Prediction of Pile Capacity Parameters using Functional Networks and Multivariate Adaptive Regression Splines

A dissertation submitted by

Shakti Suman
(213CE1052)

in partial fulfillment of the requirements
for the award of the degree of

Master of Technology
In
Civil Engineering
(Geotechnical Engineering)

Department of Civil Engineering
National Institute of Technology
Rourkela-769008, Odisha, India
May, 2015

Prediction of Pile Capacity Parameters using Functional Networks and Multivariate Adaptive Regression Splines

A dissertation submitted by

Shakti Suman
(213CE1052)

in partial fulfillment of the requirements
for the award of the degree of

Master of Technology
In
Civil Engineering
(Geotechnical Engineering)

Under the supervision of

Dr. Sarat Kumar Das

Department of Civil Engineering
National Institute of Technology
Rourkela-769008, Odisha, India

May, 2015

Department of Civil Engineering
National Institute of Technology
Odisha, India - 769008

CERTIFICATE

This is to certify that the project entitled **'Prediction of Pile Capacity Parameters using Functional Networks and Multivariate Adaptive Regression Splines'** submitted by Mr. Shakti Suman (Roll No.213CE1052) in partial fulfilment of the requirements for the award of Master of Technology in Civil Engineering (Geotechnical Engineering) at National Institute of Technology Rourkela is an authentic work carried out by him under my supervision and guidance. Further, I also certify that, this dissertation has not been submitted to any other institute or organization for the award of any other degree or diploma.

Place: Rourkela

Date: 27th May, 2015

Dr. Sarat Kumar Das
(Project mentor)
Department of Civil Engineering
National Institute of Technology
Odisha, India - 769008

ACKNOWLEDGEMENT

I would like to take this opportunity to express my deepest sense of gratitude and indebtedness to the people who rendered their kind help directly or indirectly for the completion of the project entitled as '**Prediction of Pile Capacity Parameters using Functional Networks and Multivariate Adaptive Regression Splines**'. This project would never have had seen the dawn without all those persons who helped me in form of their guidance, help or support.

I would specially like to point the contribution of my parents for their constant support towards my endeavours. Reaching here was not possible without their encouragement.

I extend my heartfelt gratitude to my mentor and guide Dr. Sarat Kumar Das for his invaluable guidance, constant motivation and steadfast support throughout the year without which the project would have been a distant reality.

I also extend my thanks to crews of the geotechnical engineering lab allowing me to use the lab facilities and for lending me a helping hand whenever it was needed.

I am also indebted to all the faculties of Department of Civil Engineering, NIT Rourkela for making me proficient and efficient enough in terms of theoretical background and understanding of the subjects.

Last but not the least, I want to say 'Thank you' to all my friends for being there for me through all ups and downs throughout my journey at National Institute of Technology, NIT Rourkela.

Shakti Suman

ABSTRACT

The soil is found to vary spatially everywhere in nature. As such, it's generally a difficult task to predict the nature of soil for any particular application with traditional methods like experimental, empirical, finite element or finite difference analysis. Analysis with traditional methods taking into factor all the varying inputs makes it a complex problem, which is difficult to solve and comprehend. This necessitates the use of statistical modelling tool for the solution to problems concerning soil.

Pile foundations are widely used in civil engineering construction. However, owing to the variable behavior of soil and the dependence of vertical pile load capacity on numerous factors, there does not exist a definite equation which can estimate the pile load accurately and include all the factors comprehensively.

Artificial intelligence techniques are known to successfully develop accurate prediction models with the obtained input and output data form laboratory experiments or field data. Therefore, the present study deals with development of prediction models for pile capacity parameters based on field and laboratory database available in literature using two recently developed artificial intelligence techniques, functional networks (FN) and multivariate adaptive regression splines (MARS).

FN is a newly developed AI technique which an extension of neural networks. It is advantageous over neural networks in terms of the use of both domain knowledge and data to build the model. MARS is an adaptive regression technique that uses non-parametric regression to develop prediction models. Previous research experience with both, FN and MARS technique have rendered them suitable for building accurate yet comprehensible prediction models in various fields of science including geotechnical engineering.

In the present study, FN and MARS were used to develop prediction models for the lateral load capacity of piles, vertical capacity of driven piles in cohesionless soil, friction capacity of piles in clay, axial capacity of piles and pullout capacity of ground anchors. In all the cases, prediction equations were provided for the developed models which were found to be simple and can be easily used by practicing geotechnical engineers. A standalone application was also developed to facilitate the calculation of required pile capacity parameters based on the prediction equations.

The prediction models built by FN and MARS were compared with different artificial intelligence (AI) techniques and empirical models available in the literature in terms of statistical parameters such as correlation coefficient (R), Nash-Sutcliff coefficient of efficiency (E), absolute average error (AAE), maximum average error (MAE) and root mean square error (RMSE). The models were also compared according to ranking index technique for two cases. FN and MARS were found to invariably outperform other AI techniques and empirical methods.

TABLE OF CONTENTS

	Page no.
Acknowledgement	iii
Abstract	iv
List of Figures	vii
List of Tables	viii
Introduction	1
Pile capacity equations	7
Literature review	17
Methodology	21
Prediction of lateral load capacity of piles in clay	31
Vertical capacity of piles in cohesionless soil	34
Friction capacity of driven piles in clay	37
Axial capacity of piles	39
Pullout capacity of ground anchor	43
Development of standalone application	46
Conclusions and future scope	47
References	49

LIST OF FIGURES

Figure 2.1 Examples of (a) end bearing and (b) friction piles

Figure 2.2: Typical arrangement of pile groups

Figure 4.1: A neural network and its equivalent functional network

LIST OF TABLES

Table 5.1: Maximum and minimum values of the data used for prediction of lateral load of piles

Table 6.1: statistical parameters for the inputs and output for vertical capacity of piles in cohesionless soil

Table 7.1: Statistical parameters for the inputs and output to predict friction capacity of piles.

Table 8. 1: Statistical parameters for the inputs and output for the bored piles

Table 8. 2: Statistical parameters for the inputs and output for the driven steel piles

Table 8. 3: Statistical parameters for the inputs and output for the driven concrete pile

Table 9.1: Statistical parameters for the inputs and output to predict pullout capacity of ground anchor

CHAPTER ONE

INTRODUCTION

Soil is a result of continuous weathering and decaying process in nature. The final nature of any soil is greatly affected by the way soil has been transported, the temperature it has been subjected to and many other factors. This leads to change in the properties of soil to vary from place to place. Conventionally, most of the time, the problems in soil mechanics are analyzed using a lot of assumptions so that the problem at hand can be simplified and a solution can be reached at. The solutions reached at this way may not give the right solution for a practical situation and evidently, we require more assumptions and adequate factor of safety when applying these solutions. These drawbacks turned the attention towards adoption of other theories such as numerical methods and analytical methods.

Thus, the concepts of mechanics, empirical correlation, experimental analysis, finite element methods became popular practices in civil engineering. However, as discussed in the above paragraph, the varying nature of soil causes spatial variability and uncertain behavior, rendering most of the traditional methods unusable as the constitutive modelling of a varying engineering material is a difficult task. Thus, came the era of using semi empirical and empirical methods which consisted of building analytical model based upon experience gained from the experimental results and field case records. The successful prediction according to these semi empirical and empirical methods' depends on the statistical or theoretical model chosen to analyze the inputs and output and the methods used to determine the model parameters (Das and Basudhar 2006).

Therefore, most of the problems associated with geotechnical engineering don't have a precise model or theory for their solution which can be reliably used for the situations. This problem mainly arises due to the incomplete and inadequate understanding of the involved phenomena and the factors affecting the output. The availability of data is also, most of the time, limited and inexact. Thus, the general practice is to use empirical solutions which may be presented in the form of equations, design charts or tables.

Piles as deep foundations are widely used in civil engineering in various structures to transfer load either to higher depths when sufficient support is not available at shallow depths or the load is high. The deep foundations are also used for soft, loose, expansive top soil or subjected to erosion, lateral or uplift loads which shallow foundations cannot carry and when scour occurrence is probable. However, there is a lot of uncertainty associated with the interaction between the pile and the surrounding soil. Hence, there is lack of a unified theory which can explain this phenomenon satisfactorily. This has led to development of quite a large number of empirical and analytical methods to model the pile behaviour and to calculate the load bearing capacity of the piles. Some of the mostly used prevalent methods can be found in Das (2006). However, owing to the ambiguous nature of soil, it is a challenging task to develop a theoretical or statistical model as the problem of pile behavior is complex and the soil parameters that affect the pile behavior is uncertain.

To overcome the difficulties associated with the empirical methods, artificial intelligence (AI) methods came into use. One of the most widely used AI techniques, artificial neural networks (ANN) came into being in the early 1960s and were used for a wide variety of problems in civil engineering. However, ANN is a black box technique (Giustolisi 2007) and the network structure of ANNs is complex. The network structure is represented in terms of weights and biases and the users do not have access to these values (Rezania and Javadi 2007). Later came the grey box techniques (Giustolisi 2007) like genetic programing (GP), SVM etc. The grey box techniques are more comprehensible than the black box technique but the user needs to set optimization parameters to build a good prediction model according to these techniques.

Another prediction tool, functional network (FN), has recently been developed and has been successfully implied in various fields such as signal processing, pattern recognition, function's approximations (Castillo et al. 1999), real-time flood forecasting, science, bioinformatics, medicine (El-Sebakhy et al. 2006), petroleum engineering (El-Sebakhy et al. 2012), structural engineering (Rajsekaran 2004), transportation engineering (Attoh-Okine 2005) and geotechnical engineering (Khan et al. 2015). Functional networks were introduced by Castillo (Castillo 1998; Castillo et al. 2000a), Castillo and Ruiz-Cobo (1992), and Castillo et al. (Castillo et al. 1998, 2000b). The FN algorithm is based upon the structure of the physical world and takes into account, both domain and data knowledge to find a relationship between the inputs and the outputs.

