A Laboratory Study on Stress Dependency of Joint Transmissivity and its Modeling with Neural Networks, Fuzzy Method and Regression Analysis

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Abstract

Correct estimation of water inflow into underground excavations can decrease safety risks and associated costs. Researchers have proposed different methods to asses this value. It has been proved that water transmissivity of a rock joint is a function of factors, such as normal stress, joint roughness and its size and water pressure therefore, a laboratory setup was proposed to quantitatively measure the flow as a function of mentioned parameters. Among these, normal stress has proved to be the most influential parameter. With increasing joint roughness and rock sample size, water flow has decreased while increasing water pressure has a direct increasing effect on the flow. To simulate the complex interaction of these parameters, neural networks and Fuzzy method together with regression analysis have been utilized. Correlation factors between laboratory results and obtained numerical ones show good agreement which proves usefulness of these methods for assessment of water inflow.

Keywords: Fractured Rock Mass, Stress Dependent Transmissivity, Neural Network, Fuzzy Method

Introduction

Joints play an important role in geo-mechanical projects in different ways. One of those is creating conduits to cross the rock mass which decreases it’s integrity and affects the hydro-mechanical properties [1, 2]. Although it is difficult to accurately predict water inflow into tunnels at the design stage, but it is very essential to make a realistic estimation of that at early stages.

Numerical methods have extended their boundaries to the field of water inflow prediction but due to the complex phenomenon of interacting parameters, it is more realistic to perform laboratory tests with setups as close as possible to the real site conditions.

A combination of data production in the laboratory and utilizing powerful analytical methods such as regression analysis, neural networks and Fuzzy logics, as indicated in the present paper, has proved to be a powerful integral tool to predict water transmissivity of rock joints.

Stress Dependency of Transmissivity of Jointed Rocks

Joint aperture can change due to stress changes, therefore transmissivity also changes accordingly.

There are well established field methods available to determine transmissivity, but they are usually time consuming and costly. An alternative solution for this is to perform laboratory tests which can provide a more versatile estimation of transmissivity and the effect of interacting parameters. This needs to be extended somehow to the field conditions in the next stage.

Research Background

Water flow through joints in rock masses is usually controlled by three main factors: fluid characteristics, joint properties and fluid pressure. Normal closure of joints due to confining stresses and dilation due to shear displacement changes water transmissivity in joints. Min et al. studied changes of permeability around underground openings due to such stress changes. They emphasized on stress relaxation as the main cause for permeability changes in tunnels [3].

Gang and Sanderson reported successful results in performing numerical analysis for

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fluid flow and deformability of jointed rock masses versus normal stress [4].

Decreasing permeability of sandstone due to increasing overburden pressure was studied by Fatt and Davis in 1952. Gray et al. in 1963 applied an axial force and lateral pressure on jointed rock samples simultaneously and studied the resulting changes in permeability. Holt also found similar trend during his tests on Triassic sandstones under three dimensional confining pressure conditions [5].

Most of the above mentioned research has been focused on stress dependent permeability of sandstone samples which is a porous media, but studies on joint transmissivity which is an important parameter in fluid flow in rock masses, has also been studied by other researchers.

The first comprehensive test on open joints was probably done by Lomize in 1951 who used rough parallel glass planes and proved the cubic power law rule for joint transmissivity [5].

This subject has recently found more attention by other researchers among which the tests by Muralidharan can be mentioned [5]. He studied fluid flow through joints on rock cores in the laboratory under different stress conditions. To simplify the case, it was assumed that the core is under no external pressure axially but it is confined laterally by a hydraulic jack. Fluid was injected into the sample at different flow rates and permeability was determined. The same test was done but with hydrostatic pressure conditions. The results show that with increasing normal pressure on joints, transmissivity is reduced due to reduction in joint aperture.

This research proves the relation between jointed rock mass permeability and stress condition due to overburden loads although the effect of joint geometry is neglected in this study. In the present paper, joint transmissivity is studied under different confining stresses and its dependency on joint roughness, sample size and fluid pressure is also determined.

Test Procedure

Instruments

A simple normal loading device is used for tests. A number of core samples from limestone blocks are selected with a rough joint in it. The samples had a variety of diameters ranging between 48 to 75 mm. The joint was normal to the axis of the core which was loaded by a hydraulic jack. Water is injected into the joint plane under pressure and water flow is measured. Figure 1 depicts the used laboratory setup.

