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As a result of the identification based on the Hammerstein model of objects of the first stage of iron ore magnetic separation, the adequacy of the model is obtained. All results of the testing of the developed identification algorithms show that the subsystem of identification of the automated process control systems of processing plants based on the Hammerstein hybrid model allows to carry out satisfactory identification of objects and, as a consequence, to improve the quality of technological processes. The study of the influence of the coefficient of various typical links on the results of identification using orthogonal parallel and parallel-recursive Hammerstein models showed that these models allow considering the differences in the properties of identifiable objects adequately.

KEYWORDS:
Hammerstein model, identification, iron ore magnetic separation, the control object.

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THE INFLUENCE OF THE CHARACTERISTICS VARIATIONS OF THE CONCENTRATING PLANT CONTROL OBJECT ON THE IDENTIFICATION RESULTS USING THE HAMMERSTEIN MODEL

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Introduction

The development and implementation of multi-level automated control systems at mining enterprises, which give the maximum economic effect, are possible only with a systematic approach to solving automation problems, when the technological process, equipment, raw materials and automation tools are considered at the same time. Even with the well-known general laws of the technological process, the conditions for its optimization are knowledge of the processed raw materials properties and the state of the technological equipment, on the one hand, and the use of sophisticated integrated automation tools, on the other hand. The control system, the selection of parameters and the control law are carried out based on a mathematical model in which the known regularities of the technological process are laid. It is not possible to create an effective control system for non-stationary technological processes based on a constant (immutable) model because the actual characteristics of the object are changing. Thus, effective control models should be sought in the direction of using a variable in the general case, a non-fixed model for a control system. Such requirements are satisfied by adaptive systems (AS), characterized in that their characteristics change (tuned) during operation. As a result, the performance of the system improves. This allows the use of an adaptive system with incomplete a priori information on external operating conditions; to produce the same adaptive systems for operation in different conditions; use adaptive systems under changing external conditions, which facilitates their operation.

One of the reasons for the non-stationary process of the iron ore beneficiation process is the change in the quality of the processed material (the size of the pieces of the original ore, the grindability, the hardness, the character of the useful component inclusion, etc.). The heterogeneity of the qualitative composition of the enriched raw material is to some extent also determined by current trends in the beneficiation process, which imply ever-expanding deep processing of poor ores, which differ significantly in geological and technological types. Another reason for the drift of the static and dynamic characteristics of the process units is their physical ageing and wear. The variations in the characteristics of the control object should be considered when modelling and identifying them in order to form the effective automatic control of ore beneficiation process.

Problem statement

Most of the control facilities at the processing plants have both dynamic and nonlinear properties. The identification of such objects often causes considerable difficulties. Some methods of identification of nonlinear dynamic objects are considered in the works [1–15; 26–31]. As the analysis of these works shows, a common technique for identifying dynamic nonlinearity is the artificial separation of these two properties. An object is represented as a combination of non-linear static and linear dynamic blocks. At the same time, N. Wiener suggested considering the serial connection in the order: dynamic block, followed by non-linearity [4–6; 14]. An alternative option is a nonlinear block, followed by a dynamic one proposed by Hammerstein and was considered in [9; 13; 15; 26–29].

However, in such a simple version, the Wiener and Hammerstein models are used extremely rarely. In most cases, the identification object is approximated by various combinations of these simple models. At the same time, studies have shown [9–13, 16, 30] that the best in terms of simplicity-quality were parallel and recursively parallel models. The study aims to analyze the possibility and results of applying these models to identify the main technological processes of beneficiation production: grinding, classification, magnetic separation.

Review of the literature

An essential feature of parallel models with an unlimited number of parallel branches was emphasized in [9–13; 16; 29–31]. The use of this class of models eliminates the solution of a very complex problem of choosing the structure of the model. The fact is that when using simple models with a limited number of blocks, it is crucial to choose the model structure or the optimal combination in which these blocks are connected. When using parallel branches, the state changes, the structure of the model ceases to play such an important role. For the vast majority of real objects, both the parallel Hammerstein model and the Wiener parallel model have approximately the same convergence.

The question of choosing the structure of a parallel model is no longer determined by the accuracy of the model, but by the possibilities of effective identification of its parameters. In this regard, the parallel Hammerstein model is more profitable, since one-dimensional orthogonal identification algorithms are possible for it [1–3], which do not impose any severe restrictions on the type of input test actions. One-dimensional algorithms for identifying the parameters of the parallel Wiener model are not orthogonal [17–20; 31]. Orthogonal algorithms for Wiener models [21–23] are multidimensional and require significant computational resources. In principle, it is possible to use not only parallel models but also sequential models containing many series-connected simple Hammerstein or Wiener models. However, this approach is not used in practice since it turned out to be difficult to formalize and is associated with simulation modelling, which requires significant computational resources [23].

