Adaptive Control and Parameter Estimation for Chemical Composition at Raw Mill in Cement Manufactory

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Abstract: This paper proposes a novel estimation algorithm and adaptive control system for composition control at a raw mill in cement manufactory. Using a little "a priori" knowledge about the controlled process, the novel algorithm avoids wrong estimates arising from the fact that the system inputs are not persistently exciting. In the new adaptive control scheme, the additional composition estimator based on our proposed algorithm and the modified minimum variance self-tuning controller are employed.

Both simulation experiments and practical operation show the new adaptive control scheme and estimation algorithm is successful. Compared with the classical least-squares algorithm, the new algorithm has a good convergence and high accuracy. The new adaptive control scheme has been implemented in an industry computer, and have used for real-time operation in a cement manufactory. The practical operation results have been very encouraging.

Key words: persistently exciting; criterion function; parameter estimation; adaptive control; computer control

1 Introduction

The objective of composition control at a raw mill in cement manufactory is to maintain chemical composition of raw meal at desired value. The control problem arises from the fact that the chemical composition of various raw materials vary from time to time, and they are not measured directly. The composition blending system is a multivariable and a coupled one and includes large time lag and nonlinearity. Therefore it is difficult to improve cement quality with classical PID controller, and one of the best solution for this problem would be to use the adaptive control. Dr. Keviczky has made great contributions to this area[1~3]. In his scheme, the composition matrix is simplified and assumed to be constant and known to simplify the control system. Therefore it can only be applied in the manufactory where the homogenous and pure raw materials are used. Nevertheless, the composition

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of raw materials used in our Chinese cement manufactory are impure and unknown and it changes considerably. In this case, if this system is still used, the controlled composition of raw meal will be deviate from the desired value. Hence, the raw materials must be estimated and the composition matrix must be adjusted timely. However, under normal operation condition the feed weights are almost invariant, i. e. the system inputs are not persistently exciting, and the conventional estimation algorithm is unsuitable without the additional signals. Using an "a priori" knowledge——the mean value of composition of raw materials, this paper introduces a new criterion function and derives a novel algorithm which avoids wrong estimates arising from the mentioned fact.

According to circumstances that the composition of raw material is complex, timevaring and unknown in Chinese cement manufactory, the linearizing and decoupling model of this process is given and a adaptive composition control scheme is presented in this paper. The main control loop with variable reference is implemented by a minimal variance self-tuning regulator, and raw material composition is estimated by the estimator based on new algorithm. Both simulation experiments and practical operation have demonstrated the goodness and efficiency of the new adaptive control system.

2 Chemical Composition Estimation

2.1 Problem Statement

There are four kinds of important oxide composition in the raw meal, including $C(\mathrm{CaO})$, $S(\mathrm{SiO_2})$, $A(\mathrm{Al_2O_3})$ and $F(\mathrm{Fe_2O_3})$. The relation between oxide composition and feed weight of raw material can be described by following equation.

$$\begin{bmatrix} C(s) \\ S(t) \\ A(t) \\ F(t) \end{bmatrix} = \begin{bmatrix} C_1 & C_2 & \cdots & C_m \\ S_1 & S_2 & \cdots & S_m \\ A_1 & A_2 & \cdots & A_m \\ F_1 & F_2 & \cdots & F_m \end{bmatrix} \begin{bmatrix} g_1(t) & & & 0 \\ & g_2(t) & & \\ & & \ddots & \\ 0 & & & g_m(t) \end{bmatrix} \begin{bmatrix} w_1(t) \\ w_2(t) \\ \vdots \\ w_m(t) \end{bmatrix}. \tag{1}$$

Where, C_i, S_i, A_i and F_i denotes four kinds of oxide composition in the raw material i, respectively. $g_i(t)$ is the raw mill dynamics to raw material i. $w_i(t)$ is the feed weight of the raw material i.

