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Multiple Model Predictive Control Based on Fuzzy Switching Scheme of a Coagulation Chemical Dosing Unit for Water Treatment Plants ⋆

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Abstract: A switching scheme based on Takagi-Sugeno fuzzy inference system is proposed in this paper to address the problems of poor transient response, rapid oscillation of plant output and long duration of switching time associated with the multiple model predictive control (MMPC) based on hard switching. A set of piecewise linear models is used to represent the system under consideration at different operating regimes. Corresponding MPC local controller is developed for each model. At each instant, the fuzzy switching system selects the appropriate model/controller pair for the system. The proposed MMPC strategy is applied to a coagulation chemical dosing unit for water purification plants. Simulation results of the proposed control scheme are promising and positive.

Keywords: Water treatment plants; coagulation process; multiple model predictive control; Takagi-Sugeno fuzzy inference system

1. INTRODUCTION

Model predictive control (MPC) is a widely accepted and useful control strategy for industrial process applications as a result of its ability to reformulate the control problem as an optimisation problem and demonstrate satisfactory performance while complying with operational and safety constraints. However, MPC is an ineffective approach to design local controllers for systems with strong nonlinearities and sudden changes in the operating conditions (Xie et al, 2008). In order to address this problem, multiple model predictive control (MMPC) strategy has been identified as a viable solution in real-life applications (Gopinathan et al., 1998; Porfirio et al., 2003; Bello et al., 2014).

MMPC as an optimal control strategy is developed using several linear models that represent separate local regions or regimes of a nonlinear system. Each linear model effectively describes distinct local region of the nonlinear system. Corresponding MPC local controller is designed for each linear model of the system. All the models are computed in parallel and the best model/controller pair is selected based on the minimum identification error at each instant (Xie et al, 2008). The switching scheme engaged for the model/controller pairs operates when another pair yields smaller identification error than the current pair. The global control input is thus generated using the parameters of the selected pair.

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In the literature, the concept of hard switching in MMPC has been discussed and investigated extensively by Narenda and Balakrishnan (1994); Giovanini and Grimble (2003); Xuelan (2012). However, MMPC hard or classic switching scheme is associated with problems that include: poor transient response; frequent switching scheme between different models and erratic behaviour when moving from one model to another (Xie et al, 2008).

In this paper, a novel switching scheme is proposed for the multiple model predictive control to address the aforementioned problems associated with hard switching scheme. Takagi-Sugeno(TS)fuzzy inference system is applied to develop a fuzzy switching scheme to select the model/controller pair that gives the best performance at each instant among the pairs in the model/controller banks. The proposed fuzzy switching multiple model predictive control strategy (FSMMPC) is applied to control a coagulation chemical dosing unit for water treatment plants. The control objective is to regulate the surface charge and pH level of the chemically treated water to meet the desired target quality levels by manipulating the flow rates of the primary coagulant, co-coagulant and lime flow rates. Performances of the proposed control strategy are evaluated using computer simulation tests.

2. MATERIAL AND METHODS

2.1 Problem Formulation

Consider a nonlinear system expressed as:

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$$\begin{cases} \dot{x} = f\left(x\left(t\right), u\left(t\right)\right) \\ y\left(t\right) = g\left(x\left(t\right), u\left(t\right)\right) \end{cases} \tag{1}$$

where $x\left(t\right) \in R^n$, $u\left(t\right) \in R^p$, $y\left(t\right) \in R^q$ stands for the state, input and output vector respectively. Piecewise linearization technique could be applied to develop multiple model system for the proposed control strategy. Assuming that the system has a number of operating points as follows:

$$\left(x^{op_i}, u^{op_i}, y^{op_i}\right), \quad i = 1, 2, \ldots, N \tag{2}$$

By using Taylor's series approximation, the nonlinear system could be linearised around these operating points. The N linearised models obtained can be expressed in the following state space model:

$$\begin{cases} \delta\dot{x}\left(t\right) = A_i \delta x_i\left(t\right) + B_i \delta u_i\left(t\right) \\ \delta y\left(t\right) = C_i \delta x_i\left(t\right) + D_i \delta u_i\left(t\right) \end{cases} \tag{3}$$

where $A_i = \frac{\partial f(x,u)}{\partial x}|\left(x^{op_i}, u^{op_i}\right)$, $B_i = \frac{\partial f(x,u)}{\partial u}|\left(x^{op_i}, u^{op_i}\right)$, $C_i = \frac{\partial g(x,u)}{\partial x}|\left(x^{op_i}, u^{op_i}\right)$, $D_i = \frac{\partial g(x,u)}{\partial u}|\left(x^{op_i}, u^{op_i}\right)$, $\Delta x_i = x_i - x^{op_i}$, $\Delta u_i = u_i - u^{op_i}$, $\Delta y_i = y_i - y^{op_i}$ and $\left(x_i, u_i, y_i\right)$ are the state, input, output variables in the i^{th} local model respectively.

