Data-Driven Modeling and Predictive Control for Boiler–Turbine Unit

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***Abstract*—This paper develops a novel data-driven modeling strategy and predictive controller for boiler–turbine unit using subspace identification and multimodel method. To deal with the nonlinear behavior of boiler–turbine unit, the system is divided into a number of local regions following the analysis of the nonlinearity distribution along the operation range, and then the corresponding measurement data are organized to identify the local models through the subspace method. By transforming local models into the same basis, the resulting multimodel system (MMS) is shown to represent the boiler–turbine unit very closely, and thus, used in designing a multimodel-based model predictive control (MMPC). As an alternative approach, a data-driven direct predictive controller (DDPC) is developed by utilizing the intermediate subspace matrices as local predictors. Online update of the predictor is also implemented on the multimodel structure to make the controller responsive to plant behavior variations. Simulation results demonstrate the feasibility and effectiveness of the proposed approach.**

***Index Terms*—Boiler–turbine unit, data-driven modeling and control, multimodel, online update, predictive control, subspace identification.**

I. Introduction

Boiler–turbine unit is widely used in modern fossil-fuel-fired power plants. The central task of a typical boiler–turbine control system is to regulate the power output to meet the demand of the grid while maintaining the drum pressure, steam temperature, and drum water level within given tolerances in order to keep the power plant to operate in a safe condition. Moreover, the derived control inputs need to satisfy the physical constraints imposed on the actuators such as the magnitude and rate saturations for the control valves.

However, control of boiler–turbine system is challenging due to its properties, such as multivariables, nonlinear, time-varying, strong coupling among variables, and large time delays. In addition, to meet the load demand at all times, large-scale power plants have to change power output frequently in a wide range of operation, and thus, nonlinear behavior becomes significant. For this reason, various control strategies have been extensively studied [1]–[15], and a multimodel strategy [16], which utilizes a combination of several linear models to approximate the nonlinear system, has been widely used to overcome the issue of nonlinearity over a wide operating range [9]–[15].

In [15], a multimodel-based H_∞ controller is designed for the boiler–turbine unit. The prediction-error method (PEM) is employed to identify the local transfer function models, and H_∞ controllers are developed based on these models to guarantee the robustness in each local-region. Then, a bumpless switchover mechanism is designed to achieve a smooth transition between the two operating regions, thus a wide range load following is attained. Besides [15], it is interesting to note that, a state-space type local linear model is adopted in most of the multimodel controllers [9]–[14] in order to take advantage of the advances in multivariable systems and control theory for linear systems. In these works, an approximation or transformation of the nonlinear system has been used to obtain the state-space model. However, for complex systems such as boiler–turbine unit, it is difficult to develop an accurate analytical model without the knowledge of thermodynamics and design specifications of many components, which has become one of the main limitations for designing controllers for real power plants.

This paper proposes the use of subspace identification (SID) method to develop state-space model directly from the input–output data of the plant [17], [18]. The SID is a noniterative robust identification method that can avoid local minima and convergence problems; therefore, it overcomes the problems of conventional PEM and is intrinsically suitable for multivariable systems [18], [19].

Because of these advantages, the subspace method has been developed steadily and widely used in process control during the past decade [20]–[24], providing models for various advanced controllers. However, most of the existing applications are on linear systems or on a small operating region of the plant, and few papers can be found on its application to highly nonlinear boiler–turbine unit. This has motivated us to extend the subspace method to nonlinear systems by combining it with the multimodel strategy.

Besides developing a model for the boiler–turbine unit, another objective of this paper is to design the controller. Among various advanced techniques in boiler–turbine control, model predictive controller (MPC) is the most popular one due to its advantages such as handling constraints in the controller design stage [6]–[12].

In [6], a dynamic matrix control (DMC) is employed for the boiler–turbine. It shows that the step-response model based on

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the test data is more suitable than the linearized model, but the performance of the proposed linear controller is still degraded for a wide range operation. In [7] and [8], nonlinear predictive controllers are designed based on the neural network model, neuro-fuzzy network and input–output feedback linearization. Although the control performance is improved, the nonlinear optimization is time consuming. Multimodel-based MPCs are developed in [9]–[12] for a wide range operation, showing better performance than the conventional predictive method. Although different kinds of objective functions and computational tools such as quadratic programming (QP), linear matrix inequalities, multiparameter programming, and genetic algorithm are adopted in these papers, they are greatly relying on analytical models. This paper provides an alternative way to build the multimodel by using only the input–output data. A typical MPC can be designed on this multimodel system (MMS) for a wide range control of the boiler–turbine.

In spite of the effectiveness of the MPC, like any other model-based controller, both the control performance and computational burden of the MPC heavily depend on the model, which has already become the "Achilles' heel" of the MPC. To alleviate this problem, a new approach, i.e., data-driven predictive controller (DDPC), is developed in this paper in the context of the multimodel and subspace method. The input–output data, which contains more information than the model, are directly used to build the predictor [25], and thus, avoid the intermediate modeling procedure to eliminate the effect of modeling mismatch.

For these reasons, we present this paper to address the modeling and control problems of boiler–turbine unit using only the input–output data, making the following contributions and advantages to the existing literatures:

1) A data-driven method is proposed to solve the modeling and control problems of the nonlinear power plant, using subspace and multimodel method.
2) A novel technique is devised to transform the local models into the combined model with common basis.
3) An online update method is proposed on the multimodel; thus, the issues of wide-range operations and plant parameter variations can be handled simultaneously.

II. System Description and Nonlinearity Analysis

The boiler–turbine system used in this paper represents the behavior of a 160-MW, drum-type, oil-fired power plant. The dynamics of this particular power plant were recorded and formulated into mathematical model by Bell and Åström [26] using both physical and empirical methods as follows:

$$\frac{dP}{dt} = 0.9u_1 - 0.0018u_2 P^{9/8} - 0.15u_3 \tag{1}$$

$$\frac{dE}{dt} = \frac{(0.73u_2 - 0.16)P^{9/8} - E}{10} \tag{2}$$

$$\frac{d\rho_f}{dt} = \frac{141u_3 - (1.1u_2 - 0.19)P}{85} \tag{3}$$

where P denotes drum steam pressure (kg/cm^2), E denotes power output (MW), and ρ_f denotes steam-water density (kg/cm^3). Control inputs into the system are valve actuator positions that control the mass flow of fuel, represented as u_1; steam to the turbine u_2; and feedwater to the drum u_3. The three control inputs are subject to magnitude and rate constraints as follows:

$$\begin{aligned} &0 \le u_1, u_2, u_3 \le 1 \\ &-0.007 \le \dot{u}_1 \le 0.007 \\ &-2 \le \dot{u}_2 \le 0.02 \\ &-0.05 \le \dot{u}_3 \le 0.05 \end{aligned} \tag{4}$$

which represent the physical limitations of the actuators.

Using the solution for ρ_f, the drum water level L (m) can be calculated using the following equations:

$$q_e = (0.854u_2 - 0.147)P + 45.59u_1 - 2.514u_3 - 2.096 \tag{5}$$

$$\alpha_s = \frac{(1 - 0.001538\rho_f)(0.8P - 25.6)}{\rho_f(1.0394 - 0.0012304P)} \tag{6}$$

$$L = 0.05(0.13073\rho_f + 100\alpha_s + q_e/9 - 67.975) \tag{7}$$

where α_s is the steam quality and q_e is the evaporation rate in kilograms per second.

To approximate the nonlinear plant with a minimum number of linear models, it is important to know the level of nonlinearity over full operation range. Therefore, the nonlinearity of the boiler–turbine unit along the whole operation range is analyzed first using the Vinnicombe gap (V-gap) metric, which is a measure of the distance between linear models around adjacent operating points [5], [12], [27].

The SID method is used to identify the linear models around the steady-state operating points, and the V-gap metric values between the adjacent linear models are calculated as shown in Table I. The gap value is bounded between 0 and 1, and a large value represents a large difference between the two linear models. Detailed method of the gap metric calculation can be found in [27].

