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Application of Autoregressive Model in the Construction Management of Tunnels

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Abstract
The unknown subsurface conditions in tunnelling projects have led to their management with many uncertainties. From these uncertainties, we can mention the geological condition of the tunnel route and the time and costs required for construction. In order to significantly reduce these uncertainties, techniques that have a high predictive power must be used. For this purpose, in this study, an autoregressive model was used to reduce the uncertainties related to geology and construction time and cost in tunnelling projects. A comparison between the predicted results and the actual values through several statistical indices showed the high-performance prediction of the autoregressive model in the prediction of tunnel resources. Also, three input parameters affecting tunnel construction time and costs, such as RQD, groundwater, and RMR, were considered. The sensitivity analysis of these parameters on the time and cost of tunnelling projects was investigated through mutual information test (MIT). The groundwater was the most effective parameter on the tunnel's time and cost.

Keywords
Autoregressive model, tunnel geology; road tunnels; construction time and costs; sensitivity analysis

Introduction

Cost overruns and delays often encounter tunnel construction projects. Delays may negatively affect the scope of tunnelling projects, which leads to severe cost overruns (Zhang et al., 2021; Xu et al., 2021). Applying contingencies and estimating risks at the project level often do not capture the multiple uncertainties in the construction process of tunnel projects (Han et al., 2021; Li et al., 2021). Predicting the duration and cost of a tunnelling project is an essential factor in determining the usefulness of a decision-making system (Bai et al., 2021; Liu et al., 2021; Pan et al., 2021).

Tunnelling, similar, but more than other geotechnical endeavours, is characterized by the influence of high uncertainties (Ritter et al., 2013). Therefore, the time and cost of the tunnel's construction can never be exactly predicted. However, it is possible to determine a range over which they vary. This can be done with any kind of probability distribution or frequency plot (Mahmoodzadeh et al., 2016; Mahmoodzadeh et al., 2022).

Researchers have developed several studies to minimize tunnel construction uncertainties (Guan et al., 2014), such as soft computing techniques (Guan et al., 2012; Leu and Adi, 2011; Bezdan et al., 2021; Rashid et al., 2019; Cuk et al., 2021; Jabar and Rashid, 2018), and hard or exploratory methods.

In recent years, significant improvements in time management and the cost of tunnelling projects have been seen. Sousa and Einstein (2012) presented a Dynamic Bayesian Networks (DBN) model to estimate the expected costs and the risk of a tunnel collapse. Einstein et al. (1999) developed Decision Aids for Tunneling (DAT) to predict and reduce construction time and cost uncertainties in tunnelling projects.

Artificial intelligence and machine learning techniques have recently shown their potential ability in different engineering problems (Kang et al., 2019a; Kang et al., 2019b; Kang et al., 2015). Mahmoodzadeh et al. (2021) have presented an innovative methodology to predict tunnelling projects' construction time and costs based on machine learning techniques. They have shown the great ability of machine learning methods to reduce uncertainties regarding time and construction costs in tunnels.

This paper uses the autoregressive (AR) model to predict geological conditions and estimate road tunnels' time and costs. A comparison between the predicted results and the actual values was made to evaluate the performance prediction of the AR model. Also, three input parameters affecting the time and costs of tunnel construction, such as rock quality designation (RQD), groundwater, and RMR, were considered. The sensitivity analysis of these parameters on the time and cost of tunnelling projects was investigated through mutual information test (MIT).

Methodology: Autoregressive (AR) Model

A time series is a sequence of measurements of the same variable(s) made over time. Usually, the measurements are made at evenly spaced times (for example, monthly or yearly). Let us first consider the problem in which we have a y-variable measured as a time series. As an example, we might have y a measure of global temperature, with measurements observed each year. To emphasize that we have measured values over time, we use t as a subscript rather than the usual i, i.e., y_t means "y" measured in time period t.

