ISA Transactions 53 (2014) 699–708

Contents lists available at ScienceDirect

ISA Transactions

journal homepage: www.elsevier.com/locate/isatrans

Data-driven modeling and predictive control for boiler–turbine unit using fuzzy clustering and subspace methods

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ARTICLE INFO

Article history:
Received 3 August 2013
Received in revised form
28 October 2013
Accepted 26 December 2013
Available online 20 February 2014
This paper was recommended for publication by Rickey Dubay

Keywords:
Boiler–turbine unit
Data-driven modeling and control
Subspace identification
Fuzzy model
Predictive control
Fuzzy clustering

ABSTRACT

This paper develops a novel data-driven fuzzy modeling strategy and predictive controller for boiler–turbine unit using fuzzy clustering and subspace identification (SID) methods. To deal with the nonlinear behavior of boiler–turbine unit, fuzzy clustering is used to provide an appropriate division of the operation region and develop the structure of the fuzzy model. Then by combining the input data with the corresponding fuzzy membership functions, the SID method is extended to extract the local state-space model parameters. Owing to the advantages of the both methods, the resulting fuzzy model can represent the boiler–turbine unit very closely, and a fuzzy model predictive controller is designed based on this model. As an alternative approach, a direct data-driven fuzzy predictive control is also developed following the same clustering and subspace methods, where intermediate subspace matrices developed during the identification procedure are utilized directly as the predictor. Simulation results show the advantages and effectiveness of the proposed approach.

1. Introduction

Boiler–turbine unit is an essential device in modern fossil-fuel-fired power plants which converts the chemical energy in fuel into mechanical energy and then into electrical energy. 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 pressure and water level in drum within given tolerances.

As the power plants increase in size and participate in grid power regulation more frequently, the control of boiler–turbine unit has been shown to be a challenge, due to the severe nonlinearity in multitude of variables over a wide operation range, tight operating constraints and large inertia behavior. Therefore, it is necessary to design advanced controllers to improve the performance of the boiler–turbine control system for economic and safe plant operation.

As a direct approach to improve the conventional PI/PID controller, auto-tuning of the PID parameters is studied in [1–3] utilizing the fuzzy logic, particle swarm optimization (PSO) and iterative feedback tuning (IFT). In [4,5], $H\infty$ controllers are proposed to enhance the robustness of boiler–turbine control system. To overcome the nonlinearity of the boiler–turbine unit, various artificial intelligence techniques have also been applied. In [6], a fuzzy auto-regressive moving average (FARMA) controller was applied to the boiler–turbine system with rules generated by using the history of input–output data. In [7], a linear quadratic regulator (LQR) controller is designed for a boiler–turbine through genetic algorithm. However, none of these controllers have dealt with the input constraints in the controller design stage; therefore, predictive controllers have been employed in recent years [8–16].

Under traditional design frameworks, predictive controller is known as the model predictive controller (MPC), where modeling is the first and foremost important step, and the controller's performance is greatly relying on the structure, accuracy and complexity of the model. In [8], a dynamic matrix controller (DMC) is employed for the boiler–turbine. It shows that the step-response model based on the test data is better than the linearized model, but the performance of the proposed linear controller is degraded for a wide-range operation. In [9,10], nonlinear predictive controllers are designed based on neural network model, neuro-fuzzy network and input–output feedback linearization. Although the control performance is improved, nonlinear optimization is time consuming and lacks robustness.

To overcome these issues the fuzzy modeling technique [17], which uses a fuzzy combination of several linear models to approximate the nonlinear behavior of the plant, has been used in the MPC design for boiler–turbine unit [11–14]. This showed better performance than the conventional predictive methods for a wide-range operation.

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http://dx.doi.org/10.1016/j.isatra.2013.12.033

Although different kinds of objective functions and computational tools such as quadratic programming [11], linear matrix inequalities [12], genetic algorithm [13,14] are adopted in these papers, it is common that, linear state-space models are used as local models in all these fuzzy MPCs because of the advances in multi-variable systems and control theory for linear systems. In these works, an approximation or transformation of the nonlinear system has been used to obtain the linear state-space model. However, for complex systems such as boiler–turbine unit, it is difficult to develop an accurate mathematical 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. Furthermore, except the reference [13], the structure of the fuzzy model is designed by simply dividing the operation range evenly, which would not guarantee the accuracy of the model.

Given these reasons, the first objective of this paper is to develop a fuzzy model for the nonlinear boiler–turbine unit when only the input–output data are available as opposed to mathematical model. Unlike the ordinary approach, we propose a novel method using fuzzy clustering [18] and subspace identification (SID) [19–21]. The clustering is used to develop the structure of the fuzzy system, and then by combining the data with the membership functions, the standard SID is extended to develop all local state-space models together at once. The resulting fuzzy model is shown to represent the boiler–turbine unit very closely, and thus used in designing the fuzzy MPC.

In spite of the effectiveness of the MPC in general, both the control performance and computational burden of the MPC heavily depend on the prediction model, which has become the “Achilles heel” of the MPC. To alleviate this problem, data-driven predictive controllers are proposed in [22] based on the SID. However, due to the fact that the SID works only for linear system identification, its application has been limited to linear systems or to a small operating region of a plant.

In the context of the fuzzy clustering and subspace identification, a new approach, data-driven fuzzy predictive controller (DDFPC), is developed in this paper. The input–output data of the plant, which would contain much richer information than the mathematical model, are directly used to build the fuzzy predictor. This also avoids the intermediate modeling procedure and eliminates the effect of modeling mismatch.

This paper is an extension of a previous work [15], in which the whole operating region is first divided by using a nonlinear analysis tool (Vinnicombe gap metric, to be specific [23]), and the corresponding data for each region are collected to identify the local model or its predictor. Compared with the method in [15], the proposed method has the following advantages (1) the fuzzy model structure and local model/predictor identification are strongly linked, thus, the integral fuzzy modeling procedure is simple and direct; (2) division of the whole operation range is determined by the clustering, thus less human intervention is needed; (3) it is more efficient since all local models can be identified together at once; (4) the resulting fuzzy controller has smooth transition between local predictors, thus provides bumpless control.

The remainder of this paper is organized as follows: Section 2 describes the boiler–turbine unit. Section 3 establishes the TS-fuzzy model of the boiler–turbine unit using fuzzy clustering and subspace identification. The DDFPC is developed in Section 4 and simulation results are given in Section 5. Finally, some conclusions are drawn in Section 6.

2. System description

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 [24] using both physical and empirical methods as shown below

Table 1
Typical operating points of the boiler–turbine unit.