TABLE I.
Typical Operating Points and V-gap Values Between Adjacent Linear Models

	#1	#2	#3	#4	#5	#6	#7
P	75.6	86.4	97.2	108	118.8	129.6	135.4
E	15.27	36.65	50.52	66.65	85.06	105.8	127
L	0	0	0	0	0	0	0
V-Gap	0.1735	0.1105	0.2252	0.2019	0.1496	0.6681	

The table shows that the level of nonlinearity increases as power level increases. Although increasing the number of local regions will improve the accuracy of the model, for the sake of simplicity, the operating range is divided into three nonequal size local regions (low load: 15.27–66 MW; middle load: 66–108 MW; high load: 108–127 MW).

III. Data-Driven Modeling of Boiler–Turbine Unit

With the divided operation region, the goal of the identification is to determine the system matrices $\{A_i, B_i, C_i, D_i\}$ and the Kalman filter gain K_i for each local model-i in such a way that the boiler–turbine system can be described in combination of a set of state-space models:

$$\begin{aligned} x_{k+1} &= A_E x_k + B_E u_k \\ y_k &= C_E x_k + D_E u_k \end{aligned} \tag{8}$$

where $u_k \in R^m$ is the input, $y_k \in R^l$ is the output, $x_k \in R^n$ is the state; $A_E = \sum_{i=1}^{M} S_i(E_k) A_i, S_i(E_k) \in \{0, 1\}, \sum_{i=1}^{M} S_i(E_k) = 1$, with M and E_k being the number of local models and the switching variable, respectively, and other system matrices, B_E, C_E, D_E, are defined in the same way.

The power output E is selected as the switching variable since its variation naturally represents various operating points of the boiler–turbine system, especially when the power plant is operating under a "constant-pressure" mode.

A. Building of Local Data Hankel Matrices

Depending on the switching variable E, a region-i can be made *active* for a period of time and *inactive* for another period of time. The experiment should be run long enough so that each region becomes active or excited sufficient number of times.

However, for a local model-i, such an experiment will make the corresponding data nonconsecutive and cannot be directly used in SID. For this reason, we arrange the data, block by block, to use the SID, where each block is a Hankel matrix composed of all the consecutive data for local region-i during its rth activation

$$Y_{i,r} = \left[\begin{array}{c} Y_{i,r}^p \\ \hline Y_{i,r}^f \end{array}\right] = \left[\begin{array}{cccc} y_0 & y_1 & \cdots & y_{j_r-1} \\ y_1 & y_2 & \cdots & y_{j_r} \\ \cdots & \cdots & \cdots & \cdots \\ y_{N-1} & y_N & \cdots & y_{N+j_r-2} \\ \hline y_N & y_{N+1} & \cdots & y_{N+j_r-1} \\ y_{N+1} & y_{N+2} & \cdots & y_{N+j_r} \\ \cdots & \cdots & \cdots & \cdots \\ y_{2N-1} & y_{2N} & \cdots & y_{2N+j_r-2} \end{array}\right].$$

Here, the output data Hankel matrix $Y_{i,r}$ is partitioned into the past $(Y_{i,r}^p)$ and the future $(Y_{i,r}^f)$ block matrices and is composed of all sampled data corresponding to region-i at its rth activation, $(y_0, y_1, \ldots, y_{2N+j_r-2})$, where N and j_r are, respectively, the row and column block numbers of $Y_{i,r}^p$ and $Y_{i,r}^f$. We should choose N larger than the order of the system n. Here, $j = j_1 + j_2 + \cdots + j_r$, which is the total number of column blocks corresponding to region-i, should be sufficiently large (typically$j \gg \max(mN, lN)$) to reduce noise sensitivity [17].

The input and noise data Hankel matrices, $U_{i,r}$ and $E_{i,r}$, can be constructed in the similar format.

Assume that the data are generated by an innovation form of the state-space model given by

$$\begin{aligned} x_{k+1} &= A_i x_k + B_i u_k + K_i e_k \\ y_k &= C_i x_k + D_i u_k + e_k \end{aligned} \tag{9}$$

where the innovation term e_k is assumed to be zero-mean white noise, and we also assume that the system is observable.

Then, by stacking up the model (9) with input–output data for a number of steps, these Hankel matrices can be used to develop the following subspace matrix equations [19]:

$$Y_{i,r}^f = \Gamma_N^i X_{i,r}^f + H_{Nd}^i U_{i,r}^f + H_{Ns}^i E_{i,r}^f \tag{10}$$

$$Y_{i,r}^p = \Gamma_N^i X_{i,r}^p + H_{Nd}^i U_{i,r}^p + H_{Ns}^i E_{i,r}^p \tag{11}$$

$$X_{i,r}^f = \Psi_Y^i Y_{i,r}^p + \Psi_U^i U_{i,r}^p + (\bar{A}_i)^N X_{i,r}^p \tag{12}$$

where $\Gamma_N^i = [\,(C_i)^T \quad (C_i A_i)^T \quad \cdots \quad (C_i A_i^{N-1})^T\,]^T$,

$$H_{Nd}^i = \begin{bmatrix} D_i & 0 & 0 & \cdots & 0 \\ C_i B_i & D_i & 0 & \cdots & 0 \\ C_i A_i B_i & C_i B_i & D_i & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ C_i A_i^{N-2} B_i & C_i A_i^{N-3} B_i & C_i A_i^{N-4} B_i & \cdots & D_i \end{bmatrix}$$

$$H_{Ns}^i = \begin{bmatrix} I & 0 & 0 & \cdots & 0 \\ C_i K_i & I & 0 & \cdots & 0 \\ C_i A_i K_i & C_i K_i & I & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ C_i A_i^{N-2} K_i & C_i A_i^{N-3} K_i & C_i A_i^{N-4} K_i & \cdots & I \end{bmatrix}$$

$$\Psi_Y^i = [\,(\bar{A}_i)^{N-1} K_i \quad (\bar{A}_i)^{N-2} K_i \quad \cdots \quad \bar{A}_i K_i \quad K_i\,]$$

$$\Psi_U^i = [\,(\bar{A}_i)^{N-1} \bar{B}_i \quad (\bar{A}_i)^{N-2} \bar{B}_i \quad \cdots \quad \bar{A}_i \bar{B}_i \quad \bar{B}_i\,]$$

in which $\bar{A}_i = (A_i - K_i C_i)$ and $\bar{B}_i = (B_i - K_i D_i)$.

The state matrices $X_{i,r}$ are defined as

$$X_{i,r} = \left[\begin{array}{c} X_{i,r}^p \\ \hline X_{i,r}^f \end{array}\right] = \left[\begin{array}{cccc} x_0 & x_1 & \cdots & x_{j_r-1} \\ \hline x_N & x_{N+1} & \cdots & x_{N+j_r-1} \end{array}\right].$$

Once all data Hankel matrices corresponding to local area-i are constructed for all activations, we can combine them together to obtain the following matrix algebraic equations:

$$Y_i^f = \Gamma_N^i X_i^f + H_{Nd}^i U_i^f + H_{Ns}^i E_i^f \tag{13}$$

$$Y_i^p = \Gamma_N^i X_i^p + H_{Nd}^i U_i^p + H_{Ns}^i E_i^p \tag{14}$$

$$X_i^f = \Psi_Y^i Y_i^p + \Psi_U^i U_i^p + (\bar{A}_i)^N X_i^p \tag{15}$$

where $Y_i^f = [\,Y_{i,1}^f \quad Y_{i,2}^f \quad \cdots \quad Y_{i,r}^f\,]$, and the data matrices, Y_i^p, U_i^p, etc., as well as the state matrices X_i^f, X_i^p can be written in the similar manner.

Remark 3.1: From the structure of $Y_{i,r}$, we can see that whenever the region-i is active, we need to keep the system operating in the region for more than $2N$ sampling time to generate sufficient data to build the Hankel matrices, and if the operating point is transited out of the region during this time, the related data would be useless.

