DEVELOPMENT OF EMPIRICAL RELATIONS FOR ENGINEERING PROPERTIES OF SOILS

Thesis

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By

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Pantnagar
December, 2020

(Pankaj Uniyal)
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CERTIFICATE-I

This is to certify that the thesis entitled "**DEVELOPMENT OF EMPIRICAL RELATIONS FOR ENGINEERING PROPERTIES OF SOILS",** submitted in partial fulfilment of the requirements for the degree of **Master of Technology** in **Civil Engineering** with major in **Soil Mechanics and Foundation Engineering** of College of Post Graduate Studies, G. B. Pant University of Agriculture & Technology, Pantnagar, is a record of *bona fide* research carried out by **Mr. Pankaj Uniyal, Id. No. 53905** under my supervision and no part of the thesis has been submitted for any other degree or diploma.

The assistance and help received during the course of this investigation have been acknowledged.

Sandeep Gupta

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CERTIFICATE-II

We, the undersigned, member of Advisory Committee of **Mr. Pankaj Uniyal**, **Id. No. 53905** a candidate for the degree of **Master of Technology** in **Civil Engineering** with major in **Soil Mechanics & Foundation Engineering** agree that the thesis entitled "**DEVELOPMENT OF EMPIRICAL RELATIONS FOR ENGINEERING PROPERTIES OF SOILS**" may be submitted in partial fulfilment of the requirements for the degree.

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LIST OF ABBREVIATIONS AND SYMBOLS

c	Cohesion
Φ	Angle of Friction
λ	Regularization Parameter (Lambda)
ρ	Spearman’s Rank Correlation Coefficient
µ	Micron
%error	Percentage of Error
%Gravel (%G)	Percentage of Gravel
%Sand (%S)	Percentage of Sand
%Fines (%F)	Percentage of Fines
σ'_v	Effective Vertical Stress
e_0, n_0	Initial Void ratio and Initial Porosity, respectively
q_u	Ultimate Bearing Capacity
Adj.R^2	Adjusted R-Squared
AASTHO	American Association of State Highway And Transportation Officials
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
ASTM	American Society For Testing and Materials
BA	Baghar Site
C	Fraction of soil coarser than 425 µm
CBR	California Bearing Ratio
C_C	Coefficient of Curvature
C_c	Compression Index
CEC	Cation Exchange Capacity
CI	Clay With Intermediate Plasticity
CPT, DCP	Dynamic Cone Penetration Test

CS, MS, FS	Coarse Sand, Medium Sand, Fine Sand ,Respectively
C_u	Coefficient of Uniformity
D_{10}	Effective Grain Size
D_{30}	Size of Sieve Hole In Which 30 % of Soil Pass Through Them
D_{60}	Size of Sieve Hole In Which 60 % of Soil Pass Through Them
DA	Dafaut Site
F_c	Consistency Factor
G	Specific Gravity
GA	Gairlekh Site
GI	Girechhina Site
HA	Harsingabagar Site
g/cc	g/cm^3
I_C	Consistency Index
ICL	Intrinsic Compression Line
IS	Indian Standards
I_v	Void Index
K	Modulus of Subgrade
KA	Kapkot Site
kPa	Kilopascal
LL	Liquid Limit
MDR	Major District Roads
MI	Silts of Intermediate Compressibility
ML	Silts of Low Compressibility
MLRA,MRA	Multiple Linear Regression Analysis
M_R	Resilient Modulus
No.	Number

ODR	Other District Roads
P#200 & R#200	Percentage of Passing & Retained on sieve no. 200, Respectively
PBT	Plate Bearing Test
PI, I_p	Plasticity Index
PL	Plastic Limit
R	Correlation Coefficient (Karl Pearson's coefficient of correlation)
R^2	Coefficient of Determination
RMSE	Root Mean Square Error
SC,SM,SW	Clayey Sand, Silty Sand & Well Graded Sand, Respectively
SL	Shrinkage Limit
SLRA	Simple Linear Regression Analysis
SPSS	Statistical Package For The Social Sciences
SPT	Standard Penetration Test
SYSTAT	Statistical Data Analysis and Scientific Visualization.
UCS	Unconfined Compressive Strength
VIF	Variance Inflation Factor
W	Percentage of Soil Passing 75µm

Introduction

Chapter 1 INTRODUCTION

1.1 Background

It is very necessary for the all infrastructural projects such as buildings, roads, dams, rails etc. to be safe and capable to withstand settlement and collapse. All the structures above or beneath the ground level, somehow related to soil. So, prior to the construction on any site, proper analysis and investigation of soil have to be done to know its strength, behaviour and design specifications. Sometimes geographical variability may be the reason for facing difficulties in predicting the behaviour of soils. Different Soil properties which comprise of physical properties (example, colour, texture, structure, and porosity), chemical properties (example, pH, salinity, organic matter, cation exchange capacity (CEC)) and mechanical properties (example, shear strength, bearing capacity, permeability, lateral earth pressure etc.) show their impact in the design consideration. Many construction errors may occur due to a lack of understanding of the properties of soil. Also for the identification and classification of soil, index properties are used. Properties like water content, density of soil, specific gravity, consistency limits (liquid limit (LL), plastic limit (PL), shrinkage limit), particle size distribution, sensitivity and activity of clay, compaction characteristics (optimum moisture content (OMC) & maximum dry density (MDD)), relative density, plasticity index (PI) etc., are classified as the index properties. Different tests have to be performed which classify the characteristics of soil used in the design specification of structures. Laboratory tests like direct shear test, triaxial test, unconfined compression test (UCS), california bearing ratio (CBR) and field tests like plate load test, standard penetration test (SPT), cone penetration test (CPT) are the strength determination tests.

Some of the above tests are easy to perform and require less time while others are time-consuming and laborious which will leads to the delay in completion of the project. Hence many researchers tried to overcome this problem by correlating the soil strength parameters and the various soil index properties. This will help in reducing the time spent on complex and sophisticated experiments. Over the years, many correlations had been proposed by various researchers mainly related to index properties which are alternatively related to fine soil. But a few numbers of researchers worked on coarse-grained soils that predicted empirical correlations between strength values and physical properties &

compaction characteristics of the soil. So this will give an area of interest regarding the further study on this topic. Hence an attempt has been made in this research which focused on the properties of soil (coarse-grained) that may be correlated with MDD and CBR value (soaked & unsoaked) of soil.

As it is a known fact that mostly Indian Highways are made of flexible pavements whose design is based on CBR test: an empirical method. CBR value is used for the design of the thickness of pavement. Procedure for the CBR test is as per IS: 2720 (Part XVI) – 1987. Determination of CBR is a very lengthy and time-consuming process, hence a suitable method is a need to correlate different parameters of soil with CBR and so that model of equations developed which compare actual and predicted CBR value. Therefore, there is a need for methods for all these researches. Regression Analysis is one which has to perform for determining the correlations between two or more variables having cause-effect relations. These relations will helpful for predicting the topic of the study. Regression method not only predicted CBR value but also give information about the percentage of error (%error) & helps in the comparison between actual and predicted terms.

1.2 Regression and Correlation Analysis

1.2.1 Regression Analysis

A Statistical tool for finding the trends between the data called Regression. It is a "best guess" at using a set of data and fitting a set of points to a graph to make some kind of prediction. Regression analysis is a set of statistical processes for developing the relationships between a dependent variable (called the 'outcome variable') and one or more independent variables (called 'predictors', 'covariates'). In this technique, the effect of variables has to compare which measured on a different scale. This will help the researchers for eliminating and developing the best fit predictive models of equations. In this research study, regression analysis plays an important role in finding the *casual-effect relationships* between the variables (i.e. Index parameters of soil). In this research, different models are developed that includes different type of dependent variable like CBR, maximum dry density (MDD) with the combination of properties of soil parameters like liquid limit (LL), plastic limit (PL), plasticity index (PI), optimum moisture content (OMC), maximum dry density (MDD), which are considered as independent variables.

1.2.2 Types of Regression

The various types of regression methods are listed below:-

A. Linear regression
B. Polynomial regression
C. Logistic regression
D. Ridge regression

A) ***Linear Regression***: - simple linear regression (SLR) models are completely based on the single input predictor variable with an output dependent variable. Results expressed as a straight line while plotting the graphs (Fig. 1.1). Let say, x is the predictor (or independent) variable and y is the outcome or dependent variable. Hence the expression for the linear regression is given below:-

$$y = a_0 + a_1 * x + \varepsilon$$

Where, a_0 is the intercept of y, a_1 is the slope of a line and ε is the error (or residual) of observation. A method named least square is used for analysing the errors in which the sum of squares of errors is to minimize.

Also, in this context more general case is Multiple - variable regression analysis (MLRA) in which a model of equation is developed having multiple predictor (or independent) variables (x_1, x_2, x_3…) and a dependent variable (y). The expression is:-

$$y = a_0 + a_1 * x_{1\,j} + a_2 * x_{2\,j} + \ldots\ldots\ldots\ldots\ldots\ a_n * x_{n\,j} + \varepsilon_j\,,$$

Where, n = no. of independent variables

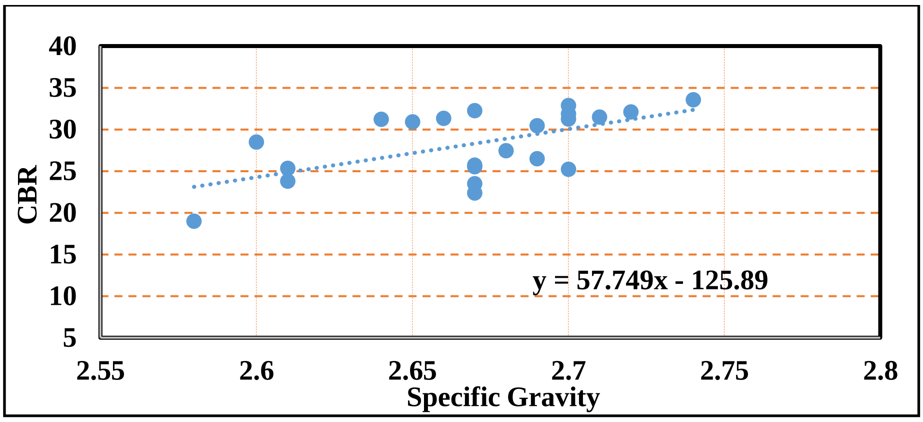


Fig. 1.1 Linear Regression

B) ***Polynomial Regression***: - non-linearly data are validated through polynomial regression. Basically, instead of a straight line, a curve line is obtained. In this case, the power of the independent variable is more than one (Fig. 1.2). The expression for this type of equation is like:-

$$y = a_0 + a_1 * x + a_2 * x^2 + \ldots\ldots\ldots\ldots\ldots\ a_k * x^k$$

Where, k signifies the degree of polynomial used.

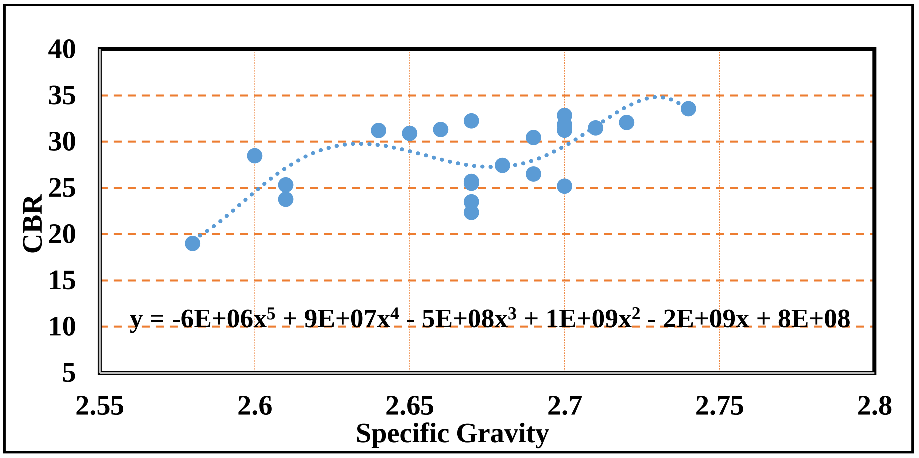


Fig. 1.2 Polynomial Regression (Degree 5)

C) ***Logistic Regression:*** **-** in this type, the nature of the dependent variable is binary (having two categories). Independent variables may continuous or binary (Fig. 1.3). It uses the *logistic function* to model the equation. The expression is as follows:-

$$p = \frac{1}{1 + b^{-(a0\ +\ a1\,*\,x1\ \ +\ a2\,*\,x2\,)}}$$

Where, x_1, x_2 are the predictors of a model, a binary response variable Y which is denoted by probability, p = P(Y=1) and b is the base of the logarithm.

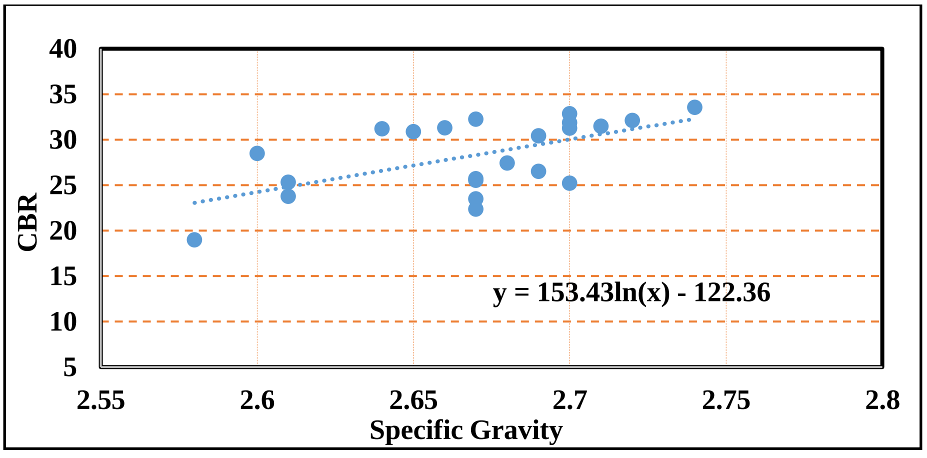


Fig. 1.3 Logistic Regression

D) ***Ridge Regression:*** **-** when a model has too many independent variables, the problem of overfitting and multicollinearity may arise. Overfitting is a condition occur when predicted data sets are too close or exact to measured data sets. Multicollinearity refers to a situation in which more than one independent variables (predictor) shows the highly perfect linear relationship. This will lead to the estimation of inaccurate coefficients, give false and insignificant results of R^2 and p-values and lower the predictability analysis of the model.

So, for analysing multiple regression data, ridge regression may be used. When there is multicollinearity between the data, the use of the least square method is not so feasible. Hence, ridge regression adds an additional regularization parameter λ (non-negative number) with the sum of squares of the regression coefficients. This regularization term helps in solving the overfitting problem of the data.

$$\text{Min}\,(\Sigma\varepsilon^2 + \lambda\,\Sigma a^2) = \text{Min}\,\Sigma(y - (a_0 + a_1 * x_1 + a_2 * x_2 + \ldots\ldots\ldots\ldots\ldots\; a_k * x_k))^2 + \lambda\,\Sigma a^2$$

The values of parameter λ (lambda) are chosen with the help of graphs called Ridge Trace (Hoerl and Kennard, 1970). The chosen value of λ should be such that after which the regression coefficient (standardize) seems to be constant. Another approach that suggests criteria for selecting the value of λ is the variance inflation factor (VIF) estimation. The value of λ should be such that all the VIF values of parameters should be less than designated value i.e. 10.

1.2.3 Correlation Analysis

In statistic, the degree to which two variables moves in relation to each other is to be measured by correlation. Change in one variable is shown by a change in the other variable, then two variables are said to be correlated and their dependence is called correlation or covariation.

A numerical index indicates the strength of correlationship between the two variables (dependent & independent). This index signifies that to what extent variables related to each other and how much proportion of predicated values are satisfied as compared to actual values. This index is known as the coefficient of correlation. This is symbolized either as R or ρ (Rho) where 'R' is known as product-moment correlation coefficient or Karl Pearson's coefficient of correlation *and* 'ρ' *is* rank difference correlation coefficient *or* Spearman's rank correlation coefficient. The term R-squared, R^2 (coefficient of determination) is a measure of the proportion of the data or their closeness to the fitted regression line. For example, as in this study, if R^2 is equal to 0.6 for an equation, it denotes that 60 percent of the data is explained by the model input equation. Its value ranges from 0 to 1.0 or in percentage from 0 to 100 %. More is the R^2 value for an equation, better it will explain or correlate the variables.

Correlation coefficient (R) ranges from -1.0 to 1.0 (Table 1.1). The interpretation of the R-value is given below:-

- ***Positive correlation***: - a value exactly 1.0 denotes the perfect positive correlation signify that with every unit increase of one variable(x), there is a proportional increase of other variables (y) (Fig. 1.5).
- ***Negative correlation***: - if there is a correspondence decrease of variable y with the increase of variable x, a negative correlation may occur. An exact value -1.0 indicate the perfect negative correlation (Fig. 1.6).
- ***Zero correlation***: - if a change in one variable (x) occur and another one (y) does not have any significant changes, it said to be Zero correlation (Fig. 1.7).

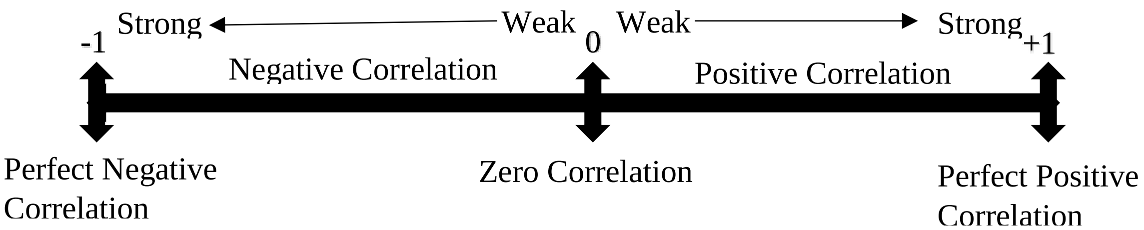


Fig. 1.4 Line Diagram of Correlation

Table 1.1 Interpretation of the R – Value

Size of the Correlation	**Interpretation**
± 1.0	Perfect Positive/Negative Correlation
±0.90 to ±0.99	Very High Positive/Negative Correlation
±0.70 to ±0.90	High Positive/Negative Correlation
±0.50 to ±0.70	Moderate Positive/Negative Correlation
±0.30 to ±0.50	Low Positive/Negative Correlation
±0.10 to ±0.30	Very Positive/Negative Correlation
±0.00 to ±0.10	No or Negligible Correlation

Table 1.2 Interpretation of the R^2 – Value

Size of R^2 Value	Interpretation
Greater than 0.9	Excellent
0.7-0.89	Good
0.4-0.69	Fair
0.2-0.39	Poor
Less than 0.2	Very Poor

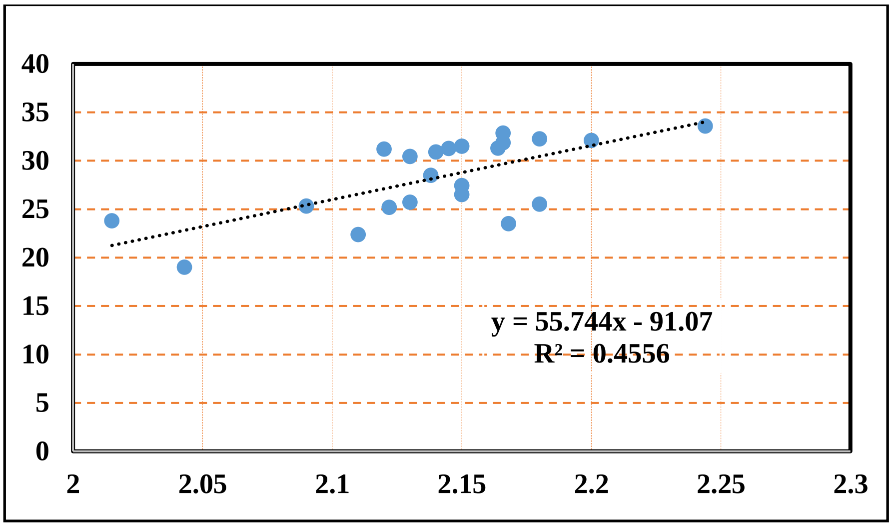


Fig. 1.5 Positive Correlation

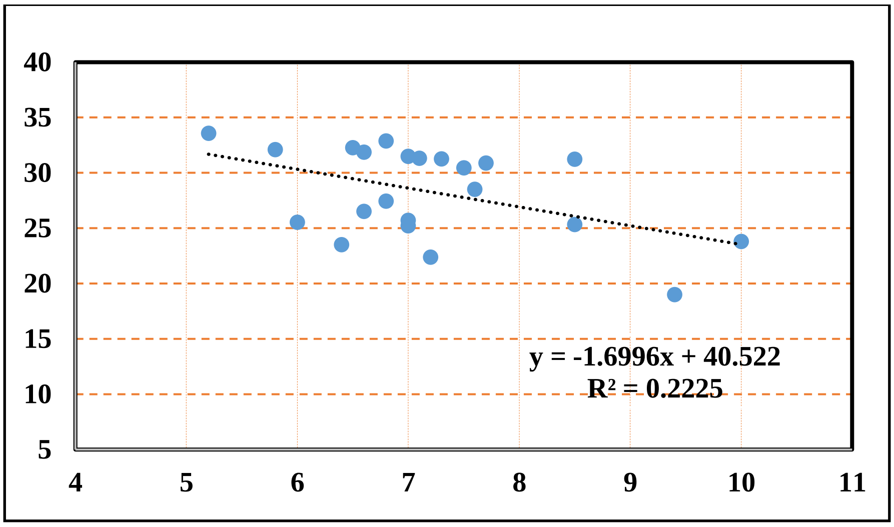


Fig. 1.6 Negative Correlation

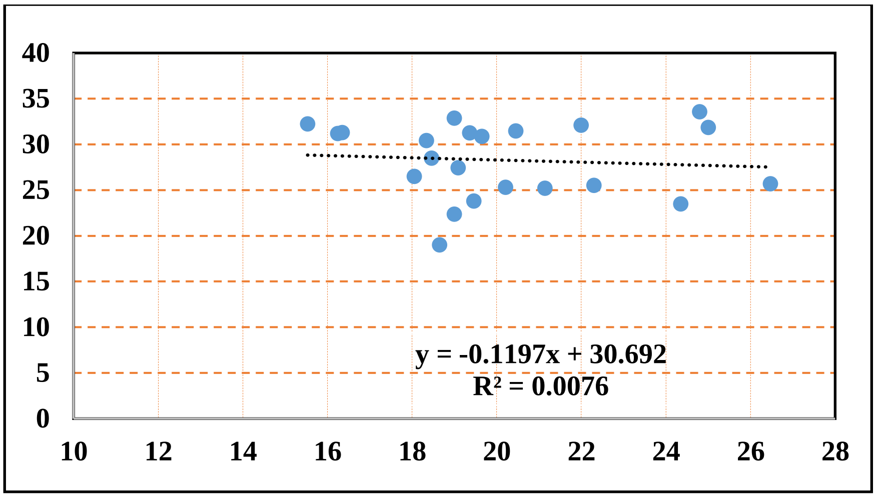


Fig. 1.7 Zero Correlation

1.2.4 General Terms Used in Regression Analysis

- **RSS (SS_{error}):-** it is known as the residual sum of squares. RSS is the deviation of the observed data from predicted model data. It plays an important role in selecting the parameters and model. For a linear regression model, $y_i=a_0+a_1*x_i + \varepsilon_i$,expression for the RSS is :

$$\mathrm{RSS} = \sum_{i=1}^{n} (\varepsilon_i)^2 = \sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathrm{y_i} - (\alpha + \beta \mathrm{x_i}))^2$$

Where, α is the estimated value of intercept a_0 and β is estimated value of slope coefficient a_1.

- **TSS (SS_{total}) :-** this is known as the total sum of squares and expressed as

$$\mathrm{TSS} = \sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathrm{y_i} - \bar{y})^2$$

Where, ȳ is mean of data.

- **Adjusted R^2:-** it is the adjustment in the value of R^2 for the determination of the number of predictor variables in the model. With the increase of the number of variables in the model, R^2 value will also increase without considering the fact that added variables may not be associated with the outcomes. Adj.R^2 penalizes those number of variables and increases only when added variables improves the model more than we would be expected by chance.

$$R^2 = 1 - \left(\frac{SS_{error}}{SS_{total}}\right)$$

$$\text{adj } R^2 = 1 - \left(\frac{(N-1)(1-R^2)}{(N-k-1)}\right)$$

Where, N is the total sample size and k is no. of independent (predictor) variable.

- **Mean Square Error (MSE) and Root Mean Square Error: -** MSE value of a data set is the average squared difference between measured and predicted values. This value tells about the quality of a predictor model and shows the closeness of data points from the regression line.

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Where, y_i is the measured values and $\hat{y}_i$ is the predicted values

RMSE is the square root of MSE value. This value is more sensitive towards the outliers point which effects the goodness of fit criteria

1.2.5 Criteria for Selecting the Regression Models

For simple regression, the goodness of fit criteria is best suited. The goodness of fit is related to the coefficient of determination (R^2), correlation coefficient (R), and R^2 adj. Also, In order to obtain the best models among the suggested models, a few criteria have to be analysed. Models should be checked for Multicollinearity. A high R^2 value is obtained from the least independent variables. For the significance of the model, the p-value should always be less than 0.05. It is assumed that residuals should be normally distributed. A hypothesis T-test has performed to check the performance of the models. Normally the variance inflation factor (*VIF*) value should be less than 10 to free from multicollinearity. A lower MSE value (nearer to zero) can give the best-fit equations.

1.3 Need for the Present Investigation

Civil engineers always encounter the problems in obtaining the representative properties of soil for the design purposes like CBR value for pavement design, strength parameters due to soil heterogeneity, especially in hilly terrain. Laboratory experiments such as CBR, direct shear test are very time-consuming. Soaked CBR takes a minimum of 4 days soaking. Sometimes due to poor handling and investigation of soil samples leads to not so accurate results. Therefore, there is a need for certain variables and procedures that are readily examined and further correlated with the parameters used for design purposes. The present analysis is therefore aimed at analysing a large number of soil samples and defining the various models equation based on model assessment parameters such as the determination coefficient (R^2), correlation coefficient (R), adjusted R^2, analysis of variance (ANOVA) test, significance test (p-value, T-test, etc.) using statistical software like M.S.Excel.

1.4 Objectives of the Present Study

The main objective of the present study is to establish the best relationship between the different properties of soil with CBR and MDD. In order to achieve this aim, the objectives listed below have been identified for the study.

1. To obtain different equations of CBR and MDD based on the Regression approaches.
2. To obtain best-suited equations with the least errors by performing different significance tests (ANOVA, T-test).
3. To analyse selected equations by implicating Ridge Regression approach.
4. To obtain the best-suited parameters for the correlation purposes based on the model evaluation parameters.

