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Implementation of Artificial Intelligence Technique to Model Arc Furnace Responses

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Abstract

Random variations of the bus voltage and power consumption of an electric arc furnace (EAF) have a significant impact on power generation equipment, transient stability of the power system network and power quality to other interconnected loads. Therefore, an accurate representation of the load's dynamic behaviour under various system disturbances is very important. This paper presents an arc furnace model using adaptive neuro-fuzzy inference system (ANFIS) in order to capture random, non-linear and time-varying load pattern of an arc furnace. To evaluate the performance of the proposed model, several case studies are presented where the outputs of the proposed model are compared with the data recorded in the real metallurgical plant.

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Abstract- **Random variations of the bus voltage and power consumption of an Electric Arc Furnace (EAF) have a significant impact on power generation equipment, transient stability of the power system network and power quality to other interconnected loads. Therefore, an accurate representation of the load's dynamic behaviour under various system disturbances is very important. This paper presents an arc furnace model using Adaptive Neuro-Fuzzy Inference System (ANFIS) in order to capture random, non-linear and time-varying load pattern of an arc furnace. To evaluate the performance of the proposed model, several case studies are presented where the outputs of the proposed model are compared with the data recorded in the real metallurgical plant.**

I. INTRODUCTION

In last few decades, the use of the Electric Arc Furnace (EAF) to produce steel in metallurgical industries has grown significantly since its first operation in the 1900s. Currently, EAF is the second most important means of steel production next to the blast furnace or basic oxygen furnace. In 2006, about 32% of steel was produced worldwide using EAF [1].

An EAF is a reactor used in the steel processing industries to charge the scraps, direct-reduced-iron (DIR) and other raw materials along with the lime and fluxes by means of both electrical and chemical energy. The heat is generated by the current passing through the electrode and by the radial energy evolved from the electrode. The other form of energy is the chemical energy that is generated as a result of combustion and the oxidizing reaction during operation. The normal operation of an arc furnace can be divided into two stages, one is the meltdown stage and the other is the refining stage. In the meltdown stage, the raw materials are melted. Then the melted materials are separated into slag and metals in the refining stage.

Due to random movements of the melting materials and random changes in arc electrode length during operation, the power consumption of the arc furnace is random and time-varying, and hence the arc current is non-sinusoidal. Consequently, the voltage-current (*v-i*) relationship of the arc furnace is complex and highly non-linear. As a consequence, arc furnaces produce harmonics and inter-harmonics of arc voltage and current in electrical networks [2-4]. Due to its random and time-varying nature, the relationship between the arc voltage and the arc power is random, which is difficult to model explicitly using mathematical equations. In addition, scraps create a condition similar to a short circuit from the secondary side of the arc furnace transformer during melting period. This causes a large current flow and voltage fluctuation. This has an adverse effect on the plant.

Due to its inherent complexity and randomness, a mathematical representation of an arc furnace is often a challenging task. However, a number of deterministic and stochastic approaches has been developed. These approaches are as follows [3-9]:

- representing the arc furnace as a time domain control voltage source. This approach is based on the piece-wise linear approximation of the voltage-current (*v-i*) characteristics of the arc furnace [3,4],
- representing the relationship between arc voltage and arc electrode length [5,6],
- representing the arc furnace as a time varying resistance [7], and
- stochastic process [8,9].

However, in most cases, simplified assumptions are used. As a result, a model often fails to capture the key features of an arc furnace. Considering the non-linear relationship between the arc voltage and the arc current and lack of knowledge associated with the process dynamics, artificial intelligence (AI) techniques can be applied to extract nonlinear relationships between the input and the output pattern of arc furnaces. In recent years, AI techniques such as artificial neural networks (ANN) and fuzzy inference systems (FIS) have been used for modelling a system where mathematical models do not exist or are ill-defined. They have also been used successfully in systems that involve complex, multi-variable processes with time-varying parameters [10-13].

