Rock and Soil Mechanics

Volume 42 | Issue 2 Article 7

6-18-2021

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Custom Citation

YAN Chang-bin, WANG He-jian, YANG Ji-hua, CHEN Kui, ZHOU Jian-jun, GUO Wei-xin, . Predicting TBM penetration rate with the coupled model of partial least squares regression and deep neural network[J]. Rock and Soil Mechanics, 2021, 42(2): 519-528.

Rock and Soil Mechanics 2021 42(2): 519–528 ISSN 1000–7598
https: //doi.org/10.16285/j.rsm.2020.5164 rocksoilmech.researchcommons.org/journal

Predicting TBM penetration rate with the coupled model of partial least squares regression and deep neural network

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Abstract: The scientific prediction of the TBM penetration rate is of great significance to the selection of hydraulic tunnel construction methods, construction schedule and cost estimation. In view of the high nonlinearity, fuzziness and complexity of TBM excavation process, and in order to improve the prediction accuracy and computational efficiency, the partial least squares regression (PLSR) has been applied to extract the principal components of the influencing parameters. Then the deep neural network (DNN) is employed to train and forecast the TBM penetration rate. A prediction model of TBM penetration rate based on the coupled method of PLSR and DNN is proposed. Based on the measured data of the double-shield TBM construction of a water conveyance tunnel in the Lanzhou water source construction project, six impact parameters including the rock uniaxial compressive strength, rock uniaxial tensile strength, cutter head thrust, cutter head speed, rock mass integrity coefficient and rock Cerchar abrasiveness index are selected to verify the prediction reasonability of the model. The fitting and prediction accuracy of the different prediction methods are compared and analyzed. The research results show that the PLSR can effectively overcome the problem of multiple collinearity between the independent variables. The extracted principal components are trained as the input layer of the DNN, which simplifies the structure of the neural network. The PLSR-DNN coupled model effectively avoids the over-fitting and inadequate fitting problems. It has the characteristics of fast convergence, stable solution and high fitting accuracy. The average relative fitting error of the PLSR-DNN prediction model is 2.96%, and the average relative prediction error is 3.27%. The fitting accuracy and prediction accuracy of the PLSR-DNN prediction model is significantly higher than those of PLSR model alone, BP neural network model and SVR model, respectively.

Keywords: tunnel boring machine; penetration rate; partial least squares regression; deep neural network; coupling prediction model

1 Introduction

With the construction of a large number of major infrastructure projects such as highways, railways, mining, urban subways, and water diversion tunnels, the tunnelling and underground construction projects are embracing significant development opportunities. The full-face rock tunnel boring machine (TBM) has many advantages in terms of high efficiency, safety and low environmental impact, and is widely used in the construction of long-distance tunnels (caverns). However, TBMs also face problems and shortcomings, such as the geological conditions sensitivity and high initial investment. The precise prediction of TBM tunnelling performance under different geological conditions is essential for construction method selection, construction schedule control and cost estimation[1–2]. Due to the influence of many factors such as geological factors, mechanical parameters, tunnelling parameters and engineering management, it is very difficult to accurately predict the tunnelling performance of TBM. Therefore, the scientific and reliable prediction of the TBM tunnelling performance under complex geological conditions has become one of the challenges requiring timely solutions.

There have been many prediction models of TBM performance evaluation developed, which can be divided into two categories: theoretical models and empirical models. The theoretical models mainly include the Sanio model[3], the dimensional model[4] and the CSM model[5]. The empirical models mainly include the simple empirical model[6–8], the NTNU model[9], the Q_{TBM} model[10], the Alber model[11], the neural network model[12–13], the RME model[14] and the multiple regression model[15–23] etc. TBM tunnelling performance evaluation indicators mainly involve construction speed (AR), net penetration rate (PR), equipment utilization (U) and tool wear[1]. Most of the current TBM tunnelling performance prediction research focuses on the net penetration rate prediction considering its importance in evaluating tunnelling performance. According to incomplete statistics, the proposed TBM net penetration rate prediction models are summarized in Table 1.

Received: 22 February 2020 Revised: 19 September 2020
This work was supported by the National Natural Science Foundation of China (41972270，U1504523), the Key Science and Technology Research Project of Henan (182102210014) and the Opening Foundation of State Key Laboratory of Shield Machine and Boring Technology (SKLST-2019-K06).
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Table 1 Summary of TBM performance prediction model parameters

Source	Model description	Method category	Prediction object	Model parameter
Tarkoy (1973) [6]	Simple model	Empirical	PR	H_T
Graham (1976) [7]	Simple model	Empirical	PR	UCS, F_n
Nelson (1983) [8]	Simple model	Empirical	FPI, PR	H_T
Sanio (1985) [3]	Sanio Model	Theoretical/ empirical	PR	I_S
Boyd (1986) [4]	Dimensional model	Theoretical/ empirical	PR	HP, SE, A, η
Rostami (1997) [5]	CSM model	Theoretical/ empirical	PR	UCS, BTS, RPM, Torque, S_c, D_c, w_t, φ, F_n
Bruland (1999) [9]	NTNU model	Empirical	PR, U, AR	DRI, BWI, CLI, UCS, RPM, F_n, S_c, J_c, D_c, α
Barton (2000) [10]	Q_{TBM} model	Empirical	PR	Q_{TBM}
Alber (2000) [11]	Alber model	Empirical	PR	UCS, RPM, RMR, F_n
Grima et al. (2000) [12]	Neural network model	Empirical	PR	CFF, UCS, RPM, Torque, D_c, F_n
Benardos et al. (2004) [13]	Neural network model	Empirical	PR	UCS, RQD, RMR, Overburden
Bieniawski et al.(2007) [14]	RME model	Empirical	AR, PR	RME
Yagiz et al. (2009) [15]	Multiple regression model	Empirical	PR	UCS, BTS, Bi, DPW, α
Gong et al. (2009) [16]	Multiple regression model	Empirical	BI, PR	UCS, Bi, J_v, α
Hassanpour et al. (2011) [17]	Multiple regression model	Empirical	FPI, PR	UCS, RQD
Delisio et al. (2014) [18]	Multiple regression model	Empirical	PR, AR	UCS, TF, RPM, J_v, D_c
Du et al. (2015) [19]	Multiple regression model	Empirical	FPI, PR	UCS, K_v
Fattahi et al. (2017) [20]	Multiple regression model	Empirical	PR	UCS, PSI, DPW, α
Liu et al. (2017) [21]	Multiple regression model	Empirical	FPI, PR	UCS, K_v, α, H
Wang et al. (2017) [22]	Multiple regression model	Empirical	PR, U, AR	RMR
Armaghani et al. (2018) [23]	Multiple regression model	Empirical	PR	UCS, BTS, RPM, RQD, RMR, TF

