MODEL OF ROOM STORAGE HEATER AND SYSTEM IDENTIFICATION USING NEURAL NETWORKS

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Abstract. This paper presents two approaches used to develop a model of Room Storage Heater. The first one consists of a dynamic model of the RSH developed by the authors using the results obtained from tests performed in a calorimetric chamber. The model was verified against the results obtained during five different charge-discharge test periods. The second approach is a new concept based on Neural Networks applications. In this approach, we suppose that we do not have a description of the RSH itself. The input data in a neural network training are as follows: the immediate paste bricks temperature, the room temperature, the electric power input and the on/off activation function of the fan. The energy released and the current brick temperature were the neural network outputs. The results of two training and test procedures are presented. In the first procedure we use the results of the tests performed in the calorimetric chamber which are sufficient to develop the dynamic model but they appear not adequate for the neural networks application. Consequently, the second NN's training and test were conducted with the modified training data set which was obtained by the simulations performed using the RSH dynamic model. Two comparison are presented : comparison of the NN's and simulation results and comparison of the NN's and calorimetric chamber test results. The NN's model accuracy seems to be very good. It is comparable with the dynamic modelization methods.

Keywords. Room Storage Heater, calorimetric chamber, system identification, neural networks.

List of Symbols

A_{vs} : RSH wall vertical area
A_{hs} : RSH wall horizontal area
h_{vs} : Convection coefficient on vertical sides
h_{hs} : Convection coefficient on horizontal sides
h_i : Internal convection coefficient
k_w : Equivalent conductivity of the RSH walls
Nu_L : Nusselt number based on vertical height
$Nu_{d_{eq}}$: Nusselt number based on internal equivalent diameter
$\dot{Q}_{in}$: Power electric input
$\dot{Q}_{out}$: Heat released
$\dot{Q}_{vs}$: Losses from the vertical surfaces
T_b : Brick temperature
T_s : RSH wall temperature

T_r : Room temperature
T_{rs} : Room wall temperature
Ra_L : Raleigh number based on vertical height
Ra_l : Raleigh number based on horizontal width
β : Volumetric thermal expansion coefficient

1. INTRODUCTION

For electrical producers and distributors, the power demand during the peak period causes many problems which reflect as much on the infrastructures necessary for the production and transport of electricity than on the production costs of energy. Many tools and management techniques can be used to reduce peak demand such as, interruptible current, bi-energy furnaces, non-electric back-up heat pumps etc. However, all these techniques do not apply to clients heated by electric baseboard heaters and these end up on the network at each peak demand produced during cold weather, hence the interest in a new technique for managing electricity consumption.

Electric Thermal Room Storage Heaters (RSH) using sensible heat can fulfill this need. They have been used in Europe for many years and more recently in the United States [1]. RSHs store heat during off-peak consumption periods (night, for example) in order to release it during peak periods. During the night, at the signal of a timer from the electricity company, the electric elements inserted in the thermal mass are activated and rise the temperature of the refractory bricks up to projected holding value. Generally a seven to eight hours are required to fully charge the RSH. After this period the electric elements are usually deactivated for the rest of the day. Often, RSH includes a fan which is controlled by a room thermostat and/or by a timer. In this case, two discharge periods are distinguished : the passive when the fan is off and the active discharge when the fan is on. The charge-discharge cycle of RSH is usually completed over a 24-hours period, shifting the heating consumption from day to night. This shift reduces the maximum power demand. In theory, it does not affect the overall consumption which could remain the same except the periods when the room is superheated due to the passive discharge which is, during these periods, greater then the room heating load.

The principal components of RSH are the follows :

- a large thermal mass, usually made of refractory bricks 70 to 200 kg ;
- electrical elements that power rating is between 1.7 and 6.0 kW ;
- an insulating layer, enclosing the refractory bricks (high density ceramic bricks) to minimize the heat losses and to reduce the wall surface temperature to around 60 ^{o}C.

RSH storage capacity can vary from 12 to 48 kWh, but typically the 12 to 24 kWh units are used more often in the residential sector.

The paper is divided into five sections. In section 1 a brief introduction and the statement of problem is presented. Section 2 presents the description of the RSH and of the experimental test conducted in calorimetric chamber. The numerical model developed based on the experimental results is presented in section 3. In the section 4 we present the new approach to develop the

RSH model using the recurrent neural networks. Some conclusions are provided in the last section.

