A SIMPLIFIED APPROACH TO NATURAL CONVECTION MODELLING IN COOLING TOWERS BY NEURAL NETWORKS

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Abstract. *This paper deals with a first approach to a natural convection problem modeling in a cooling tower. Although these phenomena are complex, a neural network approach can incorporate the main features such as the relationships between basic input variables (environment temperature, wind speed, solar irradiance) and output ones (thermal efficiency of the group). This approach requires, without any doubt, reliable experimental data regarding to actual operation of the cooling tower. In this paper, as a first approximation, this data are numerically generated following known previous behavior of each variable individually in respect to its influence on the thermal efficiency (output temperature). A multilayer perceptron network is trained with this simulated data. Up to three different behaviors are used simultaneously in the training of the same neural network in order to simulate various climatic situations. Some other patterns of operation (different from that used for training) are presented to the network and the results are compared in terms of performance and robustness. The results are very promising and show that this approach may substitute large time consuming procedures with relative good precision.*

Keywords: *neural network, natural convection, cooling tower*

1. Introduction

Thermoelectric power plants operate under Rankine cycles, where the heat rejection is an intrinsic characteristic of the process. The heat exchangers used for this rejection can be of different types, like humid exchangers, which uses natural sources of water, or dry ones with forced or natural ventilation.

Natural convection based heat exchangers had their flows driven by the buoyancy effect due to the presence of gravitational acceleration and density variation within the fluid (Bejan, 1995). The convection coefficient achieved with this natural phenomena is significantly smaller compared with the one achieved with forced flow, what obligates dry heat exchangers to become towers up to 40m, as shown in the Fig. 1.

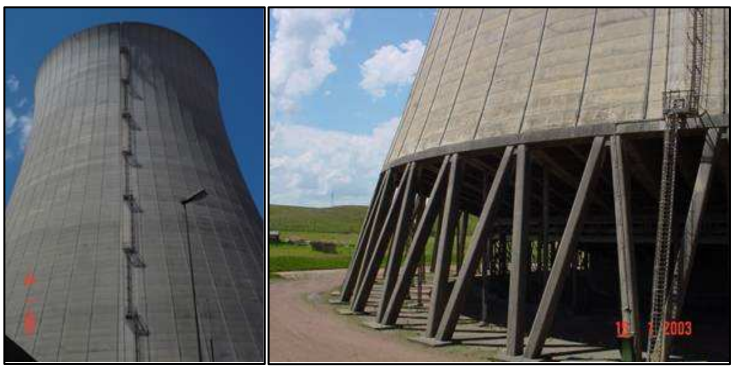

Figure 1. Dry cooling tower: general view (left) and air flow inlet (right)

In dry cooling towers, water to be cooled flows throughout heat exchanges placed in the base of tower. The temperature gradient generated in this area is responsible to feed the natural flow in addition to the chimney effect along its height.

Behavior of natural convection in a non controlled environment is a hard task to describe.

A contribution for the natural draft flow was made by Carhart, Policastro and Ziemer (1982) presenting the evaluation of 16 different algebraic models for predicting the plume raise on natural-draft cooling towers. The comparisons are made based on field data and shows that the best models can predict the tower plume behavior in 50% of the cases. Later, Carhart and Policastro (1991) presented another method to predict plume behavior based on a more physical integral model that showed good prediction results for over 75% of the cases.

An attempt to create a mathematical model for cooling towers is presented by Fraas and Ozisik (1965), were heat transfer for wet and dry towers are proposed as well as some relations to calculate its height. Following the same kind of modeling, ASHRAE (2004) proposes some very similar equations, based on heat exchanger relations.

In this way, in this paper a neural network modeling is applied to the natural convection problem on dry cooling towers. This approach follows the idea of modeling previously known behavior patterns.

2. Neural Networks

Artificial Neural Networks (ANN) may be characterized as computational models based in parallel distributed processing with particular properties such as the ability to learn, to generalize, to classify and to organize data. There are several models that have been developed for different specific computational tasks.

For Multilayer Perceptron Networks the simplest processing unit is represented by the single neuron as indicated by the figure.

