This is a peer-reviewed, accepted author manuscript of the following article: Sheil, B. B., Suryasentana, S. K., Mooney, M. A., & Zhu, H. (2020). Machine learning to inform tunnelling operations: recent advances and future trends. Proceedings of the Institution of Civil Engineers – Smart Infrastructure and Construction. https://doi.org/10.1680/jsmic.20.00011

Machine learning to inform tunnelling operations: recent advances and future trends

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Initial submission, 27 April 2020

Main text wordcount: 4980

Figures: 11

Tables: 3

ABSTRACT

The proliferation of data collected by modern tunnel boring machines (TBMs) presents a substantial opportunity for the application of machine learning (ML) to support the decision-making process on site with timely and meaningful information. The observational method is now well-established in geotechnical engineering and has a proven potential to save time and money relative to conventional design. ML advances the traditional observational method by employing data analysis and pattern recognition techniques, predicated on the assumption of the presence of enough data to describe the modelled system's physics. This paper presents a comprehensive review of recent advances and applications of ML to inform tunnelling construction operations with a view to increasing their potential for uptake by industry practitioners. This review has identified four main applications of machine learning to inform tunnelling, namely TBM performance prediction, tunnelling-induced settlement prediction, geological forecasting and cutterhead design optimisation. The paper concludes by summarising research trends and suggesting directions for future research for ML in the tunnelling space.

INTRODUCTION

Rapid urbanisation points to the use of underground space as one of the most viable, sustainable and efficient means of delivering new services and transport in congested urban areas. The use of trenchless technology in infrastructure construction is growing in popularity for its cost and environmental savings compared to conventional open excavation techniques. In these obstructed underground spaces, optimising the performance of tunnelling operations is critical to ensure safe and economical construction while also preventing damage to existing infrastructure both above and below ground.

Traditionally, tunnelling contractors have used ‘rules of thumb’ and empiricism in addition to more formal design calculations. While simplified design calculations play an important role in tunnel design and construction, optimising tunnelling operations is technically challenging due to their dependence on several complex factors such as site geology, tunnel boring machine (TBM) operational parameters and tunnel geometry (O’Dwyer et al. 2018, 2019, Phillips et al. 2019). Although a significant body of research conducted over the last thirty years has greatly enhanced our understanding of these effects and their influence on tunnelling operations, the literature contains many examples where static ‘rule-based’ design methods fail to provide satisfactory prediction of field behaviour e.g. Barla et al. (2006), Choo and Ong (2015), Sheil et al. (2016).

The proliferation of data collected by modern TBMs presents a substantial opportunity for the application of machine learning (ML) to support the decision-making process on site with timely and meaningful information (Sheil et al. 2020). The observational method is now well-established in geotechnical engineering and has a proven potential to save time and money relative to conventional design (e.g. Royston et al. 2020). ML advances the traditional observational method by employing data analysis and pattern recognition techniques, predicated on the assumption of the presence of enough data to describe the modelled system’s physics. While Shreyas and Dey (2019) present a high level overview of machine techniques for tunnelling settlement and performance prediction, a more comprehensive review of recent advances and applications of ML to inform tunnelling construction operations is necessary to increase their potential for uptake by industry practitioners. To this end, this review has identified four main applications of machine learning to inform tunnelling, namely TBM performance prediction, tunnelling-induced settlement prediction, geological forecasting and cutterhead design optimisation. The paper concludes by summarising research trends and suggesting directions for future research for ML in the tunnelling space.

MACHINE LEARNING MODELS

Overview

The practice of ML has experienced immense recent growth, driven by advances in computational performance, sensing technology and data storage. Artificial intelligence (AI), ML and deep learning are three terms often used interchangeably to describe software that behaves in an intelligent manner. ML is a subset of AI which provides systems with the ability to automatically learn and perform certain tasks without being explicitly programmed. Deep learning is a further subset of ML which uses a specific ML algorithm called 'deep' artificial neural networks, with many hidden layers, to learn from large amounts of data.

A drawback of many supervised learning techniques is the requirement for a large database of high-quality information to accurately capture the physics of the modelled system. The size of the dataset required for the training process is highly dependent on the type of ML technique adopted, its intended role (e.g. interpolation, optimisation, forecasting) and the complexity of the input-output relationship being modelled. This section provides a brief overview of ML techniques commonly applied to tunnelling operations.

Artificial neural networks

An artificial neural network (ANN) is an information processing paradigm that draws inspiration from the operation of the human brain. A network consists of multiple interconnected layers of neurons, comprising a layer of input neurons, one or more layers of 'hidden' neurons that perform operations on the data, and a layer of output neurons. Transformation of the input data is performed by the artificial neurons through the application of a nonlinear function (known as the activation function) of the sum of weighted inputs (see Fig. 1). In its simplest form (a feedforward neural network), data travels in one direction – from input to output. After each complete iteration, termed 'epochs', the network output values are compared to the target values to produce an error measurement. Feedback of the error through the network, known as 'backpropagation', is a nonlinear optimisation process which adjusts the weight and bias of each connection towards reducing the value of the cost function. In this paper the 'architecture' describes the network structure in the form n_f-…n_{hi}...-n_o where n_f, n_{hi} and n_o are the number of features, neurons in hidden layer *i* and outputs respectively.

An alternative network form is a recurrent neural network (RNN) wherein connections between units form a directed cycle. This allows the network to maintain information in 'memory' over time and therefore use historical calculations to determine outputs. Long short-term memory (LSTM) is a type of RNN that uses a 'memory cell' that can store information for long periods of time. A set of 'gates' are used to decide whether information is stored in the memory cell, when information from the memory cell is deployed in the network or when information is removed from the cell altogether (i.e. forgotten).

Fuzzy logic

Fuzzy logic (FL) involves the integration of expert knowledge and experience into a fuzzy inference system using fuzzy 'If-Then' rules to model the qualitative aspects of human knowledge. This allows an extension of binary, classic logic to qualitative, subjective and approximate situations. Takagi and Sugeno (1985) presented the first systematic investigation of fuzzy modelling. The purpose of a fuzzy inference system is to map inputs to outputs through the application of fuzzy reasoning. Fuzziness is first applied to the inputs to produce a fuzzy set using a 'membership function', $\zeta(x)$, such as the Gaussian membership function:

$$\zeta = e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{1}$$

where x is the input value and σ and c are the standard deviation and mean of the Gaussian function respectively. The resulting fuzzy set is processed using a set of If-Then rules. The results are subsequently defuzzified to produce 'crisp' outputs.

Adaptive neuro-fuzzy inference systems

Adaptive neuro-fuzzy inference systems (ANFIS) denotes the fusion of neural networks with fuzzy logic principles. The key difference to traditional neural networks is that part or all nodes in the network are modified to be 'adaptive'. This means that the outputs of the network are now dependent on the nodal parameters and the learning rule updates the parameters to minimise a prescribed error measurement. Relationships between variables are defined using fuzzy If-Then rules. ANFIS networks are typically organised in five layers as follows: (a) layer 1 is the input layer comprising the adaptive nodes and node functions and activates the fuzziness of the inputs, (b) layer 2 determines the firing strength of each rule, (c) layer 3 normalises the firing strengths, (d) layer 4 defines the consequence parameters and (e) layer 5 computes the ANFIS outputs by summing the outputs of layer 4.

Fuzzy c-means clustering

Conventional clustering techniques assign data to a cluster without consideration of the extent of its 'belonging' to that cluster. First introduced by Dunn (1974), fuzzy c-means clustering (FCM) is a clustering approach that allows a datapoint to belong to multiple clusters with varying degrees of membership. This method uses an iterative clustering technique to produce an optimal '*d*' through the minimisation of an objective function J_{FCM}:

$$J_{FCM} = \sum_{i=1}^{n_p} \sum_{j=1}^{n_c} M_{ij}^{a} \left\| x_i - d_j \right\|^2 \qquad (2)$$

where n_p and n_c are the number of datapoints and clusters respectively, M_{ij} is the membership matrix, $a > 1$ is a parameter controlling the fuzziness of the system and $\left\| x_i - d_j \right\|^2$ is the squared Euclidian distance between observation x_i and cluster centre d_j.

Classification and regression trees and random forest

Classification and regression trees (CART) are a non−parametric method that build classification or regression models in the form of a tree structure. At each tree node, a specified number of features are randomly selected and tested to achieve an optimal split of the data. Although decision trees can be highly effective, they are prone to overfitting and are sensitive to the specific dataset upon which they are trained. A robust solution to overfitting is the concept of random forests, first proposed by Breiman (2001). Random forest (RF) is an ensemble learning method that operates by building multiple decision trees and aggregating the results (see Fig. 2). Multiple different training sets (termed bootstrap samples) are generated by sampling with replacement randomly from the original data. This method builds several instances of a decision tree which produces an output $\hat{y}_i$ corresponding to each tree. All individual outputs are then averaged to obtain the final prediction, $\hat{y}$.

