DEVELOPMENT OF ARTIFICAL NEURAL NETWORK MODELS FOR SORPTION CHILLERS

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1. Introduction

Solar cooling is still a young and small but growing market with a large potential. Up to now there exists no standardised performance test method for solar cooling or combined solar cooling and heating systems. Also for these innovative systems it is important that performance determination is carried out in a standardised way in order to compare their performance with the one of a well defined reference system (conventional system). In this way energetic and environmental benefits in terms of primary energy savings and CO_2 emission reductions can be determined. For this reason and due to the fact that one established procedure to determine the performance of solar thermal systems is the CTSS-method (Component Testing – System Simulation), already standardised in European Standard series CEN/TS 12977, an extension of this method applicable for solar cooling systems and SolarCombiPlus systems (systems which provide domestic hot water, space heating and space cooling) was found to be the most promising way. With this method the annual performance of the whole system can be calculated for defined boundary and reference conditions (meteorology, load profiles) by means of a dynamic simulation of the whole system. For the suggested extension of the CTSS-method towards solar cooling systems (Frey et al., 2010) dynamic simulation models for thermally driven chillers (sorption chillers) are necessary. The main target of the work presented in this paper is to develop appropriate sorption chiller models which can be used for the extended CTSS-method. One promising way is the experimental system identification based on artificial neural networks (ANN). In this approach experimentally measured data are used to derive an ANN model which is able to predict the outlet temperatures of a sorption chiller. In the work presented, measured data of an adsorption chiller were used to develop such a model which is suitable to predict the outlet temperatures of the three hydraulic loops of the adsorption chiller. The model was validated with measured data under real working conditions. The simulated output temperatures show good agreement with the measured temperatures.

2. Testing according to the CTSS-method

For performing tests according to the CTSS-method in general, the solar thermal system does not need to be installed as a whole because this test method is based on component testing and system simulation. Due to this, the application range of the CTSS-method is very flexible because of its component-oriented approach. Hence, it is possible to apply the CTSS-method on nearly every kind of system configuration. Another important advantage of the CTSS-method is that the thermal performance of the tested systems can be easily determined for any arbitrary boundary conditions such as weather and heating/cooling load since this is done by numerical system simulations only.

2.1. Component testing

To apply the CTSS-method first of all the main components of the solar thermal system (the collector, the store(s) and the controller) are being tested separately. The aim of the component tests is the determination of all relevant component parameters required for the detailed description of the thermal behaviour of the individual components. Therefore, numerical models to describe the dynamic behaviour of the specific components are required. Parameters of these models are determined by means of parameter identification using measuring data from several specific test sequences.

2.2. System simulation

The main aim of the component tests is a detailed determination of all relevant component parameters. Based on these component parameters the annual performance of the whole system can be calculated for defined boundary and reference conditions (meteorology, load profiles) by means of a numerical simulation of the whole system. Therefore together with the hydraulic scheme of the system and the control strategies the parameters have to be implemented in a detailed dynamic and component based system simulation program like TRNSYS. Fig. 1 shows the approach of the CTSS-method according to CEN/TS 12977.

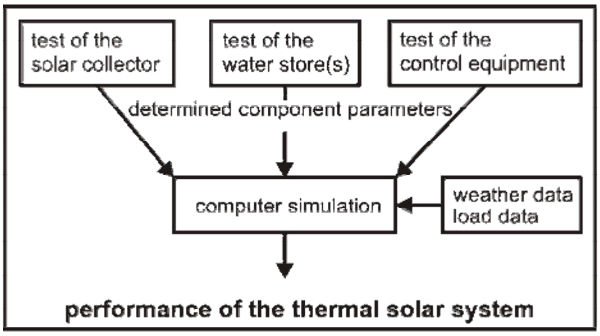


Fig. 1: CTSS-method according to CEN/TS 12977

2.3. Extension of the CTSS-method towards solar cooling and SolarCombiPlus systems

Fig. 2 shows how the approach of an extended CTSS-method applicable to solar cooling systems and SolarCombiPlus systems may look like in general. The difference to the approach of the present version of the CTSS-method according to CEN/TS 12977 (Fig.1) is that there will be one maybe even two more component tests for the cold medium production sub-system in the extended method. It will be indispensable to add one component test for sorption chillers and if necessary another one for the heat rejection unit (cooling tower, borehole or other heat sinks).

