ANALYSIS OF HEAT TRANSFER BEHAVIOR OF AN EVAPORATIVE CONDENSER USING DESIGN OF EXPERIMENTS METHODOLOGY

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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 rejected heat rate with a coefficient of determination* R^2 *of 94.7% and a root mean square error (RMSE) of 0.0259kW. The application of DoE analysis of simulated data resulted in a correlation to predict the overall heat transfer coefficient (*R^2*) of 94.7%. The higher deviation found between the experimental and the correlation was 13.28%.*

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 phenomena. Many applications in air conditioning and refrigeration fields use this effect: heat from a hot fluid is transferred to atmospheric air through direct or indirect contact in sensible and latent ways to a second fluid, usually water, which evaporates cooling the hot fluid. Due to the simultaneous heat and mass transfer in 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 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 Junior (1992), to eliminate the subjectivity of an assertion and discussions about the reliability of a conclusion is through the Design of Experiments (DoE) methodology.

Zukowski Junior (1999) used the DoE to optimize an absorption refrigeration system. Based on determination of appropriate response such as exergy efficiency, COP and ice production rate, we used the methodology that consisted of a series of experimental tests in their equipment. It was utilized the response surface methodology associated with the two-level factorial design for system optimization. Results indicate the adequacy of methodology applied in this study.

Antunes (2011) applies response surface methodology associated with two level factorial design to compare three different configurations of automatic refrigeration system.

Sacks *et al*. (1989) describe some DoE applications in traditional computational models. The authors report that output results of many computational models are restricted only to data fitting, without the perception of what is possible from application of DoE enabling experimenter to do uncertainty analysis of the prediction model with a solid statistical basis.

Ertunc and Hosoz (2006) presented application of Artificial Neural Network (ANN) to predict performance of an evaporative condenser used in a refrigeration system. A experimental system was used for experiments were performed varying the evaporator capacity, the air and water flows and air dry bulb temperature and humidity in equipment entrance. Based on experimental data an ANN model was built to provide the condenser heat rejected, refrigerant mass, the compressor power and the performance coefficient as output simulation data. Simulated results presented error in the range of 1.90 to 4.18% when compare with actual results.

2. EXPERIMENTAL SETUP

Acunha Junior and Schneider (2013) assembled an experimental laboratorial rig to perform controlled tests (Figure 1), following the ANSI/ASHRAE 64-1995 standard, based on a calorimetric essay methodology at controlled environmental conditions.

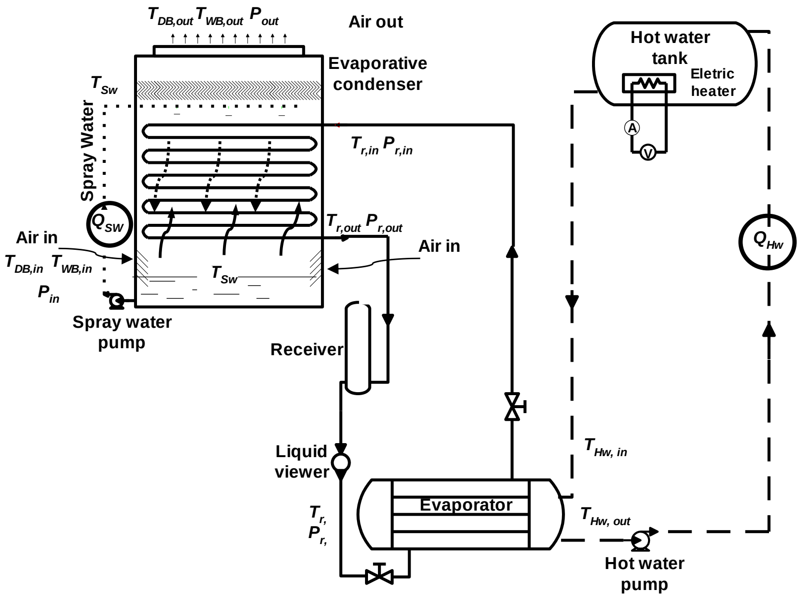

Figure 1. Test facility scheme with its main devices (Acunha Junior and Schneider, 2013)

In the experiment reported by Acunha Junior and Schneider (2013), tests were conducted along approximately 2 hours in steady state conditions. The average values of the physical parameters were statistically analyzed in order to be synthesized in a consolidate record, called hereby the experimental sample. Environmental conditions were stabilized for each sample, but they were intentionally varied from sample to sample. The complete investigation generated a 40 sample data set, built under the same heat dissipation rate at the evaporator and without replacement of the sump water.

