COMPARISON OF DIFFERENT META MODEL APPROCHES WITH A DETAILED BUILDING MODEL FOR LONG-TERM SIMULATIONS

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ABSTRACT

If detailed building models are applied for long-term simulations, for instance the prediction of the future energy demand under climate change, the computational effort can turn into a serious issue. Machine learning algorithms like Neural Networks (NN) or Support Vector Machine (SVM) could be an alternative. In this work a possible application of NN and SVM for long-term forecasts are proven and their limitations are presented. In the examined case study, with a simulation period over 30 years, the SVM is hundred fifty times and the NN ten times faster than a detailed building model. This reduction of computational effort can be useful for further studies as a uncertainty analysis of climate change.

INTRODUCTION

Buildings are responsible for 40% of all energy consumption and 36% of total CO_2 emissions in Europe (EU-Council 2010). These facts make the building sector very important for any kind of climate change mitigation strategies. To develop measures for energy and CO_2 reduction of buildings, special tools and calculation methods are necessary.

In the field of calculating the energy demand of buildings different kinds of model approaches are in use. The common models represent well-defined physical phenomena and properties. Most of the available software tools are able to handle the physical behaviour of the building combined with different types of HVAC systems. If these models are applied for long-term simulations, for instance the prediction of the future energy demand under climate change, the computational effort can turn into a serious issue. This is important when further analyses for sensitivity and uncertainty are deployed. For this reason it is necessary to use techniques with low computational effort combined with the ability to provide detailed results for energy demand and thermal behaviour of buildings. Machine learning algorithms could be a method to develop a meta model, which can provide detailed results with reduced computational effort.

In the field of building simulation, the most widely used algorithms are neural networks (NN) and support vector machines (SVM)

(Zhao and Magoulès 2012, Jain, Smith et al. 2014). The most common applications of NN and SVM for buildings are short term forecasts of heating, cooling and electric loads (González and Zamarreño 2005, Karatasou, Santamouris et al. 2006, Kavaklioglu 2011, Mustafaraj, Lowry et al. 2011, Zhang, Hong et al. 2012, Zhao and Magoulès 2012).

The primary objective in this paper is to assess the capability of neural networks and support vector machines for long-term simulations. This is going to be implemented with a comparison of the results with a detailed building simulation model.

METHODOLOGY

Neural Networks

There are many different kinds of neural networks. For the short term prediction of thermal behavior of buildings, a nonlinear autoregressive model with external inputs (NARX) are often used (Ferreira, Ruano et al. 2012). This kind of models are called serial-parallel models. A special characteristic of a NARX model is that a time delayed output of the system (for example the building) is used as input for the neural network. But for a long term prediction this model structure leads to a bias error (Isermann and Münchhof 2011).

To simulate a nonlinear dynamic system, like the thermal behavior of a building, a Nonlinear Output Error (NOE) model is more reliable (Nelles 2001). The NOE has a parallel model structure which uses the model output, but not the system output as input for the neural network. A detailed description of NARX and NOE models and their application in building simulation can be found in (Endisch 2009, Jungwirth 2014). In this paper a nonlinear dynamic neural network with NOE structure is used to develop a meta model of a building. The neural network was implemented as a General Dynamic Neural Network (GDNN) (Endisch 2009).

SVM

Support Vector Regression (SVR) is a version of SVM for regression estimation, which is necessary for problems in the field of building simulation. In this paper, an epsilon-SVR model is used to be consistent with previous literature (Jain, Smith et al. 2014). For the kernel function the Gaussian radial basis function (RBF) is chosen because the RBF is one of most widely used kernel functions (Zhao and Magoulès 2012). If the RBF is chosen, the parameter Cost (C), Epsilon (ε) and Gamma (γ) are user-defined variables. This three variables have a significant influence on the SVR outcome. In our work, the variable Gamma is defined by $γ = 1/k$, where k means the number of inputs. For Cost and Epsilon a parametric study was carried out (see section "Support Vector Machines"). The epsilon-SVR model was implemented with the statistical Software R (Team 2014) and the cran package "e1071" (Meyer, Dimitriadou et al. 2014).

