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Predictive Control Strategy for a Supercritical Power Plant and Study of Influences of Coal Mills Control on its Dynamic Responses

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Abstract—**the paper is to investigate dynamic responses of supercritical power plants (SCPP) and study the potential strategies for improvement of their responses for Grid Code compliance. An approximate mathematical model that reflects the main features of SCPP is developed. The model unknown parameters are identified using Genetic Algorithms (GA) and the model is validated over a wide operating range. A model based predictive control (MPC) is then proposed to speed up the dynamic responses of the power plant by adjusting the reference of the plant local controls instead of direct control signal applications. Simulation results have shown encouraging improvement in performance of the plant with no interference with its associated local controllers.**

Keywords - Supercritical Boiler; Mathematical Modeling; Parameter identification; Genetic Algorithms; Model based predictive control.

I. INTRODUCTION

It is well known that the Supercritical (SC) power plant is a complex process and has a large thermal inertia. Due to its once-through boiler structure, there are concerns for its dynamic response speed as there is no drum to buffer energy in the system and also there are concerns in Grid Code compliance ([1]). The first attempt towards optimal control of oil-fired SC power plants was reported in 1978 [2] with a state space model for identification and control optimization using a dynamic programming technique. Nonlinear model based predictive control (NMBPC) was reported in [3] using a reduced order physical system model to predict the next step control values. Dynamic matrix control (DMC) was published in [4] designed for SC power plants using linear model identified from step response tests. In [5], a model of an existing SC once-through power plant was reported for simulation study of plant frequency responses. The recurrent neural network modeling and modified predictive optimal control approach for coal fired SC and ultra-supercritical (USC) power plants were reported in [6] [7][8]. The paper is to study the control strategy by taking prompt actions in mill control to speed up the whole process dynamic responses.

The main contributions of the paper are: 1) a nonlinear vertical spindle mill model representing the whole milling process is integrated to a SC power plant model, which is developed by the research group at Warwick and Birmingham Universities in collaboration with the industrial partners. This has improved the whole SC power plant (SCPP) model as the previous SCPP mathematical models generally assume instantaneous response from the fuel source. In the paper, the influences of milling process capability and mill control to the whole power plant dynamic responses are investigated. 2) The paper proposed a Model Predictive Control (MPC) method to provide the updated optimal demand/set point values for the coal flow, feed water flow and the main steam valve position reference. Then those values are fed to the mill, boiler and turbine local controllers. If the amount of desired coal flow is optimally predicted in advance, there will be more stored coal in the mills to give quicker responses. The study has indicated that the proposed MPC strategy for adjusting the reference values of the plant local controls plays an important role in improving the whole plant dynamic response speeds.

II. SC POWER PLANT DESCRIPTION AND ITS MATHEMATICAL MODEL

Vertical spindle mills are the dominant types used for SC coal fired power plants ([9-10]). The raw coal enters the mill inlet tube and carries the coal to the middle of grinding rotating table. Hot primary air flows into the mill from the bottom to carry the coal output from grinding process to the classifier that is a multi-stage separator located at the top of the mill. The heavier coal particles fall down for further grinding and the pulverized coal is carried pneumatically to the furnace. Inside the boiler, the chemical energy released from combustion is converted to thermal energy. The heat is exchanged between the hot flue gas to the water through heat exchangers. The boiler contains thin tubes as heating surfaces which form the economizers (ECON), waterwall (WW), low temperature superheater (LSH), platen superheater (PSH), final stage superheater (FSH), and reheaters (RH). The water is forced at high pressure (SC pressure) inside the economizer and passes through all those heating sections. Since pressure is above the critical point, the sub-cooled water in the economizers converted to the supercritical steam in the superheaters without evaporation. The SC steam is then expanded through turbines. The high pressure (HP) turbine is energized by the steam supplied at final stage superheater and the reheaters are used to reheat the exhausted low pressure steam from the HP turbine before it returns to the IP turbine. The mechanical power is converted to electrical power by synchronous generator coupled to the turbines. In the work described in the paper, a 600MW SC power plant is selected with the boiler specifications at boiler maximum continuous rating (BMCR) shown in Table I

