COMPACTION PARAMETERS PREDICTION AND ANALYSIS FROM ATTERBERG LIMIT BY ARTIFICIAL NEURAL NET OF SOILS ALONG MOROCHO-APOSTO ROAD

M.Sc. THESIS

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HAWASSA UNIVERSITY, HAWASSA, ETHIOPIA

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ADVISOR'S APPROVAL SHEET

This is to certify that the thesis entitled "**Compaction parameters prediction and analysis from Atterberg limit by Artificial Neural Net of soils along Morocho-Aposto road**" in partial fulfillment of the Master's with specialization in Geotechnical Engineering, the graduate program of the Department/School civil engineering, and has been carried out by Meiraf Iyasu Begeje, Id No. PGGeo/022/09 under my/our supervision. Therefore, I, the student fulfilled the requirement and hence here by can submit the thesis to the department.

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We, the undersigned, members of the Board of Examiners of the final open defense by Meiraf Iyasu Begeje have read and evaluated his/her thesis entitled "**Compaction parameters prediction and analysis from Atterberg limit by Artificial Neural Net of soils along Morocho-Aposto road"**, and examined the candidate. This is, therefore, to certify that the thesis has been accepted in partial fulfillment of the requirements for the degree.

Name of the Chairperson	Signature	Date
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Name of External examiner	Signature	Date
SGS Approval	Signature	Date

DECLARATION

I, the undersigned, declare that this thesis entitled: "**Compaction parameters prediction and analysis from Atterberg limit by Artificial Neural Net of soils along Morocho-Aposto road"** is my original work, and has not been presented by any other person for an award of a degree in this or any other University, and all sources of material used for this thesis proposal have to be duly acknowledged.

Candidate:

Meiraf Iyasu Begeje

______________________ ______________________

Signature Date

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LIST OF ABBREVATIONS AND ACRONYMS

AASHTO	American Association of State Highway and Transportation Official
ANN	Artificial Neural Network
ASTM	American Society for Testing and Materials
BR	Bayesian Regularization Algorithm
IATI	International Aid Transparency Initiative
ID	Independent Data
LL	Liquid Limit
LM	Levenberg-Marquardt Algorithm
LRA	Linear Regression Analysis
MATLAB	Mathematical Labratory
MDD	Maximum Dry Density
MLRA	Multiple Linear Regression Analysis
MLP	Multilayer Perceptron Function
MP	Modified Proctor Test
MSE	Mean Squared Error
NMA	National Meteorology Agency
NN	Neural Network
OMC	Optimum Moisture Content
PI	Plasticity Index
PL	Plastic Limit
R	Correlation Coefficient
RBF	Radial Basis Function Network
ReLUs	Rectified Linear Units
SCG	Scaled Conjugate Gradient Algorithm
SEE	Standard Estimate Error
SNNPR	Southern Nations Nationalities and People's Region
SST	Residual Sum Of Square
TP	Test Pit
WMO	World Meteorological Organization

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ABSTRACT

Urbanization together with large scale industrialization and modernization has created shortage of land for construction in most countries. To overcome this problem and fulfil the need for infrastructure, land is developed using sound and cost effective engineering techniques such mechanical compaction. This method identifies important compaction parameters mainly optimum moisture content and maximum dry density and are acquired from simple laboratory testing. But when there is a limited number of laboratory equipment, budget and man power in case of larger projects which requires reasonable sizable effort, labor, time and budget, implementing other methods such developing linear relationship for determination compaction parameters of soil is a must and economical. In these study attempts to predict optimum moisture content and maximum dry density from Atterberg limit parameters by using artificial neural net analysis of soils in Morocho-Aposto road has been made. When there is a need for rehabilitating and upgrading of the road, conducting this study provides future information and used to validate findings. To conduct the study 75 data bank that includes 20 samples as primary and 55 data as secondary source were used to analyze and develop the predictive model. Samples were collected randomly from 20 pits and subjected to both Atterberg limit and Modified proctor test in accordance to AASHTO standard. The data were analyzed and computed using Neural Net. Commands where written for prediction and linear regression modeling. The data bank was trained and optimized using Levenberg-Marquardt, Bayesian regularization and Scaled Conjugate Gradient algorithm based on each criterion. Levenberg-Marquardt training algorithm is selected as the best algorithm by with the two algorithms. The study found that, LM algorithm has mean estimate error of 1.527, training time < 1 second and R value of 0.978 that predicted the models with better accuracy than SCG and BR algorithms. Therefore, the study concludes that OMC and MDD can be predicted from Atterberg limit by artificial neural net with error margin of ± 2 for soils in the study area.

- $\mathrm{OMC} = 3.65 + (0.77 * \mathrm{LL}) - (0.08 * \mathrm{PL}) - (0.9 * \mathrm{PI})$
- $\mathrm{MDD} = 1.66 - (0.006 * \mathrm{LL}) - (0.003 * \mathrm{PL}) + (0.013 * \mathrm{PI})$

Keywords: Compaction parameters, Atterberge’s limit, Artificial Neural Net, Levenberg-Marquardt, Bayesian regularization, Scaled Conjugate Gradient.

1. INTRODUCTION

1.1 Background of the study

Urbanization together with large scale industrialization and modernization has created shortage of land for construction in most countries, and has led to the development of land to fulfil the need for infrastructure. One of the cost and time effective technique is stabilization. It is usually mechanical or chemical, thermal and electrical stabilization. Mechanical compaction has occasionally been considered (Holtz, 1981). It is a processes of making soil particles to pack more closely together by reducing the air voids, generally through the mechanical means utilizing water as the lubricating medium (Sridharan, 2005). And also it enables to achieve the desired strength, compressibility and permeability characteristics of soils (AASHTO, 2003).

According to Hossam, (2016), currently used soil improvement in soft clays are acceptable on the basis that pre-knowledge of the potential problems and can lead to economic benefits if the planning, design, and construction of projects can be modified to suit the problems to provide increase of its strength, reduction of total and differential settlement, reasonable cost, and shorten construction time. But Engineers are still facing problems with clay soils as element for structural foundations. They performing and analyzing field control tests to assure that compacted fills are meeting the prescribed design specifications. These design specifications usually state the requirement of both density (as a percentage of the “maximum” density measured in a standard laboratory test), and the water content (OMC) and both parameters are dependent (Chik, 2014).

Maximum dry density (MDD) and optimum moisture content (OMC) are determined by establishing the moisture-density relationship of a material when prepared and compacted with a hammer at different moisture contents . The maximum dry density of a material for a specific compactive effort is the highest density obtainable when the compaction is carried out on the material at varied moisture contents. And OMC for a specific compactive effort is the moisture content at which the maximum density is obtained (it is the water content that results in the greatest density for a specified compactive effort) and all these are achieved by mechanical compaction.

The engineering properties, such as the strength, stiffness, resistance to Shrinkage, and imperviousness of the soil, can be improved by increasing the soil density. Compacting a material at water contents higher than the OMC results in a relatively soil structure that is swelled and that is weaker, more ductile, less pervious, softer, more susceptible to shrinking and compacting dry soil (at moisture lower than the OMC) does not achieve the specified degree of densification. According to Shackelford, (1991), many different ranges of water content and dry density for a compacting soil is used in determination of the fore mentioned soil properties.

The determination of optimum moisture content and maximum dry density is a careful and time-consuming process for specific soils and when there is a need for vast area of study. Since some soils especially clay soils are problematic because of their physical and chemical properties. And also it requires enough amounts of money and energy. Where there is scarce resource and time, developing an empirical relationship is an important task. For decades many scholars have attempted to develop empirical relationship between compaction parameters and Atterberg limit using multiple linear regression analysis (MLRA), artificial neural network (ANN) and also the combination of the two; as simple and accurate as possible. For instance, Sinha, (2008), used artificial neural network determine the optimum moisture content, permeability and maximum dry density of soils from Atterberge's limit parameter. Compaction characteristics were established from Atterberg limit index using different soil by using neural nets as model development (Najjar, 1996).

Optimum moisture content and maximum dry density of soil is going to be predicted and a with a new index property parameter called Atterberg limit on Morocho-Aposto road in Sidama zone. A representative sample is collected then, Atterberg limit and compaction is going to be conducted. By analyzing the data using MATLAB and different learning algorithms, OMC and MDD will be predicted.

1.2 Statement of the problem

Civil engineering projects mainly that are constructed in areas with conventional soil type that contain clay mineral, expansive soils, exhibit one of the most frequent problems in some part of our country (Bantayehu, 2017). Engineering problems such as Structural damage to lightweight structures (sidewalks and driveways), lifting of buildings, damage to basements, and building settlement, cracks in walls and ceilings, damage to pipelines and other public utilities, lateral movement of foundations and retaining walls due to pressure exerted on vertical walls, loss of residual shear strength causing instability of slopes are developed due to the swelling and shrinking potential of these soils when they comes into contact with water (Patel, 2019). However, different engineering techniques mainly mechanical compaction, chemical stabilization and simple soil replacement using select-materials has been implemented to minimize and solve the occurring engineering problem for decades. Mechanical compaction using Proctor test (simple and modified) in the laboratory is very beneficial for identification of the basic compaction parameters such as optimum moisture content and maximum dry density (i.e. they are important parameters in developing foundation analysis) and should be executed carefully in order to obtain practical results (Shukla, 2015).

For centuries, engineers attempted to develop empirical and mathematical relationships between important parameters in order to minimize the consumption of budget and man power that is implemented in identifying these parameters. However, developing these relationship does not always give us appropriate expected outputs because of basic human error, mistakes in the laboratory and lack of enough data sources to develop the relationship between index properties and engineering property of soils. For instance, developing relationship from Atterberg limit parameters; liquidity index determination includes determination of Casagrande's thread rolling plastic limit. These requires cautious attention mainly in the case of less plastic soils (Vardanega, 2014). Laurence D. Wesley, (2009) stated that for drying soils with higher plasticity (clay and expansive soils) it is very difficult to implement compaction since it needs considerable drying. And also, Seed & Chan, (1959), proposed that in situations with high plasticity clays (PI > 25) it may be advisable to employ a reduced density, to reduce the potential for post construction heave.

Therefore, when compacting these soils that contain clay minerals with wet of optimum moisture content, some sacrifice (time) may need to be made. And performing this same procedure carefully for lager number of sample in bigger projects is time consuming, needs lager number of machineries and laboratory equipment, soil samples, human resource and budget. Where there is a limited budget and resource, there is the need to develop predictive models using limited amount of data source and more advanced methodology with minimized error of outcome which helps to identify the expected engineering properties and characteristics of the soils with in the study area.

1.3 Research questions

1. What selection criteria is /are effective for determination of best algorithm in data optimization analysis?
2. How does the quantity and quality of data affect the impact of the predicted models on compaction parameters acquired?
3. How does the amount of clay mineral in the soil affect the duration of compaction parameter determination in the laboratory?

1.4 Objectives of the study

1.4.1 General objective

The general objective of this research was to predict optimum moisture content and maximum dry density from Atterberg limit parameters by artificial neural net analysis for soils in Morocho-Aposto road.

1.4.2 Specific objectives

The specific objective involves;

- Optimizing the data using different learning algorithm and identify the best for learning process and analysis.
- Developing linear regression model relating optimum moisture content to index properties
- Developing linear regression model relating maximum dry density to index properties of soils in the study area.

1.5 Significance of the study

Due to limited facilities, equipment and the restriction in accessibility of the resources many, engineers are still not using the appropriate procedures and specification to came up with the expected output of the laboratory tests for most engineering properties of soils.

This model provides addition ways to determine engineering properties of soils by predicting the outputs at acceptable margin of error using index property.

Also, it acquires the expected parameters with simple improvements based on soil property and allows engineers to use limited resource, time and budget effectively. In addition to this, output of this model can be used to identify other soil parameters using the same methods from the research. Therefore, the model in this study provides the necessary insight and awareness on how and what resources to implement and identifying the necessary engineering properties of soils within and beyond the study area.

1.6 Scope and limitation of the study

This study focus on developing a predictive model for compaction parameters of soils from Atterberg limit by using Artificial Neural Network (ANN). Two sets of data will be used, primary and a data bank (secondary data), to develop, train and predict the output. The study focuses on determination and implementation of artificial neural network for soils that exist around the study area. In conducting the study, there were limitations with the use of laboratory equipment. Many and different laboratory testing for the collected soil sample couldn't be directed due to the limited testing instruments and resource in the facility.

1.7 Organization of the study

This thesis contains five chapter, references and appendices; each with part coverage of specific topics. The first chapter contains the general background of the study, problem statement, objective, scope and limitation of the study, and organization of the study. Chapter two contains literature review. Chapter three covers material and methods. In Chapter four, results and discussion were presented. And the final chapter includes conclusion and recommendation for the results. Finally, the detailed laboratory test and model analysis are presented appendices.

2. LITERATURE REVIEW

2.1 General

Predictive models have gained importance as they have become ubiquitous in modern society. They enable us by generating various types of estimates in our daily lives and they are effective at telling us what is important or concrete (Kuhn, 2019). Centuries has passed when scholars used different models for prediction of different engineering properties of soil and Artificial neural network (ANN) is the recent. According to Ferentinou, (2007), artificial neural networks (ANNs) are one of the biological brain functions that are realistically used in model representation. It has a classification ability, examination, simulation and decision-making that has given them a wide application in the engineering field, and even in other fields. And it consists of a succession of layers where are systems consisting of a large number of units interconnected to each other making elementary processors (Bahmed, 2017).

2.2 ANN, activation function, learning algorithm (optimization) and epoch

Activation function represents the transfer characteristics of the individual neurons in a neural net-work in that it determines the activation behavior of the neurons to incident inputs (Kumar, 2004). The function responds to the range of incident input signals and transforms them by using a suitable learning algorithm. Though different constituent neurons may exhibit different transfer characteristics, yet most of the existing neural network architectures are held homogeneous with all the neurons in a layer characterized by the same activation.

Artificial Neural Networks can be best observed as weighted directed graphs, where the nodes are made by the artificial neurons and the connection between the neuron outputs and neuron inputs can be symbolized by the directed edges with weights. Where;

- Input layer passes the initial data into the system for further processing by successive layers of artificial neurons,
- Hidden layer is a layer in between input layers and output layers, where artificial neurons take in a set of weighted inputs and produce an output through an activation function.

- Output layer is the last layer of neurons that produces assumed outputs for the program.

In Figure 2.1, the Artificial Neural Network receives the input signal from the external world in the form of a pattern and image in the form of a vector. These inputs are then mathematically designated by the notations x(n) for every n number of inputs. Each of the input is then multiplied by its corresponding weights where their details are used by the artificial neural networks to solve a certain problem. In overall terms, these weights characteristically represent the strength of the interconnection amongst neurons inside the artificial neural network. All the weighted inputs are summed up inside the computing unit.

If the weighted sum equates to zero, a bias is added to make the output non-zero or else to scale up to the system's response. Bias has the weight and the input to it is always equal to 1. Here the sum of weighted inputs can be in the range of 0 to positive infinity. To keep the response in the limits of the desired value, a certain threshold value is benchmarked. And then the sum of weighted inputs is passed through the activation function. Activation functions are the set of transfer functions used to get the desired output. Different activation functions are shown in Figure 2.2, such as binary threshold, sigmoid, linear threshold, or probabilistic activation functions (Bhattacharyya, 2011).

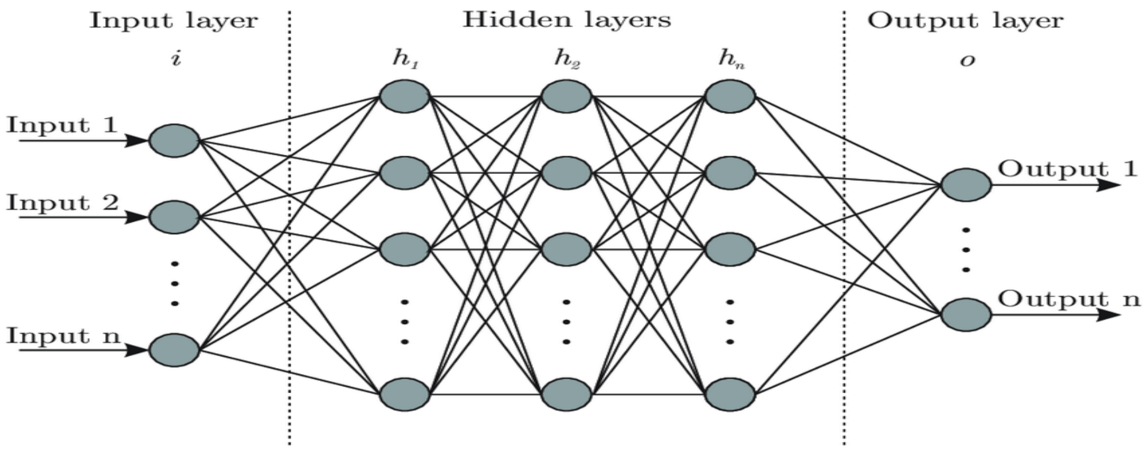

Figure 2. 1 Structure of input, output and hidden layer for ANN

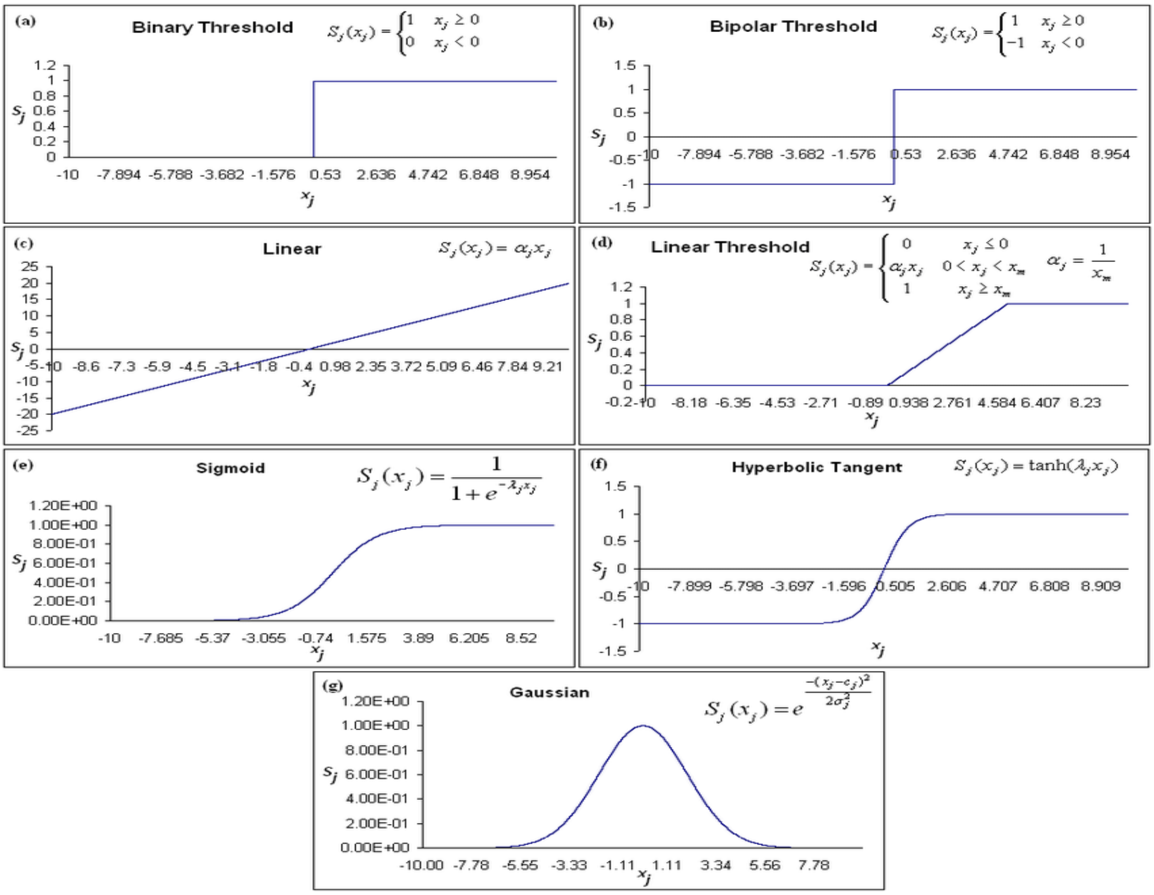

Figure 2. 2 Commonly used neural network activation functions (Bhattacharyya, 2011).

2.2.1 Learning or optimization algorithm

Learning algorithms or optimizations are procedure used to carry out the learning process in a neural network There are many different optimization algorithms. All have different characteristics and performance in terms of memory requirements, processing speed and numerical precision. This are learning problem, Gradient descent, Newton method, Conjugate gradient, Quasi-Newton method, Levenberg-Marquardt algorithm, Performance comparison and Conclusions, Bayesian regularization backpropagation, Scaled Conjugate Gradient etc..

2.2.1.1 Levenberg-Marquardt learning algorithm (LM)

Levenberg-Marquardt (LM) algorithm is back propagation algorithm is used for training the network and specifically designed to minimize sum-of-square error function. It is the most widely used optimization algorithm. LM algorithm is an iterative technique that locates a local minimum of a multivariate function that is expressed as the sum of squares of several non-linear, real-valued functions. It has become a standard technique for non-linear least-square problems, widely adopted in various disciplines for dealing data-fitting applications (S.Sapna, 2012). It is a hybrid technique that uses both Gauss–Newton and steepest descent approaches to converge to an optimal solution (Peter Wilson, 2013).

2.2.1.2 Bayesian Regularization Backpropagation learning algorithm (BR)

Bayesian regularization backpropagation is a mathematical process that converts a nonlinear regression into a "well-posed" statistical problem in the manner of a ridge regression. Bayes' theorem can be used to optimally control regularization and make ANNs more robust, parsimonious, and interpretable (Burden, 2009). It is a network training function that updates the weight and bias values according to Levenberg-Marquardt optimization. It minimizes a combination of squared errors and weights, and then determines the correct combination so as to produce a network that generalizes well.

The process is called Bayesian regularization. The algorithm can train any network as long as its weight, net input, and transfer functions have derivative functions. This function uses the Jacobian for calculations, which assumes that performance is a mean or sum of squared errors. Therefore, networks trained with this function must use either the mse or sse performance function.

2.2.1.3 Scaled Conjugate Gradient learning algorithm (SCG)

Scaled Conjugate Gradient (SCG) is a network training function that updates weight and bias values according to the scaled conjugate gradient method. The basic backpropagation algorithm adjusts the weights in the steepest descent direction (negative of the gradient). This is the direction in which the performance function is decreasing most rapidly. But, although the function decreases most rapidly along the negative of the gradient, this does not necessarily produce the fastest convergence. In the conjugate gradient algorithms, a search is performed along conjugate directions, which produces generally faster convergence than steepest descent directions (Møller, 1993).

2.2.2 Drawbacks of ANN modeling

Artificial neural networks are very effective in capturing and representing the behavior of engineering systems, they are also known to suffer from a number of shortcomings. One of the drawbacks of a neural network is that the optimum structure of ANN (for instance number of hidden layers, number of neurons, and transfer functions) should be identified a priori. This is usually done through a trial and error procedure.

The other major shortcoming is related to the black box nature of an ANN model and the fact that the relationship between input and output parameters of the system is described in terms of a weight matrix and biases that are not easily accessible to users understanding. In fact the black box nature and lack of interpretability have prevented ANNs from achieving their full potential in engineering applications (Ahangar-Asr, 2011).

2.3 Linear regression modeling

Linear regression analysis is a statistical processes for estimating the relationships between a dependent variable and one or more independent variables. The most common form of regression analysis is linear regression, in which a scholar finds the line (or a more complex linear combination) that most closely fits the data according to a specific mathematical criterion. In addition to this, it attempts to model the relationship between two variables by fitting a linear equation to observed data. One variable is considered to be an explanatory variable, and the other is considered to be a dependent variable. The mathematical equations equation (2.1) and equation (2.2) represent simple and multiple linear regression analysis respectively.

$$Y = b_0 + b_1 * x_1 \quad (2.1)$$

$$Y = b_0 + b_1 * x_1 + b_2 * x_2 + \cdots + b_n * x_n \quad (2.2)$$

Where; b_0 is constant, b_n is coefficient, Y and x are variables.