Thus, at the moment, there are several general classes of nonlinear dynamic models for describing real identification objects. The choice of the most suitable class of the model is determined by the intuition of the researcher and the capabilities of the corresponding identification algorithms developed for a specific class of models, the type of input signals, the calculation time. From the considered models of nonlinear dynamic objects, models of the Hammerstein class are convenient for rapid identification. Let's analyze the possibility of using the Hammerstein model to identify the beneficiation processes.

Materials and methods

Many iron ore beneficiation processes have a feedback model. Let's consider the identification of such processes by the parallel-recursive Hammerstein model [11].

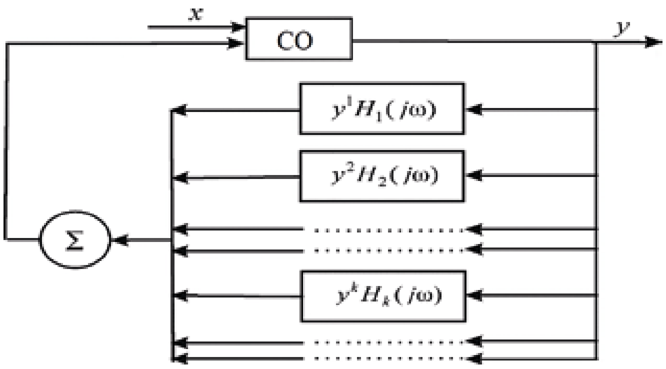

Fig.1. *Recursive inclusion of the Hammerstein model in the feedback branch*

The parallel Hammerstein model, when it is recursively included in the feedback circuit (Fig. 1) is generally described by formula (1) [11]:

$$X(j\omega)=\sum_{i=0}^{\infty} H_i(j\omega)\cdot Y^i(j\omega)\ , \tag{1}$$

where the dynamic coefficients $H_i(j\omega)$ can be any functions of frequency.

The system of linear equations, whose solution will allow us to obtain the coefficients of the model, will correspond to the power sequence of functions (1). Given the truncation of the series (1), we obtain formula (2):

$$\begin{bmatrix} Y_1^{(1)}(j\omega) & Y_1^{(2)}(j\omega) & \dots & Y_1^{(n)}(j\omega) \\ Y_2^{(1)}(j\omega) & Y_2^{(2)}(j\omega) & \dots & Y_2^{(n)}(j\omega) \\ \dots & \dots & \dots & \dots \\ Y_n^{(1)}(jw)\omega & Y_n^{(2)}(j\omega) & \dots & Y_n^{(n)}(j\omega) \end{bmatrix} \times H(j\omega)=X(j\omega)\,, \tag{2}$$

where $X(j\omega)$ – is the column-matrix of input signals, $H(j\omega)$ – is the column-matrix of unknown coefficients, $Y_k^{(n)}(j\omega)$ – is the value of model responses in k-th degrees.

Each equation of the system (2) is based on its implementation of the test impact and response. If random test effects are used to determine unknown parameters, a correlation analogue (2) should be used. The correlation equation of identification is constructed by multiplying (2) by $Y^k(-j\omega)$ and then averaging. The final formula (3) has the form:

$$R_{xy\,k}(j\omega)=\sum_{i=0}^{\infty} H_i(j\omega)\cdot R_{y^i y^k}(j\omega)\,, \tag{3}$$

where
$$\begin{cases} R_{xy^k}(j\omega)=M\{X(j\omega)\cdot Y^{(k)}(-j\omega)\}, \\ R_{y^i y^k}(j\omega)=M\{Y^{(i)}(j\omega)\cdot Y^{(k)}(-j\omega)\}. \end{cases} \tag{4}$$

In order to determine the ranges of application of these models for identifying technological objects of iron ore beneficiation, it is necessary to conduct a model study:

1) to identify the influence of the control object char-

acteristics on the value of the model coefficients and the accuracy of identification;

2) to analyze the sensitivity of the model concerning variations in the parameters of identified objects;

3) to establish the optimal number of approximating orthogonal polynomials, since more and more computational power is required to calculate each subsequent polynomial.

Experiments

Mathematical models of many apparatus of the iron ore beneficiation processing line can be represented as simple static and dynamic links and their combinations [24–25], by formula (5) and (6):

nonlinear link: $$y_{pr} = aQ^2 + bQ + c\,, \qquad (5)$$

dynamic link: $$d\frac{dy_{pr}}{dt} + y_{pr} = y\,(t-\tau)\,. \qquad (6)$$

These links correspond to the blocks of the Hammerstein model. In formulas (5) and (6): *a, b, c, d, τ* – are the control object parameters, *Q* – is the input index, *y* – is the output index. To study the effect of values of *a, b, c, d, τ* parameters on the coefficients of the Hammerstein orthogonal model we will sequentially change the values of the parameters by calculating the coefficients of the Hammerstein orthogonal model

$$R_{yg_{yk}}(j\omega) = {}^{g}H_k(j\omega)\cdot R_{g_{xi}g_{yk}}(j\omega),$$

where $$\begin{cases} R_{yg_{yk}}(j\omega) = M[Y(j\omega)\cdot G_k(Y(-j\omega))], \\ R_{g_{xi}g_{yk}}(j\omega) = M[G_i(X(j\omega))\cdot G_k(Y(-j\omega))]. \end{cases}$$

