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A STUDY OF WEAR RATE ESTIMATION OF CASTING PARTS BY SUPPORT VECTOR MACHINE

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ABSTRACT
Abrasive wear is one of the prime and mostly costly causes of secondary failure in the design and operation of mechanical machines and equipment. Wear limits must be known and measured to assure quality and durability of products by an experimental process to determine an optimum material composition. The development of wear monitoring systems for industrial processes is well recognised in the industry due to the continued demand for improved product quality and productivity. In this paper, a novel method of wear rate identification, based on a Support Vector Machine (SVM) is proposed. SVM is used to relate the wear rate and technological parameters of the wear resistant drip moulding. The SVM model for determining the wear rate of white iron casting with a low chromium content, was trained and tested by using the existing exploitation data from the Bor Flotation Plant, Serbia. The simulated results of wear prediction show that the accuracy rate of the SVM is 97%.
Keywords: SVM, wear rate, flotation balls

1. INTRODUCTION
The wear rate of flotation balls depends upon their material, mechanical-chemical characteristics obtained from the casting process and ore composition. The technology of developing flotation balls through hardness (HRC) and chemical composition has an influence on the balls' wear rate. In order to achieve the optimum process of ore milling, it is necessary to establish a relationship between the wear rate and the technological process parameters. For that purpose a Support Vector Machine (SVM) was used [1]. SVM is based on statistical learning theory and is a new achievement in the field of data-driven modelling and has been successfully implemented in classification, regression and function estimation [2]. SVM has been widely used to solve various problems in almost all scientific disciplines [3,4]. SVM requires a database that consists of a finite number of data pairs. In this study, the input database consists of the technological properties of flotation balls and measured wear rate data in the milling process. A database obtained by experimental measurement of the flotation balls’ wear rate, served for algorithm training. A trained algorithm is used for estimating the wear rate of floatation balls with new chemical compositions and mechanical characteristics. For the prediction of the flotation balls' wear rate in the process of copper ore milling, the input data are the balls hardness (HRC) and chemical composition (percentage of C, Si, Mn, Cr), and the output data are the balls wear rate during the milling process.

2. LABORATORY TESTING PROCEDURE

In order to develop an SVM model, measurements of the chemical composition of the flotation balls, as well as their wear rate during ore milling in an experimental mill were carried out. Every xperiment to measure the wear rate of the flotation balls in the laboratory mill was performed with ten balls each with a mass of 850 grams, cast from the same batch, and with the same chemical composition. Rockwell hardness testing of the floating balls was performed by the Rockwell "C" method using a 5006-УХЛ 4.2**,** ТОЧПРИБОРРОСИА aperture. The experimental results gave an average value of hardness measured for all ten balls on a specially prepared surface. Chemical composition measurements were performed by spectrochemical analysis using a METAL-LAB 75/80 (GNR-ITALIA) device.

The milling experiments were carried out to obtain the worn mass of balls per kilogram of milled ore. Milling experiments were carried out in the mill of optimum volumetric filling V=15.2 dm^3 with ϕ60 mm diameter balls (Figure 2). During the experiments, the mass of the new balls at charging was 8.5 kg, and the initial mass of copper ore was 2.5 kg. Additional ore mass of 2.5 kg was added into the mill every 12 minutes. The experiment continued until a sampled ore mass of 500 kg is milled. Based on a repeated set of experiments carried out under the same conditions, 60 experimental results are obtained. The results indicate the abrasive wear rate expressed in grams of worn mass of balls per kilogram of milled ore (g/kg). Figure 2 shows the variation of the wear rate of flotation balls as a function of Rockwell "**C**" hardness.

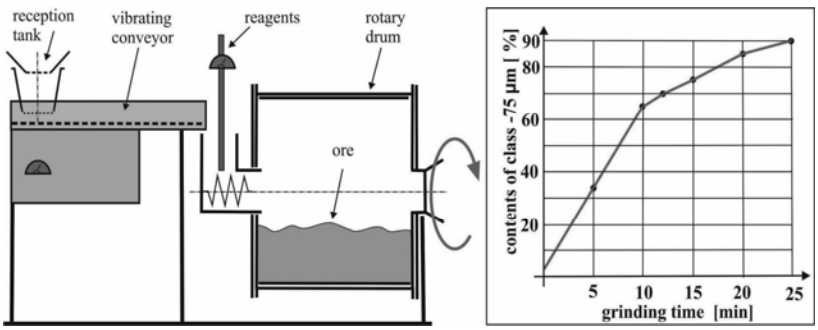

Figure 1. Experimental milling process and milling characteristic.

