International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 17 (2018) pp. 13130-13135

Artificial Neural Networks (ANN) and Kalman Filter Algorithms to Predict Output Temperatures on a Heat Exchanger

Tlatelpa-Becerro A[1*], Rico-Martínez R[2], Castro-Goméz L[3], Urquiza G[3] and Calderón-Ramírez M[2]

[1*] *Robotic Engineering Department, Escuela de Estudios Superiores de Yecapixtla-UAEM, Av. Félix Arias, Quinta Sección de los Amates, Yecapixtla Morelos, 62820, México.*

[2] *Chemical Engineering Department, Instituto Tecnológico de Celaya, Antonio García Cubas, Fovissste, Celaya Guanajuato, 38010, México.*

[3] *Mechanical Engineering Department, Centro de Investigación en Ingeniería y Ciencias Aplicadas (CIICAp)-UAEM, Av. Universidad, Chamilpa, Cuernavaca Morelos, 1001, México.*

Abstract

Artificial neural networks (ANN) were applied for the prediction of the output temperature in a heat exchanger with triangular arrangement with air-water as work fluids, currently operating at a hydroelectric power plant. Four similar heat exchanger time data series were analyzed. A feed-forward ANN configuration was used to predict the output temperatures. The ANN was trained, tested and validated using the experimental time series. In order to test the robustness of the ANN scheme as a predictor, only data from three exchangers was used to train the ANN, while data from a fourth heat exchanger was used for validation. The ANN was also coupled to a Kalman Filter in order to improve the predictions. The scheme showed to be successful and can be used in real-time to handle slowly varying behavior due to fouling implicit in the operation of the exchangers.

Keywords Heat exchanger, Kalman filter, Neural networks, Time series.

INTRODUCTION

In hydroelectric power plants, the energy generation depends on several key parameters such as the water flow, turbine efficiency and electric generator efficiency, which is related with the cooling capacity during regular operation given by heat exchangers. Heat exchangers are devices that allow the flow of thermal energy between two or more fluids at different temperatures [1]. An efficient air-cooling system leads to higher generation capacity; On the contrary, a deficient system reduces the equipment lifetime due to overheating. The cooling provided by the air flowing through the electrical generators is possible because of the heat exchangers, usually involving water flowing perpendicularly to the hot airflow (cross-flow). Water used for cooling is usually taken from the same penstock that feeds the turbines; it is usually slightly acid water that produces a corrosive attack to the heat exchangers tubing. Besides corrosion problem, mineral depositions known as fouling is often present, reducing heat exchanger capacity and even leading to complete failure [2-4]. Fouling in heat exchangers is difficult to avoid, thus modeling the heat exchanger behavior in the presence of evolving fouling deposits remains an active research topic.

In recent years, new approaches at finding the rules that describe the relevant mechanisms in complex systems have been proposed. Among them, Artificial Neural Networks (ANNs) has been successfully employed in thermal analysis by different authors [5], within the inference of discrete and continuous models that allow the description of such types of behavior. The type of ANN model plays an important role in determining the utility of the approximation, as well as in their eventual success to describe dynamic experimental behavior observed on different study systems [6].

Empirical model construction using discrete ANN models is proposed for processing power plant heat exchangers time-series data. The heat exchangers are currently in operation at one hydroelectric power plant in the state of Guerrero, México. The model proposed is given *on-line* adaptability by coupling it with a Kalman filter, thus providing a mechanism to account for the slowly varying component associated to the fouling phenomena. Such black-box approach is useful whenever the phenomenological description of a system is too complex to be used for real-time applications or it is simply unavailable or inaccurate for such purposes [6, 7].

In the remaining sections, a physical description of the system is given followed by a description of the experimental observations. In section III, the ANN architecture used here is described, along with the Kalman filter coupling. In section IV, the results achieved in the prediction of the time-series are presented, before a brief perspective given as conclusion.

PHYSICAL MODEL AND EXPRIMENTAL DATA

The heat exchanger studied here is radiator type with triangular tube arrangement and air-water as work fluids, commonly used in hydroelectric power plants (Figure 1). Its function is to cool the air that goes out of the electric generator. The air flows across the spacing between tubes with cold water flowing inside them.

