ADDIS ABABA UNIVERSITY

ADDIS ABABA INSTITUTE OF TECHNOLOGY

SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING

USE OF ARTIFICIAL NEURAL NETWORK TO PREDICT COMPACTION CHARACTERISTICS OF SOIL FROM SOIL INDEX PROPERTIES (CASE OF ADDIS ABABA)

A Research Submitted to School of Graduate Studies of Addis Ababa Institute of Technology in Partial Fulfillment of the Requirements for the Degree of Masters of Science in Civil Engineering (Geotechnical Engineering)

By

Hana Adugna

October 2021

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Advisor

Dr.-Ing. Tensay Gebremedhin

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The undersigned have examined the thesis entitled *Use of Artificial Neural Network to Predict Compaction Characteristics of Soil from Soil Index Properties (Case of Addis Ababa)* presented by Hana Adugna, a candidate for the degree of Master of Science, and hereby certify that it is worthy of acceptance.

Dr.-Ing. Tensay Gebremedhin		14/03/22
Advisor	Signature	Date
Dr.-Ing. Samuel Tadesse		15/03/22
Internal Examiner	Signature	Date
Dr.Tezera Firew		15/03/22
External Examiner	Signature	Date
	Mebruk Mohammed (Dr.-Ing.) Dean, School of Civil & Environmental Engineering	
Chairperson	Signature	Date

UNDERTAKING

I certify that research work titled ***"Use of Artificial Neural Network to Predict Compaction Characteristics of Soil from Soil Index Properties (Case of Addis Ababa)"*** is my own work. The work has not been presented elsewhere for assessment. Where material has been used from other sources it has been properly acknowledged/referred.

Signature of Student

Hana Adugna

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ABSTRACT

Soil compaction is the most commonly practiced mechanical method used to improve soil behavior and has a significant impact on earthwork structures. However, determining the compaction characteristics of soil in the laboratory requires considerable time and effort. For the purpose of attempting the problem of spending too much time and effort, ANN models that can predict the values of compaction parameters namely Maximum Dry Density (MDD) and Optimum Moisture Content (OMC) from soil index properties are developed using Artificial Neural Network (ANN). A total of 300 secondary data divided as coarse and fine grained soils were used to develop the ANN models. All data were soil laboratory test result records of different soil samples taken from Addis Ababa, Ethiopia. Percent of grain size distribution was used as input parameter for the coarse grained soils while plasticity index along with the percent fine were used as input variables for the fine grained soils. The two variables MDD and OMC were the desired outputs from the models. Supervised learning with a backpropagation algorithm was implemented to train the models using MATLAB R2020a. The models were validated using 15 primary data and the models' performance was evaluated using statistical values. The fifteen soil samples were collected from different locations in Addis Ababa. Three soil laboratory tests namely grain size analysis, Atterberg limits, and modified compaction tests were done on each sample. The outputs of the developed models were compared with the actual experimental soil laboratory test results and showed a good accuracy with a determination coefficient value of R=0.92 and R=0.81 for both maximum dry density and optimum moisture content respectively. Equations were derived for the ANN models. The models were also compared with existing regression equations developed using Addis Ababa soil type. From the research, it was concluded that the developed ANN models can be applied to predict the value of compaction parameters from soil index properties for both coarse and fine grained soils of Addis Ababa.

Keywords: ANN, Model, Compaction, Density, Optimum and Index.

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Abbreviations and Symbols

ANN	Artificial Neural Network
AI	Artificial Intelligence
AACRA	Addis Ababa City Road Authority
AAiT	Addis Ababa Institution of Technology
AASHTO	American Association of State Highway and Transportation Officials
ASTM	American Society for Testing and Materials
c	Cohesion
ECDSWC	Ethiopian Construction Design and Supervision Works Corporation
LL/W_L	Liquid Limit
MDD	Maximum Dry Density
MSE	Mean Squared Error
N.B.	Note Well
NN	Neural Network
NP	Non-Plastic
OMC	Optimum Moisture Content
PL/W_P	Plastic Limit
PI	Plasticity Index
R	Correlation Coefficient
R^2	Coefficient of Determination
RMSE	Root Mean Squared Error
SL/W_S	Shrinkage Limit
USCS	Unified Soil Classification System
φ	Angle of Internal Friction

CHAPTER 1 INTRODUCTION

1.1 Back Ground

Artificial Intelligence (AI) is one of the fastest emerging technology in the 21st century. The ability of AI to handle fuzzy and incomplete data makes it the first choice to be applied in different disciplines. The most successful artificial intelligence technology often used in geotechnical engineering applications is the artificial neural network (ANN). ANN is machine learning that mimics the way a human brain functions [1]. Their ability to learn, compute highly nonlinear problems and be applied on new and unlearned data using their generalization potential are the main reasons behind the growing rate of demand for this computational modeling tool [2].

In the field of geotechnical engineering, developing correlations between two or more soil properties is a common practice. Correlation is used to study the relationship between different soil properties and to identify the engineering properties of soil from simple index tests. There are numerous correlations between engineering and index properties of soil that have been established using statistical regression analysis. In recent times, ANN starts to override the statistical correlation methods by providing a more advanced way to build prediction models. According to former studies, soil compaction characteristics and index properties of soil are proved to have a good correlation [3]. So ANN can be applied to build prediction models that can forecast soil compaction characteristics from soil index properties.

Soil compaction is the most inexpensive and commonly practiced mechanical method used to improve soil behavior. Compaction increases the density of soil as a result of applied stress. Soil compaction has a significant impact on earthwork structures in improving slope stability, increasing the bearing capacity of subgrades, reducing swelling and shrinkage of soil caused due to volume changes and decreasing settlement issues [4]. Compaction also affects the two main engineering properties of soil, shear strength and permeability, which are essential in geotechnical engineering design. The shear strength parameter, angle of internal friction increase as the density of soil increases [5]. The permeability of soil, on the other hand, will decrease as the void ratio decreases due to the packing of soil grains together. In most cases, the shear strength and permeability requirements must be met simultaneously, implying that the soil's maximum dry density and optimum moisture content have to be obtained at the same time [3].

1.2 Problem of Statement

In construction projects particularly earthwork structures, understanding soil compaction properties is important. However, since determining the compaction parameters maximum dry density (MDD) and optimum moisture content (OMC) in the laboratory takes much time and effort, it would be useful if prediction models could be created to forecast the compaction parameters from simple index properties of soils. Employing an artificial neural network to create prediction models is the most practical solution to this problem.

1.3 Objective

1.3.1 General Objective

The general objective of this study is to develop ANN models that can predict the value of compaction characteristics, maximum dry density and optimum moisture content, from index properties of soil and evaluate models' performance.

1.3.2 Specific Objectives

The specific objective of the research is;

1. to develop an artificial neural network model that can predict the maximum dry density of soil from soil index properties.
2. to develop an artificial neural network model that can predict the optimum moisture content of soil from soil index properties.
3. to validate the prediction models using laboratory soil test results.
4. to evaluate the performance of the prediction models using some statistical parameters.

1.4 Scope of the Study

The study focused on building prediction models using ANN for Addis Ababa soil. Both coarse and fine-grained soils were considered in the study. The study used a database of 305 soil sample laboratory test results from different construction projects done in Addis Ababa. Each sample's grain size analysis, Atterberg limit and modified compaction test result were incorporated. Three laboratory tests namely grain size analysis, Atterberg limit and modified compaction test were done on soil samples used as primary data to validate the models.

1.5 Significance of the Study

The developed ANN prediction models can be used to predict the value of compaction parameters from simple soil index laboratory test results. Moreover, they are useful in minimizing the time and effort required to perform laboratory compaction tests, and can be seen as a further improvement on the existing correlation.

Using an artificial network to develop prediction models over conventional regression analysis is preferred because a complex nonlinear relationship between two or more variables can be detected using ANN models, as the amount of data points increases the accuracy of ANN improves and a variety of training algorithms can be used to create ANN models

1.6 Organization of the Research

The research paper is organized into five chapters. The first chapter begins by giving some background information related to the research work. The research problem, objective, scope and significance of the study are also discussed in this first chapter.

The second chapter reviews literature on ANN, soil compaction, and index properties of soil. Prediction models using ANN are discussed and compared with correlations of compaction properties and index properties using statistical regression analysis.

The third chapter provides a brief overview of the study methodologies and materials employed. It discusses the study area, data collection, modeling tool, data analysis, ANN development, model validation, evaluation and type of soil laboratory tests used in the study.

The fourth chapter presents the main findings of the research. The relationship between input and output parameters and the developed ANN models' property and performance is discussed. The primary soil laboratory test results, as well as the validation results of ANN models on primary data, are also presented.

The last chapter presents conclusions and recommendations based on the research results.

CHAPTER 2 LITERATURE REVIEW

2.1 Artificial Neural Network

An artificial neural network is an advanced computational tool categorized under machine learning. Machine learning, as the name suggests, is a modeling technique that uses a learning process to generate models by analyzing data. These data can be any kind of information that can be presented in the form of documents, audio, images or others [6]. In artificial neural networks, the learning process is an important behavior. It is a technique of offering the network experience in that particular area to help them acquire decision-making skills based on learned knowledge. Neural networks will construct a model that can solve a given problem by utilizing this learning ability [7]. Among other modeling tools, the artificial neural network has emerged as the finest alternative for solving a variety of real world problems across several disciplines [2].

2.1.1 Biological versus Artificial Neural Network

Artificial neural networks are imitators of the human brain, even though their approximation is highly oversimplified in terms of size and capacity. The human brain has a remarkable ability to learn and adapt to new situations. Artificial neural networks, unlike traditional computers that only accomplish a certain task based on the instructions loaded by the programmer, also can learn and adapt to new data. These are the major characteristics that an artificial neural network inherited from biological neural networks [8].

Similar to the human brain, artificial neural networks are composed of interconnected processing elements called neurons or nodes [6]. Neurons are the building block of the nervous system and are used to transmit information to other cells. The human brain contains approximately 100 billion neurons. Though each neuron is unique, they have a common structure holding a cell body also called soma, dendrites and axon. The cell body is the core part that contains the nucleus, dendrites are fibrous root like structures that receive an impulse from other neurons and an axon is a long tail like extension of a neuron that sends impulses away from the cell body to neighboring cells. The interconnection between two neurons is called synapses [9].

Following the same fashion, a multi-layer neural network has three layers known as the input, output and hidden layers. The Input layer receives initial data to the neural network whereas the output layer presents the results to the external environment. The intermediate layer between the two is called a hidden layer. The hidden layer is the layer where all computations are performed while training the network [10]. In an Artificial neural network, nodes are linked to each other using weight. The magnitude of weight determines the effect of input variables on the corresponding output values [6].

Table 2-1 Contrasts between Biological and Artificial Neural Network [11]

Biological neural network	Artificial neural network
Cell body	Node
Dendrite	Input
Axon	Output
Synapses	Weight

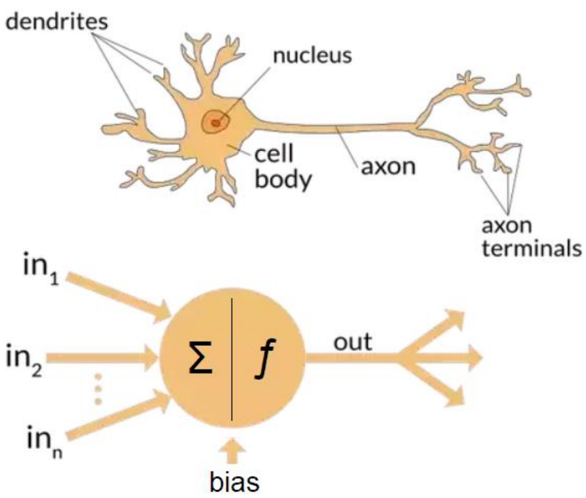


Figure 2-1 Biological vs Artificial Neural Network [12]

2.1.2 Types of Neural Network

There are different neural network types but based on their architecture, i.e. type of connection between neurons, neural networks can be broadly classified as;

i Feed-forward Neural Network and

ii Recurrent Neural Network

Feed-forward neural network architecture allows the signals to travel only in one direction from the input to the output layer. The output of any layer does not travel to other nodes in the same layer or former layers. Neural networks with such types of architecture are mostly straightforward networks. Feed-forward neural networks are suitable for modeling relationships between a set of input variables and one or more output variables [11].

Based on the number of layers it consists, a feed-forward neural network can be classified as a single-layer and a multi-layer neural network. A single-layer neural network only contains one input and one output layer. They are the simplest forms of neural networks and can compute only linearly separable problems. Multi-layer neural networks on the other hand consist of one or more hidden layers in addition to the input and output layers. These are the most commonly used neural network model in practice [10].

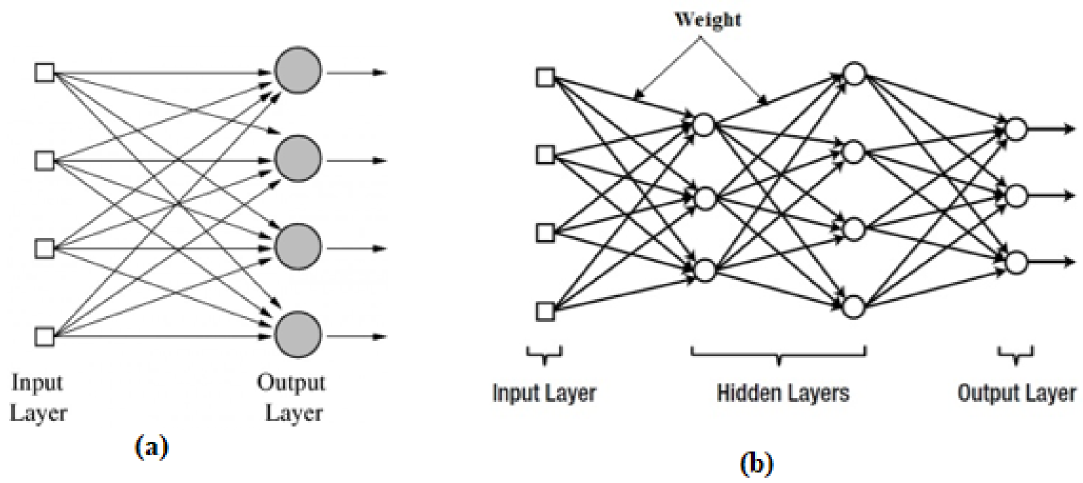


Figure 2-2 (a) A Single-Layer Neural Network (b) A Multi-Layer Neural Network [6]

Recurrent neural network or feedback architecture allows signals to travel in both forward and backward directions, forming a loop. They are computationally very powerful and suitable for many applications. In recurrent networks, there has to be at least one feedback connection. These neural networks can be applied on dynamic systems whereas the multilayer feedforward neural networks are limited to perform static problems so cannot process time-series information. Networks having a feedback architecture may get very complicated at some times [11].

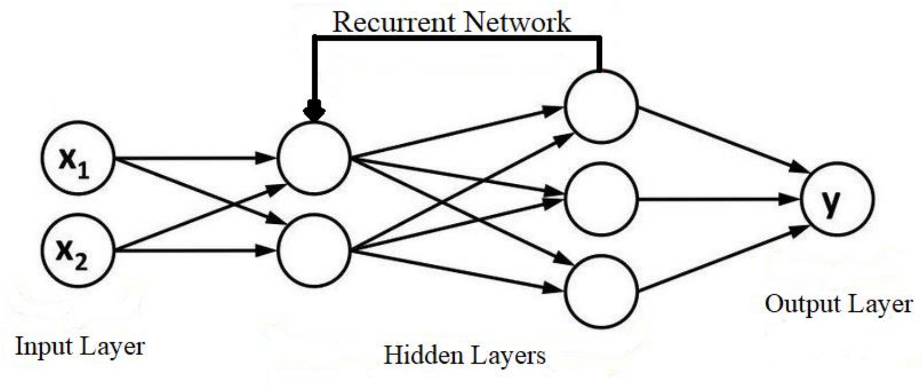


Figure 2-3 Recurrent Neural Network [13]

2.1.3 ANN Computation

Figure 2-4 shows a simplified overview of computation performed inside the feed-forward neural network.

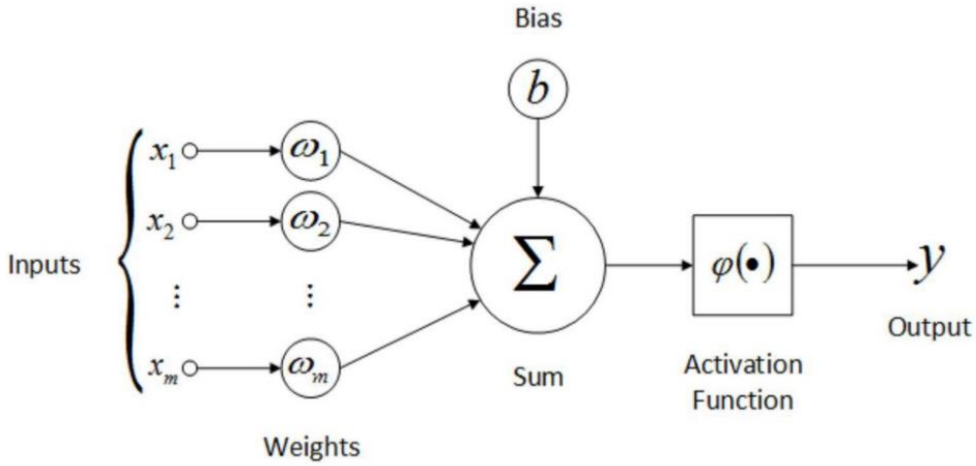


Figure 2-4 Feed-forward Neural Network [14]

The variables X_1, X_2, X_3…...X_m, W_1, W_2, W_3….. W_m, and Y represent the input, the weight and the output values respectively. As inputs travel from neurons of the input layer to the next layer neurons they will be multiplied by the weights. Then their summation will be computed when they reach the next neuron or node. Lastly, b which stands for bias will be added to the inputs' weighted sum [6].

$$\sum = \left((X1 * W1) + (X2 * W2) + \ldots\ldots + (Xm * Wm)\right) + b \qquad 2.1$$

The weighted sum then will be entered into the activation function to give the output value. There are different types of activation functions used in ANN and can be broadly classified as linear and nonlinear activation functions. Linear activation functions are represented by a straight line curve and the last output is just a linear function of the first input layer even though there are several hidden layers in between. Because the derivative or gradient of a linear function is a constant, gradient descent cannot be used to reduce error for a linear function. This type of activation function is not used in ANN especially in the hidden layers. Nonlinear activation functions are the most widely used type of activation function in ANN. Nonlinear activation functions increase the generalization ability of a neural network so as its ability to adapt to a variety of data. Nonlinear activation functions differ from one another by their curves and ranges [15]. Among these, the most commonly used type of activation functions in neural networks are the sigmoid and hyperbolic tangent function [16].

Table 2-2 Activation Functions

Activation function name	Function	Range
Binary Activation Function	$f(x) = 1\ if\ x > 0, f(x) = 0\ if\ x < 0$	(0,1)
Linear Activation Function	$f(x) = x$	(-∞,∞)
Sigmoid function	$f(x) = \frac{1}{(1 + e^{-x})}$	(0 ,1)
Hyperbolic tangent function (Tanh)	$f(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$	(-1, 1)
Sinusoidal function	$f(x) = \sin(x)$	[-1, 1]
Logistic symmetric function	$f(x) = \frac{(1 + e^{-x})}{2}$	(0, 1)
Gaussian function	$f(x) = e^{-x2}$	(0, 1]

2.1.4 Learning Methods of Neural Networks

An artificial neural network is trained through a learning process. There are three types of learning methods in artificial neural networks, these are;

- i Supervised Learning
- ii Unsupervised Learning and
- iii Reinforced Learning

Neural networks with a supervised learning method are provided with both the input and the actual output values. After training, the model output will be compared with the desired output to minimize the difference between the two. In the unsupervised learning method, only the input values are fed to the network without the actual output. The network will be allowed to discover its way to find out the output values based on the structural features in the input. The reinforced learning method is not commonly used like the above two methods. This learning method only indicates whether the output is correct or not. Like in unsupervised learning, the actual output will not be provided to the network [17].

2.1.5 Steps for Training an Artificial Neural Network

The following are major steps for training a multi-layer feed-forward neural network with supervised learning.

i Data Preprocessing

Data preprocessing is a data mining technique for converting raw data into more suitable forms for machine learning. Raw data sometimes can be noisy with some outliers, have missing information and be inconsistent because of their huge quantity and variety of sources. As data quality decreases, the results of machine learning will decrease as well. Therefore, to get an efficient neural network it is important to implement data preprocessing techniques. There are different data preprocessing techniques such as data cleaning, data reduction, data transformation and others. Data cleaning is used to remove noise from the data and improve its consistency while data reduction is used to eliminate redundancy in the data set [18]. Data transformation is a way to scale data into the same and smaller range and is important in giving all data with different measurement units an equal weight. Min-max and Z score normalization are the two commonly used data transformation methods [18].

ii Data Division

After data preprocessing, the data sets are divided into three categories called training, validation and test set with different proportions. There are several suggestions on how to divide input data into these three categories but not a single fixed way [10].

In supervised learning, a training set is a set of data with known inputs and actual outputs that are used to train the network. The model outputs are compared to the actual outputs once the inputs are fed into the network. The error will be determined as the difference between the model and the actual output. The weights are then adjusted until the error becomes as minimum as possible [19]. The gradient descent method is commonly used in supervised neural networks to adjust and modify weights based on the computed error value [6].

A validation set is a data set that is not used in the training process. They are reserved from the training set to know when to stop training the neural network and prevent overfitting. A model is said to be over-fitted when it has poor performance on the validation set while performing well on the training set. This is because the model gets very customized by the training set that it lacks generalization ability on other data sets. This is one of the problems faced in training neural network models [6].

A test set is a new data set not included in both the training and validation sets. Now the network is given only the input values without the actual output values. The network is required to provide the output values of the new test data. A test set is used to measure the network performance and its generalization ability on new data [10].

iii Define the Architecture of the Neural Network

Defining the architecture of an artificial neural network includes fixing the number of input, output and hidden neurons in each layer. The number of input neurons in an input layer is equal to the number of input variables used to train the neural network and the number of neurons in the output layer is equal to the desired number of output variables. The most controversial part is however to determine the number of hidden layers and number of hidden neurons in that layer.

Many researchers suggested different methods to determine the proper number of hidden layers required in neural networks. The number of hidden layer requirements depends on the number of training data used and the complexity of the problem under consideration. In most cases, two hidden layers are enough to solve any non-linear complex problems. Multiple hidden layers can be used in the application where accuracy is the first major criteria and if the time for training the network is not limited. The accuracy of the model can be increased by increasing the number of hidden layers, but the neural network's complexity and training time would increase. On top of that, an increasing number of hidden layers beyond the optimal value will cause overfitting. Considering the above conditions, researchers tried to develop different ways for estimating the number of hidden layers and among the suggested method a structured trial and error method is found to be the most commonly used approach [7].

iv Back Propagation

The backpropagation algorithm is the most widely used type of training algorithm in supervised learning. In a backpropagation after computing the error, i.e. the difference between the model's output and actual output, the error gets back propagated following the path from the output through the hidden layer to the primary input layers. The main aim of backpropagation is to modify the weights while this process. One cycle from the input layer to output and back from the output layer to the input layer through hidden layers is called an epoch. While training, the neural network undergoes several epochs to reach the minimum possible error within a specified range. The network is said to be trained when the error between the model output and the actual output is minimum or in a given range. The final adjusted weights of the trained network are used to calculate the output of new data sets [16].

2.2 Application of ANN

Recently, artificial neural networks have become applicable in various fields including geotechnical engineering [20]. The two most common applications of neural networks with supervised learning are classification and prediction. Classification focuses on determining which group the data belongs to, while prediction tries to estimate a specific value based on given inputs [6]. Some of the applications of ANN in geotechnical engineering include classification of soil, predicting soil compaction properties, soil permeability, slope stability, settlement of structures and others [20].

2.3 Soil Compaction

Compaction is a mechanical soil improvement method. The method allows soil particles to be arranged in a way that offers a minimal void ratio together with maximum density [21]. Natural soil found in construction sites may not always have sufficient strength to sustain structural loads. In such cases, compaction is used as one solution to enhance soil strength by increasing soil dry density. Sometimes when the prevailing soil condition is not suitable to use, replacing the natural soil with appropriate fill material is required. Here also compaction is needed to place the fill material in layers [22].

2.3.1 Factors Affecting Compaction

Compaction is mainly affected by the moisture content, soil type and amount of compaction energy used.

i Moisture Content

Water increases soil workability and is used as a lubricant permitting compaction. Soil with a higher amount of water is soft and easy to compress than soil with lower water content. Increasing moisture content will increase the dry density of soil till its maximum density is achieved. Maximum dry density is the density in which an extra increment of moisture starts to result in a reduction of soil dry density. If added, the water starts to pull soil particles away from each other. The moisture content that gives the maximum dry density is known as optimum moisture content. The effectiveness of compaction is highly affected by the moisture content especially in cohesive soils [23].

ii Soil Type

Coarse-grained soils when compacted can acquire a higher value of dry density compared to fine-grained soils. Adding some amount of fines to coarse-grained soils increases their dry density by filling the gap between the particles. But if the amount of fine is past the desired, it is going to lower the dry density value. Well-graded soils can attain better dry density than poorly graded soils. Compaction can be used on both cohesive and non-cohesive soils. Cohesion-less soils typically achieve higher dry density at lower moisture content in comparison to cohesive soils [24].

iii Amount of Compaction Energy

Compaction energy refers to the energy transferred to the soil at the time of compaction. Increasing the compaction energy on soils with constant moisture content will help to attain an increased amount of maximum dry density at a lower optimum moisture content [25].

2.3.2 Effect of Compaction on Engineering Properties of Soil

The fundamental goal of compaction is to increase shear strength, reduce soil permeability and minimize settlement under working load [21].

i Effect of Compaction on Shear Strength

Compaction increases the shear strength of soil. Compacted soil has higher cohesion and frictional angle compared to its natural state. Compacting soil at different moisture content will result in different soil strengths. Soil compacted at optimum moisture content will attain a higher strength than soil compacted at lower moisture. This is due to the fact when soil is compacted at moisture content lesser than its optimum value it becomes saturated by taking up moisture and loses strength [25].

ii Effect of Compaction on Permeability

The permeability of soil is highly affected by the water content used at the time of compaction. Previous studies proved that a coefficient of permeability of soil decreases as one goes from a water content less low than its optimum to a slightly higher moisture content value [20]. A cohesive soil compacted at its optimum moisture content will attain a lower amount of permeability relative to the one compacted at a lesser moisture content [26].

iii Effect of Compaction on Compressibility

Soil compacted at its optimum moisture content is not highly prone to settlement like the one compacted at lower moisture content than its optimum value [22].

iv Effect of Compaction on Swelling and Shrinkage

Clayey soils compacted dry of the optimum will show a swelling character when in contact with water and if they are compacted wet of the optimum value, they will tend to shrink on drying [22].

2.3.3 Compaction Laboratory Test

A laboratory compaction test must be done before field compaction to know what amount of compaction energy and moisture content is required at the field. The value of maximum dry density and optimum moisture content of soil from the laboratory test is used as a standard for the field compaction. Generally, there are two types of compaction laboratory tests called standard proctor test and modified proctor test.

The standard proctor test was developed by Ralph Roscoe Proctor in 1933. The modified proctor test also called the modified AASHTO test was standardized by the American Association of State Highway and Transportation Officials (AASHTO). The modified proctor test uses a greater energy effort than standard compaction. Using higher compaction energy will result in a higher dry density at a lower optimum moisture content [24].

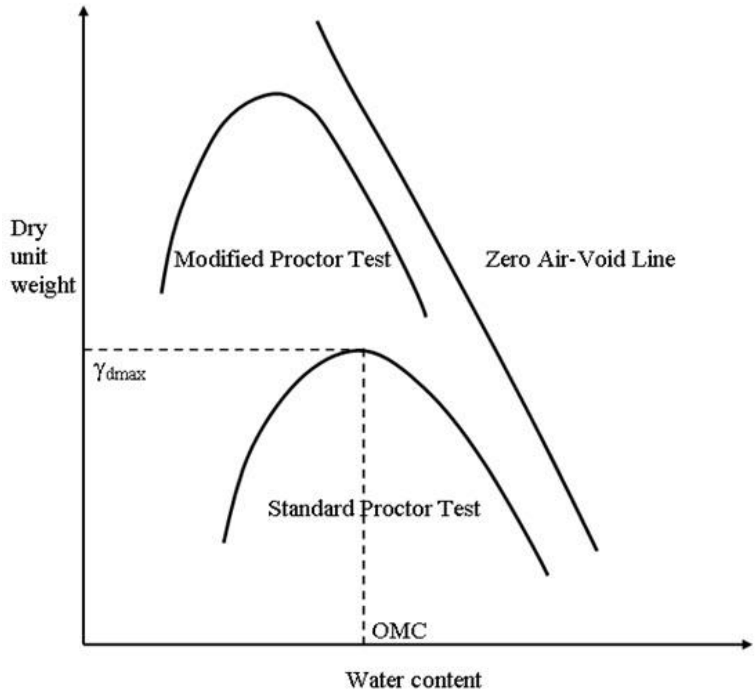


Figure 2-5 Standard and Modified Compaction Curves

During field compaction, the laboratory test results ought to be carried out into exercise as much as possible. The natural moisture content in the field has to be adjusted into the optimum value previously determined in the laboratory to achieve its maximum dry density. If the soil at the field has extra moisture content than the optimum, the soil has to get a chance to dry out and if it is less than the optimum value the amount has to be increased by whether sprinkling or adding water directly in the borrow pit. Mostly it is possible to attain the desired moisture content within the range of error between 2% to 3% [27].

Table 2-3 Compaction Laboratory Test Methods [28]

	Standard Proctor ASTM 698			**Modified Proctor ASTM 1557**		
	Method A	Method B	Method C	Method A	Method B	Method C
Material	≤20% Retained on No. 4 Sieve	> 20% Retained on No. 4 ≤20% Retained on 3/8" Sieve	>20% Retained on No. 3/8" <30% Retained on 3/4" Sieve	≤20% Retained on No. 4 Sieve	> 20% Retained on No. 4 ≤20% Retained on 3/8" Sieve	>20% Retained on No. 3/8" <30% Retained on 3/4" Sieve
For test sample, use Soil Passing	Sieve No.4	3/8" Sieve	3/4" sieve	Sieve No.4	3/8" Sieve	3/4" sieve
Mold	4"DIA	4"DIA	6"DIA	4"DIA	4"DIA	6"DIA
No. of Layers	3	3	3	5	5	5
No. of blows/layer	25	25	56	25	25	56

2.4 Soil Index Properties

Soil index properties are basic soil properties used for classification and can be determined from simple laboratory tests. The index properties are also used as indicators of some soil engineering properties. Most of the time soils with the same index properties will have similar engineering properties [24].

Soil index properties are classified into two major categories called soil grain properties and soil aggregate properties. Soil grain properties refer to individual particle properties that can be expressed in terms of size, shape and mineralogical characteristics while soil aggregate property refers to the soil mass property as a whole. Soil mass consists both the solid part and the void spaces partially or fully filled with water or air [23].

For fine-grained soils, the mineralogical property of the smallest particle is the main grain property and soil consistency is their main aggregate property. Grain size distribution and relative density, on the other hand, are the two most important grain and aggregate property of coarse-grained soils respectively [29].

2.4.1 Grain size distribution

Grain size distribution is the distribution of soil particles in a soil mass expressed in terms of their size. The distribution of soil particles and their size affects soil properties and strength. Particle size analysis is used to express the percentage proportion of different sizes of particles in the soil mass. Sieve analysis and hydrometer are the two ways to determine grain size distribution for coarse-grained soils and fine-grained soils respectively [23].

The grain size distribution of soil is presented graphically using grain size distribution curves. From the gradation curves, a soil mass can be described as well graded, uniformly graded (poorly graded) or gap graded. Well graded soil is a soil mass containing a wide range of particles size extending from gravel to fines. In a well graded soil almost all sizes of particles will have a certain amount in the total soil mass. Uniformly or poorly graded soil represents a soil mass that only contains particles of about same size. Gap graded soil describes a soil in which some of the particle sizes in between are absent. Such type of soil totally misses the amount of soil between two certain particle sizes. The gradation curves of well graded, uniformly graded and gap graded soils is presented on Figure 2-6.

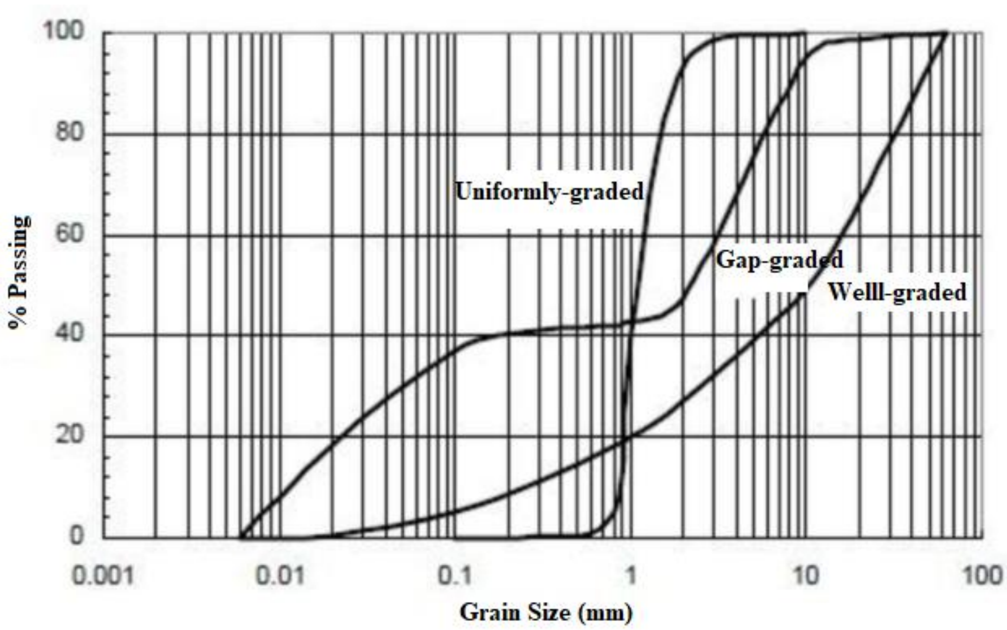


Figure 2-6 Gradation Curves

There are two parameters commonly used to define the gradation of soil as poorly graded or well graded mathematically. These are coefficient of uniformity and coefficient of curvature. Since a gap graded soil cannot be detected using coefficient of uniformity another parameter called coefficient of curvature is defined [24].

$$Cu = \frac{D60}{D10} \tag{2.2}$$

$$Cc = \frac{(D30)^2}{D60 \times D10} \tag{2.3}$$

D_{60} is the diameter of a soil particle below which 60 percent amount of particles are finer than this size and D_{10} is the particle size for which 10 percent amount of soil has particles which are finer than this size and also called effective size. D_{30} is the diameter of a soil particle below which 30 percent amount of particles are finer than this size.

Soil with a Cu value of 6 or more is a well graded gravel soil and if its Cu value is more than 4 it indicates a well graded sand. If the Cu value lowers below 2 it indicates a uniformly graded soil. Additionally, if a soil is said to be well graded it should have a coefficient of curvature Cc value in between 1 and 3 [24].

Soil classification systems are developed to classify soils in to different groups using some soil properties. The particle size of soil is one of the characteristics used as a criterion in soil classifications. Generally, soil particles can be grouped as gravel sand and fines based on their grain size. The USCS and AASHTO classification system ranged the size of gravel, sand and fine as indicated in Table 2.4.

Table 2-4 Particle Size Classification of Soil

Classification System	**Grain Size**	**Name**
USCS	4.75 mm to 75 mm	Gravel
	0.075 mm to 4.75 mm	Sand
	<0.075 mm	Fines (silt and clay)
AASHTO	2 mm to 75 mm	Gravel
	0.075 mm to 2 mm	Sand
	<0.075 mm	Fines (silt and clay)

2.4.2 Soil Consistency

The term consistency is used to describe the degree of firmness of soil. The property of fine-grained soil is highly affected by a change in moisture content and it is commonly expressed using this property. The consistency of fine-grained soil can be expressed as soft, firm, stiff or hard depending on its degree of firmness [19]. Atterberg limit is used to express and represent the soil consistency of fine-grained soils. Fine-grained soils can exhibit four different physical states called liquid, plastic, semi-solid and solid depending on their water content as explained by Swedish agriculture engineer Albert Atterberg [24]. He defined the boundaries between these states as a liquid limit, plastic limit and shrinkage limit. These are also called Atterberg limits or consistency limits. He proposed a series of tests to determine these limits [23].

i Liquid Limit

A liquid state indicates a physical state where fine-grained soil flows freely like water because of extremely high moisture content. In a liquid state, the soil attains zero shear strength and cannot resist even a very slight deformation. When the water content decreases gradually, it becomes a little stiffer and stops flowing like a liquid. As the soil gets stiffer, it starts to act plastically and gains some strength [21]. The water content in the transition between these two states, liquid and plastic state, is called liquid limit [23]. The liquid limit is designated as (LL or W_L).

ii Plastic Limit

In a plastic state, fine-grained soils have a lesser water content than the liquid limit and they can deform plastically if molded. If the water content is reduced the soil will stop deforming plastically and starts to crumble when rolled into thread. Further reduction of water content will result in a state change from plastic to semi-solid. The water content at the boundary of the plastic state and semi-solid state is called plastic limit and denoted by (PL or w_p) [24].

iii Shrinkage Limit

The state with water content below the plastic limit is called a semi-solid state. In this state, the soil crumbles when molded and any decrease in water content will result in volume change. But if the water content is further reduced below this amount it will create a condition where no more reduction of water content will cause any volume change. This is referred to as a solid state. The water content where the soil changes from semi-solid to solid state is called shrinkage limit. At the shrinkage limit, the soil has a constant volume, no further shrinkage will occur. The shrinkage limit is designated by (SL or W_S) [21].

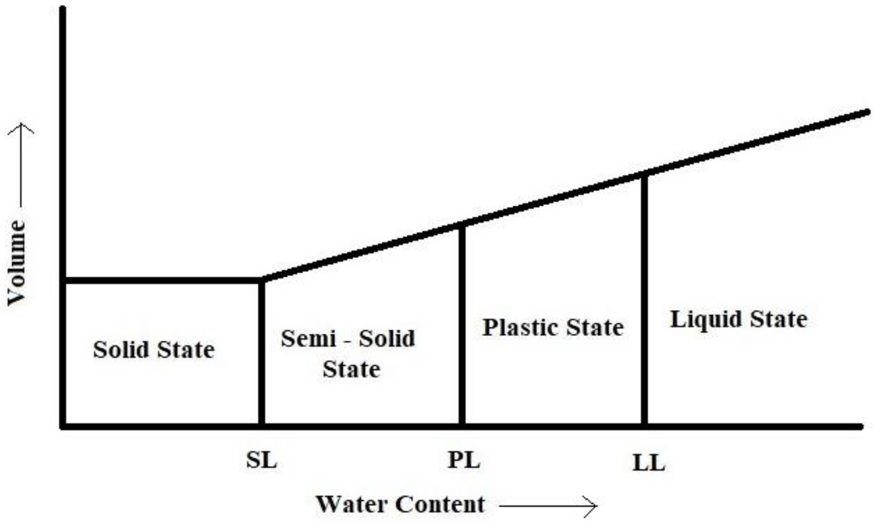


Figure 2-7 Atterberg Limits

iv Plasticity Index

The plasticity index indicates the water content range across which the soil stays plastic. Mathematically it is expressed as the difference between the liquid limit and plastic limit [23]. It is an important index property of fine-grained soil. The plasticity index is denoted by (PI or I_P). If either the plastic limit or the liquid limit cannot be identified the soil is called non-plastic (NP). If the plastic limit value is greater than that of the liquid limit, the plasticity index is considered zero not negative [29]. The PI value tells us the plasticity of the soil [21].

Table 2-5 Plasticity Index of Soil [10]

Plasticity Index	Plasticity
0	Non Plastic
1-5	Slightly Plastic
5-10	Low Plasticity
10-20	Medium Plasticity
20-40	High Plasticity
>40	Very High Plasticity

The plasticity characteristics of soil are used to classify fine grained soils in to different classes. The USCS soil classification system use plasticity chart as indicated on Figure 2-8 to classify fine grained soils. The A line on the plasticity chart is used as a border line to classify fine grained soils as a clay or silt soil. Fine grained soils plotted above the A line are clay soils and below this line are silt soils. These soil types further categorized as highly plastic and low plastic soils based on their liquid limit values. The liquid limit value of 50 is used as a limit to separate the highly plastic and low plastic soils. Soils which have a liquid limit of more than 50 are high plastic soils whereas those below 50 are low plastic soil. By combining the two criteria's that is the location relative to the A line and their value of liquid limit generally fine grained soils are classified as CH (high plasticity inorganic clay), OH (high plasticity organic clay), CL (Low plasticity inorganic clay), OL (low plasticity organic clay), MH (high plasticity inorganic silt), OH (high plasticity organic silt), ML (Low plasticity inorganic silt) and OL (low plasticity organic silt) [24].

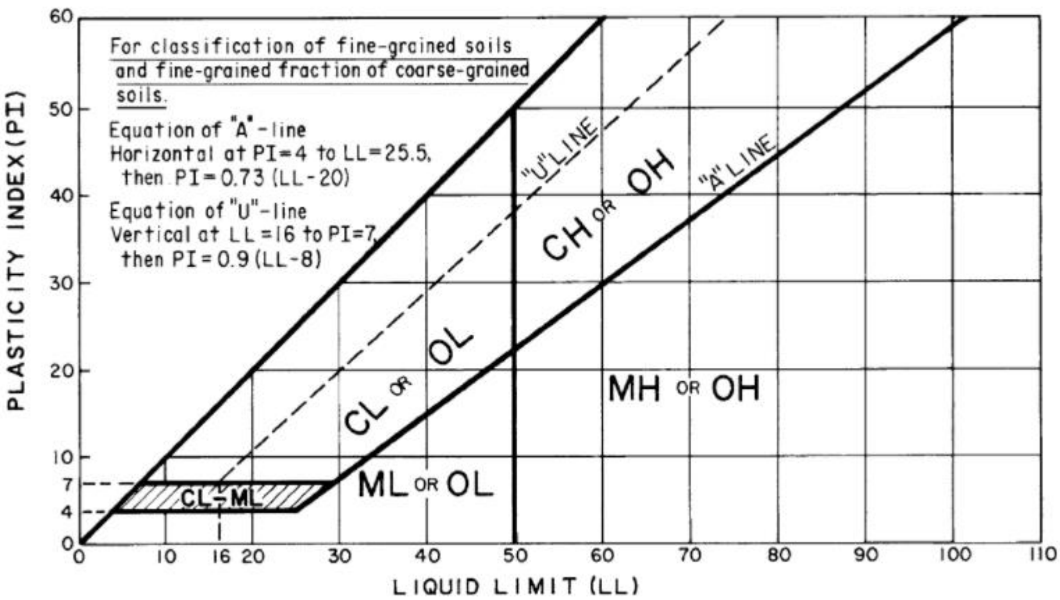


Figure 2-8 Plasticity Chart

2.5 Regression Analysis

Regression analysis can be defined as a way of fitting the best line through a series of observations. The best line fitted refers to a line that has a minimum squared difference between the observations and the line itself. Regression analysis is generally used to analyze the relationship between dependent and independent variables. The dependent variables are the outcomes that are influenced by the independent variables' values, whereas the independent variables are those variables used as a means to find out the outcomes [30]. The functional relation between the dependent and independent variables can be expressed mathematically as follows;

$$Y = f(X) \tag{2.4}$$

Where, Y denotes the dependent variable and X denotes the independent variable

But statistical relations are not perfect like a function i.e. the observations do not fall exactly on the line rather, it is a search for the best fit line relative to the others [31].

