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Performance Prediction of a Hard Rock TBM using Statistical and Artificial Intelligence Methods

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Abstract

Tunnel Boring Machines (TBMs) are extensively used to excavate underground spaces in civil and tunneling projects. An accurate evaluation of their penetration rate is the key factor for the TBM performance prediction. In this study, artificial intelligence methods are used to predict the TBM penetration rate in excavation operations in the Kerman tunnel and the Gavoshan water conveyance tunnels. The aim of this paper is to show the application of the Multivariate Linear Regression (MLR), Artificial Neural Network (ANN), and Support Vector Machine (SVM) for the TBM penetration rate prediction. The penetration rate parameter is considered as a dependent variable, and the Rock Quality Designation (RQD), Brazilian Tensile Strength (BTS), Uniaxial Compressive Strength (UCS), Density (D), Joint Angle (JA), Joint Spacing (JS), and Poisson's Ratio are considered as independent variables. The obtained results by the several proposed methods indicated a high accuracy between the predicted and measured penetration rates, but the support vector machine yields more precise and realistic outcomes.

1. Introduction

TBM performance prediction is a critical factor that can significantly impact the project's completion timeline. Hence, the fundamental determinant in the decision to employ or abstain from mechanized excavation is the excavation technique. The utilization factor refers to the duration of time that a machine spends excavating an entire project in relation to the total time or daily operation time. This coefficient is influenced by various factors including ground condition, machine type, support facilities, project management, and employee experience. In light of the recent surge in urban population growth and city development, efficient and expeditious intercity transportation has become increasingly crucial. Consequently, tunneling operations have experienced a notable increase worldwide.[1]. In the recent years, Tunnel Boring Machines (TBMs) have been increasingly utilized in tunneling operations, particularly in the excavation of large tunnels with high operating speeds. However, the complexity of TBM excavation poses a significant risk of accidents during tunneling operations. Working in environments without natural light, the possibility of falling tunnel walls, exposure to various air pollutants, and risks of explosion and fire are all factors that contribute to this risk. Failure to properly identify and control these hazards in tunnels can result in irreparable accidents. Furthermore, these tunnels are situated in high uncertainty environments, which further increases the risk of hazards. The unknown ground conditions and limited space available, due to inadequate pre-implementation studies, errors in the design and calculation steps contribute to the likelihood of hazards. Following tunneling operations, stable environmental conditions often change, which not only significantly affects the

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ground but also has consequences on its surface. The design and engineering of excavation operations necessitates a focus on minimizing risk and its associated effects through the implementation of high penetration rates. The achievement of a successful and optimal excavation operation is contingent upon a high penetration rate and the absence of any excavation-related issues. The analysis of field information is a crucial component in reducing costs and enhancing excavation operations, and the development of tools for field information analysis represents a viable means of improving excavation operations. Over the course of approximately four decades, there has been a growing recognition of the need to optimize excavation operations through the application of meta-innovative algorithms, resulting in the proposal of models for estimating penetration rates. While these models utilize only a subset of factors that impact penetration rate prediction, they are widely employed. The TBM has demonstrated high efficiency in excavating underground structures such as water conveyance tunnels, owing to its high advancement rate, continuous boring process, and simultaneous lining installation. As such, the prediction of TBM performance is a critical factor in the success of tunneling projects During the early 19th century, the growing demand for subterranean transportation and the necessity of constructing new routes and lengthy tunnels led to the emergence and advancement of tunnel boring machines (TBMs). The efficacy of these machines is influenced by a range of factors including geological conditions, rock mass properties, tunnel route slope, and technical specifications of the TBM. The evaluation of TBM efficiency and geo-technical characteristics of the site is predicated on the analysis of construction cost estimation and time scheduling for each tunneling project. TBMs offer numerous advantages for subterranean excavation projects. [4]. In urban areas, the implementation of this approach results in reduced damage zones and surface settlements. [5]. The prognostication models for TBM performance can be classified into two distinct categories: empirical models, which are the most commonly used, and theoretical or semi-theoretical models. Empirical models are typically developed by analyzing the performance of machines in previous tunneling projects. These models are primarily based on statistical analysis of rock and machine measurements, and are attractive as they consider both ground and excavation conditions to create an ideal model. However, these models are site-specific and it is challenging to establish a universal model for predicting TBM performance. From a practical standpoint, this implies that such analyses aim to consider all aspects of rock properties and TBM parameters, as well as operational and geological constraints, either directly or indirectly. The model developed at the Norwegian Institute of Technology (NTNU) is widely recognized as one of the most frequently employed empirical models. The implementation of theoretical and semi-theoretical models involves the integration of theoretical principles and empirical equations. In the context of TBM performance parameters, theoretical and semi-theoretical models are considered more reliable than empirical methods. These models possess the ability to analyze the forces acting on the cutters or the amount of specific energy required to excavate a unit volume of rock. Through analysis, these models facilitate the determination of intact rock and rock mass parameters, as well as machine parameters. The classification of TBMs has resulted in a notable model developed at the Colorado School of Mines (CSM), which has garnered considerable attention. This particular model utilizes equations to calculate the advance rate and incorporates the thrust, torque, and penetration to attain the most efficient TBM cutterhead pattern. In the field of rock engineering, it is imperative to recognize the models that have been developed in accordance with rock mass classification systems.Two such models include the QTBM [12, 13] and the Rock Mass Excavability (RME) indicator [14, 15, 16, 17]. The current investigation was conducted with the explicit objective of identifying predictive targets and determining the optimal TBM selection. Furthermore, several scholars ([18, 19, 20, 21]) have made efforts to assess the boreability of rock formations by proposing empirical equations that rely mainly on the correlations between the characteristics of individual rocks and rock masses.Tarkoy (22) proposed a theoretical framework for forecasting the rate of rock penetration by leveraging their hardness as a predictive factor. Graham (23) introduced a predictive model for determining the penetration rate of rocks possessing compressive strength within the range of 140 to 200 MPa. Farmer and Glossop [24] undertook measurements of the Rate of Penetration (ROP) of TBMs in sedimentary rock formations. The penetration rate of TBMs was assessed by Cassinelli *et al*. [25], utilizing the Rock Structure Rating (RSR) as a metric. Lislerud *et al*. [26] presented a theoretical framework aimed at improving the efficiency of TBMs in excavating lime, shale, gneiss, and basalt geological formations.According to Bamford [27], the rate of penetration of TBMs can be determined by several factors including the thrust, cone indentor index, and schmidt hammer hardness. Grima *et al.* [28] presented a pioneering approach for forecasting the performance of TBMs through the utilization of a neuro-fuzzy methodology. Delisio *et al.* [29] formulated a predictive model for the performance of TBMs in blocky rock.. Vergaraa and Saroglou [30] conducted an assessment of the performance of TBMs in ground conditions that were characterized by a mixture of different types of rock. The geological and mechanical properties of the rock mass were examined by Armetti *et al.* [31] in order to forecast the performance of the TBM. The study conducted by Kim *et al.* [32] examined the performance of TBMs by analyzing the correlation between the rock mass rating (RMR) and specific energy. Table 1 summarizes several proposed prediction models. In this study, several approaches are used to predict the performance of TBMs in two real Iranian water conveyance tunnels. TBM performance prediction using these methods was carried out in in other projects such as the Kerman tunnel, and was not yet performed for the Gavoshan water conveyance tunnel.

Table 1. TBM performance prediction models.

