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Full paper

Neural Network Modeling For Main Steam Temperature System

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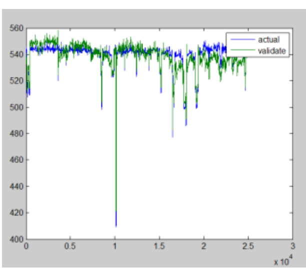
Graphical abstract



Abstract

Main Steam Temperature (MST) is non-linear, large inertia, long dead time and load dependant parameters. The paper present MST modeling method using actual plant data by utilizing MATLAB's Neural Network toolbox. The result of the simulation showed the MST model based on actual plant data is possible but the raw data need to be pre-processed for better output. Generator output, total main steam flow, main steam pressure and total spray flow are four main parameters affected the behavior of MST in coal fired power plant boiler.

Keywords: Main steam temperature; neural network; coal fired power plant

1.0 INTRODUCTION

One of the most important thermal power plant parameters is MST[1]. The steam temperature must be control within the specified limit to maintain plant nominal efficiency as well as ensuring safety for the plant equipment especially boiler tubes[2]. Successful control of MST also ensures stable load dispatch. What makes so difficult to control main steam temperature is its behavior which is non-linear, large inertia, long dead time and load dependent. It means daily load changes from 100% to 30% will have the effect to main steam temperature and the change is non-linear[3]. Typical controller applied at thermal power plant is cascade Proportional, Integral, Derivative (PID) control. Main steam temperature control is paramount in ensuring lifetime of the plant equipment, efficiency, load following capability and availability[4]. Too high temperature will result damages to boiler tubes due to thermal shocks. Too low temperature cause instability for other parameters especially main steam pressure and reheater steam temperature which subsequently cause the unit unable to achieve required load.

PID controller is selected in various industrial applications due to its simple architecture and robustness. However PID controller has some drawbacks. One of the disadvantages of PID controller is the determination of Proportional Gain (Kp), Integral Gain (Ki) and Derivative Gain (Kd) which is based on heuristic approach which require experience and knowledge. Person who tries to do the tuning need advance knowledge both in control and process. Furthermore, it is also impossible to realize perfect performance for the controller for all plant behavior that might happen[2].

2.0 THE POWER PLANT STEAM CIRCUIT

In a large utility coal fired power plant with nominal capacity of 700MW, the details and essential parameters are as follows[5]:

- Natural circulation
- Sub-critical boiler with opposed firing.
- Balanced draught system

Table 1 Plant technical data

Variables	Values
Nominal capacity	*700MW*
Main Steam Pressure	*166 Barg*
Main Steam Temperature	*541 Deg C*
Reheat Steam Temperature	*568 Deg C*
Main Steam Flow	*2365 t/hr*
Condenser Pressure	*79 mbara*
Boiler Type	*Opposed firing*

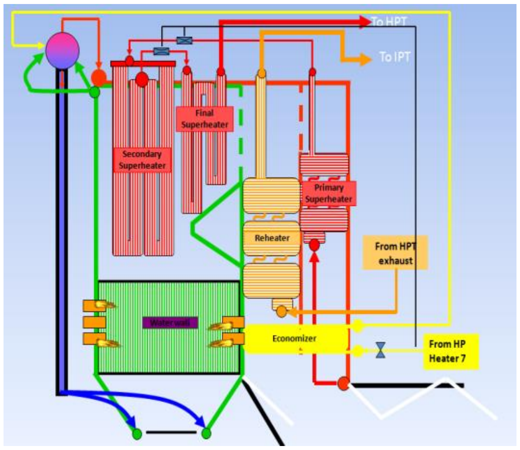


Figure 1 Steam generator configuration[5]

Figure 1 shows that the steam generator is of single drum type, natural-circulation and consists of water cooled furnace, primary superheater, secondary superheater, final superheater, reheater, economizer, downcomer pipe and riser. A balanced draught is adopted with two Forced Draught Fan (FDF), two Induced Draught Fan (IDF), two Primary Air Fan (PAF) and two Regenerative Air Preheater (RAPH)[5].