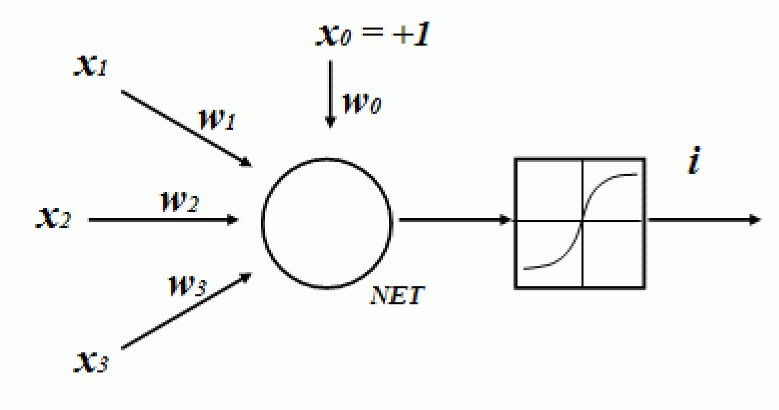

Figure 2. Single neuron unit processor (Haykin, 2001)

In Fig. 2, a sketch of a single neuron unit processor is depicted. The neuron is the most basic unit of a neural network and, as a processing unit, will receive inputs (x_i) via axons connections. Then, some transformation will be processed to the inputs in order to obtain a desired output. This transformation is carried out in two stages. First, a linear combination of all the inputs to obtain a scalar, called NET, is usually used. The coefficients of the linear transformation are called “weights” and they are denoted by w_i. In a second stage, a linear or non-linear transformation is applied to the scalar NET. The linear or non-linear function is called "activation function" and is denoted by *f*. As in natural neuron behavior, the activation function will decide when, how and whether the neuron output (*i*) will take place. As indicated in Fig. 2, there is an input with constant value ($x_0=+1$) and its respective weight (w_0), which is related to a parameter in the activation function called "threshold". For convenience, the threshold is considered as an unknown in the equation, which gives the corresponding output. The threshold defines a shift of the original activation function. This process can be written as: (Haykin, 2001)

$$i = f\left(NET\right) = f\left(\sum_{k=0}^{n} w_k x_k\right) \tag{1}$$

There are several kinds of activation functions used for the transformation such as linear (*f(x)=x*), signal (*f(x)=SIGN(x)*), sigmoid (*f(x)=1/(1+e-x)*), unit step function ($f(x)=H(x-x_0)$), hyperbolic tangent (*f(x)=tanh(x)*), etc. This single processing units can be connected each other to generate the so-called Neural Network. The ways the neurons are connected and the ways they operate are very different originating a great variety of neural networks.

Most ANNs have some sort of "training" rule whereby the weights of connections are adjusted based on training data (Demuth, 2000). Multilayer Perceptron Network is the most widely used type of neural network. A general Multilayer Perceptron Network architecture consists on a layered network fully connected, i.e., all neurons belonging to a layer are, each one, connected to the previous and the next layer. Such architecture representation is indicated by the number of input vector followed by the number of neurons on each layer (e.g. 1:12:1 indicates an ANN with one input vector followed by one layer with 12 neurons and an output layer with one neuron). Obviously, the input layer and the output layer only "put" or "receive" data from the network. The number of hidden layers and the number of hidden units in each layer needs to be determined. It depends on the complexity of the system being modeled. For a more complex system, a larger number of hidden units are needed. In practice, the optimal number of hidden units is determined by a trial and error procedure.

In the training process of neural networks, for an input pattern x_{pi} (where index p means "pattern" and index i means an input neuron), the weights (w_{pi}) adjustment will take place in the links of the neural network in order to get a desired output or, in the special case of this work, the value of the limit state function for this specific sample, y_{po} (where index p means "pattern", and o means an output neuron). After this first adjustment is achieved, the network will pick up another pair of x_{pi} and y_{po}, and will again adjust weights for this new pair. In a similar way, the process will go on until all the input-output pairs are considered. Finally, the network will have a single set of stabilized weights satisfying all the input-output pairs.

