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Towards a Generic Methodology to Model Solar Thermal Systems Using Neural Networks Through a Short Dynamic Test

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Summary

Nowadays there is no global approach to model and characterize solar thermal systems for building application from experimental data. Results of the existing approaches are valid only for specific conditions (type of climate and thermal building properties). The aim of this study is to create a generic methodology to model such systems. Neural networks (NN) proved to be suitable to tackle similar problems particularly when the system to be modeled is compact and cannot be divided up during the testing stage. Reliable “black box” NN modeling is able to identify global models of the system without any advanced knowledge about its internal operating principle. The knowledge of the system global inputs and outputs is sufficient. Results concerning the solar combisystem modeling show that a dynamic NN model is efficient to learn the dynamic of the solar system especially due to the heat storage component. NN model developed is able to predict, with a good precision degree, the annual energy performance of the system based on a learning sequence of only 12 days. Because of the NN generalization ability, it is possible to predict the solar combisystem behavior when operating under environments different from the one used during learning stage and so to characterize its performances.

Key-words: Solar thermal systems, Neural networks, Characterization, Dynamic modeling, System testing

1. Introduction

Nowadays, thermal systems for building application mix more and more energy sources. Some of them are available intermittently. Moreover, more and more systems are multi-functional. They can be used for domestic hot water preparation, space heating and space cooling too. The evaluation of their energy performances is difficult especially because a growing number of equipment are prefabricated and assembled at the factory. Therefore it is difficult to extract a sub-system of the global one in order to test it without any degradation of the whole system. Moreover, the test of each potential sub-system of the global one does not allow considering real interactions between them in a reliable way. It can distort the evaluation of the system performance. In front of this growing difficulty, system test methods based on a steady state in one hand, and methods based on components tests in a separate way in the other hand, show their limitations (Leconte, et al. 2012).

Nomenclature

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$\dot{Q}_{DHW}$	Heat flow rate supplied for the Domestic Hot Water (DHW)	(W)
A	Solar collector area	(m²)
G	Global irradiance	(W.m^{-2})
$\dot{Q}_{HE}$	Heat flow rate supplied for the Heat Emitter (HE)	(W)
$\dot{Q}_{AUX}$	Power of the auxiliary system	(W)
$\dot{Q}_{AUX,Ref}$	Power of the auxiliary system without renewable energy	(W)

To be up-to-date with the current system evolution, it becomes obligatory to consider the whole system during the modeling and test stages. So, it is crucial to take into account during this phase the system dynamic behavior and system controls, which are more and more complex.

In this paper are presented the first development results of a generic methodology modeling any solar thermal system. This new methodology can be used then to characterize any system based only on a short cycle test in a semi-virtual test bench. Following (D. Schicktanz, et al. 2014) the method can be rated as **Whole system - Indoor laboratory - Controlled dynamic conditions - Behavioral model parameters - Direct extrapolation**. *In fine*, by means of this technique, it will be possible to evaluate the performance that the tested system will have when installed in any working environment.

2. Scientific approach implemented

a. Modelling methodology to be developed

In order to be relevant and fulfill the solar thermal market requirements, the modelling methodology to be developed must respect five conditions:

1. To be generic so it can be used for several solar thermal systems for building applications: combisystem with heat pump or boiler auxiliary, absorption chiller etc.
2. To be non-intrusive so it is possible to use this method to model a system using only its inputs and outputs. No need to dismantle the system in order to test it and thus do not damaging it.
3. The method must take into account the whole system so all interactions between subsystems are modeled. The real behavior of the system will be modelled then.
4. The system procedure test must be short so the cost of the qualification test is low.
5. The method must be able to predict the system performance for several environments different from the conditions of the test. This will able the characterization of the system with the fitted method.

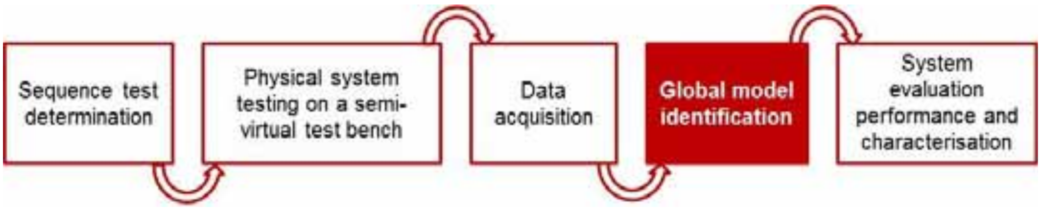

Fig. 1: Process stages of the proposed methodology

To fulfill the 1st, 2nd and 3rd conditions the most appropriate solution consists in using a black box model. In contrast with a physical detailed model, to design a black box model there is no need to know the system internal parameters such as efficiency of its sub-systems, thermal conductivities and the mechanisms of the control and regulation systems. Therefore, it is possible to identify a global model of the system without being intrusive.

