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QUALITY ANALYSIS OF TECHNOLOGICAL PROCESS CONTROL

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Abstract: *Any technological process including metallurgical processes is supported by the control system operation, accompanied by large information flows to be formed. However, the most part of this information is not used by specialists due to restricted capabilities of a human being that is, in fact, incapable of processing such information flows. It has been demonstrated that process control is significantly influenced by the human factor. This paper contains a methodology to process production information that permits the process personnel to use its potential in a more rational way to control the process. An approach has been reviewed to studying metallurgical processes using the analysis of indirect indicators of process management, namely the spectral density and auto-correlation function of main process parameters. A method to separate useful signals from noise has been studied. A method has been given to check the ACS management efficiency using primary material flows. The adopted methodology for processing experimental data permits interpreting the obtained results for their further practical application to develop new algorithms for process control and improve the existing control system.*

Keywords: *technological process control, quality analyze, operator control, melting quality*

1. Introduction

Currently, we can hardly imagine operation of any process facility without a control system. In the conditions of the market competitive struggle, enterprises are pressed to ensure safety and stability of processes and constantly improve their efficiency. Certainly, the most evident method to increase the process efficiency is improving process flow diagrams, hardware and process conditions (Xing et al., 2017). However, only a part of economy reserves can be extracted by employing this approach. The most significant effect can be obtained by quality and effective management of the process by technical staff.

Modern trends in metallurgy development are characterized by development and implementation of informational systems and technologies based on computers and computer networks having hi-end software as well as data base management systems and decision-making computer systems based on the theory of systems and systemic analysis (Bechtold & Ye, 2003; Gorai et al, 2003).

The scientific progress creates pre-requisites for improving the control quality using computational equipment, mathematical

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methods of data processing, control theory, and control automation. All these have been implemented in automated control systems. Thanks to the IT-technology development, there are modern software products and database management systems (DBMS) to solve the tasks of production control. Modern software (SW) and microprocessor equipment makes it possible to create high-level control systems comprising powerful control algorithms.

The existing control systems for melting copper-nickel sulphide feedstock in a Vanukov furnace (Vanukov process) allow controlling key parameters of the process and managing it with operator control (Bisgaard & Kulahci, 2005; Bisgaard, 2008). However, irrespective of all advantages of these systems, they are distinguished by control irrationality due to limited capabilities of operators who cannot process a large number of information flows; by manual data input, which reduces their flexibility; and by the lack of a mathematic means that would permit getting useful information from operative control data and ensure identification of values of primary process parameters. This results in the need to develop new algorithms of process control for melting copper-nickel sulphide feedstock in a Vanukov furnace.

The relevance of the study is due to the need to improve the quality of the melting products of copper-nickel sulphide feedstock in a Vanyukov furnace by stabilizing the furnace load parameters with the required accuracy, which will minimize the influence of the "human factor" (Klochkov et al., 2016).

The scientific significance of the work is to develop a methodology for analyzing the quality of process control based on indirect indicators of the operation of the furnace (spectral density and autocorrelation function of the main parameters of the technological process). An original approach to the extraction of useful information from the original numerical material is proposed, which is a set of classical methods of statistical analysis of operational control data and frequency characteristics of the parameters of the technological process (Hawkins et al, 2003; Hawkins and Deng, 2009)

The goal of the work is to improve the quality control of process control for melting copper-nickel sulphide feedstock in a Vanukov furnace.

2. The methods of melting of copper-nickel raw materials

Copper metallurgy belongs to the most energy intensive and environmentally unsafe fields of industry. Copper production is accompanied by atmosphere emissions of sulfur-containing gases, toxic oxides of metals, nitrogen oxides and greenhouse gases as well as contamination of soils and groundwaters. Processing of copper sulphide feedstock is rather complicated a task, since copper ores are comparatively poor in their composition (Kadyrov & Danilova, 2013; Katuntsov et al., 2017; Nechvoglod et al., 2012a, 2012b).

In most plants, copper production employs the scheme comprising matte smelting, matte conversion and fire refining of coarse copper intended to gradually increase the copper content in the product.

The primary role in copper production is played by matte smelting. Copper sulphide materials in most plants are melted in reverberating or electrical furnaces.

Reverberating melting of copper-nickel sulphide materials is used to melt fine feedstock (concentrates or cinder). As of now, reverberating furnaces remain primary units at copper works. However, since the requirements to integrated use of feedstock, energy saving and environmental protection become stricter, the perspectives of their future use have substantially reduced. Furthermore, reverberating furnaces use almost no heat obtained in sulfur oxidation and emitting when sulphide materials are decomposed. Therefore, recently reverberating furnaces have been gradually replaced by more advanced units.

Electrical melting of sulphide copper-nickel materials is similar in chemistry to reverberating melting, but has an advantage that fewer gases are formed in the furnace and melting products can be heated to higher temperatures. The primary disadvantage of electrical melting is high energy consumption.

Both reverberating and electrical melting are based on using additional sources of energy. However, sulphides contributing to the principal mass of copper ores and concentrates and having high calorific capacity are almost not employed. Therefore, those melting methods are employed increasingly where the combustion heat of metal sulphides (oxidizer is technical oxygen, hated air or oxygen-rich air). Such methods include blast smelting and melting of sulphide materials in a suspended state or in a melt layer (Min'ko et al., 2011; Patrushev et al., 2003).

