Prediction of hard rock TBM penetration rate based on Data Mining techniques

Modèles de prévision du taux de pénétration de tunnelier dans les roches dures

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ABSTRACT: The aim of this work is to use Data Mining tools to develop models for the prediction of hard rock tunnel boring machine (TBM) penetration rate (ROP). A database published by Yagiz (2008) was used to develop these models. The parameters of the database were the uniaxial compressive strength (UCS), an index used to quantify the brittleness and toughness and denominated peak slope index (PSI), the distance between the planes of weakness (DPW), the angle between tunnel axis and the planes of weakness (α) and the output parameter rate of penetration (ROP). The R program environment was used as a modeling tool to apply the artificial neural networks (ANN) and the support vector machine (SVM) algorithms and the corresponding models. These models were compared with two equations presented by Yagiz (2008) and Yagiz and Karahan (2011). It was concluded that the ANN model has the best performance. Moreover, these new models allowed computing the importance of the different input parameters for predicting machine performance. It was concluded that PSI is the most important parameter and UCS is the less important parameter.

RÉSUMÉ : L'objectif de cette étude s'agit d'utiliser des outils de Data Mining en vue de développer des modèles de prévision de la taux de pénétration d'un tunnelier dans les roches dures (ROP). Une base de données publiée par Yagiz (2008) a été utilisée pour développer ces modèles. Les paramètres de la base de données comprend la résistance en compression uniaxiale (UCS), un index que permettre mesurer la fragilité et la ténacité appelé d'index de pic maximal (PSI), la distance entre les plans de faiblesse (DPW), l'angle entre l'axe du tunnel et le des plans de faiblesse (α) et le paramètre de sortie dénommé de taux de pénétration (ROP). L'environnement du programme R a été utilisé comme un outil de modélisation pour appliquer les algorithmes des réseaux de neurones artificiels et des machines à vecteurs de support et leurs modèles correspondants. Ces modèles ont été comparés à deux équations présentées par Yagiz (2008) et Yagiz et Karahan (2011). On a conclu que le modèle des réseaux de neurones artificiels a été la meilleure performance. En outre, ces nouveaux modèles ont permis le calcul de l'importance des différents paramètres d'entrée pour prévoir la performance de la machine. Il a été conclu que l'PSI est le paramètre le plus important et l'UCS est le paramètre moins important.

KEYWORDS: tunnel boring machine, penetration ratio, data mining, machine learning

1 INTRODUCTION

The first question that arises when someone wants to excavate a tunnel with a tunnel boring machine is to evaluate its performance. However, this is a very complex task that requires not only the choice of a performance parameter but also of predictive models that require not only this parameter but also other input parameters. Yagiz (2008) pointed out as relevant performance parameters the penetration ratio (ROP), the ratio of excavated distance to the operating time during continuous excavation phase, and advance rate (AR), the ratio of both mined and supported actual distance to the total time. Nevertheless, according to the author, most of the forecasting models are related with the prediction of the ROP. There are many kinds of forecasting models. These include theoretical, empirical, artificial neural network, fuzzy logic, genetic algorithms and particle swarm optimization (Yagiz and Karahan 2011).

Yagiz (2008) using a statistical approach obtained a predictive equation of ROP as a function of measured engineering rock properties. Recently, Yagiz and Karahan (2011) presented a new equation to estimate ROP using the particle swarm optimization. Both studies included as independent variables the uniaxial compressive strength (UCS), an index used to quantify the brittleness and toughness and denominated peak slope index (PSI), the distance between the planes of weakness (DPW) and the angle between tunnel axis and the planes of weakness (α). Their database consisted of 153 collected data sets related to Queens Water Tunnel # 3, stage 2, New York City, USA.

The aim of this study is to develop models based on Data mining techniques such as artificial neural networks (ANN) and support vector machines (SVM) using the same database presented by Yagiz (2008) and to compare the performance of these models with the performance of the ones presented by Yagiz (2008) and Yagiz and Karahan (2011).

