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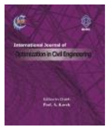

# ANALYSIS OF ROCK MASS BOREABILITY IN MECHANICAL TUNNELING USING RELEVANCE VECTOR REGRESSION OPTIMIZED BY DOLPHIN ECHOLOCATION ALGORITHM

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## ABSTRACT

During project planning, the prediction of TBM performance is a key factor for selection of tunneling methods and preparation of project schedules. During the construction, TBM performance need to be evaluated based on the encountered rock mass conditions. In this paper, the model based on a relevance vector regression (RVR) optimized by dolphin echolocation algorithm (DEA) for prediction of specific rock mass boreability index (SRMBI) is proposed. The DEA is combined with the RVR for determining the optimal value of its user-defined parameters. The optimized RVR by DEA was employed to available data given in the open source literature. In this model, rock mass uniaxial compressive strength, brittleness index ($B_i$), volumetric joint account ($J_v$), and joint orientation ($J_o$) were used as the input, while the SRMBI was the output parameter. The performances of the suggested predictive model were tested according to two performance indices, i.e., mean square error and determination coefficient. The results show that the RVR- DEA model can be successfully utilized for estimation of the SRMBI in mechanical tunneling.

**Keywords:** rock mass boreability, relevance vector regression, dolphin echolocation algorithm, TBM performance, mechanical tunneling.

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## 1. INTRODUCTION

Estimating the TBM performance is a vital phase in tunnel design, cost estimation and control as well as for the choice of the most appropriate excavation machine. Review of the

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literature shows that many methods of performance estimation and modeling for mechanical tunneling using TBM have been suggested by researchers. In this paper, the well–known research works are addressed. Sapigni et al. [1] applied rock mass classifications in predicting performance of TBM. Tarkoy [2] developed an empirical relationship between total hardness and TBM rate of penetration. Yagiz [3] used rock mass properties in predicting TBM performance under the hard-rock condition. Hassanpour et al. [4] developed new equations for predicting the performance of hard-rock TBMs in carbonate-argillaceous rocks. Gehring [5] carried out research on the influence of TBM design and machine features on performance and tool wear in rock. Also, performance prediction of hard-rock TBMs was carried out by Hamidi et al. [6] using the rock mass rating (RMR) system. Moradi and Farsangi [7] estimated the advance rate in rock TBM tunneling using the risk matrix method. Hassanpour et al. [8] introduced a regression model for hard-rock TBM performance prediction. Farrokh et al. [9] studied various models used for estimating the penetration rate of hard-rock TBMs.

Although previous efforts are valuable but in many cases, the aforesaid empirical approaches are not capable of distinguishing the sophisticated structures involved in dataset. These reasons have been the main causes of interest to better find out the interaction between rock and machine and to propose a more precise and sure model for the estimation. For doing the purpose, recently, more intelligent methods, such as artificial neural networks (ANNs) and support vector regression (SVR) are successfully applied in non-linear modeling. However, it is difficult to determine the architecture for ANNs and stochastic events are present during the building of the model (i.e. given the same training set, the different solution is often found). In contrast, solution found based on SVR is global and deterministic. But it still has the trouble to determine the parameters (e.g. insensitivity ε and penalty weight C) and choose appropriate kernel function. Relevance vector regression (RVR) is a good competitor of SVR. It is a probabilistic model similar to the SVR, but where the training takes place in a Bayesian framework [10]. The most impressive feature of this method is that it can offer good generalization performance while the inferred predictors are exceedingly sparse in that they contain relatively few non-zero weights associated with the corresponding basis functions [11]. Unlike in SVR framework where the basis functions must satisfy Mercer's kernel theorem, in the RVR case there is no restriction on the basis functions [11,12]. Also, kernel width $\sigma$ is the only parameter to be tuned in RVR model. Consequently the sparse RVR model could generalize better with very less computation time than SVR. In this study, the optimized RVR is proposed for indirect prediction of specific rock mass boreability index (SRMBI) in mechanical tunneling. The efficiency of the RVR model is tried to increase through electing the optimal value of its parameters. Some metaheuristic algorithms such as consisting of charged system search (CSS) [13] and ray optimization (RO) [14] can be used for this determination. Recently, a novel numerical stochastic optimization method inspired by dolphin echolocation behavior has been introduced. The dolphin echolocation algorithm (DEA) has been developed by Kaveh and Farhoudi [15]. In the present work, the DEA is used to select the appropriate kernel parameters of their RVR model. The goodness of each hybrid model was evaluated by using the data available in the literature. Finally, a statistical error analysis has been performed on the modeling results to investigate the effectiveness of the proposed method.