For the extension of the CTSS-method towards solar cooling systems the following steps are necessary:

- Decision which performance parameters will be required for description of the thermal behaviour of sorption chillers (and for the heat rejection unit)
- Development or modification of numerical models for sorption chillers (and for the heat rejection unit) in order to characterise their dynamic behaviour in an appropriate way
- Validation of the numerical models
- Development, implementation and validation of performance test methods for the new components
- Validation of the extended CTSS-method
- Integration of the extended CTSS-method in a future version of CEN/TS 12977 series

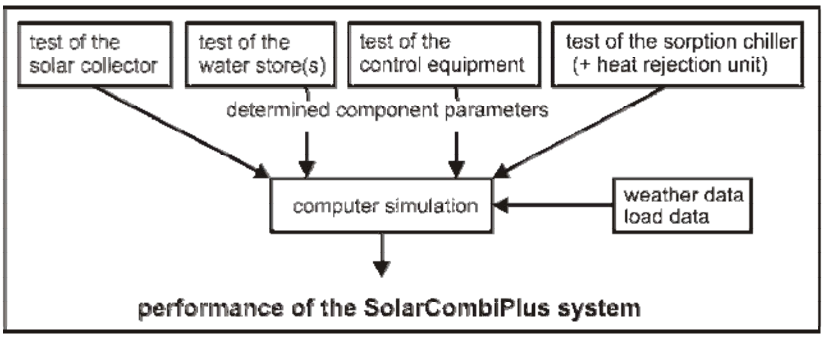


Fig. 2: Extended CTSS-method applicable to SolarCombiPlus systems

3. Dynamic simulation models for sorption chillers

One characteristic of adsorption chillers is the fact that they are periodically working chillers with partial fast temperature changes at the outlets of the hydraulic loops during one working cycle. Also sorption chillers usually have a relative high thermal mass due to their internal heat exchangers, the sorption material and the heat transfer media inside. Besides of this the inlet temperatures of sorption chillers in solar thermal systems are varying mainly as a function of the solar radiation and the ambient temperatures. As a result of this it can be summarised that all kind of sorption chillers but in particular semi-continuous chillers such as adsorption chillers are components operated in a highly dynamical way.

Dynamic simulation models of sorption chillers should allow the simulation of the real dynamic behaviour of these chillers for variable input conditions. I.e. it should be possible to simulate the thermal behaviour of the outlet temperatures of the three loops (driving circuit, heat rejection circuit, chilled water circuit) depending on the current internal operation status and on dynamic changes of the external conditions. Unfortunately, the number of available dynamic simulation models for sorption chillers is small and some existing models are due to copyright aspects not adaptable to the specific needs of the CTSS-method.

Due to the fact that a sorption chiller itself is a complicated nonlinear system it is very difficult and time-consuming to develop mathematical models of sorption chillers based on physical and thermodynamic equations including energy balances and taking into account the conservation of total mass and sorbent heat transfer as well at the thermodynamic equilibrium between solid, liquid and vapour, etc (Chow et al., 2001). One promising alternative to the development of mathematical models based on physical and thermodynamic equations is the experimental system identification based on artificial neural networks. There are several significant reasons why ANNs are such a powerful tool for experimental system identification and modelling of dynamic systems (Yang, 2008):

1. ANNs have a powerful ability to recognize accurately the inherent relationship between any set of input and output data without a physical model or even without information about the internal behaviour and even the ANN results do account for all the physics relating the output to the input data. This ability is essential independent of the complexity of the underlying relation such as nonlinearity, multiple variables and parameters. This ability is known as pattern recognition as the result of a 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.

4. Application of ANNs in the field of modelling sorption chillers

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 Yang (2008). Following is a list of the most relevant works in the field of ANN related to the work described in the present paper.

In Rosiek and Batlles (2011, 2010) a neural network is used to model a solar-assisted air-conditioning system that consists mainly of an absorption chiller, a solar collector array and a cooling tower. The main goal of that work was to estimate coefficients of performance and the cooling capacity of the absorption chiller and also to estimate the global efficiency of the total solar cooling system. As inputs the in- and outlet temperatures of the driving circuit and the chilled water circuit of the adsorption chiller, the outlet temperature and the mass flow rate of the flat-plate collector and the incident radiation intensity were used.

In order to simplify performance analysis of an ammonia-water absorption chiller Sencan (2007) used an ANN. Temperatures of the generator, condenser, absorber, evaporator and the concentration of the poor and the rich solution were used as input data. With the ANN model the coefficient of performance and the circulation ratio, defined as the ratio of the mass flow rate of the rich solution to the mass flow rate of the working fluid, can be predicted.

Sencan et al. (2007) used in their work amongst other approaches ANNs for modelling an absorption heat transformer. Also they used as inputs the temperatures of the absorber, condenser, evaporator and the generator for the ANN in order to estimate the coefficient of performance and the flow rate.

The work of Palau et al. (1999) presented a new modelling approach to simulate the performance of sorption chillers using ANNs. Inputs for the network were the environment temperature and the external heat source temperature, output was the mean cooling power produced by the sorption chiller under different inlet temperatures and ambient temperatures. The main focus of this work was on using the neutral network to control the sorption chiller.

