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Prediction of the Penetration Rate and Number of Consumed Disc Cutters of Tunnel Boring Machines (TBMs) Using Artificial Neural Network (ANN) and Support Vector Machine (SVM)—Case Study: Beheshtabad Water Conveyance Tunnel in Iran

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Abstract: Tunnel boring machines (TBMs) are designed to excavate underground spaces and widely used in tunneling, civil and mining projects. TBM performance prediction substantially deals with the evaluation of machine's penetration rate and the number of consumed disc cutters. There are various methods and equations to predict the TBMs performance in the literature. In this paper, we predicted the penetration rate and number of consumed disc cutters in Beheshtabad water conveyance tunneling project, one of the major water conveyance tunneling projects in Iran, using Artificial Neural Network (ANN) and Support Vector Machine (SVM) methods. Results showed that both approaches are very effective but SVM yields more precise and realistic findings than ANN.

Key words: TBM performance prediction, artificial neural network, support vector machine, Beheshtabad water conveyance tunnel.

Introduction

Tunnel boring machines (TBMs) are extensively used mechanical miners to excavate the tunnels and underground spaces. Because of the high price of such machines, evaluation of the excavation method is of particular importance with these machines. Therefore, the most important indicator of the performance of tunnel boring machines are the penetration rate and number of consumed disc cutters of these machines. There are various methods and equations for predicting penetration rates and number of consumed disc cutter, each of which has its own characteristics and is subject to its own specific conditions, based on rock mass parameters and machine specifications. Multivariate linear regression, neural network, support vector machine (SVM) and neuro-fuzzy adaptive inductive system are high performance methods for modeling and pattern recognition in data.

Tarkoy (1973) studied on predicting TBM penetration rates in selected rock types. Graham (1976) presented a model for penetration rate in rocks. Farmer and Glossop (1980) investigated on the rate of disc cutter penetration. Bamford (1984) proposed a rock test indices for tunnel boring machine performance. Büchi (1984) studied the influence of geological parameters on the advance rate of a tunnel drilling machine. Boyd (1986) researched regarding performance of continuous miners in hard rock

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formations. Movinkel and Johannessen (1986) studied the geological parameters affecting on hard rock tunnel boring. Martin (1988) researched at TBM tunnelling in poor and very poor rock conditions. Sapigni et al. (2002) calculated TBM performance through rock mass classification. Thuro and Plinninger (2003) investigated on rock cutting process related to hard rock tunnel boring, cutting, drilling and blasting. Roby et al. (2008) developed a disc cutter design approach. Bieniawski et al. (2008) suggested new applications of the excavability index for selection of TBM types and predicting their performance. Farrokh et al. (2011) studied analysis of unit supporting time and support installation time for open TBMs. Cho et al. (2013) evaluated cutting efficiency of linear-cutting-machine (LCM) testing and photogrammetric measurement.

Benato et al. (2015) investigated on prediction of penetration per revolution of TBM. Alsahly et al. (2016) advanced finite element modeling of excavation process by TBMs. Geng et al. (2016) studied at mechanical performance of TBM cutterhead in mixed rock ground conditions. Liu et al. (2017) suggested a predictive model of TBM performance for granite formations. Jakubowski et al. (2017) studied at multivariate linear regression and analysis of TBM performance. Maji and Theja (2017) estimated the TBM performance prediction model for rocks. Yagiz (2017) proposed new equations for predicting the field penetration index of tunnel boring machines in fractured rock mass. Seo et al. (2018) studied the influence of geological mapping on the net penetration rate prediction. Mikaeil et al. (2018) developed a fuzzy multi criteria decision-making approach for hard rock TBMs. Salimi et al. (2018) examined feasibility of developing a rock mass classification for hard rock TBMs. Giacomo et al. (2018) incorporated the geological and mechanical rock mass conditions for TBM performance prediction.

In this research, it is tried to predict the performance of TBMs using Artificial Neural Network (ANN) and Support Vector Machine (SVM) techniques in Beheshtabad water conveyance tunnel.

