

A STUDY OF FUZZY METHODOLOGY OF TUNNEL BORING MACHINE IN THE PROJECT OF LUCKNOW METRO RAIL CORPORATION

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Abstract

This work is about study on the fuzzy operation methodology of tunnel boring machines and finding the optimum solution for the best approach of tunneling. Adaptive network-based fuzzy inference system used in a mathematical model of TBM, neural networking with fuzzy logic and the fuzzy c-means clustering technique is used for soft soil and hard rock condition both with regression model developed by latest MATLAB technique to reduce error. UCS, BI, DPW, and Alpha degree constitute four geological technical variables that are utilized to develop regression equations for Rate of Penetration (ROP) to prevent unnecessary effort and save time and money in project.

Keywords

TBM, ANFIS, NN, CLUSTERING METHOD, FUZZY LOGIC, UCS, BI, DPW and ROP.

1. INTRODUCTION

LUCKNOW METRO RAIL CORPORATION was faced with the challenge of connecting the metro through densely populated city areas. Some citizens opposed trains crossing bridges close to their homes, and for security reasons, some government institutions refused to allow trains to pass close to sensitive locations like the secretariat.

LMRC had the option to build an underground segment utilizing the existing technology of tunneling because it was decided to make a particular piece of the Lucknow Metro subterranean.

1. Through Tunnel Boring Machine
2. Using Cut and Cover Method
3. NATM (New Austrian Tunneling Method)

The TBM method was an obvious choice for the majority of subterranean tunnels because to its efficacy and track record in metro areas of other cities. The nearby Underground stations for the UP line and DOWN line are connected by twin separate Bored tunnels.

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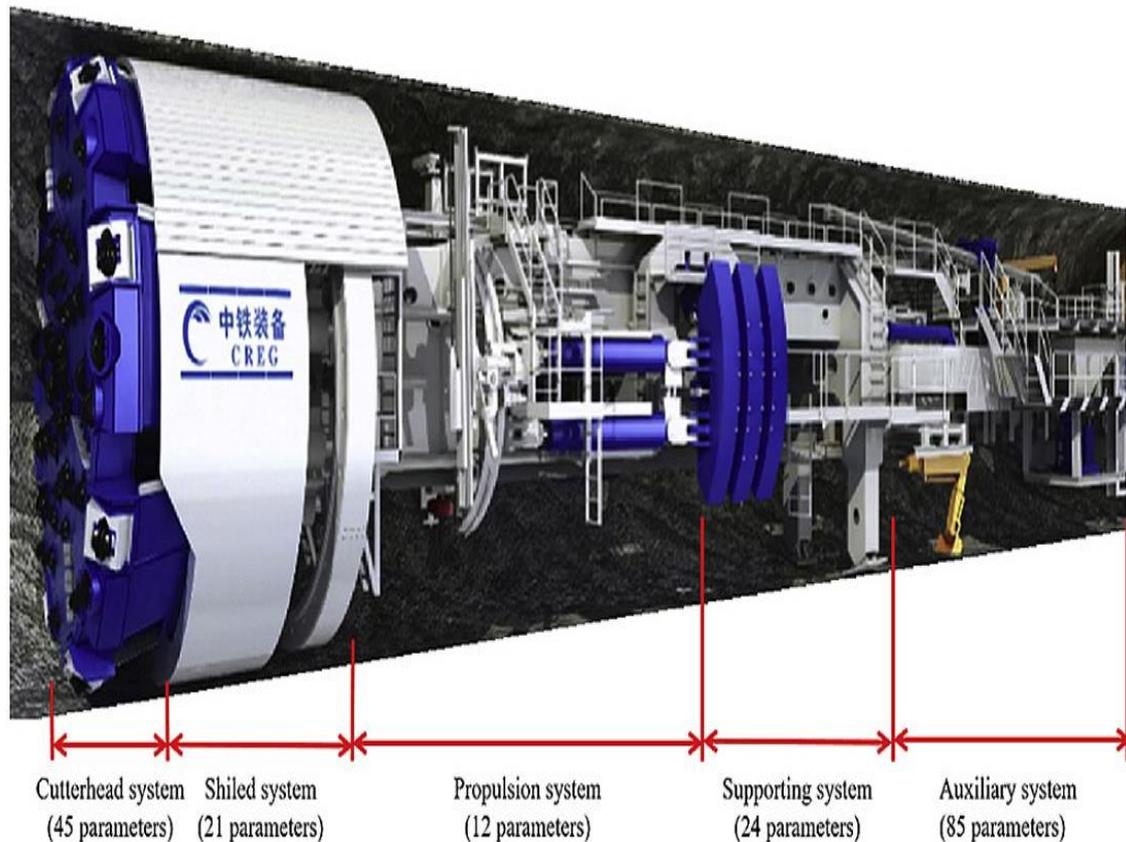


Figure 1: Tunnel Boring Machine. [29]

Currently, engineers must navigate a metro line through an underground tube while the city is home to some extremely historic structures.

