Journal of Engineering Science and Technology Review 12 (5) (2019) 75 - 90

JOURNAL OF
Engineering Science and Technology Review

www.jestr.org

Review Article

The Applications and Future Perspectives of Adaptive Neuro-Fuzzy Inference System in Road Embankment Stability

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Received 12 May 2019; Accepted 11 October 2019

Abstract

The stability of road embankment is influenced by two main factors, namely slope stability and settlement. The use of an adaptive neuro-fuzzy inference system (ANFIS) has received encouraging responses over the last decade in various research areas. This paper aims to elaborate on the previous study on the application of ANFIS to predict factors that affect the stability of road embankment. Additionally, study reports on optimization techniques using ANFIS approach such as genetic algorithms (GA), differential evolution (DE), particle swarm optimization (PSO), shuffled frog leaping algorithm (SFLA) and satin bowerbird optimization algorithm (SBO) is also discussed. It is observed that most researchers developed ANFIS models to predict soil properties. We thus present proposals for future research. Overall, this study highlights the need for ANFIS to predict the stability of road embankment. Interestingly, we find that researchers successfully use the ANFIS model with the ability to predict with acceptable accuracy. Nevertheless, our findings also revealed that no researchers had done the use of ANFIS to predict slope stability and settlement.

Keywords: Road embankment, Slope stability, Settlement, Optimization techniques, ANFIS.

1. Introduction

Road construction involves a lot of cutting and land reclamation work. Land reclamation activities require compaction processes to meet the desired performance requirements. The land that has been compacted through the reclamation process is known as an embankment. It is used when the vertical alignment of the road needs to be raised from the existing ground level to meet the design standards to avoid damage to the surface of the road. Its construction method is the longest construction technology but has always had big engineering challenges in the design process. One of the challenges occurs when it is built on soft soils. Soft soil has a large settlement rate when loaded [1–4]. Slope stability and settlement is a major factor in determining the stability of the embankment. This is supported by Al-Homoud and Tanash [5] that reveals both these factors in the assessment of earth dam stability. Recently, many researchers have reported the correlation of slope stability [6–8] and settlement [9–11] with embankment stability assessment.

Usually, at the design stage, an engineer needs to calculate the stability of the embankment using the limit equilibrium method (LEM) [12–14] or finite element method (FEM) [15–17] which has the advantage of using completely combined formulation to solve problems of settlement and slope stability. They make various assumptions and theories on some parameters due to time constraints and costs [18,19]. Therefore, the extent of their knowledge greatly affects the accuracy of predictions. This practice may result in the uncertainty of prediction accuracy compared to the actual stability on site. This problem can be solved by using the correct prediction methods and approaches.

The response to the use of artificial intelligence (AI) in various fields has been encouraging since its introduction in 1956 [20]. This is because its nonlinear prediction ability is better compared to other models. Most of the AI methods are neural networks, fuzzy logic (FL), genetic programming and hybrid approaches such as fuzzy genetic systems and neuro-fuzzy. AI core methodology such as ANFIS is a calculation model for solving complex problems for decision making. ANFIS is a combination of a fuzzy inference system (FIS) and artificial neural network (ANN) [21]. FIS is a rule-based system consisting of three conceptual components, namely rule base, data base and inference system. This combination is due to the advantages of FIS that is able to handle linguistic expressions while the ANN can learn by itself [22]. Additionally, it is a processing tool used for complex problem modelling, where relationships between variable models are unknown. It allows fuzzy systems to study the parameters by using adaptive backpropagation algorithm [21]. FIS can be generated from MATLAB software using the FL toolbox.

Al-Mahasneh et al. [23] highlight the advantages and suitability of using ANFIS for model development. Among the benefits highlighted is the ANFIS model's ability to predict accurately when it involves a known and fully understood physical relationship. In addition to producing high prediction accuracy, it also offers reasonable advantages

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ISSN: 1791-2377
doi:10.25103/jestr.125.08

in terms of simplicity, adaptability, robustness and seeks to a good generalize [24,25]. The past century has seen the rapid development of ANFIS models in geotechnical engineering for predictive purposes [26]. The main purpose of prediction is accurate and credible results [27]. Optimized fuzzy MFs is one of the right decision-making approaches [28]. While researchers often use classic approaches such as the backpropagation (BP) and the least-squares (LS) approaches, some suggest the evolution of learning algorithms in their studies. The traditional method is simple but in practice has many problems [29]. Among these problems are their convergence to a local minimum and the acceleration rate that is sensitive to the learning process [30]. Therefore, the evolutionary algorithm approach is believed to be able to solve the problem and improve the accuracy of prediction.

Over the past few years, predictions using the ANFIS approach have been relatively successful in modelling related to embankment stability predictions. It was first used in this field of study in 2002 to predict post-stage rockfill dams [31]. However, the literature review confirms that no specific study reported ANFIS's use to predict the slope stability and settlement of road embankment. Most of the existing studies are only done in a small number of areas, with the tendency to focus on soil properties related to embankment stability. In addition to sharing knowledge on the structure and model of ANFIS, there are two main objectives of this study: (i) To summarise previous studies on the development of ANFIS model to predict road embankment stability, (ii) To present the need for further research with the ANFIS approach for a more comprehensive prediction of road embankment stability. Besides, this paper is driven by the need to consider optimization techniques in ANFIS. The results of this research are expected to contribute ideas and findings to this growing field by exploring the ANFIS approach in predicting the stability of road embankment.

2. Stability of Road Embankment

An embankment refers to the amount of soil or fills material laid to construct the road on the existing ground surface, as shown in Fig. 1. It consists of a series of compacted layers to bear the load directly from the subgrade layer and distribute the traffic load to the foundation [32]. Investigation and design are two important phases of work take place during the construction of road embankments. Investigation work is intended to investigate the effects of land characteristics on the site to design and construction. It encompasses the collection of information regarding the subsoil of the embankment that needs to be identified before the design work is carried out. This is to ensure safe and economical construction of the embankment.

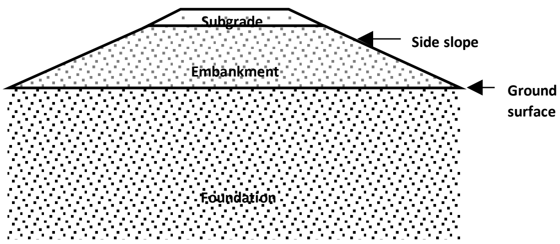

Fig. 1. Definition of embankment

The embankment component consists of a foundation and side slope that determines the degree of stability. The embankment foundation is an essential component during the design process and may be stable or unstable. This is because these components bear all the load. Soft soil such as clay and silt, as well as influenced by water, will cause instability [33–35]. Soft ground is too weak and unable to bear the load from the road [36]. This can lead to aggressive movements of soil at the embankments and consequently, large settlements and slope failures. For this reason, the embankment being constructed must be equipped with an inclinometer, settlement marker and piezometer for observe soil behaviour. This monitoring typically takes 3 to 12 months, depending on the critical level of ground movement. Additionally, this movement can occur in areas exposed to permafrost [37] and earthquake [38]. There are some researchers conducting stability studies of the embankment using ANFIS approach to measure frost heaving [39], liquefaction [40,41] and dynamic properties [42].

Typically embankments are built with varying altitudes [43–45] and fill material [46–48] according to design requirements. Geometry and materials data determine the stability performance of side slopes. The slope angle and height are geometric data used in numerical method simulations, which should be proposed prior to the design process. However, the fill materials require the determination of a large number of parameters, i.e. physical and engineering properties compared to geometric data, as shown in Table 1 [49,50]. These parameters significantly affect the workability and stability of the embankment. Some of these parameters are used in LEM and FEM to analyse settlement behaviour and embankment slope stability. Therefore, embankment stability should refer to two main criteria settlement and slope stability, as shown in Fig. 2. The slope stability of the embankment analysis is based on the factor of safety (FOS) value [51,52] and lateral deformation [53] while the settlement is based on vertical deformation [54,55].

