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The Improvements of Performance Reliability in Solar Combisystem by the Applications of Artificial Intelligence

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An interest to integrate solar collectors in heat supply systems is receiving a lot of attention. Despite perceived simplicity of solar collectors, failures can occur during the operation. Meanwhile, for the most installations, absent heat gains from solar collectors are covered by an auxiliary energy source. Thus the objective of the paper is to present the development of an automatic fault detection system, which can deal with abrupt in solar combisystems. The application of the artificial neural networks (ANN) for the fault detection has considerable advantages over other models, because the ANN can deal with complex problems, where traditional deterministic algorithms are exhausted. For the input and output layers the historical data about the fault-free operation parameters from the experimental solar combisystem and from the TRNSYS simulation tool is feed to the ANN. Learning algorithms are applied for the hidden layer in order to “train” the ANN. The results show that application of the proposed methodology increases the performance reliability of solar combisystem. The fault detection systems could be integrated in the solar combisystems, thus reducing the consumption of auxiliary energy and decreasing emissions during operation.

1. Introduction

Households in Nordic countries consume a reasonable amount of heat energy. Moreover in Latvia a large share of heat energy was produced by imported natural gas. Since the prices for energy resources are growing an interest to integrate solar collectors in heat supply systems increases.
A solar combisystem represents a unit, which combines solar collectors and an auxiliary heater, to cover both the space heating and domestic hot water loads. Nevertheless the efficiency and the performance reliability of the solar thermal energy systems still need to be improved. As reported by He et al. (2012) despite perceived simplicity of solar thermal collectors, failures can occur during the operation. As studied by de Keizer et al. (2011) over 50 % of projects reported about defective control in the first 10 y of operation, the second most common failure was the damage of a storage discharging pump.
Meanwhile a solar loop is out of order, for most of installations, absent heat gains are covered by an auxiliary energy source, where consumers cannot even notice that solar gains in a system are much lower than designed. In order to have sustainable energy systems the situation when energy resources available for “free” (like solar energy) are wasted should not be tolerated.
Thus the objective of the paper is to present the development of an automatic fault detection system, which can deal with abrupt in solar combisystems. The application of the artificial neural networks (ANN) for the fault detection has considerable advantages over other models, because the ANN can deal with complex problems, where traditional deterministic algorithms are exhausted.
The study on the fault diagnostic system for the solar waste heater in Cyprus and France was conducted by Kalogirou et al. (2008). The fault detection system could predict faults in collectors and pipes. The authors suggested to implement this kind of fault detections systems firstly in the buildings where the building management system in use already.
He et al. (2012) used adaptive resonance theory for construction of the ANN for the experimental setup of solar domestic hot water system. For the experimental setup a TRNSYS dynamic model was developed. The ANN model was trained to recognize following faults in the system: pump failure, pump degradation,

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shading and thermo-syphoning. The authors concluded that the ANN can effectively recognize a failure in the system, starting form fatal ones to slowly developing ones.

The novelty of the presented work is the development of the ANN structure capable of the description of the solar thermal systems under Nordic climate conditions. This novel methodology is applied to for the fault detections in solar combisystems. Due to authors' knowledge, no such work has been presented. As the case study a solar combisystem installed in Latvia was used. The results of the research show that integration of artificial neural network within solar combisystem increases the performance and reliability of operation.

2. Methodology

2.1 Experimental system

For the purposes of this research a solar and pellet combisystem installed in a 4-story multi-family building in Latvia was chosen. A solar combisystem represents a unit, which combines solar collectors and an auxiliary heater, to cover both space heating and domestic hot water loads. The hydraulic concept of the solar combisystem consists of 5 main components: solar collectors with hydraulic loops, a pellet boiler, heat accumulation tank, and DHW and SH loops, see for monitoring scheme by Žandeckis (2012).