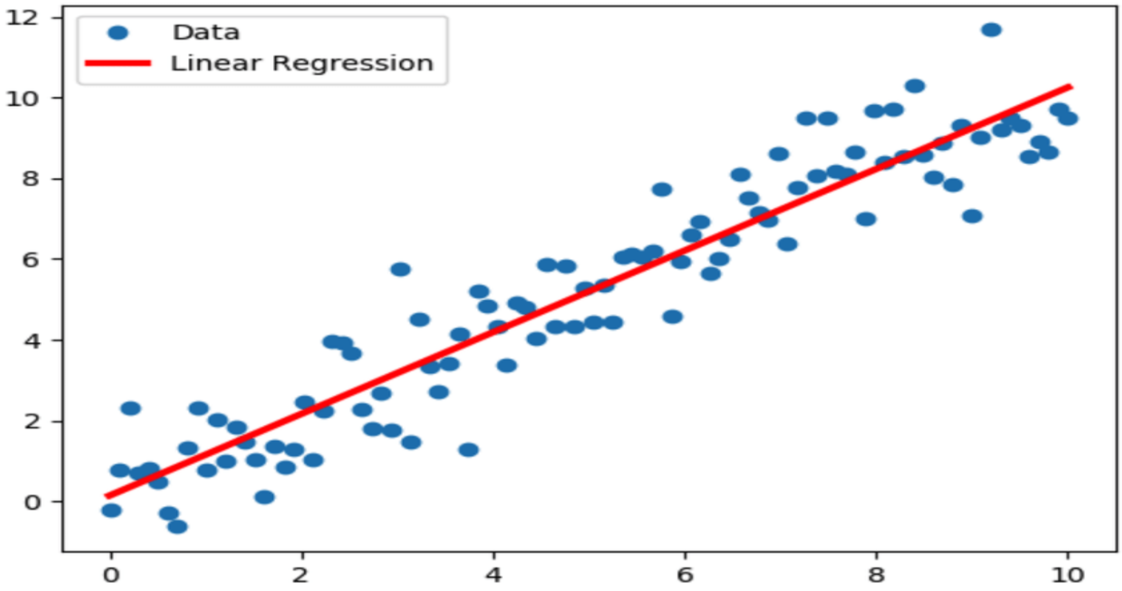

Figure 2. 3 Plot of linear regression model sample illustration (Tran, 2019)

2.4 Review on previously conducted works

A vast majority of scholars have been attempting to propose different types predictive models in-order to solve the problems related to major expense implemented issues related to laboratory tests of larger samples for the identification of compaction characteristics. Some of these predictive models are explained below.

Najjar et.al, (1996) and Sinha, (2008) proposed a model for determination permeability, maximum dry density, and optimum moisture content using artificial neural network ANN. Gunaydin, (2008), from Turkey, used 126 compaction and soil classification test that are results of nine different soil types (CH, CI, CL, GC, GM, MH, MI, ML, SC) gathered from the small dams constructed in the vicinity of Nigde (Turkey), and established models both using regression analysis and artificial neural network analysis with a strong correlations (R square value between 0.70–0.95) between the compaction parameters and soil classification properties (Gu¨naydın, 2008) ;

$$OMC = 0.323\ LL + 0.157\ PL \qquad (2.3)$$

$$MDD = 0.078\ LL + 0.062\ PL \qquad (2.4)$$

In the early 2010's, (Ashwini.T, 2013), Artificial Neural Network (ANN) was used to develop a model for compaction parameters from simple index properties tests in the laboratory. The R square values of OMC of ANN model for training and testing dataset were found to be 0.8526 and 0.7568 respectively. The R2 values of MDD of ANN model for training and testing dataset were found to be 0.8801 and 0.8071 respectively. The R2 values of OMC and MDD for simulation dataset for this parameter are 0.9463 and 0.9478 respectively.

Multiple linear regression analysis was used to develop correlation between compaction parameters and index property of nine disturbed soil sample that were collected from various sites in Penang. The accuracy of the results by MLR is verified with statistical tool such as the coefficient of correlation (R) and the standard error (SE). It was found that the linear correlation of MDD with PI has an R of 0.96 while it is R = 0.92 for correlation between OMC and PI (Mohammed.G, 2015).

Using a total of 280 values of PI and 122 values of both MDD and OMC, the reliability of the model for predicting of PI, MDD and OMC of clayey soils stabilized with different contents of lime were checked. And three models with good performance representing PI, OMC and MDD of clayey soils stabilized with lime where developed (Bahmed, 2017).

Tesfamichael, (2017), using soils from different location of Addis Abeba, Ethiopia developed compaction characteristics, optimum moisture content and maximum dry density, from Atterberg limit parameters using a total of 56 data banks, both primary and secondary data sets. And he found good correlation between the dependent and independent variables with R square value greater than 80% was found. The model is shown in the equ. below;

$$\mathrm{OMC} = (0.916 * \mathrm{PL}) - (0.030 * \mathrm{PI}) - 0.875 \quad \text{………………………………..…} \quad (2.5)$$

$$\mathrm{MDD} = 21.182 - (0.18 * \mathrm{PL}) - (0.027 * \mathrm{PI}) \quad \text{………………………………….. } \quad (2.6)$$

Karimpour, (2018), used both artificial neural networks (ANNs) and multi-linear regression (MLR) to estimate the compaction characteristics. He evaluated the study on a data bank of 728 compaction tests. Correlation between compaction parameters and index property were developed with the efficiency to predict OMC was 0.95 and 0.94 for training and testing data whereas for MDD it was slightly lower, 0.93 and 0.92 with an error range of ± 5% for OMC and MDD is 44% and 89%, respectively.

2.5 Expansive soils

Expansive soils are those that experience significant volume changes associated with changes in water contents. Expansive soils, when contact with water, swell noticeably, exert swelling pressure and show signs of low shear strength. These volume changes can either in the form of swell or in the form shrinkage and this is why they are for a while known as swell/shrink soils. When the wetness is dried up in the hot season, these soils shrink and give high shear strength. The swell/shrink phenomenon is attributed predominantly to the presence of montmorillonite clay minerals in these soils (Wang, 2016).

To prevent the structures from the damages it is necessary to improve the soil properties. Problems due to expansive soils to civil engineering structures are well realized by engineers and researchers all over the world. The damages generally noticed in the buildings are in the form of distortions in the floor (inverted dish-shaped due to moisture concentration with time in the center), cracking's in the walls (diagonal cracks extending upwards from doors and window seals), breaking of joints between structural members, etc. (Kate, 2008)

2.5.1 Mineralogy, origin and distribution of expansive soil

Expansive soils have two major origins, which are the sedimentary and basic igneous rocks. Shale and clay stones are one of the sedimentary rocks that contain montmorillonite as a constituent, limestone and marbles whether in magnesium can as well whether to clay. These constituents of the shale and clay stones contain varying amount of volcanic ash and glass, which are subsequently whether to montmorillonite. The fundamental igneous rocks are comparatively low in silica, generally about 45% to 52%. Rocks that are rich in the metallic base such as the pyroxenes, amphiboles, biotite and olivine fall within this category. Such rocks include the gabbros, basalts and volcanic glass (Alemayehu & Mesfin, 1999).

Property of soils highly depends on the grain sizes of soils. Broadly soils are classified as cohesive and cohesion less soil. The behavior of clay soils strongly depends on surface tension forces, since clays have a big specific surface as compared with their mass. The behavior of fine-grained soils depends to a large extent on the nature and characteristics of the minerals present. While the property of granular soils strongly depends on the gravitational forces (the amount of mass contained in the soils). The expansiveness of soils is due to the presence of clay minerals. Clay particles have sizes of 0.002mm or less (Das, 2007).

The grain size alone does not determine clay minerals and he emphasized that the most important property of fine-grained soils is their mineralogical composition. Clay minerals are crystalline hydrous alumino-silicates derived from parent rock by weathering. The basic building blocks of clay minerals are the silica tetrahedron and the alumina octahedron and combined into tetrahedral and octahedral sheets to form the various types of clays. Kaolinite, illite, and montmorillonite (smectite) are the common groups of clay minerals most important in geotechnical engineering studies. Clay soils consist of clay minerals. These minerals are crystalline material comprising of oxygen and silica. The structural unit of the silicates is a tetrahedron with a silica cation; positively charged, surrounded by four oxygen atoms, negatively charged. The silicates assemble themselves into sheets (Chen, 1975).

Expansive soils are widespread in the African continent, occurring in South Africa, Ethiopia, Kenya, Mozambique, Morocco, Ghana, Nigeria, etc. In other parts of the world case of expansive soils have been widely reported in countries like USA, Australia, Canada, India, Spain, Israel, Turkey, Argentina, Venezuela, etc (Alemayehu & Mesfin, 1999).

In eastern Africa, expansive soil occurs widely when compared to the other parts of Africa. Large parts of Ethiopia and Sudan are covered with black and red clay soils, as are smaller areas in Tanzania, Kenya, Uganda, Malawi, and Zambia. The associated volcanic rocks are the main cause of the black clay's formation in Ethiopia, Kenya, and Sudan (Lyon, 1971).

2.5.2 Conventional problems of expansive soils

Vast majority of soils can prove problematic in geotechnical engineering, since they expand collapse, disperse, undergo excessive settlement, and have a distinct lack of strength. Expansive soils (i.e. clay) undergo slow volume changes when change water content that occur independently of loading and are attributable to swelling or shrinkage. These volume changes can give rise to ground movement which can cause damage to low-rise buildings smaller structural support (Jose, 2012).

2.5.3 Identification of expansive soils

Techniques of identification and classification of expansive soils have phases. The first one is visual identification and recognition of soil as expansive and the second is sampling and measurement of material properties to be used as the basis for the design. In the first phase soils that can exhibit high swelling potential can be identified by field observations, mainly during reconnaissance and preliminary investigation stages. Visually they have black or grey color, wide or deep shrinkage cracks, high dry strength and low wet strength, stickiness and low traffic ability when wet, cut surfaces have a shiny appearance and appearance of cracks nearby structures.

The second phase consists of three methods which are mineralogical, indirect and direct methods. In mineralogical identification, clay mineralogy is a fundamental factor controlling expansive soil behavior. Clay minerals can be identified using a variety of techniques; the common ones are X-ray diffraction, differential thermal analysis, dye adsorption, chemical analysis, and electron microscope resolution. Due to they are time-consuming, require expensive test equipment and results can only have interpreted by specially trained technicians these methods are not suitable for routine tests (Chen, 1975).

2.6 General soil classification system

We can categorize expansive soils in the systems, which are also used for various types of soils. The general classification is based on the grain size distribution and limits of soil are AASHTO and unified soil classification system.

2.6.1 AASHTO soil classification system

AASHTO soil classification is another system, which was based on grain size and limit tests it was first developed for highway engineers (Arora, 2004). The system comprises seven groups of inorganic soils, A-l to A-7 with subgroups. A Group Index is introduced to further distinguish soils containing substantial fine-grained materials. The characteristics of various groups' fine-grained materials are defined in the figure 2.4 below.

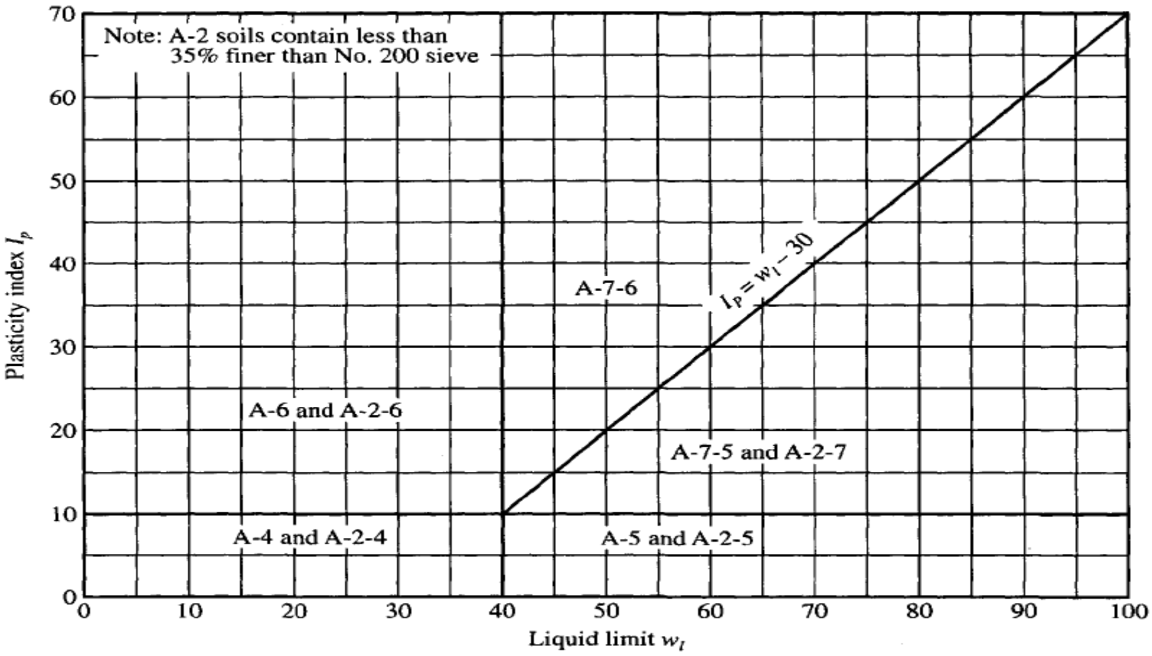

Figure 2. 4 LL Vs PI Chart in AASHTO Classification System (Murthy, 2001)

Generally, soils classified under groups A-1, A-2 and A-3 are granular materials with 35% or less passing through a No. 200(0.0075mm) sieve but A-1 and A-3 non plastic. The three groups were rank excellent to good sub-grade material accordingly. Soils with more than 35% passing a No. 200 sieve was classified under groups A-4, A-5, A-6 and A-7. These soils are typically silt and clay sort materials. Soils in those groups are placed fair to poor sub-grade material according to their order (Arora, 2004). According to this classification A-6 or A-7, may be consider as potentially expansive (John & Debora, 1992).

2.6.2 Classification of expansive soil

Different experts in expansive soil have provided classification systems for expansive soil. In those classification systems parameters determined from expansive soil identification tests, mainly one or two index properties of soil have combined. There are two ways of classifying expansive soil. The first one is a general classification system this way of classification is used for various types of soil. The other is specific to expansive soils there are some other methods of classifying expansive soil, which categorized under specific classification system (Chen, 1975).

Table 2. 1 Expansive-soil-classification-based-on-plasticity-index (Igwe, 2020)

Swell Potential	Plasticity Index (%)	
	Holtz and Gibbs (1956)	Chen (1988)
Low	< 18	0-15
Medium	15-28	10-35
High	25-41	20-55
Very High	> 35	> 35

2.7 Atterberg limit

The consistency of a fine-grained soil is largely influenced by the water content of the soil. A gradual decrease in water content of a fine-grained soil slurry causes the soil to pass from the liquid state to a plastic state, from the plastic state to a semi-solid state, and finally to the solid state. The water contents at these changes of state are different for different soils. The water contents that correspond to these changes of state are called the Atterberg limits. The water contents corresponding to transition from one state to the next are known as the liquid limit, the plastic limit and the shrinkage limit. It marks the boundaries between these stages. Often, the most necessary of those are the plastic limit and the liquid limit, which are referred to as the Atterberg limits after the man who devised them (Laurence, 2010).

The liquid limit of a soil is the water content, expressed as percentage of the weight of the oven dried soil, at the boundary between the liquid and plastic states of consistency of the soil. The soil has negligibly small shear strength. The plastic limit of a soil is the water content, expressed as a percentage of the weight of oven dried soil, at the boundary between the plastic and semi-solid states of consistency of the soil. The plastic limit for different soils has a narrow range of numerical values.

2.8 Modified proctor compaction

Soil compaction consists of closing, packing the soil particles together, so that increases the dry unit weight. Soil compaction only reduces the air void in the soil. These test is perform in accordance with AASHTO T180-D to determine the maximum dry density (MDD) and the optimum moisture content (OMC) of the soils. In early 1960's, the modified Proctor compaction test was developed as an ASTM standard. A higher and more relevant compaction standard was necessary. There were larger and heavier compaction equipment, like large vibratory compactors and heavier steel-face rollers. This equipment could produce higher dry densities in soils along with greater stability. These improved properties allowed for the transport of far heavier truck loads over roads and highways (Davis, 2008).

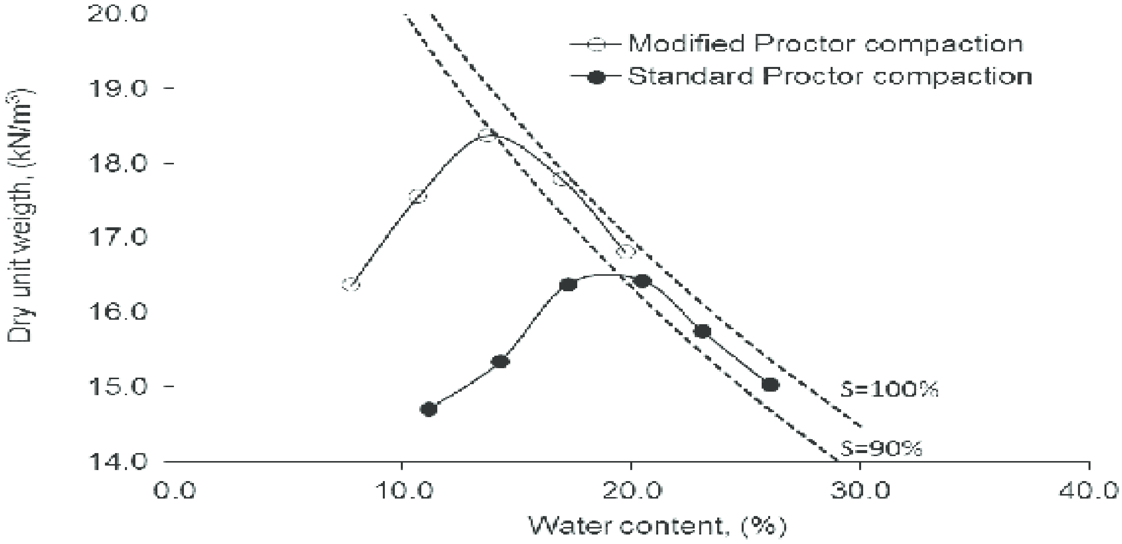

Figure 2. 5 Standard and Modified Proctor compaction curves of the soil (Yilmaz, 2016)

From the discussions above, many researchers have used different method of validation, data use, identification and development of predictive models. In this study, artificial neural network (ANN) that uses multilayer perceptron network attempts to predict and model the data set. These study implements the necessary test data of the samples and provided a better insight of the actual value compared to the trained value. And the best predictive and linear regression model for the compaction parameters of the soils in the study area is developed. In generally, the study provided additional way to identify and predict optimum moisture content and maximum dry density from index property with a text based neural net analysis using MATLAB and the known laboratory testing as an input.

3. MATERIALS AND METHODS

3.1 Description of the study area

3.1.1 General

Morocho- Aposto road is one the road way from the Hawassa-Ageremariam road section. It is designated as corridor phase three and is an extension of the mega project of Addis Ababa-Nairobi-Mombasa road that is being constructed by Ethiopian road authority (ERA) and foreign company. It is the part of Hawassa-Ageremariam road contract that has been divided into three sections by the ERA; for Hawassa–Chuko, Chuko–Yirgachefe and Yirgachefe–Ageremariam. The road section in this study cover a total of 26 kilometers (IATI, 2020).

3.1.2 Location

The road section is located in between Hawassa city and Irgalem town which is located in Sidama zone, in the Southern Nations, Nationalities, and Peoples Region. It has latitudes and longitude 7°3′N 38°28′E and 6°45′N 38°25′E, and has an elevation of 1,700 to 1, 800 meters above sea level.

3.1.3 Climate

The climatic condition of this area resembles more to that of Morocho town than Aposto town. It have a tropical savanna climate though it borders on a subtropical highland climate. There are two seasons: a lengthy though not intense wet season from March to October and a short dry season from November to February (WMO, 2017). The extra cloudiness of the wet season is sufficient to make it substantially cooler than the dry season despite a higher sun angle; however, the coolest morning temperatures, often close to freezing, occur during the dry season. Generally, the area has is categorized as, “Kolla” and it has a mean annual rainfall of 400 mm to 799 mm, and the mean annual temperature ranges from 20 °C to 24.9 °C.

3.1.4 Soil and geology

In nature, the region belongs to the category of the valley system. The earth science units within the valley locality are mainly the tip results of volcanic effort at some stage within the geological period. The full valley is caused by the method of ancient basement rocks, that are represented as genesis grading in metamorphic granites, ignimbrites (consolidated hot-ash flows) and granodiorites. Mostly the soil in this area is composed of clay and sandy soils. But exhibits the property of clay soil since most of the area is covered with clay soil.

3.2 Materials

In order to achieve the objective of the study, field and laboratory materials are used. These materials were;

1. Sampling tool including extraction and transportation of disturbed samples
2. For Atterberg's limit test: Casagrande's apparatus, mixing dish, flat glass, water dropper, labeled can, weight balance, and oven dry.
3. For compaction test; Modified Proctor test: cylindrical mold, rammer, weight balance, labeled can, and oven dry.
4. Personal computer was used to write the thesis and analyze the data (MATLAB)

3.3 Study methodology

3.3.1 Introduction

The overall workflow diagram of the study has been presented below;

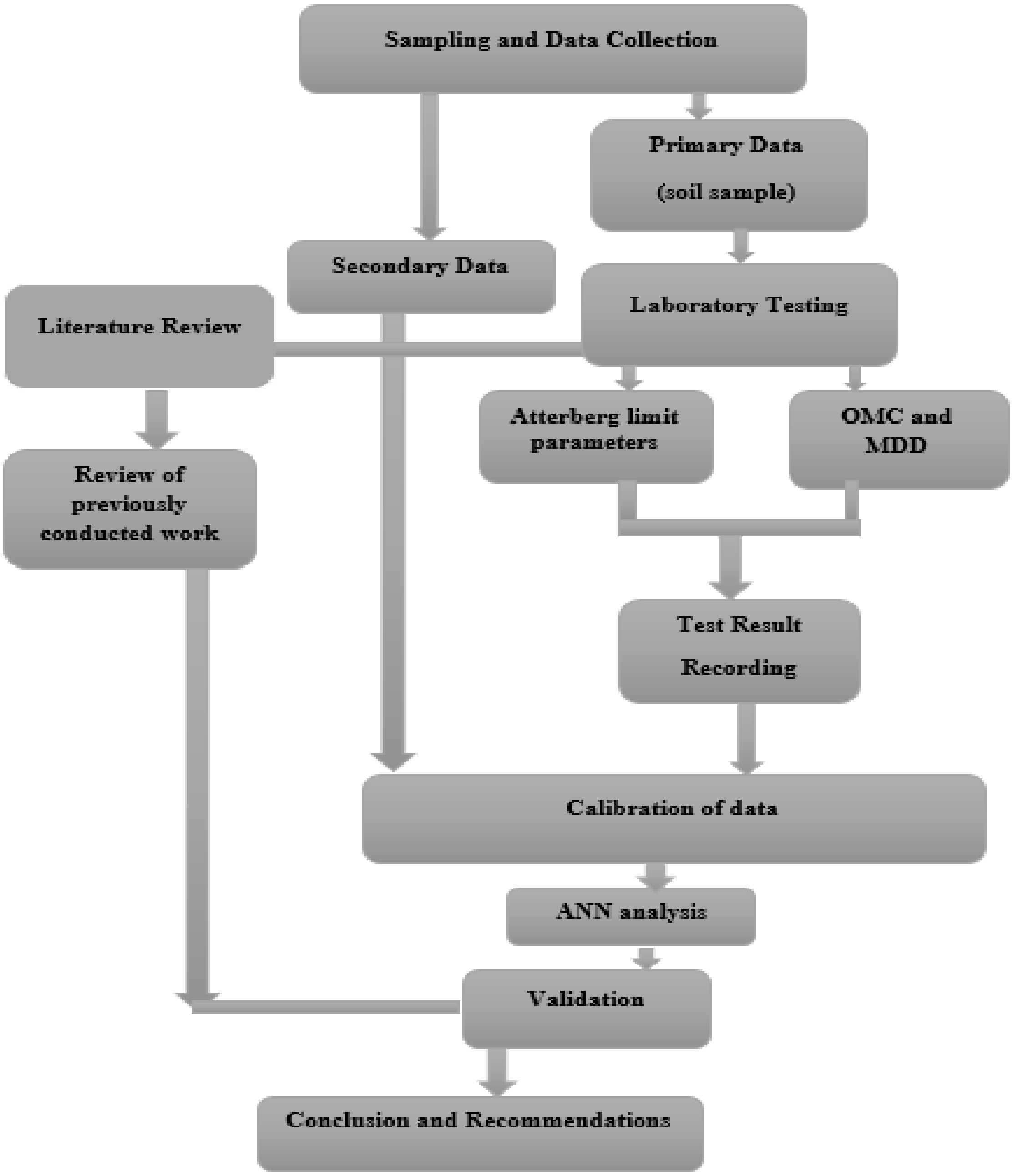

Figure 3. 1 Conceptual frame work of the study

3.3.2 Study area

In order to perform the study and reach the objectives, twenty test pits were dug from different stations that are within 100 meters to a kilometer difference. The study area map and aerial photograph of the road section are shown in figure 3.2 below. The detailed satellite map and photo graph is shown in Appendix I.

