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Coal-Fired Boiler Fault Prediction using Artificial Neural Networks

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ABSTRACT

Boiler fault is a critical issue in a coal-fired power plant due to its high temperature and high pressure characteristics. The complexity of boiler design increases the difficulty of fault investigation in a quick moment to avoid long duration shut-down. In this paper, a boiler fault prediction model is proposed using artificial neural network. The key influential parameters analysis is carried out to identify its correlation with the performance of the boiler. The prediction model is developed to achieve the least misclassification rate and mean squared error. Artificial neural network is trained using a set of boiler operational parameters. Subsequenlty, the trained model is used to validate its prediction accuracy against actual fault value from a collected real plant data. With reference to the study and test results, two set of initial weights have been tested to verify the repeatability of the correct prediction. The results show that the artificial neural network implemented is able to provide an average of above 92% prediction rate of accuracy.

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1. INTRODUCTION

In a large coal-fired power plant, effective equipment monitoring and control strategies are crucial to avoid a catastrophic accident. In existing systems, historical data are used mainly for monitoring, control and over-limit alarm; but not for fault prediction or diagnosis [1]. Furthermore, coal-fired power plant boiler (CFB) units have complex characteristics and mechanisms due to its high temperature and high pressure characteristics. The most common types of faults related to boiler in coal-fired power plant include ash deposit fouling and slagging [2]-[5], abnormal high superheater inlet temperature reading, abnormal temperature of the flue gas and the boiler's pressure reading during depressurization before start up [6].

The most common techniques in developing a power plant systems involve mathematical or causal models, data mining and artificial neural network (ANN) approach [1], [7]-[13]. The basic idea of modelling is to approximate the real geometry to an ideal geometry with an assumption that the values are perfect or accurate. It introduces uncertainties because all the material properties are dependent on the insights and the right selection of the constant property values of the actual equipment understudy [14]. Ramadhas *et al*. [15] concluded that results from their theoretical model of the complete combustion studies for a biodiesel fuelled engine were proved to be reliable and adequate, although in general it is still difficult to attain actual complete combustion. This is due to the fact that their approach is based on the numerical calculation of mass, momentum and energy equations in either one, two or three dimensions to follow the propagation of flame or combustion front within the engine combustion chamber. Whereas, ANN approach has a high degree of fault tolerance and high processing speed because of its simplified connections while dealing with complex calculations [7]. This is obtained with high accuracy without the use of technically advance developed software [16]. Moreover, ANN is able to learn the relationship between the selected input and output through a process known as network training. This approach allows user to test and explore the simulation faster and easier. To ensure that the ANN model is ready to be deployed, it is first validated using unseen data to compare its accuracy of the output against the actual output value [3].

There are a great number of studies carried out implementing ANN in prediction and replicating the behavior of an energy generation plant boiler. One of the most researched areas include fault detection and classification of a power transmission line to provide quick respond time while avoiding a trip occurance in the circuit breaker between its substations [17], [18]. As for a power plant fault diagnosis, an ANN approach is integrated with an expert system interface to improve the system's overall performance [19], [20]. In the late 90s, a predictive controller has been derived from a neural network model based nonlinear algorithm that provides an offset free closed loop behavior for a thermal power plant control [21]. A study was carried out to simulate the evolution of boiler heat absorption under realistic condition of the ash deposition in a coal fired boiler using ANN [2]. Another work by [16] reported how ANN was developed to monitor boiler's behavior and evaluate the biomass fouling as a mean of improving the existing boiler monitoring technique.

Meanwhile in a more recent work by Smrekar *et al*. [22], an ANN was developed to predict fresh steam properties for suitable combination of input parameters. In their work, they were able to identify three high impact input parameters that allows them to achieve acceptable accuracy. The parameters include mass flow rate of coal, which is dependent on the belt conveyor speed, valve openings of the steam line and the feed water pressure. Rusinowski *et al*. [23] developed an ANN model to map the influence of flue gas losses and energy losses due to unburned combustibles on the main operational parameters of the boiler. The developed model was able to confirm that the air excess ratio and flue gas temperature exert a dominant influence upon the flue gas losses. Over the past decade, these studies have shown the capability of an ANN as a tool in energy prediction and modelling.