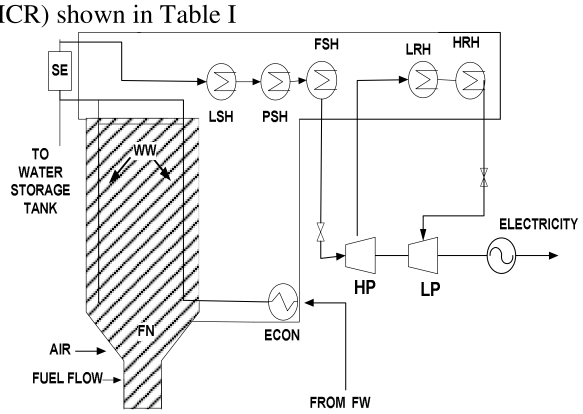

Fig.1 Schematic view of the SCPP under investigation

TABLE I. BOILER SPECIFICATION

Flow rate of superheated steam(t/h)	1780
Steam pressure (MPa) FSH outlet ECON inlet	 25.4 27.6
steam temperature (C°) FSH outlet ECON inlet	 570 288
Fuel (t/h)	Pulverized coal of 276

For the purpose of dynamic simulation studies and control system development, a nonlinear mathematical model with 20 differential equations for supercritical boiler-turbine-generator systems, rooted from physical principles, has been developed and integrated with a vertical spindle mill model [9]. Some assumptions are made to simplify the model structures which are:

- Fluid properties are uniform at any cross section, and the fluid flow in the boiler tubes is one-phase flow.
- In the heat exchanger, the pipes for each heat exchanger are lumped together to form one pipe.
- Only one control volume is considered in the waterwall.
- The dynamic behavior of the air and gas pressure is neglected.
- Only the change in internal energy is considered, the deviations or changes of kinetic energy and potential energy of fluid are neglected.

Due to page limitation, only a brief description of the model is given in the paper, the detailed procedures for the model derivation and parameter identification are reported in our work [10][11]. The boiler model is developed by deriving the nonlinear dynamics of pressure and temperature in each heat exchanger from mass and energy balance equations of a certain control volume. Those equations are strongly coupled by the equations of SC steam flow and heat flow in the boiler. The heat flow is directly related to the fuel through constant gains and fuel calorific value. It should be noted that major boiler model parameters are either calculated from steam tables or identified using the data from certain operating unit responses. The former method is more suitable for steady state system model so the latter approach has been adopted with the real power plant measured data. The turbines HP and IP are modeled by the same principles of energy conservation and simply linked to the outlet of RH and FSH outlets of the boiler. The generator nonlinear model [12] has been coupled to the turbine model through torque equilibrium with other algebraic equations. The model has two direct inputs of feedwater flow and fuel flow and one indirect input which is the valve position reference. The model equations have been implemented by MATLAB/SIMULINK so that the output scope can be easily accessed at any point in the model. The computer graphical implementation includes gains, integrators, differentiators, transfer functions in s domain, summing points, multiplication points...etc. Furthermore, Matlab stiff function (ode15s) solver has been used for numerical solution of the model during identification or verification simulations. Fig.2 shows the model blocks diagram with all combined subsystems and the symbols are listed in Table.II. The procedure of parameter identification is summarized in the next section.