1.5 Organization of Thesis

Chapter 1 stated the introduction of the problem with the objectives of the study and the need for an investigation.

Chapter 2 deals with the literature review of different researchers relevant to the work of the present study. It also conclude the critical observation from the literature review.

Chapter 3 summarizes the methodology of the work. It explain the testing procedures, material characterization and the details of the different test and parameters of soil investigated in this study. It also covers the approaches of regression used for the development of the model of equations.

Chapter 4 covers the results and discussion part of the study.

Chapter 5 contains a summary and draws conclusions. It also includes the future scope of the work in this area.

Review of Literature

Chapter 2 LITERATURE REVIEW

2.1 Introduction

Investigation of soil plays an important role in the design specification. Determination of soil parameters whether in field or laboratory is a task. It involves several tests that are time-consuming, but necessary, for the design such as CBR, standard proctor test & unconfined compression test, etc. Hence, Regression analysis is performed to determine the correlations between two or more variables having cause-effect relations.

Many kinds of literature were reviewed on the method of linear regression & multiple regression. In their research, they pointed multiple linear regression method (MLRA) as a well-known method for predicting the relationship between a set of dependent & independent variables using statistical approaches. However, MLRA is a statistical method that uses various explanatory variables to predict the outcome of a response variable. The goal of MLRA is to model the relationship between the independent (explanatory) and dependent (response) variables.

2.2 Regression Analysis of CBR Value of Fine-Grained Soil

Cathy A. Seybold *et al*. (2008) have carried out a study titled "Linear Regression Models to Estimate Soil Liquid limit and Plasticity Index from Basic Soil Properties". Atterberg's limits show the soil consistency which signifies the degree of resistance to deformation. Cohesive soils are classified by Atterberg's limits i.e. liquid limit, plastic limit, shrinkage limit. These limits are useful for interpreting soils for bearing capacity, shear strength, swelling potential & compressibility. In this study, different prediction equations were developed having a coefficient of determination, R^2 greater than 0.60. These prediction equations can be useful in Soil Survey when there is no available data (Soil Science 2008; 173; 25-34). The paper shows many researcher's work and models. Cation exchange capacity (CEC) can be an indication of mineral type & also related to LL. LL & PI prediction equation is also available in the National Soil Survey Handbook (USDA-NRCS.2005).

For modelling, pre-1999 data in the National Soil survey laboratory characterization database was used. This database contains about 10,000 horizons with measured LL and PI data, representing soils from across the continental United States, Hawaii, and Alaska. Liquid limit and Plastic limit was carried out as per ASTM D4318. SYSTAT Software (2002) was used for estimating LL and PI using the general linear model. The best regression model has a high R^2 value and the lowest root mean square error (RMSE) with a value of $p<0.05$. For determining variable collinearity, Pearson correlations were used.

As per the results obtained, lower correlation coefficients were found when correlated with PI than with the LL. Bulk density significantly correlated with LL (correlation coefficient, R = -0.55). The sand content was significantly & negatively correlated with PI (R = -0.45). Some relations developed were:-

LL = 0.655* (CLAY) + 0.406* (CEC) + 12.459 ***R^2 = 0.81*** ***RMSE = 6.8 %***

PI = 0.408 *(CLAY) + 0.434 *(CEC) - 1.525 ***R^2 = 0.71*** ***RMSE = 6.72 %***

Patel Rashmi *et al.* (2010) worked on the SPSS software version 13.0 for the statistical analyses. The paper presents the correlations between the CBR (soaked & unsoaked) and different parameters of index properties of soil and compaction characteristics. Tests were performed according to IS code specifications.

Six zones (12 samples) of Surat city, Gujrat were selected for sample collection. A total of 10 multiple linear regression equations were developed as a result. The following equations were selected whose values match nearer to the experimental value.

CBR (unsoaked) = 54.247 - 212.216* (LL) + 212.18 *(PL) + 211.937 *(PI) - 0.467* (SL) - 20.903 *(MDD) + 0.159* (OMC) **(% Error = - 6.0%)**

CBR (soaked) = 53.783 - 103.571* (LL) + 103.447 *(PL) + 103.443* (PI) - 0.077* (SL) - 21.782 (MDD) - 0.304 *(OMC) **(% Error = - 2.5%)**

Also, SPSS solution of equations was obtained, and by comparing it with the excel solution, it was observed that the percentage error was high in the SPSS model. Hence, excel solutions are preferable. From the conclusion, it may observe that CBR value varies with PI as liquid limit and plastic limit has low influence. When the PI value increases, the

CBR value decreases. Hence, clay content directly affects the CBR value. The type of soils obtained for this study was mostly the alluvium soil

The objective of the paper presented by **Singh Dharamveer *et al.* (2011)** was to establish a relationship between CBR and compaction characteristics of fine-grained subgrade soils. Also, the samples were compacted at four different levels (50, 56, 65 & 75 blows) and five different levels of moisture content on the wet and dry side of the OMC of a soil (± 2% OMC, ± 1% OMC, and OMC). Soaked and unsoaked CBR values were determined and 100 samples were prepared in the laboratory. The soil was classified (IS: 1498-1970) as CL, CH, and CI. The plasticity index was varied from 14% to 44%. OMC and MDD as found to be within the range of 7.8% to 15.5%, 17.22 to 20.90 kN/m^3, respectively. A software named SPSS (Statistical Package for the Social Science) was used for model development. Two model equations obtained for unsoaked CBR and soaked CBR are given below:-

Unsoaked CBR = 104.71 - 0.671*(w*100/OMC) + 0.239 * (density*100/MDD) - 2.004* PL $\boldsymbol{R^2 = 0.70}$

Soaked CBR = -2.213 - 0.055*(w*100/OMC) + 0.328*(density*100/MDD) - 1.147*PL $\boldsymbol{R^2 = 0.48}$

Predicted unsoaked CBR = 0.99*Measured unsoaked CBR $\boldsymbol{R^2 = 0.75}$

Predicted soaked CBR = 1.01*Measured soaked CBR $\boldsymbol{R^2 = 0.60}$

Results show that the value of soaked & unsoaked CBR decreases as the value of moisture content increases at each level. With an increase of compaction effort at constant moisture content, the value of soaked & unsoaked CBR also increases. The Paper concluded that the developed model equation validated on a large number of soils.

A technical note written by **Tiwari Binod *et al.* (2012)** reveals that compressibility is a measure of the volume change behaviour of a soil mass subject to different amounts of external pressure. Also, it is important for the evaluation of the settlement of a soil mass. The settlement of a mass of saturated clay is determined based on the consolidation characteristics of that clay. With different proportions of Kaolinite (85%), Illite (80%), Montmorillonite (90%), and Quartz (size <5μm), a total of 55 different soil specimens were prepared in the laboratory at initial moisture contents equal to the liquid limit. In this research, an attempt was made to obtain correlation equations between the compression index (C_c) of soil with liquid limit, initial void ratio (e_0), porosity (n_0), and plasticity index (PI). Also, two different equations were proposed to estimate the compression indices of remoulded clays with liquid limit—one for soils with activities less than one and the other for soils with activities greater than one. Atterberg's limit test was carried out as per ASTM D 4318-10 specification. Soil specimens were consolidated, having effective vertical stresses of 24 kPa, 48 kPa, 96 kPa. 192 kPa, 384 kPa, 768 kPa & 1536 kPa. It was assumed that 1536 kPa would account for the most representative loading conditions in the field. The final void ratio at the convergent effective vertical stress is approximately 0.4. A plot of void index (Iv) v/s log σ'v (effective vertical stress, kPa) shows that the sample having the dominating type of clay mineral and the trend of intrinsic compression line ICL was consistent and unique (like all mixtures of Montmorillonite and Quartz). Some of the correlation equations presented in this paper

$I_v = - 0.434 \ln \sigma'_v + 1.982$ ***Coefficient of Determination,*** ***$R^2 = 0.99$***

$C_c = 0.2608*(e_0)$ Activity < 1 ***$R^2 = 0.69$***

$C_c = 0.3921*(e_0)$ Activity > 1 ***$R^2 = 0.92$***

$C_c = 0.014*(PI)$ ***$R^2 = 0.95$***

$C_c = 0.0075*(LL)$ Activity < 1 ***$R^2 = 0.92$***

$C_c = 0.012*(LL)$ Activity > 1 ***$R^2 = 0.94$***

$\frac{C_c}{n_0} = 1.0584*(n_0) + 0.0885$ ***$R^2 = 0.99$***

Results show that due to the presence of Montmorillonite in the majority of samples, the compression index has a better correlation with e_0, n_0, PI, and LL.

Talukdar Dilip Kumar (2014) present a paper which shows the importance of CBR for design purposes and the runway of the airfield. It also shows the dependency of factors like OMC, MDD, and plasticity index with CBR. Microsoft Excel was used for the linear regression model. 16 soil samples were taken & soil was characterized as silts of low compressibility (ML) and silts of intermediate compressibility (MI). The standard proctor test was done as per IS: 2720 (part VII) & soaked CBR as per IS 2720 (Part XVI)-1979. From the results, it was observed that the CBR value has a significant correlation with MDD, OMC & PI. A multiple linear regression model was developed in M.S Excel and the relation is:-

CBR (soaked) = 0.127*LL + 0.0066*PL - 0.1598*PI + 1.405*MDD - 0.259*OMC + 4.618

The maximum difference between the laboratory and predicted soaked CBR was 3.67 %. From the conclusion, it was found that the CBR value decreases with the increase in the plasticity index and optimum moisture content of soil. Also, the CBR value increases with the increase in the maximum dry density.

Shirur Naveen B and Hiremath Santosh G (2014) established a relationship between CBR Value and the Physical Properties of Soil. Different soil samples were collected from different locations having liquid limit ranges between 20 & 70. Simple Linear and Multiple Regression equations were developed which correlates the CBR (soaked) values with index properties and compaction parameters. A laboratory CBR test was done as per the IS 2720 part-XVI. A total of 20 number of disturbed soil samples were collected from different locations of the Bagalkot district of Karnataka, India. Range of soil properties obtained in this paper was: Gravel= 0-17%, Sand= 20-90%, Fines (silt & clay) = 4-75%, LL= 20-66%, PL= 20-35%, OMC= 10-23%%, MDD= 1.45-2.3gm/cc and soaked CBR= 1-6%. Three soil samples were not included in the analyses as the soil was non-plastic.

The results show that the SLRA gives R^2 value 0.72, 0.78, 0.70 when correlating soaked CBR with PI, MDD, and OMC respectively. Multiple Regression equations were:-

CBR (soaked) = -4.8353 - 1.56856 *(OMC) + 4.6351 *(MDD) ***R^2 = 0.82***

CBR (soaked) = -3.2353-0.06939 *(PI) + 2.8 *(MDD) ***R^2 = 0.76***

CBR (soaked) = 6.5452 - 0.07703*(OMC) - 0.10395 *(PI) ***R^2 = 0.75***

It was found from simple linear equations that the CBR value decreases with the increase of PI and increases with an increase of MDD. Also with an increase of moisture content CBR value decreases. Results of SLRA equations reveal that there is no significant relation exists that predicts the CBR value from Liquid limit and Plastic limit.

Rakaraddi P.G. and Gomarsi Vijay (2015) shows the importance of the soaked CBR percentage (%) value considered as a strength parameter in the design of subgrade. Subgrade thickness depends on CBR value. For the higher CBR value, the design thickness of the subgrade is thinner and vice -versa. The soaked CBR test is very time-consuming as it needs too much sampling, hence it is very difficult to do with the entire road stretch within a short duration as it may lead to delay of the project and increases its cost. To overcome this problem, certain correlations were done using simple and Multiple Regression in terms of easily determining soil parameters. %Fineness (%F) and Properties like G, LL, PL, PI, OMC, and MDD were considered as independent variables which were taken for the correlation with dependent variable i.e. soaked CBR.

Different Tests were performed according to IS 2720 Part I -VI and XVI specifications. A two-degree linear regression equation was obtained between CBR-PI, CBR-OMC, CBR-MDD, and CBR-LL that give the coefficient of determination (correlation) R^2 as 0.848, 0.867, 0.887 & 0.921 respectively. Hence with increases in fines OMC increases and simultaneously MDD decreases which leads to decreases in soaked CBR value. The multiple regression equations obtained are given below

CBR = -0.26052*OMC + 5.717093*MDD $\boldsymbol{R^2=0.94}$

CBR = -0.275*LL + 0.118*PL + 0.033*F + 5.106*G $\boldsymbol{R^2=0.96}$

CBR = 0.030F - 0.426*OMC - 0.117*PI + 5.471*G $\boldsymbol{R^2=0.95}$

CBR = -0.557*OMC + 5.943*G $\boldsymbol{R^2=0.93}$

The Paper concludes that Liquid limit is considered as a higher priority for predicting soaked *CBR* value followed by OMC, MDD, and PI based on R^2 value. Equation having an R^2 value 0.961 is considered as the best equation.

Jain Vikas Kumar *et al.* (2015) had proposed a correlation of the plasticity index and compression index of Soil. It is important to get information about the rate at which compression of soil takes place, amount of settlement, coefficient of volume change (m_v), for the design consideration. The consolidation test takes a maximum of 3 weeks to complete, hence the test is time-consuming and cumbersome. So this paper aims to establish a relationship between Cc and PI through the Regression Analysis method. The paper shows some equations obtained by researchers and they were as follows:-

$C_c = 0.007 *(W_L- 10\%)$ ***Skempton (1944)***

$C_c = 0.009 *(W_L - 10\%)$ ***Terzaghi and Peck (1967)***

$C_c = 0.3* (e_0 - 0.27)$ ***Rendon- Herrero (1980)***

$C_c = 0.0102 *(Wn - 9.15)$ ***Serajjudin (1987)***

$C_c = 1.325 *PI$ ***Koppula (1981) and Wroth et al. (1978)***

$C_c =0.014*(PI+3.6)$ ***Sridharan and Nagaraj (2000)***

A graph between the compression index and the plasticity index was plotted. A total of 44 samples were tested and the best fit relation was obtained. Simple Linear Regression equation obtained from the study:-

Cc = 0.0082 *(PI) + 0.0475 ***Coefficient of Determination, R^2 = 0.89***

Results reported that with an increase in the plasticity index, the compression index increases. The Obtained equation was applicable only for the PI value ranges 5-30.

Korde Mayank and Yadav R K (2015) have given information about the correlation between CBR value and the physical properties of some soils. Like the other researchers, this study included linear regression and the multiple linear regression equation for modelling the relationship between CBR and other parameters like LL, PL, PI, OMC, and MDD. Eight numbers of samples were collected from the different locations of the JABALPUR region (M.P), India. Four days CBR soaked values were taken for the modelling.

Results of the study show that a simple linear regression relationship between PI and CBR, MDD and CBR have a coefficient of determination (R^2) value 0.799, 0.592 respectively. Also, the multiple linear regression equation had an R^2 value 0.970 that shows a good correlation between CBR and other properties.

CBR = -0.258 - 0.014*(LL) - 0.015*(PI) + 0.011*(OMC) + 2.100*(MDD) ***R^2 = 0.97***

Yashas S. R *et al.* (2016) shows the effect of California Bearing Ratio on the properties of soil and established different relationship between CBR soaked and properties of soil. 15 soil samples were taken at every 100m interval with the depth of 3 feet below the existing surface. The tests were carried out as per Indian Standards. Before analysing the data, an assumption was made that selected locations have no appreciable variation in soil characteristics & terrain conditions. Also, have the same lane distribution factor.

The study employs Regression Analysis, which is a statistical tool for the investigation of the relationship between variables. To ascertain the established relationships & results, the chi-square test ($\chi 2$) was used to examine differences with categorical variables. This test followed the two cases, the first one was goodness-of-fit which shows how closely an observed distribution matches the expected distribution and another was for estimating whether the two random variables are independent.

Hence, the paper concludes that as the Specific Gravity, Field density, Dry density & Cohesion value increase, there is also an increase in the value of soaked CBR. With a decrease in OMC, liquid limit & angle of internal friction values, the corresponding soaked CBR value is also increasing.

Dave Rima C. *et al.* (2017) shows that strong subgrade preparation is necessary to bear the stresses coming from imposed loads without shear failure and excessive deformation which is evaluated in terms of CBR value. For the investigation, the depth of collection of clayey soil was 0.3 to 0.5 feet from natural ground level & parameters were evaluated according to Indian Standards. A modified proctor test was conducted on different soil mixtures as per IS 2720 (part-16). Regression equations obtained are given below

CBR (unsoaked) = -179.64 -14.78 *(OMC)	$R^2 = 0.78$
CBR (unsoaked) = - 387.58 + 205.5 *(MDD)	$R^2 = 0.71$
CBR (soaked) = 157.39 - 13.25*(OMC)	$R^2 = 0.80$
CBR (soaked) = - 353.16+ 185.25*(MDD)	$R^2 = 0.74$

Paper concludes that with an increase in fine particles, the OMC increases. The reduction in maximum dry density was moderate because the sand and gravels used were uniformly graded. CBR values were more sensitive at a smaller amount of clay percentage.

Egbe J.G. *et al.* (2017) give information about the application of the Multilinear Regression Analysis (MLRA) model. Models predict the soil properties and provide information for the design of the foundation. Multiple Regression is one of the modelling techniques to investigate the relationship between a dependent variable and several independent variables. Different researchers show that MLRA and MATLAB programming techniques were used to estimate the required soil properties from the measured values. Forty-five (45) samples were collected from a different location (15 locations) with varying depth. A total of 270 tests were performed and soil properties like moisture content, specific gravity, liquid limit, plastic limit, CBR & grain size analysis of sizes 2.36mm, 1.18mm, 600µ, 425µ, 300µ, 212µ, 150µ, 75µ. CBR was taken as an independent variable and soil properties such as OMC, LL, PL, MDD, coarse sand (CS), medium sand (MS), and fine sand (FS) were considered as the dependent variable. The multilinear equation is as follows:-

CBR = 20.8 - 0.102*OMC - 0.162*LL - 0.120*PL + 0.145*MDD - 0.0035*CS + 0.0246*MS - 0.120*FS ***(Coefficient of Determination, $R^2 = 0.94$)***

As per the results obtained, CBR and OMC show a positive correlation. Plastic limit has a strong correlation with CBR. With a decrease of CBR value, MS and CS values increase showing a positive relation

A non-linear stochastic optimization & Multiple Linear Regression method was used for establishing a relationship between CBR (independent variable) & LL, PL, OMC & MDD (as dependent variable) were presented by **Bassey Okon *et al.* (2017)**.The lateritic soil samples were taken at a depth of 0.6 m from the natural surface. British method was used for the determination of Atterberg's limit. For soaked CBR, the specimen was cured for 6 days (temperature = 25 ± 2º C). A total of 20 soil samples were collected from three different locations & classify soil according to AASTHO. For simple regression, equation having a high coefficient of determination are:-

CBR = -3.6197*(OMC)^2 + 91.121*OMC - 564 ***$R^2 = 0.98$***

CBR = 0.0071*(PI)^2 - 0.4403*PI + 10.303 ***$R^2 = 0.92$***

Multilinear regression equations are:-

CBR (location 1) = -1.656 - 0.239*PI + 0.898*OMC ***$R^2 = 0.94$***

CBR (location 2) = -257.843 + 2.36*OMC + 128.186*MDD ***$R^2 = 0.73$***

CBR (location 3) = 90.17 + 0.415*LL - 0.815*PI - 5.481*OMC ***$R^2 = 0.65$***

Results show that the non-linear Regression Analysis has a strong relationship of CBR with PI & OMC for location 1.Soil parameters OMC, MDD from Location 2 and LL, PI, OMC from location 3 used in multiple linear analysis for predicting CBR. These values have a good impact.

The study of **Valentine Yato Katte *et al.* (2018)** was carried out on the Sangmelima - Mengong, a highway construction project. A total of 33 disturbed samples were collected. The Tests were followed according to the BIS 1377:1990 specifications.

Tests performed were the grain size analysis, liquid limit, plastic limit, modified proctor test, and CBR. A total of 12 model equations of simple and multiple regression were presented in this paper. By interpreting the results, equations that gave $R^2 = 0.819$ suited to be best as it uses only compaction characteristics. Other models could be alternatives when it comes to cost-effectiveness but with poor R^2 (coefficient of determination) value it has less predictability. The study also concluded that a model having better R^2 value is not cost-effective due to the presence of numerous soil parameters in the relation. Also in the paper, the average percentage variation was 1.68 % which signifies that the predicted value of CBR was nearest about the experimental value. The best-suited equation is presented below

$$CBR = -61.082 + 60.233 * MDD - 2.462 * OMC \qquad \boldsymbol{R^2 = 0.82}$$

Muthu Lakshmi S. *et al.* (2019) had established the correlation between CBR and Resilient Modulus of subgrade. Study reveals that in recent times, Resilient Modulus (M_R) is widely used for the pavement design instead of CBR value in software like *IIT PAVE*. According to AASHTO T 307-99(2003), M_R is to be determined by the Cyclic Triaxial Test. M_R is a material measure of subgrade stiffness and it is an estimate of the modulus of elasticity (E) of materials. Factors like material properties, stress levels influence the Resilient Modulus. Being expansive and not widely available, IRC 37:2012 accepted a few correlations used in India. Also, the method was based on American Standards, it is necessary to determine the correlation that suits Indian conditions. Five different soil samples were collected from the Chennai area.

Regression analysis was used for the correlation purpose. A modified proctor test was done for OMC and MDD values. For M_R values, Cyclic Triaxial Test was performed. Results show that group I having 3 soil came under clayey sand & silty sand (SC and SM) and group II having two soil are under well-graded sand (SW). Averaging the correlation factor, two final equations were obtained:-

For group I, $M_R = (8.95) * CBR$

For group II $M_R = (1.14) * CBR$

It was observed that the correlation factor of SC & SM soil was 7.85 higher than SW soil. Also on increasing the confining pressure, there is a decrease in M_R value.

A technical paper presented by **Faraz Md. Islamuddin *et al.*** Sept **2019** shows the relationship between index properties and CBR value through regression analysis (linear and multiple both). In this paper, the soil was stabilized with phosphogypsum and its effect as a stabilizer on the properties of soil was studied by performing experiments. The Paper presents the objective of finding the optimum percentage of phosphogypsum that mixed with soil and carry out the regression analysis to find the best-fit equation that relates index properties with CBR.

A total of 20 black cotton soil samples were collected from different locations of Madhya Pradesh within the depth of 1-1.5 meters from ground level. Laboratory tests i.e. Sieve analysis, UCS test, CBR test, standard /modified proctor test, test for Atterberg's limits and free swelling index test was performed. Study shows that .the optimum percentage of stabilizer content is 20 %, hence test were to be performed with this percentage value

Regression analysis in this paper investigated in M.S.Excel-2007 with a p-value less than 0.05 and R- square was considered as 0.5 or above for a significant relationship. A total of 7 number of models of the simple linear regression equation and 6 for multiple linear regression were obtained. The two dependent variables were CBR (soaked) and UCS on proctor value. Also, independent variables include G, LL, PL, PI, SL, free swell index (FSI), OMC, and MDD. The best model of equation among all the models was as follows:-

$$CBR = 0.533*(UCS)-0.023*(LL)-0.037*(PL)-9.59*(SP) +6.433 \qquad \boldsymbol{R^2 = 0.89}$$

The study of **Pal Krishnan *et al.* (2020)** has an attempts to develop a correlation between CBR and product of W (percentage of soil passing 75μ) & PI (plasticity index of soil). The Paper reported the work of researchers in the field of correlation analyses especially related to CBR analyses**.** Kleyn (1978), Livneh (1987), Harison (1987), Webster et al. (1992), North Carolina Department of Transportation (1998), Karunaprema and Edirisinghe (2002), shows correlation equations between CBR and DCP (Dynamic Cone Penetration) value. Also researchers like Agarwal and Ghanekar (1970, CBR- OMC &LL), Transportation Research Board (2001, CBR - weighted plasticity index, Vinod and Cletus (2008, CBR - modified liquid limit), Ferede (2010, CBR - LL& Percentage of soil particle which is passing 200micron Sieve), Transportation Research Board (2001, CBR - weighted plasticity index) had obtained various relationships.

High plastic soil (plasticity index > 17) was collected for the investigation related to CI group soil. A trend was set up between CBR (soaked) value and (W*PI). The best-fit equation obtained from the data was:

CBR (soaked) = 6551/ (W*PI)

2.3 Regression Analysis of CBR Value of Coarse-Grained Soil

Saklecha P.P *et al*. (2011) shows the importance of Regression Analysis (single and multiple) by correlating the mechanical properties with CBR value. Properties like MDD, OMC, LL, PL, and PI were taken as independent variables. A total of 387 data sets of mechanical properties and CBR value were taken from the Wardha district in the state of Maharashtra, India. The Paper also gives information about the other researcher's work as work of Jumikis (LL- OMC & PI), McRae**,** Joslin (Ohio compaction curves), Linveh**,** etc. In simple Regression Analysis, five model equations were developed i.e. Model 1: OMC vs. CBR, Model 2: MDD vs. CBR, Model 3: LL vs. CBR, Model 4: PL vs. CBR, Model 5: PI vs. CBR. The R^2 values of these models were 0.24, 0.46, 0.01, 0.00, and 0.00, respectively.

From the results obtained, simple linear regression (R^2 = 0.46) and Multiple Linear analyses models were selected and showing good correlation as compared to others.

CBR = 28.623 - 1.3407*OMC	$R^2 = 0.24$
CBR = - 61.95 + 38.38*MDD	$R^2 = 0.46$
CBR = - 73.62 + 0.26*OMC + 42.55*MDD	$R^2 = 0.47$
CBR = - 126.18 + 0.62*OMC + 0.11*LL + 58.9*MDD + 0.53*PL	$R^2 = 0.63$
CBR = - 97.94 + 0.24*OMC + 0.33*LL + 49.79*MDD	$R^2 = 0.57$
CBR = - 72.69 + 0.18*OMC + 42.13*MDD + 0.11*PI	$R^2 = 0.47$

The simple regression analysis showed that MDD has the highest effect on the CBR value of foundation soil, followed by OMC, PL, LL, and PI in decreasing order. Multiple Regression shows that a combination of soil properties MDD, OMC, LL, PI, and PL has the maximum effect on strength characteristics (CBR).

Hassan Mujtaha *et al.* (2013) study developed a predictive model between gradational parameter, compaction energy, and compaction characteristics i.e. MDD &

OMC of sandy soil. The paper shows the work of different researchers related to the correlation analyses. Omar *et al.* (2003) showed that there exists an underlying correlation between compaction characteristics and the gradational parameters of sandy soils. Joslin (1959) proposed 26 standard proctor curves called Ohio curves, which was a quick method for identifying the approximate compaction curve of a particular soil. Korfiatis and Manikopoulos (1982) developed a relationship between MDD and Grain size distribution (GSD) of granular soils. Boutwell (1961) reported that MDD and logarithm of compaction energy show a linear relationship.

