Application of Model Based Predictive Control with Kalman Filter to Natural Circulation Water Tube Boiler

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Abstract: This paper deals with the control problem of a natural circulation water tube boiler with constraint conditions. Some linearized models for the water tube boiler are proposed around some operating points, and the model based predictive control law is adopted to control the plant accounting for constraints. In this controller, the Kalman filter is used for the state estimation, and the controller is designed based on the linearized model. The control performance of the designed controller is exemplified via some nonlinear simulations around the operation point, which show it works well.

Keywords: Water tube boiler, linearization, discrete Kalman filter, model based predictive control.

1. INTRODUCTION

The industrial boilers are widely used in the thermal power plant, central heating systems, etc. The boiler system is a kind of typical nonlinear multivariable systems, and so it is known difficult to be controlled. Åström and Bell have proposed low order dynamic models for drum boiler-turbine-alternator units [1-3], and they are utilized to design various controllers for the boiler systems. However, this model is restricted to the drum boiler and not valid for another type of boiler, the water tube boiler. A nonlinear dynamic model for the water tube boiler has been proposed by Kim and Kwon in [4]. Although they have suggested an LQ regulator design using the model, it is not practical to be applied since it is a state-feedback law and has not accounted for constraint conditions.

In industrial fields, most plants have many constraint conditions. For example, because of physical limits, industrial boilers have rate and magnitude constraints of each actuator and also state constraints such as temperature and pressure etc. Furthermore, for the improved stability and performance such as energy efficiency increase, we should control industrial boilers in specific constraint conditions. Therefore we need to design a controller accounting for constraints. The predictive control law is to consider systematically constraint conditions at controller design step and also to design optimal control. It is called as MBPC(Model Based Predictive Control), RHC(Receding Horizon Control), GPC(Generalized Predictive Control), DMC(Dynamic Matrix Control), SOLO(Sequential Open Loop Optimizing control), etc., and has been researched at many variable fields [5-8].

In this paper we will propose an MBPC design with Kalman filter to control the natural circulation water tube boiler, and exemplify the performance of the controller via some nonlinear simulations using Matlab/Simulink and s-functions.

2. WATER TUBE BOILER MODEL

In this paper, a natural circulation water tube boiler is to be taken as the plant. A plant modeling for the boiler is carried out in [4], where the accomplished boiler model is as follows:

$$e_{11}\frac{dp}{dt}+e_{12}\frac{dV_{wd}}{dt}+e_{13}\frac{da_m}{dt}=Q_r+q_{fw}H_{fw}-q_sH_s,$$
$$e_{21}\frac{dp}{dt}+e_{22}\frac{dV_{wd}}{dt}+e_{23}\frac{da_m}{dt}=q_{fw}-q_s,$$
$$e_{31}\frac{dp}{dt}+e_{32}\frac{dV_{wd}}{dt}+e_{33}\frac{da_m}{dt}=Q_r-q_{dc}a_mH_c, \tag{2.1}$$

where

$$e_{11}=V_{st}\left(\rho_s\frac{dH_s}{dp}+H_s\frac{d\rho_s}{dp}\right)+V_{wt}\left(\rho_w\frac{dH_w}{dp}+H_w\frac{d\rho_w}{dp}\right)-V_t+m_tC_p\frac{dT}{dp},$$
$$e_{12}=\rho_wH_w-\rho_sH_s,$$
$$e_{13}=(\rho_sH_s-\rho_wH_w)V_r\frac{da_v}{da_m},$$
$$e_{21}=V_{st}\frac{d\rho_s}{dp}+V_{wt}\frac{d\rho_w}{dp},$$
$$e_{22}=\rho_w-\rho_s,$$
$$e_{23}=(\rho_s-\rho_w)V_r\frac{da_v}{da_m},$$
$$e_{31}=H_c(1-a_m)a_vV_r\frac{d\rho_s}{dp}-a_mH_c(1-a_v)V_r\frac{d\rho_w}{dp}+\rho_sa_vV_r\frac{dH_s}{dp}+\rho_w(1-a_m)V_r\frac{dH_w}{dp}-V_r+m_rC_p\frac{dT}{dp},$$
$$e_{32}=0,$$
$$e_{33}=H_cV_r\left[(1-a_m)\rho_s+a_m\rho_w\right]\frac{da_v}{da_m}.$$