Gaussian process regression

A Gaussian process is a collection of random variables of which any finite number follow a joint Gaussian distribution (Williams and Rasmussen, 1996). Gaussian process regression

(GPR) provides a method to perform Bayesian inference about functions in a non-parametric way. One of the key aspects of GPRs is the use of covariance functions which encodes prior assumptions about the functions one wishes to learn (in this case the measured data). This avoids reliance on algebraic mapping between inputs and outputs. The overall aim of the process is to learn a regression model of the form $y = f(x) + \epsilon$, where $f(x)$ is a latent function representing the underlying structure of the data and $\epsilon \sim N(0, \sigma^2)$ is a Gaussian noise term where σ^2 is the variance of the noise (the symbol '~' means 'distributed according to'). A GP can be completely described by a mean vector, $\mu(x)$, and covariance function $k(x,x')$ of input pairs x and x′ to describe an underlying real process f(x) as follows:

$$\mathrm{f(x)} \sim \mathcal{GP}(\mu(\mathrm{x}), k(\mathrm{x}, \mathrm{x}')) \tag{3}$$

where

$$\mu(\mathrm{x}) = \mathbb{E}[\mathrm{f(x)}] \tag{4}$$

$$k(\mathrm{x}, \mathrm{x}') = \mathbb{E}\left[\big(\mathrm{f(x)} - \mu(\mathrm{x})\big)\big(\mathrm{f(x')} - \mu(\mathrm{x'})\big)^{\mathrm{T}}\right] \tag{5}$$

Support Vector Machine/Regression

The term 'support vector regression' (SVR) denotes the application of support vector machines (SVM) to regression problems. The ε−insensitive approach first proposed by Vapnik (1995) is one of the most widely adopted SVM/SVR approaches in the literature. SVR uses either linear or non−linear kernels to map the input space into a high−dimensional feature space. The most common kernel adopted for this purpose is the radial basis function (RBF):

$$K(x_i, x) = \exp(-\gamma\ ||x_i - x_j||^2) \tag{6}$$

where γ is a kernel coefficient. A hyperplane is subsequently constructed in the feature space where the quality of fit to the data is computed using an ϵ−insensitive cost function ($L_\varepsilon(y)$) defined as follows (see Fig. 3):

$$L_{\epsilon}(y) = \begin{cases} 0 & \text{for} \quad |f(x) - y| \leq \varepsilon \\ |f(x) - y| - \varepsilon & \text{otherwise} \end{cases} \tag{7}$$

where x is the input data with target values y, $f(x)$ is the regression function, and ε is a user−defined positive value representing the maximum distance between $f(x)$ and y for which there is no loss in the cost function. According to equation (7), only predictions that have residuals greater than ε are penalised, while predictions with smaller residuals have no effect on the regression equation. Considering a linear function as an example, $f(x)$ can be defined as follows:

$$f(x) = (\boldsymbol{w} \cdot x) + b \tag{8}$$

where $\boldsymbol{w}$ is an adjustable weight vector and b is the bias. The objective is to obtain a function that has the smallest ε deviation from the target values in the training data and is also as 'flat' as possible (by minimising the Euclidean norm $||\boldsymbol{w}||^2$).

Extreme learning machine

Extreme learning machine (ELM) is a three-layer neural network i.e. it comprises a single hidden layer (Huang et al. 2004). The novelty of ELM centres around its use of randomly generated hyperparameters for the hidden layer which are not updated during training, unlike conventional neural networks (Huang et al. 2006). This significantly reduces the computational time associated with the learning process and increases the network's ability to generalise within the trained parameter space. The ELM training process involves the generation and selection of random numbers for the weight and bias matrices for the hidden layer (Huang et al. 2011). Since the number of neurons in the hidden layer is typically much less than the number of training observations, the network is an over-determined linear system. A consequence of this is that the output weight matrix is the only parameter that needs to be optimised during training, which can be undertaken using an ordinary least squares approach.

Particle swarm optimisation

Particle swarm optimisation (PSO) is an optimisation algorithm developed by Kennedy and Eberhart (1995). This approach attempts to mimic interactions in groups of social beings and the sharing of information between the group members (termed 'particles'). Rather than using a single particle to search for an optimal solution, the whole population is used where the velocities of each member are defined by both a stochastic and deterministic component. While each particle moves randomly, it is partially guided by its own (local) best position as well as the best position of the group (global). The updated velocity vector at time t+1 for particle i (v_i^{t+1}) is defined as follows:

$$v_i^{t+1} = v_i^t + \alpha\epsilon_1\left(g^* - x_i^t\right) + \beta\epsilon_2\left(x_i^* - x_i^t\right) \tag{9}$$

where ϵ_1 and ϵ_2 are two randomly initiated vectors with entries ranging between 0 and 1, α and β are the global and local learning parameters respectively, x_i is the position of particle i and g^* and x_i^* are the global and local (for particle i) best historical location.

Evolutionary algorithms

First proposed by Holland (1992), genetic algorithms (GA) are arguably the most popular variant of the evolutionary algorithm. These methods are a computational model inspired by evolution and the mechanisms of natural selection and are typically deployed as search and optimisation algorithms. The parameters of the user-defined search space are first encoded in the form of chromosomes which can in turn be grouped to form a population. The process begins by initiating a random population representing different nodes in the search space. The fitness (cost) function is then evaluated for each node to determine the fitness value. New search nodes are randomly generated by applying genetic operations on the nodes based on their fitness values. This process is repeated until an optimal solution is acquired. The purpose of the genetic operators is to combine the ‘good’ structures of each node to produce an improved search node. Common genetic operators are shown in Fig. 4 and include (a) crossover (portions of chromosomes are swapped), (b) reproduction (chromosomes with good fitness values in an old population are preserved in the new population) and (c) mutation (occasional random alteration of a chromosome).

Three alternative evolutionary algorithms include (a) genetic programming (GP), (b) gene expression programming (GEP) and (c) differential evolution (DE). The fundamental difference between these approaches lies primarily in the composition of the individuals within the respective populations. In GAs, individuals are linear chromosome strings of fixed length; in GPs, they are non-linear units with varying shapes and sizes; in GEPs, they are encoded linear strings of fixed length (similar to GA chromosomes) which are subsequently expressed as non-linear units of varying shapes and sizes; and in DEs, they are real vectors rather than binary chromosome strings.

Imperialist competitive algorithm

The imperialist competitive algorithm (ICA) is an alternative evolutionary search and optimisation algorithm proposed by Atashpaz-Gargari and Lucas (2007) and is derived from human being’s socio-political evolution. In this case, the initial population is termed ‘countries’ and is broken into two categories: (a) colony and (b) imperialist. A cost function is used to determine which countries of the initial population are the most ‘powerful’ and are therefore selected as imperialist states. The remaining countries are assigned as colonies of the imperialist states depending on the value of the cost function for each imperialist state. The imperialist state and their respective colonies are denoted an empire. The ensuing optimisation process is described by Fig. 5.

MACHINE LEARNING IN TUNNELLING

Overview

A wide range of ML techniques have been developed for tunnelling applications. Research areas have included TBM automation (Mokhtari and Mooney 2019), tunnel condition assessment (Li et al. 2017, Chen et al. 2019c), anomaly detection (e.g. Yu et al. 2018, Sheil et al. 2020), tunnel profile measurement (e.g. Xue and Zhang 2019), resilience assessment (e.g. Khetwal et al. 2019), structural defect identification (e.g. Ding et al. 2019), tunnel face stability (e.g. Hayashi et al. 2019), rockburst prediction (e.g. Liu and Hou 2019) and intelligent building information modelling (e.g. Zhao et al. 2019b). This review focuses on four tunnelling applications where the use of ML has been most prevalent: (a) TBM performance prediction, (b) tunnel-induced settlement prediction, (c) geological forecasting and (d) cutterhead design optimisation.

TBM performance prediction

A large body of research has focused on the development of improved TBM performance predictions by leveraging recent advances in ML. Table 1 presents an overview of these studies where the corresponding parameters and notation are defined in Fig. 6 (a slurry pressure balance shield machine is shown for illustrative purposes) and Table 2. Research into TBM performance has largely been confined to open mode TBM tunnelling in rock with only a handful of efforts with slurry or earth pressure balance shield TBMs in softer soils (e.g., Mooney et al. 2018, Mokhtari et al. 2020). From Table 1, it is notable that penetration rate (PR) is the most favoured measure of TBM performance, defined as the penetration along the axis of the tunnel per unit tunnelling time (i.e. does not include down times/stoppages). From Table 1, it can be observed that the input parameters are dominated by ground (rock) properties, with UCS being the most common. It is noteworthy that the selection of input parameters have predominantly been guided by empiricism from previous literature and the application of more robust 'feature engineering' techniques, such as principal component analysis (e.g. Salimi et al. 2015, 2016, 2019), in this area has been limited.

Another interesting observation is the inusitation of TBM operational (e.g. jacking force (JF), cutterhead torque (T), cutterhead rotation speed (RPM), slurry parameters, etc) and geometric parameters (e.g. tunnel diameter, distance from reception shaft, soil cover etc) as features. This is because many of the training datasets relate to a single construction project and it is a common assumption that TBM and geometric parameters remain constant during a given project and so should not be included in the ML. While this provides good predictability on a case-by-case basis (where one might wish to forecast the performance of the TBM for the current project based on the data gathered thus far), it limits the applicability of these trained ML models to other projects. This is particularly important in the case of ML models as they typically demonstrate a poor ability to extrapolate beyond their calibration space (Ahmed et al. 2010).