5. Artificial neural networks (ANN)

The human brain is a highly complex, nonlinear and parallel information-processing system with the capability to organise 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 are computational models which are inspired by biological neural networks and attempt to mimic the information processing system of the human brain.

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. 3 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 $\{x_i: 1 \leq i \leq n\}$ are weighted by parameters $\{w_{ki}: 1 \leq i \leq n\}$ 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 nonlinear 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. 4 presents an example of typical neural network architecture.

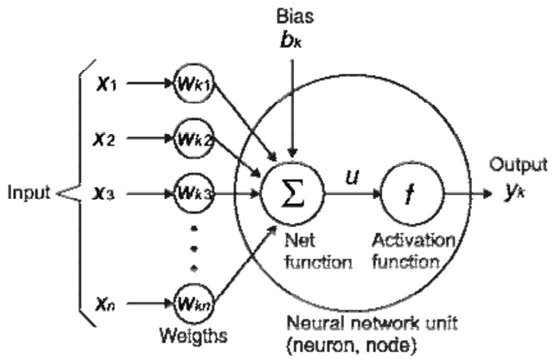


Fig. 3: Basic neural network unit (neuron, node) (McCulloch and Pitts, 1943)

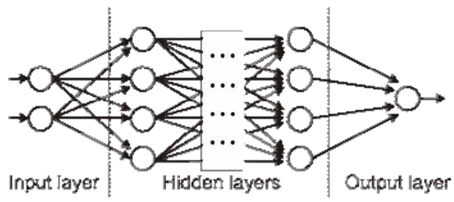
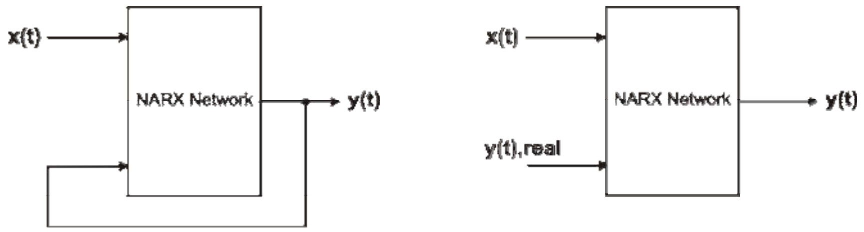


Fig. 4: Typical neural network architecture

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 coefficients 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 fixes the weights constant. Now the weights contain meaningful and important information, whereas before the 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 sorption chillers 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 three outlet temperatures of an adsorption chiller. 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. 5.



a) b)

Fig. 5: 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. 1), 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.

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

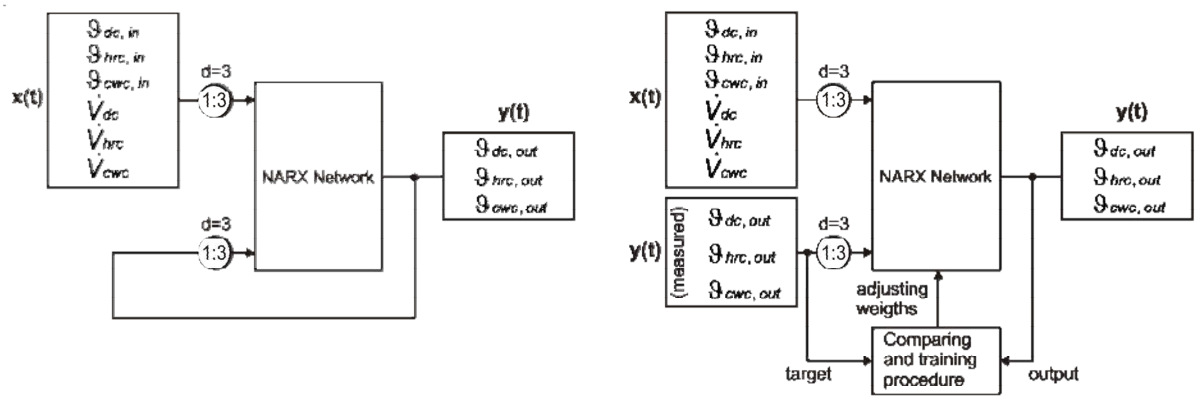
In the equation *x(t)* and *y(t)* denote the input and output of the network at the discrete time *t*. Parameter *d* represents the number of the time-delays (memory delays), which can be seen as the input-memory and output-memory order. The time-delays are used to store previous values of the x(t) and y(t) sequences. Due to this NARX-type models have also the ability to learn and to provide time-dependent information of the dynamic behaviour of the system.