2.2 Deterministic mathematical simulation model

The deterministic mathematical simulation model was developed in the environment of a transient simulation program TRNSYS 16.1 and validated by Žandeckis (2012), with the error of internal energy balance of 0.3 %. This simulation model was previously used in the research by Rochas et al. (2012), Žandeckis (2012) and Žandeckis et al. (2013).

2.3 Data collection

Data sets for the individual days with various profiles of the total beam radiation on tilted surface, and SH and DHW loads were obtained from the TRNSYS simulation model. The load of SH was obtained for outside air temperature above − 12 °C and below + 26 °C. The data sets were further split regards the characteristics of the total beam radiation at clear, broken and overcast sky conditions, and the characteristics of the DHW load for weekdays and weekends.

2.4 Data pre-processing

Pre-processing of input data was done by data spiting into 3 subsets: 70 % of data for the training set, 15 % for the validation and 15 % for the test set. Data normalization between 0 and + 1 was for logistic sigmoid transfer function and − 1 to + 1 in the case of a linear or tangent transfer function.

2.5 Architecture of artificial neural network

The mathematical model of the basic ANN structure is given in Eq(1).

$$u_k = \sum_{i=1}^{n} w_{ki} x_i = w_{k1}x_1 + w_{k2}x_2 + ... + w_{kn}x_n \tag{1}$$

Where $x_i(i=1,2,\ldots,n)$ are the input signals from n external neurons transmitted to the neuron k and w_{ki} is the weight between the i-th external input and the neuron k. The output from the summation function is u_k.

The advantages of artificial intelligence are outlined also in following studies: on the production of citric acid by Kana et al. (2012), the formation of bubble point pressure in crude oil by Cuptasanti et al. (2013), the degradation of organic pollutants in water by Capocelli et al. (2014a) and the capability of hydrodynamic cavitation by Capocelli et al. (2014b).

For input and output vectors the historical data about the fault-free operation parameters from the TRNSYS simulation tool were feed to the ANN. A non-linear autoregressive neural network (NARX) with an external input was chosen for training purposes of the ANN, because the structure of the NARX can be used for non-linear fitting and the networks of this configuration are commonly used for time-series modelling and modelling of non-linear dynamic systems (Fischer et al., 2012).

A NARX employs a real output during training instead of feeding back an estimated output. This attribute possesses an advantage of a NARX, since this network becomes more accurate. The number of neurons in an input and output layer is defined by the number of input and target variables; nevertheless there are only empirical equations for the determination of a "proper" number of hidden neurons. Generally while the number of hidden neurons increases the accuracy of ANN increases as well, however model's ability of generalization declines at the same time (Dreyfus, 2005). In this study an experimentation method was used to determine the number of neurons in a hidden layer.

2.6 Training procedure

A training procedure was carried out based on 2 main objectives: to determine best fit for a learning algorithm and to evaluate an optimal number of neurons in a hidden layer for each of the learning algorithms applied. Levenberg-Marquardt backpropagation, Broyden-Fletcher-Goldfarb-Shanno Quasi-Newton backpropagation, Conjugate gradient back-propagation with Fletcher-Reeves restarts, Conjugate gradient with Beale-Powell restarts, Scaled conjugate gradient, and Resilient Backpropagation algorithms were simulated for the best fit (Beale et al., 2010).

The simulations with 10, 15 and 20 neurons in a hidden layer were run with each of these algorithms. Moreover, for the each pair of a learning algorithm and the number of neurons in a hidden layer 5 repeated runs of the same simulation were conducted in order to exclude the influence of the initial values assigned in the network. The training procedure continued until the error of validation decreased for 6 iterations in a row. The performance of these learning algorithms was estimated based on the values obtained for a mean square error (MSE) and statistical coefficient of determination (R^2).

