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A Markov-based prediction model of tunnel geology, construction time, and construction costs

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Abstract. The necessity of estimating the time and cost required for tunnel construction has led to extensive research in this regard. Since geological conditions are significant factors in terms of time and cost of road tunnels, considering these conditions is crucial. Uncertainties about the geological conditions of a tunnel alignment cause difficulties in planning ahead of the required construction time and costs. In this paper, the continuous-space, discrete-state Markov process has been used to predict geological conditions. The Monte-Carlo (MC) simulation (MCS) method is employed to estimate the construction time and costs of a road tunnel project using the input data obtained from six tunneling expert questionnaires. In the first case, the input data obtained from each expert are individually considered and in the second case, they are simultaneously considered. Finally, a comparison of these two modes based on the technique presented in this article suggests considering views of several experts simultaneously to reduce uncertainties and ensure the results obtained for geological conditions and the construction time and costs.

Keywords: construction time and costs; continuous-space discrete-state Markov process; road tunnels; tunnel geology

1. Introduction

In today's competitive environment, the possibility of managing various construction projects, including tunnels, is of great importance (Zhang *et al.* 2021, Xu *et al.* 2021, Liu *et al.* 2021, Han *et al.* 2021, Bai *et al.* 2021, Li *et al.* 2021, Pan *et al.* 2021). One of the most important indicators in evaluating the success rate of development projects is their implementation according to the schedule and estimated costs. Experts and researchers in project management consider these two criteria as two sides of the golden triangle of project success. Given the particular complexity and volume of construction work in large tunneling projects and their long-term and high costs, recognizing the factors affecting timely non-completion and increasing the cost of these projects is of particular importance. Tunneling, similar, but more than other geotechnical endeavors, is characterized by the influence of uncertainty (Ritter *et al.* 2013). Owners, planners, designers, contractors, and other parties involved in tunneling need to consider these uncertainties in their decisions since they affect tunnel construction time and costs as well as the required and produced resources (Mahmoodzadeh *et al.* 2016).

Many studies have been developed to minimize uncertainties regarding geologic conditions and construction time and cost in tunnel projects (Guan *et al.* 2014). Soft computing techniques such as neural networks, time series, and random process approaches utilize mathematical models to predict the geology conditions along the tunnel alignment (Leu and Adi 2011, Guan *et al.* 2012, Bezdan *et al.* 2021, Jabar and Rashid 2018, Rashid *et al.* 2019, Cuk *et al.* 2021). Hard or exploratory methods, such as pilot drilling and advanced geophysical prospecting, utilize in-situ equipment. These methods have been used to detect the geology information in some specific locations along the tunnel alignment. These hard and soft methods are developed complementarily and many successful engineering applications have been well reported (Giao *et al.* 2021, Khishe and Mosavi 2020, Mosavi *et al.* 2018, Khishe

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and Mosavi 2019, Mosavi *et al*. 2016, Mosavi *et al*. 2017).

In recent years, significant improvements in time management and the cost of tunneling projects have been seen, i.e., forecasting the geological conditions of the tunnel route with the aid of the continuous-space and discrete-state Markov process. Thus, Ioannou (1987) predicted the time and cost of the tunnel required for the anticipated geological conditions. Ioannou (1987) predicted the uncertainty of geological parameters along the rock tunnel line using a continuous-space and discrete-state Markov process.

Liu *et al*. (2009) proposed a method of geological prediction for analyzing the stochastic characteristics of the geological spatial tendency. This model also used a Markov process to determine state probability along the horizontal alignment of a tunnel and applied a stochastic cyclic network simulation (CYCLONE) to analyze geological risk; there has been difficulty in doing so in traditional methods.

Recently, Hidden Markov Models (HMMs) have been proposed to analyze problems with uncertainty in transportation engineering (Mahmoodzadeh *et al*. 2019, Mahmoodzadeh *et al*. 2020a,b, Mahmoodzadeh *et al*. 2021a,b,c,d,e,f,g,h,i), and water resource engineering (Julian *et al*. 2004).

At present, construction time and cost are commonly assessed on a deterministic basis. The deterministic approach, however, does not appropriately reflect the uncertain reality. Systematic underestimation of construction costs related to infrastructure projects has been documented. The tunneling community has recognized the need to analyze the uncertainty and risks of tunnel construction.

The uncertainty in construction time and cost estimates results from the common variability of the construction performance and the occurrence of extraordinary events, such as tunnel collapses. Risks resulting from construction failures were commonly analyzed separately using techniques, such as fault tree or event tree analysis, decision trees, or risk matrixes (Aliahmadi *et al*. 2011, Jurado *et al*. 2012). Some models allowed one probabilistically to estimate the time or costs without considering the occurrence of extraordinary events. They typically used Monte – Carlo (MC) simulation (Mahmoodzadeh and Zare 2016, Mahmoodzadeh *et al*. 2019, Mahmoodzadeh *et al*. 2021a).

Full probabilistic estimates of tunnel construction time or costs were presented (Špačková and Straub 2012). Sousa and Einstein (2012) presented a Dynamic Bayesian Networks (DBN) model, which estimated the expected utility as a sum of the expected costs and the risk of a tunnel collapse. Estimations of time and cost of tunnel construction projects were subject to major uncertainties caused by uncertain geology conditions (Špačková and Straub 2013).

Einstein *et al*. (1999) developed the Decision Aids for Tunneling (DAT) that uses MCS for probabilistic prediction of construction time and costs, and consumption of resources. Vargas *et al*. (2014) developed a simulation algorithm based on MCS to estimate the time required for excavating a tunnel. DAT uses MCS for probabilistic prediction of construction time/costs and consumption of resources. It considers the geotechnical uncertainties, which are modeled utilizing a Markov process, as well as the uncertainties in the construction process. Recently, an innovative methodology to the prediction of expected ground conditions and construction time and costs in road tunnels has been proposed (Mahmoodzadeh and Zare 2016), which is an integration of the ground prediction approach based on Markov process, and the time and cost variance analysis based on MCS.

In this paper, we have used the continuous space, discrete-state Markov process, introduced by Ioannou (1987), to predict geological conditions and the MCS method to estimate the time and costs probability expected for the road tunnel construction. Initial input data are obtained through a questionnaire provided by experts in tunneling. First, the input data from each expert is obtained individually and simultaneously considered. Finally, a comparison of these two modes in the technique suggests that it is better to use the views of several expert individuals simultaneously rather than considering only the comments of an expert to reduce uncertainties and ensure more about the results obtained for geological conditions and the construction time and costs.

2. Methodology

The proposed method in this work consists of two steps: Step 1 is the probabilistic prediction of geological conditions (geology model) based on continuous-space and discrete-state Markov process. Step 2 is the probabilistic prediction of construction time and costs based on MCS (construction model).

Step 1: Probabilistic prediction of tunnel geological condition

In this study, to predict the geological conditions of the tunnel alignment, the continuous-space and discrete-state Markov process have been used. At this stage, initial input data for the geology model are obtained through a questionnaire provided by several tunneling experts. The procedure is as follows:

(1) Firstly, some geological or geotechnical parameters are considered together with the observed states according to the initial data (for example, the Rock Mass Rating (RMR) parameter with the five states: 0-20, 21-40, 41-60, 61-80 and 81-100). Then, for each parameter (e.g., parameter X), it is obtained through the questionnaire of transmission probability matrix (P_X) and transmission intensity matrix (A_X) with the aid of tunneling experts. Below the matrices of probability transition and the transmission intensity for the parameter X are shown with n states

$$P_X = \begin{bmatrix} p_{X_{11}} & p_{X_{12}} & \cdots & p_{X_{1n}} \\ p_{X_{21}} & p_{X_{22}} & \dots & p_{X_{2n}} \\ \vdots & & \ddots & \vdots \\ p_{X_{n1}} & p_{X_{n2}} & \cdots & p_{X_{nn}} \end{bmatrix} \tag{1}$$

$$A_X = \begin{cases} -C_{X_i} & , \quad i = j \\ C_{X_i} P_{X_{ij}} & \quad i \neq j \end{cases} = \begin{bmatrix} -C_{X_1} & C_{X_1} p_{X_{12}} & \cdots & C_{X_1} p_{X_{1n}} \\ C_{X_2} p_{X_{21}} & -C_{X_2} & \dots & C_{X_2} p_{X_{2n}} \\ \vdots & & \ddots & \vdots \\ C_{X_n} p_{X_{n1}} & C_{X_n} p_{X_{n2}} & \cdots & -C_{X_n} \end{bmatrix} \tag{2}$$

