A COMPARISON BETWEEN STATE-OF-THE-ART AND NEURAL NETWORK MODELLING OF SOLAR COLLECTORS

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1. Introduction

The state-of-the-art modelling of solar collectors as described in the European Standard EN 12975-2 (EN 12975, 2006) is based on equations describing the thermal behaviour of the collectors by characterising the physical phenomena, e.g. transmission of irradiance through transparent covers, absorption of irradiance on the absorber, temperature dependent heat losses and others. This approach leads to so called collector parameters that describe these phenomena, e.g. the conversion factor η_0 or the heat loss coefficients a_1 and a_2.

For more complex systems it is not always possible to describe the thermal performance with parameters having a direct "physical" meaning. In these cases often artificial neural network (ANN) modelling is successfully applied. There are several significant reasons why ANNs are such a powerful tool for modelling dynamic systems (Yang, 2008):

1. ANNs have a powerful ability to recognize accurately the inherent relationship between any set of input and output without a physical model or even without information about the internal behaviour, and yet the ANN results do account for all the physics relating the output to the input. This ability is essential independent of the complexity of the underlying relation such as nonlinearity, multiple variables and parameters. This essential ability is known as pattern recognition as the result of learning process.
2. The methodology is inherently fault tolerant, due to the large number of processing units in the network undergoing massive parallel data processing.
3. The learning ability of ANNs gives the methodology the ability to adapt to changes in the parameters. This ability enables the ANN to deal also with time-dependent dynamic modelling.

Although the state-of-the-art approach in collector modelling and testing fits most of the collector types very well there are some collector designs (e.g. "Sydney" tubes using heat pipes and "water-in-glass" collectors) which cannot be modelled with the same accuracy than conventional collectors like flat plate or standard evacuated tubular collectors. The ANN approach could be an appropriate alternative.

To compare the different approaches of modelling investigations for a conventional flat plate collector and an evacuated tubular collector have been carried out based on performance measurements according to the European Standard EN 12975. The investigations include the parameter identification (training), the comparisons between measured and modelled collector output and the simulated yearly collector yield for a solar domestic hot water system for both models. All ANNs described in the present paper were performed under the MATLAB (MathWorks, 2010) environment using the Neural Network Toolbox (MathWorks, 2010b). To carry out the simulation the neural network has been implemented in TRNSYS (2004).

The paper describes in detail the different approaches of modelling and the results of the described comparisons.

2. Application of ANN in the field of solar thermal energy

ANNs have been widely and successfully applied in various fields of mathematics, medicine, engineering, economics, meteorology, etc. Comprehensive overviews of applications of ANNs for thermal engineering and especially renewable energy systems are presented in Kalogriou (2000, 2001), Kalogriou et al. (2010) and Kwang-Tzu (2008). Following is a list of the most relevant works in the field of ANN related to the study described in the present paper:

The paper of Roberto et al. (2010) deals with the development of methods for non steady state test procedures of solar thermal collectors. The goal is to infer the collector performance for steady-state conditions in terms of the efficiency curve when only data from measurements under transient conditions are available. The authors used a Grey-box Identification Model and a Dynamic Adaptive Linear Neural network model.

In the study of Sözen et al. (2008) an approach based on ANNs was developed to determine the efficiency of flat plate solar thermal collectors. As input data the collector temperature, date, time, solar radiation, declination angle, azimuth angle and tilt angle were used.

Kalogriou (2006) used different ANNs for the prediction of the collector parameters describing the instantaneous efficiency, the incidence angle modifier coefficients at longitudinal and transverse directions, the collector time constant, the collector stagnation temperature and the collector heat capacity. As inputs of the ANN model the collector dimension, collector constructional characteristics and collector performance characteristics are used. This approach is proposed as a useful instrument for engineers to obtain the performance parameters of new collector designs without the need to perform tests. Of course the final product would have to be tested in the normal way according to the standards.

In the work of Lecoeuche and Lalot (2005) an application of ANNs was presented to predict the in-situ daily performance of solar air collectors. Output of the ANN is the outlet temperature of the collector, and inputs to the network are the solar radiation and the thermal heat loss coefficients. It was assumed that the inlet temperature and the mass flow rate of the fluid are constant.

Farkas and Géczy-Víg (2003) developed for three different kinds of solar thermal collectors (air and water collectors and a latent heat storage collector) ANN models to predict the outlet temperature of the solar collectors based on to the inlet temperature, the ambient temperature and the global solar radiation.

