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A parametric cost model for mineral grinding mills

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ABSTRACT

The adequate cost estimation of mill plants plays a crucial role in the success of feasibility studies of mining projects. Grinding is one of the most important operations in mineral processing plants and assumes a substantial share of the total milling costs. The objective of this work was to develop a set of cost functions for major grinding mill equipment. These cost models were developed using two relatively different techniques: uni-variate regression (UVR) as well as multivariate regression (MVR) based on principal component analysis (PCA). The first is appropriate for the quick estimation of costs in the early stages of project evaluation, while the second method can be helpful in the feasibility study stage. The explanatory variable in UVR was power (P), while in MVR the power and some other variables depending on the type of mill were used. The PCA technique was employed in order to omit the correlation between the independent variables in the multivariate regression. Furthermore, the scale-up factor for all mills has been calculated. The result of the evaluation of the models showed that the mean absolute error rates were less than 9.84% and 11.36% on average for the capital and operating costs of the uni-variate model, and 5.82% and 4.9% for the multivariate model, respectively.

1. Introduction

Before initiating a mining project a feasibility analysis is a key step in ensuring that the project is technically feasible, cost-effective and profitable. Consequently it is essential to identify the cost factors, which can be classified as capital and operating costs. The costs of each item are required in order to inspect the authorization of project progress (Pascoe, 1992). The overestimation or underestimation of these costs can result in a failure of project investment (Niazi et al., 2006); overestimation could result in a potentially profitable project not progressing ahead, while underestimation may cause an unviable project going progress and fail. Therefore, due to the lack of information at the initial stages of the project, the correct estimation of costs is very difficult (Gwang-Hee et al., 2004). A number of cost estimation models have been developed for this purpose. Cost models could also be implemented in the simulators which are used in plant design and optimization. Connecting models of unit operations built in the design and optimization simulators (such as MODSIM) to equipment cost estimations requires the "cost models".

Regression is among the most professional common techniques used to build appropriate cost models (Smith and Mason, 1997). Researchers including Prasad (1969), Mular (1982, 1998), Daud (1979), Stebbines (1987), Petrick and Dewey (1987), O'Hara (1980), O'Hara and Suboleski (1992), Redpath (1986), Camm (1994) and Noakes and Lanz (1993) and others have attempted to offer appropriate cost estimation models in mining and mineral processing. Almost all of them have employed exponential uni-variate regression approaches, only correlating one decision variable to a cost value (Stebbins, 1987).

Hence, despite the importance of these models in preliminary capital and operating cost estimation, the role of other effective independent variables has simply been ignored. Some of these models have now become obsolete, and updating them may also cause considerable errors. Therefore it seems that multivariate regression based on up-to-date data is the best solution for providing adequate cost estimation models.

In this research, an attempt has been made to provide two sets of univariate and multivariate regression functions for the estimation of the capital and operating costs of grinding mill equipment in mineral processing plants based on up-to-date cost data, since the comminution system contributes to about 60% of the total capital cost in concentrator equipment, 40–50% of the total operating costs, and more than 60% of the total energy consumption in processing factories (Wenzheng, 1991). Although the costs vary from mine to mine, grinding could contribute about 90% of total operating costs of comminution (Wills and Tim, 2011) and therefore estimation of costs for this section is vital.

In the next section, the specification of six main types of mills are introduced as the data structure, and also the procedure of

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regression modeling for uni-variate and multivariate regression is described. In Section 3, the ultimate cost model is provided. Furthermore, the statistical significance of the model is inspected.

2. Methodology

2.1. Data structure

A set of technical and economical data for six main types of mill, operating in mill plants in the United States, have been gathered (InfoMine Inc., 2007, 2010). Data has been classified on the basis of cost types; capital and operating and are escalated to 2010 US dollar. The capital cost (Cap.) is based on US dollars while the operating cost (Op.) is provided based on US dollars per hour. The operating cost included overhaul (parts and labor), maintenance (parts and labor), lubrication, and wear parts (such as liners and grinding media) for all mills. The overhaul cost includes both overhaul parts and labor, associated to scheduled refurbishing or replacement of major wear components such as drives, support frames, and vessels. The maintenance cost item also consists of the both maintenance parts and labor, which represents those costs associated with both unscheduled repairs and scheduled servicing of both minor and major components, excluding overhaul activities. These include all aspects of machine maintenance exclusive of fueling, lubrication, tire replacement and maintenance and replacement of those parts used directly to impart energy. It should be noted that the definite cost associated to maintenance will depend on some parameters such as ore type and abrasiveness.

