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Application of ANFIS hybrids to predict coefficients of curvature and uniformity of treated unsaturated lateritic soil for sustainable earthworks

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ABSTRACT

Unsaturated lateritic soils are complex soils to work with due to moisture effects. So, the determination of its properties requires lots of time, labor and equipment. For this reason, the application of evolutionary learning techniques has been adopted to overcome these complexities. Lateritic soil under unsaturated condition classified as poorly graded and A-7–6 group was subjected to treatment by using hybrid cement and nanostructured quarry fines in a stabilization method. The clay activity, clay content and frictional angle were determined through multiple experiments at different proportions of the additives. 121 datasets were collected through the multiple testing of treated specimens and 70% and 30% of the datasets were used in the model training and testing, respectively to predict the coefficients of curvature and uniformity (Cc and Cu) of the unsaturated lateritic soil. Fist, the multi-linear regression (MLR) model showed that the selected input parameters correlated well with the output parameters. The model performance evaluation and validation selected indicators; R^2, RMSE and MAE showed that ANFIS with 0.9999, 0.0021 and 0.0015 respectively, for the training and 0.9994, 0.0077 and 0.0059 respectively outclassed all its hybrid techniques and MLR in both training and testing. However, ANFIS-PSO with performance indicators 0.9996, 0.0062 and 0.0050 respectively (training) and 0.9989, 0.0095 and 0.0073 respectively (testing); followed by ANFIS-GA; 0.9991, 0.0094, and 0.0065 respectively (training) and 0.0089, 0.0099, and 0.0079 (testing) outclassed the other learning techniques for the Cc prediction model while ANFIS-GA; 0.9949, 0.1000, and 0.0798 respectively (training) and 0.9954, 0.0983, and 0.0807 respectively, followed by ANFIS-PSO; 0.9893, 0.1347, and 0.1011 respectively (training) and 0.9951, 0.1127, and 0.0924 respectively outclassed the other techniques for the Cu prediction model. Finally, ANFIS and its evolutionary hybrid techniques have shown their usefulness and flexibility in predicting stabilized unsaturated soil properties for sustainable earthwork design, construction and foundation performance monitoring.

Introduction

Background

Coefficients of curvature and uniformity greatly influence soil shear strength and this phenomenon affects the design and performance of compacted subgrade structures. Shear strength of soil is the basic property of soil which indicates the ability to resist structural loads. Shear strength of soil is determined through rigorous and time-consuming laboratory and/or in situ test. Consequently, models could be employed to reduce the experimental workload for assessment of the geotechnical properties of soil (Zhang et al., 2017; Muhammad et al., 2020). Owing to the small test data and restrictions in parametric limits, most available models could not provide accurate and desired result. A database that takes care of a variety of parameters is paramount in modelling accurate equations capable of predicting

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Nomenclature

ANFIS	adaptive neuro fuzzy inference system
PSO	particle swarm optimization
ACO	ant colony optimizer
GA	genetic algorithm
MLR	multi-linear regression
NQF	nanostructured/nanotextured quarry fines
R2	coefficient of determination
RMSE	root mean square error
MAE	means absolute error
HC	hybrid cement
Cc	coefficient of curvature
Cu	coefficient of uniformity
DE	differential evolution
ANN	artificial neural network
GP	genetic programming
FST	fuzzy set theory
SCC	soil compression coefficient
SFLA	shuffled frog leaping algorithm
SBO	satin bowerbird optimization
GCM	green and cleaner materials
SVM	support vector machine
XRF	x-ray fluorescence
SEM	scanning electron microscopy

multiple engineering properties of soil (Gholampour et al., 2017). For this reason, statistical regression techniques were used by many researchers (Koike and Matsuda, 2005; Anwar et al., 2016). There are concerns regarding the use of these methods because of the heterogeneous nature of soil (Potts and Zdravkovic, 1999).

Recent discoveries in the field of artificial intelligence (AI) applications have given rise in the development of accurate and dependable models for solving engineering problems (Gholampour et al., 2017; Tayfur, 2017). The breakthrough in the field of AI made it possible to produce models to adapt to difficulties associated with modelling soil behaviour (Muhammad et al 2020). AI has been considered in the field of Civil Engineering for more than one and half decade (Choobbastic et al., 2009; Ellis et al., 1995; Das and Basudhar, 2008; Daryaei et al., 2010; Farkhonde and Bolourji, 2018; Kumar and Rani, 2011; Mohammadzadeh, et al., 2019). These models range from a simple black-box model to complex distributed physics-based models. Although there are numerous AI modelling algorithms namely, genetic algorithm (GA), Ant Colony (AC), Differential Evolution (DE), Particle Swarm (PS), Artificial Neural Network (ANN), Genetic Programming (GP) and Gene Expression Programming (Tayfur, 2017; Onyelowe et al. 2021a). Artificial Neural Network (ANN), Genetic Programming (GP) and Gene Expression Programming have been widely used. However, the adaptive neuro fuzzy inference system (ANFIS) and its evolutionary hybrid learning techniques have not been widely used especially in the field of geotechnics. This hybrid operates on the learning abilities of fuzzy logic and neural networks.

Fuzzy logic is a technology used for the development of intelligent control and information systems. Fuzzy logic accomplishes machine intelligence by providing a means for representing and reasoning about human knowledge that is imprecise by nature (Gupta and Kulkarni, 2013). Zadeh (1965) was the first to propose the first theory of fuzzy sets as an extension of the traditional set theory. This theory has become more widespread after its introduction and has found various applications in different fields. The fuzzy sets allow gradual evaluation of the membership of elements in a given set described with the aid of a membership function valued in the real unit interval [0, 1]. The membership functions are usually linguistically defined. The linguistic variable is individually associated with a fuzzy number characterizing the meaning of each generic verbal term, since the linguistic variable is not directly mathematically operable (Chou and Chang, 2008). Mishra and Basu (2013) observed that the most attractive and interesting nature of the fuzzy models in relation to other classical methods commonly used in geosciences is that they can describe complex and even curvilinear multivariable problems in a transparent way. Fuzzy logic is useful in all domains of engineering. In geotechnical engineering it was introduced much later. Estimating the density of soundings on site was the subject of an approach proposed by Boumezerane et al. (2011) in which engineering judgment and qualitative information are taken into account in a fuzzy inference system.

Adaptive neuro-fuzzy inference system (ANFIS) has been in use since over a decade in geotechnical engineering applications to cope with uncertain data due to lack of precision, incompleteness, vagueness and randomness of the information as well as incorporating subjective judgment from expects into problems analysis. Fuzzy set theory (FST) provides the means for representing epistemic uncertainty using set theory and describes the concept of gradualness and bipolarity (Dubois and Prade, 1997). Since early 80′s where the first applications of FST in geotechnical engineering appeared, it has been developing intensively and currently it is employed in wide variety of problems for instance, slope stability, rock engineering, tunneling, project management, and even constitutive relation of geomaterials (Adoko and Wu, 2011). The literature reveals that researchers used fuzzy theory in different ways in order to deal with the level of complexity associated to the problems. Due to its advantages of handling epistemic uncertainty, it has been useful as predictive models, in situation where getting complete or updated data (statistical distribution parameters for example) over a period was unrealistic or impossible. Moreover, the possibility to use expert knowledge with a fuzzy reasoning approach to enhance some geotechnical problems analysis makes FST to be considered as powerful tool of describing uncertain data.

In general, fuzzy set theory (FST) is used in geotechnical engineering to handle uncertain data and subjective information. The techniques employed can be classified into four categories: basic fuzzy inference (fuzzy set/logic); advanced fuzzy inference (combining other soft computing techniques), fuzzy probability theory and Klisiński fuzzy plasticity methods (Adoko and Wu, 2011). The fuzzy logic technique can be implemented to a real application through the following three steps as suggested by Bai and Wang (2006) and is schematically represented in Fig. 1. The first stage of implementation is fuzzification, in which the fuzzifier maps crisp data into fuzzy data or membership functions. There are different membership functions such as trapezium, triangle, bell, Gaussian, and sigmoid that can be used for the fuzzification. The second stage is the fuzzy inference process, in which the fuzzy IFTHEN rule (fuzzy implication) combines membership functions with the control rules to derive the fuzzy output. Finally, defuzzification which involves the use of different defuzzifiers such as the center of gravity (COG) and middle of maxima (MoM) to convert the fuzzy outputs into crisp output (Lawal and Kwon, 2020).

Fuzzy logic has been used successfully in the field of geo-engineering in predicting the rock property and various aspects of blasting operation. Jang (1993) considered the abilities of neural network and fuzzy theory to provide adaptive neuro-fuzzy inference model. The classic method of neuro-fuzzy system is Sugeno type of fuzzy inference system that uses hybrid learning algorithm for deter-

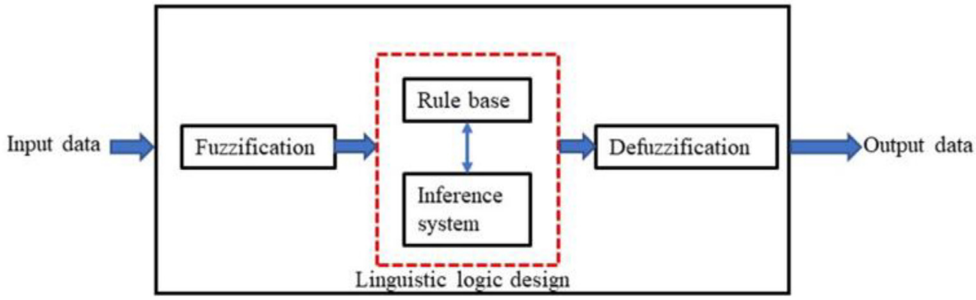


Fig. 1. Block diagram of the fuzzy logic system.

mining the parameters of the fuzzy system to train the model (Jorabiyan and Hoshmand, 2002). Adaptive neuro-fuzzy inference system (ANFIS) model is a model with a five-layer structure, emerged with a combination of fuzzy logic and artificial neural network model as presented in Fig. 2 (Dahmardeh et al., 2017). The first layer or access layer, in which membership degree of input nodes to different periods is determined using membership functions. Membership functions have different kinds, including functions that can be trapezoidal, triangular, sigmoid, Gaussian and bell-shaped functions, which generally include more general case of them. The second layer is where the inputs to each node are multiplied and the result that is the weight of rules is achieved. In the third layer, nodes normalize the weight of rules. The fourth layer is called rules layer and rules obtained in this layer. The fifth and last layer of the network contains only a single node, which calculates the total output by summing all input values together.

Fortunately, nowadays the use of modern computers allows for advanced analysis techniques and filtering of information. Traditional regression modelling is the most widely used technique as an interpretation and analysis tool (Basarir et al., 2017). More recently, some other modelling tools, such as soft computing methods, have gained popularity. One of the new evolving soft computing methods is the adaptive neuro fuzzy inference system (ANFIS) modelling. It is considered a suitable modelling tool for geosciences, since it can deal with uncertainty and cope with changing environments (Basarir et al., 2014). Nguyen and Ashworth (1985) researched rock mass classification with the help of ANFIS for multi-criteria decision modeling to select the most likely rock mass class. Kacewicz (1987) applied fuzzy set theory successfully in slope stability analysis to estimate the factor of safety of Warsaw's slope in Poland. The main soil and rock mass parameters (weight, water pore pressure, friction angle, and cohesion) were treated as fuzzy numbers. Similarly Juang et al. (1998), analyzed some existing slopes considering uncertainties based on the so called vertex method, anchored in the α-cut concept, in which uncertain soil parameters were discretized and expressed as fuzzy numbers then put into a set of intervals. The main difference here is that the problem is reduced to a series of intervals analyses and use only conventional mathematics. This approach is deterministic rather than probabilistic, that enabled them to use a PC-based computer program for slope stability analysis (PCSTABL) together with the vertex method.