Data assessment enabled to identify the volumetric flow of air and volumetric flow of spray water as the only controlled parameters, pointing out an unbalancing among the number of measured parameters to the actual controlled ones. Due to those limitations, experimental data was used to train an Artificial Neural Network, allowing for choosing and ranging a greater number of parameters and then to better assess the behavior of the evaporative condenser.

3. SIMULATION METHODOLOGY

Artificial Neural Networks (ANNs) are computational structures similar those present in the brain and used to simulate learning functions of 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. It's capable of learning from inputs, generating 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 for the modeling of extreme complexity phenomena and also to handle satisfactorily with noise and incomplete data.

The analysis of complete data set of experiment lead to the identification of some key parameters, which were chosen as the input ones for the ANN training. Table 1 displays theses parameters in accordance to Figure 1, and identifies their experimental range. Water and air mass flow rates (respectively, $\dot{m}_{sw}$ and $\dot{m}_{air}$) were not directly measured on the rig, but calculated after the data of the flow density.

Table 1. Input data ranges used in ANN training.

Parameters	**Range**
Spray water temperature (T_{sw})	22.0°C – 25.5°C
Dry bulb temperature at the entry of condenser ($T_{db,in}$)	19.7°C – 23.5°C
Wet bulb temperature at the entry of condenser ($T_{wb,in}$)	15.5°C – 19.3°C
Condensation temperature of R22 (T_r)	28.0°C – 31.0°C
Spray water mass flow rate ($\dot{m}_{sw}$)	0.075kg/s – 0.115kg/s
Air mass flow rate through the EC ($\dot{m}_{air}$)	0.105kg/s – 0.185kg/s

A Three-Layer Feed-Forward ANN with learning algorithm of back propagation. Weights were adjusted through Levenberg-Marquardt optimized training algorithm (Hagan, 2002), also employed by Ertunc *et al.* (2006) for similar applications.

The performance of an ANN can be evaluated with by the Root Mean Square Error (*RMSE*), given by

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

where N is the training data set size, a is the desired output and y is the simulated value. The agreement between predicted and actual values can be evaluated through the Determination Coefficient (R^2) shown in Eq. (2), which qualifies the model and its capacity to prediction.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(a_i - y_i)^2}{\sum_{i=1}^{N} {y_i}^2} \tag{2}$$

The experimental data set, composed of 35 selected samples of Acunha Junior (2010) experiment, was divided randomly into three groups: 70% for training, 15% for validation and 15% for testing. The training procedure consisted firstly to calculate the *RMSE* for every iteration, and then back-propagate the error by adjusting the ANN weights, until the value of *RMSE* reached a satisfactory value or the interruption of the procedure whenever a limit number of iterations were attended. To help prevent the ANN overfitting, the simulation procedure was periodically interrupted and its outputs were compared to a selected data set for validation. At the very end of the simulation, some final results were checked against experimental data. MATLAB® 7 with an ANN toolbox was used to perform the simulation.

The ANN performance is sensitive to the network configuration, leading to trial and error process. Best results were obtained with a two layer network, with 8 neurons in the first layer and 7 neurons in the second one.

In Figure 2 are plotted ANN model outputs versus experimental values for EC rejected heat rate ($\dot{q}_{cond}$) that present a *RMSE* of 0.0259kW and a R^2 of 94.7%. These results indicate a good agreement of ANN model to the experimental data, on despite of the large number of involved variables. For the purpose of the present work, the neural model achieved the objective of simulating a real experiment and allowed for a parametrical investigation.

