A support vector regression model for predicting tunnel boring machine penetration rates

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With widespread increasing applications of mechanized tunneling in almost all ground conditions, prediction of tunnel boring machine (TBM) performance is required for time planning, cost control and choice of excavation method in order to make tunneling economical. Penetration rate is a principal measure of full-face TBM performance and is used to evaluate the feasibility of the machine and predict advance rate of excavation. This research aims at developing a regression model to predict penetration rate of TBM in hard rock conditions based on a new artificial intelligence (AI) algorithm namely support vector regression (SVR). For this purpose, the Queens Water Tunnel, in New York City, was selected as a case study to test the proposed model. In order to find out the optimum values of the parameters and prevent over-fitting, 80% of the total data were selected randomly for training set and the rest were kept for testing the model. According to the results, it can be said that the proposed model is a useful and reliable means to predict TBM penetration rate provided that a suitable dataset exists. From the prediction results of training and testing samples, the squared correlation coefficient (R^2) between the observed and predicted values of the proposed model was obtained 0.99 and 0.95, respectively, which shows a high conformity between predicted and actual penetration rate.

1. Introduction

Tunnels play an essential role for urban transportation, water conveyance, storage, defense and underground mining operations. Mechanized tunneling technique has found extensive applications in tunnel constructions in recent decades. Tools for excavation range from excavators equipped with ripper teeth, hydraulic rams and roadheaders to tunnel boring machines (TBMs) of various designs. TBM refers to a machine for driving tunnels in hard or soft rock with a circular full-face cutterhead, generally equipped with disc cutters. The rock or soil is cut using these excavation tools by the rotation of the cutterhead and the blade pressure on the face.

Nowadays, many underground excavations are performed by mechanical means. By far, TBMs are the most popular method of tunnel excavation and have been widely applied to subways, railways, water conveyance projects, mines etc. In this respect, application of TBMs for excavation of long tunnels and mine galleries is generally the fastest and the most economical method.

At present, different TBM types, such as gripper, open face, earth pressure balance (EPB), slurry, single and double shield, mixed shield and convertible shield are designed to suit for the different ground conditions [1]. However, TBMs are very sensitive to adverse geotechnical conditions, such as spalling, rock bursting, squeezing, swelling and high water inflows [2]. In addition, tunneling is a high-risk industry covering geological, operational, physical and financial risks which are growing with the increase use of mechanized tunneling.

From the beginning of a tunnel excavation and during the tendering of a tunnel project, the performance of a TBM has to be estimated to achieve an accurate time schedule of the whole project. A reliable estimation of TBM performance is required for time planning, cost control and choice of excavation method in order to make tunnel boring economical rationalization.

TBM performance is measured in terms of penetration rate (PR), utilization index (UI) and advance rate (AR), which rely mainly on the geological conditions, geomechanical properties, hydrological conditions, machine design parameters, engineering and operational factors etc.

Optimal design of machine and project planning are essentially based on site geological conditions, which are fundamental factors. Due to the natural variation of geological conditions along the tunnel alignment, it is often difficult to predict exact rock mass behavior along the tunnel on the basis of site investigation [1]. With varying geotechnical conditions, TBM design is difficult to

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deal with all the possible scenarios in an optimum mode, and it has to compromise to suit the dominating geotechnical conditions, properties of rock mass and mechanical properties of material to strive an overall performance. Such difficult conditions have influences on TBM performance, and affect the overall advance of the project and the total costs.

The three main parameters affecting the TBM performance are machine design related factors, geological conditions and geomechanical properties of rocks along the tunnel axis [3–6].

The machine related factors are such as: thrust, torque, disk geometry, disk wear, disk diameter, cutter arrangement and cutterhead revolutions per minute (RPM). Further, rock properties include strength, brittleness, abrasiveness, fracture frequency, hardness, orientation of joints, faults, and bedding related to tunnel axis. These rock properties are the basis for various prediction models and are usually available from the geomechanical tests to site investigations.

Over the years, many researchers suggested a wide variety of performance prediction methods to predict and improve the TBM performance in different projects with various rock masses. However, due to the complexity of ground nature, mechanized tunneling still faces many challenges.

Due to various geotechnical conditions encountured along the tunel alignment, prediction of the performance of a TBM is a nonlinear and complex problem [7,8]. Many researches had been done to correlate TBM performance in terms of PR and AR with rock mass and machine parameters through either empirical or experimental approaches. Recently artificial intelligence (AI) based models are successfully employed by some researchers to solve this difficult non-linear problem in geotechnical projects.

Alvarez Grima et al. [4] applied a neuro-fuzzy method to predict TBM performance. Kim [9] applied fuzzy logic to establish a TBM performance model with respect to the geological and geotechnical site conditions. Acaroglu et al. [7] developed a fuzzy logic model to predict specific energy requirement for TBM performance prediction. Artificial neural networks (ANNs) are also employed to estimate the performance of TBMs in the literature [8,10,11]. Recently, particle swarm optimization (PSO) technique was applied on rock properties data in order to predict TBM penetration rates [12].

In this research, the main problem to be solved is the approximation of an unknown function from the observation of a number of known input–output datasets to predict the rate of penetration and subsequently predict TBM performance. In this regard a new model is developed to estimate the rate of penetration with both rock mass and material properties and also machine parameters.

In order to predict PR, a SVR analysis as a new machine learning (ML) algorithm is used to develop our predictive model. ML is considered as a subfield of AI and is concerned with the development of techniques and algorithms, which enable the computer to learn and perform tasks and activities. SVR is a supervised ML method based on the statistical learning theory and is capable to give good performance for a wide variety of non-linear regression problems.

2. Literature review

Many prediction models were introduced to estimate the TBM performance, which are commonly categorized as two methods, theoretical/experimental models and empirical methods [3]. The former are based on full-scale laboratory cutting tests and the latter are based on field performance of the machine and encountered rock mass properties.

One of the famous experimental models is a method developed in the Earth Mechanics Institute of Colorado School of Mines (CSM). The CSM model which is mainly based on full-scale laboratory cutting tests and database accumulated during past experiences, was developed at first by Ozdemir [13] then was updated by Rostami et al. [3] and afterward Cheema [14] suggested some modifications on it. Further, Yagiz [15] introduced the Modified CSM model, giving more precise estimation result in fractured rock mass condition by inserting rock brittleness and rock mass properties including distance between plane of weakness (DPW) and orientation of discontinuities like faults and fractures into the previous CSM model.

NTNU/NTH (Norwegian University of Science and Technology) model is one of the famous empirical TBM performance prediction methods [16], which is based on data collected from Norwegian terrains. This method was based on multiple laboratory tests and a vast amount of field experience. It takes into account intact rock as well as rock mass properties. It also utilized various machine variables to predict PR and cutter wear [17].

A wide range of empirical tests has been used to predict machine performance with varying degrees of success. These empirical predictive models have been developed based on the historical field data of TBM performance in various ground conditions. Protodyakonov [18] introduced coefficient of rock strength in order to predict PR. Punch penetration test is also used for predicting TBM performance in the literature [19–21]. More, Schmidt hammer and Shore hardness tests are together utilized for performance prediction of TBM [22,23].

With regard to the TBM penetration rate, Rostami and Ozdemir [24] developed a model for performance prediction of hard rock TBM. Barton [25] also reviewed a wide range of TBM tunnels to establish the database for estimating PR, UI and AR. Yagiz [26] utilized rock mass and material properties to construct a new empirical equation for predicting TBM performance in fractured hard rock conditions. Farrokh et al. [27] estimated PR of hard rock TBMs by studying various predictive models and application of combined models was recommended to ensure a higher degree of confidence in final estimation relative to the ground conditions and TBM types.

Influence of rock mass characteristics on TBM performance, mainly from the point of view of PR, has been investigated by some researchers. In this regard, performance of TBM has been estimated by using the empirical approaches, which two such approaches are rock mass quality for TBM (Q_{TBM}) developed by Barton [28,29] based on expanded Q system [30], and also rock mass excavability (RME) index proposed by Bieniawski et al. [31].

Rock Mass Rating (RMR) system is also used for estimating TBM performance by researchers [5,31–33]. In addition, Rock Structure Rating (RSR) [34] is used together with uniaxial compressive strength of rock for estimating the rate of penetration [35,36].

Howarth et al. [37] investigated correlation of performance of three types of drilling tool namely percussion drilling, diamond drilling and TBM with physical rock properties. Their findings show significant trends between several physical rock properties and PR for the range of rock types and drilling tools.

Gong and Zhao [38] investigated the influence of rock brittleness on TBM penetration rate using non-linear regression analysis and numerical simulation simultaneously. According to their findings the PR almost increases linearly with increasing rock brittleness index. Further, they developed a rock mass characteristics model for prediction of PR of TBM [6].

3. TBM performance parameters

A TBM is a complex set of equipment assembled to excavate a tunnel. TBM system performance is evaluated using several parameters that must be defined clearly and used consistently for proportional applications. TBM performance is commonly measured in terms of utilization index (UI), penetration rate (PR) and advance rate (AR) which rely on the site geological conditions, geomechanical properties of rock, hydrological conditions, machine design parameters, engineering, construction and operational factors.

3.1. Machine utilization index

The UI is defined as the percentage of time in boring (T_b) per unit shift time (T_{sh}) and expressed in percent [9]. The shift time includes TBM boring time and downtime or sum of time wasted by other delays (T_d) during operations of excavation.

$$\mathrm{UI} = \frac{\text{TBM boring time}}{\text{Shift time}} \times 100 = \frac{T_b}{T_{sh}} \times 100 \tag{1}$$

$$T_{sh} = T_b + T_d \tag{2}$$

where T_b is the time of operation of cutterhead, expressed in hour. The UI is usually evaluated as an average over a specified period.

The UI depends more on rock quality, equipment condition and commitment to maintenance, contractor capabilities, project conditions, environmental conditions and remoteness. In common, UI depends on rock type and properties, ground condition, machine specification and operational factors, and it may be varying from around 30 to 60% [26,39]. The reasons for the delays are mechanical breakdowns, interruptions due to haulage and auxiliary operations such as ground control and tunnel support.

3.2. Machine penetration rate

The PR is defined as a ratio of excavation distance to the operating time during tunnel construction:

$$\mathrm{PR} = \frac{\text{Distance bored}}{\text{TBM boring time}} = \frac{L}{T_b} \tag{3}$$

where PR is the average penetration rate at which the cutterhead bores rock per hour or per minute, and generally expressed in m/h or mm/min, and L is the distance that should be excavated, expressed in m or mm. Thus, the operating time is used to calculate the PR as a measure of the cutterhead advance per unit boring time.

The key parameters on the estimation of TBM performance affecting the PR, are rock strength, brittleness, toughness, weathering, joint density or discontinuity in rock mass, ground condition together with type of TBM and its specifications [26,40].

The PR can also be calculated on the basis of distance bored per cutterhead revolution and expressed as an instantaneous penetration or as averaged over each thrust cylinder cycle. The particular case of penetration per cutterhead revolution is useful for the study of the mechanics of rock cutting and is here given the notation P_{rev}:

$$P_{rev} = \frac{1000 \times \mathrm{PR}}{60 \times \mathrm{RPM}} \tag{4}$$

where P_{rev} is penetration per revolution of cutterhead, and RPM is the rate of cutterhead revolutions per minute which are expressed in mm/rev and rev/min, respectively.

