Online FOPID Control of Material Level in Steady Flow Bunker Based on Data-Driven Techniques

Hongliang Yu, Jinliang Liu, Qiang Zhang*,Xiangyu Chen
School of Electrical Engineering,University of Jinan ,Jinan,250022
E-mail: ave_zhangq@ujn.edu.cn

Abstract: In this paper,we present a fractional order proportion integration differentiation (FOPID) controller based on data-driven technology .This controller is proposed for cement raw material grinding steady flow bunker material level system system. Firstly, the pseudo-partial derivative (PPD) parameter is estimated dynamically by the state observer. Secondly, three parameters of integer order PID controller K_p, K_i, K_d are determined by PPD parameter. Then, under this circumstance, the genetic algorithm is used to determine λ, μ ,which are the other two parameters of the FOPID controller. Finally, the simulation results show that the proposed method has good control effect, and the FOPID controller is better than the integer order one.

Key Words: steady flow bunker material level; Data-driven control; FOPID controller; genetic algorithm

1 INTRODUCTION

In recent years, the term "data driven" have become very popular [1-2]. This method need not to master the exact model of the controlled object,so it can be used to solve problems in industrial processes that dynamic models are not easy to grasp. With the rapid development of data-driven technology, many scholars have excogitated a lot of new control methods. The representative methods are as follows: model-free adaptive control (MFAC) [3-5], iterative feedback tuning (IFT) [6], virtual reference feedback tuning (VRFT) [7], unfalsified control (UC) [8] methodology and others.

There are many researches on the control of cement production process.In [9], Zhang and others proposed an online updated Proportion Integration Differentiation (PID)controller. The gradient descent method is used to set the parameters,and the controller achieved the control of the calciner outlet temperature. In[10], empirical mode decomposition (EMD) combined with the least square method is researched to realize the trend extraction and identification of cement burning zone flame temperature by Lu and others.However, there are few studies on the control of steady flow bunker. The dynamic model of this process is difficult to obtain accurately,which brings a lot of difficulties to its research.

On the other hand, after years of development, PID control technology has been quite mature. Because of its simple structure, strong robustness and other characteristics, PID technique is widely used in metallurgy, electric power , machinery and other industrial processes.However, with the rapidly development of industry, the establishment of mathematical models for industrial process has put forward higher request, which is difficult for traditional integer order controller. At the same time, it has been paid more and more attention to the theory and application of Fractional Order Proportion Integration Differentiation(FOPID) control [11-13]. Due to the introduction of integral and differential orders, the controller has two more adjustable parameters, so it has a larger parameter setting range, which can obtain a more robust control effect.

For the tuning of two parameters λ,μ, we use genetic algorithm[14], which can improve the convergence and robustness of the system. As a new global optimization search algorithm, genetic algorithm has been widely used in various fields because of its simple, universal, robust and suitable for parallel processing, and has gradually become one of the important intelligent algorithms.

Based on our published result[9],we design a stabilizing online updated FOPID controller, which is to realize the optimal control of raw material grinding system through the control of feed quantity and the detection of the material position. First of all, we assume that the controller structure is integer order incremental PID. Based on PPD parameter identification observer, three PID parameters are set by the gradient descent method. Then, the other two parameters of FOPID controller are adjusted by genetic algorithm.The simulation results show that this control method can realize the effective control of the steady flow bunker material level system.

The general structure of this paper is summarized as follows. After the introduction, steady flow bunker description and the problem formulation are described in Section 2. In Section 3, a state observer is designed for PPD parameter identification. Afterwards we propose online update FOPID controller under the observer in Section 4. The simulation results by MATLAB are shown in Section 5. Finally, conclusions are drawn in Section 6.

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2 Steady Flow Bunker Description and Problem Formulation

Raw material grinding is a high energy consumption link in the cement production process. The stability of material level in steady flow bunker is the foundation of vertical mill working efficiency. The steady flow bunker process is shown in Fig.1.