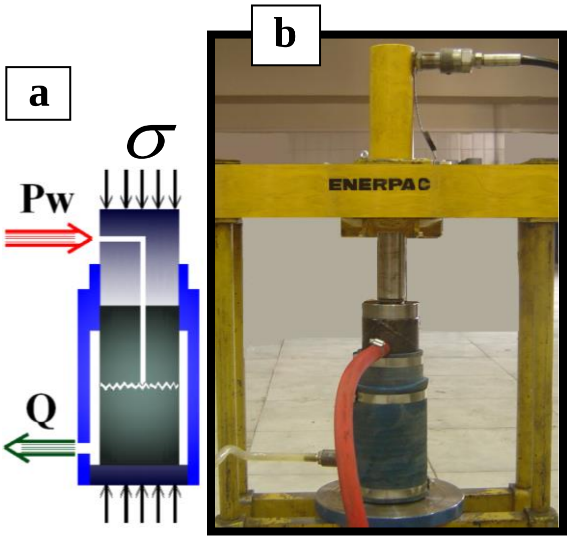


Figure 1: a) Schematic of the jointed rock sample surrounded by a cover subjected to the axial load b) The picture of the laboratory setup

Test Procedure

A number of samples were taken from limestone of Ilam formation in southern Iran with a horizontal natural joint. The rest of the samples were broken to create a new rough joint. The JRC coefficient proposed by Barton 1974 was determined for each joint. The diameter of each sample was also recorded. Joint roughness in this study was categorized in 5 classes to reduce test numbers. To convey water to the joint plane, a hole was drilled in the upper platen and further extended into the upper part of the sample. The following figure shows a close view of the two sides of the joint and the whole assembled sample.

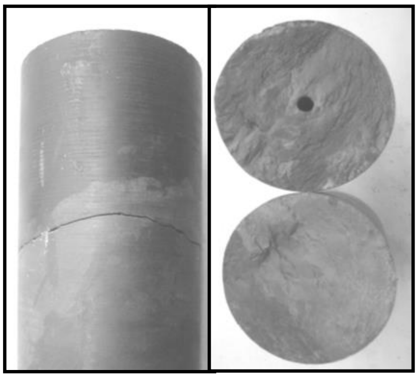


Figure 2: A sample with two sides of the joint

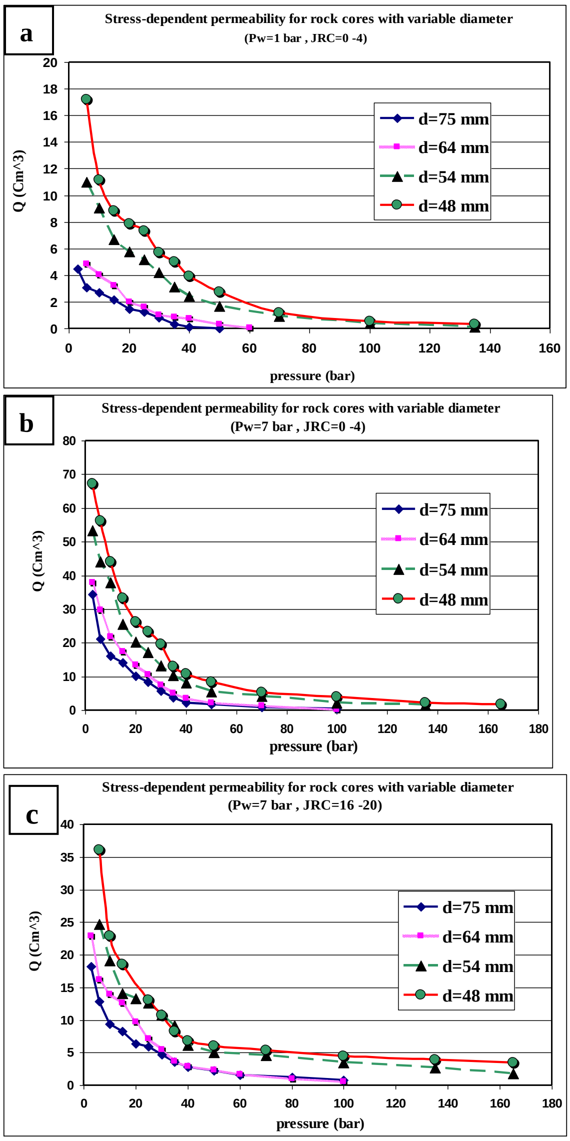


Figure 3: Volume of passed water as a function of normal stress for different joint roughness

a) JRC=0-4, water pressure=1bar

b) JRC=0-4, water pressure=7bar

c) JRC=16-20, water Pressure=7bar

All of the samples were loaded uni-axially via the upper platen. Water reached the joint plane and exited radialy from the rough joint surface and is collected by a surrounding robber bladder and conducted into a volume measuring unit.

For each test, the diameter of the sample, joint roughness, water pressure, normal confining pressure and volume of passed water are measured.

