Providing a Model to Determine of Powder Factor using Principal Component Analysis Technique

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Abstract

Objectives: Powder factor is one of the main technical and economic parameters in the design of drilling models and tunnels blasting. Therefore, the prediction and optimization of powder is so important.

Methods/Statistical Analysis: The value of powder factor is dependent upon several parameters such as geological conditions, mechanical properties of the rock and geometric design parameters. In this study, based on geotechnical properties of the rock mass in construction operations for water delivery tunnel of Seimare Dam, a suitable model has been presented to determine the powder factor using statistical methods. Findings: In this regard, PCA analysis was used to eliminate the effect of co-linearity between input variables in prediction models and coefficient of determination (R²) and mean square error (MSE) were used to assess and compare the constructed models. Comparison of models shows that the elimination of co-linearity between input variables using PCA has given better prediction results. Application: In conclusion, a model proposed to determine the Powder Factor effects on cement by using principal component analysis technique, which is valuable in civil industry.

Keywords: Powder Factor, Prediction, Principal Component Analysis, Tunnel

1. Introduction

Powder factor defines the ratio of explosives’ weight to the amount of rock that must be exploded. Increase or decrease in the value of powder factor has a direct impact on rock fragmentation. If the value of powder factor is high, smaller fragments are produced and if it is low, coarse rocks are generated that require a second explosion. Given that the purpose of blasting operations in the mines is to achieve a uniform fragmentation, powder factor not only affects the dimensions of exploded rocks but also ground vibration, rock scatter in the air, and noise pollution. Several studies have been conducted to estimate the optimal value of powder factor in mines and each has implicated certain parameters of rock mass and explosives in determining the value of powder factor. Traditional methods based on empirical relationships such as the use of physical and geomechanical properties of the rock mass, blastability index of, RQI index, drilling index (DJ), Swedish Lundborg model, Larson model, Kuznetsov model, Kuz-Ram model, modified Kuz-Ram model, Rustan model, Svedefo model, Persson-Holmberg-lee model are among the methods that have been used to estimate the powder factor. To achieve the best blast ability pattern in which all the effective parameters have been taken into account, powerful results analysis techniques should be used to predict the value of powder factor proportionate to the conditions of rock mass.

Principal Component Analysis (PCA) is a data mining technique and approach to reduce multidimensional data sets into smaller dimensions that are more prone to be analyzed. In cases where a large quantity of data is involved, several statistical methods can be used to reduce the dimensions of data and group them and thus eliminate the negative effects of co-linearity between input variables in prediction models. There are several reasons to reduce data dimensions, including the higher speed of algorithms with data of less dimensions, lower storage space required, reduced likelihood of over fitting, and increased generalization power of learning algorithms.
PCA is the most common method to achieve this goal. An objective of multiple regressions is to determine the impact of each of independent variables by keeping constant other independent variables, which is realized in the first stage via estimation of regression coefficients in the model. However, if there is a linear relationship between the independent variables, a unique answer could not be reached for variables. In this case, the problem of co-linearity arises for the regression model and causes difficulties for the researcher in accurate estimation of parameters. PCA has been used in several studies to predict various parameters in the mines, tunnels, underground spaces, and the like, the most important of which are listed in Table 1. In this research, while collecting empirical data related to explosion operations in water delivery tunnel of Seimare Dam, a model to estimate powder factor has been presented using PCA approach. The approach presented in this research article has not been investigated so far.

Table 1. Some important studies on the application of PCA

| subject          | description                                                                 |
|------------------|-----------------------------------------------------------------------------|
| penetration rate | performance prediction of hard rock TBMs                                    |
|                  | TBM Performance Prediction in Rock Tunneling                                 |
|                  | penetration rate model for rotary drilling in surface mines                  |
| blasting         | model for coal burst liability assessment                                    |
|                  | Study of the Powder Factor in surface bench blasting                        |
| fragmentation    | modeling of rock fragmentation                                              |
|                  | Dynamic failure in coal seam                                                |
| tunneling effects| Monitoring for close proximity tunneling effects on an existing tunnel      |
| cost estimation  | Hard-rock LHD cost estimation                                                |
|                  | determination of overhaul and maintenance cost in surface mining            |
| property prediction | Blended coal’s property prediction model                                 |
| Fault diagnosis  | Fault diagnosis of a mine hoist                                             |
|                  | Mine-hoist fault-condition detection                                         |