As a general observation, the Mamdani Fuzzy model is often used in geotechnical problems because of its simplicity and effectiveness to handle linguistic variables; even though other FISs are available namely the Takagi-Sugeno-Kang fuzzy (TSK) model, the Tsukamoto fuzzy model and the Singleton fuzzy model (Azimi et al., 2010). Basically, rule base, database and reasoning mechanism are three conceptual elements of a FIS. The fuzzy rules constitute the rule base and the database determines the membership functions associated with the inputs parameters to be used in the rule base while the reasoning mechanism provides the platform to derive an adequate conclusion (output) by using fuzzy logic. At this stage the extraction of a crisp set from a fuzzy set, called defuzzification is performed. Defuzzification methods include centroid of area (COA), bisector of area (BOA), mean of maximum (MOM), smallest of maximum (SOM), and largest of maximum (LOM) (Khademi et al., 2010). Many software packages are available to model FIS; one of the most commonly used being the fuzzy toolbox of Matlab.

Hou et al. (2009) used fuzzy system combined with neural network to estimate ground surface settlements based on measured data of Shanghai second Subway, and considering various kinds of factors synthetically to build an ANFIS fuzzy neural network prediction model. Comparing with the prediction results by other three kinds of methods, the validity of the ANFIS fuzzy neural network model was appraised. The study showed the potential for applying fuzzy neural networks

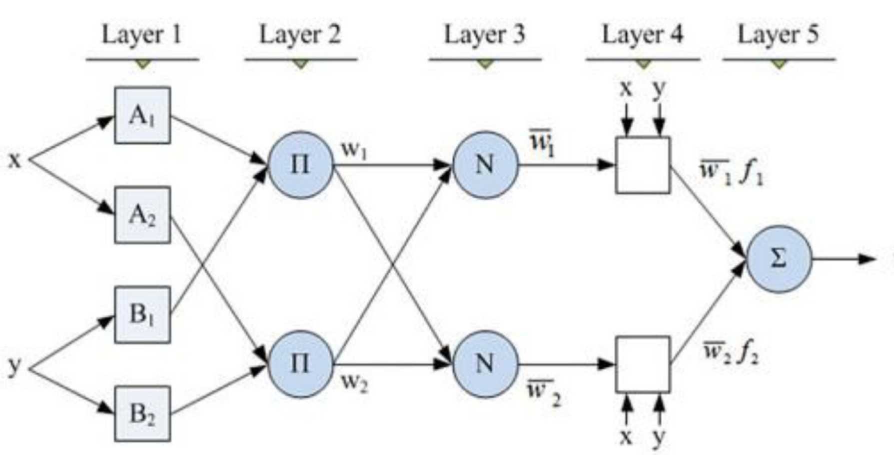


Fig. 2. A framework of ANFIS.

to ground surface settlement analysis. The predicted results from the proposed model were in good agreement with field observations and the maximum error between the model and the testing data was around 7%. Mohammed et al. (2020) studied the implementation of newly developed machine learning models called hybridized Adaptive Neuro-Fuzzy Inference System (ANFIS) with Particle Swarm Optimization (PSO) algorithm, Ant Colony optimizer (ACO), Differential Evolution (DE), and Genetic Algorithm (GA) as efficient approaches to predict settlement of shallow foundation using cohesive soil properties. The width of footing (B), pressure of footing (qa), geometry of footing (L/B), count of SPT blow (N), and ratio of footing embedment (Df/B) were considered as predictive variables. To assess the accuracy of the applied hybrid models and standalone one, multiple statistical metrics were computed and analyzed over the training and testing phases. Results indicated ANFIS-PSO model exhibited an accurate and reliable prediction data intelligent and had the highest predictability performance against all employed models.

Employing league championship optimization (LCA) technique for adjusting the membership function parameters of the adaptive neuro-fuzzy inference system (ANFIS) was carried out by Moayedi et al. (2020) for better estimation of the soil compression coefficient (SCC). The study used twelve key factors of soil, namely depth of sample, percentage of sand, percentage of loam, percentage of clay, percentage of moisture content, wet density, dry density, void ratio, liquid limit, plastic limit, plasticity Index, and liquidity index. The used data was collected from a real-world construction project in Vietnam. The hybrid ensemble of LCA-ANFIS was developed, and the best structure was determined by a three-step sensitivity analysis process. The prediction accuracy of the proposed hybrid model was compared with typical ANFIS to examine the efficiency of the combined LCA. Based on the results obtained, applying the LCA algorithm lead to a 4.88% and 6.19% decrease in prediction error, in terms of root mean square error and mean absolute error, respectively. Moreover, the correlation index indicates higher consistency of the hybrid model results.

Artificial neural networks (ANNs) have been successfully used for the soil compression coefficient (SCC) estimation. Kurnaz, et al. (2016), employed an ANN for predicting the compression and recompression indices using basic soil properties of initial void ratio, the natural water content, plasticity index, and liquid limit. It was found that this model can satisfactorily predict the compression index. As an alternative to empirical formulas for calculating the soil compression index, Park and Lee (2011) used ANN for soil information on sites over the Republic of Korea. The study proved the higher reliability of ANN compared to empirical techniques. The efficiency of three commonly used predictive models of support vector machine (SVM), ANN, and ANFIS was explored along with Monte Carlo sensitivity analysis method by Pham et al. (2019). Notably, the applied Monte Carlo method revealed the higher contribution of four input parameters namely clay, degree of saturation, specific gravity and depth of sample. Eventually, they concluded that the SVM performs more efficiently than two other colleagues.

The use of an adaptive neuro-fuzzy inference system (ANFIS) has received encouraging responses over the last decade in various research areas. Mamat et al. (2019) studied the application of ANFIS to predict factors that affect the stability of road embankment. The stability of road embankment is influenced by two main factors, namely slope stability and settlement. Additionally, looking at study reports generally 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), it is obvious that most researchers developed ANFIS models to predict soil properties. Interestingly, it was found that researchers successfully use the ANFIS model with the ability to predict with acceptable accuracy. Kalkan et al. (2009) developed ANFIS and Artificial Neural Network (ANN) models to predict the Unconfined Compressive Strength (UCS) of compacted granular soils, and the results of the ANFIS model were very encouraging, compared to the ANN model. Kayadelen et al. (2009) used ANFIS to predict the swell percentage of compacted soils, and showed that ANFIS was a more reasonable method for predicting the swelling potential of soils. Sezer et al. (2010) successfully trained an ANFIS model to predict permeability based on 20 different types of granular soils. Ikizler et al. (2012) showed that neural network and adaptive neuro-fuzzy-based prediction models could satisfactorily be used to obtain the swelling pressure of expansive soils.

The response to the use of artificial intelligence (AI) in various fields has been encouraging since its introduction in 1956 (Serenko and Dohan, 2011). This is because its nonlinear prediction ability is better compared to other models. 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) (Jang, 1993) 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 (Mittal et al., 2012; Onyelowe et al. 2021b). 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 (Jang, 1993). Al-Mahasneh et al. (2016) 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 in terms of simplicity, adaptability, robustness and seeks to a good generalize (Surajudeen-Bakinde, et al., 2018; Mishra and Mohanty, 2016).

The past century has seen the rapid development of ANFIS models in geotechnical engineering for predictive purposes (Cabalar et al., 2012a; Cabalar et al., 2012b). The main purpose of prediction is accurate and credible results (Abellan-Nebot, 2010). Optimized fuzzy is one of the right decision-making approaches (Chen, 2013). 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 (Shoorehdeli et al., 2009). Among these problems are their convergence to a local minimum and the acceleration rate that is sensitive to the learning process (Chen, 1999). 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 geotechnical engineering.

Z'lender et al. (2012) presents a concept for planning geotechnical investigation for buildings using ANFIS and they concluded that ANFIS can be used as a systematic decision support tool for engineers dealing with site characterization. To apply the developed model for any new site, it was advised that engineers could use intervals instead of exact values for input parameters. Adaptive Neuro-Fuzzy Inference System (ANFIS) model combined the neural network adaptive capabilities and the fuzzy logic qualitative approach. Neuro-fuzzy integrates the merits of both neural networks and fuzzy systems in a complementary way to overcome their disadvantage. Real-time processing of instantaneous system input and output data, offline adaptation instead of online system-error minimization, and fast learning time are some advantages of the ANFIS. The use of ANFIS extensively increased such as some applications of ANFIS in geotechnical engineering (Cabalar et al., 2012a; Cabalar et al., 2012b), reliability analysis of excavation damaged zone (Fattahi et al., 2013), prediction of soil liquefaction (Sadoghi et al., 2012). More details of ANFIS architecture can be found in (Sadoghi et al., 2012).

In a study by Rahnema et al. (2019), two Adaptive Neuro-Fuzzy Inference System (ANFIS) models, including SC-FIS model (created by subtractive clustering) and FCM-FIS model (created by Fuzzy c-means (FCM) clustering), were presented for prediction of the effective stress parameter to obtain the shear strength of unsaturated soils. The soil–water characteristic curve fitting parameter, the confining pressure, the suction, and the volumetric water content in dimensionless forms were used as input parameters for these two models. By using a trial-and-error process, a series of analyses were performed to determine the optimum methods. The quality of the ANFIS prediction ability was quantified in terms of the determination coefficient (R-square), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). The two ANFIS models were able to effectively predict the value of effective stress parameter with reasonable values of R-square, RMSE, and MAE. Sensitivity analysis implemented to determine the effect of input parameters on prediction and the results revealed that the confining pressure and the volumetric water content parameters had the most influence on prediction.

From the foregoing previous research efforts, it can be deduced that the prediction of the geotechnical engineering behavior of unsaturated lateritic soil whether treated or untreated has been look into. Meanwhile, researchers have focused on the application of ANFIS to predict various soil conditions but have not studied the learning abilities and merits of the other evolutionary hybrids of ANFIS. Hence the focus of this research work was to close the research gap existing in the harnessing of the hybrid techniques of ANFIS and predicting the gradation behavior of treated lateritic soil under unsaturated condition. The hybrid methods of ANFIS utilized in this research work were; (i) ANFIS-ACO, (ii) ANFIS-PSO, (iii) ANFIS-DE and (iv) ANFIS-GA. The results of the prediction abilities of the four hybrid techniques were compared with the prediction abilities of MLR and ANFIS in order to establish the superior learning techniques.

Further relevant reviews

Linear multivariate regression model (LMR) or Multi-linear regression (MLR)

The background is the use of multiple regressions, which is a time-honored method going back to 1908 by Pearson. This technique is applied for predicting the variance in an interval dependency, based on linear relationship of interval, dichotomous, or dummy independent variables (Esmaeili et al., 2014). In fact the linear multivariate regression (LMR) is one of the most well-known approaches for generating a multiple equations between one or more independent or input parameters and one dependent or output parameter. The linear multivariate regression (LMR) is a generalization of simple linear regression to the case of more than one independent variable, and a special case of general linear models, restricted to one dependent variable (Shakeri et al., 2020; Montgomery and Peck, 1992; Onyelowe and Shakeri, 2021). In this paper, the dependent variables which assumed as coefficient of curvature (Cc) and coefficient of uniformity (Cu) may depend on "n" independent variables (x). Generally, a typical multiple regression formulation is presented in the following format:

$$C = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n + \varepsilon \tag{1}$$

where:ε: Error of the model; $j = 0, 1\ldots n$ and β_j are the regression coefficients (Shakeri et al., 2020; Montgomery and Peck, 1992; Rezaei and Asadizadeh, 2020; Shokri et al., 2020).

Adaptive neuro-fuzzy inference system (ANFIS)

Jang in (1993) introduced an adaptive neuro fuzzy inference system (ANFIS), composed of fuzzy systems and artificial neural, based on Takagi-Sugeno fuzzy inference system. In this method, determining the parameters of membership functions is performed by least-squares and the backpropagation gradient descent using the available data. The architecture of ANFIS with two inputs as seen in Fig. 3 includes five layers and can be expressed by the following rules:

Rule 1: If × is A1 and y is B1, then f1 = p1x + q1y + r1

Rule 2: If × is A2 and y is B2, then f2 = p2x + q2y + r2

Where x and y are considered as the system inputs, A1, A2, B1, and B2 are the inputs membership functions; p1, q1, r1, p2, q2, and r2 are the parameters of output function.

According to the structure of the ANFIS, the layers can be described as follow:

Layer1: in this layer, the input values are fuzzified the by appropriate membership functions (known as fuzzification layer).

Layer 2: in this layer the weights of membership functions are obtained (rule layer).

Layer 3: in this layer the obtained weights or firing strengths of each rule are normalized (known as normalization layer).