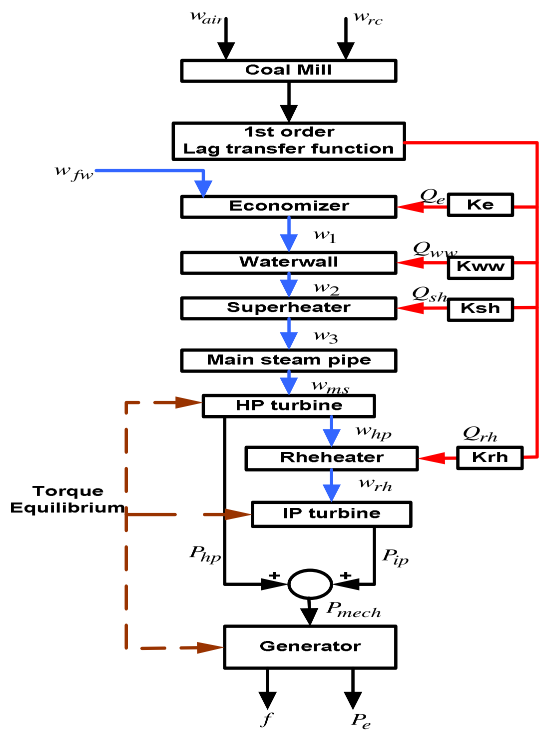

Fig.2 Mathematical model of supercritical power plan

TABLE II. LIST OF SYMBOLS IN FIG.2

w_{rc} : Raw coal flow rate (Kg/s).	w_{ms} : Main steam flow rate (Kg/s)
w_{air} : Primary air flow(Kg/s) w_{hp} : steam flow rate from HP turbine to after steam chest to the reheater (Kg/s)	w_{rh} : Reheated steam flow rate (Kg/s)
Q_e , Q_{sh}, Q_{rh}, and Q_{ww}: heat transferred from tube wall to the fluid (MJ/s)	P_{mech} : Mechanical power (MW)
w_f :Pulverized coal flow rate (Kg/s).	f : frequency (p.u)
T_{out} :Mill outlet temperature (C°).	P_e : Electrical power (MW)
w_{fw} : Feedwater flow rate (Kg/s).	w_1 , w_2 , w_3 :intermediate mass flow rates (Kg/s)

III. PARAMETER IDENTIFICATION

It is worth noticing that the physical model parameters are not known precisely. As described in the previous section, the GA optimization technique was adopted to identify the model unknown parameters. It should be mentioned that GA is robust optimization technique that is suitable for nonlinear system identification. Unlike conventional mathematical optimization methods, GA technique is able to tune all model parameters simultaneously with multi-objective optimization. Furthermore, GA produces global optimal solution for complex systems or functions because of parallel distributed search mechanism and mutation. The identification scheme is graphically represented in Fig.3. The work employed the coal mill model reported in [9] and the mill parameters are given in the reference. The rest of the plant model parameters are identified according to measured data responses of: 1) main steam temperature; 2) main steam pressure; 3) reheater pressure; 4) SC steam flow rate. The measured variable data for identification of turbine /generator parameter optimization are: 1) mechanical power; 2) electrical power; 3) system frequency. The onsite measurement data from a 600MW SC power plant is used for identification. Data set.1 has been used for identification which represents an increase in the load demand from 35% to 100% of load demand. Data sets 2, 3 and 4 are used for further model investigations. Fig.4 represents identification result while figs 5, 6, 7 show some verification results for different sets of data. It can be seen that the mathematical model reflects the main variation trends of the real power plant measurements over wide operating range although some assumption for simplifications were initially made.

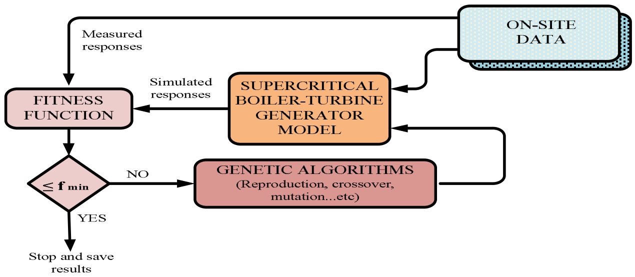

Fig.3 Identification scheme of the model using GA.

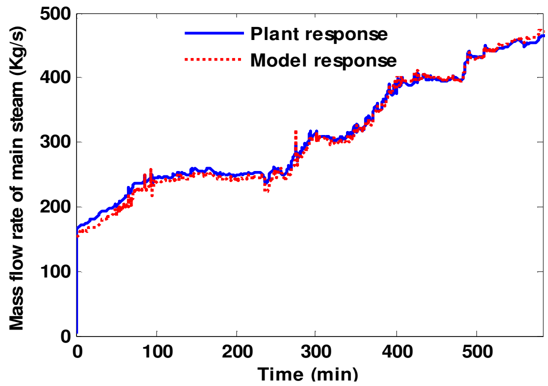

Fig.4 Mass flow (Kg/s) Data set.1 (identification)

