Cost modelling for flotation machines

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Synopsis

Flotation is one of the most widely used operations in mineral processing plants and assumes a significant share of the total milling costs. The purpose of this paper is to introduce a new set of capital and operating cost models for major flotation machines based on the application of single (SRA) and multiple regression analysis (MRA). Thirty-seven major flotation machines were analysed for this purpose. Depending on the machinery type, different technical variables such as diameter, required air flow rate, required floor space, cell volume, required air pressure, and power were considered as predictor variables, individually (in SRA) or simultaneously (in MRA). Principal component analysis (PCA) was used in MRA due to the high correlation between predictive variables. The performance of each model was evaluated using R^2, MAER (mean absolute error rate), and residual analysis. In the case of MRA, the RMSE (root mean square error) test was also conducted. Maximum obtained MAER of 13.5% and minimum R^2 of 0.86 indicated that these models could be applied as credible tools in estimation of capital and operating costs of flotation machines for design and feasibility studies.

Keywords

cost estimation, flotation machine, regression model, principal component analysis.

Introduction

Mineral processing is a vital part of mining projects and mainly involves comminution, sizing, concentration, extractive metallurgical processes, and dewatering. Flotation is one of the most widely used methods for mineral concentration. Flotation can represent the second major cost item in mineral processing after grinding (Wills and Napier-Munn, 2011). Accordingly, it is a main concern of mining project managers to select and optimize flotation circuits in order to decrease costs and increase productivity. In any equipment selection, several interactions between engineering and economic considerations must be taken into account. Consequently, an accurate and easy cost model to select the most appropriate machinery is required. Moreover, cost models could be used in flow sheet simulations applied in design and optimization. Models of unit operations built into the simulators could be improved by linking the equipment cost models (Khalesi et al., 2015).

A number of approaches can be employed with the aim of developing the cost models. A review of these methods can be found in recent papers by Niazi et al. (2006) and Huang, Newnes, and Parry (2012). Regression is one the most frequently applied techniques for cost modelling (Smith and Mason, 1997). Several cost models have been established related to mining and milling projects (Table I). One of the preliminary works was undertaken by Prasad (1969) and has been carried on in the recent work of Sayadi, Khalesi, and Khosfarman (2014). Almost all of these models have been developed based on exponential single regression approaches; correlating only one independent variable to a cost value (Stebbins, 1987). Consequently, in spite of the usefulness of these models in preliminary cost estimation, the role of other effective parameters has simply been overlooked. Some of these models have become old and updating them also may cause significant errors. Furthermore, these models mainly estimate total operating cost, and estimation of detailed operating cost items such as maintenance, lubrication, etc. is not possible. To overcome these deficiencies, this paper aims to introduce up-to-date capital and detailed operating cost models considering multiple effective factors of flotation machines. Two sets of single (SRA) and multiple regression (MRA) cost functions are presented. The first set is suitable for cost estimation at the initial phases of a project and is mainly appropriate for building rapid cost estimates where only one particular design factor of a flotation machine is accessible. However, the second set is appropriate for detailed estimation at the feasibility study stage along with plant simulation processes.

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Table I

A brief history of cost estimation in mining and milling projects

Author	Year	Theme
Mohutsiwa and Musingwini	2015	Parametric capital costs estimation for coal mines in South Africa
Sayadi *et al.*	2014	Parametric cost modeling for mineral grinding mills
Lashgari and Sayadi	2013	Overhaul and maintenance cost of loading equipment in surface mining
Sayadi *et al.*	2012	Estimating capital and operational costs of backhoe shovels
Sayadi *et al.*	2011	Hard-rock LHD cost estimation using regression techniques
McNab	2009	Simplified cost estimation for processing of iron ores
Loh *et al.*	2002	Processing equipment cost estimation
Mular	1978	Estimation of capital costs of mining and mineral processing equipment using regression analysis
Mular	1982	Estimation of capital costs of mining and mineral processing equipment using regression analysis
Mular and Poulin	1998	Estimation of capital costs of mining and mineral processing equipment using regression analysis
Camm	1994	Cost modeling for mine and mill
Noakes and Lanz	1993	Estimating the costs of mining and milling industry, using graphical or formulation methods
O'Hara	1980	Development of a set of cost formulas as estimators of capital and operating costs of mining and milling
O'Hara and Suboleski	1992	Development of a set of cost formulas as estimators of capital and operating costs of mining and milling
Pascoe	1992	Capital and operating costs of minerals engineering plants
USBM	1987	Estimation of mining and milling costs using regression analysis
Prasad	1969	Mineral processing plant design and cost estimation