Friedman (1991) postulated a modified regression technique called multivariate adaptive regression spline (MARS). MARS is a 'white box' technique used widely for predictive modelling and includes the physical laws related to the data while building a model. The underlying physical relationships of the build model can be easily presented in the form of a comprehensible model equation. No prior assumption regarding the relationship between the predictor variables and the dependent variables is made by the MARS algorithm. Thus, MARS has been found successful for building models for problems consisting a large number of variables. Recently, MARS has been used increasingly in for various application in many fields of science and technology and economy. However, literature pertaining to the use of MARS in geotechnical engineering is limited (Samui et al. 2011, Samui et al. 2014, Zhang and Goh 2014).

Therefore, the present study aims at development of prediction models for pile capacity parameters by use of FN and MARS.

Objective and scope:

The objective of this study is to develop improved prediction models for the pile capacity parameters by using FN and MARS. The versatility and flexibility of the FN and MARS allows to develop models comprehensible and fairly accurate models for complex systems when the determined inputs and output are available either from laboratory experiments or actual field data case studies. Previous experience with FN and MARS prove that they are more reliable than statistical and AI methods earlier used.

Outline of thesis

Chapter One briefly describes the background of the proposed problem and the thesis objectives and scope.

Chapter Two basic concepts of the pile foundations and the prevalent techniques in use for the design of pile foundation.

Chapter Three covers the literature review regarding the previous research works done in the area of pile foundation. Relevant works in pile foundation done using AI techniques have also been discussed.

Chapter Four briefly describes the AI techniques used in the present study, i.e., FN and MARS

Chapter Five includes the development of FN and MARS models for the lateral load capacity of piles. It explains the database used, selection of input and output variables, results of the FN and MARS modelling, their prediction equations and the comparison of the results from FN and MARS with methods previously used in the literature.

Chapter Six includes the development of FN and MARS models for the vertical capacity of piles in cohesionelss soil. It explains the database used, selection of input and output variables, results of the FN and MARS modelling, their prediction equations and the comparison of the results from FN and MARS with methods previously used in the literature.

Chapter Seven includes the development of FN and MARS models for the friction capacity of driven piles in clay. It explains the database used, selection of input and output variables, results of the FN and MARS modelling, their prediction equations and the comparison of the results from FN and MARS with methods previously used in the literature.

Chapter Eight includes the development of FN and MARS models for the axial capacity of piles. This chapter takes into consideration the bored, steel driven and concrete driven piles. It explains the database used, selection of input and output variables, results of the FN and MARS modelling, their prediction equations and the comparison of the results from FN and MARS with methods previously used in the literature.

Chapter Nine includes the development of FN and MARS models for the pullout capacity of ground anchors. It explains the database used, selection of input and output variables, results of the FN and MARS modelling, their prediction equations and the comparison of the results from FN and MARS with methods previously used in the literature.

Chapter Ten includes the development of a standalone application to calculate the pile capacity parameters based on equation predicted from FN and MARS models. The user can use this application to get the desired output if the required inputs are available.

Chapter Eleven includes the conclusions made from the present study and presents suggestions for future scope of work.

CHAPTER TWO

PILE CAPACITY EQUATIONS

Piles are deep foundation elements used to transfer the load of the superstructure to a hard strata below the soil or on a less compressible soil. Piles may be used if the immediate layer below the surface is either water or too weak to support the load of the superstructure. Piles may alos be used to resist the uplift loads caused due to winds or waves which may cause overturning of the structures. Piles are also often subjected to lateral loads such as in the case of marine structures for berthing of ships where piles are designed to brace the impact of the sea waves. Piles used in structures such as retaining walls, machine foundations and bridge are frequently subjected to both vertical and lateral loads. Generally, the use of pile foundations is recommended in the following cases:

1. Soil is soft, loose, expansive or subject to erosion.
2. Shallow foundation is unable to carry uplift or lateral loads.
3. Constraint in increasing the foundation area leads to inability of achieving the desired bearing capacity. Hence pile foundation would be recommended to achieve the permissible strength of foundation.
4. Scour is present.
5. Deep excavations next to the foundations are conducted in the future.

The two principle factors which leads into the design of pile foundations are bearing Capacity and settlement. The pile design must ensure that the soil supporting the pile is capable of carrying the pile ultimate load and the pile does not settle beyond the permissible limits.

Numerous theoretical and practical approach has been proposed by the researcher to predict the capacity and the load-settlement behavior of pile foundations. As with other types of foundations, the purpose of pile foundations is:

i. to transfer the load from the superstructure to a hard strata
ii. to keep the superstructure safe against vertical, lateral and uplift loads or combinations thereof.

Classifications of Pile Foundations

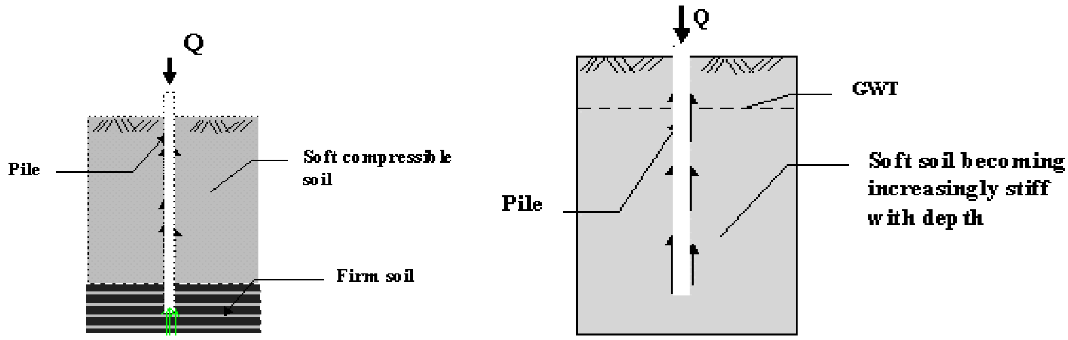
Pile foundations are classified based on material, load transfer, loading mode, size of diameter and the installation method.

Based on material

- **Timber**- varying diameter of 15 to 400 mm and length ranging from 6 to 20 m resp.
- **Steel**-range of pipe pile diameter and wall thickness is 50-4000 mm and 4-150 mm.
- **Concrete**- either fabricated or cast in place. Concrete piles are generally formed in square, triangular, circular or octagonal shapes and are fabricated in steps of one meter.
- **Polymer**-rare type of piles which are usually tubular filled with concrete.

Based on Load transfer

- **End Bearing pile (point bearing piles**) – The tip of the pile is situated on a strong stratum while the shaft is surrounded by weak soil. The bearing capacity of the pile is developed from the tip.
- **Friction piles (cohesion piles)** -Carrying capacity is developed by friction with surrounding soil.



(a) (b)

Figure 2.1 Examples of (a) end bearing and (b) friction piles (Available on http://goldfinger.007.free.fr/Stage%20PCI/driven%20piles2_fichiers/chapter1.htm Accessed on 25.05.2015)

- **Combined piles**- combined piles are used when the bearing stratum is not hard enough to support the superstructure or is at a depth up to which piling is not economical. It uses both the end bearing capacity and the frictional capacity to support the load of the superstructure. The pile is driven up to a depth where the development of frictional resistance is enough to support the load in addition with the end bearing capacity. Sometimes, the bearing area of the pile is increased so that the bearing load developed is high. To achieve this, a bulb of concrete is placed in the soft layer just above the hard layer. For bored piles, a large cone or bell shape is formed just above the hard layer. Provision of bells increase the tensile strength of the bored piles and they can be used as tension pile also.

Based on Loading Mode

- Axially loaded piles-Subject to axial compression or tension loads
- Laterally loaded piles-Subject to inclined loads at some angle.
- Moment piles-Subject to moment.

Based on diameter size

- Small diameter pile-diameter equal to or less than 600 mm but greater than 250 mm
- Large diameter pile- diameter larger than 600 mm
- Mini diameter pile- diameter less than 250 mm

Based on Installation method

- Non-displacement (bored) method- These piles are installed after driving a void in the construction area this void is later filled with concrete. The method of the excavation is decided based upon the soil profile in the construction area.
- Displacement (driven) piles. These piles are inserted into the soil without removing any soil prior to insertion and the pile is commonly installed into the soil by jacking, vibratory driving and driving.

Stages in installing a pile

The methods and the processes selected for the installation of piles, bears an importance, equal to the design process of the pile. The installation method chosen is affected by the type of pile selected, the depth of the pile and the soil profile among other environmental and economic factors. Installation by pile hammer and boring by mechanical auger are two of the most widely used methods for installation of pile.

The following factors must be kept in mind while selecting any method for the installation of piles:

- The size and the weight of the pile
- The amount of driving resistance imparted by the soil up to the desired depth of penetration of pile.
- The amount of space available and the available head room on the site

- Whether the economy and the reachability of the site allows use of cranes and other required machinery.
- Environmental factors like noise limitations and environmental pollution regulations.

Pile arrangement

A structure is very rarely built upon a single pile. Mostly, a group of piles is used to support the load from the superstructure. A pile group consists of a group of piles arranged in a specific pattern and a pile cap is provided on the top to ensure uniform loading and group action. The load is transferred to the pile cap which in turn, transfers it to the piles beneath. Each individual pile is connected to the pile cap and are spaced uniformly in a given patter. The selection of the pattern is done on the basis of the structure and the eccentricity of the load. Figure 2.2 shows the typical arrangement of pile groups generally used.

