MODELING OF BLASTING COST AT DEEWAN CEMENT QUARRY, HATTAR USING MULTIVARIATE REGRESSION

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ABSTRACT

Blasting is only the first step in the production process for mines and quarries and the cost of which is normally 8% to 12% of the total costs. Hence, reduced blasting cost is one of the main objectives of production blasting at a cement quarry. This paper presents the development of a prediction model for blasting cost per ton at Deewan cement quarry operations, located in Hattar, Pakistan. The dataset primarily consisted of a total of 12 parameters which has been analyzed using Principal Component Analysis (PCA) to account for most significant parameters. These parameters were then subsequently used to formulate a model for the prediction of blasting cost per ton in the cement quarry operations. The prediction model based on 5 statistically significant variables explains 88.1% of the variance while estimating the blasting cost per ton.

KEYWORD: *Principal Component Analysis; Linear Regression; Blasting; Cement Quarry.*

INTRODUCTION

Pakistan is amongst top twenty cement producing countries. Annual production capacity of cement in Pakistan was about 16.38 million tons in the year 2000. The installed production capacity has expanded to 41.76 million tons per annum by the year 2008-2009[1] On average, 1.6 tons of raw material is required to produce one ton of cement[2,3] Therefore, approximately 66.82 million tons of raw material is required annually to meet the installed production capacity. Hence, a mere cost saving of $1.00 per ton in producing raw materials will lead to a cumulative saving of billions of dollars[4].

Blasting design of a mine or a quarry is engineering and experience orientated, therefore a number of mining and quarrying operations hand over their blast engineering/design/ implementation to a blasting contractor with the required specialized expertise[5]. Currently, cement quarry operations focuses on minimization of the cost of raw materials production[4]. Uncontrolled cost of raw material production may result in utilization of huge amounts of money and above all, wastage of valuable natural mineral resources.

A blending optimization model for short range production planning has been designed which is based on linear programming[6]. Segarra et al[7]., developed a prediction model for mucking rate in metal ore blasting based on regression analysis. The engineering aspect at any cement quarry is not only to design the blast but also to formulate a process which minimizes the blasting cost per ton. Increase in the prices of diesel oil and ammonium nitrate has caused many cement quarry operations to find ways of reducing their blasting costs[8]. Proper blast design and planning is a major engineering task in the optimum exploitation of mineral resource. Drilling and blasting is the first phase of the production cycle but influences all costs of the other subsequent activities[8]. Proper and controlled use of explosive power can save great amounts of money[9]. Also Hudaverdi et al.,[10] formulated a blast fragmentation model using stepwise application of cluster analysis which pointed out the main parameters responsible for creating the differences between groups. These groups were then subjected to discriminant analysis and finally blast fragmentation prediction model based on multivariate regression analysis was formulated.

Massawe & Baruti[11] also designed blasting process based on regression models estimating the influence of the blast design parameters on the overall cost per ton of the material blasted. Their research emphasized the importance of three factors for an optimum blast design which include over size generation, blast hole productivity, and blasting cost per ton.

This research incorporates the use of principal component analysis (PCA)[12,13,14,15,16,17] method to first identify the significant parameters from the dataset of

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12 parameters for Deewan cement quarry, Hattar. These identified parameters were used for the development of a prediction model for blasting cost for this quarry. The blasting cost here includes the cost of all types of explosives and detonators used during bench blasting at the cement quarry.

METHODOLGY

Dataset

The dataset for this study was selected from one of the existing cement quarry operations located in Hattar, Pakistan (Coordinates; 35°50'38.61"N, 72°52'15.04"E). A satellite image showing the quarry and plant is shown in Figure 1.

Figure 1: Satellite image of Deewan cement plant and quarry operations[18]

A total of 31 numbers of blasts were studied and analyzed. The data has been taken from different benches of the same quarry and consists of 12 variables including number of holes (N), bench height (H), sub-drilling (J), burden (B), spacing (S), burden to spacing ratio (S/B), No. of blasting rows (R), hole dia (D), powder factor (PF), quantity of bottom charge (Q_b), quantity of column charge (Q_c), and stemming (T).

