Jimma University

School of Graduate Studies

Jimma Institute of Technology

School of Civil and Environmental Engineering



A Study on Correlation of California Bearing Ratio (CBR) With Index Properties of Soils on Welkite – Arekit-Hossana Road.

A Thesis Submitted to the School of Graduate Study of Jimma University in Partial Fulfillment of the Requirements for the Degree of Master of Science in Civil Engineering(Geotechnical Engineering)

By: Dino Abdela Delil

June ,2016 Jimma,Ethiopia

Jimma University

School of Graduate Studies

Jimma Institute of Technology

School of Civil and Environmental Engineering

A Study on Correlation of California Bearing Ratio (CBR) With Index Properties of Soils on Welkite – Arekit-Hossana Road.

A Thesis Submitted to the School of Graduate Study of Jimma University in Partial Fulfillment of the Requirements for the Degree of Master of Science in Civil Engineering(Geotechnical Engineering)

Dino Abdela Delil

Approved by Board of Examiners:

Dr. Yoseph Birru		
Advisor	Signature	Date
Mr. Tadesse Abebe		
Co. Advisor	Signature	Date
External Examiner	Signature	Date
Internal Examiner	Signature	Date
Chairperson	Signature	Date

ACKNOWLEDGEMENTS

First and most of all, I would like to thank almighty Allah for being with me in every moments and step I pass through.

I would like to express my warmest thanks to my advisor Dr. Yoseph Birru and Co-Advisor Mr. Tadesse Abebe for their guidance and supervision through out this research work.

A special thanks goes to Ethiopian Roads Construction Corporation Jimma District material laboratory staff members especially Mr .Teshome and Eng. Tamirat for their great help during laboratory testing of the samples.

My deepest gratitude goes to Mr. Beharu Abdela , Mr.Tadele Ahmed , Mr.Murad Delil and Eng. Sisay Tena for their unlimited help in financing and giving encouragement throughout my journey

Last but not least, my heartfelt gratitude goes to my family, friends and those who assisted me in the accomplishment of this research work.

Table of Contents

ACKNOWLEDGEMENTS	II
ACCRONYMS	V
LISTS OF TABLE	VI
LISTS OF FIGURES	VII
ABSTRACT	VIII
1. INTRODUCTION	1
1.1. Background	1
1.2 Statement of Problem	2
1.3 Objectives	3
1.3.1 General Objectives	3
1.3.2 Specific Objectives	3
1.4 Organization Of The Thesis	3
1.5 Scope of the study	4
2. LITERATURE REVIEW	5
2.1 Introduction	5
2.1.1 California Bearing Ratio(CBR)	5
2.4.1 Test Methods	5
2.4.1.1 In Situ CBR Test	6
2.4.1.2 Laboratory CBR Test	6
2.4.2 Application of CBR Value	7
2.1.2 Index Properties of Soil	7
2.1.2.1 Soil Classification	8
2.1.2.1.1 Grain Size Distribution	8
2.1.2.1.2 Moisture Content	9
2.1.2.1.3 Atterberg limit	9
2.1.2.2 Moisture Density Relationship	10
2.2 Existing CBR Prediction Methods	11
2.2.1 Universal Approaches	12
2.2.1.1 Unified Soil Classification	12
2.2.1.2 Mechanistic-Empirical Design Guide	13
2.2.2 Relationships Specific to a Region and Soil Type	15
2.2.2.1 Relationship Specific To Ethiopia	

A STUDY ON CORRELATION OF CALIFORNIA BEARING RATIO WITH INDEX PROPERTIES OF SOIL WELKITE-AREKIT- HOSANA ROAD AS CASE STUDY

7	Λ	1	6
4	U		U
	_		_

2.2.2.2 Relationship Specific To Other Regions17
3. DATA COLLECTION AND ANALYSIS25
3.1 Source of Data
4. REGRESSION AND CORRELATION ANALYSIS
4.1 General Overview
4.1.1 Selection of Variables and Model Building
4.1.2 Adequacy of The Regression Model
4.1.2.1 The Standard Error Statistics
4.1.2.2 Residual Analysis
4.1.2.3 Coefficient of Determination(R ²)
4.1.2.4 Adjusted R ²
4.1.2.5 Pearson Correlation Cofiecients
4.1.3 Hypothesis Testing of Regression
4.2 Scatter Plots
4.3 Regression analysis
4.3.1 Single Linear Regression Analysis44
4.3.2 Multiple Linear Regression Analysis46
5. DISCUSSION ON CORRELATION RESULTS49
5.1 The Developed Correlation
5.2 Evaluation of the Developed and Existing Correlations
6. CONCLUSION AND RECOMMENDATION
6.1 Conclusions
6.2 Recommendations
REFERENCE
APPENDIX A61
Single Linear Regression Statistical Summary61
APPENDIX B
Multiple Linear Regression Statistical Summary69
APPENDIX C
Laboratory Test Results

ACCRONYMS

AASHTO	American Association of State Highway and Transportation Officials
ASTM	American Society for Testing and Materials
CBR	California Bearing Ratio
DCP	Dynamic Cone Penetrometer
FCBR	Field California Bearing Ratio
LI	Liquidity Index
LL	Liquid Limit
MDD	Maximum Dry Density
NCHRP	National Cooperative Highway Research Program of United States of America
OMC	Optimum Moisture Content
PI	Plasticity Index
PL	Plasticity Limit
SPSS	Statistical Package for Social Science Software
SI	Suitability Index of de-Graft Johnson Equation
USCS	Unified Soil Classification System
R	Pearson Product Moment Correlation Coefficient
\mathbf{R}^2	Coefficient of Determination

LIST OF TABLES

Table 2-1 Symbols in the Unified Soil Classification System	12
Table 2-2 Typical California Bearing Ratio Values based on Unified Soil Classification[7]].13
Table 2- 3 Summary of correlation of CBR with index properties	22
Table 3-1 Summary Of Atterberg And Particle Size Distribution For Typical Sample	27
Table 3- 2 Summary of all test results	30
Table 4-1 Statistical Information of Dependent and Independent Variables	43
Table 4- 2 Correlation Matrix of Pearson Correlation Coefficient	43
Table 4-3 The developed correlation between CBR and Index propertie of soil	48
Table 5-1 Validation of CBR From Correlation Developed With The Actual Test Data	49
Table 5-2 Evaluation of the Developed Correlation with Control Tests	53
Table 5- 3 Comparison of The Developed and Existing Correlations	54

LIST OF FIGURES

Figure 2. 1 Description of Phases of Soil-Water System [4]10
Figure 2.2 A representative Moisture-Density relationships from a Standard Compaction
Test. [5]
Figure 3. 1 Map of study Road[36]25
Figure 3. 2 Typical flow curve diagram for sample number 27 to determine liquid limit of the
sample
Figure 3. 3 Typical moisture- density relationship graph for sample number 27
Figure 3. 4 Typical Particle size distribution for sample number 27
Figure 3.5 Typical Three-point CBR result for sample number 27
Figure 4. 1 Scatter diagram of CBR versus gravel content of the tested soil samples
Figure 4. 2 Scatter diagram of CBR versus fine content of the tested soil samples
Figure 4. 3 Scatter diagram of CBR versus sand content of the tested soil samples
Figure 4. 4 Scatter diagram of CBR versus MDD of the tested soil samples
Figure 4. 5 Scatter diagram of CBR versus OMC of the tested soil samples
Figure 4. 6 Scatter diagram of CBR versus LL of the tested soil samples
Figure 4. 7 Scatter diagram of CBR versus PL of the tested soil samples
Figure 4. 8 Scatter diagram of CBR versus PI of the tested soil sample
Figure 4. 9 Matrix plot of dependent and independent variable
Figure 4. 10 Scatter plot of independent variables with CBR
Figure 5. 1 Scattor plot between Actual CBR wit Pridicted CBR from model B-4-151
Figure 5. 2 Scatter plot between Actual CBR with Predicted CBR from model B-4-251
Figure 5. 3 Side By Side Scatter Plot Comparison Between Actual CBR With Predicted CBR
from Model B-4-1 and From Model B-4-2
Figure 5. 4 Graphical comparison of the developed model with previous correlations55

ABSTRACT

Soil properties vary from region to region and season to season as it appears naturally. studying this variation in different soil type and origin are a very important task for geotechnical engineers. To overcome the effects from this variation geotechnical engineers as well as other professionals attempt to develop empirical equations specific to a certain region and soil type in order to use the soil for different purpose. However, these empirical equations are more reliable for the type of soil where the correlation is developed .Hence, it is good practice developing empirical equations that best fit for the soil available in the area that we can access.

In the flexible pavements sub-grade is considered to be an ideal layer to resist wheel load and its CBR value is considered as the strength measuring parameter. Conducting CBR test is an expensive and time consuming procedure, moreover it is very difficult to mould the sample at a desired in-situ density in the laboratory. Furthermore, if the available soil is of a poor quality, suitable additives are mixed with soil and resulting strength of soil is assessed by CBR value which is cumbersome. To overcome such problems, the other method such as regression based models (simple & multiple) has to be used from quick and easily determined parameters.

Therefore ,this study is conducted to develop the correlation between CBR values with soil index properties specifically located along the way Welkite- Arekit –Hossana Road which is 121 km long. The study was carried out using thirty samples retrieved from this road and tested in a laboratory. By using the test result regression based statistical analysis is carried out to develop the intended correlation. The correlation development is performed in the form of an equation of CBR as a function of grain size parameters, Atterberg limits and compaction parameters by considering the effect of an individual soil properties and effect of a combination of soil properties on the CBR value.

Based on both simple and multiple linear regression analysis relatively fair correlation is obtained by combining plasticity index, percentage of fine content and maximum dry density which are basically strength determinant of fine grained soils. From the correlation analysis the equations developed are BR = 3.591 - 0.031F + 3.707MDD - 0.098PI, with coefficient of determination of $R^2 = 0.731$ for multiple linear regression and $CBR = 17.227 - 0.867 * PI + 0.013PI^2$ with coefficient of determination of $R^2 = 0.682$ single linear regression respectively. Statistical data analysis commercially available soft wares namely MINITAB, SPSS and Microsoft Excel used. After developing the correlation, comparison of predicting capacity of the developed model with control samples and previous researchers correlation have been applied for conformity. The result shows that the correlation is sufficiently accurate in determining the CBR and hence can be used for preliminary characterization purpose within the soil property ranges used in the study.

1.1. Background

The California Bearing Ratio (CBR), defined as the ratio of the resistance to penetration of a material to the penetration resistance of a standard crushed stone base material. CBR is one of the major parameters used in pavement design to assess the stiffness modulus and shear strength of subgrade material. During the early 1920s, the CBR test was developed by O. J. Porter for the California Highway Department to evaluate the bearing capacity of pavement materials in laboratory conditions [2]. Starting from then, many countries including Ethiopia have developed or adopted pavement design methods based on the CBR value of the materials.

The CBR test is essentially a measure of the shearing resistance of a soil at a known moisture and density conditions. The method of evaluating CBR is standardized in AASHTO T 193 and ASTM D 1883[4]. The value of CBR is an indicator of the suitability of natural subgrade soil as a construction material. If the CBR value of subgrade is high, it means that the subgrade is strong and as a result, the design of pavement thickness can be reduced in conjunction with the stronger subgrade. Conversely, if the subgrade soil has low CBR value it indicates that the thickness of pavement shall be increased in order to spread the traffic load over a greater area of the weak subgrade or alternatively, the subgrade soil shall be subjected to treatment or stabilization [4].

CBR test is expensive, time consuming and laborious. Obtaining a proper idea about the soaked CBR of subgrade materials over total length of the road is very difficult. So, it is not really possible to take a large number of samples. In addition, CBR test in laboratory requires a large soil sample and is laborious as well as time consuming. This would result in serious delay in the progress of the project, since in most situations the materials for earth work construction come from highly variable sources. Any delay in construction inevitably leads to rise of project cost. To overcome this situation, it is better to predict CBR value of subgrade soil with easily determinable parameters. To exercise the right judgment during various phases of professional activities, the engineer is constantly required to predict. In fact, prediction is an integral component of practice in the past developed models for estimating the CBR value on the basis of low cost, less time consumption and easiness to perform tests. Other investigators used soft computing systems like Artificial Neural Networks for correlating CBR values with LL, PL, PI, OMC, MDD and Unconfined Compressive (UCS) strength values of various soils [17].

1.2 Statement of Problem

Soil characterization gives a good insight from preliminary design to final construction of infrastructure projects such as bridges, highways, airports, seaports and railways etc., Due to the fact that Soil is diverse in formation and in character, accurate prediction of its engineering behavior is of research interest in construction engineering. As the Engineering behavior of soils vary from place to place and even with time, accurate prediction of parameters that properly characterize it depends on how much representative samples in terms of both space and time are gathered [14].

California Bearing Ratio (CBR) value is an important soil parameter for design of flexible pavements and runway of air fields. It can also be used for determination of modulus of subgrade reaction of soil by using correlation. It is one of the most important engineering properties of soil for design of sub grade of proposed roads. CBR value of soil may depends on many factors such as maximum dry density (MDD), optimum moisture content (OMC), liquid limit (LL), plastic limit (PL), plasticity index (PI), type of soil considered , permeability of soil , shear strength of the soil etc. Besides, soaked or unsoaked condition of soil also affects the value. Determination of CBR is a very lengthy , laborious and time consuming process.

Even though various attempts have been made to predict the CBR value by different researchers from samples of their respective localities, adopting those developed prediction models without adjustment leads us to misinterpretation of soil behavior due to the above stated reasons. Therefore, identification of factors that influence the soil strength, studying their relationship with CBR value and performing necessary tests on local representative soil sample can give a rational basis in speculating soil behavior, which ultimately minimizes both cost and time dedicated for carrying out actual laboratory exercise.

1.3 Objectives

1.3.1 General Objectives

The main objective of the research is to develop empirical relationship between soil index properties (indices related to gradation characteristics, maximum dry density, optimum moisture content, plastic limit, liquid limit and plasticity index) that can be used for the prediction of CBR values of soils.

1.3.2 Specific Objectives

- To establish a correlation between CBR values and soil index properties for Welkite to Hossana road subgrade soils.
- > To validate and evaluate the developed correlation using a control test results.
- > To compare the developed correlation with existing correlations.

1.4 Organization Of The Thesis

In this study, in order to accomplish the proposed objectives, basic theories and descriptions of CBR test in general and in relation to soil index property of subgrade soil is reviewed. Following that, previous studies of different researchers with concerning prediction of CBR value from basic soil index properties were reviewed. In order to have satisfactory data for utilizing the correlations, laboratory tests were conducted by the researcher on samples collected from different sections of Welkite - Arekit- Hosana road by giving emphasis to fine grained soil. Different laboratory tests done and the test results of CBR values along with the associated soil indices particularly the grain size analysis, Atterberg limits and moisture-density relationships and summary of laboratory test results were covered under data collection and analysis. Then, Statistical regression analyses of test results. Under the discussions of the obtained results the suitability of the developed correlations were examined. Finally, a generalized conclusion and recommendation was made.

1.5 Scope of the Study

The study is concerned to conduct a localized research particularly on samples that are recovered from Welkite-Arekit-Hossana Roads . For achieving objective of the study, different laboratory tests that possibly influence CBR values carried out on thirty samples that collected along the stated road. Based on this results , correlation of CBR with index properties of the soil(LL, PL, PI, MDD, Percent of Fines and OMC) developed using statistical regression. Based on the trends of the scatter plot of test results the correlation was analyzed using a linear regression model. The proposed correlation is carried out by applying a single linear regression model and multiple linear regression models with the help of Microsoft Excel , MINITAB and SPSS Softwares. Different alternatives have been tried with the help of stated soft wares. The scope of the developed correlation , discussions and result obtained are limited to the test procedures followed , the range and quantity of sample used , apparatus used , sampling areas and methods of analysis used in the subject study..

2. LITERATURE REVIEW

2.1 Introduction

2.1.1 California Bearing Ratio(CBR)

The California Bearing Ratio (CBR), defined as the ratio of the resistance to penetration of a material to the penetration resistance of a standard crushed stone base material. California Bearing Ratio is the main design input in pavement construction to assess the stiffness modulus and shear strength of subgrade material. The test was initially developed by O. James Porter for the California Highway Department during the late 1920s. "In time, Porter was able to develop the relationship between bearing ratios and pavement thicknesses for wheel loads up to 12,000 pounds and to correlate these curves with field performance". During World War II, when the military rapidly began fielding very heavy bombers and started to experience dramatic pavement failures, the Army Corps of Engineers extensively studied the CBR method for flexible pavement design and expanded it for use with much heavier loads[11].

Nowdays CBR test is the most widespread method of determining the bearing strength of the pavement materials and is fundamental to pavement design practice in most countries. The CBR test can be performed both in the laboratory and field. It is essential that the standard test procedure should be strictly followed [1]. The test may be conducted on remolded or undisturbed soil samples or on the soil in place. The samples may be tested at their natural or as molded water content (unsoaked CBR), or they may be soaked by immersing in water for four days in order to simulate highly unfavorable moisture conditions of the soil type. The CBR may be considered as the strength of the soil relative to that of crushed stone[16].

The CBR test method is most appropriate and gives the most reliable results for fine-grained soils. It can also be used to characterize the strength of pavement materials. In cohesionless soils, especially those that include large particles, the reproducibility of the test is poor [10].In the laboratory test procedure, the test samples are prepared with soils of aggregate particle size of less than 19 mm. In the case of soils where particle sizes greater than 19 mm exist, the large particles are removed from the sample and replaced with an equal mass of material that falls between the 19 mm and 4.75 mm sieve size. In the field CBR test procedure, removal of larger particles that may adversely affect the test results is not possible, and, therefore, these types of soil are likely to produce unreliable results[13].

2.1.1.1 Test Methods

The California Bearing Ratio (CBR) test may be performed either in the laboratory, typically with a recompacted sample, or in the field. The field and Laboratory CBR tests have been carried out nearly in all projects in accordance with ASSHTO T193, BS1377:1990, ASTM D 4429 and ASTM D1883-73 respectively.

2.1.1.2 In Situ CBR Test

Thus, field in-place CBR tests are used for evaluation and design of flexible pavement components such as base and subbase course and subgrades and for other applications (such as unsurfaced roads) for which CBR is the desired strength parameter. If the field CBR is to be used directly for evaluation or design without consideration for variation due to change in water content, the test should be conducted under one of the following conditions:

(a) when the degree of saturation (percentage of voids filled with water) is 80 % or greater, (b) when the material is coarse grained and cohesion less so that it is not significantly affected by changes in water content, or (c) when the soil has not been modified by construction activities during the two years preceding the test. In the last-named case, the water content does not actually become constant, but generally fluctuates within a rather narrow range. Therefore, the field inplace test data may be used to satisfactorily indicate the average load-carrying capacity.

As indicated above, field in-place tests can be used for design under conditions of nominal stability of water, density, and general characteristics of the material tested. However, any significant treating, disturbing, handling, compaction, or water change can affect the soil strength and make the prior to test determination inapplicable, leading to the need for retest and reanalysis[12].

The field CBR testing is not commonly practiced in Ethiopia. Instead, a more popular test method known as dynamic cone Penetrometer test or commonly referred as Dynamic Cone Penetration (DCP) test is widely used due to its being economical, simple and quick in operation[8].

2.1.1.3 Laboratory CBR Test

The laboratory testing for determination of CBR values is almost similar to the in situ CBR field testing as described above, except the latter soil sample is undisturbed. The test is carried out using the procedure outlined in AASHTO T193- 63 or ASTM D1883-73. The main difference between the two standards is on sample preparation[27].

CBR tests are usually made on test specimens at the optimum moisture value for the soil as determined using the standard (or modified) compaction test using method 2 or 4 of ASTM D698-70 or of D1557-70 (for the 15.2cm diameter mold).Two molds of soil are often compacted-one for immediate penetration testing and one for testing after soaking for a period of 96 hours. The second specimen is soaked for a period of 96 hours with a surcharge approximately equal to the pavement weight used in the field but in no case the surcharge weight is less than 45N. Swell readings are taken during this period at arbitrary selected times. At the end of the soaking period, the CBR penetration test is made to obtain a CBR value for the soil in saturated condition. In both penetration tests for the CBR values, a surcharge of the same magnitude as for the swell test is placed on the soil sample. The test on soaked gives information concerning the expected soil expansion beneath the pavement when the soil becomes saturated.

Penetration testing is accomplished in a compression machine using a strain rate of 1.27mm/min. Reading of load vs. penetration are taken at each 0.5mm of penetration to include the values of 2.54 and 5.08 mm and then the reading shall be continued until the total penetration is 12.7mm. The CBR values is then determined by reading from the load vs. penetration graph .The load that causes a penetration of 2.54 mm and 5.08 mm and dividing these values by the standard load 6.9 MPa and 10.3 MPa respectively required producing the same penetration in the standard crushed stone as

 $CBR (\%) = \frac{Unit \ load \ for \ 2.54 \ / 5.08 mm \ penetration \ in \ the \ test \ specimen}{nit \ load \ for \ 2.54 \ / 5.08 \ mm \ penetration \ in \ standard \ crushed \ rocks} X100-----(2.1)$

The two values are then compared, generally the CBR value at 2.54 mm will be greater than the CBR value at 5.08 mm and in such a case the former shall be taken as CBR for design purpose. If CBR for 5.08mm exceeds that for 2.54mm, the test should be repeated. If identical results follow, the CBR corresponding to 5.08 mm penetration should be taken for design[28].

2.1.1.4 Application of CBR Value

Numerous pavement design charts are published in which one enters a chart with the CBR (Structural Number) together with design traffic class and reads directly the thickness of sub base, base-course, and/or flexible pavement thickness based on expected wheel loads .Sometimes the CBR is converted to a sub grade modulus (also using charts) before entering the paving design charts using the formula[28].

The main application of California Bearing Ratio (CBR) is to evaluate the stiffness modulus and shear strength of sub grade. Generally, the sub grade soil cannot bear the construction and commercial traffic without any distress, therefore; a layer of rigid or flexible pavement is required to be laid on top of the sub grade to carry the traffic load. The determination of the thickness of the pavement layer is governed by the strength of sub grade, thus the information on the stiffness modulus and shear strength of sub grade are required before any pavement design is carried out. These parameters are necessary to determine the thickness of the overlying pavement in order to achieve optimum and economic design[8].

2.1.2 Index Properties of Soil

Soils are naturally complex, multiphase materials. They are generally a matrix of an assortment of particles (solids), fluids, and gases. Each influences the behavior of the soil mass as a whole. Unless we understand the composition of a soil mass, we will be unable to estimate how it will behave under loads and how we can use it as a construction material. Geoengineers have devised classification systems based on the results of simple, quick soil tests. These systems help us make decisions about the suitability of particular types of soils for typical Geoengineering systems[3]. These simplified tests which are indicative of the engineering properties of soils are called index properties. Index properties of cohesive

soils are used to characterize the physical and mechanical behavior of soils by making use of parameters such as moisture content, specific gravity, particle size distribution, Atterberg limits and moisture-density relationships. Such parameters are useful to classify cohesive soils and provide correlations with engineering soil properties [6].

2.1.2.1 Soil Classification

Soils exhibiting similar behavior can be grouped together to form a particular group under different standardized classification systems. A classification scheme provides a method of identifying soils in a particular group that would likely exhibit similar characteristics. There are different classification devises such as USCS and AASHTO classification systems, which are used to specify a certain soil type that is best suitable for a specific application. These classification systems divide the soil into two groups: cohesive or fine-grained soils and cohesion-less or coarse-grained soils[3].

2.1.2.1.1 Grain Size Distribution

To understand the nature of the soil, the distribution of the grain size present in the given soil mass must be known. Therefore the grain size analysis involves determining the percentage by mass of particles within the different size ranges. For coarse grained materials, the grain size distribution is determined by passing soil sample either by wet or dry shaken through a series of sieves placed in order of decreasing standard opening sizes and a pan at the bottom of the stock. Then the percent passing on each sieve is used for further identifying the distribution and gradation of different grain sizes [4].Particle size analysis tests are carried out in accordance to ASTM D 422-63. Besides, the distribution of different soil particles in a given soil is determined by a sedimentation process using hydrometer test for soil passing 0.075mm sieve size. For a given cohesive soil having the same moisture content, as the percentage of finer material or clay content decreases the shear strength of the soil possibly increases.

The selection of a soil for a particular use may depend on the assortment of particles it contains. Two coefficients have been defined to provide guidance on distinguishing soils based on the distribution of the particles. One of these is a numerical measure of uniformity, called the uniformity coefficient, Cu, defined as

 $Cu = D_{60}/D_{10}$ ------(2.2)

Where D_{60} is the diameter of the soil particles for which 60% of the particles are finer, and D_{10} is the diameter of the soil particles for which 10% of the particles are finer. Both of these diameters are obtained from the grading curve. The other coefficient is the coefficient of curvature, Cc (other terms used are the coefficient of gradation and the coefficient of concavity), defined as

 $Cc = (D_{30})^2 / D_{10} D_{60}$ ------(2.3)

where D_{30} is the diameter of the soil particles for which 30% of the particles are finer. The average particle diameter is $D_{50}[3]$.

2.1.2.1.2 Moisture Content

Change in moisture content is the most influential parameter that affects the property of soils. Moisture content is defined as the ratio expressed as a percentage of mass of water to mass of soil solids. The purpose of moisture content test is to determine the amount of water present in a quantity of soil in terms of its dry weight and to provide general correlations with strength, settlement, workability and other properties. The moisture content of soils, when combined with data obtained from other tests, produces significant information about the characteristics of the soil. For example, when the in situ moisture content of a sample retrieved from below the phreatic surface approaches its liquid limit, it is an indication that the soil in its natural state is susceptible to larger consolidation settlement. The moisture content test is carried out in the laboratory as per the procedure of AASHTO T 265 or ASTM D 2216 and in the field according to AASHTO T217.

2.1.2.1.3 Atterberg limit

Based on their mode of formation and mineralogical composition different soils respond differently for the same moisture content. Albert Atterberg, a Swedish Scientist in 1911 gave an idea of the consistency limit of cohesive soils and proposed a number of tests for defining their properties. The three Atterberg limits which are liquid limit, plastic limit and shrinkage limits are the boundary between each of the two consecutive states of the soilwater phases. Their test is performed only on that portion of a soil which passes the 425mm (No. 40) sieve[9]. A description of phases of soil-water system is shown with schematic diagram in Figure 2.1.