A total of 110 samples were selected. Out of which 40 similar samples were taken for validation purposes. Tests were done according to ASTM procedures. From the observations, it was found that all the soil samples fall within the range of medium to fine sand, with some silty sand. The range of effective grain size (D_{10}) in this paper is 0.19-0.014 mm. The range of the uniformity coefficient (C_u) varies from 1.38 to 11.76 and the curvature coefficient (C_c) was from 0.43 to 2.14. The range of MDD and OMC for modified and standard compaction test varies from 15.8 - 20.7 kN/m^3, 8.0 - 15.5 %, and 14.9 - 19.8 kN/m^3, 10.5 - 18.5 % respectively. From the development of the predictive model, it is found that C_u and compaction energy (CE) have a significant effect on the MDD (γ_{dmax}) and OMC.

Hence these two parameters were to be taken for correlation purposes. The final equations were as follows:-

γ_{dmax} (kN/m3) = 4.49*log (C_u) + 1.51*log (CE) + 10.2 ***R^2 = 0.81***

Log OMC (%) = 1.67 - 0.193*log (C_u) - 0.153*log (CE) ***R^2 = 0.71***

The standard error of estimate (SEE) for equation having R^2 value 0.81 and 0.71 is 0.51 & 0.042, respectively are quite low which signify good prediction capability of equations. The predicted values of both γ_{dmax} and OMC fall within ±5 % and ±3 % of measured values, respectively. These equations were compared against the equations obtained by Korfiatis and Manikopoulos (1982) and Omar *et al.* (2003). From the conclusions, it was reported that predictive equations were valid only for sandy soil having up to 5% gravels, fines up to 45 %, and further only for non-plastic fines.

Chen Jie-Ru *et al.* (2014) correlates the key indices and several gradation properties (D_{50}, C_u, angularity) of cohesionless soil. Parameters like dry unit weight (γ_d), in-situ porosity (n_o), and limiting densities (e_{max}, e_{min}) are the key indices. A total collection of 43 sandy and gravelly soils from 36 sites were taken. In this study, the soil was subdivided into 4 types according to nature and origin of the deposits i.e. fill, tailings, native and volcanic soil which were further classified as 8 major groups which were geologically aged sand (older than quaternary), quaternary gravel, quaternary sand, gravel fill, tailing sand, sand fill , volcanic gravel, and volcanic sand.

From the observations, it was obtained that dry density (γ_d) increases with an increase of D_{50} or $C_{u.}$ when $D_{50} < 0.3$mm, it is uniform sand and when $D_{50} > 1$mm, it is well-graded gravels. The first order equation obtained between γ_d and D_{50} fit for the uniform sands and well-graded gravels are as follows:-

$\gamma_d = 16.5 + 3*\log D_{50}$ ***Coefficient of Determination, $R^2 = 0.73$***

The above equation was valid when D_{50} value is between 0.3 and 1 mm. the study tells that the γ_d value was corrected by subtracting 1 kN/m^3 for the uniform soils and by adding 2kN/m^3 for well-graded soils. The n_o value of the volcanic sand was consistently higher than native soils because of the highly porous structures i.e. formed during deposition. Also, regression analyses were done for the void ratio and both C_u & D_{50} for all soils, except for volcanic soil.

$e_{max} - e_{min} = 0.25 + (0.038/ D_{50})$ ***$R^2 = 0.58$***

$e_{max} - e_{min} = 0.24 + (0.34/ C_u)$ ***$R^2 = 0.56$***

The paper concluded that for quaternary cohesionless soils, a correlation exists between γ_d and $D_{50.}$ The particle size and age of the soil deposit expressed in-situ porosity as their function. Also, uniformity coefficient (C_u) and particle shape control the limiting void ratios.

Reddy C N V Satyanarayana *et al.* (2016) shows the impact of variables on the precision of correlation equations of CBR of sandy soils**.** The different models of equations were developed with a single variable (MDD), two variables (% Gravel, MDD), and multi (three) variables (MDD, %Gravel, OMC) by performing linear and non-linear regression analyses. The Paper reported that most of the correlations for coarse-grained soils had R^2 values less than 0.95 and also lack in the process of identifying the influencing variables affecting CBR. Ten coarse-grained soil samples were taken from the different regions of Andhra Pradesh.

Tests like compaction (IS heavy tests), soaked CBR for coarse grained soil (IS 2720- (part XVI) 1987) were performed. Linear and non - linear analyses model equations were obtained. From the results of linear analyses, the value of the coefficient of determination (R^2) for soaked CBR Vs % fines, soaked CBR V/s %Sand, soaked CBR Vs %Gravels, soaked CBR V/s LL, soaked CBR V/s PI, soaked CBR V/s OMC, soaked CBR V/s MDD were 0.584, 0.632, 0.814, 0.688, 0.602, 0.721, 0.885 respectively. The developed correlation equations for estimating soaked CBR are given below:-

CBR = 198.69 - 93.59* MDD + 33.95* %G - 28.52*OMC - 15.38 (MDD* %G) - 5.21 (%G*OMC) +14.76(OMC*MDD) + 0.55(MDD*%G*OMC) ***R^2 = 0.98***

Nonlinear analyses equation are:-

Log CBR = 0.478 + 2.91 *log MDD + 0.536* log % G - 0.852* log (OMC) ***R^2 = 0.94***

From the conclusion, it is revealed that MDD, %Gravel and OMC are the key factors of CBR for sandy soils. With the increase of number of variables, a more precise equations may obtained. For sandy soil, nonlinear regression analyses shall be preferred for developing correlations.

Dhurgham Abdul Jaleel Rasool (2018) gives information about the models of equations that are related to soaked CBR values and parameters of properties of soil like grain size (% finer sieves, percentage of gravel, sand and fines, D_{60}, D_{30}, C_u, C_c), compaction parameters (OMC, MDD). In this study, a comparison was made by plotting the graphs of CBR values that are obtained through the equations of other researchers. Both simple and multiple regression analyses were performed. The equation of the best fit model is given below

CBR = 36.83 + 0.0196 * %F25 - 0.066 * %F9.5 + 0.102 * %F4.75 - 0.0184 * %F2.36 - 0.061 * %F1.18 - 0.180 * %F0.3 - 2.076 * MDD - 0.141 * OMC + 0.078 * G + 0.1141 * S + 0.13 * F - 6.335 * D_{10} - 0.207 * D_{30} ***R^2 = 0.95***

Also, other models of MLRA equations were within the range of 0.85 -0.91 (R^2) and 0.02- 0.28 for SLRA model equations. Results of the study show that the proposed equations of researchers Naveen and Santosh (2014) & Saklecha et al. (2011) have the closest relation with the equation proposed in this study. Also, the ANN technique proved to be valuable for the prediction of equations with higher accuracy and lesser time. Parameters like D_{60}, percentage of gravel, sand (%G, %S) are more useful for governing the SLRA equation of coarse-grained soil.

2.4 CBR Value Based on Strength Characteristics

A paper was presented by **Patel Mukesh A. and Patel H. S. (2012)** was based on the linear regression method, which may be useful to determine very time-consuming parameters. CBR value useful for flexible pavement design, coefficient of subgrade reaction (K- value) for rigid footing and unconfined compressive strength (UCS) needed for shear strength parameter of subgrade. The plate bearing test (PBT) is useful for the determination of stiffness of road subgrade (modulus of subgrade, K). This paper aims to develop a linear correlation between DCP and parameters such as UCS, CBR, KPBT, etc.

Twenty nine (29) samples were tested as per Indian Specifications. Wet sieve analysis was conducted and a modified liquid limit (W_{LM}) has been used as the characteristic property of soil which includes LL and parameter C (Fraction of soil coarser than 425 µm). The plate bearing test was carried out on a prototype cylindrical mould of 490 mm diameter and 490 mm height having a 10 mm thick steel plate with a 5 mm thick base plate.

$W_{LM} = LL\,(1-C/100)$

A simple linear model equation was in the form of $Y=a *X^b$ where Y is an independent variable i.e. MDD, KPBT, UCS, and CBR and X is the dependent variable i.e. DCP. Conclusions of the paper bring the information that due to the increase of modified Liquid limit (W_{LM}), the results of DCP decreases. Also, MDD, UCS, K-value, CBR-value increases with a decrease in DCP values.

Hamzah M. Al-Hashemi *et al*. (2016) had presented a paper that deals with the correlation between CBR and the angle of repose of granular soil. The determination of the angle of repose is quite easy; hence this factor was taken in this paper. A hollow cylinder test was done for the angle of repose. A total of 17 disturbed soil samples were collected from different locations within the Eastern Province of Saudi Arabia.

SLRA was used for establishing a relationship between soaked CBR and angle of repose. All soil samples were non- plastic. For the experimental data, the range of soaked CBR was obtained between 13.4 - 34.9 % and the angle of repose between 23.7 ° - 34.7 °. Data were incorporated into SPSS software. Soaked CBR was used as a dependent variable and angle of repose as an independent variable. Results show that the CBR value was directly related to the angle of repose. The standard error of the estimate was equal to 2.572.

Soaked CBR (%) = 1.925*(angle of repose) − 31.033 $\boldsymbol{R^2 = 0.85}$

The equation shows a highly good positive correlation between soaked CBR and angle of repose.

Magdi M. E. Zumrawi *et al.* (2016) reported that CBR test due to its simplicity and relatively low cost is being used in the determination of the bearing strength of the subgrade soil. The article shows the work of many researchers for the prediction of CBR values with undrained shear strength, dynamic cone penetrometer (DCP), and also with index properties. Correlation equation of Kleyn and Harden (field CBR and the DCP), Behera and Mishra (CBR and unconfined compression strength σ_c), Agarwal and Ghanekar (LL, PL & PI), The National Cooperative Highway Research Program (NCHRP) (percentage passing 0.075mm size sieve (W) and plasticity index (PI)), Zumrawi (CBR and placement factor), Black and Black (the ultimate bearing capacity (q_u) and CBR) were reported in their study. Two types of soil i.e. fine-grained (CH) and coarse-grained (GC) soil were selected for the investigation. Each soil having five samples and the test like sieve analysis, Atterberg's limit, compaction, unsoaked CBR, triaxial compression test (UU), specific gravity were conducted.

In this paper, a new concept was taken i.e. consistency factor (Zumrawi) F_c that includes dry density (γ_d), water content (w), void ratio (e), and soil consistency index (I_C). The Relation of this parameter may take into account for correlating with CBR and ultimate bearing capacity (q_u).

$$F_c = \frac{\gamma_d * I_C}{\gamma_w * e}$$

The following equations show the relationship between consistency factor v/s CBR and ultimate bearing capacity.

For soil 1	unsoaked CBR = 25.99*(F_c) - 33.16	***R^2 = 0.91***
For soil 2	unsoaked CBR = 2.228*(F_c) + 7.436	***R^2 = 0.94***
For soil 1	q_u (kPa) = 1678*(F_c) - 2231	***R^2 = 0.93***
For soil 2	q_u (kPa) = 251.5*(F_c) - 585.5	***R^2 = 0.97***

And then finally established a relationship between CBR and ultimate bearing capacity (q_u)

For soil 1	q_u (kPa) = 65 * (CBR - 1.5)
For soil 1	q_u (kPa) = 113 * (CBR - 12.5)

A linear trend was developed and also equations were best fitted. The developed correlations were reliable and useful in the prediction of bearing strength characteristics of foundation soils, subgrade, and embankments for design purposes.

Purwana Yusep Muslih and Nikraz Hamid (2013) shows the correlation between the CBR and shear strength in unsaturated soil conditions. Most of the natural soil present in an unsaturated condition and soil suction's effect on CBR has not been taken into account in practice. A new technique test on CBR i.e. suction-monitored CBR test was implemented by the author. Data from Suction-monitored CBR tests and suction-monitored direct shear tests on sand and sand-kaolin clay mixtures were taken for the analyses.

Suction in the soil is defined as the ability of soil to absorb additional water, hence the higher soil water content, the lower suction in the soil. Also, the change in behaviour of unsaturated soil is related to changes in suction. The paper gives information about the first investigator named Scala who developed a relationship between CBR and shear strength through number of test for obtaining CBR using static/dynamic cone penetrometers (Scala, 1956). The bearing capacity v/s CBR curve from static cone penetration and blows/inch v/s CBR curve from DCP test correlations were presented by Scala in his study. Correlations of some other researchers:-

Log CBR = 1.12 log (DCP) - 2.465 (kleyn 1975)

$$CBR = \frac{q_{u\,(kPa)}}{70}$$ (black 1961)

Danistan and Vipulanandan (2009) and Danistan and Vipulanandan (2010) proposed some relations for different soils

$S_u = -0.426*(CBR)^2 + 2.212*(CBR)$ for CH soil

$CBR = 0.56*(S_u)^{1.07}$ for CL, CH, &SC soil

Modulus of subgrade, E_s (MPa) = $17.58*(CBR)^{0.64}$ Powell et al. (1984)

$E_s = 10.34 * CBR$ (soaked) AASTHO (1993)

The test was carried out as per ASTM D 456 for Specific Gravity, D 422/63 for grain size analyses, D 4318 for Atterberg's limits, D 2487 for soil classification, and D 698 for compaction. Results report that the curve between shear strength and suction was finalized at a suction point below 80 kPa and all curves show a bilinear form. Data obtained from both shear strength-suction and CBR -suction curves taken for the correlations, valid for suction value from zero to 80 kPa. The range of R-square was between 0.87 and 0.92 which shows reasonable correlations.

2.5 Regression and Artificial Neural Networks Model Based on CBR Correlation

Taha S. *et al.* (2019) developed the CBR model using regression analysis and Artificial Neural Networks ***(ANNs)*** methods. Unbound granular material and subgrade soil was taken for investigation. About 207 Dataset of the material was collected from the reports prepared by Mansoura University Highway and Airports Engineering Laboratory, Egypt, and also, 11 different granular materials were collected from the different sites of Egypt. Tests like CBR, modified proctor compaction test, Atterberg's limits and sieve analysis have been carried out and classified according to AASTHO or ASTM standards. By using Minitab 17 and Microsoft Excel, models were selected i.e. based on the goodness of fit criteria. This criterion is based on the coefficient of determination (R^2), adjusted coefficient of determination (R^2 adj), and standard error divided by the standard deviation of the measured CBR values about the mean measured

(Se / Sy). Simple regression and multiple Regression analyses were performed. This study takes soaked CBR as a dependent variable and MDD, D60, R#4 (% retained on sieve no.4) as independent variables used in multiple regression. Also, MDD, OMC, D60, D30, %G (% of gravel), %S (% of sand), %F (% of fines), LL, P#200 & R#200 (% of passing & retained on sieve no. 200) were taken as independent variables in simple linear regression analysis. The range of R^2 varies from 0.90 to 0.92 in simple linear regression. The best fit model was selected by using the multiple regression method as it has a high R^2 value (0.928) and a p-value less than 0.05.

Model: $CBR = 76.85 * MDD + 0.946 * D_{60} - 102.68$ $\qquad$ $\boldsymbol{R^2 = 0.93}$

ANOVA (analysis of variance) test was performed to check the adequacy of the proposed model equation. A null and alternate hypothesis was conducted. Results show that the null hypothesis was rejected (p-value < 0.05), which means that there is a good correlation between the CBR and the proposed variables. Another hypothesis test (Z test) had performed for the evaluation of the performance of the proposed model. By using the software NeuroSolutions V.5 software, ANN models were described. ANN model exhibit high prediction accuracy ($R^2 = 0.97$) between the measured and predicted CBR values. ANN results show that D_{60} has a major influence as compared to MDD on CBR.

2.6 Conclusion

From the above literature, it is recognised that these analytical correlations can also be achieved by using less grain size parameters and characteristics of compaction, which are essentially useful for predicting the desirable geotechnical properties. Regression analysis (SLRA & MLRA) has been useful in identifying these relationships, but there is still a lack of other regression approaches such as logistics, ridge regression. Some of the researchers work on ANN (Artificial Neural Networks) techniques that, with an understanding of the collection of different variables, may provide more detailed results. While CBR has been linked to other soil parameters in many forms of study, if these relationships may be related to strength characteristics such as cohesion and friction values, it can be useful in providing solutions to other geotechnical problems such as a landslide. A technique like soil stabilization needed various percentages of stabilized material, so the study of regression and correlation proved to be a major impact on this area.

Materials and Methods

Chapter 3 MATERIALS AND METHODS

3.1 General

This chapter comprises the selection of sites, detail about the software packages used in this research. The methodology adopted in the present study is represented by a flow chart. The explanation of the statistical method is presented in this chapter. Different tests were performed for the determination of different properties of soil. The characterization of material was carried out in accordance with the Indian Standards.

3.2 Description of Study Area

All soil samples were collected from the different locations of District Bageshwar of Uttarakhand (Fig.3.1). These locations are prone to landslides. District Bageshwar lies in the northern part of the province of Uttarakhand (India) and is covered under the ***Kumaon Region***. The district has a geographical area of about 1687.8 km^2 having coordinates lies between latitude 29º40′ N to 30º20′ N and longitudes 79º25′ E to 80º10′ E. This district is surrounded by districts Almora, Chamoli, Pithoragarh in South, North & Northwest and East respectively of Uttarakhand state. As per the Geomorphology of the study area, soil presents under lesser Himalayas (geotectonic zone) are in major proportions. Hence, soil in these areas is subdivided into soils of summits and ridge tops, side slopes, etc. Selected areas like *Kapkot* consist of syncline type fold (high variable), *Harsila* region has an Anticline fold.

3.3 Soil Sample Collection

A total of 22 soil samples were collected from different areas of the Bageshwar district. These soil samples were taken from the different road stretches like Naugher - Bimola - Ana - Gairlekh - Lohagari (ODR), Bageshwar Girechhina motor road (SH 58), Bageshwar Dafaut road (MDR), Kapkot Karmi motor road (ODR), Bhani- Harsingabagar motor road (ODR), and Baghar site (Table 3.1).

Table 3.1 Locations of Different Sites (District Bageshwar)

S.N.	Selected Areas	Sample ID	Coordinates	
			Latitude (N)	**Longitude (E)**
1	Baghar Road	***BA 1***	30.0317278	79.8623739
2		***BA 2***	30.033606	79.857930
3		***BA 3***	30.03361111	79.85833333
4		***BA 4***	30.0345391	79.8526562
5	Bageshwar Dafaut Motor Road MDR	***DA 1***	29.77982222	79.85408889
6		***DA 2***	29.78472222	79.84833333
7	Naugher - Bimola-Ana-Gairlekh - Lohagari (Pathariya Road)	***GA 1***	29.93169444	79.55515278
8		***GA 2***	29.93444444	79.55666667
9	Bageshwar Girechhina Motor Road SH 58	***GI 1***	29.83655833	79.75221111
10		***GI 2***	29.83583333	79.75111111
11	Bhani Harsingabagar Motor Road, ODR	***HA 1***	29.98916667	79.91861111
12		***HA 2***	29.98904167	79.92355
13		***HA 3***	29.98982778	79.93205556
14		***HA 4***	29.98888889	79.93472222
15		***HA 5***	29.98833333	79.93888889
16		***HA 6***	29.98861111	79.94111111
17		***HA 7***	29.9875	79.94388889
18	Kapkot Karmi Motor Road, ODR	***KA 1***	29.99527778	79.90527778
19		***KA 2***	30.01669444	79.87819444
20		***KA 3***	30.02042222	79.87836944
21		***KA 4***	30.02249722	79.87736389
22		***KA 5***	30.03001944	79.88781944

3D images of motor area and sample collection areas were presented by using Google Earth software (Fig. 3.2 - Fig. 3.7).

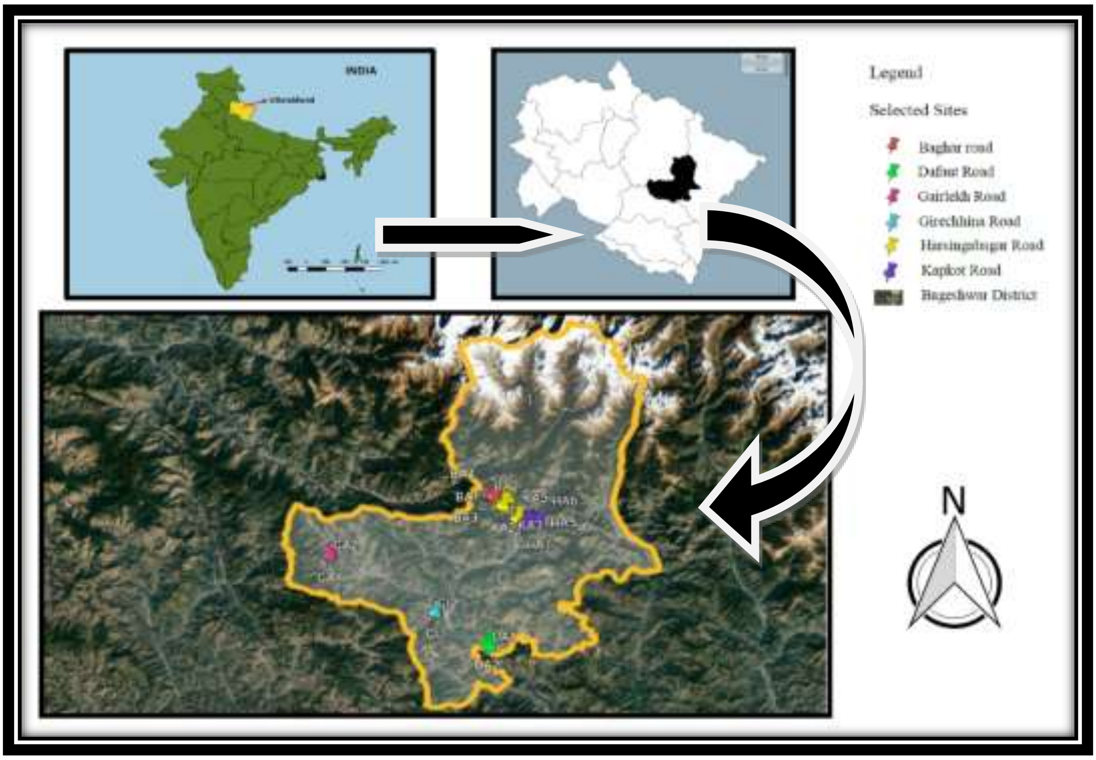


Fig. 3.1 Map of the Study Area

Fig. 3.2 Naugher - Bimola-Ana-Gairlekh - Lohagari (Pathariya road)

Fig. 3.3 Bageshwar Girechhina Motor Road

Fig. 3.4 Bageshwar Dafaut Road

Fig. 3.5 Bhani- Harsingabagar Motor Road

Fig. 3.6 Kapkot Karmi Motor Road

Fig. 3.7 Baghar Site

Figure 3.8 and Figure 3.9 shows the sample's collection sites.

(a) **(b)**

Fig. 3.8 (a) Gairlekh Site (b) Girechhina Site

(a) **(b)**

Fig. 3.9 (a) Dafut Site (b) Kapkot Site

3.4 Methodology Adopted

The methodology adopted in this research work is as shown in Fig. 3.10

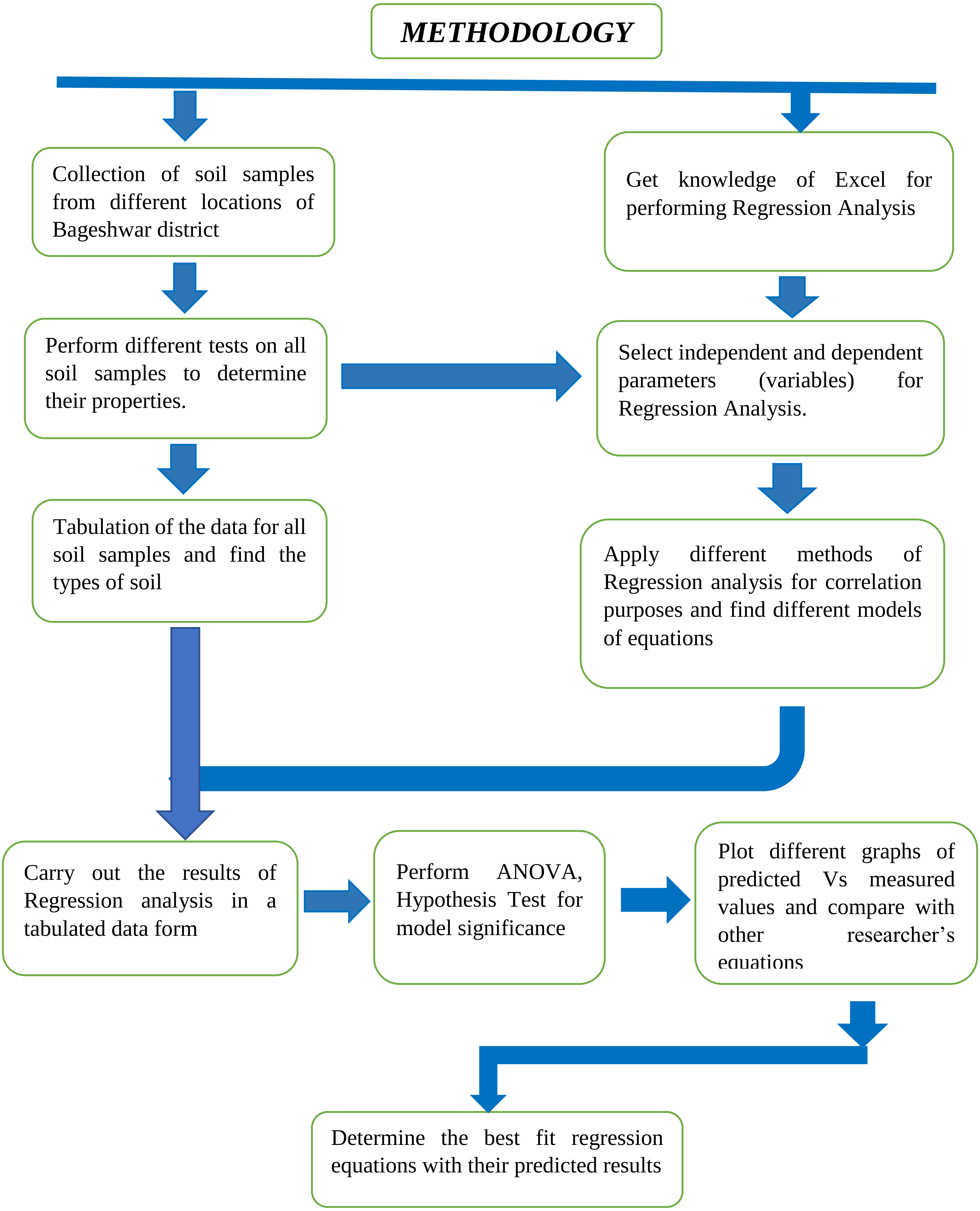


Fig. 3.10 Flowchart Showing the Methodology of the Work

3.5 Testing Methodology

Different tests are carried out for all collected soil samples as shown in Fig. 3.11. Various properties are needed for correlation purposes. These tests are followed as per IS specifications. Tests performed in this thesis are listed below:-

- Grain Size Distribution (IS: 2720 part IV -1985)
- Specific Gravity (IS: 2720 part III/sec 1,2-1980)
- Atterberg's Limit (Liquid & Plastic Limit) (IS: 2720 part V - 1985)
- Standard Proctor Compaction Test (IS: 2720 part VII - 1980)
- California Bearing Ratio Test (CBR) (IS: 2720 part XVI - 1987)

Fig. 3.11 Different Soil Samples

3.5.1 Grain Size Distribution

A soil made up of grains of different sizes is measured in terms of grain size or particle size distribution. Through sieve analysis, the soil may be classified as coarse and fine-grained soil. Grain size less than 4.75 mm sieve termed as fine-grained and more than 4.75 mm termed as coarse-grained soil. According to the test procedure, a higher aperture of the sieve is kept at the top and lower at the bottom. In this study, sieve sizes used are 40 mm, 20 mm, 10 mm, 4.75 mm for coarse-grained and 4.75 mm, 2 mm, 1.0 mm, 500µm, 425 µm, 300 µm 150 µm, 75 µm and pan for fine-grained soil.

