# MODELING SOLAR COMBISYSTEMS PERFORMANCES USING AN ARTIFICIAL NEURAL NETWORK APPROACH

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**Abstract:** This paper introduces a global Solar Combisystem model that could estimate system performances for any kind of climate and any kind of building, only from a short experimental data set. The aim of this study is to improve the "Short Cycle System Performance Test" (SCSPT) that is being developed at the French National Solar Energy Institute (INES) and that shows relevant results but its performance prediction is limited to only one environment (climate and building). This improvement would lead to a complete and reliable method to characterize SCS performances. The proposed model is based on standard equations conjugated with Artificial Neural Networks (ANN). It shows results very close to TRNSYS simulations of three detailed SCS models.

**Key words:** Solar Combisystem, Artificial Neural Network, Performance prediction, Characterization.

## 1. Background

### *1.1. Solar Combisystems: performances and market curbs*

Solar Combisystems (SCS) are solar thermal systems which provide energy for DHW and space heating demand of a building. To meet those demands, SCS use both solar energy (through solar collectors) and auxiliary energy (from one or more auxiliary heat generators: gas boiler, electric resistance…). They deal with several hydraulic loops, heat storage(s), and controller(s) (that can sometimes be advanced) to manage energy sources and meet energy demand. This aspect plays an important role to reduce auxiliary energy consumption as much as possible.

SCS can be very efficient at reducing primary energy consumption of a house. According to on-site monitoring projects realized in France, some combisystems has already saved up to 500 $kWh.m^{-2}$ collector over a year in France (Papillon et al., 2007). However, good performances of SCS are only met for very precise conditions. Unfortunately, there is no common test method nowadays to predict SCS performances. This penalizes the SCS market because there is no reliable information to help potential users to choose between products and to guarantee good performances of a SCS when installed. There is a real need for the SCS market to have a reliable test method that would be able to predict and characterize annual performances of systems.

Developing such a test is difficult because SCS performances are very sensitive, mainly to two points:

- Firstly, even though every component of a system is efficient, a little mistake in design, installation or even controllers programming can make the combisystem behave differently as it was supposed to. Its performances could be then deeply reduced. Therefore, a reliable SCS test should be done on the complete system, as it is installed in a real house, to take into account actual design, installation and control aspects in the performance evaluations;
- Secondly, combisystem performances strongly depend on climatic conditions and energy demand. Therefore, a complete methodology should be able to predict SCS performances for any "environment" (characterized in this paper by a kind of thermal efficiency of building, a kind of climate and a collector area that defines the solar resource).

### *1.2. The current SCSPT method*

Some laboratory tests are currently being developed to evaluate SCS performances. One of them, the SCSPT (Short Cycle System Performance Test), uses a "Global approach" (i.e. it tests the whole system on a test bench).

The SCSPT consists in installing the complete system on a semi-virtual test bench (i.e. that links a real thermal system with a virtual environment) and to apply a specific 12 days sequence that closely matches an annual weather cycle of one precise climate to make the SCS behave as it usually does over a year (Albaric et al., 2008). The auxiliary energy consumption of the tested SCS is recorded during the test. The “12 days” sequence allows approximating its annual consumption (and then its annual performance) with a simple extrapolation of the results (multiplication by a factor 365/12).

This method has shown relevant results (Albaric et al., 2010; Mette et al., 2010). Performances estimations are quite accurate but they are limited. The application of one test of this kind allows the evaluation of auxiliary energy consumption for only one environment (the climate and the type of building used as virtual environment) and for the sizing of the SCS during the test sequence. This is not enough to characterize the performances of the tested system for any kind of environment, for instance with the FSC method proposed by Letz (Letz et al., 2009), from only one test.

### *1.3. The envisaged improvement of the SCSPT method*

The current SCSPT method extracts only one information from a 12 days sequence whereas there would be much more to learn about each tested SCS, analyzing their inputs and outputs recorded during the test. To further develop this “Global approach”, identifying a kind of dynamical global model of the whole tested combisystem would let it be simulated with different external conditions. Its performances would be thus evaluated in a more complete way.

