Conference Proceedings

EuroSun 2014
Aix-les-Bains (France), 16 – 19 September 2014

# EXTENDED LABORATORY TEST METHOD FOR COMBINED SOLAR THERMAL AND HEAT PUMP SYSTEMS

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**Abstract**

The combination of solar thermal components with electrically driven compression heat pumps to domestic hot water and space heating systems for smaller single- and multi-family houses is by now already well known among manufacturers in the heating market. However, standardized performance test methods for such combined systems are not yet available, even though standardized test procedures are crucial for the market development by ensuring a high quality level, and also for allowing end customers to compare different system types and configurations with regard to their thermal performance in an objective, transparent and easily understandable manner. Therefore, research has been undertaken by test laboratories in different European countries during the past few years in a common effort within IEA SHC Task 44 / HPP Annex 38 with the aim of extending well established laboratory test methods for solar thermal systems and components towards heat pumps as new components. One of these extended test methods, based on the so-called component testing – system simulation (CTSS) method, is described in detail in this paper and first experiences with a brine to water heat pump are shown. For the characterization of the thermal behavior of the heat pump under dynamic operating conditions, an artificial neural network model has been developed which is also presented.

*Keywords: Combined solar thermal and heat pump system, SHP systems, laboratory test method, extension of CTSS test method, artificial neural network, dynamic heat pump model.*

## 1. Combined solar thermal and heat pump systems

Combined solar thermal and heat pump (SHP) systems are bivalent heating systems providing both domestic hot water and/or space heating for buildings. Depending on the individual technical configuration, there are several possible synergetic effects due to mutual interactions of the two sub-systems, namely the solar thermal system and the heat pump system, which may lead to high system performances. Recently, more than 100 different market available combined SHP systems have been identified in a survey (Ruschenburg and Herkel, 2012). However, further market deployment has been hindered so far, among others, by the lack of knowledge and objective, European-wide accepted performance test procedures such as laboratory test methods or common figures of merit. Hence, these have been developed meanwhile by technical experts within the IEA SHC Task 44/HPP Annex 38 “Solar and Heat Pump Systems”[1] (Task44, 2014). One of the laboratory test methods developed within this task at the Research and Testing Centre for Thermal Solar Systems (TZS) at ITW, University of Stuttgart, is based on an extension of the so-called CTSS test method towards heat pumps.

## 2. Extension of the CTSS laboratory test method towards heat pumps

The component testing – system simulation (CTSS) method is a component oriented laboratory test method originally developed for the determination of the annual thermal performance of solar thermal systems. Today this method is standardized in the European standard series EN 12977 dedicated to so-called custom built solar domestic hot water systems and to solar combi-systems applicable additionally for space heating purposes. For

[1] IEA – International Energy Agency, SHC – Solar Heating and Cooling Programme, HPP – Heat Pump Programme


doi:10.18086/eurosun.2014.03.19 Available at http://proceedings.ises.org

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 different weather data and heating loads, since this is done by numerical system simulations only. To apply the CTSS method, first of all the main components of the solar thermal system such as the collector, the store(s) and the controller are being tested separately. The aim of these component tests is the determination of all relevant component parameters required for the detailed description of the thermal behavior of the individual components. Therefore, numerical models to describe the dynamic behavior of the specific components are required. The parameters to be used in combination with these models are determined by means of parameter identification using measuring data from several specific test sequences (Frey, 2014; Frey, 2011; Drück, 2001).

This method was predominantly developed at TZS and since then it has been applied at TZS to more than 100 solar thermal systems. Already in 2007, first solar heat pump systems were investigated at TZS based on the CTSS method, where the heat pump was modeled by means of a performance map for steady-state operation with a fixed temperature difference between the inlet and outlet temperatures of the heat pump (Bachmann, 2008). However, since the operating conditions of combined solar thermal and heat pump systems installed in the field are often significantly different to steady-state behavior and of rather transient nature, this assumption can lead to inaccurate results.

