Neural Network Based Superheater Steam Temperature Control for a Large-Scale Supercritical Boiler Unit

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***Abstract*--To improve the Superheater Steam Temperature (SST) control of a large-scale supercritical coal-fired boiler generating unit, this paper presents an inverse compensation control scheme based on dynamic recurrent neural network (NN) inverse process models for the multi-stage water-spray desuperheating controllers. With proper analysis of the boiler design and operational characteristics, the inputs and outputs of the NN inverse models are determined. Then two NN inverse dynamic models of the superheater system are trained and validated with historical operating data over a wide-range of loading conditions. The trained NN inverse models are then employed as internal model controllers to improve the SST control effect by providing real-time supplementary signals to the original cascade PID controllers. The real-time steam temperature signals are fed back to adjust the input reference values of the NN controllers automatically. The controller is programmed in MATLAB and communicates with a full-scope simulator of a 600MW supercritical coal-fired power generating unit. Detailed simulation tests are carried out, which shows the new compensation control scheme can dramatically improve the SST control of the supercritical boiler.**

***Index Terms*— Dynamic recurrent neural network, inverse model, supercritical boiler, superheater steam temperature control, compensation control.**

I. INTRODUCTION

IN the 21st century, while promoting new energy power generation technologies, it is envisioned by China's energy infrastructure that the coal-dominated electricity generation trend will not change in a foreseeable future. With the purpose of energy saving, consumption reduction and environmental protection, large-scale supercritical and ultra supercritical large-scale coal-fired power generation technology with high efficiency and advanced environmental index has become the direction of leading international development. Thus far, 600MW supercritical power generating units have become the main power units in China's power grid and a growing number of 1000MW ultra-supercritical units are being put into operation successively.

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Superheater Steam Temperature (SST) is one of the key parameters in boiler operation which must be strictly controlled; either too high or too low will significantly influence the safety and efficiency of the boiler unit. For a supercritical or ultra-supercritical boiler unit with steam/water once-through circulation characteristics, any change in fuel flow, feedwater flow, or turbine governor valve opening will lead to change of unit power, main steam pressure and temperature, which is a typical three-input three-output multi-variable control system with strong coupling and nonlinearities. Its SST control is more complicated compared to that of a subcritical boiler. Therefore, it is very important for a supercritical boiler to regulate the fuel/water ratio well to ensure a relatively stable steam temperature (or Superheat Degree) near the water separator in order to facilitate the final SST control. Furthermore, multi-stage water-spray desuperheating devices are used to control the SST.

Generally, cascade PID control schemes are adopted to satisfy the steam temperature control quality requirements [1]. Since the SST has very strong nonlinear characteristics under different load, the PID controllers should be set with different optimized parameters to achieve good control effect over a wide range of loading conditions. It often costs a lot of time and effort, and is often very difficult to realize in actual operation. Thus it is always an important issue to develop more effective superheater steam temperature control methods in power station control.

In recent decades, with the development of intelligent control, artificial neural network has been extensively applied in performance prediction, modeling and control in various industrial processes due to its excellent approximation and learning ability to complicated nonlinear systems， strong adaptive ability, robustness and fault-tolerance ability [2-6]. Many research on neural networks for power station steam temperature control have also been made [7-10]. Adaptive inverse control method is with clear physical concept, and is intuitive and easy to understand. It receives widespread attention since it was first introduced and has been applied in many fields [11-15]. Specifically, when inverse system method is combined with neural network, it overcomes its own bottleneck, which is the difficulty in solving the inverse model; thus paves the way for neural network inverse method in applications to complex industrial processes [16-21].

To improve the SST control of a supercritical or an ultra-

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supercritical boiler unit, this paper presents an inverse compensation control scheme based on dynamic recurrent neural network inverse system models for the multi-stage water-spray desuperheating controllers. A typical recurrent network is used to construct the dynamic inverse models for the superheater system. Large amount of historical operational data over a wide-range of loading conditions are used for model training and validation. The trained NN inverse models are then employed as internal model controllers to improve the SST control effect by providing real-time supplementary signals to the original cascade PID controllers. The real-time steam temperature signals are fed back to adjust the input reference values of the NN controllers automatically. The aforementioned controller is programmed in MATLAB and it communicates bidirectionally with a full-scope simulator of a 600MW supercritical coal-fired power generating unit. Detailed simulation tests are made to verify the improvement of the new inverse compensation control scheme to explore relevant control rules for further engineering application.