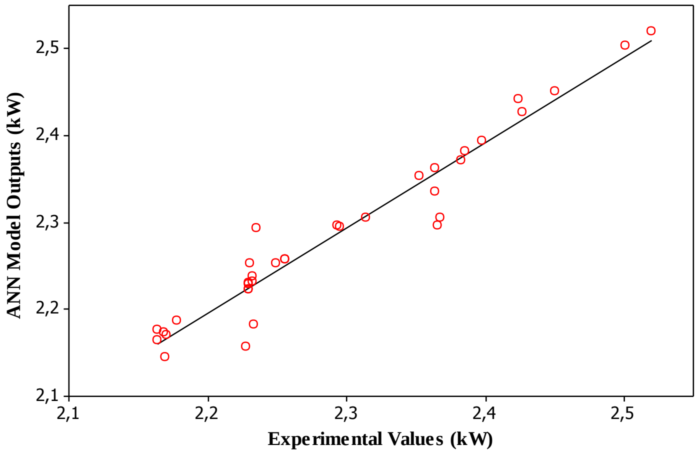

Figure 2. Experimental versus ANN output values of $\dot{q}_{cond}$.

4. RESULTS

Whenever combined effects of two or more parameters are involved on coupled phenomena, DoE is a useful methodology. It takes into account parametric combinations and detects their interactions. DoE allows for collecting appropriate data and generate valid and objective conclusions, enabling to implement a regression model to fit experimental data considering interaction effects of each parameter (Montgomery, 2001).

DoE has three basic principles: replication, randomization and blocking. Randomization refers to the order of experiments determined randomly. Blocking is a design technique used to increase the accuracy of comparisons between parameters of interest, been useful to reduce or eliminate the variance transmitted by uncontrollable variables or noises (Werkema and Aguiar, 1996). According to Montgomery (2001), replication has two important properties: estimates the experimental error and gives a more accurate parametric behavior of the experiment. In this work, isn't applied the principles of replication and randomization because the experiments are simulated and outputs will not vary with replications or with order of experiments (Almeida Filho, 2006).

The statistical analysis was based on the ANOVA (ANalysis Of VAriance) methodology, detailed in Montgomery (2001) and Box et al. (2005), and used ANN output to obtain an appropriate set of parameters to DoE application. A factorial experiment 2^6, i.e. with two levels for each parameter, was constructed totalizing a set of 65 simulated experiments: 64 factorial points and 1 center point. Table 1 shown the parameters with higher and lower values assumed to factorial points and the mean value on each range are used to define the central point. In this work, the MINITAB® 16 software was utilized in statistical analysis.

As can be seen in Table 2 all parameters and their interactions with calculated p-values. Basically, the p-value or calculated probability is the estimated probability of rejecting the null hypothesis of a study question when that hypothesis is true. In present study, the null hypothesis is the influence of parameters and their interactions in response variable ($\dot{q}_{cond}$). The confidence level (β) as defined to 0.95 and the significant level (α) as defined to (1-β), which means that they are significant at 5% with confidence level of 95%, that is to p-values less than 0.05 (or 5%) accept the null hypothesis.

Table 2. ANOVA results for 2^6 factorial design with center point for $\dot{q}_{cond}$ response variable.

Parameters	Sum of Squares	Mean Square	p-value
Main Effects	6.58434	1.09739	0.000
T_{sw}	0.69312	0.69312	0.000
$T_{db,in}$	0.6626	0.6626	0.000
$T_{wb,in}$	3.12965	3.12965	0.000
m_{air}	1.54696	1.54696	0.000
T_r	0.30338	0.30338	0.009
m_{sw}	0.24862	0.24862	0.017
2nd Order Interactions	1.51251	0.10083	0.016
$T_{db,in}$*$T_{wb,in}$	0.85226	0.85226	0.000
$T_{wb,in}$*m_{sw}	0.32071	0.32071	0.007
$T_{db,in}$*m_{air}	0.10674	0.10674	0.104
T_{sw}*$T_{db,in}$	0.09811	0.09811	0.118
T_r*$T_{db,in}$	0.07225	0.07225	0.177
T_r*m_{air}	0.01769	0.01769	0.498
T_r*T_{sw}	0.01494	0.01494	0.533
T_r*m_{sw}	0.01225	0.01225	0.572
m_{air}*m_{sw}	0.0075	0.0075	0.658
T_{sw}*m_{sw}	0.00292	0.00292	0.782
$T_{db,in}$*m_{sw}	0.00293	0.00293	0.782
T_{sw}*$T_{wb,in}$	0.00197	0.00197	0.820
T_r*$T_{wb,in}$	0.00147	0.00147	0.844
T_{sw}*m_{air}	0.00067	0.00067	0.894
$T_{wb,in}$*m_{air}	0.00008	0.00008	0.964
3rd Order Interactions	0.80618	0.04031	0.425
T_{sw}*$T_{wb,in}$*m_{air}	0.24687	0.24687	0.017
...	...	...	...
Erro Residual	0.85777	0.03729	-
Nonlinearity	0.00147	0.00147	0.848
Lack of Fit	0.85629	0.03892	-
Total	6.58434	1.09739	0.000