Type-T thermocouples were used to measure the inlet and outlet temperature of the air and water. They are located at the inlet and outlet of the heat exchanger. A Fluke 2525 Wireless Data Logger (FLUKE Corporation), was used to log the readings at one-minute increments. Time series of four radiator heat exchangers were collected from the logger and sent to a laptop computer using a wireless modem. Water pressures in and out of radiators were also measured. All pressure lines were routed to a central manifold block. Valves were manually opened to measure the pressure.

Time-series from the inlet and outlet water and air-side from four heat exchangers (HE1, HE2, HE3, and HE4) were collected. In the same manner, pressure drop during operating was also recorded.

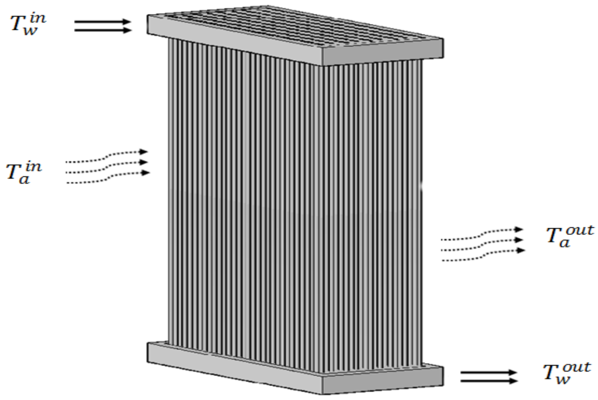

Figure 1. Air-water heat exchanger.

Figure 2 shows the time-series from 3 of these heat exchangers (HE1, HE2, and HE3) that were used to train the neural network. Figure 3 shows the time-series of heat exchanger HE4 that was used to test and validate of the developed ANN model.

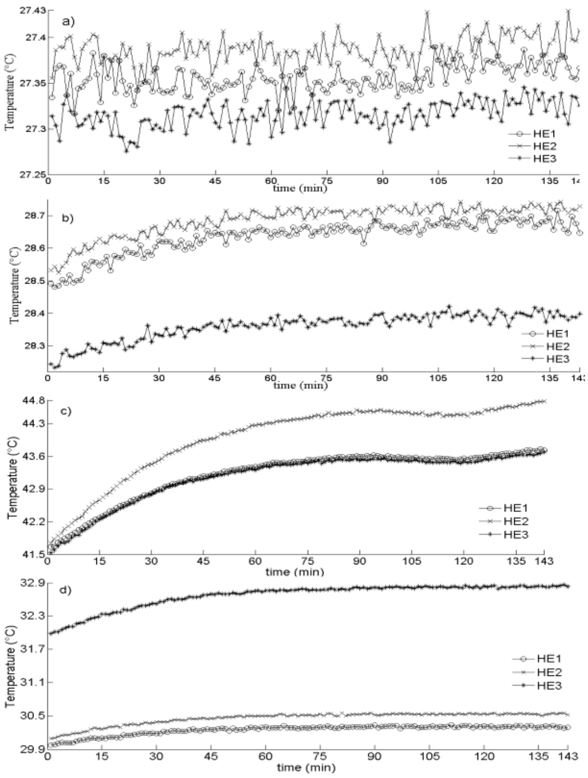

Figure 2. Experimental time-series from three different heat exchangers in operation at the plant. Water temperature: a) inlet, b) outlet. Air temperature: c) inlet, d) outlet.