Layer 4: in this layer the nodes are assumed as adaptive nodes and the weighted values of rules are calculated (known as defuzzification layer).

Layer 5: in this layer the overall output is determined through sum of the outputs of the defuzzification layer (known as output layer) (Jang et al., 1997; Akyildiz and Hudaverdi, 2020).

Ant colony optimization (ACO)

Dorigo (1992) introduced the ant colony optimization (ACO), a metaheuristic algorithm based on the behavior of real ants searching a path between their colony and a source of food.

Naturally, ants have the ability of seeking food in the shortest possible path. Each ant excretes the chemical pheromone and the pheromone trail is felt by other members of the colony. The path having more pheromones is preferred for ants. It is clear that the amount of the pheromone evaporation in longer paths is higher than shorter paths and then the shortest path is followed by ants (Dorigo and Gambardella, 1997).

Based on this fact, a series of artificial ants with artificial pheromones are applied for optimizing complicated problems. Suitable solutions for the problem are incrementally created by artificial ants according to the amount of pheromones in different paths and the quality of these stochastic solutions is continuously updated based on the existing pheromone in the path of the achieved solutions (Shishvan and Sattarvand, 2015). Fig. 4 illustrates the process of ACO algorithm and further details are accessible in literature (Dorigo et al., 2006, Saghatforoush et al., 2016).

Particle swarm optimization (PSO)

Particle swarm optimization (PSO) developed by Kennedy and Eberhart (1997) is a powerful optimization technique inspired by social behavior of bird flocking or fish schooling. PSO is an evolutionary population-based optimization technique that can be used to solve global optimization problems within a nonlinear procedure (Hajihassani et al., 2015). PSO provides a population-based search procedure in which individuals, called particles, change their positions with time. Each particle in the swarm represents a candidate solution to the optimization problem (Yagiz et al., 2018). In the PSO algorithm, a number of particles are placed in the search space of N-dimensional problem. Each particle represents a potential solution and estimates the objective function at its current position (Gordan et al., 2016; Huang et al., 2020). PSO moves particles around the search area to find a satisfactory point (Huang et al. 2020). The particles change their positions in the search space based on their experiences and those of neighboring particles, and therefore the particles make use of their own experience and those of their neighbors (Engelbrecht, 2007). These particles form a population which is technically known as a swarm (Hajihassani et al., 2015). Particles movements are steered by their own best known position, called personal best (pbest) as well as the entire particles best known position, called global best (gbest) (Hasanipanah et al., 2017; Yagiz et al., 2018; Murlidhar et al.,

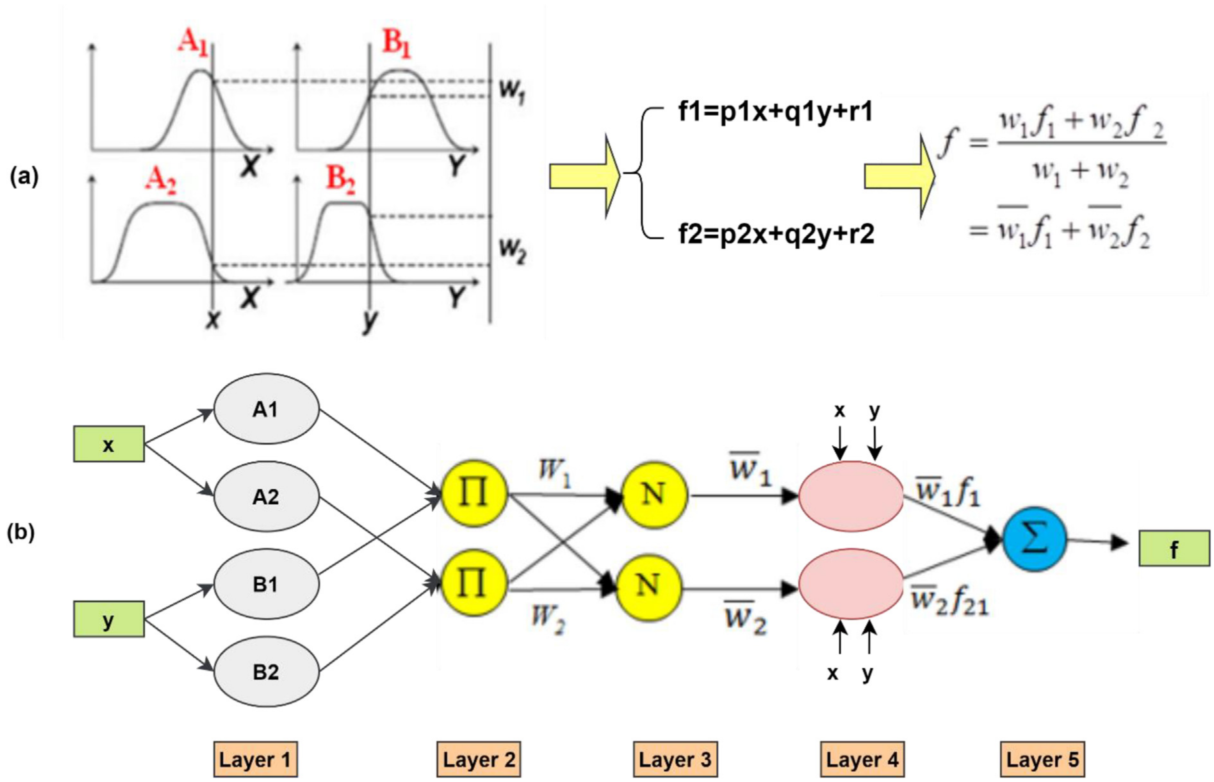


Fig. 3. (a) Takagi-Sugeno fuzzy model; (b) The structure of the ANFIS model (Jang, 1993).

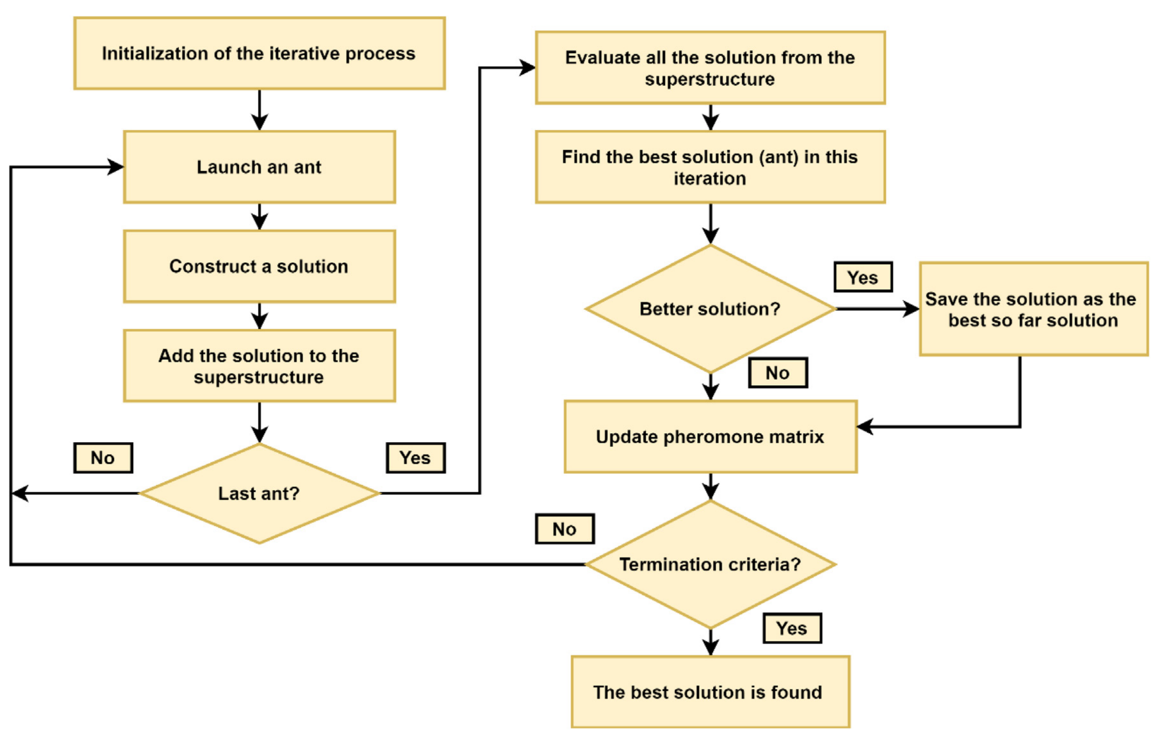


Fig. 4. The process of the ACO algorithm (Adapted from Xu et al., 2012).

2020). A particle's position and velocity in its movement process can be calculated using the following equations, respectively:

$$V_{new} = w \times V + C_1.r_1(p_{best} - X) + C_2.r_2(g_{best} - X), \quad (2)$$

$$X_{new} = X + V_{new} \quad (3)$$

where C_1 and C_2 are learning factors; X, X_{new}, V, and V_{new} denote current position, new position, current velocity, and new velocity, respectively; w is inertial weight; r_1 and r_2 are random numbers belonging to the interval [0,1] (Huang et al., 2020; Murlidhar et al., 2020; Hajihassani et al., 2015; Yagiz et al., 2018). Further information relevant to PSO applications and algorithms could be found in the literature (Yagiz and Karahan 2011; Hajihassani et al., 2018; Murlidhar et al., 2020; Hajihassani et al., 2015). The simple flow of the PSO algorithm is shown in Fig. 5.

Differential evolution (DE)

The DE algorithm is another well-known and widely used evolution algorithm that has been used in recent years for finding the globally optimal answer in a problem that has a continuous space (Storn, 2008; Storn and Price, 1997; Das et al., 2009; Chen et al., 2017). This algorithm was first introduced in 1995 by Price and Stern. DE looks for the global minimum of a multidimensional, multimodal function trying to obtain a good probability. The main idea of DE is a scheme for generating trial parameter vectors. DE differs from other evolutionary algorithms (EA) in their mechanism of generating offspring (Peralta et al., 2010). The standard DE consists of four main operations: initialization, mutation, crossover, and selection (Wang et al., 2015). In this algorithm, the initial population is usually generated using a uniform and random distribution, so the members of the population are evenly distributed in space, and at each stage of the algorithm, these members approach each other during the optimization process, and this convergence leads to smooth the optimal answer (Wang et al., 2015; Peralta et al., 2010; Shojaeian and Asadizadeh, 2020). From this population, by defining the boundaries of values and valuation, four members are randomly selected, one member being separated as the target member and the other three members as vectors 1, 2 and 3. To create a new generation in the next step, first the jump operator and then the crossover operator are applied. To apply the mutation operator and generate the mutated vector, first the difference between the 2 and 3 vectors is multiplied by the mutation step or the scale factor (numerically between 0 and 2) and added by the vector 1. After a new solution was generated using a mutation actuator and the crossover operator, the solution is compared with the previous value and is replaced if it is better (Wang et al., 2015; Peralta et al., 2010; Shojaeian and Asadizadeh, 2020).

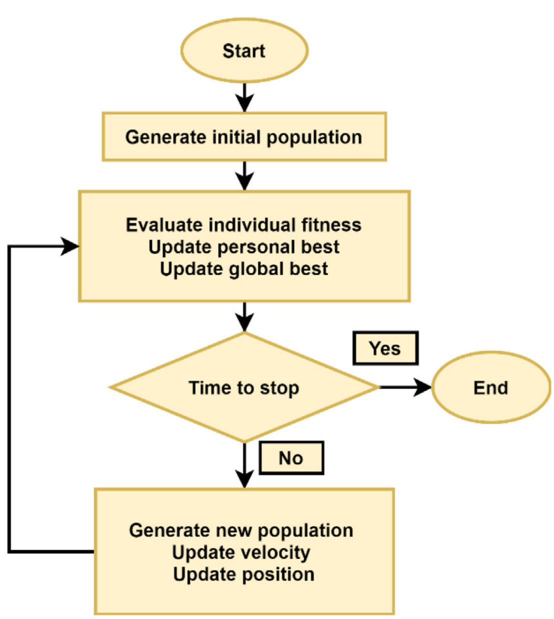


Fig. 5. Flow diagram of the particle swarm (Cheng et al., 2012; Aydın et al., 2013; Yagiz and Karahan 2011).

