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Inverse Dynamic Neuro-Controller for Superheater Steam Temperature Control of a Large-Scale Ultra-Supercritical (USC) Boiler Unit

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Abstract: The main focus of this paper is to develop an Inverse Dynamic Neuro-Controller (IDNC) by utilizing the inverse dynamic relationship of the superheater system for a large-scale ultra-supercritical (USC) boiler unit. After a recurrent neural network-based Inverse Dynamic Process Model (IDPM) has been built and trained, it is then used as a feedforward controller to improve the superheater steam temperature control. In order to eliminate the steady-state control error induced by the model and the IDPM error, a simple feedback PID compensator is added to the inverse controller. Simulation control tests are made on a full-scope simulator of the USC power generating unit to test the validity of the method. It is shown that the convergence speed of the IDNC is faster than the conventional cascaded PID control scheme. Best control result can be acquired by the IDNC together with a simple PID feedback compensator.

Keywords: Ultra-supercritical (USC) boiler, superheater steam temperature control, inverse dynamic neuro-controller, neural network, feedforward control, PID compensator.

1. INTRODUCTION

In recent years, supercritical and ultra-supercritical boiler technologies have been undertaken in modern coal-fired power plants worldwide, which are motivated by the pressing need of higher efficiency, lower generation costs and lower emissions (Susta and Khoo, 2004). The superheater steam temperature is among the most important variables for an ultra-supercritical (USC) boiler in a large-capacity fossil-fuel power generating unit, which must be controlled to be within certain upper and lower limits to ensure high efficiency and safety of the power unit. However, often it is not easily controlled with a simple PID controller since the USC boiler is a multi-input multi-output (MIMO) nonlinear system consisting of many strongly-coupled sub-systems, which leads to a large time delay and big inertia to the superheater steam temperature response. Therefore, cascaded PID controllers are generally used for superheater steam temperature control and the control logic is getting more complex with the increasing boiler capacity. Moreover, even for a cascaded control scheme with at least 2 PID control modules, the gains and time constants of these PID controllers have to be tuned frequently to achieve good control results under different loading condition and changing environment, which often costs much effort and time (Benyo, 2006). Therefore, it is of high necessity to adapt intelligent control algorithms to improve the superheater steam temperature control.

Artificial neural network is an attractive method for identifying nonlinear processes, due to its good modelling capability and its ability to learn complex dynamic behaviour of a physical system. Recently, various applications of neural networks have been widespread in process control, both in simulation and on-line implementation, including predictive control, inverse-model-based control and adaptive control (Ku, *et al*, 1992; Chi-li-Ma and Lee, 1998; Azlan, 1999; Zhang, *et al*, 2006). Feedforward and recurrent networks are the two most commonly used neural network structures for modelling, prediction and control of nonlinear dynamic systems. A feedforward network is a static mapping that model a steady-state condition of a plant. It can also be used to model dynamic behaviour of the plant by including past input and output values as additional inputs. On the other hand, a recurrent network possesses internal memory by including internal feedbacks for past values, either from network output into hidden units or from hidden units into hidden units (Ku and Lee, 1995; Gencay and Liu, 1997).

The main focus of this study is to use a recurrent neural network to model the inverse dynamic relationship of the superheater steam temperature for a large-scale ultra-supercritical (USC) boiler unit and to use the trained inverse dynamic neural network model as a feedforward controller to improve the superheater steam temperature control. Detailed simulation control tests are made on a full-scope simulator of the power generating unit to test the method.