The most common ML technique adopted for the prediction of TBM performance is a multi-layer feedforward ANN with back propagation. The main difference between the ANN models adopted in the literature is the optimal ANN architecture that was ultimately selected. Even though similar input parameters and datasets have been employed across various studies, the range of architectures that have been adopted is quite wide. For example, Armaghani et al. (2017) and Koopialipoor et al. (2019c) adopted a 7-11-1 (n_f-n_{h1}-n_o) and 5-8-32-8-1 architecture respectively for the prediction of the same dataset (the Pahang-Selangor raw water transfer tunnel (PSWRT)). It is noteworthy that the use of several hidden layers and neurons increases the likelihood of encountering overfitting. Hecht-Nielsen (1987) proved that any continuous function can be represented by a neural network using a single layer with $n_{h1} = 2n_f + 1$ nodes, albeit using significantly more complex activation functions than the conventional sigmoidal functions commonly adopted in the literature. This corresponds to an architecture of 7-15-1 and 5-11-1 respectively for these studies.

Other popular ML methods adopted in the literature include fuzzy logic, due to its ability to incorporate empirical evidence/experience and, recently, more flexible and non-linear ML algorithms such as CARTs and RFs. To develop improved methods for the determination of the optimum architecture and the avoidance of local minima, hybrid methods have also been explored by fusing ML models with optimisation algorithms such as ICA (e.g. Naghadehi et al. 2019), PSO (e.g. Armaghani et al. 2018), DE (e.g. Fattahi and Babanouri 2017) and FCM (e.g. Fattahi 2016).

Tunnelling-induced settlement prediction

Table 3 presents an overview of ML models adopted for the prediction of tunnelling-induced soil settlements, *s*, as well as tunnel convergence, *C*. Given the complex nature of tunnelling-induced settlements, the number of features used in these models are notably greater. Furthermore, these features comprise a mix of soil, tunnel geometry and TBM operational parameters. For the studies considered in this review, ANNs appear to have been the ML model of choice pre-2012, although they continue to appear in more recent literature. It is again apparent that a wide range of architectures have been explored from the 47-47-47-47-2 architecture adopted by Kim et al. (2001) to the more compact 3-4-1 architecture proposed by Hasanipanah et al. (2016) and Moghaddasi and Noorian-Bidgoli (2018).

While the integration of fuzzy systems has also been used to predict tunnel-induced settlements, the use of SVMs became popular post-2012, quickly followed by more complex and non-parametric methods such as CARTs and RFs. The prominence of these methods for settlement prediction is perhaps explained by the increased complexity of the input-output mapping process for tunnelling-induced settlements. The datasets used for predicting tunnel-induced settlements are also largely based on a single project rather than multiple projects, with the size of the dataset varying considerably (from 6 to 7650 datapoints).

Geological forecasting

Efforts to predict ahead of the TBM involve identification of geological conditions as well as the size and location of potential obstacles (Schaeffer & Mooney 2016). In these cases, it is desirable to identify changes in soil conditions as shown in Fig. 7. To obtain actionable information during tunnelling, soil conditions must be forecasted sufficiently far in advance of the TBM (typically tens of metres). This is complicated by a deterioration in the accuracy of forecasting techniques with an increase in the forecast horizons.

One approach is to consider the TBM itself as an exploratory tool. A popular implementation of this approach is to first use statistical interpolation techniques (such as kriging) to develop an initial estimate of the ground conditions at the TBM face using available borehole information as shown in Fig. 8 (Gangrade and Mooney 2019, Grasmick et al. 2020). These predictions are subsequently updated using TBM driving data to obtain a more reliable estimate of the ground immediately ahead of the TBM. This methodology has been adopted by Yamamoto et al. (2003) and Sun et al. (2018b). In particular, Sun et al. (2018b) achieved a prediction accuracy of R^2 = 0.8 using RFs.

Alternatively, ML can also be used to provide a direct mapping between TBM performance parameters and ground conditions. This approach can be considered the inverse of the techniques reviewed for TBM performance prediction. Liu et al. (2019) used SVR combined with a stacked single-target technique to identify multiple targets from a common dataset, such as UCS, BI, DPW and α; this allowed correlation between targets to be incorporated into the prediction model. The driving data used to identify the target variables included

RPM, PR, JF, T and cutterhead power (CP) where a prediction accuracy of R^2 between 0.63 and 0.83 was achieved. It is notable that R^2 = 0.83 corresponded to the UCS prediction indicating its strong correlation with TBM performance in rock. Zhang et al. (2019c) used SVM, RF and *k*-nearest neighbours (kNNs) to map RPM, T, JF and AR to rock mass type. Zhao et al. (2019a) compared the performance of eight ML models to predict geological type using feature augmentation to improve performance; a traditional ANN was found to provide the best performance. Jung et al. (2019) also used an ANN to predict the ground type from PR, JF and T with an accuracy of $R^2 > 0.9$. The PR parameter was found to be the most influential for predicting ground type, particularly across different sites. Liu et al. (2020) used a hybrid algorithm combining traditional ANNs with simulated annealing to predict rock parameters UCS, BI, DPW and α from RPM, T, JF, PR (R^2 between 0.66 and 0.85). Erharter et al. (2019, 2020) used ensemble LSTM networks to classify TBM data into rock behaviour types according to four geological 'indicators'. Yu and Mooney (2020) employed multinomial logistic regression to characterize the fractional representation of four encountered soil types (sand, clay, silt, till deposits) by an earth pressure balance TBM. The regression model was trained using RPM, AR, chamber pressure, excavated soil mass, thrust force, and 83 boring logs along the alignment.

Instead of using TBM operational parameters, Zhuang et al. (2018) used convergence displacements in rock to infer E_s and v_s through inverse analysis. This involved the use of SVR which is optimised using multi-strategy artificial fish swarm algorithm (MAFSA). The MAFSA approach is an ensemble algorithm comprising differential evolution, particle swarm optimization, adaptive step size and phased vision strategy based on artificial fish swarm algorithm (AFSA) to enhance the global search capability and improve convergence speed and optimization accuracy.

While numerous geophysical methods have been explored for forecasting geological conditions ahead of the TBM face (e.g. electromagnetic methods, electrical methods, seismic reflection methods, infrared detection methods), very few studies have explored the integration of machine learning algorithms to improve geophysical predictions. Both Alimoradi et al. (2008) and Von and Ismail (2017) used an ANN to identify rock characteristics using ground parameters obtained using Tunnel Seismic Prediction (TSP) technology. Although Von and Ismail (2017) reported a prediction accuracy of $R^2 = 0.85$, they noted that the small datasets at the beginning of a project lead to less reliable predictions.

Wei et al. (2018) documented one of the most comprehensive applications of ML to a new 'Tunnel Look-ahead Imaging Prediction System' (TULIPS). The TULIPS imaging approach comprises three sets of GPR antennae (low frequency for long-range inspection and two high frequencies to identify small objects) and seismic imaging. The pipeline of their event detection and tracking method is outlined in Fig. 9. An experimental campaign showed that buried obstacles can be successfully identified and tracked using this methodology. Those authors also recommended the development and application of more robust ML models to larger datasets including expert interpretations and ground prediction, TBM and geological exploration data.

Cutterhead design optimisation

The final research area covered by this literature review is the optimisation of the cutterhead design (see Fig. 10) which appear to have focused exclusively on tunnelling in rock. Literature in this area can be further categorised as an optimisation of (a) cutter disc layout and (b) cutter disc geometry. For the cutter layout, the optimisation process has been typically undertaken to (a) minimise eccentric forces (and therefore moments) of the whole system by maximising cutterhead symmetry, (b) maximise excavation efficiency by ensuring adjacent cutters score the tunnel face successively and (c) minimise excavation-induced stress on the cutterhead (e.g. Ji et al. 2016). Other common constraints include (a) cutter discs must remain contained within the cutterhead, (b) cutter discs must not overlap, (c) cutter discs must not interfere with manholes, ‘buckets’ or joints in the cutterhead, and (e) cutter disc positions should be easily accessible for maintenance (Rostami and Chang 2017).

An example optimisation documented by Huo et al. (2010, 2011) using a multi-objective GA and co-evolutionary GA is presented in Fig. 11. Those authors used three ‘base’ designs as the starting point for the optimisation to reflect current designs used in practice: a multi-spiral (Fig. 11(a)), ‘dynamic star’ (Fig. 11(b)) and stochastic pattern (Fig. 11(c)). Another possible reason for the use of these base designs is that the results of the optimisation process were reported to be highly dependent on the initial cutter pattern. This was also discovered by Qi et al. (2013) using grey rational analysis. Grey rational analysis (GRA) is a form of grey system theory (proposed by Deng (1982)) and solves multiple attribute decision making by combining the entire range of attribute values being considered for each alternative decision into a single value (Kuo et al. 2008). Those authors also found that the polar angle played a more important role on the cutter layout rather than radial distance from the centre point of the cutterhead. Although not discussed in those studies, these findings suggest the occurrence of local optima in these optimisation problems. While multiple alternative optimisation algorithms exist (e.g. grid search, random search), Bayesian optimisation (Brochu et al. 2010) seems suitable for this problem given its robustness to local optima. This is due to its exploration versus exploitation strategy: exploitation initially steers the search process into the direction of the local optima but exploration allows the algorithm to ‘escape’ from the local optimum towards finding an improved global optimum.

