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Predictive Functional Controller with a Similar Proportional Integral Optimal Regulator Structure: Comparison with Traditional Predictive Functional Controller and Application to Heavy Oil Coking Equipment*

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Abstract By extending the system's state variables, a novel predictive functional controller has been developed. The structure of this controller is similar to that of classical proportional integral (PI) optimal controller and includes a control block that can perform a feed-forward control of future *P*-step set points. It considers both the state variables and the output errors in its cost function, which results in enhanced control performance compared with traditional state space predictive functional control (TSSPFC) methods that consider only the predictive output errors. The predictive functional controller (PFC) has been compared with TSSPFC in terms of tracking ability, disturbance rejection, and also based on its application to heavy oil coking equipment. The results obtained show the effectiveness of the controller.
Keywords state space model, PI optimal regulator, predictive functional control

1 INTRODUCTION

The optimal control of the synthesis of petrochemicals and other related processes is of considerable significance because good control results markedly improve the dynamic performance and also enhance economic benefits. Therefore, predictive functional control (PFC)[1—3] has gained tremendous success in industrial applications. It is categorized under model predictive control (MPC)[4,5] and was first presented by Richalet and Kuntze. The control law is based on the prediction obtained from the model of the processes. Control action is calculated by minimizing the difference between the predicted process output and the reference signal over a certain time horizon. It has been proved that PFC exhibits remarkable robustness despite the model mismatch and uncontrolled dynamics[6—11]. While retaining the good features of MPC, PFC makes the control input more regular, which considerably reduces the control-calculating burden, and therefore it is highly applicable to those processes that need fast control. Till now, several research studies have been performed on PFC theory, and studies with regard to its application have made the PFC theory more significant.

However, by selecting the state space model, the system's inner states can be easily described and information of these states such as state feedback and state constraints can be effectively used when the controllers are designed[11—13]. If the states represent some physical variables, prediction of their future changes can also give important information regarding the processes. But the state space PFC algorithms that have been presented till now have not made full use of these merits[1,11].

Based on the above-mentioned merits of state space design, a novel predictive functional control method has been developed. The structure of this controller is similar to that of proportional integral (PI) optimal regulator [14] and has P-step setpoint feed-forward control. Simulation comparisons and application study show that this method has tremendous applications in chemical engineering.

2 SYSTEM MODEL AND PRESENTATION

Consider the following (SISO) discrete system with dead time

$$\bar{x}(k+1)=\bar{A}\bar{x}(k)+\bar{B}u(k-d)$$
$$y(k)=\bar{c}\bar{x}(k) \tag{1}$$

where k, u, y are the discrete time, control variable, and output variable, respectively.

$\bar{x}(k)=\left[\bar{x}_1(k),\bar{x}_2(k),\cdots,\bar{x}_n(k)\right]^{\mathrm{T}}$ is the state vector with dimension $n\times 1$, $\bar{A}$ is system matrix with dimension $n\times n$, $\bar{B}$ is the control coefficient vector with dimension $n\times 1$, $\bar{c}$ is the observer coefficient vector with dimension $1\times n$, and d is the dead time.

Extending the state space by considering $u(k-1),u(k-2),\cdots,u(k-d)$ as the system's state variables and $u(k)$ as the input

$$\boldsymbol{x}(k+1)=\boldsymbol{A}\boldsymbol{x}(k)+\boldsymbol{B}u(k)$$
$$y(k)=\boldsymbol{c}\boldsymbol{x}(k) \tag{2}$$

where

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$$\boldsymbol{A}=\begin{bmatrix} \bar{\boldsymbol{A}} & \bar{\boldsymbol{B}} & \underline{\boldsymbol{O}} & \underline{\boldsymbol{O}} & \cdots & \underline{\boldsymbol{O}} \\ \bar{\boldsymbol{O}} & 0 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & & \ddots & & \vdots \\ \bar{\boldsymbol{O}} & 0 & & 0 & & 1 \\ \bar{\boldsymbol{O}} & 0 & & \cdots & & 0 \end{bmatrix}$$

$$\boldsymbol{x}(k)=\left[\bar{\boldsymbol{x}}(k)^{\mathrm{T}}, u(k-d), u(k-d+1), \cdots, u(k-1)\right]^{\mathrm{T}}$$

$$\boldsymbol{B}=\left[\underline{\boldsymbol{O}}^{\mathrm{T}}, 0, \cdots, 0, 1\right]^{\mathrm{T}}$$

$$\boldsymbol{c}=\left[\bar{\boldsymbol{c}}, 0, 0, \cdots, 0\right] \tag{3}$$

Note that $\bar{\boldsymbol{O}}$ is the zero vector with dimension $1\times n$ and $\underline{\boldsymbol{O}}$ $n\times 1$.

Rewrite Eq.(2) as

$$\Delta\boldsymbol{x}(k+1)=\boldsymbol{A}\Delta\boldsymbol{x}(k)+\boldsymbol{B}u(k)-\boldsymbol{B}u(k-1)$$

$$y(k)=\boldsymbol{c}\boldsymbol{x}(k) \tag{4}$$

where Δ is the differencing operator, $\Delta=1-z^{-1}$.

