Academic Journal of Nawroz University (AJNU), Vol.13, No.2, 2024
This is an open access article distributed under the Creative Commons Attribution License
Copyright ©2017. e-ISSN: 2520-789X
https://doi.org/10.25007/ajnu.v13n2a1518

Prediction the Settlement of the Lightweight Road Embankments Using ANN

Ahlam Ismael Hasan [1], Ahmed Mohammad Najmalden [2], and Abdulbasit Abdulaziz Muhmood [3]

[1] Highway and bridge department, Technical College of engineering, Duhok Polytechnic University. Duhok, Kurdistan.

[2] Technical College of engineering, Duhok, Kurdistan. Polytechnic University.

[3] Transportation and highway engineering, Northern Technical University, Iraq-Mosul.

Abstract

The effectiveness of the Artificial Neural Network ANN in modelling the link between the settlement of the embankment and embankment parameters is demonstrated in this study. Data were collected from the Plaxis 3D program. Eleven factors affecting the settlement of embankments were included in this study. These factors are (Side slope (S) & Height(h) of the embankment), (Axial load, and No. of point axial load), in addition to (unsaturated unit weight (γ_{unsat}), statured unit weight (γ_{sat}), Initial void ratio (e), Friction angle (Ø), Cohesion (c), Poisson ratio (v), and modulus of elasticity (E) which are the properties of the soil under embankment). In the current study, a back-propagation neural network approach was used. The relative importance analysis showed that the soil modulus of elasticity (E) and height (h) of the embankment was the most influential parameters than other inputs. For each training validation and testing step, the correlation coefficient (R-values) of the settlement embankment dataset of the Artificial Neural Network (ANN) model were obtained to be 0.98, 0.99 and 0.97 respectively . The results revealed the validity of using Artificial Neural Networks to generate settlement embankment soil values.

Keywords: Artificial neural network, settlement, road embankment, Parametric study, Sensitivity analysis.

1. Introduction

The settlement of the embankment base is one of the most severe issues that arise during the installation of a road structure, often resulting in severe damage to the pavement structure's overlying layers. Settlement occurs due to compressive stresses on all types of soil, resulting in a reduction in the volume filled in the ground. The goal of evaluating settlement evolution during the design phase is to reduce the residual settlement at the end of construction. The infrastructure's importance determines allowable settlement, the pavement type (flexible, semi-rigid, or rigid), the possibility of differential settlement, and other factors (Marradi, Pinori, Betti, & Sciences, 2012). Researchers created several computational methods based on a constitutive model to anticipate post-construction settlement and understand its mechanism. However, these approaches can only be used to expect post-construction settlement without cyclic traffic loads. Traffic load-induced settlement generally accounted for more than 80% of all post-construction settlements (Cai, Chen, Cao, & Ren, 2018). The height of the road embankment and the vehicle's weight are two significant elements that influence the low embankment's cumulative settlement and define vehicle-load-induced emotional stress in the subsoil. Vehicle loads are treated as equal uniform static loads delivered to the pavement in road design standards to examine embankment stability. Still, the dynamic influence of vehicle loads on cumulative subsurface settlement is not considered. Meanwhile, engineers are concerned about the impact of embankment height on traffic-load-induced cumulative settlement, but there is insufficient evidence to back up their concerns (Cui, Zhang, Li, Zhang, & Wang, 2015). Because it is a mixed material, the initial moisture content of the soil sample, the cement percentage, the air bubble percentage, and the curing procedure all impact the compression strength of LWS (Lightweight soil), according to LWS. (Kim & Lee, 2002)devised a technique for estimating the unconfined compression strength of LWS in line with the mixing combination while considering the quality parameters (Yoon & Kim, 2004). The road embankment's design and construction face various challenges, including the possibility of bearing capacity failure, considerable total settlement, differential settlement, and slope instability, all of which can be caused by the embankment's weight and weak foundations. (Lu, Fang, Yao, Hu, & Liu, 2018) To address these issues, various strategies have been developed and can be applied. Modifying the embankment's load (lightweight materials, changes in embankment geometry), improving the ground (preloading, surcharging, gradual construction, excavation and replacement of soil, stone column), accelerating consolidation (vertical drainage, vacuum consolidation), retrofitting structure, and providing additional structural support for embankment construction are all examples of these techniques (Liu, Ng, Fei, & Engineering, 2007). When there is soft soil, one way of soil enhancement is to lower the weight of the embankment structure by using lightweight materials. The use of lightweight material as an embankment material has several advantages, including the ability to achieve the same volume or elevation requirement with a significantly lower weight than conventional materials, improved slope stability, embankment over high compressibility soil, and reduced ground pressure to soil retaining structures, abutments, or bridge pillars. (Somantri & Febriansya, 2019) The use of an Artificial Neural Network (ANN) is a practical method that might be suitable for this application. This method has been successfully used in various road embankment engineering applications up to this point (Goh, 1994;

Shahin, Maier, Jaksa, & engineering, 2002). Several scholars have calculated the liquefaction potential of soils like clay using the ANN (Farrokhzad, Choobbasti, & Barari, 2010; Najjar & Ali, 1998). Additionally, Artificial Neural Networks have had tremendous results in forecasting compaction parameters (Al-saffar & Khattab, 2013; Tenpe, Kaur, & Research, 2015). In addition to estimating suction efficiency (Uzundurukan, Nilay Keskin, & Selcuk Göksan, 2005). ANNs have also been successfully used to map soil layers (Choobbasti, Farrokhzad, Rahim Mashaie, & Azar, 2015). One of its objectives is to investigate how this research uses Artificial Neural Networks (ANN) to obtain a vital parameter.

1. Investigate the ANN technique's feasibility for modelling the road embankment's settlement.

2. Study the sensitivity analysis to obtain the relative effect of each parameter on the Settlement of the road embankment..

3. recognize the relative importance of every input parameter individually on the output result using Sensitivity analysis.

4. Parametric study between input parameters and input-output parameters. To realize how the parameters will affect the output.

5. The information from this study can be used to develop design guidance systems and numerical modelling.

2. Artificial Neural Networks

An artificial intelligence modelling technique known as artificial neural networks (ANNs) tries to replicate the behavior of the human nervous system and brain (Shahin, Jaksa, & Maier, 2001; Shahin, Jaksa, & Maier, 2008). Several researchers have detailed the road construction and functioning of ANNs, including (Ripley, 2007; Shahin et al., 2001)

An ANN design has three layers: an input layer, one or more hidden layers, and an output layer, where neurons are coupled by weighted interconnections that may be changed. This ANN structure is also a complete layer of interlaced receptors with many layers. Other thresholds (bias) have changing weighted connections and are associated with neurons in the output and hidden layers. The number of neurons in each layer will be selected based on the nature of the challenge.

