APPLICATION OF DESIGN OF EXPERIMENTS IN THE ANALYSIS OF AN EVAPORATIVE CONDENSER

Rodrigo Ghiorzzi Donni, rodrigo.donni@ufrgs.br
Paulo Smith Schneider, pss@mecanica.ufrgs.br
Universidade Federal do Rio Grande do Sul, PROMEC, Rua Sarmento Leite, 425, CEP 90050-170, Porto Alegre, RS, Brazil.

Ivoni Carlos Acunha Jr., ivoni.acunha@riogrande.ifrs.edu.br
Instituto Federal de Educação, Ciência e Tecnologia do Rio Grande do Sul, Refrigeração e Aquecimento, Rua Alfredo Huch, 475, CEP 96201-460, Rio Grande, RS, Brazil.

Abstract. *This work aims to apply the methodology of design of experiments in an experimental model of an evaporative condenser built in small scale, keeping geometric similarity to real size equipments. The experimental condenser has a bundle of 35 copper tubes and is assembled with 6 rows inside a glass enclosure to allow for water and air flows visualization. The system operates with R22 as working fluid under different water and air mass flow rates. The large numbers of parameters involved in this experiment makes it hard to investigate its relationship and a Artificial Neural Network (ANN) is used to simulate the condenser behavior on a more controlled base, allowing for the statistical assessment by Design of Experiments (DoE) distinguishing the parameters that actually influence the phenomena. The ANN model achieved a satisfactory prediction of the overall heat transfer coefficient with a coefficient of determination R^2 of 98,8% and a root mean square error (RMSE) of 9,33W/m²ºC. As a main result of the application of DoE using simulated data built by an ANN is a correlation to predict the overall heat transfer coefficient.*

Keywords: *evaporative condenser, design of experiments, artificial neural network, heat exchange.*

1. INTRODUCTION

Heat exchange efficiency can be increased by the aid of phase change processes. Many applications in the field of air conditioning and refrigeration systems use this effect in which heat from a hot fluid is transferred to the atmospheric air through direct or indirect contact in sensible and latent way to a second fluid, usually water, which evaporates cooling the fluid warmer. Due to the simultaneous heat and mass transfer in an evaporative heat exchanger, the process becomes more complex in comparison to the conventional system, where a sensitive phenomenon of exchange of energy takes place.

Within many factors apparently influential in the process and phenomena present in this study, it is difficult to determine objectively what parameters are important to be controlled or monitored. The only way, in agreement with Vick Jr. (1992), to eliminate the subjectivity of an assertion and discussions about the reliability of a conclusion is through the design of experiments.

2. DESIGN OF EXPERIMENTS

The method of Design of Experiments (DoE) was first developed by Fisher in 1935 and is a statistical approach to the optimization design, execution and analysis of experiments. According to Caten (1995), in a well-designed DoE, design reduces the experimental effort and allows for obtaining reliable conclusions, access to an important amount of information about the studied input parameters and the associated experimental error. In relation to the analysis, its tools enable to carry out a survey of the effect of system parameters significance on the response variable.

Werkema and Aguiar (1996) also defines an experiment as a procedure in which intentional changes are made in the parameters of a system or process in order to evaluate the possible changes experienced by the response variable and estimate their causes. A model of the process flow can be seen in Fig. 1. In the case of the evaporative condenser studied in the present work, the inputs are its dimensional characteristics, thermal and physical properties. The parameters are controlled quantities and the variables are those that cannot be controlled. The output data are experimental quantities that are also called the response of the system. It can be directly used or can be the input of other assessments of the problem.

When the experiment involves two or more factors as the object of study, the experimental design becomes indicated because it allows all the considered factors to vary allowing all possible combinations of factors and levels are possible. It was the only way to detect interactions between factors (Montgomery, 2001). It was the only way to detect interactions between factors (Montgomery, 2001). Statistical design of experiments refers to the process of planning the experiment allowing appropriate data are collected and analyzed by statistical methods resulting in valid and objective conclusions (Montgomery, 2001). The DoE methodology allow us to implement a model of regression to fit the experimental data considering the effects of interactions of the parameters (Montgomery, 2001).

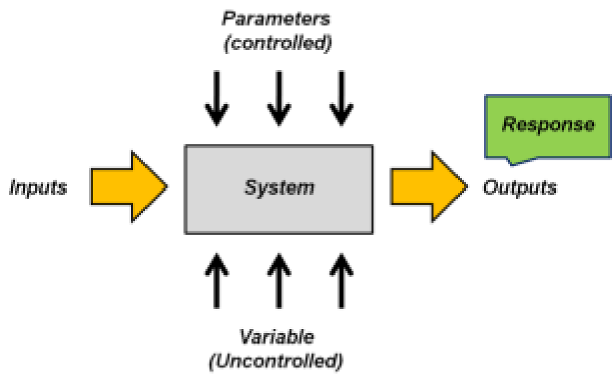

Figure 1. General model of a process or system (adapted from Montgomery, 2001)

The three basic principles of DoE are replication, randomization and blocking (Montgomery, 2001). Randomization refers to the order of the experiments or tests determined randomly (Werkema and Aguiar, 1996). The blocking is a design technique used to increase the accuracy of comparisons between factors of interest are made. It is used to reduce or eliminate the variance transmitted by uncontrollable factors or noises (Werkema and Aguiar, 1996). According to Montgomery (2001) replication has two important properties: get an estimate of experimental error and gives a more accurate estimate of the effect of the factor in the experiment.

