Artificial Intelligence for the Efficient Control of Solar Heating Systems

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Abstract

Artificial Neural Networks (ANN) are the basis of a new intelligent control concept for residential heating systems developed at Fraunhofer ISE. This artificial intelligence based concept is able to predict thermal behavior of a building and load level of a thermal storage based on measured data without using any physical model based simulation tool. This allows to improve energy efficiency and simplicity of control devices at the same time. The focus of the concept is simplicity of application, thus enabling low cost model predictive control. Up to 12% gain of energy efficiency was calculated for a current 1950's building in Southern Germany. This gain is reached without any interaction of installer or user. The ANN control approach proved to work in a real building, too.

Keywords: Artificial Neural Networks, Artificial Intelligence, Solar Thermal, Control, Heating System, Energy Efficiency

1. Introduction

Similar to biological Neural Networks (brains), Artificial Neural Networks (ANN) are able to automatically develop strategies of operation based on experience in the past. The structure of ANN is motivated by the knowledge of research in Neural Science. For an introduction to Neural Networks see for example Gurney (1997). It is obvious that such structures could be very beneficial for technical control tasks. For solar thermal heating applications ANNs seem to be useful for learning the individual thermal dynamics of a building including fossil fuel heating, the effects of passive solar heating (i.e. heating by sunlight hitting the building surface and passing window surfaces), shading and heat losses to the ambient, thus enabling the prediction of future temperature development in the building. A second application is the prediction of storage temperature distribution of the installation. These predictions do not need any physical model based simulation. The ANN is able to perform these predictions based on training from past measurement data, only. It is able to handle non-linear static and dynamic systems.

Thus, ANNs provide the back bone of a new self-learning control concept for solar thermal systems based on simple and cheap prediction methods. Local climate data, individual thermal behavior of buildings, solar passive and active gains can easily be forecasted without costly and tedious simulation. This allows not only a significant improvement of energy efficiency but also cost reduction installation and set-up of controllers.

This paper presents the description of the ANN method for the prediction of room temperatures of the building and the storage temperature development of the installation on a real building equipped with a solar thermal supported heating system. The second part shows, how ANN is used in order to control a heating system. Results on the application in a virtual environment and a real application are also shown.

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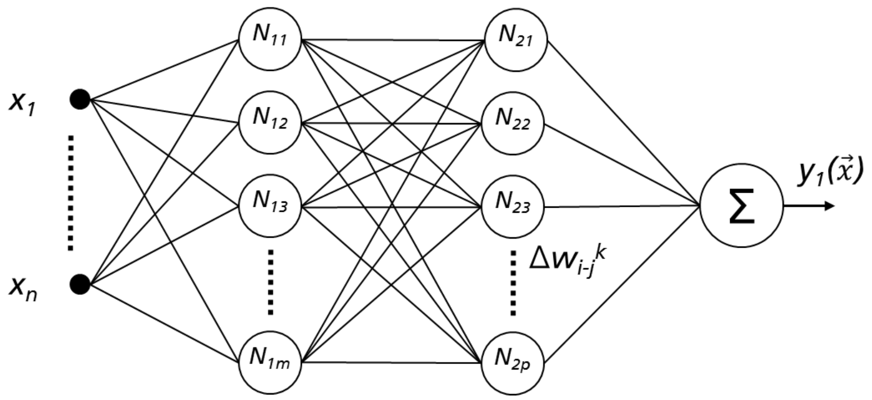

Fig. 1: 4-layer ANN Network with one input layer, 2 hidden layers and one output layer

2. Prediction using ANN Structures

ANN structures for the prediction of room temperatures and storage temperature development have been developed at the authors' institution. The ANN models consist of a 4-layer ANN structure (figure 1) including one input layer, two hidden layers and one output. Input data x_1-x_m is normalized to +/- 1 before being transferred to the first hidden layer N_{11}-N_{1n}. The calculation procedure in each neuron N is presented in figure 2. Each normalized input value is multiplied by a weight W_i and summed up. An offset is added and the sum is passed through a transfer function. In our case this is hyperbolic tangent (*tanh).* The calculation scheme for the second layer is identical. In the last layer, which is the output layer, the output of the second hidden layer N_{21}-N_{2p} is summed up and extended in order to get the output value $y_1(\vec{x})$. Figure 1 shows the ANN.

