УДК 681.5.015:622.7-52

V.B. Khotskina, Cand. Sci. (Tech.), Associate Professor

State Higher Educational Institution "National University of Krivoy Rig", Krivoy Rog, Ukraine, e-mail: valentina.hockina@mail.ru

AUTOMATIZATION OF CONTROL PROCESSES AT THE FIRST STAGE OF ORE ENRICHMENT USING QUICKLY ACTING REGRESSIVE MODELS

В.Б. Хоцкіна, канд. техн. наук, доц.

Державний вищий навчальний заклад „Криворізький національний університет", м.Кривий Ріг, Україна, e-mail: valentina.hockina@mail.ru.

АВТОМАТИЗАЦІЯ ПРОЦЕСІВ КЕРУВАННЯ ПЕРШОЮ СТАДІЄЮ ЗБАГАЧЕННЯ РУДИ З ВИКОРИСТАННЯМ ШВИДКОДІЮЧИХ РЕГРЕСІЙНИХ МОДЕЛЕЙ

Purpose. Development of high-speed multi-regression models for the operational management of the first stage of ore enrichment.

Methodology. Multifactor regression models of controlling of the first stage of grinding - classification - magnetic separation were obtained on statistical material which had been obtained in the result of passive experiment of the first stage of ore enrichment. Methodology of the research of the models of grinding mills charging optimization has been worked out taking into account the composition of complex ores and evaluation of the mass fraction of 0.056 mm class in industrial product classification.

Findings. The developed software allows us to build the model of the first stage ore enrichment and control boundary limits of input factors by projecting inception of the problem situation, correcting the models of grinding mills (ball mills) charging and classifying the process of the first stage of ore enrichment.

Originality. We have established cause-effect relationships of technological variables of enrichment facilities depending on physical and mechanical properties of ores. Dependence of process parameters on the properties of ore determined by the "production rules" input and output matrices of Petri nets. The main purpose of Petri nets is to identify problematic situations and create "production rules" which form the set of recommendations for the effective operation of the system based on the cause-effect relationships.

Practical value. The research resulted into the control system, database and software for automation of ore treatment. The methods of development of management decisions in robot and adaptive control systems of the first stage of enrichment were implemented. The practical recommendations for the effective management of the first stage of ore enrichment based on our algorithms and software have been developed.

Keywords*: process control, adaptation, decision making model, regression, forecasting*

Background. The main strategic objective of the Public Joint Stock Companies Metinvest Group till 2020 is the increase of production of the ore concentrate that contains mass fraction of iron up to 66.5% and the reduction of the specific cost of electrical energy by 15–20% [1]. These tasks are performed by an integrated management of concentrate production and business processes based on the modern automate control systems ACS and automated process control systems APCS production [2]. Modern APCS of ore enrichment work under conditions of uncertainty caused by difference in textural properties of ore to be processed and temporal variation of dynamic characteristics of the controlled objects (ball mills, classifiers, magnetic separators, etc.). The operational personnel give questionable assessment of manufacturing situations according to the types of ores to be processed. In order to meet consumers' requirements to the concentration product they deal with load redistribution between technological sections and stages that requires constant adjustment of the local control systems of ball mills of the first stage of enrichment and time identification of excitation field arising during ore concentration process [2].

When the quality of the product is determined by the order portfolio of the metallurgic plants, we can increase the concentrate production efficiency by reducing the uncertainty associated with the evaluation of textural properties of the ore through introducing of the intelligent APCS for enrichment combined with (robust-adaptive) control systems [2]. The main objective of APCS is to define the moment of change of crude ore type and identify technological process of ore production by n-factors being the fast-acting modeling elements of control systems of the first stage of ore enrichment based on instruments of fuzzy modeling, fuzzy logic, "production rules", and Petri nets.

In this case, the impact of ore properties on the operation modes of ball mills should be defined by "production rules" of input and output matrices of Petri net, based on which the matrix of changes in logical functional blocks should be compiled that can increase the accuracy of the changes (disturbances) of the properties of the ore and reduce their impact, using combined control system of the first stage of enrichment as a precondition for stabilization of the processes of flotation (PAT "Inguletskyi GZK"), agglomeration (VAT "Pivdennyi GZK"), pelletizing (PAT "Tsentralny GZK", PAT "Pivnichny GZK").

