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Local Model Network Based Multi-Model Predictive Control for a Boiler - Turbine System

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Abstract: A controller-weighted multi-model predictive control (MMPC) strategy based on local model network (LMN) is proposed to address the nonlinearity and wide operating range of the boiler-turbine (B-T) system with constraints. The LMN model of the nonlinear plant is identified off-line based on data-driven modeling method. Since each local model is valid only in local regime, different local constraints are considered in designing local predictive controllers corresponding to different local models. The local controllers are run in parallel and each controller is assigned with a weight by the implicit scheduling unit. The weighted sum of the outputs of local controllers is taken as a global control signal and applied to the plant. The efficacy of the proposed MMPC is validated by simulations on a boiler-turbine system.

***Keywords**:* Predictive control, Local model network (LMN), Boiler-turbine system, Muti-model, Simulation.

1. INTRODUCTION

The severe nonlinearity and wide operating range of boiler-turbine (B-T) system, which is strongly coupled and subject to various constraints on both inputs and outputs, bring great challenge to power system control engineers (Moon & Lee, 2009). Many attempts have been made to overcome the control difficulties of B-T system, of which model predictive control (MPC) approaches are the most prevailing, since they are able to handle the multivariable constrained problem explicitly. In view of the inability of linear MPCs in dealing with nonlinear problems, nonlinear MPCs were designed for the B-T system. A superior performance during wide range load variation can be achieved by nonlinear MPCs (Lee et al, 2010; Kong, Liu & Lee, 2016), but most of them have heavy computational burden and are in lack of model transparency. Multi-model based MPCs provide an alternative way to handle the nonlinearity, in which a combination of several linear models is used to approximate the nonlinear behavior of the B-T system (Keshavarz et al, 2010; Li et al, 2012; Wu et al, 2014). MMPCs are more flexible and easier to implement than other nonlinear control approaches, and superior control performance can also be attained.

Multi-model control systems can be constructed in many different ways. Among them, the control system based on multiple weighted controllers has received widespread attention (Rugh & Shamma, 2000; Dougherty & Cooper, 2003; Li et al, 2004), due to its transparency in structure and ease in controller design. The scheduling mechanism is important for this kind of controller-weighted system. A common method is to use fuzzy logic to deduce and calculate the weights allocated to each local controller based on some scheduling variables that reflect the operating conditions (Moon & Lee, 2011) or the deviation between model output and actual output (Pi & Sun, 1998). But so far there is no systematic method to select the parameters of the membership functions and the fuzzy rules. It often needs trial and error based on the designer's experience to make the control system show satisfactory performance. In addition, the fact that each local model is only valid in a local region is often overlooked in the design of multi-model predictive control. However, if the control inputs are not limited during the long prediction horizon, the predicted outputs of the system may exceed the valid domain of some local model over time, thus the control signal obtained must be inaccurate and may cause the deterioration of the control system.

For these reasons, in this paper controller-weighted multi-model predictive control strategy will be designed based on a local model network (LMN) to address the control problem of nonlinear B-T system. The proposed control strategy has the following novelties and advantages:

1) with the framework of local model networks, different linear models are weighted to accurately represent a nonlinear system and couple with a set of MPC controllers;

2) different validity regimes of local models are treated as constraints on the corresponding local predictive controllers to obtain the accurate local control signals;

3) the optimization of control system structure and scheduling mechanism does not need to rely on experience.

2. LOCAL MODEL NETWORK BASED MULTI-MODEL PREDICTIVE CONTROL

2.1 System Framework

A basic structure of a dynamic local model network is depicted in Fig. 1, where each local model LM_i consists of two parts (Hametner & Jakubek, 2013): the dynamic model $f_i(\cdot)$ and its validity function $\rho_i(\cdot)$. For a multivariable system with R inputs and S outputs, the output $\boldsymbol{y}(k) \in R^S$ of LMN at current k-th instant can be represented as:

$$\boldsymbol{y}(k) = \sum_{i=1}^{M} \rho_i(\boldsymbol{\phi}(k)) \cdot f_i(\boldsymbol{\varphi}(k)) \tag{1}$$

where M is the number of local models; local model $f_i(\cdot)$ $(i = 1,\ldots,M)$ is defined as a function of measurement vector $\boldsymbol{\varphi}(k) \in R^r$; and the validity function $\rho_i(\cdot)$ of the i-th local model is defined as a function of scheduling vector $\boldsymbol{\phi}(k) \in R^L$. A commonly chosen validity function in LMN is the normalized Gaussian function defined as:

$$\rho_i(\boldsymbol{\phi}) = \frac{\beta_i(\boldsymbol{\phi})}{\sum_{i=1}^{M} \beta_i(\boldsymbol{\phi})}, \quad \beta_i(\boldsymbol{\phi}) = \exp\left[-\frac{(\boldsymbol{\phi} - \boldsymbol{c}_i)^T (\boldsymbol{\phi} - \boldsymbol{c}_i)}{\sigma_i^2} \right] \tag{2}$$

where $\boldsymbol{c}_i$ and σ_i are the center and width of the Gaussian interpolation function, respectively. The validity regime of the i-th local model can be described as $\boldsymbol{\Gamma}_i \in [\boldsymbol{c}_i - \sigma_i \boldsymbol{I}_e,\ \boldsymbol{c}_i + \sigma_i \boldsymbol{I}_e]$, in which $\boldsymbol{I}_e = [1,1,...,1]^T \in R^r$.

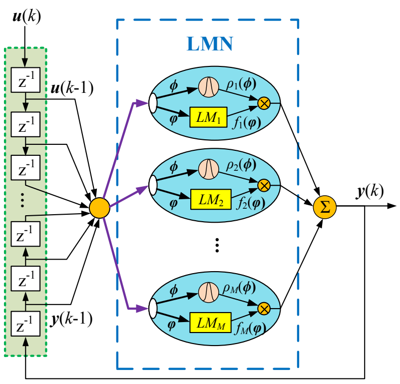

Fig. 1. A basic structure of local model network.

The proposed controller-weighted multi-model predictive control system based on LMN is shown in Fig. 2, which contains a set of local predictive controller MPC_i and an implicit scheduling unit. Each local predictive controller MPC_i is designed based on the local model LM_i in LMN. According to the scheduling vector $\boldsymbol{\phi}$ reflecting the current operating condition, the scheduling unit assigns a weight $\rho_i(\boldsymbol{\phi})$ (i.e., the validity value of each local model LM_i) at every sampling instant for each local controller MPC_i. The weighted sum of the outputs of each local controller is taken as a global control signal applied on the controlled plant.

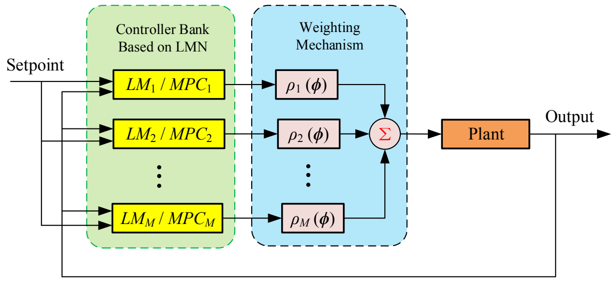

Fig. 2. LMN-based multi-model predictive control system.

2.2 Local Models

The form of the local model depends on the design of the controller and generally linear models are selected for simplicity.

Define a regression vector $\boldsymbol{\varphi}^T(k) = [-\boldsymbol{y}^T(k-1),\ldots, -\boldsymbol{y}^T(k-n_A), \boldsymbol{u}^T(k-1),\ldots,\boldsymbol{u}^T(k-n_B-1)]^T$ and a parameter vector $\boldsymbol{\theta}_i = [\boldsymbol{A}_{i1},\ldots,\boldsymbol{A}_{in_A}, \boldsymbol{B}_{i0},\ldots,\boldsymbol{B}_{in_B}]^T$ for the i-th local model LM_i, where n_A is the number of delayed input samples and n_B is the number of delayed output samples, $\boldsymbol{A}_{ij} \in R^{S\times S}, j = 1,\ldots,n_A$ and $\boldsymbol{B}_{ij} \in R^{S\times R}, j = 0,\ldots,n_B$. The output of LM_i can be expressed in a regression form:

$$\boldsymbol{y}_i^T(k) = f_i(\boldsymbol{\varphi}(k)) = \boldsymbol{\varphi}^T(k)\boldsymbol{\theta}_i, \quad i = 1,2,\ldots,M \tag{3}$$

Accordingly, the global output of the LMN is a combination of the output of each local model,

$$\boldsymbol{y}^T(k) = \sum_{i=1}^{M} \rho_i(\boldsymbol{\phi}(k)) \boldsymbol{\varphi}^T(k)\boldsymbol{\theta}_i \tag{4}$$

The identification of LMN includes choosing a suitable scheduling variable $\boldsymbol{\phi}$ and determining the number of local models M as well as the validity function $\rho_i(\cdot)$ and parameter vector $\boldsymbol{\theta}_i$. A data-driven LMN modeling method based on satisfactory fuzzy clustering technique was proposed by Zhu, Shen and Li (2016). Since this modeling method can achieve high identification accuracy with less number of local models and lower computational burden, we will use it to identify the LMN model of the B-T system. For more details about the modeling of LMN, please refer to Zhu et al. (2016, 2019).

