International Journal of Modelling and Simulation

ISSN: 0228-6203 (Print) 1925-7082 (Online) Journal homepage: http://www.tandfonline.com/loi/tjms20

Neural network ARX model for gas conditioning tower

Rezki Haddouche, Boukhemis Chetate & Mohand Said Boumedine

INTERNATIONAL JOURNAL OF MODELLING AND SIMULATION
https://doi.org/10.1080/02286203.2018.1538848

ARTICLE

Neural network ARX model for gas conditioning tower

Rezki Haddouche, Boukhemis Chetate and Mohand Said Boumedine

Automation and Electrification Department, University of M'hamed Bougara Boumerdes, Boumerdes City, Boumerdes, Algeria

ABSTRACT

This work focuses on the identification of the gas conditioning tower (GCT) operating in a cement plant. It is an important element in the cement production line. Mathematical modeling of such a process proves to be very complex. This is due to the phenomena that occur during the operation of the system. An artificial neural network-based auto-regressive with exogenous inputs (NNARX) model is constructed with the aim to study the system as well as used to control the process. Resulted models are tested and validated using data extracted on a GCT operating at Chlef cement plant in Algeria.

ARTICLE HISTORY

Received 25 August 2017

Accepted 18 October 2018

KEYWORDS

gas conditioning tower; artificial neural network; nnrx model; system identification; dust collector

1. Introduction

Cement production is a very common industrial activity in the world. However, it is highly polluting if the dust contained in the fumes generated along the cement production process is not recovered [1]. The gas conditioning tower (GCT), situated between the preheater tower and the electrostatic precipitator, is used to cool and condition the fumes coming from the preheater tower and going to the electrostatic precipitator, in order to increase the electrostatic precipitator effectiveness [2]. To ensure good recovery of the dusts in the electrostatic precipitator, optimization of the GCT functioning is necessary. For this purpose, the study and identification of the GCT are of big importance.

The study of the GCT has been the object of several research studies. Schioth studied the optimization of water injection control in the gas conditioning towers while highlighting a conventional control system order [3]. Raring presented a new vision of the GCT [4]. Bapat presented the effect of the GCT for the application of the electrostatic precipitators in the cement factories in India [5]. In the same context, the contributions of Reyes, who proposed a new control method of the fumes flow temperature in the cement plant manufacturing, and of Reigel, who analyzed the influence of the mechanism of water injector channels on the GCT efficiency, may be quoted [6,7]. Moreover, Reigel advises a cascade loop of adjustments in order to improve the reaction speed in the adjustment system.

It is to be noted that these works have helped to improve the operating efficiency not only for the GCT but also for the electrostatic precipitators. However, the analysis of existing works reveals that, on one hand, the authors have not based their studies on the GCT model, leading to think that knowledge of the GCT model can improve the GCT performances, and on the other hand, in this field, there are no works that use artificial intelligence techniques for modeling and control, such as fuzzy logic and artificial neural networks.

Artificial neural networks (ANN) are the computational models inspired by the human brain. They can be trained to produce outputs that are expected from gave inputs. In the domain of study, analysis and control of the industrial processes, this is known as a neural network application for system identification and control. The literature presents several applications in this regard. The works that may be noted in this area, which focus on the application of neural network to learn dynamic systems comportment, are of Suman [8] and Nirmaladevi [9]. In the same particular field, the works done by Tani [10–12] on neural network applications for identification and prediction the systems performances are noteworthy.

To summarize, it is our belief that the use of artificial neural networks to identify the dynamic behavior of the gas conditioning tower, based on experimental data collected directly on the actual process, will make it possible to build a model for the system. This model will be essential to design control strategies in order to optimize the GCT operation.

CONTACT Rezki Haddouche re.haddouche@univ-boumerdes.dz Automation and Electrification Department, University of M'hamed Bougara Boumerdes, Boumerdes, Algeria

Section 2 of this paper gives a description of the GCT operating principle and its position in the fumes circuit. In section 3, the procedure of neural network-based modeling and identification of the GCT is presented. Section 4gives the results of this modeling and identification and provides their analysis. Section 6 is the conclusion.

2. Gas cleaning process in cement industry

The cleaning of gas in the cement industry is a very difficult task. The modern process of cement production implies the crushing of the raw carbonated and argillaceous materials and the heating treatment of the rectified raw flour (i.e. preheated), precalcined and clinkered in the rotating kiln. After this stage, the kiln is cooled by a kiln cooler. All these operations produce a great quantity of fumes (gases and dust) whose characteristics are variable in terms of temperature values, moisture content, distribution of particles' dimension, and chemical composition [5,13]. The emission of this dust constitutes one of the principal factors of air pollution. To purify these fumes before their rejection in the atmosphere it is necessary to use an electrostatic precipitators (ESP). For the success of the operation, the ESP performances depend considerably on the equipment that is located upstream. This explains why all the electrostatic precipitators are associated with the GCT [1,3,4].

The aeraulic fumes circuit found in the cement production process presented in Figure.1 is the most frequently used one in the cement production line. The circulation of the fumes is carried out according to the evolution of the process [1]:

- The fumes go from the preheating tower to the chimney via the raw mill and electrostatic precipitator;
- In the case if the homogenization silos are full, the fumes are first directed toward the gas conditioning tower, then to the electrostatic precipitator and finally to the chimney;
- In the mixed mode, the energy provided to the raw mill is rather high. Approximately 10%–20% of the fumes are sent to the GCT and the remaining quantity to the raw mill.

One part of the generated fumes is sent toward the raw mill and the other part is directed toward the gas conditioning tower. In the raw mill, the fumes are used to dry the raw materials and then they are forwarded to the electrostatic precipitator. In the GCT, the fumes are conditioned (reduction in temperature at the lower part of the equipment with maximum resistivity) and are purified from a significant amount of dust then sent toward the electrostatic precipitator. To finish, the gases are rejected into the atmosphere via the chimney [1].

The picture in Figure 2 gives a photographic view of the cement production line. In the figure, several parts are identified: The GCT, the cyclone preheating and the chimney.

