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Application of Artificial Neural Network for Predicting Shaft and Tip Resistances of Concrete Piles

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ABSTRACT

Axial bearing capacity (ABC) of piles is usually determined by static load test (SLT). However, conducting SLT is costly and time-consuming. High strain dynamic pile testing (HSDPT) which is provided by pile driving analyzer (PDA) is a more recent approach for predicting the ABC of piles. In comparison to SLT, PDA test is quick and economical. Implementing feed forward back-propagation artificial neural network (ANN) for solving geotechnical problems has recently gained attention mainly due to its ability in finding complex nonlinear relationships among different parameters. In this study, an ANN-based predictive model for estimating ABC of piles and its distribution is proposed. For network construction purpose, 36 PDA tests were performed on various concrete piles in different project sites. The PDA results, pile geometrical characteristics as well as soil investigation data were used for training the ANN models. Findings indicate the feasibility of ANN in predicting ultimate, shaft and tip bearing resistances of piles. The coefficients of determination, R^2, equal to 0.941, 0.936, and 0.951 for testing data reveal that the shaft, tip and ultimate bearing capacities of piles predicted by ANN-based model are in close agreement with those of HSDPT. By using sensitivity analysis, it was found that the length and area of the piles are dominant factors in the proposed predictive model.

Key Words: Axial bearing capacity, artificial neural network, high strain dynamic testing, pile shaft resistance, pile tip resistance.

RESUMEN

La Capacidad Axial de Soporte (ABC, en inglés) de un pilote de construcción se determina usualmente a través de una Prueba de Carga Estática (SLT, inglés). Sin embargo, estas pruebas son costosas y demandan tiempo. La evaluación de las Dinámicas de Alto Esfuerzo de Pilotes (HSDPT, inglés), que la provee el programa de Análisis de Excavación (PDA, inglés), es una forma de aproximación más reciente para preveer la Capacidad Axial de Soporte. En comparación con la Prueba de Cargas Estática, la evaluación PDA es rápida y económica. La implementación de Redes Neuronales Arficiales (ANN, en inglés) que permita resolver problemas geotécnicos ha ganado atención recientemente debido a su posibilidad de hallar relaciones no lineales entre los diferentes parámetros. En este estudio se propone un modelo predictivo ANN para estimar la Capacidad Axial de Soporte de pilotes y su distribución. Para fines de una red de construcción se realizaron 36 pruebas PDA en pilotes de diferentes proyectos. Los resultados de los Análisis de Excavación, las características geométricas de los pilotes, al igual que los datos de investigación del suelo se utilizaron para probar los modelos ANN. Los resultados indican la viabilidad del modelo ANN en predecir la resistencia de los pilotes. Los coeficientes de correlación, R^2, que alcanzaron 0.941, 09.36 y 0.951 para la evaluación de los datos, revelan que la capacidad del pilotaje en el último rodamiento, en el cojinete del eje y en la punta que se predijeron con el modelo ANN concuerda con las establecidas a través del HSDPT. A través del análisis de respuesta se determinó que la longitud y el área de los pilotes son factores dominantes en el modelo predictivo propuesto.

Palabras clave: Capacidad Axial de Soporte; Red Neuronal Artificial; Dinámicas de Alto Esfuerzo de Pilotes; resistencia de punta.

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1. Introduction

Pile foundations are used extensively to transfer structural loads deep enough into the ground. Proper estimation of axial bearing capacity is of prime importance in designing geotechnical structures. The ultimate amount of the load, which can be carried by the pile shaft, determines the type of pile as piles are classified according to their load-transfer mechanism (friction piles and end-bearing piles). Hence, in addition to determining ultimate bearing capacity of piles, obtaining the pile shaft capacity is also of advantage (Nazir et al, 2013).

There are numerous methods for assessing pile bearing capacity and its distribution. Although many attempts have been made to develop analytical or empirical methods for pile bearing capacity estimation (e.g. Meyerhof, 1976; Vesic, 1977; Coyle and Castello, 1981), most of these methods rely on empiricism and they are site specific (Randolph, 2003). The most direct way for determining the axial bearing capacity of piles is static load test (SLT). The test is standardized by American standards test methods (ASTM D1143-07). However, conducting SLT is time consuming, expensive and difficult (Likins and Rausche, 2004). High strain dynamic testing (HSDT) of piles is a current approach for predicting the ABC of piles and its distribution. HSDT is based on one dimensional wave propagation theory and is performed by using a pile driving analyzer (PDA). In essence, in HSDT, a pile is hit by a hammer while PDA monitors and records the necessary data for implementing wave equation analysis. Consequently, through an iterative procedure using CAPWAP software, the pile bearing capacity and its distribution can be predicted. The HSDT procedure is standardized by ASTM (ASTM D4945-08).

