Intelligent Modified Predictive Optimal Control of Reheater Steam Temperature in a Large-Scale Boiler Unit

Kwang Y. Lee, *Fellow, IEEE*, Liangyu Ma, Chang-Jin Boo, Won-Hee Jung, and Sung-Ho Kim

Abstract **– A Modified Predictive Optimal Control (MPOC) scheme based on neural network modeling and Particle Swarm Optimization (PSO) techniques is proposed in this paper for Reheater Steam Temperature (RST) control of a large-scale boiler unit. A recurrent neural network is trained to directly model the temperature dynamic response of the reheater system. The neural network direct model is then used to evaluate the performance of the MPOC in search of the optimal control, where optimization is carried out with the PSO. A simplified PSO algorithm with search direction control is designed to find the nearest and optimal controls for the reheater steam temperature. To further improve the optimal search accuracy, each last-step prediction error between the direct model output and the actual RST is added to the current-step cost function to compensate for the model error. Control tests on a full-scope simulator of a large scale power generating unit have shown the validity of the proposed method.**

Index Terms **– Large-scale boiler, reheater steam temperature, modified predictive optimal control, neural network, particle swarm optimization.**

I. INTRODUCTION

STEAM temperature is among the several most important variables which must be controlled tightly within narrow margins to ensure higher operating efficiency and material safety of a large-capacity fossil fuel power generating unit. But steam temperature is often not controlled very well because a large-capacity boiler is a complex multi-input multi-output (MIMO) nonlinear system consisting of many strongly-coupled sub-systems, which brings a large time delay and big inertia to steam temperature response. To acquire good control results, often several different types of controls are applied just to control one steam temperature, and several cascaded PID controllers are included in each sub-system. The gains and time constants of these PID controllers have to be tuned frequently under different loads and changing environment due to the high nonlinearity of the boiler unit, and this often costs considerable amount of effort and time [1]. Therefore, it is a logical choice to take advantages of intelligent system techniques in improving the steam temperature control.

Artificial neural network is an attractive method for identifying nonlinear processes, due to its good modeling capability and its ability to learn complex dynamic behavior of a physical system [2],[3]. Recently, various applications of neural networks have been widespread in process control, both in simulation and on-line implementation, including predictive optimal control, inverse-model-based control and adaptive control [4]-[8].

The main focus of this paper is to design a Modified Predictive Optimal Control (MPOC) scheme based on neural network modeling and particle swarm optimization (PSO) techniques for Reheater Steam Temperature (RST) control of a large-scale boiler unit [4]. A recurrent neural network is trained to directly model the temperature dynamic response of the reheater system [9]-[11]. The neural network direct model is then used to evaluate the performance of the MPOC in search of the optimal control, where optimization is carried out with a heuristic optimization technology, Particle Swarm Optimization (PSO). The PSO is based on the analogy of a flock of birds and a school of fish [12], [13]. The PSO has been well known for providing accurate solutions with fast convergence and simple implementation in many engineering applications, such as economic dispatch and predictive optimal control. [14]-[16]. A simplified PSO algorithm with search direction control is designed and used to find the best and nearest controls. Detailed control tests are made on a full-scope simulator to validate the method.

II. MODIFIED PREDICTIVE OPTIMAL CONTROL SCHEME FOR THE REHEATER SYSTEM OF A LARGE-SCALE BOILER

A. System Introduction

The power plant under investigation is a large-scale coal-pulverized power generating unit. The feedwater pumped into the boiler will travel through several sub-systems before it becomes qualified superheated steam and is sent to the high-pressure (HP) turbine. The steam leaving the HP turbine is reheated in the boiler using the primary reheater (RH) and the final RH. The primary superheater (SH) and primary RH are respectively installed in the rear silo and front silo of the boiler's vertical gas pass. The flue gas exiting the furnace

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travels through the division SH, the platen SH, the final SH, the final RH and then passes through the paratactic primary RH and primary SH. The sketch of the boiler unit is shown in Fig. 1.