Problem. The development of complex control algorithms of ore-dressing processes are covered in scientific papers of Ye.V. Kochura, A.I. Kupin, V.I. Kornienko and others. They used in their researches various mathematical models oriented on improvement of the quality of the concentrate through optimal controlling of the first stage of enrichment [3–5].

The authors' researches of the methods of identification of the complex technological processes based on the fuzzy set theory, the theory of Petri net and the theory of R-functions allow us to project modern intelligent automated systems of control of technological processes at enrichment plants provided that the well-known computing systems phi-RMI "Siemens" (Germany) with software of high quality are used [2]. At the same time the lack of experience of personnel does not allow using such software at enrichment plants for technological sections control.

Consequently, the development of software products based on the known methods of regression modeling of complex processes using knowledge and competence of the operational staff is the way to introduce cheaper software and it can be performed at the level of engineering personnel of the enterprise.

Main part. We have conducted researches of technological sections at the plant of PAT "Tsentralny GZK" in order to develop the software "Modeling of the First Stage of Ore Enrichment". Details of the results are shown in Table. 1.

Table 1

Results of the Research of Technological Section Operation at PAT "Tsentralny GZK"

Content-of hard-processing ore (%)	Mill productivity (t / h)	Solid component of mill discharge (g/l)	Solid component in industrial products drain classifier (g / liter)	Water quantity supplied in mill download (m^3/hr)	Water amount in the charge of classifier (m^3/hr.)	Mass fraction of class in classification products (%)
1	2	3	4	5	6	7
66	193	1935	1377	54	113	56,2
66	192	1935	1377	55	114	56,3
66	194	1942	1381	55	113	56,2
65	196	1946	1383	56	114	56,2
68	191	1931	1374	54	113	56,3
67	191	1929	1372	55	114	56,4
67	187	1924	1368	53	113	56,3
68	189	1928	1371	56	113	56,2
68	189	1928	1371	55	114	56,2
66	190	1928	1371	53	114	56,4
68	192	1933	1374	56	113	56,2
68	192	1934	1373	56	115	56,1
66	193	1935	1377	54	114	56,2
66	194	1937	1377	56	113	56,2
66	195	1942	1382	56	116	56,8
66	199	1951	1388	58	116	57,3
63	201	1957	1393	60	116	57,3
63	199	1957	1392	59	115	57,4
65	201	1964	1398	58	116	58,3
63	205	1971	1403	60	118	58,3
63	205	1971	1403	59	116	58,3
62	206	1971	1403	60	119	58,3
63	206	1972	1405	61	119	58,3
64	206	1971	1405	62	119	58,3

Based on the experimental data we have developed the software for the first stage of ore enrichment in the mode of "advice to dispatcher." Outline flow chart of the task in hand is shown in Fig. 1 as an algorithm of the software development.