B. System Identification for Local State-Space Model

We can now follow the standard SID method to identify the local system matrices $\{A_i, B_i, C_i, D_i\}$ and the Kalman filter gain K_i.

Due to the stability of the Kalman filter, $(\bar{A}_i)^N = (A_i - K_i C_i)^N \to 0$ as $N \to \infty$; thus, for a large N, (15) converges to [19]

$$X_i^f = L_N^i W_i^p \tag{16}$$

where subspace matrices L_N^i and past data matrices W_i^p are defined as $L_N^i = [\,\Psi_Y^i \quad \Psi_U^i\,]$ and $W_i^p = [\,(Y_i^p)^T \quad (U_i^p)^T\,]^T$. Substituting (16) into (13), we have

$$Y_i^f = L_w^i W_i^p + L_u^i U_i^f + L_e^i E_i^f \tag{17}$$

with the subspace matrices defined by $L_w^i = \Gamma_N^i L_N^i, L_u^i = H_{Nd}^i$, and $L_e^i = H_{Ns}^i$.

With the conditions that: 1) u_k is uncorrelated with e_k; 2) u_k is persistently exciting in the order of $2N$; and 3) the number of measurements is sufficiently large, i.e., $j \to \infty$, the data Hankel matrices developed in the Section III-A can be decomposed by the QR-decomposition as follows [17]:

$$\begin{bmatrix} W_i^p \\ U_i^f \\ Y_i^f \end{bmatrix} = \begin{bmatrix} R_{11}^i & 0 & 0 \\ R_{21}^i & R_{22}^i & 0 \\ R_{31}^i & R_{32}^i & R_{33}^i \end{bmatrix} \begin{bmatrix} Q_1^i \\ Q_2^i \\ Q_3^i \end{bmatrix}. \tag{18}$$

By expanding this equation and comparing it with (17), the subspace matrices $L^i = [\,L_w^i \quad L_u^i\,]$ can be calculated as

$$L^i = [\,R_{31}^i \quad R_{32}^i\,] \begin{bmatrix} R_{11}^i & 0 \\ R_{21}^i & R_{22}^i \end{bmatrix}^{\dagger} \tag{19}$$

where † represents the Moore–Penrose pseudo-inverse. The block matrices are identified as $L_w^i = L^i(:, 1 : N(m+l))$ and $L_u^i = L^i(:, N(m+l)+1 : end)$ in MATLAB expression, representing the first $N(m+l)$ columns and the remaining columns in L^i, respectively.

The next step is to extract the system matrices from the subspace matrices. We first perform the singular value decomposition (SVD) on the subspace matrix L_w^i [17], [19]

$$L_w^i = [\,U_1^i \quad U_2^i\,] \begin{bmatrix} S_1^i & 0 \\ 0 & S_2^i \end{bmatrix} \begin{bmatrix} V_1^i \\ V_2^i \end{bmatrix} \approx U_1^i S_1^i V_1^i \tag{20}$$

where S_1^i is chosen to contain the n most significant singular values with n as the order of the model. Since $L_w^i = \Gamma_N^i L_N^i$ as defined in (17), Γ_N^i can be estimated by

$$\Gamma_N^i = U_1^i (S_1^i)^{1/2}. \tag{21}$$

From Γ_N^i, as was defined in (10) and (11), the system matrices C_i and A_i can be directly extracted.

Next, by multiplying (13) with $(\Gamma_N^i)^{\perp}$ from the left-hand side and with $(U_i^f)^{\dagger}$ from the right-hand side, we have

$$(\Gamma_N^i)^{\perp} Y_i^f (U_i^f)^{\dagger} = (\Gamma_N^i)^{\perp} H_{Nd}^i. \tag{22}$$

Considering the structure of H_{Nd}^i, as was defined in (10) and (11), (22) can be written in equations that are linear in B_i and D_i, so that they can be extracted.

Finally, from (17) and (18), we conclude

$$R_{33}^i Q_3^i = L_e^i E_i^f. \tag{23}$$

Thus, with the assumptions of the innovation term, we can get L_e^i, which equals H_{Ns}^i, as was defined in (10) and (11), and from which the Kalman filter gains K_i can be obtained [19].

Remark 3.2: Note that (17) has a potential to be used as a predictor in designing a predictive controller, because the future output is expressed as a function of future input. Furthermore, with the three aforementioned conditions, a predictive expression can be written as

$$\hat{Y}_i^f = L_w^i W_i^p + L_u^i U_i^f \tag{24}$$

which implies that by identifying the local subspace matrices L_w^i and L_u^i from the input–output data, local predictors can be directly constructed [25]. These predictors can be used directly in the predictive control without identifying all local state-space models, thus avoiding the system identification procedure required for the MPC and the resulting modeling mismatch. This will be the basis of designing an alternative control, DDPC, presented in Section IV.

C. Similarity Transformation of Local Models into the Common Basis

One important feature of the SID is that the system matrices determined may be in any basis. Thus, although all the local state-space models have been identified, it is impossible to directly combine them together to form the integrated MMS. However, by making use of the switching point information obtained during the identification experiment, all the local models can be transformed into a common basis.

Suppose the local model-i starts running at time s and switches to the local model-j at time e during its rth activation. Using the input–output data within this period and system matrices, the starting state variables of model-i, x_s^i, can be estimated first from (13) and (14)

$$x_s^i = (\Gamma_N^i)^{\dagger}(Y_{i,r}(:,1) - H_{Nd}^i U_{i,r}(:,1)) \tag{25}$$

in MATLAB expression.

Similarly, the starting state variables of model-j can also be estimated, which are denoted as x_e^j. We then calculate the ending state variables of model-i, x_e^i, by

$$x_e^i = (\bar{A}_i)^{e-s} x_s^i + \sum_{k=0}^{e-s-1} (\bar{A}_i)^{e-s-k-1} \bar{B}_i \begin{bmatrix} y_{s+k} \\ u_{s+k} \end{bmatrix} \tag{26}$$

and have

$$x_e^j = T_{ij} x_e^i \tag{27}$$

where T_{ij} is the similarity transformation matrix that brings the state vector of the local model-i into the common basis with the local model-j.

Once all starting and ending state variables corresponding to the transition between model-i and model-j are calculated, we can have:

$$[\,x_{e1}^j \quad x_{e2}^j \quad \cdots \quad x_{ek}^j\,] = T_{ij}\,[\,x_{e1}^i \quad x_{e2}^i \quad \cdots \quad x_{ek}^i\,] \tag{28}$$

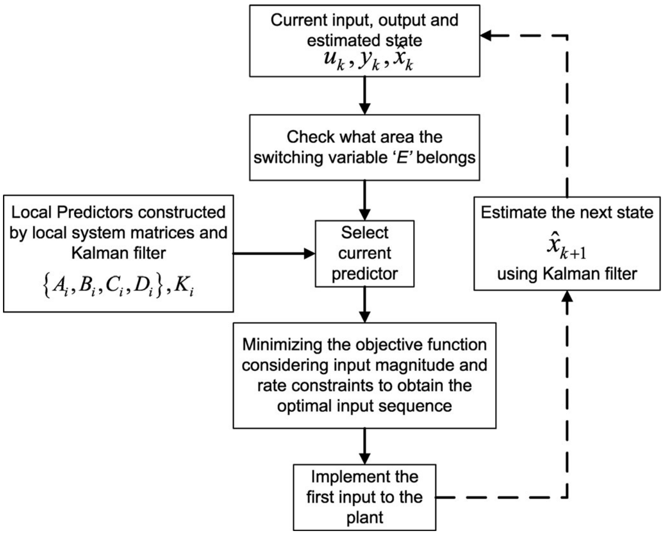

Fig. 1. Basic principle of the MMPC_S.

from which T_{ij} can be obtained and the system matrices of model-i are transformed by

$$A_i = T_{ij} A_i T_{ij}^{-1}, \;\; B_i = T_{ij} B_i, \;\; C_i = C_i T_{ij}^{-1}, \;\; K_i = T_{ij} K_i. \tag{29}$$

Following this procedure, we transfer model-1 (low load) and model-3 (high load) into model-2's (middle load) basis; then, by combining the local models, the resulting MMS can be used for approximating the behavior of nonlinear system and for controller design.

