Neural Network Applications in a Power Station

T. K Sai, K. A. Reddy

Abstract*--*The integration of Soft Computing techniques in traditional real-time systems is a promising approach to cope with the growing complexity of real-world applications. A power station is a complicated multivariable controlled plant, which consists of boiler, turbine, generator, power network and loads. The demands being placed on Control & Instrumentation engineers include economic optimization, practical methods for adaptive and learning control, software tools that place state-of-art methods . As a result, Neural network applications are explored in Measurement and Control. In real time systems, Information plays a vital role for the efficient operation and maintenance in a power station. However there are limitations on making available information online due to instrumentation limitation, hazardous environment condition etc. The Furnace Exit Gas Temperature (FEGT) is an important design and operating parameter. The furnace of a boiler is such a zone where online measurement of temperature is difficult because of high temperature and adverse conditions. Considering the complexity of power plant operating condition and number of parameters involved, the best solution to this problem lies in adopting the Neural Networks to measure FEGT in a 500 MW Thermal Power Plant. Also, Steam temperature Control is one of the most challenging control loops in a power plant boiler because it is highly nonlinear and has a long dead time and time lag. . The Superheated temperature is to be controlled by adjusting the flow of spray water to within +/- 10 deg C during transient states and +/- 5 deg C at the steady state. A neural network based Model Predictive Control (MPC) is proposed in this paper

Index Terms*-- *Neural Networks, Boiler, Superheater temperature, Furnace exit gas temperature, Measurement Control, Power Plant

I. INTRODUCTION

The Power station considered in this paper is a Fossil fired 500 MW Power Station. Boiler is a very important component of steam power plant. It costs roughly 30% of total cost of power plant Boiler is a composition of combustion and heat transfer zones. The heat transfer inside the furnace basically takes place by radiation and convection. The portion of the furnace directly exposed to the flame receives heat by radiation and all other sections receive heat by convection. The imaginary plane, which separates these two sections, is called Furnace Exit Gas Plane**.**

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T. K. Sai, received the B.Tech. Degree in Electronics and Instrumentation Engineering from Kakatiya Institute of Technology and Science (KITS), Warangal.

K. Ashoka Reddy, received the B.Tech. Degree in Electronics and Instrumentation Engineering from Kakatiya Institute of Technology and Science (KITS), Warangal.

Basically, the furnace exit point separates the radiation zone from the convection pass . The temperature in this plane is known as furnace exit gas temperature (FEGT) which cannot be measured directly due to high temperature and adverse condition. However temperature at the economizer outlet is available online, and it is possible to back-calculate this temperature using heat balance through various heat exchangers in the backward path up to the furnace exit zone and know the value of the FEGT. Considering the complexity of power plant operating condition and number of parameter involved, the best solution to this problem lies in adopting the AI method. Neural network techniques has been considered as an useful tool in the area of nonlinear parameter estimation. The design value of FEGT is in the range from 1200 deg c to 1400 deg c. FEGT provides a direct indication of the heat transfer to the furnace water walls at a particular load condition, and sets expectations for performance of the superheat and re-heat processes. If the FEGT is too high, residual fly ash will fuse to the pendants and tubes forming slag reducing the heat exchange efficiency to the tube walls. This can lead to increased soot blowing operations, tube corrosion, reduced load operation, and possible safety issues. A low FEGT value may indicate excessive radiative losses to the water walls or an incomplete combustion process resulting in lost efficiency. By online measuring and controlling the FEGT, operators can balance and optimize their combustion process and safeguard the boiler furnace.

II. CONVENTIONAL METHODS OF FEGT MEASUREMENT

A. Contact type Retractable HVT

If an accurate kinetic flue gas temperature in a furnace is required, the most common practice has been to draw a sample of gas through a ceramic radiation shield and across a thermocouple junction in a suction pyrometer (also known as a high velocity thermocouple or HVT probe). In theory, this method should provide a reliable and accurate temperature measurement. However, in practice, the response time of the instrument is long and in pulverized coal-fired furnaces the blockage from ash and damage to the shield from thermal shock poses significant problems.

B. Non Contact Type

The difficulties and limitations of contact measurement methods have encouraged the development and application of various non-contact techniques to obtain furnace gas temperature measurements on a real-time basis. Most of these techniques have been based upon measuring the thermal radiation emitted from the gas or ash particles suspended in it.

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C. Practical limitations of FEGT measurement

Sonic detection systems are quite expensive to install and their accuracy can be adversely affected by the noise of the soot-blower operation and any other steam or gas leakages. Contact-type thermocouples are not as accurate as non-contact infrared temperature sensing due to the lack of penetration of the thermowell, which is typically only 2' to 3' long. Consequently, the temperatures measured are the areas along the boiler walls, which are generally cooler than the center of the boiler, which is the desirable measurement zone. In addition, in coal fired boilers the thermowells accumulate soot and ash buildup thereby insulating the thermowell tube. This indicates a much lower operating temperature reading inside of the boiler or waste incinerator than the actual temperature, causing concern of burnout of the refractory and boiler tubes. Calculation from data points starting at the final gas-exit point, the economizer, and working back, using steam and water temperatures along the way involves too great a potential for error. Hence the continuous on-line measurement of FEGT enables the operators to monitor furnace trends and to react to undesirable conditions. For example, ash accumulation on the lower furnace walls can be reduced by initiating cleaning operations only when and as needed. This helps to avoid unnecessary tube erosion resulting from excessive cleaning operations and at the same time maintain the desired FEGT.

III. NEURAL NETWORKS FOR FEGT MEASUREMENT

NN architecture mimics the learning process of human brain. The basic architecture of NN involves interconnected neurons, which are defined in three distinct categories: input layer neurons, output layer neurons and hidden layer neurons as shown in Figure 1.

