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Application of Artificial Neural Network in Tunnel Engineering: A Systematic Review

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ABSTRACT Due to the lack of living space and the increase in population, there has been a construction boom in the underground space to improve the quality of human life. Tunnel engineering plays a vital role in the development of underground space. In addition to traditional methods, some intelligent methods such as artificial neural networks (ANNs) have been applied to various problems in the tunnel domain in recent years. This paper systematically reviews the application of ANNs from different aspects of tunnel engineering. It reveals that the backpropagation algorithm (BPA) and Levenberg-Marquardt algorithm (LMA) are the most widely used. Due to the limitations of some original models, some scholars use optimization algorithms such as particle swarm optimization (PSO) and genetic algorithm (GA) to optimize the original ANNs to obtain better prediction results. A comparison between the ANN-based methods and methods like statistical methods is conducted. Finally, the following conclusions can be drawn: (1) The recommended ratio of the training set and test set is 3:1; (2) The advantage of optimized ANNs is not apparent when the optimization algorithm varies. Additionally, the performance of ANNs is always better than that of statistical methods.

INDEX TERMS Artificial neural networks, tunnel engineering, prediction accuracy.

ABBREVIATIONS IN ALPHABETICAL ORDER

(ANFIS)	Adaptive neuro-fuzzy inference system
(AIC)	Akaike information criterion
(AF)	Application field
(ABC)	Artificial bee colony
(ANNs)	Artificial neural networks
(ANNFF)	Artificial neural network with forgetting factor
(AIER)	Average inference error rate
(ARE)	Average relative error
(BPA)	Backpropagation algorithm
(BPNN)	Backpropagation neural network
(BLR)	Bayesian linear regression
(BNC)	Bayesian network classifier
(CGA)	Conjugate gradient algorithm
(CFT)	Curve fitting toolbox
(DWF)	Daughter wavelet function
(DT)	Decision trees
(ELM)	Extreme learning machine
(FFNN)	Feedforward neural network
(FLM)	Fuzzy logic model
(GPOD)	Gappy Proper Orthogonal Decomposition
(GF)	Gaussian function
(GP)	Gaussian process
(GA)	Genetic algorithm
(GIS)	Geographic information system
(TANSIG)	Hyperbolic tangent function
(ICA)	Imperialist competitive algorithm
(KNN)	K-nearest neighbors
(KSOFM)	Kohonen self-organizing feature map
(LMA)	Levenberg-Marquardt algorithm
(LMBP)	Levenberg-Marquardt backpropagation algorithm
(LIN)	Linear function
(LMRA)	Linear multiple regression analysis
(LIR)	Linear regression
(LRM)	Logarithmic regression method
(LOGSIG)	Logistic sigmoid function

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(MABE)	Mean absolute bias error
(MAE)	Mean absolute error
(MAPE)	Mean absolute percentage error
(ME)	Mean error
(MSE)	Mean squared error
(MSEREG)	Mean squared error with Regularization
(MRNN)	Midpoint recurrent neural network
(MNN)	Modular neural network
(MLP)	Multilayer perceptron
(MOE)	Multi-object error
(MRA)	Multiple regression analysis
(MARS)	Multivariate adaptive regression splines
(NMRA)	Nonlinear multiple regression analysis
(NM)	Not mentioned
(PSO)	Particle swarm optimization
(PE)	Percentage error
(POSLIN)	Positive linear function
(PA)	Prediction accuracy
(PNN)	Probabilistic neural network
(PURELIN)	Pure linear function
(RBF)	Radial basis function
(RBFNN)	Radial basis function neural network
(RRNN)	Radius recurrent neural network
(RF)	Random forest
(ReLU)	Rectified linear units function
(RNN)	Recurrent neural network
(RE)	Reference
(RAE)	Relative absolute error
(RRMSE)	Relative root mean square error
(RMSE)	Root mean square error
(RRSE)	Root relative square error
(SCGA)	Scaled conjugate gradient algorithm
(SIG)	Sigmoid function
(SPSS)	Statistical Product and Service Solutions
(SSRE)	Sum squared relative error
(SVM)	Support vector machine
(SVMFF)	Support vector machine with a forgetting factor
(SVR)	Support vector regression
(SM)	Surrogate model
(VAF)	The variance accounted for
(TL)	Transfer learning
(TBMs)	Tunnel boring machines
(UD)	Uniform design
(WNN)	Wavelet neural network

NOMENCLATURE

(R^2)	Coefficient of Determination
(R)	Correlation coefficient
(α)	Learning rate
(t_k)	Measured output
(β)	Momentum constant
(y_k)	Predicted output produced by the ANNs
(σ)	Standard deviation
($\overline{t_k}$)	The average value of actual t_k values
($\overline{y_k}$)	The average value of actual y_k values
($N_{country}$)	The number of countries
(N_{decade})	The number of decades
(N_h)	The number of hidden neurons
(N_{imp})	The number of imperialists
(N_i)	The number of input neurons
(N_o)	The number of output neurons
(var(t_k-y_k))	The variance of t_k-y_k
(var(y_k))	The variance of y_k
(w_j)	The weight vector
(n)	Training epochs

I. INTRODUCTION

According to World Urbanization Prospects, 55% of the world's population lives in urban areas, and it is expected to increase to 68% by 2050 [1]. Together with urbanization, the overall growth of the world's population will increase the urban area by another 2.5 billion people by 2050. The growing population leads to the extensive development of underground space, which offers the possibility of improving the quality of life [2]. Tunneling is one of the methods to develop underground space using machinery such as shield TBMs. In the past few decades, researchers have been using traditional methods such as analytical methods and numerical simulation methods to solve tunnel-related problems [3], [4]. However, obtaining accurate results is not easy because many calculations require detailed external parameters and reasonable estimates. Driven by big data, ANNs are considered to be an emerging method used in tunnel engineering and have been applied to solve these tunnel-related problems.

ANNs are inspired by the biological behavior of neurons and human brain research and can help tunnel engineers establish relationships between input parameters and output parameters [5]. Shi *et al.* applied ANN to predict settlements during tunneling [6], and then the tunnel support stability was obtained [7]. Benardos *et al.* predicted the performance of TBM, mainly including the TBM advance rate, by presenting an ANN model [8]. To learn more about the hazardous geological zones in front of a tunnel face, Alimoradi *et al.* built an ANN model to classify the mechanical properties of rock mass in the zones [9]. Lau *et al.* applied RBFNN to estimate production rates on the following cycle in tunneling construction [10]. Mahdevari *et al.* estimated the unknown nonlinear relationship between the rock parameters and tunnel convergence by using the data from the Ghomroud water conveyance tunnel in Iran [11]. Rastbood *et al.* developed an ANN to predict the stresses executed on segmental tunnel lining [12]. Wu *et al.* applied ANN to verify the proposed tunnel ventilation system with variable jet speed [13]. Ribeiro e Sousa *et al.* used different types of data mining techniques ranging from ANNs to naive Bayesian classifiers to predict the type of rockburst [14].

Lai *et al.* reviewed the main developments in the field of tunnel deformation prediction system based on ANNs [15].

Lu *et al.* present applications of artificial intelligence in civil engineering [16]. However, the thorough investigation of the application of ANNs in tunnel engineering is still insufficient. Providing a brief review of the studies related to the application of ANNs in the context of the tunneling field can help plan, design, and construct tunneling projects with ANN techniques.