In this paper, an arc furnace model is proposed based on adaptive neuro fuzzy inference system (ANFIS). ANFIS is a hybrid system which is the combination of the artificial neural network and fuzzy inference system. The advantage of artificial neural networks is their adaptive learning capability that enables them to improve their performance relatively fast. On the other hand, fuzzy logic is capable of handling non-linear input/output relationship by using a set of if-then rules. It was demonstrated by the authors that both ANFIS and ANN can be used successfully for the similar type of problem. However, ANFIS proves to be a better solution tool than ANN as ANFIS utilises both advantages

of neural network and fuzzy inference system [14]. The model is tested and validated by using the recorded data from a metallurgical plant.

II. ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

The architecture of a typical ANFIS is shown in Fig. 1. [10,12]. The interconnected network consists of the following layers [10,12]:

Layer 1. This layer is known as the input layer. At this layer, the inputs x_1 and x_2 are applied and are passed without being processed to a number of neurons in Layer 2.

Layer 2. This layer is called the fuzzification layer. At this Layer, neurons perform fuzzification to the incoming inputs x_1 and x_2.

$$y_{Ai} = \mu_{Ai}$$
$$y_{Bi} = \mu_{Bi} \tag{1}$$

where, y_{Ai}, and y_{Bi} are the outputs of neurons Ai and Bi of layer 2.

Layer 3. This layer is known as the rule layer. In this layer, each neuron evaluates a single Sugeno-type fuzzy rule. The rule neurons calculate the firing strength by determining the product of the incoming signals as given below.

$$y_{\Pi i} = \prod_{j=1} x_{ji} \tag{2}$$

where, x_{ji} is the input of neuron i, and $y_{\Pi i}$ is the output of of neuron i of layer 3. In Fig. 1, the output of the 1st neuron in layer 3 is shown as follows:

$$y_{\Pi 1} = \mu_{A1}\mu_{B1} \tag{3}$$

where, μ_{A1} represents the firing strength of rule 1.

Layer 4. This layer is called the normalization layer. The neurons of this layer receive inputs from all neurons of Layer 3. Here the normalized firing strength is calculated as the ratio of the firing strength of a given rule to the sum of firing strengths of all rules as given below.

$$y_{Ni} = \frac{\mu_i}{\sum_{j=1}^{n} \mu_j} = \overline{\mu_i} \tag{4}$$

where, y_{Ni} is the output of the neuron i of layer 4, which represents the contribution of a particular rule to the final result.

Layer 5. This layer is known as the defuzzification layer. Each neuron in this layer receives inputs from the original input signals (x_1 and x_2) and the output from Layer 4. In this layer, each neuron calculates the weighted consequent value of a particular rule as given below.

$$y_i = \overline{\mu_i}(k_{i0} + k_{i1}x_1 + k_{i2}x_2) \tag{5}$$

where, $\overline{\mu_i}$ is the input of defuzzification neuron i in Layer 5, y_i is the output of defuzzification neuron I in Layer 5,
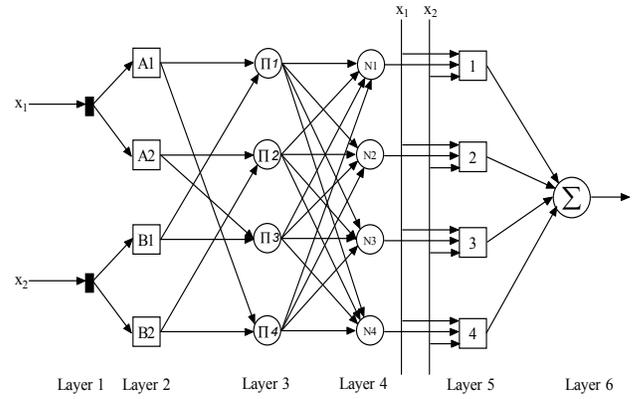

Figure 1. Typical ANFIS architecture.

and k_{i0}, k_{i1}, and k_{i2} are a set of consequent parameters of rule i.