2.7 Fault detection tool

When training process of the NARX network was finished the feedback loop within the model was closed. Within the closed loop NARX the output depends on both: on the current input to the ANN and also on the previous input and output of the network. The general mathematical definition of the closed loop NARX is given by Eq(2).

$$y(t) = f(y(t-1),..., y(t-d, x(t-1),..., x(t-d)) \qquad (2)$$

Where x(t) is the input and y(t) is the output of the network at the discrete time step t, d is a parameter representing number of time-delays and is used to store the previous values of x(t) and y(t) sequences.

The closed loop NARX was used as an integral part of a fault diagnosis tool. The aim of this developed tool was to compare the actual output values from the solar combisystem with the predicted outputs of the closed loop NARX under the same input data values. The residuals occurring between the actual and predicted output values were sent to a residual diagnosis module, proposed by Kalogirou (2008) and also used by Mavromatidis et al. (2013). The modifications were made to the original design of a residual diagnosis module, firstly, 3 consecutive states of that fault is detected where used for the detection of a fault instead of 5 used by Kalogirou (2008), secondly, the thresholds for 4 categories of faults: normal, low probability of faults, high probability of faults and failure were assigned experimentally to the system under the study.

3. Results and discussion

3.1 Model's validation

In this study an experimentation method was used for determination of number of neurons in hidden layer. The results of the structural complexity tests reveal that the saturation of the complexity for the model can be seen at the data set with the 10 neurons in hidden layer. This data set with 10 hidden neurons also had more stable learning process in comparison to other data sets, therefore the addition of neurons in hidden layer was stopped in order to avoid over-fitting of the model.

From all tested algorithms, the Levenberg-Marquardt backpropagation training algorithm was selected for further development of the ANN for solar combisystem, since it show the best MSE and R^2 statistics. The research by Fischer et al. (2012) on solar collectors and Leconte et al. (2012) on combisystems also applied the same training algorithm for studies of solar thermal energy systems.

The NARX with an external input was converted to the closed loop NARX and dynamics within the solar combisystem were simulated. The value of 96.7 % for statistical R^2 and 0.61 for the MSE was obtained for the NARX with 10 hidden neurons.

The input time series and error time series are plotted as correlations in the case when input and errors varies across lags. For the developed model all autocorrelations falls within the 95 % confidence level. For the identification of outliners an error histogram is used, see Figure 1.

The blue bars represent training data, the green bars represent validation data, and the red bars represent test data. For the NARX all errors were obtained between the − 5 and + 5, therefore no outliners with high deviation from the mean value was accounted for. Figure 1 also shows that the distribution of errors is symmetrical to the plane of zero error and has a shape of normal distribution, therefore no statistically significant over- or underestimation of the data values is present in the network.

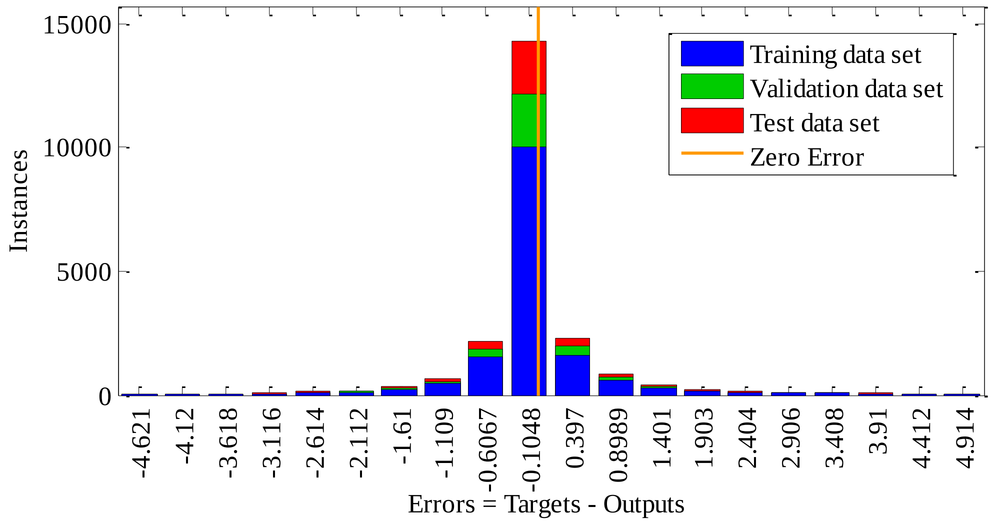

Figure 1: Error histogram with training, validation and test data set and zero error

Error autocorrelation was used for the validation of the model. For the NARX error correlations falls within the 95 % confidence level, therefore the network can be rated as valid.