Usually the outputs O_{po} from the network due to an input x_{pi} will not be the same as the desired output values y_{po} used during the training process. For each input-output pattern, the square of the error may be written as follows:

$$E_p = \frac{1}{2}\sum_k \left(y_{pk} - o_{pk}\right)^2 \tag{2}$$

where k is the number of neurons in the output layer. The average system error is given by:

$$E = \frac{1}{2P}\sum_p E_p \tag{3}$$

where P is the number of training patterns. Employing any algorithm to minimize the error function (such as downhill climbing), the weights can be evaluated and an approximated function may be obtained. A common parameter presented in any basic algorithm used to train the network (such as back-propagation) is the "learning rate" which defines the rate the learning is achieved. Such parameter must be carefully choosed to avoid numerical instabilities or overfitting problems. The generalization capability and accuracy of fitting may be estimated by the average system error evaluated with a set of patterns not used for training (Kovacs, 1996).

3. Procedure

In the heat exchange problem the rejected heat at the cooling tower is a desired variable. A well-know way to model the problem is to suppose that the water flow in the condensation circuit is constant, as well as its input temperature at the cooling tower. So, the dissipated thermal power will be expressed only as a function of outlet water temperature (t_{wo}), which is used by the neural network as a variable to be simulated.

In this work, firstly, it is assumed that the intervening factors to the outlet water temperature (t_{wo}), in other words the dissipated thermal power, are 3:

- Environment air temperature (t_a);
- Solar irradiation over the tower walls (I_t);
- Wind speed (v_w).

The built neural network will adopt these three quantities as input data, and outlet water temperature as output data.

In order to simulate properly a specific tower, some sort of consistent experimental data (at least acquired for 10 years) for ANN training should be available through an *in* situ measurement station. However this climatic set o data (t_a, I_t , v_w and t_{wo}) regarding any dry cooling tower was not available.

Since this work has the purpose to verify the use of ANN in modeling a dry cooling tower, it is proposed a simplified method that characterizes, as a first approach, the mains features of the processes or the "fingerprint" of the tower.

In this method, it is supposed that the tower presents different behavior for several climatic situations. So, dry cooling tower will have a well defined curve of operation since this curve is used at the prescribed climatic situation.

It is adopted a standard behavior for the hypothetical cooling tower regarding the variable t_{wo}, which follows a well know equation as a function of the three climatic parameters t_a , I_t *and* v_w. Physically this pattern should be seen as a series of operational points that follows a same bias and in spite of loss of accuracy, it follows the same expected physical behavior. We can imagine one pattern to each combined climatic pattern such as: winter or summer, night or day.

This pattern is obtained in a random but homogeneous fashion of the data set, which relates climatic parameters with t_{wo}. Portion of this set will be used as training data to the ANN through the back-propagation algorithm (Haykin, 2001) and another part will be used to check the fitting process with the defined criteria of Eq. (2) and Eq. (3). This stage is called "validation".

It could be imagined not only one but several patterns in order to train the neural network. This leads to a situation where the more number of used patterns, the lower is the limitation of use of the trained ANN. These tend to better represent the actual problem, where several environment data could be used.

This work shows some tests performed with one and three behavior patterns. If the neural networks could represent sufficient t_{wo} for the three patterns with the same neural network, this points out to a satisfying behavior when applied to actual data.

The function that characterizes each pattern in the system belongs to the R^4 space. In order to apply this, each curve is divided into three parts. One curve for each relation t_{wo} *versus* input environment parameter, with t_{wo} between 30 and 40°C.

The relation that describes the behavior of the cooling tower is depicted below for the three patterns.