2.1. Gas conditioning process

Gas temperature and dust resistivity affect the ESP performance. Gas conditioning is one of the means to

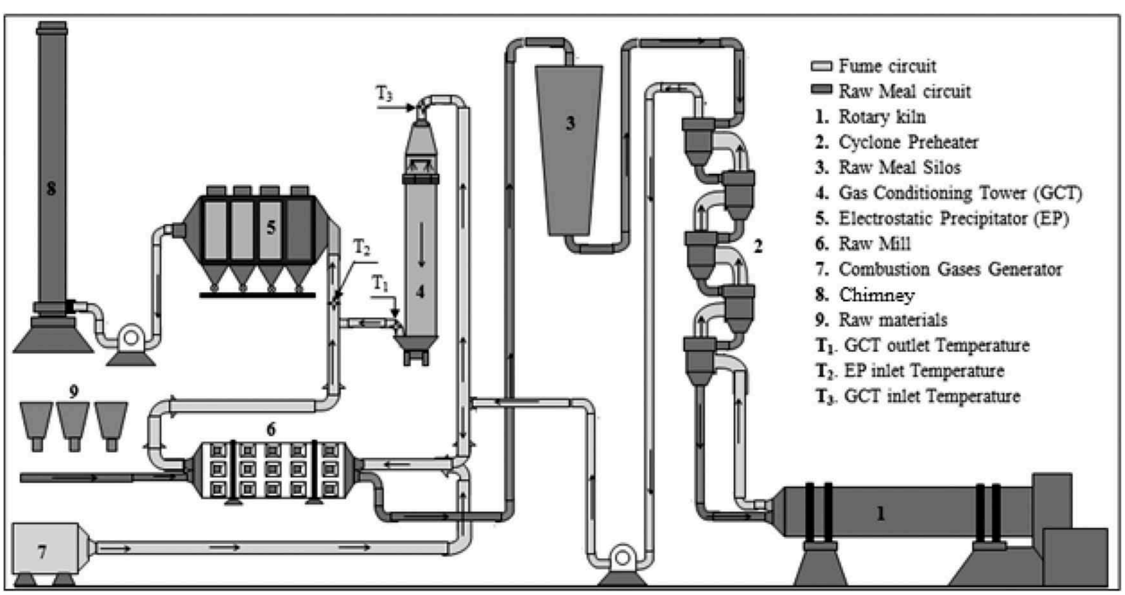

Figure 1. Fumes circuit in cement plant.

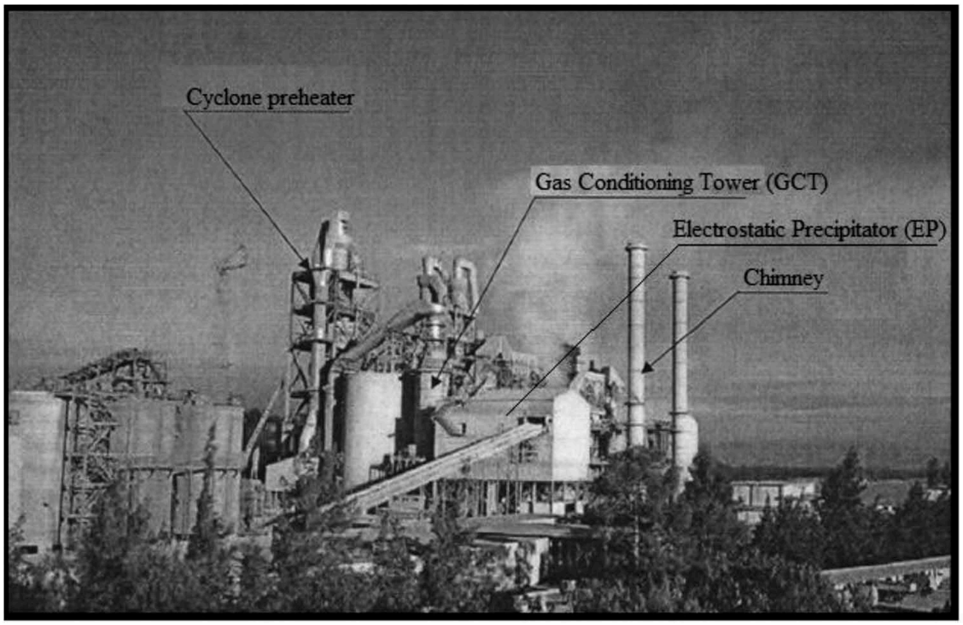

Figure 2. Photographic view of GCT in cement production line.

tackle this situation. It comprises any one or the combination of the following [5,6]:

- Reduction of gas temperature
- Increase of gas moisture content
- Dilution of gas by cold air
- Increase of the concentration of hydrophilic compounds, such as K_2SO_4, in the gas.

The moisture content of the gas is increased in the equipment called 'gas conditioning tower' (Figure 3). Gas enters at the top of the tower, flows down and exits at the bottom. Water is introduced into the gas stream at the top in tiny droplets produced by spray nozzles. As they flow down, the water droplets absorb heat from the gas and evaporate. The gas is cooled and its moisture content is increased. The inflow of water is controlled such that the entire quantity introduced at the top evaporates and no water reaches the tower bottom. In this way, the handling of dust collected at the tower bottom becomes easy. The water flow control is achieved by continuous measurement of outgoing gas temperature. For example, in the kiln section, exit gas temperature is brought down from 330°C to about 150°C and the dew point is raised from 40°C to about 60°C. The following constraints on the use of the GCT have been reported [1]:

- Gas cooled to 150°C can't be used for further heat recovery
- High cost of electric power and water
- Depending on the availability of water of acceptable quality
- Additional maintenance and unreliability due to system failures.

However, the development of a good conduit model for GCT control will allow to optimize its operation and, therefore, to optimize the performance of the electrostatic precipitator.

2.2. Gas conditioning tower control scheme

There are many control strategies of the temperatures of the fumes forwarded to the electrostatic precipitator that are applied in the cement industry [13]. All GCT control strategies cited in the literature are based on the experimental method. Moreover, the control parameters are defined by trial and error procedure.

In Chlef's cement plant, the control strategy applied is illustrated in Figure 4. In this case, the signals from the thermocouples are compared with a temperature set point, and a signal to increase or decrease the water flow is transmitted to the water flow control valve. The air flow control valve is then modulated to control the proper air-to-water ratio. Of course, the control parameters in this control strategy are defined by trial and error procedure. This operation is carried out in the installation and the start-up of the system.