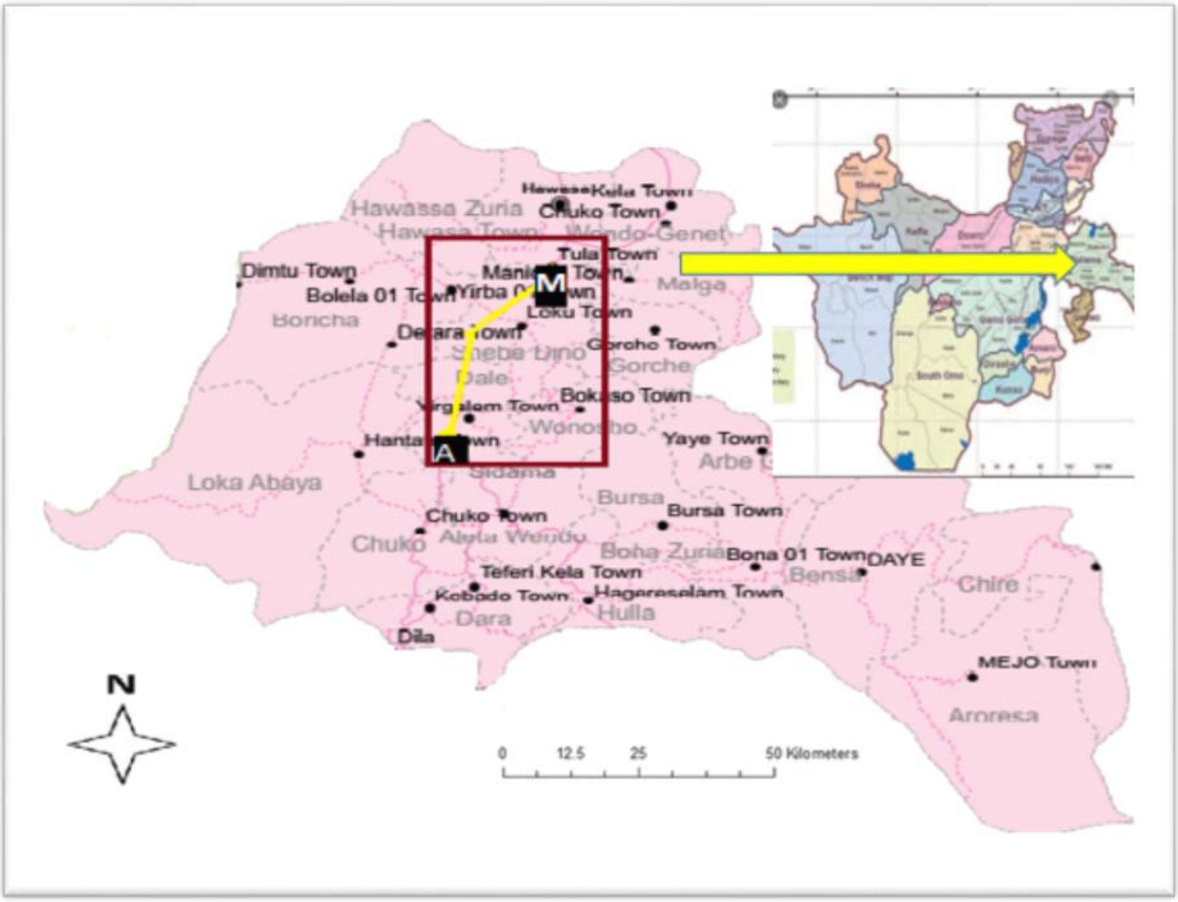

Figure 3. 2 Map of the study area containing Morocho Aposto road section

3.3.3 Data collection and soil sampling

To conduct the study primary data and secondary data source was used. Twenty primary and fifty-five secondary data was databased. In collecting the primary data, first the soil samples were collected randomly from twenty pits at a depth starting from 0.3 m to 1.5 meters beneath the ground surface in the areas along and around the road section. Then, each of disturbed samples are labelled kept in plastic bag and transported. Meanwhile, a representative data summary for laboratory results containing all the necessary about the soils from some areas of the road section are taken from a published source as a secondary data source. Description including standard deviation, variance, maximum, minimum and mean of all the 75 data is presented in Table 3.2 below.

Table 3. 1 Primary data source location by Latitude and longitudes

Test pits	Location		
	Destination	Latitudes	Longitudes
TP 1	Morocho Kutala	6°54'47.47"N	38°26'53.62"E
TP 2	Morocho Kutala	6°54'40.87"N	38°26'47.26"E
TP 3	Morocho Kutala	6°54'24.92"N	38°26'30.21"E
TP 4	Tula Town	6°57'5.38"N	38°28'32.26"E
TP 5	Morocho Shondolo	6°53'46.46"N	38°25'48.13"E
TP 6	Morocho Shondolo	6°53'18.38"N	38°25'17.46"E
TP 7	Tula Town	6°56'21.63"N	38°28'22.16"E
TP 8	Tula Town	6°56'9.64"N	38°28'19.99"E
TP 9	Tula Town	6°55'47.10"N	38°28'14.30"E
TP 10	Morocho Shondolo	6°51'59.27"N	38°23'50.78"E
TP 11	Chei-cheic	6°50'49.22"N	38°23'10.26"E
TP 12	Aposto	6°49'25.27"N	38°22'53.07"E
TP 13	Aposto	6°48'17.01"N	38°22'57.11"E
TP 14	Morocho Shondolo	6°52'46.05"N	38°24'40.29"E
TP 15	Aposto	6°46'16.61"N	38°22'39.32"E
TP 16	Aposto	6°47'8.39"N	38°22'44.90"E
TP 17	Aposto	6°45'20.72"N	38°22'34.85"E
TP 18	Aposto	6°44'59.48"N	38°22'37.21"E
TP 19	Aposto	6°44'47.90"N	38°22'37.25"E
TP 20	Aposto	6°44'37.30"N	38°22'30.78"E

Table 3. 2 Descriptive statistics of data

Variables	N	Minimum	Maximum	Mean	Std. Deviation	Variance
LL	75	25.80	64.50	42.9827	9.55969	91.388
PL	75	1.00	40.20	25.2013	6.89384	47.525
PI	75	4.20	32.90	17.4133	6.75663	45.652
OMC	75	9.00	33.10	18.8733	5.82883	33.975
MDD	75	1.24	1.83	1.5343	.15066	.023

3.4 Testing method

3.4.1 Laboratory testing

3.4.1.1 Atterberg Limit

AASHTO T 89 and AASHTO T90 has been conducted for liquid limit and plastic limit on all the 30 samples at multiple points. 100 g of the material passing the 425-µm (#40) that was sieve were obtained from each samples. Then the samples were place in the mixing dish and mixed with enough distilled water until the soil can be easily shaped into a ball. A portion of the mixed sample from the dish was removed for both liquid limit and plastic limit, about 8-g portion, determination. A Representative sample of 200gm oven-dried at 105ºC samples was taken that pass No 40(0.425 mm) and before beginning the blending to soften the material has been soaked in for 24hrs for LL and PL tests. Then according to the standards, both Atterberg limit results are determined for all the samples.

3.4.2.2 Modified compaction test

Compaction is a method of packing the soil particles by reducing the air voids within the soil through mechanical means. A particular amount of water, which causes maximum lubrication, while not changing into excess to cause hindrance is called optimum moisture content (OMC) at this stage the soil would be compacted at a density called maximum dry density (MDD).

According to AASHTO T180-D procedure, Modified proctor test, have been used to determine maximum dry density and optimum moisture contents of all the samples. Samples of soil are prepared at several moisture contents and compacted into molds of specified size, using mechanical rammers that deliver a specified quantity of compactive energy. The moist masses of the compacted samples are multiplied by the appropriate factor to determine moist density values. Moisture contents of the compacted samples has been determined and used to obtain the dry density values of the same samples.

Maximum dry density and optimum moisture content for the soil or soil-aggregate mixture has been determined by plotting the relationship between dry density and moisture content. The dry densities were plotted on the vertical axis versus moisture content on the horizontal axis and the points were connected with a smooth line, a moisture-density curves were developed. The coordinates of the peak of the curve are the maximum dry density, or just “maximum density,” and the “optimum moisture content” of the soil.

In order to determine the above curve, first the wet density and dry density must be determined using the equation (3.1) and (3.2) below:

$$Wet\ density\ (\rho_w) = \frac{wet\ mass\ (Kg)}{Measured\ volume\ of\ mold\ (m^3)} \qquad (3.1)$$

$$Dry\ density\ (\rho_d) = \left[\frac{wet\ density\ \left(\frac{Kg}{m^3}\right)}{moisutre\ content\ (\%)}\right] * 100 \qquad (3.2)$$

3.5 Data management and analysis

3.5.1 General

The link between variables is often expressed in an intended form by determining an equation connecting those variables mathematically. An experimental study, enables the collection of valid data before the establishments of the relations between variables. In carrying out the prediction and developing the linear regression model for optimum moisture content and maximum dry density, MATLAB was used.

3.5.2. Artificial neural network (ANN)

Artificial neural network is a network of neurons. The network receives input and change their internal state (activation functions) in step with the input then manufacture output depending on the input and activation functions. An artificial neural network evaluated by its Mean Squared Error which is the average squared difference between outputs and targets. Lower values are better and Regression (R) values measure the correlation between outputs and targets. An (R) value of one means a perfect relationship, zero a no valid relationship. ANNs have a classification ability, examination, simulation and decision-making that has given them a wide application in the engineering field, and even in other fields. In general, a single and multi-layer neural network (NN) consists of a succession of layers where are systems consisting of a large number of units interconnected to each other making elementary processors (Bahmed, 2017).

The analysis was conducted on all seventy-five data; consisting five variables, two dependents and three independents, in this study. Neural net analysis computation is based on a multiple layer perceptron (feedforward) network and the network architecture consists three inputs, three layers of ten neurons each (30 layers), two output layers and two outputs. A total of thirty-two hidden layers were in the neural network. It is briefly presented in the figure 3.3.

For the analysis execution of both prediction and linear modeling a text based NN analysis was used. The text based neural net analysis is composed of different command lines written with in the program. Commands or test (syntax) for each steps of predicting and linear modeling is introduced into editor window of the program. The command lines for predicting and modeling are shown in Figure 3.4 and 3.5 below. The details are shown on Appendix F

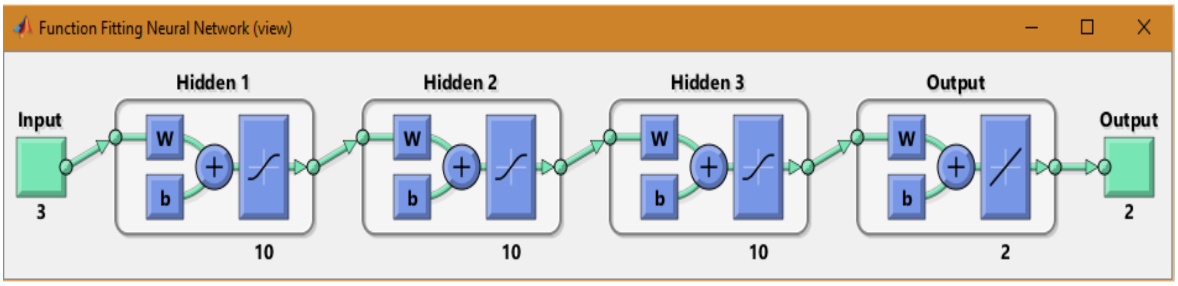

Figure 3. 3 Network architecture for 32 layers (30,2) of neural network

```
D_inputs=xlsread(name,'A:C');% inputs LL,PL,PI
D_outputs=xlsread(name,'D:E');% Outputs OMC,MDD
inputs = D_inputs'; % input to the neural net
targets = D_outputs'; % output of the neural net

% Create a Fitting Network
hiddenLayerSize = [10 10 10]; % size of the hidden layer
net = fitnet(hiddenLayerSize); % function to create the neural network

% Set up Division of Data for Training, Validation, Testing
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;
%net.trainFcn = 'trainbr';
net.trainFcn = 'trainscg';
% Train the Network
[net,tr] = train(net,inputs,targets);

% Test the Network
outputs = net(inputs);
errors = gsubtract(outputs,targets);
performance = perform(net,targets,outputs)

% View the Network
view(net)
% Plots
% Uncomment these lines to enable various plots.
figure, plotperform(tr)
figure, plottrainstate(tr)
%figure, plotfit(targets(1,:),outputs(1,:))
%figure, plotregression(targets,outputs)
%figure, ploterrhist(errors)
y=outputs';
%figure, Original OMC vs neuralnet OMC
figure,
```

Figure 3. 4 Syntax (text) for model prediction in MATLAB

```
LL=D_inputs(:,1);
PL=D_inputs(:,2);
PI=D_inputs(:,3);
OMC=D_outputs(:,1);
MDD=D_outputs(:,2);
n=length(LL);
V=[ones(n,1),LL,PL,PI];
C_1=pinv(V)*OMC;  %pinv(V) is a psudo inverse function to find the inverse of a matrix
C_2=pinv(V)*MDD;
%tbl = table(LL,PL,PI,OMC,'VariableNames',{'LL','PL','PI','OMC',});
%lm = fitlm(tbl)
```

Figure 3. 5 Syntax (text) for developing linear regression model in MATLAB

3.5.2.1 Neural network function approximation

The most useful and common neural networks in function approximation are Multilayer Perceptron (MLP) and Radial Basis Function (RBF) networks. Multiple layer perceptron is a class of feedforward artificial neural network. It consists of at least three layers of nodes: an input layer, a hidden layer and an output layer. For this study Multilayer Perceptron (MLP) networks have been used.

3.5.2.2 Calibration, validation, and testing

The network has been trained by dividing the data into three sections which is, training, validation, and testing. The term training, that is presented to the network during training, and additionally, the network is adjusted in step with its error, however validation that is employed to measure network generalization and to close training when generalization stops improving. But, testing, does no effect training and so provides an independent measure of network performance during and after training. In this thesis, the network was developed by considering 70% of data for training, 15% of data for validation and 15% of the data for testing.

3.5.2.3 Activation functions

Activation functions are mathematical equations that determine the output of a neural network. The function is attached to each neuron in the network, and determines whether it should be activated or not, based on whether each neuron's input is relevant for the model's prediction. Activation functions also help normalize the output of each neuron to a range between 1 and 0 or between -1 and 1. Tan sigmoid activation function have been introduced for the analysis purpose of the neural network.

3.5.2.4 Optimization (learning) algorithm

Optimization or learning algorithm is a procedure used to carry out the learning process in a neural network. There are many different optimization algorithms. All have different characteristics and performance in terms of memory requirements, processing speed and numerical precision. For this study three different learning algorithms; Levenberg Marquardt (LM), Scaled Conjugate Gradient (SCG) and Bayesian regularization backpropagation (BR), has been used. And based on the above listed criteria the best algorithm has been compared and selected from the learning process.

3.5.2.5 Epoch

An epoch is a degree of the number of times all of the training values are used once to update the weights. In this study, the epoch for the analysis process have been determined based on the data feed and the times requirement for computation. The epoch in this study has been fixed to 1000 for better computation.

A summarized procedure of teaching algorithms for multilayer perceptron networks was conducted accordingly:

1. The structure of the network is first defined. In the network, activation functions are chosen and the network parameters, weights and biases, are initialized.
    - Network structure is set as multiple layer perceptron feedforward network
    - The network architecture is presented.
    - Tan sigmoid was chosen as an activation function.
2. The parameters associated with the training algorithm like error goal, maximum number of epochs (iterations), etc., are defined.
    - The error goal is of 1e-3 to 1e-7 is fixed.
    - Maximum number of 1000 epoch is set.
3. The training algorithm is called.
    - Algorithm is called using the command script and RUN command.
4. simulating the output of the neural network with the measured input data. This is compared with the measured outputs. Final validation must be carried out with independent data.
    - Simulation for neural net and original data is developed and new random independent data is computed to show how the prediction works.

Then all the important results are identified, simulated and output results are compared to the original output values. And the final approximated linear regression model for the prediction analysis are presented.

3.5.3 Modeling compaction parameters

The most common form of regression analysis is linear regression, in which a scholar finds the line (or a more complex linear combination) that most closely fits the data according to a specific mathematical criterion. In addition to this, it attempts to model the relationship between two variables by fitting a linear equation to observed data. Linear regression modeling has been used to develop the regression model for this study.

3.5.4 Confidence interval

Usually, tests start by using the 95% level ($p = 0.05$), if the test at that level is passed. The 95% confidence level indicates that, although the data support the conclusion with 95% probability, there is a 5% chance that the conclusion is wrong. The probability of making an error to reject a hypothesis whereas it happens to be true is called the level of significance.

3.5.5 Correlation Coefficient (R)

Coefficient is the parameter estimate for every increase or decrease in one variable, the change of another variable. Whereas square of R is statistic representation of the proportion of variation in the dependent variable that is explained by the model. It is also the square of the correlation coefficient. The correlation coefficient measures how well the best fit line fits the sample data. The value of $R=1$ or -1 shows there is a perfect correlation but $R = -1$ shows the inverse relationship. On the other hand, $R=0$ or approaches to zero shows no valid relationship between the variables.

4. RESULT AND DISCUSSION

4.1 Index properties

Physical properties of soil from the study area were understood using successive index property tests since it is the base for understanding of index property of soils. The physical serve mainly for identification and classification purpose are commonly known as index properties which can be determined by simple laboratory tests. Index property tests of Atterberg limit, free swell and compaction test were done in laboratory and here are the result and discussion of the investigated soil. The summarized results for both Atterberg limit tests and modified compaction test is presented on Appendix H.

4.1.1 Atterberg limit

Atterberg Limits are arbitrary boundaries between every of the two states like liquid limit, plastic limit and shrinkage limit. As mentioned in section 2.4, the physical property index of all the test samples are larger than 20 %, which shows that all the soils in the study area are highly plastic. The liquid limit result ranges from 37.49% to 57.38%, the plastic limit value ranges from eighteen up to thirty-four percent and plasticity limit ranges from 3% to 28%. Summary of Atterberg limit output is presented on Table 4.1. Data analysis and laboratory test results for all samples were presented in Appendix A.

Table 4. 1 Atterberg limit results of sample from the study area

Test pits	Location			LL(%)	PL(%)	PI
	Destination	Latitudes	Longitudes			
TP 1	Morocho Kutala	6°54'47.47"N	38°26'53.62"E	44.97	33.02	11.95
TP 2	Morocho Kutala	6°54'40.87"N	38°26'47.26"E	37.49	26.85	10.63
TP 3	Morocho Kutala	6°54'24.92"N	38°26'30.21"E	42.56	33.30	9.26
TP 4	Tula Town	6°57'5.38"N	38°28'32.26"E	38.82	34.89	3.93
TP 5	Morocho Shondolo	6°53'46.46"N	38°25'48.13"E	38.02	26.86	11.16
TP 6	Morocho Shondolo	6°53'18.38"N	38°25'17.46"E	44.97	29.09	15.88

TP 7	Tula Town	6°56'21.63"N	38°28'22.16"E	50.42	23.79	26.63
TP 8	Tula Town	6°56'9.64"N	38°28'19.99"E	47.13	22.74	24.39
TP 9	Tula Town	6°55'47.10"N	38°28'14.30"E	52.23	26.55	25.69
TP 10	Morocho Shondolo	6°51'59.27"N	38°23'50.78"E	42.32	19.66	22.66
TP 11	Chei-cheic	6°50'49.22"N	38°23'10.26"E	38.20	18.23	19.97
TP 12	Aposto	6°49'25.27"N	38°22'53.07"E	45.63	20.61	25.02
TP 13	Aposto	6°48'17.01"N	38°22'57.11"E	39.29	22.85	16.43
TP 14	Morocho Shondolo	6°52'46.05"N	38°24'40.29"E	57.38	29.76	27.62
TP 15	Aposto	6°46'16.61"N	38°22'39.32"E	45.59	25.70	19.90
TP 16	Aposto	6°47'8.39"N	38°22'44.90"E	46.74	22.43	24.32
TP 17	Aposto	6°45'20.72"N	38°22'34.85"E	54.53	27.86	26.67
TP 18	Aposto	6°44'59.48"N	38°22'37.21"E	51.85	26.51	25.34
TP 19	Aposto	6°44'47.90"N	38°22'37.25"E	54.20	28.76	25.44
TP 20	Aposto	6°44'37.30"N	38°22'30.78"E	47.49	20.76	26.73

4.1.2 Modified proctor compaction

The standard proctor compaction test is performed where ordinary compaction equipment is to be used in the field. However, in some types of constructions it is required to use heavy compacting equipment in order to get better comparable results; this test need to be performed by modified proctor’s compaction test. The calculations of dry density and moisture content are identical with the ones described in the proceeding test. The compaction energy transmitted by the modified AASHTO test is about 4.5 times the energy transmitted by the standard proctor test.

The dry density was computed for each soil sample that corresponds to the twenty water content which, ranges from liquid limit up to plastic limit. In most of the cases, the soil was difficult to compact once the water content is around LL, thus it is extrapolated. Using the dry density, and its respective water content the bulk density was known and by multiplying the bulk density with the volume of the specimen the mass of the soil that is to be remolded was known and conjointly the mass for the specimen. Combined compaction curve and summarized Modified Proctor test results are presented on Figure 4.1 and Table 4.2 respectively. And all compaction laboratory tests are presented on Appendix B.

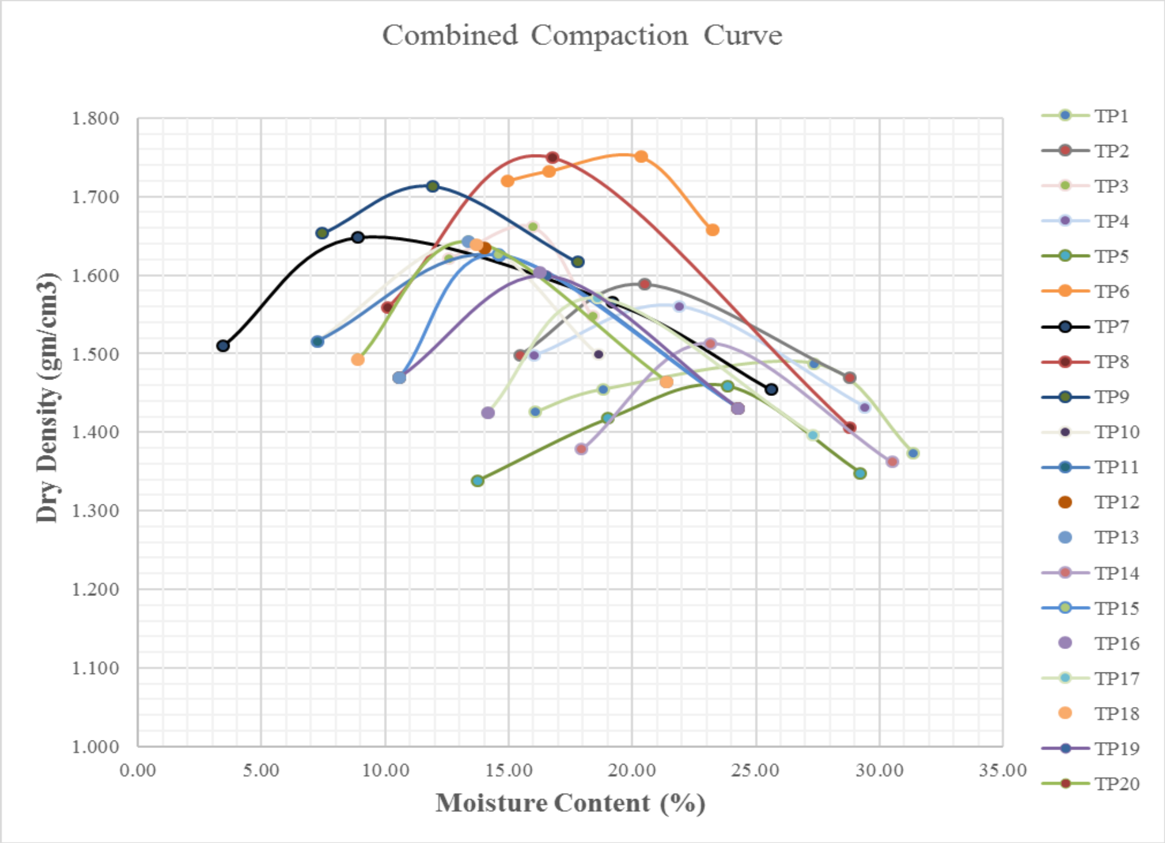

Figure 4. 1 Combined compaction curve for twenty soil sample

Table 4. 2 Summarized Modified Proctor test results

Test pits	Location			OMC (%)	MDD (gm/cm^3)
	Destination	Latitudes	Longitudes		
TP 1	Morocho Kutala	6°54'47.47"N	38°26'53.62"E	31.14	1.49
TP 2	Morocho Kutala	6°54'40.87"N	38°26'47.26"E	20.12	1.59
TP 3	Morocho Kutala	6°54'24.92"N	38°26'30.21"E	15.8	1.66
TP 4	Tula Town	6°57'5.38"N	38°28'32.26"E	21.6	1.56
TP 5	Morocho Shondolo	6°53'46.46"N	38°25'48.13"E	22.4	1.46

TP 6	Morocho Shondolo	6°53'18.38"N	38°25'17.46"E	19.4	1.756
TP 7	Tula Town	6°56'21.63"N	38°28'22.16"E	9	1.65
TP 8	Tula Town	6°56'9.64"N	38°28'19.99"E	16	1.75
TP 9	Tula Town	6°55'47.10"N	38°28'14.30"E	11.8	1.711
TP 10	Morocho Shondolo	6°51'59.27"N	38°23'50.78"E	13.8	1.64
TP 11	Chei-cheic	6°50'49.22"N	38°23'10.26"E	14.2	1.63
TP 12	Aposto	6°49'25.27"N	38°22'53.07"E	13.85	1.635
TP 13	Aposto	6°48'17.01"N	38°22'57.11"E	13.2	1.64
TP 14	Morocho Shondolo	6°52'46.05"N	38°24'40.29"E	23	1.511
TP 15	Aposto	6°46'16.61"N	38°22'39.32"E	14.8	1.625
TP 16	Aposto	6°47'8.39"N	38°22'44.90"E	16.4	1.6
TP 17	Aposto	6°45'20.72"N	38°22'34.85"E	18.2	1.552
TP 18	Aposto	6°44'59.48"N	38°22'37.21"E	13.5	1.64
TP 19	Aposto	6°44'47.90"N	38°22'37.25"E	16.4	1.6
TP 20	Aposto	6°44'37.30"N	38°22'30.78"E	13.2	1.64

4.2 Analysis of data using MATLAB

A Tan sigmoid activation function with 32 hidden layer is used for training the data. Out of the total 75 data 70 % for training, 15% for validation and 15% for testing is used. The parameters associated with the training algorithm like error goal of 1e-3 to 1e-7, maximum number of epochs of 1000 and Learning rate gradient schemes of 0.01 is assigned.