Note: A is the cross-sectional area of the tunnel; BI is the rock excavability index; Bi is the rock brittleness index; BTS is the rock tensile strength; BWI is the bit wear index; CLI is the cutter life index; CFF is the core fracture frequency; D_c is the diameter of the cutter disc; DPW is the spacing between the structural planes; DRI is the drilling rate index; F_n is the thrust of a single cutter; FPI is the field penetration index; H is the average overburden thickness above the tunnel section; HP is the hob power; H_T is total rock hardness; I_S is the point load strength; J_c is the structural plane condition; J_v is the number of structural planes per cubic meter of rock mass; K_v is the integrity factor of the rock mass; Overburden is the thickness of the overburden; PSI is the peak slope index; RME is the rock mass excavability index; RMR is the rock mass rating; RPM is the rotation speed of the cutterhead; RQD is the rock quality designation; S_C is the hob spacing; SE is the specific energy; TF is the total thrust; Torque is the torque; α is the angle between the tunnel and the structural plane; Q_{TBM} denotes Q system in TBM construction; UCS is the rock compressive strength; w_t is the blade width of the hob; φ is the contact radian between hob and rock mass.

Although the aforementioned TBM net penetration rate prediction models have their own advantages, there are also limitations of them at different levels. For example, the theoretical model is quite different from the actual situation; the simple model considers fewer influencing factors, and the prediction accuracy of the model is relatively low; some parameters in the NTNU model have poor versatility and are difficult to obtain, which limits its application [24–26]; The system parameters of the Q_{TBM} model are excessive and complex, including some parameters that are low in sensitivity to the tunnelling performance[26]. The prediction stability as well as the ability to solve nonlinear problems of the traditional multiple regression model is inadequate due to the influence of multicollinearity among independent variables. In addition, Nelson et al.[27] developed a probabilistic prediction model based on a large number of measured tunnel engineering data. The accuracy of the model's prediction mainly depends on the degree of similarity between the predicted tunnel parameters and the parameters in the database, but these parameters are not suitable for tunnel geological conditions in China. As a result, its application is also subject to restrictions[1]. Consequently, the simultaneous improvement of the prediction accuracy and the efficiency of TBM tunnelling performance, while reducing the parameter redundancy and enhancing the calculation stability, has become an urgent problem to be solved in the research of TBM net penetration rate prediction model.

Neural network possesses a strong memory-dependent learning ability and is an effective tool to tackle non-linear problems. It has been applied in the prediction of TBM tunnelling performance (see Table 1). However, when there is multiple collinearity between input variables, neural networks often face problems such as unstable learning process and slow calculation convergence speed[28]. Improving the learning efficiency of neural networks is therefore worth further research. Compared with the BP neural network, deep neural network (DNN) has better learning effect and can fit functions with high nonlinearity and complexity. Partial least squares regression (PLSR) is a multivariate data statistical analysis method that integrates the advantages of three methods including the multivariate linear regression, principal component analysis and canonical correlation analysis, which can effectively solve the problems of multi-parameters, small samples and unsteady states, and therefore having a high application value[29–30]. The outstanding advantage of this method is that by extracting the principal components that have the strongest explanatory properties to the system, it can better solve the multicollinearity effect between the independent variables. PLSR has been applied in the fields such as chemistry, finance, medicine, and engineering, and has achieved competent prediction results. However, the use of PLSR and DNN coupling method for predicting TBM tunnelling performance has not yet been reported.

In view of this, this paper proposes a prediction model for TBM net penetration rate based on coupling PLSR and DNN, with the advantages of both models being fully leveraged. The measured data from the double-shield TBM construction of the water delivery tunnel of the Lanzhou Water Source Construction Project is used to verify the superiority and rationality of the prediction model. The proposed method can provide scientific and practical reference for the evaluation and prediction of the relevant TBM tunnel construction.

2 PLSR-DNN based model coupling method

2.1 Partial least squares regression (PLSR)

PLSR is a principal component regression analysis method. Its outstanding advantage is that it can overcome the multicollinearity between multiple variables[28], and can effectively solve the multiple regression problem of multiple dependent variables to multiple independent variables. When only one dependent variable is considered, the basic principle is as follows[29–30]. Suppose there is a dependent variable *y* and *p* independent variables x_1, $x_2, x_3, \cdots, x_p$ and the number of samples is *n*, and the resulting matrix $\boldsymbol{Y} = [y]_{n\times 1}$ and $\boldsymbol{X} = [x_1, x_2, x_3, \cdots, x_p]_{n\times p}$ is formed. The components t_1 and u_1 in $\boldsymbol{X}$ and $\boldsymbol{Y}$ are extracted, respectively, where t_1 is the linear combination of x_1, x_2, x_3, $\cdots$, x_p and u_1 is the linear combination of $\boldsymbol{Y}$ ($u_1 = y$). When extracting components, all possible information in the original matrix should be included in t_1 and u_1, and the correlation between t_1 and u_1 should be maximized.

After extracting the first pair of components, the regression of $\boldsymbol{X}$ and $\boldsymbol{Y}$ to t_1 is performed, respectively. If the regression equation has reached a satisfactory accuracy at this time, the extraction can be stopped; otherwise, it continues to extract the second pair of components from the remaining information. Circulation according to this rule is performed until a satisfactory accuracy is reached. PLSR usually does not require all components to be selected for regression modelling, the selection of only the first *m* components (i.e. principal components) is sufficient to obtain a model with reasonable predictive ability. To determine the number of principal components, cross-validation analysis is usually used. If *m* components t_1, t_2, t_3, $\cdots$, t_m ($m < n$) are finally extracted from $\boldsymbol{X}$, PLSR implements the regression of the dependent variable *y* on t_1, t_2, t_3, $\cdots$, t_m and then converts it into the regression equation of $\boldsymbol{Y}$ on the original independent variable $\boldsymbol{X}$, that is, the PLSR equation. The specific process of the PLSR method is shown in Fig. 1.