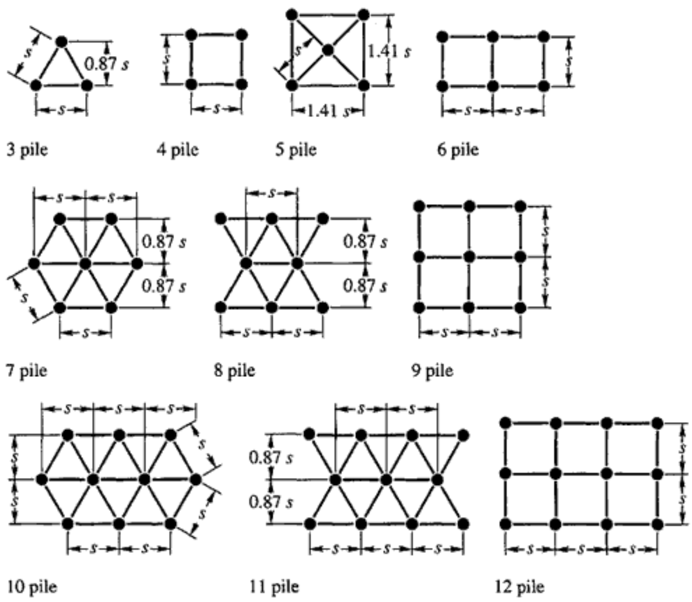


Figure 2.2: Typical arrangement of pile groups (Available on http://www.abuildersengineer.com/2012/11/number-and-spacing-of-piles-in-group.html Accessed on 25.05.2015)

DESIGN OF PILE

General considerations to be kept in mind while designing: -

- The design of the pile should be such that it is able to bear the load of the superstructure without causing any failure in the soil beneath and without causing any undesirable amount of differential or total settlement. The designed pile should be able to resist all vertical and lateral loads or combinations thereof, that may act on the foundation during the construction stage or after construction for the serviceable life of the structure.
- The installation of pile must not cause any damage to the surrounding structures.
- If deep excavations are done for the piling process, proper care must be taken to protect the surrounding soil from lateral movement.
- The material chosen to design the pile should be structurally sufficient to bear the loads that is to be transferred through it.

Design considerations: -

- First of all we find the amount of axial load each pile is subjected to in the group of piles. After that we have to decide the cross sectional area of the pile which is required (as we know the allowable bearing capacity of the soil).
- Now, we have the area required so we can choose to have any type of section (square, circular, rectangular etc) depending upon suitability and other aspects.
- Now we have to design for the reinforcement required in the pile. From the formula of Pt(% of steel) we can get the minimum requirement and compare it with the amount of steel required in the pile(we can get it by deducting concrete area from the gross area of the pile) . Depending upon the results obtained we provide reinforcement and place them according to the suitability of the sectional type of pile.
- We now design for the lateral reinforcement of the pile which is taken by practice as 0.2% of the steel requirement.(Note: - diameter of the lateral ties should not be less than

one fourth of the diameter of the main reinforcement). From the formula we calculate the pitch required (should not be less than 60mm).

- Now , depending upon the kind of strata in which it is driven additional reinforcement is provided (Eg in hard rock we provide extra reinforcement at top and bottom of pile equal to 0.3 of length of pile)

Pile Capacity from static methods

The pile capacity calculated by static methods is based on soil strength determined from laboratory or field measurements. The total bearing capacity is calculated by the addition of the tip bearing resistance and side resistance along pile shaft. The term “static” refers to the use of static soil properties to determine the bearing capacity.

Pile capacity from pile load test

The pile load test is conducted to measure the actual resistance of soil on which design can be based reliably and the test usually provides diagram showing the relationship between applied load and the corresponding settlement. There are various types of load tests which use different procedures, equipment, instrumentation and load application methods. Pile load test is considered to be as the most reliable method to determine the load capacity of pile foundations (Bowles 1988). There are several methods for obtaining pile capacity from load test some of which are:

Pile capacity from dynamic methods

Dynamic methods determine the static load capacity based on the effort required to drive the pile. They are categorized into theoretical, empirical and a combination of the two. Dynamic Formulas and Wave Equation are the common methods for estimating pile capacity on the basis of dynamic analysis. The Dynamic Formulas evaluate the total resistance of the pile based on the work done by the pile during penetration. Several researchers (e.g. Cummings 1940; Davisson 1979) have argued that the dynamic formulas are inaccurate; and statistical evaluation of the methods, carried out by Hannigan et al. (1996), has shown a wide scatter when compared with static load test results, therefore the Dynamic Formulas are not suggested for practical use. The main shortcoming of the Dynamic Formulas is that they involve uncertainties, as the energy losses in a real pile driving situation cannot be accounted for accurately (Coduto 1994) and the capacity cannot be estimated until the pile is driven (Eslami 1996). The Wave Equation is another approach to estimate pile capacity using dynamic analysis. Smith (1960) proposed a numerical solution applying the wave equation theory to pile design.

Pile capacity from in-situ tests

Cone penetration test (CPT) and standard penetration test (SPT) are mainly used for providing information about penetration resistance of soil, shear strength and pore water pressure. The data obtained from CPT or SPT are used to predict pile capacity in two methods: (1) The CPT or SPT data are correlated with conventional strength parameters of soil, such as φ or S_u and then static methods used to predict the capacity, (2) the tests' results are directly correlated with the end bearing and side resistance of pile.

The SPT has been used for pile design for over than 50 years. It has been used extensively in North and South America, UK and Japan (Coduto 1994). However, its major weakness is that it is affected by many factors like operator, drilling, hammer efficiency and rate of blows. As a result, high variability and uncertainty associate with SPT data. On the other hand, the CPT is simple, fast, provides direct readings of soil resistance and allows for considerable data to be obtained in short time. The data provided by the CPT can be interpreted empirically or analytically, so it has become preferable test for pile design.

Equations for estimating pile capacity

The ultimate load carrying capacity Q_u of a pile is given by the equation:

$$Q_u = Q_p + Q_s$$

where, Q_u= load carrying capacity of the pile point

Q_s= frictional resistance derived from the soil pile interface.

Qp = point bearing capacity

According to Terzaghi's equations, the ultimate bearing capacity of shallow foundations is

$$Q_u = 1.3c\ NC + qNq + 0.4\gamma BN\gamma$$

Point bearing capacity , Qp

$$Qp = A_p \times q_p$$

Vesic's method of estimating Qp

$$Qp = A_p \times q_p = A_p \times \sigma_o \times N_\sigma$$

Correlations for calculating Q_p with SPT and CPT results

$$q_p = 0.4 \times p_a \times N_{60} \times L/D \leq 0.4 \times p_a \times N_{60}$$

$$q_p = 19.7\, p_a\, (N_{60})^{0.36}$$

$q_p = q_c$(for granular soils)

Frictional Resistance , Qs

The friction resistance of a pile may be written as:

$$Qs = \sum p\, \Delta\, L_f$$

Correlation with SPT results

According to Meyerhof, the average unit frictional resistance**,** f_{av} for high displacement driven piles can be obtained from average SPT values as

$$f_{av} = 0.02\, p_a\, (N_{60})$$

For low displacement driven piles

$$f_{av} = 0.01\, p_a\, (N_{60})$$

$$f_{av} = 0.224\, p_{\,a}\, (N_{60})^{0.29}$$

Correlation with CPT results

Nottingham and Schmertmann (1975) provided correlation for estimating Qs using the frictional resistance f_c obtained during CPT. According to this method,

$$f = \alpha' \times f_c$$

Frictional skin resistance in clay

λ **method**

$$f_{\,av} = \lambda \times (\sigma_o + 2c_u)$$

α **method-** According to the α method, the unit skin resistance in clayey soils can be calculated as:

$f = \alpha \times c_u$, where α = empirical adhesion factor

The ultimate side resistance can thus be given as

$$Qs = \sum f \times p \times \Delta L = \sum \alpha \times c_u \times p \times \Delta L$$

$\boldsymbol{\beta}$ **method**

$$f = \beta \times \sigma_o$$

Negative skin friction

It is the downward drag force imparted on the pile by the surrounding soil. Negative skin friction can be imparted on the pile in the following conditions:

1. If there is a layer of clay over granular soil layer, then the insertion of pile causes the clay layer to consolidate which exerts a downward drag in the pile.
2. Also, if the granular layer is above the clay layer, the clay layer will consolidate due to the overburden causing a downward drag on the pile.
3. There is an increase in the vertical effective stress on the soil if the water table lowers at any depth. This induces consolidation settlement in the soil which consequently cause a downdrag on the pile.

CHAPTER THREE

LITERATURE REVIEW

Although the piles are loaded axially in most of the cases, in many cases, pile foundations are also subjected to lateral loads in addition with the axial loads. These lateral loads may be due to earth pressure, earthquake, wave or wind forces. This makes the design of pile foundation a difficult task and therefore, the design of pile foundation has attracted the attention of researchers more than any other type of foundation.

Equations provided by Hansen (1961) and Broms (1964a, b) based on earth pressure theories were the earliest attempts at prediction of laterally loaded piles. Poulos and Davis (1980) also proposed dynamic equations which were based on Winkler's soil model.

The design of laterally loaded piles is a complex problem and needs solution to non-linear differential equations. The elastic analysis adopted by Poulos and Davis (1980) is, therefore, not suitable for non-linear behavior of soil. Non-linear p-y curves were proposed by Matlock and Reese (1962) to predict the lateral load capacity of pile. Portugal and Seco e Pinto (1993) used nonlinear p-y curves and finite element method to predict the capacity of laterally loaded piles. However, all the methods stated above were found to predict the pile capacity of laterally loaded piles uncertainly due to the variations in soil properties. Hence, empirical methods such as Hansen (1961) and Broms (1964a, b) are still predominantly in use.