The main difference between genetic algorithms and differential evolution algorithms is in Selection operator. In the genetic algorithm, the chance of choosing an answer as one of the parents depends on its merit, but in the differential evolutionary algorithm, all the answers have an equal chance of being selected. The simple flow of the DE algorithm is shown in Fig. 6. Als further information relevant to DE applications and algorithms could be found in the literature (Zhang et al., 2016; Peralta et al., 2010; Chen et al., 2017; Pan et al., 2011; Wang et al., 2015; Rashid et al., 2013).

Genetic algorithm (GA)

Genetic Algorithm (GA), as a metaheuristic search technique based on natural selection and evolution process, optimize the solutions for various optimization problems (Goldberg, 1989). In GA, the possible solutions or initial population are randomly or with prior knowledge generated. Each population known as a chromosome or an individual is composed of genes and. The gens are binary strings encoded by 0 s and 1 s, but other encodings are also possible (Alipour et al., 2017)

The process of genetic algorithm is performed as follows:

The first step is generating appropriate initial population (chromosomes). Then the fitness of each generated chromosomes is evaluated according to the objective function. In next step, for improving the fitness values, new populations are generated by applying genetic operators. For this aim, chromosomes with higher fitness values are selected and using the crossover and mutation operators' new children or populations are formed and replaced with prior population (Vayenas and Peng, 2014).

The crossover operator, randomly selects a cross point along the string length of a pair of two selected chromosomes and replaces the position values between the two strings. Also the mutation operator, changes the gene values through flipping a single bit. In fact by mutation operator a small portion of genes is changed with a mutation

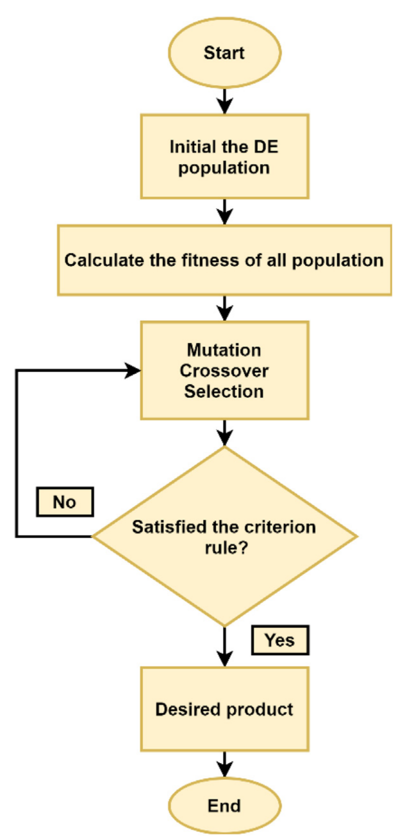


Fig. 6. The Flowchart of Basic Differential Evolution (Rashid et al., 2013).

probability. Generation and evaluation of new population continues till the stop criteria are not met. Accordingly, optimal solution is achieved by this algorithm (Monjezi et al., 2011).

Materials and methods

Materials

The reference soil was collected from a borrow pit, which has served as a source of construction soil for decades now. Fig. 7 shows the location map from where the soil was collected at a depth of 1.5 m. The soil was prepared by removing lumps and sundried for three days in open air.

Conversely, the rice husk was collected from local rice mills at Abakaliki, Nigeria rice farming is predominant and the husk a solid waste disposed indiscriminately for lack of adequate disposal management program. The husk was combusted as shown in Fig. 8. Through this procedure, the rice husk ash was generated. Furthermore, the rice husk ash was activated by blending a 5% dosage of hydrated lime by weight of the ash in order to generate the activated ash known as the hybrid cement (HC). Note, "*hydrated lime (Ca $(OH)_2$) is the quicklime combined chemically in water with 33% to 34% magnesium oxide (MgO), 46% to 48% of CaO, and 15% to 17% chemically combined with water. It is a crystal, non-flammable, odorless inorganic powder, which is soluble in water at ambient temperature. It has a melting point of 580 °C, a boiling point of 2850 °C, and a density of 2.21 g/cm^3. Its density is less than that of quicklime (3.34 g/cm^3) due to its more aqueous condition that creates pores in the structure of the solid. It is caustic with a pH of 12.8 and possesses pozzolanic characteristics, which makes it a good supplementary or alternative binder in civil engineering and earthworks*". Due to the properties outlined, hydrated lime serves as a good activator to ordinary ash materials utilized in soil stabilization. The HC is one of the major locally synthesized green binders in this exercise with improved cementing properties. In addition, quarry dust (QD) as shown in Fig. 9, was also collected from rock blasting site at Amasiri, Nigeria where aggregates are produced for construction works. The QD was further pulverized to fineness and sieved through a 200 nm sieve to generate the nanostructured quarry fines used as a second binder in the stabilization phase of this operation. These green binder materials; HC and NQF, were observed via XRF tests to meet the requirements for materials to be classified as pozzolanas (ASTM C618, 1978), as green and cleaner materials (GCM) compared to the hazardous emissions of conventional cement. Finally, the soil, HC and NQF were made ready and stored for use in the stabilization work.

Methods

Experimental program

The requirements of the British Standard International (BSI) (BS1377, 1990) were observed in conducting general tests on the materials for the purpose of characterization and classification. Under the above design conditions, the particle size analysis, compaction, Atterberg limits, specific gravity, and the angle of internal friction were conducted, which served as control experiments. In order to determine the morphology and oxides composition of the composite binder materials (RHA, HC and NQF), the scanning electron micro-

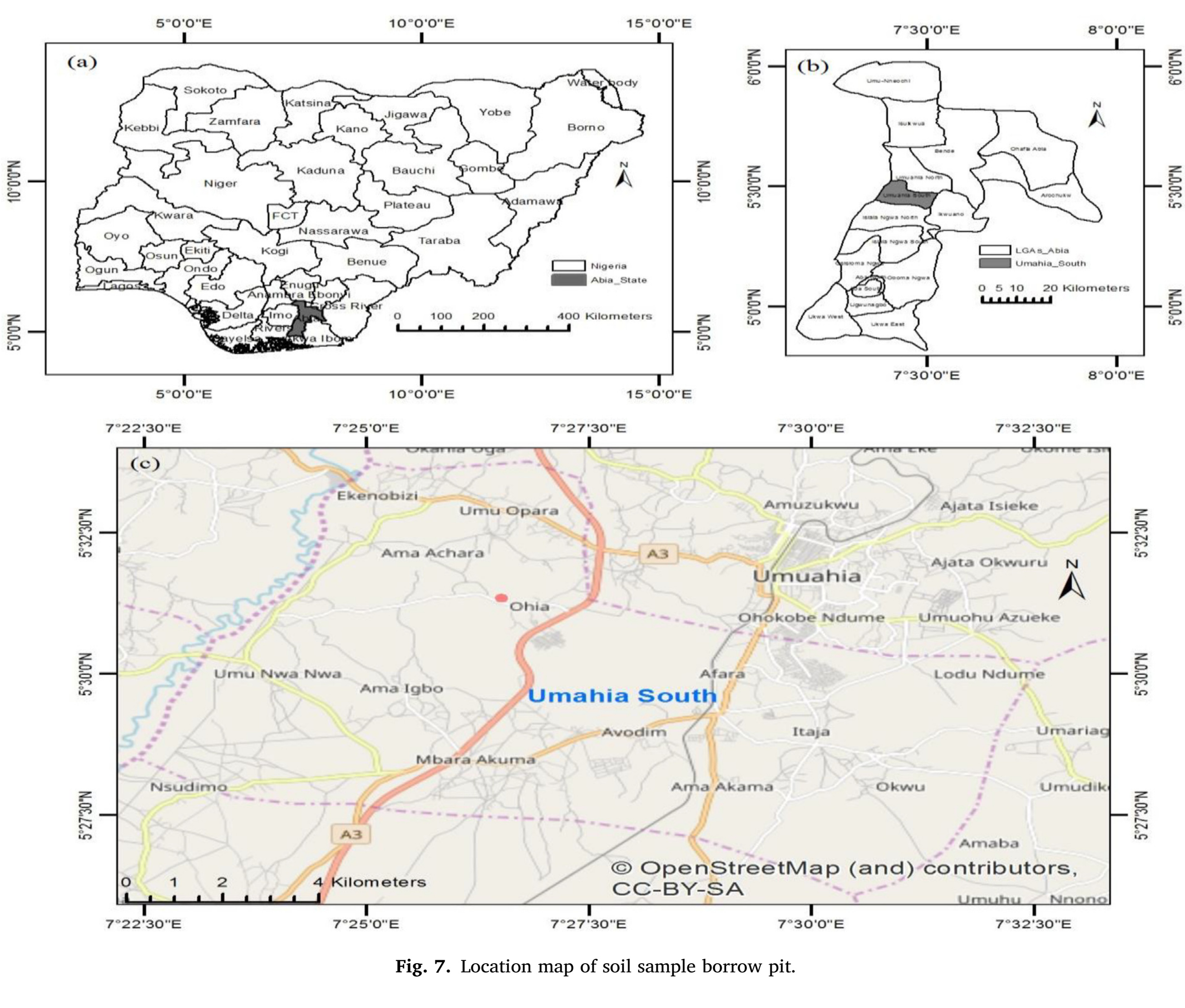


Fig. 7. Location map of soil sample borrow pit.

Fig. 8. Rice husk and ash processing by direct combustion.

Fig. 9. Quarry dust.

scopy (SEM) and the x-ray fluorescence (XRF) exposure tests were carried out in accordance with the ASTM E1621-13 (2013), and in order to achieve reliable and precise results, the samples were prepared and mixed to high homogeneity and the results were observed and recorded. Also, the UV–Vis spectrophotometer test was conducted on the NQF to determine the absorbance of the nanostructural exposure of the material. Further, the treatment exercise on the soil was conducted by mixing soil-HC and soil-NQF, in accordance with the requirements of the BS1924 (1990) and multiple data points were generated for varying dosages of HC and NQF between 0% and 12% by weight of dry soil at the rate of 0.1% and 0.01% respectively.

Models development

Predicting with linear multivariate regression (LMR). To predict the coefficient of curvature and uniformity, using intelligent methods and multivariate linear regression between input parameters and output parameters, a representative database for valid statistical analysis, consisting of 121 datasets has been created. After studies, in order to construct a predictive model of curvature coefficient and uniformity coefficient, 5 effective parameters (HC, NQF, C, Ac, and F) were used as input parameters and curvature coefficient and uniformity coefficient considered as output parameters (Table 1). Each of these 5 parameters contains 121 data. The box diagram of the input data is also shown in Fig. 10.

In the next step, the data were divided into two parts: model construction data and validation data. The ratio of 70% (85 data) was used for training data and 30% (36 data) were randomly used for test data. After describing the data, the best statistical relationships between each the input and the output data have been suggested by using the Table curve v.5.01 software which is one of the most powerful statistical software for curve and surface fitting the data. These relationships have been selected based on their R-squared coefficients and square of the average error (RMSE). Indeed, this analysis provides an opportunity to consider the interrelationship between the inputs (Hc, Nqf, C, Ac and F) and outputs (Cc and Cu) data in the further proposed relationship (Shakeri et al., 2020; Shokri et al., 2020).

After finding the best relationships between the input and the output data, each of the relationships has been considered as independent variables while the outputs were Cc and Cu. For finding the best relationship for prediction of Cc and Cu, comprehensive statistical analyses have been conducted by applying the IBM SPSS statistics software v.25 based on the LMR method. For this, the stepwise method has been used to identify the best multivariate regression relationship among the selected relationships (Shakeri et al., 2020; Shokri et al., 2020). According to Table 2, after the analysis, the best statistical relationships for Cc and Cu were obtained. To find the best relationship, three statistical parameters were selected as the best criteria. The RMSE (Eq. (4)) index is the root square of the average error between the measured and predicted data. Note that the lower the RMSE the better the model performance. Ideally, the values of RMSE and MAE (Eq. (5)) should be close to zero. Also the coefficient of determination R^2 (Eq. (6)), which is the correlation between the measured and predicted data, should be close to 1 (Asadizadeh and Hossaini, 2016). In fact, to find the best relationship, the three statistical parameters mentioned were selected as the best criteria. Table 2, shows the best values for Cc and Cu, and the Eqs. (7) and (8) for Cc and Cu, respectively, were obtained using the LMR method. Figs. 11 and 12 also show the relationship between the actual values of Cc and Cu and the values predicted and comparison of measured and predicted values by linear regression for the test data.