Utilization of artificial neural network (ANN) in civil engineering has recently drawn considerable attention. It is generally attributed to the ANN power in finding complex relationship between different parameters when the contact nature between them is unknown (Garret, 1994). Although many researchers have attempted to show the superiority of ANN in predicting the bearing capacity problems, most of them focused on the prediction of ultimate bearing capacity of piles rather than its separate shaft and tip resistances (Goh, 1995; Goh, 1996). The main objective of this study is to propose an ANN-based predictive model of bearing capacity using real PDA and site investigation data. The predictive model is built for predicting shaft, tip and ultimate resistances (Q_s, Q_p and Q_u) of piles. Nevertheless, it is worth mentioning that this study uses the CAPWAP predicted pile bearing capacity rather than the determined bearing capacity of piles through SLT.

There are several published works concerning utilization of artificial intelligence techniques for predicting ABC of piles (Chan et al. 1995; Chow et al. 1995; Abu-Kiefa, 1998; Shahin, 2001; Lok and Che, 2004; Das and Basudhar, 2006; Ardalan et al. 2009; Shahin, 2008; Shahin, 2010; Adarsh et al. 2012; Alkroosh and Nikraz, 2012). Among researchers who have addressed ANNs for predicting bearing capacity of pile foundations, Goh (1995; 1996) developed an ANN-based predictive model to estimate the ultimate load capacity of driven piles in sandy soils. His findings suggest that compared to conventional methods of pile bearing capacity estimation, ANN-based predictive model works better. In another study, Lee and Lee (1995) employed ANN for estimation of pile bearing capacity. Their study focused on small scale laboratory tests where the horizontal and vertical chamber pressure, the number of hammer blows, pile penetration depth ratio, and mean normal stress of the soil were set as inputs of the network model while the ultimate bearing capacity was selected as the model output. According to their conclusion, ANN can provide good prediction performance in bearing capacity problems. Teh et al. (1997) also addressed the workability of neural network for predicting the pile bearing capacity. Abu-Kiefa (1998) implemented ANN to predict the ABC of driven piles in cohesionless soils. For network construction purpose, he compiled the data of 59 recorded cases of good-quality pile load tests. In his study, friction angles of the soil, the effective overburden pressure around the tip of the pile, the length of the pile and its equivalent cross-sectional area were considered as input layers of the ANN model. His conclusion showed the feasibility of ANN for predicting shaft and tip resistances of piles.

However, among more recent studies, Pal and Deswal (2008) studied the ANN application in predicting the total capacity of concrete spun pipe piles. They used stress-wave data for building their ANN-based predictive model. Based on their conclusion, in comparison to support vector machines, the prediction performance provided by ANN was more reliable. Shahin and Juksa (2009) proposed an ANN-based predictive model of bearing capacity for drilled shafts. Their model dataset comprised cone penetration test results and drilled shaft load tests on 94 recorded cases. Jianbin et al. (2010) developed an ANN model for predicting the ultimate ABC of pipe piles. The influential parameters that they have considered for network construction included the effective length and diameter of pile, unit weight, cohesion and internal friction angle of soil as well as the standard penetration test (SPT) results. Benali and Nechnech (2011) suggested an ANN-based predictive model of pile bearing capacity in cohesionless soils. For training the ANN, they had collected the mechanical properties of purely coherent soil and geometrical characteristics of 80 axially loaded piles. The correlation coefficient, R, equals to 0.92 reveals the reliability of their ANN-based predictive model.

2. Methods

2.1 High Strain Dynamic Testing of Piles

It was mentioned earlier that high strain dynamic testing (HSDT) is an innovative method for estimating the ABC of piles. In dynamic testing of pile (PDA test), it is hypothesized that a pile with uniform cross section is a slender element surrounded by material with much lower stiffness. Hence, any mechanical impact through a hammer leads to downward propagation of wave (Timoshenko and Goodier, 1951; Salgado, 2008). Therefore, the principle of one dimension wave propagation theory can be implemented for piles. Details of the solution to the partial differential equations of wave propagation theory for predicting axial bearing capacity of piles can be found elsewhere (Salgado, 2008).

Nevertheless, the finite difference-based model introduced by Smith (1960) was considered as the bench mark for dynamic testing of piles. To estimate the axial bearing capacity, Smith developed a discrete solution for wave propagation in piles. In Smith's model, the pile was simulated using a number of masses attached to each other by elastic springs, while the soil was modelled by a number of springs, and linear viscous dampers to represent its behavior. However, there were some deficiencies in Smith`s model due to lack of knowledge on hammer energy and cushion characteristics. Smith`s model later on was enhanced by a group of researchers at Case Western Reserve University (Goble et al.1970; Rausche et al. 1972; Rausche et al. 1985). In their developed method also known as CASE method, it was not necessary to model the hammer and driving systems. Instead, they reported the use of force and acceleration records in a simplified model for predicting the static bearing capacity.

