Chapter 61
Comparative Study of Application of Artificial Neural Networks for Predicting Engineering Properties of Soil: A Review

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Abstract The primary aim of the synthetic neural network approach was to unravel the issues similarly that a person's brain would. The artificial neural network system was extensively applied in geotechnical engineering. Geotechnical engineering properties of soil hold the solidity of engineering structures. The engineering properties of soils are much worried about the distortion and strength of bodies of soil. Engineering properties of soil which measure the engineering behavior of soils. This review paper presents a quick overview of artificial neural network (ANN) applications of engineering properties of soil, viz. optimum moisture content, maximum dry density, permeability, shear strength parameters, and unconfined compressive strength. The review suggests that ANN with different models can predict the engineering properties of soil accurately. The survey recommends that the ANNs had been exceptionally valuable in effectively interpreting inadequate input information. This study shall help the researchers those working in the area of applications of ANN on soil behavior.

Keywords ANN · Maximum dry density · Optimum moisture content · Shear strength · Permeability · Unconfined compressive strength

1 Introduction

Artificial neural networks (ANNs) have broad applicability to unravel many problems in the engineering field. ANNs are best at identifying patterns, trends in data; they are well used for prediction purposes in geotechnical engineering. ANN consists of three layers: the input layer represents to provide raw information to the network, the hidden layer establishes between the input and output of the algorithm, and hidden

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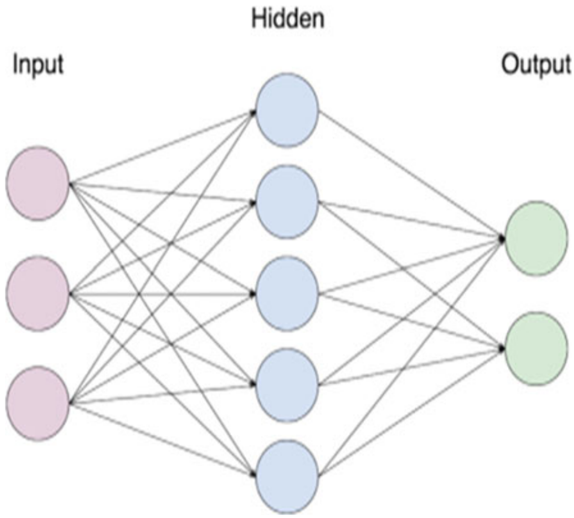
Fig. 1 Working principle of ANN



layer takes action with its input and weights from the preceding layer and applies a nonlinearity to it and sends to the output layer. The output layer in a neural network accumulates and transfers the information in a designed way. Figure 1 shows the simple working principle of the artificial neural network.

The geotechnical index and engineering properties of soils influence each other, and it depends on laboratory testing, time effects, loading effects, inherent soil variability, construction effects, human errors, errors in soil boring, sampling. From the year 1990, ANN has been utilized in various fields in geotechnical engineering like predicting soil behavior, predicting pile capacity, on earth retaining structures, site characterization, liquefaction analysis, slope stability analysis, tunnels, underground openings, and landslides assessment. The present review paper discussed applications of the artificial neural networks on different engineering properties of soil. Engineering properties of soil useful for engineering applications comprise permeability, compressibility, and shear strength parameters of the soil. Engineering properties of soils are those properties that may be used for quantifying the engineering behavior of soils. Engineering properties (Behavior of soil after application of load) of soil depends on Soil Classification, Atterbergs limits, Water content (index properties). So, the determination of those engineering properties of soil in the laboratory is a time-consuming, tedious, costly, and difficult process. The present review paper focuses on the application of various ANN models for predicting engineering properties, viz. maximum dry density (MDD), optimum moisture content (OMC), permeability, unconfined compressive strength (UCS), and shear strength parameters. These engineering properties depend on water content, dry density, bulk density, mineralogy present in the soil, liquid limit, plastic limit, plasticity index, linear shrinkage, grain size distribution, particle shape, and lots of other parameters. In ANN, these parameters were used as input parameters to predict the engineering properties of soils.

2 Literature Review

Many researchers have developed several ANN models to work out the engineering properties of various sorts of soils. The stress is given on the literature supported ANN models, input parameters; output parameters, model checking performance parameters of engineering properties of soils.

