Improving Steam Temperature Control with Neural Networks

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Abstract

The paper describes the development, installation, and testing of a neural network-based steam temperature controller for power plant boilers. Attention is focussed on the modelling and control capabilities of neural networks. Experimental data obtained from an operational coal fired power plant (Kendal Power Station, South Africa) is presented. Three key observations are made: a) the heat transfer rate from the firing system to the evaporator, superheater and reheater in a power plant boiler can be accurately modelled by using a neural network trained on noisy test data obtained from the real plant, b) once trained, such a neural network model can be used to predict the effects of firing system disturbances on heat transfer in advance, and c) the trained neural network and the backpropagation technique can be applied to adjust the firing system for minimizing the effect of firing system disturbances on steam temperature.

1. Introduction

The world today consumes vast amounts of electrical energy - the annual consumption exceeding 11.5 trillion (10^{12}) kWh [1]. Thermal power stations produce about two-thirds of all electrical power, with coal being the dominant source of this thermal energy [2]. A (much simplified) diagram of the water / steam cycle used in coal-fired thermal power stations is given in Figure 1. Condensed water is pumped to the economizer where it is heated to some point below boiling. The heated water is boiled in the evaporator and the steam is heated further in the superheater. The steam expands through a high pressure turbine where its thermal energy is converted to
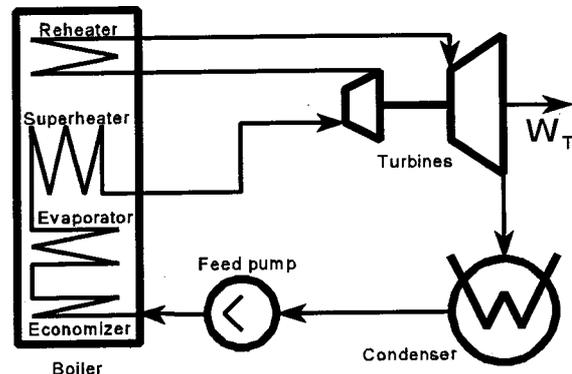

Figure 1. Simplified steam / water cycle.

mechanical work. The steam is then reheated and passed on to the low pressure turbine to produce further work. Finally, the steam is condensed to complete the cycle.

During the combustion process inside the boiler, energy is converted to heat which is discharged into the furnace space. The heat is transferred to the boiler tubes through three individual mechanisms: conduction, convection and radiation. The heat transfer rate is dependant (amongst others) on the furnace flame temperature, the flue gas temperature, flue gas velocity and the geometry of the furnace and boiler tubes [2, 3, 4].

When a power generating unit is moved from one load point to the next, the fuel flow rate to the furnace is manipulated to effect the load change. Due to the thermal inertia of the boiler, the change in steam flow rate lags behind the change in fuel flow rate. To have the generator follow the predetermined linear load ramp, the steam flow rate must be increased linearly. Therefore, it is necessary to inject a substantial quantity of additional fuel during the initial stages of the load ramp, to overcome the time lags inherent in the boiler. This technique is called over-firing, and the magnitude of over-firing is dependent on the load ramp rate. In the case of the Kendal boilers, a 5% per

minute load ramp rate requires almost 20% over-firing [5].

During a load increase, where over-firing is a positive quantity, too little steam is produced in relation to the heat transferred to the superheater and reheater. Consequently, the final steam temperatures increase. The opposite is true during generator load reductions. These temperature deviations are highly undesirable due to various mechanical and efficiency-related factors [6]. An ideal steam temperature control system should detect over-firing (and preferably other disturbances), predict the effect on steam temperature, and calculate a compensating control action.