Table 1 Average length related to each state of parameter X

State	The average length of the states (H_{X_i})
1	----------------------?
2	----------------------?
3	----------------------?
4	----------------------?

where $p_{X_{ij}}$ is the probability from state i to state j; and C_{X_i} is the transition intensity coefficient of state i

$$p_{X_{ij}} = \frac{Number\ of\ trensitions\ from\ state\ i\ to\ state\ j}{Total\ number\ of\ transitions\ out\ of\ state\ i} \quad (3)$$

$$C_{X_i} = \frac{1}{H_{X_i}} \quad (4)$$

To obtain a transmission intensity matrix, it is required to have the transition probability matrix and the transition intensity coefficient so that we can calculate it using Eq. (2). In the questionnaire for achieving the transition probability matrix and the transition intensity coefficient, for example, for a parameter with four states, each expert should complete the blank in the following matrix and in Table 1. Note that the layers on the main diameters of matrices P_X and A_X are different from the other layers. For the matrix P_X, the values of the original diameter are equal to zero because we only say that the transition has been made to change the parameter state to the state of interpolation. For the dies on the main diameter of the matrix A_X, only the C_{X_i} is considered.

$$P_X = \begin{array}{c} \\ 1 \\ 2 \\ 3 \\ 4 \end{array} \begin{array}{c} \begin{array}{cccc} 1 & 2 & 3 & 4 \end{array} \\ \begin{bmatrix} 0 & & & \\ & 0 & & \\ & & 0 & \\ & & & 0 \end{bmatrix} \end{array}$$

(2) In the entire tunnel alignment, points with equal intervals are considered to obtain the occurrence probability of each parameter state, which shows the number of these points with k and their position with t_k. For example, t_0 and t_5 respectively show positions 1 and 5.

(3) The matrix of interval transition probabilities $V_X(t_0, t_k)$ is computed.

$$V_X(t_0, t_k) = V_X(t_k - t_0) = V_X(u) = [V_{X_{ij}}(t_0, t_k)] \quad (5)$$

$$V_X(u) = e^{uA_X} = I + uA_X + \frac{1}{2!}e^2 A_X^2 + \cdots + \frac{1}{m!}e^m A_X^m + \cdots \quad (6)$$

where, $V_{X_{ij}}(t_0, t_k)$ is the probability of the parameter X being i at location t_k given that it is j at the reference location t_0. I is the identity unit matrix and m is a great number, which can be indefinite.

(4) The state probability of parameter X at location t_k, $S_X(t_k)$ is calculated according to the state probability of parameter X at the reference location $S_X(t_0)$.

$$S_X(t_k) = S_X(t_0)V_X(t_0, t_k) = S_X(t_0)e^{(t_k - t_0)A_X} \quad (7)$$

(5) The posterior interval transition probabilities $v'_{X_{ij}}(t_0, t_k)$ are updated using the Bayesian technique (Eq. (8)).

where n is the total number of parameter X states, $S'_{X_z}(t_k)$ is the posterior state probability at the observation location. t_m is the location of observations along a tunnel (m is the observations $= 1, \ldots, r$). $v_{X_{ij}}(t_k - t_0)$ is the occurrence probability of the state j of parameter X in location t_k provided that the state in the location t_0 is i. $v_{X_{qj}}(t_k - t_{m-1})$ is the occurrence probability of the state j of parameter X in location tk provided that the state in the observational location t_{m-1} is q.

(6) The state probability of parameter X at location t_k is updated using Eq. (9).

where, $S'_{X_j}(t_k)$ is the probability of the parameter X being j at location t_k ($\sum_{j=1}^{n} S'_{X_i}(t_k) = 1$). $S_{X_i}(t_0)$ is the probability of the parameter X being i at the reference location t_k. Eq. (9) outputs are probabilities of parameter X states at any considered location along the tunnel alignment. For example, $S'_{X_3}(t_4) = 0.33$ the probability of parameter X's third state at location 4 is 0.33.

$$v'_{X_{ij}}(t_0, t_k) = \begin{cases} \sum_{z=1}^{n} S'_{X_z}(t_1) \frac{v_{X_{ij}}(t_k - t_0) v_{X_{jz}}(t_1 - t_k)}{v_{X_{iz}}(t_1 - t_0)} & , \quad t_0 < t_k < t_1 \\ \sum_{q=1}^{n} S'_{X_q}(t_m - 1) \sum_{z=1}^{n} S'_{X_z}(t_m) \frac{v_{X_{qj}}(t_k - t_{m-1}) v_{X_{jz}}(t_m - t_k)}{v_{X_{qz}}(t_m - t_{m-1})}, & t_{m-1} < t_k < t_m, m = 2, \ldots \\ \sum_{z=1}^{n} S'_{X_z}(t_r) S'_{X_{zj}}(t_k - t_r) & , \quad t_r < t_k \end{cases} \quad (5)$$

$$S'_{X_j}(t_k) = \begin{cases} \sum_{i=1}^{n} S_{X_i}(t_0) v'_{X_{ij}}(t_0, t_k) & , \quad t_0 < t_k < t_1 \\ v'_{X_{ij}}(t_0, t_k) & , \quad t_{m-1} < t_k < t_m \ , \ m = 2, 3, \ldots \\ v'_{X_{ij}}(t_0, t_k) & , \quad t_r < t_k \end{cases} \quad (6)$$

(7) By performing the six above steps, it is possible to obtain the probability of all states of a parameter in all positions considered along with the tunnel alignment (k position). For example, let's consider the parameter X with three states 1, 2, and 3, for each of these states in each position considered. A probability is obtained that the summation of these probabilities in each position is equal to one. In order to obtain the occurrence probability of the parameters in the other points along the tunnel alignment (the intervals between the number k of the positions considered in step 2), for each case, they will be individually curved on the points of that fit, which will result in a profile, names parameter profile. For example, in Fig. 1 for the parameter X with three states 1, 2 and 3, the occurrence probability of each state is considered at each of 95 points (k = 95), and then for each curvilinear state, it is fixed on its points. This profile assumes the occurrence probability of all three states of parameter X in addition to 95 positions in all positions along the tunnel alignment. After obtaining the occurrence probability of all states of a parameter in all positions considered along with the tunnel alignment (k position), the smoothing spline method is used to fit a curve on the data.

(8) At this stage, several ground classes (each containing the drilling method and the specified maintenance system) should be considered concerning the parameters and state. These ground classes should be designed to be responsive to the set of predicted geological conditions. Any geological conditions that are derived from the combination of state parameters are also called geological vectors. For example,

Table 2 Identification of geologic conditions relating to the individual ground classes

Parameter X	Parameter Y	Parameter Z	Geological Vector	Ground Class
1	1	1	(1,1,1)	GC_1
1	1	2	(1,1,2)	GC_1
1	1	3	(1,1,3)	GC_3
1	2	1	(1,2,1)	GC_1
1	2	2	(1,2,2)	GC_2
1	2	3	(1,2,3)	GC_3
2	1	1	(2,1,1)	GC_3
2	1	2	(2,1,2)	GC_1
2	1	3	(2,1,3)	GC_2
2	2	1	(2,2,1)	GC_1
2	2	2	(2,2,2)	GC_3
2	2	3	(2,2,3)	GC_1

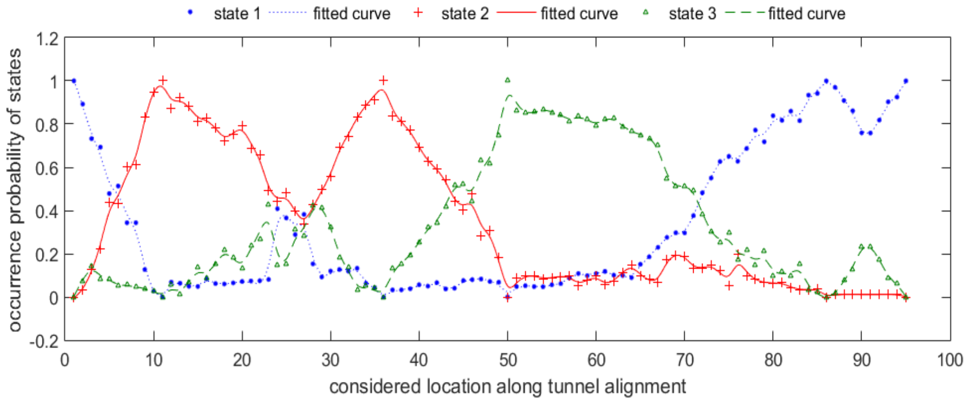

Fig. 1 Profile of parameter X

let's first consider the three parameters X, Y, and Z, respectively, with two. Three, and two states, a total of (2×3×2=)12 different vectors (or geological conditions) might occur along the tunnel alignment. Each vector is considered as (a, b, c) for the three parameters, which means that in this vector, the state 'a' of the first parameter, the state 'b' of the second parameter and the state 'c' of the third parameter occurs. These geological vectors must be divided into multiple vector sets; a ground class has to be constructed for each set. Selection of vectors in a set will be made through the questionnaire. For example, according to Table 2, each geological vector must select one of the ground classes for each of the three parameters X, Y, and Z.