	#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

$$\frac{dP}{dt} = 0.9u_1 - 0.0018u_2P^{9/8} - 0.15u_3 \tag{1}$$

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

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

where P denotes drum steam pressure (kg/cm^2), E denotes power output (MW), and ρ_f denotes steam-water density (kg/cm^3). Manipulated (input) variables of 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.

The output variables of the system is the drum pressure P (kg/cm^2), power output E (MW) and drum water level L (m). Using the solution for ρ_f, the drum water level L 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 kg/s.

Typical operating points of the boiler–turbine unit are tabulated in Table 1.

The boiler–turbine model has been investigated by many researchers for modeling and control [5–8,10–16,25], and has shown to exhibit severe nonlinearity along the whole operation range, especially in the high power region [13,5,25]. Therefore, fuzzy technique is proposed in this paper to address the nonlinearity for the modeling and control problems.

3. Data-driven fuzzy modeling of boiler-turbine unit

The following discrete fuzzy model can be used to present the boiler-turbine unit with both fuzzy inference rules and local state-space models:

$$R^i: IF \varphi_k \in M_i, \text{THEN}:$$
$$\begin{cases} x_{k+1} = A_i x_k + B_i u_k + K_i e_k \\ y_k = C_i x_k + D_i u_k + e_k, \ i = 1, 2 \ldots L \end{cases} \tag{8}$$

where R^i denotes the i-th fuzzy inference rule, L the number of fuzzy rules, M_i the fuzzy sets, $x_k \in \mathfrak{R}^n$ the state vector, $u_k \in \mathfrak{R}^m$ the control input vector, $y_k \in \Re^p$ the output vector, $e_k \in \Re^p$ the zero mean white innovation vector. The matrices A_i, B_i, C_i, D_i, K_i are local systems and observer matrices, and φ_k is the antecedent vector of the fuzzy model, which is also the clustering input, composed by current and past measurable variables of the plant.

Let ω_k^i be the normalized membership function of the fuzzy set M_i, then the fuzzy model (8) can be expressed in the global form

$$\begin{cases} x_{k+1} = A_\omega x_k + B_\omega u_k + K_\omega e_k \\ y_k = C_\omega x_k + D_\omega u_k + e_k \end{cases} \tag{9}$$

where $A_\omega = \sum_{i=1}^{L} \omega_k^i A_i$, $\omega_k^i \in [0,1]$, $\sum_{i=1}^{L} \omega_k^i = 1$, and all other matrices are defined in the same way.

Modeling of fuzzy system consists of two parts: the *premise* (structure) design and the *consequence* (local model parameters) design. In this section, we first use the fuzzy clustering to determine the structure of the fuzzy model, i.e., the number of the local models L, and the membership functions ω^i, and then the SID is used to determine the model parameters $\{A_i, B_i, C_i, D_i, K_i\}$ through the input/output data of the plant and the corresponding membership functions.

3.1. Premise design using fuzzy clustering

Clustering has been widely accepted as an effective method for designing the premise part of the fuzzy model. It classifies the data according to similarities and organizes the data into groups or clusters. The number of clusters is corresponding to the number of local models and the clustering centers can be used to calculate the membership functions. A satisfactory clustering can provide an appropriate structure design for the fuzzy model without much experience on, or nonlinear analysis of, the plant.

Before performing the clustering, it is important to select the clustering input vector φ_k. For the boiler-turbine unit, because the dynamics are greatly relying on the power level, drum pressure and water level as well as the valve positions, the clustering input is chosen as: $\varphi_k = [P_{k-1}, E_{k-1}, L_{k-1}, u_{1,k-1}, u_{2,k-1}, u_{3,k-1}]$ in this paper. Thus, the data set for clustering, $\overline{X}$, can be constructed as: $\overline{X} = \{X_k | k = 1, 2, ..., \mathrm{N}\}$ with the k-th sample $X_k = [\varphi_k, P_k, E_k, L_k]^T$, where N is the number of the samples. The goal of clustering is then to find L clustering centers V_i, $i=1, 2,\dots, L$, such that some measure of the distance between all samples X_k and the cluster centers V_i is minimum.

Among various clustering method, the Gaustafson–Kessel (G–K) clustering algorithm has been widely used recently. Based on the "covariance matrix weighted distance", the G–K clustering can perform the clustering for both the ellipsoidal and linear distributed data, thus, it is consistent with the "local linearization" idea of fuzzy modeling and provide a better modeling result compared with other clustering methods. Considering its distinct features, such as local adaptation of the distance metric to the shape of the cluster and relative insensitivity to the data scaling and initialization of the partition matrix, a modified G–K clustering algorithm [18] is employed in this paper.

The G–K clustering algorithm is an objective function-based clustering, which tries to find L clustering centers V_i, $i=1, 2,\dots, L$, and the partition matrix $U = [\mu_{ik}] \in [0,1]_{L\times \mathrm{N}}$ from the data set $\overline{X}$, such that the following objective function is minimal:

$$J(\overline{X}; U, V, A) = \sum_{i=1}^{L} \sum_{k=1}^{\mathrm{N}} (\mu_{ik})^m D_{ikA_i}^2 \tag{10}$$

where μ_{ik} is the value of the membership function of the k-th sample for the i-th fuzzy set in the data set $\overline{X}$, $m \in [1, \infty]$ is a scalar parameter which determines the fuzziness of the resulting clusters, generally set to $m=2$, and D_{ikA_i} denotes the distance between a sample X_k and a cluster center V_i, which also determines the geometrical shapes of the clustering:

$$D_{ikA_i}^2 = (X_k - V_i)^T A_i (X_k - V_i) \tag{11}$$

in which the positive definite matrix A_i is obtained by

$$A_i = [\rho_i det(F_i)]^{1/\mathrm{N}} F_i^{-1}$$
$$F_i = \frac{\sum_{k=1}^{\mathrm{N}} (\mu_{ik})^m (X_k - V_i)(X_k - V_i)^T}{\sum_{k=1}^{\mathrm{N}} (\mu_{ik})^m} \tag{12}$$

As a nonlinear optimization problem, the analytic solutions of the G–K clustering is difficult to obtain; thus an iterative method is widely used to minimize the objective function, which calculates the cluster centers at the l-th iteration by

$$V_i^{(l)} = \frac{\sum_{k=1}^{\mathrm{N}} (\mu_{ik}^{(l-1)})^m X_k}{\sum_{k=1}^{\mathrm{N}} (\mu_{ik}^{(l-1)})^m} \tag{13}$$

Then the fuzzy covariance matrix F_i and the distance value D_{ikA_i} can be updated through (12) and (11), and the partition matrix can be determined by

$$\mu_{ik}^{(l)} = \frac{1}{\sum_{j=1}^{L} (D_{ikA_i}/D_{jkA_j})^{2/(m-1)}} \tag{14}$$

until $\|U^{(l)} - U^{(l-1)}\| \le \varepsilon$, which is the termination tolerance. The detailed algorithm can be found in [18].