3.5.2 Specific Gravity (G)

Specific gravity is defined as the ratio of the mass of a given volume of material to the mass of the equal volume of water at standard temperature. In this thesis, the Pycnometer test having 1 litre capacity is used for specific gravity determination. The specific gravity of soil lies within the range of 2.65-2.85 (Fig. 3.12).

Fig. 3.12. Specific Gravity Test (Pycnometer)

3.5.3 Atterberg's Limit

The limit of moisture content at which soil changes its behaviour from one state to another is known as consistency or Atterberg's limit. Liquid limit (LL), plastic limit (PL), and shrinkage limit are referred to consistency limit. To achieve the objective of the study, liquid limit & plastic limit are determined. These properties of soil are very much effective for the fine-grained soil as it depends on the percentage of clay content as compared to coarse soil but still, coarse soil has some range of these limits.

Liquid Limit (LL) shows the limit of water content at which soil possesses low shear strength. In this test, soil samples passing through 425- micron sieve size are considered for the investigation. Grooving tool type B (as per Indian Standards) is applied at the pat of cup soil interface of the Casagrande apparatus. The graph plotted against no of blows (x-axis) on a logarithmic scale versus water content by percentage (y-axis) on a normal scale. The water content determined at 25 blows is said to sample's liquid limit (Fig. 3.13).

Fig. 3.13 Liquid Limit Test

Plastic limit (PL) indicates the limit of moisture content below which soil losses its plasticity. This test followed the procedure of rolling thread of soil sample of about 3 mm diameter and the water content corresponds to the start of crumbling of a thread is said to be the sample's plastic limit (Fig. 3.14).

Fig. 3.14 Plastic Limit Test

3.5.4 Standard Proctor Compaction Test

The need for this test is usually to set up a relationship between water content and dry density of soils compacted in a mould of given sizes. It is expressed through a curve known as the compaction curve. Compaction characteristics like optimum moisture content (OMC) and maximum dry density (MDD) are obtained with the help of the compaction curve. The moisture content at maximum dry density is said to be Optimum Moisture Content. Many engineering properties like shear strength, density, and permeability may improve by performing compaction.

Firstly in this test, about 20 kg of air-dried representative soil sample was taken which was passed through 19 mm and 4.75 mm sieve. If the retained fraction on 19 mm sieve is less than 5 % by weight of soil, 1000 ml capacity mould is used otherwise 2250 ml mould capacity is used for the test. In this thesis, most of the work was performed on large capacity mould i.e. 2250 ml which has an internal diameter of 150 mm and a height of 127.3 mm. A light compaction test was performed in this thesis. About 6.3 kg of dried soil samples were taken and mixed up with 2 or 3 % water content. At each stage of testing, water content was incremented by 1 to 2 percent. Then, the soil sample was filled in three equal layers and compacted each layer uniformly over the mould surface by giving 56 no. of blows with the help of 2.6 kg weight hammer with a free drop of 310 mm (Fig. 3.15).

Fig. 3.15 Standard Proctor Test

Further, the obtained OMC values of different samples from this test were used for the preparation of the sample for the CBR test. The range of values listed below is given by K. B. Woods (Table 3.2).

Table 3.2 Soil Classification Based on MDD Values

Range of MDD values (g/cc)	Soil Classification
Greater than 2.1	Excellent
1.9 to 2.1	Good
1.75 to 1.9	Fair to Poor
Less than 1.6	Very Poor

3.5.5 California Bearing Ratio Test (CBR)

As being the strength parameter, CBR value is used in the design of flexible pavements. Road subgrade and sub-base material are evaluated and classified by the CBR test. The thickness of subgrade is relatable to CBR value, if the value is high, then the thickness considered for the design is thinner and vice versa. In this test, a standard piston having a 50 mm diameter has penetrated the soil at the rate of 1.25 mm/minute (Fig. 3.16). 2.5 mm and 5.0 mm depth of penetration are considered for the calculation purpose. A list of the standard load is tabulated in Table 3.3

Fig. 3.16 California Bearing Ratio TesT

Table 3.3 Standard Load Values at the Specified Depth of Penetration

Depth of Penetration, mm	Standard load, kg	Unit Standard Load, kg/cm^2
2.5 mm	1370 kg	70
5.0 mm	2055 kg	105
7.5 mm	2630 kg	134
10.0 mm	3180 kg	162

The expression for the CBR value (in percentage) used for the calculation:-

$$\text{CBR (\%)} = \frac{\text{Test load corresponding chosen penetartion depth}}{\text{Standard load correpsonding to the same depth}} \times 100$$

The procedures followed in this test were as per IS 2720 - part XVI 1987. All the CBR tests were performed on remoulded soil samples with dynamically compacted. Dried samples passing through a 19 mm sieve were taken and mixed at Optimum Moisture Content (OMC) which was obtained through a compaction test. A cylindrical mould with 150 mm diameter and 175 mm height with a 50 mm height detachable extension collar and a 10 mm thick base plate was taken for the sample preparation. Soil weighing about 6 kg was taken, mixed up thoroughly with water, and compacted in the mould with 3 equal layers. Samples were compacted by using a 2.5 kg hammer with 55 no. of blows with a drop of 310 mm. A surcharge weight of about 2.5 kg was kept over the samples and covered by using filter paper. For soaked CBR, mould was immersed in the tank for 4 days soaking period (96 hours). For the penetration curves, samples were recorded at the penetration of 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 4.0, 5.0, 7.5, 10 and 12.5 mm. Corrections on load penetration curves were applied because there was a concavity (convex downwards) in the initial portion of the curve.

Table 3.4 CBR Ranges of Different Soil Materials

Types of soil	**USC soil type**	**CBR Range**
Coarse Grained soils	GW	40-80
	GP	30-60
	GM	20-60
	GC	20-40
	SW	20-40
	SP	10-40
	SM	10-40
	SC	5-20
Fine Grained soils	ML,MI	15 or less
	CL,CI	15 or less
	OL,OI	5 or less
	MH	10 or less
	CH	15 or less
	OH	5 or less

3.6 Statistical Methods and Software Used

3.6.1 Simple Regression Analysis (SRA)

In this analysis, CBR and MDD values have considered as dependent. Independent variables like OMC, MDD, LL, PL, PI, & G are those parameters that are used for finding the CBR and MDD values by correlating them through regression methods. In *Linear Regression methods*, one independent variable influences the dependent variable. In this thesis, outcomes have to analysis and if the linear model satisfies the best-fit equation, then it has to be used for predicting the values.

It is not necessary that the equation is only solved by linear behaviour, so increasing the degree of a single variable in the model provides a stronger correlation equation. So in analyses, polynomial equations have to be used for this. These equations of model correlation do not indicate that the property is explicitly connected to the parameter. Their behavioural effect may or may not be linked to other parameters.

3.6.2 Multiple Regression Analysis (MRA)

In multivariate analysis, several parameters should be chosen based on their effect on the equation that will have a higher R^2 equation, a lower MSE value, and a reduction of low percent between R^2 and adjusted R^2. Analysis may also be achieved in this study by increasing the degree of parameters in multiple regressions. A combination of variables is so chosen that their p-value should be in the permissible range.

3.6.3 Statistical Software

Microsoft Excel is used in this thesis due to its regression analysis tool. In the data analysis add-in tool, regression, correlation, ANOVA report, T-test & many more analysis tools are present. It also offers the use of a polynomial equation of up to six degrees.

3.7 Concluding Remarks

To achieve the objective of the study, experimental work has been carried out in this chapter. The results of the different tests performed in this study are discussed in the next chapter. The different models of equations with their values are obtained and compiled in the next chapter.

Results and Discussion

Chapter 4 RESULTS AND DISCUSSION

4.1 General

This chapter summarizes the results of laboratory experiments performed on a different soil sample. Different parameters obtained from the tests are further classified for statistical analysis. Different models of equations are expressed in this chapter. The criteria for the selection of models were also discussed. Different regression methods are selected for accuracy purpose of the models.

For the data analysis, M.S.Excel is used for the precision of values and different criteria of model validation and evaluation.

4.2 Geotechnical Properties of Soil Samples

4.2.1 Grain Size Distribution

For the determination of the different percentages of particle sizes, sieve analysis is performed. Obtained data are plotted on a graph called Grain Size distribution graph.

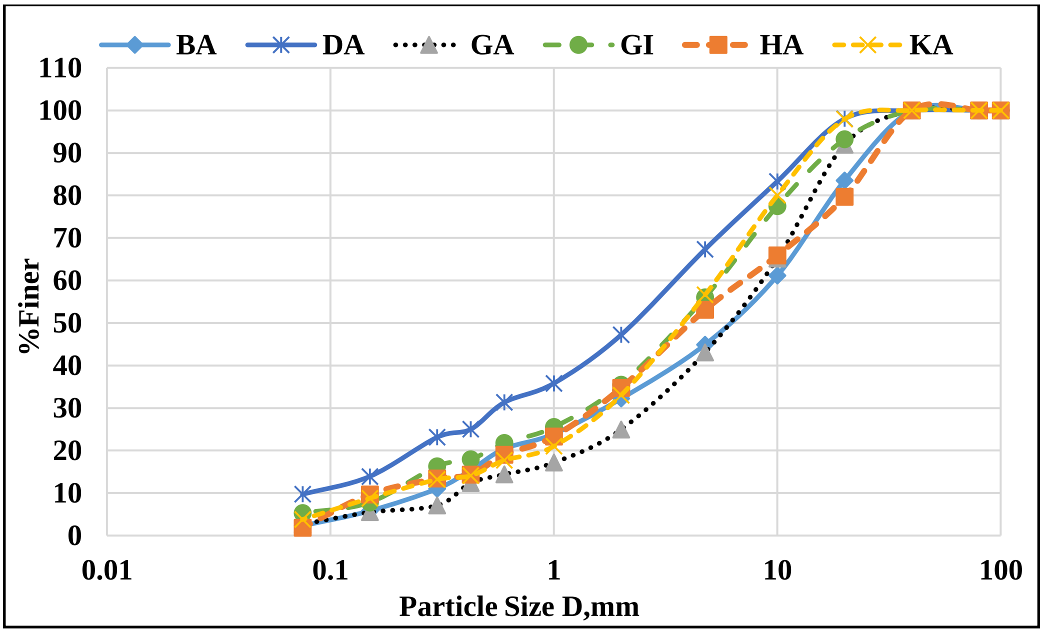


Fig. 4.1 Particle Size Distribution Curve

From the results, it is found that soil has only little to medium percentage of fines (2 to 10%). Soil fall in the range of well-graded gravel and well-graded sand. Also, some soil shows the dual nature (GW-GM, SW-SM) because of the presence of 5-12% fines classified according to IS: 1498-1970.

4.2.2 Specific Gravity

This parameter of the soil indicates strength characteristic that is used as a construction material for road and foundations. The specific gravity of all soil samples ranges between 2.58 - 2.74 as evident from Table 4.1.

4.2.3 Atterberg's Limits

As mostly, all the soil samples fall in the range of gravel (having little fines), the liquid limit ranges between 20 & 28 and the plastic limit is in between 15 - 26. The plasticity index having a minimum value of 2 with a maximum of 7 as shown in Table 4.1.

Table 4.1 Index Properties of Soil

S.No.	Sample ID	Specific Gravity	Consistency Limit		Plasticity Index (PI)	Types of Soil
			Liquid Limit (LL)	Plastic Limit (PL)		
1.	***BA1***	2.67	26.35	24.35	2.00	GW
2.	***BA2***	2.67	25.45	22.30	3.15	GW
3.	***BA3***	2.74	27.60	24.80	2.80	GW
4.	***BA4***	2.73	26.65	22.00	4.65	GW
5.	***DA1***	2.58	25.60	18.65	6.95	GW-GM
6.	***DA2***	2.61	26.34	19.46	6.88	GW-GM
7.	***GA1***	2.67	28.56	26.47	2.09	GP
8.	***GA2***	2.70	27.42	25.00	2.42	GP
9.	***GI1***	2.60	24.76	18.46	6.30	SW-SM
10.	***GI2***	2.63	23.46	16.24	7.22	SW-SM
11.	***HA1***	2.67	20.00	15.53	4.47	SW
12.	***HA2***	2.67	22.31	16.35	5.96	SW
13.	***HA3***	2.70	25.00	19.00	6.00	GW
14.	***HA4***	2.69	23.21	18.34	4.87	SW
15.	***HA5***	2.65	25.23	19.65	5.58	GW
16.	***HA6***	2.71	26.00	20.45	5.55	SW
17.	***HA7***	2.70	24.18	19.36	4.82	SW
18.	***KA1***	2.69	24.85	18.05	6.80	SW
19.	***KA2***	2.67	25.34	19.09	6.25	GW
20.	***KA3***	2.70	28.08	21.14	6.94	SW
21.	***KA4***	2.67	26.00	19.00	7.00	SW
22.	***KA5***	2.62	27.23	20.21	7.02	SW-SM

4.2.4 Compaction Characteristics

Compaction curves are used for obtaining maximum dry density and optimum moisture content values. These values are further used for obtaining CBR values and also for correlation purposes. The obtained compaction characteristics of light compaction tests are done in accordance with IS: 2720 (Part VII)-1980 as shown in figures 4.2 to 4.12.

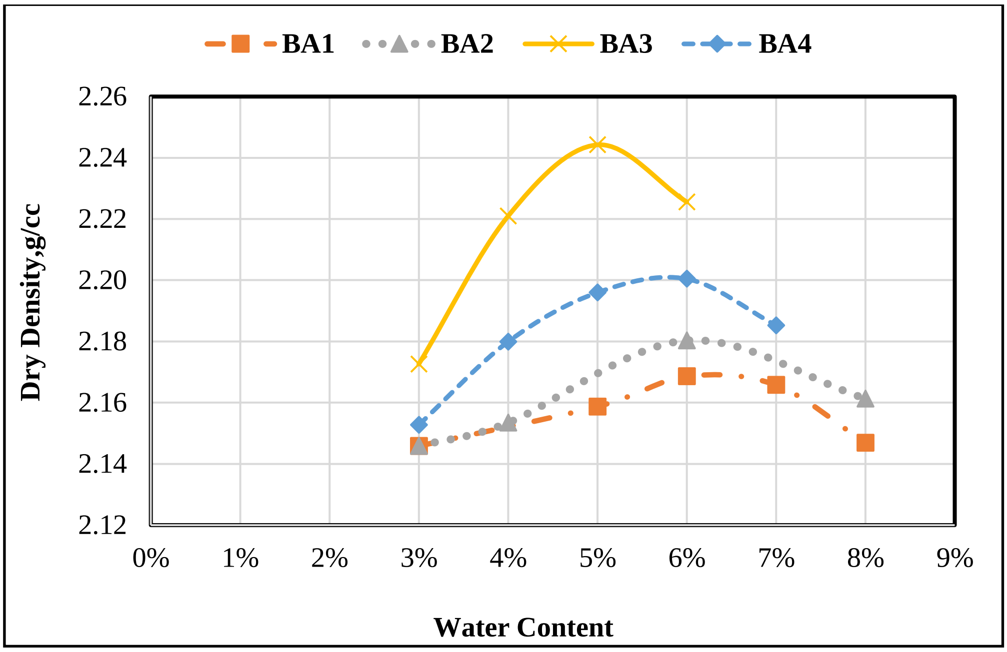


Fig. 4.2 Compaction Curves for Sample ID BA1, BA2, BA3, BA4

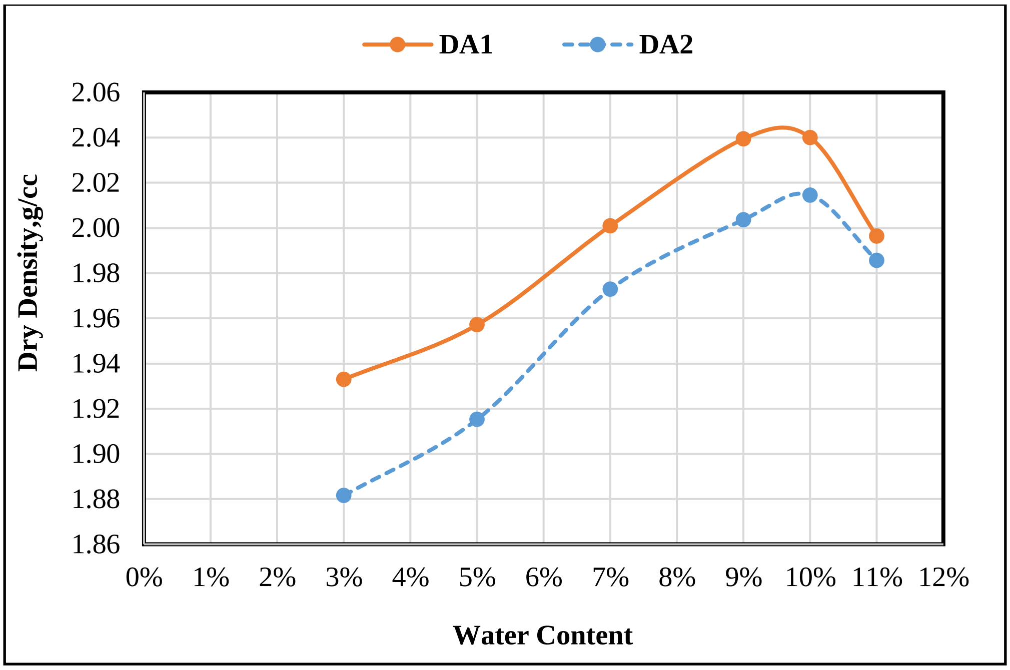


Fig. 4.3 Compaction Curves for Sample ID DA1, DA2

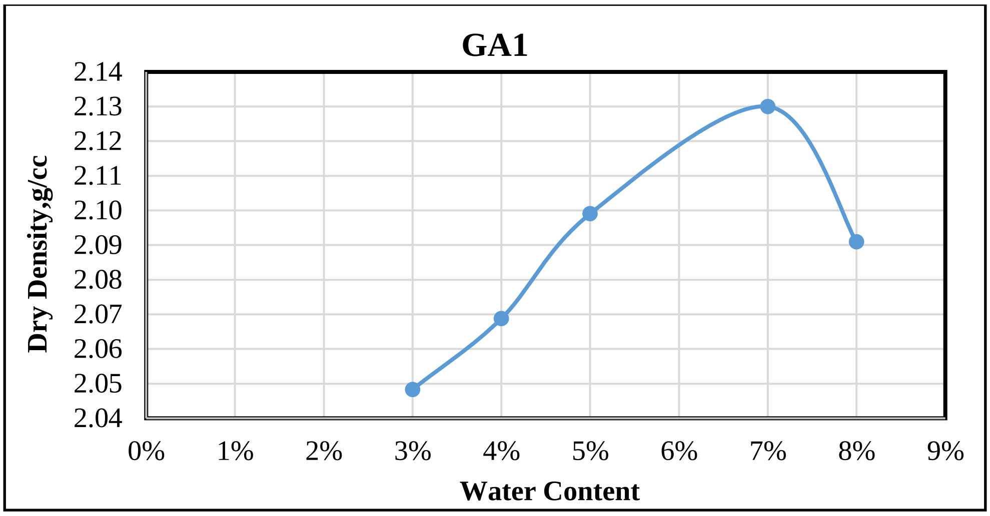


Fig. 4.4 Compaction Curve for Sample ID GA1

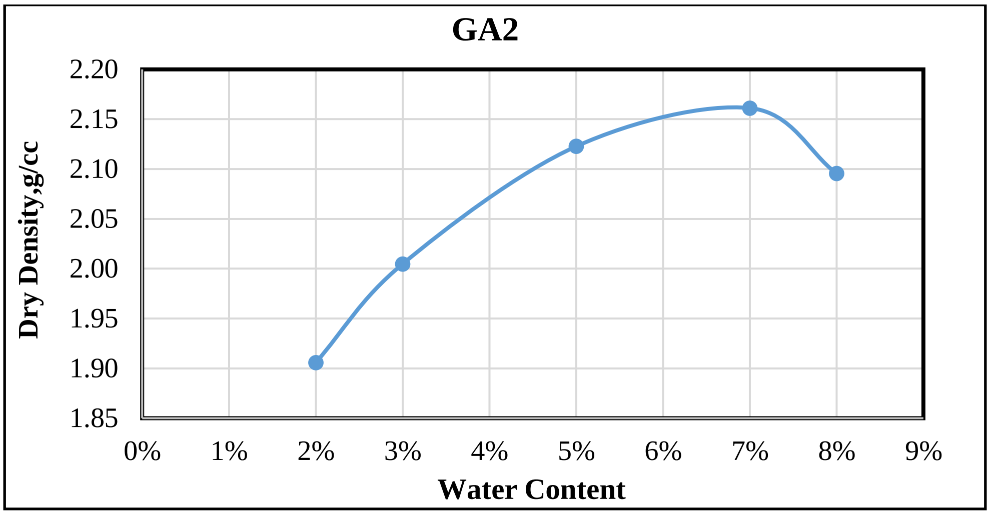


Fig. 4.5 Compaction Curve for Sample ID GA2

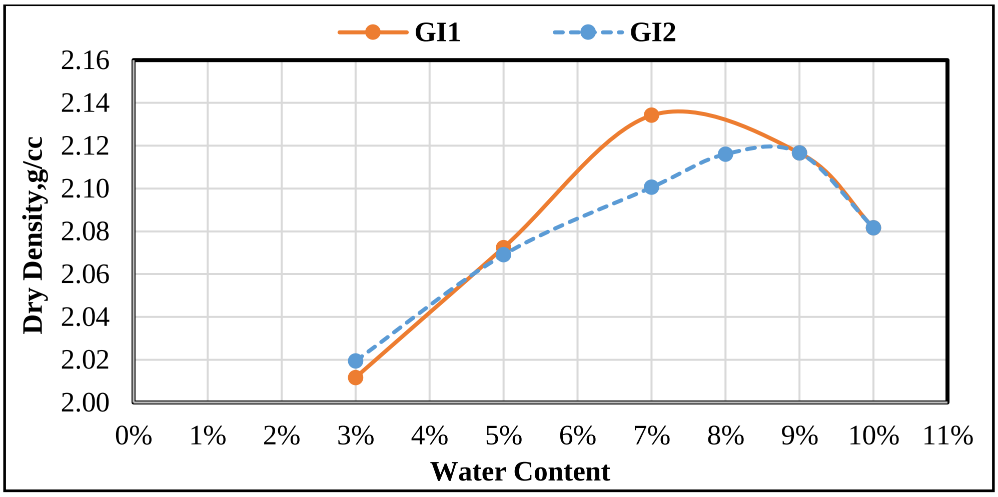


Fig. 4.6 Compaction Curves for Sample ID GI1, GI2

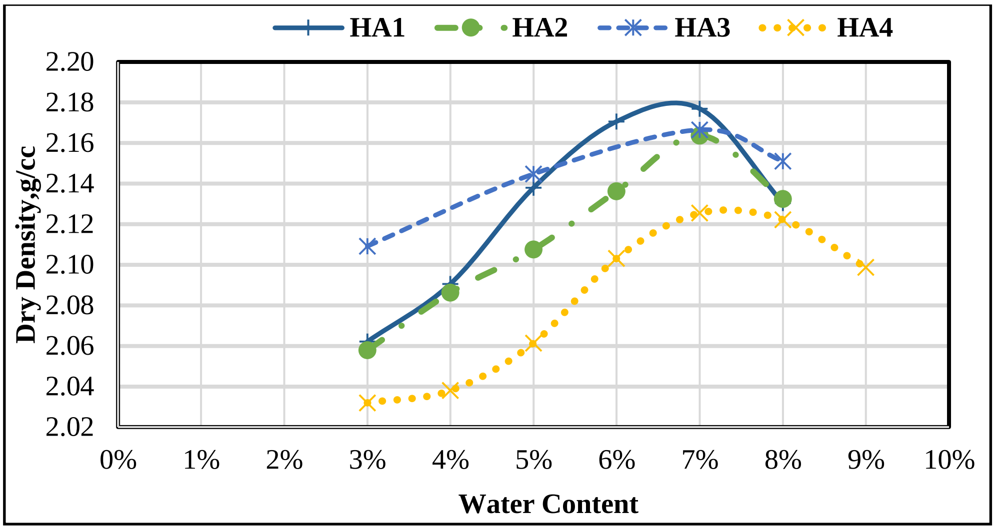


Fig. 4.7 Compaction Curves for Sample ID HA1, HA2, HA3, HA4

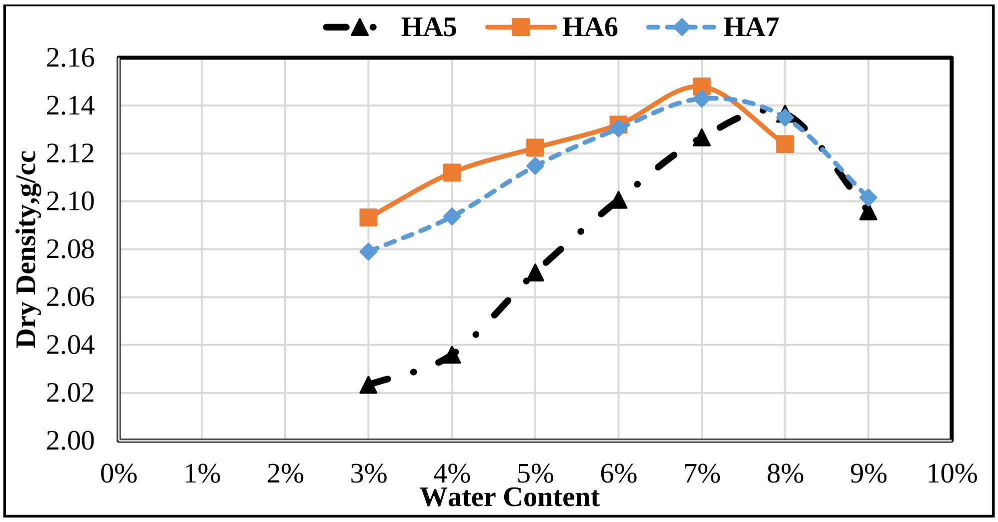


Fig. 4.8 Compaction Curves for Sample ID HA5, HA6, HA7

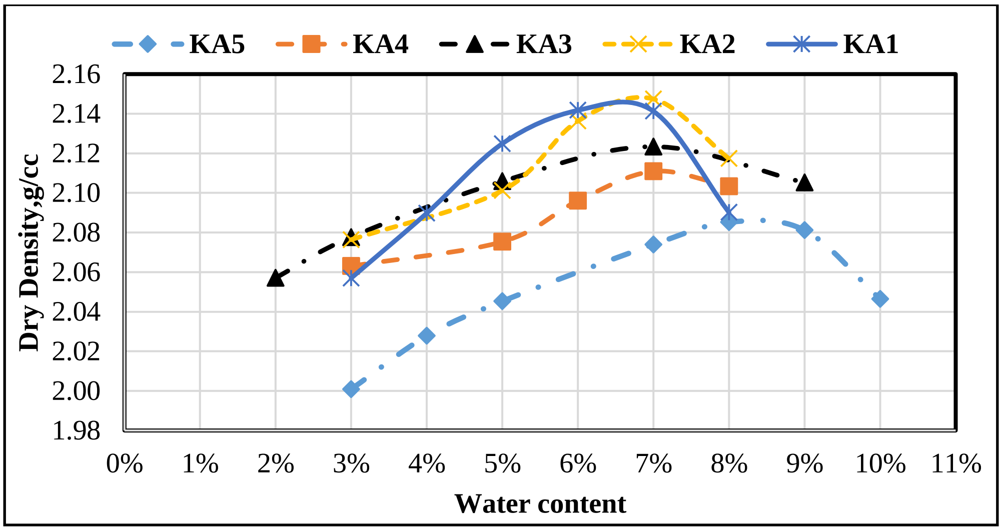


Fig. 4.9 Compaction Curves for Sample ID KA1, KA2, KA3, KA4, KA5

From the compaction curves, the maximum value of MDD is obtained for sample ID BA3 (Baghar site) i.e. 2.244 g/cm^3 and the maximum value of OMC is 10 % for sample ID DA2 (Dafaut site). The Range of OMC and MDD was in between 5.2 - 10 % and 2.015 - 2.244 g/cm^3, respectively as shown in Table 4.2.