Blast smelting is used primarily for melting lump copper ore. Oxidation blast melting of copper sulphide materials is intended to produce copper matte and remove barren rock with slug, but also to oxidize a share of sulfur of sulphides and remove it as SO2.

As compared to reverberating melting, blast melting has higher capacity, a lower temperature of off-gases and, respectively, a higher heat efficiency.

During the last years, copper production has been widely employing so called autogenic processes where the main source of heat energy is metal sulphides, which allows reducing the fuel consumption per melt (Ustinov & Baburin., 2016; Tynchenko et al., 2016; Polonik & Dudko, 2016). Currently, metal manufacturers face the task of retrofitting and upgrading to switch to the autogenic technology of sulphide feedstock processing, using these processes allows significantly reducing energy costs and sulfur emissions, improving labor conditions on work places and reducing the number of personnel involved in hazardous production, increasing the recovery of valuable metals and the feedstock usage integrity coefficient (Box and Narasimhan, 2010; Chakraborti et al., 2009; Chivel and Smurov, 2010).

The sulphide feedstock in suspended state is melted with both air and oxygen blasting. In case of oxygen-flare melting and suspended state melting (Outokumpu), the dry concentrate together with the flux is introduced into the furnace space by a jet of technical oxygen or heated oxygen-air blasting (up to 40 % O2). A dust-gas flame is formed where materials are oxidized and melted. The melted charge is dropwise supplied to the sedimentation zone, the melt is formed in the furnace that is disintegrated into matte and slag (Cruz et al., 2017; Oprea & Andrei, 2016). The primary disadvantage of these processes is high dust entrainment.

The advanced Australian metallurgy furnace technology with immersed tuyere called Ausmelt is distinguished by high efficiency and high copper recovery. Concentrates and secondary feedstock are melted in the furnace to obtain coarse copper that is periodically poured off from the furnace into scoops and delivered for refining. The advantages of this technology is that the unit can process lump materials and scrap; for furnace heating, both natural gas and carbon-containing materials and wastes can be used; almost no manual activities are required for furnace maintenance.

The Ausmelt technology is applied in industrial production of a wide range of ferrous and non-ferrous metals and in processing of various wastes at high temperatures. Ausmelt units successfully operate in China, South Africa, India and Zimbabwe. Construction is underway in one of the Ural works.

Mitsubishi Process is a complex process scheme of continuous processing of copper-containing sulphide feedstock comprising three metallurgic units: melting furnace, electrical furnace and a converter. A yield of the Mitsubishi process is coarse copper. Key disadvantages of this process include unacceptably high copper losses and impossibility to process lump feedstock in the unit (Liu et al., 2011; Mahmoud et al., 2010).

The Noranda process combines melting of charging material and conversion. The charge consisting of copper-containing sulphide materials and fluxes is purged with heated air. The charge is melted and metal sulphides are oxidized. The slag formed is removed. To increase the temperature, sometimes coal or coke are supplied with the charge. Various degree of oxygen concentration in air is used to adjust the process rate and chemical composition of products.

The Vanukov process in copper metallurgy is well developed in technological and hardware terms; it allows processing feedstock with high performance and provides high capabilities in controlling the melting process conditions.

The processed charge (ore, concentrate) is supplied to the furnace from the top through the charging device without preliminary preparation (fine grinding, deep drying, etc.). After having fallen onto the charge surface, the charge moves deep into the melt, is intensively mixed with it and melted exposed to high temperatures. As an oxidizer in the furnace, air (oxygen-air mixture, OAM) or technical oxygen is used, depending on the composition of feedstock. The purge is supplied to the melt through special tuyeres located on both sides of the bath in furnace’s sidewalls. Liquid melt products are divided into matte (sulphide melt) and slag (oxide melt) that are discharged from the unit during melting from end sides of the furnace (Thombansen et al., 2016; Prazmowski et al., 2017; Butt et al., 2016).

The physical and chemical process consists in decomposition of upper sulphides into sulphides. The basic reactions describing the melting process of the copper-nickel sulphides feedstock are given below:

$$2\,CuFeS_2 = Cu_2S + 2FeS + \tfrac{1}{2}\,S_2$$

$$2\,CuFeS_3 = Cu_2S + 4FeS + \tfrac{1}{2}\,S_2$$

$$3\,NiFeS_2 = Ni_3S_2 + 3FeS + \tfrac{1}{2}\,S_2$$

$$Cu_2S + \tfrac{3}{2}O_2 = Cu_2O + SO_2$$

$$Ni_3S_2 + \tfrac{7}{2}O_2 = 3NiO_2 + 2SO_2$$

$$\tfrac{1}{2}\,S_2 + O_2 = SO_2$$

Show that the key parameters to control the melting process are as follows: total charge consumption, total blast consumption (oxygen-air mixture - OAM), technical oxygen consumption and oxygen content in OAM. These variables are almost completely used to control the Vanukov process and they condition the copper content in the charge (Ott et al., 2000).

