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Estimation of Groundwater Seepage Risks into Tunnel Using Radial Basis Function Networks

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Abstract

In this study, Site Groundwater Rating (SGR) in the Amirkabir tunnel has been estimated using Radial Basis Function Networks (RBFNs). SGR is the first rating method that by considering the parameters like joint frequency, joint aperture, schistosity, crashed zones, karstification, soil permeability coefficient, tunnel location in the water table or piezometric surface, and the amount and intensity of annual raining in the area, classifies the tunnel path from the risk of groundwater seepage point of view. In this article, using an RBFN, an estimation of SGR along the Amirkabir tunnel path was performed. Field data obtained from primary studies in the tunnel was used to train and test the prepared network. For the testing set, modeling results showed that SGR could be predicted with the mean error of 3.57% and 4.76% using radial basis network and exact radial basis network functions, respectively. A High correlation between the SGR of the tunnel path and the network answers, confirmed the prepared RBFN.

Introduction

One of the problems of tunnels is the penetration of groundwater by engineers and workers, which creates significant risks and incidents (Maleki et al., 2022). The presence of groundwater reduces the stability of tunnel walls and roofs and, in some cases, causes severe and sudden flooding, leading to heavy losses and damage. It is impossible to determine all the efficient factors of water flow in a tunnel. Therefore, it seems complicated to accurately predict the rate of leakage. The analytical methods and equations have many applications in the calculation of water penetration rates in tunnels due to their simplification and the use of practical theory (Farhadian et al., 2021). In recent decades, scientists have tried to provide increasingly sophisticated analytical solutions to estimate the groundwater penetration into tunnels. (Agatonovic-Kustrin and Beresford 2000, Farhadian et al., 2016a). Among the most important researches on calculating water seepage into the tunnel, Goodman et al. (1965), Freeze and cherry (1979), Lei (1999), Karlsrud (2001), Lombardi (2002), and EL Tani (1999 & 2003), Perrochet and Dematteis (2007), Park et al. 2008, Gattinoni et al. 2008, Moon and Fernandez (2009), Farhadian and Katibeh (2017) and Maleki (2018) can be mentioned. The evaluation of the tunnel sections due to the risk of groundwater inflow was discussed. The analytical formulas are derived to simplify the geostructural configuration, and the input data are kept as simple as possible. An analytical solution is used to predict the groundwater flow into the tunnel based on simplified assumptions (Farhadian et al., 2016b):

1. 2-D flow and circular tunnel cross-section,
2. Homogenous and isotropic permeability,
3. The tunnel section is located under water table.

Groundwater inflow to the tunnel is one of the perilous conditions in the time of excavating underground tunnels, One of the dangerous conditions when excavating underground tunnels. The problem of groundwater penetration is very difficult to control. This is due to the fact that the prediction of low flows results in high costs and unsafe operating conditions. The high flow encourages contractors to ignore it. There are basically two problems with flow prediction. The first is that no satisfactory solutions have been proposed so far in the literature on the groundwater flow into hard rock tunnels. (Farhadian and Nikvar Hassani, 2019). The second problem is the wide variation of permeability along the tunnel section, sometimes up to six orders of magnitude. It is the responsibility of the tunnel designer to estimate the amount and location of groundwater entering the tunnel (Nikvar Hassani et al., 2016, Palmstrom and Stille, 2007, Sievanen, 2001).

An overall assessment of the groundwater inflow to the tunnel provides the basis for the designation of a drainage system. Groundwater intrusion affects both construction methods and plans. Therefore, minor errors in flow prediction can lead to long delays in comparing progress with excessive and unnecessary costs. In hard rock tunnels, it is the characteristics of the inflow that most of the inflow occurs in a few places; however, some of the inflow comes from many places. Therefore, most of the tunnel is dry. The total flow is obtained by adding the flow velocity along the length of the tunnel. This is a common phenomenon observed in hard rock tunnel projects and is the leading cause of many problems in estimating groundwater flow using standard hydrogeological solutions. (Moon and Fernandez, 2010, Butscher, 2012, Farhadian et al., 2016, Nikvar Hassani et al., 2018).

Several factors influencing the infiltration of groundwater into groundwater have been identified: (Farhadian et al., 2017):

- The size and dimension of an excavation/tunnel/water conductive zone,
- Depth of the underground excavation below the groundwater table,
- Groundwater recharge,
- Hydraulic conductivity of the rock mass/water conductive zone (geological and structural conditions).

Of the above parameters, the most important parameter in calculating the groundwater flowing in the tunnel is the permeability of the bedrock (before and after grouting) (Farhadian and Katibeh, 2015a, Brantberger et al., 1998). In addition, it has been statistically proven that the composition and thickness of the overburden play a decisive role in the water penetration rate. (Cesano, 1999, Cesano et al., 2000). However, Polla and Ritola (1989) found no correlation between excavation volume and water inflow rate. It should be noted, however, that Farhadian et al. (2016) argued that the volume of excavation (tunnel radius) plays an important role in tunneling groundwater into solid rock masses. In addition, an unpublished literature review of groundwater penetration in excavations Tolppanen, (1997) indicates that because the quantitative values cannot be compared directly due to different uses and methods of excavation, the researcher found a very weak correlation between the volume of excavation and inflow rate. In general, the existence of a weak correlation between the above parameters can be explained by the fact that in hard crystalline rock tunnels, most flows usually take place at relatively small spots or lines in the crashed zone and fractured area. (Moon and Jeong, 2011, Farhadian and Katibeh, 2015b, Moeini et al., 2018).