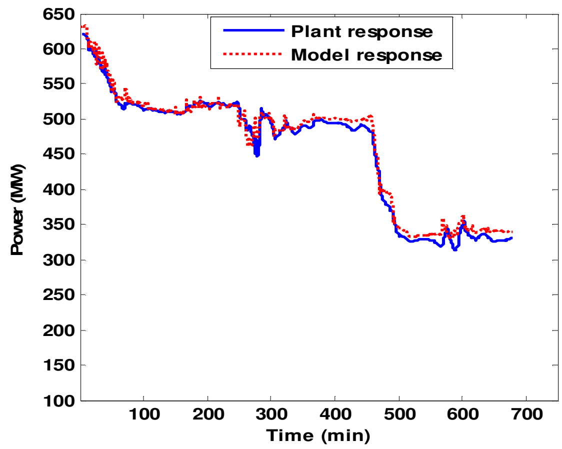

Fig.5 Electrical Power Data set.2 (verification)

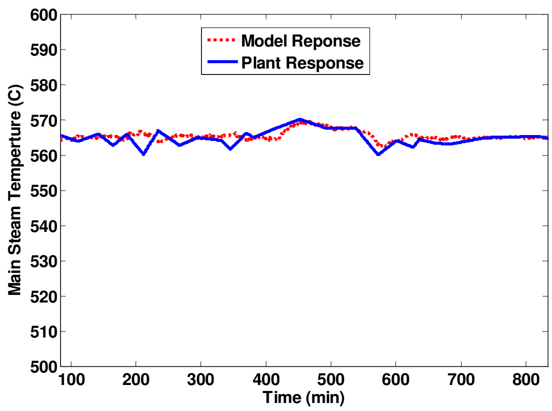

Fig.6 Main steam temperature Data set.3 (verification)

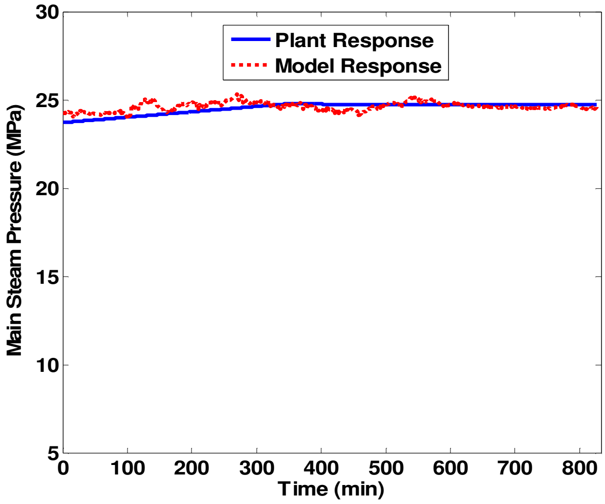

Fig.7 Main Steam pressure Data set.3 (verification)

IV. PREDICTIVE CONTROLLER DEVELOPMENT

A. *Reduced order linear model identification*

The generalized MPC algorithm includes an identified linear state space model, used for predicting the plant output variables. The plant identified linear model were investigated around nominal operating conditions (i.e. supercritical conditions). Again GA has been used to identify the linear model with portions of data set.1 and 3 to match the response of the original process model. The prediction model has four states three inputs and three outputs. the linear model which has the following form:

$$\boldsymbol{x}(k+1) = \boldsymbol{Ax}(k) + \boldsymbol{Bu}(k) \quad (1)$$

$$\boldsymbol{y}(k) = \boldsymbol{Cx}(k) \quad (2)$$

The model has four states $\boldsymbol{x}^T=[x_1 \ \ x_2 \ \ x_3 \ \ x_4]^T$, three inputs or manipulated variables $\boldsymbol{u}^T=[u_1 \ \ u_2 \ \ u_3]^T$, and three outputs.$\boldsymbol{y}^T=[y_1 \ y_2 \ \ y_3]^T = [x_2 \ \ x_3 \ \ x_4]^T$. $\boldsymbol{A}$, $\boldsymbol{B}$, and $\boldsymbol{C}$, are the normalized state space model matrices. The parameters of the digitized model are:

$$\boldsymbol{A} = \begin{bmatrix} 0.7687 & 0.05486 & 0 & 0 \\ 0.7537 & 0.05379 & 0 & 0 \\ -0.003729 & -0.0002662 & 4.041\text{e}-018 & 0 \\ 18.94 & -23.78 & 0 & 1.0001 \end{bmatrix}$$

$$\boldsymbol{B} = \begin{bmatrix} 0.008409 & 0.01259 & -0.3041 \\ 0.008181 & 0.01243 & -0.3318 \\ 0.9934 & 1.249 & 21.75 \\ 0.2056 & 0.3123 & -8.338 \end{bmatrix}, \boldsymbol{C} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

The inputs and the outputs which have been used for identification of the controlled plant are chosen as:

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \begin{bmatrix} \text{Main steam pressure (MPa)} \\ \text{Electrical Power (MW)} \\ \text{Main steam temperature (C}^{\text{O}}\text{)} \end{bmatrix}$$

$$\begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} = \begin{bmatrix} \text{Feedwater flow reference (Kg/s))} \\ \text{Raw coal flow reference (Kg/s)} \\ \text{Valve Position reference(p.u)} \end{bmatrix}$$

B. *The generalized Predictive control strategy*

A model based predictive control is developed with provisions of unmeasured disturbances and measurement noises to be used for compensation around the investigated operating conditions. Here, the linear time invariant model is used for the MPC algorithm while the process mathematical model has been used to simulate the power plant responses. The controller setup is supposed to generate such states naturally by default. In this research, the generalized predictive controller algorithm described in [13] is adopted which has been widely used for chemical or thermodynamic process control [13] [14] [15] [16]. The prediction model has been upgraded as follows:

$$\boldsymbol{x}(k+1) = \boldsymbol{Ax}(k) + \boldsymbol{B}_u\boldsymbol{u}(k) + \boldsymbol{B}_v\boldsymbol{v}(k) + \boldsymbol{B}_w\boldsymbol{w}(k) \quad (3)$$

$$\begin{aligned} \boldsymbol{y}(k) &= \boldsymbol{y}(k) + \boldsymbol{z}(k) \\ &= \boldsymbol{Cx}(k) + \boldsymbol{D}_u\boldsymbol{u}(k) + \boldsymbol{D}_v\boldsymbol{v}(k) + \boldsymbol{D}_w\boldsymbol{w}(k) + \boldsymbol{z}(k) \end{aligned} \quad (4)$$

Where $\boldsymbol{v}$ is the measured disturbance and $\boldsymbol{w}$ is the unmeasured disturbance vector, $\boldsymbol{z}$ is the measurement noise. The adopted predictive control algorithm is quite analogous to LQG procedure, but with implication of the operational constraints. The prediction is made over a specific prediction horizon. Then the optimization program is executed on-line to calculate the optimal values of the manipulated variables to minimize the objective function below:

$$\xi(k) = \sum_{i=H_w}^{H_p} \left\| \boldsymbol{y}(k+i|k) - \boldsymbol{r}(k+i|k) \right\| \mathbf{Q} + \sum_{i=0}^{H_c-1} \left\| \boldsymbol{\Delta u}(k+i|k) \right\|^2 \mathbf{R} \quad (5)$$

The weighting coefficients (**Q** and **R**), control interval (H_w), prediction horizon (H_p) and control horizon (H_C) of the performance objective function will affect the performance of the controller and computation time demands. The terms $\boldsymbol{r}$ represents the demand outputs used as a reference for MPC model and $\boldsymbol{\Delta u}$ is the change in control values for H_C number of steps. Zero-order hold method is then used to convert the control signals from discrete time to continuous time to be fed to the plant. The inputs/outputs constraints are determined according to the power plant operation restrictions, which are expressed as the maximum and the minimum allowable inputs:

$$\boldsymbol{u}_{min} \leqslant \boldsymbol{u} \leqslant \boldsymbol{u}_{max} \tag{6}$$

$$\Delta\boldsymbol{u}_{min} \leqslant \Delta\boldsymbol{u} \leqslant \Delta\boldsymbol{u}_{max} \tag{7}$$

