Probabilistic prediction of geological status of tunnel route using the Markov method

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Abstract— Minimizing the uncertainties related to the tunnels’ construction parameters is a crucial task that need to be addressed. Usually, the most uncertainties in underground structures are related to the unknown geological status. In order to probabilistically estimate these uncertainties, variety techniques have been developed, including the Markov method. This study is undertaken on a road tunnel in Iran in order to forecasting the geological status along its route using the Markov method. To access the Markov’s model input data, a number of questionnaires were distributed among the tunneling experts and eventually the mean values of the respondents were used in the model. In the next step, the results predicted by the Markov model were compared with the actual ones to evaluate the model performance. Finally, the Markov model was suggested as a powerful tool to predict tunnels’ path geology.

Index Terms— Markov method; Tunneling; Time and cost uncertainties; Geological status.

I. INTRODUCTION

Tunneling is affected by many uncertainties. Planners, owners, contractors, and designers in tunneling projects must take into account these uncertainties in their decisions (Rittera et al. 2013). Usually, geological status is considered as the most crucial factor effective on the uncertainties in tunnels construction (Mahmoodzadeh and Zare 2016). Recently, different geology forecasting approaches have been presented, which make utilize the artificial neural networks (ANNs) to predict ground status during the tunnel construction. Previous researches have considered geological hazards at the tunnel face to predict (Alimoradi et al. 2008), and tunnel settlement, or tunnel convergence (Santos and Tarsisio 2008). ANNs are applicable techniques to address the tunnels’ uncertainties because, they can explore non-linear patterns and the trends common in geological data. ANN has been widely applied and has produced successful predictions as a prediction and mapping technique in the geological engineering (Chao et al. 2018).

Another powerful technique is the Markov method. This method is one of the important stochastic approaches and applicable enough to deal with complex problems such as geological environments. The Markov method can be used as a single-step and a multiple-step memory. The advantage of single-step instead of multiple-step is that probabilistic calculations are very simpler and often a full probabilistic distribution can be found.

Chan (1981) and Ioannou (1987) estimated the uncertainty of different ground factors along the tunnel path using a discrete state Markov approach. They assumed that the ground factors are independent. However, ground factors can be correlated, for example, forecasting a factor status may depend on the other factors’ status. Qi et al. (2016) developed an approach to simulating the geological uncertainties based on coupled Markov chain. Sutanto (2007) applied real time Bayesian to propose a geological profile of a tunnel in Taiwan; however, their model failed to consider the dependency among observed variables.

Hidden Markov Models (HMMs) have been developed to analyzing the problems associated with uncertainties in the transportation engineering (Lu et al. 2009), and water resource engineering (Thyer and Kuczera 2003). In an arranged Markov approach, the state to the observer is visible directly. In the HMMs, each observation is the result of a stochastic procedure in one of different unseen states. The challenge is to specify the hidden factors from the seeable data. The advantage of utilizing HMM in the construction of tunnels is that, geological prediction errors can be reduced by updating the parameters’ status as soon as new observations is accessed during the construction.

Among the above-mentioned techniques, in this research, the Markov approach is applied to minimize the geological uncertainties along a tunnel route in Iran. Before the tunnel construction, the whole tunnel path is divided into many equal cells, then, by applying the pre-construction data in the Markov model, the status of several geological parameters is estimated along the tunnel path. Next, by combining the status of different parameters predicted along the tunnel route, the occurrence probability of several ground classes is estimated. Finally, the estimated results of the Markov model are compared with the measured ones.

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II. METHODOLOGY

The steps required in the Markov model to predict the geological status along a tunnel path are as follows:

(1) Transition probability matrix

\[ p_{ij} = \frac{T_{ij}}{\sum_{k=1}^{n} T_{ik}} \]  
(1)

Where \( p_{ij} \) is the transition intensity matrix from state \( i \) to state \( j \). \( T_{ij} \) is the transitions’ number from \( i \) to \( j \). \( \sum_{k=1}^{n} T_{ik} \) is the total transitions from \( i \) to other states, and \( n \) is the parameter states’ number.