Table II

Data description of flotation machines

Item				Min	Max	Mean	Standard deviation
Column	Sulfide	Variables	Diameter (m)	0.91	4.00	2.28	0.95
			Required air flow rate (m³/min)	8.50	850.00	212.97	261.18
		Costs	Capital (US$)	112600	393700	224558	78526
			Operating (US$/h)	3.25	11.36	6.48	2.27
	Coal	Variables	Diameter (m)	2.4	4.3	3.35	0.82
			Required air flow rate (m³/min)	850	3398	1876.25	1152.20
		Costs	Capital (US$)	179200	289400	240200	45801
			Operating (US$/h)	5.17	8.35	6.92	1.32
Self-aerating		Variables	Cell volume (m³)	0.31	85	17.20	26.22
			Required floor space (m²)	0.83	23.2	7.56	7.44
			Power (kW)	2.23	149.14	35.96	46.56
		Costs	Capital (US$)	17800	279900	74372.73	77819
			Operating (US$/h)	0.51	8.07	2.14	2.24
Standard		Variables	Cell volume (m³)	0.28	158.6	35.64	52.87
			Required air flow rate (m³/min)	0.42	85	21.11	28.42
			Air pressure required (kP)	10.34	103.42	32.95	31.29
			Power (kW)	1.11	149.14	35.94	48.79
		Costs	Capital (US$)	17600	302600	100580	95962
			Operating (US$/h)	0.51	8.73	2.89	2.77

Methodology

Data

Thirty-seven major flotation machines (16 columns, 11 self-aerating, and 10 standard cells) are considered in this study. The data descriptions are presented in Table II (InfoMine, 2013). InfoMine conducts annual surveys on costs of equipment from manufacturers and distributors; fuel, energy, and lubricant suppliers; and US mining companies and provides the data without mentioning the manufacturers' names:

➤ Column flotation: based on 36-foot, mild steel column, includes automatic sparger system, wash water system, and level control
➤ Self-aerating cells: individual cells based on a 10-cell row and including paddles, feed boxes, junction boxes, discharge boxes, skimmer drives, and motor guards, but not motors or launders
➤ Standard cells: individual cells based on a 10-cell row and including paddles, feed boxes, junction boxes, discharge boxes, skimmer drives, and motor guards, but not motors, blowers, and launders.

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The data contained technical and cost specifications of the machines. Technical parameters were diameter (D), required air flow rate (AF), cell volume (CV), required floor space (FS), required air pressure (AP) and power (P) depending on the type of flotation machine (Figure 1). These parameters were individually or simultaneously used as predictor variables in cost models.

Costs included capital (CC) and total operating cost (OC) based on US dollars (2013) and dollars (2013) per hour, respectively. Moreover, the operating costs could also be estimated in detail, *i.e.* the overhaul (parts and labour), maintenance (parts and labour) and lubrication cost items. The operating costs data is provided based on certain unit costs in the USA in 2013: electrical power, lubricant and repair labour were assumed as 0.076 US\$ per kWh, 3.32 US\$ per litre, and 37.57 US\$ per hour, respectively.

The overhaul costs (including both parts and labour) are those associated with scheduled refurbishing or replacement of major wear parts. Likewise, the maintenance costs (including both parts and labour) are associated with both unscheduled repairs and scheduled servicing of all of minor and major components, excluding overhaul actions and lubrication. The cost of operator's time was not included in this study. The data and therefore the developed models represent flotation machines with separate motors. The costs of motors are generally estimated separately. Here, for ease of use of the models, separate capital and operating cost functions for variable-speed DC motors are provided later.

Statistical approach

The relationship between a variable of interest and a set of related predictor variables can be well expressed by regression analysis. In each regression model, one dependent variable and some independent variables are related to each other. The regression is called single regression (SRA) if just one independent variable exists, while in multiple linear regression (MRA) several independent variables are correlated to the dependent variable. In this regard, independency of regressors (so-called independent variables) is a must. Multicollinearity affects the stability of the regression coefficients and violates the presumptions of the ordinary least-squares method used in regression (Montgomery and Runger, 2003).

