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Neural Network Inverse Control for the Coordinated System of a 600MW Supercritical Boiler Unit

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Abstract: A supercritical (SC) once-through boiler unit is a typical multivariable system with large inertia and non-linear, slow time-variant, and time-delay characteristics, which often makes the coordinated control quality deteriorate under wide-range loading conditions, and thus influences the unit load response speed and leads to heavy fluctuation of the main steam pressure. To improve the SC unit's coordinated control quality with advanced intelligent control strategy, the neural-network based inverse system models of a 600MW supercritical boiler unit were investigated. A feedforward neural network with time-delayed inputs and time-delayed output feedbacks was adopted to establish the inverse models for the load and the main steam pressure characteristics. Based on the model, neural network inverse coordinated control scheme was designed and tested in a full-scope power plant simulator of the given SC power unit, which showed that the proposed coordinated control scheme can achieve better control results compared to the original PID coordinated control.

Keywords: Supercritical boiler, neural network, inverse model, coordinated system, intelligent control.

1. INTRODUCTION

Supercritical (SC) and ultra-supercritical (USC) power generating units have become the dominant coal-fired power units in China and around the world (Garduno and Lee, 2005; Ma and Lee, 2011). To meet the Automatic Generation Control (AGC) requirement, these large-capacity SC/USC power units are frequently required to participate in peaking-load regulation and often work in large-scale load-following mode (Li and Wang, 2005).

Since a SC/USC boiler unit is a strongly coupled nonlinear multivariable system with large time-delay characteristics, the traditional coordinated control strategy cannot well adapt to the load regulation, and often leads to slow load response and large main steam pressure (MSP) fluctuations. Therefore, considering the stability of the power grid and the safety and economy of the power unit, it is of great importance to improve the coordinated control quality of the SC/USC power unit with advanced model-based intelligent control strategies, such as neural network inverse control or predictive optimal control method (Heo and Lee, 2008; Lee et al., 2007b, 2009, 2010; Ma and Lee, 2011).

With increasing number of SC/USC boiler units, many studies have been performed for modeling (Ding et al., 2005; Yan et al., 2012). Among them, parameter tuning for some models is complicated and the models are inaccurate. Some models are too complex to fit for intelligent coordinated controller design. Therefore, how to establish a nonlinear mathematical model with higher accuracy and simpler structure, which is suitable for intelligent controller design and applicable for a SC/USC boiler unit, remains an important open problem.

Self-adaptive inverse control method has drawn much attention in engineering applications with its advantages of clear physical concept, being intuitive and easy to understand (Dai, 2005). But solving for the inverse system model of a complex multivariable system is a bottleneck. At the same time, artificial neural networks (ANNs) have been widely used for modeling and control of complex industrial dynamic systems with impressive identification ability, strong fault tolerance and adaptive learning capability (Gencay and Liu, 1997; Lee et al., 2007a). Combining them together, ANN-model based inverse control method can overcome the difficulty of solving the inverse problem, and present promising future applications. Recently, neural network inverse control has been applied in different areas, including power plant steam temperature control and optimization (Wang et al., 2002; Lee et al., 2009, 2010; Ma and Lee, 2011).

Aimed at improving the coordinated control quality of a supercritical boiler generating unit, the neural network inverse system models for a 600MW SC boiler unit are studied. Two separate inverse models for load and MSP are constructed. The inputs and outputs of each model are determined by analyzing the correlation between input and output variables, and the coordinated control modes of the SC power generating unit. The models are built with time-delayed feedforward neural networks, trained and verified with abundant operating data. Based on the developed models, neural network inverse controllers are designed for the coordinated system of the 600MW SC power unit, which are validated by real-time control simulation tests.

