ALGORITHM FOR OPTIMIZING THE PRODUCTION PROCESS OF KAOLIN ENRICHMENT

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Abstract

An algorithm has been developed to optimize the technological process of kaolin enrichment, which is based on the theory of fuzzy sets, allowing objects to be evaluated according to their degree of belonging to a certain class and the gradient method. The dependences of the gradient values and the redistribution of weights on the initial values, as well as on the degree of correlation of the distributions of these weights, are considered.

Keywords: optimization algorithm, optimality criterion, gradient values, method of naming squares, optimization problems of parametric identification, interpolation function, optimality criteria, gradient value.

Introduction

In the process of implementing a BTS control system, one has to repeatedly face the choice of an optimization method from several alternative options. In this case , constructing a tree of goals [1] indicating relative priorities becomes insufficient, since it is necessary to take into account the subjective nature of evaluations of optimization tools and the redistribution of priorities as the system develops. It is necessary to develop methods for substantiating decisions that would better meet the conditions for optimizing systems.

When comparing alternative solutions, there is a desire to bring dissimilar goals to a single basis - the degree of their achievement .

Solving the problem of TP optimization using economic efficiency indicators as optimality criteria is complex, since it is necessary to take into account the simultaneous influence of a large number of variables on which restrictions of various types accumulate. The generalized criterion for the optimality of R-economic efficiency of a production system is a certain function of the following indicators:

R=f(C,K,D,P,U,V),

Let us consider these indicators in relation to the process of kaolin enrichment.

The cost C of manufactured products as an optimality criterion has significant drawbacks, namely, this indicator does not take into account the quality of manufactured products K and has low sensitivity to control actions. Therefore, it is inappropriate to use the C->min criterion to control the object under consideration. [6]

The role of the quality indicator K->max of manufactured products becomes clear only in pricing. Obviously, the price of higher quality products should be higher. Therefore, indicators

such as profit P and income received from sales of products are now widely used as a criterion for maximization.
However, the use of these indicators P->max and D->max in direct form is only possible for commercial products that have a certain known price. For intermediate products (such as the resulting kaolin), conditional prices have to be used.

Materials and research methods

The conditional profit indicator Y in various cases degenerates into simpler indicators. So, if the productivity of the B stage is given, then the problem of maximizing P->max becomes equivalent to minimizing the cost C->max:
P->max = C->max
A similar result is obtained when the difference between us and the cost of production is relatively small. If the price is significantly higher than the cost, then maximizing the conditional profit Y->max is equivalent to maximizing productivity B->max:
У->max = B->max
Taking into account the requirements of simplicity, completeness, equivalence and universality (including economic maximization of productivity) and technological (maximization of the target product - B $_{CPU}$) indicators, we obtain that:
V $_{ip}$ ->max = Btsp->max
Therefore, as optimality criteria, we will use such an indicator as maximizing the productivity of a given planned cost:
B $_{\text{and p}}$ ->max, C=const=C pl,
or a criterion for the maximum yield of the target product.
The fact that the relationship between the degree of goal achievement and quality indicators is not strictly defined does not create insurmountable difficulties in analysis, since the modern theory of fuzzy sets [2] allows objects to be assessed according to the degree of their belonging to a certain class. For each parameter, the technological process of kaolin enrichment, you can specify the range in which the degree of its compliance with the specified goals (μ) varies from 0 to 1 or the error from the discrepancy between the real value of the parameter and the specified value ($\overline{\mu}$) changes from 1 to 0. Dependence of the error on the value of each parameter, for example, calculation speed or modeling error , can be approximated by an analytical expression of the form

$$\overline{\mu_i} = [1 + a(\alpha_{oi} - \alpha)_i^2]^{-1}, \alpha_i \le \alpha_\alpha, (1)$$

where α_{oi} and α_i are the initial and current values of the parameter.
The quality of a system, characterized by several indicators, with a fuzzy definition of their values, is expressed by the function of intersection of fuzzy sets

$$\overline{\mu_\Sigma} = \max_i(\overline{\mu_i}), (2)$$

however, this criterion cannot be applied to the assessment of the components of the control system, since it does not capture the improvement in the quality of the system when one or more indicators change, the errors from which are not maximum. In the absence of information about the influence of individual system parameters on its quality, a composite criterion is often used, the components of which have weights determined by expert assessment

$\overline{\mu_\Sigma} = \sum_i \omega_i \overline{\mu_i}$, (3)

This criterion, however, does not take into account the dependence of the weights on the value of individual indicators [2]. It would be more appropriate to redistribute the weights in proportion to the share of the weighted error

$\omega_i' = \frac{\omega_i \overline{\mu_i}}{\sum \omega_k \overline{\mu_k}}$, (4)

but in this case, each change in the i -th indicator, leading to a change in the general criterion (3), causes a redistribution not only of ω_i, but also $\overline{\mu_i}$ to maintain the achieved value $\overline{\mu_\Sigma}$. A new set of values $\overline{\mu_i}$ requires a new redistribution of weights, and this recursion does not converge.

The problem of constructing a composite criterion is greatly simplified if we take into account that information about the weights of indicators is needed to make only one decision, and the level of quality of the system as a whole achieved at that moment does not affect the decision. To do this, it is enough to assume that the weights of the indicators are determined according to (4) according to the previous step , and the error values from them are conventionally assumed to be equal to one. In this case, the scale of the error function changes, but not its derivatives in terms of system quality indicators. It is important that this approach makes it possible to more strictly take into account the second component of the system quality criterion - the costs of improving its performance.