In this paper, both single and multiple regression analysis were conducted on the data. MATLAB software was used in order to evaluate different univariate structures for capital
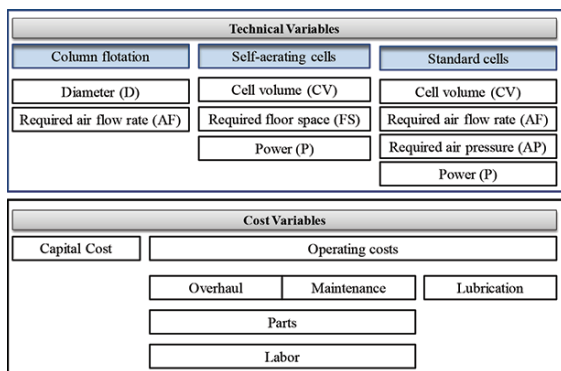
and operating costs and as a result, the power function framework of Equation [1] was chosen for the univariate model:

$$Y = aX^b \qquad [1]$$

where Y refers to capital or operating costs, X defines an independent variable (one of the machine predictor variables), and a and b are constant values (parameters) of the models.

In the case of multivariate models, the multiple linear regression framework (Equation [2]) showed promise in this research, based on testing different model structures and also on previous works (Sayadi, Khalesi, and Khosfarman, 2014).

$$Y = C + a_1 x_1 + a_2 x_2 + \ldots + a_n x_n \qquad [2]$$

where x_i defines independent explanatory variables and a_i are regression coefficients (model parameters). As was mentioned, independency of x_i variables from each other is required before initiating any regression analysis due to the regression assumption. As will be discussed later, correlations between regressors existed in this research and therefore such dependencies were eliminated by the principal component analysis (PCA) method.

For evaluation of the SRA models, R2, RMSE (root mean square error), and MAER (means absolute error rate) were carried out. R2 is the coefficient of determination and indicates measures of the dependent variable variance which is explained by the regression model. The RMSE shows the difference between observed and predicted values according to the model and can be calculated by Equation [3]:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{e,i})^2}{n}} \qquad [3]$$

where X_{obs} is the observed value, x_e the estimated value at time/place I, and n, is the number of observations.

For evaluation of the MRA models, analysis of residuals, tests of MAER values and evaluation of R2 were conducted. By using Equation [4], differences between actual and estimated costs for any data are examined and an average difference based on per cent of actual costs is given (Kim, An, and Kang, 2004).

$$MAER = \frac{1}{n}\sum_{i=1}^{n}((C_{e_i} - C_{a_i})/C_{a_i}) \qquad [4]$$

where C_e is the estimated cost, C_a the actual cost, and n the number of data. MAER values should be in low levels as much as possible.

Principal component analysis

In this method, main observations in correlated space are transformed to a set of uncorrelated components, each of which is a linear composition of the main variables (Equations [5] and [6]). The new uncorrelated variables are called principal components (PCs). As can be seen in Figure 2, neither X_1 nor X_2 is the main direction of the data, while the ellipse with main diameters PC_1 and PC_2 matches the direction of the data. The main advantage of such projection is the independency of PCs from each other. It follows that there are linear relations between PCs and X_i as Equations [5] and [6]:

$$PC_1 = w_1 X_1 + w_2 X_2 \qquad [5]$$

Figure 1—Variables of flotation machines
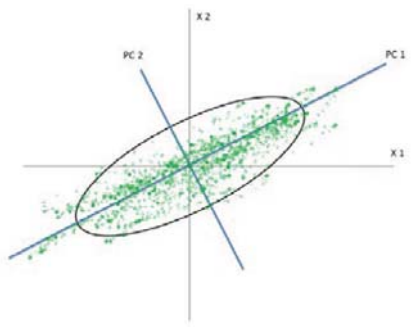
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Figure 2—PCs axis *vs.* main axis

$$PC_2 = w_1 X_1 + w_2 X_2 \qquad [6]$$

In this research, main variables of X_1, X_2 ... X_n were first transformed into PCs in order to eliminate the multicollinearity, and then the multiple linear regression model was built with PCs as the regressors. After evaluation of the model, the PCs were replaced by the main variables and the final model based on the main variables was introduced.

Steps of development of MRA models

To clarify the steps by which multivariable costs models have been obtained, the development of capital cost function for the column sulphide flotation machine (CSFM) is presented here as an example. Table III illustrates the high correlation between predictor variables for the CSFM.

