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Analysis of Boiler Operational Variables Prior to Tube Leakage Fault by Artificial Intelligent System

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Abstract. Steam boilers are considered as a core of any steam power plant. Boilers are subjected to various types of trips leading to shut down of the entire plant. The tube leakage is the worse among the common boiler faults, where the shutdown period lasts for around four to five days. This paper describes the rules of the Artificial Intelligent Systems to diagnosis the boiler variables prior to tube leakage occurrence. An Intelligent system based on Artificial Neural Network was designed and coded in MATLAB environment. The ANN was trained and validated using real site data acquired from coal fired power plant in Malaysia. Ninety three boiler operational variables were identified for the present investigation based on the plant operator experience. Various neural networks topology combinations were investigated. The results showed that the NN with two hidden layers performed better than one hidden layer using Levenberg-Maquardt training algorithm. Moreover, it was noticed that hyperbolic tangent function for input and output nodes performed better than other activation function types.

1 Introduction

A steam boiler is a covered container that furnishes a method for combustion heat to be transferred into water until the water becomes steam. The steam is then utilized for further energy conversion processes. The water wall tubes, superheater, evaporator, re-heater and economizer are the main parts of the steam boiler. These parts in the boiler are functioning in capturing the thermal energy in the combustion gases to evaporate the water into steam. Risers are installed all around the four walls of the furnace act as cooling tubes or a water wall and carry away the heat from the furnace. Adequate circulation of water must be provided in the circuit. Usually the riser tubes have more thermal loading and generate more steam because they are located opposite to the burners. Too much steaming in a riser tube is not preferable. On the heated surface, the bubbles are originated and the formation of the bubbles will be higher if there is a high rate of heat transfer to the riser. The bubbles may coalesce and form an unstable vapor film which continually collapses and reforms. Since the vapor film has much lower thermal conductivity than a liquid film, it will offer a large thermal resistance. The difference between the heat absorbed and heat transferred to the wall will be stored in the metal of the tube with the increase in its internal energy. Consequently the temperature of the metal may exceed the melting point and the tube may rupture allowing tube leakage [1].

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The use of Artificial Intelligent System (AIS) techniques is a subject of research and application in the power plants. Fast and Palméb [2] applied ANN for condition monitoring and diagnosis of a combined heat power (CHP) plant by an online monitoring system. Majidian [3] compared results of Fuzzy logic and Neural Network (NN) in life prediction of boiler tubes. Wall thickness of re-heater tubes of boiler of Neka power plant in north of Iran were measured during maintenance shutdown period. In the study of approach to early boiler tube leak detection by [4], the ANN models of flue gas humidity for steam leak detection are presented. Three structures of ANN models of flue gas humidity were built which are linear nets, radial basis function and feed forward multilayer perceptron. The models were trained with data compounded from long period of time and next decimated. Romeo and Gareta [5] presented a research on ANN for evaluating and monitoring biomass boiler to point out the advantages of ANN in these situations. The aim of the develop ANN is to produce the value of fouling index obtained by the theoretical model used for monitoring and steam output obtained by real data.

The objective of this study is to establish AIS that is able to diagnosis the boiler fault due to riser tube leakage. The selected AIS for this study are the ANN which is useful whenever a nonlinear relation between numerical data is sought. The function of the developed ANN system is to forecast the trip earlier and before the real shutdown for the ease of operator to take appropriate actions to avoid the shutdown. The data were selected from coal fired thermal power plant (TPP) in Malaysia for period of 6 months included shutdown due to boiler tube leakage.

2 Data Preparation

The acquired data consisted of the data generated from three units of boilers in the TPP. The unit selected for this project was boiler unit-1, whereby the unit was shut-down due to the leakage of the boiler tubes from 25th April 2008 until 30th April 2008. The data consisted of 1800 variable x 13000 data point based on collection in minutes. The preparation sequence is shown in figures 1 and 2.