Table 1
Statistical indicators of input and output parameters.

Type	Parameter	Symbol	Min	Max	Std. Deviation	Variance
Input	Hybrid cement (%)	Hc	0.00	12.00	0.32	12.30
	Percentage nanostructuredquarry fines (%)	Nqf	0.00	1.20	0.03	0.12
	Clay content (%)	C	23.02	24.07	0.03	0.10
	Clay activity	Ac	0.60	2.00	0.04	0.16
	Frictional angle (°)	$F(\varnothing^{\circ})$	15.00	21.60	0.19	4.36
Output	Coefficient of curvature	Cc	0.84	1.96	0.03	0.09
	Coefficient of uniformity	Cu	2.05	5.86	0.12	1.75

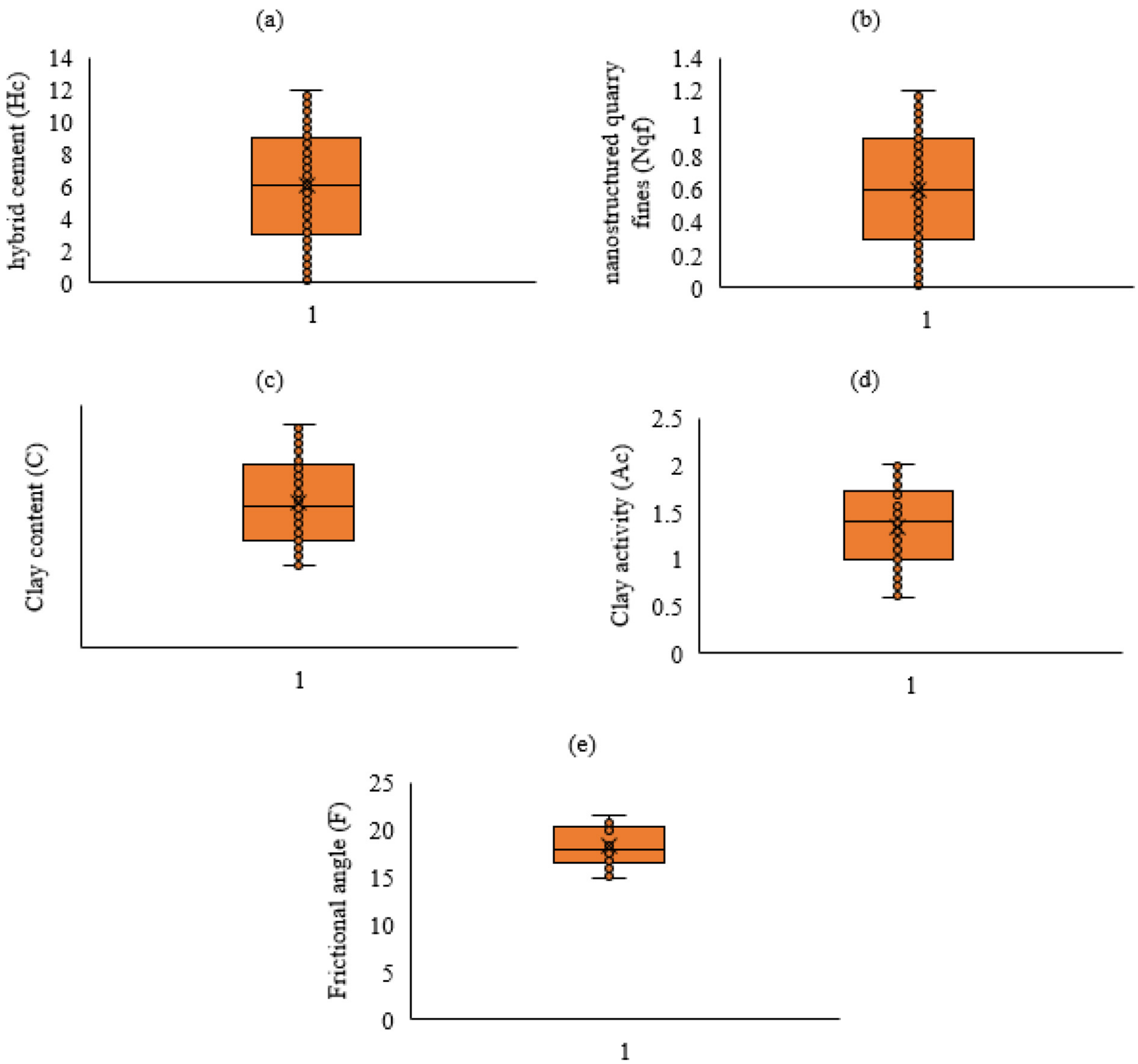


Fig. 10. Box diagrams of the input data: (a) hybrid cement (Hc), (b) percentage nanostructured quarry fines (Nqf), (c) clay content (C), (d) clay activity (Ac) and (e) frictional angle (F).

Table 2
Performance indicator values for building LMR models for Cc and Cu forecasts.

Methods	Train			Test		
	R^2	RMSE	MAE	R^2	RMSE	MAE
Cc	0.9982	0.0129	0.0104	0.9964	0.0157	0.0140
Cu	0.9931	0.1074	0.0726	0.9932	0.1124	0.0920

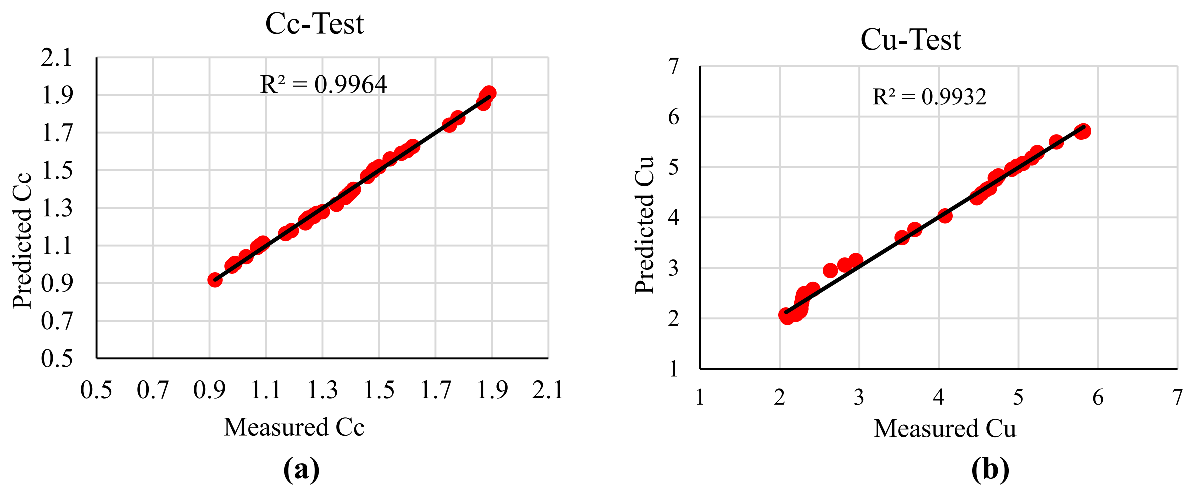


Fig. 11. The values of R-squared for LMR models, a) coefficient of curvature (Cc) and b) coefficient of uniformity (Cu).

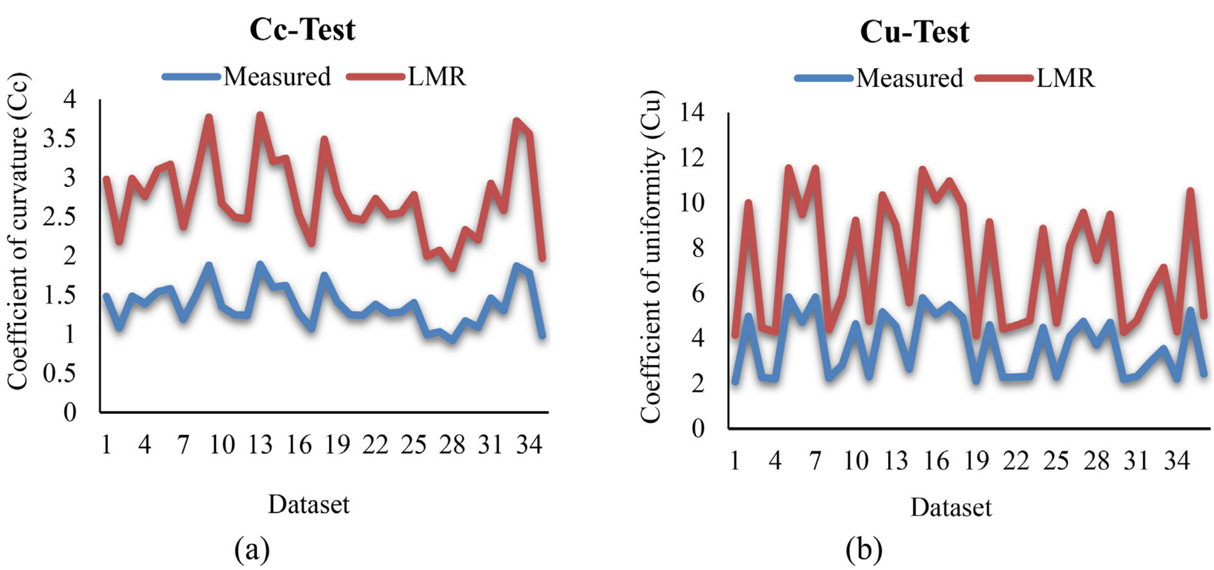


Fig. 12. Comparison of measured and predicted values using LMR model for a) coefficient of curvature (Cc) and b) coefficient of uniformity (Cu).

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\mathrm{Xipred} - \mathrm{Ximes})^2} \tag{4}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|\mathrm{Xipred} - \mathrm{Ximes}| \tag{5}$$

$$R^2 = 1 - \frac{\sum_{(i=1)}^{N}(\mathrm{Ximes} - \mathrm{Xipred})^2}{\sum_{(i=1)}^{N}(\mathrm{Ximes} - \overline{\mathrm{Ximes}})^2} \tag{6}$$

That: Xipred is the predicted values and Ximes are the measured values.

$$\begin{aligned}\mathbf{Cc} = 1.87 &+ \left((-1.04 \times \mathrm{EXP}(-\mathrm{Nqf})) + \left(\frac{-0.1 * \mathrm{LN(Ac)}}{\mathrm{Ac}^2}\right)\right)\\ &+ ((0.008 * \mathrm{Hc} * \mathrm{LN(Hc)}) + (-351503 * \mathrm{EXP}(-\mathrm{F})))\\ &+ (0.018 * \mathrm{EXP(Ac)})\end{aligned} \tag{7}$$

$$\begin{aligned}\mathbf{Cu} = -705.93 &+ \left((0.59 \times \mathrm{EXP}(-\mathrm{Hc})) + \left(-0.38 \times \mathrm{Ac}^{2.5}\right)\right)\\ &+ \left((252.58 \times \mathrm{LN(C)}) + (-0.51 \times \mathrm{F})) + \left((-0.02945) \times \mathrm{C}^{2.5}\right)\right.\\ &+ \left(\left(0.06304 \times \mathrm{Hc}^2\right) + \left(-3.39628 \times \mathrm{Nqf}^3\right)\right)\end{aligned} \tag{8}$$

Predicting with ANFIS methods. Due to the limitations of laboratory environments, artificial intelligent approaches have been developed in rapid succession. These recent developments have satisfied researchers that they could be suitable as the future of many approaches to assess parameters, more precise than ordinary approaches. For instance, forecasting the ground vibration, flyrock and back breck caused by explosions in mining, prediction of surface tension, prediction of uniaxial compressive strength in rock and concrete structures and price forecasting in economic matters utilising artificial neural networks, genetic algorithms (GAs), fuzzy logic and neuro fuzzy systems have been the attractive research topics relating to economy, mining and civil engineering in the recent years (Shakeri et al., 2020; Jahed Armaghani et al., 2018; Asadizadeh and Hossaini 2016; Monjezi et al., 2012; Shokri et al., 2020; Armaghani et al., 2016; Monjezi et al., 2013; Dehghani and Zangeneh, 2018; Alameer et al., 2020).