2. Modelling heat transfer with a NN

Many documented examples of improvements in steam temperature control, based on process models incorporated into the controller designs, exist in literature [6]. The models are used to predict the effect of disturbances and control actions prior to the (slower) process response, so that control actions can be adjusted accordingly. Due to the long dead time and time lags involved with steam temperature control (combined, typically 5 - 10 minutes [6,
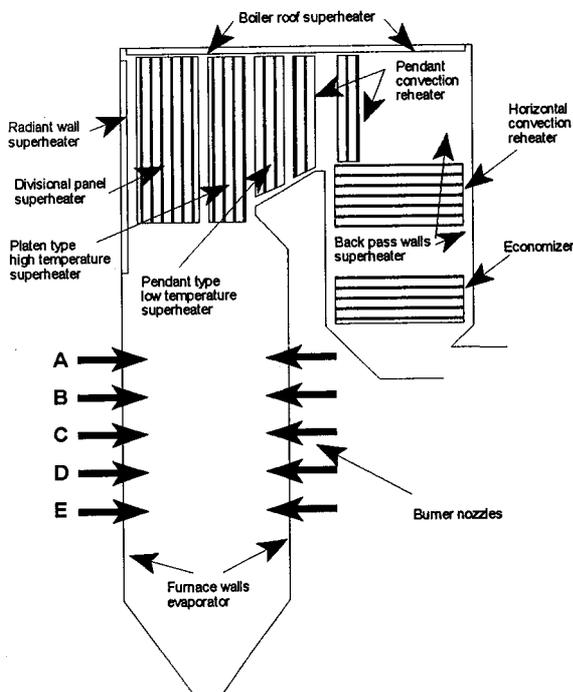

Figure 2. Typical layout of boiler elements.

7]), vast improvements in control quality may be expected from model-based control techniques, primarily due to the effective cancellation of process dead time and the predictive capabilities of the process model.

Boiler modelling, however, is no trivial exercise [8]. The boiler tube geometry and the layout of the various boiler elements are complex (Figure 2) rendering the application of analytical modelling techniques extremely difficult [9]. Additionally, the heat transfer rate varies in a nonlinear fashion with boiler load, adding to the complexity of analytical heat transfer models [10, 11]. Creating a heat transfer model based on boiler heat transfer theory, is therefore an extremely complicated task. In many cases, the modelling accuracy is poor, and the model has to be calibrated against the real system to be of any use [12].

A feasible alternative to conventional, analytical, modelling techniques is provided by neural network technology [8,13]. The nonlinear mapping capabilities of neural networks allow the creation of accurate models of nonlinear processes without needing much a priori knowledge of the process. For example, one of the most nonlinear industrial processes, being pH control in a neutralization tank, has successfully been modelled using a neural network [14]. In fact, it has been proved that a neural network with at least one hidden layer has the capability to approximate any desired nonlinear function to an arbitrary degree of accuracy, given a sufficient number of neurons [15].

Because of the multi-input, multi-output, nonlinear modelling capabilities of a neural network, it is a powerful alternative for modelling also the complex process of heat transfer inside a power plant boiler. The objective of the heat transfer model discussed here was to provide an estimate of heat pickup in the various boiler elements based on the conditions in the furnace (Figure 3). The estimated heat transfer rates can then be used in control.

Creating a neural network model may be considered as a process containing the following five steps:
a) Assign model inputs
b) Assign model outputs
c) Obtain training data
d) Determine network topology
e) Train the network.

It may be necessary to repeat the last two steps while

seeking for the optimum network size. The five steps are discussed individually below.
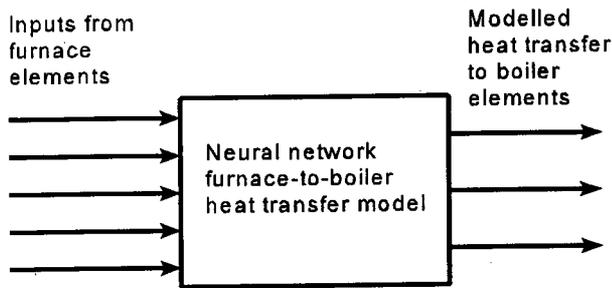
Figure 3. Furnace-to-boiler heat transfer model.

2.1 Model inputs

Inputs to the model (seven in total) were chosen as the plant measurements of factors having the greatest effect on heat transfer rate. From operating experience, these were known to be:

a) five individual mill (coal pulveriser) firing rates,
b) concentration of O_2 in flue gas,
c) fuel burner tilt angle.

From a heat transfer perspective, the total (mill) firing rate affects the total heat transfer rate. The combination of mills in service and the burner tilt position determines the elevation of the fireball in the furnace - affecting the radiant heat transfer distribution between the evaporator, superheater, and reheater. The concentration of O_2 in the flue gas is determined by the air flow rate through the boiler - affecting the convective heat transfer distribution. The concentration of O_2 in flue gas was used as input in lieu of the total air flow measurement, because of poor accuracy and repeatability of the latter measurement.

