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Nonlinear fuzzy model predictive iterative learning control for drum-type boiler–turbine system

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ABSTRACT

Advanced control strategy is necessary to ensure high efficiency and high load-following capability in the operation of modern power plant. Model predictive control (MPC) has been widely used for controlling power plant. Nevertheless, MPC needs to further improve its learning ability especially as power plants are nonlinear under load-cycling operation. Iterative learning control (ILC) and MPC are both popular approaches in industrial process control and optimization. The integration of model-based ILC with a real-time feedback MPC constitutes the model predictive iterative learning control (MPILC). Considering power plant, this paper presents a nonlinear model predictive controller based on iterative learning control (NMPILC). The nonlinear power plant dynamic is described by a fuzzy model which contains local liner models. The resulting NMPILC is constituted based on this fuzzy model. Optimal performance is realized within both the time index and the iterative index. Convergence property has been proven under the fuzzy model. Deep analysis and simulations on a drum-type boiler–turbine system show the effectiveness of the fuzzy-model-based NMPILC

1. Introduction

The boiler–turbine generation in modern power plant is the complex energy conversion system which transforms the fuel chemical energy into the electric power to meet the load demand of power system. The change of operating point right across the whole range can result in strong nonlinearity. This presents great challenge in control problem. Therefore, various advanced control strategies have appeared, e.g., the adaptive and variable structure methods [1,2], the robust approach [3–5], and the intelligent approaches [6–8].

During the past decades, power generation has undergone an extremely significant change. Much concern has been focused on economic and environmental matters instead of purely engineering issues. With these tasks, model predictive control (MPC) has been widely used in power plant control. MPC is an advanced control scheme based on a system model, in which an optimization procedure is performed to calculate optimal control actions at each sampling interval. It uses a model of the process explicitly to obtain the control signal by minimizing the objective function. So far, MPC may be the only advanced control strategy that can handle constraints, i.e. it can manipulate and control system variables in pre-defined ranges.

In MPC group, generalized predictive control (GPC) is the most widely used method in power plant control [9–13]. Hogg originally designed multivariable GPC strategy on power plant control [10]. Later on, Prasad developed a nonlinear GPC based on neural networks to control the main steam temperature and pressure, and the reheated steam temperature at several operating levels [11]. Plant nonlinearity was accounted for without resorting to on-line parameter-estimation as in self-tuning control. A nonlinear GPC based on neuro-fuzzy network is proposed in [12] for controlling the superheated steam temperature of a 200 MW power plant. Moelbak also evaluated GPC of superheater steam temperatures based on practical applications [13]. Apart from GPC, dynamic matrix control (DMC) has also been used for controlling drum-type boiler–turbine system [14,15]. With plant nonlinearity, incorporation of constraint handling is a major challenge. Paper [16] presented neuro-fuzzy modeling technique to appropriately incorporate constraint handling, and compared the scheme with

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input–output feedback linearization technique. Paper [17] present model predictive control and thermal energy storage for optimizing a multi-energy district boiler.

The existing MPCs need to further improve their learning ability when applying to the power plant. Traditionally, the self-tuning GPC is based on on-1ine model identification which requires sufficiently rich excitation of plant dynamics. This is not acceptable for security reason. Meanwhile, constraint handling, which is quite important in power plant control, is difficult to incorporate into the traditional self-tuning GPC.

Iterative learning control (ILC) has found wide application in the robotics community [18] and batch chemical process [19] as an intelligent teaching mechanism. The ILC always use the previous control error to improve the present control signal, which requires less a priori knowledge about the system dynamics and also less computational effort than many other kinds of control. Its main difference from the tradition self-tuning control is that control parameters are tuned along iteration axis, rather than time axis.

The incorporation of feedback design based on the MPC framework in the ILC leads to the model predictive iterative learning control (MPILC) [20,21]. The algorithm first utilizes MPC in the time-index for disturbance rejection, and then use ILC to eliminate persisting errors from previous runs in addition to responding to new disturbances as they occur during a run.