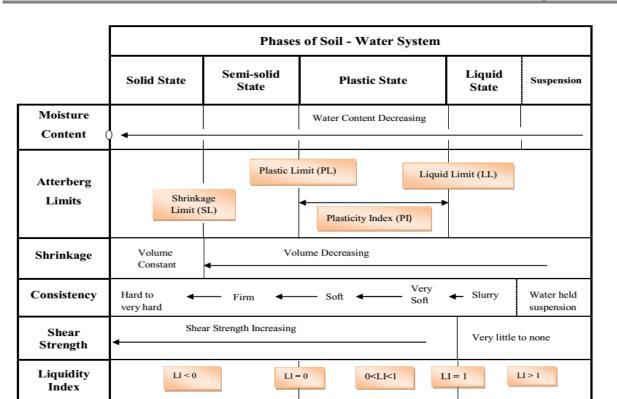


Figure 2. 1Description of Phases of Soil-Water System [4]

Liquid Limit: The liquid limit (LL) is the water content, expressed in percent, at which the soil changes from a liquid state to a plastic state and principally it is defined as the water content at which the soil pat cut using standard groove closes for about a distance of 13cm (1/2 in.) at 25 blows of the liquid limit machine (Casagrande Apparatus). The liquid limit of a soil highly depends upon the clay mineral present. The conventional liquid limit test is carried out in accordance of test procedures of AASHTO T 89 or ASTM D 4318. A soil containing high water content is in the liquid state and it offers no shearing resistance.

Plastic Limit: The plastic limit (PL) is the water content, expressed in percentage, below which the soil stops behaving as a plastic material and it begin to crumble when rolled into a thread of soil of 3.0mm diameter. The conventional plastic limit test is carried out as per the procedure of AASHTO T 90 or ASTM D 4318. The soil in the plastic state can be remolded into different shapes. When the water content is reduced the plasticity of the soil decreases changing into semisolid state and it cracks when remoulded[4].

2.1.2.2 Moisture Density Relationship

Compaction tests are performed using disturbed, prepared soils with or without additives. Normally, soil passing the No. 4 (4.75mm) or 19mm sieve is mixed with water to form samples at various moisture contents ranging from the dry state to wet state. These samples are compacted in layers in a mold by a hammer in accordance with specified nominal compaction energy. Dry density is determined based on the moisture content and the unit weight of compacted soil. A curve of dry density versus moisture content is plotted on Figure

2016

2.2 and the maximum ordinate on this curve is referred to as the maximum dry density (γ dmax). The water content at which this dry density occurs is termed as the optimum moisture content (OMC). The test is done in the laboratory according to AASHTO T 99 (Standard Proctor), T 180 (Modified Proctor) or ASTM D 698 (Standard Proctor), D 1557 (Modified Proctor)[5].

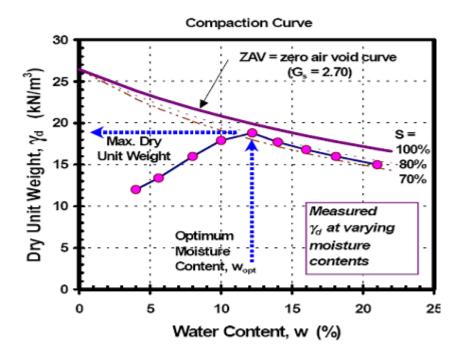


Figure 2. 2A representative Moisture-Density relationships from a Standard Compaction Test. [5]

2.2 Existing CBR Prediction Methods

Many researchers and agencies developed relationships between CBR with soil index parameters on the basis of samples obtained from a specific region and soil type. General relationships are also developed using universally accepted soil classification systems, basically based on the Unified Soil Classification System (USCS) and American Association of State Highway and Transportation Officials (AASHTO) systems. These correlation methods take a general approach and attempt to encompass many or all possible soil types. However ,most attempts have been limited in scope to a specific soil and only apply to one region, soil type, or specialized material[4].

2.2.1 Universal Approaches

2.2.1.1 Unified Soil Classification

The simplest approach to approximating the CBR value for a soil based on typical values associated with soil classification. The Unified Soil Classification System (USCS) is a standardized technique for classifying soils for engineering purposes that is widely-used in the geotechnical community [12]. Within this system, soils are classified based on the distribution of their grain sizes and the cohesive properties of their fine material. In the USCS system, soils are divided into three major categories: coarse-grained materials, fine-grained materials, and highly organic soils. These categories are further divided into soil groups the coarse-grained soils as either gravel or sand and the fine-grained soils as either silt or clay. A letter symbol represents each of these four main soil groups. which is used to further describe the soil's characteristics. These descriptors include symbols to differentiate among grain size distribution, plasticity characteristics that describe cohesive behaviour, and the nature of the organic material in a soil. Guidelines for choosing CBR values based solely on USCS soil type are found throughout the literature. A variety of USCS class soils are associated with a range of CBR values by different researchers and research institutes. A summary of reported values from several of these sources is shown in Table 2-2. Generally, these are consistent for each soil type, with minor differences among the reported values. Part of this variation may be due to the fact that some refer to compacted soils, others refer to field-measured CBR values, while some do not specify test conditions [4, 11].

Table 2-	1Symbols in	the	Unified Soil	Classification System
	•			•

Symbol	G	S	М	С	0	Pt	Н	L	W	Р
Description	Gravel	Sand	Silt	Clay	Organic Clay/Silt	Peat	High Plastic	Low Plastic	Well Graded	Poorly Graded

USCS Soil Type	USACE, US Army and Air Force	Yoder & Witczalk	US Army, Air Force and Navy and PCA	Rollings & Rollings	NCHRP*
GW	40 - 80	60 - 80	60 - 80	60 - 80	60 - 80
GP	30 - 60	35 - 60	25 - 60	35 - 60	35 - 60
GM	20 - 60	40 - 80	20 - 80	40 - 80	30 - 80
GC	20 - 40	20 - 40	20 - 40	20 - 40	20 - 40
SW	20 - 40	20 - 40	20 - 40	20 - 50	20 - 40
SP	10 - 40	15 - 25	10 - 25	10 - 25	15 - 30
SM	10 - 40	20 - 40	10 - 40	20 - 40	20 - 40
SC	5 - 20	10 - 20	10 - 20	10 - 20	10 - 20
ML	15 or less	5 - 15	5 - 15	5 - 15	8 - 16
CI	15 or less	5 - 15	5 - 15	5 - 15	5 - 15
OL	5 or less	4 - 8	4 - 8	4 - 8	
MH	10 or less	4 - 8	4 - 8	4 - 8	2 - 8
СН	15 or less	3 - 5	3 - 5	3 - 5	1 - 5
OH	5 or less	3 - 5	3 - 5	3 - 5	
Pt				< 1	
CL-ML					
GW-GM					35 - 70
GW-GC					20 - 60
GP-GM					25 - 60
GP-GC					20 - 50
GC-GM					
SW-SM					15 - 30
SW-SC					10 - 25
SP-SM					15 - 30
SP-SC					10 - 25
SC-SM					

Table 2- 2Typical California Bearing Ratio Values based on Unified SoilClassification[7]

* NCHRP: represents National Cooperative Highway Research Program of United States

2.2.1.2 Mechanistic-Empirical Design Guide

The National Co-operative Highway Research Program (NCHRP) [7] of United States of America (USA) through the "Guide for Mechanical - Empirical Design of New and Rehabilitated Pavement Structures" had been developed some correlations that clearly describes the relationship between soil index properties and CBR values based on a simple regression approach. Separate relationships were determined for coarse-grained soils that exhibit non-cohesive behavior (GW, GP, SW, and SP) and for soils with more than 12 percent fines that exhibit plastic behavior (GM, GC, SM, SC, ML, MH, CL, and CH) [7].

The CBR values were selected by choosing average values for each USCS soil type based upon sources that provide typical CBR values by classification. The index property values were selected by examining the USCS classification criteria for each soil type and choosing a typical value for that USCS soil type.

The percent passing sieve number 200 and the plasticity index parameters were combined into a composite index called the weighted plasticity index. This term, denoted by wPI, is defined as shown in equation (2.4).

wPI = (Percent passing No. 200 Sieve) x (Plasticity Index) = P200 x PI ------ (2.4)

An equation was established for soils which contain 12% fines and exhibit some plasticity. For plastic, fine-grained soils, the soil index properties chosen to correlate CBR are the percentage passing No. 200 US standard sieve or 0.075mm size sieve and plasticity index.

✓ For clean, coarse-grained, non-plastic soils where wPI = 0, the CBR were correlated with D_{60} . The best-fitted equation proposed by NCHRP for clean, coarse-grained soil provides the following prediction relationship R²=0.84

$$CBR = \begin{cases} 5\%, \text{ if } D_{60} \le 0.01 \text{mm} \\ 28.09(D_{60})^{0.358}, \text{ if } 0.01 \text{mm} \le D_{60} \le 30 \text{mm} \end{cases}$$
(2.5)
95%, if $D_{60} \ge 30 \text{mm}$

✓ For plastic, fine-grained soils CBR can be calculated as R²=0.67 $CBR = \frac{75}{1+0.278(\text{w PI})}$ -----(2.6)

Where: - wPI Weighted Plasticity Index

- PI Plasticity Index (in percent)

2.2.2 Relationships Specific to a Region and Soil Type

Currently, several models for predicting the CBR of soils for a specific soil or geographic location can be found in different literature. Many researchers trying to get soaked CBR or unsoacked CBR values by correlation using simple correlation and MLRA with the properties of soil like liquid limit, plastic limit, and plasticity index, optimum moisture content (OMC), maximum dry density (MDD) and percentage fineness, Dynamic cone penetration result, shear strength of the soil, unconfined compression result and so forth. Some of different published correlations targeting to correlate the CBR value with soil index properties specific to a certain region and soil type are presented below

2.2.2.1 Relationship Specific To Ethiopia

Here are some of the available literatures that relates CBR with different soil properties of Ethiopia.

Zelalem Worku(2010)[28], tried to predict CBR value from index properties of granular and silty-clay soils. He studied the soil data that were collected from consulting firms and used subgrade soils found around Addis Ababa as control laboratory tests. The samples were collected from the site located at Bole- Bulbula and road construction sites around Addis Ababa for the case of Granular soils and from Hageremariam, Woldia, and Addis Ababa for the case of silty-clay soils. The study showed newly developed relation is better as compared to the Mechanistic empirical method. However the relationship obtained for siltyclay soils is not compared due to weakly established correlation. The study showed that a strong correlation established between CBR, OMC and MDD with coefficient of determination of 0.863 for a sample size of 53.The developed equation for granular soil is shown below

 $CBR = -27.998 + 0.0290MC^2 + 4.796MDD^4$ where R² = 0.863------(2.7)

For the case of silty-clay soils, the study couldn't established strong reliable correlation .The maximum value attained for the coefficient of determination is 0.564 for a sample size of 106 for a correlation between CBR, LL and P200. For the sake of illustration the developed model for silty-clay soil is shown below.

Ln CBR = 4.175 - 0.029LL - 0.009P200 with R² = 0.564-----(2.8)

Yitagesu Desalegn (2012)[8]. tried to find the correlation between Cone Penetrometer (DCP) with CBR values that best suit the type of soils in Ethiopia. The soil samples under study were extracted from Jimma -Bonga road and he showed that the published correlations are not suitable to be used in Ethiopia. Consequently, a correlation had been proposed in the study to predict the CBR values of the sub grade soil from dynamic cone penetration test results. The model obtained from statistical analysis is shown below

log (CBR) = 2.954 - 1.496 log (DCPI) with R2= 0.943------(2.9)

Yared Leliso (2013)[4]. Studied forty two disturbed samples that are collected from different parts of Addis Ababa and tried to develop the correlation of CBR as a function of grain size parameter, Atterberg limits and compaction parameters by considering the effect of an individual soil properties and effect of a combination of soil properties on the CBR value. The study showed a combination of soil index properties correlates better with strength characteristic of CBR than individual soil properties. He suggested that for preliminary design purpose the correlation might be used, if the predicted CBR value is within the range of 2.2% to 10%. Otherwise, a detailed laboratory test should be carried out to obtain the actual CBR value. The developed is presented below.

CBR = -21.734 - 0.003LL - 0.137PI + 20.244MDD With R²=0.629------ (2.10)

K.Kumar et al (2014)[33]. studied about 17 samples that are collected at different intervals of sub grade soil samples from Modjo to Hawassa, in Ethiopia. From the collected samples, the basic index properties like Liquid Limit (LL), Plastic Limit (PL), Shrinkage Limit (SL), Sieve Analysis, Optimum Moisture Content (OMC) and Maximum Dry Density (MDD) have been evaluated in the laboratory. Then they tried to validated with the predicted results of CBR against different correlations available namely Agarwal and Ghanekar (1970)[20], Vinod and Cletus 2008[22], Roy et al 2009 [29], Patel and Desai 2010 [21] and concluded the following statements. The results obtained from Agarwal and Ghanekar [20] has no way matching with the experimental as well predicted CBR values. Almost all the equations are moderately validating with different samples with the experimental values with predicted values of CBR except Vinod and Cletus[22] . From NCHRP [7], the experimental and predicted values are following the trend but the values are not matching exactly.

Black (1962)[**31**]. had developed chart to estimate CBR value of cohesive soils from plasticity index and the liquidity index.

Johnson and Bhatia (1969) [24]correlated CBR with plasticity and grading using the concept of suitably index on the Ghana lateritic soil. The relationship between CBR and suitability index is shown as follows

$$CBR = (35 * SI) - 8$$
-----(2.11)

$$SI = \frac{A}{LL(Log (PI))}$$
(2.12)

Where: - SI Suitability Index value of de Graft-Johnson and Bhatia

A - Percentage passing 2.0mm sieve size

Agarwal and Ghanekar (1970)[20]tried to develop a correlation between the CBR and the liquid limit, plastic limit (PL) or plasticity index. However, they were not able to find any significant correlation among these parameters. However, they found an improved correlation when optimum moisture content (OMC) and liquid limit were included .They used 48 soil samples with CBR values not more than 9% and the standard deviation obtained was 1.8. Hence, they suggested that the correlation is only of sufficient accuracy for preliminary identification of material. They also recommended that this correlation may be of more use of derived for specific geological regions [31].The correlation developed defined as follows:

CBR = 2 - 16Log(OMC) + 0.07LL ------(2.13)

Where: - OMC Optimum Moisture Content of the soil

- LL Liquid Limit of the soil

Vinod and Cletus (2008)[22]. had proposed a correlation based on liquid limit and gradation characteristics of soils. Based on the result obtained from experimental study on lateritic soils, they suggested a correlation as defined below.

CBRs = -0.889(WLM) + 45.61-----(2.14)

where, WLM = LL (1 - C/100)-----(2.15)

Where LL is liquid limit on soil passing through 425 μ m sieve (in percentage) and C is the fraction of soil coarser than 425 μ m (percent).

 $Log(CBR) = log(\gamma dmax / \gamma w) - log(OMC) - (2.16)$

Where, $\gamma dmax$ or MDD = Maximum Dry Density and γw is unit weight of water.

soil). The following relationship is developed from their study.

Patel and Desai 2010 [21] had proposed few correlations for alluvial soils to obtain the CBR value from liquid and plastic limit. The equation for CBR as a function of different soil properties by method of regression analysis has been established. The correlations are shown below.

 $CBR = 43.907 - 0.093PI - 18.78MDD - 0.3081 - \dots$ (2.17)

Singh *et al.*(2011)[30],Tried to develop regression model to estimate soaked and unsoaked CBR values of fine grained subgrade soils , considering degree of compaction, moisture content, and various index properties of a soil. The soil samples tested at 3 moisture levels, and 4 compaction levels using modified proctor. They observed that the CBR value, both soaked and unsoaked significantly affected by change in moisture content and compaction effort. The effect of both moisture and compaction effort is more significant on the soaked CBR value. At constant moisture content, as compaction effort Increases , both the unsoaked CBR and soaked CBR value of soils decreases. Effect of compaction on soaked CBR is more dominant than compared to unsoaked CBR. The regression models developed for unsoaked CBR and soaked CBR are shown in the following Equations.

 $UCBR = 104.71 - 0.671X \left(\frac{MC}{OMC} X100\right) + 0.239X \left(\frac{Density}{MDD} X100\right) - 2.004PL ------ (2.18)$ with R²=0.70 $SCBR = -2.213 - 0.055X \left(\frac{MC}{OMC} X100\right) + 0.328X \left(\frac{Density}{MDD} X100\right) - 1.147PL ------ (2.19)$ with R²=0.48

Where, UCBR = Unsoaked CBR (%),

MC = Moisture Content (%),

OMC = Optimum Moisture Content (%),

Density = Measured or calculated density (gm/cc),

P.Muley *et al*(2013)[34]. studied three soil types namely the expansive black cotton soil, the yellow clay, and the red murrum mixed with stone dust (crusher dust) in different proportions so as to study the improvement in the CBR value of these soils. From these soils, empirical correlation developed between the CBR value and the basic soil parameters of the mix soil namely the fine content (less than 75 μ particles), D60 (particle size corresponding to 60% finer), the liquid limit and the plasticity index. The study showed correlation that is obtained from the test data predicts pretty well the soaked CBR of the mix soils with sufficient accuracy and thus can be used by practitioners to have an idea of the CBR of the soil mixed with stone dust by the basic soil parameters, that are invariably carried out for the classification purpose. The empirical relationship was developed is given on the following equation.

CBR = 0.45PI - 0.31LL - 4.19D60 - 0.43F - 0.260MC - 29.86MDD + 102.39,(R2 = 0.98)------(2.20)

Where; LL = liquid limit, PI = plastic limit, OMC = optimum moisture content in %, F = percentage fines passing from 75 micron and MDD = maximum dry density in g/cc

Ramasubbarao *et al*(,2013)[17]. observed that the use of index properties such as grain size analysis (%Gravel, %Sand, %Fines), Plasticity Characteristics (LL, PL) and Compaction Characteristics; namely MDD and OMC appears to be reasonable in the estimation of soaked CBR value of fine grained soils. The study critically reviewed some of correlations and models developed by previous researchers and have proposed a simple correlation equation for predicting of soaked CBR of compacted soils. The equation is presented below.

CBRs = 0.064F + 0.082S + 0.033G - 0.069LL + 0.157PL - 1.81MDD - 0.061OMC with (R²=0.92) ------(2.21)

D.Kumar *et al*(2014[15]. Studied silty soil samples with low compressibility (ML) and of silts of intermediate compressibility (MI) and showed CBR value of fine grained soil (ML and MI) bears significant correlation with PI, MDD and OMC. CBR value decreases with the increase in the plasticity index and optimum moisture content of soil but increases with the increase in the maximum dry density. They also stated there is a slight difference between the CBR value determined in the laboratory and computed by using multiple linear regression model involving LL, PL, PI, MDD and OMC and developed the following correlation.

CBR (soaked) = 0.127(LL) - 0.1598(PI) + 1.405(MDD) - 0.259(OMC) + 4.61 - --(2.22)

Shirur *et al.*(2014)[19]. showed that the three parameters plasticity index, maximum dry density and optimum moisture content directly affects the CBR value. From their study CBR value decreases with increase in plasticity index and CBR decreases with increase in moisture content. From their correlation analysis they stated that, large variation can be observed between experimental and predicted CBR value particularly in case of high compressible clays (CH). They showed that using maximum dry density and optimum moisture content and found a good relationship to predict the CBR Value. The empirical relation they developed is shown below

CBR = -4.8353 - 1.56856(OMC) + 4.6351(MDD) (R2 = 0.82) - (2.23)

Yadav *et al.*(2014)[18]. studied samples which covers silts and clays of all types with low, medium and high compressible soils. The study focused on the soaked CBR correlation with simple properties of fine grained soil like liquid limit, plastic limit, optimum moisture content, maximum dry density (by modified Proctor test) and % fine content in the soil (i.e. passing 75 micron sieve size particles) by multiple regression analysis .They relates CBR to the soil classification and compaction parameters. It has high regression coefficient R^2 and they suggested the relation could judiciously be used for estimating soaked CBR of fine grained soils.T he final equation obtained was given here for illustration

CBRs = -3.06 + 188.64/LL - 24.15/PL + 38.06/OMC + 0.225 MDD + 0.018/F with R2 = 0.87-----(2.24)

Rakaraddi *et al.*(2015)[15]. showed soaked CBR with respect to liquid limit has good correlation with exponential trend line have highest and as the fines increases optimum moisture content increases hence decrease in maximum dry density there by soaked CBR value decreases. Their study stated Liquid limit is considered as higher priority for predicting soaked CBR value followed by OMC, MDD and PI based on assessment factor R^2 . The correlation developed with liquid limit, plastic limit, fines and specific gravity is given below

CBR = -0.275LL + 0.118PL + 0.033F + 5.106G with R2=0.961-----(2.25)

Nguyen(2015)[13]. Investigated the effect of soil physical properties, including moisture content, plasticity index and maximum dry density, on the California Bearing Ratio (CBR) values for fine-grained soils of various locations of Melbourne, Australia. For each soil sample, the CBR tests were carried out at four different moisture contents, including the dry of optimum moisture content (OMC), OMC, wet of OMC and soaked condition. Based on their study they showed the effect of moisture content on CBR value is significant. For example, on the wet side of OMC, as moisture content increases, the CBR decreases significantly. The maximum CBR is observed at the OMC because at this moisture level, the maximum dry density and the highest strength are achieved. The influence of the plasticity index on the CBR is not clear. However, the effect of the maximum dry density on the CBR is clearly observed with the proportional relationship. The CBR increases as the maximum dry density increases. From their study, they stated the correlation of CBR and the moisture content (MC), plasticity index (PI) and maximum dry density (MDD) was found to be strong for the samples tested at OMC, wet side of OMC and soaked conditions. The correlation developed is shown below.

Log(CBR) = 4.767 + 0.843(MC) + 0.020(PI) - 1.522(MDD) with R2 = 0.75 - (2.26)

Some of predicting models published in the world concerning on the correlation of CBR using simple correlation and MLRA with the properties of soil like liquid limit, plastic limit, and plasticity index, optimum moisture content (OMC), maximum dry density (MDD) and percentage fineness with the model parameters range and their statistical results summarized on Table 2-3

S.no	Investigator	Parameters considered and their ranges	Model	Statistic al Parame ter
1	(De Graft-Johnson et al,1969)[24]		$CBR = \underline{35A} - 8$	
	ai,1909)[24]		LL(Log (PI))	
2	Agarwaland Ghanekar,1979)		CBR=2-16Log(OMC)+0.07(LL)	
3	(Satyanarayana Reddy &Pavani, 2006) [23]	FF=9.0-34.8%, LL=22-48%, MDD=1.90- 2.32g/cc, CBRs 12.232	CBRs =-0.388F-0.064LL+20.38MDD	R ² =0.96
4	(Gregory &Gross, 2007)	For cohesive soils	CBR = 0.09 cu	-
		For cohesionless soils	$CBR = \frac{q_{ultx100}}{6895}$	
5	(Vinod&Reena,2008)	C=33-65%,	CBRs= -0.889(WLM)+45.616	R ² =0.97
		LL=38.10- 63.00%,		9
		CBRs 8.596	where, WLM= LL $(1 - C/100)$	_
6	(Patel & Desai, 2010) [21]	LL=52.98- 70.78%, PL=17.09-26.8%, SL=8.03-19.5%, MDD=1.58- 1.73g/cc, OMC=17.23- 24.70%, PI=24.19-47.78%,	CBRu=17.009-0.0696Ip- .296MDD+0.0648OMC	%error= 2.5%
		CBRu=2.80- 8.94%, CBRs=1.54-4.42%		%error=
			CBRs=43.907-0.093Ip-18.78MDD- 0.3081OMC	-5%
7	(Yildirim&Gunaydin,2011))[26]	G=0-78%, S=1- 49%, F=10-99%, LL=20-89%, PL=11-43%	CBR = 0.2353G+3.0798	R ² =0.86
		MDD=1.21-2.18 g/cc,	CBR=-0.1805F+18.508	R ² =0.80

Table 2- 3Summary of correlation of CBR with index properties

		OMC=7.20- 40.20%		
			CBR=0.22G+0.045S+4.739MDD+0.122O MC	R ² =0.88
			CBR=0.62OMC+58.9MDD+0.11LL+0.53 PL-126.18	R ² =0.63
8	(YaredLeliso,2013)[4]	LL=43-72%, PL=20-45%, MDD=1.48- 1.65g/cc, OMC=17.8- 30.2%, soaked CBR=2.2- 10%.	CBR = 16.270 - 0.179*LL	R ² = 0.458
			CBR = -21.734-0.003*LL- 0.137*PI + 20.244*MDD	$R^2 = 0.629$
9	(Ramasubbarao, G.V et al,2013) [17]	Gravel=0-24%, Sand=0-40.14%, Fines(Silt+Clay)= 50-100%, LL=24.6-94.0%,	CBRs=0.064F+0.082S+0.033G- 0.069LL+0.157PL- 1.810MDD-0.061OMC	R ² =0.96
		PL=11.9-36.0%, MDD=1.25- 1.85g/cc, OMC=12.3- 35.4%, soaked CBR=0.8- 5.86%		
10	(Dilip kumar,2014) [14]	Gravel= 0-4.7%, Sand= 13-17%, Fines(silt&clay=5 9-84%, LL= 28- 37%, PL= 20-29%, PI=6.12-8.5 %,	CBR (soaked) = 0.127(LL) + 0.00 (PL) - 0.1598(PI) +1.405(MDD) -0.259(OMC) + 4.618	
		MDD= 1.62 - 1.77gm/cc, OMC= 14-16% and soaked CBR= 5.5- 6.2%		
11	(Shirur et al,2014)		CBR= -4.8353-1.56856(OMC) +4.6351(MDD)	$R^2 = 0.82$
	[19]	Gravel= 0-17%, Sand= 20-90%,	CBR = 5.09477 - 0.09323 (LL) + 0.10939	R ² =72
		1	1	1

		Fines(silt&clay)= 4-75%, LL= 20- 66%, PL= 20-35%,	(SL) + 0.022566 (SI) CBR = 5.813 - 0.007826 (LL) + 0.12097 (PL)	R ² =78
		MDD= 1.45- 2.3gm/cc, OMC= 10-23% and	CBR = -4.8353 - 1.56856 (OMC) +	
		soaked CBR= 1-	4.6351 (MDD) CBR= -3.2353-0.06939 (PI) + 2.8 (MDD)	
		6%.	CBR= 6.5452 - 0.07703(OMC) - 0.10395 (PI)	
12	(Yadav et al, 2014) [18]	Fines(silt&clay)= 76-98%,	CBRs= -3.06 +188.64/LL-24.15/PL+ 38.06/OMC + 0.225 MDD + 0.018/ F	R ² =0.87
		LL= 25-73%, PL= 17-46%,	0.225 MDD + 0.018/ F	
		PI=4.5-34%		
		MDD= 1.5- 1.8gm/cc, OMC= 8-23% and soaked CBR= 1.33-7.5%.		
13	(P.G. Rakaraddi et al,2015) [15]	Gravel= 0-28%, Sand= 0.7-37%,	CBR=-0.26052OMC+5.717093MDD	R ² =0.94 0
		Fine(silt&clay)=20 -91%, LL= 25- 78%, PL= 16-43%,		
		MDD= 1.45- 2.3gm/cc, OMC= 13-30% and soaked CBR= 0.5- 9.2%.		