Simulation approach

As a first step a detailed building model was developed using the software IDA ICE (Sahlin, Eriksson et al. 2004). The exemplary building is a multi-story dwelling. One zone at the fifth floor on the southwest corner was chosen for the further analysis (Figure 1). Based on the zone model of IDA ICE the influence of climate change on room temperatures und heating demand was analysed. The climate projection, which was used as input for the building simulation, is based on a regional climate model (REMO) (Jacob, Göttel et al. 2008) and focused on the region of Munich. To make the simulation results comparable, the climate data were split in four periods. The period 1970 – 2000 represents the current state and the periods 2000 – 2030, 2030 – 2060 and 2060 – 2090 demonstrates the future climate. The results of this analysis with IDA ICE provide the learning and test data for the machine learning algorithms.

Figure 1: Building model in IDA – ICE

In a second step, a sensitivity analysis for the weather variables was executed to detect the necessary input parameters for the NN and SVM. For the sensitivity analysis, the elementary effect method was used for detailed information (Morris 1991, Burhenne 2013).

The following weather variables were assigned with a normal distribution for every time step with a standard deviation of ± 10% :

- Ambient temperature (TAir)
- Relative humidity (RelHum)
- Direct normal radiation (DirNorm)
- Diffus horizontal radiation (Diff)
- Wind direction (WindD)
- Wind speed (WindS)

With sobol sampling a sample matrix with 100 runs was executed. The objective variables for the sensitivity analysis were heating load and overheating hours.

A parametric study was performed to define the setup for the neural network. Hence, the input parameters, the number of neurons in the hidden layers and the time delay of in- and output were varied. The test and learning phase for the parametric study was one year. After detecting the optimal parameter settings, the GDNN was trained over the period 1970 – 2000. To evaluate the ability of long term forecasting the periods 2000 – 2030 and 2060 – 2090 were used as test periods. The results of the output variables, room temperature and heating load were compared to the results of the detailed zone model from IDA ICE.

The same input variables for the GDNN were also used to develop the SVM model. To make the SVM more comparable to the GDNN, different models with and without external recurrences were analyzed. Afterwards a parametric study for the variables Cost and Epsilon were carried out. Then the developed SVM was trained over the period 1970 – 2000 and the same study was carried out as for the GDNN.

Performance criteria

The coefficient of variation (CV - RMSE) and the root mean squared error (RMSE) was utilized as the performance metric in our analysis to compare the quality of the models. Also the mean forecast error and the absolute forecast error per time step was applied.

$$CV\_RMSE = \frac{RMSE}{\bar{y}} * 100 \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{2}$$

While y_i is the observed value from the zone model, $\hat{y}_i$ is the predicted value of the meta model; $\bar{y}$ is mean of the observed values and n is the total number of observations.