Recently, the use of artificial neural networks has greatly increased the hydrogeological debate, and many researchers predict various topics, such as groundwater levels, flow, and transport (Daliakopoulos et al., 2005; Lallahem et al., 2005; Rajurkara et al., 2004; Morshed and Kaluarachchi, 1998; Imrie et al., 2000; Kompani-Zare and Zhan, 2006; Gunnink et al., 2012). Mathematical attribute models (Li et al., 2013; Wang et al., 2012), analytic hierarchical processes Ren and Xu (2011), and fuzzy extension theory Li et al., (2015) are various probabilistic mathematical techniques which widely used to assess the risk of water inflow to tunnels and coal mines. In general, the evaluation results are at an acceptable level, but subjectivity exists in the weights and scales of the evaluation indicators.

In addition, some computer intelligence techniques, such as artificial neural networks, support vector machines, and Gaussian processes, have been used to analyze landslides Grelle and Guadagno, (2013), deformation of surrounding rocks Feng et al (2004), and surface deposition. Suwansawat and Einstein, (2006); Ovidio et al., (2008), pipe failure rates Tabesh et al., (2009); Shirzad et al., (2014) and other geotechnical issues (Ocak and Seker, 2012). Several related studies have also used artificial neural networks and support vector machines to predict mine leaks, and water flows in tunnels Guo and Ma, (2010); Ren and Xu, (2011). In this study, RBFN has been used to predict SGR for the first time.

Materials and Methods

Site Groundwater Rating

Based on the preliminary studies of the tunnel sites, for the first time, Katibeh and Aalianvari (2009) provided the SGR method for dividing the tunnel path to different rates regarding the risk of groundwater seepage. In this rating system, from groundwater seepage point of view, the tunnel path is divided to 6 No risk, Low risk, Moderate risk, Risky, High risk, and Critical classes by considering parameters like joints frequency and aperture, schistosity, crashed zones, karstification, soil permeability coefficient, tunnel location in the water table or piezometric surface, and annual raining. Based on this method, the total score of the site, SGR, is calculated from the following equation (1) (Katibeh and Aalianvari, 2009):

$$SGR = [(S_1+S_2+S_3+S_4) + S_5]\, S_6 S_7 \quad (1)$$

where,

S_1 is the score of frequency and aperture of joints which is obtained using the following equation (2):

$$S_1 = 25 \times \left(\sum_{i=1}^{n} \frac{\lambda_i g e_i^2}{12\upsilon} a \right) \quad (2)$$

which, λ_i is the joint frequency (1/m), g is the earth's gravity (m sec^{-2}), e_i is the mean hydraulic joint aperture (m), υ is the kinematic viscosity of water (m^2 sec^{-1}), and a is the unit factor (sec m^{-1}) for conversion of S_1 to dimensionless form.

S_2 is the score of schistosity and ranged between 1 and 5 according to the degree of schistosity.

S_3 is the score of the crashed zone and is calculated based on crashed zone width using Table (1).

S_4 is the karstification score and is based on the intensity of karstification ranging from 10 to 100. S_5 is the soil permeability score. S_5 is calculated as follows:

$$S_5 = K \times C \quad (3)$$

where, K is the soil permeability (m/day), and C is the unit factor (day/m) for conversion of S_5 to dimensionless form. S_6 is the score of the water head above the tunnel. S6 is obtained using equation (4):

$$S_6 = \frac{H}{Ln\,(H \times d)} \times d \quad (4)$$

where, H is the water head above the tunnel and d is the unit factor (1/m) for conversion of S_6 to dimensionless form.

S_7 is the annual raining score. S_7 can be obtained by means of equation 5 regarding annual raining.

$$S_7 = \frac{P_y}{5000} \quad (5)$$

where, P_y is annual raining (mm).

Table 1- Equations for computation of S_3 (Katibeh and Aalianvari, 2009)

Type of rock	*Crashed zone width*	*S_3*
Clay base rocks	CZW	2×Log (10CZW×b)
Other rock types	CZW	100×Log (10CZW×b)

In comparison with earthen sites, parameters like crashed zone, joint frequency, and karstification have more significance in earthen sites. By contrast, in earthen sites, permeability coefficient is more important, while in rocky media, this factor is determined by frequency and aperture of joints. Therefore, in rocky site S_5 and in earthen site S_1 to S_4 are assumed to be zero. Moreover, if the tunnel is excavated in unsaturated media, S_6 will be considered as unit. Also, in areas that are unsaturated, annual precipitation is a factor that is important when drilling tunnels. If the tunnel is drilled in a saturated area, it is assumed to be a unit.

