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Forecasting tunnel path geology using Gaussian process regression

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Abstract. Geology conditions are crucial in decision-making during the planning and design phase of a tunnel project. Estimation of the geology conditions of road tunnels is subject to significant uncertainties. In this work, the effectiveness of a novel regression method in estimating geological or geotechnical parameters of road tunnel projects was explored. This method, called Gaussian process regression (GPR), formulates the learning of the regressor within a Bayesian framework. The GPR model was trained with data of old tunnel projects. To verify its feasibility, the GPR technique was applied to a road tunnel to predict the state of three geological/geomechanical parameters of Rock Mass Rating (RMR), Rock Structure Rating (RSR) and Q-value. Finally, in order to validate the GPR approach, the forecasted results were compared to the field-observed results. From this comparison, it was concluded that, the GPR is presented very good predictions. The R-squared values between the predicted results of the GPR vs. field-observed results for the RMR, RSR and Q-value were obtained equal to 0.8581, 0.8148 and 0.8788, respectively.

Keywords: engineering geology; Gaussian process regression; geomechanical parameters; tunneling; tunnel geology

1. Introduction

The mountain tunnels used for underground passage and transportation have been successful development worldwide in recent years. The construction of these tunnels inevitably encounters terrible geological conditions; however, there is still a challenge to address the construction risks when tunnelling in these complex and variable geological conditions. In Fig. 1, a number of hazards that tunnels face due to unfavorable geological conditions. Suppose the geological condition of the tunnel route is predicted before construction begins. In that case, it may be possible to predict the occurrence of such hazards by assigning an appropriate drilling method and maintenance system.

Making a good decision in the design phase of projects needs robust schedules. Tunneling, unlike any other area of civil engineering, is characterized by high degrees of uncertainty (Haas and Einstein 2002) because of ground conditions as the main incertitude source in the construction of road tunnels (Guan *et al*. 2014). To infer these unknown conditions prior to construction, we have to base ourselves on geological information near the project and on location-specific observations provided by sub-surface exploration programs. Risk assessment is one of the critical points in any project. Especially for tunnel projects (Sousa and Einstein 2012, Wang *et al.* 2017), although most constructions have been completed safely, several incidents in various tunneling projects such as injury and loss of life have resulted in delays cost overruns. Ground conditions are the main issues during the tunneling project design, minimizing uncertainties, in this case, it's an asset (Mahmoodzadeh and Zare 2016, Mahmoodzadeh *et al*. 2019). Knowing that it is not easy to predict accurately geological and geotechnical probability along tunnel alignment. Different ways, including analytical, empirical and numerical approaches, have been presented in the last few decades. All of these methods aim to determine the ground conditions ahead of the tunnel face to avoid unexpected changes in geological and geotechnical conditions and construction time and costs.

One of these methods is to use intelligent techniques such as Artificial Neural Network (ANN), time series and random process approaches which utilize mathematical models to predict the geological and geotechnical conditions along the tunnel alignment (Guan *et al*. 2014, Guan *et al.* 2012).

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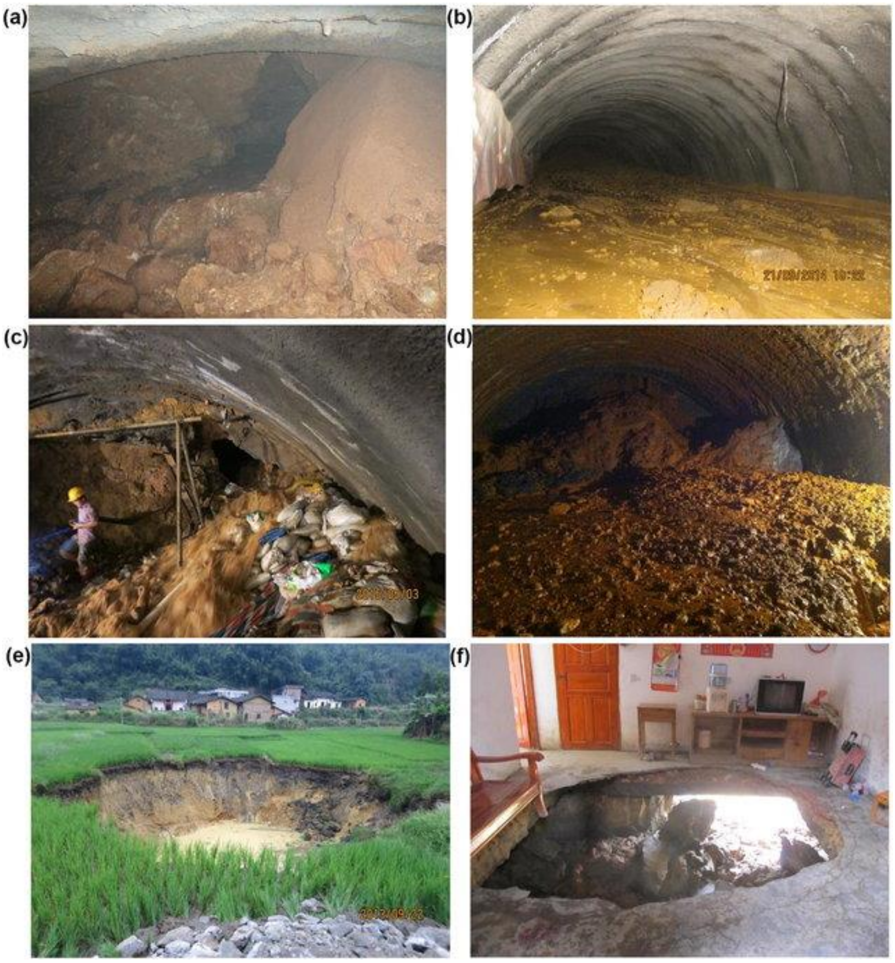

Fig. 1 A number of hazards that tunnels face due to unfavorable geological conditions (Yuan *et al*. 2019)

In recent researches, machine learning techniques have shown the potential ability to analyze the problems in the geotechnical engineering problems (Mahmoodzadeh *et al*. 2021a, Mahmoodzadeh *et al.* 2021b, Bai *et al*. 2021, Luat *et al.* 2020, Liu *et al*. 2021a, Liu *et al.* 2021b, Mahmoodzadeh *et al.* 2021c, Xiang *et al*. 2021, Dutta *et al*. 2018, Chore and Magar 2017, Cavaleri *et al.* 2017, Mahmoodzadeh *et al.* 2021d, Kundapura and Hegde 2017, Ayat *et al.* 2018, Mahmoodzadeh *et al*. 2021e).

Gaussian process (GP) is a Bayesian state-of-the-art tool for discriminative machine learning, i.e., regression, classification and dimensionality reduction. The GP model is suitable for cases that are characterized by high dimension, small sample population, and nonlinearity, it can apply the mean of the distribution as point predictions to avoid robust point predictions (Li *et al.* 2017).

Gaussian process regression (GPR) provides probabilistic models (Mahmoodzadeh *et al*. 2021f, Pal and Deswal 2010). The probabilistic models mean that Gaussian processes provide the reliability of responses to the given input data. Non-parametric models such as a Bayesian framework for GPR have recently received significant attention in the field of machine learning. GPR provides a probabilistic, non-parametric modeling approach and is being applied to various engineering problems (Liu *et al*. 2006, Mahmoodzadeh *et al*. 2021g).

GPR modeling geotechnical engineering problems is a relatively recent development (Mahmoodzadeh *et al*. 2020a, Mahmoodzadeh *et al.* 2021b). However, there is a few research on the GPR to predict ground conditions along tunnel alignment.

This paper aims to present a new intelligent, dynamic, and adaptable approach to predict geology conditions along tunnel route that can be used as a basis for developing more effective decision support systems for tunnel design and construction. For this purpose, a nonlinear GPR is applied to create a model for predicting the Rock Mass Rating (RMR), Rock Structure Rating (RSR) and Q-value parameters. In order to training the GPR model, the data of historical road tunnels are applied. Finally, in order to verify its feasibility, the GPR model, as well as other intelligent techniques, the GPR results are compared with the field-observed results.

Despite the merits of various ML approaches, according to the No-Free-Lunch (NFL) theorem, there is no ML model to solve all engineering problems as the best method successfully. Therefore, researchers have tried to evaluate the efficiency of various ML approaches for solving various optimization. As NFL theorem, we use GPR model to predict the tunnel path geological parameters. However, the key features of the aforementioned model, which motivate us to use them, is as follows:

Regression Analysis

Regression analysis is used to predict a continuous target variable from one or multiple independent variables. Typically, regression analysis is used with naturally-occurring variables, rather than variables that have been manipulated through experimentation. As stated above, there are many different types of regression, so once we've decided regression analysis should be used, how do we choose which regression technique should be applied?

