Soil Profile Prediction Using Artificial Neural Networks in Sudan

A thesis submitted in partial requirement for the M.Sc. degree in Structural Engineering to the Civil Engineering Department
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Abstract

Artificial Neural Networks (ANNs) are a form of Artificial Intelligence, which are mathematical models, inspired from the brains of certain information-processing characteristics, producing meaningful solutions, which fall beyond the reach of conventional digital computers.

In recent years, the use of ANNs has increased in many areas of engineering. In particular, ANNs have been applied to many geotechnical engineering problems and have demonstrated some degree of success.

In this study,ANNs are used for soil classification prediction in a specified locations at different depths, based on the available site investigation data from a specific area in Sudan.

Regarding the large number of the data and considerable variations in soil layers in Sudan, hundred of boreholes were selected for this study . Seven Networks are developed to predict the soil layering in specified locations in Khartoum city.In this study ,area of about 165 square kilometers of Khartoum concentrating on Blue Nile region is considered and the results are then compared with data of actual boreholes to check the ANN model's validity .

The results indicate that Artificial Neural Networks are a useful technique for predicting relationships between the input parameters of the three dimensional coordinates and the resulting soil classification and soil parameters output. So, Artificial Neural Networks can be considered as an effective tool for predicting the soil classification in Khartoum.

ملخص البحث

الشبكات العصبية الصناعية هى شكل من اشكال الذكاء الصناعي ،و التى تمثل نماذج رياضية مستوحاة من خصائص معالج المعلومات للدماغ البشري والتي تنتج حلولاً ذات معنى تفوق امكانيات الحاسبات الرقمية التقليدية .

فى الاعوام الاخيره ، كثر استعمال الشبكات العصبية الصناعية فى عدد من النواحى الهندسية . وبصفة خاصة تم تطبيقها فى كثير من فروع الهندسة الجيوتقنية ، وقد حققت درجة مقبولة من النجاح.

في هذه الدراسة ، تم استخدام الشبكات العصبية الصناعية لتخمين تصنيف وخصائص التربة في مناطق محددة واعماق مختلفة على اساس بيانات فحص المواقع المتوفرة لتلك المناطق في السودان .

مع الأخذ فى الاعتبار الكمية الكبيرة من البيانات والتباين المقدر فى طبقات التربة فى السودان ، تم اختيار مئات المواقع لهذه الدراسة لانشاء سبع شبكات تنبؤ لتخمين تصنيف وخصائص التربة في مساحة ١٦٥كيلومتر تقريبا من العاصمة الخرطوم بالتركيز على شريط النيل الازرق.وتمت مقارنة النتائج المستخلصة من شبكات التنبؤ بالبيانات الفعلية لمواقع لم يتم تعريفها في شبكات التنبؤ للتحقق من كفاءة تلك الشبكات .

النتائج تشير الى ان الشبكات العصبية الصناعية تعتبر تقنية مفيدة لاقامة علاقات بين الاحداثيات الكارتيزية ثلاثية الابعاد لاي موقع وتصنيف وخصائص التربة في المنطقة موضوع الدراسة . لذلك يمكن اعتبارشبكات التنبؤ المنشأة ادوات فعالة لتخمين نوع وخصائص التربة فى الخرطوم.

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<u>Contents</u>

List of Figures

List of Tables

Page No.

List of Symbols and Abbreviations

Symbol or Abbreviation	Description	Units (if any)
ANN	Artificial Neural Network	
C_u	The Uniformity coefficient	
C_z	The coefficient of curvature	
D_{10}	The effective size “The diameter of the particle corresponding to 10% on the particle size-plot”.	mm.
D_{60}	The diameter of the particle corresponding to 60% on the particle size-plot.	mm.
D_{30}	The diameter of the particle corresponding to 30% on the particle size-plot.	mm.
I_P or P.I.	Plasticity Index .	
W_L or L.L.	Liquid Limit .	
Wp or P.L.	Plastic Limit .	
I_L	Liquidity Index .	
F	Percentage passing No.200 sieve expressed as whole number.	
SW	Well-graded sand or gravelly sand .	
SP	Poorly-graded sand or gravelly sand .	
SM	Silty sands ,sand-silt mixture .	
SC	Clayey sand ,sand-clay mixture.	
ML	In-organic silts ,silty or clayey fine sands.	
CL	In-organic clays ,sandy clays ,silty clays.	
MH	In-organic silts of high plasticity ,elastic silts .	
CH	In-organic clays of high plasticity ,fat clays .	
C	Cohesion contributing to the shear strength of a soil .	KN/m^2
Φ	The angle of internal friction of a soil .	Degrees
N.M.C.	Natural Moisture Content .	
γ_b	Bulk density of a soil .	KN/ m^3
N-value	Standard Penetration Test value at a layer .	
B.R.R.I.	Building and Road Research Institute .	
U.of K.	University of Khartoum .	
G.P.S.	Global Positioning System .	
USCS	Unified Soil Classification System.	

List of Appendices

Chapter One

Introduction

Chapter One
Introduction

1.1 General:

Over the past three decades, there has been an increased interest in a new class of computational intelligence systems known as Artificial Neural Networks (ANNs). This type of networks (i.e., ANNs) have been found to be powerful and versatile computational tools for organizing and correlating information in ways that have proved useful for solving certain types of problems too complex, too poorly understood, or too resource-intensive to tackle using more-traditional computational methods. ANNs have been successfully used for many tasks including pattern recognition, function approximation, optimization, forecasting, data retrieval, and automatic control. This research provides an introduction to ANNs and their applications in the design and analysis of geotechnical systems. As ANNs can be a useful complement to more-traditional numerical and statistical methods, their use merits continued investigation.

Geotechnical engineering is known as an 'imprecise' area of engineering due to the fact that the soil is a material produced by nature (the ground). In many circumstances, our fundamental understanding of soil behaviour still falls short of being able to predict how the ground will behave. Under these circumstances, expert judgement plays an important role, and empirical approaches to design are widely used. Since artificial intelligence (AI) techniques can make use of heuristic knowledge (rules of thumb) or pattern matching techniques, as opposed to solving a set of mathematical equations, they should be ideally suited for application in the field of geotechnical engineering.

A variety of classification systems have been developed for soils. These systems group soils according to their general behavior under given physical conditions. Soil classification systems have been developed to provide engineers, scientists and resource managers with generalized information about the nature of a soil found in a particular location. In general, environments that share comparable soil forming factors produce similar types of soils. This phenomenon makes classification possible. Numerous classification systems are in use worldwide. The Unified System of Soil Classification, will be examined in this study.

Soil classification information can become increasingly more valuable for decision making when coupled to artificial intelligence (AI). Artificial intelligence has evolved in recent years to the point that many applications can be run using desktop computing. When linked to Soil classification, artificial intelligence can be useful for evaluating, monitoring and decision-making. Artificial Neural Networks (ANN), (Fausett 1994; Flood and Kartam 1994; Hecht-Nilsen 1990; Maren et al. 1990; Zurada 1992) [1] is a form of artificial intelligence, which, in their architecture, attempts to simulate the biological structure of the human brain and nervous system. ANNs have been applied extensively to many prediction tasks, as they have the ability to model the nonlinear relationship between a set of input variables and the corresponding outputs.

In recent times, ANNs have been applied to many geotechnical engineering problems and have demonstrated some degree of success. For example, ANNs have been used in pile bearing capacity prediction (Lee and Lee [2] 1996), stress-strain modeling of sands (Ellis et al. [3] 1995), interpretation of site investigation (Zhou and Wu [4] 1994) and seismic liquefaction assessment (Goh [5] 1994). A comprehensive list of the applications of ANNs in geotechnical engineering is given by Shahin et al.[4] (2001) who have presented the state-of the art report on the different applications (liquefaction prediction, soil classification, compaction, pile capacity, settlement analysis etc.) of ANN in geotechnical engineering. ANNs have been also used for site characterization, based on SPT (Itani and Najjar, 2000; Das and Basudhar, 2004) [4] and CPT (Juang et al., 2001) [4] results. In the majority of these applications, the data are divided into the subsets needed to develop ANN models (e.g. training, testing and validation) on an arbitrary basis. However, recent studies have shown that the way the data are divided can have a significant impact on the results obtained (Tokar and Johnson 1999) [6].

In this study,ANNs are used for soil classification prediction in a specified locations at different depths, based on the available site investigation data from actual borehole logs investigated in Khartoum state .

The results indicate that Artificial Neural Networks are a useful technique for predicting relationships between the input parameters of the three dimensional coordinates and the resulting soil classification and soil parameters output.

1.2. Scope and Objectives of the Study:

Khartoum, the capital, has population of more than 8 millions, is the largest and the most important city in Sudan. Accordingly a great development and expansion in construction is now taking place. This large urban development has occurred over a considerable area mostly of Nile silts and clays .Therefore it is necessary to establish engineering design guidelines which are requested by the construction industry in Khartoum city.

To satisfy such needs, pertinent geotechnical information and soil parameters should be compiled to serve as a data base to develop powerful networks capable of predicting the soil profile and relative soil parameters.

The main objectives of the present study can be summarized as follows:

1. To build up a powerful network capable of predicting the soil classification and soil parameters, based on previously investigated site conditions.
2. To test the ability of Artificial Neural Network method for generation of accepted results of the field of geotechnical application.

1.3. Methodology:

In the present research, data from hundreds of investigated boreholes drilled in the region were used (depth range between 5m to 50m.). It was collected from Building and Road Research Institute (B.R.R.I.) of (U.of.K). The data includes mainly: location ,depth, soil groups and soil parameters: Liquid Limit (L.L),Plastic Limit (P.L.), Plasticity Index (P.I), Natural Moisture Content (N.M.C), Bulk Density(B.D.) , Dry Density (D.D.),Standard Penetration Test values (S.P.T.-N),shear strength parameter (cohesion C and angle of internal friction Φ), the percentage passing No. 200sieve (.075mm.) and the ground water table (GWL) depth ; consolidation test results.

To locate the investigated borehole sites, a digital map of Khartoum city was used as a reference map. Global positioning system (GPS) has been used to get the exact EN co-ordinates of the sites studied (at the center point of the sites) and their respective altitudes.

Parameters used as input and output data are: location of each borehole (E, N), depth, soil group according to (U.S.C.S.), liquid limit (L.L.), plasticity index (P.I.) and standard penetration test values (N).

Available data to predict the profile was used as a general soil data base. Five sets were used for classification network as follows:

1. Global classification network: classify the soil as clay/silt or sand.
2. Sand classification network: classify sands as clayey sand or silty sand.
3. Sand grading classification network: classify the grading of sands as poor graded sand or well graded sand.
4. Clay classification network: classify clay as clays of low plasticity or clay of high plasticity.
5. Silt classification network: classify silts as silt of low plasticity or silt of high plasticity.

Two sets were used to predict the soil parameter as follows:

1. Atterberg limit network: used to predict the liquid limit and plasticity limit of fine-grained soils (silt/clay).
2. Standard penetration test network: used to predict the N-value for sands.

A multi-layer artificial neural network (ANN) with a back propagation algorithm is used to predict soil classification and soil parameters from raw data. For this purpose a neural network program is used (Neuroshell-version 2).

1.4. Outline of thesis:

Chapter (I) is an introductory chapter.

Chapter (II) presents a general summary of the literature pertaining to the subject of this thesis. A general introduction to soil classification is given including historical perspective. Then the Unified Soil Classification System is discussed followed by other classification systems, followed by the Atterberg limits and the grain size distribution. Finally the engineering soil properties and correlations are discussed.

Chapter (III) is concerned with artificial intelligence methods used in engineering mainly:Expert systems ,Artificial Neural Networks ,Evolutionary Althogrithms and Hybrid systems ,discussing learning and techniques of each method.

Chapter (IV) deals with the Artificial Intelligence Applications in several domains concentrating on Geotechnical Engineering and discussing the degree of success of Artificial Intelligence in each domain.

Chapter (V) is concerned with the soil profile and parameters prediced by the Artificial Neural Networks. In order to meet the objectives set out previously, seven modeling approaches are constructed to predict the soil classification and soil parameters, including the training and testing phases and it's results. The various forms of data representation are descibed. Special emphasis is placed on the relational data model, which is adopted by the software package used to process the information contained in the soil reports.Each of the seven models are described through : training process ,architecture used and the performance of the model .

In chapter (VI) the whole system is eventually tested for efficiency using data of new three sites investigated in the second half of year 2006, distributed over the study area. Then results and discussion for all models in the prediction phase are presented.

Chapter (VII) concludes this study by giving a general overview to the subjects discussed throughout the thesis.The conclusions concerning the various topics and proposed methods are mentioned; moreover, recommendations for further improvement and research are proposed.

Chapter Two

Classification of Soils

Chapter Two
Classification of soils

2.1 Introduction:

The term soil, as used by the civil engineer, is regarded as natural aggregate of mineral grains, with or without organic constituents, which can be separated by gentle mechanical means such as agitation in water.

In all branches of civil engineering and especially in foundation engineering, experience is a priceless asset. Indeed, the accumulated experience of generations of foundation engineers [7].

In a general way, it has been found that soils can be classified into groups within each of which the significant engineering properties are somewhat similar. Consequently, proper classification of subsurface materials is an important step in connection with any foundation job, because it provides the first clue to the experiences that may be anticipated during and after construction.

The detail with which samples are described, tested, and evaluated depends on the type of structure to be built, on consideration of economy, on the nature of the earth materials, and to some extent on the method of sampling. The samples should be described first on the basis of a visual inspection and certain simple tests that can be performed in the field as in the laboratory.

The identification and classification of the products of nature constitute an artificial procedure, because these materials are infinitely varied and do not lend themselves to separation into distinct categories. As a result, various arbitrary systems of classification have been developed, each with certain advantages and disadvantages for a particular purpose.

2.2 Description and Identification of Soils:

2.2.1 Principal types of Soil:

The principal terms used by civil engineers to describe soils are gravel, sand, silt, and clay. Most natural soils consist of a mixture of two or more of these constituents, and many contain an admixture of organic material in a partly or fully decomposed state. The mixture is given the name of the constituent that appears to have the most influence on its behavior, and the other constituents are indicated by adjectives. Thus silty clay has predominantly the properties of clay but contains a significant amount of silt, and organic silt is composed primarily of silt-sized mineral matter but contains a significant amount of organic material.

Gravels and sands are known as *course- grained* soils, and silts and clays as *fine-grained* soils. The distinction is based on whether the individual particles can be differentiated by the naked eye. The methods of describing coarse-grained soils differ from those appropriate for fine-grained soils; therefore, the procedures are discussed under separate headings.

2.2.2 Coarse-grained Soil materials:

The coarse-grained soil materials are mineral fragments that may be identified primarily on the basis of particle size.

Particles having a diameter greater than about 5mm are classified as *gravel*. However if the diameter exceeds about 200mm (8in) the term *boulder* is usually applied.

If the grains are visible to the naked eye, but are less than about 5mm in size, the soil is described as *sand*. This name is usually further modified as *coarse, medium*, or *fine*. The definitions of these terms must be chosen arbitrarily. In the United States the ASTM classification of size limits given in Table 2.1 has been adopted as standard for engineering purposes.

Table 2.1 Particle size limits of soil

Constituents, ASTM Classification

(in Millimeters)

Larger than 4.75	Gravel
4.75 to 2.00	Coarse sand
2.00 to 0.425	Medium sand
0.425 to 0.075	Fine sand
Smaller than 0.075	Fines (combined silt and clay)

A complete verbal description of a coarse-grained soil includes more than an estimate of the quantity of material in each size range. The *gradation*, *particle shape*, and *mineralogical composition* should also be noted whenever possible. The gradation may be described as *well- graded*, *fairly well-graded*, *fairly uniform*, *uniform*, or *gap-graded*. Well-graded soils contain a good representation of all particle sizes ranging from coarse to fine. The particles of uniform soils are all approximately the same size. Gap-graded soils consist of mixtures of uniform coarse-sized particles and uniform fine-sized particles, with a break in gradation between the two sizes. Any soil not well-graded may be characterized as poorly graded.

The shape of the coarse-grained particles in a soil has an influence on the density and stability of the soil deposit. The usual terms describing grain shape are rounded, angular, sub-rounded and sub-angular [(7)].

2.2.3 Fine-grained soil materials:

Inorganic silt, which constitutes the coarser portion of the microscopic soil fraction, possesses little or no plasticity or cohesion. The least plastic varieties consisting primarily of very fine rounded quartz grains are called *rock flour*. The most plastic varieties containing an appreciable quantity of flake-shaped particles are called *plastic silt*.

Clay is predominantly an aggregate of microscopic and submicroscopic *flake-shaped* crystalline minerals. It is characterized by the typical colloidal properties of plasticity, cohesion, and the ability to adsorb ions. These properties are exhibited over a wide range of water content.

The distinction between silt and clay cannot be based on particle size because the significant physical properties of the two materials are related only indirectly to the size of the particles. Furthermore, since both are microscopic, physical properties other than particle size must be used as criteria for field identification.

2.2.4 Organic Soil Materials:

Very small quantities of organic matter often have a significant influence on the physical properties of soils. Most organic soils are weaker and more compressible than soils having the same mineral composition but lacking in organic matter. The presence of an appreciable quantity of organic material can usually be recognized by the dark gray to black color and the odor of decaying vegetation that it lends to the soil.

Organic silt is a fine-grained, more or less plastic soil containing mineral particles of silt and finely divided particles of organic matter. Shells and visible fragments of partly decayed vegetable matter may also be present.

Organic clay is a clay soil that owes some of its significant physical properties to the presence of finely divided organic matter.

Highly organic soil deposits such as *peat* or *muck* may be distinguished by a dark-brown to black color, by the presence of fibrous particles of vegetable matter in varying states of decay, and by the characteristic organic odor.

Combinations of organic and mineral soil materials are not always easily recognized, particularly if the organic content is small. Nevertheless, the presence of organic matter should always be suspected if the soil has a dark-brown, dark-gray, or black color. If the organic odor cannot be distinguished, it can sometimes be brought out by a slight amount of heat.

2.3 Index Properties of Soils:

There must be procedures leading to quantitative results that may be related to the physical properties with which the engineer is directly concerned. The tests required for this purpose are known as classification tests, and the results as the index properties of the soils.

Index properties may be divided into two general types, soil *grain properties* and soil *aggregate properties*. The soil grain properties are the individual particles of which the soil is composed, without reference to the manner in which these particles are arranged in a soil deposit. Thus, it is possible to determine the grain of any soil sample, whether disturbed or undisturbed. Soil aggregate properties, on the other hand, depend on the structure and arrangement of the particles in the soil mass. Although soil grain properties are commonly used for identification purposes, the engineer should realize that the soil aggregate properties have a greater influence on the engineering behavior of a soil.

2.3.1 Soil Grain Properties:

2.3.1.1 Size of Grains:

The most important grain property of coarse-grained soil is the particle-size distribution. This is determined by performing a mechanical analysis. The size of coarse-grained constituents can be determined by means of a set of sieves. The finest sieve commonly used in the field or in the laboratory is the No.200 U.S. Standard sieve in which the width of the opening is 0.075mm. For this reason 0.075mm has been accepted as the standard boundary between coarse-grained and fine-grained materials[7].

The results of a mechanical analysis are usually presented in the form of a particle-size distribution curve. The percentage P of material finer than a given size is plotted as the ordinate to a natural scale, and the corresponding particle diameter $D_{P,}$ in millimeters, is plotted as the abscissa to a logarithmic scale. A plot of this type has the advantage that materials of equal uniformity are represented by curves of identical shape whether the soil is coarse-grained or fine-grained moreover, the shape of the curve is indicative of the grading. Uniform soils are represented by nearly vertical lines, and well-graded soils by S-shaped curves that extend across several cycles of the logarithmic scale.

The particle-size characteristics of soils can be compared most conveniently by a study of certain significant numerical values derived from distribution curves. The two most commonly used by engineers are designated as D_{10}, *The effective grain size*, and $C_u = D_{60} / D_{10}$ *the uniformity coefficient*. The effective size is the diameter of the particle corresponding to P =10per cent on the particle-size plot. Hence, 10per cent of the particles are finer and 90per cent are coarser than the effective size. It is possible to have a gap-graded soil with a large uniformity coefficient which is actually composed of two uniformly graded fractions. *The coefficient of curvature,*

$C_Z = (D_{30})^2 / (D_{10} * D_{60})$, is a value that can be used to identify such soils as poorly graded. In well- graded gravels, C_u is greater than 4 and C_Z is between 1 and 3. In well-graded sands, C_u is greater than 6 and C_Z is between 1 and 3. (See ASTM, Designation D-2487, Classification of Soils for Engineering Purposes.)

2.3.1.2 Mineralogical Composition:

The most important grain property of fine-grained soil materials is the mineralogical composition. If the soil particles are smaller than about 0.002mm, the influence of the force of gravity on each particle is insignificant compared with that of the electrical forces acting at the surface of the particle. A material in which the influence of the surface charges is predominant is said to be in the colloidal state. The colloidal particles of soil consist primarily of clay minerals that were derived from rock minerals by weathering, but that have crystal structures differing from those of the parent minerals.

The three most important groups of clay minerals are smectite, illite, and Kaolinite. They are all crystalline hydrous alumino silicates. The result of studies using the electron microscope and X-ray diffraction techniques show that the clay minerals have a lattice structure in which the atoms are arranged in several sheets, similar to the pages of a book. The arrangement and the chemical composition of these sheets determine the type of clay mineral.

The basic building blocks of the clay minerals are the silica tetrahedron and the alumina octahedron. These blocks combine into tetrahedral and octahedral to produce the various types of clay. Two- layer minerals have single tetrahedral sheet joined to a single octahedral sheet to form what is called a 1:1 lattice structure. Kaolinite is a typical two-layer mineral. In three-layer minerals a single octahedral sheet is sandwiched between two tetrahedral sheets to give a 2:1lattice structure.

2.4 Structure and Consistency of Soil Aggregate:

2.4.1 Primary and Secondary Structure:

The *primary* structure of a soil refers to the arrangement of the grains. This arrangement is usually developed during the processes of sedimentation or rock weathering. In addition, various discontinuities may arise subsequent to the deposition or formation of the soil. These constitute the secondary structure of the deposit. They correspond to such phenomena as the development of systems of joints in sedimentary rocks.

The primary structure of a soil may be described as single-grained, flocculated, or dispersed. In a single-grained structure (Fig.2.1), each grain touches several of its neighbors in such a way that the aggregate is stable even if there are no forces of adhesion at the points of contact between the grains. The arrangement may be dense or loose, and the properties of the aggregate are greatly influenced by the denseness or looseness.

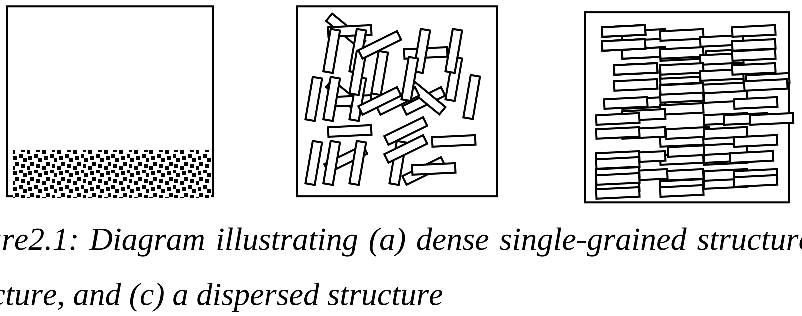


Figure2.1: Diagram illustrating (a) dense single-grained structure, (b) a flocculated structure, and (c) a dispersed structure

Figures 2.1b and 2.1c represent concepts of the structure of fine-grained soils. The oval-shaped particles represent silt grains whereas the flat-sided particles represent clay mineral platelets. In the flocculated structure (Fig. 2.1b), the edge or corner of one clay platelet tends to be attracted to the flat face of another. Consequently, the particles assume a loose but fairly stable structure that can be maintained as long as the electrical charges on the edges of the platelets remain opposite in sign to those on the faces. The degree of looseness of this arrangement depends at least in part on the nature and amount of electrolytes present during sedimentation. In the dispersed structure (Fig.2.1c), the edges, corners, and faces of the clay platelets have like electrical charges. Thus, the particles repel each other and assume nearly parallel positions. Even though the dispersed structure may be quite loose at the time of sedimentation, pressure can force the adjacent platelets into a dense state more readily than if they possessed the flocculated structure (Fig. 2.1b).

The principal types of secondary structure are cracks, joints, slickensides, and concretion. Cracks and joints are commonly formed as a result of desiccation sometime after the deposition of the material. Slickensides are polished surfaces in stiff clays that have experienced differential movement or expansion. Concretions are accumulations of carbonates or iron compounds. All these features disrupt the continuity of the soil mass and may impart to it properties significantly different from those of intact samples taken from the deposit.

2.4.2 Consistency and Sensitivity:

Undoubtedly the most significant index property of fine-grained soils in the natural state is the *consistency*. The consistency of natural cohesive soil deposits is expressed qualitatively by terms such as *soft*, *medium*, *stiff*, and *hard*. The meaning of these terms, however, varies widely in different parts of the world, depending on whether the local soils are generally hard or generally soft. Rather than rely on such vague terms, the engineer should develop his ability to estimate the compressive strength of soil.

2.4.2.1 Atterberg limits:

If the water content of a thick suspension of clay is gradually reduced, the clay-water mixture passes from a liquid state a plastic state and finally into a solid state.

It has been found that the water contents corresponding to the transitions from one state to another usually differ for clays having different physical properties in the remolded state, and are approximately equal for clays having similar physical properties. Therefore, the limiting water contents may serve as index properties useful in the classification of clays.

The significance of the limiting water contents for each physical state was first suggested by A. Atterberg in 1911.Hence, these limits are commonly known as the *Atterberg limits*, and the tests required to determine them are the *Atterberg-limit tests*. Actually, as the soil-water mixture passes from one state to another, there is no abrupt change in the physical properties. The limit tests, therefore, are arbitrary tests that have been adopted to define the limiting values.

Above the *liquid limit* w_L; the soil-water system is a suspension. Below the liquid limit and above the plastic limit w_P, the soil-water system is said to be in a plastic state. In this state the soil may be deformed or remolded without the formation of cracks and without change in volume. The range of water content over which the soil-water system acts as plastic material is frequently referred to as the *plastic range*, and the numerical difference between the liquid limit and the plastic limit is called the plasticity index I_P (often designated PI) :

$$\text{Plasticity index, } I_P = w_L - w_P \qquad \textbf{\textit{eqn 2.1}}$$

The plastic limit is the empirically established moisture content at which a soil becomes too dry to be plastic .It's used together with the liquid limit to determine the plasticity index which when plotted against the liquid limit on the plasticity chart provides a mean of classifying cohesive soils [(8)].

Somewhat below the plastic limit the soil-water system reaches the *shrinkage limit* w_S. Reduction of the water content by drying below the shrinkage limit is not accompanied by decrease in volume; instead, air enters the voids of the system and the material becomes unsaturated.

The Atterberg limits vary with the amount of clay present in a soil, on the type of clay mineral, and on the nature of the ions adsorbed on the clay surface.

The liquid limit and the plasticity index together constitute of the plasticity of a soil. Soils possessing large values of w_L and I_P are said to be highly plastic or *fat*. Those with low values are described as slightly plastic or lean. The interpretation of liquid and plastic limit tests is greatly facilitated by the use of the plasticity chart developed by A. Casagrande. In this chart (Fig. 2.2) the ordinates represent values of the plasticity index, and the abscissas represent values of the liquid limits. The chart is divided into six regions by the inclined line A having the equation $I_P = 0.73(w_L - 20)$, and the two vertical lines $w_L = 30$ and $w_L = 50$. All soils represented by points above line A are inorganic clays; the plasticity ranges from low ($w_L < 30$) to high ($w_L > 50$) with increasing values of the liquid limit. Soils represented by points below line A may be inorganic silts, organic silts, or organic clays. If they are inorganic, they are said to be of low, medium, or high compressibility, depending on whether the liquid limit is below 30, between 30 and 50, or above 50. They are organic silts, they are represented by points in the region corresponding to a liquid limit between 30 and 50 and, if they are organic clays, to a liquid limit greater than 50.

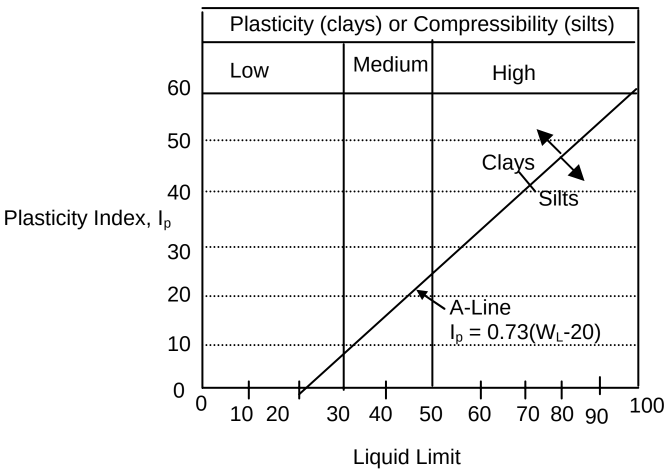


Figure 2.2: Plasticity chart (after A. Casagrande, 1948).

The distinction between organic and inorganic soils can usually be made by performing two liquid-limit tests on the same material, one starting with moist or air-dried soil, and the other with oven-dried soil. Oven-drying produces irreversible changes in organic constituents that significantly lower the liquid limit. If the liquid limit of the oven-dried sample is less than about 0.75 times that for the undrained sample, the soil may usually be classed as organic. A few inorganic clay minerals and other fine-grained soil constituents also experience irreversible changes on oven-drying; hence, the identification cannot always be based on the results of the limit tests.

The natural water content of clay is itself a useful index property of even greater significance, is the relation of the water content to the liquid and plastic limits. Those deposits having water contents close to the liquid limit are usually much softer than those with moisture contents close to the plastic limit. One of the most important index properties of natural clay deposits is, therefore, the *liquidity index*, defined the equation:

Liquidity index,

$$I_L = (w - w_P) / (w_L - w_P) = (w - w_P) / I_P \qquad \textbf{\textit{eqn2.2}}$$

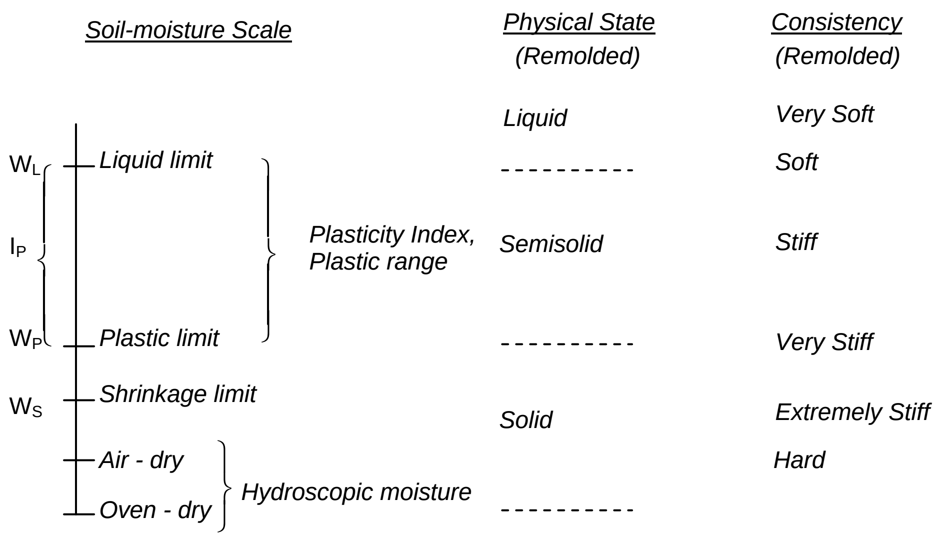


Figure 2.3: Diagram of the soil-moisture scale showing Atterberg limits, corresponding physical state, and approximate consistency of remolded soil.

It may be seen that I_L is negative for soils having water contents less than the plastic limit. As the water content increases from the plastic limit to the liquid limit, the value of I_L increases from 0 to 1.0. If the water content is greater than the liquid limit, the liquidity index is greater than 1.0. The consistency of clay in the remolded state may be estimated when the natural water content and limit values are known. The relationships are illustrated in Fig.2.3.

None of the Atterberg-limit tests is difficult to perform, although a certain amount of experience is required to develop the technique necessary to obtain reproducible results. The liquid-limit test is commonly made by means of the mechanical apparatus designed by A. Casagrande. A mixture of soil and water is plastic in the cup, and a groove 2 mm wide at its base and 8mm high is made in the center of the soil pat. The operator then turns the crank which lifts the cup to a height such that the point of contact between cup and base is 1cm above the base. The cup then falls freely from this position. The soil is at the liquid limit if 25 blows are required to cause the lower edges of the groove to come into contact with each other for a length of about 1/2in. The water content at this number of blows is the liquid limit.

The plastic limit test is performed by rolling a sample of plastic soil into a thread with a diameter of 1/8 in. If the soil does not crumble, the thread is picked up, remolded, and rolled out again. This process is repeated until the thread just begins to crumble when it reaches the diameter of 1/8 in. The water content at which crumbling takes place is defined as the plastic limit.

The shrinkage limit of a soil is determined by preparing a sample of known volume at a moisture content above the liquid limit and by drying the sample in an oven .The weight and volume of the oven-dry sample are measured. From these data and the initial water content, a computation is made of the water content at which the dried sample would be just saturated. This water content is considered to be the shrinkage limit.

2.5 Soil-Classification Systems:

2.5.1 Introduction:

Because the soil deposits of the world are infinitely varied, it has not been found possible to create a universal system of soil classification for dividing soils into various groups and subgroups on the basis of their important index properties. However, useful systems based on one or two index properties have been devised. Some of these systems are in such common use by workers in various fields involving soils that the engineer must have at least a general knowledge of them. At the same time it is essential to keep in mind that no system can adequately describe any soil for all engineering purposes. Indeed, many systems ignore the properties that are the most important from the standpoint of the foundation engineer [7].

Classification System	Grain Size, mm					
	100	10	1	0.1	0.01	0.001 0.0001
Bureau of Soils, 1890-95	Gravel	Sand	Silt	Clay		
	1	0.05	0.005			
Atterberg, 1905	Gravel	Coarse Sand	Fine Sand	Silt	Clay	
	2	0.2	0.02	0.002		
MIT, 1931	Gravel	Sand	Silt	Clay		
	2	0.06	0.002			
U.S. Dept. Agr. 1938	Gravel	Sand	Silt	Clay		
	2	0.05	0.002			
AASHTO, 1970	Gravel	Sand	Silt	Clay	Colloids	
	75	2	0.075	0.002	0.001	
Unified 1953 ASTM, 1967	Gravel	Sand	Fines (silt & clays)			
	75	4.75	0.075			

Figure 2.4: Comparison of several common textural classification systems.

2.5.2 Textural Systems

Since the particle size is probably the most obvious characteristic of a soil, it is natural that the earliest classification systems should have been based on texture alone. Indeed, many such systems have been suggested. Several of the more common are shown in Fig. 2.4 the MIT and Unified systems are commonly used by engineers, the AASHO system by highway engineers, and the Unified system by engineers charged with the design of dams and airfields.

To classify a soil according to a particular textural system, the particle-size distribution curve is usually plotted and the percentages by weight are calculated of the particles contained within each of the ranges of size specified in the system. Thus, a mixed-grained soil might be described as 3 percent gravel, 46 percent clay, according to the MIT classification.

In the textural method of classification used by soil scientists of the U.S. department of Agriculture, only three ranges of particle size are specified and material coarser than 2.0mm is excluded. Hence the percentages of sand-, silt-, and clay-size particles can be represented by a triangular chart (Fig. 2.5). After these percentages have been determined for a given sample, the point representing this mechanical composition is located on the triangular chart and the soil is given the name assigned to the area in which the point is located. If the soil contains a significant quantity of material coarser than 2.0mm, an appropriate adjective, such as gravelly or stony, is added to the textural name. Although the triangular chart does not reveal any properties of the soil other than particle-size distribution, it is widely used in various modified forms by workers in the fields of agriculture and highway engineering. Unfortunately the textural name derived from the chart does not always correctly express the physical characteristics of the soil. For example, since some clay-size particles are much less active than others, a soil described as clay on the basis of a textural system may have physical properties more typical of silt.