Table 4.2 Compaction Characteristics

S.No.	Sample ID	OMC (%)	MDD, g/cm^3
1.	***BA1***	6.4	2.169
2.	***BA2***	6.0	2.180
3.	***BA3***	5.2	2.244
4.	***BA4***	5.8	2.200
5.	***DA1***	9.4	2.043
6.	***DA2***	10.0	2.015
7.	***GA1***	7.0	2.130
8.	***GA2***	6.6	2.166
9.	***GI1***	7.6	2.138
10.	***GI2***	8.6	2.119
11.	***HA1***	6.5	2.179
12.	***HA2***	7.1	2.164
13.	***HA3***	6.8	2.167
14.	***HA4***	7.5	2.127
15.	***HA5***	7.7	2.136
16.	***HA6***	7.0	2.148
17.	***HA7***	7.2	2.142
18.	***KA1***	6.4	2.146
19.	***KA2***	6.8	2.148
20.	***KA3***	7.0	2.122
21.	***KA4***	7.2	2.111
22.	***KA5***	8.4	2.085

4.2.5 California Bearing Ratio (CBR) Test

The results of load vs penetration curves of all soil samples are presented from Figures 4.10 to 4.27.

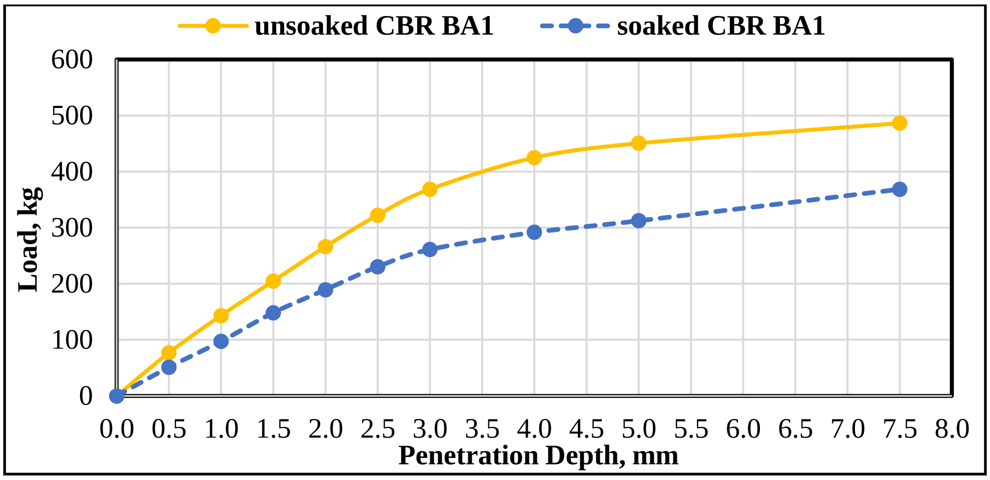


Fig. 4.10 Unsoaked and Soaked CBR Curve for Sample ID BA1

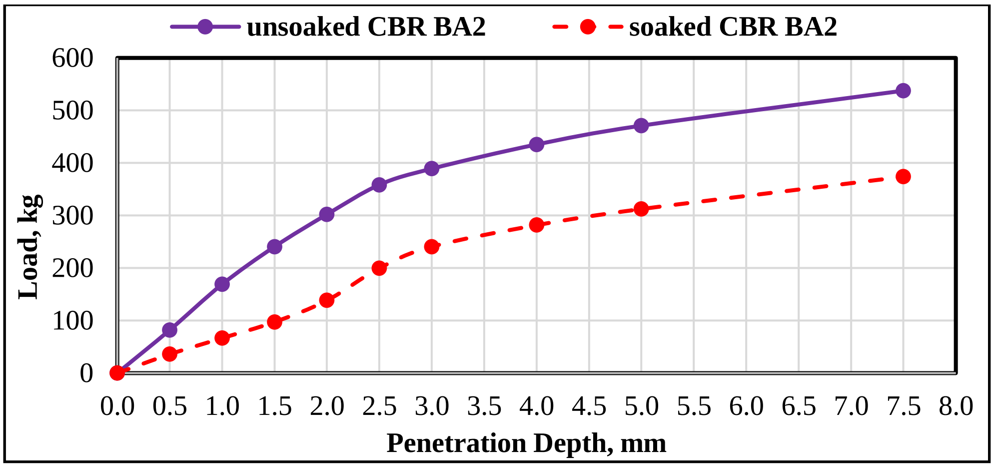


Fig. 4.11 Unsoaked and Soaked CBR Curve for Sample ID BA2

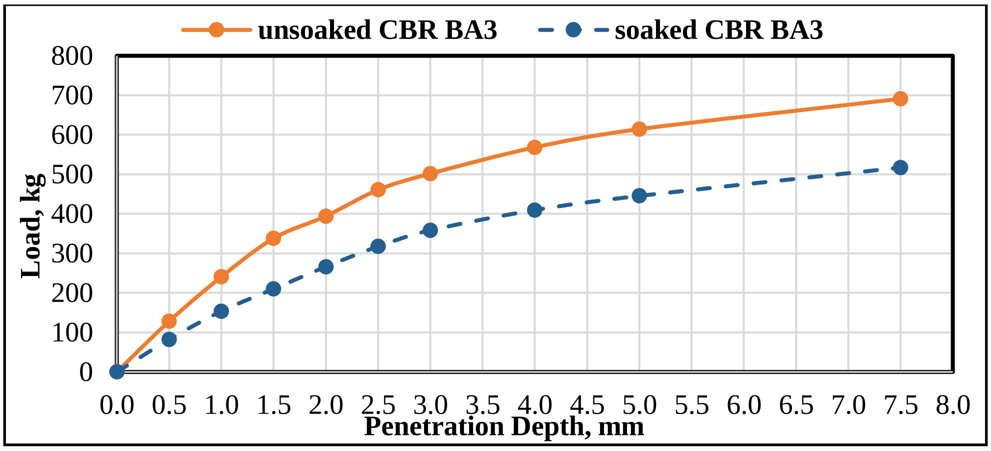


Fig. 4.12 Unsoaked and Soaked CBR Curve for Sample ID BA3

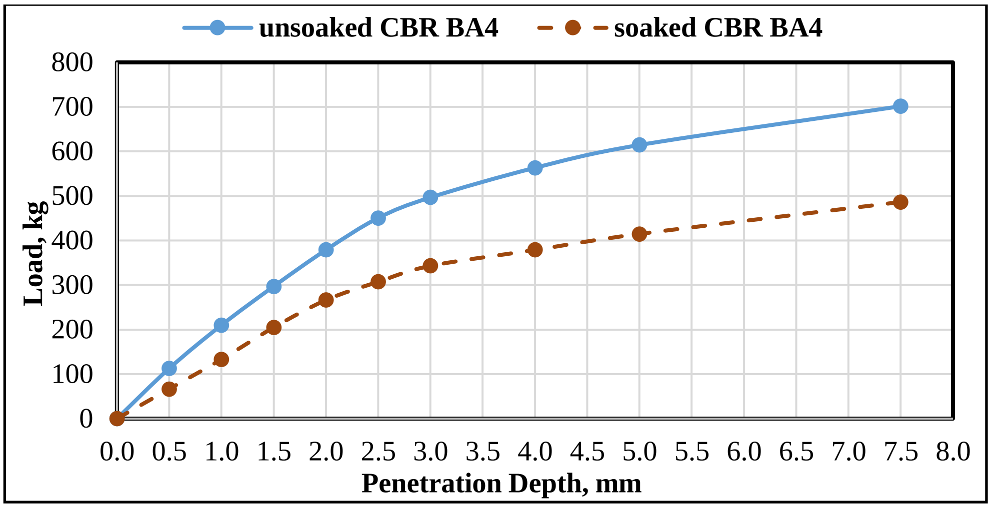


Fig. 4.13 Unsoaked and Soaked CBR Curve for Sample ID BA4

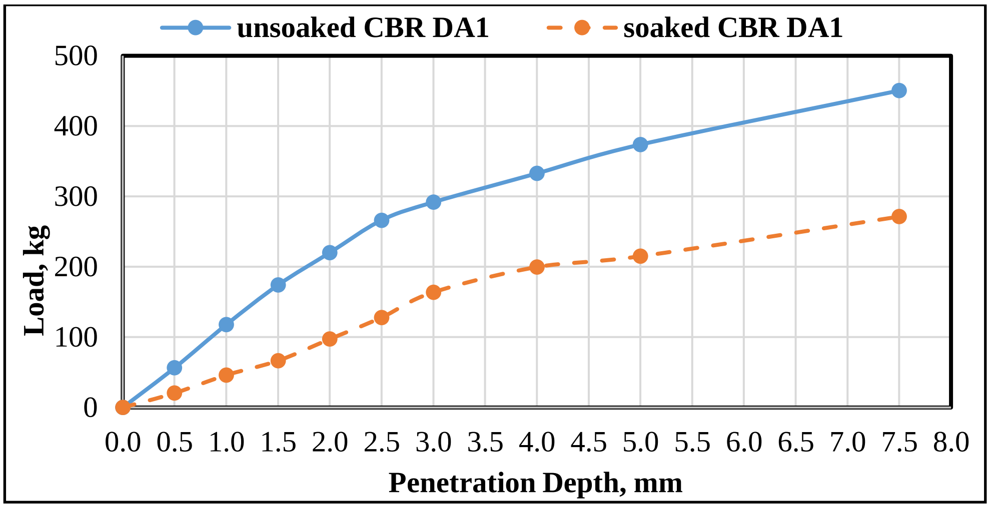


Fig. 4.14 Unsoaked and Soaked CBR Curve for Sample ID DA1

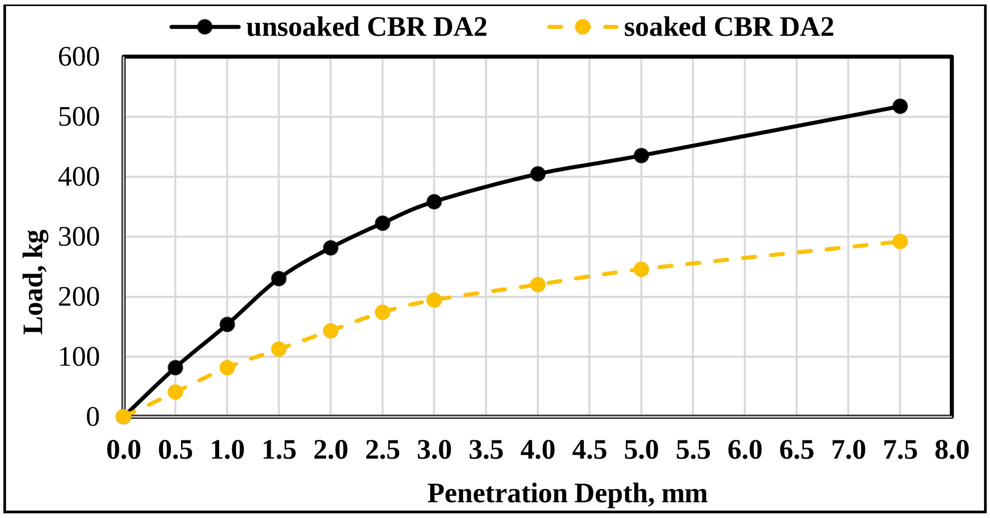


Fig. 4.15 Unsoaked and Soaked CBR Curve for Sample ID DA2

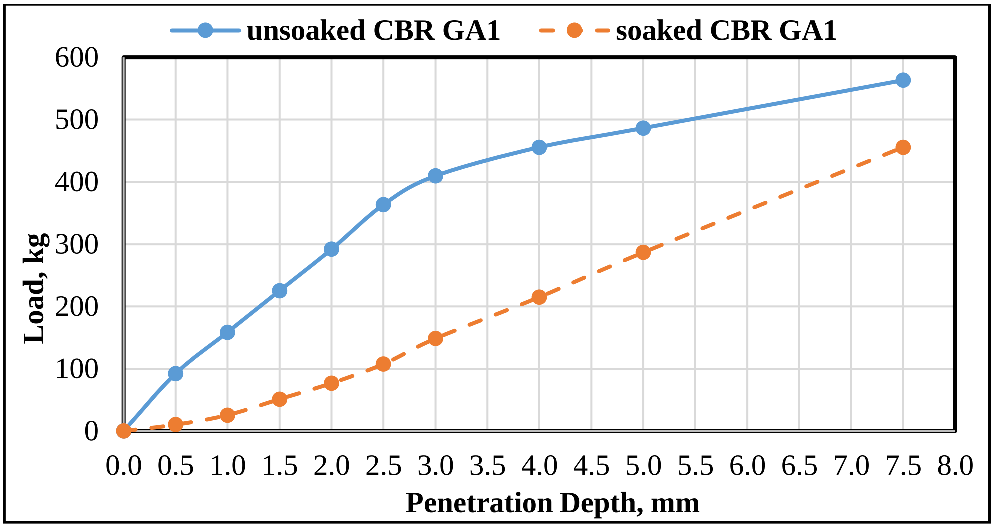


Fig. 4.16 Unsoaked and Soaked CBR Curve for Sample ID GA1

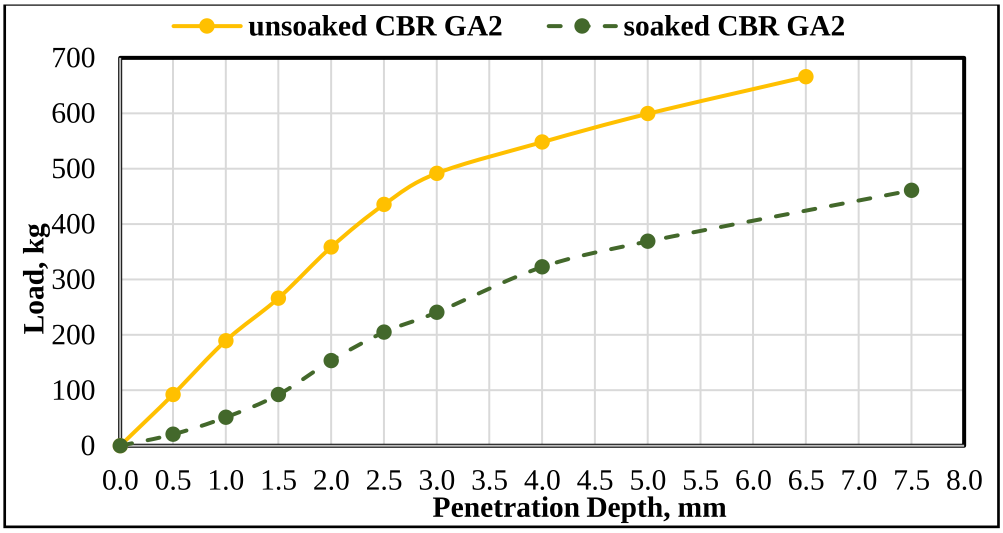


Fig. 4.17 Unsoaked and Soaked CBR Curve for Sample ID GA2

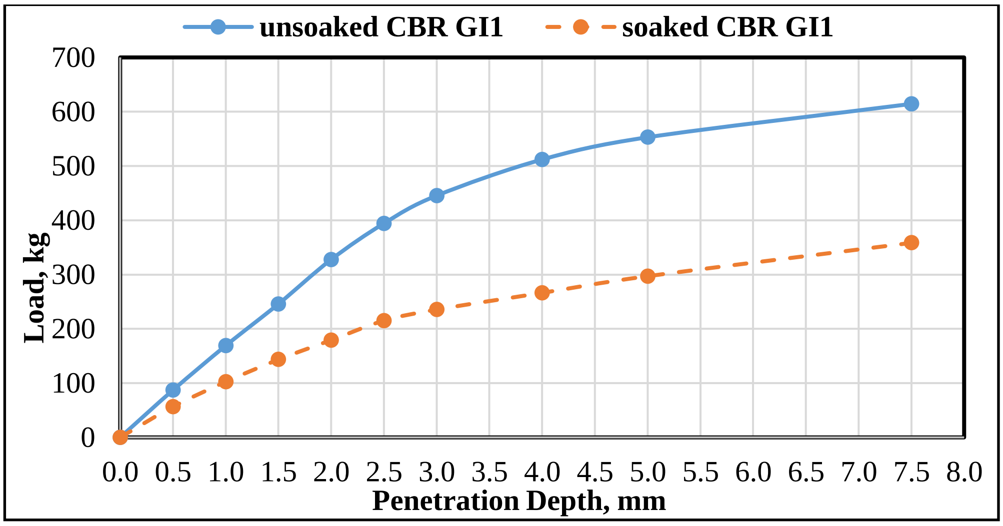


Fig. 4.18 Unsoaked and Soaked CBR Curve for Sample ID GI1

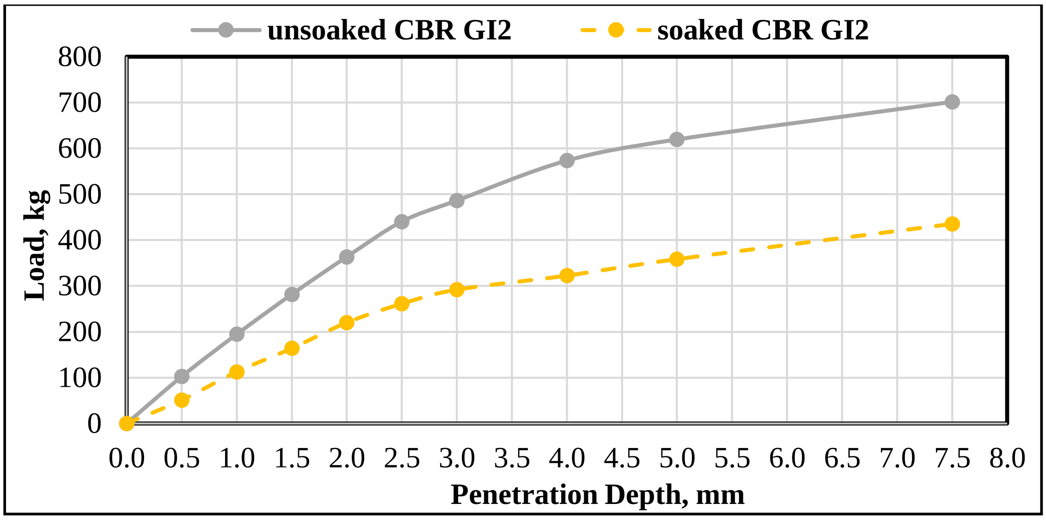


Fig. 4.19 Unsoaked and Soaked CBR Curve for Sample ID GI2

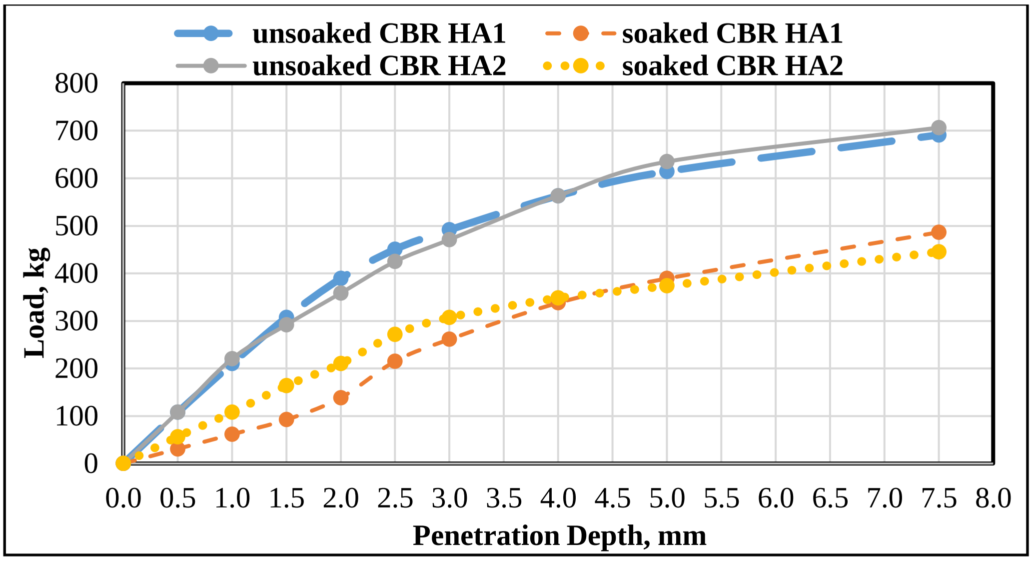


Fig. 4.20 Unsoaked and Soaked CBR Curve for Sample ID HA1, HA2

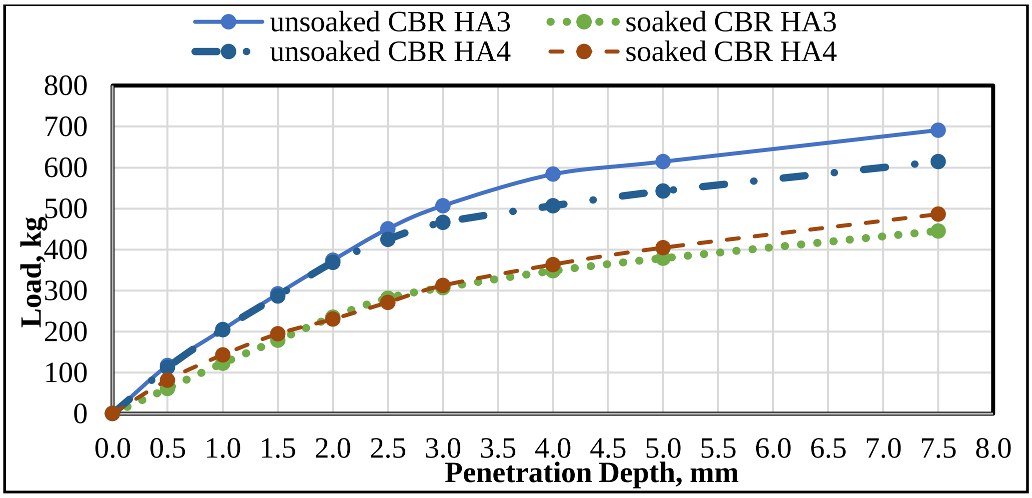


Fig. 4.21 Unsoaked and Soaked CBR Curve for Sample ID HA3, HA4

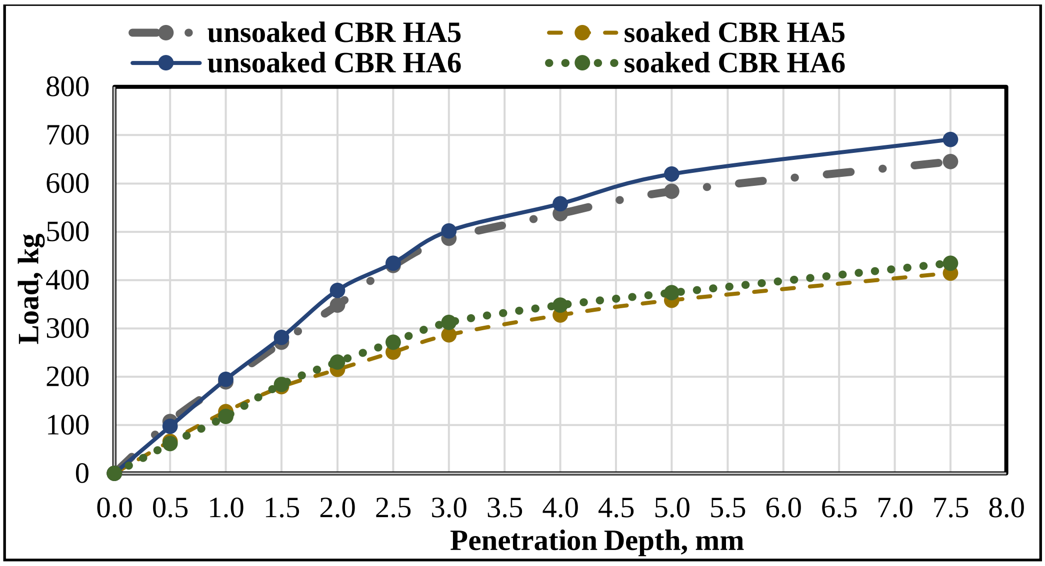


Fig. 4.22 Unsoaked and Soaked CBR Curve for Sample ID HA5, HA6

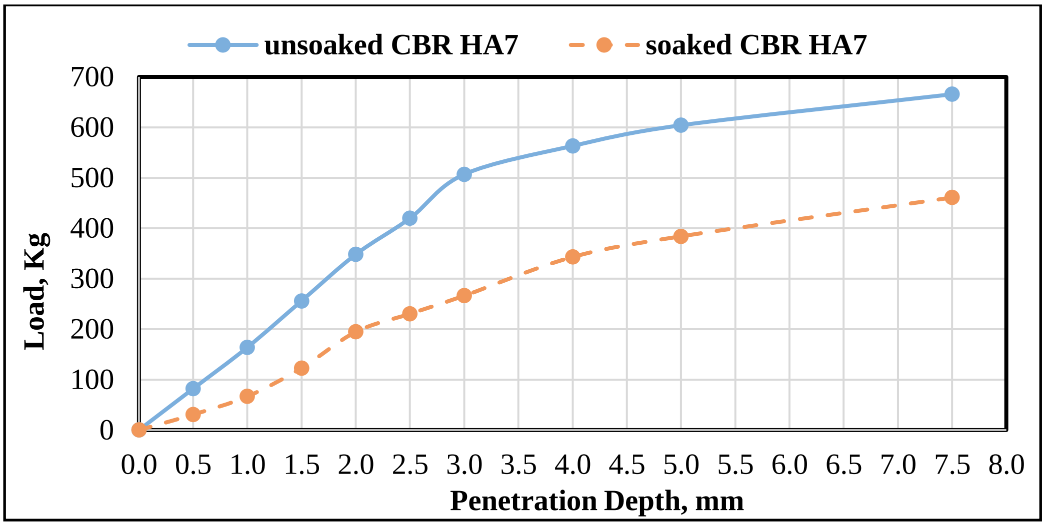


Fig. 4.23 Unsoaked and Soaked CBR Curve for Sample ID HA7

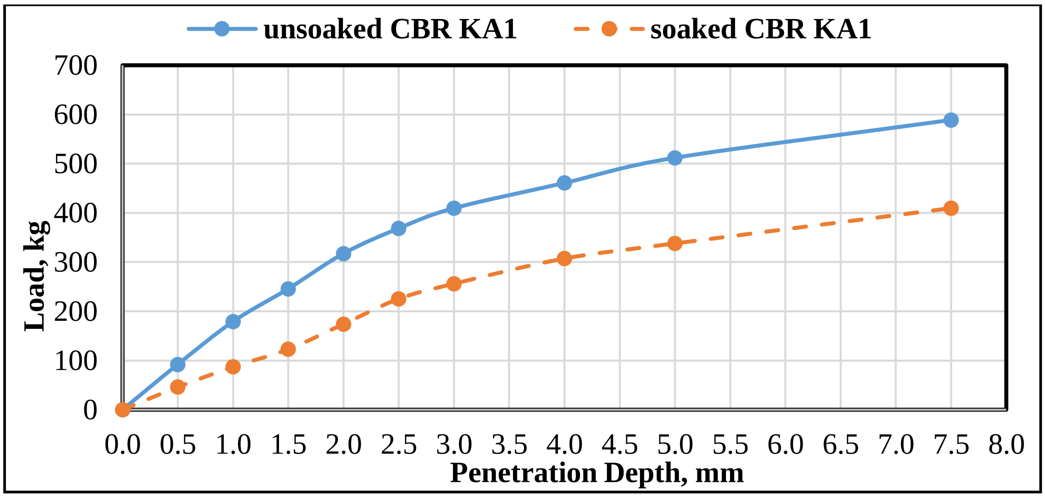


Fig. 4.24 Unsoaked and Soaked CBR Curve for Sample ID KA1

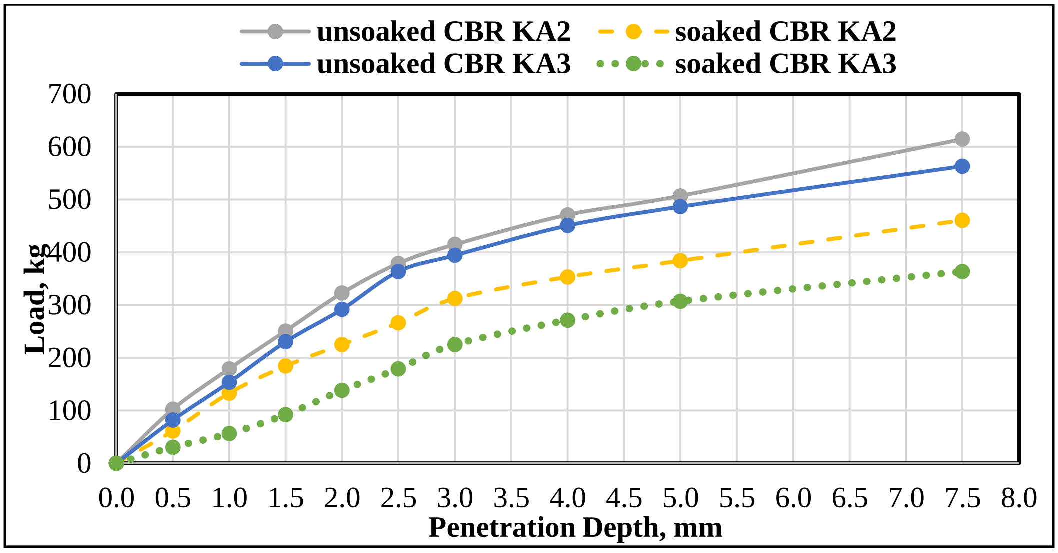


Fig. 4.25 Unsoaked and Soaked CBR Curve for Sample ID KA2, KA3

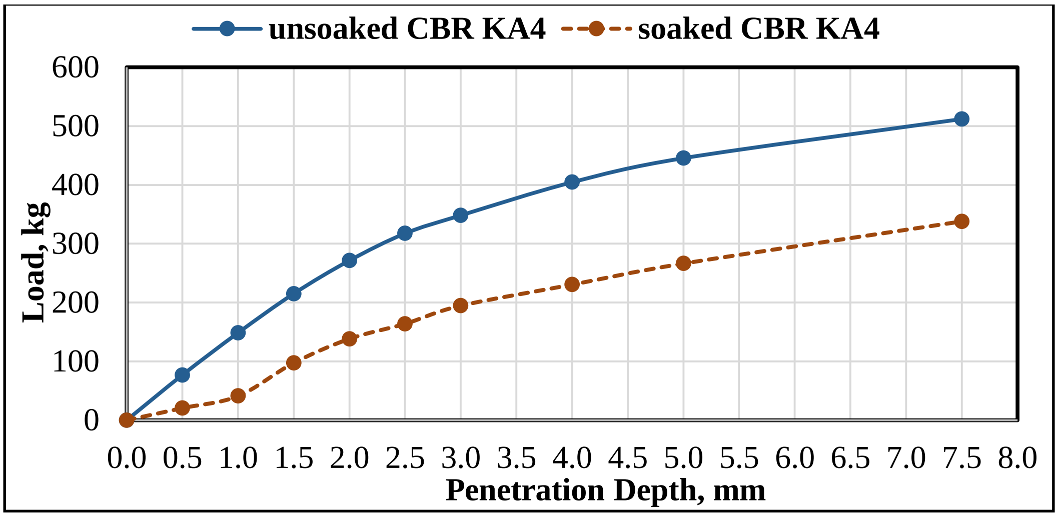


Fig. 4.26 Unsoaked and Soaked CBR Curve for Sample ID KA4

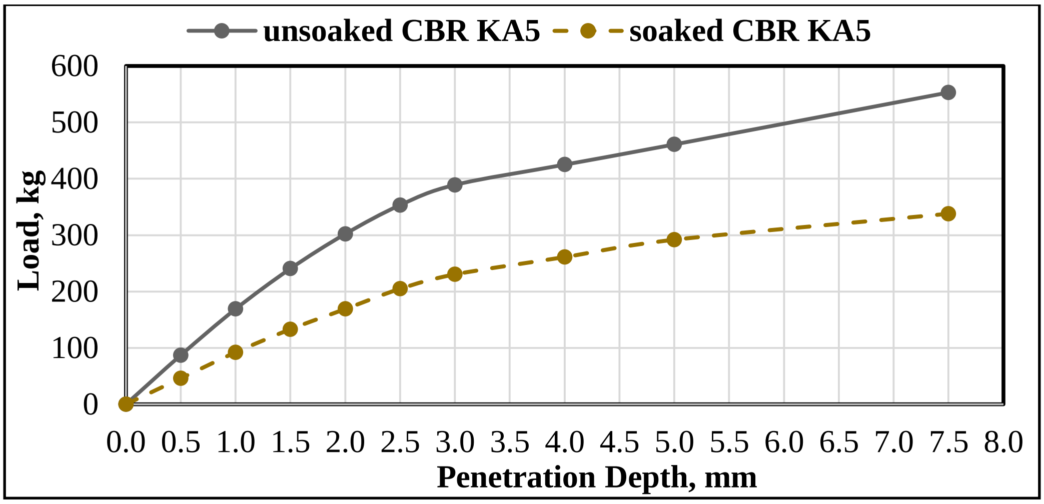


Fig. 4.27 Unsoaked and Soaked CBR Curve for Sample ID KA5

It is clear from load Vs penetration curve as shown in Figures 4.10 to 4.27**,** CBR values for the unsoaked condition are found to be a minimum value of 18.7% for sample DA1 and a maximum of 33.6% for sample BA3. Also for the soaked condition, a minimum value of 11.54% (DA1) and a maximum value of 22.91% (BA3) are obtained. It was observed from the curves that after four days soaking, the percent reduction in CBR values varies from 26 to 47% as this fact is calculated & tabulated in Table 4.3. Also, it would be observed that correction was needed for the two types of CBR curves i.e. initially concave becoming convex upward curve for the samples BA2, DA1, GA2, HA1, HA7, KA1, KA3, KA4 and continuously concave upward curve for the GA1 sample.

Table 4.3 Unsoaked and Soaked CBR Values

S.No.	Sample ID	Unsoaked CBR	Soaked CBR	% reduction (CBR value after 4 days)
1.	***BA 1***	23.43	16.24	30.68
2.	***BA 2***	25.34	18.76	25.96
3.	***BA 3***	33.60	22.91	31.81
4.	***BA 4***	32.07	21.83	31.93
5.	***DA 1***	18.7	11.54	38.28
6.	***DA 2***	23.43	12.48	46.73
7.	***GA 1***	25.47	16.24	36.23
8.	***GA 2***	31.31	20.46	34.65
