Self-Adapting Building Models and Optimized HVAC Scheduling for Demand Side Management

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ABSTRACT

The capacity of renewable power sources and especially intermittent sources like wind and PV is steadily increasing. The existing balance between production and consumption is seriously affected by these new sources. Flexible demand for example in buildings is one solution to come back to a stable system. Flexibility in buildings can be achieved by using model predictive control (MPC) with optimized scheduling for the buildings' heating, ventilation and air conditioning (HVAC) systems. Two approaches for self-adapting building models are discussed in this paper as well as different algorithms for optimization of HVAC schedules.

The two approaches for self-adapting models can be differentiated by their mathematical structure. The neural network (NN) approach is called "black-box" model. In contrast to that, the "white-box" model is a system of differential equations derived from building physics. Both models are developed to be used in model predictive control to forecast the building's thermal behavior.

Once the thermal behavior is predictable, the optimal schedule at minimal costs for the HVAC systems has to be determined with respect to thermal comfort. A schedule for HVAC components contains the information, in which time step which component is on or off. Therefore, a binary integer programming problem has to be solved.

INTRODUCTION

The increasing share of fluctuating electricity production by renewable energy evokes an increasing requirement for energy storage and demand response capacities. Recent studies revealed a considerable potential for demand response in non-residential buildings [1]. This potential mainly is connected with the thermal inertia of the buildings. This thermal inert mass could be used as storage for thermal energy. If surplus of wind energy for instance leads to low electricity prices, electrical heating systems are operated at peak load to charge the building with thermal energy. Typically, the heavier the fabric of a building is the more energy can be stored. Charging a building means in this case to raise the temperature of floors, walls and ambient air. The optimization process is necessary to find out when the HVAC systems have to operate to charge the building at minimal costs. The solution of this process is the optimal schedule for the HVAC components.

Depending on the electricity price, the MPC calculates the optimal schedule for the HVAC systems of the building with an iterative method. To provide thermal comfort inside the building, the thermal behavior of the building is predicted with a model for each optimization step. The optimized schedule is then applied to the HVAC systems of the real building. Figure 1 provides the schematic configuration of the investigated system.

Different buildings show different thermal behaviors, caused by different materials and structures. Consequently, for every individual building an individual model has to be made. To reduce the effort for modeling of different buildings, adaptive models are developed. These models have a universal structure and are shaped by fitting them to input-output-data. Input data are e.g. weather data and control signals of HVAC systems, the output signal is the room temperature.

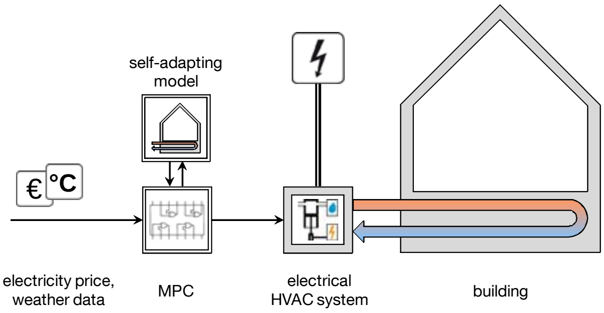

Figure 1: MPC for electrical HVAC systems

SELF ADAPTING MODELS

Initially, a detailed building model implemented in the simulation software TRNSYS generates the training data for the neural network. During the training process, the parameters of the model are adjusted. In contrast to previous publications [2], [3], [4], the neural network is trained with a parallel instead of a serial-parallel structure.

Although with a serial-parallel structure model, like the mostly used Nonlinear AutoRegressive model with eXternal inputs (NARX model) good results were shown for a prediction horizon up to 4 hours [2], prediction of more than one time-step (simulation) with this kind of model structure is expected to lead to a bias error, because of the different set ups during training and prediction [5]. Hence, for simulation a parallel structure like the Nonlinear Output Error (NOE) model is preferred in dynamic system identification [6]. Using a NOE configuration requests a dynamic NN to be used instead of a static NN, because of the feedback of the NN's output to its own input. Training dynamic NN is much more difficult because dynamic gradient calculation like Real Time Recurrent Learning (RTRL) or Back Propagation Through Time (BPTT) has to be used instead of the standard Back Propagation (BP) algorithm [7], [8].