Researchers at CEA-INES have developed an efficient method, called Short Cycle System Performance Test (SCSPT), to test solar thermal systems in controlled dynamic conditions with a view to evaluate their performances (M.Y. Haller, et al. 2013). The test method consists in testing the real system as a whole on a semi-virtual test bench: the system is plugged to thermo-hydraulic modules which “emulate” the behavior of thermal loads (DHW draw offs, space heating needs etc.) or sources (solar collectors). Those modules act according to a parallel TRNSYS simulation running in a “real-time” mode. The system to be tested is then physically linked to a virtual environment. The SCSPT procedure consists then in applying a 12 days weather test sequence. This sequence is made in order to make the system consume proportionately the same auxiliary energy during the test. The input-output data that can be harvested during the test are very representative of the system behavior. This test method is relevant to fulfil the 3rd and 4th conditions.

Classical black box models rely a lot to the data used during the design procedure. Artificial Intelligence methods are able to learn from data, so it is possible to create an efficient model with a good ability to generalize results to new data. Artificial neural networks (see section 2.2) fulfill the 5th condition. Therefore, the proposed methodology first consists in testing the system to be characterized in a semi-virtual test bench during a short sequence of time, typically 12 days and in a dynamic way. Then, harvested data will serve to design a Nonlinear Auto-Regressive with Exogenous inputs (NARX) neural network model of the system. The five steps to model and then to evaluate the performance of a system following the proposed approach are represented in (fig. 1). Basically the Neural Network learns the internal behavior of the tested system. The NN model will then be used to predict the system behavior when unseen data are presented to it and so evaluate the system performance.

b. Modelling using ANN and solar thermal energy systems application

Using Neural Networks seems to be the most powerful mathematic tool to solve this modelling problem. In fact, it was shown that neural networks are universal function approximators (Cybenko, 1989), so they can be used to approximate the system function. NN were applied successfully to solve complex, non-linear, dynamic and multivariable problems. They tolerate errors, imprecisions and missing data too (Kalogirou, 2001). Neural networks were extensively used during the last decade. Several modelling problems involving NN are nearly similar to the present research subject. In addition NN have been especially used to solve prediction modelling problems in solar energy (Mohanraja et al, 2012) (Ben Ammar et al, 2013).

The theory of ANN is well presented in (Dreyfus et al, 2004) and (Nørgaard et al, 2000). Artificial neural networks are parametric analytical functions whose concept is inspired from the human's central nervous system. A neuron, element basis of a NN, can compute values z_l from a weighted summation of its inputs x_j. The summation coefficients ω_j^l are called synaptic weights. The subscript l denotes the neuron number. The neural operation is presented in (eq. 1). The function f_l is called the neural activation function (AF).

$$z_l = f_l\left(\sum_{j=1}^{K} \omega_j^l x_j\right) \qquad \text{(eq. 1)}$$

Inter-connected neurons constitute what is commonly called a neural network. There are several NN architectures and each one is more suitable for a specific problem than others. The most famous architecture for prediction problems is the class of multi-layer perceptron (MLP). An MLP is a feed-forward network built up of neurons, arranged in layers. An MLP has an input layer, one or more hidden layers and an output layer. In (fig. 2) a MLP, with E inputs, C neurons in the hidden layer and S outputs, is presented. The s^{th} output of the network can be obtained using (eq. 2).

$$y_s = f_s^S\left(\sum_{c=1}^{C} \omega_{c,s}^S f_c^C\left(\sum_{e=1}^{E} \omega_{e,c}^C x_e\right)\right) \qquad \text{(eq. 2)}$$