2. Principal Component Analysis (PCA)

PCA is an approach providing a sequence of best linear approximations of observations in a large number of dimensions. This method has attracted the attention of many researchers in various fields in recent years. PCA is often used in different types of analysis since it is a simple non-parametric method to extract information from vague and confusing data sets. PCA provides a roadmap of how to reduce complex data sets to lower dimensions. It is a feature selection method that can be used to reduce the dimensions to enable easier evaluation of features in a space with less dimensions. PCA provides a linear transformation in which a feature vector of h dimensions is converted to feature vectors of d dimension in which h > d, so that the data are almost completely retained and the minimum mean square error is thus obtained. In other words, PCA attempts to find a linear transformation with minimum square error. In fact, the linear transformation aims to maximize $\mathbf{T}^T \mathbf{C} \mathbf{U} X - \mathbf{k}^T$ expression in which $\mathbf{C} \mathbf{U} X - \mathbf{k}$ represents the covariance matrix of data with zero mean of $X$. PCA calculates the new variables that have been obtained as a linear combination of the original variables.

3. Case Study

3.1 Introduction to Seimare Dam

Seimare Dam is located in the course of Seimare River in Badreh District in Darreh Shahr County, Ilam Province, Iran. It has a length of 417 kilometers with a slope of 0.3%, which is formed by joining together of Gharesoo and Gamasib rivers. Seimare Dam is a double-curvature arch dam with 33.0000°N 47.0000°E coordinates. Annual production of 844 GWh of hydropower energy, control and regulation of surface flows of the river, and downstream water supply are among the objectives of Seimare plan. Construction site is within folded Zagros zone in southwest. The dam is under construction on the northern flank of Ravandi anticline in Kafenil Valley. The bedrock is limestone type of Shahbazan from Asmari formation.

3.2 Data Collection

Data collection is one of the most important steps in the development of a statistical model. In this study, 12 parameters have been considered as model inputs (independent variables) and powder factor was regarded as output parameter (dependent variable) to develop the powder factor prediction model Table 2. In this regard, the data related to 290 phases of drilling and blasting operations in water delivery tunnel of Seimare Dam...
were used, from which 250 data series were applied for construction of statistical models and the remaining 40 series to test the models. Finally, coefficient of determination ($R^2$) and mean square error (MSE) were used to assess the constructed models.

3.3 Construction of Regression (Statistical) Models

All the basic assumptions of a classical regression model should be considered to construct a regression model, including the requirement of lack of co-linearity between input variables of the model. In case of co-linearity between the independent variables, the standard estimation error of regression coefficients is increased, which means increased reliability estimation distance of coefficients, and therefore the null hypothesis is often strengthened, which means a zero coefficient of regression model. Therefore, before construction and analysis of any linear regression model, the co-linearity relationship between the independent variables should be detected. There are several methods to explore co-linearity among the independent variables, including zero-order correlation (simple coefficient of correlation or Pearson correlation) between input variables or assessment of condition index (CI) for each variable. If the simple correlation coefficient between the two variables is higher than 0.8, co-linearity will be a serious problem. It should be noted that the zero-order correlation coefficient between the two variables is neither sufficient nor necessary for the existence of co-linearity. Some experts believe the condition index (CI) is the best available detector for co-linearity. CI value between 10 to 30 indicates moderate to severe co-linearity and CI>30 indicates the presence of severe co-linearity from that variable.

In this study, based on the collected data, the statistical models were constructed using SPSS software. After the discovery of co-linearity between the independent variables using CI, principal component analysis (PCA) was used to eliminate the co-linearity. In Table 3 the characteristics of powder factor regression model are shown before elimination of co-linearity.

Table 2. Effective variables (input) to construct the model of powder factor

| Diameter of the drilled holes (mm) | 2 | Uniaxial compression resistance (Mpa) | 1 |
|-----------------------------------|--|--|---|
| 0-30                              | 4 | 1 0-30 Direction of the major joint relative to direction of the tunnel |
| 30-60                             | 2 | 2 30-60 to direction of the tunnel |
| 60-90                             | 3 | 3 60-90 |
| Handle slope of secondary joint (0-90) | 6 | Handle slope of major joint (0-90) | 5 |
| Clearance of the handle of secondary joint (m) | 8 | Clearance of the handle of major joint (m) | 7 |
| 0-30                              | 10 | 1 0-30 Opening score of major joint's handle |
| 30-60                             | 2 | 2 30-60 |
| 60-90                             | 3 | 3 60-90 |
| Score (0-100) RMR                 | 12 | RQD Score (0-100) | 11 |