The back-propagation (B.P.) method is the most frequent training approach for multi-layered feed-forward networks. It's a term that's commonly used in the field of engineering. There are two elements to the B.P. algorithm. The activation processes are conveyed from the input layer to the output layer during the first phase, known as feed-forward. In the second step, referred to as the backward phase, the error discovered between the target and predicted values in the output layer is sent backwards to modify the weight and bias values of the neurons. This procedure is continued until the error is smaller than the value of the error objective. Before training a network, the inputs and outputs database for training and testing should be set up (Caglar, Arman, & Environment, 2007).

The network's hidden layer has N inputs and M neurons, with a bias of B given to each neuron. Keep in mind that the outputs of each middle layer are the inputs for the levels below. As a result, if the hidden layer's input is X and its output is A, the output layer's production is Y. This means that the network's most recent output, Y, will be constructed from the outputs of each hidden layer neuron, can evaluate them: (Caglar et al., 2007)

$$Aj= \sum_{i=1}^{n} f(XiWij + Bi) \qquad (1)$$

$$Y= \sum_{j=1}^{m} f(AjWj' + Bj') \qquad (2)$$

The transformation function, denoted by the letter f, is chosen to best suit the data. The difference (delta) between the network's actual and expected behavior is obtained by subtracting the output vector 'A' from the target or goal vector 'T.' The delta rule assesses the post-trial fluctuation in weight Wij of a connection between input and output.

$$\Delta Wij = \eta(Tj - Aj)Xi \qquad (3)$$

The weights will be calibrated after each training period ends until the difference between the output and goal values reaches a permissible limit or all training iterations have been completed .

3. Embankment properties

In order to obtain the database for use in ANN the maximum and minimum values for any properties were taken above and below of ranges mentioned in table 1, in order to make the ANN program to get a higher efficiency.

for embankment layers, the various adopted and the proportion despite the soil's characteristics and its modified shapes in terms of side slope, the height of embankment, no. of point axial load, and load. But for, the pavement layer remains constant properties.

Table 1. some properties of the embankment (دليل المهندس المقيم للمشاريع الانشائية2015)

No	Properties	pavement	embankment	subgrade(foundation)
1	Slope		(1:1 - 1:4)	
2	Height (h) (m)		(0-5)	

3	Axil load (KN)	(20 - 40)		
4	No. of point axil	(2,4)		
5	γ unsat (KN/m3)	24.5	(14-23)	**(12-21)**
6	γ sat (KN/m3)	24.5	(19-27)	**(15-24)**
7	Initial void ratio (e)	0.18	(0.3-0.9)	**(0.2-0.5)**
8	Cohesion(c) (KN/m²)		(50-75)	**(0-55)**
9	Friction angle (Ø)		(40-50)	**(0-70)**
10	Poisson ratio (v)	0.35	(0.3-0.4)	**(0.1-0.45)**
11	Modules elastic (E) (KN/m2)	30,000,000	(100,000-600,000)	**(2,000-80,000)**

4. Model Methodology

4.1. Database

Data were collected from the Plaxis 3D program. Five hundred fifty data were collected from this program. The training set was used to develop the model, the validation set was used to validate the model, and the remaining data were used to test the model. Eleven variables are used as inputs to create the N.N. model.

These variables are (Side slope (S) & Height(h) of the embankment), (Axial load, and No. of point axial load), in addition to (unsaturated unit weight (γunsat), statured unit weight (γsat), Initial void ratio (e), Friction angle (Ø), Cohesion (c), Poisson ratio (v), and modulus of elasticity (E) which are the properties of the soil under embankment). In the output layer, the settlement embankment is the variable.

4.2. Data pre-processing

Data pre-processing is required to ensure that each variable is trained with the same level of care. Additionally, pre-treatment typically hastens learning and improves convergence. Data transformation, scaling, and normalization are some examples. The output data must be scaled since the boundaries of the transfer functions used in the output stratum must be proportional to them.. (Shahin et al., 2001; Shahin et al., 2008). The scaled inputs and outputs in Fig. 1 will be in the (-1 to +1) range since the tan-sigmoid is used as a transfer function.

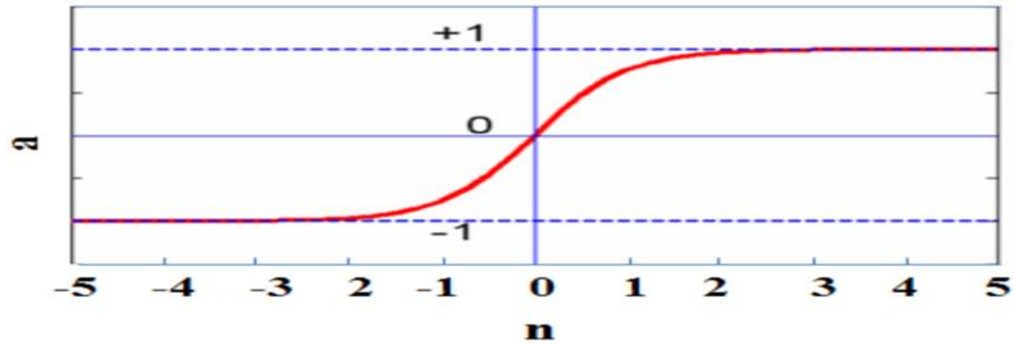
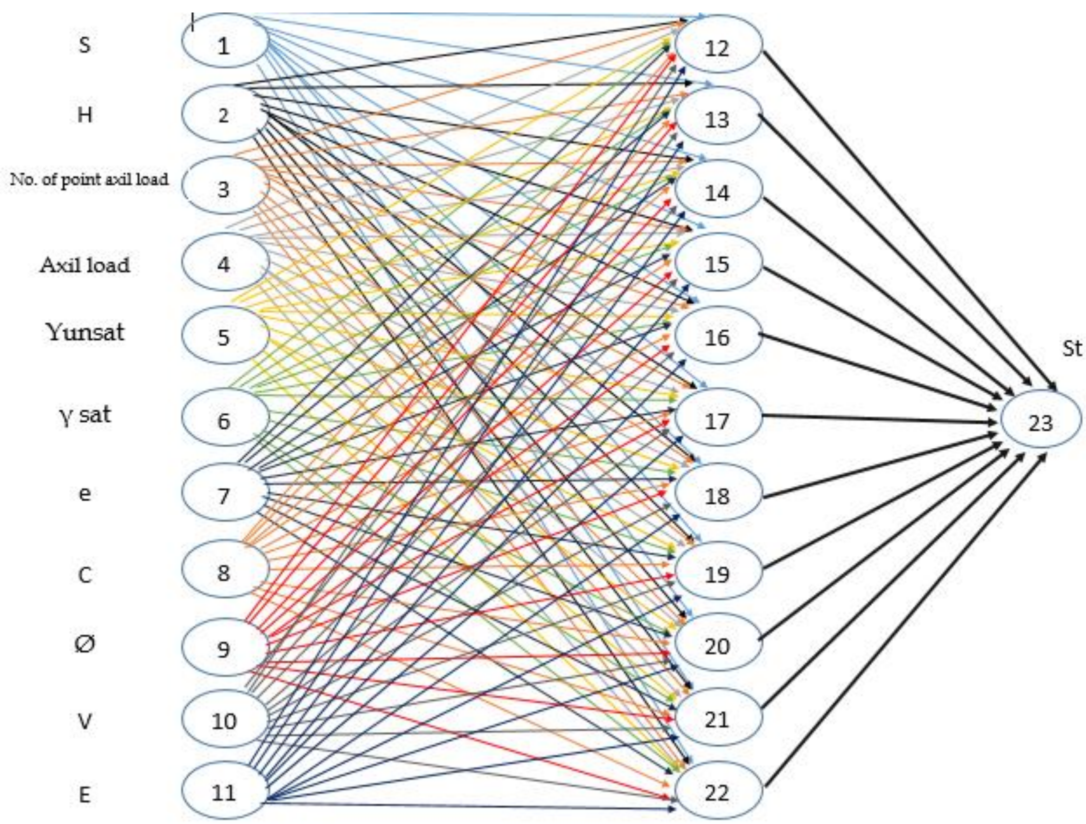