Inspite of numerous investigations, both theoretical and experimental, conducted over the years to predict the behavior and the load capacity of piles, the mechanisms governing the piles are not yet clear. Correlations were developed later, with in-situ tests in attempt to solve the problems associated with earlier empirical equations. These correlations were able to reflect the natural conditions of soil to some extent, but still they had several limitations. Based upon the results from load tests, many empirical equations developed to calculate the pile capacity of both the end bearing and friction piles based upon the soil parameters expecting to predict quick and fairly accurate estimates of the pile capacity. But, it these empirical relations were found to either oversimplifying or improperly consider the effects of certain factors. This made it imperative to use alternate methods that can not only take into consideration all the associated factors but can resolve the uncertainties associated with prediction of pile capacity to a satisfactory degree of accuracy.

Artificial intelligence (AI) techniques have gained popularity as alternate statistical method by various researchers and are found to be able to predict outputs better than the empirical methods (Das and Basudhar, 2006, Das *et al*., 2011a, Muduli et al. 2013, Tarawneh and Imam 2014). Back propagation neural networks (BPNN) was used to predict the skin friction in piles by Goh (1995). Further, Goh (1995 & 1996) used ANN to predict the ultimate load capacity of piles and found ANN to perform better than Engineering News formula, Hiley formula and Janbu formula. Many other future attempts were made to predict the pile load capacity in both cohesionless soil and clayey soil using ANN and it was inferred that ANN has a better prediction capability for pile load capacity as compared to traditional empirical methods (Chan et al. 1995, Lee and Lee 1996, Teh et al. 1997, Abu-Kiefa 1998, Goh et al. 2005, Das and Basudhar, 2006). Das and Basudhar (2006) found ANN to be better than Broms and Hansen. Samui (2008) used another AI technique, support vector machine (SVM) and found it to have a better prediction capability than ANN. Pal and Deswal (2010) developed Gaussian process regression (GPR) and SVM models on data set of Das and Basudhar (2006) and found GPR to be better than SVM. However, the observation of Pal and Deswal (2010) was based upon correlation coefficient (R) and root mean square error (RMSE) only.

Momeni et al. (2014) used a hybrid genetic algorithm (GA)-based ANN to predict the bearing capacity of piles and found GA-based ANN to be better than the conventional ANN. Zhang and Goh (2014) used MARS and BPNN to develop drivability prediction models for a database containing 4072 pile data sets with a total of seventeen variables and found MARS and BPNN to be equally efficient in terms of statistical parameters but MARS was computationally more efficient and gave a more comprehensive mathematical model.

According to Lau and Simons(1986), published literature concerning the uplift capacity of ground anchors is limited. Das (1990) also made a similar observation regarding available literature concerning the uplift capacity of anchor piles. Shahin and jaska(2003) carried out a series of 119 insitu anchor pull out tests at six different locations within Adelaide, South Australia and compared the results with contemporary methods. It was found that the contemporary methods predicted the pullout capacity of ground anchors inconsistently. Shahin and Jaska (2005) also developed an ANN model based upon the data set and found ANN to be a better prediction tool for pllout capacity of ground anchors as compared to available methods.

The better performance of ANN is ensured by repetition of the learning algorithm. However, the repetition may stop even if a local minima is reached and the process is stopped. This generally leads to the poor generalization of obtained prediction model. On the other hand, SVM has been found to have better generalization but the user needs to decide the values of the optimum values of the parameters (C) and insensitive loss function (ε) need to be fine-tuned by the user. Moreover, SVM and ANN are not able to produce a comprehensive model equation and are also called as “black box” system. Giustolisi et al. (2007) divided mathematical models into three types, black-box, grey box and white box according to their ability to explanation the functional form of the relationships between the input and output variables. The white-box models are based on physical laws where model variables and parameters are known and the underlying physical relationship can be easily explained, whereas, the functional relationships between model variables is unknown for black-box systems and needs to be determined. Black box models are data driven and the relationship between input and output is based on data. Grey-box systems are conceptual and a mathematical model can be derived for them.

FN and MARS are two recently developed AI techniques which have been successfully used to model complex problems in different fields with accurate results. They produce comprehensible prediction equations which can be used to arrive at results for a new set of data. In the present study, FN and MARS have been used to model problems associated with piles based on data sets available in literature. FN and MARS are discussed in detail in the following chapter.

CHAPTER 4

METHODOLOGY

Functional Networks

Functional Networks are a recently introduced extension of neural networks. A FN is considered as a novel generalization of neural networks as it can to take into account both data and the domain knowledge to estimate the unknown neuron functions. The initial topology of the FN can be condensed to a much simpler topology. FNs thus, eliminate the problem of neural networks being 'black boxes' by using both the domain knowledge, i.e., associative, commutative, distributive etc. and the data knowledge to derive the topology of the problem. FNs use domain knowledge to determine the structure of the network and data to estimate the unknown neuron functions. In FN, arbitrary neural functions are allowed and they are initially assumed to be multiargument and vector valued functions.

Differences between FN and ANN

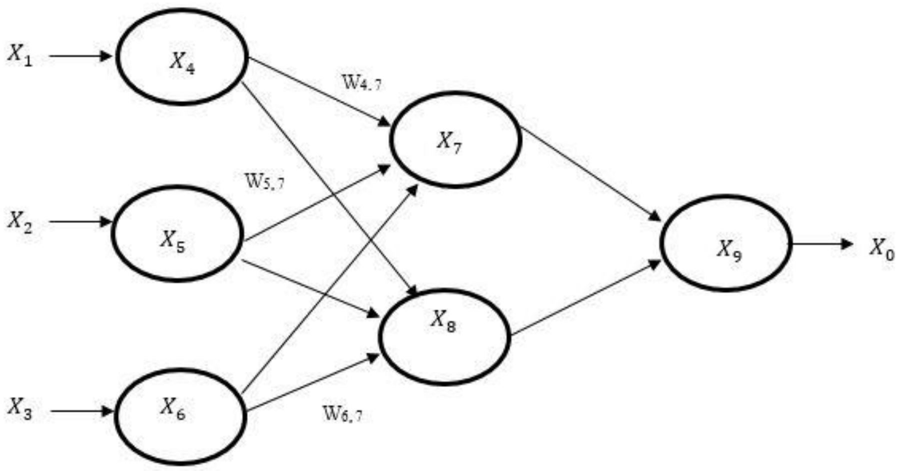
Figure 4.1 shows a typical neural network and its corresponding functional network. A FN is different from neural networks in the following respects:

1. In FN, the selection of topology is based upon both the data and the domain knowledge or a combination of the two, whereas, for neural networks, only the data is used.

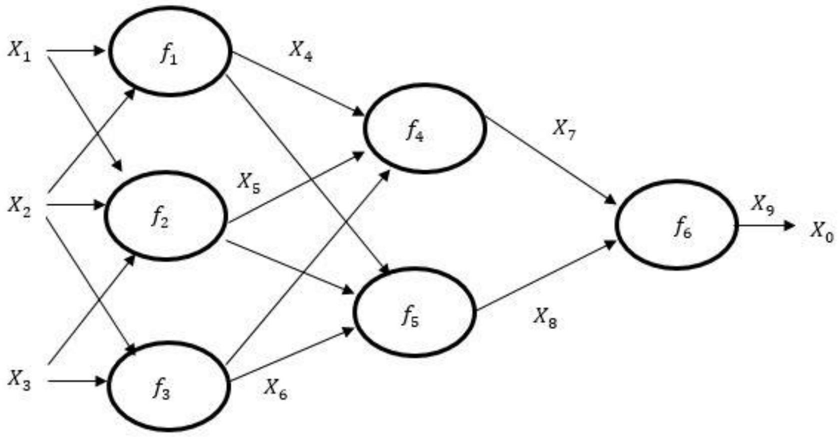
2. In FN, there are two types of learning. First, the functions are learned and this process is called as structural learning and then the function values are estimated and this process is called as parametric learning, on the other hand, neural networks, the neuron functions are assumed to be fixed and known and only the weights are learned.

3. FN can use arbitrary multiargument and vector valued functions, whereas in neural networks they are fixed sigmoidal functions.

4. In FN, several neuron outputs can be connected to the same unit by introduction of intermediate layers. This is not possible in neural networks.



(a) A neural network



(b) Functional network equivalent to the neural network in Figure 4.1 (a).

Figure 4.1: A neural network and its equivalent functional network

Working with Functional Networks

Figure 4.1 (b) shows the main elements generally encountered in every FN. They can be enumerated as:

1. Storing Units

- One layer each of input storing units and output storing units for the input data and output data respectively. For example, in Figure 4.1 (b), $x_1, x_2, x_3,$ etc. are the inputs and $f_4, f_{5.}$ are the outputs. In addition, there may be one or many layers of processing units which process inputs from the previous layer and feeds the output to the next layer, e.g. f_6 in Figure 4.1 (b).
- Intermediate storing units which contain intermediate information produced by neurons (X_4, X_5 in Figure 4.1 (b)).

2. Directed links to connect various input, output and intermediate units in accordance with the advance of the algorithm of FN.

Following are the steps required to work with functional networks:

Step 1: The physical relationship between input and output is determined.

Step 2: The initial topology of the FN is selected based on the data available in the problem. This selection of topology is done on the basis of properties and leads to selection of a single network structure. This is different to neural networks, where the topology is selected by a trial and error method.

Step 3: The network achieved in Step 2 is further is simplified using functional equations. Simpler networks which can produce the same output for the given set of inputs are searched for any given functional network. Two such complex and simpler networks are called as equivalent functional networks. This is the process of structural learning.

Step 4: For a given topology, a unique neuron function is determined that produces a set of output.

Step 5: data is collected for learning of the network.

Step 6: The data obtained in Step 5 in addition to combination of given functional families is used to estimate neuron functions. The learning may be linear or non-linear based on the linearity of the neuron functions obtained.