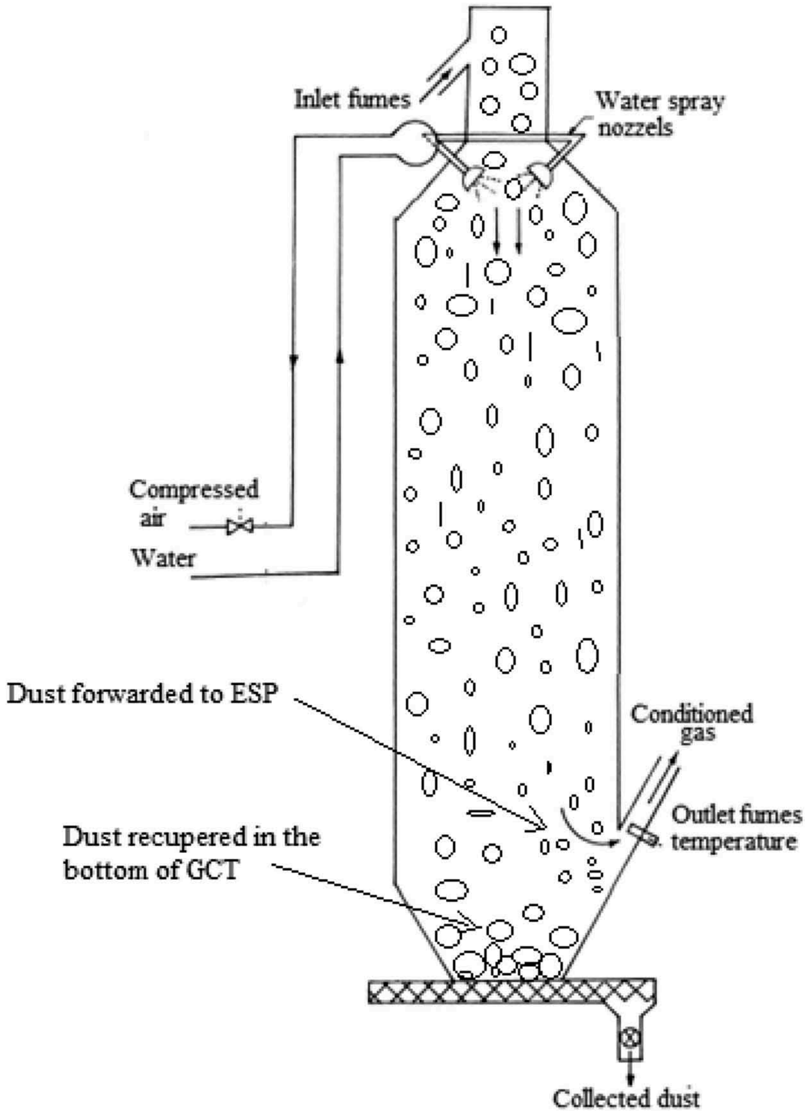

Figure 3. The GCT used in cement plant.

3. Neural network identification procedure

Identification procedure is traditionally used to establish the model parameters with a specified structure. This involves the collection of input-output data and the use of a parameters identification technique, such as least squares, to adjust the parameters of the model chosen. This procedure is suitable for the linear systems, but is not directly applicable to modeling nonlinear systems.

3.1. System identification procedure

To ensure substantially the validity of the resulting neural model, there are four steps to follow in the experimental method based on system identification [14,15]:

- Acquisition of the excitation signal by collecting input/output data file from the process,
- Selecting the model structure (adjusting the neural network: number of layers, number of neurons on each layer, number of input/output),
- Model Estimation (adjusting the neural network weights),
- Model validation.

The following flowchart summarizes the procedure adopted for neural network system identification (Figure 5).

In our case, the used neural network is a single layer neural network with eight neurons in the hidden layer, having multi inputs and a single output. The number of inputs indicates the order 'n' of the model sought to build.

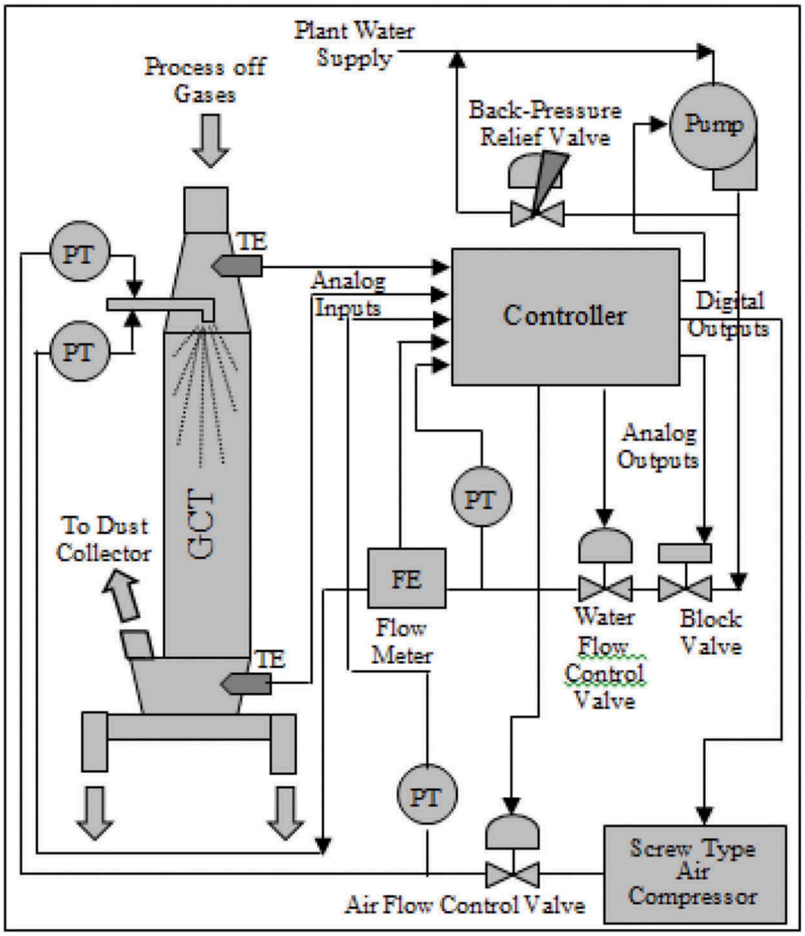

Figure 4. Algerian's GCT control scheme.

- Two inputs: first order model (n = 1);
- Four inputs: second order model (n = 2);
- Six inputs: third order model (n = 3).

It is to be noted that for each two additional inputs, the model order 'n' increases by one unit [16,17].

3.2. Experimental data collection

To collect experimental data from the gas conditioning tower, variations needs to be applied to the water flow Q (m^3/h) injected at the GCT inlet and the temperature variations T (°C) at the outlet of the tower need to be recorded. As the GCT is a slow behavior system (temperature evolution), the experimental data are collected with a sampling time equal to 6s.