As stated by Fellenius, (1999) the full power of the wave equation analysis was first realized when it was coupled with dynamic monitoring of piles. The latter can be determined by installing a pair of accelerometer and strain transducer on top of the pile (see Figure 1). Subsequently, the data recorded by aforementioned instruments are transmitted by means of a cable to PDA. The PDA will then transform the recorded data into force and velocity. In the next step, the bearing capacity of the pile is predicted using CAPWAP program. CAPWAP combines the measured force and velocity with the wave equation analysis to determine soil resistance and its distribution along the pile. The CAPWAP approach is based on an iterative curve-fitting technique in which pile response, estimated through wave equation analysis of a model pile, is matched to the measured response of the actual pile for a single hammer blow (FHWA, 2006).

Figure 1. Example of installed accelerometer (right) and strain transducer (left) on the pile.

It should be mentioned that in performing PDA tests, to obtain more reliable ABC, some criteria such as hammer weight and impact condition must be considered. For full mobilization of soil strength along pile shaft, Susilo (2006) suggested minimum hammer weight equals to 1% of the required ultimate pile capacity whereas for piles with larger expected end bearing contributions, the recommended percentage is increased to at least 2% of the ultimate pile capacity.

2.2 Artificial Neural Network

Artificial neural network is a flexible non-linear function approximation tool that estimates a relationship between given input and output parameters. Simpson (1990) reported that a specific ANN can be defined using three important components: transfer function, network architecture and learning law. More details on ANN structure are addressed elsewhere (e.g. Hecht-Nielsen, 1990; Maren, et al. 1990; Zurada, 1992; Fausett, 1994; Ripley 1996). However, study by Haykin (1999) recommends that the most well-known type of feed-forward ANNs is Multi-Layer Perceptron (MLP). In feedforward ANNs, the neurons are usually grouped into layers. Using neuron connections, signals move from input layer through the hidden layer(s) to output layer.

In essence, ANNs are composed of a set of parallel layers and several interconnected nodes or neurons. There is also a transfer or activation function along each node which transmits signals to either other nodes or output of the network. The activation function in each node is applied to the net input of that node. The net input of the node is obtained by summation of connection weights as well as a threshold value known as bias.

Among different algorithms for training ANNs, Back-propagation (BP) algorithm is recognized as the most common training algorithm (Dreyfus, 2005). Basically, BP algorithm consists of two passes; a forward pass and a backward pass. In the former, using transfer function, the outputs are calculated and the errors at the actual output unit are determined (Demuth et al. 2007). If the obtained error (mean squared difference between the actual and predicted outputs) is more than adequate, then the error is propagated back through the network and updates the individual weights. This procedure is called backward pass. Forward and backward passes are repeated several times until the error is converged to a level specified by a cost function such as mean square error (MSE) or root mean square error (Simpson 1990, Kosko 1994, Singh et al. 2004).

3. Dataset

Using the procedure suggested by ASTM (D4945-08), 36 PDA tests were conducted at various project sites in Indonesia. The tested piles were reinforced and pre-stressed concrete piles with different diameters and lengths. Most of the tests were conducted in cohesionless soils. An example of PDA test performed in one of the project sites is shown in Figure 2.

To represent soil characteristics, the results of SPT were collected. The average SPT (N) values along the pile shaft and tip were calculated. It is worth mentioning that for obtaining the average SPT (N) value around the pile tip, the Meyerhof's recommendation (1976) was considered. The average SPT (N) value for *10D* above and *4D* below the pile tip was obtained where *D* represents pile diameter.

Table 1 lists the PDA test results including ultimate bearing capacity of piles, pile set, pile shaft and tip resistances. In addition to PDA results, pile geometrical characteristic and the average SPT (N) values around the pile shaft and tip are also tabulated in Table 1.

Figure 2. PDA test

4. Model Development

The prediction performance of ANNs is closely related to the architecture of the selected network. Therefore, defining the optimum network architecture is crucial in designing ANN models. Hornik et al. (1989) mentioned that a network with one hidden layer can approximate any continuous function In ANN. Lawrence (1994) reported that in designing ANN architectures, increasing the number of the hidden layers should be the last options; instead focus should be on adding the number of hidden nodes. Nevertheless, for network construction, the optimum number of hidden nodes should be determined. Several researchers suggested that numbers of hidden nodes are related to the number of input and output parameters. In Table 2 some of the formulas suggested by a number of researchers for obtaining the optimum number of hidden nodes are presented. However, the network performance is often evaluated based on the root mean squared error (RMSE) as well as regression values. That is to say, using the trial-and-error method, several network architectures are trained with same input and output data and the network that performs best is selected as the optimum network.

