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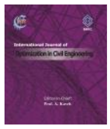

ESTIMATION OF ROADHEADER PERFORMANCE USING RELEVANCE VECTOR REGRESSION APPROACH-A CASE STUDY

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ABSTRACT

Mechanical excavators are widely utilized in civil/mining engineering projects. There are several types of mechanical excavators, such as an impact hammer, tunnel boring machine (TBM) and roadheader. Among these, roadheaders have some advantages (such as, initial investment cost, elimination of blast vibration, minimal ground disturbances and reduced ventilation requirements). The poor performance estimation of the roadheaders can lead to costly contractual claims. Relevance vector regression (RVR) is one of the robust artificial intelligence algorithms proved to be very successful in recognition of relationships between input and output parameters. The aim of this paper is to show the application of RVR in prediction of roadheader performance. The estimation abilities offered using RVR was presented by using field data of achieved from tunnels for Istanbul's sewerage system, Turkey. In this model, Schmidt hammer rebound values and rock quality designation (RQD) were utilized as the input parameters, while net cutting rates was the output parameter. As statistical indices, coefficient of determination (R^2) and mean square error (MSE) were used to evaluate the efficiency of the RVR model. According to the obtained results, it was observed that RVR model can effectively be implemented for roadheader performance prediction.

Keywords: relevance vector regression; roadheader performance; rock quality designation; schmidt hammer rebound values.

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1. INTRODUCTION

Compared to other excavation methods, the use of roadheaders has several advantages such as, reduced ventilation requirements, excavation capacity, minimal ground disturbances, improved safety, blast vibration elimination, less over excavation, flexibility and cost. Consequently, roadheaders have been utilized extensively in civil/mining engineering projects. Roadheader performance prediction for any geological formation is one of the main concerns in determining the economics of a tunneling operation. A critical issue in successful roadheader application is the ability to evaluate and predict the machine performance named net cutting rate.

Several researches are conducted to find a significant relationship between the roadheader performance and other parameters influencing roadheader performance [1-8]. Also, during the last decades, researchers have focused on developing performance estimation models for roadheaders. Fowel and Johnson [9] introduced a model based on results achieved from simulation of excavating machines in the laboratory, in which three parameters of the swept area, the cutter head advance, and the rate per minute are applied to model the rate of the roadheader performance. Copur et al. [10] applied the data collected from a roadheader at Colorado School of Mine to predict the roadheader performance based on three factors, the roadheader weight, the cutterhead power, and the roadheader penetration index. Sandbak [11] and Douglas [12] a rock classification system was used to explain the changes of roadheader advance rates at San Manuel Copper Mine in an inclined drift at an 11% grade. Bilgin et al. [13] and Bilgin et al. [14] and Ebrahimabadi et al. [15] studied a roadheader performance model based on rock quality designation (RQD) and UCS. Bilgin et al. [16] studied some geological and geotechnical factors affecting the performance of a roadheader in an inclined tunnel. Ebrahimabadi et al. [17] applied predictive models for roadheaders' cutting performance in coal measure rocks. Ebrahimabadi et al. [18] have suggested a method to predict the performance of roadheaders based on the Rock Mass Brittleness Index. Abdolreza and Siamak [19] developed a model to predict roadheader performance using rock mass properties.