These consequent parameters are learnt by the ANFIS during the training process and are used to tune the membership functions.

Layer 6. This layer is known as the summation neuron layer. This layer consists of one neuron that is used to add all the output signal from layer 5. The sum of these inputs is the ANFIS output, y_{ANFIS}, as shown below.

$$y_{ANFIS} = \sum_{i=1}^{n} y_i \tag{6}$$

A. ANFIS model training

The learning algorithm of the ANFIS model is a combination of the least-squares estimator and the gradient decent method [10]. Each iteration of the training algorithm is composed of a forward pass and a backward pass [10,12]. In a forward pass, the inputs are applied to the ANFIS. Neuron outputs are calculated layer-by-layer and rule consequent parameters are obtained. Once the forward pass has been completed, the error is determined using the following formula.

$$E = \frac{1}{2} \sum (y_d - y)^2 \tag{7}$$

where, E is the error, y_d is the desired output, and y is the actual output from ANFIS model.

Once the error is calculated, it is propagated back through the network using back propagation algorithm. During backward pass, the antecedent parameters are updated according to the chain rule [10,12]. The process continues until specific number of iteration.

B. Implementation of ANFIS model

In this application, the ANFIS is used as a tool to evaluate the real and reactive power consumption of the arc furnace. The algorithm to capture the power consumption of arc furnace uses the past data for power consumption, the present and past values bus voltage of arc furnace as input vector and corresponding power (both real and reactive) of present time as an output vector. The relationship between the input and the output vector is shown as follows:
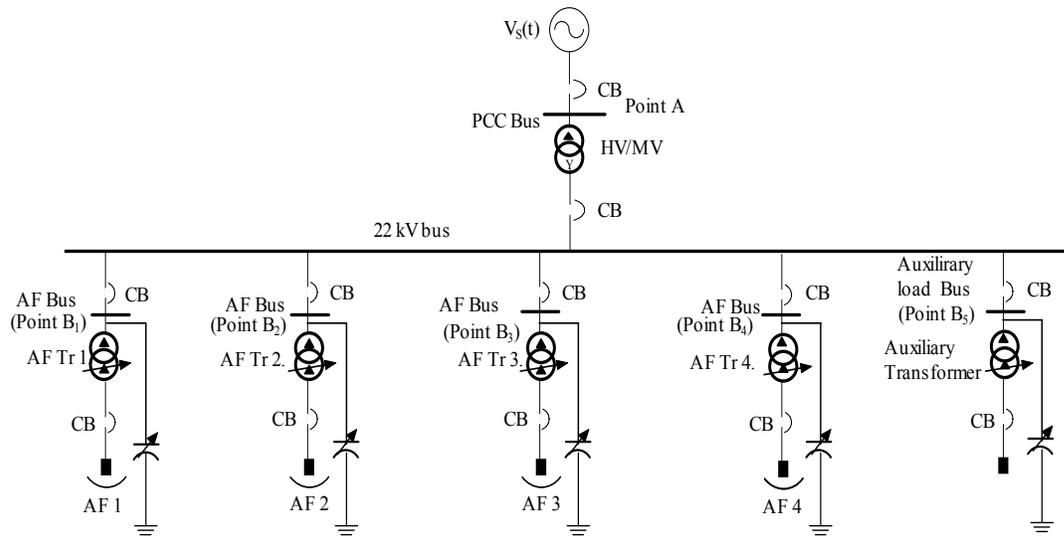
Figure 2. A metallurgical plant.

