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Robust Model Predictive Control With Bi-Level Optimization for Boiler-Turbine System

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ABSTRACT A robust model predictive control (MPC) with bi-level optimization is proposed for nonlinear boiler-turbine system. The nonlinear dynamics are described by multiple local models linearized at distinct operating points. A global linear parameter varying (LPV) model is constructed by combining the linearized local models. In order to combine the local models smoothly, an exponential weighting coefficient determined by the system states is applied. The bi-level optimization is proposed to optimize the control moves and control policy respectively. A controller model is designed as the inner optimization to calculate the suitable control policy under different operating conditions. The closed-loop robust MPC is designed to optimize the control moves to improve economic performance. Simulations under wide operating conditions have demonstrated the effectiveness of the proposed robust MPC method, by applying which the economic performance of the nonlinear boiler-turbine system is improved.

INDEX TERMS Dynamic control policy, model predictive control, nonlinear system, linear parameter varying model.

I. INTRODUCTION

The dynamics of boiler-turbine system are typically multi-variable, constrained and highly nonlinear [1]–[5]. Boiler-turbine system is a crucial component for drum-type of power plant, which transforms fuel energy into mechanical energy to drive the turbine and then generate electricity. The output electric power of boiler-turbine system is usually required to be regulated accurately according to the grid and load demand, while the internal variables such as steam pressure, temperature and drum water level should be kept within the desired ranges. Generally, drum water level needs to be adjusted to closely around the centerline of the drum, while drum steam pressure is required to be working within a safe range. Meanwhile, the input signals for various control valves need to satisfy the associated physical constraints imposed on actuators.

It is challenging to control such a complicated and highly nonlinear system as boiler-turbine system. The most intractable thing is to maintain the process working smoothly over wide operating conditions. The success of control technology depends not only on perfect control algorithm, but also on accurate model. Many efforts have been made in the modeling for boiler-turbine system. In the early models derived from first principles [2], [3], the dynamic characteristics of nonlinear system are not fully captured. This stimulated the further development of control technology for nonlinear system. In recent years, various techniques, such as fuzzy logic [6]–[8], system identification [9], [10], and piecewise affine modeling [11], are utilized to modeling the boiler-turbine system. Besides, the change of operating conditions will bring about further nonlinearities. In order to improve the control performance for the nonlinear system operating over a wide range, in [13], multiple models linearized at nine distinct operating points and a global nonlinear multi-variable compensator were designed for the GE-21 jet engine. Keshavarz *et al.* in [11] proposed the hybrid piecewise affine(PWA) model which was linearized at five typical operating points. Considering the nonlinearity of the transitional dynamics between different operating points, a multiple model LPV approach has been proposed for the modeling, and achieved satisfactory approximation. In addition, LPV model has been extensively applied to dealt with the model uncertainty [14]–[21]. In this paper, the nonlinear dynamics of the boiler-turbine system is approximated by a global LPV model established by the combination

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of multiple local models linearized at different operating points.

Due to the complexity and nonlinearity, various control strategies have been applied to the controller design for boiler-turbine system, such as gain-scheduled method [22], fuzzy control [6]–[8]. Artificial intelligence techniques are also applied to boiler-turbine controller design. In [12], genetic algorithm (GA) was applied to the control system to achieve good steady-state tracking performance. In [24], a radial basis function neural network was utilized to approximate the dynamic behaviour of the boiler-turbine system over a wide operating range. For the past few decades model predictive control(MPC), with the outstanding advantages in handling multi-variable constraints, has attracted extensively attention both in academia and in industrial [19], [25]–[27]. A new coordinated control strategy by combining min-max MPC with moving horizon estimation (MHE-MPC) was proposed in [28] to deal with the unmeasured disturbance for boiler-turbine system, in which the bounded stochastic disturbance and dead characteristics of inputs have been effectively suppressed. All of these methods applied to linear time-invariant system have achieved good tracking performance. In order to improve the control performance of nonlinear system, Zhu *et al.* in [29] investigated nonlinear predictive control strategy based on local model network for a 500 MW coal-fired boiler-turbine system, in which the nonlinear optimization problem was solved by the immune genetic algorithm. However, due to the model uncertainty, the future state predictions of robust MPC are uncertain. Only optimizing the control moves and utilizing a specified feedback control policy cannot ensure the satisfactory control. Therefore, a more sophisticated strategy is expected to optimize both the control policy and control moves at each iteration.

Motivated by these considerations, we develop the closed-loop robust MPC with bi-level optimization for the nonlinear boiler-turbine system. The main contributions are as follows:

(1) a global polytopic model representing the model uncertainty is constructed by combining multiple local models, by applying which, the accuracy of state predictions for the uncertain nonlinear system is improved.

(2) a controller model is designed to calculate the suitable control policy according to the changing operating conditions, which is obtained by solving a quadratic problem.

(3) a closed-loop robust MPC algorithm with bi-level optimization is presented, where both the control moves and the control policy are optimized, which is a more rational strategy to improve the control performance for an uncertain nonlinear system.

II. GENERAL DESCRIPTION OF BOILER-TURBINE SYSTEM

The main components of a boiler-turbine system include the furnace, drum, riser, downcomer, superheater and reheater. The heat from superheater supplied to the risers causes water boiling. Feed-water is supplied to the drum, and saturated steam is passed from the drum to the superheater and the turbine. Maintaining the water level moderate is an important criterion both for the plant protection and for the equipment safety. However, the water level may vary with the load. So the water level must be supervised closely and a good controller is required to regulate the drum water level.

Åström-Bell boiler-turbine dynamic model [2] developed for 160 MW fossil fueled boiler-turbine-alternator power generation units has been widely investigated. The model is established based on the first principle. The nonlinear model captures the essential dynamics of the boiler-turbine system, in which the drum pressure and power dynamics are described by the extention second order nonlinear model, and the drum water level dynamics is represented by an extra evaporation equation and the fluid dynamics. The nonlinear model is expressed in (1)

$$
\begin{aligned}
\dot{x}_1 &= - - 0.0018 u_2 x_1^{9/8} + 0.9 u_1 - 0.15 u_3 \\
\dot{x}_2 &= (0.073 u_2 - 0.016) x_1^{9/8} - 0.1 x_2 \\
\dot{x}_3 &= \frac{[141 u_3 - (1.1 u_2 - 0.19) x_1]}{85} \\
y_1 &= x_1 \\
y_2 &= x_2 \\
y_3 &= 0.05(0.13073 x_3 + 100\alpha_{cs} + \frac{q_e}{9} - 67.975) \qquad (1)
\end{aligned}
$$

where u_1, u_2, u_3 are the normalized inputs to the plant, namely fuel, control and feedwater actuator positions, respectively. x_1, x_2, x_3 are drum steam pressure (kg/cm^2), power output (MW), and the density of fluid in the system (kg/m^3), respectively. The output y_3 denotes the drum water level (cm), which is calculated by the following algebraic calculations α_{cs} and q_e:

$$
\begin{aligned}
\alpha_{cs} &= \frac{(1 - 0.001538 x_3)(0.8 x_1 - 25.6)}{x_3(1.0394 - 0.0012304 x_1)} \\
q_e &= (0.845 u_2 - 0.147) x_1 + 45.59 u_1 - 2.514 u_3 - 2.096 \qquad (2)
\end{aligned}
$$

where α_{cs} is the steam quality and q_e is the evaporation rate(kg/s).