In previous chapter, it was shown that it was very challenging to know which training algorithm will be the fastest for a given problem. It depends on many factors, including the complexity of the problem, the number of data points in the training set, the number of weights and biases in the network, the error goal, and whether the network is being used for pattern recognition (discriminant analysis) or function approximation (regression). In this section three algorithms were chosen; Levenberg-Marquardt, Bayesian regularization backpropagation (BR) and Scaled Conjugate Gradient are used. And based on the above listed criteria the output of each algorithm are compared and the best algorithm is selected for the learning process.

4.2.1 Training using Levenberg-Marquardt (LM)

By default, the MATLAB assigns Levenberg-Marquardt algorithm without writing syntax. As mentioned in the sections above, each algorithm produces its own values such as; performance, trial and error (epoch) point where lower value mean squared value found, the mean squared error, regression (R) values for training, validation, testing and total R. The best output results are found by continuously training the network to produce lower mean squared error (MSE) and good R values (> 95%) as much as possible.

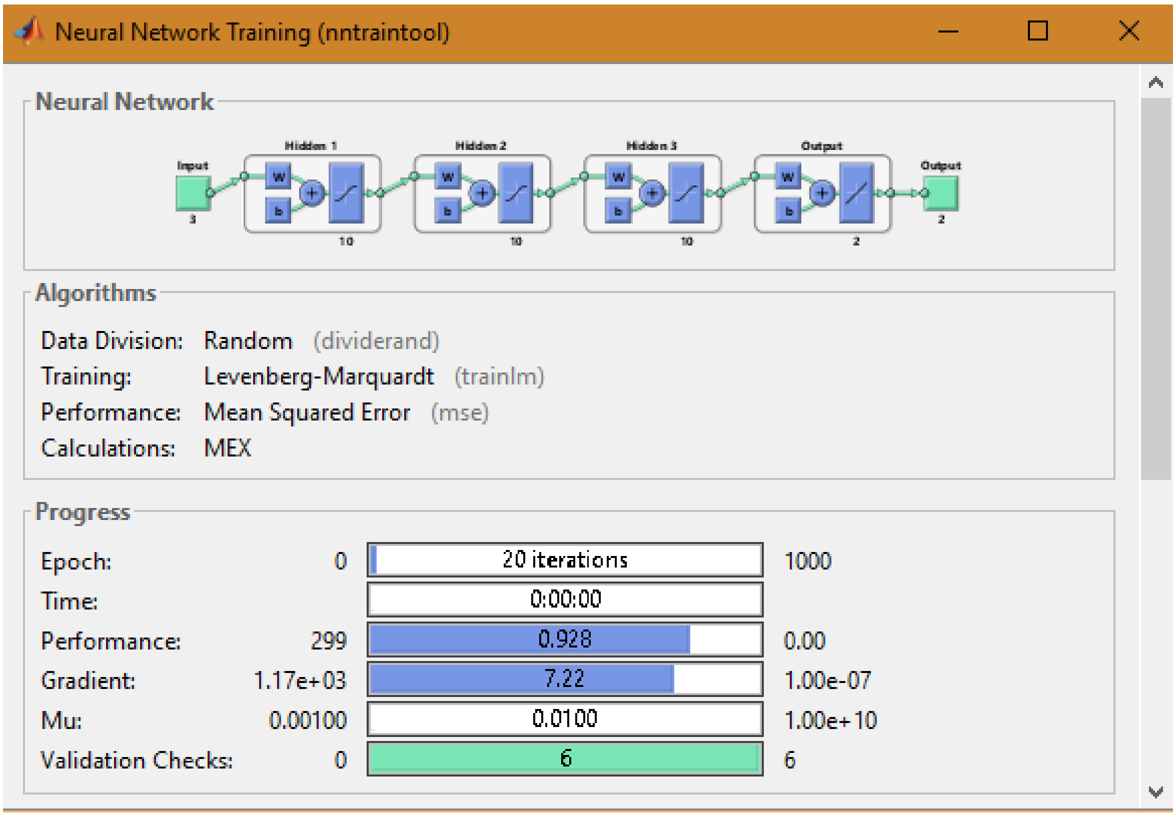

Figure 4. 2 Neural network training using LM algorithm

After training and computing algorithm for a while (5 to 8 RUN commands), the output in figure 4.2 are generated. From the figure above, it shows that the system uses LM algorithm for training the data. It has limited and specified the epoch to 20 from the total

1000 since lower value of MSE falls in between 0 and 20 epochs. The training time produced is in milli-seconds, < 1 second (0:00:00).

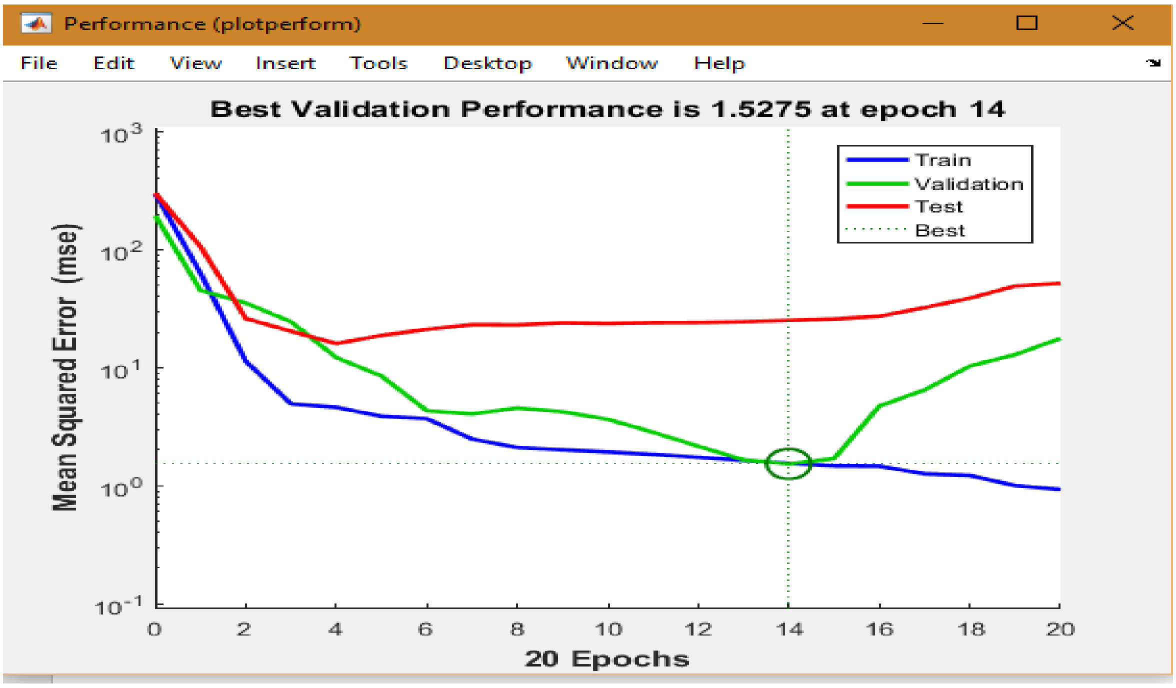

Figure 4. 3 Plot of best validation performance (Mean square error vs epoch) for LM

The performance of Levenberg-Marquardt algorithm in training the data is shown in figure 4.3 above. The figure shows a graph generated between mean squared error and 20 epochs. The data is trained, validated and tested, and best value of the computation is found. The best performance for this training is found at the 14^{th} epoch with mean squared error less than 1.6 (MSE = 1.5275).

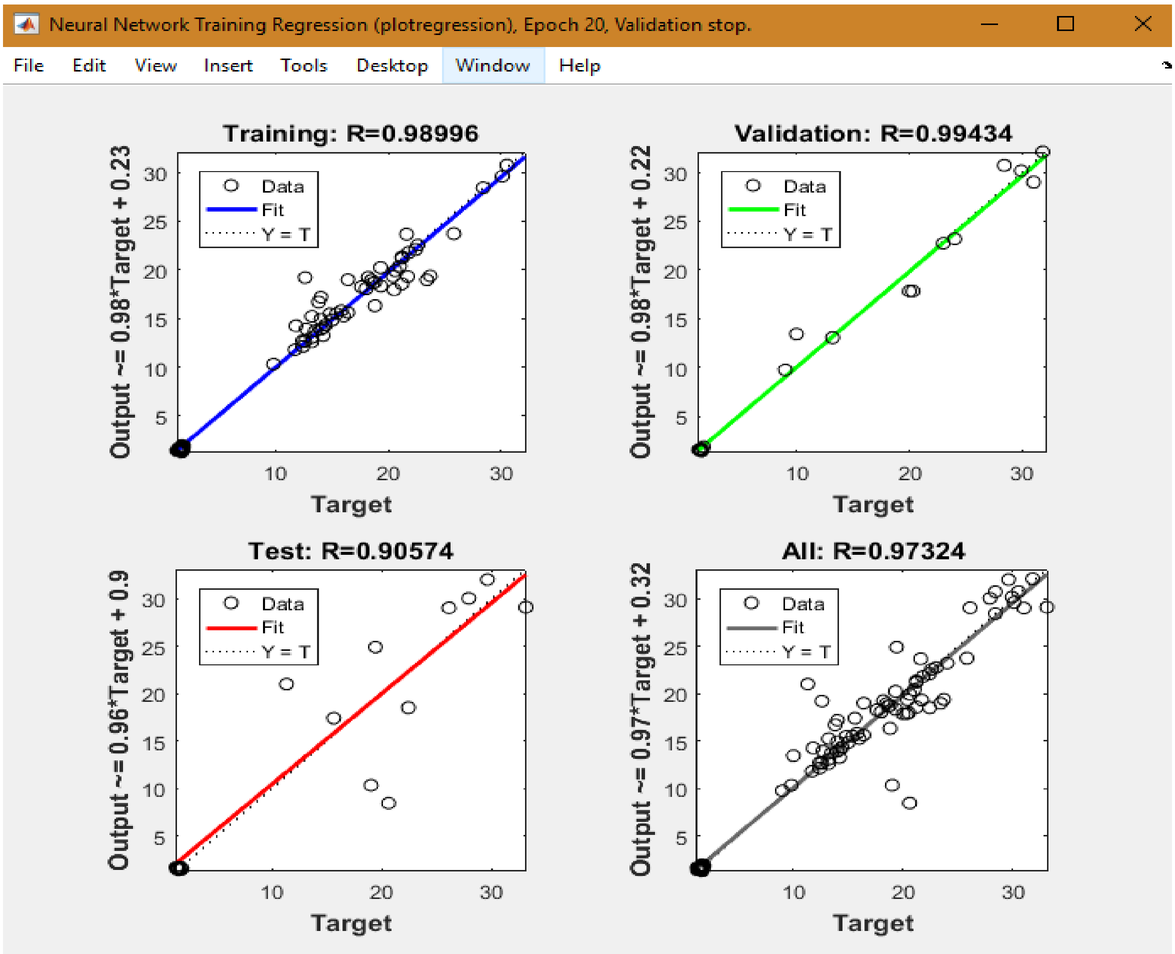

Figure 4. 4 Plots of target vs output for training, validation and test with respective R values (best) for LM

The regression (R) values for training, validation, and total R is shown in figure 4.4 above. The plot is target vs output. The analysis using LM algorithm gives the regression values that are above the standard value (95%) for most cases, for training R = 0.98996, for validation 0.99434, for testing 0.90574 and for the total R = 0.97324. And some outlier data are found in all the regression plot above.

Therefore, using all the above results and training output, the prediction output for compaction parameters, OMC and MDD, is presented as graphs in figures below. After simulation of using LM algorithm, comparison between the original OMC data and the neural net OMC (predicted) and also original MDD and predicted MDD by neural net is developed on a plot in Figure 4.5 and 4.6.

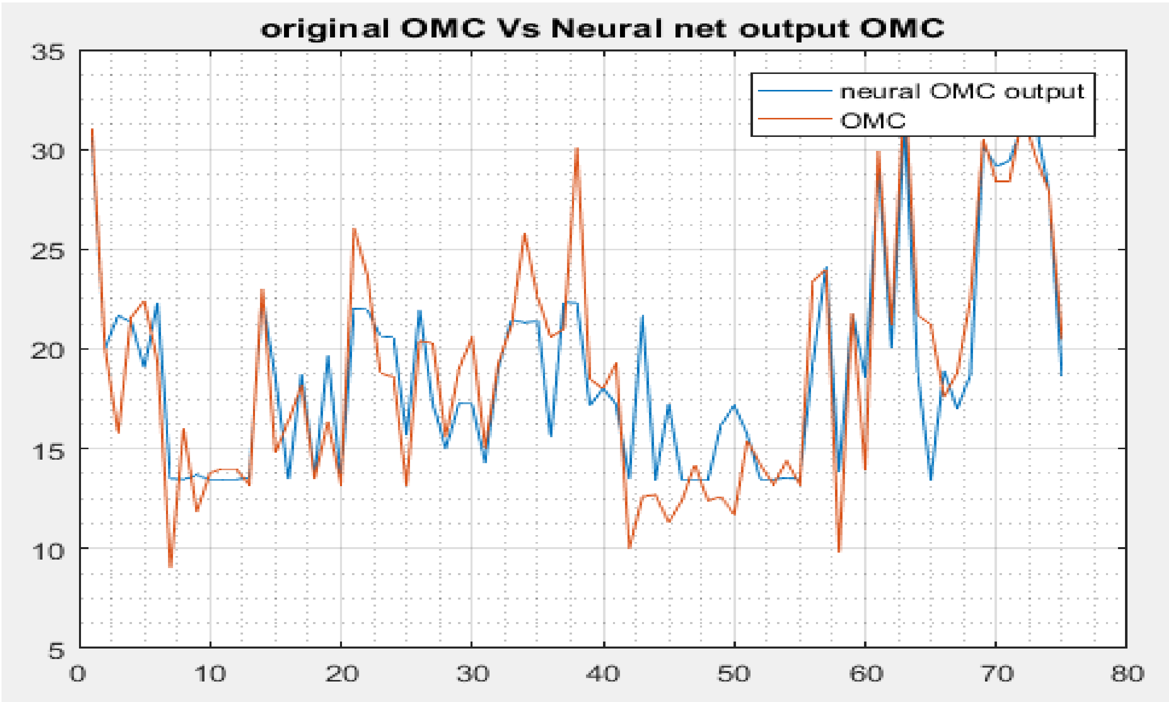

Figure 4. 5 Plot for output of original OMC vs predicted OMC using LM algorithm

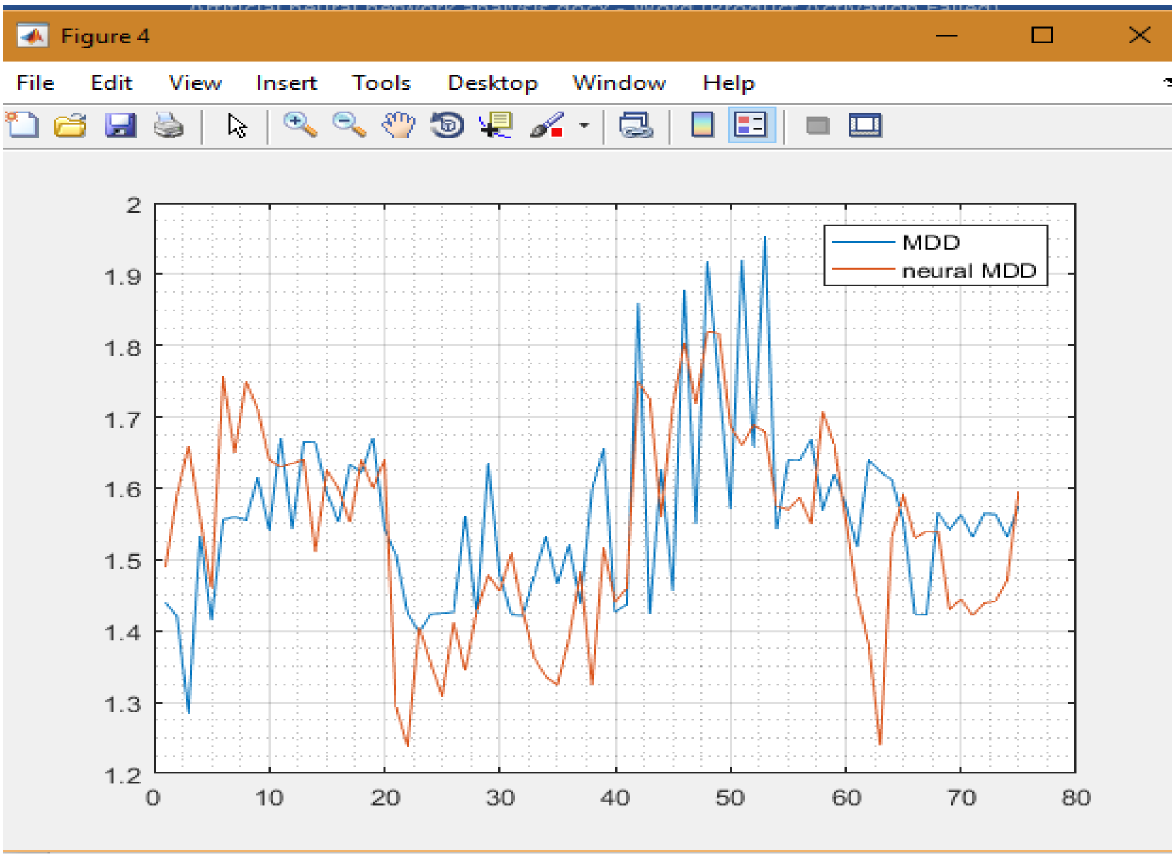

Figure 4. 6 Plot for output of original MDD vs predicted MDD using LM algorithm

4.2.2 Training by Bayesian regularization backpropagation algorithm (BR)

Bayesian regularization backpropagation algorithm was introduced into MATLAB using syntax script command, “trainbr”. It produces its own output values like that LM learning algorithm. This includes performance plots, trial and error (epoch) point where lower value mean squared value found, the mean squared error, regression (R) values for training, validation, testing and total R. The best output results are found by continuously training the network to produce lower mean squared error (MSE) and R values, greater than the standard, as much as possible. After training and computing algorithm for a sometime (2 to 5 RUN commands), the outputs are generated. In the figure 4.7 below, it shows that the system uses BR algorithm for training the data. It has limited and specified the epoch to 1000 from the total 1000 since lower value of MSE falls in between 0 and 1000 epochs. The training time produced is in seconds, < 15 second (0:00:10).

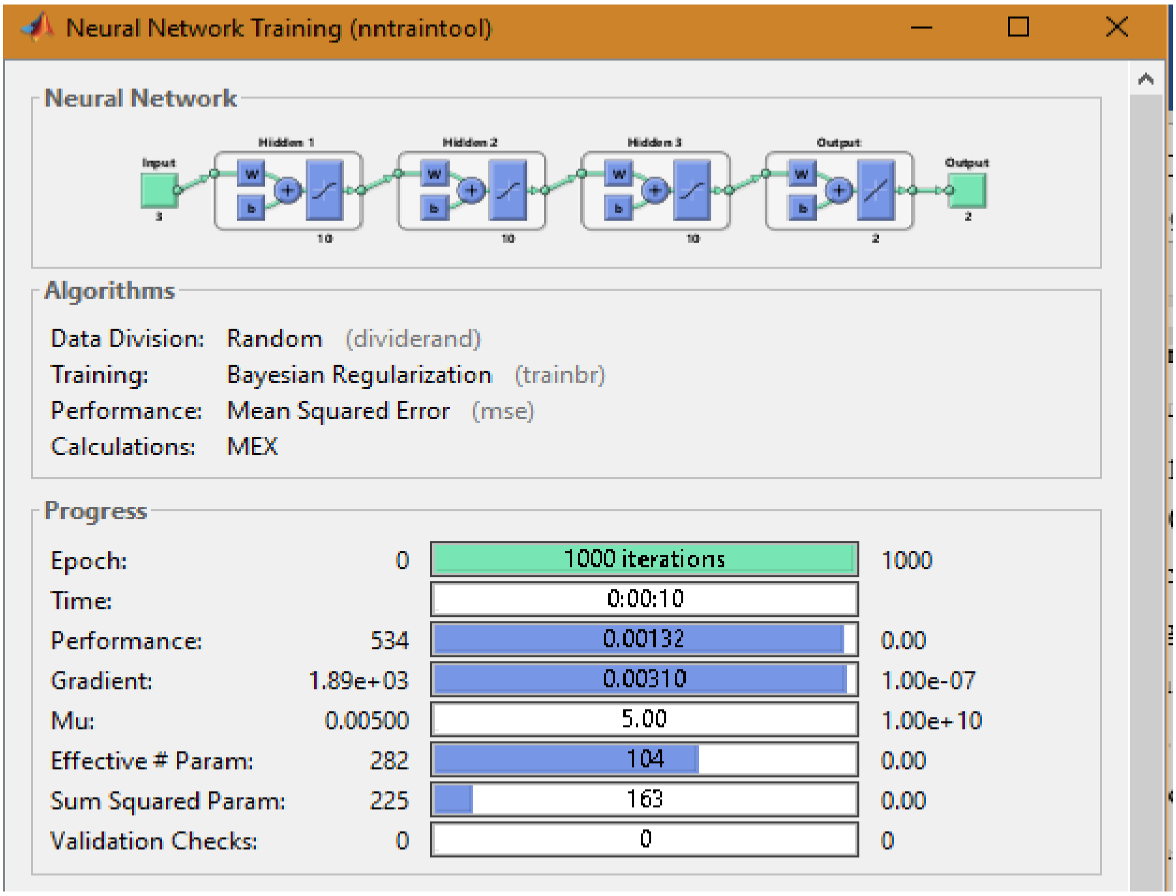

Figure 4. 7 Neural network training using BR algorithm

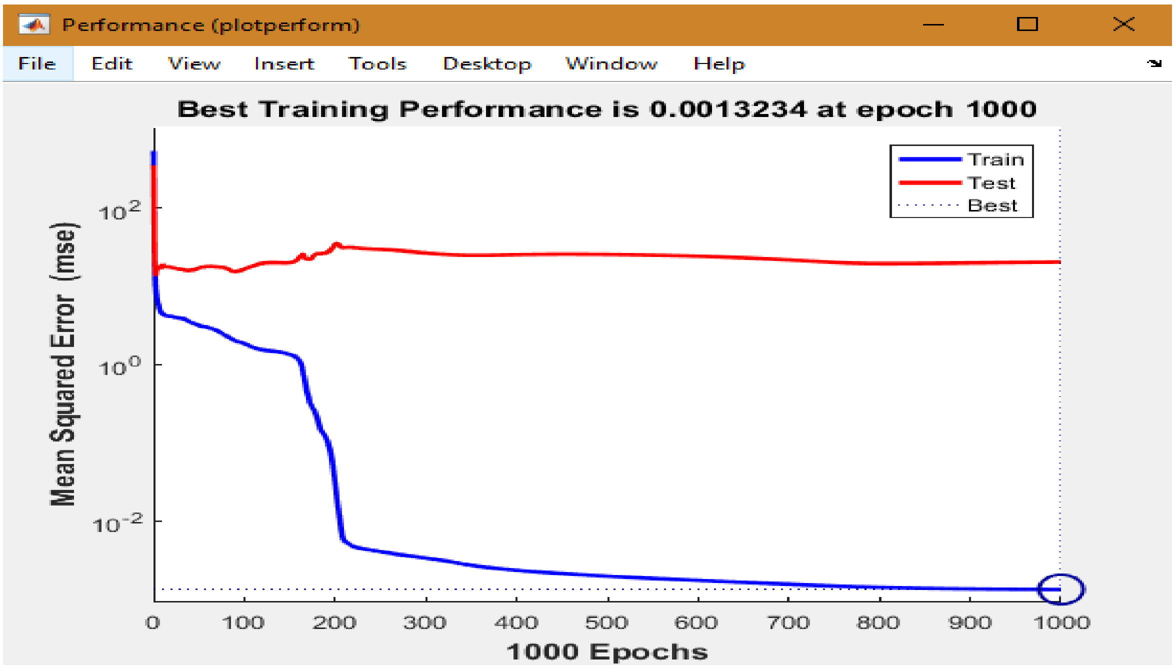

Figure 4. 8 Plot of best validation performance (Mean square error vs epoch) for BR

The performance of BR backpropagation algorithm in training the data is shown in figure 4.8 above. The figure shows a graph generated between mean squared error and 1000 epochs. The data is trained, validated and tested, and best value of the computation is found. The best performance for this training is found at the 1000th epoch with mean squared error less than 0.01 (MSE = 0.0013234).