The melting is currently controlled by process personnel based on their own experience and subjective analysis of readings of instrumentation, data of visual inspections, results of chemical analyses coming with long delays and other information of maintenance personnel on the condition of certain components of the process as well as based on preliminary calculations of material and thermal balances (Le et al., 2017).

3. Literature review

In the difficult conditions of the contemporary market, one of the main ways to ensure own competitiveness for metallurgical enterprises, which allow to ensure sustainable economic growth and increase overall production, is to ensure effective management of all available structures, resources, processes within the organization. The most important source of growth in production efficiency is a constant increase in the technical level and quality of output.

Uality control of products is an important step of any manufacturing process. It is aimed on the detecting defects in finished products and checking the process of its production. Quality control methods are applied at all stages of production, starting with the verification of materials and raw materials and ending with the control of compliance of the finished product with technical parameters.

The beginning of modern methods of control and management put so-called control cards, developed in 1924 by Shewhart Walter. The main idea was not to find and seize the defect products before they were shipped to the buyer, but how to find possibilieties to increase the yield of main products in the process. His ideas to date remain relevant. Control charts are still widely used not only in industrial enterprises for the analysis of various production processes, but also in education, medicine, services, business analysis, public administration, and so on.

In addition, Shuhart expressed the idea of continuous improvement of quality, offering a cycle of continuous process improvement, now called the "Shuhart-Deming Cycle." In recent years, this cycle has been further developed under the influence of W.E. Deming and began to be used as a tool for teamwork to improve the quality.

E. Deming. had a great influence on the development of statistical methods of control, as a quality philosophy. In the early 50's, he conducted a large-scale training of Japanese specialists in new methods of quality assurance, while paying special attention to statistical methods of quality management. His activities were so successful that in the 1960s Americans had to give Japanese firms a significant part of the sales markets, including the US itself. American scientific influence on the improvement of quality assurance systems led to the creation of the Japanese scientific school in the field of quality, among which representatives should be noted, first of all, Ishikawa Kaori and Taguchi Genichi, who made a great contribution to the development statistical methods in quality management. So Ishikawa for the first time in world practice proposed an original graphical method for analyzing cause-effect relationships, called the Ishikawa diagram. Today, it is almost impossible to find such an area of activity where Ishikawa's diagram isn't applied.

Feigenbaum Armand V. - developed the principles of total quality management and parallel (simultaneous) engineering.

Also worth mentioning is the work of Juran (Joseph M.), the developer of the principle of the "quality triad", and Masing Walter, the author of the "quality guide" as the main document of the enterprise's quality assurance system.

A great contribution to the quality assurance system in the mid-20th century was made by American scientists E. Pearson (Pearson, Egon Sharpe) and R. Fischer (Fisher, Ronald Aylmer). Among their developments, the theory of verification of statistical hypotheses was most famous. It can be noted that today, without knowledge of the theory of errors of the first and second kind, an assessment of the chosen method of statistical control is impossible.

As applied to metallurgical processes, all methods of control and quality of process control and analysis of finished products in terms of complexity can be divided into the following categories:

1) Elementary statistical methods:
   - 1.1. the Pareto diagram;
   - 1.2. cause-effect analysis (Ishikawa diagram);
   - 1.3. grouping of data by common characteristics (affinity diagram);
   - 1.4. checklists and maps;
   - 1.5. histograms and scatter diagram.
2) Intermediate statistical methods:
   - 2.1. the theory of sample research;
   - 2.2. statistical sampling control;
   - 2.3. methods for conducting statistical assessments and defining criteria;
   - 2.4. methods for planning and

calculating experiments;

2.5. correlation and regression analyzes.

3) Advanced statistical methods:

3.1. advanced methods for planning and calculating experiments;

3.2. multifactorial (dispersion) analysis;

3.3. methods of investigating operations.

Elementary statistical methods can be used by all workers of enterprises - from the top managers to the workers in the production department, in the planning, marketing, logistics and other departments.

The second group of methods is designed for engineers and technicians and specialists in the field of quality management.

The methods of the third group are intended for a limited number of engineers, since they are used for very complex quality analyzes of the process.

The main task pursued by methods of quality control of products is detection of the problem, determination of at what stage production is out of control, and taking necessary measures to correct defects and errors of the technological process.

4. The method of quality analysis of technological process control

One of the important tasks of technology and control of the technological process is the recognition of the dependences that operate in the production process and the identification of technical, technological, economic and organizational factors that help forward for increasing the efficiency of production and the quality of products (Kozlovsky et al., 2016; Klochkov, 2016). The identification of these dependences is a necessary condition for the automation of technological processes in order to facilitate the work of technologists and to obtain optimal options for conducting technological processes. The need to analyze and assess the main dependencies of metallurgical processes, especially high-power aggregates very important task (Walker et.al., 1991; Wierda, 1994). These processes are characterized by frequent mode change, quality of raw materials and uncontrolled disturbances.

Among all the disturbances acting on the technological process, it is always possible to identify fast (high-frequency) and slow (low-frequency) ones (Gitlow, 2001; Jensen et al., 2006). The fast disturbances could be for example, hunting of material flows, the mains voltage, supplied to electric power and measuring installations; the pressure of gases in the pipeline or inaccuracies in the actuation of actuating devices, which actuate the control valves, gates and metering devices (Figure 1.a). Changes in the temperature of the materials or in the concentration of any chemical component in it cannot occur at the same rate with which the costs and pressures change (Klochkov et al., 2016). These changes can be considered low – frequency (figure 1.b).