## 2. THEORY

In this section, first the literature review relevant to the RVR is presented and then, there is some descriptions about the DEA.

### *2.1 Relevance vector regression (RVR)*

The RVR, presented by Tipping [11] is actually a special case of a Gaussian process. Unlike the SVR, the uncertainty of the output estimation value can be characterized. Also, the RVR has better sparseness than the SVR, which can reduce online prediction complexity. In addition, the RVR does not need to estimate the error/margin tradeoff parameter C, which can reduce the computational time and the kernel function, does not need to satisfy the Mercer condition. For those advantages of the RVR approach compared with the SVR, RVR received great attention and is successfully employed in regression problems of estimation [16-18].

In RVR approach, supposing the system is multiple-input-single-output, given a dataset of $N$ input vectors with $N$ corresponding scalar-valued target $\{x_n,t_n\}_{n=1}^{N}$, the output $t=(t_1,...,t_N)^T$ can be expressed as the sum of an approximation vector $y=(y(x_1),...,y(x_N))^T$ The targets are from the model with additive noise:

$$t_n = y(x_n,w)+e \tag{1}$$

where $w$ is the weight vector and $e$ is the random noise. The function *y(x)* is defined as follows:

$$y(x,w)=\sum_{i=1}^{N} w_i K(x,x_i)+w_0=\sum_{i=1}^{N} w_i \Phi(x) \tag{2}$$

$\Phi(x)$; here, it is given as $\Phi(x)=\left[1,K(x,x_1),K(x,x_2),...,K(x,x_N)\right]$.

The targets can be given as $p(t_n|x_n)=N(t|y(x_n),\sigma^2)$. The likelihood of the complete dataset can be written as:

$$p(t|w,\sigma^2)=\frac{1}{2\pi\sigma^2}\exp\left\{-\frac{1}{2\sigma^2}\|t-\Phi(x)w\|\right\} \tag{3}$$

where $w=(w_0,w_1,...,w_N)$, $t=(t_1,t_2,...,t_N)$ and $\Phi$ is the $N\times(N+1)$ design matrix. Here, RVR approach adopts a Bayesian perspective and constrains $w$ and $\sigma^2$ by defining a prior probability distribution over the weights:

$$t_n = y(x_n,w)+e \tag{1}$$

$$p(w|\alpha)=\prod_{i=1}^{N} N(w_i|0,\alpha_i^{-1})=\frac{1}{2\pi^{(N+1)/2}}\prod_{i=1}^{N}\alpha_i^{1/2}\exp\left(-\frac{\alpha_i w_i^2}{2}\right) \tag{4}$$

$$p(\alpha)=\prod_{i=1}^{N} gamma\left(\alpha_i \left|a,b\right.\right) \tag{5}$$

$$p(\beta)=gamma\left(\beta\left|a,b\right.\right) \tag{6}$$

where b=$\sigma^2$, *a* is an N+1 hyper-parameter, and gamma $\left(\alpha\left|a,b\right.\right)$ is defined as

$$gamma\left(\alpha\left|a,b\right.\right)=1\Gamma(a)^{-1}b^{a}\alpha^{a-1}e^{-b\alpha}\Gamma(a)=\int_{0}^{\infty}t^{a-1}e^{-t}dt \tag{7}$$

Also, the posterior over weights can be considered through the Bayesian rule:

$$p(w\left|t,\alpha,\sigma^2\right.)=\frac{p(t\left|w,\sigma^2\right.)p(w\left|\alpha\right.)}{p(t\left|\alpha,\sigma^2\right.)}=\frac{1}{2\pi^{(N+1)/2}}\left|\sum\right|^{-1/2}\exp\left\{-\frac{1}{2}(w-\mu)^{T}\sum^{-1}(w-\mu)\right\} \tag{8}$$

where the posterior covariance and mean are defined as follows:

$$\sum=\left(\sigma^{-2}2\Phi^{T}2\Phi+A\right)^{-1} \tag{9}$$

$$\mu=\sigma^{-2}\sum\Phi^{T}t \tag{10}$$

where $A=diag\left(\alpha_1,\alpha_2,...,\alpha_N\right)$. The likelihood distribution over the training targets given by Tipping [11]:

$$p\left(t\left|\alpha,\sigma^2\right.\right)=\int p(t\left|w,\sigma^2\right.)p(w\left|\alpha\right.)dw=(2\pi)^{-N/2}\left|C\right|^{-1/2}\exp\left\{\frac{1}{2}t^{T}C^{-1}t\right\} \tag{11}$$

where the covariance is given by $C=\sigma^{-2}I+\Phi A^{-1}\Phi^{T}$. A detailed explanation of the RVR approach can be found in [19,20].