In this work, the application of simulation to obtain the results of a DoE, avoid replication and randomization because de results are the same independently of the order or randomization of the simulated experiments (Almeida Filho, 2006).

Statistical analysis is based on the methodology of ANOVA, which can be seen in detail in Montgomery (2001), Werkema and Aguiar (1996) or Box *et al.* (2005).

3. ARTIFICIAL NEURAL NETWORK

Artificial Neural Networks (ANN) are computational structures similar to those present in the brain and applied to simulate the learning functions similar to the human nervous system. Haykin (2001) defined a neural network as a massively parallel distributed processor made up of simple processing units called neurons, the basic units of an ANN, and structured according to Fig. 2. An ANN is capable of learning from inputs, and from this point, produces different outputs from those used in their training.

According to Hagan (2002), the learning capacity of an ANN makes it more flexible and powerful than a traditional parametric formulation allowing the modeling of phenomena of extreme complexity in addition to handle satisfactorily with noise and incomplete data.

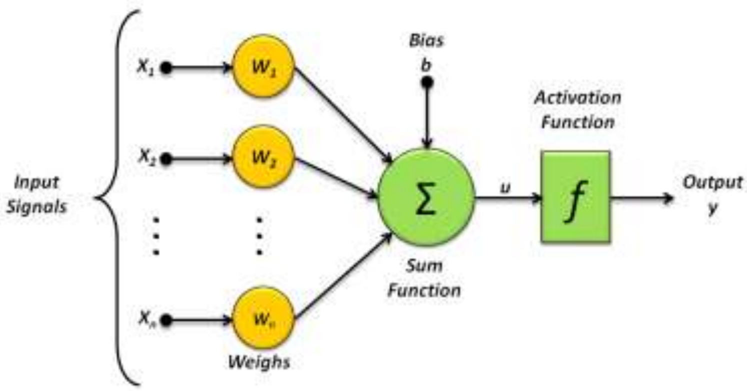

Figure 2. Nonlinear model of a neuron (adapted from Haykin, 2001)

Each neuron in an ANN receives a series of weighted inputs, i.e. each input value is multiplied by a weighing factor producing a characteristic output. Haykin (2001) describes the neuron model as having two stages. The first stage of processing is called a linear transformation where u is the sum function represented by Eq. (1):

$$u = \left(\sum_{j=1}^{n} w_j \, x_j \right) + b \quad (1)$$

where n is the number of inputs, w is the weight matrix corresponding to each entry, x is the input matrix and b is the bias value. Bias is a constant value which operates a fine tuning in the neural network. The second stage of processing consists on the application of an activation function, as occurs in biological neuron, and it defines when and how the output should occur by the output y of an ANN:

$$y = f(u) = f\left[\left(\sum_{j=1}^{n} w_j \, x_j \right) + b \right] \quad (2)$$

where f is the activation function that can take a variety of types. According Kovács (2002), the functions most commonly used are the linear, piecewise, sigmoid and hyperbolic tangent.

Usually, the architecture of a neural network is divided into three parts. In the first part, called the input layer are the input data, the second part, called the hidden layer, there may be one or more layers of neurons and the third layer, called the output layer, the output data are presented. The number of neurons in the input layer be equal to the number of entries as well as in the output layer which will contain a number of neurons equal to the amount of output, hidden layers of neurons is the amount determined by the complexity of the problem to be solved. According to Haykin (2001), a larger number of neurons in the hidden layer make the ANN more flexible to adapt to non-linear and highly complex models.

The process of training an ANN to simulate functions based on input and output data begins by adjusting the weights and subsequent comparison between the value found and the actual value. The weights are adjusted iteratively until the difference found between the simulated and actual response is within an acceptable error value or until it reaches a maximum value of iterations. With the weights properly adjusted, the ANN can be used to simulate the responses from new inputs.

The performance of an ANN can be measured by the Root Mean Square Error (*RMSE*) given by Eq. (3).

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (a_i - y_i)^2} \quad (3)$$

where N is the number of data set used in training, a is the desired output and y is the value found by the ANN.

The Mean Relative Error (*MRE*) is another coefficient used to measure the performance of RNA and is defined to be the average of the individual errors.

4. EXPERIMENTAL SETUP

Acunha Jr. (2010) developed an experimental model of an evaporative condenser built in small scale and operating with refrigerant R22 and thermo-siphon system, based on ASHRAE 64-1995. Basically, the system consists of an evaporative condenser, a heat exchanger shell and tube type (evaporator), a reservoir of liquid and a hot water tank. In order to ensure minimal heat loss to the outside of the system, the evaporator, was thermally insulated. The schematic diagram of the system can be seen in Fig. 3.

