Development of an expert system to evaluate the performance of cooling towers used in Brazilian thermal power plants

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***Abstract*— Cooling towers are equipment widely used in thermoelectric power generation units to dissipate heat from the turbine condensed exhausted steam to the environment, according to the specific thermodynamic cycle. Particularly, in electric power generation plants with steam boilers, a discontinuation of the total generation by the steam turbine may occur, if the cooling tower system stops operating. The cooling tower type assessed in this study is that of the open type, meaning that there is direct contact of hot condensed water with the drafted air in the countercurrent.**

The main objective of this development is to contribute to the design of an Expert System, presenting a methodology for the overall system random data acquisition. By analyzing the acquired operational data of cooling towers, the diagnosis can show information on operational gaps and anticipate problems to the facilities operators. The proposed data acquisition reduction is based on a neural network that, once it has been trained can be used to analyze in real-time the plant performance and, regularly, aid operators to predict extreme and abnormal operational conditions, besides better estimating the schedule of maintenance activities. Different scenarios and operating conditions of the thermoelectric plant are possible to be predicted with the neural set.

The study also provides an assessment of mass and energy balance from the thermal plant, indicating the variables values to be used on the analysis of the cooling system. A study of the variables acquired and their relevance to the control system of the unit is available, as well. Moreover, indicators that will be used to monitor the performance of cooling towers are proposed, by means of spreadsheets, in Microsoft Excel® format, allowing the indicators calculation for each set of real or fictitious data. The spreadsheet in Microsoft Excel® may simulate the cooling tower system behavior independently of the plant control system. The operator will also be allowed to predict different operational conditions or simulate extreme operating conditions, of which the tower behavior is not known.

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***Index Terms*--Process cooling, Thermal power generation, Neural networks applications, Expert systems, Fault diagnosis**

I. NOMENCLATURE

A	area (m^2)
Cp	specific heat ($J\ kg^{-1}\ K^{-1}$)
D	diameter (m)
F	force (N)
G	gravitational acceleration ($m\ s^{-2}$)
h	air input enthalpy ($kJ\ kg^{-1}$)
hfg	latent enthalpy of evaporation ($kJ\ kg^{-1}$)
h_{ws}	air saturation enthalpy ($kJ\ kg^{-1}$)
$h_{air,i}$	air input enthalpy ($kJ\ kg^{-1}$)
$h_{air,o}$	air output enthalpy ($kJ\ kg^{-1}$)
$h_{w,i}$	water input enthalpy ($kJ\ kg^{-1}$)
$h_{w,o}$	water output enthalpy ($kJ\ kg^{-1}$)
$h_{w,waste}$	waste water enthalpy ($kJ\ kg^{-1}$)
$h_{w,makeup}$	water makeup enthalpy ($kJ\ kg^{-1}$)
$h_{s,w,i}$	saturated moist air enthalpy ($kJ\ kg^{-1}$)
ID_{tower}	incrustation indicator
kf	non-dimensional pressure loss coefficient
M	mass (kg)
$m_{air,sec}$	dry air mass flow rate ($kg\ s^{-1}$)
$m_{air,i}$	input air mass flow rate ($kg\ s^{-1}$)
$m_{air,o}$	output air mass flow rate ($kg\ s^{-1}$)
m_w	water mass flow rate ($kg\ s^{-1}$)
$m_{w,i}$	input water mass flow rate ($kg\ s^{-1}$)
$m_{w,o}$	output water mass flow rate ($kg\ s^{-1}$)
$m_{w,makeup}$	makeup water mass flow rate ($kg\ s^{-1}$)
$m_{w,waste}$	waste water mass flow rate ($kg\ s^{-1}$)
p	pressure ($N\ m^{-2}$)
p_{at}	is the pressure of moist air (air vapor mixture) in a temperature T, in Pa
p_w	is the water vapor partial pressure in the temperature T, in Pa
p_{ws}	is the water vapor pressure at saturation, in Pa
Q	rejected heat (W)
RH	is the air relative humidity in the air temperature (T) in %
T	is the water temperature (°C)
t	water temperature (°C)

t_{ws} water saturation temperature (°C)

x is a ratio between the dry air and water vapor in (g kg $^{-1}$)

$x_{air,i}$ is a ratio between the dry air and water vapor in the cooling tower input (kg kg $^{-1}$)