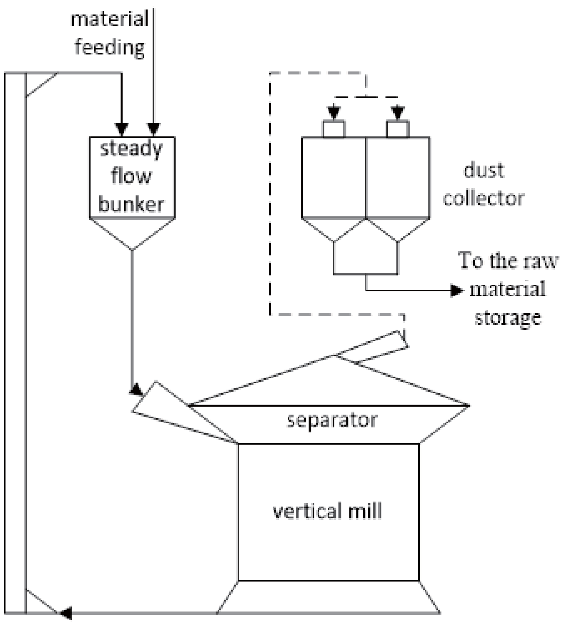

Figure 1: Grinding process of cement raw meal

In Fig.1, the raw materials are putted into the steady flow bunker for weighing. Then, the materials enter the vertical mill from feed port in the lower part of the steady flow bunker under controllable conditions. Subsequently, after full grinding of the vertical mill, the fine particles are blown by the circulating air and enter the separator for particle size screening. At the same time, the coarse particles that cannot be blown up are reintroduced into the steady flow bunker by the hoist at the bottom of the vertical mill.After this, they are regrinded together with the fine particles that fall back to the vertical mill.

From above analysis, we obtain that the material level in steady flow bunker is affected by material feeding, current of hoist in grinding, vertical mill current, dust collecting fan speed. It is worth noting that the material feeding is the most influential control quantity, the other three variables can be ignored. So the mathematical model of the steady flow bunker material level can be described as

$$\begin{aligned} c_T(k+1) = f_{map}(&c_T(k), c_T(k-1), ..., c_T(k-n_y), \\ &c_u(k), c_u(k-1), ..., c_u(k-n_u)) \end{aligned} \quad (1)$$

Where c_T and c_u are the steady flow bunker material level and the material feeding, $f_{map}(\cdot)$ is an unknown mapping function, and n_y and n_u are the delay orders of c_T and c_u respectively.

From equation(1), we can induce a general model of the steady flow bunker material level system given by

$$\begin{aligned} y(k+1) = f(&y(k), y(k-1), ..., y(k-n_y), \\ &u(k), u(k-1), ..., u(k-n_u)) \end{aligned} \quad (2)$$

Where $y \in R$ and $u \in R$ are the delay orders of y and u ,respectively.

Based on the above inferences, we designed the online undated FOPID controller with PPD technique and genetic algorithm, which structure is shown in Fig.2.

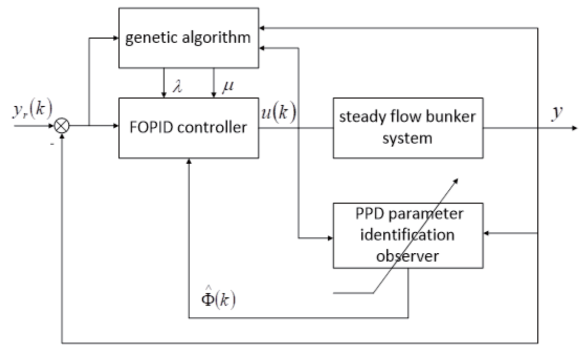

Figure 2: The diagram of online updated fractional PID controller based on PPD parameter identification observer

In order to introduce this structure in detail, the following assumptions and Lemma are required.

Assumption1. The partial derivative of the nonlinear mapping function $f(\cdot)$ in equation(2) is continuous.

Assumption2. The system equation(2) meets $\Delta y(k+1) \leq C_1|\Delta u(k)|$,for $\forall k$ and $\Delta u(k) \neq 0$, where $\Delta y(k+1) = y(k+1) - y(k)$, $\Delta u(k) = u(k) - u(k-1)$ and C_1 is an unknown constant.

Lemma1. An unknown parameter $\Phi(k)$ can be derived from the PPD parameter identification observer, which make the following equation holds

$$\Delta y(k+1) = \Phi(k)\Delta u(k) \quad (3)$$

Where

$$|\Phi(k)| \leq C_1$$

Equation (3) is the transformation of system equation (1), and it can be rewritten according to the definitions of $\Delta y(k+1)$ and $\Delta u(k)$

$$y_p(k+1) = y_p(k) + \Phi(k)\Delta u(k) \quad (4)$$

Where $y_p(k)$ is the predicted value of the model output. The next work is to design the PPD parameter identification observer.

