Artificial Neural Networks (ANN) for the Prediction of Local Outside Temperatures and Solar Yields

Wolfgang Kramer, Moritz Bitterling

Fraunhofer Institute for Solar Energy Systems (Germany)

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 data like local outside temperature, solar thermal yield, thermal behavior of a building and capacity 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 by considering the above mentioned predicted data. The current paper shows results of prediction by ANN for local outside temperature and solar yields of a solar thermal installation. The focus of the prediction method is not highest accuracy but simplicity of application, enabling low cost model predictive control. Accuracy of the local outside temperature prediction is doubled compared to a pure weather forecast data for the tested location. Solar yield prediction is also quite in line with real measurement data at the location investigated. The achieved prediction quality is reasonable and promising for improved heating system control.

Keywords: Artificial Neural Networks, Artificial Intelligence, Solar Thermal, Control, Prediction of Temperature, Prediction of Solar Yield, Heating System

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. Other applications are the prediction of storage temperature distribution and solar thermal yields of the installation. All 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 local outside temperatures and solar yields on a real building equipped with a solar thermal supported heating system. First prediction results are shown and discussed.

doi:10.18086/swc.2017.22.03 Available at http://proceedings.ises.org

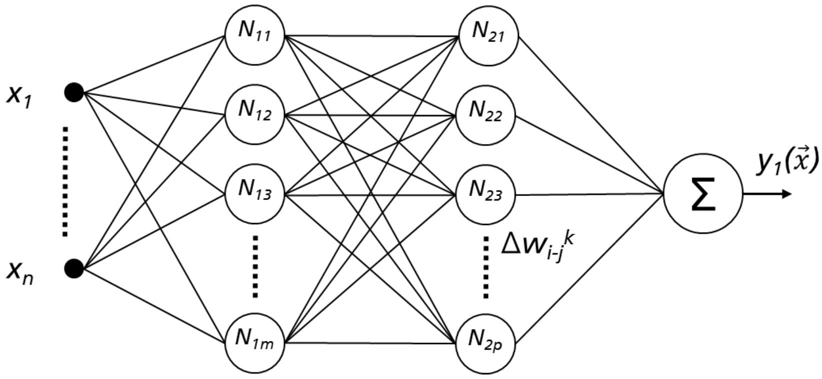

Fig. 1: 4-layer ANN Network with one input layer, 2 hidden layers and one output layer

2. Prediction using ANN Structures

ANN structures for the prediction of local outside temperatures and solar yields of a solar thermal installation 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.

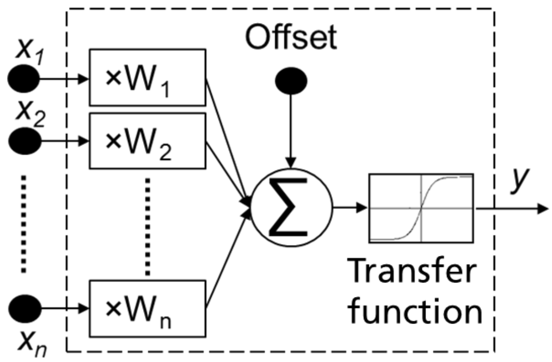

Fig. 2: Mathematical description of a neuron N_{ij}

Based 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 static ANNs. However, this has to be reevaluated for dynamic ANNs that will be used in further steps of the current work.

Training was based on measured training data from a real solar thermal heating installation, which was available for a complete year (2016) for the location of Marburg, Germany.

2.1. Prediction of Local Outside Temperature

Control of the heating system of a building is normally based on the measurement of the local temperature outside the building. Local outside temperature of a real building that is measured by a sensor mounted directly on the wall of the building differs obviously from reference temperature data of meteorological stations. When compared to local meteorological prediction, differences are expected to be even more important. On the one hand, this is due to inaccuracy in forecasting for a special location. In general, weather forecast does not account for very individual small scale local impacts on temperature. On the other hand, the local conditions of the mounting situation of the temperature sensor are not considered. This includes effects of wind, temporary exposure to irradiation, infrared cooling to the sky, heating by the wall of the building and error of local temperature measurement.