Regression analysis can be used to know whether the independent variable has an effect on the value of a dependent variable or not and to determine which independent variable has higher strength in affecting the dependent variable further more regression analysis can be used to make predictions [30].

Based on the type of relationship between the dependent and independent variables, regression analysis can be broadly classified as linear and nonlinear regression analysis. As their names indicate, linear regression assumes a linear relationship between the variables whereas nonlinear regressions are for variables related nonlinearly. When the linear regression model fails to describe the relationship between the dependent and independent variables it is more appropriate to use nonlinear regression models as an alternative. Depending on the number of independent variables used, regression models are also classified as simple and multiple regressions. If the regression model contains only one independent variable it is called a simple regression model and if it has more than one independent variable then it is called a multiple regression model [31].

2.6 Correlations using Regression Analysis

A study was conducted on nine different types of fine-grained soils found in Telengana and Andhra Pradesh, India. A regression analysis was used to show the relationship between the plastic limit and the optimum moisture content. In the study, plastic limit showed a good correlation with optimum moisture content indicating that plastic limit can be used for the prediction of compaction characteristics for fine-grained soils. The study resulted in a simple equation with a regression value of R^2=0.8404 proving the interdependence between the two variables [32].

A correlation that used to determine compaction characteristics of fine-grained soil from Atterberg limits was established using multiple linear regression analysis. A total of six soil types were used for the research purpose from Mysore city. In the research, it was concluded that compaction parameters of fine-grained soil can be estimated using liquid limit and plastic limit [33].

A functional correlation between compaction characteristics, undrained shear strength and Atterberg limits were developed using five soil samples. From the results, it was concluded that the optimum moisture content of the soil is highly affected by the modified plasticity index. Modified plasticity index (MPI) is the plasticity index when multiplied by the percentage of particles less than 425 µm [34].

A research was conducted on Addis Ababa's fine-grained soils to develop a correlation between compaction characteristics and Atterberg limits using 20 primary data and 36 secondary data. From the research, two correlations were developed with regression values of R^2=0.807 and R^2=0.835 for optimum moisture content and maximum dry density respectively. From the study, it was concluded that maximum dry density has a good correlation with plastic limit whereas optimum moisture content has a good correlation with liquid limit, plastic limit and plasticity index together [35].

2.7 Prediction Models using Artificial Neural Network (ANN)

ANN has been applied in several geotechnical engineering applications. Previous researches that are done on building a prediction model to predict the compaction characteristics of soil from index soil properties are summarized below.

A research was conducted to predict optimum moisture content and maximum dry density from index properties using simple neural networks in the United States of America. A total of 85 soil test results from 28 projects done in the continent of the United States at various locations were used for the prediction model. Three inputs including plastic limit, liquid limit and specific gravity were used. The prediction model was compared with regression equations and the prediction model using a neural network showed higher accuracy than the regression models. A higher coefficient of determination $R^2 = 0.884$ and $R^2 = 0.789$ for the maximum dry density and $R^2 = 0.884$ and $R^2 = 0.773$ for the optimum moisture content was obtained for each network [26].

A research was conducted to predict the compaction characteristics from index properties using ANN in Kerala India. The soil type used in the research was c-φ soil only. The neural network consisted of seven inputs that influence the compaction characteristics of soil. The proposed prediction model was compared with regression methods and showed a better performance with a correlation coefficient R = 0.91 and 0.92 for the maximum dry density and optimum moisture respectively [36].

An ANN-based prediction model was proposed to determine compaction, shear strength and permeability parameters from index properties using a database containing 320 soil test results from geotechnical laboratories in Brazil. A sensitivity analysis was performed to evaluate the effect of the input parameters on the compaction characteristics. Atterberg limits and fine contents of soil were found to be the most significant parameters that highly affect the compaction characteristics of the soil [3].

A neural network prediction model was developed to estimate compaction characteristics of both coarse and fine-grained soils from index properties using 200 data. In the research, it was shown that the method used for data division highly affects the ANN model. The performance of the model was checked by calculating the correlation coefficient and mean squared error. The neural networks showed a good performance with a correlation coefficient value of R = 0.951and mean squared error of MSE = 0.144 [37].

A study was conducted to check the feasibility of ANN prediction model using a database of 177 laboratory measurements. ANN model which was used to estimate the compaction parameters were developed using eight input parameters. From the research, it was concluded that ANN prediction models have higher accuracy based on the data quality and can be used in preliminary design [38].

Generally, from the previously done researches, it was recommended to increase the number of data used for modeling and to use quality data to get better performance and accuracy in the ANN prediction model.

2.8 Comparison between Regression Analysis and ANN Models

A review of a comparative study on neural networks and statistical methods used for prediction and classification in different fields of study was done formerly. A total of 73 papers that used multilayered feed-forward neural networks were compared with one of the statistical methods such as regression analysis and logistic regression. It was assessed to see if one of the methods can outperform the other in a particular way consistently. It was tried to consider the size of the sample, the number of variables used in the study, the validation method and other factors while comparing to be impartial and have the accurate conclusion about which method has the better performance [39].

The comparative study indicated that neural networks have a better potential to be used in prediction and classification problems. The main advantage of neural networks as indicated by the researchers is their potential to approximate any nonlinear function automatically. This property of neural network has high significance especially when the relationship between the variables is unknown or is complex making it difficult to solve statistically. However, finding the number of hidden layers in the neural network and the number of nodes required in this layer is not an easy task. Generally, finding the appropriate structure of the neural network is time consuming since it is done with repeated iterations. The other critic raised on neural networks is its difficulty to interpret the weights in the model building. This problem is not seen in statistical techniques since it allows the interpretation of the coefficient of variables [39].

Another research was conducted in Nigeria using both neural network and statistical techniques. The results obtained from the two methods were summarized and their ability was assessed using mean squared error (MSE) and root mean squared error (RMSE). From the results, it was clearly shown that neural networks can predict in a better way if trained with a sufficient amount of data and properly chosen inputs. Statistical methods also were established well, however, their ability to forecast was minimized when the data become larger and complex [40].

CHAPTER 3 MATERIALS AND METHODS

3.1 Study Area

The research is conducted using soil laboratory test results of different soil types found in Addis Ababa. Addis Ababa, the capital city of Ethiopia, is located at 9° 1’48’’N, 38° 44’24’’E. The average altitude of the city is 2400 meters above sea level ranging from its lowest point that is 2,326 meters to its highest point which is about 3,200 meters above sea level in the Entoto mountains to the north. Addis Ababa has a subtropical highland temperature that lies between 23°c and 11°c throughout the year [41].

According to the 2007 E.C census, the national central statistical agency puts the population of Addis Ababa to be 3,273,000. This makes Addis Ababa the largest city in the country in terms of population. The current population of the city is estimated to be around 5 million while the annual population growth rate is estimated to be 2.1 %. Generally, Addis Ababa takes 3.6% of the national population and 18% of the urban population in Ethiopia [41].

Figure 3-1 Study Area

3.2 Data Collection and Sample Size

A total of 315 soil sample laboratory test results were used in this research. The number of data points was determined by the artificial neural network's training requirements. Using a larger number of data to develop an artificial neural network is recommended to generate better generalization potential and minimize error. The 300 secondary data points were used to train the ANN models while the 15 primary data were used to validate the neural networks. The secondary data were collected from Addis Ababa Construction and Road Authority (AACRA) and Ethiopian Construction Design and Supervision Works Corporation (ECDSWC). The range of the values of the secondary data is described in Table 3-1.

Table 3-1 Range of Secondary Data

	%Gravel	%Sand	%Fine	LL	PL	PI	MDD (g/cm3)	OMC (%)
Min	0.00	1.00	1.66	26.20	15.20	4.00	1.22	7.00
Max	93.79	67.00	99.00	97.00	52.00	54.00	2.54	36.00
Mean	16.22	16.95	66.83	59.61	33.00	26.61	1.63	21.21
Median	2.89	14.00	74.00	60.00	33.00	26.00	1.59	21.00
Mode	0	7	89	71	34	23	1.5	20
Variance	594.30	137.72	682.36	207.19	41.20	94.85	0.03	31.11
Standard deviation	24.38	11.74	26.12	14.39	6.42	9.74	0.19	5.58

Primary data for validation of the developed models was attained by directly conducting soil laboratory tests on the collected samples. The samples were taken at random from various locations of Addis Ababa to ensure that the established neural networks could be used on any type of soil found in the city. The specific location of samples taken for the primary data and their depth is summarized on Table 3-2.

Table 3-2 Location and Depth of Soil Samples for Primary Data

S.N0	Sample Name	Location	Latitude	Longitude	Sample Depth (m)
1	Sample 1	Lideta	9.013333	38.738333	2.5
2	Sample 2	41 Eyesus	9.064444	38.770833	2.0
3	Sample 3	Shiromeda	9.077222	38.759444	3.0
4	Sample 4	Kore Adebabay	8.975556	38.726111	2.0
5	Sample 5	Bethel	9.0131447	38.6979849	3.5
6	Sample 6	Goro	9.0000547	38.8400869	3.0
7	Sample 7	Shegole	9.0636093	38.7157384	2.5
8	Sample 8	Ferensay Abo	9.0528866	38.7842731	3.0
9	Sample 9	Tikur Anbesa	9.023333	38.752222	2.5
10	Sample 10	Ayer Tena	8.998056	38.691944	3.0
11	Sample 11	Akaki	8.939089	38.7591322	2.0
12	Sample 12	Leghar	9.008889	38.755278	4.0
13	Sample 13	Kolfe	9.036944	38.709167	3.0
14	Sample 14	Adisu Gebeya	9.063333	38.737778	2.0
15	Sample 15	Megenagna	9.020731	38.8040915	4.0

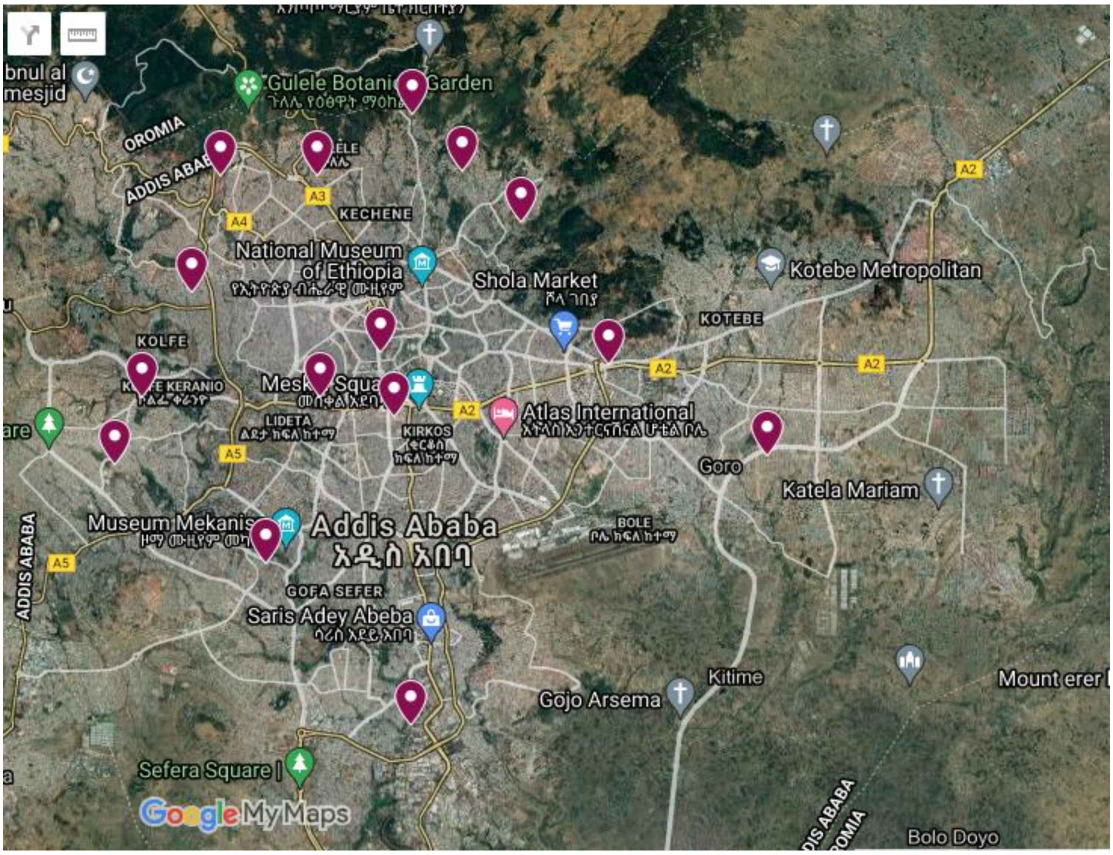


Figure 3-2 Location of Soil Samples for Primary Data

3.3 Input and Output Variables Description

The compaction characteristics of soil, maximum dry density and optimum moisture content, are the desired output variables from the developed artificial neural network models. Choosing the right input variables that are well correlated with the desired outputs has an impact on a neural network when it comes to finding a good prediction accuracy. The input variables must have a clear relationship with the output variables to influence the output's result. In the current research the whole data set was divided in to two categories as coarse and fine grained soils. Input parameters that have an effect on each soil types were. The percent of grain size distribution that was expressed in terms of percent gravel, percent sand and percent fine were used as input parameter for the AN model of coarse grained soils whereas the Plasticity index and fine content were used as input parameters for the ANN model of fine grained soils. To ensure the correlation between the suggested input parameters with the desired output variables, a scatter plot was employed. A scatter plot is used to visually display the relationship between dependent and independent variables. The input variables were used as independent variables and the output variables as dependent variables. The correlation between the input and output variables was used to decide on which variables to use as input parameters that have a significant effect on the output results.

On former works related to ANN prediction of compaction characteristics, index properties were widely used as input parameters. Not only ANN prediction but also regression analysis often used index properties to show their correlation with compaction characteristic parameters. In those researches it was proved that soil index properties have a good correlation with compaction characteristics of soil and can be used as input parameters. The most commonly used index properties to predict compaction characteristics of soil were grain size distribution and Atterberg limits. Input parameters used on former studies are summarized on Table 3-3.

Table 3-3 Input Parameters Used On Former Studies

S.NO	INPUT Parameters	Title	Researcher	Remark
1	Plastic limit, Liquid Limit, Plasticity Index, Percentage fines, Percentage sands, Percentage gravels, specific gravity	Prediction of Compaction Parameters of Soils using Artificial Neural Network	Jeeja Jayan , Dr.N.Sankar	
2	Plastic limit, Liquid Limit, , Percentage fines, Percentage sands, Percentage gravels, specific gravity	ANN prediction of some geotechnical properties of soil from their index parameters	Sandro Lemos Machado et.al (2014)	
3	Plastic limit, Liquid Limit, specific gravity	On the Identification of Compaction Characteristics by Neuronets	Yacoub M. Najjar et.al 1995	Used database from Literature which only have PL,LL and Gs
4	Plastic limit, Liquid Limit, Percentage fines, Percentage sands, Transition fine content ratio	Estimating compaction parameters of fine- and coarse-grained soils by means of artificial neural networks	Fatih Isik Gurkan Ozden (2012)	
5	Plastic limit, Liquid Limit, , Percentage fines, Percentage sands, Percentage gravels, soil type	Prediction of Soil's Compaction Parameter Using Artificial Neural Network	Raghdan Zuhair Al-saffar (2013)	
6	Plastic limit, Liquid Limit, Plasticity Index, Percentage fines, Percentage sands, Percentage gravels, specific gravity	Estimating maximum dry density and optimum Moisture content of compacted soils	K.S. Ng et al.(2015)	Using Multi Linear Regression Analysis (MLR)

3.4 Modeling Tool

The neural networks were developed using MATLAB R20202a. MATLAB is a programming language that can be used to analyze data, construct algorithms and generate models or applications. In this research, MATLAB was used for data analysis and model construction using neural networks. There are some toolboxes in MATLAB that are used to solve some specific problems. Toolboxes are collections of MATLAB functions (M-files) that extend the MATLAB environment to address a certain type of problem. Neural networks are one of those with an available toolbox in MATLAB.

In this research, the neural networks were modeled by directly coding a script into MATLAB and also using one of the neural network toolbox ‘nftool’. ‘nftool’ is a neural network fitting app used to solve a data fitting problem. It can solve complex data fitting problems arbitrarily well, given consistent data and enough neurons in its hidden layer. Script authoring allows more freedom to model neural networks the way needed than the neural network toolboxes. It is possible to change the architecture, training algorithm, learning methods and other aspects of the model as required while using script authoring for better performance.

3.5 Data Preprocessing

In machine learning, data quality is a major concern. To assure data quality, data preprocessing is required as a primary task before using raw data directly in any machine learning. There are various data preprocessing techniques. In this research data integration, data cleaning, data reduction and data transformation were the data analysis methods used before developing the neural networks.

3.5.1 Data Integration, Cleaning and Reduction

Data integration, data cleaning and data reduction are important first steps in achieving high data quality. Data integration is a way of merging data collected from different sources in the same format. This was the first challenge faced when dealing with the collected large-sized data structured differently. Even if it took some effort, it helped to avoid inconsistencies. In cases where collected data were incomplete, data cleaning was implemented. Data cleaning could be used either to eliminate or fill in missing data. The incomplete data, in this case, were all eliminated since filling a missing data may decrease the quality of data and lead to a wrong value if not done properly. Data reduction was used to remove redundancy from the data set. This required careful observation of each line of data. In this research, all data integration, data cleaning and data reduction were done manually.

3.5.2 Data Transformation

Data transformation is used to scale data into the same and smaller range, as well as to give all data with different measurement units an equal weight. Altering a measurement unit from one to another affects the result from the model if the data is not transformed. Normalization is one of the data transformation methods and is particularly useful in neural networks. Once the data is normalized, the type of unit used will no longer affect the result. To eliminate the models' dependence on the unit, all data were standardized. Min-max normalization was chosen among the various data transformation methods because of its ability to ensure all features are scaled within the same range and receive equal attention during neural network training. Normalizing or scaling data within a given uniform range helped to prevent larger values from overriding smaller ones and ensured that all data values were independent of their unit. Data normalization was done using MATLAB. In map min-max normalization for every feature, the minimum value gets transformed into a -1, the maximum into a 1 and every other value gets transformed into a decimal between -1 and 1.

$$X = \frac{value - min}{max - min}\ (newmax - newmax) + newmin\ \ [-1,1], \qquad 3.1$$

$$\text{where, X is the normalized value}$$

3.6 Neural Network Development

While developing the ANN models, the following steps were followed.

3.6.1 Data Division

The secondary data in each category that is coarse and fine grained soil were divided into three sets called training, validation and test sets. One of the approaches proposed for determining the proportion of data, the trial and error method, was used in this work. The best proportion was selected based on the resulting neural network performance. The proportion that gives a minimum value of mean squared error (MSE) and higher correlation coefficient R was taken as the best proportion to train the neural networks. For the neural networks, the proportion 70%, 15%, 15% was found to be the best proportion for training, validation and test sets respectively.

3.6.2 Define Neural Network Architecture

A two-layered feed-forward network architecture was used for the prediction models. A two-layered neural network is a neural network with one hidden layer and an output layer. The input layer is not counted since there is no calculation performed in the input layer neurons. The input layer only introduces the input data; no calculation is done. In a feed-forward neural network there is no backward travel, information only moves in the forward path to the next layer neurons.

The number of input neurons was equal to the number of input variables and the number of output neurons was equal to the number of output variables. The number of hidden neurons in the hidden layer was determined by calculating the root mean squared error (RMSE). The number of hidden neurons that gives an output with minimum RMSE for the validation set was taken as the optimum number of hidden neurons.

3.6.3 Neural Network Training

A supervised learning method was used for both neural network models. Both the input and corresponding outputs values were provided while training the neural network. The Levenberg-Marquardt algorithm (trainlm) training function was used to train the neural networks. ‘trainlm’ is often the fastest backpropagation algorithm and is suggested as a first choice supervised learning algorithm. Even though this training function takes more memory than other methods, it was chosen to train the neural networks because of its fast computation ability. Tangent hyperbolic sigmoid activation function and linear activation function were used in the hidden neurons and output neurons respectively. The tangent hyperbolic sigmoid activation function was preferred because it is differentiable and gives the output in a fixed range between -1 and 1.

3.7 Model Performance Evaluation

To assess the performance of the developed neural networks the correlation coefficient (R), mean squared error (MSE) and root mean squared error (RMSE) were calculated. The correlation coefficient R was used to measure how well the predicted values using the created neural networks match the actual experimental results. The value of the coefficient ranges from -1 to 1. As the R-value approaches 1 or -1, it indicates that the predicted values are well aligned with the actual values and when it approaches zero, it indicates that the model prediction is not well aligned with the real values.

The mean squared error (MSE) is the difference between the original and predicted values, which is determined by squaring the average difference over the data set. It is a measure of the precision between the anticipated and original values, or how close the fitted line is to the real data points. The less the MSE values, the closer the fitted line is to the original, indicating good precision between predicted and actual values.

The error rate determined as the root of the mean squared error is called root mean squared error (RMSE). Because it has the same unit as the amount represented on the y-axis, RMSE is the most simply understood statics and is a good fit indicator.

$$\mathrm{MSE} = \frac{1}{n}\sum(Yi - yi)^2 \tag{3.2}$$

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n}\frac{(Yi - yi)^2}{n}} \tag{3.3}$$

Where, Yi is the actual value and yi is the predicted value

A plot of error histogram was also used to visually display the error ranges and their redundancies.

3.8 Model Validation

The developed neural network models were validated using primary soil laboratory test results. The soil laboratory tests include grain size analysis, Atterberg limit and modified compaction. All tests were done in AAiT (Addis Ababa Institute of Technology) geotechnical laboratory. The tests were done according to the ASTM manual.

3.8.1 Grain Size Analysis

The grain size analysis was done according to ASTM manual D 1140 standard test methods for amount of material in soils finer than the No. 200 (75-µm). The samples were first soaked to find the original size of soil grains by preventing the finer particles from adhering to larger ones and washed on sieve No. 200. After drying the sample in the oven with 105^{o} C the samples were sieved with a stack of successive sieves.

3.8.2 Atterberg Limit

The Atterberg limit test was done according to ASTM D 4318 standard test methods for liquid limit, plastic limit and plasticity index of soils. Some volume of soil that passes through a sieve diameter of 0.425mm was used to perform the Atterberg limit tests. The liquid limit test was done using the Cassagrande apparatus.

3.8.3 Compaction

The compaction test was done according to ASTM D 1557 standard test methods for laboratory compaction characteristics of soil using modified effort (56,000 ft-lb/ft^3(2,700 KN-m/m^3)). The samples were air dried before the test was performed. The test method A and B were implemented using a 101 mm (4 in) diameter mold size with a volume of 944cm^3. Each soil sample was compacted in five separate layers.

The above three soil laboratory tests were done on each of the fifteen soil samples. The result from the grain size analysis and the Atterberg limit tests were used as input variables to predict the compaction characteristics. Then the value of compaction parameters maximum dry density and optimum moisture content that was found by the experimental laboratory test were compared with the values from the prediction models' output. The comparison between the two values was used to show how well the artificial neural network models can predict the value of compaction characteristics from soil index properties. The performance of the neural network models on the primary data was shown by calculating the mean squared error MSE.

3.9 ANN Model Equation Derivation

The model equation for both of maximum dry density and optimum moisture content prediction were derived by following the steps performed in creating the ANN models. The steps are normalizing input variables, calculating the weighted sum using weight and bias values and calculating the output using the activation function. This processes may be repeated a number of times based on the number of hidden layers used in the model. Finally, the output is transformed in to the original value from the normalized value. These steps are summarized on Figure 3-3.

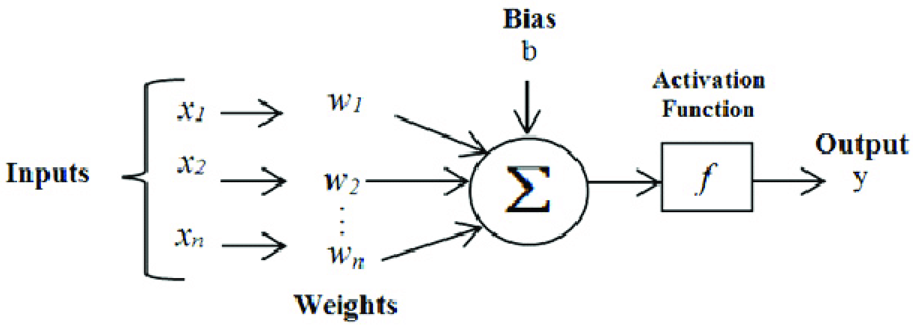


Figure 3-3 General Procedure in ANN Equation Derivation

CHAPTER 4 RESULTS AND DISCUSSION

4.1 General

In this chapter the results of the soil laboratory test on primary data, the relationship between input and output parameters, the development of the ANN models with their structure and performance, model validation using experimental data, model equation derivation and their comparison with formerly formulated regression analysis on the same area Addis Ababa are presented and discussed.

4.2 Laboratory Test Result and Discussion

Laboratory tests were used to determine the index and compaction characteristics of soil samples. Three soil laboratory tests: grain size analysis, Atterberg limit and modified compaction test were done on 15 samples used as primary data. All the laboratory tests were done according to ASTM manual.

4.2.1 Grain Size Distribution

The result of grain size distribution expresses the distribution of particle size present in a soil mass. Generally, soil can be classified as coarse and fine grained depending on the amount of soil that passes the No 200 sieve which have a size of 0.075µm. In this research coarser materials found in the soil mass were expressed as gravel or sand whereas the silt and clay particles together were expressed as fine materials. Based on the USCS classification system the particle size distribution of the soil samples was calculated in percentage as;

$$\%\ \text{Gravel} = \%\ \text{Soil passing 75 mm sieve} - \%\ \text{Soil passing 4.75 mm sieve} \qquad 4.1$$

$$\%\ \text{Sand} = \%\ \text{Soil passing 4.75 mm sieve} - \%\ \text{Soil passing 0.075 mm sieve} \qquad 4.2$$

$$\%\ \text{Fine} = \%\ \text{Soil passing 0.075 mm sieve} \qquad 4.3$$

The grain size distribution of the soil samples is summarized on Table 4-1. As can be seen from Table 4-1, out of the 15 samples 2 samples were coarse grained soil whereas the remaining 13 samples were found to be fine grained soils.

Table 4-1 Grain Size Distribution of Primary Data

S.N0	Sample Name	Gravel(%)	Sand(%)	Fine(%)	Soil Classification
1	Sample 1	1	23.5	75.5	Fine Grained
2	Sample 2	0.87	6.88	92.25	Fine Grained
3	Sample 3	12.18	14.18	73.64	Fine Grained
4	Sample 4	3.07	11.96	84.97	Fine Grained
5	Sample 5	0	4.97	95.03	Fine Grained
6	Sample 6	12.5	21.7	65.8	Fine Grained
7	Sample 7	2.75	18.75	78.5	Fine Grained
8	Sample 8	25.25	24.5	50.25	Fine Grained
9	Sample 9	8.75	20.49	70.76	Fine Grained
10	Sample 10	16.6	10.33	73.07	Fine Grained
11	Sample 11	0	24.25	75.75	Fine Grained
12	Sample 12	77.2	10.25	12.55	Coarse Grained
13	Sample 13	0.06	5.52	94.42	Fine Grained
14	Sample 14	0.17	23.1	76.73	Fine Grained
15	Sample 15	71	11.67	17.33	Coarse Grained

4.2.2 Atterberg Limits

From the Atterberg limit test the liquid limit and plastic limit were determined and plasticity index which is the difference of the two was computed. The value of liquid limit, plastic limit and plasticity index of the samples is summarized on Table 4-2.

Table 4-2 Atterberg Limit Test Result for Primary Data

S.N0	Sample Name	LL	PL	PI
1	Sample 1	65.31	38.25	27.06
2	Sample 2	49	34.23	14.77
3	Sample 3	61.68	37.52	24.16
4	Sample 4	55.95	20.29	35.66
5	Sample 5	60	28.33	31.67
6	Sample 6	69.73	39.78	29.95
7	Sample 7	65.26	35.99	28.27
8	Sample 8	57.88	36.51	21.37
9	Sample 9	59.25	39.47	19.78
10	Sample 10	68.51	38.49	30.02
11	Sample 11	54.49	35.13	19.36
12	Sample 12	47.01	31.29	15.72
13	Sample 13	73.5	50.27	23.23
14	Sample 14	46.5	30.96	15.54
15	Sample 15	39.65	30.32	9.33

4.2.3 Modified Proctor

The compaction test was done using modified proctor test method. Using a modified effort on compaction helps to achieve a higher maximum dry density at lower moisture content. The value of the two compaction parameters maximum dry density and optimum moisture content for each sample is summarized on Table 4-3.

Table 4-3 Modified Proctor Test Result for Primary Data

S.N0	Sample Name	MDD(g/cm3)	OMC(%)
1	Sample 1	1.47	20.2
2	Sample 2	1.56	25.79
3	Sample 3	1.49	21
4	Sample 4	1.55	23.66
5	Sample 5	1.67	22.01
6	Sample 6	1.49	19.3
7	Sample 7	1.41	21.82
8	Sample 8	1.65	16.77
9	Sample 9	1.52	23.26
10	Sample 10	1.54	18.6
11	Sample 11	1.48	20.63
12	Sample 12	1.9	11.7
13	Sample 13	1.55	28.04
14	Sample 14	1.66	23.12
15	Sample 15	1.93	12.3

4.2.4 Soil Classification

Based on the result of grain size distribution and Atterberg limits the type of soil were classified using Unified Soil Classification System (USCS). The coarse grained soils were classified by using the fraction percent of coarse particles present. Additionally, the value of plasticity index or their location on the plasticity chart was taken as another criterion since the samples have some amount of fines. Fine grained soils on the other hand were classified using their plasticity characteristics. Plasticity chart which is a chart of liquid limit vs plasticity index was used to show the classification of fine grained soils.

By using the location of soil samples relative to the A line and their value of liquid limit generally fine grained soils can be classified as CH (high plasticity inorganic clay), OH (high plasticity organic clay), CL (Low plasticity inorganic clay), OL (low plasticity organic clay), MH (high plasticity inorganic silt), OH (high plasticity organic silt), ML

(Low plasticity inorganic silt) and OL (low plasticity organic silt). The fine grained soils and coarse grained soils with more than 12% of fine fraction are plotted on the plasticity chart shown on Figure 4-1.

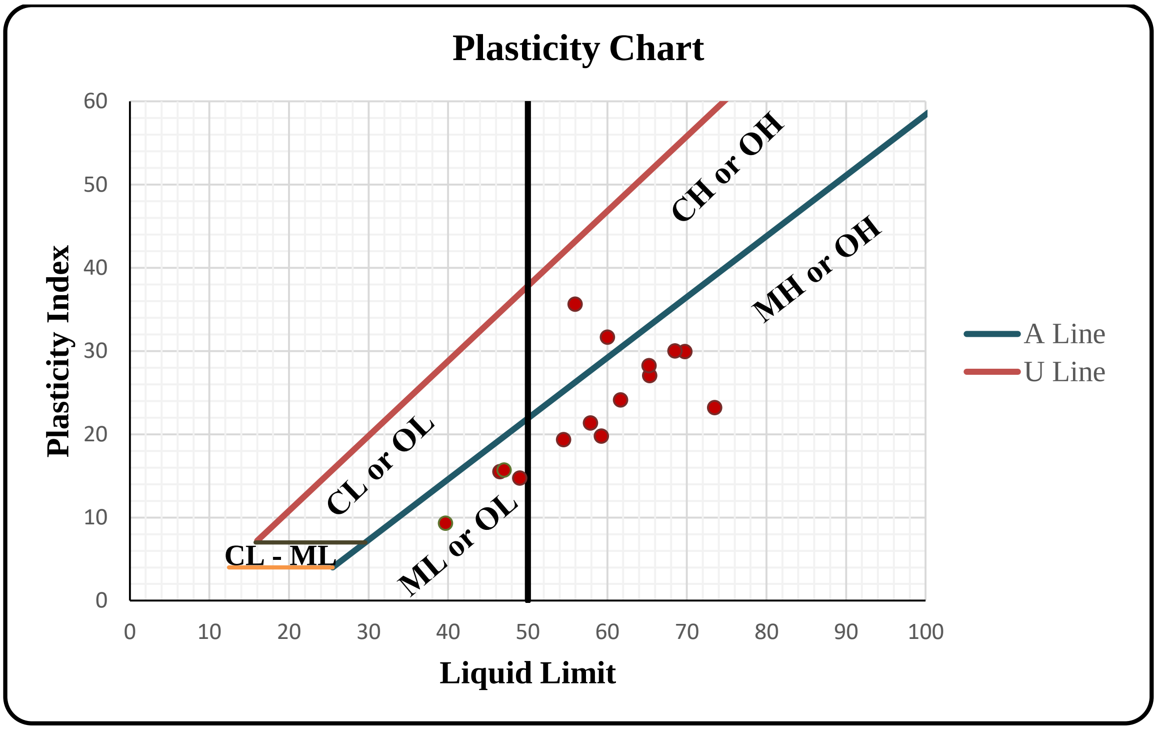


Figure 4-1 Plasticity Chart for Primary Data

From the plasticity chart on Figure 4-1 out of the 13 fine grained soil samples 2 samples were plotted above the A line with a liquid limit of greater than 50 and were classified as CH (High plasticity inorganic clay), 9 samples were plotted below the A line with a liquid limit value of more than 50 and classified as MH (high plasticity inorganic silt) and 2 samples that were plotted below the A line but have a liquid limit of less than 50 were classified as ML (low plasticity inorganic silt).

From the 15 soil samples 2 samples were found to be coarse grained soil based on the grain size distribution result. These samples have a coarse fraction of more than 50% which is larger than the No.4 sieve and were classified as gravel soils. The soil samples also have a fine content of more than 12% so by using the plasticity chart they were further classified as GM (silty gravel). The summary of soil classification of the 15 soil samples used as primary data is presented on Table 4-4.

Table 4-4 Summary of Soil Classification of Primary Data

S.N0	Sample Name	Fine Grained soil	Coarse Grained soil	Soil Classification
		Using Plasticity Chart	Gravels with fines (>12% fines)	
1	Sample 1	Below A Line LL > 50%		MH
2	Sample 2	Below A Line LL < 50%		ML
3	Sample 3	Below A Line LL > 50%		MH
4	Sample 4	Above A Line LL > 50%		CH
5	Sample 5	Above A Line LL > 50%		CH
6	Sample 6	Below A Line LL > 50%		MH
7	Sample 7	Below A Line LL > 50%		MH
8	Sample 8	Below A Line LL > 50%		MH
9	Sample 9	Below A Line LL > 50%		MH
10	Sample 10	Below A Line LL > 50%		MH
11	Sample 11	Below A Line LL > 50%		MH
12	Sample 12		Below A line	GM
13	Sample 13	Below A Line LL > 50%		MH
14	Sample 14	Below A Line LL < 50%		ML
15	Sample 15		Below A line	GM

Range of laboratory test results i.e. grain size distribution, Atterberg limit and modified compaction test of the 15 soil samples is presented on Table 4-5.

Table 4-5 Range of Laboratory Test Results of Primary Data

	Gravel (%)	Sand (%)	Fine (%)	LL (%)	PL (%)	PI (%)	MDD (g/cm3)	OMC(%)
Min	0	4.97	12.55	39.65	20.29	9.33	1.41	11.7
Max	77.2	24.5	95.03	73.5	50.27	35.66	1.93	28.04
Mean	15.43	15.47	69.10	58.25	35.12	23.06	1.59	20.54
Median	3.07	14.18	75.5	59.25	35.99	23.23	1.55	21
Variance	582.94	48.08	574.43	86.66	41.44	51.21	0.02	18.49
Standard deviation	24.14	6.93	23.97	9.31	6.44	7.16	0.15	4.30

4.3 ANN Prediction Model

Predictive modeling is a machine learning technique that uses existing data to predict expected future outcomes. It works by analyzing current and existing data and projecting what it learns on a model generated to forecast expected outcomes. A predictive model works on anything with a numerical value based on learning process. In this research predictive models were developed that can be used to forecast the value of compaction characteristics, maximum dry density and optimum moisture content, using an artificial neural network.

The total data set was divided in to two categories as coarse and fine grained soil based on their grain size distribution. Out of the 300 soil samples of the secondary data, 79 soil samples were coarse grained soils whereas the remaining 221 soil samples were fine grained soils. ANN prediction models were developed for each group separately. The models vary with each other by the type of soil used to generate the model, input parameters and models topology or structure.

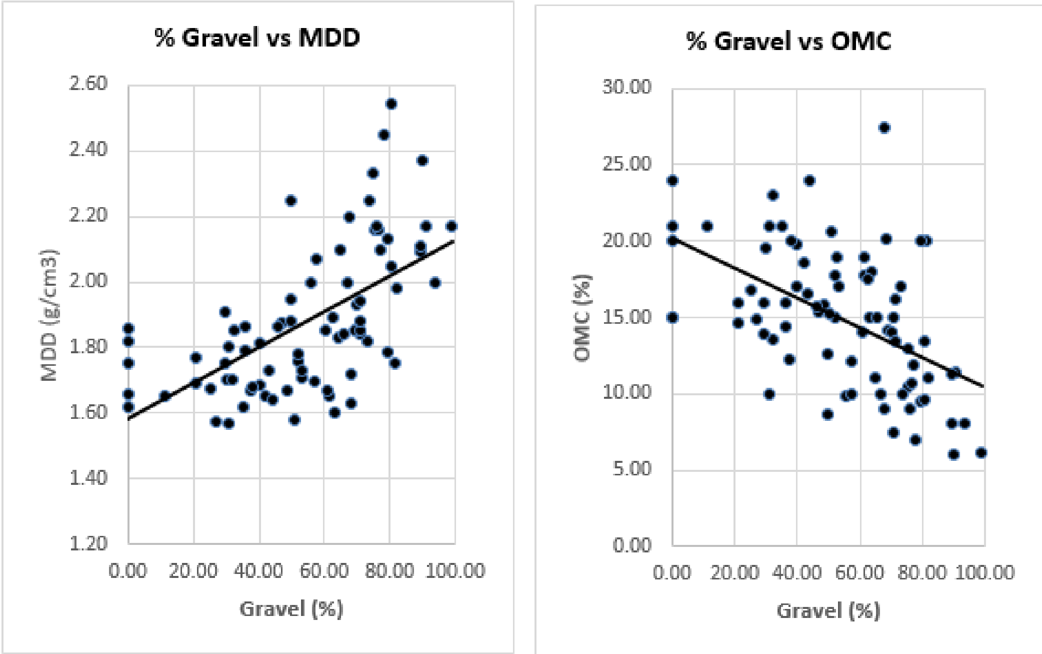
4.4 ANN Model for Coarse Grained Soil

Coarse grained soils are soils in which more than half of the total material by weight is larger than 75-micron sieve. For the coarse grained soils, ANN model was developed using a total of 79 coarse grained soil samples. Soil index properties that have significant effect on the compaction characteristics of coarse grained soils were selected as input parameters.

4.4.1 Model Input Parameters

Coarse grained soils have a different compaction characteristic when compared to fine grained soils. Coarse grained materials can be compacted to a higher value of maximum dry density than fine grained soil. Adding some amount of fines in to coarse grained soils will help to increase the dry density by filling the gaps between the coarser particles. However, if the amount of fine is increased to a value more than that required to fill the voids of the coarse grained particles, the maximum dry density will decrease. Therefore, the size and distribution of particles in a soil mass affects the compaction characteristics of coarse grained soils. Based on this, the percent of grain size distribution was selected as input variable to develop the ANN model for coarse grained soils.

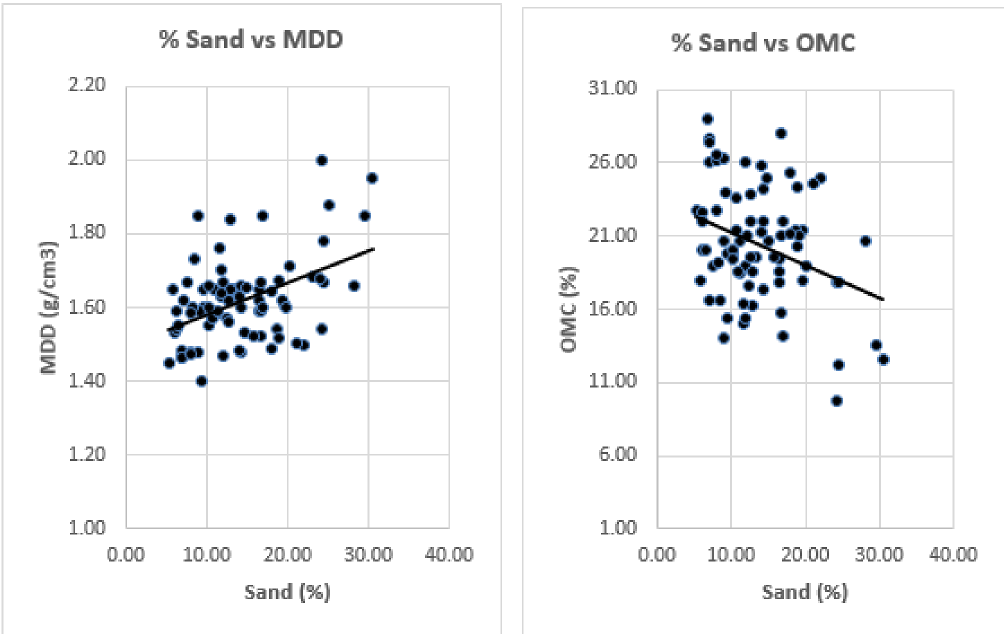
The relationship between the grain size distribution property, that is amount of coarse and fine particles expressed as gravel, sand and fine content with the two compaction parameters maximum dry density and optimum moisture content are plotted on scatter plots using the secondary data. On the scatter plot the input variables are on the X-axis whereas the output variables are plotted on the Y-axis.



