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MATHEMATICAL MODEL FOR CONTROLLING THE CLASSIFICATION PROCESS OF CRUSHED IRON RAW MATERIALS USING FUZZY LOGIC

Purpose. To model the technological process of classifying crushed iron ore raw materials at the primary grinding and classifying, and to control the classification process under unclear technological parameters.

Research methods. When modeling the classification of iron ore raw materials, methods of mathematical modeling and methods of automatic control theory, as well as the apparatus of fuzzy logic for controlling the classification process of iron ore raw materials under fluctuations in technological parameters are used.

Scientific novelty. A list of the main input and output parameters of the classification of iron raw materials, which significantly affect the separation of the crushed ore by size, was determined. The obtained parameters enable to improve the existing mathematical models of separation of the crushed ore by size at the primary grinding and classification.

Practical significance. The designed automatic control system of the primary classification of iron ore raw materials at the primary grinding and classification using fuzzy logic is to solve a number of complex problems, solutions of which are problematic using classical methods due to their high complexity and incomplete technological data. The methods of fuzzy logic formalize the dependencies regardless of their complexity, thus allow to use different parameters in controller's fuzzy logic.

Results. Analysis of the iron raw material processing at the primary grinding and classification. A list of the main technological parameters of high impact on the classification of the extracted iron raw materials and their limit values. The classifier automated control for the primary grinding and classification using the fuzzy logic controller requires the following input technological parameters: consumption of crushed ore in the classifier, density of the discharge pulp, and water consumption into the classifier. The automatic control system of the classifier using the fuzzy logic and the classifier using interactive tool for analysis of dynamic systems Simulink is developed, which is integrated with MATHLAB application package.

Key words: classification, iron ore raw materials, mathematical model, automated control, fuzzy logic.

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The problem and its connection with scientific and practical tasks. One of the most urgent tasks in the fierce competition in the world markets for iron ore raw materials is to improve the quality of iron ore concentrate [1].

The quality of iron ore concentrate is largely influenced by the stochasticity of physical-mechanical and chemical-mineralogical properties of iron raw materials coming to the primary grinding and classification of the ore processing plants. The specified factors result in deviations of technological parameters from the set ones, accordingly, in losses of iron in the ore processing.

In response, to effectively manage the processing of iron ore raw materials, it is necessary to take into account the fuzzy and incomplete data of the technological process.

Analysis of the recent research. Solutions to control physical-mechanical and chemical-mineralogical properties of the processed ore are investigated in the problem-branch research lab "Operational control and quality management of mineral raw materials" of the Ministry of Industrial Policy of Ukraine chaired by Professor A. Azaryan [2-8]. The software and hardware complexes developed by the laboratory staff allow to control in real time the quality fluctuations of iron ore raw materials coming for processing and to provide information support about the technological process of grinding and classification for the personnel of the concentrating plant.

Because of the complexity of the ore processing process, recycles and incomplete technological data of the object, it is advisable to use fuzzy logic methods for effective management of the classification process. The following issues in the context of automation of ore-processing plants are considered in a number of works [9-14].

Setting the task. To develop an automatic classifier control system using fuzzy logic.

Research material and results. Considering the specifics of the technological process, it is useful to identify the input and output sets for the classifier of the first stage grinding and classification of iron ore. When building a mathematical model for classifier control, we should use the input sets coming from the mill model: consuption of crushed ore Vpr (t/h), density of discharge pulp Sp (kg/m^3), and additionally water consumption into the classifier Vbm (m^3/h). Output parameters of the classifier are as follows: pulp density in a classifier Sz (kg/m^3), sand consumption in the unloading cycle Vp (t/h), size of discharge pulp Kz (mm) and discharge pulp productivity Pz (t/h). Expert evaluation was used to estimate the changes of fuzzy input and output variables (tabl. 1 and tabl. 2).

