

ESTIMATING CAPITAL AND OPERATIONAL COSTS OF BACKHOE SHOVELS

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Abstract. Material loading is one of the most critical operations in earthmoving projects. A number of different equipment is available for loading operations. Project managers should consider different technical and economic issues at the feasibility study stage and try to select the optimum type and size of equipment fleet, regarding the production needs and project specifications. The backhoe shovel is very popular for digging, loading and flattening tasks. Adequate cost estimation is one of the most critical tasks in feasibility studies of equipment fleet selection. This paper presents two different cost models for the preliminary and detailed feasibility study stages. These models estimate the capital and operating cost of backhoe shovels using uni-variable exponential regression (UVER) as well as multi-variable linear regression (MVLRL), based on principal component analysis. The UVER cost model is suitable for quick cost estimation at the early stages of project evaluation, while the MVLRL cost function, which is more detailed, can be useful for the feasibility study stage. Independent variables of MVLRL include bucket size, digging depth, dump height, weight and power. Model evaluations show that these functions could be a credible tool for cost estimations in prefeasibility and feasibility studies of mining and construction projects.

Keywords: loading equipment, backhoe shovel, cost estimation, multi-variable linear regression, principal component analysis, mining and construction.

1. Introduction

Earthmoving operations are an important part of construction and mining projects, and mainly include excavation, loading, site preparation, embankment construction, compacting, backfilling, surfacing and hauling. These operations are equipment-intensive, characterized by the development of large fleets (Hassanien, Moselhi 2002). Earthmoving is therefore often one of the most important operations in many mining and construction projects in terms of its effect on costs and productivity (Gransberg *et al.* 2006; Tatari, Skibniewski 2006; Park *et al.* 2010).

The owning and operation of these equipment fleets represent a considerable part of the early costs for large contractors involved in heavy construction engineering and mining projects (Skibniewski, Armijos 1990; Fan *et al.* 2008). Moreover, machine owners seek to minimize the cost of operation by optimum selection of the equipment (Zavadskas, Vilutienė 2006). Consequently, it is a main concern of equipment managers to limit and reduce the overall cost of this task. Their responsibilities include selecting and optimizing the equipment fleet, as well as reducing the cost and optimizing productivity.

In equipment planning for an earthmoving operation, a decision should be made on what machines to employ in the operation. Most assessment utilise an average operating cost over the life of the equipment (Noakes,

Lanz 1993). In making such a decision, many interactions between engineering and economic considerations must be taken into account. The process of selecting appropriate machines, however, can generally follow a decision-making path with the individual steps of selection of the type and model of the machine, determination of the number of machines and choice of the most appropriate machine.

The decision-maker should consider all the alternatives, as well as the project specification and economic issues, in order to choose the most appropriate loading equipment fleet. This decision has a significant impact on the results of the feasibility study. Therefore, managers need to have an accurate and simple cost estimation tool to select the most suitable equipment fleet, which will meet production targets and minimize overall cost (Twort, Rees 2004).

The selection and evaluation of material handling equipment is a complex procedure that requires working knowledge and experience of the techniques of cost estimation as well as knowledge of equipment management, because the work of providing cost evaluations needs the manager to be familiar with equipment management to present precise cost estimations.

In the first stages of mining and construction project evaluation, no adequate estimation of expenses is possible, because access to an expert who is knowledgeable in

both equipment management and cost estimation is not simple, adequate data is not available, and many different alternatives need to be considered. Moreover, this evaluation is time consuming and costly. Accordingly, an accurate and rapid estimation tool is beneficial for equipment managers.

A variety of equipment can be used in material handling operations. Based on its operational function, earthmoving equipment can be classified as loading (excavating) and hauling machines and some types of machines can function as both (Nichols, Day 1999). Cable shovels, hydraulic shovels, wheel loaders and backhoe shovels are the most common equipment used in loading operations.

The level of detail required in any assessment can be dependent on many factors, such as management guidelines, data source and evaluation time and budget (Noakes, Lanz 1993). It is important that the desired or necessary level of details as well as data source are clarified, prior to proceeding with cost estimation.