The objective of the work of Kalogirou et al. (1999) was to train an ANN to predict the useful energy extracted from solar domestic hot water systems and the temperature rise of the stored water with minimum of input data. Physical characteristics of the system, such as collector area, storage type, and capacity, mean storage tank heat loss coefficient, and weather conditions, such as solar irradiation at collector aperture, mean ambient air temperature and mean cold water temperature, were use as input data.

3. State-of-the-art collector testing

At present two different standardised methods are available for the determination of the collector performance:

1. The so called steady-state method (e.g. EN 12975, 2006 or ISO9806, 1995) and
2. The quasi-dynamic method (EN 12975, 2006)

Although the steady state method is still part of the European and ISO Standards it is considered out-dated by the authors because transient behaviour of the collector cannot be characterised and no distinction between diffuse and beam irradiance is considered which is important especially for concentrating collectors. Therefore the quasi-dynamic test method is considered being state-of-the-art and described briefly in the following.

3.1. Collector model

The used collector model of the quasi-dynamic test procedure is shown in equation 1. Equations 2 and 3 describe the incidence angle modifier for isotropic collectors (e.g. flat plate collector) and biaxial collectors (e.g. evacuated tubular collectors).

$$\frac{\dot{Q}}{A} = G_{hem}\eta_0\left[K_b(\theta)\frac{G_b}{G_{hem}} + K_d\frac{G_d}{G_{hem}}\right] - \left[a_1 + a_2\left(\vartheta_{fl,m} - \vartheta_{amb}\right)\right]\left(\vartheta_{fl,m} - \vartheta_{amb}\right) - c_{eff}\frac{d\vartheta_{fl,m}}{dt} \qquad \text{(eq. 1)}$$

$$K_b(\theta) = 1 - b_0\left(\frac{1}{\cos\theta} - 1\right) \qquad \text{(eq. 2)}$$

$$K_b(\theta_l,\theta_t) = K_b(\theta_l,0)\cdot K_b(0,\theta_t) \qquad \text{(eq. 3)}$$

To describe $K_b(\theta_l,\theta_t)$ the following angles of incidence (θ_l and θ_t) are used: 0°, 20°, 40°, 50°, 60°, 70° and 90°.

3.2. Test procedure

The collector is mounted under a fixed tilt angle facing the equator and operated with a fixed mass flow rate as specified by the manufacturer. Altogether four different inlet temperatures are chosen for the test, equally spread over the range of operation. Usually the lowest inlet temperature is close to ambient temperature and the highest inlet temperature is approximately 100 °C. To determine the conversion factor η_0 a day with clear sky is needed, all other days may have partly overcast sky conditions.

All quantities shown in equations 1 to 3 are either measured or calculated over the whole day to serve as input data for the parameter identification.

4. State-of-the-art parameter identification

Determination of parameters in a model by adjusting them to measured data is a well established procedure. The basic approach is usually the same for all models (Press et. al., 1992). A merit function is designed that measures the agreement between the measured data and the output of the model calculated with a particular choice of parameters. The merit function is conventionally arranged so that small values represent close agreement between the measured data and the output of the model. The parameters of the model are then adjusted to achieve a minimum in the merit function, yielding best fit parameters. The adjustment process is thus a problem in minimization in many directions and can be performed using different methods. Some methods are briefly described in the following:

4.1. Multi linear regression (MLR)

The MLR is a non iterative fast matrix method. Linear does only mean that the model is written as a sum of terms with the parameters p_m as a multiplier in front of the terms (equation 4).

$$y(x_1,x_2,x_3) = p_1\cdot f(x_1) + p_2\cdot g(x_2,x_3) + p_3\cdot h(x_1,x_2,x_3) \qquad \text{(eq. 4)}$$

The sub models $f(x_1)$, $g(x_2,x_3)$ and $h(x_1,x_2,x_3)$ in each term can be non-linear.

Suppose fitting N data points $(x_{1,i}, x_{2,i}, x_{3,i}, y_i)$, $i = 1,\ldots, N$, to a model that has m adjustable parameters p_j, $j = 1,\ldots, m$. The model predicts a functional relationship between measured independent and dependent variables (equation 5).

$$y(x_1,x_2,x_3) = y(x_1,x_2,x_3;p_1 \ldots p_m) \qquad \text{(eq. 5)}$$

The dependence on the parameters is indicated on the right hand side. These functions can be minimized using the least-square fit (see equation 6).

$$Min = \sum_{i=1}^{N} [y_i - y(x_1, x_2, x_3; p_1 ... p_m)]^2 \quad \text{(eq. 6)}$$

To perform the matrix operations needed for the minimization process typically spread sheet programs are used.

4.2. Dynamic parameter identification

Iterative parameter identification methods use the same approach as in the previous section, namely to define a merit function and to determine the best fit parameters by its minimization using the least-square fit. With non-linear dependence, however, the minimization must be performed iteratively.