Therefore, in this section, we have tried to examine the coefficient of curvature (Cc) and coefficient of uniformity (Cu) using ANFIS, ANFIS-GA/PSO/ACO/DE artificial intelligence methods. In this section, in order to predict Cc and Cu using ANFIS methods, as in LMR method, the data were divided into two categories. So the ratio of

70% (85 data) was used for training data and 30% (36 data) was used for test data. In the ANFIS-GA/PSO/ACO/DE approach, the learning algorithm for achieving good performance as well as high accuracy is adopted separately. To achieve this aim, the optimal parameters of the ANFIS model are obtained by the GA/PSO/ACO/DE algorithm. GA/PSO/ACO/DE -based ANFIS approaches are implemented using matlab codes. The optimal values of the parameters of the ANFIS model based on GA/PSO/ACO/DE for predicting Cc and Cu are listed in Table 3.

Table 3
Optimal ANFIS- GA/PSO/ACO/DE values for predicting Cc and Cu.

Parameter (ANFIS)	Description/value for Cc	Description/value for Cu
Fuzzy structure	**Sugeno-type**	**Sugeno-type**
Type of membership function of the input	Gaussian ("gaussmf")	Gaussian ("gaussmf")
Type of membership function of the output	Linear	Linear
The center of the cluster influence	0.7	0.7
Input number	5	5
Output number	1	1
Optimization approach	**GA/PSO/ACO/DE**	
Iteration number	2000	2000
No. of data for training	85	85
No. of data for test	36	36
Initial step size	0.4	0.3
The step size of the decrease rate	0.9	0.8
The step size of the increase rate	1.2	1.5
Number of fuzzy rules	6	7
Parameter (GA)	**Description/value**	
Population size	40	40
Mutation rate	0.05	0.07
Crossover	0.6	0.7
Parameter (ACO)	**Description/value**	
Initial pheromone Matrix Value	0.001	0.001
Number of construction steps	70	80
Movement steps	700	600
Pheromone decay coefficient	0.5	0.5
Parameter (DE)	**Description/value**	
Generation number	40	40
Population size Np	40	40
Mutation rate	0.05	0.05
Cross probability Cr	0.5	0.5
Parameter (PSO)	**Description/value**	
Population size	40	50
W	0.5	0.5
C1	2	2
C2	2	2

In fact, like the linear regression method to find the best prediction, the three mentioned statistical parameters were selected as the best criteria. Table 4, shows the results obtained from the ANFIS methods including; R^2, RMSE and MAE for training and test data. Like the LMR method mentioned earlier, the selection criteria for the two final models in Table 4, were based on the highest R^2 and the lowest MAE and RMSE.

According to the results obtained in Table 4, the considered smart methods have a high ability to predict Cc and Cu. Among these methods, for both Cc and Cu the ANFIS method with the highest R^2 and the lowest RMSE an MAE for training and testing data has the best performance. Figs. 13 and 14 also show the relationship between the actual values of Cc and Cu and the predicted values and comparison of measured and predicted values by ANFIS-GA/PSO/ACO/DE for the test data, which continue to show the superiority of the ANFIS method.

Results discussion

General results and materials characteristics

The soil was observed from Fig. 15 to be poorly graded soil with coefficients of curvature and uniformity as 0.84 and 2.05 respectively and classified as an A-7–6 group according to AASHTO classification method. The soil was discovered to be highly plastic with high clay content. The angle of internal friction of the soil was observed to be 15°, with clay content and clay activity of 23.02% and 2 respectively. Fig. 16 shows the compaction behavior of the lateritic soil with a maximum dry density of 1.84 g/cm^3 obtained at optimum moisture content of 16.2%. It can be observed from Table 5 that the RHA, HC and NQF showed characteristics of pozzolanas with the combined oxide compositions of SiO_2, Al_2O_3 and Fe_2O_3 as more than 70% in accordance with the appropriate testing and materials standard (ASTM C618, 1978). The behavior was important in the stabilization operation where these materials in single and composite forms were blended with soil to trigger hydration, pozzolanic, calcination, and cation exchange reactions culminating to the behavioral changes observed in the treated soil with respected to the measured parameters. Figs. 17 and 18 show the particle distribution and uv–vis spectrophotometric nanograph of the quarry dust (QD) and nanostructured quarry fines (NQF) respectively. The absorbance behavior of the NQF presented in Fig. 18 became necessary to determine the mechanism whereby size can potentially enhance cohesion between soil and nanostructured admixture which in this case is NQF. Because the nanopores are less kinetically restricted, they contribute most of the surface areas at the temperature where its isotherm is achieved during hydration under homogenous distribution of nano

Table 4
Values of performance indicators for building the ANFIS models.

Methods		Train			Test		
		R^2	RMSE	MAE	R^2	RMSE	MAE
Cc	ANFIS	0.9999	0.0021	0.0015	0.9994	0.0077	0.0059
	ANFIS-DE	0.9960	0.0193	0.0147	0.9950	0.0209	0.0176
	ANFIS-ACO	0.9959	0.0195	0.0149	0.9949	0.0211	0.0177
	ANFIS-GA	0.9991	0.0094	0.0065	0.9989	0.0099	0.0079
	ANFIS-PSO	0.9996	0.0062	0.0050	0.9989	0.0095	0.0073
Cu	ANFIS	0.9999	0.0058	0.0042	0.9992	0.0395	0.0211
	ANFIS-DE	0.9779	0.2012	0.1479	0.9793	0.2412	0.1929
	ANFIS-ACO	0.9725	0.2160	0.1629	0.9738	0.2479	0.2045
	ANFIS-GA	0.9949	0.1000	0.0798	0.9954	0.0983	0.0807
	ANFIS-PSO	0.9893	0.1347	0.1011	0.9951	0.1127	0.0924

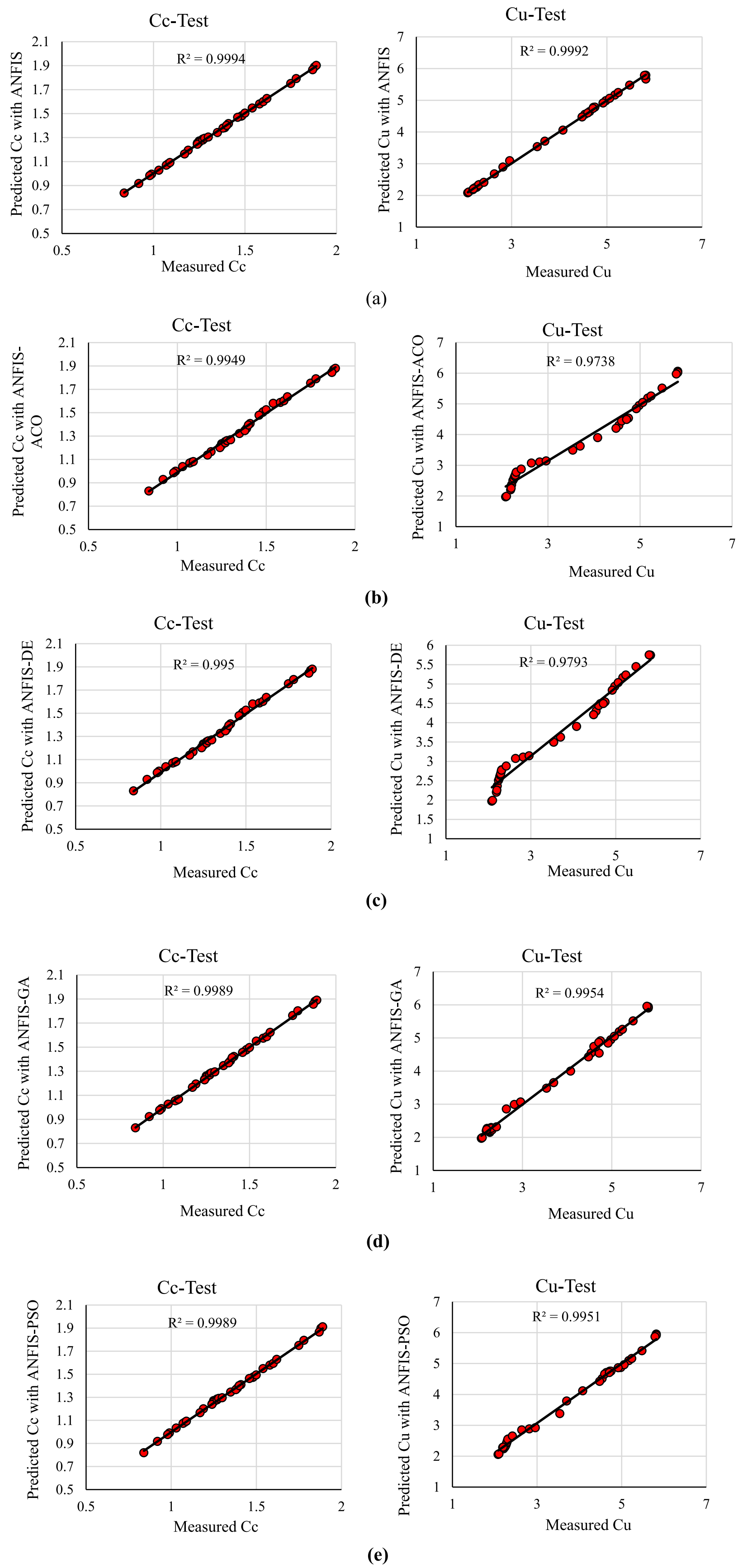
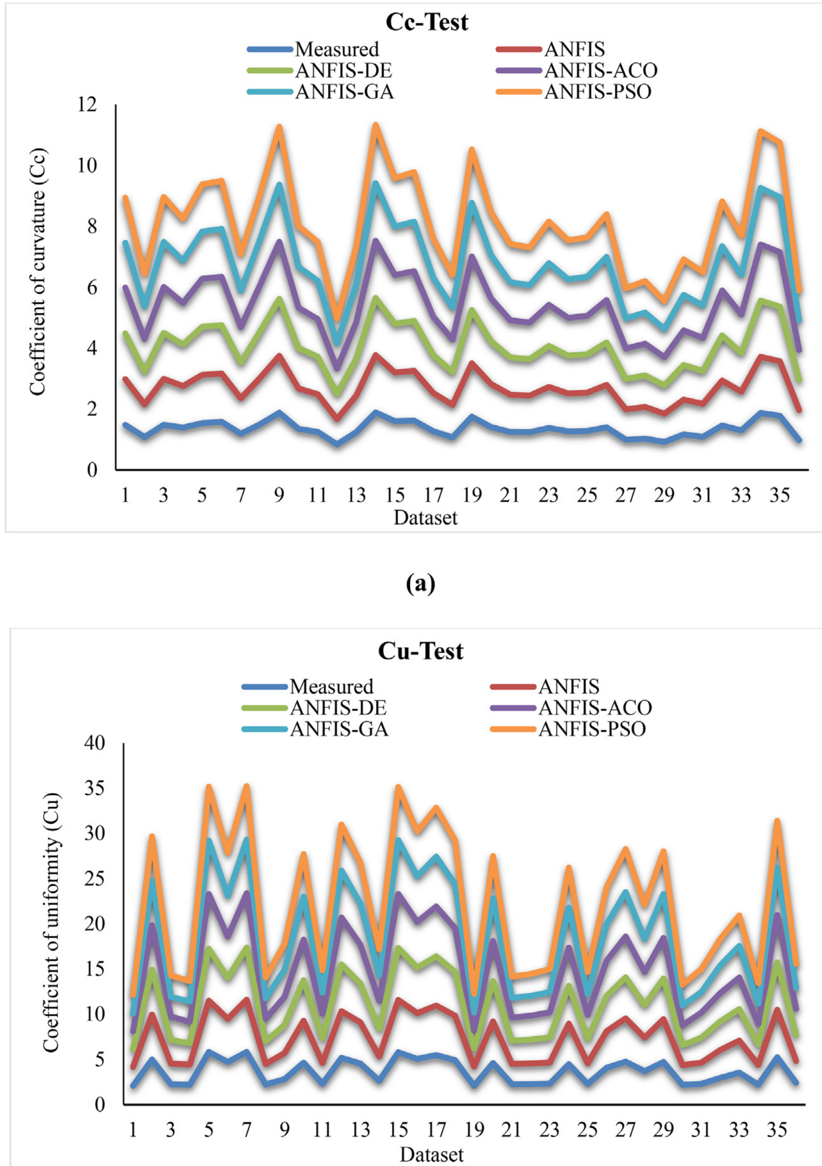


Fig. 13. The values of R-squared for predicting coefficient of curvature (Cc) and coefficient of uniformity (Cu) based on, a) ANFIS; b) ANFIS-ACO; c) ANFIS-DE; d) ANFIS-GA and e) ANFIS-PSO.