Where, CBRs= Soaked California Bearing Ratio, CBRu= Unsoaked California Bearing Ratio, D60= Diameter at 60% passing from grain size distribution (in mm), w = Percentage passing No.200 U.S. sieve (in decimal), LL= Liquid Limit of soil (in percent) and C is fraction of soil coarser than 425micron (percent), PL=Plastic Limit, SL=Shrinkage Limit, Ip =PI=Plasticity Index, MDD=Maximum Dry Density, OMC = Optimum Moisture Content (%), cu= undrained cohesion (kPa), qult=Ultimate bearing capacity (in kPa).

2016

3. DATA COLLECTION AND ANALYSIS

3.1 Description of the Study Area

The start of the road at Welkite is located at 8° 16.6 Latitude & 37° 46.4' Longitude and is found 158 km from Addis Ababa, on the Addis Ababa – Jimma trunk road. Whereas the destination point of the project, Hosana is located at 7° 33 'Latitude& 37° 51 'Longitude is 260kms away from Addis Ababa and is on the Addis Ababa –Butajira – Wolayita trunk road. The project road connects three Zones and traverses five rural Woredas and two special Woredas; namely Wolkitie special Woreda, Chaha and Gummer Woredas in Gurage Zone, Mirab Azernet Woreda in Silte zone and Limo Woreda and Hossana special Woreda in Hadya zone.

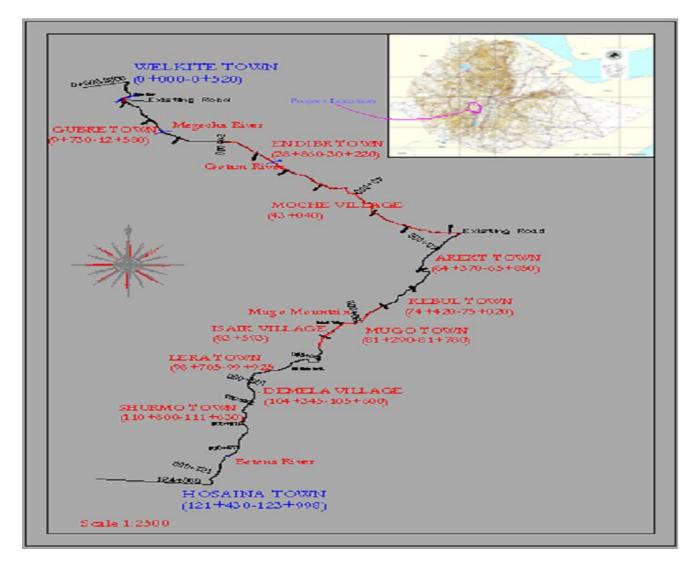


Figure 3. 1Map of study Road[36]

3.2 Source of Data

Soil samples were collected along Welkite-Arekite-Hossana road at different stretch of the roads using borrow pit. The road is 121 km long and located at Southern Nations Nationalities and Peoples Regional State Of Ethiopia. The dominant soil type on the road are red clay and brown to dark clay. The samples tested for different parameters like Atterberg limit test, compaction test, and sieves analysis, CBR tests based on AASHTO standard. The tests carried out with their respective standard numbers are presented below.

- I) Sieve analysis (AASHTO T27)
- II) Atterberg limit test (AASHTO T89-90)
- III) Compaction test (modified proctor test AASHTO T180 D)
- IV) California bearing ratio test (AASHTO T193)

The sieve analysis is done according to AASHTO T 27, Sieve Analysis of Fine and Coarse Aggregates. For sampling , the procedure outlined on AASHTO T2 is strictly followed. Accurate determination of material finer than the No. 200 sieve cannot be achieved by using this method alone. Therefore, test method ND T 11/ AASHTO T11 for material finer than the No. 200 sieve by washing is employed. When working with mixed materials that are coated, lumpy, or baked together, the material is pulverized carefully so as not to break soil grain particles.

Atterberg limit tests carried out according to AASHTO T 89 for determination of the liquid limit of the soil and AASHTO T 90 used for determination of plastic limit of the soil. Before test is undertaken the sample made to pass No.40(0.425mm) sieve according to sample preparation outlined on AASHTO T 87. For determining the water content in the laboratory AASHTO T 265 is used.

A modified proctor test conducted as per AASHTO T 180 D, through which samples compacted at five layers each compacted by 25 uniform blows using 4.54 kg weight of hammer. From the modified proctor test, after plotting moisture-density curve, a range of maximum dry density along with the optimum moisture content were obtained. Similarly, the three point CBR test was carried out, on samples remoulded with OMC using 10, 30 and 65 blows of modified proctor density and soaked for four days.

Different Laboratory tests as mentioned above were performed to characterize soils of the test site. The result obtained for each sample is attached to Appendix C of this thesis. For the sake of illustration, the laboratory test result of the typical sample is presented below from figure 3.1 to figure 3.4

Date :	10/1/2008 E.C	D ₁₀ =0.01		
Sample #:	27	$D_{30} = 0.04$		% Gravel =0.00%
Sample ID:	DO-11	$D_{60} = 0.11$		0.0070
Source:	BOROW PIT	$C_{\rm C} = 1.07$		% Sand =41.10%
Project:	THESIS WORK OF DINO ABDELA	$C_{\rm U}=8.41$	Classification MH, Sandy Elastic	
Location:	DENBER	Liquid Limit=0.59	Silt	% Silt & Clay =58.90%
Boring #:	27.00	Plastic Limit=0.38		
Depth:	1.2M	Plasticity Index=0.21	Fineness Modulus =1.39	

Table 3- 1 Summary	of Atterborg and	l Particla Siz	o Distribution	for Typical Sample
1 able 5- 1 Summary	of Atterberg and	I I al licle Siz	e Distribution	or Typical Sample

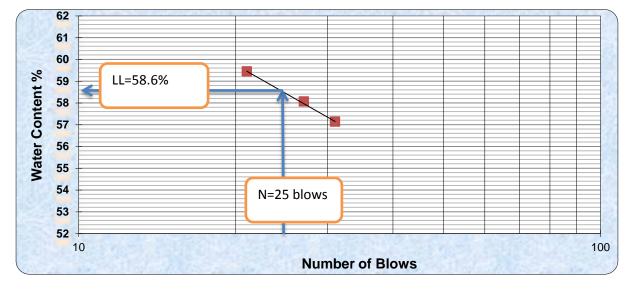
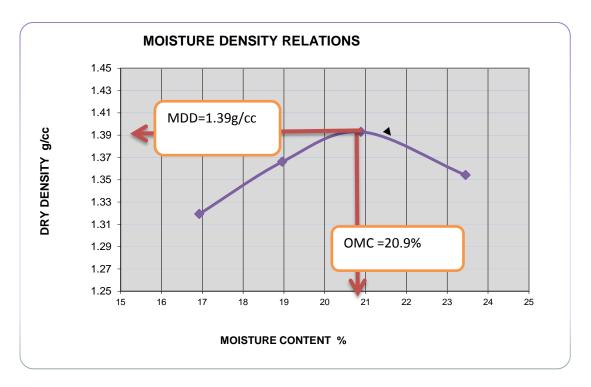
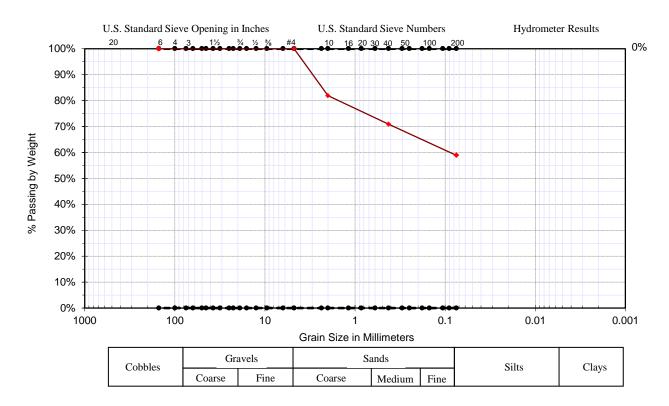


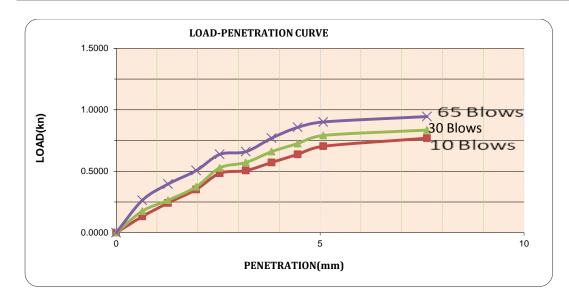
Figure 3. 2Typical flow curve diagram for sample number 27 to determine liquid limit of the sample



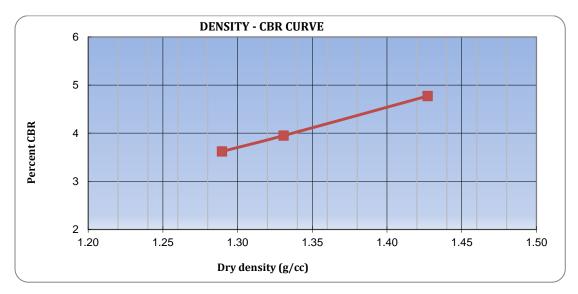








CBR at 95% of MDD (1.33g/cc)=4.2%





2016

Based on the obtained test results of plasticity and grain size distribution the soil classification was made and the result shows that all the sample are classified as fine grained soil according to AASHTO because the fine content on No.200 is greater than 35% for all samples. In accordance to the AASHTO classification system the soil is mainly classified as A-6, A-7-5 and A-7-6 and also based on USCS classification system , 13 samples classified as CL, 10 samples as MH and 5 samples as CH and 2 samples as SM. From the sieve analysis sand content 4% up to 60 % , gravel content from 0% up to 26% ,fine content from 41 % up to 96% is obtained. From Atterberg limit tests, a liquid limit value ranging from 30 up to 84% , plasticity limit value of 16up to 52 and a plasticity index value of 14 up to 39 were obtained. From the compaction test maximum dry density 1.23g/cc up to 1.9 g/cc, optimum moisture content 14% up to 37%. Consequently, after the penetration test were carried out a CBR value ranging from 2.2 % up to 8% is obtained at 95% MDD of modified AASHTO proctor density. The summarized test results presented on Table 3-2 below.

Sample	Sample	G	S	F	LL	PL	PI	MDD	OMC	95%CBR	CLASSIFICA	TION
No.	Code	(%)	(%)	(%)	(%)	(%)	(%)	(g/cc)	(%)	(%)	ASHTTO	USCS
1	AR01	2	8	90	40	22	18	1.61	21.9	4.5	A-6	CL
2	BO03	6	22	72	35	18	17	1.71	18.5	6.4	A-6	CL
3	BS01	0	17	83	67	35	32	1.48	26.2	3.4	A-7-5	MH
4	DE02	0	46	54	57	29	28	1.64	27.4	5	A-7-6	СН
5	DO10	0	16	84	68	29	39	1.53	26.5	2.8	A-7-6	СН
6	RE-18	16	22	62	30	16	14	1.9	17.2	8	A-6	CL
7	DO22	13	29	58	35	18	17	1.8	17.4	5.4	A-6	CL
8	EM02	2	11	87	41	21	20	1.58	20.7	4.3	A-7-6	CL
9	FE01	4	14	82	33	17	16	1.69	19.2	6.8	A-6	CL
10	GE01	0.3	8	92.7	84	52	32	1.3	36.8	2.5	A-7-5	MH
11	GU01	0	14	86	62	36	26	1.46	32	3.8	A-7-5	MH
12	GU02	0	43	57	55	36	19	1.53	22	6.7	A-7-5	MH
13	HO01	17	13	70	33	17	16	1.7	17.9	7.1	A-6	CL
14	HO02	12	16	72	35	18	17	1.72	18.4	6.5	A-6	CL
15	KE-02	3	36	61	59	32	27	1.23	32.8	4	A-7-5	MH
16	KB01	0.2	29	70.8	53	30	23	1.37	29.5	5.6	A-6	MH
17	JO-20	0	35	65	64	27	37	1.41	33	4.4	A-7-6	СН
18	LR01	0	4	96	72	44	28	1.44	26	4	A-7-5	MH
19	LR20	26	17	57	39	20	19	1.7	17.6	7	A-6	CL
20	WE01	0	27	73	55	34	21	1.49	26.3	5	A-7-5	MH
21	WE20	0	42	58	67	45	22	1.38	28	4.5	A-7-5	MH
22	NF04	0	59	41	56	36	20	1.54	25.5	4.3	A-7-5	SM
23	NF05	8	14	78	42	21	21	1.6	21.2	3.5	A-7-6	CL
24	MU01	2	11	87	41	21	20	1.6	20.6	4.2	A-7-6	CL
25	SE01	1	9	90	46	24	22	1.6	22	3.7	A-7-6	CL
26	SE02	13	46	41	35	18	17	1.9	14.6	8	A-6	SM
27	SE28	0	41	59	59	38	21	1.39	20.9	4.2	A-7-5	MH
28	DO-11	0	15	85	41	21	20	1.6	20	5.4	A-7-6	CL
29	TS20	0	19	81	58	25	33	1.46	27.7	2.8	A-7-6	СН
30	TS4	0	15	85	58	28	30	1.39	30	2.2	A-7-6	СН

Table 3- 2Summary of all test results

JIMMA UNIVERSITY, JIMMA INSTITUTE OF TECHNOLOGY

4. REGRESSION AND CORRELATION ANALYSIS

4.1 General Overview

Regression analysis is a statistical technique that is very useful in the field of engineering and science in modelling and investigating relationships between two or more variables. The method of regression analysis is used to develop the line or curve which provides the best fit through a set of data points. This basic approach is applicable in situations ranging from single linear regression to more sophisticate nonlinear multiple regressions. The best fit model could be in the form of linear, parabolic or logarithmic trend. A linear relationship is usually practiced in solving different engineering problems because of its simplicity[4].

In a regression analysis we are dealing with finding the relationship, called the regression function, between one variable \mathbf{Y} , called the dependent variable or the response, and several others variables \mathbf{X} i, called the independent variables or regressors. Regression function also involves a set of unknown parameters β i. If a regression function is linear in the parameters (the β 's but not necessarily in the independent variables) we call it a linear regression model. Otherwise, the model is called non-linear. Linear regression models with one independent variable is referred as simple linear models. But if it has more than one independent variable the model termed as multiple linear regression model[32].

The linear regression model may be expressed using the following equation for 'n' number of observations and for' p' number of independent variables.

The parameter β_0 is the intercept of the function. We sometimes call the other coefficients $(\beta_1, \beta_2, \dots, \beta_p)$ Partial regression coefficients, because b1 measures the expected change in Y per unit change in x1 when x2 is held constant, and b2 measures the expected change in Y per unit change in x2 when x1 is held constant and so forth for other parameters. The symbol on the right side of the equation(ϵ) is a random error with mean zero and (unknown) variance σ^2 . The random errors corresponding to different observations are also assumed to be uncorrelated random variables. The regression coefficients ($\beta_1, \beta_2, \dots, \beta_p$) can be estimated by using the method of least squares [32].

It is important to recognize that regression analysis is fundamentally different from ascertaining the correlations among different variables. Correlation determines the strength of the relationship between variables, while regression attempts to describe that relationship between these variables in more detail [28].

4.1.1 Selection of Variables and Model Building

A very important problem in many applications of regression analysis involves selecting the set of regressor variables to be used in the model. Sometimes previous experience or underlying theoretical considerations can help the analyst specify the set or regressor variables to use in a particular situation. Usually, however, the problem consists of selecting an appropriate set of regressors from a set that quite likely includes all the important variables, but we are sure that not all these candidate regressors are necessary to adequately model the response Y. In such a situation, we are interested in variable selection; that is, screening the candidate variables to obtain a regression model that contains the "best" subset of regressor variables. For making the final model to contain enough regressor variables so that in the intended use of the model perform satisfactory, there are different methods available on literatures [4].

From these methods Stepwise regression is probably the most widely used variable selection technique. The procedure iteratively constructs a sequence of regression models by adding or removing variables at each step. The criterion for adding or removing a variable at any step is usually expressed in terms of a partial F-test. Stepwise regression begins by forming a one-variable model using the regressor variable that has the highest correlation with the response variable Y. This will also be the regressor producing the largest F-statistic .The process may be either forward or backward selection[32].

4.1.2 Adequacy of The Regression Model

Fitting a regression model requires several assumptions. Estimation of the model parameters requires the assumption that the errors are uncorrelated random variables with mean zero and constant variance. Tests of hypotheses and interval estimation require that the errors be normally distributed. In addition, we assume that the order of the model is correct; that is, if we fit a simple linear regression model, we are assuming that the phenomenon actually behaves in a linear or first-order manner. The analyst should always consider the validity of these assumptions to be doubtful and conduct analyses to examine the adequacy of the model that has been tentatively entertained [32].

Several criteria may be used for evaluating and comparing the different regression models obtained. A commonly used criterion are listed below.

4.1.2.1 The Standard Error Statistics

The standard error of a statistic gives some idea about the precision of an estimate. Estimated standard errors are computed based on sample estimates, as population values are not obtainable using sample surveys.

The estimated standard error of a variable with mean \vec{x} and standard deviation of SD is given by[28]

 $\hat{\sigma} = \frac{SD}{\sqrt{n}} - \dots - (4.2)$

Where: $\hat{\sigma}$ =estimated standard error of a sample.

n=sample size

During modelling, a variable that shows the least standard error of estimates is the one to be relatively chosen.

4.1.2.2 Residual Analysis

Analysis of the residuals is frequently helpful in checking the assumption that the errors are approximately normally distributed with constant variance, and in determining whether additional terms in the model would be useful. Residuals that are far outside from the interval from normal probability plots may indicate the presence of an outlier, that is, an observation that is not typical of the rest of the data. Various rules have been proposed for discarding outliers. However, outliers sometimes provide important information about unusual circumstances of interest to experimenters and should not be automatically discarded. [32].

The residual plots usually have the different patterns that may lead us to visualize the behaviour of the regression. One of the Pattern from different cases, the residual plot may represents the ideal situation, or the variance of the observations may be increasing with time or with the magnitude of dependent variable or independent variable. Data transformation can be used for modelling the data which are out of the assumptions if necessary.

4.1.2.3 Coefficient of Determination(**R**²)

A convenient way of measuring how well the regression model performs as a predictor of the dependent variable is to compute the reduction in the sum of squares of deviations that can be attributed to regressor variables and this quantity termed the coefficient of determination, $R^{2}[4]$.

.The value of R2 is always between 0 and 1, because R is between -1 and +1, whereby a negative value of R indicates inversely relationship and positive value implies direct relationship and it is given by the equation[28].

 $R^2 = \frac{SS_R}{SS_T} = 1 - \frac{SS_E}{SS_T} - \dots - (4.3)$

Where:

$$SS_{T} = \sum_{i=1}^{n} (y - \bar{y})^{2}$$
$$SS_{E} = \sum_{i=1}^{n} (y_{i} - \bar{y}_{i})^{2}$$

And $SS_R = SS_T - SS_E$ =regression sum of squares SS_E =error sum of squares SS_T =total sum of squares y_i =ith value of the response variable \bar{y}_i =ith value of the fitted response variable. \bar{y} =average value of the response variable

4.1.2.4 Adjusted R²

Another useful criterion used to check the adequacy of a regression model is using a modified R^2 that accounts the usefulness of a variable in a model. This statistic is called the adjusted R^2 defined as:

 $R_p^2 = 1 - \frac{n-1}{n-pp} (1 - R^2)$ Where: pp=number of regressors in the regression model n=Sample size

 R_p^2 =adjusted coefficient of determination.

Maximizing the value of R^2 by adding variables is inappropriate unless variables are added to the equation for sound theoretical reason. At an extreme, when n-1 variables are added to a regression equation, R^2 will be 1, but this result is meaningless. Adjusted R^2 is used as a conservative reduction to R^2 to penalize for adding variables and is required when the number of independent variables is high relative to the number of cases or when comparing models with different numbers of independents .During regression analysis, a regression model with higher value of adjusted R^2 is usually accepted[28].

4.1.2.5 Pearson Correlation Cofiecients

Pearson's correlation coefficient or simply correlation coefficient, R, measures the strength of linear association between two measurement variables. It is calculated as: [32]

 $R = \frac{cov(x,y)}{sd(x)*sd(y)}$ (4.5)

Where:

 $cov(x, y) = \sum_{i=0}^{n} (x_i - \overline{x})(y_i - \overline{y})$ =covariance of x and y variable

 $sd(x) = \sqrt{\sum_{i=0}^{n} (x_i - \overline{x})}$ =standard deviation of variable x

 $sd(y) = \sqrt{\sum_{i=0}^{n} (y_i - \overline{y})}$ =standard deviation of variable y

The value of R ranges from -1 to +1. A value of the correlation coefficient close to +1 indicates a strong positive linear relationship (i.e. one variable increases with the other) A value close to -1 indicates a strong negative linear relationship (i.e. one variable decreases as the other increases). A value close to 0 indicates no linear relationship; however, there could be a nonlinear relationship between the variables[28].

4.1.3 Hypothesis Testing of Regression

Many problems in engineering require that we decide whether to accept or reject a statement about some parameter. The statement is called a *hypothesis*, and the decision-making procedure about the hypothesis is called *hypothesis testing*. This is one of the most useful aspects of statistical inference, since many types of decision-making problems, tests, or experiments in the engineering world can be formulated as hypothesis-testing problems

The t-test is one of the methods used to accept or reject a given hypothesis. The t- value is simply calculated as

$$t_{value} = \frac{B}{SE} = \frac{coefficient \ of \ a \ variable \ in \ the \ regression \ equation}{standard \ error \ of \ the \ estimated \ coefficient} (4.6)$$

Suppose we want to test the validity of a hypothesis, the hypothesis can be formulated as follows:

$$\begin{cases} H_0: \mu = a \\ H_1: \mu \neq a \end{cases}$$
(4.7)

For an arbitrary population value of a, here H_0 and H_1 are the null hypothesis and alternative hypothesis, respectively. Let α denote the probability of rejecting a true hypothesis (level of significance of the test), then the tabulated t-value (t-tab) that is used to test the importance of a variable in the model is obtained by reading from the t-table with $\alpha/2$ as column an n as row, and α as row and n-1 as column for two and one-sided hypothesis, respectively. Here *n*-1 denotes the degree of freedom.

By continuing in such fashion, it will be decided on the importance of each regression variable in the model. If t-cal exceeds t-tab, then H_1 is accepted; otherwise, the null hypothesis is accepted. If a=0, for instance, accepting H_0 means the particular variable has no importance in explaining.

Nowadays, commercial statistical software can provide p-values. Hence, we may not need ttables for our particular decision. The P-value is the smallest level of significance at which a variable is significant. If p- value is smaller than α , the particular variable is important in explaining the variation of the response in the model. If Z_0 is the computed value of the test statistics, then the p- value is $2[1-\phi(z_0)]$ for two-tailed test. Here, $\phi(z_0)$ is the standard normal cumulative distribution at z_0 .[28]. The p-value for each term tests the null hypothesis that the coefficient is equal to zero (no effect). A low p-value (< 0.05) indicates that you can reject the null hypothesis. In other words, a predictor that has a low p-value is likely to be a meaningful addition to your model because changes in the predictor's value are related to changes in the response variable. Conversely, a larger (insignificant) p-value suggests that changes in the predictor are not associated with changes in the response.

To study the correlation of the study parameters, the CBR value is taken as dependent variable(response) where as LL, PL, PI, Percentage of fine content(F), Percentage of sand content(S), Percentage of gravel content(G), MDD and OMC are treated as regressor(predictor) variables for the tested soils. In this work about 30 samples extracted from the roads section of Welkite-Arekit- Hosana road and various laboratory tests have been done. For achieving the goal of this work the test results taken and different kinds of relationships between CBR and other soil index properties were studied. The scatter plot of the dependent variable CBR with the regressor variable for individual independent variableFigure 4.1 to Figure 4.8 and side by side comparison of the variables is given on Figure 4.9 to 4.10 and shown below.