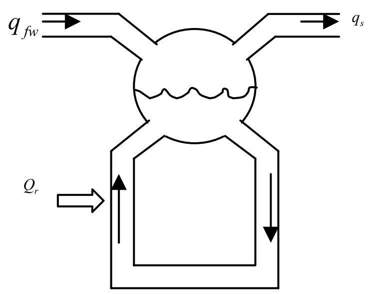

Fig. 2.1 A simple schematic of risers, drum and downcomers

The nomenclature for the model is summarized in Appendix. Plant parameters are taken as follows: $V_r=3.355m^3$, $V_{drum}=10.94m^3$, $V_{dc}=5.43m^3$, $m_r=15790kg$, $m_t=51190kg$.

The steam tables were approximated by quadratic approximations in the simulation. We suppose that the temperature of feedwater is 173.7℃. Fig 2.1 shows the simplified water tube boiler model concept for modeling [1-3].

3. MBPC WITH KALMAN FILETER FOR THE BOILER MODEL

3.1 Basic concept of predictive control

The predictive control is a control strategy to calculate control inputs to minimize the cost function assumed previously using receding horizon technique. In Fig 2.1, N_u and N_2 are called as the control horizon and the prediction horizon, respectively. In the time k, let us gain control inputs as follows:

$$u(k), u(k+1), \cdots, u(k+N_u-1). \tag{3.1}$$

Then we select the fist control inputs $u(k)$ and use it during the [k,k+1] time interval. In the next time k+1, each control horizon and receding horizon is added by each N_u and N_2 from the time k+1. And also we gain control inputs through to solve the optimization problem of cost function and select the first inputs $u(k+1)$ and use it during the [k+1,k+2] time interval. In next times, we also repeat continuously the same procedure. Fig 3.1 shows the basic concept of predictive control procedure.

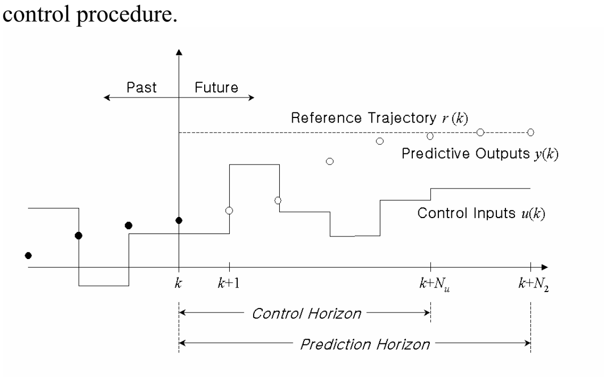

Fig. 3.1 A basic concept of predictive control

3.2 MBPC algorithm with Kalman filter for the boiler

The objective model used by MBPC is assumed that it is represented by a discrete time-invariant state space model with the controllability. This model includes the measurement noise and the plant noise. Eq. (3.2) represents the linearized plant model including noises shown in Fig 3.3.

$$\begin{aligned} \bar{x}(k+1) &= \bar{A}\bar{x}(k) + \bar{B}u(k) + \bar{B}\bar{G}w(k), \\ y(k) &= \bar{C}\bar{x}(k) + \bar{D}u(k) + \bar{R}v(k). \end{aligned} \tag{3.2}$$

Here, $u(\cdot)$ is the input vector, $y(\cdot)$ is the output vector, $\bar{x}(\cdot)$ is the state vector of the system, $v(\cdot)$ is the zero mean white Gaussian measurement noise and $w(\cdot)$ is the zero mean white Gaussian plant noise. In Eq. (3.2), the input matrix $\bar{D}$ exists in general. But when designing MBPC, it is impossible to design the controller directly considering the $\bar{D}$ term, i.e., the feedforward term. Thus to consider the $\bar{D}$ term, the model should be augmented properly using the difference operator Δ. Fig 3.2 shows the augmented system and is able to be represented by Eq. (3.3).