This study aims to review the application of ANN-based models in the field of tunnel engineering. Section 2 shows the methodology of this paper. Section 3 presents an overview of the ANNs. Section 4 demonstrates the application of ANNs in different aspects of tunnel engineering. Section 5 discusses the features of ANNs, such as architecture, transfer functions, prediction performance. In Section 6, primary conclusions and future works are summarized.

II. METHODOLOGY

The research methodology of this paper can be summarized as follows:

A. CONDUCTING A KEYWORD-BASED SEARCH

This paper employs Web of Science to perform a keyword-based searching of published papers from 1900 to 2019. The keywords include artificial neural networks and tunnel. In this step, 422 published papers are collected as a basic literature library.

B. SEARCHING TOP 100 HIGH LOCAL CITED PAPERS

Histcite pro is used to select 100 papers with the highest citation among 422 papers.

C. SEARCHING PAPERS PUBLISHED IN 2017-2019

Reviewing recently published papers can help readers know the latest developments in related research. Finally, 52 papers of the remaining 322 papers are selected.

D. SCREENING THE COLLECTED PAPERS

There are several criteria for screening the 152 papers collected in the above two steps. First, the content of the paper is directly related to tunneling engineering. Second, the model used in the paper should use at least one ANN-based model. Finally, 61 papers are extracted from the 152 collected papers.

E. REVIEWING THE PAPERS

To summarize different characteristics of the ANNs, such as the number of the hidden layers and learning rate, 61 papers are carefully reviewed.

III. OVERVIEW OF ARTIFICIAL NEURAL NETWORK

Many studies have detailed the definition and development process of ANNs [17]. ANN can be applied to approximate functions between a large number of input parameters and output parameter(s) because it has the ability of self-learning. Moreover, ANNs can learn from previous data and can help obtain useful information from the raw data. These strengths make ANNs a valuable tool for predicting some complex problems. According to different factors, ANNs can be divided into different categories (see Fig. 1).

TABLE 1. Pros and Cons of the ANNs.

.	Pros	Cons
1	It can deal with problems with uncertain or limited experience [20].	It is hard to explain how these decisions are made. Deep reasoning cannot be achieved [21].
2	There is no need to prioritize the relationship between the examined components [20].	It is challenging to determine weights and other vital parameters, such as learning rate and momentum constant.
3	It can be applied to nonlinear and multivariable problems [5, 21, 22].	It cannot perform well when extrapolation beyond the range of the data used for calibration is needed [23].
4	Its structure has high flexibility, especially the hidden layer structure, which can be designed according to the specific requirements of the actual applications [24].	When noise is captured, overfitting occurs and patterns cannot be generalized well to unseen data [18, 25]. However, keeping the model too simple may cause underfitting because the patterns in the data are not captured.
5	It has high flexibility to set multiple outputs without significantly increasing training difficulty [24].	There are no specific rules and guidelines for network design.
6	It can deal with complex regression problems or classification tasks [24].	The BPA may fall into a local optimum and has a low learning rate [26, 27].

A. ARTIFICIAL NEURAL NETWORK

Training an ANN model is a process of adjusting weights and biases until it meets the stop criteria defined by the users, or until the error converges to the minimum value initially set [18]. After establishing an ANN model, the optimal model is found by optimizing the number of hidden layer(s) and hidden nodes, the type of transfer function, and so on [19]. Table 1 lists the pros and cons of ANNs.

The ANNs in tunnel engineering can be demonstrated in three aspects: the characteristics, the modeling process, and the main types of ANN used in this field.

1) CHARACTERISTICS OF ANN

The activation function, also called the transfer function, is used for transferring the information in the artificial neurons. The derivative of SIG can be expressed according to the function itself, thus it can be applied to the most common training algorithm. Park *et al.* stated that SIG is the most efficient through its better performance [25]. Rajabi *et al.* stated that SIG is more efficient when it is compared with linear functions in general [28].

In theory, the activation function can be different from one layer to another [29]. The selection of activation functions is related to the complexity of the problem and the purpose of the model [5], [30].

The learning ability of the ANNs comes from its network topology, which mainly includes the number of layers and the number of neurons. When the ANN model is applied to

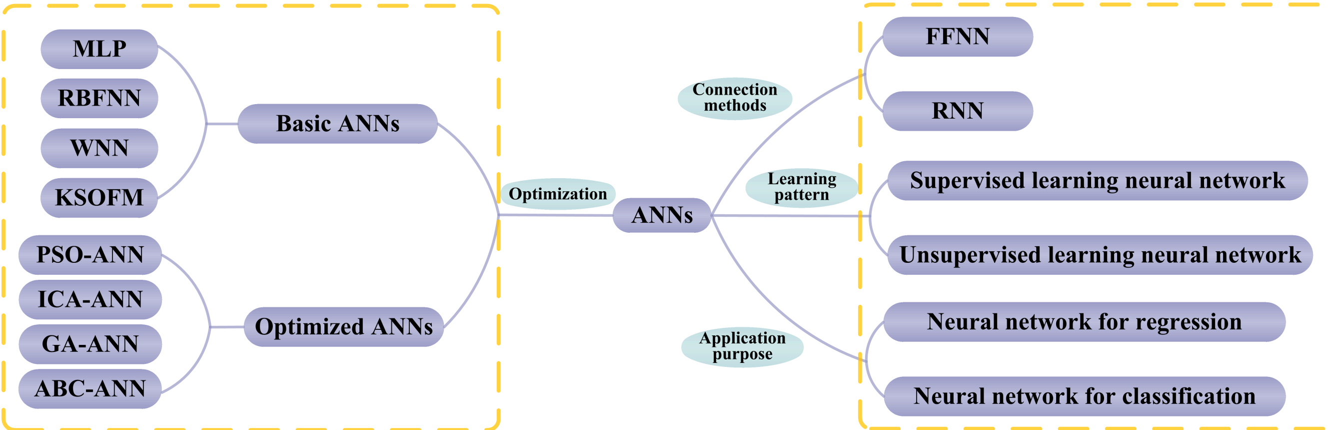

FIGURE 1. Classifications of main ANNs applied in the tunneling field.

the tunnel-related field, it always has one input layer, one or two hidden layers, and one output layer. Among these layers, one of the most critical steps in building an ANN model is to determine the number of hidden layers because mathematical adjustment operations are performed in these layers [19], [31].

The neurons in the input and output layers correspond to the input and output variables of the problem. Hidden neurons enable the network to solve complex problems and are closely related to the performance of ANNs [32].

The training algorithm automatically adjusts the weights and thresholds of neurons to minimize errors [29]. There are many existing ANN training algorithms, including BPA, LMA, the conjugate gradient method, and so forth. BPA and LMA are the most commonly used training algorithms in ANNs. LMA is 10 to 100 times faster than the usual BPA and proved to be the quickest and most robust algorithm [33], [34].

2) MODELING PROCESS OF ANN

The ratio of training, validation, and test sets is a significant factor that affects ANN's performance. So far, there is no specific method for defining the ratio of available data.

Different dimensions and scales of input parameters will lead to instability learning and a decrease in learning speed. To obtain dimensionless data, it is necessary to normalize the data before network training [35], [36].

Three main steps, including training, validation, and testing, constitutes a successful ANN. During the training process, the training algorithm is applied to update the weights and minimize the error. The validation step is the criterion for stopping the training step, and the test procedure is applied to a trained and validated ANN to measure its performance [37]. In most cases, only the training and test steps are carried out because an appropriate model can be chosen through previous experience.

Regarding the performance evaluation of the trained ANN model, Table 2 summarizes some main performance metrics.

TABLE 2. Main Performance functions of a trained ANN model.