2. SYSTEM DESCRIPTION

The power plant under investigation is a large-scale coal-pulverized, once-through ultra-supercritical (USC) boiler-turbine-generator unit. The feedwater pumped into the boiler will travel through several parts before it becomes qualified superheated steam and is sent to high-pressure (HP) turbine, among which are the coal economizer, the waterwall, the steam-water separator, the primary superheater (SH), the division SH, the platen SH and the final SH. The steam leaving the HP turbine is reheated in the boiler using the primary reheater (RH) and the final RH. The two forced draft fans and two primary air fans provide air to the air preheater. The air preheater in turn provides hot air to the pulverisers, burners, and furnace. The primary air fans also provide cold air to the pulverizers. The fuel is provided to the furnace through the pulverizers and burners. Furnace pressure is maintained at the desired value by controlling two induced draft fans. The waterwall surrounding the furnace vertically and spirally absorbs the heat of flame and gas inside the furnace area and heats the feedwater into slightly superheated steam. The steam-water separator on top of the furnace then supplies superheated steam to the primary superheater. The primary superheater and reheater are, respectively, installed in the rear silo and front silo of the boiler's vertical gas pass. The flue gas exiting the furnace travels through the division SH, the platen SH, the final SH, the final RH and the paralleled primary RH and primary SH. The coal economizers are used to raise the feedwater temperature with the flue gas before it leaves the boiler. The sketch of the boiler unit is shown in Fig. 1.

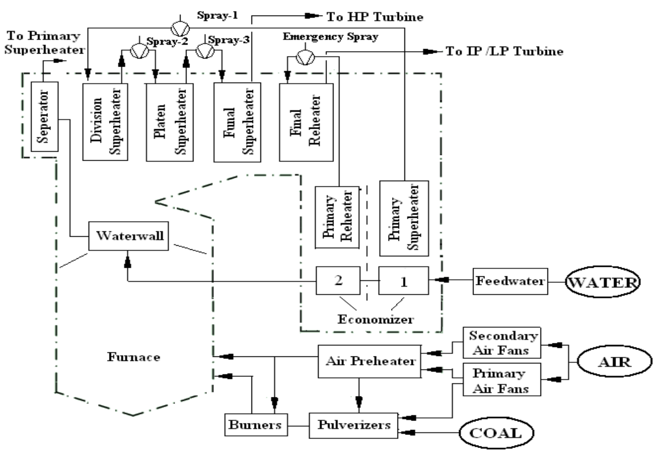

Fig. 1. Sketch of the 1000MW USC boiler unit.

3. RECURRENT NEURAL NETWORK-BASED INVERSE DYNAMIC PROCESS MODEL (IDPM)

Recurrent neural network differs from other conventional feedforward networks in that it includes recurrent or feedback connections (Elman, 1990; Ku and Lee, 1995; Gao, *et al*, 1996; Cheng, *et al*, 2002). The delays in these connections store values from the previous time step, which makes it sensitive to the history of input and output data and fit for dynamic system modelling. For convenience, the Elman network is often used for a recurrent neural network, which has *tansig* neurons in its hidden (recurrent) layer, and *purelin* neurons in its output layer (Elman, 1990). 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 recurrent network is shown in Fig. 2.

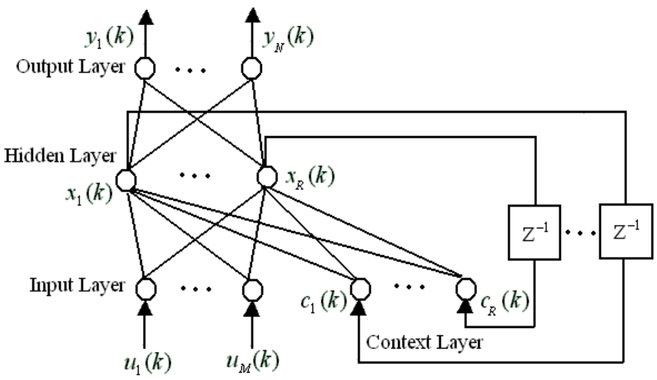

Fig. 2. Structure of the Elman recurrent network model.

As shown in Fig. 2, the outputs in each layer of the network can be given by:

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

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

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

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; $f(\cdot)$ and $g(\cdot)$ are the transfer functions of hidden layer and output layer, respectively.

