# Principal Component Analysis and Neural Networks for Predicting the Pile Capacity Using SPT

A. Benali, A. Nechnech, and D. Ammar Bouzid

***Abstract*—A neural network is, in essence, an attempt to simulate the brain. Neural network theory revolves around the idea that certain key properties of biological neurons can be extracted and applied to simulations, thus creating a simulated (and very much simplified) brain. The first important thing to understand then is that the components of an artificial neural network are an attempt to recreate the computing potential of the brain. This famous network memorizes information by a process of training, to this effect the theory of artificial neural network is developed and is applied in several fields of sciences. The geotechnical domain is among them and in particular the resolution of problems of which parameters that govern them have an uncertain character, as the case of the prediction of the pile capacity. For it we collected 120 cases of the literature, sweeping a variety of sites through the world. The model conceived by an iterative process that is, the retropropagation was validated by experimental tests and was compared with the values predicted by four of the most commonly used traditional methods. In this paper, the developed neural network model is based on the principal component analysis approach (PCA) for data analysis in the aim to improve the generalization process. The results indicate that the ANN model is able to accurately predict the capacity in several cases, including the experiments on model piles. The PCA technique shows the efficiency in the variable analysis in order to determine their relative contribution on the pile capacity and improve the generalization capacity. This study is limited for the driven piles.**

***Index Terms*—Bearing capacity, back propagation algorithm, neural networks, principal components analysis, simulation, driven piles.**

## I. Introduction

Pile foundations are used extensively around the world to support both inland and offshore structures, including nuclear plants and oil drilling platforms. They are mainly used in sites where the presence of soft soil layers would cause excessive deformation or failure of more conventional types of foundations. The two major categories of piles in common use are: friction or floating piles, whose load carrying capacity depends mostly on the amount of friction resistance that can develop at the interface between the pile shaft and the soil; and end bearing piles, which rely primarily on the concentrated soil resistance at the tip of the pile. To estimate the load-bearing capacity of the piles, therefore, one or more of several pile loading tests (PLTs) and pile dynamic analysis (PDA) tests may be performed, depending on the importance of a project. Due to the high cost and the time required for conducting such tests. Many researches reports dealing with the ultimate bearing capacity of pile foundations have been listed in the literature during the past four decades.

There are two approaches employed in the study of the behaviour of the pile foundations: theoretical and experimental. The problem of estimating the capacity of deep foundations is very complex and the mechanisms are not yet entirely understood. This can be attributed the sensitive nature of the factors affecting the behaviour of the pile. Among these factors are the stress-strain history of the soil, soil compressibility, and the difficulty in obtaining undisturbed samples of cohesionless soil, the installation effects.

In recent years, the application of in-situ testing techniques has increased for geotechnical design. This is due to the rapid development of in-situ testing instruments, an improved understanding of the behavior of soils, and the subsequent recognition of some of the limitations and inadequacies of conventional laboratory testing [1],[2], such as the standard penetration test. This test is the most frequent in-situ test in geotechnical practice because of its simplicity and affordable costs. Pile capacity determination by SPT is one of the earliest applications of this test that includes two main approaches, direct and indirect methods [3]. Most of the proposed procedures have achieved limited success in terms of providing accurate prediction of pile capacity. Although these methods reflect to some extent natural soil conditions, they have many limitations. Hence, ANN models could be an alternate approach for the above case. Several researchers [4]-[9], have attempted artificial neural networks (ANNs) for predicting bearing capacity of pile foundations. In this paper, the axial capacity of driven piles in cohesive soils has been correlated with SPT data using artificial neural networks.

The modeling advantage of ANNs is the ability to capture the nonlinear and complex relationship between the bearing capacity and the factors affecting it without having to assume a priori formula of what could be this relationship. Many authors have described the structure and operation of ANNs [10]; [11]. Although some ANN models are not significantly different from a number of standard statistical models, they are extremely valuable as they provide a flexible way of implementing them. Model complexity can be varied simply by altering the transfer functions or network structure. Traditional empirical approaches for predicting bearing capacity of piles are used: [12]; [13]; [14], [15] and others. As a result, the use of ANNs models may overcome the limitations of the traditional methods. In this paper, ANNs are used to predict the ultimate bearing capacity of piles base on standard penetration test (SPT) data. The aims of the paper

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are:

1) To analyse the variables (inputs) to choose the most pertinent by using the PCA approach (Principal Components Analysis): a multi variable analysis is carried by the PCA, in the aim to determine the principal factors which affect the bearing capacity and improve the generalization process.
2) To investigate the feasibility of the ANN technique for predicting the bearing capacity of pile in cohesionless soils;
3) To explore the relative importance of the factors affecting capacity predictions by carrying out a sensitivity analysis;
4) To compare the performance of ANN model with some of the most commonly used traditional methods; and
5) To assess the benefits and limitations of the ANN technique over traditional methods.

