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Reliability analysis of a shallow foundation on clayey soil based on settlement criteria

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Abstract

Soil is a heterogeneous medium and the involvement of its many effective attributes in geotechnical behaviour for soil-foundation system makes the prediction of settlement of shallow foundation on soil a complex engineering problem. As the understanding about the soils are improving, the variability in soil attributes is taken into consideration. As result, the present research approach has also shifted from deterministic to probabilistic approach. The present paper describes the application of two probabilistic based soft computing techniques i.e. Adaptive Network based Fuzzy Inference System (ANFIS) and Functional Network (FN) to study the shallow foundation reliability based on settlement criteria. These models are simple and reliable and can be used for routine design practice. In addition, FN and ANFIS were tested to find their adoptability for shallow foundation settlement prediction considering different soil attributes. Models performance was tested based on different fitness parameters i. e. RMSE, VAF, RSR, β, etc. Functional network (FN) model outperformed in terms of all fitness parameters (RMSE=0.0017, VAF=98.512, RSR=0.1416, NS=0.979, RPD=7.062) as compared to ANFIS (RMSE=0.0026, VAF=95.687, RSR=0.2148, NS=0.953, RPD=4.655). The results show that FN approach can be used as a reliable soft computing technique for non-linear problems like settlement of shallow foundations on soils.

Keywords: *adaptive network based fuzzy inference system; anfis; coefficient of variation; cov; functional network; reliability analysis; soil parameters.*

1. Introduction

Soil is heterogeneous complex medium, and its variation in nature due to its attributes is inevitable. Intrinsic randomness of soil formation process, inherent large uncertainty which depend upon the site condition. Shallow foundations are ubiquitous structures that process near-surface ground to transfer load to the ground. The foundation settling and soil bearing capacity are the most important factors in the construction of shallow foundations. Furthermore, the study is focussed on the settlement criteria for the shallow foundation design as it has a greater influence on failure than bearing capability (Ray et al., 2021c).

In the traditional approach, empirical calculations based on settlement criteria are employed to build shallow foundations placed on cohesive soil. The allowable bearing capacity of the shallow foundation can be calculated using the ultimate bearing capacity and dividing it by Factor of Safety (FOS). For calculating the settlement of the foundation, FOS method can be used due to its simplicity and direct method, but during this approach different uncertainties in the soil attributes into consideration (Najafzadeh, Homaei, & Farhadi, 2021a; Najafzadeh, Homaei, & Mohamadi, 2022; Pramanik, Baidya, & Dhang, 2021). Phoon (2002) in their research said about the effect on the soil property due to the variation in soil deposits and the error in testing leads to the variations in the testing data. To consider the variations in soil parameters, reliability analysis (Luat, Lee, & Thai, 2020) is done. For performing reliability analysis, input attributes of soil are taken as random variable and the effect on output due to the input were studied. In past many researchers (Ghosh, Singh, Kumar, & Maharaj, 2021; Sharma, & Jalal, 2021; Verma, Agrawal, Amorim, & Prodan, 2021; Yadav, & Shah, 2021) used probabilistic analysis, Chwała and Wengang, (2022) in their research analysed bearing capacity of spatially varied soil using the broken line random failure mechanism method. A limit analysis theorem with an upper bound is used in this approach. The suggested formulation is both computationally efficient and versatile enough to allow a failure mechanism to adjust to weaker regions in the soil domain. Reliability analysis of shallow foundation has been done for its stability having eccentric loading using various methods and it was found that First Order Second Moment method performed best (Fatolahzadeh, & Mehdizadeh, 2021). Krizek, Corotis and El-Moursi, (1977) developed models based on the probabilistic analysis for the prediction of the foundation settlement by the use of two data either together or individually i.e. SPT data or consolidation test data, whereas Pramanik et al. (2021) study the application of reliability analysis on square footing based on bearing capacity failure using fuzzy logic sets and also studied the effect of using coefficient of variation of frictional angle on it. The reliability-based technique is proposed in Simões, Neves, Antão and Guerra, (2020) study for evaluating the performance of shallow foundations built close to an existing utility tunnel.