Table 1

Technological parameters for determining the input vector of the mathematical model for the classifier control

Technological parameter	Mark	Limit value	
		min	max
Consuption of crushed ore (t/h)	Vpr	75	170
Density of discharge pulp (kg/m^3),	Sp	1400	1700
Water consumption into the classifier (m^3/h)	Vbk	200	230

Table 2

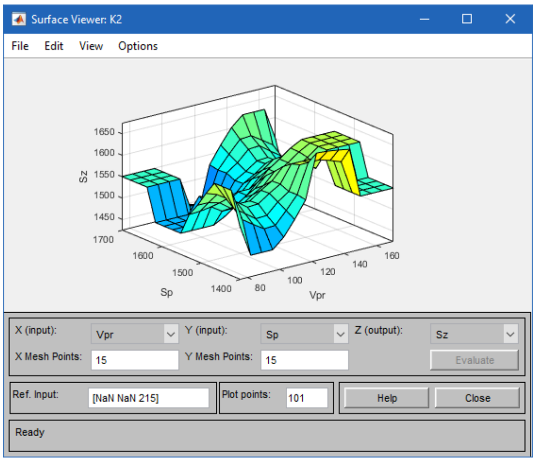
Technological parameters for determining the output vector of the mathematical model for the classifier control

Technological parameter	Mark	Limit value	
		min	max
Pulp density in a classifier (kg/m^3)	Sz	1400	1700
Sand consumption in the unloading cycle (t/h)	Vp	120	255
Size of discharge pulp (mm)	Kz	0,05	0,1
Discharge pulp productivity (t/h)	Pz	75	170

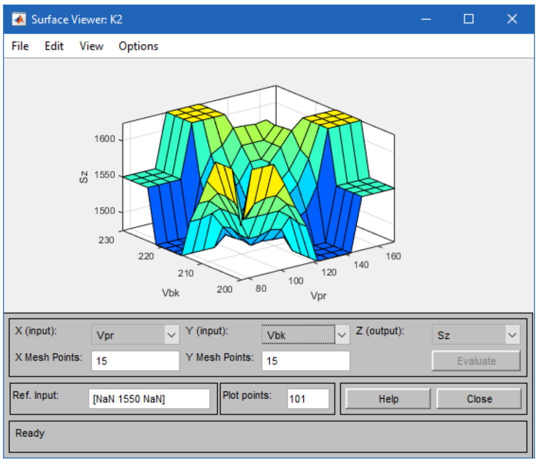
When building a mathematical model for control, we developed fuzzy rules to describe the operation of the ACS classifier of the first grinding and classification and synthesized the base of rules, membership functions and general conclusion. Using the "Fuzzy" simulation tool Simulink [15], which is integrated with MATHLAB package [16], we identified the surface of the FLC classifier for the first stage of iron ore grinding. Graphs of the synthesized FLC surface for determining the density of the discharge pulp from the classifier depending on the input technological parameters are presented in Fig. 1. The figure shows the following functional dependencies

a – [Sz] = f(Vpr, Sp), *b* – [Sz] =f (Vpr, Vbk);

c – [Sz] = f(Sp, Vbk).

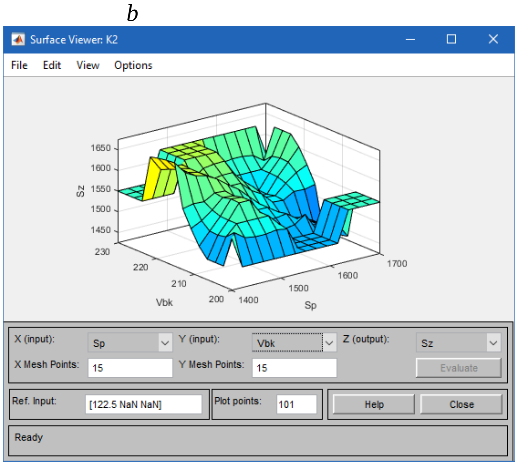


a



b

Fig. 1. The synthesized FLC surface for determining the pulp density in a classifier Sz depending on the inputs: Vpr and Sp (*a*), Vpr and Vbk (*b*), Sp and Vbk (*c*)