To obtain the data file (input/output), the intervention in the process was carried out under the following conditions:

- The variation of the water flow is between 14 m^3/h and 30 m^3/h because, on the one hand, if the water flow is lower than 14 m^3/h then the gas temperature is very high and the electrostatic precipitator loses in efficiency, and, on the other hand, if the water flow is more than 30 m^3/h, then there will be formation of sludge in the GCT bottom [13];
- The step length of the input signal (water flow) must be sufficiently large because the GCT is a slow process.

Two different sets of data are collected. The first set of data is collected in the control room. It will be used to train the neural network models because the excitation signal is a random amplitude signal (RAS). The second set of data is collected manually at the water injection valve. This set of data will be used to validate the obtained models.

3.2.1. Data collected via the control room

The first trial is made from the control room. The excitation signal of the process is a random amplitude signal (RAS). The amplitude signal is random variable and the width is set at 125 s for each impulse.

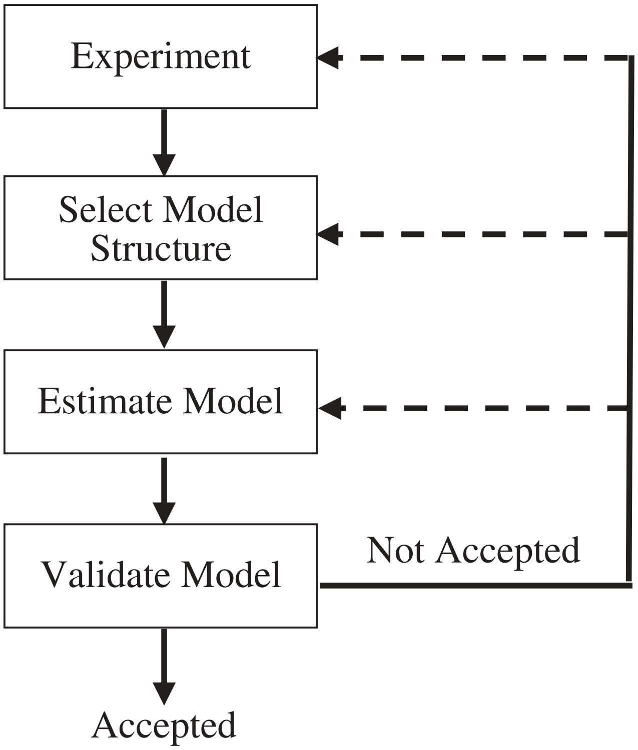

Figure 5. The system identification procedure.

Obtained data is given in Figures 6(a, b). Figure 6(a) gives the water flow variation at the inlet GCT and Figure 6(b) gives the temperature recorded at the outlet of the latter. This data will be used to train the neural network in order to build the neural network model.

3.2.2. Data collected directly from the system

The second trial is applied directly on the system. The control system is turned in manual mode, and then the water injection valve is turned on/off. The water variation is shown in Figure 7(a) and the temperature recorded is shown in Figure 7(b). This data will be used to validate the neural network model obtained.

3.3. Neural network ARX identification scheme

The direct neural network auto-regressive with exogenous input model is obtained by learning an artificial neural network based on data inputs/outputs of the gas conditioning tower. The identification scheme is given in Figure 8 and the learning algorithm used is Levenberg-Marquardt algorithm.

The neural network structure is fixed with one hidden layer which contains ten hyperbolic tangent units (f_1) and one output layer which contains one linear unit (f_2) (Figure 9).

The number of inputs (Q and T) will be fixed according to the model order to build (First order: n = 1, second order: n = 2 or third order: n = 3).

In this work, it is projected to testing three different order models according to the number of inputs of the neural network selected.

The neural network output T_n is calculated as follows:

$$T_n(k) = f_2\left(\sum_{j=1}^{m} w_{sj} f_1\left(\sum_{i=1}^{n} w_{ei,j}\, Q(k-i) + \sum_{i=1}^{n} w_{en+i,j}\, T(k-i) + w_{ej}\right) + w_s\right) \tag{1}$$

where;

$$W_e = \begin{bmatrix} w_{e1,1} & \cdots & w_{e1,m} \\ \vdots & \ddots & \vdots \\ w_{e2n,1} & \cdots & w_{e2n,m} \end{bmatrix};\ W_s = \begin{bmatrix} w_{s1} \\ \vdots \\ w_{sm} \end{bmatrix};\ W_{eb} = \begin{bmatrix} w_{e1} \\ \vdots \\ w_{em} \end{bmatrix};\ W_{sb} = w_s$$

and W_e, W_s, W_{eb}, and W_{sb} are respectively: the input weights matrix, the output weights vector, the input bias vector and the output bias vector. This weights matrix and These vectors, indicated vector θ, are the adjustable parameters to calculate during the trained operation.

3.4. Neural network-based autoregressive with exogenous part model calculation

Neural network autoregressive with exogenous part (NNARX) is a nonlinear model. In this case, the regressors are based on inspiration from linear system identification [15,17,18].

The regressors can be given by:

$$\varphi(t) = [T(t-1)\ldots\ T(t-n_a)\ Q(t-n_k)\ldots\ Q(t-n_b-n_k-1)\ ]^T \tag{2}$$

The training data are a set of inputs $Q(t)$ and outputs $T(t)$ presented in Figure 5(a,b) the training set is noted as follows:

$$Z^N = \{[Q(t), T(t)]\ t = 1, \ldots, N\} \tag{3}$$

The training objective is then to determine an optimal vector $\hat{\theta}$ which allows to obtain a neural network outputs $T_n(t)$ as close as possible to the GCT temperature outputs $T(t)$.