For this study the DF program (Spirkl, 1994) was used as reference parameter identification tool. The DF program uses the Levenberg-Marquardt algorithm for the parameter identification process. This is a well known algorithm documented in Press et al., 1992

5. Artificial neural networks (ANN)

The human brain is a highly complex, nonlinear and parallel information-processing system with the capability to organize its structural constituents, known as neurons, so as to perform certain computations like for example pattern recognition and perception many times faster than any digital computer. The basic principles believed to be used in the human brain are so-called neural networks.

Haykin (1999) defines a neural network as a massively parallel distributed processor made up of simple processing units (so called neurons), which have a natural propensity for storing experimental knowledge and making it available for use. Artificial neural networks resemble the brain with regard to two aspects: (a) the knowledge is acquired by the neural network from its environment through a learning process, and (b) interneuron connections strengths, known as (synaptic) weights, are used to store the acquired knowledge.

According to Haykin (1999) the massively parallel distributed structure and its ability to learn are the two information-processing capabilities that make it possibly for neural networks to solve complex problems. Artificial neural networks (ANNs) are computational models which are inspired by biological neural networks and attempt to mimic the information processing system of the human brain.

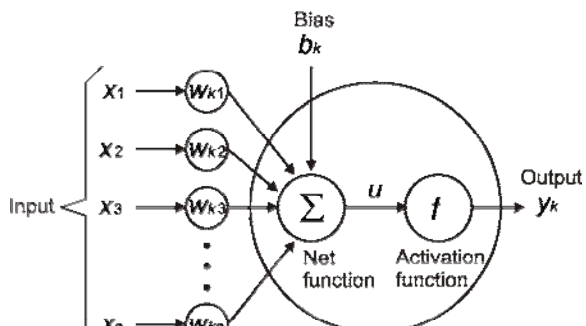


Fig. 1: Basic neural network unit (neuron, node) (McCulloch and Pitts, 1943)

The following description is taken from Yu (2002). The basic building block and the fundamental processing element of an artificial neural network is a neuron (also called basic node or unit). According to the fundamental work of McCulloch and Pitts (1943) Fig. 1 illustrates how information (input) is processed through a single neuron. Basically the neuron receives signal inputs from other sources. The inputs can either be outputs of other neurons or they can be external inputs. The inputs $\{x_i\colon 1 \le i \le n\}$ are weighted by parameters $\{w_{ki}\colon 1 \le i \le n\}$ which are called (synaptic) weights or inter-neuron connection strengths. The parameter b_k is called the bias (also called threshold value) and it is used to model the threshold. The weighted inputs are combined and summed up in a special way depending on the used network input combination method (net function). The output of the neuron is related to the input via linear or non-linear transformation which is called the activation function of the neuron.

In a neural network multiple units (neurons) are interconnected in a particular arrangement or configuration. The network usually consists of an input layer, one or more hidden layers and an output layer. Fig. 2 presents an example of typical neural network architecture.

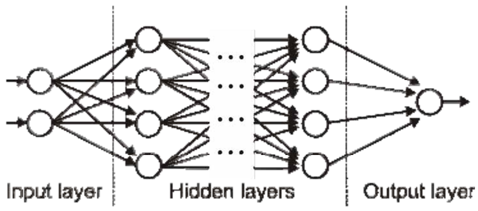


Fig. 2: Typical neural network architecture

As already mentioned one main characteristic of ANNs is their ability to learn and store information. Therefore a so called learning or training process is necessary. In the learning mode the input is presented to the network along with the desired output. Through certain training algorithms the values of weight coefficient between processing neurons are adjusted in such a way that the network attempts to produce the desired output. When the training reaches a satisfactory level the network holds the weights constant. Now the weights contain meaningful and important information, whereas before training they are random and have no meaning. After the successful training step the trained ANN model can be used to predict the output parameters as a function of the input parameters.

5.1. Modelling the solar collectors with ANNs

In the present work a NARX model (**N**onlinear **A**uto**R**egressive model with e**X**ogenous inputs) was used for modelling the thermal behaviour of two different collectors (flat plate collector and evacuated tubular collector with CPC reflector). The NARX-type model is a recurrent dynamic network which is commonly used in time-series modelling and modelling of nonlinear dynamic systems. In recurrent dynamic networks the output depends in general not only on the current input to the network but also on the current and/or previous inputs, outputs, or stages of the network. The standard NARX architecture is shown in Fig. 3.