$$P(t) = f(V(t), \quad V(t-1), \quad P(t-1)) \qquad (8)$$

$$Q(t) = f(V(t), \quad V(t-1), \quad Q(t-1)) \qquad (9)$$

III. CONFIGURATION OF A METALLURGICAL PLANT

The configuration of a typical metallurgical plant containing several arc furnaces and auxiliary loads is shown in Fig. 2. The plant is supplied by a 110 kV utility system. A step-down transformer is connected to the utility system to convert voltage level from 110 kV to 22 kV. The 22 kV bus is connected with four arc furnaces via four arc furnace transformers. The auxiliary loads are connected to the 22 kV bus via auxiliary load transformer. The arc furnace transformer is a tap changer, where the primary side voltage is 22 KV and the secondary side voltage varies from 120 V to 270 V. The rating of the auxiliary transformer is 22 kV/3.3 kV. The load pattern of this plant is similar to the load pattern of the arc furnace load as four arc furnaces consume about 85% of the total power of the plant. The important points of the plant are identified as the PCC bus (point A), arc furnace buses (point B_1, point B_2, point B_3, and point B_4) and the auxiliary load bus (point B_5). The responses of the PCC bus (point A) represent the characteristics of the entire pant, the arc furnace buses (points B_1, B_2 , B_3, and B_4) represent the characteristics of individual arc furnaces, and auxiliary load bus (point B_5) represents the combine characteristic of all auxiliary loads such as induction motor, lighting and heating load of the plant.

IV. RESULT AND ANALYSIS

About 8000 one minute interval time series data for voltage and power (both the real and reactive) consumption for different points of the plant are obtained from a metallurgical plant. Out of 8000 data, first 2000 data are selected for training and validation of the ANFIS model. The performance of the proposed model is evaluated by calculating the mean absolute percentage error (MAPE) which is given as follows:

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \frac{|y_{real} - y_{simulated}|}{\overline{y}_{real}} \qquad (10)$$

where, y_{real} is the real data from the metallurgical plant, $y_{simulated}$ is the output from the ANFIS model and $\overline{y}_{real}$ is the average of N number of real data from the plant.

A. Load response of Point A

The time series representation of the bus voltage and power consumption is shown in Fig. 3 which represents the combined characteristics of arc furnaces and auxiliary loads.

The next step is to evaluate the response of the ANFIS model when the voltage disturbances occur. After analysing the entire time series voltage data shown in Fig. 3, a voltage disturbance is identified at time of 2703 minutes. Fig. 4 represents the time series data from t=2500 minute to t=3000 minute of voltage and power consumption at the PCC bus. The output responses of the ANFIS model for the real power and the reactive power are shown in Fig. 5 and Fig. 6, respectfully.

MAPEs for the load response of the ANFIS model of the PCC bus are calculated as 2.43% for real power and 5.32% for reactive power. Moreover, from Figs. 4 and 5, it can be demonstrated that the ANFIS model is able to track the random changes of the real and the reactive power consumption due to voltage variations

B. Load response of Point B_1

The real and reactive power responses due to the variation of bus voltage at point B_1 are also investigated. In this case, similar approaches have been undertaken as in the case of load response of point A. The time series representation of the bus voltage and power consumption is shown in Fig. 7.
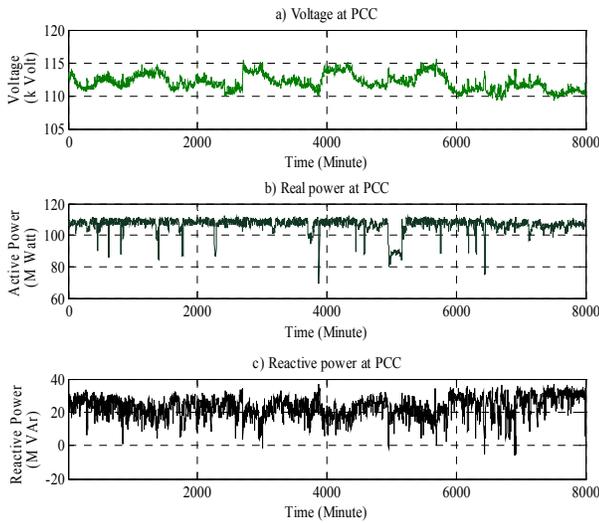
Figure 3. Time series data of a) voltage, b) real power consumption, and c) reactive power consumption at PCC (point *A*)
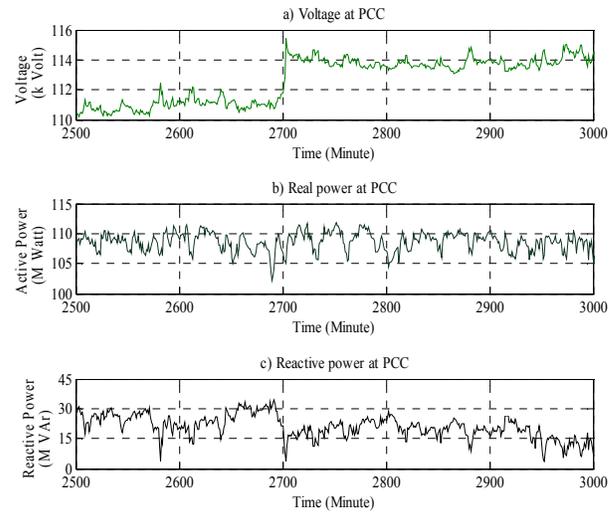
The ANFIS model is applied to evaluate the power response of arc furnace 1. In order to do this, a test case is considered which starts at t=7001 minute and finishes at t=8000 minute; this is where the arc voltage fluctuates most. The outputs of the ANFIS model are shown in Fig. 8 and Fig. 9.