After data collection, graphs of water transmissivity are plotted versus pressure for different conditions (Figure 3). In these graphs, a and b correspond to1 and 7 bars water pressure respectively. In these tests, joint roughness coefficient is between 0 and 4. Part c is for joint roughness coefficient between 16 and 20 at 7 bar water pressure. Comparing a and b shows that increasing water pressure increases water flow which results in higher permeability of the sample. With comparison between graphs b and c under constant size and water pressure, reduction of water flow is depicted as a function of JRC increase.

Figure 4 shows dependency of water flow to variable water pressure for similar joint size and roughness. For this test, a change in water pressure from 1 to 7 bars has resulted in water flow increase to more than five times.

The increase in joint roughness and size in a water flow test under 5 bars water pressure results in water flows reversely related to normal pressure on the joint (Figure 5).

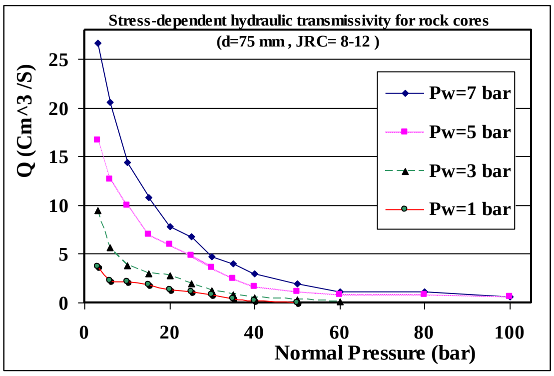


Figure 4: Effect of water pressure variation on stress dependent transmissivity in 48 mm diameter and roughness coefficient between 8 and 12

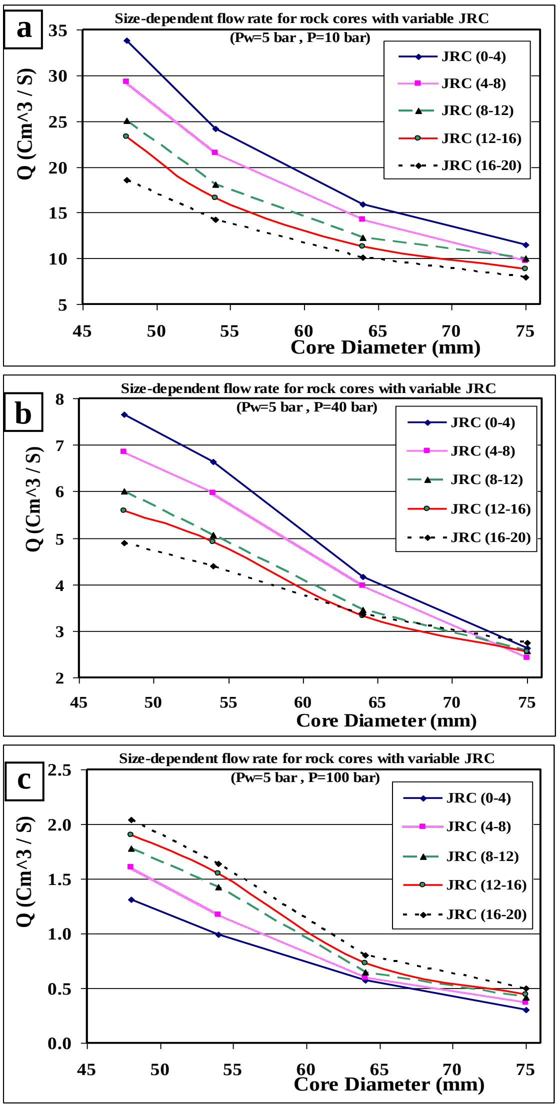


Figure 5: Effect of joint roughness on water flow rate versus diameter in 5 bars water pressure under a) low, b) medium and c) high stress condition

For low normal pressure (part a) when joint roughness increases, water flow decreases. However a different trend is observed at higher pressures (part c). It means at higher stresses better transmissivity is obtained for rougher joints. This can be explained by a good joint closure for smoother ones while rougher joints do not close as much under the same normal pressure. Part b at moderate pressure is an intermediate condition.

Figure 6 shows three stages of joint roughness effect on transmissivity under various normal pressures at 5 bar water pressure and 48 mm diameter. For better representation, a log axis is chosen for transmissivity.

