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Research article

Improved linear quadratic and proportional control system for improved liquid level system regulation in a coke fractionation tower

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ABSTRACT

A new linear quadratic regulation (LQ) control plus a proportional (P) control system is proposed for the level regulation in an industrial coke fractionation tower. The process is first stabilized using a P controller and then a subsequent LQ controller is designed for the P control system. The P control system is modeled as a generalized first order plus dead time (FOPDT) process using step-response test and the LQ-P controller is designed through a new state space structure. Performance in terms of regulatory and servo issues were investigated. Simulation results showed that the proposed method is more robust and improves performance than traditional model predictive control.

1. Introduction

Heavy oil coking is quite important to supply various petrochemical products. This kind of industrial processing technology handles different kinds of heavy oil to meet the demand of fuels and petrochemical needs [1,2]. However, control strategies may encounter difficulty since the process dynamics is rather complex and the coking kinetics is uncertain. Moreover, sensor measurement accuracy and the interactions among units, cause low performance of relevant control strategies [3,4]. It is also difficult to construct an accurate first-principle model to include main phenomena in the whole unit because of lack of detailed physicochemical processes' knowledge. What's more, control optimization using such complex models is also a tough task because of nonlinearity, time consuming calculation and even unfeasibility [5–7].

It is an attractive choice to use input/output data from process operation. In fact, though nonlinear input/output models can be obtained [8], a serious problem may arise if the process dynamics are associated with many patterns, which will lead to the deterioration of control performance if some parameters change and require repeated identification. In addition, optimization based on such complex models with large number of process parameters is also difficult [9]. Simple models can also be chosen for controller design, however, these models may result in limitations of controllers in terms of control performance and robustness. As for the industrial coke unit, many conventional control algorithms may not be very effective because of its high control specifications and the complex characteristics in the unit, which is shown as follows. First, the complexity of petrochemical process in the unit leads to the complex process dynamics. Second, the inevitable coking disturbances and change of loads cause the nonlinearity and uncertainty in each subsystem. Third, the control performance specifications for such unit are strict, which require both steady operation and small errors.

It is shown that PID (proportional-integral-derivative) control may lack enough robustness for industrial applications [10,11]. Recently, advanced control, such as model predictive control (MPC), etc., has been extensively studied, which has undergone through traditional input-output models to state space models [12–15]. A detailed review of MPC application can be seen in [16]. There have also been some research results for industrial coke unit such as adaptive control strategies [17,18], dynamic matrix control [19], predictive functional control [20], artificial intelligence online advisor based MPC [21], iterative learning MPC [22], state space model based MPC [23,24], non-minimal state space (NMSS) MPC [25,26], and so on.

Although MPC can show improved performance and effectiveness, there are still challenges for industrial coke processes. This is because the accurate input/output dynamic relationships are not easy to be obtained. Further more, the petrochemical process causes strong subsystem interactions, time-delay and disturbances of different frequencies. The coke tower switches affect the fractionation tower every several hours, while the

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Nomenclature

$G(s)$	Process transfer function (continuous domain)
K, T, τ	Process gain, time constant (or the residence time) and the time delay (continuous domain)
s	Laplace operator
$y(t)$	The real-time process output
$y(\infty)$	The final steady value of $y(t)$
U_0	The amplitude of the input step signal
Δ	The difference operator, $\Delta = 1 - z^{-1}$
$y(k)$	The discrete output variable at time instant k(discrete domain)
$u(k-d)$	The discrete input variable at time instant $k-d$(discrete domain)
k	Current time instant
f, h, d	Model coefficients (discrete domain)
$x(k)$	State space variable (discrete domain)
A_m, B_m	System matrix and control matrix (discrete domain)
$z(k)$	$z(k)^{\mathbf{T}} = [x(k)\ ,\ e(k)]$(discrete domain)
A, B	System matrix and control matrix for the augmented system (discrete domain)
J	Cost function
Q, R, Q_f	Output weighting matrix, input weighting matrix, and the terminal weighting matrix
$[k_0, k_f]$	The future optimization horizon
$\Delta u(k)$	Control input
H_{k,k_f}	Calculation matrix for control input
H_k	Hamiltonian function
p_{k+1}	The Lagrange multiplier
$G_f(z)$	Filter (discrete domain)

fractionation tower coking affect the fractionation tower over a period of weeks/months, which are difficult to be rejected. The reasons that MPC is so tough in industrial coke units have also been analyzed in [27].