Backhoe shovels are very popular for digging, loading and flattening operations. In this paper, two different cost models for backhoe shovels are presented, based on uni-variable exponential (UVER) and multi-variable linear regression (MVLRL). The UVER cost model is useful for quick cost estimation at the early stages of a project. This model is particularly suited for making quick cost

estimates where only one specific design parameter is available. While the MVLRL, based on principal component analysis (PCA), is suitable for detailed estimates at the feasibility study stage.

In order to demonstrate the capabilities of proposed cost estimation models, a case example of a real world project was performed using a particular project's conditions. The estimated costs are compared with those of the actual project records.

2. Literature review

A number of models have been established in attempts to shortcut the construction and mining cost estimating process (Table 1). These relate the cost to certain factors in a process or a unit. In these models, machine capacity usually has been used as independent variables in univariate functions (Mular, Poulin 1998; Camm 1994; O'Hara, Suboleski 1992). For instance, the cost of an excavator may be related to its bucket capacity. The relationship may be expressed in a formula or a graph. Some of these models are old, and therefore subject to modern review. Moreover, as the capital or operating cost models are univariate, the roles of the other effective parameters have simply been disregarded. Multivariate cost estimation models, on the basis of up-to-date data, will overcome these shortcomings.

Table 1. The various applications of construction and mining cost estimation

Proposed by	Year	Application
Hwang	2011	Prediction of cost indexes for construction projects using time series
Asmar <i>et al.</i>	2011	Estimation of highway project costs using project evaluation and review technology
Thal <i>et al.</i>	2010	Prediction of the required cost contingency for air force construction projects, using multiple linear regression
Sayadi <i>et al.</i>	2010a	Estimating maintenance cost of loading and hauling equipment using multiple linear regression
Sayadi <i>et al.</i>	2010b	Estimation of hoisting equipment cost for underground mines
Sonmez and Ontepeli	2009	Cost estimation of urban railway projects
R.S. Means Company	2005	Presenting cost data for all phases of building construction
Wilmot and Mei	2005	Estimation of highway construction costs indexes using neural network
Pratt	2004	Pricing construction equipment
Mular	1982	Estimation of capital costs of mining and mineral processing equipment using UVER method
Mular and Poulin	1998	UVER method
Camm	1991, 1994	Development of UVER cost functions for surface and underground mining
Noakes and Lanz	1993	Estimating the costs of mining and milling industry, using graphical or formulation methods
O'Hara and Suboleski	1992	Development of cost formulas as estimators of capital and operating costs of mining and milling
Petrich and Dewey	1987	A computer model which utilizes O'Hara's cost estimation model
Stebbins	1987	Using univariate exponential regression method for small placer mines cost prediction
USBM	1987	Estimation of mining and milling cost items, using regression analysis
Collier	1987	Fundamentals of building and construction estimating and cost accounting
Mular	1982	Estimation of mining and milling costs using regression analysis
O'Hara	1980 1981	Surface and underground mining cost estimation using exponential regression
Infomine ¹	Annually	Cost estimation guide for mine and mill equipment

¹ Cost.infomine.com

3. Data and method

3.1. Data

32 different sizes of backhoe shovels, working in construction and mining projects in the United States are considered and their economic data as well as machine specifications are considered (InfoMine 2007, 2010). The economic data are classified into two types, as capital (CC) and operating costs (OC). The CC is based on the US dollar (2010) while the OC is based on US dollars per hour. The operating costs items include overhaul (parts and labor), maintenance (parts and labor), power, lubrication and wear on parts (the cost of the operator's time is not included here) and the technical parameters are bucket size (BS), digging depth (DD), dumping height (DH), weight (W) and power (HP) (Noakes, Lanz 1993). The average and standard deviation of all the parameters and data ranges are given in Table 2.