The quality of the raw meal is usually characterized by the following three moduli:

Lime standard (LM): $$\mathrm{LM} = \frac{1000C}{2.8S + 1.1A + 0.8F}, \tag{2}$$

Aluminium modulus (AM): $$\mathrm{AM} = \frac{A}{F}, \tag{3}$$

Silica modulus (SM): $$\mathrm{SM} = \frac{S}{A + F}. \tag{4}$$

The Eq. (1)～(4) show that these moduli are interactive and oxides/moduli computations are nonlinear, that means the input/output model in multivariable is coupled and nonlinear. On the other hand, C_i, S_i, A_i and F_i are usually unknown and variable and considered as

the estimated parameters. In order to obtain good control results, C_i, S_i, A_i and F_i would be rejusted in time on the basis of estimate values for composition of raw materials.

The estimation problem can be stated as follows: given a set of raw meal composition measurement, and the feed weights of raw material are known, estimate the raw material composition.

For convenience, let us only consider the second row of Eq. (1), i. e.

$$S(t) = S_1 g_1(t) w_1(t) + S_2 g_2(t) w_2(t) + \cdots + S_m g_m(t) w_m(t).$$

In fact, the mill dynamics can be described by a first order model with a time delay

$$y_i(z) = g_i(z) w_i(z) = \frac{c_i z^{-d_i-1}}{1 - b_i z^{-1}} w_i(z).$$

Assuming $d_i = d$, the measurement equation at the kth instant is given by

$$S(k) = \sum_{i=1}^{m} S_i y_i(k) = \sum_{i=1}^{m} [S_i (b_i y_i(k-1) + c_i w_i(k-d-1)] + e(k). \tag{5}$$

Where $e(k)$ is measurement error.

For the control system, the total time delay will be in order of 30 min., and a sampling interval of 30 min. will usually be chosen, hence $d = 1$ and Eq. (5) can be rewritten as follows.

$$S(k) = \sum_{i=1}^{m} S_i y_i(k) = \sum_{i=1}^{m} [S_i (b_i y_i(k-1) + c_i w_i(k-2))] + e(k).$$

If we consider n sampling periods, the matrix equation can be obtained.

$$\Psi_n = \Omega_n \Theta + E, \tag{6}$$

$$\Omega_n = \begin{bmatrix} b_1 y_1(0) + c_1 w_1(-1) & b_2 y_2(0) + c_2 w_2(-1) & \cdots & b_m y_m(0) + c_m w_2(-1) \\ b_1 y_1(1) + c_1 w_1(0) & b_2 y_2(1) + c_2 w_2(0) & \cdots & b_m y_m(1) + c_m w_2(0) \\ \vdots & \vdots & \vdots & \vdots \\ b_1 y_1(n-1) + c_1 w_1(n-2) & b_2 y_2(n-1) + c_2 w_2(n-2) & \cdots & b_m y_m(n-1) + c_m w_2(n-2) \end{bmatrix},$$

$$\Psi_n = [S(1), S(2), \cdots, S(n)]^{\mathrm{T}},$$

$$\Theta = [S_1, S_2, \cdots, S_m]^{\mathrm{T}},$$

$$E = [e(1), e(2), \cdots, e(n)]^{\mathrm{T}}.$$

Equation (6) is a math model to estimate composition of SiO_2.

Under normal conditions, the inputs to system would not be persistently exciting, and the correct estimate results could not be obtained by the classical least-squares algorithm.

2.2 Parameter Estimation Algorithm

2.2.1 Batch Processing Algorithm

Assume the composition of mixed raw materials are non-homogenous, but the average composition is known, that is "a priori" knowledge on raw material composition, and useful for selecting sample and estimating parameter. The assumption is reasonable since the average composition can be obtained by the observation over a definite period of time.

Let us introduce a new criterion function and consider a set of n measurements.

$$J = (\Psi_n - \Omega_n\hat{\Theta}_n)^{\mathrm{T}}(\Psi_n - \Omega_n\hat{\Theta}_n) + gn[\Gamma - \frac{1}{n}(\sum_{i=1}^{n-1}\hat{\Theta}_i + \hat{\Theta}_n)]^{\mathrm{T}}[\Gamma - \frac{1}{n}(\sum_{i=1}^{n-1}\hat{\Theta}_i + \hat{\Theta}_n)]. \tag{7}$$

Where $\hat{\Theta}_n$ is a estimated parameter vector after the processing of i measurements, Γ is a vector of average composition of raw materials and g is a weighting factor, it gives more or less significance to "a priori" knowledge.