Therefore, one of the aims of the research project WPSol (Performance Testing and Ecological Assessment of Combined Solar Thermal and Heat Pump Systems) was an extension of the already standardized CTSS test method towards combined solar thermal and heat pump systems (Loose, 2011). For this purpose a dynamic laboratory test method for the heat pump as one key component of a SHP system has been developed and already successfully applied to a brine to water heat pump. In this process, the heat pump is tested in a laboratory under dynamic operation conditions and based on the hereby acquired test data an artificial neural network (ANN) model is trained in order to characterize the thermal behavior of the heat pump. Figure 1 depicts the extended CTSS method with the heat pump as an additional component schematically and shows a picture of the laboratory test facility.


**Fig. 1: Schematic procedure of the CTSS method extended to heat pump systems and picture of the laboratory test facility**

With the trained ANN model for the heat pump and numerical models for all other key components of a SHP system, which are tested conventionally according to EN 12975-2:2006 or ISO 9806 (solar collector) and EN 12977-3:2012 (hot water store), -4:2012 (combistore) and -5:2012 (controller), the annual thermal performance of the overall system can be calculated for defined reference conditions such as meteorological data and load profiles by using a component based simulation program such as TRNSYS.

## 3. Laboratory testing

The extension of the CTSS method to heat pumps proceeds in three phases. At first, there is the necessity of a dynamic heat pump test for the determination of the thermal performance of the heat pump under dynamic laboratory operating conditions, followed by the development of a dynamic simulation model for heat pumps and third the implementation into an overall system simulation deck. For the development of the dynamic heat pump test procedure a test facility for electrically driven compression heat pumps has been built at TZS.

The test facility contains two separated circuits: The *heat source circuit* is driven by a thermostat-controlled heating unit, which provides brine in the temperature range from -20 to 40 °C with a heating power up to 20 kW and cooling power up to 3 kW. It is connected to the primary side of the heat pump. The *heat sink circuit* is driven by a cooling unit, which provides water in the temperature range from 10 to 80 °C with a cooling power up to 20 kW and a heating power of 2 kW. The heat sink circuit is connected to the secondary side of the heat pump. Both circuits use 3-way-valves to control the mass flow rate of the fluids flowing through the heat pump. To improve the temperature stability and to save energy, heat recovery is applied: A part of the heat generated by the heat pump is returned from the heat sink circuit to the heat source circuit by using a heat exchanger. Figure 2 shows the hydraulic scheme of the heat pump test facility used for the determination of the thermal performance of heat pumps under dynamic operating conditions.

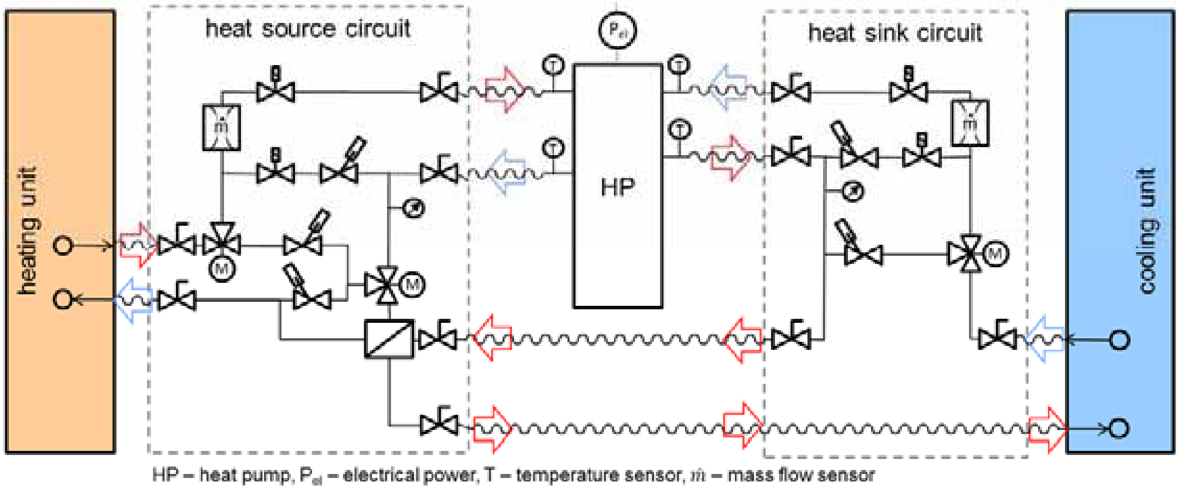


**Fig. 2: Hydraulic scheme of the heat pump test facility used for determination of the thermal performance of heat pumps under dynamic operating conditions in the context of the CTSS method**

For the determination of the thermal performance of a heat pump, the temperatures are measured at the inlets and outlets of the heat pump in time steps of 90 seconds. Additionally the mass flow rate is measured with Coriolis flow meters integrated in both hydraulic circuits. Furthermore, the electrical power consumption of the heat pump is measured and recorded. Based on these measured values all further quantities required for the evaluation can be calculated.