Table 2. Description of data

Parameter		Min	Max	Mean	St. dev.
Capital cost (CC)	M\$	0.113	16.2	3.69	3.67
Operating cost (OC)	\$/h	12.14	656	220.23	191.04
Bucket size (BS)	cu m	0.28	39.8	12.61	11.45
Digging depth (DD)	m	4.1	16.2	9.248	2.68
Dump height (DH)	m	5.1	15.9	10.22143	3.16685
Machine weight (W)	ton	8.03	811	240.5	210.6
Power (HP)	hp	54	3800	1109.8	983.16

The statistical analysis is applied and the results confirm the normal distribution of different variables, but a significant correlation is observed between independent variables (Eq. (1)):

$$\begin{matrix}
 & \text{BS} & \text{DD} & \text{DH} & \text{W} & \text{HP} \\
 \begin{matrix} \text{BS} \\ \text{DD} \\ \text{DH} \\ \text{W} \\ \text{HP} \end{matrix} & \begin{bmatrix} 1.000 & 0.865 & 0.921 & 0.976 & 0.949 \\ 0.865 & 1.000 & 0.901 & 0.868 & 0.850 \\ 0.921 & 0.901 & 1.000 & 0.886 & 0.856 \\ 0.976 & 0.868 & 0.886 & 1.000 & 0.939 \\ 0.949 & 0.850 & 0.856 & 0.939 & 1.000 \end{bmatrix}
 \end{matrix} \quad (1)$$

One of the key assumptions of linear regression analysis is that there is no multi-collinearity (mutual correlation) among the independent variables of the regression model (Sharma 1996). In multiple regression, one of the major difficulties with the usual least squares estimators is the problem of multi-collinearity, which occurs when there are near-constant linear functions of two or more of the predictor, or regressor, variables (Gunst 1983). When highly correlated explanatory parameters are used in a MVLN model, multi-collinearity causes unstable prediction of regression coefficients, numerical inaccuracies in calculating the estimates of regression coefficients, inaccurate rejection of parameters and statistical imprecision (Jennrich 1995). Consequently, the present correlation should be considered and eliminated before applying the MVLN (Gujarati 2003).

3.2. Research framework

This paper presents two different cost models for backhoe shovels. Figure 1 shows a normal material loading operation using a backhoe shovel and dump truck.

These models help the cost estimators to make a quick and up-to-date estimation of capital and operating costs with an acceptable level of accuracy for the different stages of the feasibility study. The first model estimates the costs based on the bucket size of the backhoes, using the UVER technique.

The second model is useful for in-depth estimations, and estimates the costs as functions of different specification parameters of backhoe shovels, including the bucket size (BS), digging depth (DD), dump height (DH), power (HP) and weight (W) of the machine. This model is presented using MVLN, based on PCA.

The PCA technique can be used to eliminate the correlation between independent variables. This is attained by transforming the original variables into a new set of variables, called the Principal Components (PCs). A PC is a weighted linear combination of all the original variables, which is uncorrelated with the other PCs. PCs are ordered so that the first few preserve most of the variation in all of the initial parameters. The direction of highest variance of the independent variables is represented by the first PC (PC1). The direction of the second highest variance (PC2) would be orthogonal to PC1 and the contribution of the PCs to the overall variation decreases from step to step. PCs are orthogonal by definition, so any pair of PCs will have zero correlation. The variance of the data in the corresponding PCs is represented by the eigenvalues, and the eigenvector of each PC is equal to the loading on it (Jolliffe 1986). PCs are used in conjunction with a variety of other statistical techniques. One area in which this activity has been extensive is regression analysis. In this hybrid method, the values obtained by PCA are used as inputs in the MVLN.

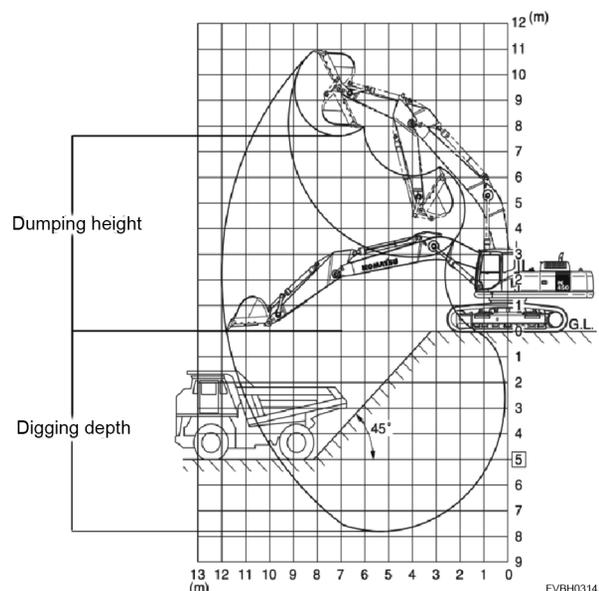


Fig. 1. A normal material loading operation by using backhoe shovel and dump truck (www.komatsu.com)