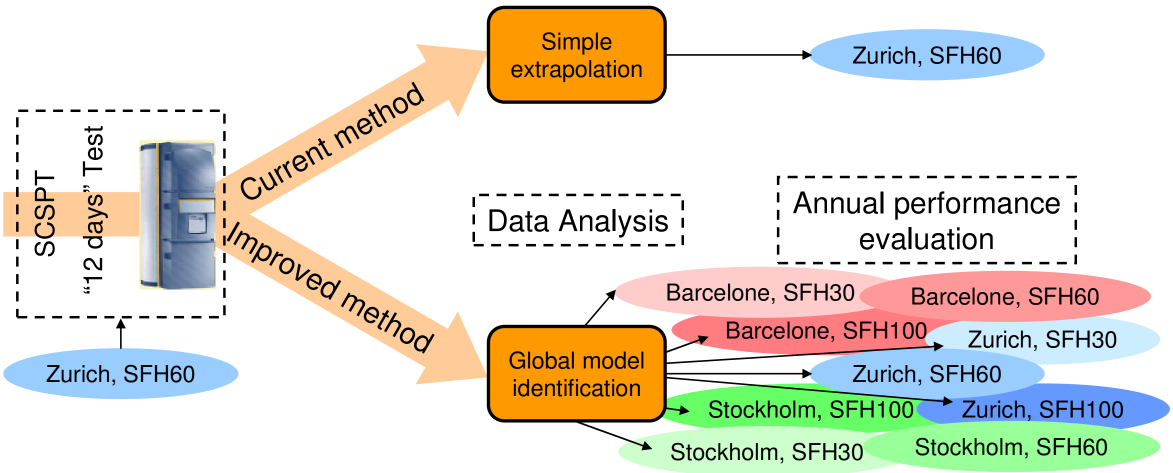


**Fig. 1: Goal of the envisaged SCSPT method improvement**

In this paper, an artificial neural network based model is built to demonstrate the feasibility of this improvement.

## 2. The proposed “Gray Box” model to learn SCS behaviors

### *2.1. General description*

The global SCS model must evaluate the powers managed by the system (outputs) functions of external variables, independent of the system (inputs). Those variables are described in Table 1.

**Tab. 1: Variables involved with the proposed global SCS model**

| | Variables | Description | Unit |
|---|---|---|---|
| Inputs | $T_a$ | Ambient temperature | [°C] |
| | $G_b$ | Beam solar radiation on a horizontal plane | [W.m$^{-2}$] |
| | $G_d$ | Diffuse radiation on a horizontal plane | [W.m$^{-2}$] |
| | $\theta_S$ | Solar zenith angle | [°] |
| | $\gamma_S$ | Solar azimuth angle | [°] |
| | $\dot{m}_{DHW}$ | DHW draw-off | [kg.hr$^{-1}$] |
| | $T_{tap}$ | Tap water temperature | [°C] |
| Outputs | $\dot{Q}_{aux}$ | Auxiliary power consume | [W] |
| | $\dot{Q}_{coll,out}$ | Power supply by collectors | [W] |
| | $\dot{Q}_{em}$ | Power received by heat emitters | [W] |
| | $\dot{Q}_{dhw}$ | Power of DHW demand | [W] |
| States | $T_{coll}$ | Mean collectors temperature | [°C] |
| | $T_{em}$ | Mean emitters temperature | [°C] |
| | $T_{room}$ | Room temperature | [°C] |
| | $T_{sto}$ | Mean storage tank temperature | [°C] |

A state space representation is chosen to form the dynamic aspect of the model. Considering the different temperatures generally controlled by a SCS when functioning, it seems relevant to call mean temperatures of the system's main elements as the dynamic states of the model (Table 1). This is all the more interesting since those temperatures can be evaluated by some equations. Finally, the relationship to identify from test data is the link between outputs on the one hand and inputs/states of the system on the other hand, which represent the real characteristic behavior of each SCS. This part to be identified must be non-linear in order to be able to face every system's behaviors.

To sum things up, the proposed model is made up of two main parts (also represented on Figure 2):

- The "White Box" part acts as a linear dynamical state feedback, supplying elements temperatures evaluation through known equations, according to external variables and energy flows within the combisystem.
- The "Black Box" part is a static non linear model that evaluates powers involve when the SCS is working according to external inputs and internal states of the system.