The local model (3) in the identified LMN can be easily transformed into a controlled auto-regressive and integrated moving average (CARIMA) model expressed as:

$$\boldsymbol{A}_i(z^{-1})\boldsymbol{y}(k) = \boldsymbol{B}_i(z^{-1})\boldsymbol{u}(k-1) + \boldsymbol{C}_i(z^{-1})\boldsymbol{\xi}(k)/\Delta \tag{5}$$

where z^{-1} is the backward shift operator, $\boldsymbol{A}_i(z^{-1})$ and $\boldsymbol{C}_i(z^{-1})$ are $S\times S$ monic polynomial matrices and $\boldsymbol{B}_i(z^{-1})$ is a $S\times R$ polynomial matrix defined as:

$$\boldsymbol{A}_i(z^{-1}) = \boldsymbol{I}_{S\times S} + \boldsymbol{A}_{i1}z^{-1} + \cdots + \boldsymbol{A}_{in_A}z^{-n_A},$$
$$\boldsymbol{B}_i(z^{-1}) = \boldsymbol{B}_{i0} + \boldsymbol{B}_{i1}z^{-1} + \cdots + \boldsymbol{B}_{in_B}z^{-n_B},$$
$$\boldsymbol{C}_i(z^{-1}) = \boldsymbol{I}_{S\times S} + \boldsymbol{C}_{i1}z^{-1} + \cdots + \boldsymbol{C}_{in_C}z^{-n_C}.$$

The operator Δ is defined as $\Delta = 1 - z^{-1}$; $\boldsymbol{y}(k)$ and $\boldsymbol{u}(k)$ are the output vector and input vector; $\boldsymbol{\xi}(k)$ is the noise vector and is supposed to be a white noise with zero mean.

2.3 Local Predictive Controllers

For each local model LM_i, a multivariable constrained model predictive controller MPC_i is designed as local controller.

The commonly used quadratic cost function (objective function) of the predictive control can be formulated and used for calculation of the optimal control input to make each output in $\boldsymbol{y}$ follow the output reference $\boldsymbol{y}_r$ in an optimal way:

$$J = \sum_{j=1}^{N_p} \left[\boldsymbol{y}(k+j) - \boldsymbol{y}_r(k+j) \right]^T \boldsymbol{Q}_0 \left[\boldsymbol{y}(k+j) - \boldsymbol{y}_r(k+j) \right] + \sum_{j=1}^{N_u} \Delta \boldsymbol{u}^T(k+j-1) \boldsymbol{R}_0 \Delta \boldsymbol{u}(k+j-1) \quad (6)$$

where N_p is the prediction horizon and N_u is the control horizon; $\boldsymbol{Q} = \boldsymbol{Q}^T > 0$ and $\boldsymbol{R} = \boldsymbol{R}^T > 0$ are symmetric weighting matrices of the output tracking errors and control input increments, respectively.

On the basis of the model (5) and Diophantine equation, the predicted outputs at future instants can be described as:

$$\hat{\boldsymbol{y}} = \boldsymbol{G}\Delta\boldsymbol{U} + \boldsymbol{f} \quad (7)$$

where $\hat{\boldsymbol{y}} = [\hat{\boldsymbol{y}}^T(k+1), \hat{\boldsymbol{y}}^T(k+2), \cdots, \hat{\boldsymbol{y}}^T(k+N_p)]^T$; $\Delta\boldsymbol{U} = [\Delta\boldsymbol{u}^T(k), \Delta\boldsymbol{u}^T(k+1), \cdots, \Delta\boldsymbol{u}^T(k+N_u-1)]^T$; $\boldsymbol{f} = \boldsymbol{H}\Delta\boldsymbol{u}(k-1) + \boldsymbol{F}\boldsymbol{y}(k)$ which can be obtained from the known inputs and outputs; $\boldsymbol{G}$, $\boldsymbol{H}$ and $\boldsymbol{F}$ are coefficient matrices derived from the Diophantine equation, see e.g. (Clarke et al,1987).

