PAPER • **OPEN ACCESS**

Data-driven modeling of heat pumps and thermal storage units for MPC

To cite this article: M Brandes *et al* 2023 *J. Phys.: Conf. Ser.* **2600** 032008

Data-driven modeling of heat pumps and thermal storage units for MPC

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Abstract. Heat pumps can play a crucial role in the European energy strategy 2050, which aims to achieve net-zero greenhouse gas emissions. When coupled with thermal energy storage and integrated with advanced control strategies, heat pump operation can be optimized to reduce carbon footprint and respond to the needs of system operators. However, to scale in a multitude of buildings, the transferability of the modeling into heterogeneous systems is crucial. In this paper, two different interpretable linear models, a hybrid (grey-box) and a fully data-driven (black-box) model are investigated. Specifically, two regression-based identification methods (SINDYc and DMDc) are used for dynamic models and the LASSO regression is used for static models. The transferability of the approach is evaluated using two real-world facilities with heterogeneous sizing and configuration. The results show a similar simulation performance for both cases with a maximum normalized RMSE of 0.41 and 0.60, respectively. This confirms the transferability of the approach that is necessary for large-scale implementation.

1. Introduction

Heat pump (HP) coupled with thermal energy storages (TESs) can be used as a source of flexibility to support energy system operation when combined with optimal predictive control [1]. However, a large number of such systems need to be aggregated for which scaleable control policies are required. To this end, data-driven modeling approaches have received considerable attention as they can reduce modeling efforts and support a cost-efficient implementation. Previous studies have shown that black-box models such as neural networks (NN) can achieve high modeling accuracy but have poor performance in sample efficiency and model interpretability [2]. For large-scale exploitation of TES units, potentially unstable models could affect energy system operation negatively and poor interpretability also raises hesitance among grid operators. Therefore, we consider linear or non-linear state-space models identified with the assistance of machine learning techniques. This facilitates model interpretability while achieving reasonable modeling accuracy and a better sample efficiency [3]. When models leverage both physics-based feature selection and machine learning methods to identify unknown model

parameters, they are classified as hybrid (grey-box) models. In contrast, fully data-driven (black-box) models utilize dependencies that extend beyond directly physics-related factors.
Extensive research has been carried out with hybrid models of HPs [4]. Models of a full heating system, consisting of a HP and a TES, to be used with MPC have been presented in [5]. However, a more systematic screening of different models and investigations into the transferability of the modelling approach are lacking. A key criterion for a large-scale rollout is the transferability of a model to different case studies [6]. Consequently, the main contribution of this research lies in conducting a systematic comparison of different data-driven models based on real-world heterogeneous variable-speed HPs combined with TES units.

2. Case study

Two case studies, the RSE Lab and NEST, with heterogeneous sizes and system configurations have been investigated in this paper. Figure 1 and Table 1 contrast the two systems regarding their main characteristics. The sampling time interval for both datasets is 1 minute. The RSE Lab is equipped with a standard setup with a hydraulically decoupled thermal buffer tank downstream of the heat pump, which is used for both heating and cooling operations [7]. In the case of NEST, additional heat can be directly injected into the storage tank from a district grid via a heat exchanger. In the cooling mode, no HP is involved and the tank is only charged with cooling energy from a district cooling grid. Despite the absence of a HP, the temperature dynamics were investigated as well. The hot water and cold water storage tanks for NEST consist of two in-series 1100-liter tanks.

System	RSE Lab	NEST
HP capacity (electric power) [kW]	7 (2)	100 (24)
Heat source	Air	Ground & District Grid
TES volume for heating/cooling [L]	300	2200

Table 1: Case-study system characteristics

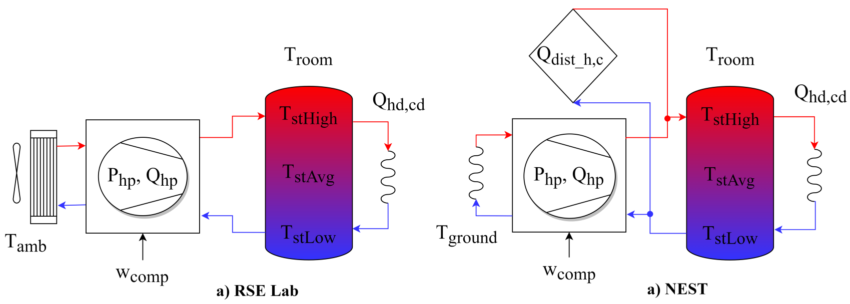

Figure 1: Schematic overview of heating system components of two case studies for heating and cooling operations: (a) RSE Lab and (b) NEST