$x_{air,o}$ is a ratio between the dry air and water vapor in the cooling tower output(kg kg $^{-1}$)

x_{ws} is a ratio between the dry air and water vapor, in the saturation temperature, in (kg kg $^{-1}$)

ΔT_w water temperature difference between input and output, in (°C or K)

ΔT_{air} air temperature difference between input and output, in (°C or K)

II. Introduction

The initial purpose of this study was the expert system development toward the support of a decision, by the thermal power plant operator. In this thermal power plant, the operational information and management system was being implemented. Together with the implantation starting, this study was also beginning, with the aim of collaborating and achieving a better use of this information, encouraging operators to cooperate with the project. The study also considers that the information return to operators is good, since it facilitates their daily tasks.

The cooling tower system was the choice for the study by the fact of being one of the cheapest project system units in the implantation and, therefore, in the conception phase it did not receive the necessary attention. But, during the operational phase, this system presented a high cost. The most common cooling tower type in Brazilian thermal power plants is the induced draft counterflow, therefore this was the system type chosen for this study. In an open cooling tower system there is direct contact between water to be cooled and air; in a counterflow cooling tower, the air enters at the base of the tower, flows upward and, usually, interfaces with the falling hot water. The induced draft cooling towers is a type of mechanical tower in which, one or more fans are located in the air outlet, to induce air through the air inlets. Figure 1 gives a scheme of this type of cooling tower system.

The main objective in this work was to contribute with the project of an Operator Support System, establishing a methodology for the system development, through analysis of operational data of the cooling towers in a thermoelectric plant. The main purpose of the operator support system is to provide information on operational deviations, anticipating the problems to the facility operator.

The methodology for development of a decision support system for the operator is based on the implementation of neural networks, which will be trained with the representative data collected when the processes is in normal operation and in other different scenarios and operating conditions of a thermal power plant.

With the methodologies for data collection improvement, accumulation and the crossing of operational data with maintenance data, the neural network will be expanded and trained to help: a) the failure diagnosis; (b) the immediate action by the operator, or (c) the failure occurrence prediction in the cooling system, when there is a tendency to this occurrence.

This study also presents the Mass and Energy Balance in the cooling tower, indicating the variables needed in order to make possible an analysis of the heat removal system. In parallel, a study of the monitored variables and their increased relevance to the system control tower is carried out.

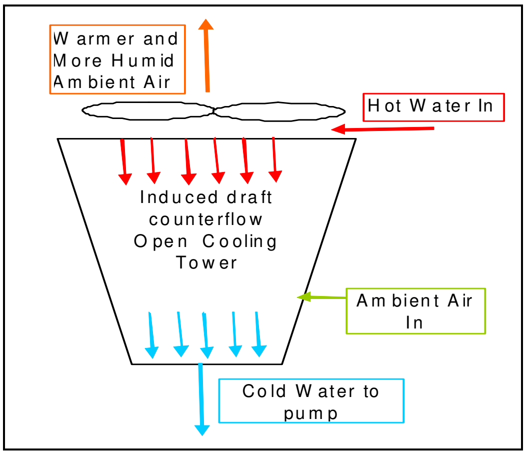

Fig. 1. Induced draft counterflow cooling tower

III. Plant Information Data

In function of the construction and operation of new thermal power plants in Brazil, the necessity of a data collection and distribution system implementation arose. These data should be distributed within the same sphere of management, for decision making at a national level.

To perform this function, the PI System® Software developed by OSIsoft, was chosen which brings all operational data into a single system that can deliver it to users at all levels of the company - from the plant floor to the enterprise level. Then the PI System® allows the management of critical parameters of plant performance. Originally the intention was to put the operation details, maintenance and management in a single system to facilitate the information dissemination for decision making.

Aiming to improve the use of the available data from the PI System®, a working group was assembled to meet with operators and managers of the thermoelectric plant: the deficiency was, then, found around the existing cooling towers. Due to their low cost of design and implementation, these systems do not receive proper consideration during the project design phase; therefore, they have a high cost when out of operation. This cost can reach up to 25% of the total operational cost of the plant, and failures in this part of a thermal power plant may lead to unplanned outages of the plant, in the case of combined cycle with steam turbines.