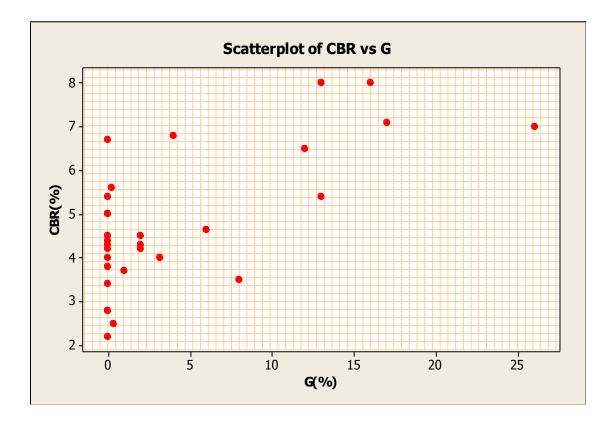


Figure 4.1 Scatter diagram of CBR versus gravel content of the tested soil samples

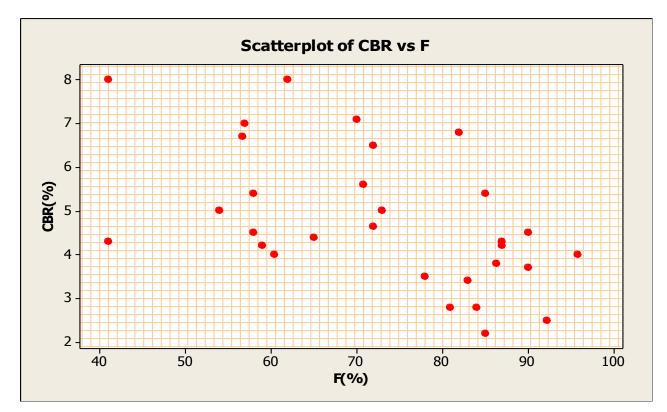


Figure 4. 2 Scatter diagram of CBR versus fine content of the tested soil samples

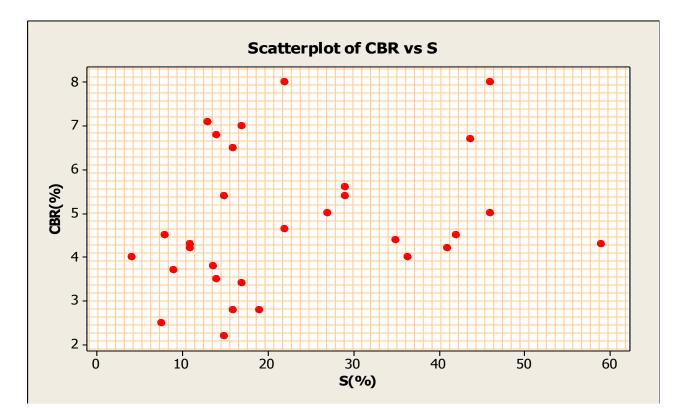


Figure 4. 3 Scatter diagram of CBR versus sand content of the tested soil samples

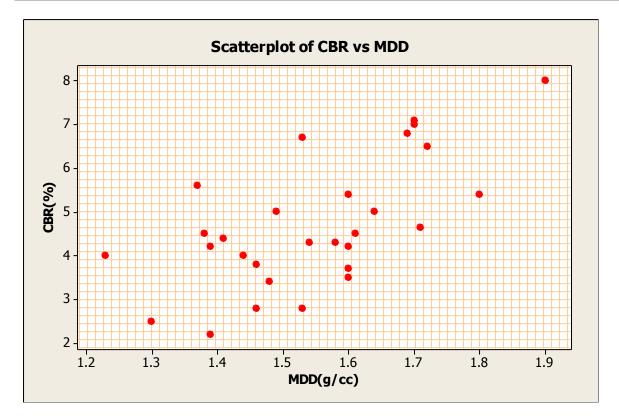


Figure 4. 4 Scatter diagram of CBR versus MDD of the tested soil samples

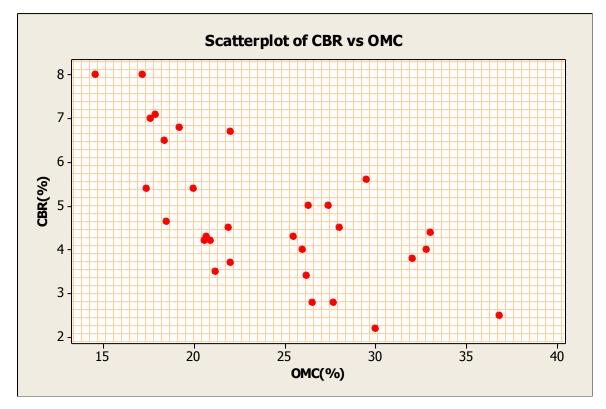


Figure 4. 5 Scatter diagram of CBR versus OMC of the tested soil samples

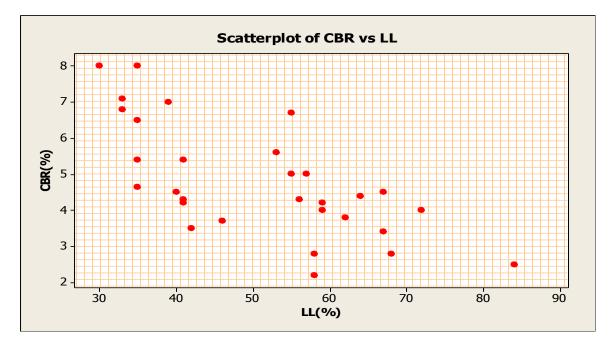


Figure 4. 6 Scatter diagram of CBR versus LL of the tested soil samples

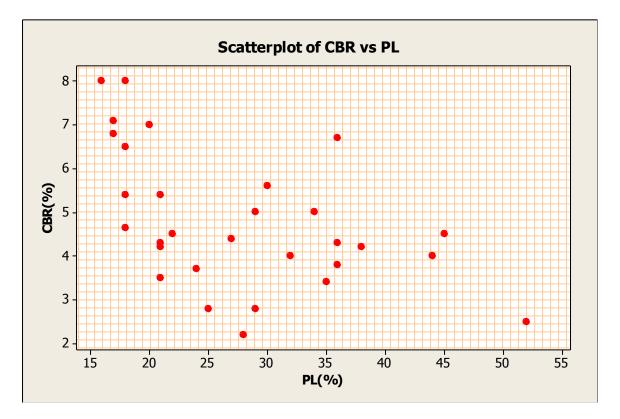


Figure 4.7 Scatter diagram of CBR versus PL of the tested soil samples

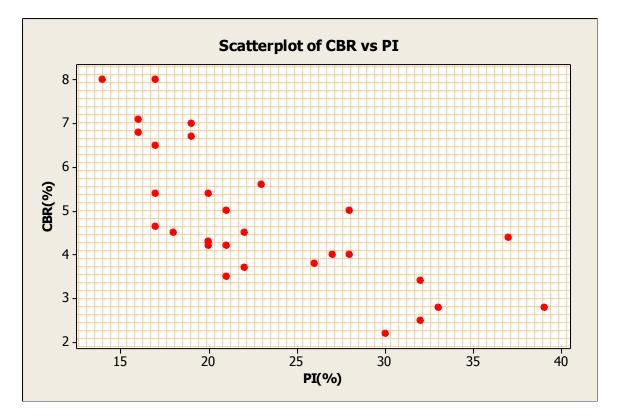


Figure 4. 8 Scatter diagram of CBR versus PI of the tested soil sample

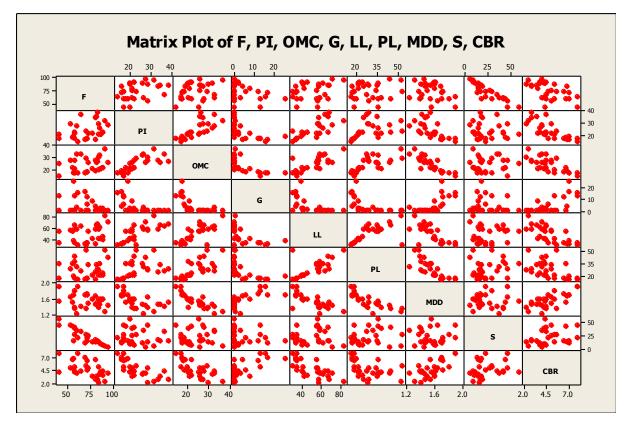


Figure 4. 9 Matrix plot of dependent and independent variable

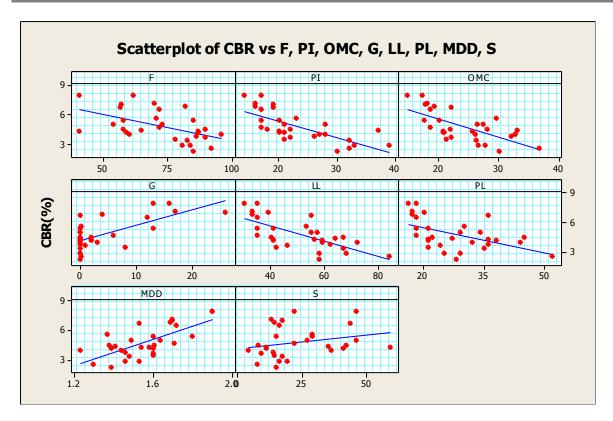


Figure 4. 10 Scatter plot of independent variables with CBR

4.3 Regression analysis

In this research work, an attempt is made to apply single linear regression model and multiple linear regression models to characterize the strength of subgrade soil from soil index parameters using a statistical approach. The general representation of a probabilistic single and multiple linear regression models are presented in the following forms:

 $Y = \beta_0 + \beta_1 x + \varepsilon \quad (4.8)$

$$Y = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 \dots + \alpha_n x_n + \epsilon$$
 (4.9)

Where, the slope (β_1) and intercept (β_0) of the single linear regression model are called regression coefficients. Similarly, coefficients α_0 , α_1 , α_2 and αn are termed multiple regression coefficients. The appropriate way to generalize this to a probabilistic linear model is to assume that the actual value of Y is determined by the mean value function (the linear model) plus the random error term, ϵ [32]. The basic assumption to estimate the regression coefficients of the single and multiple regression models is based on the least square method.

For data analysis of this thesis, commercially available software MINITAB and, a statistical package for social science software (SPSS) is employed to investigate the significance of individual regressor variables. In this study about 30 sample laboratory test results of the independent and dependent variables are used in the following regression analysis. The statistical information's of the test results are presented in Table 4-1:

	Measurment	N	Range	Minimum	Maximu m	Mean		Std. Deviation	Variance
		Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic
F	(%)	30	54.9	41	95.9	72.55	2.77	15.15	229.46
PI	(%)	30	25	14	39	23.07	1.21	6.61	43.72
OMC	(%)	30	22.2	14.6	36.8	23.93	1.03	5.65	31.92
G	(%)	30	26	0	26	4.19	1.23	6.74	45.37
LL	(%)	30	54	30	84	50.67	2.57	14.05	197.40
PL	(%)	30	36	16	52	27.60	1.74	9.51	90.46
MDD	g/cc	30	0.67	1.23	1.9	1.56	0.03	0.16	0.03
S	(%)	30	54.9	4.1	59	23.28	2.59	14.20	201.60
CBR	(%)	30	5.8	2.2	8	4.87	0.29	1.59	2.54
Valid N (listwise)		30							

Table 4- 1 Statistical Information of Dependent and Independent Variables

For determining the influence of one variable on the other, a stepwise linear regression both forward selection and backward methods using both MINITAB and SPSS software has been used and the following correlation coefficients and level of significance determined. Hereunder, the Pearson correlation coefficient matrix is shown in Table 4-2:

				Co	orrelations					
		CBR	PI	MDD	F	OMC	G	LL	PL	S
Pearson	CBR	1.000	743	.724	522	701	.672	713	537	.238
Correlation	PI	743	1.000	646	.306	.779	535	.811	.503	073
	MDD	.724	646	1.000	272	863	.685	824	769	036
	F	522	.306	272	1.000	.240	361	.199	.081	896
	OMC	701	.779	863	.240	1.000	640	.860	.729	.048
	G	.672	535	.685	361	640	1.000	653	592	091
	LL	713	.811	824	.199	.860	653	1.000	.914	.099
	PL	537	.503	769	.081	.729	592	.914	1.000	.196
	S	.238	073	036	896	.048	091	.099	.196	1.000
Sig. (1-tailed)	CBR		.000	.000	.002	.000	.000	.000	.001	.102
	PI	.000		.000	.050	.000	.001	.000	.002	.351
	MDD	.000	.000		.073	.000	.000	.000	.000	.426
	F	.002	.050	.073		.100	.025	.146	.334	.000
	OMC	.000	.000	.000	.100		.000	.000	.000	.401
	G	.000	.001	.000	.025	.000		.000	.000	.317
	LL	.000	.000	.000	.146	.000	.000		.000	.302
	PL	.001	.002	.000	.334	.000	.000	.000		.149
	S	.102	.351	.426	.000	.401	.317	.302	.149	

Table 4- 2Correlation Matrix of Pearson Correlation Coefficient

Based on the above correlation result, using Pearson correlation coefficient and significance level of the parameters there is a linear relationships between CBR and liquid limit. plasticity index and maximum dry density, optimum moisture content, and gravel content has relatively higher correlation coefficient with significance value less than 0.05. The negative sign before the Pearson coefficient indicate that the assumed parameters have opposite effect on the other parameters. For instance, the reason correlation coefficient between CBR and PI it is negative 0.743. That means for one unit increase in the value of PI, the response will be 74.3 percent decrease on the value of CBR based on this statistical result. Basically, the strength of fine grained soil has a greater association with the consistency of the soil. As a result, liquid limit and plasticity index has resulted relatively a better correlation with the strength parameter. However, the correlation with plastic a weak relationship, this is may be due to the inconsistency in limit shows relatively conducting laboratory plastic limit test and inadequacy of the number of trials considered in the test procedures. Besides, in this research work the percentage of gravel content and maximum dry density has resulted relatively higher positive correlation coefficient with the strength parameter for fine grained soil, this is due to the presence of more silty soils and some granular materials blended with the fine soils.

Different alternatives and analysis procedures used during data analysis to develop the correlation using regression methods. For this specific thesis work linear regression analyses that best fits the obtained test results have been considered. The detail outputs of the SPSS and MINITAB Software for the single and multiple linear regression analysis is presented under Appendix A of this thesis and also the summarized correlation results are presented on the next sections.

4.3.1 Single Linear Regression Analysis

Model A-1: Correlation Between CBR and Percentage of Fine (F)

Based on the resulting regression analysis for correlating CBR with F is expressed by the following single linear equation with its corresponding correlation coefficients:

CBR = 8.849 - 0.55F, with R²= 0.272, for N=30-----(4.9)

The negative sign indicates that if percentage of fine content increase the value of CBR tends to decrease. The details of the statistical out-put indicates that the relationship developed between fine content(F) and CBR is significant (α <0.05) as shown in Model A-1of Appendix A.

Model A- 2: Correlation Between CBR and Percentage of Sand (S)

Based on the resulting regression analysis after correlating CBR with sand content (s), it is observed that the result is statistically not significant (α >0.05). The developed equation is as follow and the details of the statistical out-put is shown on Model A-2 of Appendix A. CBR = 4.242 + 0.27S with R²=0.057 N=30------(4.10) Model A- 3: Correlation Between CBR and Percentage of Gravel (G)

After correlating CBR with percentage of gravel ,the following correlation developed. It is observed that the correlation coefficient is positive. It indicates there is a positive relationship between them. Even though the soil under study is mainly fine grained soil ,there might be a granular soil blended during sampling since it is extracted from the road subgrade. The correlation developed is presented below.

CBR = 4.201 + 0.159G with $R^2 = .451$ N=30------(4.11)

The details of the statistical out-put indicates that the relationship developed between G and CBR is significant ($\alpha < 0.05$) and the detail shown on Model A- 3 of Appendix A.

Model A- 4: Correlation Between CBR and Plastic Limit (PL)

Based on the resulting regression analysis for correlating CBR with PL, It is observed that the best fit between CBR and PL is using linear polynomial regression and the result obtained is Presented below

 $CBR = 37.696 - 3.133PL + 0.094PL^2 - 0.001PL^3$ with $R^2 = 0.627$ N=30------(4.12)

The details of the statistical out-put indicates that the relationship developed between fine content(F) and CBR is significant ($\alpha < 0.05$) as shown in Model A- 4of Appendix A.

Model A- 5: Correlation Between CBR and Plasticity Index (PI)

The resulting regression analysis after correlating CBR with PI is expressed by the following Quadratic linear regression model with its corresponding correlation coefficients:

The details of the statistical out-put indicates that the relationship developed between PI and CBR is significant ($\alpha < 0.05$) as shown in Model A-5 of Appendix A.

Model A- 6: Correlation Between CBR and Liquid Limit(LL)

The resulting regression analysis after correlating CBR with LL is expressed by the following Two linear equation which are almost approaches each other and the corresponding correlation with coefficients presented below.

CBR = 21.125 - 4.182 Ln(LL) with $R^2 = 0.543$ and ------(4.14)

$$CBR = 8.967 - 0.081LL$$
 With R²=0.503 N=30-----(4.15)

The details of the statistical out-put indicates that the relationship developed between LL and CBR is significant for both case ($\alpha < 0.05$) and the detail is given on Model A- 6of Appendix A.

Model A- 7: Correlation Between CBR and Maximum Dry Density (MDD)

The resulting regression analysis after correlating CBR with MDD is expressed by the following single linear equation with its corresponding correlation coefficients:

CBR = -6.087 + 7.029 * MDD, with $R^2 = 0.524$, n = 30------(4.15)

The details of the statistical out-put indicates that the relationship developed between MDD and CBR is significant (α <0.05) as shown in Model A- 7of Appendix A.

Model A- 8: Correlation Between CBR and Optimum Moisture Content (OMC)

The resulting regression analysis after correlating CBR with OMC is expressed by the following Quadratic linear regression equation with its corresponding correlation coefficients:

 $CBR = 18.369 - 0.9340MC + 0.0150MC^2$ with $R^2 = 0.582$ N=30------(4.16)

The details of the statistical out-put indicates that the relationship developed between OMC and CBR is statistically significant ($\alpha < 0.05$) and the detail is given on Model A-8of Appendix A.

From the above developed single linear regression models, based on the significant standard error (α) and coefficient of determination (\mathbb{R}^2), it was noted that the CBR value correlates relatively better with Gravel content, optimum moisture content, liquid limit, plasticity index, plastic limit and maximum dry density which is an indication for these variables to form the multiple regression variables that could yield a better correlation result. While the remaining parameters showed a weak relationship with CBR.

4.3.2 Multiple Linear Regression Analysis

In order to develop multiple linear regression model for the subject study, stepwise regression analysis is used using commercially available softwares MINITAB, SPSS and MICROSOFT EXCEL (Analysis tool pack VBA). After going through a number of alternative combinations of predictors the following correlation results are obtained as presented below

Model B-1: Correlation Between CBR with and Grain Size Analysis

The resulting regression analysis after correlating CBR with Percentage of gravel(G), percentage of sand (s) and percentage of fine (F) is expressed by the following multiple linear equations with its corresponding correlation coefficients:

$$CBR = 0.121G + 0.068S + 0.034F$$
 with $R^2 = 0.956$, Adj. $R^2 = 0.916$, $N = 30$,-----(4.17)

The details of the statistical out-put of Model A indicates that the relationship developed between CBR with grain size analysis is significant ($\alpha < 0.05$) and all predictor variables are significant($\alpha < 0.05$). Besides, the R² value of the multiple regression

analysis is better than the R^2 value of the individual parameters. For instance, the prediction capacity of sand on single linear analysis was not significant but now become significant when combined with parameters F and G. For further reference, the detail of Model B-1 is shown in Appendix B.

Model B-2: Correlation Between CBR with Atterberg Limit

The resulting regression analysis after correlating CBR with Atterberg limit (PI, LL, and PL) is found to be not significant for assumed significant level(α <0.05). The individual predicting capacity on single linear regression analysis is now changed .that may be combination effect of the other parameter. The only significant term while combining PI with PL and PI with LL is PI. The relationship using PL and LL is also not significant .Therefore the developed relationship is not presented here .

The statistical out-put of Model B indicates that the relationship developed between CBR with PI and LL, LL and PL, and PL and LL is not significant . Because α values for individual predictor is not significant rather than PI. The statistical output for the three alternative model is given on Appendix Bof this thesis under CATEGORY II

Model B-3: Correlation Between CBR with Compaction Parameters

The resulting regression analysis after correlating CBR with optimum moisture content and maximum dry density is expressed by the following multiple linear equations with its corresponding correlation coefficients:

CBR = 4.450MDD - 0.0860MC with R²=0.957 and Adj. R²=0.920, N=30-----(4.18)

The details of the statistical out-put of Model B-3 indicates that the relationship developed between CBR with OMC and MDD is significant ($\alpha < 0.05$) for both predictors. Besides, the R2 value of single linear regression analysis is also improved for the developed multiple regression model using MDD and OMC .The statistical out put is given on the AppendixB.

Model B-4: Correlation Between CBR with Grain Size Analysis, Atterberg Limit And Compaction Parameters(G, F, S, LL, PI, PL, OMC and MDD)

After going through a number of alternative combinations of predictors from Grain size analysis, compaction parameters, and Atterberg limit the following correlation results are obtained and The resulting regression analysis after correlating CBR with LL, PL, PI, OMC, G, S, F and MDD which are significant are summarized as shown on the Table 4-3

MODEL NO.	PRIDICTORS	EQUATION DEVELOPED	R ²	$\begin{array}{c} Adj. \\ R^2 \end{array}$	STANDARD DEVIATION
B-4-1		CBR=5.34MDD-0.026F-0.069PI	0.973	0.933	0.885
		CBR=3.591-0.031F+3.707MDD-			
B-4-2	F, MDD, PI	0.098PI	0.731	0.701	0.873
B-4-3		CBR=0.084S+0.048LL	0.798	0.756	2.374
B-4-4	LL, S	CBR=8.329+0.035 S-0.084LL	0.604	0.575	1.039
B-4-5		CBR=4.634MDD-0.102PI	0.967	0.93	0.973
B-4-6	MDD, PI	CBR=1.15+4.069MDD-0.114PI	0.653	0.628	0.972
B-4-7		CBR=8.974+0.036S-0.201 OMC	0.564	0.532	1.089
B-4-8	S, OMC	CBR=0.150 S+0.114 OMC	0.817	0.775	2.263
B-4-9		CBR=0.15G+0.258OMC	0.903	0.864	1.643
B-4-10	G, OMC	CBR=7.59-0.129OMC+0.89G	0.575	0.543	1.07
		CBR=6.75+0.033S-			
B-4-11		0.128OMC+0.097G	0.662	0.623	0.97
B-4-12	G, S, OMC	CBR=0.054 S+0.102 OMC+0.239G	0.927	0.884	1.45
B-4-13	MDD,F	CBR=5.171-0.044F	0.965	0.962	0.990

Table 4 2The Jameland		CDD and Indan	
Table 4- 3The developed	correlation between	UBK and Index	propertie of soli

From the above results the following correlation that are fitted with constant (intercept) are grouped on the same category and the other correlations without including intercept grouped on the other category. Based on the coefficient of determination and standard error the following equations selected with R^2 decreasing order for models fitted with including intercept.

1.	$CBR = 3.591 - 0.031F + 3.707MDD - 0.098PI$ with with $R^2 = 0.73$ (4.19)
2.	$CBR = 6.75 + 0.033S - 0.1280MC + 0.097G$ with $R^2 = 0.662$ (4.20)
3.	$CBR = 1.15 + 4.069MDD - 0.114PI$ with $R^2 = 0.653$ (4.21)
4.	$CBR = 8.329 + 0.035 S - 0.084LL$ with $R^2 = 0.604$ (4.22)
5.	$CBR = 7.59 - 0.1290MC + 0.89G$ with $R^2 = 0.575$ (4.23)
6.	$CBR = 0.15G + 0.2580MC$ with $R^2 = 0.564$ (4.24)

The statistical details of the above correlations under this section are shown in Appendix B

From models fitted without intercept model B-4-1,B-4-5, and model B-3 takes one to third rank. From those models Model B-4-1 without intercept and model B-4-2 with intercept is selected.

5. DISCUSSION ON CORRELATION RESULTS

5.1 The Developed Correlation

From the regression analysis it is observed that multiple linear regression have fairly good coefficient of determination than single linear regression analysis .Two models selected from the developed correlation that have higher coefficient of determination and based on relative significance order using standard error for further verifications.

The selected models are Model B-4-1 (CBR = 5.34MDD - 0.026F - 0.069PI With R² =0.973 and standard error =0.885) and Model B-4-2(CBR = 3.591 - 0.031F + 3.707MDD - 0.098PI with R²=0.731 and standard error =0.873). Both equations contain grain size distribution parameters(F), compaction parameter (MDD) , and Atterberg limit parameter (PI). The difference between this two model is the method of data fitting used. The first model is fitted without including the constant(intercept) while the later includes.

The validation of the correlation developed with the actual test data is studied and presented on Table 5-1

Sample code	G	S	F	LL	PL	PI	MDD	ОМС	CBR	CBR From Model B-4- 1	CBR From Model B-4- 2
AR01	2	8	90	40	22	18	1.61	21.9	4.5	5.02	5.01
BO03	6	22	72	35	18	17	1.71	18.5	6.4	6.09	6.03
BS01	0	17	83	67	35	32	1.48	26.2	3.4	3.54	3.37
DE02	0	46	54	57	29	28	1.64	27.4	5	5.42	5.25
DO10	0	16	84	68	29	39	1.53	26.5	2.8	3.30	2.84
RE-18	16	22	62	30	16	14	1.9	17.2	8	7.57	7.34
DO22	13	29	58	35	18	17	1.8	17.4	5.4	6.93	6.80
EM02	2	11	87	41	21	20	1.58	20.7	4.3	4.80	4.79
FE01	4	14	82	33	17	16	1.69	19.2	6.8	5.79	5.75
GE01	0.3	7.6	92.3	84	52	32	1.3	36.8	2.5	2.33	2.41
GU01	0	13.6	86.4	62	36	26	1.46	32	3.8	3.76	3.78
GU02	0	43.7	56.7	55	36	19	1.53	22	6.7	5.39	5.64
HO01	17	13	70	33	17	16	1.7	17.9	7.1	6.15	6.15
HO02	12	16	72	35	18	17	1.72	18.4	6.5	6.14	6.07
KE-02	3.2	36.4	60.45	59	32	27	1.23	32.8	4	3.13	3.63
KB01	0.2	29	70.8	53	30	23	1.37	29.5	5.6	3.89	4.22
JO-20	0	35	65	64	27	37	1.41	33	4.4	3.29	3.18
LR01	0	4.1	95.9	72	44	28	1.44	26	4	3.26	3.21
LR20	26	17	57	39	20	19	1.7	17.6	7	6.29	6.26
WE01	0	27	73	55	34	21	1.49	26.3	5	4.61	4.79
WE20	0	42	58	67	45	22	1.38	28	4.5	4.34	4.75

 Table 5- 1Validation of CBR From Correlation Developed With The Actual Test Data

JIMMA UNIVERSITY, JIMMA INSTITUTE OF TECHNOLOGY

A STUDY ON CORRELATION OF CALIFORNIA BEARING RATIO WITH INDEX PROPERTIES OF SOIL WELKITE-AREKIT- HOSANA ROAD AS CASE STUDY 2016

NF04	0	59	41	56	36	20	1.54	25.5	4.3	5.78	6.07
NF05	8	14	78	42	21	21	1.6	21.2	3.5	5.07	5.05
MU01	2	11	87	41	21	20	1.6	20.6	4.2	4.90	4.87
SE01	1	9	90	46	24	22	1.6	22	3.7	4.69	4.58
SE02	13	46	41	35	18	17	1.9	14.6	8	7.91	7.70
SE28	0	41	59	59	38	21	1.39	20.9	4.2	4.44	4.86
DO-11	0	15	85	41	21	20	1.6	20	5.4	4.95	4.93
TS20	0	19	81	58	25	33	1.46	27.7	2.8	3.41	3.26
TS4	0	15	85	58	28	30	1.39	30	2.2	3.14	3.17

In addition to the above tabular comparison, scatter plot of the actual CBR Versus the two chosen model is done using commercially available software MINITAB and the out put is shown on the following consecutive figures. The first two figures drawn to relate as individual effect to CBR. While the later is drawn for comparing side by side if the relationship is valid. The statistical output from MINITAB indicates the Model B-4-2 perform well in fitting the actual CBR with coefficient of determination (R^2 =73.4%) while model B-4-1 fits with R^2 =71.2.%. From these results it can be concluded that Model B-4-2 is better in representing the subject under study. Hence from now on the discussion on the next parts are based on this model. To clarify this the linear relationship between the developed and actual CBR is given below on the following equations .

