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Application of Geostatistical Modelling to Study the Exploration Adequacy of Uniaxial Compressive Strength of Intact Rock alongthe Behesht-Abad Tunnel Route

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Abstract
Uniaxial compressive strength (UCS) is one of the most significant factors on the stability of underground excavation projects. Most of the time, this factor can be obtained by exploratory boreholes evaluation. Due to the large distance between exploratory boreholes in the majority of geotechnical projects, the application of geostatistical methods has increased as an estimator of rock mass properties. The present paper ties the estimation of UCS values of intact rock to the distance between boreholes of the Behesht-Abad tunnel in central Iran, using SGEMS geostatistical program. Variography showed that UCS estimation of intact rock using geostatistical methods is reasonable. The model establishment and validation was done after assessment that the model was trustworthy. Cross validation proved the high accuracy (98%) and reliability of the model to estimate uniaxial compressive strength. The UCS values were then estimated along the tunnel axis. Moreover, using geostatistical estimation led to better identification of the pros and cons of geotechnical explorations in each location of tunnel route.

Keywords: *Behesht-Abad tunnel project, Uniaxial Compressive Strength, Geostatistical estimation, SGEMS.*

1. Introduction

Uniaxial compressive strength (UCS), as one of the most important factors on the stability of rock engineering structures, are used frequently in the design and construction of underground projects [1,2,3].The UCS of rock material can be obtained directly from laboratory tests that require many high quality specimens [4]. For instance, Coates and Parsons(1966) concluded that a minimum number of ten specimens arerequired in order to obtain reliable values for the UCS of rock material [5]. Required specimens in many laboratory tests are gathered from exploratory boreholes. Considering the large distance between exploratory boreholes, reliable prediction of geotechnical parameters in unreachable zones, based on limited sources of available datasets, is one of the most important issues in each project. Therefore, the best application of available information is of high importance [6]. Thus, application of geostatistical methods for estimation and simulation of rock mass characteristics has increased in recent years. Estimation of spatial distribution of the variable is the expected result of using geostatistical methods [7].

Geostatistics has been employed by many researchers as a tool for appraisal of rock mass characteristics. Horger et al. (1987) applied the results of geostatistical estimation/simulation of rock mass condition as input parameters for geotechnical design [8]. The results of this investigation revealed the higher accordance of the results of this design method with insitu conditions than the common design method, which is based on the mean value of datasets. Stavropoulou et al. (2007) developed a three dimensional integration of geological datasets, geostatistical, and numerical simulation [9]. Use of the geostatistical simulation outcome as input parameters in numerical modelling could provide a more efficient ground for appraisal of rock mass behaviour encountered, and minimize the need for engineering judgment. In this regard, Oh (2013), intending to estimate the values of RQD, used a combination of the results of two geophysical experiments— namely electric resistivity and seismic wave velocity— as input parameters in geostatistical simulation. He demonstrated that by means of geophysical experiment results and geostatistical methods, the cost of preliminary exploratory could be decreased in addition to the calculation of acceptable estimations of the values of intended parameters [10]. Ozturk and Simdi (2014) used cokriging in order to estimate the rock quality designation (RQD), geological strength index (GSI), rock mass modulus of elasticity (E_r), rock material modulus of elasticity (E_m), uniaxial compressive strength (UCS), and mean daily advance rate of construction in an Istanbul subway of Turkey. The results revealed that application of properly correlated datasets along with cokriging could compensate for a deficiency of usable datasets while enhancing the accuracy of geostatistical estimations [7]. All the aforementioned studies are good examples of application of geostatistical methods as powerful tools for obtaining estimation of geotechnical parameters with spatial correlation.

In this research, the Behesht-Abad water-conveying tunnel of central Iran was chosen as a case study for feasibility studies on the possibility of use of geostatistical modelling in estimation of geotechnical parameters. In some areas, due to the influence of natural obstacles, the distance between exploratory boreholes is very large. Accordingly, proper estimation of geotechnical parameters of tunnel surrounding rock mass prior to the construction stage is crucially important. Due to the significant importance of uniaxial compressive strength of rock material on the stability of the structure, this parameter was used as an input parameter of geostatistical modelling. In this study, the ability of geostatistical modelling to obtain the pros and cons of geotechnical explorations of UCS in different parts of Behesht-Abad tunnel route were assessed. Finally, the assessment of the reliability of geostatistical methods as a tool for geotechnical parameter estimation was made. The purpose of many existing studies on geotechnical parameters is the performance of geostatistical methods in parameter estimation. As a consequence, the case study of the present research was constructed to make real datasets available for comparison with geostatistical modelling results. Using geostatistical modelling for the estimation of UCS parameter in rock materials before construction phase distinguishes this study from others. Accordingly, the variogram interpretation, validation results, and geostatistical model estimation are of high importance in this study.