In this article, a new LQ-P control (linear quadratic plus P) is proposed, in which the inner P control system is viewed as a generalized process for outer LQ controller. The proposed control demonstrates improved control performance and overcomes the performance deterioration deficiency of traditional state space model based MPC under model/plant mismatches, which are very common for industrial coke units. The performance of the proposed control is illustrated through a liquid level system control case study in the coke fractionation tower.

The paper is organized as follows. Section 2 gives the new state space model using step-response test. Section 3 illustrates the proposed LQ control design. The LQ plus the P control system is detailed in Section 4. A case study on an industrial coke fractionation tower is shown in Section 5. Conclusion is drawn in Section 6.

2. New state space model through step-response test

For process system engineering problems, process control follows the procedure of first obtaining a process model and then designing a corresponding controller for the regulation of process variables. To achieve these, deriving models through step-response test is one of the most popular ways. Though most industrial processes are generally nonlinear with high degrees of uncertainties, models based on step-response test can grasp the main process characteristics. For the process uncertainties, the subsequent controller design and tuning will play an important role.

For simplicity and in accordance with the liquid level system control case study later in this article, the general first-order-plus-dead-time (FOPDT) process model is adopted.

$$G(s) = \frac{Ke^{-\tau s}}{Ts+1} \tag{1}$$

where it has three parameters: K is the process gain, T is the time constant (or the residence time) and τ is the time delay of the process.

The proposed LQ design is based on a new state space model, through which dynamic and steady control performance can be improved because the new model can enable the controller to regulate the process input and output variables. The transformation from step-response model to state space model is detailed as follows.

Eq. (1) is first transformed into the discrete formulation through sampling time T_s.

$$\Delta y(k+1) + f\Delta y(k) = h\Delta u(k-d) \tag{2}$$

where $\Delta = 1 - z^{-1}$ is the difference operator, $y(k+1)$, $y(k)$ and $u(k-d)$ are the discrete output and input variables, respectively. k is current time, f, h, d are model coefficients with

$$\begin{aligned} f &= -\exp(-T_s/T) \\ h &= K(1+f) \\ d &= \tau/T_s \end{aligned} \tag{3}$$

A state space variable is first chosen as

$$x(k)^{\mathbf{T}} = [\Delta y(k)\ ,\ \Delta u(k-1),\ \ \Delta u(k-2),\ \ \cdots,\ \ \Delta u(k-d)] \tag{4}$$

Then the corresponding state space model is

$$x(k+1) = A_m x(k) + B_m \Delta u(k) \tag{5}$$

where

$$A_m = \begin{bmatrix} f & 0 & \cdots & 0 & h \\ 0 & 0 & \cdots & 0 & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & 1 & 0 \end{bmatrix},\ B_m = \begin{bmatrix} 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \tag{6}$$

Define the output error as $e(k) = y(k) - r(k)$, where $r(k)$ is the set-point, then formulate a new state variable as

$$z(k)^{\mathbf{T}} = [x(k), e(k)] \tag{7}$$

Thus Eq. (2) is formulated as a new state space model.

$$z(k+1) = Az(k) + B\Delta u(k) \tag{8a}$$

where

$$A = \begin{bmatrix} f & 0 & \cdots & 0 & h & 0 \\ 0 & \cdots & \cdots & \cdots & \cdots & \vdots \\ 0 & 1 & 0 & \cdots & \cdots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & 1 & 0 & 0 \\ f & 0 & \cdots & 0 & h & 1 \end{bmatrix},\ B = \begin{bmatrix} 0 \\ 1 \\ 0 \\ \vdots \\ \vdots \\ 0 \end{bmatrix} \tag{8b}$$