In the blasting operation, blast hole diameters of 89mm, 102mm, 108mm, and 124mm were used in the benches of varying heights. ANFO and one of the emulsion explosive are used as column and bottom charges respectively. The range of blast-deign parameters of the quarry are listed in Table 1 below:

Table 1: Blasting design parameters of the quarry

Parameter	Description
Burden	2.5 – 5 m
Spacing	3 – 5.5m
Bench Height	4.5 – 31.21 m
Stemming	3 – 5
Powder Factor	0.35 – 0.96 Kg/m3
No. of blasting rows	1 – 4

Table 2: Eigenvalues, variance, cumulative variability, regression coefficients, and t-values of PCs

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12
Eigenvalue	3.245	2.836	2.268	1.367	0.781	0.676	0.372	0.307	0.098	0.032	0.016	0.003
Variance (%)	27.043	23.630	18.896	11.392	6.511	5.632	3.096	2.559	0.819	0.265	0.135	0.021
Cumulative %	27.043	50.673	69.570	80.961	87.473	93.104	96.200	98.760	99.578	99.844	99.979	100.000

Application of PCA on the dataset

First, the principal component analysis was conducted on the input parameters/predictor variables to find the correlation and the Principal Components. The Eigen values, variance and the cumulative variability of the Principal Components resulting from the PCA on the database are shown in Table 2

The factor loadings of the 13 parameters including output parameter (cost/ton) on the PCs are shown in Table 3.

Table 3: Factors loadings of all the thirteen (13) parameters on the PCs

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13
N	0.711	0.573	-0.070	-0.185	0.042	0.227	-0.062	-0.193	-0.161	-0.006	-0.073	-0.029	-0.002
H	-0.342	0.156	0.811	0.313	-0.045	0.177	-0.210	0.052	0.120	0.049	-0.084	-0.010	-0.002
J	-0.314	0.278	0.826	0.257	0.021	0.186	-0.101	-0.021	-0.131	-0.068	0.086	0.007	0.002
B	0.660	-0.380	0.571	-0.083	-0.147	-0.213	0.089	-0.101	0.002	0.026	-0.007	0.007	0.036
S	0.661	-0.275	0.524	0.120	-0.352	-0.098	0.224	-0.112	0.020	0.018	0.014	0.002	-0.032
S/B	-0.168	0.386	-0.315	0.521	-0.444	0.381	0.327	0.034	0.011	0.031	0.004	-0.005	0.012
R	0.719	0.539	-0.167	-0.111	0.068	0.230	-0.174	-0.166	0.179	-0.002	0.062	0.019	0.002
D	0.694	0.478	0.244	-0.191	0.163	-0.027	0.105	0.391	0.028	-0.015	0.019	-0.045	0.000
PF	-0.337	-0.167	0.313	-0.297	0.695	0.243	0.336	-0.124	0.039	0.022	-0.002	-0.003	0.000
Qb	0.092	0.908	0.083	0.175	0.215	-0.245	0.088	0.068	-0.047	0.056	-0.022	0.076	-0.002
Qc	0.370	-0.686	0.017	-0.380	-0.102	0.427	-0.079	0.202	-0.060	0.041	-0.006	0.053	-0.002
T	-0.535	0.406	0.125	-0.647	-0.290	-0.054	-0.041	-0.038	-0.030	0.145	0.044	-0.023	-0.001
C/T	0.400	-0.395	-0.199	0.681	0.379	-0.005	-0.119	0.001	-0.057	0.130	0.038	-0.024	-0.001

It can be seen that the variables relating to the horizontal dimension of the blast design (i.e. N, B, S, R, and D) have high loadings on PC1 and hence the PC1 can be termed as the *Horizontal Component*. The variables Q_b and Q_c have high loadings on PC2 and hence PC2 can be termed as *Explosive Charge Component*. Similarly, PC3 can be related to as *Vertical Component* as the variables H and J have highest loadings on this component.

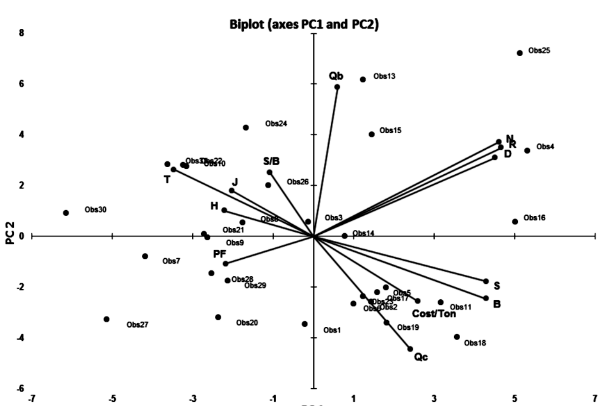

Figure 2: Biplot of parameters and observations on first two PCs

The biplot in Figure 2 shows the loadings of the parameters on the first two PCs. Together 50% of the variability is explained by the first two principal components.