The use of TUNNEL BORING MACHINE (TBM) was a smart move, however operating TBM is a challenging chore. For this task to be monitored, data must be collected, analyzed, predicted, and controlled. Estimating the tunnel-boring equipment's (TBM) efficiency of penetration is one of the difficult jobs that must be completed in order to bore a tunnel. The hazards associated with the high capital costs typical of boring operations may be decreased by estimating the machine penetration rate. The key to successful tunnel boring is the ability to predict the tunnel boring machine's effectiveness. Among the essential metrics utilized for performance prediction of these machines, The precise energy consumption of wheel cutters, which is the volume of power needed to obtain a unit volume of stone and soil.

2. LITRATURE SURVEY

Neuro-fuzzy techniques were utilized by Grima and Bruines to model TBM performance. To predict the TBM performance, Benardos and Kaliampakos used artificial neural networks. A neural network-based approach for predicting TBM performance was introduced by Zhao and Gong. Acaroglu and Ozdemir developed a fuzzy logic model to forecast the precise amount of energy needed to anticipate TBM performance. In a subsequent attempt, Yagiz proposed two nonlinear prediction tools for the estimate of TBM performance artificial neural networks and nonlinear multiple regression. Two key components of the TBM performance, including the penetration rate and utilization factor, were examined by Torabi and Shirazi using A computational social arts analytical program and a synthetic neural network. Yagiz and Karahan used the particle swarm optimization (PSO) method to predict the rate of hard-rock TBM breakthrough.

The performance of TBMs can be anticipated using an adaptive neuroscience fuzzy inference system built around Fuzzy C-Means Grouping Methodology (ANFIS-FCM), a unique data analysis technique. In this model, the rate of penetration served as the output parameter. As input variables, the intact rock brittleness (BI), alpha angle, planes of weakness, and uniaxial in nature compressible strength (UCS) were all utilized. The ANFIS-estimating FCM's capabilities are demonstrated using field data from open-access publications. Yet, as the primary function of cutters is to shatter rock, significant advances in cutter design and metallurgy have been made. Disc cutters, which are frequently used by TBMs and may cut an assortment of sandstone different types with various qualities. Hard rock TBMs have utilized single disc cutters with replacement disc rings for a long time because they have shown themselves to be effective and dependable. When tip wear developed, the V-shape (V-profile) of early disc cutters produced a sharp decline in efficiency. Constant cross-section (CCS) profiles began to take the place of V-shape ring profiles in the late 1970s in order to preserve cutting efficiency after the tip wore out. Mini disc cutters, often used after 30 cm (12 in.) in diameter, are disc cutters with a diameter of between 49 cm (19 in.) and 8 cm (3 in.). The maximum cutting forces that discs can withstand depend on the cutters' bearing capabilities, which decrease as disc diameter increases. Little discs, however, penetrate more deeply than larger discs when applied with the same force (Friant and Ozdemir, 1994).

A project's schedule and cost are significantly impacted by the ability to produce precise performance estimations when applying TBM technology. Several case studies demonstrate how performance estimate errors can lead to project delays and expense overruns. The penetration and progress rates as well as machine utilization serve as key performance indicators for TBMs. One of the main functions of a disc cutter is to cut rock, and particular efficiency, which is the amount of power needed by wheel cutters to do something, is used to identify the performance parameters for the machine. With a lower SE, the same amount of material can be produced while excavating the rock much more effectively and with comparably less expensive equipment. One of the reliable artificial intelligence methods, It has been shown that the fuzzy c-means grouping algorithm based adaptive neuro fuzzy inference system (ANFIS-FCM) is very good at identifying associations with input and output features.