3 PPD Parameter Identification Observer

Assumption3. The parameter $\Delta u(k)$ completely converges to a constant $\Omega_1 > 0$, that is, $|\ \Delta u(k)\ | \leq \Omega_1$.

Remark1. We assume that both of the input $u(k)$ and output $y(k)$ of system (1) are bounded, then we can get a large class of functions $\Delta u(k)$ that satisfies assumption 3.

Based on the above works, we can have the following equations

$$\hat{y}_c(k+1) = \hat{y}_c(k) + \Delta u(k)\hat{\Phi}(k) + k_c e_c(k) \quad (5)$$

$$e_c(k+1) = T_c e_c(k) + \Delta u(k)\tilde{\Phi}(k) \quad (6)$$

$$\hat{\Phi}(k+1) = \hat{\Phi}(k) + \Delta u(k)\Psi_c(k)(e_c(k+1) - T_c e_c(k)) \quad (7)$$

$$e_c(k+1) = T_c e_c(k) + \Delta u(k)\tilde{\Phi}(k) = R_c\tilde{\Phi}(k) \quad (8)$$

Where equation (5) is the structure of the PPD parameter identification observer, $e_c(k) = y(k) - \hat{y}_c(k)$ is the D-value between the expected value and the actual output, $\hat{\Phi}(k)$ represents an estimate of the PPD parameter, and the gain k_c is selected from the stable unit circle, such as $T_c = 1 - k_c$. Equation (6) is the output error estimated by equation (3) and (5), $\tilde{\Phi}(k) = \Phi(k) - \hat{\Phi}(k)$ is the PPD observer's output parameter estimation error. The adaptive adjustment of parameter $\Phi(k)$ can be given by equation (7), and the gain $\Psi_c(k)$ is chosen as follows

$$\Psi_c(k) = 2(|\ \Delta u(k)\ |^2 + \check{\rho})^{-1}$$

Where $\check{\rho}$ is a positive constant, therefore, $\Psi_c(k)$ is positive definite for all k . It is worth noting that the boundary of $\check{\Psi}_c(k)$ can be written as

$$|\ \check{\Psi}_c(k)\ | \geq \frac{2}{\Omega_1^2 + \check{\rho}} = \check{\gamma}_c > 0$$

Combining equation (6) and (7), the dynamic estimation error can be rewritten as equation (8) and Q_c is given by

$$R_c = 1 - \Delta u^2(k)\Psi_c(k)$$

The convergence of the system and estimation error is generalized to the following theorem.

Theorem1. Under Assumption 1-3, the globally consistent stable system (8) satisfies the equilibrium $[e_c, \tilde{\Phi}] = [0, 0]$. In addition, the estimation error $e_c(k)$ converges gradually to 0.

Proof: Consider the Lyapunov function

$$V(k) = P_c e_c^2(k) + \lambda_c \tilde{\Phi}^2(k)$$

Where λ_c, Q_c are positive constants and P_c is given by $P_c - T_c^2 P_c = Q_c$, P_c exists and is positive definite. Take the above results into equation (8) and get the result as follows

$$\begin{aligned}\Delta V(k+1) =& V(k+1) - V(k) - Q_c e_c^2(k) + 2P_c T_c \times \\ & \Delta u(k) e_c(k)\tilde{\Phi}(k) - [\lambda_c(1 - R^2) - P_c \times \\ & \Delta u^2(k)]\tilde{\Phi}^2(k) \\ =& - Q_c e_c^2(k) - [\check{\rho}\lambda_c \Psi_c^2(k) - P_c]\check{\eta}^2(k) + \\ & 2P_c T_c e_c(k)\check{\eta}(k) \\ \leq& - Q_c e_c^2(k) - [\check{\rho}\lambda_c \check{\gamma}_c^2 - P_c]\check{\eta}_c^2 + \\ & 2P_c T_c e_c(k)\check{\eta}(k) \\ \leq& - a_1 e_c^2(k) - a_2 \check{\eta}^2(k)\end{aligned}$$

Where $\check{\eta}(k) = \Delta u(k)\tilde{\Phi}(k)$, $a_1 = Q_c - \frac{1}{\varepsilon}$, $a_2 = \check{\rho}\lambda_c\check{\gamma}_c^2 - P_c - \varepsilon P_c^2 T_c^2$. If $\Delta V(k+1) \leq 0$ holds, then ε , Q_c , and λ_c must satisfy the following inequality

$$Q_c > \frac{1}{\varepsilon}, \check{\rho}\lambda_c\check{\gamma}_c^2 - P_c - \varepsilon P_c^2 T_c^2 > 0 \quad (9)$$

From the above proof and Barbalat lemma, it is proved that Theorem1 is correct, and $\lim_{k\to\infty}\check{\eta}(k) = 0$.