(a) (b)

Figure 4-2 (a) % Gravel vs MDD (b) % Gravel vs OMC

As can be seen from Figure 4-2 (a) and (b) the maximum dry density of soil increase as the amount of gravel in a soil increase while the optimum moisture content decreases.



(a) (b)

Figure 4-3 (a) % Sand vs MDD (b) % Sand vs OMC

From Figure 4-3 (a) and (b) it can be seen that as the amount of sand in a soil increase the maximum dry density of soil increase whereas the optimum moisture content decrease.

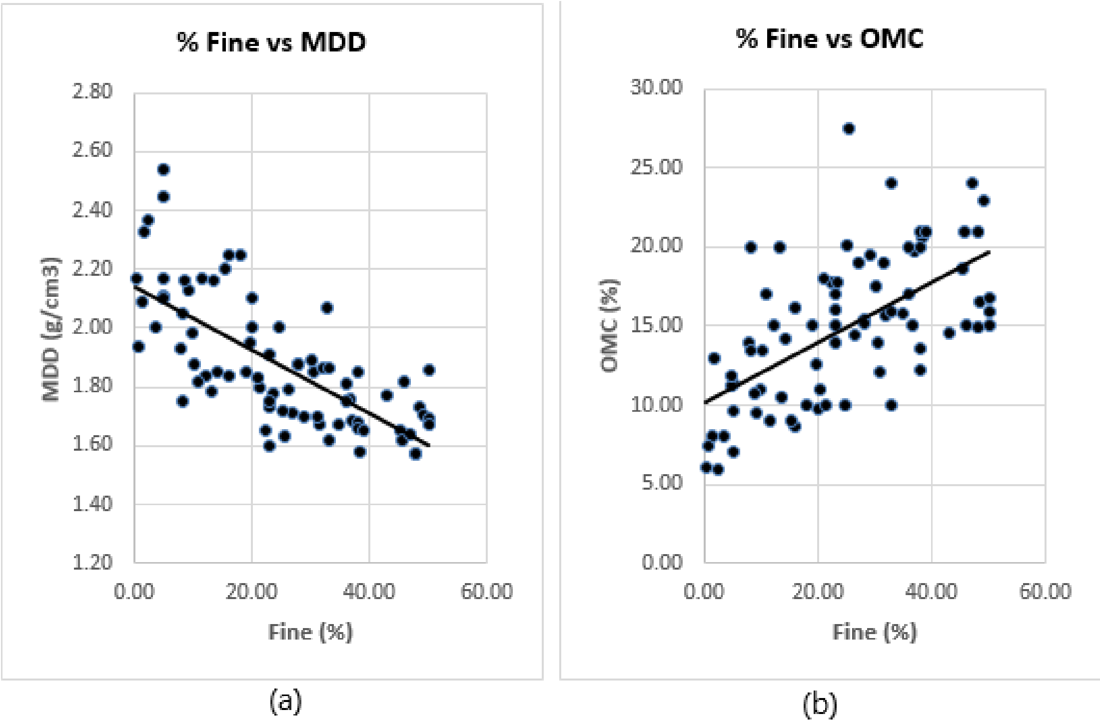


Figure 4-4 (a) % Fine vs MDD (b) % Fine vs OMC

As can be seen from Figure 4-4 (a) and (b), the value of maximum dry density of soil decreases as the fine content in the soil increase and the optimum moisture content increases with the increment of amount of fine in the soil.

Generally, from the scatter plots it can be concluded that the grain size distribution of soil has a visible relation with compaction characteristics of coarse grained soil. A soil mass with high amount of coarse grained materials can attain a higher value of maximum dry density at lower moisture content than a soil mass with high content of fine grained particles.

4.4.2 Model Structure and Performance

Considering the relationship between percent of grain size distribution and compaction characteristics, ANN models were developed to predict the maximum dry density and optimum moisture content of coarse grained soils from their grain size distribution property. The ANN models developed to predict the maximum dry density and optimum moisture content of coarse grained soils are named coarsemdd1 and coarseomc1 respectively. The architecture of the models is 3:12:1 and 3:16:1 for the maximum dry density and optimum moisture content respectively.

Neural networks with three input variables and one output were developed using different topologies. All the neural networks had only one hidden layer since it is sufficient to build a simple prediction model using ANN. Coarsemdd1 was built using three input, twelve hidden and one output neurons whereas coarseomc1 was built using three input, sixteen hidden and one output neurons. The number of neurons in the hidden layer was determined using trial and error method. The one with minimum RMSE for the validation set was chosen. The hidden and output layers, used a hyperbolic tangent sigmoid and a linear activation function respectively. The topology and activation functions used are clearly shown in Figure 4-5 and 4-6.

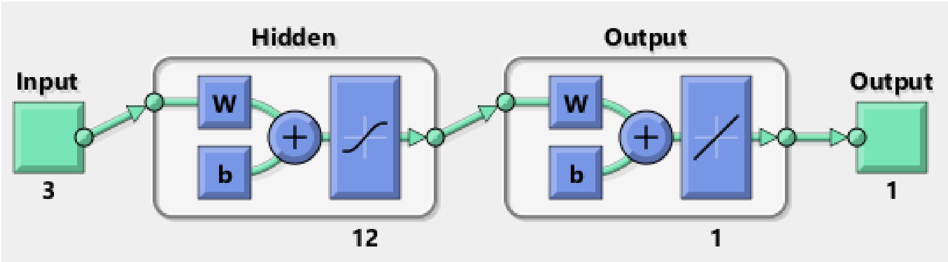


Figure 4-5 Topology of Coarsemdd1

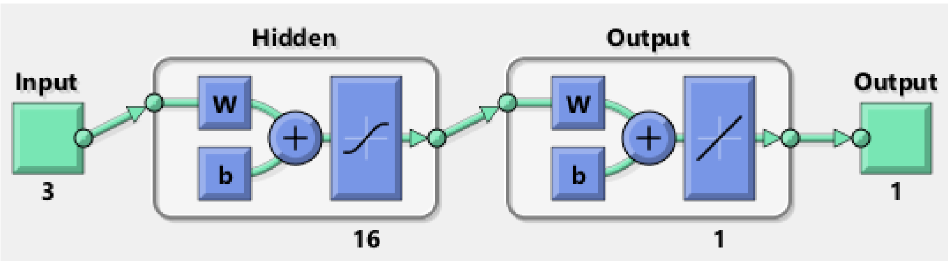


Figure 4-6 Topology of Coarseomc1

The performance of the neural networks on the test set was taken as an evaluation to select the best model since the test set is a new set of data that was neither used in training nor validation. The model's performance on the test set can tell how well it will perform on a new data set. The predicted values of maximum dry density and optimum moisture content using the developed ANN models was compared with the actual values for the coarse grained soil samples on the test set and is summarized on Table 4-6.

Table 4-6 ANN Model Prediction of Coarse Grained Soil

TEST SET							
Actual MDD	Predicted (coarsemdd1)	Error	Error Squared	Actual OMC	Predicted (coarseomc1)	Error	Error Squared
1.71	1.74	0.028	0.0008	19	16.25	2.755	7.5900
1.65	1.54	0.107	0.0115	15.4	15.76	0.355	0.1263
1.88	1.83	0.043	0.0018	14.6	9.13	5.472	29.9431
1.86	1.91	0.051	0.0026	20	19.10	0.903	0.8159
1.80	1.95	0.147	0.0216	15	14.74	0.264	0.0696
1.82	1.77	0.049	0.0024	21	17.50	3.499	12.2458
1.65	1.65	0.002	0.0000	7	10.33	3.330	11.0875
1.70	1.73	0.031	0.0009	10.5	11.41	0.909	0.8268
2.17	1.98	0.188	0.0355	17.5	18.63	1.126	1.2669
2.37	2.20	0.172	0.0296	13.5	12.93	0.569	0.3235
1.91	1.80	0.115	0.0131	20.1	21.25	1.145	1.3112
1.67	1.73	0.060	0.0036	16.8	18.35	1.547	2.3930
		MSE=	0.010			MSE=	5.667

According to Table 4-6 the error of the model coarsemdd1 while using on the test set ranges from 0.002 g/cm3 to 0.188 g/cm3 with a mean squared error of 0.010 and the error of the model coarseomc1 while using on the test set ranges from 0.264% to 5.472% with a mean squared error of 5.667.

The distribution of the error between the actual and predicted values of maximum dry density and optimum moisture content while using the model coarsemdd1 and coarseomc1 is plotted on histogram plots. As can be seen from Figure 4-7, the error between the predicted and actual value of maximum dry density on the whole data set ranges from -0.29 to +0.27 with a substantial concentration of error between 0 and -0.05. The error histogram also shows that instances near zero error are higher than the rest indicating a minimum variation between actual and predicted values.

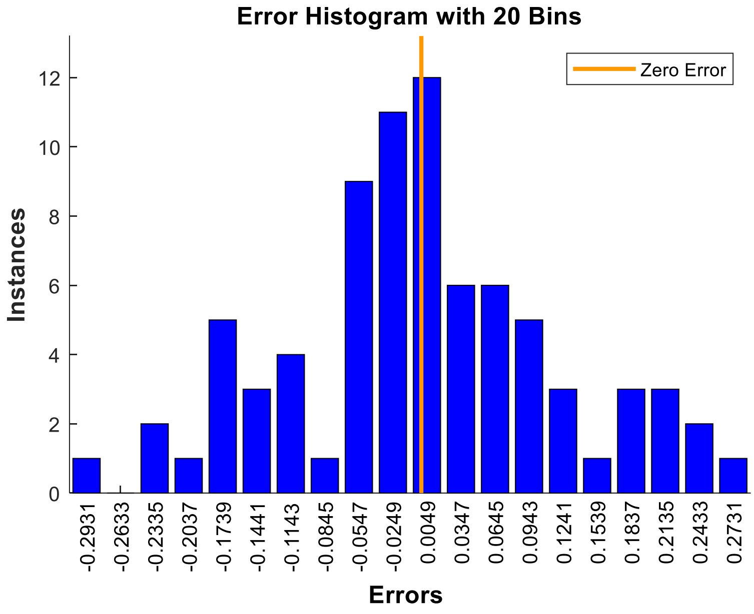


Figure 4-7 Error Histogram for Coarsemdd1

From Figure 4-8 it can be seen that the variation between the predicted and actual value of moisture content on the whole data set using coarseomc1 ranges from -7.4 up to +7.8 with a higher concentration of error between 0 and -0.16. Redundancy near zero error is also indicated to be higher than the rest values on the histogram plot.

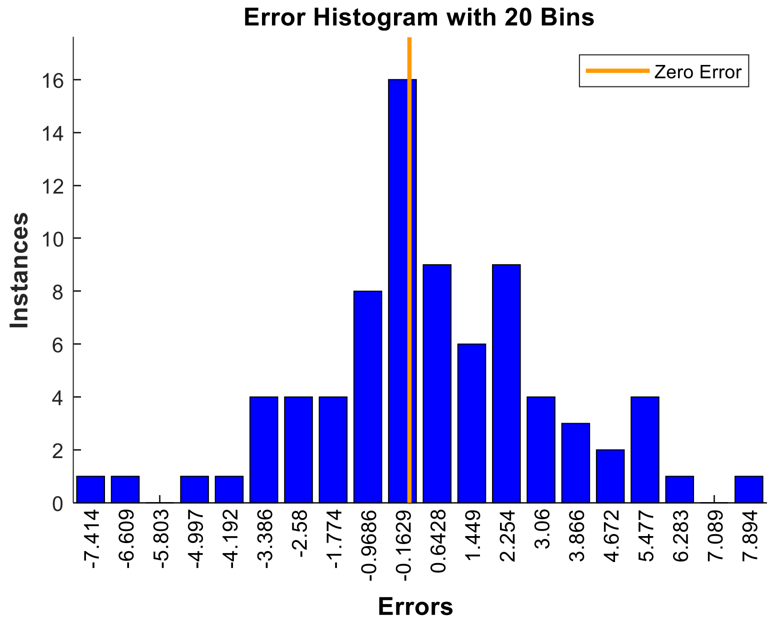


Figure 4-8 Error Histogram for Coarseomc1

4.5 ANN Model for Fine Grained Soil

Fine grained soils are soils in which more than half the total material by weight is smaller than 75-micron sieve. For the fine grained soils, ANN model was developed separately using a total of 221 fine grained soil samples. Soil index properties that have significant effect on the compaction characteristics of fine grained soils were selected as input parameters.

4.5.1 Model Input Parameters

The soil consistency limits are very important index property of fine grained soil. Soil consistency can be determined by Atterberg limits using simple laboratory tests. Plasticity index which is the numerical difference between liquid and plastic limit best expresses the physical state of fine grained soils. Plasticity index is the range of water content in which the soil remains plastic. Fine grained soils with water content between liquid limit and plastic limit stays plastic. Plasticity index is an important index property of fine grained soils. The plasticity characteristics of fine grained soils also affects its compaction property. The relation between the plasticity index and compaction parameters maximum dry density and optimum moisture content are plotted on a scatter plot.

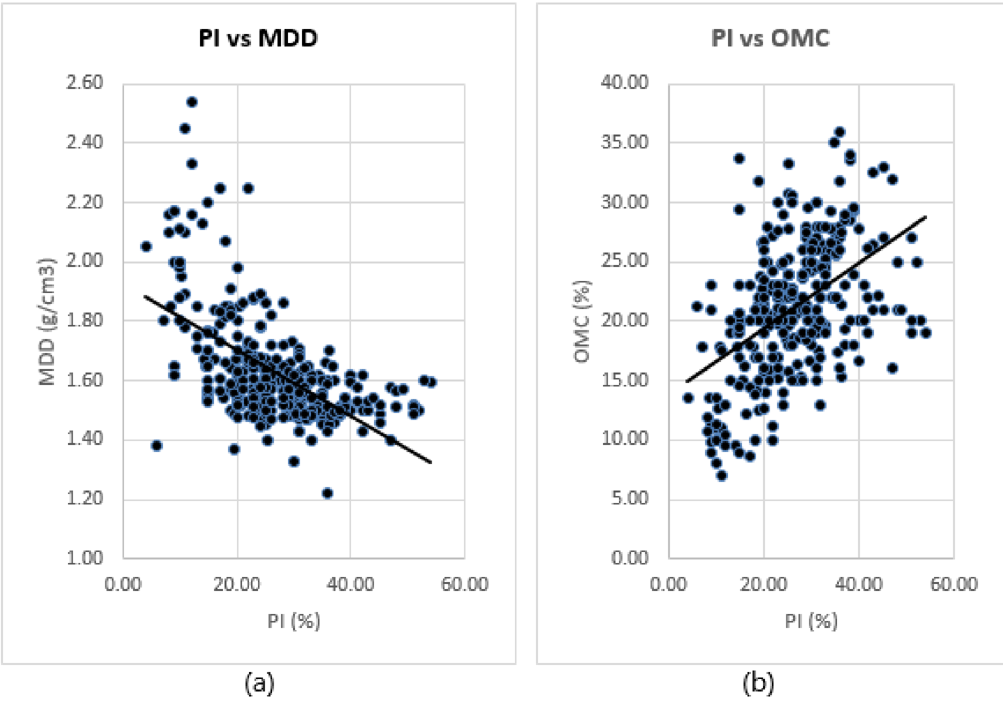


Figure 4-9 (a) PI vs MDD (b) PI vs OMC

As can be seen from Figure 4-9 (a) and (b) as the plasticity index of soil increase the maximum dry density of soil decrease whereas the optimum moisture content increase.

The amount of fine content in fine grained soil varies in different soil masses. The effect of amount of fine content in a fine grained soil on its compaction characteristics maximum dry desity and optimum moisture content is plotted on the following sacatter plot.

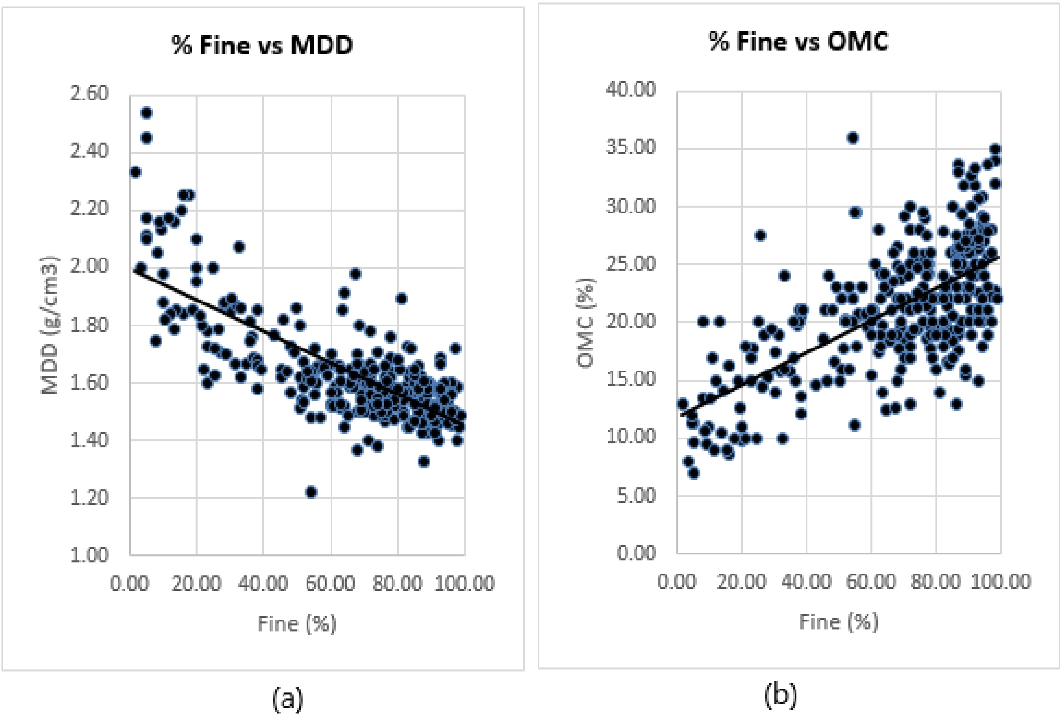


Figure 4-10 (a) % Fine vs MDD (b) % Fine vs OMC

As can be seen from Figure 4-10 (a) and (b), the value of maximum dry density decrease as the fine content in the soil increase and the optimum moisture content increase with the increment of amount of fine in the soil.

From the scatter plots it can be concluded that the plasticity of soil and its amount of fine particles have a considerable relation with compaction characteristics of fine grained soil. A soil mass with high plasticity will achieve a lower value of maximum dry density at higher moisture content when compared to low plasticity soil.

4.5.2 Model Structure and Performance

Based on the relationship between plasticity index and fine content with the compaction characteristics, ANN models were developed to determine the maximum dry density and optimum moisture content of fine grained soil using their plasticity index and amount of fine content. The ANN models developed to predict the maximum dry density and optimum moisture content of fine grained soils are named finemdd2 and fineomc6 respectively. The architecture of the models is 2:15:1 for the maximum dry density prediction and 2:8:1 for the optimum moisture content prediction.

Neural networks with two input variables and one output were developed using different topologies. All the neural networks had only one hidden layer. Finemdd2 was built using two input, fifteen hidden and one output neurons whereas fineomc6 was built using two input, eight hidden and one output neurons. The number of neurons in the hidden layer was determined using trial and error method. The one with minimum RMSE for the validation set was chosen. The hidden and output layers, used a hyperbolic tangent sigmoid and a linear activation function respectively. The topology and activation functions used are clearly shown on Figure 4-11 and 4-12.

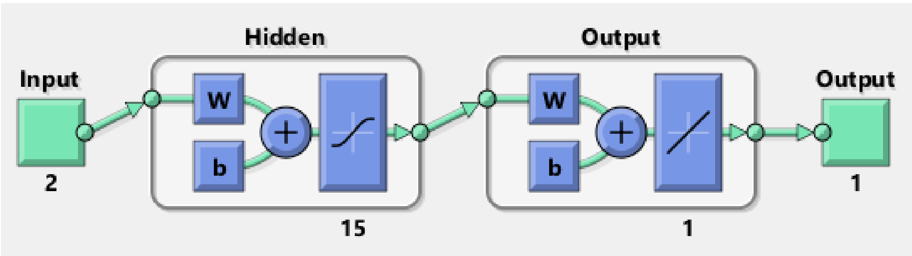


Figure 4-11 Topology of Finemdd2

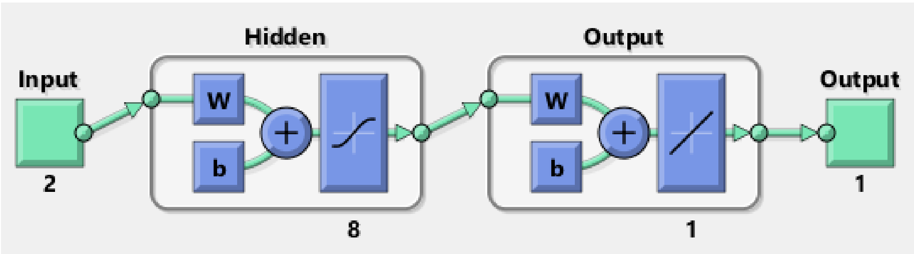


Figure 4-12 Topology of Fineomc6

The performance of the neural networks on the test set was taken as an evaluation to select the best model. The predicted values of maximum dry density and optimum moisture content using the developed ANN models was compared with the actual values for the fine grained soil samples on the test set and is summarized on Table 4-7.

Table 4-7 ANN Model Prediction of Fine Grained Soil

Test Set							
Actual MDD	finemdd2	Error	Error Squared	Actual OMC	fineomc6	Error	Error Squared
1.61	1.57	0.04	0.0016	21.4	22.04	0.64	0.4154
1.53	1.54	0.01	0.0002	17.8	20.83	3.03	9.1765
1.62	1.52	0.10	0.0095	19.8	23.00	3.20	10.2306
1.57	1.53	0.04	0.0015	20.6	20.13	0.47	0.2201
1.53	1.51	0.02	0.0004	17.6	23.58	5.98	35.8054
1.65	1.55	0.10	0.0096	21	19.29	1.71	2.9164
1.64	1.54	0.10	0.0103	24	21.40	2.60	6.7699
1.47	1.55	0.08	0.0063	21.3	21.73	0.43	0.1868
1.66	1.58	0.08	0.0062	21.1	21.34	0.24	0.0553
1.48	1.53	0.05	0.0026	27.7	25.43	2.27	5.1426
1.50	1.52	0.02	0.0005	27.1	24.58	2.52	6.3402
1.71	1.54	0.17	0.0285	26.1	25.67	0.43	0.1812
1.54	1.51	0.03	0.0011	31.8	28.19	3.61	13.0506
1.60	1.53	0.07	0.0045	24.5	24.07	0.43	0.1870
1.80	1.70	0.10	0.0103	30.6	25.73	4.87	23.7257
1.60	1.52	0.08	0.0067	25	22.07	2.93	8.6042
1.58	1.52	0.06	0.0037	19	21.45	2.45	6.0025
1.50	1.49	0.01	0.0001	26.6	24.05	2.55	6.5083
1.59	1.56	0.03	0.0007	13.9	18.89	4.99	24.9209
1.59	1.52	0.07	0.0056	12.5	19.77	7.27	52.8617
1.56	1.56	0.00	0.0000	27.5	24.34	3.16	9.9592
1.57	1.53	0.04	0.0015	25	23.83	1.17	1.3641
1.51	1.52	0.01	0.0000	22	25.38	3.38	11.4171
1.53	1.50	0.03	0.0011	25	25.05	0.05	0.0026
1.59	1.55	0.04	0.0013	15	21.94	6.94	48.1705
1.52	1.48	0.04	0.0019	20	22.57	2.57	6.5876
1.57	1.53	0.04	0.0013	23	25.31	2.31	5.3435
1.48	1.58	0.10	0.0102	25	24.18	0.82	0.6751
1.55	1.50	0.05	0.0021	22	22.98	0.98	0.9653
1.48	1.55	0.07	0.0045	19	21.39	2.39	5.7111
1.56	1.47	0.09	0.0082	16.2	19.18	2.98	8.8586
1.60	1.49	0.11	0.0118	19.4	20.45	1.05	1.1021
1.49	1.48	0.01	0.0002	26	22.82	3.18	10.1219
1.51	1.51	0.00	0.0000	21	26.16	5.16	26.6253
1.53	1.54	0.01	0.0001	21.2	20.80	0.40	0.1611
		MSE=	0.0042			MSE=	9.47

According to Table 4-7 the error of the model finemdd2 while using on the test set ranges from 0.00g/cm3 to 0.17g/cm3 with a mean squared error of 0.0042 and the error of the model fineomc6 while using on the test set ranges from 0.05% to 7.27% with a mean squared error of 9.47.

The distribution of the error between the actual and predicted values of maximum dry density and optimum moisture content on the whole data set while using the model finemdd2 and fineeomc6 is plotted on histogram plots. As can be seen from Figure 4-13, the error between the predicted and actual value of maximum dry density ranges from -0.30 to +0.36 with a substantial concentration of error between -0.05 and +0.08.

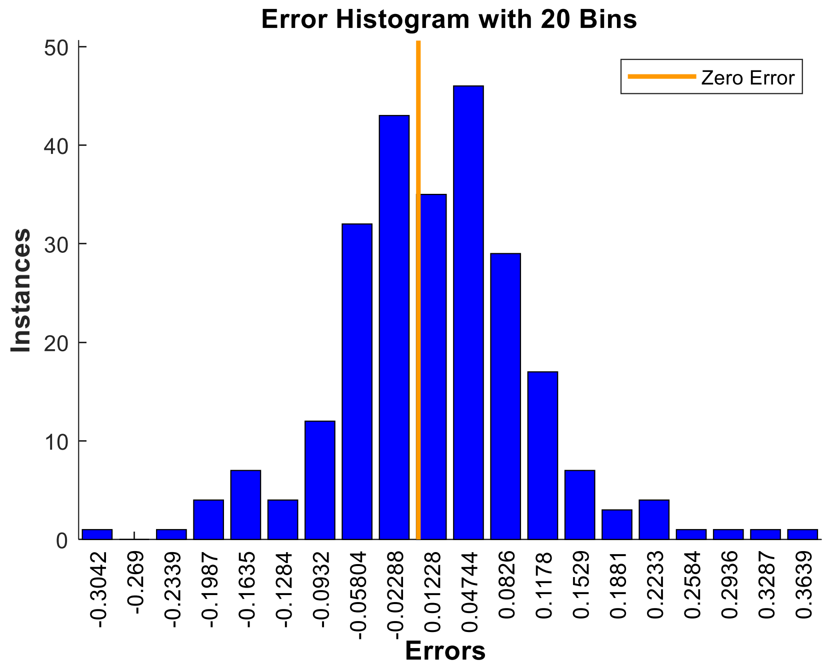


Figure 4-13 Error Histogram for Finemdd2

From Figure 4-14 it can be seen that the variation between the predicted and actual value of moisture content using fineomc6 ranges from -10.01 up to +8.2 with substantial concentration of error between -3.2 and +2.4.

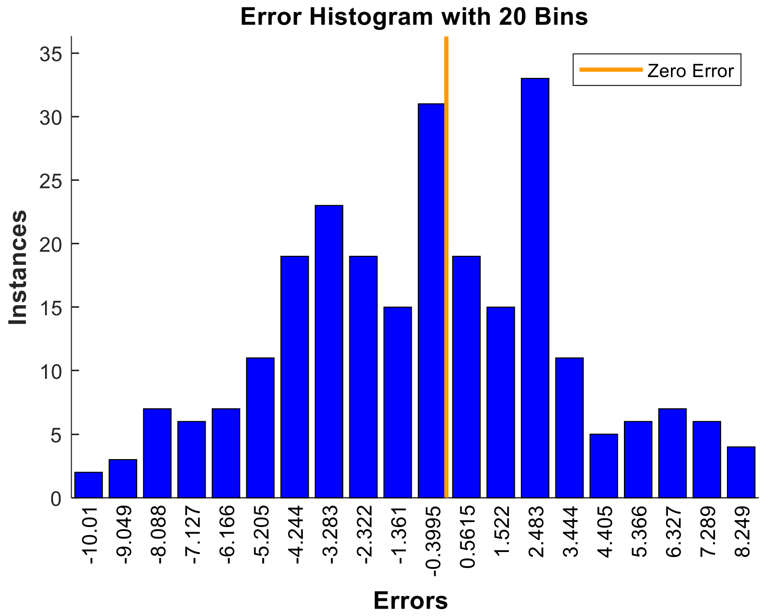


Figure 4-14 Error Histogram for Fineomc6

The correlation between the actual and predicted value of maximum dry density and optimum moisture content using both models of coarse and fine grained soils was summarized on a regression graph and a correlation coefficient R was calculated. As can be seen from the regression graph on Figure 4-15, the data points are distributed near the line Y=T (T representing the target or the actual value and Y representing the predicted model output). The best fit line also shows a minor deviation from the perfect equality line. These two are indicators of a good correlation. Additionally, the value of the correlation coefficient R= 0.92 indicates that there is a very good correlation between the actual and the predicted values of maximum dry density.

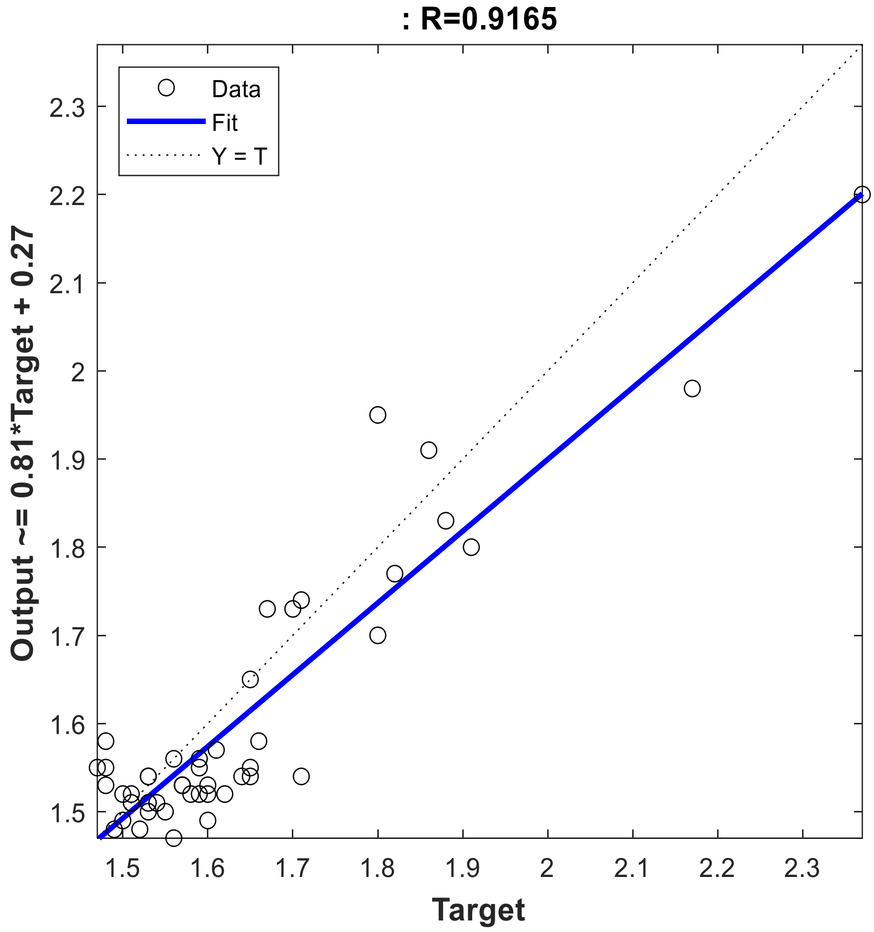


Figure 4-15 Regression Graph for Actual vs Predicted MDD

As can be seen from the regression graph on Figure 4-16, the actual and predicted values of optimum moisture content for both coarse and fine grained soils are correlated with a coefficient of regression value R= 0.81 which indicates a good correlation. The data points are also distributed near the line Y=T (T representing the target or the actual value and Y representing the predicted model output). These are all indicators of a good correlation.

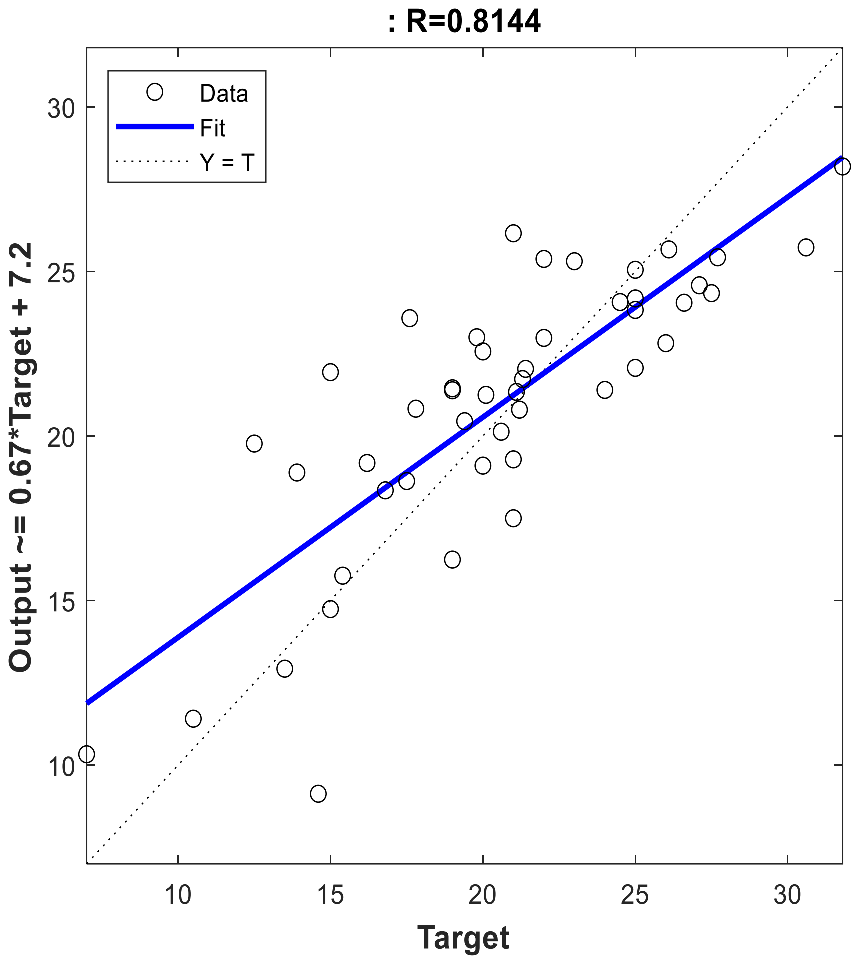


Figure 4-16 Regression Graph for Actual vs Predicted OMC

4.6 ANN Model Validation

The neural network prediction models were validated using experimental laboratory test results. The actual modified compaction test results were compared with the predicted values using the selected neural networks. According to Table 4-8, the error of the developed ANN models, for predicting maximum dry density of soils on the primary data, ranges from 0.003g/cm3 to 0.16g/cm3 with a mean squared error of 0.0042. This indicates that the developed neural networks can predict the value of maximum dry density of soil from soil index properties in a good precision with the actual value.

Table 4-8 Actual vs Predicted MDD

S.NO	Sample Name	Actual MDD (g/cm3)	Predicted MDD (g/cm3)	Error (g/cm3)	Error Squared	Variation (%)
1	Sample 1	1.47	1.55	0.081	0.007	5.246
2	Sample 2	1.56	1.54	0.023	0.001	1.489
3	Sample 3	1.49	1.55	0.062	0.004	3.986
4	Sample 4	1.55	1.52	0.033	0.001	2.126
5	Sample 5	1.67	1.51	0.157	0.025	9.386
6	Sample 6	1.49	1.62	0.135	0.018	8.305
7	Sample 7	1.41	1.55	0.140	0.020	9.013
8	Sample 8	1.65	1.52	0.127	0.016	7.668
9	Sample 9	1.52	1.57	0.045	0.002	2.877
10	Sample 10	1.54	1.54	0.003	0.000	0.207
11	Sample 11	1.48	1.54	0.060	0.004	3.887
12	Sample 12	1.9	2.00	0.096	0.009	4.807
13	Sample 13	1.55	1.51	0.044	0.002	2.844
14	Sample 14	1.66	1.53	0.134	0.018	8.060
15	Sample 15	1.93	2.06	0.134	0.018	6.499
					MSE=0.008	

As can be seen from Table 4-9, the error of the developed ANN models, for predicting optimum moisture content of soils on the primary data, ranges from 0.13% to 5.21% with a mean squared error of 5.55. This indicates that the developed neural networks can predict the value of optimum moisture content of soil from soil index properties in a good precision with the actual value.

Table 4-9 Actual vs Predicted OMC

S.NO	Sample Name	Actual OMC (g/cm3)	Predicted OMC (g/cm3)	Error (g/cm3)	Error Squared	Variation (%)
1	Sample 1	20.2	21.83	1.63	2.65	7.46
2	Sample 2	25.79	31.00	5.21	27.15	16.81
3	Sample 3	21	21.24	0.24	0.06	1.14
4	Sample 4	23.66	23.91	0.25	0.06	1.03
5	Sample 5	22.01	25.85	3.84	14.78	14.87
6	Sample 6	19.3	22.08	2.78	7.74	12.60
7	Sample 7	21.82	22.69	0.87	0.76	3.84
8	Sample 8	16.77	19.57	2.80	7.84	14.30
9	Sample 9	23.26	21.53	1.73	2.98	7.42
10	Sample 10	18.6	22.39	3.79	14.33	16.91
11	Sample 11	20.6	21.61	1.01	1.01	4.66
12	Sample 12	11.7	12.37	0.669	0.448	5.410
13	Sample 13	28.04	27.91	0.13	0.02	0.46
14	Sample 14	23.12	21.86	1.26	1.59	5.45
15	Sample 15	12.3	10.93	1.369	1.874	11.129
					MSE=5.55	

On field compaction mostly the exact maximum dry density is not achieved rather the relative compaction or percent compaction will be used. Relative or percent compaction is defined as the ratio of field dry density to laboratory maximum dry density. The relative compaction for roadways and other structures except earth dams ranges from 90% to 95% of the maximum dry density achieved during the laboratory test [42]. According to the model validation, the present ANN model prediction variation from the actual value for the maximum dry density ranges from 0.34% to 9.48%, which is within the allowable range of relative density of 90% to 95% for field compaction.

The acceptable range of moisture content on the field compaction also corresponds to the relative or percent compaction value. Using sample 10 which shows the maximum variation of OMC value, the moisture content variation was examined to see if it fits within the acceptable range or not.

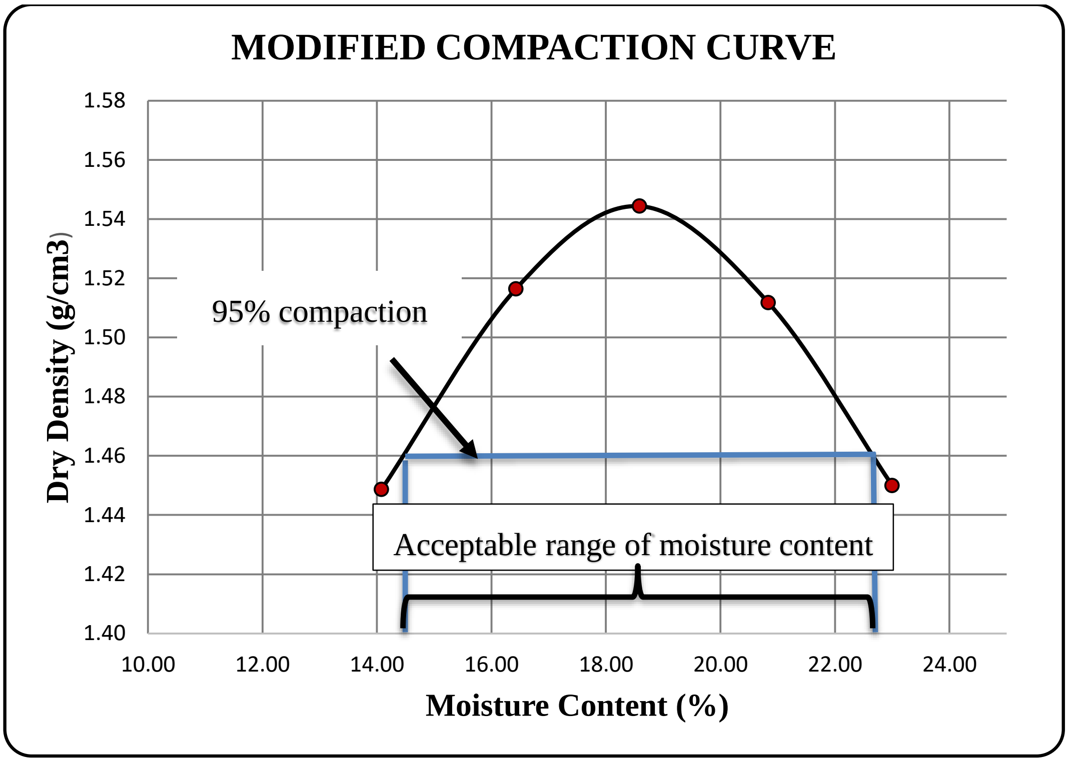


Figure 4-17 Relative Compaction

For sample 10 the actual optimum moisture content was 18.6% whereas the predicted value was 22.39%. The 95% relative compaction for this sample is 1.46g/cm3 and the acceptable range of moisture content that corresponds to the relative compaction is between 14.5% and 22.8%. As can be seen from Figure 4-17 the predicted value of moisture content 22.39% falls under the acceptable range of moisture content value. From this it can be conclude that the predicted optimum moisture contents are also found to be within the acceptable range of moisture content required for field compaction.

4.7 ANN Model Equation Derivation

The computation performed in the ANN model can be expressed by a generalized equation using the weight and biases of the neural networks. Weights and biases of the ANN model goes under several improvements during the training phase to achieve the best model with the minimum possible error. On the last stage after the ANN models are already developed the weights and biases become fixed and no further improvement will occur unless the models are trained again with different topologies, input variables or different training data set. The value of weights indicates the strength of the effect that the input variables have on the output values. The weight and bias of the ANN models are used as a coefficient and intercepts respectively. In this research equations of the ANN models which can be used to predict the value of maximum dry density and optimum moisture content were derived.