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2. COORDINATED CONTROL MODES AND SIMPLIFIED MODEL OF A SC BOILER UNIT

2.1 Coordinated Control Modes

Usually, the coordinated control system of a SC/USC boiler unit includes boiler master control (BMC), turbine master control (TMC), target load and load ramping-rate setting, target MSP and pressure rate setting, primary frequency tuning and other function loops (Zhang et al., 2007). For the 600MW supercritical boiler unit investigated in this work, based on whether BMC and TMC are put into automatic or not, there are four kinds of control modes: (1) manual mode (both BMC and TMC are in manual), (2) boiler-following mode(TMC is in manual while BMC is in automatic), (3) turbine-following mode (BMC is in manual while TMC is in automatic), and (4) coordinated control mode (both BMC and TMC are in automatic modes).

According to the inner logic difference, the coordinated control mode can be divided into Boiler-Following Based Coordinated (BFBC) mode and Turbine-Following Based Coordinated (TFBC) mode. Under BFBC mode, TMC is used to control the load by changing the valve opening of the turbine governor when load demand changes, and BMC is responsible for maintaining the MSP by changing the fuel flow. It results in faster load response and smaller load deviation, but relatively larger main steam pressure fluctuations. Under TFBC mode, BMC is responsible for controlling the load when load demand changes, and TMC is used to maintain the MSP by changing the turbine valves' opening. It results in smaller steam pressure deviation, but slower load response.

When a coal-fired power generating unit is scheduled automatically through Automatic Generation Control (AGC) by the regional grid load dispatch center, the power plant often puts the priority in meeting the power grid load demand to avoid additional penalty. Thus the BFBC mode, with its fast load response, is the preferred coordinated control mode under AGC control, and it is adopted by most SC/USC power units. For the 600MW SC power unit investigated in this paper, BFBC mode is also employed.

2.2 Simplified Model Structure of SC Boiler Unit

During the period of increasing load in a SC/USC boiler unit, the steam in the steam-water separator will convert from wet state to dry state and finally entering "once-through" stage. When a SC/USC boiler unit works in the "once-through" stage, there is no clear demarcation point between steam and water. Feedwater entering the economizer is continuously heated, evaporated and overheated, and the length of each stage changes with disturbances of fuel flow, feedwater flow and turbine governor valve opening, leading to changes in superheated steam temperature, MSP and unit power.

Therefore, a SC/USC boiler unit is normally described as a strongly coupled nonlinear model with 3 inputs and 3 outputs, as shown in Fig. 1.

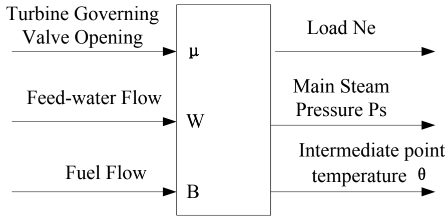


Fig. 1. Simplified model of a SC boiler unit.

3.STRUCTURE FOR LOAD AND MAIN STEAM PRESSURE INVERSE MODELS

3.1 Principle of Neural Network Inverse Model

Among different nonlinear system control methods, the inverse system method is intuitive and easy to understand, which has been applied to different industrial processes.

Based on neural network inverse system theory, if the inverse model $u = f^{-1}(y)$ of a typical SISO (single-input single-output) nonlinear system $y = f(u)$ can be approximated by a neural network model and this NN inverse model is cascaded with the original system, as shown in Fig. 2, then a quasi-linearization system $y = g(y^*)$ can be constructed and solved with linear system methods .

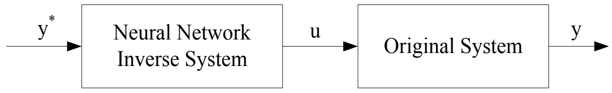


Fig. 2. Neural network inverse system principle.

After the neural network inverse system model of high precision has been established, a neural network inverse controller can be designed to realize inverse control of the original system.