The refrigerant exits the evaporator as superheated vapor and enters into the condenser leaving as liquid subcooled. Before returning to the evaporator, the fluid passes through a reservoir of liquid that is intended to maintain a constant flow of fluid thereby allowing the system to reach the steady state.

The evaporative condenser, Fig. 4, consists of an aluminum frame with glass sides for visualizing the air-water flow streams. It has a cross section of 0.25m wide by 0.51m long, totaling an area of 0.1275m². The coil is composed of 35 copper pipes with external diameter of 0.00635m, in staggered arrangement and connected to a distributor at the top and a collector at the bottom. Both have a diameter of 0.0508m and a length of 0.25m. It has 6 rows in the tubes, totaling an area of heat exchange of 2.17m².

A water distributor is placed above the coil, built in copper with 36 holes, and with a little plate of copper which allows for a uniform scattering of the sprayed water is elevated from the lower reservoir by a pump. A bypass after the discharge of the elevation pump allows for its flow control. Just above the distributor, a mist eliminator is placed made of aluminum and passage area of 1.8mm.

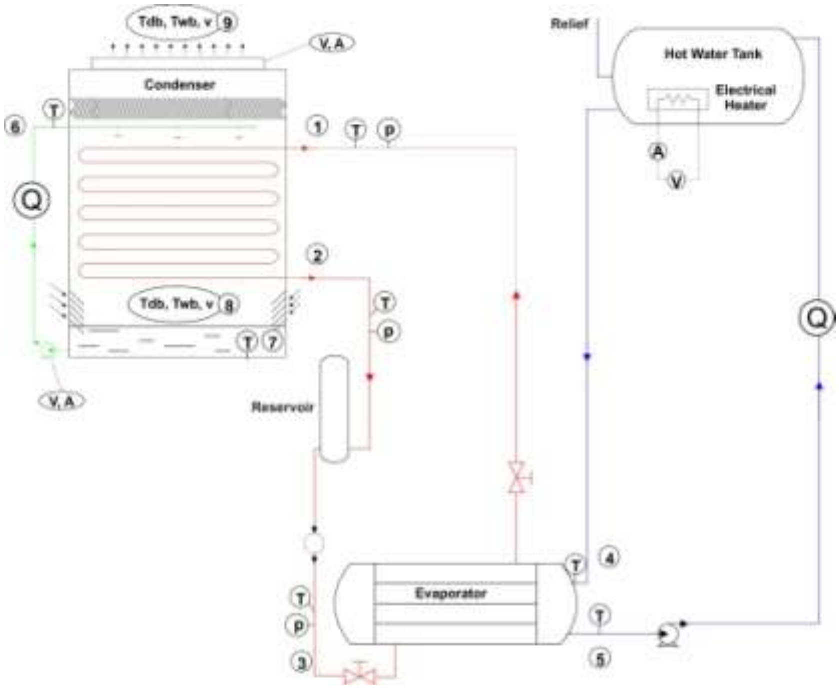

Figure 3. Schematic diagram of the system (Acunha Jr., 2010)

At the outlet of the condenser (point 9), there is a 0.200m diameter pipe that connects to a centrifugal fan of 2CV whose air flow is controlled by varying the rotation through an inverter frequency. The air inlet (point 8) is performed by the four sides with dimensions of 0.245m x 0.100m and 0.100m x 0.505m, with a total area of 0.15m². At the bottom, is located a reservoir of water (point 7) with capacity of 25 liters to collect the water dripping from the pipes and ensure that suction of the elevation pump of water sprayed does not operate in dry.

All measurement points are shown in the diagram of Fig. 3. The temperature of sprayed water, the inlet and outlet hot water temperatures in evaporator and the inlet and outlet condenser air temperatures (dry bulb and wet bulb) are obtained using thermoresistance PT-100. We obtain the R22 condensing temperature with measures of pressure and temperature of working fluid on outlet evaporative condenser. The inlet and outlet pressure of the working fluid in the condenser coil and evaporator tubes were obtained by pressure transducers. To determinate the volumetric flow of sprayed water on the condenser and the volumetric flow of hot water inside the evaporator, we used, respectively, a flow meter and a hydrometer. For the air volumetric flow we use a calibrated Venturi tube. The air mass flow rate is determined with the help of wet bulb and dry bulb temperatures acquired in the condenser outlet.