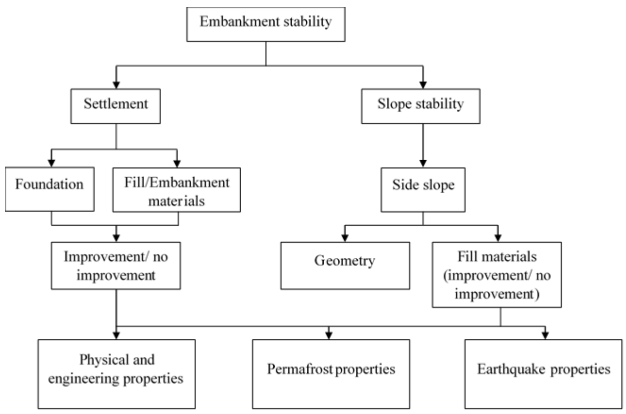

Fig. 2. Factor of embankment stability

Table 1. Parameters fill material and test procedures.

Properties	Test method
Gradation	Particle size distribution
Unit weight	Unit weight and voids in aggregate Relative density of cohesionless soils Maximum index density of soils
Specific gravity	Specific gravity of soils
Corrosion resistance	Field measurement of soil resistivity Pore water extraction
Moisture-density characteristics	Moisture-density relations
Compacted density (field)	Density of soil in place
Permeability	Permeability of soils
Shear strength	Direct shear test Triaxial test
Bearing capacity	California bearing ratio
Compressibility	One-dimensional consolidation

2.1. Recent case studies on the main factors of embankment stability.

The literature emphasized the importance of settlement and slope stability to determine the degree of embankment stability, especially after construction. These two major factors have been widely investigated as it is an essential element in subgrade construction workability [56–62]. It is evident in some case studies that confirm the importance of these factors in the road embankment stability. Throughout 2018, we find three case studies on settlement problems. Among them were Michalowski et al. [56], who conducted an investigation into the failure of a road embankment built on a section on the European route E372 in eastern Poland. During the construction of the embankment, excessive settlements resulted in the reconstruction of the embankment. However, the excessive settlement still occurring even after the reconstruction, especially in areas with culverts where displacement reaching 20 cm were found within several months.

In addition, Yao et al. [57] also reported a settlement problem on the runway of Chengde Airport, Hebei province in China. The track was built over 2400 m above the embankment which includes silty clay soil. A settlement rate data of 18 times were recorded over 298 days, with the cumulative settlement reading at the last observation is 101.972 mm. Stark et al. [58] investigated of the same problem through the analysis of road design failure on section 91 m of a connecting ramp embankment between westbound Interstate-76 and southbound Interstate-71 in Medina County, Ohio. This failure led to the Ohio Department of Transportation decided to replace the embankment with reinforced concrete bridges costing over $4.5 million.

Slope failure can cause landslides, which could cause severe damage to the road surface. The landslide occurred in the Phewa Lake area watershed in Western Nepal was reported by Vuillez et al. [59]. A total of 23 landslides along the road were reported after heavy rains in 2015. More recently, in another study, Bednarczyk [60] reported that 15 landslides occurred along the Szymbark-Szalowa road near Gorlice (SE Poland). Another case study took place at National Highway-109 in Uttarakhand, India. Pradhan et al. [61] reported that frequent occurrences of landslides along the roads during maintenance and upgrading of roads were running. There are also incidents of slope failure occurring during construction works. This similar case occurs on the Sir Solomon Hochoy Highway Extension Project along the Caribbean coastline of Trinidad and Tobago. According to Lee et al. [62], wick drains and surcharges used to stabilize the embankment may result in cracks and slope movements when subsequent fill lift is placed.

3. Overview of the Structure of ANFIS Model

The fuzzy logic system (FL) plays an important role to induce rules of observation [63]. FIS is the primary unit of the FL system that makes the decision [64]. This means FIS is the actual mapping process from a given input to output, using FL. In addition, FL has the ability to alter the qualitative aspects of human knowledge and insights into the accurate process of quantitative analysis [65]. However, FL does not have a clear method that can be used as a guide in the human transformation and takes a long time to adjust membership function (MF) [66]. Therefore, the ANN automatically adjusts the MF and reduces the error rate in the determination of rules in FL. Generally, there are six important terms in FL namely fuzzy system (FS), fuzzy inference (FI), fuzzy sets, fuzzy rules (FR), membership function (MF), and defuzzification. These six terms carry different definitions, relationships and importance based on the work done by the researchers. FS was introduced as a tool to represent and manipulate inaccurate but rather fuzzy data [67].

There are four components in FS, i.e. fuzzy rule base, fuzzifier process, inference engine and a defuzzification. The rule base contains the IF-THEN rules that include linguistic reasoning. The basis of this rule is used in inference engines for fuzzy sets to obtain a fuzzy outcome [68]. Fuzzification is the process to classify numerical measurements into fuzzy sets. It can alter crisp or fuzzy set data into linguistic values that suit the definition of linguistic variables the types of MF. FI is the process of formulating the mapping of the input given to output using FL. This mapping function is to provide the basis from which decisions can be made. This process involves three components, namely MF, IF-THEN rules and FL operators. Fuzzy sets are sets that have no crisp and contain a partial degree of membership elements. Instead, FR is a set of linguistic statements that define the relationship between input and output in FS [69]. There are two commonly used methods in FR to produce an aggregation of FR, max-min inference method and max-product method. The MF is the curve that determines how each point in the input space is mapped to the membership value or degree of membership of 0 to 1. In other words, it will map each element of the input variable to the membership grade. Then, the inference engine will perform a budget estimation to achieve the desired strategy. Due to producing a non-fuzzy result or a crisp output by a strategy, defuzzification needs to be used [70]. Defuzzification is the conversion from fuzzy quantities to exact quantities. The selection of defuzzification technique is important as it can significantly affect the speed and accuracy of the model. Many methods can be used to facilitate this conversion such as weighted average, centroid, mean-max membership and others. However, the commonly used defuzzification strategy is the centroid of the area [71–73] as is the advantage that can be used for all activated MF of the conclusions [74].

The combination of human thinking styles such as fuzzy systems with the learning and connectionist structure of neural networks is the basic idea of neuro-fuzzy systems [21]. This network simulates the FIS represented by the simple fuzzy IF-THEN rules which have the learning ability to estimate non-linear functions [75]. FIS will work when inputs containing the actual values are converted to fuzzy values via MF by using the fuzzification process [76]. Generally, fuzzy values range from 0 to 1. The basic rules and databases are important elements for decision making, as described through the FIS structure in Fig. 3. The database usually contains definitions such as information about fuzzy set parameters with defined functions for each existing linguistic variable [77]. Typically, the database development includes a determining the total linguistic value to be used for each linguistic variable, defining a universe and creating MF. There are three types of FIS used by researchers such as Mamdani [78–81], Sugeno [82–84] and Tsukamoto [85–87] fuzzy models. The differences in the three models are described in Table 2. However, the Sugeno model is more widely used compared to others.

To facilitate understanding, assume ANFIS architecture has two variable inputs: X_1 and X_2 and output f, as shown in Fig. 4. It has a function similar to the Sugeno FIS model. The two methods used in the IF-THEN rules are described as follows:

Rule 1= If x is A_1 and y is B_1 Then $f_1 = p_1x + q_1x + r_1$

Rule 2= If x is A_2 and y is B_2 Then $f_2 = p_2y + q_2y + r_2$

where A_1, A_2 and B_1, B_2 are MF for each input X_1 and X_2 while p_1, q_1, r_1 and p_2, q_2, r_2 are linear parameters in part-THEN or consequent parameters of the rule.