3. METHODOLOGY

3.1 Adaptive network-based fuzzy inference system used in a mathematical model of TBM:

Without using exact quantitative analysis, the qualitative components of human understanding and logic can be replicated by a fuzzy inference system. Information-processing software called neural networks (NNs) is modeled after research, observation and analysis on functions of the animal and human brain. A collection of interrelated components of processing that resemble neurons make up NN. The instruction process provides a set of input data into the NNs and verifies the desired output. It has been demonstrated that combining NNs with fuzzy logic (FL) can reasonably simulate the psychological procedure for making decisions for skilled. Typical NNs merely evolve the development process' values for weighting, therefore a neuro-fuzzy decision-making system combines the learning capabilities of NNs with the FL's inference process. A network structure made up of multiple nodes connected by directional links is an adaptable neural network. Each node is defined by a node function that can have either fixed or variable arguments. As soon as the fuzzy inference system (FIS) is in place, NN approaches can be used to discover the rules' underlying assumptions and resulting parameters, which are unknown, while lowering the error measure typically defined for each system variable. The system is referred to as adaptive because of this optimization process. Five levels make up the ANFIS architecture, and the model is briefly described below.

Level 1: The membership grades of a linguistic label are generated by each node R in this layer. For example, the r^{th} node's node feature could be:

$$T_r^1 = \rho_{Ar}(P) = \frac{1}{1 + \left[\left(\frac{x - k_r}{\sigma_r}\right)^2\right]^{d_r}} \quad (1)$$

here P is the each node's data, Ar is the linguistic term (listed in ascending order) attached to it, and σ_r, K_r, d_r is the parameter set that alters the MF's forms . The "Premises factors" are the name given to the variables in this level.

Level 2: The "firing intensity" of every rule in this level is determined by compounding at each node:

$$T_r^2 = Z_r = \rho_{Ar}(P) \cdot \rho_{Br}(Q) \quad r = 1,2 \quad (2)$$

Level 3: The *r*th component of this level defines the proportion of the *r*th rule's blazing strength to the sum of all rules' blazing strengths:

$$T_r^3 = \bar{Z}_r = \frac{Z_r}{\sum_{q=1}^2 Z_q} \quad r = 1,2 \quad (3)$$

This level of output will be referred to as "normalized firing" strengths for simplicity.

Level 4: All nodes r at this level are nodes functions:

$$T_r^4 = \bar{Z}_r \cdot g_r = \bar{Z}_r (\alpha_r P + \beta_r Q + \gamma_r) \quad (4)$$

Where, \bar{Z}_r is level 3's output. The term "consequent parameters" will be used to describe the parameters at this level.

Level 5: The "comprehensive outcome" of this level is calculated by a single circular component with the label "R," which adds together all of the signals coming in.

$$T_r^5 = \text{Comprehensive Outcome} = \sum \bar{Z}_r G_r = \frac{\sum Z_r g_r}{\sum Z_r} \quad (5)$$

In this work, the antecedent MFs are also identified using FCM.

3.2 The procedure of fuzzy c-means grouping

The FCM is a Bezdek-invented data grouping technique where each data point is a member of a group to the extent specified by the classification of membership of a cluster. FCM is used to distribute a set of n vector P_r , where $r = 1, 2, \dots, n$, into C fuzzy groups.. In each group, a clump center is found that minimizes the cost function of the dissimilarity measure. Thus, a quick description of the FCM algorithm's steps follows. The cluster's initial nodes are $c_r, r = 1, 2, \dots, C$. From the n points, P_1 is randomly selected, followed by P_2 and so on until P_n . The following equation is then used to build the composition of the matrix U:

$$\rho_{rq} = \frac{1}{\sum_{k=1}^c \left(\frac{g_{rq}}{g_{kq}}\right)^{2/w-1}} \quad (6)$$

The formula provides the Euclidian distance that separates the *r*th group and the *q*th value is given by the formula $g_{rq} = \|c_r - P_q\|$ and w is the fuzziness index. The cost function is then calculated using the equation shown below. If it falls below a specific threshold, the process is stopped.

$$L(U, c_1, \dots, c_2) = \sum_{r=1}^c J_r = \sum_{r=1}^c \sum_{q=1}^t \rho_{rq}^w g_{rq}^2 \quad (7)$$

A fresh c fuzzy group with $r = 1,2$ focuses on c_{rin} the final step. To figure out C, apply the equation below.

$$c_r = \frac{\sum_{q=1}^t \rho_{rq}^w x_q}{\sum_{q=1}^t \rho_{rq}^w} \quad (8)$$

3.3 Using the most recent version of MATLAB, 4 Regression Models for ROP are concluded:

Technically, because their empirical correlation coefficients to ROP are more than 0.6, qualities of boulders demonstrate the most precise factors for forecasting the ROP will be the UCS and the BI. The DPW and alpha angle are also important measures to assess ROP because they have correlation factors to ROP that are higher than 0.5. As a result, the following part will develop regression models for ROP using four (4) rock technical attributes, UCS, BI, DPW, and Alpha.