Description of the Study Area

Beheshtabad water conveyance tunnel, about 65 kilometre length and 6 metre width, is one of the biggest water supplying projects for transporting water to the central plateau of Iran. This tunnel is located near Ardal City with east north-west south direction. From the entrance portal to 17 km of the tunnel, it is located in Zagros zone and its output is in Sanandaj-Sirjan zone (Bagherpour and Rahimdel 2016). Figure 1 shows the location of Beheshtabad water conveyance tunnel. Descriptive statistics of data in Beheshtabad water conveyance tunnelling project can be seen in Tables 1 and 2.

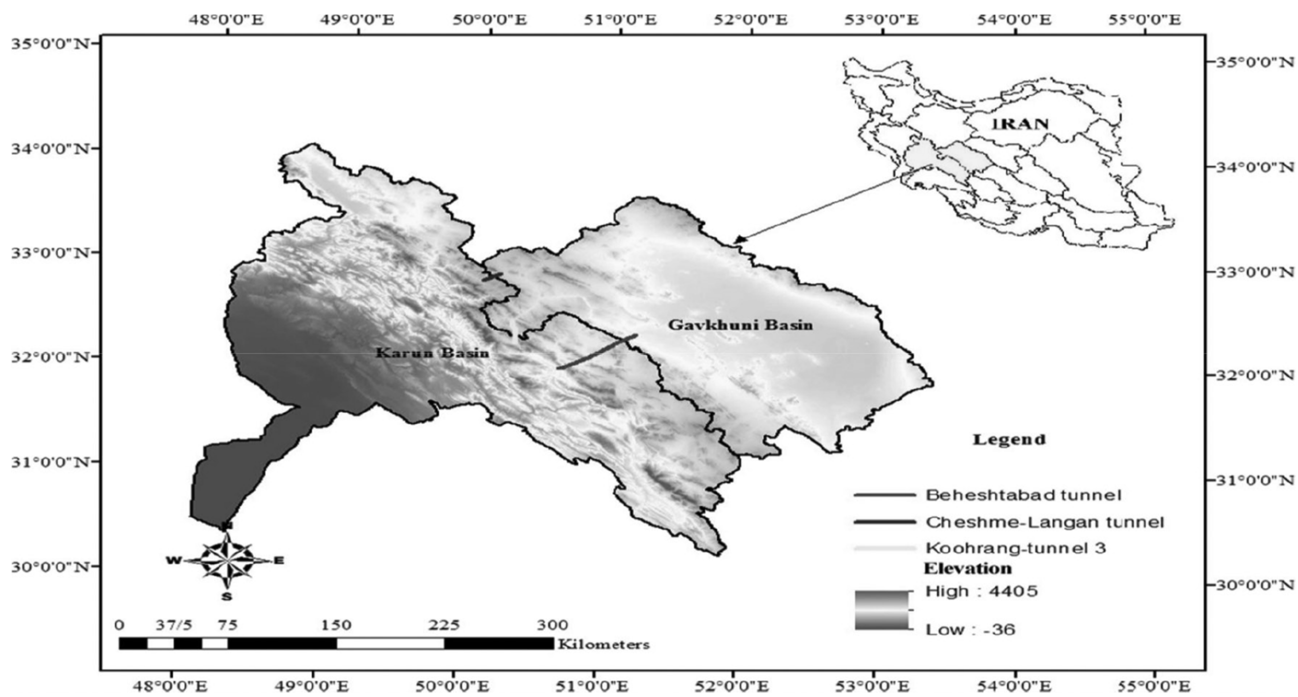

Figure 1: GIS view of Beheshtabad water conveyance tunnel (Ahmadi et al., 2018).