Researchers/models	Proposed predictive equations for TBM performance
Tarkoy [22]	$PR = 3.716-0.019 * HT, HT = HR * (HA)^{0.5}$
Farmer and glossop [24]	$PR = 624\ Fn/\sigma_{tB}$
Cassinelli *et al.* [25]	$PR = -0.0059RSR + 1.59$
Lislerud *et al.* [26]	$PR = ib * KS * Kd$
Bamford [27]	$PR = 0.5355 - 8.49 – 0.00344T – 0.000823N + 0.0137\varphi$
Innaurato [33]	$PR = \sigma c^{-0.437} - 0.047\ RSR + 3.15$
Barton [12]	$PR = 5 * QTBM^{-0.2}$ $QTBM^{-0.2} = RQD_0 / J_n * J_r / J_a * J_w / SRF * 20^9\ SIGMA/F^{10} * 20/CLI * q / 20 * \sigma_\theta$
Ribacchi and Lembo-Fazio [34]	$SP = 250\ \sigma\ cm^{-0.66},\ \sigma^{-0.66} = \sigma\ c\ \exp(RMR - 100/18)$
Bieniawski *et al.* [15]	$ARA = 0.422RME – 11.61$
Yagiz *et al.* [35]	$ROP = 1.093 + 0.029 * PSI - 0.003UCS + 0.437 * Log (\alpha) - 0.219 * DPW$
Gong and Zhao [19]	$BI = 37.06 * UCS0.26 * Bi - 0.10 * (0.84e - 0.05JV + e-0.09 * \sin(\alpha + 30)$
Hassanpour *et al.* [36]	$FPI = 0.222BRMR + 2.755$
Hassanpour *et al.* [36]	$FPI = 9.273e^{0.008GSI}$
Hassanpour *et al.* [36]	$FPI = 11.718Q^{0.098}$
Khademi Hamidi *et al.* [37]	$FPI = 4.161 + 0.091\ \sigma c + 0.077RQD + 0.117 + JC + 1.077loga$
Khademi Hamidi *et al.* [37]	$FPI = 9.401 + 0.397loga + 0.011JC^2 + (1.14 * 10^{-5})RQD^3 + (1.14 * 10^{-5})\sigma c^4$
Khademi Hamidi *et al.* [37]	$FPI = 1.828\ \sigma c^{0.313}.\ RQD^{0.207}.JC^{0.044}.\alpha^{0.012}$
Hassanpour *et al.* [20]	$FPI = \exp(0.008UCS + 0.015RQD + 1.384$
Vergaraa and Saroglou [30]	$MFPI = 2.12e^{0.02.RMR_m}$
Armetti *et al.* [31]	$FPI = 0.05 * RMR^2 - 4.22 * RMR + 137.9$
Armetti *et al.* [31]	$FPI = 0.08 * GSI^2 - 8.07 * GSI + 265.8$
Afradi *et al.* [38]	$PR = -0.0025.UCS + BTS^{0.0209} - 0.3927.RQD + C^{0.3754} - 1.4123.E + P^{0.8865} - 1.5321.D - 0.2897.JA + JS^{2.5411}$
Afradi *et al.* [38]	$PR = -0.0025.UCS + BTS^{0.0224} - 0.3999.RQD + C^{0.3779} - 1.4186.E + P^{0.8898} - 1.5398.D - 0.2811.JA + JS^{2.5497}$
Afradi *et al.* [38]	$PR = -0.0025.UCS + BTS^{0.0255} - 0.3956.RQD + C^{0.3798} - 1.4119.E + P^{0.8810} - 1.5306.D - 0.2802.JA + JS^{2.5422}$

2. Materials and Methods

The application of statistical and artificial intelligence techniques presents a novel approach that can be easily customized to tackle a wide range of optimization problems with minimal adjustments. While algorithms modify a solution during the search process, population-based algorithms consider multiple solutions based on the solution being sought. Answer-based algorithms tend to concentrate on local search areas, whereas population-based algorithms can simultaneously explore different regions of the solution space. In this section, statistical and artificial intelligence approaches are employed due to their high analytical capability and dependable outcomes. It is noteworthy that these methods are being utilized for the first time for the tunnels presented herein.

2.1. Multivariate linear regression (MlR)

Linear regression is a statistical technique that entails constructing a model of the association between a response variable and one or more explanatory variables in a linear fashion. The fundamental aim of regression analysis is to investigate the linear equation model between variables, pre-supposing that one or more explanatory variables, whose values are autonomous of other variables or subject to the researcher's control, can be instrumental in forecasting a response variable that is not reliant on explanatory and controlled variables [39]. Default regression is as follows [39]:

A) Ratio of observations of independent variables: The requisite number of observations for a given test is contingent upon the specific regression model employed. In the case of standard or ideal regression, the number of observations ought to be twenty-fold the number of independent variables, whereas stepwise regression necessitates a greater number of observations. The minimum number of observations required, or alternatively, the minimum sample size, should be no less than five times the number of independent variables.

B) Outliers: The impact of remote observations on the regression model is significant and warrants their elimination or correction to mitigate this effect. Univariate throw points can be obtained through the construction of a distribution diagram or frequency table. In contrast, statistical techniques, such as the Mahalanobis distance, or graphical methods, such as residual distribution diagrams, can be employed to identify multivariate throw points.

C) Multiplicity between independent and singular variables: Multiplicity refers to a robust correlation, approaching unity, among independent variables, whereas singularity arises when there is an exact correlation, equal to unity, among independent variables. These phenomena have implications for the interpretation of relationships between independent variables and the dependent variable, and can be assessed through examination of the correlation matrix, the square of multiple correlations, and the tolerance. In practice, many computer programs utilize default values for multiple alignments, and exclude variables that exhibit such issues from the model.

D) Normality, linearity, homogeneity of variances, and residual independence: Through the utilization of residual distribution diagrams, an examination of the residuals can be conducted. It is posited that the disparity between the observed and predicted dependent variables conforms to a normal distribution. Furthermore, it is assumed that the residuals exhibit a linear relationship with the predicted dependent variable scores, and that the residual variance remains constant across all predicted scores. Insignificant deviations from the linearity assumption are deemed to be of minimal consequence.

2.2. Artificial neural network (ANN)

The Artificial Neural Network (ANN) is a computational model that replicates the structure and functions of biological neural networks, thereby facilitating information processing. ANNs consist of numerous interconnected neurons that collaborate to solve intricate problems [40]. Similar to humans, ANNs acquire knowledge from examples and are designed to execute specific tasks such as pattern recognition and information categorization during the learning process. ANNs comprise artificial neurons or nodes that imitate biological neurons, where weighted inputs are accumulated and processed through an activation operation to generate an output. The human brain contains approximately 10^{11} neurons, and ANNs are assessed using powerful prediction tools such as curve fitting, classification, and clustering. ANNs are extensively employed in high-frequency applications, and can vary in size from a few neurons to several thousand neurons, depending on the complexity of the problem [41].Artificial neural networks (ANNs) are characterized by the reception of inputs by neurons in a specific manner, whereby the neuron is activated if the inputs are sufficient. Conversely, if the activity of the neuron falls below a predetermined threshold, it remains inactive. The inputs collected by a neuron are subsequently transmitted to an excitation function that calculates a specific output, which is then conveyed to another layer of neurons or to the network output. ANNs represent a system that processes data with specific operational properties, akin to neural networks, and have been developed to generalize mathematical models of neural networks based on certain assumptions [42].

1. The processing of data occurs within fundamental units known as neurons.
2. The exchange of information among neurons occurs through inter-neuronal communication.
3. Each of these relationships possesses a distinct weight that is multiplied in the transmission of information from one neuron to another.

4. Every individual neuron performs a computation of its output by utilizing a mobility function, which is typically non-linear in nature, to process its inputs, which are aggregated information that have been weighted. Neural networks are comprised of a collection of small datasets, commonly referred to as neurons, units, or nodes. These neurons are interconnected through directional interfaces that possess their own weight, which represents the necessary network information required to solve a given problem. The applications of neural networks are vast and include data storage and review, shape grouping, general mapping of input to output sets, similarity grouping of shapes, and optimization and solution determination despite constraints. Each neuron in a neural network has a definite state that is dependent on the outcome it receives, and typically sends its response to other neurons. Neurons within the same layer generally behave similarly, with the primary determinant of a neuron's behavior being its excitation function and the weighing interfaces through which information is received or transmitted. In most cases, neurons within a layer have the same stimulation function and communication method [42].

2.3. Support Vector machine (SVM)

The Support Vector Machine (SVM) is a powerful instrument in the domain of supervised learning, utilized for both classification and regression. Its efficacy exceeds that of its antecedents such as the perceptron neural networks. The SVM is not confined to classification, as it can also be employed as a regression methodology. The design parameters for case studies of the SVM are listed in Table 2 [43, 44].

Table 2. SVM design parameters.

Model	Kernel	Degree	ε	C	σ
$\varepsilon - SVR$	Radial basis function (RBF)	2	0.1	1000	0.5

2.4. Evaluation criteria

The coefficient of determination is a statistical measure utilized to assess the explanatory power of a model. It quantifies the proportion of variance in the dependent variable that can be accounted for by the independent variables, thereby, indicating the degree to which the model can explain the observed data. Specifically, it represents the total variation in the dependent variable as the sum of the variation explained by the regression and the variation not explained by the regression. This coefficient provides a probabilistic estimate of the correlation between two sets of data in the future, based on a defined mathematical model that conforms to existing data.

The coefficient of determination serves as a criterion for evaluating the accuracy of the regression line in representing the variables, with a higher value indicating a better fit. It also reflects the correspondence between observed and predicted values, which can be evaluated through parsing and fitting methods. The coefficient of determination ranges from zero to one, with an optimal value of one indicating perfect agreement between simulated and observed values.In the present study, the coefficient of determination (R^2) and root mean square error (RMSE) were employed as criteria for evaluating the accuracy and efficiency of the models. An R2 value of one and an RMSE value of zero were considered optimal for each criterion, respectively. Additionally, distribution diagrams and comparative graphs of observed and computed values were utilized to further analyze and compare the results.

$$R^2 = \frac{\sum_{i=1}^{N}(Xi - \bar{X})(Yi - \bar{Y})}{\sqrt{\sum_{i=1}^{N}(Xi - \bar{X})^2 \sum_{i=1}^{N}(Yi - \bar{Y})^2}} \quad (1)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Xi - Yi)^2} \quad (2)$$

At time step i, Xi and Yi represent the computational and observational values, respectively, while N denotes the total number of time steps. The mean values of computational and observational data are denoted by X¯ and Y¯, respectively [44].