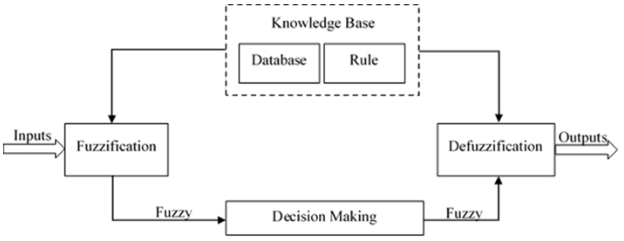

Fig. 3. Fuzzy inference system.

Table 2. The differences of three FIS model design.

Type of FIS	Description of the method of calculation of output
Mamdani	Giving the fuzzy output that needs defuzzified.
Sugeno	Using a function that gives the real number as an output.
Tsukamoto	Use a monotonous function that assigns a real number as an output.

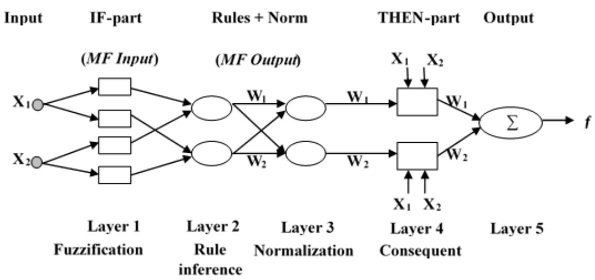

Fig. 4. Typical ANFIS architecture.

Based on Fig. 4, the ANFIS architecture has five layers with two shapes-rectangles and circles. A rectangular shape represents neurons with an adaptive node in the network, while the parameters will change during the training process. The shape of the circle depicts the neuron with an unknown parameter, i.e. fixed node.

In the first layer, the adaptive node represents MF fuzzy. Based on Eqs. 1 to 8, O_L represents the output of the node, i.e. i is the degree of MF while x or y is the input to the node.

$$O_{1,i} = \mu_{Ai}(x) \qquad i = 1,2 \tag{1}$$

$$O_{1,i} = \mu_{Bi-2}(y) \qquad i = 3,4 \tag{2}$$

where A_i and B_i are linguistic labels associated with the neuronal function, it can be any suitable fuzzy sets in parametric form. Links within this network indicate the direction of information flow between neurons and no weights provided. Bell-shaped as Eq. 3 and Gaussian MF as Eq. 4 are often used as MF inputs.

$$\mu_{(x)} = \frac{1}{1+\left[\left(\frac{x-c}{a}\right)^2\right]^b} \tag{3}$$

$$\mu_{(x)} = exp\left[-\left(\frac{x-c}{2a}\right)^2\right] \tag{4}$$

where a, b and c are MF parameters that can change shape. Also, these parameters are known as premise parameters. Output for the first layer is the MF value that is evaluated for a set of input variables.

The second layer has a fixed node. This layer plays a role as a simple multiplier. Neuron output in this layer is the result of multiplying of the signal received through the neurons to be transmitted to the next neuron. Each neuron represents a firing strength for each rule. T-norm operators such as AND are used to get output while w_i is an output representing the firing strength of each rule, as shown in Eq. 5.

$$O_{2,i} = w_i = \mu_{Ai}(x)\,\mu_{Bi}(y) \qquad i = 1,2 \tag{5}$$

The neurons present in the third layer are fixed or nonadaptive. This layer will normalize the firing strength of the previous layer. The output of each neuron in this layer is as in Eq. 6.

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1+w_2} \qquad i = 1,2 \tag{6}$$

All nodes in the fourth layer are adaptive while the output of each neuron is the result of normalized firing strength and is defined as in Eq. 7. This layer has three parameters:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \qquad i = 1,2 \tag{7}$$

where w_i is the normalized firing strength from the third layer and the $(p_i x + q_i y + r_i)$ is a polynomial parameter in modifiable neurons. This parameter is also referred to as the consequent parameters. The fifth layer has only one neuron, fixed or nonadaptive. This layer serves to calculate the overall output as the sum of all signals received from the fourth layer node. The overall output of ANFIS is described in Eq. 8.

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{8}$$

ANFIS use flow charts commonly used for predictions, as shown in Fig. 5. The modelling process is divided into three steps, i.e. development, validation and testing. Due to implementing these steps, three sets of data are used for training, testing and validation. The set of training data is used to find the optimal FIS structure and to check the data set to minimise the difference between error bias and variance [88]. A set of test data is used to examine and evaluate trained ANFIS models. Also, a test data set can check the generic FIS generalisation capability.

The model is trained so that the results are obtained with minimum error, or training data error lies within the error tolerance, which is related to error size. Parameter selection and the correct set of training and test data are important to ensure that the model can be validated [89]. A difference in the set of test data compared to the set of training data can lead to the inability of the model capture any test data characteristics. Minimum test error can be reached at the first epoch. Overfitting serves to test trained FIS on training data against checking data. It will happen past the jump point. However, the training process that occurs until the jump point is reached can reduce testing error. In addition, the model validation process is the process in which the input vector testing data set is presented to the trained FIS model to observe the way this model predicts the value that corresponds to the output data set. This means this process demonstrates the performance of the model, which can then be analysed. By using checking data, the FIS model is expected to contain parameters related to the minimum checking data model error.

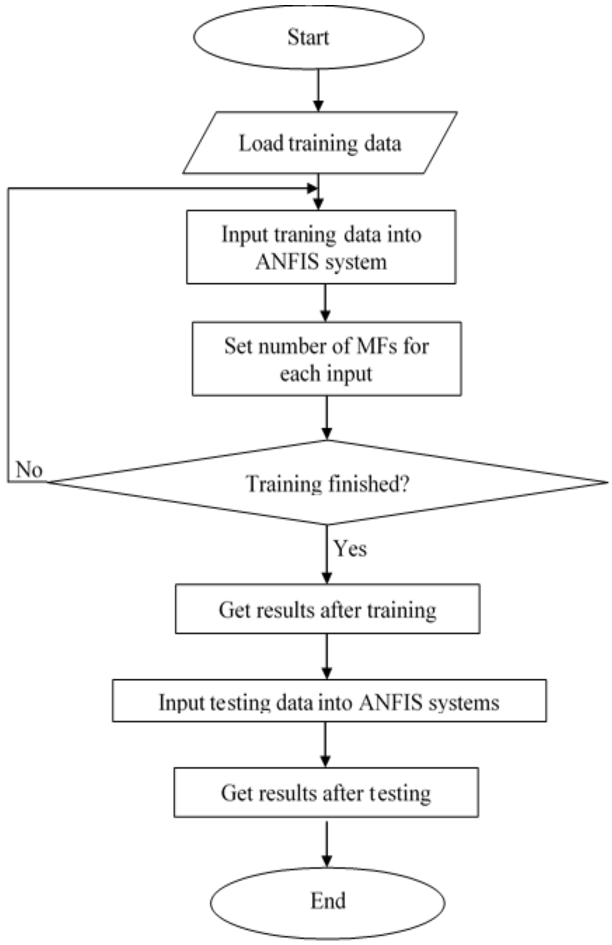

Fig. 5. ANFIS flow chart for prediction process.

The FIS generation involves the selection of model structures, i.e. by determining the number of MFs per input and output. Besides, the determination of the type and shape of the MF for the rule premise section is also performed. The grid and scatter partitioning [90] are the two methods used to generate MF. However, MATLAB software only offers grid partitioning (GP) and subtractive clustering (SC) methods [91]. GP divides the data space into smaller rectangular space called grid based on the number and type of MF [92]. When it is used, the uniformly divided grid defined by the MF with random parameter set is taken as the initial state of ANFIS. This grid will change as the parameter in MFs change during the training process [93]. Based on a survey, researchers often use this method with bell-shaped type MF because it offers many parameters that allow more degrees of freedom. SC is a clustering algorithm applied to categorize data into groups. It produces a centre of data cluster in the given data space [94]. This cluster center is the basis of fuzzy IF-THEN rules. In this case, the resulting MF is the first order Sugeno type while the MF on the premise is a gaussian type [28]. In addition, the number of fuzzy rules generated depends on the number of data clusters. The SC is different from GP in some aspects, including the number of inputs used. The SC can be used if the input number is greater than six as it can avoid the curse of dimensionality [91] problem.