4.7.1 Model Equation for MDD of Coarse Grained soil

The ANN model coarsemdd1, for prediction of maximum dry density is a two layered feed forward network with one hidden and one output layer additional to the input layer. The steps used to compute the output value inside the ANN models were followed to drive the model equation.

Step1- Normalizing Input Variables

In the ANN model the input variables are not directly used in to model training rather have to be normalized to keep the range of input variables within same scale and to ensure all input variables get equal attention during training. The min max normalization which was used in this research can be expressed using equation 4.4.

$$X(norm) = \frac{X - min}{max - min}\ (newmax - newmin) + newmin \qquad 4.4$$

Where, X(norm)is the normalized value of X (input variables)

The min and max values are the minimum and maximum values corresponding for each variable in the whole data set. The new min and new max are the minimum and maximum values in the normalization range that is -1 and 1 respectively.

Step2- Calculating Weighted Sum

The normalized input variables were then multiplied by the weight matrix IW that is found between the input and hidden layer then added to the first bias value b1 to find the weighted sum.

Table 4-10 Weight ad Bias of ANN Model coarsemdd1

Weight IW for coarsemdd1 (12x3)			Weight (LW') for coarse mdd1 (1x12)	Bias b1 for coarsemdd1 (12x1)	Bias b2 for coarse mdd1 (1x1)	Input Variables (X) (3x1)
1.36	-0.47	-4.22	-0.87	-2.72	-0.63	% G
0.91	0.78	3.21	0.94	-2.15		% S
-0.21	2.55	2.26	-1.19	-2.15		% F
0.61	-2.02	2.3	-0.80	-1.71		
1	-1.48	-3.07	1.24	0.54		
2.51	0.47	2.03	-0.93	-0.76		
-1.91	0.19	-2.74	0.70	0.57		
2.16	1.25	-3.19	-1.68	1.17		
-0.9	4.33	1.61	-1.05	3.32		
-0.44	2.32	-3.17	0.78	-1.22		
-2.36	-2.13	1.01	1.16	-2.62		
1.22	-2.17	1.68	0.49	3.55		

IW is a matrix with a dimension of 12x3 where the number of rows are equal with the number of hidden layers and the number of columns are equal with the number of input variables. b1 is the first bias matrix of size 12 x1 which was added to the product of weight and input matrices to find the weighted sum. X is a 3x1 matrix containing the input variables %G, %S and %F. The weighted sum was calculated using equation 4.5

$$Weighted\ sum \sum\ =\ IW * X(norm) + b1 \qquad 4.5$$

The matrix calculation of each row is presented as follows.

$$R1 = 1.36 * G - 0.47 * S - 4.22 * F - 2.72$$

$$R2 = 0.91 * G + 0.78 * S + 3.21 * F - 2.15$$

$$R3 = -0.21 * G + 2.55 * S + 2.26 * F - 2.15$$

$$R4 = 0.61 * G - 2.02 * S + 2.3 * F - 1.71$$

$$R5 = \ 1 * G - 1.48 * S - 3.07 * F + 0.54$$

$$R6 = 2.51 * G + 0.47 * S + 2.03 * F - 0.76$$

$$R7 = -1.91 * G + 0.19 * S - 2.74 * F + 0.57$$

$$R8 = 2.16 * G + 1.25 * S - 3.19 * F + 1.17$$

$R9 = -0.9 * G + 4.33 * S + 1.61 * F + 3.32$

$R10 = -0.44 * G + 2.32 * S - 3.17 * F - 1.22$

$R11 = -2.36 * G - 2.13 * S + 1.01 * F - 2.62$

$R12 = 1.22 * G - 2.17 * S + 1.68 * F + 3.55$

<u>Step3- Compute Activation Function Result</u>

The weighted sum is a 12x1 matrix having an entry of R1 up to R10. The weighted sum then was entered in to an activation function. The activation function used in this ANN model was a hyperbolic tangent sigmoid transfer function.

$$N = f(R) = \frac{2}{1 + \exp(-2 * R)} - 1 \qquad 4.6$$

The results found by inserting the weighted sum in to the activation function were expressed as a matrix N of size 12x1 having entry of N1 up to N10, their calculation is presented as follows.

$$N1 = tanh(R1) = \frac{2}{1 + \exp(-2 * R1)} - 1$$

$$N2 = tanh(R2) = \frac{2}{1 + \exp(-2 * R2)} - 1$$

$$N3 = tanh(R3) = \frac{2}{1 + \exp(-2 * R3)} - 1$$

$$N4 = tanh(R4) = \frac{2}{1 + \exp(-2 * R4)} - 1$$

$$N5 = tanh(R5) = \frac{2}{1 + \exp(-2 * R5)} - 1$$

$$N6 = tanh(R6) = \frac{2}{1 + \exp(-2 * R6)} - 1$$

$$N7 = tanh(R7) = \frac{2}{1 + \exp(-2 * R7)} - 1$$

$$N8 = tanh(R8) = \frac{2}{1 + \exp(-2 * R8)} - 1$$

$$N9 = tanh(R9) = \frac{2}{1 + \exp(-2 * R9)} - 1$$

$$N10 = tanh(R10) = \frac{2}{1 + \exp(-2 * R10)} - 1$$

$$N11 = tanh(R11) = \frac{2}{1 + \exp(-2 * R11)} - 1$$

$$N12 = tanh(R12) = \frac{2}{1 + \exp(-2 * R12)} - 1$$

<u>Step3- Calculation with Second Weight and Bias</u>

The result from the activation function was multiplied by the second weight matrix found between the hidden and output layer LW which has a dimension of 1x12.

$$LW = \begin{pmatrix} -0.87 & 0.94 & -1.19 & -0.80 & 1.24 & -0.93 & 0.70 & -1.68 & -1.05 & 0.78 & 1.16 & 0.49 \end{pmatrix}$$

$$MDD = LW * N + b2$$

$$\begin{aligned} MDD = & -0.87 * N1 + 0.94 * N2 - 1.19 * N3 - 0.80 * N4 + 1.24 * N5 - 0.93 \\ & * N6 - 0.70 * N7 - 1.68 * N8 - 1.05 * N9 + 0.78 * N10 + 1.16 * N11 \\ & + 0.49 * N12 - 0.63 \end{aligned}$$

<u>Step4- Denormalization of Output Values</u>

The MDD value calculated using normalized input variable is the normalized value of the original maximum dry density. So the calculated maximum dry density should be post processed and transformed to its original value following the reverse path of min-max normalization using equation 4.7.

$$MDD(predicted) = \frac{MDD - newmin}{\left(\frac{newmax - newmin}{max - min}\right)} + min \qquad 4.7$$

4.7.1.1 Sample Calculation of MDD

The sample calculation was done using one soil sample from the secondary data with the following values.

G = 35.2 S = 19.25 F = 45.56 MDD = 1.62

The first step in ANN model training was normalizing the input data using the min max normalization method. The values used in normalizing the input variables are listed on Table 4-11.

Table 4-11 Normalizing Values for MDD Inputs

x1_step1.xoffset (min)	gain ($\frac{\text{newmax-newmin}}{\text{max-min}}$)	ymin (newmin)
0	0.0202	-1
0.91	0.0302	
0.22	0.0402	

By substituting the values listed on Table 4-11 in to the min max normalization equation, equation 4-4, the input variables were transformed in to normalized value. The normalized input values are;

G = -0.288 S = -0.445 F = 0.8216

Using the developed equation, the maximum dry density of the soil sample can be calculated as follows.

$$MDD = -0.87 * N1 + 0.94 * N2 - 1.19 * N3 - 0.80 * N4 + 1.24 * N5 - 0.93 * N6 - 0.70 * N7 - 1.68 * N8 - 1.05 * N9 + 0.78 * N10 + 1.16 * N11 + 0.49 * N12 - 0.63$$

$$N1 = \tanh(1.36 * \text{G} - 0.47 * \text{S} - 4.22 * \text{F} - 2.72) = \tanh(-6.370) = -1.000$$

$$N2 = \tanh(0.91 * \text{G} + 0.78 * \text{S} + 3.21 * \text{F} - 2.15) = \tanh(-0.122) = -0.121$$

$$N3 = \tanh(-0.21 * \text{G} + 2.55 * \text{S} + 2.26 * \text{F} - 2.15) = \tanh(-1.367) = -0.878$$

$$N4 = \tanh(0.61 * \text{G} - 2.02 * \text{S} + 2.3 * \text{F} - 1.71) = \tanh(0.903) = 0.718$$

$N5 = \tanh(1 * G - 1.48 * S - 3.07 * F + 0.54) = \tanh(-1.612) = -0.923$

$N6 = \tanh(2.51 * G + 0.47 * S + 2.03 * F - 0.76) = \tanh(-0.024) = -0.024$

$N7 = \tanh(-1.91 * \mathrm{G} + 0.19 * \mathrm{S} - 2.74 * \mathrm{F}) = \tanh(-1.216) = -0.838$

$N8 = \tanh(2.16 * G + 1.25 * S - 3.19 * F + 1.17) = \tanh(-2.629) = -0.990$

$N9 = \tanh(-0.9 * \mathrm{G} + 4.33 * \mathrm{S} + 1.61 * \mathrm{F} + 3.32) = \tanh(2.975) = 0.995$

$N10 = \tanh(-0.44 * \mathrm{G} + 2.32 * \mathrm{S} - 3.17 * \mathrm{F} - 1.22) = \tanh(-4.730) = -1.000$

$N11 = \tanh(-2.36 * \mathrm{G} - 2.13 * \mathrm{S} + 1.01 * \mathrm{F} - 2.62) = \tanh(-0.163) = -0.161$

$N12 = \tanh(1.22 * \mathrm{G} - 2.17 * \mathrm{S} + 1.68 * \mathrm{F} + 3.55) = \tanh(5.545) = 1.000$

By substituting the N-values in the equation the value of MDD can be computed but since the input values were first transformed by the min max normalization the output from the equation was also a normalized value.

$$\begin{aligned} MDD = {} & (-0.87 * -1.000) + (0.94 * -0.121) + (- 1.19 * -0.878) \\ & + (- 0.80 * 0.718) + (1.24 * -0.923) + (- 0.93 * -0.024) \\ & + (-0.70 * -0.838) + (-1.68 * -0.990) + (-1.05 * 0.995) + (0.78 \\ & * -1.000) + (1.16 * -0.161) + (0.49 * 1.000) - 0.63 \end{aligned}$$

$$\mathrm{MDD} = -0.972$$

The value from the equation were transformed in to the original value using Table 4-12.

Table 4-12 Denormalizing Values for MDD Output

Ymin (newmin)	Gain $(\frac{newmax-newmin}{max-min})$	y1_step1.yoffxet (min)
-1	2.062	1.57

$$MDD(predicted) = \frac{MDD - newmin}{(\frac{newmax - newmin}{max - min})} + min$$

$$MDD(predicted) = \frac{-0.972 - (-1)}{2.062} + 1.57$$

$$MDD(predicted) = 1.58\text{g/cm3}$$

$$MDD(actual) - MDD(predicted) = 1.62g/cm3 - 1.58g/cm3 = 0.04g/cm3$$

$$\%Variation = \frac{0.04}{1.62} \times 100 = 2.47\%$$

The variation between the predicted and the actual MDD value is 0.04g/cm^3 which is a 2.47% variation indicating a very small difference between the actual and predicted value.

4.7.2 Model Equation for OMC of Coarse Grained soil

Following the same procedure as in the maximum dry density the model equation for prediction of optimum moisture content for the coarse grained soil was developed as follows.

Table 4-13 Weight ad Bias of ANN Model coarseomc1

Weight IW for coarsemdd1 (16x3)			Weight (LW') for coarse mdd1 (1x16)	Bias b1 for coarsemdd1 (16x1)	Bias b2 for coarse mdd1 (1x1)	Input Variables (X) (3x1)
-0.61	-1.51	3.30	0.60	3.25	0.73	% G
0.82	-3.38	-1.24	1.84	-3.43		% S
-0.08	1.99	-2.82	0.04	-3.17		% F
0.23	-2.80	2.30	1.10	-3.29		
1.94	-3.12	0.36	-1.99	-2.36		
-1.82	2.12	1.31	-1.02	1.89		
0.74	-3.25	1.56	0.12	-1.06		
2.69	0.78	-2.26	0.96	0.40		
-1.80	-2.05	-1.80	0.57	-0.61		
1.02	0.63	3.99	1.23	0.39		
-3.10	-0.13	1.95	0.41	-1.01		
1.04	-3.32	-1.91	-1.27	2.28		
-2.33	-1.00	-2.20	0.11	-2.72		
1.56	2.04	2.74	1.46	2.55		
-2.36	-0.08	2.95	-1.30	-2.90		
-1.19	-3.47	2.31	0.92	-3.42		

$$\begin{aligned} OMC = {} & 0.60 * N1 + 1.84 * N2 + 0.04 * N3 + 1.10 * N4 - 1.99 * N5 - 1.02 * N6 \\ & + 0.12 * N7 + 0.96 * N8 + 0.57 * N9 + 1.23 * N10 + 0.41 * N11 \\ & - 1.27 * N12 + 0.11 * N13 + 1.46 * N14 - 1.30 * N15 + 0.92 * N16 \\ & + 0.73 \end{aligned}$$

$$N1 = \tanh(-0.61 * \mathrm{G} - 1.51 * \mathrm{S} + 3.30 * \mathrm{F} + 3.25)$$

$$N2 = \tanh(0.82 * \mathrm{G} - 3.38 * \mathrm{S} - 1.24 * \mathrm{F} - 3.43)$$

$$N3 = \tanh(-0.08 * \mathrm{G} + 1.99 * \mathrm{S} - 2.82 * \mathrm{F} - 3.17)$$

$$N4 = \tanh(0.23 * \mathrm{G} - 2.80 * \mathrm{S} + 2.30 * \mathrm{F} - 3.29)$$

$$N5 = \tanh(\ 1.94 * G - 3.12 * S + 0.36 * F - 2.36)$$

$$N6 = \tanh(-1.82 * G + 2.12 * S + 1.31 * F + 1.89)$$

$$N7 = \tanh(0.74 * \mathrm{G} - 3.25 * \mathrm{S} + 1.56 * \mathrm{F} - 1.06)$$

$$N8 = \tanh(2.69 * G + 0.78 * S - 2.26 * F + 0.40)$$

$$N9 = \tanh(-1.80 * \mathrm{G} - 2.05 * \mathrm{S} - 1.80 * \mathrm{F} - 0.61)$$

$$N10 = \tanh(1.02 * \mathrm{G} + 0.63 * \mathrm{S} + 3.99 * \mathrm{F} + 0.39)$$

$$N11 = \tanh(-3.10 * \mathrm{G} - 0.13 * \mathrm{S} + 1.95 * \mathrm{F} - 1.01)$$

$$N12 = \tanh(1.04 * \mathrm{G} - 3.32 * \mathrm{S} - 1.91 * \mathrm{F} + 2.28)$$

$$N13 = \tanh(-2.33 * \mathrm{G} - 1.00 * \mathrm{S} - 2.20 * \mathrm{F} - 2.72)$$

$$N14 = \tanh(1.56 * \mathrm{G} + 2.04 * \mathrm{S} + 2.74 * \mathrm{F} + 2.55)$$

$$N15 = \tanh(-2.36 * \mathrm{G} - 0.08 * \mathrm{S} + 2.95 * \mathrm{F} - 2.90)$$

$$N16 = \tanh(-1.19 * \mathrm{G} - 3.47 * \mathrm{S} + 2.31 * \mathrm{F} - 3.42)$$

4.7.2.1 Sample Calculation of OMC

The sample calculation was done using one soil sample from the secondary data with the following values.

G = 35.2   S = 19.25   F = 45.56   OMC = 21.00

The values used in normalizing the input variables are listed on Table 4-14.

Table 4-14 Normalizing Values for OMC Inputs

x1_step1.xoffset (min)	gain $\left(\frac{\text{newmax-newmin}}{\text{max-min}}\right)$	ymin (newmin)
0	0.020	-1
0.91	0.030	
0.22	0.040	

The normalized input values are;

G = -0.288 S = -0.445 F = 0.8216

Using the developed equation, the optimum moisture content of the soil sample can be calculated as follows.

$$OMC = 0.60 * N1 + 1.84 * N2 + 0.04 * N3 + 1.10 * N4 - 1.99 * N5 - 1.02 * N6 + 0.12 * N7 + 0.96 * N8 + 0.57 * N9 + 1.23 * N10 + 0.41 * N11 - 1.27 * N12 + 0.11 * N13 + 1.46 * N14 - 1.30 * N15 + 0.92 * N16 + 0.73$$

$$N1 = \tanh(-0.61 * \mathrm{G} - 1.51 * \mathrm{S} + 3.30 * \mathrm{F} + 3.25) = \tanh(6.809) = 1.000$$

$$N2 = \tanh(0.82 * \mathrm{G} - 3.38 * \mathrm{S} - 1.24 * \mathrm{F} - 3.43) = \tanh(-3.181) = -0.997$$

$$N3 = \tanh(-0.08 * \mathrm{G} + 1.99 * \mathrm{S} - 2.82 * \mathrm{F} - 3.17) = \tanh(-6.349) = -1.000$$

$$N4 = \tanh(0.23 * \mathrm{G} - 2.80 * \mathrm{S} + 2.30 * \mathrm{F} - 3.29) = \tanh(-0.221) = -0.217$$

$$N5 = \tanh(1.94 * G - 3.12 * S + 0.36 * F - 2.36) = \tanh(-1.234) = -0.844$$

$$N6 = \tanh(-1.82 * G + 2.12 * S + 1.31 * F + 1.89) = \tanh(2.547) = 0.988$$

$$N7 = \tanh(0.74 * \mathrm{G} - 3.25 * \mathrm{S} + 1.56 * \mathrm{F} - 1.06) = \tanh(1.455) = 0.897$$

$$N8 = \tanh(2.69 * G + 0.78 * S - 2.26 * F + 0.40) = \tanh(-2.579) = -0.989$$

$$N9 = \tanh(-1.80 * \mathrm{G} - 2.05 * \mathrm{S} - 1.80 * \mathrm{F} - 0.61) = \tanh(-0.658) = -0.577$$

$$N10 = \tanh(1.02 * \mathrm{G} + 0.63 * \mathrm{S} + 3.99 * \mathrm{F} + 0.39) = \tanh(3.094) = 0.996$$

$$N11 = \tanh(-3.10 * \mathrm{G} - 0.13 * \mathrm{S} + 1.95 * \mathrm{F} - 1.01) = \tanh(1.543) = 0.913$$

$$N12 = \tanh(1.04 * \mathrm{G} - 3.32 * \mathrm{S} - 1.91 * \mathrm{F} + 2.28) = \tanh(1.889) = 0.955$$

$$N13 = \tanh(-2.33 * \mathrm{G} - 1.00 * \mathrm{S} - 2.20 * \mathrm{F} - 2.72) = \tanh(-3.412) = -0.998$$

$$N14 = \tanh(1.56 * \mathrm{G} + 2.04 * \mathrm{S} + 2.74 * \mathrm{F} + 2.55) = \tanh(3.444) = 0.998$$

$$N15 = \tanh(-2.36 * \mathrm{G} - 0.08 * \mathrm{S} + 2.95 * \mathrm{F} - 2.90) = \tanh(0.239) = 0.234$$

$$N16 = \tanh(-1.19 * \mathrm{G} - 3.47 * \mathrm{S} + 2.31 * \mathrm{F} - 3.42) = \tanh(0.365) = 0.349$$

By substituting the N-values in the equation the OMC value was computed.

$$\begin{aligned} OMC \ = {} & (0.60 * 1.000) + (1.84 * -0.997) + (0.04 * -1.000) + (1.10 * -0.217) \\ & + (-1.99 * -0.844) + (-1.02 * 0.988) + (0.12 * 0.897) \\ & + (0.96 * -0.989) + (0.57 * -0.577) + (1.23 * 0.996) \\ & + (0.41 * N11) + (-1.27 * 0.955) + (0.11 * -0.998) \\ & + (1.46 * 0.998) + (-1.30 * 0.234) + (0.92 * 0.349) + 0.73 \end{aligned}$$

$$\mathrm{OMC} = 0.466$$

Denormalizing the output value using Table 4-15

Table 4-15 Denormalizing Values for MDD Output

Ymin (newmin)	Gain $(\frac{newmax-newmin}{max-min})$	y1_step1.yoffxet (min)
-1	0.093	6

$$OMC(predicted) = \frac{OMC - newmin}{(\frac{newmax - newmin}{max - min})} + min$$

$$OMC(predicted) = \frac{0.466 - (-1)}{0.093} + 6$$

$$OMC(predicted) = 21.76\,\%$$

$$OMC(actual) - OMC(predicted) = 21\,\% - 21.76\,\% = -0.76$$

$$\%Variation = \frac{0.76}{21.76} \times 100 = 3.49\%$$

The variation between the predicted and the actual OMC value is 0.76 % moisture content which is a 3.49% variation.

4.7.3 Model Equation for MDD of Fine Grained soil

Following the same procedure, the model equation for prediction of maximum dry density for the fine grained soil was developed as follows.

Table 4-16 Weight ad Bias of ANN Model finemdd2

Weight (IW) for finemdd2 (15x2)		Weight (LW') for finemdd2 (1x15)	Bias (b1) for finemdd2 (15x1)	Bias (b2) for finemdd2 (1x1)	Input Variables (X) (2x1)
-0.76	-5.42	0.018	5.37	-0.25	PI
0.29	5.43	-0.015	-4.63		% F
-2.05	5.08	-0.064	3.72		
4.37	-3.23	-0.090	-3.07		
4.13	3.48	0.008	-2.28		
-3.75	3.89	-0.061	1.56		
-5.26	0.95	0.144	0.84		
-5.31	-1.12	-0.143	0.00		
2.79	-4.45	0.110	0.81		
5.03	1.85	-0.783	1.63		
4.80	2.89	0.666	1.98		
1.74	5.03	-0.110	3.25		
1.26	-5.36	-0.109	3.75		
2.21	-4.95	0.024	4.65		
-3.88	-3.78	-0.223	-5.43		

$$
\begin{aligned}
MDD = {} & 0.018 * N1 - 0.015 * N2 - 0.064 * N3 - 0.090 * N4 + 0.008 * N5 \\
& - 0.061 * N6 + 0.144 * N7 - 0.143 * N8 + 0.110 * N9 - 0.783 * N10 \\
& + 0.666 * N11 - 0.110 * N12 - 0.109 * N13 + 0.024 * N14 - 0.223 \\
& * N15 - 0.25
\end{aligned}
$$

$$N1 = \tanh(-0.76 * \mathrm{F} - 5.42 * \mathrm{PI} + 5.37)$$

$$N2 = \tanh(0.29 * \mathrm{F} + 5.43 * \mathrm{PI} - 4.63)$$

$$N3 = \tanh(-2.05 * \mathrm{F} + 5.08 * \mathrm{PI} + 3.72)$$

$$N4 = \tanh(4.37 * \mathrm{F} - 3.23 * \mathrm{PI} - 3.07)$$

$$N5 = \tanh(4.13 * \mathrm{F} + 3.48 * \mathrm{PI} - 2.28)$$

$N6 = \tanh(-3.75 * \mathrm{F} + 3.89 * \mathrm{PI} + 1.56)$

$N7 = \tanh(-5.26 * \mathrm{F} + 0.95 * \mathrm{PI} + 0.84)$

$N8 = \tanh(-5.31 * \mathrm{F} - 1.12 * \mathrm{PI} + 0.00)$

$N9 = \tanh(2.79 * \mathrm{F} - 4.45 * \mathrm{PI} + 0.81)$

$N10 = \tanh(5.03 * \mathrm{F} + 1.85 * \mathrm{PI} + 1.63)$

$N11 = \tanh(4.80 * \mathrm{F} + 2.89 * \mathrm{PI} + 1.98)$

$N12 = \tanh(1.74 * \mathrm{F} + 5.03 * \mathrm{PI} + 3.25)$

$N13 = \tanh(1.26 * \mathrm{F} - 5.36 * \mathrm{PI} + 3.75)$

$N14 = \tanh(2.21 * \mathrm{F} - 4.95 * \mathrm{PI} + 4.65)$

$N15 = \tanh(-3.88 * \mathrm{F} - 3.78 * \mathrm{PI} - 5.43)$

4.7.3.1 Sample Calculation of MDD

The sample calculation was done using one soil sample from the secondary data with the following values.

F = 76.88 PI = 20.00 MDD = 1.54

The values used in normalizing the input variables are listed on Table 4-17.

Table 4-17 Normalizing Values for MDD Inputs

x1_step1.xoffset (min)	gain $\left(\frac{\text{newmax-newmin}}{\text{max-min}}\right)$	ymin (newmin)
50.65	0.0414	-1
6	0.0417	

The normalized input values are;

F= 0.085 PI = -0.417

Using the developed equation, the maximum dry density of the soil sample can be calculated as follows.

$$MDD = 0.018 * N1 - 0.015 * N2 - 0.064 * N3 - 0.090 * N4 + 0.008 * N5 - 0.061 * N6 + 0.144 * N7 - 0.143 * N8 + 0.110 * N9 - 0.783 * N10 + 0.666 * N11 - 0.110 * N12 - 0.109 * N13 + 0.024 * N14 - 0.223 * N15 - 0.25$$

$$N1 = \tanh(-0.76 * \mathrm{F} - 5.42 * \mathrm{PI} + 5.37) = \tanh(7.563) = 1.000$$

$$N2 = \tanh(0.29 * \mathrm{F} + 5.43 * \mathrm{PI} - 4.63) = \tanh(-6.867) = -1.000$$

$$N3 = \tanh(-2.05 * \mathrm{F} + 5.08 * \mathrm{PI} + 3.72) = \tanh(1.430) = 0.892$$

$$N4 = \tanh(4.37 * \mathrm{F} - 3.23 * \mathrm{PI} - 3.07) = \tanh(-1.354) = -0.875$$

$$N5 = \tanh(4.13 * \mathrm{F} + 3.48 * \mathrm{PI} - 2.28) = \tanh(-3.379) = -0.998$$

$$N6 = \tanh(-3.75 * \mathrm{F} + 3.89 * \mathrm{PI} + 1.56) = \tanh(-0.379) = -0.362$$

$$N7 = \tanh(-5.26 * \mathrm{F} + 0.95 * \mathrm{PI} + 0.84) = \tanh(-0.002) = -0.002$$

$$N8 = \tanh(-5.31 * \mathrm{F} - 1.12 * \mathrm{PI} + 0.00) = \tanh(0.016) = 0.016$$

$$N9 = \tanh(2.79 * \mathrm{F} - 4.45 * \mathrm{PI} + 0.81) = \tanh(2.901) = 0.994$$

$$N10 = \tanh(5.03 * \mathrm{F} + 1.85 * \mathrm{PI} + 1.63) = \tanh(1.286) = 0.858$$

$$N11 = \tanh(4.80 * \mathrm{F} + 2.89 * \mathrm{PI} + 1.98) = \tanh(1.183) = 0.829$$

$$N12 = \tanh(1.74 * \mathrm{F} + 5.03 * \mathrm{PI} + 3.25) = \tanh(1.302) = 0.862$$

$$N13 = \tanh(1.26 * \mathrm{F} - 5.36 * \mathrm{PI} + 3.75) = \tanh(6.090) = 1.000$$

$$N14 = \tanh(2.21 * \mathrm{F} - 4.95 * \mathrm{PI} + 4.65) = \tanh(6.900) = 1.000$$

$$N15 = \tanh(-3.88 * \mathrm{F} - 3.78 * \mathrm{PI} - 5.43) = \tanh(-4.185) = -1.000$$

By substituting the N-values in the equation the MDD value is computed.

$$
\begin{aligned}
MDD \; = {} & (0.018 * 1.000) + (-\,0.015 * -1.000) + (-0.064 * 0.892) \\
& + (-\,0.090 * -0.875) + (\,0.008 * -0.998) + (-\,0.061 * -0.362) \\
& + (0.144 * -0.002) + (-0.143 * 0.016) + (0.110 * 0.994) \\
& + (-0.783 * 0.858) + (0.666 * 0.829) + (-\,0.110 * 0.862) \\
& + (-0.109 * 1.000) + (0.024 * 1.000\,) + (-0.223 * -1.000) - 0.25
\end{aligned}
$$

$$\mathrm{MDD} = \; -0.152$$

Denormalizing the output value using Table 4-18

Table 4-18 Denormalizing Values for MDD Output

Ymin (newmin)	Gain ($\frac{newmax-newmin}{max-min}$)	y1_step1.yoffxet (min)
-1	2.632	1.22

$$MDD(predicted) = \frac{MDD - newmin}{\left(\frac{newmax - newmin}{max - min}\right)} + min$$

$$MDD(predicted) = \frac{-0.152 - (-1)}{2.632} + 1.22$$

$$MD(predicted) = 1.542\ g/cm3$$

$$MDD(actual) - MDD(predicted) = 1.54 - 1.542 = -0.002\ g/cm3$$

$$\%Variation = \frac{0.002}{1.542} \times 100 = 0.13\ \%$$

The variation between the predicted and the actual MDD value is -0.002 g/cm3 which is a 0.13 % variation.

4.7.4 Model Equation for OMC of Fine Grained soil

Following the same procedure as in the maximum dry density the model equation for prediction of optimum moisture content for the fine grained soil was developed as follows.

Table 4-19 Weight ad Bias of ANN Model fineomc6

Weight (IW) for fineomc6 (8x2)		Weight (LW') for fineomc6 (1x8)	Bias (b1) for fineomc6 (8x1)	Bias (b2) for fineomc6 (1x1)	Input Variables (X) (2x1)
-2.39	2.49	-0.78	3.57	0.59	PI
-3.44	-6.31	0.17	1.15		% F
-1.52	-1.79	-0.46	0.33		
1.04	0.77	0.28	-1.96		
-5.17	3.04	0.06	-0.51		
1.52	2.70	-0.62	1.94		
-3.48	-6.01	-0.49	-4.14		
-0.23	4.07	-0.41	-3.62		

$$OMC = -0.78 * N1 + 0.17 * N2 - 0.46 * N3 + 0.28 * N4 + 0.06 * N5 - 0.62 * N6 - 0.49 * N7 - 0.41 * N8 + 0.59$$

$$N1 = \tanh(-2.39 * \mathrm{F} + 2.49 * \mathrm{PI} + 3.57)$$

$$N2 = \tanh(-3.44 * \mathrm{F} - 6.31 * \mathrm{PI} + 1.15)$$

$$N3 = \tanh(-1.52 * \mathrm{F} - 1.79 * \mathrm{PI} + 0.33)$$

$$N4 = \tanh(1.04 * \mathrm{F} + 0.77 * \mathrm{PI} - 1.96)$$

$$N5 = \tanh(-5.17 * \mathrm{F} + 3.04 * \mathrm{PI} - 0.51)$$

$$N6 = \tanh(1.52 * \mathrm{F} + 2.70 * \mathrm{PI} + 1.94)$$

$$N7 = \tanh(-3.48 * \mathrm{F} + -6.01 * \mathrm{PI} - 4.14)$$

$$N8 = \tanh(-0.23 * \mathrm{F} + 4.07 * \mathrm{PI} - 3.62)$$

4.7.4.1 Sample Calculation of OMC

The sample calculation was done using one soil sample from the secondary data with the following values.

F = 76.88 PI = 20.00 OMC = 21.4

The values used in normalizing the input variables are listed on Table 4-20.

Table 4-20 Normalizing Values for MDD Inputs

x1_step1.xoffset (min)	gain $(\frac{\text{newmax-newmin}}{\text{max-min}})$	ymin (newmin)
50.65	0.0414	-1
6	0.0417	

The normalized input values are;

F= 0.085   PI = -0.417

Using the developed equation, the optimum moisture content of the soil sample can be calculated as follows.

$$OMC = -0.78 * N1 + 0.17 * N2 - 0.46 * N3 + 0.28 * N4 + 0.06 * N5 - 0.62 * N6 - 0.49 * N7 - 0.41 * N8 + 0.59$$

$$N1 = \tanh(-2.39 * \mathrm{F} + 2.49 * \mathrm{PI} + 3.57) = \tanh(2.330) = 0.981$$

$$N2 = \tanh(-3.44 * \mathrm{F} - 6.31 * \mathrm{PI} + 1.15) = \tanh(3.487) = 0.998$$

$$N3 = \tanh(-1.52 * \mathrm{F} - 1.79 * \mathrm{PI} + 0.33) = \tanh(0.947) = 0.738$$

$$N4 = \tanh(1.04 * \mathrm{F} + 0.77 * \mathrm{PI} - 1.96) = \tanh(-2.193) = -0.975$$

$$N5 = \tanh(-5.17 * \mathrm{F} + 3.04 * \mathrm{PI} - 0.51) = \tanh(-2.215) = -0.976$$

$$N6 = \tanh(1.52 * \mathrm{F} + 2.70 * \mathrm{PI} + 1.94) = \tanh(0.944) = 0.737$$

$$N7 = \tanh(-3.48 * \mathrm{F} + -6.01 * \mathrm{PI} - 4.14) = \tanh(-1.932) = -0.959$$

$$N8 = \tanh(-0.23 * \mathrm{F} + 4.07 * \mathrm{PI} - 3.62) = \tanh(-5.335) = -1.000$$

By substituting the N-values in the equation the OMC value is computed.

$$OMC = (-0.78 * 0.981) + (0.17 * 0.998) + (-0.46 * 0.738) + (0.28 * -0.975) + (0.06 * -0.976) + (-0.62 * 0.737) + (-0.49 * -0.959) + (-0.41 * -1.000) + 0.59$$

$$\mathrm{OMC} = -0.254$$

Denormalizing the output value using Table

Table 4-21 Denormalizing Values for MDD Output

Ymin (newmin)	Gain $(\frac{newmax-newmin}{max-min})$	y1_step1.yoffxet (min)
-1	0.072	11.2

$$OMC(predicted) = \frac{OMC - newmin}{(\frac{newmax - newmin}{max - min})} + min$$

$$OMC(predicted) = \frac{-0.254 - (-1)}{0.072} + 11.2$$

$$OMC(predicted) = 21.56\ \%$$

$$OMC(actual) - OMC(predicted) = 21.4 - 21.56 = -0.16\ \%$$

$$\%Variation = \frac{0.16}{21.56} \times 100 = 0.74\ \%$$

The variation between the predicted and the actual MDD value is -0.16% moisture content which is a 0.74 % variation.

From the results it can be concluded that the developed equations, since they showed very small variation with that of the actual values, can be used as another empirical form of solution to implement the model without any software aid.

4.8 Comparison of ANN Models with Regression Analysis

Previously regression models were developed to predict the value of compaction parameters maximum dry density and optimum moisture content from Atterberg limits for the fine grained soil of Addis Ababa by [35]. From the research two correlation equations were derived for both maximum dry density and optimum moisture content.

MDD = 0.916PL - 0.030PI - 0.875 4.4

OMC = -0.18PL - 0.027PI + 21.82 4.5

Another study was also conducted to estimate compaction characteristics of fine grained soil of Addis Ababa from Atterberg limits by [43]. The following two equations were proposed to determine the value of maximum dry density and optimum moisture content using Atterberg limits.

$$MDD = 19.88 - 0.011LL - 0.17PL \quad (4.6)$$

$$OMC = 0.61LL + 0.12PL - 0.59PI + 5.38 \quad (4.7)$$

The regression models were developed using a standard compaction method while the ANN models were developed using a modified compaction method. The comparison was done using available regression models which were done on the same area with same type of soil that is Addis Ababa's fine grained soil. considering the difference of mode of compaction used, a variation of prediction is generally expected from the regression and ANN models.

The actual and predicted value of maximum dry density and optimum moisture content using the two regression analysis and the ANN model on the 13 fine grained soil samples from the primary data is presented on Table 4-22, 4-23 and 4-24.

Table 4-22 Actual vs Predicted value using Regression 1

Regression by [35]									
S.NO	Sample Name	Actual MDD (g/cm3)	Predicted MDD (g/cm3)	Error	Variation (%)	Actual 0MC (%)	Predicted OMC (%)	Error	Variation (%)
1	Sample 1	1.47	1.36	0.11	7.71	20.20	33.35	13.15	39.43
2	Sample 2	1.56	1.46	0.10	6.27	25.79	30.04	4.25	14.14
3	Sample 3	1.49	1.38	0.11	7.54	21.00	32.77	11.77	35.91
4	Sample 4	1.55	1.66	0.11	6.44	23.66	16.64	7.02	29.67
5	Sample 5	1.67	1.52	0.15	8.82	22.01	24.13	2.12	8.77
6	Sample 6	1.49	1.32	0.17	11.32	19.30	34.66	15.36	44.32
7	Sample 7	1.41	1.39	0.02	1.28	21.82	31.22	9.40	43.08
8	Sample 8	1.65	1.40	0.25	14.95	16.77	31.93	15.16	47.47
9	Sample 9	1.52	1.35	0.17	10.90	23.26	34.69	11.43	32.94
10	Sample 10	1.54	1.34	0.20	12.71	18.60	33.48	14.88	44.45
11	Sample 11	1.48	1.43	0.05	3.14	20.63	30.72	10.09	48.93
12	Sample 13	1.55	1.15	0.40	25.77	28.04	44.48	16.44	36.95
13	Sample 14	1.66	1.52	0.14	8.50	23.12	27.02	3.90	14.43

Table 4-23 Actual vs Predicted value using Regression 2

Regression by [43]									
S.NO	Sample Name	Actual MDD (g/cm3)	Predicted MDD (g/cm3)	Error	Variation (%)	Actual 0MC (%)	Predicted OMC (%)	Error	Variation (%)
1	Sample 1	1.47	1.27	0.20	13.88	20.20	33.84	13.64	40.31
2	Sample 2	1.56	1.35	0.21	13.32	25.79	30.66	4.87	15.89
3	Sample 3	1.49	1.28	0.21	13.94	21.00	33.25	12.25	36.85
4	Sample 4	1.55	1.58	0.03	1.99	23.66	20.90	2.76	11.64
5	Sample 5	1.67	1.44	0.23	13.75	22.01	26.69	4.68	17.55
6	Sample 6	1.49	1.24	0.25	17.11	19.30	35.02	15.72	44.89
7	Sample 7	1.41	1.30	0.11	7.47	21.82	32.23	10.41	47.73
8	Sample 8	1.65	1.30	0.35	20.99	16.77	32.46	15.69	48.34
9	Sample 9	1.52	1.25	0.27	17.64	23.26	34.59	11.33	32.75
10	Sample 10	1.54	1.26	0.28	18.29	18.60	34.08	15.48	45.42
11	Sample 11	1.48	1.33	0.15	10.08	20.63	31.41	10.78	52.26
12	Sample 12	1.55	1.05	0.50	32.09	28.04	42.54	14.50	34.09
13	Sample 13	1.66	1.41	0.25	15.03	23.12	28.29	5.17	18.28

Table 4-24 Actual vs Predicted value using ANN model

ANN Model of Fine Grained soil									
S.NO	Sample Name	Actual MDD (g/cm3)	Predicted MDD (g/cm3)	Error	Variation (%)	Actual OMC (%)	Predicted OMC (%)	Error	Variation (%)
1	Sample 1	1.47	1.57	0.10	6.19	20.2	21.83	1.63	7.46
2	Sample 2	1.56	1.61	0.05	3.26	25.79	31.00	5.21	16.81
3	Sample 3	1.49	1.58	0.09	5.72	21	21.24	0.24	1.14
4	Sample 4	1.55	1.52	0.03	2.12	23.66	23.91	0.25	1.03
5	Sample 5	1.67	1.51	0.16	9.83	22.01	25.85	3.84	14.87
6	Sample 6	1.49	1.61	0.12	7.62	19.3	22.08	2.78	12.60
7	Sample 7	1.41	1.54	0.13	8.44	21.82	22.69	0.87	3.84
8	Sample 8	1.65	1.59	0.06	3.78	16.77	19.57	2.80	14.30
9	Sample 9	1.52	1.57	0.05	3.42	23.26	21.53	1.73	7.42
10	Sample 10	1.54	1.57	0.03	1.71	18.6	22.39	3.79	16.91
11	Sample 11	1.48	1.54	0.06	3.89	20.6	21.61	1.01	4.66
12	Sample 13	1.55	1.55	0.00	0.29	28.04	27.91	0.13	0.46
13	Sample 14	1.66	1.60	0.06	3.75	23.12	21.86	1.26	5.45

Based on the predicted values of maximum dry density and optimum moisture content the performance of the two regression equations was compared with the current developed ANN prediction model and is summarized on Table 4-25.

Table 4-25 Performance Comparison of Regression and ANN Model

	MDD		OMC	
	Error Range (g/cm3)	Variation Range (%)	Error Range (%)	Variation Range (%)
Regression by [35]	0.02 to 0.40	1.28 to 25.77	2.12 to 16.44	8.77 to 47.47
Regression by [42]	0.03 to 0.50	1.99 to 32.09	2.76 to 15.72	11.64 to 48.34
ANN model	0.00 to 0.16	0.29 to 9.83	0.13 to 5.21	0.46 to 16.91

From Table 4-25 it can be seen that ANN model prediction performed better than the regression equations on both maximum dry density and optimum moisture content predictions. But the difference in the mode of compaction method used that is standard compaction for regression model development and modified compaction method for the ANN model development have its own significant contribution for the variation of error seen between the regression and ANN models result.

All the results discussed in this chapter indicates that artificial neural network is a convenient computational tool to predict the compaction characteristics of soil from soil index properties and have a better prediction ability than regression analysis.

CHAPTER 5 CONCLUSION AND RECOMMENDATION

5.1 Conclusion

In this research, ANN models are developed to predict the value of compaction characteristics, maximum dry density and optimum moisture content, from soil index properties for coarse and fine grained soils separately. Percent of grain size distribution was used as input parameter for the coarse grained soils while plasticity index along with the percent fine were used as input variables for the fine grained soils. The models were validated by comparing with experimental soil laboratory test results and evaluated using statistical values. The models showed a good performance with a determination coefficient value of R=0.92 and R=0.81 for the maximum dry density and optimum moisture content respectively. Equations for the ANN models were derived. The models were also compared with previously formulated regression models done in Addis Ababa. Based on the results, it is concluded that the developed ANN models can be used to predict the values of compaction characteristics from soil index properties for both coarse and fine grained soils of Addis Ababa.

5.2 Recommendation

From the research, the following points are recommended.

i To improve model performance, increase the number of data points and use high-quality data because the performance of ANN models mainly depends on the quality and the amount of data used to train the models.

ii Incorporating other soil properties that can affect the compaction characteristics of soil will improve the prediction models.

iii Even though the ANN models can give a good prediction value of compaction parameters executing the actual soil laboratory test is recommended when possible.