2.4.1. Q TBM model

Through an analysis of the relationship between the Q classification system and TBM performance, utilizing field data from the excavation of 145 tunnel projects exceeding a length of 1000 km across a diverse range of rock types, Barton [12] determined that the Q value may be infinite when estimating intrusion rate values, and that advance should be utilized instead. However, it was found that this classification system requires correction, and parameters pertaining to the interaction between rock and machine must be taken into account in order to obtain accurate values for penetration and advance rates. As such, Barton [12] has proposed the QTBM equation, which involves a few modifications to the original Q equation, and includes equations for both penetration rate and advance rate, as follows.

$$PR = 5*QTBM^{-0.2} \quad (3)$$

$$QTBM^{-0.2} = RQD_0 / J_n * J_r / J_a * J_w / SRF * 20^9 \, SIGMA/F^{10} * 20/CLI * q/20 * \sigma_\theta \quad (4)$$

$$AR = PR * U,\ AR = PR * T^m,\ U = T^m \quad (5)$$

The corrected value of Rock Quality Designation (RQD) along the axis of the tunnel is denoted as RQDo. The parameters Jn, Jr, Ja, Jw, and SRF remain unchanged, and are analogous to Q. However, Jr and Ja should be attributed to the category of joints that are most involved in tunnel excavation. F represents the average force applied to each disk in terms of tons of force, which is normalized to 20 tons of force. The Quartz content (Q) is expressed as a percentage, and the stress in the tunnel chest (σ_θ) is normalized to a depth of approximately 100 m and measured in megapascals. SIGMA denotes the compressive strength of the rock mass. The cutter life index (CLI) is imported from the Norwegian University of Science and Technology (NTNU) model. Penetration rate (PR) and advance rate (AR) are measured in meters per hour, while U represents the efficiency of the machine, and T denotes the time. The negative gradient is represented by m. In the Q TBM method, geological conditions have a greater impact than the characteristics of the device. The only parameter that reflects the device's characteristics in this method is the CLI, which is two-dimensional and affects both the material of the cutting tool and the geological characteristics of the excavation area. Hence, CLI cannot serve as a suitable benchmark for assessing the capabilities and performance of a machine. The method's independence from the technological features of the excavation process has rendered it largely autonomous from such conditions. The effectiveness of the support operation is also influenced by geological factors. Among these factors, the filling of joints is the only parameter that is somewhat less significant. This limitation is also present in the initial model of the tunneling in rock quality index. The parameters of the Q TBM method can be estimated through observation and equations or measured through simple experiments. However, the CLI parameter is the only factor that directly impacts the results, and complex experiments are required to accurately estimate it. Conversely, the factors in the Q TBM model do not necessitate complex experiments, except for the CLI. This index is applied in reverse, and approximating this factor within certain ranges will not cause significant changes in the outcome. Due to the extensive database based on the mass index of rock mass and its frequent use in mining and construction projects, accurate estimation of geological factors is possible using the Q TBM model. In projects with diverse seam structures, where only basic information and geological factors are available, and costly tests are not feasible, the Q TBM model is more appropriate. However, this method is also limited by the lower impact of excavating machine specifications and joint filling factor in their equations.

2.5. Case studies

A) Gavoshan water conveyance tunnel

The Gavoshan water conveyance tunnel with a length of 20.1394 kms is located in the south Kurdistan province. This tunnel was excavated by blasting, roadheader, and TBM. In terms of structural geological divisions, the northern half of the tunnel route is located in the Sanandaj-Sirjan zone, and its southern half is located between an ophiolite zone and the zagros thrust zone. The lithology of the tunnel route varies from sedimentary rocks including sandstone, shale, limestone, and conglomerate to igneous and metamorphic rocks including diabase, gabbro diorite, peridotite, and amphibolite [45]. Gavoshan water conveyance tunnel is located in the vicinity of Sanandaj-Sirjan and Zagros zones from the point of view of Iran's structural divisions. The route of Gavoshan water conveyance tunnel is generally divided into two north-south halves with different characteristics. The northern hemisphere is composed mainly of sedimentary rocks with an alternation of shale, sandstone, siltstone, conglomerate and slightly modified sedimentary rocks belonging to the flysch facies. The southern half is composed of igneous rocks such as diabase, gabbro, diorite, andesite, ultrabasic, and split and basalt, which represent the remnants of the oceanic crust without any special rotation. Therefore, weak, loose and abandoned rocks in the northern half and strong and good quality rocks, except in the area of faults and crushed zones in the southern half of the tunnel route. The tunnel area is located in Sanandaj-Sirjan zone in terms of structural geology. Lithological diversity, discontinuities and numerous lithological contacts are the prominent features of Gavoshan water conveyance tunnel [45]. The location of the Gavoshan water conveyance tunnel is illustrated in Figure 1.

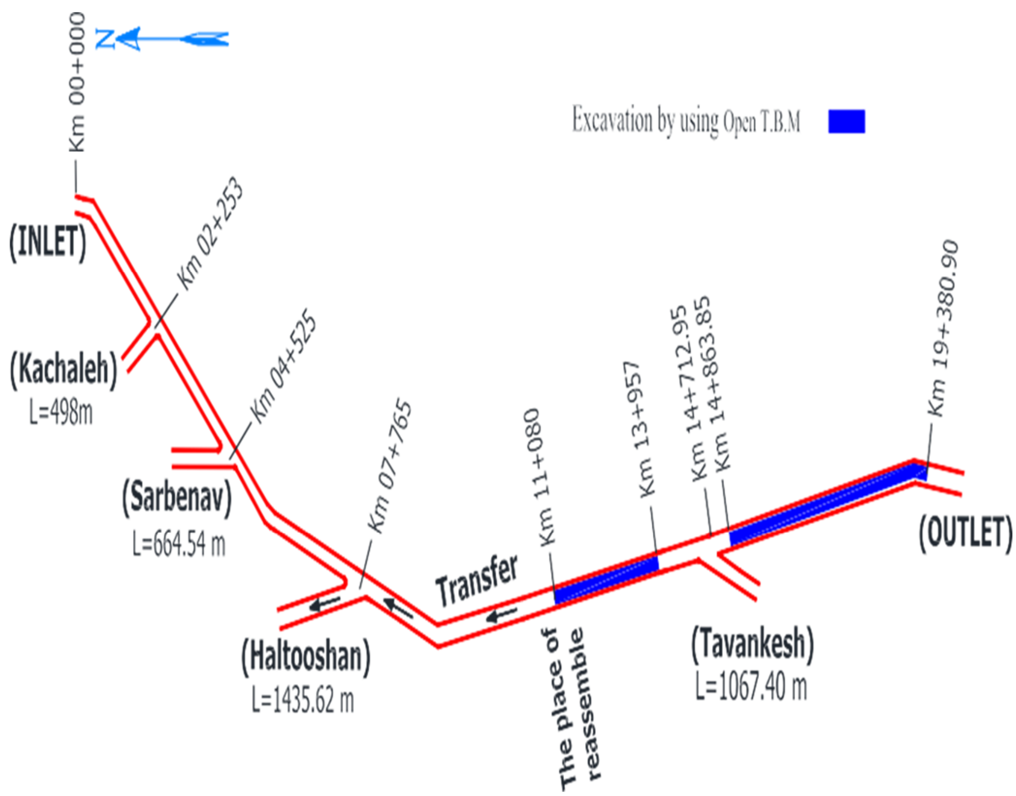

Figure1. Location of the Gavoshan water conveyance tunnel [45].

B) Kerman water conveyance tunnel

The Kerman water conveyance tunnel spans a total length of 37.9 km, consisting of a northern segment measuring 18.9 km and a southern segment measuring 19.0 km. The geological composition of the tunnel route is characterized by a diverse range of sedimentary rocks including sandstone and limestone as well as volcanic rocks such as tuff and volcanic ash. Additionally, a minor combination of diorite to granite and granodiorite is present along the route [46]. The studied area is part of the Cenozoic magmatic arc of Kerman. The extension of this strip is in the northwest-southeast direction, and its internal structure is very complex. The blocks of this area are separated from each other by faults that have continued their activity until the present time. The oldest deposits in this area are the Upper Cretaceous flysch, which can be seen in the north of the project area, and the youngest deposits are sediments of the present era. Sediments in the area include detrital sediments such as lime and calcareous conglomerate. In this area, two volcanic complexes with Eocene age have been identified, which due to their magmatic activities, large masses from granodiorite rocks to semi-deep andesitic dacites have been replaced along this area. These rocks can be divided into two main categories of prominent mountain-type granodiorites and semi-deep rocks of Mount Five. In the 10 km excavated route, the main route rocks are external and internal igneous type and include diorite, andesite, and basalt, which are lithologically rich in plagioclase feldspars [46]. The location of the Kerman water conveyance tunnel is illustrated in Figure 2.