On the geometric design of individual cutters, Xia et al. (2012) and Xia et al. (2015) used GA and multi-objective and multi-geologic conditions optimisation (MMCO) to optimise the (a) cutter cutting edge angle, (b) cutting edge width, (c) transition arc radius and (d) caulking ring width between bearings. The optimisation process sought to minimise the cutter bearing load.

SUMMARY

This review has identified an increasing trend in the use of ML in the tunnelling space with a significant increase in 2019. It is likely that this trend will persist as advancements in ML continue to be translated into practical domains for routine use and more tunnelling data is shared with the academic community. ANNs have experienced sustained popularity in this area. This is not surprising as ANNs are one of the oldest ML paradigms and are able to capture complex non-linear relationships and generalise within the trained parameter space. The second most popular technique is SVR/SVM. The non-parametric nature of these models means that model complexity remains relatively unaffected by an increase in the number of features and are therefore particularly suited to high-dimensional datasets. This may go some way to explaining their popularity, particularly for settlement predictions due to the larger number of influencing factors. These techniques have been typically coupled with optimisation algorithms to overcome the slow tuning process of the kernel hyperparameters.

The use of fuzzy-based methods such as ANFIS and FL in this area stems from their ability to incorporate human experience and their ability to deal with imprecise and noisy data typical of construction monitoring projects. These methods have not experienced the same growth, which is probably due to the increase in 'big data' in tunnelling that lends itself to training more robust algorithms. It is also apparent that there has been a significant and recent increase in the use of alternative ML algorithms such as GEP and RF. These models provide a higher level of performance for the sake of model interpretability and can therefore capture highly non-linear trends. The use of probabilistic ML techniques, such as Bayesian networks and Gaussian process regression, for underground construction applications have become more popular in recent years e.g. Zhang et al. (2016), Wang et al. (2017), Chen et al. (2019d), Zhu (2019). These methods are well-conditioned for dealing with noisy and incomplete data typical of a construction site and perform predictions within a principled framework; in light of this, they represent the most promising techniques for future applications of ML to inform tunnelling operations.

CONCLUSIONS AND FUTURE PERSPECTIVES

This paper has presented a comprehensive review of the literature exploring the use of machine learning to inform tunnelling operations. While machine learning has been used to inform a wide range of tunnelling applications, this review has identified four main areas of research, namely TBM performance prediction, tunnelling-induced settlement prediction, geological forecasting and cutterhead design optimisation. Many studies have reported the successful application of machine learning techniques in tunnelling activities with high levels of accuracy. The most popular methods adopted in the literature include artificial neural networks, support vector machines/regression and fuzzy-based methods. A clear trend is evident in the use of ML in tunnelling and this trend is likely to persist as the volume of data produced by modern TBMs continues to grow and the use of machine learning becomes more commonplace. In most instances, investigators have used empiricism (from previous literature) as the basis for the selection of model inputs where the number of features varies considerably across the literature. As the number of parameters captured by modern tunnel boring machines grows, identification of the most appropriate features for training ML models using robust techniques should be central to future research.

Despite its recent advances, machine learning in tunnelling remains a young field with many underexplored research opportunities. Some of these opportunities can be observed by contrasting the methods reviewed in this study with those adopted in other disciplines such as aerospace, healthcare, robotics, and automated vehicles (Mooney et al. 2020). In particular, there is a real need for continued application of machine learning methods employing more principled, probabilistic frameworks such as Bayesian networks and Gaussian process regression. The problems covered by this review appear well-suited to probabilistic frameworks given the uncertain nature of tunnelling operations and the prevalence of noisy data. This relieves engineers of onerous data pre-processing to denoise large training datasets. Furthermore, probabilistic frameworks provide a robust treatment of overfitting meaning large datasets are not necessarily a prerequisite and deployment of these techniques on a site-specific basis is feasible.

Another important finding of this review is that most of the studies reviewed here have been developed and validated against a single case history. Validation of these algorithms across a broader parameter space are warranted for the industry to gain confidence in these approaches. In addition, the high-risk nature of mistakes in the tunnelling industry means model interpretability is essential for take-up in practice to gain insight into the features driving predictions. It appears essential for the tunnelling industry to begin to consider how best to leverage these recent advances in machine learning to inform tunnelling operations.

REFERENCES

Acaroglu, O., Ozdemir, L. and Asbury, B., 2008. A fuzzy logic model to predict specific energy requirement for TBM performance prediction. *Tunnelling and Underground Space Technology*, *23*(5), pp.600-608.

Adoko, A.C., Jiao, Y.Y., Wu, L., Wang, H. and Wang, Z.H., 2013. Predicting tunnel convergence using multivariate adaptive regression spline and artificial neural network. *Tunnelling and Underground Space Technology*, *38*, pp.368-376.

Adoko, A.C., Gokceoglu, C. and Yagiz, S., 2017. Bayesian prediction of TBM penetration rate in rock mass. *Engineering Geology*, *226*, pp.245-256.

Adoko, A.C. and Yagiz, S., 2019. Fuzzy Inference System-Based for TBM Field Penetration Index Estimation in Rock Mass. *Geotechnical and Geological Engineering*, *37*(3), pp.1533-1553.

Ahangari, K., Moeinossadat, S.R. and Behnia, D., 2015. Estimation of tunnelling-induced settlement by modern intelligent methods. *Soils and Foundations*, *55*(4), pp.737-748.

Ahmed, N.K., Atiya, A.F., Gayar, N.E. and El-Shishiny, H., 2010. An empirical comparison of machine learning models for time series forecasting. *Econometric Reviews*, *29*(5-6), pp.594-621.

Alimoradi, A., Moradzadeh, A., Naderi, R., Salehi, M.Z. and Etemadi, A., 2008. Prediction of geological hazardous zones in front of a tunnel face using TSP-203 and artificial neural networks. *Tunnelling and Underground Space Technology*, *23*(6), pp.711-717.

Armaghani, D.J., Mohamad, E.T., Narayanasamy, M.S., Narita, N. and Yagiz, S., 2017. Development of hybrid intelligent models for predicting TBM penetration rate in hard rock condition. *Tunnelling and Underground Space Technology*, *63*, pp.29-43.

Armaghani, D.J., Faradonbeh, R.S., Momeni, E., Fahimifar, A. and Tahir, M.M., 2018. Performance prediction of tunnel boring machine through developing a gene expression programming equation. *Engineering with Computers*, *34*(1), pp.129-141.

Armaghani, D.J., Koopialipoor, M., Marto, A. and Yagiz, S., 2019. Application of several optimization techniques for estimating TBM advance rate in granitic rocks. *Journal of Rock Mechanics and Geotechnical Engineering*, *11*(4), pp.779-789.

Atashpaz-Gargari E and Lucas C (2007) Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition. In *2007 IEEE congress on evolutionary computation*, IEEE, pp. 4661-4667.

Barla, M., Camusso, M. and Aiassa, S. (2006). Analysis of jacking forces during microtunnelling in limestone. *Tunnelling and Underground Space Technology*, *21*(6):668-683.

Behnia, D. and Shahriar, K., 2015, November. Prediction of Tunnelling-induced Settlement Using Gene Expression Programming. In *49th US Rock Mechanics/Geomechanics Symposium*. American Rock Mechanics Association.

Benardos, A., 2008. Artificial intelligence in underground development: a study of TBM performance. *Underground Spaces: Design, Engineering and Environmental Aspects*, *102*, p.121.

Benardos, A.G. and Kaliampakos, D.C., 2004. Modelling TBM performance with artificial neural networks. *Tunnelling and Underground Space Technology*, *19*(6), pp.597-605.

Bouayad, D. and Emeriault, F., 2014, May. Application of the hybrid ACP/ANFIS method for the prediction of surface settlement induced by an earth pressure tunnel boring machine with consideration of the encountered geology. In *NUMGE 2014 8th European Conference on Numerical Methods in Geotechnical Engineering* (pp. 333-338). CRC Press.

Bouayad, D. and Emeriault, F., 2017. Modeling the relationship between ground surface settlements induced by shield tunneling and the operational and geological parameters based on the hybrid PCA/ANFIS method. *Tunnelling and Underground Space Technology*, *68*, pp.142-152.

Bouayad, D., Emeriault, F. and Maza, M., 2015. Assessment of ground surface displacements induced by an earth pressure balance shield tunneling using partial least squares regression. *Environmental earth sciences*, *73*(11), pp.7603-7616.

Boubou, R., Emeriault, F. and Kastner, R., 2010. Artificial neural network application for the prediction of ground surface movements induced by shield tunnelling. *Canadian geotechnical journal*, *47*(11), pp.1214-1233.

Breiman, L., 2001. Random forests. *Machine learning*, *45*(1), pp.5-32.

Brochu, E., Cora, V.M. and De Freitas, N., 2010. A tutorial on Bayesian optimization of expensive cost functions, with application to active user modeling and hierarchical reinforcement learning. *arXiv preprint arXiv:1012.2599*.

Cachim, P. and Bezuijen, A., 2019. Modelling the Torque with Artificial Neural Networks on a Tunnel Boring Machine. *KSCE Journal of Civil Engineering*, *23*(10), pp.4529-4537.