In past reliability analysis has been accomplished by many researchers (Duc Nguyen et al., 2022; Nazeeh & Sivakumar Babu, 2022; Ray, Choudhary, & Roy, 2021; Ray et al., 2021c; Ray, & Roy, 2021; Sultana, Dey, & Kumar, 2022; Dindarloo, 2015; Hajihassani, Jahed Armaghani, Marto, & Tonnizam Mohamad, 2015; Momeni, Nazir, Armaghani, & Maizir, 2015) using different method. Researcher with the help of response surface method (RSM) (Saseendran, & Dodagoudar, 2020) develop an approx. polynomial function for the calculation of bearing capacity and for the settlement of the shallow foundation on the cohesive soil using a valid range of soil parameters as an input (Babu, & Srivastava, 2007). Reliability assessment has also been used for the water quality index (Praveen, & Roy, 2021; Praveen & Roy, 2022), which is based on remote sensing data by Najafzadeh et al. (2021a, 2021b). Homaei and Najafzadeh (2020) forecast the scour depth at pile groups under regular waves, a probabilistic model was created using an artificial intelligence technique. Dodigović, Ivandić, Kovačević, & Soldo, (2021) studied the various error in reliability analysis and proposed criteria for finding the suitability of reliability methods in geotechnical engineering. Based on the proposed criteria, shallow foundation example has been used to know the applicability. ANFIS soft computing model has been found to be a good predicting model by various researcher when used for estimating wear rate of diamond wire saw, reliability analysis of gravity retaining wall, prediction of the unconfined compressive strength of stabilised soil and estimation of compression coefficient of plastic clay soil (Boumezerane, 2022; Duc Nguyen et al., 2022; Mikaeil, Haghshenas, Ozcelik, & Gharehgheshlagh, 2018; Mustafa, Samui, & Kumari, 2022; Saadat, & Bayat, 2022). Karimi (2003) used the two types of models ANFIS and FAM which are based on the neural network and fuzzy logic for studying the impact on valley which is filled with the sedimentation. Khan, Suman, Pavani, & Das. (2016) have used functional networks for the prediction of residual strength of clay. After extensive critical analysis, authors found that in conventional approach for the calculation of settlement, the variation in attributes are not considered, but by using reliability analysis approach these variations are incorporated. The purposes of present study are to perform reliability analysis of shallow foundation for the settlement criteria by using two soft computing models ANFIS and Functional Network. In addition, both ANFIS and functional network are also tested based on various assessment parameters.

2. Objective

The objective of the present study is to perform reliability analysis of shallow foundation for the settlement criteria by using two soft computing models ANFIS and Functional Network. In addition, both ANFIS and functional network are also tested based on various assessment parameters, so as to find the most reliable model for the analysis of shallow foundation for the settlement criteria

3. Methodology

In the current research, shallow foundation is being analysed based on the settlement criteria which are calculated using primary consolidation settlement eq. 1 (Arora, 2004).

$$\Delta H = H_o . C_c . \left(\frac{1}{1+e_o}\right) . \log_{10}\left(\frac{\bar{\sigma}_0 + \Delta\bar{\sigma}}{\bar{\sigma}_0}\right) \quad (1)$$

ΔH = shallow foundation settlement.
H_o = initial thickness of layer
e_o = value of void ratio
$\bar{\sigma}_0$ = initial eff. overburden pressure
C_c = compression index
$\Delta\bar{\sigma}$ = change in eff. stress

Shallow foundation settlement on clayey strata depends on following attributes γ (unit weight), C_c (compression index) and e_0 (void ratio). For the probabilistic analysis of shallow foundation these three attributes are taken as the input variables for the models to analysis using various soft computing techniques and foundation settlement taken as the output. Now to generate 100 data set, permissible range of these attributes are taken as γ from 17 to 21 kN/m^3, C_c from 0.25 to 0.96 and e_0 from 0.4 to 1 (Varghese, 2005) and from that corresponding data set of settlement are calculated using eq. 1. For using these data for the soft computing models they need to be normalized using eq. 2.

$$X_{nor} = \frac{X - X_{min.}}{X_{max.} - X_{min.}} \quad (2)$$

Where,
X_{nor} = normalized value.
X = value of the attributes.
$X_{min.}$ = minimum value of attributes.
$X_{max.}$ = maximum value of attributes.

Normalised data are to be divided into 70 % data set and 30 % data set, then these values are taken as input for training and testing of the soft computing models (ANFIS and functional network). The soft computing models then provides the appropriate normalised output. The anticipated values are converted from the normalised output data. These actual and forecast settlement values are evaluated for finding best soft computing models using various assessment parameters and various plots.

3.1 Theoretical background of models

ANFIS

System modelling which analysed using conventional mathematical tools is not suitable for the modelling the systems which are not well defined and the systems which are uncertain in nature. So, probabilistic analysis of systems needed with the help of various soft computing techniques. Soft computing helps in finding solution for the imprecision, uncertainty etc. Instead of a single technique, soft computing is a group of various types of methodologies in collaboration with Nero-computing, Genetic algorithm and Fuzzy system. The overall advantage of the neural network system is its ability of self-adaptation and also the capability to learn. Likewise, the advantage of fuzzy system is the fuzzy if-then rule which has the capability to take into account the uncertainties of the actual condition of the sites. So, to combine the advantages of both fuzzy system and neural network, a hybrid system (Jang, 1993) is formed which is known as Adaptive Network based Fuzzy Inference System (ANFIS) (Ray et al., 2021a). Based on the wide use of ANFIS by various researchers (Boumezerane, 2022; Duc Nguyen et al., 2022; Mikaeil, Piri, Shaffiee Haghshenas, Careddu, & Hashemolhosseini, 2022a; Mustafa et al., 2022; Saadat, & Bayat, 2022)in various field and its good prediction capability, selection of ANFIS model is done for this study.