For convenience, let us suppose that

$$\Gamma_n = \Gamma - \frac{1}{n}\sum_{i=1}^{n-1}\hat{\Theta}_i. \tag{8}$$

According to the extremal theorem, the necessary condition to minimize J is $\frac{\partial J}{\partial \hat{\Theta}_n} = 0$, that is

$$\begin{aligned}\frac{\partial J}{\partial \hat{\Theta}_n} &= 2\frac{\partial (\Psi_n - \Omega_n\hat{\Theta}_n)^{\mathrm{T}}}{\partial \hat{\Theta}_n}(\Psi_n - \Omega_n\hat{\Theta}_n) + 2gn\frac{\partial\left(\Gamma_n - \frac{1}{n}\hat{\Theta}_n\right)^{\mathrm{T}}}{\partial \hat{\Theta}_n}\left(\Gamma_n - \frac{1}{n}\hat{\Theta}_n\right)\\ &= -2\Omega_n^{\mathrm{T}}(\Psi_n - \Omega_n\hat{\Theta}_n) - 2gn\frac{1}{n}\left(\Gamma_n - \frac{1}{n}\hat{\Theta}_n\right)\\ &= -2\left[\Omega_n^{\mathrm{T}}\Psi_n - \Omega_n^{\mathrm{T}}\Omega_n\hat{\Theta}_n + g\Gamma_n - \frac{g}{n}\hat{\Theta}_n\right]\\ &= -2\left[(\Omega_n^{\mathrm{T}}\Psi_n + g\Gamma_n) - \left(\Omega_n^{\mathrm{T}}\Omega_n + \frac{g}{n}I_m\right)\hat{\Theta}_n\right] = 0.\end{aligned}$$

As a result, the estimator can be obtained, that is

$$\hat{\Theta}_n = \left(\Omega_n^{\mathrm{T}}\Omega_n + \frac{g}{n}I_m\right)^{-1}(\Omega_n^{\mathrm{T}}\Psi_n + g\Gamma_n). \tag{9}$$

Where I_m is a unite matrix with dimension $m \times m$.

In practice, the Eq. (9) is the classical least-squares estimator for $g = 0$, that is

$$\hat{\Theta}_n = (\Omega_n^{\mathrm{T}}\Omega_n)^{-1}\Omega_n^{\mathrm{T}}\Psi_n. \tag{10}$$

Comparing Eq. (9) and Eq. (10), it is easy to see that the new algorithm is far superior to the classical one. The new algorithm can ensure the $\left(\Omega_n^{\mathrm{T}}\Omega_n + \frac{g}{n}I_m\right)$ matrix invertible and the parameter identifiable by choosing the value of g, and result in unique and desired estimate values despite lack of persistently exciting inputs.

The above equations were derived in a form suitable for batch processing, in which the amount of data storage and computation increases with n, this is obviously undesirable for a algorithm such as self-tuning.

In order to tarck varying parameter in time, we expect to obtain the recursive form of estimator.

2.2.2 Recursive Algorithm

The recursive form for Eq. (9) can be given by a reasonable approximation in practical application. If n is large enough with respect to g, the following approximation is valid

$\left(\Omega_n^{\mathrm{T}}\Omega_n + \frac{g}{n}I_m\right) \approx (\Omega_n^{\mathrm{T}}\Omega_n)$, then (9) may be rewritten as

$$\hat{\Theta}_n = (\Omega_n^{\mathrm{T}}\Omega_n)^{-1}(\Omega_n^{\mathrm{T}}\Psi_n + g\Gamma_n). \tag{11}$$

Now the recursive form of new algorithm can be derived as follows.

On the basis of n observations, a new observation is made. Let us estimate the parameter Θ according to $n+1$ observations.

One set

$$\Psi_{n-1} = [\Psi_n^{\mathrm{T}} \vdots \psi_{(n+1)}], \quad \Omega_{n+1} = \begin{bmatrix} \Omega_n \\ \cdots\cdots \\ \omega_{n+1}^{\mathrm{T}} \end{bmatrix},$$

$$\Phi_n = (\Omega_n^{\mathrm{T}}\Omega_n)^{-1}. \tag{12}$$

The dimension of Φ_n depends on the number of estimated parameter.