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APPENDIX A: DETAILS OF SECONDARY DATA

Percent of Grain Size Distribution Property			Atterberg Limits			Modified Proctor	
%Gravel	%Sand	%Fine	LL	PL	PI	MDD g/cm3	OMC%
50.71	11.09	38.20	59.00	36.12	22.88	1.58	20.60
10.29	19.51	70.20	60.00	31.11	28.89	1.61	21.40
1.29	9.52	89.19	64.00	36.37	27.63	1.60	15.40
3.45	11.91	84.64	68.00	35.51	32.49	1.47	26.00
6.29	13.35	80.35	61.00	35.95	25.05	1.65	19.60
61.21	16.36	22.42	47.00	32.52	14.48	1.65	17.80
11.81	5.28	82.91	62.00	36.92	25.08	1.45	22.80
24.51	24.11	51.38	51.00	33.24	17.76	1.54	17.80
0.94	16.53	82.53	63.00	30.58	32.42	1.59	19.40
52.83	20.13	27.05	44.00	31.09	12.91	1.71	19.00
7.78	14.68	77.55	55.00	34.39	20.61	1.53	25.00
4.57	10.72	84.70	67.00	38.86	28.14	1.57	23.60
48.59	16.65	34.76	50.00	29.90	20.10	1.67	15.80
71.09	12.95	15.96	48.00	31.89	16.11	1.84	16.20
6.85	10.17	82.99	67.00	35.09	31.91	1.55	19.80
36.69	12.66	50.65	70.00	35.57	34.43	1.62	22.00
37.44	24.48	38.09	46.00	29.75	16.25	1.67	12.20
19.29	10.58	70.13	54.00	34.97	19.03	1.57	21.40
11.53	16.77	71.70	54.00	33.12	20.88	1.52	28.00
29.73	9.02	61.24	56.00	35.23	20.77	1.59	20.60
51.80	11.54	36.66	41.00	25.33	15.67	1.76	15.00
5.01	16.72	78.27	60.00	36.24	23.76	1.59	21.00
60.56	8.97	30.47	48.00	27.63	20.37	1.85	14.00
4.36	18.77	76.88	52.00	32.00	20.00	1.54	21.40
15.57	28.18	56.24	48.00	33.05	14.95	1.66	20.60
0.98	12.41	86.61	71.00	39.41	31.59	1.57	17.60
22.85	11.25	65.91	65.00	40.08	24.92	1.59	18.40
5.01	15.73	79.26	63.00	31.92	31.08	1.52	19.60
8.33	14.20	77.47	57.00	35.17	21.83	1.48	24.20
27.56	12.08	60.35	49.00	29.06	19.94	1.67	21.00
18.48	12.69	68.83	52.00	32.59	19.41	1.56	23.80
17.76	14.29	67.96	60.00	31.68	28.32	1.60	22.00
2.29	29.90	67.81	60.00	40.35	19.65	1.37	26.60
61.09	7.53	31.37	44.00	29.67	14.33	1.67	19.00
13.10	16.51	70.39	65.00	35.40	29.60	1.62	18.60
43.28	8.38	48.34	61.00	31.33	29.67	1.73	16.60
0.79	6.00	93.20	54.00	32.41	21.59	1.53	22.60
1.66	11.76	86.57	66.00	34.77	31.23	1.63	19.00
12.37	6.14	81.48	60.00	36.54	23.46	1.54	22.00

%Gravel	%Sand	%Fine	LL	PL	PI	MDD g/cm3	OMC%
19.23	9.28	71.49	69.00	43.74	25.26	1.40	24.00
41.92	12.84	45.24	60.00	33.55	26.45	1.65	18.60
35.20	19.25	45.56	54.00	33.84	20.16	1.62	21.00
18.00	12.69	69.31	65.00	31.97	33.03	1.62	19.60
69.05	16.86	14.09	52.00	33.44	18.56	1.85	14.20
49.80	30.52	19.69	35.00	24.70	10.30	1.95	12.60
9.48	7.15	83.36	86.00	46.19	39.81	1.62	16.60
8.48	19.75	71.78	62.00	32.07	29.93	1.60	18.00
23.63	14.20	62.17	70.00	34.52	35.48	1.66	17.40
3.75	6.17	90.08	71.00	41.63	29.37	1.59	20.00
52.00	24.47	23.53	39.00	28.12	10.88	1.78	17.80
11.89	10.91	77.20	60.00	32.43	27.57	1.65	18.60
4.42	11.75	83.83	64.00	36.92	27.08	1.64	16.40
12.26	16.86	70.89	68.00	33.45	34.55	1.60	22.00
27.23	9.54	63.23	70.00	37.62	32.38	1.65	19.80
55.74	24.19	20.07	30.00	21.05	8.95	2.00	9.80
16.70	6.85	76.45	54.00	29.86	24.14	1.47	29.00
32.45	29.51	38.04	32.00	23.57	8.43	1.85	13.60
28.03	11.77	60.20	73.00	36.67	36.33	1.70	15.40
5.38	6.55	88.07	71.00	40.57	30.43	1.55	20.00
38.68	5.78	55.53	77.00	40.13	36.87	1.65	18.00
6.73	8.18	85.09	73.00	40.05	32.95	1.60	19.20
20.45	10.25	69.29	62.00	32.75	29.25	1.66	20.00
3.31	10.13	86.56	73.00	35.86	37.14	1.60	19.40
2.00	8.00	90.00	53.00	27.00	26.00	1.59	22.70
7.00	7.00	86.00	61.00	31.00	30.00	1.48	26.00
29.00	19.00	52.00	51.00	26.00	25.00	1.67	20.30
0.00	8.00	92.00	59.00	30.00	29.00	1.48	26.20
16.00	14.00	70.00	55.00	28.00	27.00	1.63	21.30
10.00	18.00	72.00	49.00	26.00	23.00	1.65	21.10
29.00	15.00	56.00	55.00	28.00	27.00	1.65	20.70
5.00	9.00	86.00	63.00	32.00	31.00	1.48	26.30
10.00	22.00	68.00	67.00	34.00	33.00	1.50	24.90
10.00	14.00	76.00	68.00	34.00	34.00	1.49	25.80
8.00	18.00	74.00	67.00	34.00	33.00	1.49	25.30
4.00	7.00	89.00	71.00	36.00	35.00	1.46	27.60
18.00	19.00	63.00	60.00	30.00	30.00	1.52	24.30
6.00	7.00	87.00	71.00	36.00	35.00	1.47	27.40
10.00	21.00	69.00	63.00	32.00	31.00	1.50	24.60
5.00	8.00	87.00	65.00	33.00	32.00	1.48	26.60
40.00	23.00	37.00	49.00	26.00	23.00	1.69	19.80
38.00	24.00	38.00	50.00	26.00	24.00	1.68	20.00
47.00	25.00	28.00	47.00	24.00	23.00	1.88	15.40

%Gravel	%Sand	%Fine	LL	PL	PI	MDD g/cm3	OMC%
1.00	8.00	91.00	71.00	36.00	35.00	1.46	27.80
18.00	16.00	66.00	50.00	26.00	24.00	1.65	21.00
50.00	22.00	28.00	47.00	24.00	23.00	1.88	15.20
46.00	22.00	32.00	51.00	26.00	25.00	1.87	15.70
2.00	6.00	92.00	71.00	36.00	35.00	1.46	27.70
1.00	3.00	96.00	73.00	37.00	36.00	1.46	28.00
2.00	7.00	91.00	63.00	32.00	31.00	1.47	27.10
12.00	15.00	73.00	71.00	36.00	35.00	1.49	25.50
17.00	19.00	64.00	59.00	30.00	29.00	1.52	24.20
36.00	31.00	33.00	43.00	22.00	21.00	1.86	15.90
16.00	26.00	58.00	53.00	27.00	26.00	1.65	20.80
0.00	7.00	93.00	75.00	32.00	43.00	1.50	26.40
7.00	38.00	55.00	59.00	37.00	22.00	1.72	11.20
0.00	6.00	94.00	74.00	36.00	38.00	1.48	28.60
21.00	36.00	43.00	51.00	36.00	15.00	1.77	14.60
36.00	37.70	26.30	35.00	18.00	17.00	1.79	14.40
0.00	18.00	82.00	82.00	42.00	40.00	1.50	27.80
6.00	24.00	70.00	69.00	35.00	34.00	1.50	29.20
0.00	14.00	86.00	62.00	37.00	25.00	1.50	25.20
2.00	21.00	77.00	74.00	44.00	30.00	1.50	25.00
0.00	6.00	94.00	83.00	44.00	39.00	1.50	29.20
0.00	11.00	89.00	87.00	45.00	42.00	1.50	26.10
31.00	47.60	21.40	38.00	28.00	10.00	1.80	10.00
0.00	22.00	78.00	56.00	34.00	22.00	1.69	17.80
9.00	17.00	74.00	65.00	34.00	31.00	1.71	19.50
0.00	12.00	88.00	79.00	40.00	39.00	1.54	29.40
0.00	22.00	78.00	49.00	34.00	15.00	1.76	19.60
0.00	15.00	85.00	64.00	35.00	29.00	1.63	18.40
4.00	34.00	62.00	61.00	32.00	29.00	1.57	28.00
0.00	13.00	87.00	73.00	35.00	38.00	1.51	33.60
0.00	17.00	83.00	51.00	34.00	17.00	1.73	23.00
0.00	16.00	84.00	68.00	40.00	28.00	1.72	22.00
0.00	10.00	90.00	74.00	37.00	37.00	1.50	28.60
7.00	17.00	76.00	77.00	38.00	39.00	1.53	29.60
0.00	6.00	94.00	59.00	34.00	25.00	1.50	30.80
0.00	11.00	89.00	75.00	39.00	36.00	1.60	27.00
0.00	8.00	92.00	44.00	25.00	19.00	1.50	31.80
0.00	11.00	89.00	71.00	36.00	35.00	1.50	26.50
0.00	11.00	89.00	73.00	42.00	31.00	1.60	24.50
0.00	7.00	93.00	59.00	33.00	26.00	1.50	30.60
0.00	7.60	92.40	67.00	34.00	33.00	1.40	24.50
8.00	23.70	68.30	38.00	31.00	7.00	1.80	17.80
0.00	4.00	96.00	72.00	37.00	35.00	1.60	25.70

%Gravel	%Sand	%Fine	LL	PL	PI	MDD g/cm3	OMC%
0.00	10.00	90.00	70.00	39.00	31.00	1.51	26.00
30.00	41.00	29.00	47.00	32.00	15.00	1.70	19.50
0.00	5.00	95.00	77.00	40.00	37.00	1.46	29.00
0.00	3.00	97.00	69.00	38.00	31.00	1.48	28.00
0.00	6.00	94.00	70.00	38.00	32.00	1.58	28.00
3.00	25.00	72.00	60.00	31.00	29.00	1.54	25.00
10.00	22.00	68.00	53.00	33.00	20.00	1.70	19.00
0.00	9.00	91.00	77.00	34.00	43.00	1.50	32.60
0.00	33.00	67.00	88.00	52.00	36.00	1.59	26.00
0.00	8.00	92.00	77.00	38.00	39.00	1.51	24.00
0.00	5.00	95.00	73.00	44.00	29.00	1.52	27.00
0.00	10.90	89.10	71.00	37.00	34.00	1.52	26.60
0.00	49.00	51.00	46.00	26.00	20.00	1.80	16.00
0.00	28.00	72.00	47.00	23.00	24.00	1.78	13.00
0.00	27.60	72.40	82.00	43.10	38.90	1.34	37.20
0.00	40.90	59.10	43.00	22.00	21.00	1.63	19.60
0.00	35.00	65.00	45.00	25.40	19.60	1.49	22.80
0.00	2.00	98.00	55.00	29.00	26.00	1.59	22.80
0.00	1.80	98.20	80.40	45.60	34.80	1.45	35.00
0.00	16.50	83.50	70.00	33.90	36.10	1.45	21.40
0.00	10.90	89.10	67.00	37.00	30.00	1.50	26.60
0.00	5.30	94.70	65.00	31.00	34.00	1.50	27.80
0.00	7.00	93.00	46.00	26.00	20.00	1.59	26.80
0.00	12.80	87.20	61.70	31.30	30.40	1.49	26.60
0.00	11.30	88.70	80.30	44.50	35.80	1.43	31.80
0.00	36.50	63.50	46.00	28.00	18.00	1.85	13.90
0.00	35.70	64.30	46.00	27.00	19.00	1.91	12.50
0.00	32.40	67.60	46.00	26.00	20.00	1.98	12.60
0.00	12.00	88.00	64.00	34.00	30.00	1.33	25.00
0.00	9.00	91.00	72.00	41.00	31.00	1.43	30.00
0.00	25.60	74.40	51.80	28.00	23.80	1.59	24.80
0.00	13.40	86.60	68.00	35.70	32.30	1.47	24.50
0.00	44.40	55.60	57.40	28.00	29.40	1.60	29.60
0.00	2.00	98.00	72.00	34.00	38.00	1.49	34.00
0.00	28.00	72.00	51.00	28.00	23.00	1.56	30.00
0.00	13.90	86.10	75.00	38.60	36.40	1.48	27.50
0.00	12.00	88.00	64.00	34.00	30.00	1.33	25.00
0.00	9.00	91.00	72.00	41.00	31.00	1.43	30.00
0.00	28.00	72.00	80.00	38.00	42.00	1.62	19.00
0.00	18.00	82.00	73.00	41.00	32.00	1.57	20.00
0.00	28.00	72.00	71.00	40.00	31.00	1.60	21.00
0.00	11.00	89.00	77.00	42.00	35.00	1.56	22.00
0.00	31.00	69.00	79.00	43.00	36.00	1.51	16.00

%Gravel	%Sand	%Fine	LL	PL	PI	MDD g/cm3	OMC%
0.00	11.00	89.00	81.00	40.00	41.00	1.53	23.00
0.00	13.00	87.00	86.00	44.00	42.00	1.43	22.00
0.00	9.00	91.00	94.00	43.00	51.00	1.52	27.00
0.00	25.00	75.00	71.00	38.00	33.00	1.50	28.00
0.00	8.00	92.00	93.00	45.00	48.00	1.51	25.00
0.00	64.00	36.00	51.00	31.00	20.00	1.75	20.00
0.00	30.00	70.00	65.00	42.00	23.00	1.64	17.00
0.00	11.00	89.00	81.00	34.00	47.00	1.58	16.00
0.00	48.00	52.00	53.00	34.00	19.00	1.59	20.00
0.00	40.00	60.00	75.00	46.00	29.00	1.52	21.00
0.00	14.00	86.00	71.00	39.00	32.00	1.58	13.00
0.00	24.00	76.00	73.00	42.00	31.00	1.56	23.00
0.00	46.00	54.00	86.00	50.00	36.00	1.22	36.00
0.00	37.00	63.00	55.00	27.00	28.00	1.65	19.00
0.00	11.00	89.00	88.00	43.00	45.00	1.49	27.00
0.00	6.00	94.00	97.00	45.00	52.00	1.50	25.00
0.00	8.00	92.00	87.00	44.00	43.00	1.53	21.00
0.00	7.00	93.00	79.00	48.00	31.00	1.69	15.00
0.00	13.00	87.00	81.00	36.00	45.00	1.46	33.00
0.00	9.00	91.00	83.00	38.00	45.00	1.52	21.00
0.00	17.00	83.00	70.00	40.00	30.00	1.57	19.00
0.00	26.00	74.00	74.00	39.00	35.00	1.55	22.00
0.00	18.00	82.00	72.00	39.00	33.00	1.54	24.00
0.00	18.00	82.00	79.00	40.00	39.00	1.54	18.00
0.00	20.00	80.00	66.00	34.00	32.00	1.56	22.00
0.00	20.00	80.00	68.00	37.00	31.00	1.68	16.00
0.00	32.00	68.00	63.00	36.00	27.00	1.67	15.00
0.00	46.00	54.00	53.00	34.00	19.00	1.64	22.00
0.00	40.00	60.00	59.00	33.00	26.00	1.57	20.00
0.00	40.00	60.00	58.00	38.00	20.00	1.53	19.00
0.00	50.00	50.00	58.00	30.00	28.00	1.86	15.00
0.00	54.00	46.00	56.00	30.00	26.00	1.82	15.00
0.00	62.00	38.00	46.00	28.00	18.00	1.66	21.00
0.00	67.00	33.00	52.00	27.00	25.00	1.62	24.00
6.00	22.00	72.00	52.00	29.00	23.00	1.67	17.00
2.00	7.00	91.00	62.00	34.00	28.00	1.52	24.00
11.00	50.00	39.00	39.00	30.00	9.00	1.65	21.00
1.00	46.00	53.00	39.00	30.00	9.00	1.62	23.00
82.00	8.00	10.00	32.00	22.00	10.00	1.98	11.00
23.00	16.00	61.00	53.00	33.00	20.00	1.52	25.00
1.00	9.00	90.00	64.00	27.00	37.00	1.49	23.00
32.00	19.00	49.00	42.00	27.00	15.00	1.70	23.00
19.00	27.00	54.00	54.00	34.00	20.00	1.48	22.00

%Gravel	%Sand	%Fine	LL	PL	PI	MDD g/cm3	OMC%
0.00	6.00	94.00	50.00	25.00	25.00	1.55	18.00
71.00	10.00	19.00	34.00	21.00	13.00	1.85	15.00
0.00	14.00	86.00	54.00	30.00	24.00	1.50	25.00
2.00	19.00	79.00	54.00	31.00	23.00	1.48	22.00
2.00	22.00	76.00	59.00	33.00	26.00	1.62	20.00
4.00	3.00	93.00	56.00	28.00	28.00	1.56	21.00
10.00	27.00	63.00	57.00	31.00	26.00	1.53	18.00
3.00	15.00	82.00	58.00	33.00	25.00	1.49	22.00
63.00	14.00	23.00	47.00	26.00	21.00	1.60	15.00
40.00	24.00	36.00	51.00	33.00	18.00	1.81	17.00
4.00	39.00	57.00	66.00	33.00	33.00	1.48	23.00
24.00	12.00	64.00	58.00	34.00	24.00	1.45	23.00
0.00	3.00	97.00	60.00	32.00	28.00	1.48	26.00
64.00	15.00	21.00	44.00	27.00	17.00	1.83	18.00
4.00	17.00	79.00	42.00	25.00	17.00	1.57	20.00
1.00	13.00	86.00	51.00	29.00	22.00	1.66	23.00
9.00	9.00	82.00	49.00	28.00	21.00	1.57	20.00
11.00	35.00	54.00	45.00	28.00	17.00	1.61	20.00
26.00	21.00	53.00	51.00	28.00	23.00	1.64	16.00
44.00	9.00	47.00	53.00	28.00	25.00	1.64	24.00
41.00	8.00	51.00	53.00	29.00	24.00	1.52	22.00
53.00	24.00	23.00	48.00	26.00	22.00	1.73	17.00
16.00	18.00	66.00	43.00	28.00	15.00	1.60	19.00
14.00	8.00	78.00	66.00	33.00	33.00	1.54	19.00
1.00	3.00	96.00	90.00	36.00	54.00	1.60	19.00
19.00	18.00	63.00	55.00	30.00	25.00	1.61	22.00
31.00	21.00	48.00	57.00	28.00	29.00	1.57	21.00
1.00	6.00	93.00	81.00	33.00	48.00	1.56	21.00
2.00	7.00	91.00	82.00	31.00	51.00	1.51	19.00
1.00	5.00	94.00	71.00	31.00	40.00	1.60	20.00
1.00	11.00	88.00	86.00	33.00	53.00	1.60	20.00
0.00	7.00	93.00	80.00	31.00	49.00	1.57	21.00
4.00	6.00	90.00	86.00	35.00	51.00	1.49	20.00
2.00	19.00	79.00	44.00	29.00	15.00	1.54	17.00
21.00	10.00	69.00	54.00	31.00	23.00	1.54	22.00
31.00	17.00	52.00	43.00	28.00	15.00	1.54	20.00
0.00	4.00	96.00	50.00	27.00	23.00	1.51	23.00
6.00	9.00	85.00	63.00	31.00	32.00	1.64	17.00
7.00	12.00	81.00	51.00	27.00	24.00	1.89	14.00
79.29	11.49	9.22	35.80	21.80	14.00	2.13	9.50
57.39	9.77	32.84	43.00	25.00	18.00	2.07	10.00
90.73	4.23	5.04	33.50	24.50	9.00	2.17	11.39
66.86	8.40	24.74	42.00	32.00	10.00	2.00	10.00

%Gravel	%Sand	%Fine	LL	PL	PI	MDD g/cm3	OMC%
64.63	15.20	20.17	29.00	18.00	11.00	2.10	11.00
65.70	22.04	12.26	55.20	36.20	19.00	1.84	15.00
2.77	42.12	55.11	41.50	26.50	15.00	1.56	29.49
77.98	17.01	5.01	26.20	15.20	11.00	2.45	7.00
89.25	5.93	4.82	34.40	24.40	10.00	2.11	11.30
68.09	6.45	25.46	65.00	36.00	29.00	1.63	27.50
75.12	11.36	13.52	32.00	20.00	12.00	2.16	10.50
80.46	11.28	8.26	30.00	26.00	4.00	2.05	13.50
73.00	16.26	10.74	55.70	36.70	19.00	1.82	17.00
73.52	8.58	17.90	50.00	28.00	22.00	2.25	10.00
76.48	14.85	8.67	34.50	26.50	8.00	2.16	10.70
62.56	7.14	30.30	43.00	32.00	11.00	1.89	17.50
81.34	10.58	8.08	54.00	41.00	13.00	1.75	20.00
80.66	14.22	5.12	30.50	18.50	12.00	2.54	9.60
79.45	7.31	13.24	46.00	22.00	24.00	1.79	20.00
71.09	18.69	10.22	35.50	25.50	10.00	1.88	13.50
76.94	18.22	4.84	42.00	34.00	8.00	2.10	11.90
75.11	23.23	1.66	29.00	17.00	12.00	2.33	13.00
75.73	12.76	11.51	33.30	24.30	9.00	2.17	9.00
49.48	34.50	16.02	36.00	19.00	17.00	2.25	8.70
93.79	2.65	3.56	28.50	18.50	10.00	2.00	8.00
0.26	2.61	97.13	58.00	32.00	26.00	1.72	22.20
68.25	6.53	25.22	62.00	39.00	23.00	1.72	20.10
67.72	16.89	15.39	34.00	19.00	15.00	2.20	8.99
0.00	4.00	96.00	49.00	34.00	15.00	1.57	33.70
0.00	7.00	93.00	63.00	41.00	22.00	1.67	27.20
0.00	8.00	92.00	62.00	37.00	25.00	1.58	33.30
0.00	7.00	93.00	75.00	34.00	41.00	1.58	20.00
0.00	23.00	77.00	62.00	37.00	25.00	1.53	24.00
0.00	5.00	95.00	62.00	34.00	28.00	1.54	24.00
0.00	27.00	73.00	61.00	41.00	20.00	1.52	26.00
0.00	22.00	78.00	58.00	28.00	30.00	1.62	26.00
0.00	4.00	96.00	75.00	44.00	31.00	1.56	21.00
0.00	15.00	85.00	70.00	44.00	26.00	1.47	30.00
0.00	2.00	98.00	89.00	42.00	47.00	1.40	32.00
0.00	3.00	97.00	83.00	45.00	38.00	1.50	20.00
0.00	1.00	99.00	80.00	48.00	32.00	1.49	22.00
0.00	6.00	94.00	76.00	32.00	44.00	1.54	22.10
0.00	4.00	96.00	53.00	28.00	25.00	1.50	27.80
0.00	33.00	67.00	39.00	19.00	20.00	1.63	23.50
0.00	24.00	76.00	46.00	23.00	23.00	1.66	22.30
0.00	27.00	73.00	43.00	28.00	15.00	1.65	19.50
0.00	26.00	74.00	40.00	34.00	6.00	1.38	21.20

%Gravel	%Sand	%Fine	LL	PL	PI	MDD g/cm3	OMC%
0.00	26.00	74.00	62.00	36.00	26.00	1.53	22.50
0.00	15.00	85.00	51.00	36.00	15.00	1.53	20.60
0.00	23.00	77.00	54.00	31.00	23.00	1.61	27.60
0.00	20.00	80.00	52.00	28.00	24.00	1.58	19.00

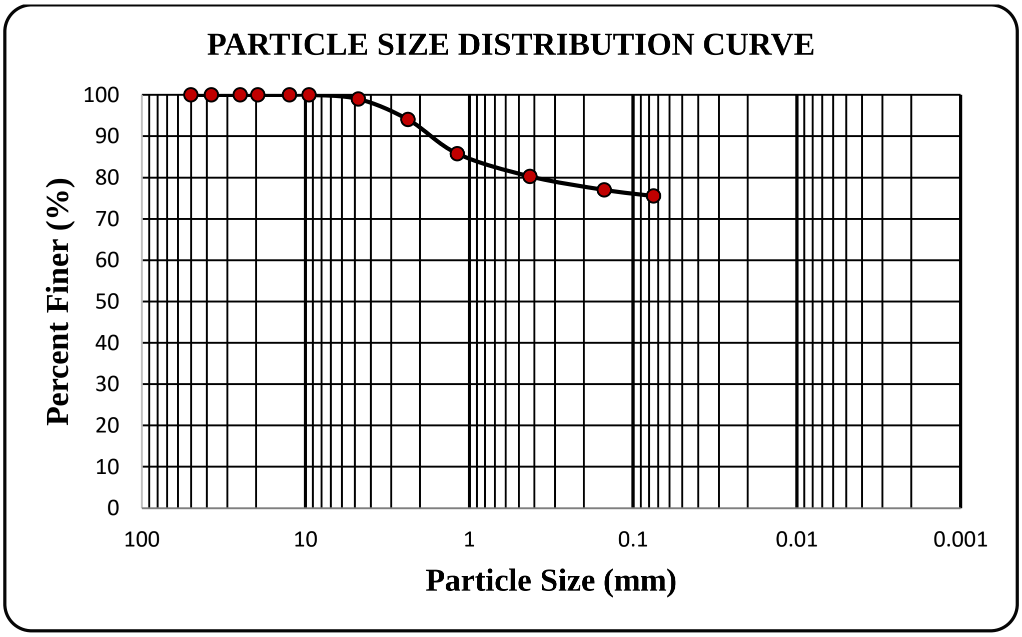
APPENDIX B: DETAILS OF GRAIN SIZE ANALYSIS TEST RESULTS

Location: Lideta

Test Method: ASTM D 1140

Total Weight = 2000g

Sieve Size (mm)	wt sieve (g)	wt sieve + dry soil (g)	Wt Retained (g)	% Retained	% Passing
50	1129	1129	0	0	100
37.5	1087	1087	0	0	100
25	1212	1212	0	0	100
19.5	1398	1398	0	0	100
12.5	1182	1182	0	0	100
9.5	1161	1161	0	0	100
4.75	574.8	594.8	20	1	99
2.36	542	642	100	5	94
1.18	326	491	165	8.25	85.75
0.425	450	560	110	5.5	80.25
0.15	274	339	65	3.25	77
0.075	412	442	30	1.5	75.5
Pan			1510	75.5	
Total			2000	100	
Gravel(%)	Sand(%)	Fine(%)			
1	23.5	75.5			

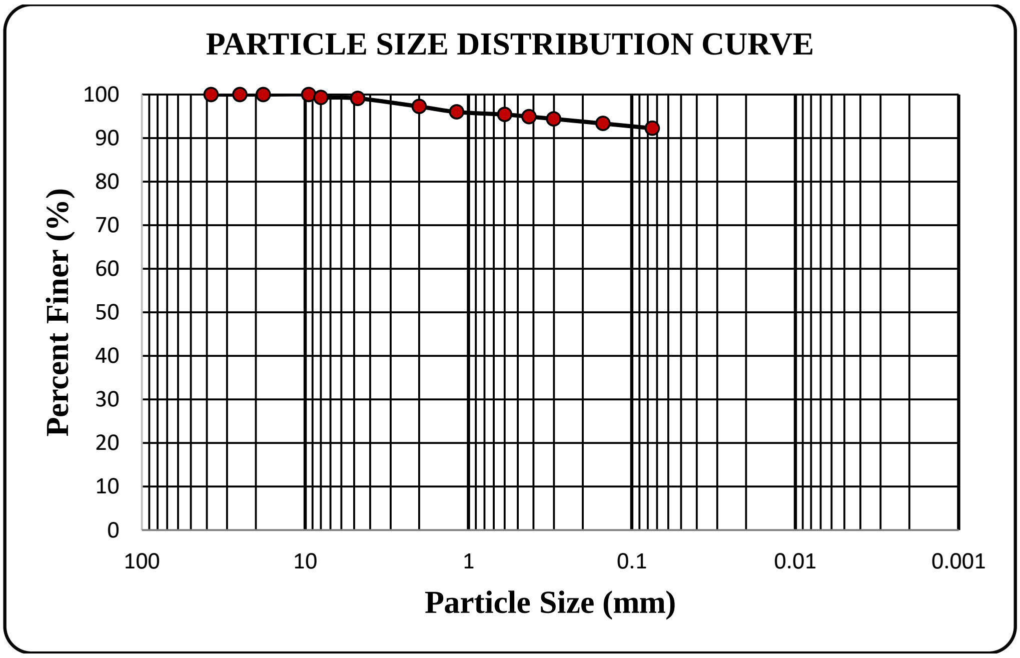


Location: 41 Eyesus

Test Method: ASTM D 1140

Total Weight = 4000g

Sieve Size (mm)	wt sieve (g)	sieve + oven dry soil (g)	Wt Retained (g)	% Retained	% Passing
37.5	1087	1087	0	0	100
25	1212	1212	0	0	100
18	625.4	625.4	0	0	100
9.5	445.2	445.2	0	0	100
8	574.8	600.8	26	0.65	99.35
4.75	428.9	437.7	8.8	0.22	99.13
2	540.3	615.8	75.5	1.8875	97.2425
1.18	459.2	509	49.8	1.245	95.9975
0.6	471.6	495.3	23.7	0.5925	95.405
0.425	449.3	468.6	19.3	0.4825	94.9225
0.3	443.4	463.8	20.4	0.51	94.4125
0.15	423.3	466.1	42.8	1.07	93.3425
0.075	409.3	453	43.7	1.0925	92.25
Pan	240.4	481.1	3690	92.25	0
Total			4000	100	
Gravel(%)	Sand(%)	Fine(%)			
0.87	6.88	92.25			

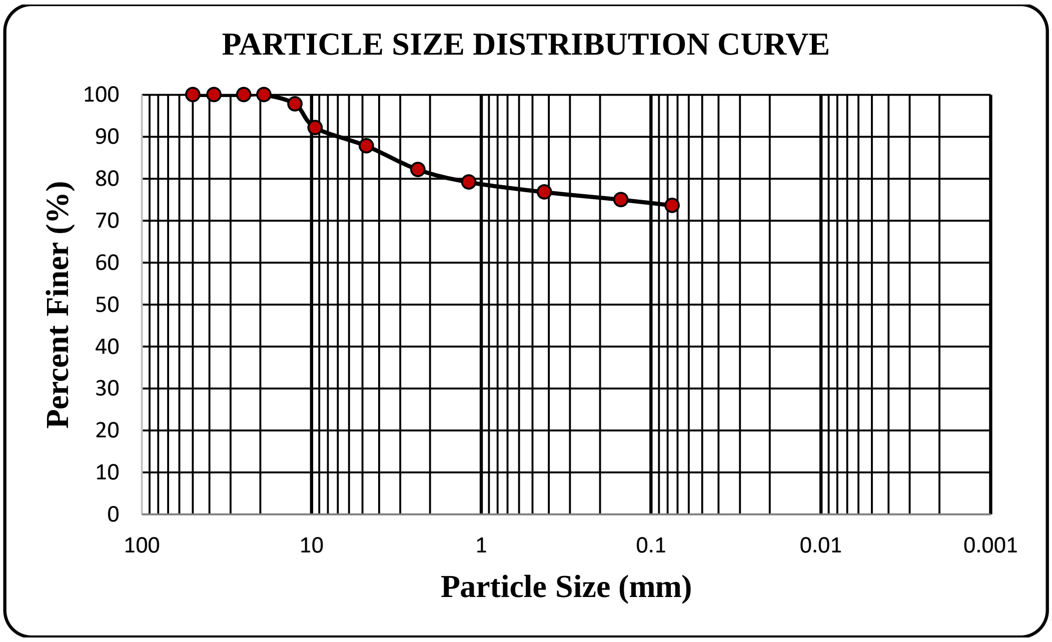


Location: Shiromeda

Test Method: ASTM D 1140

Total Weight = 5500g

Sieve Size (mm)	wt sieve (g)	wt sieve + dry soil (g)	Wt Retained (g)	% Retained	% Passing
50	1129	1129	0	0	100
37.5	1087	1087	0	0.00	100
25	1212	1212	0	0.00	100
19	1398	1398	0	0.00	100
12.5	1182	1302	120	2.18	97.82
9.5	1161	1471	310	5.64	92.18
4.75	574.8	814.8	240	4.36	87.82
2.36	542	852	310	5.64	82.18
1.18	326	491	165	3.00	79.18
0.425	450	580	130	2.36	76.82
0.15	274	374	100	1.82	75.00
0.075	412	487	75	1.36	73.64
Pan			4050	73.64	
Total			5500	100.00	
Gravel(%)	Sand(%)	Fine(%)			
12.18	14.18	73.64			

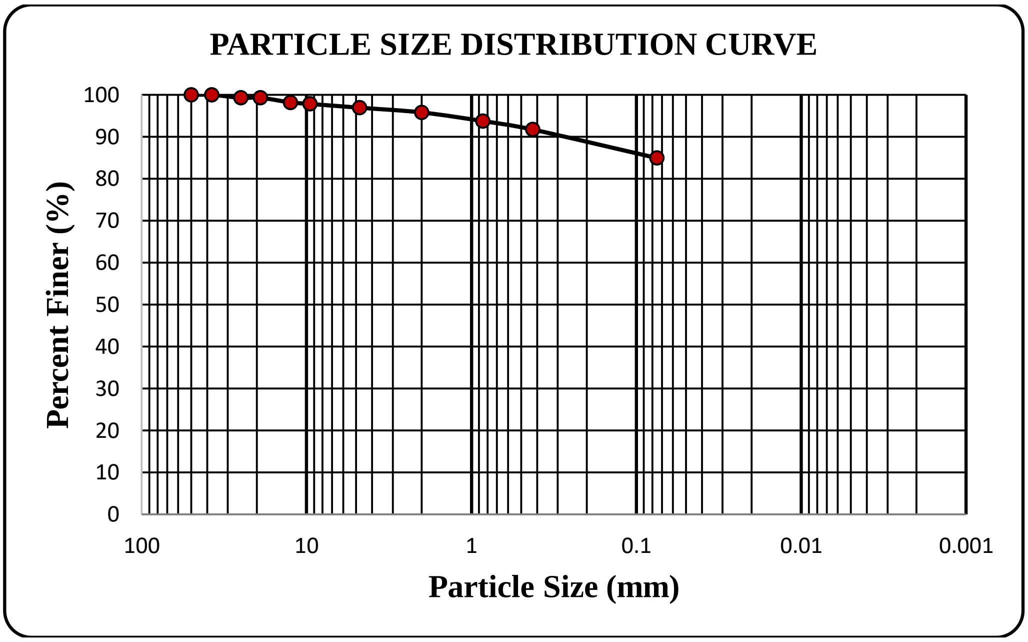


Location: Kore Adebabay

Test Method: ASTM D 1140

Total Weight = 3723g

Sieve Size (mm)	wt sieve (g)	wt sieve + dry soil (g)	Wt Retained (g)	% Retained	% Passing
50	1129	1129	0	0	100
37.5	1087	1087	0	0	100
25	1212	1238.27	26.27	0.71	99.29
19	1398	1398	0	0.00	99.29
12.5	1182	1223.04	41.04	1.10	98.19
9.5	1161	1174.62	13.62	0.37	97.83
4.75	574.8	608.12	33.32	0.89	96.93
2	542	583.65	41.65	1.12	95.81
0.85	326	402.87	76.87	2.06	93.75
0.425	450	524.57	74.57	2.00	91.74
0.075	412	664.35	252.35	6.78	84.97
Pan			3163.31	84.97	
Total			3723	100	
Gravel(%)	Sand(%)	Fine(%)			
3.07	11.96	84.97			

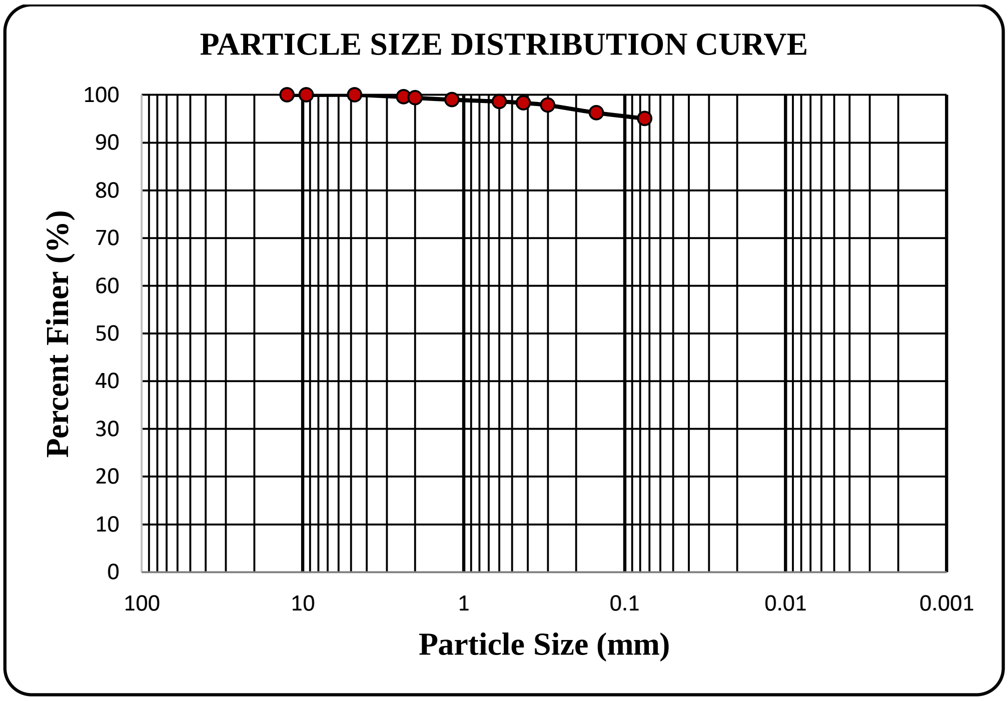


Location: Bethel

Test Method: ASTM D 1140

Total Weight = 589g

Sieve Size (mm)	wt sieve (g)	wt sieve + dry soil (g)	Wt Retained (g)	% Retained	% Passing
12.5	1182	1182	0	0	100
9.5	1161	1161	0	0	100
4.75	1129	1129	0	0	100
2.36	1087	1089.56	2.56	0.43	99.57
2	1212	1213.07	1.07	0.18	99.38
1.18	1398	1400.38	2.38	0.40	98.98
0.6	1182	1184.18	2.18	0.37	98.61
0.425	1161	1162.82	1.82	0.31	98.30
0.3	574.8	577.54	2.74	0.47	97.84
0.15	398	407.36	9.36	1.59	96.25
0.075	542	549.16	7.16	1.22	95.03
Pan	461	1020.73	559.73	95.03	0.00
Total			589	100	
Gravel(%)	Sand(%)	Fine(%)			
0	4.97	95.03			

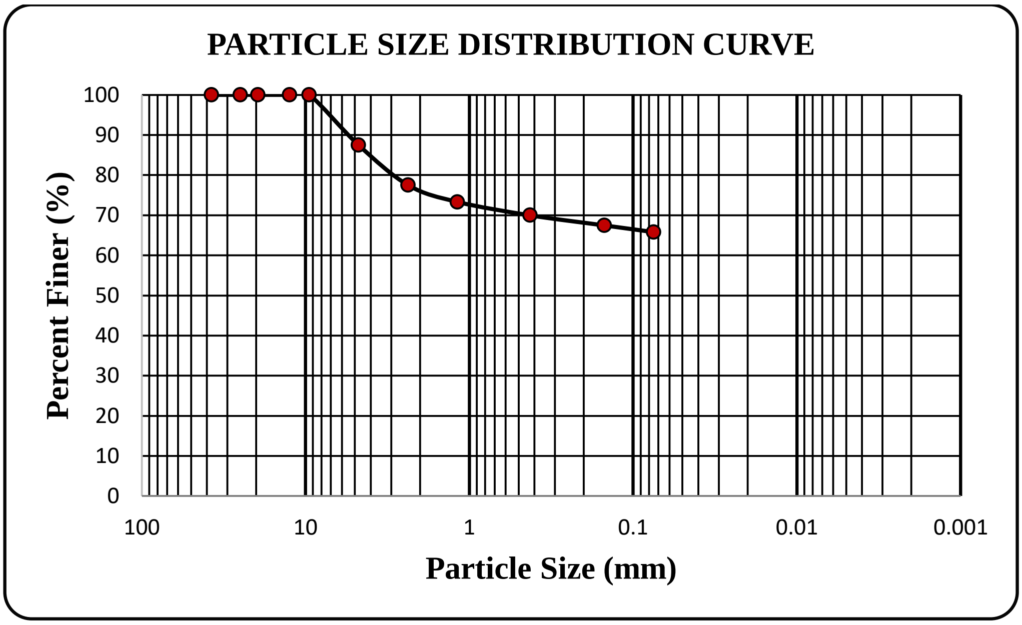


Location: Goro

Test Method: ASTM D 1140

Total Weight = 600g

Sieve Size (mm)	wt sieve (g)	wt sieve + dry soil (g)	Wt Retained (g)	% Retained	% Passing
75		0	0	0	100
63		0	0	0	100
50	1129	1129	0	0	100
37.5	1087	1087	0	0	100
25	1212	1212	0	0	100
19.5	1398	1398	0	0	100
12.5	1182	1182	0	0	100
9.5	1161	1161	0	0	100
4.75	574.8	649.8	75	12.5	87.5
2.36	542	602	60	10	77.5
1.18	326	351	25	4.17	73.33
0.425	450	470	20	3.33	70.00
0.15	274	289	15	2.50	67.50
0.075	412	422	10	1.67	65.83
Pan			395	65.83	
Total			600	100	
Gravel(%)	Sand(%)	Fine(%)			
12.5	21.7	65.8			