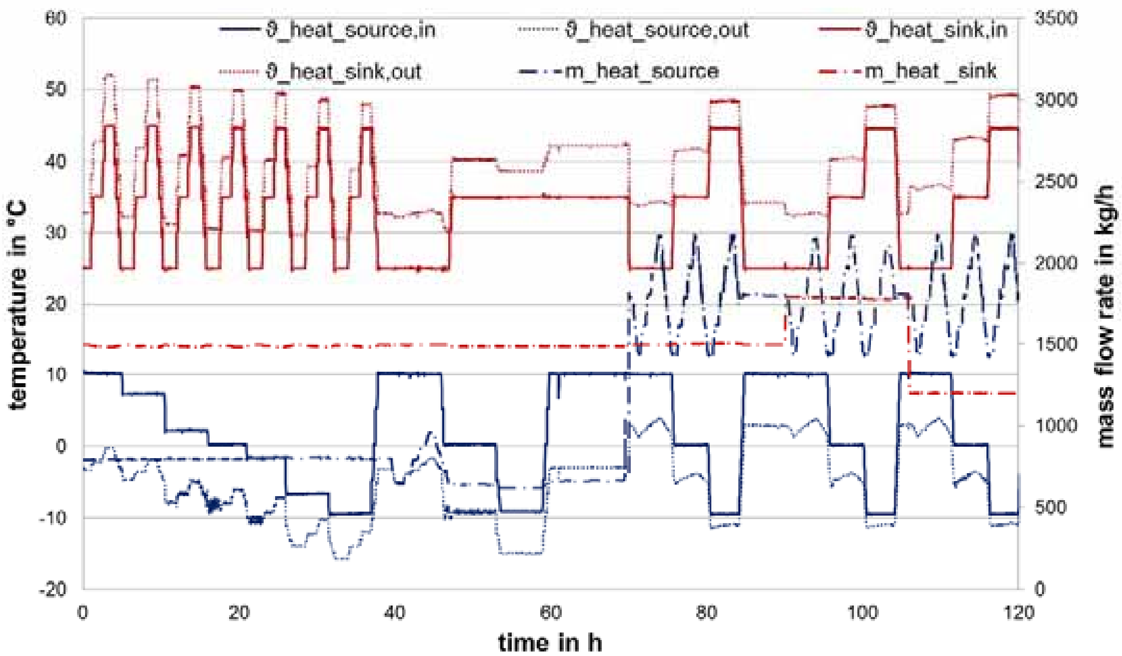


**Fig. 3: Temperatures and mass flow rates during test sequences applied to the tested heat pump**

Using the previously presented test facility, multiple test sequences have been applied to a brine to water heat pump. During all test sequences the inlet temperature of the heat source circuit ($\vartheta_{\text{heat source,in}}$), the inlet temperature of the heat sink circuit ($\vartheta_{\text{heat sink,in}}$) and the mass flow rates in both circuits ($\dot{m}_{\text{heat source}}$, $\dot{m}_{\text{heat sink}}$) have been given as fixed values to the controller of the test facility. The outlet temperatures ($\vartheta_{\text{heat source,out}}$ and $\vartheta_{\text{heat sink,out}}$) and the electrical power ($P_{el}$) consumed by the heat pump are results of the test sequences performed. Figure 3 shows as an example the inlet and outlet temperatures and mass flow rates of the heat source and sink circuits during the multiple test sequences applied to the tested heat pump.
The first test sequence applied to the tested heat pump is a quasi-stationary test sequence. It is shown in Figure 3 at the time interval between 0 and 38 h. During this sequence, the heat source and sink inlet temperatures are varied stepwise and the mass flow rates are fixed at values typical for the operation of this heat pump. Additionally different test sequences with varying inlet temperatures and mass flow rates have been applied to the tested heat pump. The test sequences are applied dynamically since there are no requirements regarding stationary conditions to be reached by the heat pump during operation. All data gathered during the test is used for training and validating of an artificial neural network model for the heat pump as described in chapter 7.