Fig.1. Sigmoid tangent transfer function (Al-Janabi, 2006)

4.3. Model architecture, optimization and stopping criteria

To forecast the values settlement of the embankment, a multi-layered feed-forward neural network using the back-propagation method was used in this study. ANN was created using the widely popular software suite. (Najemalden, Ibrahim, & Ahmed, 2020) The Levenberg-Marquardt (L.M.) backpropagation algorithm is a robust improvement approach used in neural network research because it provides strategies for speeding up the algorithm's training and convergence. (Mohanty, Jha, Kumar, & Sudheer, 2010; Najemalden et al., 2020). Initially, the Plaxis 3D database was arbitrarily separated into three groups: training data (80%), validation data (10%), and testing data (10%). The first group (80%) had employed to train various network structures. The remaining group (20%) was utilized to test and validate the predictability of each ANN model trained. The network model was then created. Our ANN model has three layers in its design. The input layer is the initial layer, and it contains eleven nodes that represent input parameters. The intermediate layer is known as the hidden layer, and it comprises eleven neurons. The output layer was the final layer, and it featured a single node that gave the soil embankment settlement. Convergence in the training process is achieved by lowering the mean squared error (M.S.E.) throughout training iterations and comparing the results to observe the general performance for the trained stages. The final ANN model's setup and properties are shown in Fig. 2 and Table 3.



Input layer Hidden layer output layer

Fig.2 Architecture of the model

Table 3. Properties of ANN model

Properties	configuration
Architecture	11.1.1
Activation function	Tan sigmoid
Learning algorithm	Levenberg-Marquardt(LM)
Mean Squared Error (MSF)	0.000623

The training process is explained in Fig (3)

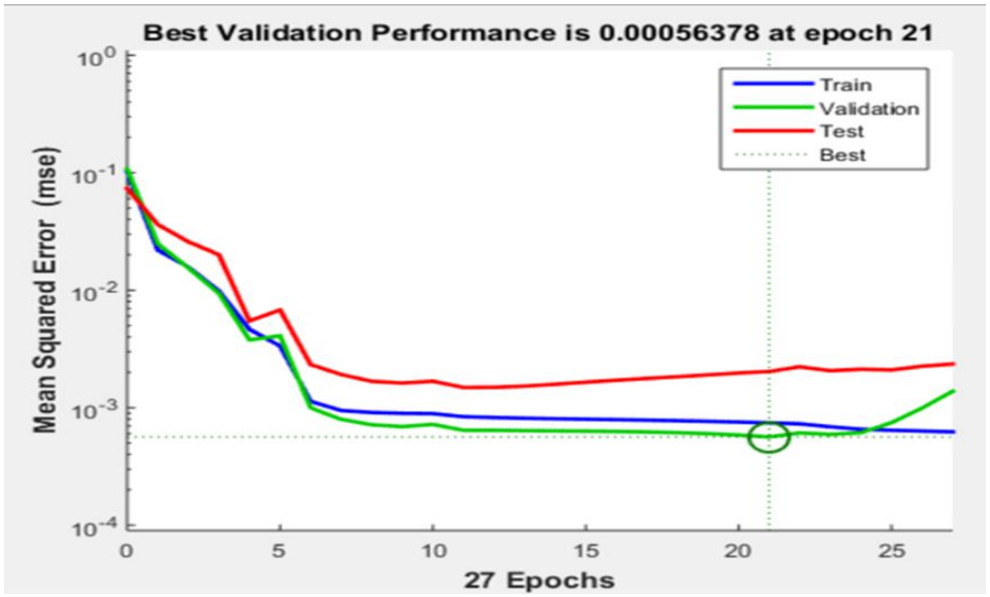


Fig (3) Training progress

Figure 4 compares the results of obtained settlement of the embankment with the neural network prediction of settlement for the training, validation, and testing stages of the ANN model with one hidden layer.

This comparison reveals that the ANN and settlement obtained by P.L.A.X.I.S. 3D are in good agreement, as seen in the graph. For each training, validation, and testing, the correlation coefficient R-values of the settlement dataset of the ANN model was founded to be 0.984.