This paper investigates the use of an ANN with a specific set of parameters to predict the boiler faulty condition in a coal-fired power plant and report the findings with the support of existing literature. The outcome of this simulation will be used as part of an ongoing study in developing an intelligent monitoring system interface for a power plant boiler condition monitoring. This paper is divided into two sections. The first section will be a brief discussion on the use of Multi-layered Perceptron (MLP) in ANN. Then, in the second section; the investigation of the implemented model are discussed to report the prediction outcome and performance.

2. MULTI-LAYERED PERCEPTRONS (MLP) NEURAL NETWORK

One of the most well documented and frequently used types of ANN is MLP [24]. An MLP is a feed forward neural network consisting of a number of neurons connected by weighted links. The neurons are organized in several layers, namely the input layer, hidden layer(s) and output layer. An example of a typical one hidden layer MLP is illustrated in Figure 1. As illustrated in Figure 1, the input layer receives an external activation vector, and passes it through the weighted connections (W_{ij}) of the neurons in the hidden layer. This process computes their activations (W_{kj}) and passes them to neurons in succeeding layers until it reaches the output layer [25]. Basically, the input vector is propagated forward through the network producing an activation vector in the output layer at the end of the process. The mapping of input vector onto output vector is in fact determined by the connection weights of the net.

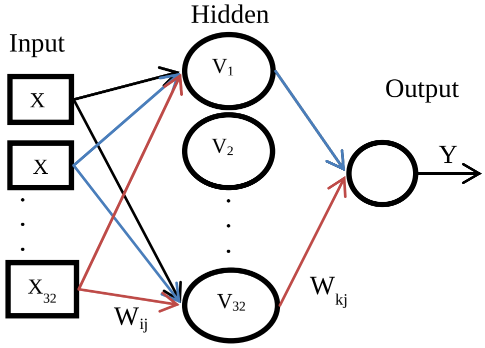

Figure 1. A topology of a general MLP with one hidden layer

Table 1. Input parameters data description

Input parameters	Dataset description	Unit
Temperature	• Boiler re-heater and superheater inlet/outlet and exchange metal temperature • Economizer inlet/outlet temperature	°C
Pressure	• Boiler drum pressure • Superheated steam pressure • Circulation pump pressure • Temperature and steam outlet pressure • Economizer inlet pressure	Bar
Flow rate	• Steam flow • Feedwater flow • Superheater water injection compensated flow	Ton/hr

One of the main components of an MLP is the training algorithm. The purpose of the training algorithm is to find the approximate solutions to minimized errors [24]. From existing literatures [26]-[28], it is evident that the most common training algorithms used for ANN model prediction and forecasting are the gradient descent methods class of algorithm. One of the preferred algorithms of this class, in terms of convergence speed, accuracy and robustness with respect to its learning parameters, is the Resilient Backpropagation (RProp) algorithm introduced by [28]. The basic principle of RProp is the direct adaptation of the weight update values Wij. It modifies the size of the weight step directly by introducing the concept of resilient update values. This results in an adaptation effort that is not distorted by an unforeseeable gradient behavior [25]. In this paper, the ANN model will use RProp as the training algorithm for this simulation for the boiler fault prediction.