II. Boiler System Description

The investigated boiler unit is a 600MW supercritical boiler, DG-1900/25.4-II type, manufactured by Dongfang Boiler Co. ltd, China. The main steam process of the boiler is shown in Fig. 1.

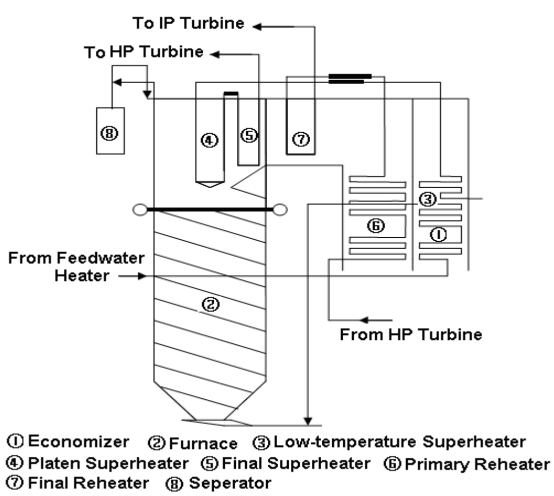


Fig. 1. Steam flow chart of a 600MW supercritical boiler.

The superheater system of the boiler is composed of four parts following the steam flow direction: 1) the roof tubes, the walls and midfeather of the real vertical flue path; 2) the Low-temperature Superheater (LSH), installed in the rear path; 3) the Platen Superheater (PSH) at the top of furnace; 4) The Final Superheater (FSH), located at above the furnace arch. The whole superheater system has a left-to-right cross before the final superheater to reduce the width-side effects induced by the uneven flue gas.

The superheater steam temperature of the supercritical boiler is controlled by both fuel/feedwater ratio and the two-stage water-spray desuperheating devices. The first-stage desuperheater is introduced to the connecting pipe between the LSH export and PSH import in order to control the PSH outlet steam temperature. The second-stage desuperheater is introduced between the PSH export and FSH import, to control the final superheater steam temperature. According to the operation manual, the final superheater steam temperature should be maintained at rated value (571 ℃) between 35% and 100% loading range with allowed deviation of ±5℃. The layout of the desuperheating system is shown in Fig. 2.

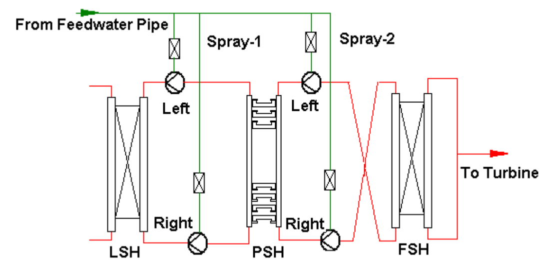


Fig. 2. Water-spray desuperheating system layout.

III. Neural Network Inverse System Principle

A. Neural Network Structure

Artificial Neural networks can be divided into feedforward networks and recurrent networks in structure [3]. The information flow of a feedforward network is one-way, transmitted from the input layer to the output layer, such as in BP network and RBF networks. A recurrent neural network differs from other conventional feedforward networks in that it includes recurrent or feedback connections [5,9,16]. 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 modeling. 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 [22-24]. 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. 3.

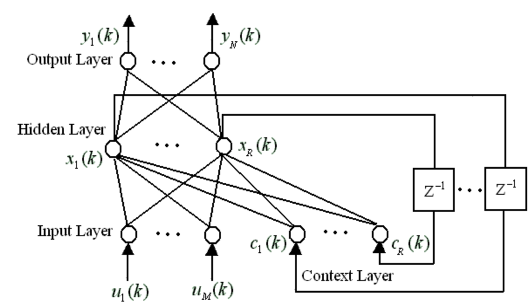


Fig. 3. Structure of the Elman recurrent network model.

As shown in Fig. 3, the outputs in each layer of an Elman network are 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; and $f(\bullet)$ and $g(\bullet)$ 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 fed 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 [22-24]. However, more accurate gradient can be evaluated by including the contributions through the recurrent neurons [5]. This gradient is then used to update the weights with the chosen back-propagation training algorithm [25]. Since Levenberg-Marquart method is fast and has robust convergence property in the off-line training, it is used for training the Elman network in this paper.