3. Methodology

3.1. Model identification methods

Two data-driven dynamic state-space modeling techniques, namely Sparse Identification of Non-Linear DYnamics with control (SINDYc) [8] and Dynamic Mode Decomposition with control (DMDc) [9] are used to identify first-order dynamic models. Kaiser et. al have shown that these two methods can be applied in a wide range of modelling tasks and the methods are closely linked in the discrete-time domain [2]. Since SINDYc is a regression-based identification method, the number of model features (complexity) can be chosen through regularization and relaxation parameters. With DMDc, the model complexity can be adjusted by selecting the number of eigenmodes resulting from singular value decomposition (SVD). Both dynamic identification methods can be used for uni- or multivariate identification. For model variables with negligible dynamics, static models, identified with Least Absolute Shrinkage and Selection Operator (LASSO) regression, have been evaluated. Non-linearities for SINDYc and LASSO were considered via a combination of bilinear and polynomial terms.

3.2. Model evaluation

Firstly, the model performance of the identification was evaluated. A screening of model characteristics, such as model type (Static/Dynamic, Linear/Non-Linear), sampling time (1 minute, 15 minutes) and the prediction horizon (1 hour, 5 hours), was conducted to identify suitable models and combinations for HP and TES variables for both case studies and operational modes (i.e., heating and cooling). The main criteria include both model error metrics (i.e., root-mean-square error (RMSE), R^2) and stability. Secondly, suitable structures of full system models (combined HP and TES model) have been selected. It is typical for the residential building sector to utilize a 15-minute sampling time, thus the more limited selection process concentrates only on models with this higher sampling time. To facilitate comparison of modelling results in different systems, the RMSE is further normalized with the standard deviation of the respective measurement. The two types of full system models that resulted from the evaluation are presented in the next subsection. Both model evaluation steps were conducted for both case studies to examine the transferability of the modelling approaches.

3.3. Selecting the model structure

The modelling approach proposed here is inspired by [5]. The HP-TES system is described by at least three states: $x = [T_{\mathrm{st}}, Q_{\mathrm{hp}}, P_{\mathrm{hp}}]$ with T_{st} either being an average temperature T_{stAvg} or two states describing the temperature at the top and bottom of the storage tank T_{stLow} and T_{stHigh}. P_{hp} is the electric power and Q_{hp} the thermal power. In practice, the only controllable variable of the system is the compressor frequency w_{comp}. With the chosen identification methods, two types of combined linear state-space models (Equation 2, Equation 3) of the following form can be selected:

$$Ex_{k+1} = Ax_k + B_u u_k + B_d d_k \ , \ y_k = Cx_k \tag{1}$$

A generic descriptor state-space representation is presented in Equation 1, where matrix E allows for the formulation of combined static and dynamic models. The HP thermal and electrical power model in Equation 3 are static.

I) Coupled fully data-driven dynamic model:

$$E = \mathbb{I},\ A,\ B_u,\ B_d,\ C = \mathbb{I} \tag{2}$$

II) Decoupled hybrid static and dynamic (mixed) model:

$$E = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix},\ A = \begin{bmatrix} a_{11} & a_{12} & 0 \\ a_{21} & -1 & 0 \\ a_{31} & 0 & -1 \end{bmatrix},\ B_u = \begin{bmatrix} 0 \\ b_{u,21} \\ b_{u,31} \end{bmatrix},\ B_d = \begin{bmatrix} 0 & b_{d,12} & b_{d,13} \\ b_{d,21} & 0 & 0 \\ b_{d,31} & 0 & 0 \end{bmatrix},\ C = \mathbb{I} \tag{3}$$

with the following definitions for the RSE Lab:

$$x = [T_{\mathrm{st}}, Q_{\mathrm{hp}}, P_{\mathrm{hp}}]^T \ , \ u = [w_{\mathrm{comp}}] \ , \ d = [T_{\mathrm{amb}}, T_{\mathrm{room}}, Q_{\mathrm{hd,cd}}]^T \tag{4}$$