If there are no constraints, the predictive control law can be obtained by minimizing the objective function (6) in the form:

$$\Delta\boldsymbol{U} = (\boldsymbol{G}^{\mathrm{T}}\boldsymbol{Q}_0\boldsymbol{G} + \boldsymbol{R}_0)^{-1}\boldsymbol{G}^{\mathrm{T}}\boldsymbol{Q}_0(\boldsymbol{Y}_r - \boldsymbol{f}) \quad (8)$$

where $\boldsymbol{Y_r} = [\boldsymbol{y}_r^T(k+1), \boldsymbol{y}_r^T(k+2), \cdots, \boldsymbol{y}_r^T(k+N_p)]^T$ is the vector of output reference trajectory.

However, almost all the actual processes are subject to certain physical conditions and only the control actions that satisfy these constraints can be truly optimal. The following hard constraints are the global constraints that all local models and controllers must satisfy.

Constraints on the magnitude of control inputs:

$$\boldsymbol{u}_{\min} \le \boldsymbol{u}(k+j-1) \le \boldsymbol{u}_{\max},\ j = 1, 2, ..., N_u \quad (9)$$

Constraints on the increment of control inputs:

$$\Delta\boldsymbol{u}_{\min} \le \Delta\boldsymbol{u}(k+j-1) \le \Delta\boldsymbol{u}_{\max},\ j = 1, 2, ..., N_u \quad (10)$$

Constraints on the controlled outputs:

$$\boldsymbol{y}_{\min} \le \boldsymbol{y}(k+j) \le \boldsymbol{y}_{\max},\ j = 1, 2, ..., N_p \quad (11)$$

In addition to the global constraints, local constraints should also be considered when designing the controllers, since each local model is locally valid. For the *i*-th local model, the local constraints are described as

$$\boldsymbol{\Gamma}_{i\min} \le \boldsymbol{\phi}(k+j) \le \boldsymbol{\Gamma}_{i\max},\ j = 1, 2, ..., N_p \quad (12)$$

where $\boldsymbol{\Gamma}_{i\min}$ and $\boldsymbol{\Gamma}_{i\max}$ are the lower and upper bound of the validity regime $\boldsymbol{\Gamma}_i$ which is already obtained during the modeling phase. The scheduling vector is defined as $\boldsymbol{\phi}(k) = [\boldsymbol{u}^T(k-1),\ \boldsymbol{y}^T(k)]^T$, so the soft constraints of each local model can be rewritten as:

$$\boldsymbol{u}_{i\min} \le \boldsymbol{u}(k+j-1) \le \boldsymbol{u}_{i\max},\ j = 1, 2, ..., N_u \quad (13)$$

$$\boldsymbol{y}_{i\min} \le \boldsymbol{y}(k+j) \le \boldsymbol{y}_{i\max},\ j = 1, 2, ..., N_p \quad (14)$$

where $[\boldsymbol{u}_{i\min}^T, \boldsymbol{y}_{i\min}^T]^T = \boldsymbol{\Gamma}_{i\min}$ and $[\boldsymbol{u}_{i\max}^T, \boldsymbol{y}_{i\max}^T]^T = \boldsymbol{\Gamma}_{i\max}$.

Taking both global and local constraints into account, the constrained predictive control problem for each local model (5) can be described as:

$$\min_{\Delta U} J(k) \quad (15)$$

$$s.t. \begin{cases} \boldsymbol{u}_{\min} \le \boldsymbol{u}(k+j-1) \le \boldsymbol{u}_{\max}, & j = 1, 2, ..., N_u \\ \Delta\boldsymbol{u}_{\min} \le \Delta\boldsymbol{u}(k+j-1) \le \Delta\boldsymbol{u}_{\max}, & j = 1, 2, ..., N_u \\ \boldsymbol{y}_{\min} \le \boldsymbol{y}(k+j) \le \boldsymbol{y}_{\max}, & j = 1, 2, ..., N_p \\ \boldsymbol{u}_{i\min} \le \boldsymbol{u}(k+j-1) \le \boldsymbol{u}_{i\max}, & j = 1, 2, ..., N_u \\ \boldsymbol{y}_{i\min} \le \boldsymbol{y}(k+j) \le \boldsymbol{y}_{i\max}, & j = 1, 2, ..., N_p \end{cases} \quad (16)$$