Fuzzy logic system
Fuzzy if-then rules

Fuzzy if-then rules are in the form of IF X THEN Y, where X and Y are labels of fuzzy rules (Zadeh, 1973) which are associated with appropriate membership functions. Due to its very concise form, fuzzy if-then rules are used which take a very important role in the human ability to take decision in cases of uncertainty and ill-defined systems.

Example: - If speed is high, then duration is short.

In the above example speed and duration denote as linguistic variables (Zadeh, 1973), high and short denotes as linguistic values that are having association with membership functions.

Fuzzy inference systems

Fuzzy inference systems are called as fuzzy models, which is fuzzy rule-based systems (Figure 1). Fuzzy inference system consists of five parts: -

- Rule base: - it consists of fuzzy if-then rules.
- Database: - it provides the membership functions for the fuzzy sets which are used in fuzzy rules.
- Decision-making unit: - it performs the decision-making operation on the rules.
- Fuzzification interface: - it converts the inputs into degrees of match with linguistic values.
- Defuzzification interface: - it converts the fuzzification results into the final output.

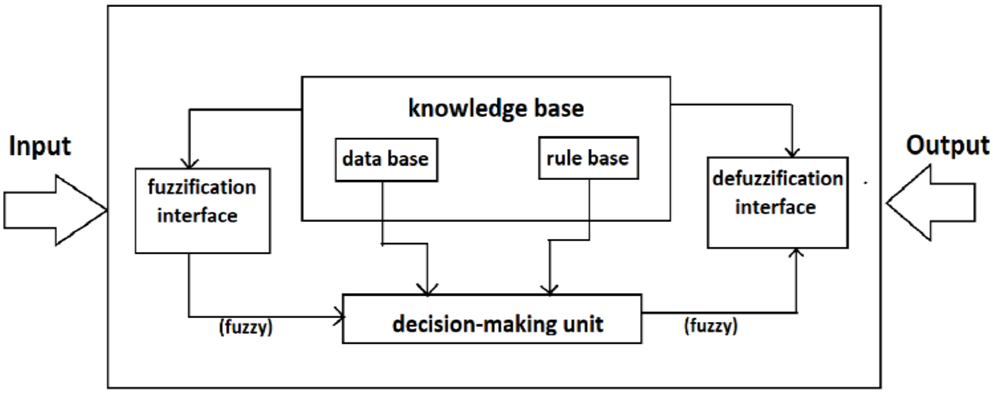

Figure 1 Fuzzy inference system

Adaptive networks

The term "adaptive network" refers to a network based topology of the system which is made of nodes which are connected by directional links (Figure 2). The nodes are adaptive in nature(Mikaeil, Haghshenas, Ozcelik, & Gharehgheshlagh, 2018b; Mikaeil, Piri, Shaffiee Haghshenas, Careddu, & Hashemolhosseini, 2022b), which means that their outputs are influenced by the parameter associated with them. The network's learning rule adjusts the parameters to reduce errors. (Werbos, 1974).

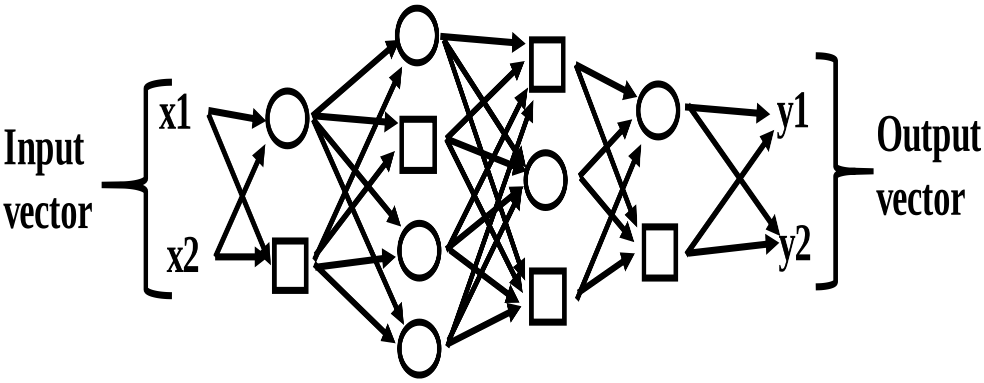

Figure 2 An adaptive network

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Functional network

Artificial neural networks are very helpful to learn and then reproduce application systems in many fields. Neural networks are basically working on the principle on which the brain works. Artificial neurons are used to build a neural network (Armaghani et al., 2020) which gives output values as a function of corresponding input values.