3.1. Fault and degradation detection tests

Abrupt (solar pump failure and solar controller failure) and incipient (loose connector) faults for clear sky and cloudy condition within the solar combisystem was simulated within developed ANN. The closed loop NARX predicted the failure of the solar pump. The results of residual generation for the simulation of solar pump failure are given in Figure 2.

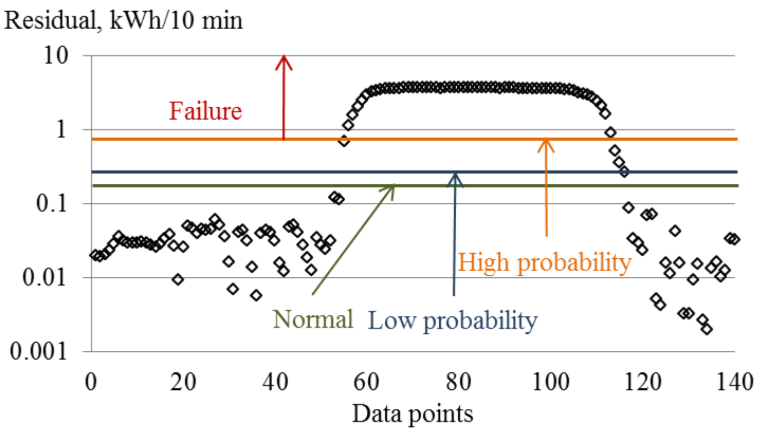

Figure 2: Residual generation for solar pump failure simulation in a logarithmic scale

Threshold values are given as follows: residuals below 0.2 kWh per 10 min are regarded as normal operation conditions, residuals below 0.4 kWh per 10 min as low probability of failure, and residuals below 0.8 kWh per 10 min as high probability of failure. All other values are translated as a failure. The lowest threshold limit was set based on the residual values observed at fault-free operation conditions.
Another simulation of abrupt fault in the solar combisystem was done regarding the failure of pump controllers, thus a solar loop pump was running at the time when the solar radiation on a collector plane was low and there was no need to start circulation in a collector loop.

Plots of raw sequences for the abrupt fault simulations are given in Figure 3, where the defined thresholds values for normal, low and high probability of failure were applied.

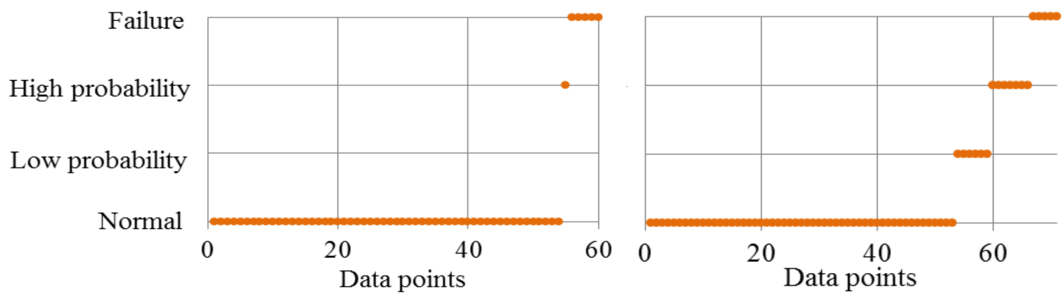

Figure 3: Plot of the raw sequence vs the functioning hour (on the left abrupt fault at clear sky conditions (solar pump failure), on the right abrupt fault under broken sky conditions (solar pump controller failure))

To detect the failure of pump controller took longer time in comparison to the pump failure simulation; see the plot of raw sequence in Figure 3, since the failure of controller was simulated under broken sky conditions. Consequently, the difference in the temperatures between solar collector loop in fault-free and faulty operation condition was not as large as in the simulation of a pump failure at sunny conditions. Since the differences in fault-free and faulty operation conditions is not great, also the value of the MSE for the fault simulation under broken sky conditions is relatively small – 1.05. Nevertheless the developed model was able to identified also fault small in magnitude.