Substituting (7) into (6), then

$$J = 2J_0 + \left[\boldsymbol{Y}_r - \boldsymbol{f}\right]^T \boldsymbol{Q}_0 \left[\boldsymbol{Y}_r - \boldsymbol{f}\right] \quad (17)$$

where $J_0 = \frac{1}{2}\Delta\boldsymbol{U}^{\mathrm{T}}(\boldsymbol{G}^{\mathrm{T}}\boldsymbol{Q}_0\boldsymbol{G} + \boldsymbol{R}_0)\Delta\boldsymbol{U} + (\boldsymbol{f} - \boldsymbol{Y}_r)^{\mathrm{T}}\boldsymbol{Q}_0\boldsymbol{G}\Delta\boldsymbol{U}$ .The last constant term in cost function (17) is independent of $\Delta\boldsymbol{U}$, so obviously $\min_{\Delta\boldsymbol{U}} J = \min_{\Delta\boldsymbol{U}} J_0$. So (15) can be reformulated as the standard constrained quadratic optimization problem:

$$\min_{\Delta U} J = \min_{\Delta U} \left\{ \frac{1}{2}\Delta\boldsymbol{U}^{\mathrm{T}}(\boldsymbol{G}^{\mathrm{T}}\boldsymbol{Q}_0\boldsymbol{G} + \boldsymbol{R}_0)\Delta\boldsymbol{U} + (\boldsymbol{f} - \boldsymbol{Y}_r)^{\mathrm{T}}\boldsymbol{Q}_0\boldsymbol{G}\Delta\boldsymbol{U} \right\} \quad (18)$$

$$s.t. \begin{cases} \boldsymbol{L}\Delta\boldsymbol{U} \le \boldsymbol{l} \\ \Delta\boldsymbol{U}_{\min} \le \Delta\boldsymbol{U} \le \Delta\boldsymbol{U}_{\max} \end{cases}$$

where $\boldsymbol{L} = [\boldsymbol{L}_1^T \quad -\boldsymbol{L}_1^T \quad \boldsymbol{L}_2^T \quad -\boldsymbol{L}_2^T \quad \boldsymbol{L}_3^T \quad -\boldsymbol{L}_3^T]^T$,

$\boldsymbol{l} = [\boldsymbol{l}_1^T \quad \boldsymbol{l}_2^T \quad \boldsymbol{l}_3^T \quad \boldsymbol{l}_4^T \quad \boldsymbol{l}_5^T \quad \boldsymbol{l}_6^T]^T$,

$$\Delta\boldsymbol{U}_{\min} = [\underbrace{\Delta u_{\min 1}, \Delta u_{\min 2} \ldots, \Delta u_{\min R}}_{1}, \ldots, \underbrace{\Delta u_{\min 1}, \Delta u_{\min 2} \ldots, \Delta u_{\min R}}_{N_u}]^T,$$

$$\Delta\boldsymbol{U}_{\max} = [\underbrace{\Delta u_{\max 1}, \Delta u_{\max 2} \ldots, \Delta u_{\max R}}_{1}, \ldots, \underbrace{\Delta u_{\max 1}, \Delta u_{\max 2} \ldots, \Delta u_{\max R}}_{N_u}]^T,$$

The matrixes $\boldsymbol{L}_1 \sim \boldsymbol{L}_3$ and vectors $\boldsymbol{l}_1 \sim \boldsymbol{l}_6$ are derived from (16) and defined as:

$$\boldsymbol{L}_1 = \begin{bmatrix} \boldsymbol{I} & \boldsymbol{O} & \cdots & \boldsymbol{O} \\ \boldsymbol{I} & \boldsymbol{I} & \boldsymbol{O} & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ \boldsymbol{I} & \cdots & \boldsymbol{I} & \boldsymbol{I} \end{bmatrix} \in R^{RN_u \times RN_u} \quad , \quad \boldsymbol{L}_2 = \boldsymbol{G} \in R^{SN_p \times RN_u} \quad ,$$

$$\boldsymbol{L}_3 = [\boldsymbol{L}_1^T \quad \boldsymbol{L}_2^T]^T ,$$

$$\boldsymbol{l}_1(k) = [\underbrace{(\boldsymbol{u}_{\max} - \boldsymbol{u}(k-1))^T}_{1}, \ldots, \underbrace{(\boldsymbol{u}_{\max} - \boldsymbol{u}(k-1))^T}_{N_u}]^T ,$$

$$\boldsymbol{l}_2(k) = [\underbrace{(\boldsymbol{u}(k-1) - \boldsymbol{u}_{\min})^T}_{1}, \ldots, \underbrace{(\boldsymbol{u}(k-1) - \boldsymbol{u}_{\min})^T}_{N_u}]^T ,$$