$$\begin{aligned} \begin{bmatrix} \bar{x}(k+1) \\ u(k+1) \end{bmatrix} &= \begin{bmatrix} \bar{A} & \bar{B} \\ 0 & I \end{bmatrix} \begin{bmatrix} \bar{x}(k) \\ u(k) \end{bmatrix} + \begin{bmatrix} 0 \\ I \end{bmatrix} \Delta u(k) + \begin{bmatrix} \bar{B}\bar{G} \\ 0 \end{bmatrix} w(k), \\ y(k) &= \begin{bmatrix} \bar{C} & \bar{D} \end{bmatrix} \begin{bmatrix} \bar{x}(k) \\ u(k) \end{bmatrix} + \bar{R}v(k), \end{aligned} \tag{3.3}$$

where $\Delta = \dfrac{1-q^{-1}}{q^{-1}}$.

In Eq. (3.3), q^{-1} is the backward shift operator. And Eq. (3.3) can be also replaced by Eq. (3.4) as follow:

$$\begin{aligned} x(k+1) &= Ax(k) + B\Delta u(k) + Gw(k), \\ y(k) &= Cx(k) + Rv(k), \end{aligned} \tag{3.4}$$

where

$$x(\cdot) = \begin{bmatrix} \bar{x}(\cdot) \\ u(\cdot) \end{bmatrix}, A = \begin{bmatrix} \bar{A} & \bar{B} \\ 0 & I \end{bmatrix}, B = \begin{bmatrix} 0 \\ I \end{bmatrix}, C = \begin{bmatrix} \bar{C} & \bar{D} \end{bmatrix},$$
$$G = \begin{bmatrix} \bar{B}\bar{G} \\ 0 \end{bmatrix}, R = \bar{R}.$$

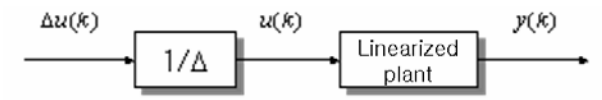

Fig. 3.2 Augmented system

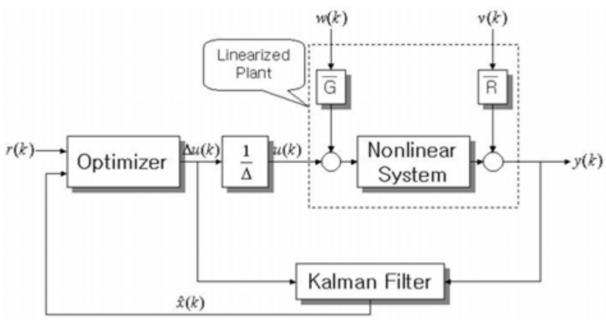

Fig. 3.3 Block diagram for the MBPC

The output prediction vector of the j step is represented by

$$\begin{aligned} y(k+j) = CA^j x(k) &+ \sum_{i=0}^{j-1} CA^{(j-i-1)} B\Delta u(k+i) \\ &+ \sum_{i=0}^{j-1} CA^{(j-i-1)} Gw(k+i) \\ &+ Rv(k+j). \end{aligned} \tag{3.5}$$

Let us take the expected value of $y(k+j)$. Then Eq. (3.5) is to be replaced by Eq. (3.6) since $E[v(\cdot)] = 0$, $E[w(\cdot)] = 0$, $E[y(k+j)] = \hat{y}(k+j)$, $E[x(k)] = \hat{x}(k)$.

$$\hat{y}(k+j) = CA^j \hat{x}(k) + \sum_{i=0}^{j-1} CA^{(j-i-1)} B\Delta u(k+i). \tag{3.6}$$

In Eq. (3.6), the state estimation vector, $\hat{x}$ can be given by Kalman filter [9].

$$e(k) = \hat{x}(k) - x(k). \tag{3.7}$$

Eq. (3.7) defines the state estimation error. Kalman filter is designed to minimize the state estimation error. The filter is constructed as follows:

$$\hat{x}(k+1) = A\hat{x}(k) + B\Delta u(k) + L(k)\left[y(k) - C\hat{x}(k)\right]. \tag{3.8}$$

Here, the Kalman filter gain $L(k)$ is calculated by the discrete Riccati equation as Eq. (3.9).