### *2.2 Dolphin echolocation algorithm*

DE mimics strategies utilized by dolphins for their hunting process. Dolphins produce a kind of voice called sonar to locate the target, doing this dolphin change sonar to modify the target and its location. This fact is mimicked here as the main feature of the new optimization method [21]. The DEA [15], simulate the dolphin's echolocation and limiting the search related by distance from the target. For defined this process more clearly, two phases are introduced: In the first phase, the algorithm evaluate all space search to form that to a general search space, so it should be looking for unexplored areas. This task is done by create a series of random locations in the search space. In the second phase concentrate to evaluate the best places from the first phase. A detailed description of the DEA can be found in [15].

## 3. PREDICTION OF SRMBI USING RVR-DEA MODEL

To prediction of SRMBI using RVR-DEA model, all relevant parameters should be determined, due to the fact that RVR work based on given data and do not have previous knowledge about the subject of prediction. Following sections describe the database and prediction of SRMBI in mechanical tunneling using RVR-DEA model.

### *3.1 Database*

Dataset applied in this study for determining the relationship among the set of input and output variables are gathered from open source literature [22]. A dataset that includes 47 case studies was employed in current study, while 37 cases (80%) were utilized for constructing the models and the remainder data points (10 cases) were utilized for models performance evaluation. Partial dataset used in this study are presents in Table 1 and the descriptive statistics of the data sets are shown in Table 2. In this database, four rock mass parameters are identified as the factors influencing the TBM penetration rate: UCS, brittleness index ($B_i$), volumetric joint account ($J_v$), and joint orientation ($J_o$) [22]. The UCS of the rock affects the formation of the crushed zone during TBM penetration. The higher the rock strength, the more load is required on the cutter. The brittleness of the rock affects the size of the crushed zone, crack initiation and propagation during rock indentation, and chip formation. A higher brittleness results in easier rock fragmentation. Because of the existence of joints, the principal stress field is changed, which affects the rock chipping process. An increase in joint spacing results in a decrease in the penetration rate. The preferred joint angle between the tunnel axis and the joint plane for optimum penetration rate is $45^0$–$60^0$. The rock mass boreability is expressed by the boreability index, defined as the ratio of the applied thrust per cutter to the penetration per revolution. It should be noted that the boreability index is a cutter force normalized by the number of revolutions per minute (RPM) and the penetration rate. Thus, it facilitates comparison of the performance of different TBMs. Because of a change in the efficiency of the cutting action at the cutter head for different cutter forces, the boreability index is not a constant. Therefore, the boreability index cannot accurately represent the rock mass boreability. The specific rock mass boreability index (SRMBI), defined as the boreability index at the critical point of penetration of 1 mm/rev and based on in situ tests, is a better representation of rock mass boreability. The SRMBI eliminates the influence of the cutter force variation on rock mass boreability.

Table 1: Partial dataset used for constructing model

| **Inputs** | | | | **Output** |
|---|---|---|---|---|
| **Jv** | **Jo** | **UCS** | **Bi** | **SRMBI ((kN/cutter/(mm/rev))** |
| 13.3 | 20 | 196.5 | 12.96 | 160.92 |
| 29.3 | 35 | 172.76 | 13.56 | 111.96 |
| 12.2 | 75 | 148.6 | 10 | 139.49 |
| 3 | 20 | 178.37 | 15.72 | 185.72 |
| 5 | 70 | 165 | 14.95 | 157.52 |
| 11.2 | 80 | 170.17 | 16.24 | 149.54 |
| 1.5 | 62.5 | 107.92 | 9.99 | 164.39 |

Table 2: Descriptive statistics of the data sets

| Variables | Input variables | | | | Output variable |
|---|---|---|---|---|---|
| | Jv | Jo (degree) | UCS (MPa) | Bi | SRMBI (kN/cutter/mm/rev) |
| **Mean** | 7.58 | 39.18 | 171.57 | 13.937 | 165.89 |
| **Standard deviation** | 7.04 | 21.72 | 35.69 | 3.113 | 25.42 |
| **Minimum** | 0 | 0 | 67.39 | 6.23 | 108.33 |
| **Maximum** | 29.3 | 80 | 240.3 | 20.93 | 210.4 |