Many different prediction models are developed by the researchers for prediction of the PR [41,42]. Amongst them three commonly applied performance correlations using empirical equations developed from data on rock testing. Graham [43] estimated the PR of TBM by UCS in the range of 140 to 200 MPa:

$$P_{rev} = 3.94 \times \frac{F_n}{\sigma_c} \tag{5}$$

where F_n is cutter load or normal force expressed in kN, and σ_c is uniaxial compressive strength of intact rock expressed in MPa. Hughes [44] also derived a relationship from mining in coal:

$$P_{rev} = 1.667 \times \left(\frac{F_n}{\sigma_c}\right)^{1.2} \times \left(\frac{2}{D}\right)^{0.6} \tag{6}$$

where D is the disc diameter in mm, and it is assumed that only one disc tracks in each kerf groove, the normal practice for TBM design. Farmer et al. [45] suggested a relationship between Brazilian tensile strength and PR in sedimentary rocks:

$$P_{rev} = 624 \times \frac{F_n}{\sigma_{tB}} \tag{7}$$

where σ_{tB} is the Brazilian tensile strength of intact rock expressed in MPa.

In this respect, Snowdon et al. [46] and Sanio [47] suggested relationships between P_{rev} and specific energy (SE) as

$$\mathrm{SE} = \frac{200 \times n_c \times r_c \times F_r}{3 \times D \times P_{rev}} \tag{8}$$

where n_c is the number of cutters on the cutterhead, r_c is the weighted average cutter distance from center of rotation in m, F_r is cutter rolling force in kN and D is TBM diameter in m. SE which is expressed in MJ/m^3, is defined as the energy requirement of disc cutters to cut unit volume of rock.

3.3. Machine advance rate

Advance rate (AR) is average speed of advancement of the tunnel and expressed in rings per day or m/day or m/shift. In this research, the AR is defined as the distance bored based upon shift time.

$$\mathrm{AR} = \frac{\text{distance bored}}{\text{shift time}} = \frac{L}{T_{sh}} \tag{9}$$

If UI and PR are expressed on a common time basis, then the AR is equated to

$$\mathrm{AR} = \frac{\mathrm{PR} \times \mathrm{UI}}{100} \tag{10}$$

AR can be varied by changes of the parameter affecting either PR or UI such as encountering very hard or poor rock, reduced torque capacity, producing suitable resistance to grippers, stoppages on various accounts like TBM maintenance, unstable invert causing train derailments, highly abrasive rock resulting cutter wear faster, break down and tunnel collapse.

These parameters are the most important factors which influenced the TBM performance. In other words, the net AR is a linear function of cutterhead RPM and the penetration of a disk per cutterhead revolution [48].

In general, AR is traced back to the two main tasks in tunneling, to mine the rock mass and to support the opening. Excavation of the rock by TBM is expressed in the PR. The support of the tunnel as well as other non-productive times (scheduled maintenance during the graveyard shift, power outages, delays in mucking, machine breakdown etc.) reduce the PR to a certain degree. This reduction is expressed in the average utilization of a TBM which ranges from 0% to about 66% [49].

4. Support vector regression

A novel kinds of ML techniques, support vector machine (SVM) was developed for solving both classification and regression problems, which maximizes predictive accuracy and avoids over-fitting simultaneously. Over the period of time many techniques and methodologies were developed for ML tasks. Amongst them SVM is relatively new method which is based on the structural risk minimization (SRM) [50] that emerged as one of the leading technique for the classification and function approximation problems.

The term SVM refers to both classification and regression methods, and the terms support vector classification (SVC) and support vector regression (SVR) is used for specification [50]. Obviously only SVR is capable to solve extrapolative problems by building a predictive model. Therefore, SVR which is applied in this research employs the SVM to tackle with problems of function approximation and regression estimation by introducing an alternative "loss function".

The SVR as a universal approach for solving the problems of high-dimensional function estimation, is based on the Vapnik–Chervonenkis (VC) theory [51,52]. If the VC dimension is low, the expected probability of error is also low, which means good generalization. Brevity, VC theory characterizes properties of learning machines, which enable them to generalize properly unseen data.

SVR is implementing the SRM inductive principle for obtaining strong generalization ability on a limited number of learning patterns. The SRM involves simultaneous attempt to minimize the empirical risk and the VC dimension [53].

Suppose that given a training set $\{(x_1,y_1), \ldots,(x_n,y_n)\} \subset R^d \times R$ where R^d is the space of the input features x_i, and y_i is the phenomenon under investigation. In SVR, the main objective is to find a function $f(x)$, that has almost ε deviation from the actual targets, y_i, given by the training data and at the same time, is as flat as possible [54]. The approximating function, $f(x_i)$, in SVR can be represented by a linear function of the form:

$$f(x_i) = \langle w_i, x_i \rangle + b \tag{11}$$

where w identifies the weight vector of the linear function having a unit length laid at right angle with the hyper-plane, and b corresponds to the threshold coefficient. SVR approximates the set of data with a linear function that is formulated in the high-dimensional feature space with the following function:

$$y = \sum_{i=1}^{N} w_i(x_i) + b \tag{12}$$

where (x_i) plays the role transferring the input vector into a feature space. In other words, (x_i) is the high-dimensional feature space, which is non-linearly mapped from the input space R^d.

The formulation of the SVR function can be more comfortable by using of the ε-insensitive loss function in the theory of error risk minimization with regularization [54].

The concept of the ε-insensitive loss function is depicted graphically in Fig. 1. Only the samples out of the $\pm\varepsilon$ margin (known as ε-insensitive tube) will have a nonzero slack variable. Normally, if the predicted value is inside the region, the loss will be zero, while if the predicted point is outside the tube, the loss is the magnitude of the difference between the predicted value and the radius ε of the tube. In other words, there is no care of errors as long as they are less than ε, but any deviation larger than this will not be accepted.

Loss function represents the fact that there is no loss for deviations smaller than ε and that larger deviations will be linearly penalized:

$$L(\xi) = \begin{cases} o & \text{if} \quad |\xi| \le \varepsilon \\ |\xi| - \varepsilon & \text{otherwise} \end{cases} \tag{13}$$

where the parameter ε is equivalent to the approximation accuracy placed on the training data points and when the data points are within $\pm\varepsilon$ range, do not contribute to the empirical error.

Flatness in the case of Eq. (12) can be ensured by minimizing the norm w^2, leading to the following convex optimization problem:

$$\min\left[\tfrac{1}{2}||w||^2 + C\sum_{i=1}^{n}\left(\xi_i^+ + \xi_i^-\right)\right]$$

$$\text{Subjected to}: \quad \begin{array}{l} (w \cdot \Phi(x_i) + b_i) - y_i \le \varepsilon + \xi_i^+ \\ y_i - (w \cdot \Phi(x_i) + b_i) \le \varepsilon + \xi_i^- \\ \xi_i^+,\ \xi_i^- \ge 0 \end{array} \tag{14}$$

where the constant $C>0$ stands for the penalty degree of the sample with error exceeding ε and slack variables ξ_i^+ and ξ_i^- are relaxation factors of the tolerable error included to cope with otherwise infeasible constraint of the optimization problem and represent the upper and lower training errors subject to ε-insensitive tube.

In the regularized risk function given by Eq. (14), the first term $(1/2)||w||^2$, is the structure risk, used to control the smoothness or complexity of the function (regularization term) and the second term $C\sum_{i=1}^{n}\left(\xi_i^+ + \xi_i^-\right)$, is the empirical risk. Thus, the SVR is formulated as minimization of both the structural and empirical risks.

The basic idea in the SVR is to map the data $X \in R^d$ into a high-dimensional feature space via non-linear mapping (Fig. 1). Kernel functions perform the non-linear mapping between the input space and a feature space. Kernel transformation is essentially a projection of the matrix from the input space into the higher dimensional feature space.

In Hilbert space [56], kernel representation is similar to inner products. Therefore, kernel function can be easily evaluated in Hilbert space. Thus the value of the kernel is equal to the inner product of two vectors x_i and x_j in the feature space $\Phi(x_i)$ and $\Phi(x_j)$, i.e. $K(x_i,x_j) = \Phi(x_i) \times \Phi(x_j)$. This means that the data within training set are moved into specified space of higher dimension through the kernel function. This plays the role making into set of input data able to separate into linear within the specified space by moving the training data into higher space.

Various kernel functions may produce different support vectors. As the typical kernel function is a kernel of radial basis function (RBF) by utilizing Gaussian distribution, this function is selected in this study as follows:

$$K(x_i,x_j) = \exp\left(-\gamma||x_i - x_j||^2\right) \tag{15}$$

where $\|\|$ is the Euclidean norm for vectors, and γ denotes the variance of the Gaussian kernel, controlling sensitivity of the kernel function.

The training problem, Eq. (14), can easily be solved in its dual formulation, obtained by constructing a Lagrange function from the objective and the constraints. Indeed, the dual formulation yields a quadratic optimization problem with a unique solution, avoiding the problem of being stuck in a local minimum. The dual formulation also provides the key to the non-linear extension of SVR.

The solution of the dual problem yields the function $f(x)$, which can be written as a linear combination of the training data, the Lagrange multipliers a_i^* and a_i, and the constant term b, whose computation stems from the Karush–Kuhn–Tucker (KKT) conditions [57,58]:

$$f(x) = \sum_{i=1}^{n}\left(a_i - a_i^*\right)\langle x_i, x\rangle + b \tag{16}$$

where n is the number of support vectors and b is a bias constant to be determined during the optimization. Only part of a_i^* and a_i has non-zero values. The sample corresponding to a_i^* and a_i is the support vector to be sought. The Lagrange multipliers verify the

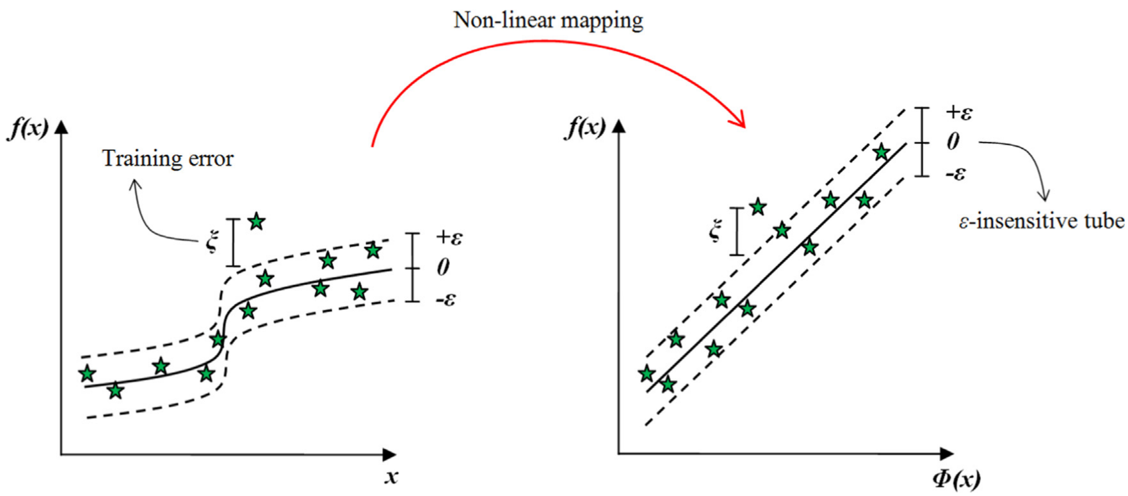

Fig. 1. Mapping a non-linear SVR into feature space and its ε-insensitive loss setting [55].

constraints:

$$\sum_{i=1}^{n}(a_i - a_i^*) = 0 \quad \text{and} \quad 0 \le a_i^*,\ a_i \le C \tag{17}$$

The KKT conditions also imply that if $a_i^*, a_i \ne C$ and $|f(x_i) - y_i| < \varepsilon$ then a_i^* and a_i must be zero. Intuitively, as errors lower than ε are tolerated, training data lying inside the so-called ε-tube will not contribute to the problem solution. In other words, not all x_i are needed to calculate $f(x)$, but only the training points x_i whose a_i^* and $a_i \ne 0$, which have approximation errors equal to or larger than ε, and are referred to as support vectors. These are the data points lying on or outside the ε-bound of the decision function. An important consequence of the above fact is that the complexity of the problem is independent of the dimension of the input space, but depends only on the number of support vectors.