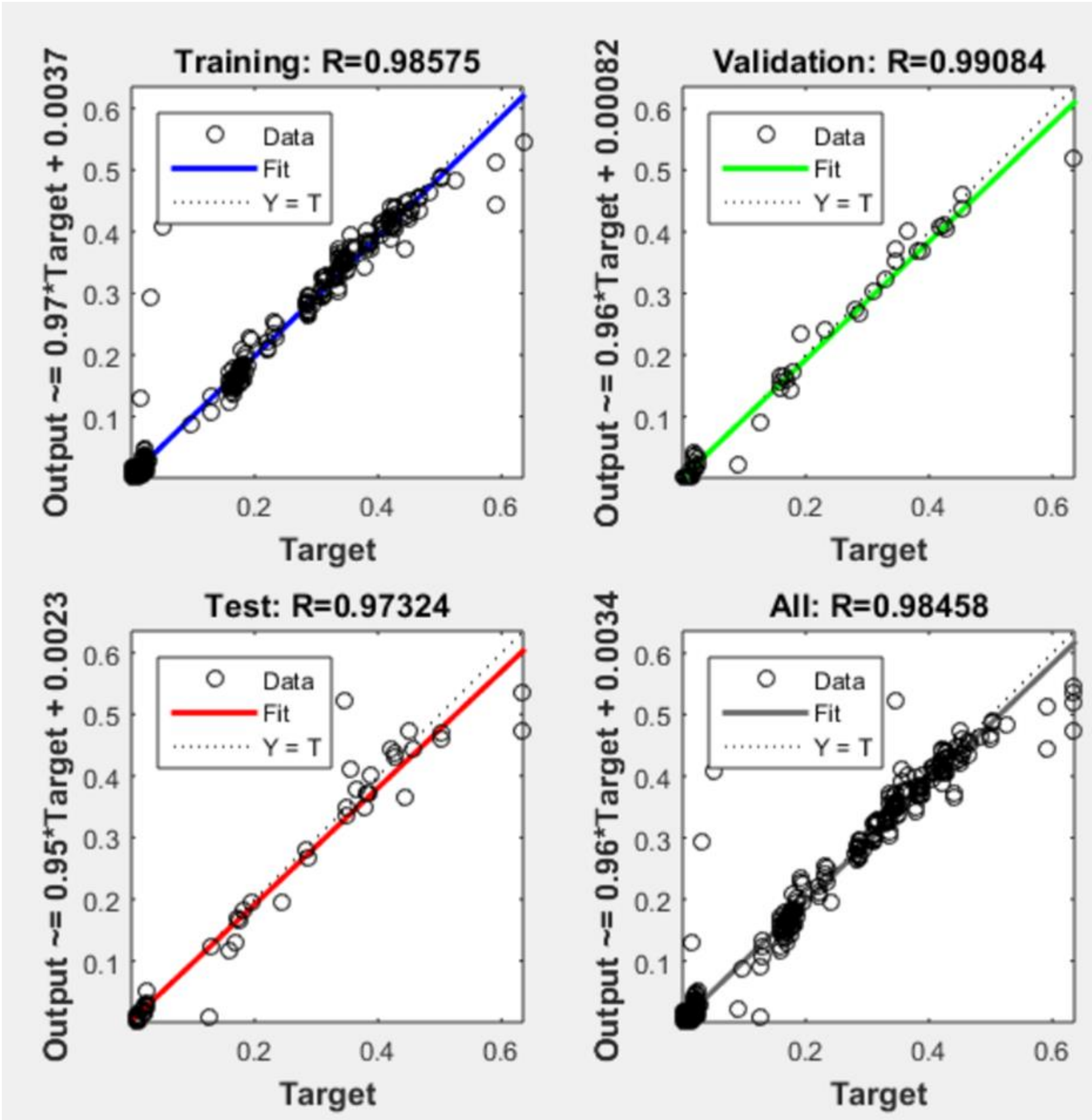


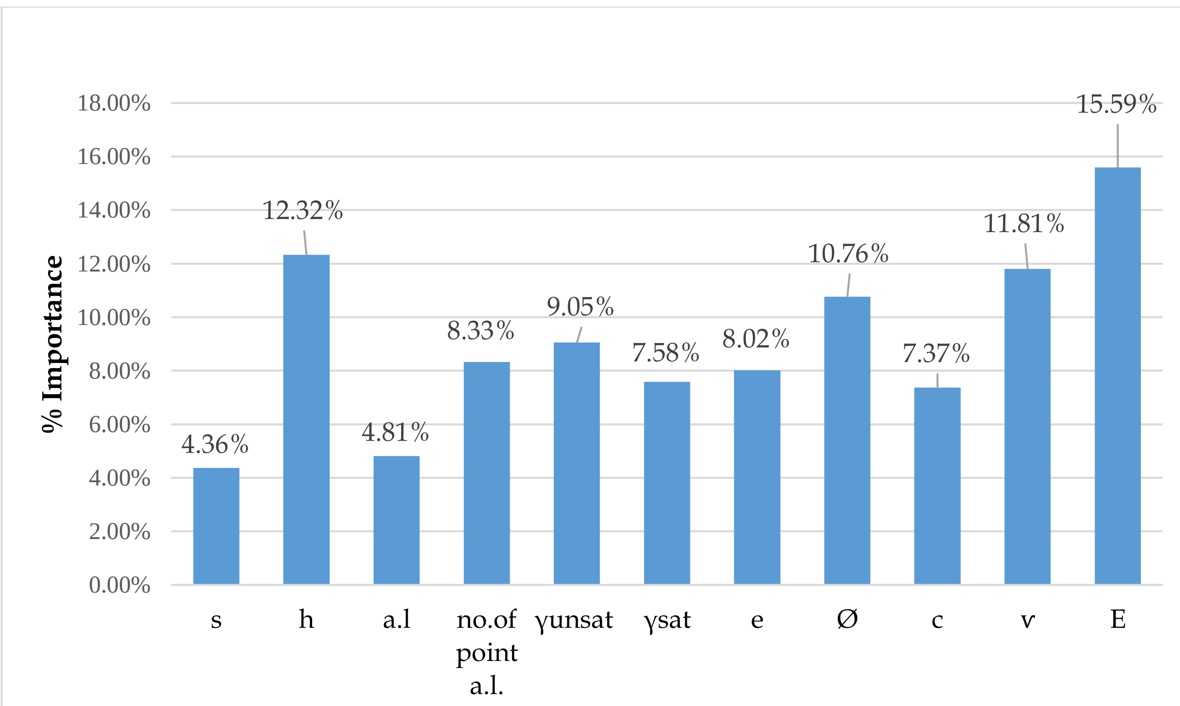
Fig. 4. Comparison of the results of settlement of the embankment (target) and settlement of the embankment prediction using a neural network (output).