RESULTS AND DISCUSSION

Sensitivity analysis

The results from the sensitivity analysis of the weather variables are shown in Figure 2 and 3. The x-axis shows the expectation μ and the y-axis shows the standard deviation σ of the distribution of elementary effects. A high value of μ means a large influence of the variable on the model output. If σ is high, a nonlinear behaviour of the variable and a major interaction with other variables occurs. Both results indicate an important role of the variables TAir, Diff and DirNorm. For that reason, they were chosen as input variables for the GDNN and SVM.
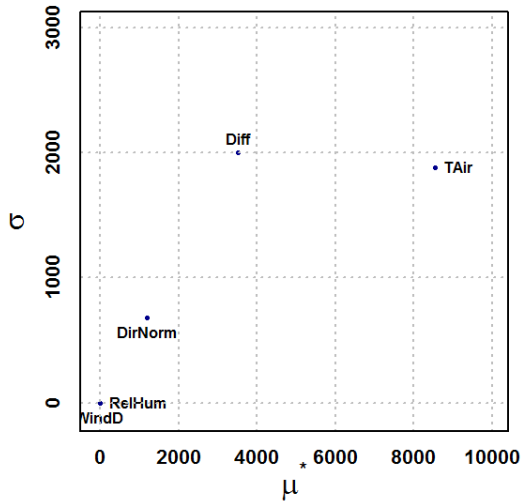
Figure 2: Results of the sensitivity analysis for the output heating demand
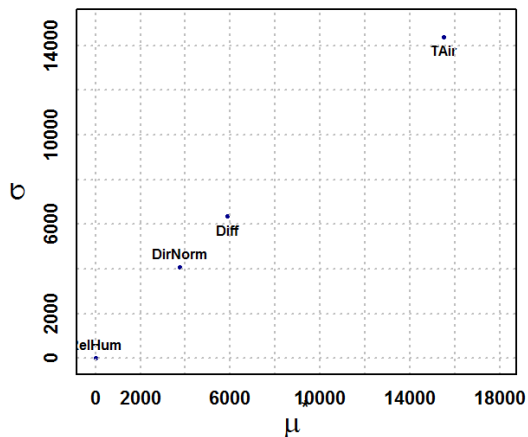
Figure 3: Results of the sensitivity analysis for the output overheating hours

Neural Network

Based on the sensitivity analysis three input variables were identified. The hours of the day [0-23] are also selected as input. This variable is represented by the sin (sh) and cosine (ch) of the daily hour as introduced in (Karatasou, Santamouris et al. 2006).
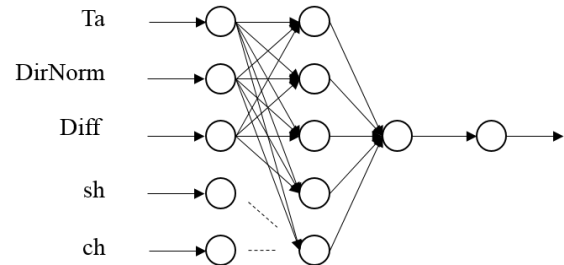

Figure 4: Schematic structure of the used neural network

The GDNN used for the parametric analysis has five inputs (Figure 4). There are also two hidden layers (h1 and h2). The first layer h1 has five neurons. The second layer h2 has one neuron. The output has a feedback-connection with the first hidden layer, with a delay of five time steps. All direct inputs have also a delay of five time steps. For the parametric study the output variable is the indoor temperature.

Parametric study

In Table 1, the variation and combination of input variables and their resulting CV and RMSE is summarized. It seems that the ambient temperature has the most influence on the model quality.

Table 1: Model quality by different inputs

Input parameter	CV-RMSE	RMSE
Ta, DirNorm, Diff, sh, ch	0.81	0.17
Ta	2.49	0.55
Ta, sh, ch	2.25	0.49
Ta, DirNorm, Diff	0.92	0.20
DirNorm, Diff	6.92	1.53
DirNorm, Diff, sh, ch	8.18	1.81
sh, ch	9.97	2.20

To compare the maximum forecast error per time step, three combinations of inputs - ambient temperature (Ta), Radiation (DirNorm, Diff) and daily hour (sh, ch) - are defined (Figure 5).

It turned out that a model with Ta as the only input has only a maximum forecast error per time step of 2 [K]. If radiation (DirNorm, Diff) is chosen for input, the error is three times higher.
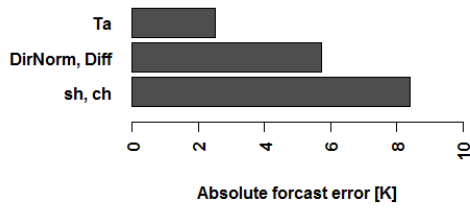