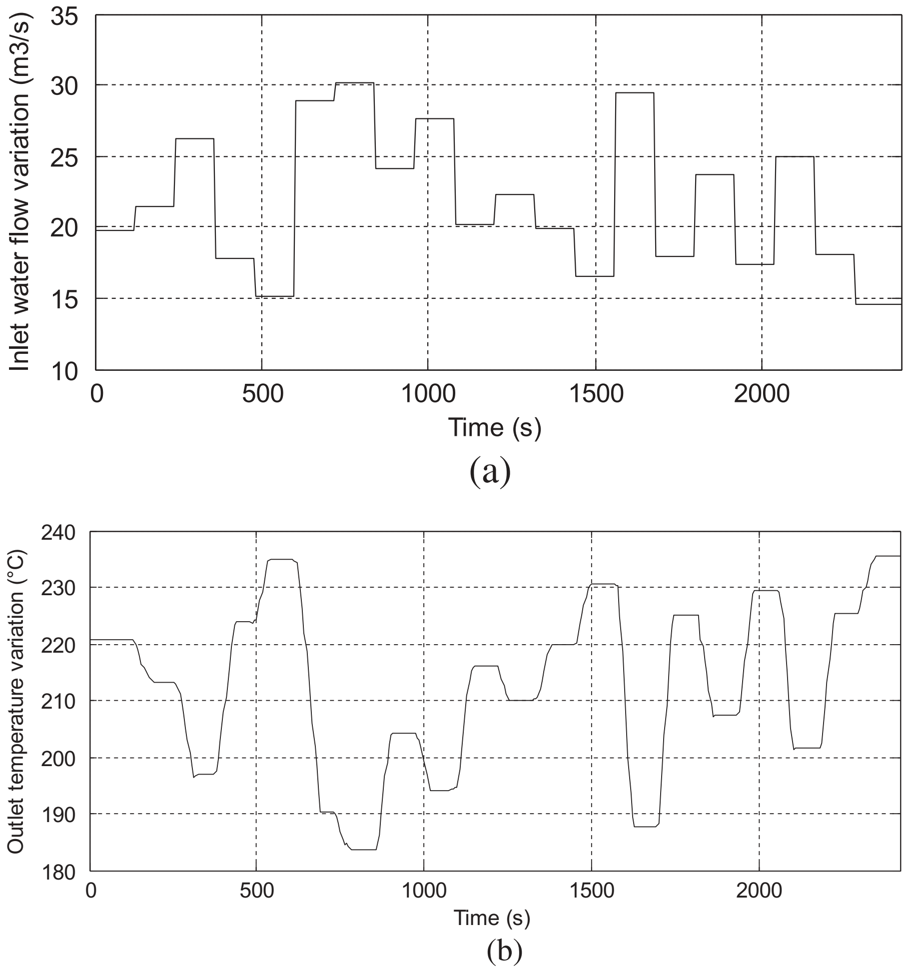

Figure 6. **a** Water flow variation (Q) at the inlet of the GCT. **b** Temperature variation (T) at the outlet of the GCT.

$$Z^N \rightarrow \hat{\theta} \tag{4}$$

A mean sum of squared error MSSE criterion is the prediction error strategy applied to calculate the weights correction as follows:

$$E_N\left(\theta, Z^N\right) = \frac{1}{2N}\sum_{t=1}^{N}[T(t) - T_n(t|\theta)]^T[T(t) - T_n(t|\theta)] \tag{5}$$

Moreover, the difference between an ARX model and an NNARX model is in the black box model chosen. In the NNARX model, the minimization of mean-square error criteria is based on the Levenberg-Marquardt algorithm.

Like the quasi-Newton methods, the Levenberg-Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function is the sum of squares (as is typical in training feed-forward networks), then the Hessian matrix can be approximated like the following [19,20]:

$$H = J^T J \tag{6}$$

And the gradient can be computed like the following, where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors.

$$g = J^T e \tag{7}$$

The Jacobian matrix can be computed through a standard back-propagation technique that is much less complex than computing the Hessian matrix.

The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the weights computing like the following:

$$W_{k+1} = W_k - \left[J^T J + \mu I\right]^{-1} J^T e \tag{7}$$

When the scalar μ is zero, it is only the Newton's method, using the approximate Hessian matrix. When μ is large, this becomes the descendant gradient with a small step size. Newton's method is faster and more accurate, near error minimum. The aim is therefore to

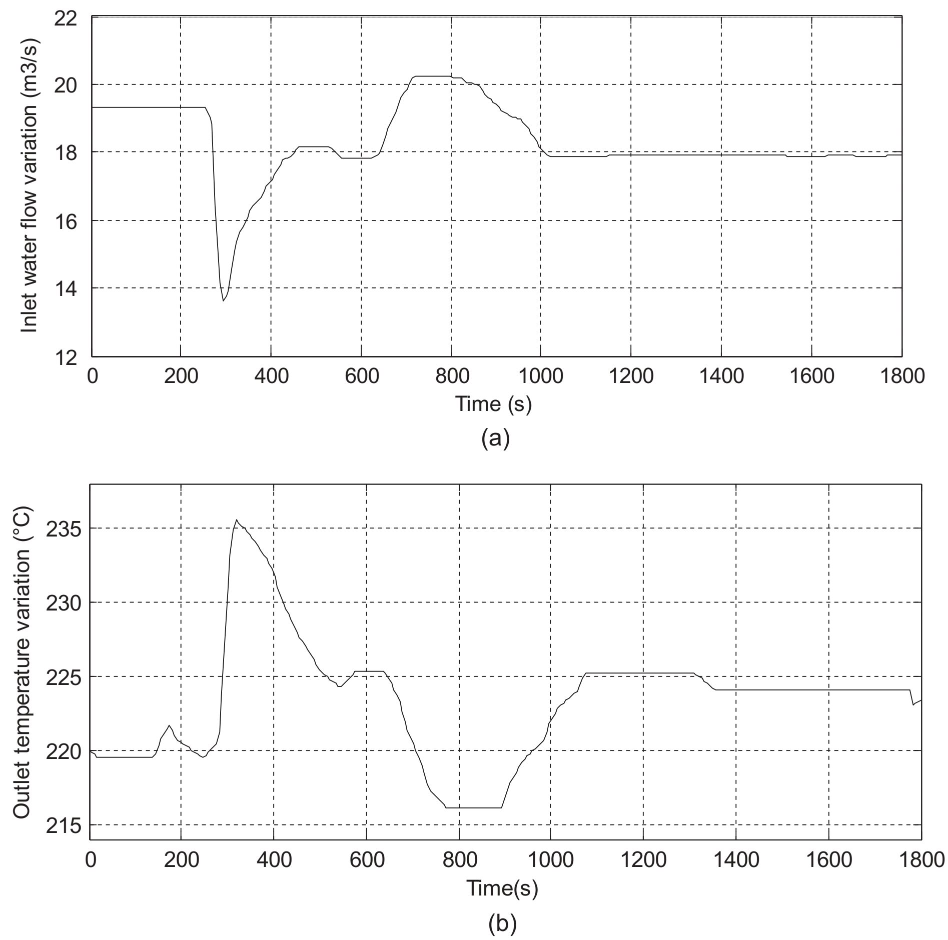

Figure 7. **a** Water flow variation (Q) at the inlet of the GCT in manual mode. **b** Temperature variation (T) at the outlet of the GCT in manual mode outlet.