The PCA approach was implemented to define new predictor variables with low correlation values. Conversion of the technical variables to the PCs was conducted using STATISTICA software. Table IV shows the main variables and the new generated PCs of the CSFM together, while Table V demonstrates the correlation matrix of the new PCs. As can be seen, the new PCs are completely independent from each other and therefore multiple regression models can be built using PCs as regressors.

Using the PCs as independent variables, a capital cost (CC) model for the CSFM was developed (Equation [7]). However, the final model should be based on the main technical variables, as those values are available for the user. Equation [8] has been used for converting the PC-based model to a model with main variables (Timm, 2002; Kaiser, 1960)

$$CC = 224\,558.3 + 54\,288.25\ PC_1 + 40\,724.7\ PC_2 \qquad [7]$$

$$Y = X_i \left(\frac{\alpha_i}{S_{i,x}} \right) - \sum \left[(\alpha_i . X_{i,ave}) / S_{i,x} + C \right] \qquad [8]$$

where X_i are main technical variables (like power or required air), α_i are calculated by multiplication of coefficients of the model based on PCs as predictors by the eigenvectors of PCs (as illustrated in Figure 3), S_{ix} and $X_{i,ave}$ are the standard deviation and mean of main variables, respectively (can be found from Table II) and C refer to constant value of PC-based model (here 224 558.3). Equation [9] shows the final capital cost model for the CSFM.

$$CC = 55\,057.22 + 70\,938.63D + 36.72AF \qquad [9]$$

Results and discussion

Single regression results

Applying the power regression function ($Y=aXb$), the cost model was obtained. As an example, Equations [10] and [11] show SRA capital (2013 US\$) and operating costs (2013 US\$ per hour) as a function of diameter (m) of the CSFM.

$$CC = 11\,8226.4D^{0.791} \qquad [10]$$

Table III

Correlation between technical variables) CSFM)

Correlations
Marked correlations are significant at p < 0.05000
N=12 (Casewise deletion of missing data)

	Mean	Std. dev.	Diameter	Required air flow rate
Diameter	2.2792	0.9471	1.000 000	0.931 963
Required air flow rate	212.9667	261.1806	0.931 963	1.000 000

Table IV

Technical variable values *vs.* generated PCs (CSFM)

X_1 (D)	X_2 (AF)	PC_1	PC_2
0.91	8.5	-1.57 581	-0.468 686
1.22	11.3	-1.33 678	-0.244 814
1.52	22.7	-1.08 193	-0.051 691
1.68	50.1	-0.88 829	-0.006 414
1.82	68	-0.73 530	0.049 652
2.1	102	-0.43 419	0.166 656
2.3	136	-0.19 282	0.223 930
2.4	170	-0.02 611	0.206 542
2.7	227	0.35 220	0.276 210
3.0	312	0.80 631	0.270 071
3.7	598	2.10 324	0.018 404
4.0	850	3.00 948	-0.439 861

Table V

Correlation coefficients between PCs of CSFM

Correlations marked correlations are significant at p < .05000 N=12 (casewise deletion of missing data)

	Mean	Std. dev.	PC_1	PC_2
PC_1	0.0	1.389 951	1.0	0.0
PC_2	0.0	0.260 839	0.0	1.0

$$\begin{array}{c} \text{Eigenvectors} \\ \begin{bmatrix} 0.707\,107 & 0.707\,107 \\ 0.707\,107 & -0.707\,107 \end{bmatrix} \end{array} \begin{array}{c} \text{PC} \\ \text{Coefficient} \\ \begin{bmatrix} 54\,288.25 \\ 40\,724.7 \end{bmatrix} \end{array} = \begin{array}{c} \text{Final} \\ \text{Coefficient} \\ \begin{bmatrix} 70\,938.47 \\ 36.721\,85 \end{bmatrix} \end{array}$$

Figure 3—Final model coefficient generation

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$$OC = 3.41D^{0.790} \qquad [11]$$

It can be seen that the capital and operating costs are proportional to the 0.791 and 0.790 power of diameter in the case of the column sulphide flotation machine. The R^2 is about 0.94 for both cases, *i.e.* 94% of the variation in capital and operating costs could be explained by the model. Tables VI to IX demonstrate results for the machines modelled in this research.