5. Results and Discussion

5.1 sensitivity analysis

Sensitivity analysis is a method for determining the impacts of the data set's inputs and outputs (Singh, Verma, Sharma, & Engineering, 2007). Once the neural network has been trained, it is vital to understand the consequences of each input parameter on the outcome result. Network performance can be enhanced by lowering training complexity and time requirements. Any input channel that generates a low sensitivity value can also be rejected and removed (Garson, 1991). This method calculates the relative importance of each input parameter to the output variable by dividing the weights of each input parameter by the sum of all input weights. Numerous studies also discovered and used this method's techniques.

(Al-Janabi, 2006; Najemalden et al., 2020; Yousif & Razzak, 2017). Figure 5 shows the relative relevance of each input variable that was calculated. As the figure indicates, the modules' elastic and height had the most considerable significant impact on the produced settlement of the embankment of the road with a value of relative importance of 15.587 and 12.324%, respectively, then followed by the Poisson ratio (v), Friction angle (Ø), unsaturated unit weight (γunsat), No. Of point axial load,Initial void ratio (e), statured unit weight (γsat), Cohesion (c), and Axial load with a relative importance of 11.805, 10.763, 9.049, 8.327, 8.016, 7.579, 7.373, and 4.808 % respectively. However, the Side slope percentage is less substantial than other road charctrcteres, with a relative importance of 4.364%



Fig(5) relative importance

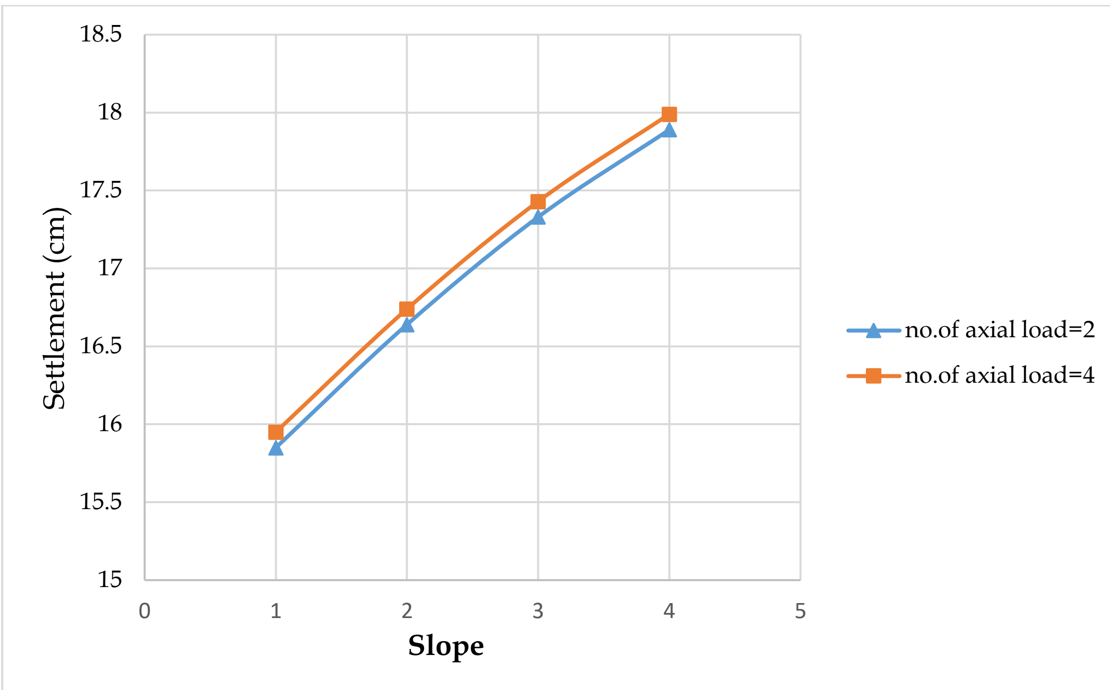
5.2 parametric study

One benefit of neural network models is their simplicity in parametric study implementation. One input parameter can be changed, and the other input parameters can be stabilized to fixed values. Due to variations in the significance of specific parameters, parametric studies allow for the model's performance to be tested by modelling the physical behaviour of settlement embankments.

5.2.1. effect of the slope with the number of axial point load

The relationship between the settlement of the embankment with the slope and the number of

axial loads is in Figures (6). The domain of slope values was (0,1:1,…..1:4), while the number of axial point load was (2,4). The settlement of the embankment is increasing with the side slope, Keeping other parameters constant. The identical connections were found by (Phutthananon et al., 2020). As shown in figure (6), the amount of settlement of the embarkment increases as a result of growing side slope of the number of axial point loads (2,4). Same relationships were reached by (Bergado, Ruenkrairergsa, Taesiri, & Balasubramaniam, 1999).

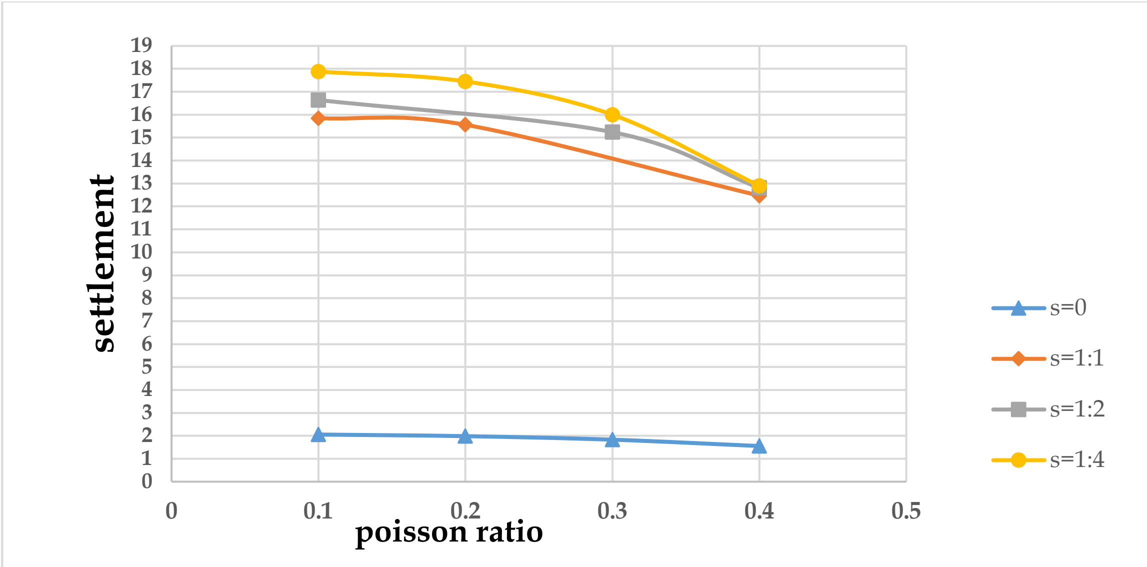


Fig(6) Effect of the side slope with number of axial point load

5.2.2. effect of the slope with Poisson ratio (v)

The correlation between the settlement embankment with the side slope and Poisson ratio(v) in figure (7). the domain of Poisson ratio (v) value was (0.1 to 0.4).