Actual CBR = 0.0132 + 0.9990 pridicted CBR from Model B - 4 - 2 with R²=0.734-(5.1)

Actual CBR = 0.1894 + 0.9657 pridicted CBR from Model B - 4 - 1 with R² = 0.712 - (5.2)

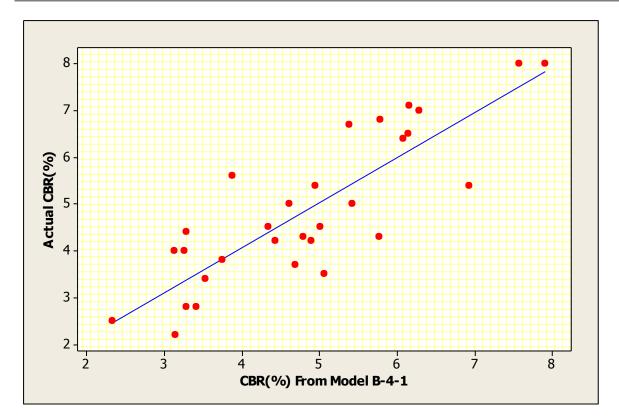


Figure 5. 1Scattor plot between Actual CBR wit Pridicted CBR from model B-4-1

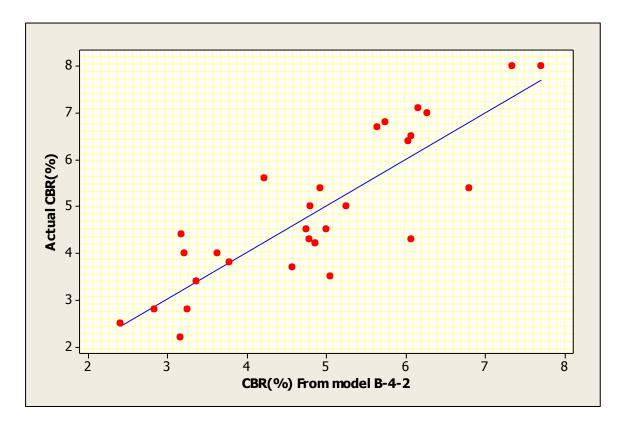


Figure 5. 2Scatter plot between Actual CBR with Predicted CBR from model B-4-2

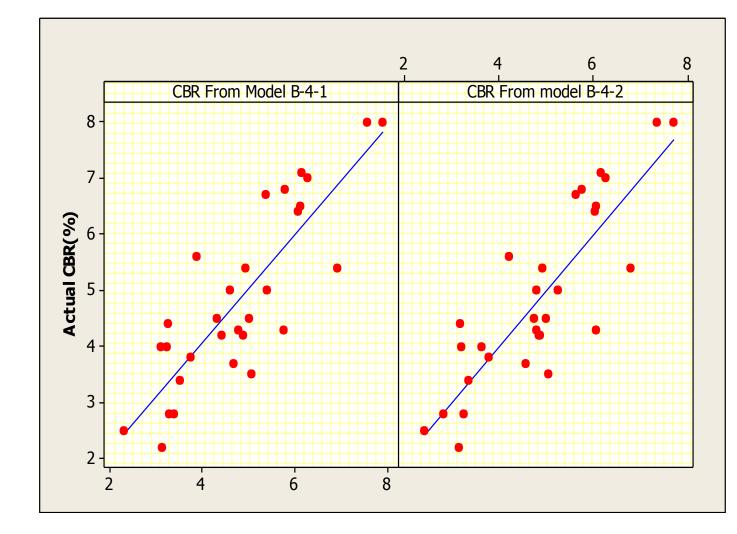


Figure 5. 3Side By Side Scatter Plot Comparison Between Actual CBR With Predicted

2016

5.2 Evaluation of the Developed Correlation

5.2.1 Evaluation of the Developed Correlation with Control Tests

In this thesis about seven separate control samples prepared and tested in laboratory to check the suitability of the developed model from other soil samples extracted from the road under study other than using the sample used in model development. The control samples laboratory result details and the CBR obtained from the developed model is given in the following table.

Sample code	G	S	F	LL	PL	PI	MDD	OMC	CBR	CBR From Model B-4-2	VARIATION %
cs1	13	41	46	64	27	37	1.405	31.7	4.8	3.75	/-21.93/
cs2	8	39	53	54	30	23	1.523	23.2	2.9	5.34	84.13
cs3	7	40	53	59	33	26	1.38	33.3	7.9	4.52	/-42.84/
cs4	2	16	82	35	18	17	1.703	19.2	3.7	5.70	53.95
cs5	22	18	60	32	17	15	1.8	16.9	5.7	6.93	21.64
cs6	0	9	91	56	31	25	1.51	25.1	3.2	3.92	22.42
cs7	1	15	84	71	27	43	1.535	19.8	3.4	2.46	/-27.55/
										AVERAGE %	39.2

Table 5- 2Evaluation of the Developed Correlation with Control Tests

The above control tests data's taken from the project of Welkite to Hosana road construction project for validation purpose. The laboratory tests and sampling of the control samples taken at different seasons during site investigation as observed from the project site investigation report. The samples location is different from the samples used for this study. From above table, control sample two shows wider variation (84.13%) compared to the predicted value. This may be due to the location of the test pit different from the samples considered in the correlation and seasonal variations. Since the soil vary from place to place and season to season, it may have different properties. On the other hand, CS1,CS5,CS6 and CS7 have a variation of 21-28%. This may be due to the location of sampling approaches to where the samples recovered and have nearly the same properties with the samples considered in the regression analysis. The other control test also shows more than 40% variation. The test shows an average variation of 39.2%. This indicates the correlation can be used for rough estimation purpose only.

In general we can conclude that even though the statistical regression analysis shows the correlation may give 73.2% accuracy in determination of the CBR, there must be a detail study in using the correlation for practical purpose and as a reference. Before using this correlation it must be checked with different soil and seasons. It also needs modification with large number of samples and advanced methods rather than simple correlation analysis.

5.2.2 Evaluation of the Developed and Existing Correlations

The suitability of existing correlations particularly the Yared Leliso[4] for CBR 2.2-10%, NCHRP's correlation for plastic soils and more than 12% fines passing 0.075 mm sieve.and Agarwal and Ghanekar's fine grained soil, Patel and Desai 2010 [21] that is chosen because it will perform well for Ethiopian soil as studied by Kumar et al (2014)[33].Therefore the comparison of calculated results of the correlations which are obtained by using the test results are shown in Table 5-3:

Sample No.	o. CBR 4-2			NCHRP[7	7]	Agarwal Ghanekar,	and 1970)[20]	(Patel &Desai,2	010)[21]	Yared Leliso,	2013[4]
		Pridicted CBR	variation(%)	Pridicted CBR	variation(%)	Pridicted CBR	variation(%)	Pridicted CBR	variation(%)	Pridicted CBR	variation(%)
1	4.5	5.01	11.23	5.86	30.22	12.58	179.58	5.25	16.66	8.27	83.84
2	6.4	6.03	-5.75	7.57	18.24	13.75	114.84	4.51	-29.49	10.45	63.27
3	8	7.34	-8.25	10.25	28.09	14.25	78.16	1.62	-79.70	14.72	84.02
4	5.4	6.80	25.92	9.17	69.83	14.18	162.51	3.16	-41.46	12.27	127.24
5	4.3	4.79	11.42	5.49	27.62	12.97	201.70	6.00	39.46	7.39	71.83
6	6.8	5.75	-15.50	7.11	4.53	13.49	98.39	4.77	-29.92	10.19	49.81
7	2.5	2.41	-3.49	3.33	33.32	9.01	260.21	5.18	107.16	-0.05	-102.11
8	3.8	3.78	-0.61	4.32	13.73	9.96	162.13	4.21	10.82	4.07	7.22
9	6.7	5.64	-15.78	8.48	26.59	12.56	87.46	6.63	-1.07	6.47	-3.41
10	7.1	6.15	-13.31	8.19	15.40	13.98	96.87	4.98	-29.89	10.39	46.34
11	6.5	6.07	-6.63	7.57	16.42	13.79	112.11	4.36	-32.99	10.65	63.87
12	4	3.63	-9.23	5.82	45.55	9.79	144.68	8.19	104.77	-0.71	-117.75
13	5.6	4.22	-24.63	5.83	4.19	10.52	87.86	6.95	24.12	2.69	-51.96
14	4.4	3.18	-27.80	4.05	-7.90	9.75	121.56	3.82	-13.21	1.55	-64.79
15	4	3.21	-19.70	3.65	-8.75	11.41	185.27	6.25	56.23	3.37	-15.87
16	7	6.26	-10.52	8.44	20.60	14.10	101.42	4.79	-31.55	9.96	42.30
17	5	4.79	-4.13	6.17	23.35	11.32	126.38	5.87	17.38	5.39	7.75
18	3.4	3.37	-0.93	3.69	8.47	11.35	233.94	5.06	48.95	3.64	7.12
19	5	5.25	5.05	6.25	24.92	11.04	120.72	2.06	-58.76	7.46	49.18
20	2.8	2.84	1.31	3.02	7.79	11.28	302.70	3.38	20.78	3.69	31.87
21	4.5	4.75	5.61	7.29	61.98	10.89	142.05	7.32	62.62	2.99	-33.61
22	4.3	6.07	41.13	10.76	150.26	11.53	168.25	5.27	22.54	6.53	51.95
23	4.2	4.86	15.64	7.49	78.22	12.92	207.59	9.41	124.06	3.35	-20.21
24	3.5	5.05	44.18	5.80	65.80	12.81	265.94	5.37	53.55	7.65	118.67
25	4.2	4.87	15.84	5.49	30.66	13.01	209.69	5.65	34.57	7.79	85.56
26	3.7	4.58	23.68	4.87	31.50	12.55	239.28	5.03	36.08	7.50	102.82
27	8	7.70	-3.78	12.35	54.34	15.39	92.44	2.15	-73.18	14.30	78.70
28	5.4	4.93	-8.76	5.61	3.83	13.21	144.67	5.84	8.09	7.79	44.32
29	2.8	3.26	16.37	3.67	30.92	10.96	291.46	4.88	74.46	3.13	11.69
30	2.2	3.17	44.03	3.83	74.25	10.41	373.03	5.77	162.26	2.12	-3.58
Average(%)			2.75		32.80		170.43		20.11		27.20

Table 5- 3Comparison of The Developed and Existing Correlations

JIMMA UNIVERSITY, JIMMA INSTITUTE OF TECHNOLOGY

Furthermore the comparison of CBR predicted from existing and developed model is given on figure 5.5.

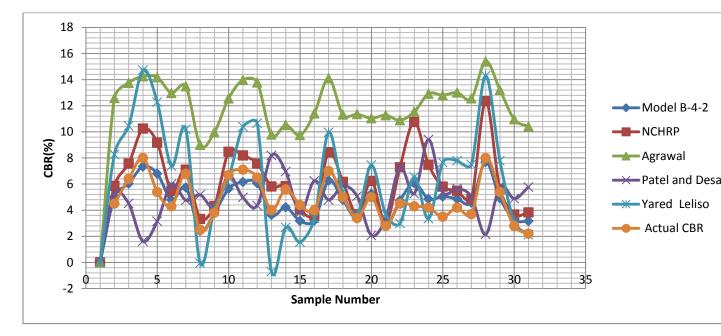


Figure 5. 4Graphical comparison of the developed model with previous correlations

As shown in Figure 5.4 and 5.5, it can be concluded that the control samples actual CBR have 12.83% variation from the newly developed model CBR value. This shows the new model may approximate the value of CBR with lesser error for rough estimation fro the soils that have the same range of Atterberg , compaction and gradation values which are used in the correlation development. In dealing the soil samples used in model development , the newly developed model B-4-2 have CBR value with variation of 3% compared to actual CBR vale. Next to model B-4-2 ,Patel and Desai 2010 [21], Yared Leliso[4] , NCHRP's have relatively good relationship to the Actual CBR. However, CBR predicted from Agrawal [20] is higher than the actual. it is magnified about 170%, it almost entirely overestimating the actual CBR value. Even though this CBR is higher , it almost exactly follow the trend line of actual CBR . However the CBR predicted from Yared[4] fluctuates much even though the average variation found to be 27% ,the NCHRP's , correlation resulted an average variation of 33% from the actual CBR values. Similarly, the Patel[21] correlation resulted average variation of 20% .

As observed above, the predicted CBR from Yared [4] correlation shows about three samples have negative value .This is may be due to the difference in test procedures and also the unique properties of the geological material where this correlation was developed. In light of the above, it is worth to note that the test results obtained from the subject study area are relatively situated better to Patel and Desai 2010 [21] in addition to developed correlation.There is a correlation from the above discussed model other than Agrawal [20] .which is following the trend line but have very high CBR value.

6. CONCLUSION AND RECOMMENDATION

6.1 Conclusions

The research was conducted to study correlation between California bearing ratio (CBR) value and index properties of soil. To achieve the objectives of the study, soil samples retrieved from different areas along Welkite-Arekit- Hosana road of Southern Nation Nationalities Peoples and Regional State of Ethiopia. About thirty samples extracted from the road section and different laboratory testes were carried out. Using this test results statistical analysis is carried out. A single and multiple linear regressions were conducted and a relationship was developed that predict the CBR values of a soil in terms of percentage of fine (F), sand (s), gravel content(G), LL, PL, PI, MDD and OMC.

From the results of this study the following conclusions are drawn:

- 1. From the single linear regression it is observed that the effect of fine , plasticity index, liquid limit, plastic limit and optimum moisture content have negative effect on CBR. That means if fine content , liquid limit, plastic limit , plasticity index, optimum moisture content tends to increase, the CBR value tends to decrease. Therefore, from this it can be concluded that the presence of much fine particles , high water content and plasticity affect soil strength.
- 2. It is observed that increasing maximum dry density and percentage of gravel content have positive effect on CBR value. For instance, if MDD or G increases CBR tends to increase. This shows coarser materials and high density soils gives better strength.
- 3. Among the single linear regression analysis the correlation between CBR and plasticity index has better correlation than other predicting parameters which is expressed in the following relationship:

 $CBR = 17.227 - 0.867 * PI + 0.013PI^2$ with $R^2 = 0.682$, n = 30

4. Relatively an improved correlation than the single regression is obtained when multiple regression is used as given below:

CBR = 3.591 - 0.031F + 3.707MDD - 0.098PI with $R^2 = 0.731$, n=30

From this combination of soil index properties (grain size analysis, Atterberg limit, and compaction parameters) correlates better than individual soil properties.

5. From control tests the predicted CBR have an average variation of 39.2% compared to the actual CBR. This indicates the correlation can be used for rough estimation purpose only and it can be concluded that even though the statistical regression analysis shows the correlation may give 73.1% accuracy in determination of the CBR, there must be a detail study in using the correlation for practical purpose and as a reference. Before using this correlation it must be checked with different soil and seasons. It also needs modification with large number of samples and advanced methods rather than simple correlation analysis.

6. From existing correlations Patel and Desai 2010 [21], NCHRP[7] demonstrated a better estimation. and followed the trend line of actual CBR value whereas Agrawal [20] over estimated.

6.2 Recommendations

The following points are some of the recommendations given by the researcher in relation to the subject study:

- 1. It is advisable to conduct frequent researches in different types of of soil, due to the fact that soil property vary from place to place and seasonally.
- 2. It is important to conduct comparative correlations between soaked and unsoaked CBR value with soil index properties.
- 3. Finally, it is important to study Ethiopian soil using advanced methods like Artificial Neural network methods other than using simple regression analysis by collecting different soil property data's available in to national database system for further study.

REFERENCES

[1] AASHTO: Standard Specifications for Transportation Materials and Methods of Sampling and Testing, Part II Methods of Sampling and Testing. 25thEdition. American Association of State Highway and Transportation Officials, Washington 2005.

[2] E. J. Yoder and M. W. Witczak, "Principles of pavement design" 2nd Ed. New York: John Wiley & Sons, 1975.

[3] Muni Budhu , "Soil Mechanics and Foundations", 3rd Ed. New York: John Wiley & Sons, 2011.

[4] YaredLeliso(2013) . "Correlation of CBR Value With Soil Index Properties f or Addis Ababa Subgrade Soils," Thesis Work, Addis Ababa University, Addis Ababa, Ethiopia.

[5]Paul W.M. and et.al, Subsurface Investigations (Geotechnical Site Characterization),FHWANHI-01-031, technical report, National Highway Institute Federal Highway Administration U.S. Department of Transportation, Ryan R. Berg & Associates Inc., Woodbury, USA, May 2002.

[6]Arora, K.R., Soil Mechanics and Foundation Engineering, Re-print Standard Publishers Distributer, NaiSarak, Delhi, 2004.

[7]National Cooperative Highway Research Program, Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement Structures, Correlation of CBR Values with Soil Index Properties, NCHRP, Transportation Research Board, National Research Council, Washington DC, 2004.

[8] Yitagesu Desalegn (2012).Developing Correlations between DCP and CBR for Locally Used Sub grade Materials, Thesis Work, Addis Ababa University, Addis Ababa, Ethiopia.

[9] Mittal,S.and Shukla,J.P., SoilTesting for Engineers, Romesh Chander KhannaPublishers Delhi (India), 2000.

[10] M. P. Rollings and R. S. Rollings, "Geotechnical materials in construction" McGraw-Hill, New York, 1996.

[11] P. M. Semen, "A generalized approach to soil strength prediction with machine learning methods" Technical Report ERDC/CRREL TR-06-15. Hanover, NH: Engineer Research and Development Center, Cold Regions Research and Engineering Laboratory, 2006.

[12] American Society for Testing and Materials. D 2487–00, Standard Practice for Classification of Soils for Engineering Purposes (Unified Soil Classification System). In Annual Book of ASTM Standards, Volume 04.08. West Conshohocken, Pennsylvania: ASTM, May 2000.

[13] BaoThach Nguyen and Abbas Mohajerani, (2015).Prediction of California Bearing Ratio from Physical Properties of Fine-Grained Soils, World Academy of Science, Engineering and Technology International Journal of Civil, Structural, Construction and Architectural Engineering Vol:9, No:2, pp.132-137.

[14]. Dilip Kumar Talukdar (2014), A Study of Correlation Between California Bearing Ratio (CBR) Value With Other Properties of Soil, International Journal of Emerging Technology and Advanced Engineering, Volume 4, Issue 1, January 2014).

[15]P.G. Rakaraddi and Vijay Gomarsi, (2015). Establishing Relationship Between CBR With Different Soil Properties. IJRET: International Journal of Research in Engineering and Technology, Volume: 04 Issue: 02 | Feb-2015, pp.182-188.

[16] M. M. E. Zumrawi (2014). Prediction of In-situ CBR of Subgrade Cohesive Soils from Dynamic Cone Penetrometer and Soil Properties, IACSIT International Journal of Engineering and Technology, Vol. 6, No. 5, pp.439-442.

[17] Ramasubbaroa, G.V., Siva Sankar, G.(2013). Predicting Soaked CBR Value Of Fine Grained Soil Using Index and Compaction Characteristics. Jordan Journal Of Civil Engineering, Vol 7, No-3. Pp.354-360.

[18] Yadav et al, (2014) .Prediction Of Soaked CBR Of Fine Grained Soils From Classification And Compaction Parameters, Int. International Journal of Advanced Engineering Research and Studies Vol.3, No..4, pp119-121.

[19] Naveen B Shirur and Santosh G Hiremath. (2014) . Establishing Relationship between CBR Value and Physical Properties of Soil.IOSR Journal of Mechanical and Civil Engineering (IOSR-JMCE), Volume 11, Issue 5 Ver. I .pp 26-30

K. B. Agarwal and K. D. Ghanekar, (1970) "Prediction of CBR from plasticity [20] characteristics of soil" Proceeding of 2nd south-east Asian conference on soil engineering, Singapore, pp. 571–6,.

[21]Patel, R. S.; and Desai, M.D. (2010). CBR Predicted by Index Properties of Soil for Alluvial Soils of South Gujarat, Indian Geotechnical Conference, Proc. IGC, Vol. I, pp.79-82.

[22]Vinod, P.; and Cletus Reena. (2008). Prediction of CBR value of Lateritic Soils using Liquid Limit and Gradation Characteristics Data, Highway Research Journal, Vol. I, No. 1, pp.89-98.

[23] Satyanarayana Reddy, C.N.V. and Pavani, K.(2006). Mechanically Stabilised Soils-Regression Equation for CBR Evaluation, Dec. 14-16, 731-734, Proceedings of Indian Geotechnical Conference-2006, Chennai, India.

[24] J. W. S. De Graft-Johnson and H.S. Bhatia, (1969)."The engineering characteristics of the lateritic gravels of Ghana" Proceedings of 7th international conference on soil mechanics and foundation engineering, Vol. 2, Mexico, pp. 13-43,.

A STUDY ON CORRELATION OF CALIFORNIA BEARING RATIO WITH INDEX PROPERTIES OF SOIL WELKITE-AREKIT- HOSANA ROAD AS CASE STUDY 20

[25]G. H. Gregory, (2007).Correlation of California Bearing Ratio with shear strength parameters" Transportation Research Record: Journal of the Transportation Research Board, Vol. 1989, pp. 148-153.

[26]Yildrim, B. and Gunaydin, O.(2011). Estimation of CBR by Soft Computing Systems, Expert Systems with Applications, ELSEVIER, 38 (2011): pp.6381-6391.

[27] Mak Wai Kin , California Bearing Ratio Correlation with Soil Index Properties,

Faculty of Civil Engineering, University of Technology, Malaysia , May 2006.

[28] Zelalem Worku, Prediction of CBR values from index Property tests, Addis Ababa University, Ethiopia, ----2010.

[29] Roy, T.K.; Chattopadhyay, B.C.; and Roy, S.K. (2009). Prediction of CBR from Compaction Characteristics of Cohesive Soil,

[30] Dharamveer Singh , K. S. Reddy, Laxmikant Yadu. Moisture and Compaction Based Statistical Model for Estimating CBR of Fine Grained Subgrade Soils .International Journal of Earth Sciences and Engineering , Volume 04, No 06 SPL, October 2011, pp 100-103

[31] M.carter and S.P.Bentley, correlation of soil properties, Pentech Press, London , 1991

[32] Douglas C. M. George C. Runger, Applied Statistics and Probability for Engineers, John Wiley & Sons, Inc. USA, third edition, 2003

[33] Kumar K., Nanduri P., Kumar N., (2014). Validation of Predicted California Bearing Ratio Values from Different Correlations. American Journal of Engineering Research (AJER), Volume-3, Issue-8, pp-344-352

[34] Pradeep Muley and P. K. Jain, (2013), Betterment And Prediction of CBR of Stone Dust Mixed Poor Soils .Proceedings of Indian Geotechnical Conference, Roorkee , Pp 1-4

[35] Fredrics, M., Standard Hand Book for Civil Engineers, McGraw-Hill Book Company, New York, 1983.