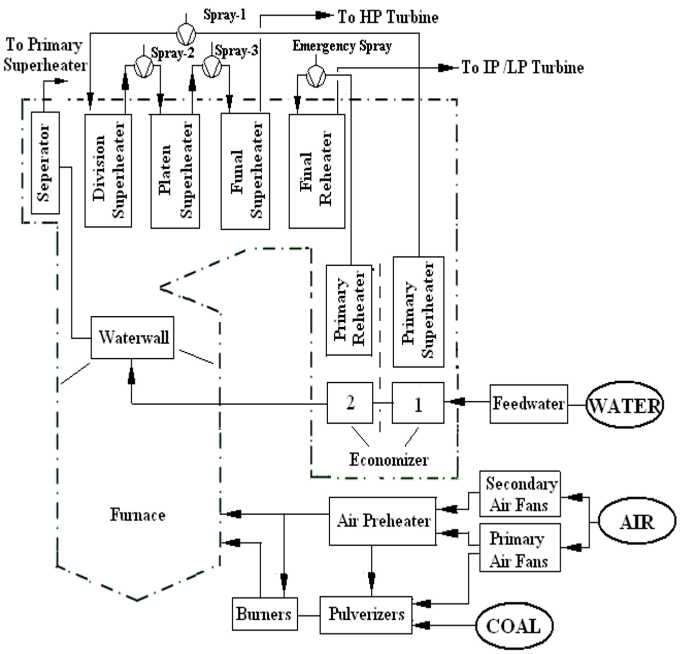


Fig.1. Sketch of the large -scale boiler unit.

For the reheater system of the boiler, a gas damper is used to adjust the reheater steam temperature by changing the flue gas proportion flowing through the primary RH and primary SH. The RST responds with larger time delay and bigger inertia after the reheater damper position is changed due to slower heat transfer between gas and steam. Thus, a steam bypass line is adapted to control the reheated steam temperature. With this steam bypass valve the RST can be controlled more quickly and accurately. An emergency water-spray valve is also added before the final reheater to avoid the over temperature of the final reheater steam under emergency case.

For the above large scale boiler unit, the RST setpoint value is fixed as 624 ℃. The emergency spray valve acts when the steam temperature is rising too fast and over 624℃ which endangers the structural safety. Under normal stable condition the emergency spray has very little opening or keeps fully closed. Thus, the reheater damper and the bypass valve will be the two control objects with the proposed MPOC scheme. However, the emergency spray valve still uses its original PID controller.

B. Structure of Reheater Steam Temperature MPOC Scheme

The overall structure of the proposed Modified Predictive Optimal Control (MPOC) scheme for RST control is shown in Fig. 2. The Unit Load Demand (ULD) and other variables needed by the MPOC will be sent from the power unit to the MPOC control program via a data interface program. The neural network direct model for the reheater system will be used as a system identification model to evaluate the performance of the MPOC in search of the optimal control, where optimization is carried out with the PSO in finding the best controls for the bypass valve and the reheater damper with iterative search. The control outputs (inputs to the reheater system) will be optimized by minimizing the tracking-error between the given RST set-point and the direct model estimation.

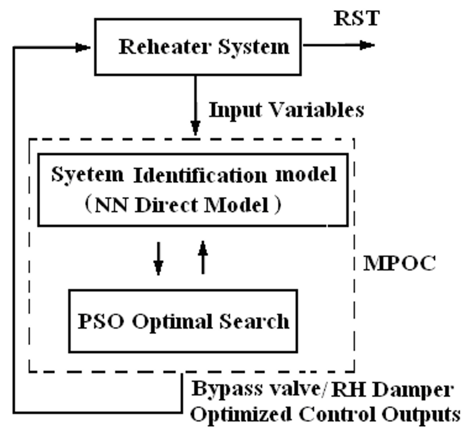


Fig. 2. Structure of the MPOC for reheated steam temperature control.

In order for the PSO to find optimal solutions against time with less iteration, the concept of *search window* is often used. A search window for a control output is a band with the possible maximum and minimum control values under different loads. The unit load (power output) is used for establishing a control window for the reheater damper based on historical data. For the given large scale boiler the control window for the reheater damper during loading-down process is shown in Fig. 3. As for the bypass valve, since it may change through 25-65% during the whole load scope according to its original control logic, we simply use 25% and 65% as its lower and upper limits during PSO control search.