Function	Range	Optimal value
MAE	[0,+∞]	0
MAPE	[0, +∞]	0
MSE	[0,+∞]	0
RMSE	[0,+∞]	0
RRMSE	[0, +∞]	0
RAE	[0%,100%]	0
RRSE	[0%,100%]	0
R	[−1,1]	-1.0, 1.0
R^2	[0,1]	1
VAF	[0%,100%]	100%

Note: R=-1.0, R=1.0 means that there is a perfect negative correlation or a perfect positive correlation between the two variables, respectively.

When using two or more performance indicator(s), the total rank method proposed by Zorlu *et al.* is commonly used to obtain the optimal model from the different results of these indicators [30], [38]–[40].

As shown in Table 1, the interpretability of the result predicted by ANNs is poor because ANN is a black-box model. Thus, sensitivity analysis is conducted to find out the relative importance of the influencing factors that affect the prediction results [28], [29], [41].

3) MAIN ANN TYPES USED IN TUNNEL ENGINEERING

Basic ANNs include MLP, RBFNN, WNN, and KSOFM (see Figs. 1 and 2). Commonly used optimized ANNs include PSO-ANN, ICA-ANN, GA-ANN, and ABC-ANN.

Among the most popular basic ANN types, MLP belongs to FFNN and contains at least one hidden layer. The advantage of the MLP is that it can be used in high nonlinear problems [42]. BPA is the most popular and efficient learning procedure in ANNs, especially for MLP [21], [30], [43].

RBFNN is an FFNN that uses radial basis functions such as a GF as the activation function [11]. Unlike BPNN, RBFNN performs in two ways: (1) is more efficient and

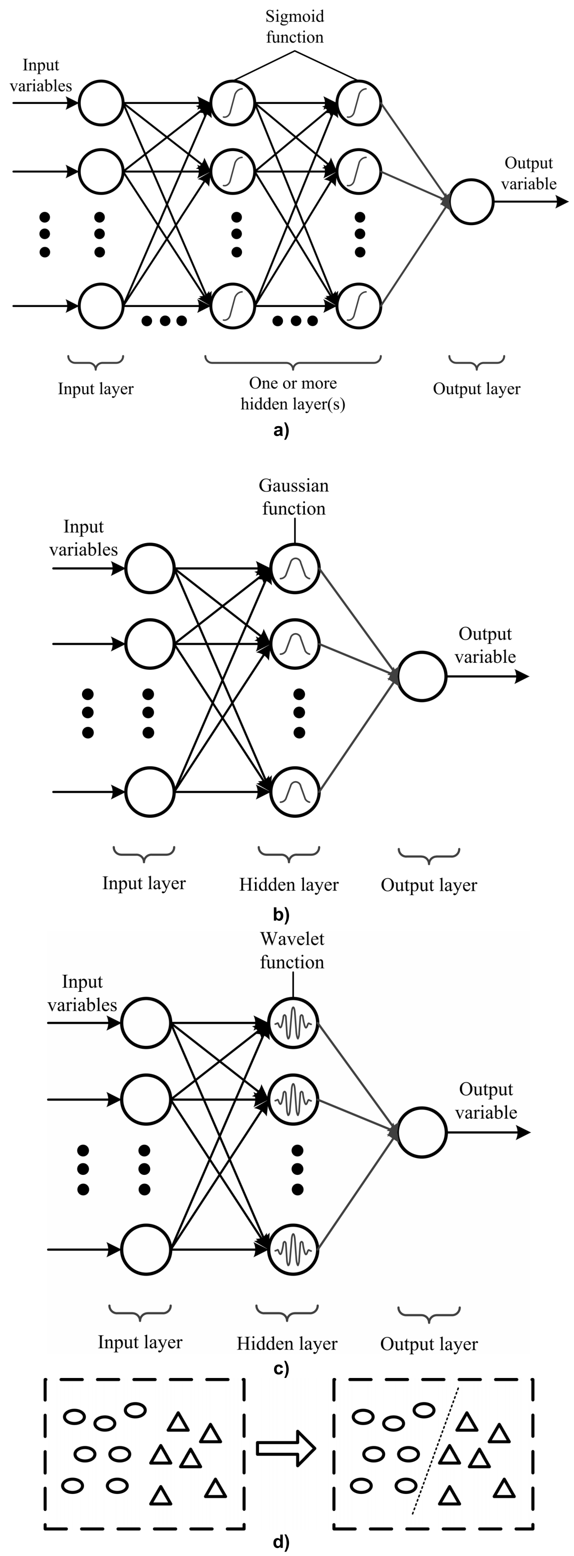

FIGURE 2. Structure or map of different basic ANNs: a) MLP; b) RBFNN; c) WNN; d) KSOFM.

straightforward, thereby reducing training time; (2) avoids falling into a local minimum and overtraining [44]. There are an input layer, hidden layer, and output layer in RBFNN, as shown in Fig. 2.

WNN is usually an FFNN composed of one input layer, one hidden layer, and one output layer. WNN uses wavelets as its activation function [21].

Among unsupervised ANNs, KSOFM is the most widely used neural networks [43]. Using KSOFM can automatically divide the dataset into multiple clusters according to the similarity of the dataset.

B. IMPROVED ARTIFICIAL NEURAL NETWORKS

Although the BPA is the most commonly used algorithm, the learning speed is relatively low and may fall into a local minimum [20], [45]. Therefore, optimization methods such as PSO, ICA, GA, and ABC are introduced to improve the performance of the network and make it easier for the network to find a global minimum. A simple comparison between these optimizers is shown in Table 3 [20], [30], [41].

IV. APPLICATIONS OF ANNs IN TUNNEL ENGINEERING

ANNs have a wide range of applications in tunnel engineering, such as tunneling-induced settlement, tunnel support stability, roadheader or TBM performance, and so forth. The reviewing results are shown in the Appendix.

A. TUNNELING-INDUCED SETTLEMENT

The application of the ANNs in tunneling-induced settlement accounts for a large part of the reviewed papers.

Many factors affect the tunneling-induced settlement, including tunnel geometry, geological conditions, and shield operation factors, and so on. In such a complex problem, the relationship between the influence parameters and the ground settlement is unknown, and it is usually nonlinear. ANNs proved to be the best way to analyze settlement data since they can predict the settlement by establishing an unknown relationship between structural features and existing settlement data [46]. One of the most challenging difficulties in ANN modeling is obtaining parameters that may be related to ground settlement [47].

Boubou *et al.* utilized ANNs and least square approximation to correlate ground surface movement and TBM operating parameters [29]. The accuracy of the model is evaluated by using the monitoring data of the Toulouse subway line B tunnel. They concluded that the most critical parameters affecting ground surface movements are the TBM's advance rate, the hydraulic pressure used for the cutting wheel, and the TBM's vertical guidance parameters.

B. THE STABILITY OF UNDERGROUND STRUCTURES

ANNs can be used to predict the stability of underground structures such as tunnels, gate roadways, and rock caves. An ANN can be applied to establish a model to depict the complicated relationship between the stable status of tunnel support and rock mechanics and construction parameters. BPNN, MLP, RBFNN are the primary neural networks for predicting the interaction of underground structure stability, tunnel support pressure, and ground-support during deep rock excavation [7], [53]–[56].

TABLE 3. A Comparison between PSO, GA, ICA and ACO.