However, in recent years, utilize of developed methods such as computational intelligence methods, which can successfully model the behavior of linear and nonlinear involved in data, is useful. Such as, Seker and Ocak [20] used machine learning methods (ZeroR, random forest, Gaussian process, linear regression, logistic regression and multi-layer perceptron) for prediction of predict roadheader performance. Faradonbeh et al. [21] used genetic programming (GP) and gene expression programming (GEP) techniques for prediction of predict roadheader performance. In this research, a database of machine performance and some geomechanical parameters of rock formations from Tabas coal mine project, the largest and fully mechanized coal mine in Iran, has been established, including instantaneous cutting rate (ICR), uniaxial compressive strength, Brazilian tensile strength, rock quality designation, influence of discontinuity orientation (Alpha angle) and specific energy. Ghasemi [22] developed a site-specific regression model for assessment of road-header cutting performance of Tabas coal mine based on rock properties such as Brazilian tensile strength, rock mass cuttability index, and alpha angle (α: is the angle between the tunnel axis and the planes of weakness. Fattahi [23] applied soft computing methods for the estimation of roadheader performance from schmidt hammer rebound values. But it should be noted that some computational intelligence methods may result in very poor generalization or even over-fitting when parameters involved in modeling are not chosen wisely. Support vector machine (SVM) used for regression, the so called support vector regression (SVR), is a suitable machine learning methodology introduced in the early 1990s [24]. However, even this capable network suffers from numerous limitations including parameters and kernel selection which may have significant effect on its prediction efficiency [25,26]. Relevance vector machine based regression (RVR) is a Bayesian sparse kernel technique used for regression having most of the SVR characteristics while avoiding its limitations [27]. It typically leads to much sparser models and correspondingly faster performance on test data as well as a sophisticated generalization error [28,29].

The RVR has not yet been used for roadheader performance prediction in any kinds of mechanical tunneling construction project. In this study, the RVR is proposed for indirect roadheader performance prediction. The goodness of RVR 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. RELEVANCE VECTOR REGRESSION

RVR is based on Bayesians approach in which a prior is introduced over the model weights and each weight is administrated by one hyperparameter. The most probable value of each hyper parameter is iteratively evaluated from the data. The model is sparser since the posterior distributions of some proportion of the weights are set to zero.

Consider a given training set of *M* regression data points $\{(x_m, y_m)\}_{m=1}^{M}$, where $x_m \in R^M$ is the input data to the actual plant and $y_m \in R$ is the output data of the actual plant and is assumed to contain Gaussian noise ε with mean 0 and variance σ^2. In high dimensional feature space *z*, the outputs of an extended linear model can be expressed as a linear combination of the response of a set of *M* basis functions as follows:

$$y(x,\omega) = \sum_{m=1}^{M} \omega_m \varphi_m(x) + \varepsilon = \omega^T \varphi + \varepsilon \tag{1}$$

Now, the predicted output $\hat{y}$ of the true value *y* is

$$\hat{y}(x,\omega) = \sum_{m=1}^{M} \omega_m \varphi_m(x) = \omega^T \varphi \; where \;\; \omega \in z \tag{2}$$

In the above nonlinear function estimation model, ω_m is the weight vector and $\varphi_m(.)$ is an arbitrary basis function (or kernel). In the present work, RBF is used as the kernel function because of its ability to reduce computational complexity of the training process.

The vector form of $\omega = [\omega_1 \cdots \omega_M]^T$ and the responses of all kernel function $\varphi(x) = [\varphi_1(x) \cdots \varphi_M(x)]^T$ maps the input data into a high dimensional feature space *z*. Hence, the obtained error signal could be stated as

$$\varepsilon_m = y_m - \hat{y}_m = N\left(0, \sigma^2\right) \tag{3}$$

The objective of relevance vector regression is to find the finest value of such that $\hat{y}(x, \omega)$ makes good predictions for unknown input data. For the RVR model in equation (2) let $\alpha = [\alpha_1 \cdots \alpha_M]^T$ be the vector of *M* independent hyperparameters, each associated with one model weight or kernel function.