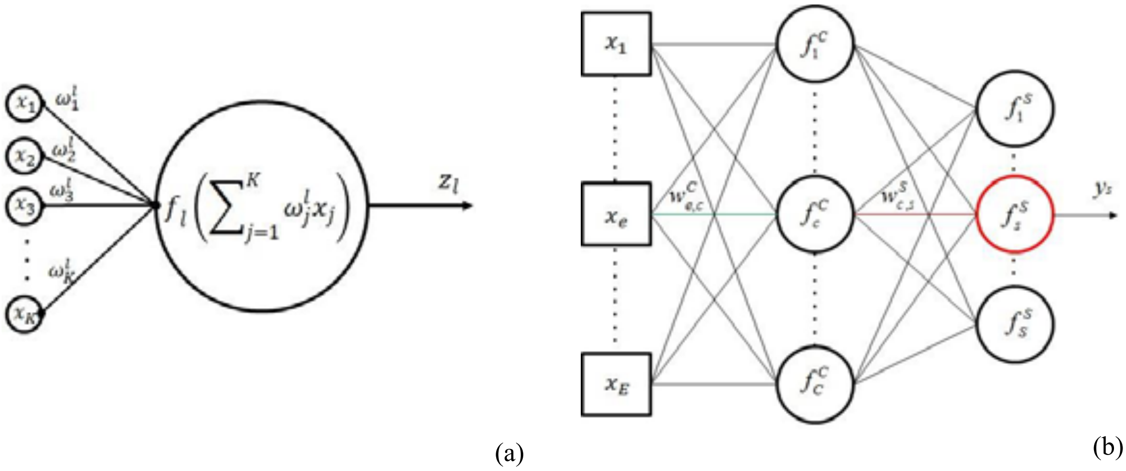

Fig. 2: neuron formal representation (a), example of a neural network MLP with one hidden layer representation

Neural network learning or training is the process of determination of an ensemble of weights so that the underlying function approximates the real system function. In fact, the objective of the training process is to minimize a cost function, with respect to weights, knowing a set of data. The short time of the system test, which is of 12 days, restricts the amount of available data for training. Therefore it is necessary to use a learning algorithm that can use a restricted data set without compromising the generalization ability of the model. For this reason it is relevant to use regularization method for the learning process. Typically, training aims to reduce the sum of squared errors see (eq. 3) with t_i the target data at the sequence time i and y_i the NN output at the same time. Regularization modifies the objective function by adding an additional term: the sum of squares of the network weights (eq. 4), q is the number of the neural network weights. By constraining the size of weights the training process produce a NN with good generalization ability (Mackay, 1992). In fact, by keeping the weights small the NN response will be smooth and so the over-fitting is supposed to be prevented. In this study the objective function optimization is done using the Levenberg-Marquardt algorithm.

$$\mathrm{sse} = \sum_{i=1}^{N}(t_i - y_i)^2 \qquad \text{(eq. 3)}$$

$$\mathrm{ssw} = \sum_{i=1}^{q}{\omega_i}^2 \qquad \text{(eq. 4)}$$

Determination of the modelling input-output configuration is crucial to develop a generic methodology. Generally, solar thermal systems physical inputs and outputs differ from one to another. They depend on the energy sources used by the system and how this latter was designed by the manufacturer. However, energy systems can be represented in terms of power transformation between the renewable energy source, the load and auxiliary system. This is why a compact configuration with three inputs: $\dot{Q}_{DHW}$, $A.G$, $\dot{Q}_{HE}$ and one output $\dot{Q}_{AUX}$ was selected. This open configuration, not particular to a specific system is relevant to develop a global method. In (Lazrak, et al. 2014) results concerning a solar combisystem modeling show that a dynamic NN model (NARX model) is more efficient than a static one. The latter does not learn the dynamic of the solar system especially due to the heat storage component, for this reason dynamic neural network (see fig. 3) was used.

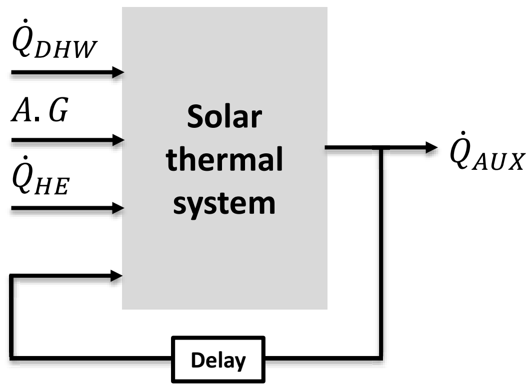

Fig. 3: NARX modelling configuration with delays for only the output

Usually, regularization does not necessary guarantee the production of efficient networks. This is why it is essential to make some data preprocessing before training. By normalizing the input and target data vectors, the neural network training will be easier, faster and all vectors will be equally taken into account during the learning process. Equation (eq. 5) will be used to pretreat the training data in order to fall between a and b, x represent a vector of data through time. It was noted that the on-off cycles of the auxiliary system generate some discontinuities in data. In order to smooth the data collected, a moving average (MA) will be applied to them.

