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Developing a Machine Learning Model for Predicting the Settlement of Bored Piles

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Abstract: Analyzing the behavior and determining the settlement of bored piles is of significant importance in construction practice. Traditional experimental methods are time-consuming and expensive, while theoretical methods often yield less reliable results. This research focuses on developing a machine learning model based on an artificial neural network, which is trained and deployed to predict pile top settlement using EXCEL software. The data used to train the model consist of results from static pile load tests conducted in Vietnam and around the world. The findings indicate that the prediction model is highly accurate in predicting pile settlement. Compared to empirical formulas, the artificial neural network model demonstrates superior performance in determining pile top settlement. Additionally, the research proposes an empirical formula that simulates the artificial neural network in EXCEL, enabling the quick estimation of pile top settlement using only a few specific parameters for the pile and soil.

Keywords: Artificial Neural Network, bored piles, pile top settlement, EXCEL formula.

1. Introduction

For high-rise buildings with large loads, the option of using pile foundations is considered the most optimal solution. During the calculation process for pile foundation design, design engineers must focus on two key aspects: pile bearing capacity and pile top displacement. The pile bearing capacity has a great influence on the overall load-bearing capacity of the building's foundation, while the pile displacement will affect the normal operation of the building as well as the overall settlement and differential settlement of the building. In addition, pile top displacement plays a crucial role in the simultaneous design of superstructures and foundation performance analysis.

Previous studies often pay special attention to the pile bearing capacity component [1], [2]. The settlement component of the pile top has not been fully given attention. The determination of the pile top displacement is generally based on the static pile tests, which are costly and time-consuming [3]. Theoretical studies on determining pile top displacement have stopped at simple models, based on many approximate assumptions, for example: Vesic (1977) [4], Gambin (1963) [5], etc. More advanced methods such as using the finite element model (FEM) or discrete model, using the Py and Tz curve method give good results in many cases [6], [7], [8]. However, accurately determining the parameters for models of this method requires a lot of effort as well as experimental results for calibration.

During the period of the 4th industrial revolution, research on applying artificial intelligence (AI) and machine learning (ML) methods in practice has shown positive results in many fields. Previous studies like Momeni (2015) [9], Al-Hamed (2014) [10], Shahnazari & Tutunchian (2012) [11] used different machine learning algorithms to determine the ultimate bearing capacity of piles and shallow foundations. Domestically, the application of artificial intelligence models in engineering in general and geotechnical engineering in particular is experiencing strong developments [12], [13].

The above mentioned studies mostly focus on analyzing and predicting the pile bearing capacity or the two components that make up the load bearing capacity: pile side friction and pile tip resistance. There has been little or no research analyzing the pile tip displacement under the effect of load. In addition, those studies often build models based on soft computing techniques, using libraries from technical programming platforms such as MATLAB or Python. These techniques, which are suitable for research problems that require writing code or using existing libraries, are difficult to implement directly for practical problems. Therefore, this study develops an artificial neural model, from building a database of bored piles, and selecting input parameters to predict results, pile top settlement is the output parameter. The model is built on the EXCEL platform, which is a friendly platform and easy to apply in practice.

2. Research Methods

2.1. Develop artificial neural network models

In 1943, Warren McCulloch and Walter Pitts [14] proposed a simple model of an artificial neuron. This is also the historical beginning of ANN. To this day, this model is still considered the foundation for most ANNs. Basically, this model consists of an input layer, hidden layers, and an output layer. Layers contain nodes (neurons) connected to each other by weights. Data is transmitted from the input layer, through the hidden layers, and ends at the output layer. During transmission, the data will be transformed to properly describe the relationship between the input and output layers. During data transformation, activation functions are used at hidden nodes to help describe nonlinear relationships. A typical artificial neural network is shown in Fig 1.

MS EXCEL is inherently a popular spreadsheet software. Since the input data is also structured in tabular form, using EXCEL to build a simple artificial neural network is feasible. To build an artificial neural network model, it is necessary to understand the rules of data transmission in that network.

First of all, the output value of any hidden node in the network is written as follows:

$$N_k = f\left(\sum_{i=1}^{n} X_i w_{ik} + b_k\right) \quad (1)$$

where: N_k - the output value of the hidden node; n - the number of input variables; w_{ik} - the weight connecting the ith variable to hidden node k; b_k - bias of hidden node k; f() - the activation function.

Data transmission diagram in an artificial neural network, which can be written in matrix form as shown in Fig 2. It can be seen that the process of data transmission and transformation in the ANN model is a series of matrix multiplications, and data transformation through the activation function.

A summary diagram of data transmission in the ANN model is shown in Fig 3. Fig 3, {X} is input vector; [W_1] is weight matrix 1, which connects from input vector to the hidden layer; {b_1} is the bias vector; {N} is the hidden note output; f() is the activation function; [W_2] if weight matrix 2, which connect from hidden layer to output layer and {b} is the output biases of output nodes.

Besides, an ANN model needs to be trained before being used. Training is a process of optimizing weights, so that the model output best matches the training data. Therefore, optimization algorithms are often used in this step.

To create an artificial neural network, some EXCEL functions that can be proposed as follows:

Matrix multiplication function:

Mmult(Matrix A, Matrix B) (2)

"Relu" activation function:

$$Relu(x) = Max\ (0,x) \quad (3)$$

"Sigmoid" activation function:

$$Sigmoid(x) = 1/(1+exp(x)) \quad (4)$$

"Tanh" activation function:

$$Tanh(x) = (exp(x)-exp(-x))/(exp(x)+exp(-x)) \quad (5)$$

Random number generator function: Rand(), generate random number in range (0,1).

Solver tool, which used to train the ANN model.

Based on the above analysis, a process for building an artificial neural network model is shown in Fig 4. It is important to note that the initial weight matrix should have small values, usually in the range (-0.1 ÷ +0.1), to ensure the weight matrix is balanced, and there is no significant difference value, causing the model to not be general.