Figure 5: Maximal forecast error per time step by different input variables

Figure 6 confirms the large influence of the variable ambient temperature. This graph demonstrates the influence on the mean forecast error by removing different input variables from the model. The Figure shows if you remove the variables for daily hour (sh, ch) the mean forecast error just rises up to 15 %. But if ambient temperature (Ta) is eliminated from the model input, the error increases up to 750 %.
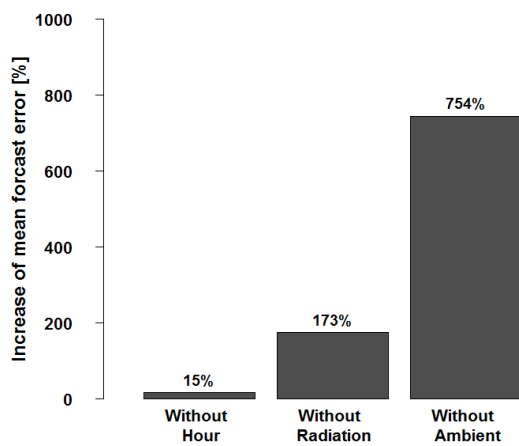

Figure 6: The influence on model quality by reducing different kind of inputs

In a next step, the GDNN structure was analysed. Therefore the number of hidden layers was fixed to two and the number of neurons varied between one to ten. Figure 7 shows the mean forecast error depending on the number of neurons of the hidden layers one and two.

Based on this graphical evaluation the minimum forecast error is achieved if the number of neurons of the firs hidden layers is set to five or seven. If the amount of neurons in- or decreases on the first layer the variance of the mean forecast error becomes larger.
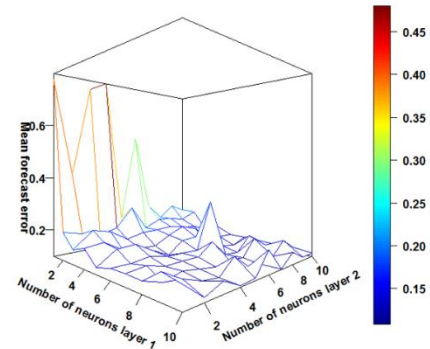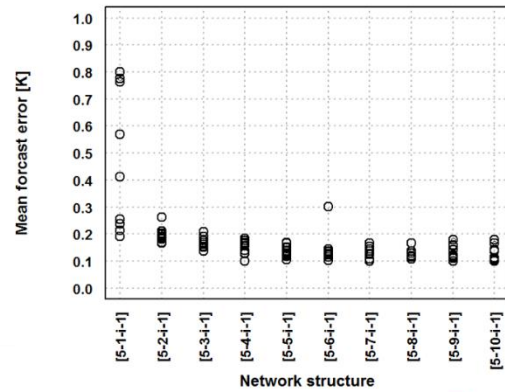

Figure 7: Analysis of the network structure by varying the number of neurons per hidden layer

To investigate the influence of the recurrences from the in- and output variables, three studies were undertaken. At first, all input variables got a delay from one to twelve time steps. Then only the output variable got different delays and after this both in- and output feedback-loops got a delay (Figure 8).
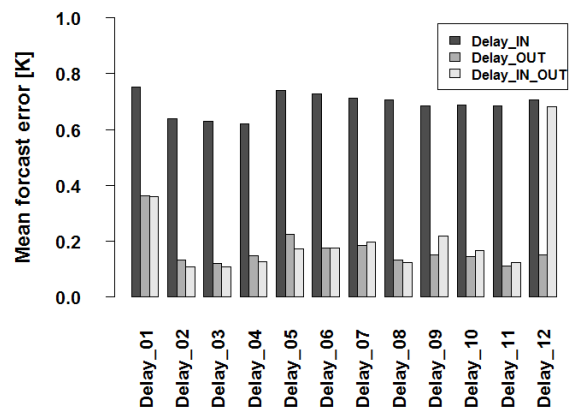

Figure 8: Influence on the mean forecast error by different delays of the input and output variables

Through comparison of the results in Figure 8 it becomes clear that a delay of the output variable has much more influence on the model quality than of the input variables. It is interesting to see that a delay of in- and output in combination, sometimes provides worse results compared to a delay only on the output variable.