2. DESCRIPTION AND EXPERIMENTAL TEST OF RSH

Two different types of RSH were tested, but the model presented in this paper concern only one of these two RSH. View and schematic of this RSH are presented in figures 1 and 2. The principal components are : the insulation layer (1), the bricks (2), the electrical elements (3) and the fan (4). The total mass is 106 kg and the dimensions are follow : high 71 cm, length 79 cm and large 17 cm. The power of the electrical elements is 2.52 kW and the RSH thermal capacity are 18 and 24 kWh.

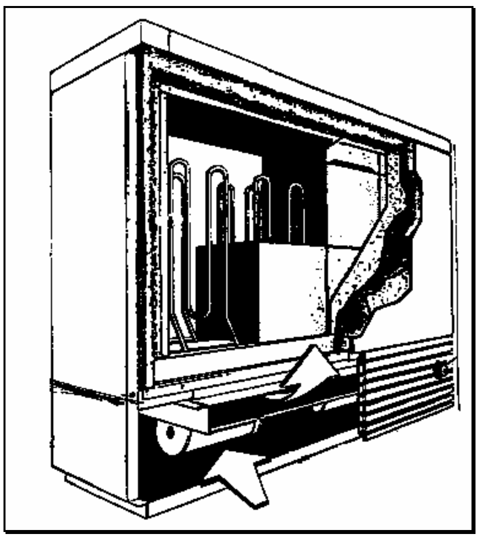

Figure 1. View of RSH

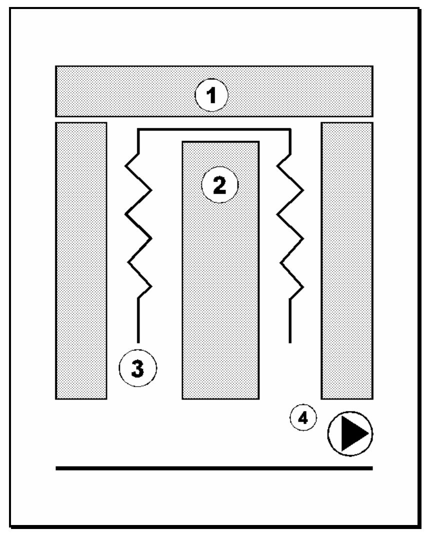

Figure 2. Schema of RSH

The tests consist in the evaluation of the thermal power released by the RSH during a 24-hour charge-discharge cycle. They were conducted at the LTEE (Laboratoire des technologies électrochimiques et des électrotechnologies d'Hydro-Québec) [2]. in the calorimetric chamber measuring 2x2x2m, very well insulated and extremely well-sealed. This calorimeter is shown in figure 3. The RSH are installed in the calorimeter across which circulates the small air flow rate in an open loop. The measurements, which step was 5 minutes, were as follows :

- calorimeter air temperature ;
- inside and outside walls temperature of the calorimeter ;
- heating or cooling powers injected into the calorimeter ;
- RSH walls temperature ;
- inside and outside walls temperature of the bricks ;
- power and on/off times of the RSH electric elements and the fan.

The thermal power released by the RSH was determined by an energy balance applying the corrective factors which consider the thermal inertia and the heat losses of the calorimeter (factors determined by sampling).

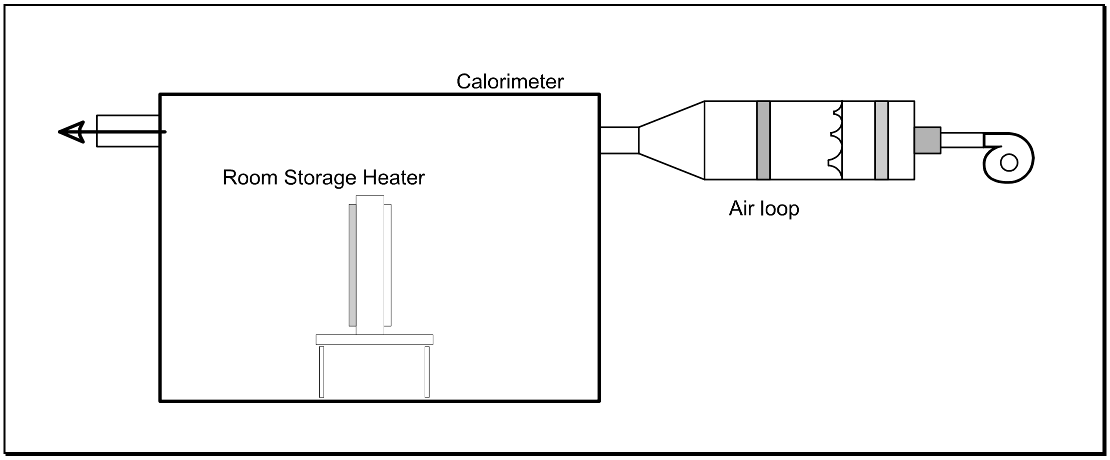

Figure 3. Schema of the calorimetric chamber

The tests provide the daily heat release profile of RSH operated according to five charge-discharge scenarios which correspond to the need to reduce the electricity network's power demand. These scenarios, shown in the table 1, were established based on the network demand profiles of the different electricity companies.