The Gaussian prior distributions of the RVR framework are chosen as

$$p\left(\frac{\omega_m}{\alpha_m}\right) = \prod_{m=1}^{M} \left(\frac{\alpha_m}{2\pi}\right)^{\frac{1}{2}} \exp\left\{-\frac{\alpha_m \omega_m^2}{2}\right\} \tag{4}$$

Here, α_M is the hyperparameter that governs each weight ω_m . The likelihood function of independent training targets $y = y_m, m = 1, \ldots, M$ can be stated as

$$p\left(\frac{y}{\omega}, \sigma^2\right) = \prod_{m=1}^{M} p\left(\frac{y_m}{\omega}, \sigma^2\right) = \frac{e^{-\frac{\left\|(y-\hat{y})^2\right\|}{2}\sigma^2}}{\sqrt{\left(2\pi\sigma^2\right)^M}} \tag{5}$$

The above likelihood function is enhanced by the prior in equation (4) defined over each weight to reduce the complexity of the model and to avoid over fitting. Now, using Bayes' rule, the posterior distribution over model weights could be calculated as follows:

$$p\left(\frac{\omega}{y}, \alpha, \sigma^2\right) = \frac{p\left(\frac{y}{\omega}, \sigma^2\right) p\left(\frac{\omega}{\alpha}\right)}{p\left(\frac{y}{\alpha}, \sigma^2\right)} \tag{6}$$

The posterior distribution in equation (6) is a Gaussian distribution function,

$$p\left(\frac{\omega}{y}, \alpha, \sigma^2\right) = N\left(\mu, \sigma^2\right) \tag{7}$$

whose covariance and mean are respectively given by

$$\sum = \left(\sigma^{-2}\varphi^T \varphi + A\right)^{-1}, \tag{8}$$

$$\mu = \sigma^{-2} \sum \varphi^T y \tag{9}$$

with $A = diag\{\alpha\}$.

Marginalization of the likelihood distribution over the training targets given by equation (5) can be obtained by integrating out the weights to acquire the marginal likelihood for the hyperparameters.

$$p\left(\frac{y}{\alpha}, \sigma^2\right) = \int p\left(\frac{y}{\omega}, \sigma^2\right) p\left(\frac{\omega}{\alpha}\right) d\omega = N\left(0, C\right) \tag{10}$$

Here, the covariance is given by $C = \sigma^2 I + \varphi A^{-1} \varphi^T$ .In equations (8) and (9), the only unknown variables are the hyperparameters α. The values of these hyperparameters are estimated using the framework of type II maximum likelihood [30].

$$p\left(\frac{y}{\alpha}, \sigma^2\right) = -\frac{1}{2}\left(M \log 2\pi + \log\left|C\right| + y^T C^{-1} y\right) \tag{11}$$

Logarithm is included in equation (11) to reduce computational complexity. Maximization of the logarithmic marginal likelihood in equation (11) over α leads to the most probable value α_{MP} which provides the maximum a posteriori (MAP) estimate of the weights.

The ambiguity about the optimal value of the weights, given by (6), is used to express ambiguity about the predictions made by the model, i.e., given an input x_*, the probability distribution of the corresponding output y_* is given by the predictive distribution

$$p\left(\frac{y^*}{x^*}, \hat{\alpha}, \hat{\sigma}^2\right) = \int p\left(\frac{y^*}{x^*}, \omega, \hat{\sigma}^2\right) p\left(\frac{\omega}{y}, \hat{\alpha}, \hat{\sigma}^2\right) d\omega \tag{12}$$

which has the Gaussian form

$$p\left(\frac{y^*}{x^*}, \hat{\alpha}, \hat{\sigma}^2\right) = N\left(Y^*, \sigma^{*2}\right) \tag{13}$$

The mean and variance of the predicted model are, respectively,

$$Y^{*} = \varphi^{T}(\mathrm{x}^{*})\mu \text{ and } \sigma^{*2} = \hat{\sigma}^{2} + \varphi^{T}(\mathrm{x}^{*})\sum\varphi(\mathrm{x}^{*}) \quad (14)$$

Maximizing the logarithmic marginal likelihood in (11) leads the optimal values of many of the hyperparameters α_m typically infnite yielding a posterior distribution in (6) of the corresponding weights ω_m that tends to be a delta function peaked to zero. Thus, the corresponding weights are deleted from the model along with its accompanying kernel function [31-34]. Hence, very few data points corresponding to nonzero weights build the RVR model and are called the relevance vectors. This results in better sparseness of RVR model than SVR model. Thus, the computation time for prediction using RVR model is reduced significantly. In this paper, the RVR model is used for prediction of roadheader performance.