$$\boldsymbol{l}_3(k) = [(\boldsymbol{y}_{\max} - \boldsymbol{f}(k+1))^T, \ldots, (\boldsymbol{y}_{\max} - \boldsymbol{f}(k+N_p))^T]^T ,$$

$$\boldsymbol{l}_4(k) = [(\boldsymbol{f}(k+1) - \boldsymbol{y}_{\min})^T, \ldots, (\boldsymbol{f}(k+N_p) - \boldsymbol{y}_{\min})^T]^T ,$$

$$\boldsymbol{l}_5(k) = [(\boldsymbol{\Gamma}_{i\max} - \boldsymbol{d}(k+1))^T, \ldots, (\boldsymbol{\Gamma}_{i\max} - \boldsymbol{d}(k+N_p))^T]^T ,$$

$$\boldsymbol{l}_6(k) = [(\boldsymbol{d}(k+1) - \boldsymbol{\Gamma}_{i\min})^T, \ldots, (\boldsymbol{d}(k+N_p) - \boldsymbol{\Gamma}_{i\min})^T]^T$$

where $\boldsymbol{d}(k+t) = [\boldsymbol{u}^T(k-1), \boldsymbol{f}^T(k+t)]^T$, $t = 1, 2, \ldots, N_p$.

The optimization problem (18) can be solved by the existing algorithms, such as *quadprog* function in MATLAB Toolbox.

2.4 Scheduling Mechanism

Compared with many existing multi-model control strategies, LMN-based multi-model control system is much simpler in designing scheduling criteria. The scheduling mechanism can be described as: first collecting the working condition parameters at the current instant to form a scheduling vector, calculating the scheduling or validity function value of each local model according to (2), and the obtained value of the function is used as the weight of the corresponding local controller. Since the local predictive controller is designed based on the local model, it is intuitive and reasonable to directly use the value of the scheduling function as the weight of the corresponding controller. Moreover, the optimization of the model set has been considered in the LMN modeling phase, that is, the number of local models/controllers and the parameters of the scheduling function have been optimized, which can avoid the blindness of selecting the number of controllers and scheduling criteria relying on experience.

3. BOILER–TURBINE SYSTEM MODEL

3.1 Nonlinear Boiler–Turbine Model

The nonlinear dynamic model of a 160MW drum–type boiler-turbine unit presented by Bell and Åström (1987) is adopted to be the controlled plant in this study. The model is described as follows:

$$\begin{cases} \dot{x}_1 = 0.9u_1 - 0.0018u_2 x_1^{9/8} - 0.15u_3 \\ \dot{x}_2 = \left(0.073u_2 - 0.016\right) x_1^{9/8} - 0.1x_2 \\ \dot{x}_3 = \left[141u_3 - \left(1.1u_2 - 0.19\right) x_1\right] / 85 \\ y_1 = x_1 \\ y_2 = x_2 \\ y_3 = 0.05(0.13073x_3 + 100\alpha_s + q_e / 9 - 67.975) \end{cases} \tag{19}$$

where

$$\alpha_s = \frac{(1 - 0.001538x_3)(0.8x_1 - 25.6)}{x_3(1.0394 - 0.0012304P)}$$

$$q_e = (0.854u_2 - 0.147)x_1 + 45.59u_1 - 2.514u_3 - 2.096$$

The three state variables x_1 , x_2 and x_3 are drum steam pressure P (kg/cm2), output power E (MW) and drum/riser fluid density ρ_f (kg/cm3), respectively. The three outputs y_1, y_2 and y_3 are drum steam pressure P, output power E and drum water-level H (m), respectively. The drum water-level H is calculated by using two algebraic calculations, the steam quality α_s (mass ratio) and the evaporation rate q_e (kg/s). The three control inputs u_1 , u_2 and u_3 are normalized positions of valve actuators that control the mass flow rates of fuel, steam to the turbine, and feed water to the drum, respectively. The control inputs are subject to magnitude and rate saturations as follows:

$$\begin{cases} 0 \le u_1, u_2, u_3 \le 1 \\ -0.007 \le \dot{u}_1 \le 0.007 \\ -2 \le \dot{u}_2 \le 0.02 \\ -0.05 \le \dot{u}_3 \le 0.05 \end{cases} \tag{20}$$

The general control objective for this kind of drum-type boiler–turbine unit is to achieve a fast power tracking while keeping the steam pressure accurately following its setpoint and eliminating the deviation of drum water level.