Once the L clustering centers V_i, $i=1, 2,\dots, L$ are obtained, we extract the input centers V_i^φ from them, which are set as the centers of the fuzzy set M_i. Then, for a given input vector φ_k, a Gaussian-type membership function can be calculated through V_i^φ:

$$w_k^i = \exp\left[-\left(\frac{\|\varphi_k - V_i^\varphi\|}{\sigma^i}\right)^2\right] \tag{15}$$

where σ^i is the width of the membership function:

$$\sigma^i = \frac{1}{\beta}\left[\frac{1}{j}\sum_{l=1}^{j} \|V_i - V_l\|\right] \tag{16}$$

with V_l, $l=1,2,\dots, j$, being the j closest centers to the center V_i. We set $j=1$ and $\beta=4$ in this paper and the normalized membership function can be calculated by

$$\omega_k^i = \frac{w_k^i}{\sum_{i=1}^{L} w_k^i} \tag{17}$$

Therefore, we have now successfully developed the premise part of the fuzzy model.

3.2. Consequence design using subspace identification

Considering the global fuzzy model (9), the problem left can now be formulated as: given the input sequence u_k, output sequence y_k and their corresponding membership functions ω_k over a time $k=1,2,\dots,\mathrm{N}$, find the state-space and the observer matrices A_i, B_i, C_i, D_i, and K_i.

Subspace identification (SID) method provides an effective way to develop the state-space model directly from the input–output data of the plant [19–21]. Based on computational tools such as QR factorization and singular value decomposition (SVD), the SID extracts the model from the subspaces of data Hankel matrices. Comparing with the conventional identification methods, the SID has several distinct advantages, such as (1) computationally efficient, especially for multivariable systems; (2) avoid local minima and convergence problems; (3) no requirement for initial conditions; and (4) the system order can be easily chosen. However, since the SID is only for linear system modeling, most of its applications have been 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.

In the previous section, although the nonlinear modeling has been handled by the fuzzy clustering, the resulting model (9) is dependent on the fuzzy membership functions, which means the global system matrices will be different for different operating point at each time step. This will make the data matrices involved in the SID grow exponentially with the size of the prediction time and the number of local models [26,27], and make it difficult to implement. To handle this problem, a simplifying assumption is made that only the input matrices B_i and D_i are dependent on the membership functions, and all other matrices except these two, i.e., A, C, K, are assumed to be independent of the membership functions (e.g., $A_i=A_j=A$, $i, j=1, 2,\ldots, L$). Under this assumption, the input data can be combined with the membership functions, before using the SID. An approximate fuzzy model is then defined as following:

$$\begin{cases} x_{k+1}=Ax_k+B_\omega u_k+Ke_k \\ y_k=Cx_k+D_\omega u_k+e_k \end{cases} \tag{18}$$

Here that $B_\omega u_k=\sum_{i=1}^{L}\omega_k^i B_i u_k=B[\omega_k\otimes u_k]$ and $D_\omega u_k=\sum_{i=1}^{L}\omega_k^i D_i u_k=D[\omega_k\otimes u_k]$, where $B=[B_1B_2\cdots B_L]$ and $D=[D_1D_2\cdots D_L]$, the membership function vector $\omega_k=[\omega_k^1\omega_k^2\ldots\omega_k^L]^T$, and $\otimes$ presents the Kronecker product. Model (18) can be rewritten as

$$\begin{cases} x_{k+1}=Ax_k+\mathrm{B}\mathrm{u}_k+Ke_k \\ y_k=Cx_k+\mathrm{D}\mathrm{u}_k+e_k \end{cases} \tag{19}$$

where $\mathrm{u}_k\equiv\omega_k\otimes u_k$ is the *mixed* input resulting from the fuzzy membership functions.

Therefore, by combining the input data with their corresponding membership functions, the SID can be extended to find the consequence of the fuzzy model. The resulting fuzzy model can be used for approximating the behavior of nonlinear system and for controller design. The algorithm of the SID is summarized in the next section.

Remark 3.1. This simplification brings a significant advantage for utilizing the SID although the nonlinear approximation ability of the fuzzy model is not fully utilized. However, since (i) the matrices B_ω and D_ω are still dependent on the fuzzy membership functions, and through which the input is coupled to the local models, and (ii) if necessary, the accuracy of the model can be improved by further adjusting the number and position of the clustering centers and membership functions, this simplification is reasonable and the resulting model can still attain a satisfactory accuracy.

3.3. Algorithm for subspace identification

The first step of SID is to construct the input and output data Hankel Matrices:

$$\mathrm{U}=\begin{bmatrix}\mathrm{U}^p\\ \mathrm{U}^f\end{bmatrix}=\left[\begin{array}{cccc} \mathrm{u}_0 & \mathrm{u}_1 & \cdots & \mathrm{u}_{j-1} \\ \mathrm{u}_1 & \mathrm{u}_2 & \cdots & \mathrm{u}_j \\ \cdots & \cdots & \cdots & \cdots \\ \mathrm{u}_{N-1} & \mathrm{u}_N & \cdots & \mathrm{u}_{N+j-2} \\ \hline \mathrm{u}_N & \mathrm{u}_{N+1} & \cdots & \mathrm{u}_{N+j-1} \\ \mathrm{u}_{N+1} & \mathrm{u}_{N+2} & \cdots & \mathrm{u}_{N+j} \\ \cdots & \cdots & \cdots & \cdots \\ \mathrm{u}_{2N-1} & \mathrm{u}_{2N} & \cdots & \mathrm{u}_{2N+j-2} \end{array}\right]$$

Here, the input data Hankel matrices U is partitioned into the past (U^p) and the future (U^f) block matrices and is composed of all *mixed* input data $(\mathrm{u}_0, \mathrm{u}_1, \cdots, \mathrm{u}_{2N+j-2})$ which is combined by membership functions, where N and j are respectively the row and column block numbers of U^p and U^f. We should choose N larger than the order of the system n and j should be sufficiently large (typically $j \gg \max(mLN, lN)$), to reduce noise sensitivity [19], where m, l, and L are dimensions of input, output variables and the number of local models.