9.	***GI 1***	28.50	15.28	46.38
10.	***GI 2***	31.20	18.28	41.41
11.	***HA 1***	32.28	21.89	32.18
12.	***HA 2***	31.11	19.32	37.89
13.	***HA 3***	32.23	19.68	38.93
14.	***HA 4***	30.34	20.26	33.22
15.	***HA 5***	30.31	18.54	38.83
16.	***HA 6***	31.49	19.54	37.94
17.	***HA 7***	31.10	19.71	36.62
18.	***KA 1***	26.53	18.59	29.92
19.	***KA 2***	27.46	19.59	28.65
20.	***KA 3***	25.16	16.44	34.65
21.	***KA 4***	22.79	14.72	35.41
22.	***KA 5***	25.16	14.87	40.89

4.3 Statistical Analysis

4.3.1 Regression Analysis

In this thesis, different equations of Simple Regression are obtained through linear, polynomial, logarithmic, exponential methods. The highest degree is chosen for the strong R^2 value in the polynomial process. Multiple Linear Analysis and Ridge Regression have been carried out to predict CBR values and MDD values by obtaining the best-fit equation with the least error. A least square method is applied to both simple and multiple regression. All the parameters of the obtained model are such that their p-value is less than 0.05. The descriptive statistics of the parameters are shown in Table 4.4.

Table 4.4 Statistical Information of the Variables (Dependent & Independent)

Type of Variables	Variable Name	No. of Samples	Mean	Ranges		Standard Deviation	Median
				Min.	Max.		
Dependent Variables	unsoaked CBR, % (UCBR)	22	28.14	18.70	33.60	3.99	29.40
	soaked CBR, % (SCBR)	22	18.05	11.54	22.91	2.99	18.67
	MDD, g/cm^3	22	2.14	2.02	2.24	0.05	2.14
Independent Variables	LL , %	22	25.44	20.00	28.56	1.99	25.53
	PL, %	22	20.18	15.53	26.47	2.93	19.41
	PI	22	5.26	2.00	7.22	1.75	5.77
	G	22	2.67	2.58	2.74	0.04	2.67
	MDD, g/cm^3	22	2.14	2.02	2.24	0.05	2.14
	OMC , %	22	7.19	5.20	10.00	1.12	7.00

4.3.2 Simple Linear Regression Analysis (SLRA)

By using the data analysis tool of Microsoft Excel, a model based on Pearson's coefficient (R) is developed. The goodness of fit criteria (based upon the coefficient of determination) is taken for the selection of the best predictive model's equations.

Model 1: Correlation between CBR and Liquid Limit (LL)

The plotted graphs show that the polynomial method (Fig. 4.29) gives a reasonable value of R^2 as compared to other methods for both unsoaked and soaked conditions. A negative correlation has been obtained from the graph.

$$UCBR = -0.0339*(LL)^5 + 4.1441*(LL)^4 - 201.81*(LL)^3 + 4895*(LL)^2 - 59130*LL + 284588 \qquad R^2 = 0.31$$

$$SCBR = -0.0216*(LL)^5 + 2.6348*(LL)^4 - 128.38*(LL)^3 + 3116.1*(LL)^2 - 37674*LL + 181519 \qquad R^2 = 0.233$$

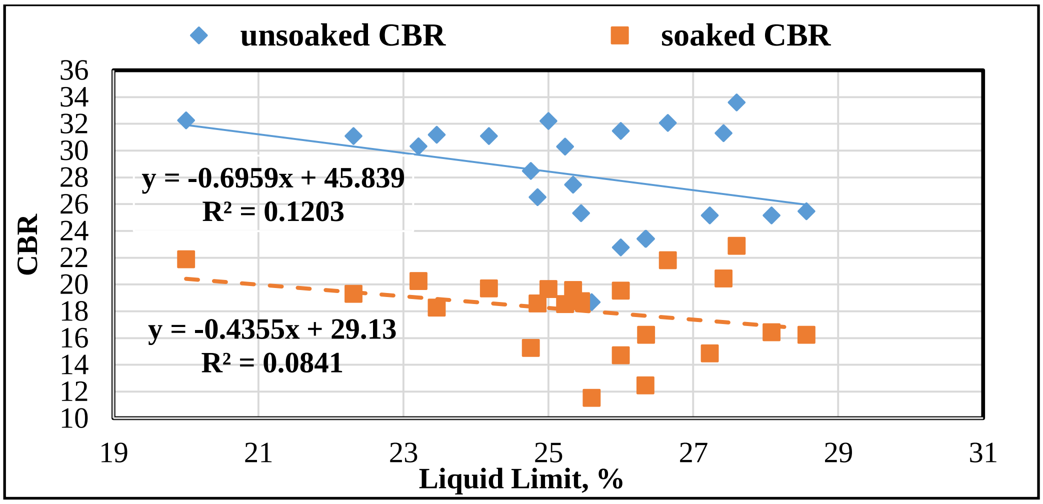


Fig. 4.28 Linear Regression Model, CBR Vs LL

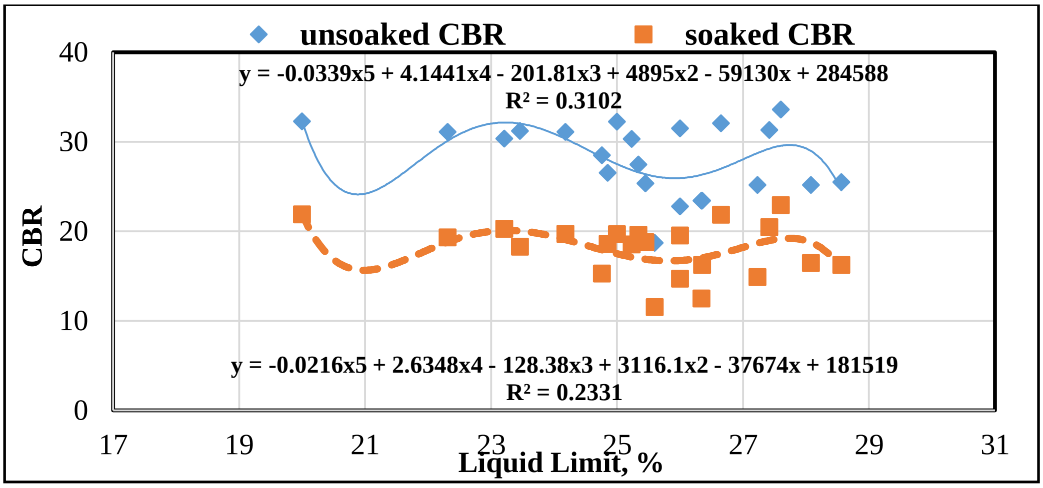


Fig. 4.29 Polynomial Method, CBR Vs LL (Degree 5)

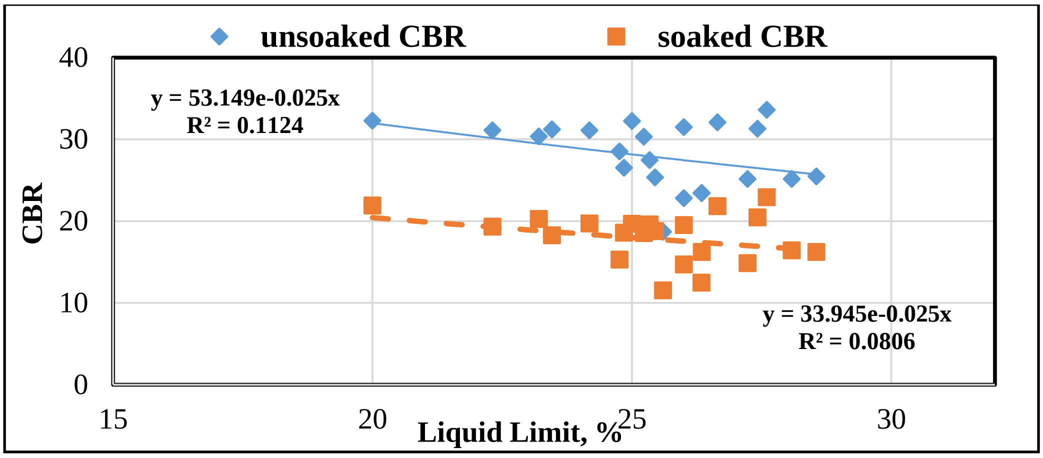


Fig. 4.30 Exponential Method, CBR Vs LL

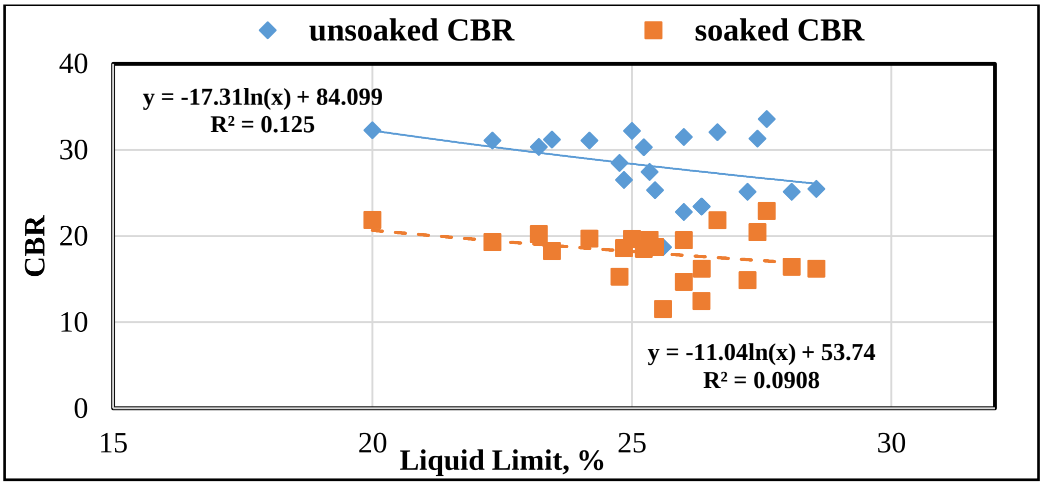


Fig. 4.31 Logarithmic method, CBR Vs LL

Model 2: Correlation between CBR and Plastic Limit (PL)

Linear, polynomial, exponential, & logarithmic regression model for soaked and unsoaked CBR vs PL have been developed and shown in figures from Fig. 4.36 to fig. 4.39.

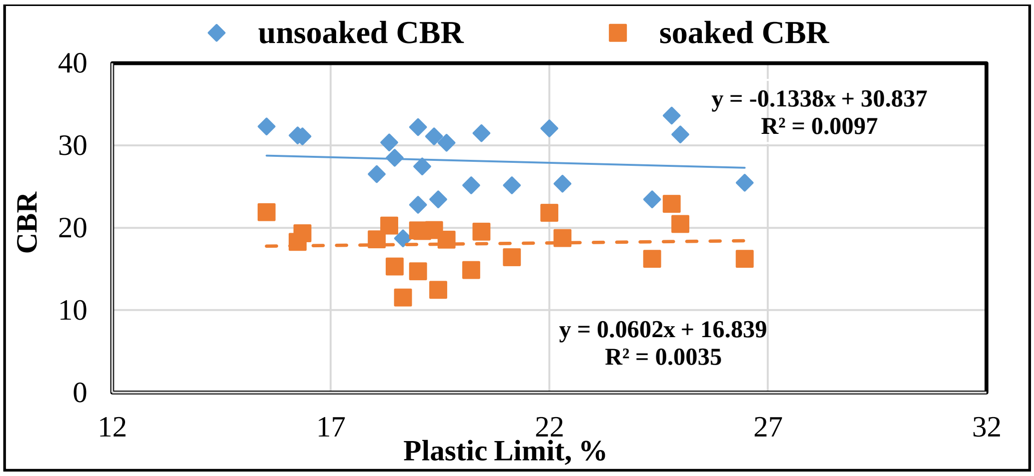


Fig. 4.32 Linear Regression Model, CBR Vs PL

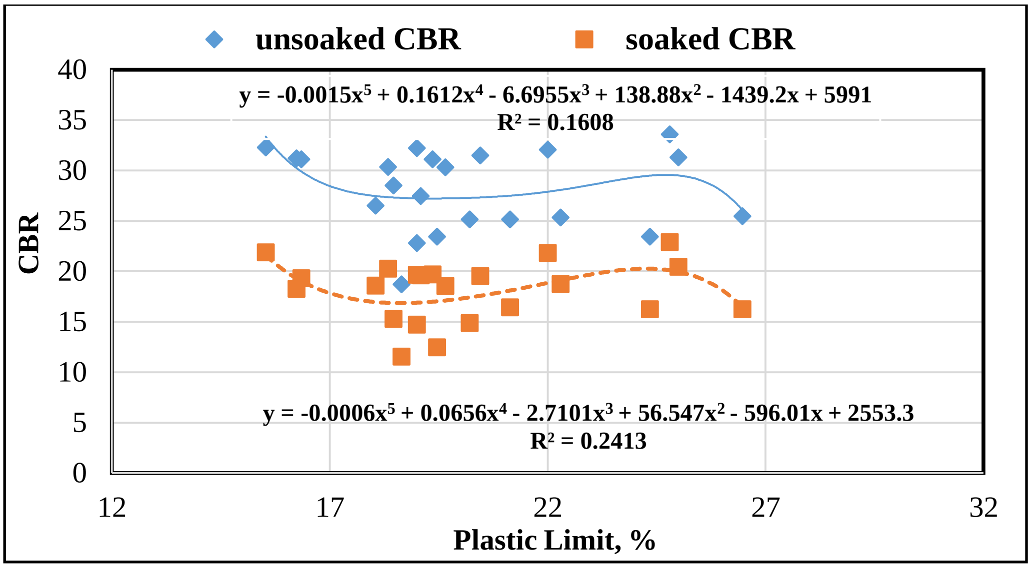


Fig. 4.33 Polynomial Method, CBR Vs PL (Degree 5)

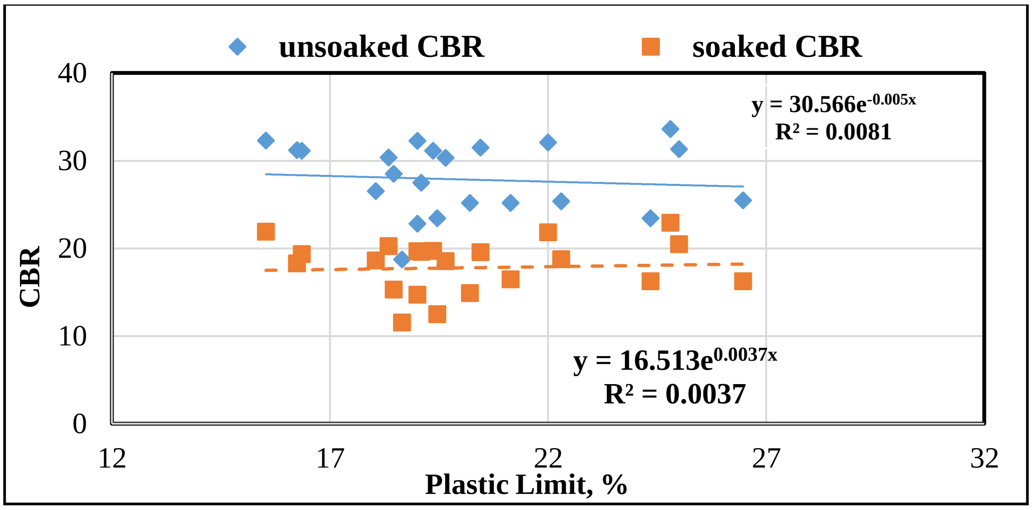


Fig. 4.34 Exponential Method, CBR Vs PL

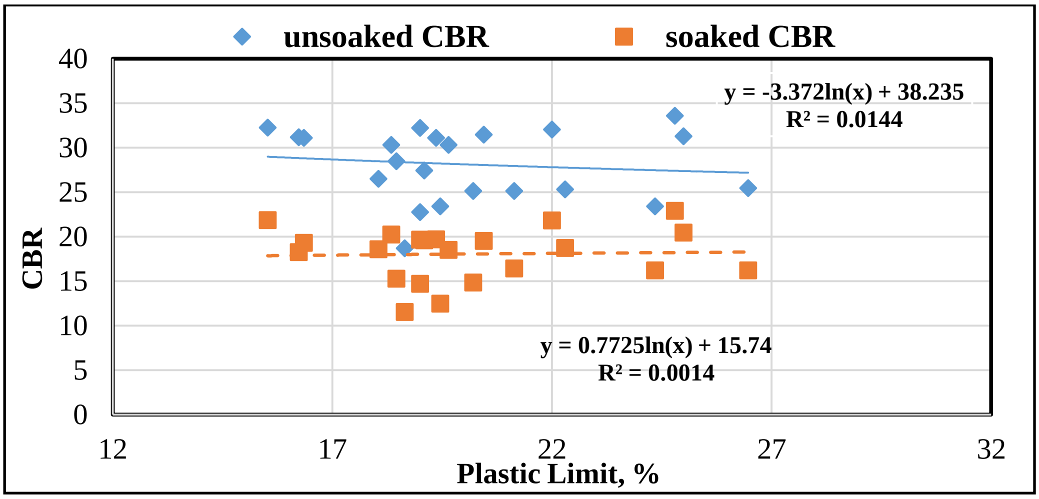


Fig. 4.35 Logarithmic Method, CBR Vs PL

It is observed from the graphs that the polynomial method (degree 5) gives the equations with sufficient R^2 value for both the conditions of CBR as compared to other methods. Also, plastic limit has no correlation with CBR because of the presence of low fines.