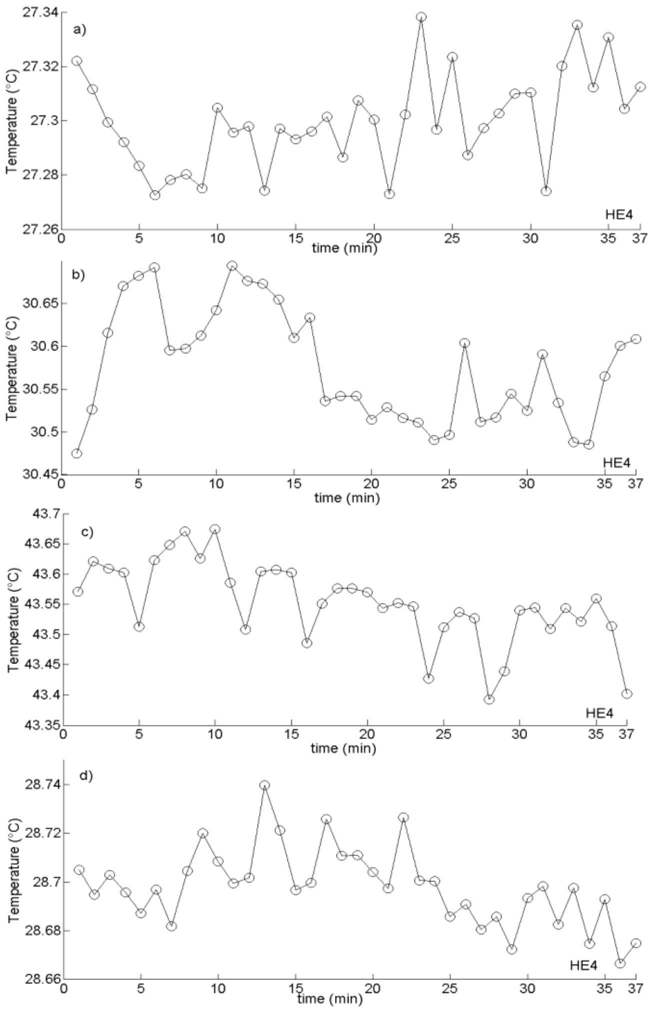

Figure 3. Time-series of heat exchanger (HE4). Water temperature: a) inlet, b) outlet. Air temperature: c) inlet, d) outlet.

THEORY

Artificial neural networks (ANN)

Artificial neural networks are known for their learning ability allowing them to be used for data simulation and prediction. They are inspired in the biology of the human brain [8]. The main disadvantage of artificial neural networks for model construction is its "black box" nature. The individual relation between the input variables and the output variables are not developed by engineering judgment so that the model is characterized as a black box. ANN consists of a number of layers with certain number of neurons. The neurons are the basic processors of the network and every connection between two neurons with a real value is called weight. Every active neuron contains an additional parameter (called bias) and there are interconnected in a variety of structures. The weights, biases and neurons number can be changed ("adapting" to the data for learning-based training) in the network layers to minimize the error between experimental and simulated values. Among the various kinds of ANNs, the feed forward neural networks have been the most popular in engineering applications. Here, a feed forward network is trained to predict the heat exchanger outlet temperatures using MATLAB neural networks toolbox (2010). The neurons in the hidden layer are nonlinear with sigmoidal activation functions.

In order to build the ANN predictor, attractor reconstruction techniques were employed [9]. These suggest the use of a delayed measurement of inlet temperatures, in addition to the current values, as well as the current pressure drop, as inputs of the ANN. The idea is similar to the employed for the construction of the so-called ARMA models [10], in the sense that delayed measurements contain information about the “memory” of the system. These ideas have been extensively used in many fields, including chemical and mechanical engineering [11-13], as well as in application of oil refinery production processes such as gasoline and enterprise manufacturing electric motors [14-15]. The ANN outputs are predictions of the values of the outlet temperatures. As the ANN training converges, it becomes a predictor of the dynamical behavior of the system and can be used for both, short and long-term predictions.

As mentioned previously, experimental time-series of the inlet temperatures and pressure drop from exchangers HE1, HE2, HE3 were used to train the network. Data from a fourth exchanger HE4, was used to validate and test the network predictions. In this manner, the robustness of the approach can be examined, since an exchanger affected by fouling will have similar behavior that the ANN coupled with the Kalman filter, should be able to reproduce.