The Legendre polynomials $G_k(x)$ are equal to [25]:

$$G_0(x) = x^0 = 1;\; G_1(x) = x^1;\; G_2(x) = (1/2)\cdot(3x^2 - 1);$$
$$G_3(x) = (1/2)(5x^3 - 3x^1);\; G_4(x) = (1/8)(35x^4 - 30x^2 + 3).$$

The ranges of changes in the link coefficients will be taken according to the results of studies [25]. Let's determine in advance the size of the statistical sample of the generated input variables. The results of simulations and the comparison of model relative errors for three variants of sample: 20, 50 and 100 elements are shown in Fig. 2. For samples of 50 and 100 elements, the errors differ insignificantly. In both cases, the maximum error practically coincides; therefore, samples of 50 elements were further used. To assess the influence of the number of orthogonal polynomials on the results of orthogonalization, the dependences of the Hammerstein model coefficients on the number of polynomials were built when the values of the input index changed over a significant range (100% change). The graphs of the obtained dependencies are shown in Fig.3.

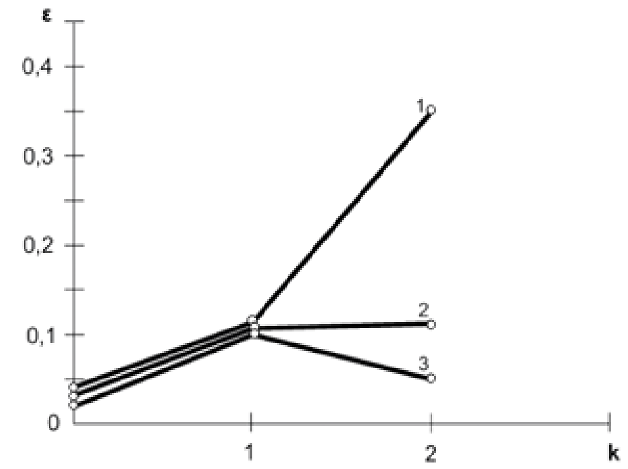

Fig. 2. *The relative error of the model for different sample sizes:1 – 20 elements; 2 – 50 elements; 3 – 100 elements*

The results obtained indicate that the coefficients H_3 and H_4 practically do not respond to changes in the state of the identification object. Therefore, an additional study was conducted in order to determine the minimum number of coefficients of the orthogonal model needed to describe the object adequately.

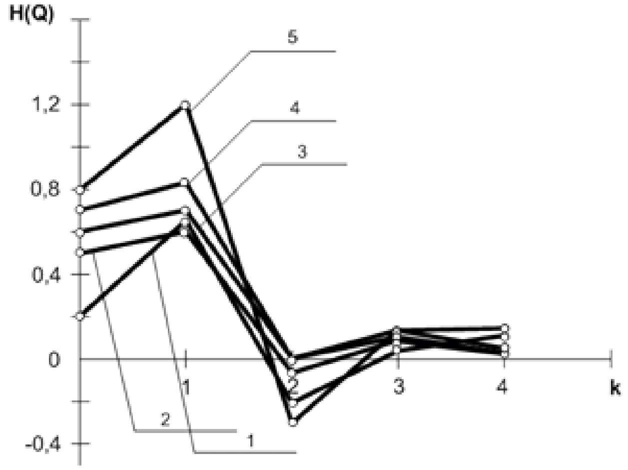

Fig. 3. *The dependence of the model coefficients on the number of polynomials for values of Q:1 – Q = 0.4; 2 – Q = 0.5; 3 – Q = 0.6; 4 – Q = 0.7; 5 – Q = 0.8*

For this purpose, the simulation results and real statistics for grinding and classification processes were compared. The simulation was carried out by several orthogonal models that differ in the number of approximating polynomials, i.e., in the number of model coefficients. The number of polynomials varied from 2 to 6, while the error of the model was determined as the relative mean-square difference between the initial indicators obtained as a result of modelling and real data. The results of the calculations are presented in Fig. 4 and demonstrate that the relative error for models with three polynomials and more differs slightly: for example, for $k = 3$ and $k = 6$, the difference is less than 0.002.

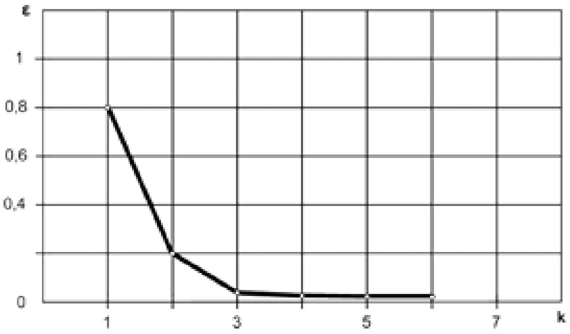

Fig. 4. *The dependence of model error on the number of orthogonal polynomials*

However, increasing the number of polynomials requires additional calculations. Therefore, models with three polynomials were used for further studies. To determine the effect of coefficients *a, b, c, d, τ* on orthogonalization coefficients, the corresponding dependencies are constructed (Fig.5, Fig. 6, Fig. 7, Fig. 8, Fig 9).