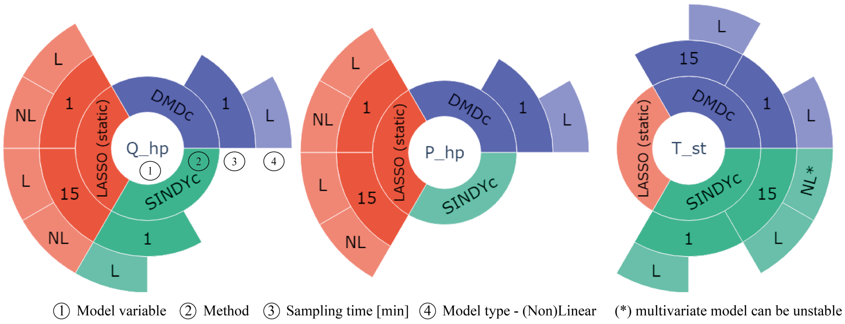

Figure 2: Screening results of feasible models

For the NEST-system the heat/cold supply from the district grid (see Figure 1) is added as an additional disturbance in the above formulation, by extending the disturbance matrix B_d in Equation 3 to capture the influence on the tank temperature in model (II). All the parts of the full system models can be identified with the introduced methods. The simulation performance of both full system models have been evaluated for the RSE Lab and NEST.

4. Results

This section first summarizes the results following the model evaluation procedure described in subsection 3.2 and then elaborates on the simulation results of the full system HP-TES models introduced in subsection 3.3.

4.1. Model screening

Figure 2 shows all feasible combinations of model variables, methods, sampling time, and model types that result in stable models. With a sampling time interval of 15 minutes, the dynamics of the HP states are not observable. Therefore no stable dynamic models can be identified with SINDYc and DMDc. Only when the number of eigenmodes in DMDc is reduced and a 1-minute sampling time is used, stable linear models can be obtained. Additionally, static linear and non-linear models always perform well for both case studies and operation modes. The storage tank states can be modeled with SINDYc and DMDc. Non-linear dynamics due to tank temperature stratification can only be modeled with SINDYc. However, evaluations presented in the next subsection show that linear models perform sufficiently well and are stable when the TES is modelled using a single or multiple states with first-order dynamics.

4.2. Model selection

Modelling results in Figure 3 are shown for both case studies and both heating and cooling modes for 1-hour and 5-hour prediction horizon. Results for the fully data-driven model for NEST are not shown because the accuracy is very low. Dependencies between the additional disturbance Q_{dist} and the HP states are identified with DMDc, which is against physical intuition. A well-performing first-order multivariate data-driven dynamic linear model as described in Equation 2 can only be identified with DMDc for the RSE Lab data. The dynamics are identified with 1-minute sampling time data and then converted to a 15-minute model. The components of the decoupled hybrid mixed model are identified separately and then combined into a state-space model as described in Equation 3. In addition to the linear models, modelling results for non-linear average tank temperature models are presented. Even though the performance is slightly better compared to linear models, it is potentially unstable. Nonetheless, in both cases, the model performance for heating and cooling modes are comparable for short prediction horizons.

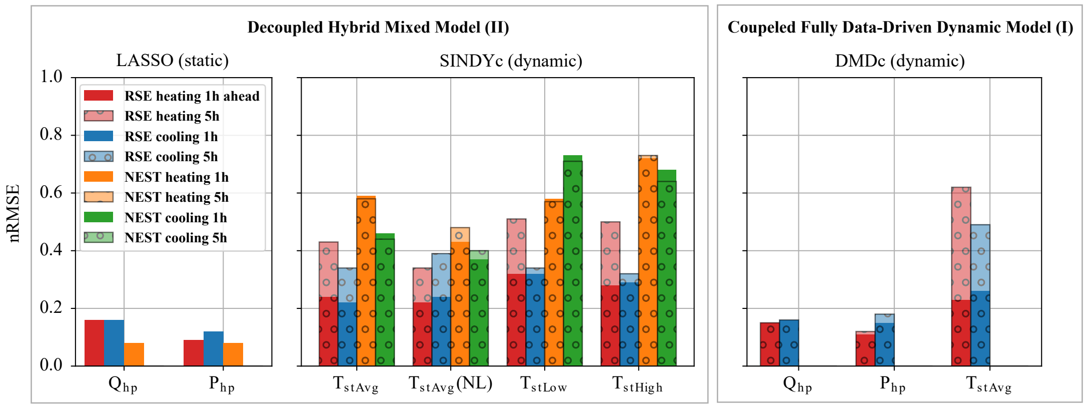

Figure 3: Model performance of selected 15 minutes sampling time models to construct coupled fully data-driven and decoupled hybrid mixed HP-TES models