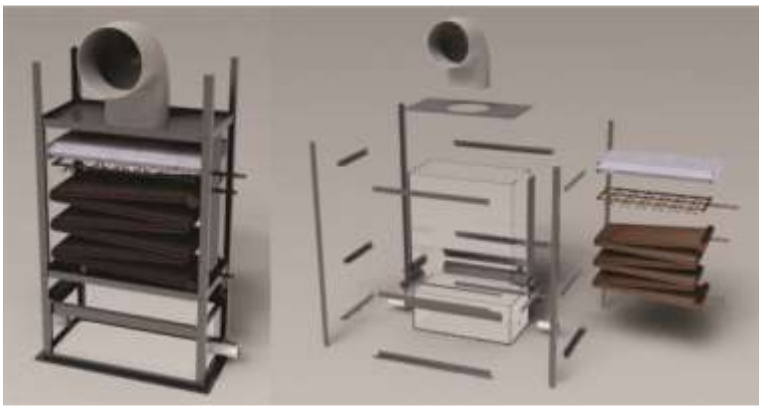

Figure 4. On the left, the virtual model of the evaporative condenser and on the right, its exploded view (Walther, 2009)

Heat absorbed in the evaporator, i.e., the cooling capacity of the system can be determined by the hot water side if we consider the system perfectly isolated, so we have Eq. (4):

$$Q_{evap} = m_{aq}(i_{aq,s} - i_{aq,e}) \tag{4}$$

where Q_{evap} [kW] is the heat absorbed in the evaporator, m_{aq} [kg/s] is the mass flow rate of hot water, $i_{aq,e}$ [kJ/kg] and $i_{aq,s}$ [kJ/kg] are respectively the enthalpies of input and output of hot water in the evaporator. The mass flow rate of refrigerant in the system can be determined based on the heat exchanged in the evaporator side of the hot water through the Eq. (5):

$$m_{r22} = \frac{Q_{evap}}{i_{r22,evap,s} - i_{r22,evap,e}} \tag{5}$$

where m_{r22} [kg/s] is the mass flow rate of refrigerant, $i_{r22,evap,e}$ [kJ/kg] and $i_{r22,evap,s}$ [kJ/kg] are respectively the enthalpies of input and output of refrigerant in the evaporator evaluated from the pressures measures at the inlet and outlet of the evaporator.

Assuming that the evaporative condenser is perfectly insulated, the heat rejected can be determined by the air side, in conformity with ASHRAE (2004), by Eq. (6):

$$Q_{cond} = m_{ar}\left(i_{ar,e} - i_{ar,s}\right) - m_{rep} i_{ag,rep} \tag{6}$$

where Q_{cond} [kW] is the heat rejected in the evaporative condenser, m_{ar} [kg/s] is the mass flow rate of air, m_{rep} [kg/s] is the mass flow rate of water replacement, $i_{ar,e}$ [kJ/kg] and $i_{ar,s}$ [kJ/kg] are respectively the enthalpies of input and output of air and $i_{ag,rep}$ [kJ/kg] is the enthalpy of water replacement.

The global coefficient of heat transfer, U [W/m^2°C], is a parameter that takes in account, among others, the internal and external coefficients of convection. All the complexity involved in the mechanisms of convective heat exchange is included in this parameter. Holman (1997) presents a definition of theoretical U. In the experimental context, the global coefficient of experimental heat transfer, U_{exp} [W/m^2°C], is estimated by Eq. (7).

$$U_{exp} = \frac{Q_{cond}}{A\left(T_{r22,cds} - T_{ag,asp}\right)} \tag{7}$$

where A [m²] is the total area of heat exchange of de evaporative condenser, $T_{r22,cds}$ [°C] is the condensation temperature of R22 and and $T_{ag,asp}$ [°C] is the sprayed water temperature.

5. SIMULATION OF DoE

In this study, experimental tests are conducted in steady state, and only the air flow and sprayed water are varied because difficulty in control the other variables. Given these limitations, we chose to use experimental data to train an ANN to make possible the variation of a greater number of system parameters. The parameters and the ranges of values of the input data used were selected from observations of Acunha Jr. (2010) and are shown in Tab. 1.

Table 1. Range of input data used for ANN training

Parameters		Range
Sprayed water temperature	$T_{ag,asp}$	22.0°C – 25.5°C
Dry bulb temperature at the entry of the condenser	$T_{db,e}$	19.7°C – 23.5°C
Wet bulb temperature at the entry of the condenser	$T_{wb,e}$	15.5°C – 19.3°C
Condensation temperature (of R22)	$T_{r22,cds}$	28.0°C – 31.0°C
Mass flow rate of water	m_{ag}	0.075kg/s – 0.115kg/s
Mass flow rate of air in the condenser	m_{ar}	0.105kg/s – 0.185kg/s

Initially, the only parameters in the controlled experiment Acunha Jr. (2010) are the volumetric flow of air and sprayed water were evaluated at temperatures of air and water to get the mass flows. As a result of the ANN to obtain, we used U_{exp}, estimated by Eq. (7), as will also be the response variable used in the application of the DoE. A series of 35 sections of experimental data was performed and the measurements of the quantities listed in Tab. 1 were acquired. The experimental data set was expanded with the use of measurement uncertainty of the sensors used in the experiment by calculating the heat exchanged considering variations of measured quantities of the same order of magnitude of the uncertainties. Thus, obtaining a set of 70 experimental data set that determine the best ANN model. The data set was divided randomly into three groups: 70% for training, 15% for validation and 15% to test the ANN.