Table 1.

Hour of day		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Scenario 1	charge																								
	fun on																								
Scenario 2	charge																								
	fun on																								
Scenario 3	charge																								
	fun on																								
Scenario 4	charge																								
	fun on																								
Scenario 5	charge																								
	fun on																								

For scenario # 3 the measured results are shown on the figure 5.

3. NUMERICAL MODEL OF RSH

For any of the different scenarios discussed in the previous section, we can divide three different operational modes:

- charge mode
- passive discharge mode (Fan off)
- active discharge mode (Fan on)

The mathematical model of the RSH is based on a thermal balance for these three modes:

$$m_b C_b \frac{dT_b}{dt} = \dot{Q}_{in} - \dot{Q}_{out} \qquad (1)$$

$$\dot{Q}_{in} = \begin{cases} Ri^2 & \text{(charge period)} \\ 0 & \text{otherwise} \end{cases} \qquad (2)$$

$$\dot{Q}_{out} = \begin{cases} \dot{Q}_{hs} + \dot{Q}_{vs} + \dot{Q}_{oth} & \text{(Fan = off)} \\ \dot{Q}_{hs} + \dot{Q}_{vs} + \dot{Q}_{dyn} & \text{(Fan = on)} \end{cases}$$

The losses from the vertical surfaces $\dot{Q}_{vs}$ are computed by:

$$\dot{Q}_{vs} = \dot{Q}_{vs}^{rad} + \dot{Q}_{vs}^{conv} = \dot{Q}_{vs}^{cond}$$

$$\dot{Q}_{vs} = \varepsilon\sigma A_{vs}\left(T_{vs}{}^4 - T_{vs}{}^4\right) + h_{vs}A_{vs}\left(T_{vs} - T_r\right) = \frac{k_{vs}A_{vs}}{l_{vs}}\left(T_b - T_{vs}\right) \qquad (3)$$

We have a similar expression for the vertical surface. In the simulation, we assume that the room surface temperature T_{rs} was the same as the room temperature T_r.

The conductivity was assumed to vary linearly with temperature:

$$k_{vs} = f\left(T_b, T_{vs}\right) = b\left(T_b - T_{vs}\right) + c \qquad (4)$$

with the constants b and c found in tables. For the vertical plates, the convection coefficient was found using

$$h_{vs} = \frac{Nu_{vs} \times k}{L_{vs}}$$

$$Nu_{vs} = \left\{ 0.825 + \frac{0.387 Ra_L{}^{1/6}}{\left[1 + \left(0.492/Pr\right)^{9/16}\right]^{8/27}} \right\}^2$$

$$Ra_L = \frac{g\beta\left(T_{vs} - T_r\right)L_{vs}{}^3}{\nu\alpha}$$

For the horizontal plate, the relation is

$$Nu_{hs} = \begin{cases} 0.54 Ra_l{}^{1/4} \rightarrow Ra_l \le 10^7 \\ 0.15 Ra_l{}^{1/3} \rightarrow Ra_l > 10^7 \end{cases}$$

The other losses during the passive energy release correspond to convective losses from the bottom of the unit which is open. We used the following quadratic relation:

$$\dot{Q}_{oth} = a_2(T_b - T_r)^2 + b_2(T_b - T_r) + c_2$$

The empirical coefficients a_2,b_2,c_2, are found from experiments. When the fan is on (active release), the convective heat release can be modeled by:

$$\dot{Q}_{dyn} = h_i A_i \frac{\left(T_r - T_{mo}\right)}{\log\left[\left(T_b - T_{mo}\right)/\left(T_b - T_r\right)\right]} \tag{6}$$

$$T_{mo} = T_b - \exp\left[\frac{-A_i h_i}{\dot{q}\rho C_p}\right]\left(T_b - T_r\right)$$

$$h_i = k_{air} \times Nu_{d\,eq} / d_{eq}$$

$$Nu_{d_{eq}} = 3.66 + \frac{0.0668\left(d_{eq}/L_s\right) Re_d \times Pr}{1 + 0.04\left[\left(d_{eq}/L_s\right) Re_d \times Pr\right]^{2/3}}$$

The non-linear system was solved using SIMULINK and the diagram of the model is shown on the figure:

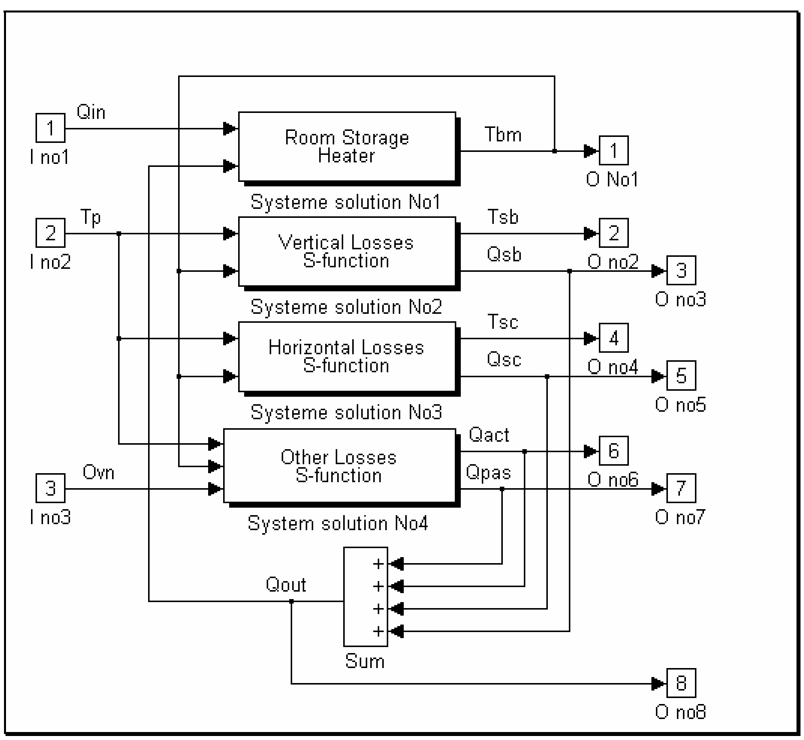

Figure 4. Diagram of the RSH model

Each of the main block is a Simulink S-function which is not given here for clarity. Some comparison data are shown on the next figure.

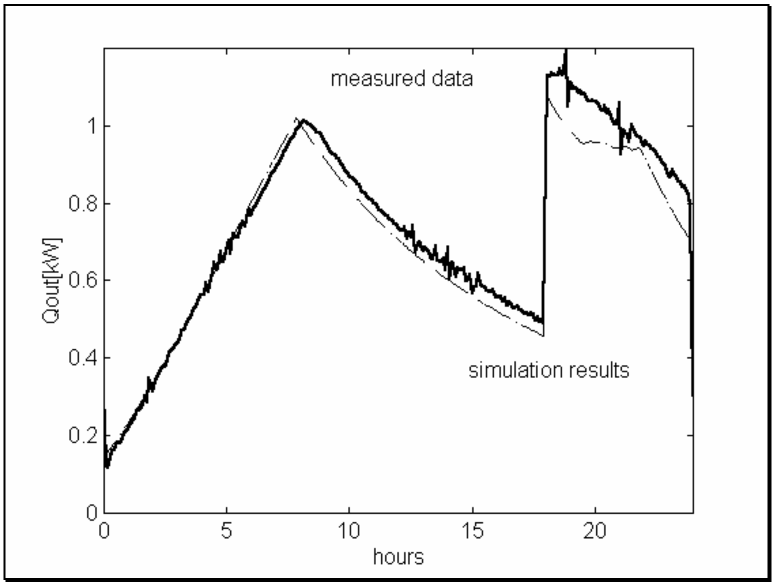

Figure 5. Comparison of the measured and simulation results

We can observe that the simulated results follow the same pattern as the measured ones. The only noticed discrepency is in the active discharge mode of operation where the measured data were somewhat higher. A possible reason is the fact that we neglected the power of the fan.