D. *Multimodel Predictive Control*

Based on the MMS developed for the boiler–turbine unit with the subspace approach, a multimodel predictive controller (MMPC_S) can be designed using the standard MPC technique, as shown in Fig. 1, with its basic working principle. The MMPC_S is tested and compared with an alternative approach in the next section, namely, the DDPC, which is a model-free controller.

IV. Data-Driven Direct Predictive Control of Boiler–Turbine Unit

With the multimodel obtained in the previous section, various advanced controllers can be designed for boiler–turbine control. However, (24) shows that by identifying the local subspace matrices L_w^i and L_u^i, a set of local predictors can be constructed directly from the input–output data without further developing the MMS, so that the intermediate modeling procedure for the MPC and the resulting modeling mismatch can be avoided. Thus, based on the multimodel and subspace idea, a *direct* predictive controller, rather than the *indirect*, i.e., the MPC, is developed in this section.

Consider the following objective function:

$$J = (\hat{y}_f - r_f)^T Q_f (\hat{y}_f - r_f) + \Delta u_f^T R_f \Delta u_f \tag{30}$$

where $Q_f = Q_f^T > 0$ and $R_f = R_f^T > 0$ are weighting matrices of output and input, respectively, and $r_f = \begin{bmatrix} r_{k+1}^T & r_{k+2}^T & \cdots & r_{k+N_y}^T \end{bmatrix}^T$ is the desired output trajectory.

Using the predictor [see (24)], the predictive output $\hat{y}_f = \begin{bmatrix} \hat{y}_{k+1}^T & \hat{y}_{k+2}^T & \cdots & \hat{y}_{k+N_y}^T \end{bmatrix}^T$ can be estimated by

$$\hat{y}_f = l_w w_p + l_u u_f \tag{31}$$

where $w_p = [\, y_{k-N+1}^T \;\; \ldots \;\; y_k^T \;\; u_{k-N+1}^T \;\; \cdots \;\; u_k^T \,]^T$ is the past output and input data, $u_f = [u_{k+1}^T \; u_{k+2}^T \; \cdots \; u_{k+N_u}^T]^T$ is the future control input, $l_w = \sum_{i=1}^{M} S_i(E_k) L_w^i(1 : lN_y, :)$, and $l_u = \sum_{i=1}^{M} S_i(E_k) L_u^i(1 : lN_y, 1 : mN_u)$ are prediction matrices, and N_y and N_u, with $N_y \geq N_u$, are, respectively, the prediction horizon and the control horizon.

A. *Integral Action for Offset Free Tracking*

In order to deal with the effect of unknown disturbances or identification mismatch, integral action is taken into account to achieve an offset free tracking performance.

To include an integral action, the noise input e_k in the state-space model [see (9)] is considered as an integrated noise, which is common in industrial processes [25]

$$e_k = e_{k-1} + a_k. \tag{32}$$

Using a difference operator $\Delta = 1 - z^{-1}$, (32) can be written as

$$e_k = \frac{a_k}{\Delta} \tag{33}$$

then (9) can be rewritten as

$$\begin{aligned} \Delta x_{k+1} &= A_i \Delta x_k + B_i \Delta u_k + K_i a_k \\ \Delta y_k &= C_i \Delta x_k + D_i \Delta u_k + a_k \end{aligned} \tag{34}$$

and following the same procedure, the prediction (31) is changed to

$$\Delta \hat{y}_f = l_w \Delta w_p + l_u \Delta u_f. \tag{35}$$

Thus, we can have

$$\hat{y}_f = \mathbf{y}_k + \zeta l_w \Delta w_p + \zeta l_u \Delta u_f \tag{36}$$

where $\mathbf{y}_k = [\, y_k^T \;\; y_k^T \;\; \cdots \;\; y_k^T \,]^T$ and

$$\zeta = \begin{bmatrix} I & 0 & \cdots & 0 \\ I & I & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ I & I & \cdots & I \end{bmatrix}.$$

The input magnitude constraint $(u_{\min}, u_{\max})$ as well as the input rate constraint $(\Delta u_{\min}, \Delta u_{\max})$ can be imposed as

$$\begin{bmatrix} I \\ I \\ \vdots \\ I \end{bmatrix} (u_{\min} - u_k) \leq \zeta \Delta u_f \leq \begin{bmatrix} I \\ I \\ \vdots \\ I \end{bmatrix} (u_{\max} - u_k) \tag{37}$$

$$\begin{bmatrix} I \\ I \\ \vdots \\ I \end{bmatrix} \Delta u_{\min} \leq \Delta u_f \leq \begin{bmatrix} I \\ I \\ \vdots \\ I \end{bmatrix} \Delta u_{\max}. \tag{38}$$

Substituting (36) into the objective function [see (30)], and at every sampling time, by minimizing (30) subject to (37) and (38), Δu_f can be calculated, and the value of u_{k+1} can be obtained and applied to the plant.

Remark 4.1: To simplify the calculation, we assume that the predictive matrices l_w, l_u are fixed over the prediction horizon N_y, which brings the optimal control sequence into a suboptimal one. This is commonly used in the literatures.

Remark 4.2: For both DDPC and MMPC in this paper, a simple hard switching is employed that directly selects the local predictor according to the switching variable. A satisfactory switching performance has been achieved due to the advantages of the proposed constrained predictive controller: 1) the boiler–turbine unit has very strict magnitude and rate constraints for the valves, which greatly limit the variations of the input signal, and the MPC can deal with these constraints in the controller design stage; 2) the DDPC proposed is an incremental type algorithm that calculates an incremental value of the input variable Δu_{k+1} based on the current input u_k, thus when a switching occurs, the variation of the manipulated variables can be relatively small; 3) by appropriately selecting the controller parameters Q_f, R_f, the variation of the input can be further constrained to achieve a smoother switching at the expense of tracking performance.

B. Online Update

For boiler–turbine plant, nonlinearity due to changing operating points and plant behavior variations (due to equipment wear, environment change, fuel variation, etc.) are two major issues. In this paper, the multimodel method is used to handle the first one, and the online update is developed for the DDPC to handle the second one.

Since we adopt the multimodel strategy, data classification is first needed according to the switching variable, which may result in nonconsecutive data. Thus, the requirement in Remark 3.1 needs to be checked before an update to see if the latest $2N$ data belongs to a region.

Consider a local predictor-i, for instance. Suppose the initial predictor is calculated using the data Hankel matrices (Y_i, U_i) composed of

$$Y_i = [\, Y_{i,1} \quad Y_{i,2} \quad \cdots \quad Y_{i,r} \,], \; U_i = [\, U_{i,1} \quad U_{i,2} \quad \cdots \quad U_{i,r} \,]$$

as in Section III; then, the procedure of update is given as follows:

Step 1: Check the switching variable E. If the current data (y_k, u_k) as well as the previous $(2N - 1)$ data all belong to model-i, go to Step 2; if not, save the current data and stop.

Step 2: If the previous $(2N–1)$ data are already used to construct the last local Hankel matrix block $Y_{i,r}, U_{i,r}$ for controller identification or update, add new data to $Y_{i,r}, U_{i,r}$. If not, build new local Hankel matrix blocks

$$\begin{aligned} Y_{i,r+1} &= [\, y_{k-2N+1}^T \quad y_{k-2N+2}^T \quad \cdots \quad y_k^T \,]^T \\ U_{i,r+1} &= [\, u_{k-2N+1}^T \quad u_{k-2N+2}^T \quad \cdots \quad u_k^T \,]^T . \end{aligned}$$

Step 3: Delete the oldest data that are in the first local Hankel matrix block $Y_{i,1}, U_{i,1}$. If the number of data left in $Y_{i,1}, U_{i,1}$ is less than $2N$, delete the whole block; if not, rebuild the local matrix using the left data.