B. Neural Network Inverse Model

The inverse system modeling is a method easy-to-understand among nonlinear system control methods. It has been applied to different industrial processes [6,8,10-5].

If the inverse model $u= f^{-1}(y)$ of a typical single-input single-output (SISO) nonlinear system $y=f(u)$ can be approximated by a neural network model and this NN inverse model is cascaded into the original system, then a quasi-linearization system $y=g(y^*)$ can be constructed and solved with linear system methods. As shown in Fig. 4, this kind of NN inverse model only includes the control input and the controlled variable. Therefore, it is called the basic-structure inverse system model [21].

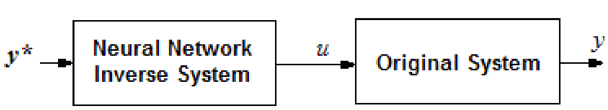


Fig. 4. Basic-structure inverse system.

To enhance the adaptability and anti-interference performance of the inverse system model, and to widen its operation range, some important process variables and disturbances in the original system can be added to the inputs of the basic-structure neural network inverse system model. In this way, an expanded-structure neural network inverse system model is constructed [21], as shown in Fig. 5.

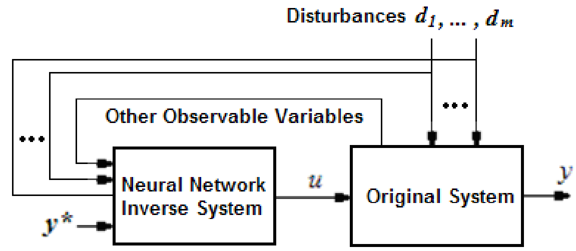


Fig. 5. Expanded-structure inverse system model.

After the NN inverse process model shown in Fig. 5 is trained with high accuracy, it can be used as a NN controller for the original system to improve its control effect.

IV. Inverse Model Development for supercritical Boiler Unit

A. Determination of Inputs and Outputs

For the boiler superheater system shown in Fig. 2, from analysis of the factors affecting superheater steam temperature, eight variables are selected as the inputs of the 1^{st}-stage NN inverse process model, and nine variables are selected as the inputs of the 2nd-stage NN inverse process model. The output of each neural network is its corresponding control input, i.e., the spray-1 or spray-2 control valve opening, as shown in Table 1.