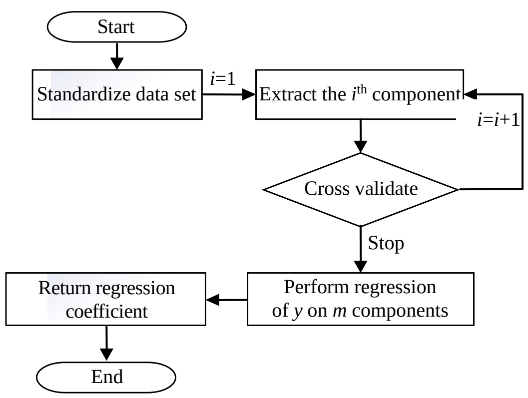

Fig. 1 Flowchart of partial least squares regression

2.2 Deep neural network model (DNN)

Neural network belongs to the category of artificial intelligence. It can reflect the highly nonlinear mapping relationship between network input parameters and output targets, reveal the nonlinear relationship contained in the sample, and simulate information processing mechanism of the brain to perform flexible processing on unknown variables that are multi-causal and complex[31]. In recent years, with the rapid development of artificial intelligence and deep learning, deep neural networks (DNN) have received great attention and applications. They combine low-level features to form more abstract high-level features through multi-layer nonlinear transformations[32]. Compared with traditional single-hidden-layer neural network (such as BP neural network), deep neural network has stronger nonlinear expression ability, and each hidden layer is fully connected. Through layer-by-layer learning, the prediction error of the model can be continuously reduced, and the problems, such as local minima and vanishing gradients of BP neural network can be avoided. The typical deep neural network model structure includes an input layer, hidden layer(s) and an output layer, as shown in Fig. 2. The deeper the structure, i.e. with more layers and nodes, the better the model training effect—a 100% fitting accuracy can even be achieved. However, the consequence is the over-fitting of the model, and the prediction effect of the model on the test data is seriously reduced. Generally, it is necessary to consider the effective depth of model training to achieve a better prediction effect without over-fitting. Therefore, although the number of hidden layers in the model has a certain impact on the prediction accuracy, it is not that the more the better. A four-hidden-layer model is given as an example in this paper. The nonlinear activation function of the hidden layer adopts the ReLU function. This activation function can improve the generalization ability of the network, avoid the vanishing gradient problem and the prediction accuracy of which is high. The activation function of the output layer adopts the traditional Sigmoid function.

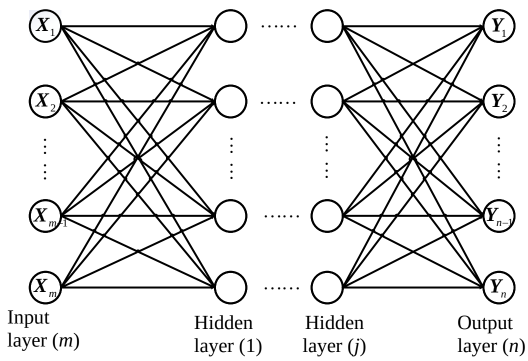

Fig. 2 Typical deep neural network model structure

2.3 Coupled modelling based on PLSR and DNN

PLSR and neural network coupled modelling method has been applied in fields such as blasting vibration prediction[28] and dam monitoring[33–34]. However, it is worth mentioning that: (a) the coupling method has not been applied to the prediction of TBM net penetration rate, and the effect of the application is unknown; and (b) the existing methods used BP neural network instead of deep neural network (DNN). Based on this, it is necessary to explore how to comprehensively utilize the respective advantages of PLSR and DNN to establish a coupled prediction model. The coupled modelling idea of PLSR and DNN is as follows: First, use PLSR to extract the principal components of the independent variables, which represent the most meaningful information for the system, and effectively solve the multicollinearity effects between variables; then, the *m* principal components extracted by PLSR are used as the input layer of the DNN, which replace the original independent variables for training and solving, so as to reduce the input nodes of the neural network, speed up the solution and enhance the stability of the model. The specific steps of PLSR and DNN coupled modelling are as follows:

(1) Standardize data set. According to the literature [35], the independent variable matrix $\boldsymbol{X}$ and the dependent variable matrix $\boldsymbol{Y}$ of the sample are standardized, and then the standardized matrices $\boldsymbol{E}_0$ and $\boldsymbol{F}_0$ are obtained, respectively.

(2) Extract the principal components. Extract a component $t_1 = E_0 w_1$ from $\boldsymbol{E}_0$, where $w_1 = \dfrac{\boldsymbol{E}_0^{\mathrm{T}}\boldsymbol{F}_0}{\left\|\boldsymbol{E}_0^{\mathrm{T}}\boldsymbol{F}\right\|}$, and $\|w_1\| = 1$, implement the regression of $\boldsymbol{E}_0$ and $\boldsymbol{F}_0$ on t_1, that is

$$\boldsymbol{E}_0 = t_1 \boldsymbol{p}_1^{\mathrm{T}} + \boldsymbol{E}_1 \tag{1}$$

$$\boldsymbol{F}_0 = t_1 \boldsymbol{r}_1^{\mathrm{T}} + \boldsymbol{F}_1 \tag{2}$$

where $\boldsymbol{p}_1$ and $\boldsymbol{r}_1$ are the regression coefficients matrices; and $\boldsymbol{E}_1$, $\boldsymbol{F}_1$ are residual matrices.

$$\boldsymbol{p}_1 = \frac{\boldsymbol{E}_0^{\mathrm{T}} t_1}{\|t_1\|^2} \tag{3}$$

$$\boldsymbol{r}_1 = \frac{\boldsymbol{F}_0^{\mathrm{T}} t_1}{\|t_1\|^2} \tag{4}$$

Confirm the convergence status. If the regression equation has converged, stop extracting the principal components; if the regression equation does not converge, continue to extract the components of the residual matrix and perform the regression analysis again.

