



The evaluation of grinding process using artificial neural network



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ABSTRACT

Ball milling has been the subject of intensive research for the past few decades. It is indeed the most encountered mineral processing operation of size reduction. Known as the most energy inefficient process, focus has mainly been on ways of reducing the energy consumption incurred by the operation. There are programs for the computer design of mineral processing circuits, and these programs contain computer simulation models for ball mill design. These models need the input of characteristic breakage parameters for the mineral of interest and these are often determined in a small size laboratory ball mill and scaled up by the program to the conditions of a full-scale ball mill. Models and simulators have been used for plant technical analysis since 1970. Some of these models and simulators were developed for mineral processing operations, whereas some were dedicated to mineral processing operations. The prominent work for the mineral processing applications includes JKSimMet, MODSIM© and its derivatives.

A neural network is able to learn complex relationships between related variables and therefore has been widely used as a tool for process modeling. It consists of many simple parallel processing units (called “neurons”), which can resemble the architecture of the human brain, and thus is capable of learning arbitrary nonlinear mappings between noisy sets of input and output factors.

The grindability properties of the calcite sample belonging to the Muğla region were investigated at batch grinding conditions based on a kinetic model. The obtained kinetic model parameters were used to estimate the product size distribution by artificial neural networks (ANN). Then, the experimental and neural network prediction results were compared.

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1. Introduction

Comminution is a process step for a wide range of industries including cement, ceramics, pharmaceuticals, paper, pigments, and minerals. Many industrial surveys have established that a significant portion of the total cost of metal production is expended in the comminution processes. The grinding operation in a ball mill is a capital- and energy intensive process. Hence, a marginal improvement in the efficiency of mill operation will be of immense economic benefit to the industry (Datta and Rajamani, 2002).

Ball milling has been the subject of intensive research for the past few decades. It is indeed the most encountered mineral processing operation of size reduction. Known as the most energy inefficient process, focus has mainly been on ways of reducing the energy consumption incurred by the operation. Perhaps the most important point is that the choice of ball size or ball size mixes to be used is dictated by some form of experience. Moreover, it is difficult to compare two

different scenarios especially if the specifications on the product from the mill are different (Katubilwa et al., 2011).

A mineral processing plant simulator is a set of computer programs that provides a detailed numerical description of the operation for an ore dressing plant. The simulator must be provided with an accurate description of the ore that is to be processed, a description of the flowsheet that defines the process and an accurate description of the operating behavior of each unit operation included in the flowsheet. The simulator uses these inputs to provide a description of the operating plant.

These basic concepts are independent of the precise nature of any particular plant that must be simulated. They lead to the development of simulation software that can be used for all possible plant configurations. The availability of such general purpose software makes computer simulation as a useful practical tool in everyday engineering. It is a difficult task to write the necessary computer code to simulate a complex ore dressing plant. Most engineers have neither the time inclination nor skill to do so and it would not be cost effective to write the code for each application. The cost in man hours to generate the code and debug it so that it can run reliably would be enormous. Computerization of any complex engineering systems is a highly specialized task and this

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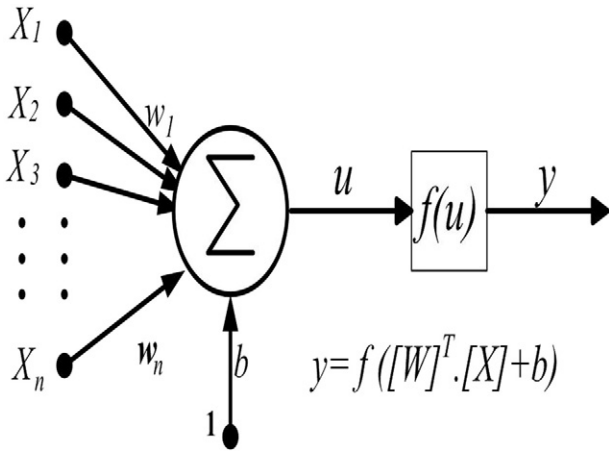


Fig. 1. The basic model of a neuron.

is true also in mineral processing and other such activities should be attempted only by specialists (King, 2001).

Models and simulators have been used for plant technical analysis since the 1970s. Some of these models and simulators were developed for mineral processing operations, whereas some were dedicated to mineral processing operations. The prominent work for the mineral processing applications includes JKSimMet (JKTech, JKSimMet, 1989), MODSIM© (King, 2001; Yan and Eaton, 1994) and its derivatives.