(b)

Fig. 14. Comparison of measured and predicted values using ANFIS- GA/PSO/ACO/DE and LMR models for a) coefficient of curvature (Cc) and b) coefficient of uniformity (Cu).

particles. Figs. 19–22 present the scanning electron microscopic arrangement (morphology) of the QD, RHA, NQF and HC. It can be noted in the Supplementary material, which is the tabulated behaviour of the soil with the addition of HC and NQF, that the tested soil properties including the output parameter; Cc and Cu of the intelligent models improved with increased addition of admixtures. This was due to the pozzolanic ability of the materials presented in Table 5, which enhanced green cementation through activation, cation exchange and hydration reactions.

Validation of models results

As mentioned, due to the limitations of laboratory environments, artificial intelligent approaches have been developed in rapid succession. These recent developments have satisfied researchers that they could be suitable as the future of many approaches to assess parameters more precise than ordinary approaches. The main aim of this paper, was predicting the coefficient of curvature (Cc) and coefficient of uniformity (Cu) based on the parameters including the hybrid

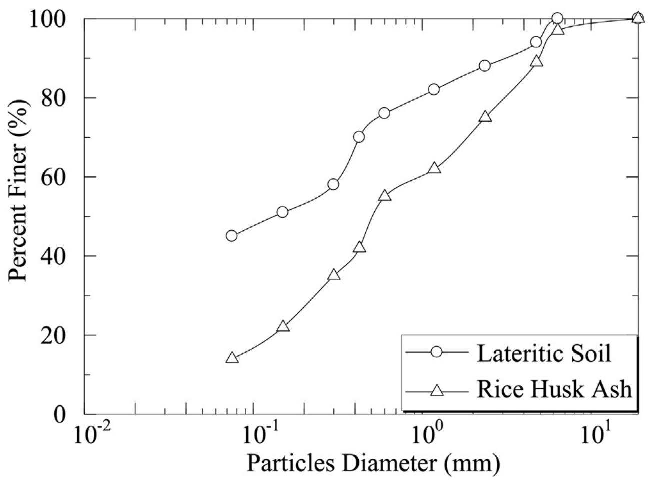


Fig. 15. Particle size distribution curve of clayey soil and rice husk ash.

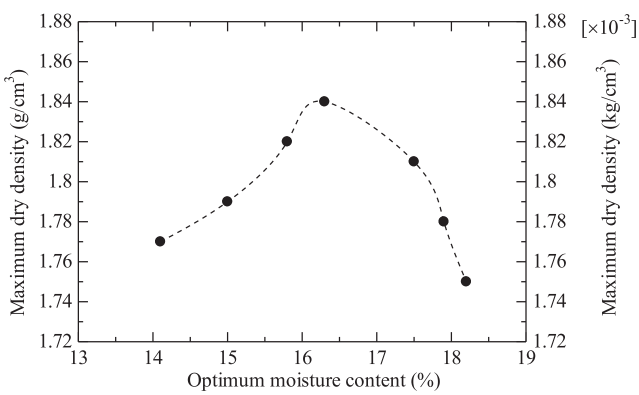


Fig. 16. Compaction characteristics of lateritic soil sample.

cement (Hc), percentage nanostructured quarry fines (Nqf), clay content (C), clay activity (Ac) and frictional angle (F). To development the relationships, firstly, the data collected from the multiple experiments were used to establish a database between the input and output data. Then, the best relationships between the outputs and each input were investigated by comprehensive statistical analyses. Subsequently, the LMR, ANFIS methods and Combined methods with ANFIS (including, ANFIS- GA/PSO/ACO/DE) were applied for predicting the Cc and Cu. The obtained results of these methods were then compared based on the highest R^2 and the lowest MAE and RMSE values for training and test stages. The best values obtained for all methods are listed in Table 6, based on the statistical indicators.

According to Table 6, all methods of ANFIS and LMR reveal high accuracy in predicting Cc and Cu values due to the high correlation of the collected data, and if we consider the best models based on the desired indicators, we can say ANFIS, ANFIS-PSO, ANFIS-GA, LMR, ANFIS-DE and ANFIS-ACO have the best performance in predicting Cc respectively. While for predicting Cu we find that, ANFIS, ANFIS-GA, ANFIS-PSO, LMR, ANFIS-DE and ANFIS-ACO have the best performance respectively (see Fig. 23).Fig. 24.

Sensitivity analysis

Sensitivity analysis was performed to determine the impact of each data on the output. Therefore, the method introduced by Yang and Zang in this study was used. All data pairs were utilized to construct a data array X as follows (Yang and Zhang, 1997; Faradonbeh et al. 2016; Khandelwal et al. 2016; Sayevand et al. 2018; Shojaeian and Asadizadeh, 2020; Asadizadeh and Rezaei 2019):

$$X = \{x_1, x_2, x_3, \cdots, x_i, \cdots, x_n\} \tag{9}$$

Each of the elements, xi, in the data array X is a vector of lengths of m, that is:

$$X = \{x_1 1, x_2 2, x_3 3, \cdots, x_{im}\} \tag{10}$$

The strength of the relation between the dataset, xi and xj, is presented as follows:

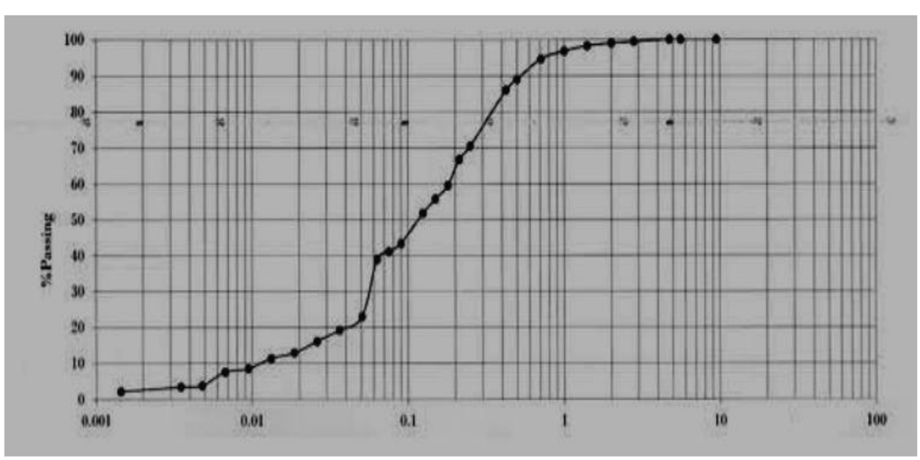


Fig. 17. Particle size distribution of quarry dust.

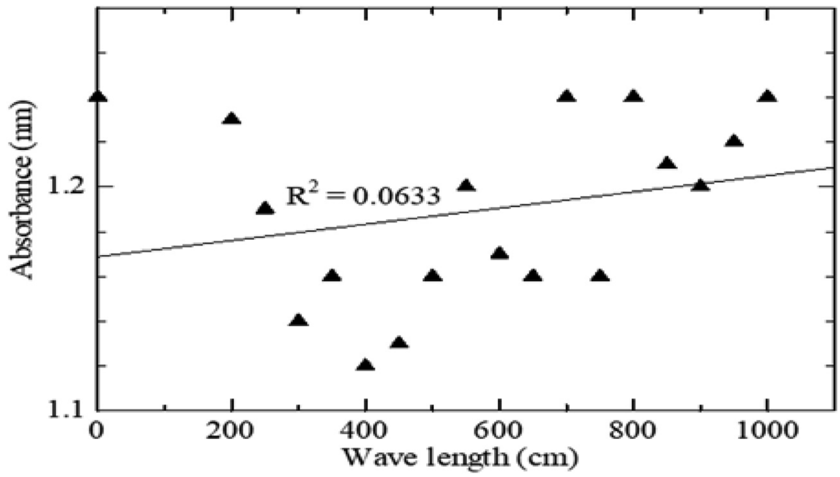


Fig. 18. UV–VIS-Spectrophotometric Nanograph of Nanostructured Quarry Fines.

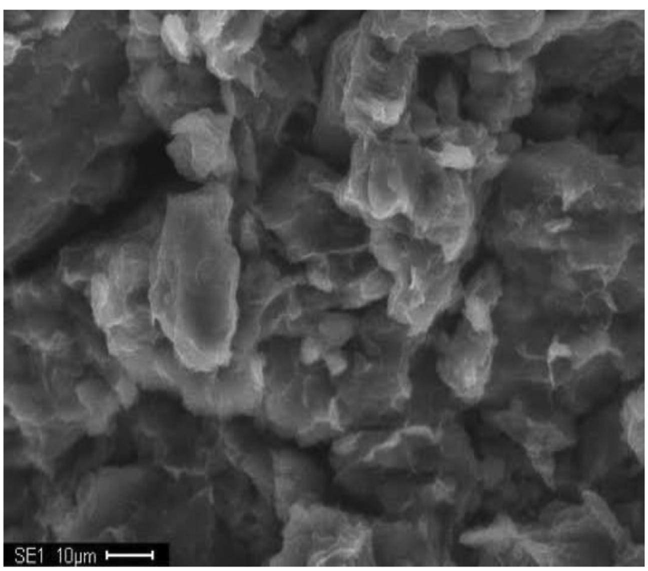


Fig. 19. SEM of Quarry Dust.

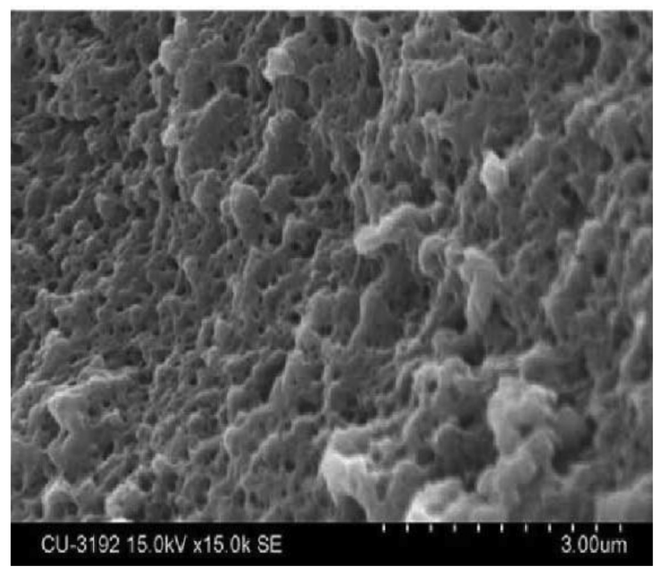


Fig. 20. SEM of RHA.

$$r_{ij} = \frac{\sum_{k=1}^{m} x_{ik}x_{jk}}{\sqrt{\sum_{k=1}^{m} x_{ik}^2 \sum_{k=1}^{m} x_{ik}^2}} \tag{11}$$

Fig. 11 shows the strengths of the relations (rij values) between the model inputs and outputs. The results showed that, F, C, H, Nqf and Ac have the most and the least effect on Cc, respectively (Fig. 11a). While the highest and lowest effects on Cu were obtained as Hc, Nqf, F, C and Ac (Fig. 11b).