Step 7: The obtained model is checked for errors and cross validated against a different set of data. The learning method of a functional network consists of obtaining the neural functions based on a set of data $U = \{I_i, O_i\}, \{i = 1,2,3,4 \ldots., n\}$. The learning process is based on minimizing the Euclidean norm of the error function, given by

$$E = \frac{1}{2}\sum_{i=1}^{n}(O_i - F(i))^2 \tag{4.1}$$

The approximate neural function $f_i(x)$ may be arranged as

$$f_i(x) = \sum_{j=1}^{m} a_{ij}\emptyset_{ij}(X) \tag{4.2}$$

Where $\emptyset$ = shape functions with algebraic expressions $(1, x, x^2, x^3 \ldots x^n)$, trigonometric functions such as $[1, sin(x), cos(x), sin(2x), cos(2x), sin(3x), cos(3x)]$, or exponential functions such as $(1, e^x, e^{2x}, \ldots.., e^{nx})$. The associative optimization function may lead to a system of linear or nonlinear algebraic equations.

The knowledge of functional equations is essential while dealing with functional networks. A Functional equation is an equation in which the unknowns are functions, excluding differential and integral equations. The most common example of functional equation is the Cauchy's functional equation:

$$f(x+y) = f(x) + f(y) \;;\; x, y \in R \tag{4.3}$$

Associativity Functional Network

This paper applies the use of associativity FNs. In general, with the use of the basic theory of functional equations, any multi-input network can be transformed to an associative network (Castillo and Ruiz-Cobo 1992, Castillo et al. 2000b).

With two inputs $x_1$and x_2 and an output, x_3, we can obtain an associative FN as follows:

$$f_s(x_s) = \sum_{i=1}^{m} a_{si}\phi_{si} \tag{4.4}$$

Where, s= number of inputs, ϕ_{si}, can be polynomial, trigonometric, exponential or any acceptable function and is called as shape function and m is the degree of functions used. The function f_3 can be expressed as:

$$f_3(x_3) = \sum_{i=1}^{m} a_{3i}\phi_{3i} \tag{4.5}$$

From the input functions, it follows that,

$$f_3(x_3) = f_1(x_1) + f_2(x_2) \tag{4.6}$$

Thus, the error in the j^{th} data is given by,

$$e_j = f_1(x_1) + f_2(x_2) - f_3(x_3) \tag{4.7}$$

To estimate the coefficients, $a_i, i = 1,2,3, \ldots\ldots m$, the sum of squared errors can be minimized as:

$$E = \sum_{j=1}^{n}\left(\sum_{i=1}^{m} a_i[\phi_i(x_{1j}) + (\phi_i(x_{2j}) - \phi_i(x_{3j})]\right)^{2`} \tag{4.11}$$

Subject to, $f(x_0) = \sum_{i=1}^{m} a_i \phi_i(x_0) = \alpha$ (4.8)

where α is a real constant.

An auxiliary function, using the Lagrangian multiplier technique can be built as:

$$E_\lambda = \sum_{j=1}^{n}\left(\sum_{i=1}^{m} a_i b_{ij}\right)^2 + \lambda\left(\sum_{i=1}^{m} a_i \phi_i(x_0) - \alpha\right), \tag{4.9}$$

where, $b_{ij} = \phi_i(x_{1j}) + \phi_i(x_{2j}) - \phi_i(x_{3j})$ (4.10)

The minimum of equation (4.9) is found from equations (4.11) and (4.12).

$$\frac{\partial E_\lambda}{\partial a_r} = 2\sum_{j=1}^{n}\left(\sum_{i=1}^{m} a_i b_{ij}\right) b_{rj} + \lambda \phi_r(x_0) = 0; \quad r = 1,2.....m, \tag{4.11}$$

$$\frac{\partial E_\lambda}{\partial \lambda} = \sum_{i=1}^{m} a_i \phi_i(x_0) - \alpha = 0 \tag{4.12}$$

The above system of equations has $(m + 1)$ equations and $(m + 1)$ unknowns and can be solved to get the coefficients $a_i, i = 1,2,3, \dots .. m$.

$$\text{In matrix form, } \begin{pmatrix} BB^T & \phi_0 \\ \phi_0^{\ T} & 0 \end{pmatrix} \begin{pmatrix} a^T \\ \lambda \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ ' \\ ' \\ 0 \end{pmatrix} \tag{4.13}$$

Where B is the matrix of coefficients $b_{ij}$and $a = \ a_1, a_2, a_3, \dots \dots a_m$. This matrix can be written in simpler form as,

$$[B]\{u\} = \{v\} \tag{4.14}$$

Solving for unknowns for any given v, we get u and thus we get the coefficients $a = a_1, a_2, a_3, \ldots \ldots a_m$. For m=1, a can be used to write the equation,

$$f_3(x_{3i}) = f_1(x_{1i}) + f_2(x_{2i}) = a_{31} + a_{32}x_{31} or, x_{31} = \frac{[f_3(x_{31}) - a_{31}]}{a_{32}} \quad (4.15)$$

Building models with FN

In the present study, the data were normalized in the range [0, 1] for FN analysis. The FN algorithm was implemented with MATLAB (Mathwork Inc. 2005).

To develop a FN model, an appropriate BF and its associated degree is selected. The model equation is derived from the analysis of training data and then the adopted model cross validated against the testing data. Though by increase in degree the obtained results would be more accurate at the same time the complexity in the model equation also increases, hence a tradeoff needs to be made between the accuracy and the complexity of the build model.

Multivariate adaptive regression splines

Multivariate adaptive regression splines (MARS), is an adaptive regression technique used to fit the relationship between a set of input variables and a dependent variable. MARS predicts the dependent variable using a non-parametric regression technique, i.e., the MARS algorithm does not make any preassumptions about the relationship between the dependent and independent variables. The data set fed to the algorithm is entirely used to create a relation between the inputs and output with the help of a set of coefficients and basis functions (BFs). This makes MARS advantageous over other statistical techniques for problems with a greater number of variables.

MARS uses a divide and conquer strategy to determine the relation between the dependent and independent variables. This includes the division of the training data set into a number of piecewise linear segments called splines of different gradients. The end points of splines are known as knots and the piece-wise linear functions or piece-wise cubic functions between two knots is known as a BF. For simplicity, only piece-wise linear functions have been discussed here and used for the prediction model of lateral load capacity of piles.

An algorithm for MARS was developed by Friedman [22] based on the above strategy. MARS fits data through a two-step process:

i. Forward stepwise algorithm: This is the step where the BFs are added. Initially, a model is constructed only with the intercept, β_0. In each subsequent step, the BF that will produce the largest decrease in the training error is added. This process continues till a predetermined maximum number of BFs is reached. This leads to an overfitted model. An adaptive regression algorithm is used to search for knot locations among all the variables.
ii. Backward pruning algorithm: This step is applied to eliminate the overfitting of the data. In this process, the terms in the model are pruned by removing terms one by one. The least effective term is removed in each pass to achieve at the best possible sub model. Model subsets are compared using the Generalized cross-validation (GCV) technique. For a data with N samples, GCV is calculated using the equation:

$$GCV = \frac{\frac{1}{N}\sum_{i=1}^{N}[Y_i - f(X_i)]^2}{[1 - \frac{M + d(M-1)/2}{N}]^2} \tag{4.16}$$

Where, M is the number of BFs, d is the penalizing parameter, N is the number of data sets and $f(X_i)$ denotes the predicted values of the MARS model. The denominator of GCV is responsible for increasing variance in case of increasing model complexity. The term $(M-1)/2$ in the denominator represents the number of knots. Thus, GCV penalizes BFs as well as knots.

To understand MARS better, consider a data set with y as an output and $X = \{X_1, X_2, X_3, \dots, X_p\}$ as an input matrix containing p variables. A model generated by MARS would be of the form,

$$y = f\left(X_1, X_2, X_3, \dots, X_p\right) + e = f(X) + e \tag{4.17}$$

Where, e is the distribution of error. The function $f(x)$ is approximated using BFs which may be piece-wise linear or piece-wise cubic functions. For simplicity, only piece-wise linear functions are discussed here. A piece-wise linear function is of the form $\max(0, x - t)$ where t is the location of a knot. It is defined as,

$$\max(0, x - t) = \{x - t, if\ x > t\ or, 0\ otherwise\} \tag{4.18}$$

Finally, $f(x)$is defined as a linear combination of BFs and their interactions and is expressed as

$$f(X) = \beta_0 + \sum_{i=1}^{M} \beta_m \lambda_m (X) \tag{4.19}$$

Where, each $\lambda_m$is a BF which can be a spline or a product of two or more splines. The coefficients β are constants estimated using the least squares method.

Building models with MARS

In the present study, the data were normalized in the range [0, 1] for MARS analysis. The MARS (Jekabsons 2010) algorithm has been implemented with MATLAB (Mathwork Inc. 2005).

The complexity and accuracy of a MARS model adopted for any particular problem depends upon the number of BF allowed in the forward phase and the maximum number of BF allowed in the final result. An increase in the number of BF allowed in the final result generally leads to a more accurate model. However, a MARS model with more number of BF is also a more complex solution and leads to a lengthy model equation. Hence, a tradeoff needs to be made between accuracy and complexity.

It is worth mentioning here that prediction equations ontained from FN and MARS modelling can be used to predict the results for a new set of data, provided all the inputs for new set lie within the maximum and minimum range of inputs used to build the model.

CHAPTER FIVE

PREDICTION OF LATERAL LOAD CAPACITY OF PILES IN CLAY

Pile foundations are frequently subjected to lateral loads due to earth pressure, earthquake, wave or wind forces in different structures along with axial load. However, very few methods are available to calculate the lateral load capacity of piles. Some equations were proposed by Poulos and Davis (1980), Matlock and Reese (1962) and Portugal and Seco e Pinto (1993) but were found to have uncertainty in predictions due to the variations in soil properties. The most widely used empirical relations are proposed by Hansen (1961) and Broms (1964a, b) but the value proposed by them are not an accurate match to the actual values encountered in field.