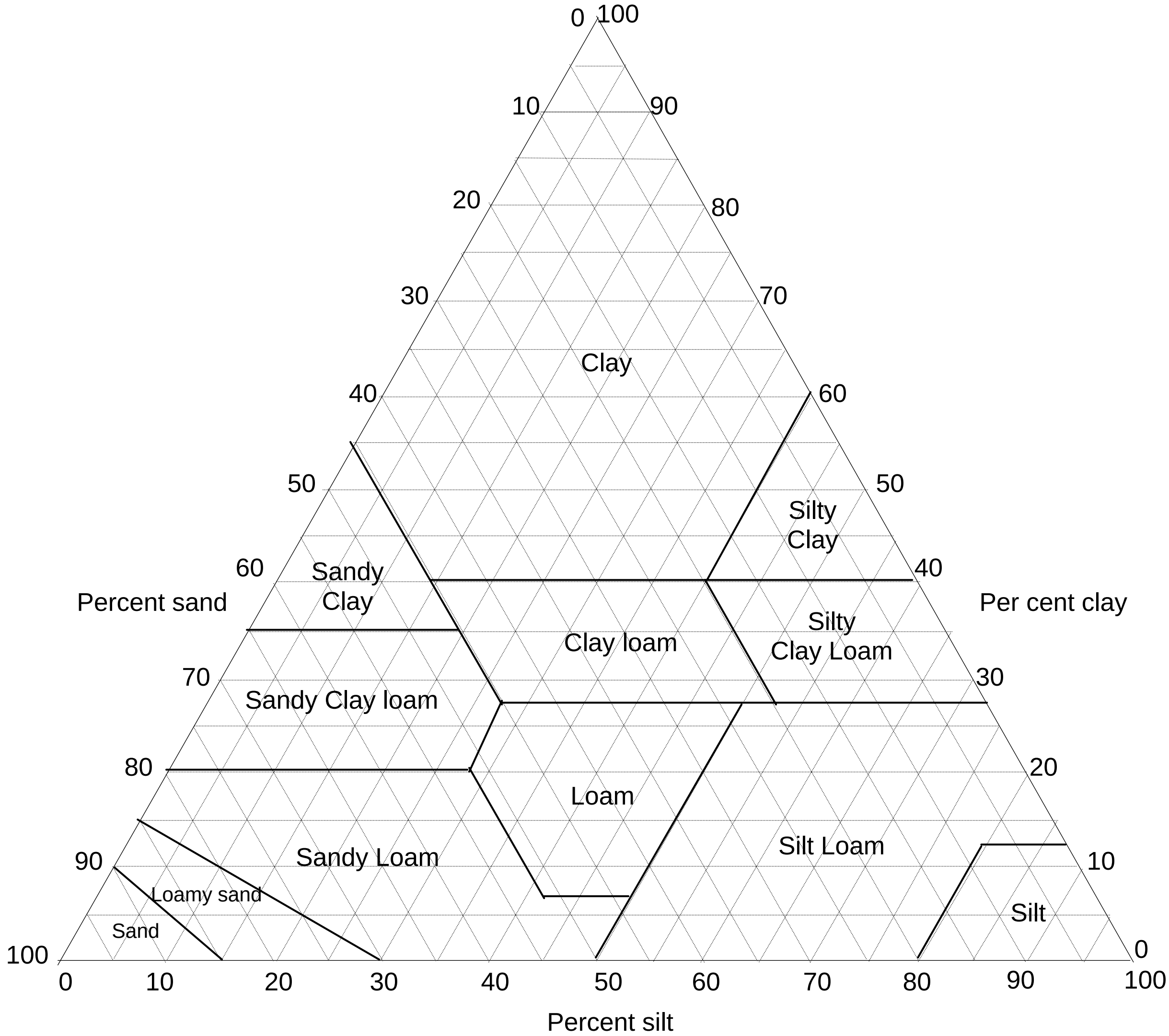


Figure 2.5: Triangular textural classification chart used by the U.S. Department of Agriculture.

2.5.3.AASHO System:

About 1928 the Bureau of Public Roads introduced a soil-classification system still widely used by highway engineers. All soils were divided into eight groups designated by the symbols A-1 through A-8. Since it was believed that the soil best suited for the sub grade of a highway is a well-graded material composed largely of sand and gravel, but containing a small amount of excellent clay binder, such a material was given the designation A-1. All other soils were grouped roughly in decreasing order of stability. The system has undergone many revisions. In the beginning, neither the percentages of the various size fractions nor the plasticity characteristics of the clay fraction were definitely specified.

In 1945 a committee of highway engineers for the Highway Research Board made an extensive revision of the Public Roads system. In 1949 and again in 1966 the American Association of state Highway Officials adopted revisions and the method are now known as the AASHO system. The characteristics of the various groups and subgroups and the classification procedure are given in Table 1.8. In the AASHO system the inorganic soils are classified in 7 groups corresponding to A-1 through A-7. These in turn are divided into a total of 12 subgroups. Highly organic soils are classified as A-8. Any soil containing fine –grained material is further identified by its *group index*; the higher the index, the less suitable the soil.

The group index is calculated from the formula

$$\text{Group index} = (F - 35)[0.2 + 0.005(w_L - 40)] + 0.01(F - 15)(I_P - 10) \qquad \textbf{\textit{eqn 2.3}}$$

In which

F = percentage passing No. 200 sieve, expressed as a whole number

w_L = liquid limit

I_P = plasticity index

The group index is always reported to the nearest whole number unless its calculated value is negative whereupon it is reported as zero. The group index is appended to the group and subgroup classification. For example, a clay soil having a group index of 25 might be classified as A-7-6(25).

2.5.4. Unified System:

The soil-classification system most widely used by foundation engineers in North America today was developed by Arthur Casagrande for the Corps of Engineers, U.S. Army. First designated as the *Anfield classification* (AC) system, it was originated to assist in the design and construction of military airfields during World War II. After the war it was adopted with minor revisions by the Corps and by the U.S. Bureau of Reclamation as the *Unified system*. In 1969, the Unified system was adopted by the American Society for Testing and Materials as a Standard Method for Classification of Soils for Engineering purposes, ASTMD-2487.

According to the Unified system the coarse-grained soils are divided into:

1- Gravel and gravelly soils; symbol G.

2- Sands and sandy soils; symbol S.

The gravels and sands are each subdivided into four groups:

a. Well-graded, fairly clean materials; symbol W.

b. Well-graded material with excellent clay binder; symbol C.

c. Poorly graded, fairly clean material; symbol P.

d. Coarse materials containing fines not included in preceding groups; symbol M.

Fine-grained soils are divided into three groups:

1. Inorganic silty and very fine sandy soils; symbol M.
2. Inorganic clays; symbol C.
3. Organic silts and clays; symbol O.

Each of these three groups of fine-grained soils is subdivided according to its liquid limit into

a. Fine-grained soils having liquid limits of 50 or less; that is, of low
to medium compressibility; symbol L.

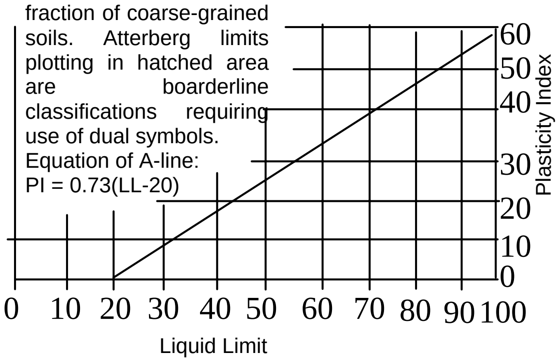
b. Fine-grained soils having liquid limits greater than 50; that is of
High compressibility; symbol H.

High organic soils, usually fibrous, such as peat and swamp soils of very high compressibility, are not subdivided and are placed in one group, symbol Pt, on the basis of visual identification. The pertinent characteristics of the various groups are given in Table 2.2.

Table 2.2 Unified Systems

Classification of Soils for Engineering Purposes

ASTM Designation D-2487

<table>
<tr><th colspan="3">Major Definitions</th><th>Group Symbols</th><th>Typical Names</th><th colspan="2"></th><th colspan="2">Classification Criteria</th></tr>
<tr><td rowspan="8">Coarse –Grained Soils More than 50% returned on No. 200 sieve</td><td rowspan="4">Gravels 50% or more of coarse fraction retained on No. 4 Sieve</td><td rowspan="2">Clean Gravels</td><td>GW</td><td>Well-graded gravel and gravel-sand mixtures, little or no fines</td><td rowspan="8">Classification on basis of percentage of fines</td><td rowspan="4">GW, GP, SW, SP, GM, GC, SM, SC Boarder line classification requiring use of dual sample</td><td colspan="2">$C_u = D_{60}/D_{10}$ > Greater than 4
$C_2 = (D_{30})^2/(D_{10} x D_{60})$
Between 1 and 3</td></tr>
<tr><td>GP</td><td>Poorly graded gravels and gravel-sand mixtures, little or no fines</td><td colspan="2">Not meeting both criteria for GW</td></tr>
<tr><td rowspan="2">Gravel with fines</td><td>GM</td><td>Silty gravels, gravel-sand-silt mixtures</td><td>Atterberg limit plot below "A" line or plasticity index less than 4</td><td rowspan="2">Atterberg limit plot in hatched area are boarderline classification requiring use of dual symbols.</td></tr>
<tr><td>GC</td><td>Clayey gravels, gravel-sand-clay mixtures</td><td>Atterberg limit plot above "A" line or plasticity index greater than 7</td></tr>
<tr><td rowspan="4">Sands More than 50% of coarse fraction passes on No. 4 Sieve</td><td rowspan="2">Clean Sands</td><td>SW</td><td>Well-graded sands and gravelly sand, little or no fines</td><td rowspan="4">Less than 5% pass No. 200 sieve More than 12% pass No. 200 sieve 5% to 12% pass No. 200 Sieve</td><td colspan="2">$C_u = D_{60}/D_{10}$ Greater than 6
$C_2 = (D_{30})^2/(D_{10} x D_{60})$
Between 1 and 3</td></tr>
<tr><td>SP</td><td>Poorly-graded sands and gravelly sand, little or no fines</td><td colspan="2">Not meeting both criteria for SW</td></tr>
<tr><td rowspan="2">Sands with fines</td><td>SM</td><td>Silty sands, sand-silt mixtures</td><td>Atterberg limit plot below "A" line or plasticity index less than 4</td><td rowspan="2">Atterberg limit plot in hatched area are boarderline classification requiring use of dual symbols.</td></tr>
<tr><td>SC</td><td>Clayey sands, sand-clay mixtures</td><td>Atterberg limit plot above "A" line or plasticity index greater than 7</td></tr>
<tr><td rowspan="6">Fine Grained Soils 50% or more passes No. 200 sieve</td><td rowspan="3">Silts and Clays Liquid Limit 50% or less</td><td rowspan="3"></td><td>ML</td><td>In-organic silts, very fine sands rock flour, silty or clayey fine sands</td><td colspan="4" rowspan="6">Plasticity Chart
For classification of fine grained soils and fine fraction of coarse-grained soils. Atterberg limits plotting in hatched area are boarderline classifications requiring use of dual symbols.
Equation of A-line:
PI = 0.73(LL-20)
</td></tr>
<tr><td>CL</td><td>In-organic clays of low to medium plasticity, gravelly clays, sandy clays silty clays, lean clays</td></tr>
<tr><td>OL</td><td>Organic silts, and organic silty clays of low plasticity</td></tr>
<tr><td rowspan="3">Silts and Clays Liquid Limit greater than 50%</td><td rowspan="3"></td><td>MH</td><td>In-organic silts, micaceous or diatomaceous fine sands or silts, elastic silts.</td></tr>
<tr><td>CH</td><td>In-organic clays of high plasticity, fat clays.</td></tr>
<tr><td>OH</td><td>Organic clays of medium to high plasticity.</td></tr>
<tr><td colspan="2">High Organic Soils</td><td></td><td>Pt</td><td>Peat, muck and other highly organic soils</td><td colspan="4">Visual – manual identification</td></tr>
</table>

2.6. Shortcomings of Engineering Classification:

The various textural systems, the AASHTO system, and the Unified system are based on the properties either of the grains themselves or of remolded material; they do not take into consideration the properties of the intact material as found in nature. It is primarily the properties of the intact material that determine the behavior of the soil during and after construction. Hence, non of the system of classification can serve as more than a starting point for adequate description of soils in the conditions under which they are encountered in the field. Nevertheless, even with these limitations, much information concerning the general characteristics of a soil can be inferred as a consequence of its proper classification according to one of the system described under the preceding subheadings. The engineer who deals with soils and foundations should commit to memory the details of at least the engineering classification system that seems most appropriate to his area of activity. He should constantly train himself to identify and classify soils in the field correctly by comparing his field descriptions of soil samples with the corresponding laboratory test results. Since all systems of soil classification just described are in common use, it is advantageous to be thoroughly familiar with each.

Still further useful information can be obtained from sources outside the field of civil engineering, particularly geology and petrology. The foundation engineer should possess knowledge of at least the descriptive terminology of these two sciences.

2.7. Engineering Properties of Soils:

To the civil engineer engaged in the design and construction of foundations, some of the important physical and engineering properties of soil are:

- Permeability,
- Elasticity,
- Plasticity,
- Cohesion,
- Angle of internal friction (Ø),
- Moisture content ,
- Density ,
- Shrink/swell potential ,
- Compressibility ,and
- Grain size distribution.

2.7.1. Permeability:

Permeability is a property indicating the ease with which water flows or passes through a material. This water movement is called percolation. The knowledge and extent of this condition is especially important in the design and construction of underground excavations. Soil texture, gradation, degree of compaction, and primary strongly influence the relative permeability of soil. Generally coarse-grained soils are much more permeable than fine grained soils [9].

2.7.2. Elasticity:

Elasticity is a property indicating ability of a material to return to its original shape or form after having been deformed by a load for a short period of time. Any load applied that exceeds the shear strength of a soil will also exceed the elastic limit of the soil, and it will not return to its original shape or form by plastic deformation.

2.7.3. Plasticity:

Plasticity is a property indicating the ability of a material to be deformed permanently without cracking or crumbling [9].

2.7.4. Cohesion:

Cohesion is a very important property contributing to the shear strength of a soil , and is the capacity to resist shearing stresses .Cohesion varies depending on water content , density and plasticity of the soil[9].

2.7.5. Angle of Internal Friction (Ø):

The angle of internal fiction is a measure of the natural angle of response of a soil. For dry sand, this angle of approximately 30 degrees observed on the side slopes of a stock pile. For clayey or clay soil, this is not the case since negative pore pressures generated by the low permeability of the soil matrix masks the expression of the frictional properties of the soil .Moderate to high plasticity clays exhibits atypical friction angle of approximately 15 degrees when pore pressures reach equilibrium.

The angle of internal friction is also the slope of the shear strength envelope, and therefore, represents the effect that increasing effective normal stress has on the shear strength of the soil .Refer to figure 2.6 for a graph of internal friction versus SPT (N-value) [9].

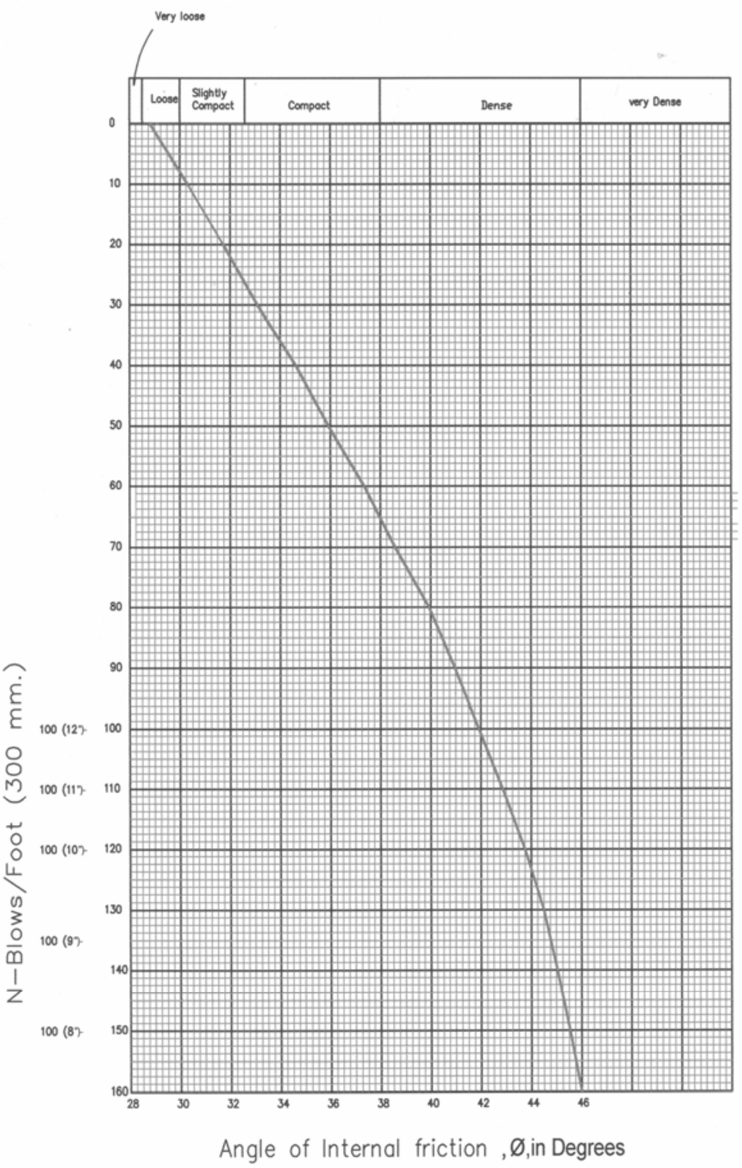


Figure 2.6.: SPT test vs. cohesion less soils' internal friction

- 25 -

2.7.6. Moisture Content:

Moisture Content is the ratio of the weight of water to the weight of solids in a given volume of soil. Moisture Content can range from a few percent for rocks to several hundred percent for very soft highly organic coastal clays .The consistency of clay may be very soft or very hard depending upon the water content. Between these extremes, the clay may be molded and formed without cracking or rupturing the soil mass.

2.7.7. Density:

Dry density is the unit weight of the solid particles of soil or rock per unit volume. Wet density is the unit weight of solid particles and the natural moisture and is used in computations for determining design values for foundations above the water table. Submerged density is wet density less the unit weight of water and is used when the foundation is below the water table. Typical values for wet density of soil range from 19.2 to 21.6 KN/m^3.

2.7.8. Shrink/Swell Potential:

Shrinking /Swelling is a property of fine grained soils, especially clays , resulting from buildup and release of capillary tensile stresses within the soil’s pore water and the varying degree of affinity for water that certain clay minerals exhibits.

2.7.9. Compressibility:

Compressibility is a property greatly influenced by soil structure and load history of the deposit. Drilled shafts or footings should not bear in a material that is susceptible to a high degree of compression (consolidation).

2.7.10. Soil Compact ability:

While the compactability is indirectly influenced by permeability, it is also directly influenced by grain size distribution. Soils consisting solely of particles within a narrow size range (Uniformly or Poorly Graded) may be difficult to compact due to lack of other particles to interlock with the predominate particle size.

Figure 2.7 is a grain size distribution chart showing some typical gradations. Well graded refers to the size of the particles being distributed over a wide range of sizes. Uniformly graded refers to the size of the particles being distributed over a narrow range of sizes. Gap graded refers to several distinct size ranges within a sample(9).

Chapter Two *Classification of Soils*

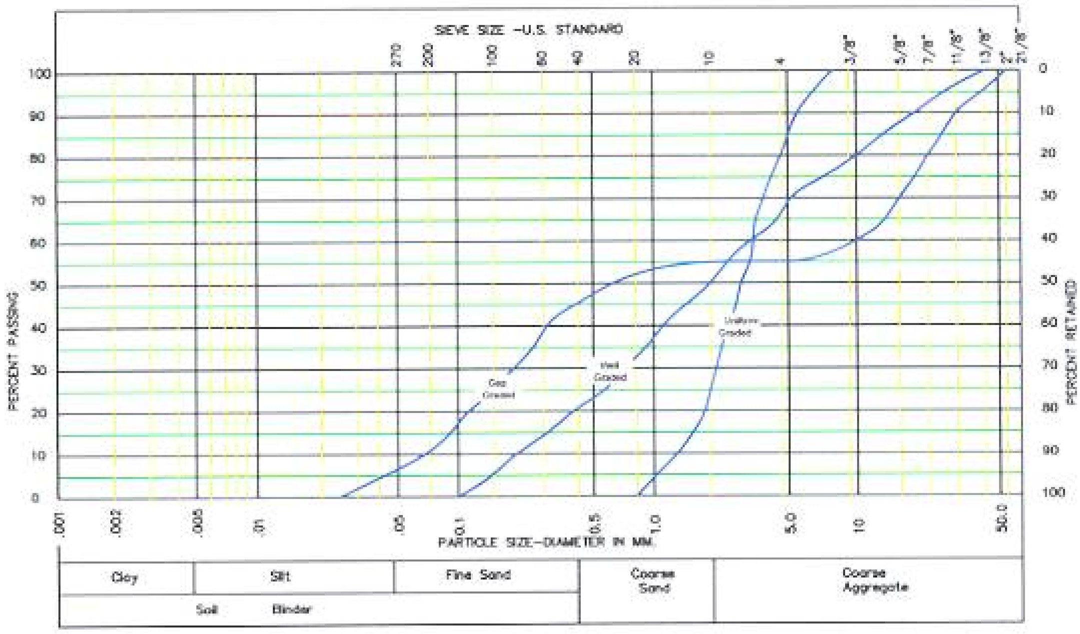


Figure 2.7.: Typical Particle size graduations (grain size distribution chart)

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Chapter Three

Artificial Intelligence Applications

Chapter Three
Artificial Intelligence Methods in Engineering

3.1. Expert System:
3.1.1. Definition:

McCarthy (2000) at Stanford University defines expert system as:
A" knowledge engineer" interviews expert in a center domain and tries to embody their knowledge in a computer program for carrying out some task." (MCCARTHY, 2000) [10].

The "knowledge acquisition" it will not only be the "knowledge" of expert that will be cloned and built into these system, but also their intuition and the way that they reason, so that the best options can be selected under any given set of circumstances [10].

An expert system can be developed by: Expert system shell software that has been specifically designed to enable quick development, AI languages, such as LISP and Prolog or through the conventional languages, such as Fortran, C++, Java, etc.

While the Expert System concept may sound futuristic, one of the first commercial Expert System, called Mycin, was already in business use 1974 (MIT, Applications of AI,2001). Mycin, which was created by Edward H. Shorliffe at Stanford University, is one of the most famous Expert system. Mycin was designed as a medical diagnosis tool. Given information concerning a patient's symptoms and test results, Mycin attempted to identify the cause of the patient's infection and suggested treatments (MIT, Applications of AI, 2001). According to McCarthy (2000), it did better than medical students or practicing doctors, provided its limitation was observed. Another example of an Expert System is Dendral, a computerized chemist. According to the Massachusetts Institute of Technology, the success of Dendral helped to convince computer science researchers that system-using heuristics were capable of mimicking the way human expert solve problem (MIT, Timeline of AI, 2001) [10].

3.1.2. Potential Applications for an Expert System:

Expert System have been developed for a variety of reasons, including: the archiving of rare skills, preserving the knowledge of retiring personnel, and to aggregate all of the available knowledge in a specific domain form several expert, (when no single expert has complete knowledge of the domain). Perhaps an expert's knowledge is needed more frequently than the expert can handle, or in places that the expert cannot travel to. The Expert System can train new employees or eliminate large amounts of the monotonous work humans do, thereby saving the expert's time for situations requiring his or her expertise. The only limit on the possible application of stored knowledge in an Expert System is what the mind can imagine.

The Expert System is an AI application that makes decisions based on knowledge and interface (the ability to react the knowledge), as defined by expert in a certain domain and to solve problem in that domain. The Expert System normally falls under the definition of Weak AI, and is one of the AI techniques that have been easiest for companies to embrace. Commercial Expert System was developed during the 1970s, and continues to be used by companies. One advantage of an Expert System is that it can explain the logic behind a particular decision, why particular questions were asked, and/or why an alternative was eliminated. That is not the case with other AI methods.

3.2. Artificial Neural Network:

Sometime the following distinction is made between the terms "neural network" and "Artificial Neural Network". "Neural Network" indicates networks that are hardware based and "Artificial Neural Network" normally refers to those which are software-based. In the following paragraphs, "Artificial Neural Network" is sometimes referred to as "Neural Network" or "Neural Computing". Neural network are an approach, which is inspired by the architecture of the human brain. In the human brain a Neural Network exists which is comprised of over 10 billion neurons; each neurons then builds hundreds and even thousands of connection with other neurons (KIMBALL, 2001) (10).

3.2.1. Definition:

Aleksandra and Morton (1995) (10), in their book “An Introduction to Neural Computing,” define Neural Computing as:

“*Neural Computing is the study of network of adaptable nodes which, through a process of learning from task examples, store experimental knowledge and make it available for use*.” (ALEKSANDER, MORTON, 1995) (10).

3.2.2. Learning:

As a Neural Network (NN) is designed, rather than begin programmed, the system learn to recognize patterns (HENGL, 2001) (10). Learning is achieved through repeated minor modification to selected neuron weights (the weight is equal to the importance of the neuron). ANN typically starts out with randomized weights for all their neurons. This means that they do not “know” anything, and must be trained. Once a NN has been trained correctly, it should be able to find the desired output to a given input; however, it cannot be guaranteed that a NN will product the correct output pattern. NN learns by either a supervised or an unsupervised learning process (Kay, 2001) (10).

3.2.2.1. The Supervised Learning Process:

A supervised learning process has a target pattern (desired output). While learning different input patterns, the weight values are changed dynamically until their values are balanced, so that each input will lead to the desired output. There are two supervised learning algorithms: forward, and Back-propagation, learning Algorithms.

3.2.2.2. The Unsupervised Learning Process:

An unsupervised Neural Network has no target outputs. During the learning process, the neural cells organize themselves in groups, according to input pattern. The incoming data is not only received by a single neural cell, but also influences other cells in its neighbourhood. The goal is to group neural cells with similar function close together. Self-organization Learning Algorithms tends to discover patterns and relationships in that data (Kay, 2001) [(10)].

3.2.3. Artificial Neural Network Techniques:

According to Sarle (1999) [(10)], there are many kinds of Artificial Neural Network. No one knows exactly how many. This dissertation only describes the most common ones.

3.2.3.1. Perceptron:

Frank Rosenblatt introduced the perceptron in 1959 (MIT, Timeline of AI, 2001) [(10)] Figure 3.1 has been devised by the author and is a very simple structure with two neuron layers that accept only binary input and values (0 or 1). The learning process is supervised and the net is able to learn basic logical operations such as AND or OR. It is also used for pattern classification purposes.

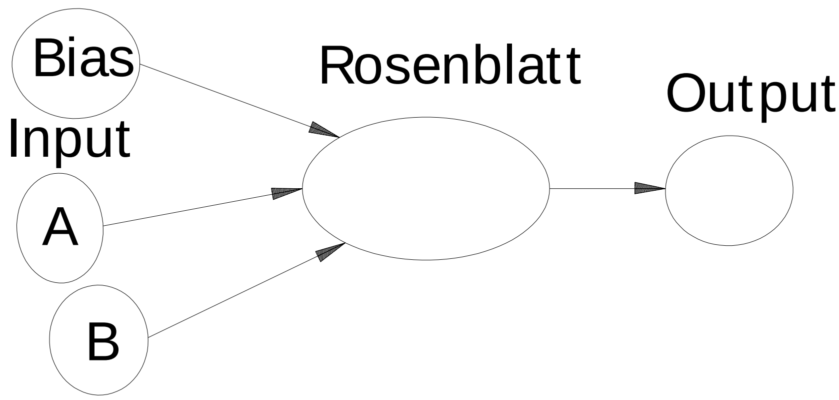


Figure 3.1: Rosenblatt Perceptron

3.2.3.2. Multi-Layer-Perceptron:

Marvin Musky and Seymour Paper first introduced the Multi-Layer-Percetron in 1969 (BUCHANAN, 2001) [10]. It is an extended perceptron and has one more hidden neuron layer between its input and output layers. Due to its extended structure, a Multi-Layer-Percetron is able to learn every logical operation. The Multi-Layer-Percetron is showed in the figure 3.2 (FROHLICH, 1996).

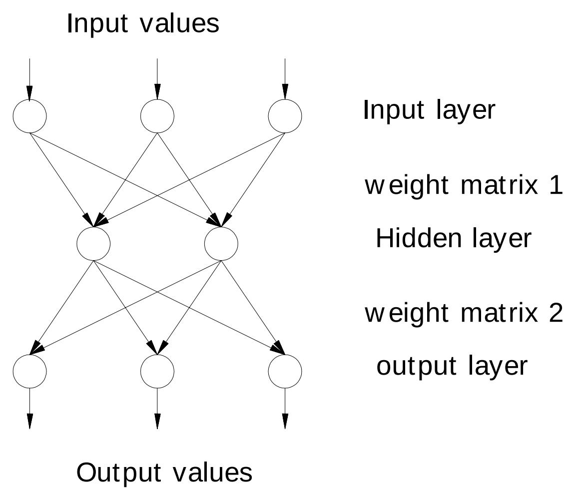


Figure 3.2:Multi-layer Perceptron (FROHLICH, 1996).

3.2.3.3. Back propagation Net:

G.E Hinton, E. Rum hart and R.J. Williams's first intro-duce the Back propagation Net in 1986. It has the same structure as the Multi-Layer-Percetron, but uses the back propagation-learning algorithm.

3.2.3.4. Hopfield Net:

Physicist J.J. Hopfield first introduced the Hopfield Net in 1982. It consists of a neuron, where each neuron is connected to every other neuron. There is no difference between input and output neuron. The main application of a Hopfield Net is the storage and recognition of patterns, e.g. image files (FROHLICH, 1996) [10]. Three nodes Hopfield Network is showed in the figure 3.3.

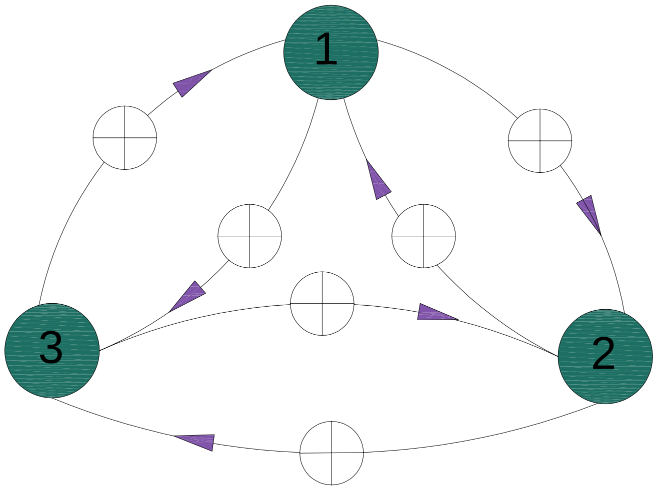


Figure 3.3: Hopfield Network (Perry 2001)

3.2.3.5. Kohonen Feature Map:

Finnish Professor Teuvo Kohonen, at the University of Helsinki, introduced the Kohonen feature Map (is showed in the figure 3.4) in 1982. Kohonen Net whose neurons compete with each other and the neuron and its neighhourhood with the smallest distance is winning.

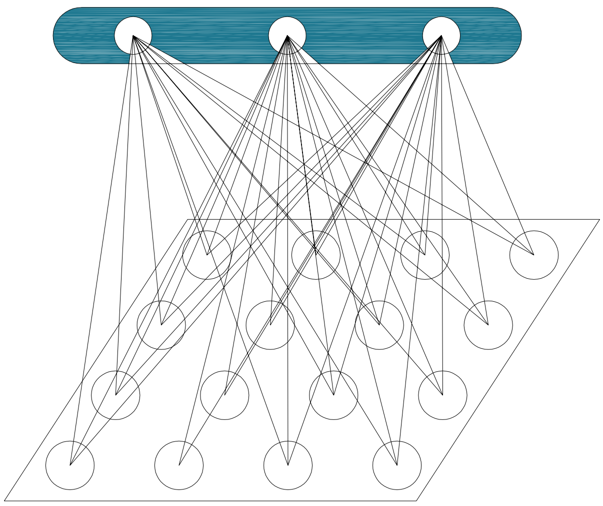


Figure 3.4: Kohonen Feature Map (NAVELLAB, 1997)

3.2.4. ANN as Method of Forecasting:

“Forecasting is essential to engineering”, (TANLER, 2001) [(10)].ANN over traditional statistical forecasting methods are that ANN do not have to fulfill any statistical assumptions and the ability to handle non-linearity, further advantages, according to Jiang et al., are that ANN is easy to learn and use, and normally requires less data preparation. Jiang et al. summarize ANN’s forecasting advantage over conventional statistical methods in the Journal of “Decision sciences”:

“Researchers believe that Neural Network approach can generalize and ’see through’ noise and distortion better the conventional statistical models” (JIANG et al., 2001) [(10)].

ANN is inspired by the architecture of the human brain, and learns to recognize patterns through repeated minor modifications to selected neuron weights. There is much kind of ANN techniques that are good at solving problem involving patterns, pattern mapping, pattern completion, and pattern classification.

ANN pattern recognition capability makes it useful to forecast time series in engineering. A Neural Network can easily recognize patterns that have too many variables for humans to see. They have several advantages over conventional statistical models: they handle noisy data better, do not have to fulfill any statistical assumptions, and are generally better at handling large amounts of data with many variables.

According to Stottler (2001) [(10)] a problem with Neural Network is that it is very difficult to understand their internal reasoning process. In my opinion, however, this is not entirely accurate. It is possible to get an idea about the learned ANN variables’ elasticity. By changing one variable at a time, and during that time looking at the changes in the output pattern, at least some information regarding the importance of the different variables will be visible. In my opinion, Neural Networks can be very flexible systems for problem solving.

3.3. Evolutionary Algorithms:

3.3.1. Definition:

After reading several Evolutionary Algorithms (EA) definitions. Howe's (1993) at the University of Pittsburgh stands out as being quite understandable and complete,

"An algorithm that maintains a population of structures (usually randomly generated initially) that evolves according to rules of selection, recombination, mutation and survival referred to as genetic operators. A shared "environment" determines the fitness or performance of each individual in the population. It also tells us that the fittest individuals are more likely to be selected for reproduction (retention or duplication), while recombination and mutations modify those individuals, yielding potentially superior ones". (HOWE, 1993) [10].

3.3.2. Branches of Evolutionary Algorithms:

There are currently four main paradigms in Evolutionary Algorithms (EA) research: Genetic Algorithm (GA), with two sub-classes and Genetic programming (GP), Evolutionary programming, and Evolution Strategy.

3.3.2.1. Genetic Algorithm:

A good definition of Genetic Algorithm (GA) is made by Obitko (1998) at the Technical University in Prague's web under the headline "Introduction to Genetic Algorithm".

"Genetic algorithms are inspired by Darwin's theory about evolution. Solution to a problem solved by genetic algorithm is evolved. Algorithm is started with a set of solution (represented by chromosomes) called population. Solution from one population are taken and used to form a new population. This is motivated by a hope, that the new population will be better than the old one. Solutions are selected to form new solutions (offspring) are selected according to their fitness- the more suitable they are the more chances they have to reproduce. This is repeated until some condition (for example number of population or improvement of the best solution) is satisfied." (OBITKO, 1998) [10].

3.3.2.2. Genetic Programming:

Genetic programming (GP) is a programming technique that extends the Genetic Algorithm to the domain of whole computer programs. In GP, populations of programs are genetically introduced to solve problems (HOEW, 1993) [(10)].

3.3.2.3. Evolutionary Programming & Evolution Strategy:

Evolution programming uses mutations to evolve population. Is a stochastic optimization strategy similar to Genetic Algorithm, but instead places emphasis on the behavioral linkage between parents and their offspring, rather than seeking to emulate specific Genetic Operators as observed in nature. Evolutionary Programming is very similar to Evolution Strategies, although the two approaches developed independently (BEASLEY, HEITKOETTER, 2001) [(10)].

3.3.3. Advantage and Disadvantages:

Examples of problems where EA have been quite successful are: Timetabling and Job-Shop Scheduling Problem (JSSP), finding the most beneficial locations for offices, etc., and typical Operational Research (OR) problems with many constraints (HEITKOTTER, BEASLEY, 2001) [(10)].
Weisman and Pollack (1995), at Ben-Gurion University, claim that GA has proven to be well suited to optimization of specific non-linear multivariable system. They explain that GA is used in a variety of application including scheduling, resource allocation, training ANNs, and selecting rules for fuzzy systems. Heitkotter and Beasley (2001) explain that,
"Gas should be used when there is no other known problem solving strategy, and the problem domain is NP-complete. That is where Gas comes into play, heuristically finding solutions where all else fails." (BEASLEY, HEITKIETTER, 2001) [(10)].

Several universities agree (HOWE, 1993) (WEISMAN, Pollack, 1995) [5] that EAs are especially ill suited for problems where efficient ways of solving them are already known.

The EA tries to mimic the process of biological evolution, complete with natural selection and survival of the fittest. EV is a useful method of optimization when other techniques are not possible. EAs seem to offer an economic combination of simplicity and flexibility, and may be the better method for finding quick solutions than the more expensive and time consuming (but higher quality)OR methods. In my opinion a hybrid system between OR and EA should be able to perform quite well(WEISMAN, Pollack, 1995) [10].

If a backward Evolutionary Algorithm is used on an accepted OR solution may be then the human eye could easily rearrange the first string in a more effective way. If EA then were to run the string through the normal forward process, the end result could be better than using EA on an unperfected start string.

3.4. Hybrid System:

3.4.1. Definition:

Gray and Kilgour at the University of Otego made a simple definition of a Hybrid system discovered during this research:

"*One that uses more than one problem-solving technique in order to solve a problem*" (GRAY, KILGOUR, 1997) [10].

There is a huge amount of interest (GRAY, KILGOUR, 1997) in Hybrid system, for example: neural-fuzzy, neural-genetic, and fuzzy-genetic hybrid system. Researchers believe they can capture the best of the methods involved, and outperform the solitary methods.