4 The FOPID parameter setting principles based on PPD parameter identification observer

The structure of PID controller is incremental, so we define the control error is

$$e(k) = y_r(k) - y(k) \quad (10)$$

In order to facilitate the setting of controller parameters, we define

$$\begin{cases} x_{c1} = e(k) \\ x_{c2} = e(k) + e(k-2) - 2e(k-1) \\ x_{c3} = e(k) - e(k-1) \end{cases} \quad (11)$$

By taking into account equation (9) and (10), the control law is chosen as

$$u(k) = u(k-1) + K_p x_{c1} + K_i x_{c2}^{\lambda} + K_d x_{c3}^{\mu} \quad (12)$$

First of all, let's make $\lambda, \mu = 1$,that is to say, we set the controller in the form of following integer order PID

$$u(k) = u(k-1) + K_p x_{c1} + K_i x_{c2} + K_d x_{c3} \quad (13)$$

The index function is given by

$$J(k) = 1/2e^2(k) \quad (14)$$

We use the gradient descent method to set the three PID parameters, that is

$$\begin{cases} \Delta K_p = -\eta\frac{\partial J}{\partial K_p} = -\eta\frac{\partial J}{\partial y}\frac{\partial y}{\partial u}\frac{\partial u}{\partial K_p} = \\ \quad -\eta e(k)\frac{\partial y}{\partial u}x_{c1} \\ \Delta K_i = -\eta\frac{\partial J}{\partial K_i} = -\eta\frac{\partial J}{\partial y}\frac{\partial y}{\partial u}\frac{\partial u}{\partial K_i} = \\ \quad -\eta e(k)\frac{\partial y}{\partial u}x_{c2} \\ \Delta K_d = -\eta\frac{\partial J}{\partial K_d} = -\eta\frac{\partial J}{\partial y}\frac{\partial y}{\partial u}\frac{\partial u}{\partial K_d} = \\ \quad -\eta e(k)\frac{\partial y}{\partial u}x_{c3} \end{cases} \quad (15)$$

Where $\frac{\partial y}{\partial u} = \hat{\Phi}(k)$ is gotten by PPD parameter identification observer.

The accurate values of K_p, K_i and K_d can be obtained by the above methods, then choose the genetic algorithm to tune λ, μ .

The objective function of genetic algorithm is set to

$$A = \int_0^{\infty}(\omega_1\ |\ e(t)\ | + \omega_2 u^2(t))dt + \omega_3 t_u \quad (16)$$

Where ω_1, ω_2 and ω_3 are weight values, t_u is rise time. Fitness function is chosen as $f = 1/A$ .The flow chart of the genetic algorithm is shown in Figure 3.

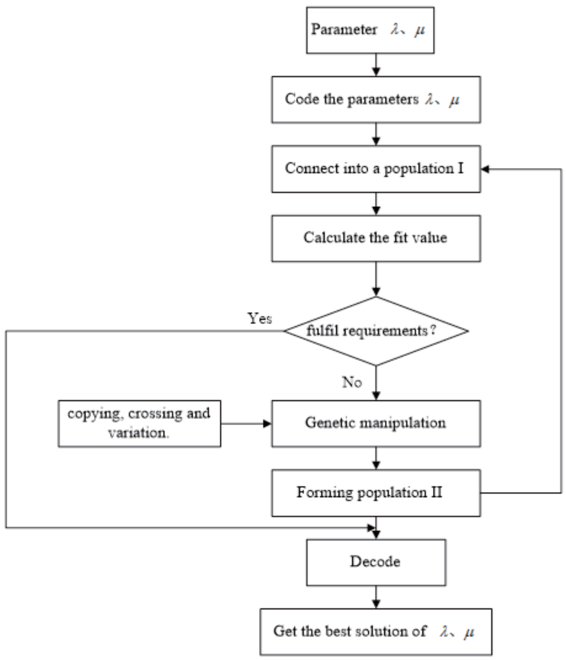

Figure 3: Setting process of λ, μ

5 Simulation

We assume that the initial material level in steady flow bunker $P_{sfb}(0) = 60\%$ and the initial material feeding $W_{mf}(0) = 160t/h$ .Then we can describe the mathematical model of steady flow bunker material level as follows[15]

$$y_T(k) = \sum_{i=1}^{3} \alpha_1 g(\alpha_2 u_T(k) + \alpha_3) \qquad (17)$$

Where $\alpha_1, \alpha_2, \alpha_3$ are system parameter matrix, the activation function, $g(\cdot)$ is sigmoid function. The expected value of material level $y_T^r = 67$.