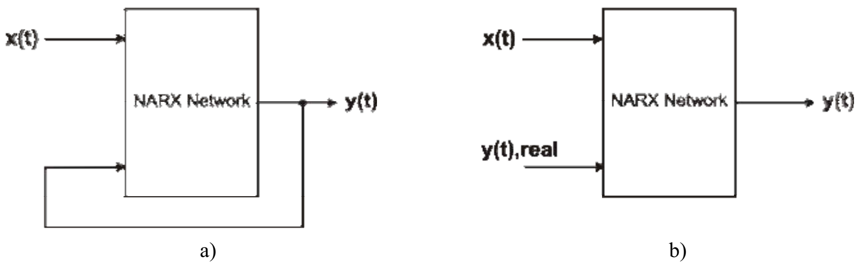


Fig. 3: NARX network architecture: a) parallel mode (closed feedback loop) b) series-parallel mode (open feedback loop)

The equation defining the NARX model (parallel mode) is shown in (eq. 7), where the value of the dependent output *y(t)* is regressed on previous values of the output and on previous values of the (exogenous) input.

$$y(t) = f\left(y(t-1),\ldots,y(t-d),x(t-1),\ldots,x(t-d)\right) \qquad \text{(eq. 7)}$$

In the equation *x(t)* and *y(t)* denote the input and output of the network at the discrete time *t*. Parameter *d* represents the number of the time-delays (memory delays), which can be seen as the input-memory and output-memory order. The time-delays are used to store previous values of the *x(t)* and *y(t)* sequences.

For efficient training often a series-parallel architecture (open feedback loop) of the NARX network as shown in Fig. 3b is preferred. This enables that during the training process the real (measured) output can be used instead of feeding back the estimated output. The main advantage of this approach is that the input to the network is more accurate. Another advantage is that series-parallel NARX network has a purely feed forward architecture, and static back-propagation can be used for training. As soon as the (open loop) training process is successful finished the feedback loop is closed (Fig. 3a).

5.2. Neural network model for modelling the flat plate collector

The selected architecture of the ANN used in this study to model the collector output of flat plate collectors is schematically illustrated in Fig. 4.

The ANN consists of an input layer representing the input variables, an output layer corresponding to the output variables and one hidden layer. The inputs to the ANN are the beam and diffuse irradiance (G_b, G_d), the incident angle of the beam irradiance (θ), the temperature difference between the collector fluid inlet temperature and ambient temperature $(\vartheta_{fl,in}-\vartheta_{amb})$[1] and the mass flow rate ($\dot{m}$). The output from the ANN is the collector output ($\dot{Q}$).

To find the ANN with the smallest deviation between measured and calculated collector output different configurations for the ANN were used. By trial and error the number of neurons in the hidden layer is chosen as 5 and the number of the tapped time-delay d is chosen as 2. In the (open loop) training procedure, the weighting coefficients are adjusted using the Levenberg–Marquardt algorithm.

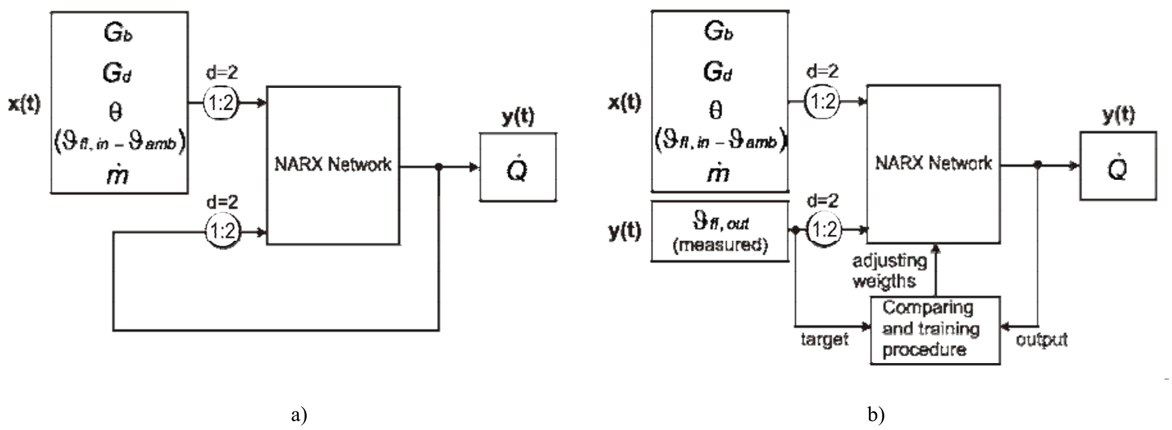


Fig. 4: Structure of the ANN for modelling the collector: a) parallel mode b) series-parallel mode (open feedback loop)

5.3. Neural network model for modelling the evacuated tubular collector

Here, instead of the incident angle of the beam irradiance (θ) the incident angle of the beam irradiance in longitudinal plane (θ_l) and in transversal plane (θ_t) were used as inputs. All other inputs and outputs of the ANN for modelling the evacuated tubular collector were the same already described in 4.2.