$$\begin{aligned} P(k+1) &= \left[A - N(k)C\right]P(k)\left[A - N(k)C\right]^T \\ &+ G\sigma_w G^T + N(k)\sigma_v N^T(k) - G\sigma_{wv}N^T(k) \\ &- N(k)\sigma_{wv}G^T, \end{aligned} \tag{3.9}$$

where $N(k) = \left[AP(k)C^T + G\sigma_{wv}\right]\left[CP(k)C^T + \sigma_v\right]^{-1}$.

$$L(k) = \left[P(k)C^T + A^T G\sigma_{wv}\right]\left[CP(k)C^T + \sigma_v\right]^{-1}. \tag{3.10}$$

To gain Kalman filter gain $L(k)$, system matrices A, B, D, and variances σ_w, σ_{wv}, σ_v and G have to be known in advance. The predictive control law is the problem which finds control inputs minimizing the performance index, or cost function as follows:

$$J(\Delta u) = \sum_{j=N_1}^{N_2}\left[r(k+j) - \hat{y}(k+j)\right]^2 + \lambda\sum_{j=0}^{N_u-1}\left[\Delta u(k+j)\right]^2. \tag{3.11}$$

Here, N_1 and N_2 are the prediction horizons, N_u is the control horizon, λ is a weighting about control increment, and $r(k+j)$ is the reference input. When $j \geq N_u$, $\Delta u(k+j) = 0$, Eq. (3.11) can be represented as follows:

$$J(\Delta u) = (r - \hat{y})^T(r - \hat{y}) + \lambda\Delta u^T\Delta u, \tag{3.12}$$

where $r = \left[r(k+N_1)\cdots r(k+N_2)\right]^T$,
$\hat{y} = \left[\hat{y}(k+N_1)\cdots\hat{y}(k+N_2)\right]^T$,
$\Delta u = \left[\Delta u(k)\cdots\Delta u(k+N_u-1)\right]^T$.

The output prediction vector $\hat{y}$ is to be represented by Eq. (3.13) from Eq. (3.6):

$$\hat{y} = F\hat{x}(k) + H\Delta u(k), \tag{3.13}$$

where $F = \begin{bmatrix} CA^{N_1} \\ \vdots \\ CA^{N_2} \end{bmatrix}$, $H = \begin{bmatrix} h_{N_1,1} & \cdots & h_{N_1,N_u} \\ \vdots & \ddots & \vdots \\ h_{N_2,1} & \cdots & h_{N_2,N_u} \end{bmatrix}$,

$$h_{j,i} = \begin{cases} CA^{j-i}B, & j \geq i \\ 0, & j < i \end{cases}.$$

Let us define

$$f = F\hat{x}(k). \tag{3.14}$$

and substituting Eqs. (3.13)~ (3.14) into Eq. (3.12), we can get

$$\begin{aligned} J(\Delta u) &= \Delta u^T\left[H^T H + \lambda I\right]\Delta u - 2(r - f)^T H\Delta u \\ &+ (r - f)^T(r - f). \end{aligned} \tag{3.15}$$

Eq. (3.15) is a cost function of the quadratic form. Thus, if the system has no constraints, we can get an optimal solution through the least square method as follows:

$$\Delta u = (H^T H + \lambda I)^{-1}H^T(r - f). \tag{3.16}$$

Then, we use only the first control increment at MBPC. Thus control inputs used really is as follows:

$$u(k) = u(k-1) + K(r - f), \tag{3.17}$$

where $K = \left[I \quad 0 \quad \cdots \quad 0\right](H^T H + \lambda I)^{-1}H^T$.

If the system has constraints, we can calculate an optimal control increment considering constraint conditions through the quadratic programming.

In the performance index of Eq. (3.15), $(r - f)^T(r - f)$ do not have an effect on the optimal solution because it is not a function of Δu. Thus, the optimal solution Δu^* can be represented as follows:

$$\begin{aligned} \Delta u^* &= \underset{\Delta u(k)}{\arg\min}\left\{\Delta u^T\left[H^T H + \lambda I\right]\Delta u - 2(r - f)^T H\Delta u\right\}, \\ &= \underset{\Delta u(k)}{\arg\min}\left\{\frac{1}{2}\Delta u^T\left[H^T H + \lambda I\right]\Delta u - (r - f)^T H\Delta u\right\}. \end{aligned} \tag{3.18}$$

The form of the quadratic programming is

$$x^* = \underset{x}{\arg\min}\left\{\frac{1}{2}x^T Px + q^T x\right\}, \ \textit{subject to } Ax \leq b, \tag{3.19}$$

where P positive definite.

