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IRON ORE GRINDING PROCESS AT THE CONCENTRATING PLANT UNDER FUZZY AND INCOMPLETE PARAMETERS

Purpose. To model the first technological phase of iron ore grinding process in the mill and classification at the concentrating plant, to control over the grinding process in terms of stochasticity of technological parameters.

Research methods. The methods of automatic control theory and mathematical modeling are to estimate transients; fuzzy logic methods are to control over the processing iron ore raw materials with fuzzy and incomplete technological parameters.

Scientific novelty. The listed iron ore processing parameters that most influence the grinding process enable to improve the existing mathematical models of processing iron ore raw materials at the first stage of grinding and classification at the ore-processing plants.

Practical significance. The fuzzy logic automatic control system of the first ore grinding and classification meets effectively the challenges that cannot be solved by classical methods due to high complexity and lack of sufficient technological data. Formalizing the rules for a fuzzy approach provides more precise result and is superior to others. Fuzzy logic can formalize the dependencies of any complexity, parameters in the controller with fuzzy logic can vary, fuzzy models are highly adaptable to expert data.

Results. The structural and functional analysis of the iron ore processing; the characteristics of technological parameters influencing the quality of grinding ore raw materials. The automated control of a first stage mill with fuzzy logic regulator consider the following technological input parameters: productivity of input ore, water consumption in the mill, ore hardness coefficient correlated with total iron content in ore, and sand consumption in the unloading cycle. A system of automatic control of the mill based on fuzzy logic was developed; a study of the operation of the mill using the Simulink tool for modeling and analysis of dynamics.

Key words: iron ore, grinding, mill, fuzzy logic, automated control, mathematical model.

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Problem statement. Processing iron ore in a first stage of grinding, classification and magnetic separation is fundamental in the enrichment plant. In the conditions of the Ore Processing Enterprise-1 PJSC "ArcelorMittal Kryvyi Rih" after the first stage of magnetic separation the content of iron in the product increases by 21%, accounting for about 50% of total sectional iron losses [1].

Note that the technological process of iron ore grinding and classification at the first stage is nonlinear and stochastic [2-5]. It is due to the fluctuations of physical-mechanical and chemical-mineralogical properties of raw materials. Therefore, the classical theory of automatic control rarely ensures a satisfactory outcome. Unclear and incomplete technological data of the object make it challenging to build an algorithm of the technological process.

Analysis of the recent research and publications Fuzzy logic is one of the most appropriate for working with nonlinear and stochastic processes. Morkun V.S. [6-8], Kupin A.I. [9-11], several domestic and foreign scientists [12-16] devoted their works to the automation of iron ore processing using fuzzy logic methods and neuro-fuzzy approaches.

The fuzzy sets and linguistic variables allow you to create an algorithm based on fuzzy logic, which is translated into program code. Such solutions are very commonly used in programming and successfully adopted in the automation of any technological process (in 1994, at the intersection of computer and other sciences L.Zadeh called them as softcomputing [17]).

Objectives of the article. To develop an automatic mill control system based on fuzzy logic.

Presentation of the main research and results. A fuzzy logic control algorithm is based on a fuzzy logic controller (FLC), which includes a fuzzy logic block (FLB). A block diagram of a fuzzy logic controller presented in Fig. 1 shows blocks 1, 2, 3 - normalization, FLB and denormalization. The fuzzy logic block 2 comprises a fuzzify unit 2.1, a rule base 2.2.1, an implication unit 2.2.2., and a defuzzify unit 2.3.