Table 1: Descriptive statistics of rock mass properties and TBM penetration rate in Beheshtabad water conveyance tunnelling project

	Uniaxial Compressive Strength (UCS)(MPa)	*Brazilian Tensile Strength (BTS) (MPa)*	*Rock Quality Designation (RQD) (%)*	*Cohesion (MPa)*	*Elasticity modulus (GPa)*	*Poisson's ratio*	*Density (g/ cm^3)*	*Joint angle (Deg.)*	*Joint spacing (m)*	*Penetration rate (m/hr)*
Mean	39.2420	6.6305	52.9871	1.0392	8.7116	0.2619	2.4547	19.0359	0.6631	6.803
N	100	100	100	100	100	100	100	100	100	100
Std. Deviation	13.49134	2.19700	7.25906	0.21394	1.37298	0.03762	0.06089	7.63606	0.29057	3.27
Minimum	25.80	5.02	35	0.75	6.39	0.22	2.30	10	0.25	0.280
Maximum	90.00	15.00	65	1.50	11.04	0.35	2.60	44	1.54	12.730
Variance	182.016	4.827	52.694	0.046	1.885	0.001	0.004	58.309	0.084	10.706
Harmonic Mean	36.2042	6.1886	51.8501	0.9976	8.5001	0.2569	2.4532	16.5898	0.5335	2.39
Geometric Mean	37.5284	6.3723	52.4459	1.0180	8.6051	0.2593	2.4540	17.7195	0.5985	5.27
Std. Error of Mean	1.34913	0.21970	0.72591	0.02139	0.13730	0.00376	0.00609	0.76361	0.02906	0.32

Table 2: Descriptive statistics of machine parameters and number of consumed disc cutters in Beheshtabad water conveyance tunnelling project

	Power (KW)	*Revolutions per minute (RPM) (cycle/min)*	*Thrust per cutter (kN)*	*Geological strength index (GSI)*	*Number of consumed disc cutter*
Mean	1108	7.7323	225.77	41.30	21.97
N	100	100	100	100	100
Std. Deviation	208.82373	1.27506	45.655	6.457	6.008
Minimum	459	5.27	150	30	11
Maximum	1315	9.91	300	72	29
Variance	43607.350	1.626	2084.341	41.687	36.091
Harmonic Mean	1044	7.5146	216.22	40.49	19.97
Geometric Mean	1081	7.6250	221.04	40.87	21.02
Std. Error of Mean	20.88237	0.12751	4.565	0.646	0.604

Material and Methods

Artificial Neural Networks (ANN)

Artificial neural networks are new computing systems and techniques for machine learning, displaying the knowledge and applying knowledge to the vast majority of output responses from complex systems. The main idea behind these networks is to some extent inspired by the way the biological nervous system functions to process data and information in order to learn and create knowledge. The key element of this idea is to create new structures for the information processing system.

This system consists of a large number of super-integrated processing elements called neurons that work together to solve a problem and transmit information through synapses (electromagnetic communications). In these networks, if a cell is damaged, the rest of the cells can compensate for it and also contribute to its reconstruction. These networks are able to learn. For example, by applying irritation to tactile neural cells, the cells remember to not go to the body and teach this system with an algorithm to correct its error. Learning in these systems is adaptive, that is, by using the examples, the weight of the synapse changes in such a way that, in the case of new inputs, the system produces the correct response.

Support Vector Machine (SVM)

Support Vector Machine (SVM) is one of the techniques for learning, which uses it for classification and regression. This method is one of the relatively new methods that have shown good performance over recent years for classification. The SVM classifier is a data linear classification, and in linear division of data, we try to select a line that has a more reliable margin. The solution to the equation is to find the optimal line for data by means of QP methods, known methods for solving constrained problems. Before dividing the line so that the machine can classify the data of high complexity, we obtain the data by the phi function into a much larger space. In order to solve the very high dimensional problem using these methods, we solve the Lagrange duality theorem for converting the minimization problem into its dual form, in which, instead of a complex phi function that brings us to a dimensional space, we use a simpler function called the kernel function, which is a function of the phi function. You can use various kernel functions, including exponential nuclei, polynomials, and sigmoids.

Evaluation Criteria

In this research, determination coefficient (R^2) and root mean square error (RMSE) were used to evaluate the accuracy and efficiency of the models. The best value for these two criteria is one and zero respectively. In addition to the above criteria, the distribution diagrams and comparative graphs of observational values are also used to compare and analyze the results.