In the controller design, the physical limitation imposed on valves should not be violated. The normalized constraints of the corresponding control valves are

$$0 < u_1, u_2, u_3 < 1 \qquad (3)$$

The constraints of the change rate of control inputs are

$$
\begin{aligned}
&|\frac{du_1}{dt}| \le 0.007 \\
&|\frac{du_3}{dt}| \le 0.05 \\
&|\frac{du_2}{dt}| \le 0.2 \quad (opening\ or\ upper\ rate) \\
&|\frac{du_2}{dt}| \le 2 \quad (closing\ or\ lower\ rate) \qquad (4)
\end{aligned}
$$

Fig. 1 illustrates the realization of the actuator dynamics.

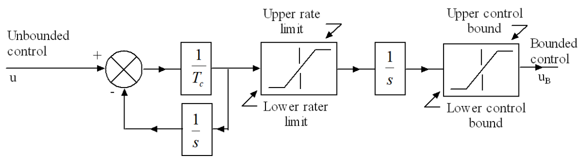

FIGURE 1. The block diagram of actuator dynamics [2].

TABLE 1. Different operating points.

	No.1	No.2	No.3	No.4	No.5	No.6	No.7
x_1	75.6	86.4	97.2	108	119	130	140
x_2	15.3	36.7	50.5	66.7	85.1	105	128
x_3	300	342	385	428	471	513	556
u_1	0.15	0.20	0.27	0.34	0.41	0.50	0.60
u_2	0.48	0.55	0.62	0.69	0.75	0.82	0.89
u_3	0.18	0.25	0.34	0.43	0.54	0.66	0.79

The dynamics of the boiler-turbine system are complex and nonlinear. Moreover, under different working conditions, the operating points may vary with the change of economic considerations. Thus causes main dynamic characteristics, such as drum pressure, power output and water level deviation to vary significantly. The collection of operating points for 160 MW boiler-turbine system is shown in table 1.

III. GLOBAL LPV MODEL

In this paper, several local linearized models are obtained for boiler-turbine system by employing Taylor's expansion approximation at different operating points. By combining the local linearized models, a global LPV model is constructed.

A. LOCAL LINEARIZED MODEL

In light of the experiences in [13], [23], several operating points (No.2,No.4,No.6) in table 1 are chosen to represent the typical operating conditions for the boiler-turbine system working over a wide range. No.2 operating point is working at 80% of half load point, No.4 is at the half load point and No.6 at 120% of the half load point.

The nonlinear boiler-turbine system (1) can be expressed in the following form:

$$\begin{aligned} \dot{x} &= f(x,u) \\ y &= g(x,u) \end{aligned} \tag{5}$$

By applying the Taylor's expansion and only retaining the linear terms, the linearized model is obtained

$$\begin{aligned} \delta\dot{x} &= \breve{A}_o\delta x + \breve{B}_o\delta u \\ \delta y &= \breve{C}_o\delta x + \breve{D}_o\delta u \end{aligned} \tag{6}$$

where $\breve{A}_o, \breve{B}_o, \breve{C}_o, \breve{D}_o$ are constant matrices defined at the operating point,

$$\begin{aligned} \breve{A}_o &= \frac{\partial f}{\partial x}|_{(x^o,u^o)}, \quad \breve{B}_o = \frac{\partial f}{\partial u}|_{(x^o,u^o)} \\ \breve{C}_o &= \frac{\partial g}{\partial x}|_{(x^o,u^o)}, \quad \breve{D}_o = \frac{\partial g}{\partial u}|_{(x^o,u^o)} \end{aligned} \tag{7}$$

For such a nonlinear system as boiler-turbine system, its operating points may vary with the operating conditions as in table 1. So the linearized local models obtained at different operating points are distinct. The corresponding matrices of the linearized model at the operating point $l(l = 1,\ldots,M)$ are given by

$$\breve{A}_l = \begin{bmatrix} 0.0018u_2x_1^{1/8} & 0 & 0 \\ -0.016x_1^{1/8} & -0.1 & 0 \\ 0.19/85 & 0 & 0 \end{bmatrix}\Bigg|_{(x_l,u_l)}$$

$$\breve{B}_l = \begin{bmatrix} 0.9 & -x_1^{9/8} & -0.15 \\ 0 & 0.073x_1^{9/8} & 0 \\ 0 & -1.1/85 & 141/85 \end{bmatrix}\Bigg|_{(x_l,u_l)}$$

$$\breve{C}_l = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ -0.147/9 & 0 & 0.05*0.13073 \end{bmatrix}\Bigg|_{(x_l,u_l)}$$

$$\breve{D}_l = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 45.59/9 & 0.845/9x_1 & -2.514/9 \end{bmatrix}\Bigg|_{(x_l,u_l)}$$

B. GLOBAL LPV MODEL CONSTRUCTED BY WEIGHTING INTERPOLATION

A local linearized model can approximate the dynamics of nonlinear process only within a small range around the operating point. Considering the transition dynamics between different operating points, a global model is expected. By combining multiple local models, the global model can be constructed by

$$\begin{aligned} \dot{x}_g &= \sum_{l=1}^{M} \alpha_l \dot{x}_l \\ y_g &= \sum_{l=1}^{M} \alpha_l y_l \end{aligned} \tag{8}$$

where the parameter vector α_l represents the normalized effectiveness that the lth local model contributes to the global model of the system. $\mathcal{T}$ is a scheduling variable representing the operating condition and $\mathcal{O}$ denotes the validity width of each local model. In order to combine M local models into a global model smoothly at each sampling instant, an exponential weighting coefficient w_k is designated for each local model l,

$$w_{l,k} = exp(\frac{-(\mathcal{T}_{cl} - \mathcal{T}_{mk})^2}{2(\mathcal{O}_l^2)}) \tag{9}$$