Finally by restating the optimization problem in terms of the kernel, it follows that $f(x)$ can be written as [54]

$$f(x) = \sum_{i=1}^{n} (a_i - a_i^*) K(x_i, x) + b \tag{18}$$

There are many ways to compute the value of b, one of which is [50]:

$$b = -\frac{1}{2}(w(y_r + y_s)) \tag{19}$$

where y_r and y_s are the support vectors, that is, any input vector which has non-zero value of either a_i^* and a_i, respectively.

Choosing optimal parameters is an important step in SVR design, which strongly affects the performance of the model. Generally for training a SVR model three parameters should be selected appropriately which are the loss function parameter ε, the penalty term C, and the Gaussian kernel parameter γ.

The parameter C can play the role minimizing the error term if rise up the real value having plus value, and while the lower of the value, the more maximizing role of the error term is doing. C is referred to the regularized constant and it determines trade-off between the empirical risk and the regularization term. Increasing the value of C will result in the relative importance of the empirical risk. The parameter γ denotes the variance of the Gaussian kernel, controlling sensitivity of the kernel function. There is no care of errors as long as they are less than loss function parameter ε, but any deviation larger than this is not accepted.

5. Development of the SVR model

Predicting the TBM penetration rate can be employed to reduce the risks related to high capital costs and time scheduling typical to excavation operations. Due to that, predicting TBM performance is one of the main issues for any mechanized tunneling projects. The proposed model is verified based on the dataset of 7.5 km long Queens tunnel project to estimate the rate of penetration via SVR algorithm.

5.1. Case study

Queens Water Tunnel No. 3 ranks as the largest and most costly construction project in the history of New York City and will improve fresh water distribution throughout the city. Once completed, the tunnel supplies about 90% of the water consumed by the city and its residents, currently at 5.7 million m^3/day [59]. Construction of the tunnel has been begun in 1970 and is expected to be complete by 2020 [60].

The tunnel will be more than 93 km long and divided into four stages. The second stage of the tunnel No. 3 built using TBM, is being constructed in two separate sections. The Brooklyn to Queens Section, which was constructed between 1997 and 2000, is investigated in this research. This section of tunnel being about 7.5 km long and 7 m in diameter was excavated beneath Brooklyn and Queens at an average depth of 200 m below the sea level in West-central Queens County with using a high power TBM model 235–282 [26].

The open hard rock TBM weighs approximately 640 t and has 10 drive trains, each rated at 315 kW. The speed of the cutterhead is 8.3 RPM, which provides a cutterhead peripheral velocity of 184 m/min. The machine can be modified to any diameter between 6.5 m and 8.5 m, making it suitable for future hard rock tunneling projects as given in Table 1.

In the study area, New York City is located at the extreme southern part of the Manhattan schist, a northeast trending and deeply eroded sequence of metamorphosed Proterozoic to Paleozoic rocks into the crystalline terrains of New England [59,60].

Geological formations are highly complex and composed of different metamorphosed igneous rock with shear zones, joint, faults, and other local weakness zones [26]. Cerchar abrasivity index for some typical samples is in the range of 3.3 to 4.3 indicating a fairly high abrasivity [59]. As shown in Fig. 2, the Brooklyn to Queens Section begins at shaft 19B, which is 9.1 m diameter and about 200 m deep, and then advances northeast till shaft 16B at an average slope down of 4.2%.

In general, the types of rocks are divided into five categories as given in Fig. 3: Mafic-to-Mesocratic Gneiss, Amphibolite and Schist (41.0%); Granitoid (Felsic) Gneiss and Orthogneiss (29.2%); Mafic-to-Mesocratic Orthogneiss (19.9%); Massive Garnet Amphibolite and larger Mafic dikes (7.3%); and Rhyodacite dike rocks (2.6%) [26].

Table 1
Specifications of the Queens TBM (Model 235–282) [8,61].

Specification	Value
Machine diameter	7.06 m
Diameter range	6.5–8.5 m
Cutters	482 mm (Series 19)
Number of disc cutters	50
Recommended individual cutter load	32 t or 70,000 lb (nominal)
Cutterhead:	
Operating cutterhead thrust	1590 t or 3500,000 lb (nominal)
Cutterhead power	3150 kW
Cutterhead speed	8.3 RPM
Cutterhead torque	3620 kN m or 2669,000 ft lb (nominal)
Thrust cylinder stroke	1.83 m (6 ft)
Conveyor capacity (approx.)	18.4 m^3/min (650 ft^3/min)
TBM weight (approx.)	640 t

5.2. Dataset

In order to develop the SVR model for predicting the PR of TBM, a database that is composed of intact rock properties including: uniaxial compressive strength (UCS), Brazilian tensile strength (BTS) and brittleness index (BI), and also rock mass properties including: distance between plane of weakness (DPW) and alpha angle (α) was used. The alpha angle is the angle between plane of weakness and TBM-driven direction. Moreover, the mechanical specifications of the machine including: specific energy (SE),

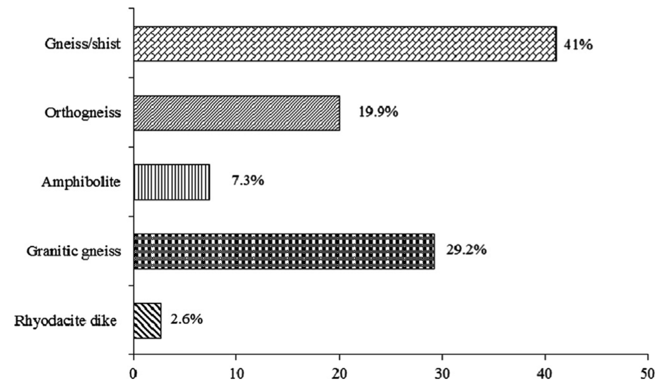

Fig. 3. Percentage of rock types encountered along the tunnel alignment [8].

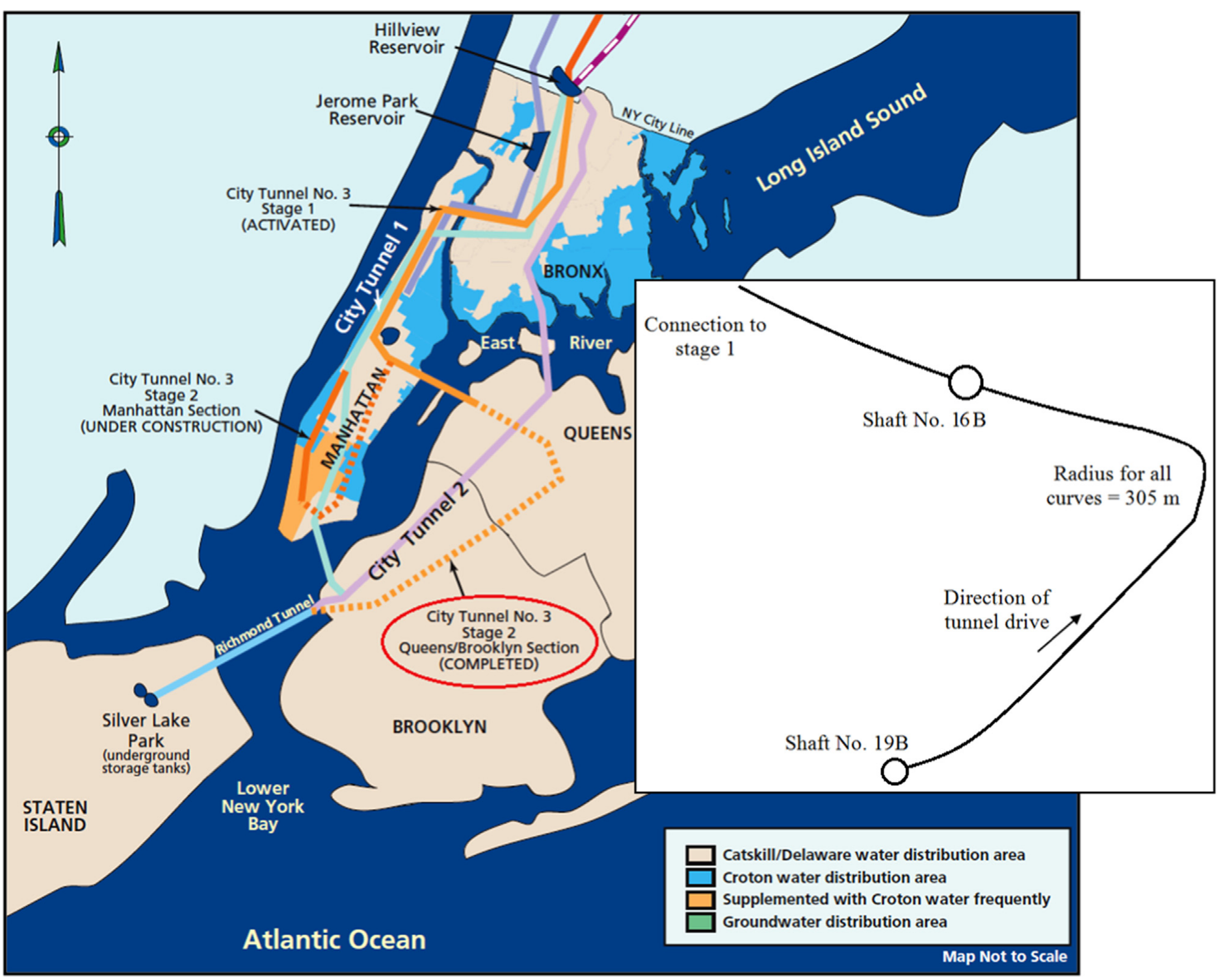

Fig. 2. Location of the first section of stage two of Queens tunnel no. 3, New York City [59,60].

Table 2
Descriptive statistics of rock and machine parameters for the model development.

Type of data		Symbol	Unit	Ave.	S.D.	Min.	Max.
Inputs	**Intact rock properties**	UCS	MPa	150.03	22.26	118.3	199.7
		BTS	MPa	9.57	0.84	7	11.4
		BI	kN/mm	34.61	8.48	25	58
	Rock mass properties	DPW	m	1.02	0.65	0.05	2
		α	Degree	44.61	23.32	2	89
	Machine parameters	SE	kW h/m^3	15.31	3.00	7.87	25.5
		TF	t	1701.05	183.69	1246.47	2031.08
		CP	kW	1204.45	198.92	642.32	1641.77
		CT	kN m	1386.17	228.93	739.24	1889.49
Output		PR	m/h	2.05	0.36	1.27	3.07

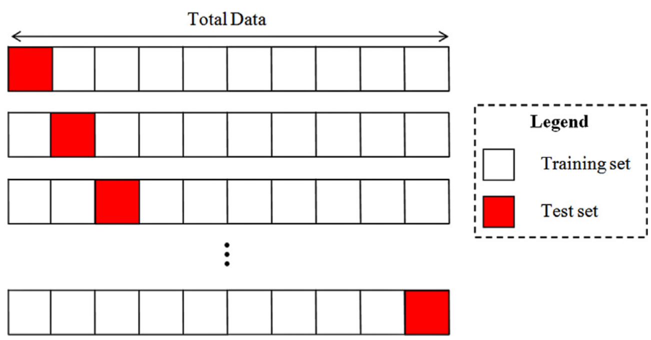

Fig. 4. Splitting dataset into two groups in each fold based on *K*-fold cross-validation.

thrust force (TF), cutterhead power (CP) and cutterhead torque (CT) are applied to enhance the accuracy of the model. The details of the parameters of 150 data points utilized for model development are given in Table 2. The main machine specifications were indicated in Table 1.