2.1 Compaction Parameters

Soil compaction is that the mechanical process whereby soil particles are forced and compress. The compaction parameters (optimum moisture content—OMC and maximum dry density—MDD) of the soil have significant importance for attaining the engineering properties of soil like bearing capacity, strength, permeability, and compressibility. OMC and MDD are determined in a laboratory for various sorts of soil called standard proctor test and modified proctor test in geotechnical engineering. ANN is often to predict the compaction parameters from different index properties of soil. Many researchers used different models, charts, curves to predict compaction parameters. "Gunaydin [1] estimates the compaction parameters using simple multiple analysis and artificial neural network. He developed five ANN models on nine different types of soils, which have several input parameters. The simplest best results were obtained from model II; input parameters were relative density (G), liquid limit (w_L), plastic limit (w_P), and grain size." "Suman et al. [2] made an exertion to create a prediction model to work out maximum dry density (MDD) and unconfined compressive strength (UCS) of cement stabilized soil. They developed three networks: functional networks (FN), multivariate adaptive regression splines (MARS), and multilinear regression model (MLR). Prediction models for both MDD- and UCS-supported FN and MARS are very inclusionary. Recently, researchers have used ANN for predicting properties of stabilized soil." Abdel-Rahman [3] developed the empirical equations to forecast compaction parameters of graded cohesionless soils. He compared the forecasted values using ANN and empirical equations with a group of laboratory tests (modified proctor tests). The ANN model grows using the computer program MATLAB 6.5. The input parameters for the ANN model were percentage passing soil from different sieves (20, 5, 2, 0.4, 0.08 mm). He concluded that based on the investigation, the notable factor which affects the MDD was the percentage passing through sieve 0.4 mm (grains of fine sand and smaller), and for OMC, the significant factor was the percentage passing through sieve 0.4 and 0.08 mm (grains of clay and silt). Tipza et al. [4] highlighted prediction models of some geotechnical properties of soil using their index parameters. A total of 580 numbers of knowledge sets have complied. Maximum dry density (MDD), optimum moisture content (OMC), permeability, and angle of internal friction were predicted using input parameters, viz. specific gravity, grain size distribution, and Atterberg limits. A multilayer perceptron (MLP) artificial neural network sets of input files on to a group of appropriate outputs. Differential statistical approaches like the coefficient of determination (COD), root mean square error (RMSE), coefficient of residual mass (CRM) were used to estimate the performance of prediction models. They concluded that laboratory tests to work out engineering properties of soil are laborious and time-consuming; it is helpful to develop forecast models to estimate engineering properties using their index properties which are easy to measure. ANN models come up with accurate predictions with experimental results. "Das et al. [5] were developed ANN models using different training algorithms; Levenberg–Marquardt algorithm (LMNN), Bayesian regularization algorithm (BRNN), and differential evaluation algorithm (DENN). LMNN was a widely used algorithm in geotechnical engineering. They concluded that BRNN has limited uses [6, 7], and still there is a wide scope of DENN algorithm in geotechnical engineering. They also used support vector machine (SVM) models for predicting MDD and UCS. SVM models are supported by statistical learning theory. The supported study developed LMNN model was best for predicting MDD and followed by BRNN and DENN. The statistical performance of SVM models is found superior to ANN models." "Shahiri and Ghasemi [8] were performed laboratory tests to work out MDD and UCS with cement and copper slag stabilized soil. They investigate the impacts of copper slag and cement with different percentages of dosages on MDD and UCS. After experimental testing, the ANN model has been developed using eight input parameters, viz. dry density, water content, liquid limit, plastic limit, P_H, copper slag content, cement content, and Curing age. In the sensitivity analysis, it had been observed that water content was the influential parameter and liquid limit, plastic limit as the least important ones. They concluded that the ANN model was ready to anticipate the elastic modulus of stabilized soil." "Alavi et al. [9] used modified ANN models to predict MDD and OMC of chemically stabilized soil. Multilayer perceptron (MLP) was used with input parameters like linear shrinkage, liquid limit, plastic limit, percentage of clay, silt, gravel, and three stabilizing additives: cement content, lime content, asphalt content. They evaluate the performance of ANN models using the coefficient of determination (R^2), mean squared error (MSE), and mean absolute error (MAE). They developed two separate ANN-based models, one for MDD and one for OMC, and also developed one combined model to see the effect. Separate models for OMC and MDD give satisfactory results with experimental results. They concluded that modified ANN models were less massive than the other models." "Salahudeen et al. [10] expand MLP models to predict MDD and OMC of cement kiln dust stabilized black cotton soil. The ten input parameters were used, viz. linear shrinkage, specific gravity, free swell, D_{10}, D_{30}, D_{60} (effective soil particle sizes), coefficient of curvature (C_c), coefficient of uniformity (C_u), liquid limit, and plastic limit. They concluded that simulation results are satisfactory with experimental results. The same statistical parameters (Alavi et al. [9]) were used for checking the performance of models." Sinha and Wang [11] developed prediction models to predict MDD, OMC, and permeability of the soil. A total of 55 different mixes were prepared with components of limestone, bentonite, dust, sand, and gravel. For training of ANN models, the program NeuralWare (2001) was used. The accuracy of the prediction models was checked using R^2 and RMSE. They concluded that, compared with experimental test results, predictions within a 95% confidence interval. ANN forecasting models become a systematic tool for the design of compacted soil earthwork. Table 1 shows the detailed summary of artificial neural networks used on compaction parameters of soil.