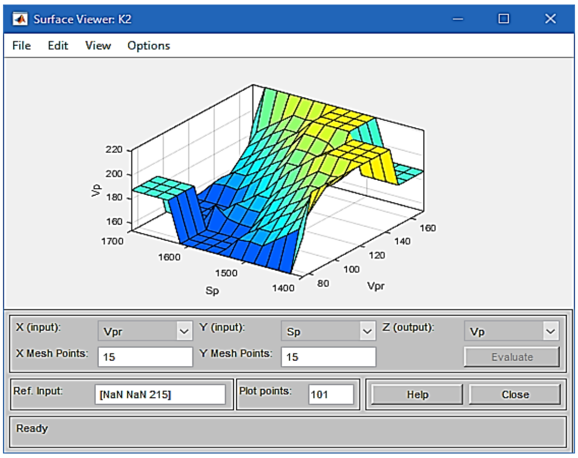
c

The research confirms the influence of the following technological parameters on the pulp density in a classifier: sand consumption, size and productivity of discharge of the classifier.

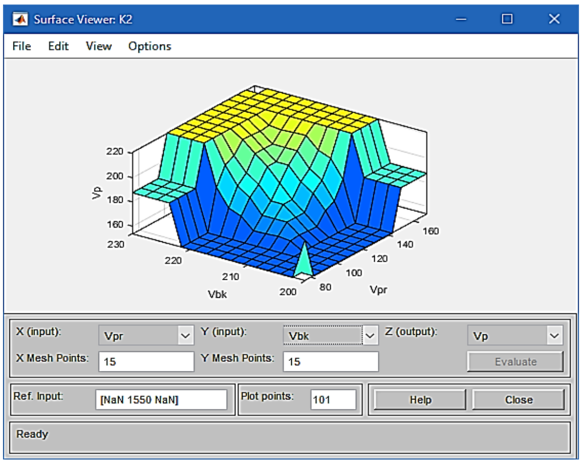
Graphs of the synthesized FLC surface for determining the sand consumption in the unloading cycle classifier are presented in Fig. 2. The figure shows the functional dependencies

a – [Vp] = f(Vpr, Sp), *b* – [Vp] =f (Vpr, Vbk),

c – [Vp] = f(Sp, Vbk).



a



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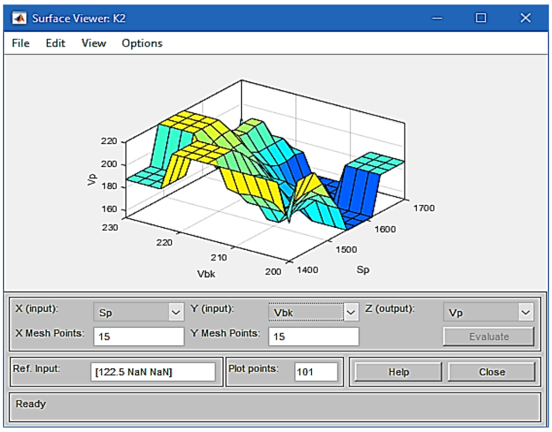


c

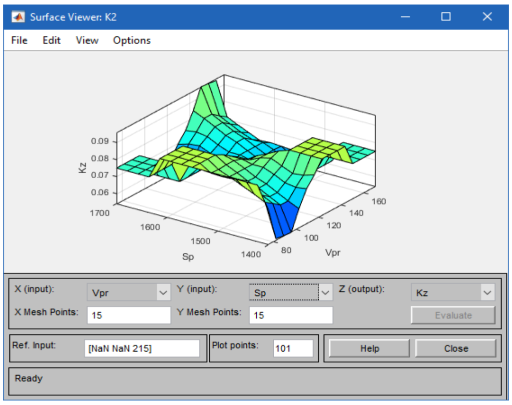
Fig. 2. The synthesized FLC surface for determining the sand consumption in the unloading cycle classifier Vp depending on the inputs: Vpr and Sp (*a*), Vpr and Vbk (*b*), Sp and Vbk (*c*)