Step 4: Combine all local Hankel matrix blocks to construct the new Y_i, U_i, perform the QR-decomposition to update the predictor-i.

Remark 4.3: Note that the unknown plant behavior variations may be significant and of various kinds; thus, it is difficult to prepare submodels or predictors for all cases. Moreover, the variations may exceed the preconfigured robustness bound of the MMS and degrade the control performance severely. Therefore, online update is an effective way to improve the performance in the case of significant unknown plant behavior variations.

Remark 4.4: Similar adaptive method can also be used for updating the MMS. However, the SVD takes much more computational time than the QR-decomposition, and thus, only the online update of the DDPC is considered in this paper.

C. Stability

Closed-loop stability in multimodel approaches has been well studied in [28], where the method of multiple Lyapunov functions has been utilized. Based on this theory, the stability analysis of the multimodel predictive control system is shown in [29], and in [10], a stable multimodel predictive controller is designed for the boiler–turbine unit.

The similar methods can also be used for the data-driven control, because the data subspace contains all the dynamics of the system. The basic idea of stability analysis for the direct use of data is given by [30] using the Lyapunov theory. These works can be extended to analyze the stability of the DDPC.

As a finite horizon predictive controller, the DDPC proposed in this paper cannot guarantee the stability even for the unconstrained linear time invariant (LTI) system and the stability depends on a good tuning of controller parameters, such as the weighting matrices Q_f, R_f and predictive and control horizons N_y, N_u.

However, considering the advantages of the DDPC, it is still a competitive controller for the boiler–turbine unit. How to develop a stable data-driven predictive controller for the boiler–turbine will be the future research.

V. Simulation Results

This section demonstrates the data-driven modeling strategy and predictive controller design for boiler–turbine unit using subspace identification and multimodel method. The accuracy of the MMS is demonstrated first, and then the proposed controllers, the MMS-based MPC and DDPC, are tested and compared with other types of predictive controllers.

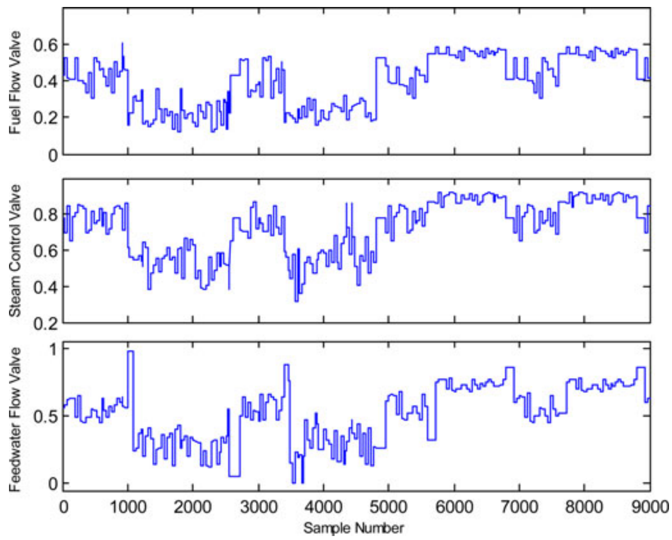

Fig. 2. Input signals used in the multimodel subspace identification method.

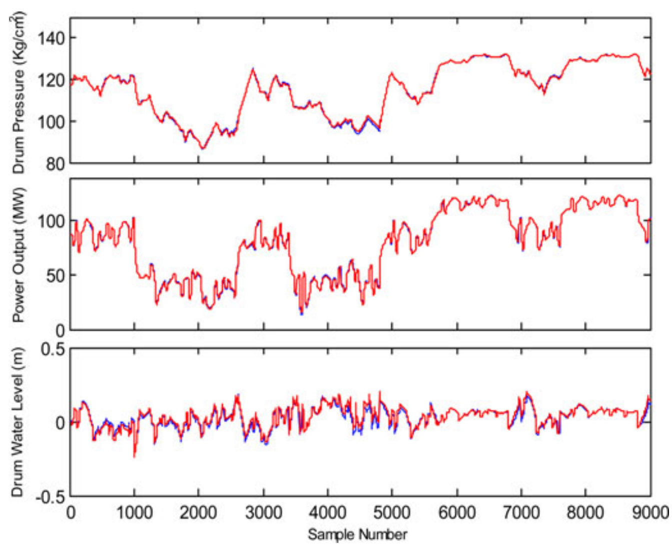

Fig. 3. Estimated and real outputs of boiler–turbine system (solid line: estimated outputs; dotted line: real outputs).

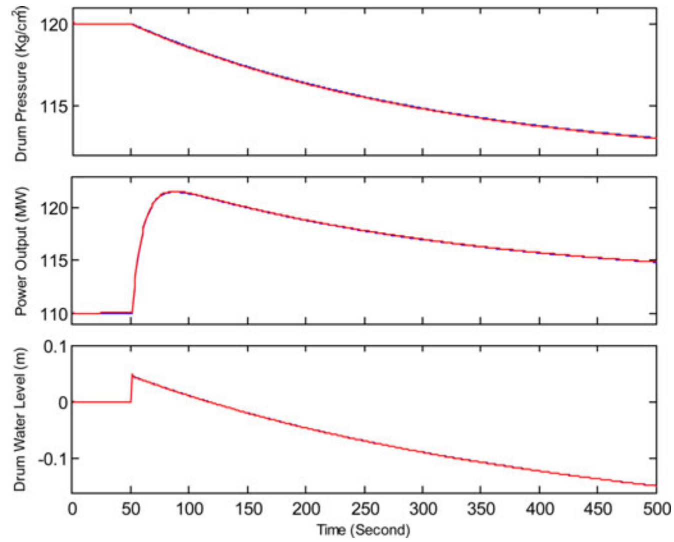

Fig. 4. Outputs of Case 1 (solid line: estimated outputs; dotted line: real outputs).

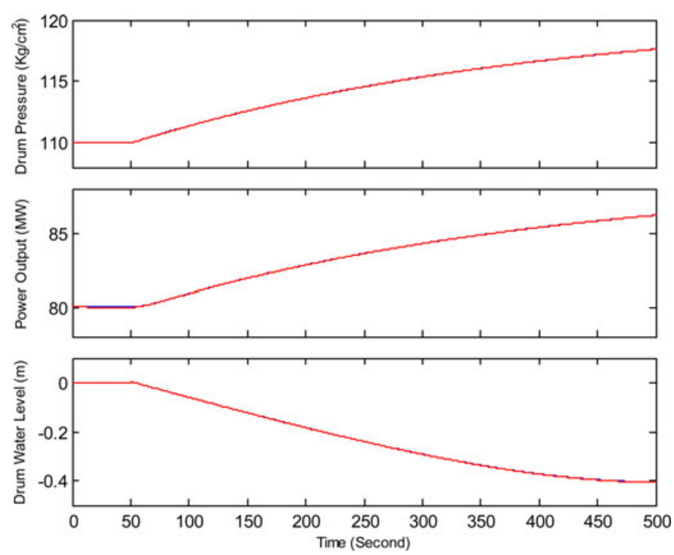

Fig. 5. Outputs of Case 2 (solid line: estimated outputs; dotted line: real outputs).

A. *Verification of MMS*

In this paper, the power output E is chosen as the switching variable, and the system is divided into three different operating regions as shown in Section II.

The input signals we used to generate data are shown in Fig. 2. Since the power output has a fast response to the variation of steam control valve, the sampling time is selected as 1 s and the identified model outputs are shown in Fig. 3 with parameter $N = 10$. From the comparison with plant outputs, the effectiveness of the proposed identification strategy is clearly demonstrated. The identified system matrices and Kalman gains for the MMS are given in the Appendix.

A single linear model developed by the SID method using the same data is also tried for comparison; however, due to the high nonlinearity of the boiler–turbine unit, it leads to a nonconvergence result.

Then, we test the predictive model through the following three step-response experiments:

Case 1: Increase the steam control valve u_2 in step from 0.9094 to 0.9894 while at the $(P, E, L) = (120, 110, 0)$ operating point.

