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An intelligent control strategy for thickening process

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ABSTRACT

Through the online measurement of the thickener operation parameters including feed flow rate, mud bed level, and underflow concentration, an intelligent control strategy for thickener underflow and flocculant addition is proposed based on the mass balance model and expert rules. Based on the strategy, some guidelines concerning controllers tuning are provided. The application of thickener modeling and optimization software in the wastewater treatment plant of mineral processing illustrates an optimal control operation with stable underflow concentration.

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1. Introduction

Due to its nonlinearity, long-time delay, and strong coupling characteristics with frequently varied boundary conditions, thickening process is known to be difficultly controlled. Thus the widespread thickener operation with poor standards, overflows with high fine particle contents and high variable underflows in many plants are understandable.

In order to resolve these problems, a fuzzy logic controller with two basic control loops was suggested by Santos et al. (1995). One is to control underflow concentration by varying the underflow pulp flow rate and the other is to regulate overflow turbidity by adjusting the flocculant addition rate. While the effect of the interaction between the two coupled control loops was not reported. Recently, Segovia et al. (2011) mentioned a multiple-input single-output (MISO) fuzzy controller to control the sludge level and underflow concentration by adjusting the underflow flow rate. The drawback is that the effect of flocculant was not considered in the MISO fuzzy controller.

On the other hand, since the development of rigorous mathematical modeling of the process of continuous sedimentation in a clarifier–thickener unit with partial differential equations (Bürger and Narváez, 2007; Garrido et al., 2003b), more advanced model-based control strategies have been proposed. Based on the sedimentation velocity of each particle affected by the time-dependent properties of the fed solids, Diehl (2008) put forward a proportional controller for controlling the inventory by calculating the mathematical model in the ideal case. Betancourt et al. (2014) suggested to using the flow rate of underflow to control the concentration and the feed property coefficient which is able to manipulate the value by modifying the flocculant concentration to control the sediment level.

Since the theoretical strategies above assume that the thickener is operated under near stationary conditions and calibrated model parameters without overload, they are difficult to perform in practice.

At the same time, with the phenomenological theory of sedimentation, the softwares for designing and simulating conventional industry thickeners have been developed (Garrido et al., 2003a; Burgos and Concha, 2005). The concentration profile in the thickener can be predicted by entering the solid feed rate and the required underflow concentration into the software. But there is no reported software for controlling thickening process.

In this work, we proposed an intelligent thickener control strategy based on the dynamic mass balance model. The "intelligent" controller is able to calculate the optimal set point of the underflow flow rate, based on the mass flow of the fed solids in thickener and the state parameters of thickening process, and automatically adjusting the controller parameters according to the trends of state parameters.

2. Mass balance model

2.1. Process parameter online measurement

Thickeners work continuously to produce a concentrated underflow and a clarified overflow. When the fed solid mass flow is determined by the upstream process, operators are used to adjusting the flow rate of underflow and flocculant to obtain the desired underflow concentration. In fact, there exist some problems in the thickener control. Mud

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bed level which makes an immediate impact on the underflow concentration is usually neglected. Online analytical instrument of overflow turbidity is replaced by manual sampling tests. Flocculant dose is adjusted according to subjective experience. What's more, thickeners often shut down due to the rakes' overloading without pressure detection. All the above factors have affected the thickening efficiency seriously.

Therefore, a complete monitoring system of thickening process should at least online measure all the variables in Table 1 (see Fig. 1).

By online measurement of mud bed level, solid mass flow of feed and underflow, mass balance model of thickening process can be built from the obtained historical data as the basic of optimal control.

2.2. Mass balance equations

Based on mass balance, changes of the total solid mass of mud bed m are mainly depending on the solid mass flow of feeding and discharging changes. Suppose the concentration of overflow is 0, the macroscopic mass balance equation is (Betancourt et al., 2013)

$$\frac{dm(t)}{dt} = Q_F(t)C_F(t)\phi_F(t) - Q_U(t)C_U(t)\phi_U(t) \tag{1}$$

where the function of total solid mass of mud bed is

$$m(t) = f_1(L_{Bed}(t)) * f_2(L_{Bed}(t), \phi_U(t)) * C_{Bed}(t) \tag{2}$$

which involves the mud bed volume function $f_1(L_{Bed}(t))$ and average solid mass fraction of mud bed function $f_2(L_{Bed}(t), \phi_U(t))$. Here we define