Cao, B.T., Freitag, S. and Meschke, G., 2016. A hybrid RNN-GPOD surrogate model for real-time settlement predictions in mechanised tunnelling. *Advanced Modeling and Simulation in Engineering Sciences*, *3*(1), p.5.

Chen, R.P., Zhang, P., Kang, X., Zhong, Z.Q., Liu, Y. and Wu, H.N., 2019a. Prediction of maximum surface settlement caused by earth pressure balance (EPB) shield tunneling with ANN methods. *Soils and Foundations*, *59*(2), pp.284-295.

Chen, R., Zhang, P., Wu, H., Wang, Z. and Zhong, Z., 2019b. Prediction of shield tunneling-induced ground settlement using machine learning techniques. *Frontiers of Structural and Civil Engineering*, *13*(6), pp.1363-1378.

Chen, X., Li, X. and Zhu, H., 2019c. Condition evaluation of urban metro shield tunnels in Shanghai through multiple indicators multiple causes model combined with multiple regression method. *Tunnelling and Underground Space Technology*, *85*, pp.170-181.

Chen, X., Zhu, H., Li, X., Lin, X. and Wang, X., 2019d. Probabilistic performance prediction of shield tunnels in operation through data mining. *Sustainable Cities and Society*, *44*, pp.819-829.

Choo, C.S. and Ong, D.E.L. (2015). Evaluation of pipe-jacking forces based on direct shear testing of reconstituted tunneling rock spoils. *Journal of Geotechnical and Geoenvironmental Engineering*, *141*(10):04015044.

Darabi, A., Ahangari, K., Noorzad, A. and Arab, A., 2012. Subsidence estimation utilizing various approaches–A case study: Tehran No. 3 subway line. *Tunnelling and Underground Space Technology*, *31*, pp.117-127.

Deng, J. (1982). Control problems of grey systems. *Systems and Control Letters*, 1, 288–294.

Dindarloo, S.R. and Siami-Irdemoosa, E., 2015. Maximum surface settlement based classification of shallow tunnels in soft ground. *Tunnelling and Underground Space Technology*, *49*, pp.320-327.

Ding, H., Liu, S., Cai, S. and Xia, Y., 2019, September. Big Data Analysis of Structural Defects and Traffic Accidents in Existing Highway Tunnels. In *International Conference on Inforatmion technology in Geo-Engineering* (pp. 189-195). Springer, Cham.

J. C. Dunn (1973) A Fuzzy Relative of the ISODATA Process and Its Use in Detecting Compact Well-Separated Clusters, , 3:3, 32-57, DOI: 10.1080/01969727308546046

Erharter, G.H., Marcher, T. and Reinhold, C., 2019. Application of artificial neural networks for Underground construction–Chances and challenges–Insights from the BBT exploratory tunnel Ahrental Pfons. *Geomechanics and Tunnelling*, *12*(5), pp.472-477.

Erharter, G.H., Marcher, T. and Reinhold, C., 2019, September. Artificial Neural Network Based Online Rockmass Behavior Classification of TBM Data. In *International Conference on Inforatmion technology in Geo-Engineering* (pp. 178-188). Springer, Cham.

Fattahi, H., 2016. Adaptive neuro fuzzy inference system based on fuzzy c–means clustering algorithm, a technique for estimation of TBM penetration rate. *Iran University of Science & Technology*, *6*(2), pp.159-171.

Fattahi, H. and Babanouri, N., 2017. Applying optimized support vector regression models for prediction of tunnel boring machine performance. *Geotechnical and Geological Engineering*, *35*(5), pp.2205-2217.

Fattahi, H. and Babanouri, N., 2018. RES-based model in evaluation of surface settlement caused by EPB shield tunneling. *Indian Geotechnical Journal*, *48*(4), pp.746-752.

Fattahi, H. and Bayatzadehfard, Z., 2019. Forecasting Surface Settlement Caused by Shield Tunneling Using ANN-BBO Model and ANFIS Based on Clustering Methods. *Journal of Engineering Geology*, *12*(5), pp.55-84.

Franza, A., Benardos, P.G. and Marshall, A.M., 2018. Use of artificial neural networks to analyse tunnelling-induced ground movements obtained from geotechnical centrifuge testing.

Gangrade, R. and Mooney, M., 2019. Incorporating Spatial Uncertainty into Site Investigations for Tunneling Applications. *Journal of Performance of Constructed Facilities*.

Gao, X., Shi, M., Song, X., Zhang, C. and Zhang, H., 2019. Recurrent neural networks for real-time prediction of TBM operating parameters. *Automation in Construction*, *98*, pp.225-235.

Ge, Y., Wang, J. and Li, K., 2013. Prediction of hard rock TBM penetration rate using least square support vector machine. *IFAC Proceedings Volumes*, *46*(13), pp.347-352.

Ghasemi, E., Yagiz, S. and Ataei, M., 2014. Predicting penetration rate of hard rock tunnel boring machine using fuzzy logic. *Bulletin of Engineering Geology and the Environment*, *73*(1), pp.23-35.

Gholamnejad, J. and Tayarani, N., 2010. Application of artificial neural networks to the prediction of tunnel boring machine penetration rate. *Mining Science and Technology (China)*, *20*(5), pp.727-733.

Goh, A.T. and Hefney, A.M., 2010. Reliability assessment of EPB tunnel-related settlement. *Geomech Eng*, *2*(1), pp.57-69.

Goh, A.T.C., Zhang, W., Zhang, Y., Xiao, Y. and Xiang, Y., 2018. Determination of earth pressure balance tunnel-related maximum surface settlement: a multivariate adaptive regression splines approach. *Bulletin of Engineering Geology and the Environment*, *77*(2), pp.489-500.

Grasmick, J.G., Mooney, M.A., Trainor-Guitton, W.J. and Walton, G., 2020. Global versus Local Simulation of Geotechnical Parameters for Tunneling Projects. *Journal of Geotechnical and Geoenvironmental Engineering*, *146*(7), p.04020048.

Grima, M.A., Bruines, P.A. and Verhoef, P.N.W., 2000. Modeling tunnel boring machine performance by neuro-fuzzy methods. *Tunnelling and underground space technology*, *15*(3), pp.259-269.

Guo, J., Ding, L., Luo, H., Zhou, C. and Ma, L., 2014. Wavelet prediction method for ground deformation induced by tunneling. *Tunnelling and underground space technology*, *41*, pp.137-151.

Hajihassani, M., Abdullah, S.S., Asteris, P.G. and Armaghani, D.J., 2019. A gene expression programming model for predicting tunnel convergence. *Applied Sciences*, *9*(21), p.4650.

Hajihassani, M., Kalatehjari, R., Marto, A., Mohamad, H. and Khosrotash, M., 2020. 3D prediction of tunneling-induced ground movements based on a hybrid ANN and empirical methods. *Engineering with Computers*, *36*(1), pp.251-269.

Hasanipanah, M., Noorian-Bidgoli, M., Armaghani, D.J. and Khamesi, H., 2016. Feasibility of PSO-ANN model for predicting surface settlement caused by tunneling. *Engineering with Computers*, *32*(4), pp.705-715.

Hayashi, H., Miyanaka, M., Gomi, H., Tatsumi, J., Kawabe, N. and Shinji, M., 2019, September. Prediction of Forward Tunnel Face Score of Rock Mass Classification for Stability by Applying Machine Learning to Drilling Data. In *International Conference on Inforatmion technology in Geo-Engineering* (pp. 268-278). Springer, Cham.

Holland JH (1992) *Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence*. MIT press.

Hu, M., Li, W., Yan, K., Ji, Z. and Hu, H., 2019. Modern machine learning techniques for univariate tunnel settlement forecasting: A comparative study. *Mathematical Problems in Engineering*, *2019*.

Huang, G.B., Zhu, Q.Y. and Siew, C.K., 2004, July. Extreme learning machine: a new learning scheme of feedforward neural networks. In *2004 IEEE international joint conference on neural networks (IEEE Cat. No. 04CH37541)* (Vol. 2, pp. 985-990). IEEE.

Huang, G.B., Zhu, Q.Y. and Siew, C.K., 2006. Extreme learning machine: theory and applications. *Neurocomputing*, *70*(1-3), pp.489-501.

Huang, G.B., Zhou, H., Ding, X. and Zhang, R., 2011. Extreme learning machine for regression and multiclass classification. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, *42*(2), pp.513-529.

Huo, J., Sun, W., Chen, J., Su, P. and Deng, L., 2010. Optimal disc cutters plane layout design of the full-face rock tunnel boring machine (tbm) based on a multi-objective genetic algorithm. *Journal of Mechanical Science and Technology*, *24*(2), pp.521-528.

Huo, J., Sun, W., Chen, J. and Zhang, X., 2011. Disc cutters plane layout design of the full-face rock tunnel boring machine (TBM) based on different layout patterns. *Computers & industrial engineering*, *61*(4), pp.1209-1225.

Jang JSR, Suni CT and Mizutani E (1997*) Neuro-fuzzy and soft computing. A computational approach to learning and machine intelligence*. Prentice Hall, New York, USA.

Ji, Z., Guo, B., Xia, Y. and Tang, L., 2016, August. TBM cutterhead structure optimization based on sensitivity analysis. In *2016 12th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications (MESA)* (pp. 1-8). IEEE.