Model 1: Linear regression model (LRM)

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$$\text{ROP (i)} = \beta_0^{(1)} + \beta_1^{(1)} \cdot \text{UCS} + \beta_2^{(1)} \cdot \text{BI} + \beta_3^{(1)} \cdot \text{DPW} + \beta_4^{(1)} \cdot \text{Alpha}$$

Model 2: Linear regression model with log(Alpha)

$$\text{ROP (ii)} = \beta_0^{(2)} + \beta_1^{(2)} \cdot \text{UCS} + \beta_2^{(2)} \cdot \text{BI} + \beta_3^{(2)} \cdot \text{DPW} + \beta_4^{(2)} \cdot \log(\text{Alpha})$$

Model 3 : Nonlinear regression model with exponential Alpha (NLRM1)

$$\text{ROP (iii)} = \beta_0^{(3)} + \beta_1^{(3)} \cdot \text{UCS} + \beta_2^{(3)} \cdot \text{BI} + \beta_3^{(3)} \cdot \text{DPW} + \beta_4^{(3)} \cdot (\text{Alpha})^{\beta_5^{(3)}}$$

Model 4: Nonlinear regression model with both exponential DPW & Alpha (NLRM2)

$$\text{ROP (iv)} = \beta_0^{(4)} + \beta_1^{(4)} \cdot \text{UCS} + \beta_2^{(4)} \cdot \text{BI} + \beta_3^{(4)} \cdot \text{DPW}^{\beta_4^{(4)}} + \beta_5^{(4)} \cdot (\text{Alpha})^{\beta_6^{(4)}}$$

3.4 Methodology for Data Processing

To increase the effectiveness of networks in recognizing the links between inputs and outputs, inputs and output data should be normalized prior to the training process. Moreover, scaling the data to reduce the biasing of the networks and improving prediction accuracy are both greatly aided by normalization. The time-consuming nature of training can be cut down through data normalization. Modeling applications with input data of various scales can greatly benefit from it. Many normalization methods, such as Z-Score normalization, Min-Max normalization, sigmoid normalization, statistical column normalization, etc, are commonly used to scale up the data, Nonetheless the Min-Max normalization method was employed for the purposes of this study. This was made possible by Min-Max normalization's ability to preserve each feature's variation following normalization. Moreover, this normalization technique can maintain all of the data's relationships. Below is how the Min-Max normalization equation is expressed:

$$Y_M = \frac{y - y_{min}}{y_{max} - y_{min}} \quad (9)$$

where Y is the dataset's original value, Y_M is the mapped value, and y_{max} (y_{min}) stands for the dataset's highest (lowest) possible raw input values.

Mean square error (MSE) and coefficient of determination (R^2) are two more established metrics used to evaluate the effectiveness of the networks in addition to normalization. The following equation is used to compute MSE:

$$\text{MSE} = \frac{1}{t} \sum_{q=1}^t (h_q - \hat{h}_q)^2 \quad (10)$$

where h_q and \hat{h}_q are the real and anticipated standard of the q th observation, accordingly, and t is the quantity of samples utilized to train or test the network. It is common practice to demonstrate the difference between measured and estimated network values using the MSE criterion. You can also compute R^2 , or the coefficient of determination, as follows:

$$R^2 = 1 - \frac{\sum_{q=1}^t (h_q - \hat{h}_q)^2}{\sum_{q=1}^t h_q^2 - (\sum_{q=1}^t \hat{h}_q^2 / t)^2} \quad (11)$$

R^2 is frequently used to illustrate the model's initial level of uncertainty. The ideal network model, which is highly improbable to be created, has $\text{MSE}=0$ and $R^2=1$.

4. Results

A specialist who is familiar with the system that needs to be simulated specifies the number of rules in a regular fuzzy inference system. However, no expert is available in the ANFIS simulation; as a result, the total number of member functions (MFs) provided for every input parameter is chosen intuitively, i.e., by charting the data sets and visually inspecting them, or just by trial and error.