Term	Populations	Iterations	Strengths	Weakness
PSO	Particles	Iterations	Compared with GA, it has a high learning speed and needs less memory [41]. Compared to other optimization algorithms, it has a comparatively simple procedure [48].	The convergence speed is affected by inertia weight [49].
GA	Chromosomes	Generations	It can solve complex and highly nonlinear problems [41].	It has difficulties in determining various parameters of the algorithm and creating appropriate function [41].
ICA	Countries	Decades	The number of iterations needed to reach the global minimum of it is equal to GA and less than PSO [50].	It can be applied to only some of the standard optimization problems [50].
ABC	Bees	-	It can get out of a local minimum and can be utilized for the optimization of multivariable, multimodal problems [51]. It can be applied to solve unimodal and multimodal optimization problems [52].	It has difficulties in determining the control parameters [51].

C. ROADHEADER PERFORMANCE AND TBM PERFORMANCE

ANNs can help predict the performance of TBM [8]. The results show that the ANN system has achieved satisfactory results in predicting the TBM advance rate. ANN is integrated with a GIS platform for tunnel performance prediction. The integrated model makes full use of GIS's capabilities in data management, storage, and visualization. The results show that the integrated GIS-ANN approach can be used as a decision support tool for tunnel engineers to predict tunnel performance [57]. Statistical methods, such as MRA, SPSS, together with ANNs, are conducted to predict TBM performance [58], [59]. For the penetration rate of TBM, the prediction accuracy of SVM, LMRA, and ANN are compared [60], [61]. In order to predict the penetration rate and advance rate of TBM, Armaghani *et al.* utilized an ANN, PSO-ANN, and ICA-ANN to make the prediction and compared the prediction ability of these methods [30], [39]. A hybrid finite element and surrogate modeling approach based on RNN is proposed to simulate and support TBM steering, which provides support for the steering decisions of tunnel engineers [62], [63].

Roadheaders can bring productivity to tunneling, mining, and civil engineering. Thus roadheader performance prediction has become one of the main issues in the economic process of underground mining. ANNs, together with KSOFM or statistical methods such as MRA, RF, zero R, etc., are applied to predict roadheaders' performance [31], [37], [43], [64].

D. GEOLOGICAL CONDITIONS

The ground condition ahead of tunnel face can be predicted by ANNs. In the literature [65], the proposed ANN model shows high efficiency in predicting ground type in front of the tunnel face. Thus, it is valuable to utilize the proposed ANN model to reduce the influence of geological conditions changes. Zhao *et al.* conducted a data-driven framework based on different methods, including ANN, XGBoost, CatBoost, DT, KNN, and BLR, to predict the geological types of stratum [24]. It reveals that the proposed ANN predictor outperforms other models. Moreover, ANN can also be applied to predict hazardous geological zones in front of the tunnel face and void behind the lining [9], [66].

E. OVERBREAK PREDICTION

Mottahedi *et al.* applied various methods, including ANNs, LMRA, NMRA, SVM, adaptive neuro-fuzzy inference system, and FLM, to predict the relationship between the causing factors and overbreak data [67]. The results indicate that specific drilling, specific charge, and rock mass rating are the most effective factors on the overbreak. Among these methods, the prediction performances of adaptive neuro-fuzzy inference systems and FLM are better than that of MRA, ANN, and SVM. ANN-based hybrid models are always being used in recent years. For example, hybrid models that combine GA and ANN, ABC and ANN are utilized to predict overbreak separately [38], [40], [68]. The results show that the prediction performance of the hybrid model is better than that of the original ANN.

F. TUNNEL CONVERGENCE

In the research field of tunnel convergence, MLP is applied frequently. Mahdevari *et al.* used MLP, RBFNN, and MRA to estimate the nonlinear relationship between the rock parameters and convergence [11]. The results show that the MLP has higher accuracy compared with the RBF and MRA. However, the prediction performance of ANN is worse than that of SVM [36]. In addition, Adoko *et al.* applied MARS, together with ANNs, to predict tunnel convergence [35]. It is concluded that the accuracy of the MARS method is lower than that of the MLP model. Zarei *et al.* utilized SPSS and discrete element methods to introduce a new convergence criterion for water conveyance tunnel, and it comes out that the ANN is more suitable than the other two methods [69]. Note that the performance of different data mining methods and statistical methods varies depending on different data.

G. OTHER APPLICATIONS

Rastbood *et al.* applied MLP to predict yield stresses and displacement of segmental tunnel lining rings based on the results obtained from the numerical method [12]. It is concluded that among all input variables, height is the most effective parameters on outputs parameters. Thus, the proposed model shows an excellent ability to predict different types of stresses and extreme values of ring displacement.

A few researchers in recent years also studied the applications of ANN in the tunnel ventilation system. To regulate the pollutant concentration, Wu *et al.* applied the ANN unit in the comprehensive dynamic model designed for tunnel ventilation systems with jet fans. Also, a new neural network was utilized to approximate the cost-to-go function that is used to optimize the performance [13]. Zheng *et al.* predicted the inside air temperature and ventilation rate of a tunnel by ANN instead of complex mathematical models. It is concluded that the average air temperature inside the tunnel is predicted more accurately than the single inside temperature at the center of the tunnel [70].

Regarding the use of ANN in rockburst and flying rock generated by blasting, the in-situ rockburst database is analyzed by ANNs, SVM, and other two different data mining techniques [14]. Based on the PNN model, Feng *et al.* predict rockburst in the deep tunnels [71]. The flyrock distance generated by blasting is predicted by three hybrid ANN models, including ICA-ANN, GA-ANN, and PSO-ANN [41]. The results show that the prediction performance of PSO-ANN is better than that of the other two methods.

Moreover, ANNs can be used to estimate next-cycle production rates in tunneling construction. Lau *et al.* utilized RBFNN to analyze the nonlinear relationship between system states and systems outputs at consecutive time events [10]. It is proved that RBFNN can help tunnel engineers forecast the production rate in the following cycle.

V. DISCUSSION

The main features and performance of different methods are summarized in this section.

A. CHARACTERISTICS OF ANN-BASED MODELS

As can be seen from the Appendix and Fig. 3, the percentage of the training set, validation set, and test set are in the intervals of [54.7%,94.1%], [0%,25%],[5.9%,39.4%], respectively. In addition, in the 50 datasets that available for analysis, the validation set is only applied in 11 datasets, which means that only the training set and test set exist in most models when ANNs are involved in the tunneling engineering field. The Appendix implied that the average percentage of the training, validation, and test set is 74.70%, 3.94%, and 21.34%, respectively (see Table 4). Besides, there are some previous recommendations that can be a guide to the ratio of the training set to the test set (see Table 5).

TABLE 4. The maximum, average, and minimum percentages of training, validation and test set.

Data set	Maximum percentage (%)	Average percentage (%)	Minimum percentage (%)
Training set	94.10	74.70	54.70
Validation set	25.00	3.94	0.00
Test set	39.40	21.34	5.90

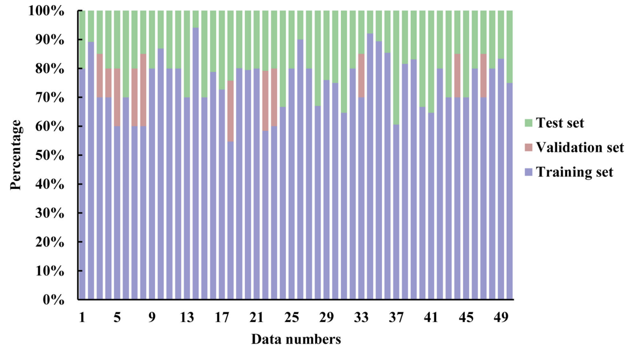

FIGURE 3. Stacked column graph of the percentages of training, validation, and test set.

TABLE 5. Recommendations of the percentages of the training set and test set.