where $\mathcal{T}_{mk}$ is the measurement of the scheduling variable at time k, $\mathcal{T}_{cl}(l = 1,2,\ldots,M)$ is the center of the scheduling variable for the lth local model, i.e., the value of the operating point, and $\mathcal{O}_l$ denotes the validity width for the lth local model. By normalizing the weighting coefficient (9), one yields

$$\alpha_{l,k} = \frac{w_{l,k}}{\sum_{l=1}^{M} w_{l,k}} \tag{10}$$

The parameter vector $\alpha_{l,k}$ is non-negative, and the following relation holds:

$$\sum_{l=1}^{M} \alpha_{l,k} = 1 \tag{11}$$

Suppose the M non-negative coefficients $\alpha_{l,k}$ (with $l = 1 \cdots M$) such that: $[A_g|B_g] = \sum_{l=1}^{M} \alpha_l [\breve{A}_l|\breve{B}_l]$. Then a global polytopic model based on the M vertices can be constructed as follows:

$$\begin{aligned} \dot{x}_g &= \sum_{l=1}^{M} \alpha_l \breve{A}_l x_l + \sum_{l=1}^{M} \alpha_l \breve{B}_l u_l \\ &= A_g x_g + B_g u_g \end{aligned} \tag{12}$$

where A_g, B_g are the coefficient matrices of the global model. By discretizing, the global dynamic model at time k is expressed as follows:

$$x_{g,k+1} = A_{g,k} x_{g,k} + B_{g,k} u_{g,k} \tag{13}$$

where k is the sampling instant. At time k, $\alpha_{l,k}$ for the local model l is known, then the current coefficient matrices $A_{g,k}$, $B_{g,k}$ are determined.

By omitting the subscript g in (13), the global model is expressed as

$$x_{k+1} = A_k x_k + B_k u_k \tag{14}$$

Let Ω denote the convex hull defined by $[\breve{A}_l|\breve{B}_l](l = 1, \ldots, M)$, *i.e.* $\Omega = \text{Co}\{[\breve{A}_1|\breve{B}_1], \ldots, [A_M|\breve{B}_M]\}$, where $[\breve{A}_l|\breve{B}_l]$ is defined as the vertex of the polytope. The corresponding nominal model of (14) is denoted as

$$\bar{x}_{k+1} = A\bar{x}_k + Bu_k \tag{15}$$

where the nominal coefficient $[A|B] = 1/L \sum_{l=1}^{L} [\breve{A}_l|\breve{B}_l]$. $\bar{x}_k$ denotes the nominal state.

Since the real-time value of the coefficient $\alpha_{l,k}$ can be obtained from (9) and (10), the real-time values of the parameters $[A_k|B_k|C_k]$ are known.

C. ECONOMIC OBJECTIVE FUNCTION

The process optimization for boiler-turbine system is a multi-objective optimization problem, more details are referred to [31]. The load-tracking, heat-rate, steam pressure, temperature and the drum water level are required to be considered. In general, priority is given to power generation. When the load demand is given, the fuel consumption and feedwater are expected to be reduced as much as possible. Meanwhile, the steam valve is expected to be opened wide enough so as to reduce the throttling losses. Similar criterion is used for the control of the feedwater valve. Thus the global economic objective function is designed as follows:

$$J = \beta_0 x_{e2,k+1}^2 + \beta_1 u_{1,k} - \beta_2 u_{2,k} - \beta_3 u_{3,k} \tag{16}$$

where $\beta_0, \beta_1, \beta_2, \beta_3$ are the weighting coefficients. x_e denotes the deviation of state variable

$$x_{e2,k+1} = |E_{uld} - x_{2,k+1}| \tag{17}$$

where E_{uld} is the unit load demand, x_{e2} denotes the error between the power generation and the load demand.

D. CONSTRAINTS ON VARIABLES OF GLOBAL LPV MODEL

The magnitudes of the control inputs in (14) are required to satisfy $0 < u_i < 1, i = 1, 2, 3$. Denote Δu_k as the deviation of manipulated variable between the current time step and the previous time step, i.e. $\Delta u_k = u_k - u_{k-1}$. Assume the sample time interval is T, the change rates of control inputs are required to satisfy

$$\begin{aligned} &|\Delta u_{1,k}| \le 0.007T \\ &|\Delta u_{3,k}| \le 0.05T \\ &|\Delta u_{2,k}| \le 0.02T \quad (\textit{opening or upper rate}) \\ &|\Delta u_{2,k}| \le 2T \quad (\textit{closing or lower rate}) \end{aligned} \tag{18}$$

IV. ROBUST MPC WITH BI-LEVEL OPTIMIZATION

Due to the model uncertainty, the future dynamics of the global LPV model is uncertain. So a controller model to cope with the model uncertainty is incorporated into the robust MPC. By adding the controller model, combining with the global dynamic model (14), the economic objective function (16) and the magnitude constraints, the new robust MPC is formulated as follows:

$$\min_{\tilde{x}_{r,k+1}, \tilde{u}_{r,k}} \sum_k \Big\{ \beta_0 x_{e2,k+1}^2 + \beta_1 u_{1,k} - \beta_2 u_{2,k} - \beta_3 u_{3,k} \Big\} \tag{19a}$$

$$s.t.\ u_k = f_{NMPC}(x_{k+1}, \tilde{x}_{r,k+1}, \tilde{u}_{r,k}) \tag{19b}$$

$$x_{k+1} = A_k x_k + B_k u_k \tag{19c}$$

$$u_{min} \le u_k \le u_{max} \tag{19d}$$

$$k = 0, \ldots, N-1$$

where $x_k = x_{k|k}$, $\tilde{x}_{r,k+1} = (x_{r,k+1}^T, \ldots, x_{r,k+N}^T)^T$ and $\tilde{u}_{r,k} = (u_{r,k}^T, \ldots, u_{r,k+N-1}^T)^T$ are the virtual reference value. N is the predictive horizon. $f_{NMPC}(x_{k+1}, \tilde{x}_{r,k+1}, \tilde{u}_{r,k})$ is the control policy determined by the nominal MPC. (19c) is the process dynamic model.

The robust MPC as in (19) is a bi-level optimization problem, the framework of which is shown in Figure 2. The outer optimization is designed to minimize the economic performance of boiler-turbine system, and the inner optimization is designed to optimize the nominal control policy. At each time step, both control moves and the control policy are optimized.

A. PREDICTION OF THE VERTEX STATES

Suppose that the state x_k in the global LPV model (14) is undetectable, the output y_k is measurable. Then the real-time value of the state can be estimated by

$$\hat{x}_k = x_{k|k-1} + L_x(y_k - C_k x_{k|k-1}) \tag{20}$$

where L_x is the Kalman filter gain for x. $\hat{x}_k$is the estimated state.