For efficient training often a series-parallel architecture (open feedback loop) of the NARX network as shown in Fig. 5b 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 the 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. 5a). All ANNs described in the present paper were performed under the MATLAB (MathWorks 2010) environment using the Neural Network Toolbox (MathWorks 2010b).

5.2. Artificial neural network model for modelling the adsorption chiller

The selected architecture of the ANN used in this study to model the outlet temperatures (hot water, cooling water, chilled water) of an adsorption chiller is schematically illustrated in Fig. 6. 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 sorption chiller fluid inlet temperatures and volume flow rates of the driving circuit ($\vartheta_{dc,in}, \dot{V}_{dc}$), heat rejection circuit ($\vartheta_{hrc,in}, \dot{V}_{hrc}$) and chilled water circuit ($\vartheta_{cwc,in}, \dot{V}_{cwc}$). The outputs from the ANN are the three fluid outlet temperatures of the sorption chiller ($\vartheta_{dc,out}$, $\vartheta_{hrc,out}$, $\vartheta_{cwc,out}$).

By trial and error the number of neurons in the hidden layer is chosen as 16 and the number of the time-delay d is chosen as 3. A nonlinear transfer function (Hyperbolic Tangent Sigmoid function) is applied as the activation function for the hidden layer, and a linear transfer function is applied for the output layer. In the (open loop) training procedure, the weighting coefficients are adjusted using the Levenberg–Marquardt algorithm.



a) b)

Fig. 6: Structure of the ANN for modelling the sorption chiller: a) parallel mode; b) series-parallel mode (open feedback loop)

6. Comparison of measured and simulated outlet temperatures and transferred energies

The investigation was carried out on a small-scaled adsorption chiller. For the (open loop) training and the verification of the ANN sorption chiller model measured input-output data which were acquired under real dynamic operating conditions were used. The solar heating and cooling system which was therefore detailed monitored is installed at the premise of the company BLS GmbH near Stuttgart, Germany providing hot and chilled water in order to heat and cool the 200 m² office area. The system consists of a solar collector array, a heat store, a back-up heater, a hydraulic switching unit, an adsorption chiller, a heat rejection unit and a floor heating/cooling system. The solar collector array consists of flat-plate solar collectors with a total collector area of 38 m² (aperture area) and is installed on the roof of the building with a 30° tilt angle facing the equator. The heat store has a storage volume of 2.000 litres and is charged and discharged via internal stratifiers. The hydraulic switching unit connects the main components (heat store, floor heating/cooling system, adsorption chiller and heat rejection unit) in order to distribute and provide hot, chilled and cooling water to the different components and loads. The adsorption chiller has a nominal cooling capacity of 8 kW. A dry cooling tower with a water spray function is used for heat rejection.

This section compares the results obtained by the ANN approach on the basis of measured and simulated outlet temperatures, transferred energies and coefficient of performance (COP) as defined in equation 2.

$$COP = \frac{Q_{cwc}}{Q_{dc}} \qquad \text{(eq. 2)}$$

In order to access the accuracy of the ANN the results were analysed in terms of the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE). The MAE and the RMSE are defined in equation 3 and equation 4.

$$MAE = \frac{1}{N} \cdot \sum_{i=1}^{N} \left| x_{i,\,simulated} - x_{i,\,measured} \right| \qquad \text{(eq. 3)}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \left(x_{i,\,simulated} - x_{i,\,measured} \right)^2}{N}} \qquad \text{(eq. 4)}$$

Here $x_{i,simulated}$ is the predicted value and $x_{i,measured}$ is the measured temperature value, i is the considered time step and N is the number of time steps in the considered period. Another figure of merit for the comparison is the difference in transferred energy ΔQ as defined in equation 5.

$$\Delta Q = Q_{simulated} - Q_{measured} \qquad \text{(eq. 5)}$$

6.1. Training of the ANN sorption chiller model

The training database consisted of 6960 data (58 hours) which were acquired with a 30 second sampling period during the summer period 2010. Fig. 7 shows the inlet temperature profiles of the three circuits which were used as input to train the ANN. The volume flow rates can be considered as constant during the whole time.