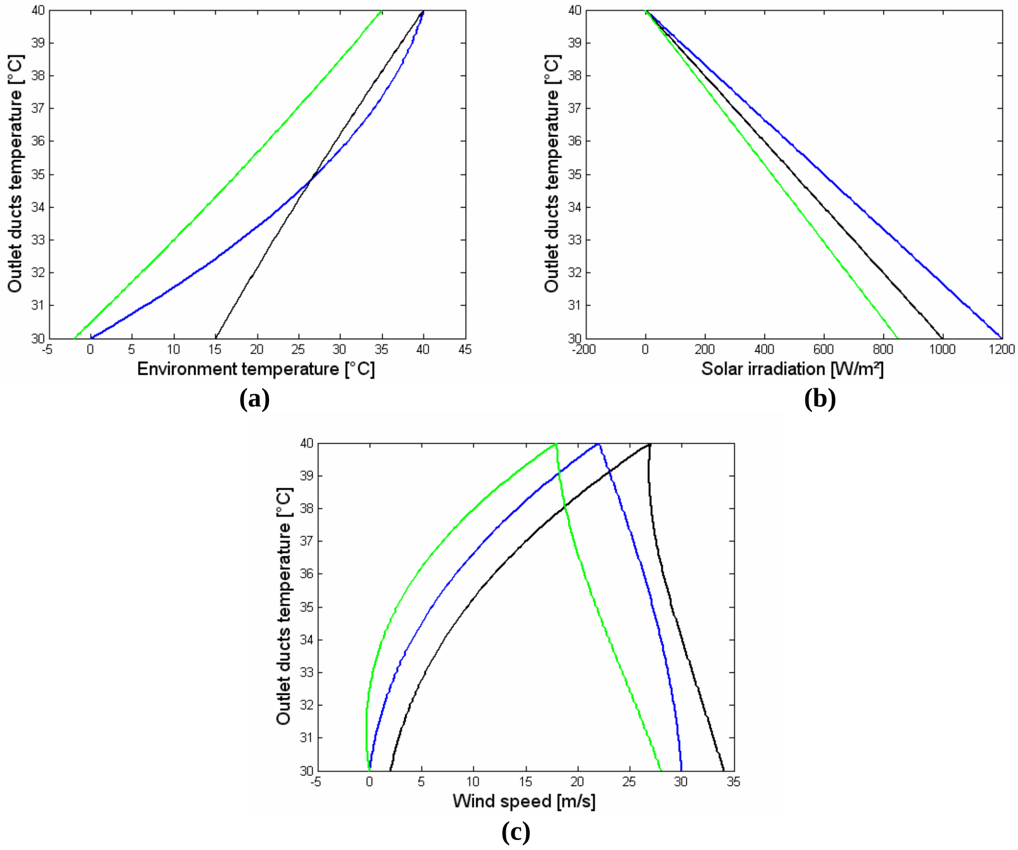

Figure 3. Three environment patterns for environment air temperature (a), solar irradiance (b) and wind speed (c) *versus* outlet water temperature duct flow

Note that the curves with same color represent the same cooling tower pattern behavior. For different patterns, this trend repeats.

In Fig. 3a the shown trend is that the greater t_a , the lower the rate heat transfer. If the input water temperature is constant this decrease will reflect in t_{wo}. In Fig. 3b it can be noticed that the solar irradiance increase the natural convection effects, accelerating the fluid flow and contributing to heat rejection.

The behavior of v_w is shown in Fig. 3c and could be separated into two regions. At slow velocities the wind has a favorable effect to the heat transfer enhancing chimney effect. At higher velocities, the flow at the top section of the cause air recirculation within the tower, restraining the local ascending flow.

A FORTRAN code was tailored to implement the ANN for a Perceptron Multilayer Network (Haykin, 2001) which uses tangent hyperbolic activation function with parameter 0,9 and learning rate η=0,1.

4. Results

Thirty points were randomly chosen from the simulated curves using only one behavior pattern. The better architecture found was (3:15:15:1), which means three input vectors followed by two layers with 15 neurons and an output layer with one neuron. Convergence criteria of 10^{-6} was used to train the net, as indicated by Eq.(3).

A total of 150 points were used to validate the ANN. In Fig. 4, the behavior curve (blue line) is shown with the validation data obtained using the trained ANN (red stars).