3. ESTIMATION OF ROADHEADER PERFORMANCE

3.1 Inputs and output data

Dataset applied in this study for determining the relationship among the set of input (Schmidt hammer rebound values and RQD) and output (net cutting rates of the roadheader for each zone) variables are gathered from open source literature [35,36]. These data recorded previously during the construction of tunnels for Istanbul's sewerage system have been evaluated. Schmidt hammer rebound values from 36 different rock zones were collected together with net cutting rates of the roadheader for each zone. Rebound tests were carried out with a Proceq N-type hammer. On any one rock type at least three sets of test were conducted, depending on the geology of the encountered rock formations. At each test point 15–20 continuous impacts were made, and the suspected low values were excluded from the calculation of a mean value (R1-values) if they satisfy Chauvenet's criterion (Test Procedure 1). Test Procedure 2: Select the peak rebound value from five continuous impacts at a point and discard the remaining values (R2-values) [37]. Test Procedure 3: Select the peak rebound value from ten continuous impacts at a point and discard the remaining values (R3-values) [38]. A detailed description of the database can be found in [35,36]. Descriptive statistics of the all data sets are shown in Table 1.

Table 1 Statistical description of dataset utilized for construction of model

Parameter		Min	Max	Average
Inputs	**RQD (%)**	0	100	53.94
	R1-value	29	63	49.78
	R2-value	30	61	47.67
	R3-value	32	64	51.75
Output	**Net cutting rate (m^3/h)**	2	25	11.39

3.2 Pre-processing of data

In data-driven system modeling, some pre-processing steps are commonly implemented prior to any calculations, to eliminate any outliers, missing values or bad data. This step ensures that the raw data retrieved from database is perfectly suitable for modeling. 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:

$$x_M = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{15}$$

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.

In addition to the normalization, mean square error (MSE) and coefficient of determination (R^2) are two conventional criteria considered to assess the efficiency of the networks. The MSE is calculated using the following equation:

$$MSE = \frac{1}{n}\sum_{k=1}^{n}(t_k - \hat{t}_k)^2 \tag{16}$$

where t_k be the actual value and $\hat{t}_k$ be the predicted value of the k^{th} observation and n is the number of samples used for training or testing the network. MSE is routinely used as a criterion to show the discrepancy between the measured and estimated values of the network. Coefficient of determination, R^2, is also calculated as

$$R^2 = 1 - \frac{\sum_{k=1}^{n}(t_k - \hat{t}_k)^2}{\sum_{k=1}^{n} t_k^{\,2} - (\sum_{k=1}^{n} \hat{t}_k^{\,2} / n)^2} \tag{17}$$

R^2 is widely used as a representation of the initial uncertainty of the model. The best network model which is unlikely to build, would have MSE=0 and R^2 =1.

4. RESULTS AND DISCUSSION

In this study, RVR model was utilized to build a model for the prediction of roadheader performance from available data, using MATLAB environment. A dataset that includes 37 data points was employed in current study, while 80% data points were utilized for constructing the model and the remainder data points were utilized for model performance evaluation. In this model, Schmidt hammer rebound values and RQD were utilized as the input parameters, while net cutting rates was the output parameter.

In RVR model, hyper parameter estimation is carried out by expectation maximization (EM) updates on the objective function [27,39]. For this RVR model, radial basis function

(RBF) kernel is used with the width parameter estimated automatically by the learning procedure [27,39] which improves generalization ability and reduces computational complexity of the training process. Thus, unlike in SVR there is no necessity for computationally expensive determination of regularization parameter by cross validation technique. Also in the RVR model confidence intervals, likelihood values and posterior probabilities could be explicitly encoded easily.