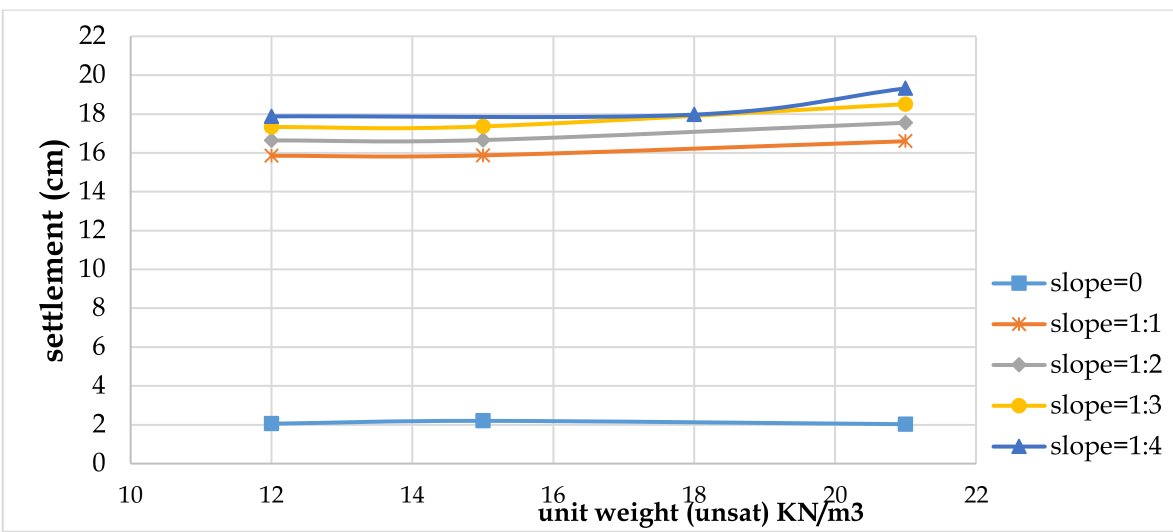
For the curve of the same value of side slope**,** settlement of the embarkment decreased due to an increase in position ratio (v). if the slope is absent or equal to (zero) settlement will reduce, and the effects of position ratio (v) will decrease in comparison to slop the amount, which means slope ((1:1,1:2,…..,ect). Same correlations were reached by (Bergado et al., 1999)



Fig(7) Effect of the slope with Poisson ratio (v)

5.2.3. effect of the slope with unit weight

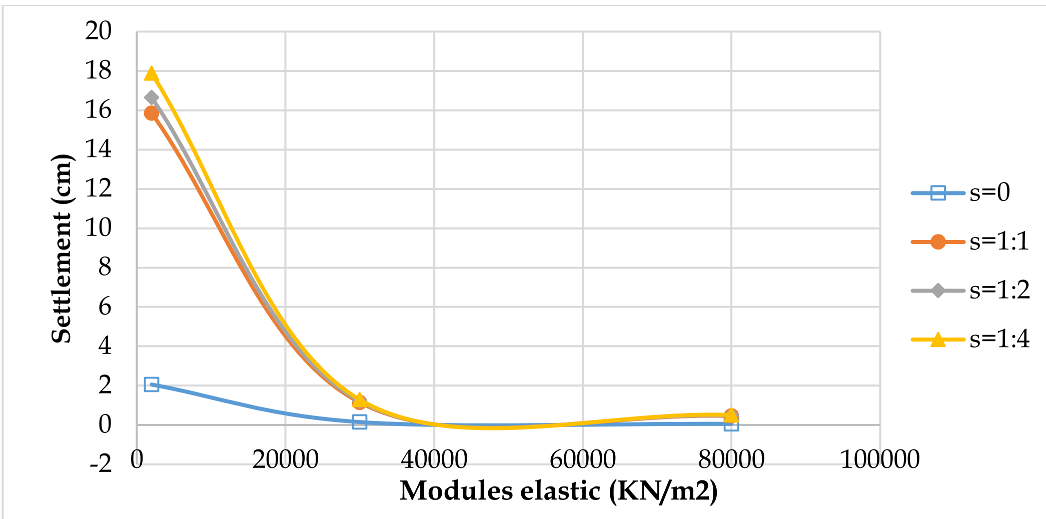
The effect between the settlement of the embankment with the side slope and unit weight is shown in figure (8). the unit weight value is (12 to 21) kN./m³. As a result of the increase in unit weight, the settlement of the embarkment shows a slow increase. The settlement will decrease, and the effects of unit weight will decline compared to the slope, if the slope is equal to (zero). Same correlations were reached by (Haghgouei, Kargar, Khosravi, Amini, & Environment, 2021)



Fig(8) Effect of the slope with unit weight

5.2.4. effect of the slope with a Modulus of elasticity (E)

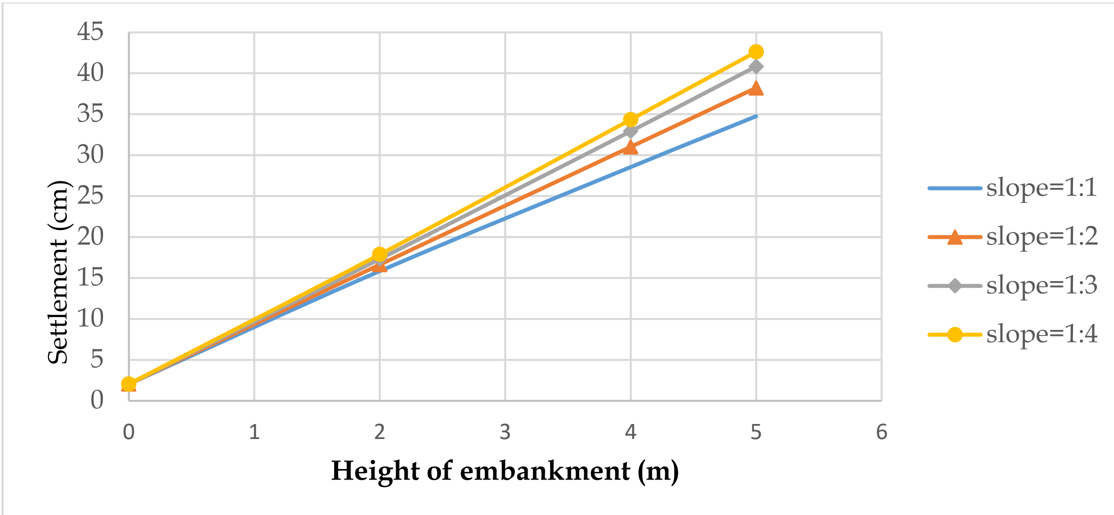
Figure (9) illustrates the settlement of the embankment with the side slope and modulus of elasticity. The modulus of elasticity is about (2000 to 80000) (kN./m^2). The curve impact of reduction occurs in settlement of the embankment as modules elastic increases. Settlement will decrease, and the effects of the modulus of elasticity (E) will reduce if slope is equal to (zero). The same connections were found by (Abusharar, Zheng, Chen, Yin, & Geomembranes, 2009)and(Zheng, Chen, Lu, Abusharar, & Yin, 2009)