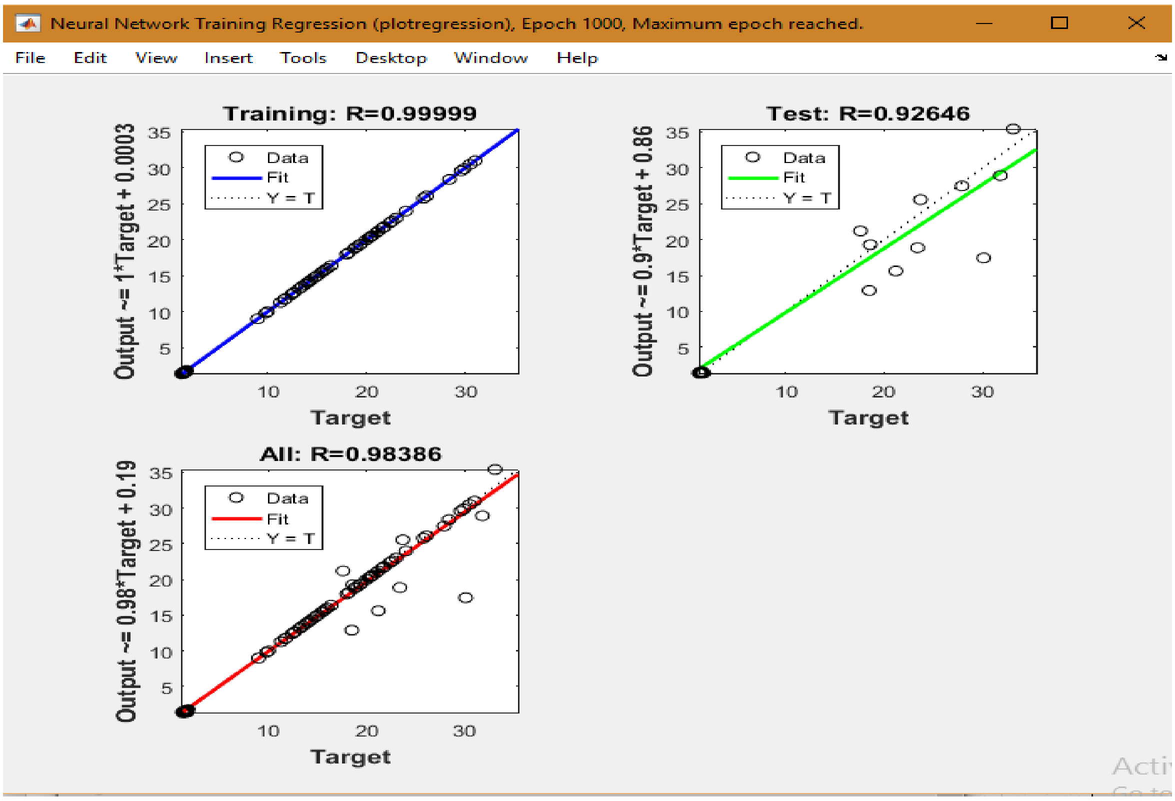

Figure 4. 9 Plots of target vs output for training and test with respective R values for BR

The regression (R) values for training, testing and total R is shown in figure 4.9 above. The plot is target vs output. The analysis using BR backpropagation algorithm gives the regression values that are above 90% for most cases; for training R = 0.99999, for testing 0.92646 and for the total R = 0.98386. Therefore, based on all the analysis outputs and the performance generated by BR algorithm, optimum moisture content and maximum dry density are predicted. And a representation of the comparison between the predicted (neural net) outputs and the original outputs of the data is presented in the figure 4.10 and 4.11.

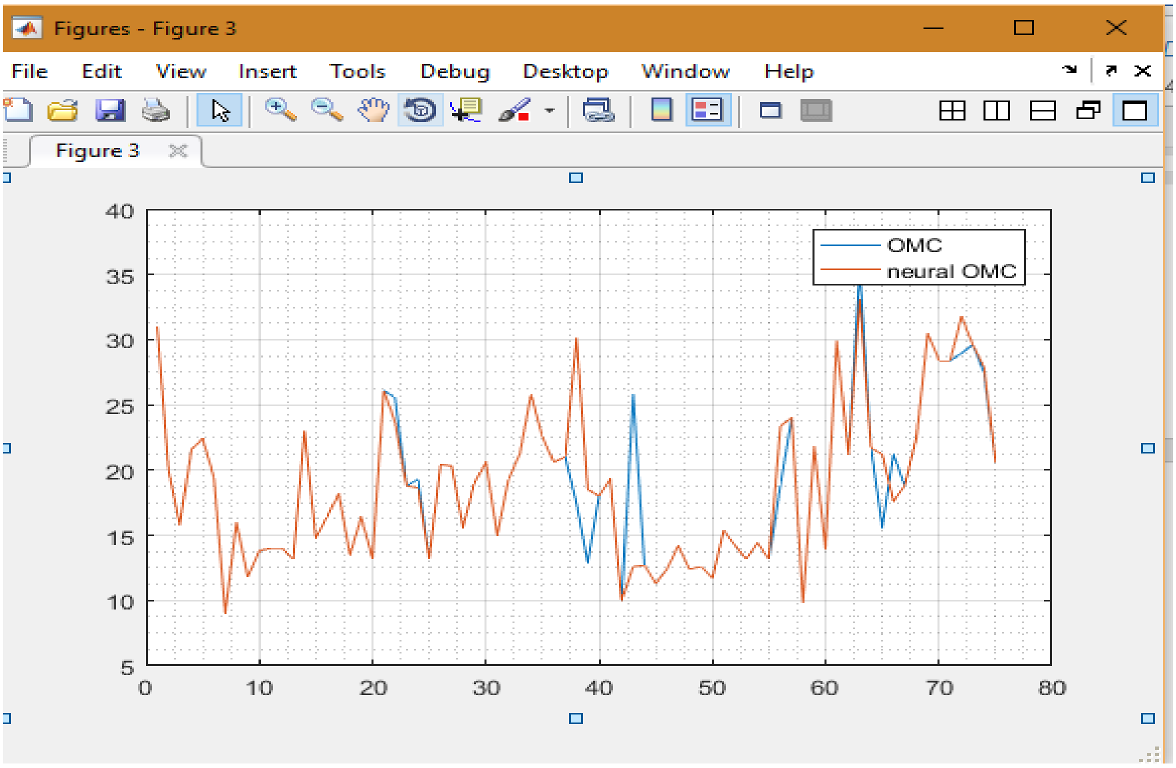

Figure 4. 10 Plot for output of original OMC vs predicted OMC using BR algorithm

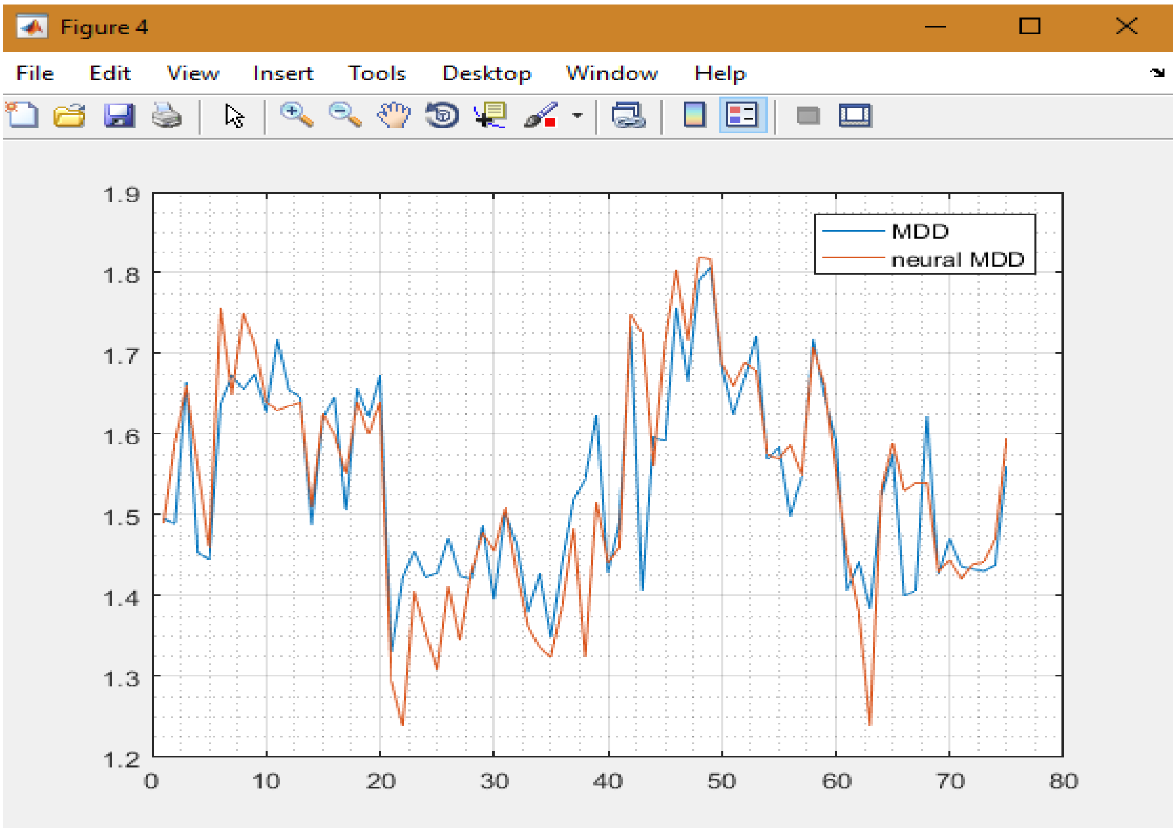

Figure 4. 11 Plot for output of original MDD vs predicted MDD using BR algorithm

4.2.3 Training using Scaled Conjugate Gradient algorithm (SCG)

The same as BR backpropagation algorithm, scaled conjugate gradient (SCG) algorithm uses syntax text command which have “trainscg” command name. SCG algorithm produces its own output values like that of LM and BR learning algorithm. This includes performance plots, trial and error (epoch) point where lower value mean squared value found, the mean squared error, regression (R) values for training, validation, testing and total R and also compares the predicted value to original data of compaction parameter.

Outputs for best results are found by continuously training the network to produce lower which produce mean squared error (MSE) and R values, greater than the standard, as much as possible. After training and computing algorithm for a sometime (1 to 6 RUN commands), the outputs are generated and presented in the figures below.

It is shown that the system uses SCG algorithm for training the data. The algorithm has limited and specified the epoch to 29 from the total 1000 since MSE of 4.5103 falls in between 0 and 23 epochs. The duration for execution of the analysis is in seconds, < 1 second (0:00:00). And also the R values for training is 0.9665, 0.9753 for validation, 0.93663 for testing and 0.96412 for all. All the outputs are presented on figure 4.12, 4.13 and 4.14 respectively. And finally the analysis outputs and the performance generated by SCG algorithm, optimum moisture content and maximum dry density are predicted. And a representation of the comparison between the predicted (neural net) outputs and the original outputs of the data is presented as plots in the figure 4.15 And 4.16 below.

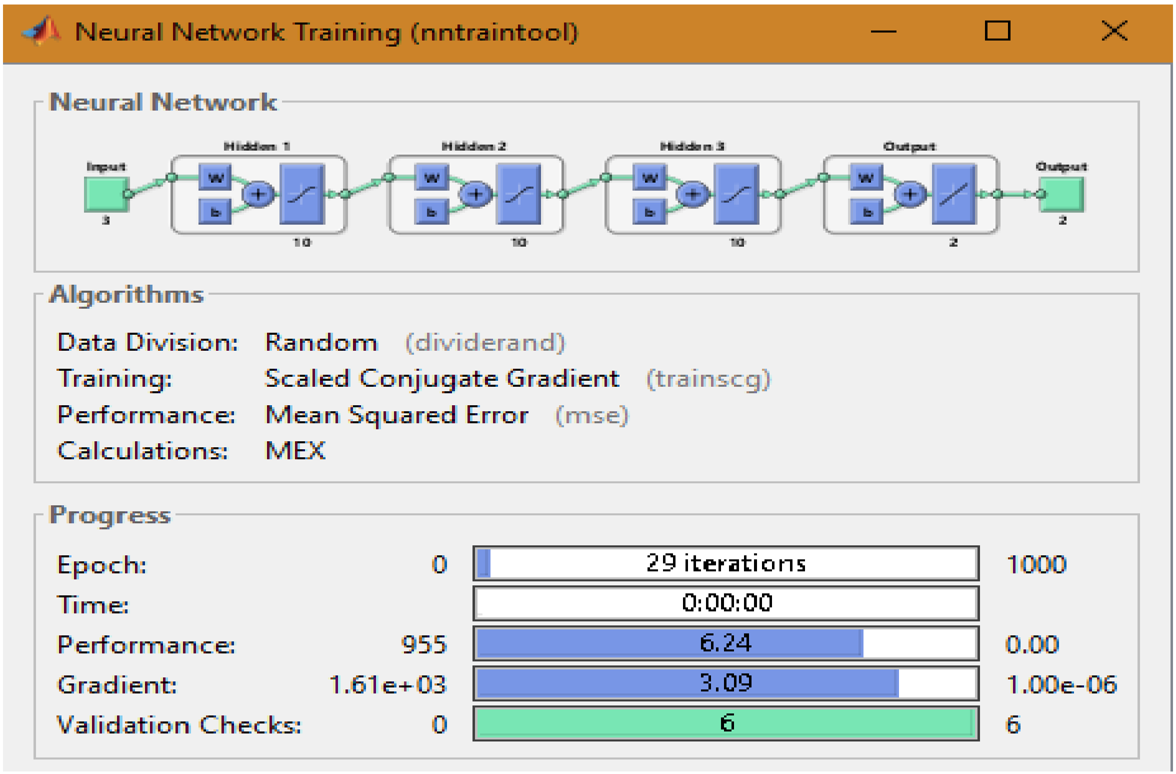

Figure 4. 12 Neural network training using SCG algorithm

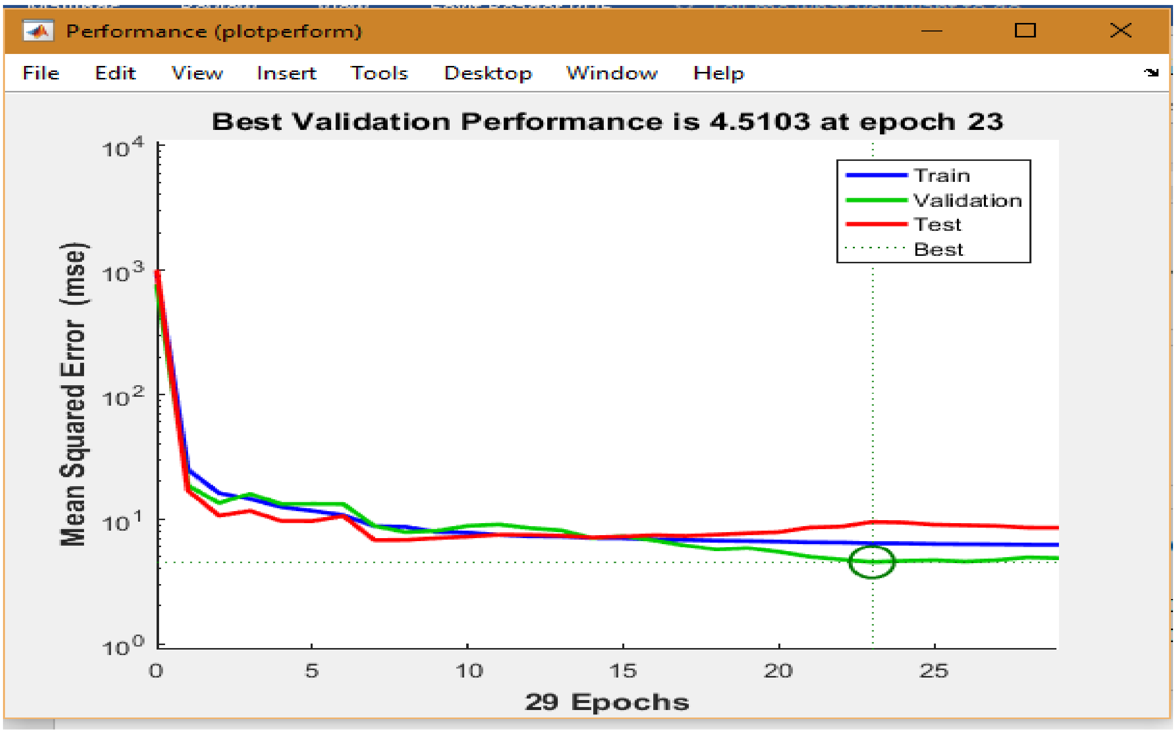

Figure 4. 13 Plot of best validation performance (Mean square error vs epoch) for SCG

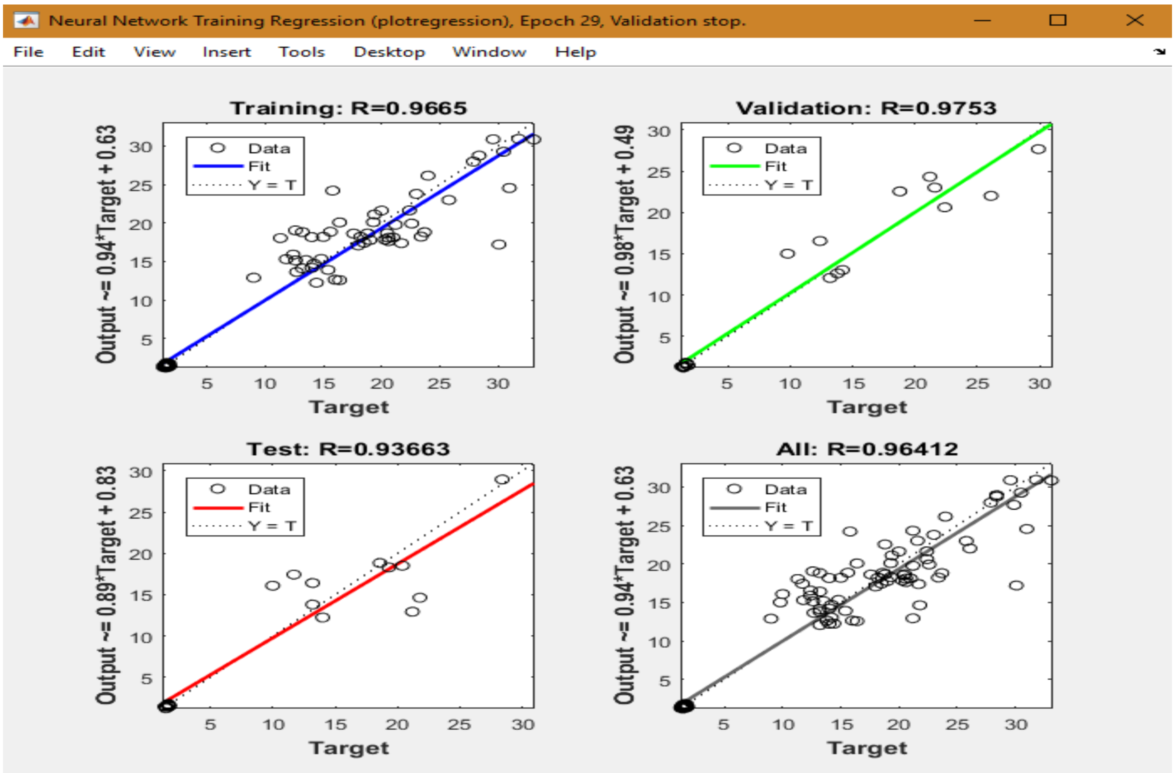

Figure 4. 14 Plot of target vs output for training and test with respective R values (best) for SCG

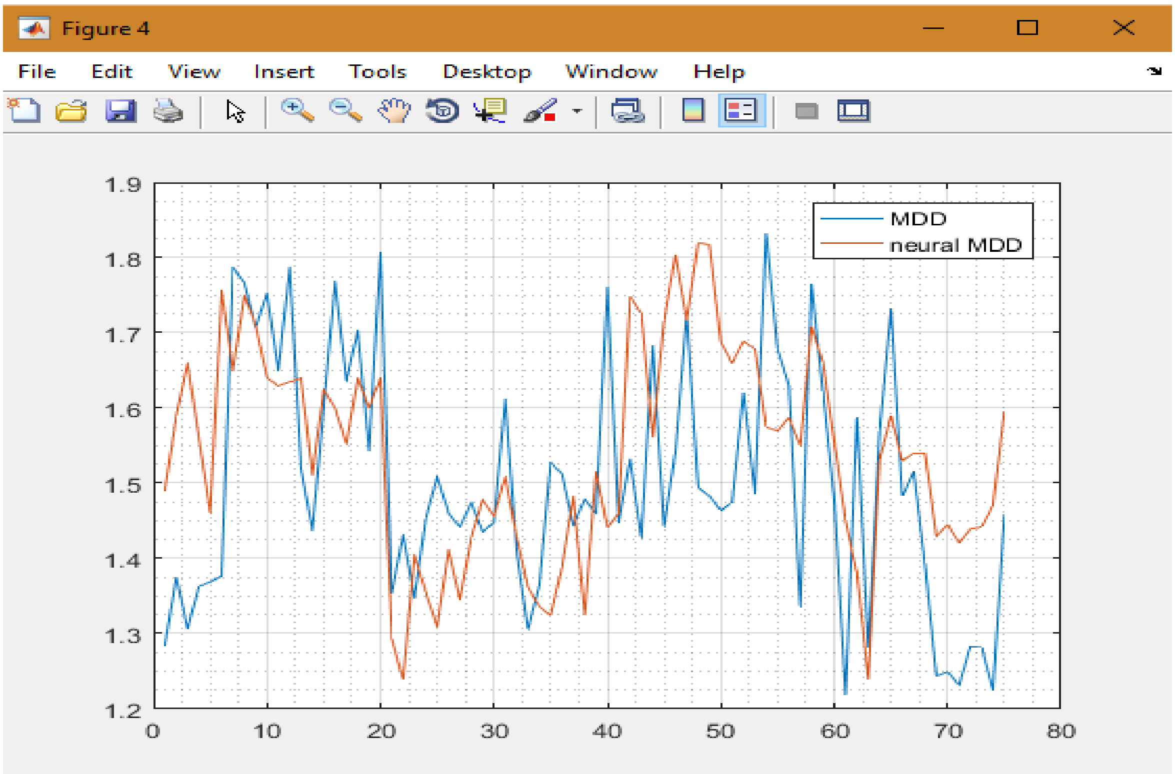

Figure 4. 15 Plot for output of original OMC vs predicted OMC using SCG algorithm

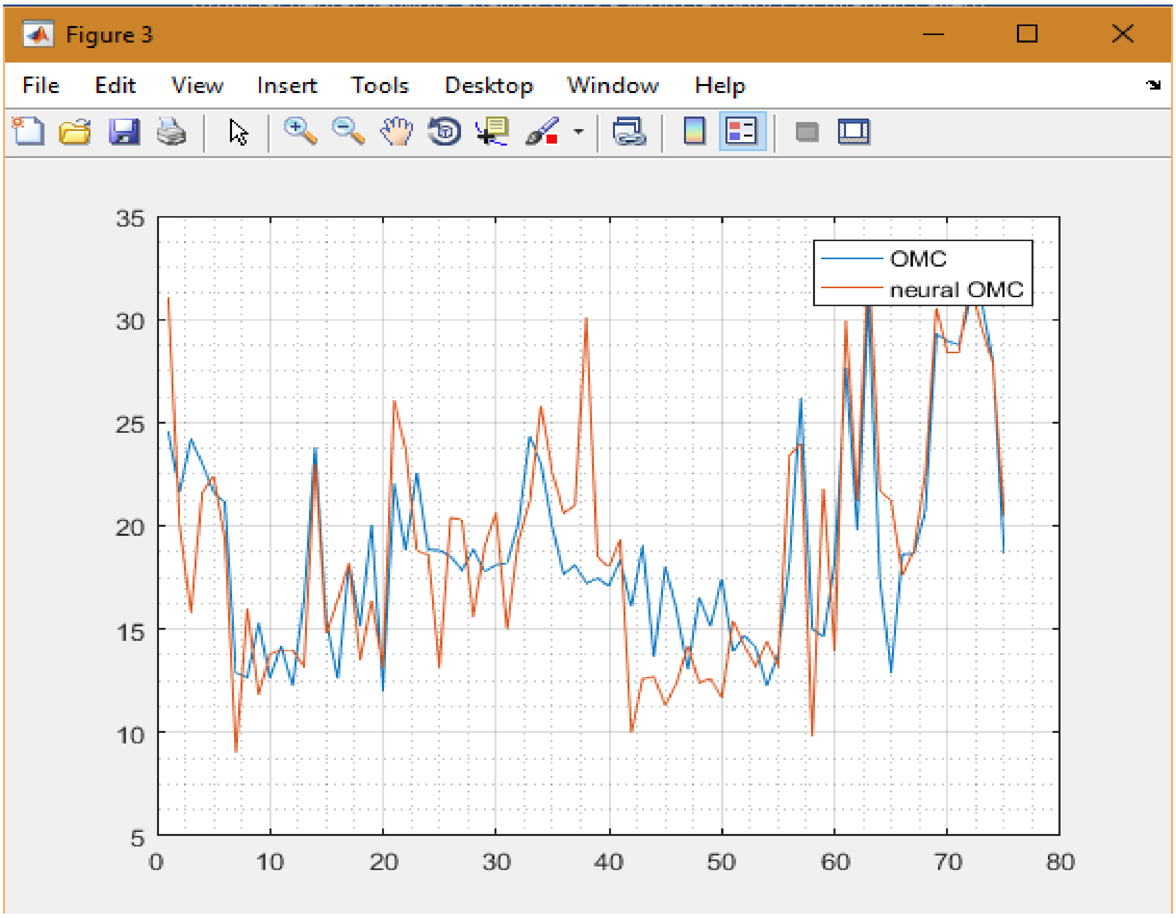

Figure 4. 16 Plot for output of original MDD vs predicted MDD using SCG algorithm

Table 4. 3 Summary of R values, MSEs and epochs of LM, BR and SCG training algorithms

Learning algoritm	Epoch (n of 1000)	Training time (sec)	Data division method	R				MSE
				Train.	Validat.	Testing	All	
LM	14	< 1	random	0.9899	0.9943	0.9057	0.973	1.5275
BR	1000	10	random	0.9999	__	0.9264	0.983	0.0013
SCG	23	< 1	random	0.9665	0.9753	0.9366	0.964	4.5103

4.3. Validation using independent data

Independent data are data sources outside the data bank. The study used three independent data sets to validate the neural net developed by each learning algorithm, are presented in table 4.4 below. The data include Atterberg limit outputs; liquid limit, plastic limit and plasticity index and compaction results (OMC and MDD).