Table 1. Dataset used for ANN-based predictive model.

No.	Pile name	Pile length (m)	Pile set (mm)	Pile area (cm²)	N_{shaft}	N_{tip}	Qu (kN)	Qs (kN)	Qp (kN)
1	kn 189	25	16	1159.25	9	30	2988	1665	1323
2	kn 204	24.7	23	1159.25	9	30	3940	1445	2495
3	kn 215	19	19	1159.25	3	10	3200	1966	1234
4	P 105 BP6	22.7	3	11309.73	7	37	6753	3649	3103
5	FE P3 BP5	23	4	11309.73	4	21	8501	6035	2466
6	FE P6 BP6	23	3	11309.73	5	21	5322	3529	1794
7	P 112 BP 12	21	3	11309.73	5	15	6089	4293	1796
8	P 108 BP 11	23	5	11309.73	3	12	8500	5903	2597
9	P 109 BP 16	23	4	11309.73	3	12	10930	6412	4518
10	P 105 B2	23	7	11309.73	4	13	11601	7211	4390
11	P 105 B6	22.7	4	11309.73	4	13	8755	5535	3220
12	P 4 A	30	7	1159.25	20	27	1347	1197	150
13	P 18 F	30	7	1159.25	20	27	950	800	150
14	P 33 C	30	6	1159.25	20	27	1176	980	196
15	P 01	34.9	8	876.5	6	10	829	789	40
16	P 02 _ 1	34.9	8	876.5	6	10	605	591	14
17	P 04	34.8	13	552.92	6	10	772	744	28
18	P 05	34.9	11	552.92	6	10	781	774	7
19	P 1 AS6BC.187	12.3	16	625	13	11	864	764	100
20	P 02 AS21ED.349	10.6	8	625	15	13	689	637	52
21	P 03 AS19ED.355	12.8	13	625	14	12	1520	1386	134
22	P01	10.3	9	735.13	18	26	500	485	15
23	P02	8.8	11	735.13	19	27	452	438	14
24	P03	10	6	735.13	18	25	584	556	29
25	P04 - 101	10	7	735.13	18	25	603	576	27
26	P06-112	10.3	6	735.13	18	26	811	768	44
27	P07-122	10	9	735.13	18	25	770	733	36
28	P08-46	10	6	735.13	18	25	748	700	48
29	P1-p330_3 sp 350	5.3	18	678.58	13	15	788	696	92
30	P2-p169 sp 350	5.3	15	678.58	13	15	794	700	94
31	P3-p144 sp 350	5.2	15	678.58	13	15	824	721	103
32	P1-E7 Squar 25	19.6	15	625	11	22	1604	1437	167
33	P2-H 5_4 Squar 25	19.7	12	625	11	22	1419	1269	150
34	P3-H 12 Squar 25	19.1	12	625	9	19	1920	1720	200
35	B2 _1	5	16	625	8	11	764	670	94
36	D4_3	7.4	17	625	13	19	650	509	141

Table 2. The proposed number of neurons for hidden layer

Heuristic	Reference
$(N_i + N_0)/2$	Ripley (1993)
$\dfrac{2 + N_0 \times N_i + 0.5\, N_0 \times (N_0^{\,2} + N_i) - 3}{N_i + N_0}$	Paola (1994)
$2N_i/3$	Wang (1994)
$\sqrt{N_i \times N_0}$	Masters (1994)
2Ni	Kaastra and Boyd (1996) and Kanellopoulas and Wilkinson (1997)

N_i: number of input neuron, N_0: number of output neuron.

To determine the optimal network architecture of the ANN model which is designed for predicting Q_s, Q_p and Q_u of piles respectively, using a MATLAB code created stochastically between -1 and 1, nine networks made of different hidden nodes in the range of 2 to 10 (based on the recommendations presented in Table 2) were trained and tested. It should be mentioned that each model was iterated 5 times.

For training the networks, Levenberg-Marquardt (LM) algorithm was used. Several studies reported that LM converges while other gradient descendent training algorithms diverge (e.g. Hagan and Menhaj, 1995). Details of this algorithm reported elsewhere (Martin et al. 1995). It is also worth mentioning that in developing ANN models, the sigmoid function was used as transfer function.

Assessments of the networks performance were made based on the obtained coefficient of determination, R^2 as well as RMSE. The former indicates the reliability and strength of the correlation between actual and predicted outputs. Table 3 lists the obtained R^2 and RMSE for training and testing datasets. As shown in this table, the fourth model which comprises 5 hidden nodes in one hidden layer performs best. The obtained R^2 and RMSE values for the selected model are 0.998, 0.942, 0.012 and 0.091 for training and testing datasets respectively. The architecture of the selected model is shown in Figure 3.