After the calculation of SGR coefficients for the intended sections in the tunnel, there must exist a criterion to evaluate the amount and size of this coefficient, based on which groundwater seepage risk into the tunnel (with a qualitative and quantitative view) can be evaluated. Predicting the rate of inflow water into the tunnel can cause the appropriate designing of drainage systems and even choosing the most appropriate excavation method, so the required preparations are performed to prevent possible risks. This was suggested based on the amounts of water inflow in Table (2) (Farhadian et al., 2012).

The larger the SGR coefficient, the more the permeated water amount to the tunnel (at least in a short time) and therefore, drainage tools and methods must be stronger and more expensive. Even sometimes, tunnel excavation methods must be revised so that the possibility of sudden and damaging incidents occurrence is decreased.

Artificial Neural Networks

An artificial neural network (ANN) is a digitized model of the human brain and a computer program that simulates how the human brain processes information. Like humans, ANNs are learned (or trained) by observing and experimenting with relevant examples of training, not programming (Agatonovic-Kustrin and Beresford, 2000). ANNs are computing algorithms that mimic the four essential functions of these biological neurons. These functions take inputs from other neurons or sources, combine them, operate on results, and display the final result (Klerfors, 1998). What makes ANNs interesting is that once the network is set up, it can learn in a self-constructive way that mimics brain functions, such as pattern recognition, classification, and optimization (Haykin, (1994); Fausett, (1994); Klerfors, (1998); Kung, (1993); Tarassenko, (2004).

ANNs were first developed in the 1940s (Lin and Chen, 2004). ANNs paid a lot of attention to various fields of study and, they are used in statistical science, engineering, computer science, artificial intelligence, etc. Much effort has been made to find practical methods for understanding the structure of systems or processes that use ANNs. There is a lot of literature on neural networks, both theoretical and practical, and a wide range of practical applications of the technique (Bishop (1995); Ripley (1996); Sato (1996) and Webb (1999). In the field of ANNs, multilayer perceptrons and RBFNs have emerged as multilayer networks (Broomhead and Lowe, 1988). In particular, the RBFN, a hybrid learning method that combined self-organized learning and supervised learning, has recently attracted attention (Moody and Darken, 1989). RBFN models built with hybrid learning methods have important advantages over multilayer perceptrons: faster convergence and no identification problems.

The Radial Basis Function Networks

RBFNs were first introduced in 1988 (Broomhead and Lowe, 1988). The basic architecture of an RBFN is shown in Fig. (1). An RBFN has three layers, including an input layer, a hidden layer and, an output layer. The input layer is composed of input data. The hidden layer transforms the data from the input space to the hidden space using a non-linear function. The output layer, which is linear, yields the response of the network.

Table 2- Qualitative and quantitative rating of tunnels site regarding water seepage based on SGR coefficient (Katibeh and Alianvari, 2009)

SGR	Tunnel rating	Class	Probable conditions for groundwater inflow into tunnel (L/sec/min)
0 - 100	I	No risk	0 - 0.04
100 - 300	II	Low risk	0.04 - 0.1
300 - 500	III	Moderate risk	0.1 - 0.16
500 – 700	IV	Risky	0.16 - 0.28
700 – 1000	V	High risk	Q> 0.28 Inflow of groundwater and mud from crashed zones is probable
1000<	VI	Critical	Inflow of groundwater and mud is highly probable

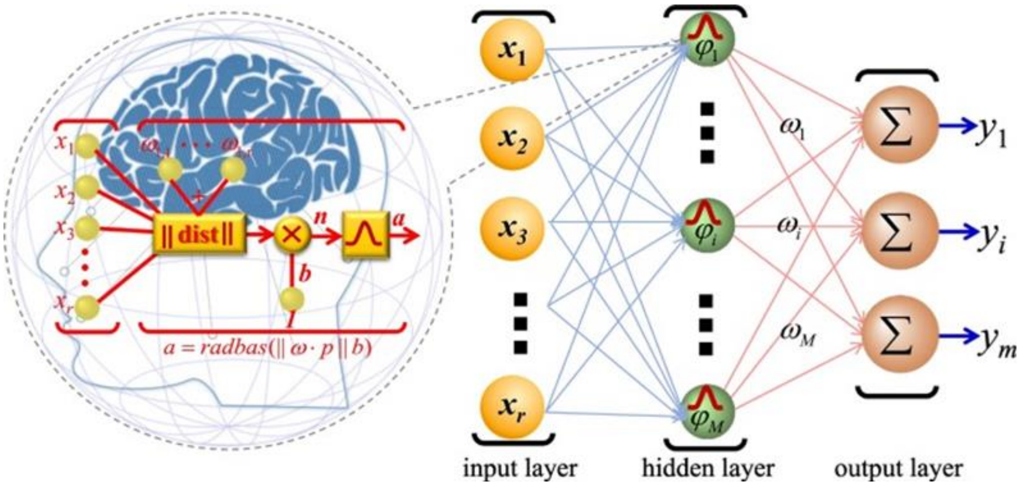

Fig. 1-The structure of RBFN (Deng et al. 2021)