4. ROOM STORAGE HEATER MODEL USING THE NEURAL NETWORKS

The numerical model presented in section 3 allows to analyze the impact of different RSH parameters on its performance (the energy released, walls temperature etc..) and to optimize the RSH conception. Suppose that this conception is already finished and we wish only to estimate the energy released by RSH. We don't have a description of RSH itself. We are given only a time series data including a time stamp, energy data (output value) and the most important parameters which have an effect on the output values. This most important parameter is, for example the RSH brick temperature because it is the on/off control value of the fan and the electric elements. If we know only these parameters, can we estimate the energy released by RSH ? The way to accomplish this is to assume that we know the form of an equation relating inputs and outputs values. We may in this case, apply a very general input-output model to the data in the hope that the appropriate model is a special case of the general model. The neural network is often used for this application, since it is a kind of general-purposes nonlinear regression model. The most commonly used neural network have several layers. The first and the last are called the input and output layer and between them are one or more hidden layers. The neurons of the input and the first hidden layer are connected by lines that have varying weights. The neurons of the first hidden layer are connected with the neurons of second layer and so on till the last hidden layer which is connected with the output layer. The inputs to a neural network can be any quantifiable variable, but, in the complex model, a considerable experience is necessary to select the proper inputs. For example, in a previous paper [3] we have predicted a building heating load without knowledge of heating load for the immediate past. For this prediction we have selected the following variables : day of a week, hour of a day, current and previous hour's solar radiation, wind speed, outside temperature and five hour's previous combined temperature. So in this neural network application we don't have selected the past output value as a part of the current input but often it is necessary to include this value to the current input. If we do it, the neural network is called recurrent since its outputs feed back into its inputs. This type of neural network was used in our approach, presented in this paper, to « identify » a Room Storage Heater. Since the energy released ($\dot{Q}_{out}$), depends on the brick temperature (T_b) which is the on/off control value of the electric elements, we consider the both as the output values. Really, the output value is ΔT_b which is the difference between the actual ($T_{b(n)}$) and the past brick temperature ($T_{b(n-1)}$). During NN's training, the known values of the past brick temperature ($T_{b(n-1)}$) are used as inputs, but during testing, the network's own past brick temperatures ($T_{b(n-1)}$) are cycled back into the inputs. This temperature was calculated as a sum of the past value ($T_{b(n-1)}$) and actual difference ΔT_b. The inputs to the neural net were :

- past brick temperature ($T_{b(n-1)}$) ;
- current room dry bulb temperature (T_r) ;
- power electric input ($\dot{Q}_{in}$) ;
- on/off activation function of the fan (binary flag 0 or 1 to distinguish the active and passive discharges).