"Fuzzy logic &fuzzy Expert system" and "Data Mining" are deliberately placed under the heading of Hybrid system. Fuzzy logic is a method that is combined with other AI techniques (Hybrid System) to represent knowledge and reality in a better way. Data Mining, does not have to be a Hybrid System, but usually is, for example: IBM's DBS (Data Mining tool), which contains technique (IBM, 2001) such as Statistics, ANN, GA, and Model quality graphics, etc. Let us now take a closer look at the methods.

3.4.2. Fuzzy Logic& Fuzzy Expert System:

Withagen at the University of Bergen explains that Lotfi Zadeh introduced fuzzy logic. He further explains that fuzzy logic resembles human reasoning, but uses estimated information and vagueness in a better way (WITHAGEN, 2001) [10]. The answers to real-world problems are rarely black or white, true or false, or start or stop. By using Fuzzy logic, knowledge can be expressed in a more natural way (fuzzy logic instead of Boolean "Crisp" logic).

3.4.2.1. Definitions:

Withagen definition of fuzzy logic is:

"It is a departure from classical two-valued sets and logic that uses "soft" linguistic (e.g. large, hot, tall) system variables and a continuous range of truth values in the interval [0, 1] rather than strict binary (True or False) decisions and assignments."(WITHAGEN, 2001) [10].

Fuzzy logic is ideal for controlling non-linear system and for modeling complex systems where an inexact model exists, or in systems where ambiguity or vagueness is common. There are over two thousand commercially available products using fuzzy logic today, ranging from washing machines to high-speed trains.

3.4.2.2. Fuzzy Expert System:

Often fuzzy logic is combined with Expert System, as the so-called Fuzzy Expert System are the most common use of fuzzy logic (KANTROWITZ et al., 2001), (HORSTKOTTE, 2000) [10]. These systems are also called "Fuzzy System" and use Fuzzy Logic instead of Boolean (crisp) logic,

Fuzzy Expert System is used in several wide-ranging fields, including: "Linear and Non-linear Control Pattern Recognition", "Operation Research","Data Analysis", "Pattern Recognition."etc…

3.4.3. Data Mining:

Data Mining is also known as Knowledge Discovery in Data bases (KDD), Data Archaeology, Data Segmentation, or Information Discovery. Port defines Data Mining.

"*Data Mining harnesses Artificial Intelligence and slick statistical tricks to unearth insights hiding inside mountains of data. The software is so thorough, and so clever at spotting relationships and associations, that it regularly makes fresh discoveries*." (PORT, 2001) [10].

Data Mining always includes AI, or that it is always a Hybrid System with different techniques gathered together. Yet that is not always true, (WELGE, 2000). Expanding our definition of Data Mining to include the process of searching for and revealing expected and unforeseen structures in data, this encompasses the issues discussed above. Port (2001) claims that data mining has taken strong root in industry. Harry R. Kola, head of strategy at IBM's BI unit, explains that data mining has become very important for companies today.

3.4.4. Conclusion:

A Hybrid System uses more than one technique, such as neural-fuzzy, neural-genetic, fuzzy expert system, data mining (most often), etc., to solve a problem. Fuzzy logic is incorporated into computer system so that they represent reality better by using "non-crop" knowledge. Often fuzzy logic is combined with Expert System, so-called Fuzzy Expert System or more simply, "Fuzzy System."

Data mining software most often uses various techniques, including Neural Networks, statistical and visualization techniques, etc., to turn what are often mountains of data into useful information. Data Mining does not always contain AI techniques. In my opinion it is quite possible that data mining will become a very useful tool companies in the competition for market shares.

Chapter Four

Artificial Intelligence Methods in Engineering

Chapter Four
Artificial Intelligence in Geotechnical Engineering

4.1. Introduction:

Artificial Neural Networks (ANNs) were started about 50 years ago .There early capabilities were exaggerated, casting doubt on the field as a whole. There is a recent renewed interest in the field, however, because of new techniques and better theoretical understanding of their capabilities.

Artificial Neural Networks (ANNs) is able to capture and represent complex input/output relationships .The motivation for the development of neural networks technology is held by scientists who are challenged to use machines more effectively for tasks currently solved by humans.

Artificial Neural Networks (ANNs) a rapidly growing facet of Artificial Intelligence (AI) , using a collection of simple processing units that are massively interconnected in order to produce meaningful behavior .

4.2. Artificial Intelligence Applications in several domains:

Artificial Intelligence techniques are used extensively in various fields such as:

4.2.1 Machine learning applications:

Which are used for:

A. Optimization: Given a set of constraints and cost function and the problem is to find an optimal solution.

B. Classification: Grouping patterns into classes.

C. Associate memory: Recalling a memory based on a partial match.

D. Regression: Function mapping.

4.2.2 Cognitive science Applications:

Which are used for:

A. *Modeling higher level reasoning* such as: language.

B. Modeling lower level reasoning such as: speech generation, audition speech recognition, vision…etc.

4.2.3 Neurobiology Applications:

Which are used for modeling models of how the brain works.

4.2.4 Mathematics Applications:

Which are used for nonparametric analysis and regression.

4.2.5 Philosophy Applications:

Which are used for modeling human soul behavior in terms of symbols like neurally based models.

4.2.6 Signal processing Applications:

Which are used for suppresses line noise, with adaptive echo canceling, blind source separation...etc.

4.2.7 Control Applications:

Which are used for backing up a truck, cab position, rear position, match with the dock get converted to steering instruction, manufacturing plant for controlling automated machines.

4.2.8 Medicine Applications:

Which are used for storing medical records based on case information.

4.2.9 Financial Application:

Which are used for time series analysis, stock market prediction ...etc.

4.2.10 Game playing Application:

Such as: back gammon, chess, goes… etc.

4.3 Artificial Intelligence in Geotechnical Engineering:

In recent years, artificial neural networks (ANNs) have been applied to many geotechnical engineering fields with some degree of success .This article describes some of these applications as follows:

4.3.1 Data Division For Developing Neural Networks Applied To Geotechnical Engineering:

In the majority of geotechnical engineering applications, data division is carried out on an arbitrary basis. However, the way the data are divided can have a significant effect on model performance, so the issue of data division and its impact on ANN model performance is investigated by Mohammed A. Shahin (2004) [(11)].
A case study of predicting the settlement of shallow foundation on granular soils was used for such scope of work. Four data division methods are investigated:

(1) Random data division.
(2) Data division to ensure statistical consistency of the subsets needed for ANN model development.
(3) Data division self-organizing maps (SOMs); and
(4) Anew data division method using fuzzy clustering.
The results indicate that the statistical properties of the data in the training, testing and validation sets need to be taken into account to ensure that the optimal model performance is achieved. It is also apparent from the results that the SOM and fuzzy clustering methods are suitable approaches for data division.

4.3.2 Prediction of coefficient of lateral Earth pressure using Artificial Neural Networks:

Prediction of lateral earth pressure ratio (K_0) based or dilatometer test results was introduced by Sarat K.Das [(12)] (2001) .Feed forward back propagation Neural networks have been used and the best model is chosen based on different statistical parameters. The best fit line for predicted K_0 (K_{0p}) and observed K_0 (K_{0obs}) , correlation coefficient , coefficient of determination , the mean and standard deviation of the ratio K_{0p}/K_{0obs} are used to compare different ANN models.
The importance of using different statistical criteria for the evaluations of the ANN model is discussed .Using sensitivity analysis, the parameter influencing the value of $K_0$are identified.
The result was presented with a high value correlation coefficient for both training and testing data. The performances of the models were governed by the input parameters. It was observed that the models should be evaluated based on different statistical parameters. A high predictactability performance of the chosen ANN model

was also observed. Based on sensitivity analysis, K_d obtained from dilameter test results found to be the most important parameter for determination of K_0value.

4.3.3 Machine Learning Classifier for seismic liquefaction potential Evaluation:

Liquefaction potential assessment has been a very important problem from the point of view of geotechnical engineering. It's well known that many factors such as soil parameters and seismic characteristics influence this problem. Various researchers have attempted to solve this problem using artificial neural networks (ANN), a sub-branch of machine learning (ML). However, many authors have missed important issues such as proper data modeling, ANN model selection, and performance evaluation of ANN for liquefaction potential assessment. Covering these aspects sudhirkumar V. Barai (2002) (13), intends to provide systematic steps to model liquefaction potential data using ML classifier (13).

Liquefaction is a phenomenon in which the strength of soil is reduced by earthquake shaking or other rapid loading. Liquefaction and related phenomena have been responsible for tremendous amount of damage in historical earthquake around the world. Determination of liquefaction potential due to an earthquake is a complex problem in the geotechnical engineering field. It is well known that factors such as soil parameters and seismic characteristic influence this problem. Recently such phenomenon has been modeled by various researchers using (ANN). This modeling was feasible since ANNs can successfully replace existing equation –based models. For seismic liquefaction potential, ANN models provide significant improvements in prediction accuracy over their statistical counterpart.

Tung et al. (1993) (13) carried out study using back prorogation based neural networks with inputs as ground shaking intensity, ground water level, depth liquefiable soil deposit and soil penetration resistance and output as liquefaction occurrence. The study was trained with a selected set of data and tested of the same domain test data and other city test data.

Goli (1994) (13) has used neural networks to model the complex relationship between seismic and soil parameters in order to investigate liquefaction potential. The networks used the standard penetration test (S.P.T.) value, fines content, grain size, dynamic shear stress, overburden stress, earthquakes magnitude, and horizontal acceleration at the ground surface as input. Goli (1996) (6) has also extended neural network study to assess liquefaction potential from cone penetration test (CPT) data.

Ural and Saba (1998) (6) used back- propagation learning algorithm to train network using actual soil records. The performance of the network model was investigated by changing the soil and seismic variables including earthquake magnitude, initial confining pressure, seismic coefficient, relative density, shear modulus, friction angle, shear wave velocity and electrical characteristic of the soil. The most efficient and global model for assessing liquefaction potential and the most significant input parameters affecting liquefaction were summarized. A forecast study was performed for the city of Izmir, Turkey. Comparisons between ANN's results and convential dynamic stress methods were made.

Above mentioned papers have missed some important issues from civil engineers perspective:

Firstly: proper data modeling issue was not well addressed.

Secondly: The basis for selection of ANN model was not clearly defined.

Last but not the least: The reliability of performance of ANN model was not well discussed. Sudhirkumar V.Barai (2002) [13] aims to discuss these aspects and to provide systematic steps to model seismic liquefaction potential data using ML classifier for civil engineering problems.

4.3.3.1 Data Modeling for Machine Learning Classifier:

In this phase the following two steps are involved:

Step (1): Data collection:

'Raw' data consist of the collected (measured, sensed, polled, observed….etc) attribute values describing objects and relations between objects in the application domain.

Data coming from systems include the results of manipulating independent or control variables. These data need to be modeled property for ML classifier. The data model represents a set of data in mathematical form. The model behaves in similar ways as the system. The data model helps in making prediction, classifying new data, trying out (what if) situations, learning about relationships in the data and optimizing the system from which it came. In achieving this goals 'raw' data must be processed before training the network.

Step (2): Preliminary Data Analysis:

Preliminary data analysis is one of essential parts in the ML data modeling. One should not forget the old saying "Garbage in-Garage out". Data can be online or off Line, continuous or discrete, coming from static or dynamic systems.

Great care is expected in presenting input, removing outliers from the data and use of prior knowledge in finding relevant inputs. The step of preliminary data analysis involves identification of methods of preprocessing and post-processing. It is general practice in ML applications to present pre-processed input data to a ML model and to obtain the required output values from post-processed outputs of a ML model. The preprocessing is the selection of appropriate data subsets for performance as well as consistency reason and the transformation of complex data for better meaningful representation.

4.3.3.2 Neural Networks As Machine Learning (ML) Classifier:

In this phase, varieties of neural network, models, such as Hopfield net, Hamming net, carpenter, Grossberg net, single-layer perception, multi-layer network…etc. can be used as ML model. The single-layer Hopfield and Hamming nets are used with binary input and output under supervised learning. The carpenter / Grossberg net, however, use unsupervised learning. The single-layer perception can be used with multi -value input and output in addition to binary data. A serious disadvantage of the single-layer networks may have open or closed convex decision regions (Lippman, 1987) [13]. One can select the model depending upon the application domain. The multi-layer network is very a popular ANN architecture and has performed well in variety of applications in several domains including applications.

In multilayer perception, the training input vectors of all the connection are adjusted to make the output layer best represent the desired output, the process is repeated many times until a predefined error is obtained or observed. By iterating through the training data many times, the neural networks are able to generalize the rules implicit in the data. The method of adjusting weights is called *learning rule*. The weights are adjusted to minimize the error between input and output vectors and the process is known as *delta-rule learning*. The most commonly used type of neural network is back-prorogation.

4.3.3.3Machine Learning Model Performance Evaluation:

Both qualitative and statistical criteria can be used for reliable ML model evaluation. These are several methods that have been used to evaluate the performance of ML: Re-substitution (R), Hold-out (H), cross validation such as leave-one-out (L) and k-fold cross validation (k), and Bootstrap (B). Bootstrap being computationally exhaustive.

Reich and Barai (1999) [13] have given qualitative nature of these basic evaluation methods. They give an idea about the reliability of these evaluation methods for given data in particular ANN model. However, they do not include any distinction between different types of errors (e.g., false positive or negative in classification); although different types of errors might be very different in terms of cost or severeness for the particular engineering application, however, there is growing interest in ML community in understanding the properties of these tests. Such properties are derived empirically from many tests on artificial and real data base.

In general, it is common to evaluate the predictive accuracy of models by cross-validation. Either K or L is acceptable. The selection of cross-validation methods is based on the size of the data. This method provides reliable estimates of the true error rate, as nearly all the cases are used for training, and all the cases are used for testing.

The estimates obtained from this test are nearly unbiased. In general K found to be more stable than L, and given its reasonable computation requirement, K is the recommended test for absolute evaluation. For small data bases one has to use L or B although there are cases where both fail. When better estimations are required and if computational resources are available one may carry out K exercise I times, which can be denoted as KI. In order to get most out of the evaluation process, Rich and Barri (1999) [(13)] recommend executing all the evaluation methods.

An important aspect when solving practical problem is obtaining the best possible performance out of the data. Therefore it is natural to wish to optimize ML program parameters. However this requires special attention related to evaluation, and finally estimating the performance of the ML model. In the first step, the data is subdivided into data for model learning and model testing. In the second step, the data for model learning is used to select the best model (i.e. learning approach) and operation parameters. In the third step, a model is created from the complete model learning set by the best approach and best operational parameters. The model is validated on the testing set.

4.3.4 Site characterization:

Systems have been developed for planning site investigation, interpreting site investigation data to generate a model of the ground conditions, classification of soil and rock, and the interpretation of geotechnical parameters.

4.3.4.1. Site Investigation planning:

SOILCON (wharry and Ashley, 1986, siller, 1987) [(14)] was one of the earliest researchers whose interest to address the problem of determining the required level of geotechnical investigation.This is based on the requirements of proposed structure and the level of information known about the site.

Smith and Oliphant (1991) [15] describe a system to assist with the planning stages of a site investigation.

The system provides suggestion as to the next stage of the site investigation. The information obtained from the subsoil exploration stage is also used to create a 2-D visual representation of the soil layers.

4.3.4.2. Interpreting Ground Conditions:

One of the earliest geotechnical knowledge-based systems (KBSs) was SITECHAR (Norkin, 1985, Rehak et al, 1985) [16]. This is a KBS which uses geometrical reasoning to develop inferences about the depositional patterns of the subsurface materials and their physical properties. It uses field and laboratory data but also takes into account existing experience of geology and geomorphology at a specific site or at similar ones. The same rule-based approach was further developed as LOGS (lok, 1987, Adams et al, 1987) [17]. LOGS treats information from several boring logs and provides the user with two dimensional subsurface profiles.

Another system which uses the integration of different types of data is described by kovalevsley and kharchenko (1992) [11].Their system is used for classifying seabed soils based on an integration of geophysical and geotechnical data e.g. compress ional and shear wave velocity section, and borehole profiles.

Toll et al (1992) [11], Toll (1994) [11], Toll (1995) [11] describe SIGMA, a KBS for interpreting ground condition of design parameters from laboratory or field test results. The approach used for correlating soil layers between boreholes (based on soil descriptions) is described by Vaptismas and Toll (1993) [11]. A similar approach was also used by Oliphant et al (1996) [15]. Their system (ASSIST) can also generate graphical representations of the ground conditions.

Kinnicut et al (1994) [11] describe a system called NOMAD which can be used for three dimensional stratigraphic characterization NOMAD can use the functionality of KRIB(kinnicutt, 1995) [11] to create ground profile from borehole data. This is done by combining geostatistical and knowledge. Based approaches.

Adams and Bosscher (1995) [11] describe the integration of geographical information systems (GIS) and knowledge-based systems for subsurface characterization. Thomagg and Altschaeffl (1994) [11], in their sketchy outline of Geosys, also suggest that a combination of tools is necessary to support the site investigation process. These developments are the logical extension of the idea of a' geotechnical site characterization work bench' suggested by Rehak et al (1995) [11].

The methods so far described for analysis and interpretation of geotechnical site investigation data make use of either geometrical reasoning or statistical techniques. Zhou and WA (1994) [11] describe the use of ANN for this purpose. Their ANN system is used to characterize the spatial distribution of rock head elevations. Similar applications relevant to ground water characterization are described by Rizzo and Dougherty (1994) [18] and Basheer et al (1996) [18]. Basheer et al (1996) [18] describe how ANNs can be used to map the variation of permeability in order to identify boundaries of a landfill.

4.3.4.3. Classification and parameter Assessment of soils:

CONE (Mullarkey, 1986, Mullarkey and fenves, 1986) [11] is a KBS that interprets raw data from the cone penetrometer (CPT) in order to check the validity of the raw data and to classify the soil types (to generate profiling). It represents an early use of fuzzy sets in geotechnical engineering. The classification is used to inter values for the shear strength of sands and clays.

Alin and Munro (1987) [11] present a very simple proto-type KBS for soil identification that uses rather simplistic text book knowledge. It provide judgment concerning the most likely foundation type under given soil and loading conditions, based on visual and physical observation of soil characteristics.

A KBS was developed by Davey-Wilson (1991) [11] for soil shear strength analysis. The system uses descriptions as input in order to enter values for friction angle (Ø). Similarly, Gillette (1991) [11] describes CASS computerized Adviser on soil strength), a KBS to assist in the selection of shear strength parameters (C and Ø) for use in stability analysis.

Agrawal et al (1994) [11] use ANN approach for predicting c' and Ø' for silty clay from dry density and water content. Davey- Wilson (1994) [11] earlier work has been much extended by Davey-wilsor and Mistry (1995) [11] which uses a case-based approach to the estimation of geotechnical parameters.

An object-oriented approach to the same problem is described by Toll and Giolas (1995) [11]. The KBS makes use of a knowledge base which is structured to represent the typical range of values for a number of geotechnical design parameters.

Neural network approach to soil classification is described by Cal (1995) [11] that use three main factors (P.L., L.L and clay content) to generate a quantitative soil classification. Goli (1995) [11] has used ANNS for modeling soil correlations.

The stress-strain behavior of soils has also been modeled using ANNS. Penumadn et al (1994) [11] have attempted to model the stress-strain behavior of clays, incorporating rate dependant behavior. Ellis et al (1995) [11] have used grain size distribution and stress history as input parameters in order to simulate stress strain behavior for sand.

4.3.4.4. Classification and Parameter Assessment of Rocks:

Rock mass classification systems make use of a set of reasonably well defined rules and are therefore ideally situated for implementation as knowledge-based systems. A number of systems have been developed, some of which have been reviewed by Coulthard (1995) [11]. These include Zhang et al (1988) [11] based on Glis qualitative classification scheme; Juang and Lee (1989) [11] and Madlu et al (1995) [11] based mainly on Bieniausskits Rock Mass Rating (RMR) system, and using fuzzy logic.

Classification systems have been developed for specific purposes have also been implemented as KBSs. Bearman et al (1990) [11] describe the development of KBS for predicting crushing requirements based on a communicating index. Koczanowski et al (1991) [11] describes a KBS for rock rip ability assessment.

ANNs have been used for rock classification. Millar and Hudson (1994) [11] describe the use of ANN method for performance monitoring of rock masses for mining geomechanics. They describe an application for the collection of data relating to the condition and subsequent classification of rock masses. They have also used ANNS to predict likely future performance of rock masses; particularly when they have been perturbed from their natural condition by mining engineering activity. CAI (1995) [11] has used ANNs to classify rocks for the purposes of blast design and Yi and Lindqvisl. (1995) [11] have used ANN model for predicting rock quality parameters.

Zhang et al (1991)[11]; Millar and Clarici (1994) [11]and Millar and Calderbank(1995)[11] have used ANNS for modeling rock deformability behavior. Input parameters include mineralogy, particle size and shape, grain compressibility….etc.

4.3.5. Foundations:

AI techniques have been used in a range of systems relating to foundations. Developers have particularly focused on conceptual design (i.e. selecting appropriate foundation types). However, there are also systems for detailed design, for foundations problems and construction. The prediction of pile capacity from site driving data is an area which has been found to be well suited to ANN Approaches.

4.3.5.1. Conceptual Design of Foundations:

A number of KBS have been developed to address the problem of selecting an appropriate type of foundation. Such a system for building foundations provide a list of all feasible foundation alternatives, based on soil conditions, water table location, depth of bedrock and the imposed loading conditions from the structure.

The system described by Stuckrath and Grivas (1990) [11] focused on the selection of bridge foundation. The system presents preliminary design options including shallow and deep foundation and ground improvement.

FOUNDATION (Rashed et al (1991) [11] also provides a preliminary module for selection of the most appropriate foundation system. In addition it has a detailed design module for performing the final design. CONCFOUND (Toll and Barr, 1995) [11] is a computer-aided learning package for preliminarily (conceptual) foundation design. The system offers a range of foundation types.

A number of KBSs have been developed specially for pile selection. PILE (Santa marina and Chmean, 1987) [11] provides a list of the most promising alternatives on technical constraints. It is then up to the user to consider additional factors (e.g. economical), in order to reach a final decision. PILEX (Elton and Brown, 1991) [11] consider timber, concrete and steel piles and takes into account geotechnical, geological, structural and environmental factors that influence the pile selection. Suppile(Wong et al, 1991) [11] evaluates of suitability of different types of piles and can estimate the required pile size and length. The selection of a pile type is performed by generating a suitability score depending on the number of problems that would exist if that pile type was used.

4.3.5.2. Detailed Design:

Yehia and Elhaj (1987) [11] are developing aKBS to assist in the selection and design of spread footings. It uses a database of previous designs and tries to match a new problem to one of the existing cases in the database. Its main purpose is the structural design of foundation and no real geotechnical design is included. A KBS (GEOTECH) has been developed by Parikgg and Rameswara Rao, (1991) [11] as an aid in shallow foundation design by calculating bearing capacity and settlement. The out put is in the form of a list of the most promising alternatives with corresponding confidence factors.

4.3.5.3. Pile Driving:

Chow et al (1995) [11] present ANN approach to the prediction of pile capacity. A stress wave matching technique is used which makes it feasible to determine the static pile capacity in real time in the field. Chan et al (1995) [11] have used ANNs as an alternative to pile driving formulas. Similarly, Goli (1996) and Lee (1996) [11]have both used ANNs to estimate the load capacity of driven piles based on the hammer characteristics, the properties of the pile, and soil, and the pile set. All these authors suggest that ANNs provide better prediction than conventional pile driving based on the geometry and the dynamic characteristics of the ground.

4.3.5.4. Foundation Construction:

Kato et al (1995) [11] outline a KBS for the planning and progress the foundation work. It selects an appropriate method of construction (for pile or slab) and incorporates these into the construction plan. Yeh et al (1991) [11] describe diagnostic Knowledge. Based system PCPILE (Prestress concrete pile) for diagnosing the damage to a pile during the construction process. Fisler et al (1993) [11], Fisler et al (1995) [11] describe a decision support system called D52 which can suggest an appropriate construction method for constructing a drilled shaft based on geotechnical information. It can also prepare a preliminary cost estimate, and suggest key specification items.

4.3.5.5. Foundation Problems:

Hadipriono et al (1991) [11] described a KBS which was under development for determining the causes of foundation failures. The system contains knowledge on possible causes for foundation failure such as soil settlement, expansive soil, soil erosion, bearing capacity failure, soil instability and foundation corrosion.

Wiseman et al (1992) [11] describe a KBS for foundations on expansive soil, extending their system for heave prediction. The system requires input about the soil and profile, the building environment (changes in drainage, vegetation) and details of existing and proposed buildings and attempts to quality the amount of heave expected.

4.3.6. Earth Retaining Structures:

Artificial intelligence systems have been developed for retaining structures, for predicting movements and analyzing failure. Hutchinson et al (1987) [11] present RETWALL, a KBS for the selection and preliminary design of earth retaining structure. the system evaluates applicability of the nine wall types that are included in its knowledge base(brick wall, block work wall, crib wall, gabions, gravity wall, railway sleeper wall, reinforced earth, reinforced concrete wall, sheet piling).Oliphant and Blockley (1989) [11] developed a KBS with a knowledge base comprising three parts, the construction process, the design process and environmental impact. The system includes 11 case studies of retaining structures and provides a narrative of the history of each one in terms of why it was selected or considered as an alternative, allowing the user to compare these with a proposed retaining wall.

A KBS for retaining wall selection and design is presented by Arockiasamy et al (1991) [11]. The system has knowledge about ten wall types including concrete gravity, cantilever, counter fort, gabions, reinforced-earth, crib, slurry, sheet-pile, tieback, and soil nailed walls. Amer & Abdel Rahman (1994) [11] describes a KBS for sheet pile selection, with links to programs for detailed design.

WADI (Chahine and Janson, 1987) [11] is a KBS developed for the preliminary diagnosis of retaining wall failures. WADI is applicable to two types' retaining walls: cantilever reinforced concrete wall sand gravity concrete or rubble walls, having maximum height of 8 meters. RETAIN (Adams et al, 1989) [11] is a KBS that allows categorization and organization of knowledge relating to failure and rehabilitation of earth retaining walls. Upon solving the failure diagnosis, a table of wall failure modes with associated certainties is produced.

Goh et al (1995) [11] have shown how neural networks can be used to estimate lateral wall movements in braced excavations. The neural network was used to synthesize data derived from finite element studies on braced excavations in clays.

4.3.7. Slopes:

4.3.7.1. Soil slopes:

Gravis & Regan (1988) [11] describe a KBS (STABCON) for evaluating slope instability and recommending appropriate types for treatment for soil slopes. It is linked to analytical methods for calculating slope stability. Hirokane et al (1990) [11] also describe a KBS for deciding on appropriate slope treatment. It includes 44 different type of slope protection ranging from vegetation and seeding through to concrete crib-work and retaining walls.

SISYPHE and XPENT (Aste et al, 1995) [11] are two KBSs for slope instability which has been developed in parallel .XPENT (Faure et al, 1988; Faure et al, 1991; Mascarelli et al, 1992; Faure et al, 1995) [11] is a KBS for assisting in slope stability analysis. It assists in diagnosing the type of landslide on the basis of information about the geology, vegetation, geomorphology (large and small scale), and hydrogeology. It can also advice on methods of stabilization based on the size of the slide, the material, accessibility of the site, etc. SISYPHE (Aste` 1992) [11] is a KBS for investigating slope instabilities. It can be used in diagnosis of a landslide as well as for hazard evaluation. For diagnosis purposes, SISYPHE provides the ability to develop three dimensional representations of the ground surface, piezometric surface and the slip surface itself.

Wang et al (1994) [11] describe a KBS for investigating potential landslides. It contains knowledge bases relating to the spatial distribution of an unstable zone, the geotechnical properties, method of assessing stability, and methods of treatment.

Winlock and Bentley (1991) [11] describe the development of a KBS the determination of planning application with respect to landslide hazard in south Wales. The system attempts to assess the landslide hazard that may affect proposed development sites and it produces output in the form of planning response options.

4.3.7.2. Rock Slopes:

Expert Slope Design System (ESDS) presented by kizil & Danby (1990) [11] and Danby and kizil (1991) [11] is a KBS to assist geotechnical engineers in the assessment of proposed slope design in open cast coal operation in the UK. Ozgenoglu &Coal (1994) [11] describe SEVDUR a KBS for slope stability analysis relating to mining operation.

Hao &Zhang (1994) [11] describe a KBS for stability analysis of rock slopes. This uses fuzzy sets for representation of joint sets. Zhou (1994) [11] uses a probabilistic approach in a KBS for the prediction of slope stability. An approach called MAQEFO-Mechanism Analysis and Quantitative Evaluation through Geological Processes is used. Moon et al (1995) [11] have also used a neural network integrated with a KBS for preliminary design of slopes.

4.3.8. Tunnels and Underground Openings:

Many of the system for rock mass classification described above have an application in design of tunneling support (Zhang et al, 1988; juang & lee, 1989; Madhu et al, 1995; Butler &franllin, 1990) [11].In addition; fairhurst & Lin (1985) [11] have discussed the use of a fuzzy methodology in the design of tunnel support system. Feng & Lin (1992) [11] also present a KBS (OSDES) for tunnel support design. The system considers rock mass classification; groundwater; type, span, and service time of opening; depth of overburden; dynamic; swelling, and rheological properties of the rock.

Ghosh et al (1987) [11] describe a KBS for deciding on rock bolt and spacing for supporting coal mine roofs. Zhang et al (1991) [11] discuss an early application of a neural network to coal mine support. Similarly, Deb et al (1994) [11] describes a neural network approach to roof stability in long wall mining. This is intended to provide real-time monitoring of leg pressure on shields in order to provide early warning of possible collapse. King & Signer (1994) [11] also describe a neural network approach to selection of roof support in mining. The neural network was used to identify patterns of discontinuities in coal mine roofs. Zhang et al (1995) [(11)] describe use of a neural network for forecasting rock deformation in Chinese colliery roadways.

Lee & Sterling (1992) [(11)] describe a neural network for identification of probable failure modes for underground openings from prior case history information. The neural network form part of a KBS for assisting with tunnel design (Sterling&Lee, 1992) [(11)]. The neural network is used to identify similar cases to that being designed. The case histories can then be extracted for the user to examine. Moon et al (1995) [(11)] have also used a neural network approach integrated with a KBS for preliminary design of tunnels.

Gokay (1993) [(11)] has made use of Hudson’s (1992) [(11)] systems approach to rock engineering to develop a KBS to assist in rock engineering decisions relating to mine excavation. The system deals with rock mass type and structure; in situ stress; hydro-geology; mining method and assist with excavation stability, location, and orientation.

SIMSECTION (Halabe & Einstein, 1994) [(11)] is a KBS that acts as the user interface for DAT (Decision Aids for Tunneling) [(11)]. The KBS assists the user with the definition of the problem and provides consistency checking before performing an analysis. Coulthard & Ciesielski (1991) [(11)] describe SAGA, a KBS to assist with the selection of a stress analysis program for rock excavation design. This can assist with choosing between ten different stress analysis packages.

Zhang et al (1993) [(11)] present a KBS for prediction of potential disaster due to excavation of tunnels or underground structures within carbonate rock areas. It is based on the knowledge of Chinese experts in karsts science and in underground engineering.

Although most Al application in tunneling has been developed rock in engineering applications, Mi and Jieliang (1989) [(11)] report on a KBS for soft ground tunneling. It has been developed to predict the value of surface settlement and the degree of damage to corresponding building caused by shield-driven tunneling. As well as estimating settlement, the system can also propose prevention and strengthening measures. Russell& Alhammad (1993) [(11)] describe a KBS framework for selection of appropriate construction methods. The approach is illustrated using a prototype KBS, called CMSA (Construction Method Selection Assistant), to select a shoring system for cut-and-cover tunneling. A KBS has also been developed for providing assistance for the planning of support for trenches (Konloly, 1986; siller, 1987) [(11)]. The system is based on two soil classification system developed by the US National Bureau of Standards in order to increase the safety of this type of excavation.

4.3.9. Mining:

Some of the A.I. systems described in the section on slopes are relevant to opencast mining operation (Kizil &Denby, 1990; Denby and Kizil, 1991; Ozgenoglu & Ocal, 1994) [11].

Similarly, some of the systems in the section on underground openings relate to deep mining operations (Ghosget al, 1987; Zhang et al, 1991; Gokay, 1993; Deb et al, 1994; King & Signer, 1994; Zhang et al 1995) [11].

Yao et al (1992) [11], Reddish et al (1994) [11], Reddish (1995) [11] present ESDAS (expert structural damage assessment system). This was developed to evaluate damage due to mining subsidence. The system uses a risk-assessment technique based on certainly factors to predict the likely damage to a particular structure that is subject to mining subsidence.

Yu & Vonpaisal (1996) [11] describe new blast damage criteria that have been developed with special reference to mining operation. It can be used for assessing damage by incorporating that vibration level, rock proprieties, site characteristic and the effect of ground support system .The approach has been used within a ground control KBS module.

4.3.10. Liquefaction:

SOLES (shyu and hryciw, 1991) [11] is a KBS to assist in the evaluation of the liquefaction potential of soil subject to earthquake excitations. SOLES considers four aspects: the earthquakes excitations, the soil prosperities, the analysis result and the overall evaluation .Chouicha et al (1994) [11] describes a new KBS called LIQUEFY. This uses five different methods for liquefaction hazard assessment and groups them according to their task.

Goh (1994) [11] has used a neural network to model the complex relationships between seismic and soil parameters in order to investigate liquefaction potential. Network uses the standard penetration test (SPT) value, fines content, grain size, dynamic shear stress, overburden stress, earthquake managinitude, and horizontal acceleration at the ground surface as inputs. GOH (1996a) [11] was also uses neural networks to assess liquefaction potential from cone penetration test (CPT) data.

4.3.11. Ground Improvement:

IMPROVE (Chameau and Sanntamarina, 1989) [11] is a KBS designed to assist in the selection of ground improvement techniques. It contains a case-based system that selects case histories that best resemble the project. Similarly, Mohamed et al (1991)[11]describe a KBS (ESPGIS) to advice on the selection of ground improvement method. EPSGIS allows the user to define the problem by specifying (with varying degrees of certainty) the nature of the ground improvement needed, subsurface condition and other relevant parameters.

Yoon et al (1994) [(11)] describes what they call a knowledge database for ground improvement technologies. This contains information on the current technologies available, classified by country of use and application. The knowledge base contains information on international/national codes of practice, design method, state of practice, and case studies.

Kotdawala & Hossain (1994) [(11)] describe a KBS (PACT) for soil compaction. The system identifies the lift thickness and molding moisture content to be used in field compaction. It has knowledge of the different types of compaction plants, and particular problems associated with compaction of particular soils. A neural network approach for soil compaction is reported by Basheer &Najjar (1995) [(11)], Najor et al (1996) [(11)]. This is intended for predicting optimum moisture content (OMC) and maximum dry density (MDD) based on soil type, grading characteristics, and consistency limits. For natural soils, they have based the prediction on only three variables: liquid and plastic limit, and specific gravity.

4.3.12. Geotextiles:

A KBS is described by Maher and Williams (1991) [(11)] that selects geosynthetic materials and performs detailed design for different geotechnical application. The knowledge incorporated in the system contains information about material selection for five different geosynthetic uses, such as stabilization to reduce erosion, separation of soil layers, reinforcement to improve soil strength, drainage material to remove water, and filtration to reduce cross plain flow of soil particles.

Edge Drain by Expert System (EDXES) has been developed by Dim Mick et al (1991)[(11)] to assist in the design and specification of the geotextile component of road pavement edge drain. This system considers commercially available geotextiles and produces a list of the ten thinnest (lightest) candidate products arranged in ascending order. The system described by Dukes et al (1994)[(11)] for road design also incorporates the design of a geotextile layer.

Mannsbart & Rest (1993)[(11)] describe a KBS design using polygeotextiles. The basis for the design is the design charts in the technical manual ‘Polyfelt Design and Practice’ and can be used for the following application: road construction, hydraulic construction, drainage system, retaining wall, and geom. embrace protection.

4.3.13. Ground Water/Dams:

Sieh et al (1988) [11] describe a KBS developed to assist in the diagnosis of seepage from embankment dams. The system attempts to define the type of problem (point source seepage, non-point seepage, sand boils, sinkhole, and drain flow), the seriousness of the problem and a recommended course of action. EXSEL (Asian et al, 1988) [11] is another KBS constructed as a diagnostic tool for seepage problem associated with dams, such as earth dams, rock fill dams, concrete dams, and roller compacted dams. Ohnishi & Solemn (1995) [11] have used a neural network approach to investigate seepage under a concrete dam founded on rock.

Engel & Beasley (1991) [11] describe a dam site selection (DSS) system. It was developed for use in a graduate-level hydrology design course and can assist with rating potential reservoir sites.

Ground water expert (GWX) presented by Davey-Wilson & May (1989) [11] and Davey-Wilson (1991) [11], is KBS that has been developed to advise on appropriate methods for ground water control in excavations. In its latest version (Davey-Wilson, 1993) [11], the knowledge base contains information on each of 26 possible methods.

Gribb& Gribb (1994) [11] and Najjar and Basheer (1996) [11] have both used neural network approaches for estimating permeability. Najjar and Basheer use thirteen input parameters including classification data (Liquid limit, activity, percent clay etc), density, type of compaction, and weight of compactor in order to predict the permeability of compacted clay liners.