In the structure of RBFNs, the input data X is an I-dimensional vector, which is transmitted to each hidden unit. The activation function of hidden units is symmetric in the input space, and the output of each hidden unit depends only on the radial distance between the input vector X and the center for the hidden unit (Lin and Chen, 2004). Different activation functions have been proposed for the hidden-layer neurons, but normally the selected one is the Gaussian function. In this paper, the Gaussian functions are applied as activation functions of the hidden layer neurons. There are six basic functions, which are recognized as having useful properties for RBFNs (Bishop, 1995; Hardy, 1971; Harpham and Dawson, 2006; Mai-Duy and Tran-Cong, 2003):

1. Multiquadratic :

$$\emptyset(\mathbf{x}) = (x^2+\sigma^2)^{1/2}\ , \quad (6)$$

Which is a case of

$$\emptyset(\mathbf{x}) = (x^2+\sigma^2)^{\alpha}\ 0<\alpha<1, \quad (7)$$

2. Gaussian:

$$\emptyset(\mathbf{x}) = \exp(-\frac{x^2}{2\sigma^2})\ , \quad (8)$$

3. Inverse multiquadratic :

$$\emptyset(\mathbf{x}) = (x^2+\sigma^2)^{-\beta}\ ,\ \beta > 0. \quad (9)$$

4. Thin plate spline:

$$\emptyset(\mathbf{x}) = (\frac{x}{\sigma})^2 \ln(\frac{x}{\sigma}). \quad (10)$$

5. Cubic:

$$\emptyset(\mathbf{x}) = x^3. \quad (11)$$

6. Linear:

$$\emptyset(\mathbf{x}) = x, \quad (12)$$

Where $\emptyset(\mathbf{x})$ is the basis function, σ is the width of the basis function, $x=||x - c_k||$, where x is the training data, c_k is the center of the kth neuron in hidden layer and, $||.||$ is the Euclidean norm.

The RBFN, a class of single hidden layer feedforward networks, is expressed as a linear combination of radically symmetric nonlinear basis functions and takes the following form:

$$u(\mathbf{x}) = \sum_{k=1}^{m} W_k \emptyset_k(\mathbf{x}) + w_0 \quad (13)$$

Where $\emptyset_k(\mathbf{x})$ is the response of the hidden neuron. W_k is the connecting weight between the kth hidden neuron and the output unit, w_0 is the bias term, and $u(\mathbf{x})$ is the output of the network.

In the Learning Phase of the RBFNs, the center and width are decided first. It takes advantage of the well-defined meanings of the RBFN parameters. The centers are highly related to the density of data points. Without using the class label, K-means is the most typical method to divide the samples into different clusters (Kiernan et al., 1996; Mendoza et al., 2009; Moody, 1991; Moody and Darken, 1989). It minimizes the distance between the center and the samples in that cluster. Since the class label is available in a classification problem, the supervised method could be used. Learning Vector Quantization (LVQ) algorithm was proposed by Kohonen for vector quantization and classification tasks (Vogt, 1993; Kohonen, 1990). Different from unsupervised clustering, each cluster center belongs to a class. A center is moved closer to samples in the same class and away from samples belonging to a different class. The decision tree can be used to separate the feature space into different regions. Each region represents the center of the RBFN (Kubat, 1998; Yoo and Sethi, 1995).

The next step is the selection of the width for each center. The width can be determined by computing the variance of all samples in a cluster (Brizzotti and Carvalho, 1999; De Castro et al., 1999). K-nearest-neighbor algorithm is sometimes applied, and the width is calculated as the mean of distances among the centers belonging to other K-nearest hidden neurons (Mak and Cho, 1998; Musavi et al., 1992; West and Dellana, 2009). The next phase is to find the weights after the centers and widths are decided. They can be easily found by linear optimization using any linear least-squares methods. Gradient Descent and Singular Value Decomposition (SVD) are two popular methods (Kiernan et al., 1996; Bruzzone and Prieto, 1999; Mak and Cho, 1998).

Case Study: Amirkabir Tunnel

Amirkabir tunnel, located northwest of Tehran, Iran, is designed and being operated to transfer water from the Amirkabir dam to Tehran. One of the difficulties in this project is groundwater inflow into the tunnel while doing the excavation operations. In this study, SGR for this tunnel was predicted using RBF networks.

Geology of the Area

In the performed geological studies, the tunnel was divided into 14 different geological units that generally encompass various sedimentary-volcanic sets from the Karaj formation. Its petrology generally includes an alteration of tuff, sandstone, fine-grained conglomerates, and siltstone, lava and, agglomerate parts. In this study, we deal with investigating the SGR from kilometers 3.1 to 14.1 of the tunnel. As shown in Fig. (2), it is divided into 9 geological engineering sections, Gta2 (sandstone and tuff layers), Gta3 (sandstone layers, tuff, and micro conglomerate), Gta4-1 (sandstone, tuff), Gta4-2 (tuff, in sandstone sections and micro conglomerate), Sts1 (tuff, siltstone, layers of sandstone and micro conglomerate), Sts2-1 (tuff, limestone), Sts2-2 (tuff, limestone, shale and siltstone), Tsh-1 (Sandstone, Shale, Siltstone), and Cz (tuff, sandstone, and micro conglomerate) (SCE Company, 2006) (Fig. 2).