Table 4. 4 Independent data (ID) set for validation of the predictive model

Locations	Indep. data	LL (%)	PL (%)	PI	OMC (%)	MDD (g/cm^3)
6°56’24”N-38°28’22”E	ID 1	42.22	27.21	15.01	23	1.3
6°55’43”N-38°28’07”E	ID 2	31.43	23.04	8.39	15	1.51
6°51’54”N-38°23’45”E	ID 3	52.8	26.12	26.68	11.5	1.64

Table 4. 5 Results of validation using LM, BR and SCG algorithm for ANN analysis

Algorithm	Neural net OMC			Neural net MDD		
	ID 1	ID 2	ID 3	ID 1	ID 2	ID 3
LM	23.6610	24.1797	13.3519	1.4703	1.4355	1.5368
BR	56.2293	26.1814	15.7301	1.0496	1.5929	1.5387
SCG	19.7134	18.4945	17.6527	1.5407	1.5058	2.0200
Original value	23	15	11.5	1.3	1.51	1.64
Error LM	0.66	9.17	1.1519	0.1	0.12	0.11
Error BR	33.22	11.18	4.231	0.4	0.1	0.002
Error SCG	3.29	3.49	6.15	0.24	0.01	0.48

The table 4.5 above shows that the previously discussed three algorithms predicting the outputs for OMC and MDD from three independent data sets using Atterberg limit outputs (LL, PL and PI) as an input data.

It is found that, the difference between the original and predicted outputs using LM and SCG training algorithms is smaller than Bayesian regularization (BR) backpropagation algorithm for most cases. In addition to this, maximum dry density is predicted with the most reasonable variation compared to the original values by all the for mentioned optimization algorithms.

4.4 Linear regression modeling

Prediction and data analysis using neural net is considered to be a black box modeling (i.e. how the approximation is one is not clear because it doesn't have a simple mathematical representation). To represent prediction and data analysis by using mathematical equation one method that we apply is linear regression. Basically, these method tries to find a mathematical equation between dependent and independent variables given the value at each instant of time.

Let's say we have a function Y which depends on the values of X. The simplest formula that we can use to relate these two variables can be;

$$Y = \beta_0 + \beta_1 X;) \quad \text{...(4.1)}$$

where β_0- intercept and β_1 coefficient.

Again, let's assume Y is a multi-variable function which is dependent on the variables $(X_1, X_2, \ldots, X_n)$. Here also we can use a simple regression to represent Y in terms of X;

$$Y = f(X_1, X_2, \ldots, X_n) \quad \text{.. (4.2)}$$

Therefore;

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \quad \text{.. (4.3)}$$

If we create a matrix X, whose column is $(X_1, X_2, \ldots, X_n)$;

$$X = [X_1, X_2, \ldots, X_n]. \quad \text{.. (4.4)}$$

And a matrix constant of β whose rows are the coefficients $(\beta_1, \beta_2, \ldots, \beta_n)$ is represented in equation below;

$$\beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ . \\ \beta_n \end{bmatrix} \quad \text{.........} \quad (4.5)$$

Since we have three independent variables (LL, PL, PI) and two dependent (OMC and MDD), we have to normalized and standardize the matrix by using pseudo- inverse matrix (these matrix enables the system to assume the non-squared matrix as squared matrix). And Y_1 & Y_2 represent OMC and MDD respectively, and X_1, X_2, X_3 represent LL, PL, PI respectively. Then using the script developed on MATLAB that was presented in figure 3.5 of subsection 3.5.2, the linear models for both OMC and MDD are developed and shown in equation 4.6 and 4.7 below;

$$\text{OMC} = 3.65 + (0.77 * \text{LL}) - (0.08 * \text{PL}) - (0.9 * \text{PI}) \quad \text{.........} \quad (4.6)$$

$$\text{MDD} = 1.66 - (0.006 * \text{LL}) - (0.003 * \text{PL}) + (0.013 * \text{PI}) \quad \text{.........} \quad (4.7)$$

By using independent data set that was mention in Table 4.4. of section 4.3, it is found that for over majority of the independent data used as an inputs, the outputs predicted has small range of error compared to the original vales of the independent data. It predicted optimum moisture content (OMC) and maximum dry density (MDD) at a marginal error range of ± 2 which was in the acceptable standard of marginal range of error. In addition to this, comparison between previous works has been carried out. And it is found that, the model predicted both OMC and MDD with a better accuracy (85%) than the models developed by Gunaydin (2008), Tesfamichael (2017) and Karimpour (2018) when using independent data sets from Table 4.4.

5. CONCLUSIONS AND RECOMMENDATIONS

In-order to develop prediction models for maximum dry density and optimum moisture content of good accuracy, a total of 75 data bank were used. The test results for every samples were organized and a generalized relationship between two compaction parameters and Atterberg limit has been found from the laboratory tests. A text based neural-net analysis and linear regression modeling for soils of Morocho-Aposto road were developed and discussed in the previous section. In this section, conclusions and recommendations were made;

5.1 Conclusions

From the previous discussion, it is found that MDD is better predicted than OMC for most cases using the three algorithms. But in one case, optimum moisture content is better predicted than maximum dry density when using BR and LM algorithm than (SCG). The correlation coefficient R of Levenberg-Marquardt training algorithm was found to be 0.973 that is much more acceptable than the SCG and BR optimization algorithms. And also the Epoch for finding our best value (i.e. the point at which smallest Mean Square error is found) when training our data is much better. In addition to this, the training time required by LM optimization algorithm was way smaller than that of BR and SCG learning algorithms. But LM performance is relatively poor on pattern recognition problems. And also the storage requirements of LM are larger than SCG and BR algorithm tested. It requires more time on function approximation problems and needs more time for large networks. Therefore, despite some draw backs, the study concludes that OMC and MDD can be predicted from Atterberg limit by artificial neural net with error margin of ± 2 using LM as optimization algorithm for soils in the study area.

5.2 Recommendations

1. More advanced neural networks such Rectified Linear Units (ReLUs) for the hidden layer with a combination of problem specific optimization or learning algorithms is recommended to predict outcomes with more accurate prediction values. And also using more hidden layers for training the network results in better prediction.
2. Compaction test parameters can be incorporated with other soil index parameters. Therefore, extending this work for further identification can be studied in the near future. For instance, using OMC to predict MDD and CBR or using the results of this study to identify other engineering properties is recommendable.
3. Due to the variant nature of soils, entire study can be implemented on to other soil (such as; clayey soils, silty soils) types which are located in Ethiopia and the southern region.
4. The study's results are limited to the soils that are only located in the study area. Therefore, in order to acquire more practicable outcome, it is recommended that, a detailed study should be done in other areas with different soil types around this region in the near future.

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APPENDICES

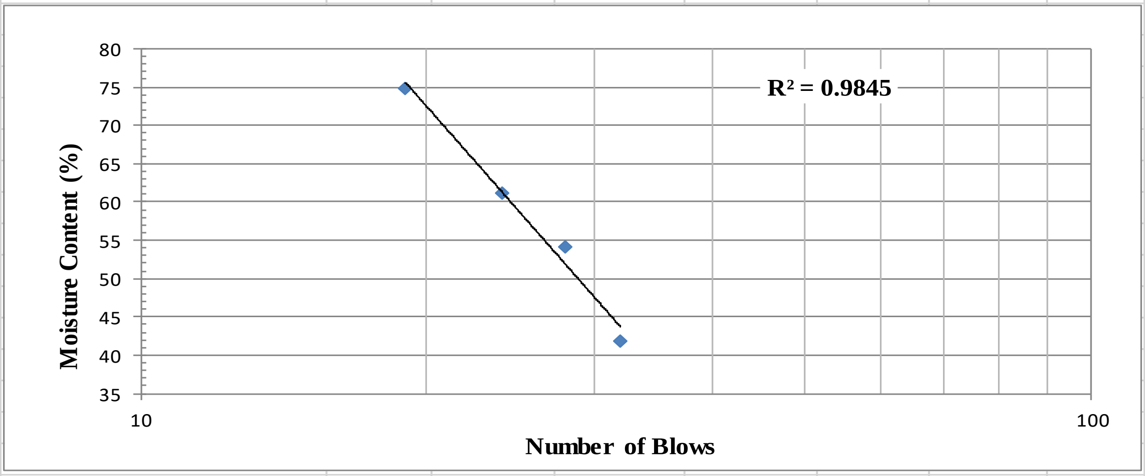
Appendix A: Atterberg limit result

Table A. 1 Atterberg limit result for soil sample one

	Hawassa University Institute of Technology Civil Engineering Department Geotechnical Laboratory	Atterberg Limit

Project:-	Geotechnical Investigation Program
Sampled by:-	Meiraf Iyasu
Station:-	
Sample of:-	Disturbed
Depth:-	1-3 meters
Method used:-	AASHTO T 89 and AASHTO T90
Date tested:-	

		LIQUID LIMIT				PLASTIC LIMIT		
		1	2	3	4	1	2	3
No.of Blows	N	32	28	24	19			
Can No.	n	A9	F3	C4	D5	FA3	TA1	G8
Wt. Can + Wet Soil	g	30	32	37.3	27.4	26.8	27	28.5
Wt Can + Dry Soil	g	26.8	28.9	35	24.1	24.8	25.7	26.6
Wt. water	g	3.2	3.1	2.3	3.3	2	1.3	1.9
Wt. of Can	g	20.2	20.6	19	19.7	19.62	20.8	21
Wt. of Dry Soil	g	6.6	8.3	16	4.4	5.18	4.9	5.6
No.of Blows	N	32	28	24	19			
Moisture Content	%	48.48	37.35	14.38	75.00	38.61	26.53	33.93
						AVERAGE PLASTIC LIM IT		
						33.02		



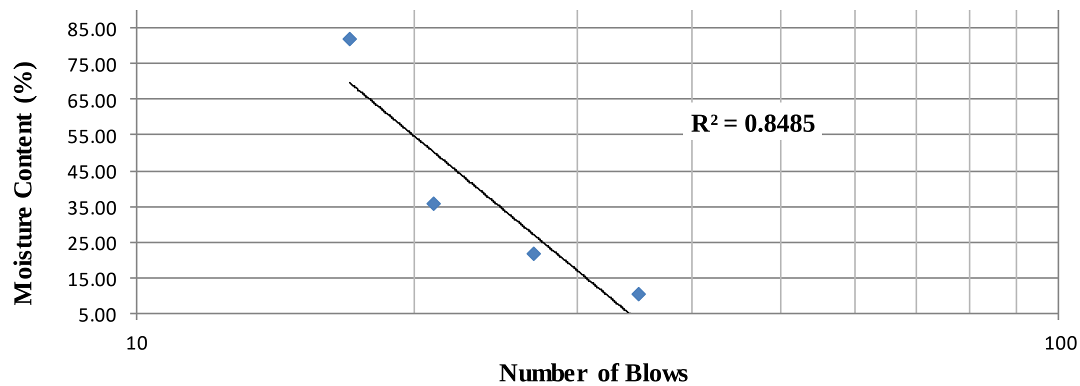
Liquid Limit, LL or wL	**(%)**	44.97
Plastic Limit, PL or wp	**(%)**	33.02
Plasticity Index, PI	**(%)**	11.95

Table A. 2 Atterberg limit result for soil sample two

	Hawassa University Institute of Technology Civil Engineering Department Geotechnical Laboratory	Atterberg Limit

Project:-	Geotechnical Investigation Program
Sampled by:-	Meiraf Iyasu
Station:-	
Sample of:-	Disturbed
Depth:-	
Method used:-	AASHTO T 89 and AASHTO T90
Date tested:-	

		LIQUID LIMIT				PLASTIC LIMIT		
		1	2	3	4	1	2	3
No.of Blows	N	35	27	21	17			
Can No.	n	Z31	F2	A4	B6	W11	P23	Z8
Wt. Can + Wet Soil	g	33	33.2	33.5	34.2	31.3	28.2	28.3
Wt Can + Dry Soil	g	31.8	31	30	27.8	29.3	25.6	26.7
Wt. water	g	1.2	2.2	3.5	6.4	2	2.6	1.6
Wt. of Can	g	20.5	20.8	20.2	20	20.4	18	20
Wt. of Dry Soil	g	11.3	10.2	9.8	7.8	8.9	7.6	6.7
No.of Blows	N	35	27	21	17			
Moisture Content	%	10.62	21.57	35.71	82.05	22.47	34.21	23.88
						AVERAGE PLASTIC LIM IT		
						26.85		



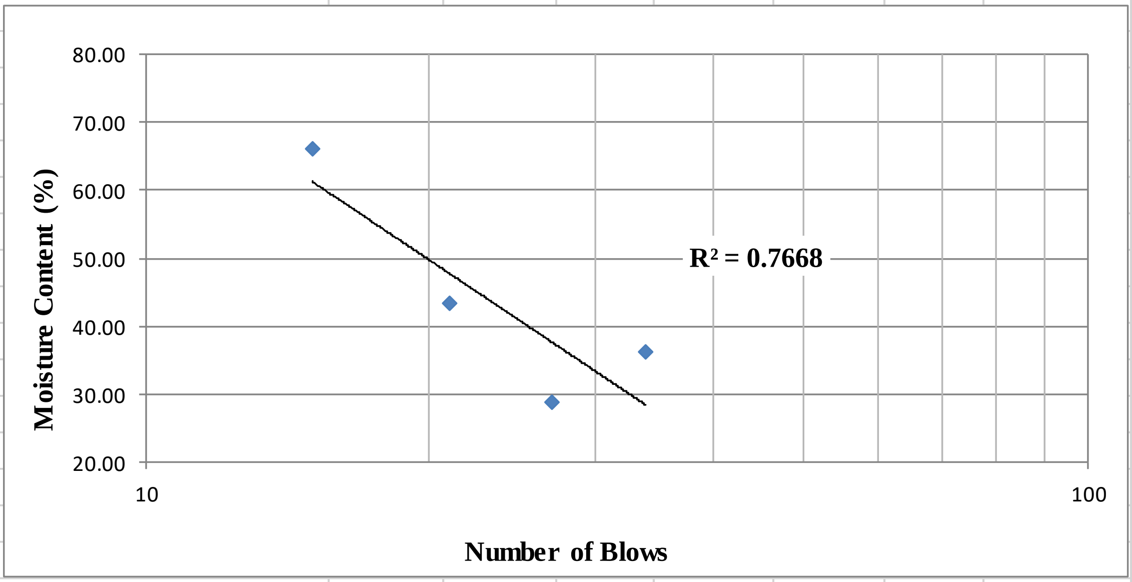
Liquid Limit, LL or wL	**(%)**	37.49
Plastic Limit, PL or wp	**(%)**	26.85
Plasticity Index, PI	**(%)**	10.63

Table A. 3 Atterberg limit result for soil sample three

	Hawassa University Institute of Technology Civil Engineering Department Geotechnical Laboratory	Atterberg Limit

Project:-	Geotechnical Investigation Program
Sampled by:-	Meiraf Iyasu
Station:-	
Sample of:-	Disturbed
Method used:-	AASHTO T 89 and AASHTO T90
Date tested:-	

		LIQUID LIMIT				PLASTIC LIMIT		
		1	2	3	4	1	2	3
No.of Blows	N	34	27	21	15			
Can No.	n	DA	GT	G4	B4	W8	B10	S6
Wt. Can + Wet Soil	g	32	31.9	32.2	32.3	28.4	28.7	28.1
Wt Can + Dry Soil	g	28.8	29	28.2	27.4	25.7	25.7	26.8
Wt. water	g	3.2	2.9	4	4.9	2.7	3	1.3
Wt. of Can	g	20	19	19	20	19.6	18	19
Wt. of Dry Soil	g	8.8	10	9.2	7.4	6.1	7.7	7.8
No.of Blows	N	34	27	21	15			
Moisture Content	%	36.36	29.00	43.48	66.22	44.26	38.96	16.67
						AVERAGE PLASTIC LIM IT		
						33.30		



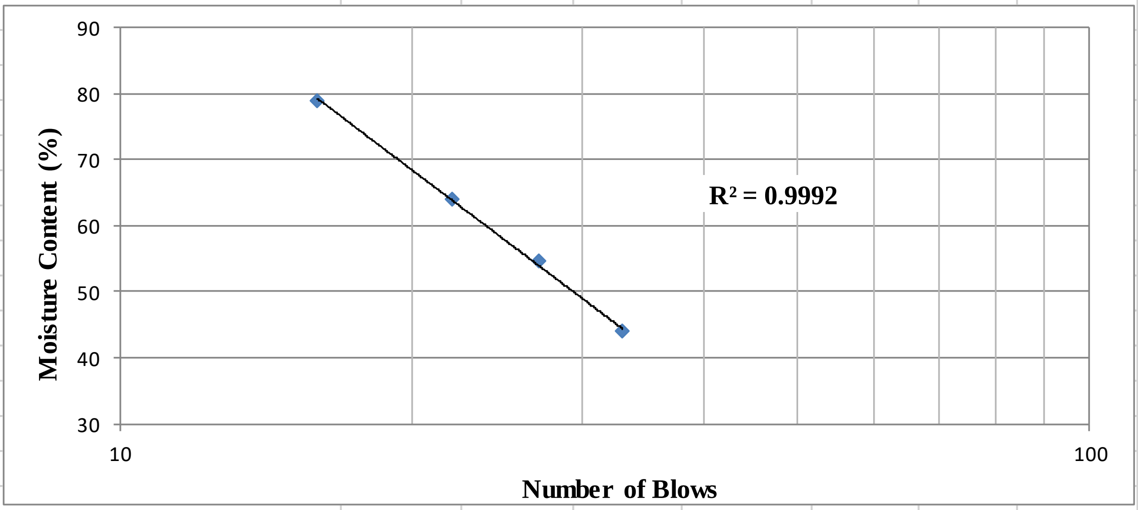
Liquid Limit, LL or wL	**(%)**	42.56
Plastic Limit, PL or wp	**(%)**	33.30
Plasticity Index, PI	**(%)**	9.26

Table A. 4 Atterberg limit result for soil sample four

	Hawassa University Institute of Technology	Atterberg Limit
	Civil Engineering Department	
	Geotechnical Laboratory	

Project:-	Geotechnical Investigation Program
Sampled by:-	Meiraf Iyasu
Station:-	
Sample of:-	Disturbed
Method used:-	AASHTO T 89 and AASHTO T90
Date tested:-	

		LIQUID LIMIT				PLASTIC LIMIT		
		1	2	3	4	1	2	3
No.of Blows	N	34	27	22	16			
Can No.	n	Z8	F2	Z3	B6	A4	W11	P2
Wt. Can + Wet Soil	g	35.6	32.8	34.8	34	31.1	28.8	25.4
Wt Can + Dry Soil	g	33.2	29.2	31.7	28.3	27.8	27	23.5
Wt. water	g	2.4	3.6	3.1	5.7	3.3	1.8	1.9
Wt. of Can	g	20	20.5	20.7	20.5	20.1	20.4	18
Wt. of Dry Soil	g	13.2	8.7	11	7.8	7.7	6.6	5.5
No.of Blows	N	33	27	22	16			
Moisture Content	%	18.18	41.38	28.18	73.08	42.86	27.27	34.55
						AVERAGE PLASTIC LIM IT		
						34.89		



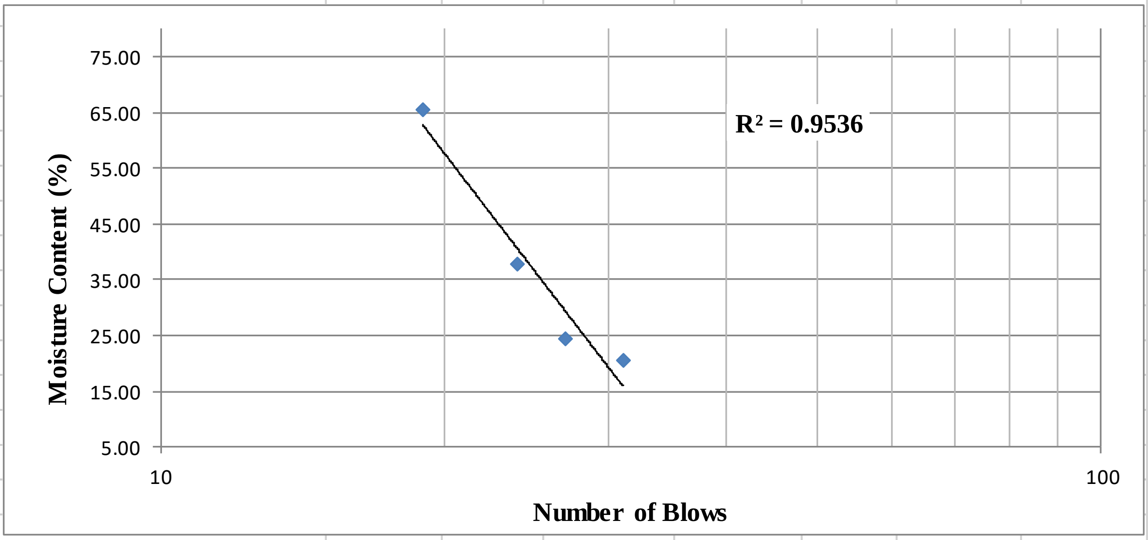
Liquid Limit, LL or wL (%)		38.82
Plastic Limit, PL or wp (%)		34.89
Plasticity Index, PI (%)		3.93

Table A. 5 Atterberg limit result for soil sample five

	Hawassa University Institute of Technology Civil Engineering Department Geotechnical Laboratory	Atterberg Limit

Project:-	Geotechnical Investigation Program
Sampled by:-	Meiraf Iyasu
Station:-	
Sample of:-	Disturbed
Method used:-	AASHTO T 89 and AASHTO T90
Date tested:-	

		LIQUID LIMIT				PLASTIC LIMIT		
		1	2	3	4	1	2	3
No.of Blows	N	35	27	24	17			
Can No.	n	GT2	A4	FA3	Z11	G8	GT24	TA1
Wt. Can + Wet Soil	g	35	27.2	33.1	33	28.4	30	28.5
Wt Can + Dry Soil	g	32.1	25.2	29.5	27.9	26.3	28	27
Wt. water	g	2.9	2	3.6	5.1	2.1	2	1.5
Wt. of Can	g	18	17	20	20.1	21	19	19
Wt. of Dry Soil	g	14.1	8.2	9.5	7.8	5.3	9	8
No.of Blows	N	31	27	24	19			
Moisture Content	%	20.57	24.39	37.89	65.38	39.62	22.22	18.75
						AVERAGE PLASTIC LIM IT		
						26.86		



Liquid Limit, LL or wL	**(%)**	38.02
Plastic Limit, PL or wp	**(%)**	26.86
Plasticity Index, PI	**(%)**	11.16

Appendix B: Modified Proctor compaction test results

Table B. 1 Modified Proctor compaction test results for sample one

Hawassa University Institute of Technology		Modified Compaction for Moisture Density Relation of Soil				
Civil Engineering Department						
Geotechnical Laboratory						

Project:-	Geotechnical Investigation Program
Sampled by:-	
Station:-	
Sample of:-	Disturbed
Method used:-	AASHTO T-180
Date tested:-	

A	Mold	No.	1	2	3	4
B	Wt. of Mold + Wet Soil	grams	8774	8927	9280	9089
C	Wt. of Mold	grams	5258	5258	5258	5258
D	Wt. Wet Soil	grams	3516	3669	4022	3831
E	Volume of Mold	cu.cm.	2124	2123	2123	2123
F	Wet Density	gr/cu.cm.	1.655	1.728	1.894	1.805
G	Container	No.	FA3	GT2	A3	Z3
H	Wt. Cont + Wet soil	grams	73	70.9	72	70
I	Wt. Cont + Dry soil	grams	65.6	63	61	58.3
J	Weight of Water	grams	7.4	7.9	11	11.7
K	Weight of Container	grams	19.6	21	20.8	21
L	Weight of Dry Soil	grams	46	42	40.2	37.3
M	Moisture Content	%	16.09	18.81	27.36	31.37
N	Dry Density	gr/cu.cm.	1.426	1.455	1.487	1.374