3.2 Load and MSP Inverse Model Structure

As shown in Fig. 1, a SC boiler unit can be simplified as a 3-input 3-output model. Considering the strong coupling among the inputs and outputs and the diversity of the unit's coordinated control modes, if this model structure is selected to build the inverse model of the load and main steam pressure, the reversibility of the model is difficult to guarantee, and it is not suitable for inverse controllers' design. In addition, the unit power is related directly to the main steam temperature (MST) before the turbine governor valve, not the intermediate point temperature. The MST of a supercritical boiler unit not only depends on the feedwater-coal ratio, but also is greatly affected by the water-spray attemperators during dynamic loading process. The model in Fig. 1 does not take the water-spray attemperators into account, so it may lead to large load prediction error.

For the simplified system of a SC power unit shown in Fig. 3, main steam pressure P_S, main steam temperature T_S and turbine governor value opening μ are the three most important variables directly related to the turbine load. Main steam pressure P_S is affected by boiler fuel flow B, feedwater flow W and turbine governor value opening μ. To facilitate the design of the inverse coordinated controller, the inverse model structure is determined with the following considerations: (1) The MSP model and the unit load model are built respectively to make each model simpler in structure and reversible. (2) Since BFBC mode has faster load response under AGC than other coordinated control modes, the inverse model development is based on BFBC mode.

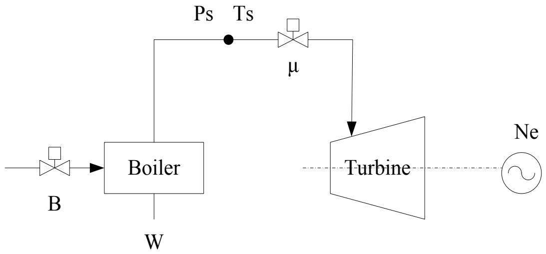
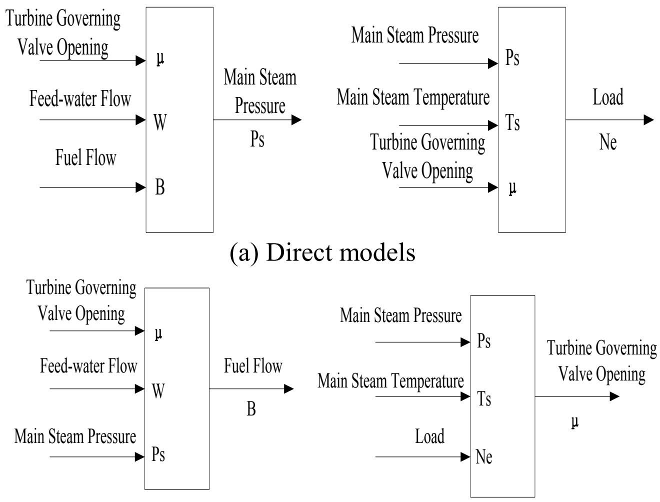


Fig. 3. Schematic diagram for supercritical power unit.

Based on the above consideration, two separate direct models for the MSP and the unit load are set up as shown in Fig. 4(a). Corresponding to the BFBC mode, turbine governor valve opening is responsible for adjusting the unit load, and fuel flow is for maintaining the main steam pressure. Thus the two inverse models are formed as shown in Fig. 4 (b). It can be easily seen that the reversibility of the two inverse models are guaranteed, and the models are with simple structure and fit for inverse coordinated controller design.



(a) Direct models

(b) Inverse models

Fig. 4. Direct/inverse models for load and MSP of a SC unit.

4. NEURAL NETWORK INVERSE MODEL DEVELOPMENT AND VALADITION

4.1 Structure of Neural Network Inverse Models

In this work, a standard BP (or feed-forward) neural network with time-delayed inputs and output feedbacks is applied to establish the inverse dynamic system models for the load and the MSP of a 600MW SC boiler unit.

For the two BP network inverse models, the current and delayed values of the 3 inputs are used as the model inputs. The delayed value of the fuel flow (or turbine valve opening) is also introduced as the model's input. The current value of fuel (or turbine valve opening) is used as the model output. Thus the two dynamic inverse models both have 7 inputs and 1 output, as shown in Fig. 5. The BP model has been implemented using Matlab Neural Network Toolbox. The hidden-layer and the output-layer activation functions adopt Matlab *purelin* function and *tansig* function, respectively; and the Levenberg-Marquardt (LM) algorithm (trainlm) is used for model training.