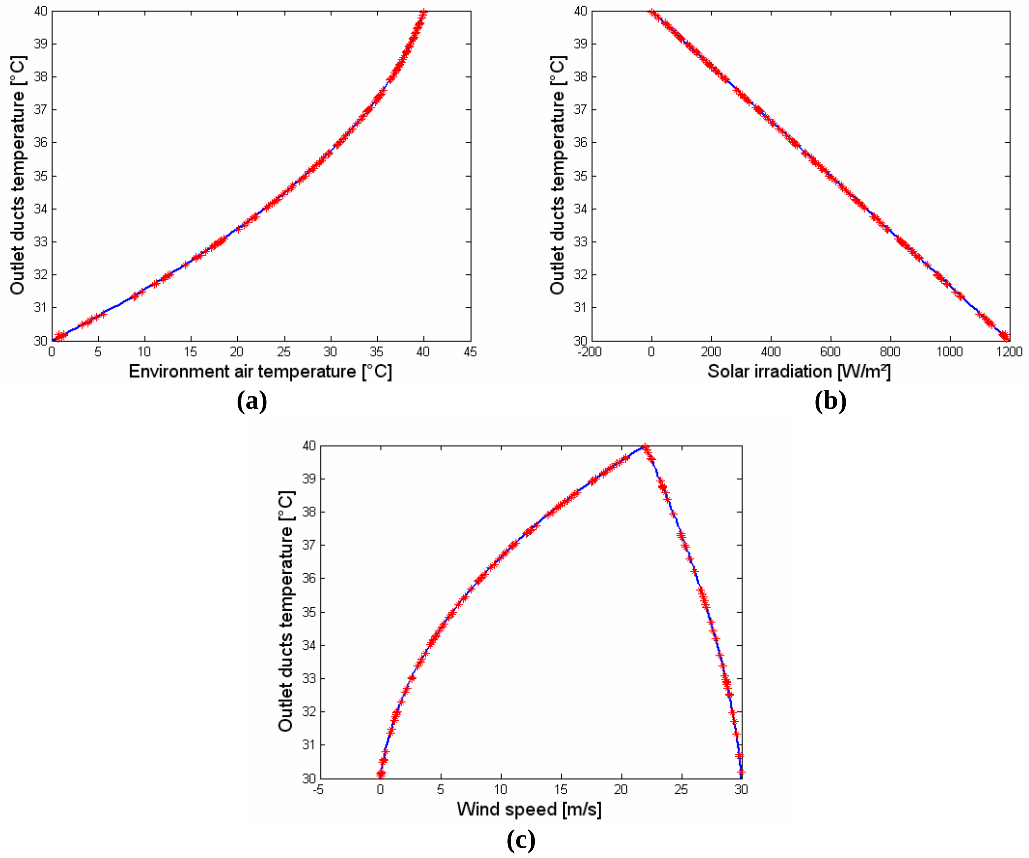

Figure 4. Validation data for outlet water temperature obtained with a trained neural network for 1 pattern along with the expected pattern

In Fig. 4, the validation points follows the same trend, always very close to the behavior curves, showing that a training set of very little number of points was sufficient to capture the whole behavior of the phenomenon. In this case, the error criterion for the validation points, as indicated by Eq. (3), was about 10^{-4}.

It should be emphasized that the v_w behavior is a challenge to the trained ANN since it has two distinct regions with different trends. So, there are no single relation between t_{wo} and t_a , I_t and v_w. Nevertheless the trained ANN was able to distinguish the different trends as indicated.

For the case of three patterns simulated with the same ANN, it is expected a greater difficult. For that reason the ANN that presented better results was one with (3:15:10:1), which means three input vectors followed by two layers with 15 neurons and an output layer with one neuron. Convergence criteria of 10^{-6} was used to train the net, as indicated by Eq.(3)..

One hundred points randomly chosen from the three curves in Fig. 3 were used to train the ANN. This way, the quantity of data is approximately equal for the three patterns and equally distributed along the domain.

The training process was finished within one minute and the convergence error criteria, as depicted by Eq. (3), attain the value of 10^{-6}, as in the precedent test.

As indicated, five hundred points were generated for validation purposes. The ANN was able to predict the expected values, Fig. 5, with an acceptable error of 0,37 x10^{-4}.

Observing Fig. 5 one could notice that the ANN generates good results for the almost the entire domain. The validation error criterion was slightly higher due to regions with deviations of the expected behavior.

This deviation is more pronounced in Fig. 5a with respect to the environment air temperature. So it is outstanding the trend perception. The ANN was able to identify which of the 3 patterns belongs to the input pattern, generating a precise result of the t_{wo}.