Using (12)gives

$$\Phi_{n+1} = (\Omega_{n+1}^{\mathrm{T}}\Omega_{n+1})^{-1} = \left\{[\Omega_n^{\mathrm{T}} \vdots \omega_{n+1}]\begin{bmatrix} \Omega_n \\ \cdots\cdots \\ \omega_{n+1}^{\mathrm{T}} \end{bmatrix}\right\}^{-1},$$

$$= [\Omega_n^{\mathrm{T}}\Omega_n + \omega_{n+1}\omega_{n+1}^{\mathrm{T}}]^{-1} = [\Phi_n^{-1} + \omega_{n+1}\omega_{n+1}^{\mathrm{T}}]^{-1}. \tag{13}$$

According to the following indentity[4]

$$(A + BC^{\mathrm{T}})^{-1} = A^{-1} - A^{-1}B(I + C^{\mathrm{T}}A^{-1}B)^{-1}C^{\mathrm{T}}A^{-1}. \tag{14}$$

(13) becomes:

$$\Phi_{n+1} = \{\Phi_n^{-1} + \omega_{n+1}\omega_{n+1}^{\mathrm{T}}\}^{-1} = \Phi_n - \Phi_n\omega_{n+1}[I + \omega_{n+1}^{\mathrm{T}}\Phi_n\omega_{n+1}]^{-1}\omega_{n+1}^{\mathrm{T}}\Phi_n.$$

Note $[I + \omega_{n+1}^{\mathrm{T}}\Phi_n\omega_{n+1}]$ is a scalar, then suppose

$$\rho_{n+1} = [I + \omega_{n+1}^{\mathrm{T}}\Phi_n\omega_{n+1}]^{-1}. \tag{15}$$

The above equation may be rewitten as

$$\Phi_{n+1} = \Phi_n - \rho_{n+1}\Phi_n\omega_{n+1}\omega_{n+1}^{\mathrm{T}}\Phi_n = [I - \rho_{n+1}\Phi_n\omega_{n+1}\omega_{n+1}^{\mathrm{T}}]\Phi_n. \tag{16}$$

Suppose $\hat{\Theta}_{n+1}$ denotes estimated value of parameter based on $n+1$ observations,

$$\begin{aligned}
\hat{\Theta}_{n+1} &= \Phi_{n+1}[\Omega_{n+1}^{\mathrm{T}}\Psi_{n-1} + g\Gamma_{n+1}] \\
&= \Phi_{n+1}[\Omega_n^{\mathrm{T}} \vdots \omega_{n-1}]\begin{bmatrix} \Psi_n \\ \cdots\cdots \\ \psi_{(n+1)} \end{bmatrix} + g\Phi_{n+1}\Gamma_{n+1} \\
&= \Phi_{n+1}[\Omega_n^{\mathrm{T}}\Psi_n + \omega_{n-1}\psi_{(n+1)}] + g\Phi_{n+1}\Gamma_{n+1} \\
&= \Phi_{n+1}[\Phi_n^{-1}\hat{\Theta}_n - g\Gamma_n + \omega_{n+1}\psi_{(n+1)}] + g\Phi_{n+1}\Gamma_{n+1} \\
&= \Phi_{n+1}[\Phi_n^{-1}\hat{\Theta}_n + \omega_{n+1}\psi_{(n+1)}] + g\Phi_{n+1}(\Gamma_{n+1} - \Gamma_n).
\end{aligned}$$