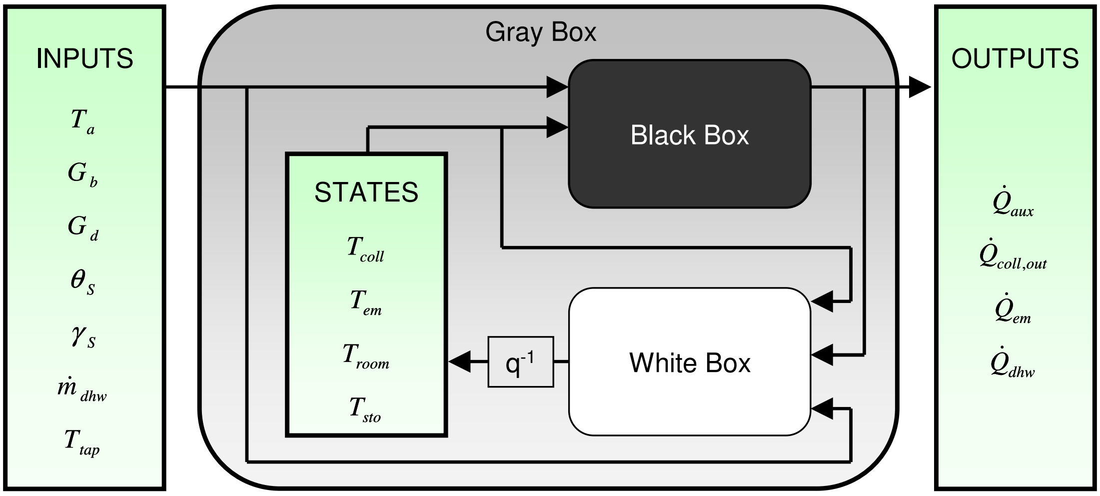


**Fig. 2: Architecture of the "Gray Box" model proposed to model SCS behavior from SCSPT experimental results**

This way, the global SCS model forms a "Block oriented Slate-Gray" model according to Ljung (Ljung, 2010). This shape of model has shown good results in different scientific field.

### *2.2 The "White Box" part*

The "White Box" part contains equations of combisystem elements: auxiliary energy system, storage tank, solar collectors, heat emitters and building. In order to eventually propose this method as a future normative test, equations are principally based on several standards and need almost only characteristic parameters of the system.

So far, this part has been built to model SCS using gas boiler as auxiliary energy system and radiators as heat emitters but the "Gray Box" architecture seems flexible enough to be adapted to other elements (like heating floor for instance) for the next steps of this work.

The mean collectors temperature is evaluated by the collector model described in (Perers, 1997). This model is based on the well-known "Hottel-Whillier-Bliss" equation for flat plate solar collectors that is adapted to characterize almost every kind of collectors, except ICS collectors. It has been widely used for standards (EN 12975-2, 2006; ASHRAE 93-86, 1986). It is also used during the SCSPT test as part of the virtual environment.

The radiator model used to evaluate the mean temperature of the heat emitter is based on standard parameters, calculated with (EN 442-2, 1996). This model is also used during the SCSPT test as part of the virtual environment.

The building model used to react with the global SCS model is the one defined in the international standard (ISO 13790, 2008). Every heat transfer coefficients and the internal capacity can be calculated out of architectural and physical parameters of the building. So far, parameters used are calculated to have three building models similar to the IEA SHC Task32 reference ones (Heimrath and Haller, 2007): SFH30, SFH60 and SFH100 (i.e. buildings with space heating loads respectively of $30kWh.m^{-2}$, $60kWh.m^{-2}$ and $100kWh.m^{-2}$ over a year for Zurich climate). This model is also used during the SCSPT test as part of the virtual environment.