Functional network (Castillo, Cobo, Manuel Gutiérrez, & Pruneda, 1999) is a basically the most important and new of neural based network system that uses the data knowledge and domain knowledge to form the structure of the network. In functional network arbitrary neural functions are allowed and taken as multi-argument.

Based on the arrangement of the elements of the neural based network system the outputs are written in several formats and that results in a system of functional equations. The main step in functional network for the development of the model is the learning procedure (Castillo, Gutiérrez, Cobo, & Castillo, 2000) along with the help of the domain and data knowledge.

i. Structural Learning: - during the development of structure based on learning procedure and with the use of initial topology and the properties of the system to be deigned.

ii. Parametric Learning: - During the learning there is estimation of the neuron functions and the parameters which are linked with them from the available data.

Elements of functional network: -

1. Layers of storing units
   a) Layer of input storing units: - This layer consists of input data x_1, x_2, etc.
   b) Several intermediate layers of storing unit which are used to evaluate the inputs of previous layer and the outputs are provided to the next layer, f_6.
   c) Layer containing output storing units: - it contains output data f_4, f_5.
2. Layers of neuron: - In this layer the neurons are having network that works as computing unit that uses the input data which is being provided by the preceding layer to evaluate and gives an output result data for the intermediate or the output layer. Layer for the computation i.e. computing units, f_1, f_2, f_3.
3. Set of directed links: - On the right side, these are utilised to connect the previous layer or input layer to the following intermediate layer or output layer. These directed connections are used to indicate the flow of information in a specific direction. The network structure is used to power the intermediary functions. Example $x_7 = f_4(x_4, x_5, x_6)$ as in Figure 3.

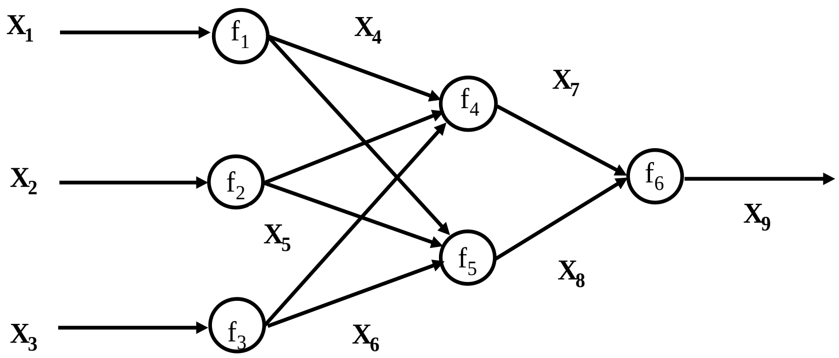

Figure 3 Functional network

3.2 Model performance assessment indexes

Performance Assessment of soft computing ANFIS and functional network models performed by the help of following indexes: -

Nash-Sutcliffe efficiency (NS) calculate the power of prediction of different models. Higher the value towards 1 more will be the predictive power (Jain, & Sudheer, 2008).

$$NS=1-\frac{\sum_{i=1}^{n}(d_i-y_i)^2}{\sum_{i=1}^{n}(d_i-d_{mean})^2} \quad (3)$$

Root Mean Square Error (RMSE) shows the prediction error of the soft computing models. More the value nearer or equal to 0 more is the accuracy in prediction (Kisi, Shiri, & Tombul, 2013).

$$RMSE=\sqrt{\frac{1}{N}\sum_{i=1}^{n}(d_i-y_i)^2} \quad (4)$$

Variance Account Factor (VAF) shows the model performance. Closer the VAF value to 100% more the desired model performance (Gokceoglu, 2002).

$$VAF=(1-\frac{var(d_i-y_i)}{var(d_i)})\times 100 \quad (5)$$

R^2 and Adj. R^2 (Babu, & Srivastava, 2007) shows how much the model used variability in soil attributes. More the values closer to 1 and also closer to each other depicts the best model used.

$$R^2=\frac{\sum_{i=1}^{n}(d_i-d_{mean})^2-\sum_{i=1}^{n}(d_i-y_i)^2}{\sum_{i=1}^{n}(d_i-d_{mean})^2} \quad (6)$$

$$AdjR^2=1-\frac{(n-1)}{(n-p-1)}(1-R^2) \quad (7)$$

Performance Index (PI) value shows the level of soft computing model's performance (Ray & Roy, 2021).

$$PI=adj.R^2+0.01VAF-RMSE \quad (8)$$

Bias Factor value shows the estimation diversion of the models. If value is greater than 1, it shows model is overestimating and if it less than 1 then model is underestimating and if it is 1 then the model is unbiased (Prasomphan & Machine, 2013).

