Proceedings of BS2013:
13th Conference of International Building Performance Simulation Association, Chambéry, France, August 26-28

SELF-ADAPTING BUILDING MODELS FOR MODEL PREDICTIVE CONTROL

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ABSTRACT

The capacity of intermittent power 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. Buildings provide a huge potential for flexible electricity demand. This flexibility can be addressed by using model predictive control (MPC) with optimized scheduling for the buildings' heating, ventilation and air conditioning (HVAC) systems. Therefore, it is necessary to have detailed simulation models of each single building. To avoid the huge effort of setting up lots of different building models, two approaches for self-adapting building models are discussed in this paper. Those approaches can be differentiated by their mathematical structure. The neural network (NN) approach is called "black-box" model. In contrast to that, the physical "white-box" model is a system of differential equations with free parameters. These models are parameterized by measured data and 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 can be determined with respect to thermal comfort.

The investigations show, that the difference between the training phase and the prediction phase is decisive for the quality of the forecast. If test and training data are similar (e.g. same season), both models deliver satisfying results.

INTRODUCTION

The increasing share of fluctuating electricity production by renewable energy evokes an increasing requirement for energy storage and demand side management capacities. The adaptation of the buildings energy consumption to flexible energy price has a high potential for integration of renewables [1]. On the one hand, it decreases the necessity for expansion of the grid, on the other hand, consumers could benefit from lower energy costs. The potential for demand response in buildings is mainly connected with their thermal inertia. 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 construction 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 a flexible 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.

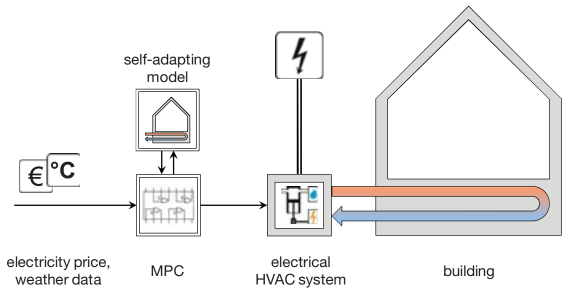

Figure 1: Concept for MPC application

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.

NEURAL NETWORKS

Neural networks (NN) are a black box approach of system identification. Black box models need hardly any information about the system. In the following section, an overview of theory and recent studies is given.

Theory and recent studies

In the last years numerous studies on modeling buildings thermal behavior with neural networks were published [2], [3], and [4]. Because of the nonlinear characteristic of the buildings thermal behavior, nonlinear model structures show satisfying adaptation results and are discussed in recent publications [5] and [6]. Nonlinear AutoRegressive model with eXternal inputs (NARX) models use the system output y as an input of the neural network during training, to learn the dynamic behavior of the system. Models with this configuration are called serial-parallel models.

Although the NARX models are supposed to be used for a one step prediction, it is possible to use them for simulation as an approximation (prediction of more than one time-step). But this is expected to lead to a bias-error, since they are not trained in that configuration [7].

This is why in dynamic system identification parallel models like the Nonlinear Output Error model (NOE) are preferred when the model is applied for simulation [8]. Because of the feedback and delay of the neural networks output $\hat{y}$ to its input, it transforms into a dynamic neural network. The neural network now depends on its own previous outputs as well as on its inputs. Training dynamic neural networks in a parallel configuration is much more difficult than training static ones in a serial parallel configuration. Dynamic gradient calculation like Real Time Recurrent Learning (RTRL) or Back Propagation Through Time (BPTT) has to be used for calculating the gradient of the dynamic neural network instead of the standard Back Propagation (BP) algorithm, which can used for static neural networks only [9], [10]. Figure 2 shows the difference between a parallel model and a serial-parallel model during the training. The shown Tapped Delay Lines (TDL) are used to delay the signals for any number of positive integral time steps (e.g. one TDL can delay one signal by the time steps 0,1,4 and 8; feedback signals have to be delayed by a time step higher than 0).

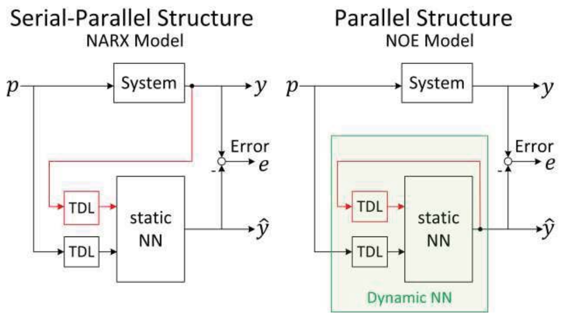

Figure 2: Difference between a serial–parallel model and a parallel model structure

In this context, the purpose is to apply the neural network model in the model predictive control for the HVAC systems. The aim is to develop the HVAC schedule at least for the next day. Therefore, the model should provide reliable simulation results for at least the next 24 hours. To accomplish that, it is necessary to use a parallel model structure.