2.2 Model outputs

The network outputs were chosen as the modelling objectives, i.e.

a) evaporator (including economizer) heat transfer rate
b) superheater heat transfer rate
c) reheater heat transfer rate.

Originally, absolute heat transfer rates were modelled, but it will be shown later how modelling accuracy was improved by configuring outputs to represent heat transfer rates of the elements in relation to total heat transfer.

2.3 Acquisition of training data

The training process of a neural network requires masses of training data consisting of input-output pairs. A series of steady state tests was performed on Kendal Unit 3 to obtain data for training the neural network model. The test data had to be sufficiently rich in heat transfer characteristics so that the neural network trained on it would be able to predict heat transfer rates outside the normal operating regime (for example, with mills biassed away from the normal common setpoint). The richness of the data was ensured by assigning for each test, randomly generated settings to each of the furnace elements assigned as model inputs.

A total of 129 tests was designed in this way. One hour was allocated for performing each test, i.e. fifteen minutes to set up the furnace elements, thirty minutes to let the boiler settle out, and fifteen minutes for data capturing. Ninety-five process values (pressures, temperatures, and flow rates) were recorded. For each test the individual mill loads, O_2 measurement, and burner tilt angle were used directly as model inputs in the training data set. The enthalpy of water and steam were calculated at 26 positions in the cycle, where after the total heat transfer rates to the evaporator, superheater and reheater were calculated and used as target model outputs in the training data set.

2.4 Network training

From the 129 sets of test data, 116 sets were used as training data for the neural network and 13 sets were used as test data. The purpose of the test data sets was to determine how accurately the neural network represented data sets that it had not been trained on. In other words, testing data was used to determine the generalization capabilities of the neural network.

The PC programme Brainmaker [16] was used to train the neural networks. The weights were adjusted after completion of every training run. Histograms of the weight values were then updated. The histograms were used as an indication of the degree of saturation of the neural network

(weights saturating at -8 or +8), which in turn, indicates whether the neural network was too small [16]. A training session typically consisted of 6000 training runs through the 116 training data sets. The neural network RMS output errors on training data sets were recorded after each training run. Then the 13 sets of test data were run through the network without training to obtain the RMS error on testing data. During the training session, the weights of the neural network were saved to a file every 50 training runs so that an optimum set of weights could be selected afterwards.

After a training session the RMS error during the training phase and RMS error during the testing phase were plotted against the number of training runs. While both errors decreased, the neural network was constructively learning the input-output mapping. When the error on training data decreased while the error on testing data increased, it suggested that the neural network was learning specific data sets and its generalization capabilities were decreasing [16].
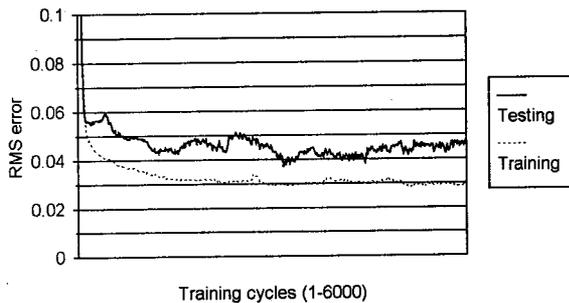

Figure 4. Evolution of error during training.

Figure 4 shows the evolution of error during a typical training session. Initially, the training and testing errors were very large, but these reduced rapidly during the first few training runs. The error on training data was (as expected) lower than the error on testing data. The averages of both errors decreased until, after many training runs, the error on testing data started to increase due to the loss of generalization. A neural network selected from the area of minimum error on testing data was deemed to have the best input-output mapping. Since the network weights were saved every 50 training runs, the network closest to the minimum RMS error on testing data was selected as the final result of the training session. For example, the

network weights saved after training run 3100 in Figure 4 were used as the best training run.

The training process described above was repeated four times on similar sized networks with weights initialized differently. The networks trained differently and had different best run errors. The set of neural network weights giving the lowest error was selected as the best possible with the specific topology.

2.5 Network topology

The following notation will be used to describe neural network topology: Input Neurons : 1st Hidden Neurons : 2nd Hidden Neurons : . . . : Output neurons. For example: 7:15:5:3, refers to a neural network with two hidden layers, 7 input neurons, 15 neurons in the first hidden layer, 5 neurons in the second hidden layer, and 3 output neurons. The bias neurons are not indicated, but it may be assumed that every layer, except the output later, has one bias neuron, of which the output was set to unity.