## II. Descriptive Analysis of Variables

### A. Literature Review

Despite the important advances realized in the domain, the dimensioning of piles remains a difficult problem, connected to complex behavior mechanisms and still ill-known. Although understanding of the factors affecting pile capacity is needed in order to obtain accurate bearing capacity prediction, most traditional methods include; geometry state, mechanical state, soil compressibility state. The database is extracted from literature and is resumed in Table I. The main factors affecting the capacity are summarized in Table II

TABLE I: Organization of the Database

<table>
<tr><th>Surface of data</th><th>Country</th><th>Site</th><th>Number of total data</th></tr>
<tr><td rowspan="12">Bouafia and Benali (2002) [16]</td><td>Belgium</td><td>Kallo</td><td>2</td></tr>
<tr><td>USA</td><td>SF Francisco , Seattle</td><td>4</td></tr>
<tr><td>The Netherlands</td><td>Amsterdam</td><td>1</td></tr>
<tr><td>Canada</td><td>Vancouver</td><td>2</td></tr>
<tr><td>Greece</td><td>-</td><td>3</td></tr>
<tr><td>Japan</td><td>Osaka</td><td>8</td></tr>
<tr><td>Malaysia</td><td>Port klang</td><td>2</td></tr>
<tr><td>Thailand</td><td>Bangkok</td><td>7</td></tr>
<tr><td>Croatie</td><td>-</td><td>2</td></tr>
<tr><td>Palestine</td><td>-</td><td>4</td></tr>
<tr><td>UAE</td><td>Sharjah, Dubai, Ajman, Ras-El-Kheimah</td><td>40</td></tr>
<tr><td>-</td><td>-</td><td>18</td></tr>
<tr><td>Lee and Lee (1996) [17]</td><td>-</td><td>-</td><td>27</td></tr>
</table>

### B. Statistical Analysis

The statistical parameters considered include the mean, standard deviation, minimum, maximum, and range. In this part, the statistical parameters studied represent the entire database (Table II). The depth of the water table is not included in this study; its effect is already reflected in the measured SPT blow count down. Burland and Burbidge [18] recommended no correction to N be taken for overburden pressure or submergence. However, for sand and gravel, they take the correction proposed by [19]. In this study, we take the correction proposed by [19] for sand or gravel below the water table when N > 15 as follows:

$$N_{corrected} = 15 + 0.5(N - 15) \tag{1}$$

TABLE II: Statistical Analysis of the Database

| Statistical parameters | B (m) | D (m) | D/B | σ'v (Kpa) | Ocrb | Rg | Nspte | φ' (°) | Qt exp (KN) |
|---|---|---|---|---|---|---|---|---|---|
| Minimum | | | | | | | | | |
| All data | 0,040 | 0,150 | 3,750 | 75,000 | 0,400 | 0,000 | 6,060 | 14,280 | 205,0 |
| Maximum | | | | | | | | | |
| All data | 2,000 | 75,000 | 62,500 | 780,600 | 1,960 | 1,000 | 414,000 | 40,000 | 42116,90 |
| Range | | | | | | | | | |
| All data | 1.73 | 74,850 | 58,750 | 705,600 | 1,560 | 1,000 | 407,940 | 25,720 | 41911,90 |
| Mean | | | | | | | | | |
| All data | 0.807 | 15,513 | 22,339 | 220,329 | 1,220 | 0,778 | 69,459 | 31,718 | 6841,310 |
| Standard deviation | | | | | | | | | |
| All data | 0.348 | 14,406 | 13,303 | 168.000 | 0.250 | 0,335 | 103,001 | 6,053 | 7916,085 |

These corrections were applied on all case records in the database used in the present study. Soil compressibility within the depth of influence of a foundation requires the assignment of soil properties that can accurately reflect this compressibility. The SPT is of one the most commonly used tests in practice for measuring the compressibility of cohesionless soils. Although it is not the most accurate in situ method for measuring soil compressibility, it is used extensively worldwide. Consequently, for the purpose of this study and from an already done study, the average SPT blow count/300mm (Nspte) over the influence of the foundation is used as a measure of soil compressibility.

$$N_{spte} = \frac{1}{D+3B} \int_{0}^{D+3B} Nspt \, .dz \tag{2}$$

These variables include: B: Pile diameter; D: Pile penetration depth; D/B : Slenderness; $R_g$ : Roughness of the pile/soil interface; $N_{spte}$ : Number of blows equivalent; $\sigma'_v$ : Overburden pressure at the pile point; φ': Internal angle of friction; $O_{crb}$ : Overconsolidation ratio; $Q_t$ : Total pile capacity.