The ANN architecture is a feed forward four-layer regular network with 7 neurons in the input layer, two hidden layers with 9 neurons each and 2 neurons in the output layer (Figure 4). As there is currently no rigorous way to determine an optimum number of neurons in the hidden layers, the choice in the number of neurons is somewhat arbitrary. This choice reflects a compromise between the computational effort required to train the ANN and an estimate of the minimum number of neurons needed to capture the underlying dynamics. This compromise is tested during the process of validation of our results: in this particular case the optimum number of neurons was determined based on the minimum value of MSE of the training and prediction sets. The optimization was achieved using the Polak-Ribiere conjugate gradient along with the backpropagation algorithm for training. As part of the validation, an ANN with 9 neurons per hidden layer was found to yield qualitative and quantitative results similar to the ANN used here. The minimum MSE was 0.00048.

The input neurons of the ANN are linear, while the neurons in the hidden and output layer are nonlinear with sigmoidal activation function, since this activation function gives values between 0 and 1, the network inputs and target values were accordingly normalized to the range [0.1, 0.9] [16]. It is important to remark that seven inputs were fed to the network: the two inlet temperatures at the current time and at a previous time with delay τ (τ = 1min), the outlet temperatures are a previous time and the pressure drop in the water-side. The network is trained to predict the current state: outlet temperatures ($T_w^{out}(t)$ y $T_a^{out}(t)$). This input-output configuration is schematically depicted in Figure 4.

In order to provide adaptive capabilities to the model and improve the predictions in the presence of slowly varying time dependent behavior, such as the produced by the fouling phenomena, a hybrid strategy, involving coupling of the ANN with a Kalman Filter, is proposed. The idea is to provide the model with a mechanism to account for the deviations observed improving the robustness of the overall model.

The Kalman filter is a numerical tool composed of dynamical equations and has been extensively used for stochastic estimation and noise filtering applications [17-18]. It is an optimal filter in the sense that it minimized the covariance matrix of the error on the experimental measurements.

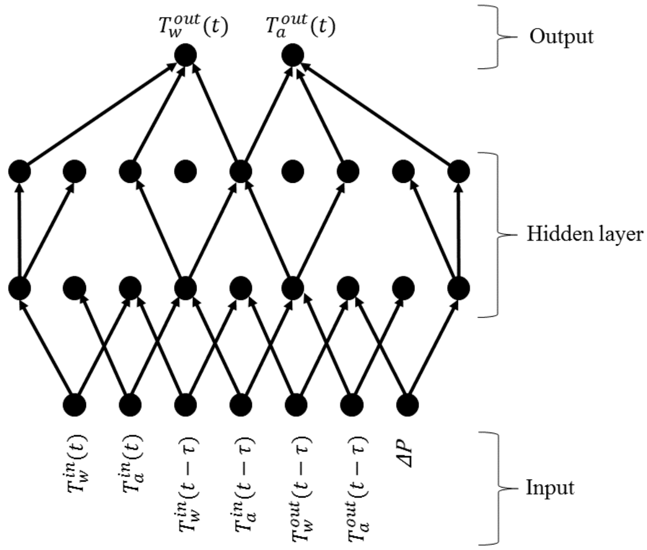

Figure 4. ANN architecture used. $T_w^{in}(t)$, $T_a^{in}(t)$, $T_w^{in}(t-\tau)$, $T_a^{in}(t-\tau)$, $T_w^{out}(t-\tau)$, $T_a^{out}(t-\tau)$ are the inputs to the ANN wich represent the current state of the system and ΔP is the value of the operating parameter. The outputs of the ANN $T_w^{out}(t)$, $T_a^{out}(t)$ are the prediction of the outlet temperatures. Only a few connections of the fully interconnected neurons are depicted.