As it was previously been said, the initial purpose of the work is the establishment of an Operator Support System, to precede the occurrence of undesirable operating status in a cooling tower, thus anticipating the corrective actions that may be necessary, or better planning for remedial actions, in the case of outages.

To the development of this system, operational data of three Brazilian thermal power plants were analyzed. These three power plants have different types of gas turbine: they use natural gas as fuel and operate in combined cycle. The analysis of the operational data was done to examine the information in the plant and that which was, actually, available in the PI system, what is fundamentally a history of macro variables for the plant operation. In parallel, a study has been done on the state of the art of the cooling tower systems, in order to identify the variables that will be needed to develop the expert system.

IV. Mass and Energy Balance

A survey, of the international literature relating to cooling tower system and its simulation by 2008 [2, 3, 4, 5, 6, 7, 8, 10], showed that the use of mass and energy balance for a cooling tower were sufficient to predict the operation or perform the necessary calculations for any design case.

The initial survey conducted for the three thermal power plants concluded that all of them are dealing with a wet cooling tower-type, with water evaporation and countercurrent induced flow. This system is part of a steam circuit, which typically consists of the following components: steam turbine, condenser, and boiler or heat recover steam generator, when working in a combined cycle gas turbine. The heat removed by the condenser is transferred to a cooling tower, which, in turn, transfers this heat to the atmosphere.

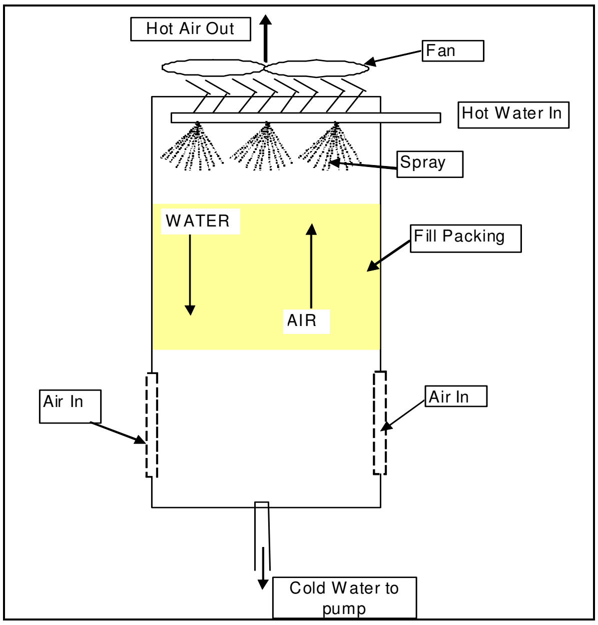

Fig. 2. Scheme of fluid flow in a wet induced countercurrent type cooling tower.

The cooling towers of the wet type use the evaporation of a small fraction of water that enables the cooling of the remaining not evaporated water, circulating through a cooling tower. The heat from the stream of water is transferred into the air, increasing its temperature and humidity, and then the air in these conditions is discharged into the atmosphere. In Fig.2, a diagram of the fluid flow, in a wet induced countercurrent type cooling tower, is shown.

The warm water, from the heat source, is distributed by gravity on the filling surface, by a type of spray showers. Air is simultaneously blown from the bottom onto the wet surface of the filler, causing the evaporation of the water, thus removing the water heat. The cooled water is collected in a cooling tower well and is pumped back to the condenser. One of the most advantageous features of the project with cross-flow of air is the low internal loss of cargo, which means a greater flow. The cross-flow towers have, generally, two entrances in opposite sides of the air.

The thermodynamic analysis [1, 10, 12, 13] obtained the equations needed to analyze the cooling tower operation. These equations are presented below. For these equations, use the caption presented in Fig. 3 and definitions presented in the Nomenclature.

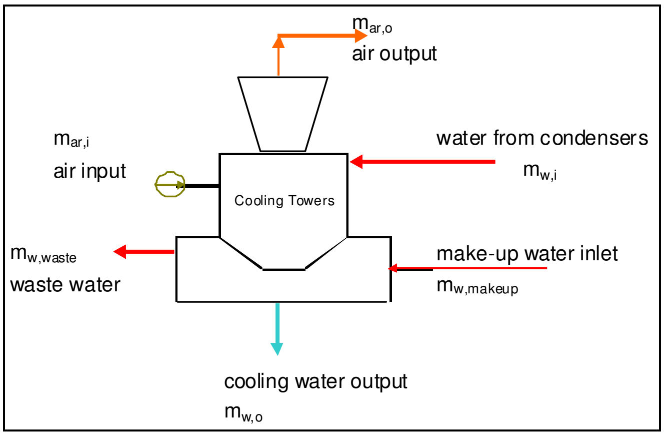

Fig. 3. Cooling tower scheme and mass flow rate abbreviations used.