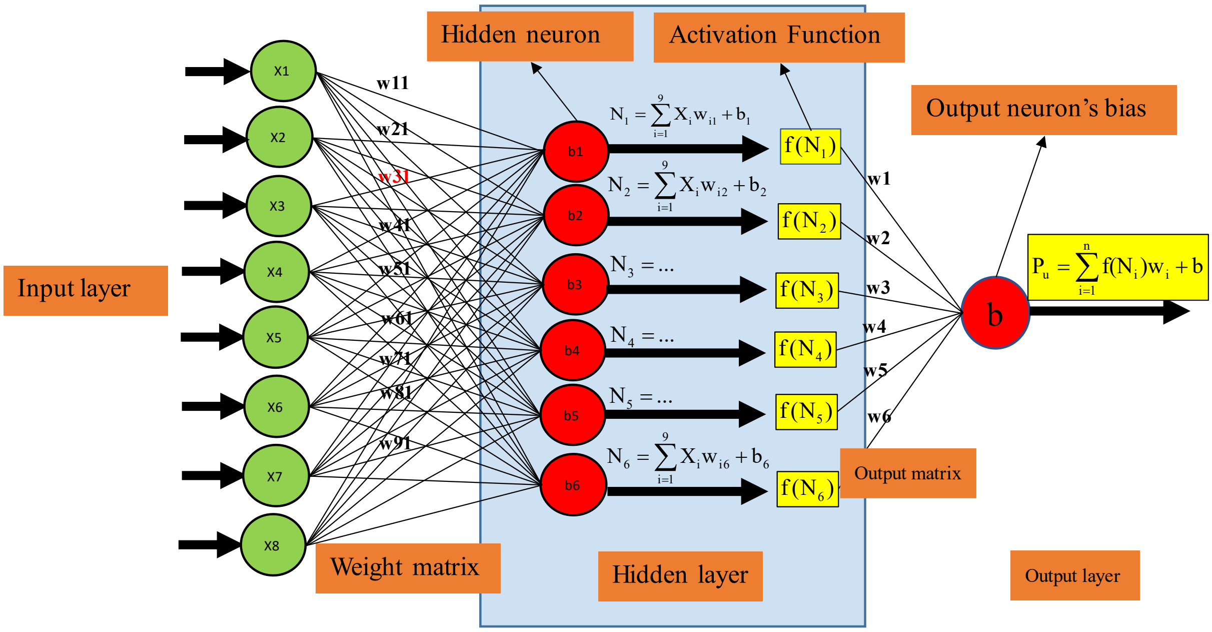


Fig 1. Artificial neural network structure

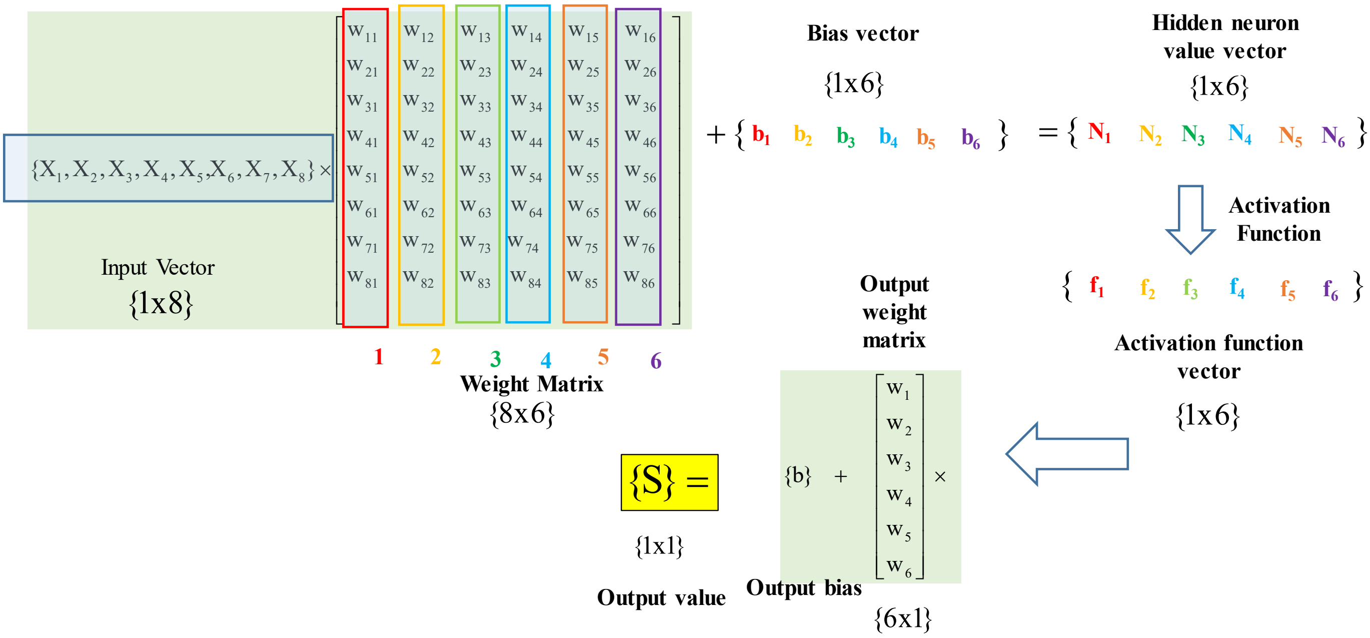


Fig 2. Data transmission diagram in an artificial neural network in matrix form

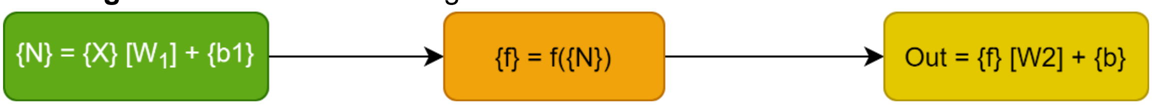


Fig 3. A summary diagram of data transmission in the ANN model

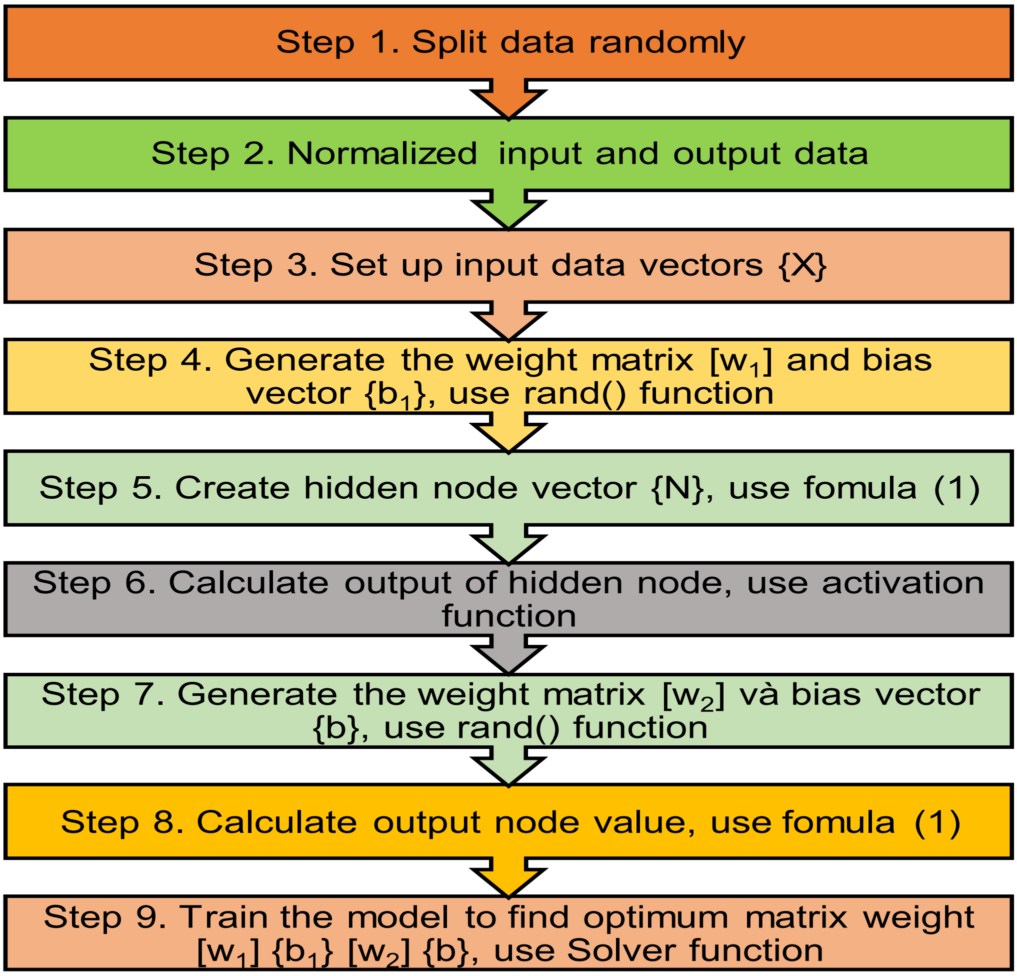


Fig 4. Diagram of building an artificial neural network on EXCEL

2.2. Database collection

Building and training a machine learning model to achieve a certain accuracy depends greatly on the input database. Based on the analysis and selection of input parameters, related to pile bearing capacity, this study collects and selects an input database of 64 results of static pile load tests, accompanied by information about the results of SPT of the soil. To make the results of the problem more general, static pile load test data were selected to be distributed in several regions of the world especially 4 piles in Vietnam.