An Elman neural network can be created and trained according to the back-propagation algorithm with MATLAB Neural Network Toolbox. 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 (Elman, 1990; Cheng, *et al*, 2002). However, more accurate gradient can be evaluated by including the contributions through the recurrent neurons (Ku and Lee, 1995). This gradient is then used to update the weights with the chosen back-propagation training function (Demuth, *et al*, 2007). Since Levenberg-Marquart method is fast and has robust convergence property in the off-line training, it is used for training the Elam network in our work.

The inputs and outputs of an inverse dynamic process model (IDPM) for a given system can be determined after analyzing the system and the problem carefully based on the inverse control principle (Widrow and Plett, 1997; Chi-Li-Ma and Lee, 1998). Then a neural network-based IDPM can be built and trained with enough historical inputs/outputs data sequence. The training process is shown in Fig. 3.

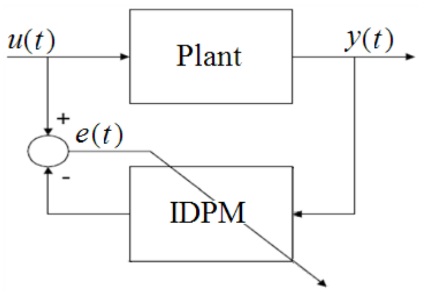

Fig. 3. Training of the IDPM.

Assuming the network which reflects the inverse dynamic process has been obtained through a training process described in Fig. 3, it can then be used as a feedforward controller by replacing the input of the inverse model with the expected setpoint y_{ref}. How the IDPM is applied as a feedforward controller is shown in Fig. 4. If the network represents the exact inverse, the control output $u_r(k)$ produced by the network will drive the system future output $y(k+1)$ to y_{ref}.

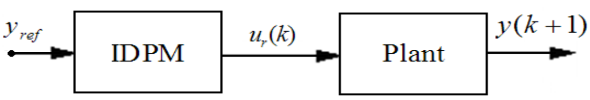

Fig. 4. The IDPM used as a feedforward controller.

Since an inverse dynamic process model expressed by the neural network is not a complete inverse but an approximation, it may generate a steady-state error when it is used as a feedforward controller. Therefore, a supplementary signal $E(k)$ is needed to eliminate the steady-state error induced by modelling error and other disturbances. The supplementary signal $E(k)$ can come from the output of a feedback PID compensator. This combined control scheme with an IDPM feedforward controller and a simple PID feedback compensator is shown in Fig. 5.

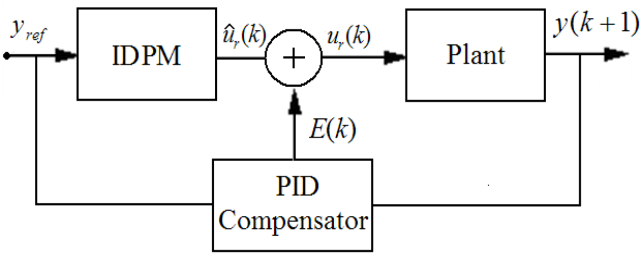

Fig. 5. Inverse control scheme with a PID compensator.

4. IDPM DESIGN FOR SUPERHEATER STEAM TEMPERATURE CONTROL

4.1 IDPM Structure

By isolating the superheater system from the whole USC boiler unit and carefully analyzing the most important peripheral influence variables of the superheater steam temperature, the inverse model structure for superheater steam temperature control with the 2nd-stage and 3rd-stage de-superheating water is designed.

It is noticed that the superheater system is not a simple SISO system. Many variables influence the superheater steam temperature, such as air, feedwater, coal flow, reheater/superheater damper position and several water-spray attemperators. Therefore, the IDPM should include all these factors.

According to the original USC boiler control logic, the spray-2 and the spray-3 are used for controlling the platen superheater outlet temperature and the final superheater outlet temperature, respectively. Since we plan to use only one neural network to control both, the spray-2 and the spray-3 valves, the neural network should include 2 outputs, i.e., the spray-2 and the spray-3 control demands. At the same time, the platen SH outlet steam temperature and the final SH outlet steam temperature are included in the inputs. The inputs and outputs of the neural network IDPM are shown in Table 1.