OMC	31
MDD	1.49

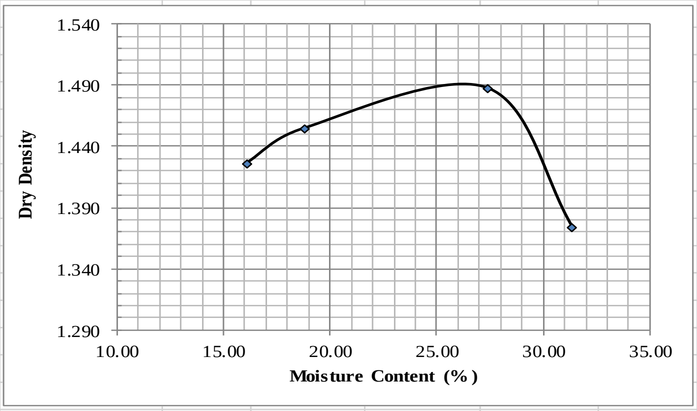


Table B. 2 Modified Proctor compaction test results for sample two

	Hawassa University Institute of Technology	Modified Compaction for Moisture Density Relation of Soil
	Civil Engineering Department	
	Geotechnical Laboratory	

Project:-	Geotechnical Investigation Program
Sampled by:-	
Station:-	
Sample of:-	Disturbed
Method used:-	AASHTO T-180
Date tested:-	

A	Mold	No.	1	2	3
B	Wt. of Mold + Wet Soil	grams	8919.3	9311	9265
C	Wt. of Mold	grams	5247	5247	5247
D	Wt. Wet Soil	grams	3672.3	4064	4018
E	Volume of Mold	cu.cm.	2123	2123	2123
F	Wet Density	gr/cu.cm.	1.730	1.914	1.893
G	Container	No.	GTZ2	Z11	D5
H	Wt. Cont + Wet soil	grams	77.8	71.2	70.5
I	Wt. Cont + Dry soil	grams	71	63	61
J	Weight of Water	grams	6.8	8.2	9.5
K	Weight of Container	grams	27	23	28
L	Weight of Dry Soil	grams	44	40	33
M	Moisture Content	%	15.45	20.50	28.79
N	Dry Density	gr/cu.cm.	1.498	1.589	1.470

OMC	20
MDD	1.59

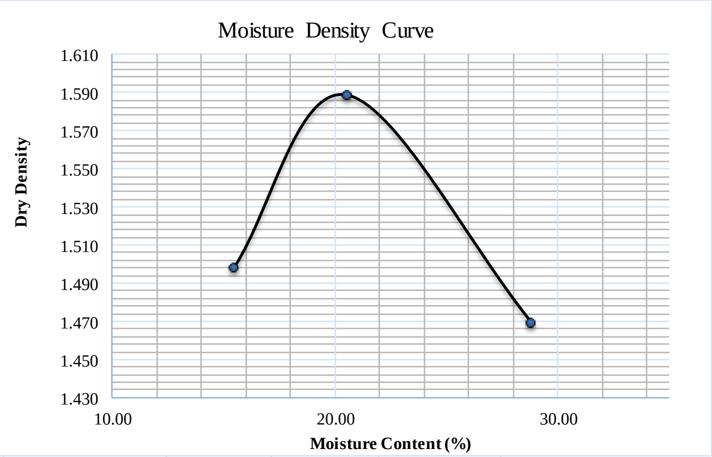


Table B. 3 Modified Proctor compaction test results for sample three

	Hawassa University Institute of Technology	Modified Compaction for Moisture Density Relation of Soil
	Civil Engineering Department	
	Geotechnical Laboratory	

Project:-	Geotechnical Investigation Program
Sampled by:-	
Station:-	
Sample of:-	Disturbed
Method used:-	AASHTO T-180
Date tested:-	

A	Mold	No.	1	2	3
B	Wt. of Mold + Wet Soil	grams	8869.3	9339.9	9201.5
C	Wt. of Mold	grams	5249	5249	5249
D	Wt. Wet Soil	grams	3874.5	4090.9	3890
E	Volume of Mold	cu.cm.	2123	2123	2123
F	Wet Density	gr/cu.cm.	1.825	1.927	1.832
G	Container	No.	G1	F4	HT-1
H	Wt. Cont + Wet soil	grams	78.6	86.5	79.01
I	Wt. Cont + Dry soil	grams	72	77.4	70
J	Weight of Water	grams	6.6	9.1	9.01
K	Weight of Container	grams	19.5	20.5	21
L	Weight of Dry Soil	grams	52.5	56.9	49
M	Moisture Content	%	12.57	15.99	18.39
N	Dry Density	gr/cu.cm.	1.621	1.661	1.548

OMC	15.8
MDD	1.66

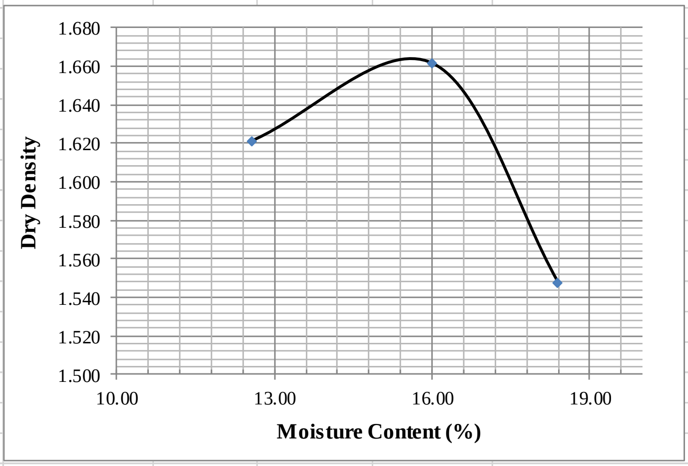


Table B. 4 Modified Proctor compaction test results for sample four

	Hawassa University Institute of Technology	Modified Compaction for Moisture Density Relation of Soil
	Civil Engineering Department	
	Geotechnical Laboratory	

Project:-	Geotechnical Investigation Program
Sampled by:-	
Station:-	
Sample of:-	Disturbed
Method used:-	AASHTO T-180
Date tested:-	

A	Mold	No.	1	2	3
B	Wt. of Mold + Wet Soil	grams	8947.5	9297	9192.9
C	Wt. of Mold	grams	5258	5258	5258
D	Wt. Wet Soil	grams	3689.5	4039	3934.9
E	Volume of Mold	cu.cm.	2123	2123	2123
F	Wet Density	gr/cu.cm.	1.738	1.902	1.853
G	Container	No.	FA2	G44	A77
H	Wt. Cont + Wet soil	grams	68.6	81.3	87
I	Wt. Cont + Dry soil	grams	62	70.5	72
J	Weight of Water	grams	6.6	10.8	15
K	Weight of Container	grams	20.8	21.2	21
L	Weight of Dry Soil	grams	41.2	49.3	51
M	Moisture Content	%	16.02	21.91	29.41
N	Dry Density	gr/cu.cm.	1.498	1.561	1.432

OMC	21.6
MDD	1.56

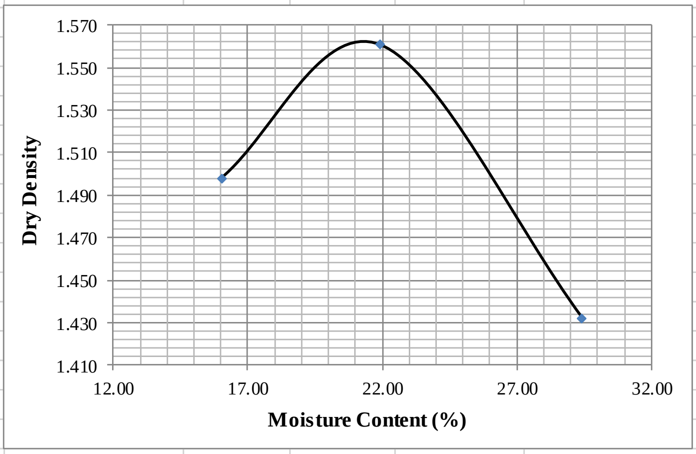


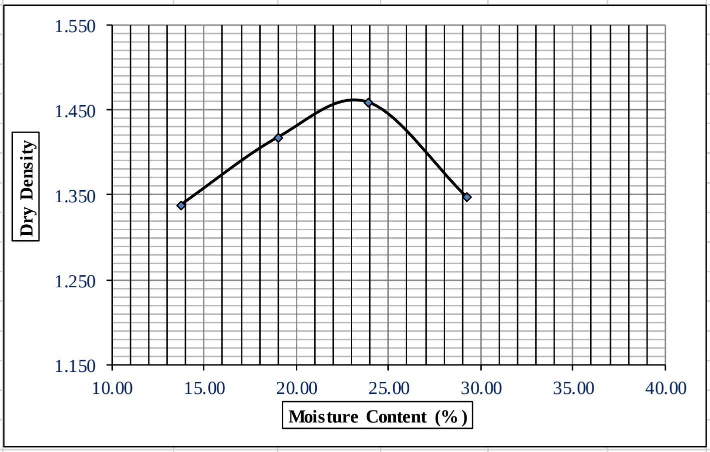
Table B. 5 Modified Proctor compaction test results for sample five

Hawassa University Institute of Technology	Modified Compaction for Moisture Density Relation of Soil
Civil Engineering Department	
Geotechnical Laboratory	

Project:-	Geotechnical Investigation Program
Sampled by:-	
Station:-	
Sample of:-	Disturbed
Method used:-	AASHTO T-180
Date tested:-	

A	Mold	No.	1	2	3	4
B	Wt. of Mold + Wet Soil	grams	8489.5	8839.2	9095.2	8956.3
C	Wt. of Mold	grams	5258	5258	5258	5258
D	Wt. Wet Soil	grams	3231.5	3581.2	3837.2	3698.3
E	Volume of Mold	cu.cm.	2123	2123	2123	2123
F	Wet Density	gr/cu.cm.	1.522	1.687	1.807	1.742
G	Container	No.	B6	B8	G10	Z8
H	Wt. Cont + Wet soil	grams	68.8	78.5	68.5	71.6
I	Wt. Cont + Dry soil	grams	63	69	59	60
J	Weight of Water	grams	5.8	9.5	9.5	11.6
K	Weight of Container	grams	20.8	19	19.2	20.3
L	Weight of Dry Soil	grams	42.2	50	39.8	39.7
M	Moisture Content	%	13.74	19.00	23.87	29.22
N	Dry Density	gr/cu.cm.	1.338	1.418	1.459	1.348