Thus, when trying to improve efficiency of a heating control system by considering future outside temperature development, it seems reasonable to use a more precise method of forecasting the local temperature. Instead of relying on weather forecast temperature only, ANN is able to deliver more precise information on future local temperature development. The big advantage of ANN is its self-learning capability. Just by automatically analyzing local measurement data such a system is able to predict local temperature development without any physical simulation model behind. The complex non-linear characteristics of the local climate is taken into account with this simple approach.

Such an ANN correlates real measured temperature and data from a weather forecast. Apart from the temperature data itself more variables like solar irradiation, wind speed and direction, hour of the day and day of the year are taken into account. This additional data deliver implicitly important information on the position of the sun, local shading, and heating by irradiation. The ANN is trained by combining historical locally measured temperature data and collected historical weather forecast data provided by meteoblue 2017.

Figure 3 shows the capability of an ANN to perform such a prediction. An ANN has been trained to predict the local outside temperature with a forecast horizon of one hour, based on historical data from a regional weather forecast provided by meteoblue and measurement data. The static ANN consisted of 4 inputs (temperature forecast one hour ahead (1), time (2), date (3) and current local temperature (4)), 2 hidden layers of 10 neurons each and one output (local temperature one hour ahead). Wind and irradiation data did not further improve the forecast. This is due to the fact that the sensor in this case never sees solar irradiation and is well protect from wind effects.

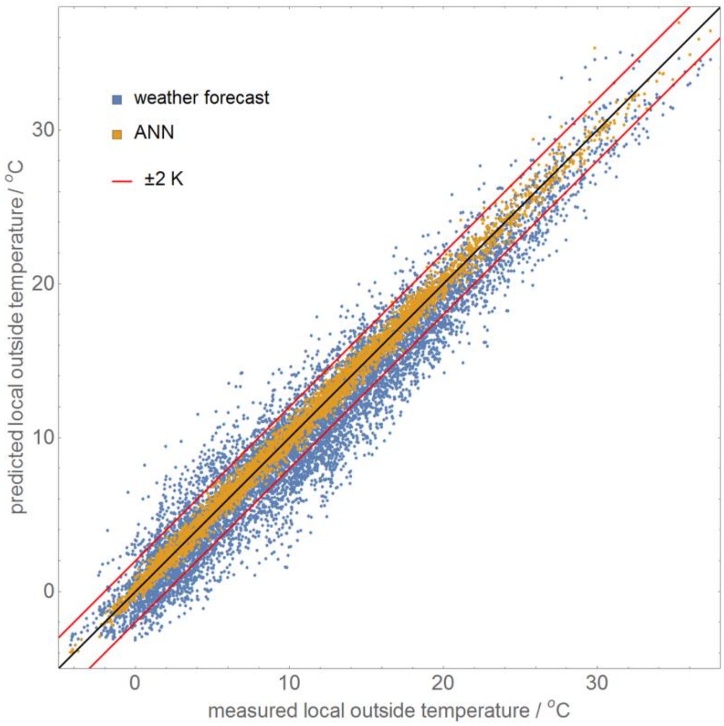

Fig. 3: Prediction of local outside temperature of a building

The results show an improvement in standard deviation from 1.9 K to 1.1 K when comparing pure weather forecast temperature data and ANN prediction with the real locally measured outside temperature. The mean deviation is corrected from 0.9 K to 0 K. At first glance this seems possibly disappointing. However, it has to be stressed that this improvement could be automatically generated in a real application without dealing with any tedious parameterization. Compared to many other prediction methods, it is somehow “for free”.