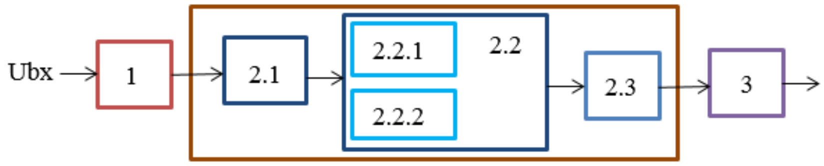


Fig. 1. A block diagram of a fuzzy logic controller

The algorithm of FLB operation can be represented as an input-output model and set by the equations (1). The physical variables converted into fuzzy ones through the fuzzify operation (fuzz) are determined by the task of fuzzy functions as triangles, trapezoids, bell-shaped functions. The inverse converting into physical variables is performed by the defuzzify operation (dfz) either by the methods of the center of gravity, or the center of the area, or the mean maximum. [18].

$$\{R_i\}_{i=1}^{k} = \begin{cases} R_1 : A_1 \circ r_1 = A_1(A_{11} \to A_{21}) = B_1; \\ R_2 : A_2 \circ r_2 = A_2(A_{12} \to A_{22}) = B_2; \\ \vdots \\ R_k : A_k \circ r_k = A_k(A_{1k} \to A_{2k}) = B_k; \end{cases}$$

$$A_i(i = \overrightarrow{1,k}) = fuzz(x_i), A_{ji} = fuzz(x_j, x_i); \tag{1}$$

$$B = \bigcup_{i=1}^{k} B_i, z = dfzB$$

where R_i is a rule, $\{R_i\}_{i=1}^{k}$ is a rule base; ○ is a composition of fuzzy relations; → is a fuzzy implication; $A_i(i = \overrightarrow{1,k})$ is a local conclusion; *B* is a general conclusion; *fuzz* is the fuzzify operation; *dfz* is the defuzzify operation.

The FLB processes the fuzzy sets, whose output signal is determined by the tasks of setting fuzzy implication and composition.

The FLC is used in nonlinear systems or systems with nonlinear external influences, in systems with a long delay time.

To create a base of linguistic rules for a fuzzy system with two inputs and one output, the data as multiple pairs require:

$$(x_1(i), x_2(i), d(i)), i = 1,2...,$$

where $x_1(i)$, $x_2(i)$ are the signals supplied to the FLC input; $d(i)$ is the expected value of the output signal.

The Mamdani's fuzzy logic control algorithm is a set of heuristic rules for controlling a control object. Fuzzy sets and fuzzy logic are to represent linguistic terms and evaluate compound rules.

When controlling a mill of the first stage of iron ore grinding, a number of fuzzy input parameters simultaneously affect it, they are: productivity of input ore, t / h; water consumption, m^3/h; ore hardness correlated with the total iron content in the ore; sand consumption in the unloading cycle, t/h.

When transporting iron ore pulp from the mill to the classifier, its initial parameters that affect the operation of the classifier need to be considered. Therefore, the computational model for the mill is multifaceted. The fuzzy and incomplete input and output vectors and their relationship in the control of the first grinding in the mill have the general form shown in Fig. 2. The technological parameters of the input and output vectors depicted above are given in Tables 1 and 2. Here are the minimum and maximum allowable limits of the input and output vectors of the technological grinding process in the mill set by experts.

According to results of production processes, the output vector parameters [Vpr, Sp] vary in a wide range and depend on the values of the input vectors [Pm, Vbm, Km, Vp]. The presented block diagram in Fig. 2 developed an automatic control system (ACS) for a mill based on fuzzy logic (Fig. 3), and performed the study on the mill using a Simulink tool for modeling and analysis of dynamic systems. [19]. The pictured ACS includes a Fuzzy Regulator to control the grinding process of iron ore in the mill. The ACS based on fuzzy logic represents blocks that specify the inputs of the vector [Pm, Vbm, Km, Vp], and the outputs of the vector [Vpr, Sp]. The blocks have models which display the values of the received inputs. Each of these blocks represents the set average value of the interval for each parameter and the variance of this interval within the specified norms. The developed computational model of the system considers the mill as a typical aperiodic link of the first order, because any process of grinding the ore has inertia. The ACS uses the Fuzzy Logic Controller with Ruleviewer as the main regulating and control device, which operates according to the Mamdani's algorithm rules of fuzzy logic. See Fig. 4 for a graphical depiction of membership functions.