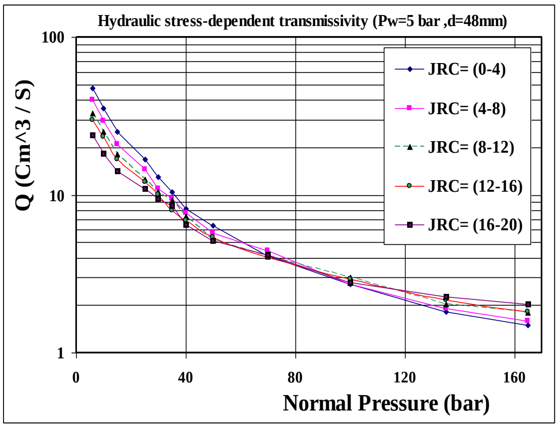


Figure 6: Three stages of joint roughness effect on stress dependent hydraulic transmissivity in 48 mm diameter and 5 bars water pressure

Fracture Flow Rate Estimation by Indirect Methods

Although experimental tests usually have properly responded to encountered problems in science, but they are costly and time consuming. This fact holds true for all laboratory activities related to geosciences especially in hydrogeomechanic activities. Therefore, new estimation methods such as statistical methods, artificial neural networks and Fuzzy logic systems have been used for solving these problems. in the present study, these new methods have been employed to estimate the laboratory pressure dependent flow rate in fractured rock masses by taking into account the effect of joint roughness coefficient, sample size and water pressure.

Artificial Neural Networks ($ANN's$)

In general, neural networks are nonlinear mathematical systems. The network is simulated to human brain functioning. A neural network is a parallel and big processor comprising of simple processing units. These networks are capable of solving problems which do not have a precision mathematical relationship between their input and output parameters.

Back Propagation Neural Network (BPNN)

A Back Propagation (BP) neural network is a multilayer perceptron feed forward which uses back/reverse error propagation algorithm for training. This algorithm is a general and applicable technique. A BPNN consists of one input layer, one or more hidden layers and one output layer. This Network is considered as a feed forward tool, because there is no unit internal connection between output of a processing and inputs of a node in previous layers. [6]

Training of Back Propagation Neural Network

Training is a phenomenon which through known input and output data, releases optimum weight for inputs of any single cell of the neural network. The network learns the patterns after several runs. The error decreases as the number of runs increases and comes to its minimum in a proper round of running. In this study 60% out of 450 total data sets were used for training and 10% for validation and the rest for testing.

Data Preparation and ANN Structure

Data Preparation is usually the most complicated part of *ANN's* application. Part of this complication is due to selection of actual occurred cases which provide proper patterns. Another part is due to the changing the scales of training data (i.e. normalizing the input and output data). For this purpose, the values are normalized in the interval (-1, 1) using Eq. (1).

$$p_n = 2\frac{p - p_{\min}}{p_{\max} - p_{\min}} - 1 \qquad (1)$$

The main reason for normalization of the data to the two above intervals is that active functions such as sigmoid ones are not able to differentiate between two large values. In other words the network would go wrong when the huge amounts are concerned. In such cases the training process will face difficulties. This is called "network saturation". [7]

In order to determine the optimum neural network, their performances were tested with the help of two parameters namely correlation coefficient (R) and Root of Mean Square Errors (RMSE). For this purpose, neural networks with different number of hidden layers and neurons, different activation functions and training functions were tried and the best of them was selected. The best network is the one with higher correlation coefficient and lower RMSE. For estimation of water seepage value (Q) an optimized model of neural network was build after several executions. This model has seven neurons in its hidden layer with sigmoid tangent activation function. Such a model contains four input neurons representing pore pressure, normal loading pressure, joint roughness coefficient and sample size. The output would be a single neuron representing the volume of water seepage (Q). Figure 7 depicts a simple view of the model used for estimation of the value of Q. Figure 8, illustrates the correlation between measured values in laboratory and predicted values by neural network for training and test data. The correlation coefficients for training and test data are 97.1% and 95.7% respectively.

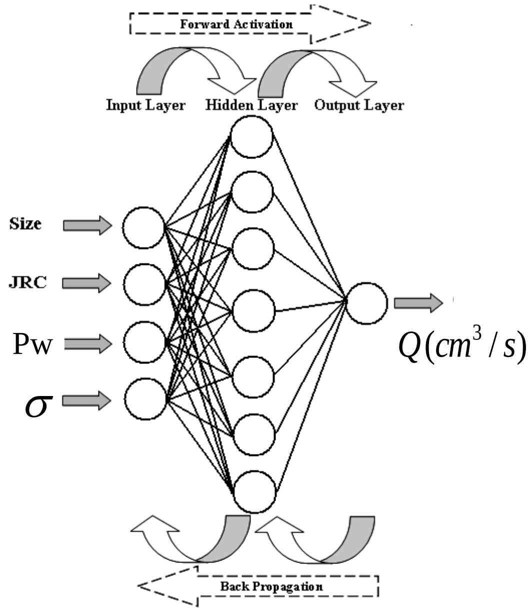


Figure 7: Back propagation neural network used for flow rate estimation

Fuzzy Logic Method

The Fuzzy logic is based on Fuzzy set theory in which a Fuzzy collection is considered as a collection that has no certain boundary and any of its members has a relative degree of membership. Specification of type and number of parameters related to membership functions is the most important problem in Fuzzy logic. The membership function is a function which fuzzifies the input space. In other words, each input value is normalized in the [0, 1] interval. There are many Fuzzy membership functions such as triangular shaped, Trapezoidal-shaped, Gaussian curve and sigmoid-shaped [7].