3.2 LMN Model of B-T System

In order to fully stimulate the nonlinearity of the B-T system under different operating conditions, three uncorrelated modified pseudo-random sequences with adjustable frequency and amplitude are respectively applied to the three manipulated variables to generate identification data, as shown in Fig. 3. The LMN model of the B-T system is obtained by using the data-driven modeling method proposed in Zhu, Shen & Li (2016). The comparison between the model outputs and the actual outputs is shown in Fig. 4, where the model error e_P of drum steam pressure, e_E of output power and e_H of drum water-level at each sampling instant are also shown. Obviously, the resulting LMN has very high prediction accuracy even with only three local models.

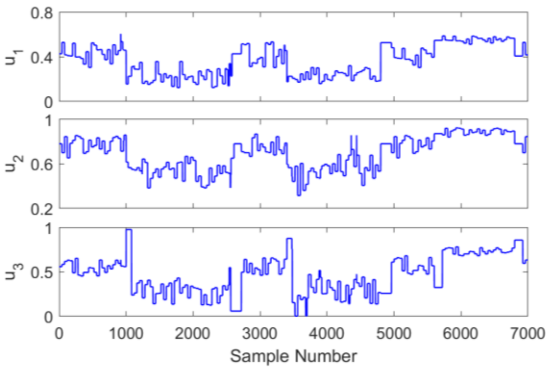

Fig. 3. Excitation inputs used for model identification.

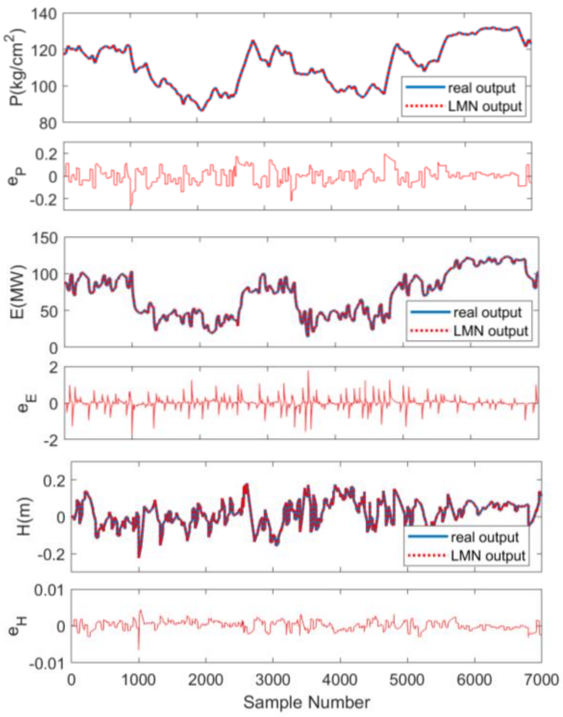

Fig. 4. Comparison of model outputs and real outputs.

4. SIMULATIONS

Based on the identified LMN model of the B-T system, a multi-model predictive control system similar to that shown in Fig. 2 is designed, which contains three local predictive controllers. Several simulation scenarios are presented to evaluate the performance of the proposed control strategy. In the simulations, the parameters of the three local controllers are chosen the same, except for the prediction model: $T_s = 1s$, $N_P = 30$, $N_u = 5$, $Q_0 = I_3$ and $R_0 = 0.5I_3$.

Case 1: Wide-range step response test. Some equilibrium operating points of the B-T model (19) was given by Bell & Åström (1987). Assume that there is a wide step disturbance from #1 to #7 operating point, i.e., the setpoints of y_1, y_2 and y_3 have a step change from (75.6, 15.27, 0) to (135.4, 127, 0). Fig. 5 show the outputs and control inputs of the B-T system, respectively. Comparing the result with that of the similar tests in other literatures such as Wu et al. (2012) and Pan et al. (2015), we know that our control system has better control performance since it can track the setpoints more quickly and has less transient time, overshoot and small water-level fluctuation. Meanwhile, the manipulated variables meet all the constraints of inequalities (16).

Case 2: Wide-range ramp tracking test in nominal case. We simulate the automatic generation control (AGC) mode and the reference tracking trajectory is chosen as: first, output power ramps from #4 to #7 operating point at an increasing rate of 0.415 MW/sec; then it ramps from #7 to #1 operating point at a decreasing rate of 0.284 MW/sec; finally, it ramps from #1 to #4 operating point at an increasing rate of 0.25 MW/sec. The reference for the drum steam pressure is changed in proportion to the load, while the reference for the drum water level is kept at zero. The output responses and control inputs for this tracking case are shown in Fig. 6. It can be seen that in the case of wide-range rapidly-changing operating conditions, the drum pressure and output power can accurately track their setpoints and the fluctuation of drum water-level is small.