$$\frac{\mathrm{x} - x_{min}}{x_{max} - x_{min}}(b-a) + a \qquad \text{(eq. 5)}$$

c. *The solar combisystem characterization FSC method*

After developing a good neural network model of the tested systems, it can be used to elaborate different simulations in several environments. Results of numerous annual simulations of the tested systems can be smartly used to characterize its performances with a simple curve, thanks to the FSC procedure (Letz, et al. 2009). The FSC method considers that annual fractional energy savings f_{sav} defined in (eq. 6) of a solar combisystem can be expressed as a quadratic function of the fractional solar consumption FSC, a dimensionless quantity which only depends on the environment of the system. It almost represents the maximum f_{sav} that a solar combisystem can reach for a given location. Each system is then characterized by its own simple parabola. In this way, for two different systems, the one of which parabola is above the other is the more efficient.

$$f_{sav} = 1 - \frac{Q_{AUX}}{Q_{AUX,Ref}} \qquad \text{(eq. 6)}$$

d. *Systems tested on the experimental test bench*

A numerical validation of the methodology using data from a simulated SCSPT test was done in (Lazrak, et al. 2014). In the current study a real standard solar combisystem is considered to validate the methodology using real experimental data. A drawing of the system is represented in (fig. 4). The distinguishing features of this system can be briefly described by the following:

1. The energy transfer to the storage tank or for DHW is done by intern heat exchangers.
2. The condensing boiler could heat up directly the water returning from the space heating emitter.
3. The condensing boiler can heat up simultaneously the storage tank and the space heating emitter.

4. The volume of the storage tank is about 735.9 litres.

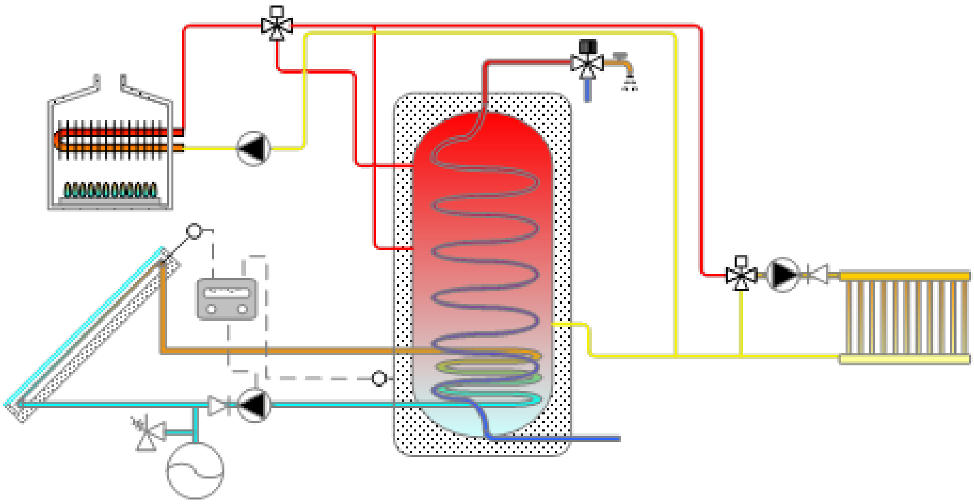

Fig. 4: Solar combisystem modelled in the present work

A second system was derived from the standard one. There is no physical difference between the two systems but they control algorithm of the second one was optimized so that the performance of the system get improved. The second system will be denoted as “optimized system”.

Each system has been tested according to the SCSPT procedure under the following environment: Zurich climate, an SFH60 building type and with 16.1 m² of solar collector area. Those boundary conditions were emulated, only the system was real. As mentioned in section 2.1. the test is applied to the whole system exactly like it can be found in the market. In this way all interactions between sub-systems will be taken into account. Measurements of input-output temperatures and flow rates in the different system loops (DHW, solar collector and HE) will be used to form the input-output model configurations.

3. Results and discussion

a. System modelling

Input-output data harvested during the two tests have been used to design two dynamic artificial neural networks modelling each system. An example of untreated data used for training is represented in (fig. 7). The 12 days of the test sequence were applied successively without interruption.

The two models were created according to the indications mentioned in section 2.2. Using the MATLAB2012b Neural Network Tool Box, various network architectures, number of neurons in the only hidden layer, weight initialisations, activation functions and learning strategies etc. have been investigated to find the optimal combination that can provide the best results. Features of the two ANN, among those tested, that gave best results are presented in Tab.1 and their modelling configurations in (fig. 5) and (fig.6). Those two models were adopted for the present work.