Table 3. Regression model of powder factor before elimination of co-linearity

| VAR (Constant) | B   | SIG | CI  | Std. Error | R-SQUARED | MSE  | R-SQUARED | MSE  | TOTAL PREDICTION | TEST |
|----------------|-----|-----|-----|------------|------------|-------|-----------|-------|-----------------|------|
| UCS            | -0.052 | 0.37 | 5.102 | 0.06  |
| RQD            | -0.290 | 0.02 | 7.956 | 0.12  |
| RMR            | 0.021   | 0.85 | 9.544 | 0.11  |
| DIJPS1         | 0.194   | 0.00 | 10.838 | 0.05  |
| DDR1           | 0.084   | 0.01 | 13.750 | 0.03  |
| JS1            | 0.337   | 0.00 | 15.992 | 0.10  |
| JAPP1          | 0.004   | 0.95 | 19.389 | 0.07  |
| DIJPS2         | 0.158   | 0.00 | 20.364 | 0.05  |
| DDR2           | -0.045  | 0.23 | 27.819 | 0.04  |
| JS2            | 0.245   | 0.01 | 38.485 | 0.10  |
| JAPP2          | -0.131  | 0.01 | 61.883 | 0.05  |
| D              | 0.425   | 0.00 | 100.372 | 0.03  |

SIG . TOTAL 0.00
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CI in Table 3 indicates moderate to severe co-linearity between independent variables, which is also evident in Table 4. The numbers marked with red color indicate the presence of co-linearity caused by that variable. In Table 5, the significance levels of null hypothesis for zero-order correlation coefficient are shown. Null hypothesis for zero-order correlation coefficients states: “zero-order correlation between these two variables is zero”. If this value in Table 5 is close to zero, it suggests that this hypothesis can be rejected with a confidence level close to 100%. In other words, we can say with 100% confidence that there is a correlation between the two variables.

Then, after the detection of co-linearity, its impact is eliminated using principal component analysis (PCA) and a new model is constructed. The results of the new statistical model are listed in Table 6. According to this table, assessment of CI values can indicate the impact of PCA in severe reduction of co-linearity impact in the constructed model. The results presented in Table 7 and 8 also confirmed this point.

The general results of statistical models are listed in Table 9. The best regression model to predict the powder factor functions according to Figure 1 and 2.

### Table 4. Zero-order correlation coefficients for the detection of co-linearity between variables

|       | UCS  | RQD  | RMR  | DIPJS1 | DDR1 | JS1  | JAPP1 | DIPJS2 | DDR2 | JS2  | JAPP2 | D    |
|-------|------|------|------|--------|------|------|-------|--------|------|------|-------|------|
| UCS   | 1.000| .229 | .237 | .259   | -.199| .028 | -.100 | .061   | -.114| .307 | -.240 | -.199|
| RQD   | .229 | 1.000| .823 | -.267  | -.011| .703 | .669  | -.014  | -.021| .649 | -.628 | .291 |
| RMR   | .237 | .823 | 1.000| -.170  | -.043| .610 | .862  | .125   | .018 | .531 | -.711 | .254 |
| DIPJS1| .259 | -.267| -.170| 1.000  | -.072| -.507| .192   | .147   | -.088| .045 | .032  | -.599|
| DDR1  | -.199| -.011| -.043| -.072  | 1.000| -.106| .043   | .033   | .284 | -.079| -.023 | .175 |
| JS1   | .028 | .703 | .610 | -.507  | -.106| 1.000| -.527  | .117   | -.032| .256 | -.339 | .331 |
| JAPP1 | -.100| -.669| -.862| .192   | .043 | -.527| 1.000  | -.045  | -.107| -.386| .621  | .327 |
| DIPJS2| .061 | -.014| .125 | .147   | .033 | .117 | -.045  | 1.000  | .189 | -.315| -.065 | .251 |
| DDR2  | -.114| -.021| .018 | -.088  | .284 | -.032| -.107  | .189   | 1.000| -.185| .009  | .196 |
| JS2   | .307 | .649 | .531 | .045   | -.079| .256 | -.386  | -.315  | -.015| 1.000| -.513 | .146 |
| JAPP2 | -.240| -.628| -.711| .032   | -.023| -.339| .621   | -.065  | .009 | -.513| 1.000| -.211|
| D     | -.199| .291 | .254 | -.599  | .175 | .331 | -.327  | -.251  | .196 | .146 | -.211| 1.000|