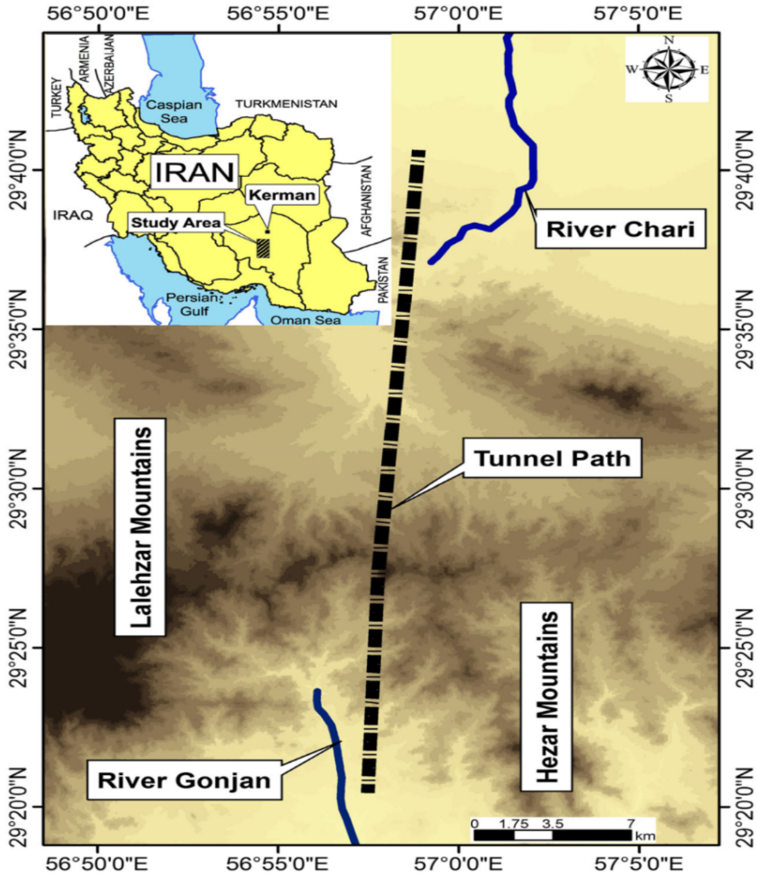

Figure 2. Location of Kerman water conveyance tunnel [46].

2.6. TBM specifications

The selection of the appropriate type of excavating machine is a crucial aspect in the implementation of mechanized tunnel excavation. The initial step involves the technical selection of at least two different types of full-length machines, which is based on an examination of the geological conditions and project schedule. The geological and geo-technical conditions of the surrounding rock, as well as the type of materials that comprise it, are significant factors that have always posed challenges in tunnel implementation. The presence of discontinuities, layer changes, permeability, and other related issues must be carefully considered during the pre-decision stage to ensure the appropriate selection of the machine. Additionally, the project schedule plays a critical role in determining the type of machine to be used. For instance, the selection of an open cross-section machine is influenced by the usual time required for concreting and final lining of the tunnel in each country, which is dependent on the level of manpower training and technology available. Therefore, it is imperative to carefully consider this aspect to ensure timely project execution. After the initial selection of the machine based on technical and executive criteria, economic considerations must also be taken into account. With the advancement of technology, tunnel excavating machines have made significant progress in the recent years, and are now categorized into two general types: soil excavating and rock excavating. Some machines are also classified as shielded or open. However, due to the rocky nature of the tunnel route, this report will only provide a brief introduction to tunnel excavating machines in rock. The specifications of the TBMs used for the two water conveyance tunnels are given in Tables 3 and 4.

Table 3. Specifications of the TBM for the Gavoshan water conveyance tunnel [45].

Parameter	Value
TBM type	Open TBM hard rock (S112) from German Hernknscht Company
Main drive	180 ton
Disc cutters	7 double & 20 singles & 6 Scraper plate
Advanced cylinders	4 * 1600 mm / 340 mm

Table 4. TBM specifications for the Kerman water conveyance tunnel [47].

Parameter	Value
TBM type	Double shield hard rock TBM
Cutterhead diameter	4665 mm
Number of disc cutters	27
Center discs No./size/wear limit	1 to 8/432 mm/25 mm

2.7. Database

For the considered case studies, the input (dependent) and output (independent) variables through the analyses are listed in Table 5. For this step, the data of the two tunnels was merged. Descriptive statistics and parameters can be seen in Table 6.

Table 5. Dependent and independent variables.

Input	Rock Quality Designation (RQD) (%), Brazilian Tensile Strength (BTS) (MPa), Uniaxial Compressive Strength (UCS) (MPa) Density (D) (gr/cm^3), Joint Angle (JA) (deg.), Joint Spacing (JS) (m), Poisson's ratio
Output	Penetration Rate (PR) (m/h)

Table 6. Descriptive statistics of the two studied areas.

	RQD (%)	BTS (MPa)	UCS (MPa)	D (gr/cm^3)	JA (deg.)	JS (m)	Poisson's Ratio	PR (m/h)
Mean	**53.53**	**10.86**	**104.50**	**2.45**	**28.69**	**0.67**	**0.27**	**1.21**
N	200	200	200	200	200	200	200	200
Std. Deviation	18.08	2.57	39.19	.10	8.64	0.38	0.05	0.58
Minimum	10	5.00	30.00	2.30	14	0.2	0.15	0.40
Maximum	90	14.99	180.00	2.70	53	1.6	0.40	2.93
Variance	326.96	6.61	1536.20	0.01	74.75	0.14	0.00	0.34
Std. Error of mean	1.27	0.18	2.77	.00	0.61	0.02	0.00	0.04
Harmonic mean	44.92	10.13	88.56	2.44	26.00	0.47	0.25	0.97
Geometric mean	49.77	10.52	96.75	2.45	27.36	0.56	0.26	1.08

2.8. Sensitivity analysis of parameters

According to the conventional definition, sensitivity analysis involves examining the impact of output variables on the input variables of a statistical model. This systematic approach entails modifying the inputs of a statistical model to ascertain the extent to which varying values of an independent variable influence a specific dependent variable, given a set of assumptions. It is important to note that this technique is subject to certain limitations, as the parametric values and assumptions of each economic model are subject to change and error. Large-scale sensitivity analysis examines the potential impact of these changes and errors on the results of the model. Sensitivity analysis methods can be classified into three main groups: mathematical, statistical (probabilistic), and graphic. This classification helps to determine the appropriate method for a variety of models and their respective benefits. Mathematical methods are useful for both definite and probabilistic models, while statistical methods are commonly used for probabilistic models. Graphic methods, on the other hand, can be used for any type of model. In the realm of system analysis, sensitivity analysis pertains to evaluating and approximating the degree of sensitivity exhibited by the predicted behavior of a system, or its output, in response to variations in the values of the independent variables, or its input. In this research work, we analyze the sensitivity of TBM parameters to demonstrate how these parameters are affected.

3. Results of Analyses

3.1. Prediction model for penetration rate by MLR

In order to develop a predictive model for the penetration rate, a linear regression analysis was conducted on the available database. The resulting regression coefficients were presented in Table 7, and Equation 6 was derived to describe the linear relationship between the independent variables and the penetration rate. The distribution and fitting diagram between the measured and predicted penetration rates are depicted in Figures 3 and 4, respectively.

$$PR = 1.006-0.001 * RQD - 0.001BTS - 0.004UCS - .0008D - 0.006JA + 0.100JS + 0.680P \quad (6)$$

Table 7. Regression coefficients of linear regression model.