The performance of ANN is strongly affected by the topography of the network, i.e. the number of hidden layers and number of neurons in each layer. Thus, a very small number of neurons will not be able to adjust the model to data (underfitting) while a large number of neurons will fit to the data, but will not be able to predict satisfactorily the output data from entries not used in the training of the ANN (overfittig).

There are no definitive methods capable of predicting the optimal number of layers and neurons in a neural network (Haykin, 2002) to determine the best network topology must be found by trial and error. The activation function, f, chosen for the hidden layer is the tangent sigmoid type while for the output layer was applied a linear function. Thus, this study will be used a Three-Layer Feed-forward ANN with a learning algorithm of Backpropagation and the weights are adjusted through the training algorithm optimized Levenberg-Marquardt (Hagan, 2002), also used by Ertunc *et al.* (2006).

The training procedure is to calculate the *RMSE* for each iteration and back-propagate the error by adjusting the ANN weights until the value of *RMSE* is satisfactory or simulation reaches a maximum value of iterations. To help prevent overfitting of the ANN, periodically every certain number of iterations of the simulation is stopped and the data selected for validation are used to check the performance of the ANN. At the end of the simulation, the data selected for testing will be used for checking the quality of the predictions of the ANN compared with the experimental data. The ANN toolbox implemented in MATLAB® 7 software was used in this work to perform the simulation.

Based on simulation data of ANN, we obtain an appropriate set of parameters to application of design. Given a factorial experiment 2^6, i.e. with two levels for each parameter, we construct an ANN simulation to use in a DoE and totalizing a set of 65 simulated experiments: 64 factorial points and 1 center point. In Tab. 1, we shown the parameters with higher and lower values used and the intermediary values are the mean of them. In this work, the MINITAB® 16 software was utilized in the statistical analysis of experiment.

6. RESULTS AND DISCUSSION

6.1. ANN Simulation

As the performance of ANN is sensitive of the network configuration, was performed a trial and error process that results in a two layer network with 8 neurons in the first layer and 7 neurons in the second layer. A plot of the predicted versus experimental values of evaporative condenser heat rejected through the simulation in shown in the Fig. 5. The predictions to experimental overall heat transfer coefficient (U_{exp}) results in a *MRE* of 1.57%, a *RMSE* of 9.3W/m²°C and a coefficient of determination (R^2) of 98.8%. These results indicate a good agreement of the ANN model with the experimental data despite a large number of variables involved. For the purpose of this work, the neural model has achieved the objective of simulate a real experiment with an evaporative condenser taking the advantage of allow us to vary parameters with couldn't be controlled in a real experiment and studied the behavior of phenomena involved.

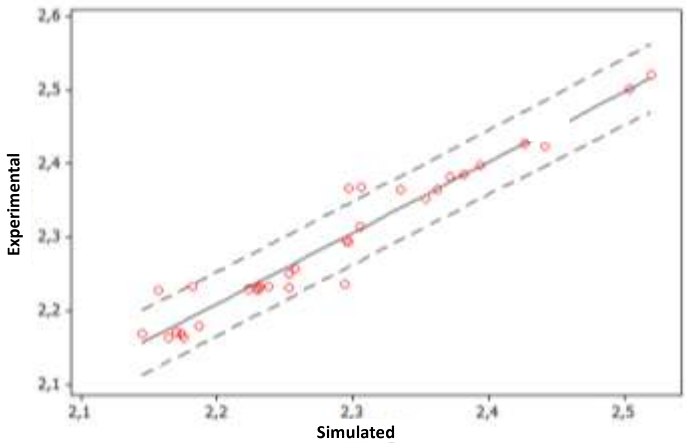

Figure 5. Experimental values versus simulated values with ANN model to U_{exp}.

6.2. DoE Analisys

As from the analysis of the simulation of experiment we obtain the results shown in Tab. 2. As it can be verified in Tab. 2, the main effects of each parameter over the mean response of the variable (U_{exp}) are statistically significant at level of 5%, except the $T_{r22,cds}$ who presented a poor significance. It's possible to see in table that the parameters strongly influents in process are $T_{ag,asp}$, $T_{db,e}$, $T_{wb,e}$, m_{ar} and m_{ag}. These results also are displayed in the graph of the Fig.

6. The red points represent the center points used to measure effects of nonlinearity in relationship between the parameters and between your interactions.

Table 2. Results of variance analysis (ANOVA).