The present chapter is an attempt to develop prediction models for lateral load capacity of piles in clay using FN and MARS. Different statistical criteria like correlation coefficient (R), Nash-Sutcliff coefficient of efficiency (E) (Das and Basudhar 2008), absolute average error (AAE), maximum absolute error (MAE) and root mean square error (RMSE) are used to compare the MARS and FN models with ANN (DENN, BRNN) models and existing empirical models, Broms(1964a,b) and Hansen (1961). A ranking system (Abu-Farsakh and Titi 2004) using rank index (RI) has also been followed to compare the different models based on four criteria: (i) the best fitness calculations (R and E) for predicted lateral load capacity (Qp) and measured lateral load capacity (Qm), (ii) arithmetic calculations (mean, μ and standard deviation, σ) of the ratio, Qp/Qm (iii) 50% and 90% cumulative probabilities (P_{50} and P_{90}) of the ratio, Qp/Qm. and (iv) the probability of pile load capacity within 20% accuracy level in percentage using histogram and lognormal probability distribution of Qp/Qm.

Database

In the present study the database of Das and Basudhar (2008) has been considered. Das and Basudhar (2008) have developed an ANN model with this data. Each sample has four inputs viz. diameter of pile (D), length of pile (L), eccentricity of load (e), and undrained shear strength of soil (S_u) and one output, measured lateral load capacity (Q_m). The statistical parameters for the inputs and output are shown in Table 5.1.

Table 5.1: Maximum and minimum values of the data used for prediction of lateral load of piles

Input	D (mm)	L (mm)	E (mm)	S_u (kPa)	Q_m (N)
Maximum	33.3	300	50	38.8	225
Minimum	6.35	130	0	3.4	29.5
Mean	17.8	278.9	44.2	9.9	72.8
Standard Deviation	6.1	52.8	14.7	10.1	36.9
Range	26.95	170	50	35.4	195.5

Summary

In this chapter, an attempt has been made to develop prediction models for the lateral load capacity of piles in clay using two recently developed statistical modelling methods; MARS and FN. Based on the results of MARS and FN models and the discussion that follows, the following conclusions can be drawn:

(a) the performance of MARS and FN is better than other AI techniques such as ANN and empirical methods like Hansen and Broms.

(b) According to RI, FN is the best prediction technique followed by MARS, ANN, Broms and Hansen.

(c) For the MARS model, S_u is the most important input whereas, for FN model, L is the most important input.

(d) Prediction Model equations for both MARS and FN are given, which can be used by practicing geotechnical engineers to predict the lateral load capacity of pile in clay.

CHAPTER SIX

VERTICAL CAPACITY OF PILES IN COHESIONLESS SOIL

Piles as deep foundations are of paramount importance in civil engineering due to their wide use in various structures to transfer load either to higher depths when sufficient support is not available at shallow depths or the load is high. Thus, the design of pile foundation has attracted many researchers and various equations are available to calculate the load bearing capacity of piles in different soil conditions. However, due to the uncertainty associated with the interaction between the pile and the surrounding soil, most of these equations do not produce consistent equations and/or are not accurate. Hence, the design process of pile foundation is not yet entirely comprehensible and there is a lack of equation that can be universally applied to all soil conditions with surety.

Consequently, the present chapter is an attempt to develop prediction models for vertical capacity of piles in cohesionless soil using MARS and FN. Different statistical criteria like correlation coefficient (R), absolute average error (AAE), maximum absolute error (MAE), root mean square error (RMSE) and normalized mean bias error (NMBE) are used to compare the MARS and FN models with the works done in previous literature.

Database

In the present study, the database of Abu-Keifa (1998) has been considered which contains 59 load test records compiled by Darrag (1987) for driven piles in sand. Each sample has five inputs viz. cross sectional area of pile (D), length of pile (L), effective overburden pressure (σ_v') at the tip of the pile, and the angle of shear resistance at the shaft ($\emptyset_{shaft}$) and at the tip ($\emptyset_{tip}$) of the pile with one output, total pile capacity (Q_{total}). The statistical parameters for the inputs and output are shown in Table 6.1.

Table 6.1: statistical parameters for the inputs and output for vertical capacity of piles in cohesionless soil

	$\emptyset_{shaft}$	$\emptyset_{tip}$	σ_v' (kN/m^2)	L(m)	A(m^2)	Q_{total} (kN)
Maximum	39	41	475	47.2	0.6568	5604
Minimum	28	31	38	3	0.0061	75
Mean	34.87288	36.40678	179.7966	17.49322	0.134407	2207.627
Standard deviation	2.1125	2.090079	81.68994	7.89681	0.102209	1221.407
Range	11	10	437	44.2	0.6507	5529

Summary

This chapter dealt with development of prediction models for load-bearing capacity of piles in cohensionless soil using two recently developed statistical modelling methods; MARS and FN. The prediction models based upon the results from MARS and FN models were also provided. Based on the results of MARS and FN models and the discussion that follows, the following can be concluded:

- Based on a comparison of correlation coefficients, the performance of MARS and FN is better than GRNN.
- In terms of the values of MAE, AAE, RMSE and NMBE, a FN model with higher degree was found to best. GRNN model was found to be better than the MARS model and a FN model with low degree in terms MAE, AAE, RMSE and NMBE.
- Based on the trade-off between the accuracy of the model and the complexity of the model equation, the MARS and FN can be argued to be better prediction techniques as

they produce simpler model equations with fairly accurate results in comparison with GRNN where the model equations are complex and difficult to comprehend.

CHAPTER SEVEN

FRICTION CAPACITY OF DRIVEN PILES IN CLAY

Friction capacity of piles in clay is an important factor that profoundly affects the ultimate load carrying capacity of the piles. But, there is a lack of comprehensible and accurate formula to calculate the friction capacity of piles. Goh (1995) used artificial neural network for the prediction of the friction capacity of piles. However, no prediction equation was provided to calculate friction capacity for a new data set.

Consequently, in the present chapter, FN and MARS have been used to develop prediction models for friction capacity of piles driven in clay. The results obtained in the present study are compared with prediction models developed using neural networks (Goh 1995) in previous studies available in literature and other available methods, β method (Burland 1973) and method of Semple and Ridgen (1986). Prediction equations to calculate the friction capacity based upon the developed FN and MARS method have also been provided.

Database

The database available in Goh (1995) was used to develop prediction models for the friction capacity of pile. The database were compiled from load test records available in Vijayvergiya and Focht (1972), Flaate and Selnes (1977) and Semple and Ridgen (1986) for driven piles in clay. The driven piles result available in Flaate and Selnes (1977) were mainly related to timber piles while driven piles result available in other sources related mainly to steel pipe piles. The friction capacity (f_s) present in the database was calculated using compression load tests on pile after allowing for end bearing where the unit end bearing was assumed to be equal to 9*s_u at the tip of the pile. The determination of undrained shear strength, s_u was done using unconfined compression tests. However, for very soft and soft clays, s_u was calculated using vane shear test.

Pile length (L), pile diameter (D), mean effective stress (σ_v') and the undrained shear strength (s_u) were used as the inputs to develop the FN and MARS models. The friction capacity of piles (f_s) was the model output. The statistical parameters for the inputs and output are shown in Table 7.1.

Table 7.1: Statistical parameters for the inputs and output to predict friction capacity of piles

	L(m)	D(cm)	σ_v'(kPa)	s_u (kPa)	f_s (kPa)
Maximum	96	76.7	718	335	192.1
Minimum	4.6	11.4	19	9	8
Mean	21.55385	31.45231	124.4092	62.16308	40.84769
Standard deviation	16.24329	16.47713	126.8554	59.56669	36.23642
Range	91.4	65.3	699	326	184.1

Summary

The present chapter dealt with development of prediction models for friction capacity of driven piles in clay using FN and MARS techniques. The database used by Goh (1995) was used to develop the prediction models. The results obtained from the present study were compared with results obtained previously in literature using BPNN and previous methods available to calculate the friction capacity of piles in terms of statistical parameters and values of AAE, MAE and RMSE. Based on the comparison, it was found that the FN and MARS techniques are better prediction tools for friction capacity of piles. Prediction equations for the FN and MARS models were provided which can be used by the practicing geotechnical engineers.

CHAPTER EIGHT

AXIAL CAPACITY OF PILES

As discussed earlier in the text, a number of methods are already available for the calculation of axial capacity of the piles. However, most of these methods are either empirical or semi-empirical, rendering them unable to produce consistent and accurate values of the axial capacity of piles. The previous experience in design of pile foundations has shown that the methods that correlate the CPT data with the axial capacity of piles produce comparatively better results. This is due to the fact that the CPT results generally provide a clear view of the soil properties which reflect in the determination of the pile capacity. However, a comparison of the available CPT based methods suggests that the results obtained from them are neither consistent nor accurate. Therefore, there is a need to develop alternative prediction models based on CPT data which are able to produce more accurate results consistently.

Consequently, in the present chapter, FN and MARS have been used to develop prediction models for axial capacity of piles. Four models were developed based upon the data set present in Alkroosh and Nikraz (2011). One models each were developed for the bored piles, driven steel piles and driven concrete piles. A model was also developed combined for the driven piles, both steel and concrete.

Database

This study uses data set present in Alkroosh and Nikraz (2011) to develop the prediction models for axial capacity of piles. The data set was generated based upon results obtained from 50 bored pile load tests and 58 driven pile load tests (30 steel pile load tests and 28 concrete pile load tests) as well as the related CPT data. For the bored piles, four factors influencing pile capacity are considered as input for the FN and MARS model. They are:

1. pile diameter (D)
2. pile embedment length (L)
3. weighted average cone point resistance over pile tip failure zone (q_{c-tip})
4. weighted average cone point resistance along pile shaft ($q_{c-shaft}$)

The interpreted failure load, Q_u is the output of the model. The statistical parameters for the inputs and output for the bored piles are shown in Table 8. 1.