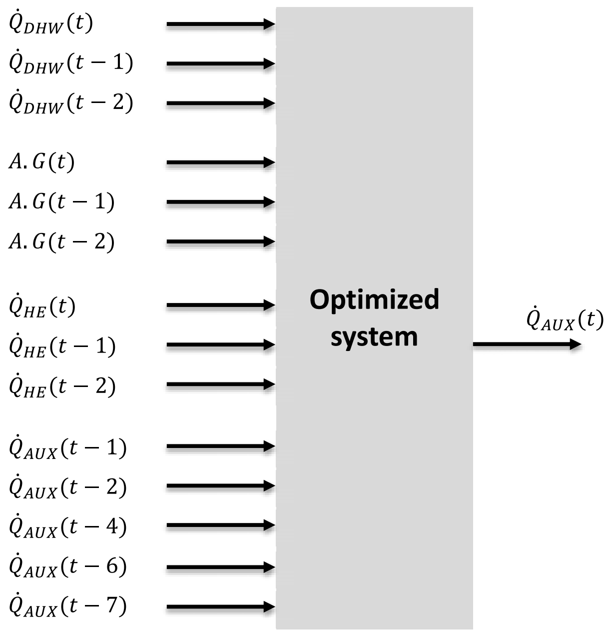

Fig. 5: Input-Output NARX modelling configuration for the optimized system used during training

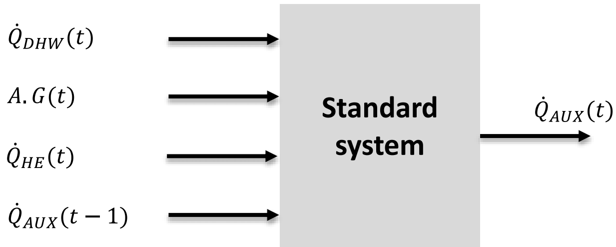

Fig. 6: Input-Output NARX modelling configuration for the standard system used during training

Tab. 1: Features of the two neural network used in the present work

Model	Normalization range	No. of neurons	MA window	Input and Output layer AF	Feed-back delays	Input delays
Of standard system	±0.5	8	Five Time Steps (TS)	$\frac{1-e^{-2x}}{1+e^{-2x}}$	One TS	none
Of optimized system		3			Five TS	Two TS

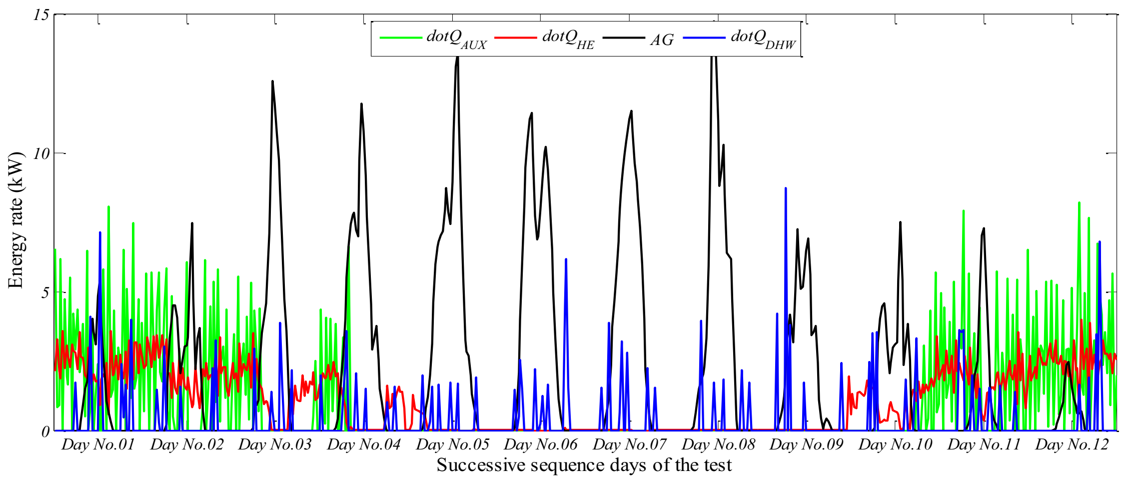

Fig. 7: Inputs and output evolution in function of time used for training, case of the optimized system

In order to validate the methodology, the two models have to be tested, in closed-loop, using unseen data from different environements. To do so, the two neural networks have been used to do 36 annual simulations in different environements, each environement is made up of a climate site, a building type and a solar collector area. In Tab. 2 elements of each environement are described. To test physically the two systems in 36 conditions is clearly impossible, this is why two physical detailled TRNSYS models were built and validated so that they are very close to the real systems. Prediction results of the NN models will be compared to those of the TRNSYS models which represent here the reference.