Eq. (3.19) is implemented as a QP command by Matlab with the form of QP command.

$$x^* = QP(P, q, A, b). \tag{3.20}$$

Comparing Eq (3.18) with Eq. (3.19), we can get the following solution:

$$\Delta u^* = QP(P, q, A, b), \tag{3.21}$$

where $P = H^T H + \lambda I, q = -H^T(r - f)$.

The constraint condition of Eq. (3.21) is expressed as $A\Delta u \leq b$. Let us $\Delta u(k) \in R^n$ and

$$\Delta u_{\min} \leq \Delta u(k) \leq \Delta u_{\max}. \tag{3.22}$$

Eq. (3.22) is the constraint condition for the control increment. Eq. (3.23) and Eq. (3.24) are to express Eq. (3.22) as the matrix inequality forms of $A\Delta u \leq b$. Here I is an $n \times n$ identity marix.

$$\begin{bmatrix} I & 0 & \cdots & 0 \\ 0 & I & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & I \end{bmatrix} \begin{bmatrix} \Delta u(k) \\ \Delta u(k+1) \\ \vdots \\ \Delta u(k+N_u-1) \end{bmatrix} \le \begin{bmatrix} \Delta u_{\max} \\ \Delta u_{\max} \\ \vdots \\ \Delta u_{\max} \end{bmatrix}. \quad (3.23)$$

$$-\begin{bmatrix} I & 0 & \cdots & 0 \\ 0 & I & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & I \end{bmatrix} \begin{bmatrix} \Delta u(k) \\ \Delta u(k+1) \\ \vdots \\ \Delta u(k+N_u-1) \end{bmatrix} \le -\begin{bmatrix} \Delta u_{\min} \\ \Delta u_{\min} \\ \vdots \\ \Delta u_{\min} \end{bmatrix}. \quad (3.24)$$

Eq. (3.25) is the constraint condition for the control amplitude. Eq. (3.26) is to represent Eq. (3.25) as an inequality for the control increment.

$$u_{\min} \le u(k) \le u_{\max}. \quad (3.25)$$

$$u_{\min} - u(k-1) \le \Delta u(k) \le u_{\max} - u(k-1). \quad (3.26)$$

Eq. (3.27) and Eq. (3.28) are to express Eq. (3.26) as the matrix inequality form of $A\Delta u \le b$.

$$\begin{bmatrix} I & 0 & \cdots & 0 \\ I & I & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ I & I & \cdots & I \end{bmatrix} \begin{bmatrix} \Delta u(k) \\ \Delta u(k+1) \\ \vdots \\ \Delta u(k+N_u-1) \end{bmatrix} \le \begin{bmatrix} u_{\max} - u(k-1) \\ u_{\max} - u(k-1) \\ \vdots \\ u_{\max} - u(k-1) \end{bmatrix}. \quad (3.27)$$

$$-\begin{bmatrix} I & 0 & \cdots & 0 \\ I & I & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ I & I & \cdots & I \end{bmatrix} \begin{bmatrix} \Delta u(k) \\ \Delta u(k+1) \\ \vdots \\ \Delta u(k+N_u-1) \end{bmatrix} \le -\begin{bmatrix} u_{\min} - u(k-1) \\ u_{\min} - u(k-1) \\ \vdots \\ u_{\min} - u(k-1) \end{bmatrix}. \quad (3.28)$$

Eq. (3.23)~(3.24) and Eq. (3.27)~(3.28) can be represented at once by the matrix inequality form as follows:

$$A\Delta u \le b, \quad (3.29)$$

where I_t is $nN_u \times nN_u$ identity matrix, $\Delta u \in R^{nN_u}$.