According to Table 2, there are three ground classes, where the ground classes 1, 2 and 3 (GC_1, GC_2, and GC_3) contain six, two, and four geological vectors, respectively. Now, with the aid of geological vectors, it is necessary to obtain the occurrence probability of each ground class in each of the considered positions (position k).

To describe this methodology, we shall describe the ground class No. 3 (GC_3) that includes four geological vectors as shown in Table 2

$$V_{31} = (1,1,3) \qquad V_{32} = (1,2,3) \qquad V_{33} = (2,2,1) \qquad V_{34} = (2,2,2)$$

If each geological vector is considered as (i,j,k), to identify the occurrence probability of each ground class in a given location along tunnel alignment, the occurrence probability of i, j and k states inside the location must be identified. Afterwards, the obtained probabilities for each geological vector must be multiplied by each other. Suppose the ground class includes several geological vectors. In that case, such calculations must be performed for each geological vector inside the related location and added up to obtain the occurrence probability of that ground class inside the relevant location. In the following, considering the above discussions, the procedure for obtaining the ground class No. 3 (GC_3) inside the location k has been presented

$$P[g(k) belongs\ to\ GC_3] = P[g(k) = V_{31}\ or\ g(k) = V_{32}\ or\ g(k) = V_{33}\ or\ g(k) = V_{34}]$$

$$\begin{aligned}
&= P[g(k) = V_{31}] + P[g(k) = V_{32}] + P[g(k) = V_{33}] + P[g(k) = V_{34}] \\
&= P[X(k) = 1\ \&\ Y(k) = 1\ \&\ Z(k) = 3] \\
&+ P[X(k) = 1\ \&\ Y(k) = 2\ \&\ Z(k) = 3] \\
&+ P[X(k) = 2\ \&\ Y(k) = 2\ \&\ Z(k) = 1] \\
&+ P[X(k) = 2\ \&\ Y(k) = 2\ \&\ Z(k) = 2] \\
&= \big[P[X(k) = 1] * P[Y(k) = 1] * P[Z(k) = 3]\big] \\
&+ \big[P[X(k) = 1] * P[Y(k) = 2] * P[Z(k) = 3]\big] \\
&+ \big[P[X(k) = 2] * P[Y(k) = 2] * P[Z(k) = 1]\big] \\
&+ \big[P[X(k) = 2] * P[Y(k) = 2] * P[Z(k) = 2]\big]
\end{aligned}$$

Notice:

$P[g(k) belongs\ to\ GC_3]$ is defined as the occurrence probability of third ground class in the location k.

$g(k)$ is defined as the parameter state in the location k.

$X(k)$ is the parameter X state in the location k.

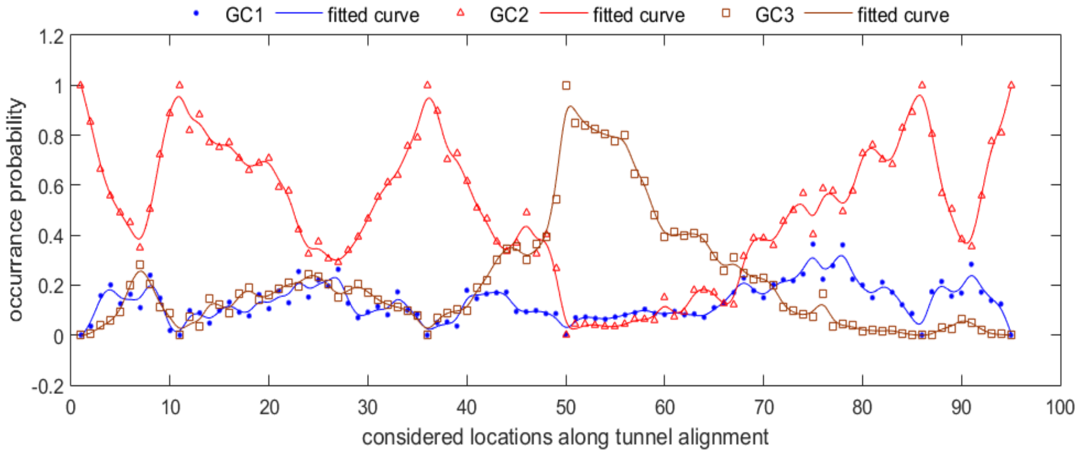

Fig. 2 Ground class profile

$Y(k)$ is the parameter Y state in the location k.
$Z(k)$ is the parameter Z state in the location k.
$P[X(k) = i]$ is the occurrence probability of state i for parameter X in the location k.
$P[Y(k) = i]$ is the occurrence probability of state j for parameter Y in the location k.
$P[Z(k) = i]$ is the occurrence probability of state q for parameter X in the location k.

After obtaining the occurrence probability of each of the ground classes considered in all positions (k position) for each class, the smoothing spline method is used to fit a curve on the data. Thus, the occurrence probability of the ground class in addition to the k positions, in all other situations will be obtained along with the tunnel alignment. In this case, the obtained profile is called the ground class profile, which gives the occurrence probability of each ground class in any position along the tunnel alignment. In each of the situations, the sum of the probabilities of ground classes is equal to one. Fig. 2 shows an example of a ground class profile that has three classes.

Access to the ground class profile is the last step of the geology model, and this data will be used in the construction model (step 2).

Step 2: Probabilistic Prediction of Construction Time and Costs

At this stage, with the advantage of the questionnaire according to Table 3, experts are asked to provide the minimum (Min), most likely (ML) and maximum (Max) values of time and costs for each of the considered ground class per each meter of tunnel construction based on the experience of previous projects in the similar manners. So far, here are the construction time and costs for each meter of ground classes available, as well as the ground class profile, which can be used to determine the minimum, most likely, and maximum time and costs of each of the ground classes in any location along the tunnel alignment.

The MCS is used to obtain the construction time and costs of the tunnel. The reason is that the estimated construction time and costs of ground classes by experts are per meter of tunnel construction, thus, the entire tunnel alignment is divided into one-meter equal parts. In each section, in accordance with the ground class profile, each

Table 3 The construction time and costs per each meter for all considered ground classes

GC	Construction time per one meter (days)			Construction cost per one meter ($)		
	Min	Ml	Max	Min	Ml	Max
1	……….?	……….?	……….?	……….?	……….?	……….?
2	……….?	……….?	……….?	……….?	……….?	……….?
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.

ground classes occur with a certain probability that the occurrence probability of time and costs of these classes is also the same in each section. The MCS is repeated up to a specified number. In each repetition, the non-deterministic values of construction time and costs within each considered meter along the tunnel alignment are determined randomly based on the distributions and the input data. At the end of each repetition, one final construction time and cost is obtained, displayed in a time-cost scattergram as a point. After all the repetitions have been finished, the stored values are used to plot the time-cost scattergram and prepare the probabilistic function relating to the execution of the above items. It is worth noticing that since the minimum, most likely, and maximum construction time and costs have been obtained from questionnaires, it is preferable to use the triangular distribution function in choosing the distribution function to simulate MC. Finally, a time-cost scattergram is obtained according to Fig. 3, which can be used as an optimal mode wherever the compaction points are closer. In addition, with the aid of this graph, the maximum and minimum construction time, costs can be obtained as these values are closer to each other, which results in less uncertainty and more precise decision-making can be made in the initial planning.

3. Garan road tunnel case study

In this section, both the project and the probabilistic prediction of construction time and costs are explained in detail in the followings:

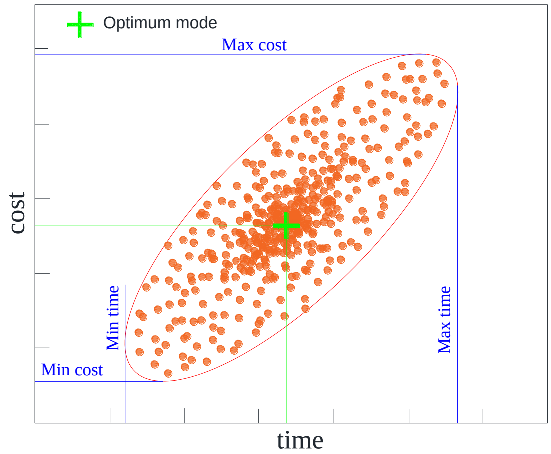

Fig. 3 The time – cost scatter gram

3.1 The project

The new road between Sanandaj and Marivan, in the northwest of Iran, is an under-construction. Due to passage through the Zagros mountains, several tunnel projects, including Garan, Hamru, and Gezerdareh, have been implemented or under construction. The old Sanandaj-Marivan road is one of the most dangerous roads in Iran, with many accidents happening every year and causing financial losses and death of human beings. The length of the old Sanandaj-Marivan road is 126 km. On the new road, the length will be reduced to 105 kilometers, reducing the travel time and accidents.