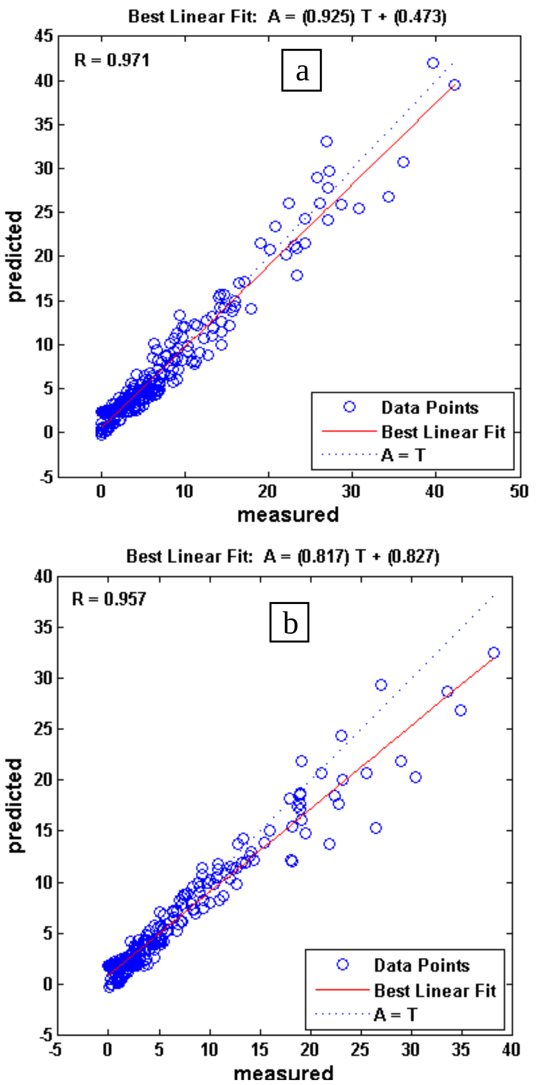


Figure 8: Correlation between measured and predicted values for training (a) and test data(b)

Fuzzy Inference System

In Fuzzy inference system, a set of conditional rules are used to relate input and output membership functions. A simple example of the "if-then" condition is as follows:

If x is A and y is B then z is C

In general, there are five steps for constructing the Fuzzy inference process: [7]

1. Fuzzification of input variables,
2. Application of the Fuzzy operator (AND or OR) in the antecedent,
3. Implication from the antecedent to the consequent,
4. Aggregation of the consequents across the rules,
5. Defuzzification of outputs.

There are two methods in Fuzzy inference system, Mamdani method and Sugeno method. In Sugeno Fuzzy method of inference system which used in this study on the contrary of Mamdani method, the output membership functions are either linear or constant [8].

Fuzzy Model Construction by ANN

Definition of membership function and Fuzzy rule is the most important parts of Fuzzy model construction. Researchers mostly apply the try and error method for adjustment of these parameters, but this method is often a time consuming process which needs much experiment. Therefore, the idea of applying learning algorithms for Fuzzy systems was considered. These algorithms are the same as those used in neural networks. These models are called neuro-Fuzzy systems. Actually the ANN provided properly ways for adjustment the Fuzzy models parameter by existing data and makes the manual way possible in shorter time [9].

In this study triangle membership function was used for each input parameter. The applied model is the Sugeno model which applies the liner membership function for output parameter. The data used for determining the Fuzzy rules and membership function were the same data used for training the ANN. Initially a Fuzzy model was built through try and error process. Then the parameters of this model were used for training in neural network. The introduced membership functions defined by neural network after training are shown in Figure 9.