APPENDIX A

Single Linear Regression Statistical Summary

Model A-1:Statistical Analysis For Correlation Between CBR and F

Model Summary

		[
				Std.	Change S	tatistics			
				Error of	R				
		R	Adjusted	the	Square	F			Sig. F
Model	R	Square	R Square	Estimate	Change	Change	df1	df2	Change
1	.522 ^a	.272	.246	1.38452	.272	10.462	1	28	.003
2	.545 ^b	.297	.245	1.38571	.025	.952	1	27	.338
3	.545°	.297	.216	1.41187	.000	.009	1	26	.926

a. Predictors: (Constant), F

b. Predictors: (Constant), F, F²

c. Predictors: (Constant), F, F², F⁴

a. Dependent Variable: CBR

b. Predictors: (Constant), F

c. Predictors: (Constant), F, F2

d. Predictors: (Constant), F, F2, F4

Model A- 2: Statistical Analysis ForCorrelation Between CBR and	1 S
---	-----

Model Summary									
				Std.	Change Statistics				
			Adjusted	Error of	R				
			R	the	Square	F			Sig. F
Model	R	R Square	Square	Estimate	Change	Change	df1	df2	Change
1	.238 ^a	.057	.023	1.57597	.057	1.684	1	28	.205
2	.323 ^b	.105	.038	1.56366	.048	1.443	1	27	.240
3	.326 ^c	.106	.003	1.59205	.002	.046	1	26	.832
4	.351 ^d	.123	017	1.60825	.017	.479	1	25	.495

a. Predictors: (Constant), S

b. Predictors: (Constant), S, S2

c. Predictors: (Constant), S, S2, S3

d. Predictors: (Constant), S, S2, S3, S5

ANOVA ^a							
Мо	del	Sum of Squares	df	Mean Square	F	Sig.	
1	Regression	4.183	1	4.183	1.684	.205 ^b	
	Residual	69.543	28	2.484			
	Total	73.727	29				
2	Regression	7.710	2	3.855	1.577	.225 ^c	
	Residual	66.016	27	2.445			
	Total	73.727	29				
3	Regression	7.826	3	2.609	1.029	.396 ^d	
	Residual	65.900	26	2.535			
	Total	73.727	29				
4	Regression	9.065	4	2.266	.876	.492 ^e	
	Residual	64.662	25	2.586			
	Total	73.727	29				

a. Dependent Variable: CBR

b. Predictors: (Constant), S

c. Predictors: (Constant), S, S2

d. Predictors: (Constant), S, S2, S3

e. Predictors: (Constant), S, S2, S3, S5

Model Summary									
				Std.	Change Statistics				
			Adjusted	Error of	R				
			R	the	Square	F			Sig. F
Model	R	R Square	Square	Estimate	Change	Change	df1	df2	Change
1	.672 ^a	.451	.431	1.20229	.451	23.004	1	28	.000
2	.692 ^b	.480	.441	1.19217	.028	1.477	1	27	.235
3	.699 ^c	.489	.430	1.20370	.010	.485	1	26	.492
4	.703 ^d	.494	.413	1.22114	.005	.262	1	25	.613

Model A- 3: Statistical Analysis ForCorrelation Between CBR and G

a. Predictors: (Constant), G

b. Predictors: (Constant), G, G2

c. Predictors: (Constant), G, G2, G3

d. Predictors: (Constant), G, G2, G3, G5

ANOVA ^a							
Mo	del	Sum of Squares	df	Mean Square	F	Sig.	
1	Regression	33.253	1	33.253	23.004	.000 ^b	
	Residual	40.474	28	1.445			
	Total	73.727	29				
2	Regression	35.353	2	17.676	12.437	.000 ^c	
	Residual	38.374	27	1.421			
	Total	73.727	29				
3	Regression	36.056	3	12.019	8.295	$.000^{d}$	
	Residual	37.671	26	1.449			
	Total	73.727	29				
4	Regression	36.447	4	9.112	6.110	.001 ^e	
	Residual	37.280	25	1.491			
	Total	73.727	29				

a. Dependent Variable: CBR

b. Predictors: (Constant), G

c. Predictors: (Constant), G, G2

d. Predictors: (Constant), G, G2, G3

e. Predictors: (Constant), G, G2, G3, G5

Model 8	Model Summary												
				Std.	Change Statistics								
			Adjusted	Error of	f R								
			R	the	Square	F			Sig. F				
Model	R	R Square	Square	Estimate	Change	Change	df1	df2	Change				
1	.537 ^a	.288	.263	1.36877	.288	11.352	1	28	.002				
2	.607 ^b	.368	.322	1.31332	.080	3.414	1	27	.076				
3	.792 ^c	.627	.584	1.02810	.259	18.059	1	26	.000				

Model A- 4: Statistical Analysis ForCorrelationBetween CBR and PL

a. Predictors: (Constant), PL

b. Predictors: (Constant), PL, PL2

c. Predictors: (Constant), PL, PL2, PL3

AN	OVA ^a					
Мо	del	Sum of Squares	df	Mean Square	F	Sig.
1	Regression	21.268	1	21.268	11.352	.002 ^b
	Residual	52.459	28	1.874		
	Total	73.727	29			
2	Regression	27.157	2	13.578	7.872	.002 ^c
	Residual	46.570	27	1.725		
	Total	73.727	29			
3	Regression	46.245	3	15.415	14.584	.000 ^d
	Residual	27.482	26	1.057		
	Total	73.727	29			

a. Dependent Variable: CBR

b. Predictors: (Constant), PL

c. Predictors: (Constant), PL, PL2

d. Predictors: (Constant), PL, PL2, PL3

Model A- 5: Statistical Analysis For Correlation Between CBR and PI

Model	Model Summary											
				Std. Change Statistics								
			Adjusted	Error of	R							
			R	the	Square	F			Sig. F			
Model	R	R Square	Square	Estimate	Change	Change	df1	df2	Change			
1	.743 ^a	.551	.535	1.08681	.551	34.419	1	28	.000			
2	.826 ^b	.682	.658	.93206	.130	11.069	1	27	.003			
3	.833 ^c	.695	.659	.93074	.013	1.077	1	26	.309			

a. Predictors: (Constant), PI

b. Predictors: (Constant), PI, PI2

c. Predictors: (Constant), PI, PI2, PI3

AN	OVA ^a		ANOVA ^a										
Mod	del	Sum of Squares	df	Mean Square	F	Sig.							
1	Regression	40.654	1	40.654	34.419	.000 ^b							
	Residual	33.072	28	1.181									
	Total	73.727	29										
2	Regression	50.271	2	25.135	28.933	.000 ^c							
	Residual	23.456	27	.869									
	Total	73.727	29										
3	Regression	51.203	3	17.068	19.702	$.000^{d}$							
	Residual	22.523	26	.866									
	Total	73.727	29										

a. Dependent Variable: CBR

b. Predictors: (Constant), PI

c. Predictors: (Constant), PI, PI2

d. Predictors: (Constant), PI, PI2, PI3

Model A- 6:StatisticalAnalysisFor Correlation Between CBR and LL

Model	Model Summary											
				Std.	Change Statistics							
			Adjusted	Error of	R							
			R	the	Square	F			Sig. F			
Model	R	R Square	Square	Estimate	Change	Change	df1	df2	Change			
1	.713 ^a	.508	.491	1.13770	.508	28.959	1	28	.000			
2	.737 ^b	.543	.509	1.11756	.034	2.018	1	27	.167			
3	.778 ^c	.606	.560	1.05748	.063	4.155	1	26	.052			

a. Predictors: (Constant), LL

b. Predictors: (Constant), LL, LL2

c. Predictors: (Constant), LL, LL2, LL3

AN	OVA ^a		1		1	
Mo	del	Sum of Squares	df	Mean Square	F	Sig.
1	Regression	37.484	1	37.484	28.959	.000 ^b
	Residual	36.242	28	1.294		
	Total	73.727	29			
2	Regression	40.005	2	20.003	16.016	.000 ^c
	Residual	33.722	27	1.249		
	Total	73.727	29			
3	Regression	44.652	3	14.884	13.310	.000 ^d
	Residual	29.075	26	1.118		
	Total	73.727	29			

a. Dependent Variable: CBR

b. Predictors: (Constant), LL

c. Predictors: (Constant), LL, LL2

d. Predictors: (Constant), LL, LL2, LL3

Model A- 7: Statistical Analysis ForCorrelation Between CBR and MDD

Model S	Model Summary											
Std. Change Statistics												
			Adjusted	Error of	R							
			R	the	Square	F			Sig. F			
Model	R	R Square	Square	Estimate	Change	Change	df1	df2	Change			
1	.724 ^a	.524	.507	1.11964	.524	30.813	1	28	.000			
2	.761 ^b	.579	.548	1.07173	.055	3.559	1	27	.070			

a. Predictors: (Constant), MDD

b. Predictors: (Constant), MDD, MDD2

AN	ANOVA ^a										
Mo	del	Sum of Squares	df	Mean Square	F	Sig.					
1	Regression	38.626	1	38.626	30.813	.000 ^b					
	Residual	35.100	28	1.254							
	Total	73.727	29								
2	Regression	42.714	2	21.357	18.594	.000 ^c					
	Residual	31.012	27	1.149							
	Total	73.727	29								

a. Dependent Variable: CBR

b. Predictors: (Constant), MDD

c. Predictors: (Constant), MDD, MDD2

Model A- 8: Statistical Analysis ForCorrelation Between CBR and OMC

Model	Model Summary											
	Std. Change Statistics											
			Adjusted	Error of	R							
			R	the	Square	F			Sig. F			
Model	R	R Square	Square	Estimate	Change	Change	df1	df2	Change			
1	.537 ^a	.288	.263	1.36877	.288	11.352	1	28	.002			
2	.607 ^b	.368	.322	1.31332	.080	3.414	1	27	.076			
3	.792 ^c	.627	.584	1.02810	.259	18.059	1	26	.000			

a. Predictors: (Constant), OMC

b. Predictors: (Constant), OMC, OMC2

c. Predictors: (Constant), OMC, OMC2, OMC3

AN	ANOVA ^a										
Mod	lel	Sum of Squares	df	Mean Square	F	Sig.					
1	Regression	21.268	1	21.268	11.352	.002 ^b					
	Residual	52.459	28	1.874							
	Total	73.727	29								
2	Regression	27.157	2	13.578	7.872	.002 ^c					
	Residual	46.570	27	1.725							
	Total	73.727	29								
3	Regression	46.245	3	15.415	14.584	.000 ^d					
	Residual	27.482	26	1.057							
	Total	73.727	29								

a. Dependent Variable: CBR

b. Predictors: (Constant), OMC

c. Predictors: (Constant), OMC, OMC2

d. Predictors: (Constant), OMC, OMC2, OMC3

APPENDIX B

Multiple Linear Regression Statistical Summary

Model B-1: Correlation Between CBR with and Grain Size Analysis

Model Summary

				Std.	Change S	Statistics			
			Adjusted	Error of	R				
		R	R	the	Square	F			Sig. F
Model	R	Square	Square	Estimate	Change	Change	df1	df2	Change
1	.672 ^a	.451	.431	1.20229	.451	23.004	1	28	.000
2	.736 ^b	.541	.507	1.11927	.090	5.308	1	27	.029

a. Predictors: (Constant), G

b. Predictors: (Constant), G, S

ANOVA^a

		Sum of		Mean		
Mo	del	Squares	df	Square	F	Sig.
1	Regression	33.253	1	33.253	23.004	.000 ^b
	Residual	40.474	28	1.445		
	Total	73.727	29			
2	Regression	39.902	2	19.951	15.926	.000 ^c
	Residual	33.825	27	1.253		
	Total	73.727	29			

a. Dependent Variable: CBR

b. Predictors: (Constant), G

c. Predictors: (Constant), G, S

Coefficients^a

	Unstandar Coefficier		andardized Standardized ficients Coefficients				95.0% Confidence Interval for B	
			Std.				Lower	Upper
Mo	odel	В	Error	Beta	t	Sig.	Bound	Bound
1	(Constant)	4.201	.260		16.174	.000	3.669	4.733
	G	.159	.033	.672	4.796	.000	.091	.227
2	(Constant)	3.385	.429		7.898	.000	2.506	4.265

A STUDY ON CORRELATION OF CALIFORNIA BEARING RATIO WITH INDEX PROPERTIES OF SOIL WELKITE-AREKIT- HOSANA ROAD AS CASE STUDY 2016

G	.165	.031	.699	5.340	.000	.102	.229
S	.034	.015	.302	2.304	.029	.004	.064

a. Dependent Variable: CBR

B. BETWEEN F,G,S

Model S	ummary									
				Std.	Change Statistics					
			Adjusted	Error of	R					
		R	R	the	Square	F			Sig. F	
Model	R	Square ^b	Square	Estimate	Change	Change	df1	df2	Change	
1	.900 ^a	.810	.804	2.26422	.810	123.976	1	29	.000	
2	.949 ^c	.901	.894	1.66668	.090	25.522	1	28	.000	
3	.978 ^d	.957	.952	1.11872	.056	35.147	1	27	.000	

a. Predictors: F

b. For regression through the origin (the no-intercept model), R Square measures the proportion of the variability in the dependent variable about the origin explained by regression. This CANNOT be compared to R Square for models which include an intercept.

- c. Predictors: F, G
- d. Predictors: F, G, S

A	NOVA ^{a,b}						
		Sum of		Mean			
Μ	odel	Squares	df	Square	F	Sig.	
1	Regression	635.587	1	635.587	123.976	.000 ^c	
	Residual	148.673	29	5.127			
	Total	784.260 ^d	30				
2	Regression	706.481	2	353.240	127.164	.000 ^e	
	Residual	77.779	28	2.778			
	Total	784.260 ^d	30				
3	Regression	750.469	3	250.156	199.880	$.000^{f}$	
	Residual	33.791	27	1.252			
	Total	784.260 ^d	30				

a. Dependent Variable: CBR

b. Linear Regression through the Origin

c. Predictors: F

d. This total sum of squares is not corrected for the constant because the constant is zero for regression through the origin.

e. Predictors: F, G

f. Predictors: F, G, S

Coefficients^{a,b}

	benncients							
-		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
			Std.				Lower	Upper
M	odel	В	Error	Beta	t	Sig.	Bound	Bound
1	F	.062	.006	.900	11.134	.000	.051	.074
2	F	.051	.005	.743	11.077	.000	.042	.061
	G	.221	.044	.339	5.052	.000	.132	.311
3	F	.034	.004	.490	7.903	.000	.025	.043
	G	.199	.030	.306	6.728	.000	.139	.260
	S	.068	.011	.359	5.928	.000	.044	.091

a. Dependent Variable: CBR

Model B-2: Correlation Between CBR with Atterberg Limit

Model S	ummary								
				Std.	Change S	Statistics			
			Adjusted	Error of	R				
		R	R	the	Square	F			Sig. F
Model	R	Square ^b	Square	Estimate	Change	Change	df1	df2	Change
1	.861 ^a	.741	.732	2.64658	.741	82.967	1	29	.000

a. Predictors: LL

b. For regression through the origin (the no-intercept model), R Square measures the proportion of the variability in the dependent variable about the origin explained by regression. This CANNOT be compared to R Square for models which include an intercept

AN	ANOVA ^{a,b}											
		Sum of		Mean								
Mo	del	Squares	df	Square	F	Sig.						
1	Regression	581.133	1	581.133	82.967	.000 ^c						
	Residual	203.127	29	7.004								
	Total	784.260 ^d	30									

a. Dependent Variable: CBR

b. Linear Regression through the Origin

c. Predictors: LL

d. This total sum of squares is not corrected for the constant because the constant is zero for regression through the origin.

A STUDY ON CORRELATION OF CALIFORNIA BEARING RATIO WITH INDEX PROPERTIES OF SOIL WELKITE-AREKIT- HOSANA ROAD AS CASE STUDY

Co	Coefficients ^{a,b}												
		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B						
			Std.				Lower	Upper					
M	Model B Error		Beta	t	Sig.	Bound	Bound						
1	LL	.084	.009	.861	9.109	.000	.065	.103					

a. Dependent Variable: CBR

b. Linear Regression through the Origin

E	Excluded Variables ^{a,b}											
М	odel	Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance						
1	PI	.194 ^c	.332	.743	.063	.027						
	PL	236 ^c	332	.743	063	.018						

a. Dependent Variable: CBR

b. Linear Regression through the Origin

c. Predictors in the Model: LL

Model S	ummary								
				Std.	Change S	Statistics			
			Adjusted	Error of	R				
		R	R	the	Square	F			Sig. F
Model	R	Square ^b	Square	Estimate	Change	Change	df1	df2	Change
1	.970 ^a	.940	.938	1.27173	.940	455.923	1	29	.000
2	.978 ^c	.957	.954	1.09264	.017	11.285	1	28	.002

a. Predictors: MDD

b. For regression through the origin (the no-intercept model), R Square measures the proportion of the variability in the dependent variable about the origin explained by regression. This CANNOT be compared to R Square for models which include an intercept

c. Predictors: MDD, OMC

AN	ANOVA ^{a,b}											
		Sum of		Mean								
Mo	del	Squares	df	Square	F	Sig.						
1	Regression	737.359	1	737.359	455.923	$.000^{\circ}$						
	Residual	46.901	29	1.617								
	Total	784.260 ^d	30									
2	Regression	750.832	2	375.416	314.453	.000 ^e						
	Residual	33.428	28	1.194								
	Total	784.260 ^d	30									

a. Dependent Variable: CBR

b. Linear Regression through the Origin

c. Predictors: MDD

d. This total sum of squares is not corrected for the constant because the constant is zero for regression through the origin.

e. Predictors: MDD, OMC

C	oefficients ^{a,b}							
	Unstandardized		Standardized			95.0%	Confidence	
	Coefficients		Coefficients		Interval fo		or B	
			Std.				Lower	
Μ	odel	В	Error	Beta	t	Sig.	Bound	Upper Bound
1	MDD	3.164	.148	.970	21.352	.000	2.861	3.468
2	MDD	4.449	.403	1.363	11.037	.000	3.624	5.275
	OMC	086	.026	415	-3.359	.002	139	034

a. Dependent Variable: CBR

b. Linear Regression through the Origin

Model B-4: Correlation Between CBR with Grain Size Analysis, Atterberg Limit And Compaction Parameters(G, F, S, LL, PI, PL, OMC and MDD)

CORRELATIONS INCLUDING INTERCEPT Category I

Model Summary

					Change Statistics					
		R	Adjusted	Std. Error of the	R Square	F			Sig. F	
Model	R	Square	R Square	Estimate	Change	Change	df1	df2	Change	
1	.743 ^a	.551	.535	1.08681	.551	34.419	1	28	.000	
2	.809 ^b	.654	.628	.97223	.102	7.989	1	27	.009	
3	.855 ^c	.731	.700	.87340	.077	7.456	1	26	.011	
4	.865 ^d	.749	.683	.89746	.018	.541	3	23	.659	

a. Predictors: (Constant), PI

b. Predictors: (Constant), PI, MDD

c. Predictors: (Constant), PI, MDD, F

C	oefficients ^a							
		Unstandardi	zed	Standardized			95.0%	Confidence
		Coefficients		Coefficients	Coefficients		Interval for B	
							Lower	Upper
Μ	odel	В	Std. Error	Beta	t	Sig.	Bound	Bound
1	(Constant)	8.997	.731		12.300	.000	7.499	10.496
	PI	179	.031	743	-5.867	.000	242	117
2	(Constant)	1.150	2.852		.403	.690	-4.702	7.003
	PI	114	.036	472	-3.183	.004	187	040
	MDD	4.070	1.440	.419	2.826	.009	1.115	7.024
3	(Constant)	3.591	2.714		1.323	.197	-1.987	9.169
	PI	098	.033	406	-3.002	.006	165	031
	MDD	3.707	1.300	.382	2.851	.008	1.034	6.379
	F	031	.011	293	-2.731	.011	054	008
4	(Constant)	3.147	5.077		.620	.541	-7.355	13.650
	PI	104	.041	431	-2.504	.020	190	018
	MDD	3.327	2.313	.343	1.438	.164	-1.457	8.111
	F	027	.012	259	-2.207	.038	053	002
	OMC	.034	.074	.120	.460	.650	118	.186
	G	.043	.036	.180	1.179	.250	032	.117
	PL	003	.029	017	096	.924	063	.058

a. Dependent Variable: CBR

A. MODEL WITH LL, S, G, PI, MDD, OMC

Model Summary

				Std.	Change Statistics					
			Adjusted	Error of	R					
		R	R	the	Square	F			Sig. F	
Model	R	Square	Square	Estimate	Change	Change	df1	df2	Change	
1	.713 ^a	.508	.491	1.13770	.508	28.959	1	28	.000	
2	.778 ^b	.605	.575	1.03918	.096	6.561	1	27	.016	
3	.866 ^c	.749	.684	.89682	.145	3.313	4	23	.028	

a. Predictors: (Constant), LL

Predictors: (Constant), LL, S

Predictors: (Constant), LL, S, G, PI, MDD, OMC

AN	ANOVA ^a										
			10		_	~					
Mo	odel	Sum of Squares	df	Mean Square	F	Sig.					
1	Regression	37.484		37.484	28.959	.000 ^b					
	Residual	36.242	28	1.294							
	Total	73.727	29								
2	Regression 44.570		2	22.285	20.636	.000 ^c					
	Residual	29.157	27	1.080							
	Total	73.727	29								
3	Regression	55.228	6	9.205	11.444	.000 ^d					
	Residual	18.499	23	.804							
	Total	73.727	29								

a. Dependent Variable: CBR

b. Predictors: (Constant), LL

c. Predictors: (Constant), LL, S

d. Predictors: (Constant), LL, S, G, PI, MDD, OMC

2016

с.

b.

C	oefficients ^a							
		Unstandardiz	ad	Standardized			95.0% Confider	
	Coefficients		Coefficients				Interval for B	
			Std.				Lower	Upper
Μ	odel	В	Error	Beta	t	Sig.	Bound	Bound
1	(Constant)	8.967	.790		11.355	.000	7.349	10.584
	LL	081	.015	713	-5.381	.000	112	050
2	(Constant)	8.329	.763		10.915	.000	6.763	9.894
	LL	084	.014	744	-6.115	.000	113	056
	S	.035	.014	.312	2.561	.016	.007	.063
3	(Constant)	.428	4.827		.089	.930	-9.556	10.413
	LL	003	.029	027	103	.919	064	.058
	S	.027	.012	.244	2.216	.037	.002	.053
	PI	101	.048	418	-2.086	.048	201	001
	OMC	.034	.073	.120	.460	.650	118	.186
	G	.070	.035	.295	2.003	.057	002	.142
	MDD	3.322	2.311	.342	1.437	.164	-1.459	8.103

a. Dependent Variable: CBR

B. MODEL WITH OMC, G, S

Model	Model Summary												
				Std. Error	Error Change Statistics								
		R	Adjusted	of the	R Square	F			Sig. F				
Model	R	Square	R Square	Estimate	Change	Change	df1	df2	Change				
1	.701 ^a	.491	.473	1.15774	.491	27.005	1	28	.000				
2	.758 ^b	.575	.544	1.07696	.084	5.358	1	27	.028				
3	.814 ^c	.663	.624	.97801	.087	6.739	1	26	.015				

a. Predictors: (Constant), OMC

b. Predictors: (Constant), OMC, G

c. Predictors: (Constant), OMC, G, S

el	Sum of Squares	df	Mean Square	F	Sig.	
Regression	36.196	1	36.196	27.005	.000 ^b	
Residual	37.530	28	1.340			
Total	73.727	29				
Regression	42.411	2	21.206	18.283	.000 ^c	
Residual	31.316	27	1.160			
Total	73.727	29				
Regression	48.857	3	16.286	17.026	.000 ^d	
Residual	24.869	26	.957			
Total	73.727	29				
	Regression Residual Fotal Regression Residual Fotal Regression Residual Fotal	Regression 36.196 Residual 37.530 Total 73.727 Regression 42.411 Residual 31.316 Total 73.727 Regression 48.857 Regression 48.857 Residual 24.869 Total 73.727	Regression 36.196 1 Residual 37.530 28 Total 73.727 29 Regression 42.411 2 Residual 31.316 27 Total 73.727 29 Residual 31.316 27 Regression 48.857 3 Residual 24.869 26	Regression 36.196 1 36.196 Residual 37.530 28 1.340 Total 73.727 29 21.206 Regression 42.411 2 21.206 Residual 31.316 27 1.160 Total 73.727 29 29 Regression 48.857 3 16.286 Residual 24.869 26 .957 Total 73.727 29 10.286	Regression 36.196 1 36.196 27.005 Residual 37.530 28 1.340 1 Total 73.727 29 29 1 Regression 42.411 2 21.206 18.283 Residual 31.316 27 1.160 1 Total 73.727 29 1 1 Regression 42.411 2 21.206 18.283 Residual 31.316 27 1.160 1 Total 73.727 29 1 1 Regression 48.857 3 16.286 17.026 Residual 24.869 26 .957 1 Total 73.727 29 1 1	

a. Dependent Variable: CBR

- b. Predictors: (Constant), OMC
- c. Predictors: (Constant), OMC, G
- d. Predictors: (Constant), OMC, G, S

			Count														
		Unstandard	lized	Standardized			95.0%	Confidence									
		Coefficients		Coefficients			Interval for	r B									
							Lower	Upper									
Model		В	Std. Error	Beta	t	Sig.	Bound	Bound									
1	(Constant)	9.598	.935		10.268	.000	7.684	11.513									
	OMC	198	.038	701	-5.197	.000	276	120									
2	(Constant)	7.590	1.228		6.179	.000	5.070	10.110									
	OMC	129	.046	459	-2.810	.009	224	035									
	G	.089	.039	.378	2.315	.028	.010	.169									
3	(Constant)	6.750	1.162		5.811	.000	4.362	9.137									
	OMC	128	.042	454	-3.060	.005	214	042									
	G	.097	.035	.408	2.744	.011	.024	.169									
	S	.033	.013	.297	2.596	.015	.007	.060									

Coefficients^a

a. Dependent Variable: CBR

Category II CORRELATION WITH EXCLUDING INTERCEPT

A. WITH MDD, PI , F, OMC, LL, PL , G

Model S	ummary										
				Std.	Change Statistics						
			Adjusted	Error of	R						
		R	R	the	Square	F			Sig. F		
Model	R	Square ^b	Square	Estimate	Change	Change	df1	df2	Change		
1	.970 ^a	.940	.938	1.27173	.940	455.923	1	29	.000		
2	.983 ^c	.967	.965	.95758	.027	23.149	1	28	.000		
3	.986 ^d	.973	.970	.88546	.006	5.747	1	27	.024		
4	.988 ^e	.976	.969	.89670	.003	.832	4	23	.519		

a. Predictors: MDD

b. For regression through the origin (the no-intercept model), R Square measures the proportion of the variability in the dependent variable about the origin explained by regression. This CANNOT be compared to R Square for models which include an intercept.

- c. Predictors: MDD, PI
- d. Predictors: MDD, PI, F
- e. Predictors: MDD, PI, F, G, PL, S, OMC

AN	OVA ^{a,b}					
		Sum of				
Mod	del	Squares	Df	Mean Square	F	Sig.
1	Regression	737.359	1	737.359	455.923	.000 ^c
	Residual	46.901	29	1.617		
	Total	784.260 ^d	30			
2	Regression	758.585	2	379.293	413.640	.000 ^e
	Residual	25.675	28	.917		
	Total	784.260 ^d	30			
3	Regression	763.091	3	254.364	324.428	.000 ^f
	Residual	21.169	27	.784		
	Total	784.260 ^d	30			
4	Regression	765.766	7	109.395	136.050	.000 ^g
	Residual	18.494	23	.804		
	Total	784.260 ^d	30			

a. Dependent Variable: CBR

b. Linear Regression through the Origin

c. Predictors: MDD

d. This total sum of squares is not corrected for the constant because the constant is zero for regression through the origin.