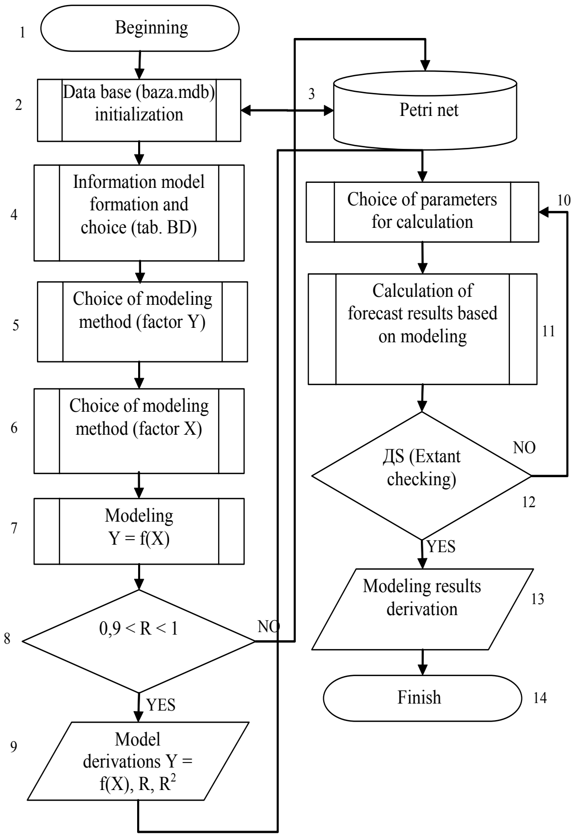

Fig. 1. "Modeling of the First Stage of Ore Enrichment" software development algorithm

The software allows us to build models of the first stage of ore enrichment. We can build two multifactorial models with the following modifications:

1. The dependence of the mass fraction of a class by industrial products classification, % (*Y*) on the input factors (productivity of the mill t / h. (x1), solid content of mill discharge g / liter (x2), solid content in the discharge of industrial products classifier g / l (x3), the quantity of water supplied in the mill charge m^3 (x4), water flow in classifier charge, m^3. (x5).

2. The dependence of the mill productivity *t / h. (Y)* on the input factors (solid content of mill discharge g / liter (x1), solid content in the discharge of industrial products classifier g / liter (x2), quantity of water supplied in the download mill m^3 (x3), water flow in the load classifier m^3/hr. (x4), mass fraction of industrial products in the class-certification by classes, % (x5).

To receive a modification of the model we can replace one of the input parameters (first model parameter x2 or x1 parameter of the second model) by index content of hard-processing ore, %.

During the formation of these models, we can select any number of input factors (from 1 to 5). Indices, as an information models, are given in Table. 1. These tables were obtained during studies of technological sections in the factory of PAT "Tsentralny GZK" for the period from 6.00 a.m. to 11.45 a.m. with a 15-minutes interval. So these figures represent the primary configuration of the system.

Fig. 2–8 is graphic representation of the data of Table 1 in the form of time series. Each division of the x-axis corresponds to 15-minutes interval of the study.

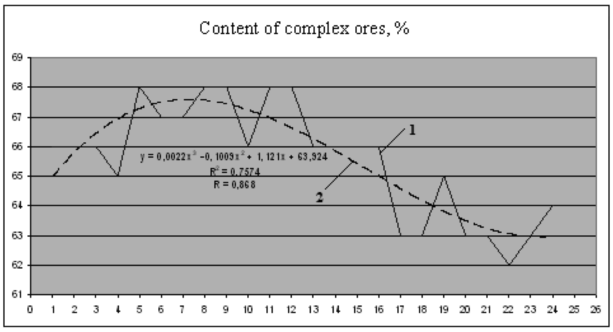

Fig. 2. Time dependence of the hard-processing ore content: 1 is hard-processing ore enrichment data; 2 is the 3rd degree polynomial model

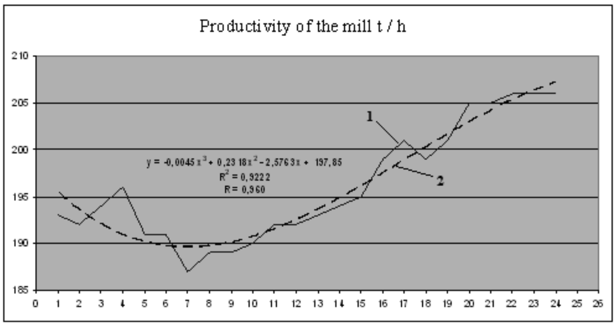

Fig. 3. Time dependence of the mill performance: 1 is mill performance data; 2 is the 3rd degree polynomial model