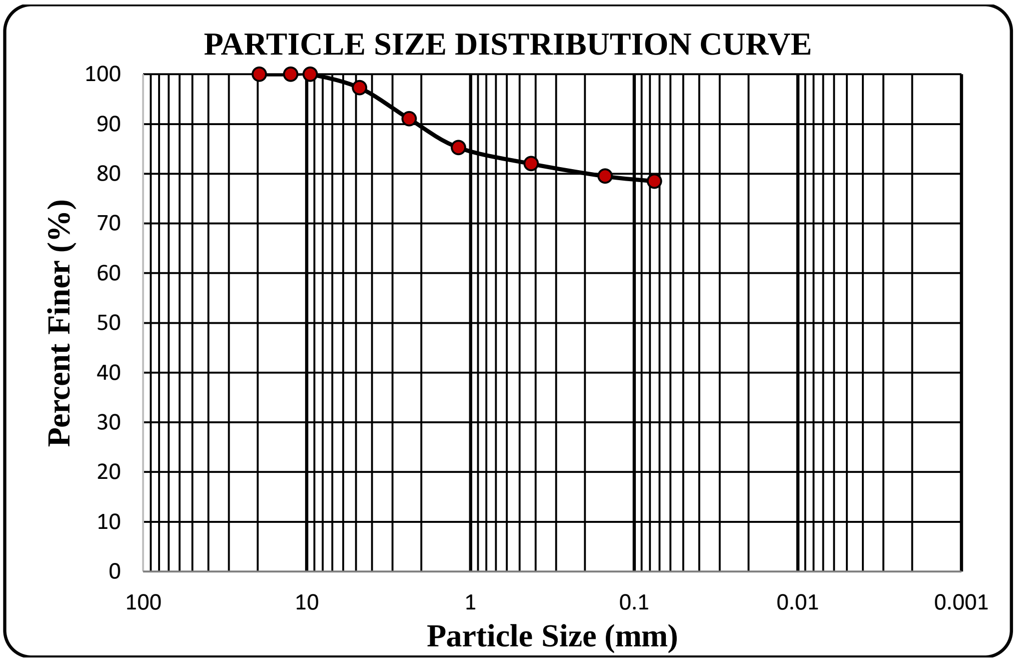


Location: Shegole

Test Method: ASTM D 1140

Total Dry Weight = 2000

Sieve Size (mm)	wt sieve (g)	wt sieve + dry soil (g)	Wt Retained (g)	% Retained	% Passing
19.5	1398	1398	0	0.00	100.00
12.5	1182	1182	0	0.00	100.00
9.5	1161	1161	0	0.00	100.00
4.75	574.8	629.8	55	2.75	97.25
2.36	542	667	125	6.25	91.00
1.18	326	441	115	5.75	85.25
0.425	450	515	65	3.25	82.00
0.15	274	324	50	2.50	79.50
0.075	412	432	20	1.00	78.5
Pan			1570	78.5	
Total			2000	100	
Gravel(%)	Sand(%)	Fine(%)			
2.75	18.75	78.5			

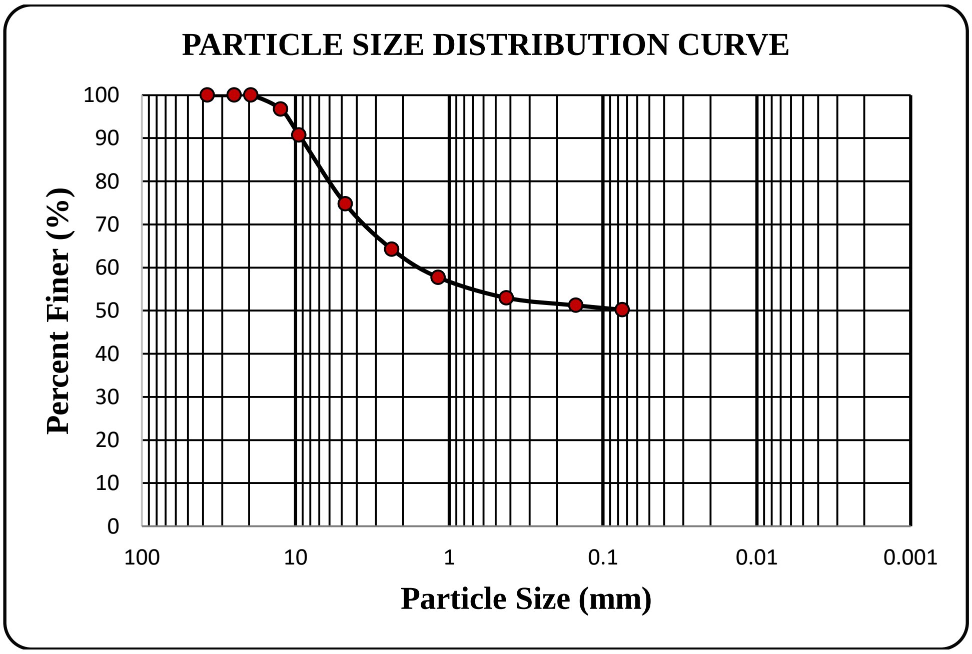


Location: Ferensay Abo

Test Method: ASTM D 1140

Total Weight = 2000g

Sieve Size (mm)	wt sieve (g)	wt sieve + dry soil (g)	Wt Retained (g)	% Retained	% Passing
75		0	0	0	100
63		0	0	0	100
50	1129	1129	0	0	100
37.5	1087	1087	0	0	100
25	1212	1212	0	0	100
19.5	1398	1398	0	0	100
12.5	1182	1247	65	3.25	96.75
9.5	1161	1281	120	6.00	90.75
4.75	574.8	894.8	320	16.00	74.75
2.36	542	752	210	10.50	64.25
1.18	326	456	130	6.50	57.75
0.425	450	545	95	4.75	53.00
0.15	274	309	35	1.75	51.25
0.075	412	432	20	1.00	50.25
Pan			1005	50.25	
Total			2000	100	
Gravel(%)	Sand(%)	Fine(%)			
25.25	24.5	50.25			

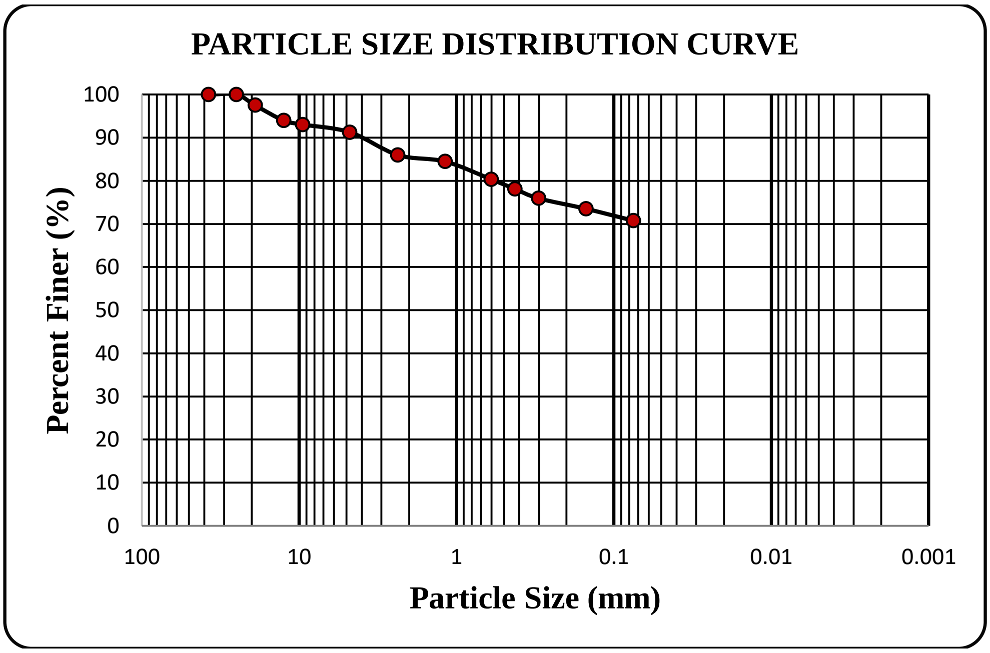


Location: Tikur Anbessa

Test Method: ASTM D 1140

Total Weight = 590g

Sieve Size (mm)	wt sieve (g)	wt sieve + dry soil (g)	Wt Retained (g)	% Retained	% Passing
37.5	1087	1087	0	0	100
25	1212	1212	0	0	100
19	1398	1412.77	14.77	2.50	97.50
12.5	1182	1202.89	20.89	3.54	93.96
9.5	1161	1166.41	5.41	0.92	93.04
4.75	574.8	585.34	10.54	1.79	91.25
2.36	398	429.1	31.1	5.27	85.98
1.18	461	469.93	8.93	1.51	84.47
0.6	326	350.38	24.38	4.13	80.34
0.425	450	463.21	13.21	2.24	78.10
0.3	445	457.81	12.81	2.17	75.93
0.15	274	288.25	14.25	2.42	73.51
0.075	412	428.24	16.24	2.75	70.76
Pan	240.4	657.87	417.47	70.76	0.00
Total			590	100	
Gravel(%)	Sand(%)	Fine(%)			
8.75	20.49	70.76			

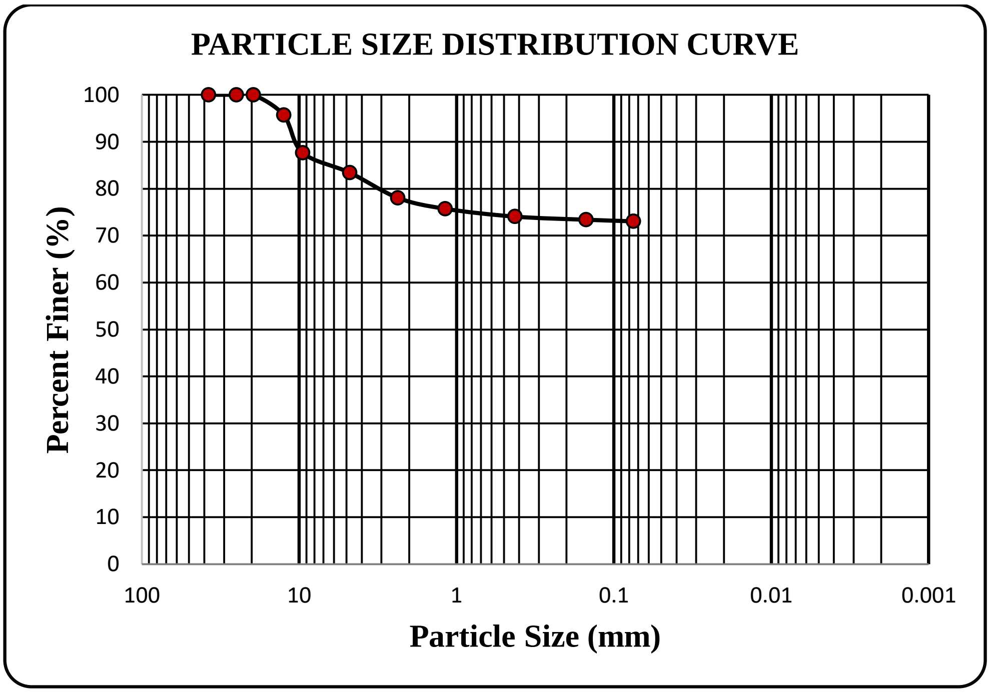


Location: Ayertena

Test Method: ASTM D 1140

Total Weight = 1500g

Sieve Size (mm)	wt sieve (g)	wt sieve + dry soil (g)	Wt Retained (g)	% Retained	% Passing
37.5	1087	1087	0	0.00	100
25	1212	1212	0	0.00	100
19.5	1398	1398	0	0.00	100
12.5	1182	1247	65	4.33	95.67
9.5	1161	1281	120	8.00	87.67
4.75	574.8	638.8	64	4.27	83.40
2.36	542	622	80	5.33	78.07
1.18	326	361	35	2.33	75.73
0.425	450	475	25	1.67	74.07
0.15	274	284	10	0.67	73.40
0.075	412	417	5	0.33	73.07
Pan			1096	73.07	
Total			1500	100	
Gravel(%)	Sand(%)	Fine(%)			
16.6	10.33	73.07			

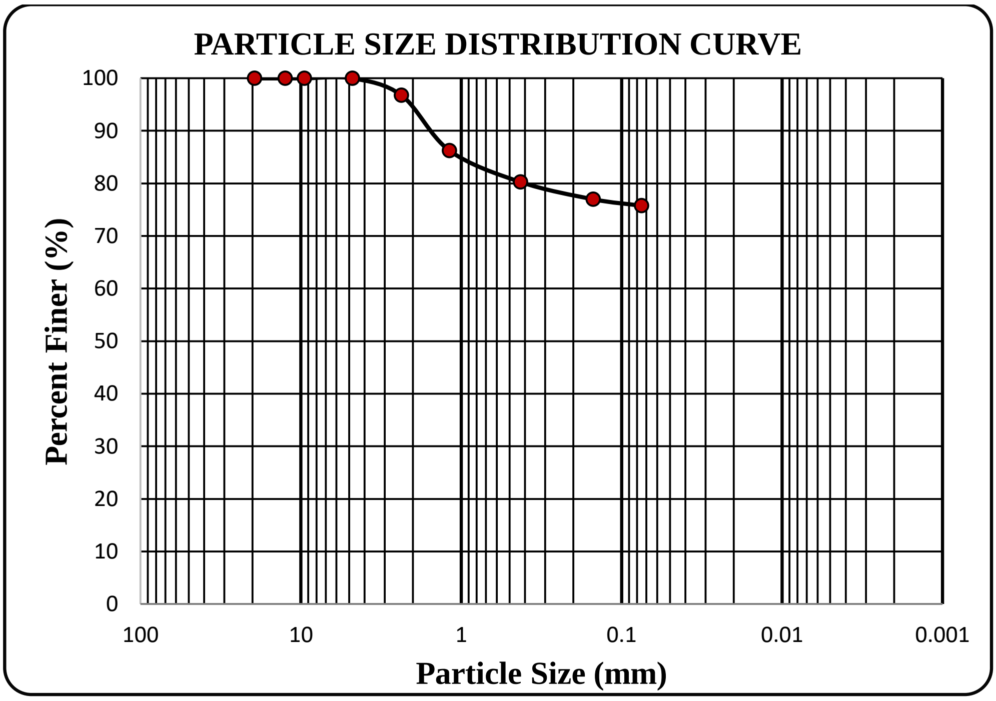


Location: Akaki

Test Method: ASTM D 1140

Total Dry Weight = 2000g

Sieve Size (mm)	wt sieve (g)	wt sieve + dry soil (g)	Wt Retained (g)	% Retained	% Passing
19.5	1398	1398	0	0	100
12.5	1182	1182	0	0	100
9.5	1161	1161	0	0	100
4.75	574.8	574.8	0	0	100
2.36	542	607	65	3.25	96.75
1.18	326	536	210	10.5	86.25
0.425	450	570	120	6	80.25
0.15	274	339	65	3.25	77
0.075	412	437	25	1.25	75.75
Pan			1515	75.75	
Total			2000	100	
Gravel(%)	Sand(%)	Fine(%)			
0	24.25	75.75			

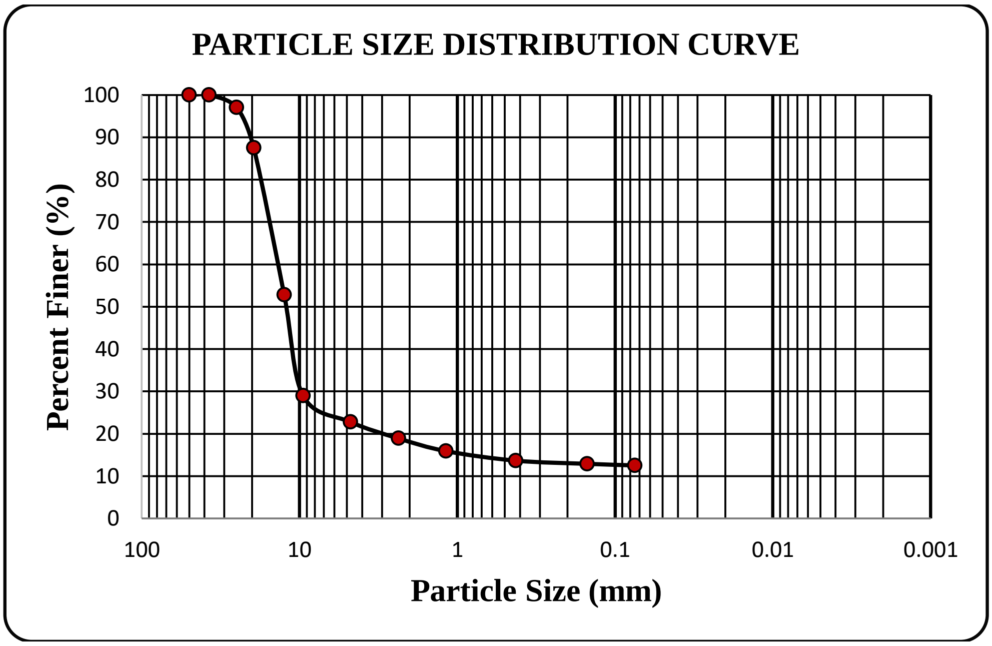


Location: Leghar

Test Method: ASTM D 1140

Total Weight = 4000g

Sieve Size (mm)	wt sieve (g)	wt sieve + dry soil (g)	Wt Retained (g)	% Retained	% Passing
75		0	0	0	100
63		0	0	0	100
50	1129	1129	0	0	100
37.5	1087	1087	0	0	100
25	1212	1330	118	2.95	97.05
19.5	1398	1778	380	9.5	87.55
12.5	1182	2572	1390	34.75	52.8
9.5	1161	2111	950	23.75	29.05
4.75	574.8	824.8	250	6.25	22.8
2.36	542	697	155	3.875	18.925
1.18	326	446	120	3	15.925
0.425	450	540	90	2.25	13.675
0.15	274	304	30	0.75	12.925
0.075	412	427	15	0.375	12.55
Pan			502	12.55	
Total			4000	100	
Gravel(%)	Sand(%)	Fine(%)			
77.2	10.25	12.55			

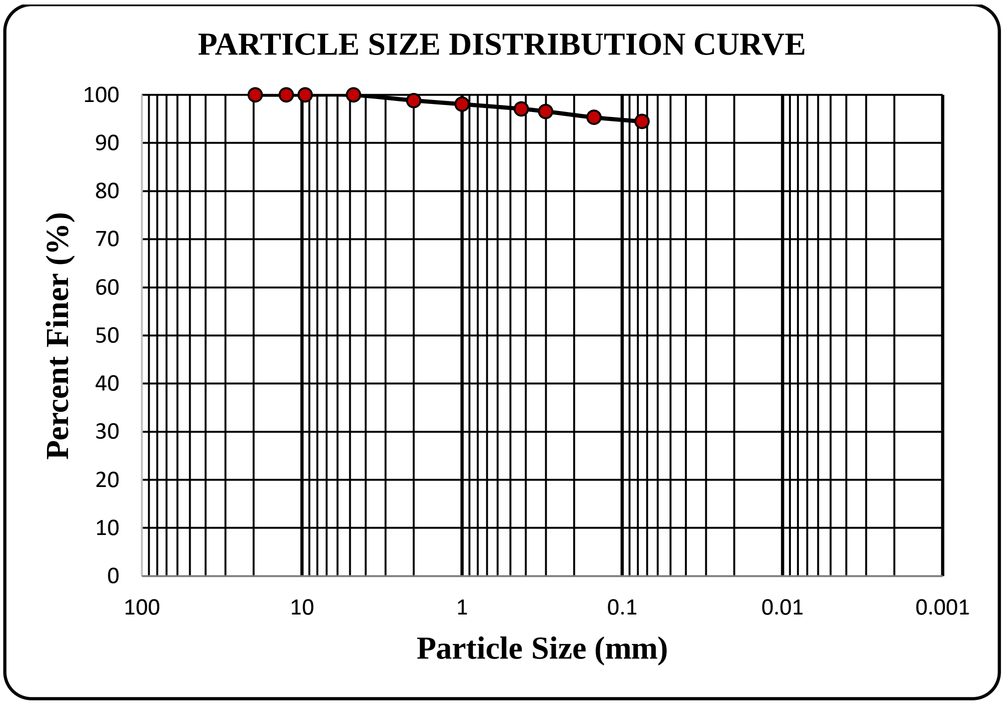


Location: Kolfe

Test Method: ASTM D 1140

Total Weight = 2000g

Sieve Size (mm)	wt sieve (g)	wt sieve + dry soil (g)	Wt Retained (g)	% Retained	% Passing
19.5	1398	1398	0	0	100.00
12.5	1182	1182	0	0	100.00
9.5	445.2	445.2	0	0	100.00
4.75	427.7	429.00	1.3	0.07	99.94
2	539.8	562.5	22.7	1.14	98.80
1	514.3	529.6	15.3	0.77	98.04
0.425	447.8	467.4	19.6	0.98	97.06
0.3	443	453.6	10.6	0.53	96.53
0.15	423	447.9	24.9	1.25	95.28
0.075	409.7	427	17.3	0.87	94.42
Pan	336.5	336.7	1888.3	94.42	0
Total			2000	100	
%Gravel	%Sand	%Fine			
0.06	5.52	94.42			

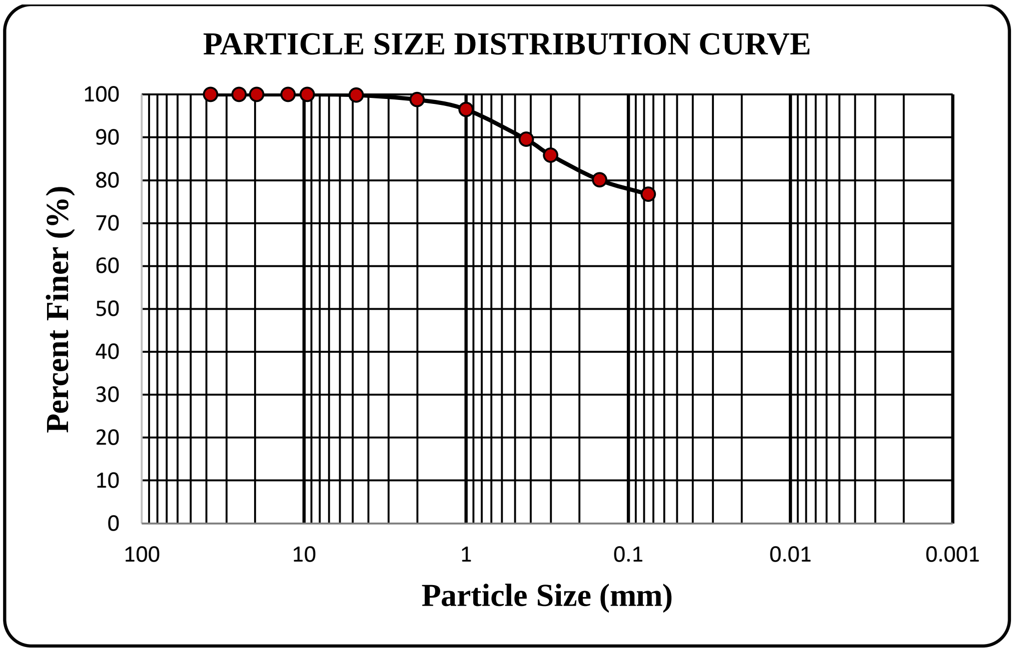


Location: Adisu Gebeya

Test Method: ASTM D 1140

Total Weight = 2000g

Sieve Size (mm)	wt sieve (g)	sieve + oven dry soil (g)	Wt Retained (g)	% Retained	% Passing
50	1129	1129	0	0	100
37.5	1087	1087	0	0	100
25	1212	1212	0	0	100
19.5	1398	1398	0	0	100
12.5	1182	1182	0	0	100
9.5	1161	1161	0	0	100
4.75	428.8	432.2	3.4	0.17	99.83
2	377.3	398.6	21.3	1.065	98.76
1	521.8	567.4	45.6	2.28	96.48
0.425	458.9	598.3	139.4	6.97	89.51
0.3	309.2	382.9	73.7	3.685	85.83
0.15	263.2	378.5	115.3	5.765	80.06
0.075	410.1	476.8	66.7	3.335	76.73
Pan	347.3	349.6	1534.6	76.73	
Total			2000	100	
Gravel(%)	Sand(%)	Fine(%)			
0.17	23.1	76.73			

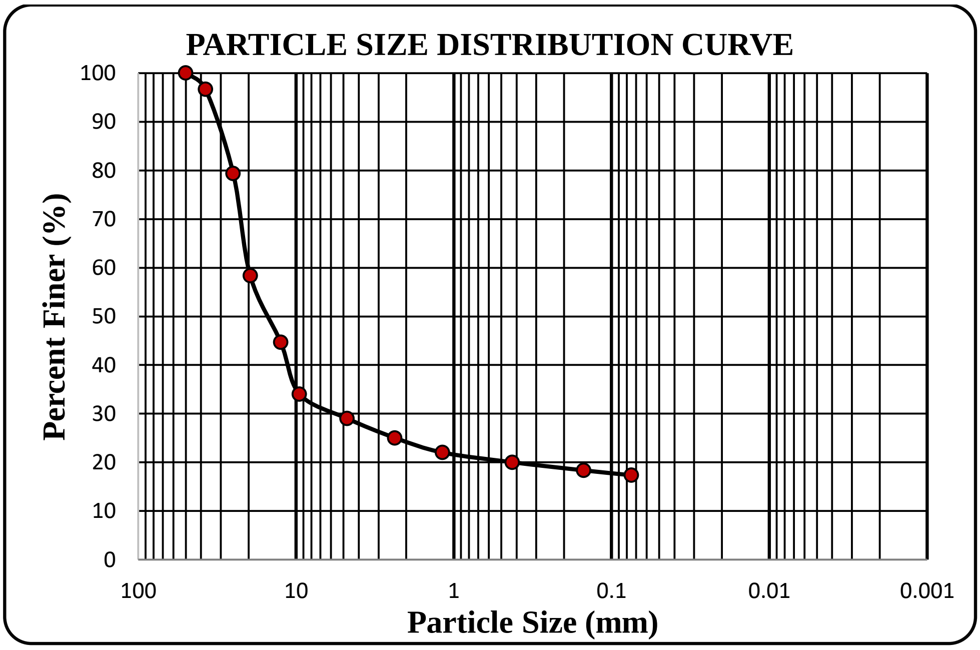


Location: Megenagna

Test Method: ASTM D 1140

Total Weight = 3000g

Sieve Size (mm)	wt sieve (g)	wt sieve + dry soil (g)	Wt Retained (g)	% Retained	% Passing
75		0	0	0	100
63		0	0	0	100
50	1129	1129	0	0	100
37.5	1087	1187	100	3.3	96.66
25	1212	1732	520	17.3	79.33
19.5	1398	2028	630	21	58.33
12.5	1182	1592	410	13.6	44.67
9.5	1161	1481	320	10.6	34.00
4.75	574.8	724.8	150	5.00	29.00
2.36	542	662	120	4.00	25.00
1.18	326	416	90	3.00	22.00
0.425	450	510	60	2.00	20.00
0.15	274	324	50	1.67	18.33
0.075	412	442	30	1.00	17.33
Pan			520	17.3	
Total			3000	100	
Gravel(%)	Sand(%)	Fine(%)			
71.00	11.67	17.33			

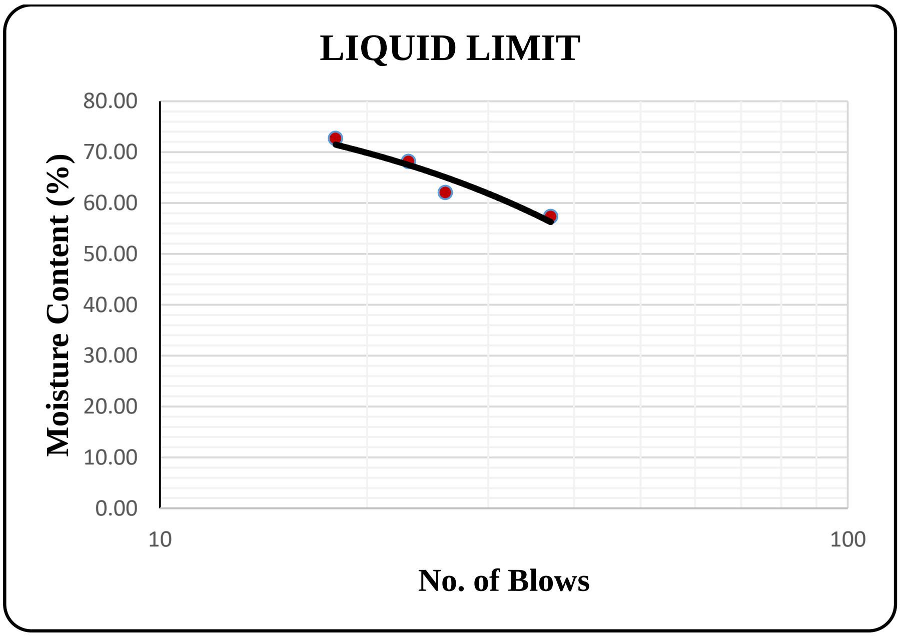


APPENDIX C: DETAILS OF ATTERBERG LIMIT TEST RESULTS

Location: Lideta

Test Method: ASTM D 4318

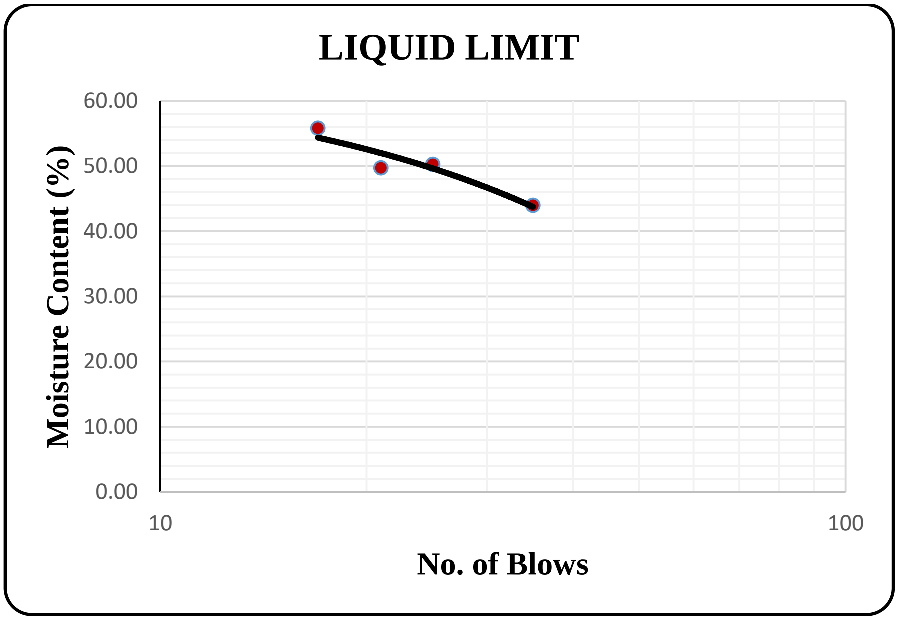
Atterberg Limit						
	Liquid limit				Plastic limit	
Number of blows	35	26	23	18		
Weight of can + wet soil (g)	77.3	78	79.5	70.9	54.6	50.9
Weight of can + dry soil (g)	60.5	60	59.6	53.6	47.6	45.6
Weight of can (g)	31.2	31	30.4	29.8	30.6	30.6
Weight of water (g)	16.8	18	19.9	17.3	7	5.3
Weight of dry soil (g)	29.3	29	29.2	23.8	17	15
Moisture content (%)	57.34	62.07	68.15	72.69	41.18	35.33
Average (%)					38.25	
	LL=65.31				PL = 38.25	



Location: 41 Eyesus

Test Method: ASTM D 4318

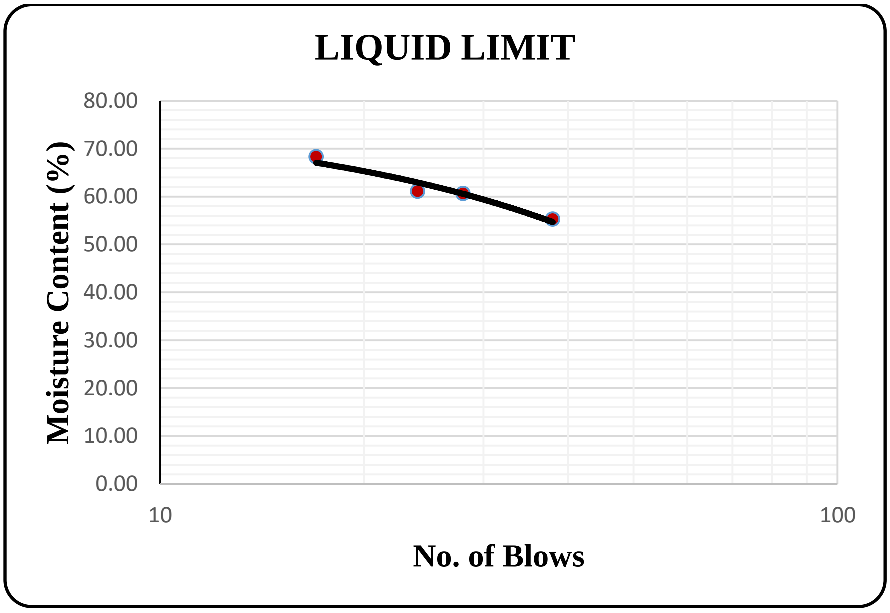
Atterberg Limit						
	Liquid limit				Plastic limit	
Number of blows	17	21	25	35		
Weight of can + wet soil (g)	47	41	51	50	25	24
Weight of can + dry soil (g)	35.9	32.7	39.3	38.7	22.4	22
Weight of can (g)	16	16	16	13	15	16
Weight of water (g)	11.1	8.3	11.7	11.3	2.6	2
Weight of dry soil (g)	19.9	16.7	23.3	25.7	7.4	6
Moisture content (%)	55.78	49.70	50.21	43.97	35.14	33.33
Average (%)					34.23	
	LL=49				PL = 34.23	



Location: Shiromeda

Test Method: ASTM D 4318

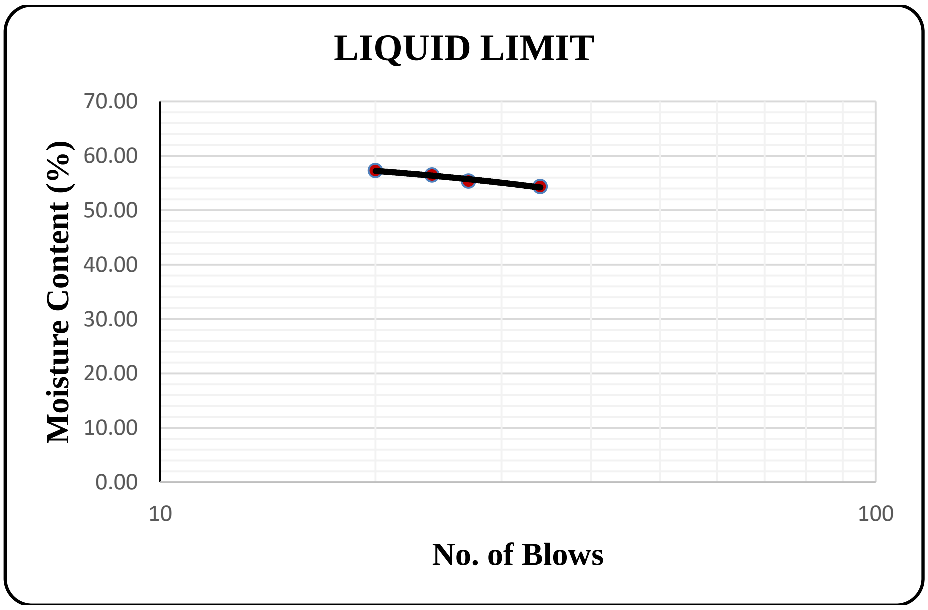
Atterberg Limit						
	Liquid limit				Plastic limit	
Number of blows	35	28	24	17		
Weight of can + wet soil (g)	60.32	61.5	59.6	62.3	59.4	48.36
Weight of can + dry soil (g)	49.6	49.8	48.3	49.6	52	43.2
Weight of can (g)	30.2	30.5	29.8	31	30.5	30.5
Weight of water (g)	10.72	11.7	11.3	12.7	7.4	5.16
Weight of dry soil (g)	19.4	19.3	18.5	18.6	21.5	12.7
Moisture content (%)	55.26	60.62	61.08	68.28	34.42	40.63
Average (%)					37.52	
	LL=61.68				PL=37.52	



Location: Kore Adebabay

Test Method: ASTM D 4318

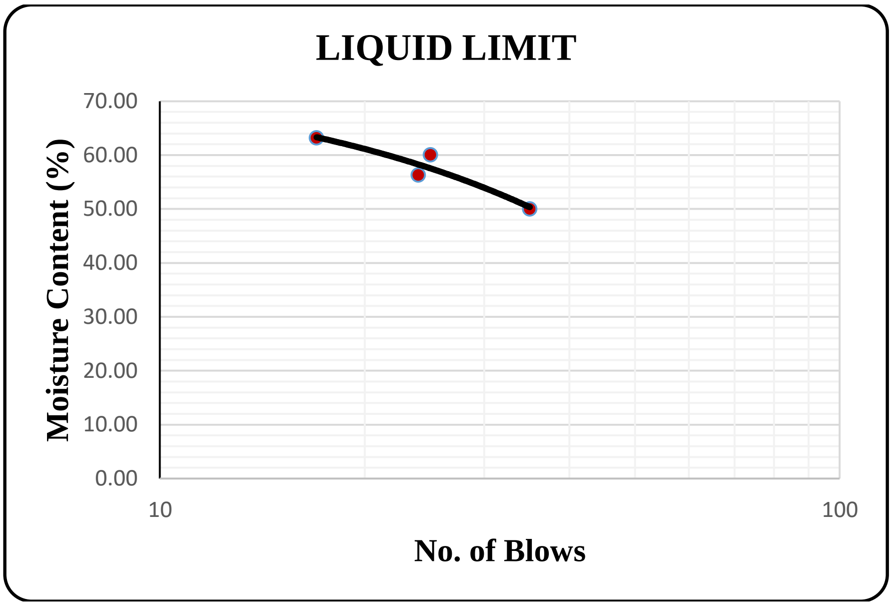
Atterberg Limit						
	Liquid limit				Plastic limit	
Number of blows	34	27	24	20		
Weight of can + wet soil (g)	43.44	43.21	43.11	43.06	15.25	14.92
Weight of can + dry soil (g)	36.45	36.15	35.96	35.84	14.83	14.57
Weight of can (g)	23.58	23.39	23.3	23.24	12.79	12.82
Weight of water (g)	6.99	7.06	7.15	7.22	0.42	0.35
Weight of dry soil (g)	12.87	12.76	12.66	12.6	2.04	1.75
Moisture content (%)	54.31	55.33	56.48	57.30	20.59	20
Average (%)					20.29	
	LL=55.95				PL = 20.29	



Location: Bethel

Test Method: ASTM D 4318

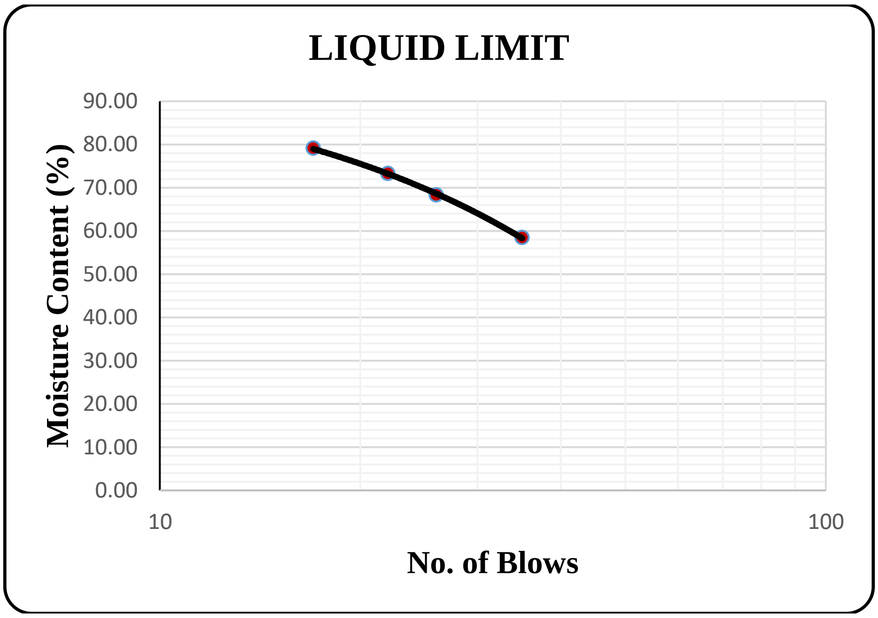
Atterberg Limit						
	Liquid limit				Plastic limit	
Number of blows	17	24	25	35		
Weight of can + wet soil (g)	45	168	56	48	132	21
Weight of can + dry soil (g)	33	159	41	37	131	19
Weight of can (g)	14	143	16	15	125	14
Weight of water (g)	12	9	15	11	1	2
Weight of dry soil (g)	19	16	25	22	6	5
Moisture content (%)	63.16	56.25	60	50	16.67	40
Average (%)					28.33	
	LL=60				PL=28.33	



Location: Goro

Test Method: ASTM D 4318

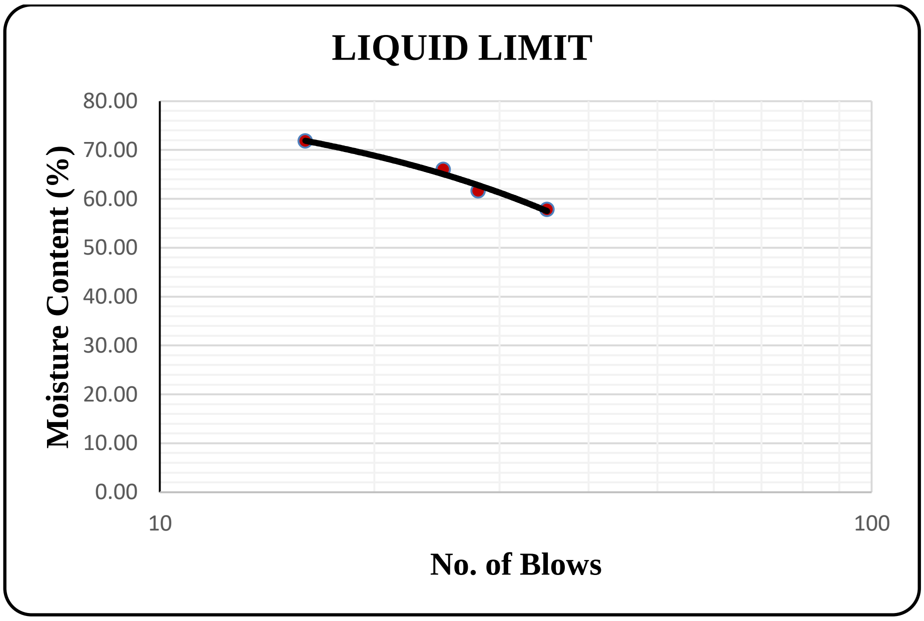
Atterberg Limit						
	Liquid limit				Plastic limit	
Number of blows	35	26	22	17		
Weight of can + wet soil (g)	70.8	76.5	80.7	70	57.8	56.8
Weight of can + dry soil (g)	55.6	58.2	59.6	52.6	50	49.4
Weight of can (g)	29.6	31.4	30.8	30.6	30.6	30.6
Weight of water (g)	15.2	18.3	21.1	17.4	7.8	7.4
Weight of dry soil (g)	26	26.8	28.8	22	19.4	18.8
Moisture content (%)	58.46	68.28	73.26	79.09	40.21	39.36
Average (%)					39.78	
	LL=69.73				PL = 39.78	



