MODEL-PREDICTIVE CONTROL OF A RESIDENTIAL HEATING SYSTEM WITH MACHINE-LEARNING BASED MODELS, FORECASTS AND SIGNAL-PROCESSING

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Overview

The conversion of space heating for private households to climate-neutral energy sources is an essential component of the energy transition, as this sector as of 2018 was responsible for 9.4 % of Germany's carbon dioxide emissions [1]. In addition to reducing demand through better insulation, the use of heat pumps fed with electricity from renewable energy sources, such as on-site photovoltaics (PV) systems, is an important solution approach.

Advanced energy management and control can help to make optimal use of such heating systems. Optimal here can e.g. refer to maximizing self-consumption of self-generated PV power, extended component lifetime or a grid-friendly behavior that avoids load peaks. A powerful method for this is model predictive control (MPC), which calculates optimal schedules for the controllable influence variables based on models of the system dynamics, current measurements of system states and predictions of future external influence parameters.

In this paper, we will discuss three different use cases that show how artificial intelligence can contribute to the realization of such an MPC-based energy management and control system. This will be done using the example of a real inhabited single family home that has provided the necessary data for this purpose and where the methods are implemented and tested. The heating system consists of an air-water heat pump with direct condensation, a thermal stratified storage tank, a pellet burner and a heating rod and provides both heating and hot water. The house generates a significant portion of its electricity needs through a rooftop PV system.

Methods

For the realization of a model predictive control, methods from the field of machine learning were now applied in a threefold way:

1. The considered heat pump is very complex due to the special design of direct condensation and difficult to represent by physical models. Therefore, a hybrid modeling approach was used, combining manufacturer's look-up tables with long-short-term memory (LSTM) neural networks. This model is used for off-line simulations of the heating system as well as a basis for model predictive control.
2. Among other inputs, the model predictive control needs predictions of future heat consumption as input variables in order to be able to optimize the heat supply and use of the intermediate storage tank accordingly. Based on extensive historical measurement data, the random forest approach was used to create a predictor that provides the desired heat load predictions.
3. The data-based modeling of the heating system also requires the correct recording of heat outflows from the heat storage tank. Unfortunately, the corresponding measurements for the retrieval of hot freshwater for shower or kitchen were strongly disturbed by electromagnetic coupling of other measurement signals. Here a decision tree approach was chosen to clean the freshwater signals offline, and then also for cleaning the live freshwater data online.

The programming of the methods presented above was done in Python using the machine learning library KERAS [2] and the optimization and MPC environment CasADi [3] Methodologically, the work builds on numerous prior works where artificial intelligence methods have already been used to model and control heating systems, e.g. Géczy-Víg used a MLP neural network for modelling the layer stratification temperatures in a storage tank of a solar thermal system [4]. Gilani et al., developed a hybrid black box-greybox model based on ANN to characterize thermal responses in a test cell aimed for HVAC MPC [5]. Antão et al. described a technique for identification and model predictive control of non-linear systems with ANNs based on the Tensor Flow framework [6].

Results

For the modelling of the stratified storage, attempts with existing physical models have not shown satisfying results so that it was decided to use a hybrid model that makes use of machine learning techniques. The hybrid model consists of an LSTM based neural network for the thermal storage system. This is coupled with a linear regression model for the heat pump since the thermal output power is not an available measurement.

Simulations based on the model show good agreement with the measured values, with an RM SE of 1.923 for Winter, and an RMSE of 1.060 for Summer, see Fig. 1. The model is a suitable predictor for the given states and depicts accurately the non-linear behavior of the system.

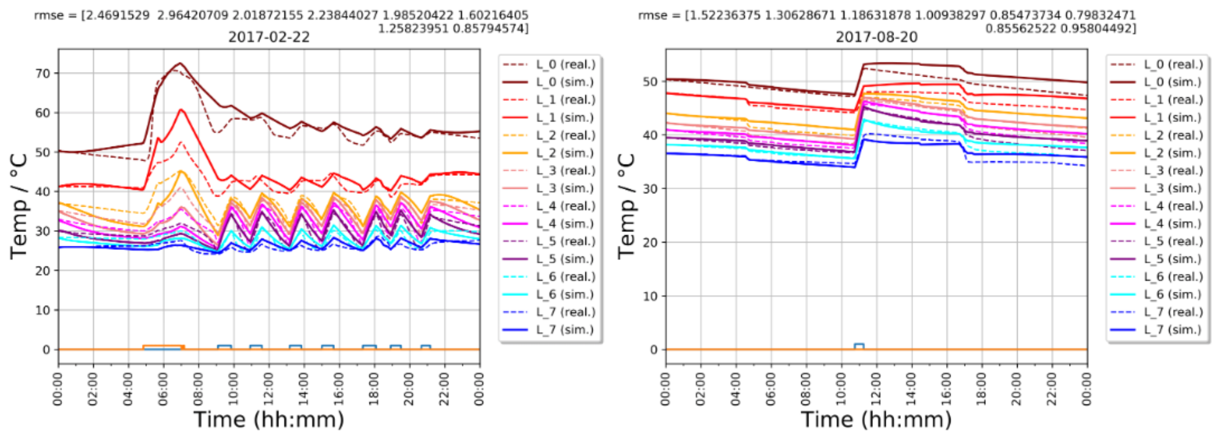

Figure 1. Simulation with one step ahead prediction. Depicted are the real vs. predicted values with the LSTM-ANN model. The starting conditions are the temperatures at the beginning of each day. On the left, a winter day simulation is showcased, on the right a summer day.

For the thermal load forecasting two random forest models were developed. The R2 score of the prediction on the test data of 2017 resulted in 43.2% for the conventional heaters with an RMSE of 0.236, and 73.1% for the underfloor heating with an RMSE of 0.707. These results show that a good relation exists between the ambient temperature and the underfloor heating, the model was able to capture in a good sense the given parameters. For the heater's case, the accuracy was lower, showing that a better feature set should still be determined or other modeling approaches should be explored. However, the models were deemed good enough for the given purposes.

The decision tree model for handling the data disturbances show the correct removal of the noise signals such as negative values in "square" shaped noise, and other random noise. The accuracy of the model is 99% with 98.2 % true positives and 1.77% of true negatives in the test set

Conclusions

The practical use of Machine Learning algorithms for modelling, prediction and optimal control of an energy system was demonstrated. The models demonstrated good accuracy while showing suitalble complexity and have thus proved to be a good option for the implementation of complex energy management applications such as MPC. The application of Machine Learning methods is increasing in many fields of the energy sector. This work demonstrated that Machine Leaning can also be applied for advanced control of energy systems and that Machine Learning can help to implement MPC in real applications.

References

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