Penetration Rate Analysis

Predicting TBM Rate of Penetration Using ANN

The number of input parameters is nine including Uniaxial Compressive Strength (UCS) (MPa), Brazilian Tensile Strength (BTS) (MPa), Rock Quality Designation (RQD) (%), Cohesion (MPa), Elasticity modulus (GPa), Poisson's ratio, Density (g/cm^3), Joint angle (Deg.), Joint spacing (m) and the number of output parameter is one (Rate of penetration). A schematic of ANN structure applied for database is shown in Figure 2.

As shown in Figure 3, the convergence of the training data and validation data is 0.97531 and 0.94557, respectively. The introduction of the raw data reduces the speed and precision of the network and shows the success of network in learning and its accurate estimated test data with a regression of 0.92545. Moreover, it depicts the linear regression between the input and output data of the entire network. Based on this diagram, the total network regression is 0.95667 which implies on relation between measured or actual data (target) and predicted (output) data.

Figure 4 shows mean square error vs. epochs of Beheshtabad water conveyance tunnel for penetration rate prediction. The plot consists of three lines for three different steps of training, validation, and test. MSE is the mean of the squared error between the desired output and the actual output of the neural network. As it seems, the epoch (each iteration of learning) in which the best network is obtained is 17 and the best validation performance is 2.45 at epoch 17.

Determination coefficient (R^2), root mean square error (RMSE), and output equation achieved from the artificial neural network (ANN) to be used to predict the TBM penetration rate in the Beheshtabad water conveyance tunnel are shown in Figure 5. This graph

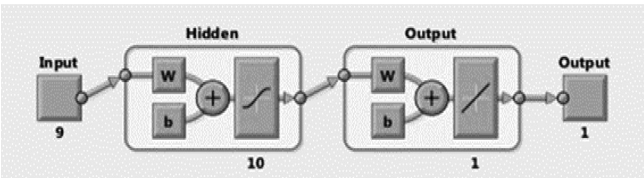

Figure 2: ANN structure for penetration rate prediction in Beheshtabad water conveyance tunnel excavation.