Fig. 3 presents the graphs of the synthesized FLC surface for determining the size of the drain from the classifier; Fig. 4 presents the productivity of the drain classifier. The first figure shows the functional dependencies

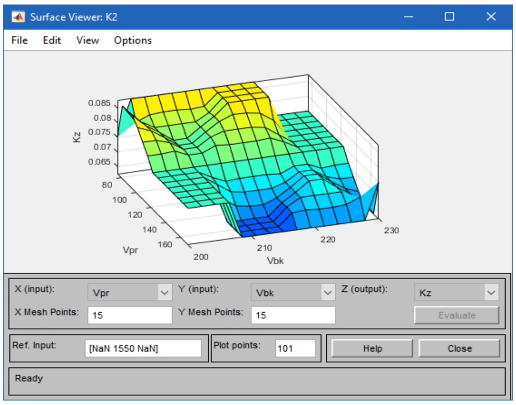
a – [Kz] = f(Vpr, Sp), *b* – [Kz] =f (Vpr, Vbk),
c – [Kz] = f(Sp, Vbk);

the second figure shows

a – [Pz] = f(Vpr, Sp), *b* – [Pz] = f (Vpr, Vbk),
c – [Pz] = f(Sp, Vbk).



a



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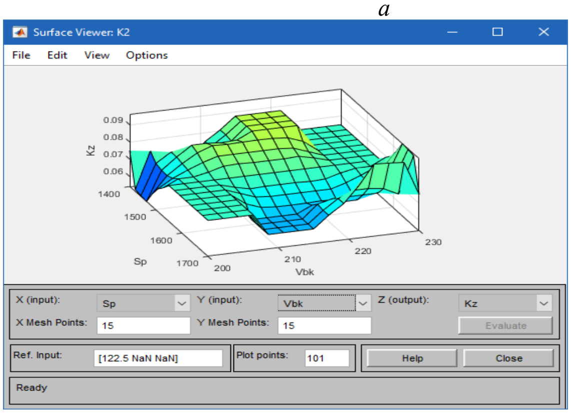
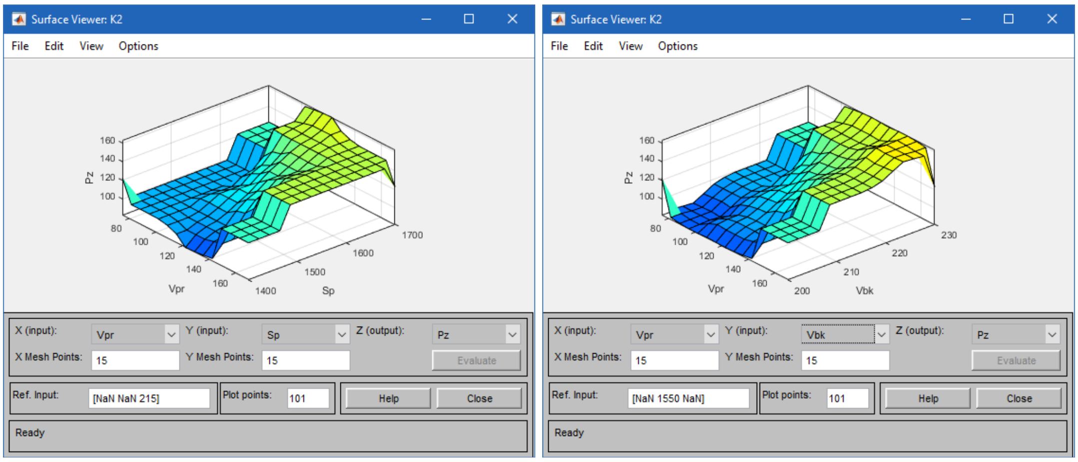