First two simulated faults were abrupt in their nature; therefore third fault simulation covered an incipient fault – a loose connector. This type of fault can be attributed to the faults which possess alternating nature, thus don’t have a clear pattern and are hard to detect.

The fault detection test of loose connector within the NARX had following statistics for the MSE: 1.05 $(kWh/10\ min)^2$ at broken sky conditions and 2.30 $(kWh/10\ min)^2$ at sunny day. The obtained values for the performance of the network has a reasonable value, since at sunny day an incipient fault will have a higher influence on the performance of system and thus are easier to isolate. For cloudy weather condition fault isolation within the network becomes a more complex problem. The plot of raw sequence for the incipient fault detection in cloudy day is given in Figure 4.

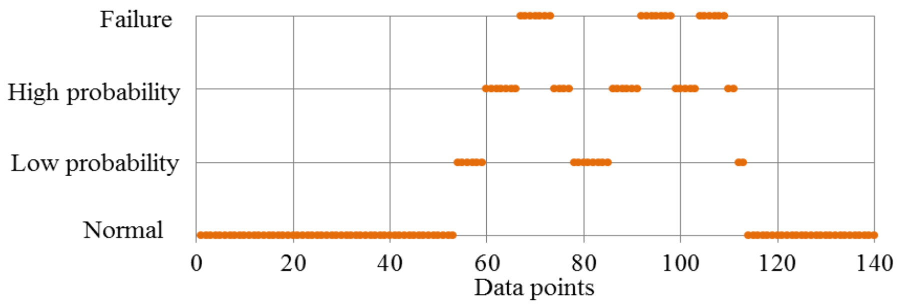

Figure 4: Plot of the raw sequence against the functioning hour (incipient fault simulation at broken sky conditions (loose connection failure))

The pattern of fault detection is the case of loose connection failure has an alternating nature, since the fault signal varied over simulation time and moreover the solar radiation on a collector plane was not constant also. Nevertheless the developed NARX could detect the presence of the incipient fault within the solar combisystem. The fault detection tools proposed can be adapted for the wide range of solar combisystems, as well as used for both: owners of solar combisystems and research facilities. The remote monitoring of the system is possible with the neural networks. The input parameters used for the simulation are commonly found in solar installations; therefore the cost of integration of neural network into existing system would be relatively easy.

4. Conclusions

Despite perceived simplicity of solar collectors, failures can occur during the operation. For the most installations, absent heat gains from solar collectors are covered by an auxiliary energy source. Therefore within the research fault detection tool by the application of closed loop non-linear autoregressive neural network and programming language in the MatLab environment is developed. This developed model detected two types of faults: abrupt and incipient. As abrupt faults the malfunction in solar pump was tested and as incipient faults the malfunction of solar controller due to loose connector. Faults were detected both for clear sky and cloudy condition. The results of the research show that integration of artificial neural network within solar combisystem increases the performance and reliability of operation. The fault detection tool can be used for both: owners of solar combisystems and research facilities. The fault detection tool can be further integrated for the on-site operation at various types of solar combiystems and added to the real-time monitoring system. The fault detection systems could be integrated in the solar combisystems, thus reducing the consumption of auxiliary energy and decreasing emissions during operation. In the context of the European Union the developed model can be used by research facilities and manufactures or renewable energy technologies to align with the targets set in for energy policy.

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