(3) Determine the number of principal components. According to the cross-validation analysis method[34], for $i = 1, 2, \cdots, n$, the sum of squares of the prediction errors of the dependent variable $\boldsymbol{Y}$ can be defined as PRESS_h, and there is

$$\mathrm{PRESS}_{hj} = \sum_{j=1}^{p}\sum_{i=1}^{n}(y_{ij} - \hat{y}_{hj(-i)})^2 \tag{5}$$

When PRESS_h is the minimum, the corresponding *h* value is the determined number of principal components. If the regression equation is unstable and the fitting error is large, the equation is very sensitive to the change of the sample, and the value of PRESS_h increases at this time[36].

(4) Train coupled model. The *m* principal components obtained in the previous step are used as the input layer of the deep neural network for training and solving.

(5) Predict. The parameter matrix to be predicted is standardized, and then substituted into the PLSR model to obtain the corresponding principal component matrix, which is then used as the input layer of the deep neural network for training, and finally the predicted value is calculated.

It can be seen that the TBM net penetration rate prediction model based on the coupled modelling method of PLSR and DNN leverages the fundamental advantages of the two methods, which not only solves the problem of parameter multicollinearity, avoids overfitting, but also improves the performance stability and prediction accuracy of the model, and thus presenting high engineering application value.

3 Project overview

The Lanzhou Water Source Construction Project is located in Yongjing County, Linxia Prefecture and Xigu District, Lanzhou City, Gansu Province. It uses Liujiaxia Reservoir on the Yellow River as a water source to supply water to Lanzhou City. The project includes the main infrastructures of water intakes, water conveyance tunnels, water conveyance pipelines and water plants. Among them, the water conveyance tunnel is a controlled project with a total length of 31.57 km. The construction adopts TBM as the main method and drilling and blasting to provide auxiliary support. The designed excavation diameter of the tunnel is 5.46 m, and the diameter after the installation of lining is 4.60 m [37]. The TBM construction section is about 26.0 km long and is constructed by two double-shield TBMs operating towards each other at the same time. The section length constructed by TBM1 is 12.426 km, and by TBM2 is 13.259 km [38]. TBM1 enters from the No. 5 construction adit. The total length of the adit is 3.544 km. The designed longitudinal slope is –2.37%, which is for downhill tunnelling; TBM2 enters from the No. 6 construction adit, and commences tunnelling towards the tunnel entrance along the direction of the main tunnel. The TBM excavation section of the main water conveyance tunnel adopts uphill excavation, and the designed longitudinal slope is 0.1%. The main design parameters of the two TBMs refers to the literature[39].

The average buried depth of the water conveyance tunnel is about 500 m, and the maximum overburden thickness is 918 m. During the TBM excavation process, the lithology of the strata along the tunnel is mainly quartz schist, diorite, granite, Cretaceous argillaceous sandstone, and metamorphic andesite. Quartz schist: the rock is hard mainly with flaky structure and well-developed schist. Diorite: the rock is hard and strong in weathering resistance, with less joint development and good rock integrity. Granite: the rock is hard with strong resistance to weathering, mostly present in the form of veins originated by invasion. The rock is well connected to the surrounding rock and has good rock mass integrity. Cretaceous argillaceous sandstone:

changes of local occurrences are relatively significant with relatively developed joints due to the influence of tectonic structure. The rock mass has fair rock mass integrity and is prone to disintegration once in contact with water. Metamorphic andesite: rock has strong weathering resistance. The rock mass lacks joints and has good integrity. The engineering geological profile of the water conveyance tunnel line is shown in Fig. 3.

According to *Code for engineering geological investigation of water resources and hydropower* (GB50487-2008)[40] Appendix N: Classification Method of Surrounding Rocks, type III is main surrounding rock type, accounting for 47.5%; types II and IV are second, accounting for 35.7% and 15.3%, respectively; occurrence of Category V is low, accounting for about 1.5%. The groundwater types along the water conveyance tunnel are mainly Quaternary pore phreatic water and bedrock pore phreatic water. The tunnel is generally located below the groundwater level. The maximum water inflow of the TBM1 construction section is estimated to be 400 m^3/h. In general, the surrounding rock conditions are suitable for using the TBM tunnelling method.

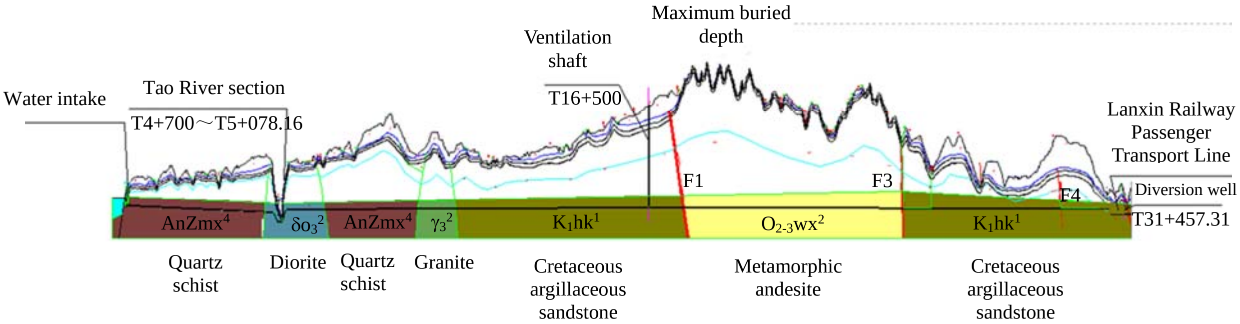

Fig. 3 Engineering geological section of the water conveyance tunnel

4 Coupled prediction model

4.1 Parameter selection and data sources

There are a variety of factors affecting the net penetration rate of TBM, including surrounding rock geological conditions, mechanical conditions, excavation parameters, and construction management level. Research and practice have shown[1] that the commonly used factors and indicators for the prediction of TBM net penetration rate mainly include rock uniaxial compressive strength, rock uniaxial tensile strength, rock abrasivity, structural planes, rock mass integrity coefficients, mechanical parameters, tunnelling parameters, groundwater and ground stress. In view of the construction characteristics of the double-shield TBM, it is difficult to directly observe and check the surrounding rock conditions of the face. At present, most of the parameters used to characterize the discontinuity of the rock mass are subjectively estimated by the engineers, and these parameters cannot be directly used in the prediction and analysis[1]. Tunnelling parameters include cutterhead thrust, cutterhead speed, cutterhead torque and penetration, etc. Among them, the cutterhead thrust and cutterhead speed are actively controlled, while the parameters such as cutterhead torque and penetration are driven. Therefore, the cutterhead thrust and cutterhead speed can be selected during analysis. Although groundwater has a certain impact on the TBM excavation rate, it is generally believed that the groundwater condition has little effect on the net penetration rate, and the impact of groundwater is difficult to quantify. Since there is no high in-situ stress in the area where the Lanzhou water source tunnel project is located, this study did not consider the impact of high in-situ stress. The parameters commonly used in the prediction model are shown in Table 1.