c

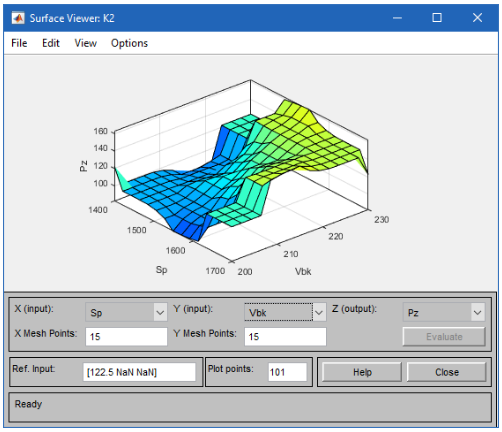
Fig. 3. The synthesized FLC surface for determining the size of discharge pulp classifier Kz depending on the inputs: Vpr and Sp (*a*), Vpr and Vbk (*b*), Sp and Vbk (*c*)

In the Simulink modeling environment, an ACS based on fuzzy logic was developed to control the technological process of iron ore distribution in the classifier by adding the classifier control unit C to the model of Fuzzy Logic Controller (see Fig. 5).



a *b*

Fig. 4. The synthesized FLC surface for determining the discharge pulp productivity classifier Pz depending on the inputs: Vbm and Sp (*a*), Vbm and Vpr (*b*), Sp and Vpr *(c)*



c

The given influence is a set of inputs: consuption of the crushed ore Vpr and density of the discharge pulp Sp from a mill and water consumption into the classifier Vbk are added. The model uses the output sets: the density of the discharge pulp Sz, sand consumption in the unloading cycle Vp, the size of discharge pulp Kz and the discharge pulp productivity Pz from the classifier.

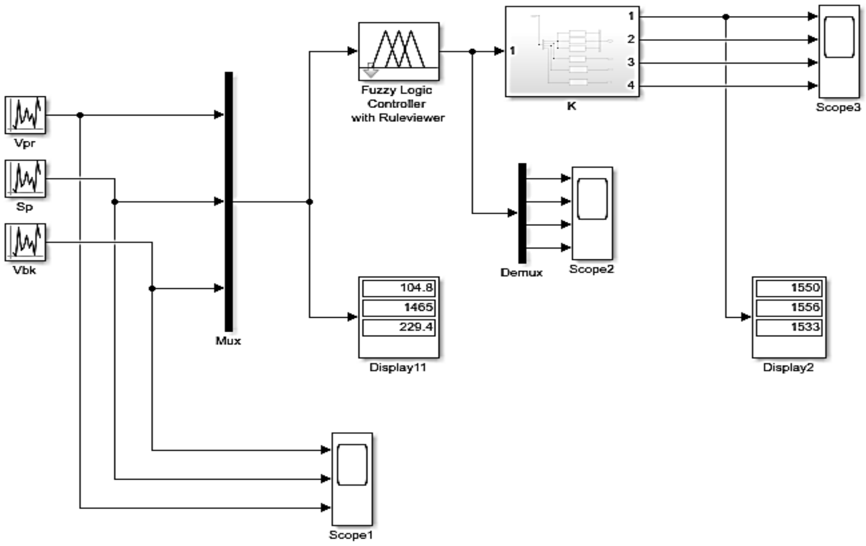
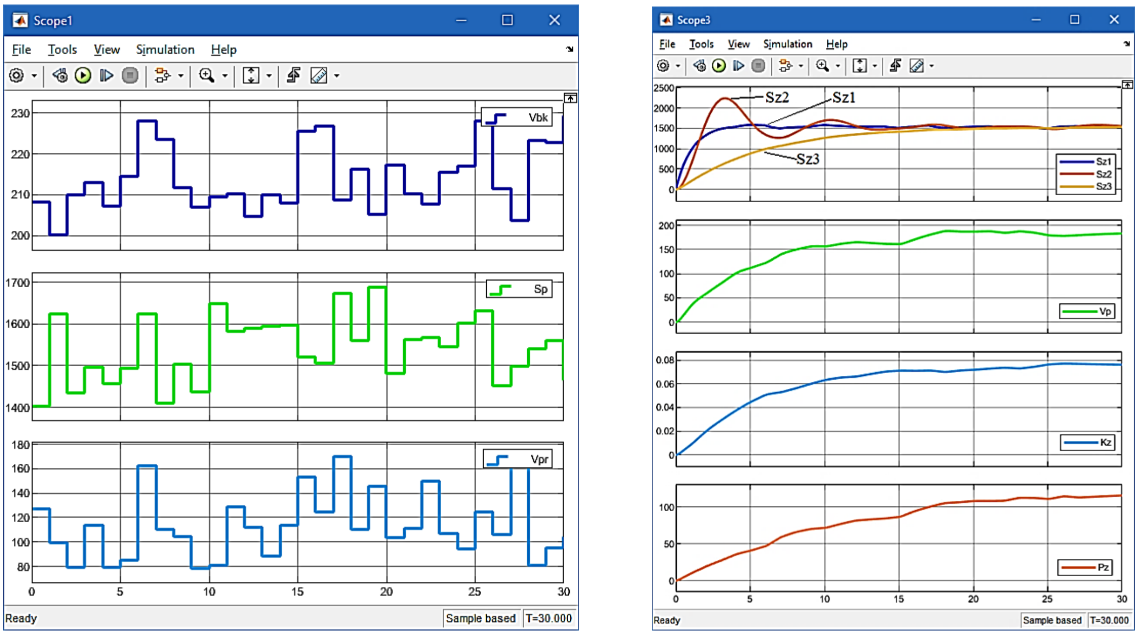