In this work, in contrast to the previous publications, a nonlinear dynamic neural network with a NOE structure is used for modeling the thermal behavior of a building. The neural network was implemented within the Layered Digital Dynamic Network (LDNN) introduced in [10] and advanced and renamed (General Dynamic Neural Network, GDNN) in [9]. The schematic structure of the used NN is shown in Figure 3, where $\underline{p}$ is the system input, $\widetilde{IW}$ and $\widetilde{LW}$ are the input and layer weight matrices respectively, $\underline{b}$ is the bias vector and $\underline{\hat{y}}$ is the output. For calculating the output $\underline{a}$ of each layer the transfer function $\underline{f}(\underline{n}) = \tanh(\underline{n})$ is used. A detailed description of calculating the neural network output can be found in [9] and [10].

Application of neural networks for indoor climate simulation

The neural network has 7 inputs, two hidden layers with each 5 neurons and one output. The output has a feedback-connection to the first hidden layer, so that the outputs (state) of the last 4 time steps serve as additional inputs for the current time step. All direct inputs have a delay (TDL) of 0, 1, 2, 3 and 4.

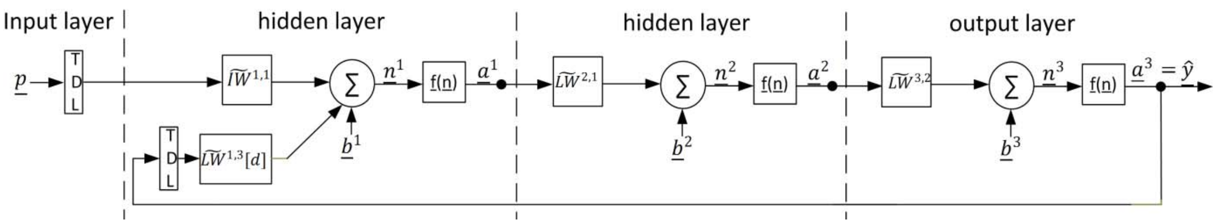

Figure 3: Schematic structure of the used NN

STATE SPACE MODEL

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 [11]. The universal structure of this set of energy balances shapes a state space model with identifiable parameters [12].

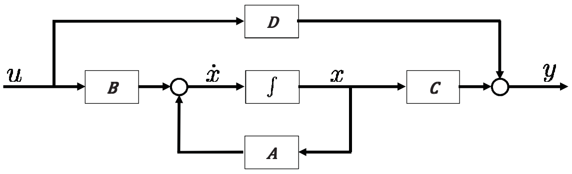

Figure 4: Block diagram for state space model

The equations below show the mathematical structure of a state space model.

$$\dot{\boldsymbol{x}} = \boldsymbol{A} \cdot \boldsymbol{x} + \boldsymbol{B} \cdot \boldsymbol{u}$$
$$\boldsymbol{y} = \boldsymbol{C} \cdot \boldsymbol{x} + \boldsymbol{D} \cdot \boldsymbol{u}$$

The variables have the following meaning:

$\boldsymbol{x}$ = state vector, e.g. storage temperatures
$\dot{\boldsymbol{x}}$ = derivative of state vector
$\boldsymbol{y}$ = output vector, e.g. room temperature
$\boldsymbol{u}$ = input vector, e.g. heating power, ambient temperature
$\boldsymbol{A}$ = system matrix
$\boldsymbol{B}$ = input matrix
$\boldsymbol{C}$ = output matrix
$\boldsymbol{D}$ = feedthrough matrix

The vector $\boldsymbol{x}$ represents the states of a system. Concerning the thermal behavior of a building, the state is quantified by the temperatures of the thermal storages. In the example presented below, the storages are the thermal mass of the buildings fabric and the thermal mass of the heating system. The input signals of the system are summarized in the input vector $\boldsymbol{u}$. In this case, input signals are weather conditions (e.g. ambient temperature, solar radiation), control signals (e.g. inlet temperatures, mass flows) and occupation. The only output is the room temperature. Therefore, the output vector $\boldsymbol{y}$ degenerates to a scalar. The interactions between the storages, the inputs and outputs are characterized by the parameter matrices $\boldsymbol{A}$, $\boldsymbol{B}$, $\boldsymbol{C}$ and $\boldsymbol{D}$. The components of these matrices represent physical parameters like masses, heat capacities, heat transfer coefficients etc. The values of these parameters are estimated in a system identification process [13]. The number of signals on the input and output side defines the dimension of the state space model.