Table 8. 1: Statistical parameters for the inputs and output for the bored piles

	D(mm)	L(m)	q_{c-tip} (MPa)	$q_{c-shaft}$ (MPa)	Q_u (kN)
Maximum	1800	27	47.9	20.1	9653
Minimum	320	5.6	1.6	1.4	356
Mean	606.22	10.714	17.614	8.83	2215.2
Standard Deviation	334.11	5.13	10.12	4.51	2402.63
Range	1480	21.4	46.3	18.7	9297

For the driven Piles, five factors influencing pile capacity are considered as input for the FN and MARS model. They are:

1. equivalent pile diameter (Deq)
2. pile embedment length (L)
3. weighted average cone point resistance over pile tip failure zone (q_{c-tip})
4. weighted average sleeve friction over shaft length (f_s)
5. weighted average cone point resistance along pile shaft ($q_{c-shaft}$)

The interpreted failure load, Q_u is the output of the model. The statistical parameters for the inputs and output for the driven piles are shown in Table 8. 2 and Table 8. 3.

Table 8. 2: Statistical parameters for the inputs and output for the driven steel piles

	D(mm)	L(m)	q_{c-tip} (MPa)	f_s (kPa)	$q_{c-shaft}$ (MPa)	Q_u (kN)
Maximum	660	36.3	23.9	131	17.6	4460
Minimum	273	8.5	0	18	1.4	490
Mean	398.6	18.11333	6.516667	54.76667	9.283333	1560.9
Standard Deviation	101.7102	8.039392	7.632391	23.20443	5.681554	1137.054
Range	387	27.8	23.9	113	16.2	3970

Table 8. 3: Statistical parameters for the inputs and output for the driven concrete pile

	D(mm)	L(m)	q_{c-tip} (MPa)	f_s (kPa)	$q_{c-shaft}$ (MPa)	Q_u (kN)
Maximum	625	25.8	18.6	205	15.7	5455
Minimum	250	8	1.1	25	2.5	600
Mean	402.1429	13.27321	7.360714	81.21429	6.207143	1529.286
Standard Deviation	88.25115	4.180385	3.464137	49.65694	3.168926	1093.436
Range	375	17.8	17.5	180	13.2	4855

Summary

The present chapter dealt with the development of prediction models for axial capacity of piles using FN and MARS techniques. The database from Alkroosh and Nikraz (2011) was used to develop separate models for the bored piles, driven steel piles and driven concrete piles and a combined model for the driven piles, both steel and concrete. The results obtained from the present study were compared with results obtained previously in literature using GEP in terms of statistical parameters. Based on the results of the statistical parameters for the developed models, it was inferred that MARS has a better prediction capability for the prediction of the axial capacity of piles. It was also noticed that the FN and MARS techniques are better at prediction than the GEP technique. Prediction equations for the FN and MARS models were provided which can be used by the practicing geotechnical engineers.

CHAPTER NINE

PULLOUT CAPACITY OF GROUND ANCHOR

The structural stability of marquees depends on the pullout capacity of the anchors which transfer the tensile forces from the structures to the surrounding soil, thus resisting these forces by through the shear resistance of the soil. These anchors, less than one meter in length, may have different shapes and diameters and are traditionally made up of steel. They can be driven into ground by different installation techniques e.g. using a sledge hammer or using a hydraulic ram combined with a drilling rig. The length of the anchor embedment, diameter and surface roughness of anchor, properties of the soil in which the anchor is placed and the technique used for the installation of the anchor are some of the factors that affect the pullout capacity of ground anchors. Most of the equation available to calculate the pullout capacity of ground anchors are based on these factors. However, the most of the present methods apply also to the axial capacity of single piles, and the methods available for marquee anchors are very rudimentary. Nevertheless, the available single pile methods can be reasonably expected to apply equally to marquee anchors as such ground anchors are effectively micro-piles - the two are thus analogous, only the scale being different. The available methods to calculate the pullout capacity of ground anchors have been found to be inexact and incomplete.

Consequently, in the present chapter, FN and MARS have been used to develop prediction models for pullout capacity of ground anchors. The results obtained in the present study are compared with prediction models developed using GP (Senapati 2013) and ANN (Shahin and Jaska 2005) in previous studies available in literature. Ranking of FN, MARS, GP and ANN has also been done in accordance with the ranking system developed by Abu-Farsakh and Titi (2004).

Database

The data set used by Shahin and Jaska (2005) to develop ANN model for prediction of pullout capacity of ground anchor was used in the present study. ANN model for prediction of pullout capacity of ground anchors was based on a data set based upon results obtained from carrying out 119 in situ pullout tests on rough mild steel anchors can be found in Shahin and Jaksa (2003). The tests covered a wide range of geotechnical conditions and soil types e.g. river deposited slit and sand, clay gravel, fine grained sand, medium grained sand, very expansive black earth clay and hard and hard and dry red brown clay and thus included both cohesive and cohesionless soils. Different shapes of anchors including circular, hexagonal and star dropper were used and these anchors were embedded vertically in the ground at various embedment depths (400, 600 and 800 mm). Anchors were driven into ground by different installation techniques, viz., using a sledge hammer or using a hydraulic ram combined with a drilling rig. Five variables, including the anchor equivalent diameter (D_{eq}), embedment length (L), average cone tip resistance (q_{c-tip}) along the embedment length, average sleeve friction (f_s) along the embedment length and the installation technique were used as the inputs. Static installation was assigned a value of 1 and dynamic installation was assigned a value of 2. The ultimate pullout capacity (Q_u) was used as the input. The statistical parameters for the inputs and output are shown in Table 9.1.

Table 9.1: Statistical parameters for the inputs and output to predict pullout capacity of ground anchors

	D_{eq} (mm)	L(mm)	q_{c-tip} (MPa)	f_s (kPa)	Installation technique	Q_u (kN)
Maximum	44.60	800.00	3.55	179.71	2.00	3.80
Minimum	25.00	400.00	0.95	12.22	1.00	0.29
Average	30.81	579.83	1.93	57.59	1.59	1.75

Standard deviation	7.68	119.93	0.57	40.28	0.49	0.77
Range	19.60	400.00	2.60	167.49	1.00	3.51

Summary

The present chapter dealt with development of prediction models for pullout capacity of ground anchors using FN and MARS techniques. The database used by Shahin and Jaska (2005) based upon the experimental results available in Shahin and Jaska (2003) was used to develop prediction model. The results obtained from the present study were compared with results obtained previously in literature using GP and ANN in terms of statistical parameters. FN and MARS were also compared with GP and ANN in terms of their prediction performance by means of ranking system. Based on the statistical parameters, it was found that the FN and MARS techniques are a better prediction tool for pullout capacity of ground anchors. Also, based upon the ranking system, it was found that FN had the best performance followed by MARS, GP and ANN. Prediction equations for the FN and MARS models were provided which can be used by the practicing geotechnical engineers.

CHAPTER TEN

DEVELOPMENT OF STANDALONE APPLICATION

As discussed in the earlier chapters, prediction equations have been provided for the FN and MARS prediction models developed in this study. These equation are comprehensible and can easily be used by the practicing geotechnical engineers to calculate different pile capacity parameters. To facilitate the users interested in using the equations provided in this study, a need was felt to provide a standalone application that can be run on any computer by the user without delving deep into the intricacies of the equations. Keeping in mind this fact, a standalone application has also been developed as a part of this work which can be run on any computer equipped with windows operating system. The user just needs to enter the value of the required inputs to get the desired output. It was tried to keep the application as informative as possible at every step and an example run is shown through use of screenshots later in this chapter.

The source code of the application was written in Python programming language. Python is a high level programming language widely used across many fields for its simplicity. Python was chosen as the programming language for writing the source code for its ease of readability of code and maximum information can be included in less number of lines of code. The functionality in the present study was mainly concerned with mathematics and printing instructions. Python includes these functionalities in a simple to way.

Summary

The present chapter dealt with development of a standalone application to calculate the pile capacity parameters if the required inputs are available to the user. The developed application is interactive and provides adequate information at each step.

CHAPTER ELEVEN

CONCLUSIONS AND FUTUTRE SCOPE

Conclusion

The present study was an attempt to develop prediction models for the pile capacity parameters using two recently developed AI techniques, FN and MARS. Prediction models were developed to calculate the lateral load capacity of piles, vertical capacity of driven piles in cohesionless soil, friction capacity of piles in clay, axial capacity of piles and pullout capacity of ground anchors. The results obtained from the FN and MARS models were compared with other AI techniques previously used in the literature based upon statistical criteria like R, E, AAE, MAE and RMSE. Ranking system was also followed in some cases to assess the performance of the models. Based on the results obtained in the previous chapters and related discussions, the following conclusions can be drawn:

- For the prediction of lateral load capacity of piles, according to comparison done on the basis of statistical parameters (R, E, MAE, AAE, RMSE) and properties of $Q_p\ /Q_m$ (μ, σ, cumulative distribution, log-normal distribution), MARS and FN models were found to be better than other AI techniques like DENN and BRNN and empirical methods like Hansen and Broms. Based on the rank index technique also, FN was found to be the best model followed by MARS, DENN, BRNN, Broms and Hansen.
- For the prediction of vertical capacity of driven piles in cohesionless soil, based upon comparison of R, the performance of MARS and FN was better than GRNN. GRNN was found to better in terms of error parameters but the prediction equations derived from FN and MARS model were much simpler and comprehensible as compared to prediction equation derived from GRNN. Thus, FN and MARS would be more easier to use as a prediction tool

- For prediction of friction capacity of driven piles in clay, FN and MARS were found to better than ANN in terms of statistical parameters and values of AAE, MAE and RMSE.
- For prediction of axial capacity of piles, FN and MARS were found to better than GEP in terms of statistical parameters.
- For prediction of pullout capacity of ground anchors, FN and MARS were found to better than GP and ANN in terms of statistical parameters. Also, based upon the ranking system, it was found that FN had the best performance followed by MARS, GP and ANN.
- Model equations for both MARS and FN are given, which can be used by practicing geotechnical engineers to predict the required pile capacity parameters when the appropriate input data are available.
- A standalone application was developed to facilitate the calculation of pile capacity parameters using the provided model equation.