(2) Transition intensity matrix

\[
A_x = \begin{bmatrix}
-C_{X_1} & C_{X_1}p_{X_12} & \cdots & C_{X_1}p_{X_1n}
C_{X_2}p_{X_21} & -C_{X_2} & \cdots & C_{X_2}p_{X_2n}
\vdots & \vdots & \ddots & \vdots
C_{X_n}p_{X_n1} & C_{X_n}p_{X_n2} & \cdots & -C_{X_n}
\end{bmatrix}
\]  
(2)

\( C_{X_i} \) dictates the coefficient of transition intensity of state \( i \).

(3) Interval probability matrix

\[ V_X(u) = \left\{ v_{Xij}(u) \right\} \]  
(3)

Where \( v_{Xij}(u) \) is the occurrence probability of state \( j \) for parameter \( X \) at cell \( L \) spaced \( u \) from cell \( O_0 \).

(4) Occurrence probability of states of a parameter

\[ S_X(u) = \sum_{i=1}^{n} S_{X1}(0) \cdot v_{Xij}(u) \]  
(5)

Where \( S_{X1}(u) \) is occurrence probability of state \( i \) of parameter \( X \) in location \( O_0 \).

III. ENGINEERING APPLICATIONS

The Hamru tunnel on in Iran is considered as the engineering application of this study.

The under-construction road between Marivan and Sanandaj is located in the northwest of Iran. The previously Sanandaj-Marivan road was 87 km. After the construction of the new road, the distance is decreased to 63 km. This research is undertaken on the Hamru tunnel with 1312m length and a cross-section of 97 m². In Fig. 2, the location map of the tunnel is depicted. Three types of geological units distinguishable along the tunnel path such as Limestone, Siltstone, and Shale. In Fig. 3, the geological map of the tunnel is depicted.

IV. THE GEOLOGICAL PREDICTION MODEL OF HAMRU TUNNEL

According to pre-construction data, lithology, groundwater, and RMR parameters to estimate along the tunnel path. For each parameter, several states were observed before the tunnel construction.

1. Lithology
   - State I: limestone-Li; state II: Shale-Sh; state III: sequence of shale limestones and sand shales-ShL; IV: sequence of Shale and Limestone-LSh
   - RMR
     - State I: < 20; state II: 20 – 40; state III: 41 - 60
   - Groundwater
     - State I: dry; state II: wet; state III: dripping; state IV: flowing

The average length of the above-mentioned states along the tunnel route are estimated by the tunneling experts as in Table 1.

| TABLE 1 Average Length And Transition Intensity Coefficient Of Each State. |
|------------------------|--------|-----------------|-----------------|
| Parameter | State | Average length (m) | \( C_{X} \) (m⁻¹) |
| Lithology | Li     | 400              | 0.0025          |
|           | Sh     | 100              | 0.0100          |
|           | ShL    | 630              | 0.0015          |
|           | LSh    | 180              | 0.0055          |
| RMR       | < 20   | 380              | 0.0062          |
|           | 20 - 40| 870              | 0.0011          |
|           | 41 - 60| 60               | 0.0035          |
| Groundwater | Dry   | 100              | 0.0100          |
|            | Wet    | 300              | 0.0033          |
|            | Dripping | 700            | 0.0014          |
|            | Flowing| 210              | 0.0047          |

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In the next step, using Eq. (2) the transition intensity matrices were calculated as follows.

Lithology:

\[
P_t = \begin{bmatrix}
1 & 0.11 & 0.82 & 0.07 \\
0.07 & 0 & 0.67 & 0.26 \\
0.22 & 0.13 & 0 & 0.65 \\
0.32 & 0.07 & 0.61 & 0
\end{bmatrix}
\]

\[
A_t = \begin{bmatrix}
1 & 2 & 3 & 4 \\
0 & 0.0002 & 0.0020 & 0.0001 \\
0.0007 & -0.0100 & 0.0067 & 0.0026 \\
0.0003 & 0.0001 & -0.0015 & 0.0009 \\
0.0008 & 0.0001 & 0.0015 & -0.0025
\end{bmatrix}
\]

RMR:

\[
P_d = \begin{bmatrix}
1 & 2 & 3 \\
0 & 0.93 & 0.07 \\
0.89 & 0 & 0.11 \\
0.35 & 0.65 & 0
\end{bmatrix}
\]

\[
A_d = \begin{bmatrix}
1 & 2 & 3 \\
0 & 0.0026 & 0.0024 & 0.0001 \\
0.0009 & -0.0011 & 0.0001 \\
0.0058 & 0.0107 & -0.0166
\end{bmatrix}
\]