A program code was developed to do training of the ANN. This means to determine the most suitable values of W_i for each neuron in order to get the best fit between measured input and output training data of the ANN. Main challenges of the training process are overfitting, convergence, termination method, being trapped in local minima, required processing power to perform an epoch of training and required RAM to perform an epoch of training.

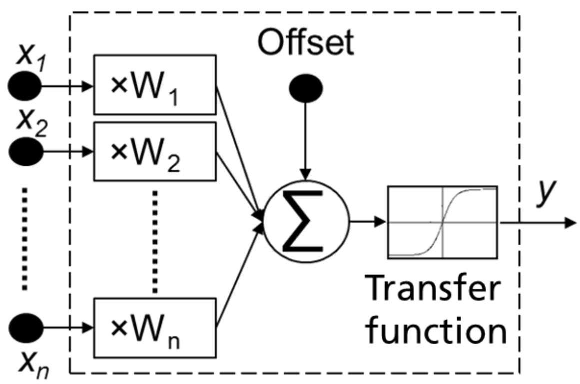

Fig. 2: Mathematical description of a neuron N_{ij}

Based on the local conditions of weather data and a real individual building construction a trial and error approach was used to choose the most suitable topology. The most important criteria were accuracy of prediction, robustness of the training result and computation time. Overfitting can be avoided by minimizing the size of the ANN. A maximum of 2 hidden layers with not more than 15 neurons each proved to be appropriate for the application presented in this paper. The trials carried out showed that at least for the data that was available a simple termination rule could be defined by stopping the training after a fixed number of training epochs. The developed algorithm follows a supervised training approach and incorporates several training features including weight correction, momentum modification and temperature as described by Haykin (2005) in order to avoid being trapped in local minima. Required processing power and RAM does not seem to be a problem for the presented dynamic ANNs.

2.1. Prediction of Room Temperature and Storage Load Status

Control of the heating system of a building is normally based on the measurement of the local temperature outside the building. A heating curve which has to be adjusted to the thermal behavior of the building defines the temperature of the heating circuit. Sometimes, on top of that some limited correction to the heating circuit temperature is made by taking into account the current room temperature of a reference room representing the typical behavior of the building.

Experience shows, that the optimum adjustment is hard to find and takes a lot of time. Therefore, in very many cases the applied heating curve does not reach the most efficient status. Besides this, the control approach is only based on the current status of outside temperature (and possibly room temperature). This means, that the future development of the room temperature is not taken into account. Effects like future passive solar gains, change of outside temperature or reduced heating demand due to the approaching night temperature reduction are neglected.

However, the ANN control approach is able to account for all these effects. Using internet based weather forecast data, it is based on the future prediction of the room temperature development. It accounts for effects like passive solar gains, shading of the building, microclimatic influences and position of the sun.

It is important to state, that the ANN is able to account for all these effects implicitly. That means, it is sufficient to deliver the time dependent necessary raw input data to the system which show an influence on the room temperature and the measured room temperature in the building. No separate calculation of energy flow, irradiation reaching the building or other physical data is done. The system is able to correlate this data which results in a black box dynamic model for the room temperature forecast.

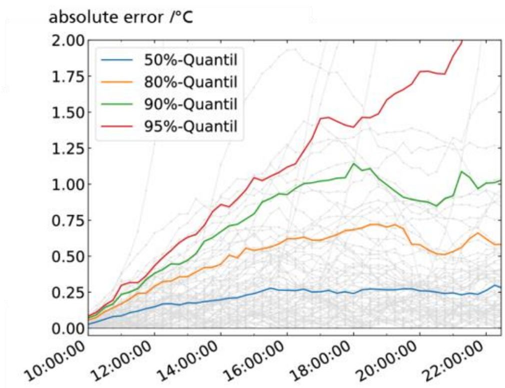

Fig. 3: Prediction of the room temperature using a rolling prediction based on 4 weeks historical data

Figure 3 shows the capability of an ANN to predict the room temperature of a real building. The building is situated in Marburg, Germany. It has a low specific heat demand of 45 kWh/m²a.