- e. Predictors: MDD, PI
- f. Predictors: MDD, PI, F

g. Predictors: MDD, PI, F, G, PL, S, OMC

Co	Coefficients ^{a,b}											
		Unstandar Coefficien		Standardized Coefficients			95.0% Interval fo	Confidence r B				
Mo	odel	В	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound				
1	MDD	3.164	.148	.970	21.352	.000	2.861	3.468				
2	MDD	4.635	.325	1.420	14.246	.000	3.968	5.301				
	PI	102	.021	480	-4.811	.000	146	059				
3	MDD	5.337	.420	1.635	12.708	.000	4.476	6.199				
	PI	069	.024	321	-2.832	.009	118	019				
	F	026	.011	376	-2.397	.024	048	004				
4	MDD	3.256	2.314	.998	1.407	.173	-1.532	8.044				
	PI	104	.041	486	-2.501	.020	189	018				
	F	.006	.048	.082	.118	.907	094	.106				
	OMC	.032	.073	.156	.443	.662	119	.184				
	G	.076	.063	.116	1.197	.243	055	.206				

2016

PL	003	.029	019	114	.910	064	.057
S	.033	.051	.176	.651	.521	072	.138

a. Dependent Variable: CBR

b. Linear Regression through the Origin

B. WITH LL, S, OMC, MDD, PI, PL,F,G

Model S	ummary								
				Std.	Change S	Statistics			
			Adjusted	Error of	R				
		R	R	the	Square	F			Sig. F
Model	R	Square ^b	Square	Estimate	Change	Change	df1	df2	Change
1	.861 ^a	.741	.732	2.64658	.741	82.967	1	29	.000
2	.894 ^c	.799	.784	2.37405	.058	8.040	1	28	.008
3	.988 ^d	.976	.969	.89670	.178	34.653	5	23	.000

a. Predictors: LL

b. For regression through the origin (the no-intercept model), R Square measures the proportion of the variability in the dependent variable about the origin explained by regression. This CANNOT be compared to R Square for models which include an intercept

c. Predictors: LL, S

d. Predictors: LL, S, G, F, PI, OMC, MDD

AN	OVA ^{a,b}					
		Sum of		Mean		
Mod	lel	Squares	df	Square	F	Sig.
1	Regression	581.133	1	581.133	82.967	.000 ^c
	Residual	203.127	29	7.004		
	Total	784.260 ^d	30			
2	Regression	626.449	2	313.225	55.575	.000 ^e
	Residual	157.811	28	5.636		
	Total	784.260 ^d	30			
3	Regression	765.766	7	109.395	136.050	$.000^{\mathrm{f}}$
	Residual	18.494	23	.804		
	Total	784.260 ^d	30			

a. Dependent Variable: CBR

b. Linear Regression through the Origin

c. Predictors: LL

d. This total sum of squares is not corrected for the constant because the constant is zero for regression through the origin.

e. Predictors: LL, S

f. Predictors: LL, S, G, F, PI, OMC, MDD

Co	efficients ^{a,l})						
		Unstandar Coefficien		Standardized Coefficients			95.0% Interval fo	Confidence or B
			Std.				Lower	Upper
Mo	odel	В	Error	Beta	t	Sig.	Bound	Bound
1	LL	.084	.009	.861	9.109	.000	.065	.103
2	LL	.047	.015	.488	3.114	.004	.016	.079
	S	.084	.029	.444	2.836	.008	.023	.144
3	LL	003	.029	034	114	.910	064	.057
	S	.033	.051	.176	.651	.521	072	.138
	F	.006	.048	.082	.118	.907	094	.106
	PI	100	.048	470	-2.074	.049	200	.000
	OMC	.032	.073	.156	.443	.662	119	.184
	G	.076	.063	.116	1.197	.243	055	.206
	MDD	3.256	2.314	.998	1.407	.173	-1.532	8.044

a. Dependent Variable: CBR

- b. Linear Regression through the Origin
 - C. OMC, S, LL, PI, LL, MDD, G,F

Model S	ummary								
				Std.	Change Statistics				
			Adjusted	Error of	R				
		R	R	the	Square	F			Sig. F
Model	R	Square ^b	Square	Estimate	Change	Change	df1	df2	Change
1	.879 ^a	.772	.764	2.48345	.772	98.159	1	29	.000
	2								
2	.951 ^c	.904	.897	1.64316	.132	38.244	1	28	.000
3	.963 ^d	.927	.919	1.45511	.024	8.705	1	27	.006
4	.988 ^e	.976	.969	.89670	.049	12.025	4	23	.000

a. Predictors: OMC

b. For regression through the origin (the no-intercept model), RSquare measures the proportion of the variability in the dependent variable about the origin explained by regression. This CANNOT be compared to R Square for models which include an intercept.

c. Predictors: OMC, G

d. Predictors: OMC, G, S

e. Predictors: OMC, G, S, PL, F, PI, MDD

AN	OVA ^{a,b}					
		Sum of				
Mo	del	Squares	df	Mean Square	F	Sig.
1	Regression	605.401	1	605.401	98.159	.000 ^c
	Residual	178.859	29	6.168		
	Total	784.260 ^d	30			
2	Regression	708.660	2	354.330	131.234	.000 ^e
	Residual	75.600	28	2.700		
	Total	784.260 ^d	30			
3	Regression	727.091	3	242.364	114.465	$.000^{\rm f}$
	Residual	57.169	27	2.117		
	Total	784.260 ^d	30			
4	Regression	765.766	7	109.395	136.050	.000 ^g
	Residual	18.494	23	.804		
	Total	784.260 ^d	30			

a. Dependent Variable: CBR

b. Linear Regression through the Origin

c. Predictors: OMC

d. This total sum of squares is not corrected for the constant because the constant is zero for regression through the origin.

e. Predictors: OMC, G

- f. Predictors: OMC, G, S
- g. Predictors: OMC, G, S, PL, F, PI, MDD

Co	efficients ^{a,t})						
		Unstandardized Coefficients		Standardized Coefficients			95.0% Interval fo	Confidence or B
			Std.				Lower	Upper
Mo	odel	В	Error	Beta	t	Sig.	Bound	Bound
1	OMC	.183	.018	.879	9.908	.000	.145	.221
2	OMC	.150	.013	.721	11.272	.000	.123	.177

A STUDY ON CORRELATION OF CALIFORNIA BEARING RATIO WITH INDEX PROPERTIES OF SOIL WELKITE-AREKIT- HOSANA ROAD AS CASE STUDY 2016

	G	.258	.042	.396	6.184	.000	.173	.344
3	OMC	.102	.020	.491	5.087	.000	.061	.143
	G	.239	.038	.367	6.383	.000	.162	.316
	S	.054	.018	.287	2.950	.006	.016	.092
4	OMC	.032	.073	.156	.443	.662	119	.184
	G	.076	.063	.116	1.197	.243	055	.206
	S	.033	.051	.176	.651	.521	072	.138
	PI	104	.041	486	-2.501	.020	189	018
	PL	003	.029	019	114	.910	064	.057
	MDD	3.256	2.314	.998	1.407	.173	-1.532	8.044
	F	.006	.048	.082	.118	.907	094	.106

a. Dependent Variable: CBR

b. Linear Regression through the Origin

D. WITH MDD, F, G, OMC, PI

Model S	ummary								
				Std.	Change S	Statistics			
			Adjusted	Error of	R				
		R	R	the	Square	F			Sig. F
Model	R	Square ^b	Square	Estimate	Change	Change	df1	df2	Change
1	.970 ^a	.940	.938	1.27173	.940	455.923	1	29	.000
2	.982 ^c	.965	.962	.99027	.025	19.828	1	28	.000

a. Predictors: MDD

b. For regression through the origin (the no-intercept model), R Square measures the proportion of the variability in the dependent variable about the origin explained by regression. This CANNOT be compared to R Square for models which include an intercept.

c. Predictors: MDD, F

AN	ANOVA ^{a,b}										
		Sum of		Mean							
Mo	del	Squares	df	Square	F	Sig.					
1	Regression	737.359	1	737.359	455.923	.000 ^c					
	Residual	46.901	29	1.617							
	Total	784.260 ^d	30								
2	Regression	756.802	2	378.401	385.874	.000 ^e					
	Residual	27.458	28	.981							
	Total	784.260 ^d	30								

a. Dependent Variable: CBR

b. Linear Regression through the Origin

c. Predictors: MDD

d. This total sum of squares is not corrected for the constant because the constant is zero for regression through the origin.

e. Predictors: MDD, F

Co	efficients ^{a, l})						
		Unstandar	dized	Standardized			95.0% (Confidence
	Coefficients		Coefficients			Interval for	or B	
			Std.				Lower	Upper
Mo	odel	В	Error	Beta	t	Sig.	Bound	Bound
1	MDD	3.164	.148	.970	21.352	.000	2.861	3.468
2	MDD	5.171	.465	1.584	11.118	.000	4.218	6.123
	F	044	.010	635	-4.453	.000	064	024

a. Dependent Variable: CBR

b. Linear Regression through the Origin

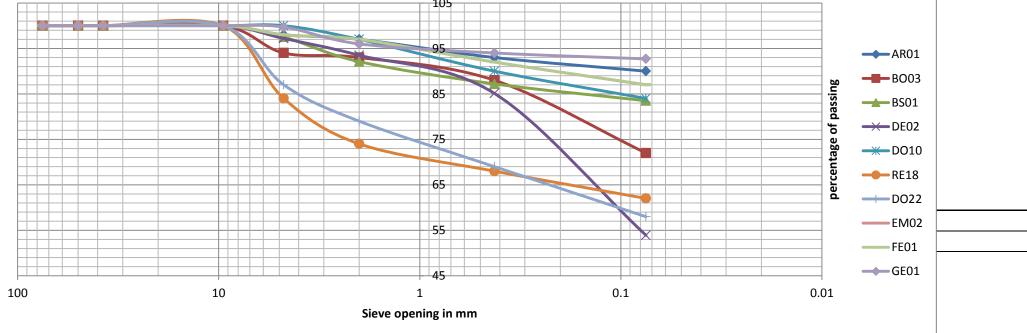
APPENDIX C

Laboratory Test Results

2016

A STUDY ON CORRELATION OF CALIFORNIA BEARING RATIO WITH INDEX PROPERTIES OF SOIL WELKITE-AREKIT- HOSANA ROAD AS CASE STUDY

				PARTICLE SIZ	E DETERMINAT	ION	
	TEST METHOD-AA	SHTO T27				W	ET SIEVING
					CUMULATIVE PE	ERCENTAGE OF P	ASSING
Size size in mm					SAN	MPLE CODE	
	AR01	BO03	BS01	DE02	DO10	RE18	DO22
75	100	100	100	100	100	100	100
50	100	100	100	100	100	100	100
37.5	100	100	100	100	100	100	100
9.5	100	100	100	100	100	100	100
4.75	98	94.0	97.5	97.2	100	84.0	87
2	97	93	92.1	93.5	97	74.0	79
0.425	93	88	87.2	85.1	90	68.0	69
0.075	90	72	83.5	53.9	84	62.0	58



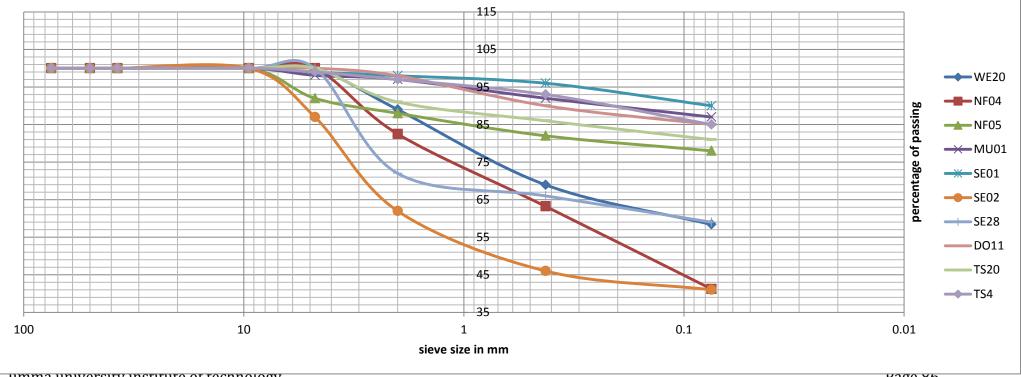
A STUDY ON CORRELATION OF CALIFORNIA BEARING RATIO WITH INDEX PROPERTIES OF SOIL WELKITE-AREKIT- HOSANA ROAD AS CASE STUDY **2016**

	TEST METHOD-A	AASHTO T27					T SIEVING	
				C	UMULATIVE PI	ERCENTAGE (OF PASSING	
Size size in mm					SA	MPLE CODE		
	GU01	GU02	HO01	HO02	KE02	KB01	JO20	LR
75	100	100	100	100	100	100	100	
50	100	100	100	100	100	100	100	
37.5	100	100	100	100	100	100	100	
9.5	100	100	100	100	100	100	100	
4.75	100	84.9	83	88	96.8	99.8	100	
2	87.3	79.8	76	81.0	95.2	87	82	
0.425	86.3	69.1	72	73	88.4	75	69	
			95					5U02 1001 1002 E02 B01 D20 R01 R20
00	10		1	(D.1	(0.01	F
		sieve	size in mm					

2016

A STUDY ON CORRELATION OF CALIFORNIA BEARING RATIO WITH INDEX PROPERTIES OF SOIL WELKITE-AREKIT- HOSANA ROAD AS CASE STUDY

				CUMU	ULATIVE PER	RCENTAGE O	F PASSING	
Size size in mm					SAM	PLE CODE		
	WE20	NF04	NF05	MU01	SE01	SE02	SE28	
75	100	100	100	100	100	100	100	
50	100	100	100	100	100	100	100	
37.5	100	100	100	100	100	100	100	
9.5	100	100	100	100	100	100	100	
4.75	100	100	92	98.1	99	87.0	100	
2	89.0	82.5	88	97.0	98	62.0	72	
0.425	68.9	63.2	82	92	96	46	66	
								-



Jimma university institute of technology

Раде 86

	ATER	BERG LIMI	Г TEST -A	ASHTO T89	9-90		
sample code	e Trial No. LIQUID LIMIT	1	2	3	4	PLASTIC	LIMIT
AR01	Water content, %	36.98%	38.74%	40.03%	42.78%	22.08%	22.06%
	No. of blows	34	29	23	18		
	LL	40		PL	22	PI	18
BO03	Water content, %	34.3 %	33.7 %	35.3 %	36.2 %	18.5 %	18.0 %
	No. of blows	34	28	22	16		
	LL	35.00		PL	18	PI	17
BS01	Water content, %	64.12	66.41	68.29	71.05	32.29	31.93
	No. of blows	34	28	24	19		
	LL	67.00		PL	35	PI	32
DE02	Water content, %	55.35	56.47	57.69	59.35	28.02	29.03
	No. of blows	33	28	22	18		
	LL	57.00		PL	29	PI	28
DO10	Water content, %	65.09	66.44	67.43	70.59	29.29	28.40
	No. of blows	34	29	24	19		
	LL	68.00		PL	29	PI	39
RE-18	Water content, %	33.01	30.92	29.08	26.97	0.16	0.16
	No. of blows	33	28	23	18		
	LL	30.00		PL	16	PI	14
DO22	Water content, %	32.2 %	34.5 %	35.5 %	37.9 %	18.6 %	17.4 %
	No. of blows	34	28	22	16		
	LL	35.00		PL	18	PI	17
EM02	Water content, %	36.2 %	42.9 %	47.9 %		21.0 %	20.9 %
	No. of blows	32	22	16			
	LL	41.00		PL	21	PI	20
FE01	Water content, %	36.2 %	42.9 %	47.9 %		21.0 %	20.9 %
	No. of blows	32	22	16			
	LL	33.00		PL	17	PI	16
GE01	Water content, %	77.90	83.18	85.43	87.37	31.87	32.63
	No. of blows	34	29	23	19		
	LL	84.00		PL	52	PI	32
GU01	Water content, %	58.5 %	60.6 %	64.1 %		35.7 %	35.9 %
	No. of blows	35	29	19			
	LL	62.00		PL	36	PI	26
GU02	Water content, %	52.55	54.24	57.04		36.34	36.20
	No. of blows	32	28	19			
	LL	55.00		PL	36	PI	19
HO01	Water content, %	32.3 %	33.6 %	33.8 %		18.0 %	15.8 %
	No. of blows	33	23	16			
	LL	33.00		PL	17	PI	16
HO02	Water content, %	33.4 %	34.0 %	35.0 %	36.7 %	18.3 %	17.7 %
	No. of blows	33	28	23	19	1010 /0	1111 /0
	LL	35.00	20	PL	12	PI	17
KE02	Water content, %	55.68	57.80	61.20	62.02	31.86	32.46
	No. of blows	33	28	23	18	51.00	52.40
	LL	59.00	20	PL	32	PI	2
	Water content, %	52.34	49.60	57.87	32	28.98	30.29
	No. of blows	32.34	28	19		20.70	30.27

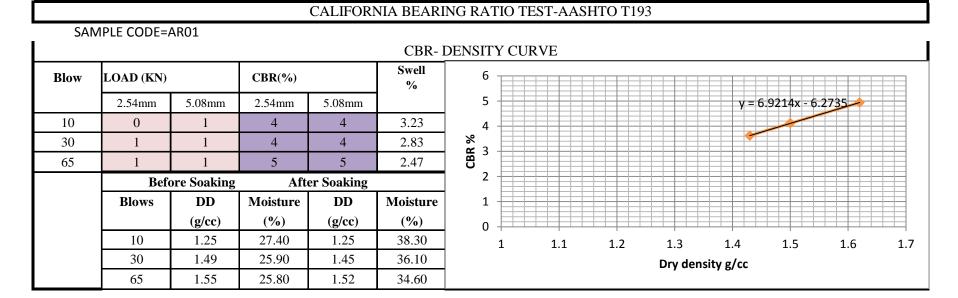
	ATE	RBERG LIMI	Г TEST -	AASHTO T8	9-90		
			LIQU	ID LIMIT		PLASTI	C LIMIT
sample code	Trial No.	1	2	3	4		
	Water content, %	61.4 %	62.4 %	65.6 %		26.7 %	28.2 %
	No. of blows	34	28	22			
JO20	LL	64.00		PL	27	PI	37
	Water content, %	68.10	70.54	73.50	75.62	44.19	43.75
	No. of blows	33	29	22	17		
LR01	ш	72.00		PL	44	PI	28
	Water content, %	36.5 %	38.3 %	41.3 %		20.2 %	20.0 %
	No. of blows	34	25	19			
LR20	ш	39.00		PL	20	PI	19
	Water content, %	54.1 %	54.8 %	55.7 %		34.3 %	33.3 %
	No. of blows	33	28	24			
WE01	LL	55.00		PL	34	PI	21
	Water content, %	64.46	66.65	68.89		44.26	44.93
	No. of blows	34	29	23			
WE20	LL	67.00		PL	45	PI	22
	Water content, %	64.46	66.65	68.89		44.26	44.93
	No. of blows	34	29	23			
NF04	LL	56.00		PL	36	PI	2
	Water content, %	49.3 %	51.8 %	57.7 %		32.8 %	39.0 %
	No. of blows	33	28	24			
NF05	LL	42.00	20	PL	21	PI	2:
	Water content, %	37.0 %	43.6 %	48.2 %		25.1 %	17.1 %
	No. of blows	32	22	16		2011 /0	1111 /0
MU01	LL	41.00	22	PL	21	PI	20
	Water content, %	34.0 %	43.4 %	48.2 %		25.1 %	17.1 %
	No. of blows	33	23	17		23.1 /0	17.170
SE01	LL	46.00	23	PL	24	PI	2
5201	Water content, %	44.94	45.70	45.96	47.08	24.58	23.19
	No. of blows	35	29	23	19	21.50	25.17
SE02	LL	35.00	27	PL	18	PI	17
0202	Water content, %	68.10	70.54	73.50	75.62	44.19	43.75
	No. of blows	33	29	22	17	11.19	13.75
SE28	LL	72.00	27	PL	44	PI	28
0220	Water content, %	57.1 %	58.1 %	59.5 %		38.1 %	38.0 %
	No. of blows	31	27	21		50.1 %	50.0 %
DO11	LL	59.00	21	PL	38	PI	2:
0011	Water content, %	57.1 %	58.1 %	59.5 %		38.1 %	38.0 %
	No. of blows	31	27	21		50.1 /0	30.0 /0
TS20	LL	41.00	21	PL	21	PI	20
1320	Water content, %	55.90	57.78	FL 59.10	61.49	26.60	22.78
	No. of blows					20.00	22.18
TS4	LL	33 58.00	28	23 PL	18 25	DI	3
134			EC AT				
	Water content, %	55.35	56.47	57.69	62.05	28.02	28.31
D502	No. of blows	33	28	22	18	DI	
DE02	LL	58.00		PL	28	PI	30

A STUDY ON CORRELATION OF CALIFORNIA BEARING RATIO WITH INDEX PROPERTIES OF SOIL WELKITE-AREKIT- HOSANA ROAD AS CASE STUDY 2016

	·		MODIFIE	ED PROCT	OR TEST	-AASHTO	D T180 D					
ample code	Trial No.	1	2	3	4	ample code	е	Trial No.	1	2	3	4
	Moisture content (%)	15.01387	18.74387	22.06057	24.53014		Moisture c	ontent (%	17.64706	19.14557	22.11855	23.43927
	Dry Density (g / cm3	1.511215	1.573228	1.601098	1.556487		Dry Densit	y (g / cm3	1.488701	1.564419	1.566544	1.505807
AR01		MDD 1.61	g/cc	OMC	21.9%	FE01		MDD 1.69	g/cc		OMC :	19.2%
	Moisture content (%	16.95554	17.62306	18.5567	21.1386		Moisture c	ontent (%	29.52768	34.65748	37.33691	42.3865
	Dry Density (g/cm3	1.65323	1.688688	1.697633	1.632715		Dry Densit	y (g / cm3	1.252559	1.279664	1.297893	1.212186
BO03	MDD 1.71	g/cc		OMC 18.59	6	GE01		MDD 1.3g	/cc		OMC 36.89	6
	Moisture content (%	23.4375	24.50947	25.63758	26.90238		Moisture c	ontent (%	24.97247	29.91847	33.53888	35.95361
	Dry Density (g/cm3	1.358602	1.4006	1.46447	1.446906		Dry Densit	y (g / cm3	1.347189	1.452454	1.436345	1.346768
BS01	MDD 1.48	g/cc		OMC 26.29	6	GU01		MDD 1.46	g/cc		OMC	32%
	Moisture content (%	20.21238	23.73188	28.84311	33.52973		Moisture c	ontent (%	15.59176	18.99254	22.99376	26.42954
	Dry Density (g/cm3	1.564635	1.615257	1.63157	1.546098		Dry Densit	y (g / cm3	1.442535	1.508187	1.531888	1.456727
DE02	MDD 1.64	g/cc		OMC 27.49	6	GU02		MDD 1.53	g/cc		OMC 22%	
	Moisture content (%	23.29914	26.21334	28.33083			Moisture c	ontent (%	14.05405	16.80912	19.04762	23.33333
	Dry Density (g/cm3	1.457115	1.527172	1.485098			Dry Densit	y (g / cm3	1.620222	1.694461	1.693842	1.581539
DO10	MDD 1.53	g/cc		OMC 26.5%	6	HO01		MDD 1.7g	/cc		OMC 17.9%	6
	Moisture content (%	14.75724	15.48588	17.35424	18.63153		Moisture c	ontent (%	15.57377	16.8254	18.48185	20.83333
	Dry Density (g/cm3	1.803529	1.870831	1.901225	1.85337		Dry Densit	y (g / cm3	1.725198	1.768404	1.800531	1.759254
RE-18	MDD 1.9g	/cc		OMC 17.29	6	HO02		MDD 1.72	g/cc		OMC	18.4%
	Moisture content (%			17.35424	18.63153		Moisture c	ontent (%	27.26664	30.43178	33.89292	37.13438
	Dry Density (g/cm3	1.803529		1.901225			Dry Densit	y (g / cm3	1.123507	1.210307	1.221216	
DO22	MDD 1.9g			OMC 17.29		KE02		MDD 1.23	0.		OMC 32.89	6
	Moisture content (%						Moisture c					
	Dry Density (g/cm3			1.566544			Dry Densit			1.367272		
EM02	MDD 1.58			OMC 20.79		KB01		MDD 1.37			OMC 29.59	
	Moisture content (%						Moisture c	•				
	Dry Density (g/cm3	-		1.412624	1.395414		Dry Densit			1.571523		1.501435
JO20	MDD 1.41			OMC 33%		SE01		MDD 1.6g			OMC 22%	
	Moisture 14.81276			37.46863			Moisture c					
	Dry Densit 1.403251		1.425289	-			Dry Densit					1.35413
LR01	MDD 1.44	g/cc		OMC 26%		SE02	L	MDD 1.9g	/CC		OMC 14.69	6

A STUDY ON CORRELATION OF CALIFORNIA BEARING RATIO WITH INDEX PROPERTIES OF SOIL WELKITE-AREKIT- HOSANA ROAD AS CASE STUDY 2016