Selecting a subset of principal components

The scree graph and the cumulative variability of the PCs are shown in Figure 3. Judged solely on the basis of size of variance and other criteria available in literature[12,14,17] only the first four PCs are needed to be retained while the last eight PCs can be ignored because most of the variance in the data has been retained and redundant information exists in the remaining PCs.

An additional way of retaining the PCs can be based on the coefficients and their respective *t*-values form the regression of output parameter (cost/ton) on PCs. A high *t*-value implies that the coefficient was able to be estimated with a fair amount of accuracy and it can be concluded that the variable in consideration has a significant impact on the dependent variable[19]. Boneh & Mendieta[20] have also based their selection of PCs on the regression coefficients and their respective *t*-values.

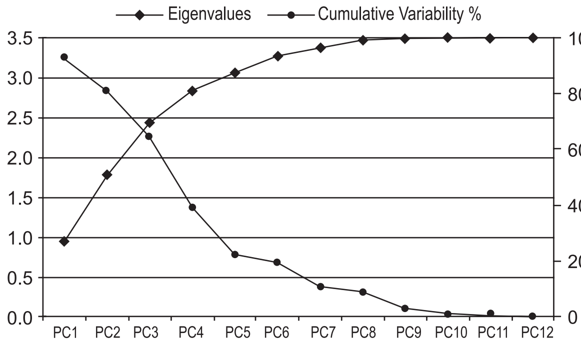

Figure 3: Scree graph and plot of cumulative variability of PCs

By considering the values of regression coefficients, and t-statistics, the fifth and eleventh component seemed to be relatively important for prediction of dependent variable (Cost/Ton), despite the fact that they account for only 6.51% and 0.14% of the total variance in the predictor variables respectively. Therefore, six principal components namely PC1, PC2, PC3, PC4, PC5, and PC11 were retained for further analysis. These six numbers of PCs collectively account for 87.61% of total variance in the original data.

Reduction of variables

Various techniques exist for reduction of original variables on the basis of principal components. These have been discussed thoroughly by Jollifee[21]. Out of these available techniques, the technique named "B2" is the most effective and gives a reasonable subset of variables[12]. This technique states that:

"If p variables are to be retained, a variable is associated with each of the last (K-p) components in a way that the variable has the largest coefficient in the component (eigen vector) under consideration and which has not already been associated with a previously considered component and then these (K-p) variables are rejected"

On the basis of above technique, the rejected and retained variables are discussed in section 3.

RESULTS AND DISCUSSION

The rejected and retained variables are listed in Table 4

Table 4: Rejected and retained input variables/parameters after PC Analysis

Rejected Variables	Retained Variables
Sub-Drilling (J)	Number of Holes (N)
Burden (B)	Bench Height (H)
Spacing to Burden Ration (S/B)	Spacing (S)
Number of Blasting Rows (R)	Powder Factor (PF)
Hole Dia (D)	Bottom Charge (Qb)
Column Charge (Qc)	Stemming (T)

The retained variables were then subjected for formulation of a statistical model basis on regression analysis. The retained blasting parameters after PCA and their possible values are depicted in Table 5.

Table 5: Description of the input and output parameters in the reduced dataset

Type	Parameter	Abbreviation	Description
Input	Number of Holes	N	3 – 10
	Bench Height	H	4.5 – 31.21 m
	Spacing	S	3 – 5.5 m
	Powder Factor	PF	0.35 – 0.96 Kg/m3
	Bottom Charge	Qb	40 –660 Kg
	Stemming	T	3 – 5 m
Output	Cost/Ton	C/T	7.75 – 12.59

It can be seen from the Table 5 that some of the input parameters have a high variation in their values especially for N, PF, and Q_b which is due to the difference in size of the blast. The bigger the size of blast, the larger are the values of the parameters N, PF, and Q_b are.