2.2 Permeability

Permeability is a capacity of soil to permit water passes through it. Permeability is an extremely important engineering property of soil because the designer should know the standards of liquid flow, as groundwater conditions are frequently experienced on construction projects. Permeability is determined in the laboratory for various sorts of soil using a constant head and falling head permeability test. ANN can be used to predict permeability from index parameters of soil. In the present review paper, Tipza et al. [4] and Sinha et al. [11] already discussed prediction of permeability in 2.1.

"Erzin et al. [12] developed ANN and MRA models for determining the hydraulic conductivity of fine-grained soil. They performed a falling head permeability test on silty sand and marine clays in the laboratory. ANN models were developed individually on silty sand and marine clays and one generalized model developed which contains different soils compacted to different states using experimental data. The input parameters were water content, dry density, D_{10}, D_{30}, D_{60}, D_{85}, D_{100}. The performance of both models was checked by the coefficient of correlation, variance (VAF), and RMSE. They concluded that ANN models are better than MRA for determining the hydraulic conductivity of varied soils." Chapuis [13] assessed methods to predict the saturated hydraulic conductivity, permeability of sand and gravel. Recently, researchers have used neural networks, fuzzy logic, and regression to work out the permeability of coarse and fine-grained soils. El-Sebakhy et al. [14] present functional networks are good to approach to work out the permeability of soils. Permeability prediction has been a provocation for geotechnical engineers. In this study, functional networks were used to predict permeability in a carbonate reservoir. They concluded that developed functional networks give reliable and proper results.

2.3 Shear Strength Parameters

The ability of soil to help a stacking from a structure, or to help its overburden, or to sustain a slope in equilibrium is governed by its shear strength. There are two shear strength parameters called cohesion (c) and the angle of internal friction (ϕ). Shear strength parameters are used for earth and rockfill dam design, earth pressure problems, highway and airfield design, foundation design, and stability of slopes. Cohesion depends upon water content, the grain size of soil particles, minerals,

Table 1 Summary table of application of ANNs on MDD and OMC

S. No.	Author	Year	Model/algorithm	Input parameters	Output parameters	Accuracy/performance parameters	References
1	Gunaydin	2008	MLP	G, w_L, w_P, grain size	MDD, OMC	SRA, MRA	[1]
2	Suman et al.	2016	FN, MARS, MLR	w_L, w_P, PI, % sand, % gravel, moisture content, cement content	MDD, UCS	Statistical analysis	[2]
3	Abdel-Rahman	2008	ANN	Gradation percentage	MDD, OMC	Statistical analysis	[3]
4	Tipza et al.	2014	MLP	Grain size distribution, G, Atterberg limits	permeability, MDD, OMC, effective friction angle	COD, RMSE, CRM	[4]
5	Das et al.	2010	BRNN, LMNN, DENN, SVM	w_L, PI, % clay fraction, % sand, % gravel, cement content, moisture content	MDD, UCS	MAE, AAE, RMSE, statistical analysis	[5]
6	Shahiri and Ghasemi	2017	MLP	Water content, dry density, w_L, w_P, P_H, curing age, copper slag content, cement content	MDD, OMC	Statistical analysis	[8]
7	Alavi et al.	2010	MLP	w_L, w_P, Linear shrinkage, % Gravel, % Clay, % silt, lime content, cement content, asphalt content	MDD, OMC	Coefficient of determination (R^2), MSE, MAE	[9]
8	Salahudeen et al.	2018	MLP	G, linear shrinkage, free swell, D_{10}, D_{30}, D_{60}, C_u, C_c, w_L, w_P	MDD, OMC	Coefficient of determination (R^2), MSE	[10]