The performance of a multi layered neural network mainly depends on its generalization capacity, which in return depends on the data. The data analysis can be carried out by using different statistical tools; among them we find the principal component analysis. In this study the main objective of the PCA is the determination of the contribution rate of variables in the studied problem. Each variable is relative to one component. Thus, according to the component order, we can classify the different variables effects. Next, we compare these results with the sensitivity analysis of the relative importance of the neural network model input variables.

## III. Principal Components Analysis Of The Variables

### A. Definition

The PCA technique was first introduced by Karl Pearson in 1901. It is a descriptive technique which allows the study of dependency that exists between the variables. Mathematically, the PCA is a linear orthogonal projection technique which projects multidimensional observations represented in a subspace of m dimensions (m is the number of observed variables) in a subspace with low dimensions ($L$ < m) by maximizing the projection variables.

Practically, for modeling a process using the PCA, the variables for this process are collected in an $X^b$ matrix. Whether m the number of variables and N the number of observations for each variable, $X^b$ is given by (3),

$$\begin{bmatrix} x_1(1) & x_2(1) & \dots & x_m(1) \\ x_1(2) & x_2(2) & \dots & x_m(2) \\ . & . & \dots & . \\ . & . & \dots & . \\ x_1(N) & x_2(N) & \dots & x_m(N) \end{bmatrix} \quad (3)$$

where $x_1(1)$ represents the value of the first variable of the first observation.

As a preliminary, in order to make the result independent of the used units for each variable, a necessary pretreatment comprises of centering and reducing variables. Each $X_j$ column is given by (4),

$$X_j = \frac{X_j^b - M_j}{\sigma_j} \quad (4)$$

where

$X_j^b$ is the $j^{th}$ column of the $X^b$ matrix and $M_j$ is its mean given by (5),

$$M_j = \frac{1}{N}\sum_{k=1}^{N} x_i(k) \quad (5)$$

And $\sigma_j^2$ is its variance which will be determined by using the equation (6)

$$\sigma_j^2 = \frac{1}{N}\sum_{k=1}^{N}\left(x_i(k) - M_j\right)^2 \quad (6)$$

The new matrix for the normalized data is noted (7)

$$X = [X_1 \dots X_m] \quad (7)$$

The correlation matrix is given by: (8)

$$\sum = \frac{1}{N-1} X^T X \quad (8)$$

The estimation of PCA parameters is summarized in an estimation of proper values and vectors of the correlation matrix Σ. A spectral decomposition of this latter allows writing (9).

$$\sum = P\Lambda P^T = \sum_{i=1}^{m} \lambda_i P_i P_i^T \quad (9)$$

where $p_i$ is the $i^{th}$ proper vector of $\Sigma$, $\lambda_i$ is the corresponding proper value and Λ is the diagonal matrix for proper vectors.

If there're q linear relationships between the $X$ columns, we shall have q zero proper values and the $X$ matrix can be represented by the first (m-q) = $L$ principal components corresponding to none zero proper values. However, it is rare to have proper values equal to zero in reality (quasi-linear relations, noise…etc). So, it is necessary to determine the number $L$ representing the number of proper vectors corresponding to dominants proper values. A number of rules are proposed in the literature to determine the number of $L$ components to deduct [20] where most are heuristic. In our study, we utilized the method of cumulated percentages of the total variance (PVC). The basis of this method, each principal component is representative of a portion of the variance of data for the studied process. The proper values of the correlation matrix are measured from this variance and can so be utilized in the selection of the number of principal components. The implementation was done with the aid of an Excel Stat Software [21]

### B. Results and Discussion

The cumulative variances of relative contributions for principal components to the total variance of data are given in Table III. Considering the distribution values, the three first which have 90% of the total variance of variables were chosen and the remaining can be neglected; because they don't have an important impact on the information.

Table III also shows that the first proper value is 6.039, it corresponds to a percentage of 67.09% of the variance, and it expresses part of the information explained by the first axis. The second proper value is 1.204 and corresponds to a percentage of 13.37%, the third proper value is 0.86 and corresponds to a percentage of 9.62%, these results show: The first three proper values represent and synthesise better the information. As a matter of fact, the information explained by the first, second and the third axes is 90%. The plan formed by the axis one and two explains to its self 80% of the information.

Fig. 1 illustrates a graphical representation of proper values in function with the principal components axes ($F_1$, $F_2$,…$F_i$) and which confirm that the three first principle components present 90% of the variance ($F_i$ are the Axes of Principal Components).