4.3.14. Roads and Earthworks:

Pears et al (1986) [11] describe a KBS begin developed for the evaluation of road corridors taking into account finance, safety, and engineering geological criteria. The system will give a cost for each potential road corridor and a probability of failure with in its design life, as well as a summary of the main advantages and disadvantages of each alignment.

Goh (1993) [11] describes a KBS (PAVEDKB) for deign of flexible road pavements. The KBS assists with selection of appropriate soil parameters for the sub grade and also for properties of the pavement materials. It is linked to algorithmic routines for linear elastic analysis of the pavement structure.

Dukes et al (1993) [11] describe a KBS (ROAD) for deign of primary and major road high ways. It is based on AASHTO deign procedures, and allows the inclusion of geotextile layer. It considers the mechanical and filtration properties of the geotextile the design.

Amirkhanian &Baker (1992) [11] describe a KBS of selecting equipment for earthmoving operations. The system interprets information concerning the soil condition at a site, operator performance and required earthmoving operation. PACT (Kotdawala &Hossain, 1994) [11] is a KBS that focuses on field compaction. It has knowledged the different types of compaction plant, and particular problem associated with compaction of particular soils.

4.3.15. Discussion:

A number of artificial intelligence (AI) systems have been developed for geotechnical application. Many of the system developed are simple prototype, i.e. they have been developed to show that the techniques could be useful. Relatively few are being used commercially at present. However, as the area develops, and more system were developed beyond the prototype has, we should see an increase in the use of AI system in practice.

The majority of the earlier systems used simple rule-based technologies. As time has progressed more complex form of representation have been adopted, e.g. form-based, object oriented. We are now seeing a limited number of case-based systems being applied in geotechnical engineering and no doubt this area will develop further. The use of neural network has developed rapidly and a considerable number of geotechnical applications are now available. Genetic algorithms have yet to be exploited as geotechnical engineering tools but they will certainly have application in the synthesis (conceptual design) area.

Knowledge-based system developers identify different intended uses for their system. Some authors see their knowledge-based system developing to the stage of becoming ‘expert system’ where they would be capable of reasoning at the level of a human expert. They would see the role of their system as replacing human expertise. This is often the case with developers relatively new to the field who do not appreciate the enormous difficulties of acquiring the knowledge required for such a system.

However, as the area of AI has progressed, more seasoned developers now see their systems in a support role, as decision support tools or, assistants’. AI tools in this way, rather than pretending that such system will replace human expertise. We must also convey this change of philosophy to potential users. There is otherwise a danger that engineers in practice will see AI system as a threat rather than something that will benefit them (Toll, 1990) [11].

Developers are also finding that AI technology is good for some aspects of solving engineering problem, but that other approaches are still valid for many applications. Therefore, we are increasingly seeing the development of hybrid system which mixes Knowledge-based, neural network, case based, probabilistic and algorithmic approaches.

4.4. Conclusion:

A large number of artificial intelligence (AI) systems have now been developed for geotechnical application. Although many of the system described are simple prototypes, some systems are progressing beyond the developmental prototype phase. Therefore, we should soon start to see an increase in the use of AI systems in geotechnical practice.

It is suggested that AI systems should be developed as decision support tools or ‘assistants’ rather than pretending that AI systems will develop to the stage where they could replace human expertise. It should also be recognized that AI techniques are good for some aspects of solving engineering problem, but that other approaches are still valid for many application. Therefore, the way forward will be the development of hybrid system which mixes Knowledge-based, neural network, case based, probabilistic and algorithmic approaches.

Chapter Five

Soil Profile Prediction Using Artificial Neural Networks

Chapter Five
Soil Profile Prediction Using Artificial Neural Networks

5.1. Introduction:

The geotechnical characteristics including layering and (stratification) and engineering properties of underlying soil in the cross-borehole region is a human intensive process and is subjected to the presence of statistical and systematic errors. Improving of the reliability of soil layering interpolation, will lead to cost reduction and improved operation planning.

In this chapter, Using a multi-layer perceptron Artificial Neural Network (ANN) with a back propagation algorithm ,a prototype approach has been developed that uses a model system to predict soil properties in specified locations in different depths, based on the available site investigation produced data from selected sites in Sudan. The results are then compared with unused data of actual boreholes to check the ANN model’s validity. For this purpose, a neural network program , "Neuroshell 2"(7) used.

5.2. Data Collection:

The recognition of soil layers begins with data collection. The data used in this research was collected from borehole logs in the studied area, which was executed by Building and Road Research Institute (B.R.R.I.) of University of Khartoum (U.of K.).

To locate the investigated borehole sites, a digital map of Khartoum city was used as a base map. Global Positioning System (G.P.S.) has been used to read the exact E N co-ordinates of the sites studied and their respective altitudes.

Usually, the boreholes depths range between 5 to 50 m., and the data include mainly: Site name and location, borehole number and location(E,N), depth, soil group symbol(USCS), and other soil parameters such as liquid limit (LL), plasticity index (PI) and standard penetration test N-value (SPT- N).

5.3. Data Normalization:

Because the activation function transfers the output of a neuron to values between 0 and 1.0, the training set in App.1 would be normalized before presenting it to the model. The expression[19] used for normalizing the data is given by :

$$Normalized(value) = \frac{Actual(value) - Minimum(value)}{Maximum(value) - Minimum(value)} \qquad \text{...eqn(5.1)}$$

The output must also be normalized. To convert the normalized output to actual values the following equation was used:

$$Model(value) = Model(output) * [Max.(value) - Min.(value)] + Min.(value). \qquad \text{...eqn(5.2)}$$

5.4 Data Base:

The data include 255 borehole logs of 63 sites in an area of more than 165 square kilometers from center and east of Khartoum .The study area and the scatter of the data can be observed in figure (5.1).

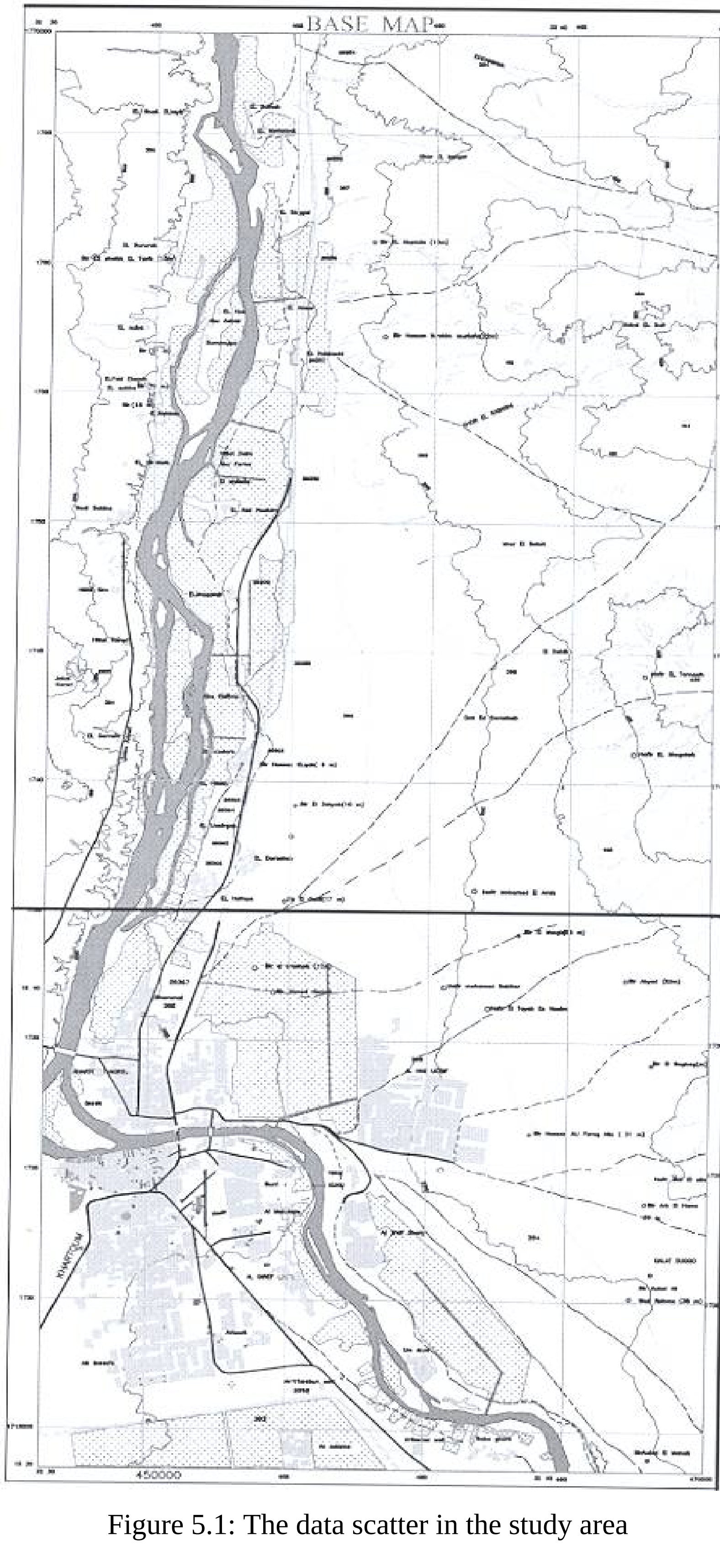


Figure 5.1: The data scatter in the study area

5.5 Artificial Neural Network Modeling:

Artificial neural networks have several advantages when used as classifiers of complex data sets. They normally require no assumptions on the data distribution and can be trained with relatively small sample sets. Further, they are robust classifiers that require little data preparation prior to use; however, the selection of a suitable architecture and the subsequent lengthy training time of the network have often been perceived as a disadvantage to the acceptability of such classifiers.

5.5.1. Selection of input and output parameters:

Regarding the available data and their quality, a decision was made to use the sand parameters in “model 1”, the clay/silt parameters in “model 2” and the soil classification in “model 3, model 4, model 5, model 6 and model 7”. The soil class is determined by the Unified Soil Classification System (USCS) according to the particle size analysis and Atterberg limits. In this study each group is assigned with a certain number as follows :

GW	GP	GM	GC	SW	SP	SM	SC	ML	CL	MH	CH
1	2	3	4	5	6	7	8	9	10	11	12

where G, S, M and C respectively represent gravel, sand , silt and clay and W, P, L and H stand for well-graded, poor-graded, low plasticity and highly plastic. For example GW would represent well-graded gravel, SC would be sandy clay and ML would be low plasticity silt.

The soil type in the study area is limited to the last eight groups of the above table. So, in the test oversize grains are excluded which cause soils of the same size property may to fall in different categories. Besides, noticing the non homogeneity of the soil masses, soil categories can be expected to change due to little variations in the amount of fines. Therefore, the following two groups were selected in order to represent the data to the neural network.

SW	SP	SM	SC	ML	CL	MH	CH
Sand				Clay/Silt			
2				3			

In selection of the above numeric group signs the general particle size has been considered.

5.5.1.1. Standard penetration test (S.P.T.) network" model 1":

In "model 1" the network inputs include the borehole coordinates (easting "E", and northing "N")and soil layer depth in each borehole, and the output would be the layer S.P.T. (N-value" blows/ft") . In "model 1" if the actual number of S.P.T (N-value" blows/ft") is greater than 50 is stated as 51.

5.5.1.2. Atterberg limits network" model 2":

In "model 2" the network inputs include the borehole coordinates (easting "E", and northing "N")and soil layer depth in each borehole, and the output would be the clay/silt layer parameters (liquid limit "L.L."& Plastic index "P.I."). In "model 2" the plastic limit "P.L."is neglected since it can be calculated from the following equation :

$$P.L. = L.L - P.I. \qquad \textbf{\textit{...eqn(5.3)}}$$

5.5.1.3. Global classifier network" model 3":

In "model 3" the network inputs include the borehole coordinates (easting "E", and northing "N") and soil layers depths in each borehole, and the output would be the layer soil classification .In order to classify the layers to coarse grained soil or sand and fine grained soils or clay/silt two output nodes were used and the soil class representative of the layers would be 0 and 1 respectively.

In other words, the output column" node 1" indicates occurrance of sand if it's value is 1,and no occurrence if 0, and "node 2"indicates occurrance of clay/silt if it's value is 1,and no occurrence if 0.In which sand and clay/silt classifier units is the final figure of both columns used to classify the soil in this network.

5.5.1.4. Sand classifier network" model 4":

In "model 4" the network inputs include the borehole coordinates (easting "E", and northing "N") and soil layer depth in each borehole, and the output would be the layer soil classification as sand "if any".

The output column" node 1" indicates ocurrance of silty sand "SM" if it's value is 1,and no occurrance if 0, and "node 2"indicates ocurrance of clayey sand "SC" if it's value is 1,and no occurrence if 0.In which sand classifier units is the final figure of both columns used to classify the soil in this network.

5.5.5. Sand grading classifier network" model 5":

In "model 5" the network inputs include the borehole coordinates (easting "E", and northing "N") and soil layer depth in each borehole, and the output would be the layer sand grading "if any".

The output column" node 1" indicates ocurrance of well graded sand "SW"if it's value is 1,and no occurrence if 0, and "node 2"indicates ocurrance of poorly graded sand "SP" if it's value is 1,and no occurrence if 0.In which sand grading classifier units is the final figure of both columns used to classify the soil in this network.

5.5.1.6. Clay classifier network" model 6":

In "model 6" the network inputs include the borehole coordinates (easting "E", and northing "N") and soil layer depth in each borehole, and the output would be the layer classification as clay "if any".

The output column" node 1" indicates ocurrance of clay of low plasticity"CL" if it's value is 1,and no occurrence if 0, and "node 2"indicates ocurrance of clay of high plasticity "CH" if it's value is 1,and no occurrence if 0.In which clay classifier units is the final figure of both columns used to classify the soil in this network.

5.5.1.7Silt classifier network" model 7":

In "model 7" the network inputs include the borehole coordinates (easting "E", and northing "N") and soil layer depth in each borehole, and the output would be the layer classification as silt "if any".

The output column" node 1" indicates ocurrance of silt of low plasticity"ML" if it's value is 1,and no occurrence if 0, and "node 2"indicates ocurrance of silt of high plasticity "MH" if it's value is 1,and no occurrence if 0.In which clay classifier units is the final figure of both columns used to classify the soil in this network.

5.5.2 Training, Testing and Verifying Data Sets:

The back propagation neural network software program, "Neuroshell 2", based on the back-propagation procedure was utilized for this study. This package allows for the generation of networks with arbitrary layers, nodes per layer, link connections between layers, and other fundamental network design components. Generally, it is preferred that the user conduct several experimental runs with the neural network to learn which combinations of parameters are adequate to produce meaningful results. The network is working to solve an unknown solution space through exploration of that space. Each network training session begins by searching random starting points, and then proceeds with respect to the user identified parameters. Although the user may decide to retain identical network structures and parameters in consecutive runs, the network may train to slightly different solutions, on the basis of different set of random weights being automatically chosen at the network initialization time. Different initial conditions may start the network on a path towards a different local minimum solution.

As stated before, although the training data are usually used on a random basis, some points should be considered. The most important point is that Neural Networks in the generalization and control stages are not capable of predicting cases which does not lie in the range of the training data. In other words they are more able to interpolate than extrapolate. Therefore the training data should contain the boundary values for each variable. Selection of the training, testing and verification data has a vital role in the training process and an improper combination may obstruct convergence.

5.5.2.1 The Network Architecture:

Training the network with any architecture using the backpropagation algorithm is a very crucial and usually time-consuming process. Nevertheless, this process is what will enable the network to detect, classify or identify the features in question. Careful consideration is given to the architecture used.

Ward Nets are the most powerful nets. Backprop nets are more global than the local GRNN and PNN nets, meaning they may not pick up small details as well, but consequently could generalize better on noisy data. The most powerful backpropagation nets are the Ward nets, and the one with three hidden layer slabs is the default program network.

All backpropagation algorithms comes with a choice of Momentum weight updates. Momentum means that the weight updates not only include the change dictated by learning rate, but include a portion of the last weight change as well.

All supervised backpropagation networks include the Calibration feature, which prevents overtraining (thereby greatly reducing training time), and increases the network's ability to generalize well on new data.

Up to three hidden layers were tested for each network and using the trial and error method, the number of hidden neurons, the suitable training method, effective parameters in training process such as rate of learning, momentum, and the number of necessary epochs were determined.

It is recommended that if you do decide to use a three layer net, use the Gaussian activation function in the hidden layer. This is usually the most powerful three layer net. For all backprop nets, including Ward nets and three layer nets, you may want to try using the linear activation function in the output slab if your output is not categories, i.e., it is a continuous value. If the net starts giving wild or huge errors when you do this, reduce the number of hidden neurons and possibly the learning rate. Use of the linear activation function in the output layer often gives better accuracy across the entire output range, and is very powerful when combined with a Gaussian in a hidden slab (which Ward nets have)[(20).]

5.5.2.2 Modeling learning types:

In order to meet the objectives set out above, three modeling approaches are investigated to choose the most powerful one . In order to investigate the relationship between the proportion of the data used for training and validation and model performance, the available data are divided into their respective subsets. A novel approach proposed in this work, which uses a self-organizing with output backprop nets with the available data. The data patterns are divided equally into training and testing sets.

Using Ward Nets architecture supervised backpropagation networks include the Calibration feature. The first modeling approach was enough and satisfied for the most of the networks.

4.5.2.3 Training the networks:

The changes in the error value can be observed versus the number of epochs while the training process is in progress. Besides, the final error values are plotted in histograms demonstrating individual errors for each input data. When the training has stopped, Root Mean Square error is calculated for each of the training, testing and verification phases and compared. Then the actual values of each output variable are plotted versus the expected values to discuss the network performance. The more the plotted points are close to the bisector of the coordinates the more effective is the training and the actual and desired sets of data would be well correlated.

4.5.2.4 Performance of the trained networks:

After completion of the training process, it is important to check the performance and reliability of the selected networks.Training results were evaluated by computing the R value, the coefficient of multiple determination. It compares the accuracy of the model to the accuracy of a trivial benchmark model wherein the prediction is just the mean of all of the samples. An R value approaching 1 indicates a good model fit, and an R value near 0 indicates a poor fit. Correlation Coefficient r (Pearson's Linear Correlation Coefficient), is a statistical measure of the strength of the relationship between the actual vs predicted outputs. The r coefficient can range from -1 to +1. The closer r is to 1, the stronger the positive linear relationship, and the closer r is to -1, the stronger the negative linear relationship. When r is near 0, there is no linear relationship. R is a much better measure of the closeness of actual and predicted values than r. Comparison of actual to predicted outputs performed on the test data confirmed the network's training success.

Percent within 5%, 10%, 20% and 30% and over 30% - These boxes list the percent of network answers that are within the specified percentage of the actual answers used to train the network. If the actual answer is 0, the percent cannot be computed and that pattern is not included in a percentage group. For that reason and for rounding, the total computed percentages may not add up to 100.

5.6. Prediction models:

5.6.1. SPT prediction model:

The SPT prediction model "model 1" is used to estimate the standard penetration test (N-value Blows/ft) for sand layers for known borehole coordinates and layer depth. The process of selecting the proper number of the hidden neurons with the trial and error method ,the network architecture characteristics are shown in Figure 5.2 and Table 5.1 , the efficiency of the training is stated below:

Patterns processed: 2146

Output:	*N-value*
R squared:	*0.3853*
r squared:	*0.3856*
Mean squared error:	*120.494*
Mean absolute error:	*8.144*
Min. absolute error:	*0*
Max. absolute error:	*45.708*
Correlation coefficient r:	*0.6210*
Percent within 5%:	*25.163*
Percent within 5% to 10%:	*13.141*
Percent within 10% to 20%:	*21.994*
Percent within 20% to 30%:	*12.209*
Percent over 30%:	*27.493*
Learning time :	*2:19:59 (hhh:mm:ss.)*

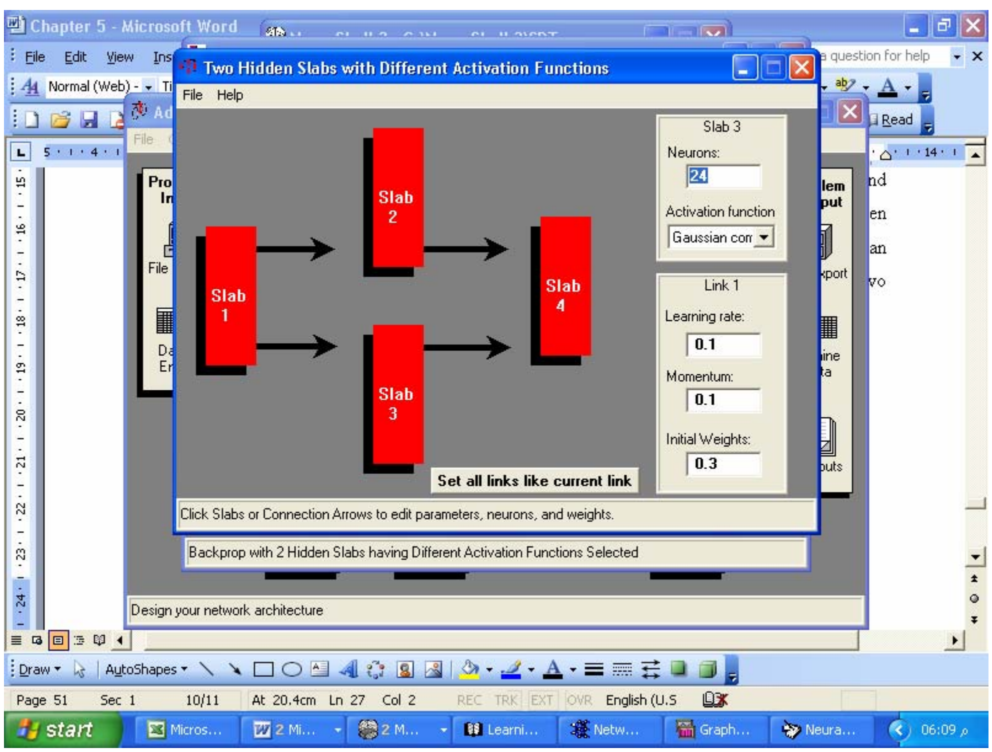


Figure (5.2):A two hidden slab backpropogation architecture used for SPT prediction model.

Table 5.1:SPT model architecture parameters:

Parameter	Selected option
Architecture	Multiple hidden slab with different activation functions (Ward nets)
No. of hidden layers	2
Slab 1 no. of neurons	3
Slab 2 no. of neurons	24
Slab 3 no. of neurons	24
Slab 4 no. of neurons	1
Slab 1 scale function	Linear [-1,1]
Slab 2 activation function	Gaussian
Slab 3 activation function	Gaussian Complement .
Slab 2 activation function	Logestic
Learning rate	0.1
Momentum	0.1
Initial weight	0.3

5.6.2. Atterberg limits prediction model:

The Atterberg limits prediction model “model 2” is used to estimate the liquid limit and plastic index for clay/silt layers for known borehole coordinates and layer depth. The process of selecting the proper number of the hidden neurons with the trial and error method ,the network architecture characteristics are shown in Figure 5.3 and Table 5.2 , the efficiency of the training is stated below:

Patterns processed: 1915

Output:	*L.L.*	*P.L.*
R squared:	*0.5384*	*0.5846*
r squared:	*0.5423*	*0.5864*
Mean squared error:	*254.341*	*201.334*
Mean absolute error:	*11.341*	*9.685*
Min. absolute error:	*0.001*	*0*
Max. absolute error:	*91.628*	*78.264*
Correlation coefficient r:	*0.7364*	*0.7657*
Percent within 5%:	*14.360*	*6.945*
Percent within 5% to 10%:	*15.405*	*7.154*
Percent within 10% to 20%:	*24.961*	*13.211*
Percent within 20% to 30%:	*16.762*	*10.548*
Percent over 30%:	*27.572*	*44.648*
Learning time(hhh:mm:ss.) :	*3:20:00*	

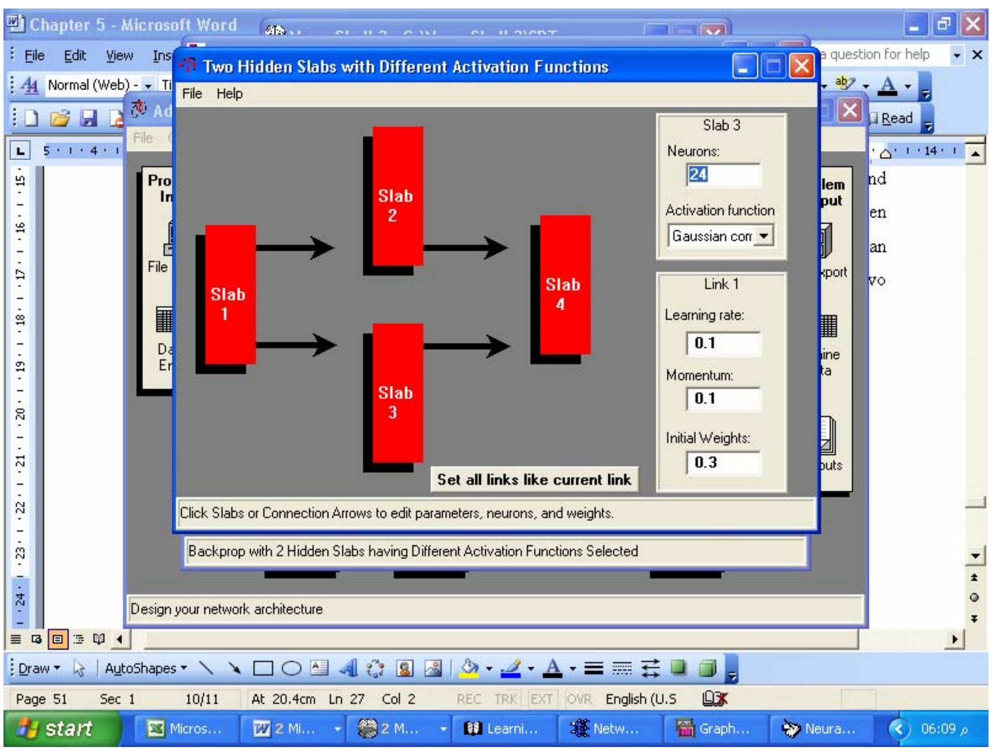


Figure (5.3):A two hidden slab backpropogation architecture used for Atterberg limits prediction model.

Table 5.2:Atterberg limits model architecture parameters:

Parameter	Selected option
Architecture	Multiple hidden slab with different activation functions (Ward nets)
No. of hidden layers	2
Slab 1 no. of neurons	3
Slab 2 no. of neurons	24
Slab 3 no. of neurons	24
Slab 4 no. of neurons	2
Slab 1 scale function	Linear [-1,1]
Slab 2 activation function	Gaussian
Slab 3 activation function	Gaussian Complement.
Slab 2 activation function	Logestic
Learning rate	0.1
Momentum	0.1
Initial weight	0.3

5.6.3. Global classifier prediction model:

The Global classifier prediction model "model 3" is used to estimate the layer general soil classification "coarse grained soils or sand against fine grained soils or clay/silt" for known borehole coordinates and layer depth. The process of selecting the proper number of the hidden neurons with the trial and error method ,the network architecture characteristics are shown in Figure 5.4 and Table 5.3, the efficiency of the training is stated below:

Patterns processed: 6236

Output:	*Sand*	*Clay/silt*
R squared:	*0.4962*	*0.4861*
r squared:	*0.5002*	*0.4899*
Mean squared error:	*0.124*	*0.126*
Mean absolute error:	*0.226*	*0.229*
Min. absolute error:	*0*	*0*
Max. absolute error:	*1.000*	*1.000*
Correlation coefficient r:	*0.7072*	*0.7000*
Percent within 5%:	*27.245*	*11.690*
Percent within 5% to 10%:	*4.025*	*4.153*
Percent within 10% to 20%:	*5.580*	*6.591*
Percent within 20% to 30%:	*4.410*	*4.586*
Percent over 30%:	*15.667*	*15.779*
Learning time(hhh:mm:ss.) :	*2:38:00*	

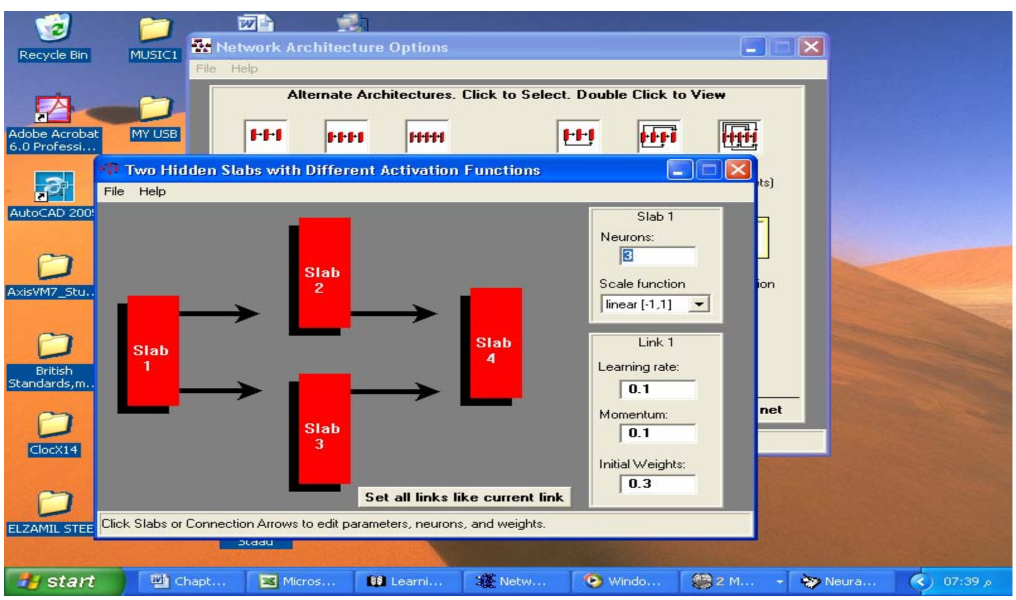


Figure (5.4):A two hidden slab backpropogation architecture used for Global classifier prediction model.

Table 5.3:global classifier model architecture parameters:

Parameter	Selected option
Architecture	Multiple hidden slab with different activation functions (Ward nets)
No. of hidden layers	2
Slab 1 no. of neurons	3
Slab 2 no. of neurons	29
Slab 3 no. of neurons	29
Slab 4 no. of neurons	2
Slab 1 scale function	Linear [-1,1]
Slab 2 activation function	Gaussian
Slab 3 activation function	Gaussian complement
Slab 4 activation function	Logestic
Learning rate	0.1
Momentum	0.1
Initial weight	0.3

5.6.4. Sand classifier prediction model:

The Global classifier prediction model "model 4" is used to estimate the layer specific soil classification "clayey sand SC against silty sand SM if existed" for known borehole coordinates and layer depth. The process of selecting the proper number of the hidden neurons with the trial and error method ,the network architecture characteristics are shown in Figure 5.5 and Table 5.4, the efficiency of the training is stated below:

Patterns processed: 6240

Output:	*C1*	*C2*
R squared:	*0.3445*	*0.4331*
r squared:	*0.3524*	*0.4334*
Mean squared error:	*0.138*	*0.061*
Mean absolute error:	*0.246*	*0.117*
Min. absolute error:	*0*	*0*
Max. absolute error:	*1.000*	*1.000*
Correlation coefficient r:	*0.5937*	*0.6584*
Percent within 5%:	*4.135*	*3.397*
Percent within 5% to 10%:	*1.490*	*0.272*
Percent within 10% to 20%:	*2.949*	*0.497*
Percent within 20% to 30%:	*2.612*	*0.304*
Percent over 30%:	*19.119*	*7.821*

Learning time(hhh:mm:ss.) : *2:12:30*

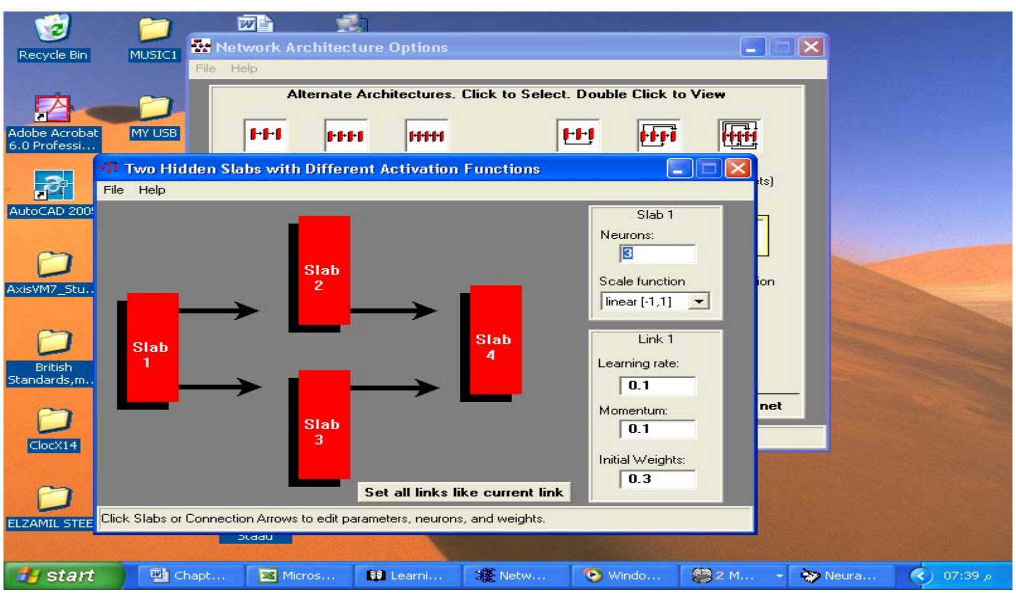


Figure (5.5):A two hidden slab backpropogation architecture used for Sand classifier prediction model.

Table 5.3:global classifier model architecture parameters:

Parameter	Selected option
Architecture	Multiple hidden slab with different activation functions (Ward nets)
No. of hidden layers	2
Slab 1 no. of neurons	3
Slab 2 no. of neurons	29
Slab 3 no. of neurons	29
Slab 4 no. of neurons	2
Slab 1 scale function	Linear [-1,1]
Slab 2 activation function	Gaussian
Slab 3 activation function	Gaussian complement
Slab 4 activation function	Logestic
Learning rate	0.1
Momentum	0.1
Initial weight	0.3

5.6.5. Sand grading classifier prediction model:

The Global classifier prediction model “model 5” is used to estimate the layer specific soil classification “well graded sand Sw against poorly graded Sp if existed” for known borehole coordinates and layer depth. The process of selecting the proper number of the hidden neurons with the trial and error method ,the network architecture characteristics are shown in Figure 5.6 and Table 5.5, the efficiency of the training is stated below:

Patterns processed: 6240

Output:	*SW*	*SP*
R squared:	*0.4298*	*0.2896*
r squared:	*0.4327*	*0.2973*
Mean squared error:	*0.065*	*0.047*
Mean absolute error:	*0.125*	*0.099*
Min. absolute error:	*0*	*0*
Max. absolute error:	*1.000*	*1.000*
Correlation coefficient r:	*0.6578*	*0.5452*
Percent within 5%:	*2.708*	*0.032*
Percent within 5% to 10%:	*0.337*	*0.048*
Percent within 10% to 20%:	*0.689*	*0.208*
Percent within 20% to 30%:	*1.026*	*0.304*
Percent over 30%:	*8.269*	*6.554*
Learning time(hhh:mm:ss.) :	*3:58:00*	

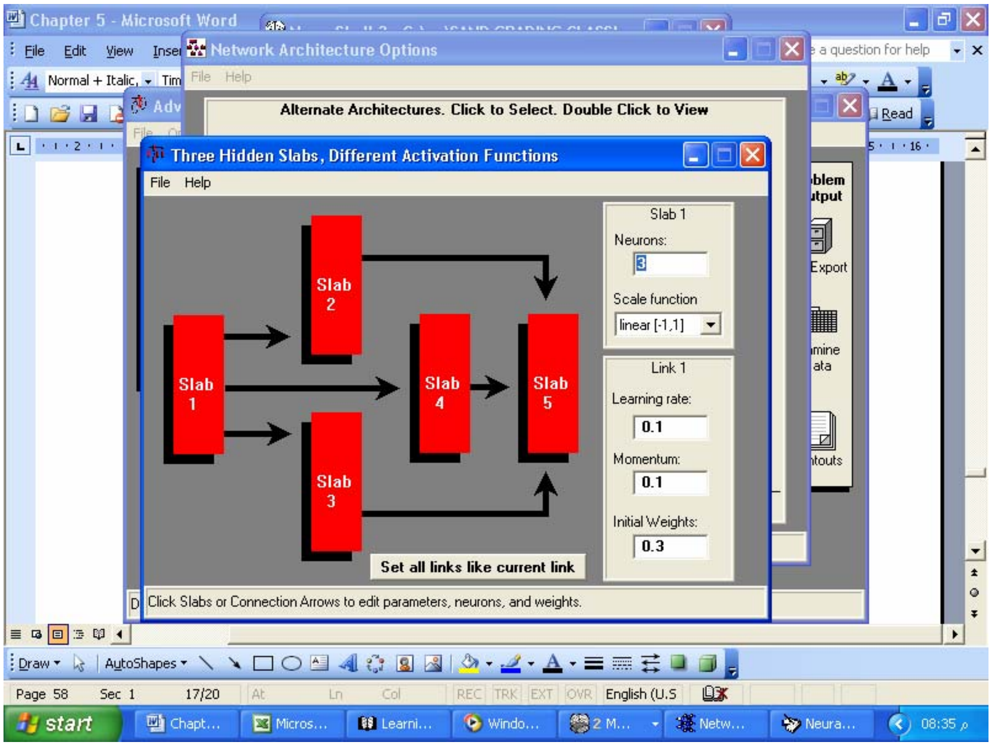


Figure (5.6):A three hidden slab backpropogation architecture used for sand grading classifier prediction model.