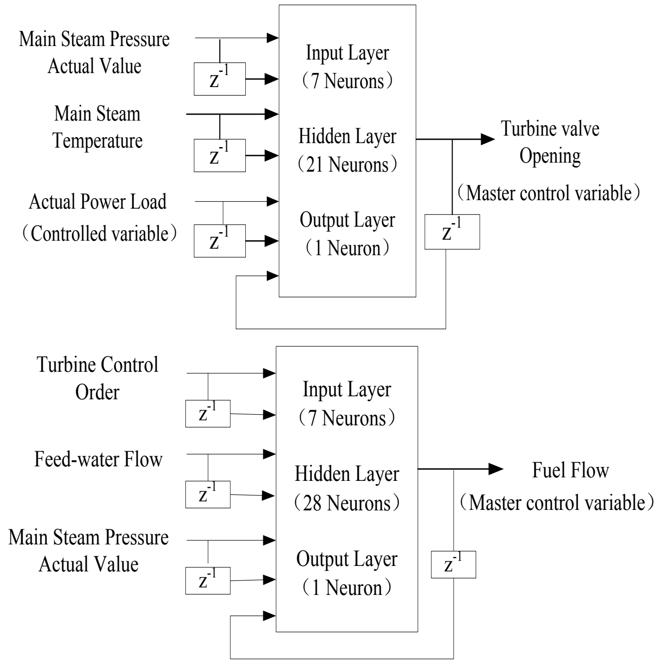


Fig. 5. Structure of the 2 Inverse models.

4.2 Training of Neural Network Inverse Models

The neural network models should be trained with sample data set after the models' inputs, outputs and structures are determined. To make a NN model fully represent the dynamic and static characteristics of the controlled object, the training data should be rich enough to contain different operating conditions under which the model will be applied.

In this paper, the training data are obtained from the full-scope simulator of a 600MW SC boiler unit. During data acquisition, the simulator is operating in BFBC mode, and the feed-water control, water-spray attemperator controls, air flow control, et al., are all put into automatic modes. In our work, 11,927 sets of data are collected from the simulator with the sampling period of 2s, including different steady-state data between 600MW and 420MW load levels and the dynamic transient data between different load levels with the load ramping rate of 12MW/min. Matlab Neural Network

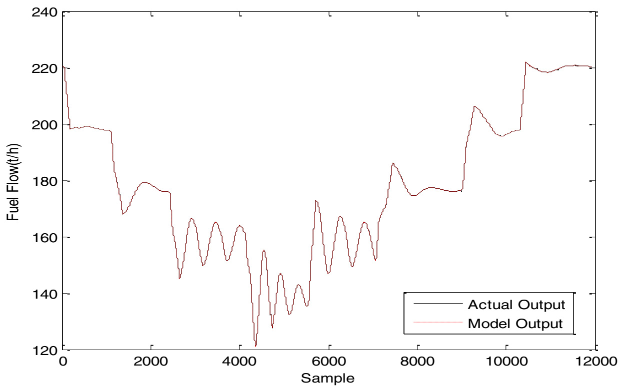
Toolbox functions are then used to construct the NN inverse models.

Number of hidden nodes in a neural network has great influence on its performance. In this work, the hidden-layer nodes of the 2 NN models are determined by trial and error. The final model structures and the mean squared errors (MSE) of the two models after 1000 training cycles are shown in Table 1.