An AR model is when a value from a time series is regressed on previous values from that same time series. For example, y_t on y_{t-1}.

$$\boldsymbol{y_t = \beta_0 + \beta_1 y_{t-1} + \epsilon_t} \tag{1}$$

In this regression model, the response variable in the previous time period has become the predictor, and the errors have our usual assumptions about errors in a simple linear regression model. The order of an AR is the number of immediately preceding values in the series that are used to predict the value at the present time. So, the preceding model is a first-order AR, written as AR(1).

If we want to predict y this year (y_t) using measurements of global temperature in the previous two years (y_{t-1}, y_{t-2}), then the autoregressive model for doing so would be:

$$\boldsymbol{y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \epsilon_t} \tag{2}$$

This model is a second-order autoregression, written as AR(2) since the value at time t is predicted from the values at times $t-1$ and $t-2$. More generally, a k^{th}-order AR, written as AR(k), is a multiple linear regression in which the value of the series at any time t is a (linear) function of the values at times $t-1$, $t-2$, …, $t-k$.

Data preparation

To investigate the performance prediction of the AR model in the tunnel geology, construction time, and construction cost, a road tunnel of 1900m length in Iran with a cross-section of 97m^2 was considered. The Lithology of the tunnel route is mainly composed of Sand Shales, Shale and Limestone. The tunnel was excavated using the top heading and benching method. The support system used in the 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

In the database, three parameters of RMR, RQD, and groundwater were considered the important geological parameters in the tunnelling projects.

RMR system is a geomechanical classification system for rocks developed by Bieniawski **(1989)**. It combines the most significant geologic parameters of influence. It represents them with one overall comprehensive index of rock mass quality, which is used to design and construct excavations in rock, such as tunnels, mines, slopes, and foundations. Over the years, the RMR system has been successively refined. More case records have been examined, and the reader should be aware that Bieniawski has significantly changed the rating assigned to different parameters. The following discussion is based upon the 1989 version of the classification (Bieniawski 1989). The following six parameters estimate the strength of rock mass using the RMR system:

Uniaxial compressive strength of rock material
Rock Quality Designation (RQD)
Spacing of discontinuities
Condition of discontinuities
Groundwater conditions
Orientation of discontinuities

Each of the six parameters is assigned a value corresponding to the characteristics of the rock. These values are derived from field surveys and laboratory tests. The sum of the six parameters is the RMR value, which lies between 0 and 100. The classification of the RMR system is provided in Table 1.

Table 1 The classification for the RMR system (Bieniawski 1989).

RMR	0-20	21-40	41-60	61-80	81-100
Class No.	I	II	III	IV	V
Rock quality	Very poor	Poor	Fair	Good	Very good

RQD is a measure of rock core quality taken from a borehole. RQD signifies the degree of jointing or fracture in a rock mass measured in percentage, where RQD of 75% or more shows good quality hard rock, and less than 50% shows low quality weathered rocks. Table 2 shows the values of RQD of various grades of rocks. RQD is calculated by taking a rock core sample from a borehole, and the lengths of all sound rock pieces, which are a minimum of 100 mm long, are summed up and divided by the size of the core run.

Table 2 Quality of rocks and their RQD

Rock Quality	RQD [%]
Very poor (Completely weathered rock)	< 25
Poor (weathered rocks)	25 – 50
Fair (Moderately weathered rocks)	51 – 75
Good (Hard Rock)	76 – 90
Very Good (Fresh rocks)	91 – 100

Results and discussion

Geology prediction of the tunnel route

In order to examine the performance prediction of the AR model in the geology prediction of a tunnel route, the status of the parameters, including RMR, RQD, and groundwater, are predicted along the tunnel route. For this purpose, the status of these parameters from Km 0 + 000 to Km 0 + 300 was used as the training datasets, and their status from Km 0 + 300 to Km 0 + 350 was used as the test datasets. An overview of the database is provided in Table 2. The AR prediction results for these three parameters are shown in Fig. 1. As in Fig. 1, the results predicted by the AR model are in good agreement with the actual ones along the tunnel route. Therefore, considering the datasets applied in this study, the AR model has the potential ability in the prediction of tunnel geological parameters along the tunnel route.

Table 2 An overview of the database.