The ratio between dry air and water vapor will be calculated by the equation below, using properties of dry air and water from ref. [11, 12, 13]:

$$x = 0.62198 * p_w / (p_{at} - p_w) \tag{1}$$

where:

$$p_w = p_{ws} * RH/100 \tag{2}$$

$$p_{ws} = \exp\left((77.3450 + 0.0057 * T - 7235/T)/T^{8.2}\right) \tag{3}$$

The dry air flow calculation at the tower entrance will be calculated by the equation below:

$$m_{air,sec} = m_{air,i} / (1 + x_{air,i}) \tag{4}$$

Below, the calculation method for the air mixture flow, leaving the tower, is presented:

$$m_{air,o} = (x_{air,o} - x_{air,i}) * (m_{air,i} / (1 + x_{air,i})) \tag{5}$$

The enthalpy calculation for the air input is performed by equation 6:

$$h = 1.006 * t + x * 1.84 * t + 2.502 \tag{6}$$

The enthalpy calculation for the saturated air is made by equation 7:

$$h_{ws} = 1.006 * t_{ws} + x_{ws} * 1.84 * t_{ws} + 2.502 \tag{7}$$

Equation 8 does the air output enthalpy calculation:

$$h_{air,o} = \left(h_{air,i} * m_{air,i} - m_{w,o} * h_{w,o} + h_{w,i} * m_{w,i} + h_{w,makeup} * m_{w,makeup} - h_{w,waste} * m_{w,waste}\right)\big) / m_{air,o}$$

$$h_{air,o} = (h_{air,i} * m_{air,i} - m_{w,o} * h_{w,o} + h_{w,i} * m_{w,i} + h_{w,makeup} * m_{w,makeup} - h_{w,waste} * m_{w,waste}) / m_{air,o} \tag{8}$$

The air mixture ratio in the cooling tower output is calculated by the equation below:

$$x_{air,o} - x_{air,i} = \left(m_{w,makeup} - m_{w,waste}\right) / m_{air,i} \tag{9}$$

Then, two indicators are introduced to predict the degradation of a cooling tower: the tower efficiency and the incrustation indicator of the tower.

The tower efficiency is calculated as showed by equation 10:

$$\varepsilon = \left(h_{air,o} - h_{air,i}\right) / \left(h_{s,w,i} - h_{air,i}\right) \tag{10}$$

The incrustation indicator is calculated as below:

$$ID_{torre} = \Delta T_w \,/\, \Delta T_{air} \tag{11}$$

The cooling towers study concluded that 11 process variables have a significant influence on the towers performance results, which are: temperature and humidity of the input air; temperature, pressure and flow rate of input water; temperature and pressure of output water; temperature, pressure and flow rate of replacement water; and temperature, pressure and flow rate of waste water.

V. PI Data Analysis

The data collected by the PI software or even the thermoelectric control system, were found not to be complete, or were distributed in various databases and the chronological information was not always available. The fact is that PI software, though existing in all thermoelectric power plants analyzed, was not wholly implemented in any of the units, so the PI is restricted to a few process variables; in the future, as they are solving the problems, other necessary variables will be implemented.

Out of the three thermoelectric plants that provided their complete data, only a part may be used at the moment. The first thermoelectric power plant that had the data discarded, it was because the automatic data collection, in the cooling tower system, did not exist. Another thermoelectric power plant, which had the data discarded, was due to the fact that, despite having such data, they were not available in the PI system. The thermoelectric power plant, which was chosen for study, despite the fact that it did not have all the necessary data, these could be obtained from indirect form, calculated from other existing variables.

Therefore, the initial idea of setting up an Operator Support System was divided into creating a neural network to study the tower state planned, in order to anticipate any unwanted operational status and, in the future, when the complete information is available, to have the roll-out specialist.