Tab. 2: Climates, building types and collector areas used to form the 36 simulation environments

Climate	Building	Collector area (m²)
Zurich	SFH100	10
Stockholm	SFH60	13
Barcelona	SFH30	16
		19

The most interesting criterion to evaluate the performance of a solar thermal system is to measure its energy consumption during a specific period of time. This allow to characterize its performance (see section 2.3. and paragraphs below). For these reason, the power consumed by the auxiliary system, output of the models, will be integrated in time to measure the annual consumption prediction of the two systems. Estimation results are presdented in (fig. 8) and (fig. 9).

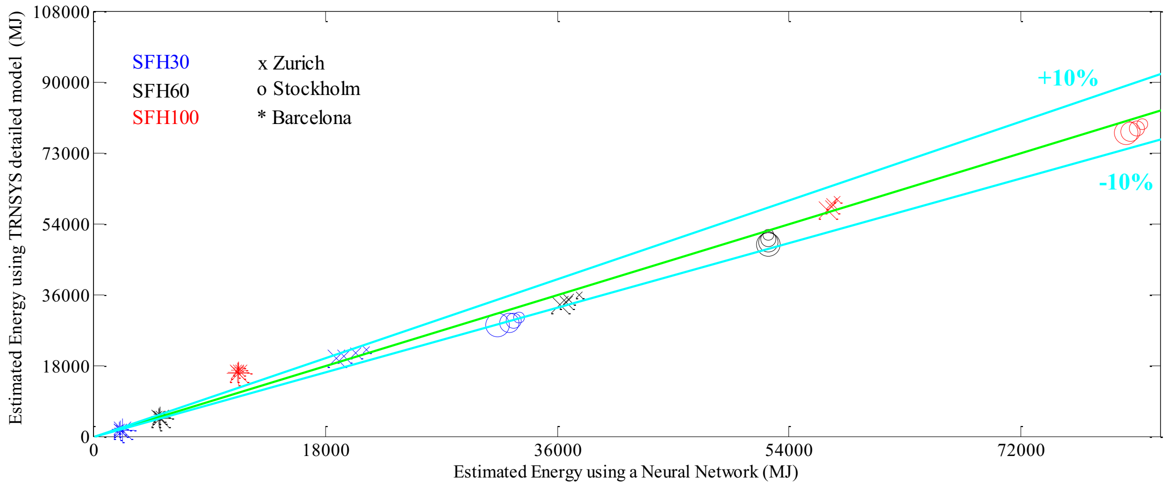

Fig. 8: Comparison between the annual energy consumption of the standard system predicted and calculated respectively by the NN model and the TRNSYS model

Each point in the graphs represents two simulations but in one specific environment (boundary conditions): one with a NN model and the second using the reference model. Each point gives an idea on how the energy estimated using the NN model is close to the reference one. Symbols, colours and the size of symbols denote, respectively, the climate, building type and the collector area used during each simulation. The size of the symbol is proportional to the collector area.

On the whole, predictions of the black box models and the detailed TRNSYS simulations are very close. In fact, coefficients of determination, R^2, for the two systems are about 0.98. Differences between both methods to estimate system energy consumption are almost within the ±10% range (line in light-blue) for all simulations. For low heat demand simulations (environment with Barcelona as climate for instance), absolute differences are not excessive but the low energy level makes those differences proportionally higher.

It can be noted also on this two figures that the neural model of the optimized system has learn the physical behaviour of the system more effectively that the other model. In fact, the latter does not differentiate a lot between collector areas like the first model.

Some environments are not realistic e.g. they do not respect the rules of designing a solar combisystem such as combining a high solar collector area with a low heat demand. For those types of environments, predictions are less accurate but still acceptable. In general neural networks do not work effectively in extrapolation mode. This means that if a set of data is very different from the one used during the learning process the neural network predictions will not be good. Neural network estimation abilities stay good as long as means and variances of its inputs have values close to those used during training.