TABLE III: PROPER VALUES

| | F1 | F2 | F3 | F4 | F5 | F6 | F7 | F8 | F9 |
|---|---|---|---|---|---|---|---|---|---|
| Proper Value | 6.039 | 1.204 | 0.866 | 0.359 | 0.307 | 0.138 | 0.046 | 0.036 | 0.006 |
| % variance | 67.098 | 13.375 | 9.624 | 3.983 | 3.408 | 1.531 | 0.510 | 0.403 | 0.067 |
| % cumuler | 67.098 | 80.473 | 90.097 | 94.081 | 97.488 | 99.019 | 99.529 | 99.933 | 100.000 |

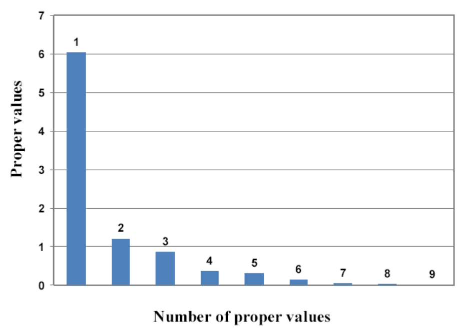

Fig. 1. Histogram representing the proper values (test of the bearing capacity)

### C. Contribution of Variables in Principal Axes (Components)

The disposition of variables on different axes of the principle components, and the contribution to the axis formation is function of many parameters. In this study we used the CTR factor, defined as the variables contribution to construct the principal components. In other words, this parameter (CTR) enabled us to determine the contribution of the variables to the total capacity. For this study, we concentrate on the values given by the CTR parameter.

Basing on the order of these components, we can draw important remarks concerning the effect of the different variables on the pile capacity. The first component designs the pile depth (D), the overconsolidation ratio ($O_{crb}$), and the angle of friction ($\varphi'$). The second component is connected to the overburden pressure ($\sigma'_v$), the pile – soil interface roughness ($R_g$), and the number of blows ($N_{spte}$). The third component corresponds to the pile diameter ($B$) and the slenderness ratio (D/B). Following the CTR values, the best represented variables on the different axis and in a descending order are presented respectively in Tables IV, V and VI

We conclude that the PCA technique enabled us also to determine the importance of the variables on the phenomena (the pile bearing capacity). The different used variables (B,D, D/B, $O_{crb}$, $N_{spte}$, $\varphi'$, $\sigma'_v$ and $R_g$) participate respectively with the following percentages, 17.5%, 14%, 49.44%, 13.89%, 22.27%, 14%, 25.5%, and 15%.These values are considered so important, and for that we can consider them being the relevant variables for the problem studied.

TABLE IV: PARAMETERS FORMING THE FIRST PRINCIPAL AXIS (PILE CAPACITY)

| variable | CTR (%) |
|---|---|
| D | 14,017 |
| $O_{crb}$ | 13,889 |
| $\varphi'$ | 13,996 |

TABLE V: PARAMETERS FORMING THE SECOND PRINCIPAL AXIS (PILE CAPACITY)

| variable | CTR (%) |
|---|---|
| $\sigma'_v$ | 25.486 |
| $R_g$ | 15.001 |
| $N_{spte}$ | 22.277 |

TABLE VI: PARAMETERS FORMING THE THIRD PRINCIPAL AXIS (PILE CAPACITY)

| variable | CTR (%) |
|---|---|
| B | 17.528 |
| D/B | 49.447 |

## IV. NEURAL NETWORK MODELING

### A. Overview of the Neural Network Modeling

The types of neural networks used in this study are multilayer perceptrons (MLPs) that are trained with the back propagation algorithm. A comprehensive description of back propagation can be found in [10]; [11]; [22]. The typical MLP consists of a number of processing elements (called neurons, or units) that are usually arranged in layers: an input layer, an output layer, and one or more hidden layers. Each processing element in the specific layer is joined to the processing element of other layers via weighted connections. The input from each processing element in the previous layer is multiplied by an adjustable connection weight.

This combined input then passes through a nonlinear transfer function (sigmoid or purelin function) to produce the output of the processing element. The output of one processing element provides the input to the next processing elements. In this work, the ANN model is developed with flexible and useful software for this type of application; the MATLAB release 7.0.[23]. The data used to calibrate and validate the model were obtained from literature and included a series of 120 axially loaded piles (Table1).

NN: Neural Network; ANN: Artificial Neural Network; MPLs: Multilayer perceptrons; ANN – MP: Artificial Neural Network – Multilayer perceptron.

### B. Model Inputs and Outputs

The ANN is considered as a black box system as it is unable to explain the underlying principles of prediction and the effect of inputs on the output. Therefore, interpretation of weights may be considered to the subject of future research. Recently, a number of investigators have advocated the use of connection weights to interpret the input variable contributions in neural networks [24]-[26].