After modeling, a comparison between estimated values of net cutting rates by the RVR model and measured values for data sets at training and testing phases is shown in Fig. 1. As shown in Fig. 1, the results of the RVR model in comparison with actual data show a good precision of the RVR model.

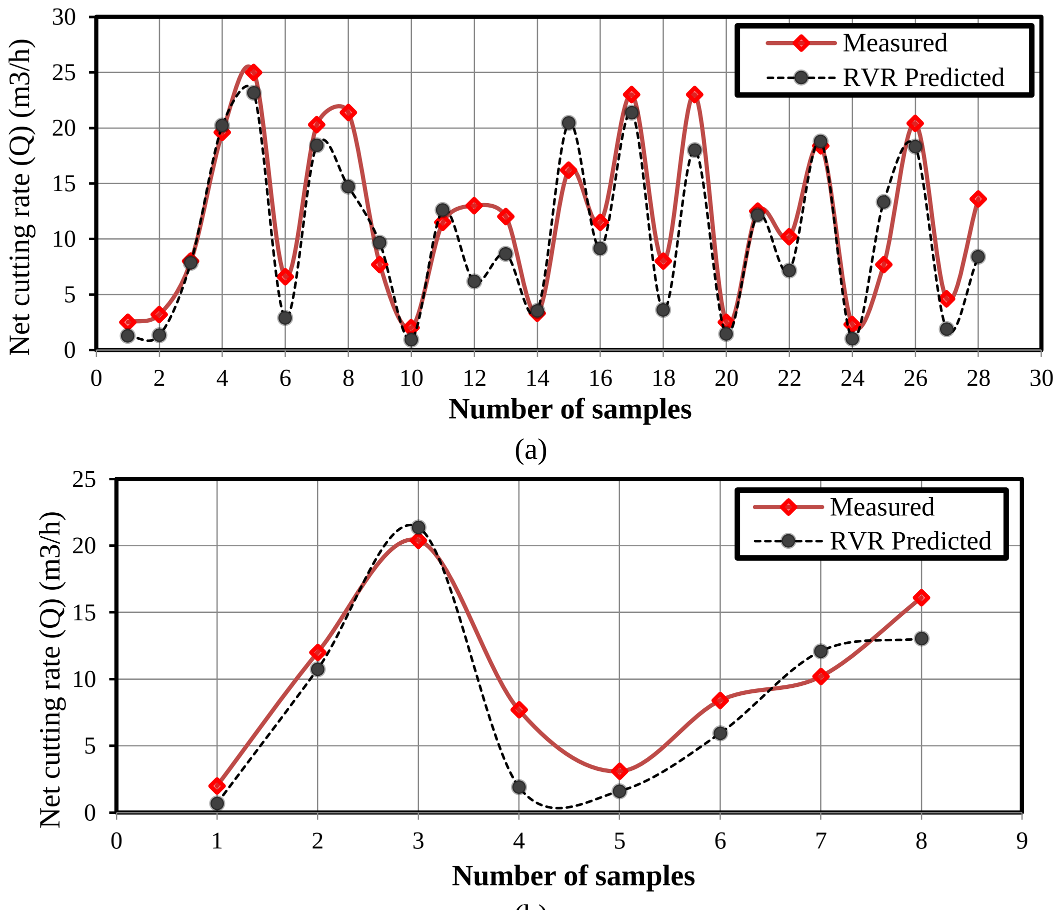
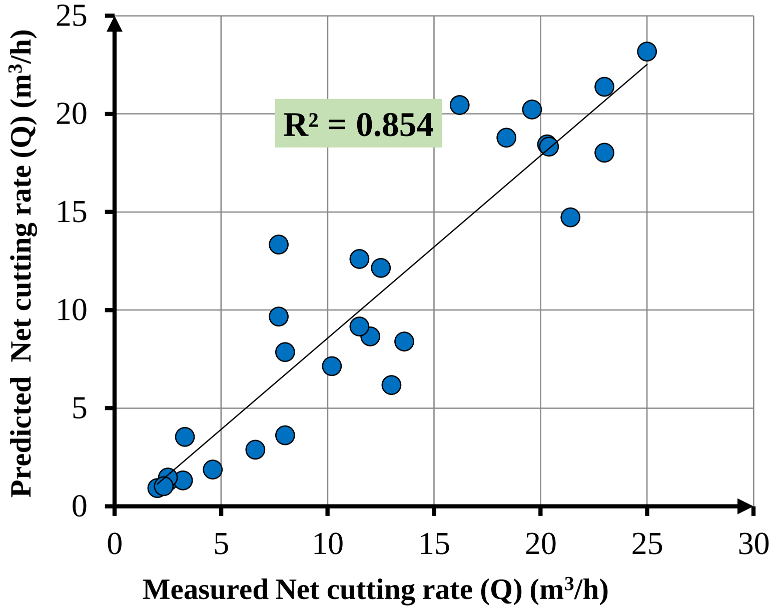
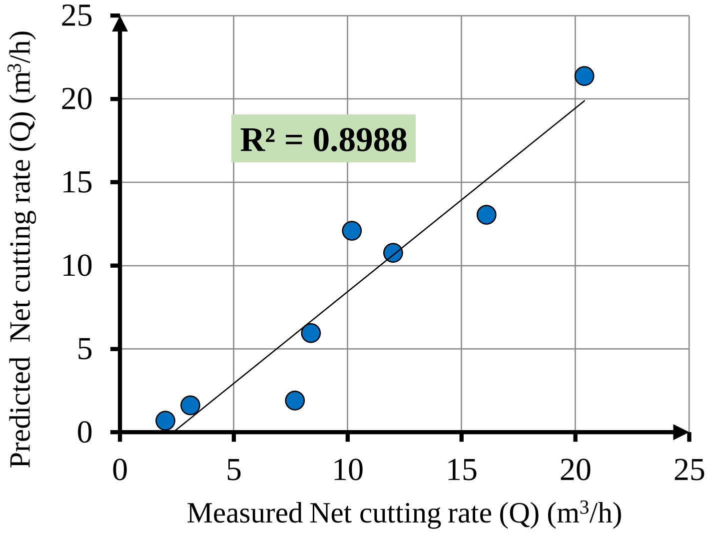