Modelling accuracy will be presented as the RMS error between model and target outputs across the 129 sets of training & testing data.

Thirty different feedforward neural network topologies were tested to obtain the optimum nonlinear mapping of the furnace input elements to the boiler output elements. As no firm network sizing theory has been established, experimentation with different neural network sizes was done to obtain the smallest neural network that still had good accuracy. In all cases the training method described above was followed. The network sizes tested, ranged between zero and 160 hidden neurons in zero to three hidden layers.

Various output schemes were tested. As a first attempt, the networks were configured with ten outputs, since heat transfer was calculated for ten sub-sections of the evaporator, superheater, and reheater. Although the RMS error averaged over the ten outputs was acceptable (4.75 %), a few large and unrepeatable errors were evident on some of the individual boiler sub-sections. The reason for the poor modelling is believed to be that the individual boiler components receive gas streams that differ in temperature and velocity, and the sizes of the sub-sections are not large enough to represent the average heat transfer.

Small changes in furnace conditions cause a redirection of these gas streams which then has a large effect on heat transfer. This was observed in practice too, where the right-hand side of the reheater requires more desuperheating than the left-hand side for certain burner tilt angles, and less for other angles.

Due to the large errors, and because no real need exists for modelling heat transfer rates to the individual sub-sections, the heat transfer rates of the sub-sections were combined into the tree main boiler sections: evaporator, superheater, and reheater. This modification reduced the modelling error for similar sized networks (Table 1).

Output Characteristic	Size	RMS Error
Individual sub-sections	7:50:10	4.750 %
Combined sections	7:50:3	4.054 %

Table 1. Comparison of individual to combined output heat transfer models.

Since the modelling ability of the neural network seemed to improve somewhat when the complexity of the output pattern was reduced, a test was devised to establish the ability of a neural network to model only one specific boiler section. The output training data was split into three groups, one for heat transfer to each of the three combined boiler sections, i.e. evaporator, superheater, and reheater. Three neural networks were created and trained individually on the tree sets of data. No major difference in modelling accuracy was noted between this three-network model and a single-network model of comparable size (Table 2).

Output Characteristic	Size	RMS Error
Single-network	7:15:3	5.17 %
Three-network	7:5:1	5.26 %

Table 2. Comparison of single-network to three-network heat transfer models.

Another variation in output scheme was tested - and proved to significantly increase modelling accuracy. The concept was to model heat transfer in the evaporator, superheater, and reheater in relation to the sum total heat transfer. Heat transfer rates to the three main boiler components are quite linear relative to boiler fuel input (or total heat transfer). When changing boiler load, variations in absolute heat

transfer are far greater than variations in relative heat transfer. Inaccuracies in a model of absolute heat transfer (as discussed up to now), overshadow the subtle changes in relative heat transfer.

Since the total boiler heat transfer rate is reasonably proportional to fuel flow, this did not need to be modelled. What had to be modelled were the changes in heat transfer to the individual boiler components, relative to total heat transfer. In this way the model could be trained on variations in heat distribution, which could be superimposed on the linear (relative to fuel flow) heat transfer rate. Consequently, neural networks trained on relative heat transfer rates displayed a significant improvement in modelling accuracy in comparison to networks trained on absolute heat transfer rates (Table 3).

Output Characteristic	Size	RMS Error
Absolute heat transfer	7:15:3	5.17 %
Relative heat transfer	7:15:3	3.33 %

Table 3. Comparison of absolute to relative heat transfer models.

Since these neural network models were trained on heat transfer rates relative to the total heat transfer rate, the sum of the neural network outputs should ideally have been unity. This was not the case in reality, where the sum of the model outputs was close to, but usually not equal to unity. Varying with different models and model inputs, the sum of the model outputs ranged between 0.97 and 1.03.

Because the sum of the model outputs should be 1.00, it was possible to correct any deviations from unity by proportionally adjusting the model outputs. The correction was done by dividing the three model outputs by the sum of the uncorrected model outputs. Once again, a substantial increase in modelling accuracy resulted (Table 4).

Output Characteristic	Size	RMS Error
Uncorrected outputs	7:15:3	3.33 %
Corrected outputs	7:15:3	2.82 %

Table 4. Comparison of uncorrected to corrected heat transfer models.