Which, the results of 02 piles were implemented at the Kenton Project, Nha Be district, Ho Chi Minh City. The piles in this project were tested in static compression according to TCVN 269-2002, using counterweights, combined with Extensometer Model A9 probes to measure axial deformation, to measure axial force, and displacement of each pile body segment. In addition, a static compression test of 02 piles was carried out at the Ben Van Don Apartment project, District 4, Ho Chi Minh City, according to TCVN 9393 - 2012. This test uses counterweights combined with a torsional anchor system, along with the Geokon 4200 strain gauge system installed along the pile shaft. Some data on static pile load tests around the world are referenced from the Federal Highway Administration (FHWA) [15]. These experiments are mainly performed in the form of loading at each level. The results measured the load-pile top displacement relationship.

Based on the working characteristics of the pile, parameters that have a direct influence will be selected to predict pile top settlement. Specifically: (1) Load applied to the top of the pile (P); (2) Total pile length (L_t); (3) Length of the pile in the ground

(L_s); (4) Average SPT index along the pile body (N_{sh}); (5) Average SPT index at pile tip (N_t); (6) Pile diameter (D); (7) Elastic modulus of pile materials (E); Output parameter: Settlement at pile tip (S). The input parameters are illustrated in Fig 5.

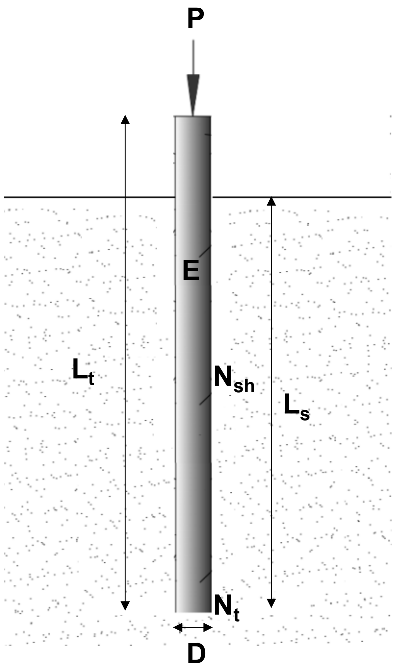


Fig 5. Input parameters of the model

The dataset consists of 563 measurement points from 64 bored piles at various test load levels. The author uses 75% of the data for training and 25% for testing to evaluate the model. A summary of database statistical parameters is presented in Table 1, including the minimum, mean, maximum, median, and standard deviation (denoted as SD) values of all parameters used in this study. One important point to note is that to help input variables have equal importance to the model output, all data (including input and output parameters) are normalized within the range [0; 1]. Normalization is the process of changing the min-max range of input variables while still retaining the relationship rules between them. The normalization formula is written as follows:

$$X_i = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{6}$$

With output parameter S, this parameter will be normalized to Log(S). To explain this standardization, it can be seen that, without standardization, the P-S relationship has a strongly nonlinear relationship, making it is very difficult for the model to learn the necessary rules. After using the P-Log(S) form, this relationship can approximately be considered linear, making the model more convenient for learning the relationship rules. An example of normalizing pile top settlement is shown Fig 6.

To evaluate the degree of correlation between variables, a correlation matrix is used. The correlation value r between any two variables is determined by the formula:

$$r_{x,y} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{X})(y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{X})^2 \sum_{i=1}^{n}(y_i - \overline{Y})^2}}} \tag{7}$$

where: $\overline{X}, \overline{Y}$ - is the average value of the variables x, y; n – is the number of samples of variables x, y;

The r value is in the range (-1; 1), negative values mean negative correlation. The larger the value, the higher the correlation between variables. Usually, variables are considered linearly independent, when the correlation between them is in the range (-0.8; 0.8). It can be observed that the correlation between the input variables and the output Log(S) is small, as shown in Table 2, indicating that the variables can be considered linearly independent. The relationship between L_t and L_s can be approximated as a linear dependence because these two parameters essentially characterize the pile length. However, in terms of pile performance, the pile section buried in the soil works differently from the pile section above the soil, so the study recommends not eliminating any variables, but keeping all L_t and L_s variables.

It can be seen that the input values of the pile load test data set show the coverage of the values, the parameters are all within the common range of piles in practice, as shown in Fig 7. This proves that the research results can be applied in many real case studies.

Table 1. Statistical characteristics of variables used in the study

	P	L_t	L_s	N_{sh}	N_t	D	E	S
Unit	(N)	(mm)	(mm)	-	-	(mm)	(Pa)	(mm)
Total	563	563	563	563	563	563	563	563
Min	0	4876.8	4140.02	12.24	17.5	127	9.69E+08	0
Max	16964000	76000	76000	273.82	400	2865.12	3.42E+10	234.19
Mean	3233946	15257.52	14591.48	59.24	119.07	937.44	2.94E+10	20.63
SD	2955526	16519.59	16295.64	57.37	121.31	491.61	5.03E+09	36.20

