Development of a model of an agent identifying the noise signal in a ball drum mill

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Abstract. This work is devoted to the topical issue of identifying the noise signal arising during the operation of a ball drum mill. An approach to the development of a model of an agent identifying a given noise signal is presented. Having a sufficiently large number of measurements of the parameters of the technological process, the relationship between noise and all the quantities influencing it was derived in the form of a system of linear equations. For the analysis of expert data, a model in the MatLab environment, the Simulink simulation application was developed. This model is a model of the agent for estimating the noise of the mill, which can then be used to analyze the state of the lining, regulate the operation of the mill, or make predictions with predictive control.

1. Introduction

Modern control systems for technological processes must not only provide the required performance while using the minimum amount of energy resources, but also the safety of production equipment. This need is confirmed by the fact that breakdowns, and as a result of downtime, equipment cause significant economic harm to the enterprise, which is not covered by the profit received when the equipment operates at “maximum capacities” [1–7].

This paper discusses the issue of identifying the noise signal generated by a ball drum mill (BDM). This signal can be identified and subsequently used to control the ore grinding process, taking into account changes in the internal states of the equipment.

The paper proposes a variant of the development of a software agent that evaluates the change in the parameters of the technological process in conjunction with the change in the state of the BDM, which leads to a change in the situation affecting the choice of technological control regulations.

2. Technological process of grinding

The technological process of wet grinding (figure 1) is quite complex, the work of the BDM cannot be considered separately from the work of the classifying apparatus, since there is a feedback that affects the material balance in the mill drum.
The input flows entering the mill are the feedstock intended for grinding $Q_p$, water $Q_w$ (the mill performance depends on the proportions of water to the crushed raw material), grinding balls (ceramic or metal) $Q_b$, as well as the sandy fraction that has not passed the classifying apparatus and returned into the $Q_s$ mill. These flows implement the material balance inside the drum of the mill, on which the performance of its work will depend.

If, for example, the studies carried out by the specialists of the Central Technological Laboratory of JSC "APATIT" found that the water flow rate into the mill should be proportional to the productivity of the mill feed conveyor for ore [1]:

$$Q_w = (0.25 + 0.28) \cdot Q_p$$

then the flow rate of balls entering the mill can be controlled only by the value of its productivity. The number of balls added to the mill must be changed, since in the process of grinding, balls lose their properties as a result of mechanical damage and the performance of the BDM decreases.

The change in the weight of the ball charge can be determined using a standardized indicator $\psi$ — the consumption of balls per 1 ton of processed ore.

$$\Delta Q_b = -\psi \cdot \int_{t_0}^{t_1} Q_{shi} dt$$

where $Q_{sh}$ is the productivity of the mill for the original ore, t / h.

Thus, ideally, by creating a certain balance of water, balls and processed raw materials, it is possible to achieve a certain productivity of the mill, but in a real situation there is an additional factor that significantly affects the technological process. This factor is the state of the mill drum lining, which deteriorates over time under the influence of shock loads from the balls. At the same time, a change in the state of the lining leads to an increase in the internal volume of the mill drum, which in turn leads to a change in the material balance inside the mill, and ultimately affects the specific productivity. With a critical change in the state of the lining, the mill breaks down, which leads to a stoppage of the technological process, downtime, unplanned repairs, and, as a result, to financial losses.

3. Analysis of the mill lining state

The process of grinding ore with the help of the BDM is continuous, the mill stops only at maximum wear of the lining for its replacement, while the state of the lining can be assessed only by the noise emitted by the mill, or the mill stops in accordance with the production schedule after a certain operating time. In this article, noise does not mean actual sound pollution, but vibrations present in the mill housing. Microphones capable of recording sound are not suitable for use in an industrial workshop due to the fixation of extraneous noise.

Thus, hereinafter, the noise is understood as a useful signal picked up by the vibration sensor from the grinding area.
The total (average) potential of all interacting elements within the "mill" system will most likely be represented by the grinding area noise signal read by the sensor. This signal is the result of all participants in the interaction, reflecting their mutual behaviour.

Consider a noise signal, more than 7000 unit values (figure 2).

As it can be seen in the figure, this signal contains both low-frequency and high-frequency components. The noise signal during the study was subjected to spectrum singularity analysis (track method) using CaterpillarSSA 3.30 software to identify the principal components. The analysis revealed a large number of periodic components in the mid-frequency range, which is obviously due to the frequency of operation of the moving parts of the machine, and a large number of high-frequency components with low energy values, which do not give any significant contribution to the overall signal.

By analysing this signal, it is possible to reveal the presence in it of areas similar to each other, described by the signature functions.