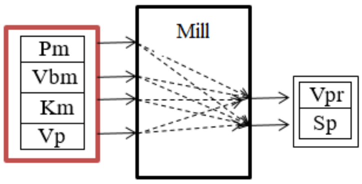


Fig. 2. A block diagram of input and output vectors and their interactions in the control of the first-stage grinding in the mill

Table 1

Technological fuzzy parameters for determining the input vector of the computational model for the mill control

Technological parameter	Mark	Limit value	
		min	max
Productivity of input ore, t / h	Pm	75	170
Water consumption, m^3/h	Vbm	80	120
Ore hardness	Km	3	20
Sand consumption in the unloading cycle, t / h	Vp	120	255

Table 2

Technological fuzzy parameters for determining the output vector of the computational model for the mill control

Technological parameter	Mark	Limit value	
		min	max
Consumption of crushed ore, t / h	Vpr	75	170
Pulp density in a mill, t / h	Sp	1400	1700

The membership functions of the selected fuzzy variables of FLC inputs and outputs (Fig. 4) have five input and output variables. The methods of defuzzifying, implication, and limits of input and output variables for membership functions are chosen in this window. Then, the synthesized membership functions and their selected types, and the determined limits of membership functions.

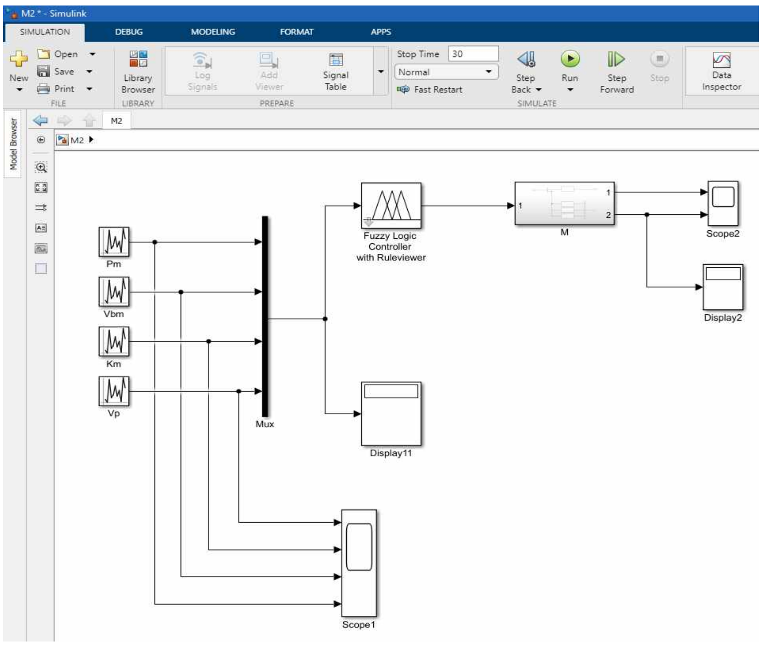
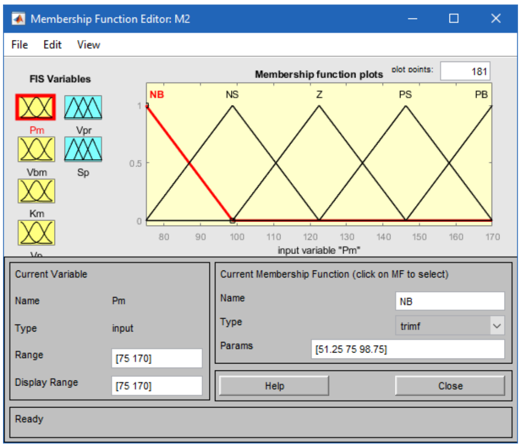
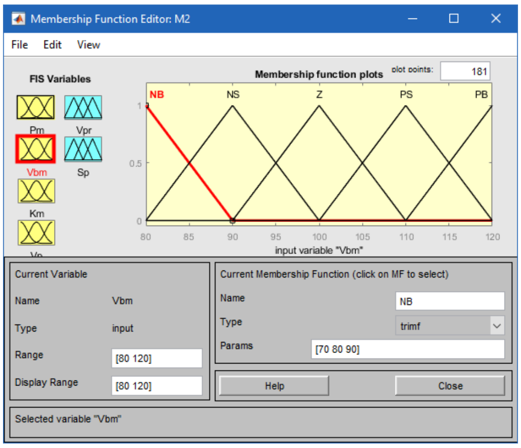