Multiple regression results

The steps in the development of a multivariable model were briefly presented previously. As was mentioned, the validity of regression models like Equation [9] were tested by different statistical approaches. Figure 4 shows the residuals of the capital cost model of the CSFM, confirming their correct normal distribution. Table X represents the coefficients of the final MRA models (a_1, a_2, a_3) and new intercept (a_0) along

Table VI

Single regression analysis for column (sulphide) flotation machine (CSFM)

Explanatory variable	Model description	Capital cost	Operating costs							Lubrication cost
			Total operating cost	Overhaul			Maintenance			
				Parts	Labour	Total	Parts	Labour	Total	
Diameter (m)	a	118 226.4	3.410 613	0.493 788	0.462 357	0.914 055	0.914 055	0.861 211	1.7752	0.673 749
	b	0.791 01	0.790 883	0.790591	0.795 579	0.791 869	0.791 869	0.792 835	0.7923	0.793 598
	R^2	0.9379	0.9377	0.9391	0.9375	0.9369	0.9369	0.9387	0.9378	0.9383
	MAER	4.86	4.88	4.77	4.86	4.83	4.83	4.85	4.84	4.82
	RMSE	113.90	0.61	0.23	0.23	0.32	0.32	0.31	0.44	0.27

Table VII

Single regression analysis for column (coal) flotation machine (CCFM)

Explanatory variable	Model description	Capital cost	Operating costs							Lubrication cost
			Total operating cost	Overhaul			Maintenance			
			Parts	Labour	Total	Parts	Labour	Total		
Diameter (m)	a	95 523.91	2.754 794	0.4006	0.3691	0.7697	0.74 194	0.7013	1.4433	0.543 649
	b	0.765 573	0.765628	0.7614	0.7780	0.769 50	0.76 200	0.7603	0.76 122	0.76 731
	R^2	0.9284	0.9290	0.9282	0.9285	0.9284	0.9315	0.9271	0.9294	0.9246
	MAER	11.63	11.45	12.02	11.89	11.64	11.80	11.53	11.66	11.53
	RMSE	94.46	0.51	0.19	0.19	0.27	0.26	0.26	0.36	0.23

Table VIII

Single regression analysis for self-aerating flotation machine (SAFM)

Explanatory variable	Model description	Capital cost	Operating costs							Lubrication cost
			Total operating cost	Overhaul			Maintenance			
				Parts	Labour	Total	Parts	Labour	Total	
Cell volume (m^3)	a	23 907.727	0.690	0.098	0.092	0.190	0.186	0.175	0.361	0.137
	b	0.469	0.469	0.474	0.474	0.474	0.467	0.467	0.467	0.469
	R^2	0.8655	0.8655	0.8671	0.8700	0.8685	0.8611	0.8624	0.8618	0.8665
	MAER	11.63	11.45	12.02	11.89	11.64	11.80	11.53	11.66	11.53
	RMSE	110.92	0.59	0.23	0.22	0.31	0.31	0.30	0.43	0.26

Table IX

Single regression analysis for standard flotation machine (SFM)

Explanatory variable	Model description	Capital cost	Operating costs							Lubrication cost
			Total operating cost	Overhaul			Maintenance			
				Parts	Labour	Total	Parts	Labour	Total	
Cell volume (m^3)	a	25 351.280	0.715	0.103	0.101	0.174	0.196	0.185	0.381	0.146
	b	0.452	0.457	0.460	0.449	0.496	0.452	0.453	0.452	0.450
	R2	0.9561	0.9571	0.9618	0.9541	0.9776	0.9561	0.9561	0.9561	0.9552
	MAER	10.82	11.99	9.93	10.91	15.55	10.90	10.55	10.73	10.56
	RMSE	108.32	0.58	0.21	0.21	0.27	0.30	0.29	0.42	0.26