According to the graphs, the coefficient H_1 is independent of the parameters. It is determined only by the type of orthogonal polynomial, and the proposed procedure can determine the rest of the coefficients for all considered parameter ranges. That is, almost all the processes of iron ore beneficiation can be identified using orthogonal parallel Hammerstein models.

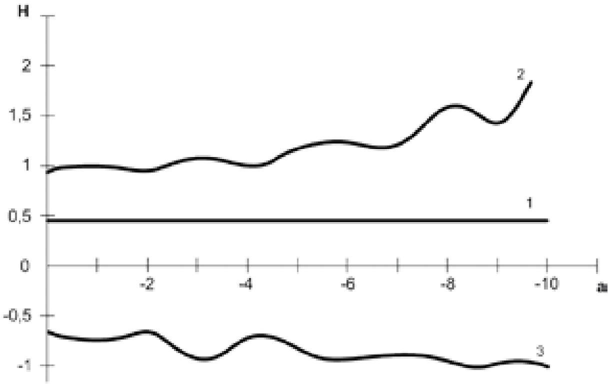

Fig. 5. *The dependence of model coefficients on the parameter a: 1 – $H_0(a)$; 2 – $H_1(a)$; 3 – $H_2(a)$*

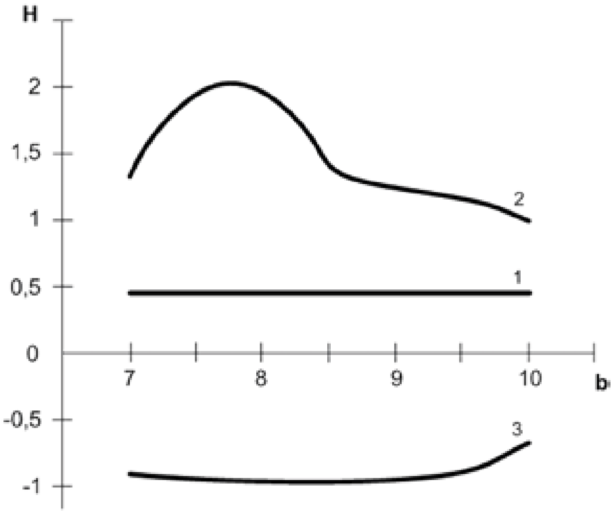

Fig. 6. *The dependence of model coefficients on the parameter b: 1 – $H_0(b)$; 2 – $H_1(b)$; 3 – $H_2(b)$*

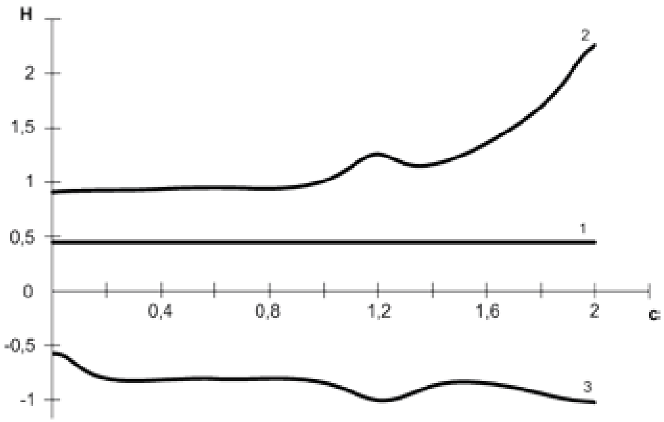

Fig. 7. *The dependence of model coefficients on the parameter c: 1 – $H_0(c)$; 2 – $H_1(c)$; 3 – $H_2(c)$*

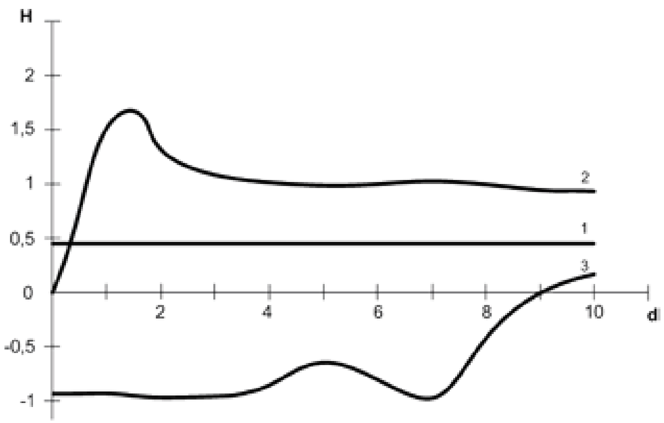

Fig. 8. *The dependence of model coefficients on the parameter d: 1 – $H_0(d)$; 2 – $H_1(d)$; 3 – $H_2(d)$*