Case 2: Decrease the feedwater flow valve u_3 in step from 0.5149 to 0.3149 while at the (110, 80, 0) operating point.

Case 3: Decrease the fuel flow control valve u_1 in step from 0.3085 to 0.1085 while at the (100, 60, 0) operating point.

From the simulation results shown in Figs. 4–6, we can find that the proposed predictive model has satisfactory approximation accuracy. Figures also show the behavior of the boiler–turbine unit, which can guide us in controller design:

1) Steam control valve can quickly change the power output; however, since the fuel entering into the unit does not change, the power output will return to the previous level

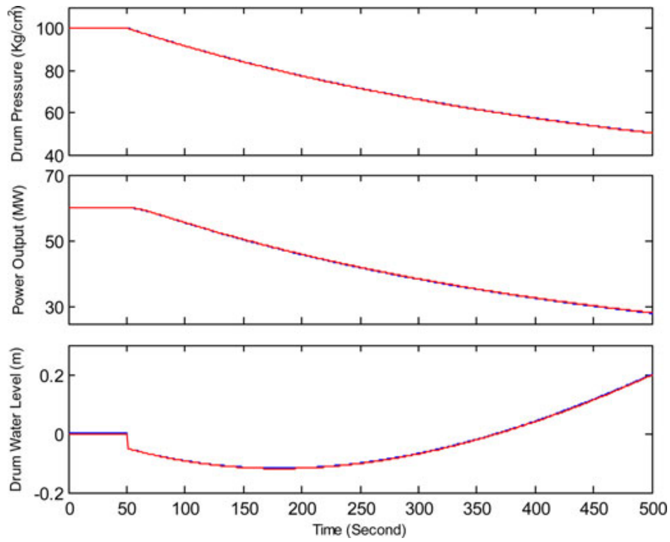

Fig. 6. Outputs of Case 3 (solid line: estimated outputs; dotted line: real outputs).

after a while, and what changed is the stored thermal energy in the drum, represented as "drum pressure."

2) Fuel flow valve can change the power output and drum pressure ultimately; however, this influence has the characteristics of a large inertia.
3) The drum water level has an obvious "shrink and swell" characteristic.

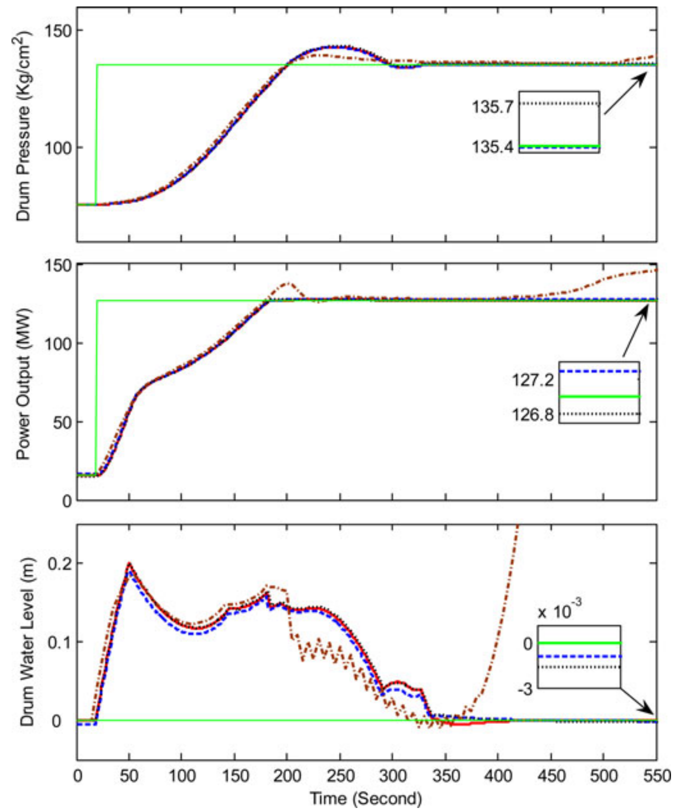

Fig. 7. Performance of the boiler-turbine unit in the CCS mode: Output Variables (solid: DDPC_IO; dotted: MMPC_S; dashed: MMPC_T; dotted-dashed: DMC; solid light: reference).

B. Testing of Predictive Controllers

The designers of this boiler–turbine unit model provide seven typical operating points along the operation range, as shown in Table I. To cover this wide range of operation, a transition from the lowest load point to the highest is considered. Such a wide range operation is achieved by the use of three local predictive controllers to overcome the significant nonlinearity.

Two commonly used operating modes in modern power plant, coordinated control scheme (CCS) mode and automatic generation control (AGC) mode, are considered in the comparison study:

1) CCS Mode: In the CCS mode, the demands of the power plant are given by operators. The control mission is tracking the expected operating points of drum pressure and output power while maintaining the drum water level constant.

First, an operating point change from (75.6, 15.27, 0) to (135.4, 127, 0) is considered, three different multimodel predictive controllers and a single linear model predictive controller are tested for comparison:

1) Data-driven direct predictive controller with integral action and online update (DDPC_IO) proposed in Section IV. A total of 2000 data are used to identify three local predictors as initial ones.
2) MPC based on the MMS model developed using the subspace method in Section III (MMPC_S).
3) MPC based on the multiple state-space models derived from the Taylor series approximation of the nonlinear model (MMPC_T): The models are derived at three operating points (86.4, 36.65, 0), (118.8, 85.06, 0), and (135.4, 127, 0) to represent the dynamics of low, middle, and high operation regions, respectively.
4) Dynamic matrix controller (DMC) using the step response model developed based on the test data around the operating point (108, 66.65, 0) [3]. This point is in the middle of the whole operation range; thus, it is adopted here to develop a model for this single linear model-based controller.

For all three multimodel based controllers, the sampling time is set as 1 s and a prediction horizon $N_y = 10$ s and control horizon $N_u = 10$ s are adopted. For the linear DMC, the predictive and control horizons are set as $N_y = N_u = 600$ s with sampling time being set as 5 s. The weighting diagonal matrices Q_f, R_f for all four controllers are given as: $Q_f = I_{N_y} \otimes Q, R_f = I_{N_u} \otimes R$, with diagonal elements

$$Q = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 10 \end{bmatrix}, \quad R = \begin{bmatrix} 2 & 0 & 0 \\ 0 & 80 & 0 \\ 0 & 0 & 0.2 \end{bmatrix}$$

and $\otimes$ presents the Kronecker product.

The simulation results in Figs. 7 and 8 show that three multimodel-based predictive controllers have satisfactory performance while the DMC has failed in the wide range operation. The reason is that the step response model built around one point

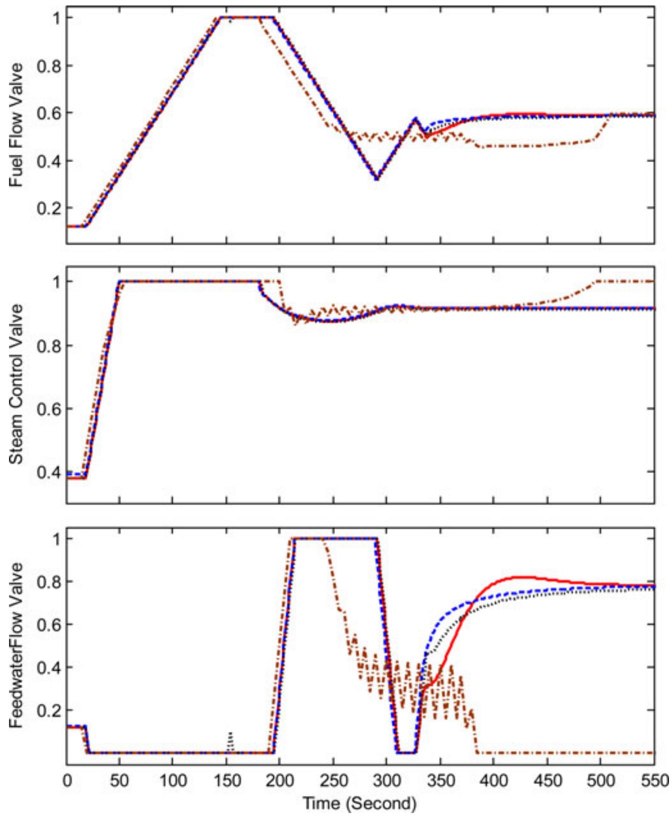

Fig. 8. Performance of the boiler-turbine unit in the CCS mode: manipulated variables (solid: DDPC_IO; dotted: MMPC_S; dashed: MMPC_T; dotted-dashed: DMC).