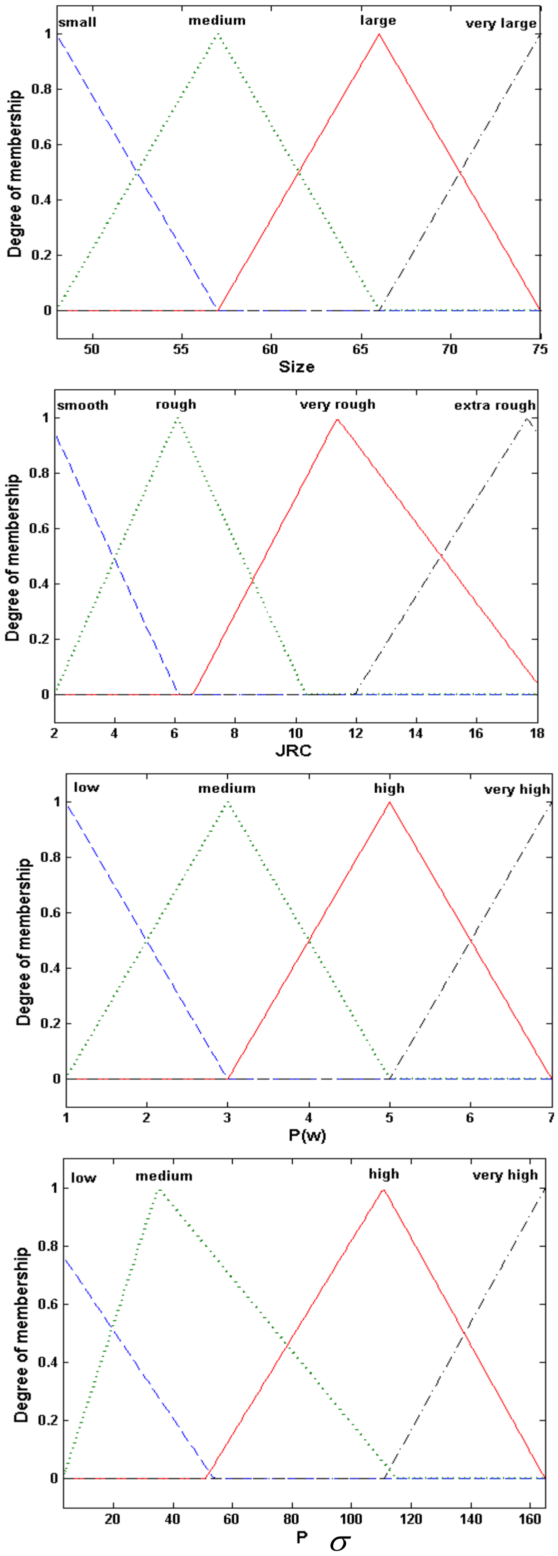


Figure 9: Membership function for input parameters after training by neural network

Correlation between measured values and the values predicted by neuro-Fuzzy model built up in this study, before and after training, is shown in Figure 10. In these graphs “a“ represents the graph related to training and “b“ represents the graph related to testing of the model. Correlation coefficient between predicted and measured data for training and test data is 99.3% and 98.3%. It is noticeable that correlation coefficient (R) for neuro-Fuzzy model is higher than that of Fuzzy model. The difference is much higher in the case of test data

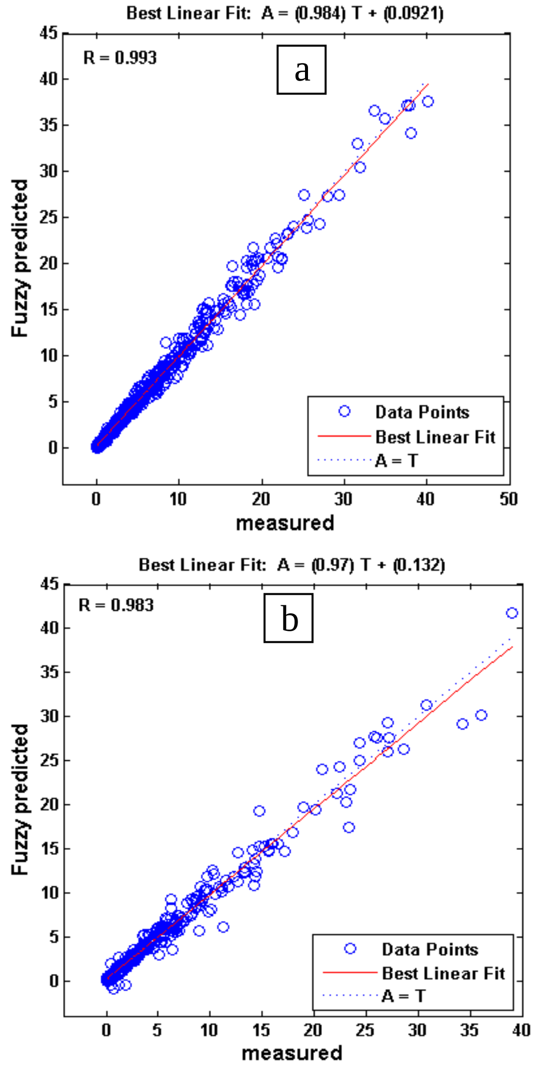


Figure 10: Correlation between measured values in laboratory and predicted values by neuro-Fuzzy model for training (a) and test data (b).