When predicting the net penetration rate of TBM, the selection of influencing parameters is not necessarily the more the better. On the one hand, the model will be more complicated and inconvenient to apply when considering more parameters; on the other hand, some parameters are relatively difficult to obtain accurately, and the correlation of these parameters with the TBM net penetration rate is not sufficient, and thus the influence of these parameters over the model's prediction accuracy is not significant. Ultimately, the selection of model parameters should consider the availability of parameters, the accuracy of prediction, the complexity of the model, and their use in previous studies [1]. According to the above analysis, the six parameters including rock uniaxial compressive strength (UCS), rock uniaxial tensile strength (BTS), cutterhead thrust (TF), cutterhead rotation speed (RPM), rock mass integrity factor (K_v) and rock abrasivity (CAI) are selected and used as independent variables. In the TBM construction database of the water conveyance tunnel of the Lanzhou Water Source Construction Project, 50 sets of representative measured data are selected as the final sample data after the removal of some variability data that might affect the modelling. The descriptive statistics of the different variables in the sample data are given in Table 2. Among them, the parameters such as the uniaxial compressive strength, uniaxial tensile strength, rock mass integrity coefficient and abrasivity index are obtained through indoor tests; the tunnelling parameters such as cutterhead thrust, cutterhead rotation speed and TBM net penetration rate are acquired through the daily geological report kept at the tunnel construction site.

Table 2 Descriptive statistics of the database variables

Variable	UCS /MPa	BTS /MPa	TF /(10^3 kN)	RPM /(r/min)	K_v	CAI	PR /(mm/min)
Range	50.00	9.000	6.550	3.400	0.400	2.350	31.840
Minimum	20.00	1.000	3.200	4.200	0.450	0.750	38.500
Maximum	70.00	10.000	9.750	7.600	0.850	3.100	70.340
Average	50.70	5.320	6.010	6.020	0.630	2.020	55.480
Standard deviation	16.537	3.437	2.123	0.911	0.123	0.944	7.624

4.2 Parameter correlation analysis

The correlation coefficients between different variables are calculated, see Table 3. It can be seen from the table that there is a high correlation between the independent variables. For example, the uniaxial compressive strength of rock has a high correlation with the thrust and the speed of the cutterhead. There is also a high correlation between the uniaxial tensile strength of the rock, the thrust and the speed of the cutterhead. This is because the excavation parameters such as cutterhead thrust and cutterhead speed are actually dynamically adjusted according to the geological conditions of the surrounding rock. In general, the higher the strength of the surrounding rock, the greater the thrust required, so there is an obvious correlation between them, and the correlation between these parameter variables tends to be detrimental to the modelling and analysis of the TBM net penetration rate.

The problem of multicollinearity between independent variables will cause errors in the prediction model[41]. Traditional multiple linear regression and neural network methods cannot eliminate this multicollinearity problem. Commonly used solutions include principal component regression, stepwise regression, and PLSR. However, the principal component regression does not fully consider the relationship between the extracted principal components and the dependent variables, which leads to a decrease in prediction accuracy. Stepwise regression tackles the influence of multiple correlations by eliminating highly correlated variables, which leads to a significant reduction in model interpretability, and a decrease in model fitting accuracy and prediction. Based on this, it is necessary to use PLSR to eliminate the effects of multicollinearity among variables.

Table 3 Correlation coefficient matrix between variables

Independent variable	PR	UCS	BTS	TF	RPM	K_v	CAI
PR	1	–0.858	–0.840	–0.862	–0.847	–0.726	–0.724
UCS		1	0.868	0.862	0.856	0.645	0.854
BTS			1	0.904	0.729	0.671	0.874
TF				1	0.770	0.656	0.845
RPM					1	0.635	0.675
K_v						1	0.408
CAI							1

It can be known from engineering practice that within a single formation, there is a positive correlation between the net penetration rate and the thrust and speed of the cutterhead, and the net penetration rate increases with the increase of the thrust and speed. However, for complex geological conditions, especially formations where soft and hard rocks alternately appear, the relationship between net penetration rate and cutterhead thrust and rotation speed becomes complicated, sometimes showing a negative correlation (see Table 3). This observation, however, is not inconsistent with the positive correlation between the net penetration rate and the thrust and speed of the cutterhead under the condition of a single formation. The reason is that the strength and abrasion resistance of different lithologies are quite different, resulting in a great difference in the net penetration rate. Under hard rock conditions, the net penetration rate is always low even when the thrust and speed of the TBM cutterhead are high; while in soft rock conditions, the net penetration rate is relatively high even when the thrust and speed of the cutterhead are low. Therefore, a negative correlation between the TBM net penetration rate and the cutterhead thrust and speed under complex geological conditions is in line with the actual operation situation[42]. It should be noted that this conclusion is based on the data of the thrust and rotation speed of the cutterhead of the double-shielded TBM cutterhead of the water conveyance tunnel of the Lanzhou Water Source Construction Project. The regularity outside this range needs to be verified.

4.3 Modelling and effect analysis

The PLSR is performed using Minitab, the change in PRESS value with the increase in the number of principal components can be calculated (see Fig. 4).