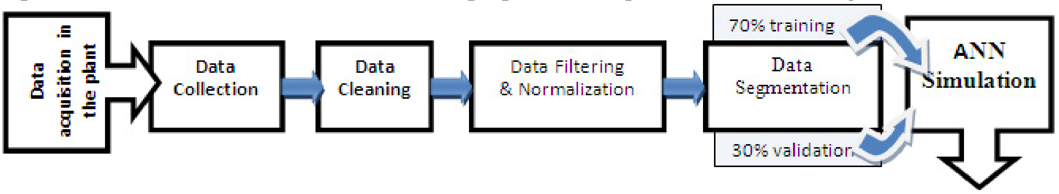

Figure 1: The sequence of data processing from the plant CC room to the output from the ANN.

The erroneous data will affect the data normalization because it will produce error to the ANN system. Hence, filtering is essential step to be done to delete all the erroneous data. After data filtering, the data need to be normalized or stabilized in order to make sure that the ANN model will detect the data. The data was normalized hundreds into the value between 0 and 1 by using the equation shown below.

$$\text{Normalization equation} = \frac{X - Xmin}{Xmax - Xmin} \qquad (1)$$

Training and validation had been classified into 70% training and 30% validation. After training and validation the ANN model by using different activation function and training algorithms, the best combination of activation function with certain training algorithms which produced the smallest root mean square error (RMSE) would be selected to undergo the validation part.

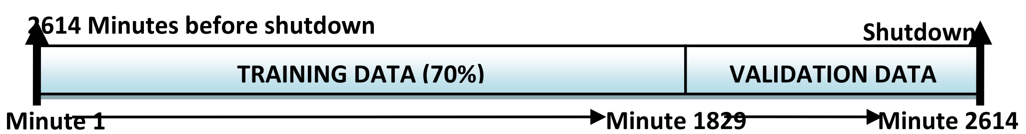

Figure 2: Data duration starting from the steady operation till the unit shutdown.

3 NN Topologies

There are 9 types of multidimensional minimization backpropagation training algorithms. Only 4 types were selected in the hidden layer to produce different errors of output. The ANN model coding had been constructed based on the number of hidden layers used and types of function (for training and validation). This part is the most crucial part whereby simulating each coding is time consuming.

3.1 Training Algorithms

There are 4 types of training algorithms Function of these four training algorithms is for the convergence of the algorithms of models from ten to one hundred times faster than other algorithms in the NN MATLAB Toolbox.

3.2 Activation Functions

There are three types of activation functions used in ANN which consists of linear, tan-sigmoid and log sigmoid. The linear transfer function calculates the neuron's output by simply returning the value passed to it. Log-Sigmoid Transfer Function is commonly used in back-propagation networks, in part, because it is differentiable. Multi-layer NN alternatively can use Tan-Sigmoid Transfer function other than Log-Sigmoid [6].

The performance of the network was calculated by using RMSE as shown in eqn.2 in order to find out the weights that minimize error. The smallest the error, the better the output obtained. Then, the desired output obtained from MATLAB will be compared with the actual output and finally will come up with several recommendations and discussions.

$$RMSE = \frac{1}{Q}\sum(t(k) - a(k))^2 \qquad (2)$$

Where k is the number of iterations, Q is the total number of iterations (epochs), t is the target output, and a is the actual output.

4 Results and Discussion

After undergo the data processing procedure, the data were shortlisted into 32 important variables based on plant operator experience. The variables were shortlisted based on the critical sensors that contributed to the trip of that particular unit of boiler. Among all those 32 variables, there are several variables that had been identified to contribute to the trip before the real shutdown.

4.1 Analysis of the ANN training results.

The coding of the NN was carried out using MATLAB software. After identifying V20 as the very important variable, the data were fed into the real ANN model for further rationalization to obtain the acceptable and justified results. Based on the results presented in figure 5, the behavior of the data for the first 200 minutes of operation is very steady even though there are other sensors that had affected by the possible tube leakage faults. However, after the sensors of V20 started to fluctuate un normally and reached the high alarm at minute 2612, which is represented by value 1 in figure 3, the unit is shutdown 3 minutes later.