Location: Shegole

Test Method: ASTM D 4318

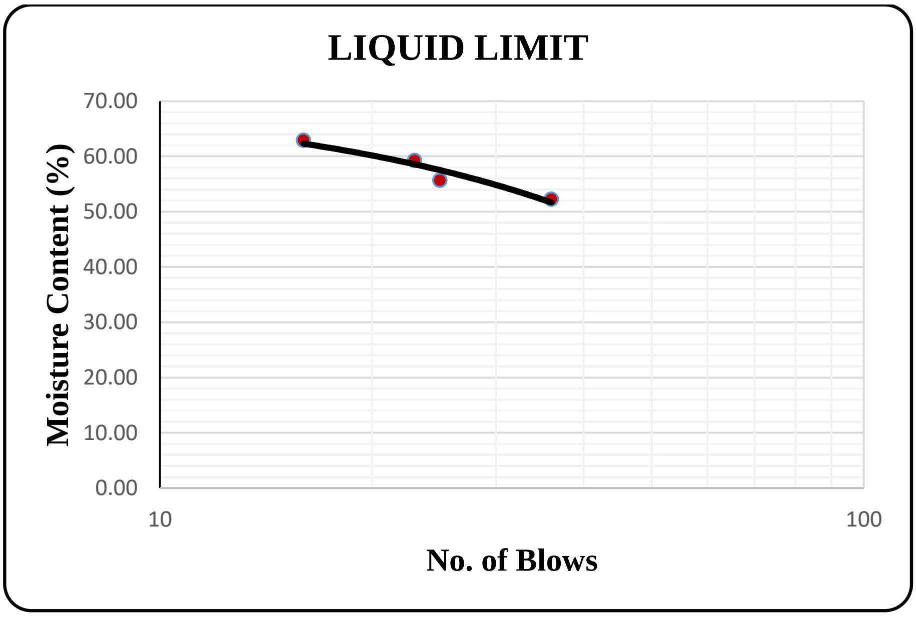
Atterberg Limit						
	Liquid limit				Plastic limit	
Number of blows	35	28	25	16		
Weight of can + wet soil (g)	63.25	64.3	65.32	60.21	50.21	48.61
Weight of can + dry soil (g)	51	51.3	51.6	48	44.8	44
Weight of can (g)	29.8	30.2	30.8	31	30.5	30.5
Weight of water (g)	12.25	13	13.72	12.21	5.41	4.61
Weight of dry soil (g)	21.2	21.1	20.8	17	14.3	13.5
Moisture content (%)	57.78	61.61	65.96	71.82	37.83	34.15
Average (%)					35.99	
	LL=65.05				PL = 35.99	



Location: Ferensay Abo

Test Method: ASTM D 4318

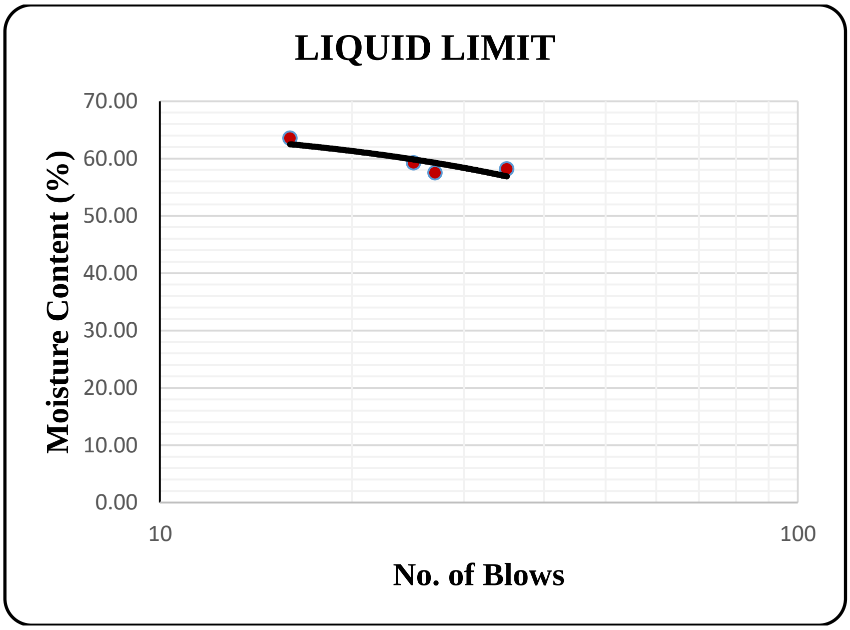
Atterberg Limit						
	Liquid limit				Plastic limit	
Number of blows	35	25	23	16		
Weight of can + wet soil (g)	72.6	60.8	63.8	62.7	69	63
Weight of can + dry soil (g)	58.6	50	51.3	50	58.2	54.8
Weight of can (g)	31.8	30.6	30.2	29.8	30.6	30.6
Weight of water (g)	14	10.8	12.5	12.7	10.8	8.2
Weight of dry soil (g)	26.8	19.4	21.1	20.2	27.6	24.2
Moisture content (%)	52.24	55.67	59.24	62.87	39.13	33.88
Average (%)					36.51	
	LL=57.88				PL = 36.51	



Location: Tikur Anbesa

Test Method: ASTM D 4318

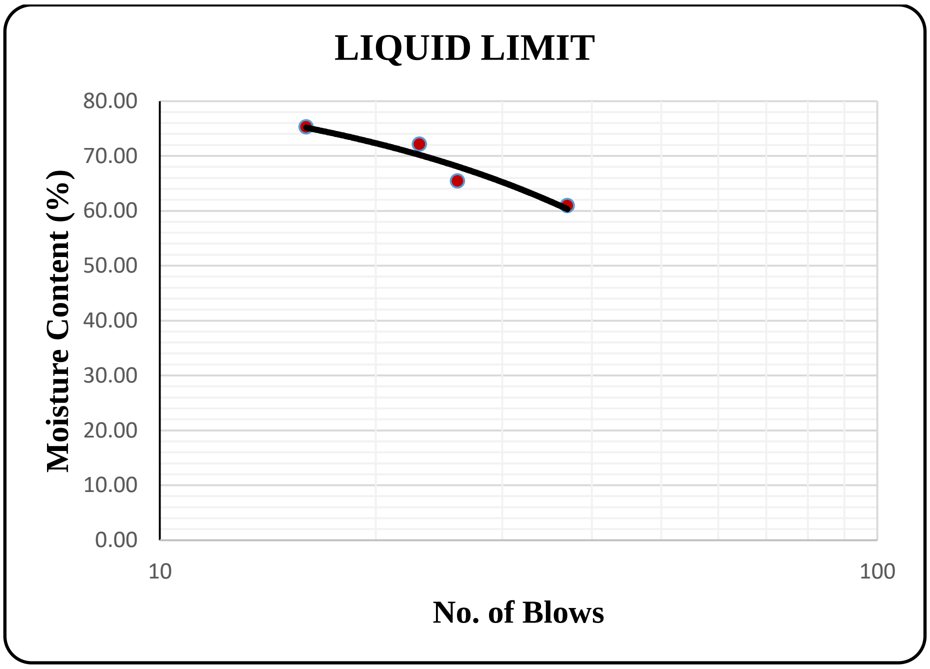
Atterberg Limit						
	Liquid limit				Plastic limit	
Number of blows	16	25	27	35		
Weight of can + wet soil (g)	48.02	42.6	50.1	47.47	21.23	20.26
Weight of can + dry soil (g)	35.426	32.51	37.63	35.81	18.88	19.74
Weight of can (g)	15.6	15.48	15.94	15.76	15.32	15.72
Weight of water (g)	12.594	10.09	12.47	11.66	2.35	0.52
Weight of dry soil (g)	19.826	17.03	21.69	20.05	3.56	4.02
Moisture content (%)	63.52	59.25	57.49	58.15	66.01	12.94
Average (%)					39.47	
	LL=59.25				PL=39.47	



Location: Ayertena

Test Method: ASTM D 4318

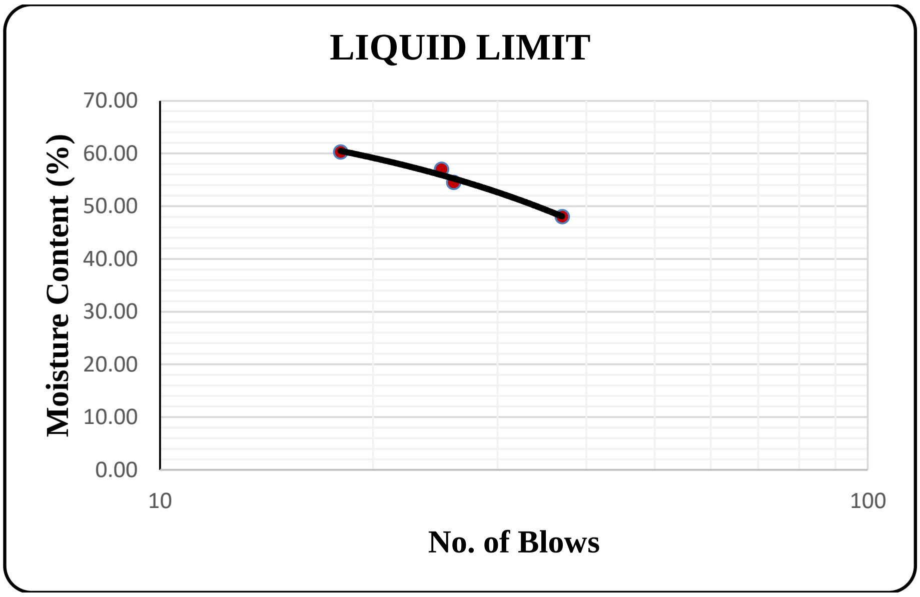
Atterberg Limit						
	Liquid limit				Plastic limit	
Number of blows	37	26	23	16		
Weight of can + wet soil (g)	76.3	78.5	80.4	81.5	52.8	56.8
Weight of can + dry soil (g)	59.3	59.4	59.7	59.3	47	49.1
Weight of can (g)	31.4	30.2	31	29.8	30.6	30.6
Weight of water (g)	17	19.1	20.7	22.2	5.8	7.7
Weight of dry soil (g)	27.9	29.2	28.7	29.5	16.4	18.5
Moisture content (%)	60.93	65.41	72.13	75.25	35.37	41.62
Average (%)					38.49	
	LL=68.51				PL = 38.49	



Location: Akaki

Test Method: ASTM D 1140

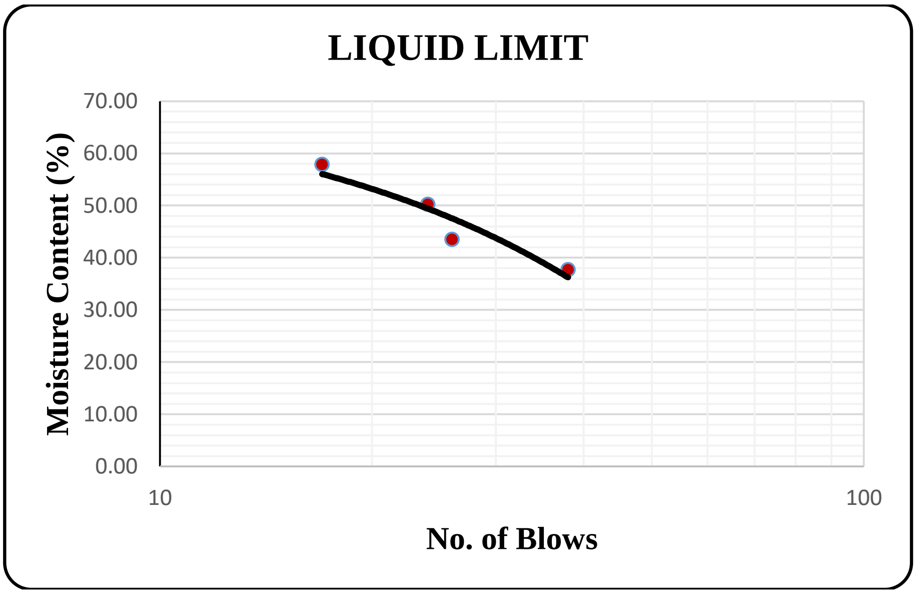
Atterberg Limit						
	Liquid limit				Plastic limit	
Number of blows	37	26	25	18		
Weight of can + wet soil (g)	78.9	76.8	73.5	70.5	59.6	56.2
Weight of can + dry soil (g)	63.4	61	58	55.2	52	49.6
Weight of can (g)	31.1	32	30.8	29.8	30.6	30.6
Weight of water (g)	15.5	15.8	15.5	15.3	7.6	6.6
Weight of dry soil (g)	32.3	29	27.2	25.4	21.4	19
Moisture content (%)	47.99	54.48	56.99	60.24	35.51	34.74
Average (%)					35.13	
	LL=54.49				PL = 35.13	



Location: Leghar

Test Method: ASTM D 4318

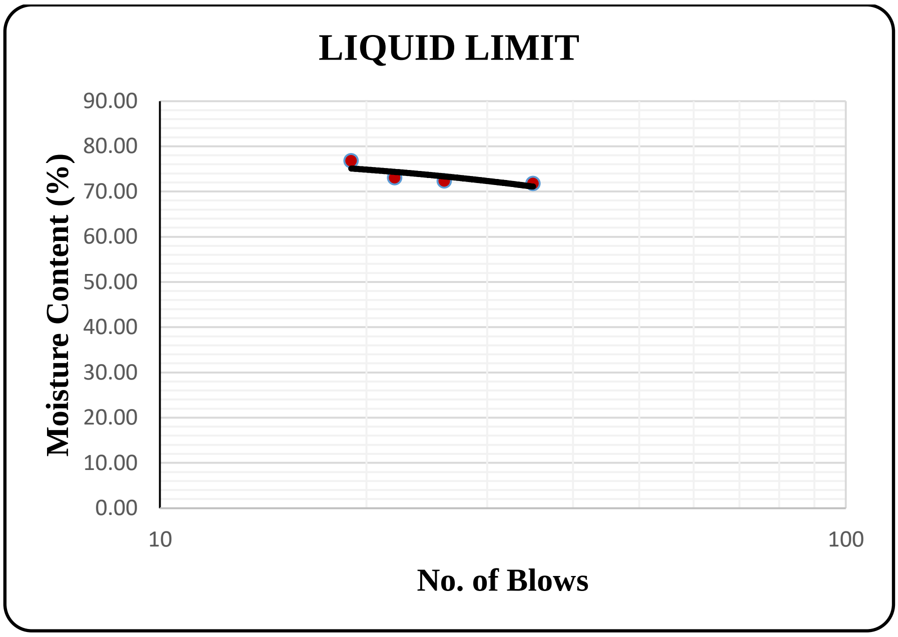
Atterberg Limit						
	Liquid limit				Plastic limit	
Number of blows	35	26	24	17		
Weight of can + wet soil (g)	68.5	75.6	71.4	69.6	50.8	56.8
Weight of can + dry soil (g)	57.9	61.9	57.9	55.6	45.8	50.8
Weight of can (g)	29.8	30.4	31	31.4	30.6	30.6
Weight of water (g)	10.6	13.7	13.5	14	5	6
Weight of dry soil (g)	28.1	31.5	26.9	24.2	15.2	20.2
Moisture content (%)	37.72	43.49	50.19	57.85	32.89	29.70
Average (%)					31.30	
	LL=47.01				PL = 31.29	



Location: Kolfe

Test Method: ASTM D 4318

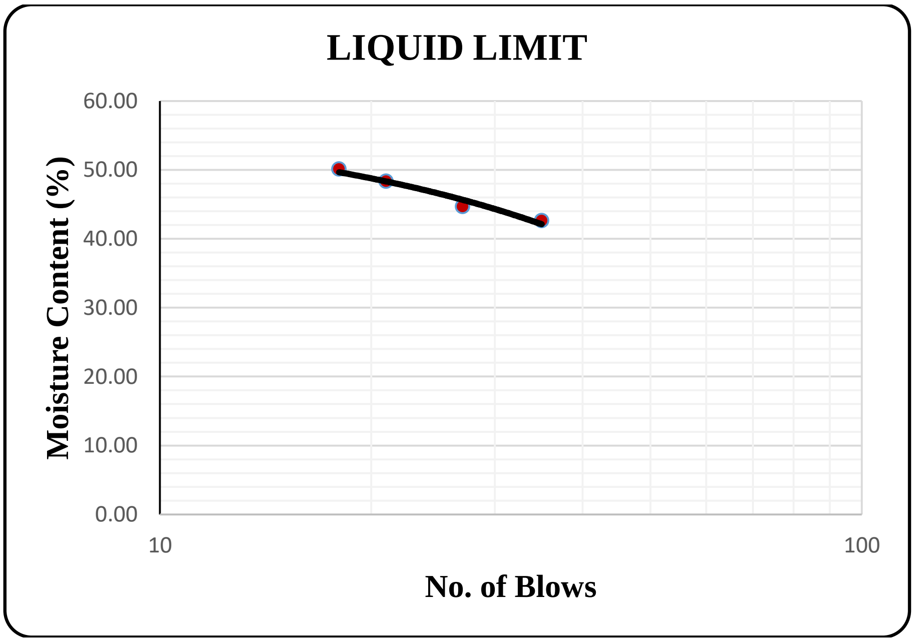
Atterberg Limit							
	Liquid limit				Plastic limit		
Number of blows	19	22	26	35			
Weight of can + wet soil (g)	29.45	34.65	30.22	33.16	29.12	22.61	31.7
Weight of can + dry soil (g)	23.38	26.59	24.1	25.89	26.13	20.23	26.32
Weight of can (g)	15.47	15.55	15.64	15.76	20.28	15.42	15.61
Weight of water (g)	6.07	8.06	6.12	7.27	2.99	2.38	5.38
Weight of dry soil (g)	7.91	11.04	8.46	10.13	5.85	4.81	10.71
Moisture content (%)	76.74	73.01	72.34	71.77	51.11	49.48	50.23
Average (%)					50.27		
	LL=73.5				PL=50.27		



Location: Adisu Gebeya

Test Method: ASTM D 4318

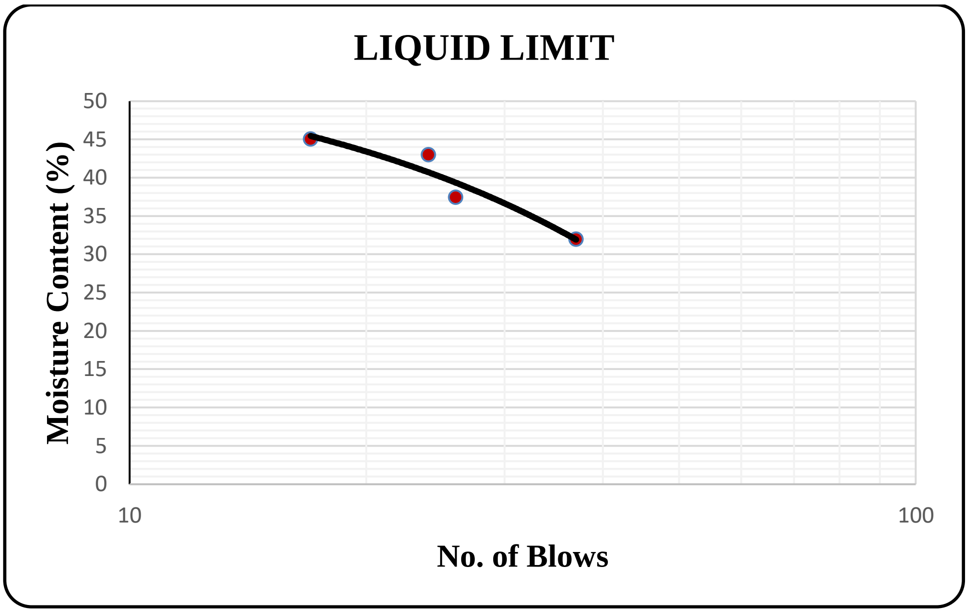
Atterberg Limit							
	Liquid limit				Plastic limit		
Number of blows	18	21	27	35			
Weight of can + wet soil (g)	53	53.05	44.78	47.31	26	29.78	28.08
Weight of can + dry soil (g)	40.47	40.72	35.81	37.99	23.36	26.23	25.63
Weight of can (g)	15.46	15.22	15.74	16.12	15.67	15.94	15.44
Weight of water (g)	12.53	12.33	8.97	9.32	2.64	3.55	2.45
Weight of dry soil (g)	25.01	25.5	20.07	21.87	7.69	10.29	10.19
Moisture content (%)	50.10	48.35	44.69	42.62	34.33	34.50	24.04
Average (%)					30.96		
	LL = 46.5				PL=30.96		



Location: Megenagna

Test Method: ASTM D 4318

Atterberg Limit						
	Liquid limit				Plastic limit	
Number of blows	37	26	24	17		
Weight of can + wet soil (g)	70	80	68.5	63.4	64.7	62.5
Weight of can + dry soil (g)	60.6	66.3	57.2	53	57.3	54.6
Weight of can (g)	31.2	29.7	30.9	29.9	30.6	30.6
Weight of water (g)	9.4	13.7	11.3	10.4	7.4	7.9
Weight of dry soil (g)	29.4	36.6	26.3	23.1	26.7	24
Moisture content (%)	31.9728	37.43	42.97	45.02	27.72	32.92
Average (%)					30.32	
	LL=39.65				PL = 30.32	

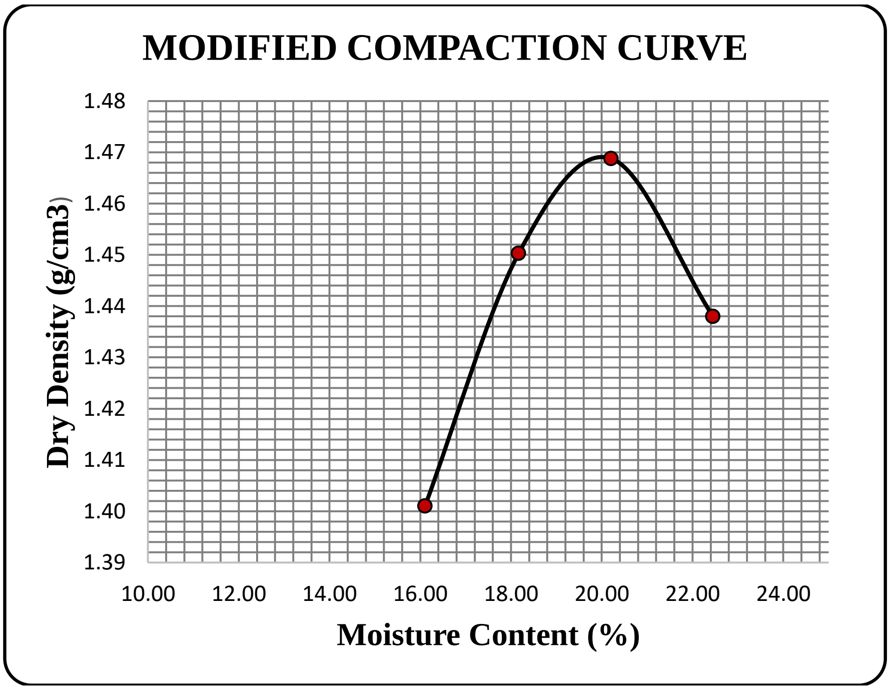


APPENDIX D: DETAILS OF MODIFIED COMPACTION TEST RESULTS

Location: Lideta

Test Method: ASTM D 1557

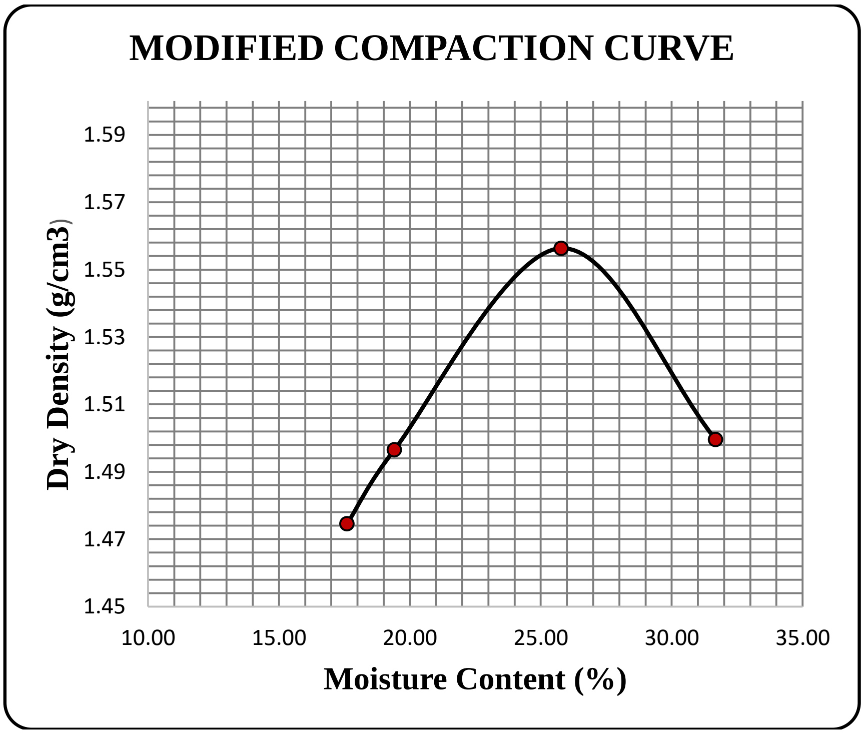
Modified Proctor				
	Density			
Trial Number	1	2	3	4
weight of wet soil + mold (g)	7097	7179	7228	7223
weight of mold (g)	5561	5561	5561	5561
weight of wet soil (g)	1536	1618	1667	1662
volume of mold (g)	944	944	944	944
bulk density of soil (g/cm3)	1.63	1.71	1.77	1.76
	Moisture content			
can number	AB	T-2	MD4	DS7
wet soil + can (g)	174	180.4	184.6	170.3
dry soil + can (g)	154	157.4	158.8	145
weight of can (g)	29.8	30.8	31.1	32.3
weight of water (g)	20	23	25.8	25.3
weight of dry soil (g)	124.2	126.6	127.7	112.7
moisture content (%)	16.10	18.17	20.20	22.45
dry density of soil (g/cm3)	1.40	1.45	1.47	1.44
	MDD = 1.47g/cm3		OMC =20.2%	



Location: 41 Eyesus

Test Method: ASTM D 1557

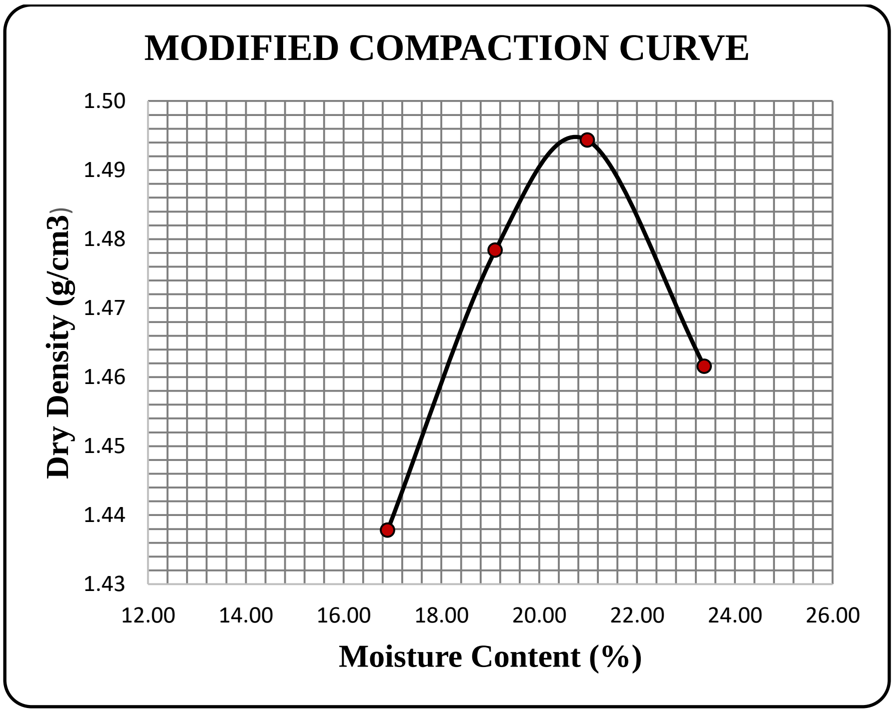
Modified Proctor				
	Density			
Trial Number	1	2	3	4
weight of wet soil + mold (g)	6225	6275	6436	6452
weight of mold (g)	4588	4588	4588	4588
weight of wet soil (g)	1637	1687	1848	1864
volume of mold (g)	944	944	944	944
bulk density of soil (g/cm3)	1.73	1.79	1.96	1.97
	Moisture content			
can number	LL3	PL1	PL2	PL2
wet soil + can (g)	101.1	85.8	75.3	67.4
dry soil + can (g)	88.3	74.5	63	54
weight of can (g)	15.6	16.3	15.3	15.1
weight of water (g)	12.8	11.3	12.3	13.4
weight of dry soil (g)	72.7	58.2	47.7	42.3
moisture content (%)	17.61	19.42	25.79	31.68
dry density of soil (g/cm3)	1.47	1.50	1.56	1.50
	MDD = 1.56g/cm3		OMC =25.79%	



Location: Shiromeda

Test Method: ASTM D 1557

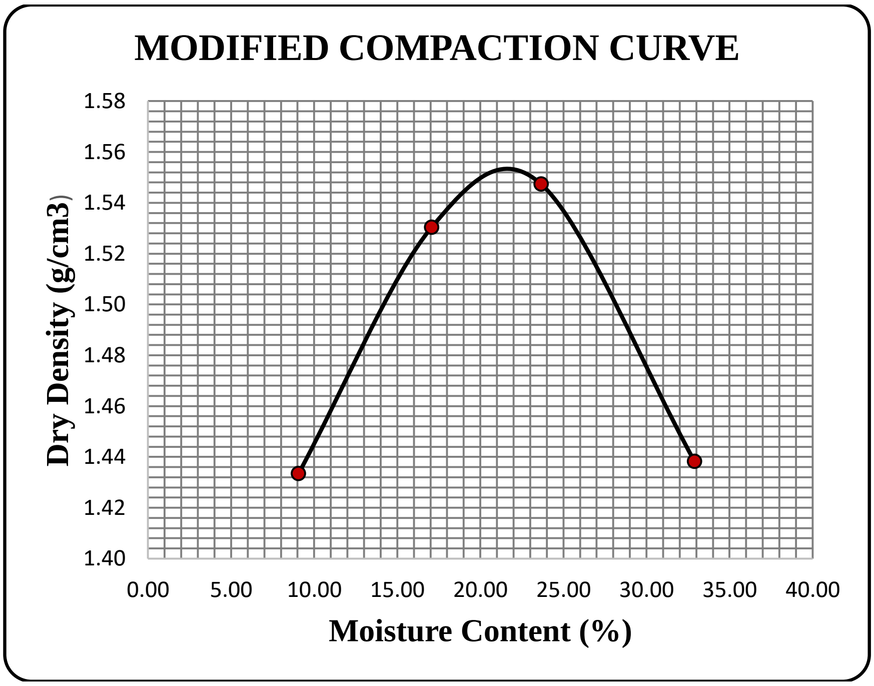
Modified Proctor				
	Density			
Trial Number	1	2	3	4
weight of wet soil + mold (g)	7147.7	7223.2	7267.7	7263.2
weight of mold (g)	5561	5561	5561	5561
weight of wet soil (g)	1587	1662	1707	1702
volume of mold (g)	944	944	944	944
bulk density of soil (g/cm3)	1.68	1.76	1.81	1.80
	Moisture content			
can number	MD	M32	MD4	5RW
wet soil + can (g)	165.5	175	163.6	163.3
dry soil + can (g)	146	152	140.6	138.5
weight of can (g)	30.6	31.6	31	32.4
weight of water (g)	19.5	23	23	24.8
weight of dry soil (g)	115.4	120.4	109.6	106.1
moisture content (%)	16.90	19.10	20.99	23.37
dry density of soil (g/cm3)	1.44	1.48	1.49	1.46
	MDD = 1.49g/cm3		OMC =21%	



Location: Kore Adebabay

Test Method: ASTM D 1557

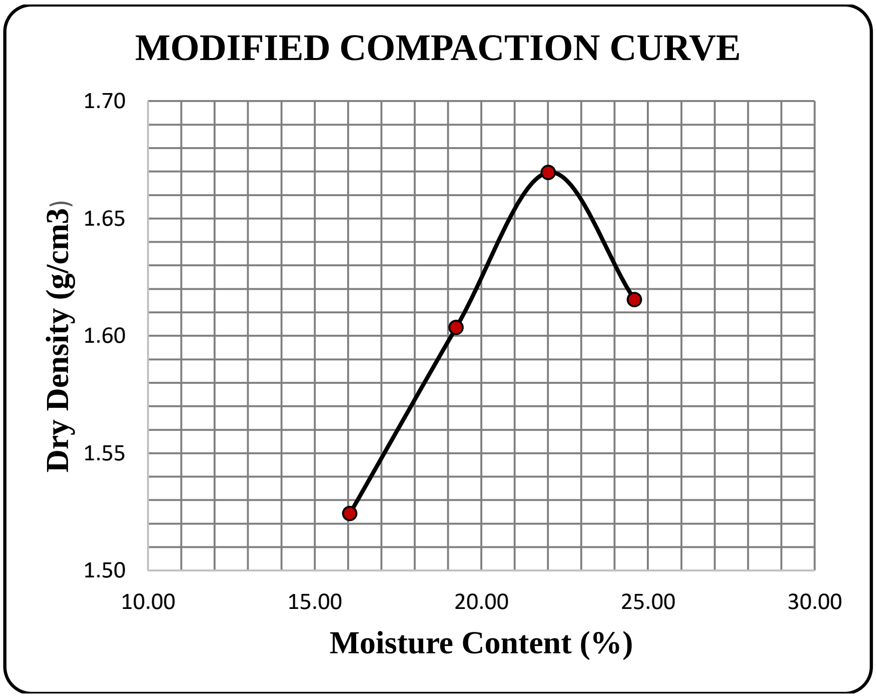
Modified Proctor				
	Density			
Trial Number	1	2	3	4
weight of wet soil + mold (g)	6904	7131	7252	7250
weight of mold (g)	5350	5350	5350	5350
weight of wet soil (g)	1554	1781	1902	1900
volume of mold (g)	994	994	994	994
bulk density of soil (g/cm3)	1.56	1.79	1.91	1.91
	Moisture content			
can number	BD-2	T-30	T2	KJ-2
wet soil + can (g)	234.5	228.2	225.8	223
dry soil + can (g)	220.8	204.7	195.7	184.4
weight of can (g)	69.6	67.1	68.5	67.1
weight of water (g)	13.7	23.5	30.1	38.6
weight of dry soil (g)	151.2	137.6	127.2	117.3
moisture content (%)	9.06	17.08	23.66	32.91
dry density of soil (g/cm3)	1.43	1.53	1.55	1.44
	MDD = 1.55g/cm3		OMC =23.66%	



Location: Bethel

Test Method: ASTM D 1557

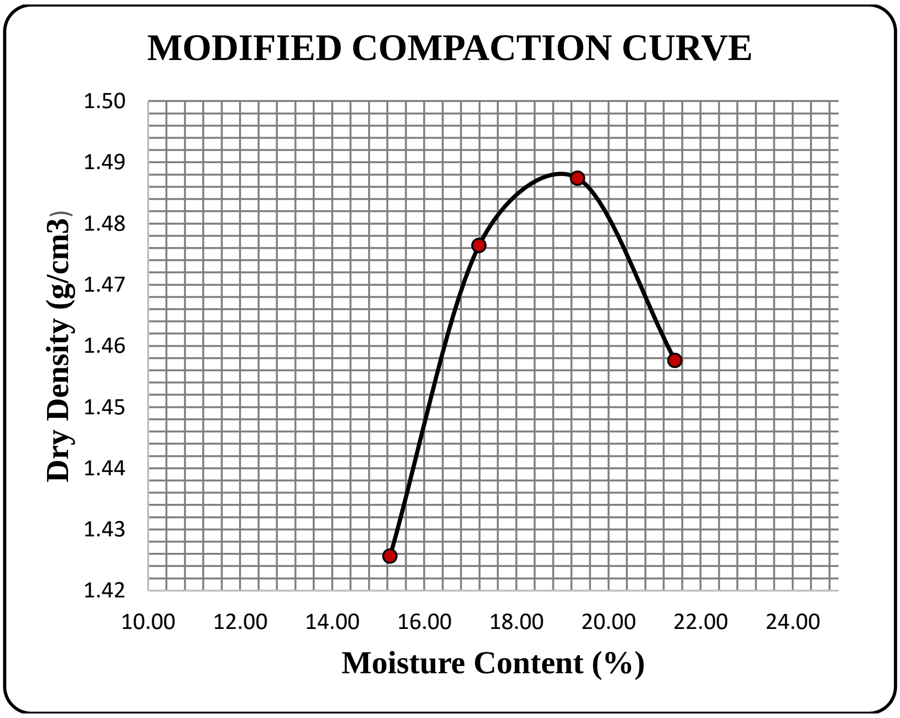
Modified Proctor				
	Density			
Trial Number	1	2	3	4
weight of wet soil + mold (g)	6380	6515	6633	6610
weight of mold (g)	4710	4710	4710	4710
weight of wet soil (g)	1670	1805	1923	1900
volume of mold (g)	944	944	944	944
bulk density of soil (g/cm3)	1.77	1.91	2.04	2.01
	Moisture content			
can number	AB3	PL2	PLTA	ABL5
wet soil + can (g)	99	71.3	79.4	99.64
dry soil + can (g)	87.44	62.34	67.91	82.96
weight of can (g)	15.45	15.78	15.71	15.14
weight of water (g)	11.56	8.96	11.49	16.68
weight of dry soil (g)	71.99	46.56	52.2	67.82
moisture content (%)	16.06	19.24	22.01	24.59
dry density of soil (g/cm3)	1.52	1.60	1.67	1.62
	MDD=1.67g/cm3		OMC = 22.01%	



Location: Goro

Test Method: ASTM D 1557

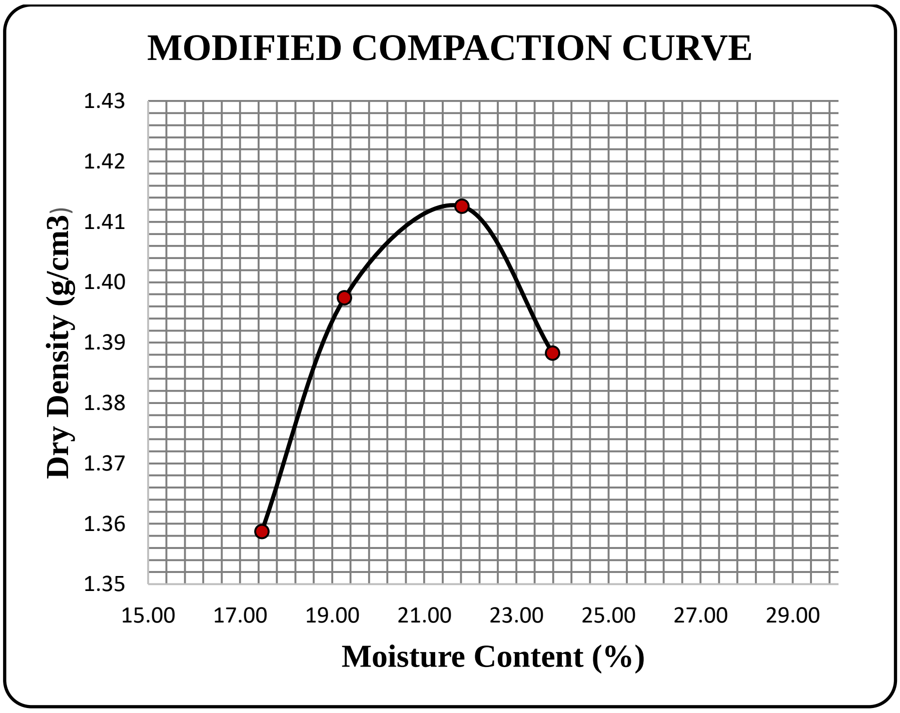
Modified Proctor				
	Density			
Trial Number	1	2	3	4
weight of wet soil + mold (g)	7112	7194	7237	7232
weight of mold (g)	5561	5561	5561	5561
weight of wet soil (g)	1551	1633	1676	1671
volume of mold (g)	944	944	944	944
bulk density of soil (g/cm3)	1.64	1.73	1.77	1.77
	Moisture content			
can number	K3	ST3	44W	K2
wet soil + can (g)	176.3	160	185.2	170.8
dry soil + can (g)	157	140.9	160.2	146.2
weight of can (g)	30.5	29.8	30.9	31.5
weight of water (g)	19.3	19.1	25	24.6
weight of dry soil (g)	126.5	111.1	129.3	114.7
moisture content (%)	15.26	17.19	19.33	21.45
dry density of soil (g/cm3)	1.43	1.48	1.49	1.46
	MDD = 1.49g/cm3		OMC =19.3%	