The MAPEs for the real and reactive power of arc furnace 1 are calculated as 1.23% and 6.15% respectively. Moreover, like the previous case, the ANFIS model is able to track the random pattern of the power consumption of arc furnace 1.

C. Load response of Point B_3

The real and reactive power responses due to the variation of bus voltage at point B_3 are also investigated. In this case similar approach has been undertaken as in the case of load response of point A. The time series representation of the bus voltage and power consumption is shown in Fig. 10.

Like the previous section, the ANFIS model is applied to evaluate the power response of arc furnace 3. To evaluate the performance of the proposed model, a test case is considered which starts at t=6001 minute and finishes at t=7000 minute; this is where the arc voltage fluctuates most. The outputs of the ANFIS model are shown in Fig. 11 and Fig. 12.

The MAPEs for the real and reactive power of arc furnace 3 are calculated as 2.13% and 8.23% respectively. Moreover, like the previous case studies, the ANFIS model is able to track the random pattern of the power consumption of arc furnace 3.
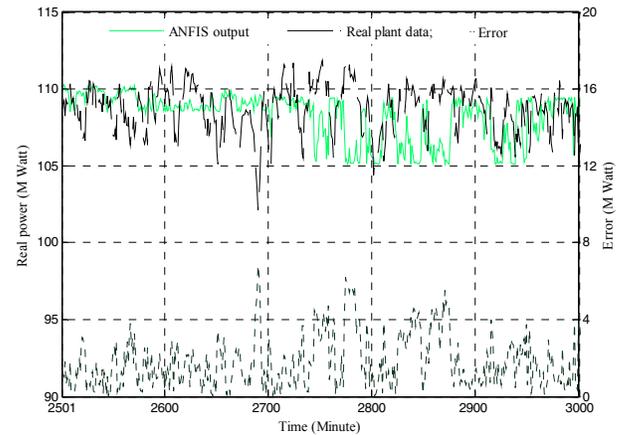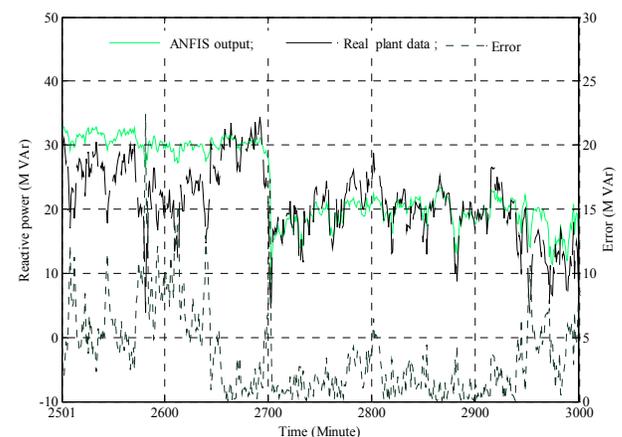

Figure 4. Time series data from time of 2500 minutes to time of 3000 minutes of a) voltage, b) real power consumption, and c) reactive power consumption at PCC bus.