### *3.2 Pre-Processing of Data*

In data-driven system modeling methods, some pre-processing steps are usually implemented prior to any calculations, to eliminate any outliers, missing values or bad data. This step confirms that the raw data retrieved from database is perfectly proper for modeling [23-25]. In order to softening the training procedure and improving the accuracy of prediction, all data samples are normalized to adapt to the interval [0,1] according to the following linear mapping function:

$$x_M = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{12}$$

where $x$ is the original value from the dataset, $x_M$ is the mapped value, and $x_{min}$ ($x_{max}$) denotes the minimum (maximum) raw input values, respectively. It is to be noted that model outputs will be remapped to their corresponding real values by the inverse mapping function ahead of calculating any performance criterion [26,27].

### *3.3 Tuning Parameters for the DEA*

To develop an accurate RVR model, the training, and validation processes are the important steps. In the training process, a set of input-output patterns is repeated to the RVR. The model training stage includes choosing a criterion of fit (Root mean squared error) and an iterative search algorithm to find the network parameters that minimizes the criterion. The control parameters used for running the DEA shown in Table 3.

Table 3: The control parameters used for running the DEA

| **Parameter** | **Value** |
|---|---|
| Maximum iterations number | 80 |
| Population number (number of locations) | 25 |
| Effective radius | 5 |
| power: the degree of the curve | 2.88 |
| PP1: the convergence factor of the first loop | 0.095 |

### *3.4 Performance criterion*

In this paper, the difference between the output of the model and the real output is considered as the error and represented in two ways, including mean squared error (MSE) and squared correlation coefficient ($R^2$) were chosen to be the measure of accuracy. Let $t_k$ be the actual value and $\hat{t}_k$ be the predicted value of the $k^{th}$ observation and $n$ be the number of observations, then MSE and $R^2$ could be defined, respectively, as follows:

$$MSE = \frac{1}{n}\sum_{k=1}^{n}(t_k - \hat{t}_k)^2 \tag{13}$$

$$R^2 = 1 - \frac{\sum_{k=1}^{n}(t_k - \hat{t}_k)^2}{\sum_{k=1}^{n} t_k^2 - \frac{\sum_{i=1}^{n}\hat{t}_k^2}{n}} \tag{14}$$

## 4. RESULTS

In this study, RVR-DEA model was utilized to build a prediction model for the forecasting of SRMBI in mechanical tunneling from available data, using MATLAB environment. All data (47 cases) were randomly divided into two subsets: 80% of the total data was allotted to training data of model construction and 20% of the total data was allocated for test data used to assess the reliability of the developed model. In this model: UCS, $J_o$, $J_v$ and $Bi$ were utilized as the input parameters, while the SRMBI was the output parameter.

After modeling, a correlation between estimated values of SRMBI by the RVR-DEA model and measured values for training and testing phases is shown in Fig. 1. Also, a comparison between predicted values of SRMBI by the RVR-DEA model and measured values for 47 data sets at training (37 data sets) and testing (10 data sets) phases is shown in Fig. 2. As shown in Figs. 1 and 2, the results of the RVR-DEA model in comparison with actual data show a good precision of the RVR-DEA model.