The present study is undertaken on Garan tunnel of 1900 m length and cross-section of 97 m^2 as part of the under-construction Sanandaj-Marivan road. The entrance of the Garan tunnel is considered the eastern mouth (to the Sanandaj-S) and its outlet is considered the western (to the Marivan-M). In Fig. 4, the location of the Garan tunnel is shown.

The Lithology of the tunnel route is mainly composed of Sand Shales, Shale and Limestone. In Fig. 5, the geological profile of the Garan tunnel is illustrated.

Garan tunnel has been excavated using top heading and benching method. The support system used in the Garan tunnel construction is as follows.

IPE 180 - Spacing 0.75-1.5 m

Rock bolts: Fully grouted, φ25 mm, L: 4-6 m

Shotcrete: 22cm-Reinforced by 2 layer mesh φ6@100×100 mm

Depending on the ground conditions, during the tunnel construction, the spacing of the IPEs have changed.

3.2 Prediction models of Garan tunnel

Design and construction decisions in tunneling depend on such geologic parameters as rock type, joint density, RMR, faulting, joint appearance, degree of weathering and groundwater characteristics. Considering the initial information, three parameters of lithology, RMR and groundwater, have been examined in the study and the states relevant to each parameter have been presented.

The lithology parameter with four states (state 1: limestone (Li), state 2: Shale (Sh), state 3: sand shales and shale limestone sequence (ShL), and state 4: Limestone and shale sequence (LSh). Parameter RMR with three states (state 1: < 20, state 2: 20 to 40, and state 3: 41 to 60). Groundwater parameter with four states (state 1: dry, state 2: wet, state 3: dripping, and state 4: flowing).

It should be noted that the groundwater is effective on the RMR parameter and is part of the RMR rating. Also, the parameters considered are dependent. Considering the initial data on this tunnel, including the water springs in the area, it became clear that the groundwater parameter could be important in this tunnel, so the groundwater parameter itself is also considered. In addition, any of the parameters that affect the ground conditions can be considered, provided that the initial data is available to them. Therefore, if the selected parameters are interdependent, the quality will not decrease.

All four borehole positions and entrance and exit portals are used as observations in the Bayesian technique to update the parameter and ground class profiles, with the considered parameter states of Garan road tunnel shown in Fig. 5.

In order to obtain the required initial data in the geology model, six questionnaires were submitted to the six tunneling experts according to the materials presented in the previous sections. Experts with master's and Ph.D. degrees in rock mechanics and geotechnical engineering, with at least ten years of experience in the field of tunnel construction, are selected. After completion of the questionnaires by the experts, input data required for the geology model was obtained for each of them. In Table 4, the input data obtained by the first expert is presented. Further, the data was used as input in MATLAB software, in which all the steps were coded. In coding, 95 positions (k = 95) were considered at a distance of 20 meters in relation to each other along the tunnel alignment. In these situations, the occurrence probability of each state and each ground class is obtained by entering input data. Finally, for each expert, a parameter profile was obtained according to the completed questionnaire. In Figs. 6 and 7, the lithology parameter profile is shown for the first and sixth experts, respectively. From the comparison of Figs. 6 and 7, the difference between the results for the first and sixth experts can be seen. As it can be noticed from the parameters profiles, there are six existing positions along with the tunnel alignment, in which the probability of one of the states is equal to 1 and probability of other states equal to zero, which are related to four boreholes and two tunnel entrance and exit portals. These positions are referred to as observational positions, where the occurrence of states is definite for each parameter. These data have already been provided to experts in the questionnaire.

A total of 48 conditions or geological vectors (4 × 3 × 4=48) are obtained from the combination of the states of the parameters. In order to present several ground classes in this paper, the experience of previous projects is being used in the same conditions. Finally, Table 5, including 5 ground classes, was accessed by interviewing several experts, including senior engineers, project managers, and

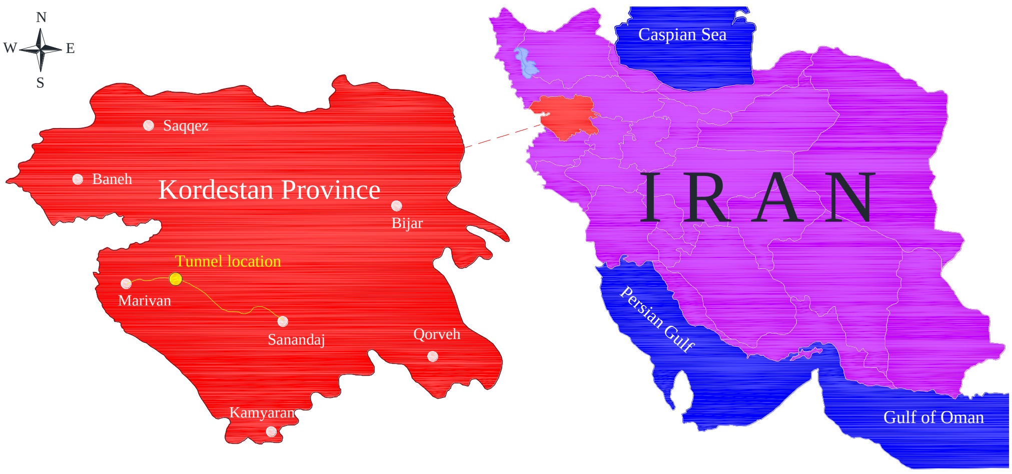

Fig. 4 Project location of Garan tunnel

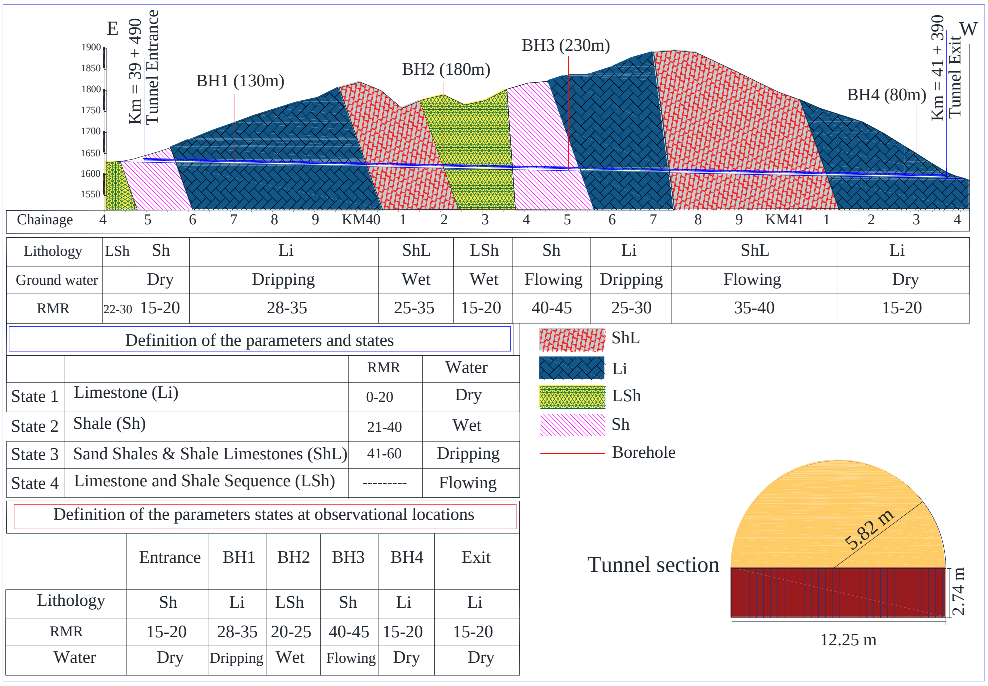

Fig. 5 Geologic profile and location of boreholes along Garan tunnel alignment

Table 4 The input data from experts' opinions used in the geological model

Expert	Parameter	State	H_{Xi} [m]	C_{Xi} [m^{-1}]	A_X
Expert 1	Lithology	1	450	0.0023	$\begin{bmatrix} -0.0023 & 0.0010 & 0.0008 & 0.0005 \\ 0.0014 & -0.0031 & 0.0011 & 0.0006 \\ 0.006 & 0.0016 & -0.0025 & 0.0003 \\ 0.0005 & 0.0002 & 0.0006 & -0.0013 \end{bmatrix}$
		2	320	0.0031	
		3	390	0.0025	
		4	740	0.0013	
	RMR	1	950	0.0010	$\begin{bmatrix} -0.0010 & 0.0002 & 0.0008 \\ 0.0009 & -0.0021 & 0.0012 \\ 0.0014 & 0.0006 & -0.0020 \end{bmatrix}$
		2	460	0.0021	
		3	490	0.0020	
	Groundwater	1	520	0.0019	$\begin{bmatrix} -0.0019 & 0.0008 & 0.0005 & 0.0006 \\ 0.0012 & -0.0035 & 0.0010 & 0.0013 \\ 0.0002 & 0.0004 & -0.0014 & 0.0008 \\ 0.0009 & 0.0003 & 0.0011 & -0.0023 \end{bmatrix}$
		2	280	0.0035	
		3	670	0.0014	
		4	430	0.0023	