The storage tank is one of the proper parts of a combisystem. Unlike elements presented above, this part is not modeled during the SCSPT. The goal of this model is to give information about the energy stored in the tank. Since there is not enough variables and parameters available to have a detailed storage tank model, equations come down to a simple energy balance, completed by a heat capacitance $C_{sto}$ and a heat loss parameter $(UA)_{sto}$ to be roughly estimated (Equation 1).

$$C_{sto}\frac{dT_{sto}}{dt}=\dot{Q}_{aux,out}+\dot{Q}_{coll,out}-\dot{Q}_{em}-\dot{Q}_{dhw}-(UA)_{sto}\left(T_{sto}-T_{amb,sto}\right) \text{(eq. 1)}$$

The equation above-mentioned needs an estimation of $Q_{aux,out}$, the power supplied by the auxiliary system. That is why a gas boiler model is also employed in the "White Box" part. The one currently used is taken from the French thermal regulation for building (RT2005, 2006). It evaluates the energy losses of the boiler according to the heat demanded with a simple second-order polynomial. Parameters of the polynomial are calculated with characteristic powers and losses of the boiler, determined by standards - like the (EN677, 1998) for instance.

For numerical computing, all equations described in this section are calculated with an explicit discretization scheme.

### 2.3. The "Black Box" part

The "Black Box" part is a pure numerical model. It learns the characteristic behavior of the tested SCS by identifying its parameters from a test data analysis. A specific model must be adapted to face non-linear behaviors of combisystems.

Artificial Neural Networks (ANNs) are widely appealed to different research projects nowadays, even in solar energy field because, as Kalogirou highlights (Kalogirou, 2001), they can learn from examples, are fault tolerant and are able to deal with non-linear problems. Therefore, ANNs are adapted in the "Black Box" part.

A mathematical neuron is presented on Figure 3.

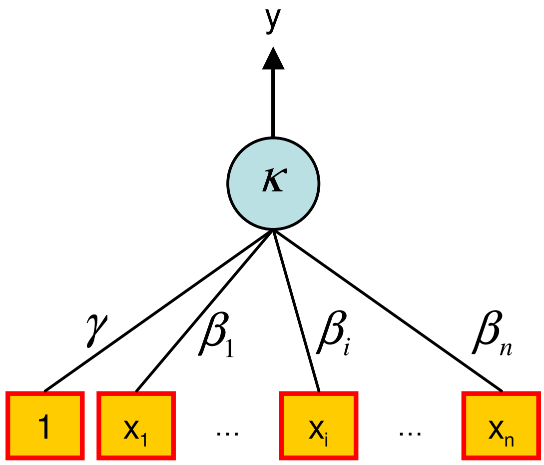


**Fig. 3: Representation of an artificial neuron**

Neuron inputs $x_i$ come from other neurons outputs or model inputs. Those signals are transmitted to the neuron through connections called "synapses". Synaptic weights $\beta_i$ are linked to each connection. There are several ways to combine neuron inputs with their corresponding synaptic weights. In this model, a simple linear combination, as described in Equation 2, is used. The result of this combination $\upsilon$ is the argument of a transfer function $\kappa$ (taken as a sigmoid for every neuron in this paper). The outcome y is the activation of the neuron.

$$\begin{cases}\upsilon=\gamma+\sum_{i=1}^{n-1}\beta_i x_i \\ y=\kappa(\upsilon)\end{cases} \text{(eq. 2)}$$

ANNs are built linking neurons together and with the model inputs and outputs. When presenting a training data set, an optimization algorithm searches the best synaptic weights set to minimize a cost function. For this work, the cost function is the sum of squared error over the training sequence, to be minimized by the Levenberg-Marquardt algorithm (Marquardt, 1963), completed by Bayesian regularization (Mackay, 1992).

An important inputs and outputs pre-processing step helps both the training procedure and the capacity of the "Gray Box" model to simulate correctly the SCS behavior for any environment. It consists in creating regressions of raw temperatures and heat flows in order to have reduced criterions of the interaction between the system, the building and the climate, at the bounds of the ANN. The network would simulate more easily the system's behavior in different loads and climatic conditions.