In an attempt to identify which of the input variables has the most significant impact capacity predictions using ANN model, a sensitivity analysis is carried out on the trained network. A simple and innovative technique proposed by [27] is used to interpret the relative importance of the input variables by examining the connection weights of the trained network. For a network with one hidden layer, technique involves a process of partitioning the hidden output connection weights into components associated with each input node. The sensitivity analyses are repeated for networks trained with different initial random weights in order to test the robustness of the model in relation to its ability to provide information about the relative importance of the different factors affecting the bearing capacity of deep foundations. The results of the sensitivity analysis are discussed later.

### C. Data Division and Processing

Recent studies have found that the way the data are divided can have a significant impact on the results obtained [28]. Like all empirical models, ANNs are unable to extrapolate beyond the range of their training data. Consequently, in order to develop the best possible model, given the available data, all patterns that are contained in the data need to be included in the training set. If all the available patterns are used to calibrate the model, the best way of improving generalization ability of the model is if all of the patterns are also part of the validation set. Consequently, it is essential that the data used for training, testing and validation represent the same population [29]. In this present study, several random combinations of the training, testing, validation sets are tried until three statistically consistent data sets are obtained. The statistical parameters considered include the mean, standard deviation, minimum, maximum, and range. Despite trying numerous random combinations of training, testing, and validation sets, there are still some slight inconsistencies in the statistical parameters for the training, testing, and validation sets that are most closely matched (Table 7). The data ranges used for the ANN model variables are given in Table VII.

The next step in the development of the ANN model is dividing the available data into their subsets. In this work, the data were randomly divided into three sets: a training set for model calibration, a testing set and an independent validation set for model verification. In total, 65 tests were used for model training, 15 tests for model testing and 40 for model validation. Once available data are divided into their subsets, the input and output variables are pre-processed, in this step the variables are normalized between -1.0 and 1.0.

TABLE VII: ARTIFICIAL NEURAL NETWORK INPUT and OUTPUT STATISTICS

| statistical parameters | B (m) | D (m) | D/B | $\sigma'_v$ (KPa) | $O_{crb}$ | $R_g$ | $N_{spte}$ | φ' (°) | Qt (KN) |
|---|---|---|---|---|---|---|---|---|---|
| Minimum | | | | | | | | | |
| All data | 0.040 | 0.150 | 3.750 | 75.000 | 0.400 | 0.000 | 6.060 | 14.280 | 205.000 |
| Training set | 0.040 | 0.150 | 3.750 | 75.000 | 0.400 | 0.000 | 6.060 | 14.280 | 205.000 |
| Validation set | 0.040 | 0.150 | 3.750 | 83.140 | 0.452 | 0.000 | 7.920 | 14.91 | 271.000 |
| Maximum | | | | | | | | | |
| All data | 2.000 | 75.000 | 62.500 | 780.600 | 1.960 | 1.000 | 414.000 | 40.000 | 42116.90 |
| Training set | 1.200 | 75.000 | 62.500 | 780.600 | 1.960 | 1.000 | 349 | 40.000 | 42116.9 |
| Validation set | 2.000 | 75.000 | 57.14 | 596.5 | 1.960 | 1.000 | 404.000 | 40.000 | 36984.4 |
| Range | | | | | | | | | |
| All data | 1.73 | 74.850 | 58.750 | 705.600 | 1.560 | 1.000 | 407.940 | 25.720 | 41911.90 |
| Training set | 1.96 | 74.850 | 58.750 | 705.600 | 1.560 | 1.000 | 342.94 | 25.720 | 41911.90 |
| Validation set | 1.73 | 67.5 | 50.43 | 698.000 | 1.560 | 1.000 | 407.940 | 25.720 | 39362.5 |
| Mean | | | | | | | | | |
| All data | 0.807 | 15.513 | 22.339 | 220.329 | 1.220 | 0.778 | 69.459 | 31.718 | 6841.310 |
| Training set | 0.729 | 19.07 | 24.36 | 213.28 | 1.056 | 0.865 | 77 | 29.63 | 7992.320 |
| Validation set | 0.807 | 21.2 | 26.82 | 189.66 | 1.137 | 0.865 | 69.459 | 31.718 | |
| Standard deviation | | | | | | | | | |
| All data | 0.348 | 14.406 | 13.303 | 168.000 | 0.250 | 0.335 | 103.000 | 6.05 | 7916.085 |
| Training set | 0.408 | 15.04 | 12.58 | 171 | 0.384 | 0.386 | 108 | 5.608 | 8398 |
| Validation set | 0.348 | 14.74 | 11.205 | 174.39 | 0.375 | 0.34 | 103 | 6.45 | 7532.2 |

### D. *Model Architecture*

Following the data division and the pre-processing, the optimum model architecture (i.e., the number of hidden layers and the corresponding number of hidden nodes) must be determined. It should be noted that a network with one hidden layer can approximate any continuous function if sufficient connection weights are used [30]. Therefore, one hidden layer was used in the current study. The optimal number of hidden nodes obtained by trial and error approach in which the network is trained with a set of random initial weights and a fixed learning rate of 0.3, a momentum term of 0.01, a tansigmoidal transfer function for hidden layer nodes, and pureline transfer function for the output layer nodes. The designed ANN has three layers, eight neurons in the input layer, six neurons in the hidden layer and one neuron in the output layer.