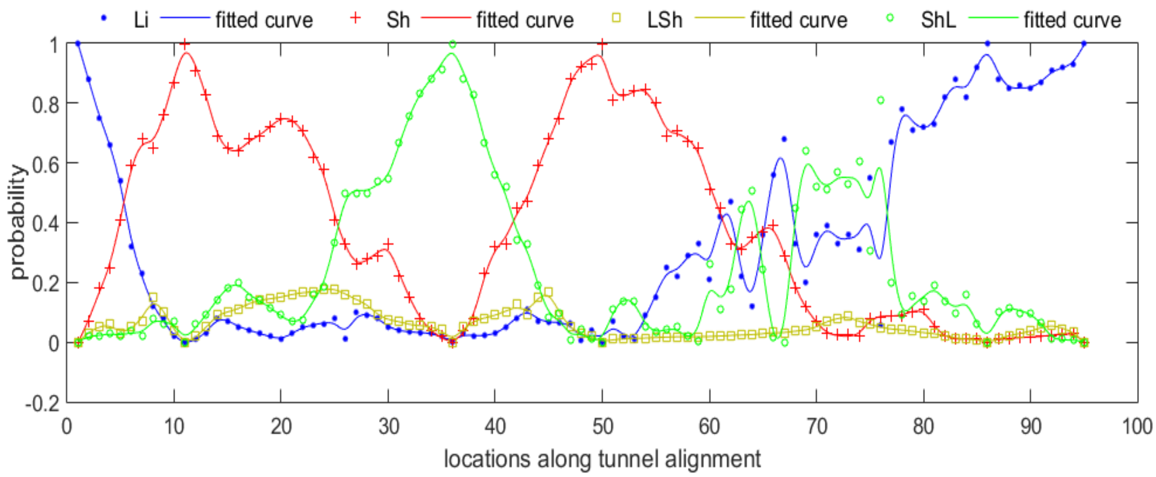

Fig. 6 Lithology parameter profile by using first expert inputs

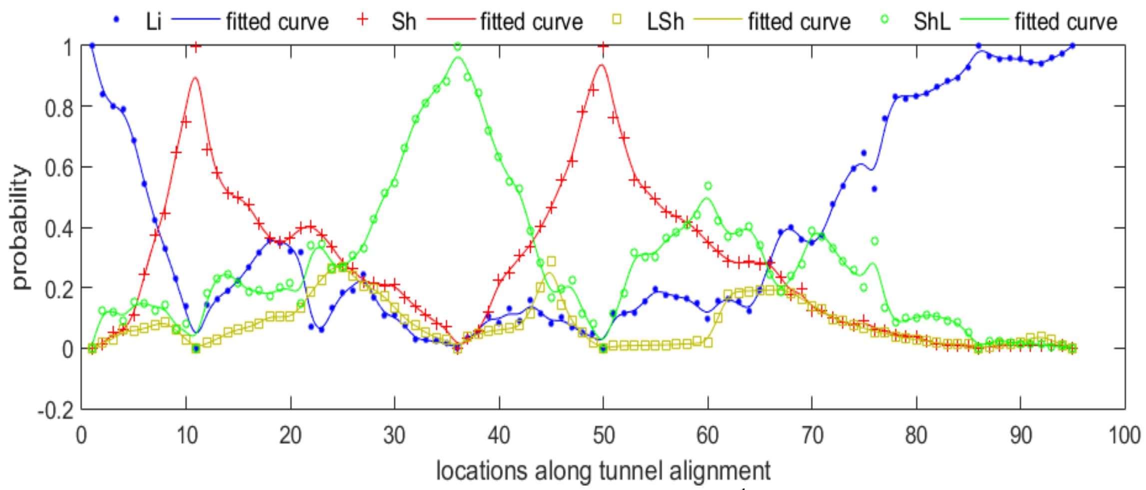

Fig. 7 Lithology parameter profile by using 6th expert inputs

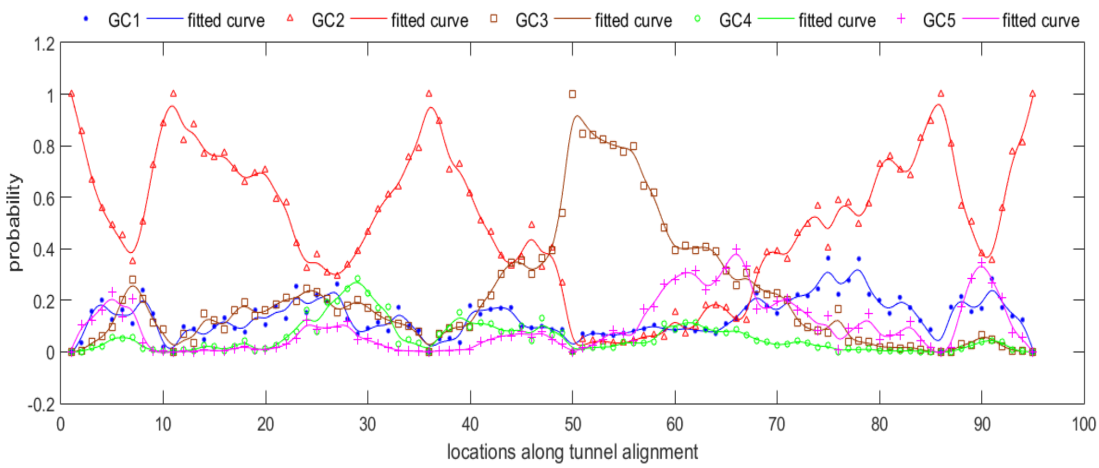

Fig. 8 Ground class profile by using 3rd expert inputs

consultants. All the experts have come up with a final answer in consultation. After this step, by providing the classes defined to the expert, each of them identified a set of vectors among the 48 existing geological vectors for each ground class, for example, the second expert has acted according to Table 6.

In the next step, with the help of the results obtained for each expert, a ground class profile was obtained using the method described in the preceding sections, which is for the third and fifth experts, in forms Figs. 8 and 9, respectively. From the comparison of these forms, one can see the change that is due to the difference in opinion of the experts in the questionnaire.