The output and noise Hankel matrices Y and E can be constructed in the similar format. Then by stacking up the model (19) with input–output data for a number of steps, these Hankel matrices can be used to develop the following subspace matrix equations [21]:

$$Y^f=\Gamma_N X^f+H_{Nd}U^f+H_{Ns}E^f \tag{20}$$

$$Y^p=\Gamma_N X^p+H_{Nd}U^p+H_{Ns}E^p \tag{21}$$

$$X^f=\Psi_Y Y^p+\Psi_U U^p+(\overline{A})^N X^p \tag{22}$$

where

$$\Gamma_N=[C^T \quad (CA)^T \quad (CA^{N-1})^T]^T,$$

$$H_{Nd}=\begin{bmatrix} D & 0 & 0 & \cdots & 0 \\ CB & D & 0 & \cdots & 0 \\ CAB & CB & D & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ CA^{N-2}B & CA^{N-3}B & CA^{N-4}B & \cdots & D \end{bmatrix},$$

$$H_{Ns}=\begin{bmatrix} I & 0 & 0 & \cdots & 0 \\ CK & I & 0 & \cdots & 0 \\ CAK & CK & I & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ CA^{N-2}K & CA^{N-3}K & CA^{N-4}K & \cdots & I \end{bmatrix},$$

$$\Psi_Y=[(\overline{A})^{N-1}K \quad (\overline{A})^{N-2}K \quad \cdots \quad \overline{A}K \quad K],$$
$$\Psi_U=[(\overline{A})^{N-1}\overline{B} \quad (\overline{A})^{N-2}\overline{B} \quad \cdots \quad \overline{A}\overline{B} \quad \overline{B}]$$

in which $\overline{A}=(A-KC)$, $\overline{B}=(B-KD)$.

Similarly, the state matrix X is defined as:

$$X=\begin{bmatrix} X^p \\ X^f \end{bmatrix}=\left[\begin{array}{cccc} x_0 & x_1 & \cdots & x_{j-1} \\ \hline x_N & x_{N+1} & \cdots & x_{N+j-1} \end{array}\right]$$

Owing to the stability of the Kalman filter, $(\overline{A})^N=(A-KC)^N\to 0$ as $N\to\infty$; thus for a large N, (22) converges to [21]:

$$X^f=\mathrm{L}_N W^p \tag{23}$$

where subspace matrices L_N and past data matrices W^p are defined as: $\mathrm{L}_N=[\Psi_Y \quad \Psi_U]$ and $W^p=[(Y^p)^T \quad (U^p)^T]^T$.

Substituting (23) into (20), we have:

$$Y^f=\mathrm{L}_w W^p+\mathrm{L}_u U^f+\mathrm{L}_e E^f \tag{24}$$

with the subspace matrices defined by $\mathrm{L}_w=\Gamma_N \mathrm{L}_N$, $\mathrm{L}_u=H_{Nd}$ and $\mathrm{L}_e=H_{Ns}$.

With the conditions that (*i*) u_k is uncorrelated with e_k, (*ii*) u_k is persistently exciting in the order of $2N$, and (*iii*) the number of measurements is sufficiently large, i.e., $j\to\infty$, the data Hankel matrices can be decomposed by the QR-factorization as follows [19]:

$$\begin{bmatrix} W^p \\ U^f \\ Y^f \end{bmatrix}=\begin{bmatrix} R_{11} & 0 & 0 \\ R_{21} & R_{22} & 0 \\ R_{31} & R_{32} & R_{33} \end{bmatrix}\begin{bmatrix} Q_1 \\ Q_2 \\ Q_3 \end{bmatrix} \tag{25}$$

By expanding this equation and comparing it with (24), the subspace matrices $\mathrm{L}=[\mathrm{L}_w \quad \mathrm{L}_u]$ can be calculated as:

$$\mathrm{L}=[R_{31} \quad R_{32}]\begin{bmatrix} R_{11} & 0 \\ R_{21} & R_{22} \end{bmatrix}^{\dagger} \tag{26}$$

where † represents the Moore–Penrose pseudo-inverse. The block matrices are identified as $\mathrm{L}_w=\mathrm{L}(:, 1:N(Lm+l))$ and $\mathrm{L}_u=\mathrm{L}(:, N(Lm+l)+1:end)$ in MATLAB expression, representing the first $N(Lm+l)$ columns and the remaining columns in L, 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 [19,21]:

$$L_w = [U_1 \quad U_2]\begin{bmatrix} S_1 & 0 \\ 0 & S_2 \end{bmatrix}\begin{bmatrix} V_1 \\ V_2 \end{bmatrix} \approx U_1 S_1 V_1 \tag{27}$$

where S_1 is chosen to contain the n most significant singular values with n as the order of the model. Since $L_w = \Gamma_N L_N$ as defined in (24), Γ_N can be estimated by:

$$\Gamma_N = U_1 {S_1}^{1/2} \tag{28}$$

From Γ_N, as was defined in (20) and (21), the system matrices C and A can be directly extracted.

Next, by multiplying (20) with the orthogonal complement $(\Gamma_N)^{\perp}$ from the left-hand side and with $(U^f)^{\dagger}$ from the right-hand side, we have:

$$(\Gamma_N)^{\perp} Y^f (U^f)^{\dagger} = (\Gamma_N)^{\perp} H_{Nd} \tag{29}$$

Considering the structure of H_{Nd}, as was defined in (20) and (21), (29) can be written in equations that are linear in B and D, so that they can be extracted.

Finally, from (24) and (25), we conclude

$$R_{33} Q_3 = L_e E^f \tag{30}$$

Thus, with the assumptions on the innovation term, we can get L_e which equals H_{Ns}, as was defined in (20) and (21), and from which the Kalman filter gains K can be obtained [21].

The whole procedure of the modeling can be summarized as Fig. 1.

3.4. Fuzzy model predictive control

Based on the fuzzy model developed for the boiler-turbine unit with the clustering and subspace approach, a fuzzy model predictive controller (FMPC_S) can be designed using the standard MPC technique, with the working principle shown as following:

Step 1. Calculate the next instant fuzzy membership function ω_{k+1} from the antecedent vector $\varphi_{k+1} = [P_k, E_k, L_k, u_{1,k}, u_{2,k}, u_{3,k}]$ using (15),(17);

Step 2. Calculate the global model parameters $B_\omega = \sum_{i=1}^{L} \omega_k^i B_i$, $D_\omega = \sum_{i=1}^{L} \omega_k^i D_i$, and form the predictor using matrices $\{A, B_\omega, C, D_\omega, K\}$;

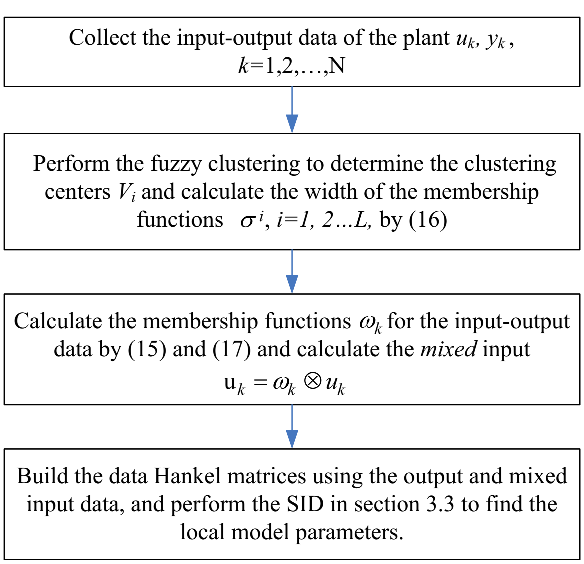

Fig. 1. Procedure of the data-driven fuzzy modeling.