The dynamic ANN consisted of 8 inputs (figure 4). Date, time, day of the week, surface temperature of a wood stove, heating circuit temperature and from a weather forecast (data by meteoblue 2017) hourly local outside temperature, global normal irradiation and cloudiness factor. Output is the room temperature. The back propagation of the room temperature transforms the system into a dynamic one. Time step is 15 minutes. The ANN network consists of 2 hidden layers with 12 neurons each. The ANN algorithm has been combined with a Linear System Approach (LSI) as described by Chen (1999) in order to be able to handle non-linear (ANN) and linear (LSI) behavior of the building.

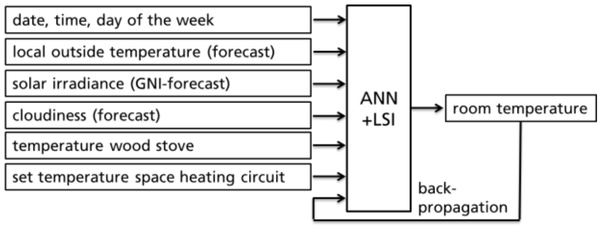

Fig. 4: Dynamic ANN+LSI Module with backpropagation for the prediction of room temperature development

First the LSI is applied to identify the linear part of the behavior. The residues are treated with the ANN. In the analyzed building, the behavior was mainly linear. However, short trials on other buildings showed, that non-linear behavior can also be significant. The combined non-linear – linear approach using ANN and LSI seems to be robust and universal for a general application in buildings.

Continuous rolling learning using the measured data from the 4 last weeks was applied every day during the heating period. The graph shows the results for 100 days. Every day the forecast starts a 9:00h in the morning and is done for the next 13.5 hours. Prediction for the first hours is good. For more than 95% of data the accuracy is better than 0.5 K for the first 3 hours. This is a very good value, since there are always some unpredictable additional heat sources or sinks like for example opening of the windows or unexpected cooking or ironing.

Prediction of the storage load status is done in a similar way. Prediction quality is lower than for the room temperature. Deviation from the real temperature is better than 15 K for 90% of the predictions during the first 4 hours. This is due to non-predictable hot water tapping. However this prediction quality is still sufficient for an efficient operation of the ANN control algorithm.

3. Control Approach using ANN

A new approach for controlling the heating system in buildings using ANN has been developed. This approach relies on the strong performance of ANN combined with a Linear System Identifier approach (LSI) predicting room temperature and storage load status. The control approach is based on the ANN+LSI prediction shown in figure 4. Output of the prediction is the room temperature development in the future hours. The only input parameter which can be varied by the control system is the heating circuit temperature. Changing this temperature leads to a different room temperature development. The task of the control system is to find the lowest heating circuit temperature leading to the future desired room temperature. The desired room temperature is defined by the user and described by a temperature-time table. Deviation from the desired temperature is calculated for 1, 2, 3 and 4 hours in advance. Each deviation is weighted by a factor in order to differentiate the importance of sooner and later deviations. The algorithm determines the heating circuit temperature allowing the lowest sum of weighted deviations.

Switch on/off of the boiler is also done by an ANN+LSI approach. ANN+LSI forecast is used to predict the development of the different storage temperatures. If the future storage temperatures are in line with the calculated needed heating circuit temperatures in the future, there is no need to switch on the boiler. The prediction of the future storage temperature includes solar gains, reduced heat demand if the wood stove is delivering additional heat or due to demanded nightly room temperature reduction. The boiler is switched on in order to deliver the minimum storage temperature to keep the calculated future heating circuit temperatures.