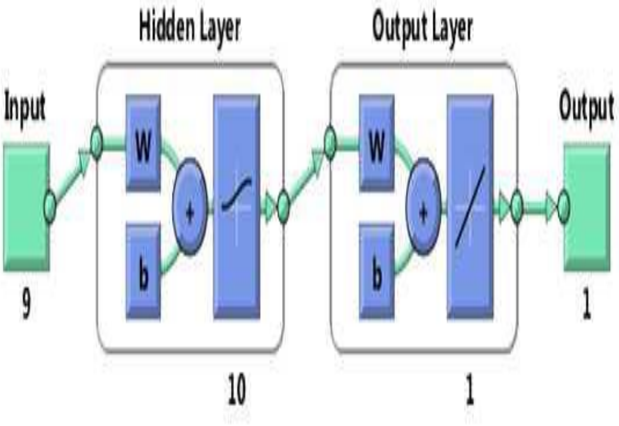

Figure 1 The Schematic diagram of a feed forward-back propagation network

The important parameters selected at the input of the neural network are those parameters which are having maximum influence on FEGT, are as listed below.

1. Feed Water Flow
2. Coal Flow
3. Air Flow
4. Secondary Air Temperature
5. Primary air flow to Coal flow ratio
6. 02%
7. Burner Till Position
8. Mill Combination in service
9. Cleanliness Factor

The input data are presented through input layer neurons and the response of the input data is presented at output layer neurons. Neurons are connected by scalar functions known as weights that take part in the learning process of networks. In back propagation algorithm, which is widely used in training of NNs, a series of input and output data is presented to the system. Each hidden layer neuron and output layer neuron process this input data by multiplying its corresponding weights, and using a transfer function. Neural networks operate by recognizing and accounting for relationships among several input variables in an effort to correctly predict an output variable. The input variables are multiplied by a "weight", added to other variable-weight products and sent through an activation function (the hyperbolic tangent, logistic, and Gaussian distribution are examples). This new value is then multiplied by a second weight and the process repeated for as many layers as the network designer has used . For error back-propagation networks, the predicted output variable is compared to the actual value and the difference is then accounted for and distributed back through the weighted connections with each weight adjusted accordingly[11,15]. The FEGT is derived from the weights and biases of the trained feed forward back propagation neural network[8,9,11]. Weights and biases of all layers of neurons were combined with transfer functions of NN model to achieve an NN equation pattern as the following steps[11,19,20,21,22,23,24]. Results The learning of the network is carried out through adjusting the weights by continuous iterations and minimizing the error between the measured analyser value and ANN model predicted response [3].The 9 input layer nodes with the 1st bias node connected to 10 nodes of hidden layer. Thus, there are 90 values of weights and 10 values of biases on the layers between input and hidden layer. On the hidden layer, the 'tansig' transfer function is used to calculate the sum of the 90 weighted inputs ($W_{i,j}$) and the 10 biases (bt_j). The sum of weights and biases in hidden layer is displayed on Eq. (1).

$Z_j = f_t(W_{i,j} X_i + bt_j)$, i = 1,2,3,4,5,6,7,8,9 j = 1,2,3,…,10 (1)

where, Z_j is the 10 outputs of hidden layer
f_t is the 'tansig' transfer function of hidden layer
$W_{i,j}$ is the weights from input layer i to hidden layer j
X_i is the 9 inputs of input layer
bt_j is the 10 biases of hidden layer

The 10 nodes of hidden layer connected to one node of output layer. It means the layers between hidden layer and output layer have 10 values of weights rows and one value of bias. On the output layer, the 'purelin' transfer function is used to calculate the sum of the 10 weighted inputs (Wj) and one bias (bp).The sum of weights and bias in output layer is displayed on Eq. (2).

$Y = f_p(W_j Z_j + bp)$, j = 1,2,3,…,10 (2)

where, Y is the output – FEGT estimation
f_p is the 'purelin' transfer function of output layer
W_j is the weights from hidden layer j to output layer
Z_j is the 10 inputs of hidden layer
bp is the bias of output layer

Neural network training is made more efficient if certain pre-processing steps are performed on training data set. The input data to be applied to network and the target data for training and testing is to be normalized in the range of the activation function. It is also to be seen that the normalized values of input and target data samples do not fall in the saturation regions of the activation function characteristic curve to avoid unrealistic network response. Hence all data samples are normalized in the range of-0.9 to +0.9 as the range of tan-sigmoid activation function is from -1 to +l. In this case the target value is measured with HVT probe.

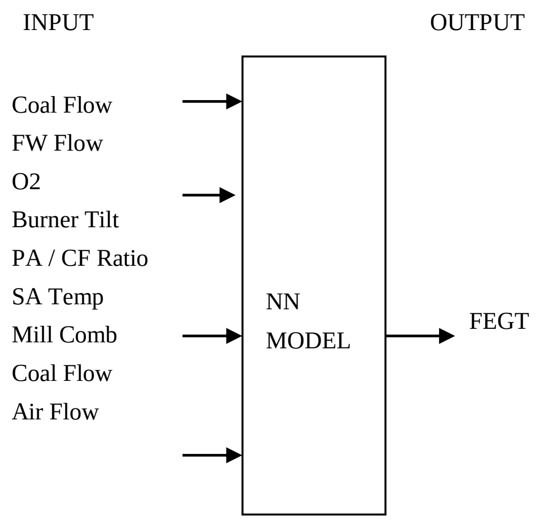

Figure 2 Neural Network Parameters

As shown in figure 2 there are 9 inputs and 1 output. The measured and predicted FEGT shown in Figure 3 indicates that the trained network is performing reasonably good in prediction.