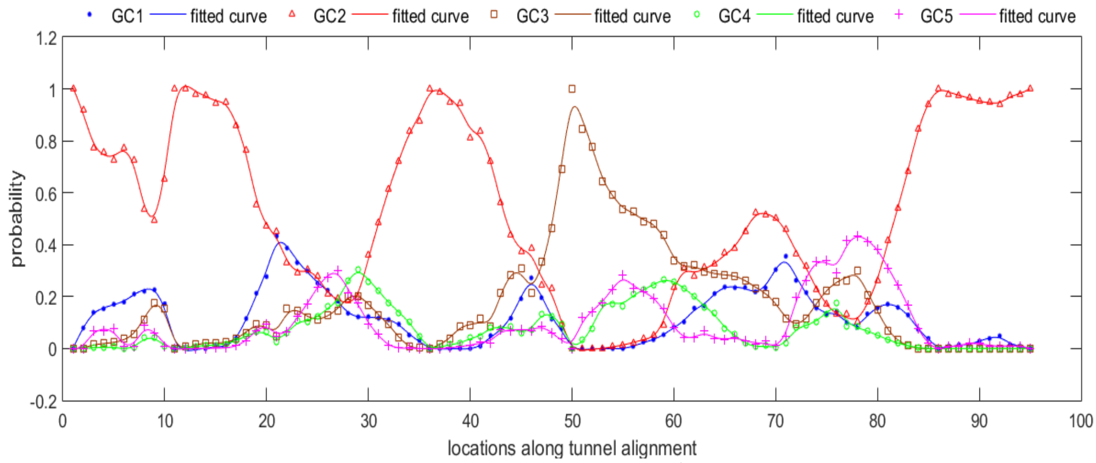

Fig. 9 Ground class profile by using 5th expert inputs

Table 5 The specifications and construction methods of the ground classes

Ground Class	Specifications
GC_1 (very weak)	Sidewall drif Method - Support : IPE 180 , spacing 0.5-0.7 m and Shotcrete :20cm reinforced by 2 layer mesh φ8@100×100 mm
GC_2 (weak)	Central Diaphragm Method - Support: IPE 180, spacing 0.7-1 m and Shotcrete: 20cm reinforced by 2 layer mesh φ8@100×100 mm
GC_3 (weak to medium)	Top Heading & Benching Method - Support: IPE 180, spacing 1-1.4 m and Shotcrete: 18cm reinforced by 2 layer mesh φ8@100×100 mm
GC_4 (medium)	Top Heading & Benching Method - Support : Rockbolts: fully grouted, φ24 mm, L: 4-7 m, spacing 2.7 × 2.7 Shotcrete: 14 cm, reinforced by 2 layer mesh φ6 @100×100 mm
GC_5 (medium to good)	Top Heading & Benching Method - Support: Rockbolts: fully grouted, φ24 mm, L: 3-5 m, spacing 2.2 × 2.2 Shotcrete: 12, reinforced by 1 layer mesh φ6 @100×100 mm

Table 6 Identification of geological conditions relating to the individual ground classes

Ground Class	Lithology parameter state	RMR parameter state	Groundwater parameter state
I	1,2,3,4	1	2,3,4
	1	2	4
II	1,2	2	1,2,3
	1,2,3,4	1	1
	2,3	2	4
	3,4	2	3
	4	2	2,4
III	3,4	2	1
	1,2,3,4	3	3,4
	3	2	2
IV	2,3,4	3	2
V	1	3	2
	1,2,3,4	3	1

So far, the geology model has been fully completed for each expert, and this data is being used to carry out the construction model. In the first phase of the construction model, each expert estimates the minimum, most likely and maximum construction time and costs for the ground classes per meter. The construction model inputs obtained by experts have been presented in Table 7.

The entire tunnel alignment was then divided into one-meter sections (1900 sections). In each section, for each expert, according to the ground class profile, the occurrence probability of the ground classes and the occurrence probability of the estimated time and costs exist. In order to reach the total construction time and costs of the tunnel, all time and costs must be combined in all parts. As within each section, each ground class occurs with a certain probability (the ground class profile) and to estimate the total construction time and costs, the MCS method was used. For this purpose, Primavera Risk Analysis (PRA) software was used for performing MCS. The distributive function used in these simulations was a triangular distribution function based on the availability of minimum, most likely and maximum construction time and costs values. In this work, we monitor the improvement of the performance by increasing the number of simulations from 1000 through 2000. However, we didn't see further improvement after 1100 simulations. Therefore, we run the MC for 1100 instances of simulations. During simulations, the prepared software is repeated to a specified number of

Table 7 The construction model's inputs obtained by experts

Expert	Parameter		GC1	GC2	GC3	GC4	GC5
Expert 1	Construction time of one meter [days]	Max	1.84	1.72	1.39	1.28	1.05
		Ml	1.67	1.42	1.17	1.00	0.84
		Min	1.38	1.27	1.01	0.86	0.72
	Construction cost of one meter [US$]	Max	12263	11835	11012	9698	8418
		Ml	11954	11666	10611	9226	7873
		Min	11724	11334	10430	8931	7333
Expert 2	Construction time of one meter [days]	Max	1.43	1.36	1.10	1.00	0.95
		Ml	1.28	1.20	1.05	0.94	0.90
		Min	1.22	1.12	0.98	0.81	0.68
	Construction cost of one meter [US$]	Max	12250	11850	11100	9700	8460
		Ml	11950	11600	10600	9200	7800
		Min	11700	11310	10450	8850	7350
Expert 3	Construction time of one meter [days]	Max	1.55	1.50	1.25	1.12	1.00
		Ml	1.40	1.25	1.15	1.00	0.95
		Min	1.30	1.20	1.00	0.85	0.70
	Construction cost of one meter [US$]	Max	13660	12800	12250	10800	10400
		Ml	12800	12200	11500	10280	9520
		Min	12260	11850	11100	9430	8700
Expert 4	Construction time of one meter [days]	Max	1.80	1.70	1.35	1.27	1.10
		Ml	1.60	1.38	1.20	0.98	0.85
		Min	1.40	1.22	0.95	0.82	0.67
	Construction cost of one meter [US$]	Max	13800	13150	12670	11550	10900
		Ml	13300	12750	12200	11240	10200
		Min	12570	11900	11420	10430	9500
Expert 5	Construction time of one meter [days]	Max	2.10	1.93	1.68	1.52	1.34
		Ml	1.86	1.63	1.30	1.25	1.12
		Min	1.59	1.41	1.14	1.03	0.95
	Construction cost of one meter [US$]	Max	13940	13630	13150	12590	12400
		Ml	13510	13350	12760	12130	11670
		Min	12900	12600	12580	11750	11200
Expert 6	Construction time of one meter [days]	Max	1.85	1.72	1.38	1.25	1.15
		Ml	1.63	1.42	1.24	1.02	0.94
		Min	1.35	1.28	0.90	0.83	0.72
	Construction cost of one meter [US$]	Max	13600	12800	12260	10850	10340
		Ml	12890	12170	11520	10260	9610
		Min	12350	11900	11240	10100	8900

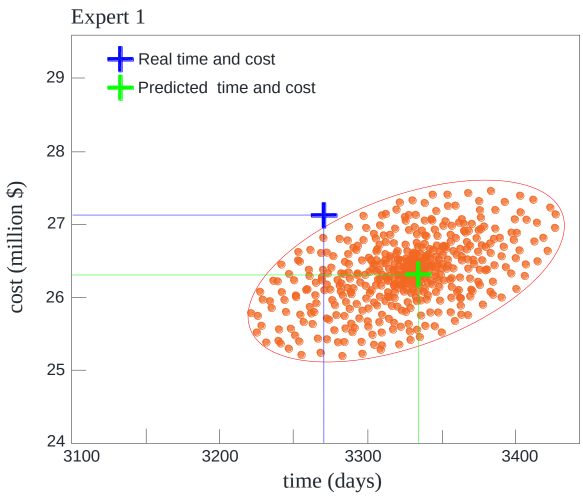

Fig. 10 The time–cost scatter gram - expert 1

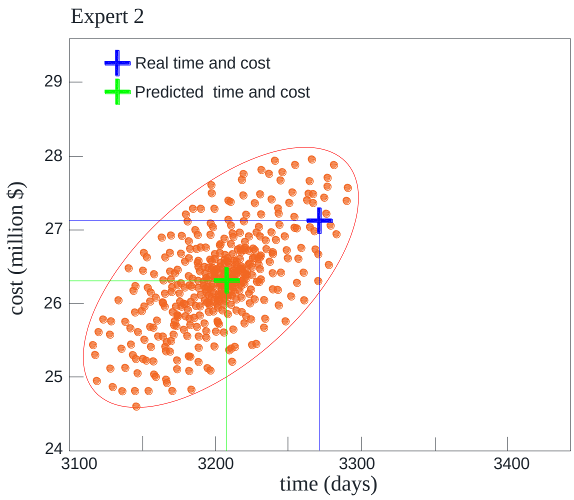

Fig. 11 The time–cost scatter gram - expert 2

repetitions. In each repetition, the non-deterministic values of construction time and costs are determined randomly based on the distributions and the input data. The PRA software stores the estimated total construction time and costs at the end of each repetition. After all the repetitions have been finished, the stored values are used for plotting the time-cost scattergrams. Finally, a time-cost scattergram was obtained for each expert according to Figs. 10-15. In these scattergrams, it is usually considered as an optimal mode in predicting the construction time and costs of the