### Table 5. Significance level (Sig) of null hypothesis for zero-order correlation coefficients

|       | UCS  | RQD  | RMR  | DIPJS1 | DDR1 | JS1  | JAPP1 | DIPJS2 | DDR2 | JS2  | JAPP2 | D    |
|-------|------|------|------|--------|------|------|-------|--------|------|------|-------|------|
| UCS   | .    | .000 | .000 | .001   | .329 | .057 | .167   | .034   | .000 | .000 | .001  | .000 |
| RQD   | .000 | .    | .000 | .000   | .429 | .000 | .412   | .370   | .000 | .000 | .000  | .000 |
| RMR   | .000 | .000 | .    | .003   | .246 | .000 | .000   | .024   | .386 | .000 | .000  | .000 |
| DIPJS1| .000 | .000 | .003 | .    | .128 | .000 | .001   | .010   | .303 | .000 | .104  | .355 |
| DDR1  | .001 | .429 | .246 | .128   | .    | .046 | .249   | .303   | .000 | .104 | .355  | .003 |
| JS1   | .329 | .000 | .000 | .000   | .046 | .    | .000   | .031   | .305 | .000 | .000  | .000 |
| JAPP1 | .057 | .000 | .000 | .001   | .249 | .000 | .    | .237   | .044 | .000 | .000  | .000 |
| DIPJS2| .167 | .412 | .024 | .010   | .303 | .031 | .237   | .    | .001 | .000 | .151  | .000 |
| DDR2  | .034 | .370 | .386 | .081   | .000 | .305 | .044   | .001   | .    | .002 | .443  | .001 |
| JS2   | .000 | .000 | .000 | .240   | .104 | .000 | .000   | .000   | .002 | .    | .000  | .010 |
| JAPP2 | .000 | .000 | .000 | .306   | .355 | .000 | .151   | .443   | .000 | .    | .000  | .000 |
| D     | .001 | .000 | .000 | .003   | .000 | .000 | .000   | .001   | .010 | .000 | .    | .000 |
Table 6. Regression model of powder factor after elimination of co-linearity impact

| VAR          | B   | SIG | CI | Std. Error | TOTAL PREDICTION | TEST  |
|--------------|-----|-----|----|------------|-----------------|-------|
| (Constant)   | .196| .123| 1.00 | 0.13       | R-SQUARED      | MSE   |
| UCS          | -0.110 | .683 | 1.393 | 0.07        | .6410          | 0.1790 | 0.2999 | 1.1313 |
| RQD          | -0.238 | .000 | 1.402 | 0.05        | .1790          | 0.2999 | 1.1313 |
| RMR          | -0.117 | .200 | 1.404 | 0.05        | .2999          | 1.1313 |
| DIPJS1       | 0.420 | .011 | 1.405 | 0.06        | .2999          | 1.1313 |
| DDR1         | 0.024 | .005 | 1.406 | 0.06        | .2999          | 1.1313 |
| JS1          | -0.001 | .811 | 1.406 | 0.05        | .2999          | 1.1313 |
| JAPP1        | -0.061 | .000 | 1.406 | 0.05        | .2999          | 1.1313 |
| DIPJS2       | 0.455 | .001 | 1.407 | 0.06        | .2999          | 1.1313 |
| DDR2         | -0.036 | .000 | 1.407 | 0.09        | .2999          | 1.1313 |
| JS2          | 0.219 | .237 | 1.407 | 0.10        | .2999          | 1.1313 |
| JAPP2        | -0.198 | .393 | 1.425 | 0.11        | .2999          | 1.1313 |
| D            | -0.235 | .449 | 11.383 | 0.15        | .2999          | 1.1313 |

Table 7. Zero-order correlation coefficients for the detection of co-linearity between variables