It is worth noting that in designing the ANN models, 80 percent (29 out of 36) of the datasets were assigned randomly for training purpose, and the last 20 percent was used for testing the performance of the model.

Table 3. ANN model performances.

Model No.	Nodes in hidden layers	Network Result																			
		Iteration 1				Iteration 2				Iteration 3				Iteration 4				Iteration 5			
		Train		Test		Train		Test		Train		Test		Train		Test		Train		Test	
		R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
1	2	0.974	0.078	0.761	0.136	0.978	0.064	0.910	0.515	0.902	0.096	0.674	0.392	0.988	0.089	0.879	0.153	0.961	0.081	0.853	0.250
2	3	0.980	0.065	0.674	0.288	0.978	0.166	0.783	0.226	0.990	0.065	0.832	0.152	0.982	0.104	0.842	0.149	0.976	0.133	0.891	0.155
3	4	0.994	0.071	0.783	0.178	0.994	0.043	0.906	0.135	0.990	0.058	0.784	0.149	0.992	0.037	0.637	0.217	0.968	0.036	0.861	0.194
4	5	0.998	0.016	0.896	0.155	0.998	0.040	0.904	0.107	0.998	0.012	0.942	0.091	0.998	0.019	0.774	0.177	0.998	0.095	0.758	0.157
5	6	0.998	0.017	0.763	0.156	0.998	0.032	0.776	0.252	0.998	0.021	0.794	0.237	0.998	0.024	0.605	0.277	0.998	0.033	0.777	0.117
6	7	0.998	0.022	0.721	0.167	0.998	0.028	0.740	0.187	0.998	0.043	0.629	0.209	0.998	0.031	0.921	0.125	0.998	0.067	0.790	0.168
7	8	0.998	0.049	0.850	0.150	0.998	0.116	0.885	0.139	0.998	0.044	0.589	0.231	0.998	0.033	0.784	0.189	0.998	0.020	0.785	0.211
8	9	0.998	0.051	0.851	0.185	0.998	0.042	0.571	0.262	0.998	0.039	0.752	0.201	0.998	0.098	0.870	0.262	0.998	0.072	0.767	0.291
9	10	0.998	0.038	0.706	0.321	0.998	0.055	0.794	0.202	0.998	0.088	0.887	0.282	0.998	0.075	0.715	0.371	0.998	0.061	0.727	0.299

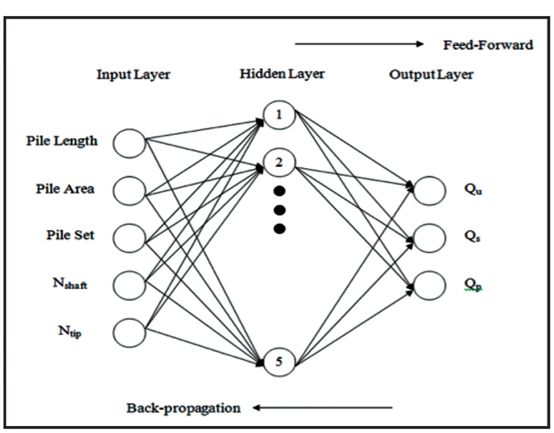

Figure 3. Architecture of the selected ANN-based predictive model.

5. Result and discussion

The reliability of the ANN-based predictive model of bearing capacity can be seen in Figures 4 to 6. These figures show the predicted Q_s, Q_p and Q_u of piles versus their measured values. Figure 4 shows a comparison between predicted and measured Q_s for training and testing data. The obtained R^2 values equal to 0.999 and 0.941 suggest the reliability of the model in predicting Q_s.

Similarly Figure 5 suggests that the predicted Q_p is in good agreement with the measured Q_p. As displayed in Figure 5-b, the coefficient of determination equals to 0.936 for testing data recommends the feasibility of the ANN-based predictive model of bearing capacity.