2.2. Prediction of Solar Yield of a Solar Thermal Installation

A second ANN has been used to do a one-hour prediction of the solar yield. The product of temperature difference between collector inlet and outlet and the rotation speed of the pump was taken as an indicator of solar yield. The reason for using such an indicator instead of real yield data is the availability of data. In a future commercial application, data of real solar yield is not always available. Therefore, a control system has to work with such an indicator.

Training of the network has been performed with historical weather forecast data and measured data from one year. The appropriate ANN consists of two hidden layers with 12 neurons each. The input data given to the network were date (1), time (2), storage tank temperatures at top (3) and bottom (4) and predicted data from a weather forecast for radiation (5), ambient temperature (6) and cloud cover (7) as well as the measured solar heat input during the previous hour (8). The data was split into a training set and a validation set. Figure 4 shows quite reasonable agreement between prediction and measurement.

The accuracy of the predicted total daily solar yield is shown in figure 5. 80% of the daily solar yield data is predicted with an accuracy better than 15.2 % when compared to the average daily solar yield.

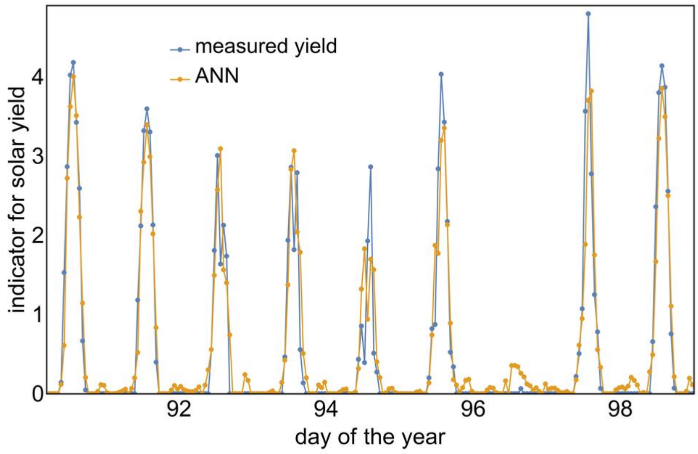

Fig. 4: Prediction of hourly mean solar yield indicator and comparison with measured data

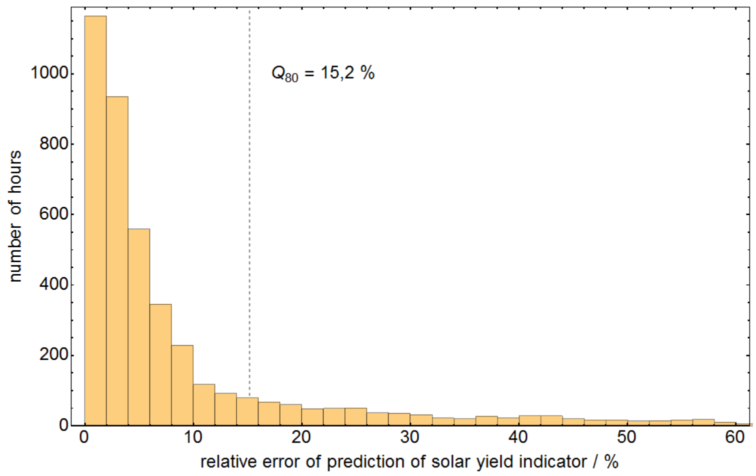

Fig. 5: Accuracy of prediction of solar yield indicator

3. Discussion of the Results

The results shown in this paper have been created by training ANNs for one single local site for one individual building in an urban environment in the city of Marburg, Germany based on real measured data and historical weather forecast data. The accuracy communicated is only valid for these individual conditions. Accuracy under different conditions is expected to be of similar magnitudes but have to be checked. In the case of the black box model ANN, this can only be done by statistical methods. A limited comparison of the ANN method presented with other statistical approaches for different sites and different types of training data showed comparable accuracy, though.