| UCS | RQD | RMR | DIPJS1 | DDR1 | JS1 | JAPP1 | DIPJS2 | DDR2 | JS2 | JAPP2 | D |
|-----|-----|-----|--------|------|-----|-------|--------|------|-----|-------|---|
| 1.00 | -0.488 | 0.331 | -0.350 | -0.265 | -0.078 | 0.049 | 0.071 | -0.180 | -0.156 | -0.012 | -0.041 |
| -0.488 | 1.000 | 0.102 | -0.107 | -0.084 | -0.028 | 0.021 | 0.020 | -0.055 | -0.065 | -0.009 | -0.012 |
| 0.331 | 0.102 | 1.000 | 0.073 | 0.056 | 0.016 | -0.010 | -0.015 | 0.038 | 0.033 | 0.003 | 0.009 |
| -0.350 | -0.107 | 0.073 | 1.000 | -0.059 | -0.017 | 0.010 | 0.016 | -0.040 | -0.033 | -0.002 | -0.009 |
| -0.265 | -0.084 | 0.056 | -0.059 | 1.000 | -0.014 | 0.010 | 0.011 | -0.030 | -0.030 | -0.003 | -0.007 |
| -0.078 | -0.028 | 0.016 | -0.017 | -0.014 | 1.000 | 0.005 | 0.003 | -0.009 | -0.009 | -0.003 | -0.002 |
| 0.049 | 0.021 | -0.010 | 0.010 | 0.005 | 1.000 | -0.001 | 0.005 | 0.015 | 0.003 | 0.001 | 0.002 |
| 0.071 | 0.020 | -0.015 | 0.016 | 0.003 | -0.001 | 1.000 | 0.008 | 0.003 | -0.001 | 0.002 |
| -0.180 | -0.055 | 0.038 | -0.040 | -0.030 | -0.009 | 0.005 | 0.008 | 1.000 | -0.017 | -0.001 | -0.005 |
| -0.156 | -0.065 | 0.033 | -0.033 | -0.030 | -0.015 | 0.015 | 0.003 | -0.017 | 1.000 | -0.010 | -0.003 |
| -0.012 | -0.009 | 0.003 | -0.002 | -0.003 | -0.003 | 0.003 | -0.001 | -0.001 | 1.000 | 0.000 |
| -0.041 | -0.012 | 0.009 | -0.009 | -0.007 | -0.002 | 0.001 | 0.002 | -0.005 | -0.003 | 1.000 |

Table 8. Significance level (Sig) of null hypothesis for zero-order correlation coefficients

| s  | UCS | RQD | RMR | DIPJS1 | DDR1 | JS1 | JAPP1 | DIPJS2 | DDR2 | JS2 | JAPP2 | D |
|----|-----|-----|-----|--------|------|-----|-------|--------|------|-----|-------|---|
| .  | .000 | .000 | .000 | .000 | .000 | .108 | .217  | .132  | .002 | .007 | .424  | .256 |
| .  | .000 | .052 | .045 | .091  | .328  | .370 | .378  | .192  | .151 | .443  | .424 |
| .  | .000 | .052 | .123 | .190  | .398  | .434 | .408  | .276  | .302 | .483  | .445 |
| .  | .000 | .045 | .123 | .177  | .394  | .434 | .401  | .264  | .301 | .486  | .442 |
| .  | .000 | .091 | .190 | .177  | .412  | .439 | .429  | .317  | .316 | .479  | .457 |
| .  | .108 | .328 | .398 | .394  | .412  | .470 | .484  | .445  | .408 | .483  | .489 |
| .  | .217 | .370 | .434 | .434  | .439  | .470  | .494  | .466  | .407 | .478  | .494 |
| .  | .132 | .378 | .408 | .401  | .429  | .484  | .494  | .449  | .481 | .496  | .487 |
| .  | .002 | .192 | .276 | .264  | .317  | .445  | .466  | .449  | .395 | .493  | .470 |
| .  | .007 | .151 | .302 | .301  | .316  | .408  | .407  | .481  | .395 | .434  | .482 |
| .  | .424 | .443 | .483 | .486  | .479  | .483  | .478  | .496  | .493 | .434  | .500 |
| .  | .256 | .424 | .445 | .442  | .457  | .489  | .494  | .487  | .470 | .482  | .500 |

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4. Conclusion

Powder factor is one of the most important technical and economic parameters in the design of drilling patterns and tunnel blasting, which is dependent upon various parameters such as geological conditions, rock mechanical properties, and geometric design parameters. For this reason, prediction and optimization of powder factor is of high importance. Several empirical equations have been presented to predict the powder factor; however, since these relationships have been usually developed based on specific geological conditions, they cannot be used for all conditions. In this study, based on geomechanical properties of the rock mass, statistical methods as well as principal component analysis (PCA) were used to predict and optimize the powder factor. Thus, data from 290 phases of drilling and blasting operations for water delivery tunnel of Seimare Dam were collected, from which 250 items of data were used to construct the statistical models and another 40 items to test the models obtained. In this respect, PCA algorithm was used to eliminate the negative effect of co-linearity between input variables in prediction models and $R^2$ as well as MSE parameters were used to assess the constructed models. Comparisons showed that the elimination of co-linearity between the input variables has given better prediction results in statistical models.

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Table 9. General results of statistical models

|                  | WITHOT PCA | WITH PCA |
|------------------|------------|----------|
| $R^2$            | 0.641      | 0.641    |
| MSE              | 0.2559     | 0.2999   |
| TOTAL PREDICTION | 0.179      | 0.179    |
| TEST             | 1.2777     | 1.1313   |

Figure 1. The coefficient of determination results of statistical model to predict powder factor using PCA.

Figure 2. Predicted results of statistical models optimized for a 40-member test data.
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