As given above (Table 2), the datasets including both rock properties and machine parameters are used together to develop SVM model in order to predict TBM penetration.

5.3. Data normalization

Before training and modeling, the data had to be normalized for keeping them in the prescribed range of 0 and +1. Dimensionless input data are necessary to improve the learning speed and the stability of the models. In addition, because input parameters have different units, normalization causes dimensionless. Normalizing the data was performed as

$$X^{ij}_{Norm} = \frac{X^{ij} - X^{j}_{min}}{X^{j}_{max} - X^{j}_{min}} \tag{20}$$

where X^{ij}_{Norm} is the scaled value and X^{ij} is the original data in *i*th row and *j*th column, respectively, X^{j}_{max} and X^{j}_{min} are the respective maximum and minimum values of each related *j*th column.

To avoid over-fitting in SVR model developing, two different sets namely training and testing sets are defined, which are used for learning and testing the predictive function, respectively. Cross-validation is a solution to split the whole data in different training sets and test sets, and to return the averaged value of the prediction scores obtained with the different sets.

5.4. K-fold cross-validation

In the cross-validation procedure, the training data is clustered into several classes or folds. Sequentially a fold is considered as the validation set and the rest are for training. As shown in Fig. 4 in *K*-fold cross-validation, the training data is randomly split into *K* mutually exclusive subsets of equal size. The SVR decision rule is obtained using $K-1$ of the subsets and then is tested on the subset left out. This procedure is repeated *K* times and in this mode each subset is used for validating once. Averaging the validation error over the *K* trials gives an estimate of the expected generalization error.

5.5. Non-linear SVR designing

A non-linear regression, in principle, is to search for the optimized value of a non-linear objective function. Hence the procedure of prediction of TBM performance with a non-linear SVR-based model can be carried out as follows:

First, the important data and information affecting PR of TBM are collected. Second, training and testing datasets are specified. Third, the model was trained and reasonable parameters of SVR structures are obtained. Finally, the trained model is applied on the test data to predict the PR. This procedure is depicted in Fig. 5.

The performance of SVR depends on an appropriate selection of the combination of three important parameters which control SVR quality: penalty parameter *C*, ε of ε-insensitive loss function, and γ which controls the amplitude of the Gaussian RBF kernel function and therefore, controls the generalization aptitude of SVR.

C is a regularization parameter that controls the trade-off between maximizing the margin and minimizing the training error. This trade-off makes SVR rather different from traditional error minimization problems and very robust to outliers. If *C* is too small then insufficient stress would be placed on fitting the training data. On the contrary, if *C* is too large then the SVR model would over-fit the training dataset.

There is no single accepted procedure for estimating these parameters. In practice, the parameters *C* and γ are varied through a wide range of values and the optimal performance assessed using a separate validation set or a technique such as cross-validation for verifying performance using only the training set [62,63]. In our research, a 10-fold cross-validation was used to realize the optimum combination of these parameters. Besides, a SVR-implementation known as "ε-SVR" in the LIBSVM 3.17 software library [64], which is executed under MATLAB software, was utilized to train the proposed SVR model.

The LIBSVM package utilizes a fast and efficient method known as sequential minimal optimization (SMO) for solving large quadratic programming problems and thereby estimating function parameters *b*, a_i^* and a_i in Eq. (18). The SMO algorithm gives an efficient way of solving the dual problem arising from the derivation of the SVR. SMO decomposes the overall quadratic programming problem into sub-problems. There are two components in SMO: an analytic method for solving of the two Lagrange multipliers; and a heuristic one for choosing multipliers in optimization [65].

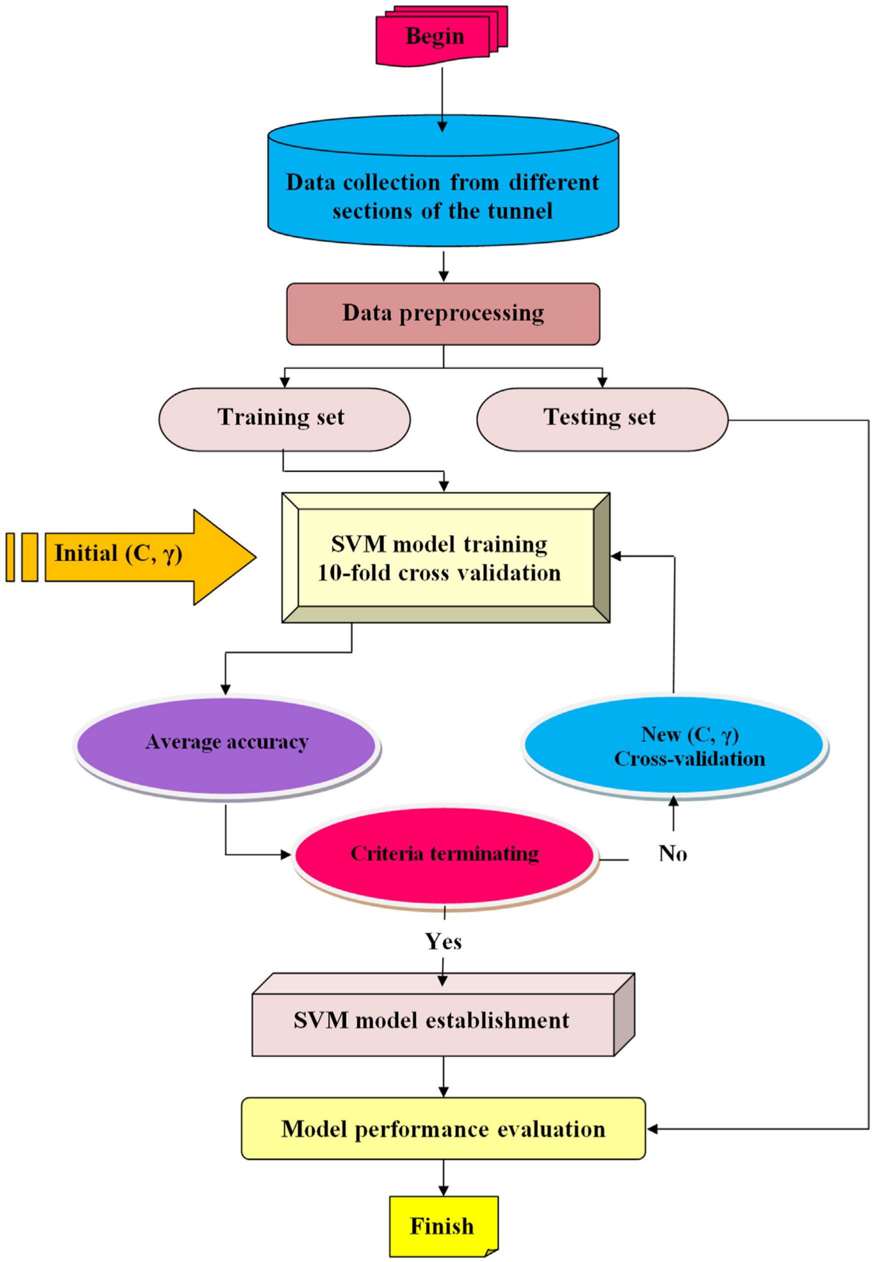

Fig. 5. Flow chart of developing SVR-based model.

A dataset of 150 data points from Queens Water Tunnel was used to train and test the proposed SVR model. In order to find out the optimum values of the parameters and preventing the over-fitting, 80% of the total data (120 data points) were selected randomly for the training set and the rest (30 data points) were kept for testing the model. We investigated all the combinations of parameters C and γ over a $\log_2$ range of values [66,67], so that in the range of $[2^{-6},2^{10}]$ for C with step sizes of $2^{0.2}$ (1.149), and in the range $[2^{-7},2^{1}]$ for γ with step sizes of $2^{0.1}$ (1.072). This function was defined in two loops for each combination of C and γ, and continues for 6561 times (81×81).

The parameter ε is referred to as the tube size (Fig. 1), and is defined as the approximation accuracy placed on the training data points. The optimal value for ε depends on the type of noise present in the data, which is usually unknown. In order to make the learning process stable, the insensitivity zone in ε-insensitive loss function in this research is assumed 0.1.

Finally, we pick and choose the optimum C and γ with the lowest cross-validation error and the highest squared correlation coefficient (R^2). According to the results of modeling, the best values of MSE and R^2 are obtained where $\log_2 C$ and $\log_2 \gamma$ are 6.6 and -5.4, respectively.

The R^2 is a statistic that is most commonly used to summarize the relationship between two variables. In other words, it is a performance measure of the association between two random variables which is defined in terms of the deviations of the coordinates of two variables from their mean values and is given by the product moment formula [68,69]:

$$R^2 = \frac{(1/n)\sum_{i=1}^{n}(x_i - m_x)(y_i - m_y)}{\sigma_x \sigma_y} \tag{21}$$

where n is the number of data; x_i, …, x_n are the data values for the first variable; m_x is their mean; and σ_x is their standard deviation; y_i, …, y_n are the data values for the second variable; m_y is their mean; and σ_y is their standard deviation. R^2 value varies between closed range of [0,1]. The larger the R^2 becomes, the stronger the relationship between the variables has become.

Obviously, the square of the correlation coefficient is called the coefficient of determination [69]. The typical performance function mean squared error (*MSE*), was used for training the model as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - Y_i^*}{Y_i}\right|^2 \tag{22}$$

where Y_i is the observation value, Y_i^* is the predicted value and n is number of input-output data pairs. *MSE* is a measure of stopping the training process to prevent over-fitting of the model. Fig. 6 shows a schematic view of the learning of a model. As it can be observed, the *MSE* during the training process decreases and

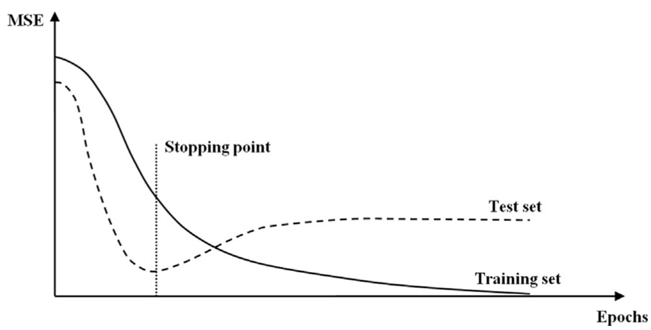

Fig. 6. Schematic view of the *MSE* versus epochs during learning an intelligent model.

Table 3
Results of 10-fold cross-validation and optimal values of R^2 and *MSE*.