We chose GPR because:

- GPR directly captures the model uncertainty. For example, in regression, GPR directly gives a distribution for the prediction value, rather than just one value. This uncertainty is not directly captured in neural networks.
- When using GPR, we can add prior knowledge and specifications about the shape of the model by selecting different kernel functions. For example, based on the answers to the following questions, we may choose different priors. Is the model smooth? Is it sparse? Should it be able to change drastically? Should it be differentiable? This capability gives researchers flexible models, which can be fit to various kind of datasets.

In Fig. 2, the GPR prediction stages of the geological or geotechnical parameters is shown schematically.

In the next section, the GPR is described. In section 3, the application of the GPR model in order to predict the geology conditions along tunnel alignment is expressed. The GPR model is applied to an engineering application of Hamru road tunnel in section 4 and the predicted results are compared with field-observed results. Discussion and conclusions are described in section 5.

2. Gaussian Process Regression (GPR)

A Gaussian procedure (GP) is a gathering $\mathcal{F}$ of arbitrary factors $F_{x_1}, F_{x_2}, ...$ for which any finite subset of the factors has a joint multivariate Gaussian conveyance. The factors are listed by components x of a set $\mathcal{X}$. For any finite length vector of lists $x = [x_1, x_2, ..., x_n]^T$, we have a comparing vector $\boldsymbol{F}_x = [F_{x_1}, F_{x_2}, ..., F_{x_n}]^T$ of factors that has a multivariate Gaussian (or ordinary) distribution, where the components of $\mu(x)$ are given by an earlier mean capacity $\mu(x_i)$, and k is the portion work. The portion takes two files x_i andx_j, and gives the covariance between their comparing factors F_{x_i} and F_{x_j}. Given vectors of lists x_i andx_j, k restores the framework of covariances between all sets of factors where the first in the pair originates from F_{x_i} and the second from F_{x_j}. Note that each F_{x_i} is barely Gaussian, with mean $\mu(x_i)$ and difference $k(x_i, x_i)$ (Mahmoodzadeh *et al.* 2021h).

Assume we have a capacity $f(x)$ that we might want to upgrade. Further, assume that f can't watched legitimately, yet that an arbitrary variable F_x can be seen that is listed by a similar space as f and whose normal esteem is f, i.e., $\forall\ x \in\ \mathcal{X}, E[Fx] = f(x)$. Specifically, we accept that our earlier conviction about the capacity f complies with a Gaussian procedure with earlier mean μ and part k. Assume that F_x is a perception of $f(x)$ that has been tainted by zero-mean, i.i.d. Gaussian clamor, i.e., $F_x = f(x) + \epsilon$, where $\epsilon \sim \mathcal{N}(0, \sigma_\epsilon^2)$. Subsequently, $f(x)$ is a shrouded variable whose back appropriation we can derive in the wake of watching tests of F_x at different areas in the space. The subsequent deduction is called Gaussian procedure relapse (Mahmoodzadeh et al. 2021i).

Give x a chance to be the arrangement of perceptions focuses and $\boldsymbol{F_x}$ be the subsequent genuine esteemed perceptions. We need to process the back appropriation of some new point $\hat{x} \in \mathcal{X}$. The appropriation will be Gaussian with mean and difference,

$$\boldsymbol{F}_x \sim \mathcal{N}\{\mu(x), k(x, x)\} \tag{1}$$

$$\mu(\hat{x}|x) = \mu(\hat{x}) + k(\hat{x}, x) k(x, x)^{-1}\ (\boldsymbol{F}_x - \mu(x)) \tag{2}$$

$$\sigma^2(\hat{x}|x) = k(\hat{x}, \hat{x}) - k(\hat{x}, x) k(x, x)^{-1}\ k(x, \hat{x}) \tag{3}$$

Note that the backward application deceives the portion network of watched area focuses, thus it can be figured once and used to assess the back at numerous focuses in the space.

Since the issue is to find an ideal of the obscure capacity, the final step is to process the ideal of the subsequent back mean $x^R = argmax_{\hat{x} \in \mathcal{X}}\ \mu(\hat{x}|x)$. This, all in all, can't be processed in shut structure, and requires the utilization of some strategy for capacity streamlining. Despite the fact that not ideal, another strategy is just to restore the x_i from x with the biggest watched esteem F_{x_i}. This has the functional reaction that the method won't restore a point that has never been assessed, including some insurance from an inaccurate earlier.

3. GPR model of geology conditions prediction

As noted in the previous section, GPR requires samples to use as a training dataset to help them make predictions. These inputs can vary depending on the type of the project and the type of problem. Since the main focus of this paper is on the geology prediction along tunnel route, different geological and geomechanical parameters such as RMR, Rock Quality Designation (RQD), lithology, underground water conditions, etc. can be taken into consideration.

In this paper, the distances from the tunnel entrance are considered inputs xi, and the status of a geological or geotechnical parameter is considered outputs y_i. For example, the status of the RQD parameter, can be varied from zero to 100%.

The initial number of data (x_i, y_i) for a tunnel project may not be sufficient to be used as the initial inputs for the GPR. We need more inputs for training, as much as they are, GPR provides more accurate predictions. For this reason, in the presented technique, in addition to using the initial data on the tunnel (observational locations), the historical tunnels that are excavated and their field-observed data are available, are used. The stages of forecasting the status of a geological or geotechnical parameter are given below:

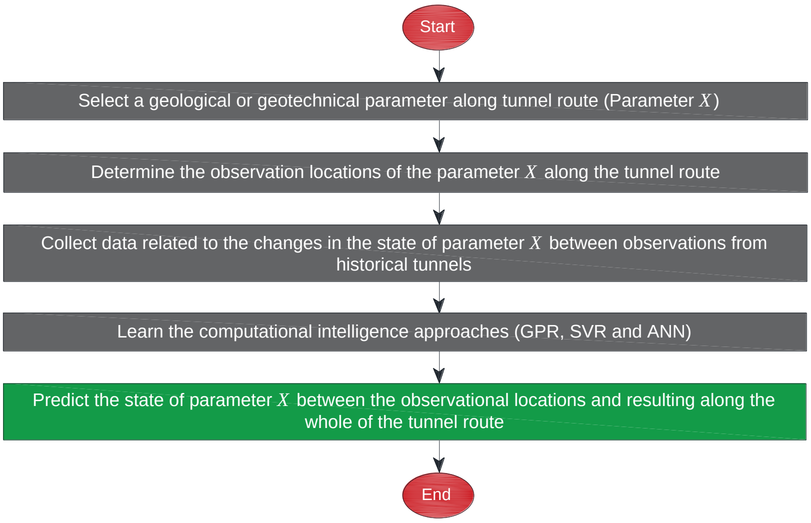

Fig. 2 A summary of the steps involved in this article

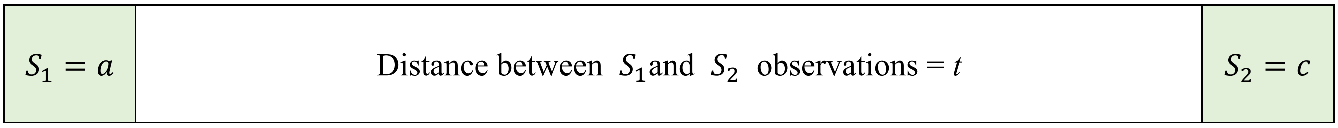

Fig. 3 The position of the two observations S_1 and S_2 at the distance t from each other, where the status of the parameter X are a and c respectively

1. According to Fig. 3, we consider two observational positions S_1 and S_2 that we want to predict the state of the parameter X at the distance t.
2. Determine the status of the parameter X in the positions S_1 and S_2, as shown in Fig. 3, which is respectively a and c.
3. In other historical tunnels, we look for two positions, such as S_1 and S_2, spaced at or near distance t. S_1 is similar to S'_1 and S_2 has the same position as S'_2. For a similar situation, for example, if in position S_1 the conditions of the parameter X is a, then it should be in the same position as S'_1.
4. In the interval between the positions S'_1 and S'_2, we specify yi values (or status of the parameter X) for each xi. The data obtained between the two positions S'_1 and S'_2 is called a dataset. Similarly, we can look at the number of n sets of data from other positions such as S'_1 and S'_2 in the historical tunnels, and, as shown in Fig. 4, we obtain the values of the input of each case the GPR model.
5. As shown in Fig. 4, we put all datasets of S'_1 and S'_2 parallel to S_1 and S_2, and each of n sets of data obtained is considered as the input of the GPR model in the interval between S_1 and S_2.
6. After obtaining input data and applying them to the GPR, for each x_i^* the corresponding y_i^* will be predicted in-between S_1 and S_2. In the following, for any distance in the tunnel route, we act in the manner described above so that we can predict the probability of occurrence of the parameter status in other tunnel locations.

