CHAPTER 2

LITERATURE REVIEW

M. Fast [2009] has presented a paper on *Application Of Artificial Neural Networks To The Condition Monitoring And Diagnosis Of A Combined Heat And Power (CHP) Plant*. In his paper stated that the objective of his study has been to create an online system for conditioning monitoring and diagnosis of a combined heat and power plant in Sweden [13]. The artificial neural network (ANN) models were integrated on a power generation information manager server in the computer system of the combined heat and power plant. The CHP components were simulated with ANN and the models were integrated in a power generation information manager (PGIM) server in the computer system of the CHP plant.

The plant system was divided into its basic components, and each component was modeled separately. Data from the plant was delivered as 5-min averages, covering three months of operation. Before using any data for training, the data had to be filtered and outliers (removed). Also all transient operations were removed since 5-min average data only permitted modeling of the steady state operation. The selection of input and output parameters, for each individual model, was based on the availability of reliable plant data as well as true needs. All ANN models were subjected to a sensitivity analysis in order to assess which input parameters were of significance for each model.

The performance of a gas turbine is determined by the ambient conditions and using these conditions as input parameters to the ANN model is a natural course of action. The two discrete load cases were represented by two ‘switches’ (‘1’ and ‘0’), enabling the NN to differentiate between two modes of operation based on load. In boiler model, only two inputs (temperature and pressure of feedwater) were required for the ANN boiler model in order to obtain predictions of the steam properties and the mass flow rate of pellets. With proper training, data and parameter selection, it is also feasible to achieve very high prediction accuracies. The condition of a plant could be monitored while simultaneously economically evaluating deviations.

The parameters of HRSG, district heat and input parameters of the boiler, e.g. fuel and air flow rates and air temperature is included to see the effects on the power output. Other parameters like drain pressure and the Curtis pressure have been used as input parameters in order to increase the accuracy of the ANN model. The ANN models are found to have very good prediction accuracy. By predicting the power output with good accuracy, online monitoring system for the plant and the assessment of degradation of the performance of the plant can be implemented.

In the paper of *Comparison of Fuzzy logic and Neural Network in life prediction of boiler tubes* written by *A. Majidian* [2009], wall thickness of reheater tubes of boiler of Neka power plant in north of Iran are measured during maintenance shutdown period [1]. This study has investigated the thickness dependency versus time and it shows that about 40% of tube failures occur in furnace water wall tubing and several primary mechanisms have been found responsible for the boiler tube failure experienced in power plant boilers. Secondary failure mechanisms (adjacent tube washing / impact) also can produce a tube failure and always a concern after an initial failure.

By implementing ANN, two cases were considered. First, the data of all leading tubes of all bundles were used as input and next, 10 selected tubes were chosen. In order to get the best approximation for wall reduction, multi-layer feed forward Neural Network (ANN) is used. Typically, the more the neurons in hidden layer, the more powerful the network. The number of neurons in the hidden layer is varied to give the network enough power to solve the problem.

Since the objective of this study is to find the minimum remaining life of a set of tubes in the boiler, the worst tube is sought or in other words, seeking for the tube that has the lowest thickness or a redundant wall thickness with a membership value of one and is prone to highest loss of wall thickness or a wall thickness reduction rate with a membership value of one as well. Using ‘tansig’ as activation function causes the network to approach the solution faster than when using ‘logsig’.

From the results, ANN model with one neuron in hidden layer predicts 70% and 31% longer life compared with ANN model with three neurons in hidden layer hence, the number of neurons affect the results of maximum wall reduction rate. The results indicate that wall thickness reduction rate accelerates with time. The choice of activation function may be significant influence on the results of network. Increasing the number of neurons in hidden layer will decrease the number of calculation steps with subsequent decrease in sum-squared error.

For prevention of utility destruction in power plant, the early boiler tube leak detection is highly enviable. In the study of *Approach to Early Boiler Tube Leak Detection with Artificial Neural Networks* by *A. Jankowska* [2007], the ANN models of flue gas humidity for steam leak detection are presented. The author mentioned that, the plant shutdown, breakdown and catastrophes can be avoided by implanting early detection of faults.

There are several methods of steam leak detection. Hence, the method of steam leak detection can be specified as by implementing acoustic monitoring devices, steam and water balance testing method, monitor the humidity of flue gas whereby the humidity can be caused by water added to combustion chamber, changing fuel hydrogen or steam leaks.

The advantages of using artificial intelligence methods approach to steam leak detection can be named as new devices or signals besides DCS are not necessary, expected earlier leak detection because of using many measured signals and no apparent interdependencies, expected solution portability between like plants [12]. 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. The learning, testing and validation subsets were distinguished and reconstruction, validation of missing and fault values of measured data is necessary stage in off-line and special in on-line mode of models application.

Hence, due to averaging and generalization properties of ANN external process disturbance were sufficient well presented in model. The tested ANN model gave promising results in early detection of tube boiler faults, but very limited number of faults cases was in disposal [12].

Luis M. Romeo [2006] had presented a research on *Neural Network For Evaluating Boiler Behavior* and the objective of the research is to present the methodology of NN design and application for a biomass boiler monitoring and point out the advantages of NN in these situations [8]. This paper proposes the use of an artificial feed-forward neural networks based model in order to evaluate the biomass boiler fouling.

There are 2 techniques that could be used to develop an accurate boiler monitoring; theoretical thermal modelization and neural networks simulation. The first technique requires strong hardware and software to solve non-linear mathematical operation. However, neural networks simulation technique is able to deal with complex calculation, obtaining accurate results without needing of high developed software. The aim of the develop NN is to produce the value of fouling index obtained by the theoretical model used for monitoring and steam output obtained by real data.

Multilayer feed-forward NN is the structure used in the work where the information goes from the input to the output throughout intermediate layers in a unidirectional way. The methodology applied to develop NN could be theoretically divided in four stages: structure or architecture design, training, validation and use. The NN is training with the available inputs and mean square error (MSE) is registered.

The higher the influence of the absent input in the training is, the more increased the MSE value is, and more important the eliminated input variables are to solve the problem. All the results have been validated with real and equation-based monitoring data. Agreement between data and NN results is excellent and also has been pointed out that the NN is a stronger tool for monitoring.

On the other hand, R.J. Patton [1994] had proposed in his paper on *A New Approach For Detecting And Isolating Faults In Nonlinear Dynamic Processes Using Neural Networks*. Two stages involved and demonstrated in a laboratory 3 tanks system. The first is to generate residual signals based in comparison between actual and predicated states and the second stage of fault detection and isolation, a neural network is trained to classify characteristics contained in the residuals [14]. A neural network is used to examine the possible fault or abnormal feature in the system outputs and gives a fault classification signal to declare whether the system is fault or not.

A laboratory 3-tank system is used as a test bed to demonstrate the method presented in the paper. The NN detects a fault using pattern recognition techniques and activates an alarm signal. In the training of NN to classify faults, output node values of 0.1 and 0.9 are used to indicate fault-free and faulty cases. If fault patterns are known to occur for specific faults, this information could be stored in the neural network by choosing the training set of the neural network to co-ordinate with known faults. The results show that the NN-based fault diagnosis scheme can detect faults in nonlinear dynamic system reliably providing sufficient training.