Step	Best *C*	Best γ	$MSE_{Opt.}$	$R^2_{Opt.}$
1st	256.0000	0.0078	0.0024	0.9051
2nd	97.0059	0.0192	0.0047	0.9353
3rd	55.7152	0.0385	0.0020	0.8905
4th	294.0668	0.0078	0.0036	0.9589
5th	84.4485	0.0090	0.0037	0.9119
6th	16.0000	0.0084	0.0013	0.9772
7th	**97.0059**	**0.0237**	**0.0013**	**0.9903**
8th	13.9288	0.1250	0.0034	0.8012
9th	128.0000	0.0179	0.0025	0.9626
10th	16.0000	0.1250	0.0019	0.9818
Average of the best results in SVR model			0.0027	0.9315

finally tends to zero (solid line). But, the *MSE* during the testing process decreases at first, and then increases so that eventually does not tend to zero (dashed line). This phenomenon in the process of learning an intelligent model is called over-fitting which in term means memorizing (learn by heart) versus learning. Thus, before increasing of the error the process of training should be stopped, this indicates in the figure by stopping point.

The details of the results of 10-fold cross-validation operation in each step are listed in Table 3. As it can be seen, the best results with high accuracy and low error, are obtained in step seven correspond to 0.9903 and 0.0013 for R^2 and *MSE*, respectively.

Fig. 7 presents the best result of cross-validation in a 3D surface plot to check for local minimization. As it can be observed, *C* and γ have been calculated in an order that corresponding *MSE* is located in global extremum point with value of 0.00125. This indicates that *C* and γ are optimum because of *MSE* was calculated in a global minimization condition and the model does not over-fit. In our research, the stopping point to pause the training process, which yields minimum error and maximum R^2 simultaneously, is the 64th epoch.

Fig. 8 illustrates the best result of cross-validation in a 3D surface plot to check for local maximization. This indicates that *C* and γ are optimum because of R^2 was calculated in a global maximization condition corresponding to the value of 0.99.

The compared predicted and measured of the PR results of training data is depicted in Fig. 9. The SVR model outputs (SVR predicted PR) are plotted versus the targets (measured PR). The best linear fit is indicated by a solid line. As shown, maximum of R^2 for training data is obtained 0.99, which shows a high conformity between predicted and actual PR values.

5.6. Applying the trained model on the testing data

Finally, the trained model is applied on testing samples to predict PR. As mentioned, choosing optimal parameters of *C*, ε and γ is an important step in SVR design, which strongly affects the performance of the model. According to the cross-validation results, the best parameters of *C*, ε and γ for our dataset which lead to simultaneous minimum *MSE* and maximum R^2, are implemented 97.01, 0.1 and 0.0237, respectively, to test accuracy of the model.

The values of *C*, ε and γ are obtained from training the SVR model (Table 3) and may be changed for different datasets. As mentioned parameter "*C*" determines trade-off between training error and VC dimension. Parameter "ε" is the insensitivity zone in

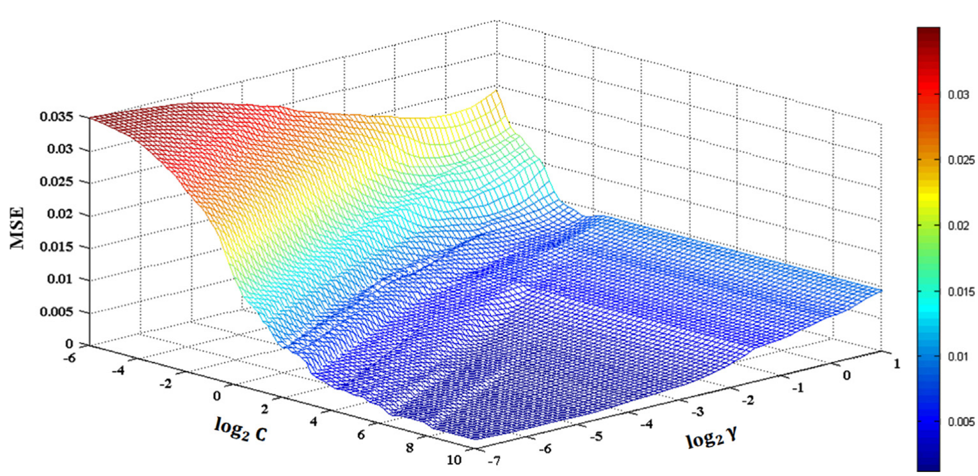

Fig. 7. 3D view of *MSE* versus $\log_2 C$ and $\log_2 \gamma$ in the best step by cross-validation.

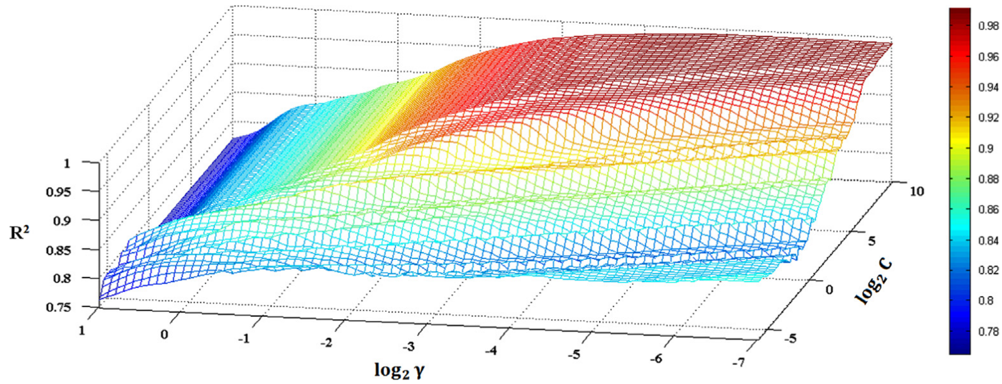

Fig. 8. 3D view of R^2 versus $\log_2 C$ and $\log_{2}\gamma$ in the best step by cross-validation.

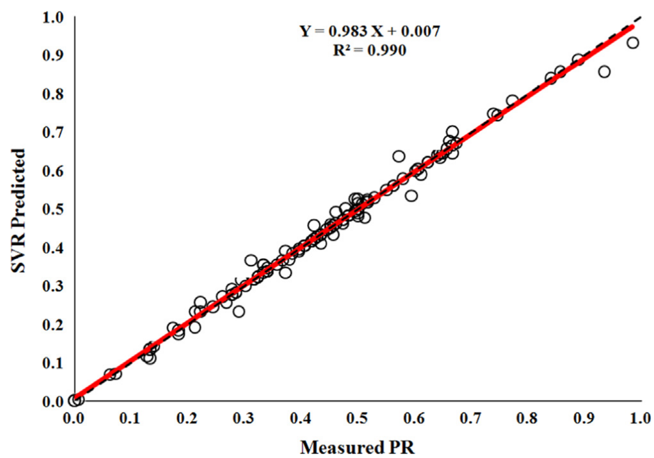

Fig. 9. Squared correlation coefficient for the SVR model training (dashed line is for $R^2=1$).

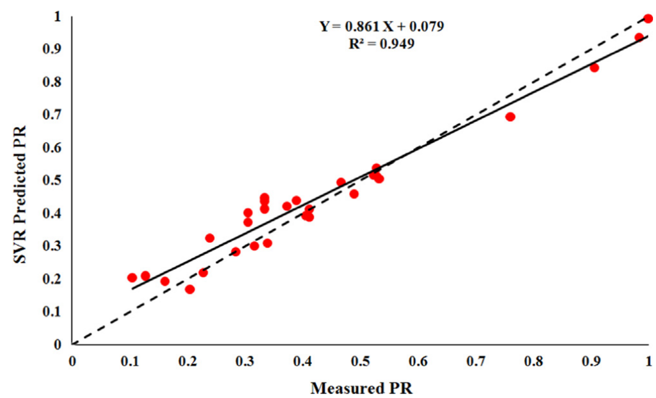

Fig. 10. Testing the SVR model with 20% of the data (dashed line is for $R^2=1$).

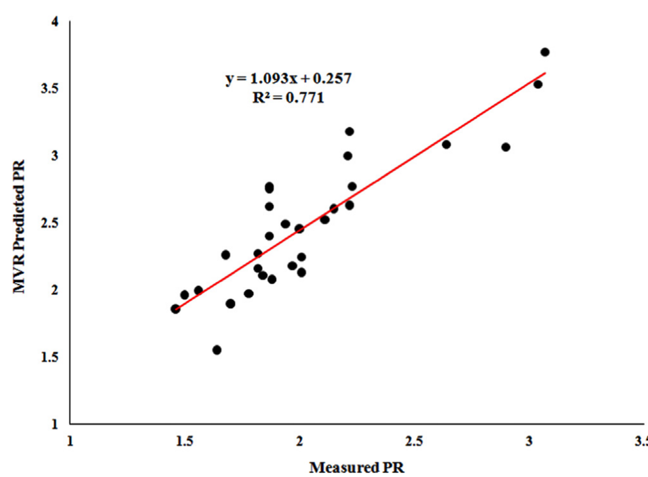

Fig. 11. Coefficient of determination for the MVR linear regression.

ε-insensitive loss function and "γ" is parameter of the Gaussian kernel function, which controls sensitivity of the kernel function.

Fig. 10 illustrates the graphical output provided by regression analysis for the normalized testing data. It is observed that the predicted values are less scattered and are close to measured values signified by its closeness to the line of equality (dashed line). From this figure, SVR has good performance for regression, which proves that the model has stable and reliable prediction ability. Therefore, the proposed SVR model is feasible and effective for prediction of TBM penetration rate and can be put into use.

From the prediction results of training and testing samples, the *MSE* and R^2 between the observed and predicted values of SVR model are found to be 0.0013 and 0.9903 respectively for training data, and 0.0034 and 0.9493 respectively for testing data.

5.7. Linear regression using MVR

In statistics, multi-variable regression (MVR) is an approach to model the relationship between a dependent variable and a set of independent variables. In MVR, data are modeled using linear functions and unknown model parameters are estimated from the data. In this research, a relationship between the dependent variable of PR and the independent variables of geomechanical rock properties and machine parameters is established using MVR method applying SPSS software as follows:

$$\begin{aligned}\mathrm{PR} = 2.0556 &- (0.0024 \times \mathrm{UCS}) - (0.0098 \times \mathrm{BTS}) + (0.0039 \times \mathrm{BI}) \\ &- (0.0296 \times \mathrm{DPW}) - (0.0052 \times \alpha) - (0.1091 \times \mathrm{SE}) \\ &- (0.0004 \times \mathrm{TF}) - (0.1154 \times \mathrm{CP}) + (0.1027 \times \mathrm{CT})\end{aligned} \quad (23)$$

The parameters used in this equation were defined in Table 2. The MVR analysis was done by the same dataset, which were used in the SVR training. In other words, 80% of the total data were selected for the training set and the rest were kept for testing the MVR model. The predicted values of MVR are illustrated in Fig. 11. As it is seen, R^2 of this method is 0.7715 and MSE is 5.327, which shows a poor correlation between the parameters and very low accuracy. Comparing the obtained results shows the relatively higher level of accuracy of non-linear SVR algorithm in comparison with the MVR linear regression.

6. Results and discussion

Although mechanized tunneling has many advantages, TBMs are still encountered with frequent stoppages in some geological conditions due to uncertainties regarding to the estimation of TBM penetration rate. AI-based algorithms such as SVR can be employed for this purpose and applied on a suitable dataset to evaluate PR dynamically in each advance cycle prior to excavation.

In mechanized tunneling the TBM cutterhead is rotated and thrust into the rock surface, causing the cutting discs to penetrate and break the rock at the tunnel face. The interrelationship between cutter wear, machine advancement, mucking and support installations requires an evaluation of many geological conditions, geomechanical rock properties and machine parameters affecting TBM penetration rate.