In the next section, an engineering application of the GPR is presented on Hamru tunnel to predict the status of the parameter X along the tunnel route.

4. Engineering application

4.1 Engineering background

The new road between Sanandaj and Marivan is an under-construction project in the northwest of Iran. Due topassage through the Zagros roads, 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 kilometers. On the new road, the length will be reduced to 105 kilometers, reducing the travel time and accidents.

The present study is undertaken on Hamru tunnel of 1312 m length and cross-section of 97 m^2 as part of the under-construction Sanandaj-Marivan road. The entrance of the Hamru tunnel is considered the eastern mouth (to the Sanandaj-S) and its outlet is considered the western (to the Marivan-M). In Fig. 5, the location of the Hamru tunnel is shown.

Five types of geological engineering units are identifiable and distinguishable in the tunnel route: Limestone, Shale, Shale with Limestone, Shale with Siltstone, and Limestone with Siltstone. In Fig. 6, the geological profile of the Hamru tunnel is shown along with the position of the five boreholes. Because in the later sections of the data from the parameter RMR is used, in Table 1 it’s status is shown in the borehole positions and entrance and exit portals of the tunnel.

Previous datasets from n case parallel with S_1 and S_2			
$S'_{11} = a$	t	$S'_{21} = c$	$x_{1i} = x_{11}, x_{12}, \dots, x_{1t}$ $y_{1i} = y_{11}, y_{12}, \dots, y_{1t}$
⋮	⋮	⋮	⋮
$S'_{n1} = a$	t	$S'_{\mathrm{n}2} = c$	$x_{ni} = x_{n1}, x_{n2}, \dots, x_{nt}$ $y_{ni} = y_{n1}, y_{n2}, \dots, y_{nt}$
Predict the status of a parameter between S_1 and S_2 by using the previous data in GPR model			
$S_1 = a$	t	$S_2 = c$	$x_i^* = x_1^*, x_2^*, \dots, x_t^*$ $y_i^* = y_1^*, y_2^*, \dots, y_t^*$

Fig. 4 Presentation of accessing the GPR input data from previously excavated tunnels

Table 1 RMR status in the observational locations

Tunnel chainage (m)	RMR
SM40 + 920 (Entrance)	40
SM41 + 273 (BH1)	5
SM41 + 543 (BH2)	20
SM41 + 740 (BH3)	15
SM41 + 973 (BH4)	25
SM42 + 133 (BH5)	0
SM42 + 232 (Exit)	20

4.2 Sample selection and model establishment

In this paper, RMR parameter has been considered in order to predict the geology conditions with the help of GPR along the tunnel route. The reason for choosing the RMR parameter is that it can be used to estimate the status of several other parameters such as Rock Structure Rating (RSR), Q-value, maximum unsupported span, etc. Therefore, the RMR parameter is very important in the construction of underground spaces, especially tunnels.

For GPR, a squared exponential covariance function (Eq. (4)) is considered concerning the parameter setting. The kernel is very simple, it takes only two parameters, the length between points and the average distance of them from the mean. Already it is supposed to have zero mean vector, so the distribution is around zero. To match a signal with noise, their covariance is calculated by (Eq. (4)), nearby points will have high covariance and thus highly correlated. In the other hand, using squared exponential, it is not possible to extrapolate more than l units between any two points.

$$k(x_p, x_q) = \sigma_f^2 exp\left(-\frac{1}{2}(x_p - x_q)^T M(x_p - x_q)\right) = \sigma_f^2 exp\left(-\frac{1}{2}\sum_{i=1}^{D}\frac{(x_{p,i} - x_{q,i})^2}{l_i^2}\right) \quad (4)$$

where, $M = diag(l)^{-2}$, $l = [l_1, l_2, \dots, l_D]^T$ and $\theta = (lnl_1, \dots, lnl_D, ln\sigma_f)$ are the hyper-parameters.

The kernel normally contains hyper-parameters such as the length-scale, the signal variance, and the noise variance. These are usually not assumed to be known but rather are learned from the data. As the posterior distribution over the hyper-parameters is generally difficult to obtain, the full Bayesian inference of the hyper-parameters is generally not used. Instead, a point estimate of the hyper-parameters is usually computed by maximizing the log-marginal likelihood. This is similar to parameter estimation by maximum likelihood and is also referred to as type-II maximum likelihood. Here, the hyper-parameters are tuned using the automatic hyper-parameter optimization method given in MATLAB with the 'fitrgp' function.

Three primary hyperparameter tuning approaches have been proposed in literatures, including random search, grid search, metaheuristic-based search (smart search) although there are also other approaches which are less popular. Unlike the "dumb" alternatives of grid and random search, metaheuristic-based hyperparameter tuning, including PSO, is much less parallelizable. Instead of producing all the candidate points up front and investigating the batch in parallel, metaheuristic-based tuning approaches pick a few hyperparameter settings, investigate their performance, then determine where to sample next. These methods are intrinsically iterative and sequential process, which is not parallelizable. On one hand, making fewer evaluations and reducing the total time complexity are the primary goal of any computation algorithm and on the other hand, metaheuristic-based search algorithms require computation time to find out where to place the next set of samples. Besides, metaheuristic-based search algorithms also contain parameters of their own that need to be tuned. These shortcomings motivate us to choose random search, which has the least time and space complexity.

Considering the Bergstra theorem that stated that "if the close-to-optimal region of hyperparameters occupies at least 5% of the grid surface, then random search with 60 trials will find that region with high probability", The hyperparameters of the GPR method was optimized with a random search approach as follows: the values of hyperparameter are modeled with an exponential

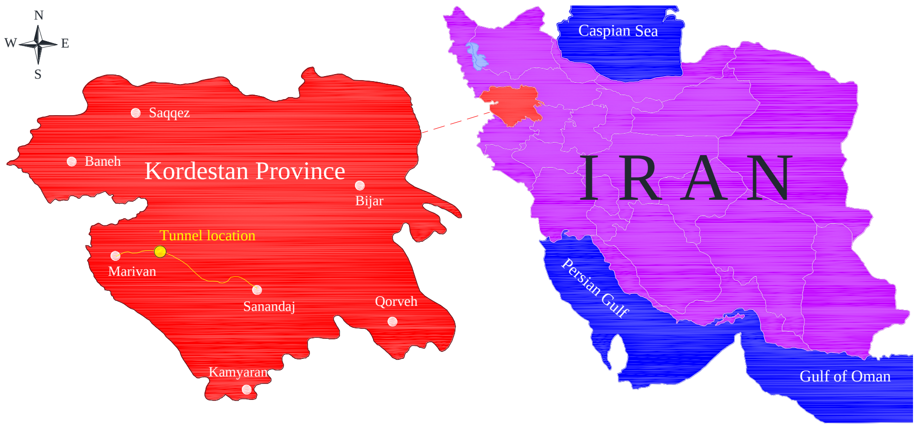

Fig. 5 Location of Hamru tunnel

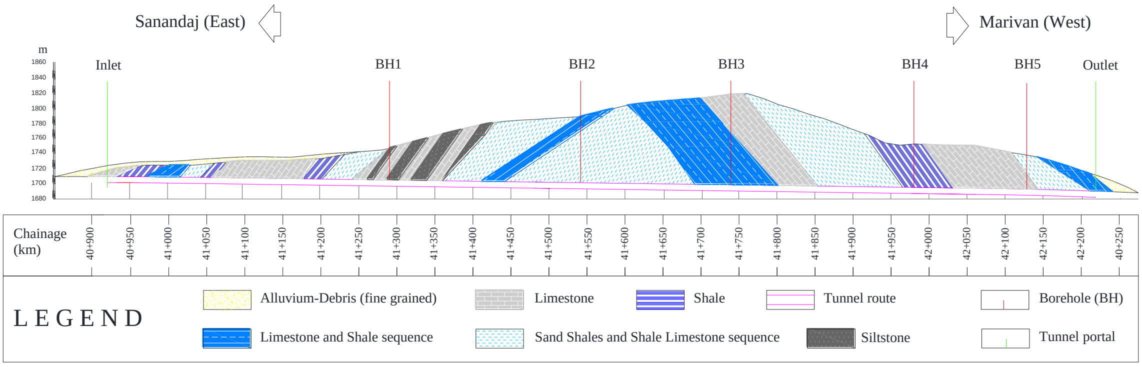

Fig. 6 Geological map of Hamru tunnel

Table 2 Input data to train the GPR model to predict the RMR parameter state between entrance and borehole 1

