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Permeability zoning of Amirkabir water transfer tunnel using support vector machine (SVM) method

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Abstract

The rock mass permeability is one of the most important parameters regulating to the groundwater flow through the fracture's rocks. The permeability distribution is an important part of estimating inflow into tunnels. The common methods to rock mass permeability estimation such as lugeon tests are expensive and very time consuming. The use of intelligent methods to estimate or classify data, especially in engineering problems, has been common in recent decades. Many algorithms have been designed and optimized for this purpose. Support vector machines (SVM) is one of these methods. In this paper, using the SVM method, the Amirkabir tunnel has been classified from the permeability point of view. In order to optimize the parameters of this algorithm, random search method has been selected. The results show that the accuracy of modelling using this method based on experimental data is around 94.59%. Based on this result, amount 85% of tunnel length is classified in the low permeability category and water inflow into tunnel from this part of tunnel is negligible

Keywords: *Amirkabir tunnel, Permeability, classification, Support Vector machine*

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Extended Abstract:

1. Introduction

Groundwater inflow is one of the key issues impacting the process of design and construction for tunnel projects, particularly for open face excavation methods. During tunneling, extensive water inflow may cause unpredictable down time for the construction and may also introduce secondary effects of groundwater draw down to the above ground, leading to ground movement or settlement impacts to sensitive buildings and utilities. Estimating groundwater inflow into tunnels is a difficult art, even if done carefully (Heuer 1995; El Tani 2003). The difficulties arise from several sources: the geological conditions for the project site may not be properly understood; actual conditions may violate the assumptions of the inflow equations; the data as collected may have limitations arising from the testing program that are not accounted for in the analysis; the data may be improperly analysed; and the field investigation may not have found the areas providing most of the inflow. Permeability is a key parameter in seepage computation, and the relationship between rock mass properties and permeability is often complex and difficult to understand by using conventional statistical methods. Neural-network-based methods can be employed to develop more-accurate permeability correlations, but the correlations from these methods have limited generalization and the global correlations are usually less accurate compared to local correlations.

2. Materials and methods

Recently, support-vector machines (SVMs) based on statistical-learning theory have been proposed as a new intelligence technique for both prediction and classification tasks. The formulation of SVMs embodies the structural-risk-minimization (SRM) principle, which has been shown to be superior to the traditional empirical-risk-minimization (ERM) principle employed by conventional neural networks. This new formulation deals with kernel functions, allows projection to higher planes, and solves more-complex nonlinear problems. SRM minimizes an upper bound on the expected risk, as opposed to ERM, which minimizes the error on the training data. In this paper, using the SVM method, the Amirkabir tunnellength has been classified from the permeability point of view. The using data are as: overburden (m), lugeon value, head of water above tunnel, joint aperture (mm), JRC and rock mass permeability. The summary of data are shown in table1.

Table1. Summary of statistical information of used data

Max	Min	Standard deviation	Average	Parameter
660	65	137.7	320.6	Overburden(m)
23.45	0	5.2	4.4	Lugeon
535	55	126.5	251.8	H(m)
11	1	3.2	8.5	JRC
10	0.01	1.8	0.5	Aperture(mm)
2.35e-6	5e-8	5.2e-7	4.56e-7	Permeability(m/s)

Radial Basis Function (RBF) was used in this research. In order to classify the permeability, at first rock mass permeability was classified in three classes, median permeability, low and very low permeability. (Table 2)

Table2. Permeability classification

Permeability Classification	Permeability(m/s)
Median Permeability	>1e-6
Low Permeability	1e-6≤1e-7
Very Low Permeability	1e-7<

Table 3 shows the results of data classification and modelling.

Table3. Accuracy of SVM modeling for permeability classification

Accuracy of test data	Accuracy of training data	
٪ ۹۰/۹۰	٪ ۹۴/۵۹	Accuracy
۲۲	۸۸	Data No.
۰/۲۳	۰/۳۵	Time(s)

The cross-validation method has been used to avoid over-fitting.. In order to optimize the parameters of this algorithm, a random search method has been selected. The results show that the accuracy of modeling using this method based on experimental data is around 94.59%. Based on this result, amount 85% of tunnel length is classified in the low permeability category and water inflow into tunnel from this part of tunnel is negligible

3. Conclusion

In this research Support vector classifier method has been used for Permeability zoning of Amirkabir water transfer tunnel.The use of this method has lead to good results in the classification of rock masses along the tunnelRandom search method has been used as a model selection method for tuning the model parameters. Based on obtained results, accuracy of the classification method is about 86.36% and proposed method in this research can be a good option in initial studies about classification of rock mass. Review of frequency classification curves of overburden, aperture, head of water above tunnel and confusion matrixs show that the general pattern of permeability class has been remaind and the classification error is around 3.64% and negligible

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