water demand model performed with an RMSE of 0.60 L/min, MAE of 0.25 L/min, MAPE of 0.03, R2 of 0.40, and G of 0.22. The DHW demand $Q_{\text{tapwater-DHW}}$ was calculated using the tap water demand, average DHW tank temperature, and inlet DHW tank temperature.

**HP model**

The water-to-water HP extracted heat from the PVT system and charged the SH tank and the DHW tank. Unsteady PVT operating conditions (HP source) and water thermal storage tank conditions (HP sink) required that the HP continuously adapt its electricity consumption. A summary of the measurements, including performance data such as coefficient of performance (COP), is given in Appendix B. The HP’s energy efficiency varied during start-up and shut-down moments and during phases of partial load, especially at low compressor speeds [48]. To sufficiently capture the dynamic behaviour of the HP, Underwood [48] suggested fully dynamic modelling, which likely requires artificial intelligence methods. Mathioulakis et al. [49] proposed the use of ANNs for HP performance prediction. In the present study, we developed an ANN (Fig. 4) which was a NARX based on Eq. (4). The ANN predicted the electricity consumption of the HP. Control of the HP $\beta$ had three modes: charging DHW tank $\beta_{\text{DHW}}$, charging SH tank $\beta_{\text{SH}}$, and idle mode. The best configuration for electricity consumption $P_{\text{HP}}$ (kWh) was found with three input delays, three feedback delays, and a hidden layer size of 20, resulting in an hourly performance with an RMSE of 0.15 kWh, MAE of 0.09 kWh, MAPE of 0.15, R2 of 0.92, and G of 0.72.

**Method validation**

We developed a system model of a building and heating system, including models of the weather forecasting, the SH tank, the SH demand, the DHW tank, the DHW demand, and the HP. The models of the system components were validated offline using measurement data between November 2017 and April 2018. Compared to other studies, the models showed a good performance prediction.

The system model was integrated into an online MPC that used dynamic programming as optimisation method. In the original research article [7], we achieved a prediction performance of HPs electricity consumption of RMSE between 0.17 kWh and 0.22 kWh, which is an improvement against prior studies that used simplified MPC modelling methods. The system model, furthermore, performed fast with low computational effort. For the computation of the system model, a computational time of less than 1 s was achieved using MATLAB and an industrial box-PC with Intel core i7-6700TE.
Fig. 4. Artificial neural network (ANN) to obtain the electricity consumption of the HP ($P_{HP}$) based on the ambient temperature ($T_{amb}$), temperature of DHW and SH return to the HP ($T_{sink-to-HP}$), global and horizontal solar radiation ($Q_{gsr-hsr}$), SH tank temperature for HP control ($T_{SH}$), DHW tank temperature for HP control ($T_{DHW}$), control output ($\beta$), and degree minutes ($^\circ m$).

processor and RAM8GB-DDR4. For the optimisation method, assuming a state space of 1200 decisions, the current system model, thus, can be simulated within 20 min of computational time.

The current system model implements various modelling techniques for the system components. The modelling techniques were chosen to accurately represent the dynamic behaviour of the system components. We note that the system model was configured to act as a plug-and-play solution, which means that the models of the components can be replaced in case that more accurate and faster performing models of the components are developed.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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APPENDIX A 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.

Root Mean Square Error

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (e_i - o_i)^2}$$

Mean Absolute Error

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |e_i - o_i|$$

Mean Absolute Percentage Error

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{|e_i - o_i|}{o_i} \right|$$
Coefficient of Determination

\[ R^2 = 1 - \frac{\sum_{i=1}^{n} (o_i - e_i)^2}{\sum_{i=1}^{n} (o_i - \bar{o})^2} \]

Goodness of Fit

\[ G = 1 - \frac{\sqrt{\sum_{i=1}^{n} (e_i - o_i)^2}}{\sqrt{\sum_{i=1}^{n} (o_i - \frac{1}{n} \sum_{i=1}^{n} o_i)^2}} \]

**APPENDIX B  Experimental data for heat pump**

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

Experimental data for heat pump \( \text{COP}_{\text{HP}} \) vs. \( P_{\text{HP}} \): the heat pump regulates the electricity consumption of the compressor according to \( P_{\text{HP min}} = 0.42 \text{ kW}, P_{\text{HP max}} = 2.7 \text{ kW}, \) and \( \Delta P_{\text{HP}} = 0.06 \text{ kW}; \) box plots for \( P_{\text{HP min}} \leq P_{\text{HP}} \leq P_{\text{HP max}} \).
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