3.1. Performance indices

The correlation coefficient (R), the coefficient of determination (R^2), the root mean square values (RMSE), the variance account for (VAF) and the mean squared error (MSE) are some performance index that is often used to check the performance of the prediction model. The performance of the model is assessed by comparing the output calculated against the actual data. The correlation coefficient is a statistical measure that measures the strength of the relative movement relationship between the two variables. As with Eq. 9, the correlation coefficient takes the value between -1.0 to 1.0. A high correlation value approaching 1.0 shows that this prediction model has good accuracy. A model with R values of more than 0.8 indicates a strong correlation between the measured values predicted [95]. The coefficient of determination, also known as the multiple correlation coefficient is the measure of the model's ability to predict or explain the results of linear regression. More specifically, as shown in Eq. 10, the proportionate variance in dependent variables with independent variables predicted or explained by linear regression. In general, a high R^2 value indicates that the model has a good prognosis. RMSE, as shown in Eq. 11 is also known as the root mean square deviation is a measure commonly used for the difference between the values predicted by the model. It works to aggregate these differences into one measure of predictive power. Low RMSE value indicates a highly accurate model. VAF such as Eq. 12 is often used to verify the accuracy of the model, by comparing the actual output to model output estimates. It means the VAF shows the level of difference between two sets of variance data: measured and predicted values. VAF value close to 100% shows small variability and, consequently better prediction capabilities. MSE as in Eq. 13 is the non-negative measure of the quality of the estimator's performance, and the value closer 0 is the best. Where, $y_{prd.i}$ is the predicted value, $y_{exp.i}$ is the measured value, y_m is the mean value, and N is the number of data.

$$R = \sqrt{1 - \frac{\sum_{i=1}^{N}\left(y_{prd.i} - y_{exp.i}\right)^2}{\sum_{i=1}^{N}\left(y_{prd.i} - y_m\right)^2}} \quad (9)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(y_{prd.i} - y_{exp.i}\right)^2}{\sum_{i=1}^{N}\left(y_{prd.i} - y_m\right)^2} \quad (10)$$

$$RMSE = \sqrt{\frac{\sum_{i=0}^{N}\left(y_{prd.i} - y_{exp.i}\right)^2}{N}} \quad (11)$$

$$VAF = \left[1 - \frac{var\left(y_{prd} - y_{exp}\right)}{var\left(y_{prd}\right)}\right] x100 \quad (12)$$

$$MSE = \frac{1}{N}\sum_{i=0}^{N}\left(\left|y_{prd.i} - y_{exp.i}\right|\right)^2 \quad (13)$$

4. Modelling of Road Embankment Stability

In this section, we summarise and review the factors that describe the stability of the road embankment in recent studies that use ANFIS approach. It covers the ANFIS model structure as well as the input and output parameters used by the researchers. Statistics on the number of researchers reporting on the use of the ANFIS model for research related to the stability of road embankment in recent years are presented in Fig. 6. As previously discussed, the main factors are a settlement and slope stability. Related factors are physical properties, engineering properties, permafrost properties, earthquake properties and others. A number of researchers have reported the physical properties of the ANFIS approach, which includes soil water content, soil compaction, internal soil stability and soil aggregates stability. Some other researchers report on engineering properties such as soil shear strength, soil bearing capacity, soil swelling and soil permeability. Besides, researchers who report permafrost properties include frost heaving, while soil liquefaction and dynamic soil properties are earthquake properties. Among the related factors are soil erosion and groundwater levels. Table 3 present the prediction input and output parameters.

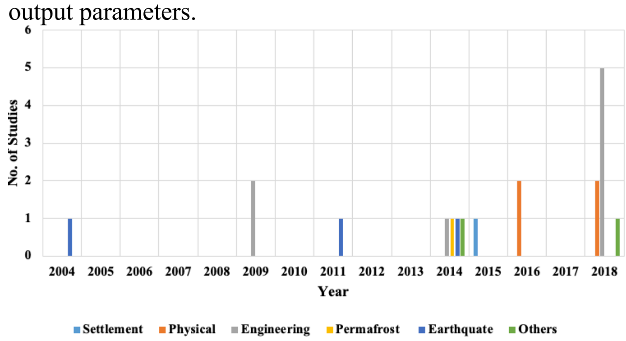

Fig. 6. Applications of ANFIS models for road embankment stability.

Table 3. A summary of investigations on ANFIS modeling relates to embankment stability.

Stability factors	Parameter inputs	Parameter outputs	The best evaluation indices	References
Settlement	*e, w, LL, PL, PI,* G_s	Compression index	*R*=0.900, RMSE=0.032	Demir [101]
Soil liquefaction	*N, fc,* σ_o*',CSR,* φ	Safety of factor	*R*=0.98, RMSE=0.27	Kayadelen [40]
Soil liquefaction	*N, fc, z,* $□_b$, *w*	Water table and earthquake magnitude	R^2=0.9979	Kumar et al. [41]
Soil compaction	*w,* $□_b$, *EC*	Soil cone index	R^2=0.979, RMSE=0.0621	Abbaspour-Gilandeh and Abbaspour-Gilandeh [104]
Soil water content	*PSD,* $□_b$, *n,* θ_r, θ_e	Saturated soil water content	R^2=0.5527, RMSE=0.0733	Fashi [103]
Swelling	*t,* h_{EPS}	Lateral swelling pressure, vertical swelling pressure	R^2=0.998, RMSE=3.052	Ikizler et al. [98]
Shear strength	*fc, Cc, LL,* $□_b$	Effective friction angle	*R*=0.890, RMSE=1.90	Kayadelen et al. [97]
Shear strength	σ_n, *MS, c,* φ	Unsaturated shear strength	R^2 (train)=0.9912, R^2=0.999	Jokar and Mirasi [106]
Shear strength	*PSD*	Unconfined compressive strength	R^2(train)=0.9868, R^2(valid)= 0.9848, R^2(test)=0.9941	Kalkan et al. [96]
Internal stability	*PSD,* c_u, c_c	Status of stability	RMSE (train)= 0.011, RMSE (test)= 0.027, RMSE(total)= 0.038	Xue and Xiao [102]
Aggregates stability	*CEC, pH, OM, fc, fd*	Geometric mean diameter, Mean weight diameter	R^2=0.97, RMSE=0.06 R^2=0.94, RMSE=0.05	Marashi et al. [105]
Dynamic soil properties	σ_3, *fc, rc*	Shear modulus, Damping ratio	R^2=1 R^2=1	Akbulut et al. [42]
Bearing capacity	*zc,* A_r, c_r	Bearing capacity of soft soil	R^2(train)=0.989, R^2(test)=0.960	Bunawan et al. [108]
Bearing capacity	*c,* D_c, l_c, d_s, φ_s	Bearing capacity of stone column	R^2(train)= 0.986, R^2(test)= 0.979 RMSE(train)= 2.06, RMSE (test)= 1.45	Das and Dey [109]
Bearing capacity	q_c, f_s, l_p, D_p	Bearing capacity of piles	R^2(train)= 0.970, R^2(test)= 0.960 RMSE(train)= 0.0594, RMSE (test)= 0.0647	Harandizadeh et al. [110]
Erosion	R_e, *K,* l_s, *S, C, P,* M_f	Soil erosion	R^2=0.8275, RMSE= 1.4276	Islam et al. [112]
Frost heaving	*w,* $□_d$, V_f, H_w, *PI,* S_c	Frost heaving ratio	*R*=0.987, RMSE= 0.382	Yiming et al. [39]
Permeability	M_c, σ_n, *c,* φ, θ_w, θ_s, s_r, u_e, *n*	Unsaturated soils permeability	R^2= 0.9605, RMSE= 1.63E−05m/s, VAF= 96.0531%	Jokar et al. [111]
Groundwater level	R_r, I_r, P_r	Groundwater level	R^2=0.96, RMSE= 0.02	Emamgholizadeh et al. [100]