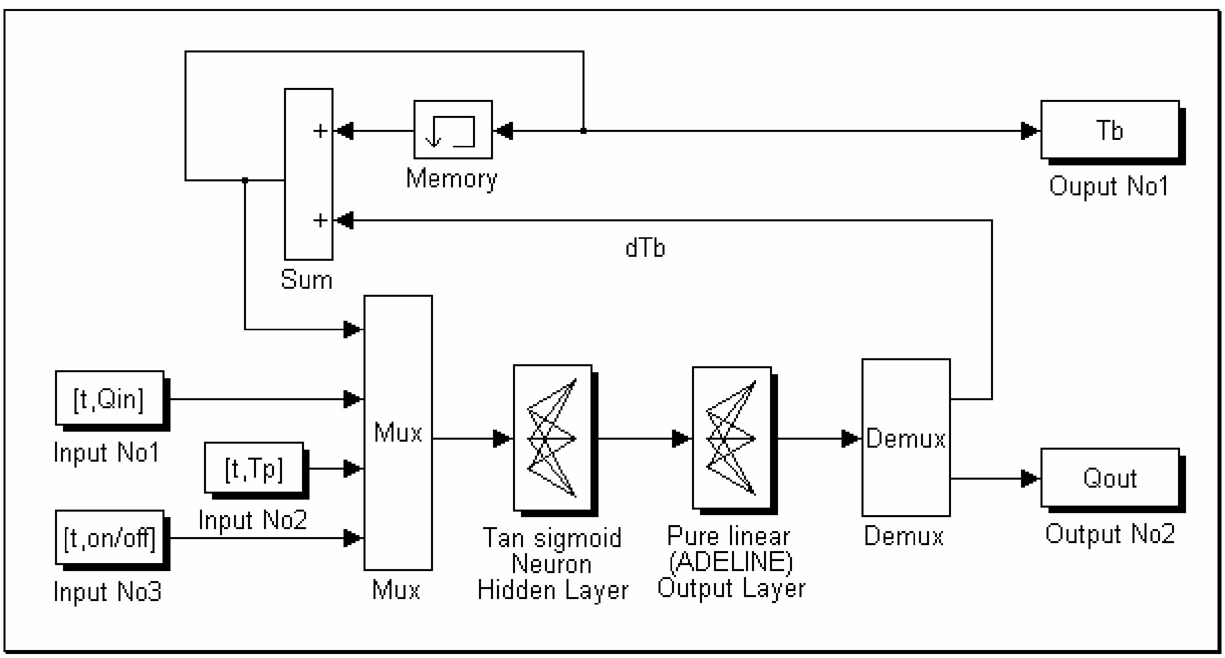

Figure 6. Neural networks schematic diagram

The figure 6 shows neural network schematic diagram. The neural network used in this study have one input, one output and one hidden layer containing 10 neurons. The tan sigmoid function was the activation function for the hidden units while the output layer was linear. The method used was the Levenberg-Marquard method. The training for the neural network was done using 40% of the measured data (set of 574 inputs and outputs data) in the calorimetric chamber during the five charge-discharge scenarios described in section 2 of this paper, while the tests were conducted with 100% of the measured data for these scenarios. The results of these tests concerning only the energy released by RSH are presented in the table 2. The coefficient of variation *CV* is the root mean square *RMS* error (between the energy released obtained by neural network and the one measured in calorimetric chamber) divided by the mean value of the testing data set. We present also the relative error *RE*, in order to compare the sum of energy exchanged by RSH (including Q_{in} and Q_{out}) during 24 hours. This error was calculated by the following equation :

$$RE = \frac{\left|\sum\left(Q_{NN} - Q_{measured}\right)\right|}{\sum\left|Q_{measured}\right|}$$

Table 2.

	CV [%]	RMS [W]	Relative Error [%]
Scenario #1	3.0	21.02	1.0
Scenario #2	6.0	46.95	4.0
Scenario #3	3.0	22.35	2.0
Scenario #4	3.0	25.89	1.0
Scenario #5	7.0	68.79	5.0

The comparison of the brick temperature differences (ΔT_b) measured and obtained by NN's is presented on the figure 7.

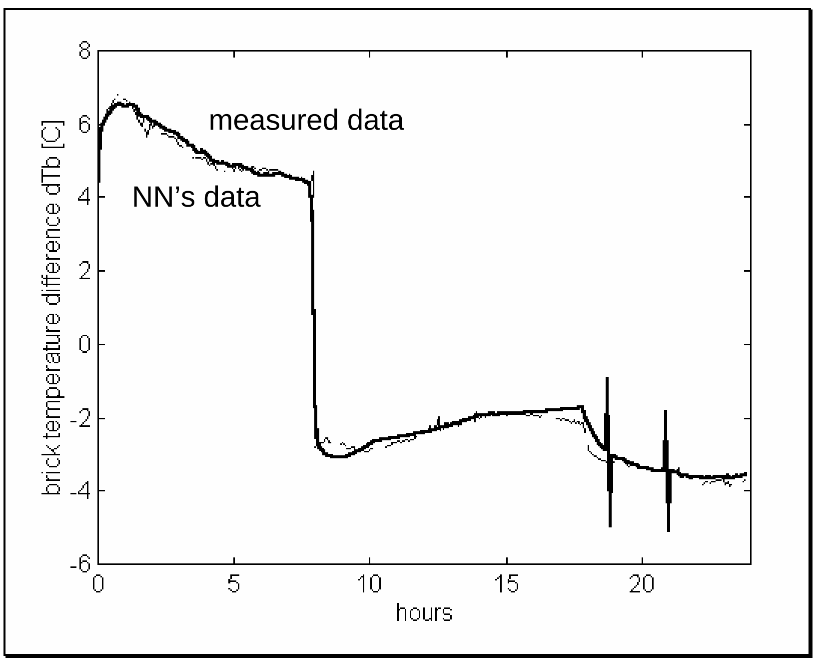

Figure 7. Comparison of the ΔT_b measured and obtained by NN's

According to this comparison and to the errors presented in the table 2, the testing results of neural network seem very good. However, we know that the training and testing data sets contain only one value of electric elements power. We know also that, the room temperature varies during the calorimetric tests. Hence, to know the NN's behavior when the electric power or the variation of the room temperature is different, we have tested the NN with a fixed room temperature. Since we do not have the measured data with the fixed room temperature, the results of this test are compared to the simulation results obtained using the numerical model presented in section 3. The figure 8 shows the comparison of the brick temperature, which is the one of outputs values, obtained by simulation and by NN's application. We can find that the NN's model does not give the adequate results when the inputs values behavior is different than that in training data set. This conclusion is particularly important for the room temperature because the training data set seems to contain enough values of this temperature.