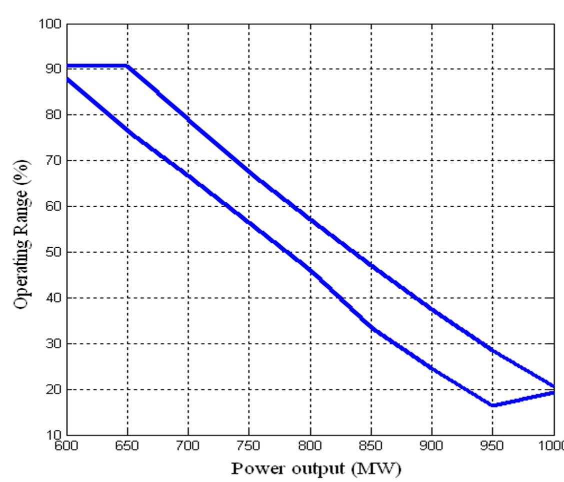


Fig. 3. Reheater damper control search window for loading-down process.

III. Development of Neural Network-Based Direct Model for Reheater System

A. *Recurrent Neural Network*

A recurrent neural network is used to build the direct model for the reheater system of the large-scale boiler unit. Recurrent neural network differs from other conventional feedforward networks in that it includes recurrent or feedback connections [7], [9]-[12]. The delay in this connection stores values from the previous time step, which makes it sensitive to the history of input data and fit for dynamic system modeling. For convenience, the Elman network is often used as a recurrent neural network, which has *tansig* neurons in its hidden (recurrent) layer, and *purelin* neurons in its output layer. This combination is special in that a three-layer network with these transfer functions can approximate any function (with a finite number of discontinuities) with arbitrary accuracy if the hidden layer has enough neurons. The structure of an Elman network is shown in Fig. 4.

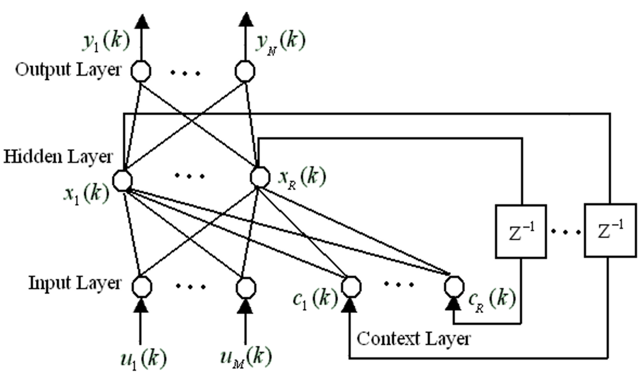


Fig.4. Structure of the Elman network model.

As shown in Fig. 4, the outputs in each layer of the Elman network can be given by:

$$x_j(k) = f(\sum_{i=1}^{M} W1_{i,j} u_i(k) + \sum_{i=1}^{R} W3_{i,j} o\_c_i(k)) \quad (1)$$

$$c_i(k) = x_i(k-1) \quad (2)$$

$$y_j(k) = g(\sum_{i=1}^{R} W2_{i,j} x_i(k)) \quad (3)$$

Where, $W1_{i,j}$ is the weight that connects node *i* in the input layer to node *j* in the hidden layer; $W2_{i,j}$ is the weight that connects node *i* in the hidden layer to node *j* in the output layer; $W3_{i,j}$ is the weight that connects node *i* in the context layer to node *j* in the hidden layer; *f*(•) and *g*(•) are the transfer functions of hidden layer and output layer, respectively.

An Elman network can be created and trained according to back-propagation algorithm with MATLAB Neural Network Toolbox [18]. When the entire input sequence is presented to the network, its outputs are calculated and compared with the target sequence to generate an error sequence. For each time step, the error is back propagated to find gradients of errors for each weight and bias. This gradient is actually an approximation, because the contributions of weights and biases to errors via the delayed recurrent connection are ignored. However, more accurate gradient can be evaluated by including the contributions through the recurrent neurons [10]. This gradient is then used to update the weights with the chosen back-propagation training function. Since Levenberg-Marquart method is fast and has robust convergence property in the off-line training, it is used for training the Elam network.

The inputs and outputs of a direct model for the reheater system can be determined by analyzing the system structure and the problem carefully. Then a neural network-based direct model can be built and trained with enough historical inputs/outputs data sequence.

B. *Reheater System NN Direct Model*

By isolating the reheater system from the rest of the boiler unit and analyzing the most important peripheral influence variables of the RST carefully, the inputs/outputs of the direct model were determined as shown in Table 1. It shows that the reheater system is not a simple SISO system. There are many variables which influence the reheater steam temperature, such as air, feedwater, coal flow, reheater damper position, bypass valve opening and emergency water-spray attemperator, etc. Therefore, the reheater system direct model should consider all these important factors.