Tunnel chainage (m)	RMR									
SM40 + 920 (Entrance)	40	40	40	40	40	40	40	40	40	40
SM40 + 945	35	50	60	20	35	40	50	35	25	35
SM40 + 970	30	55	70	20	35	40	30	30	30	30
SM40 + 995	10	55	60	15	35	35	35	35	35	35
SM41 + 020	10	50	50	25	40	35	30	25	20	25
SM41 + 045	35	30	30	30	25	30	35	30	20	25
SM41 + 070	40	20	30	30	35	25	15	25	25	20
SM41 + 095	40	20	25	35	30	15	15	20	25	35
SM41 + 120	30	20	30	25	30	10	15	15	20	40
SM41 + 145	20	15	50	20	20	10	15	15	20	35
SM41 + 170	15	15	55	15	15	10	20	10	15	30
SM41 + 195	20	10	30	15	20	5	25	10	20	20
SM41 + 220	20	15	20	10	25	5	25	15	15	20
SM41 + 245	25	15	15	10	20	10	15	10	10	10
SM41 + 269	15	15	5	5	5	10	10	5	10	10
SM41 + 273 (BH1)	5	5	5	5	5	5	5	5	5	5

probability density function, which produces values for each hyperparameter to be investigated according to the models' performance in the validation set. After 60 iterations with differently produced values from the probability functions, the hyperparameters that generated the highest accuracy are selected and stored.

Section 3 clearly explained how to collect data in order to train the GPR model by investigating historical tunnels. As mentioned earlier, there are seven observation positions along the Hamru tunnel path. In these situations, the status of the RMR, RSR and Q-value parameters is clear. In order to obtain the training data in this study, 27 road tunnels that were almost geologically similar to the Hamru tunnel were examined. In all these tunnels, changes in the status of

Table 3 Input data to train the GPR model for predict the RMR parameter state between borehole 1 and borehole 2

Tunnel chainage (m)	RMR									
SM41 + 273 (BH1)	5	5	5	5	5	5	5	5	5	5
SM41 + 300	5	10	5	5	15	10	15	15	5	5
SM41 + 317	15	25	10	30	25	25	30	5	10	20
SM41 + 334	30	35	20	15	10	5	15	5	10	10
SM41 + 351	25	40	25	15	15	10	25	15	35	15
SM41 + 368	45	35	20	10	25	20	55	75	30	5
SM41 + 385	30	25	30	15	35	40	50	70	15	20
SM41 + 402	25	20	35	30	20	25	30	55	35	30
SM41 + 419	25	15	5	30	25	10	35	35	50	40
SM41 + 436	45	5	25	20	35	35	20	30	25	35
SM41 + 453	55	10	35	15	35	25	30	15	20	30
SM41 + 470	40	15	20	25	30	15	35	10	35	20
SM41 + 487	35	10	15	30	25	5	40	15	20	5
SM41 + 504	25	15	20	35	30	15	30	20	15	10
SM41 + 521	20	15	20	30	25	30	40	10	15	5
SM41 + 543 (BH2)	20	20	20	20	20	20	20	20	20	20

Table 4 Input data to train the GPR model to predict the RMR parameter state between borehole 2 and borehole 3

Tunnel chainage (m)	RMR									
SM41 + 543 (BH2)	20	20	20	20	20	20	20	20	20	20
SM41 + 547	15	20	25	25	20	25	20	30	15	30
SM41 + 561	15	20	25	20	20	25	20	30	15	35
SM41 + 575	15	25	30	25	20	25	15	35	10	40
SM41 + 589	15	25	25	20	15	20	20	35	10	20
SM41 + 603	20	30	20	15	10	15	10	30	15	15
SM41 + 620	25	25	15	15	5	15	10	25	20	15
SM41 + 634	25	20	15	10	5	20	15	25	20	70
SM41 + 651	15	20	15	25	5	15	15	15	15	70
SM41 + 665	10	25	20	25	15	15	10	15	20	65
SM41 + 679	10	20	15	20	15	20	15	20	35	55
SM41 + 693	10	25	10	10	20	20	5	15	45	55
SM41 + 707	15	15	10	10	25	25	5	15	65	40
SM41 + 721	15	15	15	10	20	25	10	15	40	35
SM41 + 735	15	10	15	15	20	15	10	15	20	25
SM41 + 740 (BH3)	15	15	15	15	15	15	15	15	15	15

RMR, RSR and Q-value parameters were carefully examined. For each parameter, data were obtained from positions in previous tunnels that showed variations at approximately the same distances as the distances between observation positions in the Hamru tunnel. Depending on the status of the RMR, RSR and Q-value parameters in the Hamru tunnel route, different amounts of training data were obtained for the distances between the observed positions.

For example, to reach the initial data between two observations of the tunnel entrance and borehole 1, spaced 373 meters apart, 10 datasets were obtained after studying 27 historical tunnels (it is not necessary to have exactly a distance of 373 meters, in this case 373± 20 meters are considered). In the Hamru tunnel, the status of the RMR parameter in the entrance portal and borehole 1 locations, is 40 and 5, respectively. The 10 input datasets obtained from historical tunnels for the RMR parameter between the two observations are presented in Tables 2-7, respectively.

The prediction method in this paper is based on the holdout method in which the data obtained from previous tunnels are used as training data, and the data between the observed positions in the Hamru tunnel route are used as a test. The training procedure is a way that training is done separately for the distances of observation situations with the help of the data obtained in Tables 2-7. That is, first, with the help of Table 2, which is the training data related to the distance between the Hamru tunnel entrance and borehole 1, training is done and the status of each parameter in the distance between these two observations in the Hamru tunnel path is determined. The same procedure is repeated for the distances between other observation positions in the Hamru tunnel path until the status of all the

Table 5 Input data to train the GPR model for predict the RMR parameter state between borehole 3 and borehole 4

Tunnel chainage (m)	RMR									
SM41 + 740 (BH3)	15	15	15	15	15	15	15	15	15	15
SM41 + 746	15	25	10	30	20	15	20	5	15	25
SM41 + 762	25	30	20	40	25	20	15	20	20	25
SM41 + 778	35	30	15	50	15	25	25	20	15	30
SM41 + 794	40	25	45	50	30	25	15	10	20	35
SM41 + 810	40	20	50	55	30	35	5	25	15	30
SM41 + 826	55	30	45	65	35	45	10	25	10	40
SM41 + 842	55	30	40	75	30	45	15	20	10	35
SM41 + 858	50	35	40	75	35	40	25	15	5	40
SM41 + 874	55	45	50	65	35	35	20	15	25	35
SM41 + 900	55	35	45	65	30	40	15	20	25	30
SM41 + 916	50	30	45	55	30	35	20	20	15	25
SM41 + 932	45	30	45	50	20	30	20	15	15	10
SM41 + 948	35	30	35	45	25	30	25	25	20	15
SM41 + 964	35	25	30	30	25	25	20	15	20	25
SM41 + 973 (BH4)	25	25	25	25	25	25	25	25	25	25

Table 6 Input data to train the GPR model for predict the RMR parameter state between borehole 4 and borehole 5

Tunnel chainage (m)	RMR									
SM41 + 973 (BH4)	25	25	25	25	25	25	25	25	25	25
SM41 + 986	20	25	15	25	20	25	10	30	20	25
SM41 + 999	20	35	20	15	20	30	5	25	20	15
SM42 + 012	15	40	25	10	25	35	5	25	20	5
SM42 + 025	20	40	20	15	25	35	5	20	25	0
SM42 + 038	20	35	20	10	20	30	15	30	10	5
SM42 + 051	25	35	10	25	20	35	20	30	15	5
SM42 + 064	30	35	10	10	20	30	15	15	15	5
SM42 + 077	25	25	5	5	10	25	20	0	5	10
SM42 + 090	20	15	0	10	10	20	20	0	0	10
SM42 + 103	15	15	5	10	5	15	10	5	5	0
SM42 + 116	5	5	5	0	5	10	5	5	5	5
SM42 + 129	0	5	0	0	0	5	0	0	0	0
SM42 + 133 (BH5)	0	0	0	0	0	0	0	0	0	0

Table 7 Input data to train the GPR model for predict the RMR parameter state between borehole 5 and exit

Tunnel chainage (m)	RMR									
SM42 + 133 (BH5)	0	0	0	0	0	0	0	0	0	0
SM42 + 141	0	5	0	0	10	0	0	5	0	5
SM42 + 149	5	15	5	10	15	5	5	25	10	20
SM42 + 157	15	40	15	10	15	5	10	25	35	20
SM42 + 165	15	40	20	5	25	0	5	15	30	15
SM42 + 173	15	55	35	0	30	5	5	15	30	10
SM42 + 181	45	55	30	5	30	5	5	10	35	5
SM42 + 189	50	75	30	5	30	5	5	10	35	5
SM42 + 197	55	75	25	15	25	35	0	15	30	10
SM42 + 205	55	75	25	15	30	35	20	25	30	10
SM42 + 213	50	70	20	10	30	30	20	25	35	30
SM42 + 221	30	15	15	10	25	30	25	20	35	15
SM42 + 229	20	15	15	10	20	25	25	10	30	20
SM42 + 232 (Exit)	20	20	20	20	20	20	20	20	20	20

Table 8 GPR predictions for RMR parameter along the tunnel route.