As a qualitative experiment, the trained ANN with 1 and 3 patterns are subjected to validation data not belonging to any of the used curves. The ANN is asked to solve for trends not used for training.

Statistical results shows that the trained ANN with 1 pattern generated results with a large standard deviation from expected results while for the ANN trained with 3 patterns generated a lower standard deviation. This shows that as the number of patterns is increased so increases the ability of the ANN in modeling complex phenomena with unknown data set.

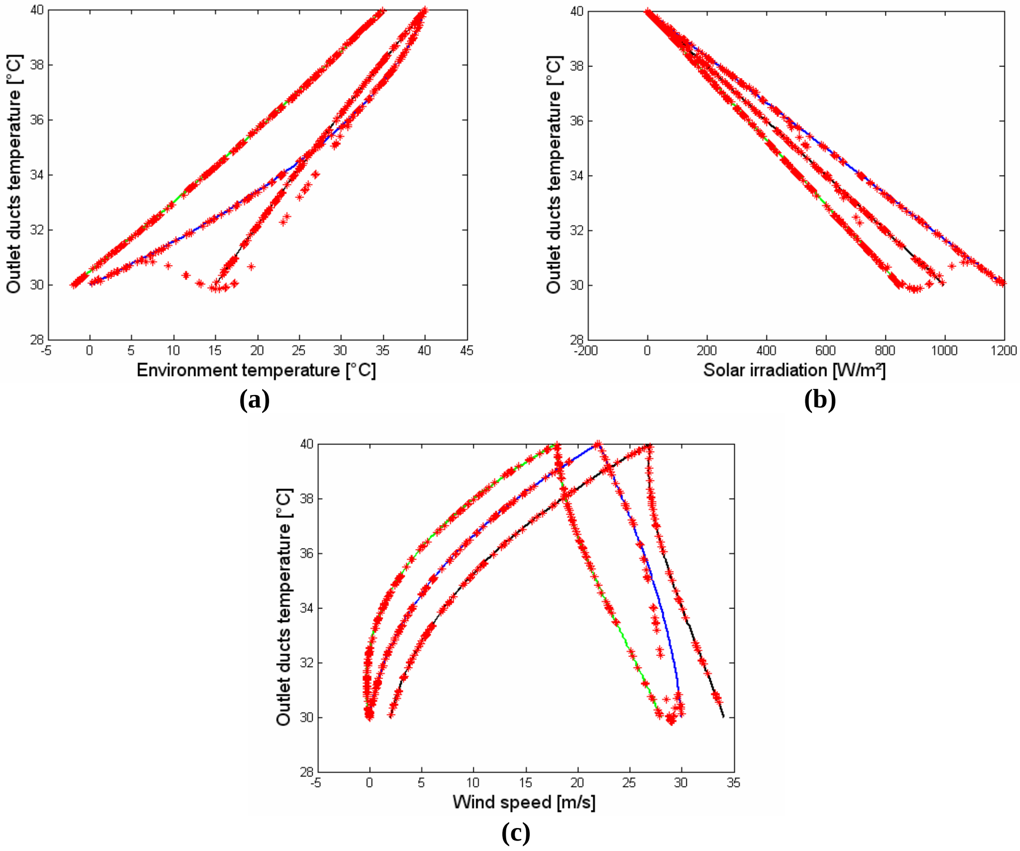

Figure 5. Validation data for outlet water temperature with 3 pattern behaviors obtained from a trained ANN along with the 3 expected behaviors

5. Conclusion

The ANN used to model the natural convection phenomena in a dry cooling tower could be recommended according to the results presented in this paper.

Non single behavior in non-linear problems is a circumstance where ANN could be explored. The behaviors that follows trends similar to those numerically simulated in this paper, despite of the simplification of the actual problem, are adequate for the engineering point of view and have potential of applicability in real life cases.

It is suggested that a deeper study should be conduced to identify the intervening parameters. The model theory could lead to better results and fewer efforts to train since only non dimensional numbers would be used.

It is also suggested to set up a measurement station at a cooling tower to obtain experimental data. Weather records could be used if obtained from a close enough station and coupled with t_{wo} record data from the power plant.

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