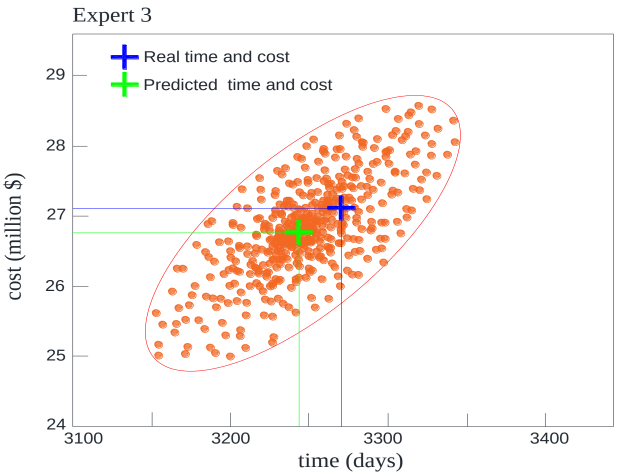

Fig. 12 The time–cost scatter gram - expert 3

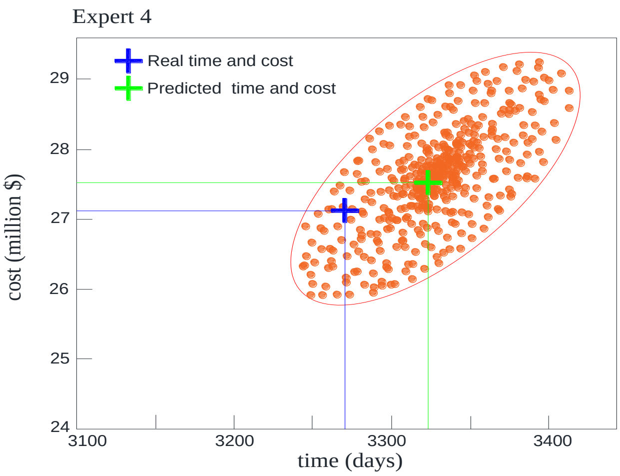

Fig. 13 The time–cost scatter gram - expert 4

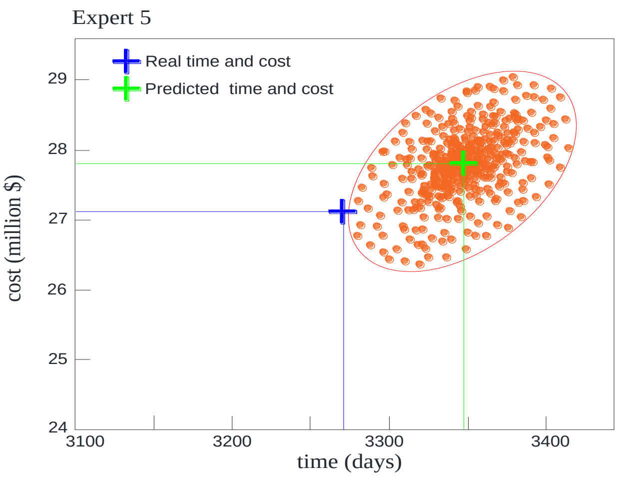

Fig. 14 The time–cost scatter gram - expert 5

tunnel, where the focus of the simulation points has been most concentrated. The Garan road tunnel project has already been completed and; therefore, in each of the scattergrams, the real-time and costs of the project are compared with the time and costs predicted by the method mentioned in this paper. Differences can be made with the comparison of the time-cost scattergrams of experts.

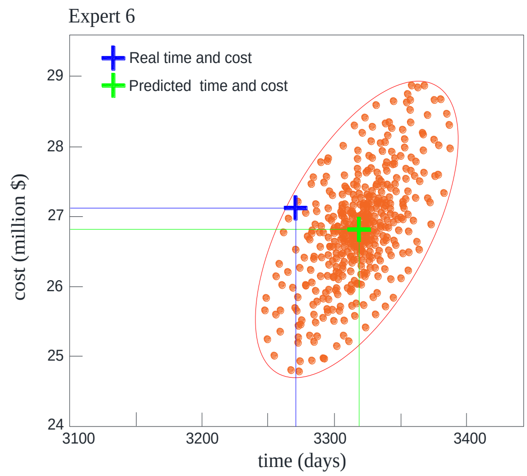

Fig. 15 The time–cost scatter gram - expert 6

Now, the question that arises here is which expert's results should be considered in the initial planning? The answer is simple; in this article, we have the real construction time and costs for the tunnel project, and it can easily be determined that the obtained result for which expert is closer to reality. However, we are managing projects by implementing the described method and the project has not begun yet; hence, the real construction time and costs are not available to determine which expert data to be used. Therefore, in this study, in addition to obtaining the results of forecasting geological conditions and construction time and costs separately for each expert, all of their views have been combined to achieve these results. To do this, first in the coding for the geology model, the occurrence probability of all the parameters for all experts together in each of the 95 positions considered along the tunnel alignment was obtained. This time the fitted curve on data was collected for all experts. In this stage, all the inputs averaged from experts' opinions for the geology and construction models are presented in Tables 8 and 9, respectively.

Finally, the parameters and the ground class profiles were obtained from the experts' opinions according to Figs. 15-19. Correspondingly, in the construction model, the time-cost scattergram was obtained for the total expert opinion according to Fig. 19. From the comparison of Fig. 20 with Figs. 10-15, it can be seen that if the whole of expert opinions is used, more accurate, reliable and less uncertain results can be achieved. Of course, among experts, there may be individuals or people who are close to real construction time and costs, and the results are accurate, but it is not possible to identify them at the initial planning stage. In the inputs of the method presented in this article, the views of the experts are used together. For this purpose, the smoothing spline method is used to fit a curve on the data. It performs the interpolation of the inter-order background using smoothing spline polynomials. Spline interpolation consists of the approximation of a function by means of series of polynomials over adjacent intervals with continuous derivatives at the end-point of the intervals. Smoothing spline interpolation enables to control of the variance of the residuals over the data set. Six experts are

Table 8 The input data averaged from all experts' opinions for the geological model

Expert	Parameter	State	H_{Xi} [m]	C_{Xi} [m^{-1}]	A_X
All experts	Lithology	1	347	0.0028	$\begin{bmatrix} -0.0028 & 0.0013 & 0.0004 & 0.0011 \\ 0.0012 & -0.0027 & 0.0008 & 0.0007 \\ 0.0013 & 0.0004 & -0.0022 & 0.0005 \\ 0.0007 & 0.0004 & 0.0002 & -0.0013 \end{bmatrix}$
		2	359	0.0027	
		3	436	0.0022	
		4	730	0.0013	
	RMR	1	641	0.0015	$\begin{bmatrix} -0.0015 & 0.0005 & 0.0010 \\ 0.0011 & -0.0017 & 0.0006 \\ 0.0004 & 0.0010 & -0.0014 \end{bmatrix}$
		2	569	0.0017	
		3	690	0.0014	
	Groundwater	1	680	0.0014	$\begin{bmatrix} -0.0014 & 0.0007 & 0.0004 & 0.0003 \\ 0.0008 & -0.0021 & 0.0011 & 0.0002 \\ 0.0008 & 0.0003 & -0.0017 & 0.0006 \\ 0.0003 & 0.0005 & 0.0003 & -0.0011 \end{bmatrix}$
		2	460	0.0021	
		3	570	0.0017	
		4	870	0.0011	

Table 9 The input data averaged from all experts' opinions for the construction model

Expert	Parameter		GC1	GC2	GC3	GC4	GC5
Expert 1	Construction time of one meter [days]	Max	1.76	1.65	1.35	1.24	1.09
		Ml	1.57	1.38	1.18	1.03	0.93
		Min	1.37	1.25	0.99	0.86	0.74
	Construction cost of one meter [US$]	Max	13252.1	12677.5	12073.6	10864.6	10153
		Ml	12734	12289.3	11531.8	10389.3	9445.5
		Min	12250.6	11815.6	11203.3	9915.16	8830.5