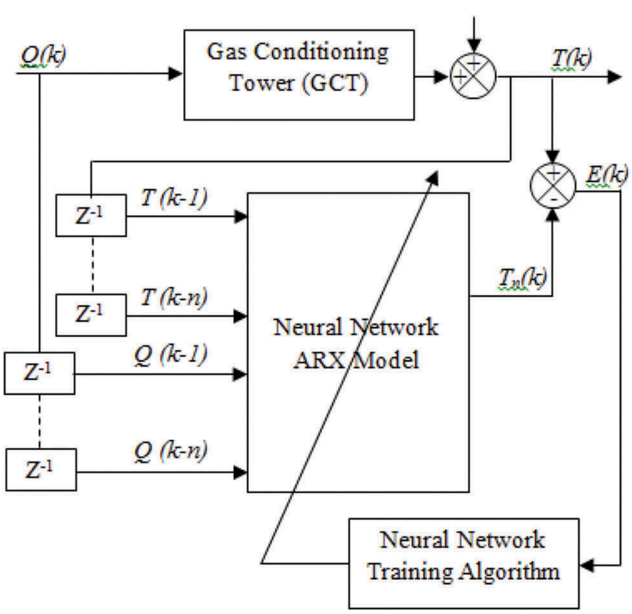

Figure 8. NNARX model identification scheme for GCT.

shift toward the Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step increases the performance function. In this way, the performance function is always reduced at each iteration of the algorithm.

4. Results and discussion

Three different models are selected: first-order model, second-order model, and third-order model. The models are trained using data collected in the real process, and the results are illustrated in Figures10-12.

Figure 10 shows the trained result of the first-order model (n = 1). In this case, the neural network has two inputs for each iteration: water flow inlet $Q(k-1)$ and outlet measured temperature $T(k-1)$.

Figure 11 shows the trained result of the second-order model (n = 2). In this case, the neural network

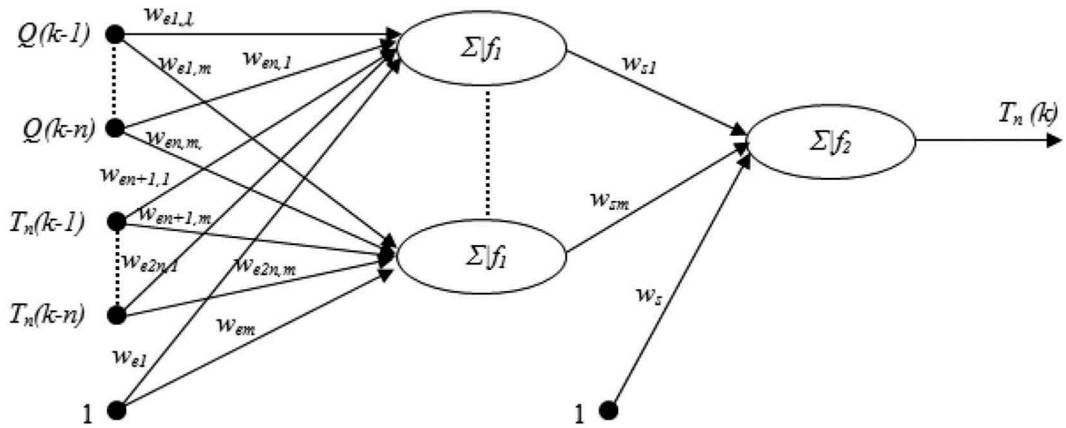

Figure 9. Neural network structure with one hidden layer.

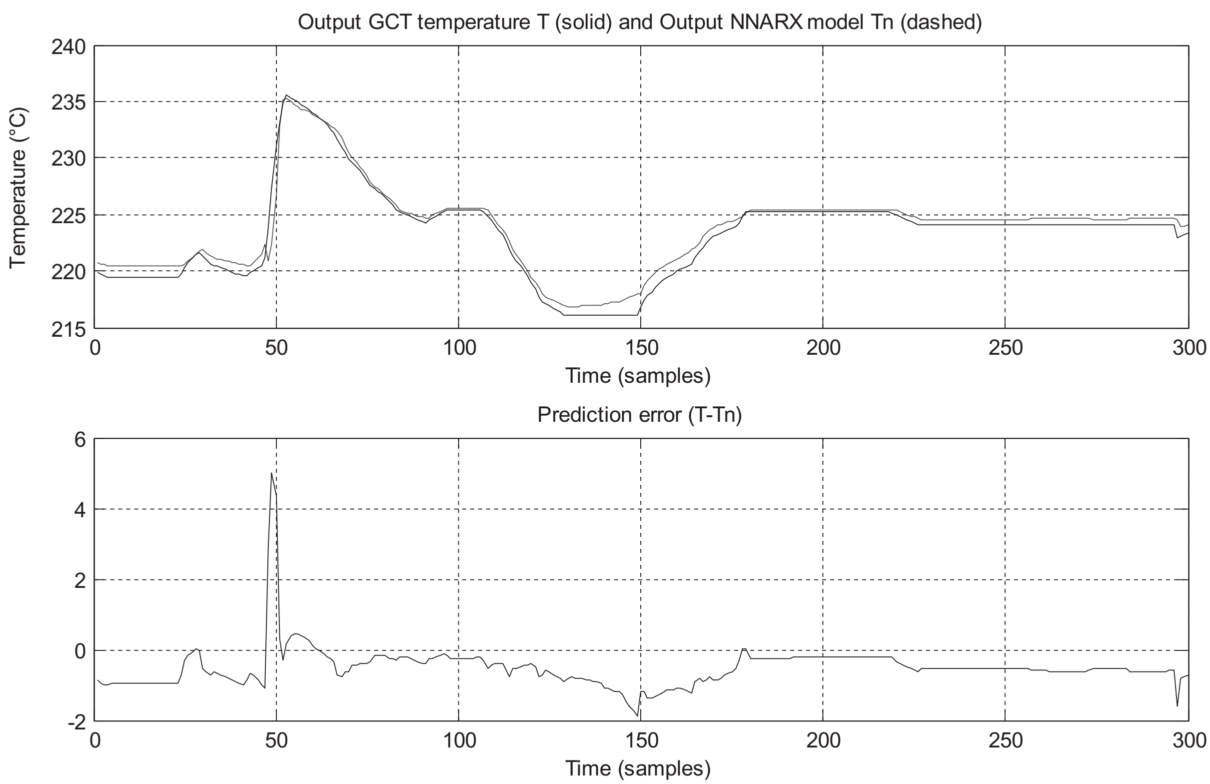

Figure 10. Trained result and validation of the first order.

has four inputs for each iteration: water flow inlet (*Q(k-1), Q(k-2)*) and outlet measured temperature (*T(k-1),T(k-1)*).