Since the purpose of using the trained neural network model of our building is to implement it in a model predictive control with the aim to optimize costs depending on the flexible electricity rate for at least the next day, it should provide reliable results for simulating the next 24 hours. To accomplish that, it is necessary to use a parallel model structure.

The training process is successful, if the original model and the self-adapting model show approximately the same behavior during later simulations.

To generate data for the first training phase, the TRNSYS building is simulated for 26 days with the implemented control of HVAC systems. Figure 2 shows the result of simulating the neural network model for the next two days by using the standard controller compared to the performance of the TRNSYS model. The deviation between both simulated room temperatures is always less than 1 K.

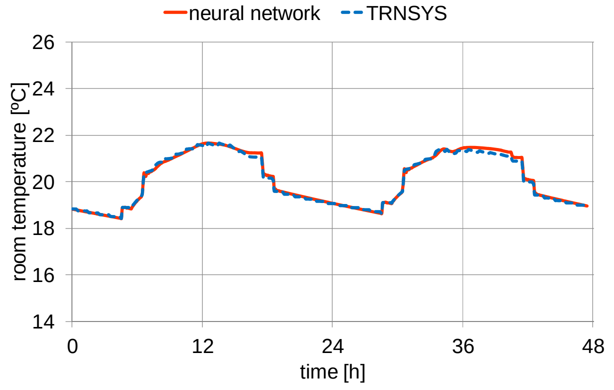

Figure 2: Simulation results under standard conditions and standard test data

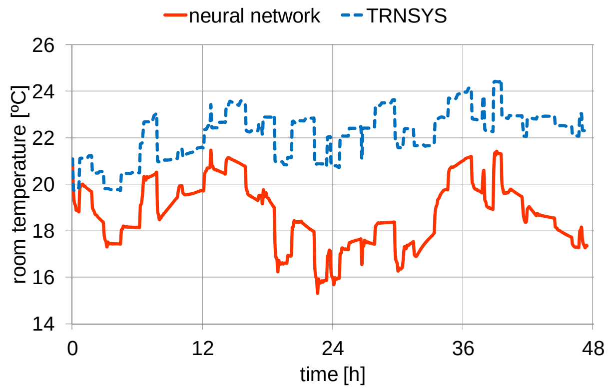

Figure 3: Simulation results under standard conditions with random test data

Additionally, the performance of the neural network is tested by using test data, which is generated with a different operation mode of the building technology. Figure 3 shows the results of the same trained neural network as before, now with the test data of the "new" operation mode. Because this test data contains correlations and values that are not included in the training data, the results are very poor.

The deviation between the simulation results could be lowered by using a wider range of training data. This data includes unconventional operation modes of the HVAC-Systems. While other conditions are left as mentioned before, satisfying results are delivered (Figure 4).

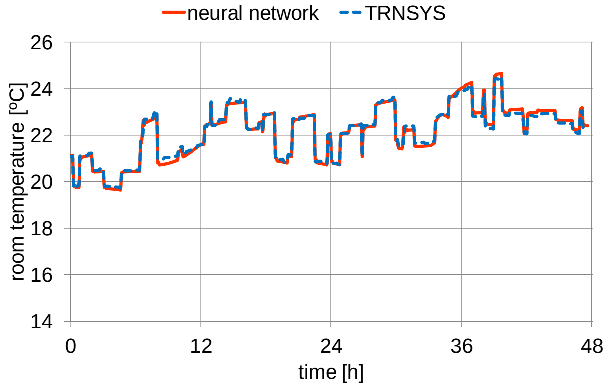

Figure 4: Simulation results under random conditions with random test data

In the ongoing investigation the neural network approach is compared with a white-box model with regard to adaptation time and deviation of simulation results. This model consists of several coupled energy balances, taking into account the internal energy of thermal masses [9]. The universal structure of this set of energy balances shapes a state space model with identifiable parameters [10]. The initially unknown parameters (e.g. masses, heat capacities, heat transfer coefficients) in the system of energy balances are estimated in a system identification process [11]. Figure 5 shows the first results for parameter identification with a state space model. In this case, the model has been trained with the data of one week. Training data on the input side are weather conditions and control signals, the only output signal is the room temperature. The number of signals on the input and output side defines the dimension of the state space model.