Table 5.5:Sand grading classifier model architecture parameters:

Parameter	Selected option
Architecture	Multiple hidden slab with different activation functions (Ward nets)
No. of hidden layers	3
Slab 1 no. of neurons	3
Slab 2 no. of neurons	25
Slab 3 no. of neurons	25
Slab 4 no. of neurons	25
Slab 5 no. of neurons	2
Slab 1 scale function	Linear [-1,1]
Slab 2 activation function	Gaussian
Slab 3 activation function	Hyperbolic Tangential

Slab 4 activation function	Gaussian complement
Slab 5 activation function	Logestic.
Learning rate	0.1
Momentum	0.1
Initial weight	0.3

5.6.6. Clay classifier prediction model:

The Clay classifier prediction model “model 6” is used to estimate the layer specific soil classification “Clay of low plasticity CL against Clay of high plasticity CH if existed” for known borehole coordinates and layer depth. The process of selecting the proper number of the hidden neurons with the trial and error method ,the network architecture characteristics are shown in Figure 5.7 and Table 5.6, the efficiency of the training is stated below:

Patterns processed: 6235

Output:	*CL*	*CH*
R squared:	*0.3109*	*0.4113*
r squared:	*0.3135*	*0.4124*
Mean squared error:	*0.078*	*0.072*
Mean absolute error:	*0.153*	*0.133*
Min. absolute error:	*0*	*0*
Max. absolute error:	*1.000*	*1.000*
Correlation coefficient r:	*0.5599*	*0.6422*
Percent within 5%:	*0.770*	*1.315*
Percent within 5% to 10%:	*0.321*	*0.449*
Percent within 10% to 20%:	*0.850*	*1.171*
Percent within 20% to 30%:	*1.139*	*0.497*
Percent over 30%:	*9.976*	*10.778*

Learning time(hhh:mm:ss.) : 4:50:15

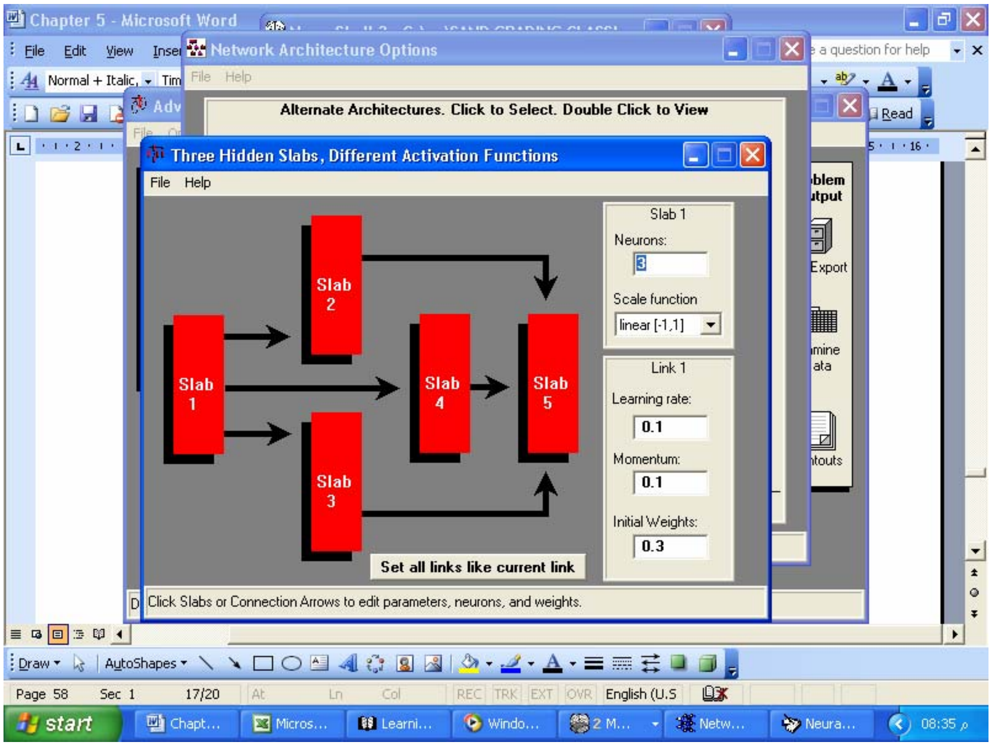


Figure (5.7):A three hidden slab backpropogation architecture used for Clay classifier prediction model.

Table 5.6:Clay classifier model architecture parameters:

Parameter	Selected option
Architecture	Multiple hidden slab with different activation functions (Ward nets)
No. of hidden layers	3
Slab 1 no. of neurons	3
Slab 2 no. of neurons	25
Slab 3 no. of neurons	25
Slab 4 no. of neurons	25
Slab 5 no. of neurons	2
Slab 1 scale function	Linear [-1,1]
Slab 2 activation function	Gaussian
Slab 3 activation function	Hyperbolic Tangential

Slab 4 activation function	Gaussian complement
Slab 5 activation function	Logestic.
Learning rate	0.1
Momentum	0.1
Initial weight	0.3

5.6.7. Silt classifier prediction model:

The Clay classifier prediction model “model 7” is used to estimate the layer specific soil classification “Silt of low plasticity ML against Silt of high plasticity MH if existed” for known borehole coordinates and layer depth. The process of selecting the proper number of the hidden neurons with the trial and error method ,the network architecture characteristics are shown in Figure 5.8 and Table 5.7, the efficiency of the training is stated below:

Patterns processed: 6236

Output:	*ML*	*MH*
R squared:	*0.2875*	*0.0561*
r squared:	*0.2924*	*0.0576*
Mean squared error:	*0.105*	*0.031*
Mean absolute error:	*0.192*	*0.060*
Min. absolute error:	*0*	*0*
Max. absolute error:	*1.000*	*1.000*
Correlation coefficient r:	*0.5407*	*0.2399*
Percent within 5%:	*1.042*	*0*
Percent within 5% to 10%:	*0.401*	*0*
Percent within 10% to 20%:	*1.106*	*0*
Percent within 20% to 30%:	*1.235*	*0*
Percent over 30%:	*14.144*	*3.368*

Learning time(hhh:mm:ss.) : 3:24:15

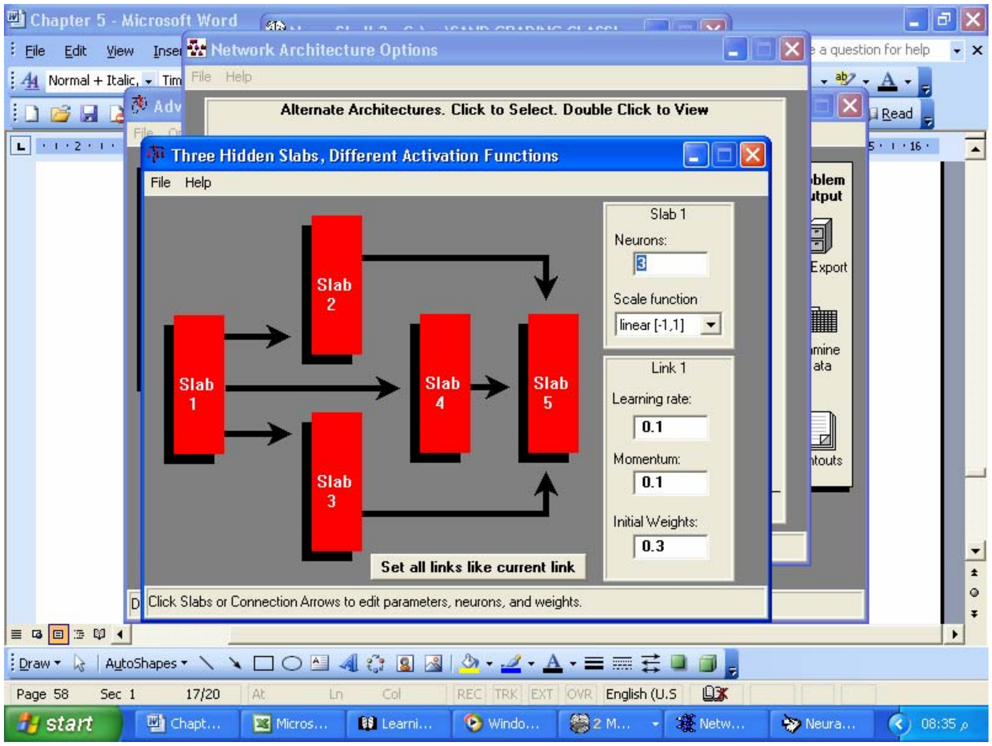


Figure (5.8):A three hidden slab backpropogation architecture used for Silt classifier prediction model.

Table 5.7:Silt classifier model architecture parameters:

Parameter	Selected option
Architecture	Multiple hidden slab with different activation functions (Ward nets)
No. of hidden layers	3
Slab 1 no. of neurons	3
Slab 2 no. of neurons	25
Slab 3 no. of neurons	25
Slab 4 no. of neurons	25
Slab 5 no. of neurons	2
Slab 1 scale function	Linear [-1,1]
Slab 2 activation function	Gaussian
Slab 3 activation function	Hyperbolic Tangential

Slab 4 activation function	Gaussian complement
Slab 5 activation function	Logestic.
Learning rate	0.1
Momentum	0.1
Initial weight	0.3

Chapter Six

Discussion of the Results

Chapter Six
Discussion of the Results

6.1. Introduction:

ANN expert systems consisting of Multi-layer Perceptron have been developed to predict soil classification and soil parameters based on the available site investigation data from 580 square kilometers area of Khartoum and results of soil classification and characteristics as outputs of these systems are compared with actual data investigated in the second half of year 2006 by B.R.R.I. of U. of K. to check the ANN models validity.

6.2. Area of Study:

The soil classification and soil parameters assessment ANN model results are compared with actual values for three investigated sites in the second half of year 2006 namely Areeba co., Alneelain University and Hassan &Alaabid co. sites with known Boreholes coordinates and depths to perform ANN models accuracy.

6.3 Models Validation:

Upon completion of the learning and verification stage successfully, a prediction study is investigated. The purpose of the model validation phase is to ensure that the model has the ability to generalize within the limits set by the training data, rather than simply having memorized the input–output relationships that are contained in the training data. Once the training, testing and validation phases are successfully accomplished, the neural network obtained can be used as a practical model for soil classification and parameters prediction.

For this purpose, a data set separate from the training phase is used. After making necessary computations, the input data set (see the attached CD) is prepared. This data used for the trained networks.

6.4. Results and discussion:

6.4.1. First case study:

Areeba building in Burri:

After a completion of the learning stage with a satisfactory degree of success for each model (see input data in attached CD), the actual data and ANN predicted data are presented in appendix (A),these data set are presented in Figures (6.1,6.2,6.3 and 6.4) .

Figure (6.1-a) shows that the ANN predicted layer is clayey sand of thickness varies from (0.0 to 4.5) m., where the actual top layer of clayey sand of thickness varies from (0.0 to 2.5) m. (which falls within the range of predicted layer) .The relatively low plastic index indicates that the fines content liquid limit may be clay of low plasticity .The second layer of borehole no.1 is clay of low plasticity of thickness varying from (2.5 to 7.5) m. which is the same as the predicted but of thickness varies from (4.5 to 9.0) m. The final layer is clay of high plasticity of thickness varying from (7.5 to 10.0) m. predicted as clay and silt of high plasticity of thickness varying from (9.0 to 10.0) m .Generally the ANN predicted borehole no. 1 stratification is of no major difference of investigated soil classification.

Figure (6.1-b) shows that the second borehole consists of a one layer of clay of low plasticity; ANN prediction gives one layer of clay and silt of low plasticity, which is slight differ from the actual.

Figure (6.2-a) shows that the actual SPT values ranging from 38 to over 50 blows/ft. in borehole no. 1,where the predicted values shows that SPT values ranging from 38 to over 46 blows/ft. within the range of the actual values. Figure (6.2-b) shows a same actual and predicted SPT lines with depth have the same trend line with slight difference in values.

Figures (6.3-a,b) shows that the results of liquid limits are in the range of 47 to 56 % and 47 to 58 % respectively ,where the actual results are 43 to 50 % and 45 to 51 % respectively . Figures (6.4-a,b) shows that the results of predicted plastic index values are approaching actual values with same trend lines , i.e. Atterberg limits model demonstrates some degree of success especially for plastic index.

Chapter Six Discussion of

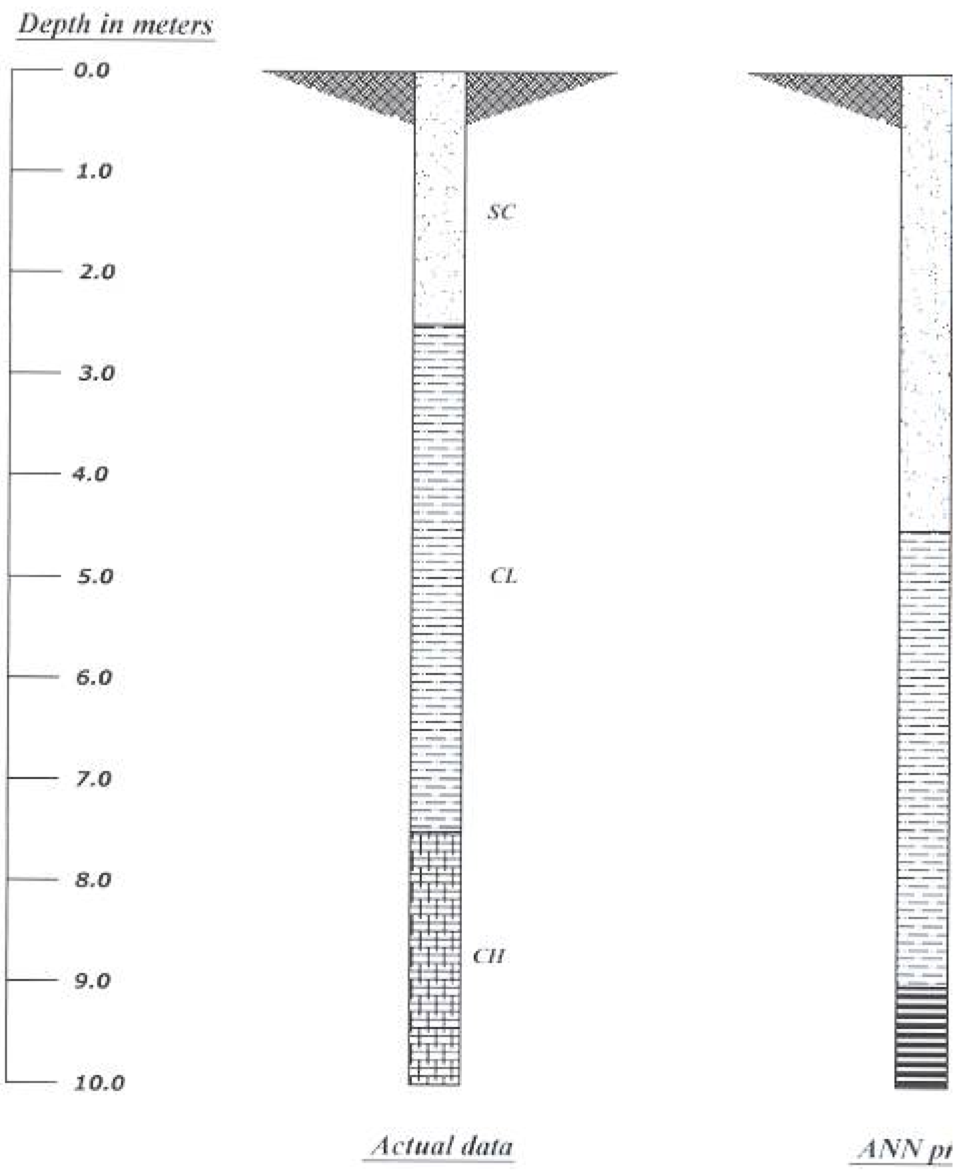
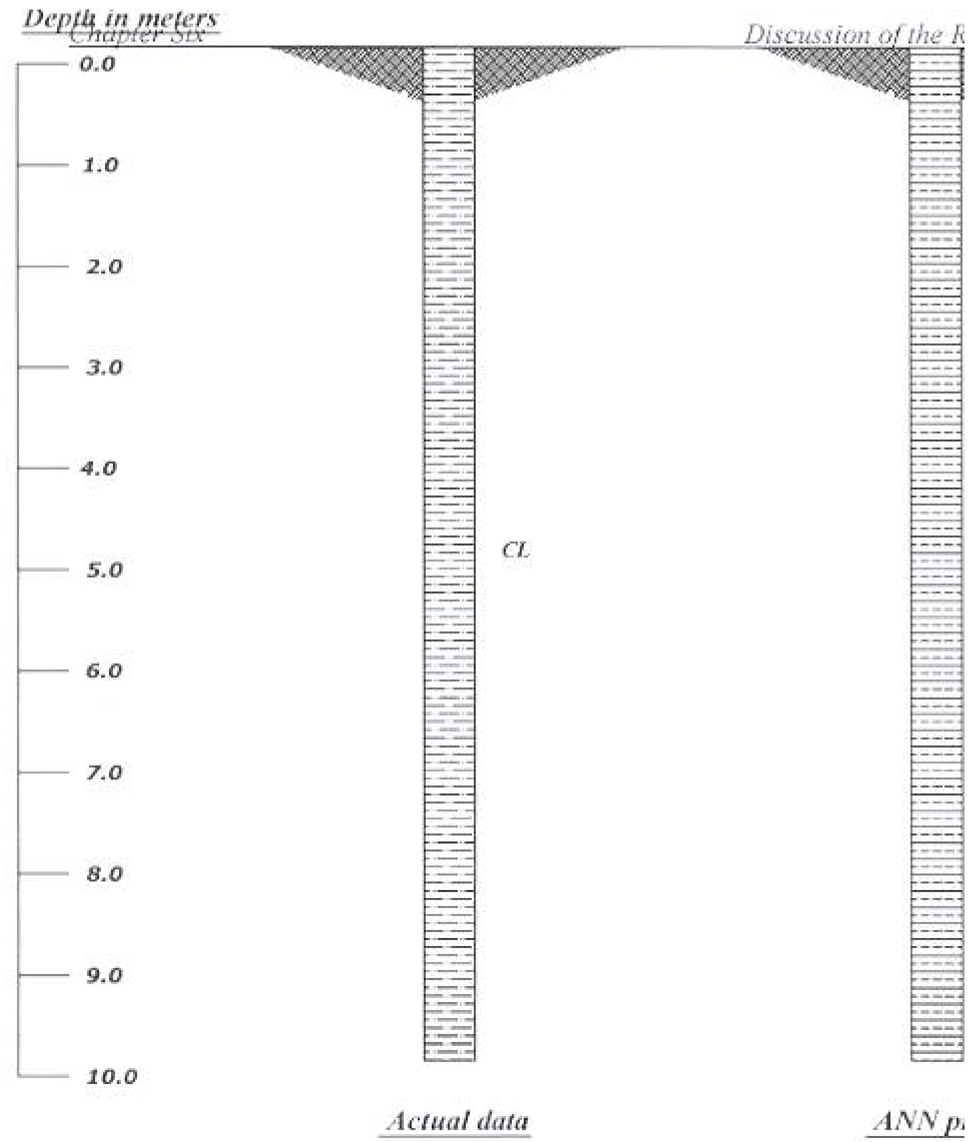


Figure 6.1:Comparison between actual and ANN predicted soil classification results for Areeba co. site :

(a) Borehole no.1,

***(b) Borehole no.2*.**

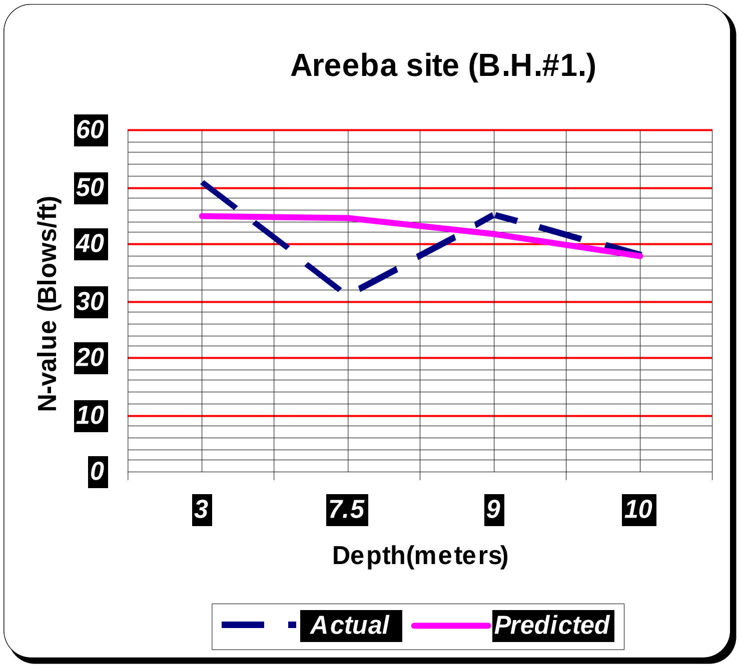


(b)

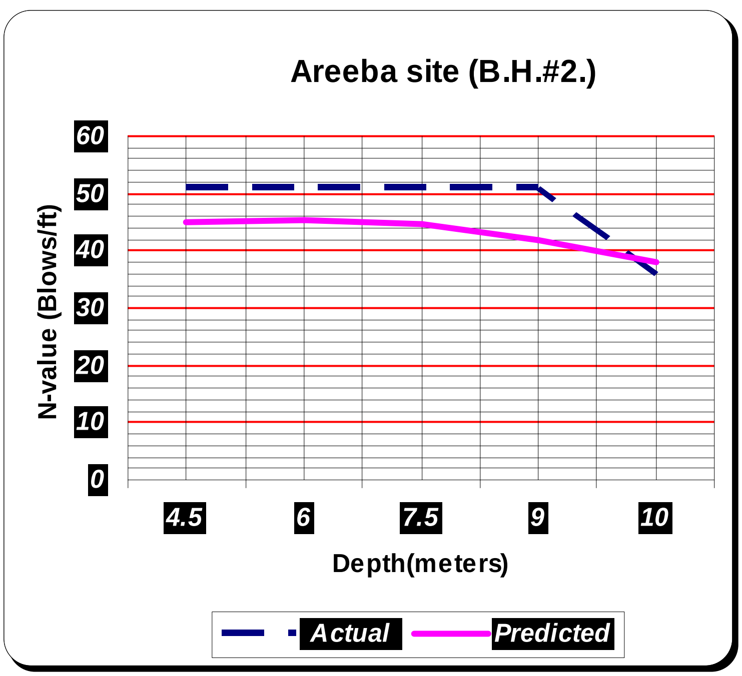
Figure 6.1:Comparison between actual and ANN predicted soil classification results for Areeba co. site :

(a) Borehole no.1,

(b) Borehole no.2

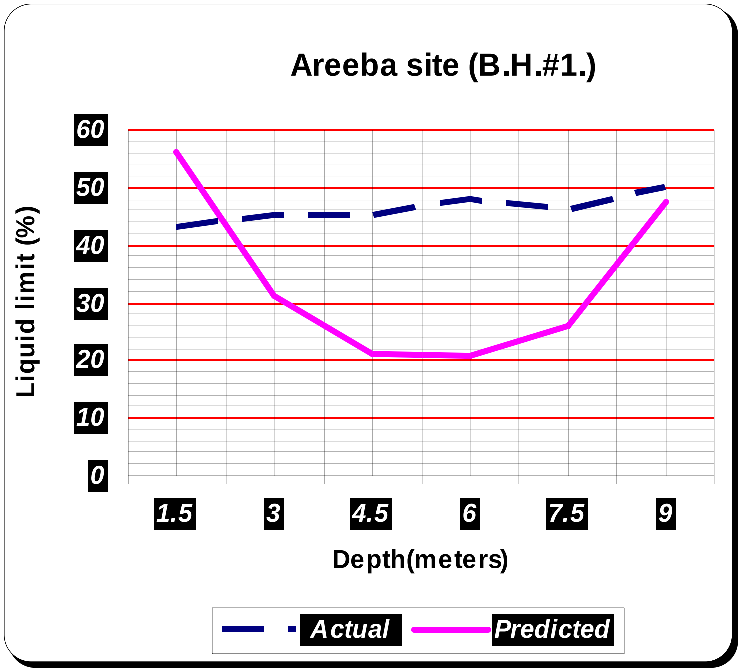


(a)

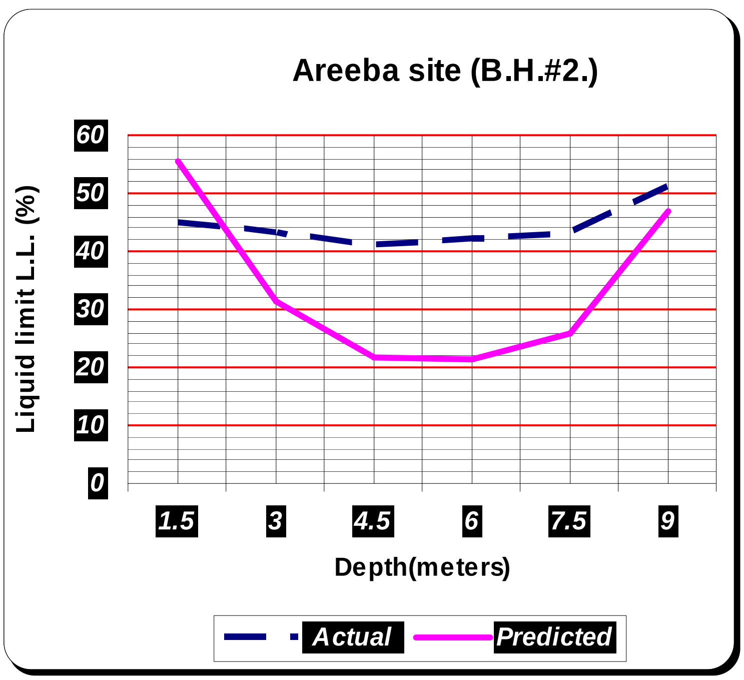


(b)

Figure 6.2:Comparison between actual and ANN predicted SPT for Areeba co. site. (a)Borehole no.1, (b)Borehole no.2.



(a)

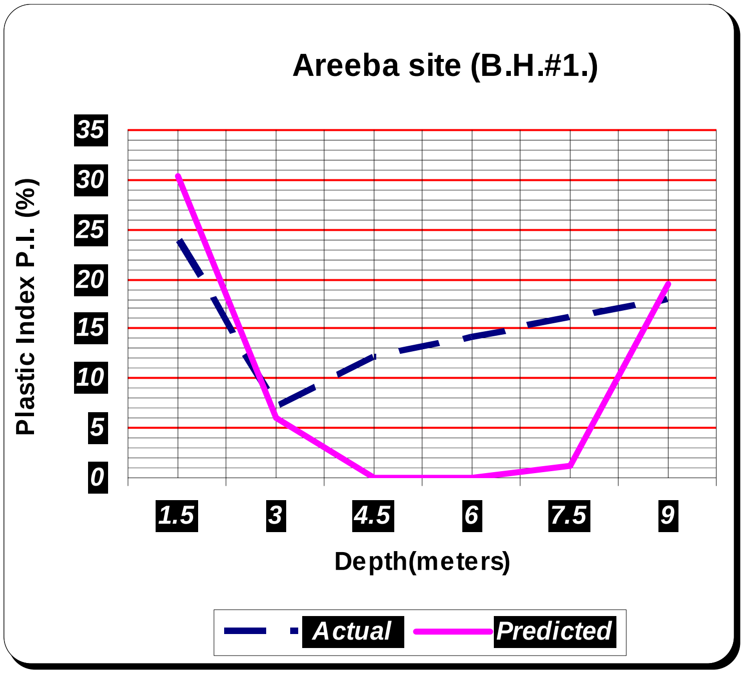


(b)

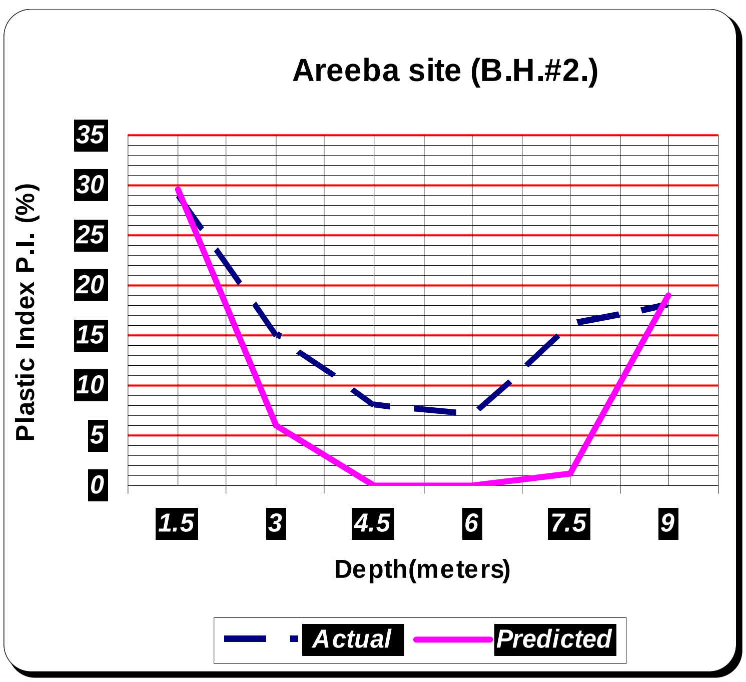
Figure 6.3:Comparison between actual and ANN predictedliquid limit (L.L.) for Areeba co. site.

(a)Borehole no.1,

(b)Borehole no.2.



(a)



(b)

Figure 6.4:Comparison between actual and ANN predicted plastic index (P.I.) for Areeba co. site.

(a)Borehole no.1,

(b)Borehole no.2.

6.4.2. Second case study:
Elneelain University in Elmogran:

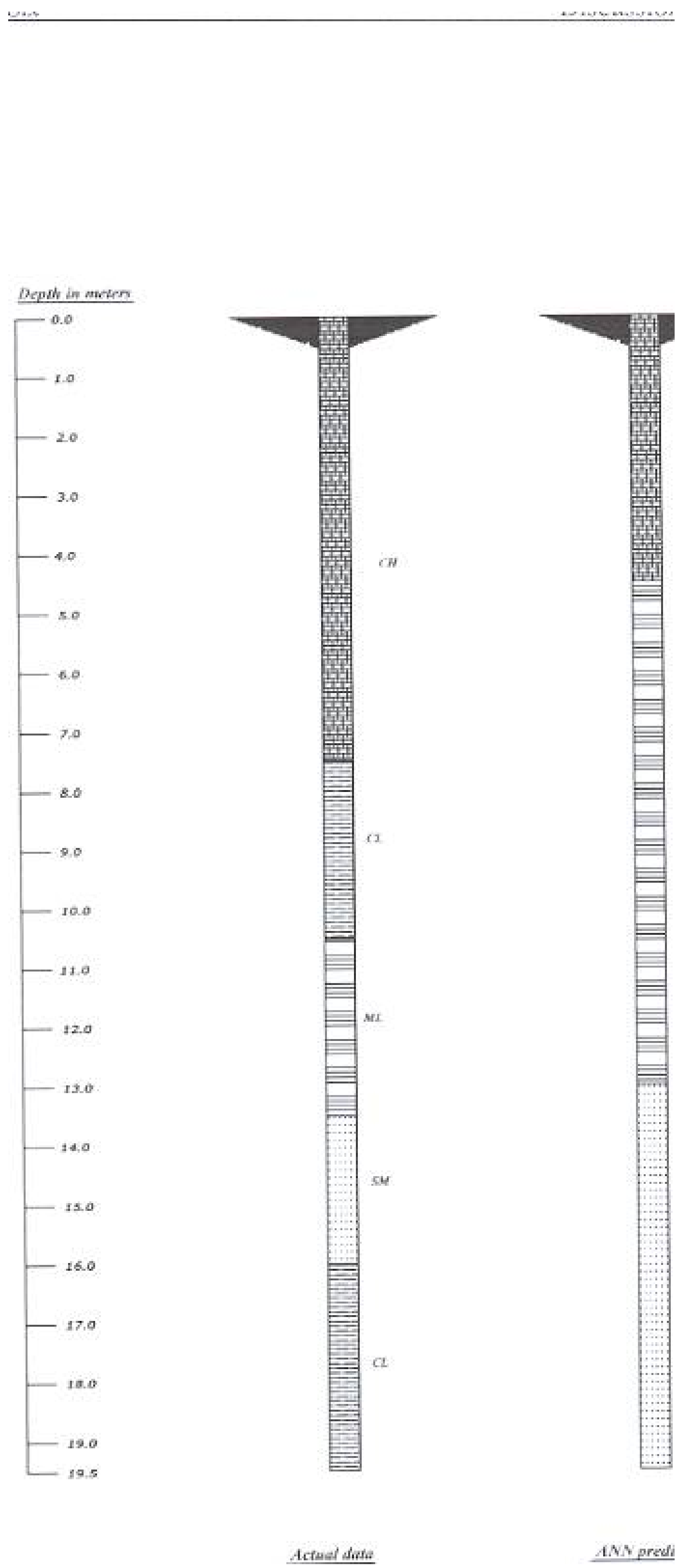
For known boreholes coordinates and depths which entered as inputs and the ANN prediction results were listed in Appendix (B), and compared with actual values as in Figures (6.5,6.6,6.7 and 6.8).

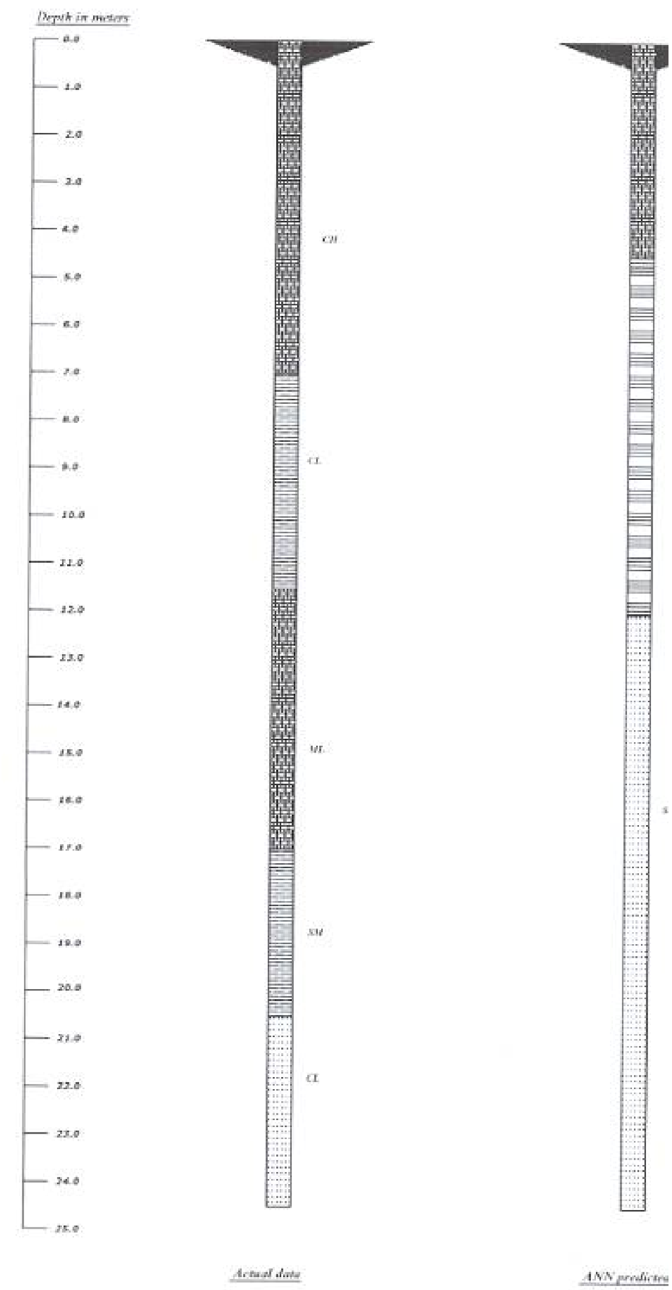
Figure (6.5) shows that the ANN predicted layer soil classification indicates reliable stratum with a little variation in depth of some layers when compared with the actual layers for a three boreholes in Elneelain University in Elmogran area. This comparison shows acceptable prediction.

Figure (6.6) shows that the ANN predicted sand parameter (SPT) produces close values to actual ones especially in borehole no. 3 .The maximum variation in borehole no. 1 (={46-12}/46 =73.9%),that is due to limited data in the study area for the SPT .

Figure (6.7) shows that the ANN predicted clay parameter (liquid limit) is close to the actual values with the same trend lines in specific ranges , beside usually the top layers produces a considerable variations (for example in borehole no. 2 at 1.50 m. depth variation =73-37=36%).