Groundwater:

\[
P_w = \begin{bmatrix}
1 & 2 & 3 & 4 \\
0 & 0.27 & 0.63 & 0.10 \\
0.12 & 0 & 0.67 & 0.21 \\
0.16 & 0.41 & 0 & 0.43 \\
0.21 & 0.32 & 0.47 & 0
\end{bmatrix}
\]

\[
A_w = \begin{bmatrix}
1 & 2 & 3 & 4 \\
-0.0100 & 0.0027 & 0.0063 & 0.0010 \\
0.0003 & -0.0033 & 0.0022 & 0.0006 \\
0.0002 & 0.0005 & -0.0014 & 0.0006 \\
0.0009 & 0.0015 & 0.0018 & -0.0022
\end{bmatrix}
\]

To estimate the geological status along the tunnel path, first the whole tunnel path was divided into 10 m segments. 6 cells were calculated as follows.

\[
\text{Entrance portal (10 m)}
\]

In Fig. 4, the observational cells are shown in green. However, due to the data accessibility for the observational cells, the parameters’ status within them were considered deterministically. Hence, the status of each parameter within these cells was determined as in Table 2.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Lithology</th>
<th>RMR</th>
<th>Groundwater</th>
</tr>
</thead>
<tbody>
<tr>
<td>State1</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>State2</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>State3</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>State4</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

Now, the matrices and the data presented in Table 2 are used as the Markov model’s inputs. The Markov model predicts the occurrence probability of each parameter state within the unknown cells. The parameter profiles produced by the Markov model are depicted in Figs. 5-7.

**Fig. 5. The lithology parameter profile**

**Fig. 6. The RMR parameter profile**

**Fig. 4. Quantity and location of observational cells**

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According to the states of the parameters, 48 (4×3×4) geology vectors can be occurred during the tunnel path. These 48 vectors are classified into several Ground classes as in Table 3. To estimate the occurrence probability of each class along the tunnel path, we consider the vectors as (a, b, c), in which state ‘a’ is related to lithology, state ‘b’ is related to RMR, and state ‘c’ is related to groundwater. Now, as in Table 3, for each geology vector, a ground class should be selected.

<table>
<thead>
<tr>
<th>Ground Class</th>
<th>Lithology states</th>
<th>RMR states</th>
<th>Groundwater states</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1,2,3</td>
<td>1</td>
<td>2,3,4</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>2</td>
<td>1,2,3,4</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>2</td>
<td>2,3,4</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>2</td>
<td>3,4</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>2</td>
<td>2,3</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>3</td>
<td>3,4</td>
</tr>
<tr>
<td></td>
<td>2,3,4</td>
<td>2</td>
<td>3,4</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>2</td>
<td>2,3</td>
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<tr>
<td></td>
<td>4</td>
<td>3</td>
<td>3,4</td>
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<td>1</td>
<td>3</td>
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<td>2,3,4</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>3</td>
<td>1,2</td>
</tr>
<tr>
<td></td>
<td>2,3,4</td>
<td>3</td>
<td>3</td>
</tr>
</tbody>
</table>

The occurrence probability of each ground class estimated by the Markov model along the tunnel path is shown in Fig. 8.

Finally, based on Fig. 8, the final ground class estimated using the Markov model is depicted in Fig. 9(a). Also, in Fig. 9(b), the ground classes measured during the Hamru tunnel construction is depicted. Looking at Fig. 9, the ability of the Markov model developed by this study to predict the geological status of tunnels’ path is significant. Lastly, this article recommended the Markov model developed by this research to predict the geological status of road tunnels’ path.

V. CONCLUSIONS

Minimizing the geological uncertainties in the tunneling project is a crucial task that need to be addressed. To this end, this article developed a model based on the Markov method to estimate the occurrence probability of different geological statuses and ground classes along a tunnel path. By comparing the estimated results with the measured ones, it was concluded that the Markov model developed by this study have a good ability in the tunnels’ path geology prediction.

It is suggested that the performance estimation of the proposed model by this study be investigated for other tunneling types such as urban tunnels.

REFERENCES


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