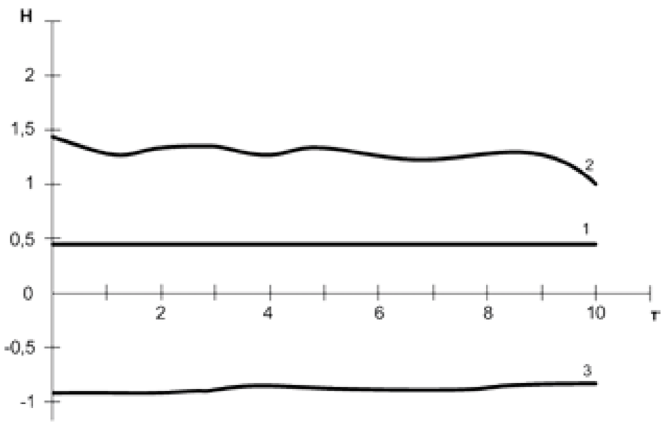

Fig. 9. *The dependence of model coefficients on the parameter τ: 1 – $H_0(\tau)$; 2 – $H_1(\tau)$; 3 – $H_2(\tau)$*

Let's investigate the error of identification. To do this, we determine the relative errors of the models depending on each parameter of the identified link. Based on formulas $y_{pr} = aQ^2 + bQ + c$ and $d \cdot dy_{pr}/dt + y_{pr} = y\,(t-\tau)$ random values of input parameters from a given range are generated. Since the equations for modelling are consistent with the structure of the mill and the classifier models [25], the value of the input parameter Q was generated using a random number generator in the range close to the range of change in the initial ore mill performance ($Q = 0.5 \div 0.7$

according to the data [25] for the mill). By the model (5), (6), the corresponding output indicators are calculated. To determine the errorε, another 50 input values are generated by which the coefficients of the orthogonal parallel-recursive Hammerstein model are verified. As a result, the errors of the model coefficients are obtained when each of the coefficients of the equations (5) (6) is changed. Fig.10, Fig. 11, Fig. 12, Fig. 13, Fig. 14 demonstrate the influence of coefficients a, b, c, d, τ on the model error ε. In all cases, the smallest errors near the values that correspond to the real parameters of the object are observed. In order to determine the sensitivity of the orthogonal model concerning changes in each of the parameters a, b, c, d, τ of the identification object, the following studies were conducted. Each of a, b, c, d, τ received consecutive gains of 1%, 10% and 100% of its nominal value, corresponding to research [25].

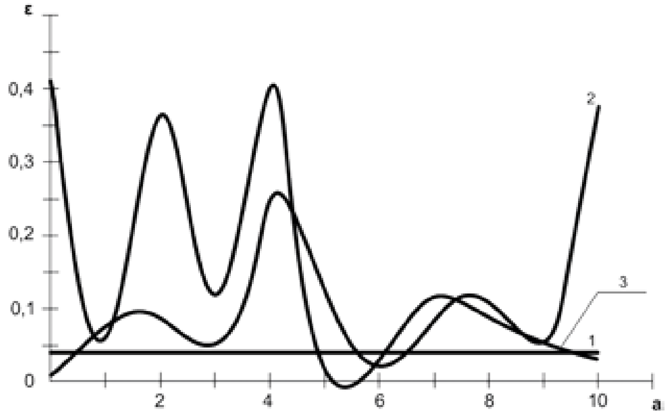

Fig. 10. *The dependence of the identification error for the model coefficients on the parameter a:*
1 – coefficient error H_0; 2 – coefficient error H_1; 3 – coefficient error H_2

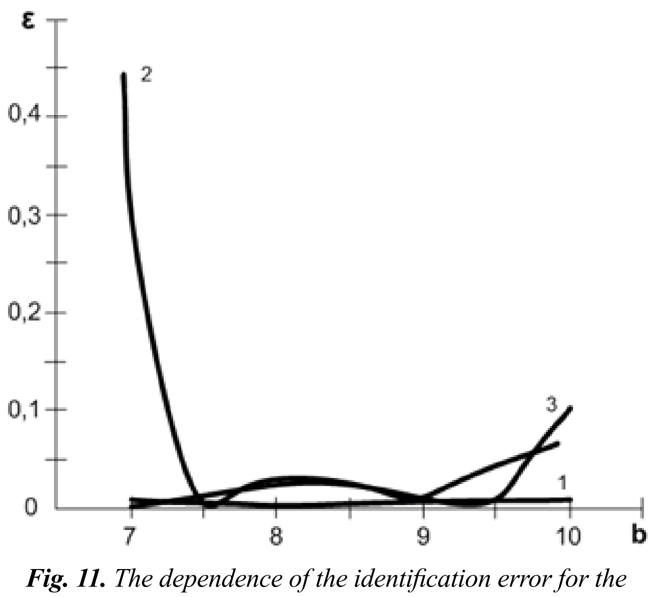

Fig. 11. *The dependence of the identification error for the model coefficients on the parameter b:*
1 – coefficient error H_0; 2 – coefficient error H_1;
3 – coefficient error H_2