Parameters	**Degrees of Freedom**	**Sum of Squares**	**Mean of the Sum of Squares**	**F-Statistic**	**p-Value**
$T_{ag,asp}$	1	0.69312	0.69312	18.59	0.000
$T_{db,e}$	1	0.6626	0.6626	17.77	0.000
$T_{wb,e}$	1	3.12965	3.12965	83.92	0.000
m_{ar}	1	1.54696	1.54696	41.48	0.000
$T_{r22,cds}$	1	0.30338	0.30338	8.13	0.009
m_{ag}	1	0.24862	0.24862	6.67	0.017
$T_{db,e}*T_{wb,e}$	1	0.85226	0.85226	22.85	0.000
$T_{wb,e}*m_{ag}$	1	0.32071	0.32071	8.60	0.007
$T_{db,e}*m_{ar}$	1	0.10674	0.10674	2.86	0.104
$T_{ag,asp}*T_{db,e}$	1	0.09811	0.09811	2.63	0.118
$T_{r22,cds}*T_{db,e}$	1	0.07225	0.07225	1.94	0.177
$T_{r22,cds}*m_{ar}$	1	0.01769	0.01769	0.47	0.498
$T_{r22,cds}*T_{ag,asp}$	1	0.01494	0.01494	0.40	0.533
$T_{r22,cds}*m_{ag}$	1	0.01225	0.01225	0.33	0.572
$m_{ar}*m_{ag}$	1	0.0075	0.0075	0.20	0.658
$T_{ag,asp}*m_{ag}$	1	0.00292	0.00292	0.08	0.782
$T_{db,e}*m_{ag}$	1	0.00293	0.00293	0.08	0.782
$T_{ag,asp}*T_{wb,e}$	1	0.00197	0.00197	0.05	0.820
$T_{r22,cds}*T_{wb,e}$	1	0.00147	0.00147	0.04	0.844
$T_{ag,asp}*m_{ar}$	1	0.00067	0.00067	0.02	0.894
$T_{wb,e}*m_{ar}$	1	0.00008	0.00008	0.00	0.964
$T_{ag,asp}*T_{wb,e}*m_{ar}$	1	0.24687	0.24687	6.62	0.017
...	...	...	...	...	...
Residual Error	23	0.85777	0.03729	-	-
Effect of Nonlinearity	1	0.00147	0.00147	0.04	0.848
Lack of Fit	22	0.85629	0.03892	-	-
Total	64				

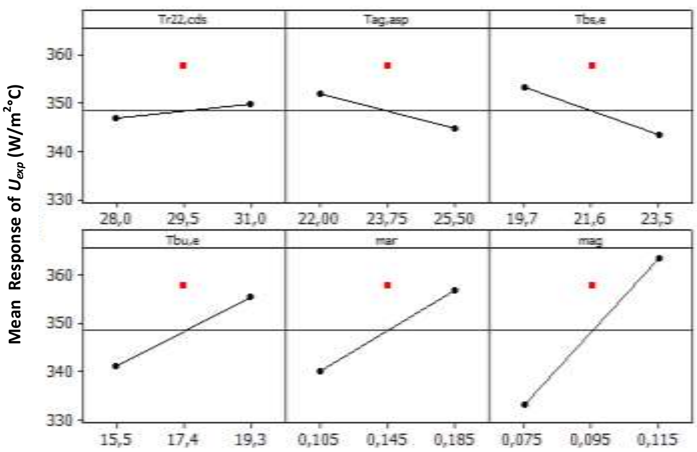

Figure 6. Graph of main effects of each parameter over the mean response of the variable U_{exp}

Likewise, in the same table are presented the second-order interactions effects in the experiment and notice an influence of interactions between $T_{ag,asp*}T_{db,e}$ and $T_{ag,asp}*m_{ag}$. All these interactions are shown in the Fig. 7. According to Montgomery (2001), the third-order and higher interactions are negligible in the most of the cases and are used to compute the error.

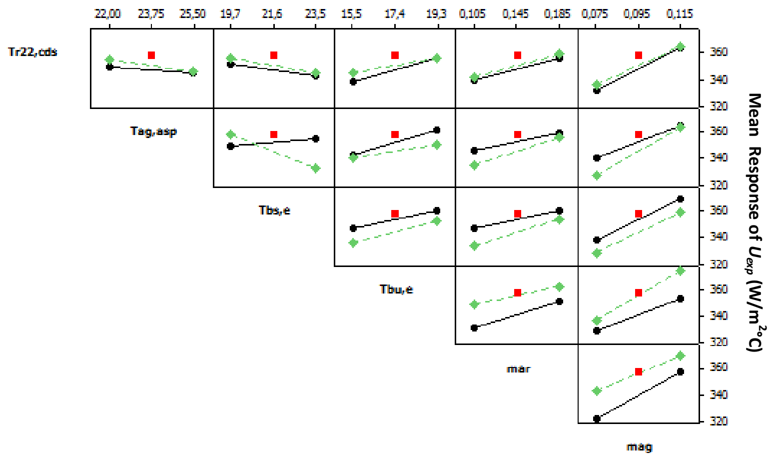

Figure 7. Graph of interactions effects of each pair of parameter over the mean response of the variable U_{exp}

To ensure the adequacy of the statistical model, we should verify the condition of standard distribution of the error with zero mean and standard deviation constant. This condition is verified in Fig. 8a where it is shown the normal probability plot of standardized residuals and haven't indications of any discordance with conditions above. Also the condition of no interaction between experiments is demonstrated in graph of Fig. 8b.