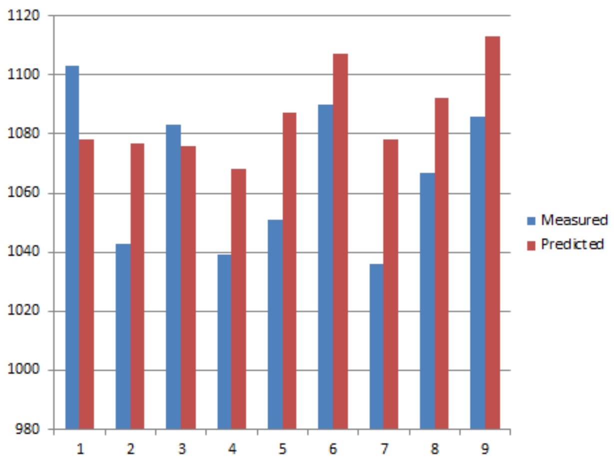

Figure 3. Sample Measured versus predicted FEGT

IV. NEURAL NETWORKS FOR SUPERHEATER TEMPERATURE CONTROL

Proper control of Superheated steam temperature is extremely important as high temperature can damage the superheater or high pressure turbine and low temperature will reduce the efficiency of power plant.

Thus for economical operation:

[1] It is important to maintain rated main steam temperature and pressure and reheat steam temperature within extremely close limits for higher cycle efficiency and avoidance of overstresses.

[2] The rate of change in steam temperature should be within the limits imposed by thermal stresses.

[3] The use of spray water should be minimized.

4.1 Conventional Superheater temperature control

The conventional superheater(SH) temperature control loop is shown in figure 4. The Main Steam (MS) temperature is influenced by three variables, namely Main Steam flow, Heat input and Drum pressure. To control the MS temperature as per the setpoint value, the inlet steam temperature is modulated by changes in spray water. As the dynamic response of superheated steam temperature to the inlet steam temperature is very sluggish, the control system will set into oscillations if the MS temperature is controlled directly by spray water flow. Hence a Cascade Control is envisaged. The Master controller (MC) has the set point value for the final superheated steam temperature and sets the required superheater inlet steam temperature to the Slave controller (SC). The SC responds to this and the disturbance of inlet steam temperatures and modulates the spray water flow rates. The general layout of Cascaded Steam temperature control loop is shown in Figure I. The Slave controller (TC2) reduces the intensity of effects of these disturbances on the final superheater steam temperature. The process under the control of Slave controller consist of control valve, Desuperheater and Temperature Sensor. The overall order of this system is third order which can be controlled by a PI control configurations. The Master controller (TC 1) is of sixth order and hence a PID configuration is used. Conventional Proportional-Integral-Derivative (PID) based controllers were used to control the spray vales that regulate the injection of water into the steam header. The control is difficult because there is a significant dead time between the addition of the spray water and the effect on steam temperature. This problem is compounded because the system response changes as the MW load on the turbine is changed and the boiler-firing rate is adjusted to produce the required steam flow.

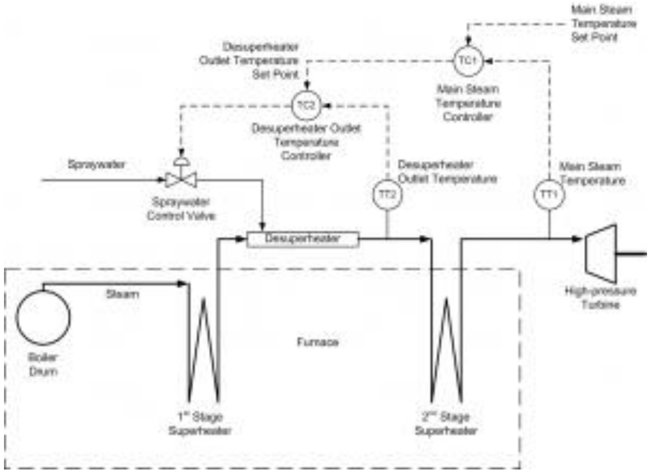

Figure 4.Conventional SH temperature control loop

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4.2 Predictive Control

Predictive control is becoming a valuable control strategy for higher control requirements i.e., tighter, faster regulation or tracking in the industrial world. Using predictive control, a process is regulated by specifying the desired plant output at a particular instance or instances in the future. Then the controller action, which minimises the predicted error is calculated. As MPC relies of the prediction of the controlled variable, a model of the process is compulsory.With the increasing interest to Artificial Neural Networks (ANN) as a modelling tool for industrial processes, the concept of ANN models used with MPC appeared. Artificial neural networks (ANNs) as a process model for control purposes conceive the following superiority points as compared with other conventional modeling methods:

(1) Models derived from first principles are usually difficult and/or costly to develop for processes that are not well understood or very complex. Additionally, to evaluate model parameters and to make models concise enough for online execution, assumptions and simplifications are inevitable and compromise model accuracy.

(2) ANNs provide a general approach for extracting process dynamics from input-output data only. Their learning ability makes them versatile and friendly for practical applications. In addition to their great power for approximating complex functionality, the compact form and high speed of information retrieval make ANNs very suitable for online use.

Model Predictive Control (MPC) is widely adopted in industry as an effective means to deal with large multivariable constrained control problems. The main idea of MPC is to choose the control action by repeatedly solving on line an optimal control problem. This aims at minimizing a performance criterion over a future horizon, possibly subject to constraints on the manipulated inputs and outputs, where the future behavior is computed according to a model of the plant . The general principle of predictive control can be explained as “At each consecutive sampling instant k, the control inputs u(k) = u(k|k), u(k +1|k), . . . , u(k + Nu −1|k) are calculated, assuming u(k + p|k) = u(k + Nu −1|k) for p ≥Nu, where Nu is the control horizon. The applied notation ‘u(k + p|k)’ means the prediction of the control input value for the future time k + p, performed at the time k. The control inputs are calculated in such a way as to minimize differences between the predicted controlled outputs y(k + p|k) and the foreseen set points for these outputs y^{sp}(k+p|k) over the prediction horizon N (p = 1, 2, . . .,N). Then, only the first element u(k|k) of the calculated sequence is applied to the process, i.e., u(k) = u(k|k). At the next sample (k + 1), there occurs a new measurement of the process outputs and the whole procedure is repeated, with the prediction horizon of the same length N, but shifted by one step forward”. This principle is presented in Figure 5 and 6.