Figure 3 shows the filtered signal of the noise sensor for the BDM. On an interval of 812 discrete samples, 2 large-scale cooperative strikes were identified (the corresponding signatures are highlighted by a rectangle). According to the results of computational experiments, ~ 5 signatures are identified per hour (smoothing order 4, signature length 12 counts), with decreasing the duration of signature formation to 10 counts, the number of identification facts increases sharply. The optimal duration for identifying cooperative strikes (signatures), according to the results of a computational experiment, is proposed to set from 12 to 15 discrete reports with a smoothing order of 4. The signature has the property of self-similarity, that is, it can be identified on smaller scales. This event can be interpreted as uniform wear of the protective coating associated with a minor cooperative impact.
With a significant increase in the number of signatures, it can be concluded that there is significant wear of the lining and the need for scheduled repair.

You can try to use the noise signal to change the operating mode of the mill, since it is influenced not only by the state of the lining, but also by the proportions of the components that make up the material balance inside the drum.

4. Identification of the noise function

It is obvious that the level of noise emitted by the mill during operation is influenced by several factors. Mathematically, it is not possible to derive an exact function describing this influence. Having a sufficiently large number of measurements of the parameters of the technological process, the relationship between noise and all the quantities influencing it can be represented in the following form:

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\begin{align*}
S_1 &= k_1e^{Q_{u1}} + k_2e^{Q_{o1}} + k_3e^{Q_{p1}} + k_4e^{Q_{nec1}} + k_5e^{\omega_{uA}} + k_6e^{W_1} \\
S_2 &= k_1e^{Q_{u2}} + k_2e^{Q_{o2}} + k_3e^{Q_{p2}} + k_4e^{Q_{nec2}} + k_5e^{\omega_{uA2}} + k_6e^{W_2} \\
S_3 &= k_1e^{Q_{u3}} + k_2e^{Q_{o3}} + k_3e^{Q_{p3}} + k_4e^{Q_{nec3}} + k_5e^{\omega_{uA3}} + k_6e^{W_3} \\
S_4 &= k_1e^{Q_{u4}} + k_2e^{Q_{o4}} + k_3e^{Q_{p4}} + k_4e^{Q_{nec4}} + k_5e^{\omega_{uA4}} + k_6e^{W_4} \\
S_5 &= k_1e^{Q_{u5}} + k_2e^{Q_{o5}} + k_3e^{Q_{p5}} + k_4e^{Q_{nec5}} + k_5e^{\omega_{uA5}} + k_6e^{W_5} \\
S_6 &= k_1e^{Q_{u6}} + k_2e^{Q_{o6}} + k_3e^{Q_{p6}} + k_4e^{Q_{nec6}} + k_5e^{\omega_{uA6}} + k_6e^{W_6}
\end{align*}
\]

This system is a system of linear equations in which it is possible to express the relationships between the amount of balls, water, ore, sands coming from the hydro cyclone, the speed of the engine and the state of the lining with each other. In fact, the system is a kind of "material balance equation". In this work, it is proposed to evaluate the state of the lining with a value from 0 to 1 (1 new lining, 0 critical state in which it is necessary to replace it to prevent breakage of the BDM). It should be noted that an expert gives an assessment of the state of the lining during experimental studies.

Practically carrying out a number of experiments, it is possible to obtain the necessary initial data for solving this system and determining the unknown coefficients $k$, after which, by expressing the last term, it is possible to obtain an expression of the state of the lining from all other parameters, and then track it during the technological process.

For the analysis of expert data, a model was developed in the MatLab environment, shown in figure 4. In fact, this model is a model of the noise estimation agent of the BDM, which can later be used to analyze the state of the lining, regulate the operation of the BDM, or to make predictions with proactive control.

In figure 5, the results of its functioning are presented, superimposed on the statistical data that were selected for calculating the coefficients, it is obvious that the functional dependence has the same form as in the tuning data, but the signal is received with some delay, and is lower than the average noise value used for tuning.
After discussing the result of the model’s work with specialists working in production and working directly with the BDM, a conclusion was made about the functional incompleteness of the system of equations (1). Since the temperature changes significantly during the crushing process as a result of the friction of the balls and the friction of the processed raw materials, it was decided to take into account the term describing it in the system of equations (1). Since the form of the system of equations has not fundamentally changed, this article does not provide its form. Figure 6 shows the simulation results taking into account the temperature and in comparison with the noise signal and the result of the model from figure 4.

It can be seen from the results that with a sufficiently fast change in the noise signal, the model is not able to fully assess its average value, but in the remaining sections the quality of its work is satisfactory.

Figure 4. Noise identification agent BDM.

Figure 5. Simulation results.

Figure 6. Simulation results taking into account temperature changes.
5. Conclusion
It should be noted that the use of such a parameter as the noise level in the BDM and in other technological facilities can significantly affect the service life of equipment and the continuity of the technological cycle, due to timely scheduled preventive maintenance [2,8]. The article proposes a model of an agent estimating the noise level in the BDM, which can be used both for modelling the automatic control system of the BDM and for predicting changes in the noise level and, consequently, the states of the lining. This work was carried out with the financial support of the Russian Foundation for Basic Research (project No. 20-07-00914).

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