Note: φ=friction angle, φ_s=friction angle of stone column, $□_b$=bulk unit weight, $□_d$=dry unit weight, θ_e= field capacity, θ_r=wilting point, θ_s=saturated volumetric water content, θ_w=volumetric water content, σ_o'=effective overburden stresses, σ_n= normal stress, σ_3=confining pressure, A_r=improvement area ratio, *c*=cohesion, c_c=coefficient of curvature, c_r= cohesion ratio, c_u=coefficient of uniformity *C*=vegetation cover and management factor, *Cc*=coarse content, d_s=spacing between the stone column, D_c= diameter of stone column, D_p=diameter of pile, *e*=void ratio, *fc*= finest content, *fd*=fractal dimension, f_s=sleeve friction, h_{EPS}=thickness of EPS geofoam, H_w=groundwater level, I_r=irrigation returned flow, *CEC*=cation exchange capacity, *CSR*=cyclic stress ratio, *EC*=electrical conductivity, *K*=soil erodibility factor, l_c=length of stone column, l_p=length of pile, l_s=slope length, *LL*=liquid limit, *n*=porosity, *N*=N-value(SPT), M_f=microbes factor, *MS*=matric suction, *OM*=organic matter, *P*=support practice factor, P_r=pumping rates, *PI*=plasticity index, *PL*=plastic limit, *PSD*=particle size distribution, q_c=cone tip resistance, *rc*=rubber content, R_e=rainfall erosivity factor, R_r=rainfall recharge, *S*=steepness factor, S_c=ion content, s_r=soil suction at residual water content conditions, *t*=time, u_e=air-entry value, V_f=frost penetration rate, *w*=moisture content, *z*=depth, *zc*=column height.

Research in this field began in 2004 by predicting earthquake properties, i.e. shear modulus and the damping coefficient of the sand samples. This study was conducted by Akbulut et al. [42] by comparing the statistical performance rating of three developed models, i.e. ANFIS, ANN and multiple regression analysis methods (MRM). The ANFIS model is trained using the hybrid learning algorithm approach. The SC method is used to determine the optimum number and form of FR. The statistical performance assessment for all three developed models is shown in Table 4. The results show that the ANFIS model is an alternative method that can predict more accurately compared to the ANN and MRM methods. The authors conclude that it can have an impact on efforts towards encouraging other researchers to use ANFIS in their study.

Table 4. Statistical performance for ANFIS model [42].

Models	R^2 (shear modulus)	R^2 (damping ratio)
ANFIS	1	1
ANN	0.84	0.65
MRM	0.72	0.63

After nearly five years without any development, two articles on the prediction of engineering properties were published in 2009. Among these reports is the purpose of predicting unconfined compression strength (UCS) of granular soils. Kalkan et al. [96] performed comparisons of the developed models of ANFIS and ANN. Both of these models use seven input parameters such as clay (%), fine silt (%), coarse silt (%), fine sand (%), medium sand (%), coarse sand (%) and gravel. A total of 84 soil samples with different particle size distribution were compacted at optimum water content. Both of these models were trained with 64 samples while 20 samples forecasted UCS. The SC method was used to determine the number and form of FR. The statistical performance of both models is shown in Table 5. The value of R^2 for UCS forecasts for ANFIS and ANN models were 0.99 and 0.86. The results show that ANFIS is the best model for predicting UCS.

Table 5. The performance indices of the ANFIS and ANN models developed [96].

Models	R^2
Traning	
ANFIS	0.9912
ANN	0.8637
Performance in the prediction	
ANFIS	0.999
ANN	0.8668

Kayadelen et al. [97] developed two Sugeno ANFIS models to predict the angle of shearing resistance of soils. ANFIS I model has 16 linear parameters, 16 nonlinear parameters, 55 neurons and 16 FR. ANFIS II model has eight linear parameters, 12 nonlinear parameters, 22 neurons and 2 FR. The SC and GP methods are used for the ANFIS I and ANFIS II models to generate the Gaussian MFs for each input variable. Input parameters used are the percentage of fine-grained the percentage of coarse-grained, liquid limit and bulk density. A total of 122 data sets were used, 75 for training, 32 for testing and 15 for validation. Due to optimize parameters, hybrid learning algorithms are used in both models. Based on statistical performance, ANFIS I model has a high accuracy prediction with an R-value of 0.89 compared to ANFIS II with 0.86. RMSE for ANFIS I and ANFIS II models are 1.90 and 2.06 respectively. The results of this study found that the ANFIS I model can be used for the prediction of the angle of shearing resistance of soils.

In the two years that follow, there was no development until in 2011, Kayadelen [40] developed two types of ANFIS models to predict the safety factor for liquefaction of soils. With the 569 sets of data provided, 400 data sets were used for training, and the remaining 169 data sets were performed for testing. The standard penetration test, percentage of finest content, effective overburden stresses, cyclic stress ratios and angle of shearing resistance are the ANFIS I model input parameters, while ANFIS II model consists of the standard penetration test, the percentage of finest content, cyclic stress ratios and angle of shearing resistance. The ANFIS I model has 72 linear parameters, 36 nonlinear parameters, 176 neurons and 72 FR. In contrast, the ANFIS II model has 81 linear parameters, 36 nonlinear parameters, 193 neurons and 81 FR. Based on the results obtained, all of these models give satisfactory agreement in terms of the statistical evaluation criteria. ANFIS model has the best R-value of 0.98. When the models are compared through RMSE, ANFIS II model has the lowest value of 0.21. The authors conclude that based on the assessment and from the statistical performance, it is clear that these two models have good prediction ability.

For almost three years thereafter, no researcher appeared to report research activities in this area. However, in 2014, more studies emerged with various findings presented. They are beginning with Ikizler et al. [98] who studied the engineering properties of swelling pressures of expansive soils using Sugeno's ANFIS model. Two ANFIS models were successfully developed. The ANFIS I model was developed to predict lateral swelling while ANFIS II model predicts vertical swelling. The FR of ANFIS I and ANFIS II are 12 and 16, respectively. Inputs for these two models are time and thickness of EPS geofoam. A total of 139 data sets are provided, of which 103 were randomly selected to be used for training purposes while 36 were used for testing. The ANFIS I model has MFs of 3 and 4 while ANFIS II has 4 Gaussian types that are found to yield the best results. After training the models, performance tests produced the same R^2 both models, i.e. 0.998. RMSE for ANFIS I and ANFIS II models are 3.052 and 3.25 respectively. This means that the ANFIS I model has better predictive capabilities than ANFIS II because of the lower RMSE value.

The prediction of permafrost properties reported by Yiming et al. [39] uses the ANFIS model to predict soil frost heaving. The model was developed with six inputs, 21 FRs using SC method and one output. The input parameters consist of initial water content, initial dry unit weight, frost penetration rate, groundwater level, plasticity index and ion content while frost heaving ratio is the output parameter. The ANFIS model is trained using hybrid learning algorithms namely BP and LS. This study has made comparisons of statistical performance between the ANFIS models and the backpropagation neural network. The result of the regression analysis namely, the value of R and RMSE for the ANFIS model are 0.987 and 0.382, respectively. Based on these results, the ANFIS model has a higher prediction accuracy than the backpropagation neural network model. The authors also suggest that ANFIS models can be the better choice and is a powerful tool for predicting frost heaving hazard in seasonally frozen regions.