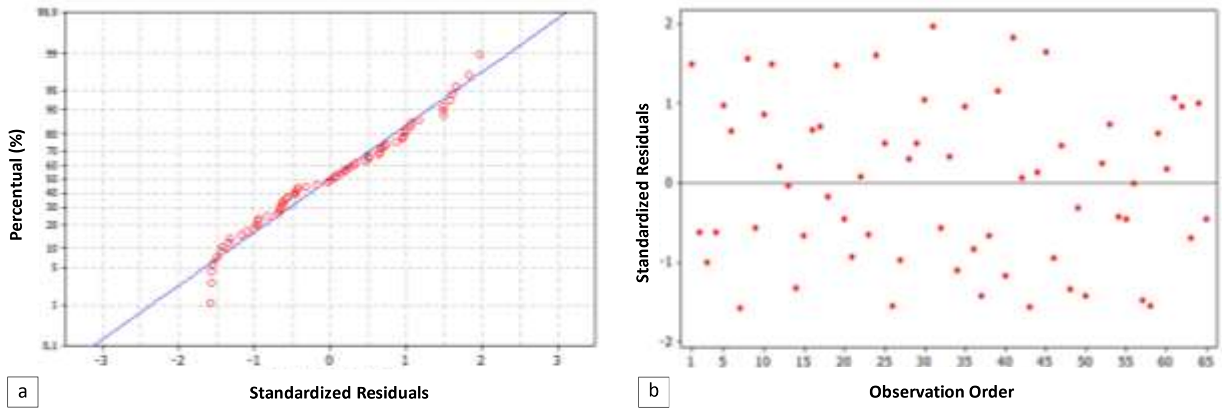

Figure 8. (a) Normal probability plot of standardized residual and (b) standardized residual versus observation order.

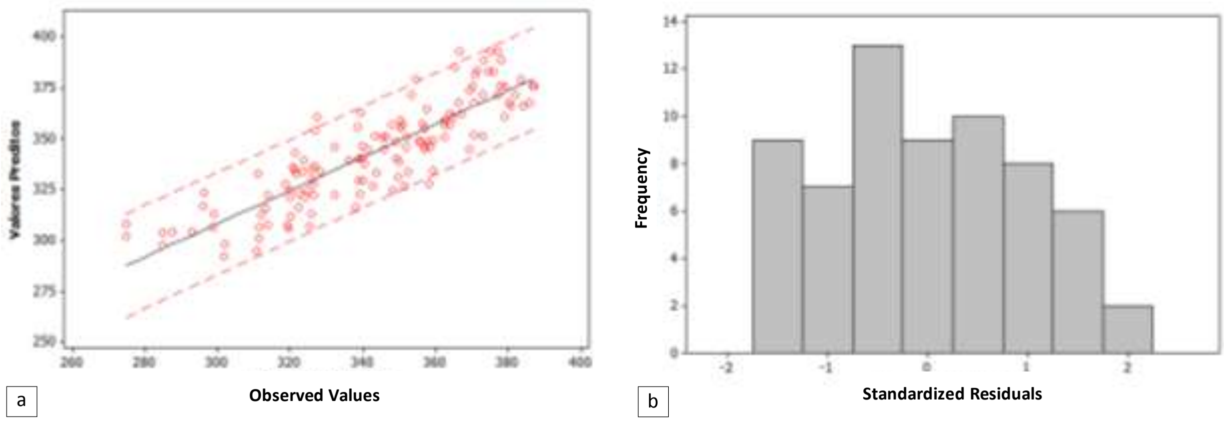

Figure 9. (a) Simulated values (with DoE model) versus predicted values and (b) the histogram of standardized residual

The adjusted model of regression obtained with the experimental data is shown in Eq. (8) and its capacity to predict values to U_{cond} is shown in Fig. 9a and presented a R^2 of 75.2%. Figure 9b displays the histogram of standardized residuals for Eq. (8). Both figures not demonstrate any inconsistence or discrepancy. The validation results of statistical analysis makes possible to take conclusion more consistent about behavior of the phenomena evolved in the experiment.

Equation (8) shows a correlation between parameters $T_{ag,asp}$, $T_{db,e}$, $T_{wb,e}$, m_{ar} e m_{ag} but the parameter $T_{r22,cds}$, as represents the energetic condition of internal flow, is not present, indicating as the value of U_{exp} is not affected by the internal flow condition for the evaporative condenser model adopted in this experiments. The largest percentage error was found to be 8.89% and the lowest was less than 0.1%. The *RMS* was 3.69% and the R^2 was 75.2%. The regression model used has significant 0.01% (Tab. 2), showing that well-adjusted.