Applying XLSTAT package on the reduced subset of the original database, a mathematical equation (Eq. 1) was developed to predict the blasting cost/ton with the help of input parameters:

$$Cost/Ton = 19.605 - 0.031N + 0.006H - 0.290S - 0.455PF - 3.84E\text{-}05Qb - 2.056T \quad (1)$$

Table 6: Multiple regression model for the prediction of blasting cost/ton

Parameter	Coefficient	St. Error	t-value	Pr > t
Constant	19.605	1.100	17.819	< 0.0001
N	-0.031	0.074	-0.415	0.681
H	0.006	0.014	0.396	0.695
S	-0.290	0.144	-2.011	0.056
PF	-0.455	0.766	-0.595	0.558
Qb	3.84E-05	0.001	0.069	0.945
T	-2.056	0.162	-12.684	< 0.0001
n = 31	**R2 = 0.881**	**Ra2 = 0.851**	**MSE = 0.200**	**RMSE = 0.448**

Table 6 summarizes the detailed results of regression analysis on the reduced dataset.

The Coefficient of Determination (R2) value of 0.881 shows that the predicting line of regression has a good fit to the original blasting cost per ton values and accounts for 88.1% of the variability in the original data. A graphical comparison of the predicted blasting cost/ton with the actually observed/ measured blasting cost/ton from the dataset is depicted in Figure 4 and Figure 5. This shows that the most of the information from the dataset has been explained by six retained variables.

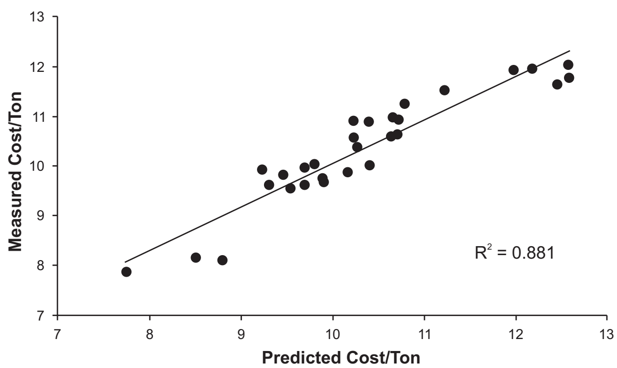

Figure 4: Correlation between predicted cost/ton with observed/ measured cost/ton

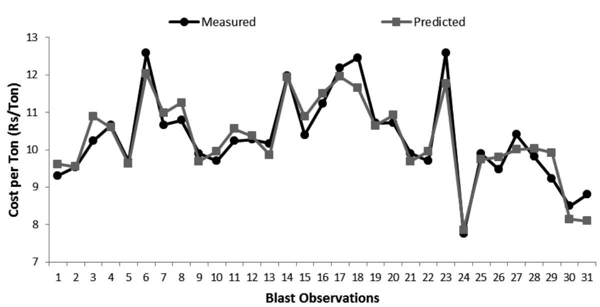

Figure 5: Comparison of predicted cost/ton with observed/ measured cost/ton

CONCLUSIONS

The recent increase in the prices of diesel oil and ammonium nitrate has caused many operations to re-examine their blasting methods to find ways of reducing costs. Blasting cost at a cement quarry shares 8% to 12% of the total costs and hence reducing blasting cost can save a huge amount of finance. Blasting operations of Deewan cement quarry were studied in this research. The dataset consisted of twelve parameters and PCA was used to bring to light the most significant blasting design parameters. Out of those twelve parameters, six were selected on the basis of their high variance in the data. These six parameters were subsequently subjected to regression analysis to develop a prediction model for estimating the blasting cost based on the retained parameters.

The resulting regression model accounted for 88.1% of the variation in the blasting cost per ton and it was statistically significant. The model resulted in this research was developed under the given set of conditions specific to Deewan cement quarry, Hattar. However, it is believed that similar models can be developed for other quarry operations to make it more generalized. Prediction of blasting cost/ ton will help the decision-makers at Deewan cement quarry to control their blasting cost and organizing their blasting schedule. They can effectively plan their annual blasting budget in an accurate way.