The experimentally obtained realizations of random signals in addition to valid information on the actual change of the investigated parameter also contain disturbance. In this connection, when processing the experimental data, it becomes necessary to separate the valid signal from the disturbance (Woodall & Thomas, 1995; Woodall & Montgomery, 1999). Since the measurement errors in each experiment are independent random variables, their temporal realization is close to that of normal white noise and is not correlated with a valid signal.

To solve this problem, we can use the formula [3,4]:

$$R_X(\tau) = \lim_{T \to \infty} \frac{1}{2T} \int_{-T}^{T} x(t) \cdot x(t+\tau) dt \approx \frac{1}{T} \int_{0}^{T} x(t) \cdot x(t+\tau) dt \quad (1)$$

where T is the interval of supervision of the random process (duration of realization).

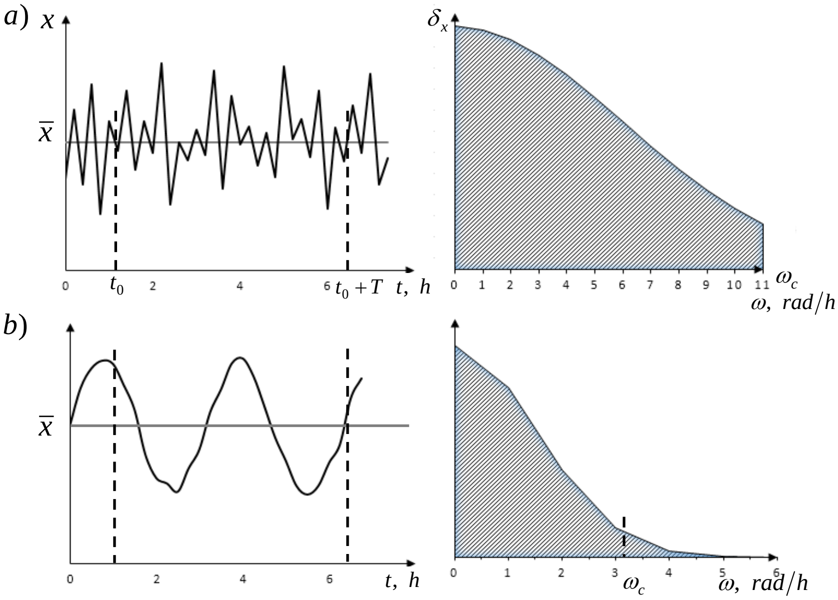

Figure 1. High-frequency (a) and low-frequency (b) oscillations (left, - changing in time, right - spectral density)

In the general case, the implementation can be given by a continuous curve or by discrete points. If the integral is replaced by a sum, then the value of the correlation function can be found from the relation (2):

$$R_x(\tau) \approx \frac{1}{N-\tau} \cdot \sum_{i=0}^{N-\tau} \overset{0}{x}_i \cdot \overset{0}{x}_{i+\tau} \qquad (2)$$

$\overset{0}{x}_i$ – is the centered value of the function at time $t_i = i \cdot \Delta$, $\overset{0}{x}_i = x_i - \bar{x}$, $i = \overline{0, N-\tau}$;

$\overset{0}{x}_{i+\tau}$ – is the centered value of the function at time $t = t_i + \tau$.

therefore,

$$R_\varphi(\tau) = R_x(\tau) + R_f(\tau) \qquad (3)$$

Where $R_\varphi(\tau)$ – total correlation function of the initial implementation $\varphi(t) = x(t) + f(t)$;

$R_x(\tau)$ – correlation function of valid signal $x(t)$;

$R_f(\tau)$ – correlation function of disturbance $f(t)$.

The correlation function describes the degree of correlation (correlation ratio) between the previous and next signal values.

When the value of τ is increased, the correlation between the values of $x(t)$ and $x(t+\tau)$ is getting weaker and the correlation function ordinates are decreased.

This primary property of correlation functions can be explained as follows: in case of small shifts, the integral sign (1) covers the products of multipliers usually having the same signs and so most products will be positive and the integral value will be high. As the shift is increased, the integral sign will cover more and more multipliers having opposite signs and the integral values will be decreased.

For very large shifts $(\tau \to \infty)$, the multipliers of $\overset{0}{x}(t)$ and $\overset{0}{x}(t+\tau)$ are almost independent and the number of positive products is equal to the number of negative products, and the integral value tends toward zero.

These discussions also show that the faster a random signal changes in time, the faster the correlation function is decreased.

For stationary random processes possessing the property of ergodicity, the separation of the valid signal from the disturbance can be performed by the moving average method (Park et al., 2017; Pruteanu & Cărăusu, 2017; Raz & Chval, 2017).