Step 3. Minimize the objective function considering input magnitude and rate constraints to obtain the optimal input sequence;

Step 4. Implement the first input in the input sequence to the plant;

Step 5. Estimate the new state vector using the Kalman filter K, and go back to Step 1.

The FMPC_S is tested and compared with an alternative approach in the next section, namely the data-driven fuzzy predictive controller (DDFPC), which is a model-free controller.

4. Data-driven fuzzy predictive control of boiler–turbine unit

With the fuzzy model obtained in the previous section, various advanced controllers can be designed for boiler–turbine control. However, Eq. (24) 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 conditions mentioned in Section 3.3, a predictive expression can be written as:

$$\hat{Y}^f = L_w W^p + L_u U^f \tag{31}$$

where $W^p = [(Y^p)^T \quad (U^p)^T]^T$ is the past input–output data Hankel matrix, U^f is the future input data Hankel matrix, and $\hat{Y}^f$ is the prediction of the future data Hankel matrix. This implies that by identifying the subspace matrices L_w and L_u from the input–output data and corresponding membership functions (i.e., from the mixed input–output data), fuzzy predictor can be directly constructed without completing the fuzzy model; therefore, the intermediate modeling procedure for the MPC and resulting modeling mismatch can be avoided. Thus, based on the fuzzy technique and subspace idea, a *direct* predictive controller, rather than the *indirect*, i.e., the MPC, will be developed in this section.

Now, consider the objective function

$$J = (\hat{y}_f - r_f)^T Q_f (\hat{y}_f - r_f) + \Delta u_f^T R_f \Delta u_f \tag{32}$$

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

Using the predictor (31), the predictive output $\hat{y}_f = [\hat{y}_{k+1}^T \quad \hat{y}_{k+2}^T \quad \cdots \quad \hat{y}_{k+N_y}^T]^T$ can be estimated by:

$$\hat{y}_f = l_w w_p + l_u \Omega u_f \tag{33}$$

where $w_p = [y_{k-N+1}^T \quad \cdots \quad y_k^T \quad \mathrm{u}_{k-N+1}^T \quad \mathrm{u}_k^T]^T$ is the past output and the mixed input data, $u_f = [u_{k+1}^T \quad u_{k+2}^T \quad \cdots \quad u_{k+N_u}^T]^T$ is the future control input, $l_w = L_w(1:lN_y, :)$ and $l_u = L_u(1:lN_y, 1:mLN_u)$ are prediction matrices, and N_y and N_u, $N_y \geq N_u$ are, respectively, the prediction horizon and the control horizon, and Ω the matrix consisting of the future fuzzy membership functions:

$$\Omega = \begin{bmatrix} \omega_{k+1} \otimes I_m & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \omega_{k+N_u} \otimes I_m \end{bmatrix}$$

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

To include an integral action, the noise input e_k in the state-space model (19) is considered as an integrated noise which is common in industrial processes [22]:

$$e_k = e_{k-1} + a_k \tag{34}$$

Using a difference operator $\Delta = 1 - z^{-1}$, (34) can be written as:

$$e_k = \frac{a_k}{\Delta} \tag{35}$$

then Eq. (19) can be rewritten as

$$\Delta x_{k+1} = A\Delta x_k + B\Delta u_k + K a_k$$
$$\Delta y_k = C\Delta x_k + D\Delta u_k + a_k \tag{36}$$

and following the same procedure, the prediction (33) is changed to:

$$\Delta \hat{y}_f = l_w \Delta w_p + l_u \Omega \Delta u_f \tag{37}$$

Thus, we can have:

$$\hat{y}_f = \mathbf{y}_k + \zeta l_w \Delta w_p + \zeta l_u \Omega \Delta u_f \tag{38}$$

where $\mathbf{y}_k = [y_k^T \quad y_k^T \quad \cdots \quad y_k^T]^T$ 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:

$$\begin{bmatrix} I \\ I \\ \vdots \\ I \end{bmatrix} (u_{\min} - u_k) \le \zeta \Delta u_f \le \begin{bmatrix} I \\ I \\ \vdots \\ I \end{bmatrix} (u_{\max} - u_k) \tag{39}$$

$$\begin{bmatrix} I \\ I \\ \vdots \\ I \end{bmatrix} \Delta u_{\min} \le \Delta u_f \le \begin{bmatrix} I \\ I \\ \vdots \\ I \end{bmatrix} \Delta u_{\max} \tag{40}$$

Substituting (38) into the objective function (32), and minimizing (32) subject to (39) and (40) at every sampling time, the future input sequence Δu_f can be calculated, and the first input in the sequence,u_{k+1}, can be obtained and applied to the plant.

Remark 4.1. To simplify the calculation, during the implementation, we assume that the matrix Ω *is* composed by the fuzzy membership function ω_{k+1} over the entire prediction horizon N_u, which brings the optimal control sequence into a suboptimal one. This is commonly used in the fuzzy MPC literatures.

5. Simulation results

This section demonstrates the data-driven modeling strategy and predictive controller design for boiler-turbine unit using fuzzy clustering and subspace identification method. The accuracy of the fuzzy model is demonstrated first, and then the proposed controllers, the FMPC_S and DDFPC, are tested and compared with other types of predictive controllers.

5.1. Verification of the fuzzy system

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. Although increasing the number of the clusters L will improve the accuracy of the model, for the sake of simplicity, we set $L=5$. The identified model outputs are shown in Fig. 3. 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 non-convergent result.