TABLE 1. STRUCTURE OF THE REHEATER SYSTEM DIRECT MODEL

Inputs (9)	
(1)	Boiler demand
(2)	Turbine demand
(3)	Forced draft fan demand
(4)	Primary air fan demand
(5)	Coal feeder demand
(6)	Feedwater pump demand
(7)	Emergency Water-Spray valve demand
(8)	Reheater damper demand
(9)	Bypass valve demand
Output (1)	
(1)	Final reheated steam temperature

The NN direct model will be used to predict RST under different inputs. Thus, we need data of different steady-state conditions and dynamic transient processes to train the network. If the data used for network training are not sufficient we can not count on the direct model to give an accurate temperature prediction over a wide-range operation. Therefore, data selection is a very important factor during the model development. In this work, following conditions are included in the original training data, totaling 2664 groups: (1) different steady-state conditions (100%, 95%, …, 60% load levels); (2) different dynamic load-changing conditions (load change from 100% to 95%, from 95% to 90%, …, from 65% to 60%).

For the designed direct NN model with 9 inputs and 1 output, its optimal hidden neuron number can be determined with a MATLAB optimal search program, which is fixed as 15. Then the network is trained with the above 2664 groups of the original data. With 75-epoch training the final mean-squared error (MSE) of the direct model is 6.3681e-5. The training result is shown in Fig. 5.

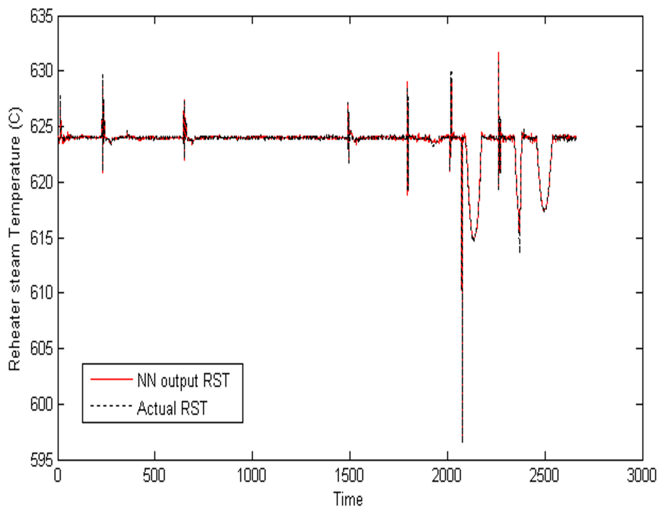


Fig. 5. Neural network direct model training results.

IV. Optimal Control Search with Particle Swarm Optimization (PSO)

A. Particle Swarm Optimization (PSO)

The Particle Swarm Optimization (PSO) algorithm was created based on the simulation of birds flocking in two-dimensional space [13]. The position and velocity of each particle represents the position and velocity of a bird. The position and velocity vectors are both represented by X-Y coordinates. The flocking of birds around food is used as a model to represent the optimization of a function. Each particle (bird) saves its best value so far (called *pbest*) and its current position. Also each particle knows the best *pbest* among the group (called *gbest*), which is the best value any particle in the group has had so far. By knowing its own best value (*pbest*), the particle knows its own personal experience. With knowledge of the group's best (*gbest*), the particle knows the overall performance of the group. Each particle modifies its position by changing its velocity. The velocity of each particle can be updated by

$$v_i^{k+1} = wv_i^k + c_1 * rand_1 * (pbest_i - u_i^k) + c_2 * rand_2 * (gbest - u_i^k) \tag{4}$$

where v_i^k is velocity of particle i at iteration k, w is weighting function, c_1 and c_2 are weighting factors, $rand_1$ and $rand_2$ are random numbers between 0 and 1, u_i^k is current position of particle i at iteration k, $pbest_i$ is the pbest of particle i, and *gbest* is the best value so far in the group among the *pbest*s of all particles

The weighting function in (4) is usually adjusted as

$$w = w_{\max} - (w_{\max} - w_{\min}) * iter / iter_{\max} \tag{5}$$

where $w_{\max}$ is the initial weight, $w_{\min}$ is the final weight, $iter_{\max}$ is the maximum iteration number and $iter$ is the current iteration number. Using the above equations, a certain velocity, which gradually brings the particles close to *pbest* and *gbest* can be calculated. The current position (search point in the solution space) can be modified by

$$u_i^{k+1} = u_i^k + v_i^{k+1} \tag{6}$$

The model using (4) is called the Gbest model. The model using (5) in (4) is called the Inertia Weights Approach (IWA). Fig. 6 shows the concept the search point by the PSO.