REFERENCES

1. *State Bank of Pakistan (2010) The State of Pakistan's Economy – First Quarterly Report 2008-2009. State Bank of Pakistan. Available from: http://www.sbp.org.pk/reports/quarterly/FY09/first/Section_2.pdf (Accessed 15 August 2010).*

2. *Austin, G.T. (1984). Shreve's Chemical Process Industries, 5th ed., New York: McGraw Hill Book Company.*

3. *Carr, D.D. (1994). Industrial Minerals and Rocks. 6th ed., Littleton, Colorado: Society of Mining, Metallurgy, and Exploration, Inc.*

4. *Asad, M.W.A. (2008). Multi-Period Short Range Production Planning for Cement Quarry Operations, Unpublished Post Doctoral Research Thesis, NWFP University of Engineering & Technology, Peshawar, Pakistan.*

5. *Hartman, H.L. (1987). Introductory Mining Engineering. USA: John Wiley & Sons, Inc.*

6. *Asad, M.W.A. (2010). 'Implementing a Blending Optimization Model for Short Range Production Planning of Cement Quarry Operation', Journal of Mining Science, Vol.46 No.5, pp.525-535.*

7. *Segarra, P., Sanchidrián, J.A., López, L.M, & Querol, E. (2010). 'On the Prediction of Mucking Rates in Metal Ore Blasting'. Journal of Mining Science, Vol.46 No.2, pp.167-176.*

8. Konya, C.J. (2011). Controlling Drilling and Blasting Costs. [online] Technical report, Intercontinental Development Corporation, Inc: Available from: http://www.idc-pbs.com/ images/graphics/Controlling_Drilling_and_Blasting_Costs.pdf (Accessed 19 September 2011)

9. Persson, P.A., Holmberg, R., & Lee, J. (1994). Rock Blasting & Explosives Engineering. US: CRC Press LLC.

10. Hudaverdi, T., Kulatilake, P.H.W.S., & Kuzu, C. (2011). 'Prediction of Blast Fragmentation Using Multivariate Analysis Procedures'. International Journal for Numerical and Analytical Methods in Geomechanics, Vol.35, pp.1318-1333.

11. Massawe, A.T.S., & Baruti, K.R. (2011). 'Regression Models of the Impact of Rockmass and Blast Design Variations on the Effectiveness of Iron Ore Surface Blasting'. Scientific Research, Engineering, Vol.3, pp.55-62.

12. Jolliffe, I.T. (2002). Principal Component Analysis, 2nd ed., New York: Springer-Verlag Inc.

13. Shlens, J. (2005). A Tutorial on Principal Component Analysis. [online] Available from: http://www.cs.princeton.edu/picasso/mats/PCA-Tutorial-Intuition_ip.pdf (Accessed 07 April 2010).

14. SAS Institute Inc. (2011). Principal Component Analysis. [online] SAS Tutorial, SAS Institute Inc. Available from: http://support.sas.com/publishing/pubcat/chaps/55129.pdf (Accessed 28 January 2011).

15. University of California. (2011). Chapter 5: Prinicpal Component Analysis. [online] Lecture Notes. Department of Plant Sceinces: University of California. Availabale from: http://www.plantsciences.ucdavis.edu/agr206/AGR206files/AGR206Lectures/AGR206Ch05PCA.doc (Accessed 12 October 2011).

16. Lilly, D.P., Cory, J., & Hissem, B. (2009). 'The Use of Prinicipal Component Analysis To Integrate Blasting Into The Mining Process'.Paper presented at the 2009 Oxford Business & Economics Conference Program. 24-26 June 2009, St. Hugh College, Oxford University, Oxford, UK.

17. Harlow, L.L. (2005). The Essence of Multivariate Thinking :Basic Themes and Methods. New Jersey: Lawrence Erlbaum Associates, Inc.

18. Google Earth. (2011). Google Earth Inc. 2011, Coordinates; 35°50'38.61"N, 72°52'15.04"E, Imagery Date 27/06/2010 (Viewed 18 March 2011).

19. Trochim, W. (2006). The T-test. [online] Research Methods Knowledge Base: Available from: http://www.socialresearchmethods.net/kb/stat_t.php (Accessed 03 October 2011)

20. Boneh, S., & Mendieta, G.R. (1994). 'Variable Selection in Regression Models Using Principal Components'. Communications in Statistics - Theory and Methods, Vol.23, pp.197-213.

21. Jollifee, I.T. (1972). 'Discarding Variables in a Principal Component Analysis. I: Artificial Data'. Applied Statistics, Vol.22 No.2, pp.160-173.