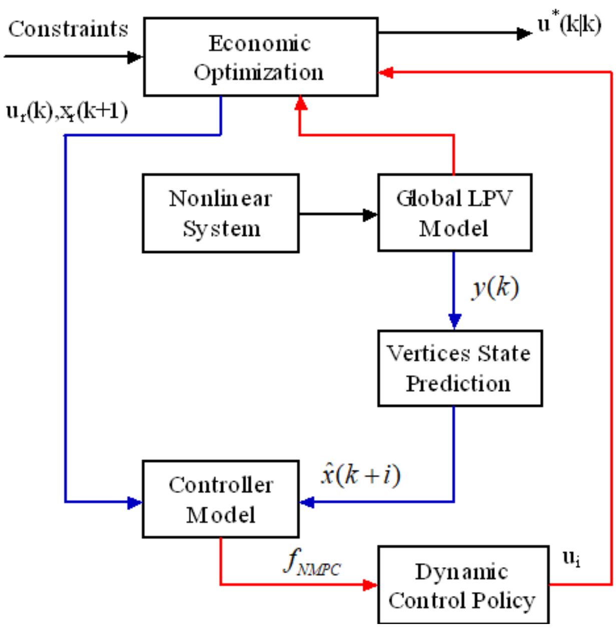

FIGURE 2. Framework of the closed-loop robust MPC with bi-level optimization.

Although the estimated state at the next time step can be obtained by the state observer, the future estimated state $x_{k+1+i|k}, i \geq 1$ cannot be obtained. In order to obtain a correct prediction of the process future behavior for the polytopic model, the open-loop model predictive control method is applied, which is proposed by Ding in [32] by optimizing the vertex control moves to improve the dynamic prediction. For the uncertain nonlinear system, the control moves at future time step are uncertain. So, in this paper, a controller model is designed to determine the decision variables according to the updating nominal control policy at each time step. Let the control horizon and the predictive horizon be the same N. For the polytopic model, the vertex control moves dependent on the vertex values of polytope, are defined by $u_{k|k}, u^{l_0}_{k+1|k}, \ldots, u^{l_{N-2}\cdots l_0}_{k+N-1|k}, l_j \in \{1,\ldots,L\}, j \in \{0,\ldots,N-2\}$. The vertex next state predicted at time k can be obtained by

$$x^{l_0}_{k+1|k} = \breve{A}_{l_0} x_{k|k} + \breve{B}_{l_0} u_{k|k} \tag{21}$$

$$x^{l_i\cdots l_0}_{k+j+1|k} = \breve{A}_{l_i} x^{l_{i-1}\cdots l_0}_{k+j|k} + \breve{B}_{l_i} u^{l_{i-1}\cdots l_0}_{k+j|k} \tag{22}$$

where $j \in \{1,\ldots,N-1\}$, $l_i \in \{1,\ldots,L\}$, $i \in \{0,\ldots,N-1\}$.

Based on (14), the future estimated states of the global LPV model are predicted by

$$\begin{aligned} x_{k+1|k} &= A_k x_{k|k} + B_k u_{k|k} \\ &= \sum_{l_0=1}^{L} \alpha_{l_0,k}[\breve{A}_{l_0} x_{k|k} + \breve{B}_{l_0} u_{k|k}] \\ &= \sum_{l_0=1}^{L} \alpha_{l_0,k} x^{l_0}_{k+1|k} \end{aligned} \tag{23}$$

$$\begin{aligned} x_{k+2|k} &= A_{k+1} x_{k+1|k} + B_{k+1} u_{k+1|k} \\ &= \sum_{l_1=1}^{L} \alpha_{l_1,k+1}[\breve{A}_{l_1} \sum_{l_0=1}^{L} \alpha_{l_0,k} x^{l_0}_{k+1|k} \\ &\quad + \breve{B}_{l_1} \sum_{l_0=1}^{L} \alpha_{l_0,k} u^{l_0}_{k+1|k}] \\ &= \sum_{l_1=1}^{L} \sum_{l_0=1}^{L} \alpha_{l_1,k+1}\alpha_{l_0,k} x^{l_1 l_0}_{k+2|k} \\ &\ \vdots \end{aligned} \tag{24}$$

Assume $x(k|k) = \hat{x}(k)$. Then the state estimated prediction at the future time can be written in a vector form

$$\begin{bmatrix} x_{k+1|k} \\ x_{k+2|k} \\ \vdots \\ x_{k+N|k} \end{bmatrix} = \sum_{l_0\cdots l_{N-1}=1}^{L} \left(\prod_{h=0}^{N-1} \alpha_{l_h,k+h} \begin{bmatrix} x^{l_0}_{k+1|k} \\ x^{l_1 l_0}_{k+2|k} \\ \vdots \\ x^{l_{N-1}\cdots l_0}_{k+N|k} \end{bmatrix}\right) \tag{25}$$

where $\sum_{l_0\cdots l_{N-1}=1}^{L} (\prod_{h=0}^{N-1} \alpha_{l_h,k+h}) = 1, i \in \{1,\ldots,N\}$.

According to (25), the state predictions $x_{k+i|k}, i \in \{1,\ldots,N\}$ are parameter dependent. As in [33], all the vertex state predictions can be denoted by adopting a tree-type structure, in which the total number of the prediction vertex $\mathcal{L}$ is dependent on the number of multiple local models L and the predictive horizon N, that is $\mathcal{L} = L^N$.

Based on the equations (23) and (24), the future prediction of the global LPV at the future time is expressed as

$$\begin{aligned} &\begin{bmatrix} x^{l_0}_{k+1|k} \\ x^{l_1 l_0}_{k+2|k} \\ \vdots \\ x^{l_{N-1}\cdots l_0}_{k+N|k} \end{bmatrix} = \begin{bmatrix} \breve{A}_{l_0} \\ \breve{A}_{l_1}\breve{A}_{l_0} \\ \vdots \\ \prod_{i=0}^{N-1} \breve{A}_{l_{N-1-i}} \end{bmatrix} x_{k|k} \\ &+ \begin{bmatrix} \breve{B}_{l_0} & 0 & \cdots & 0 \\ \breve{A}_{l_1}\breve{B}_{l_0} & \breve{B}_{l_1} & \ddots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ \prod_{i=0}^{N-2} \breve{A}_{l_{N-1-i}}\breve{B}_{l_0} & \prod_{i=0}^{N-3} \breve{A}_{l_{N-1-i}}\breve{B}_{l_1} & \cdots & \breve{B}_{l_{N-1}} \end{bmatrix} \\ &\times \begin{bmatrix} u_{k|k} \\ u^{l_0}_{k+1|k} \\ \vdots \\ u^{l_{N-2}\cdots l_1 l_0}_{k+N-1|k} \end{bmatrix} \end{aligned} \tag{26}$$