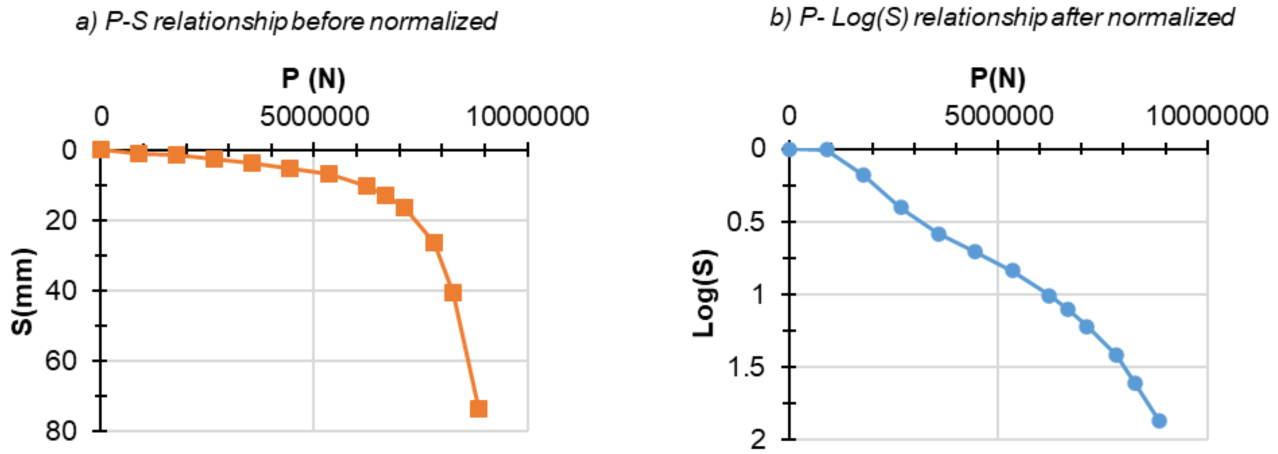
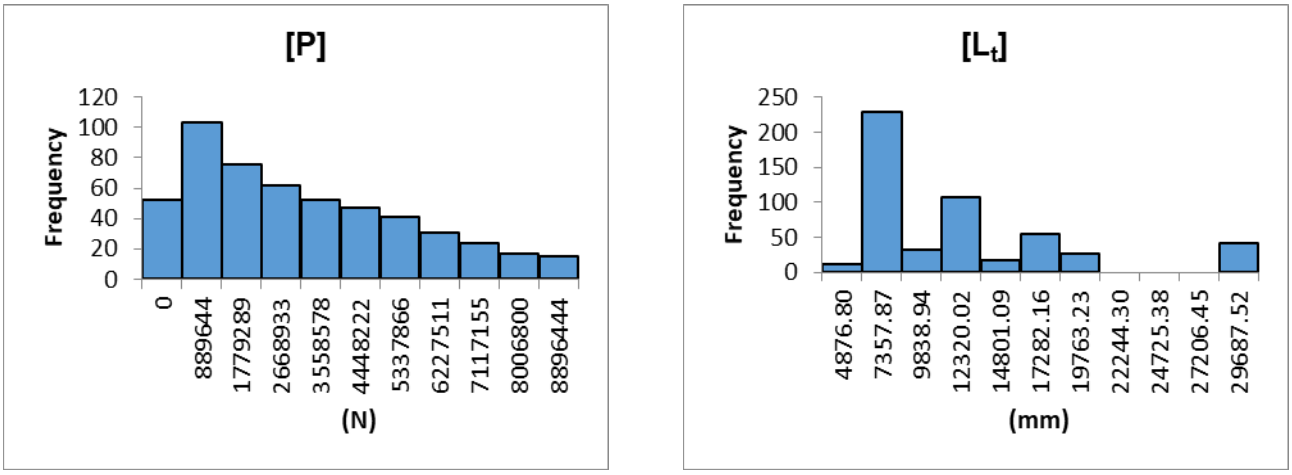


Fig 6. Standardized pile tip settlement

Table 2. Correlation matrix of research parameters

	P	*L_t*	*L_s*	*N_{sh}*	*N_t*	*D*	*E*	*Log(S)*
P	1							
L_t	0.3636	1						
L_s	0.3712	0.9933	1			SYM		
N_{sh}	0.0148	-0.1618	-0.1552	1				
N_t	0.1288	-0.2835	-0.2812	0.1169	1			
D	0.2531	0.0076	0.0120	-0.2429	0.6012	1		
E	-0.0848	-0.1628	-0.2014	0.0325	-0.2321	0.0496	1	
Log(S)	0.5279	0.0129	-0.0074	-0.0045	0.0905	0.0235	0.0359	1



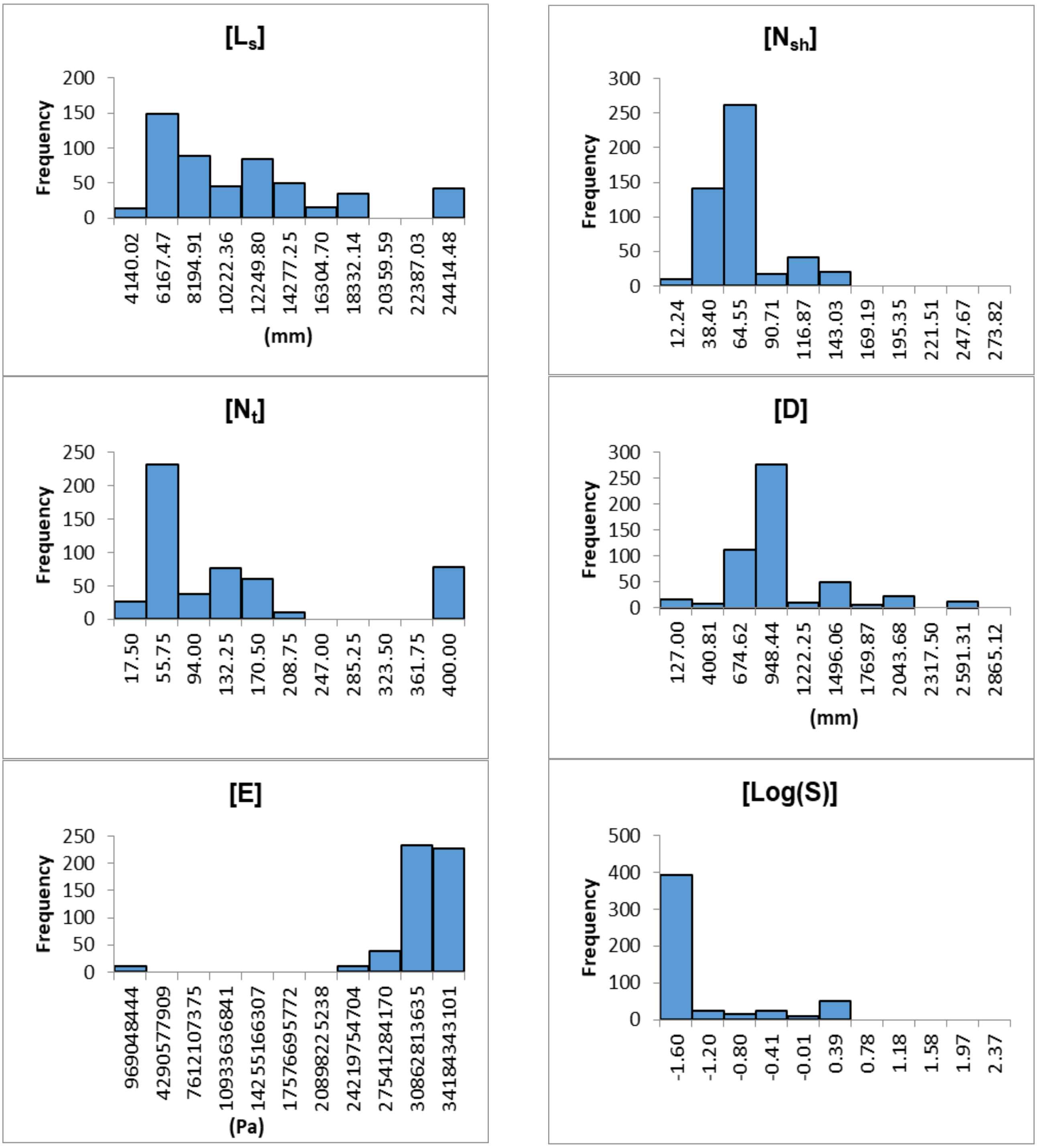


Fig 7. Data distribution chart of parameters used in this study

2.3. Performance indicator

In this study, the evaluation of machine learning models was performed using statistical measures such as Mean Absolute Error (MAE), coefficient of determination (R^2), and Root Mean Square Error (RMSE). Overall, these criteria are common methods for quantifying the performance of AI algorithms. More specifically, MAE and RMSE represent the difference in error between the actual and estimated values. Meanwhile, R^2 evaluates the correlation between the actual values and the predicted values. Quantitatively, lower RMSE and MAE indicate better performance of the models. On the contrary, higher R^2 indicates better performance of the model. MAE, RMSE, and R^2 are expressed as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|a_i - \hat{a}_i\right| \quad (8)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(a_i - \hat{a}_i)^2} \quad (9)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(a_i - \hat{a}_i)^2}{\sum_{i=1}^{N}(a_i - \hat{a})^2} \quad (10)$$

where a_i is the actual output, $\hat{a}_i$ is the predicted output, and N is the number of samples used.