The MPILC has been well established for linear system. Considering nonlinear industry process, it usually need to linearize the error trajectory equation at some specific operating point, mostly using Taylar expansion. For certain class of nonlinear model, this could be very effective. While power plant dynamics can change in a large operating range, the model errors would inevitable introduce additional perturbations that would persist through the subsequent iterations without further corrections. Large model error may cause big computing burden for ILC.

The system nonlinearity must be taken into theoretical consideration in the MPILC design procedure to promise a higher control performance. The knowledge of thermo dynamics and design specification of many components are quite important for developing a more accurate nonlinear model. The Takagi–Sugeno fuzzy model [22] is described by fuzzy IF-THEN rules which represents local input–output relations of a nonlinear system. The main feature is to express the local dynamics of each fuzzy implication by a linear system model. The overall fuzzy model of the system is achieved by fuzzy "blending" of the local linear system models. This modeling technique is particularly suitable for those plants whose dynamic changes with operating point [23]. With a higher model exactness, the iteration process can be greatly reduced and the trajectory tracking property can be improved.

Thermal power plant are quite similar to chemical process in that both of them have typical overdamped nonlinear dynamics, significant interactions, large model errors, active constraints, and wide load changing range. The objective of this paper is to derive a nonlinear model predictive iterative learning control (NMPILC) based on fuzzy modeling technique. Due to the load dependent characteristic of the power plant, fuzzy models could be used to approximate the plant by local models at different operating points. The nonlinear predictive control can be devised incorporating all the local MPCs designed using the respective local linear models. Simulation results show that the proposed NMPILC can well control the power plant under wide operating range.

2. Problem description

For the MIMO discrete-time nonlinear system where the run length is fixed and consists of N sample steps, the input–output relationship can be written in the form of

$$y = F(u, d) \tag{1}$$

where F is some nonlinear mapping, and y, u, d are the output, the input and the disturbances, respectively. The dimensions of input and output are n_u and n_y.

Define the input, output and disturbance sequences as

$$\begin{aligned}
\mathbf{u} &\triangleq \begin{bmatrix} u^T(0) & u^T(1) & \cdots & u^T(N-1) \end{bmatrix}^T \in R^{n_u N} \\
\mathbf{y} &\triangleq \begin{bmatrix} y^T(1) & y^T(2) & \cdots & y^T(N) \end{bmatrix} \in R^{n_y N} \\
\mathbf{d} &\triangleq \begin{bmatrix} d^T(1) & d^T(2) & \cdots & d^T(N) \end{bmatrix} \in R^{n_y N}
\end{aligned} \tag{2}$$

The nonlinear mapping F can be modeled by the T–S fuzzy model:

$$R^i : \text{If}\, Z_1(t)\, \text{is}\, A_{i1}\, \text{and} \ldots \text{and}\, Z_p(t)\, \text{is}\, A_{ip},\ \text{then}\, y^i = G^i u - P^i \quad i = 1, 2, \ldots r \tag{3}$$

where R^i denote the fuzzy implication R in the ith rule, $Z_1(t)\ldots Z_p(t)$ are variables of the premise of implication, $A_{i1}\ldots A_{ip}$ are fuzzy sets in the premise, P^i represents the collective effects of disturbance, bias errors, measurement noise in the ith sub-area. G^i is the ith sub-model impulse response coefficient matrix.

By causality, the structure of G^i is lower-block triangular form as follow:

$$\mathbf{G}^i = \begin{bmatrix} g^i_{1,0} & 0 & \cdots & 0 \\ g^i_{2,0} & g^i_{2,1} & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ g^i_{N,0} & \cdots & \cdots & g^i_{N,N-1} \end{bmatrix} \in R^{n_y N \times n_u N} \tag{4}$$

where $g^i_{pq} \in R^{n_y \times n_u}$ is the output response at time p to independently applied unit pulse inputs at time q.