A neural network has been used to address complex and irregular features of nonlinear systems, and has been applied to expert systems in various fields with proven advantages and improved predictions in many applications (Brown and May, 2005; Han and Wang, 2009; Duarte et al., 2001; Li and Park, 2009; Pacella and Semeraro, 2007; Karacan, 2008; Mansa et al., 2008). Using time-series data and multivariate analysis, a neural network was used to predict the real time system and detect faulty operation (Hong and May, 2004). A neural network is able to learn complex relationships between related variables and therefore has been widely used as a tool for process modeling. It consists

of many simple parallel processing units (called “neurons”), which can resemble the architecture of the human brain, and thus is capable of learning arbitrary nonlinear mappings between noisy sets of input and output factors. Neurons in the network are interconnected such that the knowledge is stored in the weighted connections between them. Networks consist of several layers of neurons that receive, process, and transmit critical information regarding the relationships between the input variables and corresponding responses (as in Fig. 1). Each neuron contains the sum of its weighted inputs filtered by a nonlinear sigmoidal transfer function (Behzadi et al., 2009). The networks incorporate “hidden” layers of neurons that do not interact with the outside world, but assist in performing such tasks as classification and feature extraction for the information provided by the input and output layers.

The grindability properties at different powder filling ratios of calcite sample belonging to the Muğla region was investigated at batch grinding conditions based on a kinetic model. For this purpose, firstly, five different mono-sized fractions were prepared between 1.7 mm and 0.106 mm. S_i and $B_{i,j}$ (selection and breakage distribution functions) equations were determined from the size distributions at different grinding times and the model parameters (S_i , a_b , α , γ , β and ϕ_j) for different powder filling ratios. The objective of the present study is to analyze the experimentally determined data and to compare the statistically obtained data using model parameter from outputs of neural network model.

2. Theory

2.1. Kinetic model

When breakage is occurring in an efficient manner, the breakage of a given size fraction of material usually follows a first-order law (Austin et al., 1981, 1984). Thus, the breakage rate of material that is in the top size interval can be expressed as:

$$\frac{dw_1}{dt} = S_1 w_1(t) \tag{1}$$

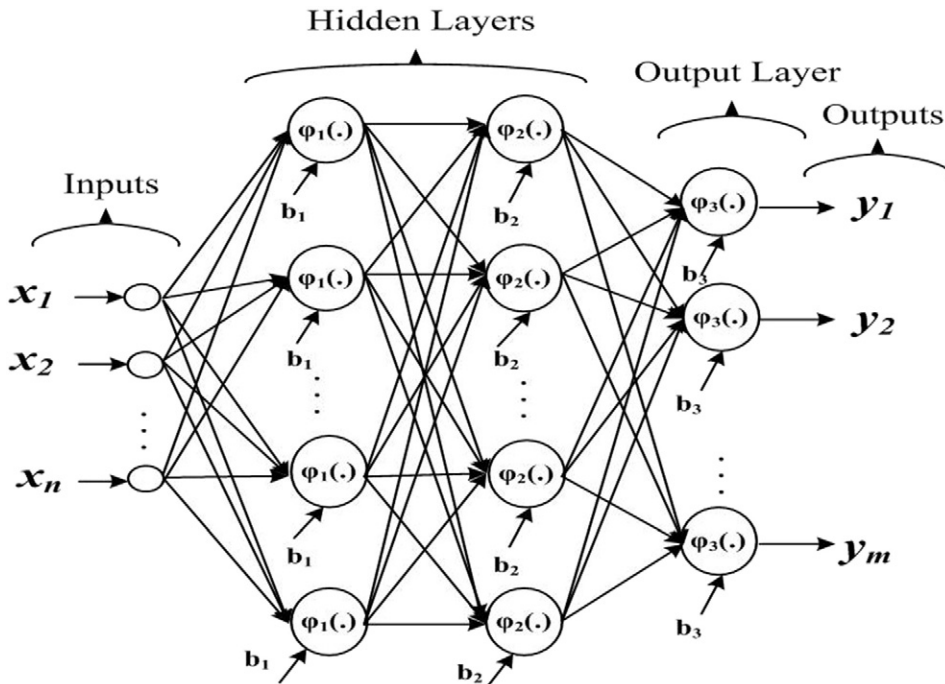


Fig. 2. Structure of 2-hidden layer MLPNN.

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