2.1 Current Main Steam Temperature Control

Current main steam temperature control in the power plant utilizing two stages control as per Figure 2. The first stage control is feedforward PID control which the main objective is to control the Secondary Superheater Outlet Steam Temperature at 452 Deg C at 700MW. The second stage control is feedforward cascade PID control in which the main objective to control boiler outlet steam temperature at 541 Deg C at 700MW[5].

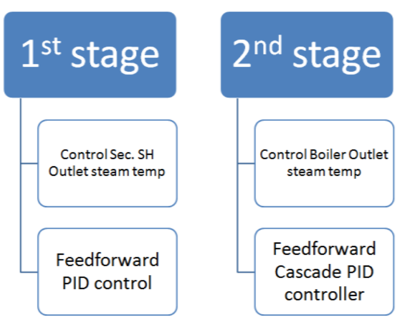


Figure 2 Current control

- First Stage Control - Main steam temperature control at The Power Plant utilizing overall plant automated plant control system. First stage main steam temperature control or also known as primary spray control is part of automatic plant control loop where main control parameters with its feedback are drawn into one logic and loop sheet. The main features are as follows:

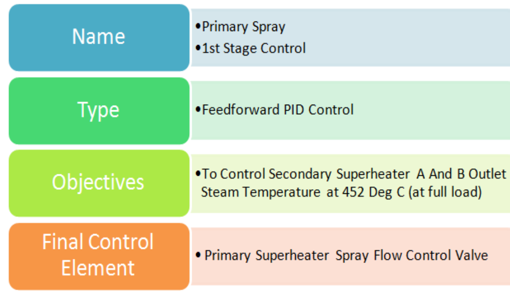


Figure 3 Main features for first stage control

- Second Stage Control - Second stage control objective is to control boiler outlet main steam temperature at 541 Deg C during full load. Second stage temperature control is the continuity from the first stage control and both are important in ensuring successful temperature control. The main features are as follows:

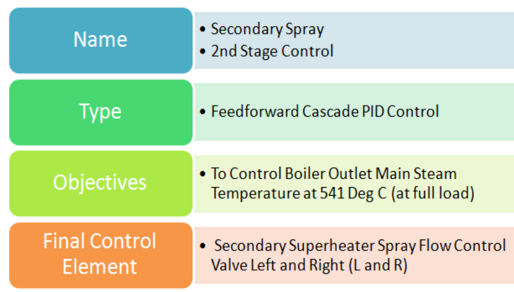


Figure 4 Main features for second stage control

3.0 NEURAL NETWORK INVERSE SYSTEM

3.1 Neural Network (NN)

Starting from 18th century, human being already starts thinking of building intelligent machine. However it is not until the 20th century that the study of neuro science start gaining its pace and human start to understand further about human brain and try to replicate it[6]. Santiago Ramon y Cajal introduced important conceptual insight that the nervous system is made up of discrete signaling elements called neurons[6]. However actual breakthrough in neural network came in 1943 when McCulloch and Pitts published their paper that introduced term "Boolean Brain"[7]. Because of the "all-or-none" behavior for nervous activity, any neural events and its relation can be treated by Boolean logic[7]. There are many progress in understanding human brain and reflected it to artificial neural network but one of the most significant work is by John von Neumann which reflected McCulloch and Pitts ideas during the design of first digital computers. John von Neumann discussing the comparison between computing machines and living organisms, where both displaying the "all-or-none" behavior[8]. Around the same time, Hebb's publication in 1949 introduced several hypotheses about the neural substrate of learning and memory which is famously known as Hebb's learning rule or Hebb's synapse[9]. Hebb's publication continues to spur more work on neural network and inspire diverse computational neural network models. Turing Test which was introduced by Alan Turing in 1950 suggested that computer can be considered intelligent if a human communicating by teletype fail to differentiate the computer from the human being[10].Not until publication of Rosenblatt's Perceptron that the area of neural network research receives a huge boost. Rosenblatt's demonstrate his algorithm capability of pattern recognition that could learn, the convergence proof of Perceptron learning scheme and its ability to classify linearly separable pattern classes[11-14]. Rosenblatt's model further refined by Minsky and Papert in the 1960s; its computational properties were thoroughly analyzed[15]. Since then, there is numerous researches in neural network areas convene and many neural network models are introduced.