The discrete Kalman filter deals with the general estimation problem of state x defined by the following lineal stochastic equation:

$$x_k = Ax_{k-1} + w_{k-1} \tag{1}$$

For a measurement z given by:

$$z = Hx_k + v_k \tag{2}$$

Where w_{k-1} and v_k are white Gaussian noise variables for the process and measurement respectively, being independent variables with normal distribution [$p(w) \approx N(0, Q)$, $p(v) \approx N(0, R)$] and constant covariant matrices given by **Q** and **R** respectively. In the absence of noise, **A** is a constant matrix that relates the previous state x_{k-1} with the current one x_k, while **H** relates the state x_k with the measurement z_k. $\hat{x}_k^-$ is the *a priori* estimation of the state at time *k* using information at time *k-1*. The filter estimates x_k as a linear combination of $\hat{x}_k^-$ and the error of the previous measurement, the difference between z_k and its prediction $\boldsymbol{H}\hat{x}_k$, multiplied by a gain K, as follows:

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-) \quad (3)$$

Matrix K is the so-called Kalman-gain and it is calculated from the error covariance, P, between the current state and *a priori* estimation of the same in such a way that it minimizes the error covariance *a posteriori*. The calculations are as follows:

$$P_k^- = AP_{k-1}A^1 + Q \quad (4)$$

$$K_k = \hat{P}_k^- H^T\left(H\hat{P}_k^- H^T + R\right)^1 \quad (5)$$

$$\hat{P}_k = (1 - K_k H)\hat{P}_k^- \quad (6)$$

The Kalman filter has been employed for nonlinear problems using linearization (the so-called extended Kalman filter) [19]. Here, a modification is introduced by replacing the linear estimation with the ANN prediction, in this manner one achieves a compensation of the model error. Further description has been given in [17-18].

RESULTS AND DISCUSSIONS

Time-series from HE4, Figure 3, were used for testing and validating the ANN predictions. Inlet temperatures (Figure 3 a) and c)), along with the pressure drop, were used as network inputs in order to predict the outlet temperatures ($T_w^{out}(t)$ and $T_a^{out}(t)$, depicted in panels b) and d) of Figure 2). Figure 5 illustrates the comparison between observed and predicted values of the outlet temperatures.

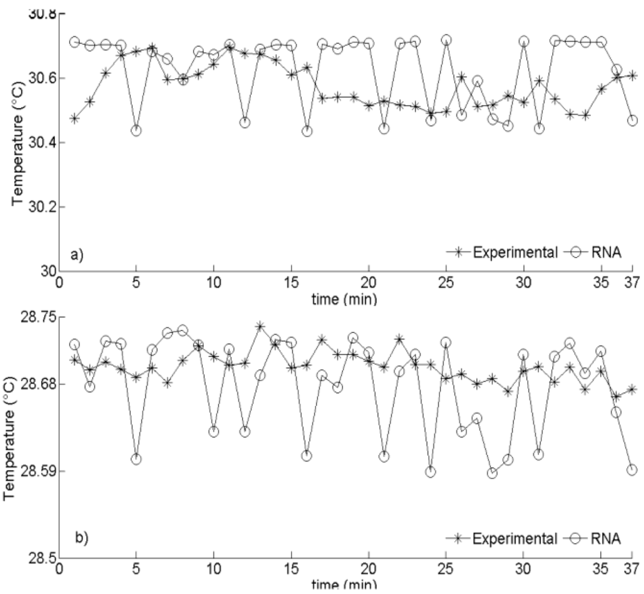

Figure 5. Comparison of predicted and observe outlet temperatures for HE4. a) water temperature. b) air temperature.

These results have a relative error (RE) between predicted and experimental points below 0.008% and 0.004% for T_w^{out} y T_a^{out} [20].

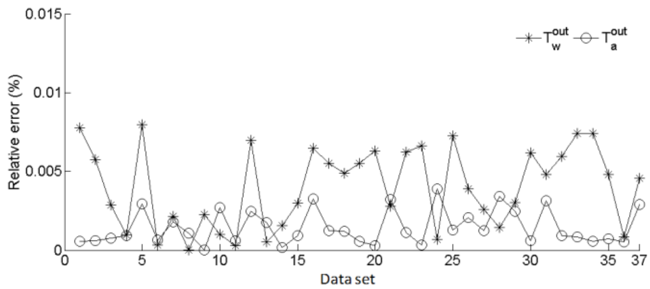

Figure 6. Relative Error for ANN predictions.