2. The Behesht-Abad water conveying tunnel

The Behesht-Abad water conveying tunnel, with a length of 65 kilometres and a diameter of 6 metres,is one of the largest ongoing projects in central Iran. It aims to provide the central parts of the country with water for drinking, industrial, and agricultural purposes via conveying water from the Behesht-Abad river, which has a capacity of 1070 cubic metres of water. Based on geotechnical studies, the tunnel route was divided into 42 parts from an engineering geology point of view. The LANDSAT satellite imageand profile of the final 11 kilometres of the tunnel route is shown in Figure 1 [17].

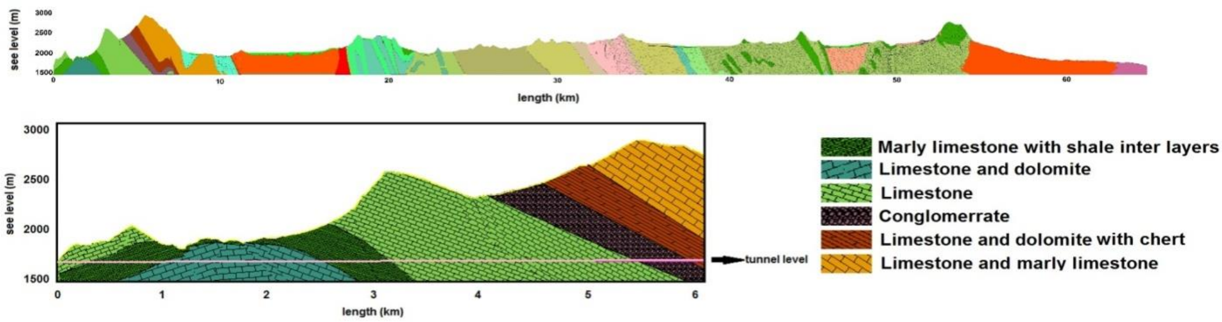


Fig. 1. geological profile of the tunnel route [17]

Proper estimation of geotechnical parameters along the tunnel route is of high importance due to the long distance between the boreholes and the high magnitude of the project. Thus,this project used the SGEMS program to evaluate the reliability of the conducted exploratory work and estimate the compressive strength of intact rock along the tunnel axis. Calculation of error estimation variance, along with estimated values in each point, is one of the advantages of geostatistical estimation methods [12]. In fact, kriging error specifies an estimated level of reliability [6].

3. Geostatistical estimation

Geostatistics is an interpolation method that aims to gain an understanding of behaviour of natural phenomena using a limited set of data [11,12]. In use of geostatistics, the first step would be obtaining a variogram related to the regional correlation of the parameter of interest [11]. Mathematical description of an empirical variogram would be as follows [13,14].

$$\gamma(h) = \frac{1}{2N}\sum_{i=1}^{N}[Z(x+h) - Z(x)]^2 \tag{1}$$

where γ(h) is half of semivariogram, Z(x) is the function stochastic variable related to its location x, Z(x+h) is the function of stochastic variable in location x+h, and N is the number of double points which contribute in obtaining the variogram.

The estimation of the intended parameter in unreachable zones could be implemented directly after obtaining a variogram with acceptable correlation. The applied estimator in geostatistical modelling is kriging, which was first introduced by Krig in 1951. The kriging estimator for attaining the value of a variable at an intended point can be identified using the following equation:

$$Z^*(x_0) = \sum_{i=1}^{m} w_i Z(x_i) \tag{2}$$

where $Z^*(x_0)$ is the estimated values of the variable in unsampled (unreachable) points, w_i is the numerical values of kriging weight, and $Z(x_i)$ is the available value of the parameter in the vicinity of the point. The kriging estimator is regarded as the unbiased estimator, though it should contain no systematic errors as well as having a minimum variance of estimation. The overall sum of kriging coefficients must be equal to one in order to fulfil the first requirement: namely,that it contains no systematic error.