The inputs regression vector is presented in Equation 3.

$$\varphi(t) = \begin{bmatrix} \dot{Q}_{sol,net} / G_{ref} \\ \dot{Q}_{sh} / \dot{Q}_{sh,nom} \\ \left(T_{room} - T_{set,room}\right) / \left(T_{set,room} - T_{a,d}\right) \\ \left(T_{room} - T_{a}\right) / \left(T_{set,room} - T_{a,d}\right) \\ \left(T_{store} - T_{set,dhw}\right) / 100 \end{bmatrix} \text{(eq. 3)}$$

The net input solar irradiation on collectors plane $Q_{sol,net}$ (i.e. that takes into account $T_{coll}$ and collectors optical and thermal losses) is divided by a reference irradiation $G_{ref}$ (taken as $1000 W.m^{-2}$). The heat delivered by radiators to building rooms $Q_{sh}$ is divided by the nominal power of radiators (which depends on the thermal quality of the building and the climate). The room temperature is compared with both the room temperature set-point $T_{set,room}$ and the ambient temperature $T_a$. Difference between $T_{set,room}$ and design ambient temperature $T_{a,d}$ is used to weight those comparisons. The mean storage tank temperature is compared with the DHW set point temperature $T_{set,dhw}$. Since there are no obvious limits to this comparison, it is only divided by 100 to reduce the variation of this criterion.

The nominal power of the boiler $Q_{aux,nom}$, the reference solar radiation and the nominal power of radiators are used to compose the outputs regression vector, presented by Equation 4.

$$y(t) = \begin{bmatrix} \dot{Q}_{aux} / \dot{Q}_{aux,nom} \\ \dot{Q}_{coll} / \left(A_{coll} G_{ref}\right) \\ \dot{Q}_{em} / \dot{Q}_{sh,nom} \end{bmatrix} \text{(eq. 4)}$$

To have a first evaluation of this approach, the DHW demand $Q_{dhw}$ is supposed to be fulfilled. So this "Gray Box" output is not considered at the bounds of the ANN to make its learning easier in a first place.

Finally the global structure of the neural network chosen to be part of the "Black Box" is presented on Figure 4. It is composed of one output layer and one hidden layer, for which the right complexity (number of neurons) has to be tested from several trainings to match the SCS behavior as best as possible.

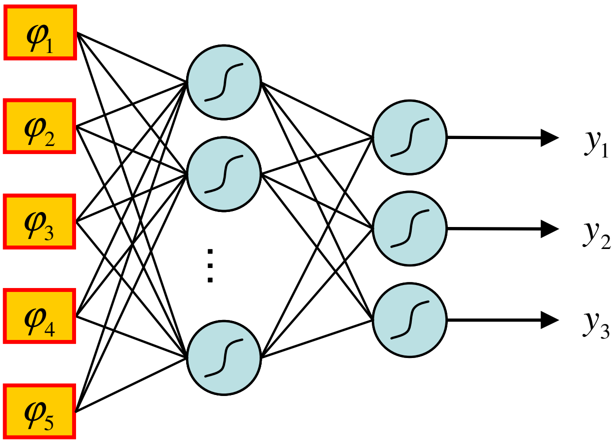


**Fig. 4: Representation of the neural network considered in the "Black Box" part**

For a given network complexity, the optimization algorithm to train neural network from a data set is also applied several times with different initial weights using the Nguyen-Widrow method (Nguyen and Widrow, 1990) to enhance the ANN trainings. In this paper, the best "Gray Box" model is selected thanks to TRNSYS simulation comparisons, according to the process described below.

## 3. Validation of this approach

### *3.1. Protocol*

To validate this approach, three detailed combisystems models (called SSC1, SSC2 and SSC3 below) are used within TRNSYS. Training data sets for neural network are calculated from a simulation of the "12 days" sequence. Trained "Gray Box" models are then used to do the 27 annual simulations presented in Table 2, corresponding to 3 climates, 3 buildings and 3 collector areas (defined as A1, A2 and A3 below, to be chosen according to the volume of the storage tank and usual sizing considerations). Annual results of these simulations are then compared to the corresponding TRNSYS simulations ones. The scheme of this process is represented on Figure 5.