The selection of a subset of PCs to use as independent variables of MVLR depends on the nature of the data. The main objective in many applications of PCA is to replace the elements of original variables by a much smaller number of PCs, which nevertheless discard only a small amount of the variation of the original variables and useful information. In these cases the number of PCs selected to use as independent variables in the MVLR is an important issue. But, in the cases in which the major objective of using the PCA technique is to solve the problem of multi-collinearity, all PCs can be contributed to the MVLR model (Jolliffe 1986). Concerning the present study, all scores obtained from the PCA technique are used as regressor variables in the MVLR model. Performing the MVLR, the relationship between costs (as dependent variables) and PCs (as independent variables) are established.

In order to estimate the cost as a function of the original variables, the eigenvectors of the correlation matrix are multiplied in MVLR coefficients (B coefficients). Since, when applying the PCA technique, all the variables are standardized, it is necessary to transform them to their initial positions with actual means and standard deviations as follow:

$$x^* = (x - m) / sd, \tag{2}$$

where: x^* is the standardized value of the original variable (x) and m and sd represent the mean and standard deviation of x .

To assess the performance of the models, the Mean Absolute Error Rates (MAER) of different functions are calculated as follows (Kim *et al.* 2004):

$$MAER = \left[\sum |(C_e - C_a) / C_a| \cdot 100 \right] / n, \tag{3}$$

where: C_e is the estimated backhoe shovel cost, C_a is the actual backhoe shovel cost, and n is the number of data.

4. Results

4.1. Univariate exponential regression

Applying the UVER, two different sets of functions are developed for estimation of the capital and operating costs of backhoe shovels as functions of different machine specific parameters. The UVER functions are in the form of $Y = a \times (\text{parameter})^m$, where Y is the estimated cost. Whereas a and m are constants determined by the regression analysis. Eqs (4) and (5) show UVER functions to calculate capital and operating costs as functions of bucket size of backhoe shovels and the relationships are expressed as graphs in Figs 2 and 3.

$$CC(\$) = 34076 \times BS^{0.932}, R^2 = 95.0\%; \tag{4}$$

$$OC(\$ / h) = 32.91 \times BS^{0.765}, R^2 = 93.7\%. \tag{5}$$

The following equations show UVER functions based on the other backhoe shovel specification parameters:

$$CC(\$) = 164.3 \times DD^{4.256}, R^2 = 68.6\%; \tag{6}$$

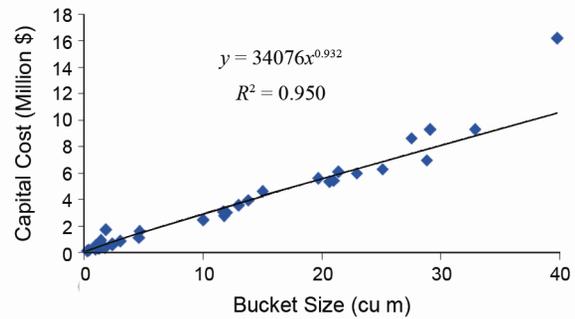


Fig. 2. UVER result for capital cost

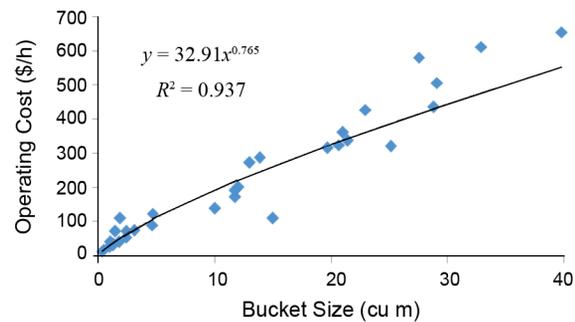


Fig. 3. UVER result for operational cost

$$CC(\$) = 435.8 \times DH^{3.698}, R^2 = 85.1\%; \tag{7}$$

$$CC(\$) = 4.279 \times W^{1.096}, R^2 = 97.1\%; \tag{8}$$

$$CC(\$) = 878.2 \times HP^{1.176}, R^2 = 93.9\%; \tag{9}$$

$$OC(\$ / h) = 0.091 \times DD^{3.340}, R^2 = 74.8\%; \tag{10}$$

$$OC(\$ / h) = 0.079 \times DH^{3.268}, R^2 = 85.4\%; \tag{11}$$

$$OC(\$ / h) = 0.003 \times W^{0.893}, R^2 = 94.5\%; \tag{12}$$

$$OC(\$ / h) = 0.238 \times HP^{0.971}, R^2 = 93.7\%. \tag{13}$$

4.2. Multiple regression analysis

Performing the PCA technique on these five backhoe shovel parameters to describe their interrelation pattern, the number of PCs will usually be equal to the number of independent original variables. Table 3 shows the eigenvectors of the correlation matrix that represent the matrix of the weights for the PCs, which demonstrates the relative importance of each standardized parameter in the PC calculations (He, Ma 2010).

Table 3. Eigenvector of correlation matrix

	BS	DD	DH	W	HP
PC ₁	-0.4577	-0.2837	0.2550	-0.1631	0.7864
PC ₂	-0.4348	0.6541	-0.5865	-0.1340	0.1452
PC ₃	-0.4430	0.4333	0.6805	0.2903	-0.2620
PC ₄	-0.4538	-0.3275	-0.0078	-0.6497	-0.5145
PC ₅	-0.4463	-0.4434	-0.3576	0.6701	-0.1648

The eigenvalue of the correlation matrix is shown in Table 4. There are no multi-collinearities between PCs, because they are uncorrelated, and the regression calculations are also simplified. If all the PCs are submitted to the MVLr, then the outcome is equal to the model attained by least squares, so the significant variances caused by multi-collinearities have not departed. However, estimation of the least squares predictions via MVLr based on PCA may be more stable than common calculation (Flury, Riedwyl 1988). Therefore, in this study all five PCs were selected as inputs to the MVLr model.

Table 4. Eigenvalue of correlation matrix

	Eigenvalue	Total Variance %	Cumulative Eigenvalue	Cumulative %
PC ₁	4.61	92.14	4.61	92.14
PC ₂	0.21	4.22	4.82	96.36
PC ₃	0.11	2.16	4.93	98.52
PC ₄	0.06	1.18	4.99	99.70
PC ₅	0.01	0.30	5.00	100.00

To identify non-significant PCs and derive the best estimation functions for the costs of a backhoe shovel, MVLr is performed on the PC scores using stepwise variable selection procedures (Sousa et al. 2007). Tables 5 and 6 summarize the results of the MVLr model on the capital and operating costs of these equipments, respectively. The regression coefficients of PCs are highlighted in the “B” Column. The “Beta” coefficients are the standardized regression coefficients. It is important to note that the advantage of “Beta” coefficients in comparison with “B” coefficients is that their magnitudes facilitate the assessment of the relative contribution of each PC in the estimation function. As indicated in Tables 5 and 6, PC₁ is the most effective variable in the cost functions (with regard to “Beta” coefficient). A t-Test is used to assess the significance of the regression coefficients. The significant variables are given in bold in Tables 5 and 6. Eqs (14) and (15) show the relationships between costs and PCs:

$$CC(\$) = -1648260 \times PC_1 - 1516023 \times PC_2 - 973745 \times PC_3 + 3690728; \tag{14}$$