Percentage of the training set	Percentage of the test set	Reference/s
70%~80%	20%~30%	[72]
75%	25%	[73]
80%	20%	[74]
2/3	1/3	[75, 76]

According to Tables 4 and 5, setting the ratio of the training set to the test set to 3:1 is suggested in the future tunneling-related research.

The performance of the ANNs depends mainly on the architecture, namely the number of input, hidden and output layers, and the number of neurons in the hidden layer(s).

Some scholars believe that neural networks with a single hidden layer are sufficient to approximate any function [20], [43], [77]–[80]. The strength of an ANN model with one hidden layer is that it can decrease the complexity of a model [81]. Other scholars consider that two hidden layers can meet the requirements to solve high complexity problems [19]. Jung *et al.* stated that the number of hidden layers is restricted to two because additional hidden layers could trigger the vanishing gradient problem in the activation function [65]. Two or more hidden layers are known as a way to solve the overfitting problem. However, the performance of ANNs is not improving with more than two layers [18]. In practice, some scholars decided the number of hidden layers by the trial and error method or experience [5], [28], [47].

In conclusion, single hidden layer networks can be applied in most problems, especially in linear or low nonlinear problems. However, in nonlinear problems, two-layer networks are more proper to be utilized while the difficulty in optimization and risk of overdetermined ambiguity exists. One to three layers are reckoned to be sufficient for most of the problems [82]. More hidden layers may cause issues like huge calculation.

Numerous empirical equations are proposed to guide the determination of the number of hidden neurons (see Table 6) [20], [30], [38], [40], [81]. After the range of N_h is determined, the trial and error method is conducted to obtain the optimal value of N_h [20], [28], [30], [40], [41], [83], [84].

TABLE 6. Equations for determination of the hidden neurons.

Heuristic	References
$\leq 2 \times N_i + 1$	[78]
$3N_i$	[85]
$(N_i + N_O)/2$	[86]
$[2 + N_o \times N_i + 0.5N_o \times (N_o^2 + N_i) - 3]/(N_i + N_O)$	[87]
$2N_i/3$	[88]
$\sqrt{N_i \times N_O}$	[89]
$2N_i$	[90] [91]
$3N_i/2$	[92]

Data in Fig. 4 illustrates that the number of hidden layers is mostly set to be one (36 datasets), followed by two (20 datasets) and three (4 datasets). When $N_h = 1$, the number of hidden neurons is always between 3 and 24, and the average number is 13 (see Fig.4 a)). Figs. 4 b) and c) indicates that when $N_h = 2$, both the numbers of the neurons in the first hidden layer and the second hidden layer are either beyond 20 or between 3 and 13. Only in a few cases, $N_h = 3$ is applied.

Although the learning rate, the momentum constant, and the training epochs are three essential parameters determined by experience, their values are not given in some cases. Note that the success of the training process varies with the selection of the momentum coefficient [58].

The values of the learning rate and momentum constant in the collected papers are fluctuant, the learning rate is from 0.01 to 0.7, and the momentum constant is from 0.01 to 0.9(see Appendix). The magnitude orders of learning rate values are either 10^{-1} or 10^{-2}. The learning rate should be decided through the trial and error method until the gradient descent process is working correctly. The training speed will be slow when the learning rate is too low. However, oscillations will occur when the learning rate is too large. Thus, the momentum coefficient is proposed to promote the process of computation, which can fasten the learning speed and keep the change of the weight stable. Most of the magnitude orders of the momentum coefficient are equivalent to those of the learning rate, i.e., either 10^{-1} or 10^{-2} except in two cases [55], [84]. Moreover, different value domain of momentum constant have been proposed by different researchers, such as 0.4-0.9 [93], 0.0-1.0 [94], [95], close to 1.0 [96], [97]. The value of the training epochs in the reviewed papers is mostly from 13 to 10000. However, the training epochs value was set to be 600000 by Leu *et al.* [7], which is far beyond other cases. Most values of the training epochs are lower than 1000, only in several cases are they beyond 1000. Besides, the average value of the training epochs is 1534.

In summary, the determination of the learning rate and the momentum coefficient should be determined together. The magnitude orders of these two factors are always set to be the same. Additionally, the initial training epochs can be set to 1500 and then decided by the trial and error method.

Regarding the training algorithm, as shown in Fig. 5, the BPA is the most commonly used algorithm in all the collected

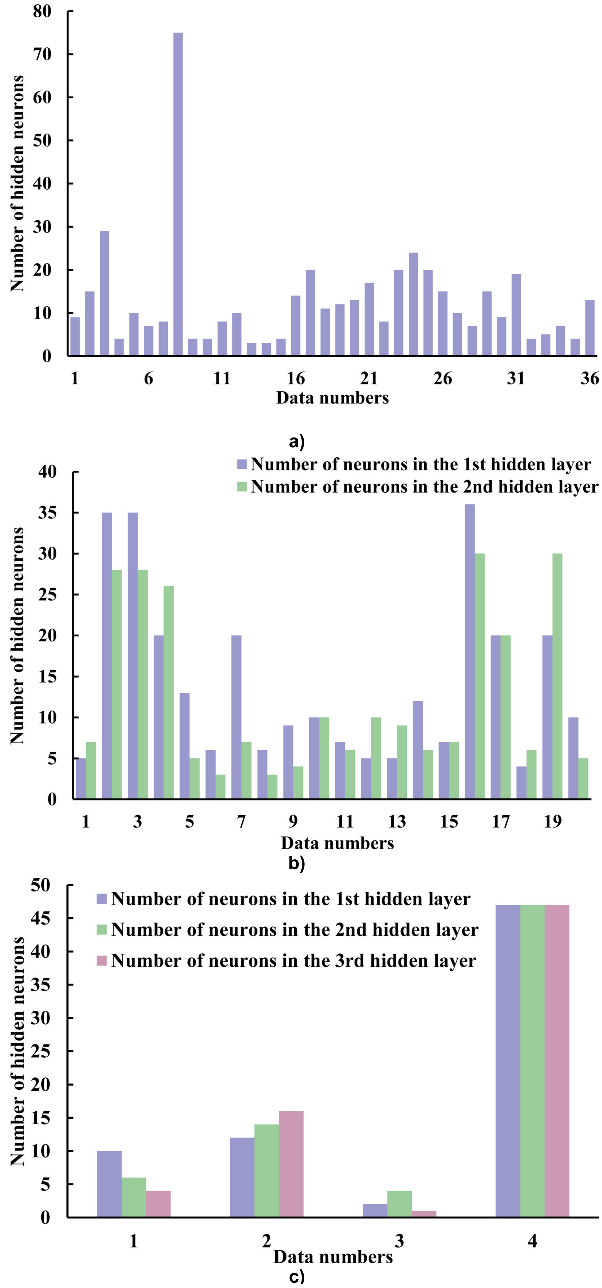

FIGURE 4. The number of hidden neurons: a) one hidden layer; b) two hidden layers; c) three hidden layers.

cases, and LMA is the second widely used one, followed by LMBP, CGA, SCGA, PSO, RBF, ICA and GA. In conclusion, BPA and LMA are used to train the ANNs in most cases. However, because of the limitations of these two algorithms, some optimization algorithms such as ICA, PSO, and GA have been utilized to optimize the original ANNs to obtain better prediction results.