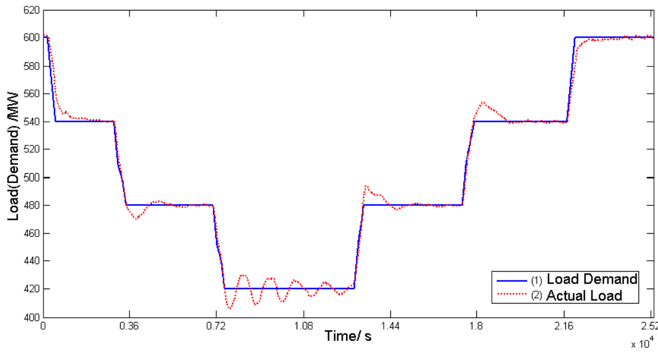
TABLE I

INPUTS/OUTPUTS SELECTION OF THE NN INVERSE MODELS

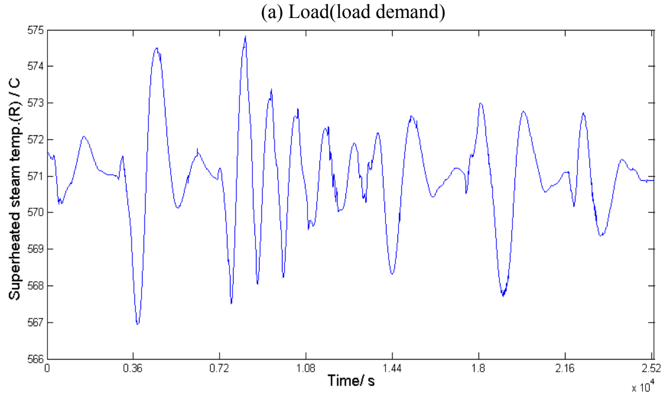
Inverse model	1st-stage water-spray desuperheating system	2nd- stage water-spray desuperheating system
Inputs	(1) Coal flow (Kg/h) (2) Air flow (Km^3/h) (3) Feedwater flow to waterwall (Kg/h) (4) Feedwater press. (MPa) (5) Feedwater temp. (C) (6) Main steam press. （MPa） (7) LSH out steam temp. (left) (C) (8)PSH out steam temp.(left) （C）	(1) Coal flow (Kg/h) (2)Air flow (Km^3/h) (3)Feedwater flow to waterwall (Kg/h) (4)Feedwater press. (MPa) (5)Feedwater temp.(C) (6)Main steam press. （MPa） (7)Spray-1 water flow (left) (Kg/h) (8)PSH out steam temp(left) （C） (9)FSH steam temp (right) （C）
Output	(1)Spray-1 valve opening (left) （%）	(1)Spray-2 valve opening (left) （%）

B. Training of the NN Inverse Models

In order for the model to fully reflect the static and dynamic features of the system, the network training data should be as extensive as possible, covering different steady-state load conditions and dynamic loading-up and loading-down process data. In this paper, 25,314 groups of data (sampling time 1s) are collected, including steady-state data at 600MW, 540MW, 480MW, 4200MW load levels, and the dynamic transition data when loading-up or loading-down between the four load levels with load changing rate of 10MW/min and pressure changing rate of 0.5MPa/min. During data collection process, the feedwater pumps, superheated steam temperature, airflow, etc. are all put in auto state, controlled by the original control system units. Fig. 6(a) shows the load demand and the actual load curves in data extraction process, 6(b) is final superheater steam temperature change curves.



(a) Load(load demand)



(b) Final superheater steam temperature

Fig. 6. Training sample data acquisition.

To reduce the sample size used for neural network training and facilitate model convergence within shorter time, one out of ten samples among the 25,314 groups of data are extracted and used for network training (interval 10s). Then the Elman neural network models are built using MATLAB and trained with improved Levenberg-Marquardt algorithm [14]. The training process is illustrated in Fig. 7.

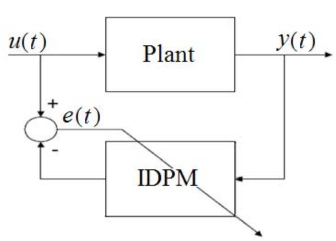
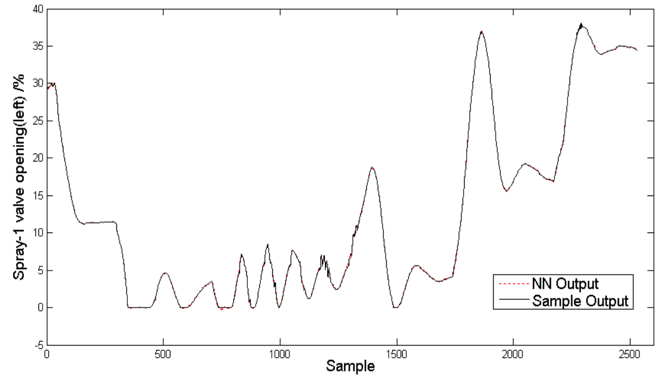
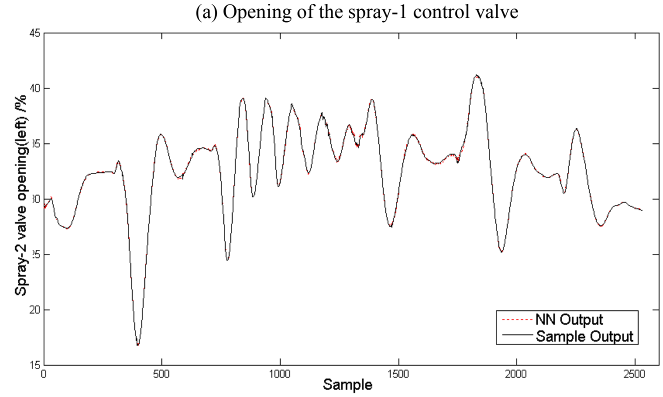


Fig. 7. Training process of the inverse dynamic process model.