The expert system development will require a longer time for data collection (at the time, the plant had less than two years of operation), with a significant improvement in data collection procedures, with operational and maintenance reports for the cooling towers and, preferably, providing all data chronologically integrated in a single database.

VI. Neural Network Development

This study opted for the use of ANN (Artificial Neural Network), anticipating the trend of the variable process [01]. The advantage of using neural network in this study is the fact that it does not require the comprehension of heat and mass transfer, which are very complex phenomena to be expressed by mathematical formulations. From this ANN trend, then, an expert system which predicts the operating state of a cooling tower will be developed.

With the mass and energy balance of a cooling tower, and added to the process data contained in the PI data bank, it was possible to calculate the output parameters of the neural network. But, as commented previously, the implementation work of the PI data bank was not fully completed and, therefore, all the data are not available in this bank.

Another problem was found in the process data quality, instruments with readings totally outside the expected values were detected, and in the maintenance records consulted it was found that they had undergone regular measurements, but they had not been recorded properly, due to PI problems. These process variables with problems could be replaced by data obtained through the presence of other instruments in the vicinity that provided the data in a direct (instrument with the same type of measurement) or indirect form (process variable calculated from other variables).

The relative humidity was one of the process variables that mostly presented problems and has undermined the neural network simulations and training. The relative humidity values, obtained from PI database and presented most of the time, was 100%, despite the present dry climate. These data were replaced by data provided by the nearest regional weather station [14] plus available data, which showed the region characterization well. Fig. 4 presents the relative humidity values obtained from the thermoelectric power plant PI databank and the meteorological station.

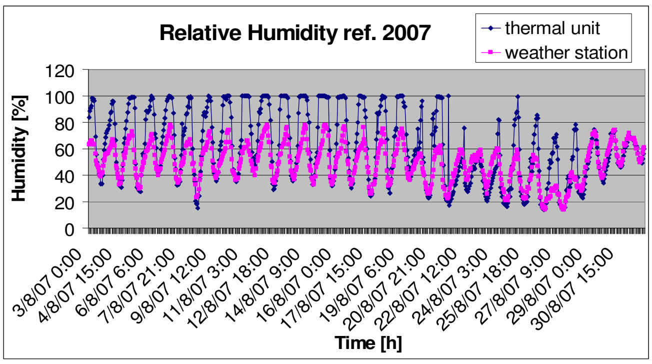

Fig. 4. Relative humidity of thermal init x weather station

Other process variables that presented problems were the flows, but these were calculated indirectly from other available flows in the PI databank. Thus, the 11 variables of the training process required for the ANN resulted. Due to problems with these variables, not much time was invested in them to improve the ANN, but their technical and economic feasibility were simply demonstrated, together with the necessity of an improved monitoring to collect historical data for future use.

The ANN was created with three layers: an input layer with nine neurons to represent the input variables; a hidden layer with 17 neurons, to propagate the information representing the various operating states; and an output layer with three neurons, representing the exits. The choice of this configuration is due to the fact that it has represented well the simulation of cooling towers, in previous studies [1, 4, 5]. The method of training was the feed-forward back-propagation network.

Both the ANN and the training methodology algorithms have a simple implementation, independently of the language adopted. As the PI software had an interface for exporting data into spreadsheets compatible with Microsoft Excel®, the Visual Basic® (VB), from Microsoft, was adopted as a programming language and all the final tests were performed in Excel® spreadsheets. Due to ease of training and testing, the ANNs were originally developed using the MatLab® [16] with their Neural Network Toolbox, and the training function with feed-forward back-propagation network, fitting network and, by linear layer. Out of the three methods, the first two were more accurate, and among them there were no significant differences. As feed-forward back-propagation networks are known and disclosed, they were adopted for the algorithms transfer to the Visual Basic® (VB).

The training is a supervised learning, i.e, an associative learning in which the network is trained by providing it with input and matching output patterns. In this case the system which contains the neural network is provided with a correct answer (output) for every input pattern (self supervised). Weights, associated with the inputs, are determined to allow the network to produce answers as close as possible to the known correct answers.

The first term, "feed-forward" describes how this neural network processes and recalls patterns. In a feed-forward neural network, neurons are only connected foreword. Each layer of the neural network contains connections to the next layer (for example, from the input to the hidden layer), but there are no connections back. The term "back-propagation" describes how this type of neural network is trained. Back-propagation is a form of supervised training. When using a supervised training method, the network must be provided with both sample inputs and anticipated outputs. The anticipated outputs are compared against the actual outputs for given input. Using the anticipated outputs, the back-propagation training algorithm then takes a calculated error and adjusts the weights of the various layers backwards from the output layer to the input layer. For more details in feed-forward back-propagation network see [15].