Figure 1. Comparison between measured and estimated net cutting rates for a) training datasets, b) testing datasets

Furthermore, a correlation between estimated values of net cutting rates by the RVR model and measured values for data sets at training and testing phases is shown in Fig. 2.



(a)



(b)

Figure 2. Correlation between measured and estimated net cutting rates for a) training datasets, b) testing datasets

Also, performance analysis of the RVR model for predicting net cutting rates is shown in Table 2. The performance indices obtained in Table 3 indicate the high performance of the RVR model that can be used successfully to the estimation of the net cutting rates.

Table 2: Performance analysis of the RVR model for predicting net cutting rates

Description		MSE	R^2
RVR model	Training	0.0345	0.854
	Testing	0.0224	0.899

5. CONCLUSION

Performance prediction of roadheaders plays a crucial role in the successful application of such machines in mining and civil industries. The more precise prediction accomplished, the more effective cutting and production rates achieved. In this study, the RVR technique has been used for estimating the roadheader performance. It is observed that the Schmidt hammer rebound values and RQD have major effect on the roadheader performance. So, the model was generated based on relevant properties. The following conclusions can be drawn:

- The RVR with MSE=0.0224 and R^2= 0.899 is a reliable system modeling technique for predicting roadheader performance with highly acceptable degree of accuracy and robustness.
- This study shows that the RVR approach can be applied as a powerful tool for modeling of some problems involved in tunnel engineering.

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