Jung, J.H., Chung, H., Kwon, Y.S. and Lee, I.M., 2019. An ANN to predict ground condition ahead of tunnel face using TBM operational data. *KSCE Journal of Civil Engineering*, *23*(7), pp.3200-3206.

Kennedy J and Eberhart R (1995) Particle swarm optimization. In *Proceedings of ICNN95-International Conference on Neural Networks*. IEEE, vol. 4, pp. 1942-1948.

Khamesi, H., Torabi, S.R., Mirzaei-Nasirabad, H. and Ghadiri, Z., 2015. Improving the performance of intelligent back analysis for tunneling using optimized fuzzy systems: case study of the Karaj Subway Line 2 in Iran. *Journal of Computing in Civil Engineering*, *29*(6), p.05014010.

Khatami, S.A., Mirhabibi, A., Khosravi, A. and Nahavandi, S., 2013, October. Artificial neural network analysis of twin tunnelling-induced ground settlements. In *2013 IEEE International Conference on Systems, Man, and Cybernetics* (pp. 2492-2497). IEEE.

Khetwal, S., Pei, S. and Gutierrez, M., 2019, September. A Data-Driven Approach for Direct Assessment and Analysis of Traffic Tunnel Resilience. In *International Conference on Inforatmion technology in Geo-Engineering* (pp. 168-177). Springer, Cham.

Kim, C.Y., Bae, G.J., Hong, S.W., Park, C.H., Moon, H.K. and Shin, H.S., 2001. Neural network based prediction of ground surface settlements due to tunnelling. *Computers and Geotechnics*, *28*(6-7), pp.517-547.

Kohestani, V.R. and Bazarganlari-Lari, M.R. and Asgari-marnani, J. 2017. Prediction of maximum surface settlement caused by earth pressure balance shield tunneling using random forest. *Journal of AI and Data Mining*, *5*(1), pp.127-135.

Kongsomboon, T., Suwansawat, S. and Sunthornjak, S., Predicting Ground Deformations Induced by Shield Tunneling Using Correlation Coefficient–ANN Technique. In *Proceedings of the World Tunnel Congress and 36th General Assembly*, Vancouver, Canada. Tunnelling association of Canada.

Koopialipoor, M., Nikouei, S.S., Marto, A., Fahimifar, A., Armaghani, D.J. and Mohamad, E.T., 2019a. Predicting tunnel boring machine performance through a new model based on the group method of data handling. *Bulletin of Engineering Geology and the Environment*, *78*(5), pp.3799-3813.

Koopialipoor, M., Tootoonchi, H., Armaghani, D.J., Mohamad, E.T. and Hedayat, A., 2019b. Application of deep neural networks in predicting the penetration rate of tunnel boring machines. *Bulletin of Engineering Geology and the Environment*, *78*(8), pp.6347-6360.

Koopialipoor, M., Fahimifar, A., Ghaleini, E.N., Momenzadeh, M. and Armaghani, D.J., 2020. Development of a new hybrid ANN for solving a geotechnical problem related to tunnel boring machine performance. *Engineering with Computers*, *36*(1), pp.345-357.

Koukoutas, S.P. and Sofianos, A.I., 2015. Settlements due to single and twin tube urban EPB shield tunnelling. *Geotechnical and Geological Engineering*, *33*(3), pp.487-510.

Kuo, Y., Yang, T. and Huang, G.W., 2008. The use of grey relational analysis in solving multiple attribute decision-making problems. *Computers & industrial engineering*, *55*(1), pp.80-93.

Lai, J., Qiu, J., Feng, Z., Chen, J. and Fan, H., 2016. Prediction of soil deformation in tunnelling using artificial neural networks. *Computational Intelligence and Neuroscience*, *2016*.

Li, S.J., Zhao, H.B. and Ru, Z.L., 2012. Deformation prediction of tunnel surrounding rock mass using CPSO-SVM model. *Journal of central south university*, *19*(11), pp.3311-3319.

Li, X., Lin, X., Zhu, H., Wang, X. and Liu, Z., 2017. Condition assessment of shield tunnel using a new indicator: The tunnel serviceability index. *Tunnelling and Underground Space Technology*, *67*, pp.98-106.

Ling, F., Jingcheng, W., Yang, G., Chuang, L. and Langwen, Z., 2013, May. Prediction of TBM penetration rate based on the model of PLS-FNN. In *2013 25th Chinese Control and Decision Conference (CCDC)* (pp. 1295-1299). IEEE.

Liu, Y. and Hou, S., 2019, September. Rockburst Prediction Based on Particle Swarm Optimization and Machine Learning Algorithm. In *International Conference on Inforatmion technology in Geo-Engineering* (pp. 292-303). Springer, Cham.

Liu, K. and Liu, B., 2019. Intelligent information-based construction in tunnel engineering based on the GA and CCGPR coupled algorithm. *Tunnelling and Underground Space Technology*, *88*, pp.113-128.

Liu, B., Wang, R., Guan, Z., Li, J., Xu, Z., Guo, X. and Wang, Y., 2019. Improved support vector regression models for predicting rock mass parameters using tunnel boring machine driving data. *Tunnelling and Underground Space Technology*, *91*, p.102958.

Liu, B., Wang, R., Zhao, G., Guo, X., Wang, Y., Li, J. and Wang, S., 2020. Prediction of rock mass parameters in the TBM tunnel based on BP neural network integrated simulated annealing algorithm. *Tunnelling and Underground Space Technology*, *95*, p.103103.

Mahdevari, S. and Torabi, S.R., 2012. Prediction of tunnel convergence using artificial neural networks. *Tunnelling and Underground Space Technology*, *28*, pp.218-228.

Mahdevari, S., Torabi, S.R. and Monjezi, M., 2012. Application of artificial intelligence algorithms in predicting tunnel convergence to avoid TBM jamming phenomenon. *International Journal of Rock Mechanics and Mining Sciences*, *55*, pp.33-44.

Mahdevari, S., Haghighat, H.S. and Torabi, S.R., 2013. A dynamically approach based on SVM algorithm for prediction of tunnel convergence during excavation. *Tunnelling and underground space technology*, *38*, pp.59-68.

Mahdevari, S., Shahriar, K., Yagiz, S. and Shirazi, M.A., 2014. A support vector regression model for predicting tunnel boring machine penetration rates. *International Journal of Rock Mechanics and Mining Sciences*, *72*, pp.214-229.

Maher, J., 2013. A Machine Learning Approach to Predicting and Maximizing Penetration Rates in Earth Pressure Balance Tunnel Boring Machines. Report. Colorado School of Mines.

Martins, F.F. and Miranda, T.F., 2013. Prediction of hard rock TBM penetration rate based on Data Mining techniques. In *18th International Conference on Soil Mechanics and Geotechnical Engineering* (Vol. 2, pp. 1751-1754). Presses des Ponts.

Marto, A., Hajihassani, M., Kalatehjari, R., Namazi, E. and Sohaei, H., 2012. Simulation of longitudinal surface settlement due to tunnelling using artificial neural network. *International Review on Modelling and Simulations*, *5*(2), pp.1024-1031.

Mehrnahad, H. and Zekrabad, M.K., 2018. Prediction of Tunnelling-Induced Surface Settlement with Artificial Neural Networks, Case Study: Mashhad Subway Tunnel. *Journal of Engineering Geology*, *12*, p.135.

Mikaeil, R., Naghadehi, M.Z. and Sereshki, F., 2009. Multifactorial fuzzy approach to the penetrability classification of TBM in hard rock conditions. *Tunnelling and Underground Space Technology*, *24*(5), pp.500-505.

Mikaeil, R., Naghadehi, M.Z. and Ghadernejad, S., 2018. An extended multifactorial fuzzy prediction of hard rock TBM penetrability. *Geotechnical and Geological Engineering*, *36*(3), pp.1779-1804.

Minh, V.T., Katushin, D., Antonov, M. and Veinthal, R., 2017. Regression models and fuzzy logic prediction of TBM penetration rate. *Open Engineering*, *7*(1), pp.60-68.

Mobarra, Y., Hajian, A. and Rezazadeh Anbarani, M., 2013. Application of Artificial Neural Networks to the Prediction of TBM Penetration Rate in TBM-driven Golab Water Transfer Tunnel. In *International Conference on Civil Engineering Architecture & Urban Sustainable Development* (Vol. 27).

Moeinossadat, S.R. and Ahangari, K., 2019. Estimating maximum surface settlement due to EPBM tunneling by Numerical-Intelligent approach–A case study: Tehran subway line 7. *Transportation Geotechnics*, *18*, pp.92-102.

Moeinossadat, S.R., Ahangari, K. and Shahriar, K., 2018a. Control of ground settlements caused by EPBS tunneling using an intelligent predictive model. *Indian Geotechnical Journal*, *48*(3), pp.420-429.

Moeinossadat, S.R., Ahangari, K. and Shahriar, K., 2018b. Modeling maximum surface settlement due to EPBM tunneling by various soft computing techniques. *Innovative Infrastructure Solutions*, *3*(1), p.10.

Moghaddasi, M.R. and Noorian-Bidgoli, M., 2018. ICA-ANN, ANN and multiple regression models for prediction of surface settlement caused by tunneling. *Tunnelling and Underground Space Technology*, *79*, pp.197-209.