## 4. Simulation models for heat pumps

In order to extend the CTSS method towards combined solar thermal and heat pump (SHP) systems, numerical models describing the thermal behavior of heat pumps under dynamic operating conditions are required. Unfortunately, the number of available simulation models for heat pumps is relatively small and some existing models are due to copyright aspects not adaptable to the specific needs of the CTSS method.

Quasi steady-state performance map models (i.e. black box models) are the most widespread heat pump models in dynamic simulation programs like e.g. TRNSYS. Therein, a restricted number of sampling points from performance map measurements is used either to interpolate in-between those points or to fit a two-dimensional polynomial plane. These models use the inlet-temperature of the heat source and the desired outlet-temperature on the heat sink side of the heat pump to calculate its thermal output and its electricity demand (Dott, 2013). Typical implementations of quasi steady-state performance map models for heat pumps in simulation software packages are for example the TRNSYS Types 504, 505, 665 and 668 from the TESS library 2011. Usually only the standard measurements according to EN 14511:2011 are available as input for this kind of simulation models. The extension of black box steady-state models for the inclusion of dynamic effects such as for icing and defrosting or for the thermal inertia in the condenser or evaporator has been described e.g. by Afjei (1989). In contrast to heat pump models based on performance maps, a component-based model has been developed by Hornberger (1994), which models the thermodynamic cycle of the heat pump. A modification of the Hornberger model implementing dynamic features of the Afjei model has been undertaken by Marx (2011). This combined TRNSYS Type was again modified for the refrigerant R410A for the project WPSol. Several parameter identification procedures have been applied to this model in combination with measured data. However, a characterization of the thermal behavior of the heat pump with acceptable accuracy was not possible so far. Therefore, within the project WPSol a methodology for modelling heat pumps based on experimental system identification with Artificial Neural Networks (ANNs) has been developed. There are several reasons why ANNs are such a powerful tool for modelling dynamic systems (Yang, 2008) based on experimental data:

(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 behavior of the system itself. The ANN results can account for all physical effects relating the output to the input. This ability is essentially 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 a learning process.

(2) The ANN methodology is in principle 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 power to adapt to changes in the parameters. This capability enables the ANN to deal also with time-dependent dynamic modelling.

At the Research and Testing Centre for Thermal Solar Systems (TZS) at ITW very good experiences with regard to ANNs have already been gained in the past, e.g. with the simulation of other thermo-technical components such as solar collectors and thermally driven chillers (Frey, 2011; Fischer, 2012).

## 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 biological 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 (ANN) 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 connection 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 possible 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) Figure 4 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 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. Figure 5 presents an example of typical neural network architecture.

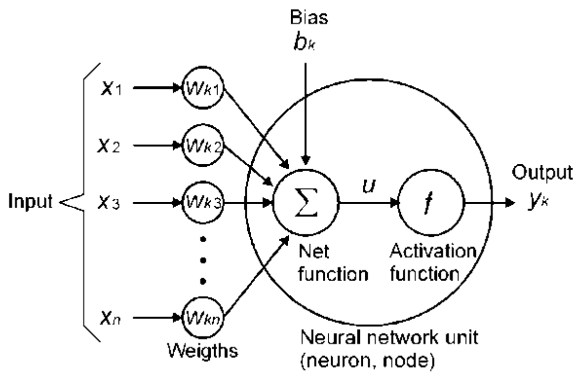


**Figure 4: Basic neural network unit (neuron, node) (McCulloch and Pitts, 1943)**

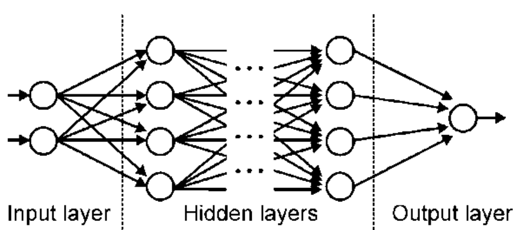


**Figure 5: Typical neural network architecture**

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 holds the weights constant. Now the weights contain meaningful and important information, whereas before the training they have random values and no meaning (Kalogirou and Sencan, 2010). After the successful training step, the trained ANN model can be used to calculate the output parameters as a function of the input parameters.