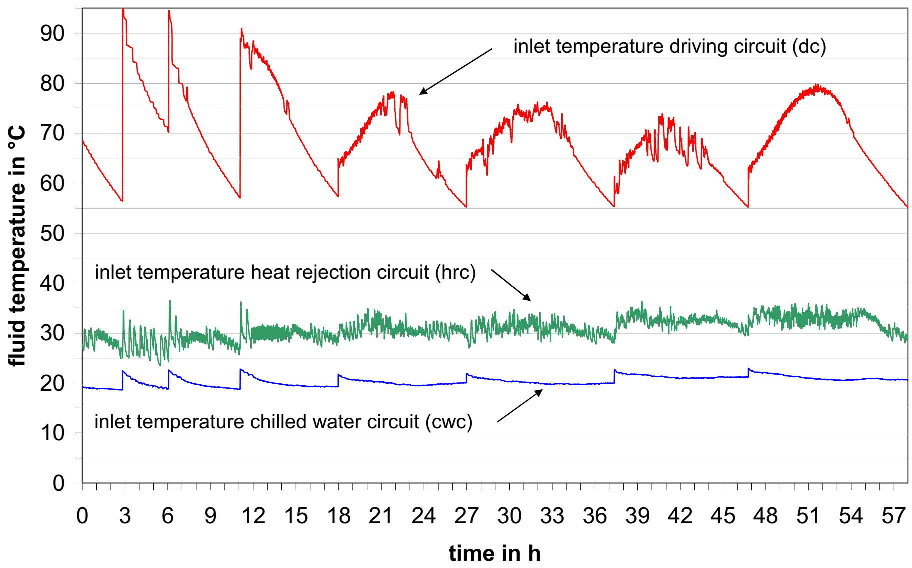


Fig. 7: Measured inlet temperatures of the driving, heat rejection and chilled water circuit used for the training sequence

Fig. 8 illustrates the comparison of the measured and simulated outlet temperature of the driving circuit for a part of the used training sequence. The ANN model shows a very good agreement between the measured and simulated temperatures. For the whole training sequence the Mean Absolute Error (MAE) of $\vartheta_{dc,\,out}$ is 0.5 K and the Root Mean Square Error (RMSE) of $\vartheta_{dc,\,out}$ is 1.2 K. The difference in the transferred energy ΔQ_{dc} is about 12 MJ (0.6 %). As it can be seen in Tab. 1 and 2 the quality of the results of all three circuits are in the same range.

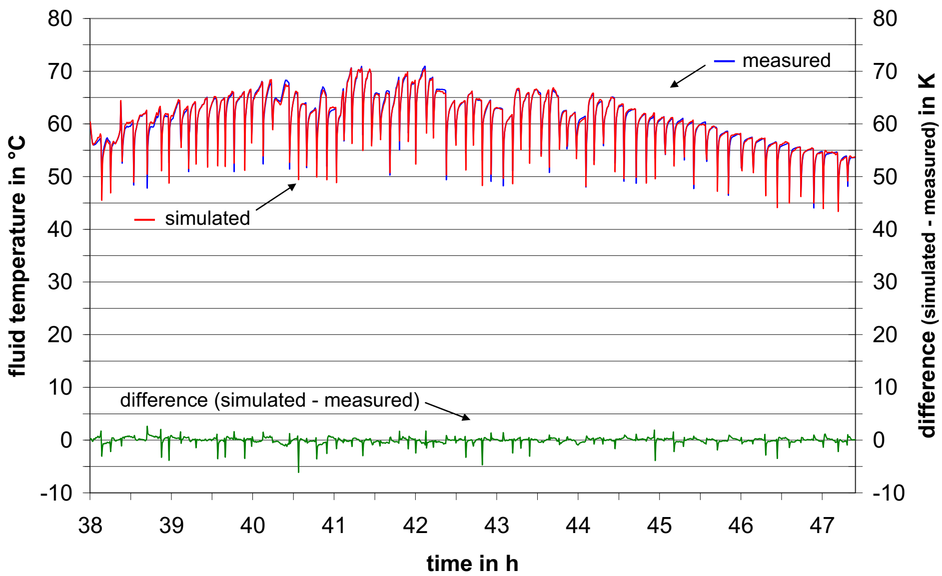


Fig. 8: Comparison of measured and simulated outlet temperature of the driving circuit (training)

Tab. 1: ANN sorption chiller model error analysis for the outlet temperatures (training)

Term	MAE in K	RMSE in K
$\vartheta_{dc,\,out}$ (driving circuit)	0.5	1.2
$\vartheta_{hrc,\,out}$ (heat rejection circuit)	0.3	0.7
$\vartheta_{cwc,\,out}$ (chilled water circuit)	0.3	0.5

Tab. 2: Energy balance and COP (training)

Term	Measurement Energy	Simulation Energy	Error	Error in %
driving circuit	2002 MJ	2014 MJ	12 MJ	0.6
heat rejection circuit	-3071 MJ	-3067 MJ	4 MJ	-0.1
chilled water circuit	985 MJ	981 MJ	-4 MJ	-0.4
COP	0.492	0.487	-0.005	-1.0

6.2. Validation of the ANN sorption chiller model

In order to evaluate the reliability of the developed ANN model a specific test sequence was created. This sequence consists of 990 measurement data (8.25 hours) which were also acquired during the summer period 2010. The inlet temperature profiles of the driving, heat rejection and chilled water circuit which were used for the test sequence are depicted in Fig. 9. The volume flow rates can be considered as constant during the whole test sequence.