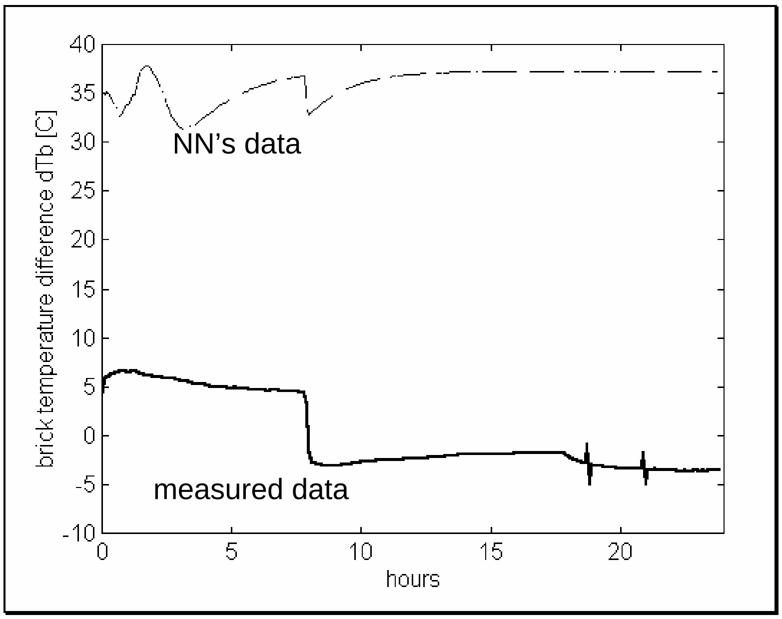

Figure 8. Comparison of the ΔT_b obtained by simulation model and by NN's

The question is « why the results of the test conducted with 100% of measured data for five scenarios are correct and they are unacceptable when the inputs pattern change ? ». In [4] the authors have analyzed the several factors that influence NNs learning, such as : (1) input pattern sequencing and related notion of persistently exciting, (2) the effect of normalizing techniques and input scaling on the rate of convergence and (3) the concept of learning in environments with a nonunique solution. In our case, the first factor is particularly pertinent and consequently to response to question mentioned above we have analyzed the training data set. We can conclude that there are following reasons to obtain those unacceptable results :

- the variation of room temperature in experimental data set is always similar to the variation of the brick temperature ;
- there is only one value of the electric power used during the calorimetric test ;
- the using of the on/off activation function of the fan is not enough.

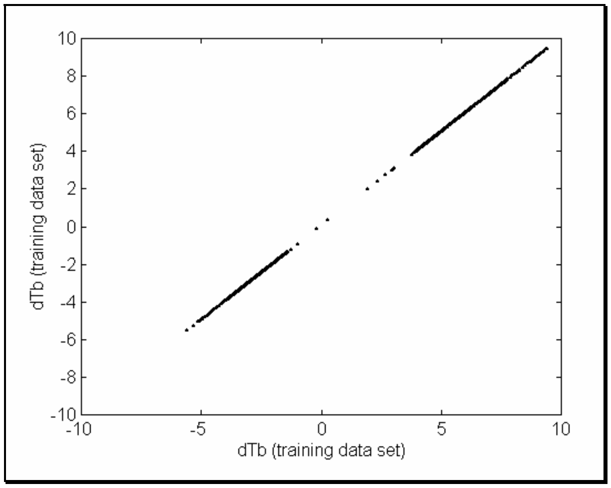

Figure 9. Distribution of ΔT_b in the training data set

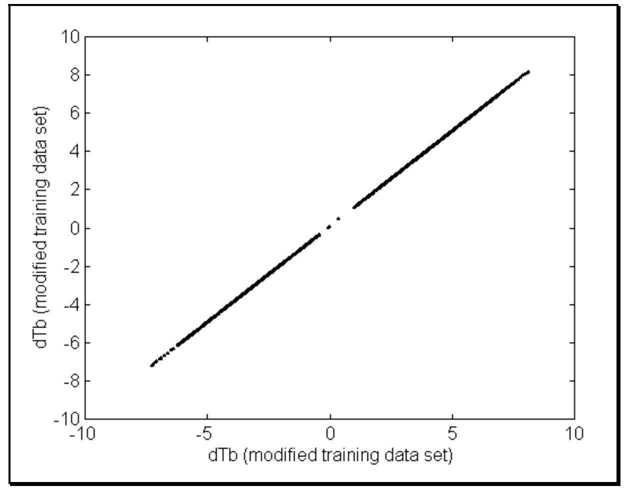

Figure 10. Distribution of ΔT_b in the modified training data set

Otherwise, the training data set is not adequate because the outputs, it means the brick temperature and the energy released, do not cover the output domain. According, for example, to the figure 9, we find that the training data set does not contain the brick temperature difference (ΔT_b) between -2 to 4 ^oC. This is similar for the other output value, it means for the RSH energy released. The training data set must then be modified in order to cover the outputs domain. Since it was difficult to remake the experiments in the calorimetric chamber, we have made these modifications using the numerical model described in the previous section. During the simulations performed by this model the following assumptions are taken into account :

- three values of the RSH electric power are used during the charge period, it means 2.1, 2.4 and 2.7 kW ;
- the charge-discharge frequency is more important then that during the test in calorimetric chamber. The charge time depend on the electric power used. Three or four discharge periods, alternatively active and passive, follow each charge period.
- the variation of the room temperature is sinusoidal and it varies between 15 ^oC and 50 ^oC ;
- the simulations were performed for 130 hours, it means for quite the same period then the five scenarios described in section 2.