This white box model had to adapt the same TRNSYS simulation model as described above. The results of the original TRNSYS model and the adaptive white box model are shown in Figure 5. The deviation between both graphs is mostly significantly below 0,5 K.

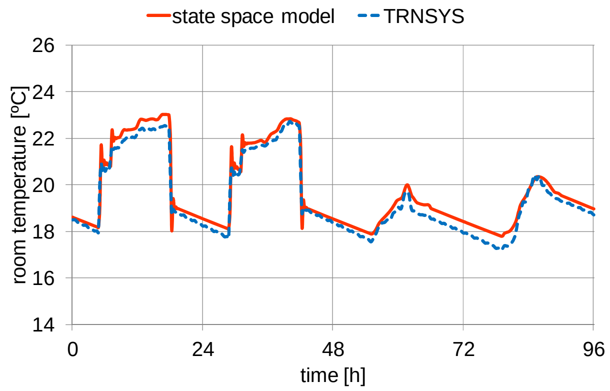

Figure 5: Simulation results, state space model

The preliminary results show, that neural networks need a wide range of training data to reproduce the buildings' thermal behavior. Subject of further investigations is to find solutions (e.g. combination of white- and black-box model) for shortening adaptation time and minimize the range of necessary training data.

OTIMIZATION OF HVAC SCHEDULES

Besides the development of adaptive building models, optimization is a main part of a model predictive control. It calculates an optimized schedule for electric HVAC systems like a heat pump or a chiller. The resolution of the optimization is 15 minutes, which leads to 96 binary variables per day. Each variable represents the state "on" or "off" for one timestep.

We started with a detailed TRNSYS-model of a single room. This office accommodates 16 employees and is equipped with active floor slabs for heating and cooling, radiators and ventilation. Thermal power is generated by a heat pump and a chiller respectively. Input parameters for the simulation are information on weather, occupancy, schedules for heating and cooling and a flexible electricity tariff.

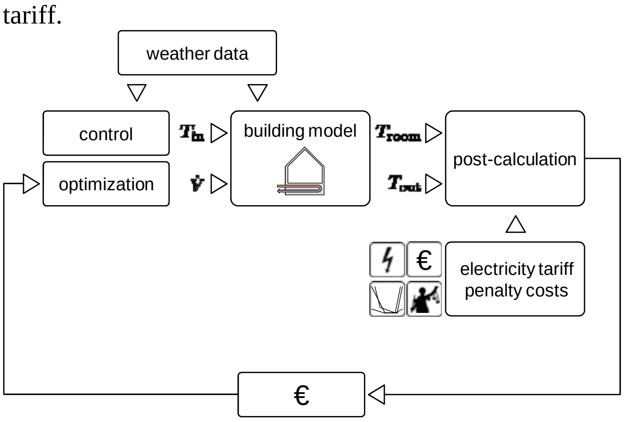

Figure 6: Schematic optimization process of the MPC

As can be seen in Figure 6, the optimization calls the building model with a certain set of variables, which represent the schedules. The building model simulates the building including the HVAC system and delivers a temperature profile and a load profile. The post-calculation, gives the total cost, depending on the flexible electricity tariff and a penalty function. In order to reduce the cost, the optimization algorithm varies the schedule and recalls the building simulation in an iterative process.

To gain first experience with optimizing heating and cooling schedules, GenOpt [12] and TRNSYS were used. To gain more flexibility, GenOpt was replaced by a self-developed optimization framework written in LabVIEW. Besides more influence on the optimization algorithm, it is possible to replace building model in TRNSYS by a self adapting model, as described before.