To make it easy to understand, the closer MAE and RMSE get to 0, the more accurate the model is. The value of R^2 ranges from -∞ to 1, and the closer R^2 approaches 1, the more accurate the model is.

In EXCEL, you can quickly build evaluation criteria functions as follows:

Correlation coefficient function:

R^2 **= RSQ(Array1, Array2)**

Root Mean Squared Error function:

RMSE **= SQRT(SumQ(Ar)/CountA(Ar))**

Mean absolute Error function:

MAE = **ABS(Sum(Ar)/CountA(Ar))**

where Ar = Array1-Array2; Array1, Array2 are two arrays containing the actual value and predicted value of the model.

3. Results and Discussions

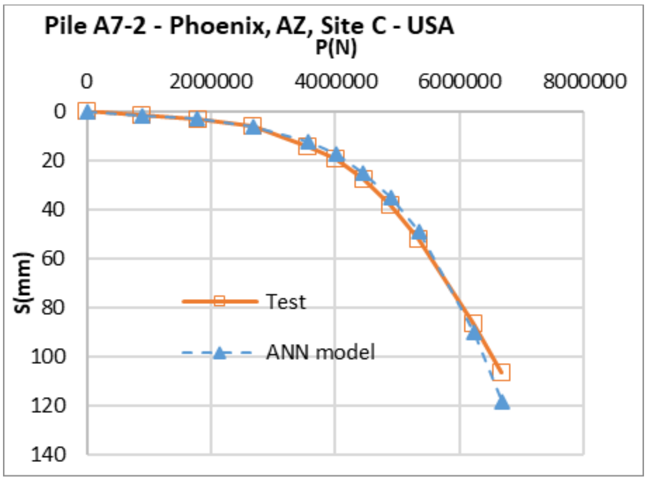
3.1. Develop and train Artificial Neural Network models

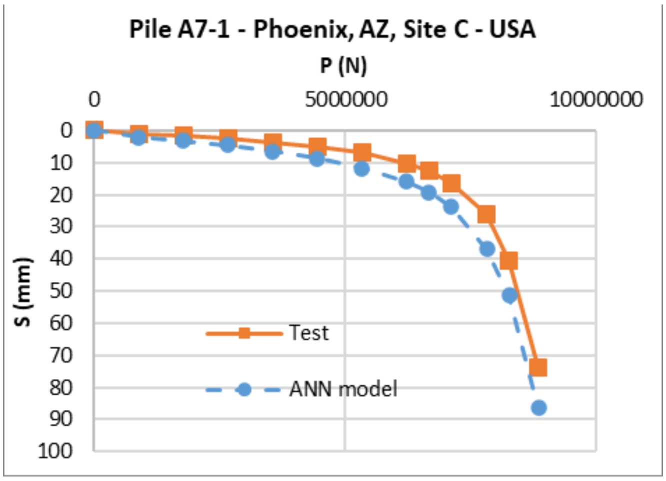
In this study, Artificial Neural Networks model is built on the EXCEL platform. The model architecture is described in Table 3. It's important to note that this model architecture was chosen based on a trial and error method. The hyperparameters of the model are selected based on the best results obtained on the training data set.

Table 3. ANN model architecture used in this study

Parameter	Meaning	Value
N	Number of input variables	7
Number of hidden layers	-	1
Number of hidden neurons	-	6
Hidden neuron activation function	The type of activation function of the nodes in the hidden layer	Tanh()
Output neuron activation function	The type of activation function of the nodes of the output node	Linear()
Training algorithm	The algorithm optimizes the weights and biases of the model	GRG
Weight constraints	Allowable range of weights when optimizing	(-0,1 ÷ 0.1)

3.2. Model analysis results





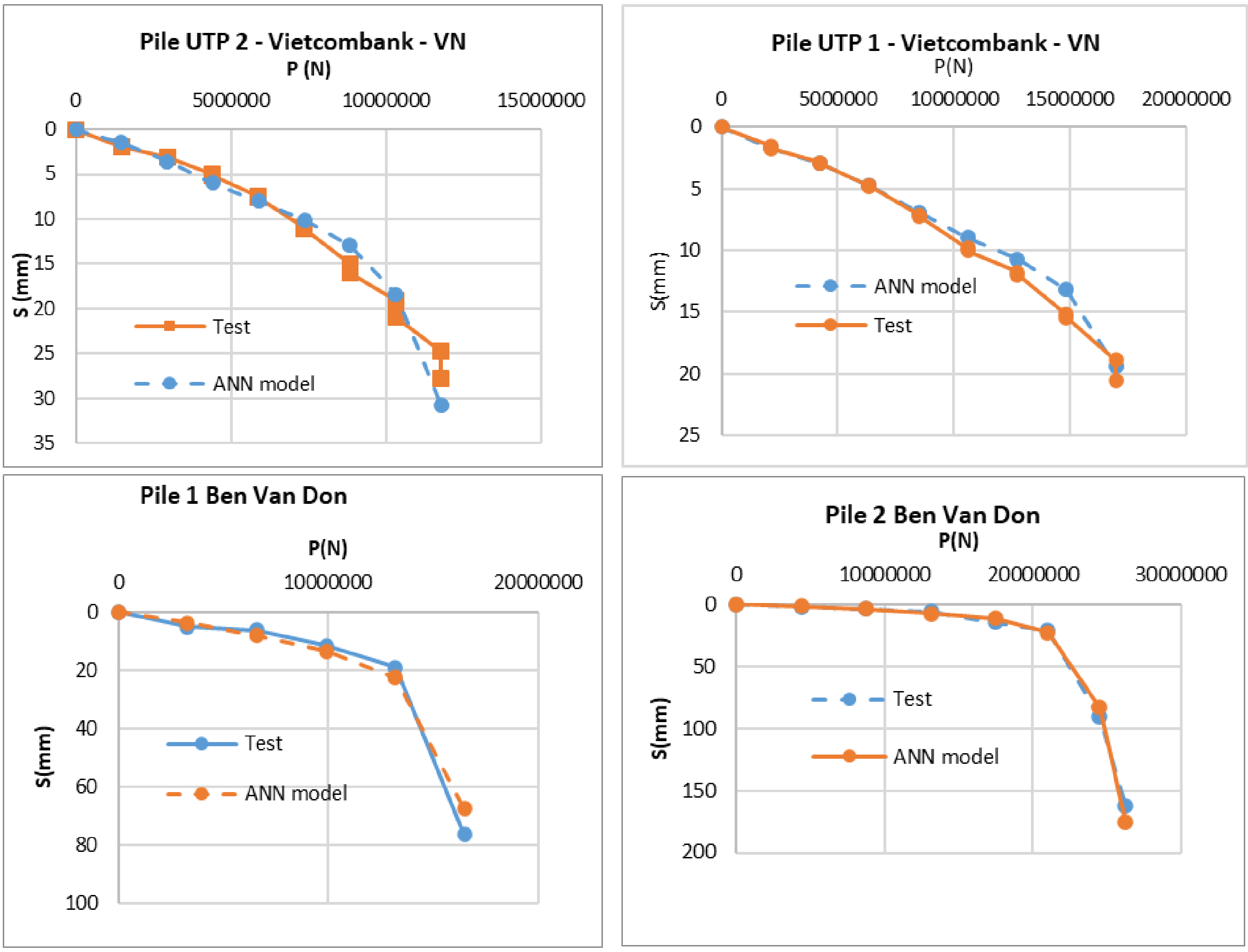


Fig 8. The ability to predict settlement results of the ANN model for piles in the data set

The pile settlement (S) is determined inversely based on the Log(S) function according to the following formula:

$$S_i = 10^{Log(S)} \tag{11}$$

The results of pile settlement prediction with 04 piles in Vietnam and some typical piles in the USA under different load levels are collected by the author.