4. Results of a Real Building Tests

The ANN controller approach was tested in a real building. The question to be answered was whether the ANN approach can cope with a real control environment. The building is shown in figure 5. It is equipped with a 18 m² flat plate collector field, a 1000 L thermal storage, a 10 kW Pellet Boiler. The heated surface area is 200 m², the yearly heat demand is 45 kwh/m². It is located in Marburg, (Germany)

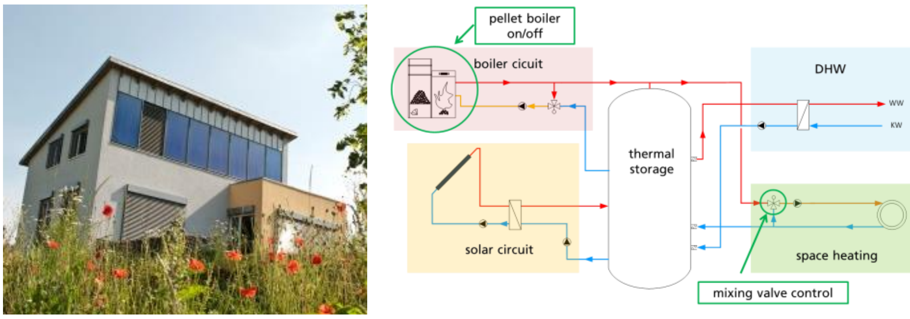

Fig. 5: Test building and simplified hydraulic scheme. ANN-controlled actuators control the mixing valve of the space heating circuit and the on/off switch of the pellet boiler

The ANN controller controls the mixing valve of the space heating circuit and the on/off switch of the pellet boiler. All other control actions are taken by the conventional controller already implemented in the building. This means in particular control of the fresh water heat exchanger. The ANN controller was tested during the heating period 2017/2018. Some typical results are shown in Figure 6. The top graph shows the heating circuit temperature defined by the ANN controller. For comparison the heating circuit temperature which would be defined by the conventional controller of the building is also shown. The second graph shows the time dependent set-value of the room temperature and the measured room temperature. The third graph shows the collector temperature representing solar irradiation.

The heating circuit temperature of the ANN differs significantly from the conventional controller. Although the conventional controller also takes into account the real room temperature there is only a small reduction, when the room temperature exceeds the desired value. When the room temperature is significantly below the desired value, the ANN rises the temperature of the heating circuit to its limit of 60°C. This allows for fast reaching of the desired room temperature after for example a holiday period with reduced heating (i.e. 3.4.2018). When passive solar gains help to reach the room temperature, ANN reduces the heating circuit temperature or even switches completely off the heating circuit (i.e. 6.4. and 7.4.2018), which reduces heat demand of the boiler.

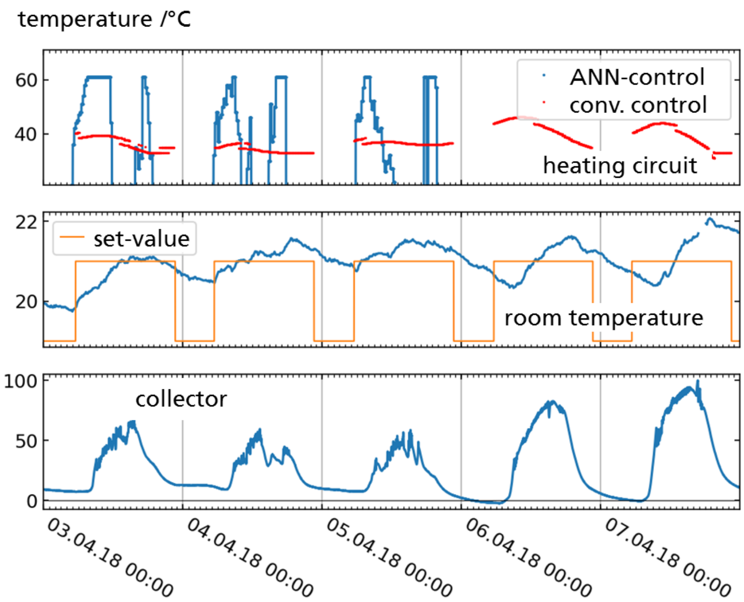

Fig. 6: ANN-controller acting in a real building (typical example)