Fig. 5. The ACS classifier based on fuzzy logic in the technological process of grinding iron ore

The Fuzzy Logic Controller output generates a control signal and is essentially a corrective effect. The signal is introduced into the control system of iron ore processing in the classifier and keeps it in the regulatory state. Using ACS based on fuzzy logic to control iron ore processing in the classifier enables to study the influence of input parameters presented in Fig. 6 *a*, and the output parameters in Fig. 6, *b*.



a *b*

Fig. 6. Modeling the control processing iron ore in the classifier on the base of fuzzy logic: *a* - input sets and *b* - output sets

When setting the inputs [Vpr, Sp, and Vbk] labeled in Fig. 6, *a*, the output sets change as shown in the graphs of Fig. 6, *b*. The first graph shows the three functional dependencies Sz1 = f(t), Sz2 = f(t) and *Sz3 = f(t)*, the second graph shows Vp = f(t), the third graph shows Kz = f(t) and the fourth graph shows Pz = f(t).

The control unit classifier C presents the transfer functions on the basis of analytical calculations and experimental data. The influence of transfer functions on the initial dependence of the change in the pulp density of the classifier discharge Sz = f(t) was investigated. The classifier C is represented by three links: 1 is aperiodic $W(s)=\dfrac{1}{s+1}$, 2 and 3 are vibrational: $W(s)=\dfrac{1}{s^2+0.5s+1}$ and $W(s)=\dfrac{1}{s^2+6s+1}$.

These results indicate that the shortest time of 5 s, at which the transient process of changing the density of the discharge pulp in the classifier, is Sz1 = f(t). Transition time with the first and second oscillating links is 20 seconds. When the oscillating link constant time is doubled, the oscillating process of the classifier discharge density is Sz3 = f(t) and the time of the transient process significantly increases. When determining the sand consumption in the unloading cycle Vp, size of discharge pulp Kz and discharge pulp productivity Pz, the classifier is represented as an aperiodic link. The modeling results are visualized in a graph presented in Fig. 6, *b* and show that the transition time is about 20-25 s for the discharge size Kz and pulp productivity Pz. The transition process remains oscillatory for the sand consumption in the unloading cycle Vp.