	Training data			Testing data		
	RMR	RQD	Groundwater	RMR	RQD	Groundwater
Count	300	300	300	50	50	50
Mean	57.34	58.45	1.42	45.98	60.39	2.69
Std	24.23	20.94	3.46	24.27	17.40	0.94
Min	2	7	0	9	22	0.39
25%	38.75	43	0	20	50	2.14
50%	56	59.65	0.00001	48	60	2.67
75%	79	77	0.84	62.50	71	3.16
Max	98	97	18.94	88	97	4.92

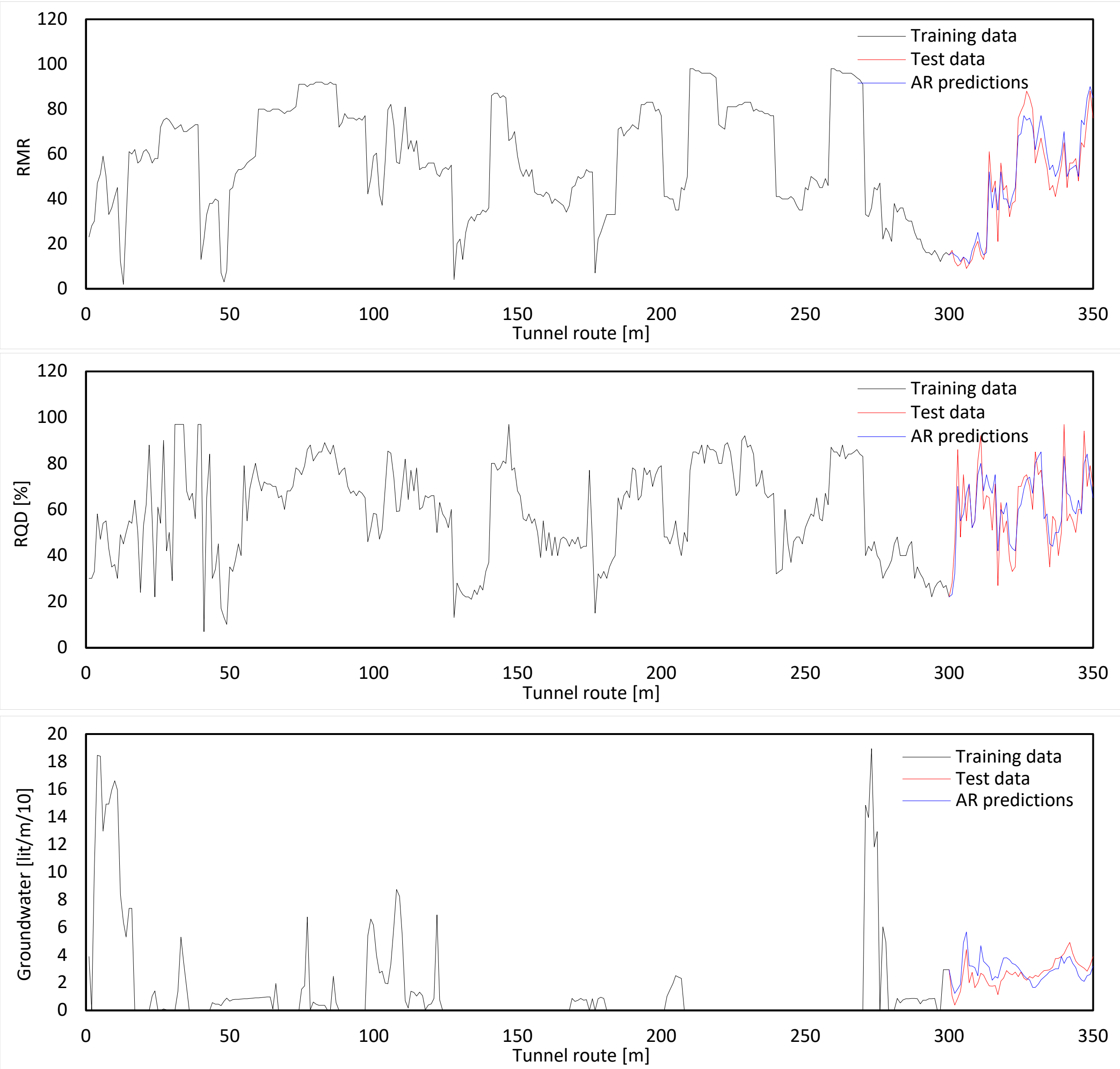

Fig. 1. AR model predictions along the tunnel route for three parameters: RMR, RQD, and groundwater.