Fig. 3. A fuzzy logic mill ACS in the grinding process of iron ore

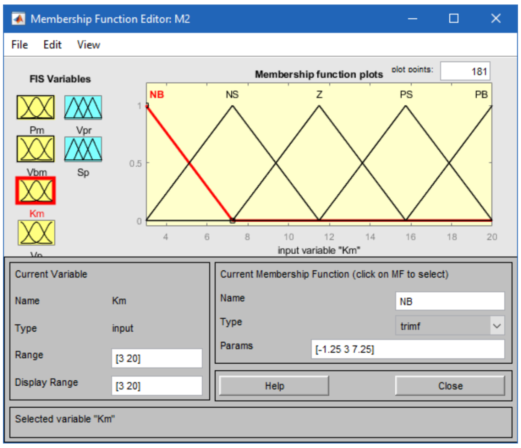
a



b



c



d

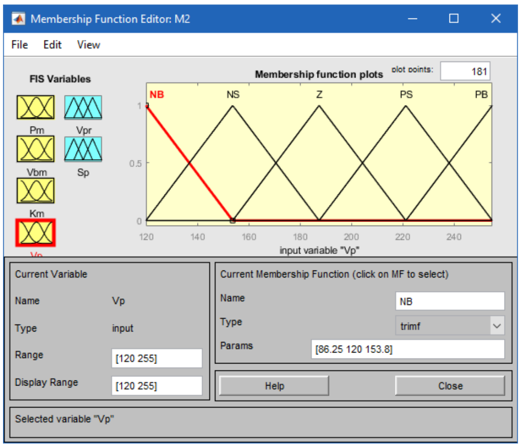


Fig. 4. The membership functions fuzzy variables of inputs and outputs for productivity of input ore (*a*), water consumption in a mill (*b*), ore hardness (*c*) and circulating loading (*d*)

Form and synthesize the FLC rule base. One of the rules presented looks like the following form in Fig. 5, *b*

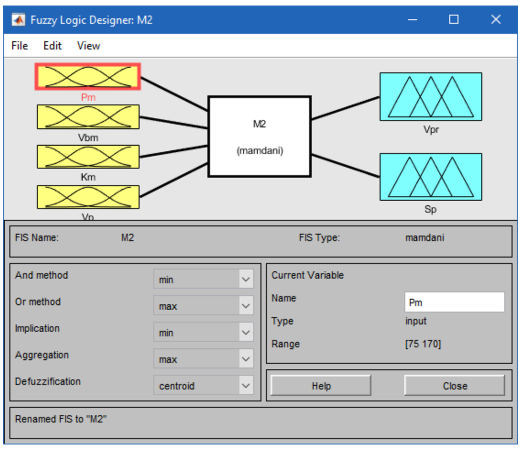
R_t (M): If (Pm is PB) ^ (Vbm is Z) ^ (Km is Z) ^ (Vr is Z) then (Vpr is PB) ^ (Vp is Z).

The other rules are similar to the presented in fig. 5 *b*.

After synthesizing the rule base, the FLC surfaces were determined to calculate the consumption of crushed ore in the mill Vpr (Fig. 6). Here, the synthesized RNL surfaces for the consumption of crushed ore are presented by the functional dependencies

$$Vpr = f(Pm, Vbm), Vpr = f(Pm, Km), Vpr = f(Pm, Vp), Vpr = f(Vbm, Vp).$$

a



b

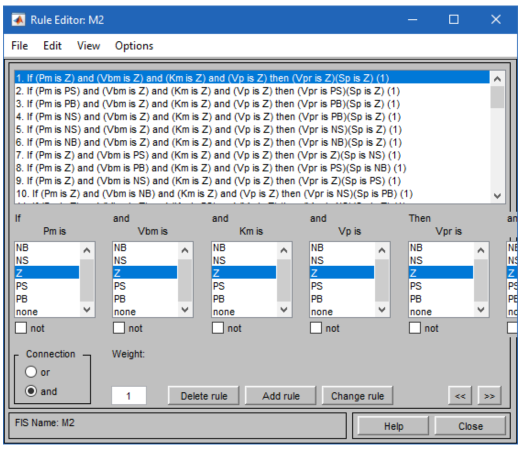


Fig. 5. The membership functions of the selected inputs and outputs (*a*) and knowledge base model (*b*)