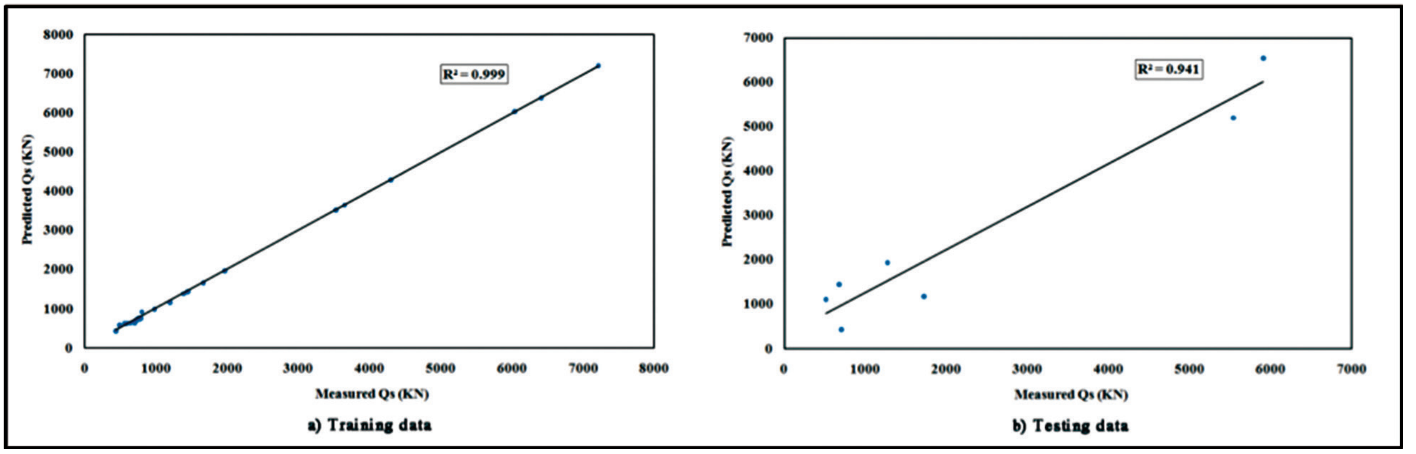

Figure 4. Shaft bearing capacity (Qs) of piles predicted by ANN model versus their measured values.

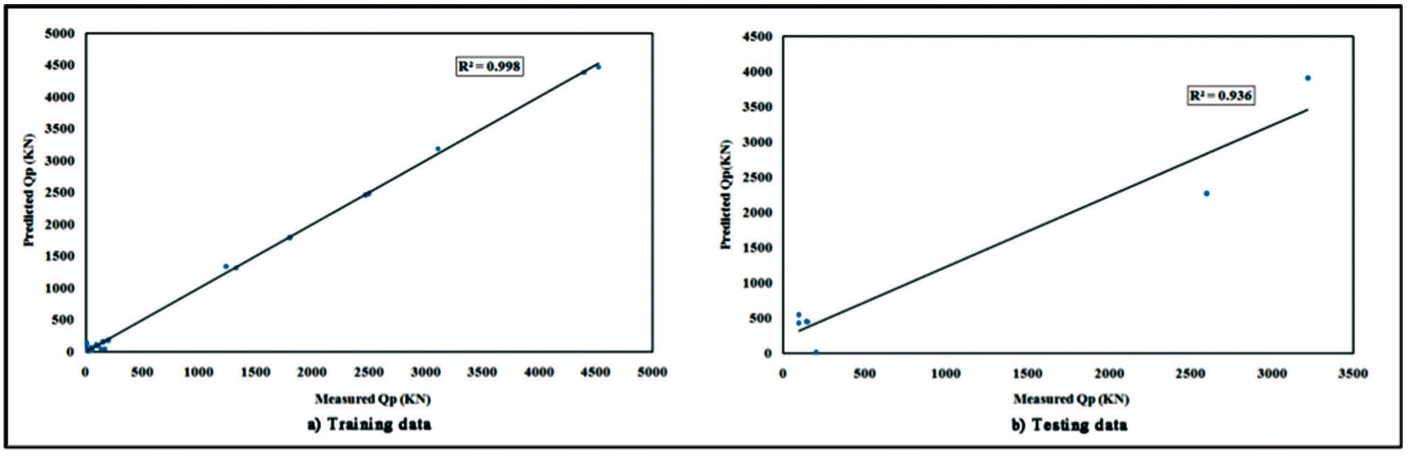

Figure 5. End-bearing capacity (Q_p) of piles predicted by ANN model versus their measured values.

In Figure 6, a comparison is made between the measured and predicted Q_u of piles for both training and testing data. Coefficient of determination equals to 0.951 for testing data suggests that the ANN-based predictive model is good enough in capturing the ultimate bearing capacity of piles.