$$OC(\$ / h) = -86.305 \times PC_1 - 62.27 \times PC_2 + 220.229. \tag{15}$$

Table 7 summarizes the coefficients of determination for the models. As can be observed in the “R-square” (the coefficient of determination) column in Table 7, about 96.37% of variation in the operating cost of backhoe shovels is explained by the proposed MVLr model. R-square has a weakness; each additional variable used in the equation will, at least, result in a higher R-Square, even when the new variable causes the equation to become less efficient. The adjusted R-Square (adj R²) value is an attempt to correct this shortcoming by adjusting both the numerator and the denominator of R-square by their respective degrees of freedom (Gujarati 2003). It is adjusted by dividing the error sum and total sums of squares through their respective degrees of freedom (Eq. (16)) (Gujarati 2003):

$$adjR^2 = 1 - [(Res\ SS / df) / (Total\ SS / df)], \tag{16}$$

where *Res SS* is the error sums of squares, the *Total SS* is the total sums of squares and *df* is their respective degree of freedom.

The eigenvectors of the correlation matrix (Table 3) are multiplied by the “B” coefficient calculated using MVLr (Tables 5 and 6) to obtain the costs as functions of the original variables. Then the new standardized coefficients are transformed to their initial position, by Eq. (2). The final MVLr cost estimation functions are presented as follows:

$$CC = 81770BS + 110325DD - 186064DH + 5.946W + 1786.3HP + 129073; \tag{17}$$

$$OC = 4.99BS - 1.193DD + 3.554DH + 0.00028W + 0.067HP - 10.69. \tag{18}$$

Table 5. Regression summary for capital cost (\$) for backhoe shovel

	Beta	Std. Error of Beta	B	Std. Error of B	T(26)	P-value
Intercept			3690728	111147.1	33.2058	0.000000
PC1	-0.964430	0.030784	-1648260	52611.3	-31.3290	0.000000
PC2	-0.189797	0.030784	-1516023	245890.3	-6.1654	0.000002
PC3	-0.087324	0.030784	-973745	343269.2	-2.8367	0.008716
PC4	-0.038305	0.030784	-578859	465197.5	-1.2443	0.224479
PC5	-0.010976	0.030784	-330291	926394.0	-0.3565	0.724318

Table 6. Regression summary for operating cost (\$/h) for backhoe shovel

	Beta	Std. Error of Beta	B	Std. Error of B	T(26)	P-value
Intercept			220.229	7.029	31.331	0.000
PC1	-0.970	0.037	-86.305	3.327	-25.939	0.000
PC2	-0.150	0.037	-62.272	15.551	-4.004	0.000
PC3	-0.015	0.037	-8.592	21.709	-0.396	0.695
PC4	0.014	0.037	11.025	29.420	0.375	0.711
PC5	-0.024	0.037	-37.833	58.587	-0.646	0.524

Table 7. MVLR coefficients of determination

	R-square	Adjusted R-square
Capital Cost	0.754	0.9706
Operating Cost	0.9637	0.9567

The estimated costs can be updated as follows:

$$C_x = (I_x \times C_{2010}) / I_{2010} \quad (19)$$

where C indicates cost and x and I are proposed year and cost index, respectively.

4.3. Model performance

In this study, each model’s performance is measured with the MAER, which was determined with Eq. (3). The MAER obtained from the UVER and MVLR models for cost estimation functions are presented in Table 8. As is observed, the MAER values are smaller for the multiple regression analyses for both the capital and the operating costs, therefore, by using MVLR functions the capital and operating costs can be estimated with a error no more that 13.85% and 11.44% in cases of capital and operating costs, respectively, while these bounds for UVER functions is about 19.49 and 20.89 for capital and operating costs, respectively.

Table 8. The MAER obtained from the UVER and MVLR

	UVER	MVLR
Capital Cost	19.49	13.85
Operating Cost	20.89	11.44

5. Case example

Sungun Copper Mine is located in East Azerbaijan province approximately 125 Km east of the city of Tabriz is one of the main copper deposits of Iran. Feasibility studies were shown that open pit mining technique is the most appropriate method for Sungun Copper Mine (Bazzazi *et al.* 2009). By using open-pit method, the waste to ore ratio in this mine will be 1.8:1 and an amount of 384 million tons of ore with 0.665 percentage of copper grade can be mined. Total Sungun Copper Mine’s life is evaluated to be 31 years with an annual production of 7 million tons in the first 5 years and 14 million tons for the remaining 26 years (Karan Darya Co. 2011). Fig. 4 shows the location map of Sungun Copper complex.