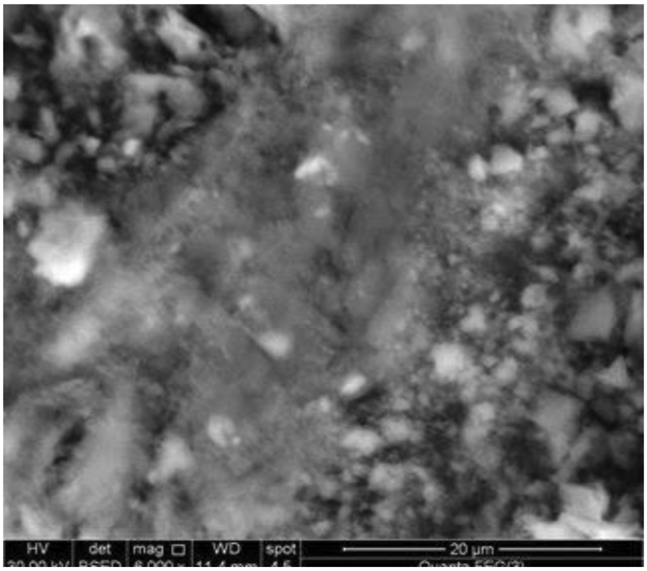


Fig. 21. SEM Nano Quarry Fines.

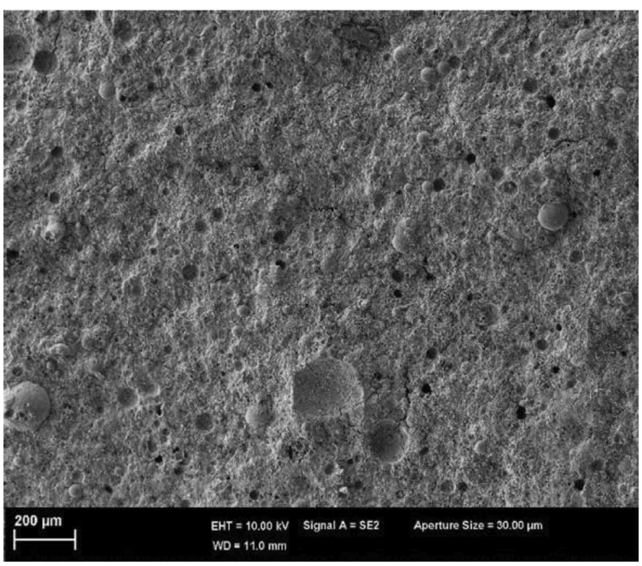


Fig. 22. SEM of Hybrid Cement.

Conclusions

The adaptive neuro fuzzy inference system (ANFIS) and its selected evolutionary hybrid learning techniques; ANFIS-PSO, ANFIS-GA, ANFIS-ACO and ANFIS-DE have been employed in forecasting the coefficients of curvature and uniformity of unsaturated lateritic soil treated with the combined influence of hybrid cement and nanostructured quarry fines (NQF). The multi-linear regression or the linear multivariate regression was also employed as a base regression model to check the conformity or the correlation between selected parameters of the model exercise. Preliminary test results showed that the soil was a problematic soil classified as A-7–6 group and poorly graded with high clay content. It was also observed that the rice husk ash, quarry dust and its nanostructured type (NQF) showed high aluminosilicate content to be classified as pozzolanas by appropriate testing and material standard. The following were concluded from the foregoing prediction model;

- The MLR (LMR) showed that the selected input parameters of the model exhibited close correlation with the output parameters beyond 0.95.
- The outcome of the performance evaluation and model validation selected indicators; R^2, RMSE and MAE for both training and testing showed that ANFIS outclassed all its hybrid techniques and MLR. However, ANFIS-PSO followed by ANFIS-GA outclassed ACO and DE techniques and of course MLR on both training and testing for the Cc model prediction. But, for the Cu model prediction, ANFIS-GA followed by ANFIS-PSO outclassed again ACO and DE techniques and of course the MLR.
- The sensitivity analysis of model parameters degree of importance and influence showed acceptable results with F showing the greatest influence on Cc model behavior and Ac as the lowest influential. This model behavior shows the effect of angle of internal friction between materials particles on curvature which is a shape function in the gradation of soils. Meanwhile, clay content (C), HC and NQF also showed good influence on the Cc model prediction. Secondly, Cu model prediction was influenced most by HC and NQF in equal proportion. This also shows the contribution of various particle sizes of HC and NQF, which were uniformly distributed in the admixture-soil blend. Again, Ac was the least influential. However, F and C also showed considerable contribution to the behavior of the Cu evolutionary model prediction.
- Generally, ANFIS and its evolutionary hybrids have shown to be good learning techniques in predicting with the properties of treated lateritic soil with great accuracy.

Table 6
The best predicted values of R^2, RMSE and MAE for forecasting Cc and Cu.

Methods		Train			Test		
		R^2	RMSE	MAE	R^2	RMSE	MAE
Cc	ANFIS	0.9999	0.0021	0.0015	0.9994	0.0077	0.0059
	ANFIS-DE	0.9960	0.0193	0.0147	0.9950	0.0209	0.0176
	ANFIS-ACO	0.9959	0.0195	0.0149	0.9949	0.0211	0.0177
	ANFIS-GA	0.9991	0.0094	0.0065	0.9989	0.0099	0.0079
	ANFIS-PSO	0.9996	0.0062	0.0050	0.9989	0.0095	0.0073
	LMR	0.9982	0.0129	0.0104	0.9964	0.0157	0.0140
Cu	ANFIS	0.9999	0.0058	0.0042	0.9992	0.0395	0.0211
	ANFIS-DE	0.9779	0.2012	0.1479	0.9793	0.2412	0.1929
	ANFIS-ACO	0.9725	0.2160	0.1629	0.9738	0.2479	0.2045
	ANFIS-GA	0.9949	0.1000	0.0798	0.9954	0.0983	0.0807
	ANFIS-PSO	0.9893	0.1347	0.1011	0.9951	0.1127	0.0924
	LMR	0.9931	0.1074	0.0726	0.9932	0.1124	0.0920

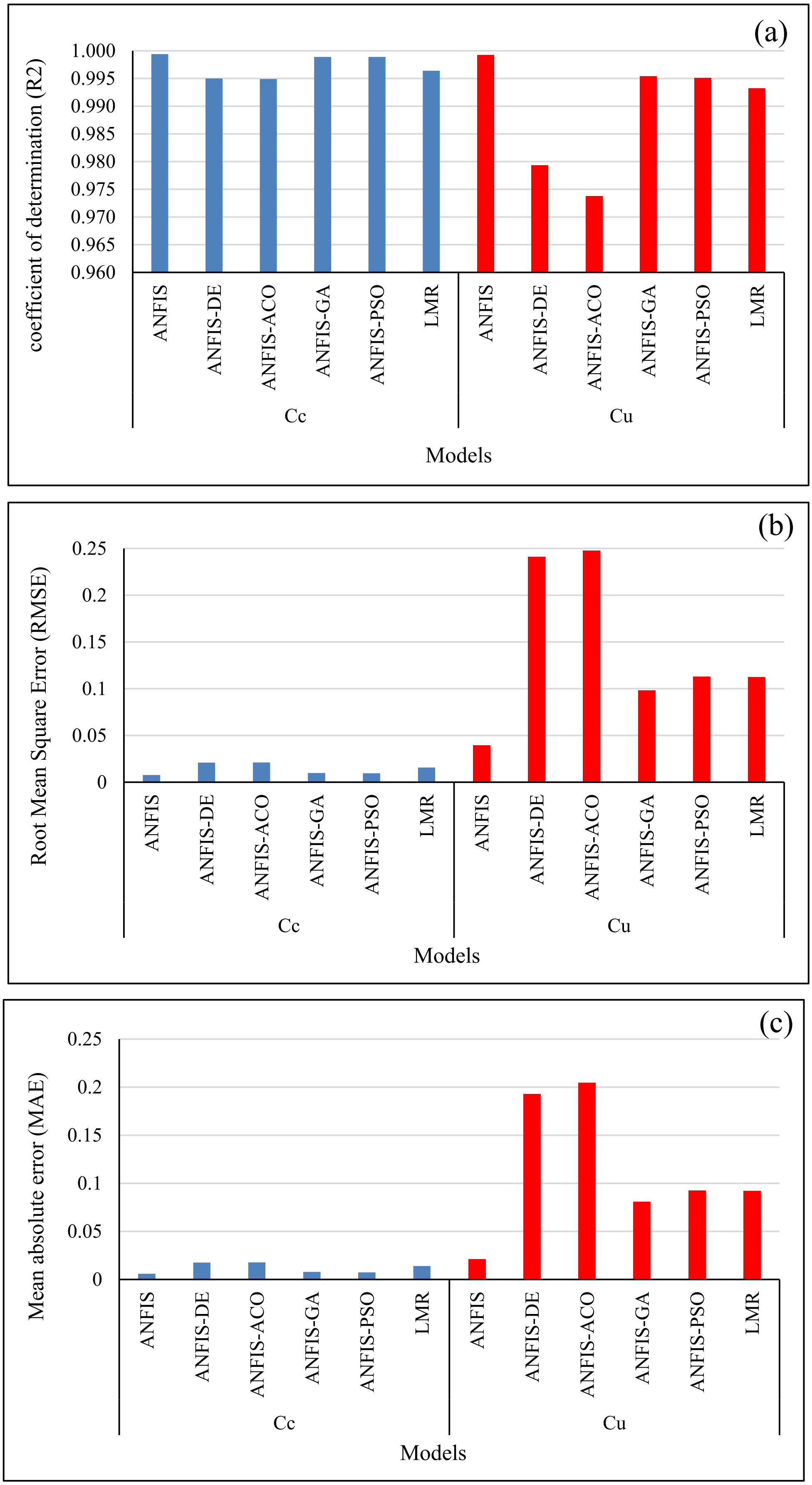
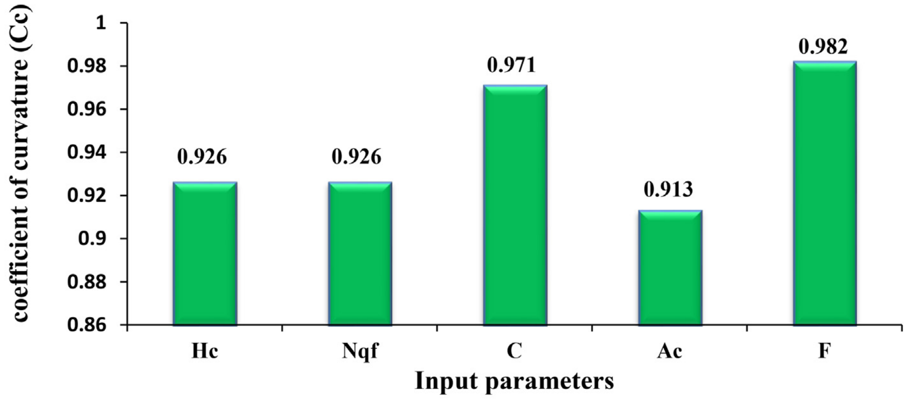
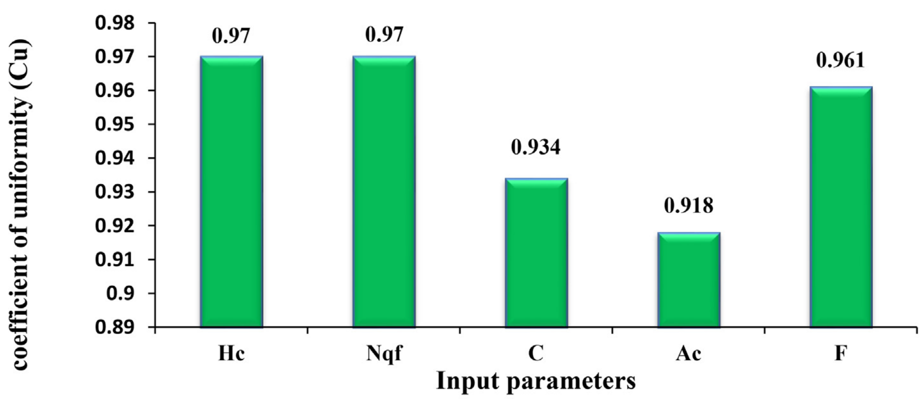


Fig. 23. Comparison of predicted values of, a) R^2, b) RMSE and c) MAE for forecasting Cc and Cu.



(a)



(b)

Fig. 24. Sensitivity analysis to determine the impact of each data on the output for a) coefficient of curvature (Cc) and b) coefficient of uniformity (Cu).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.clema.2021.100005.

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