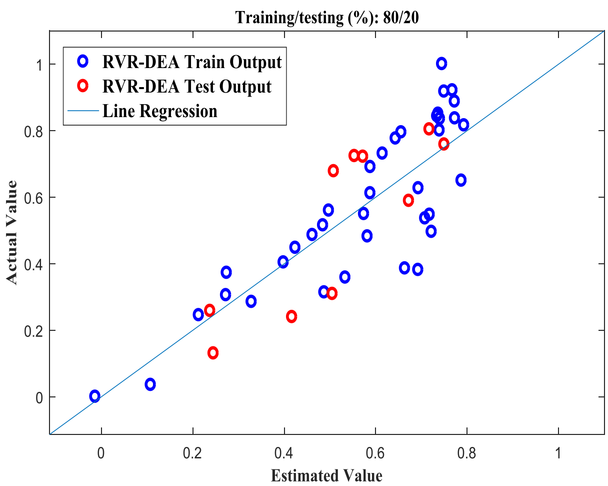
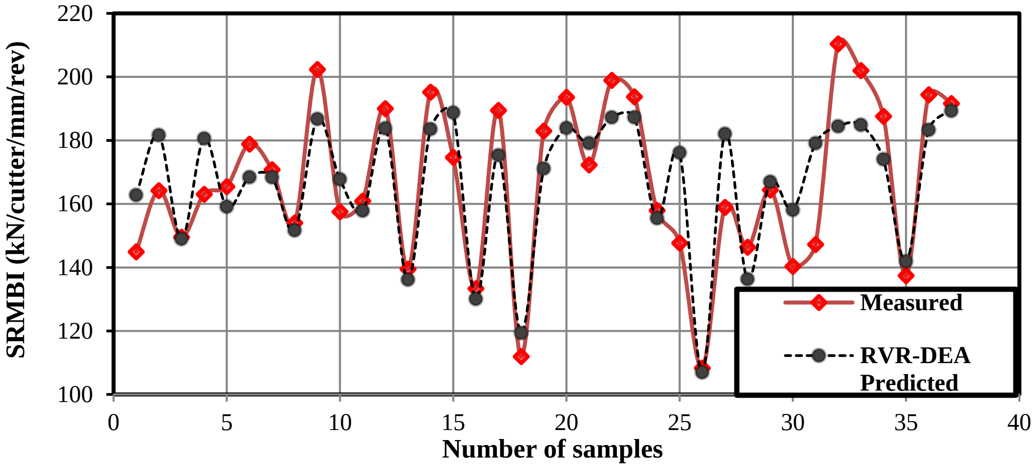
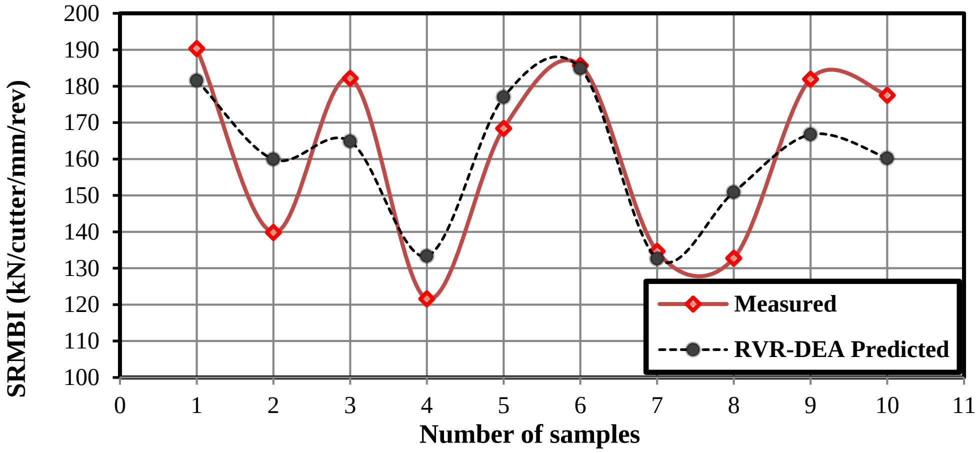



Figure 1. Correlation between measured and estimated SRMBI using RVR-DEA model for training and testing datasets




(a)




(b)

Figure 2. Comparison between measured and predicted SRMBI for a) training data, b) testing datasets

As it was mentioned, it seems that RVR-DEA model is a good method in forecasting of SRMBI during testing and training steps. However, this strong statement needs more approvals. As a matter of fact, there is one question which is yet required to be answered in this section: whether different fractions of training and testing data may change the performance of the models? This question would require many attempts with different fractions of data to show how the performance of the models may change with different numbers of training and testing data.

According to Fig. 3 and Table 4, the MSE and $R^2$ of RVR-DEA model (for training/testing=80/20) is less than that of the other models in almost all of the cases indicating that it can be a better choice for prediction process. It is worth mentioning that the presented model was developed based upon the limited sets of data and cannot be generalized for all the slopes. However, it is open for more development if more data are available.