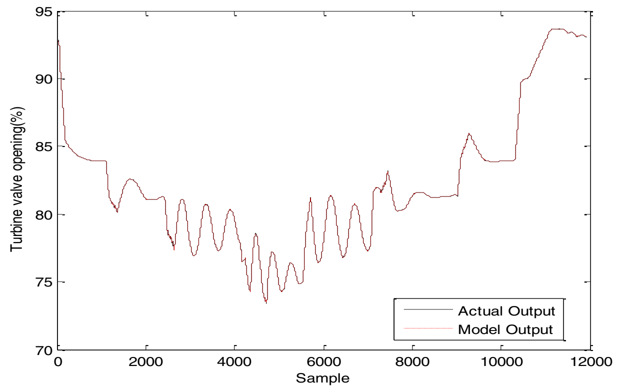
Table 1. Training results of the 2 models

Inverse Model Category	Model Structure	MSE
Main Steam Pressure	7-21-1	1.3726×10^{-7}
Load	7-28-1	3.3205×10^{-7}

The calculating results of the two dynamic BP network models are shown in Fig. 6. It is evident that the dynamic BP network models with time-delay inputs and output feedback are with high fitting precision.



(a) Fuel flow

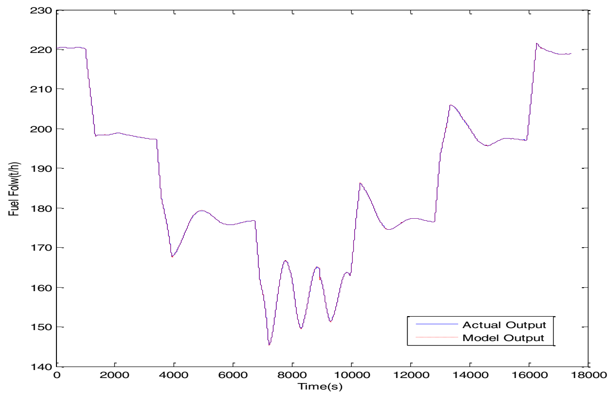


(b) Turbine valve opening

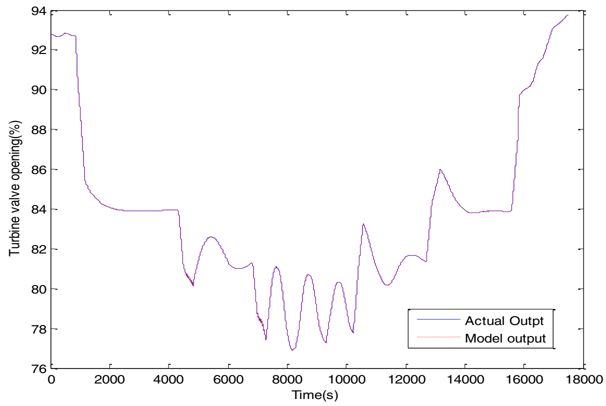
Fig. 6. Training results of the 2 NN inverse models.

4.3 Model Verification for Load-Changing Conditions

To verify the on-line dynamic prediction performance of the trained models, tests are carried out under a wide range of loading conditions. During loading-down process from 600MW to 420MW with the ramping rate of 10MW/min, the models' real-time outputs are compared with those of the power plant simulator in Fig. 7. It can be seen that the two dynamic inverse models predict the actual outputs with a small MSE error.



(a) Fuel flow



(b) Turbine valve opening

Fig. 7. On-line test of the NN inverse models.

5. INVERSE CONTROL SCHEME DESIGN

5.1 Inverse Compensation Control Scheme

After the 2 inverse models have been trained with sufficient accuracy, the NN inverse coordinated controllers can be constructed, which can directly replace the original PID coordinated controllers to adjust the fuel flow and turbine valve opening to keep MSP and follow load demand. For the control action to take place, the last input of each inverse model, as shown in Fig. 4(b), needs to be replaced with the desired reference output of the unit load or the MSP. The direct inverse control scheme is shown in Fig. 8.

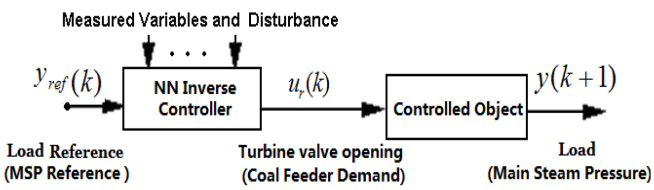


Fig. 8. Direct inverse coordinated control scheme.