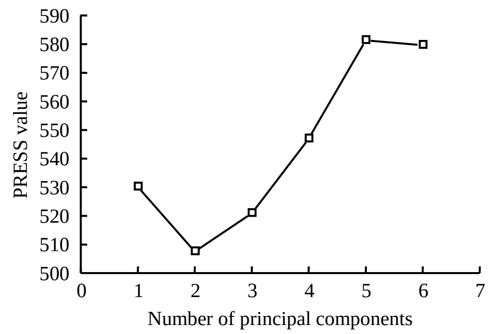

Fig. 4 Variation of the PRESS value with increase of principal component

As seen from Fig.4, the PRESS value is the lowest when two principal components are extracted. Thus, only the two principal components t_1 and t_2 need to be extracted. The expression of the two principal components is

$$\begin{bmatrix} t_1 \\ t_2 \end{bmatrix} = \begin{bmatrix} -0.437 & 0.077 \\ -0.433 & 0.222 \\ -0.433 & 0.118 \\ -0.401 & -0.347 \\ -0.342 & -0.717 \\ -0.399 & 0.635 \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} \hat{X}_1 \\ \hat{X}_2 \\ \hat{X}_3 \\ \hat{X}_4 \\ \hat{X}_5 \\ \hat{X}_6 \end{bmatrix} \tag{6}$$

where $\hat{X}_1, \hat{X}_2, \hat{X}_3, \hat{X}_4, \hat{X}_5, \hat{X}_6$ are the standardized values of UCS, BTS, TF, RPM, K_v, and CAI,

DOI: 10.16285/j.rsm.2020.5164

respectively.

The two principal components t_1 and t_2 extracted by PLSR are used as the input layer of the deep neural network. At this time, the number of neuron nodes in the input layer is reduced from six to two, and the output layer has only one node, which is the TBM net penetration rate (PR). This helps achieve dimensionality reduction. It is very important to determine the number of nodes in the hidden layer of a deep neural network, as it is the direct cause of the "overfitting" phenomenon during training and has a great impact on the performance of the model[32]. After calculation, it is found that when the number of hidden layer neurons is 80, the correlation coefficient between the measured and predicted values of PR is the highest, and the error is also the smallest. Therefore, the number of neurons in each layer of the deep neural network can be determined to be (2, 80, 80, 80, 80, 1). After training and testing the neural network, 50 sets of PR prediction values are obtained. The comparison between the actual measured value and the predicted value is shown in Figs. 5 and 6.

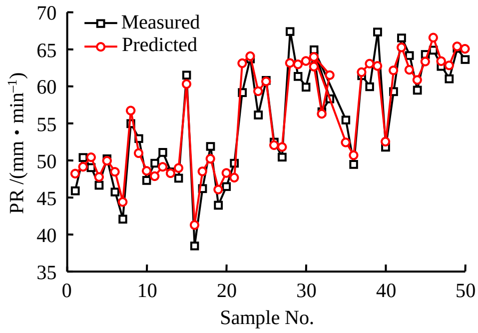

Fig. 5 Comparison between the measured PR and predicted PR

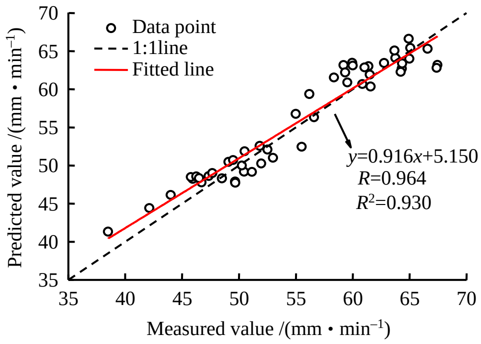

Fig. 6 Scatter plot of PR

As displayed in Fig.5, the measured and predicted values of PR in the 50 sets of sample data are very close. While Fig. 6 shows that the errors between the measured PR value and the predicted value are small, and the linear fitting of the two is close to the 1:1 line, and the correlation coefficient R is 0.964. The calculation results show that among the 50 groups of PR prediction values, the maximum relative error is 7.35%, the average relative error is 2.96%, and the overall relative error is relatively small. From this analysis, it can be seen that the fitting accuracy of the coupled prediction model of TBM net penetration rate is reasonably high.

5 Comparison and verification

5.1 Comparison of model fitting accuracy

In order to further verify the fitting accuracy of the TBM net penetration rate prediction model established by the PLSR-DNN coupling method, several prediction models for TBM net penetration rate estimation are established based on the 50 sets of data used above. These include a PLSR model, a DNN model, a BP neural network model and a support vector regression (SVR) model. The comparison of the fitting effects of the five PR prediction models is shown in Table 4.

It can be seen from Table 4 that the correlation coefficient R between the PR predicted value and the measured value obtained by the PLSR-DNN coupled model is the highest, the average relative error is the smallest, and the fitting accuracy is generally better than the other four prediction models. Among the five prediction models listed in Table 4, the PLSR prediction model has the worst fitting accuracy, which also shows that although the PLSR analysis method can mitigate the multicollinearity effect between the independent variables, its ability to deal with nonlinear problems is poor as a linear analysis method, and thus not recommended to be used on its own; as an effective tool for dealing with nonlinear problems, DNN models have competent fitting accuracy. Combining the two can achieve a sound fitting. For the three machine learning algorithms of DNN, BP neural network and support vector regression, DNN achieved the best fitting effect.

Table 4 Comparisons of fitting accuracy for different prediction models

Parameter	Correlation coefficient R	Maximum error /(mm • min^{-1})	Average error /(mm • min^{-1})	Maximum relative error /%	Average relative error /%
PLSR	0.921	7.01	2.35	15.15	4.42
DNN	0.956	6.37	1.98	12.56	3.67
PLSR-DNN	0.964	4.57	1.76	7.35	2.96
BPNN	0.940	8.12	2.11	18.29	3.99
SVR	0.945	5.89	2.75	13.22	4.03

5.2 Comparison of model prediction accuracy

In order to further analyse the applicability and rationality of different methods and verify the prediction accuracy of the TBM net penetration rate based on the PLSR-DNN coupled model, 15 sets of measured data were randomly selected from the TBM construction database of the water conveyance tunnel of the Lanzhou Water Source Construction Project. The PR values predicted by the PLSR model, DNN model, PLSR-DNN model, BP neural network model, and SVR model are compared with the actual measured values, and the relative error of the five prediction models are calculated, as shown in Fig. 7.