While the ANN shows the general tendency of the dynamics, but not some of the high-frequency component of the time-series. In order to further improve this prediction, the Kalman filter is introduced.

Figures 7 and 8 show the comparison between experimental, ANN alone, and ANN assisted by the Kalman Filter for water and air outlet temperatures respectively. Clearly, the predictions are improved capturing the high-frequency variation.

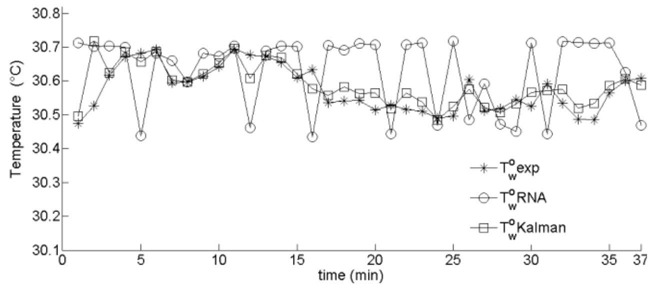

Figure 7. Comparison of water outlet temperature predictions.

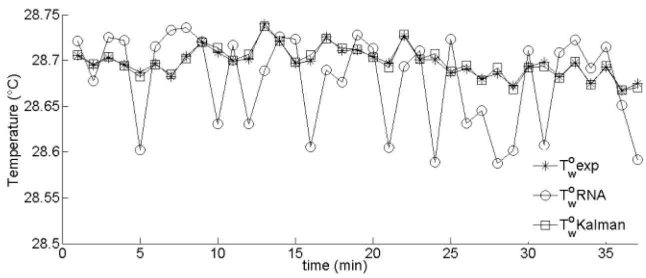

Figure 8. Comparison for air outlet temperature predictions.

Furthermore, has can be appreciated in Figure 9 de maximum relative error drops dramatically for the air temperature prediction, and it is also reduced for the water outlet temperature prediction.

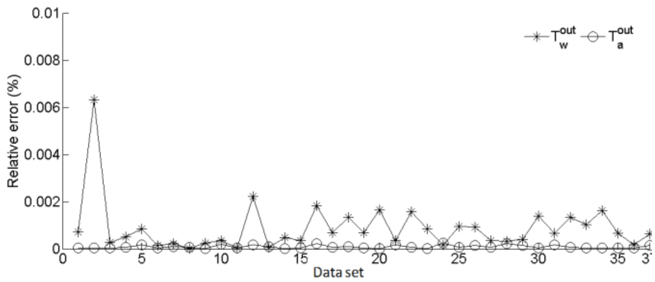

Figure 9. Relative error for the Kalman filter assisted ANN strategy.

CONCLUSIONS

The aim of this work is to develop a framework for heat exchanger behavior prediction for real-time applications. Here, the strategy was successfully tested with data from four cross-flow heat exchangers in operation at a hydroelectric power plant. By using an Artificial Neural Network coupled with a Kalman filter, a robust predictive model is constructed. By lumping the experimental data from four different exchangers, one achieves a “general” predictor, since one may assume that the efficiencies of the exchangers are different because they will exhibit different degrees of corrosion and fouling. Furthermore, the corrective capabilities of the Kalman Filter, provide an adapting mechanism, in principle capable of handling the slowly evolving change in efficiency related to the operation of the exchangers due to corrosion and fouling.
Currently, laboratory experiments are being developed, in order to further test these capabilities and prove this model framework as the basis for control and optimization applications.

ACKNOWLEDGMENTS

We acknowledge the Mexican Council of Science and Technology (CONACYT) for the scholarship granted for the development of this project.

REFERENCES

[1] Kakaç, S., Liu, H., Pramuanjaroenkij, A., 2012, Heat exchanger, selection, rating and thermal design, CRC PRESS, Taylor & Francis Group, Boca Raton, EUA, Chap. 1.