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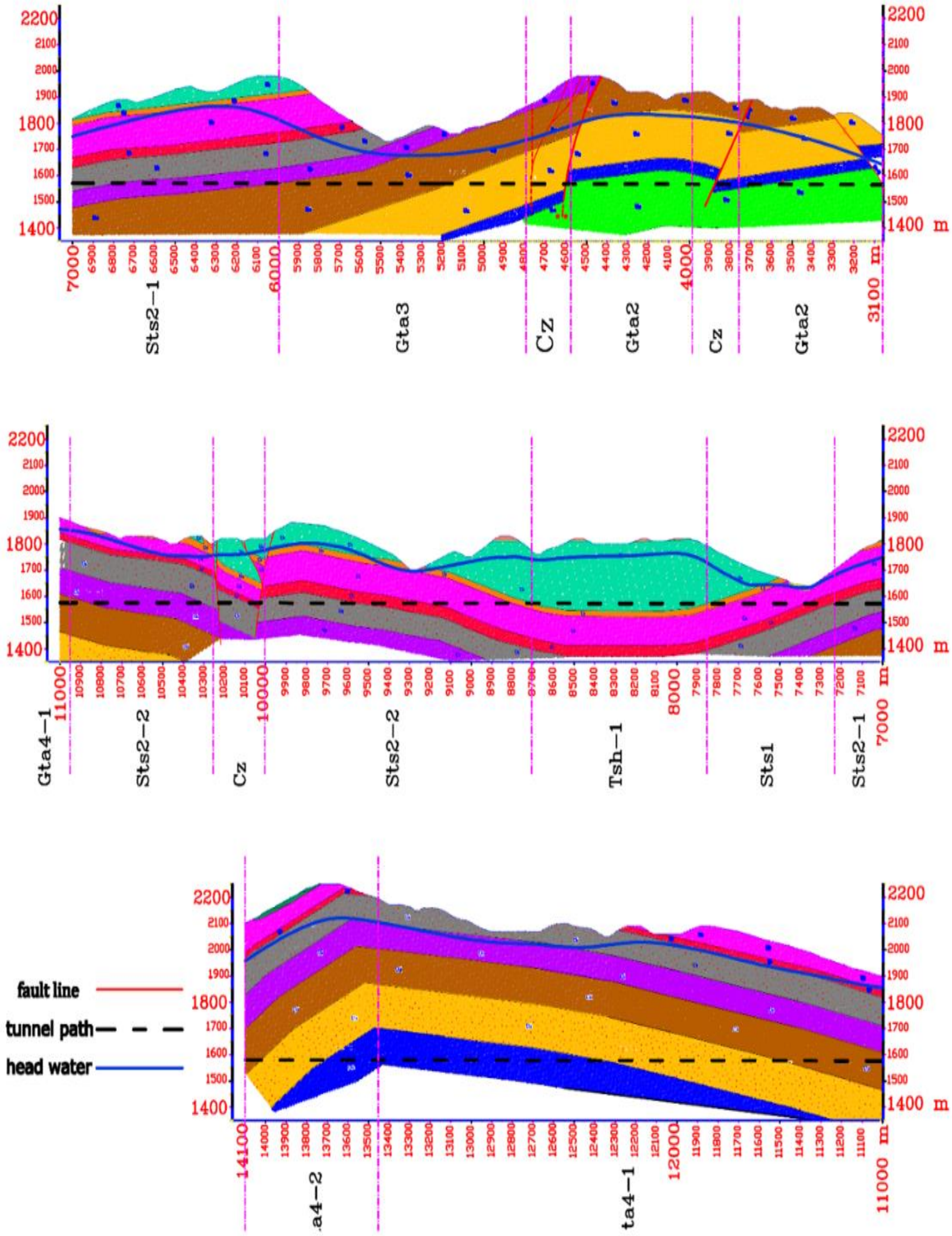

Fig. 2- Geological sections of Amirkabir tunnel (km 3.1 to 14.1) (SCE Company, 2006).

Rating of Amirkabir Tunnel Site (in terms of groundwater seepage hazards based on SGR coefficient)

Field data obtained from the Amirkabir tunnel showed two sets of joints in the rock mass. Considering parameters like joint aperture, tunnel's excavation depth, the width of crashed zones, and height of groundwater table above the tunnel axis, SGR coefficients are calculated in 110 sections of the tunnel path (each 100 meters), the summary of which is shown in Table 3 and Fig. (3). As obtained from the results, SGR method divides the tunnel path to 5 various rates regarding groundwater seepage hazard. Among 110 excavated sections in the tunnel path, 70 sections are located in No risk, 20 sections in Low risk, 3 sections in Moderate risk, 11 sections in risky, and 6 sections in critical class.