Model		Unstandardized coefficients B	Unstandardized coefficients Std. Error	Standardized coefficients Beta	t	Sig.
1	(Constant)	1.006	0.370		2.721	0.007
	RQD (%)	-0.001	0.001	-0.022	-0.799	0.426
	BTS (MPa)	-0.001	0.007	-0.004	-0.113	0.910
	UCS (MPa)	-0.004	0.001	-0.249	-6.400	0.000
	D (g/cm^3)	-0.008	0.154	-0.001	-0.049	0.961
	JA	-0.006	0.002	-0.085	-2.866	0.005
	JS (m)	0.100	0.043	0.065	2.319	0.021
	Poisson's ratio	0.680	0.033	0.763	2.475	0.000

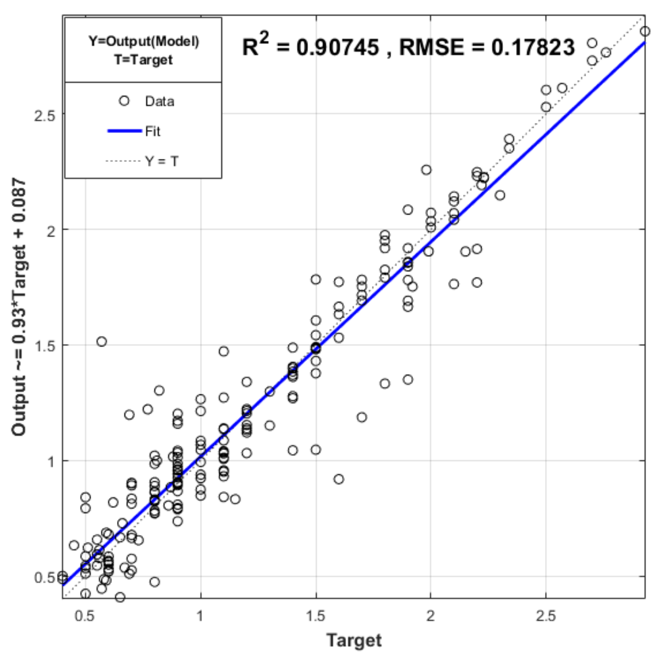

Figure 3. Distribution diagram obtained by MLR.

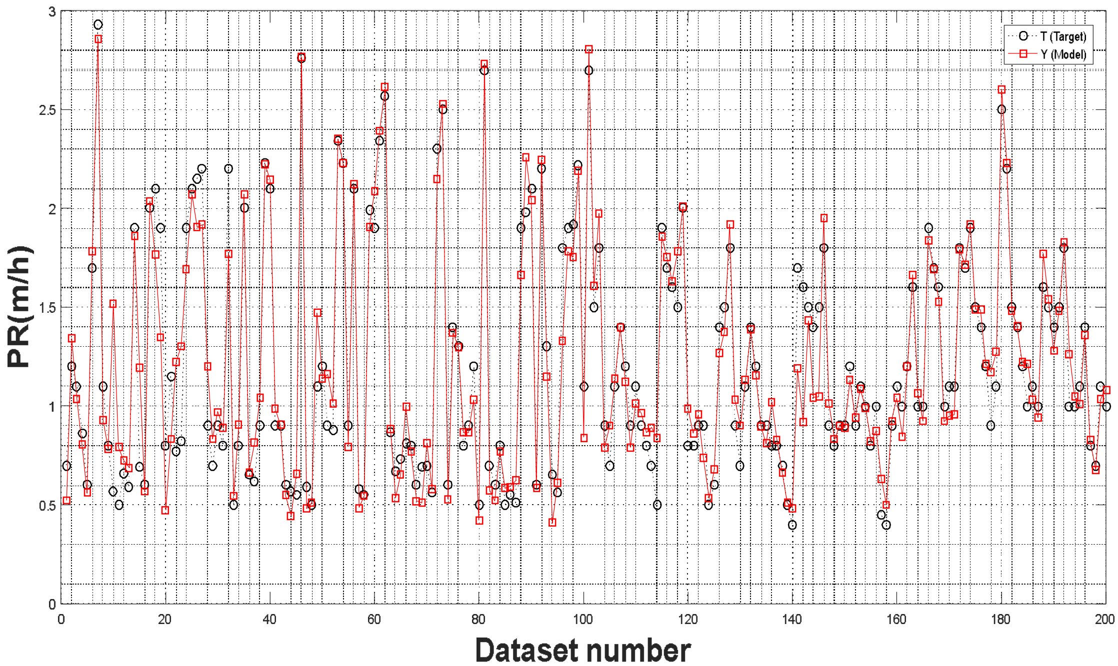

Figure 4. Fitting diagram given by MLR.

3.2. Prediction model for penetration rate by ANN

The utilization of ANN has been employed in the database to predictive model for penetration rate. R^2, RMSE, distribution diagram, and fitting diagram of TBM penetration rate have been presented in Figures 5 and 6.

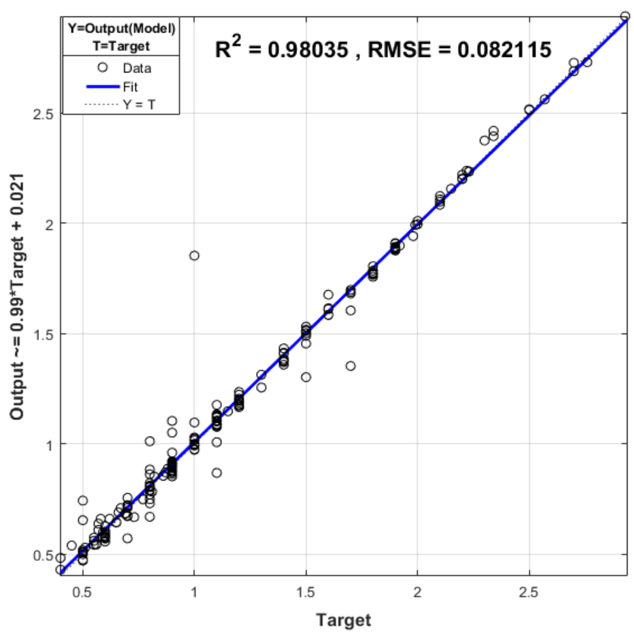

Figure 5. Distribution diagram obtained by ANN.

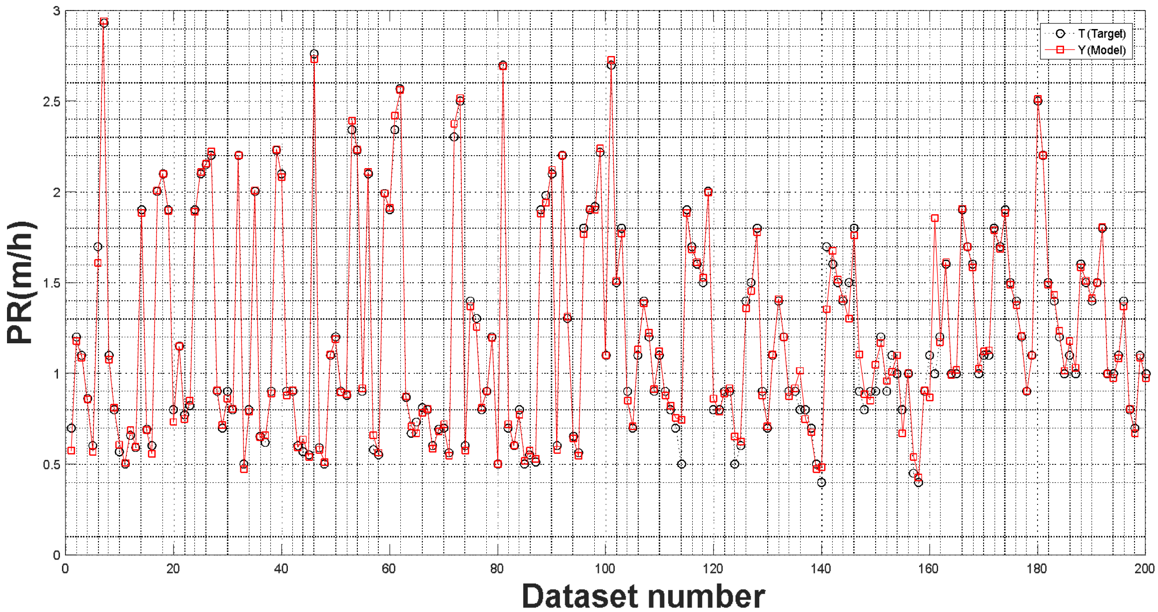

Figure 6. Fitting diagram obtained by ANN.

3.3. Prediction model for penetration rate by SVM

Figure 7 displays R^2, RMSE, and Support Vector Machine (SVM) utilized for the prediction of penetration rate. Figure 8 presents fitting diagram of the measured values or target and the predicted values by the SVM predictive model.

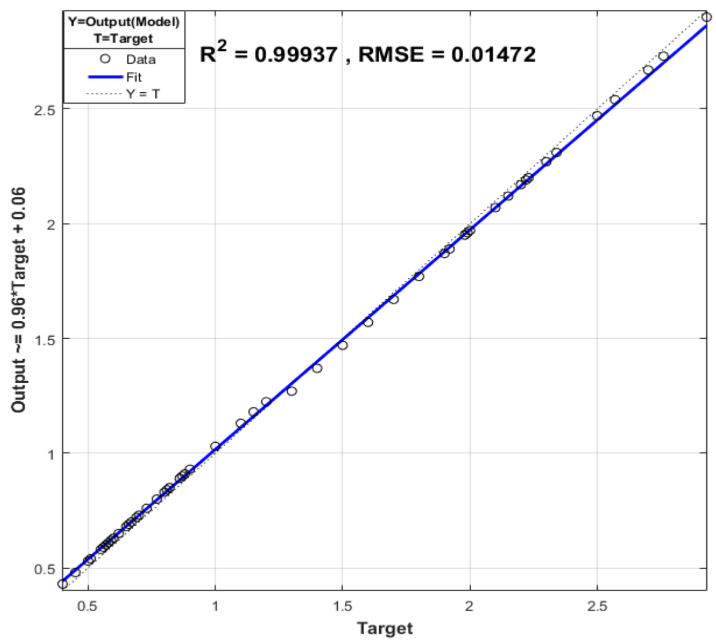

Figure 7. Distribution diagram obtained with SVM.