To further test the accuracy of the identified fuzzy model, another group of data in the medium-high power region are used for validation as shown in Figs. 4 and 5. Severe nonlinearity is distributed within this region according to previous studies [13,15]. From the comparison between model outputs and plant outputs, it can be seen that the fuzzy model has very high

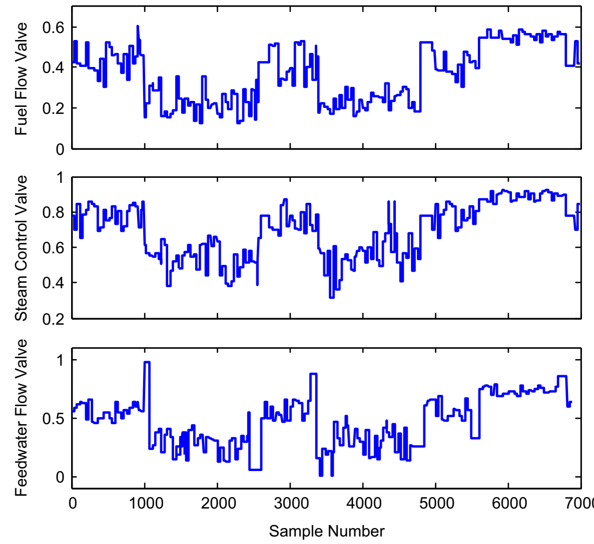

Fig. 2. Input signals used in the fuzzy subspace identification method.

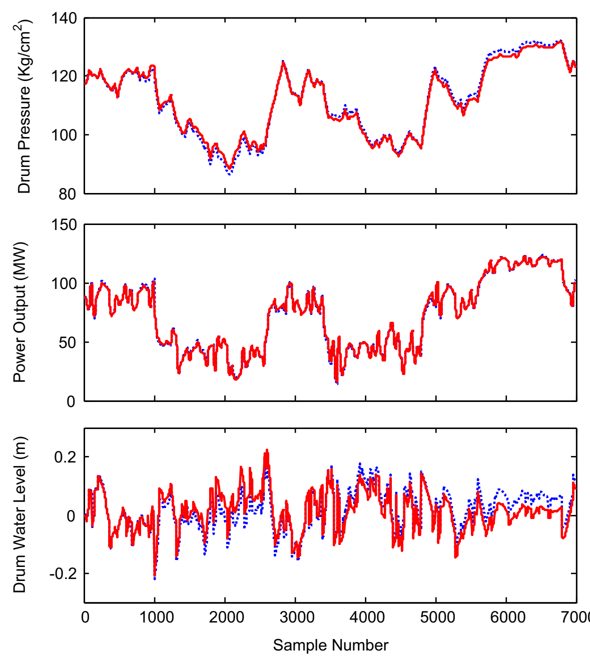

Fig. 3. Fuzzy model identification for the boiler-turbine unit (solid-red: estimated outputs; dotted in blue: real outputs). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

precision for the power output, which is the most important variable for the boiler–turbine unit. It can also capture the drum pressure and water level dynamics correctly in terms of trend and time constant. The figure shows a little offset for the drum pressure and water level outputs; however, it is acceptable for controller design and can be easily reduced by increasing the number of fuzzy rules or further tuning of the fuzzy membership functions. The effectiveness of the proposed identification strategy is clearly demonstrated by the results.

5.2. Testing of predictive controllers

The designers of this boiler-turbine unit model provide 7 typical operating points along the operation range as shown in Table 1. To cover this wide range of operation, a transition from the lowest load point to the highest is considered. Such a wide range

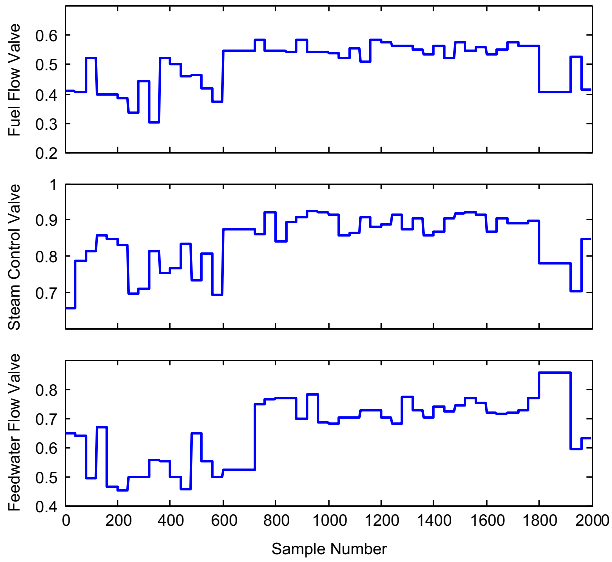

Fig. 4. Input signals used in the fuzzy model verification.

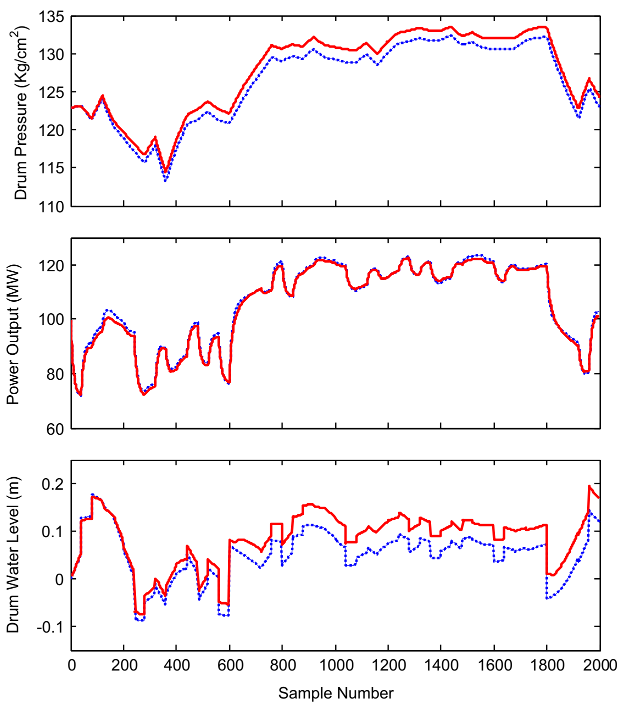

Fig. 5. Fuzzy model verification in the medium-high power region (solid in red: estimated outputs; dotted in blue: real outputs). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

operation is achieved by the use of fuzzy 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 for comparison:

5.2.1. CCS mode

In the CCS mode the demands of the power plant is 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.

The first case is designed to show the overall control performance of the fuzzy subspace based controllers over a wide operation range. At $t=50$ s, the operating point (P, E, L) changes from (75.6, 15.27, 0) to (135.4, 127, 0), then at $t=400$ s it changes again to (110, 80, 0).