The above equations (25) and (26) can be summarized as

$$\begin{bmatrix} x_{k+1|k} \\ x_{k+2|k} \\ \vdots \\ x_{k+N|k} \end{bmatrix} = \mathcal{A}_k x_{k|k} + \mathcal{B}_k \times \begin{bmatrix} u_{k|k} \\ u^{l_0}_{k+1|k} \\ \vdots \\ u^{l_{N-2}\cdots l_1 l_0}_{k+N-1|k} \end{bmatrix} \tag{27}$$

where

$$\mathcal{A}_k = \sum_{l_0\cdots l_{N-1}=1}^{L} (\prod_{h=0}^{N-1} \alpha_{l_h,k+h} \times \begin{bmatrix} \breve{A}_{l_0} \\ \breve{A}_{l_1}\breve{A}_{l_0} \\ \vdots \\ \prod_{i=0}^{N-1} \breve{A}_{l_{N-1-i}} \end{bmatrix} \tag{28}$$

$$\mathcal{B}_k = \begin{bmatrix} \breve{B}_{l_0} & 0 & \cdots & 0 \\ \breve{A}_{l_1} B_{l_0} & \breve{B}_{l_1} & \ddots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ \prod_{i=0}^{N-2} \breve{A}_{l_{N-1-i}} \breve{B}_{l_0} & \prod_{i=0}^{N-3} \breve{A}_{l_{N-1-i}} \breve{B}_{l_1} & \cdots & \breve{B}_{l_{N-1}} \end{bmatrix} \tag{29}$$

The combination coefficients α_{lh}, $h \in \{0, \ldots, N-1\}$ for each local model are known. The future real control moves $u_{k+j|k}$, for any $j > 0$, are uncertain and can be defined by

$$u_{k+j|k} = \sum_{l_0\cdots l_{j-1}=1}^{L} \left\{ \left\{ \prod_{h=0}^{j-1} \alpha_{l_h,k+h} \right\} \times u^{l_{j-1}\cdots l_0}_{k+j|k} \right\} \quad j = 1 \ldots N-1 \tag{30}$$

where

$$\sum_{l_0\cdots l_{i-1}=1}^{L} (*) = \sum_{l_0=1}^{L} \cdots \sum_{l_{i-1}=1}^{L} (*)$$

The future real control moves $u_{k+j|k}, j \in \{1, \ldots, N-1\}$ are parameter dependent. Since $\sum_{l_i=1}^{L} \alpha_{l_i} = 1$, each $u_{k+j|k}$ is uncertain and can be regarded as a convex combination of its vertex control moves $u^{l_{j-1}\cdots l_0}_{k+j|k}, j \in \{1, \ldots, N-1\}$. Hence, in the new closed-loop robust MPC, the control moves are determined by the nominal MPC control policy f_{NMPC} at each time step.

B. INNER OPTIMIZATION PROBLEM DETERMINING THE CONTROL POLICY

In the closed-loop MPC with bi-level optimization, the inner optimization problem is a nominal MPC, which is designed to optimize the control policy. At each time step, the optimal control policy is obtained by solving the following Quadratic Program (QP):

$$\min_{u_i} \sum_i \left\{ (\bar{x}_{i+1} - x_{r,i+1})^T Q (\bar{x}_{i+1} - x_{r,i+1}) + \sum_i (u_i - u_{r,i})^T R (u_i - u_{r,i}) \right\} \tag{31a}$$

$$s.t.\ \bar{x}_{i+1} = A\bar{x}_i + Bu_i \tag{31b}$$

$$u_{min} \leq u_i \leq u_{max} \tag{31c}$$

$$i = k, \ldots, k+N-1$$

where Q, R are the weighting matrices for states and control moves, respectively. (31b) is the nominal model. $\{x_{r,i+1}, u_{r,i}\}$ is the virtual reference variables at time i.

C. SOLUTION FOR THE INNER OPTIMIZATION

It is intractable to solve the bi-level optimization problem (19) in real time. Li in [27] has proposed a successful way to solve this kind of problem by transforming the bi-level optimization problem into a tractable single-level optimization problem. The main idea to do that is to convert the effective inequality constraints into equality constraints, then to solve the equivalent QP problem by utilizing the first order optimality conditions. Since physical constraints can never be violated at any time. Suppose that a bound on a decision variable at each time step is either active or inactive for all the realizations of the system. By removing the inactive bounds and transforming all the active bounds into equality constraints, a QP problem with equality constraints equivalent to (31) is formulated. Then, the equivalent QP problem is solved by using the first order optimality condition,

$$2\tilde{A}^T\tilde{Q}\tilde{A}\bar{x}_0 - 2\mathbf{x}^T_{r,1}\tilde{Q}\tilde{A} + 2(\tilde{A}^T\tilde{Q}\tilde{B}^T + \tilde{Q}\tilde{B} + \tilde{R})\mathbf{u}_i + 2\tilde{B}^T\tilde{Q}\tilde{A}\bar{x}_0 - 2x^T_{r,1}\tilde{Q}\tilde{B} - 2\mathbf{u}^T_r\tilde{R} + \boldsymbol{\lambda}^+ - \boldsymbol{\lambda}^- = 0 \tag{32a}$$

$$\mathbf{u}_{min} \leq \mathbf{u}_i \leq \mathbf{u}_{max} \tag{32b}$$

where (32a) is stationary condition. $\boldsymbol{\lambda}^+$ and $\boldsymbol{\lambda}^-$ are the Lagrange multipliers. Complementarity constraints on the decision variables are as follows:

$$\boldsymbol{\lambda}^+(\mathbf{u}_i - \mathbf{u}_{max}) = 0, \boldsymbol{\lambda}^-(-\mathbf{u}_i + \mathbf{u}_{max}) = 0, \quad \boldsymbol{\lambda}^+, \boldsymbol{\lambda}^- \geq 0 \tag{33}$$

The decision variables $\mathbf{u}_i$ are determined by

$$\mathbf{u}_i = (\tilde{A}^T\tilde{Q}\tilde{B}^T + \tilde{Q}\tilde{B} + \tilde{R})^{-1} \times [-(\tilde{A}^T + \tilde{B}^T)\tilde{Q}\tilde{A}\bar{x}_0 + (\tilde{A}^T + \tilde{B}^T)^T\tilde{Q}\mathbf{x}_{r,1} + \tilde{R}^T\mathbf{u}_r - (\lambda^+ - \lambda^-)/2] \tag{34}$$

Since only the first control move is sent to the plant and implemented, partial information of $\boldsymbol{u}_i$ is required. An identity matrix $\boldsymbol{I}_{pu}$ is designed to pick up the values of the effective decision variables at the current time step. Thus, $\mathbf{u}_k = \boldsymbol{I}_{pu} \times \mathbf{u}_i$.