With these heuristically motivated adjustments made to the heat transfer model, it was possible to decrease the modelling error from 5.2 % to 2.8 % for similar sized

networks. The heat transfer model with corrected relative heat transfer outputs was the most accurate configuration achieved with the neural network model, and for this reason, it was the configuration used in the heat distribution controller.

Once the final neural network model output configuration had been established, different network sizes were tested to find the smallest network with a good representation of the heat transfer. As before, four training exercises, starting with different randomised initial weights, were done on every selected size. The 7:15:3 network had the best accuracy (Table 5).

| Size | Modelling Error | | | |
	Evaportr	Superhtr	Reheater	Average
7:30:15:3	1.971 %	1.938 %	4.654 %	2.85 %
7:15:10:3	1.846 %	2.058 %	4.662 %	2.86 %
7:15:3	1.861 %	1.961 %	4.641 %	2.82 %
7:10:3	2.519 %	2.709 %	5.380 %	3.54 %
7:5:3	2.424 %	2.326 %	5.591 %	3.45 %

Table 5. Modelling errors with different sized networks.

3. Steam temperature controller

For any arbitrary steam flow rate, some design rates of heat transfer to the superheater and reheater exist (Figure 5). The design heat transfer rates are adequate to raise the enthalpy of the steam and obtain the desired outlet steam temperatures. Deviations from design heat transfer rates would cause temperature deviations had it not been for the closed loop automatic control system keeping steam temperatures at setpoint. Since the rate of closed loop control action is dictated by the long process time constants, the closed loop correction is quite slow.

Large disturbances such as load ramps occur on the fire side of the boiler, resulting in large and almost instant changes in the distribution of the heat discharge. These rapid changes in heat distribution are the cause of major steam temperature deviations. Since these major disturbances occur on the fire-side, it is sensible to eliminate it at the source. It would not be possible to prevent load changes, but it may be possible to maintain
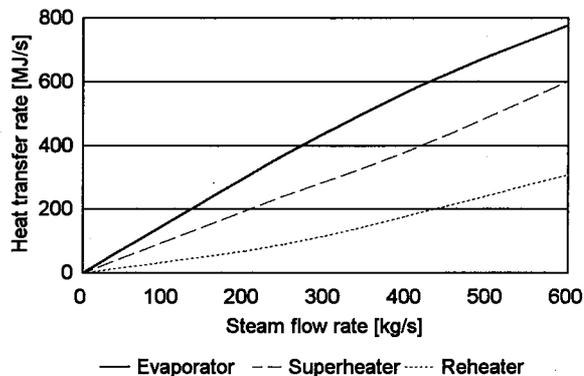

Figure 5. Design heat transfer rates.

the design heat flow rate to the superheater and reheater during a load ramp. Maintaining design heat transfer rates to the superheater and reheater will improve steam temperature regulation. Any excess or deficit heat can be directed towards the evaporator where it will not directly affect steam temperatures. The control elements available for manipulating heat distribution are: individual mill firing rates, furnace air flow rate (O_2 setpoint), and burner tilt angle.

During load up-ramps excess heat flow exists due to over-firing. It is desirable to direct the excess heat to the evaporator to assist the boiling process. In doing so, heat transfer to the superheater and reheater can be kept to design (based on steam flow) to prevent temperature increases. During down-ramps a deficit in heat flow rate exists due to under-firing. Then heat must be directed away from the evaporator to the superheater and reheater in order to maintain steam temperatures. Directing the heat away from the evaporator will also reduce boiling and assist in decreasing the steam flow rate.

3.1 Controller Design

The controller was designed to maintain the optimal heat transfer rate to the superheater and reheater, and operated iteratively in two phases: the first was a prediction of error in heat transfer, and the second was to adjust the elements on the firing side to minimize these errors. Errors in heat transfer were obtained by passing the furnace conditions as inputs to the previously designed neural network heat transfer model and comparing its

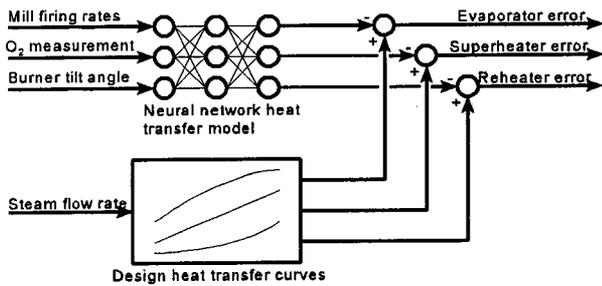outputs with the design heat transfer rates based on steam flow (Figure 6).