The discussion of the results

Let us assume that at the initial stage of work, costs are distributed unevenly among indicators, i.e. have weights ϑ_i. In this case, the composite quality criterion will have the form

$M = a_1 \sum \omega_i \overline{\mu_i} + a_2 \sum \vartheta_i (1 - \overline{\mu_i})$, (5).

The first term characterizes the error from the discrepancy between the system indicators and the given values, the second - the costs of eliminating this discrepancy. As a result of performing the work, a certain effect must be achieved, which can be measured in fractions of the initial error value:

$M(\overline{\mu_i} = 1) = a_1; \;\; M(\overline{\mu_i} = 0) = a_2;$

$\Delta M = a_1 (1 - \frac{a_2}{a_1}); \;\; a_1 + a_2 = 1.$

Equation (5) can be represented as:

$M = a_2 + \sum (a_1 \omega_1 - a_2 \vartheta_i) \overline{\mu_i}$. (6)

Here a_1 and a_2 are dimensionless coefficients, the ratio of which determines the efficiency of the work performed. Since criterion (6) is intended to compare alternatives that reduce the error for each indicator by the amount $\Delta\overline{\mu_i}$, the coefficients a_1 and a_2 should be considered as derivatives of the resulting error and costs by weighted average components. Assuming that every optimization solution is efficient, i.e. $\Delta M > 0$, coefficients and a_1 can a_2 be obtained by expert assessment, based on the specific situation in which alternatives are considered and the relative complexity of the solution. Obviously, for given a_1 and, a_2 preference should be given to the solution that minimizes the criterion M. However, in the Pareto optimal region, a more in-depth analysis of alternatives is required, taking into account, in particular, the uneven distribution of costs between error components. Despite the complexity of a comparative assessment of costs for each indicator in a complex solution, taking into account weights ϑ_i becomes appropriate if we keep in mind that the costs of various resources are directly aimed not at changing $\overline{\mu_i}$, but at changing the system quality indicators α_i associated with $\overline{\mu_i}$ dependency (1).

Let's imagine that costs are associated with changes in system indicators by the expression

$\Delta 3_i = 3'_{\alpha i} \Delta\alpha$, (7)

Moreover, as the system develops, unit costs decrease as its functionality accumulates . [11] The change in errors as the indicator changes is a derivative $\mu'_{\alpha i}$. Then the following relations are valid:

$$\Delta 3_i = \frac{3'_{\alpha i}}{\overline{\mu}'_{\alpha i}} \Delta\overline{\mu_i} = r_i \Delta\overline{\mu_i}\ . \ (8)$$

$$\Delta 3\Big|_{\Delta\overline{\mu}=1} = \sum_k r_k\ ,\ (9)$$

$$\Delta M = a_1 \sum \omega_i \Delta\overline{\mu_i} - a_2 \sum \vartheta_i \Delta\overline{\mu_i}\ ,\ (10)$$

$$\vartheta_i = r_i : \sum_k r_k\ .\ \text{(eleven)}$$

Here $\Delta\mu_i$ it is defined as the difference between the error values before and after the next step, counting from the initial state of the system. In this case, changing conditions may require correction of the dependence of costs on errors. [13] Obviously, the change in the error components should ensure movement along the normal to the hypersurface of equal level M . If several options give the same value of M , the option that leads to the maximum value of the gradient M is selected at the next solution step.

Equation of the normal at a point $\overline{\mu_i} = 1, i = \overline{1,n}$:

$$\frac{1-\overline{\mu_1}}{a_1\omega_1 - a_2\vartheta_1} = \frac{1-\overline{\mu_2}}{a_1\omega_2 - a_2\vartheta_2} = \ldots = C\ .\ (12)$$

Criterion gradient value

$$|gradM| = \sqrt{\sum_{i=1}^{n}(a_1\omega_i - a_2\vartheta_i)^2} = \sqrt{n[a_1^2 D(\omega) - 2a_1a_2\operatorname{cov}(\omega,\vartheta) + a_2^2 D(\vartheta)] + \frac{1}{n}(a_1 - a_2)^2}\ ,\ (13)$$

where $D(\omega), D(\vartheta)$ are the variances of the weights of the error components and the costs of changing the system parameters; $\operatorname{cov}(\omega,\vartheta)$ - covariance of weights ω_i and ϑ_i.

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Research results:

In the case considered, when moving along the normal, the difference in the weights of individual indicators, as well as the rate of change in the resulting damage, decreases, i.e. the speed of approaching the parameters of the optimized system to the specified ones decreases. [17]

The advantage of such a decision-making procedure is the ability to take into account any changes in external conditions in the process of multi-stage work, for example, the relative value of various system parameters, the dependence of the error on quality indicators, and the distribution of costs for improving various indicators. On the other hand, focusing on maintaining a high rate of reduction in the resulting error is especially relevant for creating complex human-machine systems with limited resources, since this strategy allows maintaining the user's interest in continuing the work.

Based on the above methodology, an optimization algorithm for the kaolin enrichment process has been developed. Below are the optimization results.

Table 1

No.	Control parameter	Values according to technological	Degree of affiliation	Optimal value
1.	Temperature 0 C	20-35 C	Average 0.5	28 C
2.	pH (acidity of the environment)	1.5-2.6	Average0.75	2.2-2.3
3.	Titer of bacteria suspension	1.5-2.5 million cells in 1 ml	Large 0.9	2.0 million 1ml
4.	Mineral Particle Sizes	3-5 microns	Small 0.25	3 microns
5.	Air supply quantity	0.5 to 2l/m ^{3}	Average 0.6	1.5 l/min

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