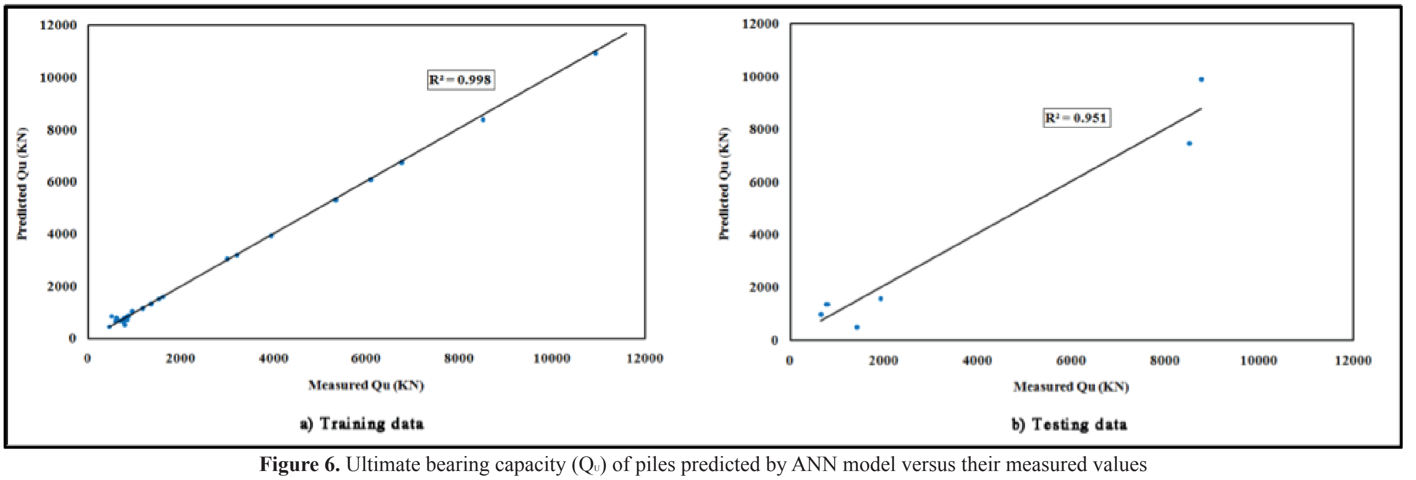

Figure 6. Ultimate bearing capacity (Q_u) of piles predicted by ANN model versus their measured values

To have a better understanding of the prediction performance of ANN, in Figures 7 to 9 the predicted Q_S, Q_P, and Q_U are checked against their measured values for testing dataset. In fact, the idea behind using testing dataset is to verify the generalization capability of proposed neural network model. Close agreement between measured and predicted values suggests that by using pile geometrical characteristics, pile set and the results of SPT insitu test, the ANN-based predictive model can be implemented for estimating Q_S, Q_P, and Q_U of piles.

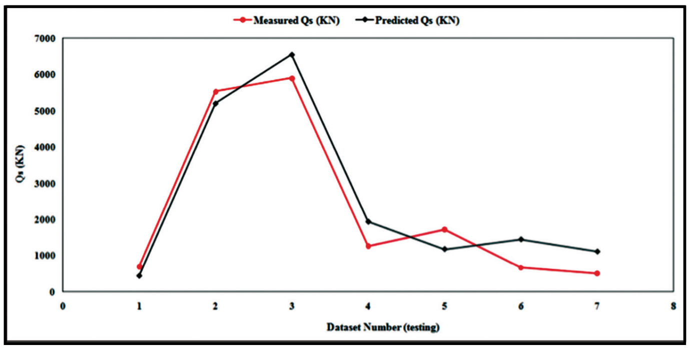

Figure 7. ANN-model performance in predicting pile shaft resistance (testing data).

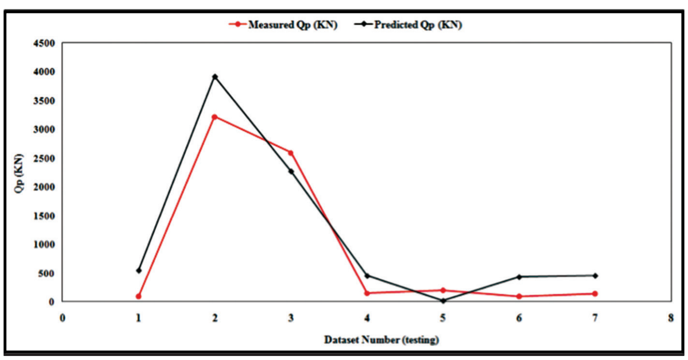

Figure 8. ANN-model performance in predicting pile tip resistance (testing data).

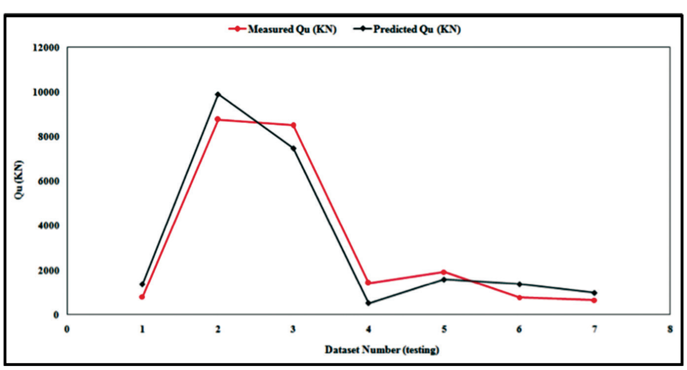

Figure 9. ANN-model performance in predicting ultimate bearing capacity of piles (testing data).