Table 1. IDPM structure for SH temperature control.

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)	Superheater damper demand
(8)	Platen SH outlet steam temperature
(9)	Final SH outlet steam temperature
Outputs (2)	
(1)	Spray-2 control demand
(2)	Spray-3 control demand

4.2 Training Data Preparation

The inverse neural network controller can be viewed as a feedforward controller. Its main function is to provide fast control when the unit load demand is changed. Thus, we need data for wide range operating conditions, both steady-state and dynamic transient processes to train the neural network. If the data used for network training is not sufficient we cannot count on the inverse controller to give reliable control demands under different operating conditions. Therefore, data selection is a very important factor during the IDPM development.

In our work, following conditions are included in the original training data, totalling 1894 groups: (1) different steady-state conditions, 100%, 95%, … ,65% load levels; (2) load change from 100% to 95% load levels; (3) load change from 95% to 90%; (4) load change from 90% to 85%; (5) load change from 85% to 80%; (6) load change from 80% to 75%; (7) load change from 75% to 70%; (8) load change from 70% to 65%.

4.3 Training and Development of the IDPM

For the designed IDPM neural network with 9 inputs and 2 outputs, its optimal hidden neuron number can be determined with a MATLAB optimal search program. The optimal number of hidden neurons thus found is 17. Then the network is trained with the above 1894 groups of data. The training process of this IDPM for superheater system temperature control is shown in Fig. 6. The training mean-squared error (MSE) curve is shown in Fig. 7.

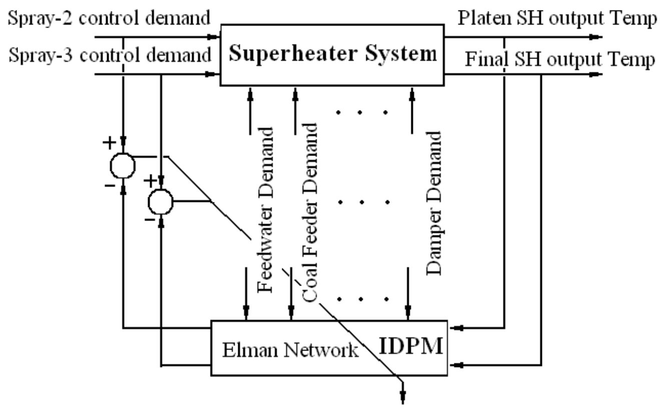

Fig. 6. Training of the IDPM for superheater steam temperature control.

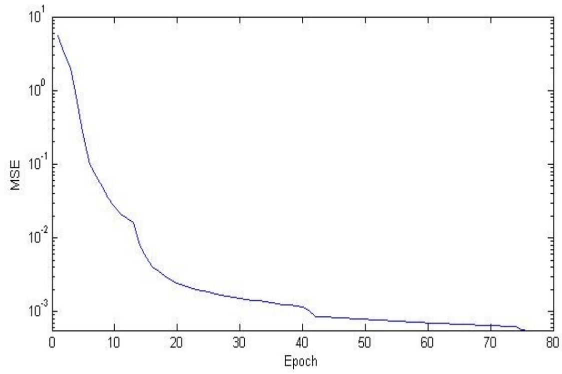

Fig. 7. Convergence of the SH IDPM training.

The outputs of neural network are compared with the actual control demands (data used for training) in Fig. 8 and Fig. 9. The dashed lines are the outputs of the neural network.

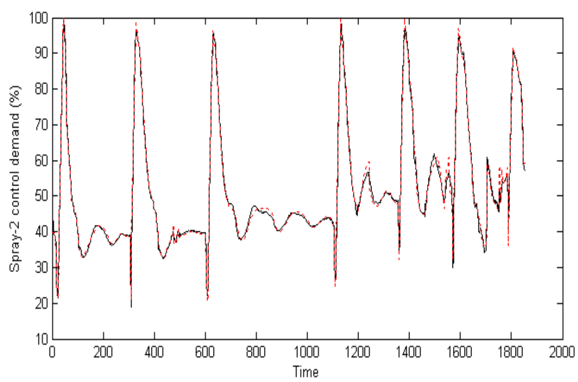

Fig. 8. Spray-2 control demand.