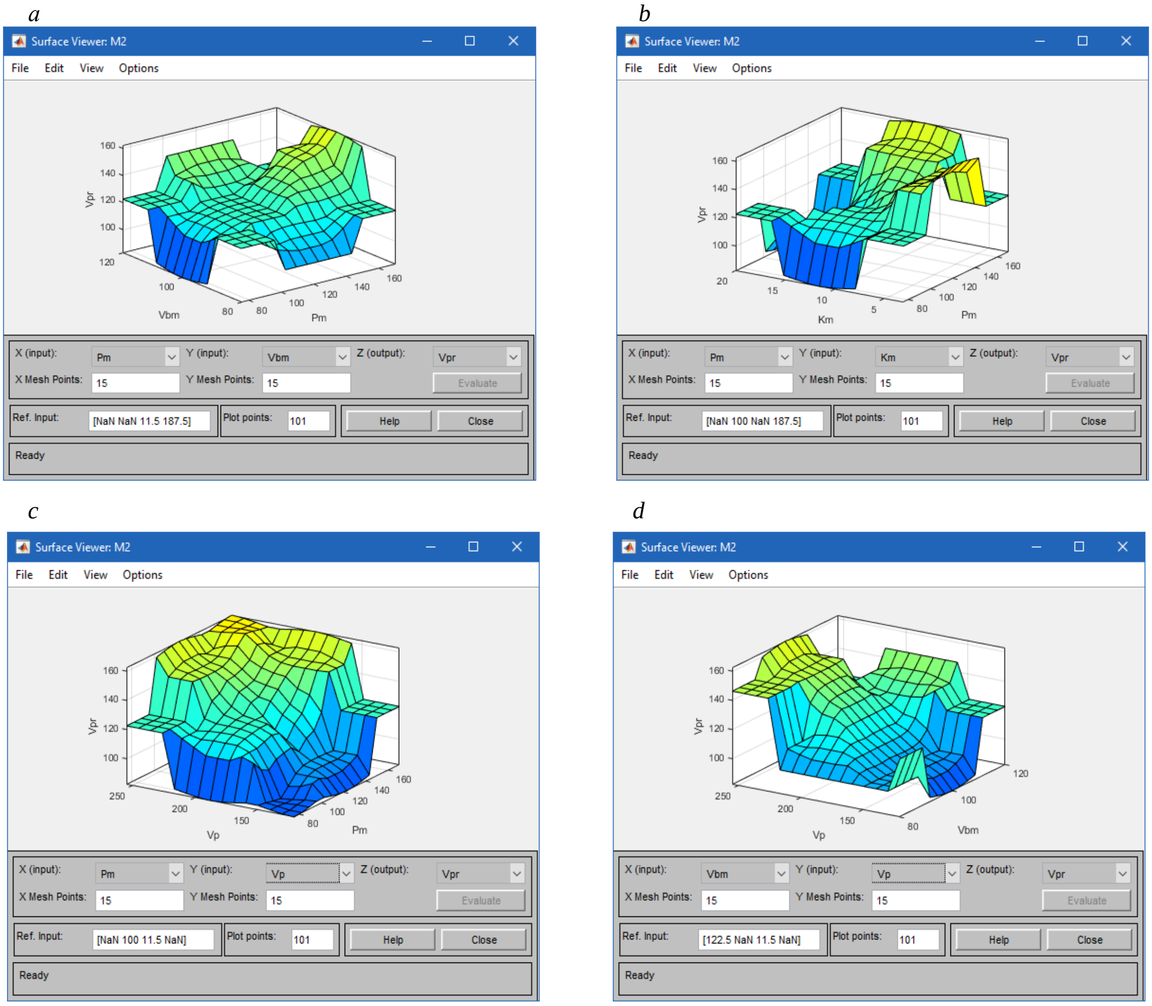
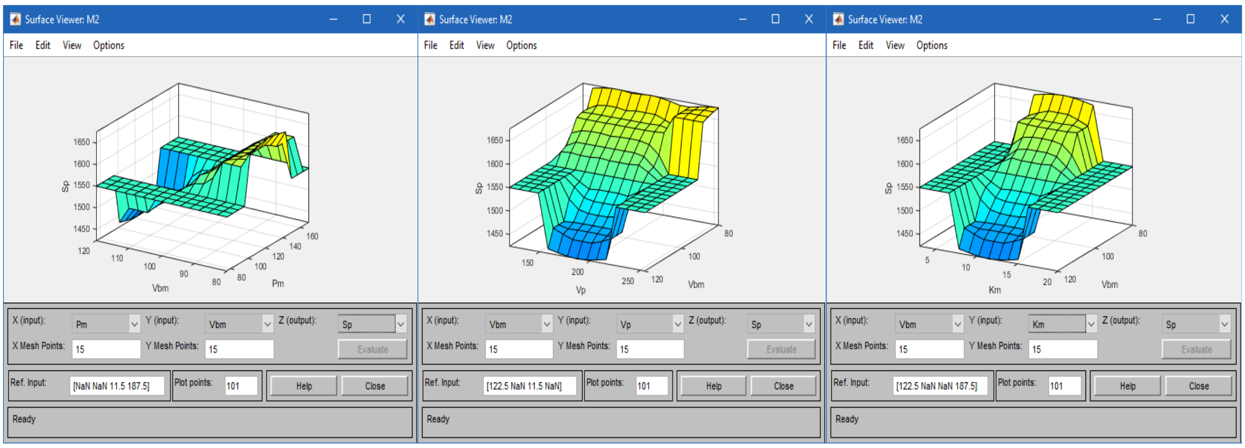