Table 3- Classification of 110 excavated sections in Amirkabir tunnel path from kilometers 3.1 to 14.1 based on groundwater seepage hazard by SGR method.

water inflow risk	Number of section	length (m)	%
No risk	70	6920	63
Low risk	20	2110	19
Moderate risk	3	310	3
Risky	11	1140	10
High risk	0	0	0
Critical	6	520	5
summation	110	11000	100

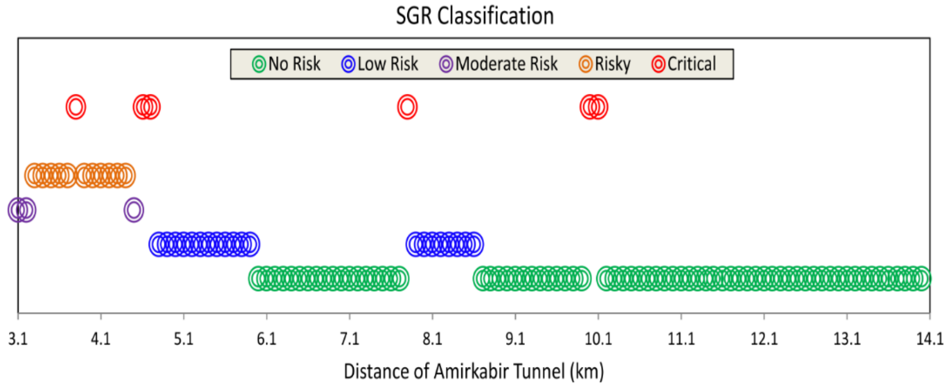

Fig. 3- Classification of 110 excavated sections in Amirkabir tunnel path from kilometers 3.1 to 14.1 based on groundwater seepage hazard by SGR method

The proposed RBF model

In this study, using MATLAB software, an RBFN was designed to predict SGR. Because rock type of the Amirkabir tunnel site, parameters like joint aperture, joint frequency and karstification are concerned. S_5, permeability coefficient parameter was considered zero because this parameter is hidden in rock media, joints frequency, and their aperture, and other factors. The amount and intensity of annual raining in the area is concerned when the tunnel is excavated in the unsaturated zone, so because the Amirkabir tunnel is located in the saturated zone from kilometer 3.1 to 14.1, the score of this factor was considered 1, automatically. On the other hand, due to the lack of schistosity and karstification outcrop in the tunnel path, the coefficient of these two parameters in all the sections was considered zero. Consequently, joint frequency, joint aperture, JRC, JCS of each set of joints, water head, overburden, and the score of crashed zones (S_3) were selected as the network's input parameters, and various SGR classes were considered as output. The data used for training and testing the prepared network was acquired from the primary studies in the Amirkabir tunnel. The optimum network was constructed by testing several models and repeating them. Each ANN was trained with 3/4 of the data set, and remaining was used to evaluate their accuracy and trend stability. The values of each class and the class frequency for SGR classification in all data and training data are shown in Fig. (4). A preprocessing of input and output data was performed, and they were normalized between [-1, 1] thereafter. In order to normalize the data, the following formula was used:

$$x = 2\frac{x - \min x}{\max x - \min x} - 1 \quad (14)$$

It is clear that after finishing the simulation, the converse of the above functions were exerted. The learning rate of the network was measured by target functions during the learning process. At last, the network with the least error and highest regression coefficient was selected. The network error was calculated through the following equation:

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Network error for training data (testing) = {number of training data (testing) which are not located in their own class/ total number of used data for training (testing)}.

Due to random selection of the training and testing data and also network weights, the results were different. All networks were operated 10 times, and the average was considered as the final result.

Results and Discussions

After the determination of network structure, SGR was predicted.

Gaussian Spread Determination

One of the most important issues in the design of RBFNs is Gaussian spread determination. MATLAB software uses newrb and newrbe functions for constructing an RBFN. This process was performed by newrb and newrbe functions. To determine optimal Gaussian spread, several networks with variable spread values from 0 to 1 and 0.02 spacing were constructed. Fig. (5) and (6) show the percentage mean value of network error after 10 runs related to the Gaussian spread values of the newrb and newrbe functions.

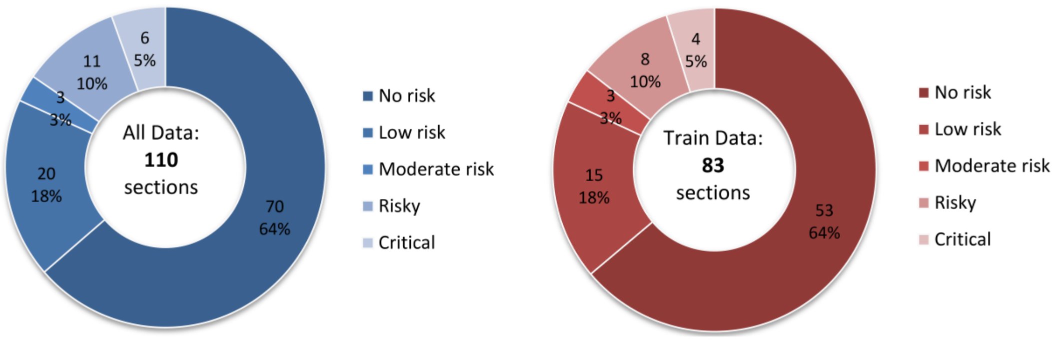

Fig.4- Analysis of each class and the class frequency for SGR classification in all data and training data