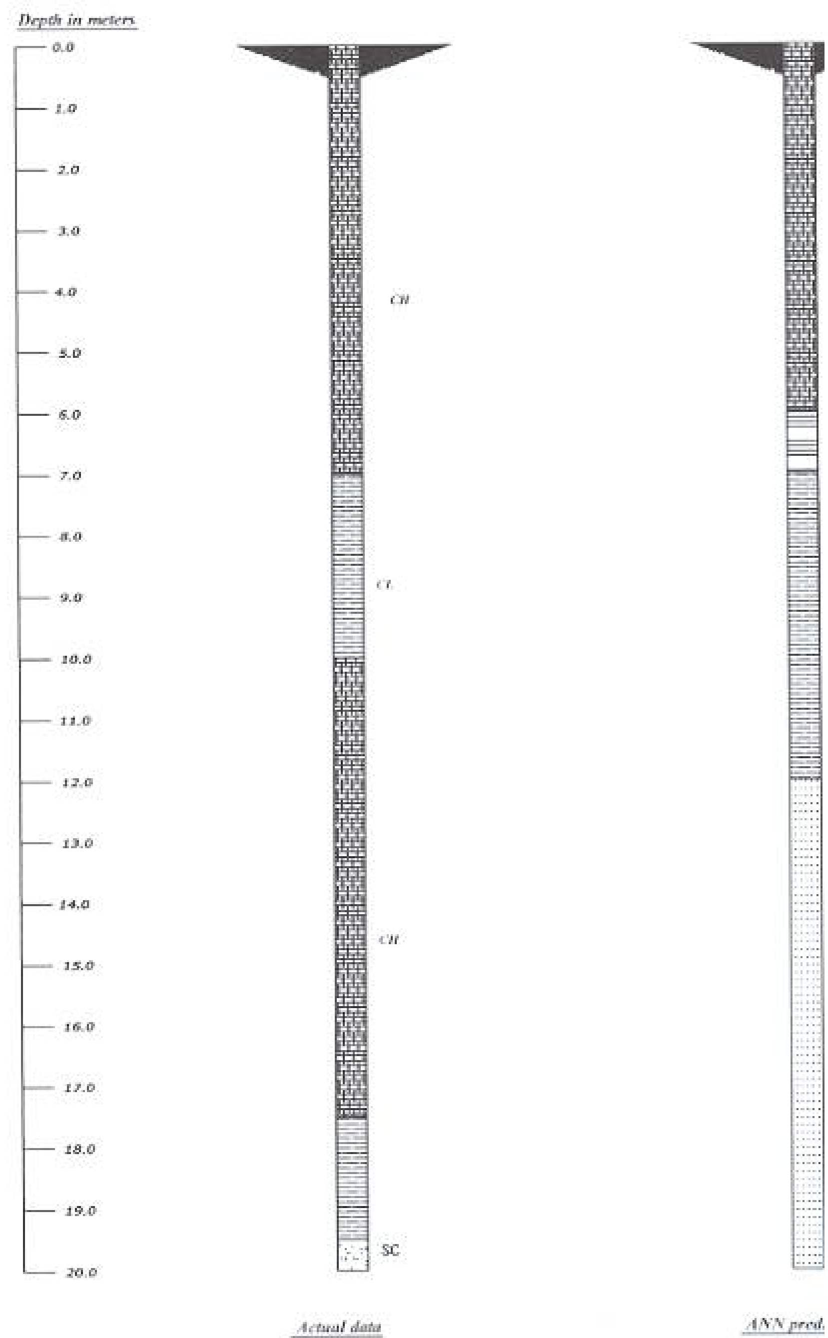
Figure (6.8) shows that the ANN predicted clay parameter (plastic index) almost approaching the exact values with considerable differences in the top layers of the three boreholes in Elneelain University.


Depth in meters
0.0
1.0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
9.0
10.0
11.0
12.0
13.0
14.0
15.0
16.0
17.0
18.0
19.0
19.5
CH
CL
ML
SM
CL
Actual data
ANN predi


Depth in meters
0.0
1.0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
9.0
10.0
11.0
12.0
13.0
14.0
15.0
16.0
17.0
18.0
19.0
20.0
21.0
22.0
23.0
24.0
25.0
CH
CL
ML
SM
CL
Actual data

(b)

94



(c)

Figure 6.5:Comparison between actual and ANN predicted classification results for Elneelain University site :

(a)Borehole no.1,

(b)Borehole no.2,

(c) Borehole no.3.

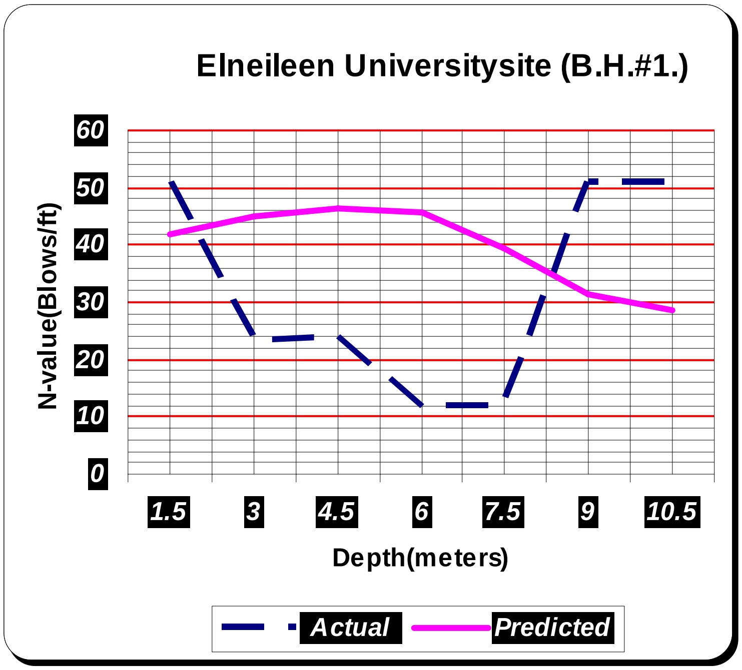


Figure 6.6-a

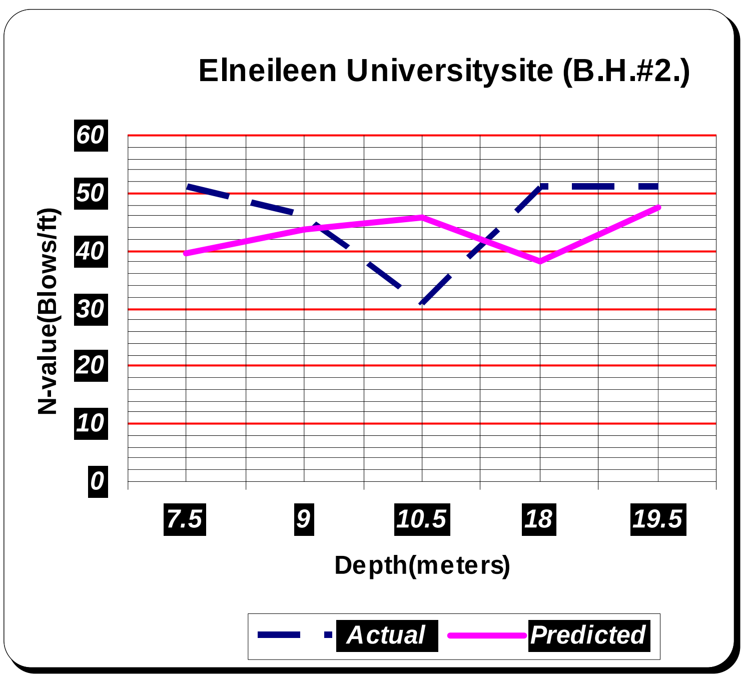


Figure 6.6-b

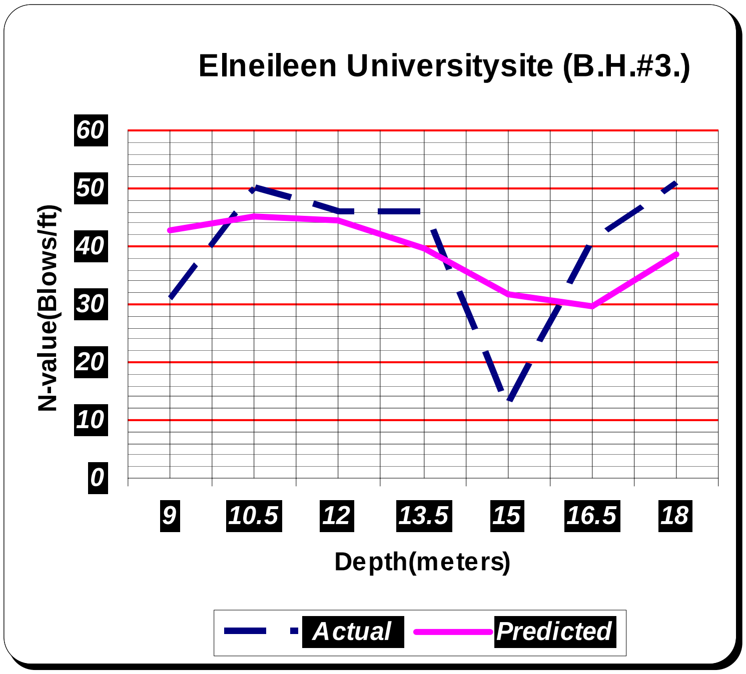


Figure 6.6-c

Figure 6.6:Comparison between actual and ANN predicted SPT for test Elneelain University site.

(a)Borehole no.1,

(b)Borehole no.2,.

(c)Borehole no.3.

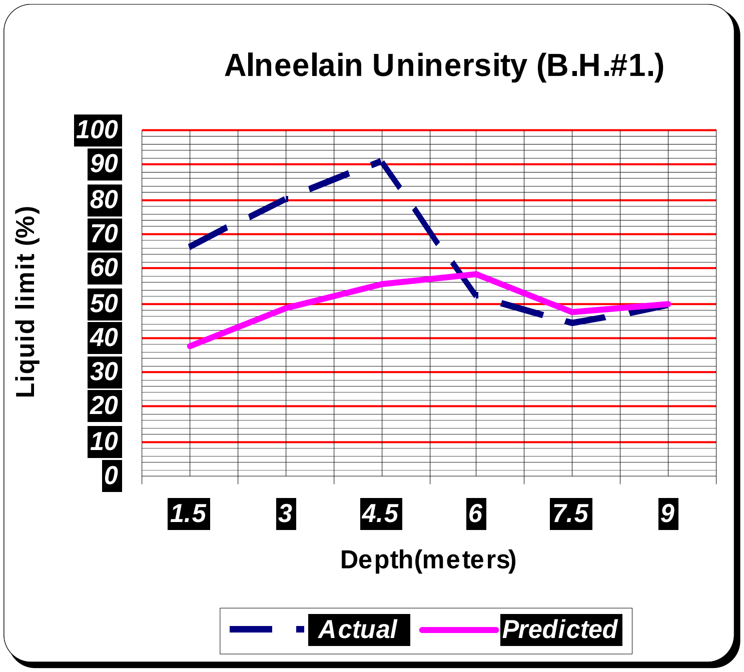


Figure 6.7-a

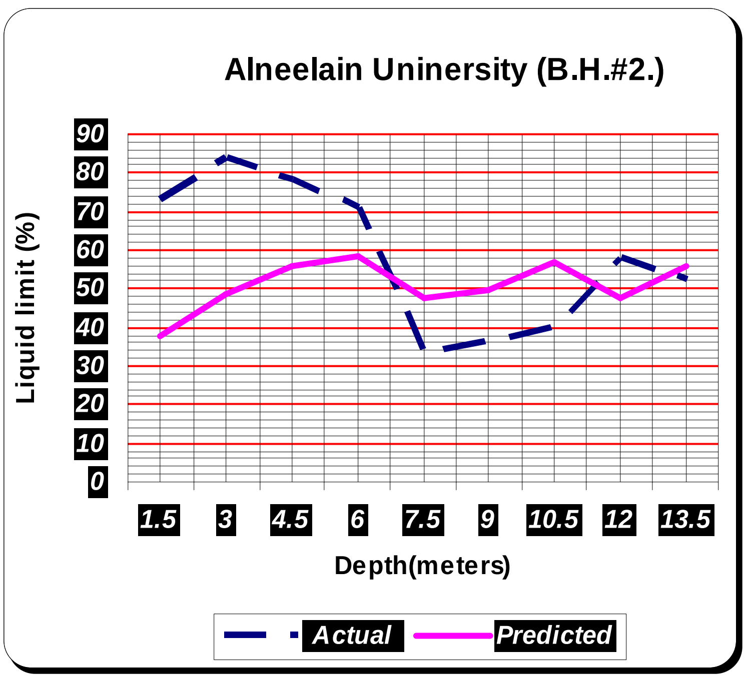


Figure 6.7-b

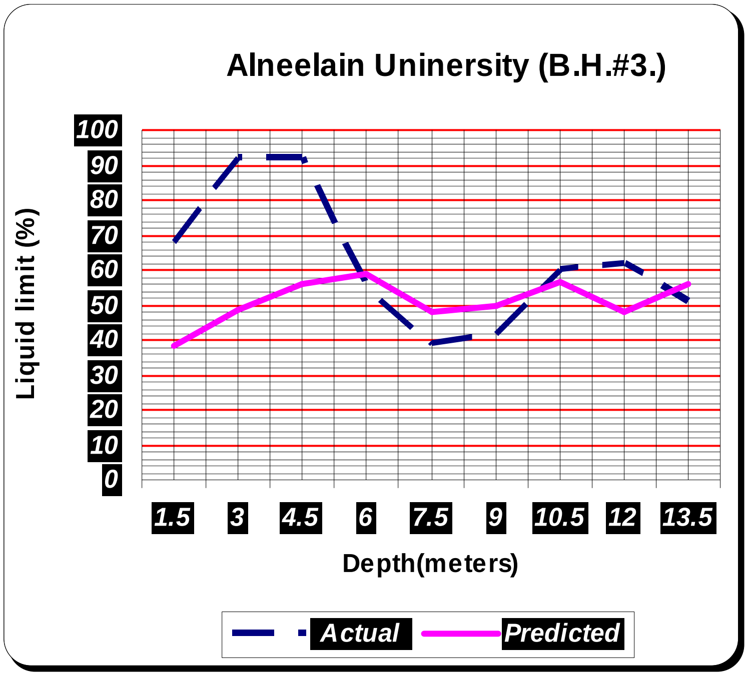


Figure 6.7-c

Figure 6.7:Comparison between actual and ANN predictedliquid limit (L.L.) for Elneelain University site.

(a)Borehole no.1,

(b)Borehole no.2,

(c)Borehole no.3.

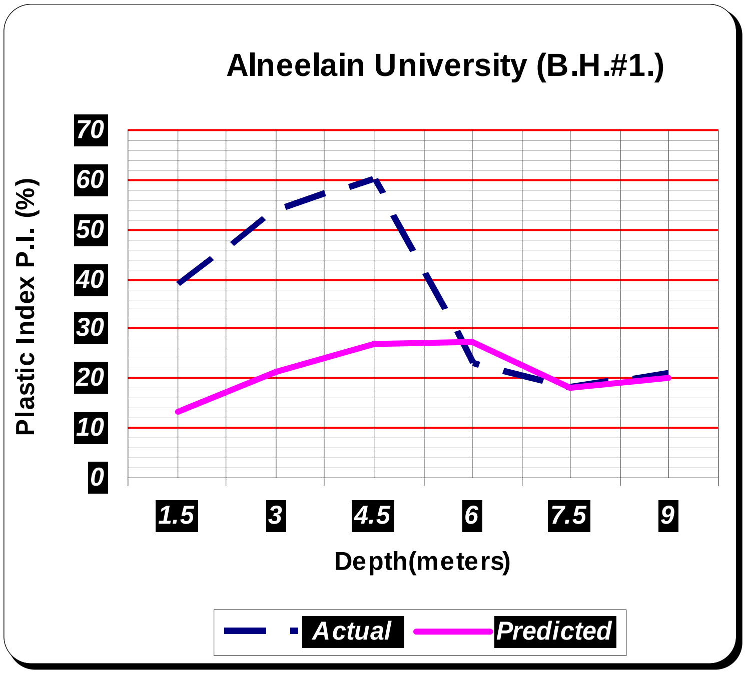


Figure 6.8-a

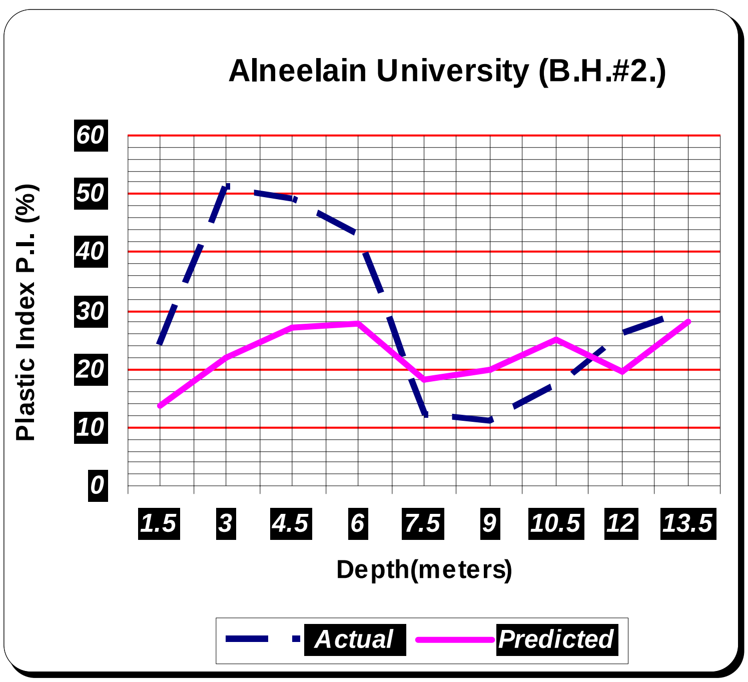


Figure 6.8-b

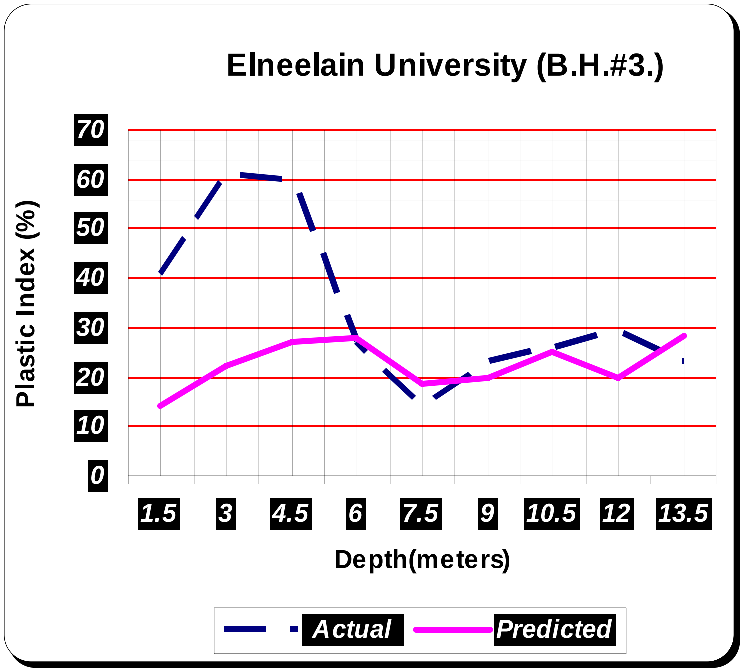


Figure 6.8-c

Figure 6.8:Comparison between actual and ANN predicted plastic index (P.I.) for Elneelain University site.

(a)Borehole no.1,

(b)Borehole no.2,

(c)Borehole no.3.

6.4.3. Third case study:
Hassan &Alaabid co. in University near Africa Street:

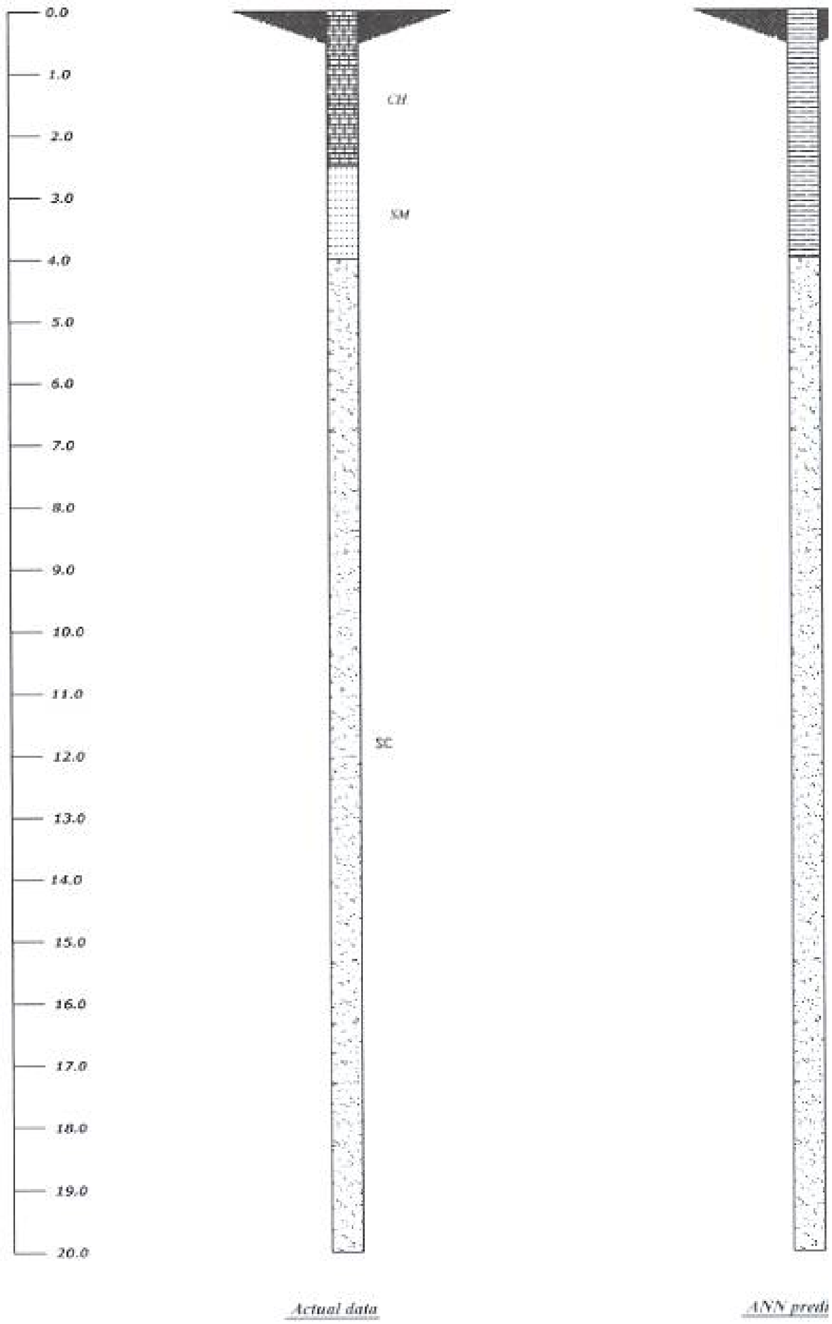
For known boreholes coordinates and depths which entered as inputs the ANN prediction results were listed in Appendix (C) ,and compared with actual values in Figures (6.9,6.10,6.11 and 6.12).

Figure (6.9) shows that the ANN predicted stratum for the four boreholes in Hassan & Alaabid co. site is of the same layer main group (sand or clay),but of differences in subgroups some examples of such differences are shown in table (6.1) below:

Table (6.1): Some differences in ANN predicted and actual soil classification in Hassan &Alaabid co.site

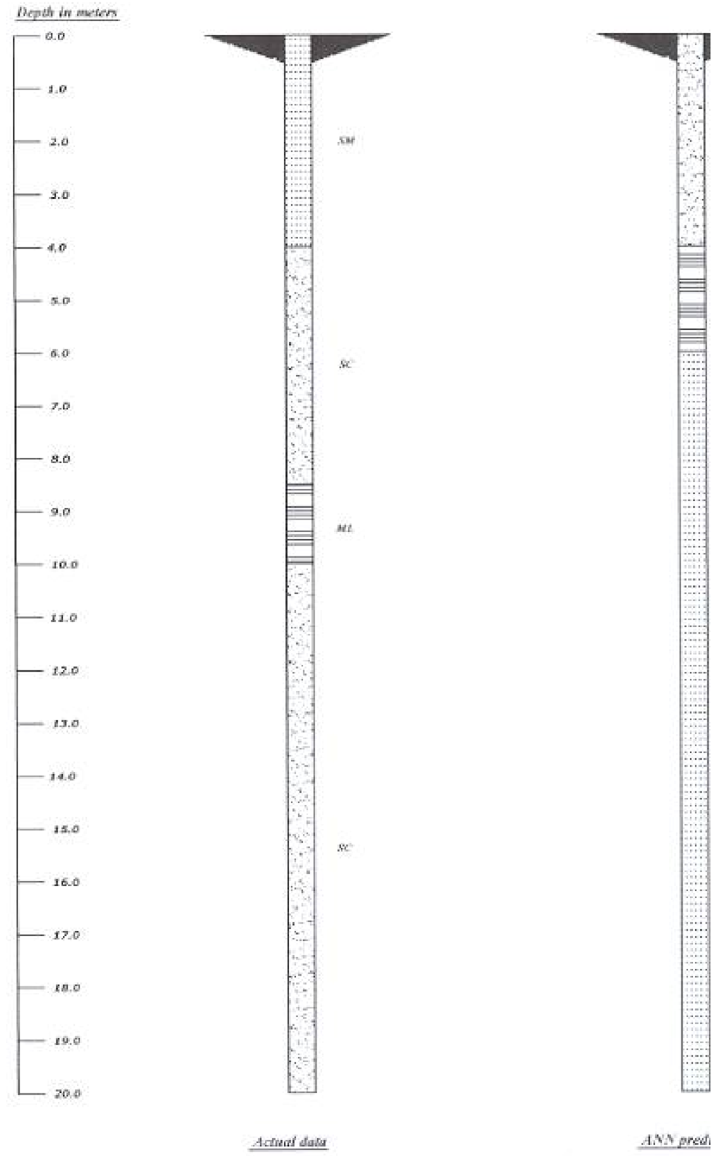
Borehole No.	Actual soil class	Predicted soil class
1	*CH*	*CL*
2	*SM*	*SC*
3	*SC*	*SM*
4	*SC/SP*	*SC/SW*

Figure (6.10) shows that the ANN predicted N-value are typical to actual values in specific locations with slight differences in others .Figures (6.11) and (6.12) present the differences of only two points of Atterberg limits which is not enough to study the differences in ANN predicted values .Because of nonlinearity of the produced models it’s important to compare the predicted values of three or more points with actual values of the same points to perform the accuracy of such model.


0.0
1.0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
9.0
10.0
11.0
12.0
13.0
14.0
15.0
16.0
17.0
18.0
19.0
20.0
CH
SM
SC
Actual data
ANN predi

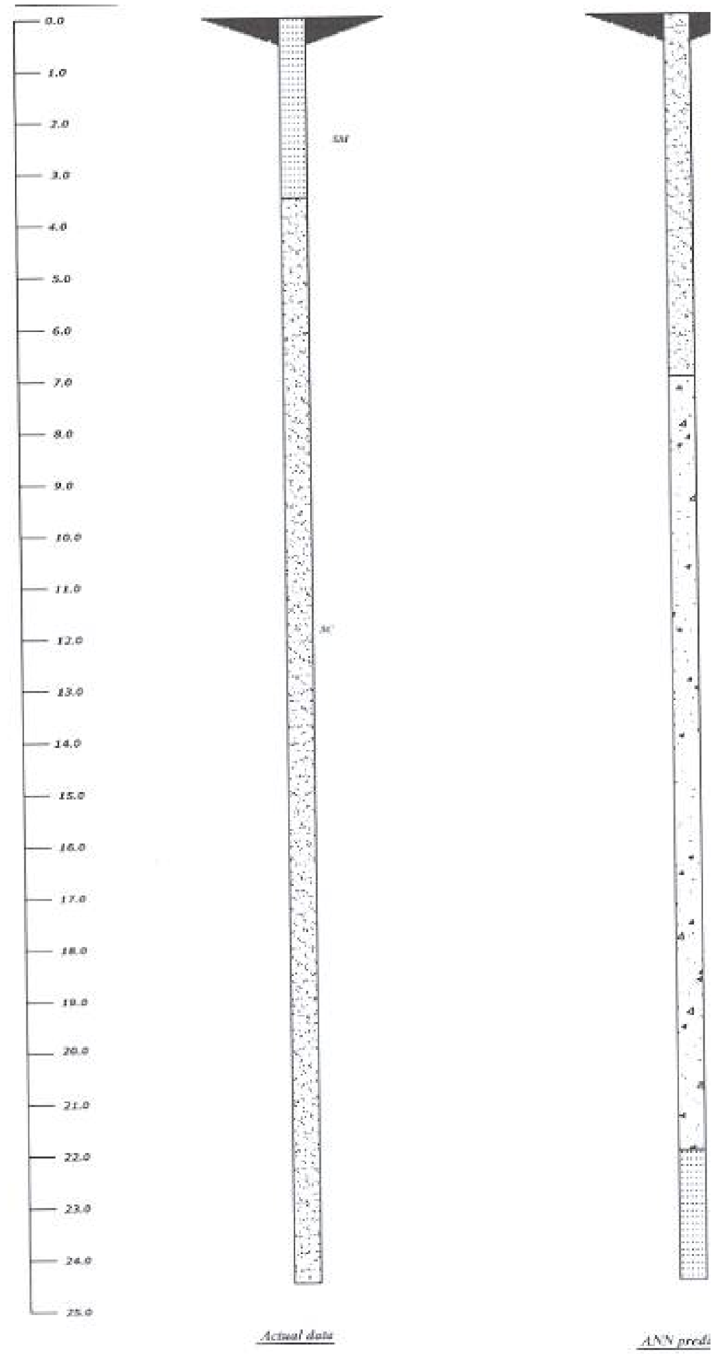
(a)

103


Depth in meters
0.0
1.0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
9.0
10.0
11.0
12.0
13.0
14.0
15.0
16.0
17.0
18.0
19.0
20.0
SM
SC
ML
SC
Actual data
ANN predi

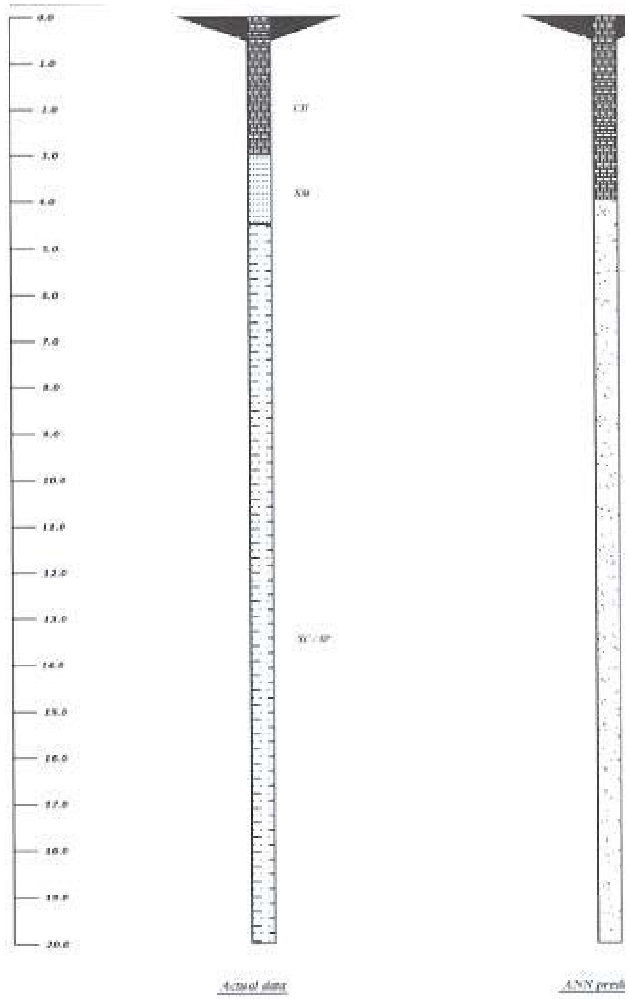
(b)

104


0.0
1.0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
9.0
10.0
11.0
12.0
13.0
14.0
15.0
16.0
17.0
18.0
19.0
20.0
21.0
22.0
23.0
24.0
25.0
SM
Actual data
ANN predi

(c)

105



(d)

Figure 6.9:Comparison between actual and ANN predicted soil classification results for Hassan &Alaabid co. site :

(a)Borehole no.1,

(b)Borehole no.2,

(c) Borehole no.3,

(d) Borehole no.4.

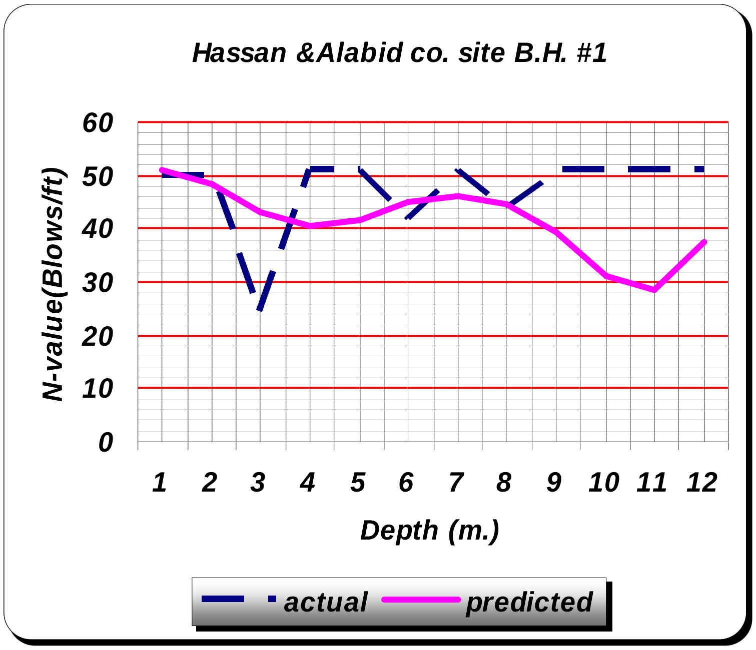


Figure 6.10-a

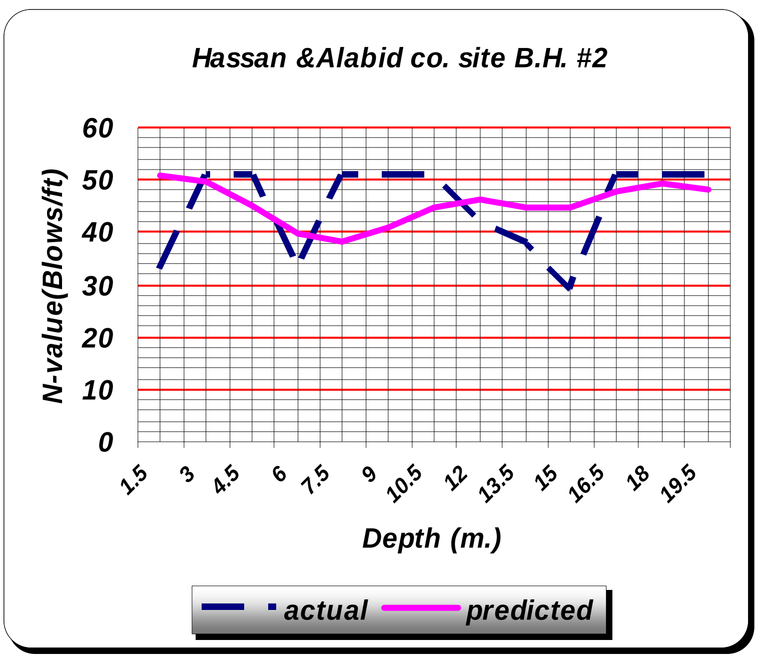


Figure 6.10-b

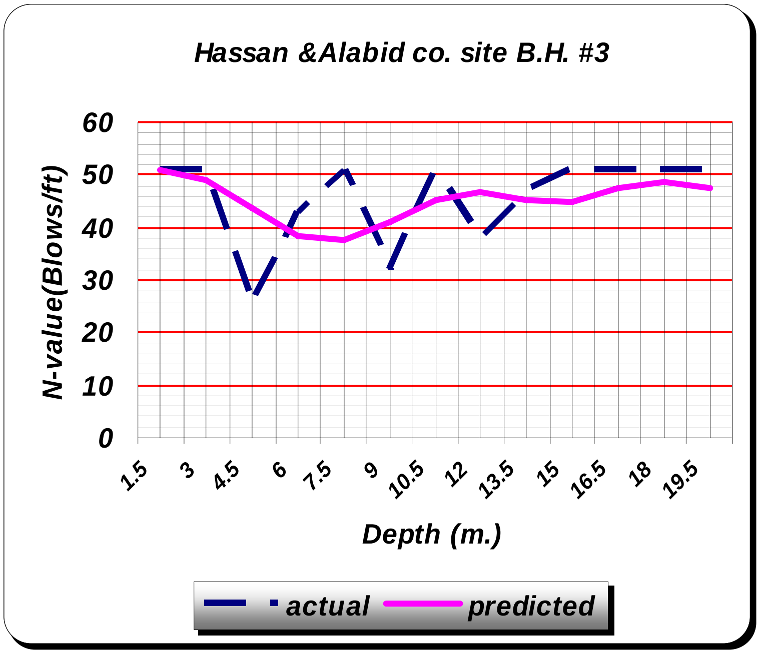


Figure 6.10-c

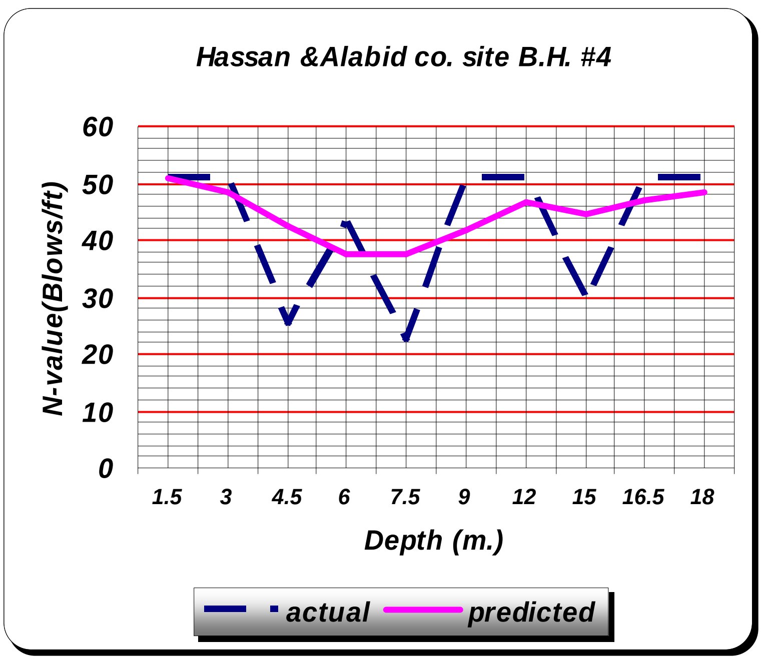


Figure 6.10-d

Figure 6.10:Comparison between actual and ANN predicted SPT for Hassan &Alaabid co. site.