Figure 6. Estimating errors in heat transfer.

Once the predicted heat transfer errors are available, the new control action must be calculated. The backpropagation technique is a practical and easily applied method of obtaining the derivatives of the error on the inputs of the model (Figure 7) [17]. Errors on the superheater and reheater outputs were backpropagated through the neural network model to obtain the derivatives of the errors in relation to the inputs. (Errors on the evaporator output were ignored as it had no direct bearing on steam temperature.)
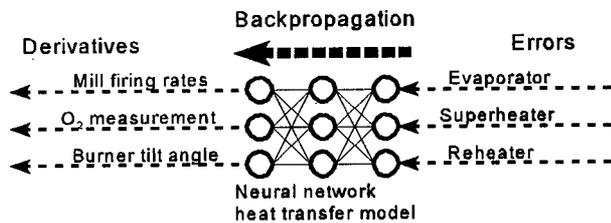

Figure 7. Obtaining error derivatives.

With the derivatives of the errors in relation to the network inputs available, the network inputs were adjusted in proportion to the derivatives and a new error estimate obtained. The new error was again backpropagated to obtain new derivatives. This process was followed iteratively until the errors converged. Process restrictions such as control element limits, manual operation, mills out-of-service, and the requirement of meeting total fuel demand were considered during the adjustment phase. After convergence, the adjusted inputs of the neural network model were used as setpoints to the corresponding control elements.

3.2 Catering for control limitations

Depending on the process conditions, it was not always possible to cancel out the entire error on heat transfer. Therefore, after adjusting the furnace elements, some error in heat transfer to the superheater or reheater remained. Because the errors were expressed numerically in quantities of heat excess or deficit, precise adjustments to the desuperheating spraywater flow rate could be calculated. The final control action therefore consisted of two components: firstly, the firing system was manipulated to reduce the heat transfer errors as much as possible, and secondly, any remaining error was compensated for by adjusting the degree of normal temperature control.

3.3 Adaptation

To compensate for unmodelled process changes (sooting of boiler tubes etc.) the neural network model outputs were multiplied by long-term, self-adjusting correction factors to keep the model accurate. The heat transfer design curves were also provided with self-adjustment to enable the furnace elements to return to their normal operating points while the standard temperature controls compensate for the shift in heat transfer.

3.3 Implementation

The data processing algorithms, neural network model, control strategy, and user interface were programmed in Borland C++ [18]. The entire programme ran on a 100 MHZ Pentium PC. An RS485 data communications link was established with the existing ABB unit control system to obtain process data and to send control signals to the plant. The standard boiler control system was modified to accept the advanced control signals when a watchdog square-wave signal was present to provide a failsafe scheme and to enable the advanced controls to be turned off during development and for comparative test purposes.

4. Results

The expected results of the Optimal Heat Distribution (OHD) controller were that, during load ramps, mill firing

rates, burner tilt angle, and O_2 concentration would be biassed away from the "normal" settings while the heat distribution controller regulated heat transfer to the reheater and superheater. This control action worked very well on the mills and burner tilts, but the desired effect could not be achieved on O_2 concentration. The latter was established to be as a result of incorrect fuel flow measurement during transient conditions - which negatively affected the true fuel-air ratio and therefore O_2 manipulation was not accurate.
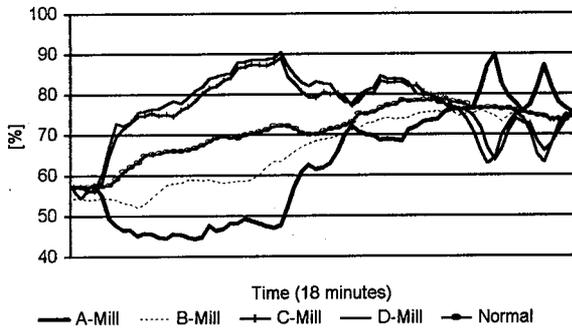

Figure 8. Biased mill fuel flows under OHD control compared to normal.