$$\sum_{i=1}^{n} w_i = 1 \tag{3}$$

For fulfilment of the second requirement- namely, having minimum variance of estimation- the function of variance of estimation should be obtained and then minimized. Variance of estimation in common ordinary kriging is obtained via following equation.

$$\delta_E^2 = 2\sum_{i=1}^{n} w_i \overline{\gamma}(v, v_i) - \overline{\gamma}(v, v) - \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \overline{\gamma}(v_i v_j) \tag{4}$$

where δ_E^2 is variance of estimation, $\bar{\gamma}(v, v_j)$ the mean value of variogram, while one of the h vector's ends starts in it h block and the other end goes to an unknown block. $\bar{\gamma}(v_i, v_j)$ is also the mean value of the variogram, while one end of h vector starts from the v_i block leading the other end of the vector to block v_j. The w is coefficient of kriging where the values of w_i are chosen in a way that causes the minimum possible outcome for variance of estimation. This optimization problem can be solved using Lagrangian coefficients. Considering μ as Lagrangian coefficient, the following partial derivatives must be equal to zero.

$$\frac{\partial\left[\sigma_E^2 - 2\mu\left(\sum_{i=1}^{n} w_i - 1\right)\right]}{\partial w_i} = 0 \qquad i = 1,2,3,\ldots n \tag{5}$$

This equation is in fact a linear equation set including n+1 number of equations and n+1 number of unknown parameters (including n number of w_i and one Lagrangian coefficient μ) which can be solved by means of matrix methods.

$$A = \begin{bmatrix} w_{11} & w_{12} & \ldots & w_{1n} & 1 \\ w_{21} & w_{22} & \ldots & w_{2n} & 1 \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ w_{n1} & w_{n2} & \ldots & w_{nn} & 1 \\ 1 & 1 & \ldots & 1 & 0 \end{bmatrix}$$

$$B = \begin{bmatrix} w_{1v} \\ w_{2v} \\ \ldots \\ w_{3v} \\ 1 \end{bmatrix}, \quad X = \begin{bmatrix} w_1 \\ w_2 \\ \ldots \\ w_3 \\ -\mu \end{bmatrix} \tag{6}$$

$$AX = B \text{ or } x = A^{-1}B$$

where matrix elements for A, X, and B are variogram values of sampling points, Kriging estimation coefficients, and variogram of the distance between sampling and estimated points, respectively.

4. Geostatistical modelling of uniaxial compressive strength of intact rock

The distribution of test results were investigated prior to geostatistical modelling. The distribution of reliable information about UCS in the tunnel route is shown in Figure 2. Statistical information and histograms of reliable UCS test results are represented in Figure 3.