In term of (13)

$$\begin{aligned}
\hat{\Theta}_{n+1} &= \Phi_{n+1}[(\Phi_{n+1}^{-1} - \omega_{n+1}\omega_{n+1}^{\mathrm{T}})\hat{\Theta}_n + \omega_{n+1}\psi_{n-1}] + g\Phi_{n+1}(\Gamma_{n-1} - \Gamma_n) \\
&= \hat{\Theta}_n + \Phi_{n+1}\omega_{n+1}(\psi_{(n+1)} - \omega_{n-1}^{\mathrm{T}}\hat{\Theta}_n) + g\Phi_{n+1}(\Gamma_{n+1} - \Gamma_n) \\
&= \hat{\Theta}_n + \Xi_{n+1}(\psi_{(n+1)} - \omega_{n+1}^{\mathrm{T}}\hat{\Theta}_n) + g\Phi_{n+1}\Delta_{n+1}
\end{aligned} \tag{17}$$

where

$$\Xi_{n+1} = \Phi_{n+1}\omega_{n-1}, \tag{18}$$

$$\Delta_{n+1} = g[\Gamma_{n+1} - \Gamma_n]. \tag{19}$$

Using (16) gives

$$\begin{aligned}\Xi_{n+1} &= [\Phi_n - \rho_{n+1}\Phi_n\omega_{n+1}\omega_{n+1}^{\mathrm{T}}\Phi_n]\omega_{n+1} \\ &= \Phi_n\omega_{n+1}[I - \rho_{n+1}\omega_{n+1}^{\mathrm{T}}\Phi_n\omega_{n+1}] \\ &= \Phi_n\omega_{n+1}\rho_{n+1}[1/\rho_{n+1} - \omega_{n+1}^{\mathrm{T}}\Phi_n\omega_{n+1}] \\ &= \Phi_n\omega_{n+1}\rho_{n+1} = \frac{\Phi_n\omega_{n+1}}{1 + \omega_{n+1}^{\mathrm{T}}\Phi_n\omega_{n+1}}. \end{aligned} \tag{20}$$

From (8)

$$\Gamma_{n+1} = \Gamma - \frac{1}{n+1}\sum_{i=1}^{n}\hat{\Theta}_i = \Gamma - \frac{1}{n+1}[\sum_{i=1}^{n-1}\hat{\Theta}_i + \hat{\Theta}_n] = \frac{1}{n+1}[n\Gamma + \Gamma_n - \hat{\Theta}_n]. \tag{21}$$

To sum up, the recursive algorithm be expressed by the equations (17), (19), (20) and (21).

From the new algorithm, it is shown for a large enough value of n, Γ_{n+1} tends to Γ_n and Δ_{n+1} tends to zero. So Eq. (17)can be written as

$$\hat{\Theta}_{n+1} = \hat{\Theta}_n + \Xi_{n+1}[\psi_{(n+1)} - \psi_{n+1}^{\mathrm{T}}\hat{\Theta}_n]. \tag{22}$$

That shows the new recursive algorithm tends to the classical RLS algorithm, and it implies the new one is convergent. The simulation results later reported show that the new recursive algorithm has good convergence and is more accuruate than the classical RLS algorithm. This new algorithm is also suitable for the other oxide.

3 Adaptive Control System

3.1 Linearizing and Decoupling Model

As mentioned is Section 2.1, the composition blending system is a coupled and nonlinear one. This makes it difficult to design the control system and also to adjust the regulator on-line, thus the requirement for linearizing and decoupling the model is proposed.

In order to linearize and decouple the model, some reasonable approximations must be made according to specific circumstances.

In fact, an ideal raw material blending process can be described by the following equation, in which raw mill dynamics is ignored temporarily.

$$\begin{bmatrix} C(t) \\ S(t) \\ A(t) \\ F(t) \end{bmatrix} = \begin{bmatrix} C_1 & C_2 & 0 & 0 \\ S_1 & S_2 & S_3 & 0 \\ A_1 & A_2 & 0 & 0 \\ F_1 & F_2 & 0 & F_4 \end{bmatrix} \begin{bmatrix} w_1(t) \\ w_2(t) \\ w_3(t) \\ w_4(t) \end{bmatrix}. \tag{23}$$