By trial and error the number of neurons in the hidden layer is chosen as 4 and the number of the time-delay d is chosen as 2. The same training algorithm as for the flat plate collector was used.

For both type of collectors the (open loop) training of the ANN model was carried out by using measured input-output data which were acquired under quasi-dynamic conditions according to the test procedure described in the European Standard EN 12975-2 (EN 12975, 2006) at the Research and Testing Centre for Thermal Solar Systems (TZS) of ITW, University of Stuttgart.

[1] Investigations not presented in this paper have shown that the term $(\vartheta_{fl,in}-\vartheta_{amb})$ has to be used as input instead of using $\vartheta_{fl,in}$ and ϑ_{amb} as separate inputs. This approach enables the ANN to deal also with collector inlet ambient temperatures that were not used during the training process.

6. Comparison of measured and calculated collector output

For this study two solar collectors, one flat plate collector and one evacuated tubular collector with CPC reflector were tested according to section 3. State-of-the-art parameter identification was performed using the method described in section 4.2 and compared to the results using an artificial network (ANN) as described in section 5.2 and 5.3 respectively. This section compares the results obtained by the two approaches on the basis of measured and calculated collector output data. The figure of merit for the comparison is the difference in transferred energy ΔQ ($[\Delta Q]$ = J), calculated as the sum of absolute error for each time step i as defined in equation 8.

$$\Delta Q = \sum_{i=1}^{N} \left| Q_{i,cal} - Q_{i,meas} \right| \quad \text{(eq. 8)}$$

6.1. Flat plate collector

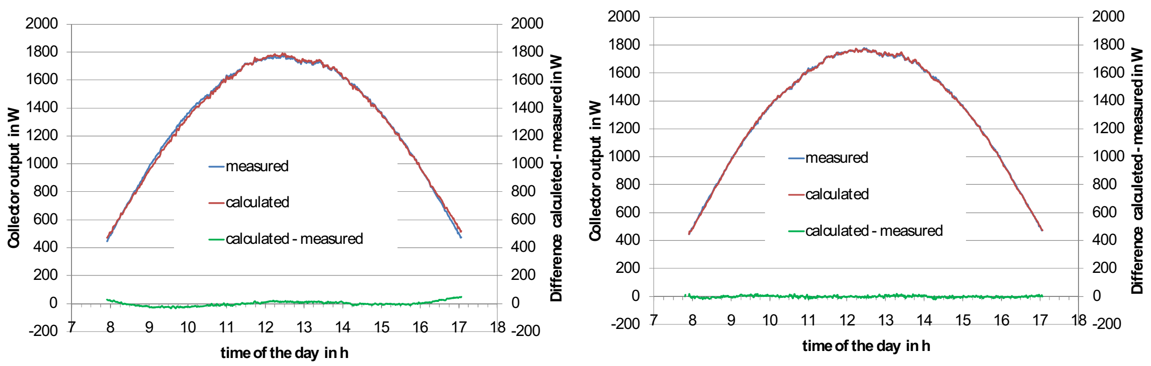
The investigation was carried out on a flat plate collector with an aperture area of 2.17 m² with a Cu-Cu absorber. The absorber sheet with a thickness of 0.2 mm is connected to the riser tubes (10 in parallel) and manifolds using ultrasonic welding. The absorber uses a selective coating. Mineral wool with a thickness of 60 mm is used as backside thermal insulation. Tab. 1 shows the collector parameters determined using the state-of-the-art collector test method.

Tab. 1: Collector parameter describing the thermal performance of the flat plate collector under investigation

η_0	b_0	K_d	a_1 W m^{-2} K^{-1}	a_2 W m^{-2} K^{-2}	c_{eff} J m^{-2} K^{-1}
0.815	0.119	0.948	3.577	0.019	12870

Fig. 5 shows the comparison of the measured and calculated collector output for the state-of-the-art and the ANN modelling for the used test sequence at $(\vartheta_{fl,m} - \vartheta_{amb}) \approx 0$ K under clear sky conditions (Q_{meas} = 43374 kJ). The state-of-the-art model shows a very good agreement between measured and calculated collector output. The difference in the transferred energy is 436 kJ (1 %). At certain angles of incidence the calculated collector output shows slight differences to the measured output. The main reason is the incidence angle modifier model, which has to be used during the state-of-the-art testing and which does not perfectly fit flat plate collectors.