$$\text{Bias Factor}=\frac{1}{N}\sum_{i=1}^{n}\frac{y_i}{d_i} \quad (9)$$

RSR (Moriasi et al., 2007) shows error index. Value closer to 0 shows higher predictive power.

$$RSR=\frac{RMSE}{\sqrt{\frac{1}{N}\sum_{i=1}^{n}(d_i-d_{mean})^2}} \quad (10)$$

Normalized Mean Bias Error (NMBE) shows the level of prediction of the model of values far from the mean. Model for prediction is best if NMBE equal to 0 (Ray & Roy, 2021).

$$NMBE(\%)=\frac{\frac{1}{N}\sum_{i=1}^{n}(y_i-d_i)}{\frac{1}{N}\sum_{i=1}^{n}d_i}\times 100 \quad (11)$$

Mean Absolute Percentage Error (MAPE) (Ray et al., 2021a) indicates the accuracy in the prediction of settlement, which is good if value is nearer to 0.

$$MAPE=\frac{1}{N}\sum_{i=1}^{n}\left|\frac{d_i-y_i}{d_i}\right| \quad (12)$$

Relative Percentage Difference (RPD) shows the performance of the model and is calculated using eq. 13 and referred by the Table1 (Ray & Roy, 2021).

Table 1 RPD values for evaluating models

RPD	Performance
<1	Very poor level
1.0 - 1.4	Poor level
1.4 - 1.8	Fair level
1.8 - 2.0	Good level
2.0 - 2.5	Very good level
> 2.5	Excellent level

$$RPD=\frac{SD}{RMSE} \quad (13)$$

Willmott's Index (WI) indicates shallow foundation settlement prediction error level by soft computing models. Index range 0 to 1 and index value = 1 indicates good model for prediction as error is least (Deo, R. Samui, & Kim, 2016).

$$WI=1-\left[\frac{\sum_{i=1}^{N}(d_i-y_i)^2}{\sum_{i=1}^{N}(|y_i-d_{mean}|+|d_i-d_{mean}|)^2}\right] \quad (14)$$

Mean Bias Error (MBE) and Mean Absolute Error (MAE) indicates error in prediction of foundation settlement and ideal value for the parameter is 0 (Raventos-Duran, Camredon, Valorso, Mouchel-Vallon, & Aumont, 2010).

$$\text{MBE}=\frac{1}{N}\sum_{i=1}^{n}\left(y_i-d_i\right) \quad (15)$$

$$\text{MAE}=\frac{1}{N}\sum_{i=1}^{n}\left|\left(y_i-d_i\right)\right| \quad (16)$$

Legate and McCabe's Index (LMI) shows the divergence of the model in prediction and the parameter range is (-∞, 1) (Legates, & McCabe, 2013; Ray et al., 2021c).

$$\text{LMI}=1-\left[\frac{\sum_{i=1}^{N}|d_i-y_i|}{\sum_{i=1}^{N}|d_i-d_{mean}|}\right] \quad (17)$$

Expanded uncertainty (U_{95}) shows the model's performance for the prediction of foundation settlement on short-term basis. Smaller the value high the performance of model (Ray & Roy, 2021).

$$U_{95}=1.96(SD^2+RMSE^2)^{1/2} \quad (18)$$

t-statistic lower value shows the model's superiority in prediction of the values. (Stone, 1993).

$$\text{t-stat}=\sqrt{\frac{(N-1)MBE^2}{RMSE^2-MBE^2}} \quad (19)$$

Global Performance Indicator (GPI) analysis the model using various other parameters of assessment in single value (Ray, Choudhary, & Roy, 2021b). Higher the value of GPI higher is the accuracy of model.

$$\text{GPI}=MBE\times RMSE\times U_{95}\times t_{stat}\times(1-R^2) \quad (20)$$

Reliability Index (β) is an index for evaluating the reliability analysis. Higher the value of reliability index indicates better the model performed (USACE, 1997).

$$\beta=\frac{C-D}{\sqrt{\sigma_C^2+\sigma_D^2}} \quad (21)$$

Here d_i and y_i are the observed and predicted i^{th} value, d_{mean} is the average of observed value, SD is the standard deviation, σ_D is standard deviations of demand (D) and σ_C is standard deviations of capacity (C).

4. Results and discussion

Shallow foundation of dimension (1.5 m x 3 m) resting at a depth D_f (= 1.0 m) on a cohesive soil having hard strata at a depth of 5m is considered. The values of soil parameters used as input are normalized and used for the reliability analysis using ANFIS and functional network.