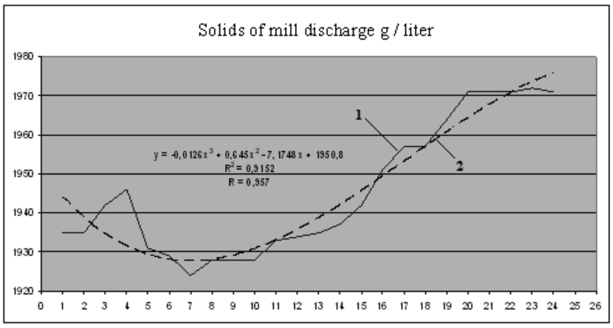

Fig. 4. Time dependence of the solid component in mill discharge: 1 is the data of the solid component in mill discharge; 2 is the 3rd degree polynomial model

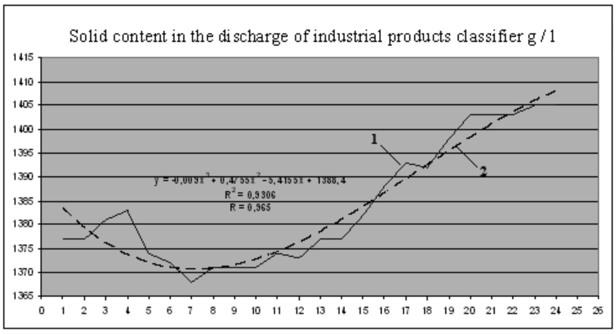

Fig. 5. Time dependence of the solid component in industrial products: 1 is the data of the solid component in drain classifier; 2 is the 3rd degree polynomial model

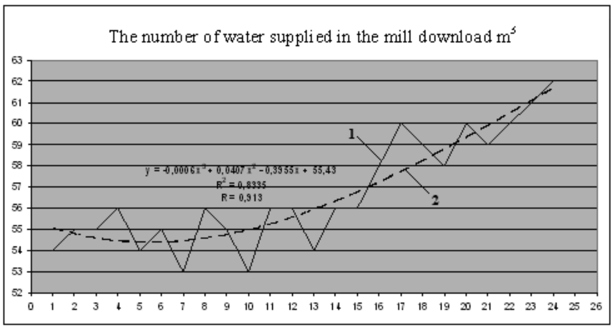

Fig. 6. Time dependence of the water amount supplied for mill charge: 1 is data about the amount of water supplied to the mill; 2 is the 3rd degree polynomial model

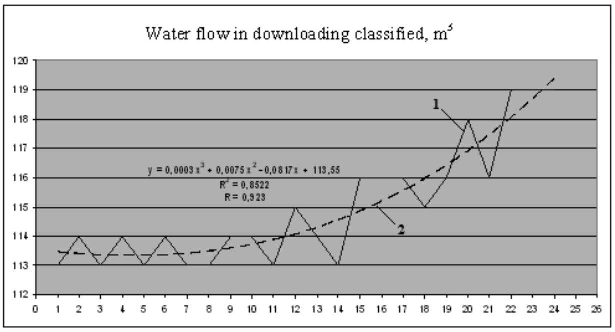

Fig. 7. Time dependence of water consumption in the classifier charge: 1 the data about water consumption in the classifier charge; 2 is the 3rd degree polynomial model

We have chosen the optimal model of time dependence for each of the chosen indicators. It is a polynomial model of the 3rd degree. The Fig. 2–8 shows the time dependence of the study parameters such as content of hard-processing ore, mill productivity, content of solid component in mill discharge, content of solid component in industrial product of classifier discharge, the amount of water supplied to the mill charge, water flow in the classifier charge, and mass fraction in industrial product classification. The figures show the polynomial model dependence of these parameters on the time. We have calculated corresponding coefficients of determination R^2 and correlation R of the parameters under research. The correlation coefficient R is within the range of 0.868–0.965, which is quite high. This proves the probability of the studies. This serves an input data to construct multivariate models.