4.3. Full HP-TES system simulation

Figure 4 shows two-day simulations, for both case studies and both operational modes. For the RSE lab, the coupled fully data-driven dynamic model (I) and the decoupled hybrid linear mixed tank temperature model (II) are depicted. In this case, the normalized RMSEs of all three states $T_{\mathrm{st}}, Q_{\mathrm{hp}}, P_{\mathrm{hp}}$ of model (II) are 0.41, 0.16, 0.10, respectively. The corresponding normalized RMSEs are 0.60, 0.07, 0.04 for NEST. Moreover, the RSE Lab system has long charging and discharging periods. The tank temperature model mainly deviates from the true behaviour when the temperature in the TES reaches its peak. The tank temperature model (I) drifts off as the simulation time increases, particularly when the HP is operated in cooling mode. The reason is a delay of the HP states of one time step (i.e., 15 minutes) introduced by the conversion from 1 to 15 minutes. The HP states are only presented for model (II) because the behaviour is similar to model (I). The NEST model, with its large GSHP and frequent periodic tank charging and discharging behaviour, only shows some deviations from the true system behaviour for long-term operations of the HP. The tank temperature model for heating and cooling modes performs similarly.

5. Conclusion

Key to the model design and evaluation process was the ease of model interpretation provided by the methods used. The transparency ensures the choice of stable and intuitive models. The results show that the methodology can be applied to systems with different scales which indicates transferability. The decoupled hybrid model has proven to be more suitable for use in an optimal control framework. It provides good performance for short-term prediction and long-term simulation. In contrast, the fully data-driven dynamic model suffers from a delay of the HP dynamics, leading to a drift of the tank temperature for long-term simulations. By manually assigning the HP-states one time step earlier for each iteration, the model can be used for predictive control. Additionally, linear first-order two-state tank temperature models show only slightly worse performance than the one-state model. To further improve model accuracy, non-linear features can be added.

In the future, extended tank temperature two-state models would allow for a more accurate state-of-charge estimation. Additionally, a more detailed model evaluation analysis consisting of complexity, sample efficiency, and prediction error analysis can be used to evaluate the benefits and drawbacks of non-linear features in detail. Lastly, to enhance the robustness of the conclusions regarding the transferability of the modelling approach, future work includes investigations on more systems with heterogeneous configurations such as different sizes and

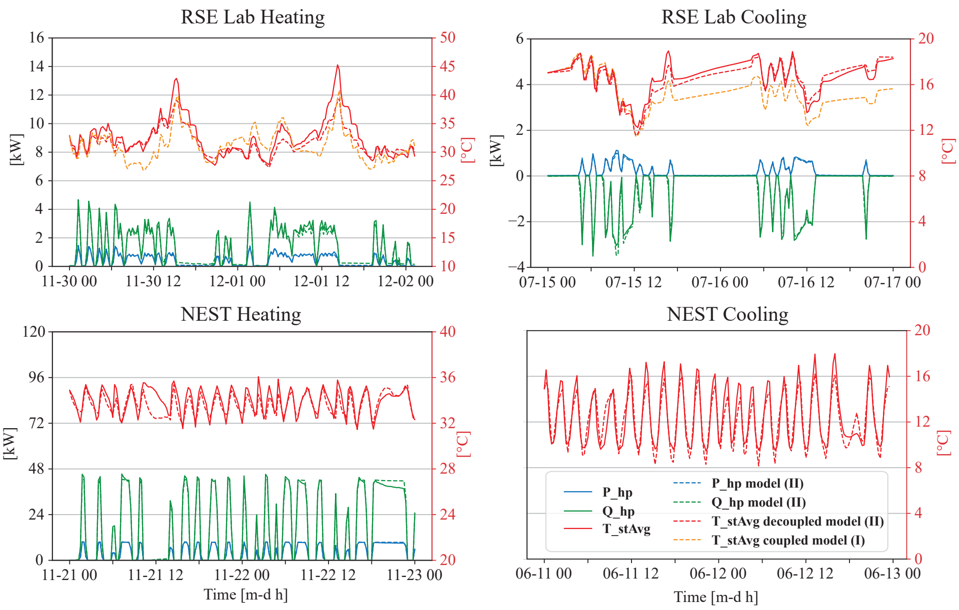

Figure 4: Simulation performance of the coupled fully data-driven dynamic model (I) for RSE Lab and decoupled hybrid mixed model (II) for both case studies in the heating mode

heat injection setups for thermal energy storages.

Acknowledgments
This research has been conducted within the SWEET PATHFNDR project funded by the Swiss Federal Office of Energy SFOE (grant Nr. SI/502259-01).

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