The results show in Fig 8 that the predicted values of the dataset closely approximate the test values for both domestic and international piles. This demonstrates the ANN model's strong predictive capability in determining the load-settlement relationship at the pile top.

3.3. Comparison with other studies

The calculated results are compared with the two models of Vesic and Gambin as follows

Results by Vesic [4]:

$$S = \frac{PL}{A_t.E} + Cp.\frac{P_t}{D.q_p} + Cs.\frac{(P - P_t)}{L.q_p} \tag{12}$$

in which: P – Axial force on the pile top; L – Pile's length; A_t – Pile tip cross-sectional area; E – Young Modulus of pile material; Cp- Experimental coefficient (0.09 for sandy soil); q_p – bearing capacity of pile tip soil, $q_p = \frac{40N_t.L}{D} \le 400N_t$; P_t – Axial force transmitted to pile tip, approximately P_t = 0.5P; C_s – Experimental coefficient, $C_s = 0.93 + 0.16\sqrt{\frac{L}{D}}C_p$

The results of calculating pile settlement according to Vesic are not completely consistent, the linear regression line deviates quite far from the standard regression line, shown in Fig 9. In addition, the evaluation criteria also give poor results when the correlation coefficient (R^2, R) is low and the error criteria (MAE, RMSE) is high, shown in Table 4. It can be seen that the linear model according to Vesic cannot accurately predict pile settlement, which has a nonlinear load-settlement relationship.

Results by Gambin [5]: In this study, the Gambin method is improved on the Winkler coefficient model, shown in Fig 10. The pile is divided into sections, the interaction between the pile and the ground is replaced by Winkler spring-type connections. Accordingly, the pile tip settlement is determined based on the load transmission method, by assuming the reaction force (settlement) of the pile tip, then calculating backwards.

The results in Fig 11 and Table 5 show that the ANN model can predict pile head settlement closer to the experimental results than the other two methods, the Vesic Formula and the Gambin-Winkler model. The two traditional models of Vesic and Gambin-Winkler allow the prediction of pile settlement in linear elastic form, while the ANN model allows the prediction of pile settlement in nonlinear form. This is specifically shown for all three evaluation criteria in Table 5, the ANN model is superior with R^2 =0.98, RMSE =4.51 mm and MAE =1.32mm for 6 typical piles included in settlement prediction.

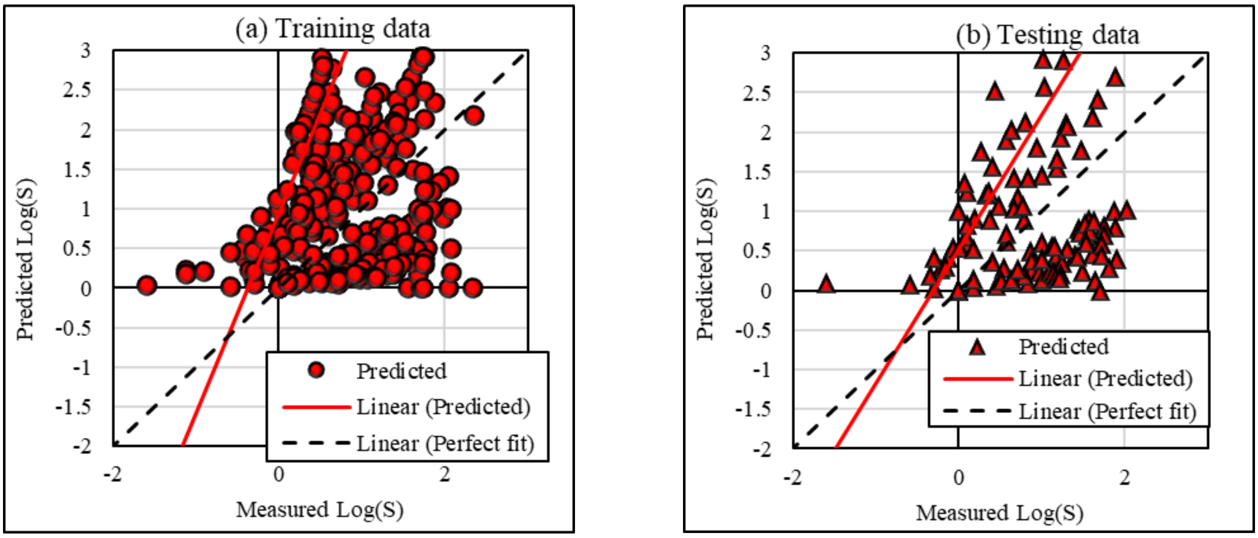


Fig 9. Calculation results of pile top settlement according to Vesic's formula

Table 4. Results of evaluation criteria according to Vesic formula

Assessment criteria	R^2	R	MAE	RMSE
Training data	0.060	0.246	2.686	7.247
Testing data	0.051	0.227	1.756	5.296