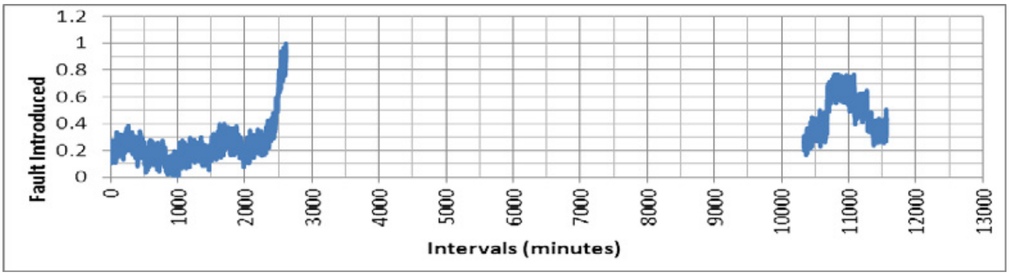

Figure 3: the ANN results of V20

Next step of this study is to model the NN network to produce a NN model that finally could forecast the trip earlier and before the real shutdown. The data selected was based on the 32 variables and fed into the NN model whereby the data is the normalized data which consists of all data before the real shutdown.

The data undergone training and validation and there are 2 types of hidden layers used. First model is constructed by using only one hidden layer with 10 neurons and the other model was constructed by using 2 hidden layers with 10 neurons. The neurons used in the model are only up to 10 neurons because the RMSE will be much higher than 0.5 and even up to 1.0 if using more than 10 neurons. The reason of using only 1 and 2 hidden layers is because the RMSE for 3 or more hidden layers will be constant. Hence, the ANN model was simulated with only up to 2 hidden layers.

For ANN model with 1 hidden layer, there are two types of activation functions that have been combined together and used. The combinations are Purelin + Logsig (P+L), Tansig + Logsig (T+L), Purelin + Tansig (P+T) and so on. There are about 9 combinations of activation functions that had been simulated in this 1 HL model. Each combination produces different RMSE under different number of neurons, from 1 neuron up to 10 neurons. Hence, the smallest RMSE produced under certain combination of activation function and certain number for neurons will be taken as the best combination for respective training algorithms. The RMSE of the 9 combinations x 10 neurons x 4 training algorithm are obtained and grouped in tabulation form. The results are shown in figure 4 (a).

For 2 HL model, there are 27 combinations of activation functions that have been simulated and each combination produced different values of RMSE at different number of neurons. However, the ANN model is constructed with only 1 and 2 hidden layers because the 3 hidden layers model are constantly producing the value of RMSE which similar to the model with 2 hidden layers. The RMSE of the 27 activation combinations X 10 neurons X 4 training algorithm are obtained and grouped in tabulation form. The results are shown in figure 4 (b). Each combination of the activation functions are simulated under different training algorithms because each training algorithms produces different functions as mentioned previously. The data has been compared graphically for the ease of analysis.

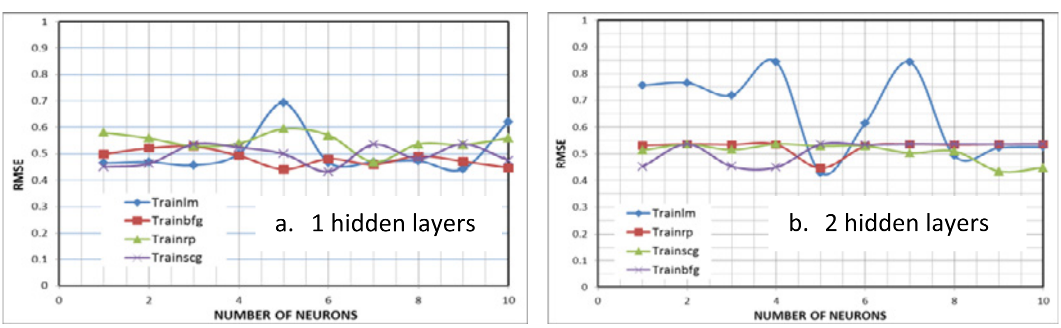

Figure 4: Comparison of training functions of (a) 1 hidden layer, (b) 2 hidden layers