2 REVIEW OF DATA MINING IN TUNNELLING

Feng et al. (2004) presented a novel machine learning method, termed support vector machine (SVM), to obtain a global optimization model in conditions of large project dimensions, such as tunnels, small sample sizes and nonlinearity. A new idea is put forward to combine the SVM with a genetic algorithm. The results indicate that the established SVMs can appropriately describe the evolutionary law of deformation of geo-materials at depth and provide predictions for the future time steps with acceptable accuracy and confidence. Liu et al. (2004) introduced the SVM regression algorithm for the design of tunnel shotcrete-bolting support parameters. Suwansawat and Einstein (2006) attempt to evaluate the potential as well as the limitations of ANN for predicting surface settlements caused by EPB shield tunneling and to develop optimal neural network models for this objective. Gajewski and Jonak (2006) presented the results of a research work using ANN to classify the signals of machining forces typical for particular worn cutting tools. Javadi (2006) explored the capabilities of neural networks to predict the air losses in compressed air tunneling. Yoo and Kim (2007) demonstrated that an integrated Geographical information system-Artificial Neural Network (GIS–ANN) approach can be used effectively as a decision support tool for making tunneling performance predictions that are required in routine tunnel design works. Boubou et al. (2010) analyzed ground movements induced by tunnelling and their correlation with TBM operation parameters using a nonlinear least square approximation and an ANN. Measured ground movements are reproduced with reasonable agreement by each of the two approaches. Lui et al. (2011) proposed a predictive control strategy for earth pressure balance during excavation, where an earth pressure prediction model taking advance speed and screw conveyor speed as the control parameters is established by means of least squares support vector machine (LS-SVM). The simulation results demonstrate that their method is very effective to control earth pressure balance. Jiang et al. (2011) presented an integrated optimisation method for the feedback control of tunnel displacement which combines the SVM, particle swarm optimisation (PSO) and numerical analysis methods. Lü et al. (2012) proposed an efficient approach for probabilistic ground-support interaction analysis of deep rock excavation using the ANN and uniform design. Mahdevari and Torabi (2012) developed a method based on ANN for prediction of convergence in tunnels. Darabi et al. (2012) preformed tunnel stability analysis and subsidence prediction using empirical, numerical, neural network and statistical methods. Mohamadnejad et al. (2012) used three approaches to predict the vibrations in excavations. The vibrations were predicted using several widely used empirical methods and two intelligence science techniques namely general regression neural network (GRNN) and SVM. They conclude that the SVM technique is more precise than the other used methods. Pourtaghi and Lotfollahi-Yaghin (2012) presented an alternative method of maximum ground surface settlement prediction caused by tunnelling, which is based on integration between wavelet theory and ANN, or wavelet network (wavenet). The simulation results indicate excellent learning ability compared to the conventional back-propagation neural network with sigmoid or other activation functions. Mahdevari et al. (2012) employed well-known Artificial Intelligence based methods, SVM and ANN, to predict the ground condition of a tunneling project. They concluded that the performance of the SVM model is better than the ANN model and a high conformity was observed between predicted and measured convergence for the SVM model.

3 ARTIFICIAL NEURAL NETWORKS AND SUPPORT VECTOR MACHINES

Artificial Neural Networks are intended to be an approximation to the architecture of the human brain. These networks consist of processing units (nodes) interconnected according to a given configuration. The multi-layer perceptron (Figure 1) is the most popular configuration (Haykin 1999).

The nodes are constituted by: a set of connections (w_{ij}), each one labeled by a weight, which has an excitatory effect for positive values and inhibitory effect for negative ones; an integrator (g), which reduces the n input arguments (stimuli) to a single value; and an activation function (f) which can condition the output signal, by introducing a component of non-linearity in the computational process.

In the present paper the network weights are initially randomly generated within the range [-0.7, +0.7] and it is used the logistics activation function (1 / (1 + exp (-x)). Then, the training algorithm is applied adjusting successively the weights, stopping when the slope of the error is approximately zero or after a maximum number of iterations. The prediction is made by adding the contribution of all connections activated.

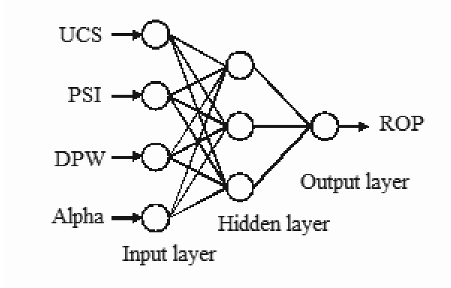

Figure 1. Example of a multilayer perceptron.

The SVM (Cortes and Vapnik 1995) were originally designed for classification problems based on the separation of two classes of objects using a set of functions known as kernels (Figure 2). In this process, called mapping, the classes are separated by hyperplanes being used one iterative optimization algorithm to find the hyperplane that provides the largest separation between the classes. This separation is related to a set of support vectors in the feature space.