At time k, if no bound is active, the Lagrange multipliers are zero. When some bounds on the decision variables are active, the complementarity constraints and Lagrange multipliers can be substituted for equality constraints. Then the controller model at time kth is formulated by

$$\mathbf{u}_k = \boldsymbol{I}_{pu} \times (\tilde{A}^T\tilde{Q}\tilde{B}^T + \tilde{Q}\tilde{B} + \tilde{R})^{-1} \times [-(\tilde{A}^T + \tilde{B}^T)\tilde{Q}\tilde{A}\bar{x}_k + (\tilde{A}^T + \tilde{B}^T)^T\tilde{Q}\mathbf{x}_{r,k+1} + \tilde{R}^T\mathbf{u}_{r,k}] \tag{35}$$

At time k, only the values of the decision variable, not the reference variables, are applied into the closed-loop MPC.

So the combination of the virtue reference variables can be defined as a new vector variable $\mathbf{t}$, which is used as an auxiliary variable to adjust the optimization of the robust MPC,

$$\mathbf{t}_k = \boldsymbol{I}_{pu,k} \cdot \Phi \cdot [(\tilde{A}^T + \tilde{B}^T)^T \tilde{Q} \boldsymbol{x}_{r,k+1} + \tilde{R}^T \mathbf{u}_{r,k}] \tag{36}$$

where $\Phi = (\tilde{A}^T \tilde{Q} \tilde{B}^T + \tilde{Q}\tilde{B} + \tilde{R})^{-1}$.

Then, rewrite (35) in linear form as follows:

$$\mathbf{u}_k = K_x \bar{x}_k + \mathbf{t}_k \tag{37}$$

where

$$K_x = -\boldsymbol{I}_{pu} \cdot \Phi \cdot (\tilde{A}^T + \tilde{B}^T)\tilde{Q}\tilde{A} \tag{38}$$

Thus the nominal control policy is obtained as in (37). Check the physical constraints, once some decision variable is saturated, the value of the corresponding decision variable is set to its bound. Then the rest of the decision variables within the bounds are optimized in the robust MPC. So active constraints are required to be added into (37). Here a vector matrix $\boldsymbol{I}_{\delta_k}$ is introduced to specify the active constraints. The controller model with active constraints can be expressed as follows:

$$\mathbf{u}_k = \boldsymbol{I}_{\delta_k} K_x \bar{x}_k + \mathbf{t}_k \tag{39a}$$

$$(\boldsymbol{I} - \boldsymbol{I}_{\delta_k}) \cdot \mathbf{t}_k = \mathbf{u}_b \tag{39b}$$

where the vector $\mathbf{u}_b$ represents all the active bounds. $\boldsymbol{I}_{\delta_k} \in R^{n_u \times n_u}$ is a diagonal matrix consisting of 0's or 1's. If any bound on the decision variables $u_{r,k}$ is active, the corresponding element in I_{δ_k} is set to 0, else set to 1. The active bounds on the decision variables are obtained iteratively by using the heuristic approach proposed in [27]. Substituting the control policy (19b) with equations (39a) and (39b), the bi-level optimization problem (19) is then transformed into a single-level one.

D. SINGLE ROBUST MPC

According to the constrained control policy (39), the controller model for the uncertain process at time k can be approximately expressed as follows:

$$u_{p,k} = K_{x,k} x_{p,k} + K_{t,k} t_k \tag{40}$$

where $K_{x,k} = \boldsymbol{I}_{\delta_k} K_x$, the subscript p in the variables $\{u_{p,k}, x_{p,k}\}$ is used to differentiate the uncertain variable values from their nominal value. The uncertain process model at time k is formulated by

$$x_{p,k+1} = A_k x_{p,k} + B_k u_{p,k} \tag{41}$$

Based on (27) and (40),(41), the extended vector $\xi_k = (u_{p,k-1}, x_{p,k+1}, x_{p,k})$ is defined. Then equations (27) and (40),(41) can be summarized as follows:

$$\xi_{k+1} = \boldsymbol{G}_{\xi,k} \xi_k + \boldsymbol{G}_{t,k} t_k, \quad k = 0, \ldots, N-1 \tag{42}$$

where

$$\boldsymbol{G}_{\xi,k} = \begin{bmatrix} 0 & 0 & K_{x,k} \\ 0 & A_k & B_k K_{x,k} \\ 0 & \begin{matrix} L_x C_{k+1} A_k \\ +(\mathcal{B}_k - L_x C \mathcal{B}_k) K_{x,k} \\ +L_x C_{k+1} B_k K_{x,k} \end{matrix} & (\mathcal{A}_k - L_x C \mathcal{A}_k) \end{bmatrix} \tag{43}$$

$$\boldsymbol{G}_{t,k} = \begin{bmatrix} K_{t,k} \\ B_k K_{t,k} \\ L_x C_{k+1} B_{k+1} K_{t,k} + (\mathcal{B}_k - L_x C \mathcal{B}_k) K_{t,k} \end{bmatrix} \tag{44}$$

Equation (42) is then transformed into the following explicit formulation:

$$\begin{aligned} \xi_{k+1} &= (\prod_{i=0}^{k} \boldsymbol{G}_{\xi,k-i})\xi_0 + \sum_{i=0}^{k} \left((\prod_{j=0}^{k-1-i} \boldsymbol{G}_{\xi,k-j}) \boldsymbol{G}_{t,i} t_i \right) \\ &= \boldsymbol{G}_{\xi t,k} \begin{pmatrix} t_0 \\ \vdots \\ t_{N-1} \end{pmatrix} + \boldsymbol{G}_{\xi\xi,k} \xi_0 \end{aligned} \tag{45}$$

where

$$\boldsymbol{G}_{\xi\xi,k} = \prod_{i=0}^{k} \boldsymbol{G}_{\xi,k-i},$$

$$\boldsymbol{G}_{\xi t,k} = \sum_{i=0}^{k} (\prod_{j=0}^{k-1-i} \boldsymbol{G}_{\xi,k-j}) \boldsymbol{G}_{t,i}.$$

Suppose the initial estimation $\hat{x}_0$ is correct. Then the closed-loop model is obtained

$$u_{p,k} = G_{u1,k} \begin{pmatrix} t_0 \\ \vdots \\ t_{N-1} \end{pmatrix} + G_{u2,k} \begin{pmatrix} u_{-1} \\ \hat{x}_0 \end{pmatrix}, \ k = 0, \ldots, N-1 \tag{46}$$

$$x_{p,k+1} = G_{x1,k} \begin{pmatrix} t_0 \\ \vdots \\ t_{N-1} \end{pmatrix} + G_{x2,k} \begin{pmatrix} u_{-1} \\ \hat{x}_0 \end{pmatrix}, \ k = 0, \ldots, N-1 \tag{47}$$

where the $G_{u1,k}, G_{u2,k}, G_{x1,k}, G_{x2,k}$ are uncertain parameters.