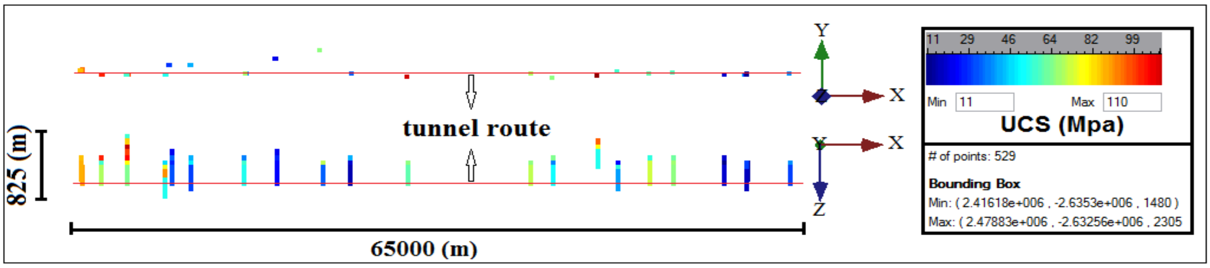


Fig. 2. distribution of reliable UCS test results in boreholes

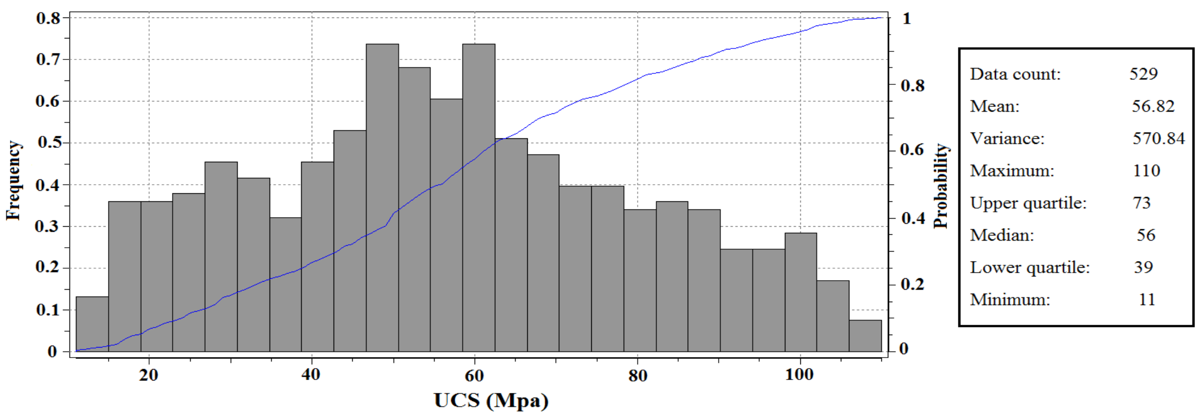


Fig. 3. Histogram of values of UCS obtained from laboratory tests

Figure 2 reveals that the reliable values of UCS in some boreholes are due to different reasons: such as lack of availability of standard specimens, and the decision of experts that the values of this parameter do not exist. This fact shows the importance of using different approaches in order to make efficiency gains from the available datasets. Thus, in this research, geostatistical estimation of UCS in the distances between boreholes was obtained.

Three aspects of applied datasets should be assessed prior to geostatistical estimation.

Drift: examining the availability of drift in the applied datasets is one of the most important steps in geostatistical studies [12]. Use of geostatistical methods will be possible if there is no drift discernible in the datasets. In the case of drift occurrence, it should be omitted before construction of the variography [6]. Observation of the trend of parameter changes with regard to the depth is an easy method to check the existence of drift [12]. The employed datasets were checked prior to the construction of the model and carrying out the estimation. It was concluded that there is no drift in the applied datasets.

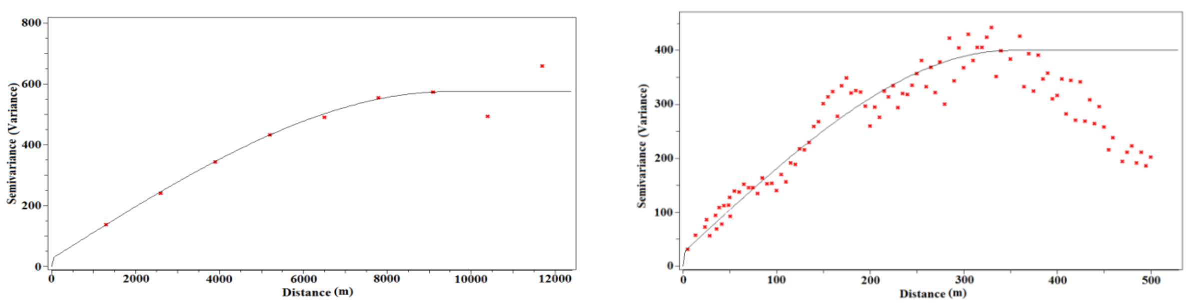
Outliers: since the variance is a square operator, even a single outlier can have a significant negative impact on the obtained results.The best choice, therefore, is to remove the outliers where possible [18]. In cases where removal of the outliers could lead to significant reduction in number of datasets, one method of correction is to truncate the outlier to its neighbouring values. Using a logarithm of the datasets could be another way to reduce the impact of outliers [12]. Developed appraisals disclosed that in some points, the values of UCS were hugely different to their neighbouring values. In some of these points, referring to experts, and the available history and documents of the values of UCS, along with consideration of the lithology and rock type, the abnormal values were truncated to standard ones. In some other points,the outliers were omitted due to a lack of information needed for adjusting the values of UCS.

Anisotropy: the variograms take into account the difference between points without considering their orientation, while the majority of geological phenomena are anisotropic and variograms can be constructed in different orientations [6]. Ellipses of anisotropy can be obtained by plotting the variogram in different orientations [13]. In this research, due to the distribution of the boreholes along a tunnel axis (Fig. 3), variograms could be obtained practically in the vertical direction and the horizontal direction parallel to the tunnel axis. Therefore, the variograms in these directions were constructed.