Concerning the transfer function, as can be seen in Fig. 6, the most commonly applied transfer functions are TANSIG, LOGSIG, and PURELIN alternately. It can be concluded that the SIG, TANSIG, and LOGSIG functions are always applied in the hidden layers; however, the PURELIN functions are always utilized in the output layers in the

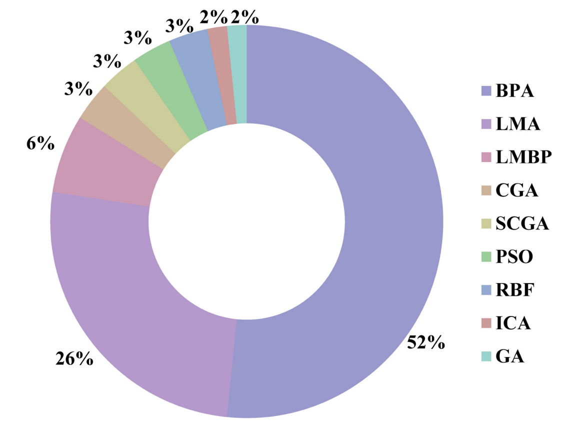

FIGURE 5. Percentages of training algorithms in the ANNs applied in the tunneling field.

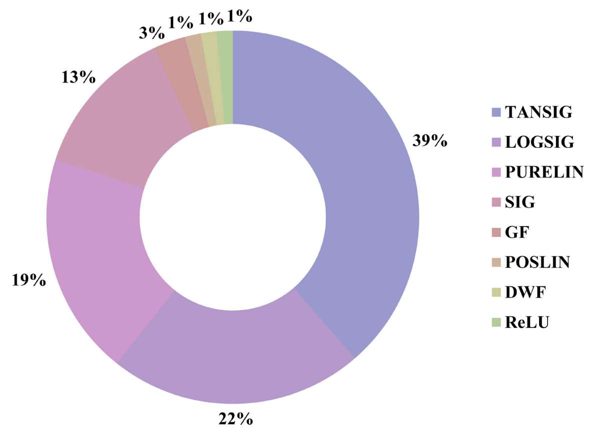

FIGURE 6. Percentages of transfer functions in the ANNs applied in the tunneling field.

ANNs. Although the transfer functions should be determined by the specific situation of the real problems, it is recommended that the SIG, including the TANSIG and LOGSIG, can be firstly tried for the hidden layers, and the PURELIN functions can be firstly tried for the output layers.

TABLE 7. Comparison of ANNs and other methods.

RF	Application area	Comparison results
[6]	Settlement	MNN>BPNN
[21]		WNN>ANN
[22]		GP>SVM>ANN
[83]		SVMFF>ANNFF
[84]		MLP>MRA
[81]		PSO-ANN>ANN
[98]		ANFIS>CFT>ANN
[5]		FLM>BPNN>MRA
[20]		ICA-ANN>ANN>LMRA
[99]		TL>RNN>SVM
[49]		PSO-SVR>PSO-BPNN>PSO-ELM
[53]	Stability	BPNN>LRM
[56]		MLP>RBFNN
[58]	TBM performance	BPNN>NMRA
[59]		ANN>SPSS
[31]		ANN>MRA
[60]		ANN>LMRA
[30]		ICA-ANN>PSO-ANN>ANN
[61]		SVM>ANN
[39]		PSO-ANN>ICA-ANN>ANN
[24]	Geological conditions	ANN>XGBoost, CatBoost, RF, DT, SVR, KNN, BLR
[18]	Overbreak	ANN>NMRA>LMRA
[67]		ANFIS>FLM>ANN>SVM>NMRA>LMRA
[38]		GA-ANN>ANN
[68]		ABC-ANN>ANN
[40]		ABC-ANN>ANN
[11]	Tunnel convergence	MLP>RBFNN>MRA
[36]		SVM>ANN
[35]		MLP>MARS
[69]		MLP>SPSS
[70]	Rockburst and flying rocks	PSO-ANN>ICA-ANN>GA-ANN

Note: The '>' means the performance of the left model outperforms the right one.

B. PREDICTION ACCURACY OF ANN BASED MODELS

ANN-based models such as ICA-ANN, PSO-ANN are compared with a bunch of methods, including data mining methods (such as SVM, RF), statistical methods (such as LMRA, NMRA). Different prediction functions or methods are conducted to estimate the accuracy of the models.

Concerning the prediction accuracy, different prediction functions are introduced to compare the efficiency of different methods. The most used prediction functions are R^2, RMSE, MSE, MAE, R, VAF, RRSE, RAE, and RRMSE. The corresponding functions have been shown in Table 2.

According to the review results, the comparison results between the ANNs and other methods are listed in Table 7. It illustrates that when comparing the ANN models with the optimized ANN models, most of the optimized ANN models outperform the original ANN models [11], [56]. Moreover, the advantage of optimized ANNs is not apparent when the optimization algorithm varies. For example, in literature [30], [56], the performance of ANN optimized by ICA is better than ANN optimized by PSO. However, in literature [39], an opposite conclusion is drawn: the performance of PSO-ANN is better than that of ICA-ANN.

In addition, Table 7 demonstrates that the performance of ANNs always outdoes that of statistical methods, including MRA, LRM, SPSS, and MARS. Moghaddasi *et al.* have obtained a similar conclusion before [20].

The performance of the ANFIS model is better than the ANN model in two cases. Besides, the comparison can obtain opposite results when comparing SVM with the ANNs. However, the conclusion cannot be decided yet because of a lack of datasets. Nevertheless, the abovementioned conclusions can provide a reference in the tunnel engineering field.

TABLE 8. The review results of 61 published papers.