$x_i(m)$	RMR	$x_i(m)$	RMR	$x_i(m)$	RMR	$x_i(m)$	RMR
25	38.47	508	30.71	825	17.89	1139	21.03
50	36.98	525	27.22	836	15.19	1152	20.03
75	34.00	542	27.73	852	15.19	1165	22.54
100	31.02	559	27.24	868	18.40	1178	19.05
125	29.03	576	24.75	884	24.40	1191	13.56
150	26.54	593	20.26	900	26.40	1204	11.07
175	26.06	610	21.77	916	29.91	1213	09.08
200	23.57	623	21.28	932	30.92	1220	05.59
225	22.09	637	15.14	948	36.42	1225	01.60
250	20.10	651	11.80	964	35.93	1229	00.30
275	17.62	665	15.31	980	36.43	1237	00.30
300	17.13	679	23.80	996	38.44	1245	03.10
325	14.14	693	21.81	1012	36.45	1253	12.10
350	09.16	707	26.82	1044	32.96	1261	19.59
373	05.09	721	31.82	1053	28.47	1269	17.60
390	05.09	735	35.82	1060	28.98	1277	20.60
407	09.18	749	35.83	1066	25.49	1285	23.10
424	19.68	763	33.84	1079	25.25	1293	25.11
441	15.69	777	36.34	1092	25.25	1299	29.11
458	22.19	791	30.85	1105	22.01	1307	32.61
474	32.19	805	28.36	1113	21.01		
491	33.20	815	20.88	1126	21.02		

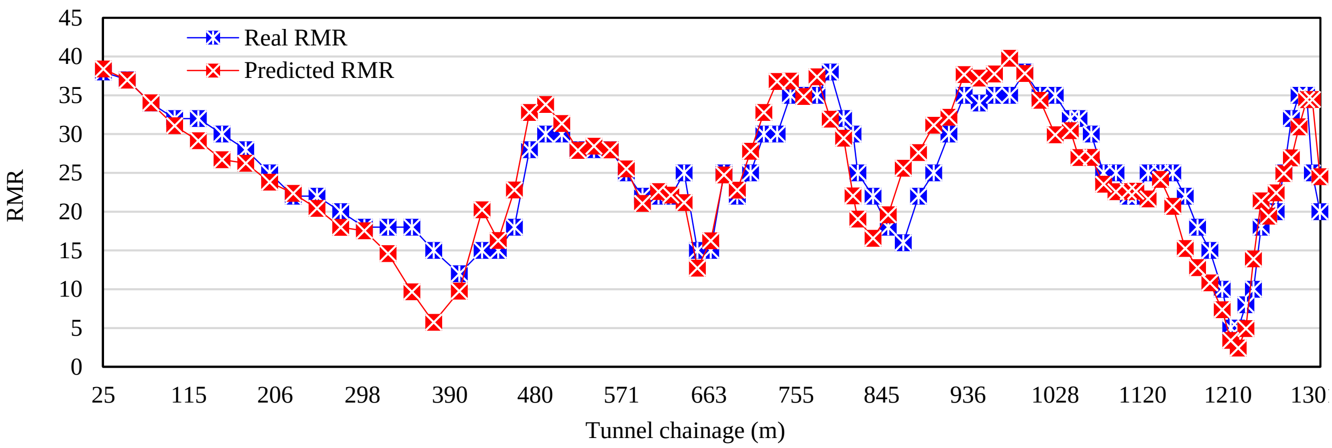

Fig. 7 Comparison of the field-observed results of the RMR parameter with the GPR result

considered parameters in the Hamru tunnel path is predicted.

4.3 Results analysis and comparison

After training the GPR model, several points along the Hamru tunnel route were given to the model. For each point, the predictions for the RMR parameter was obtained according to Table 8. This projection in Fig. 7 is shown for the parameters of RMR, in the graph of the GPR. Since the tunnel project has already been constructed, and the field-observed data of the RMR parameter is accurately available, so to validate the GPR model for use in future tunneling projects, the predicted values of RMR were compared with the field-observed RMR according to Fig. 7. Comparing the field-observed (actual mode) state of RMR with the predicted state, we can see the high accuracy of the GPR model in predicting geological and geotechnical parameters along the tunnel route using the technique presented in this paper. Therefore, this technique can be very important in the early stages of planning a tunnel construction project and reduce the uncertainties associated with the geology conditions along the tunnel route to an acceptable level.

The regression result's predictive performance and the R-squared value are given in Fig. 8 for the corresponding