As seen in Fig. 7, the PR value predicted by the PLSR-DNN coupled model is the closest to the measured value, and its relative prediction error is the smallest. The maximum relative prediction error in the 15 sets of verification data is 8.33%, and the average relative prediction error is 3.27%. After verification and comparison, it is found that the best prediction effect is achieved by the PLSR-DNN coupled, outperforming the other four, which further proves the effectiveness and reliability of the coupled prediction model. It can be seen that the prediction accuracy can be guaranteed by coupling the two methods. In summary, the TBM net penetration rate prediction model established by the coupling method of PLSR and DNN is reasonable and effective.

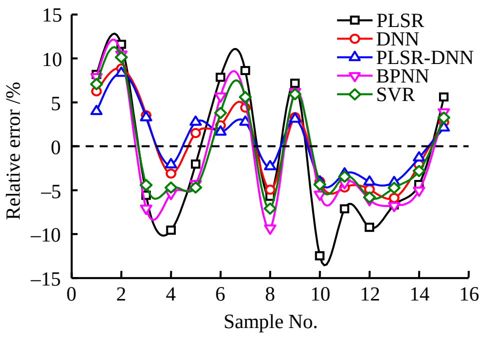

Fig. 7 Comparisons of relative prediction errors for different models

6 Discussion

Based on the measured data of the double-shield TBM construction of the water conveyance tunnel of the Lanzhou Water Source Construction Project, this paper proposes a new TBM net penetration rate prediction model. The significant advantages of this model are: (1) The model leverages the advantages of the methods of PLSR and DNN and avoids their respective shortcomings, and has high fitting and prediction accuracy. (2) The selected sample data sources cover igneous rocks, sedimentary rocks and metamorphic rocks, including hard rocks and soft rocks. The types of surrounding rocks cover a wide range, thus having a strong universality in terms of surrounding rock geological conditions. (3) The rock mass parameters and tunnelling parameters are comprehensively considered, and the parameter selection is also comprehensive.

However, the proposed prediction model is also subject to certain application conditions and has limitations. For example, given the TBM equipment has been selected, the change of mechanical parameters (hob diameter, cutter spacing, etc.) cannot be considered; fault fracture zone and other adverse geological conditions are excavated using drilling and blasting, so that the data samples under different geological conditions are relatively limited.

In general, the TBM net penetration rate prediction model proposed in this paper demonstrates significant advantages in parameter multicollinearity processing and prediction accuracy. In situations where consideration of the changes of TBM mechanical parameters is not required and tunnel geological conditions changes are not complicated, the TBM net penetration rate prediction model proposed in this paper gives superior performance, and can be extended to and provide a scientific reference to construction evaluations and predictions of similar TBM tunnelling projects.

7 Conclusion

(1) The principal components of independent variables that are more explanatory to the dependent variables are extracted by the PLSR, and input into the new neural network, thus reducing the input dimension of the neural network, simplifying the network structure, and overcoming the influence of multicollinearity among the independent variables.

(2) Using the PLSR-DNN coupled model to predict the net penetration rate of TBM, avoiding the overfitting and insufficient-fitting problems faced by when the two methods are used alone, and the model demonstrates advantages of fast convergence speed, high stability and fitting accuracy.

(3) The PLSR-DNN coupled model is used to predict the net penetration rate of TBM, and has achieved competent fitting accuracy and prediction result. The relative errors of fitting and prediction are below 10%, the average relative error of fitting is 2.96%, and the average relative error of prediction is 3.27%. The coupled model outperformed the prediction models established by PLSR and DNN methods, respectively, and also outperformed the BP neural network model and the support vector regression model.

(4) In view of the complexity of geological conditions, the diversity of mechanical equipment and the randomness of construction, it is very difficult to accurately predict the net penetration rate of TBM. The TBM net penetration rate prediction model established by the coupling method of PLSR and DNN is suitable for tunnel (cavern) projects with similar conditions as this research.

The applicability of the prediction model under other conditions needs to be verified by more engineering examples, so that the model can be continuously improved.

References

[1] LIU Quan-sheng, LIU Jian-ping, PAN Yu-cong, et al. Research advances of tunnel boring machine performance prediction models for hard rock[J]. Chinese Journal of Rock Mechanics and Engineering, 2016, 35(Suppl.1): 2766–2786.

[2] WU Xin-lin, ZHANG Xiao-ping, LIU Quan-sheng, et al. Prediction and classification of rock mass boreability in TBM tunnel [J]. Rock and Soil Mechanics, 2020, 41(5): 1721–1729, 1739.

DOI: 10.16285/j.rsm.2020.5164

[3] SANIO H P. Prediction of the performance of disc cutters in anisotropic rock[J]. International Journal of Rock Mechanics and Mining Sciences & Geomechanics Abstracts, 1985, 22(3): 153–161.

[4] BOYD R J. Hard rock continuous mining machine: Mobile Miner MM-120[C]//Rock Excavation Engineering Seminar. Queensland: University of Queensland, 1986: 618–626.

[5] ROSTAMI J. Development of a force estimation model for rock fragmentation with disc cutters through theoretical modeling and physical measurement of crushed zone pressure[D]. Colorad: Colorado School of Mines, 1997.

[6] TARKOY P J. Predicting TBM penetration rates in selected rock types[C]//Proceedings of the Ninth Canadian Rock Mechanics Symposium. Montreal: [s. n.], 1973.

[7] GRAHAM P C. Rock exploration for machine manufacturers[J]. Exploration for Rock Engineering, 1976: 173–180.

[8] NELSON P P. Tunnel boring machine performance in sedimentary rock[D]. Ithaca: The Graduate School of Cornell University, 1983.

[9] BRULAND A. Hard rock tunnel boring[D]. Trondheim, Norway: Norwegian University of Science and Technology (NTNU), 1999.

[10] BARTON N R. TBM tunneling in jointed and faulted rock[M]. Boca Raton: CRC Press, 2000: 170–175.

[11] ALBER M. Advance rates of hard rock TBMs and their effects on project economics[J]. Tunnelling and Underground Space Technology, 2000, 15(1): 55–64.

[12] GRIMA M A, BRUINES P A, VERHOEF P N W. Modeling tunnel boring machine performance by neuro-fuzzy methods[J]. Tunnelling and Underground Space Technology, 2000, 15(3): 259–269.