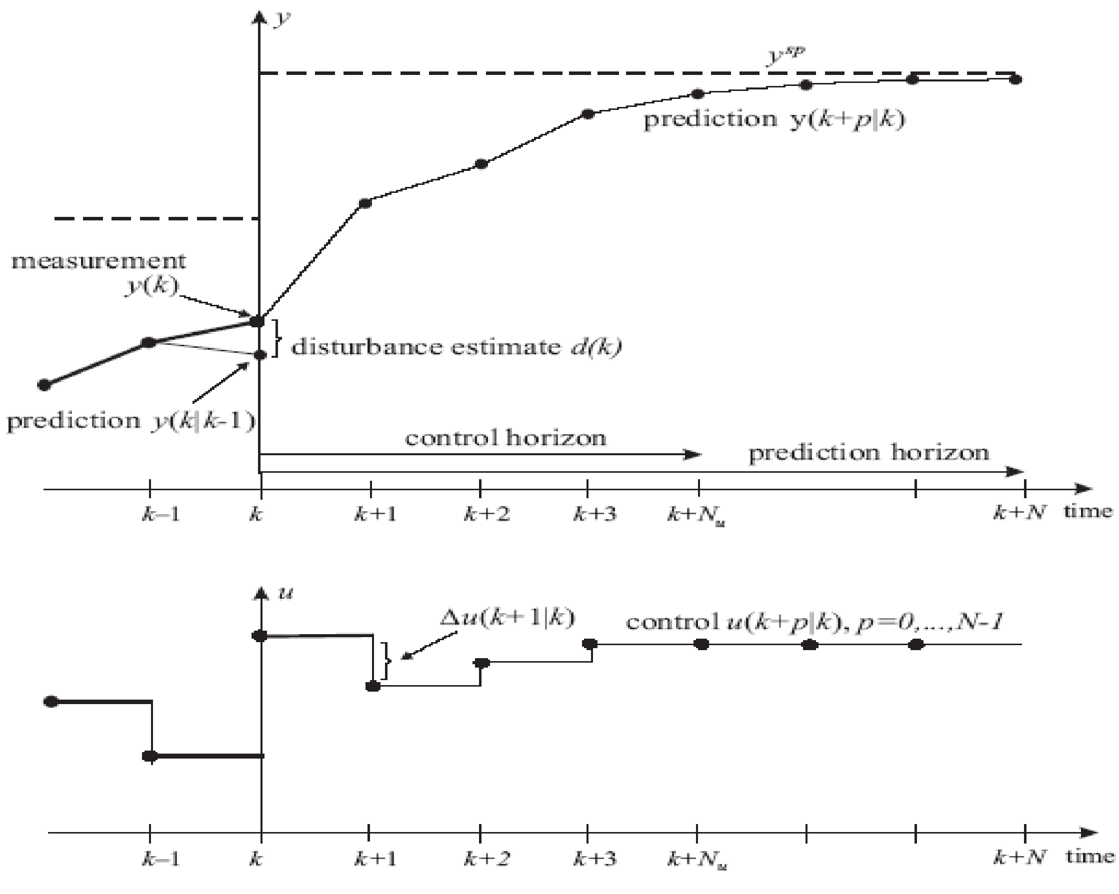

Figure 5. Concept of predictive control

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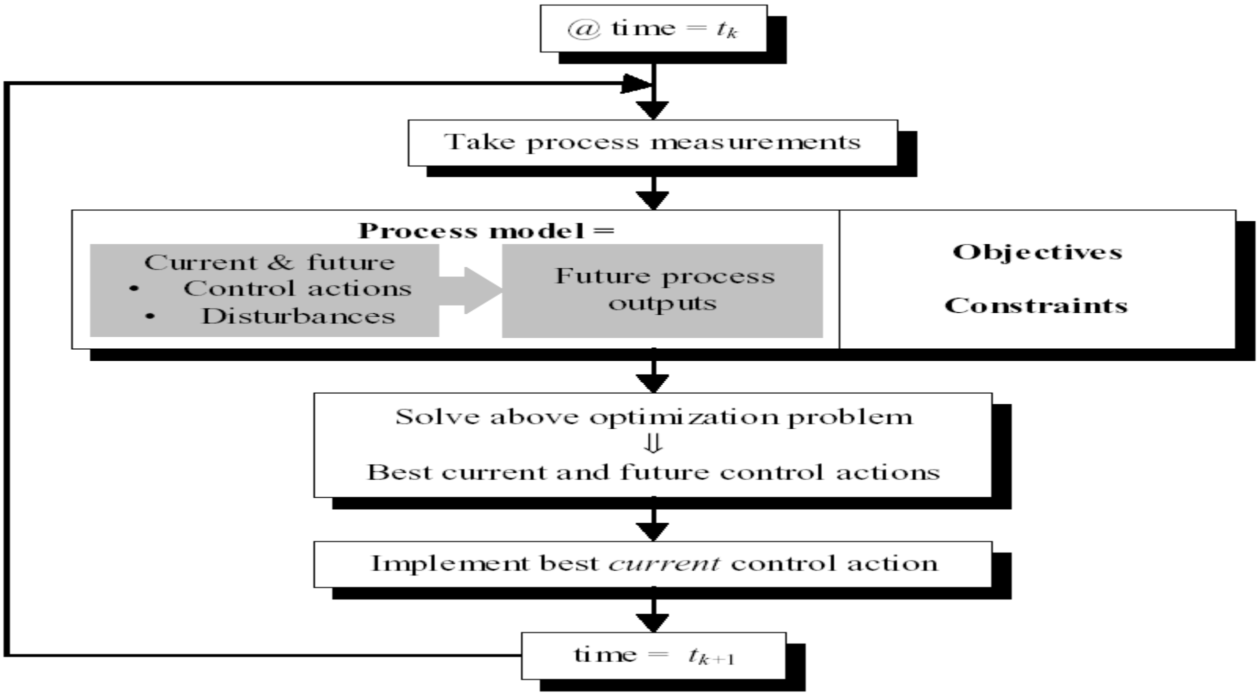

Figure 6. MPC principle

4.3 MPC strategy

An MPC strategy can be implemented using either an identified input-output model or a physical state-space model based on first principles. But, getting a physical model involves complicated computations and total dynamics of sub-systems cannot be incorporated, as it will increase the order of the system. . Hence, it is important to construct a data-based model for the power plant. This would give a system behaviour close to the actual plant behaviour with a model of complexity much less than the actual physical model. Figure 7 shows a typical set up of a MPC in a power plant.