The applicability of Eq. (8) to determine the overall heat transfer coefficient in condensers with different construction characteristics of the experimental model adopted in the tests could not be confirmed, though the parameters used in this equation are not tied by construction characteristics specific.

$$U_{cond} = -836{,}18 + 51{,}42 * T_{ag,asp} + 52{,}16 * T_{db,e} + 11{,}14 * T_{wb,e} + 210{,}40 * m_{ar} - 2840{,}44 * m_{ag} - 2{,}30 * T_{ag,asp} * T_{db,e} - 0{,}67 * T_{ag,asp} * T_{wb,e} + 84{,}99 * T_{ag,asp} * m_{ag} + 91{,}21 * T_{wb,e} * m_{ag} \tag{8}$$

Figure 10 shows a graph with the theoretical overall heat transfer coefficient calculated (based on data from 35 experimental samples) using some classical correlations for external heat transfer coefficient presented in Facão (1999) and the internal heat transfer coefficient obtained with the correlation of Chato (1930) (apud Bejan, 1995). The correlations of Acunha Jr. (2010), Niitsu *et al.* (1967) (apud Facão, 1999) and Eq. (8) was best approached the real values. It should be noted that correlations of Acunha Jr. (2010) and this work aims to estimate the value of U_{cond} differently of the others that have been developed only for determining the heat transfer coefficient between the film of water (around the tubes) and the external air flow.

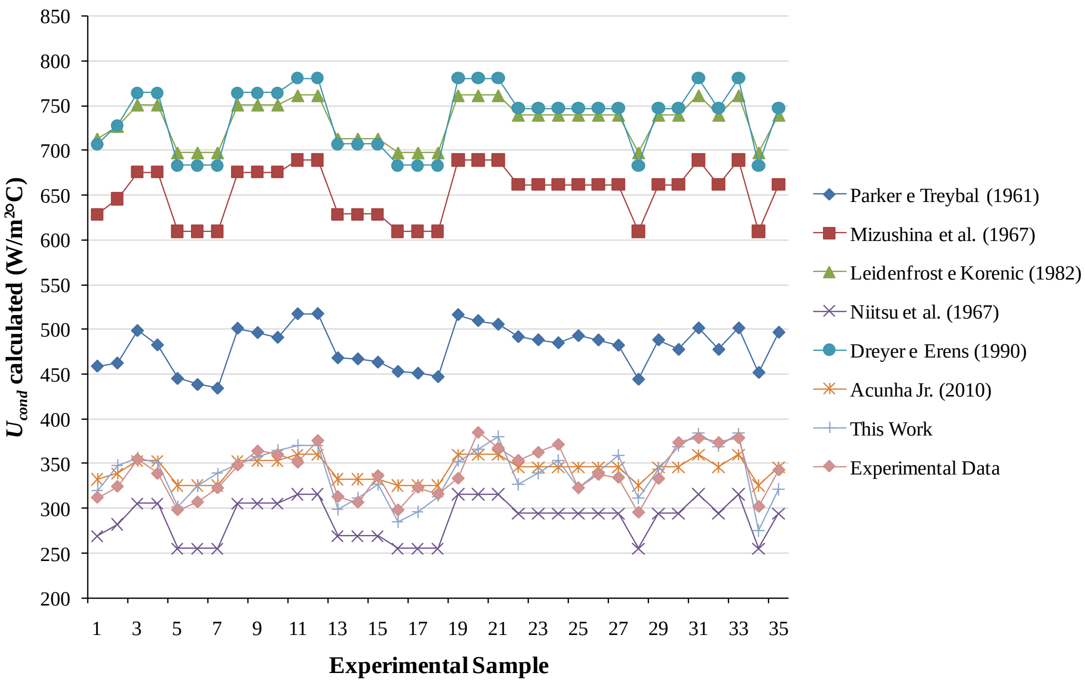

Figure 10. Overall heat transfer coefficient calculated with experimental data and correlations.

7. CONCLUSIONS

In practice, experimenters often not think about the statistical aspects that are relevant in an experimental study because they unknown. Not always the way experiments are conducted allows us to establish the complete identity between all the factors involved in a process or system. The extreme care with the measurements obtained from sensors and data acquisition, with accuracy in applying the correct techniques to measure quantities of other experimental care are often not observed also in the assembly planning of the experiment.

In this study, it is possible to verify the efficiency of the use of simulation techniques to obtain an ANN from simulated experimental data for application to design of experiments, allowing the testing in practice would be excessively complex and expensive.

Since there were no replication of the experiments, because they are simulated, was not possible to estimate the pure error, i.e. the error related only to uncertainty of measurement. Only the error of fitting of the model was possible to determinate. The effects of nonlinearity were not significant, demonstrating that relationships are essentially linear.

It is noted that mass flow of water spray is a factor of great influence in the global coefficient of heat transfer. This comes to agree with literature, confirming that the PE model adopted is correct. The condensation temperature of the refrigerant inside the condenser was not influential in the global coefficient of heat transfer, being removed from the model.

The methodology of experimental design enable simulated complex experiments could be performed simply and with good accuracy with a EMR of 3,69% and maximum error of 8,89%. Thus, this work could apply the proposed methodology with great success.

8. REFERENCES

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