## 6. Development of numerical models for heat pumps based on ANN

The main requirement for the numerical model is the ability to describe the dynamic thermal behavior of the heat pump in an accurate way. I.e. the model has to be able to calculate the outlet temperatures of the two circuits (heat source and heat sink) and the electrical power consumption of the heat pump with adequate precision. Another requirement is that for the modelling process no information about the internal configuration of the heat pump is required.

All ANNs used for the work described in the present paper were performed under the MATLAB (Mathworks, 2010a) environment using the Neural Network Toolbox (Mathworks, 2010b).

### *6.1 Modelling heat pumps with ANNs*

The selected input and output quantities of the ANNs used in this study to model the outlet temperatures and the electrical power consumption of a heat pump are schematically illustrated in Figure 6. The so-called feed-forward 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 heat pump fluid inlet temperatures and volume flow rates of the heat source circuit ( $\vartheta_{\text{heat source, in}}$ ; $\dot{m}_{\text{heat source}}$ ) and the heat sink circuit ( $\vartheta_{\text{heat sink, in}}$ ; $\dot{m}_{\text{heat sink}}$ ). The outputs from the ANN are the two fluid outlet temperatures ( $\vartheta_{\text{heat source, out}}$ ; $\vartheta_{\text{heat sink, out}}$ ) and the electrical power consumption of the heat pump ( $P_{\text{el}}$ ) under the assumption that the outlet volume flow rates are identical to the inlet volume flow rates.

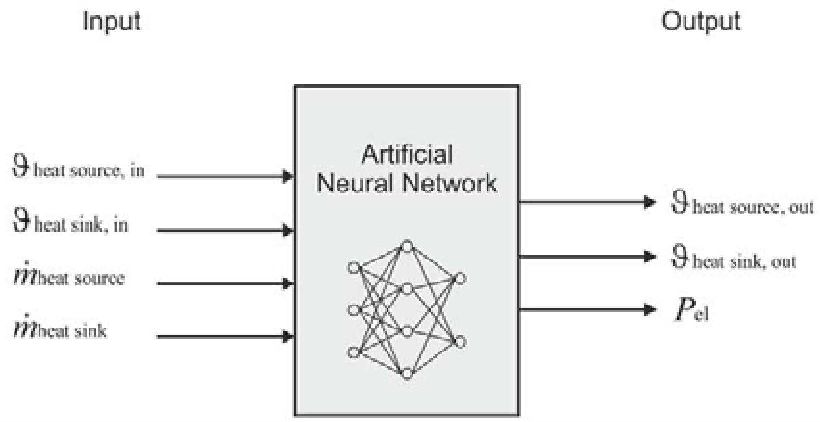


**Figure 6: Input and output quantities of the ANN for modeling heat pumps**

### *6.2 Assessment criteria of the model performance*

In general, the performance of the model itself can be assessed by means of regression analysis between the model output (calculated values) and measured values. The criteria used here for assessing the performance of the ANN model are the *Mean Absolute Error* (MAE), the *Root Mean Square Error* (RMSE) and the *Index of Agreement* (IA). The *MAE* and the *RMSE*, that is more sensitive to extreme values than the MAE, are defined in Eq. 1 and Eq. 2.

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

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

Here $x_{i,calculated}$ is the value determined by the ANN and $x_{i,measured}$ is the corresponding measured value, i is the considered time step and N is the number of time steps in the considered period.

The dimensionless *Index of Agreement* ($0 \le IA \le 1$), proposed by Willmott (1981), is intended to characterise the ability of a model to calculate reality accurately. There is no deviation between calculated and measured values if IA = 1; the larger the deviation, the lower the value of IA. The *Index of Agreement* is defined as:

$$IA = 1 - \frac{\sum_{i=1}^{N} \left( x_{i,\,calculated} - x_{i,\,measured} \right)^2}{\sum_{i=1}^{N} \left( \left| x_{i,\,calculated} - \overline{x}_{measured} \right| + \left| x_{i,\,measured} - \overline{x}_{measured} \right| \right)^2} \quad \text{(eq. 3)}$$

Here $\overline{x}_{i,\,measured}$ is the mean of the measured values in the considered period.