The smoothed value of the function $\varphi(t)$ at any point is taken as its average value in some interval $2l\Delta$ with the center at the point t. When t changes, this interval slides along the t axis. Thus, the total random function $\varphi(t)$ is divided into a smoothed stationary random function $x(t)$ (valid signal), the ordinates of which are calculated from the formula (4) and on the disturbance determined which are calculated from the formula (5)

$$x_i = \frac{1}{2 \cdot l + 1} \cdot \sum_{k=-l}^{l} \varphi_{i+k} , \tag{4}$$

$$f_i = \varphi_i - x_i . \tag{5}$$

As can be seen from (4), the larger the interval $2l\Delta$, the better the smoothing. However, for a very large value of *l*, the function itself is smoothed $x(t)$.

Since the disturbance is a white noise type signal, the correlation function $R_f(\tau)$ decreases rapidly with increasing τ. This allows us to take as the criterion determining the degree of attenuation $R_f(\tau)$, the ratio

$$\lambda = \frac{\left|R_f(\tau)\right|_{\max}}{D_f} \tag{6}$$

Here $\left|R_f(\tau)\right|_{\max}$ is the maximum absolute value of the correlation function $R_f(\tau)$ for $\tau > 0$, D_f - variance of disturbance.

As follows from (6), the largest damping $R_f(\tau)$ occurs with a minimum value of the criterion λ. This allows the length of the interval $2l$ at which $\lambda = \min$ to be considered optimal in the sense of approximating the disturbance $f(t)$ to a signal such as white noise.

Obtaining the probabilistic characteristics of random signals - correlation functions $R(\tau)$ makes it possible to identify the object of research, to prepare the necessary information for solving a number of other problems. These include, for example, the synthesis of automatic control systems in the presence of random disturbance, etc.

The spectral density of random effects could be calculated from the formula (7):

$$S(\omega) = \frac{D \cdot \lambda}{\pi \cdot \left(\lambda^2 + \omega^2\right)} \tag{7}$$

where D and λ - the dispersion and the damping coefficient of the correlation function of disturbance.

The physical essence of spectral density consists in the fact that it characterizes the signal power distribution along the frequency content (Leinonen, 2006). The wider is the spectral density chart (Fig. 1, a) and the higher are the frequencies represented in the spectral density, the faster are changes in time. The narrower is the spectral density chart (Fig. 1, b) and the lower are the frequencies represented in the spectral density, the slower are changes in time.

The wider is the spectral density chart $S_x(\omega)$, the narrower is the chart of the respective correlation function $R_x(\omega)$, and vice versa. This corresponds to the physical essence of the process: the wider is the spectral density chart, e.g., the higher are the frequencies represented in the spectral density, the higher is the variability degree of a random process and the narrower are correlation function charts. In other words, the correlation between the spectral density type and the time function type will be reverse as compared to the correlation between the correlation functions and the time function type (Mackey, 2014; Zhang et al., 2010).

Individual peaks on the chart of spectral density indicate that the random process is mixed with hidden periodic components that are related with disturbances affecting the process.

As a measure of the mean frequency of the disturbance x ω_c, it is possible to apply the frequency ω at which the energy of a portion of the spectrum in the range $0 \le \omega \le \omega_c$ is a large part (for example, 90%) of the entire dispersion D_x of the signal $x(t)$.

$$\int_0^{\omega_c} S_x(\omega)d\omega = 0,9 \cdot \int_0^{\infty} S_x(\omega)d\omega = 0,9 \cdot D_x \qquad (8)$$

Then the required quantity can be determined by solving equation (8).

If it turned out that:

$$\omega < \omega_c \qquad (9)$$

then the disturbance $x(t)$ is referred to as low-frequency, otherwise to high-frequency.

Practical application of the methods described above, let us consider the example of the process of melting copper-nickel sulfide raw materials in the melt layer (the Vanukov process), which is the most effective for the processing of sulfide materials.

5. The quality analyzes of melting process control

Figure 2 shows the graphs reflecting the capacity of the furnace for one day with a discreteness level of 1 minute, during which three different operation crews shifted the melt (crew 1 from 0.00 to 8.00, crew 2 from 8.00 to 16.00 and crew 3 from 4 pm to 4 pm). From the preliminary analysis of the graph it follows that each of the crew is characterized by a character of the conduct of the process that is substantially different from the other crews. It is very clear that different operators completely differently control the loading of the furnace. The night crew, working from 0.00 to 08.00 hours, is clearly distinguished by the randomness of the loading actions.