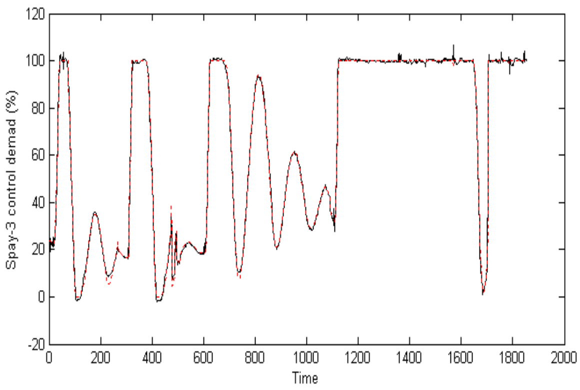

Fig. 9. Spray-3 control demand.

5. CONTROL SIMULATION TESTS

After the inverse dynamic process model (IDPM) has been trained, it can be used as a feedforward controller for spary-2 and spray-3 control valves by replacing the model's 9th input, the final SH outlet steam temperature, with its setpoint, while other inputs still using their original values for the unit. For this USC boiler unit, the setpoint value of the superheater steam temperature is fixed at 613 ℃.

Control simulation tests have been carried out on a full-scope simulator of the USC boiler-turbine-generator unit. For the unit load change from 100% full-load to 90% load, three different control schemes are tested: (1) the original cascaded PID controller, (2) the feedforward inverse neuro-controller, and (3) the feedforward inverse controller with a PID compensator. The control result of the original cascaded PID controllers is shown in Fig. 10. Fig. 11 is the result of the feedforward inverse neuro-controller. Fig. 12 is the control result of the feedforward inverse controller together with a PID compensator.

From Fig. 10, we find that the spray-3 control valve has a very long stabilization time. From Fig. 11, it can be seen that the stabilization time of the superheater steam temperature is shortened with the feedforward inverse controller. But a small steady-state control error exists due to the modeling error of the IDPM. From Fig. 12, we observe the best control result with shorter stabilization time and accurate steady-state value by an inverse controller together with a simple PID compensator.

By comparing Fig. 10 and Fig. 12, it is noticed that the responses of the spray-2 and spray-3 control valves under the original cascaded PID control and the inverse control are quite different. But the final superheated steam temperatures are both very close to its set point value 613℃. That is because, for a USC boiler, the superheated steam temperature is not only influenced by the spray-type steam attemperators, but also greatly influenced by another important factor, the coal-water ratio.

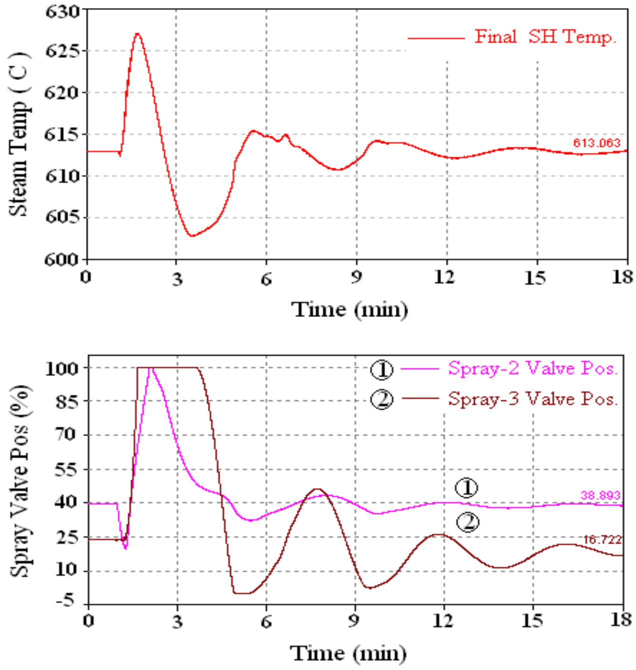

Fig. 10. Control results of the original cascaded PID control.