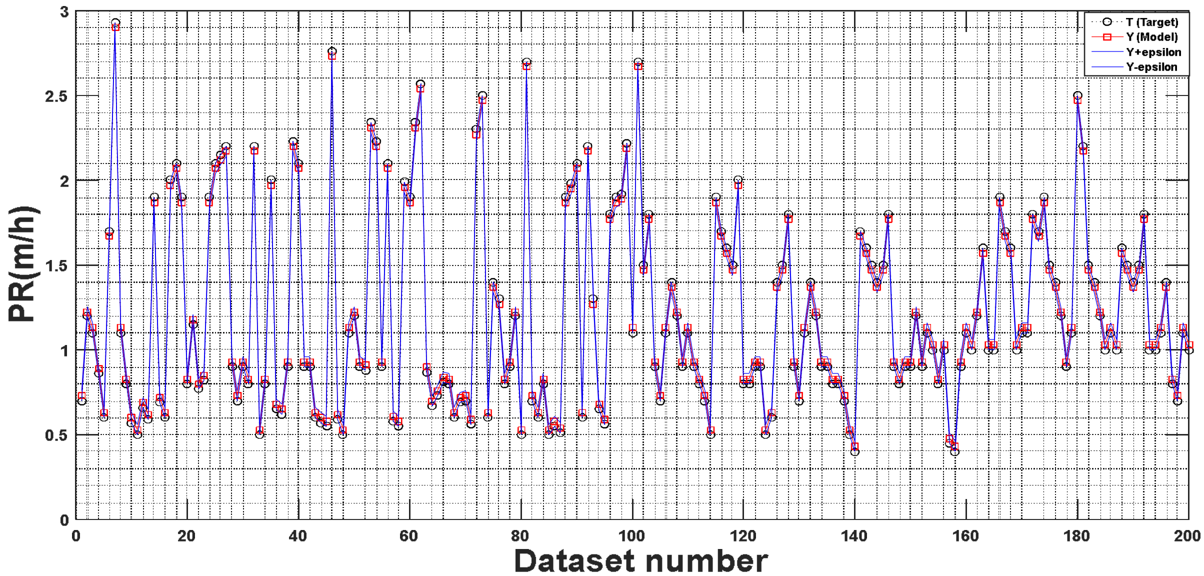

Figure 8. Fitting diagram by SVM.

3.4. Estimation of penetration rate using Q TBM

The determination coefficient, the root means square error, and Q TBM for predicting penetration rate are shown in Figure 9. Matching graph of measured values or target and the predicted values by Q TBM predictive model is shown in Figure 10.

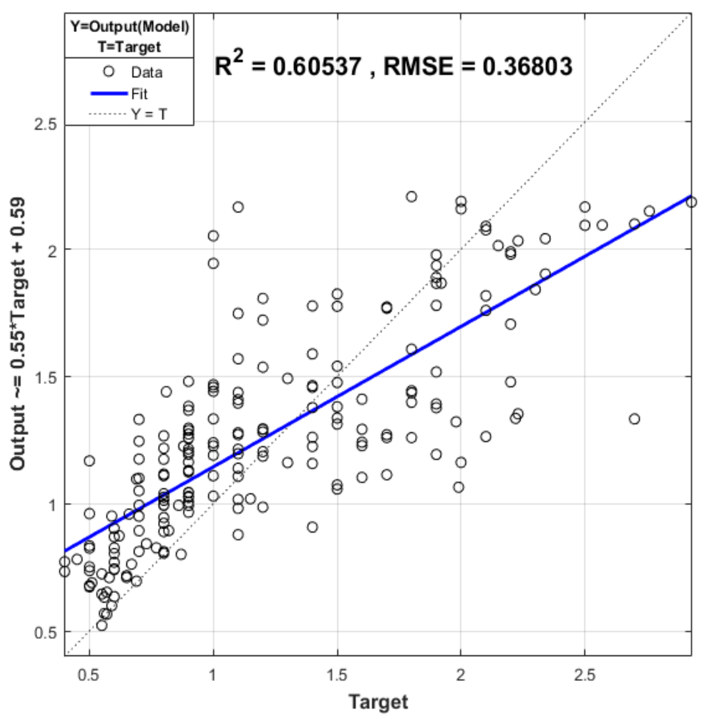

Figure 9. Distribution diagram obtained with Q TBM.

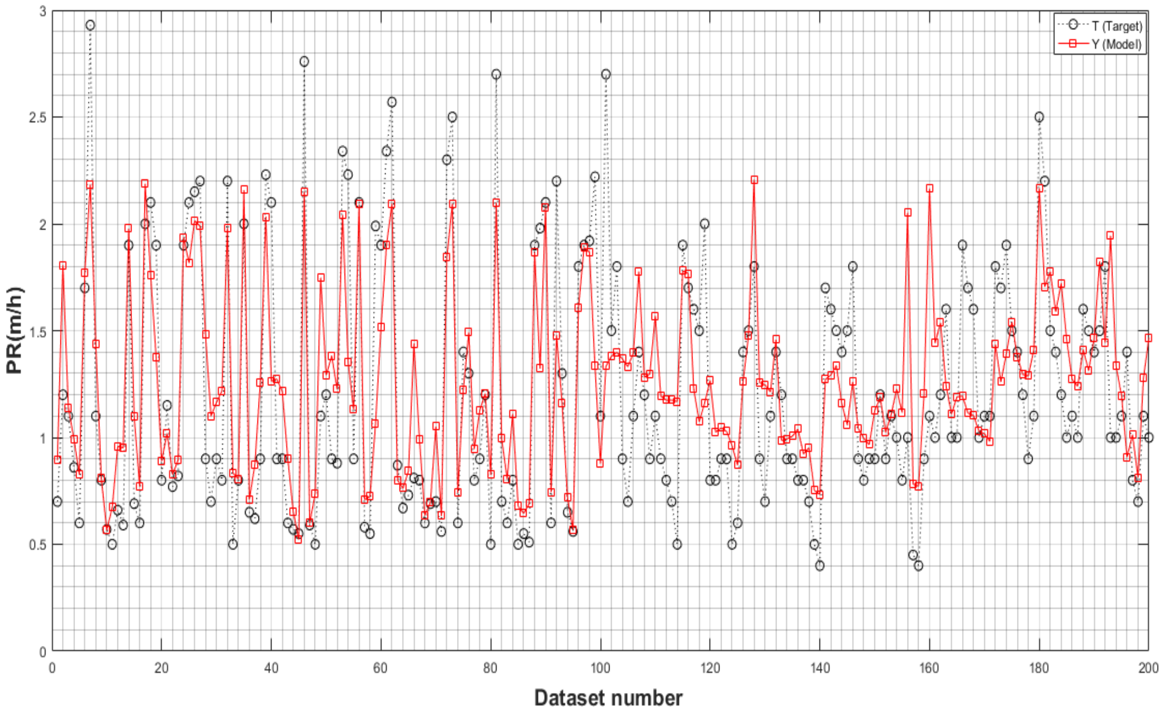

Figure 10. Fitting diagram by Q TBM.

3.5. Comparison of achieved results with results of Q TBM

In this part, the achieved results (predicted values) using MLR, ANN, and SVM are compared with the measured values (target). Moreover, these predicted values are also compared to the obtained values using the Q TBM model, the most extensively used TBM performance prediction model. Figure 11 and Table 8 show the superiority of the models obtained in this study compared to the Q TBM one.

3.6. Sensitivity analysis

Sensitivity analysis is a widely used method in various fields to assess the impact of changes in independent variables on a dependent variable, while holding a set of assumptions constant. This technique involves a thorough examination of the influence of diverse sources on a mathematical model, under both deterministic and stochastic conditions. It is commonly employed in disciplines that deal with one or more input variables and aim to measure the behavior of a function or relation based on them. The analysis is based on the constraints assumed for each of the independent or dependent variables, and is predicated on input variables that affect the output variable. Sensitivity analysis is also known as "if-then" analysis or simulation analysis, as it enables the prediction of the output of a decision based on a range of variables. In this study, we analyzed the sensitivity of the parameters. As you can see in Figures 12 and 13, the UCS parameter has the most impact on modeling. Also the effect of the parameters is shown in Figure 12.

Table 8. Model analysis.