The optimization problem is to find the control moves for each manipulated variable, i.e. the MPC control law:

$$\min_{\Delta\boldsymbol{u},\ldots,\Delta\boldsymbol{u}(k+1+H_C)} \xi(k) \quad \text{subject to (6) and (7)}$$

The quadratic programming (QP) solver, with active set method or interior point method, is commonly used to solve control law problem of the MPC. In the interest of predictive controllers for thermal power stations, the generalized MPC approaches and DMC algorithms are reported for control of power plants once-through and drum type units. [3][4][5][7][14][15][16][17]. To show the influences of coal mill control on the plant output responses, a controller is implemented to regulate the primary air fan and the other is implemented to regulate the coal feeder speed. Both receive the MPC coal flow signal as adjuster for their reference. With the MPC strategy described above, simulations have been conducted. The whole package of the proposed strategy is shown in fig.8. Simulation results are presented in the next section.

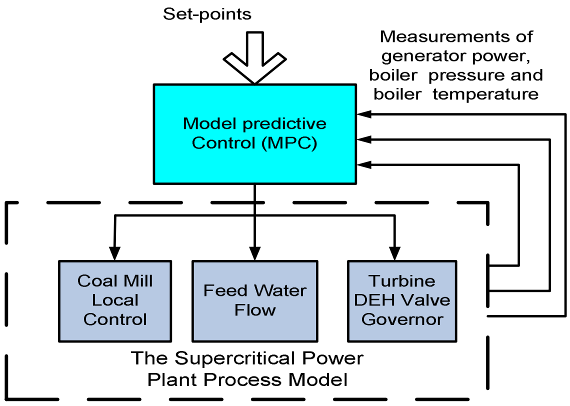

Fig.8 Predictive controller scheme

V. SIMULATION STUDIES

MPC tuning is finalized by selection appropriate values for the prediction horizon H_p, control horizon H_C, and weighting matrices **Q** and **R.** The control interval, prediction, and control horizons are found to be 1, 35, 5seconds respectively. **Q**= [1 1 1] and **R**=[0.1 0.1 0.1]. Simulating different scenarios have lead to this selection. In this scenario, a step change of ±20MW in the power is assumed as set-point signal, the pressure set-point is rescheduled from look-up table which relates the power set-point to the pressure, and the temperature set-point is constant of 570C°. In the reported results for Case A represent the improved case with using MPC as correction to the mill local control, boiler feedwater flow, and turbine valve controller and Case B represent existing milling and plant performance. From the reported results, the improvements are obvious in case of using the MPC without violating the practical constrains of the various plant variables. Thus the primary air fan and feeder speed can be regarded as other supplementary means to improve the power primary response, not only acting the turbine expansion valves.

Furthermore, the boiler steam pressure and temperature have less fluctuation around the set-point which helps in extending the life of the equipment. The pulverized coal flow to the furnace, the feedwater flow, and valve position are mentioned in fig.10, more pulverized coal is discharged to the furnace from the mills per time unit which means more coal is combusted and more energy is delivered from the boiler to give quicker responses. Hence, the MPC and its associated strategy for reference correction control play an important role in improving the plant responses and satisfying the regulations of the national grid code. Especially when increasing the grinding capability of the mills and pulverized coal discharging speed. Fig.11 shows major mill variables. High mill differential pressure and primary air pressure are created to carry more coal flow to the burners. Also higher raw coal is initially dropped in the mill because of the improved feeder speed response. The mass of raw coal and pulverized coal in the mill is higher to provide the required flow of pulverized coal in a timely manner. The only penalty which has been paid is that more current, and consequently, power is consumed from the mills to increase the grinding capability of the mills.