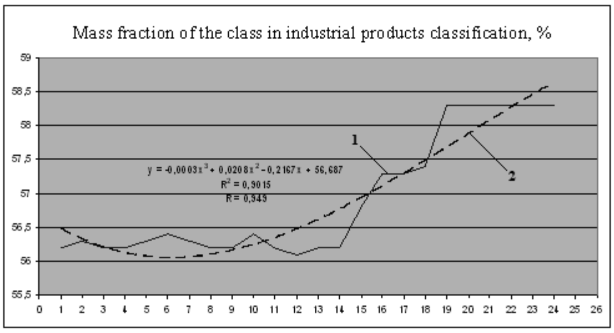

Fig 8. Time dependence of the mass fraction of the class in classification of industrial products: 1 is the mass fraction of the class in classification of industrial products; 2 is the 3rd degree polynomial model

All the input data of the parameters of the ball mill must meet technological requirements of the first stage of enrichment. For this purpose, each of the indicators should be measured by the appropriate sensors and should be in the range. Threshold limits for each parameter information model are shown in Table 2.

Table 2

Threshold limits for information model indices

Index	Lower bound	Upper bound
Hard-processing ore content, %	50	70
Mill productivity t / h	180	250
Solid component in mill discharge, g / liter	1900	2100
Solid component in industrial products, g / liter	1350	1500
Quantity of water supplied in the Mill charge m^3	50	80
Water amount in classifier charge, m^3	110	130
Mass fraction of class in industrial products classification, %	50	62

If a parameter is outside the boundaries, the corresponding sensor is activated. Once the corresponding sensor is activated, a problem situation arises, to which the Petri net reacts immediately. It characterizes the different versions of the enrichment process and produces a matrix of coefficients that characterize the corresponding reduction (factor -1), an increase (factor 1) or stay in the current state (rate 0) of the relevant index.

After this, the input data given in Table 1 is adjusted. Thus Petri net reacts immediately to the problem situation and changes the input model.

All incoming data is stored in the database baza.mdb, which is the default directory. Database consists of two tables of input Model and Model2. Table Model storages incoming data from PAT "Tsentralny GZK". Table Model2 has simulation data (data obtained by means of simulation). When adding input data, we have an option of removal, correction or adding new entries to the model.

The signals Petri net result into the input data change. Each parameter decreases, remains constant or increases by one step. The change of the step in absolute terms is determined by the operator during the analysis of the results.

In case of any problem situation the Petri net has several options for further development of the process. Each of them is inserted as input data into the simulation model and is calculated. We analyze the correlation for both the single factor (analysis of input factors depending on the time factor) and the model index calculated.

The choice of maximum correlation coefficient (in the range from 0.9 to 1) suggests the optimal variant of the enrichment process through modeling by the Petri net.

In constructing the first model $Y = f(X)$, where Y is a mass fraction of a class in industrial products of the classification; the input factors X (from 1 to 5) are chosen. Then both the linear dependence of the selected function Y on descriptive factor X and the coefficients of determination R^2 and correlation R are displayed. It is recommended to build a model based on five factors, where the correlation coefficient is the highest.

In our case, the factors x1, x2, x3, x4, x5 are selected. And the linear model has the form of this dependence:

$$Y = -0{,}156 \times x1 + 0{,}002 \times x2 + 0{,}122 \times x3 - 0{,}011 \times x4 + 0{,}137 \times x5 - 99{,}408.$$

The coefficients of model determination and correlation let to 1. This reflects the maximum level of dependence of Y on the input X (x1, x2, x3, x4, x5). In our case the coefficient of determination R^2 = 0.94089, and the correlation coefficient R = 0.96999.

After receiving the multifactor model $Y = f(X)$, let us calculate the mass fraction of the class –0.056 mm for the parameters set by a user.

Factors are inserted manually or are generated randomly. When data are inserted manually, control for entering a number of local data and the corresponding ranges for each indicator is provided. If you pass the mouse over the box on any kind of indicators, the information on its thresholds is displayed.

When data are generated randomly, a random number is generated from the range limit for each parameter. In such a way the user can change the input data to calculate the mass fraction of the class.

At the last stage, if the button "Calculate" is pressed, the screen displays the calculated value of the mass fraction of a class in industrial product of classifier, as well as corresponding hard-processing ore content (boundaries from 70 to 50%) and the circulating loading (boundaries from 100 to 150%)

$$Y = -0{,}156 \times x1 + 0{,}002 \times x2 + 0{,}122 \times x3 - 0{,}011 \times x4 + 0{,}137 \times x5 - 99{,}408 = 56{,}17160.$$

If the calculated index does not belong to the range from 50 to 62%, a report about correction of input parameters is displayed in order to continue the technological process. Thus, a user seeing positive or negative regression coefficients, can adjust the input data to obtain the result within given range.