With this environment different optimization algorithms and penalty functions can be tested for different typical days. The results shown in Figure 8 are optimized with the Hooke-Jeeves algorithm [13].

The penalty function is shown in Figure 7. The blue graph defines the range of comfort, which is between 20 °C and 26 °C for this example. This function is called dead band (DB), because of its zero section. If the range of comfort is left, there are high penalties. We found out, that results might be improved by combining the DB-function with a value function that points on a particular temperature near the border of the range of comfort. For heating conditions the function is f(x)=abs(x-21). By adding up DB and the value function the penalty is calculated. It is applied only during working hours from 7:00 till 19:00 o'clock, to create a sort of night set back.

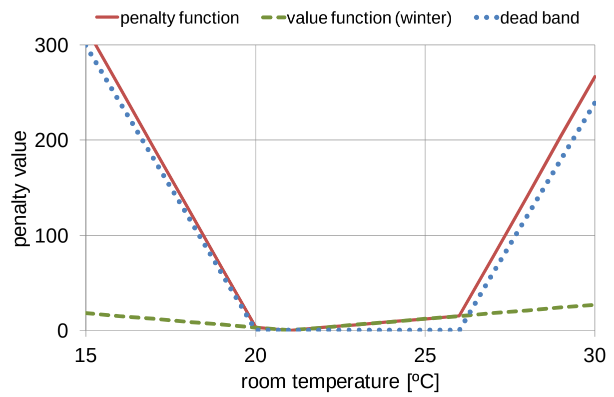

Figure 7: Penalty functions

Figure 8 shows the results for an optimized heating schedule for a Tuesday in winter. The heating power of standard operation is shown as blue area. The red area shows the resulting heating power of an optimized schedule. It can easily be seen, that the time of operation is shifted to the period of low electricity tariff, given in black. Optimized operation does not use radiators in contrast to standard operation where they run till 18:00 o'clock. With standard operation (blue curve), room temperature rises higher than for optimized operation (red curve). Due to less and well planned operation during periods of low electricity tariff, the optimization reduces costs by 47%.

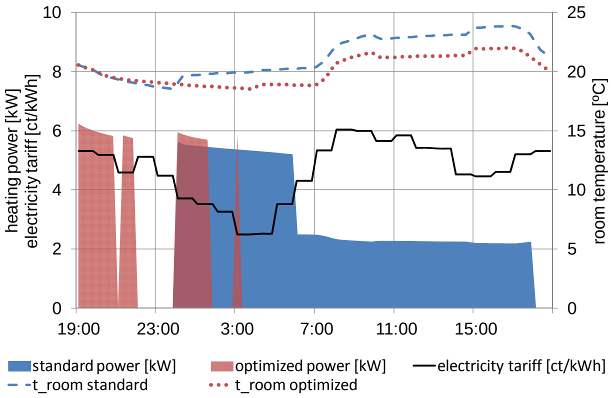

Figure 8: Results for scheduled heating

A major point for embedded building automation controllers is a good balance between computation time and optimization results. Therefore different optimization algorithms and penalty functions must be tested and compared. To optimize computational effort, a variation of the schedules resolution will be tested. This means that the resolution decreases with the forecast horizon. For example, if the resolution is reduced to one hour for the second half day, the number of optimization variables can be reduced from 96 to 60. A rolling horizon optimization of the schedules also has to be implemented as a further step.

SUMMARY

Both adaptive modeling approaches show promising preliminary results concerning their ability to reproduce a buildings thermal behavior. In contrast to physical models, neural network models need a wider range of training data. One disadvantage of physical models is the fact, that a basic structure of energy balances has to be predestined. Therefore, a minimum of knowledge about the modeled building is necessary. In contrast to that, the black box character of the neural network approach needs hardly any information about a building. As a consequence, it is assumed to be applicable for a wider range of objects. Concerning HVAC scheduling, the presented results show that costs can be minimized significantly by Hooke-Jeeves algorithm. Nevertheless, more extensive investigations should deliver improved algorithms with shorter computation time. Finally, it is necessary, to test the separately developed approached for adaptive models and optimization algorithms in integrated systems.

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