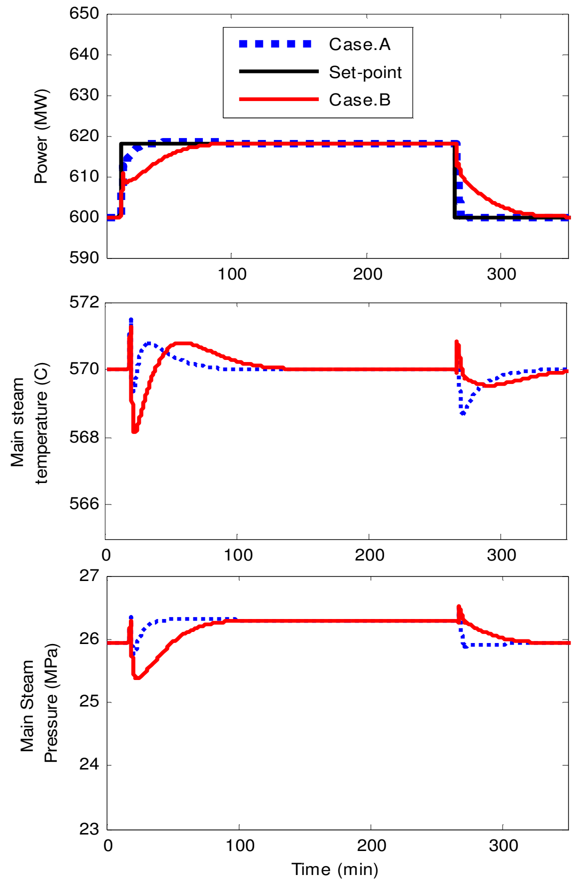

Fig.9 Controlled variables of the SCPP

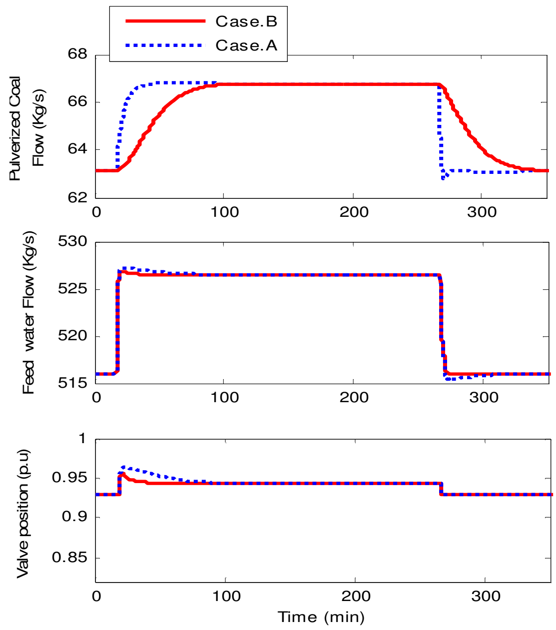

Fig.10 input variables to the boiler-turbine-generator system

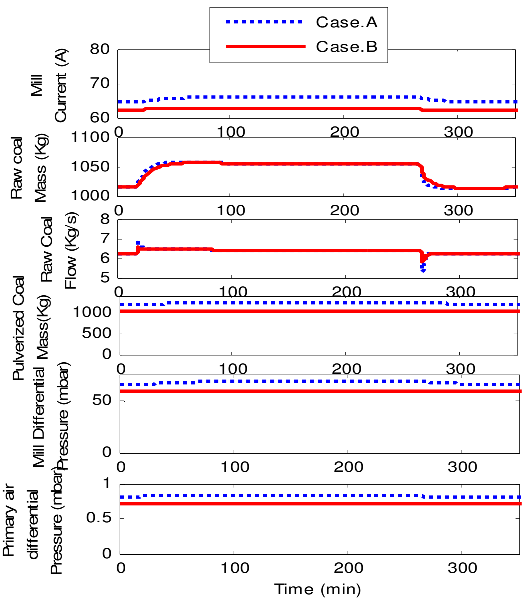

Fig.11 variables of each mill in service

VI. CONCLUSION AND FUTURE RESEARCH

In this paper, a complete power plant process model including fuel preparation milling process. The model prepared a platform for us to investigate the influences of mill control to the whole power plant responses. A new strategy of applying model predictive control is reported and the new contribution for the strategy is to use the MPC to update the control set-up/desired values instead of tuning the individual local loop controllers. This improved the power plant responses over the existing control strategy. As a future recommendation, it is suggested to extend the method of modeling and control to ultra-supercritical power plant.

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