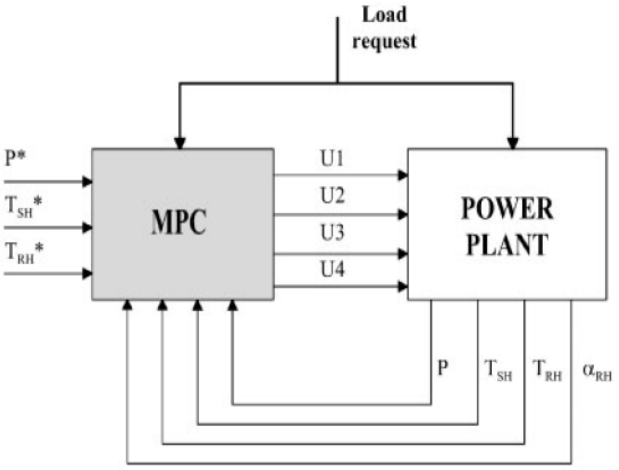

Figure 7. Typical MPC in a Power Plant

P-steam pressure
T_{SH}- superheater steam temperature
T_{RH}- reheater steam temperature
α_{SH}- superheater spray valve opening
*- Predicted values
U1 to U4 control inputs

4.4 Data collection

Extensive data from an actual plant was taken from two thermal power plants of 200 MW and 500 MW units. Dates for data collection are chosen based on 10% variation from normal value. For 500 MW units the duration was 15 seconds and 5760 sets of data per day were collected and total number of days was 8. For 200 MW units the duration was 60 seconds and 1440 sets of data per day were collected and total number of days was 7. A sample data sheet for stage I and II units is given in Appendix IV and V respectively. An Artificial Neural Network (ANN) is used to model the complete boiler. An ANN is trained with the help of measured data from the boiler process and then is used in a control system. It is also possible to train the ANN online and update the parameters continuously to keep the performance within some quality measure. Creating an ANN is nothing but a nonlinear system identification process, resulting in a nonlinear model. Schematic of NN predictive controller is given in figure 8.

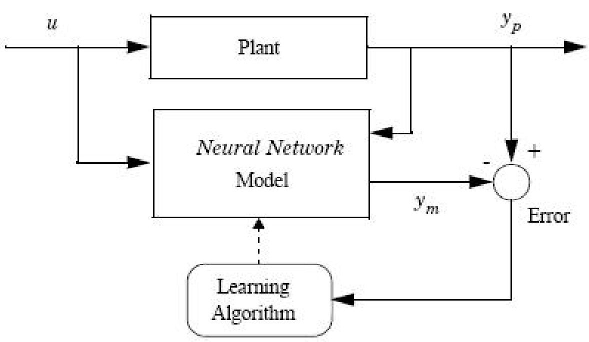

Figure 8. ANN predictive control structure

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INPUTS: MS Temperature, MS pressure, drum level, Feed Water Flow Rate, Fuel Flow Rate, Attemperator Spray Flow Rates, Flue Gas Temperatures, Air Flow, Excess Oxygen, Furnace Pressure

OUTPUTS: Main Steam Temperature

The FFNet uses a *supervised* learning algorithm besides the input pattern; the neural net also needs to know to what category the pattern belongs. Learning proceeds as follows: a pattern is presented at the inputs. The pattern will be transformed in its passage through the layers of the network until it reaches the output layer. The units in the output layer all belong to a different category. The outputs of the network as they are now are compared with the outputs as they ideally would have been if this pattern were correctly classified: in the latter case the unit with the correct category would have had the largest output value and the output values of the other output units would have been very small. On the basis of this comparison all the connection weights are modified a little bit to guarantee that, the next time this same pattern is presented at the inputs, the value of the output unit that corresponds with the correct category is a little bit higher than it is now and that, at the same time, the output values of all the other incorrect outputs are a little bit lower than they are now. (The differences between the actual outputs and the idealized outputs are propagated back from the top layer to lower layers to be used at these layers to modify connection weights. This is why the term *back propagation network* is also often used to describe this type of neural network.

4.5 Simulation of ANN:

Parametric model of the plant is developed using system identification toolwith Graphic User Interface (GUI). This model is used in the design of ANN predictive controller. Figure 9 to 12 show the plants measured and predicted model output, error, 5 step ahead prediction and step response for stage-II units .