With the assumption that δ is very small, the linear models could represent the nonlinear model adequately. The discretized state space model of the N linearised models yields a family of piecewise linear system represented as:

$$\left.\begin{array}{l} x\left(k+1\right) = A_i x_i\left(k\right) + B_i u\left(k\right) + b_i \\ y\left(k\right) = C_i x\left(k\right) + D_i u\left(k\right) + d_i, \end{array}\right\} \; i = 1, 2, \ldots, N \tag{4}$$

where $x\left(k\right) \in X_i$, X_i represents the corresponding operating region of the state space in which i represents the nonlinear system model. These linear models could be used to develop corresponding MPC local controllers for the system.

2.2 Model Predictive Control Formulation

The control strategy of the MPC is to find a sequence of control signals $\Delta u\left(k\right)$, $\Delta u\left(k+1\right)$, …, $\Delta u\left(k+M+1\right)$ that yield the predicted outputs $y\left(k+1|k\right)$, $y\left(k+2|k\right)$, …, $y\left(k+P|k\right)$, in accordance to some desired reference signal vector $r\left(k+1|k\right)$, $r\left(k+2|k\right)$, …, $r\left(k+P|k\right)$. The span of the control sequence, M, is referred to as the control horizon, while that of the predicted output, P, is called the prediction horizon. Although, the computed control values are based on P time steps, only the first move is implemented and a new sequence of control inputs is computed at the next sampling instant. The following cost function is chosen to implement the proposed control strategy:

$$J\left(u\right) = \underbrace{min}_{\Delta u(k),\ldots,\Delta u(k+M-1)} \; S_y\left(k\right) + S_u\left(k\right) + S_{\Delta u}\left(k\right) \tag{5}$$

subject to:

$$u_{min} \leq u\left(k+i-1\right) \leq u_{max}, \; for\; i = 1\; to\; M \tag{6}$$

$$\Delta u_{min} \leq \Delta u\left(k+i-1\right) - \Delta u\left(k+i-2\right) \leq \Delta u_{max}, \; for\; i = 1\; to\; M \tag{7}$$

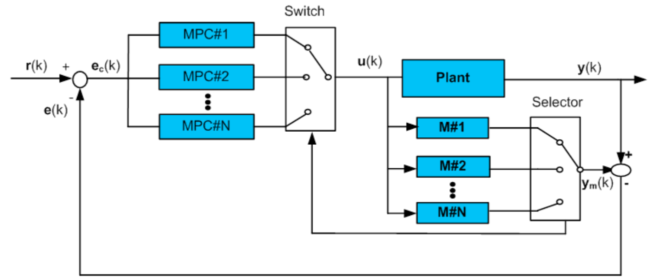

Fig. 1. Multiple model predictive control scheme

$$y_{min} \leq y\left(k+i\right) \leq y_{max}, \; for\; i = 1\; to\; P \tag{8}$$

where

$$S_y\left(k\right) = \sum_{i=1}^{P}\sum_{j=1}^{n_y}\left\{w_j^y\left[r_j\left(k+i\right) - y_j\left(k+1\right)\right]\right\}^2 \tag{9}$$

$$S_u\left(k\right) = \sum_{i=1}^{M}\sum_{j=1}^{n_u}\left\{w_j^u\left[u_j\left(k+i-1\right) - \overline{u}_j\right]\right\}^2 \tag{10}$$

$$S_{\Delta u}\left(k\right) = \sum_{i=1}^{M}\sum_{j=1}^{n_u}\left\{w_j^{\Delta u}\Delta u\left(k+i-1\right)\right\}^2 \tag{11}$$

$\mathbf{r}\left(k\right)$ is the reference vector, $\mathbf{y}\left(k+j|k\right)$ is the j-step ahead predicted output given the present output measurements, w_j^y is the positive definite output error weighting matrix, w_j^u and $w_j^{\Delta u}$ are the positive semi definite input and input increment weighting matrices. $\overline{u}_j$ is the nominal value of input j. The weighting matrices and the prediction horizon parameters, P, and the control horizon M are the tuning parameters which can be used to shape the closed-loop response of the system (Yu et al., 1992; Shamsaddinlou et al., 2013).

2.3 Multiple Model Predictive Control Scheme

Multiple Model Predictive Control (MMPC) is realised by defining models that adequately describe different operating conditions of the system. It includes the design of a local controller for each of the predefined models, identification of the appropriate model and selection of the appropriate control signals at each instant (Mazinan and Sadati, 2008).

Fig. 1 shows the block diagram of a typical switching MMPC control scheme. M#1, M#2,…,M#N are the N models in Fig. 1, which are connected in parallel with the actual process. $\mathbf{y}\left(k\right)$ is the output vector of the process, $u_1(k)$, $u_2(k)$,…, $u_N(k)$ are the control actions to each of the corresponding models and the $\mathbf{u}(k)$ is the final control action. $\mathbf{r}\left(k\right)$ is the reference trajectory, $\mathbf{y}_m\left(k\right)$ is the predictive output of the selected model, $\mathbf{e}\left(k\right)$ is the error between plant output and predictive output of the selected model, and $\mathbf{e}_c\left(k\right)$ is meant to correct plant-model mismatch.

2.4 Tagaki-Sugeno Switching Scheme

The fuzzy switching (FS) mechanism proposed in this study is based on TS fuzzy rules of form (Roger-Jang et al., 1997):

$$R_i: \; if\; x_j\; is\; A_j^{(i)}\; then\; u\; is\; f_i\left(x_j\right) \tag{12}$$