**Tab. 2: Definition of the 27 (3x3x3) environments for annual simulation**

| Building | Climate | Collector area |
|---|---|---|
| SFH30 | Stockholm | A1 |
| SFH60 | Zurich | A2 |
| SFH100 | Barcelona | A3 |

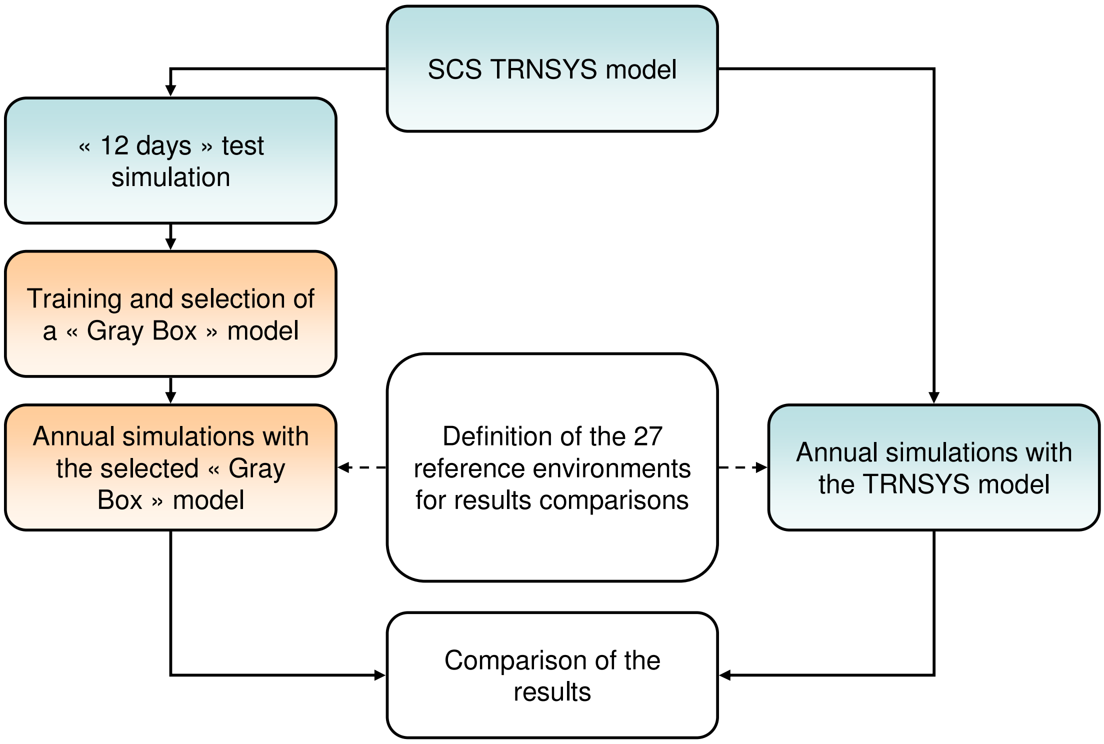


**Fig. 5: Process for the validation of the proposed approach from a detailed SCS model**

TRNSYS "12 days" and annual simulations are done with a 3 minutes time step. TRNSYS "12 days" simulations data are processed to train "Gray Box" model with a 30 minutes time step, which seems a good compromise between sufficient precision of the system's behavior and quite smooth signals for the network.

### *3.2. Results*

Figure 6, Figure 7 and Figure 8, presented below, show the comparison between the TRNSYS model results and the best "Gray Box" model results, for each of the three tested SCS. They represent estimations by both types of model of annual energy consumed by the boiler (blue stars), supplied by the collectors (green stars) and received by the radiators (red stars) of the tested SCS for the 27 simulations. The statistical regression coefficient $R^2$ is also noticed on these figures, for each energy evaluation.