The overall prediction performance (for all dataset) of the ANN-based model is summarized in Table 4. In this table, apart from R^2, RMSE and value account factor (VAF) were also used to control the capacity performance of the model. For determining RMSE and VAF, equations 1 and 2 were used respectively.

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y-y')^2}, \tag{1}$$

$$VAF = [1 - \frac{var\,(y-y')}{var\,(y)}]\times 100, \tag{2}$$

In the aforementioned equations, y and y′ denote the obtained and estimated values, respectively and N is the total number of data. It is worth mentioning that the model is excellent if the RMSE is zero and VAF is 100.

Table 4. Performance indices of the predictive model

Output	R^2	RMSE	VAF (%)
Q_P	0.982	0.081	98.199
Q_S	0.984	0.075	98.361
Q_U	0.988	0.064	98.770

Overall, the general trend of the results shows that ANN as a method which does not require prior assumptions and can provide a relatively reliable solution for assessing the pile bearing capacity and its distribution. Although direct determination of pile bearing capacity through SLT is still recommended due to the amount of uncertainties in other semi empirical methods (Momeni et al, 2013), the use of proposed ANN-based predictive model is of advantage as it can reduce the required number of PDA tests in each project.

6. Sensitivity Analysis

Sensitivity analysis was performed to recognize the importance of each input variable on the axial bearing capacity of piles. For this reason, the strength of the relations between the output parameters and the input parameters was evaluated using cosine amplitude method (CAM). This use of this sensitivity analysis is reported in several studies (Yang and Zhang, 1997; Jong and Lee, 2004). To utilize CAM, all data pairs were expressed in common U-space. The data pairs used to construct a data array U is defined as:

$$U = \{u_1, u_2, u_3 \ldots, u_i, \ldots, u_n\} \tag{3}$$

The elements ui in the array U is a vector of lengths m that is:

$$u_i = \{u_{i1}, u_{i2}, u_{i3} \ldots, u_{im}\} \tag{4}$$

Therefore, each data pair can be considered as a point in m-dimensional space, where each point requires m-coordinates for a full description. The strength of relation between data pairs, ui and uj, is represented by the following equation:

$$r_{ij} = \frac{\sum_{k=1}^{m} u_{ik}u_{jk}}{\sqrt{\sum_{k=1}^{m} u_{ik}^2 \sum_{k=1}^{m} u_{jk}^2}} \tag{5}$$

The strength of the relation (r_{ij} value) indicates the influence of different input parameters on one of the output parameters. The larger the value of r_{ij} becomes, the higher is the effect on the output. For example, if the output has no relation with the input, then the r_{ij} value is zero, while the value of r_{ij} closer to 1 expresses the further influence of the input parameter. Nevertheless, the obtained strength of relations of the problem in hand is shown in Figure 10. This figure suggests that the most influential parameters on Q_S, Q_P and Q_u are pile area and pile length.

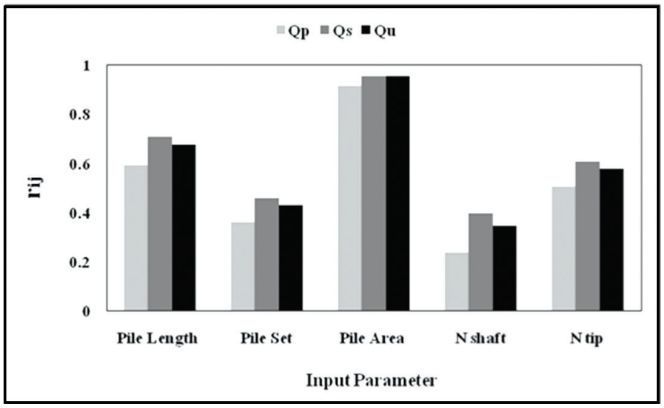

Figure 10. Strengths of relation (rij) between Q_S and Q_P and input parameter

8. Summary and Conclusion

To develop an ANN-based predictive model for estimating the axial bearing capacity of piles, 36 PDA tests were performed on different concrete piles with various diameters and lengths. The tests were mostly performed in cohesionless soils. For network construction purpose, the PDA results, pile length and cross sectional area, and the average SPT (*N*) values along the pile shaft and tip were used as inputs while the pile bearing capacity and its distribution were set as outputs. Through a trial-and-error procedure, it was found that a network with five hidden nodes in one hidden layer yields the best performance. The coefficients of determination equal to 0.941, 0.936, and 0.951 for testing data revealed the reliability of the proposed ANN model in predicting the shaft, tip and ultimate bearing capacities of piles, respectively. Additionally, through a sensitivity analysis, it was found that the pile length and cross sectional area are the most influential parameters in predicting the bearing capacity of piles.

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