Figure 9 shows the final results of the parametric study. The GDNN has two hidden layers with each of them having five neurons. The input and output variables have a delay of five time steps. The forecast error of the indoor temperature indicates reliable results for further investigations with a maximum of 0.9 [K].
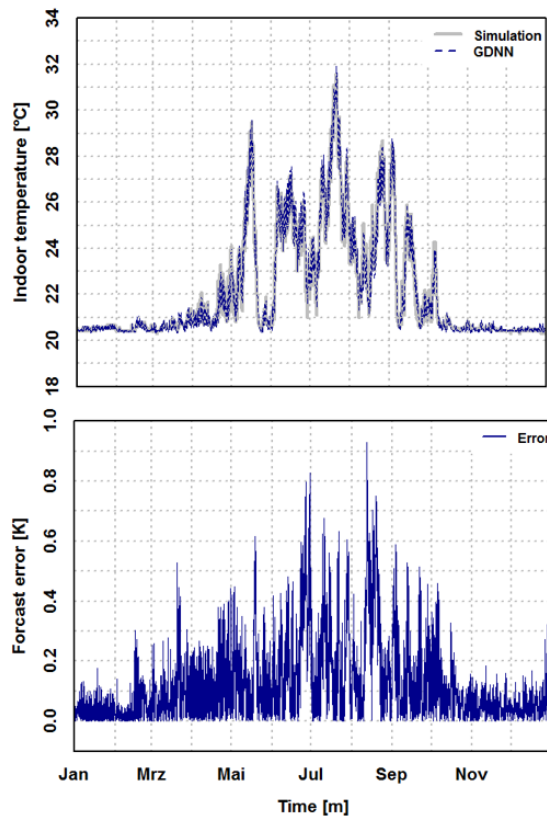

Figure 9: Results of the GDNN [5,5,5,1]_D5 with the output "Indoor temperature"

Long-term prediction of the GDNN

In a next step, the GDNN was trained over 30 years across the period from 1970 – 2000 and tested for the periods 2000 – 2030 and 2060 – 2090. For the period 2000 – 2030 the forecast offers usable results. The absolute forecast error of a time step is between 1.2 and 1.4 [K] (Figure 10). The results for the period 2060 – 2090 present an error of 6 [K], which is too large for a reliable analysis.

The reason for the increase of the error is probably caused by the large differences of weather data from the learning and testing phase. The climate projection demonstrates an exponential rise of the ambient temperature. Therefore the difference between learning phase (1970 – 2000) and first test phase (2000 – 2030) is smaller than in the second test phase (2060 – 2090).
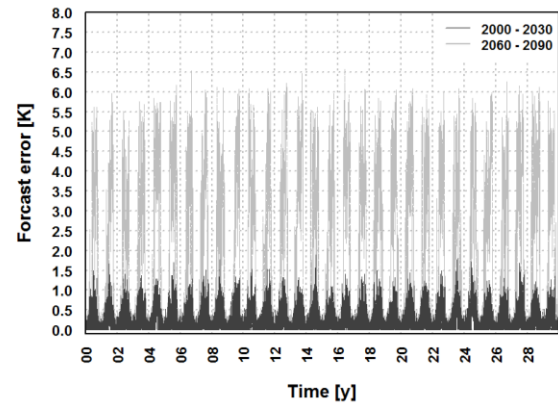

Figure 10: Absolute forecast error per time step for the output indoor temperature

The results for the output variable heating load are presented in Figure 11. The absolute forecast error rises during the period 2000 – 2030 up to 300 [W] and during the period 2060 – 2090 to 900 [W]. The difference of the energy demand for heating between the detailed zone model and the GDNN in the period 2000 – 2030 is 0.8%. Hence, between 2060 – 2090 there are is variance of 46 %.
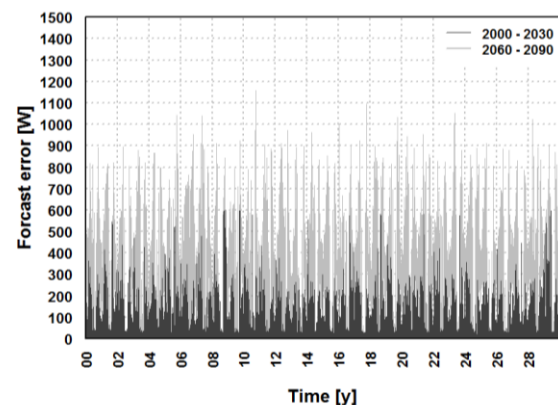