4.1. Construction and interpretation of the variogram

The most important step in use of geostatistical methods is to obtain the variogram with high correlation. This step has a significant impact on the behaviour and results of the model [11, 19]. Accordingly, accurate interpretation and construction of the variogram are among the prerequisites of modelling [13]. The interpretation and description of the variograms is discussed in the following.

As was mentioned above, the only practical way of constructing a variogram is in horizontal and vertical directions. Thus, variograms of UCS datasets in these two directions were calculated and constructed, and are represented in Figure 4. The parameters of these variograms are shown in Table 1.



A B

Fig. 4. A) Horizontal variogram of UCS values in the direction of the tunnel axis. B) Vertical variogram of UCS values.

Table 1. a) properties of horizontal variogram of UCS values in direction of tunnel; b) properties of vertical variogram of UCS

	type of variogram	nugget effect	sill	(A)
a	spherical	25	575	9477
b	spherical	25	400	350

Some of the valuable information obtained from appraisal of variograms is as follows:

1. As is obvious from the horizontal variograms, the impact distances are very large (A: 9744 m) and comprise a significant part of the location under study.This is an indicator of the proper spatial correlation of the UCS values in the studied location.

2. Behaviour at the originof coordinates and in central parts is an indicator of the level of continuousness of regional variable and homogeneity of the environment, which defines the range of the variogram [13]. Low values of the slope of the horizontal variogram in these parts indicate high levels of continuousness, vastness of the structural region, and homogeneity of the environment for application of geostatistical estimation of UCS. As can be seen in the horizontal variogram, slope in these parts is low and thus indicates high continuity, vastness structural region, and homogeneity of the environment in geostatistical terms.

3. As shown in Figure 1 and Table 1, the maximum sill of horizontal variogram of UCS values is almost equal to the overall variance of employed datasets and conforms to the initial condition of the datasets.

4. Short scale variance (nugget effect): the nugget effect in the variogram could be a result of measurement errors, geological structures, or correlation in a scale shorter than distances between sampling points [13]. The value of variance could differ in each direction. In order to develop a variogram, the lowest possible value of nugget effect in different directions should be used. In this study, the final nugget effect for the horizontal variogram was selected based on the nugget effect of the vertical direction. It could be identified that the nugget effect has a small value in comparison with the overall variance of the variogram, which is an indicator of high spatial correlation and smallness of randomly structured parts.

5. Average scale variance (geometric anisotropy): geometric anisotropy is related to phenomena that have different impact in different directions [13]. Due to the geometry of the boreholes, acquisition of ellipse of anisotropy was not possible. Therefore, only the comparison of horizontal and vertical variograms was practical. In comparing the impact distances of these two variograms, it is clear that the anisotropy in a vertical direction is way more than its value in a horizontal direction, and that changes in UCS in this direction occur faster.

6. Largescale- variance (regional anisotropy): these kinds of anisotropy appear whenever the roof (sill) of the variogram cannot reach the theoretical variance of dataset and does not cover the variance of whole complex [13]. The difference between maximum and minimum roof (sill) of variance in variograms can be a sign of this kind of anisotropic structure. In this study, the difference between sill of horizontal and vertical variograms refers to this issue. Figure 5 shows the three general structures of variance in analysing the variograms of UCS.

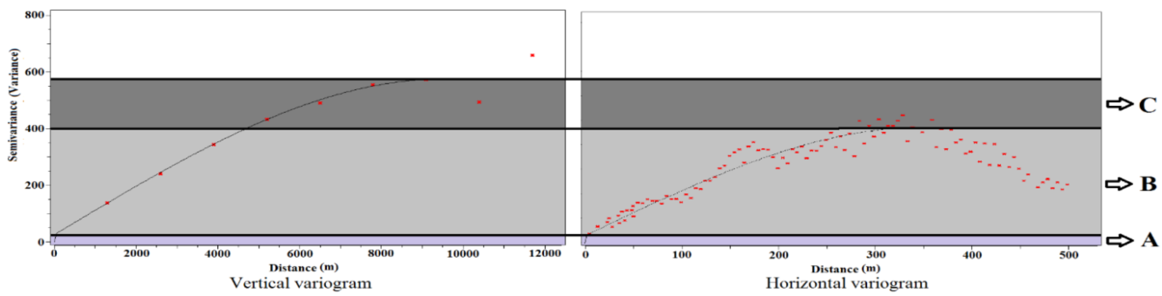


Fig. 5. general structures of variance: a) first structure (nugget effect), b) second structure (geometric anisotropy), and c) third structure (regional anisotropy)

According to points one to three, above, about the appraisal of variograms, it can be concluded that UCS in the region of the project has a good spatial correlation, and that using geostatistical methods to estimate this parameter along the tunnel route is reliable.