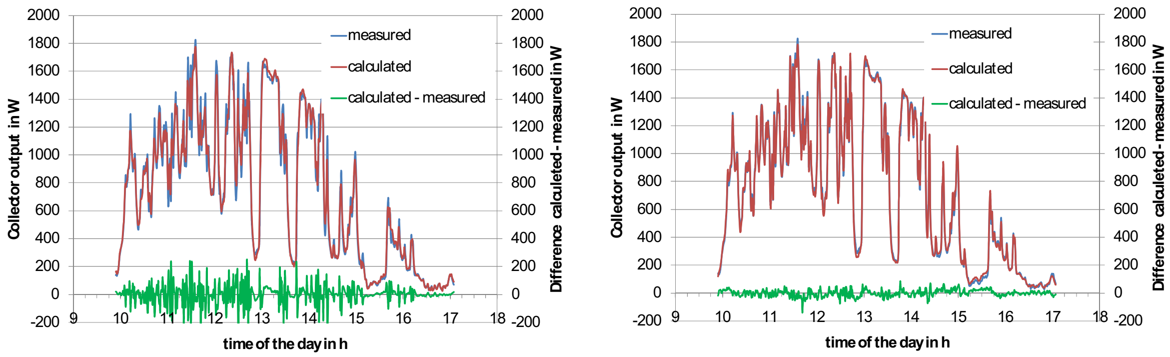
The ANN model shows an even better agreement, since it is not restricted to limited number of parameters. The difference in transferred energy is 184 kJ (0.4 %).



a) b)

Fig. 5: Measured and calculated collector output flat plate collector: a) state-of-the-art collector modelling b) ANN modelling

Fig. 6 shows the comparison of the measured and calculated collector output for the state-of-the-art and the ANN modelling for the used test sequence at $(\vartheta_{fl,m} - \vartheta_{amb}) \approx 25$ K under broken clouds conditions (Q_{meas} = 19040 kJ). Again the ANN model shows the better agreement between measured and calculated collector output. This time the mean reason is the fact that the state-of-the-art approach uses a 1-node model, approximating the transient behaviour of the collector by one effective thermal capacity (c_{eff}) at mean fluid temperature ($\vartheta_{fl,m}$). This approach leads to over- and under prediction, respectively, in case of rapidly changing input values. The difference in transferred energy yields to 1160 kJ (6.1 %) with the state-of-the-art approach and to 477 kJ (2.5 %) by using ANN.



a) b)

Fig. 6: Measured and calculated collector output flat plate collector: a) conventional collector modelling; b) ANN modelling

6.2. Evacuated tubular collector

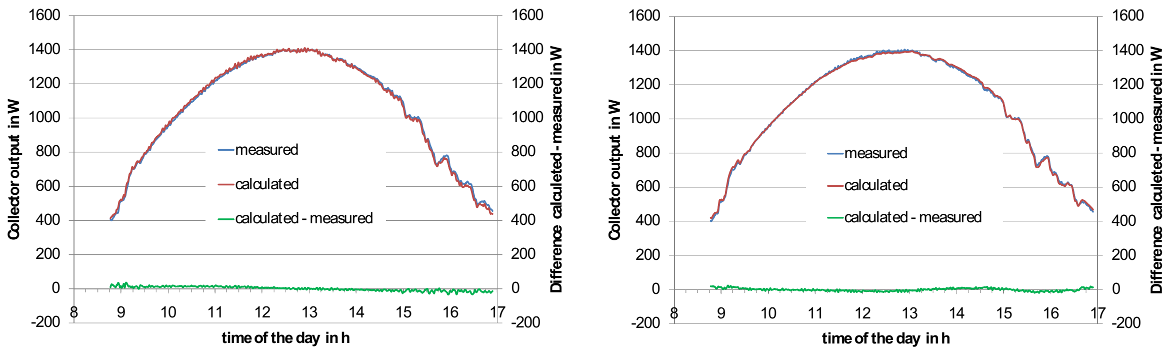
The investigation was carried out on an evacuated tubular collector with an aperture area of 1.9 m² using "Sydney" tubes and a CPC reflector. The heat from the absorber is transferred to the heat transfer fluid by an aluminium heat transfer sheet and copper U-tube. Tab. 2 shows the collector parameters determined using the state-of-the-art collector test method.

