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Predicting the Operational Efficiency of High-Pressure Roller Crushers

O. A. Ivashchuk[a], *, O. D. Ivashchuk[a], **, V. I. Fedorov[a], *, and A. I. Shtana[a], ******

[a]Belgorod State University, Belgorod, 308015 Russia
**e-mail: ivaschuk@bsu.edu.ru*
***e-mail: ivaschuk_o@bsu.edu.ru*
****e-mail: fedorov_v@bsu.edu.ru*
*****e-mail: 1335477@bsu.edu.ru*

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Abstract—Models based on regression analysis for predicting the operational efficiency of high-pressure roller crushers are considered. A systematized and structured production database is created and statistically analyzed. The consistency of the data is verified. The parameters with the greatest influence on the productivity are identified. The basic structure of the mathematical models is determined, and the limits on their applicability are assessed. Predictive mathematical models are developed. Their adequacy is verified, and their precision is established in assessing the productivity of mills at an enrichment plant where the mineral composition of the incoming ore varies.

Keywords: high-pressure roller crushers, iron ore, ore crushing, regression analysis, modeling, operational efficiency, prediction

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As the global economy develops, there is growing demand for all kinds of mineral resources, of which the most important is iron ore. By 2024, mineral extraction in Russia will have increased by 10–15% and demand for iron ore will rise from 331 to 380 million t (by 14.8%), according to the predictions in [1].

Enrichment plants process iron ore and produced concentrate with high iron content. The processing costs depend greatly on the crushing of the minerals in special equipment.

The principles for determining the operational efficiency of such equipment and identifying means of increasing the efficiency are well known. Besides traditional methods—based on physicochemical models [2–6] and standard methods of optimal process control [7–11]—smart data analysis may be employed [12–14].

However, problems associated with predicting the operational efficiency of crushing equipment are often superficially discussed. If the assessment of the productivity fails to take account of the ore's mineral composition, which is a key factor, the results are of no practical value.

In that context, we need to develop a reliable method of predicting the productivity of mills with different composition and properties of the incoming ore, on the basis of appropriate research. Satisfactory analysis of the relation between crusher performance and the parameters of the incoming ore permits prediction of the output, which is extremely important in economic planning at enrichment enterprises, especially on switching to different ore.

We have developed models for predicting the operational efficiency of mills at enrichment enterprises on the basis of regression analysis. Specifically, we consider an enrichment enterprise in the Belgorod region, which is known as a world leader in iron production.

The operational characteristics of the mills are collected for primary statistical analysis. A database covering all the necessary parameters is created. Shift and daily data in which even one of the necessary parameters is missing are disregarded.

After verifying that the data are correct and consistent, we eliminate the shift characteristics and create a database solely of daily data. Then this database is divided into four parts containing the general operational characteristics of specific production sections. In each subdivision of the database, days on which the mills operate for less than 24 h are disregarded.

By assessing the pair correlations of the granulometric composition and all the ore-processing parameters with the mill productivity Q, we are able to select the most significant characteristics. For each one, we determine the pair correlation coefficient with the factors Q, $Q^{0.5}$, $Q^{1.2}$, Q^2, Q^3, and $Q^{0.2}$.

Then, in order to derive an adequate regression relation, we eliminate possible multiple correlations. As a result, we select the following parameters: the content (by mass) of specific mineralogical types; the ease of enrichment (W); and the content of the ≤0.045 mm class in the concentrate (C_1). The mineralogical types chosen are micaceous hematite–magnetite (Fe), biotite–hematite (B), and magnetite (M)

To assess the applicability of standard correlation analysis and multiparametric regression analysis, we verify that the model parameters conform to a normal distribution (by means of Statistica 6.0 software). The assumption of a normal distribution is confirmed.

In the next stage, in order to assess the relation between Q and the selected parameters, we analyze the dependences of Q, $Q^{0.5}$, $Q^{1.2}$, Q^2, Q^3, and $Q^{0.2}$ on the corresponding combination of characteristics, in the form $Q^i = A_0 + A_1M^j + A_2(B)^k + A_3W^1 + A_4C_1^m + A_5\mathrm{Fe}^n$, where i, j, k, l, m, and n may take the values 1, 0.5, 1.2, 2, 3, and 0.2; and A_z are the regression coefficients.

The best result for the first data subdivision is $Q^2 = A_0 + A_1M^2 + A_2\left(\frac{B}{M}\right)^2 + A_3W^2 + A_4C_1^2 + A_5\mathrm{Fe}^{3/2}$, with determination coefficient $R = 0.77$.

A dependence of this form is also satisfactory for the second data subdivision. In that case, we may combine the data in these two subdivisions and analyze the resulting aggregate database. The same dependence is obtained, with $R = 0.785$.