Fig. 6. The synthesized FLC surface for the consumption of crushed ore in a mill Vpr depending on the inputs Pm i Vbm (*a*), Pm i Km (*b*), Pm i Vp (*c*), Vbm i Vp (*d*)

In Fig. 7, the following functional dependencies show the synthesized FLC surfaces for determining the pulp density in a mill,

$$Sp = f(Pm, Vbm),\ Sp = f(Vbm, Vp)\ і\ Sp = f(Vbm, Km).$$



a *b* *c*

Fig. 7. The synthesized FLC surface for determining the pulp density in a mill depending on the inputs Pm i Vbm (*a*), Vbm i Vp (*b*), Vbm i Km (*c*)

We modeled the impact of the technological input parameters on the output parameters during the grinding iron ore in the mill, by scattering the technological parameters under tables 1 and 2 with the corresponding rules; Fig. 8 shows the search for the general overview.

The Simulink model (see Fig. 3) with the input technological parameters (see Fig. 9) is simulated and shown in Fig. 10. When applying the inputs to the model (see Fig. 9), the changes in the outputs are like in the graphs of Fig. 10: pulp density in a mill *Sp=f(t)* (graph *a*) and the consumption of crushed ore at the outlet of the mill for different time constants of the aperiodic link of the transfer function – *Vpr = f(t)* (graph *b*).