The values of the presented evaluation criteria are determined for all output quantities (i.e. outlet temperatures and electrical power consumption) of the ANN model of the heat pump.

## 7. Results and discussion

A feed-forward ANN with a so-called sigmoid transfer function in the hidden layer and a linear transfer function in the output layer was selected. By trial and error the number of neurons in the hidden layer was determined to 8 in order to obtain the best fit between calculation and measurement. This results in a so-called 4-8-3 architecture. In the training procedure, the weighting coefficients were adjusted using the Levenberg-Marquardt algorithm.

Measured data were acquired under dynamic operating conditions. The prepared database consists of 4,622 input-output data patterns. 122 data patterns were selected arbitrarily and assigned as the training database. The remaining 4,500 data patterns are used for validating the ANN model.

Figures 7 and 8 show for the validation database a comparison of the measured and the calculated fluid outlet temperatures for the heat sink circuit and the electrical power consumption of the heat pump. Apart from a few exceptions the ANN heat pump model calculates the temperatures with an accuracy of ± 1 K and the electrical power consumption with an accuracy of ± 100 W.

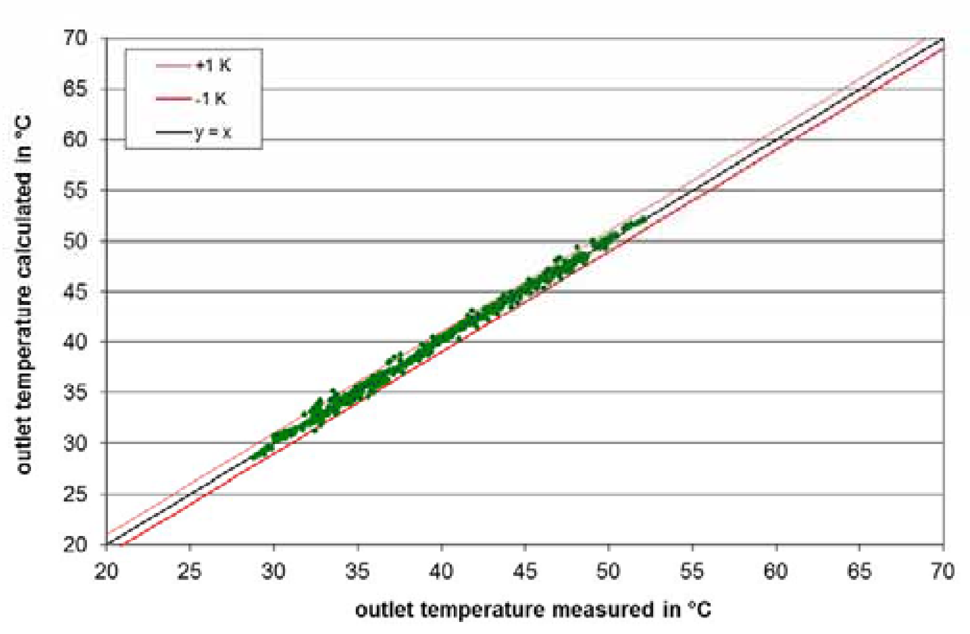


**Figure 7: Comparison of measured and calculated fluid outlet temperature of the heat sink circuit of the heat pump**

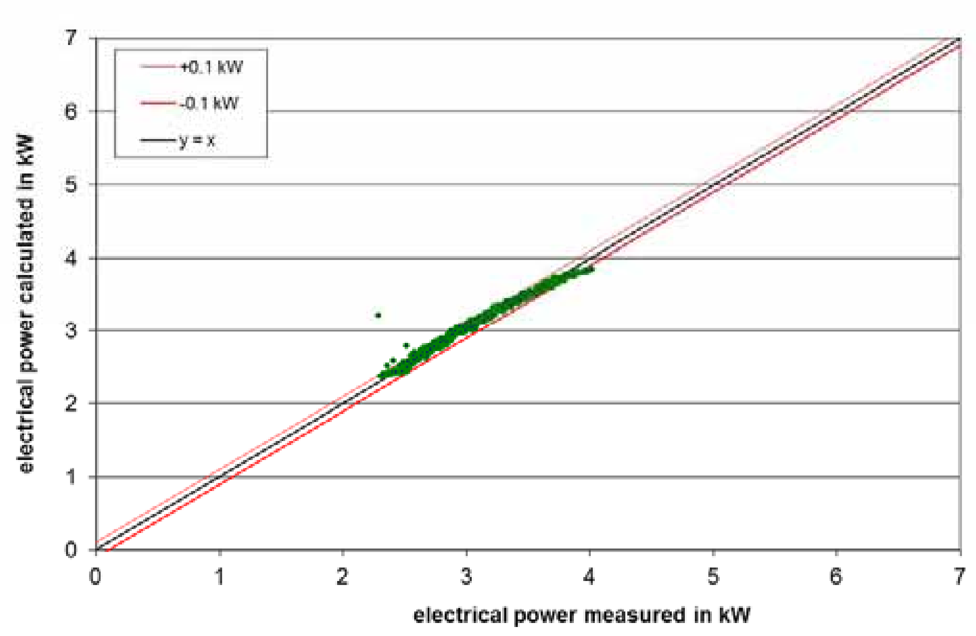


**Figure 8: Comparison of measured and calculated electrical power consumption of the heat pump**

The ANN calculations for the outlet fluid temperature of the heat sink circuit and the heat source circuit result in a Root Mean Square Error of 0.72 K and 0.53 K respectively. The RMSE for the electrical power consumption of the heat pump is 0.09 kW. Further results are presented in Tables 1 and 2.

**Tab. 1: Results of the validation**

| Term | MAE | RMSE | IA |
|---|---|---|---|
| heat sink circuit | 0.26 K | 0.72 K | 0.9985 |