The parameters of the PPD parameter identification observer are chosen as $k_c = 0.8, \check{\rho} = 0.1$ and $\Phi(0) = 1$ .The initial values of the PID parameters are selected as $\eta = 1.5, K_p(0) = 0.3, K_d(0) = 0.2$,and $K_i(0) = 0.02$.. The simulation results of the system are shown in Fig.4,5,6.

As we have seen, the actual value is better able to track expectations with the solid line in Fig.4. The material feeding finally stabilized at 168 from Fig.5. Fig.6 shows the adaptive results for the three parameters of the PID controller.

The upper and lower bounds of parameters are [0 2] , $P_c = 0.6$ and $P_m = 0.01$,terminating evolution algebras $G = 50$.

Run genetic algorithm to get λ, μ , the control effect such as the dotted line in Fig.4.

Obviously, the FOPID controller has better control performance than the integer order PID controller.

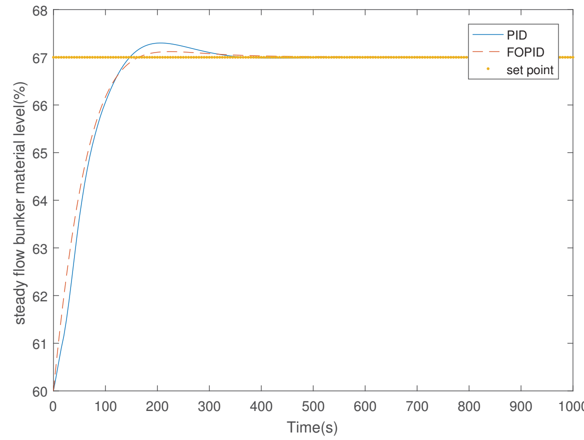

Figure 4: the time response of steady flow bunker material level

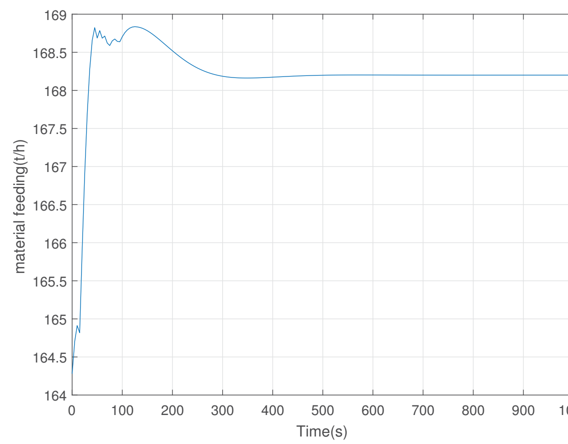

Figure 5: the time response of material feeding

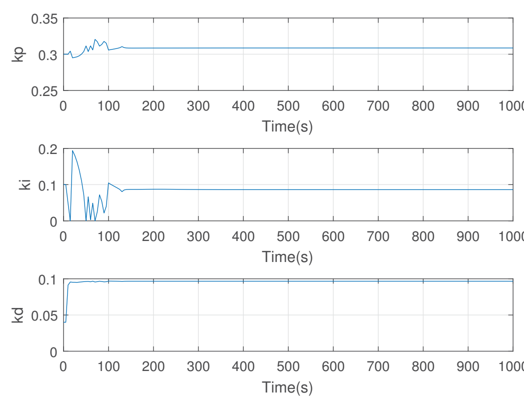

Figure 6: the time response of PID controller parameters

6 Conclusions

In this paper, a FOPID controller has been presented for the steady flow bunker material level system of cement raw material mill. The nonlinear system is controlled by data-driven method. Based on the PPD parameter identification observer and the integer PID controller, the tracking of the expected value is achieved. After tuning parameters by genetic algorithm, a FOPID controller has been designed, and the simulation shows that it has better control effect than the traditional method. However, this method is proposed in an ideal environment, the unknown disturbances in the actual situation are not taken into account. This is the main problem that needs to be solved in the future.

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