3.2 Backpropagation (BP) Learning Algorithm

Backpropagation (BP) is a learning algorithm and originally derived by Werbos[16] in different field but was made popular by McClelland and Rumelhart[17] in the neural network application. Currently BP learning neural network is the most popular neural network algorithm[6]. In BP, the learning rate and the initial value of the weights are specified by the user at the start of the process. It is also important to note that the number of hidden layers determines how effective the algorithm perform. The user must use find the correct number of hidden layers based on heuristic approach. Too few hidden layer can limit the ANN algorithm's learning capabilities while too many hidden layers result the algorithm to memorize the process.

To accelerate the convergence of the BP algorithm, momentum learning is introduced[17]. The updated weight equations are as follows[17]:

Output Layer

$$\mathbf{W_k^{New} = W_k^{Old} + \Delta W_k(t)}$$

Hidden Layer

$$\mathbf{W_j^{New} = W_j^{Old} + \Delta W_j(t)}$$

Where,

$$\mathbf{\Delta Wk(t) = \eta\delta oY^T + \alpha\Delta Wk(t\text{-}1)} \text{ and}$$
$$\mathbf{\Delta Wj(t) = \eta\delta yX^T + \alpha\Delta Wj(t\text{-}1)}$$

Where α is momentum positive constant, t indicates iteration and (t-1) indicates previous iteration.

4.0 NEURAL NETWORK MODEL STRUCTURE

The input and output for the neural network models are as per Table 2:

Table 2 Input-output parameters for neural network model

Input	Output
Generator Output (MW) Total Main Steam Flow (t/hr) Main Steam Pressure (Bar) Total Spray Flow (t/hr)	Boiler Outlet Main Steam Temperature (Deg C)

To get higher accuracy main steam temperature modeling, the input and output selected must be adequate and with minimum noise. Thus, the training data for neural network are taken from actual plant data from 15th September 2012 12:01 AM until 30th September 2012 23:59 PM. Meanwhile, the validation data taken from 1st October 2012 12:01 AM until 20th October 2012 23:59 PM. Data taken with one minute interval. Neural network selected have four inputs and one output with two hidden layer. The hidden layer takes tansig and logsig as transfer function. The hidden layers contain ten neurons and five neurons respectively. The neural network model is using Gradient Descent With Momentum and Adaptive Learning Rate Backpropagation training methods.

4.1 Raw Data Preprocessing

Data mining from actual plant are exposed to a lot of noise which can deterred good neural network performance. As such, raw data preprocessing is needed to prepare smoother data before being fed to the network. Multiple 1-D Multivariate Denoising method is selected for raw data preprocessing. Figure 5 and 6 are the summary of the output of the denoising process. Both training and checking data undergoes the pre-processing step and the outcome showed smoother curve after denoising step.

5.0 NEURAL NETWORK MODEL TRAINING RESULT

The neural network main steam temperature modeling was built using Matlab Neural Network Toolbox. The network is trained using Gradient Descent With Momentum and Adaptive Learning Rate Backpropagation algorithm. After 2683 iterations of training, the model's Mean Square Error reaches 8.3268 x 10-7. The result comparing neural network model output and validation data are shown in the Figure 7.