Figure 12 shows the trained result of the third-order model (n = 3). In this case, the neural network has six inputs for each iteration: water flow inlet (*Q(k-1), Q(k-2), Q(k-3)*) and outlet measured temperature (*T(k-1),T(k-2), T(k-3)*).

These figures indicate that the NNARX models adapt excellently the nonlinear dynamics of the GCT. The training algorithm forces the NNARX models to converge quickly to the desired recurrent neural network models. Moreover, in the case of the first order model, the prediction error (Figure 10) is in the range of [−2, + 6], and in the case of the second and third order models, the prediction error (Figures 11 and 12) is in the range of [−2, + 2].

Furthermore, the prediction error peaks (at Time ≃ 48 and Time ≃ 295) in the second-order model are less than the prediction error peaks obtained in the cases of the first and the third order models.

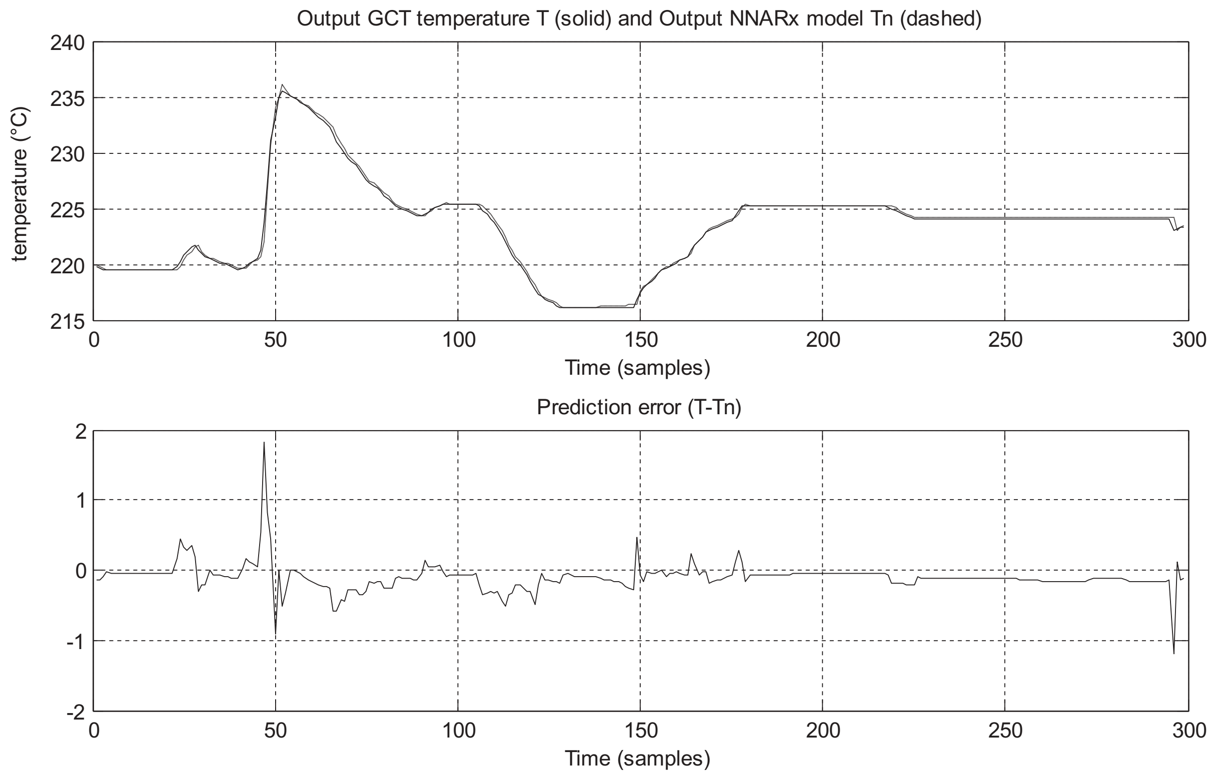

Figure 11. Trained result and validation of the second order.

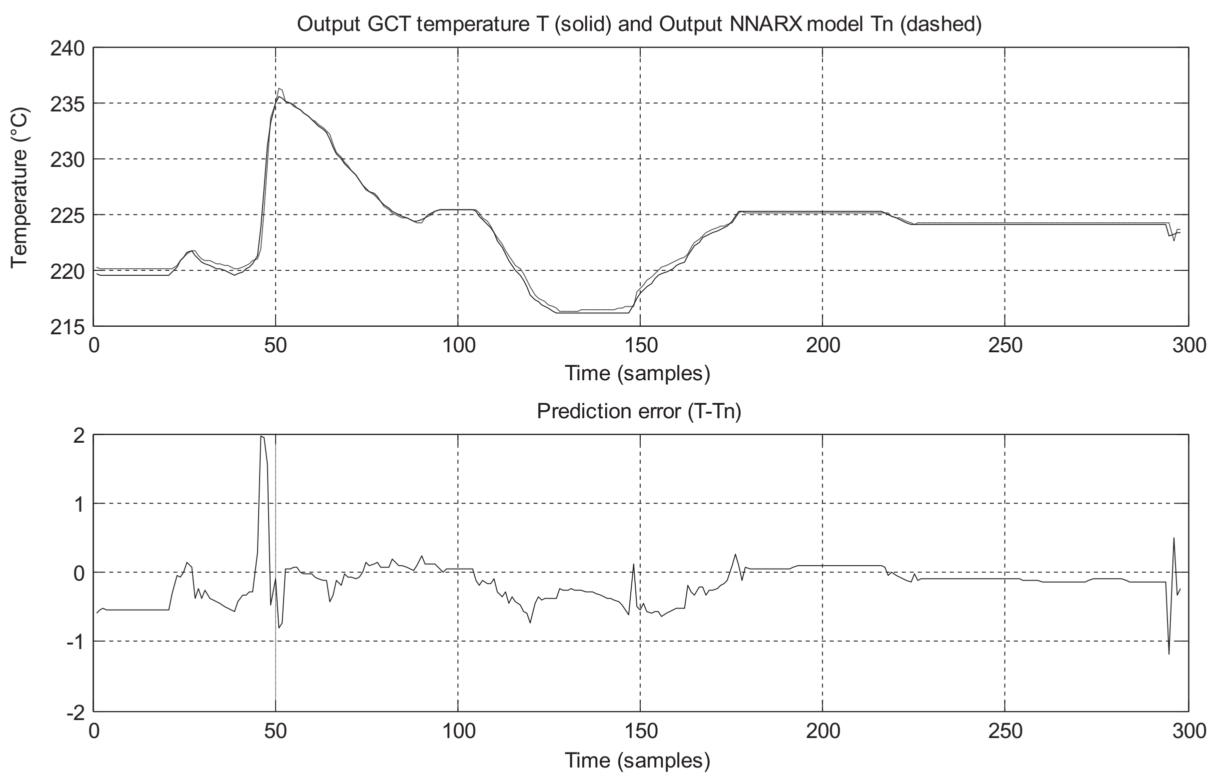

Figure 12. Trained result and validation of the third order.