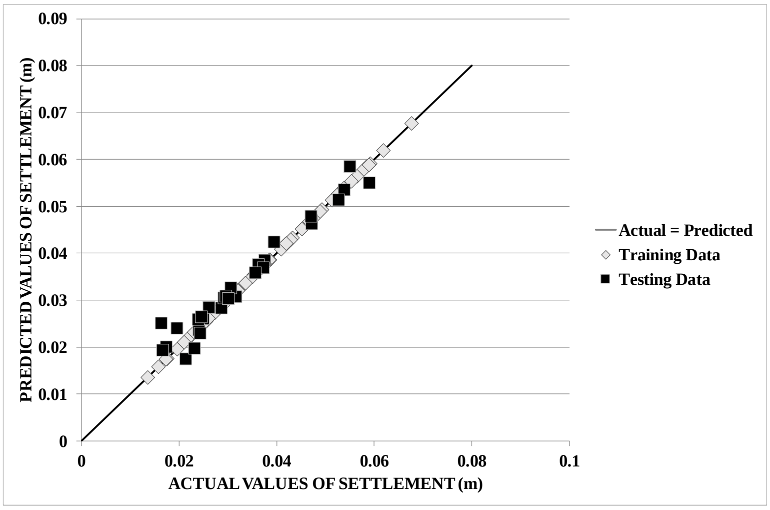

Figure 4 Training and testing plot of ANFIS model for settlement of the foundation

Figure 4 shows the plot of actual values of settlement and predicted values of settlement of shallow foundation for training data and testing data using ANFIS model which maximum values are closer to the actual equal to predicted value line i.e. model prediction capability is high.

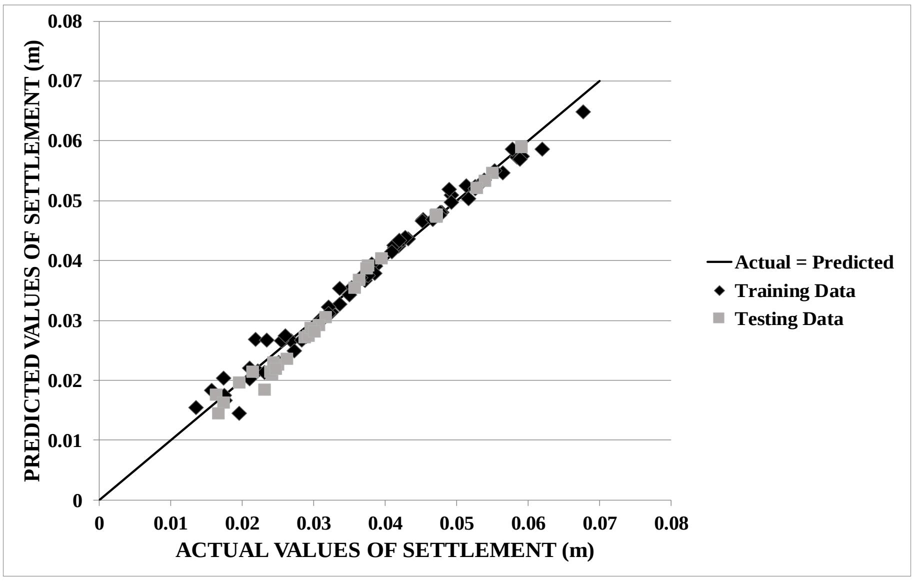

Figure 5 Training and testing plot of Functional Network model for settlement of the foundation

The above figure (Figure 5) is the plot between actual values of settlement and predicted values of settlement of shallow foundation for training and testing data using functional network model which shows that the values are very much closer to the actual equal to predicted value line which means model prediction power is high.

Table 2 Performance assessment of ANFIS and functional model

Parameters	ANFIS		Functional Network	
	Training	Testing	Training	Testing
NS	0.9434	0.9539	0.9654	0.9799
RMSE	0.0055	0.0026	0.0032	0.0017
VAF	95.2346	95.6871	97.546	98.5127
R^2	0.8945	0.9539	0.9354	0.9799
Adj. R^2	0.8889	0.9485	0.9216	0.9776
PI	1.8500	1.9028	1.9158	1.9611
Bias Factor	1.1120	1.0359	0.9564	0.9637
RSR	0.2250	0.2148	0.1658	0.1416
NMBE (%)	2.3041	2.0067	-2.7564	-2.6283
MAPE	0.0850	0.0767	0.0652	0.0512
RPD	3.5231	4.6551	5.1560	7.0622
WI	0.9125	0.9877	0.9546	0.9953
MAE	0.0030	0.0019	0.0020	0.0013
MBE	0.0010	0.0007	-0.0011	-0.0009
LMI	0.8090	0.8112	0.8542	0.8681
U95	0.0304	0.0242	0.0265	0.0239
t-stat	1.3451	1.4246	2.1654	3.1774
GPI	3.137×10^{-9}	2.737×10^{-9}	-3.112×10^{-9}	-2.261×10^{-9}
β	3.1543	3.6012	3.2035	3.3512

Both the models are analysed on the basis of various parameters (table 2) variance account factor (VAF), the root mean square error (RMSE), R^2 (Coefficient of determination), Adj. R^2 (adjusted determination coefficient), Mean Absolute Error (MAE), Performance Index (PI), root mean square error to observation's standard deviation ratio (RSR), NS (Nash-Sutcliffe efficiency), the bias factor, the Legates and McCabe's (2013) Index (LMI), Normalized Mean Bias Error (NMBE), Relative Percent Difference (RPD), Mean Absolute Percentage Error (MAPE), expanded uncertainty (U95), t-statistic, Global Performance Indicators (GPI) and reliability index value (β).