In consideration of $w_2(t)/w_1(t) = \text{const.}$, let us choose new input/output vectors instead of the original ones

$$U = [u_1 \quad u_2]^{\mathrm{T}} = [w_3(t)/w_1(t) \quad w_4(t)/w_1(t)]^{\mathrm{T}}, \tag{24}$$

$$Y = [y_1 \quad y_2]^{\mathrm{T}} = [1/LM \quad 1/AM]^{\mathrm{T}}. \tag{25}$$

Then the linearizing and decoupling model can be derived from Eq. (1)~(4):

$$Y = AU + B. \tag{26}$$

Where

$$A = \begin{bmatrix} 2.8S_3/D & 0.8F_4/D \\ 0 & F_4/D' \end{bmatrix}, \tag{27}$$

$$B = \begin{bmatrix} D_1 \\ D_2 \end{bmatrix}, \tag{28}$$

$$D_1 = \{2.8S_1 + 1.1A_1 + 0.8F_1 + [w_2(t)/w_1(t)](2.8S_2 + 1.1A_2 + 0.8F_2)\}/D, \tag{29}$$

$$D_2 = \{F_1 + F_2[w_2(t)/w_1(t)]\}/\{A_1 + A_2[w_2(t)/w_1(t)]\}, \tag{30}$$

$$D' = S_1 + S_2[w_2(t)/w_1(t)], \tag{31}$$

$$D = 100C_1 + 100C_2. \tag{32}$$

Here S_3 and F_4 are usually assumed known, the others are unknown and variable and considered as the estimated parameters.

3.2 Self-Tuning Control System

On the basis of the new model, the multivariable self-tuning control system is proposed. Its block scheme and simplified flow sheet are respectively shown in Fig1. and Fig. 2.

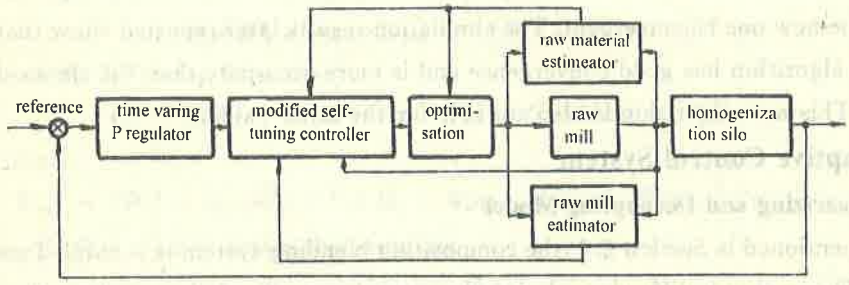

Fig. 1 The block scheme of self-tuning control system

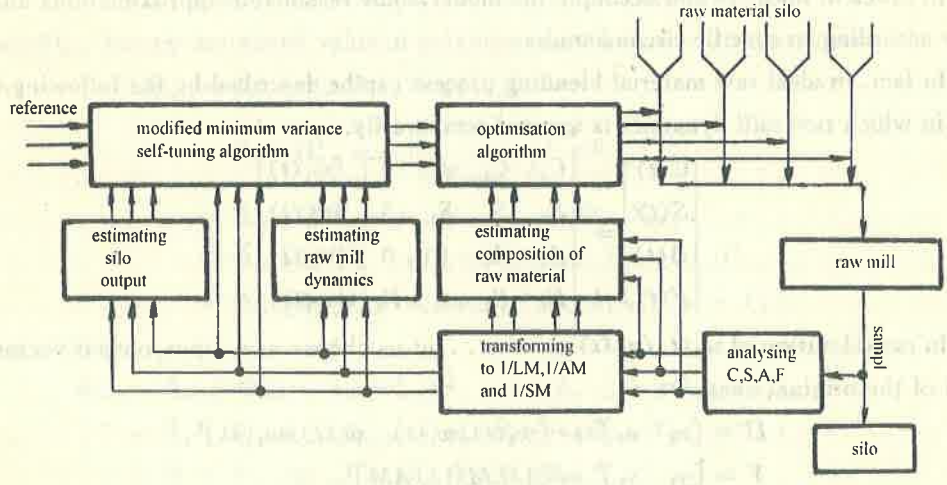

Fig. 2 The simplified flow sheet of self-tuning control system

Here the inner control loop consists of a modified MIMO minimum variance self-tuning (MIMO-MV-ST) regulator with required average for finite time and time-varying pro-

portional regulator is in the outer control loop. The composition estimator based on the new algorithm is employed to adjust the related computation matrix.