Tab. 2: Collector parameter describing the thermal performance of the evacuated tubular collector under investigation

η_0	K_d	a_1 W m^{-2} K^{-1}	a_2 W m^{-2} K^{-2}	c_{eff} J m^{-2} K^{-1}
0.872	1.026	0.986	0.006	40860

Incident angle	0°	20°	40°	50°	60°	70°	90°
$K_{\theta b}(\theta_l)$	1.00	0.99	0.94	0.89	0.79	0.64	0.00
$K_{\theta b}(\theta_t)$	1.00	1.00	1.01	1.10	1.12	1.32	0.00

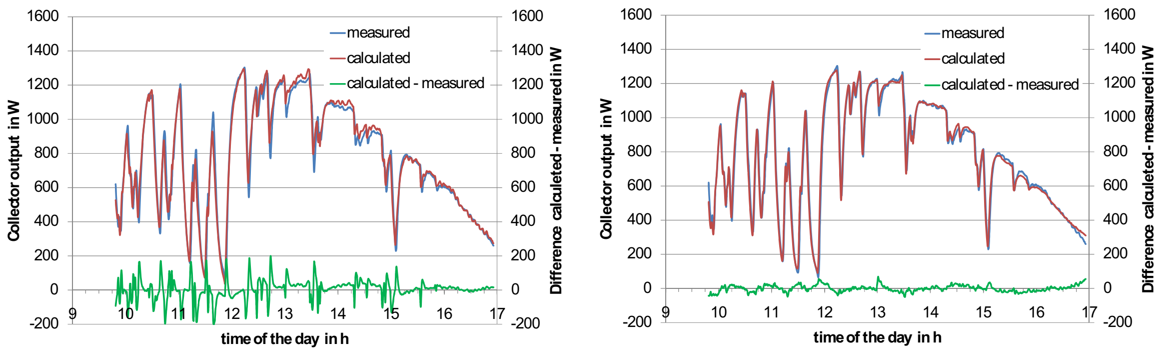
In Fig. 7 the comparison of the measured and calculated collector output is shown for the state-of-the-art and the ANN modelling for the used test sequence at $(\vartheta_{fl,m} - \vartheta_{amb}) \approx 0$ K under clear sky conditions (Q_{meas} = 30964 kJ). Due to the more advanced incidence angle modifier model (eq. 3) used for evacuated tubular collectors, the state-of-the-art approach gives almost as good results as the ANN approach. The difference in transferred energy yields 307 kJ (1 %) (state-of-the-art) and 200 kJ (0.6 %) (ANN).



a) b)

Fig. 7: Measured and calculated collector output evacuated tubular collector: a) conventional collector modelling; b) ANN modelling

Fig. 8 shows the comparison of the measured and calculated collector output for the state-of-the-art and the ANN modelling for the used test sequence at $(\vartheta_{fl,m} - \vartheta_{amb}) \approx 85$ K under broken clouds conditions ($Q_{meas} = 20075$ kJ). The difference in transferred energy yields 1015 kJ (5.1 %) (state-of-the-art) and 856 kJ (4.3 %) (ANN), showing again a better agreement between measured and calculated collector output for the ANN approach.



a) b)

Fig. 8: Measured and calculated collector output evacuated tubular collector: a) conventional collector modelling; b) ANN modelling

7. Dynamic system simulation

Section 6 shows that the ANN approach yields a slightly better agreement between measured and calculated collector output than the state-of-the-art approach. To be a true alternative, however, it must also be possible to use the ANN collector in a dynamic system simulation together with other components of a solar thermal system.

To evaluate this ability a solar domestic hot water system (SDHW system) was defined and implemented in the simulation tool TRNSYS. Fig. 9 shows a sketch of the solar domestic hot water system and Tab. 3 the most relevant used system parameter. The simulations were performed for a single family house (located in Würzburg, Germany) occupied by 4 persons with a domestic hot water draw off of 200 l/d at 45 °C. The following tapping cycle was used: 80 l at 7 am, 40 l at 12 am and 80 l at 7 pm.

To implement the ANN which was generated under the MATLAB environment the TRNSYS “TYPE 155-Calling MATLAB” was used. This TYPE enables the communication between the two software packages TRNSYS and MATLAB. The communication is realised by a so called Component Object Model (COM) interface which launches MATLAB at every single TRNSYS time step as a separate process.

The ANN was implemented in the TRNSYS deck parallel to the collector. Using this approach the collector

TYPE 132 and the ANN receive always the same input values, thus the collector yield of the collector type and the ANN can be compared directly. In the simulation the output of the collector TYPE 132 is used as input for the other types.