Kumar et al. [41] successfully produced a report on predicting earthquake properties. In this study, the comparison of ANFIS model performance and multiple linear regression (MLR) was done to predict soil potential liquefaction. Five input parameters are used: depth, SPT-N value, bulk density, particle size finer than 0.075 mm and natural or field moisture content. The liquefaction potential assessment in this study uses the analytical method presented by Idriss and Boulanger [99] in 2006. The results of this method are used to develop prediction models using ANFIS, and MLR approaches. A variety of parameter values, i.e. earthquake magnitude (6.0, 7.0 and 8.0 in Richter scale) and water table (0, 2, 4, 6 and 8 in m from ground surface) are used for parametric studies. GP method with triangle type MF is used to generate FIS for input variables while MF linear type is used for output variables. The hybrid learning algorithm is used as an optimization technique for FIS training. Output parameters in the ANFIS model are designed to be answered in like or unlike format. Comparison of predictive performance among ANFIS models is shown in Table 6. Based on statistical performance, the ANFIS model has a better liquefaction potential than the MLR model. The authors conclude that the ANFIS model can be used effectively and highly reliable because of its more accurate prediction ability.

Table 6. Performance statistics of ANFIS and MLR models [41].

Water level (m)	Earthquake magnitude (Richter scale)	ANFIS		MLR	
		R^2	RMSE	R^2	RMSE
0	6	0.9943	4.490	0.5866	71.47
0	7	0.0079	3.995	0.7154	72.58
6	8	0.9922	3.606	0.4325	85.08

Emamgholizadeh et al. [100] conducted further studies on other properties. He developed ANFIS and ANN models to predict groundwater levels. The data collected for nine years are pumping rates, rainfall recharge and irrigation return flow which is used as input parameters for both models. This study uses hybrid and BP type algorithm learning while MF on the input and output are a trapezoid and linear type, respectively, proven to yield the best result. The statistical ratings are as presented in Table 7 that shows that the ANFIS model is better than the ANN model in the test phase. The authors conclude that the strength of the ANFIS model is due to the combination of both neural networks and fuzzy logic. Therefore, it has the potential to yield benefits based on the advantages of both methods in a single framework.

Table 7. The best performance indices of the models developed [100].

Models	R^2	RMSE
ANN	0.83	1.06
ANFIS	0.96	0.02

In 2015, the study returned to a state of scarcity in a publication with only one reported by Demir [101]. His report is related to settlement as the main factor in embankment stability. He compared ANFIS model performance with genetic expression programming (GEP) to predict the compression index of soils. A total of 299 sets of data comprising five input parameters namely natural water content, liquid limit, plastic index, specific gravity and void ratio are used to develop three predictive models for each of these approaches. The composition of split data sets for training and tests are 233 and 66, respectively. The MF of each input variable is generated using the GP method while hybrid learning algorithms with MF type triangles are selected to optimize parameters. The ANFIS I model has 243 linear parameters, 45 nonlinear parameters, 524 neurons and 243 FS while the ANFIS II models have 64 linear parameters, 48 nonlinear parameters, 158 neurons and 64 FS. In contrast, the ANFIS III model has nine linear parameters, 18 nonlinear parameters, 35 neurons and 9 FS. The *R* and RMSE are selected as statistical verification criteria to find out the performance of each model as presented in Table 8. The ANFIS model produces satisfactory results with *R*-value between 0.900 and 0.850, while RMSE ranges from 0.032 to 0.900. Overall, the approach used in this study is very encouraging, based on the results of the model evaluation. The authors conclude that the five input parameters used are reasonable to predict the compression index of soils.

Table 8. Performance statistics indices of the models [101].

Performance index	ANFIS			GEP		
	Model I	Model II	Model III	Model I	Model II	Model III
R	0.900	0.870	0.852	0.910	0.870	0.866
RMSE	0.032	0.090	0.037	0.029	0.034	0.035

Throughout 2016, only two articles were successfully published on physical properties. Xue and Xiao [102] developed three models using BP, particle swarm optimization (PSO) - BP and ANFIS to predict internal stability of soils. This study uses a hybrid learning method to train FS while SC is used to optimize the amount of FR. The Sugeno type ANFIS model is developed with six input parameters, 14 rules (14 input MFs and 14 output MFs) and one output parameter. Clay content, fines content, sand fraction, gravel fraction, the coefficient of uniformity and coefficient of curvature are the input parameters used for training and testing. After the model is trained, the Gaussian MF type is used on input parameters. This ANFIS model has 98 linear parameters, 168 non-linear parameters and 205 neurons. The number of data sets used for the training and verification is 50 and 12, respectively. Table 9 shows the performance evaluations for the three models. Based on the comparison of statistical performance, the ANFIS model is able to predict the internal stability of soils under seepage accurately. The authors conclude that this model has the capability to interpolate input parameters and can predict under various situations. In addition, the author also suggested that the ANFIS model is used to predict other criteria as proposed by the literature with correct input data. Hence, the development of the ANFIS model is more attractive compared to some other criteria.

Table 9. Comparison of the performance indices of model developed [102].

Models	RMSE		
	Training	Testing	Total
ANFIS	0.011	0.027	0.038
BP	0.073	0.413	0.486
PSO-BP	0.033	0.072	0.105

The evaluation studies for estimating saturated soil water content with ANFIS model approach were conducted by Fashi [103]. Input parameters such as medium porosity (P), sand (%), silt (%), clay (%), organic carbon (%) (OC), permanent wilting point (PWP), field capacity (FC) and bulk density (BD) are used to develop saturated soil water content pedotransfer functions (PTFs). An evaluation of the contributions of various MFs is made by the author based on the estimation of saturated groundwater content as each type of MF has an important role in the implementation of the

ANFIS approach. In this study, the development of the ANFIS model is based on the best selection of inputs. Therefore, there are five ANFIS models developed with multiple inputs and MFs used. The statistical performance for all the best PTFs is shown in Table 10. The P1 model has the best predictive accuracy feature. The authors concluded that the results of this study are encouraging. The authors also suggested that the approach of using the ANFIS model can be used for modelling saturated soil water content. Also, the author also proposed fine and medium textured classes to be considered as input parameters in future studies.

Table 10. Model performance indices during validation for the best selected PTFs [103].

Models	Input variables	R^2	RMSE	MF (Input)	MF (Output)	Epoch
P1	Sand, Silt, Clay	0.5527	0.0733	gauss2mf	Constant	150
P2	Sand, Silt, Clay, BD	0.5265	0.0779	gaussmf	Constant	150
P3	Sand, Silt, Clay, P	0.5218	0.0745	gaussmf	Constant	150
P4	Sand, Silt, Clay, P, BD	0.4977	0.0792	trapmf	Constant	150
P5	Sand, Silt, Clay, P, BD, OC	0.519	0.0804	gbellmf	Constant	150

In 2017, no reports were reported by researchers. However, this activity re-emerged in 2018, when a total of eight articles were successfully published based on recent advances. The breakdown of the number of publications for physical, engineering and other properties are 2.5 and 1 respectively. The use of ANFIS for physical properties reported by Abbaspour-Gilandeh and Abbaspour-Gilandeh [104] is to predict soils cone index values as criteria for soil compacting. Linguistic variables such as very low (VL), low (L), medium (M), high (H) and very high (VH) are used for fuzzification of input and output parameters. 5 MF triangles are used for each input variable parameter as it produces high accuracy. MF at the output is of linear type. The composition of the training data sets and validation is 80% and 20% based on the 450 empirical data provided. Hybrid optimization methods are used for ANFIS model training with 30 epochs. The assessment of statistical parameter rating found that R^2 and RMSE were 0.979 and 0.0621, respectively. The predicted results of the ANFIS model show that the measured value is almost the same as the predicted value. The author concludes that ANFIS can become a powerful tool, where the data generated from this model has very high compatibility with experimental data. Therefore, this model can be used as a fast, accurate design method with low cost.