Hidden layer neuron numbers of the two neural network models are optimized through trial-and-error search. The structure of the two models is finally determined as 9-17-1, 8-16-1. With 50 epochs of training cycles, the networks achieved the mean-square error (MSE) of 3.17e-5 and 5.44e-5, respectively. The outputs of the trained neural networks are compared with the training data in Fig. 8. It can be seen the two neural network inverse models have very higher fitting precision.



(a) Opening of the spray-1 control valve

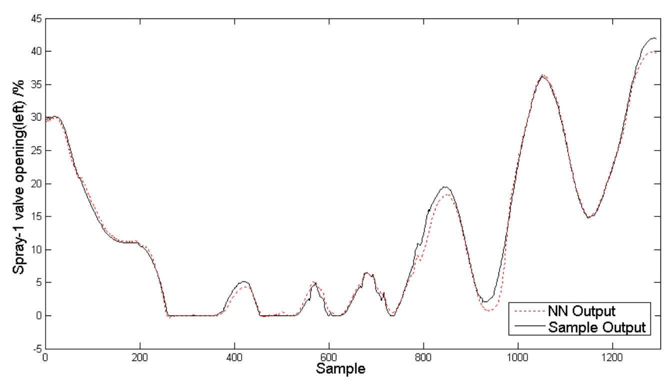


(b) Opening of the spray-2 control valve

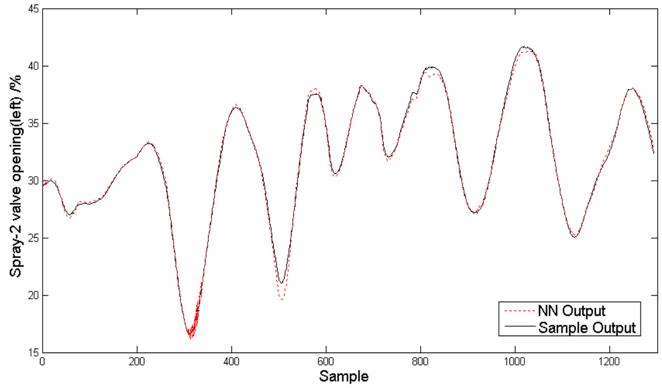
Fig. 8. Outputs of the trained NN models.

C. *Validation of the NN Inverse Models*

In order to validate the trained models under other working condition, changing unit load continuously between 600MW, 540MW, 480MW, 420MW with a different loading rate of 5MW/min., 12926 groups of data are gathered (sampling period 1s) and, again, one out of ten samples (1293 groups of data) are extracted and used for model validation. The results are shown in Fig. 9. It can be seen that the trained inverse process models also have very good prediction performance for the validating data.



(a)Spray-1 valve opening



(b)Spray-2 valve opening

Fig. 9. Model validation under different work condition.

V. NN Inverse Model Based Control

A. Inverse Compensation Control

After the off-line training has been finished with sufficient accuracy, two NN inverse controllers can be constructed based on the trained models，which can directly replace the original cascade PID controllers to control the spary-1 and spray-2 valves. For the control action to take place, the last input of each model needs to be replaced with desired reference output of the corresponding steam temperature. The direct inverse control scheme is shown in Fig. 10.

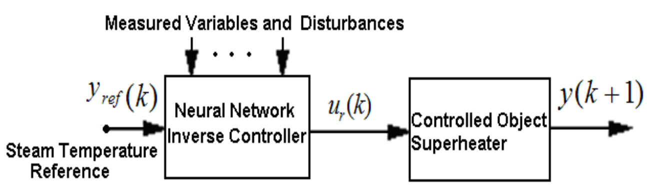


Fig. 10. Direct inverse control scheme for SST.

As illustrated in Fig. 5 and Table 1, the setpoint for spray-1 should be the expected value of the PSH outlet temperature. The setpoint for spray-2 should be the expected value of the final superheater steam temperature. All other inputs for both inverse dynamic process models are the endogenous inputs coming from real-time simulation of the plant.

For complex power generating units, out of operation safety and reliability consideration, it is often not allowed to abandon the original control logic. Because of this, the best compromising solution is to provide a supplementary signal to the original control demand to improve the steam control effect. In our work, the inverse compensation control scheme is adopted by adding supplementary signal coming from the NN inverse controller to the original cascade controller's output, as shown in Fig. 11.