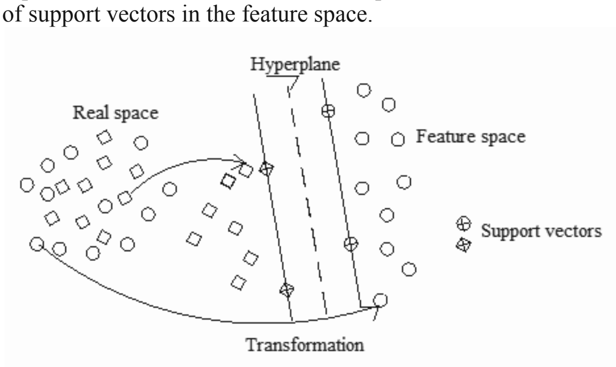

Figure 2. Example of the SVM transformation.

Both in classification and regression methods there is an error function to minimize subjected to some constraints. In this paper it will be used the popular Kernel with Radial Basis which presents less hyperparameters and smaller numerical difficulties than other kernels (eg, polynomial or sigmoid) (Cortez 2010):

$$k(x, y) = \exp\left(-\gamma \|x - y\|^2\right), \gamma > 0 \qquad (1)$$

In addition to the parameter of the kernel, γ, two more parameters are used: the penalty parameter, C, and ε, the width of the ε-insensitive zone.

The performance of models was assessed using the Mean Absolute Deviation (MAD, Equation 2), the Root Mean Squared Error (RMSE, Equation 3) and the Pearson's product-moment correlation coefficient (R).

$$MAD = \frac{1}{N} \times \sum_{i=1}^{N} \left| y_i - \hat{y}_i \right| \qquad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \left(y_i - \hat{y}_i \right)^2}{N}} \qquad (3)$$

where N denotes the number of examples, y_i the desired value and $\hat{y}_i$ the estimated value by the considered model.

4 DATABASE AND PREVIOUS EQUATIONS FOR ROP

The database used in this study was presented by Yagiz (2008) and is composed of 153 data sets collected from 151 different locations from a tunnel excavated in fractured igneous and metamorphic rock in New York City. The independent variables present in the database are UCS, Brazilian Tensile Strength (BTS), PSI, DPW and α and the dependent variable is ROP. However, according to Yagiz (2008), BTS is the property that presents the lowest correlation with the ROP. Therefore, it was excluded from the dataset.

Table 1 presents some statistical attributes from the database.

Table 1. Statistics of the input and output parameters.

Parameter	*Min*	*Mean*	*Max*	*Std. Dev.*
Inputs				
UCS (MPa)	118.30	149.89	199.70	22.09
PSI (kN/mm)	25	34.64	58	8.42
DPW (m)	0.050	1.023	2.00	0.642
α (º)	2	44.57	89	23.21
Output				
ROP *(*m/h)	1.27	2.05	3.07	0.36

Yagiz (2008) performed several statistical analyses with the database to develop a predictive equation of TBM performance. The commercial software package for standard statistical analysis (SPSS) allowed the author to generate several models and to obtain empirically the best predictive equation of ROP:

$$ROP\ (m/h) = 1.093 + 0.029\,.PSI - 0.003\,.UCS + 0.437\,.Log(\alpha) - 0.219\,.DPW \tag{4}$$

Yagiz and Karahan (2011) using partial swarm optimization obtained the following equation:

$$ROP\ (m/h) = -0.0041\,.UCS + 0.0292\,.PSI - 0.4016\,.DPW^{0.584} - 1.6756\,.\alpha^{-0.217} + 2.827 \tag{5}$$

Table 2 shows the values of the errors and Pearson's product-moment correlation coefficient (R) using a linear regression between the measured and the predicted values obtained with both equations and using all the dataset. A slight improvement was obtained from equation 4 to equation 5.

Table 2. Performances of Equations 4 and 5.

Parameter	*Eq. 4*	*Eq. 5*
MAD	0.184	0.178
RMSE	0.216	0.207
R	0.815	0.817

5 PREDICTION OF ROP USING ANN AND SVM

The ANN and SVM were applied using the R program environment (R Development Core Team 2010) which is an open source freeware statistical package. This software can be used with other packages that allow performing DM analyses. Therefore, a specific program R-Miner developed by Cortez (2010) was used to apply the SVM and the ANN and evaluate their behaviour under a different set of metrics. It must be emphasized that R-Miner allows the application of other DM algorithms and was already applied before by Martins and Miranda (2012).