After analyzing models with different coefficients, we select a model with the minimum possible mean deviations and the maximum R

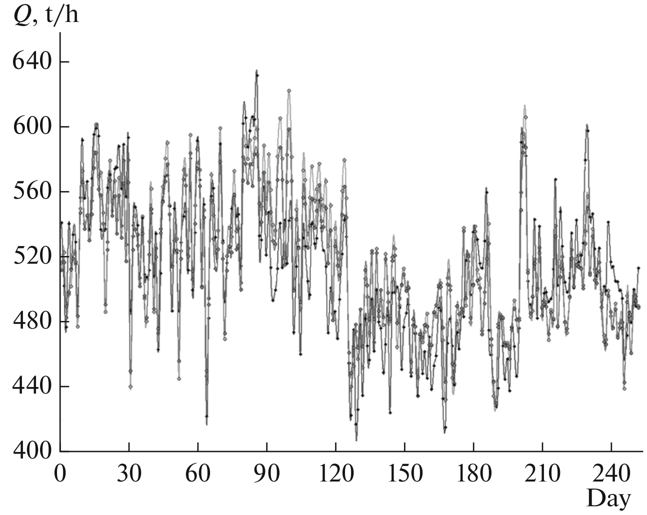

Fig. 1. Mean daily values of the actual productivity and the predicted Q curve for the aggregate data in mill sections *1* and *2*.

$$Q = \sqrt{\left(-3\,280\,533 + 25\mathrm{Fe}^{3/2} + 877W^2 - 58C_1^2 - 15M^2 - 600B^2\right)}.$$

The predicted and calculated Q values are in good agreement for this model: the mean deviation ΔQ_{me} is no more than 0.25%. In Fig. 1, we show the mean daily values of the actual productivity and the predicted Q curve.

Analogously, the regression formula for the third data subdivision is $Q^{3/2} = A_0 + A_1M^{3/2} + A_2(B)^{3/2} + A_3W^{3/2} + A_4C_1^{3/2} + A_5\mathrm{Fe}^{3/2}$.

We obtain the model

$$Q = \sqrt[3]{\left(-94386.8 + 68.6\sqrt[3]{\mathrm{Fe}}^2 + 181.9\sqrt[3]{W}^2 - 30.3\sqrt[3]{B}^2 + 6.0\sqrt[3]{C_1}^2 - 1.3\sqrt[3]{M}^2\right)^2}.$$

The mean deviation ΔQ_{me} is no more than 0.2%.

Since the operational system for these three sections is the same, we may attempt to formulate a common model. However, regression analysis shows that this is unsatisfactory.

For the fourth data subdivision, the best result is $Q^{1/5} = A_0 + A_1M^{1/5} + A_2(B)^{1/5} + A_3W^{2/3} + A_4C_1^6 \times 10^{-8} + A_5\mathrm{Fe}^3$.

The model takes the form

$$Q = \Big(-15.91 + 0.91\times10^{-4}\mathrm{Fe}^3 + 1.274\sqrt[3]{W}^2 - 0.702\times10^{-12}C_1^6 - 0.274\sqrt[5]{M} - 0.169\sqrt[5]{B}\Big)^5.$$

In Fig. 2, we show the mean daily values of the actual productivity and the predicted Q curve for the fourth data subdivision. The mean discrepancy over the period is no more than 0.35%.

With model parameters close to the mean, the regression formulas correspond to the following confidence levels: with 0.95% probability, the actual productivity is within ±1% of the calculated value (around ±2% for the fourth subdivision). However, at the boundaries of this interval, higher values are seen: ±5, ±8, and ±15% for the three models describing all the sections.

As a result, the models are applicable when M = 80.28–89.03, B = 4.77–9.93, W = 67.96–68.27, and C_1 = 72.33–88.63.

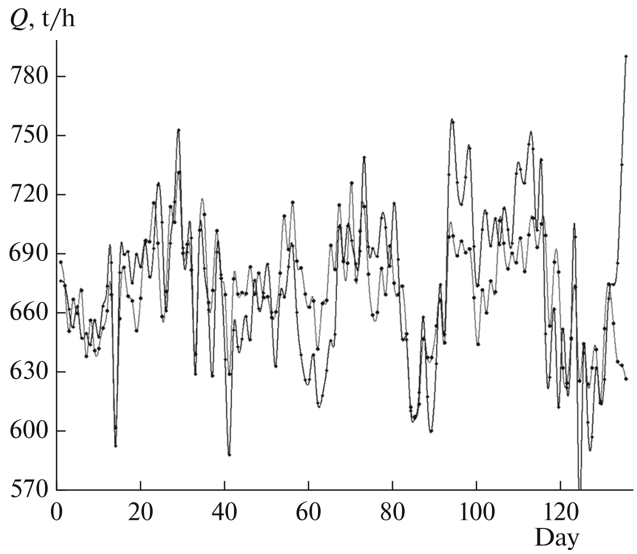

Fig. 2. Mean daily values of the actual productivity and the predicted Q curve for the fourth mill section.

Estimates show that the compliance χ^2 with a normal distribution is no more than 13.5 for all the regression models, with a critical value of 31.

CONCLUSIONS

(1) We have developed mathematical models characterizing the causal relations between the mill productivity at an enrichment enterprise and the mineral composition of the incoming ore and verified their adequacy and accuracy.

(2) We have obtained predictive models of the mill productivity with $R = 0.8$ for the first and second sections; $R = 0.68$ for the third section; and $R = 0.7$ for the fourth. This indicates that the models provide satisfactory predictions.

(3) The proposed models permit effective assessment and prediction of the expected daily mill productivity, which may be used as the main parameter in economic planning of plant output.

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