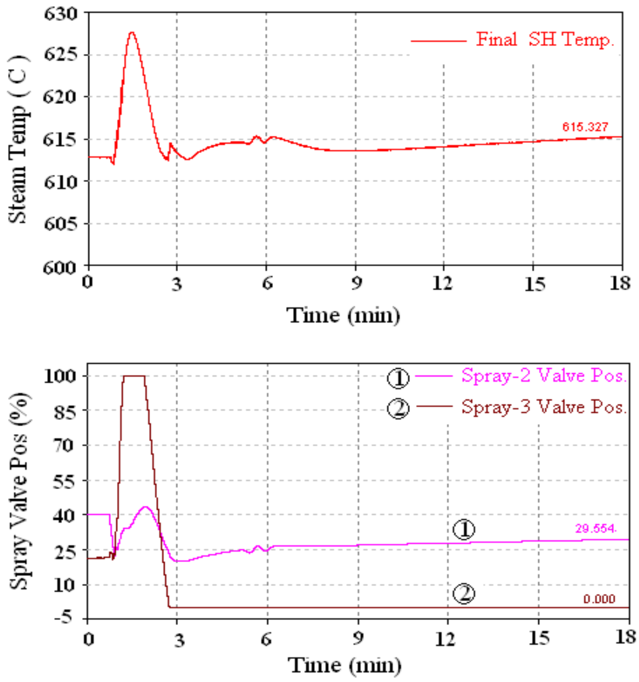

Fig. 11. Control result of the IDPM-based neuro-controller.

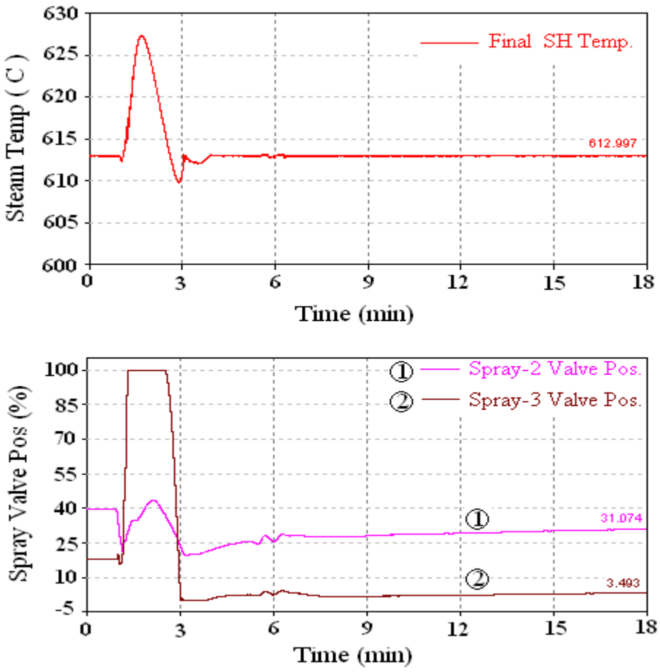

Fig. 12. Control result of the inverse controller with a PID compensator.

6. CONCLUSION

In this paper, a recurrent network based inverse dynamic process model (IDPM) concept is developed and used as a feedforward controller to improve the superheater steam temperature control for a large-scale ultra-supercritical (USC) boiler unit. The main purpose of an inverse dynamic neural controller is to shorten the stabilization time of the control process. In order to eliminate the steady-state control error induced by the modelling error of the inverse model, a simple feedback PID compensator is added to the inverse controller. Simulation control results from a full-scope simulator of the 1000MW power generating unit have demonstrated the validity of the control scheme in improving the superheater steam temperature control.

Since the superheater system of the USC boiler is a very complex nonlinear MIMO system, the superheater steam temperature is influenced by many factors. The selection of the input variables for the IDPM model and the selection of the data for model training both influence the control effect greatly. Other IDPM structures and different input combinations will be investigated and tested to achieve better control results in future work.

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