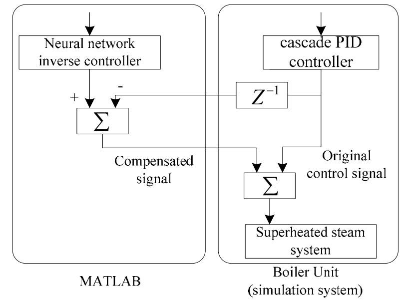


Fig. 11. Inverse compensation control schematic.

B. Steam Temperature Reference Value Calculation

Neural network inverse model itself is a kind of approximation of the inverse system. The imperfection of the model structure and the incomplete training sample will both lead to modeling error. When the NN models are used as real-time controllers, the actual operating condition also will be different from the model training or validating condition, thus producing control error. In addition, the SH outlet steam temperature cannot be changed instantaneously when the difference between the setpoint and current temperature is big. Therefore, the use of fixed steam temperature setpoints in NN controllers not necessarily bring good control effect. As a solution, real-time steam temperature signals are introduced to adjust the input reference values of the NN controllers automatically [8]. The reference SH outlet temperatures at time k for the 2 inverse NN controllers $T_{1ref}(k)$ and $T_{2ref}(k)$ are adjusted by:

$$T_{1ref}(k)= T_1(k)+sat[T_{1sp}-T_1(k)] \tag{4}$$

$$T_{2ref}(k)= T_2(k)+sat[T_{2sp}-T_2(k)] \tag{5}$$

where, $T_1(k)$ and $T_2(k)$ are the outlet temperatures at time k for the PSH and the FSH, respectively; T_{1sp} and T_{2sp} are the setpoints of the outlet temperatures for the PSH and the FSH, respectively; sat[.] is the saturation function defined by the ramp rate, which limits the change of the reference value to be within the ramp rate.

For simplicity's sake, the saturation function may take a simple linear form, thus (4) and (5) can be rewritten as:

$$T_{1ref}(k)= T_1(k)+K_{1sat}* [T_{1sp}-T_1(k)] \tag{6}$$

$$T_{2ref}(k)= T_2(k)+ K_{2sat}* [T_{2sp}-T_2(k)] \tag{7}$$

where $K_{1\mathrm{sat}}$ and $K_{2\mathrm{sat}}$ are called saturation factors. The function of a saturation factor is similar to the proportional coefficient of a PID controller. Its value has significant effect on the control quality of a NN inverse model controller, thus should be set reasonably through experiments.

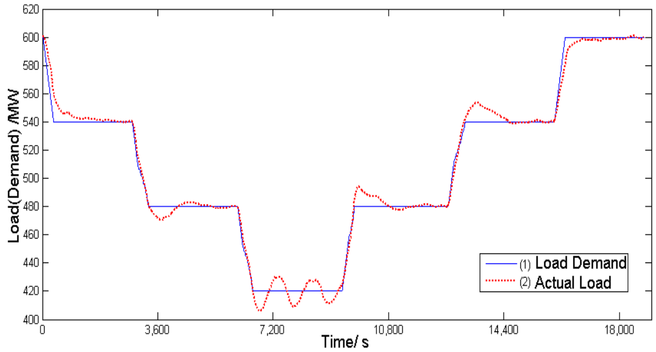
VI. Control Simulation Tests

A. Control Tests for Two Different Conditions

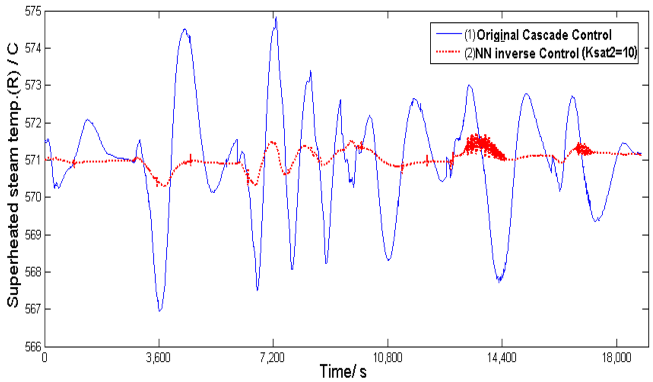
Based on the neural network inverse compensation control scheme shown in Fig. 11, the control procedure developed in MATLAB realizes SST real-time control by communicating with the full-scope simulator of a 600 MW coal-fired supercritical unit. Detailed control simulation tests are made. In the tests, the saturation factors for 1st-spray and

2nd-spray NN controllers are given fixed values, i.e., K_{1sat} = 1 and K_{2sat} = 10.