The figure 10 shows that the modified training data set contains more values of the brick temperature difference (ΔT_b) between -2 to 4 ^oC than the previous training data set, but it does not contain many values between 0 and 1 ^oC. To explain that, it should be noted that the ΔT_b is positive only when the electric elements are on. Consequently, it is clear that, when these elements, which power is equal or greater then 2.1 kW, are on, the ΔT_b is rarely between 0 and 1^oC.

The neural network was trained the second time using the modified training data set including 1560 data records. The tests were conducted with the measured data for the five same scenarios mentioned above and with the modified scenario #1, called here scenario #1A. This modification consist in the fixed room temperature while during the scenario #1 this temperature was variable.

The inputs used during the tests were the following measured data : the room temperature T_r, the power input $\dot{Q}_{in}$ and the fan on/off activation function. The measured brick temperature, which was also the input parameter during the first NN's training, was used only as initial value during the first step, later this temperature was calculated taking into account the ΔT_b which is the NN's output that feeds back into the inputs. The coefficient of variation *CV*, root mean square error *RMS* and relative error previously defined are presented in the table 3. The figure 11 shows the comparison of the RSH released energy obtained by the NN's model and in the calorimetric chamber for the scenario #3.

Table 3.

	CV [%]	RMS [W]	Relative Error [%]
Scenario #1	6.0	44.93	1.0
Scenario #1A	5.0	37.85	1.0
Scenario #2	7.0	49.11	3.0
Scenario #3	6.0	41.12	0.0
Scenario #4	6.0	43.37	2.0
Scenario #5	4.0	35.36	1.0

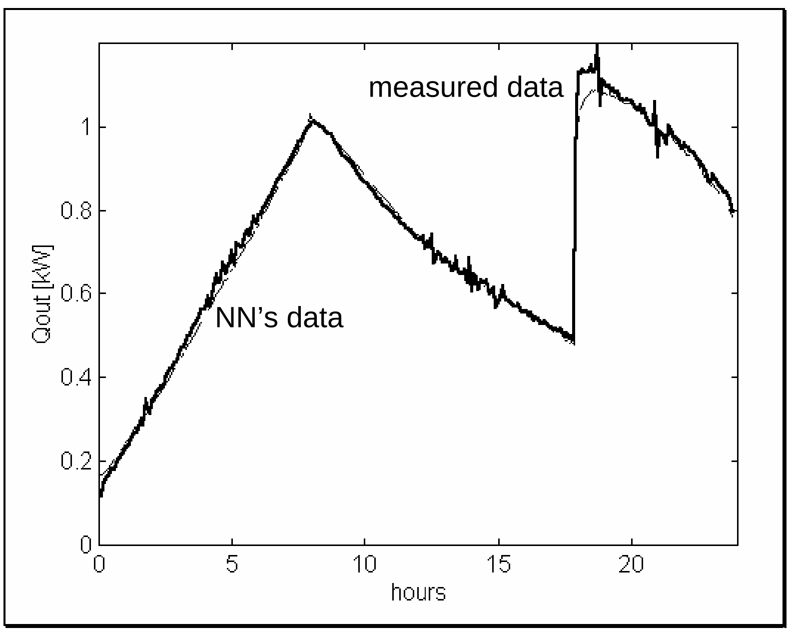

Figure 11. Comparison of the measured results and obtained by modified NN's

Even if the simulation results were used as the training data set, the comparison with the experimental results shows that the accuracy of the NN's model is very good. The modification of the training data set allows to obtain the acceptable coefficient of variation *CV* for the variable and fixed room temperature and for the electric power different than that used in training test (2.52 kW in the test against 2.1, 2.4 or 2.7 kW during the NN's training).

5. CONCLUSIONS

The presented new approach using the NN's is quite comparable with the dynamic model obtained by the modelization methods. The use of neural networks seems very appropriate in the system identification problems when the description of the studied apparatus is not given or when its optimization is not necessary.

Significant improvement occurred after the modification of the training data set using the simulation results. These results allow to conclude that to apply the NNs to system identification problems, the experimental tests in calorimetric chamber must be conducted in order to provide the adequate training and testing data that cover better the outputs domain. It seems, however, that a further research of the effect of training and testing data set construction on the results of system identification is needed.

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