Figure 5. Real power consumption of PCC bus.

Figure 6. Reactive power consumption of PCC bus.

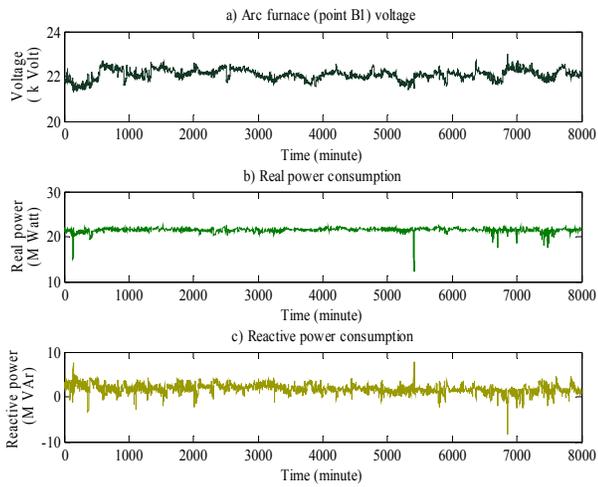2008 Australasian Universities Power Engineering Conference (AUPEC'08)

Figure 7. Time series data of a) voltage, b) real power consumption, and c) reactive power consumption at arc furnace 1 (point B_1).
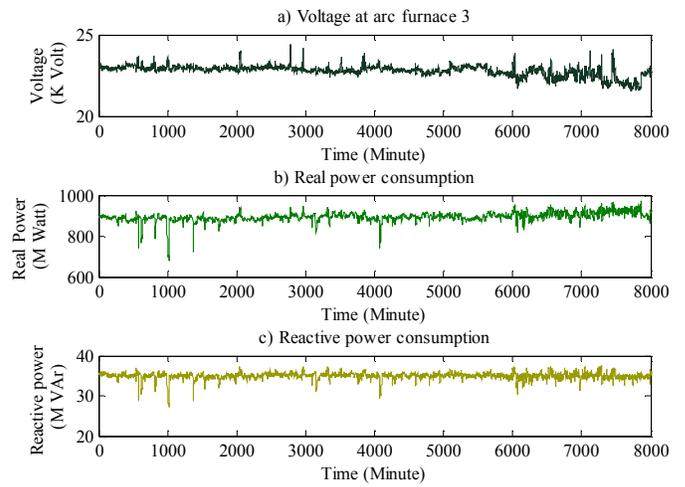

Figure 10. Time series data of a) voltage, b) real power consumption, and c) reactive power consumption at arc furnace 3 (point B_3).
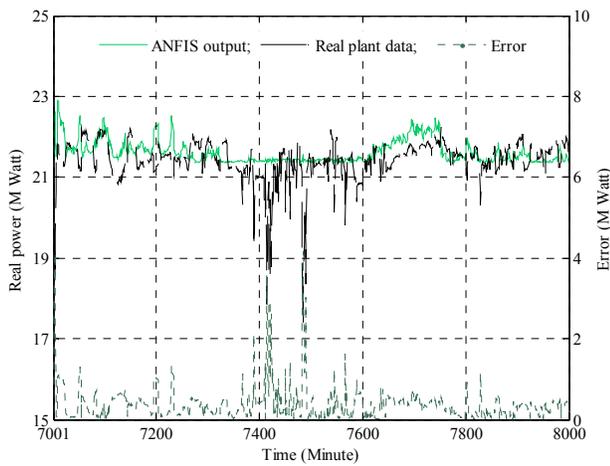