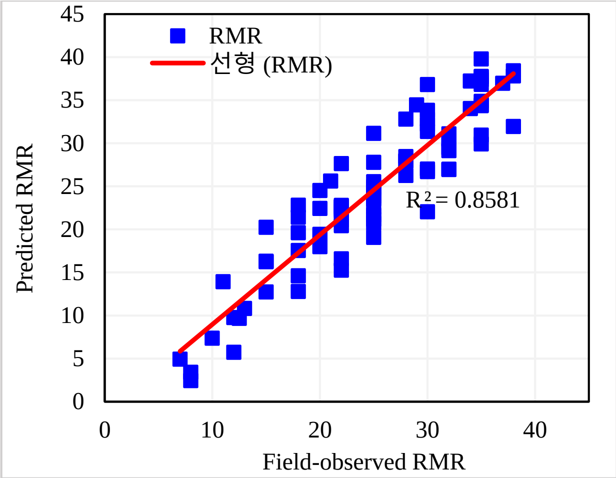

Fig. 8 Predictive performance of GPR on RMR parameter

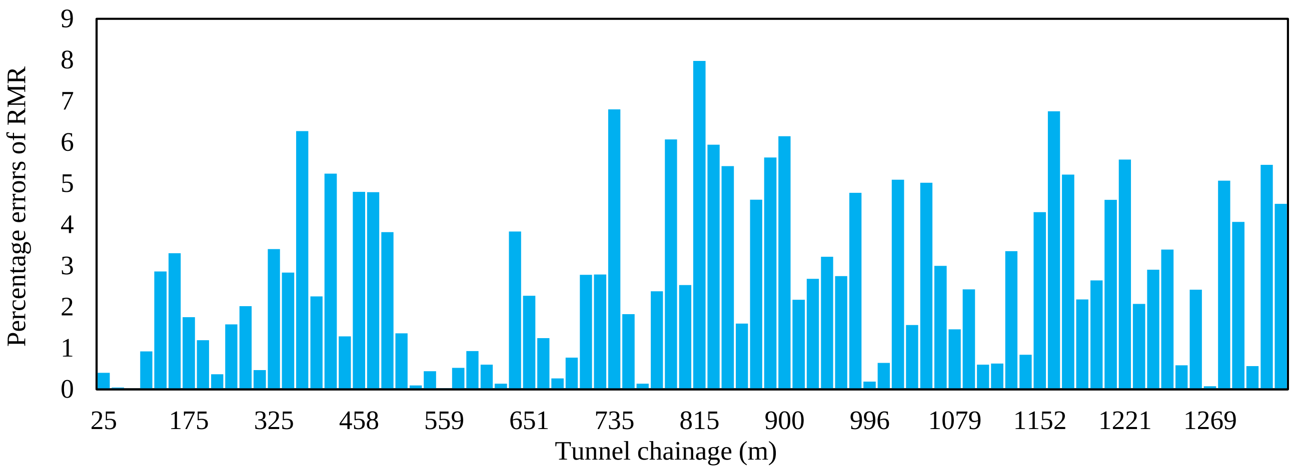

Fig. 9 Predictive percentage errors of GPR

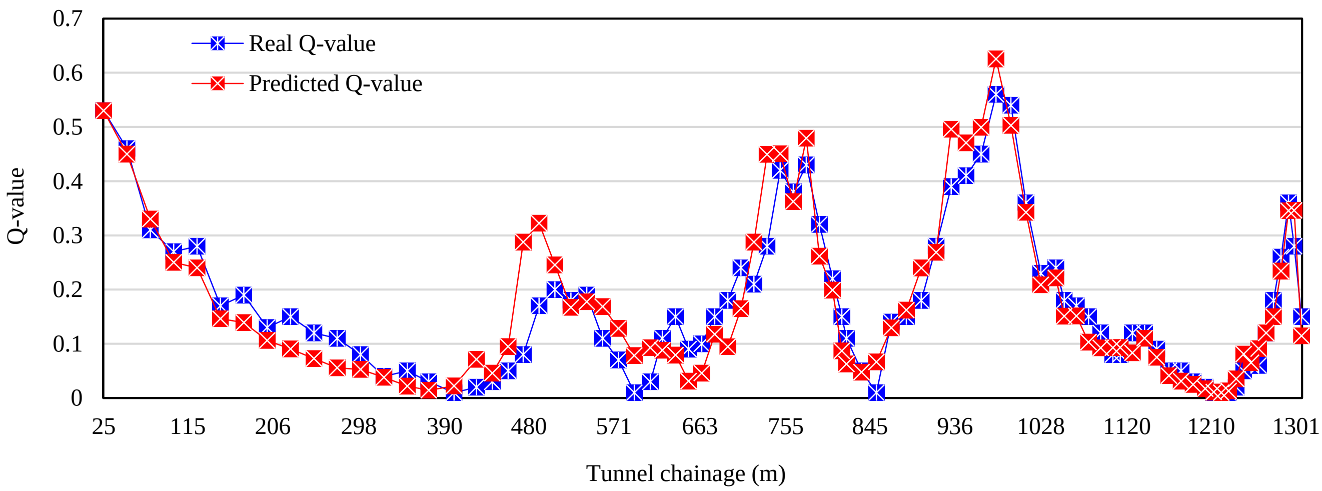

Fig. 10 Comparison of the actual state of the Q-value parameter with the GPR prediction

predicted value by the GPR versus the field-observed RMR parameter in tunnel. Again, the *R-squared* value indicates that the GPR technique performs very well in predicting the geology conditions along the tunnel's route. The predictive percentage errors in Fig. 9 have shown this more obvious. The GPR produces the small average predictive percentage error values, which are no more than 2.71.

Also, predictions are made on the tunnel route similar to the first parameter for the Q-value and RSR parameters. The high accuracy in the predicted results can be seen (Figs.

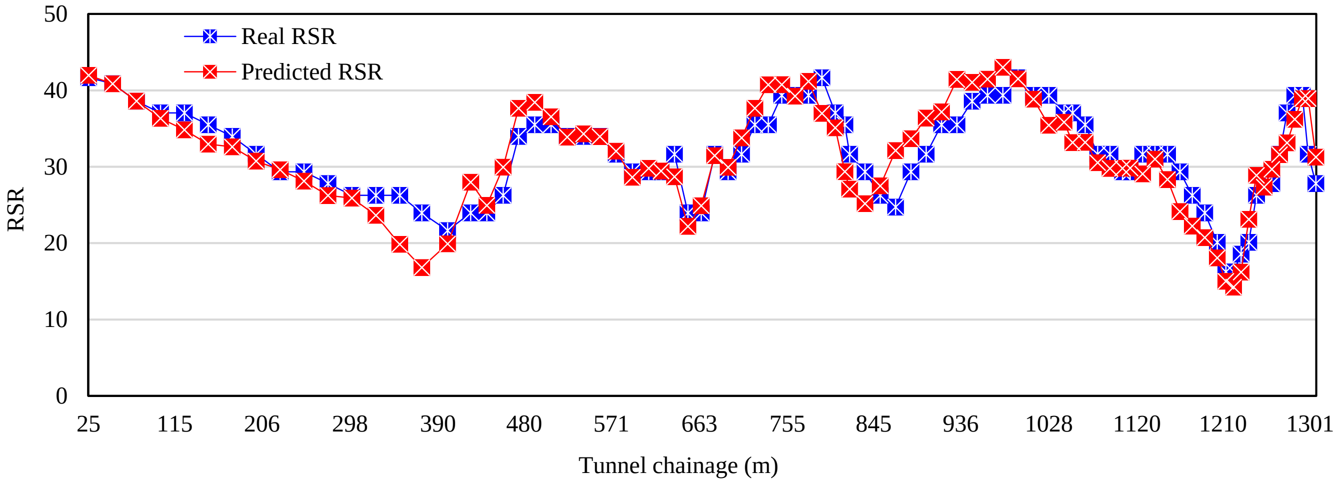

Fig. 11 Comparing the actual mode of the RSR parameter with the GPR prediction

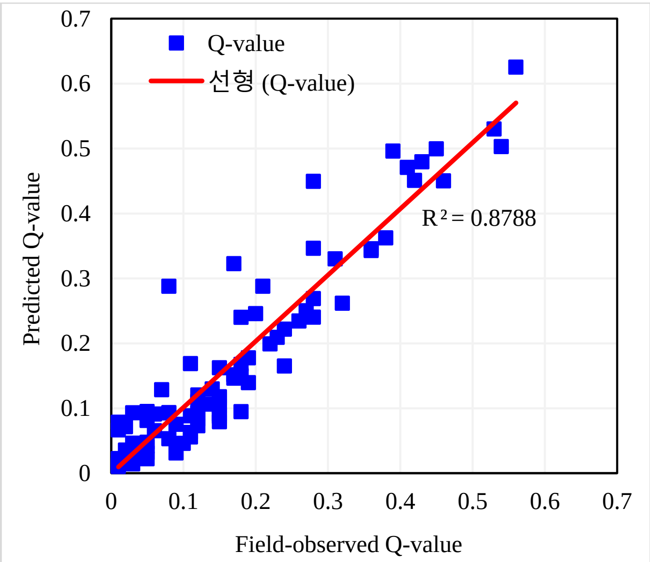

Fig. 12 Predictive performance of Q-value parameter

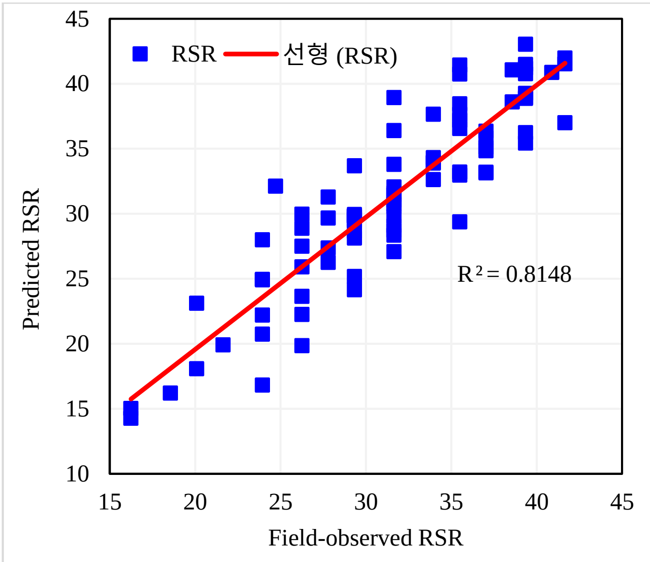

Fig. 13 Predictive performance RSR parameter

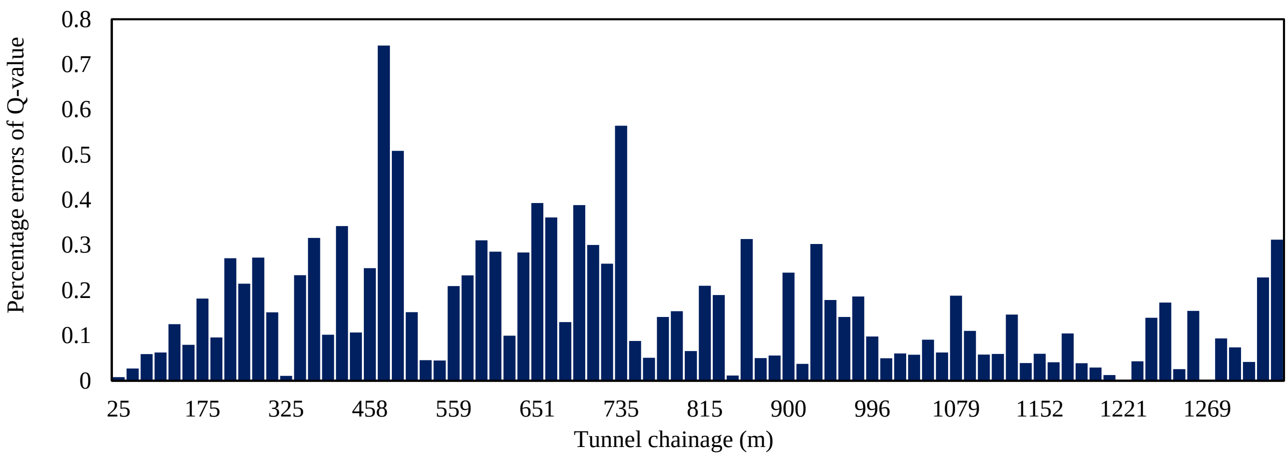

Fig. 14 Predictive percentage errors of Q-value

10 and 11).

