



Fuzzy modeling and stable model predictive tracking control of large-scale power plants



Xiao Wu^{a,*}, Jiong Shen^a, Yiguo Li^a, Kwang Y. Lee^b

^a Department of Energy Information and Automation, Southeast University, Nanjing 210096, China

^b Department of Electrical and Computer Engineering, Baylor University, One Bear Place #97356, Waco, TX 76798-7356, USA

ARTICLE INFO

Article history:

Received 21 November 2013

Received in revised form 17 June 2014

Accepted 6 August 2014

Available online 2 September 2014

Keywords:

Power plant

Stable model predictive control

Subspace identification

Fuzzy clustering

TS-fuzzy model

ABSTRACT

This paper develops a stable model predictive tracking controller (SMPTC) for coordinated control of a large-scale power plant. First, a Takagi–Sugeno (TS) fuzzy model is established to approximate the behavior of the boiler–turbine coordinated control system (CCS) using fuzzy clustering and subspace identification (SID). Then, an SMPTC is designed based on the fuzzy model to track the power and pressure set-points while guaranteeing the input-to-state stability and the input constraints of the system. An output-based objective function is adopted for the proposed SMPTC so that the controller could be directly applicable for the data-driven model. Moreover, the effect of modeling mismatches and unknown plant variations has been overcome by the use of a disturbance term and steady-state target calculator (SSTC). Simulation results for a 600 MW power plant show that an off-set free tracking performance can be achieved over a wide range load variation.

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1. Introduction

Thermal power plant is the most widely used facility for power generation, which is composed by the boiler, turbine and generator to transform the fuel chemical energy into electric energy.

For a thermal power plant, the main task of the control system is to regulate the power output to meet the demand of the grid while maintaining the throttle pressure within a given tolerance to keep the power plant in a safe operating condition. Such an object is generally achieved by the multi-loop proportional–integral–derivative (PID) controllers, under either the boiler-following or turbine-following control mode [1]. However, in the context of increasing power demand as well as the energy and environmental issues, power plants are increasing in size and becoming more complex in order to achieve high efficiency and the scale of economy. Therefore, power plants present a challenging control problem owing to the behaviors such as: severe nonlinearity over a wide operation range, tight operating constraints, strong coupling among the multitude of variables, unknown disturbances and plant parameter variations. Consequently, the conventional PI/PID based controllers are no longer sufficient in meeting performance specifications, even if they are well tuned at a given load level; thus, various control strategies have been extensively studied [1–20].

As a direct approach to improve the conventional PI/PID controller, auto-tuning of the PID parameters is studied in [1–4] utilizing the fuzzy logic, particle swarm optimization (PSO) and iterative feedback tuning (IFT). In [5], a single linear controller is designed on the basis of careful choice of the operating range to avoid severe nonlinearity. In [6], a gain-scheduled l^1 -optimal approach is designed for the boiler–turbine unit based on the linear parameter varying model. In [7,8], H_∞ controllers are proposed to enhance the robustness of power plant control system. To overcome the nonlinearity of the power plant, various artificial intelligence techniques have also been applied. In [9], a fuzzy auto-regressive moving average (FARMA) controller was applied to the boiler–turbine system with rules generated using the history of input–output data. In [10], a linear quadratic regulator (LQR) controller is designed for the boiler–turbine through the genetic algorithm.

However, none of these controllers except [6] have dealt with the input constraints in the controller design stage; therefore, model predictive controller (MPC) has been employed in recent years. In [11], a dynamic matrix control (DMC) is employed for the boiler–turbine.

* Corresponding author. Tel.: +86 13645166145; fax: +86 25 83795951.

E-mail addresses: wux@seu.edu.cn (X. Wu), shenj@seu.edu.cn (J. Shen), lyg@seu.edu.cn (Y. Li), Kwang.Y.Lee@baylor.edu (K.Y. Lee).

It shows that the step-response model based on the test data is better suited than using the linearized mathematical model, but the performance of the proposed linear controller is degraded in a wide range operation. In [12,13] nonlinear predictive controllers are designed based on the neural network model and input–output feedback linearization. Although the control performance is improved, the nonlinear optimization is time consuming and lacks robustness.