COMPARISON OF NEURAL NETWORK AND STATE SPACE MODEL

In this section, the two different self-adapting building models are compared. The adaptive models have to reproduce the thermal behavior of a simplified building which consists out of one room. This building is modeled in the simulation software TRNSYS and is used as a data generator instead of a real building. This TRNSYS model delivers the room-temperature for the single-zone-building depending on different external and internal influences. The main characteristics of this model are illustrated in Figure 5.

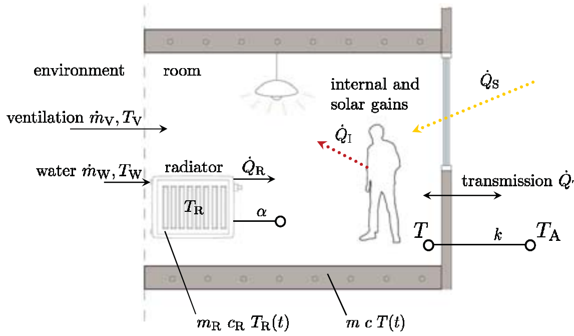

Figure 5: Single-zone-building as data generator

In detail, the following input and output signals were created by the TRNSYS model and used for the model comparison, Table 1.

Table 1: Model inputs and output

	description	type
$\dot{Q}_{\mathrm{S}}$	horizontal radiation	
T_{A}	ambient temperature	
$\dot{Q}_{\mathrm{I}}$	internal gains	
$\dot{m}_{\mathrm{W}}$	radiator water flow rate	inputs
T_{W}	radiator inlet temperature	
$\dot{m}_{\mathrm{V}}$	supply air flow rate	
T_{V}	supply air temperature	
T	room temperature	output

The room temperature was simulated as a function of the inputs for different seasons. During the estimation process, input data and output data from the TRNSYS model was fed to both adaptive models for a limited time period, e.g. for one month. The free model parameters were determined to minimize the deviation between the room temperature simulated by the TRNSYS model and the output temperature of the adaptive models.
In the following part the results for different estimation and prediction periods are presented and interpreted. As comparison criterion the mean absolute error (MAE) between the room temperature $T_{Model,i}$ predicted by the adaptive model and the room temperature $T_{TRNSYS,i}$ simulated by the TRNSYS model was calculated for each prediction

period. The mean absolute error is calculated by the following formula:

$$MAE = \frac{1}{n} \cdot \sum_{i=1}^{n} \left| T_{Model,i} - T_{TRNSYS,i} \right|$$

Every prediction period consist of discrete time steps i with a length of 15 minutes. The total number of time steps of one period is denoted by n.

The following diagram shows the temperature curves for four days in March (Thursday, Friday, Saturday and Sunday). In this case, the TRNSYS generated data of all days in March were used for parameter estimation.

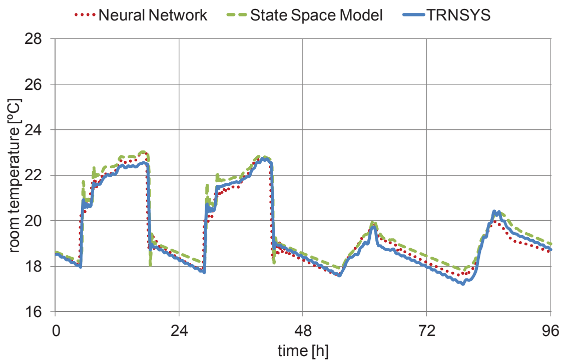

Figure 6: Estimation in March, Prediction for March

Over the whole period of 31 days, the deviation between the simulated temperature and the predicted temperatures is very low. The medium average error between the TRNSYS model and the neural network is 0,3 K and 1,3 K for the state space model, respectively.

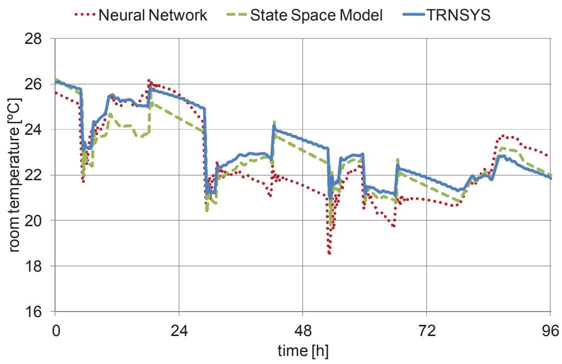

Figure 7: Estimation in March, Prediction for April

The prediction error increases, if the adaptive models are estimated with the data of one month and are tested with the input data from another month. Like in the previous case, both models were estimated with the TRNSYS data of March. But in this case, the adaptive models have to predict the room temperature for April. To illustrate the results for April, the temperature curves from one Thursday to Sunday are shown exemplarily. The MAE increases to 1,4 K (NN) and 2,58 K (SS). The prediction error is relatively low thanks to the reason, that March and April are both part of the same season. In one season, the operation modes of the HVAC systems and the ambient temperatures lie in a narrowly limited range. It is possible for both adaptive models to identify parameters, which are valid for one whole season.