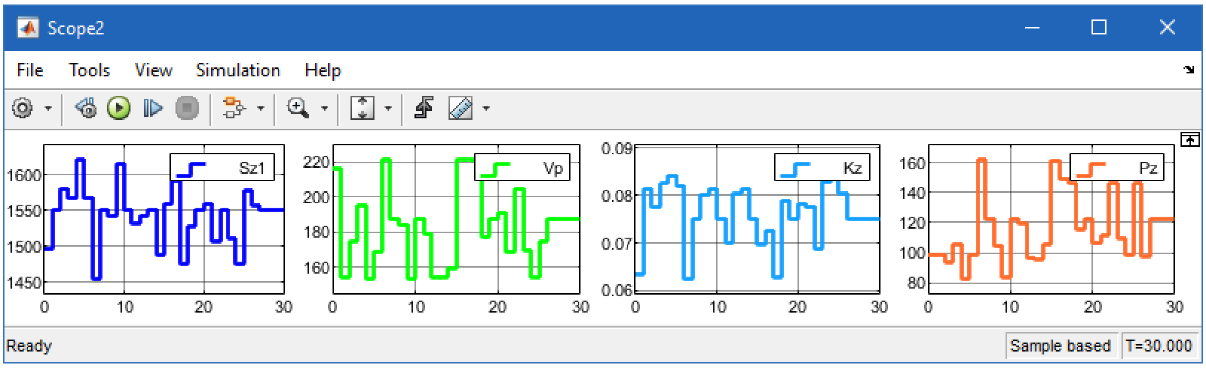
The influence of input vector parameters on initial functional dependencies like classifier pulp density Sz, sand consumption in the unloading cycle Vp, size of discharge pulp Kz and discharge pulp productivity Pz was moduled with the following change of values: crushed ore consumption Vpr, pulp density Sp and water consumption Vbk. Study data on the changes in the input technological parameters of the classifier are given in table 3.

Table 3

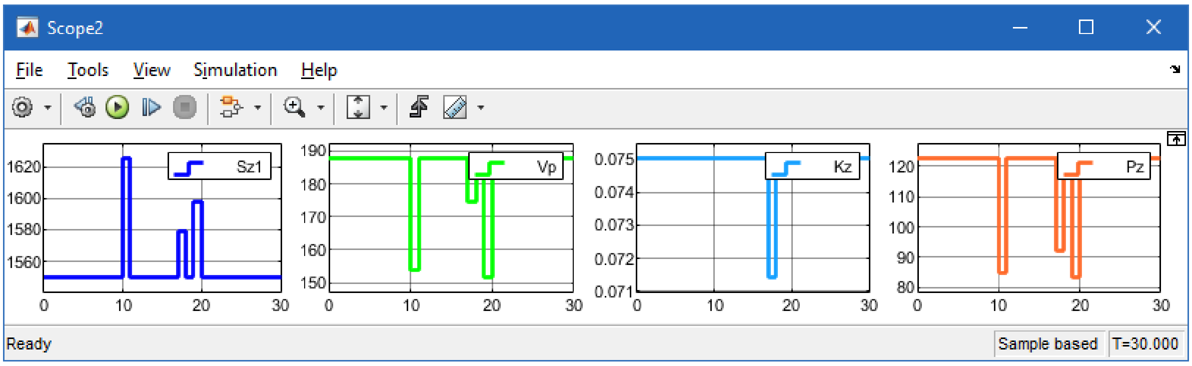
Data on changes in input technological parameters of the classifier

Mark	Limit value							
	Experiment №							
	1		2		3		4	
	min	max	min	max	min	max	min	max
Vpr, t/h	75	170	100	600	100	600	100	600
Sp, kg/m^3	1400	1700	1700	2000	1400	1700	1400	1700
Vbm, m^3/h	200	230	200	230	200	230	255	400

The above performance in Fig. 7 shows that Fuzzy Logic Controller with Ruleviewer forms the following outputs: density of the classifier pulp discharge Sz – 1550 kg /m^3, sand consumption in the unloading cycle Vp – 190 t / h, size of discharge pulp Kz – 0.075 mm and discharge pulp productivity in the classifier Pz – 120 t / h.