According to Eq. (26)～(28) and the mill dynamics, the control model can be described as follows:

$$Y(k) = A(z^{-1})Y(k-1) + B(z^{-1})U(k-d) + E(k), \tag{33}$$

where $A(z^{-1}) = A_0 = \begin{bmatrix} a_{01} & 0 \\ 0 & a_{02} \end{bmatrix}$, $B(z^{-1}) = B_0 = \begin{bmatrix} b_{01} & b_{02} \\ 0 & b_{02} \end{bmatrix}$,

$d = 1$, and $e(k)$ is a disturbance sequence.

According to the minimum variance theory, the optimal control strategy is

$$U(k) = \hat{B}_0^{-1}[Y_r - \hat{A}_0^{-1}Y(k)] \tag{34}$$

where Y_r refers to the required reference value of the output, $\hat{A}_0$ and $\hat{B}_0$ denote the estimation values and they can be obtained by using the classical recursive least-squares algorithm.

In order to achieve a good control result, Y_r would be replaced by the time varying reference value Y_{rm}. That results in the following modified MV-ST control law.

$$U(k) = \hat{B}_0^{-1}[Y_{rm} - \hat{A}_0^{-1}Y(k)] \tag{35}$$

where $Y_{rm} = Y_r - \dfrac{k}{n-k}[\hat{Y}_a(k) - Y_r]$ for $k = 1, 2, \cdots, (n-1)$; and $Y_{rm} = y_r$ for $k = n$. Here n is the assumed filling time. $\hat{Y}_a(k)$ is a prediction at kth instant for the actual average value.

In fact, the measurements of the silo output cannot be used for feedback. Therefore, the silo output must be estimated using the following first order model.

$$G_s(z^{-1}) = \frac{b_0}{1 + a_1 z^{-1}} I \tag{36}$$

where I is the unit matrix and $b_0 = v(k)/q(k)$, $a_1 = a_1(k) = -[q(k) - v(k)]/q(k)$. Here k is the discrete time and $q(k) = \sum_{i=1}^{k} v(i) + q(0)$ is the instantaneous silo content; $v(k)$ stands for the quantity of raw meal fed to silo during the kth interval.

4 Simulation Experiments and System Implementation

In order to verify the feasibility of new estimation algorithm and adaptive control scheme, a complete blending process has been simulated on a computer and the simulation experiments have been made as follows.

4.1 Experiment 1 Comparison of New and Classical Estimation Method

Here the choices of initial values for both algorithms in recursive form are the same, that is $\hat{\Theta}_0 = 0$; $P_0 = 10^3 I$. Fig. 3 shows that the estimate values resulting from the classical LS algorithm are far away from the actual values. The silica contents of lime s_1 is always greater than the actual value and the silica contents of day s_2 is always smaller than the actual value. Fig. 4 shows that the new algorithm is accurate and has good convergence

compared with the classical one. Of course the weighting factor g has a significant influence on convergence, and it could not be discussed in this paper due to the limitation of space.

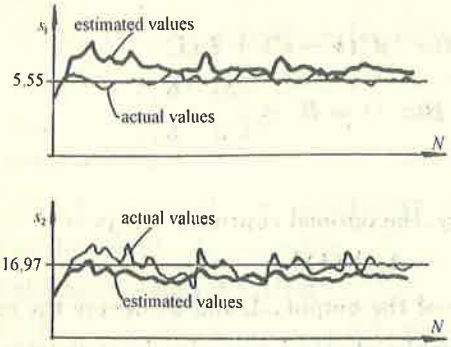

Fig. 3 Result of the classical RLS algorithm

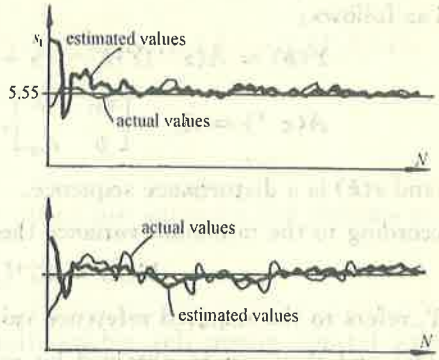

Fig. 4 Result of the new algorithm

4.2 Experiment 2 Comparison of New Control Scheme and Old One for Step Disturbance

Assume the silica content of lime and clay is subjected to a step increment disturbance with 1% of mangnitude. In this case, if such ST control scheme without composition estimator as Keviczky proposed is still used, then the LM at silo output, as shown in Fig. 5, is far away from the desired values. However, using the new control scheme with composition estimator, the silo output, as can be shown in Fig. 6, is close to the desired values.