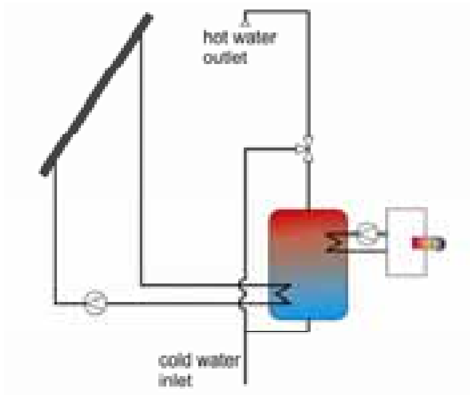


Fig. 9: Schematic drawing of the solar domestic hot water system

Tab. 3: Main system parameter for the SDHW TRNSYS simulation

System parameters for SDHW system concepts	value
Collector area flat plate collector, m²	4.34
Total heat store volume, l	300
Auxiliary volume for domestic hot water preparation, l	150
Set temperature for domestic hot water, °C	52.5
Overall heat loss capacity rate of store, W K^{-1}	2.5
Total pipe length of collector loop, m	20
Inner diameter of collector loop pipe, mm	13
Maximum heat store temperature, °C	80
Temperature difference collector start-up, K	10
Temperature difference collector shut-off, K	2
Fluid heat capacity (collector loop and hot water loop), J kg^{-1} K^{-1}	4180

Tab. 4 shows the yearly collector yield of the flat plate collector calculated using the collector TYPE 132 and the ANN collector model. Compared to the state-of-the art approach the collector output of the ANN within the dynamic system simulation is overestimated by 1.2 %. What seems to be a good agreement turns out to be still quite far away from the defined goal.

The analysis of the simulation data revealed the fact that the generated ANN is not able to handle periods without mass flow through the collector. No flow conditions have not been part of the state-of-the-art test sequences and could thus not be trained and remembered by the ANN. The consequence of this “lack of knowledge” is the calculation of some unrealistic collector outlet temperatures.

Tab. 4: Comparison of the yearly collector yield calculated using the collector TYPE 132 and the ANN

	TYPE 132 kWh a^{-1}	**ANN kWh a^{-1}**	**Deviation %**
Yearly collector yield flat plate collector	1724	1745	+ 1.2

Since the results of the TRNSYS simulation using the evacuated tubular collector shows the same effects and does not deliver further finding it is not presented in this paper.

8. Conclusions

Artificial neural networks are a powerful tool that can be used to characterize the thermal behavior of solar collectors. However special care has to be taken during the training process to cover all operation conditions that will be encountered during the future usage of the ANN.

To use ANNs instead of the state-of-the-art collector model as a reliable tool in dynamic system simulation special test sequences have to be designed. These test sequences need to cover a large range of operating conditions, including no flow conditions. In case the system simulation shall be performed with a heat transfer fluids that differ from the one used for testing, also a variety of different fluids to cover different values of the fluids' specific heat capacity is needed during testing.

The investigations also showed that the determination of the ANN that fits the thermal performance of the collector the best depends on the expertise of the user and can be quite time consuming. Especially when ANNs based test method should become part of European or international standards an algorithm is needed which ensures a reliable and fast determination of the best ANN.

If the above presented improvements have been made artificial neural networks can become an interesting alternative to the state-of-the-art collector models used today.

9. Nomenclature

Symbol	Unit	Quantity
A	m²	Collector area
a_1	W m^{-2} K^{-1}	Heat loss coefficient
a_2	W m^{-2} K^{-2}	Temperature dependent heat loss coefficient
b_0	-	Factor to calculate the incidence angle modifier for beam irradiance
b_k	-	Bias
c_{eff}	J m^{-2} K^{-1}	Effective collector heat capacity
d	-	Number of the time-delays
η_0	-	Conversion factor
ϑ_{amb}	°C	Ambient temperature
$\vartheta_{fl,in}$	°C	Fluid inlet temperature
$\vartheta_{fl,m}$	°C	Mean fluid temperature
$\vartheta_{fl,out}$	°C	Fluid inlet temperature
G_b	W m^{-2}	Beam irradiance
G_d	W m^{-2}	Diffuse irradiance
G_{hem}	W m^{-2}	Hemispherical irradiance
i	-	Index of the time step
$K_b(\theta)$	-	Incidence angle modifier for beam irradiance
K_d	-	Incidence angle modifier for diffuse irradiance
θ	°	Incident angle of the beam irradiance
θ_l	°	Incident angle of the beam irradiance in longitudinal plane
θ_t	°	Incident angle of the beam irradiance in transversal plane
$\dot{m}$	kg s^{-2}	Mass flow rate of the heat transfer fluid
N		Number of time steps
Q_{cal}	J	Transferred energy (calculated)
Q_{meas}	J	Transferred energy (measured)
$\dot{Q}$	W	Collector output
ΔQ	J	Difference in transferred energy
t	s	Time
w_{ki}	-	Synaptic weights

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