AF	RE	Model	Training set number	Validation set number	Test set number	Hidden layers number	N_i-N_h-N_o	α	β	n	Transfer function	Training algorithm	Performance
I	[6]	BPNN	328 (92.1%)		28 (7.9%)	1	11-24-3					BPA	0.000-0.0356(R^2) 1264-7664(MSE) 26.5-70.0(MAE) 0.320-0.401(R)
		MNN										BPA	0.575(R)
	[47]	BPNN				1	13-20-1			2000		BPA	7.33(RMSE)
	[100]	BPNN				2	6-5-9-1	0.05		3500	LOGSIG	BPA	15%(SSRE)
	[19]	MLP				2	14-12-6-1	0.7	0.5	10^4	TANSIG	BPA	0.6806(R^2) 41.65%(PE)
	[101]	BPNN +GIS				1	7-15-1	0.01	0.01	5000	SIG	BPA	96.06%(PA)
	[102]	BPNN	35(85.4%)		6(14.6%)		9-NM-1		0.9			BPA	2.46%(PE)
	[29]	BPNN	262(60.6%)		170(39.4%)	2	11-7-7-1			1000	SIG-SIG-SIG	BPA	7.96%(RMSE)
	[21]	ANN	40(81.6%)		9(18.4%)	1	13-10-1	0.01		200	SIG	CGA	4.45(RMSE) 3.2925(MAE) 0.7949(R^2) 0.89443(R)
		WNN	40(81.6%)		9(18.4%)		13-7-1				DWF	CGA	3.8719(RMSE) 3.1068(MAE) 0.8447(R^2) 0.9562(R)
	[28]	ANN	1225(70%)		215(30%)	2	12-20-20-1	0.1	-	200	LOGSIG	LMBP	0.00005(RMSE)
	[103]	BPNN	101(89.4%)		12(10.6%)	3	47-47-47-47-2	0.1	0.9	5922	LOGSIG- LOGSIG- LOGSIG- LOGSIG	BPA	22.9% (AIER)
	[82]	BPNN				2	9-36-30-1	0.3	0.9	3000	LOGSIG	BPA	-
	[42]	ANN	133(83.1%)		27(16.9%)	1	6-15-1	0.5	0.6	500	TANSIG- TANSIG	LMA	
	[22]	ANN	66%		33%	1	18-9-1			18	LOGSIG	BPA	0.8031(R^2) 13.0(RMSE)
		SVM											0.9682(R^2) 12.8(RMSE)
		GP											0.9858(R^2) 35.6(RMSE)
	[83]	ANNFF+ SVMFF				1	NM-5-NM					SCGA	
	[104]	PSO-ANN	33(75%)		11(25%)	1	10-13-2					PSO	0.926(R^2) 0.149(RMSE)
	[84]	MLP	11(64.7%)		6(35.3%)	1	8-19-1	0.01	0.9	1000	TANSIG- PURELIN	BPA	0.84(R) 1.99(RMSE) -1.3(ME) 10.31(AIC)
		MRA											0.72(R) 2.97(RMSE) 1.57(ME) 15.07(AIC)
	[81]	ANN	114(80%)		29(20%)	1	3-4-1					LMA	0.940(R^2) 0.064(RMSE)
		PSO-ANN				1	2-5-1						0.968(R^2) 0.052(RMSE)
	[98]	ANN	48(70%)	10(15%)	10(15%)	2	7-4-6-1				TANSIG- TANSIG- PURELIN	BPA	5.089(σ) 1.927(MSE) 3.423(MAE) 5.099(RMSE) 0.274(RRMSE) 0.142(MOE) 0.860(R^2)
		ANFIS+ CFT											4.044-4.573(σ) 9.29-24.89(MSE) 2.76-2.87(MAE) 4.11- 4.77 (RMSE) 0.230-0.296 (RRMSE) 0.12-0.15(MOE) 0.896-0.913(R^2)
	[63]	RRNN+SM +GPOD				2	1-10-10-1				LOGSIG- POSLIN	LMA	
		MRNN				1	1-7-1				TANSIG- PURELIN	LMA	
	[49]	PSO-BPNN	83.33%		16.67%							BPA	0.02051(MSE) 0.1432(RMSE) 0.612%(MAPE)
		PSO-SVR+ PSO-ELM										PSO	
	[99]	RNN	16(80%)		4(20%)	2	1-10-5-1						0.728%(ARE)
		TL+ SVM											0.281%-1.753% (ARE)
	[25]	ANN	152(70%)	32(15%)	32(15%)					13		LMA	

TABLE 8. ***(Continued.)*** **The review results of 61 published papers.**

AF	RE	Model	Training set number	Validation set number	Test set number	Hidden layers number	N_i-N_h-N_o	α	β	n	Transfer function	Training algorithm	Performance
I	[5]	BPNN	70%		30%	2	12-20-30-4	0.2		300	LOGSIG	LMA	96.45%(VAF) 0.00017(MSE) 0.0035(MABE) 0.9778(R^2)
		MRA+ FLM											61.82%-97.22% (VAF) 0.00014-0.00912 (MSE) 0.0031-0.0965 (MABE) 0.6532-.982(R^2)
	[20]	ANN	114(80%)		29(20%)	1	3-4-1					BPA	0.9377(R^2) 93.77%(VAF) 0.062(RMSE)
		ICA-ANN										ICA	0.9729(R^2) 97.29%(VAF) 0.045(RMSE)
		LMRA											0.9036(R^2) 90.36%(VAF) 0.086(RMSE)
II	[54]	ANN+UD	55(64.7%)		30(35.3%)	1	*7-20-1*				LOGSIG-PURELIN	BPA	
	[7]	BPNN	165(67%)		55(33%)	1	13-13-1	0.6	0.5	600000	SIG	BPA	0.1123(RMSE)
		BPNN	190(76%)		60(24%)	1	14-17-1						0.1491(RMSE)
	[56]	MLP	70%	15%	15%	2	15-5-10-1				TANSIG	BPA	99.48%(R^2) 0.03883(RMSE) 0.02825(MAE)
						2	17-5-15-1						99.91%(R^2) 0.1793(RMSE) 0.1252(MAE)
		RBFNN				1	15-5-1					RBF	99.21%(R^2) 0.0506(RMSE) 0.0409(MAE)
						2	17-3-12-1						93.18%(R^2) 1.5581(RMSE) 1.0781(MAE)
	[53]	BPNN	162(75%)		54(25%)	1	NM-8-NM				TANSIG-PURELIN	BPA	0.999(R^2)
		LRM											0.960(R^2)
	[55]	BPNN	80%		20%	2	9-7-6-1	0.1	0.001	300	TANSIG-TANSIG-PURELIN	BPA	0.172(MSE)
III	[58]	BPNN	121(80.1%)		30(19.9%)	1	4-8-1	0.1	0.95		TANSIG	BPA	0.104(RMSE) 69.188(VAF) 0.85(R)
	[8]	ANN	8(72.7%)		3(27.3%)	2	8-9-4-1			5000	TANSIG-PURELIN	LMA	$1.4*10^{-27}$ (MSE)
	[57]	BPNN	52(54.7%)	20(21.1%)	23(24.2%)	1	7-4-4 7-4-2	0.2	0.8		SIG	BPA	0.87-0.99(R^2) 0.38-2.54 (RMSE) 0.52-1.54 (MAE)
		NMRA											0.119(RMSE) 61.5(VAF) 0.79(R)
	[30]	ANN	80%		20%	1	7-11-1				SIG	LMA	0.666(R^2) 0.071(RMSE) 66.148(VAF)
		PSO-ANN											0.905(R^2) 0.034(RMSE) 66.148(VAF)
		ICA-ANN											0.912(R^2) 0.035(RMSE) 91.194(VAF)
	[43]	MLP+KSOFM	60%	20%	20%	1	3-14-1	-	-		TANSIG-TANSIG	LMA	0.973(R) 5.494(MSE)
	[62]	Hybrid SM (RNN +PSO)	100(66.7%)	-	50(33.3%)	1	6-20-1	-	-	-	SIG	PSO	3.5% (RRMSE)
	[59]	ANN	31(79.5%)		8(20.5%)	3	*4-2-4-1-1*						0.998(R^2)
		SPSS											0.668(R^2)
	[60]	ANN	-	-	-	1	3-3-1	-	-	199	TANSIG-PURELIN	LMA	0.88(R^2)
		ANN					4-4-1			21	LOGSIG-PURELIN		0.88(R^2)
		LMRA											0.70(R^2)
	[61]	ANN											0.92545(R) 0.91522(R^2) 0.95183(RMSE)
		SVM											0.978(R^2) 0.4849(RMSE)
	[37]	ANN	14(58.4%)	5(20.8%)	5(20.8%)	1	2-3-1			50	LOGSIG	LMBP	1.062(MSE)
	[39]	ANN	80%		20%	1	8-12-1					LMA	0.706(R^2)
		PSO-ANN											0.961(R^2)
		ICA-ANN											0.951(R^2)