To overcome these issues, the fuzzy modeling technique [21], which uses a combination of several linear models to approximate the nonlinear behavior of the plant, has been widely used in controller design for a wide range power plant operation [14–19], resulting in better performance than the conventional MPC methods. In [14–18], various kinds of MPCs are proposed on the Takagi–Sugeno (TS) fuzzy model for the boiler–turbine coordinated system, utilizing different computational algorithms, such as linear matrix inequalities (LMIs) [14], genetic algorithm (GA) [15,17], quadratic programming (QP) [16], and iterative learning [18]. In [19], a generalized predictive controller (GPC) is designed on the basis of neuro-fuzzy network model to control the steam temperature system of a 200 MW power plant. However, the stability of the control system which is desirable for industrial processes such as thermal power plant cannot be guaranteed by all of the aforementioned approaches, except [14,15].

On the other hand, it is common that, state-space models are used as local models in these fuzzy controllers [8,14–17] 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 models. However, for complex systems such as large-scale power plant, it is difficult to develop an accurate analytical model without the knowledge of thermodynamics and design specifications of many components, and this has become one of the main limitations in designing controllers for real power plants. Moreover, except [15] the structure of the fuzzy model is designed by simply dividing the operation range evenly, which greatly affects the accuracy of the model.

For these reasons, we propose a stable model predictive tracking controller (SMPTC) based on the data-driven fuzzy model to solve power plant control problems. Firstly, a TS fuzzy model is developed to approximate the behavior of the coordinated control system (CCS) in the power plant. Compared with the ordinary methods which linearize the nonlinear mathematical model around different operating points [8,14–18], we propose the use of fuzzy clustering [22] and subspace method [23–25] to identify the local state-space model directly from input–output data. To overcome the nonlinearity of the power plant, fuzzy clustering is first used to develop the structure of the fuzzy system and the membership functions, and then by combining the data with the membership functions, the SID is extended to develop all local state-space models.

The SMPTC is then designed on the developed fuzzy model to achieve a satisfactory power output and throttle pressure performance, while satisfying the input constraints and guaranteeing the closed-loop system stability. To improve the output tracking performance of the conventional stable MPC, an output-based objective function is used in the SMPTC formulation. Offset-free control is also achieved, even in the case of modeling mismatches and unknown plant behavior variations, by introducing a disturbance term and steady-state target calculator (SSTC) [26,27]. It is shown that the SMPTC can be realized by solving a set of linear matrix inequalities (LMIs), which is known to be a computationally efficient algorithm [14,28–30].

The proposed modeling and control approaches are applied to the CCS in a 600 MW large-scale power plant simulator. The remainder of this paper is organized as follows: Section 2 describes the power plant. Section 3 establishes the TS-fuzzy model of the CCS using fuzzy clustering and subspace identification. The SMPTC 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 power plant under consideration is a 600 MW oil-fired drum-type boiler–turbine–generator unit shown in Fig. 1. The model of this plant is developed from the first-principles as used in a power plant simulator and is validated in the MATLAB environment. The model is grouped into boiler, turbine, feedwater, and condenser modules and composed of 31 subsystems and 12 control valves associated with physical processes as shown in Fig. 1 [3].

As two of the most critical variables in a power plant, the power output E and throttle pressure P are controlled by the CCS through manipulating primarily the fuel flow valve u_1 and turbine governor valve u_8 . However, the variables are strongly coupled and the fuel flow has a relatively large thermal inertia property to the power and pressure. Moreover, the frequent unit load demand change brings severe nonlinearity to the CCS, and furthermore, the equipment wear, environmental change, fuel variation, etc., will result in significant disturbances and plant behavior variations. Therefore, advanced control techniques are needed to overcome the weaknesses of the conventional controllers.

3. Data-driven fuzzy modeling of the boiler–turbine coordinated control system

Subspace identification (SID) method provides an effective way to develop the state-space model directly from the input–output data of the plant [23,24]. Based on computational tools such as QR-factorization and singular value decomposition (SVD), the SID extracts the model from 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, the SID is only for linear system identification, while the power plant has inherent nonlinearity due to the load variations [12–20]. In [20], the whole operating region of the plant is first divided by using a nonlinear analysis tool (Vinnicombe gap metric, to be specific [31]), and the corresponding data for each region are collected to identify the local models separately. Then, switching point information is utilized to transform all local models into a common basis to form an integrated multi-model system. Although the resulting model can approximate the plant behavior closely, the modeling procedure is complex and greatly relying on human knowledge and intervention. As an alternative to the approach in [20], the fuzzy modeling strategy is adopted in this paper to solve the nonlinear problem by combining the fuzzy clustering with the SID.

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