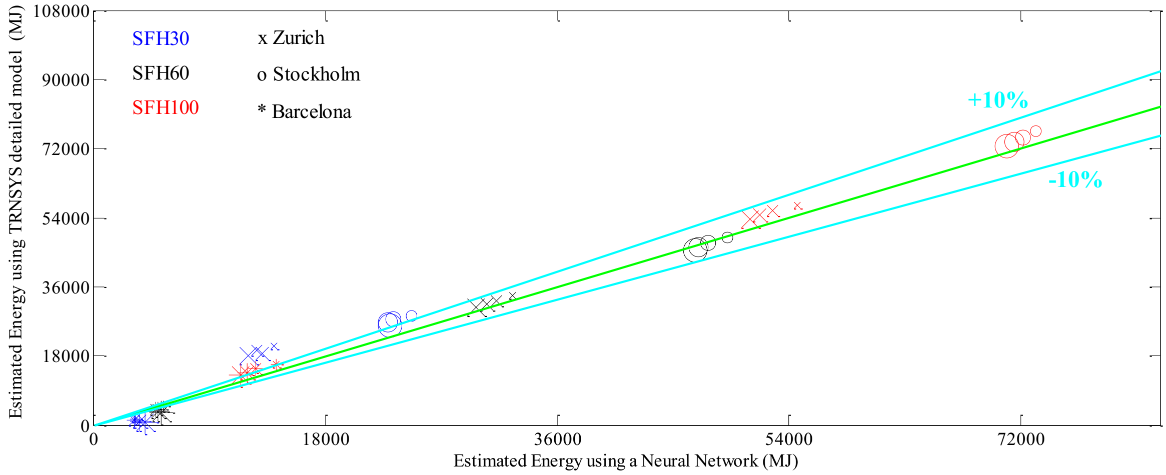

Fig. 9: Comparison between the annual energy consumption of the optimized system predicted and calculated respectively by the NN model and the TRNSYS model

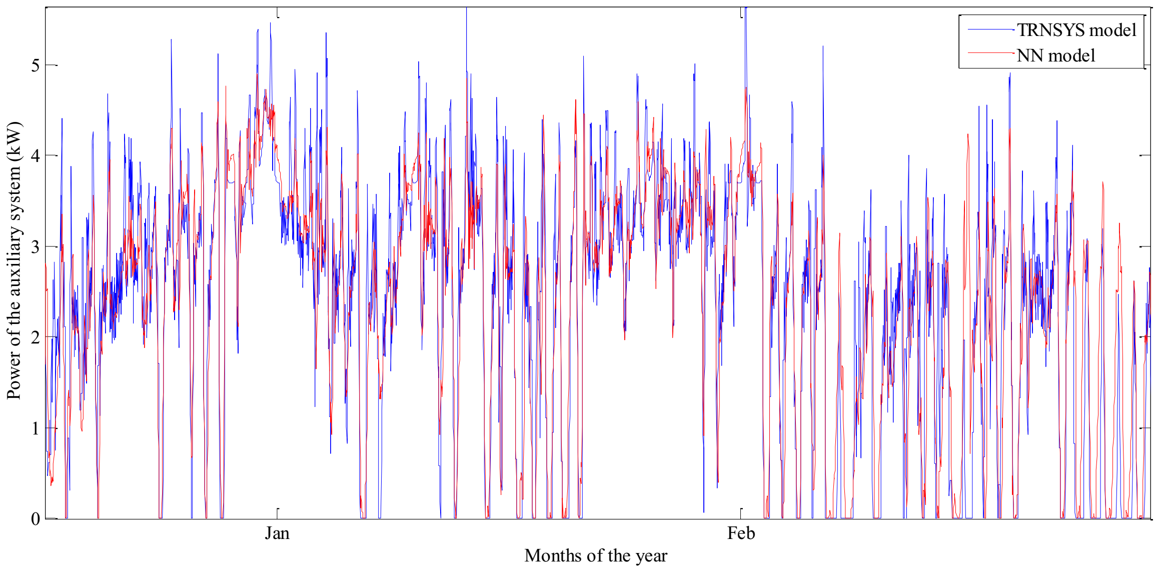

Fig. 10: NN and TRNSYS outputs evolutions in function of time, case of the optimized system and the environment formed with Zurich climate, SFH60 and 13 m² of collector area

In (fig. 10) are represented evolutions of the energy rate estimated by the NN and calculated by the TRNSYS detailed model. The figure shows that the neural network model is capable to predict, with a good degree of accuracy (R^2 around 0.92), not only the annual energy but also its rate.

b. System characterization

In (fig. 11) each combisystem is characterised from black box model results, according to the FSC method. The distribution of the points is following the quadratic function of the fractional solar consumption FSC which is in agreement with what was showed in the FSC method theory. Characterization of systems using the FSC method is a visual way to compare energy performances of different systems. In the present work, it appears clearly that the optimization of the regulation system of the combisystem improve significantly its performances by about 20%. This percentage is a bit lower for environments with low FSC and a bit greater for environments with high FSC. The construction of a characterization curve could help engineers to better design the solar collector area. In fact, for a given site and a building type it is possible to estimate how much the collector area will affect the performance of the system.