Based on the data of RMSE for each training algorithms, the best training algorithm for hidden layer2 is trainlm with the combination of tansig, purelin and tansig T+P+T activation functions. Under the combination of T+P+T activation functions with 8 neurons in hidden layer1 and 5 neurons in hidden layers2, the trainlm had produced the RMSE value of 0.429. In his boiler monitoring by ANN,

4.2 Analysis of the ANN validation results.

The next step which is the validation step whereby in this step, the model will simulated by using different coding to finally produce the final forecasted graph which is important to prove that the trips are able to be forecasted earlier before the real shutdown. Figure 5 represents the forecasted forecast trip is known as the "Predicted RMSE" and the real trip is known as "Actual RMSE".

The results shown in figure 5 are the predicted (forecast) and the actual trips. That predicted trip ultimately occurs before the real trip. The predicted trip in blue lines occurs after 150 minutes of operation whereby it can forecast the trip about 10 minutes earlier before the real trip (red dotted lines) which occur after 160 minutes of operation. The data is classified as trip once it reaches the value (‘1’). The difference between the actual and predicted RMSE is essential and has been proven in this study that with the gap of 10 minutes, the real trip is possible to be eliminated or avoided which will ensure the boiler unit running continuously. Since this ANN system is a continuous-learning system, the future trip that will occur in the future can be forecasted again since the ANN system will detect it earlier. This forecast trip will actually help the plant operator to take premature or prevention actions to prevent the real trip that will occur after a few minutes.

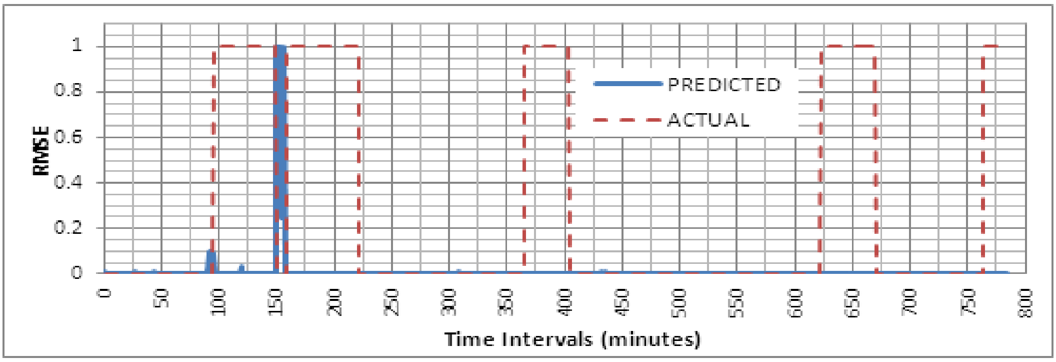

Figure 5: The actual and ANN prediction of the variable 20

5 Conclusions

The results of ANN are very sensitive to number of neurons. It might have different result in each run even with fixed number of neurons. Increasing the number of neurons in hidden layer will decrease the number of calculation steps with subsequent decrease in the root mean square error. The variable “Low Temp Superheater Right Wall Outlet before Superheater Dryer” is the main contributor to the shutdown. However, this study only focuses on studying and identifying the behavior of the variables and the ANN modeling instead of confirming the main contributor. Based on the knowledge gained in developing this set AIS, it is recommended to utilize it as a ground work for the future development and validation of other AIS to minimize the effect of boiler tube leakage. By such technology, the plant shutdown, breakdown and catastrophes can be avoided by implanting early detection of faults

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