The predictive performance and the *R-squared* values of the Q-value and RSR regression results are given in Figs. 12 and 13, respectively.

The predictive percentage errors of the Q-value and RSR are given in Figs. 14 and 15, which that are no more than 0.038 and 2.27, respectively.

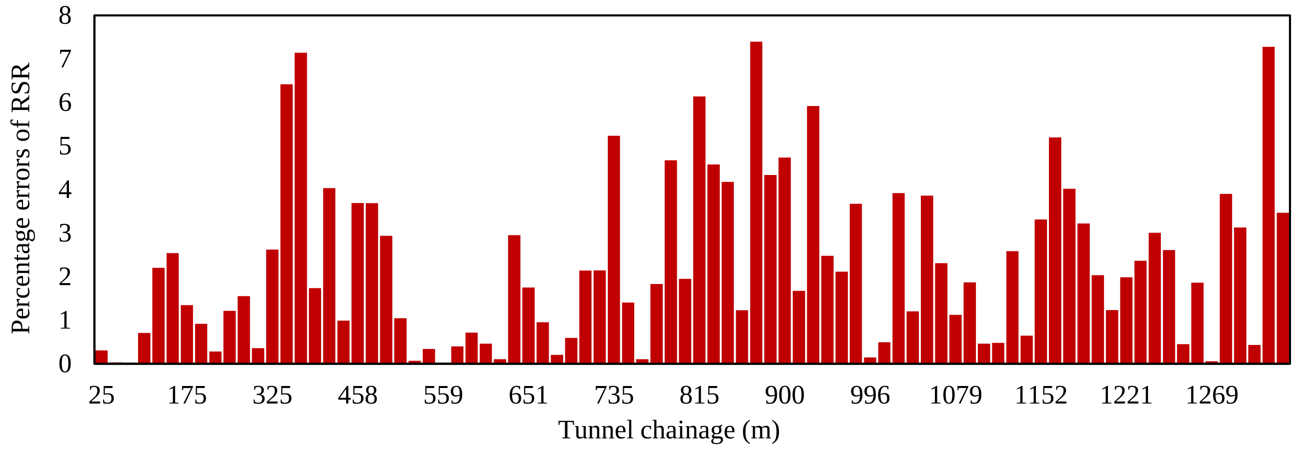

Fig. 15 Predictive percentage errors of RSR

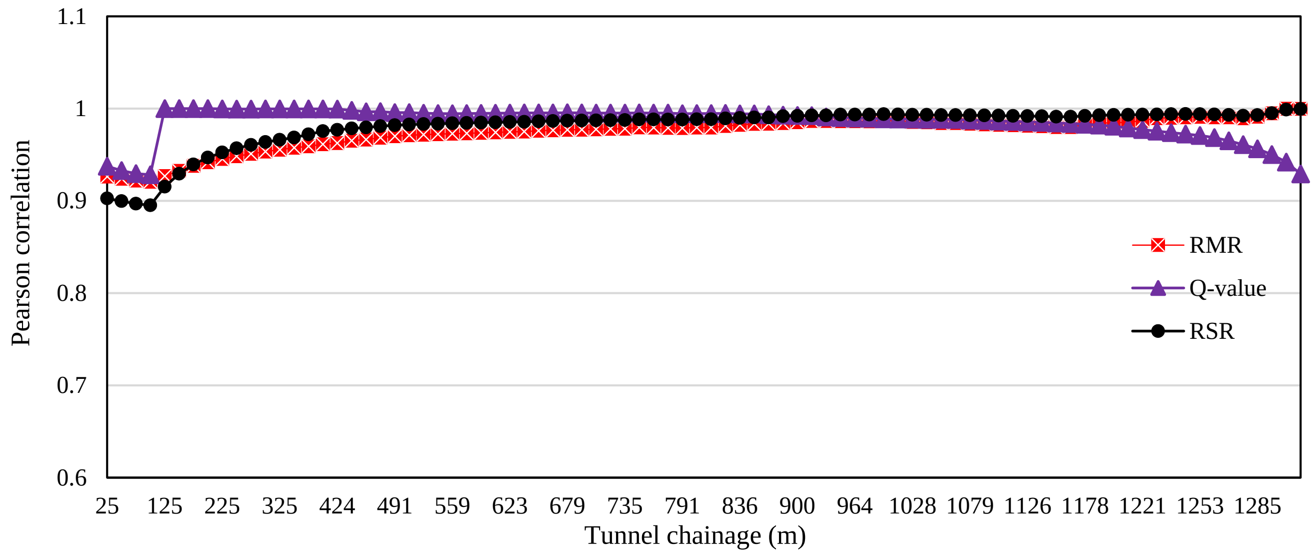

Fig. 16 Pearson correlation between the predicted and actual values of RMR, Q-value and RSR using the GPR model

Regression has a close correlation with the correlation coefficient, meaning that if there is a correlation between the variables studied, the regression can be used to test the research hypotheses. The stronger correlation between the variables is a sign of more accurate predictions. The regression difference with the correlation coefficient is that regression is followed by prediction, while the correlation coefficient only compares the degree of dependence between the two variables. The correlation coefficient between -1 and +1 is volatile. In other words, if the two societies have a complete and direct correlation, their correlation coefficient is estimated as +1 and if they are completely inverse correlations, their correlation coefficient is estimated as -1. As two societies or two variables lack correlation, their correlation coefficient will be zero.

According to Fig. 16, the correlation between the predicted and actual values of RMR, Q-value and RSR is shown. As can be seen, the predicted results have a correlation coefficient close to +1 relative to the actual one. Therefore, it can be said that with the help of GPR model, accurate results can be obtained in predicting the geological and geotechnical parameters along the tunnel route.

Table 9 A summary of the results obtained by GPR

Parameter	Mean absolute error (MAE)	R^2
RMR	2.710	0.8581
RSR	2.270	0.8148
Q-value	0.038	0.8788

Table 9 summarizes the predicted results by the GPR. So, according to the predicted results and comparing them with the field-observed state, it can be said that the GPR is an important technique that can predict the status of the geology conditions parameters along the tunnel route in high accuracy and can reduce the uncertainties to an acceptable level.

6. Discussion

Undoubtedly, reducing the uncertainties about the geology conditions in tunneling projects is one of the most serious issues. The most important of these uncertainties are

Table 10 Comparison of the performance of four methods

Parameter	Method	RMSE	Score	MAE	Score	R^2	Score	Rank
RMR	GPR	0.42	4	2.710	4	0.8581	4	36
RSR		0.64	4	2.270	4	0.8148	4	
Q-value		0.015	4	0.038	4	0.8788	4	
RMR	SVR	0.86	1	3.18	1	0.7837	1	9
RSR		1.31	1	3.72	1	0.7512	1	
Q-value		0.042	1	0.081	1	0.8493	1	
RMR	OLS	0.57	2	2.95	2	0.8219	2	19
RSR		0.92	2	2.55	2	0.7832	2	
Q-value		0.033	2	0.063	2	0.8640	3	
RMR	ANN	0.45	3	2.80	3	0.8311	3	26
RSR		0.58	3	2.39	3	0.8021	3	
Q-value		0.027	3	0.045	3	0.8637	2	

Table 11 Comparison of the GPR performance of this research and previous researches.