Mohammadi, H., Farsangi, M.E., Rahmannejad, R. and Poor, H.N., 2007. TBM Advance Rate Prediction: An Artificial Neural Network Approach. In *Third National Congress in Civil Engineering*, Tabriz, Iran.

Mohammadi, S.D., Naseri, F. and Alipoor, S., 2015. Development of artificial neural networks and multiple regression models for the NATM tunnelling-induced settlement in Niayesh subway tunnel, Tehran. *Bulletin of Engineering Geology and the Environment*, *74*(3), pp.827-843.

Mokhtari, S. and Mooney, M.A., 2019. Feasibility study of EPB shield automation using deep learning. In *Tunnels and Underground Cities. Engineering and Innovation Meet Archaeology, Architecture and Art* (pp. 2691-2699). CRC Press.

Mokhtari, S., Navidi, W., and Mooney, M.A. White Box Regression (Elastic Net) Modeling of Earth Pressure Balance Shield Machine Advance Rate, *Automation in Construction*, 2020, 115(103208).

Mokhtari, S. and Mooney, M.A., Predicting EPBM Advance Rate Performance using Support Vector Regression Modeling, Tunnelling and Underground Space Technology, 2020, in review.

Mooney MA, Yu H, Mokhtari S, Zhang X, and Zhou X. EPB TBM Performance Prediction on the University Link U230 Project. Proc. North American Tunneling Conference, Washington D.C., June 24-27, 2018.

Mooney, M., Yu, H., Gangrade, R. EPB Shield TBM Automation using the Autonomous Vehicle Framework, Proc. North American Tunneling, Nashville, TN, June 7-10, 2020.

Naeini, S.A. and Khalili, A., 2017. Settlement Prediction for Tehran Subway Line-3 via FLAC3D and ANFIS. *International Journal of Geotechnical and Geological Engineering*, *11*(7), pp.612-617.

Naghadehi, M.Z., Samaei, M. and Ranjbarnia, M., Superior Modeling of Hard Rock TBM Performance Using Novel Predictive Analytics Methodologies.

Neaupane, K.M. and Adhikari, N.R., 2006. Prediction of tunneling-induced ground movement with the multi-layer perceptron. *Tunnelling and underground space technology*, *21*(2), pp.151-159.

Ninic, J., Stascheit, J. and Meschke, G., 2011. Prediction of tunnelling induced settlements using simulation-based artificial neural networks. In *Proceedings of the Second International Conference on Soft Computing Technology in Civil, Structural and Environmental Engineering, page paper* (Vol. 26).

Ninić, J., Stascheit, J. and Meschke, G., 2013, September. Simulation-based steering for mechanized tunneling using an ANN-PSO-based meta-model. In *The Third International Conference on Soft Computing Technology in Civil, Structural and Environmental Engineering, Civil-Comp Press* (pp. 801-811).

O'Dwyer, K.G., McCabe, B.A., Sheil, B.B. and Hernon, D.P. (2018). Blackpool South Strategy project: analysis of pipe-jacking records. *Proceedings of Civil Engineering Research in Ireland (CERI 2018).*

O'Dwyer, K.G., McCabe, B.A., Sheil, B.B. (2019). Interpretation of pipe-jacking and lubrication records for drives in silty soil. *Underground Space.* DOI: 10.1016/j.undsp.2019.04.001

Ocak, I. and Seker, S.E., 2013. Calculation of surface settlements caused by EPBM tunneling using artificial neural network, SVM, and Gaussian processes. *Environmental earth sciences*, *70*(3), pp.1263-1276.

Oraee, K., Khorami, M.T. and Hosseini, N., 2012, February. Prediction of the penetration rate of TBM using adaptive neuro fuzzy inference system (ANFIS). In *Proceeding of SME annual meeting and exhibit, from the mine to the market, now it's global, Seattle, WA, USA* (pp. 297-302).

Phillips, B.M., Royston, R., Sheil, B.B. and Byrne, B.W. (2019) Instrumentation and monitoring of a concrete jacking pipe. In *International Conference on Smart Infrastructure and Construction (ICSIC)*, Cambridge.

Pourtaghi, A. and Lotfollahi-Yaghin, M.A., 2012. Wavenet ability assessment in comparison to ANN for predicting the maximum surface settlement caused by tunneling. *Tunnelling and Underground Space Technology*, *28*, pp.257-271.

Qi, G., Zhengying, W., Jun, D.U. and Yiping, T., 2013, September. A cutter layout optimization method for full-face rock tunnel boring machine. In *International Conference on Intelligent Robotics and Applications* (pp. 727-737). Springer, Berlin, Heidelberg.

Qiao, J., Liu, J., Guo, W. and Zhang, Y., 2010, November. Artificial neural network to predict the surface maximum settlement by shield tunneling. In *International Conference on Intelligent Robotics and Applications* (pp. 257-265). Springer, Berlin, Heidelberg.

Rafiai, H. and Moosavi, M., 2012. An approximate ANN-based solution for convergence of lined circular tunnels in elasto-plastic rock masses with anisotropic stresses. *Tunnelling and Underground Space Technology*, *27*(1), pp.52-59.

Ramezanshirazi, M., Sebastiani, D. and Miliziano, S., 2019, July. Artificial Intelligence to Predict Maximum Surface Settlements Induced by Mechanized Tunnelling. In *National Conference of the Researchers of Geotechnical Engineering* (pp. 490-499). Springer, Cham.

Rostami, J. and Chang, S.H., 2017. A closer look at the design of cutterheads for hard rock tunnel-boring machines. *Engineering*, *3*(6), pp.892-904.

Royston, R., Sheil, B.B. & Byrne, B.W. (2020) Monitoring the construction of a large-diameter caisson in sand. *Proceedings of the ICE - Geotechnical Engineering*. In press.

Saadallah, A., Egorov, A., Cao, B.T., Freitag, S., Morik, K. and Meschke, G., 2019. Active learning for accurate settlement prediction using numerical simulations in mechanized tunneling. *Procedia CIRP*, *81*, pp.1052-1058.

Salimi, A. and Esmaeili, M., 2013. Utilising of linear and non-linear prediction tools for evaluation of penetration rate of tunnel boring machine in hard rock condition. *International Journal of Mining and Mineral Engineering*, *4*(3), pp.249-264.

Salimi, A., Moormann, C., Singh, T. and Jain, P., 2015, November. TBM performance prediction in rock tunneling using various artificial intelligence algorithms. In *11th Iranian and 2nd regional tunnelling conference Iran*.

Salimi, A., Rostami, J., Moormann, C. and Delisio, A., 2016. Application of non-linear regression analysis and artificial intelligence algorithms for performance prediction of hard rock TBMs. *Tunnelling and Underground Space Technology*, *58*, pp.236-246.

Salimi, A., Rostami, J. and Moormann, C., 2019. Application of rock mass classification systems for performance estimation of rock TBMs using regression tree and artificial intelligence algorithms. *Tunnelling and Underground Space Technology*, *92*, p.103046.

Santos Jr, O.J. and Celestino, T.B., 2008. Artificial neural networks analysis of Sao Paulo subway tunnel settlement data. *Tunnelling and underground space technology*, *23*(5), pp.481-491.

Schaeffer, K. and Mooney, M.A. Examining the Influence of TBM-Ground Interaction on Electrical Resistivity Imaging ahead of the TBM, *Tunnelling & Underground Space Technology*, 2016, 58 (82-98),

Shao, C., Li, X. and Su, H., 2013, September. Performance prediction of hard rock TBM based on extreme learning machine. In *International Conference on Intelligent Robotics and Applications* (pp. 409-416). Springer, Berlin, Heidelberg.

Sheil, B.B., Curran, B.G. and McCabe, B.A. (2016). Experiences of utility microtunnelling in Irish limestone, mudstone and sandstone rock. *Tunnelling and Underground Space Technology*, *51*:326-337.

Sheil, B.B., Suryasentana, S. and Cheng, W.-C. (2020) An assessment of anomaly detection methods applied to microtunnelling. *Journal of Geotechnical and Geoenvironmental Engineering*. In press.

Shi, J., Ortigao, J.A.R. and Bai, J., 1998. Modular neural networks for predicting settlements during tunneling. *Journal of Geotechnical and Geoenvironmental Engineering*, *124*(5), pp.389-395.

Shi, M., Zhang, L., Sun, W. and Song, X., 2019a. A fuzzy c-means algorithm guided by attribute correlations and its application in the big data analysis of tunnel boring machine. *Knowledge-Based Systems*, *182*, p.104859.

Shi, S., Zhao, R., Li, S., Xie, X., Li, L., Zhou, Z. and Liu, H., 2019b. Intelligent prediction of surrounding rock deformation of shallow buried highway tunnel and its engineering application. *Tunnelling and Underground Space Technology*, *90*, pp.1-11.

Simoes, M.G. and Kim, T., 2006. Fuzzy modeling approaches for the prediction of machine utilization in hard rock tunnel boring machines. In *Conference record of the 2006 IEEE industry applications conference forty-first IAS annual meeting* (Vol. 2, pp. 947-954). IEEE.

Song, X., Shi, M., Wu, J. and Sun, W., 2019. A new fuzzy c-means clustering-based time series segmentation approach and its application on tunnel boring machine analysis. *Mechanical Systems and Signal Processing*, *133*, p.106279.