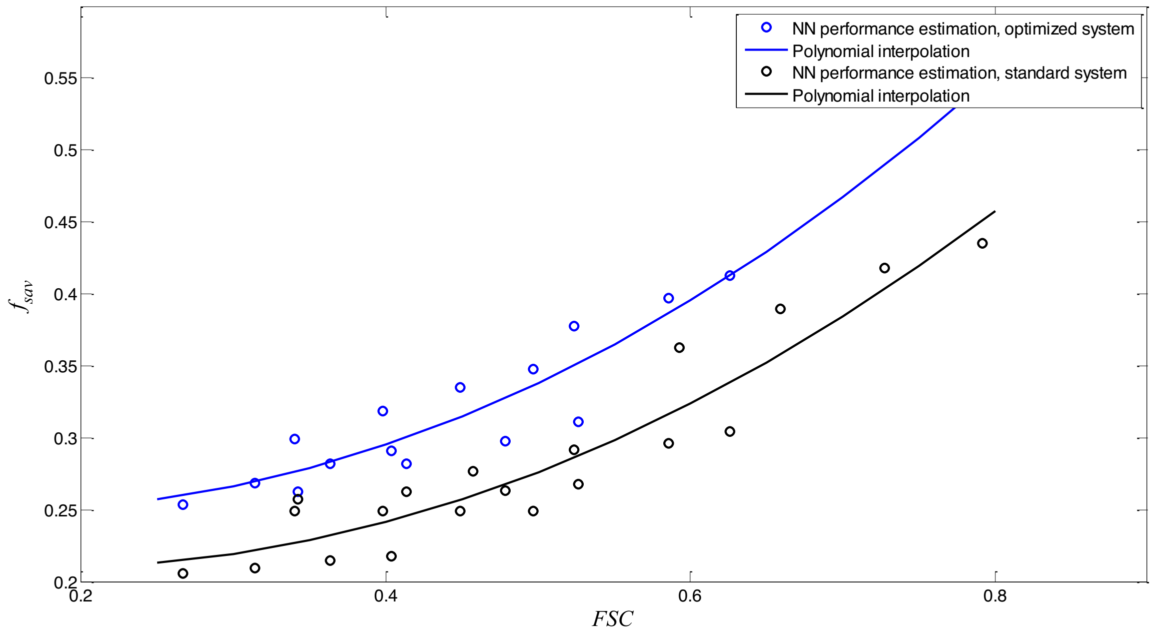

Fig. 11: Characterization curves of the optimized and standard systems

Finally in the case of solar combisystems using the proposed approach for modelling and the FSC method for characterization, it will be possible to establish a strategy for energy labelling. In fact, by superimposing characterization curves of several systems on the same drawing, it will be possible to locate regions where, for a given conditions (*FSC*), the system must be of class A or B etc. in the image of refrigerators for instance.

4. Conclusion and perspectives

In the present paper, some first results of the development of a new methodology to model solar thermal energy systems are presented. This methodology is supposed to be generic and able to be applied to systems as we can find them in the market, no need to dismantle the system in order to characterize it. The NN models developed are able to predict with a good precision degree the annual consumption of two tested systems based on a short learning sequence of only 12 days. In fact, by means of the NN generalization ability it is possible to predict the system behavior in various environments (other climate types and other building types) different from the one used during the NN learning. Prediction errors are almost in the range of ±10% and R^2 coefficients for energy rates are about 0.92 for non-extreme environments. Thanks to this approach the characterization of a real solar combisystem is done according to the FSC method without any extra test.

Neural network limitations appear in extreme conditions. In fact, NN predictions are poor for some environments very different from the one used during the physical test.

Future works will be concentrated in the development of an optimal method to build the learning data set. Using data from different climates and conditions seems to be relevant. This certainly will improve the generalization ability of the neural model and might reduce the sequence length too. The extension of the methodology to other solar thermal configuration systems will be done too.

5. Acknowledgment

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