Firstly, the control test is made for the same load-changing condition as the condition under which the NN model training data are extracted. The control result is compared with that of the original cascade PID controllers in Fig. 12.



（a）Load(Load demand)

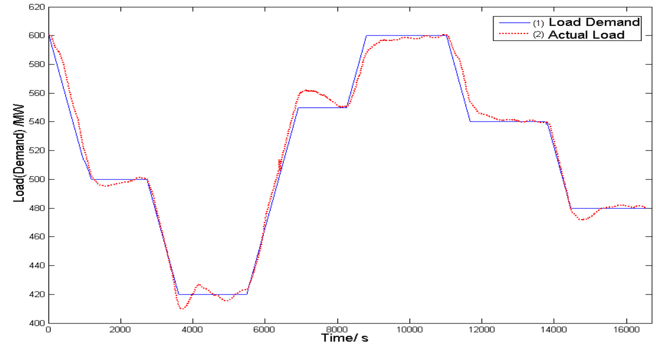


（b）Superheated steam temperature

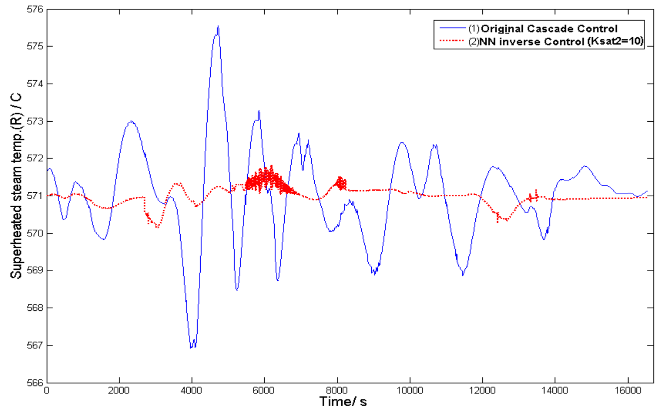
Fig. 12. Control test under the training condition.

It can be seen from Fig. 12, with the original cascade PID controllers, the superheated steam temperature changes between 567 and 575℃ during the whole load-changing process. The deviation from the setpoint is about ±4℃. The overshoot is big, the stabilizing time is long and the control quality differs at different loading points. Especially, under 420MW, the steam temperature stabilization needs quite long time. While, with the NN inverse compensation control scheme, the steam temperature always keeps between 570 and 572 ℃ during the whole loading process. The deviation from the setpoint never exceeds ±1℃, and the steam temperature stabilization is very fast.

For further validation of the control scheme, a different loading condition is tested. The load is changed with load changing rate of 5MW/min and pressure changing rate of 1MPa/min, in turn, from 600MW to 500MW, to 420MW, to 550MW, then to 600MW, et al. The control results with two different schemes are compared in Fig. 13. As before, in the whole loading range the neural network compensation control has far better control quality than the original cascade PID controllers.



（a）Load(Load demand)



（b）Superheated steam temperature

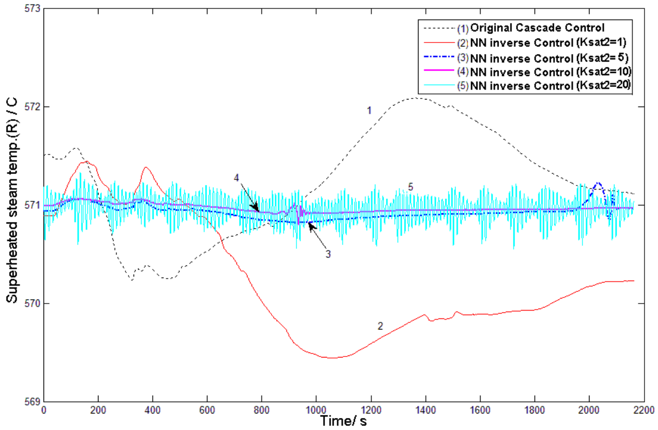
Fig. 13. Control test under different loading conditon (load rate 5MW/min, pressure rate 1MPa/min).