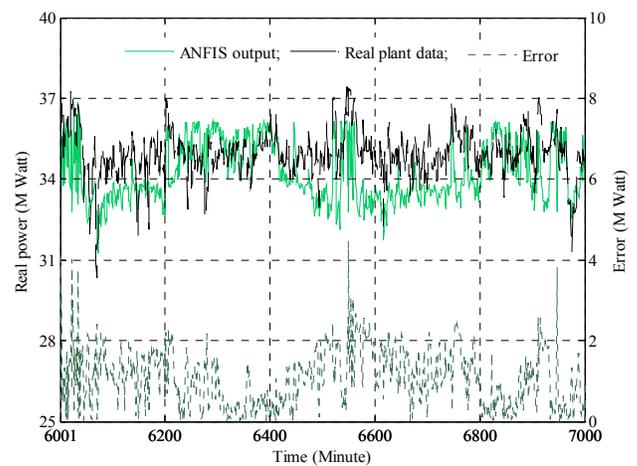Figure 8. Real power consumption of arc furnace 1.
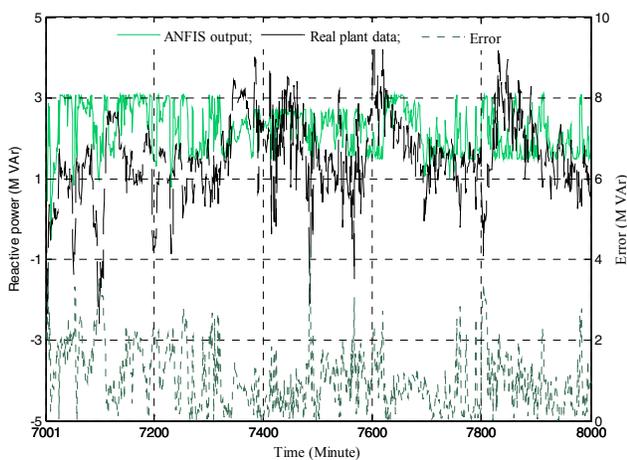

Figure 11. Real power consumption of Arc furnace 3.

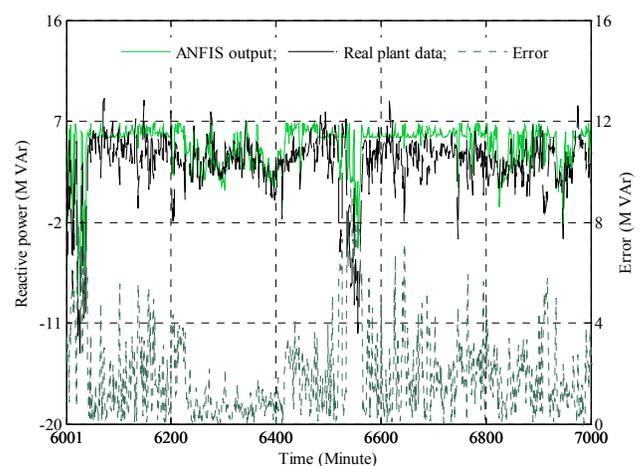

Figure 9. Reactive power consumption of arc furnace 1.

Figure 12. Reactive power consumption of arc furnace 3.

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V. Conclusion

In this paper, a new approach to model arc furnace power response is demonstrated using ANFIS model. The performance of the proposed model is evaluated using several case studies. Obtained results clearly demonstrate an applicability of the artificial intelligent approach to the arc furnace modeling problem. The performance of the model was evaluated by measuring the mean absolute percentage error (MAPE). It was demonstrated that the MAPEs for ANFIS model are significantly low. The proposed model can be applied in various process industries that involve arc furnace applications. A new energy management system based on artificial intelligence techniques can be developed using proposed ANFIS model. As a result, industrial plants would be able to improve their energy consumption and maximise the production. Moreover, an intelligent control system based on artificial intelligence techniques to control the movement of arc electrode can be developed using the proposed models. As the arc electrode length plays an important role in metal and slag production, an intelligent arc electrode controller can assure the proper positioning of the arc electrode that would optimise the production of metal and slag.

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