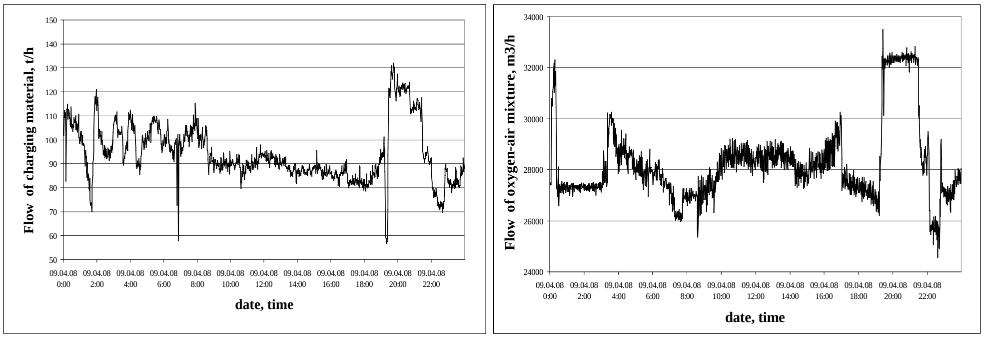

Figure 2. Change of parameters of loading of the Vanukov furnace during one day

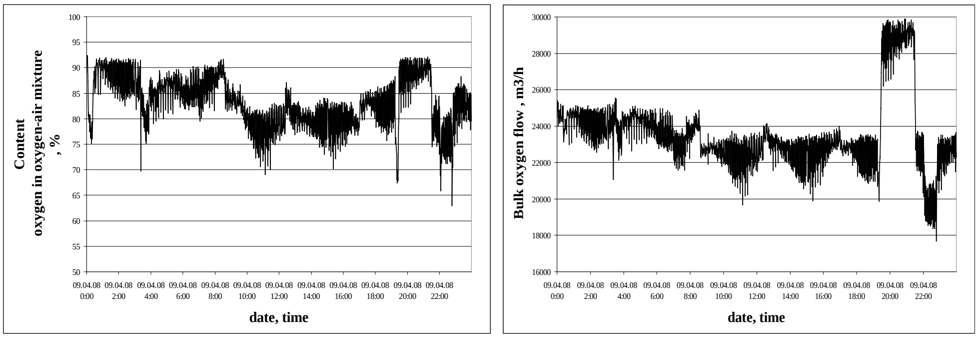

Figure 2. Change of parameters of loading of the Vanukov furnace during one day (continued)

Figure 2 shows that the work of crew 1 and crew 3 is characterized by a constant targeted intervention in process control with a significant amplitude of the control actions for loading. The presented character of management, probably, is connected with aspiration of operators-technologists independently to support the set levels of components of a capacity, not relying on existing circuits of stabilization.

However, the actions of the operators-technologists during the crew 1 and the change of 3 are excessively chaotic in comparison with similar actions during crew 2, when the changes in the capacity values were more smooth.

But, despite the clearly observed differences in capacity control, the average daily batch capacity for each individual crew is almost the same (Table 1) and falls within the range of 90 ... 100 t/h.

Table 1. Statistic data of technological variables

Statistical indicators	Crew number	Flow of charging material, t/h	Flow of oxygen-air mixture, m^3/h	Content oxygen in oxygen-air mixture, %
Range	1	57,88-120,86	25970-32312	69,74-92,40
	2	79,84-108,81	25370-29227	69,09-91,60
	3	56,74-132,00	24553-33500	62,96-92,02
Average	1	100,30	27837	86,34
	2	90,21	28069	80,91
	3	92,70	28839	82,85

Based on the available data for each of the technological changes under consideration, we plot the autocorrelation functions and the spectral densities of the burden charge (figure 3).

Analyzing the behavior of the graphs of the autocorrelation function of charging charge for each crew, it is possible to draw conclusions regarding the methods of conducting smelting by operators of different crews. Thus, the actions of crew 1 should be considered unsuccessful, since the autocorrelation function characterizes them as sharply chaotic. The work of this crew is characterized by an unnecessarily frequent intrusion into the proceeding process, which is expressed by the presence and alternation of the amplitude of the autocorrelation function on both sides of zero. The system "remembers" its past by loading the charge materials for 10-13 minutes, which is about 2-3 less than in the other crews for the same day. The actions of crew 2 and crew 3 can be regarded as satisfactory.