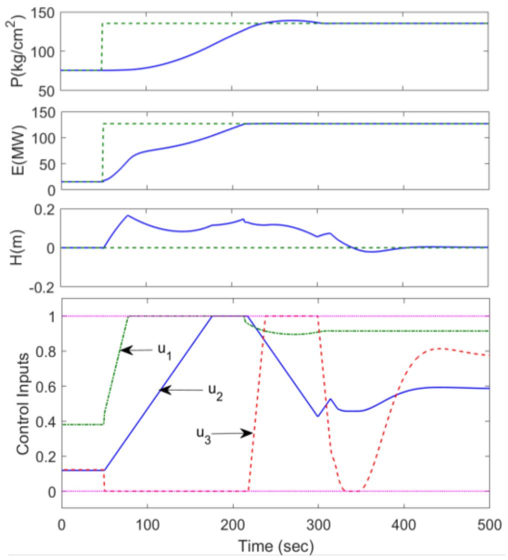

Fig. 5. Outputs and control inputs under the wide-range step disturbances.

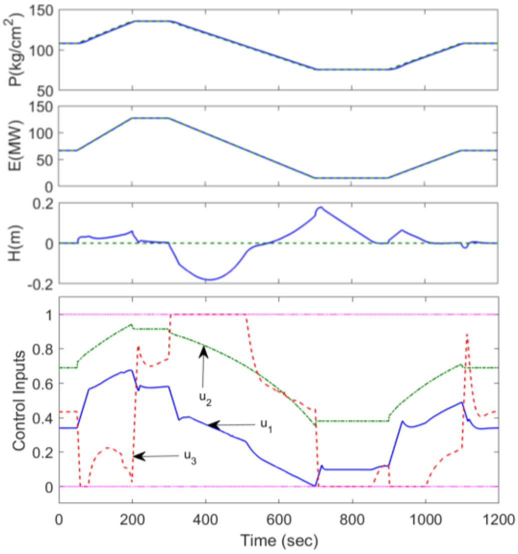

Fig. 6. Outputs and control inputs under wide-range ramp tracking in nominal case.

Case 3: Wide-range ramp tracking test in the case of model mismatch. Assume that the coefficients of the nonlinear state model of the B-T system in (19) are all changed to 50% of their original values, which indicates the dynamic behavior of the system has changed significantly; and the setpoints of outputs are set the same as in Case 2. The outputs and control inputs for this tracking case with model uncertainty are shown in Fig. 7. It can be observed that good tracking of the load demand and drum pressure is obtained even if the dynamic behavior of the B-T unit has changed and the maximum fluctuation of drum water level is just slightly larger than that of Case 2, which indicates that our control strategy has strong robustness.

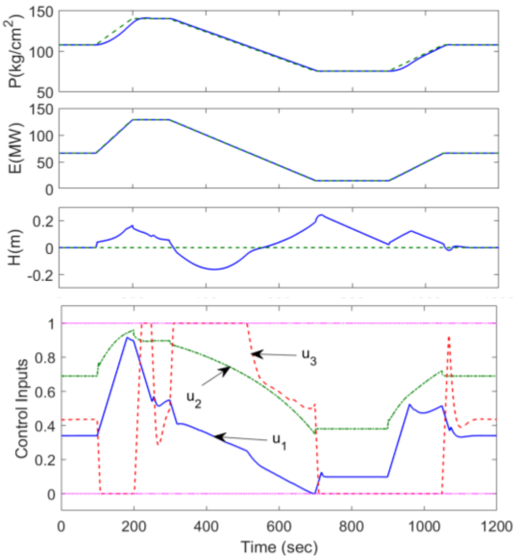

Fig. 7. Outputs and control inputs under wide-range ramp tracking in the presence of model mismatch.

5. CONCLUSIONS

A controller-weighted multi-model predictive control strategy based on LMN is designed in this paper, where different valid regions of each local model are treated as local constraints in the design of the local predictive controllers. Since the number of local models/controllers and the parameters of scheduling functions have been optimized in the LMN modeling phase, the structure and scheduling mechanism of the control system are more reasonable and do not rely on experience. Simulation results on a drum-type B-T system demonstrate the superior performance of the proposed control strategy: the control and control-move constraints can be easily meet; the satisfied tracking performance can be attained over a wide operation range; and it has good robustness against model uncertainty. The proposed control strategy can also be applied in any other plants or processes.

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