OMC	22.4
MDD	1.46



Appendix C: Best training performance with respect to MSE

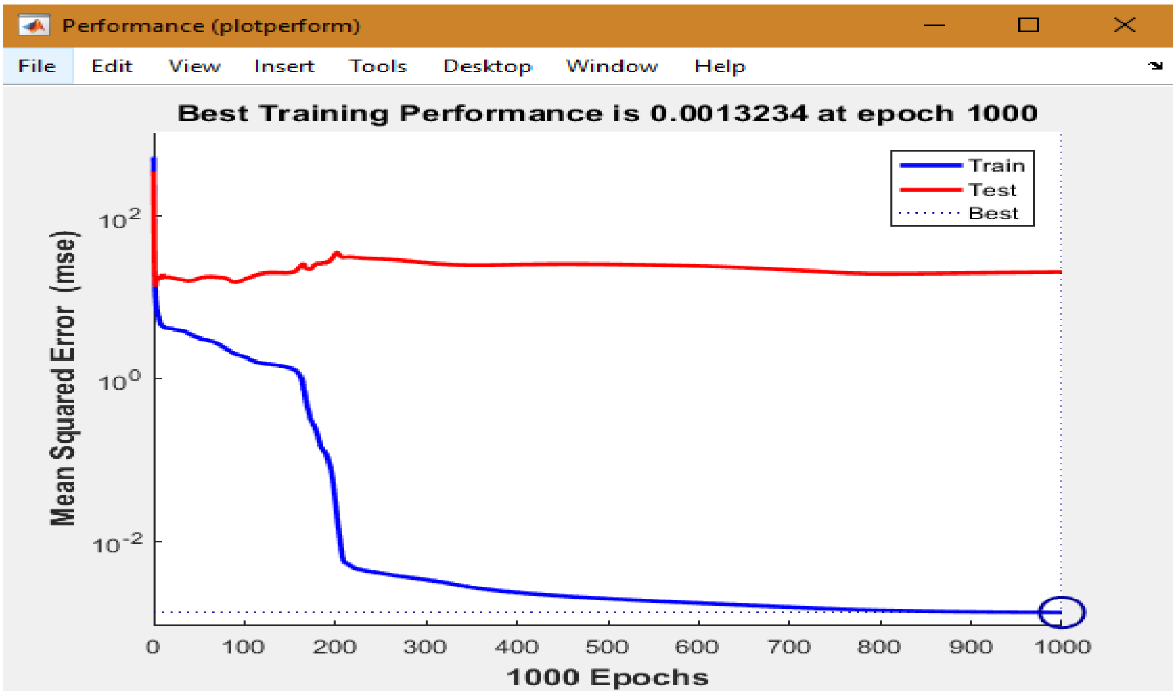


Figure C. 1 Plot of best performance for MSE vs Epoch for LM

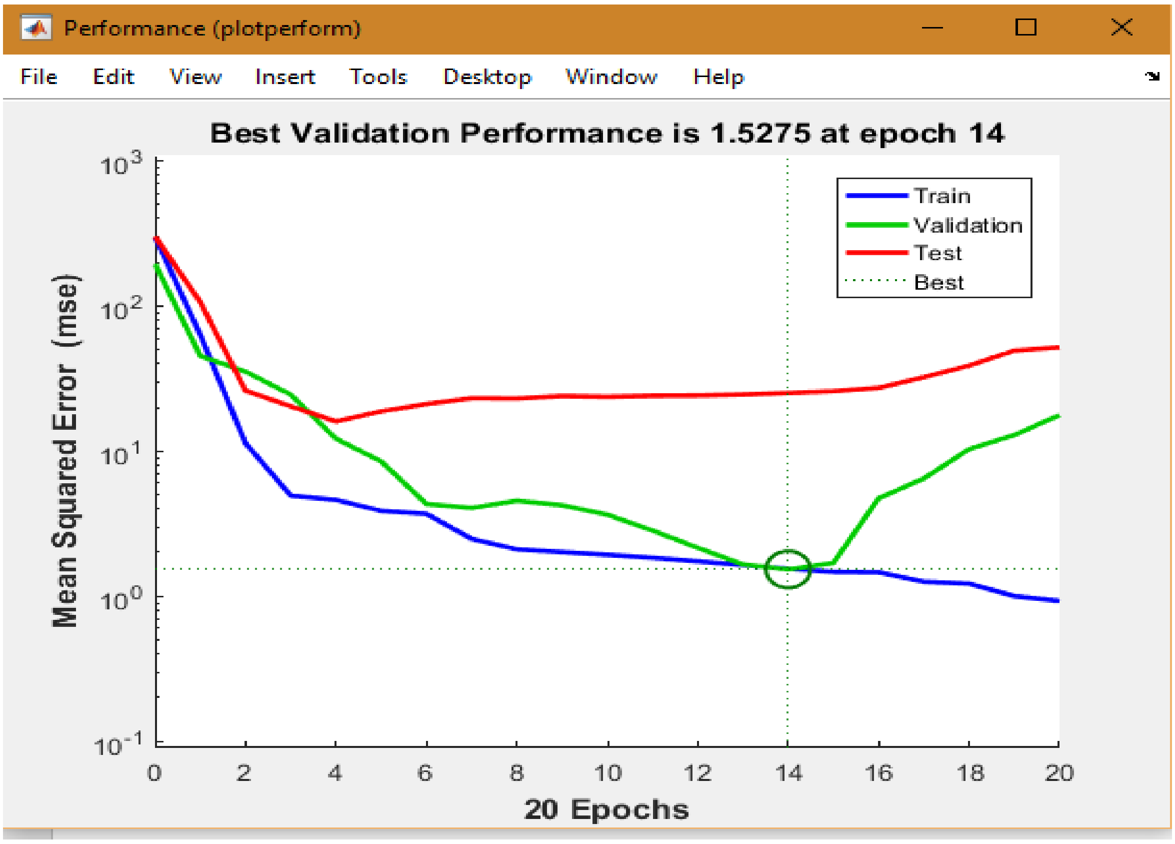


Figure C. 2 Plot of best performance for MSE vs Epoch for BR

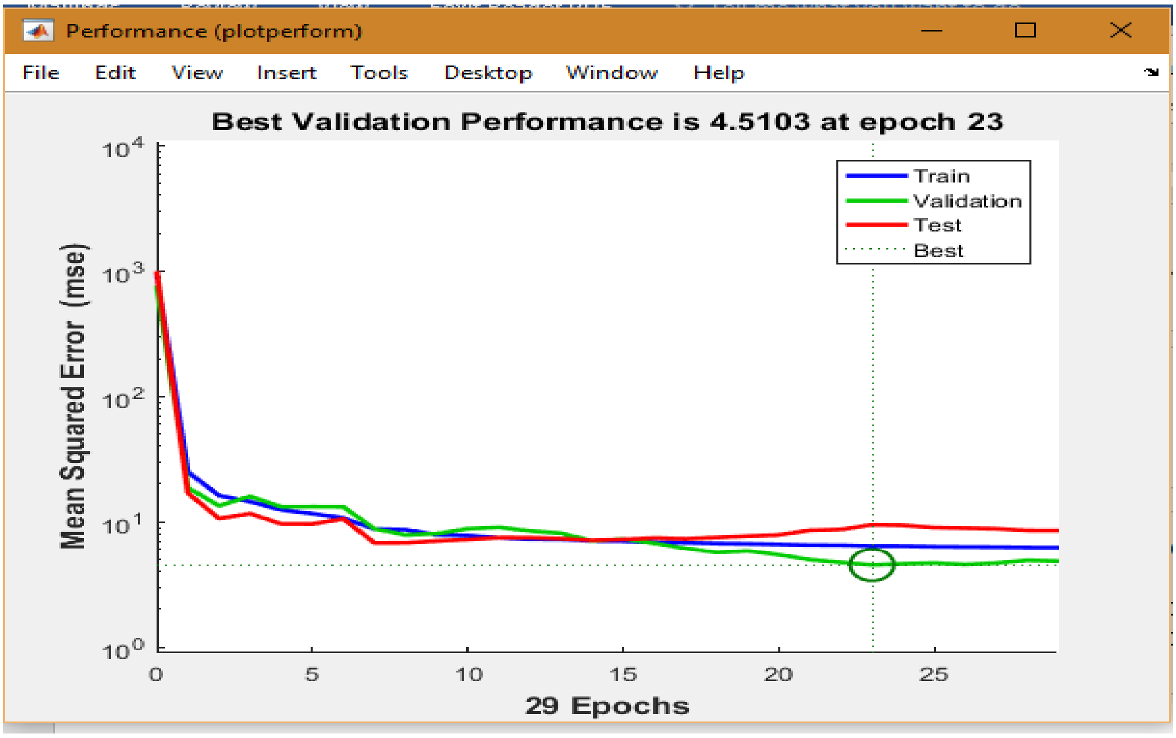


Figure C. 3 Plot of best performance for MSE vs Epoch for SCG

Appendix D: Regression (R) values for different training algorithm

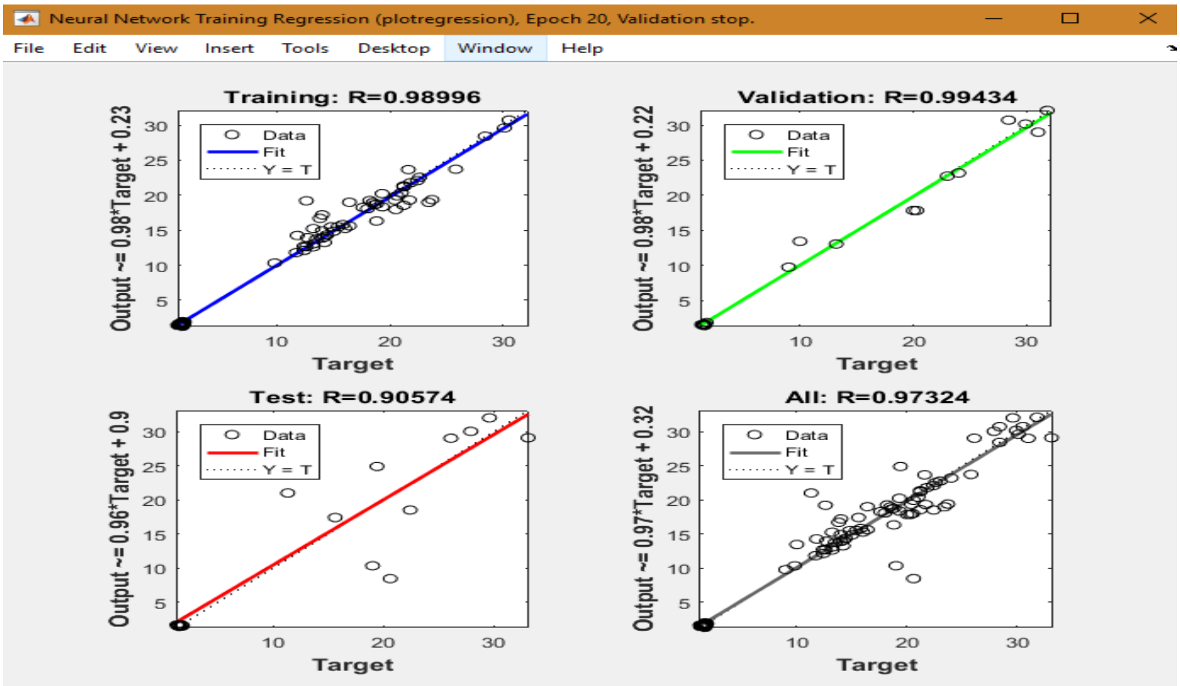


Figure D. 1 R values for training, validation, test and all R using LM

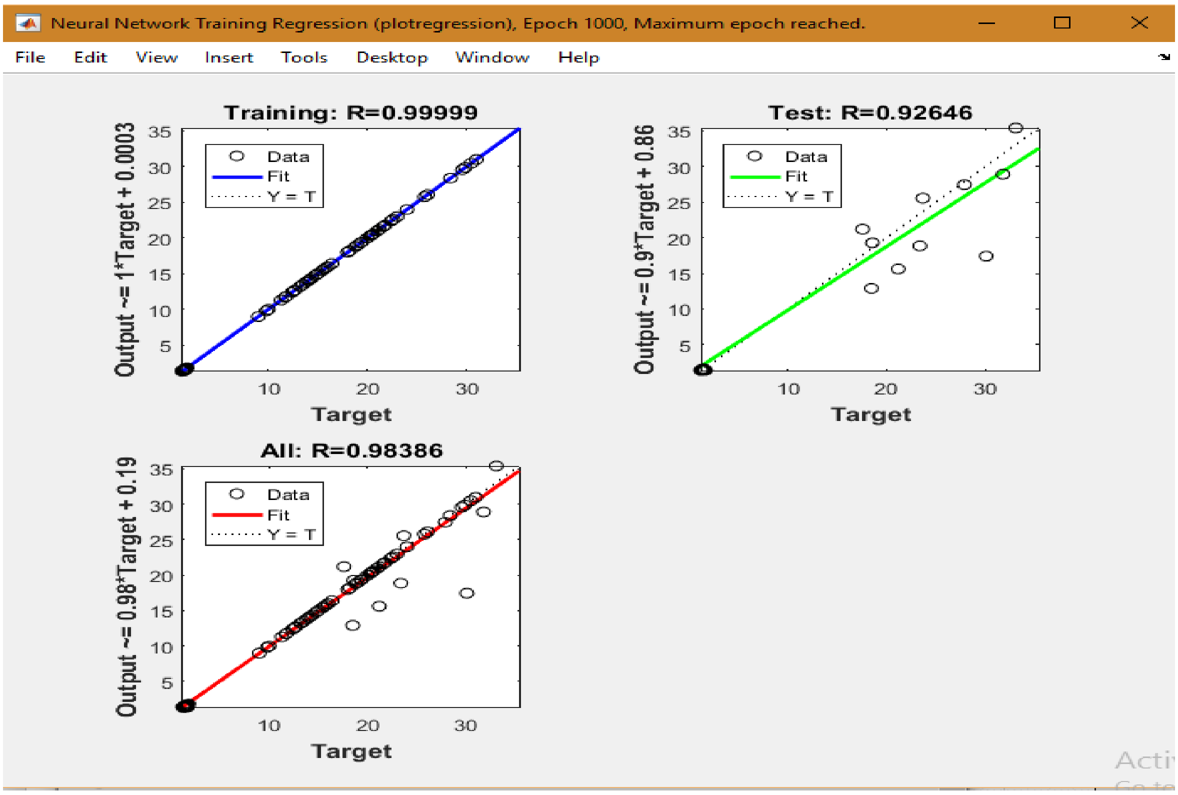


Figure D. 2 R values for training, validation, test and all R using BR

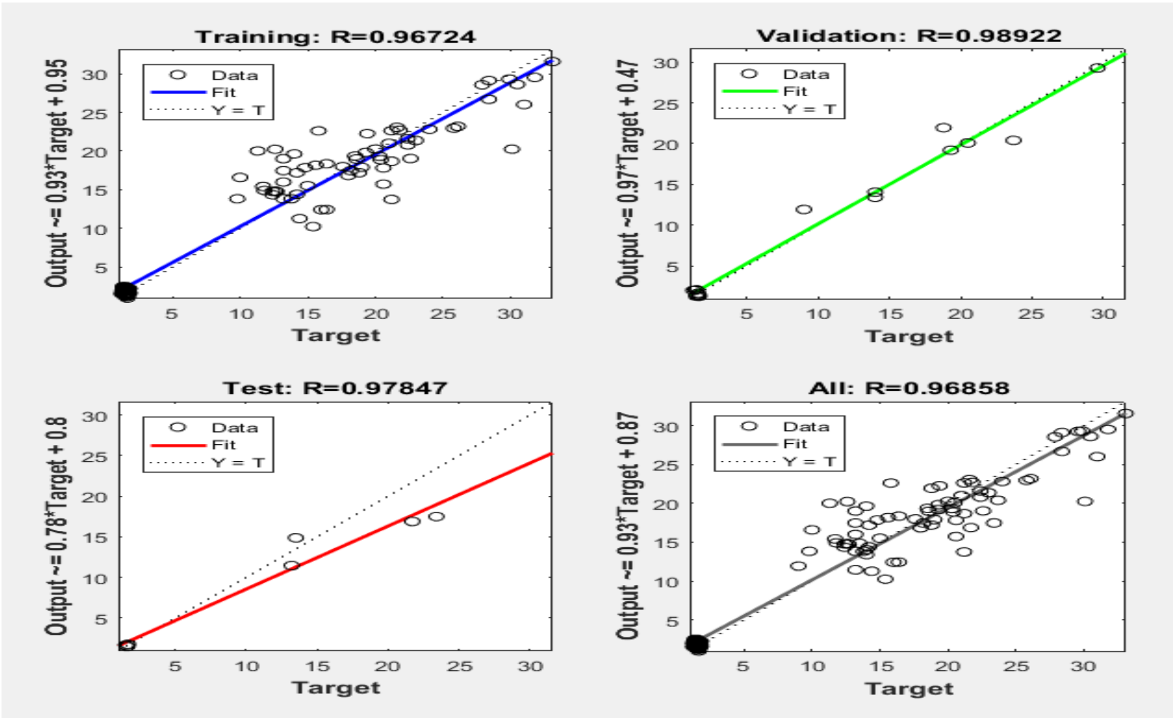


Figure D. 3 R values for training, validation, test and all R using SCG

Appendix E: Neural network training outputs using different training algorithm

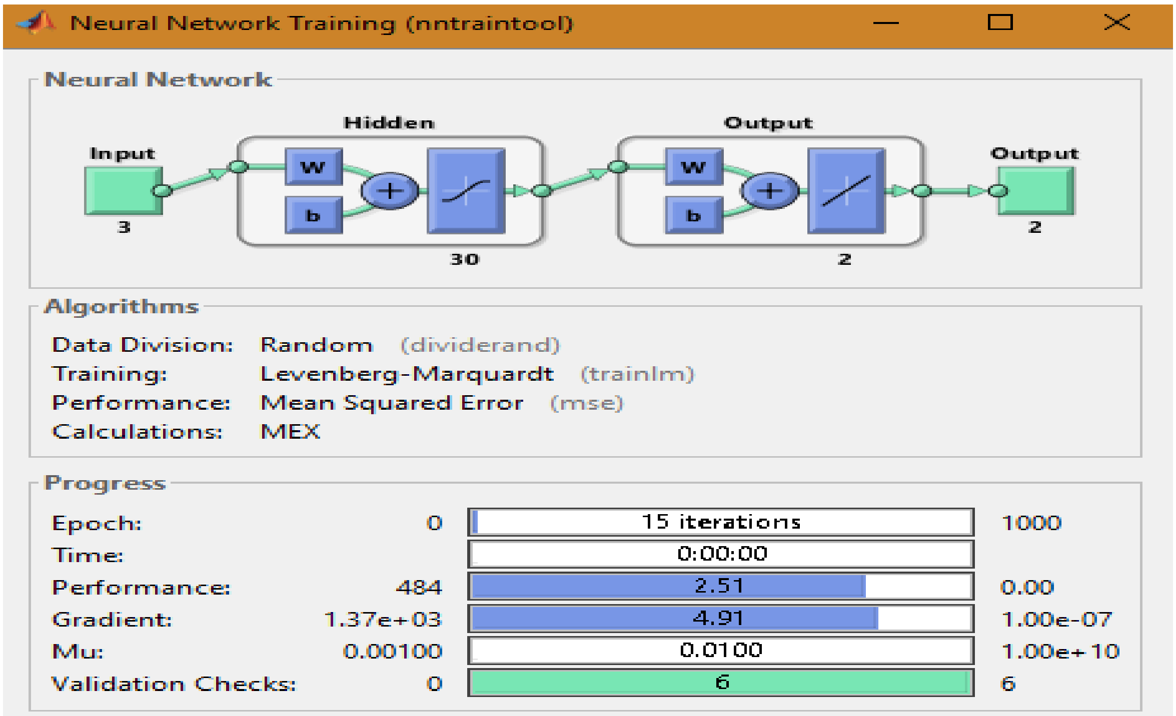


Figure E. 1 Neural network training output using Levenberg-Marquardt

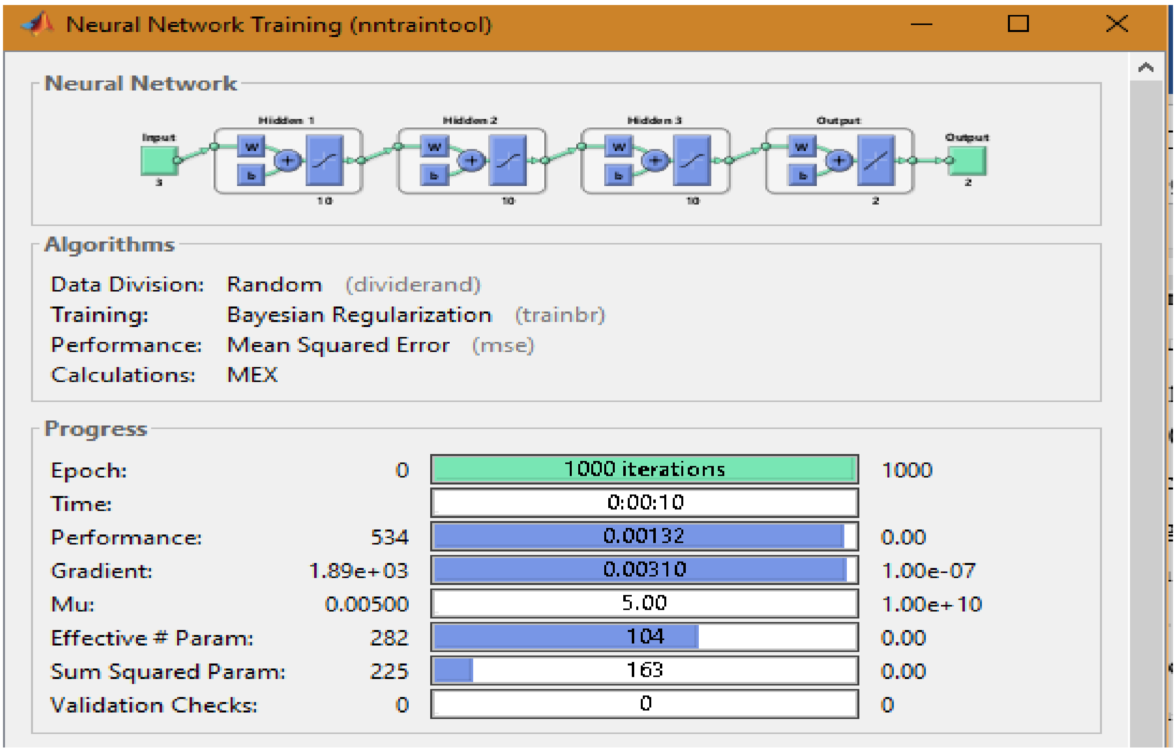


Figure E. 2 Neural network training output using Bayesian regularization

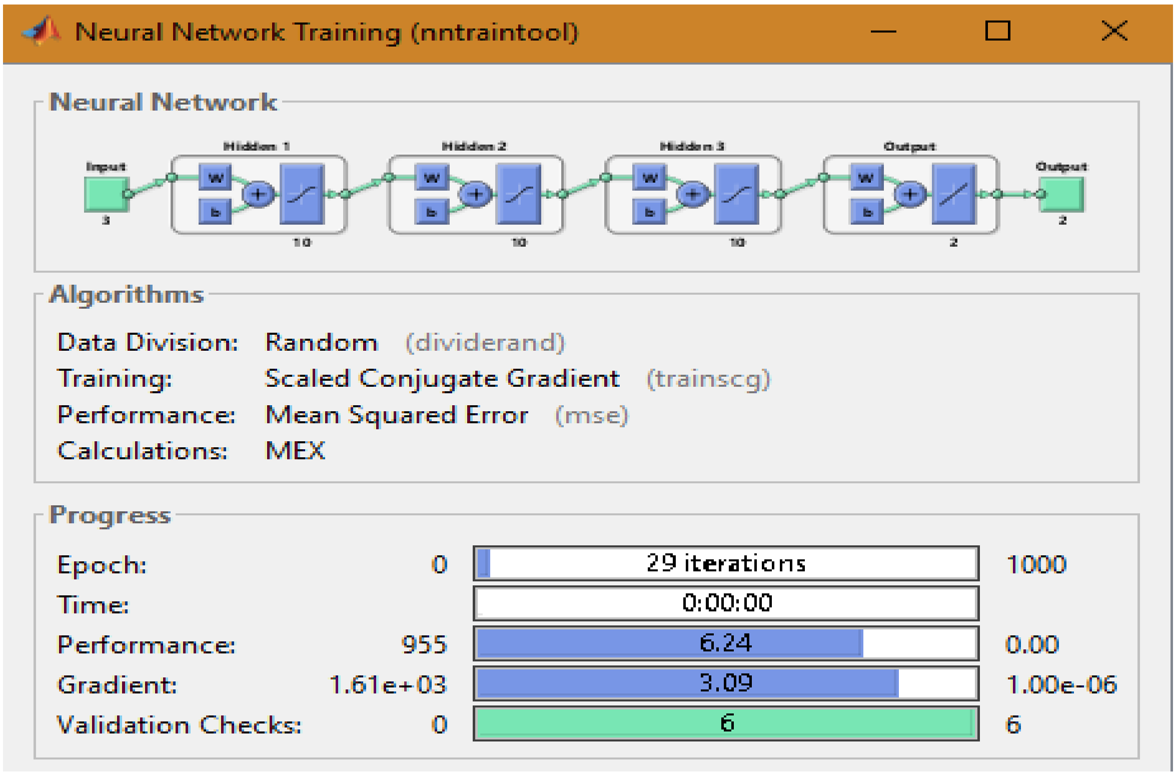


Figure E. 3 Neural net training output using scaled conjugate gradient

Appendix F: Syntax for neural network analysis and linear algorithm development

```
LL=D_inputs(:,1);
PL=D_inputs(:,2);
PI=D_inputs(:,3);
OMC=D_outputs(:,1);
MDD=D_outputs(:,2);
n=length(LL);
V=[ones(n,1),LL,PL,PI];
C_1=pinv(V)*OMC;  %pinv(V) is a psudo inverse function to find the inverse of a matrix
C_2=pinv(V)*MDD;
%tbl = table(LL,PL,PI,OMC,'VariableNames',{'LL','PL','PI','OMC',});
%lm = fitlm(tbl)
```

Figure F. 1 Syntax for linear regression modeling on MATLAB editor window

```
name='C:\Users\hp\Desktop\New_matlab_file\Book1.xlsx';
D_inputs=xlsread(name,'A:C');% inputs LL,PL,PI
D_outputs=xlsread(name,'D:E');% Outputs OMC,MDD
inputs = D_inputs'; % input to the neural net
targets = D_outputs'; % output of the neural net

% Create a Fitting Network
hiddenLayerSize = [10 10 10]; % size of the hidden layer
net = fitnet(hiddenLayerSize); % function to create the neural network

% Set up Division of Data for Training, Validation, Testing
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;
%net.trainFcn = 'trainbr';
%net.trainFcn = 'trainscg';
% Train the Network
[net,tr] = train(net,inputs,targets);

% Test the Network
outputs = net(inputs);
errors = gsubtract(outputs,targets);
performance = perform(net,targets,outputs)

% View the Network
view(net)
```

Figure F. 2 Syntax for neural net analysis on MATLAB editor window

Appendix H: Secondary and primary data summary

Table H. 1 Primary data summary for twenty soil samples

Sample	LL (%)	PL (%)	PI (%)	OMC (%)	MDD (g/cm^3)
1	44.9	33	11	25.2	1.375
2	37.6	26.9	10.7	20	1.328
3	42.9	33.4	9.5	15.8	1.432
4	38.8	34.6	4.2	21.6	1.442
5	38.4	26.9	11.5	22.4	1.437
6	56.7	29.2	27.5	19.4	1.537
7	50	23.6	26.4	9	1.829
8	47.3	22.4	24.9	16	1.461
9	52.4	26.1	26.3	11.8	1.605
10	42.4	19.6	22.8	13.8	1.605
11	38	18.3	19.7	14	1.758
12	45.4	20.7	24.7	14	1.687
13	39.4	22.8	16.6	13.2	1.74
14	57.2	29.7	27.5	23	1.562
15	45.9	25.8	20.1	14.8	1.715
16	46.8	22.9	23.9	16.4	1.655
17	54.2	27.8	26.4	18.2	1.639
18	51.8	26.5	25.3	13.3	1.695
19	54.2	28.7	25.5	16.4	1.648
20	47.6	20.9	26.7	13.2	1.747

Table H. 2 Secondary data for fifty-five soil samples

Sample Number	Stations (m)	LL (%)	PL (%)	PI (%)	OMC (%)	MDD (g/cm^3)	Soil Classification (ASSHTO)
1	0+050-0+150	41.6	28.3	13.3	26.1	1.294	A-7-6(4)
2	0+150-0+350	36.5	24.1	12.4	23.7	1.239	A-6(6)
3	0+550-0+650	39.7	28.3	11.4	18.8	1.405	A-6(2)
4	0+750-0+950	35.2	23.8	11.4	18.6	1.355	A-6(0)
5	0+950-1+150	33.8	23.8	10	13.2	1.309	A-4(0)
6	1+250-1+450	34.4	22.4	12	20.4	1.412	A-2-6(0)
7	1+450-1+550	34.6	20	14.6	20.3	1.345	A-6(3)
8	1+550-1+750	34.6	23.8	10.7	15.6	1.428	A-6(1)
9	1+750-1+950	33	18.6	14.4	19	1.478	A-6(4)
10	1+950-2+250	32.2	19.3	12.9	20.6	1.456	A-6(3)
11	2+050-2+150	29.2	20.6	8.6	15	1.509	A-2-4(0)
12	2+250-2+450	36.6	25.4	11.2	19.3	1.428	A-6(3)
13	2+650-2+850	41.6	35.1	6.5	21.2	1.362	A-5(1)
14	2+850-3+050	38.8	34.6	4.2	25.8	1.336	A-4(1)

15	3+050-3+150	34.2	26.8	7.4	22.6	1.324	A-6
16	3+150-3+250	28.6	18.3	10.3	20.6	1.389	A-6
17	3+350-3+450	37	23.2	13.8	21	1.483	A-6
18	3+450-3+750	38.4	23	15.4	30.1	1.324	A-2-6
19	3+550-3+650	35.9	20.6	15.3	18.5	1.516	A-2-6
20	3+750-3+850	27.1	21.7	6	18	1.441	A-4
21	3+850-3+950	34	21.1	12.9	19.3	1.46	A-2-6(1)
22	9+100-19+200	37.1	19.9	17.2	10	1.749	A-6
23	12+120-12+220	36.5	24.4	12.1	12.6	1.725	A-6
24	12+220-12+320	41	21	20	12.7	1.561	A-2-7
25	12+520-12+620	35.1	21.2	13.9	11.3	1.716	A-6
26	13+020-12+150	36.4	18.3	18.1	12.4	1.804	A-2-6
27	13+500-13+600	40.2	18.5	21.7	14.2	1.717	A-6
28	13+600-13+700	34.8	16.9	17.9	12.4	1.82	A-7
29	18+100-18+200	25.8	15.8	10	12.6	1.817	A-7
30	18+300-18+400	29.6	17.7	11.9	11.7	1.688	A-2-6
31	18+600-18+700	29.5	14.3	15.2	15.4	1.66	A-6
32	19+200-19+300	42	23.2	18.8	14.2	1.689	A-7
33	19+300-19+400	30.9	14.1	16.8	13.2	1.679	A-2-6
34	19+400-19+500	54.9	22	32.9	14.4	1.575	A-7
35	19+500-19+600	43.7	23.2	20.5	13.2	1.57	A-7
36	19+700-19+800	54.4	27.9	26.5	23.4	1.587	A-7
37	19+800-19+900	57.4	31	26.4	24	1.55	A-7
38	19+900-20+000	54.5	25.9	28.6	9.8	1.708	A-7
39	52+500-52+700	54.6	1	26.6	21.8	1.661	A-2-7
40	56+740	46.6	28	18.6	14	1.556	A-7
41	62+200-62+300	52.2	36.4	15.8	29.9	1.45	A-7
42	62+900-63+000	55.5	28.4	27.1	21.2	1.38	A-7
43	62+800-62+900	64.5	37.5	27	33.1	1.24	A-7
44	62+700-62+800	50.6	28	22.6	21.7	1.532	A-7
45	62+600-62+700	42.5	20.8	21.7	21.2	1.59	A-7
46	62+500-62+600	34	22.8	11.1	17.6	1.53	A-6
47	62+400-62+500	33.2	22.8	10.4	18.8	1.54	A-6
48	62+300-62+400	45.8	29.1	16.7	22.4	1.54	A-7
49	62+100-62+200	56.3	38.1	18.2	30.5	1.43	A-2-7
50	62+000-62+100	56.2	36.5	19.7	28.4	1.445	A-2-7
51	61+900-62+000	55	37.8	17.2	28.4	1.421	A-2-7
52	61+800-61+900	62.3	40.2	22.1	31.8	1.439	A-2-7
53	61+700-61+800	62	40.1	21.9	29.6	1.442	A-2-7
54	61+600-61+700	53.4	36.5	16.8	27.9	1.471	A-7
55	61+500-61+600	46.3	28.2	18.1	20.5	1.597	A-7

Appendix I: Satellite image and generalized map of the study area

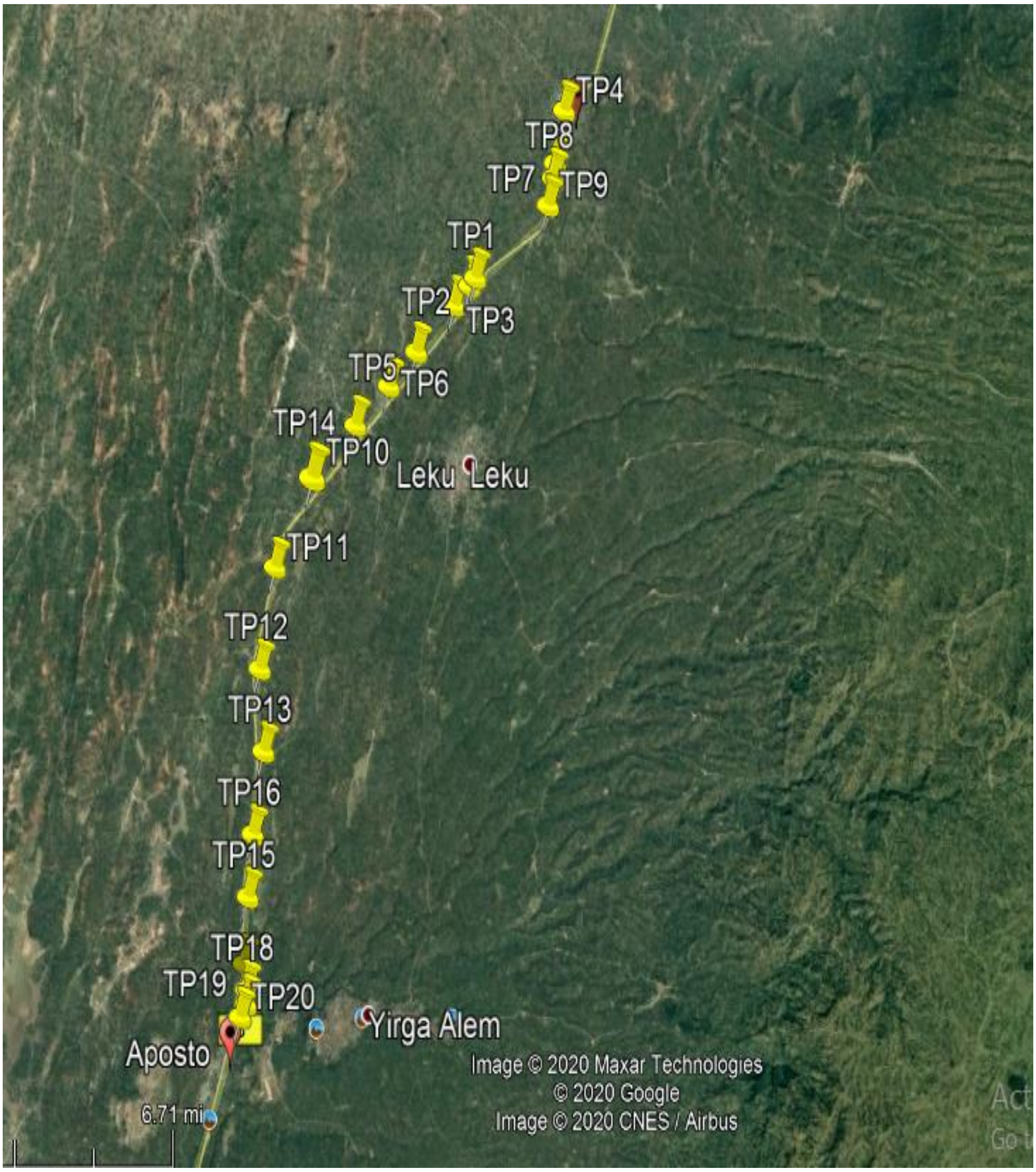


Figure I. 1 Satellite image of Morocho-Aposto road section

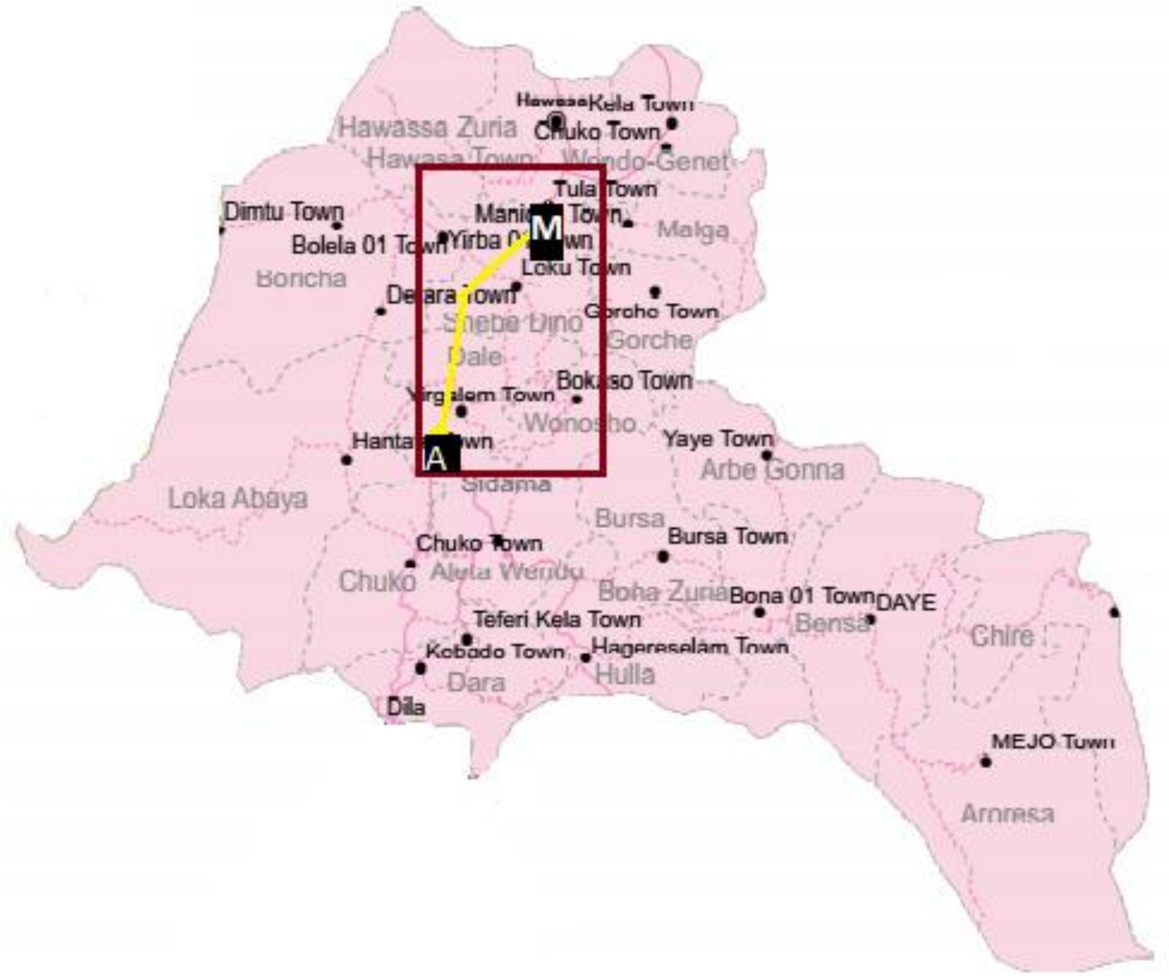


Figure I. 2 Generalized map of the study area