5. Conclusion

Based on the obtained results by the application of neural network-based autoregressive with exogenous part (NNARX) model identification, it can be stated that the model NNARX is an adequate model type to describe the complex and dynamic systems. Regarding the identification results, the three models obtained are acceptable. However, the results show that the second-order NNARX model yields better performance and higher accuracy than the first and the third order NNARX models.

Also, the obtained model can be used to select the GCT controller structure, to compute the GCT controller parameters and to analyze the dynamics of the GCT and to enable automatic diagnosis. These results are very interesting because they are based on the experimental data.

In addition, neural networks based identification is an effective approach to the identification of systems, as is shown by the good results obtained.

Acknowledgments

Experimental data are collected at the Chlef's Cement Plant.
Industrial zone; Oued Sly – BP 54.02310 Oued Sly, Chlef, Algeria.

Disclosure statement

No potential conflict of interest was reported by the authors.

Notes on contributors

Rezki Haddouche was born in Algeria on January 7, 1977. He received his Master of Science degree in Automation from Mouloud MAMMERI Tizi-Ouzou University, Algeria, in 2002 and his Magister degree in Process Control and Automation from Alger's Polytechnic school in 2006. At present, he is a Doctoral candidate at Boumerdes University. His research interests include neural networks, system identification and modeling. Currently, Mr. Haddouche is a teacher researcher at the Mouloud MAMMERI, Tizi-Ouzou University.

Boukhemis Chetate Professor of the Boumerdès University (Algeria). He is, in one hand, the Director of the Research Laboratory on the Electrification of Industrial Enterprises and, in another hand, Editor and reviewer of International Journals in Electrical Engineering. Boukhemis Chetate has an original scientific contribution in many domains in electrical engineering, such as: Electrical Energy Saving; Electric drives; Automatic control; Artificial intelligence; Industrial applications, etc.

Mohand Said Boumedine Professor of the Boumerdès University (Algeria). He received his Master of Science degree in Automation from Boumerdes University, Algeria, and his PhD. degree in Process Control and Instrumentation Engineering from AGH University, Poland. Currently, Mr. Boumedine is a teacher researcher at the Boumerdes University.

ORCID

Rezki Haddouche http://orcid.org/0000-0002-6141-6013
Boukhemis Chetate http://orcid.org/0000-0002-6118-9877
Mohand Said Boumedine http://orcid.org/0000-0003-4277-543X

References

[1] Zimwara D, Mugwagwa L, Chikowore TR Air pollution control techniques for the cement manufacturing industry: a case study for Zimbabwe. CIE 42 Proceedings; 2012 July 16-18; Cape Town, South-Africa.

[2] Berubre RA Effective temperature control for cement kiln off-gases. 2012; www.cheresources.com/cementkiln.shtml

[3] Schioth M. Better control of cooling tower water injection of electrostatic precipitators. 1997; Cem, Concr, Plasters, Lime. 825(2):104–110.

[4] Raring DL. A new look at evaporative gas cooling and conditioning in the cement industry. IEEE Transaction Ind Appl. 1979;IA-15(4):357–364.

[5] Bapat JD. Application of ESP for gas cleaning in cement industry – with reference to India. J Hazard Mater. 2001;B81:285–308.

[6] Reyes V 2001 Method of regulating the flue gas temperature and voltage supply in an electrostatic precipitator for a cement production plant. United States Patent, N° US 6,293,787 B.

[7] Reigel SA, Doyle CD Evaporative cooler. United States Patent, N° 3842615. 1974.

[8] Ghosh SK, Sarkar P. A unified approach for identification and control of delta operator systems using neural networks. Int J Modelling Simulation. 2013;33 (2):67–76.

[9] Nirmaladevi M, Arumugam S. VLSI Implementation of Artificial Neural Networks— A survey. Int J Modelling Simulation. 2010;30(2):148–154.

[10] Jani DB, Mishra M, Sahoo. PK. Application of artificial neural network for predicting performance of solid desiccant cooling systems- A review. Renewable Sustainable Energy Rev. 2017;80:352–366.

[11] Jani DB, Mishra M, Sahoo. PK. Performance prediction of rotary solid desiccant dehumidifier in hybrid air-conditioning system using artificial neural network. Appl Thermal Eng. 2016;98:1091–1103.

[12] Jani DB, Mishra M, Sahoo PK. Performance prediction of solid desiccant - vapor compression hybrid air-conditioning system using artificial neural network. Energy. 2016;103:618–629.

[13] Boumedine MS, Haddouche R, Chetate B. Improvement of operation performances of the evaporative tower and the electrostatic precipitator for a cement factory. AMSE J Model Meas Control, Serie B. 2013;82(1): 77-91.

[14] Morgaard M, Ravn O, Poulsen NK. NNSYSID and NNCTRL tools for system identification and control with neural network. Comput Control Eng J. 2012;12 (1):29–36.
[15] Morgaard M, Ravn O, Hansen LK et al. 1996. The NNSYSID toolbox – A MATLAB toolbox for system identification with neural networks. IEEE proceeding, International Symposium on Computer-Aided Control System Design, Dearborn,Michigan, USA; 1996 September 15-18.
[16] Morgaard M, Ravn O, Poulsen N. K.NNSYSID-toolbox for system identification with neural networks. Math Comput Modeling Dynamical Syst. 2002;8 (1):1–20.
[17] Morgaard M Department of automation, technical university of denmark. release notes - neural network based system identification toolbox, Technical Report 00-E-891. 2000
[18] Saifizi M, AbMuin MZ, SazaliYaacob and al. Comparison of ARX and ARMAX models for thermoelectric refrigerator. 2013. 2nd International Conference on Mechanical Engineering Research ICMER, Kuantan, Pahang, Malaysia.
[19] Hagan MT, Demuth HB, Beale MH. Neural Network Design. Boston, MA: PWS Publishing; 1996.
[20] Hagan MT, Menhaj M. Training feedforward networks with the Marquardt algorithm. IEEE Trans Neural Networks. 1994;5(6):989–993.