Multivariate Regression

Regression analysis defines relation between depended variable (Y) and predictor parameters (X_1, X_2, …, X_n). Commonly, linear regression model is used to predict this relation and can express it in the following form: [10]

$$y = \beta_1 + \beta_2 x_2 + ... + \beta_n x_n \quad (2)$$

Where β is unspecified parameter, X is the predictor parameter, Y is depended variable. If the variance of Y is constant we can approximate the unspecified parameters with least square method until the error between measured and predicted values is minimized. In this study, multivariate linear regression was applied to estimate the relation between core seepage (Q) as depended parameter and values of sample size (D), joint roughness coefficient (JRC), pore pressure (P_w), and normal pressure (σ) as predictor parameters.

The twin-logarithmic model has been used in multivariate nonlinear regression analysis for predicting Q in this study. The equation representing this model can be written in the following form:

$$Y = a X_1^{b_1} X_2^{b_2} ... X_n^{b_n} \quad (3)$$

where Y is the predicted value corresponding to the dependent variable (response), a is the intercept, X_1, X_2, and X_n are the independent variables and b_1, b_2, and b_n are the regression coefficients of X_1, X_2, and X_n. Taking logarithms of both sides of Eq. (3) converts the model into the following linear form:

$$\log Y = \log a + b_1 \log X_1 + b_2 \log X_2 + ... + b_n \log X_n \quad (4)$$

Eq. (4) can be written as the linear regression function as follows:

$$Y' = a' + b_1 X_1' + b_2 X_2' + ... + b_n X_n' \quad (5)$$

where, Y' is the logarithm of the predicted value, X_1', X_2', and X_n' are the logarithms of the independent variables where a' is the logarithm of value a. [11]

Results Obtained from Multivariate Linear Regression

To determine the unknown regression coefficients the data used for training neural network were employed. According to Eq. (2) and the results which obtained from multivariate linear regression:

$$Q = 33.03 - 0.387 \times (D) - 0.293 \times (JRC) + 2.326 \times (Pw) - 0.274 \times (\sigma) \quad (6)$$

where, Q= core seepage, cm^3/s

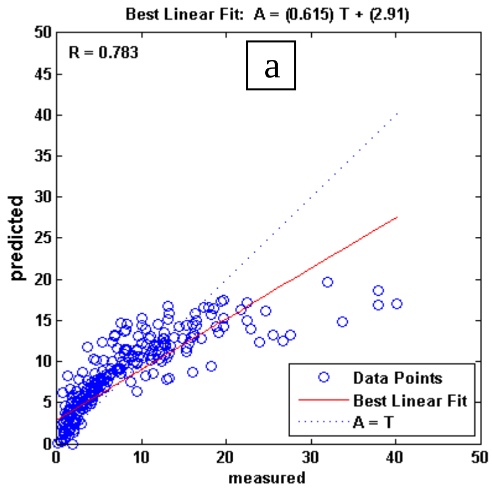
P_w= water pressure, bar

D= core diameter, mm

JRC= joint roughness coefficient

σ = normal pressure applied on joint, bar

To verify the capability of generalization of regression model the new data set was used. For this purpose the test data of neural network and neuro-Fuzzy model were employed. The results of calculating the regression coefficients for both data used for determining regression coefficient and new data are shown in Figure 11. Correlation coefficient between predicted values by multivariate liner regression and experimental data are 78.3% and 75.8% respectively. These coefficient values are within the accepted range for engineering purposes.



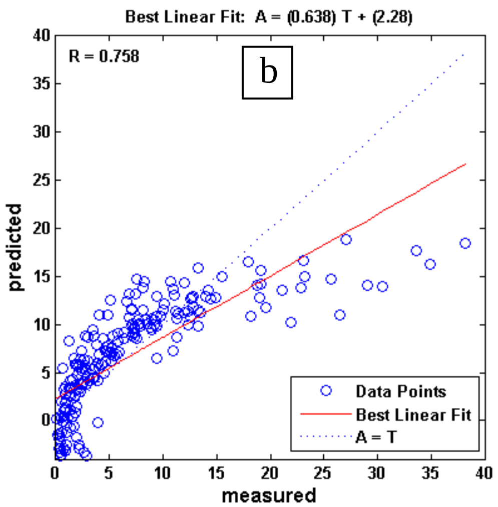


Figure 11: Correlation between measured values in lab and predicted values by regression for data set using in determined of unknown coefficient (a) and new data (b)