Reference	Method	Output	RMSE	R^2
Mahmoodzadeh *et al*. (2020a)	GPR	Maximum settlement caused by urban tunneling [mm]	8.08	0.96
Mahmoodzadeh *et al*. (2020b)	GPR	RMR	---	0.9501
		Tunnel construction time [days]	---	0.9130
		Tunnel construction cost [USD]	---	0.9198
Mahmoodzadeh *et al.* (2021b)	GPR	Uniaxial compressive strength [MPa]	0.5216	0.9955
Mahmoodzadeh *et al*. (2021c)	GPR	Rock quality designation [%]	1.80	0.9433
Mahmoodzadeh *et al*. (2021d)	GPR	RMR	0.8144	0.9937
		Tunnel construction time [days]	0.009	0.9911
		Tunnel construction cost [USD]	13.3496	0.9861
Mahmoodzadeh *et al*. (2021e)	GPR	Disc cutter life of TBM [m^3/cutter]	107.3554	0.8866
Mahmoodzadeh *et al*. (2021f)	GPR	Water inflow into tunnels [m^3/h]	5.77	0.9714
Mahmoodzadeh *et al.* (2021g)	GPR	Sidewall displacement of underground caverns [mm]	0.0066	0.9947
Mahmoodzadeh *et al*. (2021h)	GPR	Rock quality designation [%]	0.1540	0.987
This study	GPR	RMR	0.42	0.8581
		RSR	0.64	0.8148
		Q value	0.015	0.8788

the geomechanical and geotechnical conditions along the tunnel route. The uncertainty of these conditions, in turn, increases the uncertainty about the time and costs of the tunnel construction. Therefore, reducing the uncertainty about the geological and geomechanical conditions along the tunnel route is necessary. Usually, before constructing the tunnels, we are faced with a lack of initial data on geology conditions. Under such circumstances, the appropriate maintenance system and the proper excavation method cannot be considered, also, the construction time and costs of the tunnel cannot be estimated carefully. In order to reduce these uncertainties, the GPR technique was used to predict the geology conditions along the tunnel route. To illustrate the correct functioning of the GPR, it was used in a case study of Hamru road tunnel.

In order to predict the geology conditions along the Hamru tunnel route, the RMR, RSR and Q-value parameters were considered. First of all, before the construction of the tunnel, the data on the parameters were available only in entrance and exit portals and borehole locations. Initial input data for model training were obtained for the distance between each observation position separately from other historical tunnels where data were available after construction. Then the status of the RMR, RSR and Q-value parameters was predicted along the tunnel route.

Now we want to compare the capabilities of the other three methods, including support vector regression (SVR), artificial neural networks (ANN), and orthogonal least square (OLS), with the proposed GPR method. For this purpose, all the prediction steps described for the GPR method were applied to each of these methods. Finally, the evaluation statistical indices results of root mean square error (RMSE), MAE, and R^2 for these methods were obtained as in Table 10. The prediction performance of the four models for the RMR parameter from high to low is GPR (RMSE: 0.42; MAE: 2.71; R^2: 0.8581), ANN (RMSE: 0.45; MAE: 2.80; R^2: 0.8511), OLS (RMSE: 0.57; MAE: 2.95; R^2: 0.8219), and SVR (RMSE: 0.86; MAE: 3.18; R^2: 0.7837).

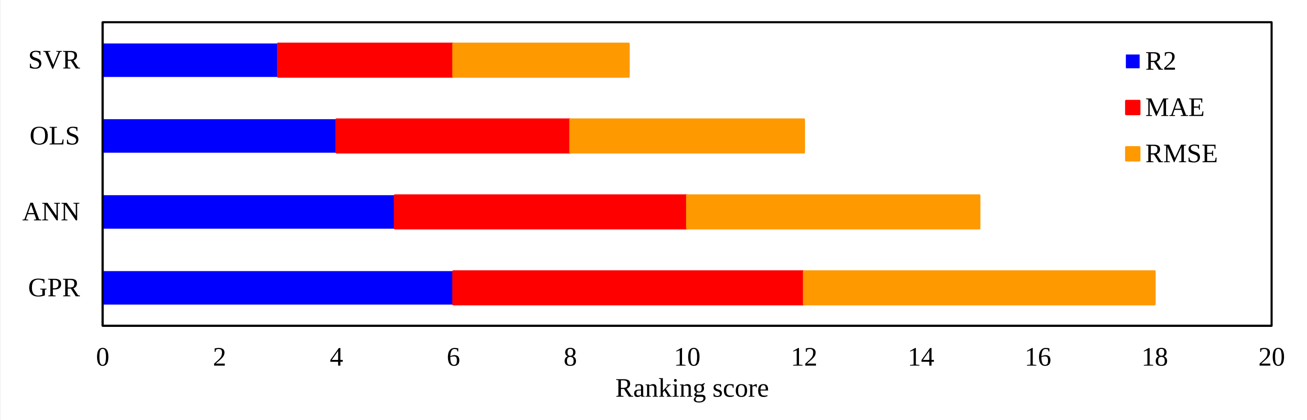

Fig. 17 Intuitive display of comprehensive ranking of four models

The prediction performance of the four models for the RMR parameter from high to low is GPR (RMSE: 0.64; MAE: 2.27; R^2: 0.8148), ANN (RMSE: 0.58; MAE: 2.39; R^2: 0.8021), OLS (RMSE: 0.92; MAE: 2.55; R^2: 0.7832), and SVR (RMSE: 1.31; MAE: 3.72; R^2: 0.7512).

The prediction performance of the four models for the RMR parameter from high to low is GPR (RMSE: 0.015; MAE: 0.038; R^2: 0.8788), ANN (RMSE: 0.027; MAE: 0.045; R^2: 0.8637), OLS (RMSE: 0.033; MAE: 0.063; R^2: 0.8640), and SVR (RMSE: 0.042; MAE: 0.081; R^2: 0.8493).

To more analyze the predictive performance of the applied models, Fig. 17 shows the results of overall ranking graphically. Lastly, the comprehensive ranking indicates that the GPR model is the most robust and accurate model compared to the other models.

In Table 11, a comparison between the results of the proposed GPR model of this research and the GPR results of the previous researches done on the other geomechanical problems is provided. Clearly, in all the researches, the GPR model has presented robust and acceptable results.

7. Conclusions

In this work, the effectiveness of the GPR method in estimating geological or geotechnical parameters of road tunnel projects was explored. The GPR model was trained with data of old tunnel projects. To verify its feasibility, the GPR technique was applied to Hamru tunnel on Sanandaj-Marivan highway in Iran to predict the state of three geological/geomechanical parameters of RMR, RSR, and Q-value. Finally, in order to validate the GPR approach, the forecasted results were compared to the field-observed results. From this comparison, it was concluded that, the GPR is presented very good predictions. The R^2 values between the predicted results of the GPR vs. field-observed results for the RMR, RSR and Q-value were obtained equal to 0.8581, 0.8148 and 0.8788, respectively.

The capability of the GPR model was also compared with three methods of SVR, OLS, and ANN. The prediction performance of the four models for the RMR parameter from high to low is GPR (RMSE: 0.42; MAE: 2.71; R^2: 0.8581), ANN (RMSE: 0.45; MAE: 2.80; R^2: 0.8511), OLS (RMSE: 0.57; MAE: 2.95; R^2: 0.8219), and SVR (RMSE: 0.86; MAE: 3.18; R^2: 0.7837).

The prediction performance of the four models for the RMR parameter from high to low is GPR (RMSE: 0.64; MAE: 2.27; R^2: 0.8148), ANN (RMSE: 0.58; MAE: 2.39; R^2: 0.8021), OLS (RMSE: 0.92; MAE: 2.55; R^2: 0.7832), and SVR (RMSE: 1.31; MAE: 3.72; R^2: 0.7512).

The prediction performance of the four models for the RMR parameter from high to low is GPR (RMSE: 0.015; MAE: 0.038; R^2: 0.8788), ANN (RMSE: 0.027; MAE: 0.045; R^2: 0.8637), OLS (RMSE: 0.033; MAE: 0.063; R^2: 0.8640), and SVR (RMSE: 0.042; MAE: 0.081; R^2: 0.8493).

Lastly, considering the data used in this study, compared to the other models, the statistical evaluation indices indicated that the GPR model is the most robust and accurate model to predict geomechanical parameters of RMR, RSR, and Q-value along road tunnels path.

In future works, the GPR model presented in this work is suggested to predict RMR, RSR, and Q-value in other tunnels by using newer data with various input parameters, the most accurate algorithms be identified and the most influential parameters on the considered parameters be specified. Also, given that various geological and geotechnical issues can be very important to predict, it is suggested that the prediction models presented in this work be used to predict them, and their ability to solve these problems be examined.

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