[2] Ranjbar, K., 2010, “Effect of flow induced corrosion and erosion on failure of a tubular heat exchanger,” Material and Design, 31, pp. 613-619.

[3] Kuznicka, B., 2009, “Erosion-corrosion the heat exchanger tubes,” Engineering Failure Analysis, 16, pp. 2382-2387.

[4] Usman, A., Nusair Khan, A., 2008, “Failure analysis of heat exchanger tubes,” Engineering Failure Analysis, 15, pp. 118-128.

[5] Mohanraj, M., Jayaraj, S., Muraleedharan, C., “Applications of artificial neural networks for thermal analysis of heat exchangers - A review,” International Journal of Thermal Sciences, 90, pp.150-172.

[6] Rico-Martinez, R., Krischer, K., Kevrekidis, I.G., Kube, M.C., Hudson, J.L., 1992, “Discrete- vs. continuous-time nonlinear signal-processing of Cu electrodissolution data,” Chemical Engineering Communications, 118, pp. 25-48.

[7] Rico-Martinez, R., Anderson, J.S., Kevrekidis, G., 1996, “Self-consistency in neural network-based NLPC analysis with aplication to time-series processing,” Computer chem. Engng, 20, pp. 1089-1094.

[8] Haykin, S., 1999, Neural networks and learning machines, McMaster University, Canada, Chap. 1.

[9] Takens, F., “Detecting strange attractors in turbulence,” Dynamical Systems and Turbulence, 898, pp. 366-381.

[10] Granger, C.W., Joyeux R, R., 1980, “An introduction to long-memory time series models and fractional differencing,” Journal of time series analysis, 1(1), pp. 15-29.

[11] Xie, G.N., Wang, Q.W., Zeng, M., Luo, L.Q., 2007, “Heat transfer analysis for shell-and-tube heat exchanger with experimental data by artificial neural networks approach,” Applied thermal engineering, 27, pp. 1096-1104.

[12] Pacheco-Vega, A., Sen, M., Yang, K.T., McClain, R.L., 2001, “Neural network analysis of fin-tube refrigerating heat exchanger with limited experimental data,” International journal of heat and mass transfer, 44, pp. 763-770.

[13] Islamoglu, Y., 2003, “A new approach for the prediction of the heat transfer rate of the wire-on-tube type heat exchanger use of an artificial neural networks model,” Applied thermal engineering, 23, pp. 243-249.

[14] Tatwawadi, V.H., Modak, J.P., Chilbule, S.G., 2010, “Mathematical modelling and simulation of working of an enterprise manufacturing electric motors,” International Journal of Industrial Engineering, 17(4), pp. 341-359.

[15] Mithat Zeydan, 2008, “The comparison of artificial intelligence and traditional approaches In FCCU modeling,” International Journal of Industrial Engineering, 15(1), pp. 1-15.

[16] Khataee, A.R., Kasiri, M.B., 2010, “Artificial neural networks modeling of contaminated water treatment processes by homogeneous and heterogeneous nanocatalysis,” Journal of molecular catalysis a: Chemical, 331, pp. 86-100.

[17] Ramírez-Álvarez, E., González-Figueredo, C., Rico-Martínez, R., 2010, “Reference Models assisted by nonlinear Kalman filters as a strategy for real-time bifurcation detection,” 20th European Symposium on Computer Aided Process Engineering ESCAPE20.

[18] Ramírez-Álvarez E., Calderón Ramírez, M., Rico-Martínez, R., González-Figueredo, C., Parmananda, P., 2013, "Detecting Bifurcations in an Electrochemical Cell Employing an Assisted Reference Model Strategy," The journal of physical chemistry, 117, pp.535-540.

[19] Ljung, L., 1979, "Asymptotic behavior of the extended Kalman filter as a parameter estimator for linear systems," Automatic Control, IEEE Transactions on, 24(1), pp. 36-50.

[20] Islamoglu, Y., Kurt, A., Parmaksizoglu, C., 2005, "Performance prediction for non-adiabatic capillary tube suction line heat exchanger an artificial neural network approach," Energy Conversion and Management, 46, 223-232.