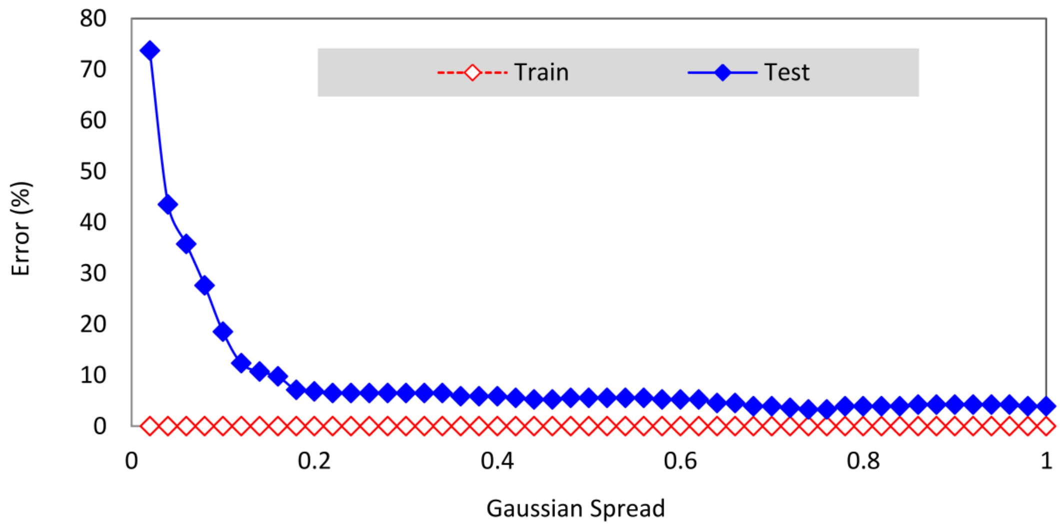

Fig. 5- The percentage of the mean value of network error related to the amounts of Gaussian spread (newrb function)

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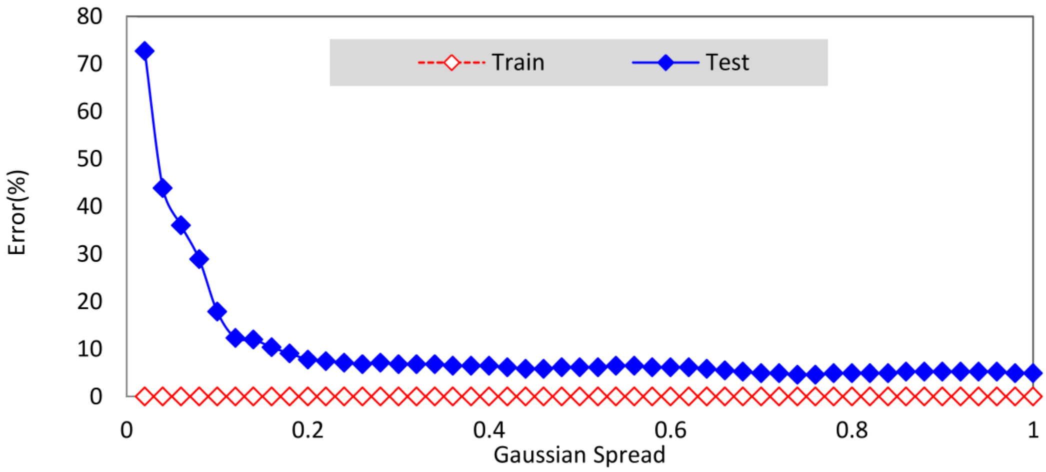

Fig. 6- The percentage of the mean value of network error related to the amounts of Gaussian spread (newrbe function)

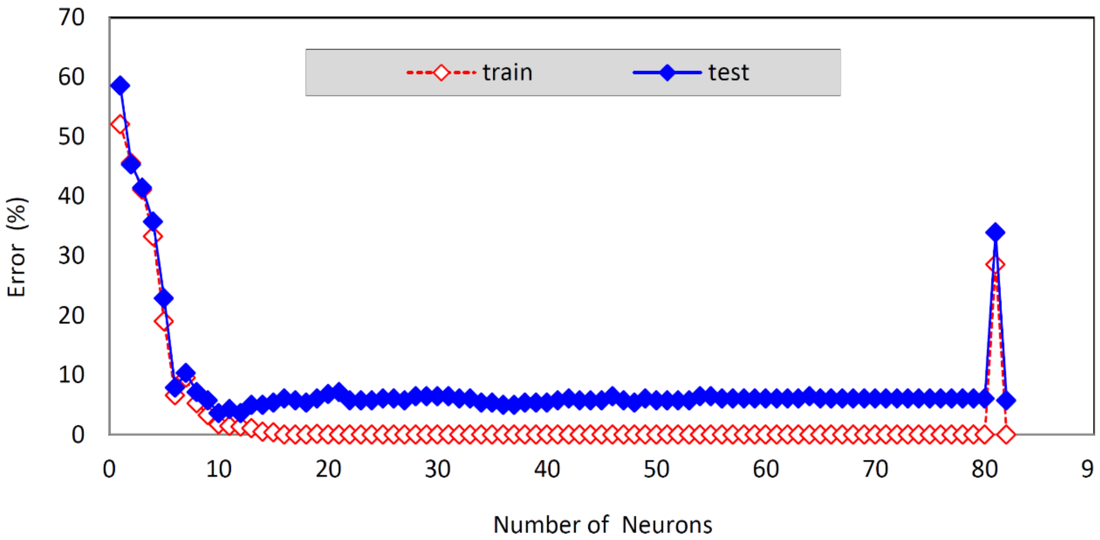

Fig. 7- The percentage of the mean value of network error related to the neurons' number of the hidden layer

As observed in Fig. 5 and Fig. 6, with a Gaussian spread of 0.74, the least error occurred for structured networks by newrb and newrbe functions.