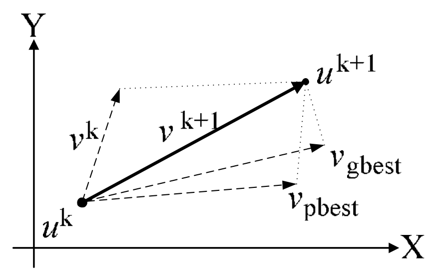


Fig. 6. Concept of modification of a search point by the PSO.

The above basic particle swarm optimization (bPSO) has some disadvantages, such as relapsing into local extremum, slow convergence in velocity and low convergence in precision in the later evolution. Recently, a simplified PSO is proposed to overcome the disadvantages of the bPSO [17]. The simplified PSO (sPSO) discards the concept of particle velocity and reduces the bPSO from the second order to the first order difference equation. The evolutionary process is only controlled by the variables of the particles position. The experimental results of some classic benchmark functions have shown that the sPSO greatly improves the convergence velocity and precision in the evolutionary optimization [17]. With this new sPSO the position of each particle is updated by

$$u_i^{k+1} = w * u_i^k + c_1 * rand_1 * (pbest_i - u_i^k) + c_2 * rand_2 * (gbest - u_i^k) \tag{7}$$

The simplified Particle Swarm Optimization (sPSO) algorithm will be used in search of the best controls for the reheater damper and the bypass valve of the boiler unit.

B. Optimal Control Search with sPSO

The sPSO procedure runs 10 iterations with 10 particles before the optimal controls are sent to the reheater system [4],[16]. The operation of sPSO is outlined in Fig. 7.

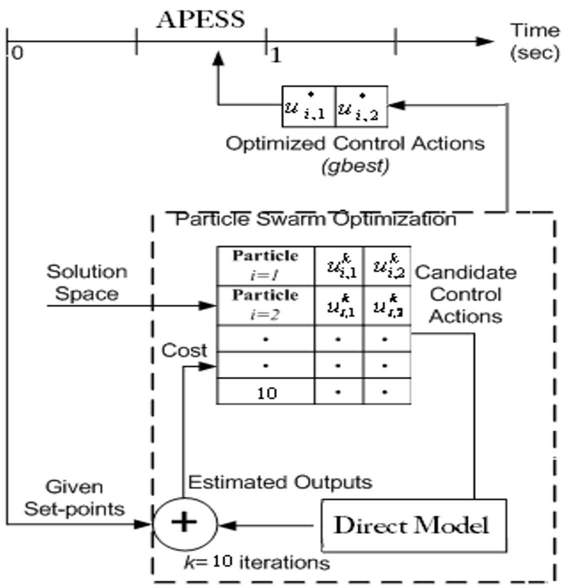


Fig. 7. Operation of the sPSO section of the MPOC.

The candidate control actions are provided to the direct model, with which the reheater steam temperature of the boiler unit is estimated. The estimated output T_e is compared with the current set-point *SP_RST* in a cost function, the Mean Square Error (MSE) between T_e and its set-point *SP_RST*, which is

$$Cost = (T_e - SP\_RST)^2 \tag{8}$$

To make further efforts to reduce the single-step RST prediction error of the neural direct model, each of the last-step error $\Delta^{'}$ between the network's predictive output $T_e^{'}$ and the actual reheater steam temperature $T_a^{'}$ is calculated and added to the cost function for current-step search of the best controls with PSO. The modified cost function with error compensation is:

$$Cost^{'} = (T_e + \Delta^{'} - SP\_RST)^2 \tag{9}$$

It is noted that the reheater damper and the bypass valve have very clear control direction in an actual power plant operation, which is based on the relationship between actual RST T_a and its setpoint *SP_RST*. If $T_a > SP\_RST$, the damper will go down and the bypass will go up from the current position. On the other hand, if $T_a <$ SP_RST, the damper will go up and the bypass will go down from the current position. In fact, there are many combinations of controls for reheater damper and bypass valve in each step which can meet the temperature control demands. In order to avoid oscillation during the search a special search direction control factor *Dir* can be added to (7) to obtain an optimal combination for the reheater bypass and the damper, which are the nearest to their last-step positions. With this new directional sPSO, the position of each particle is updated by