(continued)

Table 1 (continued)

S. No.	Author	Year	Model/algorithm	Input parameters	Output parameters	Accuracy/performance parameters	References
9	Sinha and Wang	2008	ANN (NeuralWare)	Density of solid phase, fineness modulus, effective grain size, w_L, w_P	Permeability, MDD, OMC	Coefficient of determination (R^2), RMSE	[11]

and promise between the particles, whereas angle on internal friction depends upon water content, particle size distribution, dry density, the shape of particles, and surface texture. These parameters were determined in the laboratory using a direct shear test, triaxial test, vane shear test, and unconfined compression test. ANN can predict the parameters accurately of various sorts of soils. Table 2 shows the detailed summary of artificial neural networks used on shear strength parameters of soil. "Mousavi et al. [15] developed new nonlinear solutions to work out shear strength parameters using linear genetic programming (LGP). An experimental database was established after conducting unconsolidated undrained and unsaturated triaxial tests. They concluded that LGP models were better than regression models. The factors, viz. fine-grained content, D_{30}, C_u, w_L, water content, and dry soil unit weight, represent the behavior of shear strength parameters. Out of that water content and dry soil unit weight effectively affects shear strength parameters." Iyeke et al. [16] were 83 soil samples collected from Nigeria. They concluded the appliance of those models will help to scale back cost and time. ANN predicts the shear strength parameters for lateritic soils exceed the empirical methods. Kiran and Lal [17] investigated the MLP model to work out cohesion and angle of internal friction. They used soil within the state of Jharkhand (India). Input parameters should be the same as earlier researchers, but they used bulk density (BD) and dry density (DD) separately. The model showed the best performance for the prediction of cohesion and angle in internal friction. Eidgahee et al. [18] evaluated shear strength parameters of granulated waste rubber using the group method of data handling (GMDH) algorithm. GMDH gives well-founded results for shear strength and vertical strain. "Kayadelen et al. [19] conducted consolidated drained triaxial tests (CID) in a laboratory and predict the angle of shearing resistance (ϕ) using gene expression programming (GEP), ANN, and ANFIS models. This study shows that GEP models give exceed results than ANN and ANFIS."

Khan et al. [20] predicted residual friction angle using SVM, ANN, and FN models. They concluded that FN is best than ANN for predicting the residual strength of clay. "Khanlari et al. [21] utilized MLP and radial basis function (RBF) approach to predict friction angle and cohesion of soils. They used different percentages of soil passing on sieve No. 200, 40, 4, PI, and bulk density as an input layer. This study gives the results of the MLP-ANN model performed better than RBF-ANN." Lee et al. [22] developed ANN models to estimated unsaturated shear strength (Apparent Cohesion Cmax). Test investigations of unsaturated soils are exorbitant, tedious, and hard to lead; for that purpose, they formulated the connection between nonlinear unsaturated shear strength and matrix suction in a hyperbolic form. Ly et al. [23] developed a support vector machine (SVM) for prediction of cohesion and angle of internal friction. SVM models performed well prediction and moisture content, w_L, w_P were found most affected factors on soil shear strength. "Sezer [24] utilized three different algorithms scaled conjugate gradient (SCG), gradient descent method with momentum term (GDM), Levenberg–Marquardt (LM) for predicting shear development in clean sand. The input parameters are counting on the particle shape, i.e., roundness, sphericity, area-perimeter fractal dimension, etc. Tests were employed on 33 differing types of sands." Sezer [25] again performed the estimation of the angle