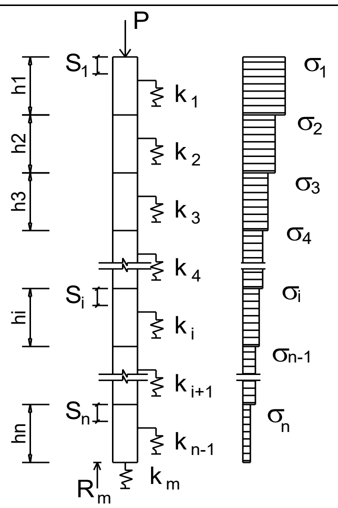


Fig 10. Pile behavior analysis according to Gambin - Winkler model

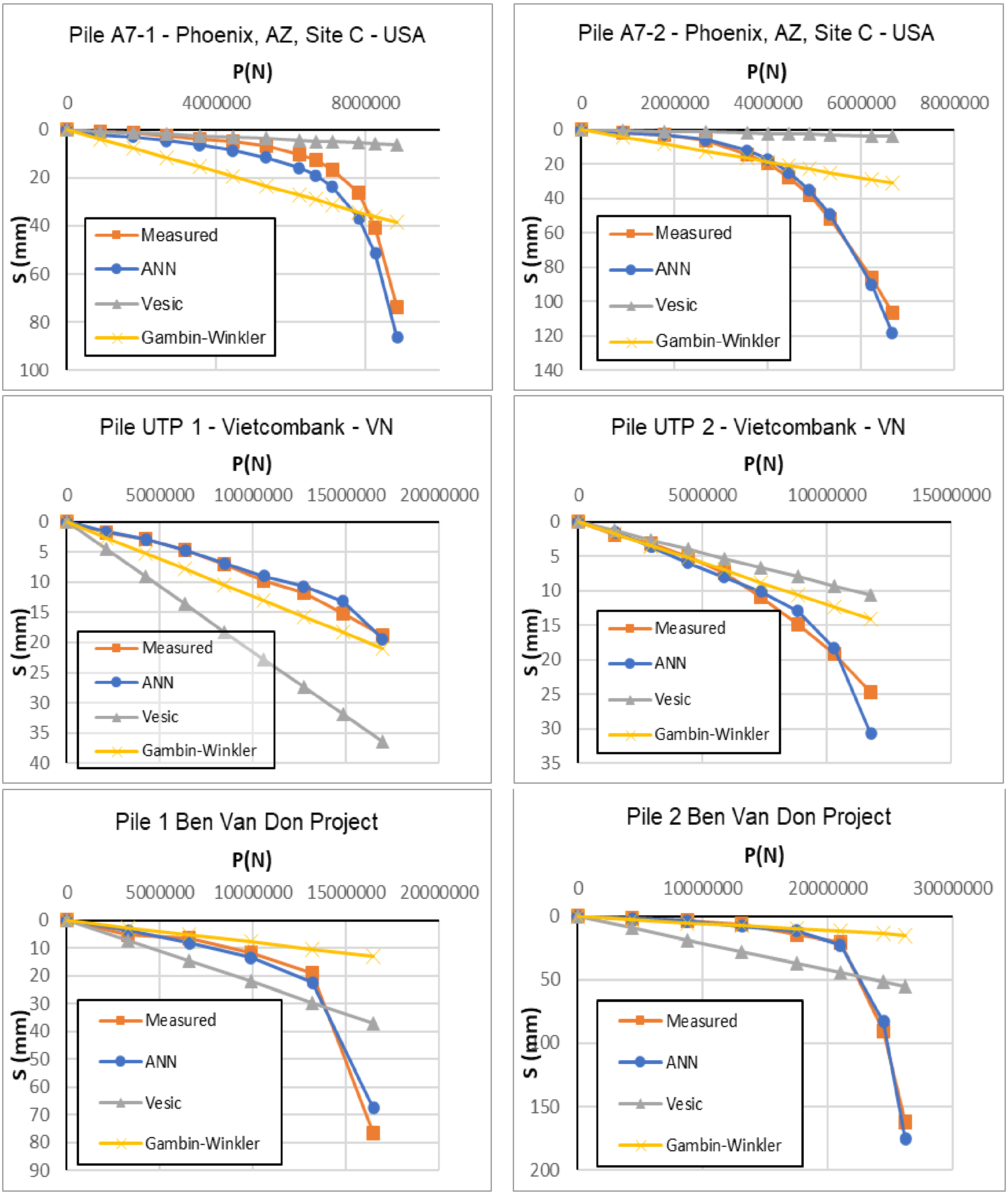


Fig 11. Comparison results of calculating settlement of models

Table 5. Evaluation criteria results for 6 test piles in this study

Criteria	ANN	Vesic	Gambin-Winkler
R^2	0.98	0.22	0.25
MAE, mm	1.32	8.77	7.09
RMSE, mm	4.51	28.65	28.11

3.4. Analyze input variables importance

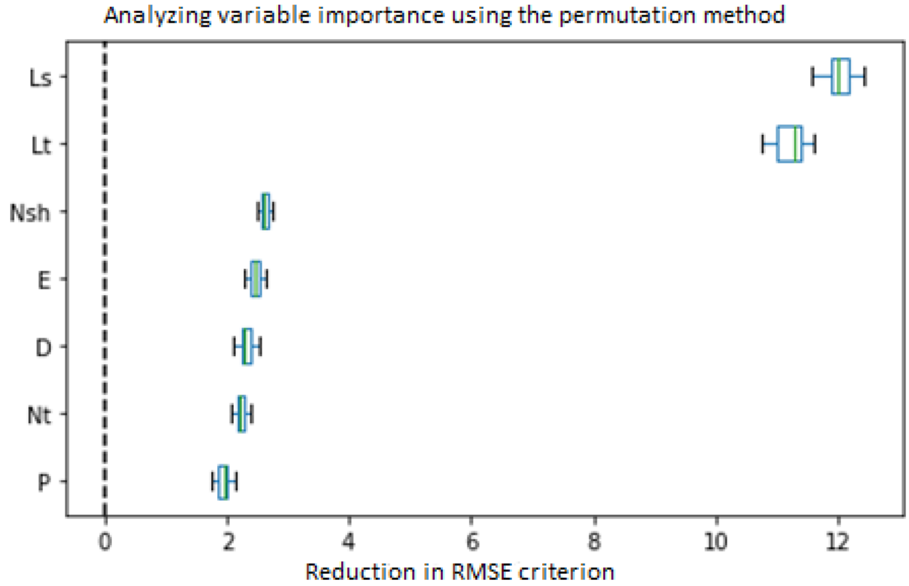


Fig 12. Importance of input variables in permutation method

One of the important advantages of data-driven models such as artificial neural networks is that the model can be used to assess the importance of input parameters to the output data (here, pile top settlement). Based on the identification of important variables, people can focus more on accurately determining those variables, to increase the reliability as well as the predictive ability of the model. One of the commonly used methods for assessment is the Permutation feature importance method. This method has been presented in detail in the tutorial accompanying the scikit-learn library [16] and the document by Breiman (2001) [17].

The results (Fig 12) show that, after 20 analyses for each input variable, the parameters related to pile length (L_s, L_t) have the highest importance. This seems to imply that pile length is the most important parameter affecting the accuracy of the pile settlement prediction model. The remaining parameters such as pile parameters (D, E) and soil index (Nsh, Nt) along with pile top load (P) are all of equal importance and do not greatly affect the accuracy of the prediction model.

4. Conclusion

The research results are a set of data including 64 static pile compression test results in Vietnam and the world, along with 563 data points to serve the model training shows. Standardize the output data, use the Log(S) normalization function to simplify the nonlinear relationship between load - and displacement, helping the model easily grasp the nonlinear relationships.

Build and train the ANN model using Excel software to predict pile top settlement with high accuracy. The model effectively demonstrates its ability to predict the nonlinear relationship between load and pile top displacement. A comparison with two traditional methods demonstrates the model's superior ability to calculate pile settlement. Comparison with 02 traditional methods shows the superior ability of the model in calculating pile settlement.

The results also show that parameters characterizing the pile length have the greatest influence on the calculation results. This model can be further refined to improve the ability to predict pile foundation settlement.