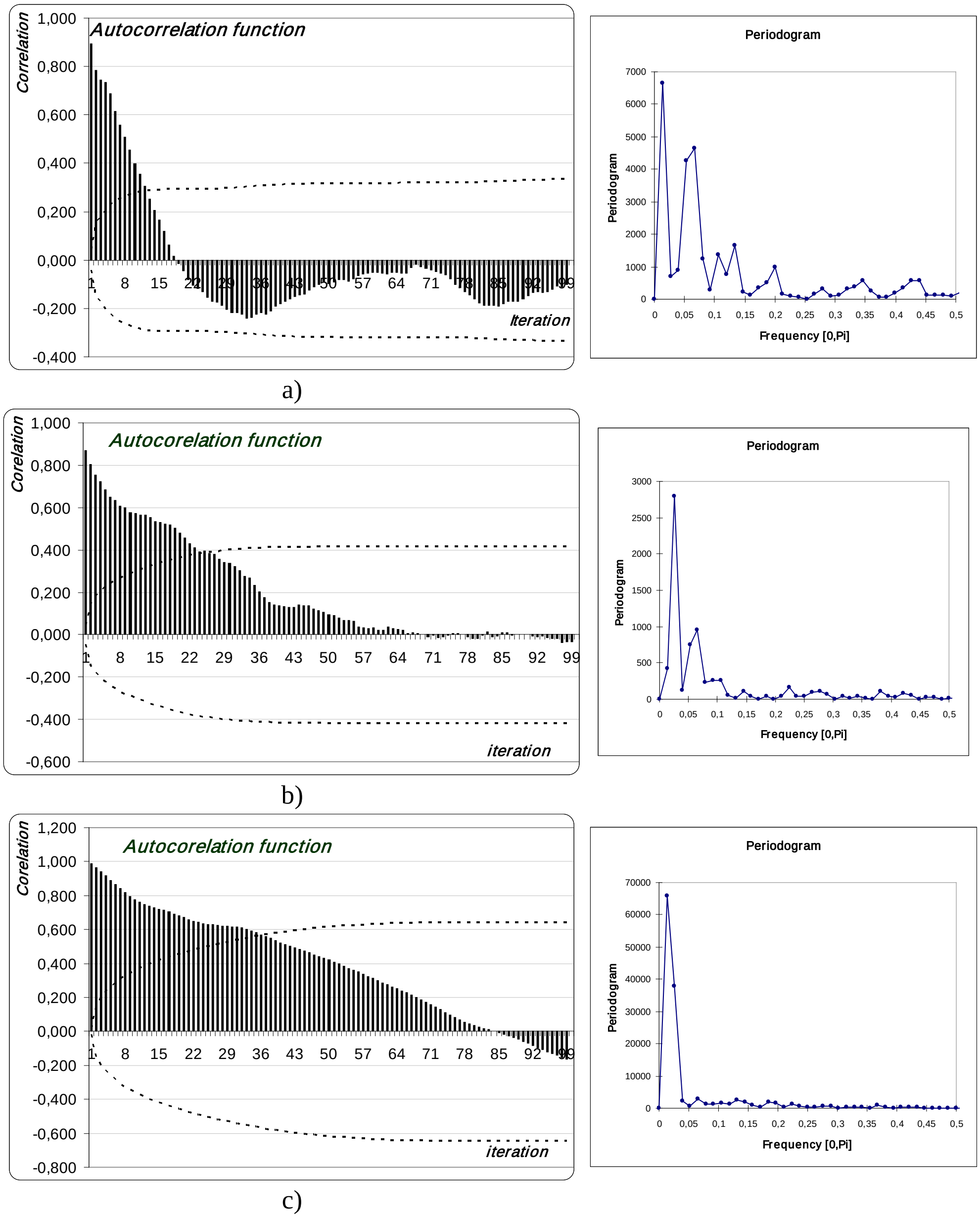

Figure 3. a) Crew 1 (с 0.00 до 8.00); b) crew 2 (с 8.00 до 16.00); c) crew 3 (с 16.00 до 24.00)

Analysis of the graphs of spectral densities (Figure 3) confirms the presence of significant differences in the control of the process. Thus, the spectrum of crew 1 is characterized by multiple high-frequency peaks, which reflects the process of conducting in the oscillatory mode with a rapid change in the setting of the download speed. The managing spectra of the second and third crews are characterized by single peaks, that is, the effects on the process are time-consuming, and therefore purposeful in a strategic sense.

6. The useful signal separation from the random noise

Apart from useful information on changes of the parameter under study, the data for the process progress (Figure 2) contain noise caused by the measurement error; triggering inaccuracy of actuators operating control valves, gate valves, batchers; oscillations of mains voltage supplied to electrical and measuring units; oscillations of gas pressure in the mains. Therefore, it is required to separate a useful signal from the noise.

The above methodology allows calculating frequency characteristics of signals when the process of each crew is controlled. All the identified characteristics of process parameters are given in the summary Table 2.

Useful signal dispersion (Table 2) for each process parameter is approximately 3-5 times different from the total signal dispersion. This shows that the noise signal makes a solid contribution into the total signal. This noise should be captured and smoothed.

Table 2. The frequency characteristics of the parameters of the Vanukov process

Statistical indicators	Crew number	Flow of charging material, t/h	Flow of OAM, m^3/h	Content oxygen in OAM, %
Signal dispersion	1	69,26	1111068	13,55
	2	18,17	450705	15,48
	3	279,17	5305399	29,14
Useful signal dispersion	1	20,54	454628	5,07
	2	6,08	150300	5,64
	3	98,36	2005603	6,07
Quadratic mean deviation	1	8,32	1054,07	3,68
	2	4,26	671,35	3,93
	3	16,71	2303,35	5,40
Attenuation coefficient, day^1	1	0,0114	0,7042	0,0863
	2	0,0082	0,3963	0,0123
	3	0,0105	0,5412	0,0654
Frequency oscillations, rad/day	1	9,90	18,00	2,90
	2	5,00	8,00	1,50
	3	7,21	11,64	1,87

Separating a random signal from the noise by the moving average method allowed determining the attenuation degree of the correlation function of each parameter. The closer is the attenuation coefficient to zero, the less are the signal noise. In this manner, the noisiest parameter is the OAM consumption, since it has the attenuation coefficient within 0.3-0.7 days^{-1}, which is almost 50 times more than the charge consumption attenuation coefficient (0.008-0.012 days^{-1}) and the attenuation coefficient of oxygen content in OAM (0.06-0.013 days^{-1}).

By checking the ratio of (9), we conclude that the charge consumption and the OAM consumption can be conditionally referred to high-frequency oscillations. This is caused by frequent oscillations of consumptions due to random changes in conveyors and feeders characteristics and gas pressure oscillations in the mains. The oxygen content in OAM can be conditionally referred to low-frequency oscillations. This can be explained by the fact the concentrations can't be changed abruptly, and their changes are smooth.