Table 2 Summary table of application of ANNs on shear strength parameters

S. No.	Author	Year	Model/algorithm	Input parameters	Output parameters	Accuracy/performance analysis	References
1	Mousavi et al.	2011	LGP	% FC, % CC, D_{10}, D_{30}, D_{60}, C_u, C_c, w_L, water content, soil unit weight and dry soil unit weight	Cohesion (c), angle of internal friction (ϕ)	RMSE, MAE	[15]
2	Iyeke et al.	2016	MLP	Plasticity index (PI), percentage of particles passing sieve No. 200, G, w_L, w_P	Cohesion (c), angle of internal friction (ϕ)	Coefficient of determination (R^2), RMSE, MAE	[16]
3	Kiran and Lal	2015	MLP	Water content, w_L, w_P, dry density, bulk density, % gravel, % sand, % silt, % clay	Cohesion (c), angle of internal friction (ϕ)	RMSE, fractional bias (FB), normalized mean square error (NMSE), model (MB)	[17]
4	Eidgahee et al.	2018	ANN and group method of data handling (GMDH)	Normal stress (σn), horizontal strain (εh), C_u, C_c, D_{50}	Cohesion (c), angle of internal friction (ϕ)	RMSE, MAE, MSE	[18]
5	Kayadelen et al.	2009	Gene expression programming (GEP), ANN, adaptive network-based interference system (ANFIS)	% of coarse-grained soil, % of fine-grained soil, bulk density, w_L	Angle of internal friction (ϕ)	Coefficient of determination (R^2), RMSE, standard deviation (σ)	[19]
6	Khan et al.	2015	ANN, SVM, FN	w_L, w_P, plasticity index, % of clay fraction	Residual friction angle	Coefficient of efficiency (E), absolute average error (AAE), maximum average error (MAE) and root mean square error (RMSE)	[20]

(continued)

Table 2 (continued)

S. No.	Author	Year	Model/algorithm	Input parameters	Output parameters	Accuracy/performance analysis	References
7	Khanlari et al.	2012	MLP-ANN, radial basis function (RBF-ANN)	Percentages of passing the No. 200, 40 and 4 sieves, plasticity index (PI), and density (ρ)	Cohesion (c), angle of internal friction (ϕ)	RMSE, MAE, coefficient of determination (R^2)	[21]
8	Lee et al.	2003	ANN	% sand fraction, and clay and silt fraction, void ratio (e), OMC, c, ϕ	Apparent cohesion (Cmax)	Coefficient of determination (R^2)	[22]
9	Ly et al.	2020	SVM	Moisture content, G, e, w_L, w_P	Cohesion (c), angle of internal friction (ϕ)	RMSE, MAE, coefficient of determination (R^2)	[23]
10	Sezer	2011	Gradient descent method with momentum term (GDM), scaled conjugate gradient (SCG) and Levenberg–Marquardt (LM)	% gravel, % sand, % silt–clay, C_u, C_c, normal stress (σ), e, relative density, D_{10}, r (roundness), s (sphericity), DR (area–perimeter fractal dimension) and current relative deformation	Angle of internal friction (ϕ)	MSE	[24]
11	Sezer	2013	Multiple regression models (MRM), ANFIS, ANN	Relative density, area-perimeter fractal dimension (D_r), regularity (r), D_{10}, C_c	Angle of internal friction (ϕ)	RMSE, coefficient of determination (R^2)	[25]

of shearing resistance (ϕ) of uniform sands using ANFIS and multiple correlation models (MRM).

2.4 Unconfined Compressive Strength

The unconfined compressive strength is that the load per unit area at which the cylindrical specimen of a cohesive soil falls after applying pressure. The undrained shear strength of the soil is one half of the unconfined compressive strength and it is determined in the laboratory. Suman et al. [2], Das et al. [5], and Shahiri et al. [8] also worked on the application of ANN on Unconfined compressive strength which is already discussed in 2.1. Narendra et al. [26] developed MLP, RBF, and genetic programming (GP) mathematical models to predict the unconfined compressive strength of cement stabilized soft ground soil. The input parameters were curing period, water content, w_L, liquidity index, clay water-cement ratio, cement content. The MLP network gives better results compared to RBF and GP for predicting the unconfined compressive strength of clayey soil.

3 Discussion and Conclusions

The engineering properties of soil depend on soil structure, permeability, swelling, pore water pressure, shrinkage, compressibility, stress–strain relationship, and shear strength parameters. The evolution of accurate engineering properties is a difficult task. The review confirms the application of ANNs completing a spread of classification, prediction, optimization, and modeling-related task in geotechnical engineering. The accuracy for predicting the engineering properties of soil depends on the input parameters. ANN algorithm is favorably used for predicting the engineering properties of soil. The important input parameters which affect the MDD of soils were water content, liquid limit, plastic limit, percentage of fine-grained soil, and relative density, whereas, on OMC, input parameters were the percentage of gravel, percentage of sand, coefficient of uniformity, coefficient of curvature, D_{10}, D_{30}, D_{60}, additive content. For cohesion, the most affected factors were water content, grain size distribution, and liquid limit of soil. Most researchers were to see the model performance using statistical approaches like coefficient of determination (R^2), MSE, RMSE, and MAE. Laboratory tests to work out engineering properties of soil are laborious and time-consuming; it is desirable to develop prediction ANN models to estimate these properties using index parameters.

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