Any failure of the machine performance can lead to serious cost escalation and extensive construction delay. Due to that,

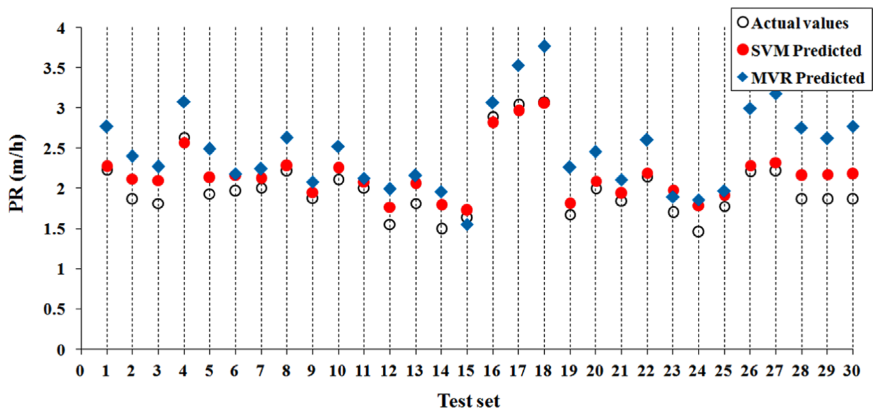

Fig. 12. Comparison of the predicted and actual PRs.

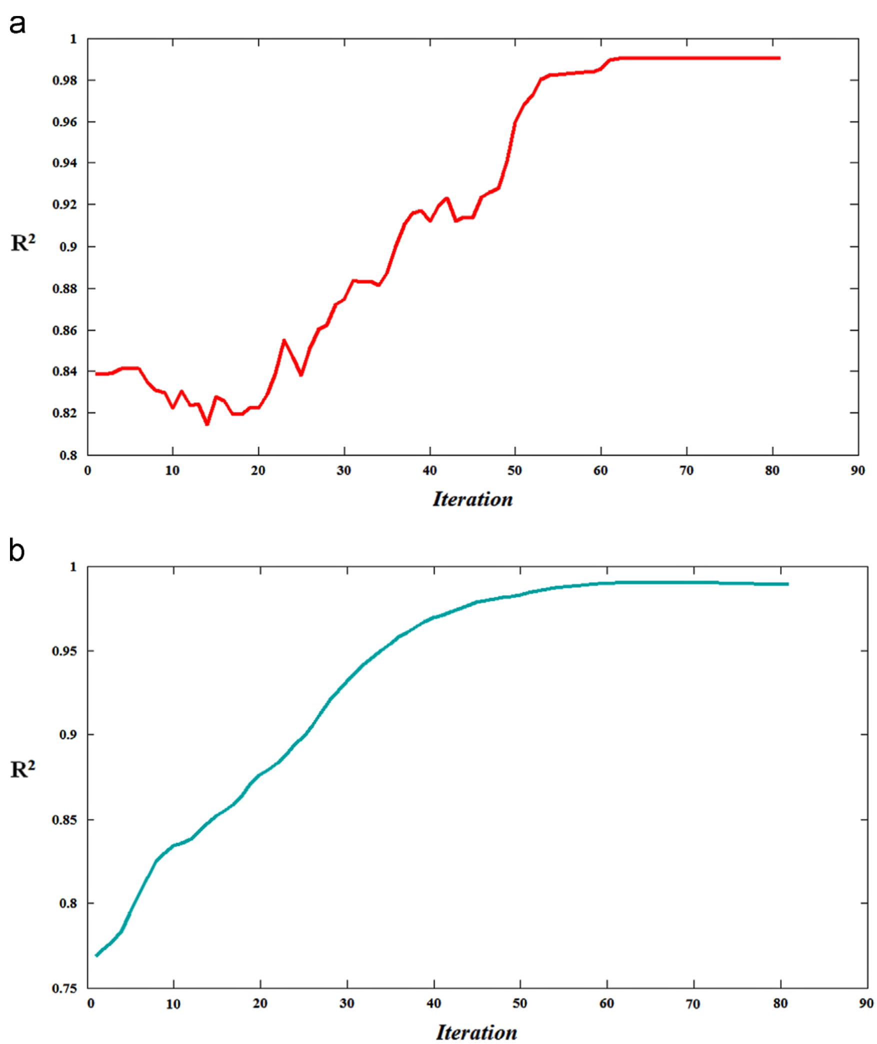

Fig. 13. 2D view of R^2 versus 81 iterations of C and γ. (a) R^2 versus iterations of C and (b) R^2 versus iterations of γ.

prediction of PR depends on both rock engineering properties and machine specifications.

Since a TBM is a system that provides thrust, torque, rotational stability, muck transport, steering, ventilation, and ground support, this research in addition to consider geological conditions and intact and mass rock properties, covers the mechanical characteristics of the machine to enhance the accuracy of the predictive SVR model.

Running the SVR model, it was observed that this algorithm gives accurate prediction of PR compared to the measured ones. In a sense, the complexity of a function's representation by SVR is independent of the dimensionality of the input space, and depends only on the number of support vectors. In addition, this approach demands the optimal selection of only a few number of control parameters such as C, ε and γ when compared with other AI algorithms.

In estimating predictive efficiency of the SVR model, the results are compared with measured values and MVR linear regression; computing indices such as R^2 and *MSE* are used to evaluate the prediction accuracy of the model. From the prediction results of testing samples, R^2 between the observed and predicted values of SVR and MVR models are found to be 0.949 and 0.771, respectively. The SVR and MVR predicted PR values are compared with actual measured ones in Fig. 12. These results show a high conformity between SVR predicted and actual PR values.

The 2D view of the R^2 versus iterations of C and γ are depicted in Fig. 13. As mentioned, the stopping point to pause the training process, which yields minimum *MSE* and maximum R^2 simultaneously, is the 64th epoch. The 2D view of the *MSE* versus iterations of C and γ are also depicted in Fig. 14.

One of the most important factors for the prediction of the cost and finishing time of a TBM tunneling project is the correct prediction of the overall performance of the machine. Since SVR is an algorithm learning statistically by searching the optimal separated hyper-plane and applying support vectors to solve the regression problem, it shows higher performance with regard to PR prediction. In addition, SVR has the character able to avoid over-fitting and local extremum problem through the principal of SRM.

Thus, a first peculiarity of SVR is its root in the risk minimization theory where given a training set the aim is to find a function that minimizes an empirical risk based on a loss function. The second peculiarity of SVR is the kernel trick. The idea is to map the input data into a high-dimensional feature space F by a function $\Phi : \mathbb{R}^d \rightarrow \mathscr{F}$. Then, a linear regression in this new space is equivalent to a non-linear regression in the original space.

According to the results obtained from this research, SVR is a useful and reliable means to predict the rate of penetration. This algorithm is proved suitable tool when relationship between dependent and independent variables cannot easily be understood.

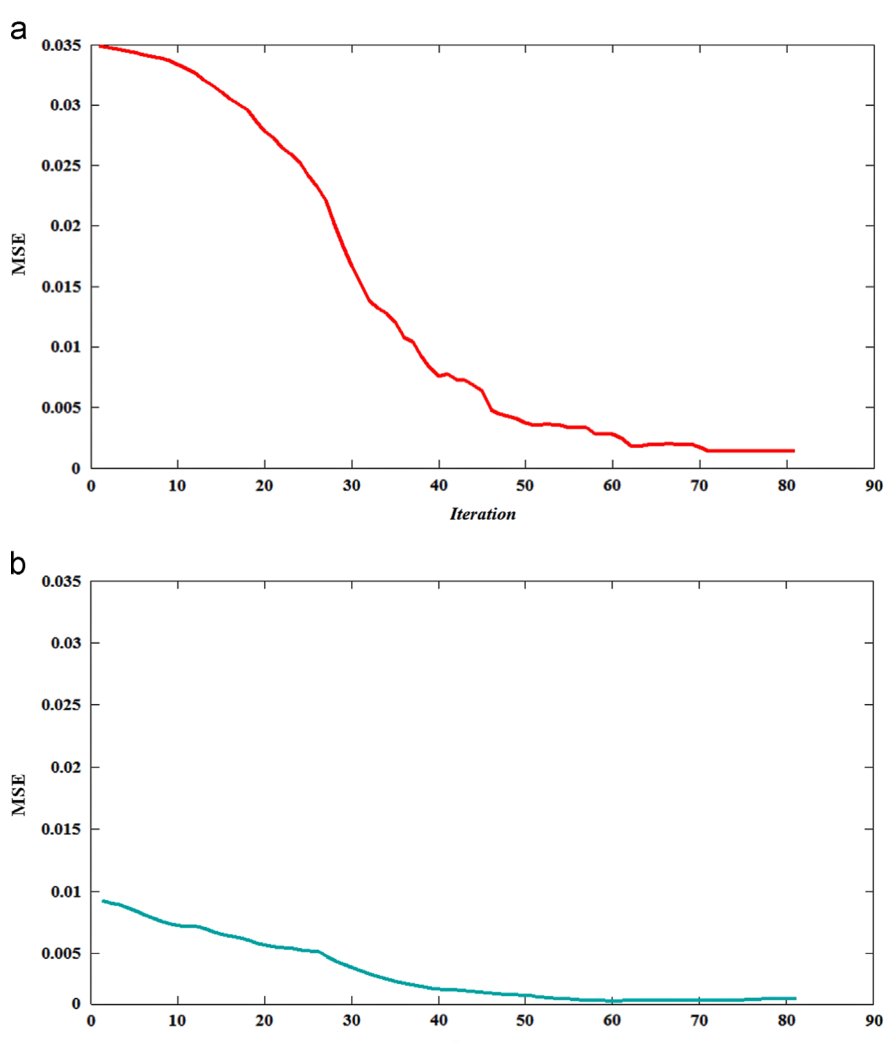

Fig. 14. 2D view of *MSE* versus 81 iterations of C and γ. (a) *MSE* versus iterations of C and (b) *MSE* versus iterations of γ.

After assessment of the proposed SVR model, a parametric study is surveyed to estimate the impact of the machine parameters and rock properties on the machine PR. In this procedure the relative influence of each parameter on the PR is identified as linear trend and the results are shown in Fig. 15. A 45° dashed line is an assumed line where predicted and actual rates are the same ($R^2=1$).