In Table 2 can be observed that all main parameters are relevant in heat rejection rate with 5% of significance, because obtained p-values less than 0.05. Likewise in 2nd order interactions only $T_{db,in}$*$T_{wb,in}$ e $T_{wb,in}$*$\dot{m}_{sw}$ were significant, and in 3rd order interactions, only interaction T_{sw}* $T_{wb,in}$ *$\dot{m}_{air}$ obtained with prescribed significance. The nonlinearity effects aren't influential in rejected heat rate, so a linear model could be appropriate. According to Montgomery (2001), the 3rd order and higher interactions are negligible in most cases therefore the high order interactions were used to determinate lack of fit error since isn't replication of experiments making it impossible calculate pure error (Box *et al.*, 2005).

Figure 3 shows the most significant effects of each parameter on the mean response of the rejected heat rate, with a significant level of 5%, while Figure 4b brings 2nd order effects on that same output.

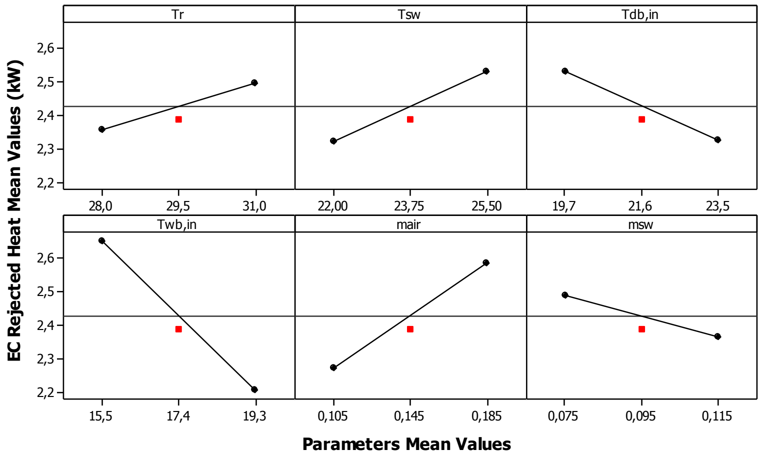

Figure 3. Graph of main effects of each parameter over the mean response variable ($\dot{q}_{cond}$).

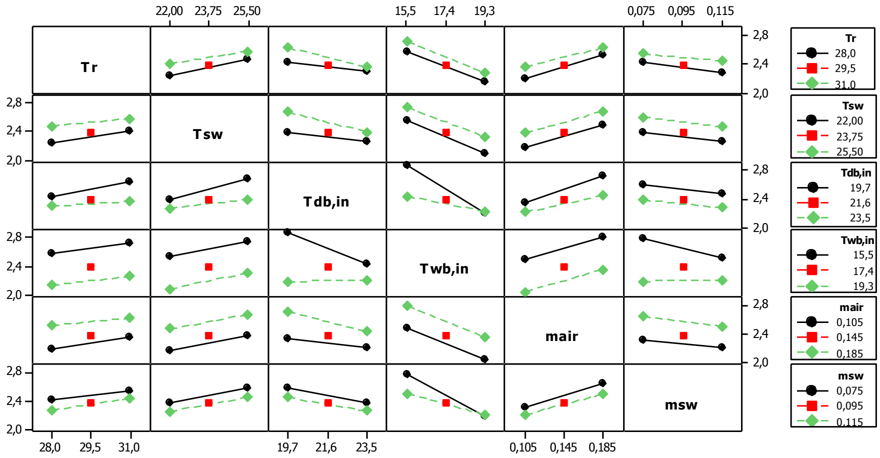

Figure 4. Graph of interactions effects of each parameter pair over mean response variable ($\dot{q}_{cond}$).

