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

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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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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:

$$R^i: IF\varphi_k\in M_i, \text{THEN}:$$

$$\begin{cases}x_{k+1}=A_ix_k+B_iu_k+K_ie_k\\ y_k=C_ix_k+D_iu_k+e_k,\ i=1,2...L\end{cases} \tag{8}$$

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