Influence of Neurons' Number of the Hidden Layer in Network Error:

As mentioned, the application of the newrb functions is a method for constructing RBF networks. Adding neurons into the RBF network consecutively, this process continued until the error was less than the goal value or reached to maximum determined neurons' number (total numbers of training data). In contrast, the neurons' number of newrbe function was constant and equal to the total number of training data. In this study, the influence of neurons' number of the hidden layer on the network`s error was investigated by newrb function. Fig. (7) shows the percentage of the mean value of network error after 10 runs related to the neuron's number of network hidden layer.

As observed in Fig. (7), with a network including 12 neurons in the hidden layer, the least error occurred for training and testing sets.

Optimal Network

After performing the above stages, the networks with the Gaussian spread value of 0.74 were constructed and by which SGR was modeled. Considering the selection of random training and testing data and thereupon the weights, network error values in every run were different. Table 4 contains data about the percentage of minimum, maximum, and mean network error values after 10 runs.

The performance of the trained network was investigated by Regression analysis. To do so, network output and target vector were given to the postreg function. As a result, this function gave three parameters, two of which were m and b calculated from slope and intercepts of plot the network output vs. target vector. The third variable returned by postreg was the correlation coefficient between outputs and targets. The higher correlation coefficient the more compatible of predicted data and target vector and the more performance of the network (Demuth and Beale, 1998). Fig. (8) shows the regression analysis resulted from modeling SGR for test data.

Fig. (8) shows the SGR classification (measured data) and predicted this classification for testing data (using RBF). According to this figure, the coefficient of correlation (R^2) of the RBFN model is 0.9931. This high coefficient of correlation shows the accordance between the results of the RBFN model and measured data. Also, the following values are obtained as the output of the postreg function:

- Slope: 0.99
- Y-intercept: 0.051

Regarding regression analysis resulted values, it can be concluded that a perfect compatibility exists between the results obtained from the proposed RBFN and SGR.

Table 4- Network errors for training and testing data

Data set	training data (newrb function)	testing data (newrb function)	training data (newrbe function)	testing data (newrbe function)
Minimum network error (%)	0	0	0	0
Maximum network error (%)	2.44	10.71	0	7.14
Mean of network error (%)	1.42	4.76	0	3.57

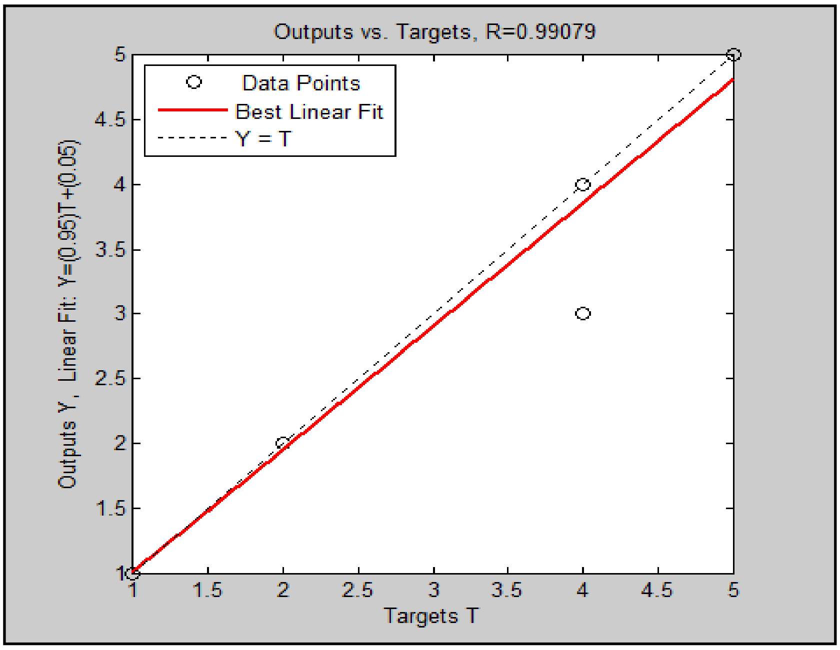

Fig. 8- Regression analysis resulted from modeling SGR for testing data

Conclusion

In this study, RBFN was used to predict the SGR for the Amirkabir tunnel. In addition, network structure and the optimum network were also determined. Distance between the joints, joint aperture, JRC and JCS of each joint set, water head, overburden and score of crashed zones (S_3) were selected as input parameters, while various SGR classes were considered as network output. The data required for network training were obtained from preliminary studies in the path of the Amirkabir tunnel. The results of this research showed that with the help of an RBFN, SGR could be predicted well. Also, high regression analysis proves the very good conformity between results gained from SGR and predicted by the RBFN.

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