Fig(9) Effect of the slope with Modulus of elasticity (E)

5.2.5. effect of the slope with Hight of embarkment (h)

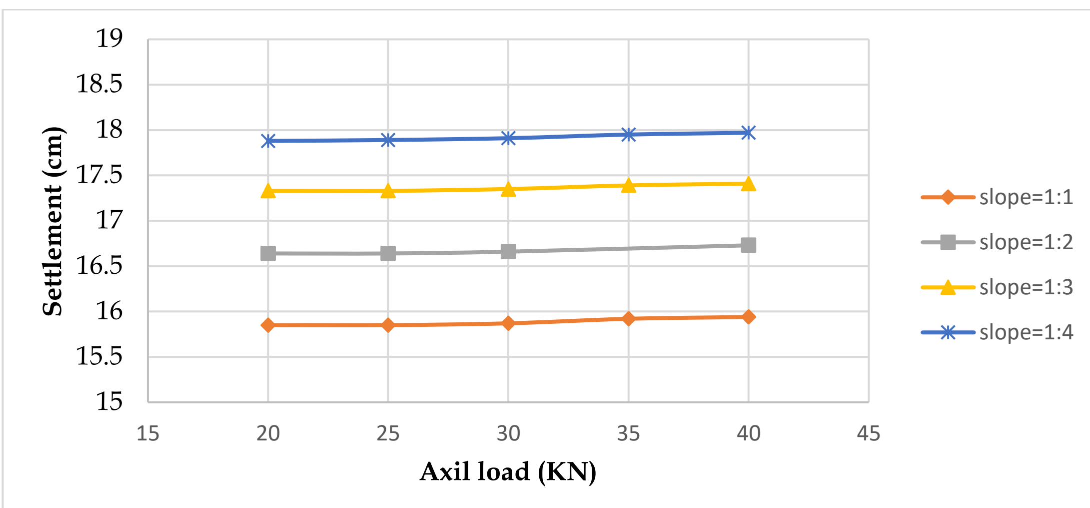
Influence the settlement embankment with the slope and height of embarkment as illustrated in figure (10). The rate height of embankment is equal to (0 to 5) m. settlement of embankment higher increased with the increase in height. These relationships were also discovered by(Bergado et al., 1999; Zheng et al., 2009).



Fig(10) Effect of the slope with Hight of embankment (h)

5.2.6. effect of the slope with axial load

The effects of the settlement embankment on the slope and axial loads as illustrated in figure (11). the load amuont was (20 to 40) kN. Settlement of the embankment increased with the increase in axial load. The identical results were found by(Duda & Siwowski, 2021)



Fig(11) Effect of the slope with axial load

6. Conclusions

This study examing using ANN program to find the settlement of road embankment .

The following conclusions may be taken based on the findings of this study:

1• ANN can obtain the settlement of the embankment with accuracy in the data field used to develop the ANN model.

2• The most appropriate network design was obtained via a tan-sigmoidal transformation and comprised of a three-layer back-propagation model, eleven input neurons, a single hidden layer involving one neuron, and one output layer containing one neuron.

3• As per the sensitivity analysis, the inputs variables can be arranged according to their relative importance as follows: (Side slope (S) & Height(h) of the embankment), (Axial load, and No. of point axial load), in addition to (unsaturated unit weight (γunsat), statured unit weight (γsat), Initial void ratio (e), Friction angle (Ø), Cohesion (c), Poisson ratio (ѵ), and modulus of elasticity (E) which are the properties of the soil under embankment).

4• The results of the parametric study displayed that the value of settlement of the embankment increased with the raised (grown) in the importance of (Side slope(S) & Height(h) of the embankment), (Axial load(a.L), and No. of point axial load and also with the reduction in the (Poisson ratio (ѵ), and modulus of elasticity (E)).

Nomenclatures

St	settlement
ANN	Artificial Neural Network
S	slope
h	Height
a.L	Axil load
γ_{unsat}	unsaturated unit weight
γ_{sat}	statured unit weight
e	void ratio
Ø	Friction angle
c	Cohesion
ѵ	Poisson ratio
E	Modulus of elasticity
M.S.E.	Mean Squared Error
LM	Levenberg-Marquard