| heat source circuit | 0.22 K | 0.53 K | 0.9986 |
| el. power consumption | 0.05 kW | 0.09 kW | 0.9897 |

**Tab. 2: Energy balance and seasonal performance factor SPF for the considered sequence**

| Term | Measurement Energy | Calculation Energy | Error (absolute) | Error (relative) |
|---|---|---|---|---|
| heat sink circuit | -1,893 kWh | -1,906 kWh | -13 kWh | 0.67 % |
| heat source circuit | 1,391 kWh | 1,396 kWh | 5 kWh | 0.42 % |
| el. power consumption | 496 kWh | 495 kWh | -1 kWh | -0.21 % |
| SPF | 3.817 | 3.851 | 0.034 | 0.89 % |

Table 2 summarizes the transferred energies of the two circuits and the electrical power consumption of the heat pump and the related error, which is 0.67 % at the most. The SPF (seasonal performance factor) for the considered time sequence of 3.849 determined by means of numerical calculations corresponds within 0.89 % with the result of 3.815 determined on the basis of the measurements.

## 8. Validation of the specific numerical model based on in-situ measurement data

In addition to validation data acquired from laboratory test facility measurements the same type of heat pump has been installed and monitored in a real application. A detailed description of the monitored solar thermal and heat pump system can be found e.g. in Loose and Drück (2013). The data gathered during this in-situ measurement has been used to validate the specific numerical ANN model. For this purpose, the inlet temperatures and flow rates from the in-situ measurement have been used as input data for the simulation program. The control signal for switching the heat pump on and off required by the specific numerical model has been generated from the measured electrical power based on the in-situ measurement data. The results to be compared are the delivered heat and the heat pump's consumption of electrical energy. The comparison between measured (meas) and calculated (calc) results of the daily generated heat ($Q_{heat\ sink}$) and electrical energy ($E_{el}$) consumed by the heat pump is plotted as an example for one month in Figure 9.