Location: Shegole

Test Method: ASTM D 1557

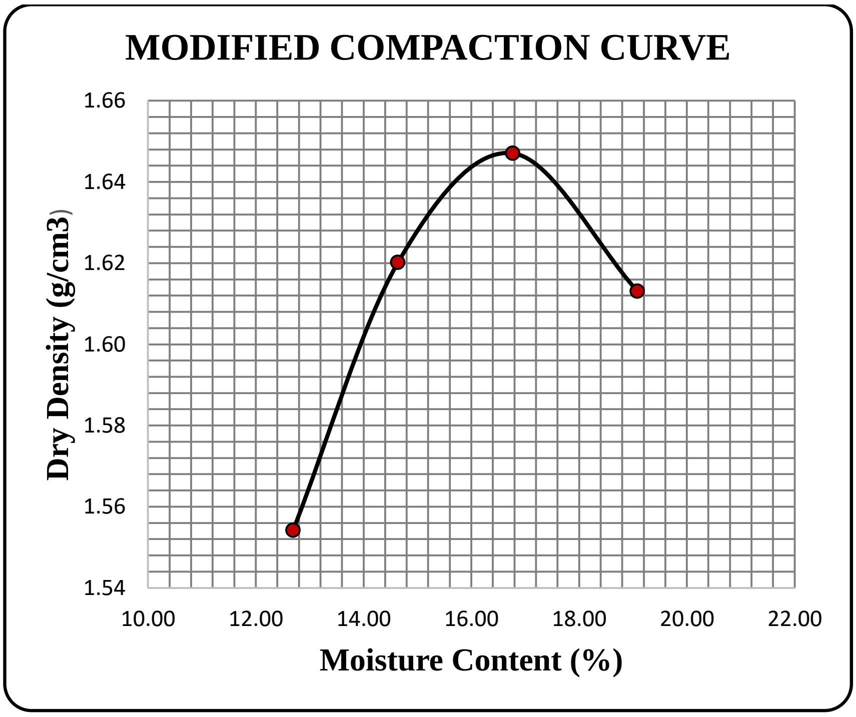
Modified Proctor				
	Density			
Trial Number	1	2	3	4
weight of wet soil + mold (g)	7068	7134	7185	7183
weight of mold (g)	5561	5561	5561	5561
weight of wet soil (g)	1507	1573	1624	1622
volume of mold (g)	944	944	944	944
bulk density of soil (g/cm3)	1.60	1.67	1.72	1.72
	Moisture content			
can number	AB	T-2	MD4	DS7
wet soil + can (g)	174.4	167.2	176.6	172
dry soil + can (g)	153	145	150.5	145
weight of can (g)	30.5	29.8	30.9	31.5
weight of water (g)	21.4	22.2	26.1	27
weight of dry soil (g)	122.5	115.2	119.6	113.5
moisture content (%)	17.47	19.27	21.82	23.79
dry density of soil (g/cm3)	1.36	1.40	1.41	1.39
	MDD = 1.41g/cm3		OMC =21.82%	



Location: Ferensay Abo

Test Method: ASTM D 1557

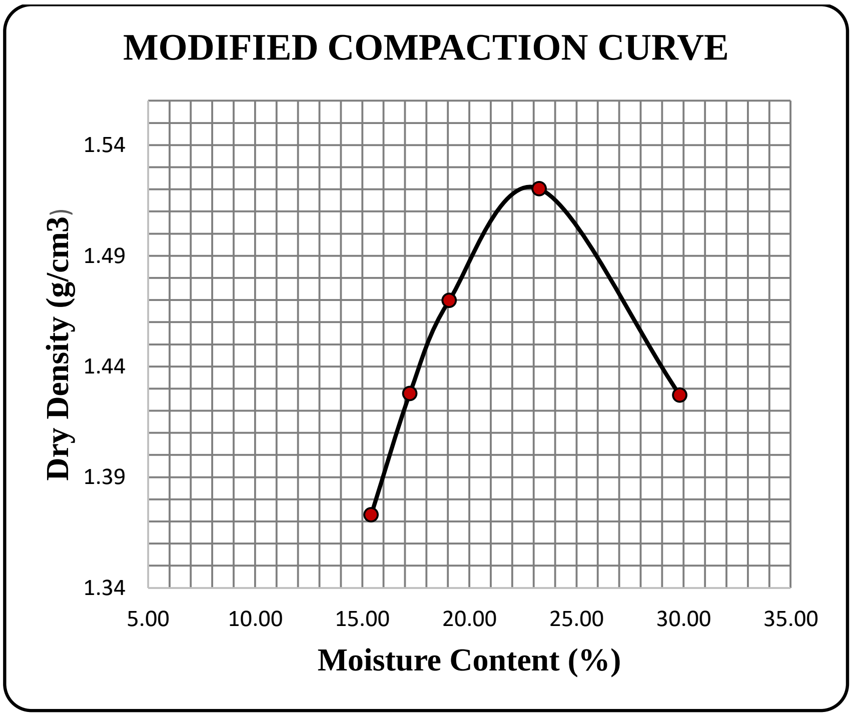
Modified Proctor				
	Density			
Trial Number	1	2	3	4
weight of wet soil + mold (g)	7214	7314	7377	7374
weight of mold (g)	5561	5561	5561	5561
weight of wet soil (g)	1653	1753	1816	1813
volume of mold (g)	944	944	944	944
bulk density of soil (g/cm3)	1.75	1.86	1.92	1.92
	Moisture content			
can number	NB	22-T	CC	D23
wet soil + can (g)	164.6	160.8	183.5	180.7
dry soil + can (g)	149.6	144.2	161.6	157
weight of can (g)	31.4	30.8	31	32.8
weight of water (g)	15	16.6	21.9	23.7
weight of dry soil (g)	118.2	113.4	130.6	124.2
moisture content (%)	12.69	14.64	16.77	19.08
dry density of soil (g/cm3)	1.55	1.62	1.65	1.61
	MDD = 1.65g/cm3		OMC =16.77%	



Location: Tikur Anbesa

Test Method: ASTM D 1557

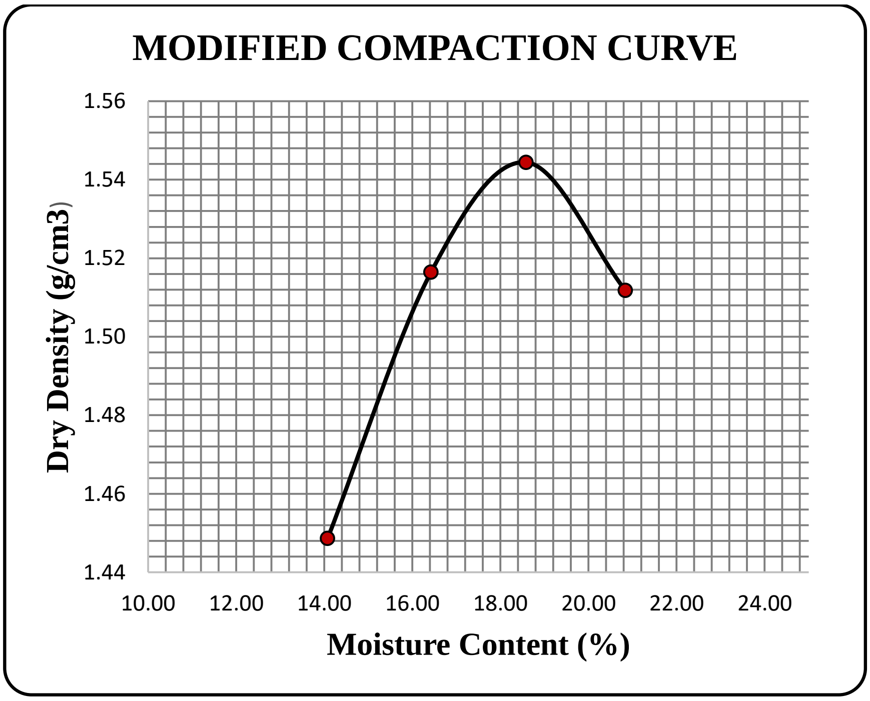
Modified Proctor					
	Density				
Trial Number	1	2	3	4	5
weight of wet soil + mold (g)	7057	7141	7213	7330	7310
weight of mold (g)	5561	5561	5561	5561	5561
weight of wet soil (g)	1496	1580	1652	1769	1749
Volume of mold (g)	944	944	944	944	944
Bulk density of soil (g/cm3)	1.58	1.67	1.75	1.87	1.85
	Moisture content				
can number	COMPAC	Test3	1	8	24
wet soil + can (g)	101.6	101.1	94.6	103.61	95.7
dry soil + can (g)	90.18	88.56	81.24	86.97	77.35
weight of can (g)	16.14	15.77	11.17	15.43	15.84
weight of water (g)	11.42	12.54	13.36	16.64	18.35
weight of dry soil (g)	74.04	72.79	70.07	71.54	61.51
moisture content (%)	15.42	17.23	19.07	23.26	29.83
dry density of soil (g/cm3)	1.37	1.43	1.47	1.52	1.43
	MDD=1.52g/cm3			OMC=23.26%	



Location: Ayertena

Test Method: ASTM D 1557

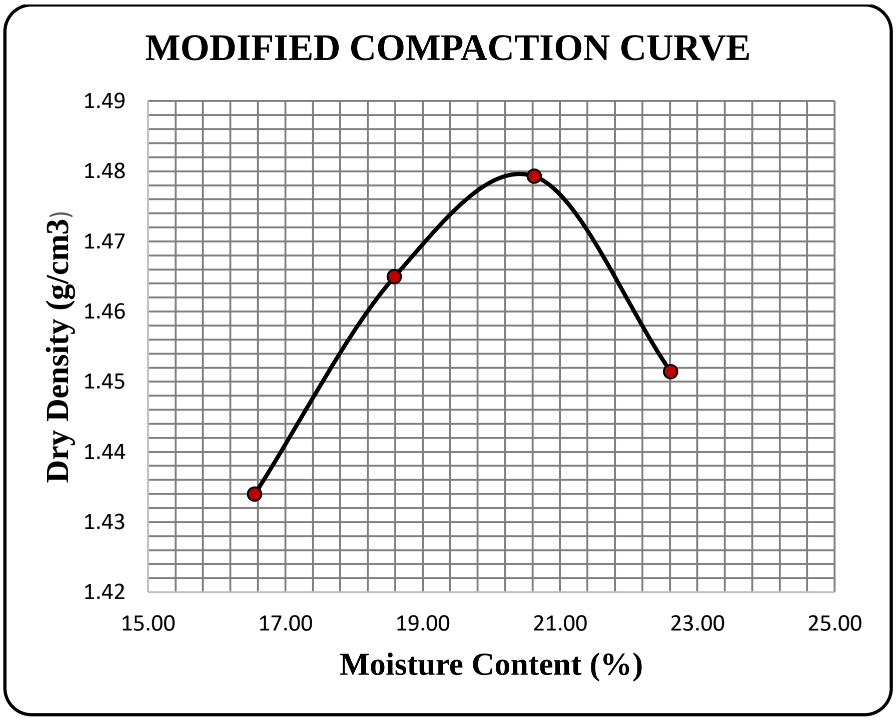
Modified Proctor				
	Density			
Trial Number	1	2	3	4
weight of wet soil + mold (g)	7121	7228	7290	7285
weight of mold (g)	5561	5561	5561	5561
weight of wet soil (g)	1560	1667	1729	1724
volume of mold (g)	944	944	944	944
bulk density of soil (g/cm3)	1.65	1.77	1.83	1.83
	Moisture content			
can number	KS	MM	KJ3	DD2
wet soil + can (g)	170.4	160.5	190.5	176.9
dry soil + can (g)	153	142.3	165.5	152
weight of can (g)	29.4	31.5	31	32.5
weight of water (g)	17.4	18.2	25	24.9
weight of dry soil (g)	123.6	110.8	134.5	119.5
moisture content (%)	14.08	16.43	18.59	20.84
dry density of soil (g/cm3)	1.45	1.52	1.54	1.51
	MDD = 1.54g/cm3		OMC =18.6%	



Location: Akaki

Test Method: ASTM D 1557

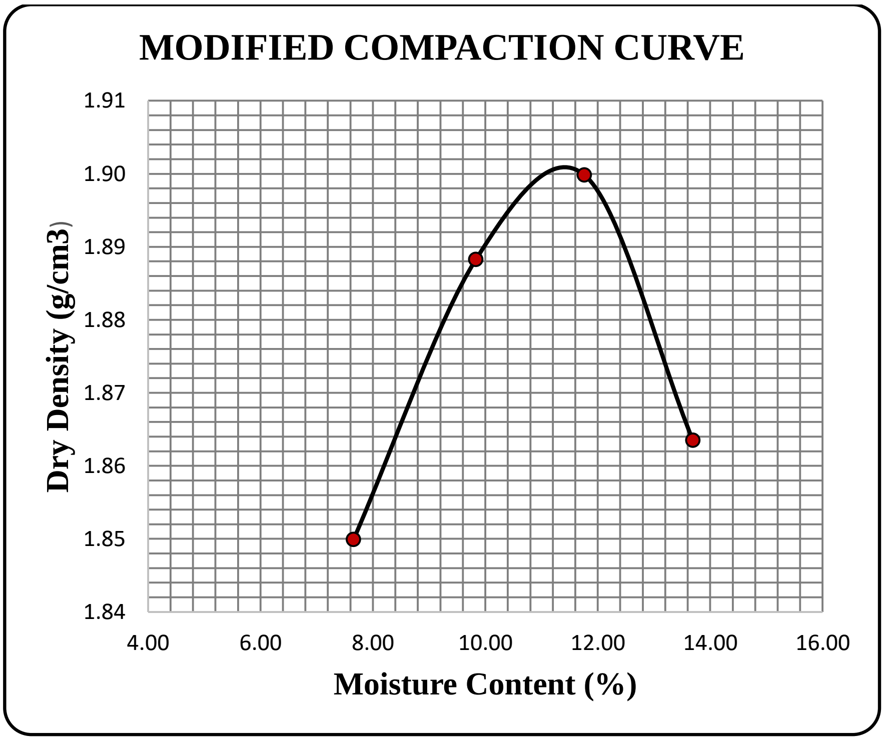
Modified Proctor				
	Density			
Trial Number	1	2	3	4
weight of wet soil + mold (g)	7139	7201	7245	7241
weight of mold (g)	5561	5561	5561	5561
weight of wet soil (g)	1578	1640	1684	1680
volume of mold (g)	944	944	944	944
bulk density of soil (g/cm3)	1.67	1.74	1.78	1.78
	Moisture content			
can number	JS3	K2	CC2	MD4
wet soil + can (g)	170	170.9	185.3	176.8
dry soil + can (g)	150.2	149	158.9	150
weight of can (g)	30.6	31.2	30.9	31.5
weight of water (g)	19.8	21.9	26.4	26.8
weight of dry soil (g)	119.6	117.8	128	118.5
moisture content (%)	16.56	18.59	20.63	22.62
dry density of soil (g/cm3)	1.43	1.46	1.48	1.45
	MDD = 1.48g/cm3		OMC =20.63%	



Location: Leghar

Test Method: ASTM D 1557

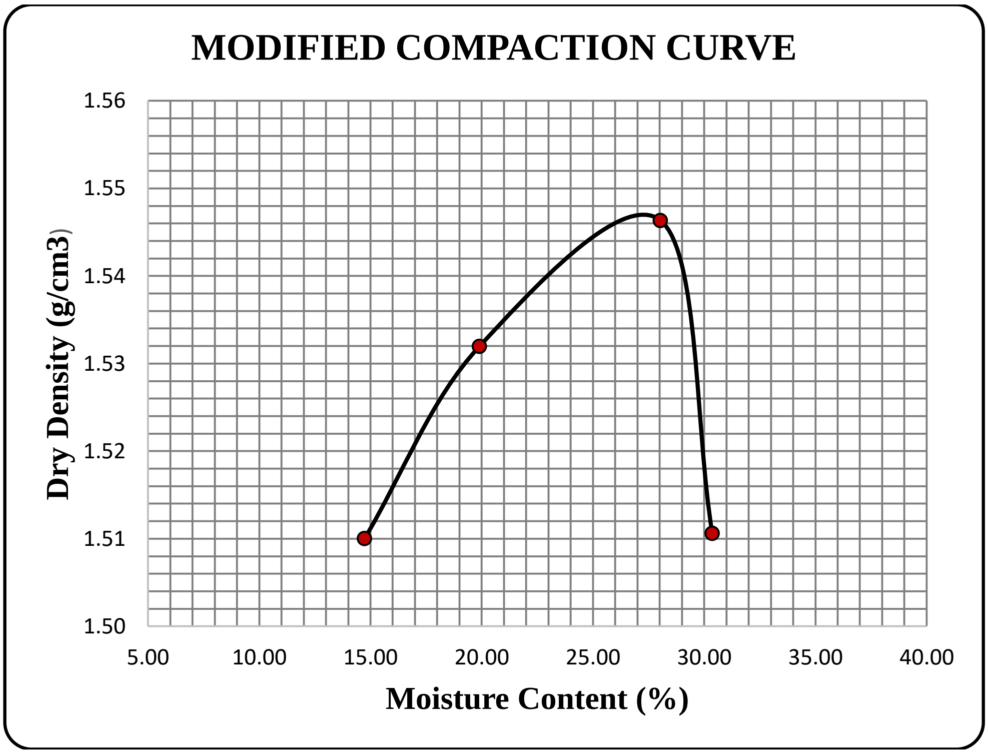
Modified Proctor				
	Density			
Trial Number	1	2	3	4
weight of wet soil + mold (g)	7441	7519	7565	7561
weight of mold (g)	5561	5561	5561	5561
weight of wet soil (g)	1880	1958	2004	2000
volume of mold (g)	944	944	944	944
bulk density of soil (g/cm3)	1.99	2.07	2.12	2.12
	Moisture content			
can number	AB	T-2	MD4	DS7
wet soil + can (g)	163	174.4	175.6	175.5
dry soil + can (g)	153.6	161.6	160.4	158
weight of can (g)	30.8	31.4	31.2	30.2
weight of water (g)	9.4	12.8	15.2	17.5
weight of dry soil (g)	122.8	130.2	129.2	127.8
moisture content (%)	7.65	9.83	11.76	13.69
dry density of soil (g/cm3)	1.85	1.89	1.90	1.86
	MDD = 1.9g/cm3		OMC =11.7%	



Location: Kolfe

Test Method: ASTM D 1557

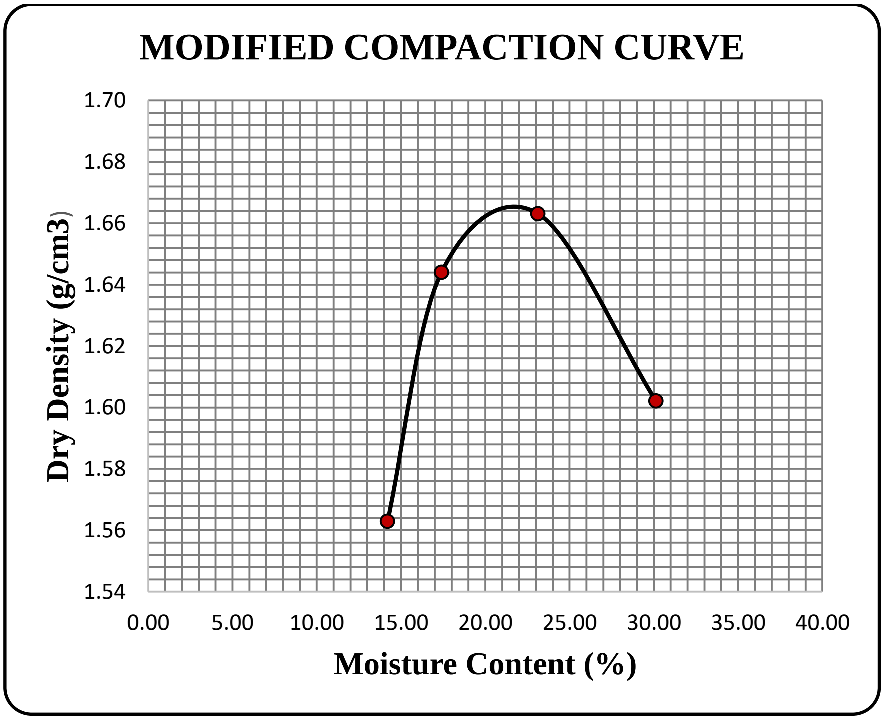
Modified Proctor				
	Density			
Trial Number	1	2	3	4
weight of wet soil + mold (g)	7215	7295	7430	7420
weight of mold (g)	5561	5561	5561	5561
weight of wet soil (g)	1654	1734	1869	1859
volume of mold (g)	944	944	944	944
bulk density of soil (g/cm3)	1.75	1.84	1.98	1.97
	Moisture content			
can number	2C	3A	ComR	mc3
wet soil + can (g)	104.6	94.65	88.7	74
dry soil + can (g)	92.74	81.6	72.89	60.7
weight of can (g)	15.64	16.03	16.5	16.9
weight of water (g)	11.86	13.05	15.81	13.3
weight of dry soil (g)	77.1	65.57	56.39	43.8
moisture content (%)	15.38	19.90	28.04	30.37
dry density of soil (g/cm3)	1.51	1.53	1.55	1.50
	MDD=1.55g/cm3		OMC=28.04%	



Location: Adisu Gebeya

Test Method: ASTM D 1557

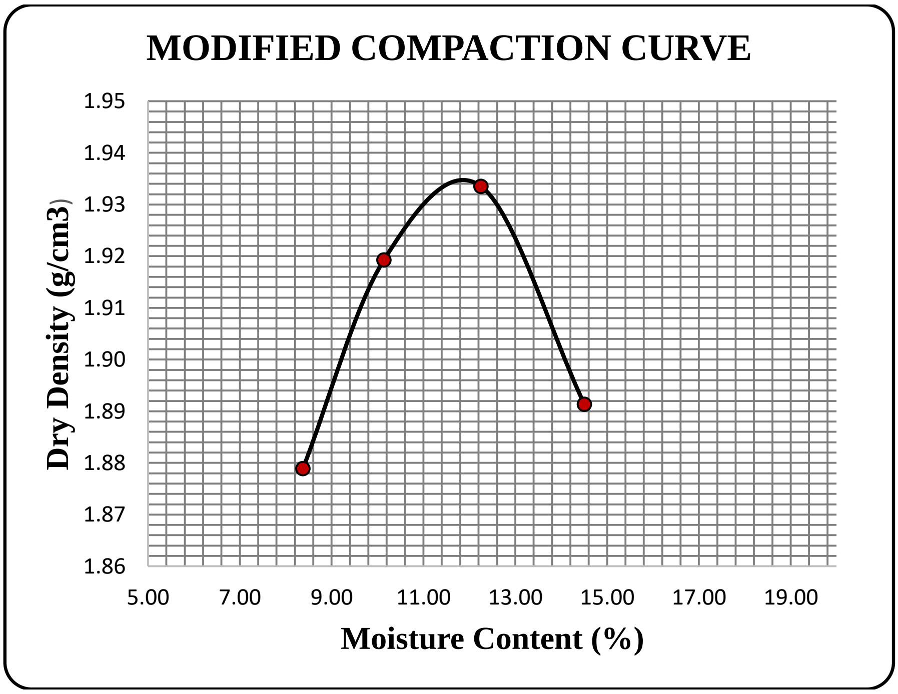
Modified Proctor				
	Density			
Trial Number	1	2	3	4
weight of wet soil + mold (g)	6273	6410	6521	6556
weight of mold (g)	4588	4588	4588	4588
weight of wet soil (g)	1685	1822	1933	1968
volume of mold (g)	944	944	944	944
bulk density of soil (g/cm3)	1.78	1.93	2.05	2.08
	Moisture content			
can number	zz	P6-2	1	Ms2
wet soil + can (g)	98	101	98.1	103
dry soil + can (g)	87.8	88.4	82.5	81.7
weight of can (g)	16	16	15	11
weight of water (g)	10.2	12.6	15.60	21.3
weight of dry soil (g)	71.8	72.4	67.47	70.7
moisture content (%)	14.21	17.40	23.12	30.13
dry density of soil (g/cm3)	1.56	1.64	1.66	1.60
	MDD = 1.66g/cm3		OMC =23.12%	



Location: Megenagna

Test Method: ASTM D 1557

Modified Proctor				
	Density			
Trial Number	1	2	3	4
weight of wet soil + mold (g)	7483	7557	7610	7605
weight of mold (g)	5561	5561	5561	5561
weight of wet soil (g)	1922	1996	2049	2044
volume of mold (g)	944	944	944	944
bulk density of soil (g/cm3)	2.04	2.11	2.17	2.17
	Moisture content			
can number	AB	T-2	MD4	DS7
wet soil + can (g)	160.8	170.9	166.6	174.1
dry soil + can (g)	150.8	158	151.8	156.2
weight of can (g)	31.4	30.8	31	32.8
weight of water (g)	10	12.9	14.8	17.9
weight of dry soil (g)	119.4	127.2	120.8	123.4
moisture content (%)	8.38	10.14	12.25	14.51
dry density of soil (g/cm3)	1.88	1.92	1.93	1.89
	MDD = 1.93g/cm3		OMC =12.3%	



APPENDIX E: MATLAB SCRIPT FILE FOR Coarsemdd1

```
%importdata
x = input;
t = outputmdd;
m = length(t);


%select training function type
trainFcn = 'trainlm'; % Levenberg-Marquardt
backpropagation.


% Choose Input and Output Pre/Post-Processing Functions
net.input.processFcns = {'removeconstantrows','mapminmax'};
net.output.processFcns =
{'removeconstantrows','mapminmax'};


% Setup Division of Data for Training, Validation, Testing
net.divideFcn = 'dividerand';  % Divide data randomly
net.divideMode = 'sample';  % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;


% Create a Fitting Network
hiddenLayerSize = 12;
net = fitnet(hiddenLayerSize,trainFcn);


% Choose a Performance Function
net.performFcn = 'mse';  % Mean Squared Error


% Choose Plot Functions
net.plotFcns =
{'plotperform','plottrainstate','ploterrhist', ...
    'plotregression', 'plotfit'};


% Train the Network
[net,tr] = train(net,x,t);


% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y)
```

```
% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1};
valTargets = t .* tr.valMask{1};
testTargets = t .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)

% View the Network
view(net)


% Plots
figure, plotperform(tr)
figure, plottrainstate(tr)
figure, ploterrhist(e)
figure, plotregression(t,y)
figure, plotfit(net,x,t)

% RMSE of the ANN
tTrain = net(x(:,tr.trainInd));
tTrainTrue = t(tr.trainInd);
sqrt(mean((tTrain - tTrainTrue ).^2))
tVal = net(x(:,tr.valInd));
tValTrue = t(tr.valInd);
sqrt(mean((tVal - tValTrue ).^2))
ttest = net(x(:,tr.testInd));
ttestTrue = t(tr.testInd);
sqrt(mean((ttest - ttestTrue).^2))

% optimize the number of neurons in the hidden layer using
their RMSE
for i = 1:30

  % defining the architecture of the network
  hiddenLayerSize = i;
  trainFcn = 'trainlm';
  net = fitnet(hiddenLayerSize,trainFcn);
  net.divideFcn = 'dividerand';  % Divide data randomly
  net.divideMode = 'sample';  % Divide up every sample
  net.divideParam.trainRatio = 70/100;
  net.divideParam.valRatio = 15/100;
  net.divideParam.testRatio = 15/100;

  % Training the ANN
  [net,tr] = train(net,x,t);

  % Determine the error of the ANN

  tTrain = net(x(:,tr.trainInd));
```

```
  tTrainTrue = t(tr.trainInd);
  tVal = net(x(:,tr.valInd));
  tValTrue = t(tr.valInd);
  ttest = net(x(:,tr.testInd));
  ttestTrue = t(tr.testInd);
  rmse_train(i) = sqrt(mean((tTrain - tTrainTrue ).^2)); %
RMSE of Training set
  rmse_val(i) = sqrt(mean((tVal - tValTrue ).^2)); % RMSE
of Validation set
  rmse_test(i) = sqrt(mean((ttest - ttestTrue).^2));% RMSE
of test set

end

% select optimal number of hidden neurons
plot(1:30,rmse_train); hold on;
plot(1:30,rmse_val);
plot(1:30,rmse_test);hold off;

% retrain the network with optimal number of hidden neurons
  hiddenLayerSize = 10;
  trainFcn = 'trainlm';
  net = fitnet(hiddenLayerSize,trainFcn);
  net.divideFcn = 'dividerand';  % Divide data randomly
  net.divideMode = 'sample';  % Divide up every sample
  net.divideParam.trainRatio = 70/100;
  net.divideParam.valRatio = 15/100;
  net.divideParam.testRatio = 15/100;

  % Training the ANN
  [net,tr] = train(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y)


% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1};
valTargets = t .* tr.valMask{1};
testTargets = t .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)


% RMSE of the ANN
tTrain = net(x(:,tr.trainInd));
tTrainTrue = t(tr.trainInd);
sqrt(mean((tTrain - tTrainTrue ).^2))
```

```
tVal = net(x(:,tr.valInd));
tValTrue = t(tr.valInd);
sqrt(mean((tVal - tValTrue ).^2))
ttest = net(x(:,tr.testInd));
ttestTrue = t(tr.testInd);
sqrt(mean((ttest - ttestTrue).^2))


% View the Network
view(net)


% Plots
figure, plotperform(tr)
figure, plottrainstate(tr)
figure, ploterrhist(e)
figure, plotregression(t,y)
figure, plotfit(net,x,t)



w1 = network22.IW(1,1);
w2 = network22.LW(2,1);
b1 = network22.b(1);
b2 = network22.b(2);
```

APPENDIX F: MATLAB SCRIPT FILE FOR Coarseomc1

```
%importdata
x = input;
t = outputomc;
m = length(t);


%select training function type
trainFcn = 'trainlm'; % Levenberg-Marquardt
backpropagation.


% Choose Input and Output Pre/Post-Processing Functions
net.input.processFcns = {'removeconstantrows','mapminmax'};
net.output.processFcns =
{'removeconstantrows','mapminmax'};


% Setup Division of Data for Training, Validation, Testing
net.divideFcn = 'dividerand';  % Divide data randomly
net.divideMode = 'sample';  % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;


% Create a Fitting Network
hiddenLayerSize = 16;
net = fitnet(hiddenLayerSize,trainFcn);


% Choose a Performance Function
net.performFcn = 'mse';  % Mean Squared Error


% Choose Plot Functions
net.plotFcns =
{'plotperform','plottrainstate','ploterrhist', ...
    'plotregression', 'plotfit'};


% Train the Network
[net,tr] = train(net,x,t);



% Test the Network
y = net(x);
e = gsubtract(t,y);
```

```
performance = perform(net,t,y)

% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1};
valTargets = t .* tr.valMask{1};
testTargets = t .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)

% View the Network
view(net)


% Plots
figure, plotperform(tr)
figure, plottrainstate(tr)
figure, ploterrhist(e)
figure, plotregression(t,y)
figure, plotfit(net,x,t)

% RMSE of the ANN
tTrain = net(x(:,tr.trainInd));
tTrainTrue = t(tr.trainInd);
sqrt(mean((tTrain - tTrainTrue ).^2))
tVal = net(x(:,tr.valInd));
tValTrue = t(tr.valInd);
sqrt(mean((tVal - tValTrue ).^2))
ttest = net(x(:,tr.testInd));
ttestTrue = t(tr.testInd);
sqrt(mean((ttest - ttestTrue).^2))

% optimize the number of neurons in the hidden layer using
their RMSE
for i = 1:30

  % defining the architecture of the network
  hiddenLayerSize = i;
  trainFcn = 'trainlm';
  net = fitnet(hiddenLayerSize,trainFcn);
  net.divideFcn = 'dividerand';  % Divide data randomly
  net.divideMode = 'sample';  % Divide up every sample
  net.divideParam.trainRatio = 70/100;
  net.divideParam.valRatio = 15/100;
  net.divideParam.testRatio = 15/100;

  % Training the ANN
  [net,tr] = train(net,x,t);

  % Determine the error of the ANN
```

```
  tTrain = net(x(:,tr.trainInd));
  tTrainTrue = t(tr.trainInd);
  tVal = net(x(:,tr.valInd));
  tValTrue = t(tr.valInd);
  ttest = net(x(:,tr.testInd));
  ttestTrue = t(tr.testInd);
  rmse_train(i) = sqrt(mean((tTrain - tTrainTrue ).^2)); %
RMSE of Training set
  rmse_val(i) = sqrt(mean((tVal - tValTrue ).^2)); % RMSE
of Validation set
  rmse_test(i) = sqrt(mean((ttest - ttestTrue).^2));% RMSE
of test set

end

% select optimal number of hidden neurons
plot(1:30,rmse_train); hold on;
plot(1:30,rmse_val);
plot(1:30,rmse_test);hold off;

% retrain the network with optimal number of hidden neurons
  hiddenLayerSize = 16;
  trainFcn = 'trainlm';
  net = fitnet(hiddenLayerSize,trainFcn);
  net.divideFcn = 'dividerand';  % Divide data randomly
  net.divideMode = 'sample';  % Divide up every sample
  net.divideParam.trainRatio = 70/100;
  net.divideParam.valRatio = 15/100;
  net.divideParam.testRatio = 15/100;

  % Training the ANN
  [net,tr] = train(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y)

% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1};
valTargets = t .* tr.valMask{1};
testTargets = t .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)


% RMSE of the ANN
tTrain = net(x(:,tr.trainInd));
tTrainTrue = t(tr.trainInd);
sqrt(mean((tTrain - tTrainTrue ).^2))
```

```
tVal = net(x(:,tr.valInd));
tValTrue = t(tr.valInd);
sqrt(mean((tVal - tValTrue ).^2))
ttest = net(x(:,tr.testInd));
ttestTrue = t(tr.testInd);
sqrt(mean((ttest - ttestTrue).^2))


% View the Network
view(net)


% Plots
figure, plotperform(tr)
figure, plottrainstate(tr)
figure, ploterrhist(e)
figure, plotregression(t,y)
figure, plotfit(net,x,t)



w1 = network59.IW(1,1);
w2 = network59.LW(2,1);
b1 = network59.b(1);
b2 = network59.b(2);
```

APPENDIX G: MATLAB SCRIPT FILE FOR Finemdd2

```
%importdata
x = input;
t = outputmdd;
m = length(t);


%select training function type
trainFcn = 'trainlm'; % Levenberg-Marquardt
backpropagation.


% Choose Input and Output Pre/Post-Processing Functions
net.input.processFcns = {'removeconstantrows','mapminmax'};
net.output.processFcns =
{'removeconstantrows','mapminmax'};


% Setup Division of Data for Training, Validation, Testing
net.divideFcn = 'dividerand';  % Divide data randomly
net.divideMode = 'sample';  % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;


% Create a Fitting Network
hiddenLayerSize = 15;
net = fitnet(hiddenLayerSize,trainFcn);


% Choose a Performance Function
net.performFcn = 'mse';  % Mean Squared Error


% Choose Plot Functions
net.plotFcns =
{'plotperform','plottrainstate','ploterrhist', ...
    'plotregression', 'plotfit'};


% Train the Network
[net,tr] = train(net,x,t);


% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y)
```

```
% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1};
valTargets = t .* tr.valMask{1};
testTargets = t .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)

% View the Network
view(net)


% Plots
figure, plotperform(tr)
figure, plottrainstate(tr)
figure, ploterrhist(e)
figure, plotregression(t,y)
figure, plotfit(net,x,t)

% RMSE of the ANN
tTrain = net(x(:,tr.trainInd));
tTrainTrue = t(tr.trainInd);
sqrt(mean((tTrain - tTrainTrue ).^2))
tVal = net(x(:,tr.valInd));
tValTrue = t(tr.valInd);
sqrt(mean((tVal - tValTrue ).^2))
ttest = net(x(:,tr.testInd));
ttestTrue = t(tr.testInd);
sqrt(mean((ttest - ttestTrue).^2))

% optimize the number of neurons in the hidden layer using
their RMSE
for i = 1:30

  % defining the architecture of the network
  hiddenLayerSize = i;
  trainFcn = 'trainlm';
  net = fitnet(hiddenLayerSize,trainFcn);
  net.divideFcn = 'dividerand';  % Divide data randomly
  net.divideMode = 'sample';  % Divide up every sample
  net.divideParam.trainRatio = 70/100;
  net.divideParam.valRatio = 15/100;
  net.divideParam.testRatio = 15/100;

  % Training the ANN
  [net,tr] = train(net,x,t);

  % Determine the error of the ANN

  tTrain = net(x(:,tr.trainInd));
```

```
  tTrainTrue = t(tr.trainInd);
  tVal = net(x(:,tr.valInd));
  tValTrue = t(tr.valInd);
  ttest = net(x(:,tr.testInd));
  ttestTrue = t(tr.testInd);
  rmse_train(i) = sqrt(mean((tTrain - tTrainTrue ).^2)); %
RMSE of Training set
  rmse_val(i) = sqrt(mean((tVal - tValTrue ).^2)); % RMSE
of Validation set
  rmse_test(i) = sqrt(mean((ttest - ttestTrue).^2));% RMSE
of test set

end

% select optimal number of hidden neurons
plot(1:30,rmse_train); hold on;
plot(1:30,rmse_val);
plot(1:30,rmse_test);hold off;

% retrain the network with optimal number of hidden neurons
  hiddenLayerSize = 10;
  trainFcn = 'trainlm';
  net = fitnet(hiddenLayerSize,trainFcn);
  net.divideFcn = 'dividerand';  % Divide data randomly
  net.divideMode = 'sample';  % Divide up every sample
  net.divideParam.trainRatio = 70/100;
  net.divideParam.valRatio = 15/100;
  net.divideParam.testRatio = 15/100;

  % Training the ANN
  [net,tr] = train(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y)


% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1};
valTargets = t .* tr.valMask{1};
testTargets = t .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)


% RMSE of the ANN
tTrain = net(x(:,tr.trainInd));
tTrainTrue = t(tr.trainInd);
sqrt(mean((tTrain - tTrainTrue ).^2))
```

```
tVal = net(x(:,tr.valInd));
tValTrue = t(tr.valInd);
sqrt(mean((tVal - tValTrue ).^2))
ttest = net(x(:,tr.testInd));
ttestTrue = t(tr.testInd);
sqrt(mean((ttest - ttestTrue).^2))


% View the Network
view(net)


% Plots
figure, plotperform(tr)
figure, plottrainstate(tr)
figure, ploterrhist(e)
figure, plotregression(t,y)
figure, plotfit(net,x,t)



w1 = network22.IW(1,1);
w2 = network22.LW(2,1);
b1 = network22.b(1);
b2 = network22.b(2);
```

APPENDIX H: MATLAB SCRIPT FILE FOR Fineomc6

```
%importdata
x = input;
t = outputomc;
m = length(t);


%select training function type
trainFcn = 'trainlm'; % Levenberg-Marquardt
backpropagation.


% Choose Input and Output Pre/Post-Processing Functions
net.input.processFcns = {'removeconstantrows','mapminmax'};
net.output.processFcns =
{'removeconstantrows','mapminmax'};


% Setup Division of Data for Training, Validation, Testing
net.divideFcn = 'dividerand';  % Divide data randomly
net.divideMode = 'sample';  % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;


% Create a Fitting Network
hiddenLayerSize = 8;
net = fitnet(hiddenLayerSize,trainFcn);


% Choose a Performance Function
net.performFcn = 'mse';  % Mean Squared Error


% Choose Plot Functions
net.plotFcns =
{'plotperform','plottrainstate','ploterrhist', ...
    'plotregression', 'plotfit'};


% Train the Network
[net,tr] = train(net,x,t);



% Test the Network
y = net(x);
e = gsubtract(t,y);
```

```
performance = perform(net,t,y)

% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1};
valTargets = t .* tr.valMask{1};
testTargets = t .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)

% View the Network
view(net)


% Plots
figure, plotperform(tr)
figure, plottrainstate(tr)
figure, ploterrhist(e)
figure, plotregression(t,y)
figure, plotfit(net,x,t)

% RMSE of the ANN
tTrain = net(x(:,tr.trainInd));
tTrainTrue = t(tr.trainInd);
sqrt(mean((tTrain - tTrainTrue ).^2))
tVal = net(x(:,tr.valInd));
tValTrue = t(tr.valInd);
sqrt(mean((tVal - tValTrue ).^2))
ttest = net(x(:,tr.testInd));
ttestTrue = t(tr.testInd);
sqrt(mean((ttest - ttestTrue).^2))

% optimize the number of neurons in the hidden layer using
their RMSE
for i = 1:30

  % defining the architecture of the network
  hiddenLayerSize = i;
  trainFcn = 'trainlm';
  net = fitnet(hiddenLayerSize,trainFcn);
  net.divideFcn = 'dividerand';  % Divide data randomly
  net.divideMode = 'sample';  % Divide up every sample
  net.divideParam.trainRatio = 70/100;
  net.divideParam.valRatio = 15/100;
  net.divideParam.testRatio = 15/100;

  % Training the ANN
  [net,tr] = train(net,x,t);

  % Determine the error of the ANN
```

```
  tTrain = net(x(:,tr.trainInd));
  tTrainTrue = t(tr.trainInd);
  tVal = net(x(:,tr.valInd));
  tValTrue = t(tr.valInd);
  ttest = net(x(:,tr.testInd));
  ttestTrue = t(tr.testInd);
  rmse_train(i) = sqrt(mean((tTrain - tTrainTrue ).^2)); %
RMSE of Training set
  rmse_val(i) = sqrt(mean((tVal - tValTrue ).^2)); % RMSE
of Validation set
  rmse_test(i) = sqrt(mean((ttest - ttestTrue).^2));% RMSE
of test set

end

% select optimal number of hidden neurons
plot(1:30,rmse_train); hold on;
plot(1:30,rmse_val);
plot(1:30,rmse_test);hold off;

% retrain the network with optimal number of hidden neurons
  hiddenLayerSize = 16;
  trainFcn = 'trainlm';
  net = fitnet(hiddenLayerSize,trainFcn);
  net.divideFcn = 'dividerand';  % Divide data randomly
  net.divideMode = 'sample';  % Divide up every sample
  net.divideParam.trainRatio = 70/100;
  net.divideParam.valRatio = 15/100;
  net.divideParam.testRatio = 15/100;

  % Training the ANN
  [net,tr] = train(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y)

% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1};
valTargets = t .* tr.valMask{1};
testTargets = t .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)


% RMSE of the ANN
tTrain = net(x(:,tr.trainInd));
tTrainTrue = t(tr.trainInd);
sqrt(mean((tTrain - tTrainTrue ).^2))
```

```
tVal = net(x(:,tr.valInd));
tValTrue = t(tr.valInd);
sqrt(mean((tVal - tValTrue ).^2))
ttest = net(x(:,tr.testInd));
ttestTrue = t(tr.testInd);
sqrt(mean((ttest - ttestTrue).^2))


% View the Network
view(net)


% Plots
figure, plotperform(tr)
figure, plottrainstate(tr)
figure, ploterrhist(e)
figure, plotregression(t,y)
figure, plotfit(net,x,t)



w1 = network59.IW(1,1);
w2 = network59.LW(2,1);
b1 = network59.b(1);
b2 = network59.b(2);
```