It is possible observe the impact on output of all parameters, with a special remark to $T_{wb,in}$, the most significant one. T_r, T_{sw} and $\dot{m}_{air}$ lead to a direct variation on $\dot{q}_{cond}$, whereas $T_{db,\mathrm{in}}$, $T_{wb,in}$ and $\dot{m}_{sw}$ behave on the opposite sense. Figure 4 presents experiment effects of 2nd order and confirms interactions between $T_{db,in}$ *$T_{wb,in}$ (with $\dot{q}_{cond}$ negative influence) and $T_{wb,in}$*$\dot{m}_{sw}$ (with $\dot{q}_{cond}$ positive influence). Red dots represent center points used to evaluate nonlinearity effects of parameters and their interactions.

Surfaces displayed on Figure 5 show the behavior of the EC rejected heat rate $\dot{q}_{cond}$ for 5 pairs of independent parameters, spanning along their experimental range, while the remaining experimental parameters were taken as fixed values, around the mean value of their respective ranges.

Figure 5a displays $\dot{q}_{cond}$ as a function of the condensation temperature T_r and the spray water temperature T_{sw}. It can be seen that there is a gain of heat released to the external air throughout the EC even with the reduction on the thermodynamic cycle efficiency, due to the increase of both temperatures.

Figure 5b shows the interactions of inlet air dry bulb and wet bulb temperatures $T_{db,in}$ and $T_{wb,in}$, affecting significantly $\dot{q}_{cond}$. The greater range span of each of these parameters, the greater is the potential of heat exchange through the water film and the air flow. This behavior is even more stronger for lower $T_{db,in}$ values. In case of $T_{db,in}$*$T_{wb,in}$, which their difference represents the relative humidity of input air flow, verified a rejected heat rate reduction in function of air flow saturation condition through the EC and reducing latent exchange energy potential.

Figure 5c shows $\dot{q}_{cond}$ as a function of the inlet air wet bulb temperature $T_{wb,in}$ and the spray water temperature T_{sw}. there was a directly proportional increase on heat rejection in regard to T_{sw} and an inversely proportional one for $T_{wb,in}$. Likewise, Figure 5d shows $\dot{q}_{cond}$ as a function of $T_{wb,in}$ and T_r and the similar behavior it is noted.

Figure 5e presents $\dot{q}_{cond}$ as a function of the air mass flow rate $\dot{m}_{air}$ and the inlet air dry bulb temperature $T_{wb,in,}$ showing that the combination of higher values of $\dot{m}_{air}$ together with lower values of $T_{wb,in}$ increase EC heat rejection rate because air mass flow rate exchange increase in EC driven by exchange latent potential increase (by difference of partial steam pressure).