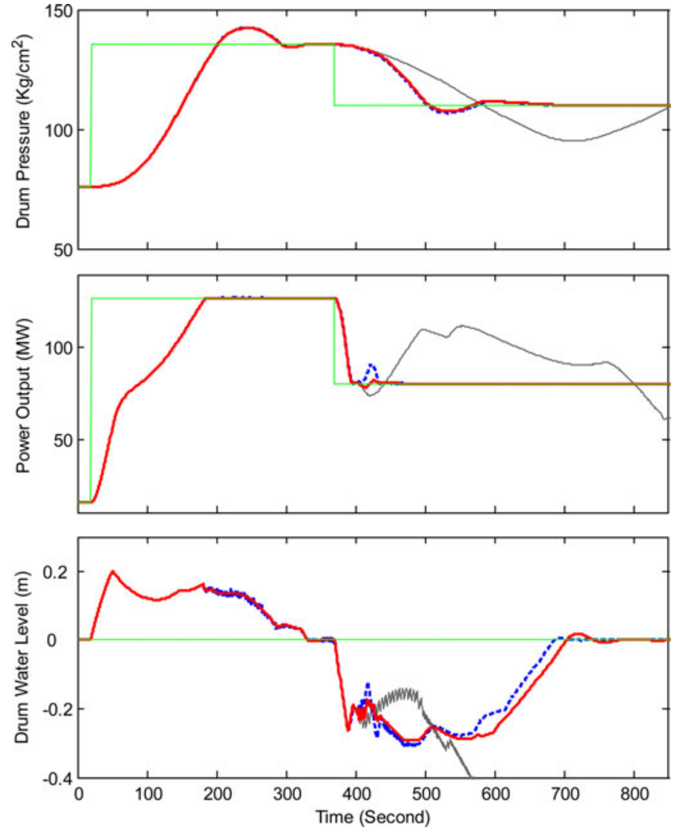

Fig. 9. Performance of the boiler-turbine unit with parameter changes at $t = 400$ s in the CCS mode: output variables (solid: DDPC_IO; solid light: DDPC_I; dashed: single linear_DDPC_IO; dotted: reference).

is not enough to capture the nonlinear behavior of the unit in the full operating range.

Predictor switching occurs at $t_1 = 58$ s (low-middle) and $t_2 = 152$ s (middle-high) for DDPC_IO and MMPC_S, and $t_1 = 57$ s (low-middle) and $t_2 = 152$ s (middle-high) for MMPC_T, and smooth switching performance is achieved in output variables.

The three multimodel-based controllers have almost the same performance. However, in MMPC_S, additional computation for SVD as well as system matrix estimation and transformation are needed. In MMPC_T, the exact analytical model of power plant is required first to build a Taylor series approximation model, which greatly limits its application; moreover, affine terms exist in the state-space model [8], [9], increasing the controller design complexity and computational burden.

Due to the unavoidable modeling mismatch, we can also observe tracking offset in MMPC_S and MMPC_T, when integral action is not included.

Note that the QP-based predictive controller and QR-decomposition-based online update are both computationally efficient. For the DDPC_IO, controller calculation takes 0.1211 s and the predictor update takes 0.03285 s for each step during the simulation. (MATLAB R2006a is used on our PC: 2.00 GHz Core-i7 CPU, 8 G memory).

To further illustrate the effect of multimodel strategy and online update, data-driven predictive controller without online-update (DDPC_I) and a single linear data-driven predictive controller with online update (single linear_DDPC_IO) are compared with the DDPC_IO. A wide range operating point change from (75.6, 15.27, 0) to (135.4, 127, 0) and then to (110, 80, 0) is considered, and a significant unknown plant variation is assumed such that from $t = 400$ s, all parameters in the models (1)–(3) change to their 80% level. The simulation results are shown in Figs. 9 and 10.

The results demonstrate a significant advantage and effectiveness of the proposed DDPC_IO, which can handle both issues of operating point changes and considerable unknown plant variations. Under the same multimodel configuration, a satisfactory transition performance is attained for the DDPC_I in the nominal case. However, it cannot handle the effect of significant unknown plant variations, making the controller fail after $t = 400$ s. For the single linear_DDPC_IO, predictor identified at low-load region is employed as the initial one. During the operating point change, since the new data obtained are not sufficient to capture the dynamics of current region in time, the system keeps oscillating during the transition and bigger bump is observed when considerable plant behavior variation occurs.

2) AGC Mode: In AGC mode, the boiler–turbine unit follows the load demand from the grid that is given by the automatic dispatch system (ADS) and generally requires that the power plant tracks the load demand rapidly. We also consider the load following over a wide range of operation: the power demand rises from 15.27 to 127 MW in the rate of 0.7449 MW/s, while the pressure demand rises from 75.6 to 130 kg/cm^2 at the

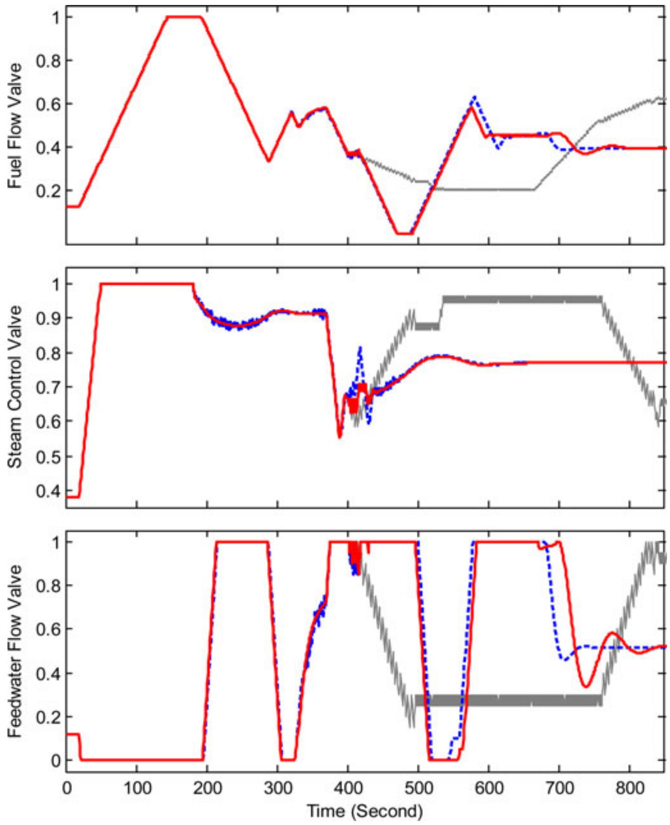

Fig. 10. Performance of the boiler-turbine unit with parameter changes at $t = 400$ s in the CCS mode: manipulated variables (solid: DDPC_IO; solid light: DDPC_I; dashed: single linear_DDPC_IO).