In addition, the software provides the graphical interpretation of Y function for each X parameter.

According to the principle described above, the model of mill capacity depending on the input factors is built.

Based on real data obtained during the control by the first stage of the ore enrichment process at PAT "Tsentralny GZK" the models of ball mill performance and mass fracture of the class –0.056 mm have been built. Decisions on correction of loading of ball mills of the first stage are performed by an operator using both the Petrie net and the *"Modeling of the First Stage of Ore Enrichment" software*.

The study of the models for control of the first stage of ore enrichment in conditions of PAT "Tsentralny GZK" resulted into the following: water consumption has been reduced by 6%; ball mills capacity of the first stage ore enrichment has been increased by 3%; and energy cost per one ton of concentrate has been decreased by 10% in comparison with manual supervisory control.

Conclusions. The algorithm and software for the first stage of ore enrichment controlling allows:

1. Building up multifactor models of mass fraction class -0.056 mm of products classification and mill productivity which depend on factors selected by a user.

2. Computing the simulation results for a given input parameter, thus predicting results of the chosen mill productivity of the first stage and the yield of preparation products -0.056 mm.

3. Adjustment and control of the input and output factor values and the parameters calculated, using boundary limit factors.

4. Visual inspection of the data of a single factor model and get the result in graphical mode for each individual parameter model.

References / Список літератури

1. Babets, Ye.K. (2011), "Technical-economic indicators of mining enterprises of Ukraine for 2009-2010", GP "NIHRI", Krivoy Rog, Ukraine.

Технико-экономические показатели горнодобывающих предприятий Украины в 2009–2010 гг. : сб. науч. трудов / под. ред. Е. К. Бабца. − Кривой Рог: ГП „НИГРИ", 2011. − 309 с.

2. Khorolskiy, V.P., Hotskina, V.B., Khorolska, T.V. and Babets, Ye.K. (2008), *Intehrovane intelektualne upravlinnia tekhnolohichnymy protsessamy v ekonomichnykh systemakh korporatyvnykh pidpryemstv hirnycho-metalurhiinoho kompleksu Ukrainy* [Integrated Intelligent Control of Technological Processes in Economic Systems of Corporate Mining and Metallurgic Complex], monograph, Sich, Dnepropetrovsk, Ukraine.

Інтегроване інтелектуальне управління технологічними процесами в економічних системах корпоративних підприємств гірничо-металургійного комплексу : монографія / [В.П. Хорольський, В.Б. Хоцкіна, Т.В. Хорольская, Е.К. Бабец ; під. ред. В.П. Хорольського]. – Дніпропетровськ : Січ, 2008. – 443 с.

3. Kochura, Ye.V. (1996), "Development of scientific bases of automation processes magnetic ore enrichment for energy saving", Abstract of Dr. Sci. (Tech.) dissertation, Dnepropetrovsk, Ukraine.

Кочура Е.В. Развитие научных основ автоматизации процессов магнитного обогащения руд с целью энергосбережения : автореферат дис. на соиск. научн. степени докт. техн. наук / Е.В. Кочура. – Днепропетровск, 1996. – 41 с.

4. Kupin, A.I. (2008), *Intellektualna identyficatsiia ta keruvannia v umovakh protsessiv zbahachuvalnoi tekhnolohii* [Intelligent Identification and Control of Process in Concentration Technologies], KTU, Kryvyi Rih, Ukraine.

Купін А.І. Інтелектуальна ідентифікація та керування в умовах процесів збагачувальної технології / Купін А.І. – Кривий Ріг : Видавництво КТУ, 2008. – 204 с.

5. Kornienko, V.I. (2009), "Hierarchical adaptive control of ore-preparation processes by the synergistic principle with intelligent forecasting", *Scientific Bulletin of National Mining University*, no. 11, pp. 61−66.