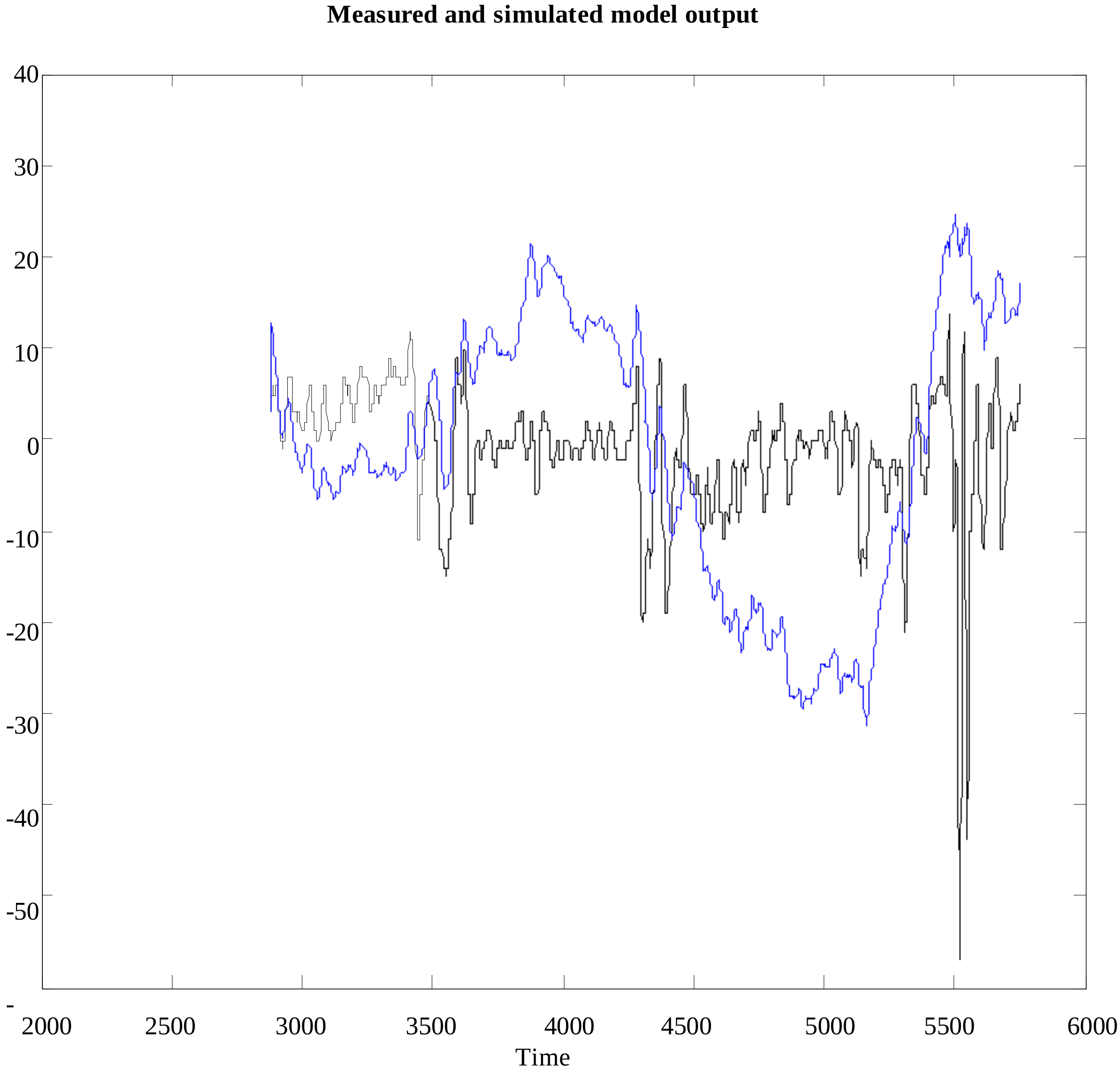

Figure 9. Measured and simulated model output stage-II unit

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Measured minus simulated model output