4.2. Estimation of UCS in borehole surroundings

Ordinary kriging was used for estimation of UCS values after construction of the variogram. For estimation of this parameter along the tunnel axis, the dividing process was done in the whole tunnel route with 325 cubic blocks at a size of 200 m: the tunnel axis passes through the blocks'centres and each block represents the condition of 100 m of tunnel vicinity. The centre coordinate of these blocks was used for geostatistical modelling in order to represent the estimated values with their coordinates. In fact, this can be assumed to be a virtual exploratory network of boreholes with distances of 200 m along the tunnel axis. Distribution of estimated UCS and variance of estimation error is shown in Figure 6.

According to Figure 6, variance of estimation error in the central part is higher than in other parts,indicating a lower reliability of estimation results in this region. The reason for this could be the large distance of sampling points of UCS in this area. To do more assessments of the reliability of geostatistical estimation results, the model was validated and analysed.

4.3. Cross Validation of estimation results in unreachable zones

In this study, 100 of UCS's initial values were randomly chosen for cross validation of estimation results. Then, chosen values were ostracized separately from initial values in ten groups of 10 members each, and the rest of the values were used for estimation of UCS in these points. The estimated and actual values of these points were regressed linearly as shown in Figure 7. Linear regression results revealed that correlation coefficient of estimated and actual values is approximately 98%. Validation showed that the proposed model of variogram is highly precise in estimating the UCS changes in the vicinity of the project. Moreover, estimation based on the proposed model has high level of reliability.

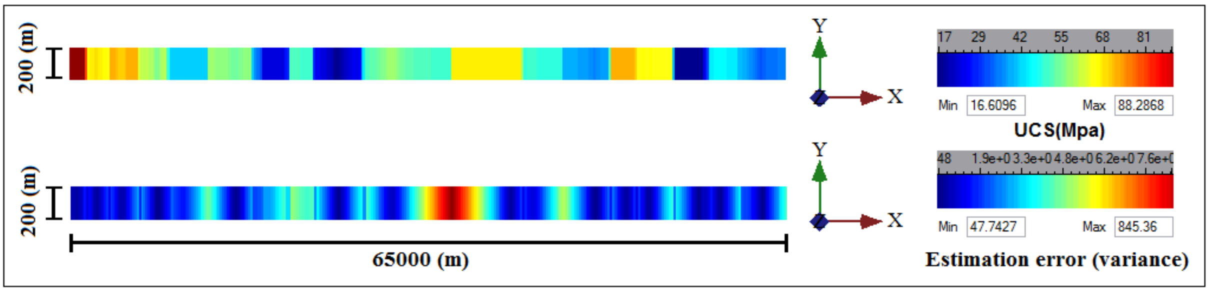


Fig. 6. Distribution of estimated UCS and variance of estimation error along the tunnel axis