In related work, Marashi et al. [105] in their study evaluated and compared ANFIS capabilities with multiple linear regressions (MLR) to obtain the pedotransfer function between the soil aggregate stability indices, mean weight diameter (MWD) and geometric mean diameter (GMD). A total of 101 samples were used for two sets of readily measured factors data. These data sets are used separately as inputs for predicting MWD and GMD. The three commonly used MF types are trimf, gaussian curve (gaussmf) and gaussian combination (gauss2mf) with the different number of epochs segregated by genetic command1 to get the best training efficiency with minimum error. ANFIS training uses Sugeno's FIS structure with GP. The hybrid-learning algorithm is used to identify Sugeno type parameters. MF of FIS is trained by BP and LS methods. Model evaluation criteria are presented as in Table 11. Based on the evaluation of these models, the ANFIS model shows better potential for predicting the stability index of soil aggregates compared to the MLR model, which has a low prediction accuracy.

Table 11. Model performance evaluation of MLR and ANFIS using the first dataset (P1) and the second dataset (P2) [105].

Models	MWD		GMD	
	R^2	RMSE	R^2	RMSE
First dataset (P1)				
MLR	0.78	0.18	0.58	0.12
ANFIS	0.92	0.10	0.90	0.07
Second dataset (P2)				
MLR	0.90	0.11	0.85	0.09
ANFIS	0.97	0.06	0.94	0.05

The prediction of engineering properties of unsaturated soils shear strength performed by Jokar and Mirasi [106] was successfully carried out using the cluster approach. In this study, the two fuzzy clusterings are SC (S-ANFIS) and fuzzy c-means clustering (F-ANFIS), which are used to create an ANFIS model with a minimum number of FR. A total of 10 ANFIS models were developed using five semiempirical models consisting of five S-ANFIS models and five F-ANFIS models. The input parameters for ANFIS models were obtained from experiments in laboratories, and they are net normal stress, matric suction, effective cohesion and angle of frictional resistance. Comparison through statistical performance is performed between two ANFIS models and the empirical model. The epochs are set to 2000 for initial FIS training. After the training evaluation, the validation and testing process found that all the developed ANFIS models yield almost equal measured and predicted values. The statistical performance assessment, i.e. R^2 for training, validation and testing using input parameters proposed by [107] are 0.9868, 0.9848 and 0.9941, respectively. The authors conclude that all the ANFIS models display a high ability to predict shear strength. The ANFIS models can also be used in future studies to predict the soil-water characteristic curve with nonlinear relationships with inputs.

Besides, Bunawan et al. [108] predicted bearing capacity of cohesive soft soils reinforced with soil-cement columns. This study developed two prediction models using ANFIS and ANN methods. The ANFIS model has 108 linear parameters, 18 nonlinear parameters and 78 neurons. A total of 21 FRs with three input parameters, i.e. column height/ground model height, improvement area ratio, and cohesion ratio were used to develop the ANFIS model. The statistical performance of the test data, R^2 for the ANFIS and ANN models, are 0.960 and 0.903, respectively. Overall, the performance comparison between the two models shows that the ANFIS model overcomes the ANN model. The authors also suggested that the ANFIS model can be used as a powerful and feasible tool to predict the bearing capacity of cohesive soft soils reinforced with soil-cement columns.

Relevant work has also been done by Das and Dey [109] to predict the bearing capacity of a stone column. A total of 105 data sets consisting of data of stone and sand columns obtained from previous technical literature were used to train and test ANFIS models. This study developed three ANFIS models: ANFIS-E (experimental data as input), ANFIS-A (analytical or numerical result as input) and ANFIS-EA (experimental data and analytical or numerical result as input). The input parameters used in this study are the diameter of the stone column, undrained cohesion of soft soil, the length of the stone column, the spacing between the stone column, and friction angle of stone column material while bearing capacity is the output parameter. The performance statistics of the predictive accuracy of training and test data are as shown in Table 12. Based on these performance statistics, the ANFIS model-EA has a smaller RMSE but a larger R^2 compared to the other two models. Therefore, the ANFIS-EA model has a greater ability to predict more accurately. The authors concluded that larger data sets would yield better precision.

Table 12. Statistical performance for ANFIS model [109].

Models	R^2	RMSE
Traning		
ANFIS-E	0.971	7.55
ANFIS-A	0.960	8.26
ANFIS-EA	0.986	2.06
Testing		
ANFIS-E	0.964	7.4
ANFIS-A	0.940	7.9
ANFIS-EA	0.979	1.45

Next, Harandizadeh et al. [110] used ANFIS to predict the bearing capacity of piles. Two improved ANFIS models were developed using a combination of the group method of data handling (GMDH) and fuzzy polynomial (FP). A total of 72 sets of data are used to train and test these models. Cone tip resistance, sleeve friction of cone penetration test, length and diameter of the pile are used as the input parameters. The ANFIS-GMDH model is optimized using the gravitational search algorithm. Both models were developed with 10 FR to be trained with a hybrid training algorithm in the ANFIS structure. The performance of both models is compared to multiple linear regression (MLR) and multiple linear and nonlinear regression (MNLR). Table 13 shows that the FP-GMDH model has the best predictive capabilities compared to other models. MLR produces a larger computational error followed by MNLR, where the RMSE values are 0.163 and 0.132, respectively. Based on ANFIS model performance, the writer concludes that soft computing tools can help to solve any problems in geotechnical engineering.

Table 13. Summary of performance indices for bearing capacity of piles [110].

Models	R^2	RMSE
Traning		
ANFIS–GMDH	0.965	0.065
FP–GMDH	0.970	0.0594
Testing		
ANFIS–GMDH	0.940	0.082
FP–GMDH	0.960	0.0647
MLR	0.810	0.163
MNLR	0.850	0.132

The ANFIS model developed by Jokar et al. [111] intended to predict unsaturated soils permeability (k_{unsat}). A total of 4660 records from 245 types of land were acquired and collected from around the world to be used as data to model $k_{unsat.}$ The data set includes nine soil parameters, i.e. suction, saturated permeability, $k_{unsat,}$ initial saturation, void ratio, specific gravity, uniformity coefficient, clay content, silt content and sand content. SC was used and trained by ANFIS using the hybrid learning algorithm. The optimum number of epochs is 100 while the number of clusters between 35 and 50 with 43 rules. The results of the training, validation and testing found that the ANFIS model has good predictive ability, as shown in Table 14. Good relationships can be seen between the measured and predicted k_{unsat}. The author suggested the ANFIS model developed in this study to be used to predict used k_{unsat} in geotechnical engineering design. It can save time and reduce costs without requiring complicated experiments.

Table 14. The performance indices of ANFIS model [111].

Performance index	Training	Validation	Test	Total
R^2	0.9657	0.9455	0.9510	0.9605
RMSE (m/s)	2.40E−05	1.39E−05	4.77E−06	1.63E−05
VAF (%)	96.5737	94.5501	95.1001	96.0531

The prediction of other properties, i.e. soil erosion based on the revised universal soil loss equation (RUSLE) model parameter was conducted by Islam et al. [112]. Erosivity factor, soil erodibility factor, slope length and steepness factor, vegetation cover and management factor, support practice factor and microbes factor are the RUSLE parameters. Model evaluation on method combination and the various ANFIS configurations, i.e. MF types, MF counts, optimization methods and epoch numbers were conducted to obtain the best prediction. The 500 epochs are used to obtain minimum RMSE during the training period while the ANFIS network is trained using hybrid learning methods. A total of 60 data sets are provided with four triangular MF (trimf) inputs used in this study. Sugino type FIS is generated by genfis1 using GP of the data. The best performance errors obtained are 1.4276 and 0.8275 for R^2 and RMSE, respectively. The authors conclude based on the results of this study that the ANFIS model is able to predict soil erosion within a short period of time even though no performance comparison was made with other models. This is because the authors believe that the results obtained show some confidence in the use of ANFIS models to predict soil erosion.