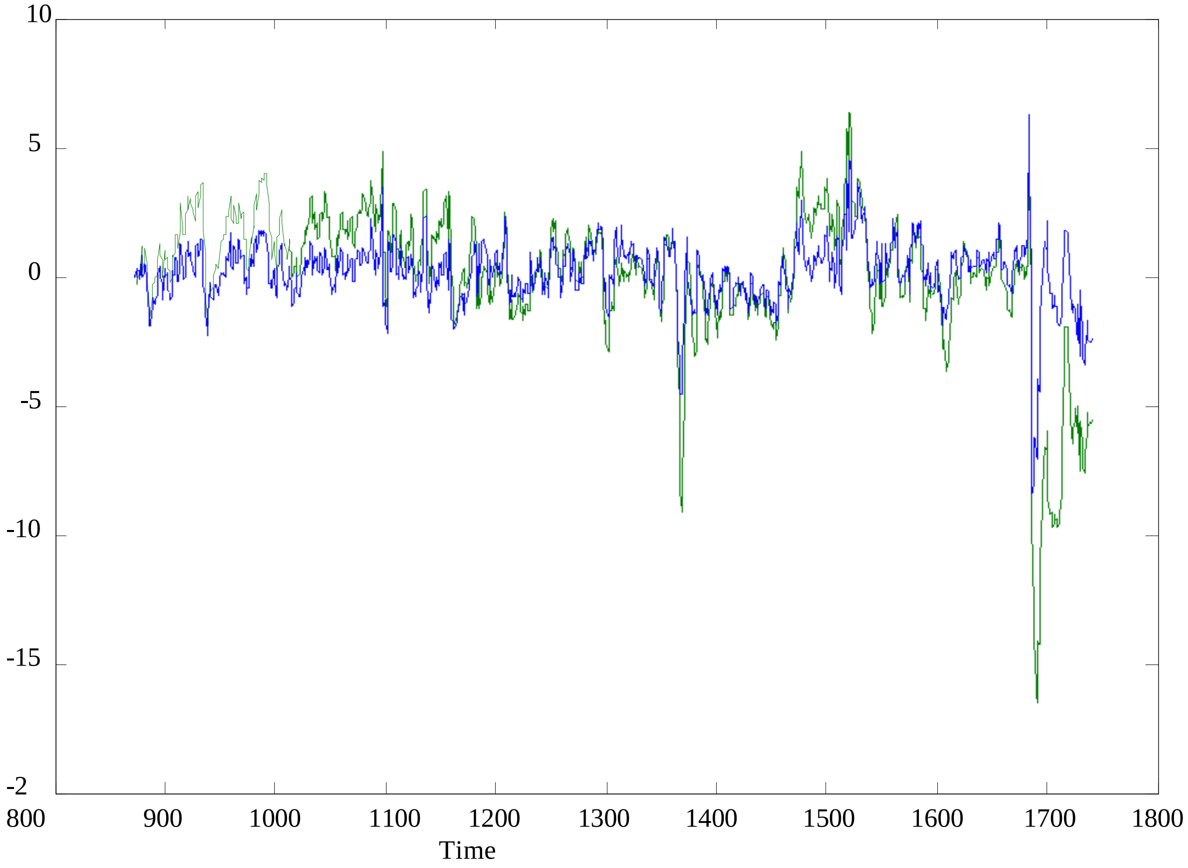

Figure 10. Model error stage-II unit

Measured and 5 step predicted output

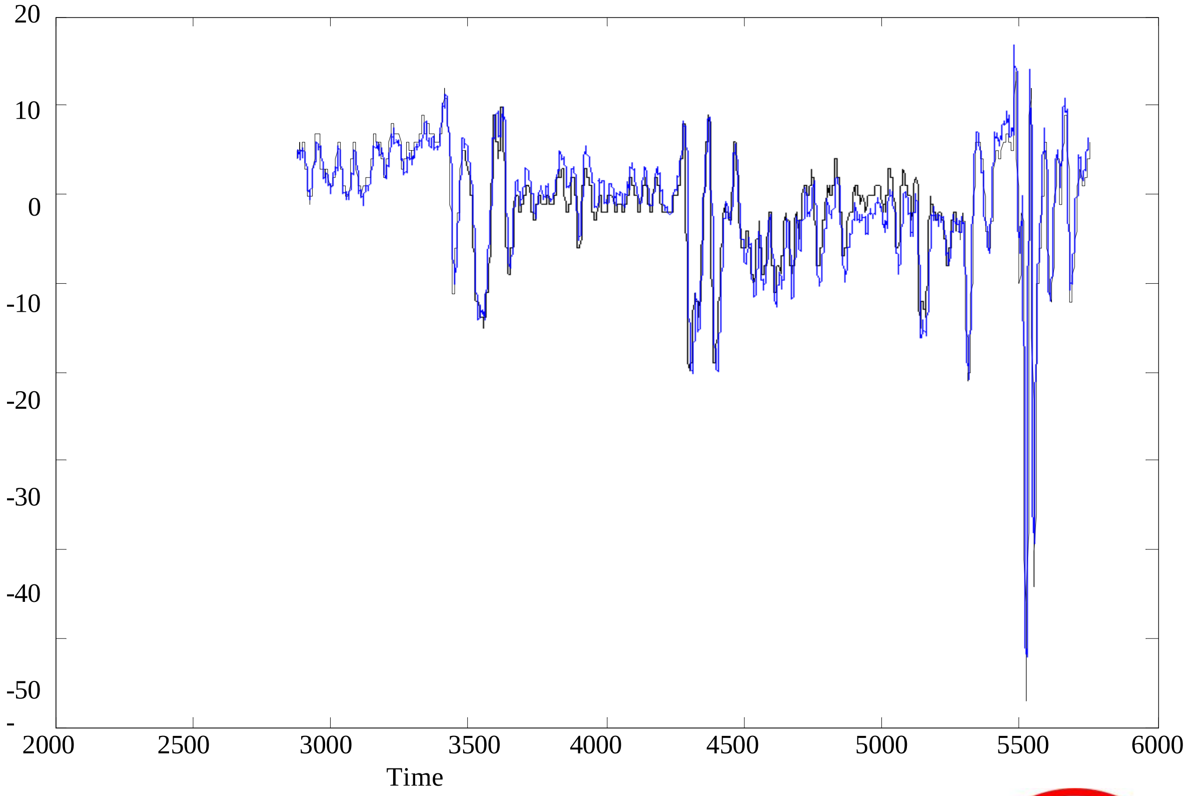

Figure 11. Prediction output stage-II unit

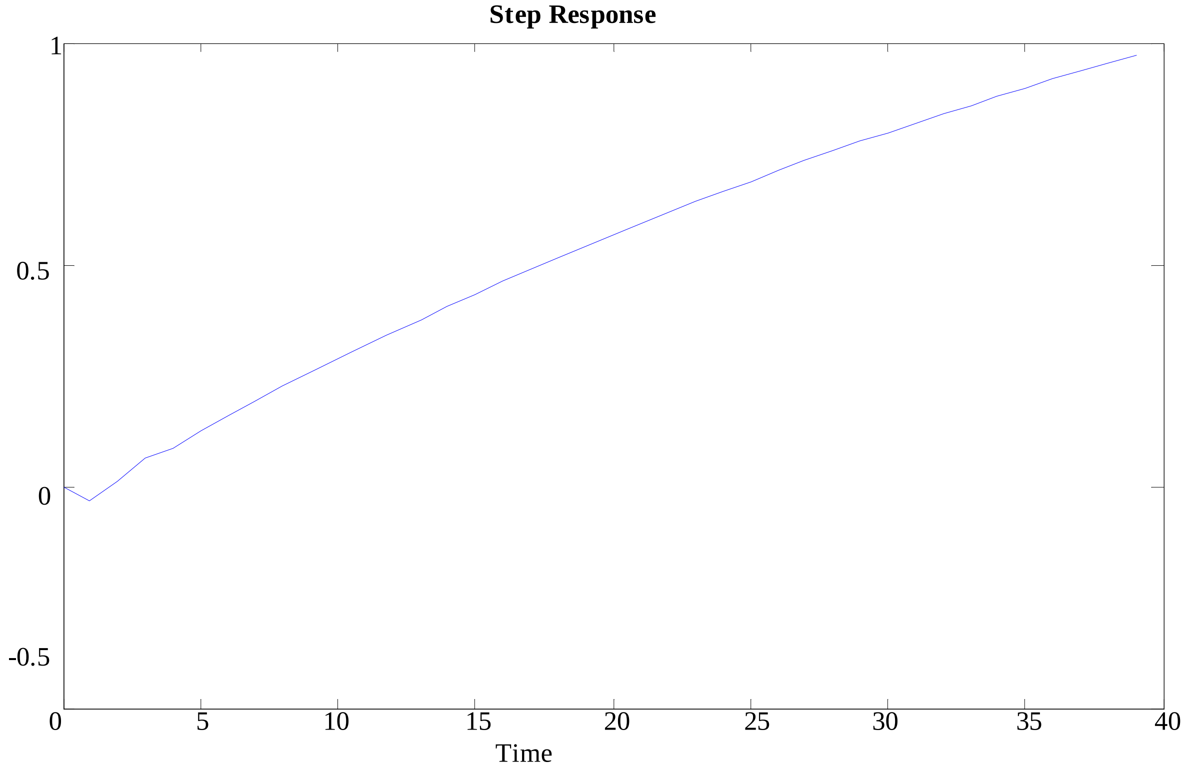

Figure 12. Model step response stage-II unit

4.6 Results

The data is taken from an actual plant to provide the input/output data for the system. The ANN consists of many neurons, which utilize a sigmoid function in each hidden layer. There are simulation parameters, which are the number of neurons in the hidden layer of the ANN, and the number of epochs to train the ANN. Figures 13 to 14 show results of the simulation