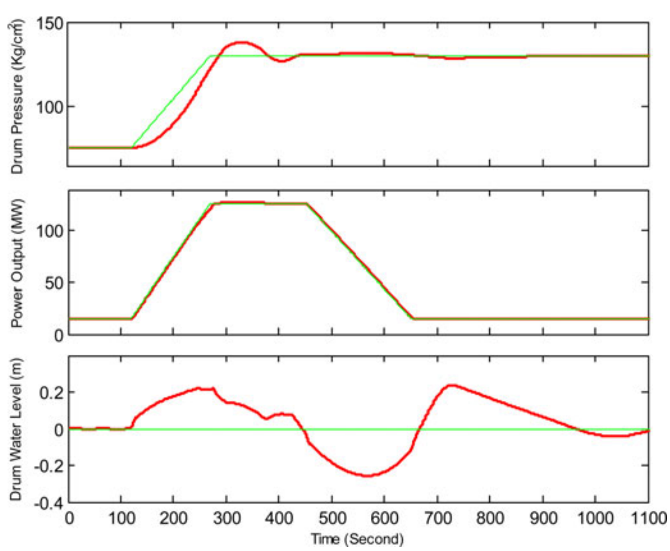

Fig. 11. Performance of the boiler–turbine unit in AGC mode: output variables (solid: DDPC_IO; dotted: reference).

rate of 0.3627 kg/(cm^2·s) first, then a "constant pressure" operation mode is considered while the power demand decreases to 15.27 MW at the rate of 0.5587 MW/s. The simulation results in Figs. 11 and 12 show that in a wide operating range, the proposed DDPC_IO has a very good performance, which drives the plant to follow the load demand very closely.

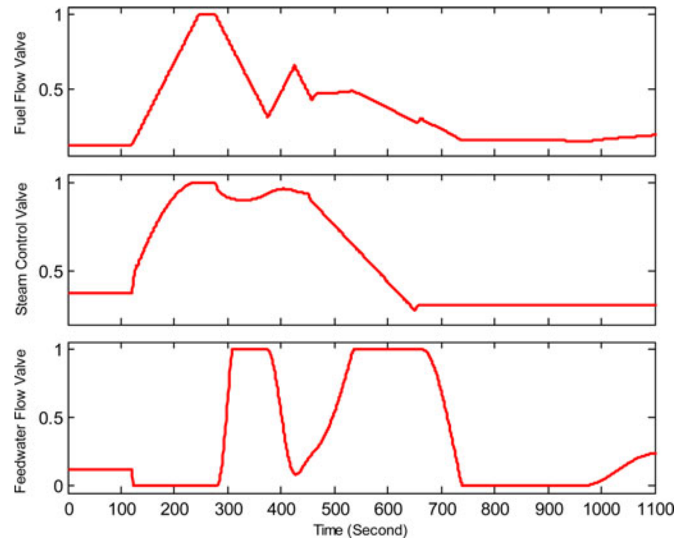

Fig. 12. Performance of the boiler–turbine unit in AGC mode: manipulated variables (solid: DDPC_IO).

VI. Conclusion

In order to solve the problem of modeling and control of a highly nonlinear boiler–turbine unit, a new data-driven modeling and predictive control strategy is proposed using subspace and multimodel method. The MMS has a good approximation accuracy of the boiler–turbine unit and is suitable for advanced controller design, resulting in a MMS-based predictive controller. Following the multimodel and subspace method, a direct data-driven predictive controller is proposed as an alternative method, which can achieve a wide range offset-free tracking control while dealing with the input constraints. An online update strategy is proposed on the multimodel to further increase the robustness of the system, and thus both the wide range transition and severe unknown plant behavior variation issues can be solved simultaneously. Due to their data-driven nature, the proposed modeling and control method are flexible and can easily be adapted to other types of systems without knowing mathematical models of the plant.

Appendix
Local State-Space Models for the MMS

$$A_1 = \begin{bmatrix} 0.7740 & 0.5150 & 0.0768 & 0.1827 \\ -0.1176 & 1.2681 & 0.0401 & 0.0950 \\ 0.2715 & -0.6353 & 0.9185 & -0.2201 \\ 0.0716 & -0.1628 & -0.0255 & 0.9423 \end{bmatrix}$$

$$B_1 = \begin{bmatrix} -0.5793 & -4.9414 & 0.1133 \\ -0.2278 & -2.5868 & 0.0254 \\ -0.4848 & 5.3330 & 0.0441 \\ 0.0155 & 1.6438 & 0.0590 \end{bmatrix}$$

$$A_2 = \begin{bmatrix} 1.0004 & -0.0007 & -0.0063 & 0.0000 \\ -0.0247 & 0.9683 & 0.1460 & 0.0011 \\ 0.0109 & 0.0128 & 0.9329 & -0.0013 \\ 0.0004 & 0.0008 & -0.0020 & 0.9995 \end{bmatrix}$$

$$B_2 = \begin{bmatrix} -0.5977 & 0.4526 & 0.1015 \\ -0.2863 & -8.7254 & 0.0087 \\ -0.3867 & 4.0809 & 0.0909 \\ 0.0274 & 0.0983 & 0.0502 \end{bmatrix}$$

$$A_3 = \begin{bmatrix} 0.9962 & -0.0421 & 0.0933 & -0.0152 \\ -0.0051 & 0.9626 & 0.0938 & -0.0126 \\ 0.0059 & 0.0150 & 0.9400 & 0.0036 \\ -0.0003 & 0.0065 & -0.0100 & 1.0023 \end{bmatrix}$$

$$B_3 = \begin{bmatrix} -0.7064 & -5.6263 & 0.1223 \\ -0.2967 & -5.6189 & 0.0190 \\ -0.4021 & 3.5415 & 0.0700 \\ 0.0770 & 0.6135 & 0.0473 \end{bmatrix}$$

$$C_1 = \begin{bmatrix} -30.1969 & 73.5549 & 0.4119 & 23.4449 \\ 15.4142 & -41.0206 & 0.6268 & -12.7787 \\ -0.4873 & 1.2606 & -0.0024 & 0.5219 \end{bmatrix}$$

$$D_1 = \begin{bmatrix} -0.0001 & -0.0010 & -0.0001 \\ -0.0176 & 0.0235 & 0.0028 \\ 0.2491 & 0.4716 & -0.0148 \end{bmatrix}$$

$$C_2 = \begin{bmatrix} -1.4408 & -0.0540 & -0.0517 & 0.0002 \\ -0.0853 & -1.3452 & 0.8404 & 0.0067 \\ 0.0067 & -0.0045 & -0.0156 & 0.1274 \end{bmatrix}$$

$$D_2 = \begin{bmatrix} 0.0000 & -0.0001 & 0.0002 \\ 0.0051 & 0.0013 & -0.0021 \\ 0.2565 & 0.5681 & -0.0116 \end{bmatrix}$$

$$C_3 = \begin{bmatrix} -7.4787 & 10.7703 & 4.0773 & 5.8199 \\ 3.8801 & -8.4273 & -1.7844 & -4.2661 \\ 0.0089 & -0.0080 & -0.0157 & 0.0846 \end{bmatrix}$$

$$D_3 = \begin{bmatrix} -0.0003 & 0.0001 & 0.0001 \\ 0.0171 & 0.0002 & -0.0045 \\ 0.2585 & 0.6174 & -0.0137 \end{bmatrix}$$

$$K_1 = \begin{bmatrix} -0.3182 & -0.5327 & 1.5916 \\ -0.0985 & -0.2639 & -1.8575 \\ 0.0444 & 0.0795 & -0.5331 \\ -0.0589 & 0.1404 & 7.8867 \end{bmatrix}$$

$$K_2 = \begin{bmatrix} -0.6941 & 0.0213 & 0.0590 \\ 0.0354 & -0.6149 & -0.6252 \\ -0.0260 & 0.0109 & -0.8756 \\ 0.0345 & -0.0212 & 7.7132 \end{bmatrix}$$

$$K_3 = \begin{bmatrix} -0.3224 & -0.4226 & -0.2707 \\ -0.1517 & -0.3019 & -5.0615 \\ 0.0217 & -0.0003 & -2.6495 \\ 0.0240 & 0.0162 & 10.8760 \end{bmatrix}.$$

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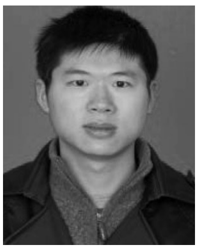

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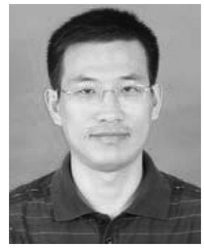

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