Substituting (46) and (47) into formulation (19), the bi-level robust MPC (19) can be transformed into the following single-level optimization:

$$\min_{t_k} \sum_{k} \Big\{ \beta_0 x_{e2,k+1}^2 + \beta_1 u_{1,k} - \beta_2 u_{2,k} - \beta_3 u_{3,k} \Big\} \tag{48a}$$

$$s.t. \ u_{p,k} = G_{u1,k} \begin{pmatrix} t_0 \\ \vdots \\ t_{N-1} \end{pmatrix} + G_{u2,k} \begin{pmatrix} u_{-1} \\ \hat{x}_0 \end{pmatrix} \tag{48b}$$

$$x_{p,k+1} = G_{x1,k} \begin{pmatrix} t_0 \\ \vdots \\ t_{N-1} \end{pmatrix} + G_{x2,k} \begin{pmatrix} u_{-1} \\ \hat{x}_0 \end{pmatrix} \tag{48c}$$

$$u_{min} \le u_{p,k} \le u_{max} \tag{48d}$$

$$(\boldsymbol{I} - \boldsymbol{I}_{\delta_k}) \cdot \mathbf{t}_k = \mathbf{u}_b \tag{48e}$$

$$k = 0, \ldots, N-1$$

According to (48), at each iteration, the control policy is calculated by the controller model (48b). Then by solving

Algorithm 1 Overall Heuristic Algorithm

Step 0 Initialize (x_0, u_{-1}). Pre-specify the weighting matrices Q, R, and coefficient matrices $\beta_0, \beta_1, \beta_2, \beta_3$.
Step 1 Calculate x_{k+1} by (20).
Step 2 Obtain $x_{r,k+1}, u_{r,k}$ by solving the open-loop optimization problem (19) without considering the control policy (19b).
Step 3 Substituting $x_{r,k+1}, u_{r,k}$ into (31), obtain $u_i (i = 1, \ldots, N-1)$ by solving (31).
Step 4 Check if any one (or more) decision variable violates the physical constraints in (31c), then go to step 5; otherwise, go to step 7.
Step 5 Set the decision variable that beyond constraint bound to the bound values, set the corresponding $\delta_k = 0$. Then update u_i.
Step 6 Substitute u_i into (19a), resolve the optimization problem (19), go to step 3.
Step 7 Calculate $u_{p,k}$ by equations (35) and (38).
Step 8 Solve the single-level optimization problem(48).
step 9 Increase k, go to step 1.

the optimization problem (48), a set of control moves are obtained. Note that only the current optimal control move $u^*_{k|k}$ is implemented in the plant.

E. OVERALL SOLUTION TO ROBUST MPC WITH MODEL UNCERTAINTY

A heuristic method is utilized to solve the robust MPC with model uncertainty. First, an initial solution $u_{p,k,0}$ is obtained by solving problem (19) without any active bounds. Then, the decision variables are substituted into (31c) to judge if any of the decision variables which have not been set to the constraint bounds exceed the physical constraints. For the active constraints, the corresponding decision variables are set to their bounds, meanwhile the equivalent equality constraints are added into the inner optimization (31). Repeat the procedure until all the decision variables in the solution are either fixed to their bounds or within the constraint bounds. Thus the controller model is obtained as in (39), and the control policy for the uncertain process model is approximated with (40). Finally, a newly closed-loop robust MPC with updating control policy is formulated as in (48).

Remark 1: Any decision variable set to its bound value will remain valid for the subsequent iterations.

Remark 2: The solution is not globally optimal only if the repeated procedure involves all the active bounds.

V. SIMULATION RESULTS

The robust MPC with controller model based on the global LPV model is designed for the boiler-turbine system. The objective is to minimize the economic performance of the system. Simulation experiments are carried out to investigate the performance of the proposed strategy. The sampling time interval is set be 1s. In order to cover the whole dynamics for the boiler-turbine system operating in a wide range, the local models used to construct a global LPV model are linearized at operating points No.2, No.4, No.6, respectively. The corresponding coefficient matrices are as follows:

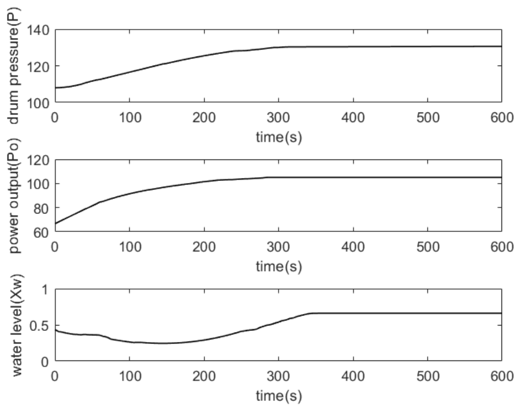

FIGURE 3. Dynamic response of states from operating point No.4 to No.6.

$$\breve{A}_1 = \begin{bmatrix} 0.001729 & 0 & 0 \\ 0.02794 & -0.1 & 0 \\ 0.002235 & 0 & 0 \end{bmatrix}$$

$$\breve{A}_2 = \begin{bmatrix} 0.002230 & 0 & 0 \\ -0.02872 & -0.1 & 0 \\ 0.002235 & 0 & 0 \end{bmatrix}$$

$$\breve{A}_3 = \begin{bmatrix} 0.002712 & 0 & 0 \\ -0.0294 & -0.1 & 0 \\ 0.002235 & 0 & 0 \end{bmatrix}$$

$$\breve{B}_1 = \begin{bmatrix} 0.9 & -150.8613 & -0.15 \\ 0 & 11.01288 & 0 \\ 0 & -0.1294 & 1.6588 \end{bmatrix}$$

$$\breve{B}_2 = \begin{bmatrix} 0.9 & -193.91068 & -0.15 \\ 0 & 14.15548 & 0 \\ 0 & -0.01294 & 1.65884 \end{bmatrix}$$

$$\breve{B}_3 = \begin{bmatrix} 0.9 & -238.88356 & -0.15 \\ 0 & 17.4385 & 0 \\ 0 & -0.01294 & 1.65884 \end{bmatrix}$$

$$\breve{C}_1 = \breve{C}_2 = \breve{C}_3 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 6.5365e-3 \end{bmatrix}$$