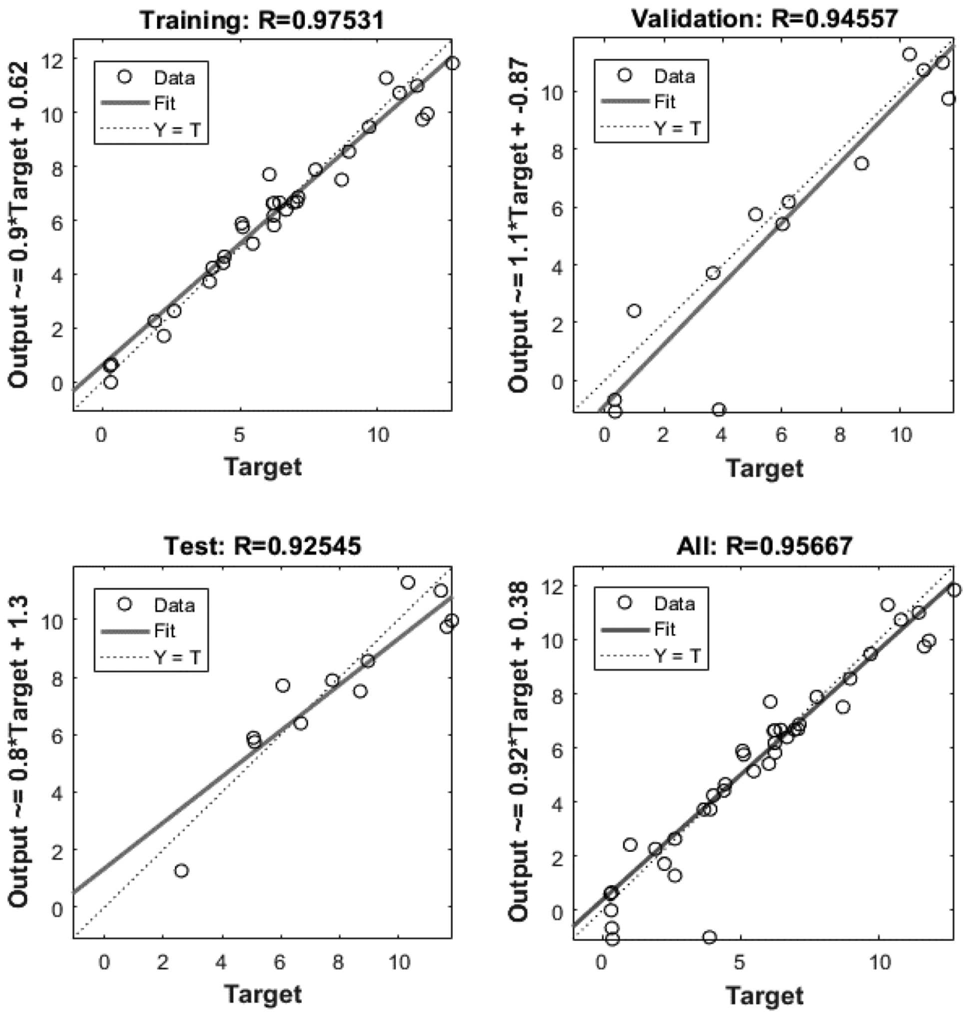

Figure 3: Results of network training regression, network validation, network testing regression and entire network for penetration rate prediction in Beheshtabad water conveyance tunnelling project.

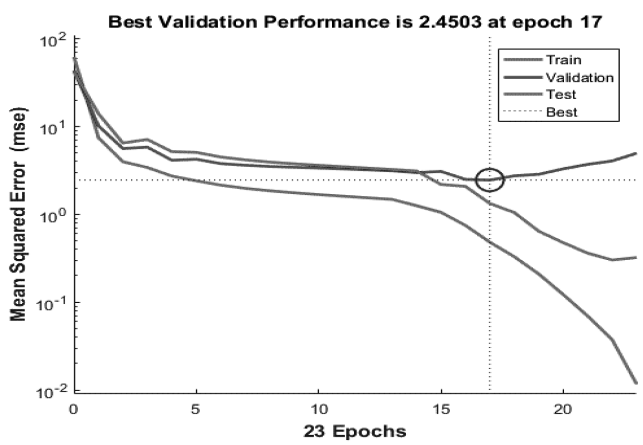

Figure 4: Mean square error versus epochs of penetration rate prediction in Beheshtabad water conveyance tunnelling project.

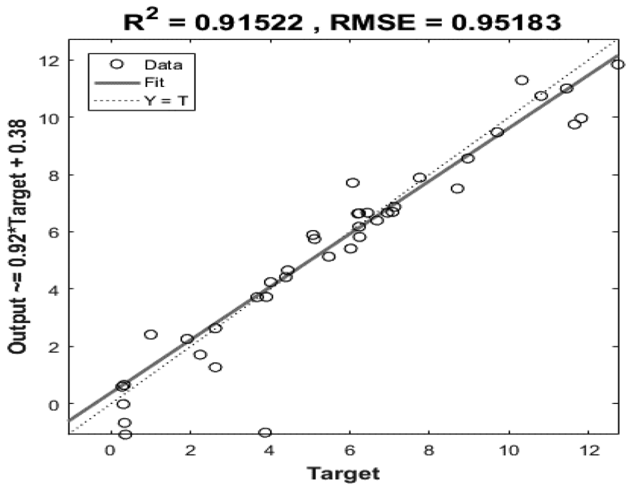

Figure 5: Output graph (relation between measured and predicted data) obtained from penetration rate analysis using ANN in Beheshtabad water conveyance tunnelling project.

represents the fitting line between the values predicted by the ANN model with the best fit line $y = x$. As it is clear from this form, most predicted and measured values, or targets, are set apart from a few points on the bisector line, indicating that the measured and predicted values are equal to $y = x$. The compliance graph of the measured values of the penetration rate or target and the predicted values of the penetration rate by the ANN predictive model is shown in Figure 6.