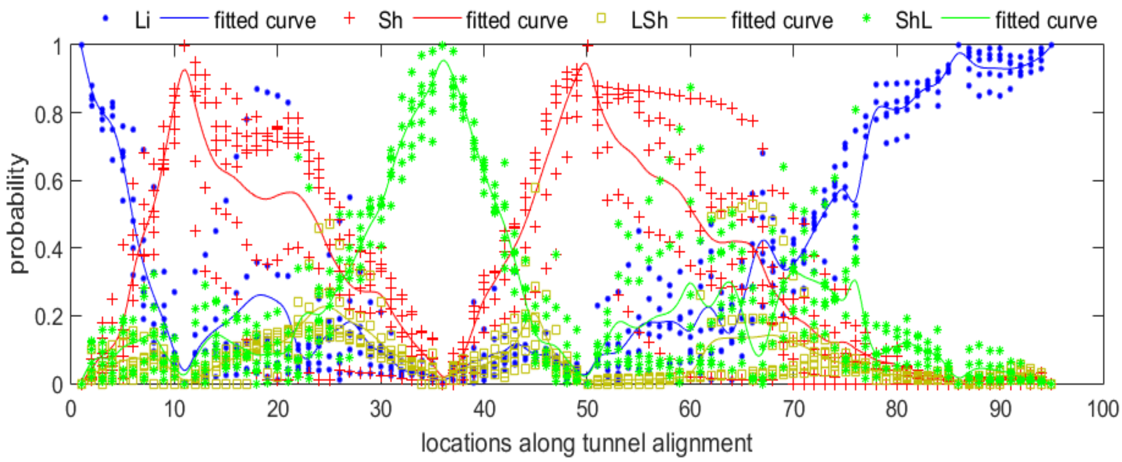

Fig. 16 Lithology parameter profile for all experts

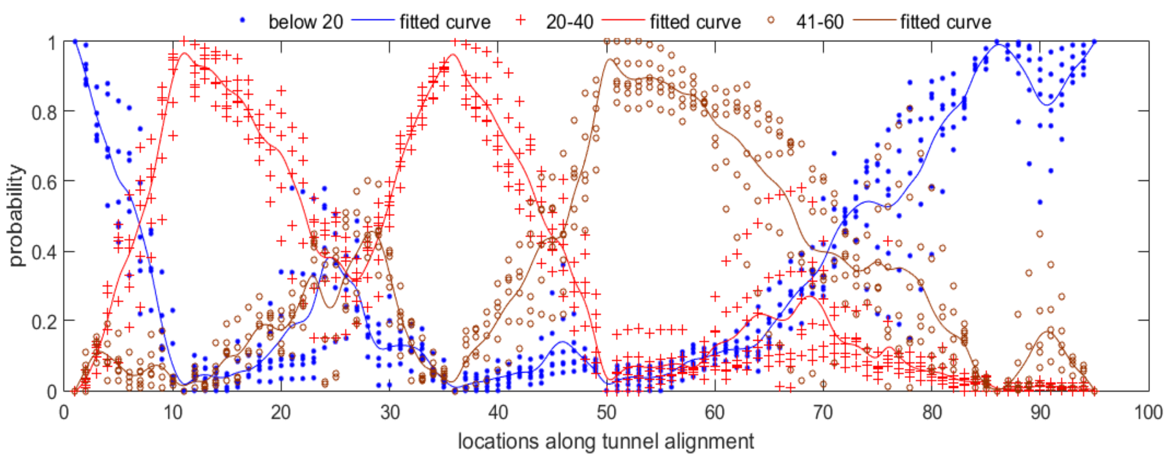

Fig. 17 RMR parameter profile for all experts

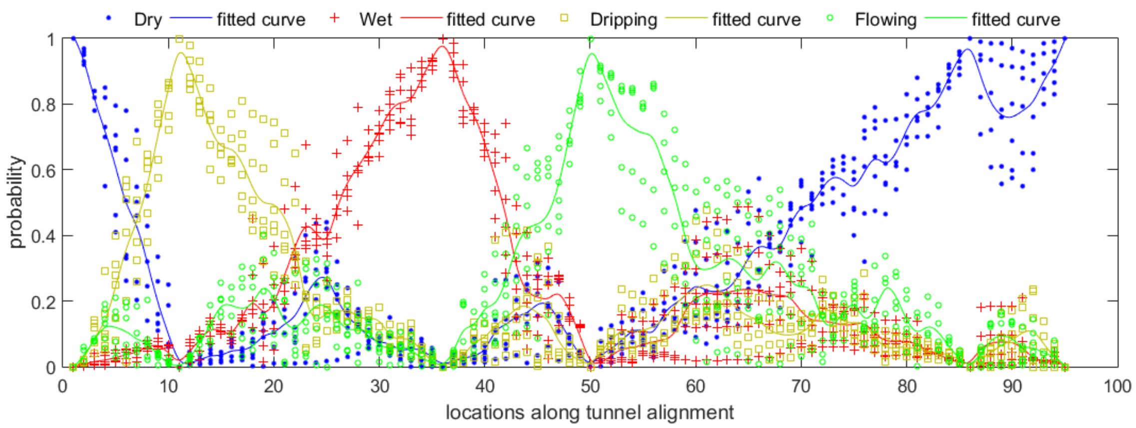

Fig. 18 Groundwater parameter profile for all experts

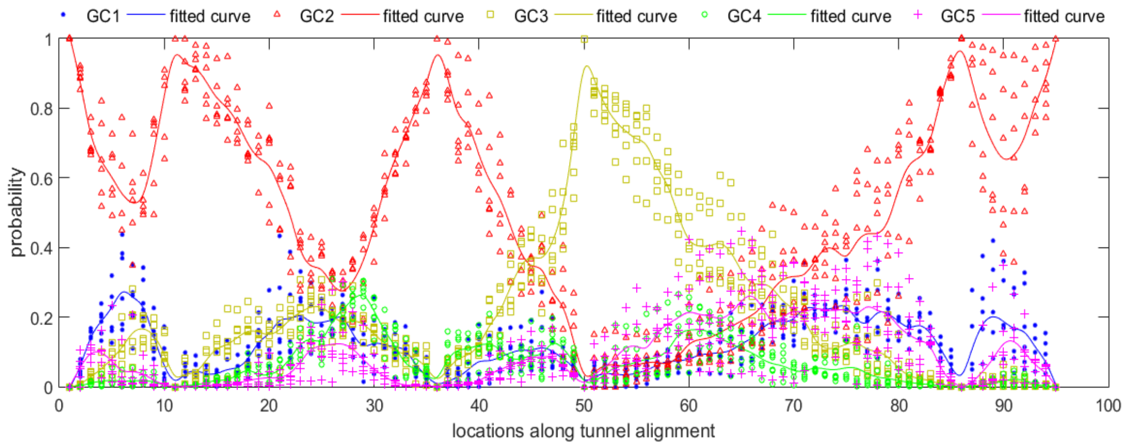

Fig. 19 Ground class profile for all experts

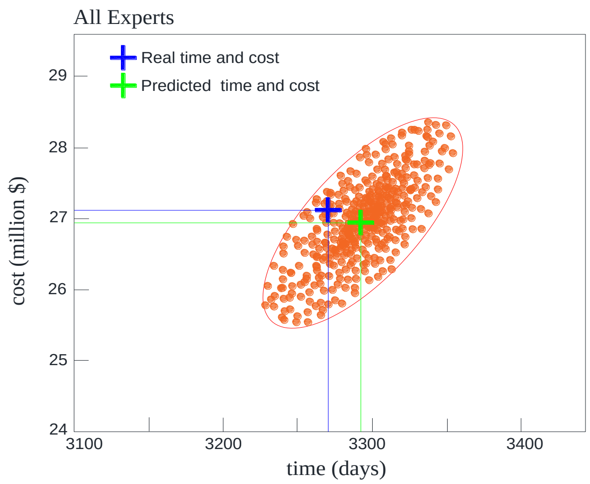

Fig. 20 The time–cost scatter gram for all experts

selected in this study and more experts can be used to achieve better accuracy because the more experts are, the more accurate and reliable results are obtained.

4. Conclusions

In tunneling projects, initial planning is regularly associated with a high risk caused by unknown subsurface conditions. As a result, during the planning phase of the projects, different techniques can be used to predict the geological conditions along the tunnel alignment and then to predict the construction time and cost. One of the most important techniques is the use of a continuous-space, discrete-state Markov process. This paper predicts the continuous-space, discrete-state Markov process, coded in MATLAB software, and the geological conditions along the Garan road tunnel. Subsequently, with the advantage of these predicted conditions, simulations for each expert's input data were carried out with the aid of MCS in the PRT software to reach the time-cost scattergram. In another case, geological conditions and the construction time and costs of the tunnel were obtained by simultaneously examining the views of all experts as inputs in MATLAB and PRT software.

Consequently, it is concluded that experts obtained different results according to the questionnaire they completed, whether these results are close to real value or not. In the meantime, the Garran road tunnel project was completed and the construction time and costs estimations of each expert were compared, and it was found that better results for some experts were obtained from the rest. However, it should be noted that this method predicts the construction time and costs of the tunnel in the early stages of work and before starting to construct the tunnel. At that stage, it cannot be determined which expert opinions are more accurate and better than the rest. First, it might be convenient to consider an expert's data that differ from the actual state. To solve this problem, the results were compared for each expert with the results in which the views of all experts were simultaneously affected. Hence, it is concluded that the simultaneous impact of all expert opinions can reduce uncertainties to a significant degree for predicted construction time and costs and more accurately predicted the results.

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