$$A = \begin{bmatrix} I_t \\ -I_t \\ Q^T \\ -Q^T \end{bmatrix}, \quad b = \begin{bmatrix} \Phi_1 \\ \Phi_2 \\ \Phi_3 \\ \Phi_4 \end{bmatrix}, \quad Q = \begin{bmatrix} I & I & I & \cdots & I \\ 0 & I & I & \cdots & I \\ 0 & 0 & I & \cdots & I \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & I \end{bmatrix} \in R^{nN_u \times nN_u},$$

$$\Phi_1 = \begin{bmatrix} \Delta u_{\max} \\ \Delta u_{\max} \\ \vdots \\ \Delta u_{\max} \end{bmatrix} \in R^{nN_u}, \quad \Phi_2 = \begin{bmatrix} -\Delta u_{\min} \\ -\Delta u_{\min} \\ \vdots \\ -\Delta u_{\min} \end{bmatrix} \in R^{nN_u},$$

$$\Phi_3 = \begin{bmatrix} u_{\max} - u(k-1) \\ u_{\max} - u(k-1) \\ \vdots \\ u_{\max} - u(k-1) \end{bmatrix} \in R^{nN_u}, \quad \Phi_4 = \begin{bmatrix} -u_{\min} + u(k-1) \\ -u_{\min} + u(k-1) \\ \vdots \\ -u_{\min} + u(k-1) \end{bmatrix} \in R^{nN_u}.$$

4. SIMULATION

To apply the MBPC to the nonlinear boiler system, the model should be linearized at some operating points. Let us take an operating point of the natural circulation water tube boiler plant as given in Table 4.1. The linearized model of the objective boiler model can be derived at the operating point as follows:

$$\dot{x} = Ax + Bu,$$
$$y = Cx + Du.$$

Table 4.1 The operating point

$p = 4.1926$	$V_{wd} = 7.2245$	$a_m = 0.5332$
$q_s = 4.807$	$q_{fw} = 4.807$	$Q_r = 9999.19$

Table 4.2 The linearized model at the operating point

A	$\begin{bmatrix} 0.00001982 & 0 & 0 \\ 0.00103049 & 0 & -0.02705983 \\ 0.00179506 & 0 & -0.03950403 \end{bmatrix}$
B	$\begin{bmatrix} -0.00152088 & -0.00029170 & 0.00000087 \\ -0.00168927 & 0.00121701 & 0.00000158 \\ 0.00013685 & 0.00002624 & 0.00000190 \end{bmatrix}$
C	$\begin{bmatrix} 1 & 0 & 0 \\ -0.00371640 & 0.00593877 & 0.03141064 \\ 0 & 0 & 0 \end{bmatrix}$
D	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix}$

Table 4.2 shows coefficient matrices of the linearized state space model at the operating point of Table 4.1. In Table 4.2, the input, output, and state variables are taken as follows:

- state variables : $x_1 = p, x_2 = V_{wd}, x_3 = a_m$,
- input variables : $u_1 = q_s, u_2 = q_{fw}, u_3 = Q_r$,
- output variables : $y_1 = p, y_2 = l, y_3 = q_s$,

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}, \quad u = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix}, \quad y = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}.$$

Due to the limit constraints of actuators, it is assumed that there exist input constraints as follows:

$$0 \le u_1 \le 16(kg/s), -0.35 \le \dot{u}_1 \le 0.35,$$
$$0 \le u_2 \le 16(kg/s), -0.9 \le \dot{u}_2 \le 0.9,$$
$$0 \le u_3 \le 35000(kJ/s), -1000 \le \dot{u}_3 \le 1000.$$

The following values are chosen as parameters for the simulation:

$$N_1 = 1, N_2 = 120, \mathrm{N_u} = 2, \lambda = 0.00001, T_s = 1\sec,$$

$$\overline{R} = 0.001\begin{bmatrix} 1 & 0 & 0 \\ 0 & 0.1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \overline{G} = 0.001\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 100 \end{bmatrix},$$

$$\sigma_w = 0.001\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \sigma_v = 0.001\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \sigma_{wv} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}.$$

The sampling time T_s for discrete system is taken as 1sec. And the pressure reference input is a step input changed +0.2 MPa at 50sec. The drum level reference input maintains at the operating point. And the steam mass flow rate reference input is a step input changed +0.2 kg/s at 800sec. The following figures show the simulation results.