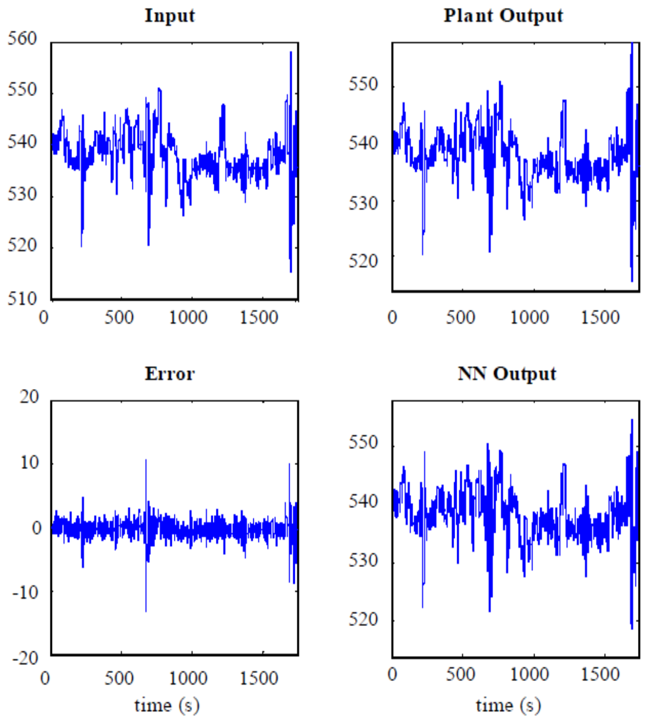

Figure 13. Predicted MS Temperature (training)

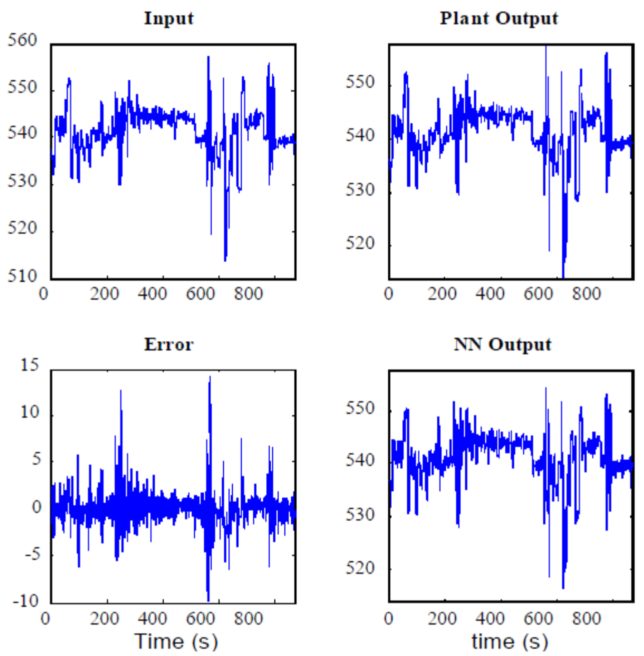

Figure 14. Predicted MS Temperature (testing)

V. CONCLUSION

The purpose of this paper is to demonstrate the neural network applications in a Power Station. The FEGT online measurement is derived from Neural Networks. FEGT can be used as the primary indicator to establish the scheme for automatic soot blowing or to alert the operator to start the manual soot-blowing operation.

If FEGT exceeds the original design value, this indicates that the furnace is dirty and the operator should initiate the furnace soot blowing and the soot blowing should be stopped when FEGT has been reduced below the original design value. The over-blowing in the furnace is wasting the energy and can also create soot blower erosion problem in the water wall tube. The Superheater temperature control is implemented with NN based MPC which is more effective and efficient. Hence, the proposed approach makes it possible to easily build high-performance tailor-made controllers for any specific control loop in the Power Plant thereby optimizing power plant efficiency and cost. The boiler system is a kind of typical nonlinear multivariable systems, and so it is known difficult to be controlled**.** Modeling by physical principle is very complex.Hence ANN based modeling tool is very handy method of improving the control syste. These techniques can be be applied to other measurement and control domains of Power Station.

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BIOGRAPHIES

T. K. Sai, received the B.Tech. degree in electronics and instrumentation engineering from Kakatiya Institute of Technology and Science (KITS), Warangal, in 1986 and the M.Tech. (part time) degree from NIT, Warangal in 2002 in Instrumentation and is currently with NTPC . His research interests include power plant measurement and control, Soft computing & data mining in power plants . He is Senior Member of IEEE with 3 years in Senior Member grade and Fellow of IEI.

K. Ashoka Reddy, received the B.Tech. degree in electronics and instrumentation engineering from Kakatiya Institute of Technology and Science (KITS), Warangal, in 1992 and the M.Tech. degree from Jawaharlal Nehru Technical University, Kakinada, India, in 1994 in Electronics. He received the Ph.D degree from the Indian Institute of Technology Madras, Chennai, India, in 2008 in the field of Biomedical Instrumentation. He is currently Prinicipal and Professor with the Faculty of Electronics and Instrumentation Engineering, KITS. His research interests include biomedical instrumentation, digital signal processing , instrumentation and soft computing.