Reference

1. Abusharar, S. W., Zheng, J.-J., Chen, B.-G., Yin, J.-H. J. G., & Geomembranes. (2009). A simplified method for analysis of a piled embankment reinforced with geosynthetics. Geotextiles and Geomembranes, 27.1: 39-52
2. Al-Janabi, K. (2006). *Laboratory leaching process modeling in Gypseous soils using Artificial Neural Network (ANN)*. PhD Thesis. PhD Thesis). University of Technology, Baghdad, Iraq
3. Al-saffar, R., & Khattab, S. J. A.-R. E. J. (2013). Prediction of soil's compaction parameter using artificial neural network. *Al-Rafidain Engineering Journal (AREJ), 21.3: 15-27*
4. Bergado, D., Ruenkrairergsa, T., Taesiri, Y., & Balasubramaniam, A. J. P. o. t. I. o. C. E.-G. I. (1999). Deep soil mixing used to reduce embankment settlement. Proceedings of the Institution of Civil Engineers-Ground Improvement,, 3.4: 145-162
5. Caglar, N., Arman, H. J. B. o. E. G., & Environment, t. (2007). The applicability of neural networks in the determination of soil profiles. *Bulletin of Engineering Geology and the Environment, 66.3: 295-301*.
6. Cai, Y., Chen, Y., Cao, Z., & Ren, C. J. A. G. (2018). A combined method to predict the long-term settlements of roads on soft soil under cyclic traffic loadings. *Acta Geotechnica, 13.5: 1215-1226*
7. Choobbasti, A., Farrokhzad, F., Rahim Mashaie, S., & Azar, P. J. J. o. t. S. A. I. o. C. E. (2015). Mapping of soil layers using artificial neural network (case study of Babol, northern Iran). *Journal of the South African Institution of Civil Engineering, 2015, 57.1: 59-66*.
8. Cui, X., Zhang, N., Li, S., Zhang, J., & Wang, L. J. A. J. o. G. (2015). Effects of embankment height and vehicle loads on traffic-load-induced cumulative settlement of soft clay subsoil. *Arabian Journal of Geosciences, 8.5: 2487-2496*.
9. Duda, A., & Siwowski, T. W. J. T. I. G. (2021). Stability and settlement analysis of a lightweight embankment filled with waste tyre bales over soft ground. Transportation Infrastructure Geotechnology, 9.4: 467-491.
10. Farrokhzad, F., Choobbasti, A., & Barari, A. J. T. N. (2014). Artificial neural network model for prediction of liquefaction potential in soil deposits. Neural computing and applications, 24.3: 891-900
11. Garson, D. G. (1991). Interpreting neural network connection weights.
12. Goh, A. T. J. J. o. G. e. (1994). Seismic liquefaction potential assessed by neural networks. *Journal of Geotechnical engineering, 120(9), 1467-1480*
13. Haghgouei, H., Kargar, A., Khosravi, M. H., Amini, M. J. J. o. M., & Environment. (2021). Semi-analytical study of settlement of two interfering foundations placed on a slope. *Journal of Mining and Environment, 12(2), 457-470*
14. Kim, Z., & Lee, C. J. J. o. K. G. S. (2002). Mechanical characteristics of light-weighted foam soil consisting of dredged soils. *Journal of Korean Geotechnical Society, 18(4), 309-317.*
15. Liu, H., Ng, C. W., Fei, K. J. J. o. G., & Engineering, G. (2007). Performance of a geogrid-reinforced and pile-supported highway embankment over soft clay: case study. *Journal of Geotechnical and Geoenvironmental Engineering, 133(12), 1483-1493.*
16. Lu, Z., Fang, R., Yao, H., Hu, Z., & Liu, J. J. I. J. o. G. (2018). Evaluation and analysis of the traffic load–induced settlement of roads on soft subsoils with low embankments. *Journal of Geotechnical and Geoenvironmental Engineering, 133(12), 1483-1493*.
17. Marradi, A., Pinori, U., Betti, G. J. P.-S., & Sciences, B. (2012). The use of lightweight materials in road embankment construction. *Procedia-Social and Behavioral Sciences, 53, 1000-1009*
18. Mohanty, S., Jha, M. K., Kumar, A., & Sudheer, K. J. W. r. m. (2010). Artificial neural network modeling for groundwater level forecasting in a river island of eastern India. *Water resources management, 24(9), 1845-1865*
19. Najemalden, A. M., Ibrahim, S. W., & Ahmed, M. D. J. J. E. S. T. (2020). Prediction of collapse potential for gypseous sandy soil using ANN technique. Journal of Engineering Science and Technology, 15(2), 1236-1253
20. Najjar, Y. M., & Ali, H. E. (1998). CPT-based liquefaction potential assessment: A neuronet approach. Paper presented at the Geotechnical earthquake engineering and soil dynamics III. (pp. 542-553). ASCE
21. Phutthananon, C., Jongpradist, P., Jongpradist, P., Dias, D., Baroth, J. J. C., & Geotechnics. (2020). Parametric analysis and optimization of T-shaped and conventional deep cement mixing column-supported embankments. Computers and Geotechnics, 122, 103555.
22. Ripley, B. D. (2007). Pattern recognition and neural networks: Cambridge university press.
23. Shahin, M. A., Jaksa, M. B., & Maier, H. R. J. A. g. (2001). Artificial neural network applications in geotechnical engineering. Australian geomechanics, 36(1), 49-62
24. Shahin, M. A., Jaksa, M. B., & Maier, H. R. J. E. J. o. G. E. (2008). State of the art of artificial neural networks in geotechnical engineering. Electronic Journal of Geotechnical Engineering, 8(1), 1-26.
25. Shahin, M. A., Maier, H. R., Jaksa, M. B. J. J. o. g., & engineering, g. (2002). Predicting settlement of shallow foundations using neural networks. Journal of geotechnical and geoenvironmental engineering, 128(9), 785-793.
26. Singh, T., Verma, A., Sharma, P. J. G., & Engineering, G. (2007). A neuro-genetic approach for prediction of time dependent deformational characteristic of rock and its sensitivity analysis. Geotechnical and Geological Engineering, 25(4), 395-407
27. Somantri, A. K., & Febriansya, A. (2019). The Effect of EPS Addition to Soil Stabilized with Fly Ash as Lightweight Fill Materials for Embankment Construction. In Journal of Physics: Conference Series (Vol. 1364, No. 1, p. 012077). IOP PublishingIn Journal of Physics: Conference Series (Vol. 1364, No. 1, p. 012077). IOP Publishing
28. Tenpe, A., Kaur, S. J. I. J. o. S., & Research. (2015). Artificial neural network modeling for predicting compaction parameters based on index properties of soil. International Journal of Scientific Research, 4(7), 1198-1202
29. Uzundurukan, S., Nilay Keskin, S., & Selcuk Göksan, T. J. J. o. A. S. (2005). Artificial Neural Network Modelling for Estimation of Suction Capacity. Journal of Applied Sciences, 5(4), 712-715

30. Yoon, G., & Kim, B. J. J. o. t. K. G. S. (2004). Compressibility and characteristics of light-weighted foam soil. J Korean Geotech Soc, 20(4), 5-13.
31. Yousif, S. T., & Razzak, A. A. A. (2017). Artificial neural networks modeling of elasto-plastic plates: Scholars' Press.
32. Zheng, J., Chen, B., Lu, Y., Abusharar, S., & Yin, J. J. G. I. (2009). The performance of an embankment on soft ground reinforced with geosynthetics and pile walls. Geosynthetics International, 16(3), 173-182
33. جمهورية العراق وزارة العمال والسكان. دليل المهندس المقيم للمشاريع الانشائية2015. الطبعة الثانية. من الرابط. https://www.scribd.com/doc/