The next example shows, that significant problems appear, when the time periods of estimation and prediction lie in different seasons.

The temperature curves shown in Figure 8 represent the results for September of adaptive models trained in March. The prediction error in this case is above an acceptable level, but not extremely high. The mean absolute error is 3,0 K (NN) and 4,8 K (SS).

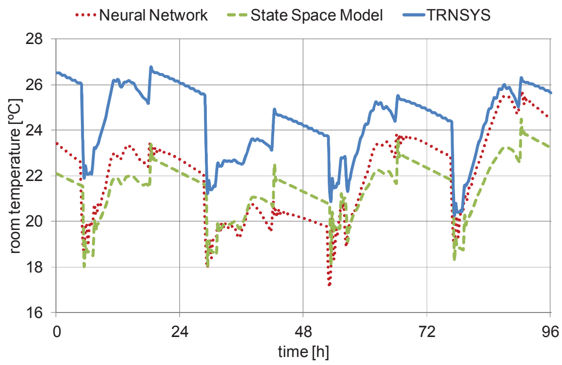

Figure 8: Estimation in March, Prediction for September

The prediction error could be lowered by enlarging the training period from one month to one year. For the results shown in Figure 9, the adaptive models had to predict the temperature for September as described in the example above, but were estimated with TRNSYS data of one year. Thus, the estimated models show acceptable predictions for a large horizon. By extending the estimation period to one year, the prediction error was reduced by approximately 50 % compared to the previous example. The mean average error is 1,1 K in case of the neural network an 2,4 K for the state space model.

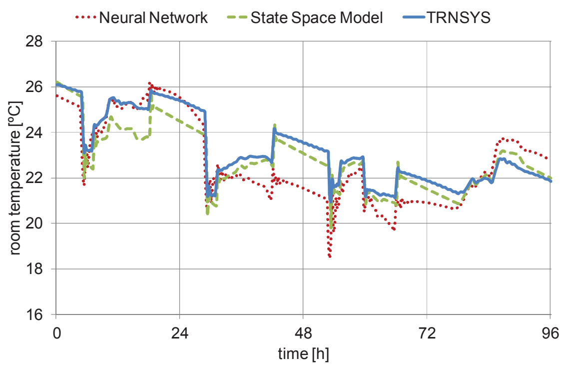

Figure 9: Estimation during one year, Prediction for September

The discussion above focused on the prediction error as comparison criterion. In future applications, the necessary calculation time to estimate a models parameter might be interesting. At present, both adaptive models were tested on common personal computers. In case of the state space model, the time required for determining the models parameters laid always below half a minute. In contrast to that, it took up to half an hour to adapt the neural network.

CONCLUSION AND OUTLOOK

The results show, that the two approaches are generally able to reproduce a building's thermal behavior. The quality of the room temperature forecast is significantly depending on the set of input data used for the training period of the model. If the training had similar conditions as the test phase, the outputs of both models deliver a good forecast for the indoor temperature. With these trained models, a model predictive control could be able to optimize the operation times of the HVAC system. This optimization allows the building to react to different internal or external signals, for example a flexible electricity tariff or own consumption of renewables.

At the moment especially the neural network shows significant deviations, when the conditions for testing vary considerably from the training conditions. Because of its physical background, the state space model generates qualitatively good results, even if the test conditions differ very much from the training conditions. Anyway, the forecast error is above the acceptable tolerance range.

Both approaches have very different characteristics: One advantage of the neural network is its flexibility. It needs hardly any information about the building and its building services to reproduce the thermal behavior. But it delivers results of low quality, if the training period varies from the test period. The state space model has a physical structure, which defines a certain framework of parameters. It needs general information about the building and its building services. This means, little adaptations are necessary for each single building. In contrast to the neural network, a state space model delivers qualitatively good results for a wide forecast range.

With both approaches having different advantages a combined model could be very helpful. The further investigations should analyze how to implement the best aspects of the two models into one hybrid model. The presented adaptive models only predict the thermal behavior, respectively the indoor temperature of a building. New outputs to be predicted could be added to the models, to increase the quality of the forecast. For example humidity or concentration of CO_2 in the indoor air could improve future investigations.

In the ongoing scientific project the model predictive control will be implemented in a real building. This pilot experiment should validate the theoretical results and could form the basis for buildings to play an active role in a future renewable energy system.

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