[13] BENARDOS A G, KALIAMPAKOS D C. Modeling TBM performance with artificial neural networks[J]. Tunnelling and Underground Space Technology, 2004, 19: 597–605.

[14] BIENIAWSKI Z, CELADA B, GALERA J M. TBM excavability: prediction and machine-rock interaction[C]// Proceedings of RETC. Toronto: [s. n.], 2007: 1118–1130.

[15] YAGIZ S, GOKCEOGLU C, SEZER E, et al. Application of two non-linear prediction tools to the estimation of tunnel boring machine performance[J]. Engineering Applications of Artificial Intelligence, 2009, 22(4): 808–814.

[16] GONG Q M, ZHAO J. Development of a rock mass characteristics model for TBM penetration rate prediction[J]. International Journal of Rock Mechanics and Mining Sciences, 2009, 46(1): 8–18.

[17] HASSANPOUR J, ROSTAMI J, ZHAO J. A new hard rock TBM performance prediction model for project planning[J]. Tunnelling and Underground Space Technology, 2011, 26(5): 595–603.

[18] DELISIO A, ZHAO J. A new model for TBM performance prediction in blocky rock conditions[J]. Tunnelling and Underground Space Technology, 2014, 43: 440–452.

[19] DU Li-jie, QI Zhi-chong, HAN Xiao-liang, et al. Prediction method for the boreability and performance of hard rock TBM based on boring date on site[J]. Journal of China Coal Society, 2015, 40(6): 1245–1256.

[20] FATTAHI H, MORADI A. Risk assessment and estimation of TBM penetration rate using RES-based model[J]. Geotechnical and Geological Engineering, 2017, 35: 365–376.

[21] LIU Q S, LIU J P, PAN Y C, et al. A case study of TBM performance prediction using a Chinese rock mass classification system–Hydropower Classification (HC) method[J]. Tunnelling and Underground Space Technology, 2017, 65: 140–154.

[22] WANG Jian, WANG Rui-rui, ZHANG Xin-xin, et al. Estimation of TBM performance parameters based on rock mass rating (RMR) system[J]. Tunnel Construction, 2017, 37(6): 700–707.

[23] ARMAGHANI D J, FARADONBEH R S, MOMENI E, et al. Performance prediction of tunnel boring machine through developing a gene expression programming equation[J]. Engineering with Computers, 2018, 34: 129–141.

[24] GONG Qiu-ming, ZHAO Jian, ZHANG Xi-hu. Performance prediction of hard rock TBM tunneling [J]. Chinese Journal of Rock Mechanics and Engineering, 2004, 23(Suppl.2): 4709–4714.

[25] GONG Q M. Development of a rock mass characteristics model for TBM penetration rate prediction[D]. Singapore: Nanyang Technological University, 2005.

[26] ZHU Dian-hua, SONG Li-wei, GUO Wei. Establishment and implementation of TBM performance prediction model under rock classification conditions[J]. Journal of Machine Design, 2018, 35(1): 22–28.

[27] NELSON P P, ALJALIL Y A, LAUGHTON C. Tunnel boring machine project data bases and construction simulation[R]. Austin, Texas: The University of Texas at Austin, 1994: 708–712.

[28] SHI Xiu-zhi, WU Yong-meng, TANG Li-zhong, et al. Application of neural network model with partial least

square regression in prediction of peak velocity of blasting vibration[J]. Journal of Vibration and Shock, 2013, 32(12): 45–49.

[29] WOLD S, ALBANO C, DUNN M, et al. Pattern regression finding and using regularities in multivariate data[M]. London: Analysis Applied Science Publication, 1983.

[30] WANG Hui-wen. Partial least squares regression method and its application[M]. Beijing: National Defense Industry Press, 1999: 24–35.

[31] XIONG Fan, HU Zhi-ping, REN Xiang, et al. Matlab-based BP neural network applied to the prediction of TBM advance rate[J]. Modern Tunnel Technology, 2017, 54(5): 101–107.

[32] XIE Jia-ying, GUO Peng. Deep neural network modeling on power curve based on multi-variable selection[J]. Huadian Technology, 2019, 41(8): 27–31.

[33] DENG Nian-wu, QIU Fu-qing. Application of neural network model with partial least-squares regression into interpretation on observation data of dam[J]. Chinese Journal of Rock Mechanics and Engineering, 2002, 21(7): 1045–1048.

[34] LÜ Bei-bei, YANG Yuan-fei. Dam monitoring model based on coupling of partial least square regression and artificial neural network modern tunnel technology[J]. Yellow River, 2013, 35(3): 84–85, 89.

[35] SHANG Kun-bo. Research on data modeling method based on partial least squares and neural network[D]. Beijing: North China Electric Power University, 2014: 78–85.

[36] ZHANG Heng-xi. Analysis method and application of small sample multivariate data[M]. Xi'an: Northwestern Polytechnical University Press, 2002: 102–108.

[37] YAN Chang-bin, JIANG Xiao-di, YANG Ji-hua, et al. Prediction of TBM cutter consumption considering geological suitability and disc cutter diameter[J]. Tunnel Construction, 2018, 38(7): 1243–1250.

[38] GUO Wei-xin, YANG Ji-hua, QI San-hong, et al. Cause analysis and treatment measures of double shield TBM blocked in granite stratum[J]. Resources Environment and Engineering, 2017, 31(5): 610–613.

[39] YAN Chang-bin, FAN Ming-hui, CHEN Kui, et al. Analysis on TBM cutter consumption based on the particle size distribution of rock debris[J]. Journal of China Coal Society, 2020, 45(12): 4216–4227.

[40] Ministry of Water Resources of People's Republic of China. GB50487－2008 Code for engineering geological investigation of water resources and hydropower[S]. Beijing: China Planning Press, 2009.

[41] KULKAMI S G, CHAUDHARY A K, NANDI S, et al. Modeling and monitoring of batch processes using principal component analysis (PCA) assisted generalized regression neural networks (GRNN)[J]. Biochemical Engineering Journal, 2004, 18(3): 193–210.

[42] YAN Chang-bin, JIANG Xiao-di. Prediction model of TBM net penetration rate based on parameters of rock mass and tunneling[J]. Modern Tunneling Technology, 2020, 57(2): 26–32.