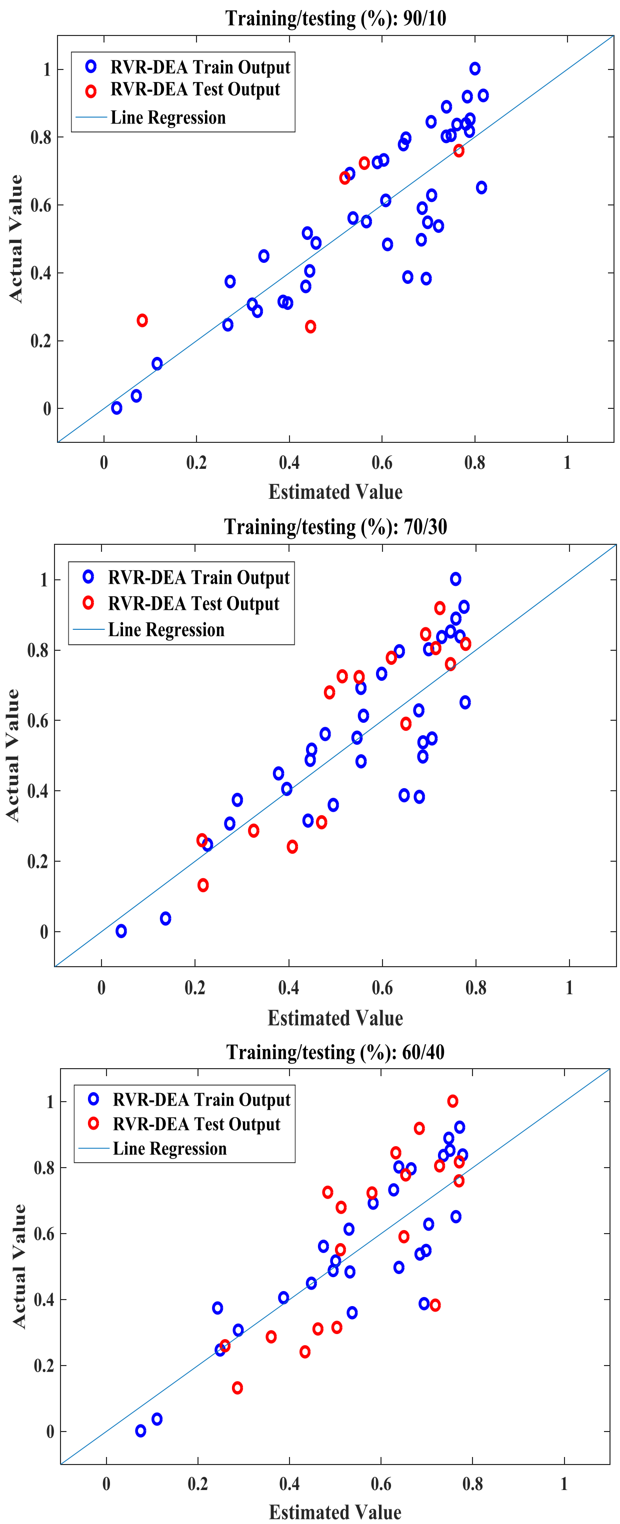



Figure 3. Comparing the performance of RVR-DEA model with different fractions of training and testing data.

Table 4: Comparing the performance of RVR-DEA model with different fractions of training and testing data

| **Training/testing (%)** | **Model** | **MSE (Train)** | **MSE (Test)** | **$R^2$ (Train)** | **$R^2$ (Test)** |
|---|---|---|---|---|---|
| 90/10 | RVR-DEA | 0.014385 | 0.02465 | 0.8753 | 0.7915 |
| 80/20 | RVR- DEA | 0.017238 | 0.01780 | 0.8457 | 0.8511 |
| 70/30 | RVR- DEA | 0.01680 | 0.01811 | 0.8426 | 0.8930 |
| 60/40 | RVR- DEA | 0.01381 | 0.02797 | 0.8676 | 0.7900 |

## 5. CONCLUSIONS

Prediction of the TBM performance is a crucial issue in the tunnel projects excavated by full face tunneling machines. A large number of models have been introduced to estimate TBM performance based on properties of the both rock and machine. However, predicting the TBM performance is a nonlinear and multivariable complex problem that depends on many variables. Thus, it cannot be accurately modeled using a simple linear regression method. There are various techniques of nonlinear analysis utilized for estimating the TBM performance. In this study, an optimized RVR by DEA was used to investigate the SRMBI in mechanical tunneling. This study focused on predicting performance of TBM in different geological settings. Nevertheless, the methodology proposed in here can be applied to predict performance of other types of TBM. The following conclusions were obtained:

- The model proposed in this study are able to successfully predict the SRMBI in mechanical tunneling.
- Application of DEA significantly increases the speed and accuracy of finding optimal values of kernel parameters.

Implementation of the optimized RVR combined with metaheuristic algorithms can be applied as a powerful tool for modeling of non-linear problems encountered in excavation.

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