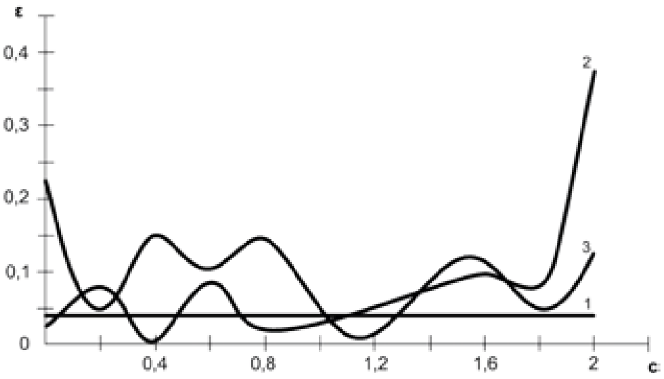

Fig. 12. *The dependence of the identification error for the model coefficients on the parameter c:*
1 – coefficient error H_0; 2 – coefficient error H_1;
3 – coefficient error H_2

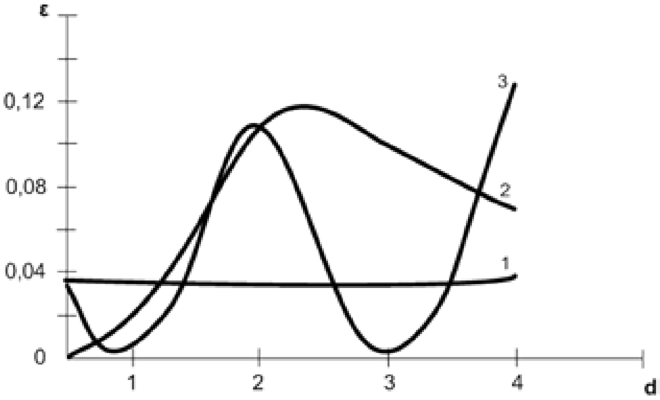

Fig. 13*. The dependence of the identification error for the model coefficients on the parameter d:*
1 – coefficient error H_0; 2 – coefficient error H_1;
3 – coefficient error H_2

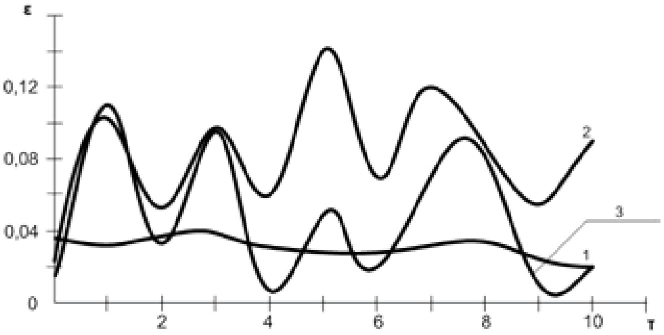

Fig. 14. *The dependence of the identification error for the model coefficients on the parameter τ:*
1 – coefficient error H_0; 2 – coefficient error H_1;
3 – coefficient error H_2

In this case, the corresponding relative change (sensitivity) of each of the model coefficients was determined:

$$\delta = \frac{|H_{in} - H_{ch}|}{H_{in}}.$$

Where H_{in} – is the value of the model coefficient at the initial parameter value, H_{ch}–is the value of the model coefficient when the parameter value is changed by 1%, 10%, and 100% from the initial value. Sensitivity is considered satisfactory if a change in the parameter of the object by 1% causes a change in the coefficients of the model by 2%.

Results

The results of the study are presented in Fig. 15, Fig. 16, Fig. 17, Fig. 18, Fig. 19. According to the obtained relations, the coefficients of the model are characterized by good sensitivity: when changing the parameters of the control object by 1%, the relative change in the coefficients is in the range from 4% to 20%.