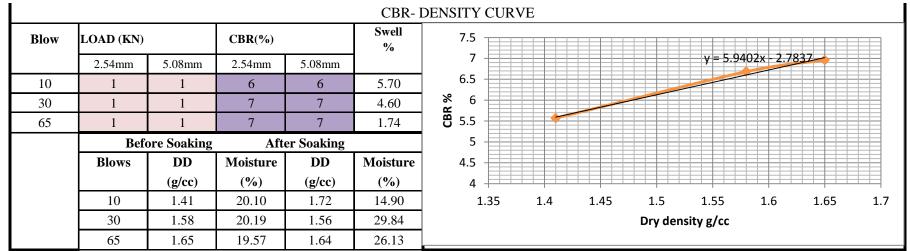
			MODIFIE	ED PROCT	OR TEST	-AASHTO	D T180 D					
sample code	Trial No.	1	2	3	4	ample cod	е	Trial No.	1	2	3	4
	Moisture content (%)	15.01387	18.74387	22.06057	24.53014		Moisture	content (%	17.64706	19.14557	22.11855	23.43927
	Dry Density (g / cm3	1.511215	1.573228	1.601098	1.556487		Dry Densi	ty (g / cm3	1.488701	1.564419	1.566544	1.505807
AR01		MDD 1.61	g/cc	OMC	21.9%	FE01		MDD 1.69	g/cc		OMC	19.2%
	Moisture content (%	16.95554	17.62306	18.5567	21.1386		Moisture	content (%	29.52768	34.65748	37.33691	42.3865
	Dry Density (g/cm3	1.65323	1.688688	1.697633	1.632715		Dry Densi	ty (g / cm3	1.252559	1.279664	1.297893	1.212186
BO03	MDD 1.71	g/cc		OMC 18.5%	6	GE01		MDD 1.3g	/cc		OMC 36.89	%
	Moisture content (%	23.4375	24.50947	25.63758	26.90238		Moisture	content (%	24.97247	29.91847	33.53888	35.95361
	Dry Density (g/cm3	1.358602	1.4006	1.46447	1.446906		Dry Densi	ty (g / cm3	1.347189	1.452454	1.436345	1.346768
BS01	MDD 1.48	g/cc		OMC 26.29	6	GU01		MDD 1.46	g/cc		OMC	32%
	Moisture content (%	20.21238	23.73188	28.84311	33.52973		Moisture	content (%	15.59176	18.99254	22.99376	26.42954
	Dry Density (g/cm3	1.564635	1.615257	1.63157	1.546098		Dry Densi	ty (g / cm3	1.442535	1.508187	1.531888	1.456727
DE02	MDD 1.64	g/cc		OMC 27.49	6	GU02		MDD 1.53	g/cc		OMC 22%	
	Moisture content (%	23.29914	26.21334	28.33083			Moisture	content (%	14.05405	16.80912	19.04762	23.33333
	Dry Density (g/cm3	1.457115	1.527172	1.485098			Dry Densi	ty (g / cm3	1.620222	1.694461	1.693842	1.581539
DO10	MDD 1.53	g/cc		OMC 26.5%	6	HO01		MDD 1.7g	/cc		OMC 17.99	%
	Moisture content (%	14.75724	15.48588	17.35424	18.63153		Moisture	content (%	15.57377	16.8254	18.48185	20.83333
	Dry Density (g/cm3	1.803529	1.870831	1.901225	1.85337		Dry Densi	ty (g / cm3	1.725198	1.768404	1.800531	1.759254
RE-18	MDD 1.9g	/cc		OMC 17.29	6	HO02		MDD 1.72	g/cc		OMC	18.4%
	Moisture content (%			17.35424				· ·	27.26664			
	Dry Density (g/cm3			1.901225	1.85337			ty (g / cm3		1.210307		
DO22	MDD 1.9g			OMC 17.29		KE02		MDD 1.23			OMC 32.89	6
	Moisture content (%			22.11855				•	23.65963		35.38547	
	Dry Density (g/cm3			1.566544					1.324942	1.367272	1.352072	
EM02	MDD 1.58			OMC 20.79		KB01		MDD 1.37			OMC 29.59	
	Moisture content (%			33.98158				•	15.59176			
1020	Dry Density (g/cm3			1.412624	1.395414	6501	Dry Densi		1.507734	1.571523		1.501435
JO20	MDD 1.41			OMC 33%		SE01	Moisture	MDD 1.6g		19 05011	OMC 22%	22 45122
	Moisture • 14.81276 Dry Densit 1.403251		29.61987 1.425289	37.46863 1.320623			-		16.92913 1.319285			23.45133 1.35413
	MDD 1.44			OMC 26%		5502		MDD 1.9g		1.300005	OMC 14.69	
LR01	1.44 בסוייון 1.44	g/ll		UIVIC 20%		SE02		ד מסואון 1.98	/		UNIC 14.67	′0



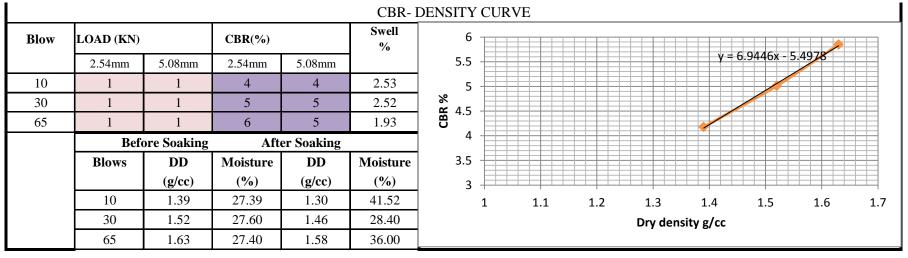
SAMPLE CODE=BO03

					CBR-1	DENSITY CURVE
Blow	LOAD (KN)		CBR(%)		Swell %	
	2.54mm	5.08mm	2.54mm	5.08mm		9 y = 19.957x - 26.492
10	1	1	6	6	2.64	8
30	1	1	7	7	2.15	
65	1	2	10	10	1.55	
	Bef	ore Soaking	Aft	er Soaking		6
	Blows	DD	Moisture	DD	Moisture	5
		(g/cc)	(%)	(g/cc)	(%)	4
	10	1.60	11.19	1.62	21.85	1.5 1.55 1.6 1.65 1.7 1.75 1.8 1.85
	30	1.68	11.42	1.73	20.07	Dry density g/cc
	65	1.80	8.30	1.84	17.31	

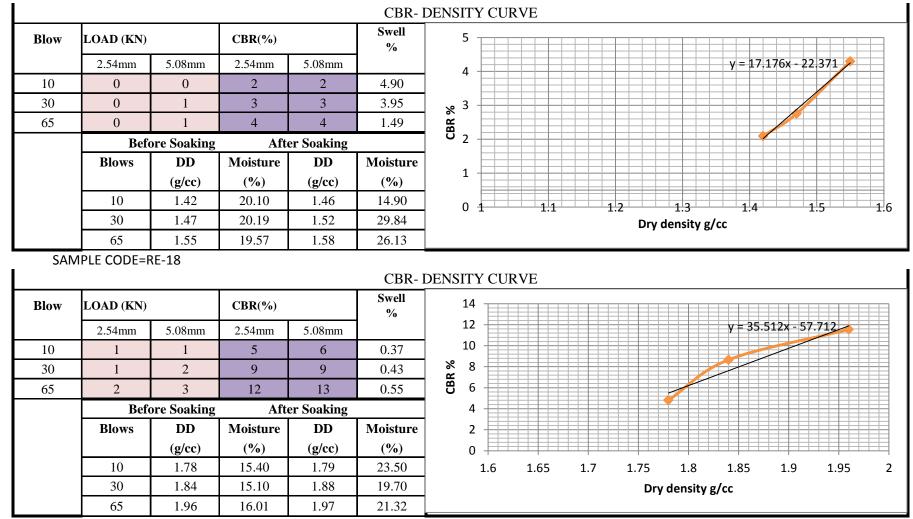
SAMPLE CODE=BS01



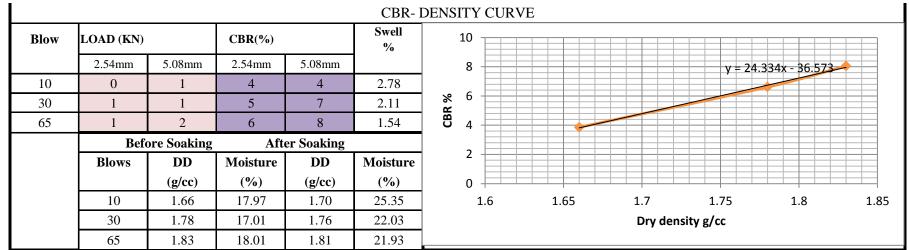
SAMPLE CODE=DE02



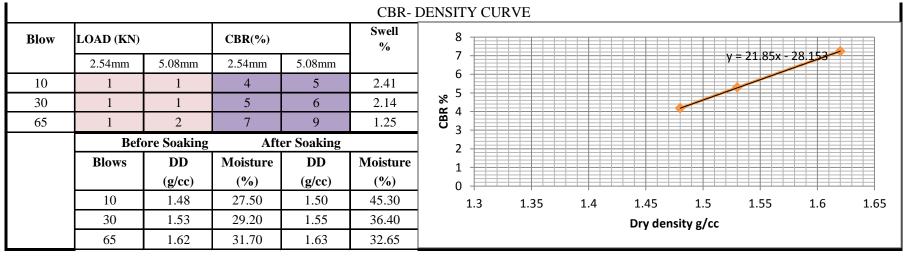
SAMPLE CODE=D010



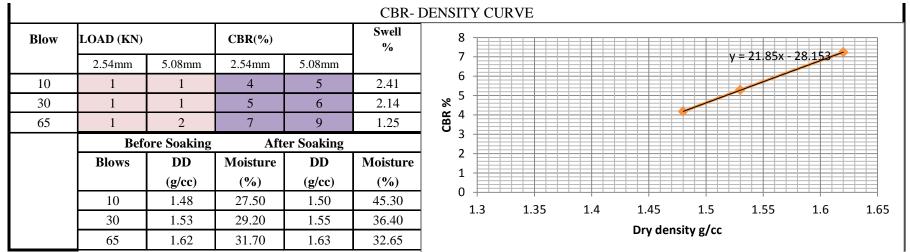
SAMPLE CODE=DO22



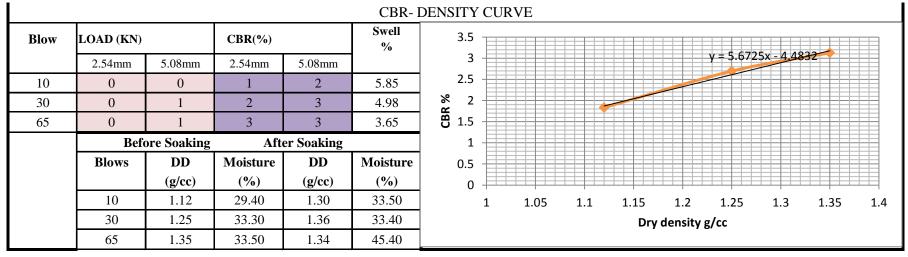
SAMPLE CODE=EM02



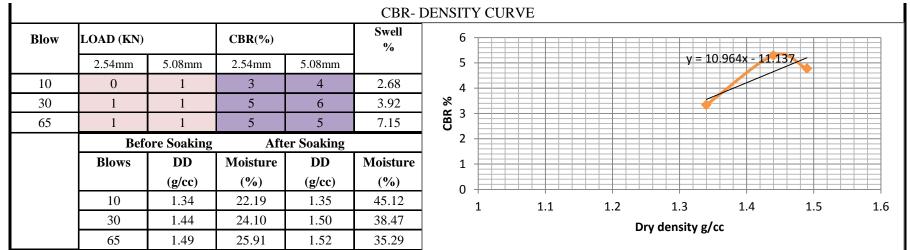
SAMPLE CODE=FE01



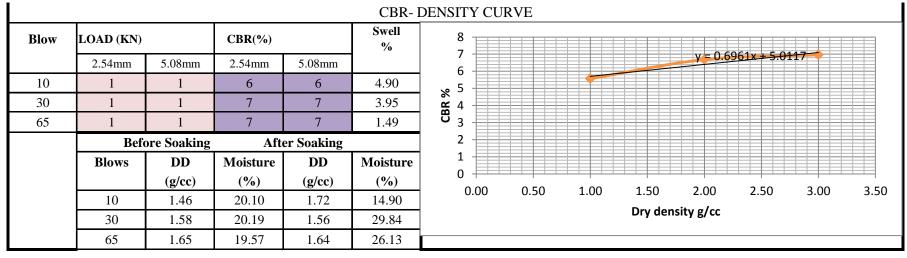
SAMPLE CODE=GE01



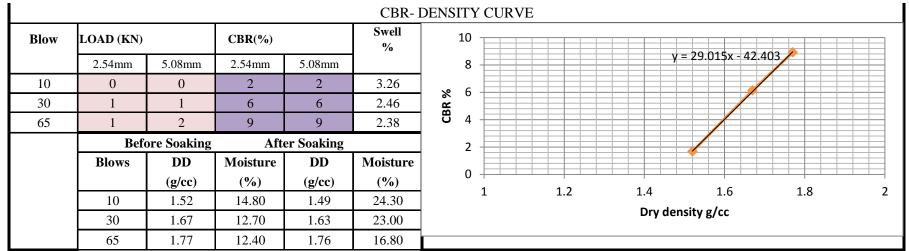
SAMPLE CODE=GU01



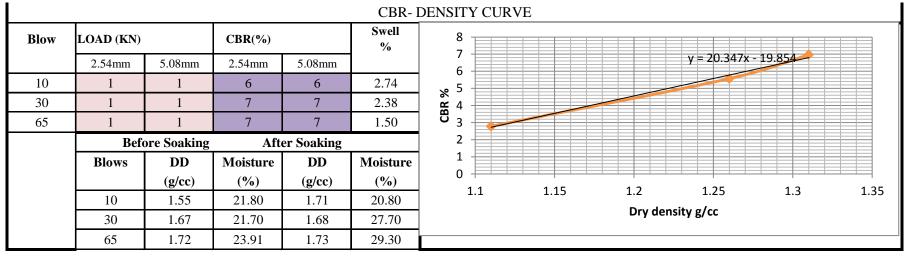
SAMPLE CODE=GU02



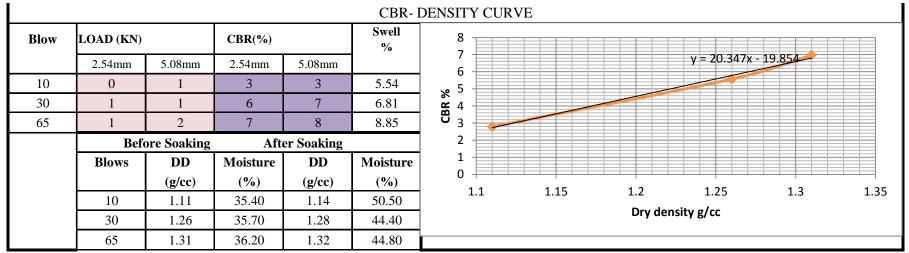
SAMPLE CODE=HO01



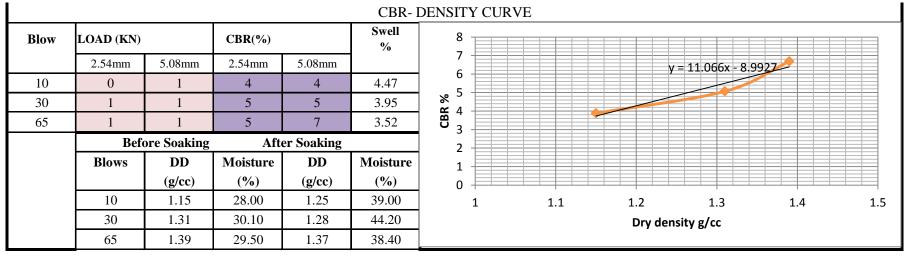
SAMPLE CODE=HO02



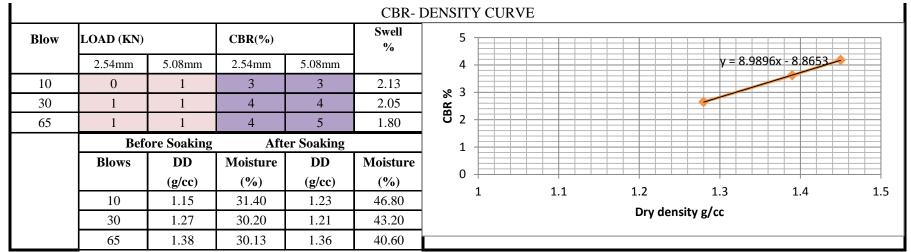
SAMPLE CODE=KE02



SAMPLE CODE=KB01



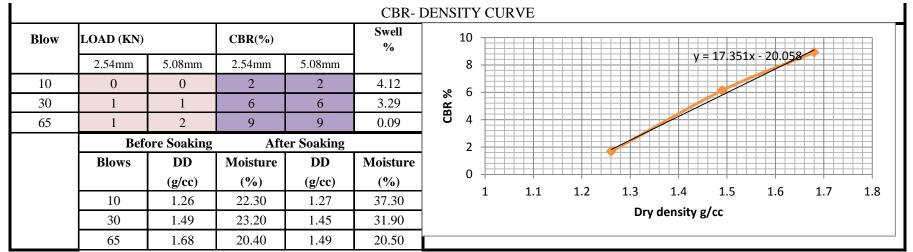
SAMPLE CODE=JO20



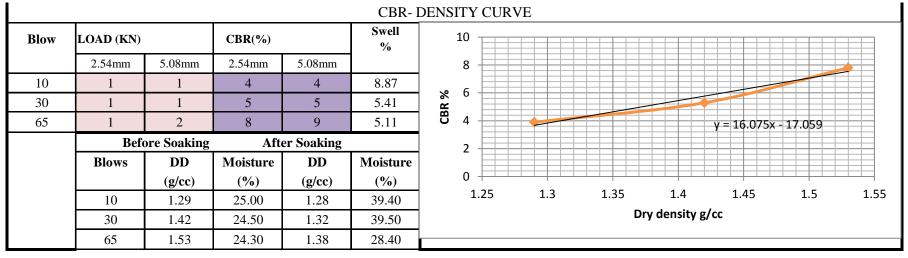
SAMPLE CODE=LR01

					CBR- I	NSITY CURVE				
Blow	LOAD (KN)		CBR(%)		Swell %	6				
	2.54mm	5.08mm	2.54mm	5.08mm		5		y = 9.7	015x - 8,9095	
10	0	1	3	4	2.13	. 4				
30	0	1	4	4	2.05	8 3				
65	1	1	4	5	1.80	8 2				
	Bef	ore Soaking	Aft	er Soaking		1				
	Blows	DD	Moisture	DD	Moisture					
		(g/cc)	(%)	(g/cc)	(%)	0	1.2	1.2	1.4	 1 F
	10	1.28	21.40	1.23	36.80	1 1.1	1.2	1.3	1.4	1.5
	30	1.39	20.20	1.21	33.60		Dry de	ensity g/cc		
	65	1.45	20.14	1.36	30.60					

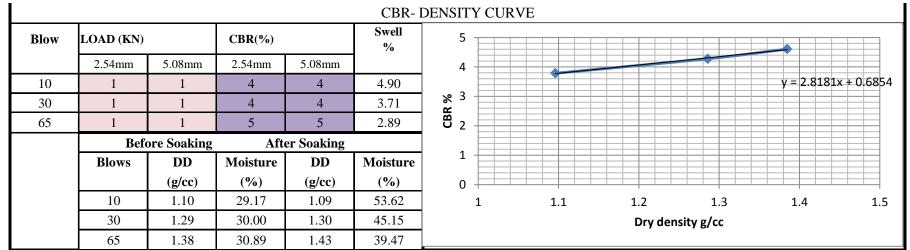
SAMPLE CODE=LR20



SAMPLE CODE=WE01



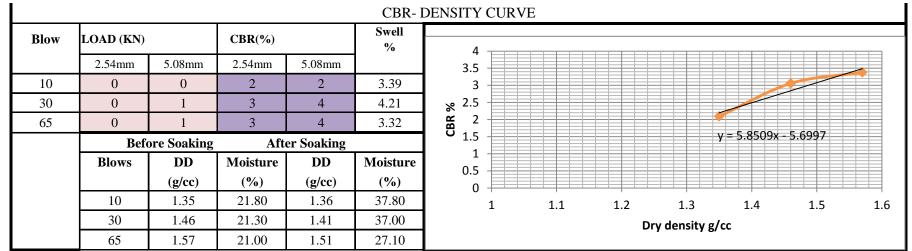
SAMPLE CODE=WE20



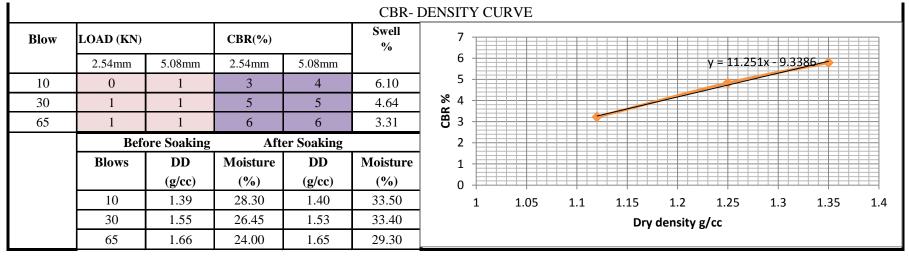
SAMPLE CODE=NF04

					CBR- I	DENSITY CU	RVE					
Blow	LOAD (KN)		CBR(%)		Swell	6						
	2.54mm	5.08mm	2.54mm	5.08mm		5						
10	0	0	2	2	4.90	4					y = 11.74	x - 12.90
30	0	1	4	5	3.71	%						
65	0	1	4	5	2.89	CBR 3						
	Bef	ore Soaking	Aft	er Soaking		2						
	Blows	DD	Moisture	DD	Moisture	1						
		(g/cc)	(%)	(g/cc)	(%)	0						
	10	1.30	23.00	1.35	37.90	1	1.1	1.2	1.3	1.4	1.5	1.6
	30	1.44	21.20	1.45	31.20			D	ry density g/	/cc		
	65	1.53	23.20	1.64	28.10							

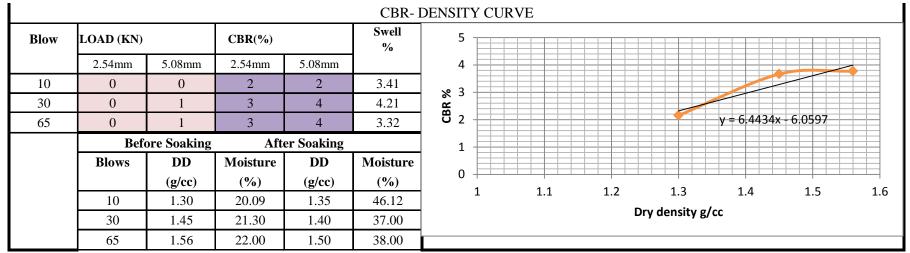
SAMPLE CODE=NF05



SAMPLE CODE=MU01



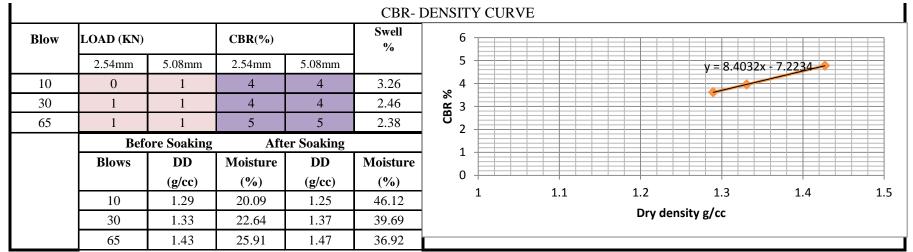
SAMPLE CODE=SE01



SAMPLE CODE=SE02

					CBR- I	DENSITY CURV	VЕ				
Blow	LOAD (KN)		CBR(%)		Swell %	12					
	2.54mm	5.08mm	2.54mm	5.08mm		10			y = 8.	7347x - 7.1604	
10	1	2	5	8	5.93	8					
30	1	2	7	9	4.90	6 6 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8					
65	1	2	8	10	3.74	8 4					
	Bef	ore Soaking	Aft	er Soaking		2					
	Blows	DD	Moisture	DD	Moisture						
		(g/cc)	(%)	(g/cc)	(%)	0	1.2	1.4	1.0	1.0	
	10	1.71	17.09	1.72	26.30	1	1.2	1.4	1.6	1.8	2
	30	1.83	20.10	1.85	32.10			Dry dens	sity g/cc		
	65	1.93	23.40	1.94	33.40						

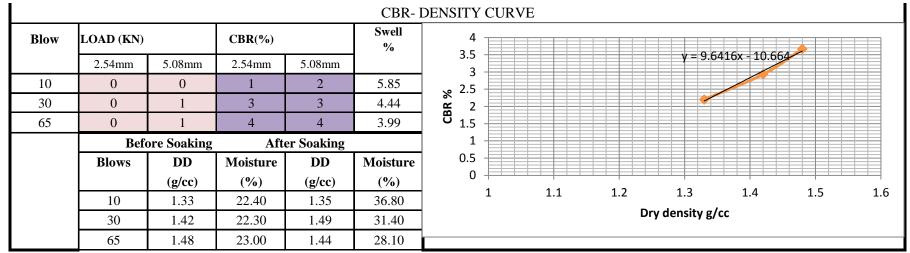
SAMPLE CODE=SE28



SAMPLE CODE=D011

					CBR- I	DENSITY CUF	RVE					
Blow	LOAD (KN)		CBR(%)		Swell %	7						
	2.54mm	5.08mm	2.54mm	5.08mm		6						
10	1	1	4	4	2.90	5						
30	1	1	5	5	2.66	% 4						
65	1	1	5	6	1.72	B 3			Y	= 6.8453x -	5.0872	
	Bef	ore Soaking	After Soaking			2						
	Blows	DD	Moisture	DD	Moisture	1						
		(g/cc)	(%)	(g/cc)	(%)	0	1.25	1.4	1 4 5	<u> </u>		 1 C
	10	1.36	18.80	1.37	31.90	1.3	1.35	1.4	1.45	1.5	1.55	1.6
	30	1.52	18.00	1.48	29.60		Dry density g/cc					
	65	1.57	18.70	1.53	28.20							

SAMPLE CODE=TS20



SAMPLE CODE=TS4

					CBR-1	DENSITY CUR	V E						
Blow	LOAD (KN)		CBR(%)		Swell %	3							
	2.54mm	5.08mm	2.54mm	5.08mm		2.5				y = 3.5423	5x - 2.8719		
10	0	0	2	2	5.85	2							
30	0	0	2	2	4.98	% ¥ 1.5							
65	0	0	3	2	3.65	Hange 1.5							
	Bef	ore Soaking	After Soaking			1							
	Blows	DD	Moisture	DD	Moisture	0.5							
		(g/cc)	(%)	(g/cc)	(%)	0 							
	10	1.25	27.40	1.25	38.30	1	1.1	1.2	1.3	1.4	1.5	1.6	
	30 1.49 25.90 1.45 36.10 Dry density g/cc												
	65	1.55	25.80	1.52	34.60								