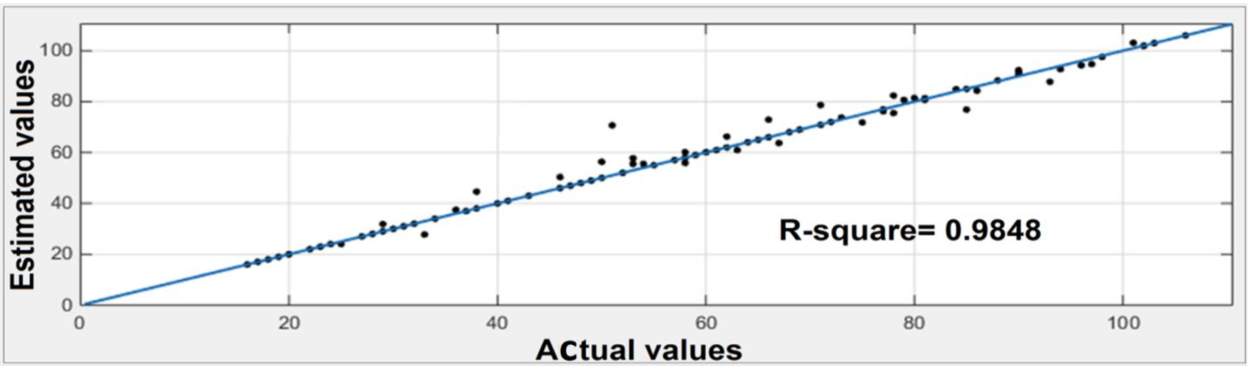


Fig. 7. Linear regression of estimated and actual values

5. Analysis of geostatistical estimations along the tunnel axis

As was mentioned previously, one of the main purposes of this research is to assess the adequacy of conducted experiments and explorations in order to estimate UCS along the tunnel axis. One of the benefits of estimation using geostatistical methods is calculating the variance of estimation error along with estimated values at each point. Thus, after ensuring the validity of the geostatistical model, the strengths and weaknesses of UCS experiments in the project environment were analysed. In addition to pros and cons of explorations and experiments, the reliability of estimation is also characterized by examining the variance of estimation error in each part, which was evaluated in the vicinity of exploratory boreholes (Fig. 8).

As can be seen in Figures 8 and 9, in the middle part of the exploratory boreholes, the variance of estimation error has a larger value than both the other regions, and the overall variance which is the consequence of the large distance between sampling points of UCS. The changes of this parameter along the tunnel axis were investigated in order to explore further the impact of sampling point on the amount of variance of estimation error (Fig. 9).

It is obvious from Figure 9 that variance of geostatistical estimation is least at borehole points and increases by receding from these boreholes. However, the amount of this error is not the same at different locations, which is a result of the difference in the amount of conducted exploration and experiment in each borehole. This variety could be identified clearly at location of boreholes 5, 7, 8, and 13. The valid results of UCS experiment in these points are less than the others, which causes a higher variance of estimation error.

According to distribution of exploration datasets and variance of estimation error, it could be concluded that the amount of UCS experimentation in most part of the project is adequate. However, there are some regions, such as the distance between boreholes 10 and 12, and also 5, 7, 8, and 13, which need more exploration. One of the purposes of estimating the values of UCS is classification of rock mass quality along the tunnel route. As a result, the estimated values of this parameter was rated and classified based on a RMR classification system. The conducted procedure is represented in Figure 10. It is obvious that a small part of whole tunnel route has been classified as weak rock mass. However, it is suggested that further exploration is conducted in the areas with poor quality ofrock, and also the regions where we lack exploratory datasets.

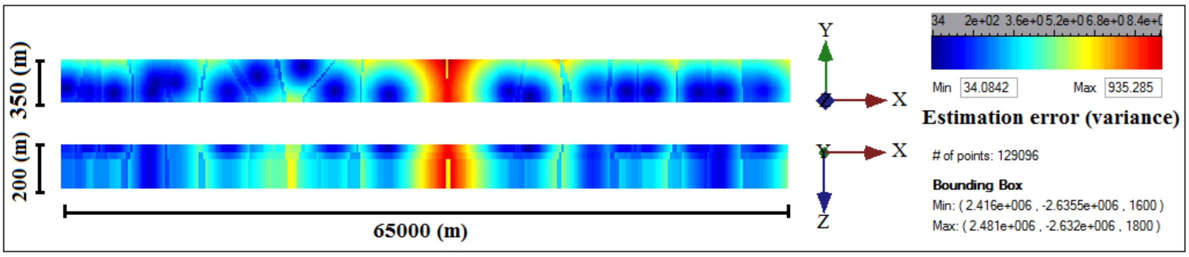


Fig. 8. Distribution of the variance of estimation error in the vicinity of exploratory boreholes