Predicting TBM Rate of Penetration Using SVM

Through this modelling, similar to previous approach, the parameters are those nine input parameters and one output parameter (ROP). Determination coefficient (R^2), root mean square error (RMSE), and output equation obtained from the support vector machine model (SVM) which is used to predict the TBM penetration rate in the Beheshtabad water conveyance tunnel are illustrated in Figure 7. The compliance graph of the measured values of the penetration rate or target and the predicted values of the penetration rate by the SVM predictive model is shown in Figure 8. SVM design parameters of Beheshtabad water conveyance tunnel for penetration rate prediction are listed in Table 3.

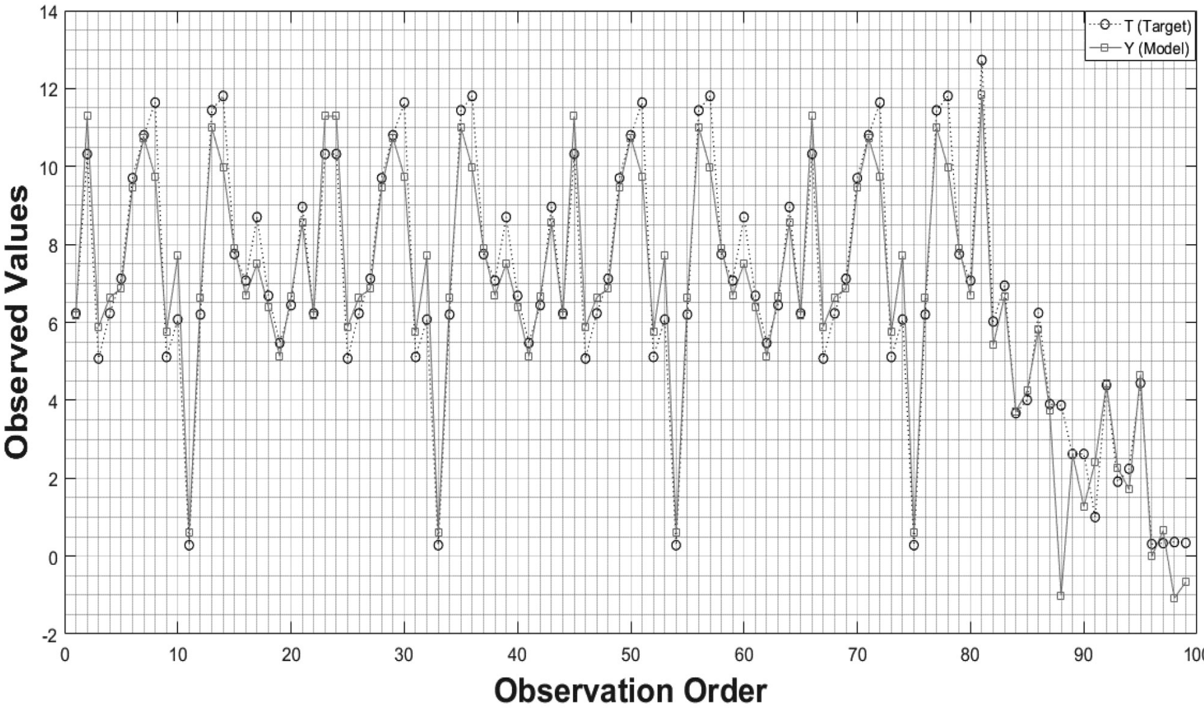

Figure 6: The compliance graph of the measured values of the penetration rate (target) and the predicted values (model) using ANN in Beheshtabad water conveyance tunnel.