The coefficient matrices of nominal model (15) are

$$A = \begin{bmatrix} 0.0022 & 0 & 0 \\ -0.0101 & -0.1 & 0 \\ 0.0022 & 0 & 0 \end{bmatrix}$$

$$B = \begin{bmatrix} 0.9000 & -194.5518 & -0.1500 \\ 0 & 14.2023 & -0.0500 \\ 0 & -0.0518 & 1.6588 \end{bmatrix}$$

$$C = \breve{C}_1 = \breve{C}_2 = \breve{C}_3$$

Based on equations (9),(10),(11), the widths of each local model are pre-specified as $\mathcal{O}_1 = 5.4$, $\mathcal{O}_2 = 5.5$, $\mathcal{O}_3 = 5.3$, respectively. The filter gain $L_0 = [1; 1; 1]$ and the prediction horizon $N = 3$.

The dynamic response and economic performance of the robust MPC is first tested under different operating conditions. The weighted coefficients $\beta_0 = 0.01$, $\beta_1 = 15$,

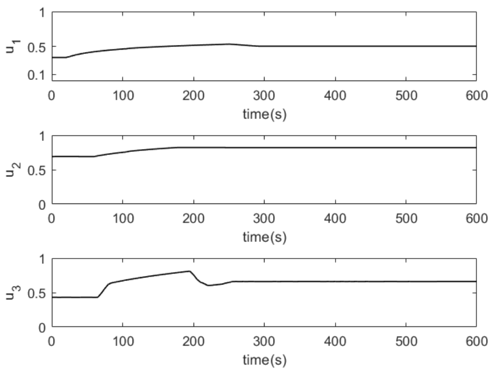

FIGURE 4. Control variables.

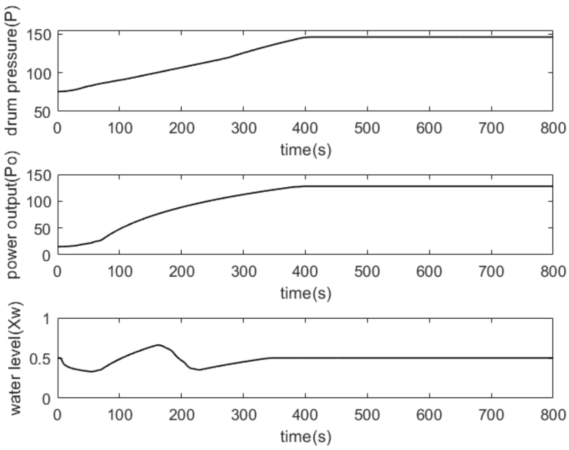

FIGURE 5. Dynamic response of states from operating point No.1 to No.7.

$\beta_2 = 5.27$, $\beta_3 = 6.77$, and the weighting matrices $Q = \text{diag}\{0.01; 0.01; 0.01\}$, $R = \text{diag}\{10; 10; 10\}$. When the operating condition is varying from operating point No.4 to No.6, the dynamic responses of the states of boiler-turbine system under are shown in Fig. 3, and the response of the control variables are adjusted as in Fig. 4. According to (48),The transient economic performance of the bi-level robust MPC for this simulation is 134.1073. It is seen that the dynamic responses of drum pressure P, power output Po, and water level Xw, increase smoothly with time and ascends up to the higher stable conditions at time about 300s, indicating that the constructed global LPV model (14) can perfectly describe the transient dynamic characteristic of the boiler-turbine system. Seen from Fig. 4, throughout the transient process, u_1, u_2, u_3 are kept within the allowable ranges (3), and the change rates of the control variables meet the restriction (4).

The performance of the proposed control method based on the global LPV model is demonstrated in the next simulation for the boiler-turbine system operating over a wide range, for instance, from operating point No.1 to No.7, as in Figs. 5 and 6. From Fig. 5, we notice that the drum pressure P and power output Po gradually increase to the higher stable operation conditions. Due to the swell-and-shrink effect, the water level Xw declines initially and then rises up to the climax, then Xw drops to a the final stable value as the drum pressure P increases. Note that it takes longer time to reach the stable

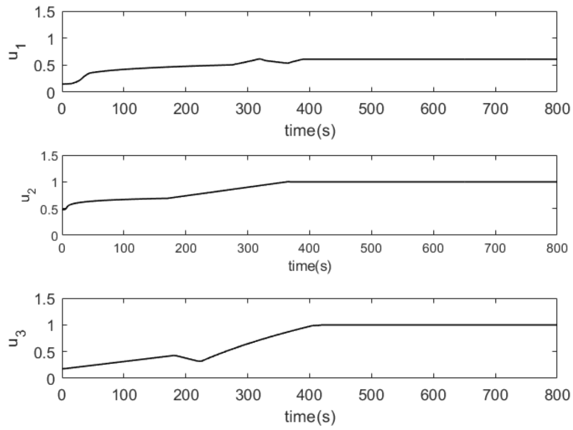

FIGURE 6. Control variables.

condition. As shown in Fig. 6, the steam control valve u_2 and feedwater flow valve u_3 hit the bounds at time 365a and 400s, respectively, and keep it to the end. while the fuel flow valve u_1 always meets the designated range.

The simulation results show that the proposed closed-loop robust MPC with bi-level optimization for nonlinear boiler-turbine system has good performance. Different from the tracking MPC, the proposed MPC method emphasizes on the economic performance, in which the operating points are slightly changed. Besides, the global LPV model accurately describes the dynamic performance of the nonlinear boiler-turbine system, thus improve the transient performance when the operation conditions vary from one operating point to another.

VI. CONCLUSION

A closed-loop robust MPC with bi-level optimization for the control of boiler-turbine system is proposed. A global LPV model with load-dependent parameters is established to represent the uncertain process for the boiler-turbine system operating over a wide range. A bi-level optimization, including a quadratic program as the inner optimization and an economic optimization in the outer, is designed to improve the control performance. A heuristic algorithm is introduced to transform the bi-level optimization problem into a single one, thus the computational complexity is greatly reduced. The simulation shows that the proposed strategy is able to deal with the model uncertainty effectively.

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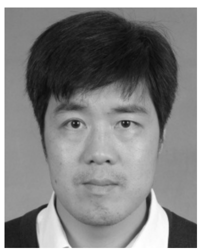

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