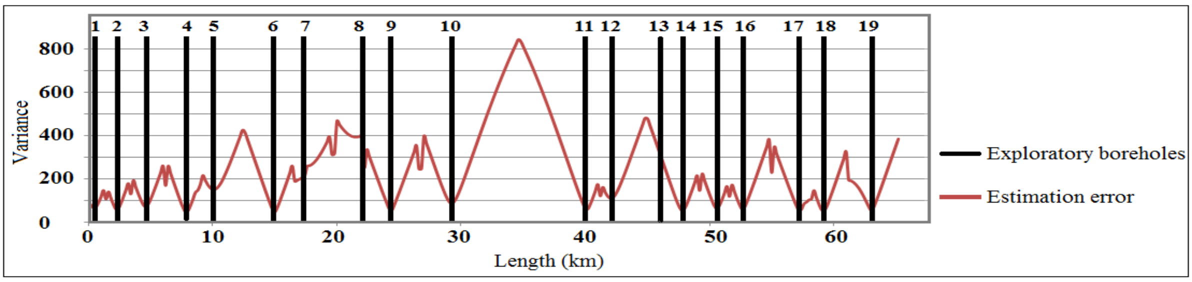
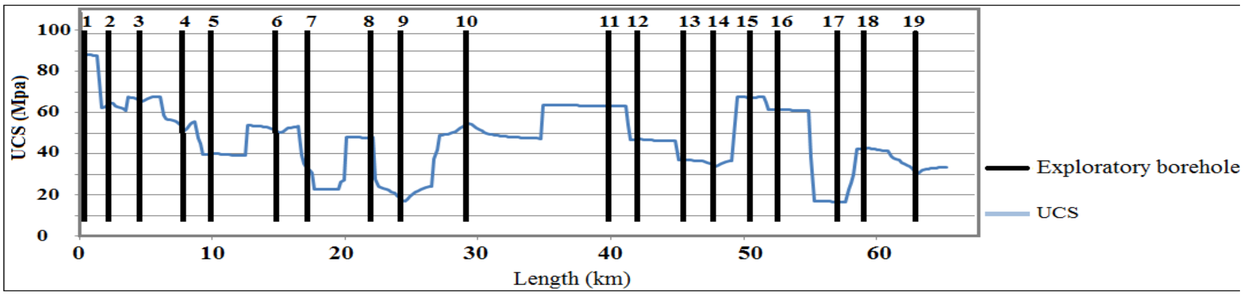


Fig. 9. Variance of estimation error along the tunnel axis



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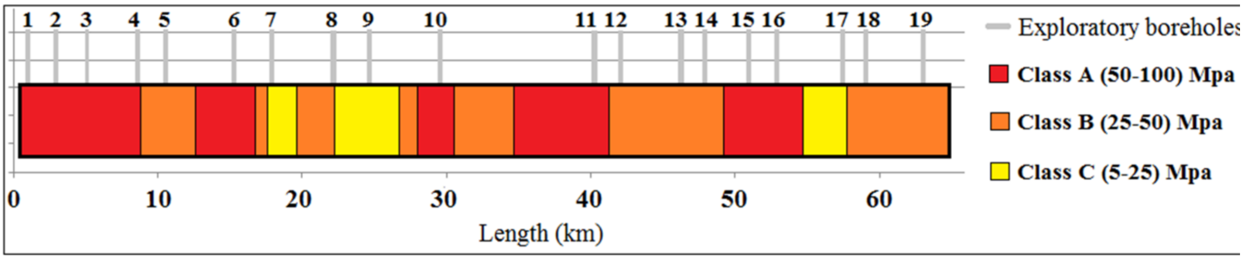

B

Fig. 10. a) geostatistical estimation values of UCS along the tunnel axis, b) classification of geostatistical estimation results for UCS along the tunnel axis

6. Conclusion

UCS is a key factor in stability analyses of rock engineering projects and which is obtained from laboratory tests carried out on the specimens attained from exploratory boreholes. Considering the long distances between exploratory boreholes in geotechnical projects, estimation of UCS between those boreholes is of high importance. In this study, UCS values along the tunnel axis of Behesht-Abad in central Iran were estimated using SGEMS software. The results of variography revealed the proper spatial correlation of distribution of the values of this parameter in the study area and suitability of use of geostatistical methods for estimation purposes. Validation results revealed that the geostatistical model has high precision (98%) and that estimated results for those sampling points which have a lower space than the impact distance meet the high compliance with the conditions governing the project. Furthermore, using geostatistical estimation led to better identification of the pros and cons of geotechnical explorations in each location of tunnel route. Assessment and analysis of geostatistical estimation results revealed that the amount of UCS experiments in most part of the project are adequate. However, there are some regions, such as the distance between boreholes 10 and 12, and also 5, 7, 8, and 13, which need more exploration.

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