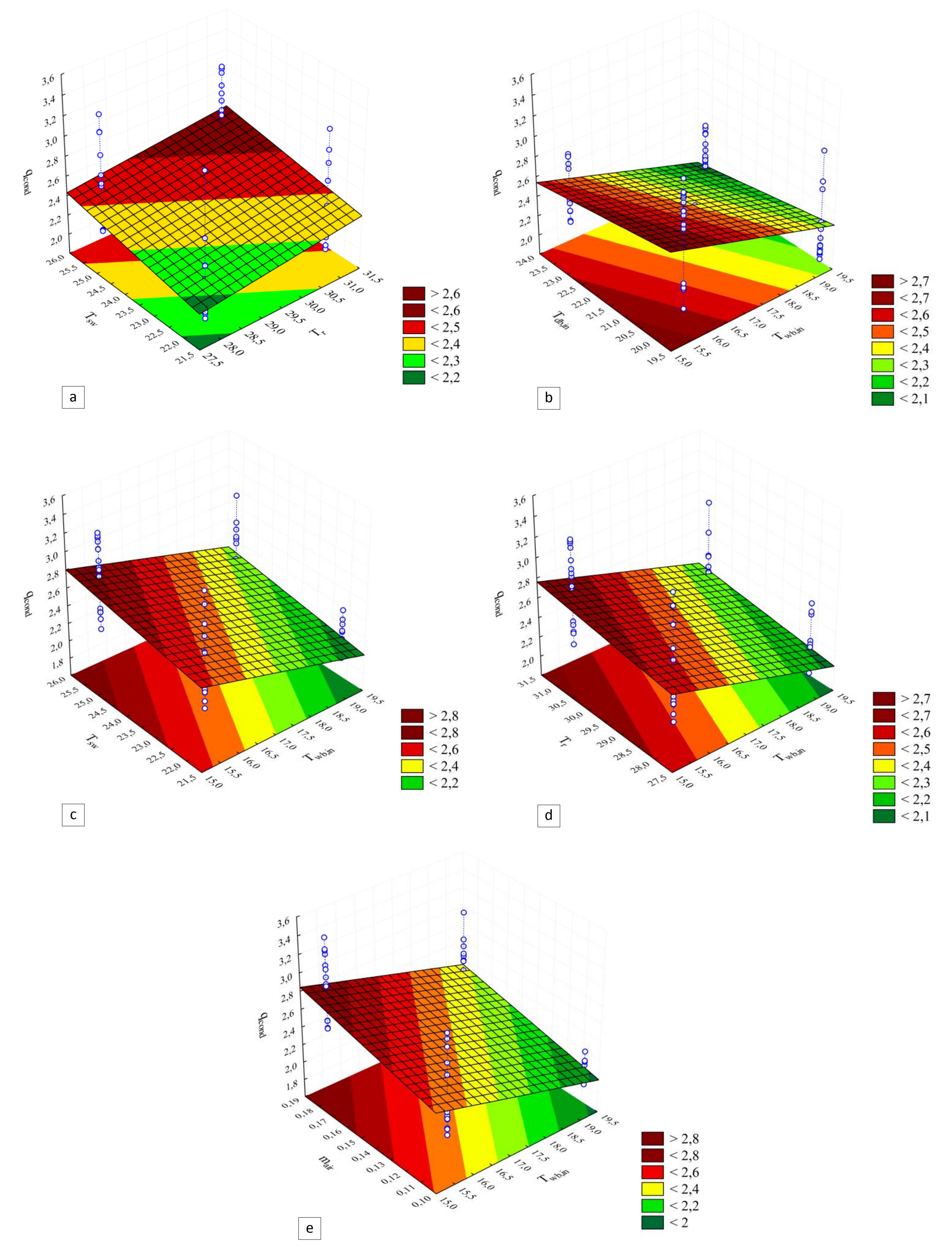

Figure 5. Graphs of EC rejected heat rate ($\dot{q}_{cond}$) as function of (a) condensation temperature and spray water temperature, (b) dry bulb and wet bulb temperature, (c) spray water temperature and wet bulb temperature, (d) condensation temperature and dry bulb temperature and (e) air mass flow rate and dry bulb temperature.

Equation (3) presents a model for the predict capacity of mean rejected heat ($\bar{q}_{cond}$) as a function of 6 independent parameters. The adjusted regression was obtained by factorial design, based on experimental data, and its behavior is shown in Figure 6a, for a correlation coefficient R^2 of 79.3% which signifies that model explains 79.3% of the variability of mean rejected heat. The maximum error found was 13.28%. Figure 6b displays a standardized residual histogram for Eq. (3), showing a distribution close to the normal one.

$$\bar{q}_{cond} = 2{,}43 + 0{,}301T_r + 0{,}301T_{sw} + 0{,}096T_{db,in} - 0{,}098T_{wb,in} + 15{,}49\dot{m}_{air} - 35{,}53\dot{m}_{sw} \\ -0{,}012T_rT_{db,in} - 0{,}012T_{sw}T_{db,in} + 0{,}032T_{db,in}T_{wb,in} - 0{,}537T_{db,in}\dot{m}_{air} + 1{,}863T_{wb,in}\dot{m}_{sw} \quad (3)$$