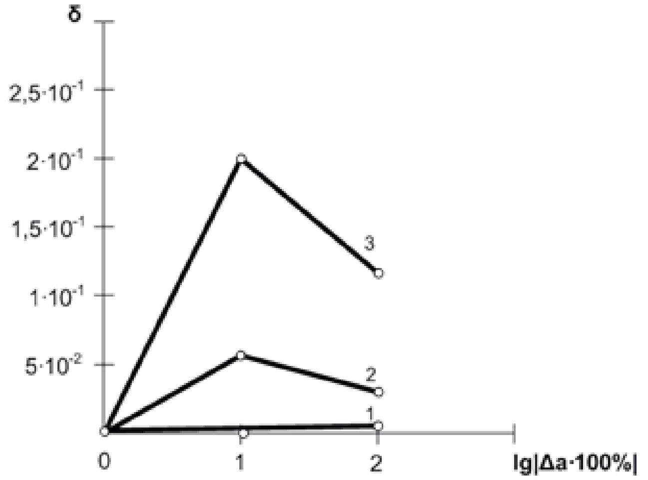

Fig. 15. *The dependence of the sensitivity of the model coefficients on the change of parameter a:*
1 – coefficient sensitivity H_0; 2 – coefficient sensitivity H_1;
3 – coefficient sensitivity H_2

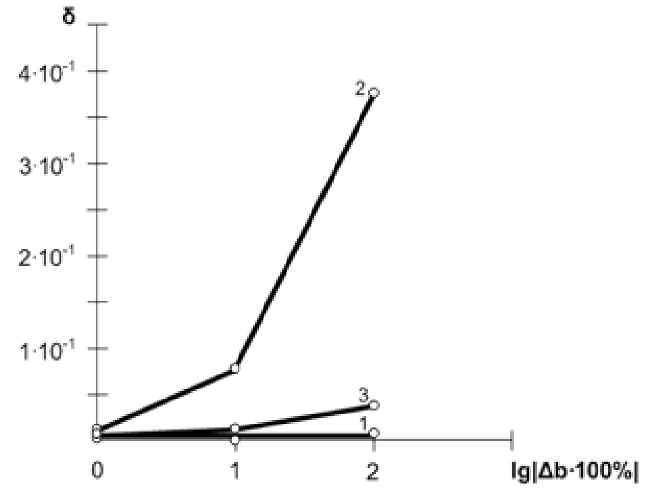

Fig. 16. *The dependence of the sensitivity of the model coefficients on the change of parameter b:*
1 – coefficient sensitivity H_0; 2 – coefficient sensitivity H_1;
3 – coefficient sensitivity H_2

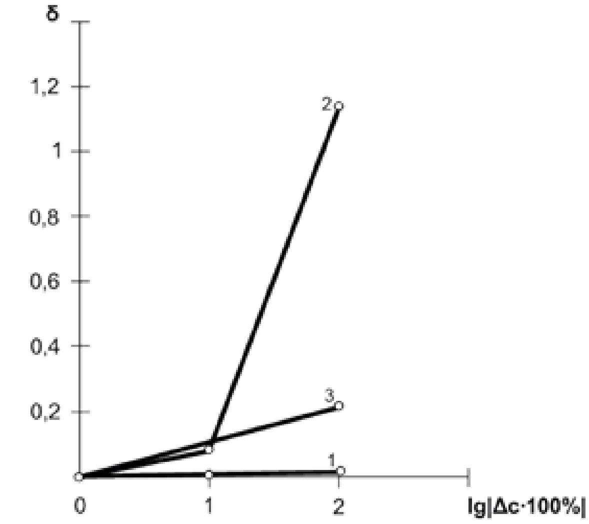

Fig. 17. *The dependence of the sensitivity of the model coefficients on the change of parameter c:*
1 – coefficient sensitivity H_0; 2 – coefficient sensitivity H_1;
3 – coefficient sensitivity H_2

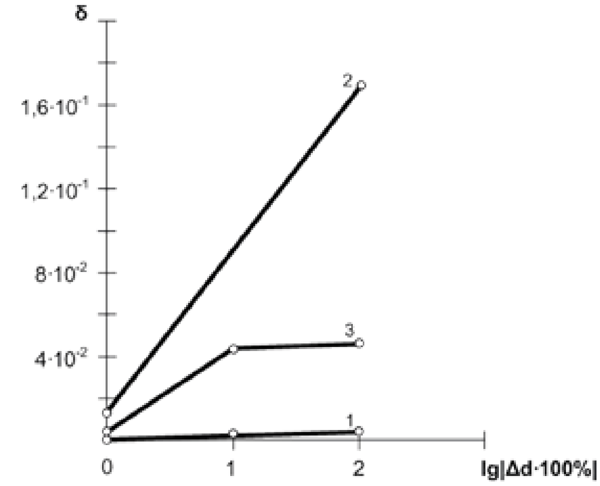

Fig. 18. *The dependence of the sensitivity of the model coefficients on the change of parameter c:*
1 – coefficient sensitivity H_0; 2 – coefficient sensitivity H_1;
3 – coefficient sensitivity H_2