a



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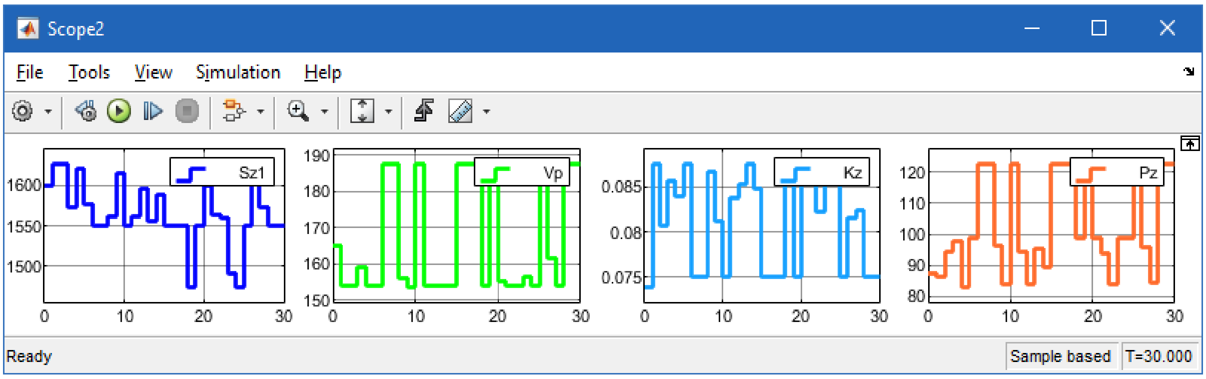

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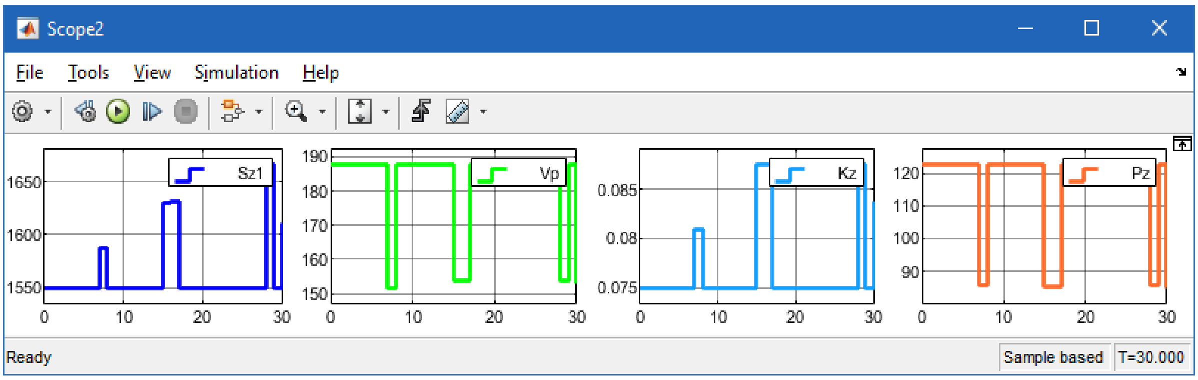

d

Fig. 7. Modeling results according to Table 3: *a*, *b*, *c* and *d* - experiments, respectively №1 – №4

Changing the inputs affects the average value of the classifier outputs. Changing the Vpr minimum value of 100 t/h to the maximum value of 600 t/h (experiment Table 3 №3) has the greatest influence on the initial functional dependencies: the density of the classifier discharge pulp Sz, the sand consumption in the unloading cycle Vp, the size of discharge pulp Kz and discharge pulp productivity Pz.

Conclusions and directions for further research. Studies have shown that, when controlling the classifier of the primary iron ore processing using the fuzzy logic controller, it is reasonable to rely on the corresponding technological input parameters: consumption of crushed ore, the density of the mill discharge pulp and water consumption into the classifier. In this case, the model of the classifier as an object under control is sufficiently represented in an aperiodic transfer function.

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