Model	R^2	RMSE
MLR	0.90	0.17
ANN	0.98	0.08
SVM	0.99	0.01
Q TBM	0.60	0.36

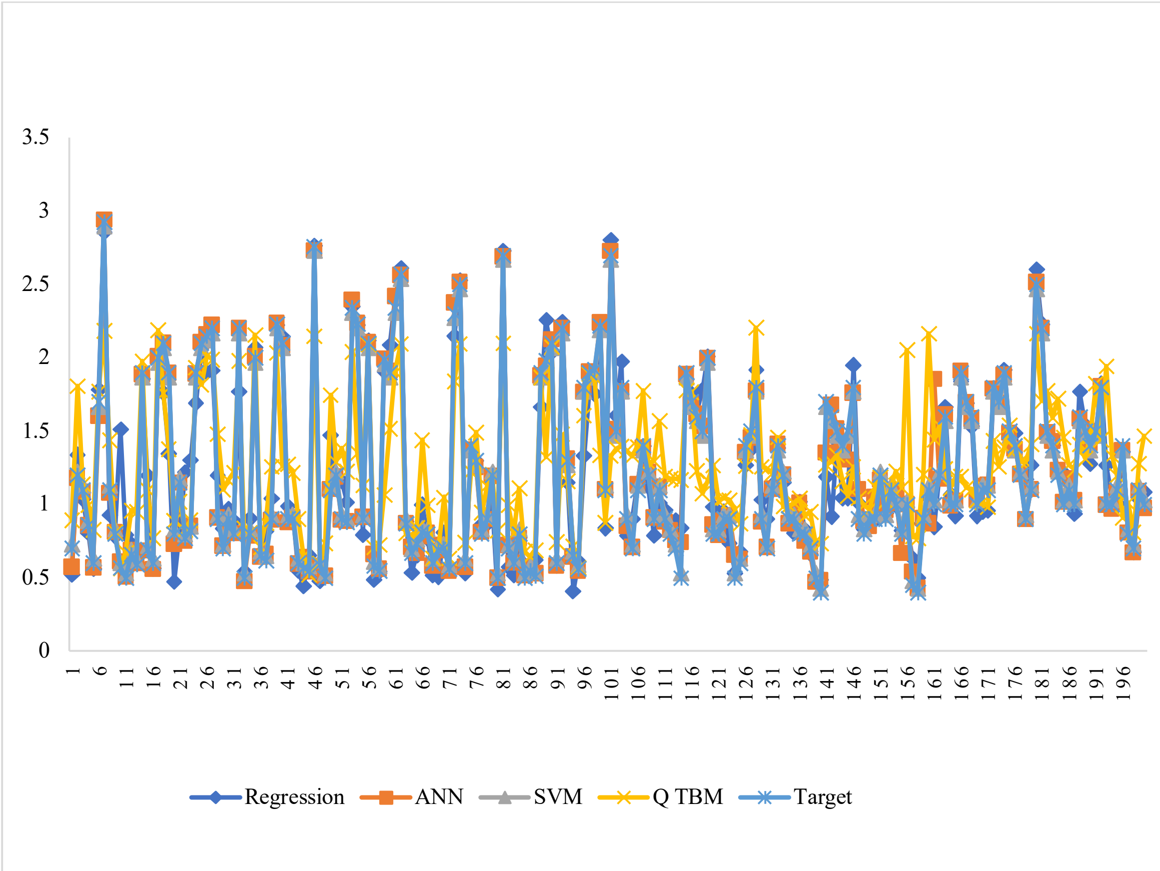

Figure 11. Comparison of achieved results with results of Q TBM.

As can be seen, the SVM and ANN approaches yield the closest values to the actual values, respectively.

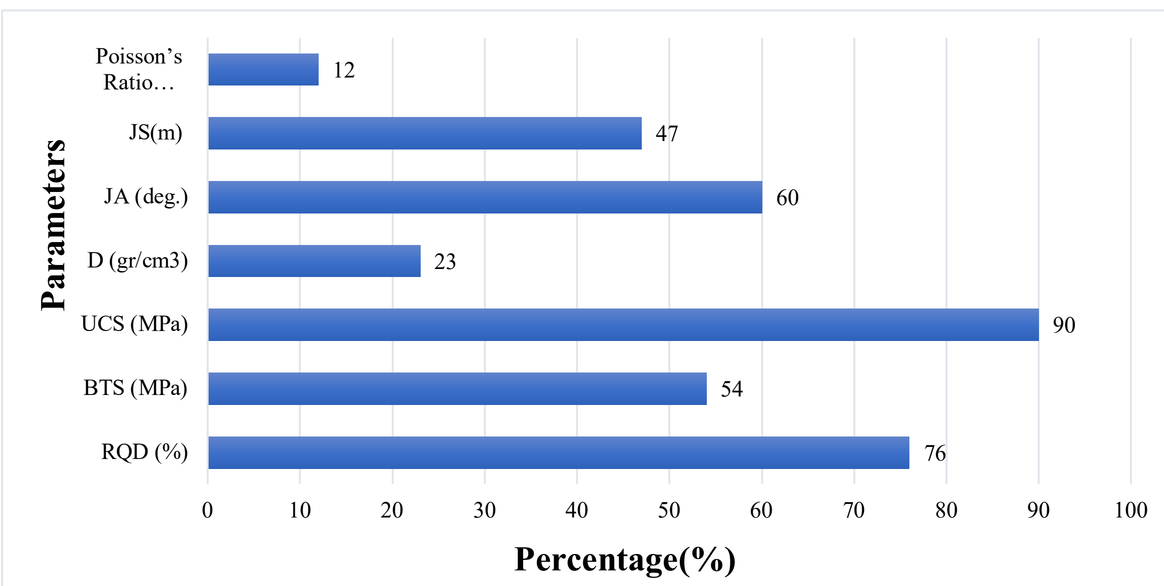

Figure 12. Parameter sensitivity analysis diagram.

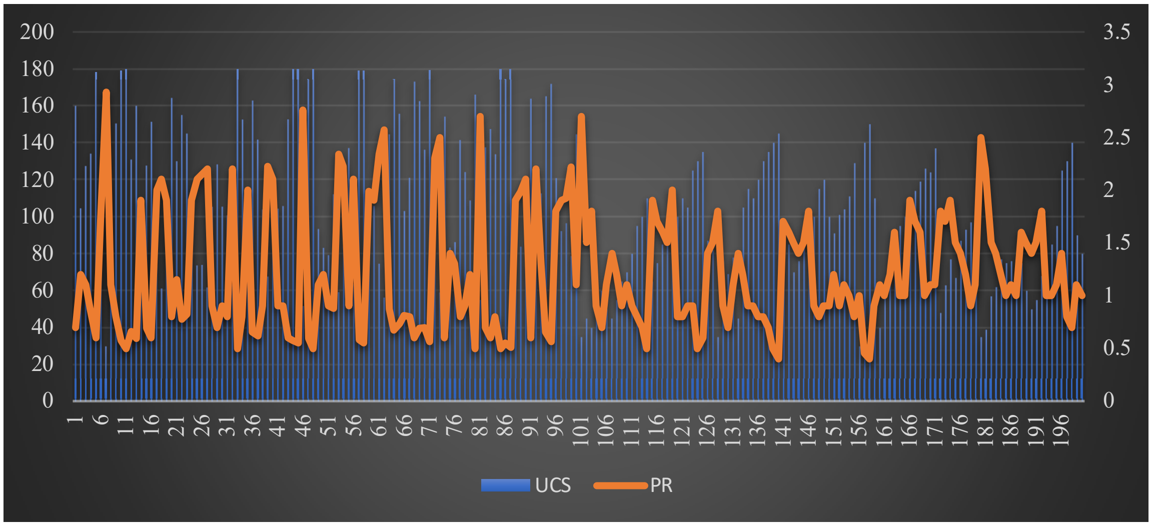

Figure 13. Impact of UCS on PR.