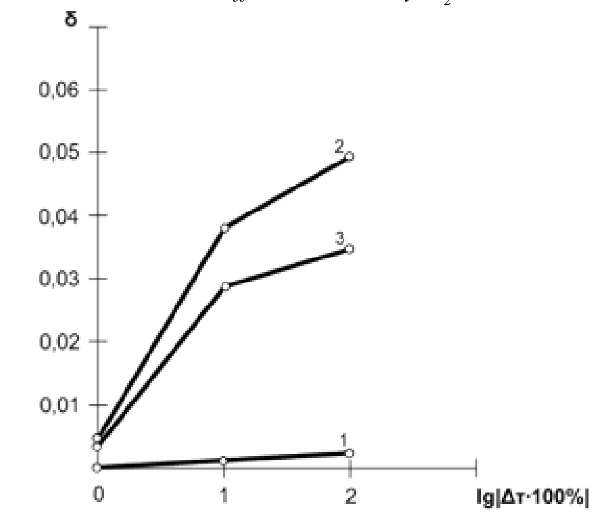

Fig. 19. *The dependence of the sensitivity of the model coefficients on the change of parameter τ:*
1 – coefficient sensitivity H_0; 2 – coefficient sensitivity H_1;
3 – coefficient sensitivity H_2

Discussion

Thus, identification using orthogonal parallel and parallel-recursive Hammerstein models allows to account for differences in the properties of identifiable objects adequately and can be used for most fundamental processes of iron ore beneficiation, with an optimal number of orthogonal polynomials. As a result of the identification based on the Hammerstein model of objects of the first stage of iron ore magnetic separation, the adequacy of the model is obtained, which corresponds to the coefficient of determination R2 $\geq$ 0.96. All results of the testing of the developed identification algorithms show that the subsystem of identification of the automated process control systems of processing plants based on the Hammerstein hybrid model allows to carry out satisfactory identification of objects and, as a consequence, to improve the quality of technological processes. Algorithms for the identification of technological process objects have been implemented at Kryvbas Mining and Processing Enterprises, which are part of the Association "Ukrrudprom", as well as several other enterprises.

Conclusions

The scientific novelty is that for identification the processes of magnetic beneficiation of iron ore by the criterion of minimum error, it is advisable to use a recursive-parallel model of Hammerstein. The study of the influence of the coefficient of various typical links on the results of identification using orthogonal parallel and parallel-recursive Hammerstein models showed that these models allow considering the differences in the properties of identifiable objects adequately. These models are characterized by high sensitivity – when the characteristics of an object change by less than 1%, the model coefficients change by 4%–20%. The optimal number of orthogonal polynomials for identifying the control objects of the mineral processing industries is three since with a further increase in the number of polynomials the error practically does not change $\Delta\varepsilon \leq 0.002$) and the number of calculations increases.

The practical significance is that for the objects of the technological line of iron ore beneficiation, which are characterized by nonlinear, dynamic, non-stationary properties, is advisable to use Hammerstein class models for their approximation. The simple model of Hammerstein describes the real object inaccurately and therefore cannot be recommended for identification of such nonlinear dynamic objects as technological processes of iron ore beneficiation.

CONFLICT OF INTEREST

The authors declare no conflicts of interests.

CONTRIBUTION

Porkuian O.V. and ***Morkun V.S.*** were responsible for research concept and design, Morkun N. made critical revision and final approval of article, ***Gaponenko I.A.*** was responsible for data analysis and interpretation.

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ВЛИЯНИЕ ВАРИАЦИЙ ХАРАКТЕРИСТИК ОБЪЕКТА УПРАВЛЕНИЯ ОБОГАТИТЕЛЬНОГО ПРОИЗВОДСТВА НА РЕЗУЛЬТАТЫ ИДЕНТИФИКАЦИИ С ПРИМЕНЕНИЕМ МОДЕЛИ ГАМЕРШТЕЙНА

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Целью исследования является анализ возможности и результатов применения ортогональных параллельных и параллельно-рекурсивных моделей Гамерштейна для выявления основных технологических процессов обогащения: измельчения, классификации, магнитной сепарации.

С целью определения областей применения этих моделей для идентификации технологических объектов обогащения железной руды определено влияние характеристик объекта управления на величину коэффициентов модели и точность идентификации, чувствительность модели к вариациям, проанализированы параметры идентифицируемых объектов, установлено оптимальное количество аппроксимирующих ортогональных многочленов. Таким образом, идентификация с использованием ортогональных параллельных и параллельно-рекурсивных моделей Гамерштейна позволяет адекватно учитывать различия в свойствах идентифицируемых объектов и может использоваться для большинства фундаментальных процессов обогащения железной руды с оптимальным количеством ортогональных многочленов.

В результате идентификации на основе модели Гамерштейна объектов первой стадии магнитной сепарации железной руды получена адекватность модели. Все результаты тестирования разработанных алгоритмов идентификации показывают, что подсистема идентификации АСУ ТП перерабатывающих предприятий на основе гибридной модели Гаммерштейна позволяет проводить удовлетворительную идентификацию объектов и, как следствие, повышать качество технологических процессов. Изучение влияния коэффициента различных типовых звеньев на результаты идентификации с использованием ортогональных параллельных и параллельно-рекурсивных моделей Гамерштейна показало, что эти модели позволяют адекватно учитывать различия в свойствах идентифицируемых объектов.

Ключевые слова: модель Гамерштейна, идентификация, магнитная сепарация железной руды, объект управления.

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