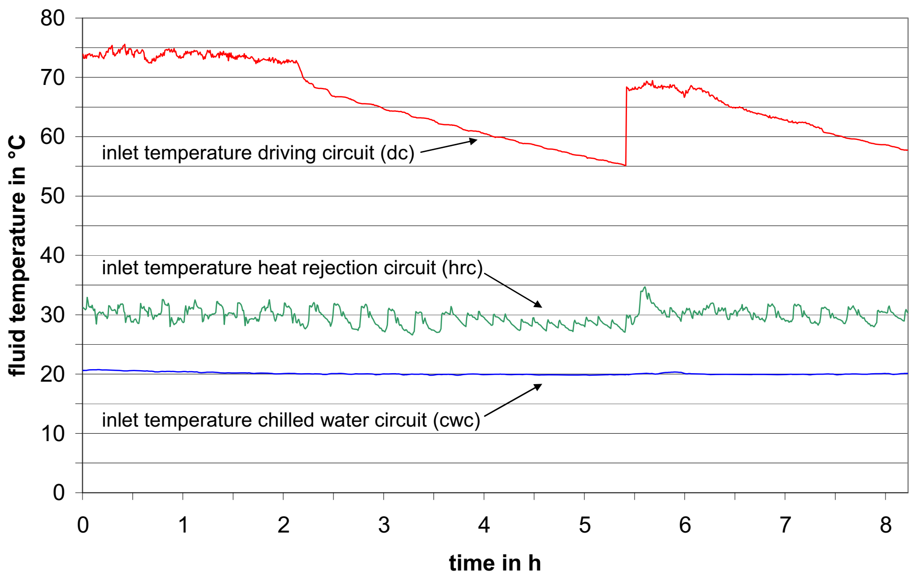


Fig. 9: Measured inlet temperatures of the driving, heat rejection and chilled water circuit (test sequence)

Fig. 10-12 shows the comparison of the measured and simulated outlet temperatures of the three circuits.

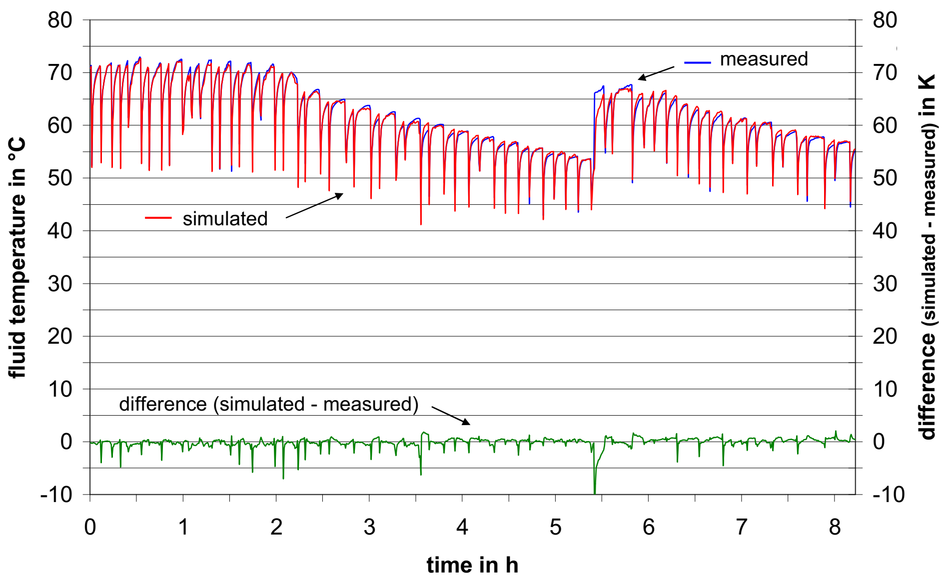


Fig. 10: Comparison of measured and simulated outlet temperature of the driving circuit (test sequence)