Figure 11: Absolute forecast error per time step for the output heating load

Support Vector Machines

With the structure of the GDNN it is possible to use internal recurrences for the input and output variables. In a standard Support Vector Regression there are no internal recurrences. Based on the results above, the information of the past time steps of the output has a remarkable influence on the model quality. For that reason SVR with and without external recurrences of the output $y(t)$ is analysed.

Table 2: Model quality by different inputs with and without external recurrences

Input parameter	CV – RMSE	RMSE
Ta, DirNorm, Diff, sh, ch	5.71	1.26
y(t − 1), Ta, DirNorm, Diff, sh, ch	0.49	0.10
y(t − 1), y(t − 2), y(t − 3), Ta, DirNorm, Diff, sh, ch	0.48	0.09

The results in Table 2 illustrate a model without external recurrences of the output $y(t)$, a model with one recurrence with a delay of one time step and a model with three external recurrences with a delay of one to three time steps. The recurrences have a large effect on the model quality. The improvement of the model quality between one and three external recurrences can be neglected. For that reason the model with one external input is chosen for the further analysis.

Parametric study

To improve the model accuracy a parametric study, based on a grid search of Epsilon (ε) [0,1] and Cost (C) [1,1000] was fulfilled. Figure 12 shows the results. Epsilon has a significant influence on the model quality (CV) for a detailed explanation of the meaning of ε and C see (Dong, Cao et al. 2005). For the further analysis Epsilon was chosen to be 0.083 and Cost to be 32.
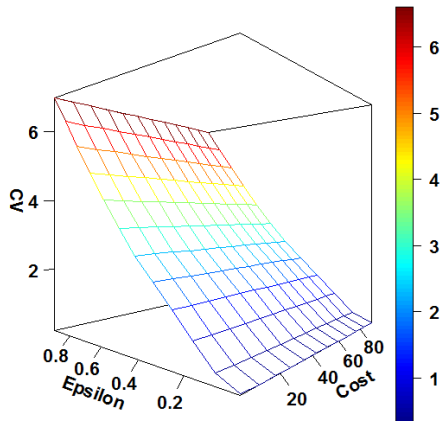

Figure 12: Analysis of the parameters Cost and Epsilon and their effect on the model quality - coefficient of variation (CV)

Long-term prediction of the SVR

For the long term prediction, the SVR was also trained for a 30 years period (1970 – 2000). The testing periods are 2000 – 2030 and 2060 – 2090. The results for the output indoor temperature are shown in Figure 13. The forecast error per time step during the period 2000 – 2030 is always smaller than 1 [K]. These results demonstrate the opportunity of using a SVR for long term prediction. However, for the period

2060 - 2090 there is a forecast error of to 5 [K] which is not applicable for further analysis. The reason for this increasing error is probably the same as for the GDNN.
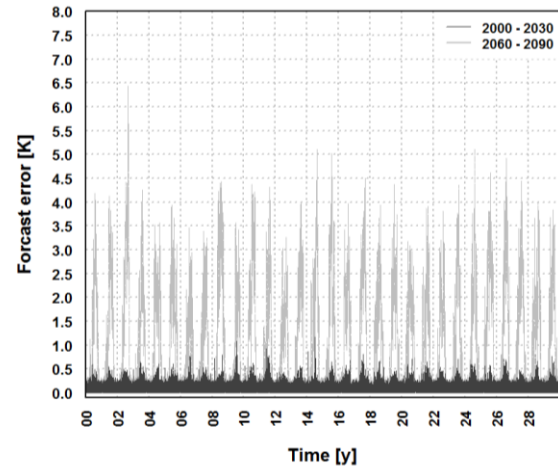