As shown in table-2 the NS value for ANFIS is closer to 1 and that of functional network is also which shows that the predictive power of both the models are high. If both the models are compared functional network is having higher predictive power as compared to ANFIS. RMSE value for both ANFIS and functional network is closer to zero means both models have less error, but functional network is having lesser error as compared to ANFIS. The value of VAF of both the models are closer to 100%. But it can be seen that the value of VAF is more for functional network as compared to ANFIS, so functional network exhibits a better performance. Values of R^2 and Adj. R^2 are closer to 1 and also closer to each other for both the models i.e. Functional network shows most of the variability in soil parameters as compared to ANFIS. Both the models are performing good as per the PI value. As the value of bias factor is closer to 1 for both the models (bias factor for ANFIS and functional network are 1.035 and 0.963 respectively) shows that the predicted output is very less biased or deviated from the actual value. RSR value of both ANFIS and functional network are closer to zero but functional network shows lesser error as compared to ANFIS in prediction. NMBE value for both ANFIS and functional network shows that both models are normally predicted. The value of MAPE of both the models shows the high prediction accuracy, but functional network has higher prediction accuracy as compared to ANFIS. RPD value for both ANFIS and functional network are 4.655 and 7.062 respectively shows that functional network model works more accurately as compared to ANFIS, as the RPD value of ANFIS is lower than functional network. As the value of WI for both the models are closer to 1(i.e. for ANFIS and functional network WI values are 0.987 and 0.995 respectively) so, both are having lower degree of model prediction error. Both the models ANFIS and functional network are having very low MAE and MBE which means both the models are working good and the predicted values are very less deviated from actual values. As per the table 2, value of LMI is closer to 1 for both ANFIS and functional network i.e. both shows lower divergence between observed and predicted values. Both ANFIS and functional network models are having good short-term performance as the value U_{95} (as per the table 2) for both the models are very small. The value t-stat for both the models are very small which indicates both ANFIS and functional network models are having superior performance. Value of GPI for ANFIS is more than that of functional network which shows that ANFIS have greater accuracy as compared to functional network. If both ANFIS and functional network are evaluated on the basis of reliability index then both ANFIS and functional network have high reliability index (β) i.e. between 3 and 4 (Baecher & Christian, 2003; USACE, 1997) (as per the table 2), which implies that the models are having a good performance.

The other criteria such as the cumulative probability of the ratio (Qp/Qm), has also been considered for evaluation (Abu-Farsakh, & Titi, 2004; Das, & Basudhar, 2006). The value of 50% cumulative probability (P_{50}) and the 90% cumulative probability (P_{90}) values for ANFIS are 0.9897 and 1.0903 and for functional network are 1.0061 and 1.0714 respectively (from Figure 6). As the values are closer to 1 indicates that the variation in ratio Qp/Qm is very small and these models are giving a high performance.

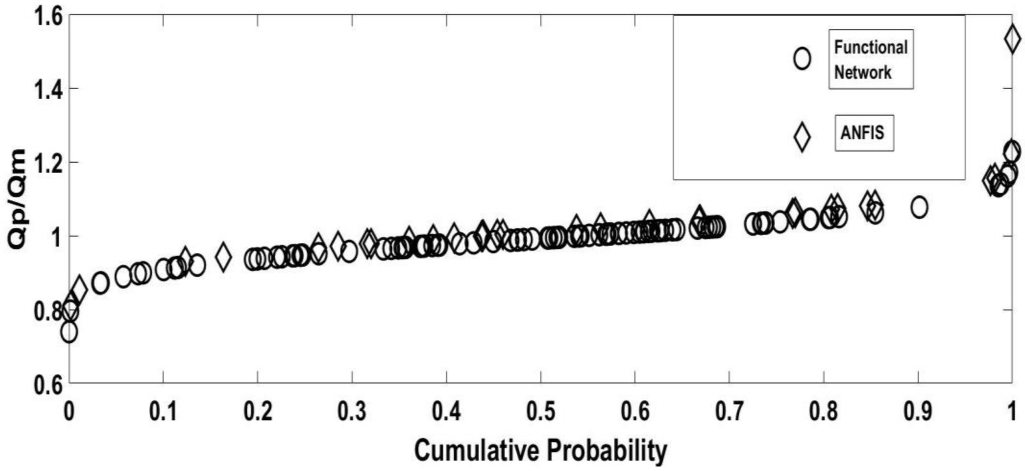

Figure 6 Cumulative probability plots of Q_p/Q_m for different models for testing data

The lognormal distributions of the Q_p/Q_m for the models of the testing data are shown in Figure 7. On the basis of the plot (in Figure 7), it can be observed that the probability of settlement within ± 20% accuracy level (as shown with the shaded area under the lognormal distribution plot of Q_p/Q_m) for functional network is more than the ANFIS.