To terminate the training process, the criterion used is: the scaled mean squared error with regularization performance function (MSEREG), it measures network performance as the weight sum of two factors: the mean squared error and the mean squared weights and biases between the actual and predicted values of all outputs over all patterns is monitored until no significant improvement in the error occurs. This was achieved at approximately 90000 training epochs.

### E. *Model Validation*

As a result of training, Tables VIII, VIX and VX show that the network ANN1 produced 6x8 weights and 6 bias values connecting the input layer to the hidden layer, 1x6 weights and one bias value connecting the hidden layer to the output layer for the model.

TABLE VIII: CONNECTIONS WEIGHT OF THE FIRST HIDDEN LAYER

| W (i,j) | $j^{th}$ input | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| $i^{th}$ neural | -0.34269 | -1.2823 | -0.8537 | 0.2851 | -0.18189 | 0.17483 | -0.81106 | -0.28265 |
| | 1.1991 | -0.44158 | -0.48513 | -0.54981 | -0.97668 | -0.70477 | 0.4544 | -0.19646 |
| | -1.1074 | -0.3853 | -0.72629 | 0.6297 | -0.44002 | 0.72524 | -0.10684 | -0.77743 |
| | 0.39691 | 0.69517 | -0.8436 | 0.10951 | -0.54352 | 0.79597 | -0.54135 | -0.58342 |
| | 0.51494 | -0.035535 | 0.73414 | -0.37146 | -0.56504 | -0.10218 | 0.71434 | 0.89817 |
| | 0.77425 | 0.79287 | 0.16991 | 0.052489 | -0.55107 | 0.0032257 | -0.2712 | 0.89677 |

TABLE IX: BIASES OF THE FIRST HIDDEN LAYER

| b (i) |
|---|
| 0.40594 |
| -0.67187 |
| -0.62815 |
| -0.45991 |
| 0.54765 |
| -0.93626 |

TABLE X: CONNECTIONS WEIGHT OF THE SECOND HIDDEN LAYER

| w (i) | -1.1454 | -0.18371 | 0.1476 | -0.16427 | 0.087622 | -0.069076 |
|---|---|---|---|---|---|---|

The second hidden bias is:

b = - 0.2667

The performance of the optimum ANN model in the training set is shown in Fig. 2, and the predictive ability of the model in the validation is depicted in Fig.3. It should be noted that the validation is done for 40 tests (ANN1). These results demonstrate that the ANN model has a strong capability to stimulate the complex behavior of pile. The error distribution of the predicted capacity is also shown in Fig.4.

Table XI summarizes the results of comparison between the usual statistical parameters of model predictions and measured values. The statistical parameters for both model prediction and measured values are closely matched which gives the best generalization of the model.

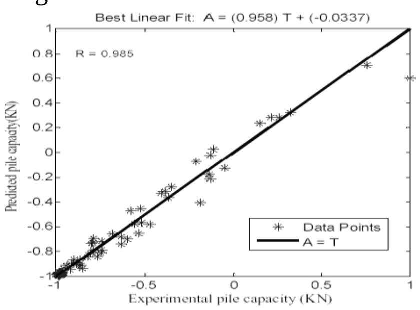


Fig. 2.The learning of the ANN1 model

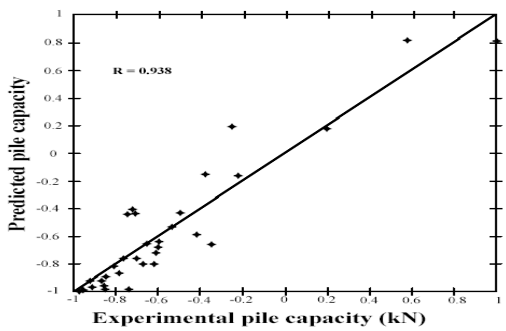


Fig. 3. Generalized model to predict the bearing capacity of pile (ANN1 model)