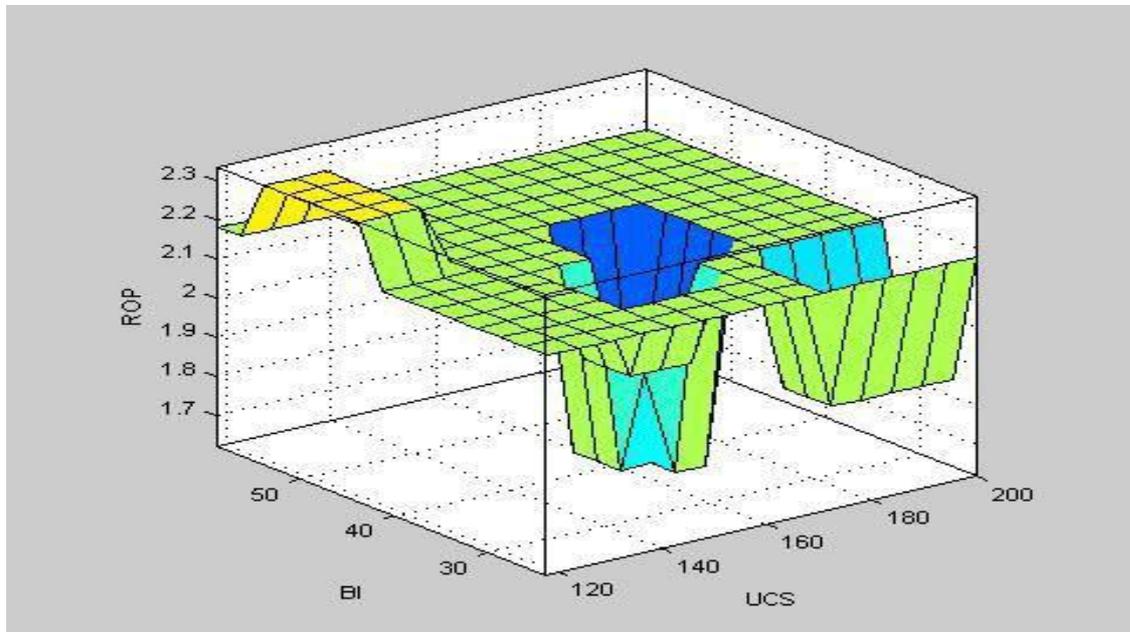


Figure 2: Fuzzy logic surface. [30]

