Adaptive control of ore pulp thinning in ball mills with the increase of their productivity

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Abstract
The optimal control problem and its solution algorithm for magnetic separation processes based on clear-fuzzy block predictive model are formulated.

Key words: OPTIMAL CONTROL, PREDICTIVE MODELS, MAGNETIC SEPARATION

Almost all modern industries operate under the conditions, when, on the one hand it is necessary to provide a high competitive product quality and on the other hand, to minimize the resource consumption.

The solution of such problems is relevant for enterprises of beneficiation industry too, due to a large energy-consuming of iron ore beneficiation technological processes.

Essentially, this problem can be viewed as the problem of optimal control synthesis [1-3]. With respect to the beneficiation processes the main quality indicator of the product is the useful component content in the concentrate. Therefore, in optimal control problem statement it is advisable to formulate both the limitations and the optimality criterion considering this indicator. According to research results [4], in developing of mathematical and algorithmic support of APCS only due to more accurate model it is possible to reduce the uncertainty in the optimal controls determination by 15%.

The recent years investigations [5-8] allow to construct models and to conduct their positive identification due to the possibility to take into account the physical features of the control object and particularly the pulp characteristics, even for such complex dynamic objects, which include processing facilities objects [9, 10].

In this case, the methods based on predictive models demonstrate the best control performance [11, 12].

The predictive control algorithms are described in many studies, but their basis is the predictive control theory with a model [13, 14]. This approach allows to use the different types of models in the control circuit, making possible to use the fuzzy or the hybrid (fuzzy-clear) models for this purpose. In [15] the Hammerstein hybrid model as a predictive model for the iron ore magnetic separation process control is proposed.

The similar models were considered in [16] as applied to the control of a simpler technological objects and showed a good result.

The aim of this paper was the optimal control system development of the first stage of the iron ore magnetic separation based on a hybrid Hammerstein model. The first stage of magnetic separation is considered as a control object with *n* inputs and *m* outputs: a vector of input variables $\overline{u} = [u_1,...,u_n]^T$, a vector of output variables $\overline{y} = [y_1,...,y_m]^T$. In this case, *n*=2, *m*=3. The control variables: the ore flow rate to the mill $u_1=Q_1$ and the water flow rate to classifier $u_2=Q_2$. The output variables: the performance on the intermediate product $y_1=Q_{int}$, the iron content in the middling product $y_2=\beta_{middl.}$ and the iron losses in the magnetic separator tailings $y_3=\beta_{tail.}$ The optimization was performed under the constraints of $\beta_{tail} \le \beta_{tail.opt}$, $\beta_{pr} \ge \beta_{pr.opt}$.

As an optimization criterion the quadratic functional was considered:

$$J(\overline{x}_t,\overline{u}_t,T_p,T_c) = \sum_{i=t}^{t+T_c}((\overline{x}_i - r_x)R(\overline{x}_i - r_x) + (\overline{u}_i - r_u)Q(\overline{u}_i - r_u)) \rightarrow \min, \tag{1}$$

where r_x and r_u – is the parameters specifying the object movement on the prediction horizon, T_p; *R* and *Q* – is the symmetric positive definite weighting matrices;

$T_c \le T_p$ – is the control horizon; $\overline{x}_t$ - state vector.

Such object can be approximated by Hammerstein model, ie, a set of series-connected blocks - nonlinear static and linear dynamic [17, 18]. In this case, the non-linear block is represented by fuzzy Takagi - Sugeno knowledge base [19, 20]:

if u_1 is $A_{1,i1}(u_1)$ and ... and u_{n_u} is $A_{n_u,i_{n_u}}(u_{n_u})$,

then $\nu_h = d^h_{i_1,...i_{nu}}$, (2)

where $A_{j,i_j}(u_j) = \dfrac{u_j - a_{j,i_j-1}}{a_{j,i_j} - a_{j,i_j-1}}$, $\quad a_{j,i_j-1} \le u_j \le a_{j,i_j}$,

$A_{j,i_j}(u_j)$ - is the i_j-th prior fuzzy set for the *j*-th input; $d^h_{i_1,...i_{nu}}$ -is the consequence of rule, M_j – is the number of fuzzy sets in the area of *j*-th input, $\beta_{i_1,...i_{nu}}$ - is the weighting coefficients characterizing the validity of fuzzy rules. A dynamic block is approximated by difference equations:

$$\overline{y}(k+1) = \sum_{i=1}^{n_a} A_i \overline{y}(k-i+1) + \sum_{i=1}^{n_b} B_i f(\overline{u}(k-i-n_d+1)) \tag{3}$$

where $\overline{y}(k),...,\overline{y}(k-n_a+1)$ and $\overline{u}(k-n_d),...,\overline{u}(k-n_b-n_d+1)$ - are the inputs and outputs on the respective steps.Considering (2) eq.(3) takes the form:

$$\overline{y}(k+1) = \sum_{i=1}^{n_a} A_i \overline{y}(k-i+1) + \sum_{j=1}^{N_R} \sum_{i=1}^{n_b} B_i d_j \beta_j (\overline{u}(k-i-n_d+1)) \tag{4}$$

The model obtained in this way (4) contains parameters A_i and B_i, characterizing the linear unit, and a parameter d_j, characterizing the fuzzy block.

To identify the parameters the iterative procedure is proposed [15]. An algorithm considering the need to identify two blocks of the hybrid model (the block (2) and (4)) and imposed constraints is proposed.

The determination of the optimal control actions is carried out according to the following principles. The prediction of the control object behavior on the prediction horizon T_{pr} is calculated by model (4). The resulting prediction is compared with the desired values of the system state vector and the value of $(\overline{x} - r_x)$ is determined. The optimal control actions are determined from (1).

Conclusions

The proposed identification algorithms based on Hammerstein hybrid models allow to avoid nonlinear optimization and simplify the calculation. The industrial tests of developed adaptive control algorithms have shown that their use allows to reduce the dispersion of adjustable parameters by 17-24%, and the duration of transients by 14-23%, which ultimately leads to a reduction of energy consumption while providing the required product quality.

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