Prediction time and cost of tunnel construction

In this article, 350 datasets, including three input parameters of RMR, RQD, and groundwater and two output parameters of construction time and construction cost, were used to evaluate the AR model's performance in predicting the time and cost required for tunnel construction. Three hundred data were applied for training and 50 data for tests. The correlation matrix of the datasets is shown in Fig. 2.

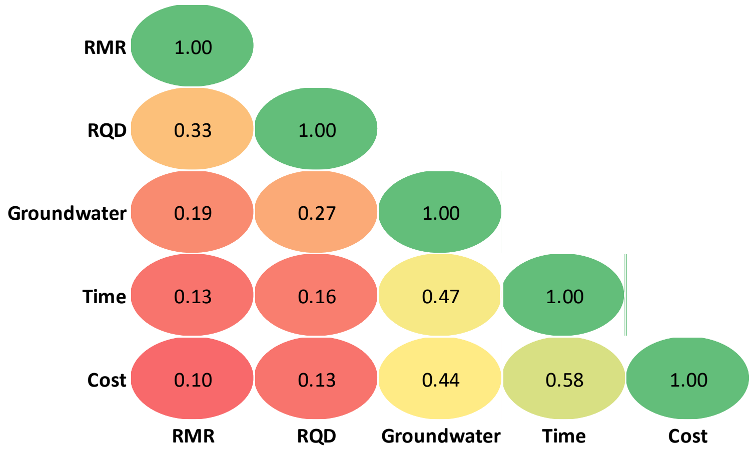

Fig. 2. The correlation matrix of the datasets.

The AR model predictions for both construction time and construction cost are depicted in Fig. 3 and compared with the actual ones. According to Fig. 3, the AR results are very close to the actual ones. Therefore, it shows that the AR model's ability to predict the time and cost of tunnel construction is high. Also, it can be understood from these results that the three parameters of RMR, RQD, and groundwater considered in the datasets are effective parameters for the time and cost of tunnel construction. If the parameters are not selected correctly, then the correct performance of the model can not be expected.