$$V_{Bed}(t) = f_1(L_{Bed}(t)) \tag{3}$$

$$\phi_{Bed}(t) = f_2(L_{Bed}(t), \phi_U(t)) \tag{4}$$

where V_{Bed} is the volume of mud bed and ϕ_{Bed} the average solid mass fraction of mud bed, which is obtained from the prediction model with mud bed level and underflow solid mass fraction as input variables. And the average concentration (kg/m^3) of mud bed function C_{Bed} that appeared in Eq. (2) satisfies the following formula

$$\begin{aligned} C_{Bed}(t) &= \frac{m_{bed}(t)}{V_{bed}(t)} \\ &= \frac{m_{bed}(t)}{\frac{m_{bed}(t) * \phi_{Bed}(t)}{\rho_{solid}} + \frac{m_{bed}(t) * (1-\phi_{Bed}(t))}{\rho_{water}}} \\ &= \frac{\rho_{solid} * \rho_{water}}{\rho_{water} * \phi_{Bed}(t) + \rho_{solid} * (1-\phi_{Bed}(t))} \end{aligned} \tag{5}$$

where ρ_{solid} is the solid density (kg/m^3). Similarly, feed concentration function C_F and underflow concentration function C_U can be calculated from ϕ_F and ϕ_U, respectively.

Table 1
Information of online measured variables.

Icon	Symbol	Measured objects
FT (feed)	Q_F	Feed volumetric flow (m^3/h)
DT (feed)	ϕ_F	Feed solid mass fraction (%)
FT (flocculant)	Q_{Floc}	Flocculant volumetric flow (m^3/h)
PT	P_{Rake}	Rake torque (N*m)
LT	L_{Bed}	Bed level (m)
AT	T_{Over}	Overflow turbidity (mg/l)
DT (underflow)	ϕ_U	Underflow solid mass fraction (%)
FT (underflow)	Q_U	Underflow volumetric flow (m^3/h)

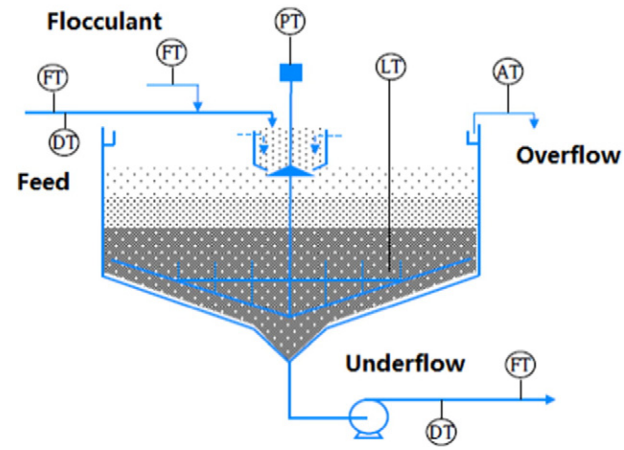

Fig. 1. Thickening process measurement.

2.3. Average solid mass fraction of mud bed prediction model

The average solid mass fraction of mud bed prediction model can be obtained by using the partial least-squares (PLS) regression algorithm. Here, we rewrite Eq. (4) as follows

$$y = \phi_{Bed}(t) = f_2(L_{Bed}(t), \phi_U(t)) = f_2(X) \tag{6}$$

where the input matrix X is composed of mud bed level and underflow solid mass fraction, and the output vector y is the corresponding average solid mass fraction of mud bed.

First, X is normalized processing. Then given the nonlinearity of the thickening process, X is converted to the active matrix X_A. The elements a_{ij} of row i column j of X_A can be obtained by

$$a_{ij} = \exp\left(-\frac{\left\|x_i - c_j\right\|^2}{\sigma_j^2}\right) \quad i, j = 1, 2 \cdots n \tag{7}$$

where x_i is the input vector of row i of data samples and c_j is the centered parameters which satisfies

$$c_j = x_j \tag{8}$$

and σ_j is the width parameter of Gaussian function which satisfies

$$\sigma_j = \frac{1}{n}\sum_{i=1}^{n}\left\|x_i - x_j\right\|. \tag{9}$$

Finally, X_A and y can be decomposed as follows (Geladi and Kowalski, 1986; Qin, 1998)

$$\begin{cases} X_A = TP^T + E_h \\ y = X_A b + F_h \end{cases} \tag{10}$$

where b is the regression vector obtained in accordance with PLS algorithm.

3. Control objective and strategies

In order to maintain stable and efficient in the continuous thickening process, the controller is required to meet the following objectives.

(1) Ensure stable thickener operation by minimizing "short circuit" or overloaded conditions.
(2) Stabilize the underflow concentration, thereby improving the performance of downstream processes.
(3) Improve the clarity of the overflow water and prevent the loss of mineral particles.

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