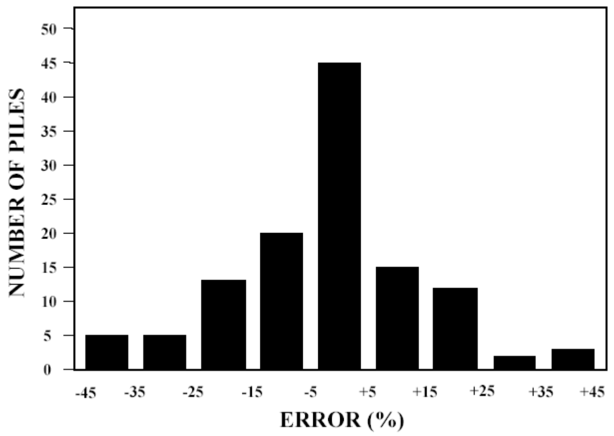


Fig. 4. Error distribution of the predicted capacity for all pile tests

TABLE XI: COMPARISON BETWEEN STATISTICAL PARAMETERS OF PREDICTED VALUES AND MEASURED VALUES

| Variable output | Mean | Standard deviation | Minimum | Maximum | Range |
|---|---|---|---|---|---|
| Measured values Qt | 6608.85 | 5532.25 | 270.5 | 23633 | 23362.5 |
| Model prediction Qt | 7484 | 7639.46 | 336 | 23295 | 22960 |

## V. TRADITIONAL METHODS FOR CAPACITY PREDICTION

Many traditional methods for capacity prediction of deep foundations are presented in the literature particularly the empirical methods. The predictive ability of ANN1 model in validation set was made using four empirical techniques and they were also compared with actual measurements of pile capacities. These methods are those proposed by [12], [13], [14] and [15]. These methods are chosen as they are commonly used; represent the chronological development of capacity prediction, and the database used in this work contains most parameters required to the calculate capacity by these methods (Table XII).

TABLE XII: COMPARISON OF ARTIFICIAL NEURAL NETWORK AND TRADITIONAL METHODS FOR PILE CAPACITY PREDICTION

| Approaches considered | ANN | Meyerhof (1976) | Coyle and Castello (1981) | API (RP2A, 1984) | Randolph (1985) |
|---|---|---|---|---|---|
| $R^2$ | 0.88 | / | / | / | / |
| MSERG (%) | 4.8 | / | / | / | / |
| MSE (%) | / | Between 23% and 25% | | | |

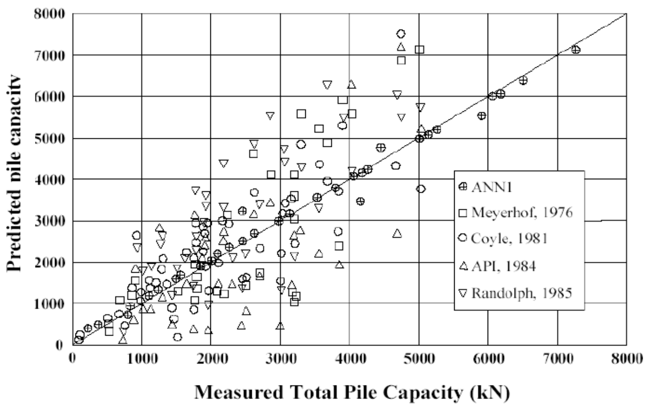


Fig. 5. Comparison of Predicted and measured total pile capacity

TABLE XIII: ARTIFICIAL NEURAL NETWORK RESULTS

| Data set | $R^2$ | MSERG (%) |
|---|---|---|
| Training set | 0.94 | 3.8 |
| Validation set | 0.88 | 4.8 |

The ANN model performs better than the traditional methods for all the four performance measures considered. As just mentioned, the coefficient of determination, $R^2$, the MSERG, and MSE obtained using the ANN and the four traditional methods are summarized in Table XIII. Fig.5 shows the relationship between measured and predicted values of the four methods. ANN predictions show few scatters in the data points than the predictions of all other methods.

The predictive performance of the optimal neural network model is summarised in Table 13. The results indicate that the ANN model performs well with an $R^2$ of 0.88, an MSERG of 4.8% for the validation set.

## VI. COMPARISON WITH OTHER METHODS

To measure the model performance, we take a numerical example described in Table XI. The studied case is an IPE 400 embedded in sandy soil in Kallo site in Belgium. The interpretation of the load test curve gives value of 3474 KN. The obtained result is compared with the different approaches based on SPT, presented in Table XII (1: Canadian code (CFEM; 1985) [34] 2: [31]; 3: [32]; 4: [33]; Qu: Ultimate pile capacity).

The coefficient of variation values (COV) shows a divergence between the Aoki and De'Alencar method and the other prediction approaches witch give a good agreement with the measured value. The developed model shows best predictive ability with low Variation Coefficient (COV= 4.77%).