TABLE 8. ***(Continued.)*** **The review results of 61 published papers.**

AF	RE	Model	Training set number	Validation set number	Test set number	Hidden layers number	N_i-N_h-N_o	α	β	n	Transfer function	Training algorithm	Performance
Ⅲ	[31]	ANN	80%		20%	1	*4-10-1*				TANSIG-PURELIN	BPA	0.987(R^2) 98.7%(VAF) 1.183(RMSE) 0.745(MAPE)
		MRA											0.965(R^2) 96.48%(VAF) 1.84(RMSE) 1.545(MAPE)
	[64]	MLP	90%		10%	1		0.3	0.2	500			0.877(R) 11.158(MAE) 17.318(RMSE) 47.75%(RAE) 48.45%(RRSE)
		ZeroR +RF +GP +LIR +LRM											-0.187-0.770(R) 10.567-23.367(MAE) 22.85-35.75(RMSE) 45.22%-100%(RAE) 63.9%- 100%(RRSE)
Ⅳ	[24]	ANN	70%		30%	2	NM-20-7-NM	0.01		500	ReLU	BPA	0.212(MSE)
		XGBoost+ CatBoost+ RF+SVR+ KNN+DT +BLR											0.0581-0.2685 (MSE)
	[65]	BPNN	5057 (78.8%)		1357 (21.2%)	2	9-6-3-1		0.9		TANSIG	LMBP	0.989(R^2)
	[9]	BPNN	92(70%)		39(30%)	3	6-12-14-16-1			200		SCGA	0.884(R)
	[66]	ANN	800(94.1%)		50(5.9%)	1	12-75-4	0.01		200		BPA	$7.62*10^{-6}$(MSE)
Ⅴ	[68]	ANN	80%		0.2	1	9-7-1					LMA	0.8987(R^2) 0.0915(RMSE)
		ABC-ANN										BPA	0.9428(R^2) 0.0668(RMSE)
	[18]	ANN	39(80%)		10(20%)	2	6-13-5-1			1000	SIG-TANSIG-LIN	BPA	0.1(MSE) 0.945(R^2)
		MRA											0.694-0.708(R^2)
	[38]	ANN	80%		20%	1	7-10-1					BPA	70.319(VAF) 0.693(R^2) 0.108(RMSE)
		GA-ANN										GA	88.030(VAF) 0.881(R^2) 0.074(RMSE)
	[40]	ANN				1	8-8-1					LMA	0.923(R^2) 0.4277(RMSE)
		ABC-ANN											
	[67]	ANN	232(86.9%)		35(13.1%)	2	5-6-3-1				TANSIG-TANSIG-SIG	BPA	4.64(MSE) 0.93(R^2) 2.15(RMSE)
		MRA+FLM +SVM +ANFIS											0.84-0.97(R^2) 1.38-3.30 (RMSE)
Ⅵ	[35]	MLP	234(60%)	60~78 (15%~20%)	88~96 (20%~25%)	2	8-20-26-1	0.05	0.01	200	TANSIG-LOGSIG-PURELIN	LMBP	95.81%(VAF) 0.29(RMSE) 0.13(RRMSE) 0.976(R^2)
		MARS											94.26%(VAF) 0.42(RMSE) 0.18(RRMSE) 0.962(R^2)
	[11]	MLP	36(60%)	12(20%)	12(20%)	2	9-35-28-1	0.05	0.01	300	TANSIG-LOGSIG-PURELIN	BPA	0.9358(R^2) 0.084(MSEREG)
		RBFNN	70%		30%						GF	RBF	0.645(R^2) 1.972(MSEREG)
		MRA											0.352(R^2) 9.431(MSEREG)
	[69]	MLP	60%	25%	15%	3	7-10-6-4-1				TANSIG-TANSIG-LOGSIG-PURELIN	LMA	0.0611(RMSE)
		SPSS											0.830(R^2)
	[36]	ANN	60%	20%	20%	2	9-35-28-1	0.05	0.01	300	TANSIG-LOGSIG-PURELIN	LMA	0.872(R^2) 0.631(MSE)
		SVM											0.965(R^2) 0.143(MSE)
Ⅶ	[12]	MLP	70%	10%	20%	2	5-7-4-1				TANSIG	BPA	0.041(RMSE)
	[10]	RBFNN				1	7-4-1				GF	RBF	0.61(MAE)
	[41]	ICA-ANN	80%		20%	1	6-9-1				LIN or SIG	BPA	0.958(R^2) 0.045(RMSE)
		PSO-ANN											0.959(R^2) 0.044(RMSE)
		GA-ANN											0.932(R^2) 0.058(RMSE)

TABLE 8. ***(Continued.)*** **The review results of 61 published papers.**

AF	RE	Model	Training set number	Validation set number	Test set number	Hidden layers number	N_i-N_h-N_o	α	β	n	Transfer function	Training algorithm	Performance
Ⅶ	[14]	ANN					9-NM-1						
	[70]	ANN	70%	15%	15%	1	6-15-2				TANSIG	LMA	0.93-0.95(R)
		ANN				1	6-29-2						0.005-0.054(MSE) 0.052-0.181(MAE)
		SVM +KNN +BNC+DT											
	[71]	PNN	83(89.2%)		10(10.8%)		6-NM-1						

Note:
a) In the AF column, I: Tunneling-induced settlement, Ⅱ: The stability of underground structures, Ⅲ: Roadheader performance and TBM performance, Ⅳ: Geological conditions, Ⅴ: Overbreak prediction, Ⅵ: Tunnel convergence, Ⅶ: Other applications.
b) The first and last data in the column "N_i-N_h-N_o" means the neuron numbers in the input, output layer, respectively. The several middle data in this column means the neuron numbers in the hidden layer(s). For example, 47-47-47-47-2 means that there are 47 and 2 neurons in the input, output layers, respectively. Moreover, there are 47, 47, 47 neurons in the first, second, third hidden layer, respectively.

VI. CONCLUSIONS AND FUTURE WORKS

This paper reviews the based-ANN models and optimized-ANN models utilized in tunneling engineering problems. The characteristics and modeling process of the ANNs are described; the main ANN types are introduced. Additionally, the application area of the ANNs in tunnel engineering is divided into several fields, including tunneling-induced settlement, the stability of underground structures, the performance of roadheaders and TBMs, the prediction of geological conditions, the prediction of overbreak, tunnel convergence and so forth. The characteristics of these related references have been discussed and the following major conclusions are reached:

- The average percentage of the training set, validation set, and test set is 74.7%, 3.94%, and 21.34%, respectively.
- In most cases, one hidden layer is capable of solving linear problems. Two hidden layers are enough to solve nonlinear problems. More hidden layers may cause issues like huge calculation.
- The determination of the learning rate and the momentum coefficient should be determined together. The magnitude orders of these two factors are always set to be the same. Additionally, the initial training epochs can be set to 1500 and then decided by the trial and error method.
- It is recommended that the SIG, including the TANSIG and LOGSIG, can be firstly tried for the hidden layers, and the PURELIN functions can be firstly tried for the output layers.
- BPA and LMA are used to train the ANNs in most cases. However, the BPA may be trapped in local minima; this kind of limitation calls for optimization. As a result, algorithms such as ICA, PSO, and GA have been utilized to optimize the original ANNs to obtain better prediction results.
- Most of the optimized ANN models outperform the original ANN models. The advantage of optimized ANNs is not apparent when the optimization algorithm varies. Additionally, the performance of ANNs always better than that of statistical methods.

Note that this research has potential limitations. Depending on the search criteria, there is no guarantee that all relevant literature can be searched. Nevertheless, several suggestions for future works can be proposed according to the review results as follows: (1) it is recommended to set the ratio of the training set to the test set to 3:1 in the tunneling-related research. (2) The usage of optimization algorithms in the ANN models is suggested in the future to prevent trapping in local minima and obtain a better performance. There may be differences between the performance of different optimized ANN models such as PSO-ANN, ICA-ANN, GA-ANN, and ABC-ANN. Thus it is meaningful to compare the performance of different optimized ANN models applied in various problems. (3) The data amount is one of the most critical aspects of the application of ANNs. More data can bring more precision to the model. Therefore, big data and data mining will lead to an application boom in the engineering field.

APPENDIX

See Table 8.

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