(a)Borehole no.1,

(b)Borehole no.2l,

(c) Borehole no.3,

(d) Borehole no.4.

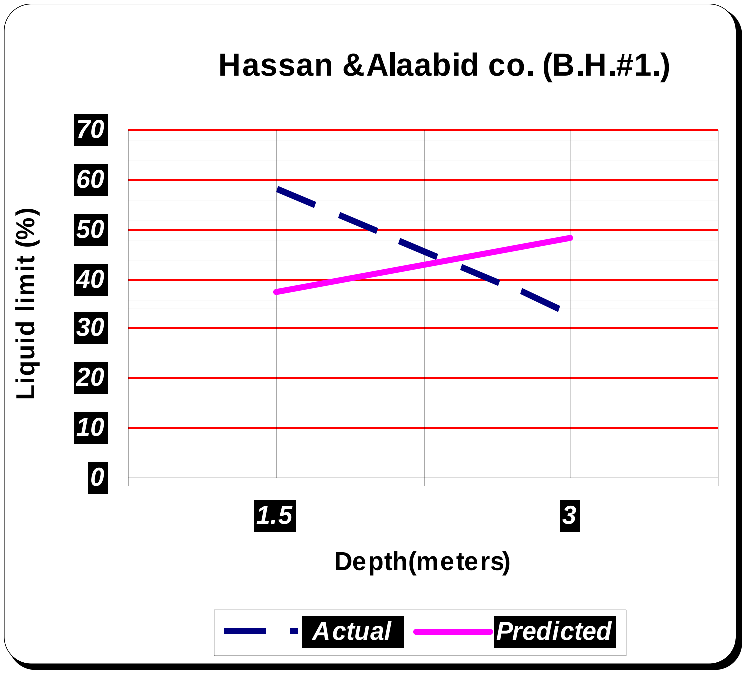


Figure 6.11-a

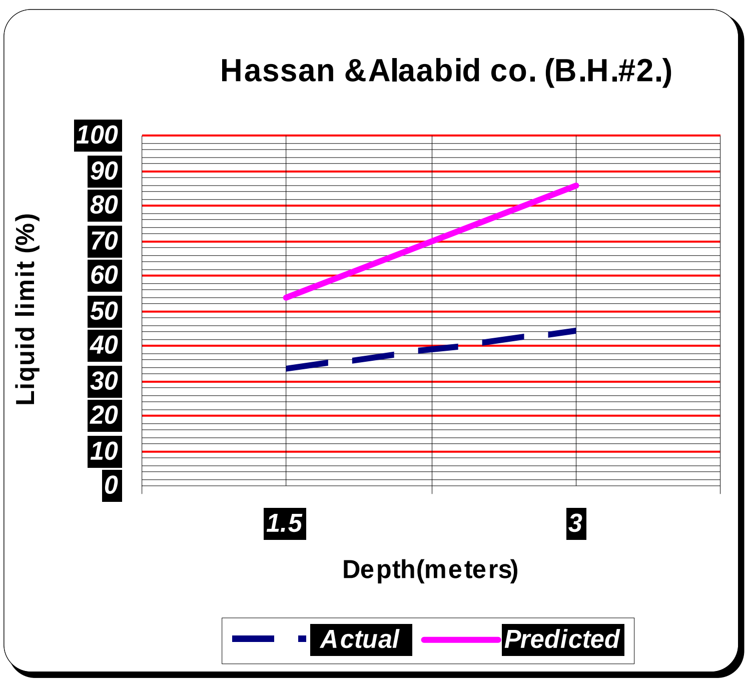


Figure 6.11-b

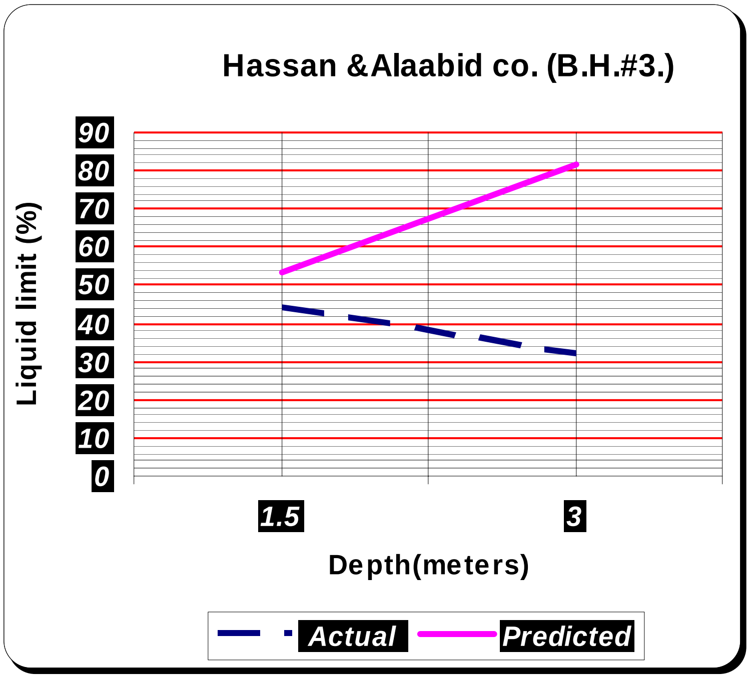

Hassan &Alaabid co. (B.H.#3.)
Liquid limit (%)
90
80
70
60
50
40
30
20
10
0
1.5
3
Depth(meters)
Actual
Predicted

Figure 6.11-c

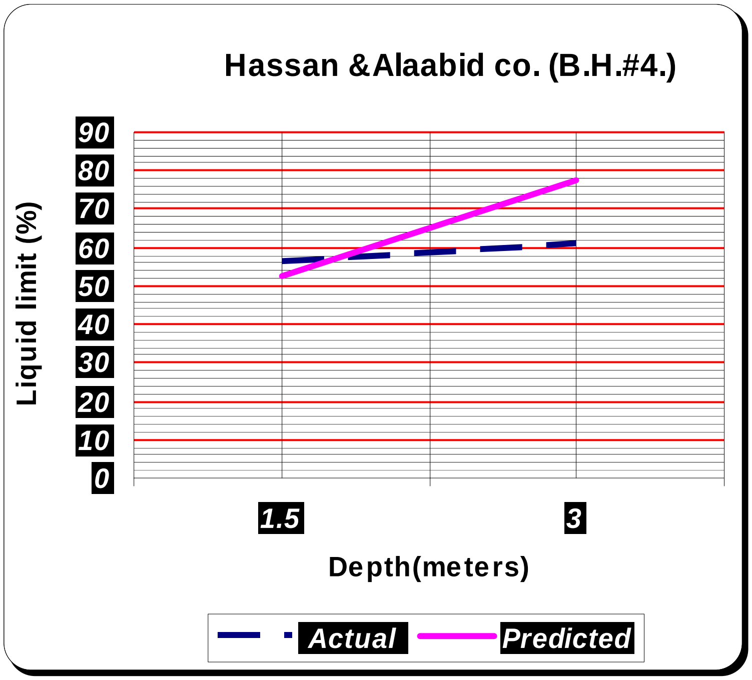


Figure 6.11-d

Figure 6.11:Comparison between actual and ANN predicted liquid limit (L.L.) for Hassan &Alaabid co. site.

(a)Borehole no.1,

(b)Borehole no.2,

(c) Borehole no.3,

(d) Borehole no.4.

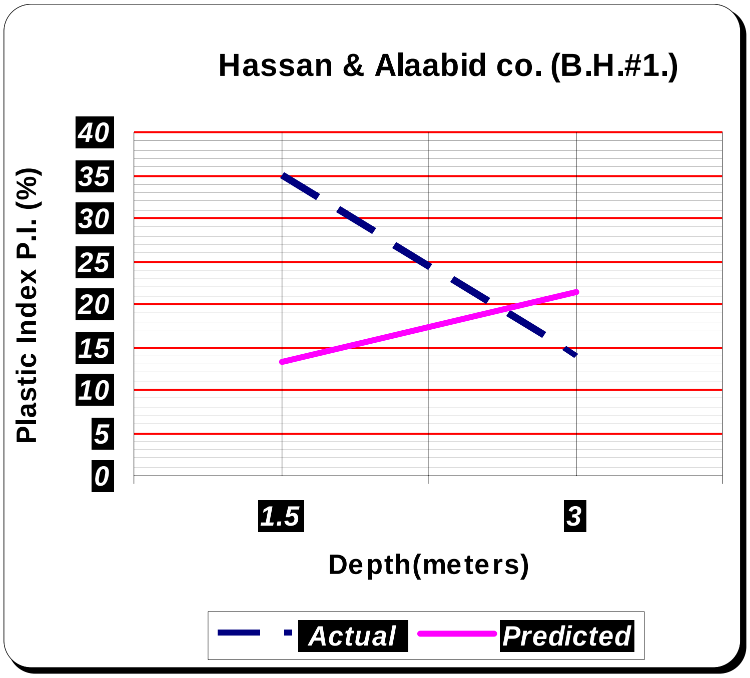


Figure 6.12-a

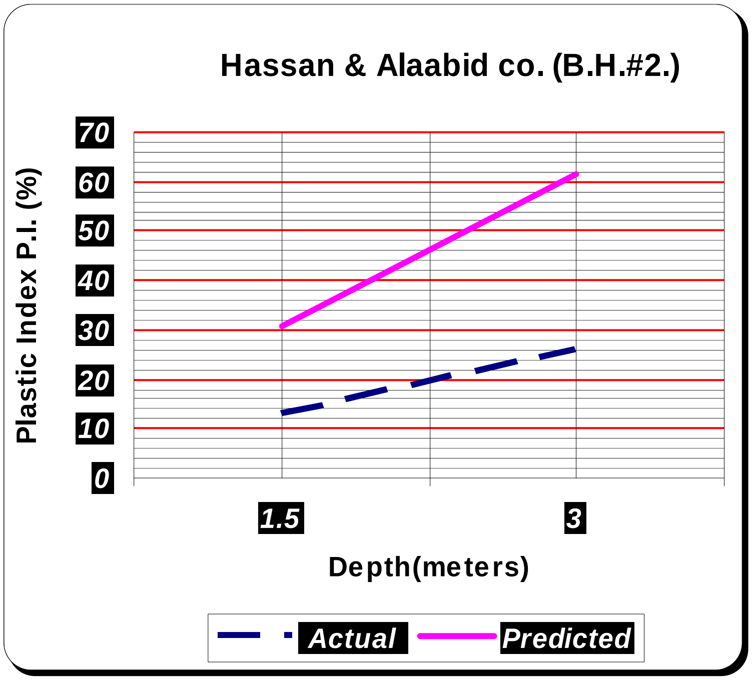


Figure 6.12-b

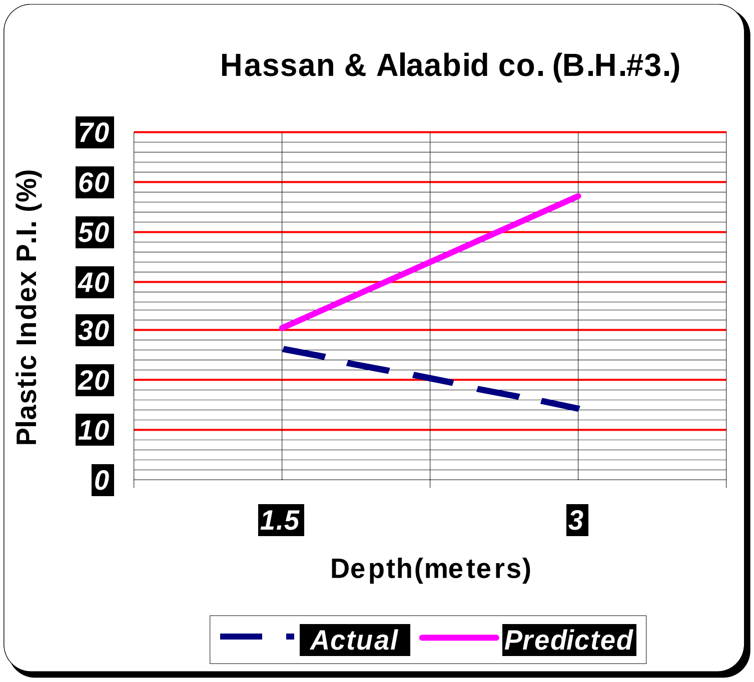

Hassan & Alaabid co. (B.H.#3.)
Plastic Index P.I. (%)
70
60
50
40
30
20
10
0
1.5
3
Depth(meters)
Actual
Predicted

Figure 6.12-c

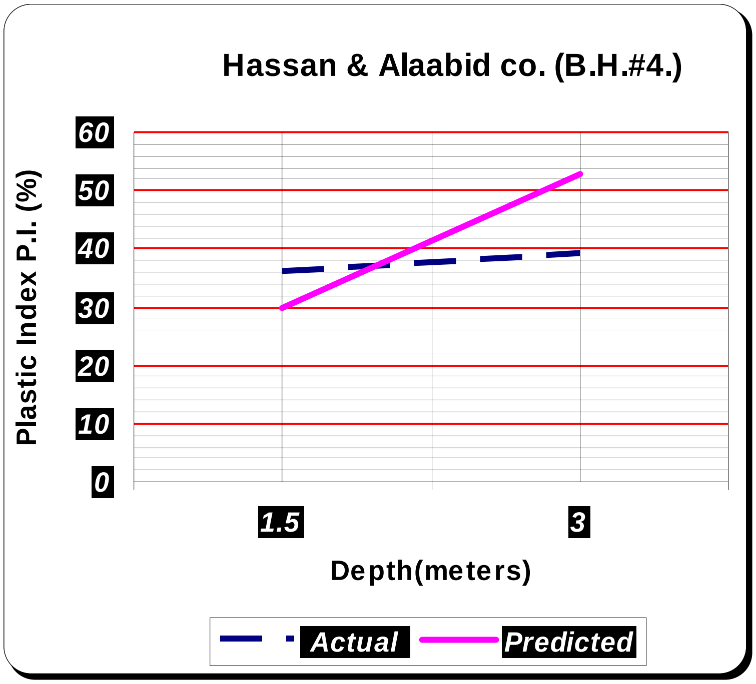


Figure 6.12-d

Figure 6.12:Comparison between actual and ANN predicted plastic index (P.I.) for Hassan &Alaabid co. site.

(a)Borehole no.1,

(b)Borehole no.2.

(c) Borehole no.3,

(d) Borehole no.4.

6.5. Training of Networks Time factor:

In this study, as the training of the networks are in progress, it has been observed that the network powerful statistical indicators (The coefficient of multiple determination R squared and Pearson's linear correlation coefficient r) are increased as the training time is increased for the same network architecture characteristics .The correlation coefficient against SPT network training time are plotted in Figure (6.13) and the polynomial equation for such relationship has been investigated so it is expected to get 95% correlation factor after training the network about 35 hours.

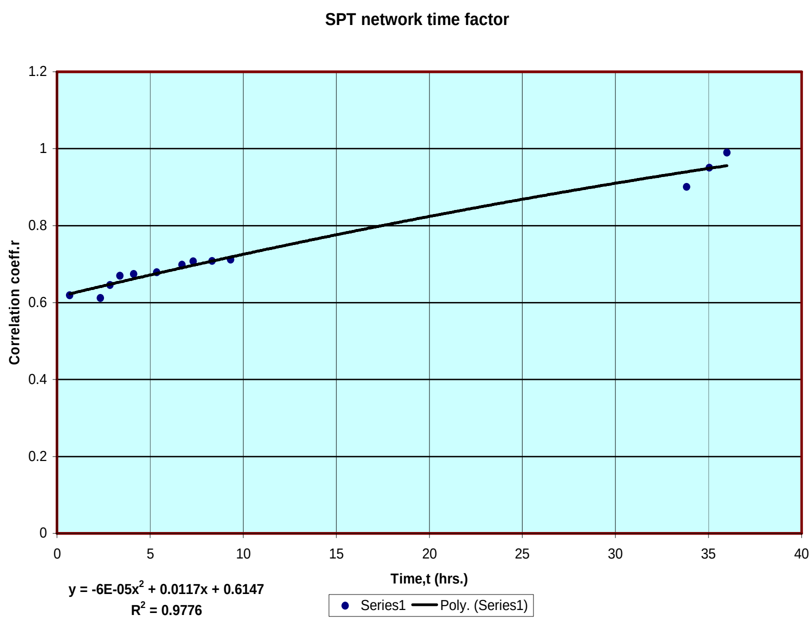


Figure 6.13:Statisical indicators (r) improvement through time For SPT network .

Chapter Seven

Conclusions and Recommendations for Future Studies

Chapter 7
Conclusion &Recommendations for Future Studies

7.1. Conclusions:

Artificial Neural Networks method is an effective tool in solving complex, nonlinear and causal problems. Neural networks have been applied in solving a wide variety of problems. The consistencies, accuracy, volume of learning data, are the factors, which the ability of this method depends on.

In this study, ANN were used to predict the soil profile and parameters in Khartoum city based on raw data carried out during the past decades in Sudan. Based on the results obtained, the following conclusions have been found:

1. In spite of the fact that the tested boreholes were presented to the network in the training process, it can be stated that the trained ANN are capable of predicting variations in the soil profile with an acceptable level of confidence.
2. In case of problems dealing with different variables with different ranges and dimensions, the application of separate networks of each variable is a good choice.
3. Constructed Atterberg limits model shows a good performance in prediction especially for plasticity index.
4. Constructed SPT model shows acceptable performance in prediction
5. ANNs are efficient tools when used as pattern classifier; cases concerning decision making based on previous experiments
6. ANNs are efficient in interpolation more than extrapolation.
7. Increasing training time leads to reliable results.
8. Soil profile ANN prediction networks cannot replace site investigation, but they can reduce the total number of boreholes, which will lead to cost reduction and improved operation planning.
9. ANNs may be used as a good decision support and source of information for soils.

7.2. Recommendations for Future Work:

Based on this study, the following recommendations for future work may be feasible:

a. Increasing training process time may lead to better results for prediction of soil profile and parameters in the studied area.
b. Using modern ANN software may decrease training time.
c. Connect inputs of three dimensional coordinates in Khartoum digital map to the outputs of produced networks in the same environment.
d. The soil classification modeling may be spread to all area of Sudan if raw data are available.
e. Other soil parameters can be entered as outputs of the ANNs such as: shear parameters (Cohesion C and Friction angle Φ), Relative density D_R, Cone Penetration Test continuous values q_c... etc.

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Appendix (A)

Actual and ANN predicted soil classification &parameters for Areeba co. site in Burri zone.

Appendix (A):
Areeba co. site:
1. Atterberg limits Network results:

B.H.#	E	N	DEPTH	ACTUAL L.L	PREDICTED L.L	ACTUAL P.I.	PREDICTED P.I.
1	453112	1725600	1.5	43	56.06184143	24	30.3981563
1	453112	1725600	3	45	31.18198275	7	6.04707677
1	453112	1725600	4.5	45	21.02824137	12	0
1	453112	1725600	6	48	20.84465438	14	0
1	453112	1725600	7.5	46	25.84381549	16	1.14506859
1	453112	1725600	9	50	47.5524251	18	19.59892
2	453160	1725608	1.5	45	55.38355076	29	29.6967136
2	453160	1725608	3	43	31.22274629	15	6.03980496
2	453160	1725608	4.5	41	21.67781335	8	0
2	453160	1725608	6	42	21.35468142	7	0
2	453160	1725608	7.5	43	26.00002244	16	1.25122227
2	453160	1725608	9	51	46.93307039	18	18.9872752

2. SPT Network results:

B.H.#	E	N	DEPTH	ACTUAL N-VALUE	PREDICTED N-NALUE
1	453112	1725600	3	51	44.75028389
1	453112	1725600	7.5	31	44.57818591
1	453112	1725600	9	45	41.75606734
1	453112	1725600	10	38	37.95160661
2	453160	1725608	4.5	51	44.90097733
2	453160	1725608	6	51	45.32201137
2	453160	1725608	7.5	51	44.59568412
2	453160	1725608	9	51	41.81694052
2	453160	1725608	10	36	38.00486425

3. Global classifier Network results:

B.H.	E	N	DEPTH	SAND	SAND(predicted)	CLAY/ SILT	CLAY/ SILT(predicted)
1	453112	1725600	1.5	1	0.70171324	0	0.301268138
1	453112	1725600	2.5	1	0.78346444	0	0.221819391
1	453112	1725600	3	0	0.805692428	1	0.200138462
1	453112	1725600	4.5	0	0.742438114	1	0.261793843
1	453112	1725600	6	0	0.611670288	1	0.388701114
1	453112	1725600	7.5	0	0.579265775	1	0.420642015
1	453112	1725600	8.5	0	0.603840771	1	0.396981615
1	453112	1725600	9	0	0.62839647	1	0.373050238
1	453112	1725600	10	0	0.69344086	1	0.309560448
2	453160	1725608	1.5	0	0.714819705	1	0.288414284
2	453160	1725608	3	0	0.812950113	1	0.192905028
2	453160	1725608	4.5	0	0.740829832	1	0.263203791
2	453160	1725608	6	0	0.613976913	1	0.386399853

2	453160	1725608	7.5	0	0.583420442	1	0.416787382
2	453160	1725608	8.5	0	0.605913373	1	0.39536618
2	453160	1725608	9	0	0.629285398	1	0.37268285
2	453160	1725608	10	0	0.693200579	1	0.31039726

4. Sand classifier Network results:

B.H.#	E	N	DEPTH	SM	SM(PREDICTED)	SC	SC(PREDICTED)
1	453112	1725600	1.5	0	0	1	0.222972294
1	453112	1725600	2.5	0	0	1	0.277783237
1	453112	1725600	3	0	0	0	0.295974501
1	453112	1725600	4.5	0	0	0	0.271220952
1	453112	1725600	6	0	0	0	0.160348989
1	453112	1725600	7.5	0	0	0	0.078307793
1	453112	1725600	8.5	0	0	0	0.059443016
1	453112	1725600	9	0	0	0	0.0591137
1	453112	1725600	10	0	0.017515617	0	0.073420492
2	453160	1725608	1.5	0	0	0	0.242089665
2	453160	1725608	3	0	0	0	0.306948871
2	453160	1725608	4.5	0	0	0	0.261254347
2	453160	1725608	6	0	0	0	0.145529821
2	453160	1725608	7.5	0	0	0	0.070904728
2	453160	1725608	8.5	0	0	0	0.055865768
2	453160	1725608	9	0	0	0	0.056827191
2	453160	1725608	10	0	0.014269781	0	0.072986365

5. Sand grading classifier Network results:

B.H.#	E	N	DEPTH	SW	SW(PRED.)	SP	SP(PRED.)
1	453112	1725600	1.5	0	0	0	0.02088621
1	453112	1725600	2.5	0	0	0	0.01658217
1	453112	1725600	3	0	0	0	0.01266568
1	453112	1725600	4.5	0	0	0	0.00015801
1	453112	1725600	6	0	0	0	0
1	453112	1725600	7.5	0	0	0	0
1	453112	1725600	8.5	0	0	0	0
1	453112	1725600	9	0	0	0	0.00042932
1	453112	1725600	10	0	0	0	0.00533637
2	453160	1725608	1.5	0	0	0	0.02514312
2	453160	1725608	3	0	0	0	0.01386454
2	453160	1725608	4.5	0	0	0	0.00097485
2	453160	1725608	6	0	0	0	0
2	453160	1725608	7.5	0	0	0	0
2	453160	1725608	8.5	0	0	0	0.00100048
2	453160	1725608	9	0	0	0	0.00336041
2	453160	1725608	10	0	0	0	0.00823349

6. Clay classifier Network results:

B.H.#	E	N	DEPTH	CL	CL(PRED.)	CH	CH(PRED)
1	453112	1725600	1.5	0	0.009225561	0	0.408623036
1	453112	1725600	2.5	0	0.032476327	0	0.289527699
1	453112	1725600	3	1	0.041317913	0	0.262656844
1	453112	1725600	4.5	1	0.062657401	0	0.294805244
1	453112	1725600	6	1	0.12134123	0	0.282115787
1	453112	1725600	7.5	1	0.263931378	0	0.02920257
1	453112	1725600	8.5	1	0.335992613	0	0
1	453112	1725600	9	0	0.34464881	1	0
1	453112	1725600	10	0	0.308881104	1	0
2	453160	1725608	1.5	1	0.015021926	0	0.39330371
2	453160	1725608	3	1	0.052064109	0	0.237016192
2	453160	1725608	4.5	1	0.0767878	0	0.247634797
2	453160	1725608	6	1	0.136472634	0	0.22156324
2	453160	1725608	7.5	1	0.283773131	0	0
2	453160	1725608	8.5	1	0.364387969	0	0
2	453160	1725608	9	0	0.378126169	1	0
2	453160	1725608	10	0	0.35053231	1	0

7. Silt classifier Network results:

B.H.#	E	N	DEPTH	ML	ML(PRED.)	MH	MH(PRED.)
1	453112	1725600	1.5	0	0	0	0.03671977
1	453112	1725600	2.5	0	0	0	0.0483822
1	453112	1725600	3	0	0	0	0.05188792
1	453112	1725600	4.5	0	0.14131501	0	0.04937307
1	453112	1725600	6	0	0.32646846	0	0.05736449
1	453112	1725600	7.5	0	0.32834768	0	0.07485136
1	453112	1725600	8.5	0	0.3851093	0	0.08297119
1	453112	1725600	9	0	0.47314883	0	0.08584543
1	453112	1725600	10	0	0.77589189	0	0.08819166
2	453160	1725608	1.5	0	0	0	0.04017602
2	453160	1725608	3	0	0	0	0.05465037
2	453160	1725608	4.5	0	0.15897566	0	0.05091555
2	453160	1725608	6	0	0.3409281	0	0.0584153
2	453160	1725608	7.5	0	0.35583366	0	0.07545426
2	453160	1725608	8.5	0	0.42786412	0	0.08351882
2	453160	1725608	9	0	0.52512531	0	0.08635626
2	453160	1725608	10	0	0.83078911	0	0.08838321

Appendix (B)

Actual and ANN predicted soil classification &parameters for Elneelain University in Elmogran zone.

Appendix (B):
Elneelain University site:
1. Atterberg limits Network results:

B.H.#	E	N	DEPTH	ACTUAL L.L	PREDICTED L.L	ACTUAL P.I.	PREDICTED P.I.
1	447869	1724767	1.5	66	37.46321712	39	13.3687938
1	447869	1724767	3	80	48.35836691	54	21.5039884
1	447869	1724767	4.5	91	55.55060902	60	26.9749786
1	447869	1724767	6	52	58.35905842	23	27.4448599
1	447869	1724767	7.5	44	47.4526486	18	18.1481241
1	447869	1724767	9	49	49.8610265	21	20.0181416
2	447832	1724786	1.5	73	37.88111748	24	13.833518
2	447832	1724786	3	84	48.6263804	51	21.8216269
2	447832	1724786	4.5	78	55.73800168	49	27.1459691
2	447832	1724786	6	71	58.66157461	43	27.6409604
2	447832	1724786	7.5	33	47.70115695	12	18.2980919
2	447832	1724786	9	36	49.68813388	11	19.88628
2	447832	1724786	10.5	40	56.87019991	17	25.1948895
2	447832	1724786	12	58	47.5823314	26	19.4135257
2	447832	1724786	13.5	52	55.8040988	30	28.0321074
3	447798	1724804	1.5	68	38.25488991	41	14.2516673
3	447798	1724804	3	92	48.85120775	61	22.089781
3	447798	1724804	4.5	92	55.88697637	60	27.2780987
3	447798	1724804	6	55	58.91934094	27	27.8029882
3	447798	1724804	7.5	39	47.90933415	14	18.4222463
3	447798	1724804	9	42	49.50761215	23	19.7494377
3	447798	1724804	10.5	60	56.84329076	26	25.2222676
3	447798	1724804	12	62	48.05583295	29	19.8102102
3	447798	1724804	13.5	51	56.13717876	23	28.2268561

2. SPT Network results:

B.H.#	E	N	DEPTH	ACTUAL N-VALUE	PREDICTED N-NALUE
1	447869	1724767	7.5	51	41.79917581
1	447869	1724767	9	23	44.83600797
1	447869	1724767	10.5	24	46.22934817
1	447869	1724767	11.5	12	45.56640219
1	447869	1724767	13.5	12	39.4605489
1	447869	1724767	15	51	31.22972357
1	447869	1724767	16.5	51	28.66816516
2	447832	1724786	7.5	51	39.48235139
2	447832	1724786	9	46	43.57878727
2	447832	1724786	10.5	31	45.63147012
2	447832	1724786	18	51	38.09034372
2	447832	1724786	19.5	51	47.49633471
3	447798	1724804	9	31	42.76446881
3	447798	1724804	10.5	50	45.28368178
3	447798	1724804	12	46	44.3583101
3	447798	1724804	13.5	46	39.55074518

3	447798	1724804	15	12	31.83141669
3	447798	1724804	16.5	41	29.79348665
3	447798	1724804	18	51	38.73568197

3. Global classifier Network results:

B.H.	E	N	DEPTH	SAND	SAND(predicted)	CLAY/ SILT	CLAY/ SILT(predicted)
1	447869	1724767	1.5	0	0.083958407	1	0.919812304
1	447869	1724767	3	0	0.079645917	1	0.923015085
1	447869	1724767	4.5	0	0.08072573	1	0.920883921
1	447869	1724767	6	0	0.102781051	1	0.897574183
1	447869	1724767	7	0	0.144090555	1	0.854920129
1	447869	1724767	7.5	0	0.174010932	1	0.824085677
1	447869	1724767	9	0	0.268740169	1	0.726452446
1	447869	1724767	10	0	0.321590827	1	0.672810648
1	447869	1724767	10.5	0	0.354906136	1	0.639820669
1	447869	1724767	12	0	0.537764326	1	0.461865371
1	447869	1724767	13	0	0.668426429	1	0.334628486
1	447869	1724767	13.5	1	0.684630175	0	0.318584331
1	447869	1724767	15	1	0.596984448	0	0.4028504
1	447869	1724767	16	1	0.564297931	0	0.434252922
1	447869	1724767	16.5	0	0.568585591	1	0.430077319
1	447869	1724767	18	0	0.610451373	1	0.389830361
1	447869	1724767	19.5	0	0.620177361	1	0.3814609
2	447832	1724786	1.5	0	0.067695335	1	0.935996828
2	447832	1724786	3	0	0.062717732	1	0.93992552
2	447832	1724786	4.5	0	0.062910237	1	0.938748402
2	447832	1724786	6	0	0.082844917	1	0.917661992
2	447832	1724786	7	0	0.121083571	1	0.878186356
2	447832	1724786	7.5	0	0.148897856	1	0.849523599
2	447832	1724786	9	0	0.236745438	1	0.758911945
2	447832	1724786	10	0	0.284520052	1	0.710308006
2	447832	1724786	11.5	0	0.415692259	1	0.58181596
2	447832	1724786	12	0	0.490574917	1	0.509120493
2	447832	1724786	13.5	0	0.649440933	1	0.354274588
2	447832	1724786	15	0	0.561666534	1	0.438651522
2	447832	1724786	16.5	0	0.527771681	1	0.471168837
2	447832	1724786	17.5	0	0.555086926	1	0.444816467
2	447832	1724786	18	0	0.569839673	1	0.430676979
2	447832	1724786	19	0	0.585245388	1	0.416312967
2	447832	1724786	20	0	0.570359276	1	0.431751464
2	447832	1724786	20.5	1	0.549762145	0	0.452409168
2	447832	1724786	22	1	0.442523216	0	0.559058459
2	447832	1724786	23.5	1	0.304837525	0	0.695714181
2	447832	1724786	25	1	0.184471008	0	0.815558264
3	447798	1724804	1.5	0	0.052322067	1	0.95127335
3	447798	1724804	3	0	0.046944722	1	0.955659656
3	447798	1724804	4.5	0	0.046530544	1	0.95515555
3	447798	1724804	6	0	0.064669356	1	0.935957489
3	447798	1724804	7	0	0.100127415	1	0.899368879
3	447798	1724804	7.5	0	0.126009615	1	0.872699972

3	447798	1724804	9	0	0.207639781	1	0.788456403
3	447798	1724804	10	0	0.251039787	1	0.744208596
3	447798	1724804	11.5	0	0.372885207	1	0.624739575
3	447798	1724804	13	0	0.591347264	1	0.412387516
3	447798	1724804	14.5	0	0.567596824	1	0.434596729
3	447798	1724804	16	0	0.489371015	1	0.509832844
3	447798	1724804	17.5	0	0.518292755	1	0.481819256
3	447798	1724804	18	0	0.533646241	1	0.467074817
3	447798	1724804	19	0	0.550917134	1	0.450858292
3	447798	1724804	19.5	1	0.548802734	0	0.453322349
3	447798	1724804	20	1	0.538065478	0	0.464270716

4. Sand classifier Network results:

B.H.#	E	N	DEPTH	SM	SM(PREDICTED)	SC	SC(PREDICTED)
1	447869	1724767	1.5	0	0	0	0.2922244
1	447869	1724767	3	0	0	0	0.33242643
1	447869	1724767	4.5	0	0	0	0.312776939
1	447869	1724767	6	0	0	0	0.243801696
1	447869	1724767	7	0	0	0	0.19179817
1	447869	1724767	7.5	0	0	0	0.167751606
1	447869	1724767	9	0	0.136065199	0	0.105694396
1	447869	1724767	10	0	0.184788589	0	0.075210978
1	447869	1724767	10.5	0	0.190720331	0	0.064552251
1	447869	1724767	12	0	0.214918551	0	0.048945855
1	447869	1724767	13	0	0.238608046	0	0.045242004
1	447869	1724767	13.5	1	0.244413389	0	0.043865229
1	447869	1724767	15	1	0.24586547	0	0.046278324
1	447869	1724767	16	1	0.289699435	0	0.061429974
1	447869	1724767	16.5	0	0.344727004	0	0.073782497
1	447869	1724767	18	0	0.589487376	0	0.111696137
1	447869	1724767	19.5	0	0.599181624	0	0.124660259
2	447832	1724786	1.5	0	0	0	0.287642516
2	447832	1724786	3	0	0	0	0.321089626
2	447832	1724786	4.5	0	0	0	0.29479757
2	447832	1724786	6	0	0	0	0.222107132
2	447832	1724786	7	0	0	0	0.169556696
2	447832	1724786	7.5	0	0	0	0.145573816
2	447832	1724786	9	0	0.181150265	0	0.08475493
2	447832	1724786	10	0	0.22978585	0	0.056026813
2	447832	1724786	11.5	0	0.248804165	0	0.035744208
2	447832	1724786	12	0	0.261691696	0	0.033535707
2	447832	1724786	13.5	0	0.291888714	0	0.031335383
2	447832	1724786	15	0	0.287350304	0	0.036776412
2	447832	1724786	16.5	0	0.378533791	0	0.067639325
2	447832	1724786	17.5	0	0.540181592	0	0.098658794
2	447832	1724786	18	0	0.615596148	0	0.111666614
2	447832	1724786	19	0	0.663802151	0	0.127089167
2	447832	1724786	20	0	0.55394669	0	0.135133802
2	447832	1724786	20.5	1	0.469686953	0	0.139510329
2	447832	1724786	22	1	0.34180198	0	0.143731232