3.7. Results and discussion of present work and previous model

In this part, the previously developed models are examined and compared with the suggested models of this research work. Several researchers have been studied TBM performance. For instance, Mikaeil *et al.* [50] studied at prediction of TBM penetration rate with generalized regression neural network in hard rock condition. Bejari *et al.* [51] presented a model for simultaneous effects of joint spacing and joint orientation on the penetration rate of a single disc cutter. Frough *et al.* [52] evaluated the TBM utilization using rock mass rating system. Dehghani *et al.* [53] suggested the estimation of penetration rate of tunnel boring machines using Monte-Carlo simulation method. Moosazadeh *et al.* [54] studied at simulation of tunnel boring machine utilization. In this study, several approaches are used to predict the performance of TBMs in two real Iranian water conveyance tunnels and the achieved results compared to those models in which similar approaches applied. The aim of this paper is to show the application of the Multivariate Linear Regression (MLR), Artificial Neural Network (ANN), and Support Vector Machine (SVM) for the TBM penetration rate prediction. As shown in Table 9 and Figure 14, the findings of the previous models were examined with the obtained results of this research work, and it was found that the best model is in accordance with the TBM performance prediction using the SVM approach. The validation dataset serves as a means to impartially assess the performance of a model trained on the training dataset, while simultaneously adjusting the model's hyperparameters. However, it is important to note that the evaluation process becomes increasingly biased as the model's performance on the validation dataset is incorporated into the model's configuration. The purpose of the validation set is to assess the performance of a given model, primarily for frequent evaluations. As machine learning engineers, we utilize this dataset to refine the hyperparameters of the model. Consequently, the model may occasionally encounter this data, but it does not actively "learn" from it. Instead, we leverage the results obtained from the validation set to update higher-level hyperparameters. Thus, the validation set indirectly influences the model's behavior. It is worth mentioning that the validation set is also referred to as the development set, as it plays a crucial role during the developmental phase of the model. Validation the proposed the best model with data, which are not used in the ANN model, as can be seen in Figure 15.

Table 9. Results of present work and previous models.

Model	R^2	RMSE
Yagiz [55]	0.66	0.21
Zare Naghadehi *et al.* [56]	0.72	0.18
Adokoet *et al.* [57]	0.66	0.22
New MLR model (This study)	0.90	0.17
New ANN model (This study)	0.98	0.08
New SVM model (This study)	0.99	0.01

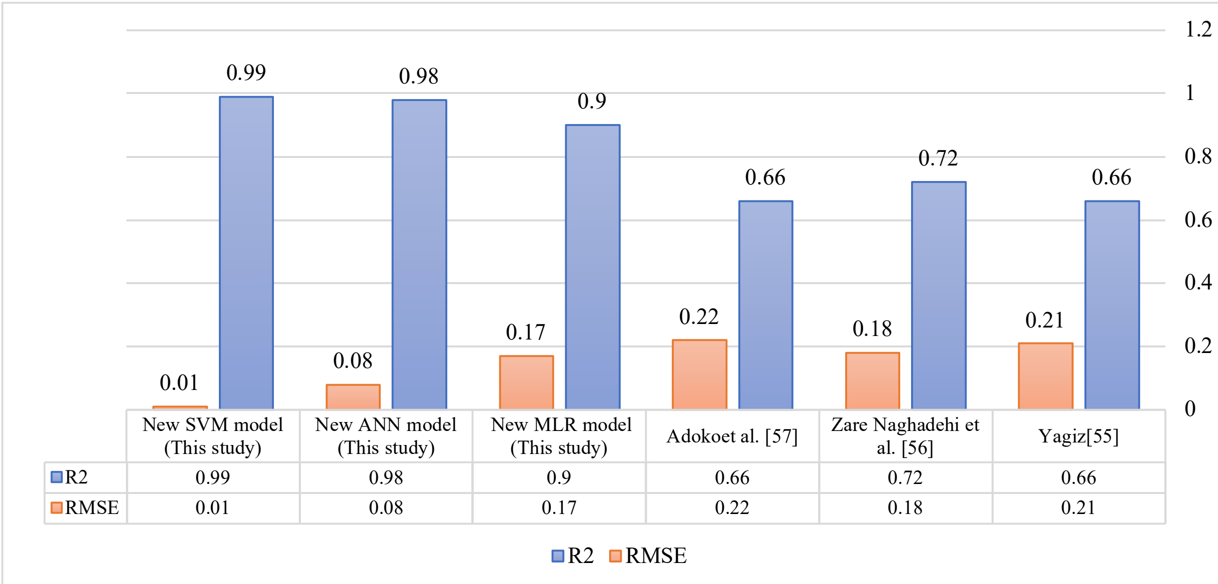

Figure 14. Comparison of proposed models and previous models.

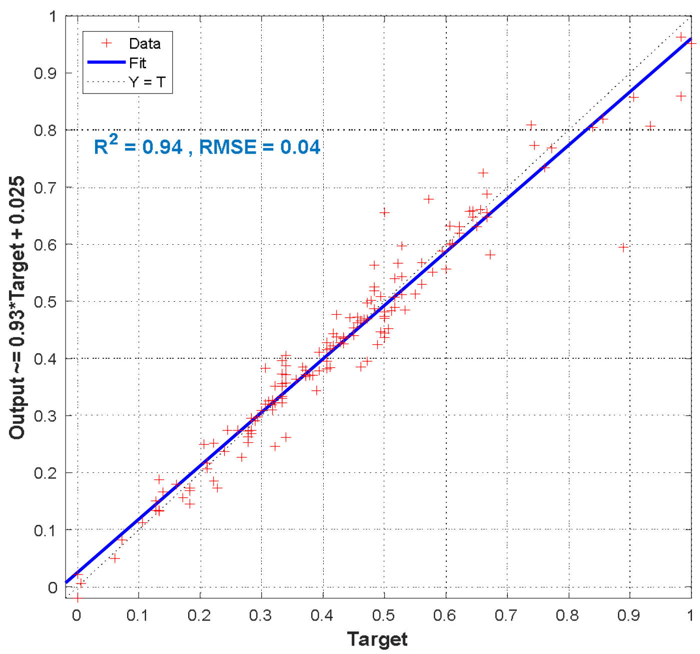

Figure 15. Validation of the proposed best model with data that is not used in ANN model.

Table 10. Validation Datasets that are not used in ANN model.

Dataset	R^2	RMSE
Dataset 1	0.65	0.21
Dataset 2	0.72	0.36
Dataset 3	0.40	0.14
Dataset 4	0.32	0.46
Dataset 5	0.57	0.12
Dataset 6	0.94	0.04

4. Conclusions

The escalating global population has led to an imperative need for energy resources, thereby, rendering the construction of water conveyance tunnels via TBM tunneling method a crucial issue. This undertaking poses significant challenges in terms of the requisite construction investment, estimation of total excavation time, and project completion time. Tunnel boring machines have demonstrated remarkable efficiency in excavating tunnels, particularly water conveyance tunnels, owing to their high excavating speeds, integrated excavating, and simultaneous installation of a support system. Accurate prediction of the rate of penetration plays a pivotal role in determining the investment required and the completion time of the tunneling project. In this study, a database primarily established from machine parameters and field data for predicting the TBM penetration rate in the Kerman and Gavoshan water conveyance tunnels is presented. A Multivariate Linear Regression (MLR), an Artificial Neural Network (ANN), and a Support Vector Machine (SVM) were applied to the database. The results showed that the three applied methods are able to give results in good agreement with the real penetration rate values. The determination coefficient for MLR, ANN, and SVM approaches were found as 0.90, 0.98, and 0.99, respectively, indicating SVM contributes to a more precise and realistic outcome as it is able to give a higher determination coefficient. Moreover, the QTBM model was applied to the database. The relationship between measured and predicted data showed all three approaches are capable to predict the performance of TBMs more accurate (R^2 = 0.90, 0.98, 0.99) than the QTBM model (R^2 = 0.60).

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پیش‌بینی عملکرد ماشین حفار تمام مقطع (TBM) سنگ سخت با استفاده از روش های آماری و هوش مصنوعی

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چکیده:

ماشین حفار تمام مقطع (TBM) به طور گسترده برای حفاری فضاهای زیرزمینی در پروژه‌های عمرانی و معدنی استفاده می‌شوند. ارزیابی دقیق نرخ نفوذ عامل کلیدی برای پیش‌بینی عملکرد ماشین حفار تمام مقطع (TBM) است. در این تحقیق از روش‌های هوش مصنوعی برای پیش‌بینی نرخ نفوذ ماشین حفار تمام مقطع (TBM) در عملیات حفاری در تونل انتقال آب کرمان و تونل انتقال آب گاوشان استفاده شده است. هدف این مقاله نشان دادن کاربرد رگرسیون خطی چند متغیره (MLR)، شبکه عصبی مصنوعی (ANN) و ماشین بردار پشتیبان (SVM) برای پیش‌بینی نرخ نفوذ ماشین حفار تمام مقطع (TBM) است. پارامتر نرخ نفوذ به عنوان یک متغیر وابسته در نظر گرفته شده و شاخص کیفی سنگ (RQD)، مقاومت کششی برزیلی (BTS)، مقاومت فشاری تک محوری (UCS)، چگالی (D)، زاویه بین ناپیوستگی ها (JA)، فاصله بین امتداد ناپیوستگی ها (JS)، و نسبت پواسون به عنوان متغیرهای مستقل در نظر گرفته شده است. نتایج نشان می دهد روش ها کارایی بسیار بالایی دارند با این تفاوت که ماشین بردار پشتیبان برتری نسبی خاصی نسبت به سایر روش ها دارد.

کلمات کلیدی: ماشین حفار تمام مقطع، رگرسیون خطی چند متغیره، شبکه عصبی مصنوعی، ماشین بردار پشتیبان.