The simulation results of Figs. 4.1~3.3 show good control performance. However, it can be seen that there exists a little offset error at Figs. 4.1~4.3 due to the difference between the nonlinear model and the linearized model at the specific operating point. Fig. 4.4 shows the estimation performance of the discrete Kalman filter, and it can be seen that it works very well. As shown in Figs. 4.5~4.7, there is no differences between the control inputs and the actuater outputs except for an effect of the noise, which means that the MBPC is designed completely accounting for input constraint conditions.

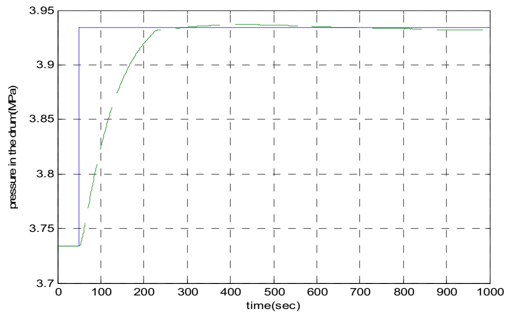

Fig. 4.1 Reference input(real line) and output response(dashed line) of the pressure in the drum(MPa)

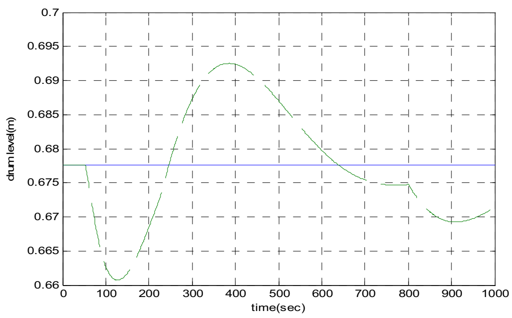

Fig. 4.2 Reference input(real line) and output response(dashed line) of the drum level(m)

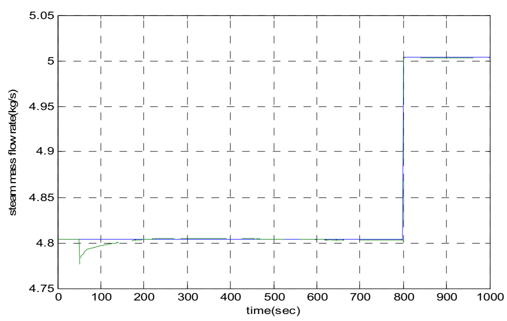

Fig. 4.3 Reference input(real line) and output response(dashed line) of the steam mass flow rate(kg/s)

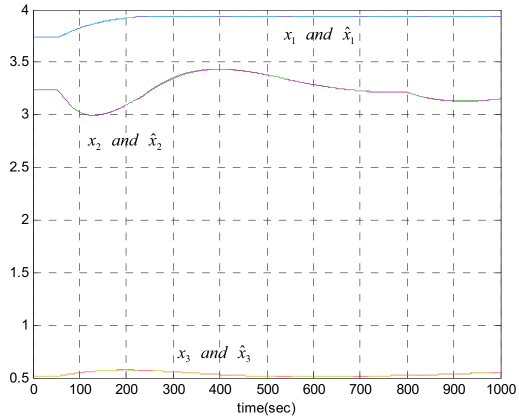

Fig. 4.4 The sate values x (real line) the state estimation values $\hat{x}$ (dashed line)

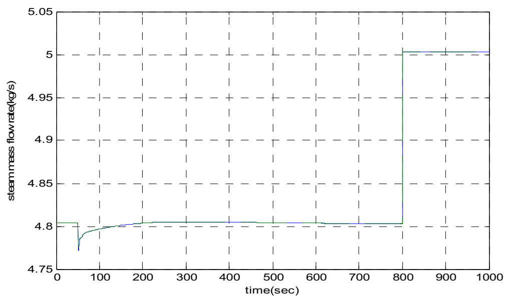

Fig. 4.5 Control input(real line) and actuator output(dashed line) of the steam mass flow rate(kg/s)