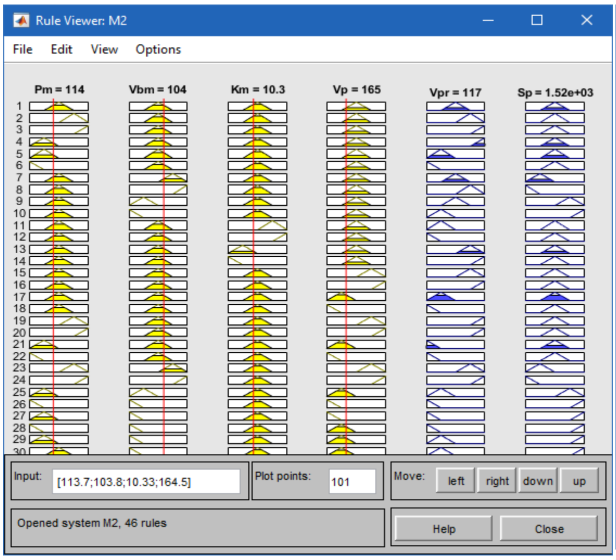


Fig. 8. Fuzzy overview defuzzifying

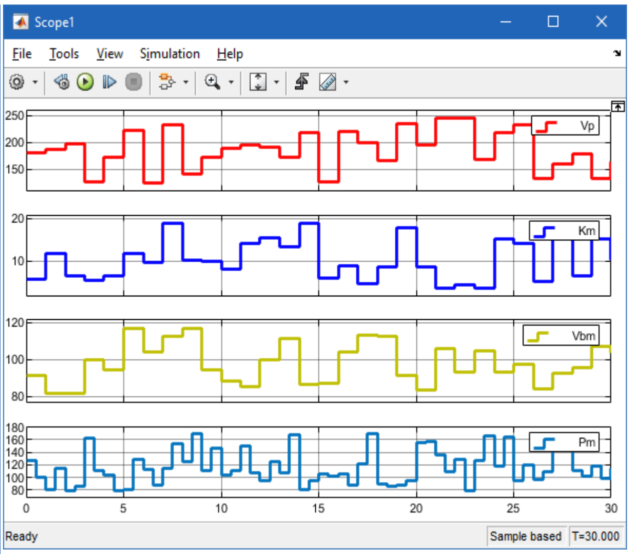


Fig. 9. A diagram of input technological parameters for FLC processing in control over the first grinding

a *b*

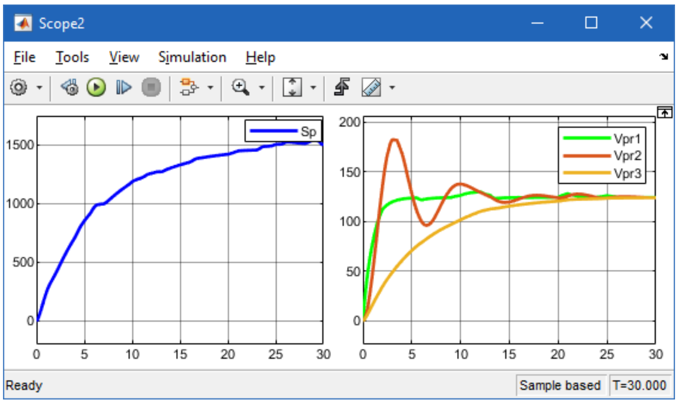


Fig. 10. An FLC in modeling the mill control system for the first- stage grinding ore: *a* - pulp density in a mill, *b* - consumption of crushed ore at the outlet of the mill

The mill control model described as a transfer function came from analytical calculations and experimental data. Thus, the initial dependence of the change in consumption of crushed ore at the outlet of the mill – *Vpr = f(t)* is represented by three different links: 1 – aperiodic $W(s)=\frac{0.08}{s+1}$, 2 and 3 − respectively oscillating: $W(s)=\frac{0.08}{s^2+0.5s+1}$ and $W(s)=\frac{0.08}{s^2+6s+1}$.

Data gained from these studies indicate that for the consumption of crushed ore at the outlet of the mill – *Vpr = f(t)* the time before transition process ends is 25 seconds for all the above links. Doubling the time constant of the oscillating link leads to the oscillating changes in the consumption of crushed ore at the outlet of the milll – *Vpr = f(t)* and the time of the transition increases. The outlets for determining the density of the drain pulp from the mill *Sp = f(t)* (graph *b*) remain unchanged over time after 25 seconds.

Conclusions and direction of further research. To sum up, simulating the automated control of the mill for the first grinding ore based with the fuzzy logic controller suggests the following technological inputs: input ore productivity, water consumption in the mill, ore hardness (correlates with iron content in the ore) and sand consumption in the unloading cycle. It suffices to model the mill control object as an aperiodic or oscillating transfer function.

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