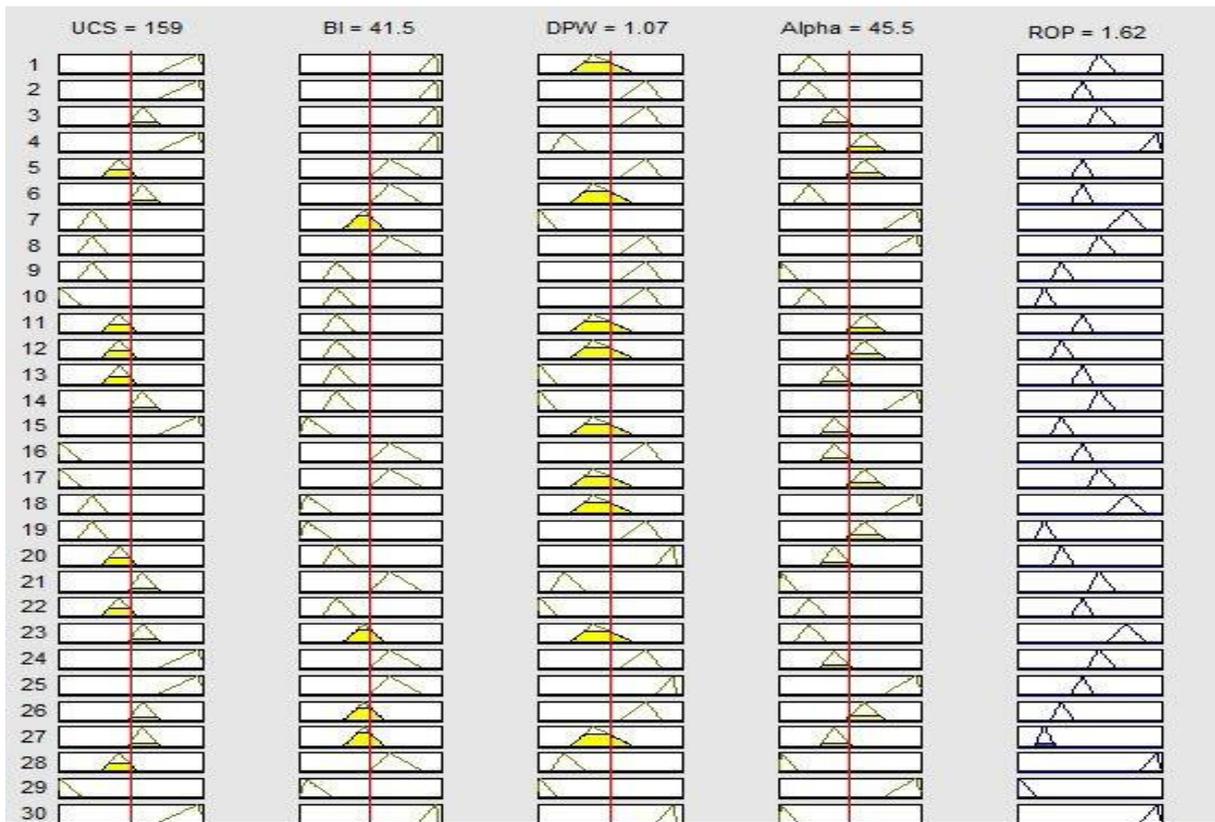


Figure 3: Fuzzy logic rules viewer [30]

Using the MATLAB environment, the ANFIS-FCM model was used to this study's prediction model to calculate the TBM penetration rate from the available data. In order to estimate TBM performance, the ANFIS-FCM model's fuzzy architecture is depicted in Fig 4. The current study used a dataset with 153 data points, 122 of which (or 80%) were used to build the model while the other 31 data points were used to assess the model's performance. Table 1 provides more information on the parameters of the ANFIS-FCM model.

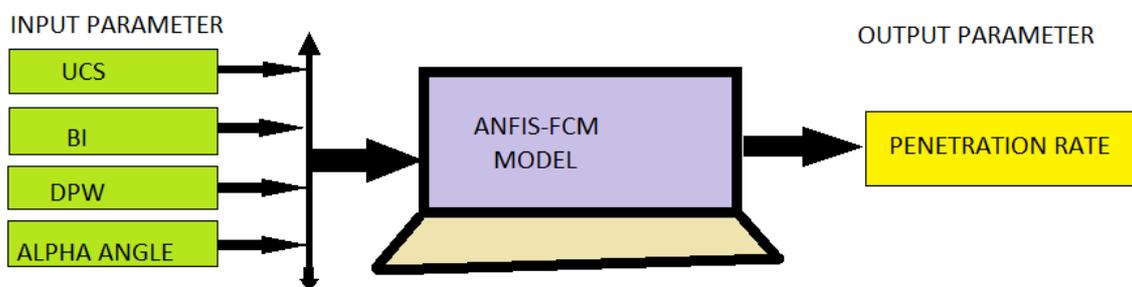


Figure 4: An ANFIS-FCM Strategy Structure

Table 1
Modeling components for the ANFIS-FCM

Parameter	Description
Type of participation duty	Gaussian
participants perform produce	Linear
Density of vertices	57
numerous linear factors	25
various nonlinear parameters	40
Numerous parameters in total	65
Total pairs of training data	122
combinations of test data in numerical	31
quantity of fuzzy rules	5

5. Conclusion and Discussion

The forecast and evaluation of its utilization factor are two of the most crucial elements influencing how well TBM performs. In actuality, TBM tunneling projects are more productive when the utilization factor is accurately identified and calculated. Since the goal of the current study is to anticipate the utilization approach in sandy soil tunneling (metropolitan environment), correct locating and calculating the utilization proportion helps to avoid potential machine damage as well as excessive project costs and time. However, there are always unknown and unforeseen events in underground operations, requiring the use of smart data analysis techniques.

In this study, the hard rock TBM penetration rate was estimated using the ANFIS-FCM method. The UCS, BI, DPW, and alpha angle of intact and bulk rocks, among others, have been discovered to significantly affect TBM penetration. Consequently, the model was created using relevant properties. It can be concluded that ANFIS-FCM is a dependable method of system modeling that forecasts penetration rate with a very respectable level of resilience and accuracy.

With $R^2= 0.6765$ and $MSE= 0.0257$. This study highlights the potential of the ANFIS-FCM technique as a powerful tool for simulating several tunnel engineering-related problems.

When the outcomes of the various generated models were compared, the created model, which was based on the regression model and ANN-FCM, was discovered to have a superior capacity for training multiple linear regression and multi-layer perceptron neural networks. Last but not least, given the importance of figuring out the utilization factor in tunneling project procedures.

It is advised to research and compare this coefficient in soft lands with other prediction techniques like the support vector machine, genetic programming, and regression tree technique, as well as compare it with the findings of this study.

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