TABLE XIV: PILE GEOMETRY AND SOIL PROPERTIES

| Soil properties | Pile geometry | Nspt |
|---|---|---|
| C = 0<br>$\varphi = 35.2°$<br>$\gamma_d = 15.6$ KN/m$^3$ | IPE400<br>*D* = 14m (embedment length) | *Nb* = 42<br>*Ns* = 30<br>Nspte = 33 |

TABLE XV: COMPARISON OF A NEURAL NETWORK MODEL AND OTHER METHODS

| methods | 1 | 2 | 3 | 4 | ANN model | Test result |
|---|---|---|---|---|---|---|
| Qu (KN) | 3045.4 | 3787 | 5786 | 2966 | 3640 | 3474 |
| COV (%) | 12 | 9 | 66 | 14.6 | 4.77 | - |

## VII. SENSITIVITY ANALYSIS OF THE RELATIVE IMPORTANCE OF ARTIFICIAL NEURAL NETWORK INPUT VARIABLES

The result of the sensitivity analyses are shown in Table 16. It can be seen that $N_{spte}$ has the most significant effect on the predicted capacity when the network is retrained with different initial weights. However, the relative importance of the remaining input variables changed depending on which initial weights were used. Although σ'$_v$ was found to be the most important input in all trials, the variables D/B, $N_{spte}$, $R_g$, φ’ and D have a tendency of having the same contribution. The remaining variables B and $O_{crb}$ look to have the same effect. The analysis carried out indicate that as expected, σ’$_v$, $N_{spte}$, $\varphi'$, D and D/B are the most important factors affecting pile capacity with average relative importance equal respectively to 16.14%, 14.15%, 12.46%, 12.69%and 13.27%. The results also indicate that $R_g$, $O_{crb}$ and $B$ have a moderate impact on pile capacity with average relative importance respectively equal to 11.16%, 10.54%, and 9.77%.

TABLE XVI: SENSITIVITY ANALYSES OF THE RELATIVE IMPORTANCE OF ARTIFICIAL NEURAL NETWORK INPUT VARIABLES

| | Relative importance for input variable (%) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Trial n°. | B | D | $N_{spte}$ | $R_g$ | φ' | $O_{crb}$ | D/B | σ'$_v$ |
| 1 | 7.32 | 14.33 | 14.49 | 12.48 | 11.39 | 8.89 | 14.33 | 16.4 |
| 2 | 10 | 11 | 15 | 10 | 14 | 12 | 12 | 17 |
| 3 | 12 | 12.71 | 12.95 | 11 | 12 | 10.75 | 13.5 | 15 |
| Average | 9.77 | 12.69 | 14.15 | 11.16 | 12.46 | 10.54 | 13.27 | 16.14 |

## VIII. CONCLUSIONS

ANNs were used to simulate the mechanical behavior of an axially loaded pile and more particularly the prediction of the bearing capacity. The ANNs used were MLPs that were trained with the back-propagation algorithm.The principal aim of this study is to show the efficacy of this approach to estimate the total pile capacity in cohesionless soils.

A database containing 120 case records of actual field measurements for capacity was used for model development and verification. The optimum network architecture and internal parameters were found to be as follows: 6 hidden layer nodes; a learning rate of 0.3; a momentum of 0.01; a tansigmoidal transfer function for the hidden layer nodes and a pureline transfer function for the output layer nodes. A sensitivity analysis was carried out to study the relative importance of the factors that affect a pile capacity. The results of the ANN model were compared with the results of the experimental tests and with those obtained from other traditional methods. The results indicate that the ANN model was capable of accurately simulating the pile capacity by using eight simple parameters as model inputs (i.e., B, D, D/B, $R_g$, $\varphi'$, $O_{crb}$, $N_{spte}$, and $\sigma'_v$). The results obtained also demonstrate that the ANN method performs better than the traditional methods. A neural network performance depends mostly on its generalization capacity, which in return depends on the data.

The application of the PCA technique on the study of variables before the learning process of an ANN model enabled us to determine the importance of the variables on the phenomena to study (pile bearing capacity).

The sensitivity analysis indicates that the SPT blow count, the overburden the pressure at the pile point, the pile slenderness, and the internal angle of friction, the penetration depth, the roughness of the pile/soil interface, the pile diameter and the overconsolidation ratio are most important factors affecting pile capacity in cohesionless soils. ANNs have the advantage that once the model is trained, it can be used as an accurate and quick tool for estimating the total bearing capacity without need of using table or charts.

Like all empirical models, the range of applicability of ANNs is constrained by the data used in the model calibration phase and ANNs should thus be recalibrated as new data becomes available. Despite of these limitations, the results of this study indicate that ANNs have a number of significant benefits that make them a powerful and practical tool for pile capacity prediction in cohesionless soils.

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