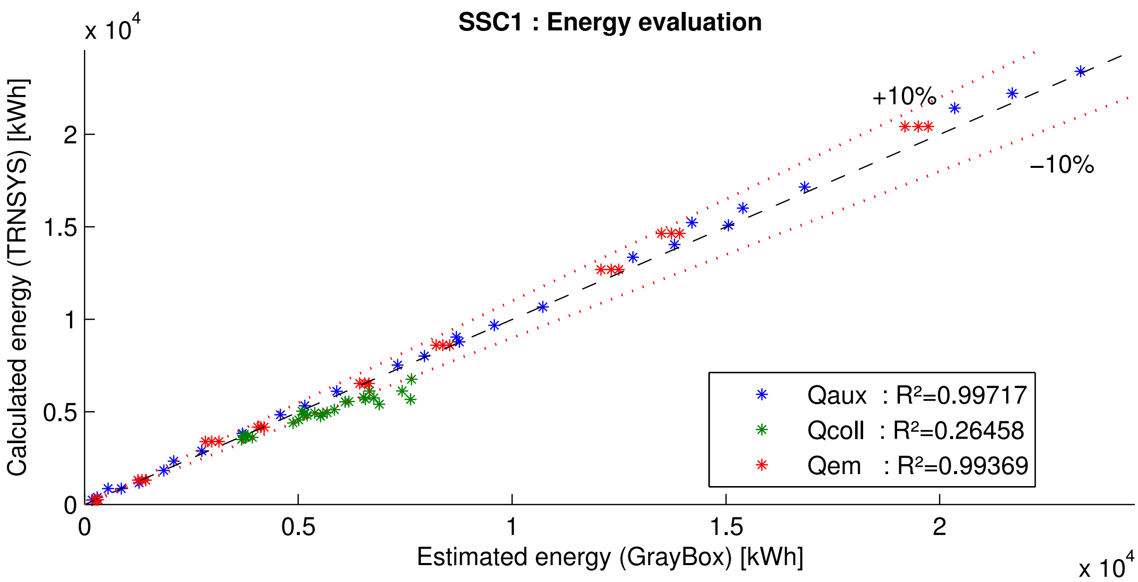


**Fig. 6: Comparison of annual energy evaluations between the TRNSYS model of SSC1 and its "Gray Box" model selected**

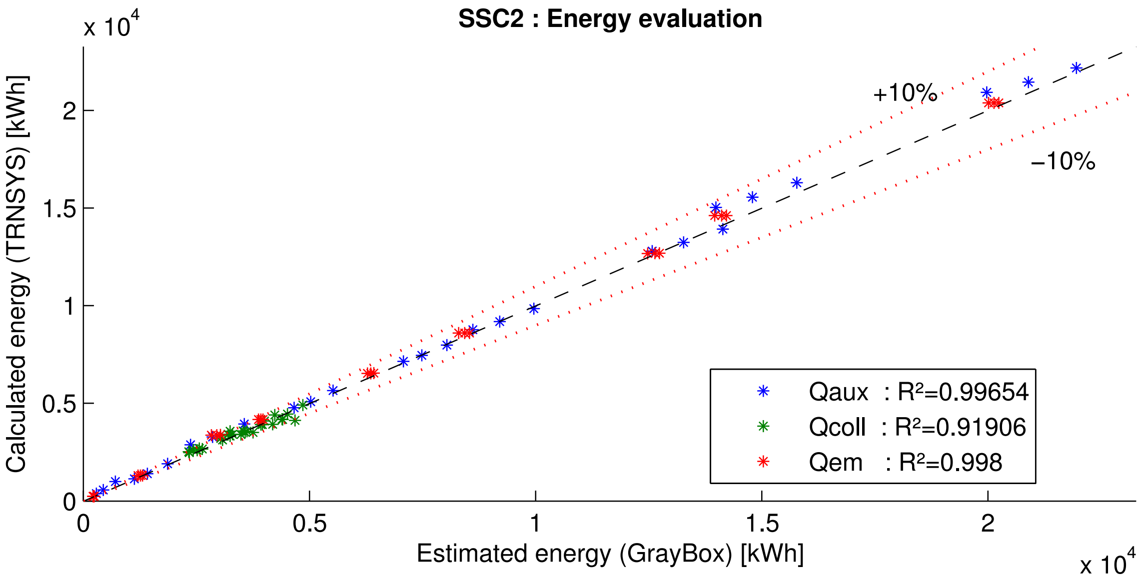


**Fig. 7: Comparison of annual energy evaluations between the TRNSYS model of SSC2 and its "Gray Box" model selected**

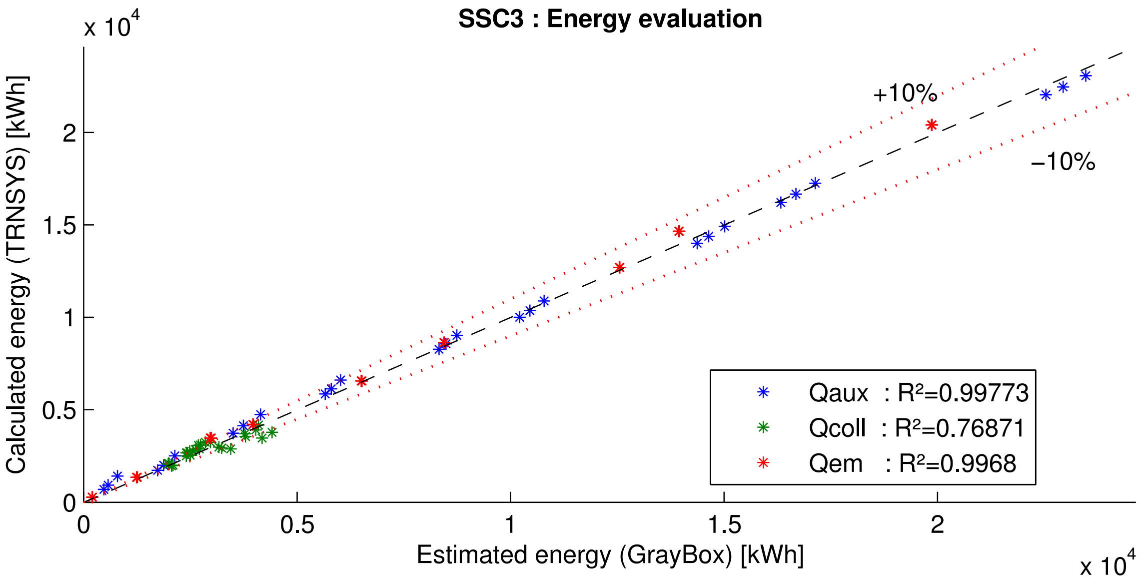


**Fig. 8: Comparison of annual energy evaluations between the TRNSYS model of SSC3 and its "Gray Box" model selected**

This approach seems to be relevant since for the three combisystem models tested, energy estimations are really close to the corresponding TRNSYS calculations, within +/-10% precisions for most simulations. "Grey Box" models seem precise enough to characterize SCS performances.

Globally, estimations are less accurate for $Q_{coll}$. It seems that the training sequence does not let the tested system activate all of its control function. Moreover, there should be more information about the heat storage to be more precise on how the system controls the solar loop. (Statistical regression coefficient is very low in this case because the energy $Q_{coll}$ doesn't vary as much as other energy from one simulation to the other. That makes one flawed estimate have a more important effect on $R^2$).

Simulations that seem a little harder to model represent environment that require few auxiliary energy and that have large solar resource. Actually, those environments involve mainly the Barcelona climate, which imply different weather conditions compared to the Zurich climate used as reference for the test sequence.

Figures above also show that accuracy of the "Gray Box" models depends on the kind of system. SSC2's behavior seems easier to learn.

This “Grey Box” modeling is very acceptable for the characterization of the three tested combisystems. Therefore, this study shows that the new approach is promising in order to predict thermal efficiency of combisystem.