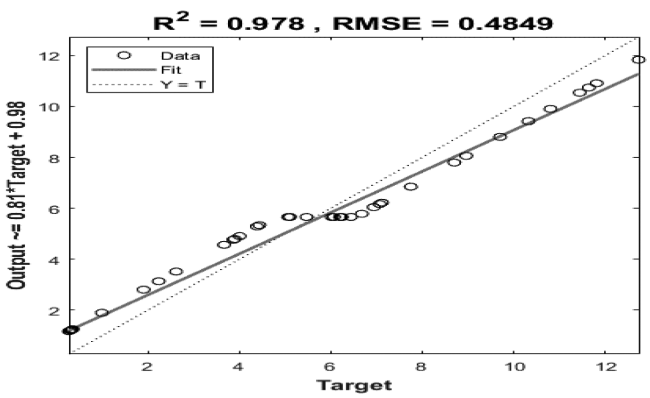

Figure 7: Output graph (relation between measured and predicted data) obtained from penetration rate analysis using SVM in Beheshtabad water conveyance tunnelling project.

Table 3: SVM design parameters of Beheshtabad water conveyance tunnel for penetration rate prediction

Model	*Kernel*	*Degree*	ε	C	σ
$\varepsilon - SVR$	*Radial Basis Function (RBF)*	2	0.1	1000	0.5

Number of Consumed Disc Cutter

Similarly, analyses have been conducted to yield prediction models for number of consumed disc cutter through these approaches—ANN and SVM. In this

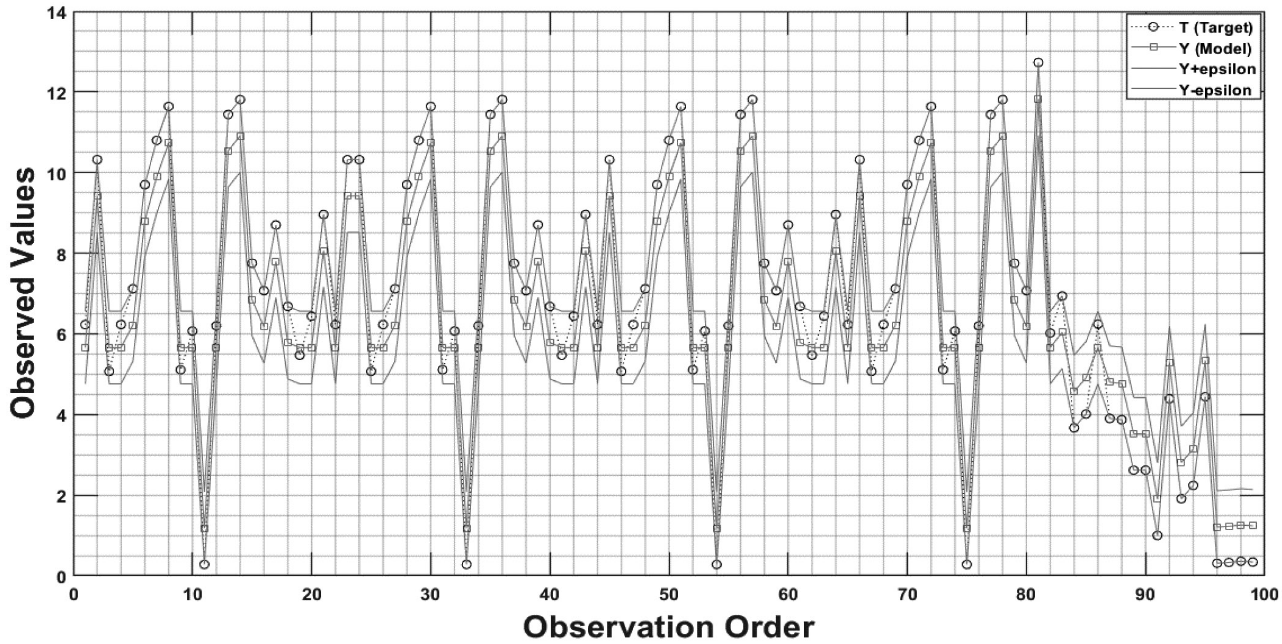

Figure 8: The compliance graph of the measured values of the penetration rate (target) and the predicted values (model) using SVM in Beheshtabad water conveyance tunnel.