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Appendix A. Structure of the EXCEL table to use contact formulas

B	C	D	E	F	G	H	K
P	Lt	Ls	Nsh	Nt	D	E	MTKNT (LogS)
0	0.0205705	0.028492	0.143955	0.082353	0.231911	0.902473	0.077647908
0.033891	0.0205705	0.028492	0.143955	0.082353	0.231911	0.902473	0.298370001
0.067782	0.0205705	0.028492	0.143955	0.082353	0.231911	0.902473	0.487763211
0.101674	0.0205705	0.028492	0.143955	0.082353	0.231911	0.902473	0.657671608
0.135565	0.0205705	0.028492	0.143955	0.082353	0.231911	0.902473	0.809055925
0.169456	0.0205705	0.028492	0.143955	0.082353	0.231911	0.902473	0.942416711
0.203347	0.0205705	0.028492	0.143955	0.082353	0.231911	0.902473	1.066755814
0.237238	0.0205705	0.028492	0.143955	0.082353	0.231911	0.902473	1.202458042
0.254184	0.0205705	0.028492	0.143955	0.082353	0.231911	0.902473	1.283256581
0.27113	0.0205705	0.028492	0.143955	0.082353	0.231911	0.902473	1.37768715
0.298243	0.0205705	0.028492	0.143955	0.082353	0.231911	0.902473	1.565849387
0.315188	0.0205705	0.028492	0.143955	0.082353	0.231911	0.902473	1.711243572
0.337218	0.0205705	0.028492	0.143955	0.082353	0.231911	0.902473	1.936477359
0	0.0004286	0.008556	0.143955	0.082353	0.28757	0.902473	-0.06142457
0.033891	0.0004286	0.008556	0.143955	0.082353	0.28757	0.902473	0.209493532
0.067782	0.0004286	0.008556	0.143955	0.082353	0.28757	0.902473	0.480041309
0.101674	0.0004286	0.008556	0.143955	0.082353	0.28757	0.902473	0.770517273
0.135565	0.0004286	0.008556	0.143955	0.082353	0.28757	0.902473	1.080879109
0.15251	0.0004286	0.008556	0.143955	0.082353	0.28757	0.902473	1.238799336
0.169456	0.0004286	0.008556	0.143955	0.082353	0.28757	0.902473	1.394940469
0.186402	0.0004286	0.008556	0.143955	0.082353	0.28757	0.902473	1.54658317
0.203347	0.0004286	0.008556	0.143955	0.082353	0.28757	0.902473	1.69143052
0.237238	0.0004286	0.008556	0.143955	0.082353	0.28757	0.902473	1.955089503
0.254184	0.0004286	0.008556	0.143955	0.082353	0.28757	0.902473	2.073092772

Appendix B. Regression formula based on Artificial Neural Network has been trained in EXCEL to determine the pile top settlement value S(mm)

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=((-0.600489705216556*(((1/(1+EXP(-(((-0.468776628790025*B2+-
0.266682571891782*C2+0.124768700008979*D2+0.399972155392599*E2+0.323597726987388*F2+0.15653670
7629331*G2+-0.407027992144072*H2)+-1.37396297769659)*2))))*2)-1)+3.07587140548582*(((1/(1+EXP(-
(((1.63511934366891*B2+-0.423736500106807*C2+-2.16593076068899*D2+-
5.35568281053685*E2+4.0531508069391*F2+-6.07071951309046*G2+-
1.04694541482673*H2)+2.17300434525059)*2))))*2)-1)+0.344811392525002*(((1/(1+EXP(-(((-
0.313410414263851*B2+0.370364137949135*C2+0.15134293607182*D2+0.404870867297975*E2+0.352991200
680117*F2+-0.0413084035090411*G2+0.170236411231718*H2)+1.39189786178793)*2))))*2)-1)+-
4.3636875860018*(((1/(1+EXP(-(((-5.21034009960122*B2+-
5.14709458170011*C2+1.80148361215971*D2+0.711024591740444*E2+7.86791667523458*F2+2.02490806842
416*G2+-1.413450789499*H2)+0.616674694794617)*2))))*2)-1)+4.36777985221*(((1/(1+EXP(-
(((3.56987633269998*B2+1.23690421070275*C2+2.454669756374*D2+11.8907018311146*E2+2.115997262195
11*F2+8.81802436276201*G2+-4.86578147804534*H2)+-1.16885840048915)*2))))*2)-
1)+2.8569669677433*(((1/(1+EXP(-(((-3.8864788711009*B2+1.16919902385962*C2+-5.83077871972677*D2+-
1.95708248148237*E2+1.33187004428507*F2+9.8762773514557*G2+4.70455410558154*H2)+-
5.48456195726928)*2))))*2)-1)+8.22528496628169*(((1/(1+EXP(-(((-
2.98657091174006*B2+4.58112355294569*C2+-4.51032518141412*D2+-
2.64483235836588*E2+6.76881591200181*F2+3.54743597041204*G2+-
10.4711413536149*H2)+8.87959639622427)*2))))*2)-1)+3.25465835015256*(((1/(1+EXP(-(((-
5.74215149141753*B2+-2.57444366789805*C2+-0.835282981756777*D2+-1.62680991139892*E2+-
0.906806212196266*F2+3.81959424564757*G2+-1.86137162364403*H2)+0.493609917112262)*2))))*2)-
1)+1.55724416731427*(((1/(1+EXP(-(((2.77228574248722*B2+0.79368232659102*C2+-
0.0333028553663127*D2+-0.388595563395093*E2+-
0.39035883246853*F2+0.304595831197884*G2+1.33547121543709*H2)+1.83856858796418)*2))))*2)-
1)+8.80906569683276*(((1/(1+EXP(-(((-1.47307779024677*B2+-
2.73895874341775*C2+0.515537148160081*D2+0.17936229328582*E2+-1.73847855674929*F2+-
3.98249394575356*G2+-2.3974750068742*H2)+3.55786797768772)*2))))*2)-1)+-5.3210783989847*(((1/(1+EXP(-
(((1.76198639637415*B2+-2.51477153717323*C2+1.59894389632975*D2+-0.33433518260573*E2+-
5.15888223530224*F2+3.71333935671939*G2+1.35868451698779*H2)+-2.78173546417603)*2))))*2)-1)+-
1.05025622757389*(((1/(1+EXP(-(((-1.37179793577859*B2+-0.416848683482649*C2+-
0.579588401635947*D2+0.637173299114886*E2+0.873088624554774*F2+0.490736677628383*G2+-
0.650406878860619*H2)+-0.0771228561966379)*2))))*2)-1)+-3.27988106885117*(((1/(1+EXP(-(((-
6.84199126142833*B2+-3.03163144949923*C2+-4.4891470743464*D2+-12.6409616262714*E2+-
0.620796468960259*F2+3.01194837938257*G2+-4.30490952469618*H2)+4.33701617272917)*2))))*2)-
1)+8.18771320955401*(((1/(1+EXP(-(((1.79862562327768*B2+4.23106559078384*C2+-
4.41690718803399*D2+3.31123269294321*E2+-3.70905318835966*F2+-
0.905886289211572*G2+3.68505038939738*H2)+-3.72594528415605)*2))))*2)-1)+-
8.56872392985598*(((1/(1+EXP(-(((-4.1224144051609*B2+-
1.63181031321347*C2+1.28475777763959*D2+2.32461677991795*E2+-1.44297663442136*F2+-
3.46484920209706*G2+-2.73282384250334*H2)+1.86557711935525)*2))))*2)-1)+-
7.76459311066199*(((1/(1+EXP(-(((-2.63447401449355*B2+-
2.41472153561294*C2+2.42949911103848*D2+2.46871894455217*E2+3.06468265507497*F2+1.455313033891
94*G2+-2.75109004005678*H2)+2.95578554985131)*2))))*2)-1)+3.27592925870841*(((1/(1+EXP(-(((-
0.77529141160183*B2+-0.817885176053783*C2+-1.72031671827667*D2+1.56707664405523*E2+-
1.39344062559176*F2+4.04726955430744*G2+-1.04457335803722*H2)+-1.21149965942234)*2))))*2)-1))+-
1.09446881293618)
```