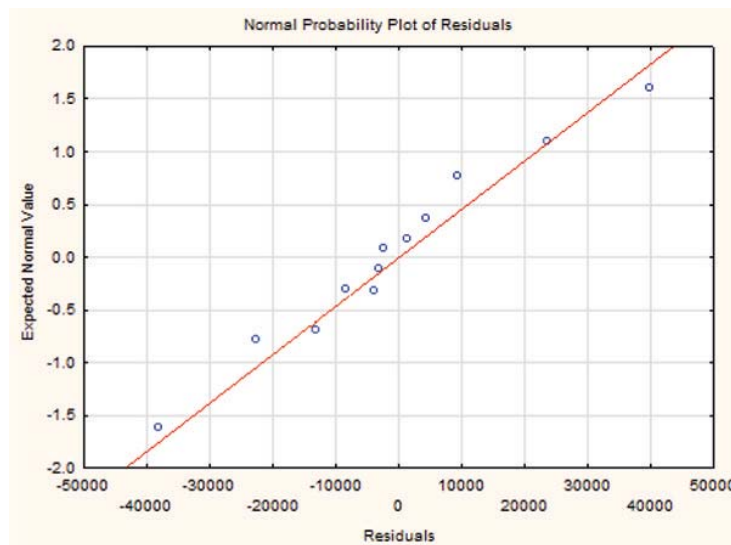# Cost modelling for flotation machines

Figure 4—Residual analysis for MVR capital cost of the CSFM
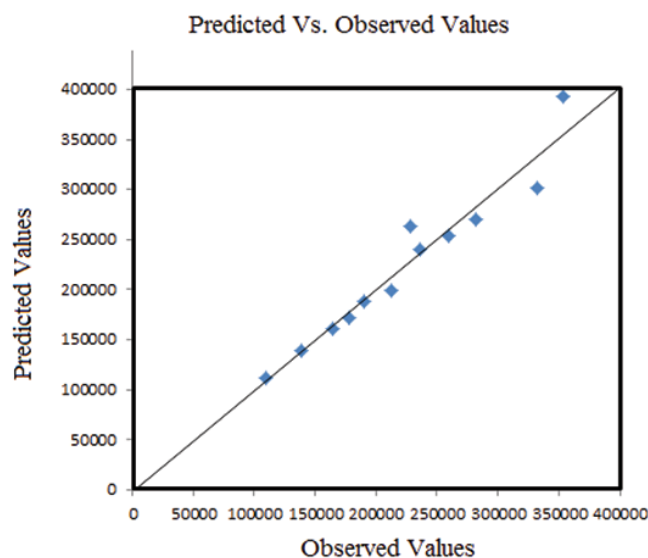

Figure 5—Observed *vs.* predicted values of MVR capital cost for the CSFM

with the MAER. As an example, the validity of the developed model in reproducing the measured data of capital costs for the CSFM machine is demonstrated in Figure 5.

Cost model for variable-speed DC motors

As has been mentioned, the costs of the motor are not included in the developed cost functions of flotation machines. Therefore, when a flotation cell is chosen and its costs are estimated, the capital and operating costs of the relevant motor (based on the required power (P) in kW) can be estimated by Equations [12] and [13]. Motors are assumed to be variable speed with 1150 r/min drive rating. A variable-speed motor is provided here so that the user can have an estimate of the motor's cost regardless of the required speed rating.

$$CC = 863.6 \times P^{0.7186} \quad R^2 = 0.9952, \text{ MAER} = 3\% \qquad [12]$$

$$OC = 0.1114 \times P^{0.9344} \quad R^2 = 0.9998, \text{ MAER} = 1\% \qquad [13]$$

Discussion

Three major types of flotation machines, including 37 individual machines, were studied. The explanatory variable in SRA was either diameter or cell volume; whereas in MRA (depending on the machine type), different technical variables such as diameter, required air flow rate, required floor space, cell volume, required air pressure, and power were considered as predictor variables simultaneously.

The models were classified into capital and operating costs. Moreover, the operating cost was detailed in different cost items. The cost models are valid within a certain range, indicated in Table II, and major extrapolation should be avoided.

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Table X

Coefficients of multivariable cost models (Y = a0 + a1x1 + a2x2+ a3x3 + ...)