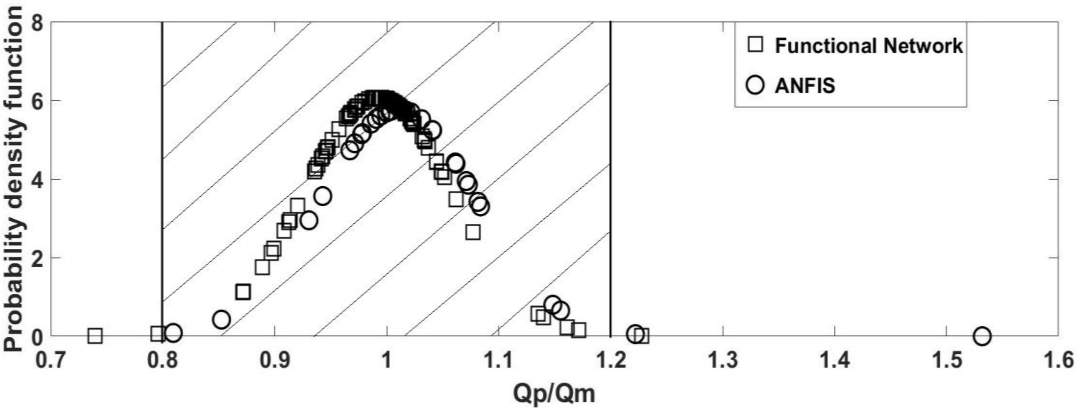

Figure 7 Log normal distribution of Qp/Qm for ANFIS and functional network models for testing data

Table 3 Performance assessment using various parameters of ANFIS and functional model for 10 data set.

Parameters	ANFIS		Functional Network	
	Training	Testing	Training	Testing
NS	0.9401	0.9417	0.9790	0.9821
RMSE	0.0035	0.0021	0.0022	0.0012
VAF	95.1253	96.0775	97.4332	98.4446
R^2	0.9125	0.9417	0.9546	0.9821
Adj. R^2	0.9208	0.9125	0.9621	0.9732
PI	1.8512	1.8712	1.9123	1.9565
Bias Factor	0.9454	0.9664	0.9523	0.9777
RSR	0.2865	0.2415	0.1628	0.1336
NMBE (%)	-3.8645	-3.4912	-1.3291	-1.2115

Parameters	**ANFIS**		**Functional Network**	
	Training	**Testing**	**Training**	**Testing**
MAPE	0.0786	0.0593	0.0523	0.0352
RPD	3.6548	4.1410	7.3250	7.4842
WI	0.9563	0.9853	0.9658	0.9960
MAE	0.0025	0.0017	0.0011	0.0009
MBE	-0.0020	-0.0012	-0.0010	-0.0004
LMI	0.7320	0.7568	0.7820	0.8709
U95	0.0185	0.0176	0.0182	0.0173
t-stat	1.0530	2.0930	1.1150	1.1534
GPI	-5.856×10^{-9}	-5.469×10^{-9}	-2.430×10^{-10}	-1.737×10^{-10}
β	3.9561	4.7862	4.1240	4.2314

Now our models are developed. To check the working and validity of models so that it can be used in the future for finding settlement of shallow foundation, coefficient of variation (COV) for γ (unit weight), C_c (compression index), e_0 (void ratio) are taken as 5%, 30% and 3% respectively (Griffiths, & Fenton, 2007; Jones, Kramer, & Arduino, 2002) and generated 10 data set for all the parameters. Then, reliability analysis of these 10 data set are done using both ANFIS and functional network model. The actual and predicted values of settlement of shallow foundation are used to find the parameters for the analysis of models. As shown in the table 3 the values of the parameters are closer to the values obtained during the development of the models. This shows that models prediction power is high.

5. Conclusions

In this research work, two soft computing techniques (ANFIS and Functional Network) were analyzed for the probabilistic study of settlement of shallow foundation on a clayey soil. The ANFIS and functional network models were compared in terms of various parameters, which showed that both the models are well capable in prediction of the settlement of shallow foundation. Further, it was found that Functional Network model outperformed in terms of various fitness parameters. Therefore, Functional Network model can be considered as a reliable soft computing technique for predicting the settlement of shallow foundation on clayey soils. Also the models were checked for the future application using COV, which results that models are having high predictive power.

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