UCBR = - 0.0015*(PL)^5 + 0.1612*(PL)^4 - 6.6955*(PL)^3 + 138.88(PL)^2 - 1439.2*PL + 5991 ` ***R^2 = 0.161***

SCBR = -0.0006*(PL)^5+ 0.0656*(PL)^4 - 2.7101*(PL)^3 + 56.547*(PL)^2 - 596.01*PL + 2553.3 ***R^2 = 0.241***

Model 3: Correlation between CBR and Plasticity index (PI)

Linear, polynomial, exponential, & logarithmic regression model for soaked and unsoaked CBR VS PI have been developed and shown in figures from Fig. 4.36 to fig. 4.39.

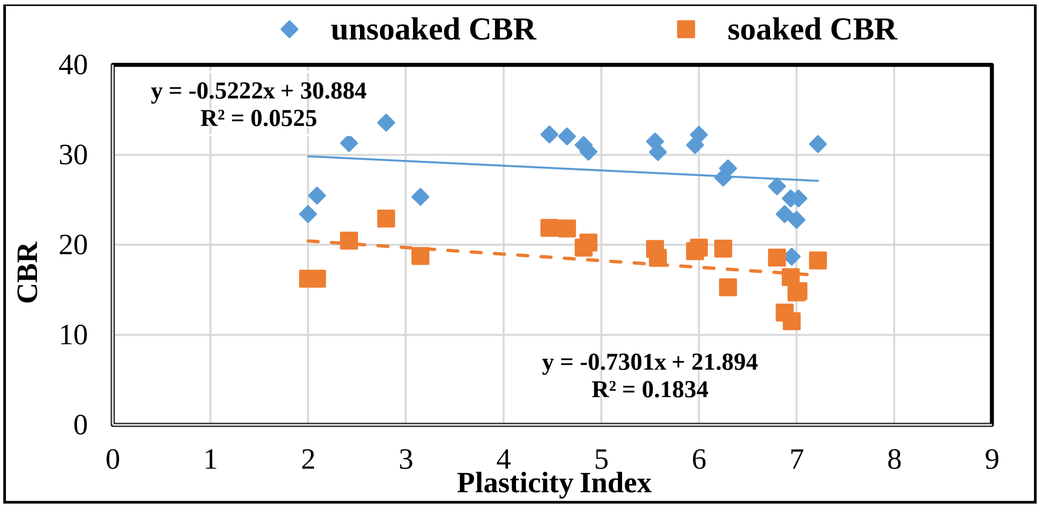


Fig. 4.36 Linear Regression model, CBR Vs PI

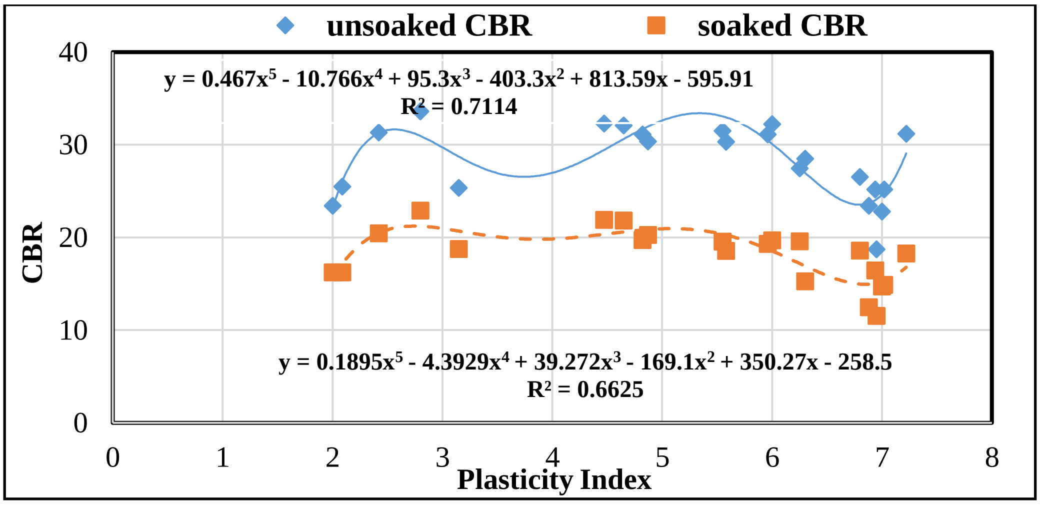


Fig. 4.37 Polynomial Method, CBR Vs PI (Degree 5)

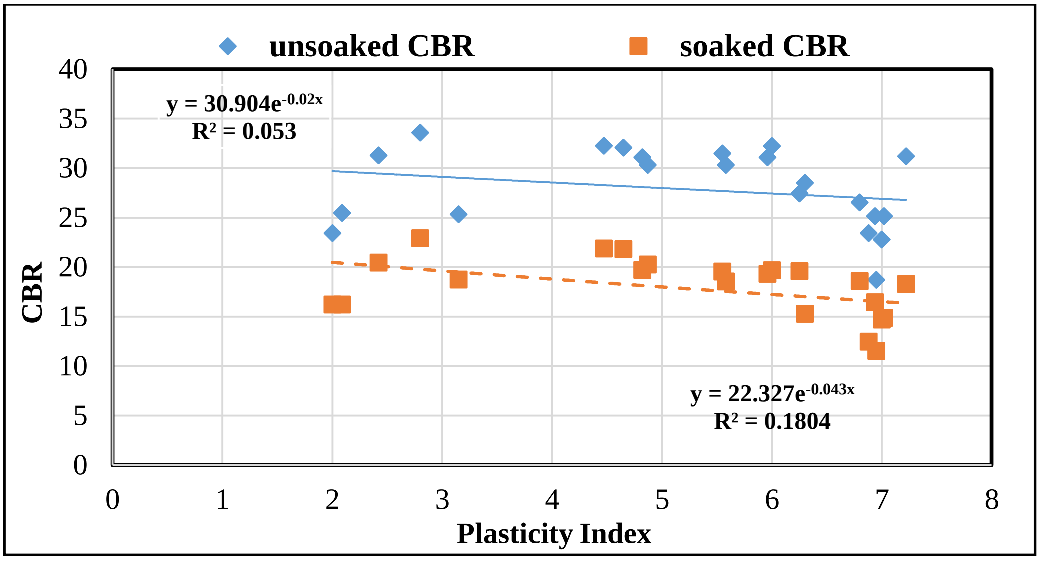


Fig. 4.38 Exponential Method, CBR Vs PI

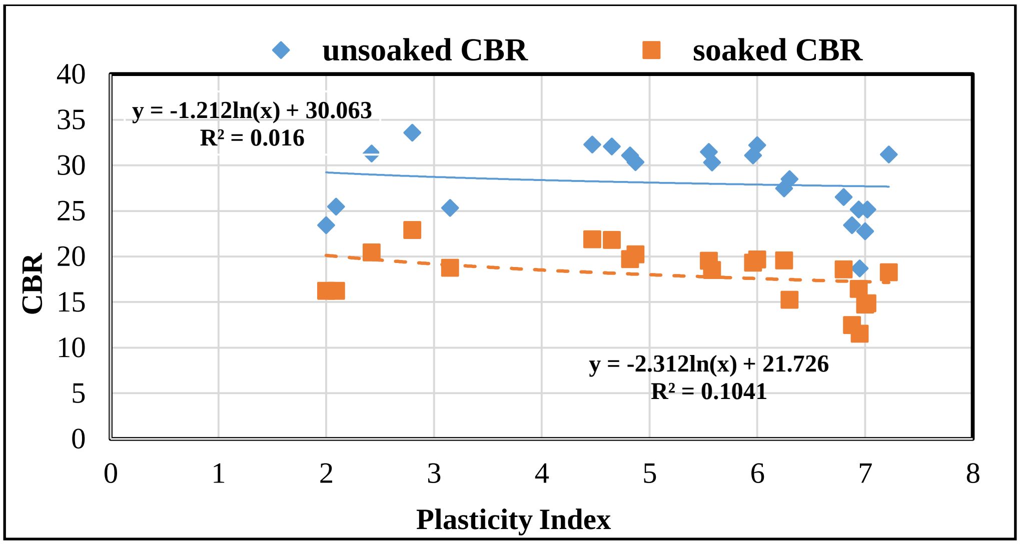


Fig. 4.39 Logarithmic Method, CBR Vs PI

Fig. 4.37 of the polynomial method shows a good value of R^2 when the curve has a degree of 5. Other method does not give so much better results. Hence, this methods is taken for correlating the PI values.

$$UCBR = 0.467*(PI)^5 - 10.766*(PI)^4 + 95.3*(PI)^3 - 403.3*(PI)^2 + 813.59*PI - 595.91$$

$$R^2 = 0.71$$

$$SCBR = 0.1895*(PI)^5 - 4.3929*(PI)^4 + 39.272*(PI)^3 - 169.1*(PI)^2 + 350.27*PI - 258.5$$

$$R^2 = 0.66$$

Model 4: Correlation between CBR and Specific Gravity (G)

For soaked and unsoaked CBR vs G, a linear, polynomial, exponential, & logarithmic regression model was developed and shown in the figures from Fig. Fig. 4.40 to fig. 4.43.

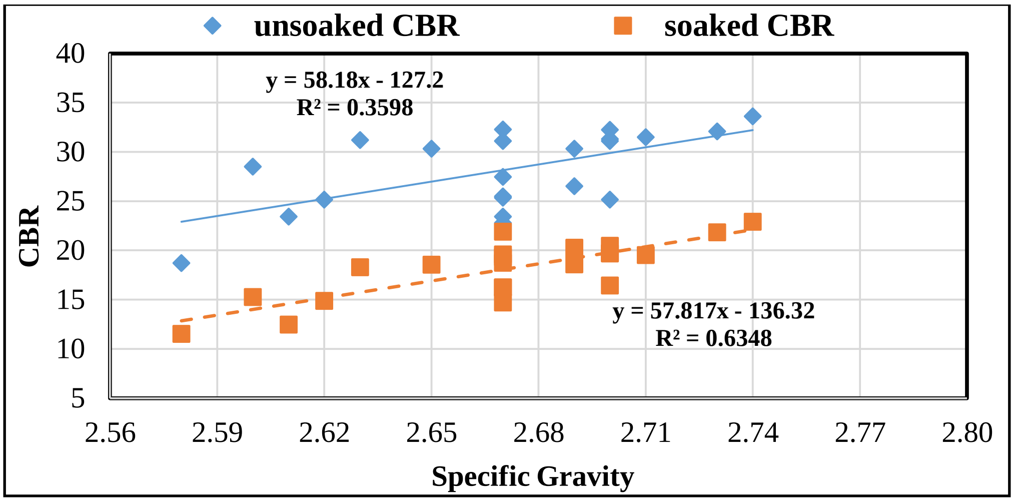


Fig. 4.40 Linear Regression Model, CBR Vs G

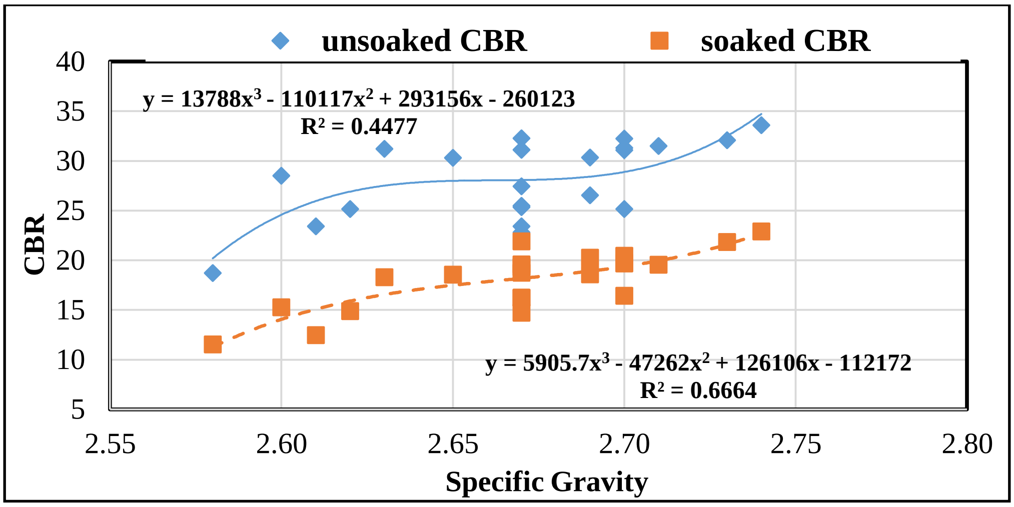


Fig. 4.41 Polynomial Method, CBR Vs PI (Degree 3)

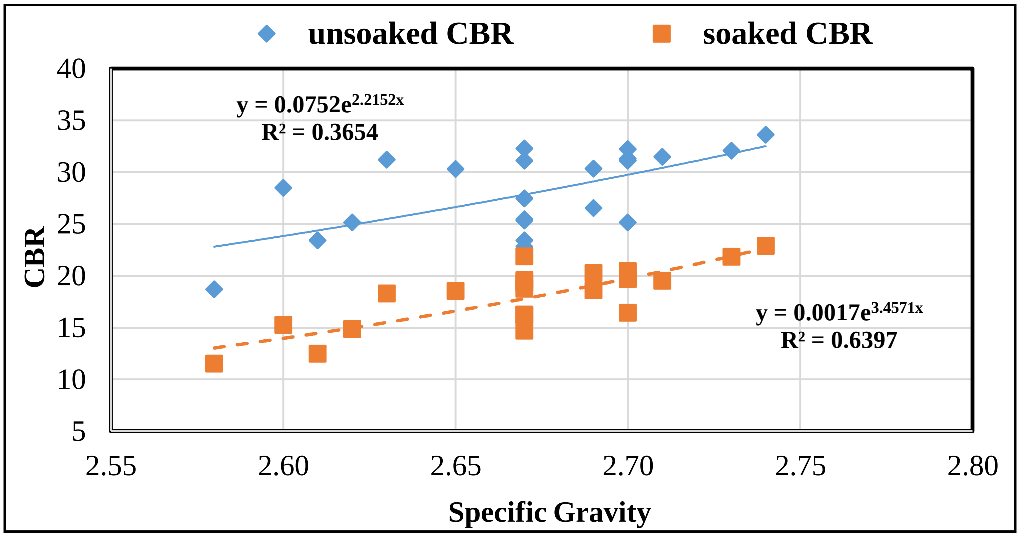


Fig. 4.42 Exponential Method, CBR Vs G

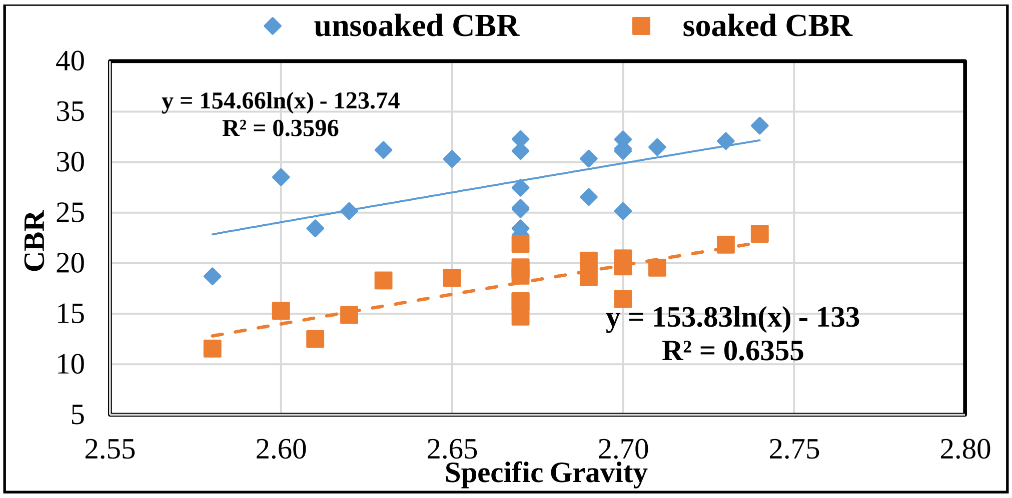


Fig. 4.43 Logarithmic Method CBR Vs G

From Fig 4.40 to Fig. 4.43, a better R^2 value is obtained for soaked CBR while R^2 of unsoaked CBR is very low. Results of linear and exponential methods give a satisfactory correlation of specific gravity with soaked CBR conditions with least error. Obtained equations are given below:-

SCBR = 57.817*G - 136.32 ***R^2 = 0.64***

SCBR = $0.0017 e^{3.4571 G}$ ***R^2 = 0.64***

UCBR = 58.18*G - 127.2 ***R^2 = 0.36***

UCBR = $13788(G)^3 - 110117(G)^2 + 293156(G) - 260123$ ***R^2 = 0.45***

Model 5: Correlation between CBR and OMC

. For soaked and unsoaked CBR vs OMC, a linear, polynomial, exponential, & logarithmic regression model was developed and shown in the figures from Fig. Fig. 4.40 to fig. 4.43.

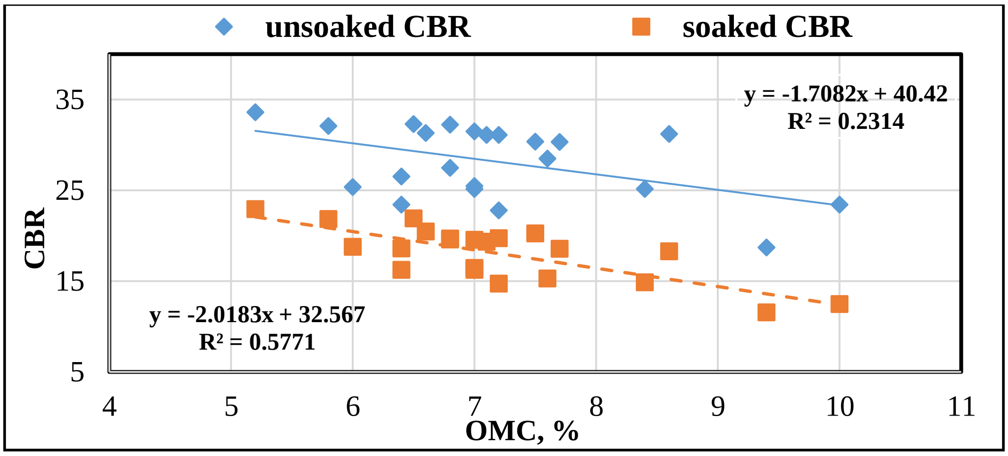


Fig. 4.44 Linear Regression Model, CBR Vs OMC

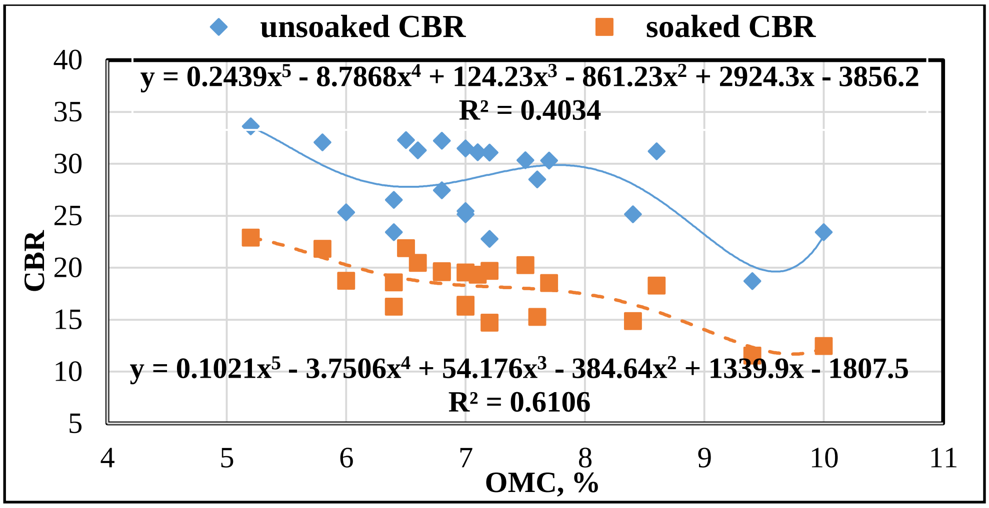


Fig. 4.45 Polynomial Method, CBR Vs OMC (Degree 5)

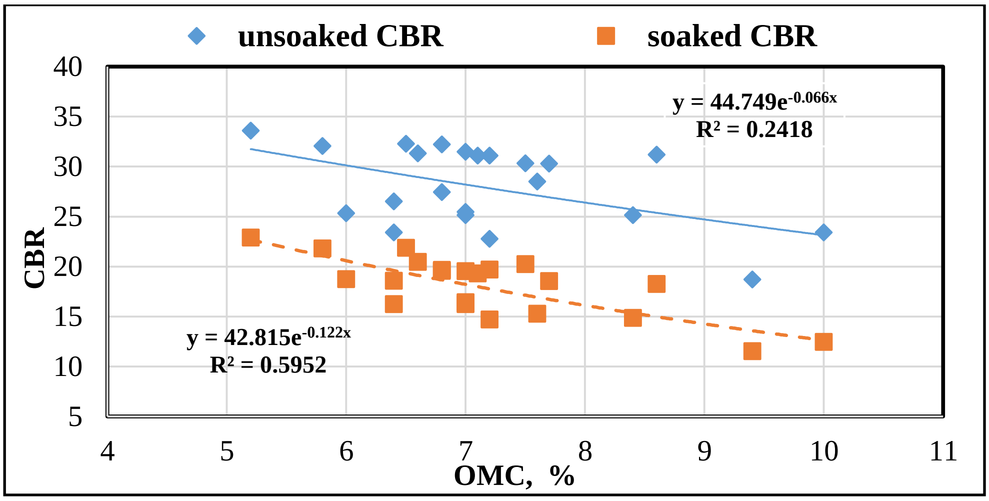


Fig. 4.46 Exponential Method, CBR Vs OMC

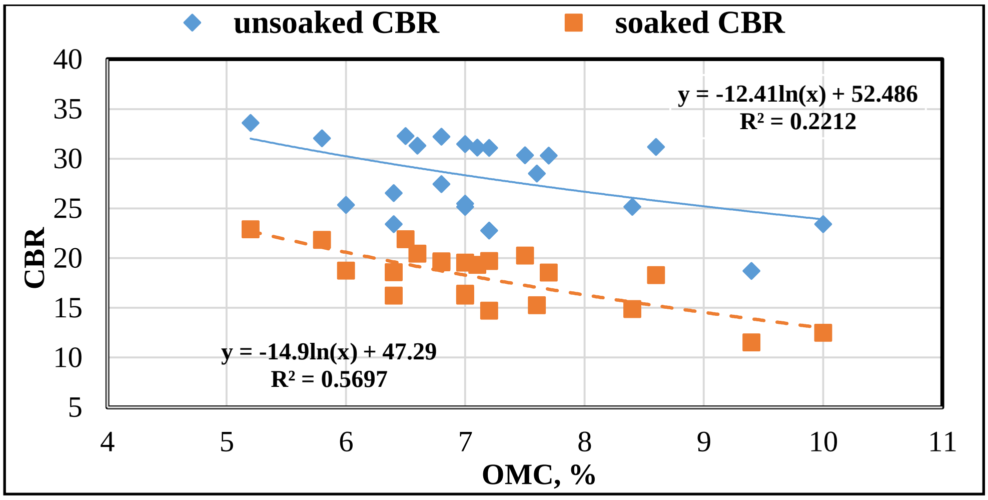


Fig. 4.47 Logarithmic Method, CBR Vs OMC

From the graph (Fig. 4.44*)*, it was found that a negative correlation exists between CBR and OMC. Linear and exponential methods of regression analysis for soaked CBR vs OMC are better correlated with OMC as compared to polynomial method in terms of low error value. For unsoaked CBR, polynomial method give satisfactory result. Fitted equations for both soaked and unsoaked condition are given below:-

SCBR = - 2.0183*OMC + 32.567 ***R^2 = 0.58***

SCBR = 42.815*e$^{-0.122*OMC}$ ***R^2 = 0.60***

UCBR = 0.2439*(OMC)^5 - 8.7868*(OMC)^4 + 124.23*(OMC)^3 - 861.23*(OMC)^2 + 2924.3*(OMC) - 3856.2 ***R^2 = 0.40***

Model 6: Correlation between CBR and MDD

A linear, polynomial, exponential, & logarithmic regression model for soaked and unsoaked CBR vs MDD was developed and shown in the figures from Fig. 4.48 to Fig. 4.51.