Machine type	Explanatory variables	Coefficients	Capital cost	Operating costs							Lubrication cost
				Total operating costs	Overhaul			Maintenance			
					Parts	Labour	Total	Parts	Labour	Total	
Column, sulphide	Intercept	a_0	55 057.22	1.5927	0.2284	0.2129	0.4272	0.4272	0.3947	0.8219	0.3112
	D	a_1	70938.63	2.0429	0.2974	0.2801	0.5478	0.5478	0.5219	1.0697	0.4070
	AF	a_2	36.7212	0.0011	0.0001	0.0001	0.0003	0.0003	0.0003	0.0005	0.0002
	MAER			4.98	4.98	4.94	5.07	5.04	5.04	4.93	4.98	5.08
	R^2			0.9417	0.9416	0.9427	0.9409	0.9408	0.9408	0.9420	0.9414	0.9417
Column, Coal	Intercept	a_0	-7769.630	-0.19 900	-0.0088	-0.0359	-0.0448	-0.0235	-0.0431	-0.0667	-0.06008
	D	a_1	88 745.590	2.545 99	0.358 75	0.348 56	0.707 31	0.668 26	0.642 32	1.310 59	0.514 09
	AF	a_2	-26.29080	-0.00075	-0.0001	-0.0001	-0.0002	-0.0002	-0.0002	-0.0003	-0.00016
	MAER			3.3	3.3	3.42	3.4	3.41	3.28	3.33	3.31	3.37
	R^2			0.9509	0.9509	0.9471	0.9495	0.9483	0.9511	0.9493	0.9502	0.9490
Self-aerating	Intercept	a_0	24 976.6	0.7206	0.1021	0.0951	0.1971	0.1951	0.1840	0.3791	0.1425
	CV	a_1	4130.6	0.1190	0.0172	0.0160	0.0331	0.0327	0.0304	0.0632	0.0236
	FS	a_2	1114.9	0.0319	0.0045	0.0050	0.0094	0.0086	0.0078	0.0164	0.0068
	P	a3	-624.4	-0.0179	-0.0025	-0.0024	-0.0049	-0.0051	-0.0047	-0.0098	-0.0036
	MAER			13.48	13.55	13.09	13.88	13.45	13.19	13.56	13.37	13.43
	R^2			0.9940	0.9939	0.9943	0.9939	0.9941	0.9941	0.9940	0.9940	0.9937
Standard	Intercept	a_0	30 240.78	0.8330	0.1216	0.1146	0.2241	0.2307	0.2162	0.4469	0.1728
	CV	a_1	-5415.50	-0.1552	-0.0241	-0.0206	-0.0527	-0.0419	-0.0396	-0.0814	-0.0306
	AF	a_2	10 220.11	0.2944	0.0422	0.0392	0.0871	0.0795	0.0739	0.1534	0.0573
	AP	a_3	-13354.40	-0.3664	-0.0568	-0.0472	-0.1242	-0.1011	-0.0944	-0.1955	-0.0746
	P	a_4	2312.0450	0.0649	0.0111	0.0085	0.0252	0.0175	0.0170	0.0345	0.0133
	MAER			3.05	5.05	3.56	2.56	11.78	3.4	3.06	3.12	2.81
	R^2			0.9997	0.9993	0.9996	0.9997	0.9988	0.9996	0.9997	0.9996	0.9997

The most expensive machine is a type of flotation column that has capital and operating costs of about $394 000 and $11 per hour, respectively. The capital cost of a CSFM and CCFM is proportional to the 0.79 and 0.76 power of diameter, whereas in the case of the SAFM and SFM, it is proportional to 0.47 and 0.45 of the cell volume, respectively. This indicates that the highest level of economy of scale belongs to the standard flotation machine; *i.e.* the SFM cost advantage increases with increasing size of the machine. The R^2 values between 0.87% and 0.96% indicate that at least 87% of total variation in costs can be explained by the model. The lowest MAER of SRA belongs to the CSFM (4.86%) that designates the cost model with the maximum accuracy. In the MRA cases, this property is owed to the SFM (3.05%).

Conclusion

Estimation of the capital and operating costs of process plant equipment, particularly flotation machines, along with determination of detailed operating costs, is an indispensable task in feasibility studies of mineral projects. Almost all of the current models are obsolete and need to be updated. Moreover, the majority of the available models have a univariate structure, and the role of other operative variables has simply been disregarded. A new up-to-date statistical cost model for flotation machines (column as well as coal and sulphide, self-aerating, and standard) has been developed.

Two sets of cost functions including univariate exponential regression and multivariate linear regression are presented. Individual cost functions are presented for each operational cost item category such as overhaul (parts and labour), maintenance (parts and labour), power and lubrication items. However, costs can vary from mine to mine and from time to time, and should be adjusted for conditions specific to the operation based on local unit costs (such as electrical power, lubricants, and repair labour), and annual cost index of mineral processing equipment. The proposed cost models are reliable in device specifications ranged as noted in Table II, and over- extrapolation could result in misguiding estimates.

The MAER, RMSE, R^2, and residual analysis methods were applied for the evaluation of the models. Maximum MAER of 13.5% and minimum R^2 of 0.86 indicate that these models can be used as a reliable tool in cost estimation of flotation machines at the pre-feasibility and even feasibility study level of projects.

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