Figures 8 and 9 show coal mill and burner tilt biassing during a 100 MW load ramp at 15 MW/min. Due to the excess heat entering the furnace during the upward ramp, the upper mills were biassed down in load, while the lower mills were biassed up, to regulate heat flow to the superheater & reheater (Figure 8). Burner tilts were biassed downwards to add to the heat shift (Figure 9). O_2 biassing is not shown since it varied more with fuel flow than with setpoint changes.
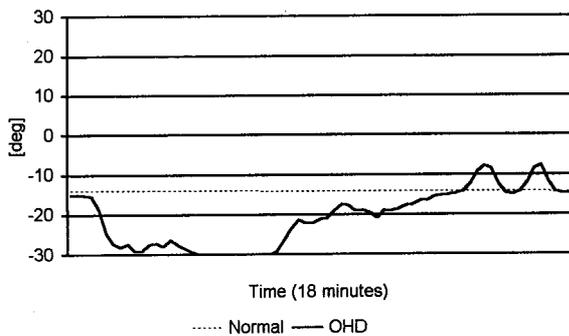

Figure 9. Burner tilt biassing during load ramp.

The biassing actions were generated to keep heat transfer rates to design. Substantial improvements in heat transfer

rates were achieved on both superheater and reheater under OHD control. In most cases the regulation of heat transfer to the reheater was not as good as the superheater due to the lack of control over the furnace air flow rate (due to the incorrect fuel flow measurement). Heat transfer to the superheater with, and without, OHD control recorded during a 150 MW downward load ramp at 15 MW/min is shown in Figure 10. Steam temperatures are compared in Figure 11.
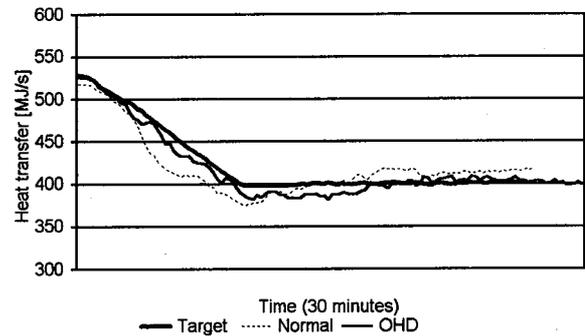

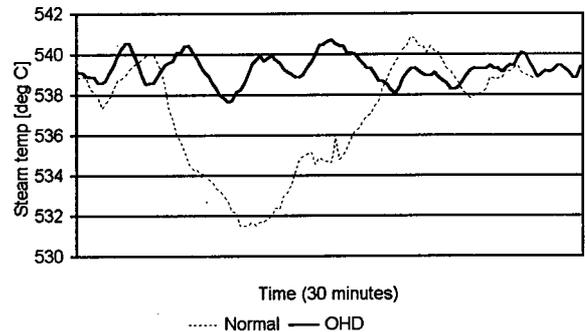Figure 10. Heat transfer rate to superheater during down-ramp.

Figure 11. Effect of OHD control on main steam temperature.

As noted earlier, OHD control regulated heat transfer to the superheater and reheater and shifted any excess or deficit heat to the evaporator. This shift in heat increased or decreased the steam production, which directly affected boiler pressure. The gain of the pressure control loop was therefore increased and this caused oscillations between pressure and fuel (fuel being the manipulated variable of the pressure controller). Reducing the gain of the pressure controller did not effectively solve the problem, because the

heat shift was not constant - causing a variable process gain. The effect of the oscillations can be seen in the last quarter of Figures 8 and 9.

5. Conclusion

This paper described the development of a neural network steam temperature controller for a large power plant boiler. The controller utilized a neural network model of heat transfer between the furnace flame and main boiler components. The neural network was trained on test data captured during a series of tests designed to extract the necessary heat transfer characteristics. Various output configurations were tested and the modelling of heat transfer relative to total heat transfer was found to be the most accurate. The neural network was then utilized in a steam temperature controller. The backpropagation technique was successfully applied for adjusting furnace elements. The controller was found to work as designed, and substantial improvements in heat transfer rates and steam temperature regulation were observed. As the controller was designed with no consideration for boiler pressure, the increase in the gain of the pressure control loop (due to the heat shifted to the evaporator) resulted in oscillatory behaviour in the pressure control loop.

Future research could include the incorporation of boiler pressure regulation into the control objective.

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