The ANN and SVM were tested in predicting the ROP being adopted an assessment scheme using 10 runs in a 10-fold cross-validation (Efron and Tibshirani, 1993), where the records were divided into 10 parts of equal size. Sequentially, each subset was tested with the adjusted model with the leftover records. The overall performance is given by the mean values of the errors (MAD and RMSE) and the Pearson's product-moment correlation coefficient (R) in 10 runs.

The errors (MAD and RMSE) and the Pearson's product-moment correlation coefficient (R) obtained during the training phase of the models that allow evaluating the performance of ANN and SVM are presented in Table 3. It can be seen that both algorithms have good behavior. However there is a slightly better performance of SVM.

To evaluate the importance given by the models to the input parameters it is necessary to perform a sensibility analysis. In this analysis each parameter is changed over its range of variation, while maintaining the others constant, and calculated the variance of the output parameter. The input parameter that induces a higher variance in the output parameter is the most important one. The relative importance is given in Table 4. Based on these results, we can state that both techniques give almost the same importance to all the parameters. The most influential parameters is PSI, followed by α and DPW. The less important parameter is UCS. The database used in this paper corresponds to a rock mass with a lot of joints and faults. This can explain the low influence of the UCS in the machine performance. PSI translates the influence of rock toughness and brittleness in machine performance. Therefore it is understandable its great influence on ROP.

Table 3. Performances of ANN and SVM obtained in the training phase.

Parameter	*ANN*	*SVM*
MAD	0.196	0.192
RMSE	0.234	0.231
R	0.760	0.765

Table 4. Relative importance (%) of the input parameters.

Parameter	*ANN*	*SVM*
UCS	5.49	5.33
PSI	65.94	65.90
DPW	12.39	11.69
α	16.18	17.08

Table 5. Metrics obtained adjusting the models with all the dataset.

Parameter	*ANN*	*SVM*
MAD	0.163	0.185
RMSE	0.195	0.227
R	0.838	0.796

Figures 3 and 4 show the comparisons between the measured and predicted ROP for ANN and SVM. It can be seen for both models that for ROP values between 1.5 and 2.5 the set of points is near the 45º slope line. Outside this range it seems that the ANN model provides better results. The errors and R associated to these figures are presented in Table 5.

It can be seen that the ANN models have lower errors and higher R than the SVM.

Comparing the results of Tables 2 and 5 it is possible to conclude that the ANN model has better performance than the Equations 4 and 5.

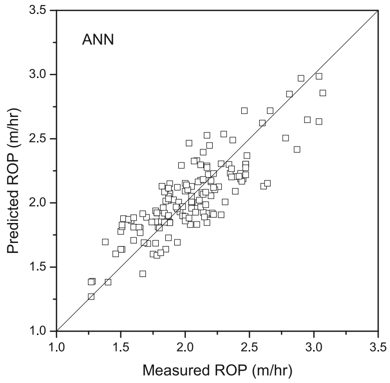

Figure 3. Comparison between the measured and predicted ROP from the ANN model.

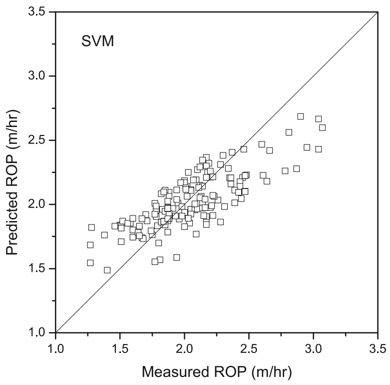

Figure 4. Comparison between the measured and predicted ROP from the SVM model.

6 CONCLUSIONS

Using a database of geotechnical data published by Yagiz (2008) ANN and SVM algorithms were applied in order to develop new models to predict the machine performance.

In the training phases, using a cross-validation scheme, the SVM algorithm had slightly better performances than the ANN algorithm. However, using the induced model with all dataset, the ANN gives lower errors and greater R than SVM.

When all the dataset is used ANN had even better performance than the models presented by Yagiz (2008) and Yagiz and Karahan (2011).

The most important input variable is PSI and the less important input one is UCS.

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