5. Results of a Virtual Building Test

The test in the real building was mainly meant to see whether the ANN algorithm is able to run in a real environment without problems. However, the question of energy savings was answered by simulating different buildings with ANN-Controller. The basis for the comparison were two building types. One close to the building which was used for the real building test. This means a modern well insulated building with low heat demand (i.e. 45 kWh/m²a) and a rather high heat demand building corresponding to the building stock of the 1950's in Germany (i.e. 150 kWh/m²a). For both buildings three simulations where conducted. On with the heating curve independent from outside temperature at constant temperature (worst case, if the heating curve is not adapted), a second one with optimized conventional heating curve and a third one with ANN-Controller approach. Both simulations were done with climatic data of Freiburg, Germany. Heat transfer to the building is by radiators. The optimization of the conventional heating curve was done in such a way, that more than 80% of the daytime in the heating period is within a limit of maximum 2K below set-value. Approximately the same comfort was reached by the ANN Controller.

Figure 7 shows that in a modern building with low heat demand the effect of either optimizing a conventional heating system or using an ANN controller is low. However, existing buildings with higher heat demand can gain significant energy efficiency by optimization. Optimizing a conventional heating curve can improve the system by up to 5%. ANN improves efficiency even more significantly by up to 12% under Freiburg climatic conditions.

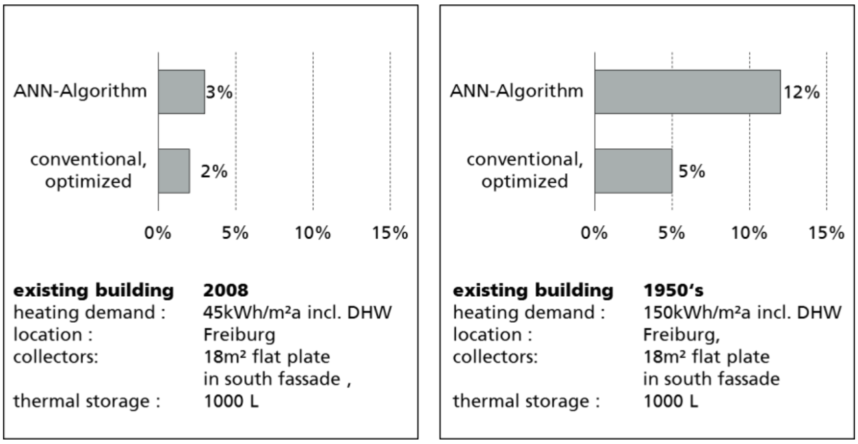

Fig. 7: Energy savings by using the ANN controller approach for 2 different applications

6. Discussion of the Results and Conclusion

A new artificial intelligence control approach using Artificial Neural Networks provides a powerful concept which can significantly improve energy efficiency and reduce implementation cost at the same time. Higher improvements of energy efficiency can be reached in the existing building stock than in new buildings with low heat demand. This due to the fact that modern buildings normally show a higher thermal capacity to heat demand ratio than old buildings. Therefore, temporary overheating can be stored more efficiently in the thermal building capacity. Old buildings with a less favorable thermal capacity to heat demand ratio are more sensitive to unnecessary heat supply to the building.

Up to 12% gain in energy efficiency was calculated for existing 1950's buildings under southern Germany climatic conditions. Other climatic conditions and other low thermal capacity buildings might lead to even higher savings. This has to be further investigated.

Besides the benefit of energy savings the ANN approach allows for automatic adjustment of the heating controller to the individual buildings. Its strength is its simplicity in application by relying on local measured and simple weather forecast data, only. This is a very big advantage, since optimization of current heating controllers demand a high labor cost. The installer has to come at least twice at different periods of the heating season in order to minimize the necessary heating circuit temperatures. ANN does not need such an effort since it automatically adapts to the individual conditions of the building and the environment.

7. Acknowledgment

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