Answering the question of “How accurate is the ANN approach?” in a general sense is not possible. The ANN training approach can be regarded as a sort of sophisticated non-linear regression of input and output data. It is the same as asking how precise is a least-square method for linear correlation of data. This depends on the data, not on the method itself.

Unlike in simulations based on physical models, each site and building needs a new creation of an ANN model by training with individual data. The advantage of ANN is, that this model building procedure can be realized in an automatic way, whereas physical models often need tedious parameter identification for adjusting the model to individual conditions.

An important feature of ANN is that inaccurate input data is less of a problem than for other approaches, since systematic inaccuracy is automatically compensated by the self-learning feature. The same holds for missing data or physically incomplete data with regard to the physical model. Simple weather forecast data, which is easily available for almost every place on earth, is sufficient to make the ANN approach work. For example calculating the solar yield of a solar thermal installation by a physical model needs a precise array of irradiation at any time. Such irradiation data is not easily available from simple weather forecast data. However, the ANN approach is able to process successfully such simple data. By feeding not only the ANN with the irradiation data from the weather forecast but also other inputs like time of the day, month, forecast of cloudiness, current outside temperature, temperatures of the thermal storage and others if necessary (i.e. barometric pressure, wind speed and direction, humidity etc.) the ANN is able to correlate these values with the individual output of the installation. This correlation inherently includes technical characteristics of the heating installation, thermo-physical properties of the building, passive heating, shading effects and others. As long as there is a systematic correlation of input data and the desired output (solar yield in this case), the system is able to generate a black box model describing this dependence. Accuracy depends on careful selection of input data, accuracy of input data, ANN topology and training method, of course.

4. Conclusion and Outlook

A new control approach using Artificial Neural Networks provide a powerful concept that could significantly improve energy efficiency and reduce cost at the same time. It is not expected, that ANN is more precise than other modelling approaches. Its strength is its simplicity in application by relying on local measured and simple weather forecast data, only. Parametrization as needed in physical models is not necessary. The ANN model describing individual characteristics of the building and the heating installation under local weather conditions can be created automatically. First results of using an ANN approach for predicting local outside temperatures and solar yields of a real installation show, that it is possible to use such an approach in order to avoid costly simulation methods. Future improvement is expected after more work on optimum ANN structures and training methods. Current work on ANNs with back propagation shows that dynamic ANN structures are even more appropriate for predicting future status several hours in advance. However, computational requirements and calculation speed have to be carefully monitored.

Further steps will include the prediction of inside room temperatures of a building and the development of the level of charge capacity in the thermal storage using the ANN approach and the implementation of complete control algorithm for a solar thermal heating installation. First results on the prediction of the stratification in thermal storage are also very promising (Kramer et al. 2017).

Further validation in order to provide information of the general applicability and limitations on different sites and in different buildings is needed.

5. Acknowledgment

This research was conducted within the project „Neuronale Netzwerke für die Anwendung in der Solarthermie“ (Neural Networks for the application in solar Thermal)(ANNsolar) and is supported by the German Ministry of Economics (Bundesministerium für Wirtschaft, BMWi) under the grant number FKZ 325548 and supported by the project executing organization PTJ Jülich. The responsibility for the content of this paper lies completely with the authors.

6. References

Gurney, K., 1979. An Introduction to Neural Networks, UCL Press Limited, London

Haykin,S., 2005. “Neural Networks – A Comprehensive foundation”, Pearson Prentice Hall, 2nd Edition

Kramer, W., Bohrer, J., Bitterling, M., 2017. Künstliche Neuronale Netzwerke für die Anwendung in der Solarthermie, Poster, in Ostbayerisches Technologie-Transfer-Institut e.V. -OTTI-, Regensburg, 27. Symposium Thermische Solarenergie, Bad Staffelstein, p.p. 36-37, 2017

Meteoblue. „http://www.meteoblue.com,“ 16 01 2017. [Online].