Data obtained from the training were analyzed by the difference of the collected or calculated values from data obtained by ANN, in absolute values, as shown in Table I.

It is also important to note that this study uses the defaults values by the program manufacturer, and no effort was developed to reduce the error.

TABLE I
DATA OF COOLING TOWER EFFICIENCY

	Difference between the value		
	Read and calculated by the ANN for Water temperature output the tower	Spreadsheet calculus and the ANN efficiency for the cooling tower	Spreadsheet calculus and the ANN incrustation for the cooling tower
Maximum	1.5460	0.1115	6.1898
Average	0.2603	0.0157	0.3768
Minimum	0.0003	0.0000	0.0006

The Matlab® [16] and its Neural Toolbox allow the construction of the graph that presents the quadratic errors during training of ANN, through the command "Performance". An example of this graph is presented in Fig. 5.

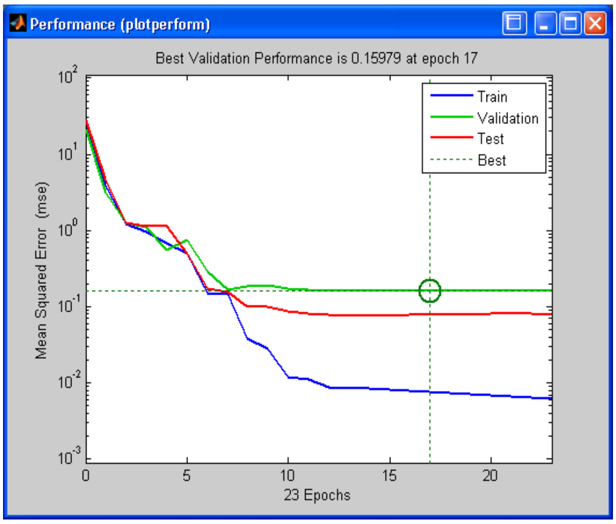

Fig. 5. Command "Performance" shows the graph of the quadratic errors of the training.

VII. CONCLUSION

In this study, the balance of mass and energy in the cooling tower system of a thermoelectric power plant was conducted and the variables that may be used to achieve a performance analysis of the tower were pointed out. These variables were chosen from the database of a PI System®, in the thermoelectric power plant studied.

From the use of these data, it may be shown how the calculated indicators can be used for the monitoring of technical and operational problems in a cooling tower: the cooling tower efficiency (ε) and incrustation rate (ID). These indicators may, also, show to the operators that an incrustation process has been initiated and, in the future, they will even indicate the anticipated need to stop the operation for cooling system maintenance. Thus, this system can warn about a not planned downtime, increasing the thermoelectric power plant availability.

The trained ANNs have always used the default program settings; the results analysis was done especially for the evaluation of the quadratic error. Another possible evaluation method is the surface errors analysis that could be used to increase the ANN reliability, but this was not done, in this work, due to the lack of reliable historical data. In future works, with more reliable historical data, the use of this evaluation is advisable.

Even without any concern with the ANN improvement, the errors were very low. Data analysis is the most critical development point, and this could lead to success or failure of the ANN. These data could be of greater confidence if cross-checked with maintenance information, from the thermoelectric power plant, and values, such as the water and air flow inside the cooling tower, could be obtained indirectly by improving the results of the ANN.

The ANN training duration is negligible when compared to the time spent for data collection, calculation and data analysis. The ANN type has a small influence on results, but from the moment they are seeking the improvement of this ANN, the difference tends to decrease, leading us to evaluate the ANN response time when the required response time of applications is very fast.

This study has also shown that the greatest efforts in developing these Operator Support Systems occur in a very long time: these efforts comprise, mainly, data collection and selection for the periods of normal operation of the cooling towers, in various operational scenarios, or during a failed operation, what should be very well characterized.

Please note that the use of neural networks do not imply the requirement of understanding the phenomena of heat and mass transfer, which is really very complicated to be expressed by mathematical formulations.

VIII. ACKNOWLEDGMENT

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