Scope of future work

The MARS and FN models developed in this study were based upon the results obtained from experiments done on scaled models in laboratory. The prediction equations provided work best when the input data entered lies within the range of inputs used to build the models. The range of the inputs pertaining to actual field data usage may not always lie within the input range used in this study. Therefore, appropriate dimensional analysis and scaling effects have to be taken into consideration to apply the results in actual field practice. The equations presented in this study can be modified so that they can be applied directly to the field studies.

References

Abu-Farsakh, M. Y., Titi, H.H., 2004. Assessment of direct cone penetration test methods for predicting the ultimate capacity of friction driven piles. J. Geotech. Geoenv Engg., 130 (9), 935–944.

Abu-Kiefa, M.A., 1998. General regression neural networks for driven piles in cohesionless soils. J. Geotech. Geoenv Engg., ASCE , 124, (12), 1177–1185.

Alkroosh I. and Nikraz H., 2013. Evaluation of Pile Lateral Capacity in Clay Applying Evolutionary Approach. Int. J. of GEOMATE, 4(1), 462-465.

Attoh-Okine N.O., 2005. Modeling incremental pavement roughness using functional network, (2005). Can. J. Civ. Eng.32, 899–905.

Broms, B.B., 1964a. Lateral resistance of piles in cohesive soils. J. Soil Mech. Found Engg., ASCE, 90 (SM. 2), 27–63.

Broms, B.B., 1964b. Lateral resistance of piles in cohesionless soils. Journal of Geotechnical Engineering, 90, 123-156.

Burland, J.B. 1961. Shaft friction of piles in clay- a simple fundamental approach. Ground Engg., 6(3), 1-15

Castillo, E., 1998. Functional Networks. Neural Processing Letter, 7, 151–159.

Castillo, E., and Ruiz-Cobo, R. 1992. Functional Equations in Science and Engineering, New York: Marcel Dekker.

Castillo, E., Cobo, A., Gomez-Nesterkin, R., Hadi, A.S., 2000b. A general framework for functional networks. Networks, 35(1), 70–82.

Castillo, E., Cobo, A., Gutierrez, J. M., and Pruneda, E., 1998. An introduction to functional networks with applications, Kluwer, Boston.

Castillo, E., Cobo, A., Gutierrez, J. M., Pruneda, R. E., 1999. Working with differential, functional and difference equations using functional networks. Applied Mathematical Modelling, 23, 89-107

Castillo, E., Cobo, A., Manuel, J., Gutierrez, J. M., and Pruneda, E., 2000a. Functional networks: A new network-based methodology, Comput. Aided Civ. Infrastruct. Eng., 15, 90–106

Chan, W.T., Chow, Y.K. and Liu, L. F., 1995. Neural network: an alternative to pile driving formulas. J. Comput Geotech, 17, 135–156.

Coduto, D. P. 1994. Foundation Design. New Jersey: Prentice-Hall Inc.

Das, S. K. and Basudhar, P. K. , 2006. Undrained lateral load capacity of piles in clay using artificial neural network. Computers and Geotechnics, 33, 454-459.

Das, S. K., Basudhar, P. K., 2008. Prediction of Residual Friction Angle of Clays Using Artifical Neural Network, Engineering Geology, 100(3-4), 142-145

Das, S.K., Biswal, R.K., Sivakugan, N., and Das, B., 2011. Classification of slopes and prediction of factor of safety using differential evolution neural networks. Environ. Earth. Sci., Springer, 64, 201–210.

Das, S.K., Sivakugan, N., 2010. Discussion of: intelligent computing for modeling axial capacity of pile foundations. Can. Geotech. J. 47, 928-930.

El-Sebakhy E. A., Faisal K.A., Helmy T., Azzedin F., Al-Suhaim A., 2006. Evaluation of Breast Cancer Tumor Classification with Unconstrained Functional Networks Classifier. *Proceeding of the 4th ACS/IEEE international conference on computer systems and applications,* 281–287.

El-Sebakhy E.A., Al-Bokhitan S.Y., 2008. Estimating PVT properties of crude oil system based on functional networks, Petroleum science and engineering.

El-Sebakhy, E.A., Asparouhov, O., Abdulraheem, A., Al-Majed, A., Wu, D., Latinski, K., Raharja, I., 2012. Functional networks as a new data mining predictive paradigm to predict permeability in a carbonate reservoir, Expert Systems with Applications, 39, 10359-10375.

Friedman, J., 1991. Multivariate adaptive regression splines. Ann. Stat. 19, 1–141.

Gandomi, A. H., Yun, G. J. and Alavi, A. H., 2013. An evolutionary approach for modeling of shear strength of RC deep beams. Materials and Structures, DOI 10.1617/s11527-013-0039-z.

Giustolisi, O., Doglioni, A., Savic, D.A., Webb, B.W., 2007. A multi-model approach to analysis of environmental phenomena. Environmental Modelling & Software, 22 (5), 674–682.

Goh, A. T. C., 1996. Pile driving records reanalyzed using neural networks. J. Geotech. Engg., ASCE, 122 (6), 492–495.

Goh, A. T. C., 1995. Empirical design in geotechnics using neural networks. Geotechnique , 45 (4), 709–714.

Hamid, M and Reza, R., 2010. The estimation of rock mass deformation modulus using regression and artificial neural networks analysis. The Arabian Journal for Science and Engineering, 35(1A), 205-217.

Hansen, B., 1961. The ultimate resistance of rigid piles against transversal force. Copenhagen, Danish Geotechnical Institute, Bulletin No. 12., 5–9.

Jekabsons G., ARESLab: Adaptive Regression Splines toolbox for Matlab/Octave, 2011, available at http://www.cs.rtu.lv/jekabsons/

Lau DS, Simmons JV. Interpretation of field tests on small-scale ground anchors. In: Specialty geomechanics symposium: interpretation of field testing for design parameters, Adelaide, Barton (IEAust); 1986. p. 85–8.

Lee, I. M and Lee, J. H., 1996. Prediction of pile bearing capacity using artificial neural networks. Comput Geotech., Vol. 18, No. 3, pp. 189–200.

Long, J., and M. Wysockey. 1999. Accuracy of Methods for Predicting Axial Capacity of Deep Foundations. Geotechnical Special Publication, 88: 181-195

MathWork Inc., 2005. Matlab User's Manual, Version 6.5. Natick (MA).

Matlock, H. and Reese, L. C., 1962. Generalized solutions for laterally loaded piles. Trans ASCE, 127, 1220–48.

Muduli, P.K., Das, M.R., Samui, P., Das, S.K. (2013). Uplift Capacity of Suction Caisson in Clay Using Artificial Intelligence Techniques. Marine Georesources & Geotechnology, 31:4, 375-390

Pal, M. and Deswal, S., 2010. Modelling pile capacity using Gaussian process regression. Computers and Geotechnics, 37, 942-947.

Portugal, J. C. and Seco e Pinto, P. S., 1993. Analysis and design of pile under lateral loads. Proceedings of the 11th international geotechnical seminar on deep foundation on bored and auger piles, Belgium, 309–313.

Poulos, H. G. and Davis, E. H., 1980. Pile foundation analysis and design, New York: Wiley.

Rajasekaran, S. (2004) Functional Networks in Structural Engineering. J. Comput. Civ. Eng. 2004.18:172-181

Rao K.M., Suresh Kumar V., 1996. Measured and predicted response of laterally loaded piles. In: Proceedings of the sixth international conference and exhibition on piling and deep foundations, India, 1.6.1–1.6.7

Rezania, M., Javadi, A., 2007. A new genetic programming model for predicting settlement of shallow foundations. Can. Geotech. J. 44, 1462 1472.

Samui, P., 2008. Prediction of friction capacity of driven piles in clay using the support vector machine**.** Canadian Geotechnical Journal, 45 (2), 288-295.

Samui, P., Das. S, and Kim , D., 2011. Uplift capacity of suction caisson in clay using multivariate adaptive regression spline. Ocean Engineering, 38, (17–18), 2123-2127.

Semple, R.M., Rigden, W.J., 1986. Shaft capacity of driven pipe piles in clay. Ground Engg., 19(1), 11-17

Senapati, S., 2013. MODELLING OF GEOTECHNICAL STRUCTURES USING MULTIVARIATE ADAPTIVE REGRESSION SPLINE (MARS) AND GENETIC PROGRAMMING (GP), M.Tech. Thesis, National Institute of Technology, Rourkela, India.

Shahin MA, Jaksa MB. Modelling the pullout capacity of marquee ground anchors. Research Report No. R174, School of Civil and Environmental Engineering, The University of Adelaide, Adelaide; 2003.

Tarawneh, B. and Imam, R., 2014. Regression versus Artificial Neural Networks: Predicting Pile Setup from Empirical Data, KSCE Journal of Civil Engineering, 18(4), 1018-1027.

Teh , C.I., Wong, K. S., Goh, A. T. C., Jaritngam, S., 1997. Prediction of pile capacity using neural networks. J. Computing in Civil Engg., ASCE, 11 (2), 129–138