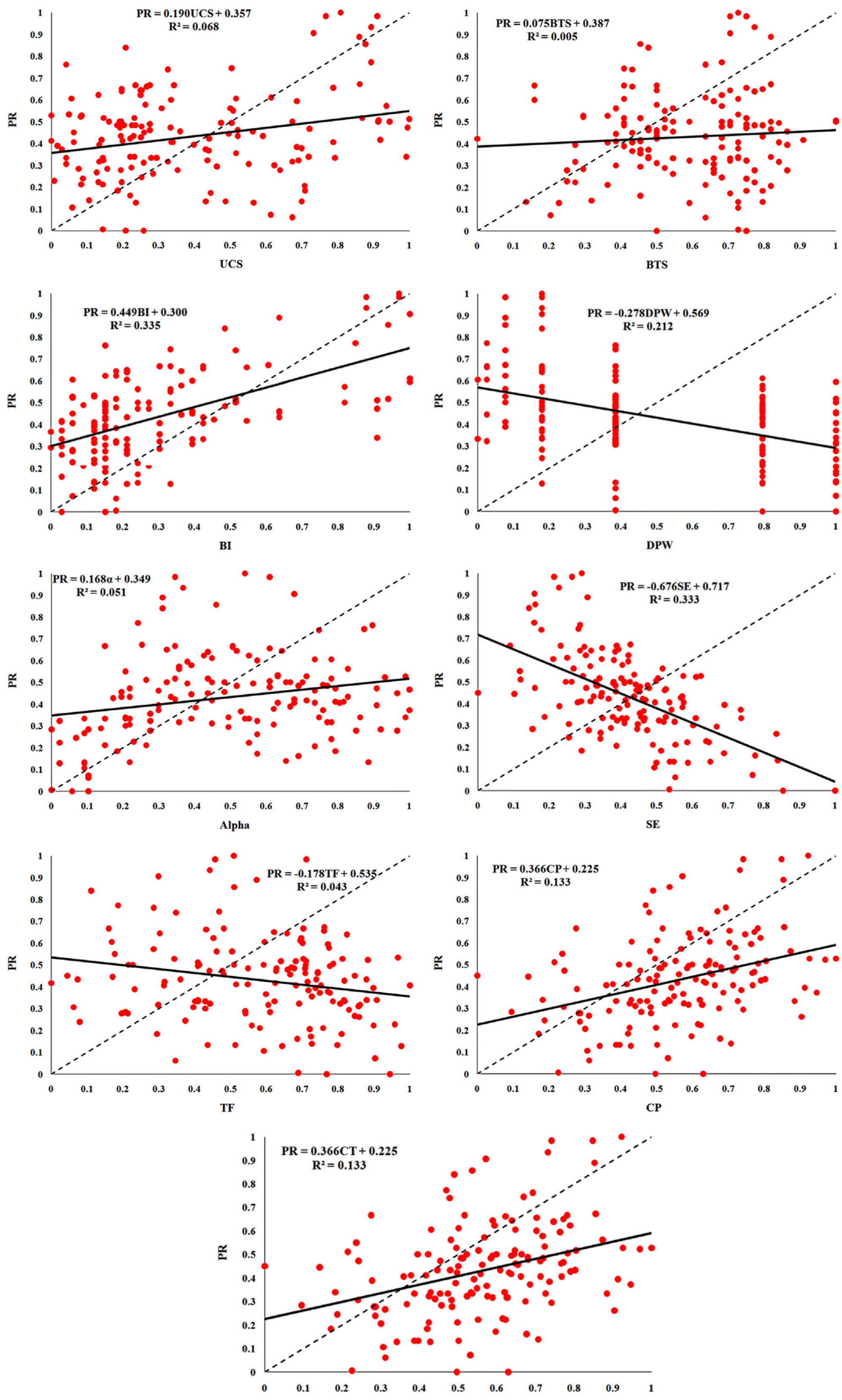

Fig. 15. Relative influence of each input parameter on PR in term of normalized data.

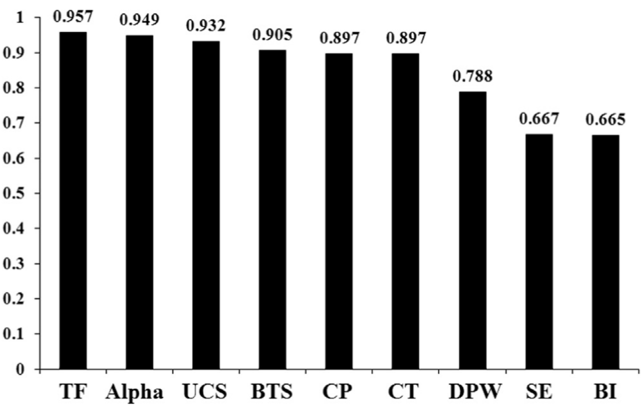

Fig. 16. Sensitivity analysis of the input parameter of the SVR model.

Simultaneously, the result of performing sensitivity analysis in the proposed SVR model is shown in Fig. 16. Sensitivity analysis is performed varying the desired parameter and maintaining fixed values for the other parameters. The parameter to be analyzed varied between its minimum and maximum values of the dataset. The larger the value of the input parameters, the greater the effect the corresponding input unit has on the output unit. It is observed that TF, α, UCS and BTS parameters played a more important role and are the most effective factors on PR and on the other hand the BI and SE are the least effective ones.

During tunnel excavation with a TBM, the thrust and torque produced in the machine as reactions from the rock vary depending on the properties of the rock. Therefore, it is necessary for the TBM operator to control the PR and rotating speed of the cutterhead in accordance with the rock properties so that maximum degree of the capability of the machine can be achieved [70].

In general, greater thrust and torque are produced in excavation of harder rock leading to decrease PR and vice versa. Therefore, based on our findings the rock strength and the thrust force of the machine are the most important parameters which affect machine PR.

Obviously, the higher the quartz content of the rock mass, the more abrasion loss of the cutter happens. Thrust force is one of the basic criteria for judging the hardness of the bedrock [71].

On the other hand, regarding the cutters without any form of wear, the complete torsional resistance acting on the cutterhead during the excavation process can be depended on seven torque components [72], which the dynamic fluctuation characteristics of the excavation torque are mainly determined by the cutting torque generated by the cutting forces of the cutters.

To relate the geomechanical characteristics of a rock mass with the mechanical characteristics of a TBM, it is important to recognize the capabilities of a TBM and to understand the limitations of its applicability. In other words, if geological conditions and rock properties vary in a complex manner, excavation by TBM would not be advantageous, because a TBM cannot generally cope with sudden changes in geology [70].

Additionally, the PR or AR of TBM determines the payment schedule based on progress milestones. A tunneling project may be executed well from a technical point of view, but a lack of appreciation of the time aspect may turn the technically sound project into a financially unsatisfactory situation [49]. Therefore, project evaluation of TBM tunneling requires knowledge about the time of tunnel completion and, consequently, about TBM penetration rate.

7. Conclusions

Successful application of TBM tunneling is directly related to reliable prediction of PR which is used for a project schedule and its related costs. However, rock mass properties strongly affect the TBM penetration rate, utilization index and advance rate, the knowledge about machine design according to site geotechnical conditions is also necessary for reducing the uncertainties in tunnel construction. In this regard, machine specifications such as thrust, torque and cutterhead power have main influence on the rate of penetration.

Due to importance of the mechanical properties on the machine performance, this research in addition to consider intact rock properties including: UCS, BTS and BI, and rock mass properties including: DPW and α; also covers the mechanical properties of the machine including: SE, CP, TF and CT to enhance the accuracy of the predictive SVR model. In this regard, a new and robust SVR model is introduced to estimate the potential non-linear relationship between the parameters affecting PR of TBM.

In order to examine the predictive efficiency of the proposed SVR model, a real dataset of 150 data points pertaining to the Queens Water Tunnel, the USA, was used. When applying SVR, the goodness of fit is determined by the penalty factor C and the Gaussian kernel function parameter γ. Performance evaluation of the developed model was fulfilled by calculating R^2 and *MSE* between the model outputs and actual PRs. From the prediction results of training and testing samples, the *MSE* and R^2 between the observed PR and predicted values of SVR model are 0.0013 and 0.9903 respectively for training data, and 0.0034 and 0.9493 respectively for testing data. These results show an acceptable accuracy of the model.

MVR linear regression is also applied on the same dataset for comparison of the results. The R^2 and *MSE* obtained from this method is 0.7715 and 5.327, respectively. Comparing the SVR results with MVR linear regression reveals that an acceptable accuracy of the proposed SVR model.

SVR uses a non-linear mapping, based on a kernel function, to transform an input space to a high dimensional space and then looks for a non-linear relation between inputs and outputs data. SVR not only has a rigorous theoretical background but also can find global optimal solutions for problems with small training samples, high dimensions and non-linearity.

The SVR performance in comparison with the MVR method shows a good accordance with the actual data. The SVR gain achievable over simple prediction methods such as MVR is satisfactory to justify its deployment for TBM performance prediction.

In order to develop SVR model in this research, a dataset including both rock properties and machine parameters is used together for predicting TBM penetration rate. Due to that, the result obtained from this research is independent, new and different from previous studies. However, this research may be continued in order to compare results of the proposed SVR model with conventional methods or other numerical techniques when a reliable and comparable dataset is available.

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References

[1] Zhao J, Gong QM. Keynote: rock mechanics and excavation by tunnel boring machine—issues and challenges. In: Proceedings of the ISRM international symposium and fourth Asian rock mechanics symposium. Singapore; 2006.
[2] Delisio A, Zhao J, Einstein HH. Analysis and prediction of TBM performance in blocky rock conditions at the Lötschberg Base Tunnel. Tunnelling