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 coordinated control effect (Ma and Lee, 2011). In our work, the inverse compensation control scheme is adopted by adding 2 supplementary signals coming from the NN inverse controllers to the original coordinated controllers' outputs, as shown in Fig. 9.

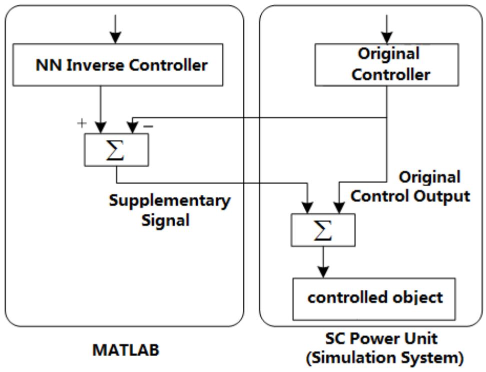


Fig. 9. Inverse compensation control schematic.

5.2 Load and MSP Reference Real-time Updating Method

A neural network inverse model itself is a kind of approximation of the inverse system. The imperfection of the model structure and the incomplete training samples will both lead to modeling error. When the NN inverse models are used as real-time controllers, the actual operating condition will also be different from the model training or validating conditions, thus producing control error. In addition, the load and MSP cannot be changed instantaneously when the difference between the setpoint and current temperature is big. Therefore, the use of fixed load and MSP setpoints in the NN controllers not necessarily brings good control effect. As a solution, real-time load $Ne(k)$ and MSP signals $P_t(k)$ at kth step are introduced to adjust the input reference values of the NN controllers at k+1 step automatically. The reference Load and MSP values, $L_{ref}(k+1)$ and $P_{ref}(k+1)$, are adjusted by:

$$L_{ref}(k+1) = L_{ref}(k) - k_1(Ne(k) - L_{sp}) \quad (1)$$

$$P_{ref}(k+1) = P_{ref}(k) - k_2(P_t(k) - P_{sp}) \quad (2)$$

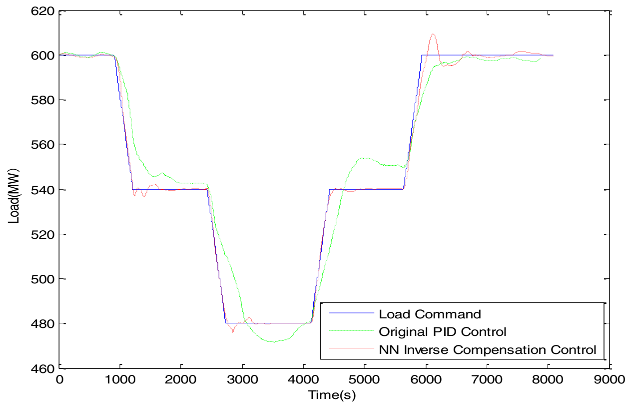
where, k_1 and k_2 are two saturation factors related to load and MSP error, respectively.

6. INVERSE CONTROL SIMULATION TESTS

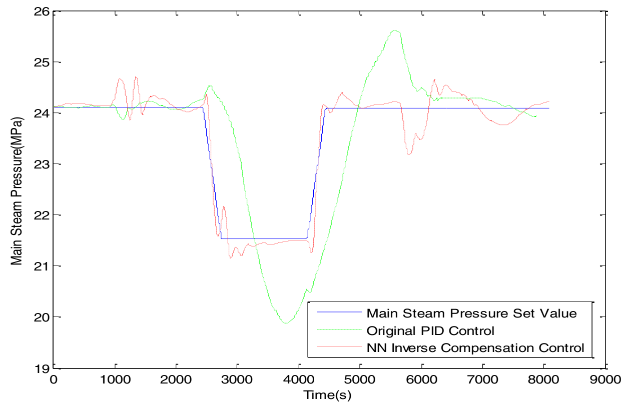
Based on the NN inverse control compensation scheme, detailed control simulation experiments are made with the full-scope simulator of a 600MW SC boiler unit.