The dispersion and the quadratic mean deviation of furnace charge oscillations (table 2) for all crew s are greatly dispersed. Crew 2 characterized by a smooth progress of the process has reached the quadratic mean deviation of furnace charge of 4.26 t/h for the average charge value of 90.21 t/h. Crew 1 characterized by a chaotic progress of the process has the quadratic mean deviation of furnace charge of 8.32 t/h for the average charge value of 100.30 t/h.

However, crew 3 operation indicators described as satisfactory exceed crew 1 operation indicators, since they have the quadratic mean deviation of furnace charge of 16.71 t/h for the average charge value of 92.70 t/h. This dispersion of crew 3 operation indicators is explained by process personnel intervening the process. This is well illustrated by Fig. 2, which shows that the operator's control over the process from 4PM to 8PM was smooth. However, at 8AM the charge consumption has greatly decreased, which naturally caused the operator to intervene the process. 8PM to 12PM show an endeavor to stabilize the charge consumption at the specified level. In general, crew 3 actions are evaluated as satisfactory. The process personnel manage to maintain the required level of the process.

The dispersion and the quadratic mean deviation of oxygen content in the OAM for all crew does not change greatly, since the OAM quality does not change within the process control interval.

7. The research results discussion

The analysis of the Vanukov process control quality has shown that at this stage of the Vanukov furnace operation there is a process control issue. The charge and technical oxygen consumption are greatly influenced by the process personnel (multiple peaks of high frequencies - Fig. 3). Process control by many operators has a significant impact on the Vanukov process control. Crew 1 actions are unsuccessful since the operation of this crew is described by aggressive process control due to a frequent unregulated intervention into the process. However, in order to efficiently control the Vanukov process, these actions are not necessary and disturb the process as we believe. Too frequent process interventions stir it introducing additional disturbances into the furnace operation. Crew 2 and 3 actions can be regarded as satisfactory.

The noise signal is detected very well. It means that it is required to separate a useful signal from noise.

A high dispersion in oscillations of furnace charge parameters (Table 1) also shows insufficiently accurate process control by process personnel or no respective software that would allow eliminating inconsistencies of process control in an expedient manner. It is more likely that these both trends take place, which does not permit stabilizing charge parameters with the required accuracy.

Based on the data obtained for the Vanukov furnace control quality, we can formulate the task of controlling the subject of study. In practice, this task is divided into several tasks of lower complexity. The most convenient method of such separation is frequency decomposition based on conditional separation of disturbances into high and low frequency depending on comparison results of their frequency spectra with frequency characteristics of the Vanukov furnace. The control task is regarded as a combination of subtasks intended to suppress disturbances of various frequencies. In this manner, the compensation of high and low frequency disturbances can be assigned to various APCS subsystems based on frequency decomposition. The general control task will then be divided into the tasks solved by the high and low frequency subsystems.

So the melting process of the copper-nickel sulphide feedstock in the Vanukov furnace belongs to complicated and hardly formalized processes functioning in the condition of high uncertainty: insufficiency of knowledge, uncertainty of description, noise, and measurement errors. Therefore, the process control based on traditional modeling is low efficient and it is required to develop new methods and approaches to process description.

8. Conclusions

The studies have identified that the furnace charge parameters have a significant stochastic dispersion. All furnace charge parameters (charge consumption, OAM consumption, technical oxygen consumption and oxygen content in OAM) are affected by significant noise, both random and that originated from the process personnel. The signals of these parameters are extremely noisy (figure 2). This indicates the need to improve the process control system.

The methodology of separating a random signal from noise by the moving average method has proved to be efficient. This permits defining the attenuation degree of the correlation function of each parameter and building charts of the auto-correlation function and spectral density of furnace charge parameters (figure 2). The analysis of these charts has shown that the Vanukov process is greatly influenced by the human factor, which also proves the need to develop new process control algorithms.

The obtained data allowed for the frequency decomposition of the Vanukov furnace control task based on conditional separation of disturbances into high and low frequency depending on comparison results of their frequency spectra with frequency characteristics of the Vanukov furnace. Therefore, the charge and OAM consumption are referred to high-frequency oscillations. The changes in oxygen content in the OAM can be referred to low-frequency oscillations.

The proposed evaluation methodology for process control quality based on the analysis of frequency function can be used to develop a new generation of control and stabilization methods for process parameters as well as process control systems in metallurgy.

The use of such methods and process control systems will allow stabilizing furnace loading parameters and support them without large fluctuations in the future, increase the predictability of melting products and the amount of SO2 emissions into the atmosphere, which will improve the technical and economic parameters of the melting process of copper-nickel sulphide feedstock in a Vanukov furnace and improve the technological parameters of further pyrometallurgical rework. All this will ensure resource-saving by keeping the technological process in a mode close to optimal.

In order to increase the process control quality for melting the copper-nickel sulphide feedstock in the Vanukov furnace, it is required to implement new control algorithms that would allow for stabilization and rigid linkage between furnace charge parameters and minimize the influence of the human factor.

Summarizing, we should emphasize the possibility of using both the methodology and the results obtained to improve the quality control of the melting process of copper-nickel sulphide feedstock in a Vanukov furnace. The universality of the proposed method makes it possible to recommend it for other technological processes.

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