Defining the expected output as $r(k)$, the output error is

$$e(k)=y(k)-r(k) \tag{5}$$

Combining Eqs.(4) and (5)

$$e(k+1)=e(k)+\boldsymbol{cA}\Delta\boldsymbol{x}(k)+\boldsymbol{cB}u(k)-\boldsymbol{cB}u(k-1)-\Delta r(k+1) \tag{6}$$

Defining

$$z(k)=\begin{bmatrix} e(k) \\ \Delta\boldsymbol{x}(k) \end{bmatrix} \tag{7}$$

as the new state variables and combining Eqs.(4) and (6), a new system is derived

$$z(k+1)=\tilde{\boldsymbol{A}}z(k)+\tilde{\boldsymbol{B}}u(k)-\tilde{\boldsymbol{B}}u(k-1)+\tilde{\boldsymbol{c}}\Delta r(k+1) \tag{8}$$

where

$$\tilde{\boldsymbol{A}}=\begin{bmatrix} 1 & \boldsymbol{cA} \\ \tilde{\boldsymbol{O}} & \boldsymbol{A} \end{bmatrix}, \tilde{\boldsymbol{B}}=\begin{bmatrix} \boldsymbol{cB} \\ \boldsymbol{B} \end{bmatrix}, \tilde{\boldsymbol{c}}=\begin{bmatrix} -1 \\ \tilde{\boldsymbol{O}} \end{bmatrix} \tag{9}$$

$\tilde{\boldsymbol{O}}$ is the zero vector with dimension $(n+d)\times 1$

The derived Eq.(8) is used to design a novel predictive functional controller.

3 PFC CONTROL ALGORITHM

3.1 Cost function

Consider the following optimal problem over a certain horizon

$$J=\sum_{j=1}^{P} z^{\mathrm{T}}(k+j)\boldsymbol{Q}_j z(k+j) \tag{10}$$

where P is the number of fitting points, $\boldsymbol{Q}_j$ is the symmetrical weighted matrix with dimension $(n+d+1)\times(n+d+1)$, generally

$$\boldsymbol{Q}_j=\mathrm{diag}\{q_{j1}, q_{j2}, \cdots, q_{j(n+1)}, 0, \cdots, 0\} \quad 1\leqslant j\leqslant P \tag{11}$$

(1) Usually, $q_{j1}\neq 0$, which means the output error must be considered in the cost function. $q_{j2}, \cdots, q_{j(n+1)}$ can be adjusted to regulate the system's state vector increments $\Delta\bar{\boldsymbol{x}}(k)$.

(2) Considering $\boldsymbol{Q}_j=0, j<N_P$ indicates that the optimizing time starts at time $k+N_P$, which can consider the impact of the system's dead time effectively. Considering $N_P=P$ indicates only one-point prediction.

(3) Considering $\boldsymbol{Q}_j=\mathrm{diag}\left\{q_{j1}, 0, \cdots, 0\right\}$ indicates that only output errors are weighted; in this case, the cost function is reduced to the input-output type, which means this method is equivalent to the traditional state space predictive functional control method (TSSPFC).

3.2 State prediction and controller design

The inputs of PFC are associated with specific base functions which are set according to the process nature and set points, namely the linear combination of these.

$$u(k+i)=\sum_{j=1}^{N}\mu_j f_j(i) \tag{12}$$

where μ_j are the weighted coefficients, $f_j(i)$ are the values of the base functions at the sampling time i, and N is determined by the system's model and expected set point.

Combining Eqs.(8) and (12), the future prediction of the system is

$$z(k+1)=\tilde{\boldsymbol{A}}z(k)+\tilde{\boldsymbol{B}}\sum_{j=1}^{N}\mu_j f_j(0)-\tilde{\boldsymbol{B}}u(k-1)+\tilde{\boldsymbol{c}}\Delta r(k+1)$$

$$\begin{aligned} z(k+2)&=\tilde{\boldsymbol{A}}^2 z(k)+\tilde{\boldsymbol{A}}\tilde{\boldsymbol{B}}\sum_{j=1}^{N}\mu_j f_j(0)-\tilde{\boldsymbol{A}}\tilde{\boldsymbol{B}}u(k-1)+\tilde{\boldsymbol{B}}\sum_{j=1}^{N}\mu_j f_j(1)-\tilde{\boldsymbol{B}}\sum_{j=1}^{N}\mu_j f_j(0)+\tilde{\boldsymbol{A}}\tilde{\boldsymbol{c}}\Delta r(k+1)+\tilde{\boldsymbol{c}}\Delta r(k+2) \\ &=\tilde{\boldsymbol{A}}^2 z(k)+\left(\tilde{\boldsymbol{A}}\tilde{\boldsymbol{B}}-\tilde{\boldsymbol{B}}\right)\sum_{j=1}^{N}\mu_j f_j(0)+\tilde{\boldsymbol{B}}\sum_{j=1}^{N}\mu_j f_j(1)-\tilde{\boldsymbol{A}}\tilde{\boldsymbol{B}}u(k-1)+\tilde{\boldsymbol{A}}\tilde{\boldsymbol{c}}\Delta r(k+1)+\tilde{\boldsymbol{c}}\Delta r(k+2) \end{aligned}$$

$$\vdots$$