3. BOILER OPERATIONAL PARAMETERS

Generally, a physical model requires an exact number of parameters values for calculations. Hence, the choices are dictated by the equation representing the processes involved. This limits the choice of input and output parameters by the “cause and effect” relations [22]. Unlike a physical model, the input and output parameters in ANN modelling are mostly selected on the basis of the objective of the modelling and the boiler’s operators’ experience. In fact, the input parameters are usually optimized to compromise between the number of parameters and the desired accuracy of the ANN prediction.The final set of input parameters was defined on the basis of observations related only to the boiler unit, advice and feedback from the plant operator, removal of parameters that has non-effective factors on the faulty scenario and any redundant readings from the same sensors [29]. The input parameters and their dataset description are listed in Table 1.

The parameters listed are important to monitor the overall performance of the boiler. Primarily, the temperature of the steam produced in the boiler is dependant on the superheater and reheater to reach its optimum temperature before it is transferred to the turbine. Therefore, the water supply and fuel flow rate leading to the burner need to be at the right pressure and temperature level to provide the exact amount of combustion for the steam production. Likewise, the water leaving the high pressure feedwater heater needed to be raised to reach the saturation temperature to correspond to the boiler drum pressure as a safety measure. This is achieved through the economizer by exchanging heat with the gas leaving the superheater in the temperature and pressure inlet and outlet tube up to the stack. Hence, a summary of the dataset that corresponds to the temperature, pressure and flow rate of the boiler efficiency are identified in Table 1.

Next step is to feed the selected parameter data to the network for simulation. Firstly, it is known that the starting values of the weights in a network have a significant effect on the training process [30], [31]. Achieving this requires coordination between the training set normalization, the choice of training function and the choice of weight initialization. To evaluate how much influence each assumed initial weights has on the output and thereby to identify the best initial weight for the simulation, a sensitivity analysis was performed. The first initial set of the weight (W1) value was set to zero and the second initial set of weights (W2) is a pre-selected and randomized value set. These weights are applied to the same selected data set in order to examine how much it changed the accuracy of the misclassified rate (MCR) produced when using RProp. The training and testing result are recorded and saved accordingly for analysis and comparison. In order to compare the result fairly, the following criteria were set:

a. Data normalization is important to avoid bias and noise disturbances. Since the target output is set to be either 0 for normal and 1 for faulty; all the sample data are normalized and scaled to be between 0 and 1 using the Min-Max normalization method Equation (1).

$$\text{Data normalized} = \frac{(\text{Ax} - Ax_{Min})}{(Ax_{Max} - Ax_{Min})} \tag{1}$$

Where Ax represents the original data value before normalization

b. The network consists of 3 layers; input layer, one hidden layer and one output layer. In the hidden layer, there are 32 hidden neurons, and two output value of 0 and 1 for the output layer. The number of iterations for each epoch is set to 500 and each data set will be trained for 10 runs.
c. The selected training algorithm used for this simulation is RProp due to its high speed convergence, accuracy and robustness. By setting the learning rate to its default value of 0.1, all the weights in the network converge roughly at the same speed.
d. One of the most common forms of activation function is the Hyperbolic tangent sigmoid function Equation (2). This function is selected because they are more likely to produce outputs that are on average close to zero [32].

$$f(x) = \tanh(x) \tag{2}$$

e. One pre-randomized data set was used for each ANN model. This is to ensure that the same data were used in training and testing. This provided the common platform for comparison of results for different initial weights set.
f. The same proportion of data for training, and testing was used for each ANN (70% training and 30% testing).
g. To determine the minimum difference between the answer of the output neuron Y and the target value of Z, the minimization of the error using Mean Squared Error (MSE) method Equation (3) is used, where Zj is the target output and Yj represents the output of the network.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Z_j - Y_j\right)^2 \tag{3}$$

h. To evaluate the performance of the network in achieving an acceptable accuracy rate, the Miss-Classification Rate (MCR) shown in Equation (4) is used where TP represents true positive, TN represents true negative and TS is the total number of samples.

$$\text{MCR (\%)} = \left(1 - \frac{\sum TP + \sum TN}{\sum TS}\right) \text{x } 100\% \tag{4}$$

4. RESULTS AND ANALYSIS

In this paper, data from a local thermal power plant containing 1286 training data and 551 testing data are pre-randomized and normalized for the ANN model. The selected network is a three layer MLP with 32 input parameters and two target classes of 0 and 1. The hidden layer consists of 32 hidden neurons and a sigmoid function is used as the activation function. MATLAB platform is used to conduct this simulation in a 2.20GHz Intel® Core™ i5-5200U CPU with 8GB RAM.