2	447832	1724786	23.5	1	0.49940352	0	0.088596989
2	447832	1724786	25	1	0.792474204	0	0
3	447798	1724804	1.5	0	0	0	0.282137468
3	447798	1724804	3	0	0	0	0.309328251
3	447798	1724804	4.5	0	0	0	0.277249142
3	447798	1724804	6	0	0	0	0.201862451
3	447798	1724804	7	0	0	0	0.149337365
3	447798	1724804	7.5	0	0.021535531	0	0.125657557
3	447798	1724804	9	0	0.226168928	0	0.066584714
3	447798	1724804	10	0	0.273505784	0	0.039666678
3	447798	1724804	11.5	0	0.292944796	0	0.021996154
3	447798	1724804	13	0	0.332797655	0	0.02030613
3	447798	1724804	14.5	0	0.330446997	0	0.024267771
3	447798	1724804	16	0	0.361057969	0	0.047855686
3	447798	1724804	17.5	0	0.566949816	0	0.09714057
3	447798	1724804	18	0	0.640073467	0	0.112335807
3	447798	1724804	19	0	0.687558105	0	0.132119427
3	447798	1724804	19.5	0	0.650127951	1	0.138086169
3	447798	1724804	20	0	0.579103948	1	0.143429092

5. Sand grading classifier Network results:

B.H.#	E	N	DEPTH	SW	SW(PRED.)	SP	SP(PRED.)
1	447869	1724767	1.5	0	0	0	0
1	447869	1724767	3	0	0	0	0
1	447869	1724767	4.5	0	0	0	0
1	447869	1724767	6	0	0	0	0
1	447869	1724767	7	0	0.0190239	0	0
1	447869	1724767	7.5	0	0.0330275	0	0
1	447869	1724767	9	0	0.0240989	0	0
1	447869	1724767	10	0	0	0	0.04356136
1	447869	1724767	10.5	0	0	0	0.07487501
1	447869	1724767	12	0	0	0	0.11945068
1	447869	1724767	13	0	0	0	0.09495274
1	447869	1724767	13.5	0	0	0	0.07607979
1	447869	1724767	15	0	0	0	0.02275374
1	447869	1724767	16	0	0	0	0
1	447869	1724767	16.5	0	0.0109525	0	0
1	447869	1724767	18	0	0.1629874	0	0
1	447869	1724767	19.5	0	0.287354	0	0
2	447832	1724786	1.5	0	0	0	0
2	447832	1724786	3	0	0	0	0
2	447832	1724786	4.5	0	0	0	0
2	447832	1724786	6	0	0	0	0
2	447832	1724786	7	0	0.0200558	0	0
2	447832	1724786	7.5	0	0.033494	0	0
2	447832	1724786	9	0	0.0206572	0	0
2	447832	1724786	10	0	0	0	0.04391694
2	447832	1724786	11.5	0	0	0	0.1138368
2	447832	1724786	12	0	0	0	0.1152192
2	447832	1724786	13.5	0	0	0	0.07045523
2	447832	1724786	15	0	0	0	0.01799088

2	447832	1724786	16.5	0	0.0133384	0	0
2	447832	1724786	17.5	0	0.1105589	0	0
2	447832	1724786	18	0	0.1639854	0	0
2	447832	1724786	19	0	0.2527599	0	0
2	447832	1724786	20	0	0.2950792	0	0
2	447832	1724786	20.5	0	0.2985948	0	0
2	447832	1724786	22	0	0.2696683	0	0
2	447832	1724786	23.5	0	0.2493508	0	0.03424271
2	447832	1724786	25	0	0.3130857	0	0.06606437
3	447798	1724804	1.5	0	0	0	0
3	447798	1724804	3	0	0	0	0
3	447798	1724804	4.5	0	0	0	0
3	447798	1724804	6	0	0	0	0
3	447798	1724804	7	0	0.0210061	0	0
3	447798	1724804	7.5	0	0.033887	0	0
3	447798	1724804	9	0	0.0175521	0	0
3	447798	1724804	10	0	0	0	0.04420006
3	447798	1724804	11.5	0	0	0	0.11112751
3	447798	1724804	13	0	0	0	0.08451361
3	447798	1724804	14.5	0	0	0	0.02975455
3	447798	1724804	16	0	0	0	0
3	447798	1724804	17.5	0	0.1125216	0	0
3	447798	1724804	18	0	0.1646615	0	0
3	447798	1724804	19	0	0.2486991	0	0
3	447798	1724804	19.5	0	0.273321	0	0
3	447798	1724804	20	0	0.2853532	0	0

6. Clay classifier Network results:

B.H.#	E	N	DEPTH	CL	CL(PRED.)	CH	CH(PRED)
1	447869	1724767	1.5	0	0.476715347	1	0.509119152
1	447869	1724767	3	0	0.218179596	1	0.418788646
1	447869	1724767	4.5	0	0.092056182	1	0.275799482
1	447869	1724767	6	0	0.032020333	1	0.087560763
1	447869	1724767	7	0	0	1	0.007843515
1	447869	1724767	7.5	1	0	0	0
1	447869	1724767	9	1	0	0	0
1	447869	1724767	10	1	0	0	0
1	447869	1724767	10.5	0	0	0	0
1	447869	1724767	12	0	0	0	0.115307154
1	447869	1724767	13	0	0	0	0.175425351
1	447869	1724767	13.5	0	0.003115824	0	0.1849216
1	447869	1724767	15	0	0.03922864	0	0.153317224
1	447869	1724767	16	0	0.067791	0	0.114915011
1	447869	1724767	16.5	1	0.083820571	0	0.095494383
1	447869	1724767	18	1	0.111809945	0	0.03534292
1	447869	1724767	19.5	1	0.072414719	0	0
2	447832	1724786	1.5	0	0.484667873	1	0.499408959
2	447832	1724786	3	0	0.223438514	1	0.418248628
2	447832	1724786	4.5	0	0.093085517	1	0.286355987
2	447832	1724786	6	0	0.029449706	1	0.102140767

2	447832	1724786	7	0	0	1	0.021311027
2	447832	1724786	7.5	1	0	0	0
2	447832	1724786	9	1	0	0	0
2	447832	1724786	10	1	0	0	0
2	447832	1724786	11.5	1	0	0	0.07731694
2	447832	1724786	12	0	0	1	0.117421834
2	447832	1724786	13.5	0	0.007366827	1	0.173567884
2	447832	1724786	15	0	0.052575424	1	0.133909261
2	447832	1724786	16.5	0	0.09995648	1	0.079237085
2	447832	1724786	17.5	0	0.123442462	1	0.0448393
2	447832	1724786	18	1	0.124887279	0	0.02669694
2	447832	1724786	19	1	0.1008732	0	0
2	447832	1724786	20	1	0.052544411	0	0
2	447832	1724786	20.5	0	0.027050489	0	0
2	447832	1724786	22	0	0	0	0
2	447832	1724786	23.5	0	0	0	0
2	447832	1724786	25	0	0.077813615	0	0
3	447798	1724804	1.5	0	0.491478747	1	0.490725307
3	447798	1724804	3	0	0.227429939	1	0.419159089
3	447798	1724804	4.5	0	0.092962974	1	0.298265964
3	447798	1724804	6	0	0.025993251	1	0.118380426
3	447798	1724804	7	0	0	1	0.036315127
3	447798	1724804	7.5	1	0	0	0.007793485
3	447798	1724804	9	1	0	0	0
3	447798	1724804	10	1	0	0	0
3	447798	1724804	11.5	0	0	1	0.078069468
3	447798	1724804	13	0	0	1	0.157820373
3	447798	1724804	14.5	0	0.049832791	1	0.134186274
3	447798	1724804	16	0	0.098544055	1	0.081409954
3	447798	1724804	17.5	0	0.135920248	1	0.036288678
3	447798	1724804	18	1	0.13571694	0	0.020221128
3	447798	1724804	19	1	0.107577083	0	0
3	447798	1724804	19.5	0	0.082840317	0	0
3	447798	1724804	20	0	0.055314835	0	0

7. Silt classifier Network results:

B.H.#	E	N	DEPTH	ML	ML(PRED.)	MH	MH(PRED.)
1	447869	1724767	1.5	0	0.17111292	0	0.04302652
1	447869	1724767	3	0	0.10243419	0	0.0558312
1	447869	1724767	4.5	0	0.22856094	0	0.06363384
1	447869	1724767	6	0	0.52319084	0	0.06287129
1	447869	1724767	7	0	0.56734634	0	0.06785722
1	447869	1724767	7.5	0	0.49914353	0	0.0769731
1	447869	1724767	9	0	0.31059861	0	0.11624915
1	447869	1724767	10	0	0.31546481	0	0.14233548
1	447869	1724767	10.5	1	0.3262395	0	0.15524577
1	447869	1724767	12	1	0.3145979	0	0.17972633
1	447869	1724767	13	1	0.25440689	0	0.17205165
1	447869	1724767	13.5	0	0.21432925	0	0.16126597
1	447869	1724767	15	0	0.10093092	0	0.11950207

1	447869	1724767	16	0	0.04434488	0	0.09437564
1	447869	1724767	16.5	0	0.01980941	0	0.08304763
1	447869	1724767	18	0	0	0	0.05801578
1	447869	1724767	19.5	0	0	0	0.06555599
2	447832	1724786	1.5	0	0.15348315	0	0.04317482
2	447832	1724786	3	0	0.09652988	0	0.05596911
2	447832	1724786	4.5	0	0.22494312	0	0.06374947
2	447832	1724786	6	0	0.52614239	0	0.06274891
2	447832	1724786	7	0	0.57028067	0	0.06785221
2	447832	1724786	7.5	0	0.50046538	0	0.07708798
2	447832	1724786	9	0	0.31076729	0	0.11645818
2	447832	1724786	10	0	0.31606041	0	0.14255916
2	447832	1724786	11.5	0	0.32946747	0	0.17571047
2	447832	1724786	12	0	0.31507734	0	0.17986709
2	447832	1724786	13.5	0	0.21441675	0	0.16126932
2	447832	1724786	15	0	0.10134914	0	0.11964321
2	447832	1724786	16.5	0	0.02145194	0	0.08378876
2	447832	1724786	17.5	0	0	0	0.06495611
2	447832	1724786	18	0	0	0	0.05920672
2	447832	1724786	19	0	0	0	0.06049824
2	447832	1724786	20	0	0.01157341	0	0.07725324
2	447832	1724786	20.5	0	0.03882955	0	0.08734958
2	447832	1724786	22	0	0.10201573	0	0.10281937
2	447832	1724786	23.5	0	0.08549427	0	0.08338263
2	447832	1724786	25	0	0.00612638	0	0.03723364
3	447798	1724804	1.5	0	0.13883169	0	0.04330711
3	447798	1724804	3	0	0.09194455	0	0.05609158
3	447798	1724804	4.5	0	0.22180229	0	0.06385098
3	447798	1724804	6	0	0.52889836	0	0.06262717
3	447798	1724804	7	0	0.57301541	0	0.0678431
3	447798	1724804	7.5	0	0.50170575	0	0.07719013
3	447798	1724804	9	0	0.31092987	0	0.11663798
3	447798	1724804	10	0	0.31659763	0	0.14274952
3	447798	1724804	11.5	0	0.33002608	0	0.17587566
3	447798	1724804	13	0	0.25478911	0	0.17212608
3	447798	1724804	14.5	0	0.13529369	0	0.13358509
3	447798	1724804	16	0	0.04662796	0	0.09531952
3	447798	1724804	17.5	0	0	0	0.06588317
3	447798	1724804	18	0	0	0	0.0601875
3	447798	1724804	19	0	0	0	0.06168238
3	447798	1724804	19.5	0	0	0	0.06914678
3	447798	1724804	20	0	0.01594213	0	0.07950601

Appendix (C)

Actual and ANN predicted soil classification &parameters for Hassan &Alaabid co. in Alamaarat zone.

Appendix(C):
Hassan & Alaabid co. site :
1. Atterberg limits Network results:

B.H.#	E	N	DEPTH	ACTUAL	PREDICTED	ACTUAL	PREDICTED
				L.L	L.L	P.I.	P.I.
1	447869	1724767	1.5	58	37.46321712	35	13.3687938
1	447869	1724767	3	33	48.35836691	14	21.5039884
2	452348	1719407	1.5	33	53.68786554	13	30.8008502
2	452348	1719407	3	44	85.92400969	26	61.5477015
3	452334	1719340	1.5	44	53.58665562	26	30.6172085
3	452334	1719340	3	32	81.82134445	14	57.3021363
4	452359	1719282	1.5	56	52.74179239	36	29.6963745
4	452359	1719282	3	61	77.61241679	39	52.8268884

2. SPT Network results:

B.H.#	E	N	DEPTH	ACTUAL N-VALUE	PREDICTED N-NALUE
1	447869	1724767	1.5	50	51
1	447869	1724767	3	50	48.42425828
1	447869	1724767	4.5	24	43.22899099
1	447869	1724767	6	51	40.50133648
1	447869	1724767	7.5	51	41.79917581
1	447869	1724767	9	42	44.83600797
1	447869	1724767	10.5	51	46.22934817
1	447869	1724767	12	44	44.69758117
1	447869	1724767	13.5	51	39.4605489
1	447869	1724767	15	51	31.22972357
1	447869	1724767	16.5	51	28.66816516
1	447869	1724767	18	51	37.39668735
2	452348	1719407	1.5	33	50.89131979
2	452348	1719407	3	51	49.52274652
2	452348	1719407	4.5	51	45.06234931
2	452348	1719407	6	33	39.84883175
2	452348	1719407	7.5	51	38.11104002
2	452348	1719407	9	51	40.93034383
2	452348	1719407	10.5	51	44.88366166
2	452348	1719407	12	42	46.16927816
2	452348	1719407	13.5	38	44.6595838
2	452348	1719407	15	29	44.68922452
2	452348	1719407	16.5	51	47.67708506
2	452348	1719407	18	51	49.20446746
2	452348	1719407	19.5	51	48.11599698
3	452334	1719340	1.5	51	51
3	452334	1719340	3	51	49.0906287
3	452334	1719340	4.5	25	43.86049276
3	452334	1719340	6	43	38.46388835
3	452334	1719340	7.5	51	37.42710203
3	452334	1719340	9	32	41.04360942

3	452334	1719340	10.5	51	45.32562199
3	452334	1719340	12	38	46.64178826
3	452334	1719340	13.5	47	45.0420546
3	452334	1719340	15	51	44.77218495
3	452334	1719340	16.5	51	47.44530039
3	452334	1719340	18	51	48.74740383
3	452334	1719340	19.5	51	47.36919249
4	452359	1719282	1.5	51	51
4	452359	1719282	3	51	48.44716331
4	452359	1719282	4.5	25	42.58810306
4	452359	1719282	6	43	37.4779173
4	452359	1719282	7.5	22	37.43549884
4	452359	1719282	9	51	41.6732785
4	452359	1719282	12	51	46.80307992
4	452359	1719282	15	29	44.48346995
4	452359	1719282	16.5	51	47.14201511
4	452359	1719282	18	51	48.37759761

3. Global classifier Network results:

B.H.	E	N	DEPTH	SAND	SAND (predicted)	CLAY/ SILT	CLAY/ SILT (predicted)
1	447869	1724767	1	0	0.085657102	1	0.91850726
1	447869	1724767	2.5	0	0.080835589	1	0.922183005
1	447869	1724767	3	1	0.079645917	0	0.923015085
1	447869	1724767	4	1	0.079159711	0	0.922801552
1	447869	1724767	4.5	1	0.08072573	0	0.920883921
1	447869	1724767	6	1	0.102781051	0	0.897574183
1	447869	1724767	7.5	1	0.174010932	0	0.824085677
1	447869	1724767	9	1	0.268740169	0	0.726452446
1	447869	1724767	10.5	1	0.354906136	0	0.639820669
1	447869	1724767	12	1	0.537764326	0	0.461865371
1	447869	1724767	13.5	1	0.684630175	0	0.318584331
1	447869	1724767	15	1	0.596984448	0	0.4028504
1	447869	1724767	16.5	1	0.568585591	0	0.430077319
1	447869	1724767	18	1	0.610451373	0	0.389830361
1	447869	1724767	19.5	1	0.620177361	0	0.3814609
1	447869	1724767	20	1	0.607672381	0	0.394166823
2	452348	1719407	1.5	1	0.407684672	0	0.591330873
2	452348	1719407	3	1	0.475958927	0	0.525074348
2	452348	1719407	4	1	0.570136355	0	0.434036371
2	452348	1719407	4.5	1	0.605078014	0	0.400186669
2	452348	1719407	6	1	0.560198472	0	0.443095979
2	452348	1719407	7	1	0.472766055	0	0.526530787
2	452348	1719407	8.5	1	0.473677373	0	0.521962315
2	452348	1719407	9	0	0.513197228	1	0.481856807
2	452348	1719407	10	0	0.616255227	1	0.378524105
2	452348	1719407	10.5	1	0.666389961	0	0.328810328
2	452348	1719407	12	1	0.802410075	0	0.196631883
2	452348	1719407	13.5	1	0.880557876	0	0.123122217
2	452348	1719407	15	1	0.854649524	0	0.153110116
2	452348	1719407	16.5	1	0.787454226	0	0.22382736

2	452348	1719407	18	1	0.727841309	0	0.283877104
2	452348	1719407	19.5	1	0.711813396	0	0.297478959
2	452348	1719407	20	1	0.714891753	0	0.29343389
3	452334	1719340	1.5	1	0.403173048	0	0.595807703
3	452334	1719340	3	1	0.469431249	0	0.531484082
3	452334	1719340	3.5	1	0.515606522	0	0.486856109
3	452334	1719340	4	1	0.563664184	0	0.440395367
3	452334	1719340	5.5	1	0.597213628	0	0.40765379
3	452334	1719340	7	1	0.4721072	0	0.527242392
3	452334	1719340	8.5	1	0.471495656	0	0.524109647
3	452334	1719340	10	1	0.614128607	0	0.380562733
3	452334	1719340	11.5	1	0.755533032	0	0.241705215
3	452334	1719340	13	1	0.869887378	0	0.132320723
3	452334	1719340	14.5	1	0.870667901	0	0.135552226
3	452334	1719340	16	1	0.81174759	0	0.198492666
3	452334	1719340	17.5	1	0.741635836	0	0.270389094
3	452334	1719340	18	1	0.724944598	0	0.28684441
3	452334	1719340	19	1	0.708150392	0	0.302226544
3	452334	1719340	20	1	0.710528916	0	0.297917836
3	452334	1719340	21	1	0.72188226	0	0.284922868
3	452334	1719340	22	1	0.731574348	0	0.274285115
3	452334	1719340	23	1	0.733063719	0	0.272570177
3	452334	1719340	24	1	0.723805106	0	0.282152742
3	452334	1719340	25	1	0.703236287	0	0.30338943
4	452359	1719282	1	0	0.407401215	1	0.591725977
4	452359	1719282	2	0	0.421127271	1	0.578134553
4	452359	1719282	2.5	0	0.443573077	1	0.556347267
4	452359	1719282	3	1	0.479693381	0	0.521405756
4	452359	1719282	4	1	0.573801146	0	0.430434313
4	452359	1719282	4.5	1	0.60806756	0	0.397235419
4	452359	1719282	6	1	0.560844065	0	0.442417902
4	452359	1719282	7.5	1	0.451800977	0	0.545875028
4	452359	1719282	9	1	0.514671549	0	0.480418844
4	452359	1719282	10.5	1	0.66771542	0	0.327546635
4	452359	1719282	12	1	0.803223157	0	0.195886899
4	452359	1719282	13.5	1	0.880720671	0	0.123023199
4	452359	1719282	15	1	0.854543428	0	0.153280418
4	452359	1719282	16.5	1	0.787842252	0	0.223457289
4	452359	1719282	18	1	0.729385665	0	0.282283797
4	452359	1719282	19.5	1	0.714099905	0	0.295117013
4	452359	1719282	20	1	0.71720933	0	0.291044786

4. Sand classifier Network results:

B.H.#	E	N	DEPTH	SM	SM(PREDICTED)	SC	SC(PREDICTED)
1	447869	1724767	1	0	0	0	0.269468426
1	447869	1724767	2.5	0	0	0	0.324908608
1	447869	1724767	3	1	0	0	0.33242643
1	447869	1724767	4	1	0	0	0.326308907
1	447869	1724767	4.5	0	0	1	0.312776939
1	447869	1724767	6	0	0	1	0.243801696
1	447869	1724767	7.5	0	0	1	0.167751606

1	447869	1724767	9	0	0.136065199	1	0.105694396
1	447869	1724767	10.5	0	0.190720331	1	0.064552251
1	447869	1724767	12	0	0.214918551	1	0.048945855
1	447869	1724767	13.5	0	0.244413389	1	0.043865229
1	447869	1724767	15	0	0.24586547	1	0.046278324
1	447869	1724767	16.5	0	0.344727004	1	0.073782497
1	447869	1724767	18	0	0.589487376	1	0.111696137
1	447869	1724767	19.5	0	0.599181624	1	0.124660259
1	447869	1724767	20	0	0.527892977	1	0.126965395
2	447869	1719407	1.5	1	0.359732213	0	0.255081056
2	447869	1719407	3	1	0.66129205	0	0.15593668
2	447869	1719407	4	1	0.749056838	0	0.048301063
2	447869	1719407	4.5	0	0.757209562	1	0.005641161
2	447869	1719407	6	0	0.648538146	1	0
2	447869	1719407	7	0	0.475347309	1	0
2	447869	1719407	8.5	0	0.195097808	1	0
2	447869	1719407	9	0	0.13018304	0	0
2	447869	1719407	10	0	0.055989448	0	0.074086499
2	447869	1719407	10.5	0	0.043471094	1	0.13301087
2	447869	1719407	12	0	0.083106209	1	0.363610464
2	447869	1719407	13.5	0	0.110491546	1	0.618705872
2	447869	1719407	15	0	0.016128552	1	0.82132248
2	447869	1719407	16.5	0	0.023428808	1	0.927169157
2	447869	1719407	18	0	0.25831323	1	0.948597325
2	447869	1719407	19.5	0	0.494790195	1	0.837873945
2	447869	1719407	20	0	0.506374135	1	0.752518005
3	447869	1719340	1.5	1	0.40598296	0	0.227078831
3	447869	1719340	3	1	0.704479342	0	0.138084735
3	447869	1719340	3.5	1	0.753870584	0	0.088608575
3	447869	1719340	4	0	0.777667441	1	0.042194735
3	447869	1719340	5.5	0	0.708706057	1	0
3	447869	1719340	7	0	0.446426799	1	0
3	447869	1719340	8.5	0	0.165675521	1	0
3	447869	1719340	10	0	0.041941489	1	0.100478636
3	447869	1719340	11.5	0	0.053825147	1	0.315239467
3	447869	1719340	13	0	0.111560648	1	0.569329382
3	447869	1719340	14.5	0	0.035203203	1	0.787875109
3	447869	1719340	16	0	0	1	0.91185635
3	447869	1719340	17.5	0	0.154907122	1	0.954232423
3	447869	1719340	18	0	0.270800255	0	0.949909149
3	447869	1719340	19	0	0.482280372	0	0.896365252
3	447869	1719340	20	0	0.540065065	0	0.750863008
3	447869	1719340	21	0	0.470959289	1	0.521587774
3	447869	1719340	22	0	0.353650825	1	0.311615542
3	447869	1719340	23	0	0.246327704	1	0.180176269
3	447869	1719340	24	0	0.173980478	1	0.107232419
3	447869	1719340	25	0	0.134319546	1	0.066100147
4	447869	1719282	1	0	0.319736489	0	0.195897256
4	447869	1719282	2	0	0.568406181	0	0.190443431
4	447869	1719282	2.5	0	0.66753668	0	0.162478346
4	447869	1719282	3	1	0.738488636	0	0.12296678
4	447869	1719282	4	1	0.798235142	0	0.037921603

4	447869	1719282	4.5	0	0.79127548	1	0.003998103
4	447869	1719282	6	0	0.626863885	1	0
4	447869	1719282	7.5	0	0.311330185	1	0
4	447869	1719282	9	0	0.087507547	1	0.02844371
4	447869	1719282	10.5	0	0.025253762	1	0.190606747
4	447869	1719282	12	0	0.07433913	1	0.430306722
4	447869	1719282	13.5	0	0.092069351	1	0.676934247
4	447869	1719282	15	0	0	1	0.855575557
4	447869	1719282	16.5	0	0.013143393	1	0.939608348
4	447869	1719282	18	0	0.281405225	1	0.950596018
4	447869	1719282	19.5	0	0.561951445	1	0.835770199
4	447869	1719282	20	0	0.567688019	1	0.748908571

5. Sand grading classifier Network results:

B.H.#	E	N	DEPTH	SW	SW(PRED.)	SP	SP(PRED.)
1	4447869	1724767	1	0	0.7203012	0	0
1	4447869	1724767	2.5	0	0.891345	0	0
1	4447869	1724767	3	0	0.9176961	0	0
1	4447869	1724767	4	0	0.9140501	0	0
1	4447869	1724767	4.5	0	0.8837251	0	0
1	4447869	1724767	6	0	0.7002299	0	0
1	4447869	1724767	7.5	0	0.5368266	0	0
1	4447869	1724767	9	0	0.494068	1	0
1	4447869	1724767	10.5	0	0.5132144	0	0
1	4447869	1724767	12	0	0.5587561	1	0
1	4447869	1724767	13.5	0	0.6177683	1	0
1	4447869	1724767	15	0	0.660133	1	0
1	4447869	1724767	16.5	0	0.6534629	0	0.00450629
1	4447869	1724767	18	0	0.6035883	0	0
1	4447869	1724767	19.5	0	0.5626747	1	0
1	4447869	1724767	20	0	0.5605741	0	0
2	452348	1719407	1.5	0	0	0	0
2	452348	1719407	3	0	0	0	0
2	452348	1719407	4	0	0.0441951	0	0
2	452348	1719407	4.5	0	0.0832936	0	0
2	452348	1719407	6	0	0.2618794	1	0
2	452348	1719407	7	0	0.4412792	0	0
2	452348	1719407	8.5	0	0.738961	0	0
2	452348	1719407	9	0	0.8135811	0	0
2	452348	1719407	10	0	0.8997891	0	0
2	452348	1719407	10.5	0	0.9135356	0	0
2	452348	1719407	12	0	0.8562609	1	0
2	452348	1719407	13.5	0	0.7173344	0	0.03237548
2	452348	1719407	15	0	0.6828471	1	0
2	452348	1719407	16.5	0	0.8089162	0	0
2	452348	1719407	18	0	0.9446894	0	0
2	452348	1719407	19.5	0	0.9524965	0	0
2	452348	1719407	20	0	0.9167243	0	0
3	452334	1719340	1.5	0	0	0	0
3	452334	1719340	3	0	0.0008911	0	0
3	452334	1719340	3.5	0	0.0298794	0	0

3	452334	1719340	4	0	0.065961	0	0
3	452334	1719340	5.5	0	0.2260306	1	0
3	452334	1719340	7	0	0.4824705	1	0
3	452334	1719340	8.5	0	0.7655023	0	0
3	452334	1719340	10	0	0.9029203	0	0
3	452334	1719340	11.5	0	0.8760159	0	0
3	452334	1719340	13	0	0.7393808	1	0.04336112
3	452334	1719340	14.5	0	0.6657506	1	0.0268955
3	452334	1719340	16	0	0.7633415	1	0
3	452334	1719340	17.5	0	0.9249959	1	0
3	452334	1719340	18	0	0.9604511	1	0
3	452334	1719340	19	0	0.9871209	1	0
3	452334	1719340	20	0	0.9494202	1	0
3	452334	1719340	21	0	0.8230061	0	0
3	452334	1719340	22	0	0.6068768	0	0
3	452334	1719340	23	0	0.3747685	0	0
3	452334	1719340	24	0	0.180222	0	0
3	452334	1719340	25	0	0.0325795	0	0
4	452359	1719282	1	0	0	0	0
4	452359	1719282	2	0	0	0	0
4	452359	1719282	2.5	0	0	0	0
4	452359	1719282	3	0	0.0049853	0	0
4	452359	1719282	4	0	0.070187	0	0
4	452359	1719282	4.5	0	0.1134174	1	0
4	452359	1719282	6	0	0.297728	1	0
4	452359	1719282	7.5	0	0.5739275	1	0
4	452359	1719282	9	0	0.819151	0	0
4	452359	1719282	10.5	0	0.8933272	0	0
4	452359	1719282	12	0	0.8094057	1	0.02512653
4	452359	1719282	13.5	0	0.6659106	1	0.07903525
4	452359	1719282	15	0	0.6621755	1	0.0293324
4	452359	1719282	16.5	0	0.8209697	1	0
4	452359	1719282	18	0	0.9686731	1	0
4	452359	1719282	19.5	0	0.9875241	1	0
4	452359	1719282	20	0	0.9614121	1	0

6. Clay classifier Network results:

B.H.#	E	N	DEPTH	CL	CL(PRED.)	CH	CH(PRED)
1	4447869	1724767	1	0	0.887113419	1	0
1	4447869	1724767	2.5	0	0.659034524	1	0
1	4447869	1724767	3	0	0.498757443	0	0
1	4447869	1724767	4	0	0.156792733	0	0
1	4447869	1724767	4.5	0	0.049676664	0	0
1	4447869	1724767	6	0	0	0	0
1	4447869	1724767	7.5	0	0	0	0
1	4447869	1724767	9	0	0	0	0
1	4447869	1724767	10.5	0	0.12155929	0	0
1	4447869	1724767	12	0	0.270685888	0	0
1	4447869	1724767	13.5	0	0.26468519	0	0
1	4447869	1724767	15	0	0.176321227	0	0
1	4447869	1724767	16.5	0	0.096828801	0	0

1	4447869	1724767	18	0	0.06557259	0	0.135684921
1	4447869	1724767	19.5	0	0.086746638	0	0.212578324
1	4447869	1724767	20	0	0.098226306	0	0.250733866
2	452348	1719407	1.5	0	0.132877226	0	0.310906321
2	452348	1719407	3	0	0.021406748	0	0.215153878
2	452348	1719407	4	0	0	0	0.201524903
2	452348	1719407	4.5	0	0	0	0.171190664
2	452348	1719407	6	0	0.062019073	0	0.01278542
2	452348	1719407	7	0	0.116273774	0	0
2	452348	1719407	8.5	0	0.065023501	0	0.091466376
2	452348	1719407	9	0	0.035890128	0	0.178021561
2	452348	1719407	10	0	0.005202349	0	0.268242321
2	452348	1719407	10.5	0	0.002284087	0	0.241041815
2	452348	1719407	12	0	0.001291279	0	0.103515939
2	452348	1719407	13.5	0	0	0	0.101381367
2	452348	1719407	15	0	0	0	0.071460933
2	452348	1719407	16.5	0	0	0	0
2	452348	1719407	18	0	0	0	0
2	452348	1719407	19.5	0	0.000197031	0	0.031985129
2	452348	1719407	20	0	0.003725877	0	0.055255696
3	452334	1719340	1.5	0	0.167553607	0	0.227823442
3	452334	1719340	3	0	0.047863714	0	0.17269123
3	452334	1719340	3.5	0	0.022983142	0	0.182649452
3	452334	1719340	4	0	0.008735275	0	0.1843233
3	452334	1719340	5.5	0	0.036280259	0	0.059082054
3	452334	1719340	7	0	0.121158132	0	0
3	452334	1719340	8.5	0	0.066970021	0	0.04249408
3	452334	1719340	10	0	0	0	0.217896921
3	452334	1719340	11.5	0	0	0	0.111422924
3	452334	1719340	13	0	0	0	0.061987612
3	452334	1719340	14.5	0	0	0	0.077155784
3	452334	1719340	16	0	0	0	0
3	452334	1719340	17.5	0	0	0	0
3	452334	1719340	18	0	0.00197514	0	0
3	452334	1719340	19	0	0.006264039	0	0
3	452334	1719340	20	0	0.012293961	0	0.037427462
3	452334	1719340	21	0	0.024033832	0	0.070110273
3	452334	1719340	22	0	0.043955698	0	0.075430602
3	452334	1719340	23	0	0.069303766	0	0.054115031
3	452334	1719340	24	0	0.086343654	0	0.030800859
3	452334	1719340	25	0	0.074306179	0	0.035759649
4	452359	1719282	1	0	0.250839403	1	0.233596412
4	452359	1719282	2	0	0.152934282	1	0.147941369
4	452359	1719282	2.5	0	0.105636933	1	0.146806831
4	452359	1719282	3	0	0.064381093	0	0.163000539
4	452359	1719282	4	0	0.013524788	0	0.1964673
4	452359	1719282	4.5	0	0.006682445	0	0.180431005
4	452359	1719282	6	0	0.056851871	0	0.008080062
4	452359	1719282	7.5	0	0.101885883	0	0
4	452359	1719282	9	0	0.014146679	0	0.099840884
4	452359	1719282	10.5	0	0	0	0.205395591
4	452359	1719282	12	0	0	0	0.07202293

4	452359	1719282	13.5	0	0	0	0.05287395
4	452359	1719282	15	0	0	0	0.047505676
4	452359	1719282	16.5	0	0	0	0
4	452359	1719282	18	0	0.005132482	0	0
4	452359	1719282	19.5	0	0.014703507	0	0.00226506
4	452359	1719282	20	0	0.01961249	0	0.018706527

<u>7. Silt classifier Network results:</u>

B.H.#	E	N	DEPTH	ML	ML(PRED.)	MH	MH(PRED.)
1	4447869	1724767	1	0	0	0	0.06835439
1	4447869	1724767	2.5	0	0	0	0.04639673
1	4447869	1724767	3	0	0	0	0.03597089
1	4447869	1724767	4	0	0	0	0.0173412
1	4447869	1724767	4.5	0	0	0	0.01349331
1	4447869	1724767	6	0	0	0	0.02414298
1	4447869	1724767	7.5	0	0	0	0.03034714
1	4447869	1724767	9	0	0	0	0.02876539
1	4447869	1724767	10.5	0	0	0	0.03211417
1	4447869	1724767	12	0	0	0	0.01009584
1	4447869	1724767	13.5	0	0	0	0
1	4447869	1724767	15	0	0	0	0
1	4447869	1724767	16.5	0	0	0	0
1	4447869	1724767	18	0	0	0	0
1	4447869	1724767	19.5	0	0	0	0
1	4447869	1724767	20	0	0	0	0
2	452348	1719407	1.5	0	0	0	0.0013357
2	452348	1719407	3	0	0	0	0
2	452348	1719407	4	0	0	0	0
2	452348	1719407	4.5	0	0	0	0
2	452348	1719407	6	0	0.01228564	0	0
2	452348	1719407	7	0	0.02142959	0	0.00736794
2	452348	1719407	8.5	0	0.03442583	0	0.02690476
2	452348	1719407	9	1	0.03465123	0	0.03123653
2	452348	1719407	10	1	0.02907455	0	0.02699522
2	452348	1719407	10.5	0	0.02758467	0	0.01643548
2	452348	1719407	12	0	0	0	0
2	452348	1719407	13.5	0	0	0	0
2	452348	1719407	15	0	0.09349478	0	0
2	452348	1719407	16.5	0	0	0	0
2	452348	1719407	18	0	0	0	0.00449597
2	452348	1719407	19.5	0	0	0	0
2	452348	1719407	20	0	0	0	0
3	452334	1719340	1.5	0	0	0	0.00313836
3	452334	1719340	3	0	0	0	0
3	452334	1719340	3.5	0	0	0	0
3	452334	1719340	4	0	0	0	0
3	452334	1719340	5.5	0	0.01014377	0	0
3	452334	1719340	7	0	0.02146902	0	0.00779325
3	452334	1719340	8.5	0	0.0312072	0	0.02570224
3	452334	1719340	10	0	0.01926079	0	0.02362399

3	452334	1719340	11.5	0	0.00358763	0	0
3	452334	1719340	13	0	0	0	0
3	452334	1719340	14.5	0	0.05381259	0	0
3	452334	1719340	16	0	0.02084741	0	0
3	452334	1719340	17.5	0	0	0	0.00266406
3	452334	1719340	18	0	0	0	0.00553429
3	452334	1719340	19	0	0	0	0.00181734
3	452334	1719340	20	0	0	0	0
3	452334	1719340	21	0	0	0	0
3	452334	1719340	22	0	0.00387222	0	0
3	452334	1719340	23	0	0.04141524	0	0
3	452334	1719340	24	0	0.0662426	0	0
3	452334	1719340	25	0	0.08968474	0	0.00998135
4	452359	1719282	1	0	0	0	0.00386546
4	452359	1719282	2	0	0	0	0.00192317
4	452359	1719282	2.5	0	0	0	0.00067791
4	452359	1719282	3	0	0	0	0
4	452359	1719282	4	0	0	0	0
4	452359	1719282	4.5	0	0.00221523	0	0
4	452359	1719282	6	0	0.01269335	0	0
4	452359	1719282	7.5	0	0.02316066	0	0.01277327
4	452359	1719282	9	0	0.02407201	0	0.02671607
4	452359	1719282	10.5	0	0.00395441	0	0.00911308
4	452359	1719282	12	0	0	0	0
4	452359	1719282	13.5	0	0	0	0
4	452359	1719282	15	0	0.06659185	0	0
4	452359	1719282	16.5	0	0	0	0
4	452359	1719282	18	0	0	0	0.00526015
4	452359	1719282	19.5	0	0	0	0
4	452359	1719282	20	0	0	0	0