Fig. 4. Location map of Sungun Copper Complex

The site preparation project for Sungun Copper Complex, including over burden removal, access-road construction and smelter complex site preparation began in the fourth quarter of 2010. The site plan of the project has been shown in Fig. 5.

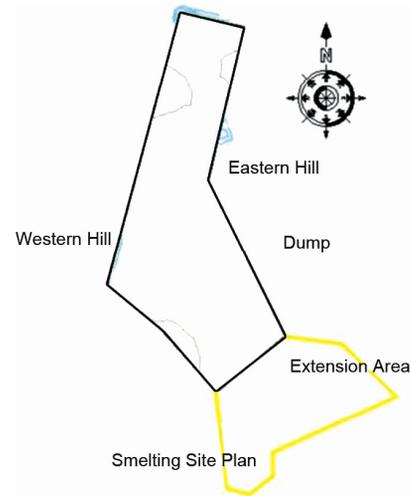


Fig 5. Site plan of Sungun Copper Complex (Karan Darya Co. 2011)

This project needs about 1.3 million m³ of excavation and overburden removal operation including soil and rocky soil removal operations. The equipment fleet used in this project is listed in Table 9.

Table 9. Equipment fleet used in the project

Equipment	Number
Backhoe shovel	20
Wheel loader	14
Dozer	17
Truck	62
Grader	4
Compactor	4
Tractor	1
Truck, water	2

Table 10 lists the model, number and specification of backhoe shovels used in this project.

Table 10. Backhoe shovels used in the project

Model	Number	BS (cu m)	DD (m)	DH (m)	W (ton)	HP
Komatsu PC220	5	1.28	6.7	7.035	22.84	168
Komatsu PC200	4	1.17	6.89	6.095	20.63	155
Hyundai 250LC	2	1.07	6.05	6.86	25.49	163
Hyundai 320LC	2	1.14	6.37	7.05	32	237
New Holland E265 BJ	1	1.1	7.01	7.7	28.27	184
New Holland E215 BJ-ST	3	1.223	6.7	9.47	21.7	150
Daewoo Doosan 230	3	0.92	6.61	6.985	21.5	163

MVLR model has been used to estimate operational cost of backhoe shovels. Table 11 shows the estimated cost of each machine by using proposed MVLR model vs. the actual operational costs calculated from in site operations as well as the calculated MAER values.

Table 11. Estimated vs. actual operational costs

Model	Estimated operational cost (\$/h)	Estimated operational cost (\$/h)	MAER (%)
Komatsu PC220	24.02	27.18	11.63
Komatsu PC200	19.03	22.24	14.43
Hyundai R250 LC	22.79	24.52	7.05
Hyundai R320 LC	28.41	27.32	3.99
New Holland E265 BJ	26.19	28.93	9.47
New Holland E215 BJ-ST	31.18	29.75	4.81
Daewoo Doosan 230	21.81	25.54	14.60
Average MAER:		9.43%	

Regarding to the number of backhoe shovels used in the project, the total operational cost of backhoe shovel fleet is estimated about 483.78 US\$/hour, while the actual in site operational cost of these equipment is recorded as 523.34 US\$/hour.

6. Conclusions

The objective of this paper was to establish reliable cost estimating models for backhoe shovels which are popular for material handling in mining and construction projects. For this, regression techniques have been adopted due to the mathematical background and their explanatory values. Based on the collected data, two cost estimation models in the form of uni-variable exponential regression (UVER) and multi-variable linear regression (MVLR) have been developed. These models are quick, easy and accurate tools and can be useful for making accurate decisions about the size of the loading equipment fleet in construction and mining projects. The UVER model presents a rough estimate suitable for preliminary cost estimations while the MVLR model is more detailed with reasonable accuracy and can be appropriate for detailed estimates in feasibility studies.

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