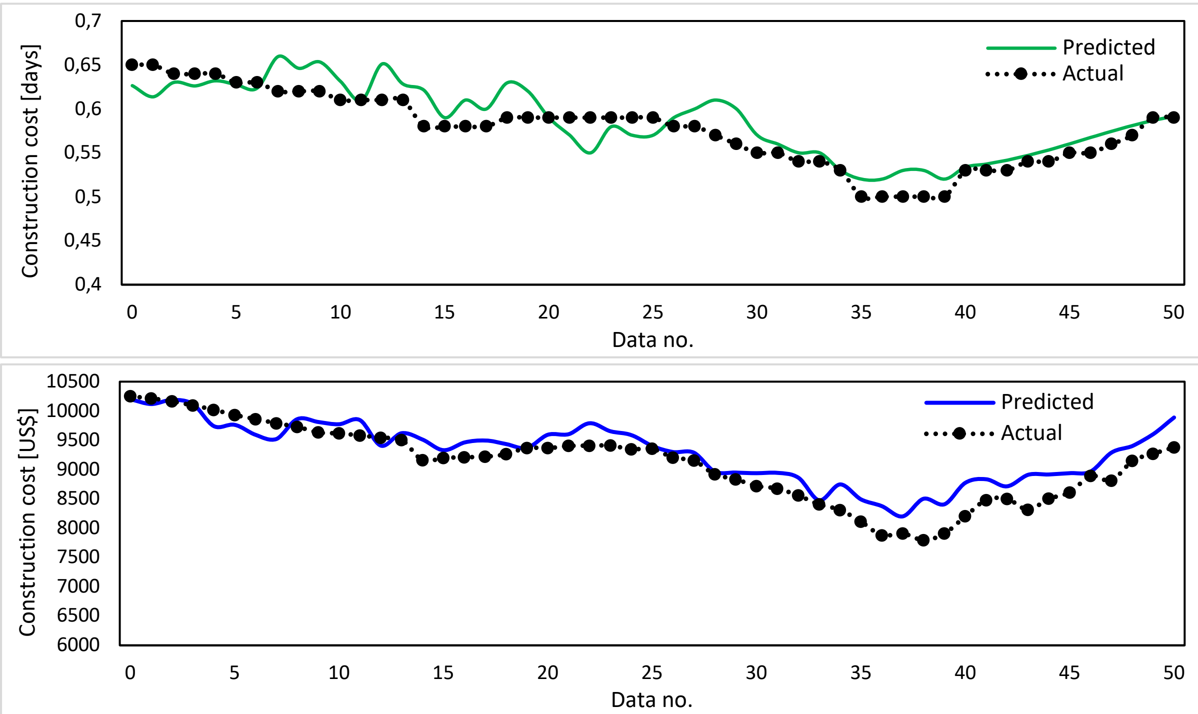

Fig. 3. Comparison of AR model predictions with the actual time and cost of tunnel construction.

The correlation coefficient (R^2) for the construction time and construction cost predictions versus the actual ones are shown in Fig. 4. As in Fig. 4, the R^2 value made by the AR model in the prediction of time and cost is equal to 0.7760 and 0.9128, respectively. The AR model was more accurate in predicting the construction cost than the construction time. This is because the parameters considered in the datasets (RMR, RQD, and groundwater) have a greater impact on cost. Therefore, the type of data and parameters used in forecasting models can significantly impact forecasting results.

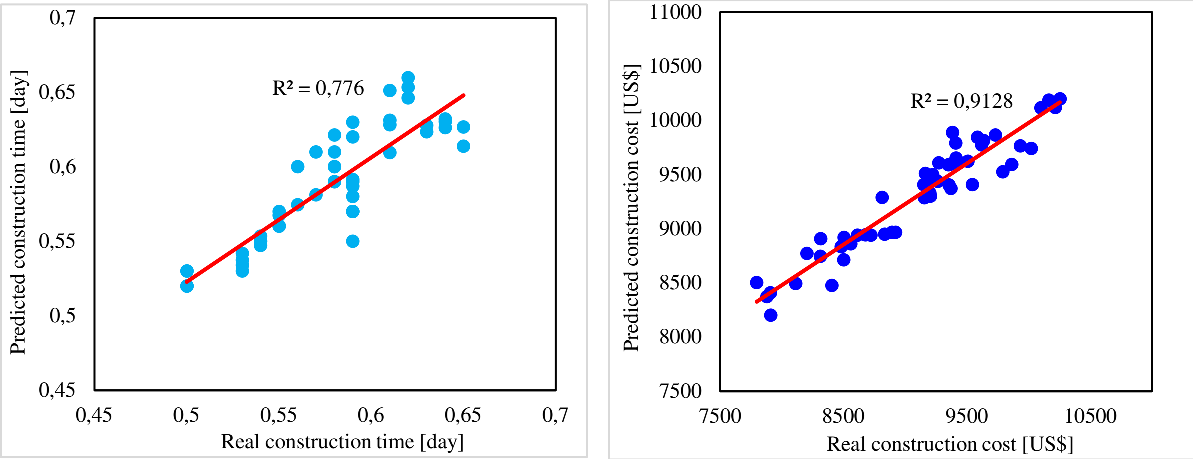

Fig. 4. R^2 values of the predicted construction time and construction cost versus actual ones.