In Table 2, the network simulation result implementing both initial weight setups for W1 and W2 are reported. Based on the result, it is evident that the selected training algorithm (RProp) was able to compute the training in an average of 1.42 milliseconds for 500 iterations using W1. From the observation, it was also able to achieve the highest accuracy for MSE of 0.0317, while achieving a very good MCR of 3.53%. Meanwhile, when the initial weight W2 was applied, the training result has a slight improvement. Based on the outcome, although it took 1.63 millisecond to compute; the MSE achieved is 0.0254 and it has a lower misclassification rate of 2.71%.

Table 2. Training and Testing Results of Multilayer Perceptron Neural Networks

	Weight Sample	MSE	Misclassified rate
Training result	W1	0.0317	3.53%
	W2	0.0254	2.71%
Testing result	W1	0.0487	5.86%
	W2	0.0491	6.06%

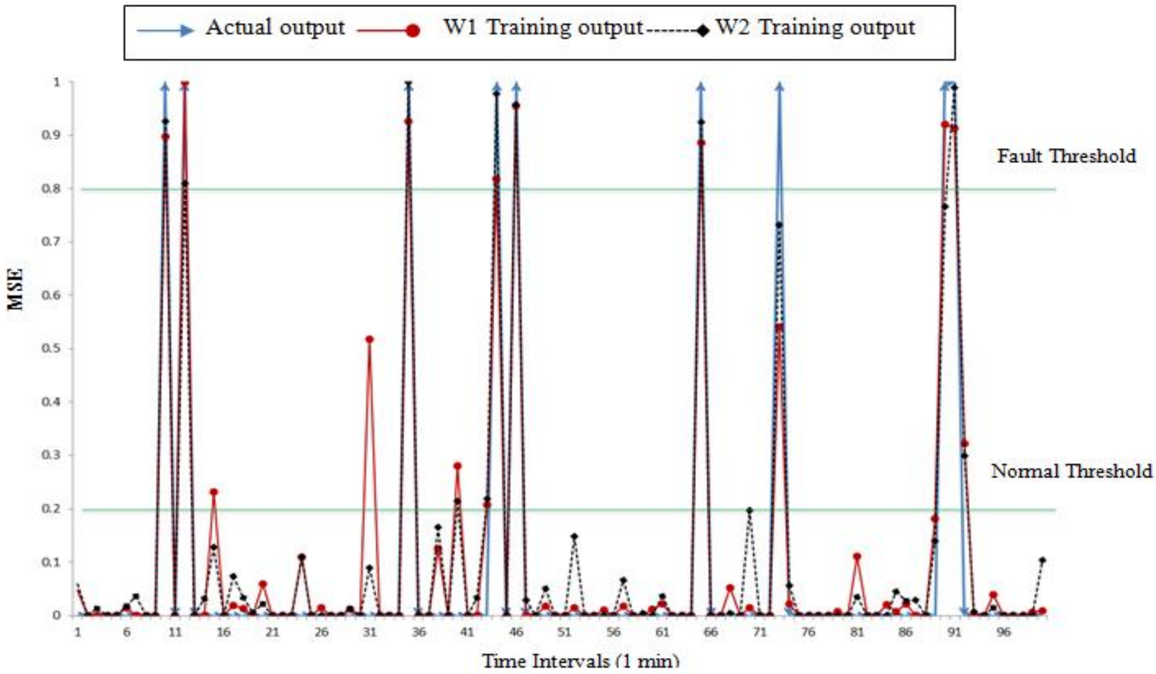

Figure 2. Initial weight setup comparison for the fault prediction

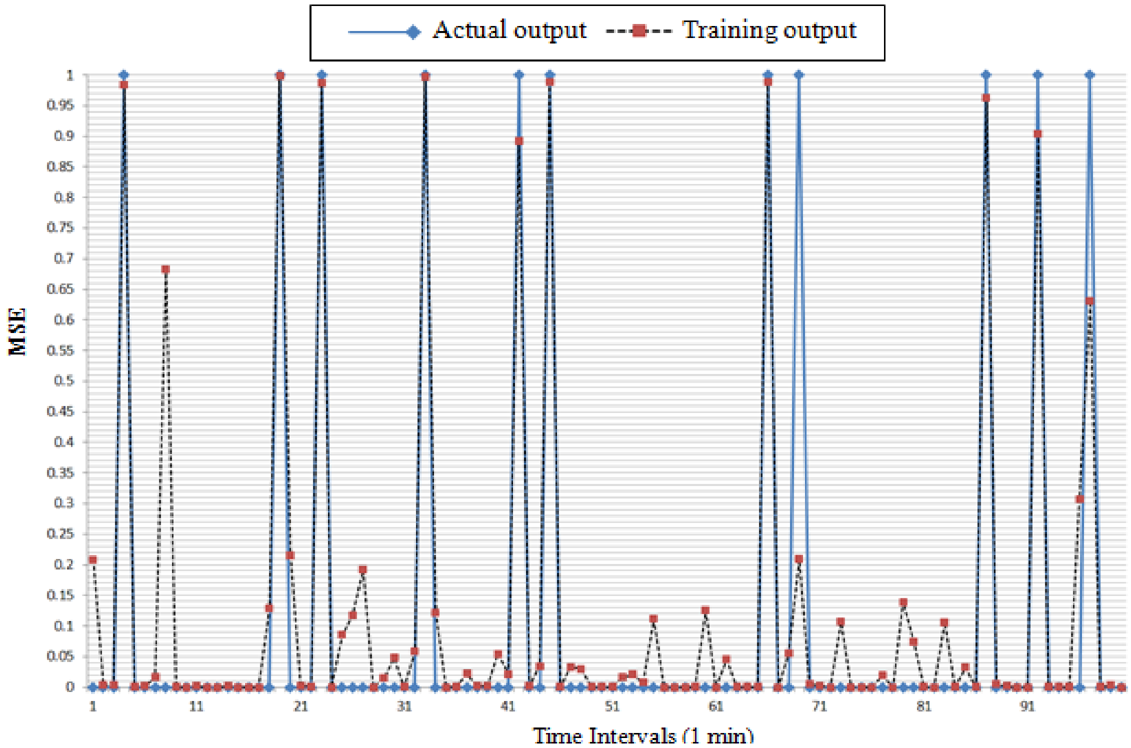

Figure 3. Training result of the ANN model using W2

To check for the best parameter setup for the ANN in this investigation, the testing results of the same data set sample are also recorded for comparison. Although the computation time recorded is the same with the training result; there is a significant difference in the MSE and MCR recorded. The testing sample for W1 produces an average of 0.0487 for its MSE with a very small difference of 2.33% higher MCR of

5.86% compared to the training outcome presented in Table 2 for W1. Meanwhile a small difference of MSE and MCR value is recorded when the initial weights are modified using W2, an average of 0.0491 for its MSE and 6.06% MCR respectively.

In Figure 2, a sample of 100 predicted output were extracted from a continuous recorded simulation of 1286 simulated data sample to compare them against the actual measured output. Here, the initial weight for W2 shows a better accuracy rate of 95.5% compared to W1 for the first 100 sample of 1 minute intervals training. Based on the fault and normal threshold line in Figure 2, predicted output from randomized initial weights shows more data points that has the least prediction error compared to the predicted output using zeros as initial weights. However, when the network using random weights (W2) is presented with new set of data for testing, the recognition rate had a slight drop resulting into 91.8% output prediction accuracy, see Figure 3 and Figure 4. This may be due to the fact that data used for testing has never been used to train the network. The accuracy rate may improve if more data are collected and used for training in future work to allow better learning rate for the network.