5. Optimization Approach

Training efficiency is enhanced by using optimization methods that serve to learn about training data [21]. ANFIS has two commonly used learning algorithms, namely BP and hybrid methods, to minimize errors between measured and predicted data. Recently, researchers have shown an increased interest in the development of ANFIS predictive models with various optimization approaches. It is divided into two types: derivative-based and derivative-free methods. However, derivative-free methods are often used because they do not require derivation of the objective function and are more robust to find the global minimum [113]. Metaheuristic algorithms are part of the derivative-free method and are divided into two categories, namely evolutionary algorithms and intelligent swarm algorithms [114]. Evolutionary algorithms and swarm intelligent algorithms are based on the biological evolution and social behaviour of animals. Among the popular examples of evolutionary algorithms are genetic algorithms (GA) and differential evolution (DE) while particle swarm optimization (PSO), shuffled frog leaping algorithm (SFLA) and satin bowerbird optimization algorithm (SBO) are swarm intelligent algorithms. Each algorithm has its own advantages in terms of computational complexity, convergence speed, accuracy and the number of control parameters.

Holland [115] in 1975 introduced GA and received a good response to date due to its simplicity, easy execution, efficiency and flexibility [116]. It is also known as a search method that can be used to model evolution systems and to solve problems. It is very effective for optimization tasks in situations where multiple inputs interact with each other to produce a large number of output possibilities [117]. Due to this advantage, researchers used GA with ANFIS widely for predictable tasks [118–122], control systems [123–125], classification [126,127], optimization [128–130] and decision making [131,132]. However, there are also investigators comparing ANFIS model performance between GA and PSO [119,132–135], DE [133,135,136], BP [135,137], ant colony optimization (ACO) [132,135], simulated annealing [137,138] and others.

An alternative algorithm other than GA is DE which was first introduced in 1995. It is known as a highly effective global optimizer as it is a simple mathematical model with a large and complex natural evolution process [139]. Its purpose of development was to replace the mutation and classical crossover schemes of the GA. Recent developments highlighted by Vasan and Simonovic [140] in 2010 suggested the DE algorithm to achieve the best optimal solution in its study. It has the advantage of faster and more robust in numerical optimization in finding global optimum than genetic algorithms [141]. Recently, some researchers compared ANFIS prediction models between DE and GA [118,133,136,142–144], particle swarm optimization (PSO) [142,143,145], ant colony optimization for continuous domains (ACOCD) [118], firefly algorithm (FA) [145] and found that the use of DE has the best predictive performance.

Optimization methods based on intelligent swarm techniques have improved over the past few decades. The use of PSO dominates in this technique as it is flexible in many cases. It was introduced by Kennedy and Eberhart [146] based on the simulation of social behaviour reviewing global optima. Subsequently, Shi and Eberhart [147] introduced the inertial weight parameters to produce better performance. PSO has been successfully used in various fields and applications. Recently, some researchers used ANFIS - PSO for predicting work [148–151], control systems [152,153] and classification [154,155]. Researchers also compared the performance of the ANFIS model between PSO with GA [156,157], BP [152], ACO [132,155], FA [155] and found that ANFIS-PSO can produce better results.

Among the latest discoveries in intelligent swarm techniques is the one highlighted by Chen et al. [158] who use SFLA as an optimization method and successfully solves the problem of non-linear dimensions. SFLA was first introduced in 2003 by Eusuff and Lansey [159]. This algorithm is very efficient for discrete data because of its high speed in reaching convergence [160]. In recent years, the literature on the development of the ANFIS-SFLA model [158,161–164] is on the rise. Some studies have compared the performance of the ANFIS model between SFLA and GA [164], and PSO [158].

In addition, Samareh Moosavi and Bardsiri [165] have introduced SBO to customize ANFIS components through small and reasonable changes in the variables. After it was introduced, some researchers used this algorithm and found that the results were very positive in various developed AI models [166–168]. In another study, some researchers compared the performance of the AI model using SBO with GA [168]. At the same time, Tian et al. [169] introduced a new algorithm based on SBO and the no free lunch theorem, i.e. multi-objective satin bowerbird optimizer (MOSBO). Through the comparisons made with other benchmark models, it was found that this algorithm not only has excellent optimization capability, but it also improves the accuracy and stability of the projection simultaneously.

6. Discussion and Future Perspective

The first objective of this paper is to summarize previous studies on the development of the ANFIS model to predict the stability of the road embankment. Result discussions begin with the use of ANFIS to predict the main factors of stability of road embankment. Based on literature surveys from 2004 to 2018, only Demir [101] conducted a prediction study on soil settlement that can be used on ground foundation and embankment. The findings reveal that there is no comprehensive study to predict the stability of the embankment by linking two significant factors of settlement and slope stability. In contrast, secondary factors related to embankment stability, such as soil and permafrost properties, are being implemented. The findings are not expected and suggest that this study is done in the future.

The selection of input parameters is also an essential factor in developing predictive models. Since no investigators predict the stability of road embankment that makes a settlement and slope stability as output, it is recommended that maximum deflection, maximum deflection location, maximum settlement and FOS. These input parameters are relevant based on literature, supported and used by some researchers in their study [170–173]. It is suggested that these parameters are further investigated to be considered as input parameters of the AI prediction model in future studies.

One of the most important current discussions in the development of the ANFIS model is the more efficient optimization approach to the performance of embankment stability predictions. Many researchers use optimization techniques with hybrid approaches (classic algorithms), namely BP and LS. Also, the classic algorithm has difficulty calculating the gradient in each step, and the use of chain rule can cause local minimum problems and very slow convergence of the parameters [10,165]. Nonetheless, there is research comparing the performance of the classical algorithm models with evolutionary and swarm intelligence algorithms. The results of these comparisons show that evolutionary and swarm intelligence algorithms produce better result precision compared to classic algorithms [135,137,174]. These findings further support the idea that researchers develop a predictive model of stability of road embankment approach ANFIS with optimization method using evolutionary and swarm intelligent algorithms such as GA, DE, PSO, FLA and SBO.

7. Conclusion

Researchers from various countries have successfully published a total of 19 research studies related to road embankment stability using the ANFIS approach. This good response to ANFIS is due to its ability to reduce search space dimensions by distributing input information over the network. Advantages and benefits through a combination of neural networks and fuzzy logic in a framework are the strengths of the ANFIS model, a researchers' choice for use in predictive model development studies.

This paper examines the importance of developing road embankment stability prediction models with ANFIS applications. One of the more significant findings of this study is the limited number of researchers who predict road embankment stability by linking settlement and slope stability. Although many researchers developed ANFIS models for soil properties, it has been shown that this field of study is still poorly understood, possibly due to limited literature. More research in this area would mean a start of more novel research in the road and geotechnical engineering. By increasing the projection of road embankment stability, researchers can select appropriate input parameters to avoid underfitting of models. This effort can also help in choosing the appropriate number and the type of MF.

Overall, many researchers developed the ANFIS Sugeno model with hybrid learning algorithm and SC type cluster method. Based on a literature review in this paper, the ANFIS approach yields better accuracy than the ANN, MLR, MNLR, MRM and GEP methods. However, the accuracy of the results is dependent on optimization techniques, as some researchers compared the classic approaches to algorithms (BP and LS) with the PSO. On the other hand, many researchers used evolutionary and swarm intelligent algorithms in different fields and have proven to yield amazing performance results. It will be even more interesting if there are more predictive project performance reviews with optimization techniques such as GA, DE, PSO, SFLA and SBO. In addition, the cluster method approach also affects the accuracy of results as it is proven by some researchers who compare ANFIS model performance based on conventional cluster method (GP and SC) with fuzzy c-means.

Based on the discussion presented in this paper, it can be concluded that the evidence and the results of the study can give some contribution to the current literature. Hence, the findings of this study have important implications for future practice. This is because the information and findings presented are beneficial to researchers, especially in the field of road embankment stability with the ANFIS approach.

Acknowledgements

The authors dedicate their appreciation to the Ministry of Education Malaysia (MOE) for providing sponsorship under the Federal Training Gift Scheme (HLP) for the success of this project. A special thank you to the Department of Polytechnic and Community College (JPPKK) and Politeknik Ungku Omar (PUO) due to providing the facilities for this project.

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