The proposed DDFPC and FMPC_S are compared with another MPC built on the Taylor series approximation model (FMPC_T) [11], in which seven local models are derived at the typical operating points in Table 1 and connected by the triangular fuzzy membership functions to form the fuzzy model.

For all three 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. The weighting diagonal matrices Q_f,R_f for all controllers are given as: $Q_f=I_{N_y}\otimes Q, R_f=I_{N_u}\otimes R$, with diagonal elements:

$$Q=\begin{bmatrix}1 & 0 & 0\\ 0 & 1 & 0\\ 0 & 0 & 100\end{bmatrix}, R=\begin{bmatrix}2 & 0 & 0\\ 0 & 80 & 0\\ 0 & 0 & 2\end{bmatrix}.$$

The simulation results in Figs. 6 and 7 show that the three controllers have almost the same performance. The power output and the drum pressure have rapid response to the load change, and then approach to the expected operating points while the drum water level jumps and then gradually return to zero after a period of fluctuation. All the three manipulated variables are within the magnitude and rate constraints. The results show that a satisfactory control of the boiler-turbine for a wide range operation can be achieved.

However, in FMPC_S, additional computation for SVD as well as system matrix estimation are needed. In FMPC_T, the exact analytical model of power plant is required first to build a Taylor series approximation model, which greatly limits its applicability; moreover, affine terms exist in the state-space model [11–13,16], increasing the controller design complexity and computational burden. Due to the unavoidable modeling mismatch, we can also observe tracking offset in FMPC_S and FMPC_T, when integral action is not included.

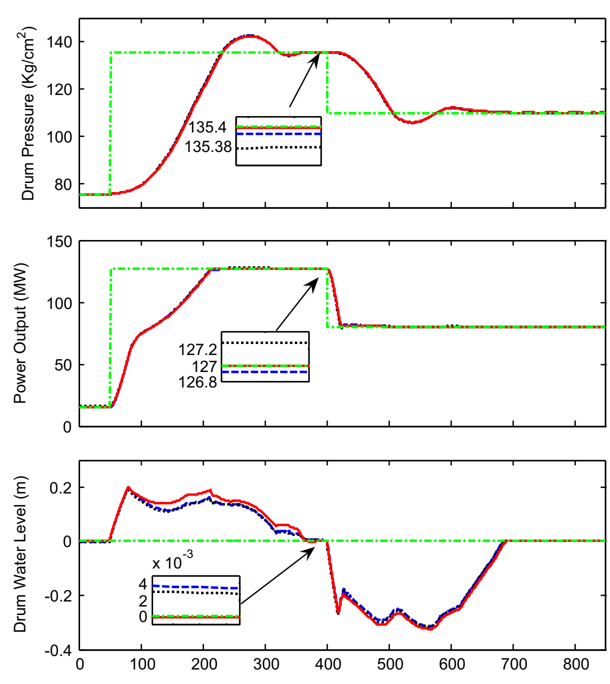

Fig. 6. Performance of the boiler-turbine unit in the CCS mode: Output Variables (solid in red: DDFPC; dashed in blue: FMPC_S; dotted in black: FMPC_T; dot-dashed in green: reference). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

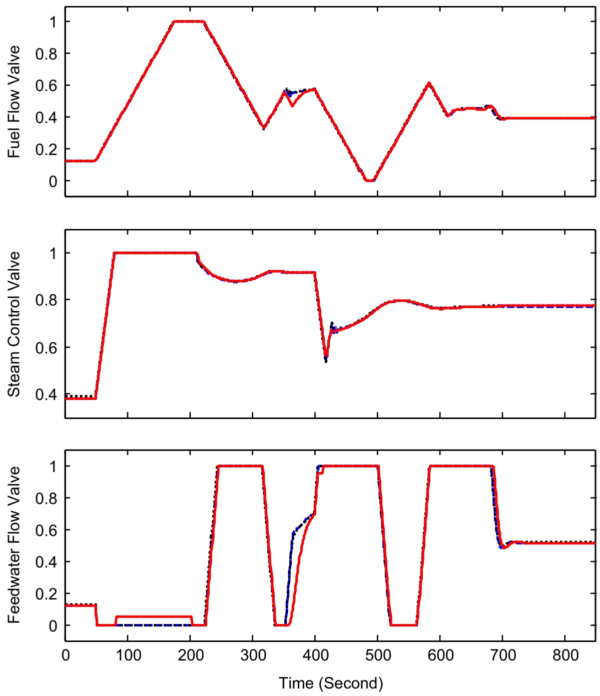

Fig. 7. Performance of the boiler-turbine unit in the CCS mode: Manipulated Variables (solid in red: DDFPC; dashed in blue: FMPC_S; dotted in black: FMPC_T). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

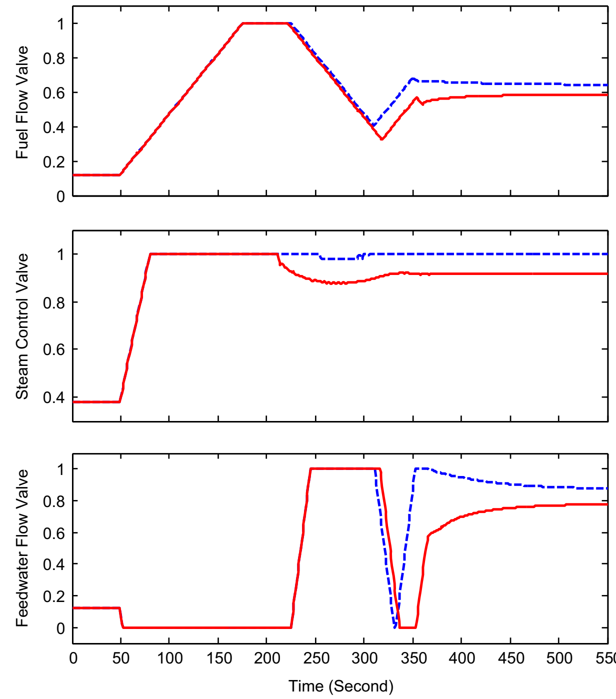

Fig. 9. Performance of the boiler-turbine unit in the CCS mode: Manipulated Variables (solid in red: FMPC_S; dashed in blue: linear_MPC_S). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