Underground Space Technol 2013;33:131–42. http://dx.doi.org/10.1016/j.tust.2012.06.015.
[3] Rostami J, Ozdemir L, Nilsen B. Comparison between CSM and NTH hard rock TBM performance prediction models. In: Proceedings of the annual technical meeting: Institute of Shaft Drilling Technologys (ISDT). Las Vegas, Colorado School of Mines, Golden, CO, USA; 1996. p. 11.
[4] Alvarez Grima M, Bruines PA, Verhoef PNW. Modeling tunnel boring machine by neuro-fuzzy methods. Tunnelling Underground Space Technol 2000;15(3):259–69. http://dx.doi.org/10.1016/S0886-7798(00)00055-9.
[5] Sapigni M, Berti M, Bethaz E, Busillo A, Gardone G. TBM performance estimation using rock mass classification. Int J Rock Mech Min Sci 2002;39(6):771–88. http://dx.doi.org/10.1016/S1365-1609(02)00069-2.
[6] Gong QM, Zhao J. Development of a rock mass characteristics model for TBM penetration rate prediction. Int J Rock Mech Min Sci 2009;46:8–18. http://dx.doi.org/10.1016/j.ijrmms.2008.03.003.
[7] Acaroglu O, Ozdemir L, Asbury B. A fuzzy logic model to predict specific energy requirement for TBM performance prediction. Tunnelling Underground Space Technol 2008;23:600–8. http://dx.doi.org/10.1016/j.tust.2007.11.003.
[8] Yagiz S, Gokceoglu C, Sezer E, Iplikci S. Application of two non-linear prediction tools to the estimation of tunnel boring machine performance. Eng Appl Artif Intell 2009;22:808–14. http://dx.doi.org/10.1016/j.engappai.2009.03.007.
[9] Kim T. Development of a fuzzy logic based utilization predictor model for hard rock tunnel boring machines. PhD thesis. Dept Mining Eng, Colorado School of Mines; 2004.
[10] Benardos AG, Kaliampakos DC. Modeling TBM performance with artificial neural networks. Tunnelling Underground Space Technol 2004;19:597–605. http://dx.doi.org/10.1016/j.tust.2004.02.128.
[11] Tiryaki B. Application of artificial neural networks for predicting the cuttability of rocks by drag tools. Tunnelling Underground Space Technol 2008;23(3):273–80. http://dx.doi.org/10.1016/j.tust.2007.04.008.
[12] Yagiz S, Karahan H. Prediction of hard rock TBM penetration rate using particle swarm optimization. Int J Rock Mech Min Sci 2011;48(3):427–33. http://dx.doi.org/10.1016/j.ijrmms.2011.02.013.
[13] Ozdemir L. Development of theoretical equations for predicting tunnel borability. PhD dissertation. Dept Mining Eng, Colorado School of Mines; 1977.
[14] Cheema S. Development of a rock mass boreability index for the performance of tunnel boring machines. PhD dissertation. Dept Mining Eng, Colorado School of Mines; 1999.
[15] Yagiz S. Development of rock fracture and brittleness indices to quantify the effects of rock mass features and toughness in the CSM model basic penetration for hard rock tunneling machines. PhD dissertation. Dept Mining Eng, Colorado School of Mines; 2002.
[16] Bruland A. Hard rock tunnel boring. PhD dissertation. Norwegian University of Sciences and Technology, Trondheim; 1998.
[17] Tarkoy PJ. Simple and practical TBM performance prediction. Geomech Tunnelling 2009;2(2). http://dx.doi.org/10.1002/geot.200900017.
[18] Protodyakonov MM. Mechanical properties and drillability of rock. In: Proceedings of the fifth symposium on rock mechanics. University of Minnesota; 1962. p. 103–118.
[19] Pariseau WG, Fairhurst C. The force-penetration characteristics for wedge penetration into rock. Int J Rock Mech Min Sci 1967;4(2):165–8. http://dx.doi.org/10.1016/0148-9062(67)90041-1.
[20] Lundberg B. Penetration of rock by conical indenters. Int J Rock Mech Min Sci Geomech Abstr 1974;11(6):209–14. http://dx.doi.org/10.1016/0148-9062(74)90127-2.
[21] Yagiz S. Assessment of brittleness using rock strength and density with punch penetration test. Tunnelling Underground Space Technol 2009;24:66–74.
[22] Tarkoy PJ. Rock index properties to predict tunnel boring machine penetration rates. Report to NSF. No. NSFG136468—PB 239 664. USA; 1974. p. 48.
[23] Tarkoy PJ, Hendron AJ. Rock hardness index properties and geotechnical parameters for predicting tunnel boring machine performance. Report to NSF. No. GI-36468/NSF-RA-7-75-030. USA; 1975. p. 347.
[24] Rostami J, Ozdemir L. A new model for performance prediction of hard rock TBMs. In: Bowerman LD et al., editors. Proceedings of the rapid excavation and tunneling conferences (RETC). Boston, USA; 1993. p. 793–809.
[25] Barton NR. TBM performance estimation in rock using QTBM. Tunnels Tunnelling Int 1999;31:41–8.
[26] Yagiz S. Utilizing rock mass properties for predicting TBM performance in hard rock condition. Tunnelling Underground Space Technol 2008;23(3):326–39. http://dx.doi.org/10.1016/j.tust.2007.04.011.
[27] Farrokh E, Rostami J, Laughton C. Study of various models for estimation of penetration rate of hard rock TBMs. Tunnelling Underground Space Technol 2012;30:110–23. http://dx.doi.org/10.1016/j.tust.2012.02.012.
[28] Barton NR. TBM tunneling in jointed and faulted rock. London: Taylor & Francis; 2000.
[29] Movinkel T, Johannessen O. Geological parameters for hard rock tunnel boring. Tunnels Tunnelling 1986;18(4):45–8.
[30] Barton NR, Lien R, Lunde J. Engineering classification of rock masses for the design of tunnel support. Rock Mech Rock Eng 1974;6(4):189–236. http://dx.doi.org/10.1007/BF01239496.
[31] Bieniawski ZT, Celada B, Galera JM. TBM excavability; prediction and machine and rock interaction. In: Proceedings of the rapid excavation and tunneling conferences (RETC). Toronto, Canada; 2007.
[32] Bieniawski ZT, Celada B, Galera JM, Alvares MH. Rock mass excavability (RME) index. Paper no. PITA06-254. ITA World Tunneling Congress, Korea; 2006.
[33] Khademi Hamidi J, Shahriar K, Rezai B, Rostami J. Performance prediction of hard rock TBM using Rock Mass Rating (RMR) system. Tunnelling Underground Space Technol 2010;25:333–45. http://dx.doi.org/10.1016/j.tust.2010.01.008.
[34] Wickham GE, Tidemann HR, Skinner EH. Ground support prediction model: RSR concept. In: Proceedings of the rapid tunneling and excavation conference. New York: SME/AIME; 1974. p. 691–707.
[35] Cassinelli F, Cina S, Innaurato N, Mancini R, Sampaolo A. Power consumption and metal wear in tunnel boring machines: analysis of TBM operation in hard rock. Tunneling 1982;82:73–81.
[36] Innaurato N, Mancini A, Rondena E, Zaninetti A. Forecasting and effective TBM performances in a rapid excavation of a tunnel in Italy. In: Proceeding of seventh international congress on rock mechanics. Aachen, Germany; 1991. p. 1009–1014.
[37] Howarth DF, Adamson WR, Berndt JR. Correlation of model tunnel boring and drilling machine performances with rock properties. Int J Rock Mech Min Sci Geomech Abstr 1986;23(2):171–5. http://dx.doi.org/10.1016/0148-9062(86)90344-X.
[38] Gong QM, Zhao J. Influence of rock brittleness on TBM penetration rate in Singapore granite. Tunnelling Underground Space Technol 2007;22:317–24. http://dx.doi.org/10.1016/j.tust.2006.07.004.
[39] Engineer Manual, EM 1110-2-2901. Tunnels and shafts in rock: engineering and design. Washington: Department of the Army, US Army Corps of Engineers; 1997.
[40] Wu S, Qian B, Gong Z. The time and cost prediction of tunnel boring machine in tunneling. Wuhan Univ J Nat Sci 2006;11(2):385–8. http://dx.doi.org/10.1007/BF02832128.
[41] Tarkoy P. Predicting TBM penetration rates in selected rock types. In: Proceeding of the ninth Canadian rock mechanics symposium, Montreal: Mines and Resource Press; 1973. p. 263–274.
[42] Sundin N, Wanstedt S. Boreability model for TBMs. In: Proceeding of the first North American rock mechanic symposium. Texas: Balkema Press; 1994. p. 311–318.
[43] Graham PC. Rock exploration for machine manufactures. In: Bieniawski ZT, editor. Proceeding of the exploration for rock engineering. Johannesburg, South Africa. Rotterdam: Balkema; 1976. p. 173–80.
[44] Hughes HM. The relative cuttability of coal-measures stone. Min Sci Technol 1986;3(2):95–109. http://dx.doi.org/10.1016/S0167-9031(86)90250-1.
[45] Farmer I, Garrity P, Glossop N. Operational characteristics of full face tunnel boring machines. In: Proceeding of the rapid excavation and tunneling conference (RETC). Chapter 13, SME Publication; 1987.
[46] Snowdon RA, Ryley MD, Temporal J. A study of disc cutting in selected British rocks. Int J Rock Mech Min Sci Geomech Abstr 1982;19(3):107–21. http://dx.doi.org/10.1016/0148-9062(82)91151-2.
[47] Sanio HP. Prediction of the performance of disc cutters in anisotropic rock. Int J Rock Mech Min Sci Geomech Abstr 1985;22(3):153–61. http://dx.doi.org/10.1016/0148-9062(85)93229-2.
[48] Tatiya RR. Surface and underground excavations—methods, techniques and equipment. London: Taylor & Francis; 2005.
[49] Alber M. Advance rates of hard rock TBMs and their effects on project economics. Tunnelling Underground Space Technol 2000;15(1):55–64. http://dx.doi.org/10.1016/S0886-7798(00)00029-8.
[50] Gunn SR. Support vector machines for classification and regression. (Technical report). University of Southampton, School of Electronics and Computer Science; 1998.
[51] Cortes C, Vapnik V. Support vector networks. Mach Learn 1995;20(3):273–97. http://dx.doi.org/10.1023/A:1022627411411.
[52] Vapnik V, Golowich S, Smola A. Support vector method for function approximation, regression estimation, and signal processing. In: Mozer MC, Jordan MI, Petsche T, editors. Advances in neural information processing systems. Cambridge: MIT Press; 1997. p. 281–7.
[53] Basak D, Pal S, Patranabis DC. Support vector regression. Neural Inf Process Lett Rev 2007;11(10):203–24.
[54] Vapnik V. The nature of statistical learning theory. 2nd ed.. New York, NY: Springer-Verlag; 1995.
[55] Smola AJ, Scholkopf B. A tutorial on support vector regression. Stat Comput 2004;14(3):199–222. http://dx.doi.org/10.1023/B:STCO.0000035301.49549.88.
[56] Courant R, Hilbert D. Methods of mathematical physics. New York, NY: Interscience; 1953.
[57] Karush W. Minima of functions of several variables with inequalities as side constraints. MSc dissertation. Dept Math, University of Chicago; 1939.
[58] Kuhn HW, Tucker AW. Nonlinear programming. In: Second Berkeley symposium on mathematical statistics and probabilistics. Berkeley; 1951. p. 481–492.
[59] Khalighi BB, Diehl JJ. High performance tunnel boring machine for Queens Water Tunnel No. 3: A design and case history. In: Proceeding of the rapid excavation and tunneling conference (RETC). Chapter 11, SME publication; 1997.
[60] Baskerville CA, Mose GD. The separation of the Hartland formation and Ravenswood granodiorite from the Fordham gneiss at Cameron's line in the New York City area. Northeastern Geol 1989;11(1):22–8.
[61] Merguerian C, Ozdemir L. Rock mass properties and hard rock TBM penetration rate investigations, Queens tunnel complex, NYC Water Tunnel No. 3, stage 2. In: Robinson RA, Marquardt JM, editors, rapid excavation and tunneling conference (RETC); 2003. p. 1019–1036.
[62] Cherkassky V, Mulier F. Learning from data: concepts, theory and methods. New York, NY: Wiley; 1998.

[63] Shawe-Taylor J, Cristianini N. Kernel methods for pattern analysis. Cambridge: Cambridge University Press; 2004.
[64] Chang CC, Lin CJ. LIBSVM: A library for support vector machines. Taipei: Dep Comput Sci Inf Eng, National Taiwan University; 2012. ⟨http://www.csie.ntu.edu.tw/~cjlin/libsvm⟩.
[65] Platt JC. Sequential minimal optimization: a fast algorithm for training support vector machines. Microsoft Research Tech. Report MSR-TR-98-14, Microsoft, Redmond, Washington; 1998.
[66] Zhang H, Wang YJ, Li YF. SVM model for estimating the parameters of the probability-integral method of predicting mining subsidence. Min Sci Technol 2009;19(3):385–8. http://dx.doi.org/10.1016/S1674-5264(09)60072-7.
[67] Hsu CW, Chang CC, Lin CJ. A practical guide to support vector classification. Taipei: Dep Comput Sci Inf Eng. National Taiwan University; 2010. ⟨http://www.csie.ntu.edu.tw/_cjlin/libsvm⟩.
[68] Bird J. Engineering mathematics. 4th ed. Oxford: Routledge; 0-7506-5776-6.
[69] DeCoursey WJ. Statistics and probability for engineering applications with Microsoft Excel. New York, NY: Elsevier; 0-7506-7618-3.
[70] Morimoto T, Hori M. Performance characteristics of a tunnel boring machine from the geomechanical viewpoint. Int J Rock Mech Min Sci Geomech Abstr 1986;23(1):55–66. http://dx.doi.org/10.1016/0148-9062(86)91666-9.
[71] Jung HS, Choi JM, Chun BS, Park JS, Lee YJ. Causes of reduction in shield TBM performance—a case study in Seoul. Tunnelling Underground Space Technol 2011;26:453–61. http://dx.doi.org/10.1016/j.tust.2011.01.001.
[72] Zhang K, Yu H, Liu Z, Lai X. Dynamic characteristic analysis of TBM tunneling in mixed-face conditions. Simul Modell Pract Theory 2010;18:1019–31. http://dx.doi.org/10.1016/j.simpat.2010.03.005.