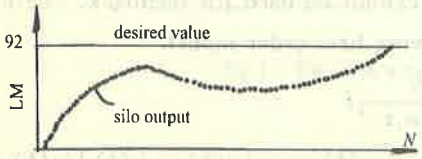

Fig. 5 Results of old control scheme for step increment disturbance

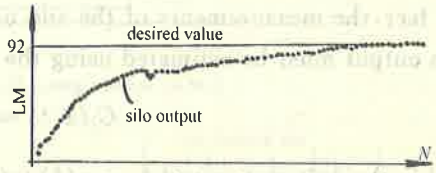

Fig. 6 Results of new control scheme for step increment disturbance

4.3 Experiment 3 Comparison of New Control Scheme and Old One for Sinusoidal Disturbance

Assume the silica content of lime and clay is subjected to a sinusoidal disturbance with 1% of mangnitude. The control result without composition estimator is shown in Fig. 7, and the fluctuation of silo output is very great. Fig. 8 shows the fluctuation of silo output

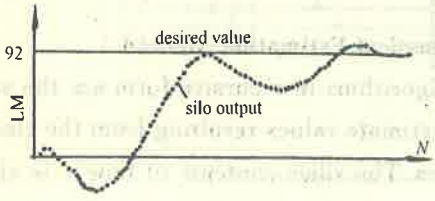

Fig. 7 Result of old control scheme for sinusoidal disturbance

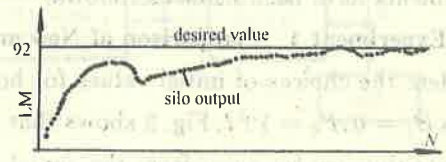

Fig. 8 Result of new control scheme for sinusoidal disturbance ($g=0.2$)

in effectively rejected.

4.4 System Implementation and Operation Results

The adaptive composition control system have been implemented on a PMC-88 computer. The total program with 30kB includes twenty-six subprograms and completes the following works: computation, control, measurement, diagnosis, indication, etc. This new control system has been used for one years in a cement manufactory.

The practical operation results have been very encouraging, and the variance of the silo output has been brought down by 39%, from 2.63 to 1.61.

5 Conclusions

In our proposed algorithm, using "a priori" information on the parameters, the wrong estimates due to lack of persistently exciting inputs are avoided without applying additional signals. The estimate values of new algorithm approximate to the actual values compared with ones of the classical algorithm. This algorithm provided a new approach to solve the problem on composition estimation for blending process.

On the basis of the analysis on static characteristics of blending process, its model is linearized and is partly decoupled by choosing new input/output vectors. For this model is based on the case that the composition matrix is not simplified, it is accurate and has strong suitability comparing with that one presented by Keviczky[3].

To introduce the composition estimator and the modifed MV controller is the master key to success for the new control scheme. The new system has overcome the faults of Keviczky's scheme which is unsuitable for this case the composition of raw materials is complex, time-varing and unknown. As a result, the saticfactory output values can be obtained, despite the great variations of composition of raw material.

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水泥生料磨机系统化学成分的自适应控制和参数估计

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摘要:本文针对水泥生料磨机系统的成分控制问题,提出了一种新型参数估计算法和自适应控制系统.新算法利用被控过程的先验知识避免了由于输入信号不"持续激励"而引起的估计错误.在新控制系统中,增设了基于新算法的成分估计器并采用了改进最小方差自校正控制器.

仿真实验和实际应用结果都已证实:估计算法和控制方案是成功的.与普通最小二乘法相比,新算法具有更好的收敛性和更高的精度.控制方案已在工业控制机上实现,并用于水泥厂实时控制,运行结果是令人鼓舞的.

关键词:持续激励;准则函数;参数估计;自适应控制;计算机控制

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