Корнієнко В.І. Ієрархічне адаптивне керування процесами рудопідготовки за синергетичним принципом з інтелектуальним прогнозуванням / В.І. Корнієнко // Науковий вісник Національного гірничого університету. – 2009. – № 11. – С. 61−66.

Мета. Розробка швидкодіючих моделей багатофакторних регресій для оперативного управління першою стадією збагачення руди.

Методика. На статистичному матеріалі, отриманому в результаті проведення пасивного експерименту першої стадії збагачення руди, побудовані багатофакторні регресійні моделі керування першою стадією: подрібнення – класифікація – магнітна сепарація, та розроблена методика дослідження моделей оптимізації завантаження кульових млинів з урахуванням вмісту важкозбагачуваних руд та оцінки масової частки класу -0,056мм у промпродуктах класифікації.

Результати. Розроблене програмне забезпечення дозволяє будувати моделі першої стадії збагачення руди та контролювати граничні межі вхідних факторів шляхом прогнозування моменту виникнення проблемної ситуації та корекції моделей завантаження кульового млина й процесу класифікації першої стадії збагачення.

Наукова новизна. Розв'язано актуальну наукову задачу зі встановлення причинно-наслідкової залежності технологічних параметрів змінних комплексу збагачення від фізико-механічних властивостей руд. Залежність технологічних параметрів від властивостей руд визначається „правилами продукції" вхідних і вихідних матриць мереж Петрі. Головна мета мереж Петрі – виявлення проблемної ситуації та створення „правил продукції", що на основі причинно-наслідкових зв'язків формують набір рекомендацій для ефективної роботи системи.

Практична значимість. Результати роботи реалізовано у вигляді розробленої системи керування, бази даних і програмного забезпечення з автоматизації технологічних процесів збагачення руд, у тому числі знайшли використання методи розробки управлінських рішень у робастних і адаптивних системах керування першою стадією збагачення, розроблені практичні рекомендації щодо ефективного керування першою стадією збагачення руди на основі створеного алгоритму та програмного забезпечення.

Ключові слова: *процес, керування, адаптація, прийняття рішень, моделі, регресії, прогнозування*

Цель. Разработка быстродействующих моделей многофакторных регрессий для оперативного управления первой стадией обогащения руды.

Методика. На статистическом материале, полученном при проведении пассивного эксперимента первой стадии обогащения руды, построены многофакторные регрессионные модели управления первой стадией измельчения – классификации – магнитной сепарации, и разработана методика исследования моделей оптимизации загрузки шаровых мельниц с учетом содержания труднообогатимых руд и оценки массовой доли класса -0,056 мм в промпродуктах классификации.

Результаты. Разработанное программное обеспечение позволяет построить модели первой стадии обогащения руды и контролировать границы входных факторов путем прогнозирования момента возникновения проблемной ситуации, коррекции моделей загрузки шаровой мельницы и процесса классификации первой стадии обогащения.

Научная новизна. Решена актуальная научная задача по установлению причинно-следственной зависимости технологических параметров переменных комплекса обогащения от физико-механических свойств руды. Зависимость технологических пара-

метров от свойств руд определяется „правилами продукции“ входных и выходных матриц сетей Петри. Главная цель сетей Петри – определение проблемной ситуации и создание „правил продукции“, которые на основе причинно-следственных связей формируют набор рекомендаций для эффективной работы системы.

Практическая значимость. Результаты работы реализованы в виде разработанной системы управления, базы данных и программного обеспечения по автоматизации технологических процессов обогащения руды, также использованы методы разработки управленческих решений в робастных адаптивных системах управления первой стадией обогащения, разработаны практические рекомендации относительно эффективного управления первой стадией обогащения руды на основе созданного алгоритма и программного обеспечения.

Ключевые слова: *процесс, управление, адаптация, принятие решений, модели, регрессии, прогнозирование*

Рекомендовано до публікації докт. техн. наук Є.В. Кочурою. Дата надходження рукопису 02.07.13.