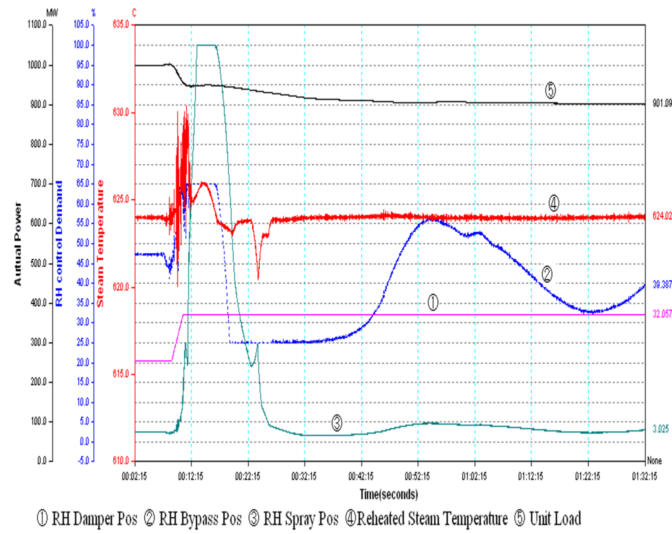
$$\begin{aligned} u_i^{k+1} &= w * u_i^k + c_1 * rand_1 * Dir * (pbest_i - u_i^k) \\ &\quad + c_2 * rand_2 * Dir \times (gbest - u_i^k) \end{aligned} \tag{10}$$

where *Dir* is the directional control vector, whose value takes either $[1, -1]^T$ or $[-1, 1]^T$ under different cases.

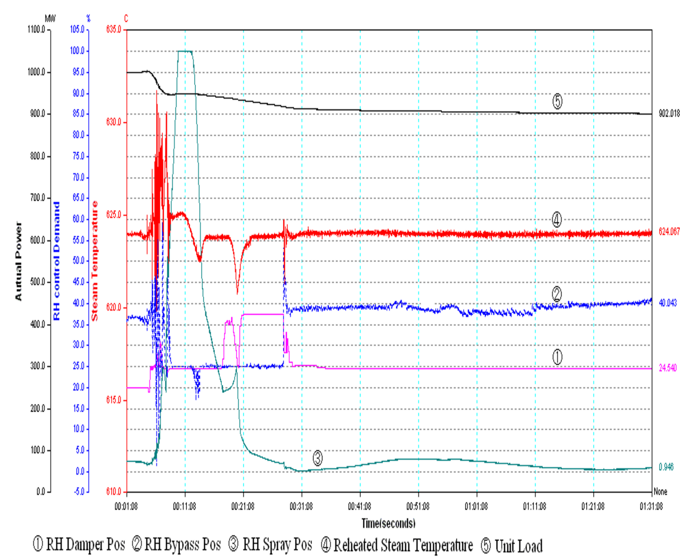
V. Control Simulation Tests

After the neural network direct model has been trained, it is used as a system online identification model for performance evaluation of the MPOC, in which the sPSO searches for the optimal controls for reheater damper and bypass valve.

In order to test the above MPOC scheme some simulation tests have been made on a full-scope simulator for the large scale power generating unit. The control results with the original control logic in the simulator and the proposed MPOC scheme are compared by changing the unit load from 100% to 90% load and from 100% to 75% load, with respective results shown in Figs. 8 and 9.