Results Obtained from Multivariate Nonlinear Regression

Multivariate linear regression is capable of estimating stress dependent flow. Since any single parameter affecting flow has a nonlinear relationship the following multivariate nonlinear equation is proposed to enhance the accuracy:

$$Q = 56\frac{Pw^{0.8}}{D^{3.9} \times JRC^{0.05} \times \sigma^{1.1}} \qquad (7)$$

where, Q= core seepage, lit/s
Pw= water pressure, bar
D= core diameter, cm
JRC= joint roughness coefficient
σ = normal pressure applied on joint, bar

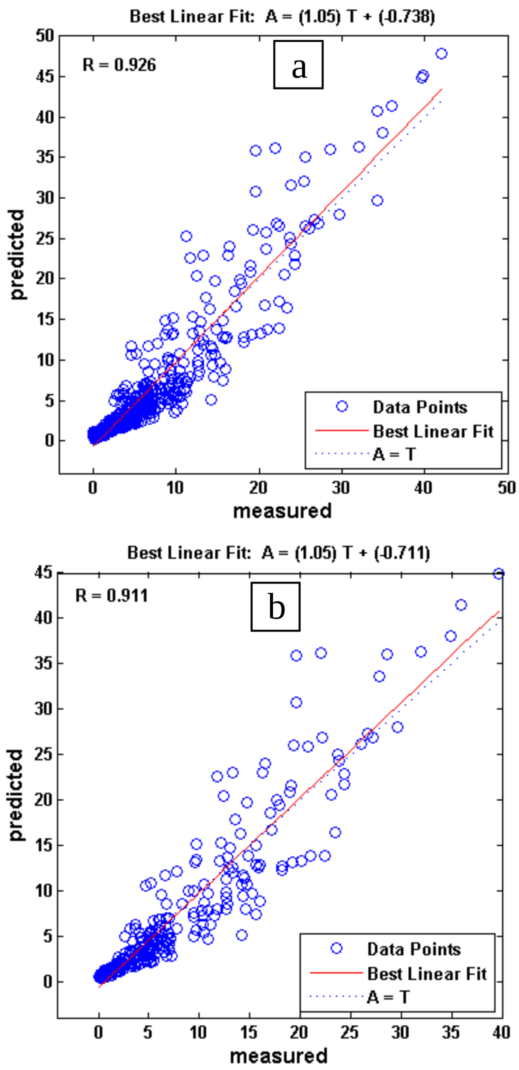


Figure 12: Correlation between measured values in lab and predicted values by regression for data set using in determined of unknown coefficient (a) and new data (b).

In order to determine the regression coefficient of Eq. (4) and to evaluate its accuracy all already used for testing and training have been employed. The Results of calculating the multivariate nonlinear regression coefficients are shown in Figure 12. The coefficient of correlation between the values estimated by multivariate nonlinear regression and laboratory values with training and test data are 92.6% and 91.1% respectively.

Summary

According to the test results, higher water pressure causes higher water flow. On the other hand, following parameters result in transmissivity reduction:

1. Increase in normal pressure
2. Higher joint roughness at low-moderate normal pressure
3. Increase in core diameter (or area of water flow) which causes more resistance to the flow.

The results obtained from prediction of core flow rate value by four methods (artificial neural network, neuro-Fuzzy logic and multivariate linear and nonlinear regression) are presented in table (1). In this table coefficient of correlation (R) and root of mean square error (RMSE) are also shown. Clearly the model which has the higher coefficient of correlation and lower RMSE is preferred.

Table 1: A comparison between results obtained from different methods used in this study

MODEL	R% (train)	R% (test)	RMSE (train)	RMSE (test)
Neural network	97.1	95.7	0.0019	0.0026
Neuro- Fuzzy	99.3	98.3	0.0029	0.0041
Multivariate linear regression	78.3	75.8	0.0053	0.0058
Multivariate nonlinear regression	92.6	91.1	0.0038	0.0046

The reason for a better result by neuro-Fuzzy model might be the uncertainty of input measurement values and outputs. It is believed that Fuzzy method has a better capacity in dealing with these problems.

Conclusions

- Increasing water pressure from 1 to 7 bars causes five times increase in water flow volume. This dependency is also not linear.
- In low normal stresses, water flow is inversely related to joint roughness. However, at high stress levels, higher JRC values cause more flow. This effect is more pronounced for bigger core sizes.
- Water flow through joint was never dropped to zero even at high normal stresses. This is due to the fact that a joint never closes completely.
- Among used methods in this study, Neuro-Fuzzy approach causes higher accuracies. Coefficient of correlation between predicted and measured lab results for training and testing stages are 99.3% and 98.3% respectively. This drops to 97.1% and 95.7% for neural network method and to 92.6% and 91.1% for nonlinear multivariable regression analysis. For linear multivariable regression method these values are as low as 78.3% and 75.8% percent respectively.

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