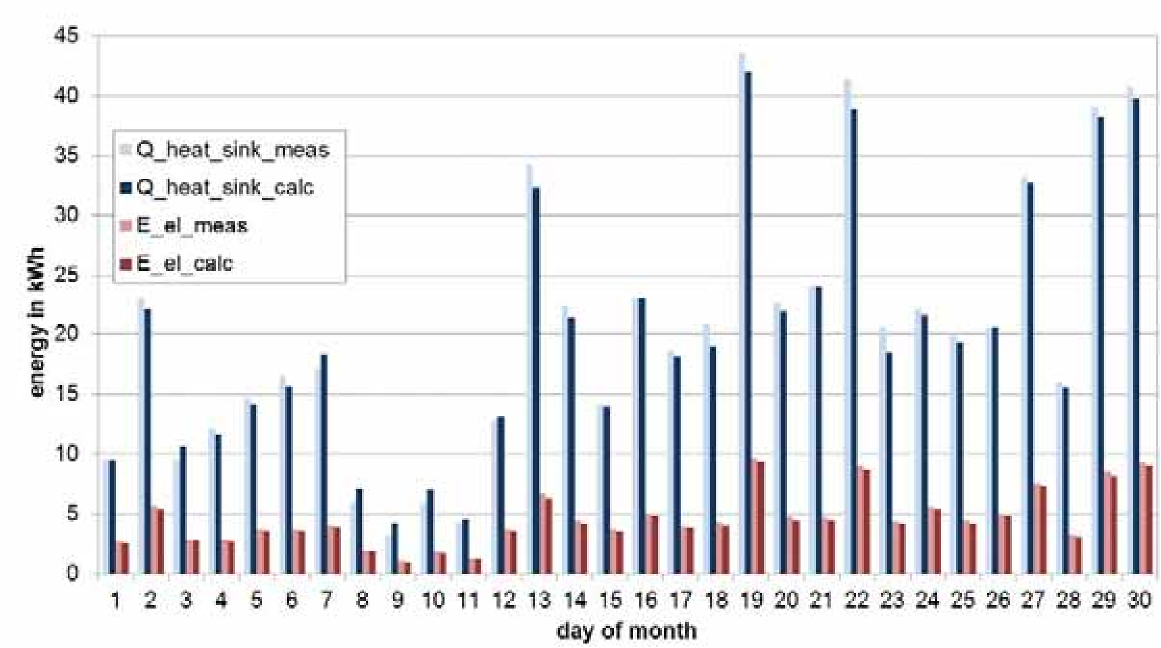


**Fig. 9: Comparison between measured and calculated results of the daily generated heat ($Q_{heat\ sink}$) and electrical energy ($E_{el}$) consumed by the heat pump**

The calculated daily values for heat generated by the heat pump and the energy consumed by the heat pump show good compliance with the measured daily values. Over the whole month, the electrical energy is underestimated by about 4 % and the generated heat is underestimated by about 2.5 %. Determined on the basis of the measurement data the monthly $SPF_{HP,meas}$ is 4.40. Compared to the $SPF_{HP,calc}$ of 4.49 the monthly $SPF_{HP,calc}$ is overestimated by about 2 %.

## 9. Conclusion and outlook

The CTSS laboratory test method standardized in the EN 12977:2012 series for solar thermal systems has been extended towards combined solar thermal and heat pump systems including the development of a dynamic heat pump test procedure. In this context also an Artificial Neural Network model for the characterization of the thermal behavior of heat pumps under dynamic operating conditions has been developed. A representative laboratory test applying the newly developed extended CTSS method including test sequences, calculation and validation, has been shown exemplary for a brine to water heat pump. The method described in this paper can in principle also be applied to air to water heat pumps if a climate chamber is available for the operation of the heat pump with defined ambient temperature and humidity. Due to the successful development of the extended CTSS test method, the long-term goal is the implementation of this test procedure into appropriate European standards such as the EN 12977 series.

The ANN modelling approach for heat pumps can be considered as very powerful tool for the calculation of the dynamic thermal behavior of the heat pump in this type of component oriented laboratory test procedure. However, the method is still limited by its underlying “black-box” approach, which does not allow insight in the inner processes and thus no physical interpretations. As outlook, the project WPSol will therefore be extended with the aim of developing a so-called “model-based ANN”, i.e. a grey-box model, which combines the advantages of the black-box approach with the ones of theoretical physical models. By doing so, also parameter variations and optimizations would be possible to calculate the performance of modified configurations without the need for a new laboratory test each time.

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**Acknowledgement:** The work described above was part of the research project WPSol (Performance Testing and Ecological Assessment of Combined Solar Thermal and Heat Pump Systems), which was partly funded by the German Federal Ministry of Economic Affairs and Energy (BMWi), based on a decision of the German Bundestag by Projektträger Jülich (PTJ) under grant number 0325967A. The authors gratefully thank for the support and carry the full responsibility of the content of this publication.