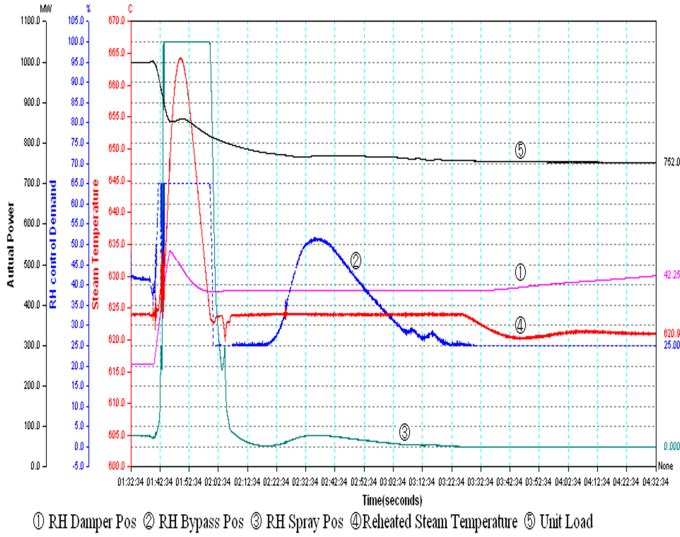


(a) The original PID control

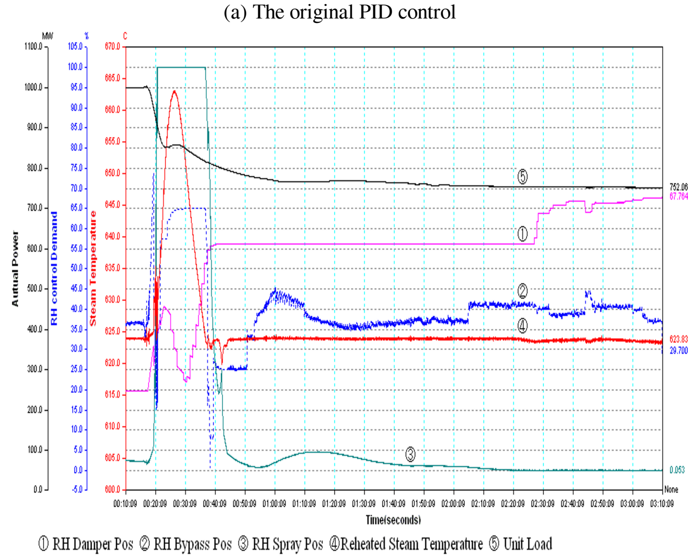


(b) The MPOC control

Fig. 8. Damper, bypass and RST responses due to load change from 100% to 90%.



(a) The original PID control



(b) The MPOC control

Fig. 9. Damper, bypass and RST responses due to load change from 100% to 75%.

From Figs. 8(a) and 8(b) it can be seen that both the original PID control and MPOC schemes give similar control results for the reheater steam temperature (curve 4) after the unit load is changed form 100% to 90%. However, the reheater damper's opening (curve 1) with MPOC is smaller than that with the original control, which leads to smaller amount of water-spray flow (curve 3) and better economical efficiency of the unit. It can be also seen that the bypass valve responses faster and gets stabilized in shorter time with the MPOC.

From Figs 9(a) and 9(b) it can be seen that the MPOC scheme gives a better control result for the reheater steam temperature than the original control over time when the unit load is changed significantly, from 100% to 75%. This improvement is acquired by faster and optimized adjustments for the reheater damper and the bypass valve with the PSO optimal search. It has been noticed that the maximum transient RSTs in Figs. 9 (a) and 9(b) are too high to be true in an actual load-changing process, which shows that the reheater model of the simulator needs further improvement.

VI. Conclusions

A Modified Predictive Optimal Control (MPOC) scheme is proposed for and applied to Reheater Steam Temperature (RST) control of a large-scale power generating unit. A neural network-based direct model is built and trained with enough historical operating data of the unit. The neural network direct model is used as a system on-line identification model in evaluating the performance of the MPOC and for optimal control search with the Particle Swarm Optimization technology. A simplified PSO algorithm with directional control vector is designed in search of optimal controls for reheater damper and bypass valve.

Control tests on a simulator for the large-scale power generating unit have shown that the MPOC works well for RST control by giving faster and optimized controls for the reheater damper and bypass vlave than the original control in the simulator. However, because the reheater system of the large-scale boiler unit is so complex and influenced by many factors, the MPOC scheme used for reheater steam temperature control needs further study and more tests in future work.

Another thing should be mentioned. Since the MPOC uses PSO to search for optimal controls in each step, it needs more calcualtion than other control schemes, such as a traditional PID controller, an inverse controller, etc. In this simulation tests the data acquisition and data sending period of the simulator is 1s. In order for the MPOC to have enough time to finish the PSO search, a computer of higher performance is recommended to run the control program.

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VIII. Biographies

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Sung-Ho Kim received his B.S. degree in Mechanical Engineering from Yeungnam University, Korea, in 1991, and M.S. degree in Mechanical Engineering from Kyungpook National University, Korea, in 1995. Since 1995 he has been with Doosan Heavy Industries & Construction Company, Ltd., Korea, where he is a Principal Engineer of Plant Control System Team in the Corporate R&D Institute, Taejon, Korea. He has been involved in developing advanced control system for boiler unit. His interests are control, operation and modeling of fossil power plant.