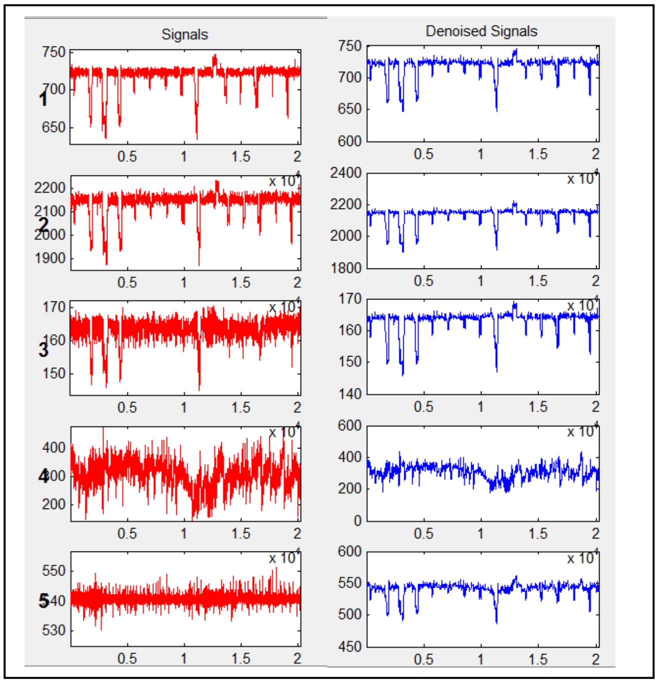


Figure 5 Training data denoising

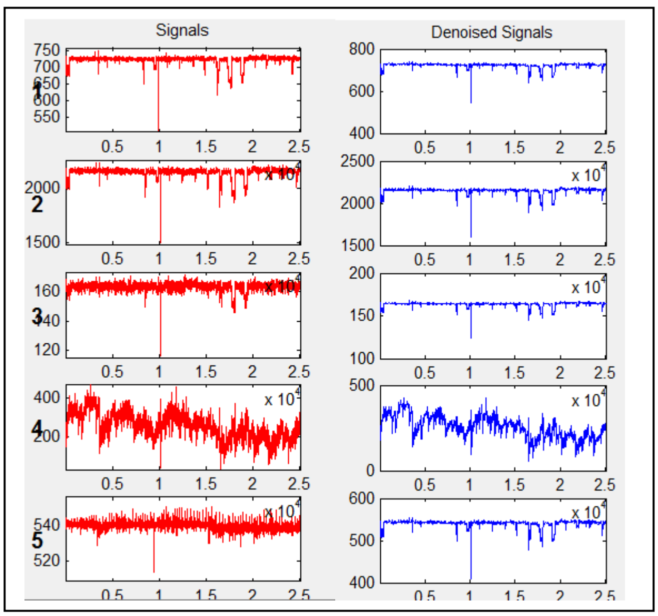


Figure 6 Validation data denoising

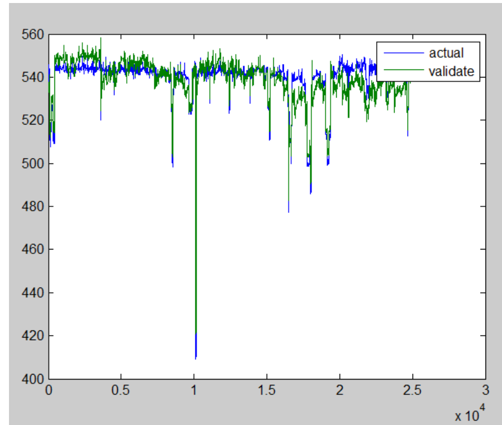


Figure 7 Neural network modeling output vs. validation data with data

■7.0 CONCLUSION

Main steam temperature modeling using neural network based on actual plant data is possible given the raw data is adequately pre-processed. Generator output, total main steam flow, main steam pressure and total spray flow are four main parameters affected the behavior of main steam temperature in coal fired power plant boiler.

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