Figure 13: Absolute forecast error per time step for the output indoor temperature

The outcome of the forecast for the output variable heating load is presented in Figure 14. Both test periods present a reliable forecast error, less than 300 [W]. The differences in the energy demand between the detailed zone model in IDA – ICE and the SVR is among 3% (2000 – 2030) and 7% (2060 – 2090). These results indicate that in this case the SVR is applicable for long term predictions.
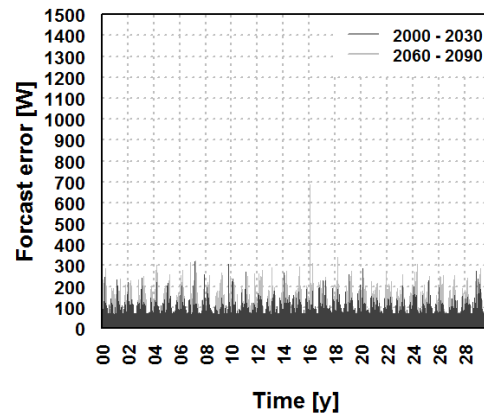

Figure 14: Absolute forecast error per time step for the output heating load

Comparison of the different model approach

When comparing the models by the coefficient of variance, the SVR demonstrates slightly better results than the GDNN (Table 3). Both models illustrates for the period 2000 – 2030 the ability of reliable long term prediction. Hence, if the test data are varying to strong from the learning data, as is the case in period 2060 - 2090, the error increases in both methods.

Table 3: Quality of the different model types for the output indoor temperature

Model	CV-RMSE	RMSE
GDNN 1 Year	0.78	0.16
GDNN (2000-2030)	1.63	0.36
GDNN (2060-2090)	10.22	2.45
SVR 1 Year	0.49	0.10
SVR (2000-2030)	0.87	0.21
SVR (2060-2090)	6.30	1.51

As mentioned in the introduction the computational effort could be an issue for long term simulations, as for example to analyze the influence of climate change on energy demand of buildings. In Table 4 a comparison of computational effort of the machine learning algorithms and the detailed building model is shown. A one-year simulation of the case study the GDNN and SVR just needs 3% of the simulation time compared to the detailed model. To simulate a 30 year period the GDNN is ten times and the SVR more than hundred fifty times faster as the detailed building model. This could be an advantage for further investigations as a uncertainty analysis based on climate data.

Table 4: Computational effort of different model types and training phases for the output indoor temperature

Model	Mean forecast erorr [K]	Computational effort [s]
GDNN 1 Year	0.11	00.98
SVR 1 Year	0.08	00.72
IDA_ICE 1Year	--	33.00
GDNN (2000-2030)	0.25	75.00
SVR (2000-2030)	0.21	05.30
IDA_ICE (2000-2030)	--	810.00

CONCLUSION

In this paper, the capability of neural networks and support vector machines for long-term forecasting in the field of building simulation was discussed. Both methods demonstrate the ability to predict long-term simulations. However the forecast error increases rapidly if the input data varies from learning data. This was clearly shown with the results of the period 2060 – 2090. The advantage of the meta models are the reduced computing time compared to detailed building model. The SVR is hundred fifty times faster than the detailed model for simulating a 30 year period.

In a next step a further analysis about the length of the learning period will be fulfilled to produce reliable results of both meta models for the whole climate data (2000 – 2090). After this, the meta models are used for a uncertainty analysis based on climate change.

Using the time delayed output variable as an input presents a large influence on the model quality. Therefore the structure of the General Dynamic Neural Network (GDNN) works well for long-term predictions. This is due to the fact that the time delayed recurrence of the output variable is also developed with the GDNN. Whereas external recurrences are necessary for a comparable application of the Support Vector Regression.

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