## 4. Conclusion and outlook

The study presented in this paper offers a basis to get ahead with a complete method to characterize SCS that could lead to develop a standardization method from performance evaluation (and eventually complete the European norm (EN 15316-4-3, 2008) for instance) and to plan a combisystems performance labeling.

The next step is to arrange this methodology to fit current lab tests and so to be able to evaluate combisystem performance in a complete and reliable way.

This starts with developing a process to select only one “Gray Box” model trained from a test data set or to handle results from several ones to have a unique performance characterization. Currently, most of trained “Gray Box” models show good results but they don’t calculate exactly the same estimations. Moreover few of them can be “over-trained” (i.e. they can’t simulate the SCS behavior correctly but for the only training sequence). Those ones have to be sought out and put aside.

Another important point is to consider how the tested SCS supply DHW. The current “Grey Box” model estimates that the demand is fulfilled but it should take into account the temperature of DHW delivered more precisely to have right performances evaluations.

Moreover, the methodology has to be adapted to other kind of SCS in order to be able to characterize any type of SCS, considering equations for other elements like heating floor for instance, in the “White Box” part.

The methodology must even be further improved by studying a different way to model the energy storage, that takes into account the quality of the heat stored (with a multi-nodes storage model or an exergy calculation for instance). Some other leads could probably also act in this way like for instance studying other regression vectors and optimizing the test sequence to get more information about the tested SCS behavior in the training data set.

## 5. Acknowledgment

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