Špačková, O. and Straub, D., 2013. Dynamic Bayesian network for probabilistic modeling of tunnel excavation processes. *Computer‐Aided Civil and Infrastructure Engineering*, *28*(1), pp.1-21.

Sun, Y., Feng, X. and Yang, L., 2018a. Predicting tunnel squeezing using multiclass support vector machines. *Advances in Civil Engineering*, *2018*.

Sun, W., Shi, M., Zhang, C., Zhao, J. and Song, X., 2018b. Dynamic load prediction of tunnel boring machine (TBM) based on heterogeneous in-situ data. *Automation in Construction*, *92*, pp.23-34.

Suwansawat, S. and Einstein, H.H., 2006. Artificial neural networks for predicting the maximum surface settlement caused by EPB shield tunneling. *Tunnelling and underground space technology*, *21*(2), pp.133-150.

Takagi, T. and Sugeno, M., 1985. Fuzzy identification of systems and its applications to modeling and control. *IEEE transactions on systems, man, and cybernetics*, (1), pp.116-132.

Tao, H., Jingcheng, W. and Langwen, Z., 2015, May. Prediction of hard rock TBM penetration rate using random forests. In *The 27th Chinese Control and Decision Conference (2015 CCDC)* (pp. 3716-3720). IEEE.

Tsekouras, G.J., Koukoulis, J. and Mastorakis, N.E., 2010. An optimized neural network for predicting settlements during tunneling excavation. *WSEAS TRANSACTIONS on SYSTEMS*, *9*(12), pp.1153-1167.

Vapnik, V. “The nature of statistical learning theory,” Springer-Verlag: New York, 1995.

Von, W.C. and Ismail, M.A.M., 2017, October. Evaluation of tunnel seismic prediction (TSP) result using the Japanese highway rock mass classification system for Pahang-Selangor Raw Water Transfer Tunnel. In *AIP Conference Proceedings* (Vol. 1892, No. 1, p. 030011). AIP Publishing LLC.

Wang, F., Gou, B., Zhang, Q., Qin, Y. and Li, B., 2016. Evaluation of ground settlement in response to shield penetration using numerical and statistical methods: a metro tunnel construction case. *Structure and Infrastructure Engineering*, *12*(9), pp.1024-1037.

Wang, C., Osorio-Murillo, C.A., Zhu, H. and Rubin, Y., 2017. Bayesian approach for calibrating transformation model from spatially varied CPT data to regular geotechnical parameter. *Computers and Geotechnics*, *85*, pp.262-273.

Wei, L., Magee, D.R. and Cohn, A.G., 2018. An anomalous event detection and tracking method for a tunnel look-ahead ground prediction system. *Automation in Construction*, *91*, pp.216-225.

Williams, C.K. and Rasmussen, C.E., 1996. Gaussian processes for regression. In *Advances in neural information processing systems* (pp. 514-520).

Xia, Y.M., Wu, F., Cheng, L. and Zhang, Z.H., 2012. Optimal Design of Disc Cutter Structure Parameter Based on Genetic Algorithm. In *Applied Mechanics and Materials* (Vol. 130, pp. 919-922). Trans Tech Publications Ltd.

Xia, Y., Zhang, K., and Liu, J. 2015. Design optimization of TBM disc cutters for different geological conditions. *World journal of engineering and technology*, *3*(4).

Xu, H., Zhou, J., G Asteris, P., Jahed Armaghani, D. and Tahir, M.M., 2019. Supervised machine learning techniques to the prediction of tunnel boring machine penetration rate. *Applied Sciences*, *9*(18), p.3715.

Xue, Y.D. and Zhang, S., 2019, September. A Fast Metro Tunnel Profile Measuring Method Based on Close-Range Photogrammetry. In *International Conference on Inforatmion technology in Geo-Engineering* (pp. 57-69). Springer, Cham.

Yagiz, S., Gokceoglu, C., Sezer, E. and Iplikci, S., 2009. Application of two non-linear prediction tools to the estimation of tunnel boring machine performance. *Engineering Applications of Artificial Intelligence*, *22*(4-5), pp.808-814.

Yagiz, S. and Karahan, H., 2011. Prediction of hard rock TBM penetration rate using particle swarm optimization. *International Journal of Rock Mechanics and Mining Sciences*, *48*(3), pp.427-433.

Yagiz, S. and Karahan, H., 2015. Application of various optimization techniques and comparison of their performances for predicting TBM penetration rate in rock mass. *International Journal of Rock Mechanics and Mining Sciences*, *80*, pp.308-315.

Yamamoto, T., Shirasagi, S., Yamamoto, S., Mito, Y. and Aoki, K., 2003. Evaluation of the geological condition ahead of the tunnel face by geostatistical techniques using TBM driving data. *Tunnelling and underground space technology*, *18*(2-3), pp.213-221.

Yan, K., Dai, Y., Xu, M. and Mo, Y., 2020. Tunnel Surface Settlement Forecasting with Ensemble Learning. *Sustainability*, *12*(1), p.232.

Yu, Y., Workman, A., Grasmick, J.G., Mooney, M.A. and Hering, A.S., 2018. Space-time outlier identification in a large ground deformation data set. *Journal of Quality Technology*, *50*(4), pp.431-445.

Yu, H.J. and Mooney, M.A., Logging the As-Encountered Ground Condition with EPBM Data using Supervised and Semi-Supervised Learning, *Tunnelling & Underground Space Technology*, 2020, in review.

Zhang, W., 2020. MARS Use for Determination of EPB Tunnel-Related Maximum Surface Settlement. In *MARS Applications in Geotechnical Engineering Systems* (pp. 121-136). Springer, Singapore.

Zhang L, Wu X, Qin Y, et al. 2016. Towards a fuzzy Bayesian network based approach for safety risk analysis of tunnel-induced pipeline damage. *Risk Analysis*, 36(2): 278-301.

Zhang, L., Wu, X., Ji, W. and AbouRizk, S.M., 2017. Intelligent approach to estimation of tunnel-induced ground settlement using wavelet packet and support vector machines. *Journal of Computing in Civil Engineering*, *31*(2), p.04016053.

Zhang, P., Chen, R.P. and Wu, H.N., 2019a. Real-time analysis and regulation of EPB shield steering using Random Forest. *Automation in Construction*, *106*, p.102860.

Zhang, L., Wu, X., Liu, W. and Skibniewski, M.J., 2019b. Optimal Strategy to Mitigate Tunnel-Induced Settlement in Soft Soils: Simulation Approach. *Journal of Performance of Constructed Facilities*, *33*(5), p.04019058.

Zhang, Q., Liu, Z. and Tan, J., 2019c. Prediction of geological conditions for a tunnel boring machine using big operational data. *Automation in Construction*, *100*, pp.73-83.

Zhang, W.G., Li, H.R., Wu, C.Z., Li, Y.Q., Liu, Z.Q. and Liu, H.L., 2020. Soft computing approach for prediction of surface settlement induced by earth pressure balance shield tunneling. *Underground Space*.

Zhao, Z., Gong, Q., Zhang, Y. and Zhao, J., 2007. Prediction model of tunnel boring machine performance by ensemble neural networks. *Geomechanics and Geoengineering: An International Journal*, *2*(2), pp.123-128.

Zhao, J., Shi, M., Hu, G., Song, X., Zhang, C., Tao, D. and Wu, W., 2019a. A Data-Driven Framework for Tunnel Geological-Type Prediction Based on TBM Operating Data. *IEEE Access*, *7*, pp.66703-66713.

Zhao, W., Wei, Y., Liu, B., Liu, S. and Xiao, L., 2019b, September. Design and Application of Automatic Monitoring and BIM Technology to the Construction of Shield-Bored Underneath Building. In *International Conference on Inforatmion technology in Geo-Engineering* (pp. 493-501). Springer, Cham.

Zhou, J., Shi, X.Z., Du, K., Qiu, X.Y., Li, X.B. and Mitri, H.S., 2016, July. Development of the ground movements due to shield tunnelling prediction model using random forests. In Proc., 4th Geo-China Int. Conf (pp. 108-115).

Zhou, J., Shi, X., Du, K., Qiu, X., Li, X. and Mitri, H.S., 2017. Feasibility of random-forest approach for prediction of ground settlements induced by the construction of a shield-driven tunnel. *International Journal of Geomechanics*, *17*(6), p.04016129.

Zhou, J., Bejarbaneh, B.Y., Armaghani, D.J. and Tahir, M.M., 2019. Forecasting of TBM advance rate in hard rock condition based on artificial neural network and genetic programming techniques. *Bulletin of Engineering Geology and the Environment*, pp.1-16.

Zhu M, Zhu H, Wang X, et al. Quantitative Analysis of Seasonal Uncertainty of Metro Tunnel's Long-Term Longitudinal Settlement via Hierarchy Bayesian Network. In Proc. International Conference on Information technology in Geo-Engineering. Springer, Cham, 2019: 279-291.

Zhuang, D.Y., Ma, K., Tang, C.A., Liang, Z.Z., Wang, K.K. and Wang, Z.W., 2019. Mechanical parameter inversion in tunnel engineering using support vector regression optimized by multi-strategy artificial fish swarm algorithm. *Tunnelling and Underground Space Technology*, *83*, pp.425-436.