analysis, there are four input and one output parameter. Input parameters are: Power (kW), Revolutions per minute (RPM) (cycle/min), Thrust per cutter (kN), Geological Strength Index (GSI) and output parameter is the number of consumed disc cutter. Determination coefficient (R^2), root mean square error (RMSE), and the relation between target and output in ANN and SVM approaches used to predict the TBM number of consumed disc cutter in Beheshtabad water conveyance tunnel are shown in Figures 9 and 10, respectively.

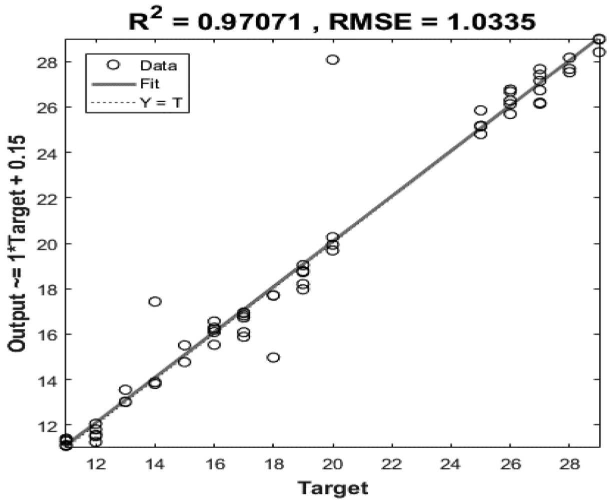

Figure 9: Output graph (relation between measured and predicted data) obtained from disc cutter consumption analysis using ANN in Beheshtabad water conveyance tunnel construction.

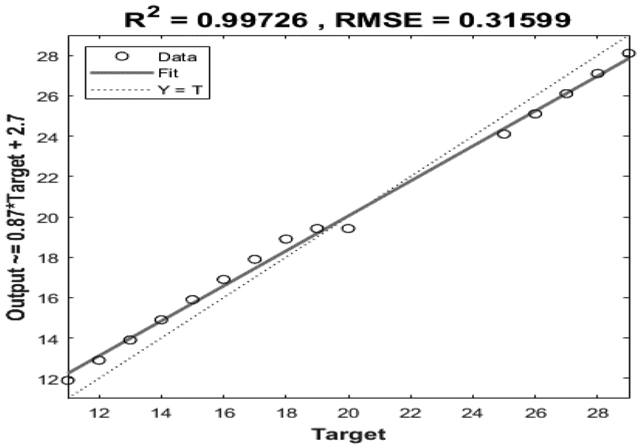

Figure 10: Output graph (relation between measured and predicted data) obtained from disc cutter consumption analysis using SVM in Beheshtabad water conveyance tunnelling project.

Comparison of Results Achieved from Artificial Neural Network (ANN) and Support Vector Machine (SVM)

After comparing the findings obtained from both ANN and SVM approaches, it can be concluded that the SVM is a more acceptable method than ANN for prediction of penetration rate and number of consumed disc cutters. Comparison data for both methods are listed in Tables 4 and 5, respectively.

Table 4: Results of penetration rate prediction using ANN and SVM

Model	R^2	*RMSE*
ANN	0.915	0.951
SVM	0.978	0.484

Table 5: Results of number of consumed disc cutter prediction using ANN and SVM

Model	R^2	*RMSE*
ANN	0.970	1.033
SVM	0.997	0.315

Conclusions

In this study, a database primarily established from field observations, rock formation properties and TBM penetration rates as well as the number of consumed disc cutters through the excavation of a tunnelling project, Beheshtabad water conveyance tunnel in Iran. The database was then analyzed using Artificial Neural Network (ANN) and Support Vector Machine (SVM) to obtain predictive models for the penetration rate and the number of consumed disc cutter of TBMs. Results showed that SVM yields more precise and realistic findings than ANN.

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Contents