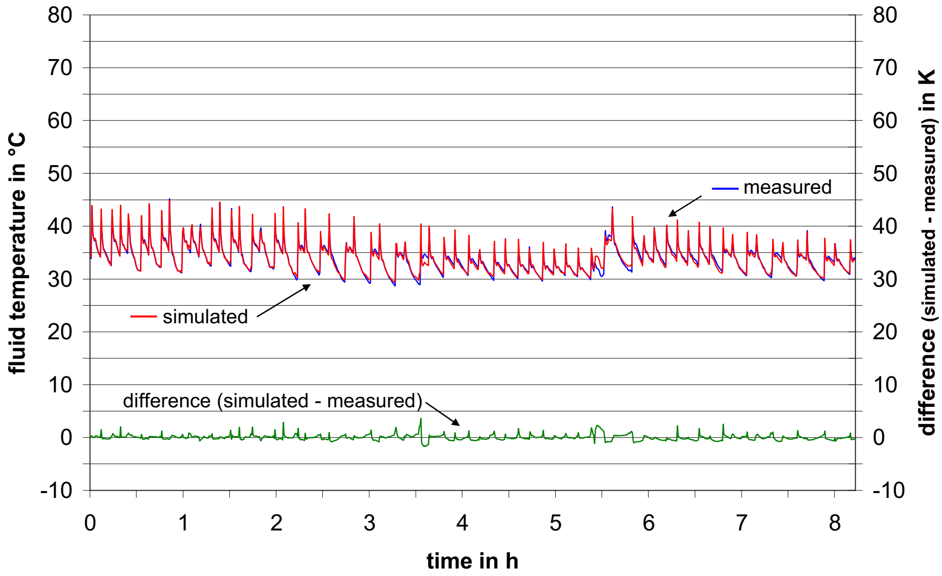


Fig. 11: Comparison of measured and simulated outlet temperature of the heat rejection circuit (test sequence)

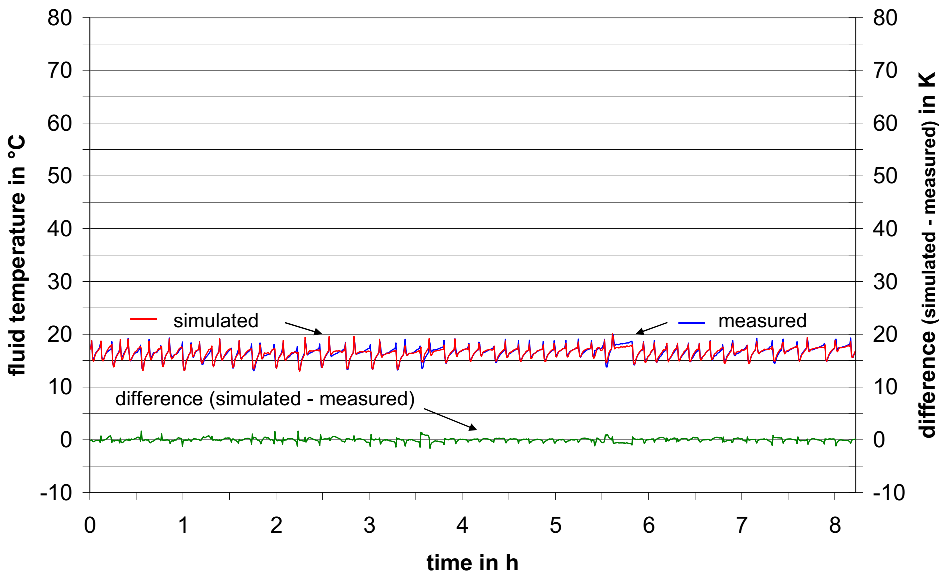


Fig. 12: Comparison of measured and simulated outlet temperature of the chilled water circuit (test sequence)

All three figures (Fig. 10-12) indicate clearly the very good agreement between the measurement and the simulated results in terms of the dynamic behaviour. Moreover the figures show that the obtained errors of the simulated outlet temperatures are quite low. Tab. 3 presents the MAE and the RMSE for the test results shown in Fig. 10-12. For all circuits the MAE is only 0.6 K and the RMSE is 1.0 K or even better. Tab. 4 summarizes the transferred energies and the obtained error which is in the worst case 2.0 %. The COP of the simulation with 0.561 agrees within 1.1 % with the result of 0.567 determined on the basis of the measurements. In conclusion the obtained results can be considered as very satisfactory

Tab. 3: ANN sorption chiller model error analysis for the outlet temperatures (test sequence)

Term	MAE in K	RMSE in K
$\vartheta_{dc,\,out}$ (driving circuit)	0.6	1.0
$\vartheta_{hrc,\,out}$ (heat rejection circuit)	0.3	0.5
$\vartheta_{cwc,\,out}$ (chilled water circuit)	0.2	0.3

Tab. 4: Energy balance and COP (test sequence)

Term	Measurement Energy	Simulation Energy	Error	Error in %
driving circuit	266 MJ	271 MJ	5 MJ	2.0
heat rejection circuit	-439 MJ	-441 MJ	-2 MJ	-0.4
chilled water circuit	151 MJ	152 MJ	1 MJ	0.5
COP	0.567	0.561	-0.006	-1.1

7. TRNSYS simulation

As already mentioned above one main part of the CTSS-method is the system simulation. Here the annual performance of the whole system has to be calculated for defined boundary and reference conditions. Therefore together with the hydraulic scheme of the system and the control strategies all components have to be implemented in a detailed dynamic and component based system simulation program like TRNSYS.