Meanwhile, the cost of the operator's time is not incorporated here. Our database and consequently the developed models cover mills with separate motors (except for the tower mill) and therefore the cost of purchasing and operating the motors (including the cost of energy) has not been considered. It also implies that costs of mills with integral motors (as in wraparound drives) cannot be estimated with the developed models. The capital and operating costs of motors are usually estimated separately from the other costs of the mills. Particularly, the operating cost of energy depends on the real throughput and efficiency of equipment and also the properties of the material being ground (such as hardness). Bond's method or empirical models could be used to estimate the real consumption of energy and then the cost could be evaluated.

Before modeling the costs, the relative shares of each operating cost item were investigated (Fig. 1). In the rod, ball (wet and dry) and tower mills, the wear part has the highest share and maintenance ranks second, but in the roller mill and the SAG mill this is reversed. The lubrication item has the lowest share for all mills, as can be seen in Fig. 1.

Technical parameters of the six considered mills with their statistics are presented in Table 1. All dimensions are in meters (m) and power (P) is in kilowatts (kW). The range of power of the mills (Table 1) used in the model development should be considered in order to not extrapolate the models too much.

2.2. Regression modeling procedure

The scheme of the modeling process is presented in Fig. 2. All the steps were carried out until the adequacy of the models was accepted. The final models were tested with performance evaluations such as residual analysis, lack of fit testing, and examination of the effects of influential points. Moreover the MAER (Mean Absolute Error Rate) measure was used as a means of comparison between the models. The MAER is defined as follows (Kim et al., 2004):

$$\mathrm{MAER} = \frac{\sum \left| \left(\frac{C_e - C_a}{C_a} \right) \times 100 \right|}{n} \tag{1}$$

where C_e is the estimated mill costs, C_a is the actual (from the database) mill costs, and n is the number of data used in regression model building.

2.2.1. Uni-variate regression

After choosing the regressor variables, the structure of the model should be selected. Cost models of mineral grinding mills have historically applied the power function platform (Mular, 1982, Mular and Poulin, 1998; Pascoe, 1992). In these models, the mill power has been selected as the explanatory variable.

Here, considering power (P) as the regressor variable, different mathematical functions have been examined using the MATLAB curve fitting toolbox. Among all the functions tested, the power function in the form of Cost = $a(\text{power})^b$ showed more consistency with the data, where a and b are constants determined by regression analysis.

By approving the power function it is possible to give a preliminary cost estimation in terms of the "scale-up factor". The earliest mention of this concept was found in 1947 as the "rule of six-tenths (Williams, 1947). Based on this rule the approximate costs can be obtained, if the cost of a similar item of a different size or capacity is known. The following equation shows the scale-up function (Ramer et al., 2008).

$$Cost_2 = Cost_1 \times \left(\frac{S_2}{S_1} \right)^{Se} \tag{2}$$

where $Cost_2$ is the approximate cost ($) of equipment of size S_2 (cfm, Hp, ft^2, or suchlike), $Cost_1$ is the known cost ($) of equipment of corresponding size S_1 (same units as S_2), and S_2/S_1 is the ratio known as the size factor (dimensionless). Se in this equation is the scale-up factor which is obtained based on power (b) in the cost's uni-variate function. In this research the size factor is based on mill power as P_2/P_1. The usage of P is common in equipment selection, since based on the knowledge of the equipment's power estimating the capacity is easier.

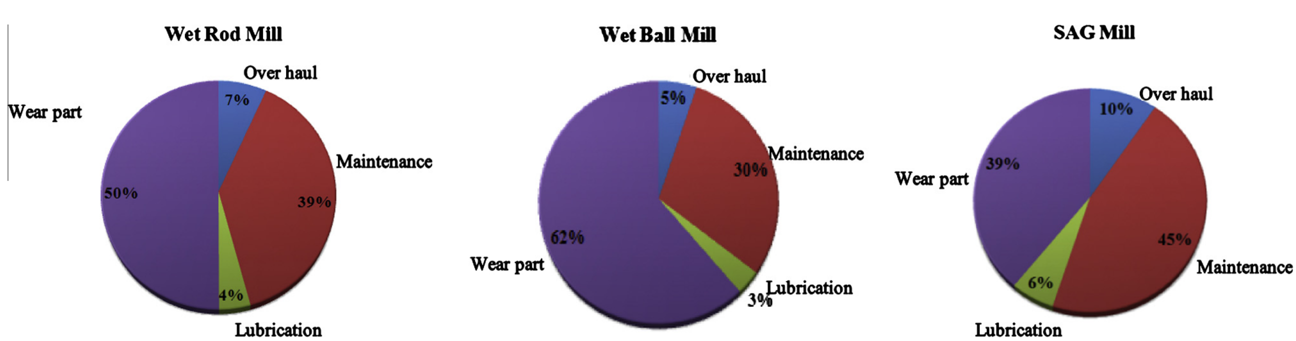

Fig. 1. Relative share of each operating cost item.