Sensitivity analysis of the parameters

To accurately predict the time and cost of tunnel construction, the impact of factors should be comprehensively studied and evaluated. In this study, three input parameters, including RMR, RQD, and groundwater, were considered effective parameters for the tunnel's construction time and cost. However, the sensitivity of these parameters individually is unclear on time and cost parameters and needs more study to reveal it. In this study, the mutual information test (MIT) proposed by Verron et al. (2008) is used to investigate the impact of the input parameters on the model output. The MIT is a filtering technique applied to capture the desired relationship between each parameter and the label. This measure is the interdependence between parameters and shows the relationship's strength. The information gain can calculate the mutual information size between the parameters:

$$Gain(Y,X) = Ent(Y) - \sum_{v=1}^{V} \frac{|Y^v|}{|Y|} Ent(Y^v) \tag{3}$$

Where v indicates the number of all possible values for X, Y^v is the set Y related to when x takes x_v and *Ent(Y)* is the entropy of the information. As $Gain(Y,X)$ increases, the correlation between X and Y is increased.

Lastly, according to the score of the parameters in the MIT method, the importance degree of the input parameters on time and cost was calculated. The results obtained by the MIT method are illustrated in Fig. 5 for each input parameter. Looking at Fig. 5, it is revealed that all the three parameters of RMR, RQD, and groundwater with important scores of 1. 48, 1.35, and 1.85 in the prediction of construction time parameter, and with important scores of 1.67, 1.59, and 2.21 in the prediction of construction cost parameter, respectively, have great impacts on the time and cost of tunnels' construction. But, their impact on the construction cost is more than their impact on construction time. Also, the impact of groundwater parameters on both construction time and construction cost is more.

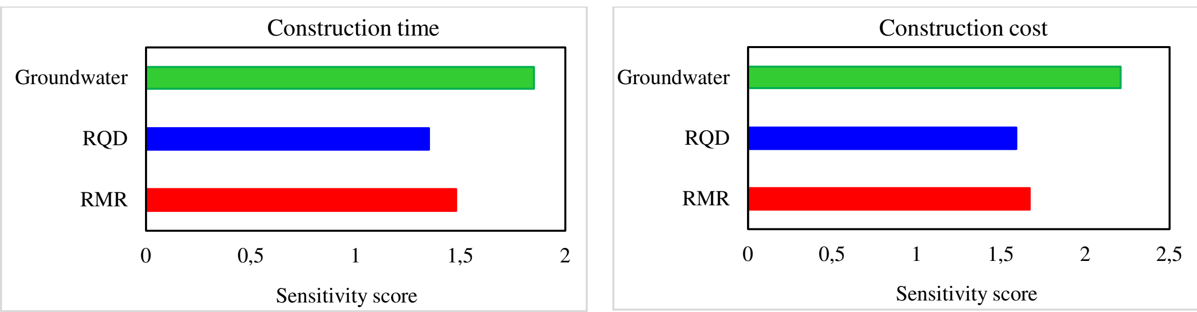

Fig. 5. Sensitivity analysis of the input parameters on the time and cost of tunnel construction.

Conclusions

The unknown subsurface conditions in tunnelling projects have led to their management with many uncertainties. In this study, an AR model was used to reduce the uncertainties related to geology and construction time and cost in tunnelling projects. Three hundred fifty datasets, including three input parameters of RMR, RQD, and groundwater, and two output parameters of construction time and construction cost. were applied in the AR model. Three hundred datasets were used for training and 50 datasets for the test. The MIT method was used to investigate the sensitivity analysis of the parameters. The obtained results in this study lead to the following conclusions:

- The performance prediction of the proposed AR model in the prediction of the tunnel route's geology is very good.
- The performance prediction of the proposed AR model in the prediction of construction time and cost of tunnels is very high.
- Three input parameters of RMR, RQD, and groundwater considered in the datasets significantly affected the construction time and construction cost.
- The sensitivity analysis using the MIT method showed that, among three parameters of RMR, RQD, and groundwater, the groundwater parameter impacts the time and cost of tunnel construction.
- Three parameters of RMR, RQD, and groundwater are more effective on construction time than construction cost.
- This work's significance is that it allows geotechnical engineers to determine the usefulness of a decision-making system in a tunnelling project.

Given that there are different types of tunnels, and depending on the type of tunnel, the parameters affecting the construction time and costs can be different, the investigation of the AR model capability presented in this article on the different types of tunnels, such as urban tunnels is suggested.

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