In order to use the newly developed ANN sorption chiller model for the extended CTSS-method it must also be possible to use the ANN sorption chiller model within a dynamic system simulation together with other components of a solar thermal system. To evaluate this ability a solar cooling system was defined and implemented in the simulation tool TRNSYS (2004). 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 implementation of a modified ANN sorption chiller model[1] in TRNSYS was carried out successfully so that for the future it will be possible to perform yearly simulations of the whole solar cooling system.

8. Conclusions

For the suggested extension of the CTSS-method towards solar cooling systems among others dynamic simulation models for sorption chillers are necessary. Most of the already existing simulation models are due to various aspects not applicable for the extension of the CTSS-method. On the other hand it is very difficult and time-consuming to develop new mathematical models of sorption chillers based on physical and thermodynamic equations. One alternative to the development of such models is the experimental system identification based on artificial neural networks (ANN). The main advantage of this approach respective the application to a testing method for sorption chillers is that only very limited information about the internal behaviour of the system is necessary and that it is applicable for all kind of sorption chillers. Moreover after the successful system identification the controller of the sorption chiller is implemented in the derived ANN model as an integral part.

In the work presented experimental measured data were used to derive an ANN model of an adsorption chiller. The developed model was validated with measured data under real operating conditions. The measurements and the simulation results show very good agreement in the highly dynamic thermal behaviour of the sorption chiller. For all three circuits of the sorption chiller the Mean Absolute Error (MAE) is max. 0.6 K and the Root Mean Square Error (RSME) is max. 1.0 K. The difference of the transferred energy is 2.0 % or lower. The relative deviation of the COP is about -1.1 %. The ANN sorption chiller model presented in this work allows the simulation of the dynamic behaviour of a real adsorption chiller for variable input conditions. The developed ANN model of the sorption chiller has been successfully also implemented in TRNSYS. By this another precondition to use ANN models for the suggested extension of the CTSS-method is fulfilled. The next step is the development and definition of testing sequences for sorption chillers on a test facility so that it is possible to derive the ANN sorption chiller model based on laboratory test results.

[1] Here a modified ANN model was used. The main difference compared to the model described in this paper is the operation of the model without using volume flow rates of the three circuits as input data.

It is expected that at the beginning of next year a first proposal for a standardised performance test procedures for solar thermal cooling systems based on ANNs will be available. This will be a remarkable step forward towards advanced and flexible test procedures in the field of solar thermal technology.

9. Acknowledgement

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10. Nomenclature

Symbol	Unit	Quantity
b_k	-	bias of the neuron
COP	-	coefficient of performance
d	-	number of time-delays
i	-	considered time step
MAE	K	mean absolute error
n	-	number of synaptic weights
N	-	number of time steps in the considered period
$Q_{simulated}$	J	transferred energy (simulated)
$Q_{measured}$	J	transferred energy (measured)
ΔQ_{cwc}	J	difference in the transferred energy (chilled water circuit)
ΔQ_{dc}	J	difference in the transferred energy (driving circuit)
ΔQ_{hrc}	J	difference in the transferred energy (heat rejection circuit)
$RMSE$	K	root mean square error
t	-	discrete time
$\dot{V}_{cwc}$	$m^3\ s^{-2}$	volume flow rate of the chilled water circuit of the sorption chiller
$\dot{V}_{dc}$	$m^3\ s^{-2}$	volume flow rate of the driving circuit of the sorption chiller
$\dot{V}_{hrc}$	$m^3\ s^{-2}$	volume flow rate of the heat rejection circuit of the sorption chiller
w_{ki}	-	(synaptic) weights
$x_{i,simulated}$	-	simulated value in the considered time step
$x_{i,measured}$	-	measured value in the considered time step
$x(t)$	-	input of the neural network at the discrete time t
$y(t)$	-	output of the neural network at the discrete time t
$\vartheta_{cwc,\ in}$	°C	fluid inlet temperature of the chilled water circuit of the sorption chiller
$\vartheta_{cwc,\ out}$	°C	fluid outlet temperature of the chilled water circuit of the sorption chiller
$\vartheta_{dc,\ in}$	°C	fluid inlet temperature of the driving circuit of the sorption chiller
$\vartheta_{dc,\ out}$	°C	fluid outlet temperature of the driving circuit of the sorption chiller
$\vartheta_{hrc,\ in}$	°C	fluid inlet temperature of the heat rejection circuit of the sorption chiller
$\vartheta_{hrc,\ out}$	°C	fluid outlet temperature of the heat rejection circuit of the sorption chiller

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