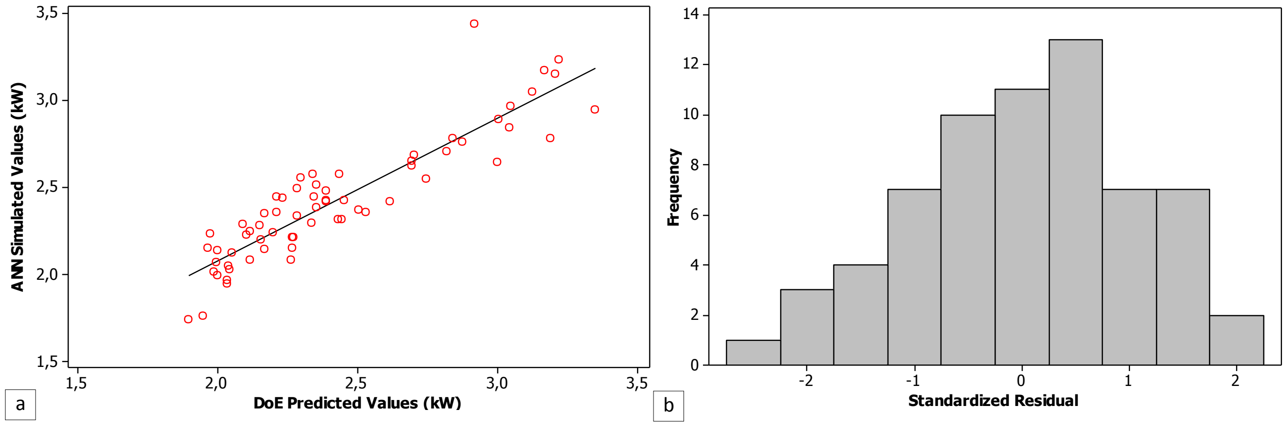

Figure 6. (a) ANN simulated values versus DoE predicted values and (b) the histogram of standardized residual.

Figure 7 shows a graph with theoretical rejected heat rate calculated using some classical correlations to external heat transfer coefficient presented in Facão (1999) and the internal heat transfer coefficient obtained with correlation of Chato (1930) (apud Bejan, 1995). Coefficients were calculated upon experimental data from 35 independent and steady state experimental samples. The correlations of Acunha Junior (2010), Niitsu et al. (1967) (apud Facão, 1999) and Eq. (8) was best approached real values. It should be noted that correlations of Acunha Junior (2010) and this work aims to estimate the rejected heat rate differently of others that have been developed only for determining heat transfer coefficient between film of water (around the tubes) and external air flow.

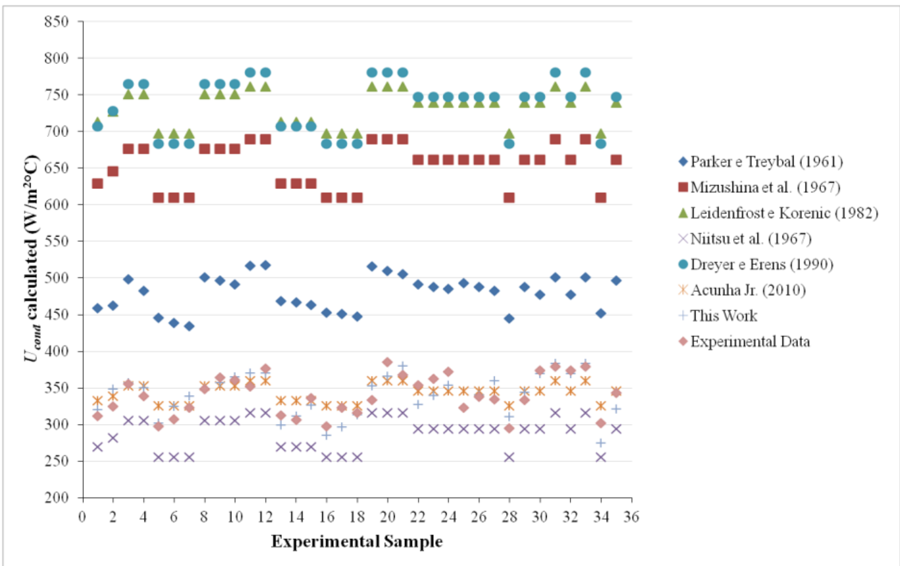

Figure 7. Overall heat transfer coefficient calculated with experimental data and correlations.

5. CONCLUSIONS

When performing experiments often statistical considerations that are relevant in an experimental study are unknown. Not always how the experiments are conducted allow us establish a complete relationship between all factors involved in a process or system. The greatest care with measurements acquired from sensors and data acquisition devices or with accuracy in applying correct techniques to measure experimental quantities often are not observed with equal care in design of experiment.

In this study, it is possible to verify the simulation techniques efficiency to obtain an ANN from experimental data to design of experiments application, allowing the performance of experiments which would be complex in practice.

The methodology of PE enabled simulated complex experiments could be performed simply and with good accuracy with a maximum error of 13.28%. Thus, this work could apply the proposed methodology with great success.

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