When the unit load is changed in turn from 600 MW, to 540 MW, to 480 MW, and then back to 540 MW and to 600 MW, with the load ramping rate of 12 MW/min and the pressure changing-rate of 1 MPa/min, the NN inverse compensation control results are compared with the original coordinated control results in Fig. 10.

It can be seen from Fig. 10 that, with the original coordinated control scheme, the maximum load control deviation is ±5 MW and the control quality are obviously different at different load level. The MSP control overshoot is relatively large and the stabilizing time is long. With the NN inverse compensation control scheme, load can track the instruction completely, and the MSP deviation is less than ±0.5MPa, and stabilizing time is short.



(a) Load

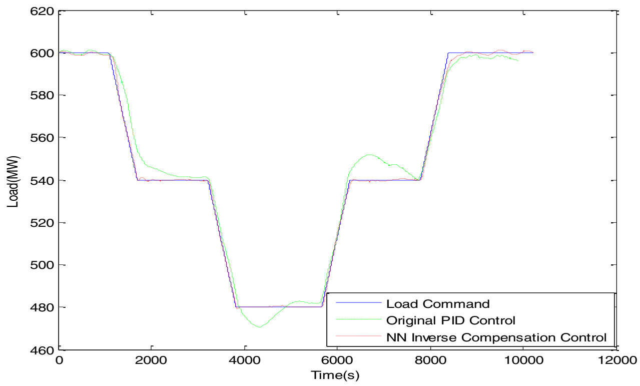


(b) Main steam pressure

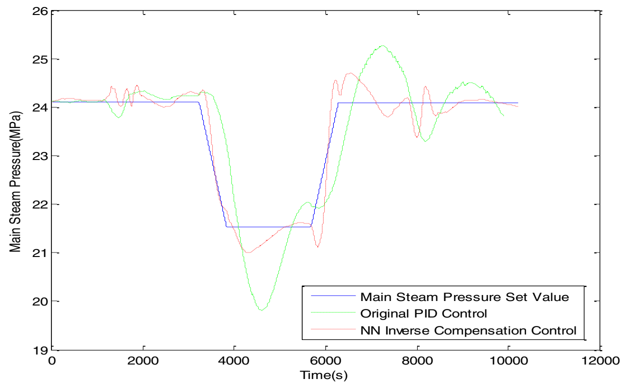
Fig. 10. Control test under training condition.

For the above experiments, the load changing rate and the pressure changing rate are consistent with the model training condition. To test the inverse coordinated control effect under an operating condition different from the training samples, we change the load ramping rate to 6 MW/min, and keep the pressure-changing rate at 1 MPa/min. Again, we drop load from 600MW to 480MW then back to 600MW. The load and MSP control effects are compared in Fig. 11.

We can see from Fig. 11 that, under the validation condition, the NN inverse control also achieves better results than the original PID control. The load can completely track the load instruction and the MSP deviation is less than ±0.5MPa. The overshoot is smaller and the stabilizing time is shorter.



(a) Load



(b) Main steam pressure

Fig. 11. Control test under validation condition.

7. CONCLUSION

To improve the coordinated control quality of a supercritical power generating unit, the dynamic feedforward neural network inverse models for the load and main steam pressure (MSP) are developed. Based on the trained models, the NN inverse coordinated controllers are designed, programmed and tested in the full-scope simulator of a 600MW SC power unit. Simulation experiments showed that the proposed NN inverse coordinated control method has better performance in load responsiveness, steam pressure overshoot and control accuracy, compared to the original scheme.

It should be pointed out that a supercritical power unit is a complicated nonlinear system. There are many factors influencing the load and main steam pressure. Selection of input variables, neural network structure, and the choice of training data, all have influence on the final control effect. In addition, real-time tuning of the NN inverse models still needs further research.

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