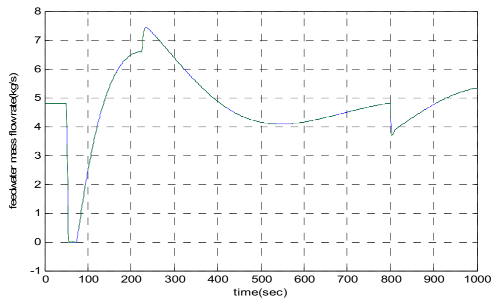

Fig. 4.6 Control input(real line) and actuator output(dashed line) of the feedwater mass flow rate(kg/s)

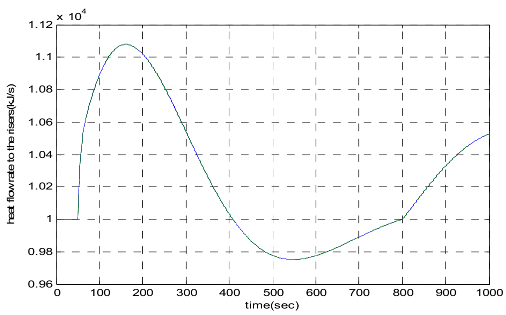

Fig. 4.7 Control input(real line) and actuator output(dashed line) of the heat flow rate to the risers(kJ/s)

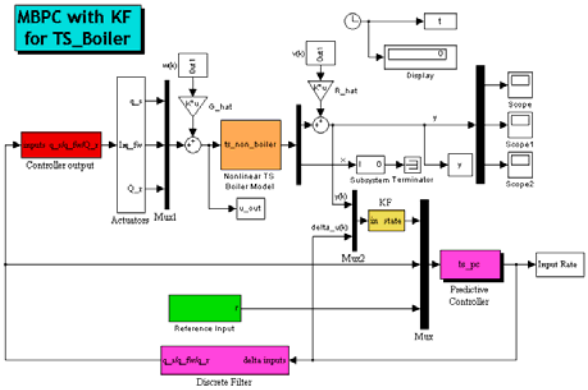

Fig. 4.8 The structure of MBPC with Kalman filter implemented by Matlab/Simulink

5. CONCLUSIONS

In this paper, we have dealt a control problem of a water tube boiler for power plants. The boiler model is proposed in [4], and the MBPC with Kalman filter is adopted to control the boiler plant accounting for constraint conditions efficiently. We have proposed a linearized model at an operating point and designed the MBPC. The performance of the control system is checked via some nonlinear simulations, which exemplify the control law works well. It requires further study to get rid of or reduce offset error.

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APPENDIX: Nomenclature

p : pressure of steam in drum(MPa)

t : time

ρ_s, ρ_w : the specific density of steam, water and feedwater(kg/m^3)

H_s, H_w, H_{fw} : the specific enthalpy of steam, water and feedwater(kJ/kg)

H_c : the specific enthalpy of condensation ($=H_s - H_w$)

V_{wt}, V_{st} : the total volume of water and steam in the risers, drum and downcomers(m^3)

V_t : the total volume of the risers, drum and downcomers($=V_{wt}+V_{st}$)

m_t : the total mass of the risers, drum and downcomers(kg)

m_r : the mass of the risers(kg)

C_p : the specific heat of the metal($kJ/kg^{\circ}C$)

T : the temperature of metal($^{\circ}C$) (=the temperature of the steam and the water in the risers, drum and downcomers)

Q_r : the heat flow rate to the risers(kJ/s)

q_s : the steam mass flow rate(kg/s)

q_{fw} : the feedwater mass flow rate(kg/s)

V_{drum} : the volume of the drum(m^3)

V_r, V_{dc} : the volume of the risers and downcomers(m^3)

V_{wd} : the volume of water in the drum (m^3)

a_v : the average steam-volume fraction in the flow at the riser

a_m : the steam-mass fraction in the flow at the riser outlet

q_r : the mass flow rate of the risers(kg/s)

q_{dc} : the mass flow rate of the downcomers(kg/s)

l : the drum water level(m)

A : the wet surface of the drum(m^2)

k : the friction coefficient of the downcomer