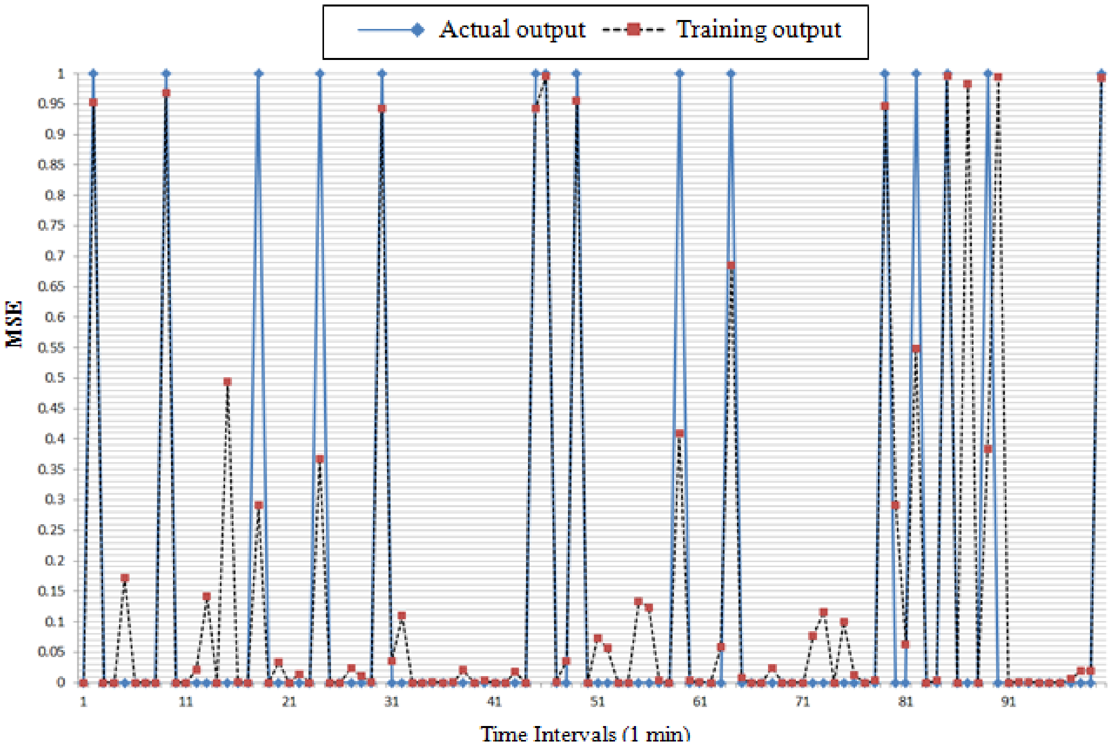

Figure 4. Testing result of the ANN model using W2

5. CONCLUSION

The primary target of this paper was to investigate an implementation of ANN for a fault predictive tool for a CFB to facilitate plant operators to identify and narrow down the operational boiler parameters that causes the fault quickly. From the analysis of the simulation using the ANN method, it has shown a good performance of the system that predicts the condition of the listed parameters in Table 1 with a satisfactory comparison supported by the experimental values. The developed model was able to provide an indication of the importance of the various input parameters, in terms of the effects of variation in their output values. Moreover, the initialization of the random weights in the method also results in an improved accuracy rate of 97.3% during training and a slight difference of 93.9% accuracy in the testing phase. To conclude, the proposed model using random weights perform better and can be used to predict the CFB fault operational parameters accurately.

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