To sum up, under different test conditions, the NN inverse compensation control scheme gets bigger improvement both from overshoots and stabilization time than the original cascade PID controllers, which validates the excellent performance of the inverse compensation control scheme.

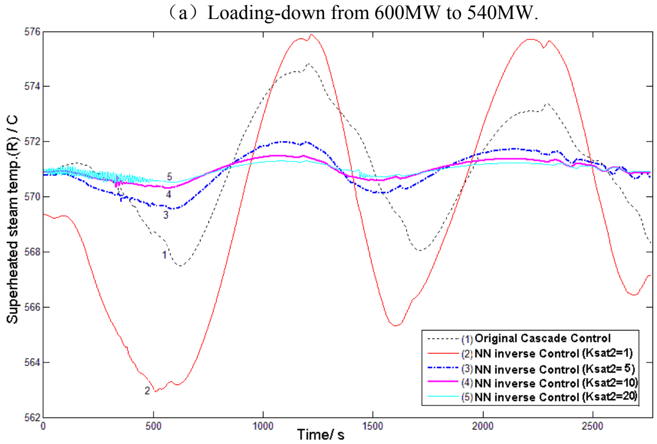
It is worth mentioning that the data used for training of the neural network inverse models are gathered by changing the unit load with the original cascade PID controllers, but the results of the inverse compensation control are much better than those of the original cascade PID controllers when the NN models are used for real-time control, which highlights the significance and meaningfulness of this research.

B. NN Controller Performance Tests with Different Saturation Factors

It is pointed out in Section V that the values of the saturation factors in (6) and (7) have great influence on the performance of the neural network controllers. Therefore, control tests with different saturated factors are further made. In the following tests, the saturation factor of the lst-stage NN controller, K_{1sat}, is fixed to 1, and only the saturated factor value for the 2nd-stage NN controller, K_{2sat}, is changed. Tests are made in turn when K_{2sat} takes values 1, 5, 10 and 20. The control results for the SST over different load scope are compared with that of the original cascade PID controllers in Fig. 14.



（a）Loading-down from 600MW to 540MW.



（b）Loading-down from 480MW to 420MW

Fig. 14. Performance of the NN controllers under different saturation factor values.

From Fig. 14 we can observe the following: 1) When K_{2sat} value is 1, NN compensation control gets very poor control result, even worse than the original cascade PID controllers. Under this situation, T_{2ref} (k) always equals T_{2sp} and takes fixed setpoint value 571 ℃, thus the steam temperature real-time feedback signal does not play any role. 2) With the K_{2sat} value increasing, NN compensation control effect is more and more obvious. When K_{2sat} takes value 10 or so, the control effect is the best. 3) When K_{2sat} is further increased to 20, oscillation appears for the superheater steam temperature for a part of the loading section, indicating that the compensation is too strong and K_{2sat} should be appropriately reduced.

VII. Conclusion

To improve the superheater steam temperature (SST) control of a 600MW supercritical boiler unit, the expanded-structure inverse dynamic process models for the 2-stage water-spray desuperheating system are established based on typical dynamic recurrent neural network. The trained NN inverse models are then employed as inverse model controllers to improve the SST control effect by providing real-time supplementary signals to the original cascade PID controllers. The real-time steam temperature signals are fed back to adjust the input reference values of the NN controllers automatically. It is verified through control simulation tests with the full-scope simulator of a 600MW supercritical boiler unit that the proposed control scheme is a great improvement both in control speed and overshoot compared to the original cascade PID controllers.

The superheater system in a large-scale supercritical boiler unit is a very complex nonlinear system. There are many factors influencing the SST. Selection of the input variables, the neural network structure and the training data for the inverse system models, all have influence on the final control effect, needing further study. In addition, some other factors leading to changes in SST characteristics are not considered during the inverse process model development, such as the changes in the coal characteristics, in the boiler structure during maintenance, in the boiler performance over time, etc. Finally, on-line tuning or correction of the inverse system models needs further study.

Acknowledgment

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VIII. References

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