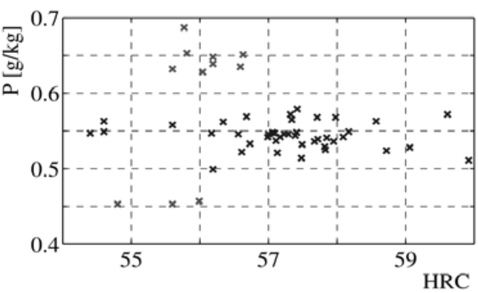

Figure 2. Experimental results: wear rate vs. Rockwell Hardness

3. MODEL IMPLEMENTATION

SVM includes several different functions, such as: classification, regression, and clustering etc., which permits its application in managing different production processes [5]. In this study, the SVM regression function and appropriate learning SVR algorithm are used. The SVR algorithm consists of two phases: the training (off- line) phase, and the test (online**)** phase. Experimental results from Table 1 are used for development of the SVM model. Data from a set of 43 experiments are used for training the SVR algorithms, while another 17 datasets are used for testing the SVR. As shown in Table 1, there is an input vector whose attributes represent the input data of the SVR algorithm (HRC, Cr, Mn, C, Si), and wear rate of flotation balls (P) as an output value.

3.1. Training phase

The SVR algorithm belongs to the class of algorithms where a complete training database is given to algorithm at the beginning of training with the task of detecting the specific relationships of the database set [6]. By detecting this relationship, the learning system is trained for new input data. The SVR algorithm is used for training the parameters of the regression function. In the test phase, the trained regression function is used for the estimation of the flotation balls' wear rate for a new input vector. In the training phase, the algorithm has input data (training dataset from Table 1), as well as appropriate output data that represents the measured values of the wear rate of the flotation balls. Based on these data, the SVR algorithm sets the parameters of the regression function, in order to model an appropriate set of data in the best possible way. Setting the parameters of the regression function actually represents learning about the way of solving the set problem.
Regression function form is:

$$\boldsymbol{f}(\mathbf{x}) = \sum_{j=1}^{l} \beta_j^* k(\mathbf{x}_j, \mathbf{x}) + b^* \tag{1}$$

where: β_j^* - difference of optimum values of Lagrange multipliers, l - number of experimental results for training, b^* - regression function threshold, k -selected kernel function [7].

3.2. Test phase

After parameters optimisation, the regression function is used for estimating the wear rate of the flotation balls for a new input vector (Table 1). Figure 3 shows the comparison of flotation balls' wear rate obtained for the algorithm test dataset, and measured values of wear rate for the same input data. The figure shows the small difference between the flotation balls' wear rate obtained by the developed SVR algorithm and the measured data. Results show that the developed SVM model can be used for accurate prediction of the abrasive wear rate of floating balls.

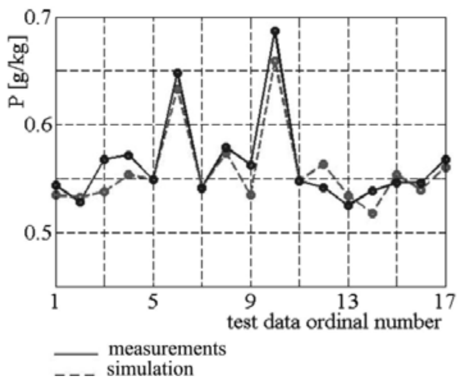

Figure 3. Comparison between measured and simulated flotation balls' wear rate.

The process of development and verification of the SVM model performance is simulated in the Matlab software package using functions svdatanorm, svr and svroutput [8]. In this analysis the mean error was Δ=0.0074, while mean absolute error was |Δ|=0.0125. Using the developed SVM model, wear rate of the flotation balls with hardness of between 55-59 HRC, for two different chemical compositions of melted metal was obtained (Figure 4). Results show that hardness level had a decisive impact on the wear rate of flotation balls: for lower values for hardness, wear rate decreases with the increase in the percentage of Mn in the alloy.

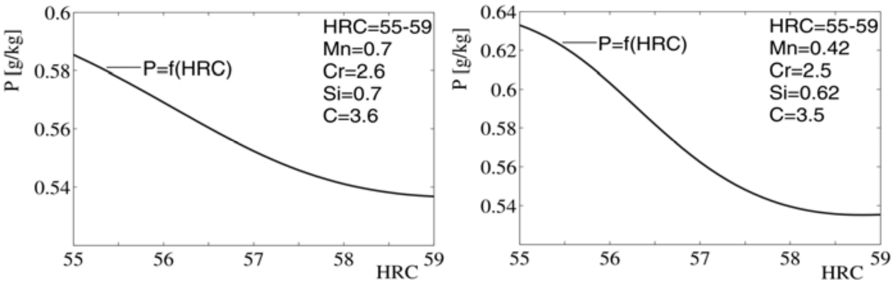

Figure 4. Wear rate of flotation balls vs. hardness (HRC).

4. CONCLUSIONS

An SVM model was constructed to relate the wear rate and technological parameters of the wear resistant drip moulding. The model was tested and used for the prediction of wear rates of floating balls in real operating conditions. The proposed SVM model is capable of accurately predicting the floating ball wear rate. In order to improve the precision of the SVM model predictions, it is necessary to improve the performance of the experimental mill, for determining the wear rate and to achieve higher wear rates with shorter experiment duration. Also, to build an efficient regression model for ball wear estimation, kernel selection methodologies should be explored to find an optimal kernel including the type of kernel and kernel parameters.

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