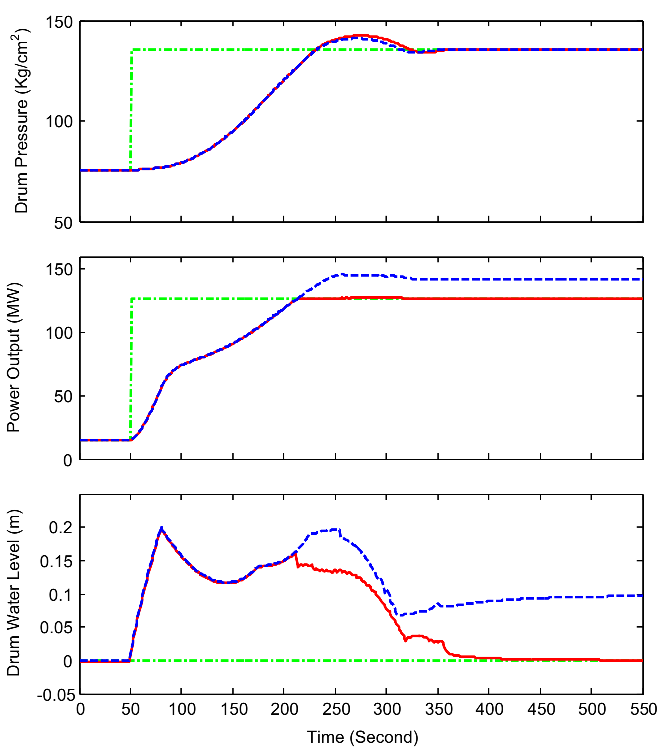

Fig. 8. Performance of the boiler-turbine unit in the CCS mode: Output Variables (solid in red: FMPC_S; dashed in blue: linear_MPC_S; dot-dashed in green: reference). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

To further illustrate the effect of the fuzzy strategy, a linear MPC (linear_MPC_S) based on the state-space model identified around (108, 66.65, 0) operating point is used for comparison. A wide range operating point change, from (75.6, 15.27, 0) to (135.4, 127, 0), is considered and the simulation results are shown in Figs. 8 and 9. Although the linear_MPC_S has the similar performance with fuzzy_MPC_S at low-medium load operating range, where the nonlinearity is small, the control performance is degraded at the high load level, where the nonlinearity is strong. Due to the severe modeling mismatches, large tracking offsets in power output and drum water level are shown for the linear_MPC_S.

5.2.2. AGC mode

In AGC mode, the boiler-turbine unit follows the load demand from the grid which is given by the Automatic Dispatch System (ADS) and generally it 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 MW to 127 MW in the rate of 0.7449 MW/s, while the pressure demand rises from 75.6 kg/cm^2 to 130 kg/cm^2 in the 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 in the rate of 0.5587 MW/s. The simulation results in Figs. 10 and 11 show that in both "variant pressure mode" and "constant pressure mode" the proposed DDFPC and FMPC_S can drive the power output to follow the load demand very closely while regulating the drum pressure and water level gradually reach the set-points. The effectiveness of the proposed controllers for a wide range operation is demonstrated.

6. 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 fuzzy clustering and subspace identification method. The fuzzy model has a good approximation accuracy of the boiler-turbine unit and is suitable

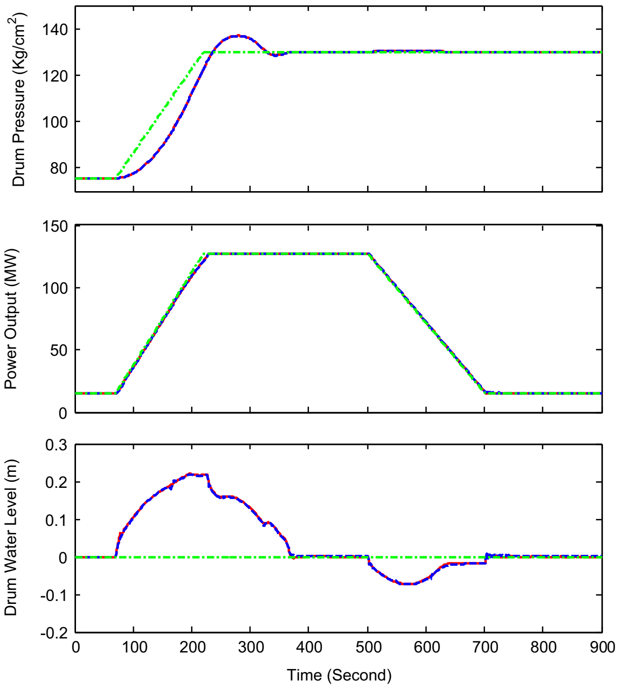

Fig. 10. Performance of the boiler-turbine unit in AGC mode: Output Variables (solid in red: DDFPC; dotted in blue: FMPC_S; dot-dashed in green: reference). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

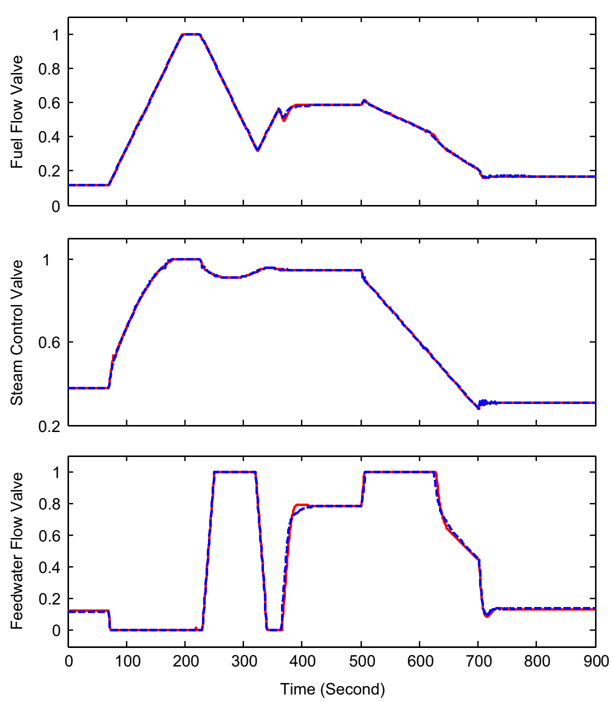

Fig. 11. Performance of the boiler-turbine unit in AGC mode: Manipulated Variables (solid in red: DDFPC; dotted in blue: FMPC_S). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.),

for advanced controller design, resulting in a fuzzy model predictive controller. Following the same clustering and subspace method, a direct data-driven fuzzy predictive controller is proposed as an alternative method, which can achieve a wide range offset-free tracking control while dealing with the input constraints. 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.

Acknowledgment

This work was supported in parts by the National Natural Science Foundation of China (NSFC) under Grant 51076027, Grant 51036002 and Grant 51306082, the Scientific Research Foundation of Graduate School of Southeast University under grant ybjj1120, and the U.S. National Science Foundation under grant ECCS 0801440.

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