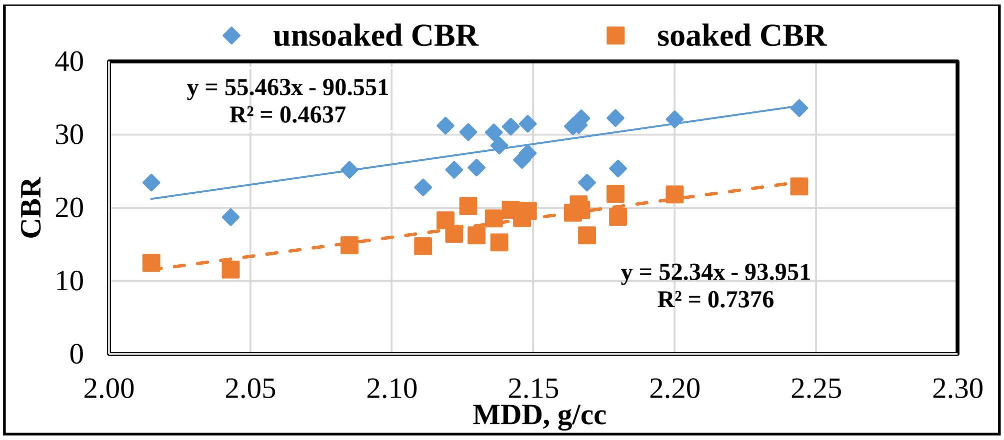


Fig. 4.48 Linear Regression Model, CBR Vs MDD

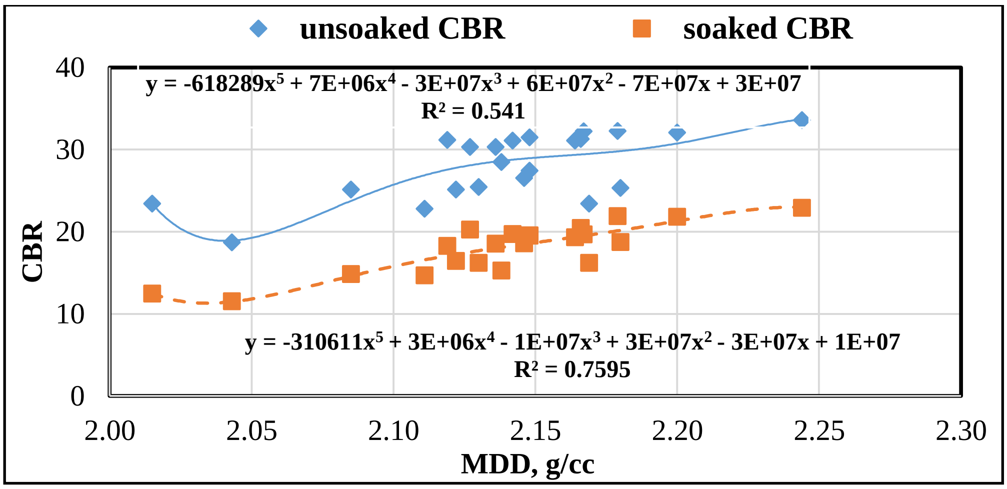


Fig. 4.49 Polynomial Method, CBR Vs MDD (Degree 5)

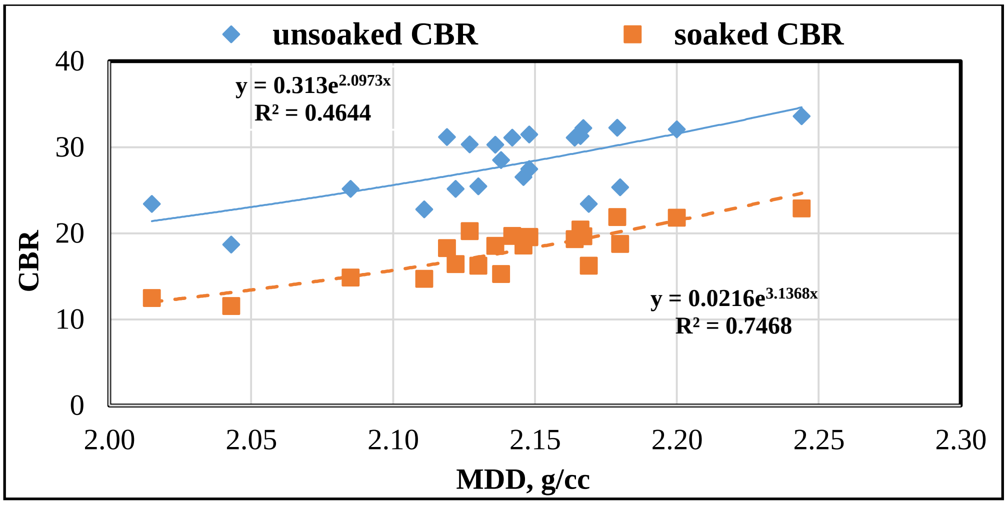


Fig. 4.50 Exponential Method, CBR Vs MDD

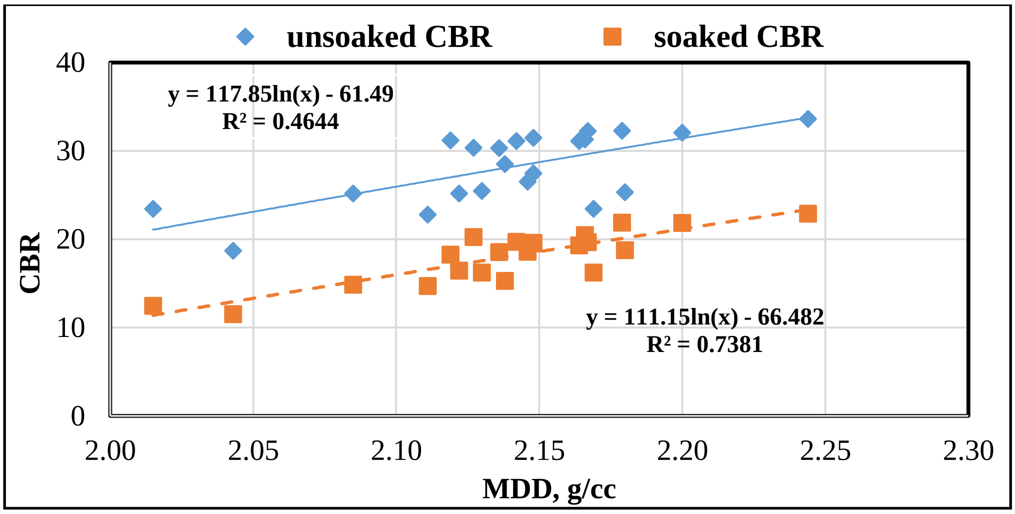


Fig. 4.51 Logarithmic Method, CBR Vs MDD

. Fig. 4.48 shows a very good positive correlation of MDD with CBR. The R^2 value of all the methods for the soaked condition represents a good value which shows MDD as an important parameter for predicting CBR values. The Linear method gives the higher R^2 value with least error.

SCBR = 0.0216*e$^{3.1368*MDD}$ ***R^2 = 0.75***

SCBR = 52.34*MDD - 93.951 ***R^2 = 0.74***

UCBR = 55.463*MDD - 90.551 ***R^2 = 0.46***

UCBR = - 618289(MDD)^5 + 7E+06(MDD)^4 - 3E+07(MDD)^3 + 6E+07*(MDD)^2 - 7E+07*(MDD) + 3E+07 ***R^2 = 0.54***

Model 7: Correlation between MDD and OMC

Fig. 4.52 shows a very good negative correlation between OMC and MDD

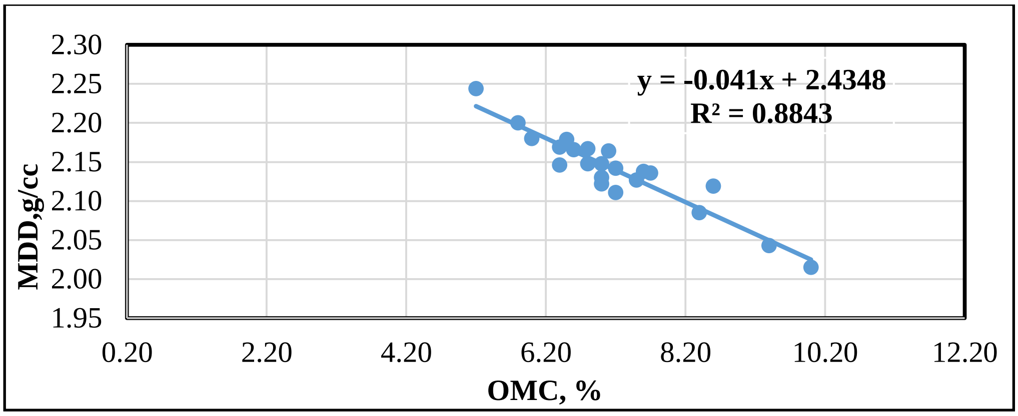


Fig. 4.52 Linear Regression Model, MDD Vs OMC

It is clear from Fig. 4.52 that a high R^2 is obtained for MDD, hence the linear method is sufficient for correlating the MDD values. A linear approach gives us a best-fit equation because it gives a low error value. No need to carried out polynomial, exponential, & logarithmic regression analysis.

MDD= - 0.041*OMC + 2.4348 ***$R^2 = 0.88$***

Model 8: Correlation between MDD and Specific Gravity

A linear approach is selected for correlating the MDD and G values and presented in Fig. 4.53.

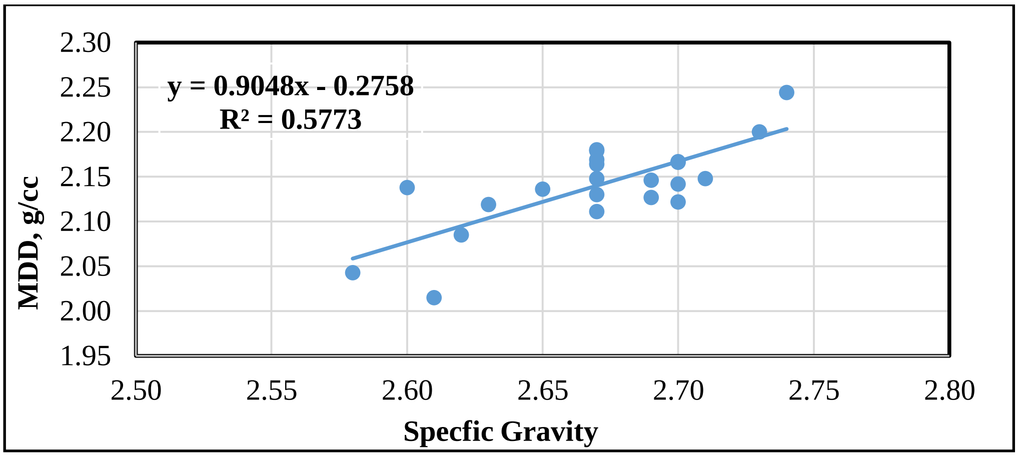


Fig. 4.53 Linear Regression Model, MDD Vs G

A positive correlation with a high value of correlation coefficients (R = 0.76) is obtained from the graph.

MDD = 0.9048*G - 0.2758 ***$R^2 = 0.58$***

Model 9: Correlation between MDD and Plasticity Index (PI)

Linear and polynomial methods give satisfactory results of MDD and PI and shown in figures 4.54 & 4.55. The R^2 value of polynomial method for degree 5 are high as compared to lower degree of polynomial.

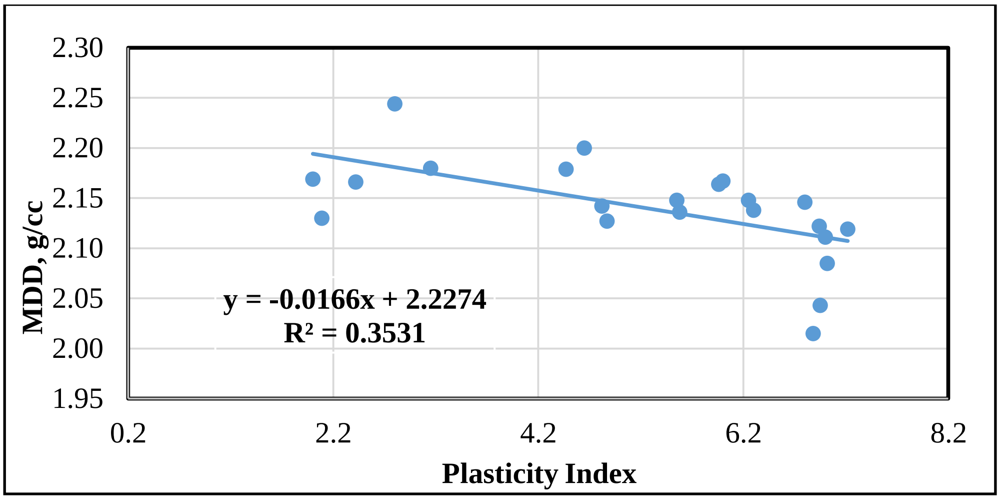


Fig. 4.54 Linear Regression Model, MDD Vs PI

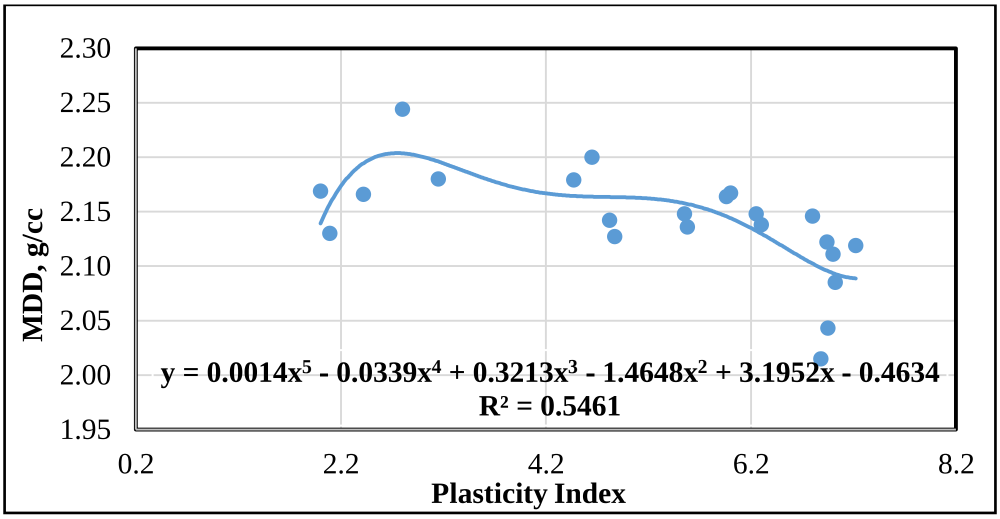


Fig. 4.55 Polynomial Method, MDD Vs PI

From the plotted graphs, it is found that the plasticity index shows a reasonable negative correlation with MDD and polynomial method is selected because it gives a high R^2 value.

$$MDD = 0.0014*(PI)^5 - 0.0339*(PI)^4 + 0.3213*(PI)^3 - 1.4648(PI)^2 + 3.1952*(PI) - 0.4634$$

Coefficient of Determination, *R^2* = *0.55*

Model 10: Correlation between Unsoaked and Soaked CBR values

A linear relation between unsoaked and soaked CBR of the measured values gives an idea about the prediction of the soaked CBR values from this obtained relation (Fig. 4.56).

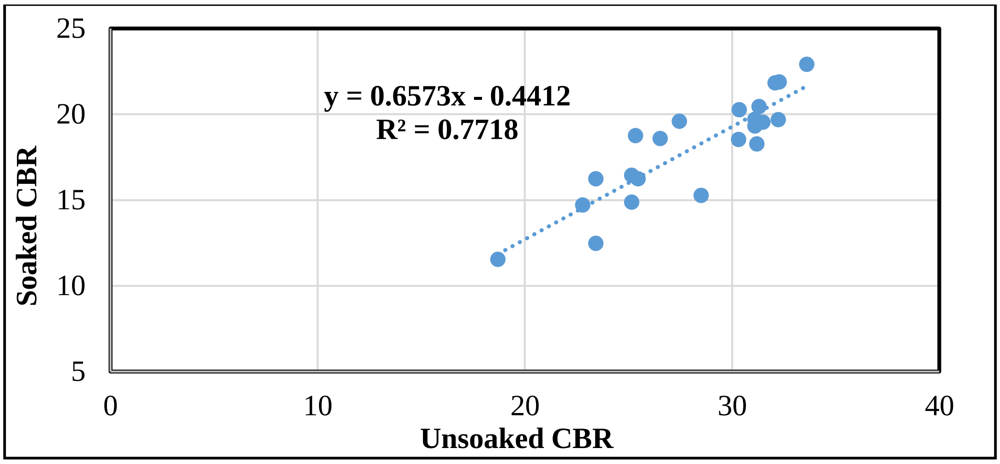


Fig. 4.56 Measured values of Unsoaked CBR and Soaked CBR

Soaked CBR = 0.6573*Unsoaked CBR - 0.4412 **R^2 = 0.772**

A ratio of UCBR/OMC was correlated against soaked CBR value and obtained result as shown in Fig. 4.57 gives a positive correlation (R = 0.94) with high R^2 value (0.875)

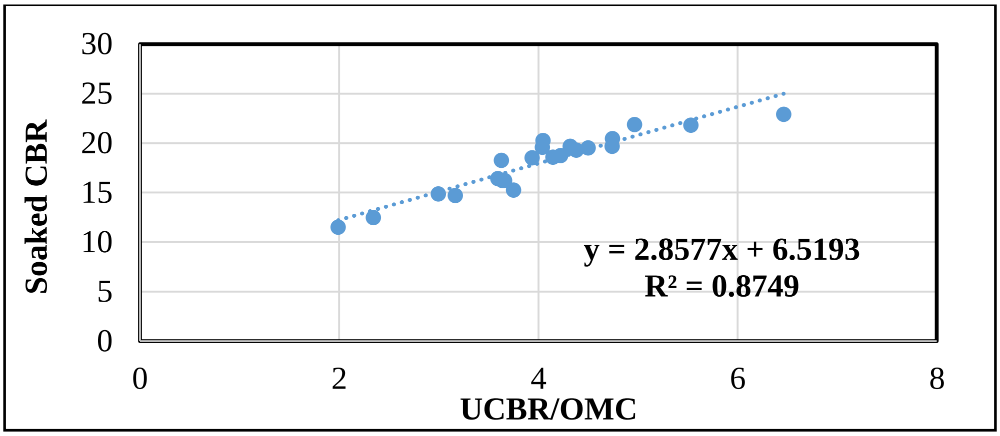


Fig. 4.57 UCBR/OMC Vs SCBR

Result of Fig. 4.57 shows that the factor UCBR/OMC is well suited for correlating the soaked CBR value. Also, the standard error is low for this factor.

SCBR = 2.858 *(UCBR/OMC) + 6.519 ***R^2 = 0.87***

The results of simple regression analysis show that from the linear, polynomial, exponential methods, polynomial methods proved to be effective in finding best-fit model equations. Compaction parameters (OMC, MDD) and specific gravity show a better correlation with soaked CBR (Table 4.6). For unsoaked parameters G and MDD are effective. A high R^2 value (0.738) of correlation of MDD with soaked CBR was found in this study. Also, a very good negative correlation was found between MDD and OMC (R^2

= 0.884). The results of developed models are present in Table 4.5. Also, Table 4.6 shows the different values of correlation coefficients plotted in a correlation matrix.

Table 4.5 Summary of Developed Model Using Simple Regression Analysis

Model No.		Correlation of CBR with		Regression Model	R	R^2
1.	A	LL	L^{Φ}	$UCBR = -0.6959(LL) + 45.839$	- 0.346	0.120
				$SCBR = -0.4355(LL) + 29.13$	- 0.290	0.084
	B		P^{Φ}	$UCBR^{\#} = -0.0339(LL)^5 + 4.1441(LL)^4 - 201.81(LL)^3 + 4895(LL)^2 - 59130(LL) + 284588$	0.557	0.310
				$SCBR^{\#} = -0.0216(LL)^5 + 2.6348(LL)^4 - 128.38(LL)^3 + 3116.1(LL)^2 - 37674(LL) + 181519$	0.483	0.233
	C		E^{Φ}	$UCBR = 53.149e^{-0.025(LL)}$	- 0.335	0.112
				$SCBR = 33.945e^{-0.025(LL)}$	- 0.285	0.081
	D		Log^{Φ}	$UCBR = -17.31\ln(LL) + 84.099$	- 0.354	0.125
				$SCBR = -11.04\ln(LL) + 53.74$	- 0.302	0.091
2	A	PL	L^{Φ}	$UCBR = -0.1338(PL) + 30.837$	- 0.098	0.0097
				$SCBR = 0.0602(PL) + 16.839$	- 0.059	0.0035
	B		P^{Φ}	$UCBR^{\#} = -0.0015(PL)^5 + 0.1612(PL)^4 - 6.6955(PL)^3 + 138.88(PL)^2 - 1439.2(PL) + 5991$	0.401	0.161
				$SCBR^{\#} = -0.0006(PL)^5 + 0.0656(PL)^4 - 2.7101(PL)^3 + 56.547(PL)^2 - 596.01(PL) + 2553.3$	0.491	0.241
	C		E^{Φ}	$UCBR = 30.566e^{-0.005(PL)}$	- 0.090	0.0081
				$SCBR = 16.513e^{0.0037(PL)}$	- 0.061	0.0037
	D		Log^{Φ}	$UCBR = -3.372\ln(PL) + 38.235$	- 0.120	0.0144
				$SCBR = 0.7725\ln(PL) + 15.74$	- 0.037	0.0014
3.	A	PI	L^{Φ}	$UCBR = -0.5222(PI) + 30.884$	- 0.230	0.053
				$SCBR = -0.7301(PI) + 21.894$	- 0.428	0.183
	B		P^{Φ}	$UCBR^{\#} = 0.467(PI)^5 - 10.766(PI)^4 + 95.3(PI)^3 - 403.3(PI)^2 + 813.59(PI) - 595.91$	0.843	0.711
				$SCBR^{\#} = 0.1895(PI)^5 - 4.3929(PI)^4 + 39.272(PI)^3 - 169.1(PI)^2 + 350.27(PI) - 258.5$	0.814	0.663
	C		E^{Φ}	$UCBR = 30.904e^{-0.02(PI)}$	- 0.230	0.053
				$SCBR = 22.327e^{-0.043(PI)}$	- 0.424	0.180
	D		Log^{Φ}	$UCBR = -1.212\ln(PI) + 30.063$	- 0.126	0.016
				$SCBR = -2.312\ln(PI) + 21.726$	- 0.322	0.104
4.	A	G	L^{Φ}	$UCBR = 58.18(G) - 127.2$	0.600	0.360
				$SCBR^{\#} = 57.817(G) - 136.32$	0.797	0.635
	B		P^{Φ}	$UCBR^{\#} = 13788(G)^3 - 110117(G)^2 + 293156(G) - 260123$	0.669	0.448

				$SCBR = 5905.7(G)^3 - 47262(G)^2 + 126106(G) - 112172$	0.816	0.666
	C		E^{Φ}	$UCBR = 0.0752e^{2.2152(G)}$	0.604	0.365
				$SCBR = 0.0017e^{3.4571(G)}$	0.800	0.640
	D		Log^{Φ}	$UCBR = 154.66\ln(G) - 123.74$	0.599	0.359
				$SCBR = 153.83\ln(G) - 133$	0.797	0.636
5	A	OMC	L^{Φ}	$UCBR^{\#} = -1.7082(OMC) + 40.42$	- 0.481	0.231
				$SCBR^{\#} = -2.0183OMC + 32.567$	- 0.760	0.577
	B		P^{Φ}	$UCBR = 0.2439(OMC)^5 - 8.7868(OMC)^4 + 124.23(OMC)^3 - 861.23(OMC)^2 + 2924.3(OMC) - 3856.2$	0.635	0.403
				$SCBR = 0.1021(OMC)^5 - 3.7506(OMC)^4 + 54.176(OMC)^3- 384.64(OMC)^2 + 1339.9(OMC) - 1807.5$	0.782	0.611
	C		E^{Φ}	$UCBR = 44.749e^{-0.066(OMC)}$	- 0.492	0.242
				$SCBR = 42.815e^{-0.122(OMC)}$	- 0.771	0.595
	D		Log^{Φ}	$UCBR = -12.41\ln(OMC) + 52.486$	- 0.470	0.221
				$SCBR^{\#} = -14.9\ln(OMC) + 47.29$	- 0.754	0.569
6	A	MDD	L^{Φ}	$UCBR^{\#} = 55.463(MDD) - 90.551$	0.681	0.464
				$SCBR^{\#} = 52.34(MDD) - 93.951$	0.859	0.738
	B		P^{Φ}	$UCBR = -618289(MDD)^5 + 7E+06(MDD)^4 - 3E+07(MDD)^3 + 6E+07(MDD)^2 - 7E+07(MDD) + 3E+07$	0.736	0.541
				$SCBR = -310611(MDD)^5 + 3E+06(MDD)^4 - 1E+07(MDD)^3 + 3E+07(MDD)^2 - 3E+07(MDD) + 1E+07$	0.872	0.760
	C		E^{Φ}	$UCBR = 0.313e^{2.0973(MDD)}$	0.681	0.464
				$SCBR^{\#} = 0.0216e^{3.1368(MDD)}$	0.866	0.750
	D		Log^{Φ}	$UCBR = 117.85\ln(MDD) - 61.49$	0.681	0.464
				$SCBR = 111.15\ln(MDD) - 66.482$	0.859	0.738
Correlation of MDD with						
S7	OMC		L^{Φ}	$MDD^{\#} = - 0.041*OMC + 2.4348$	0.940	0.884
S8	G		L^{Φ}	$MDD^{\#}= 0.9048*G - 0.2758$	0.76	0.577
S9	A	PI	L^{Φ}	$MDD^{\#} = - 0.0166*PI + 2.2274$	0.594	0.353
	B		P^{Φ}	$MDD = 0.0014*(PI)^5 - 0.0339(PI)^4 + 0.3213(PI)^3 - 1.4648(PI)^2 + 3.1952*PI - 0.4634$	0.739	0.546
Correlation of Soaked CBR with						
S10	UCBR / OMC			$SCBR =2.858 *(UCBR/OMC) + 6.519$	0.94	0.875

 # Model selected for correlation

L^{Φ} = Linear, P^{Φ} = Polynomial, E^{Φ} = Exponential, Log^{Φ} = Logarithmic, S=SLRA

Table 4.6 Correlation Matrix of Pearson Correlation Coefficient

Pearson Correlation	LL	PL	PI	G	OMC	MDD	UCBR	SCBR
LL	1							
PL	0.813	1						
PI	-0.226	-0.751	1					
G	0.146	0.373	-0.459	1				
OMC	-0.068	-0.407	0.604	-0.821	1			
MDD	-0.085	0.297	-0.594	0.760	-0.940	1		
UCBR	-0.347	-0.098	-0.229	0.600	-0.481	0.681	1	
SCBR	-0.290	0.059	-0.428	0.797	-0.760	0.859	0.879	1

4.3.3 Multiple Regression Analysis (MRA)

Through the findings of simple regression analysis and with the application of M.S. Excel, the most relevant variables were found to be G, OMC, MDD, PI, LL, and PL, which give regression models the best match. Obtained models equations are categorised into two cases i.e. listed below:-

Case 1: variables having only single variable terms have categorised in this case.

Model 1: SCBR = - 152.704 + 1.013*OMC + 76.094*MDD

Model 3: SCBR = - 126.24 + 24.7502*G + 36.547*MDD

Model 7: SCBR = - 282.737 + 41.989*G +2.512*OMC + 79.728*MDD

Model 8: UCBR = - 562.381 + 68.179*G + 7.177*OMC + 166.765*MDD

Model 9: SCBR = - 108.051 -0.29054*LL + 0.4432*OMC + 60.893*MDD

Model 10: SCBR = - 155.88 + 0.572*PI + 0.998*OMC + 77.505*MDD

Model 11: SCBR = -111.5 - 0.213*LL - 0.063*PL + 0.4394*OMC + 62.2*MDD

Model 13: SCBR = - 283.3 + 0.119*PI +41.458*G + 2.422*OMC + 80.659*MDD

Model 14: UCBR = - 563.901 + 0.326*PI + 66.721*G + 6.931*OMC +169.319*MDD

Model 17: SCBR = - 237.461 - 0.379*LL+ 46.181*G + 1.794*OMC + 60.259*MDD

Model 18: UCBR = - 520.554 - 0.3501*LL + 72.050*G + 6.514*OMC+148.779*MDD

Model 19: SCBR = - 258.307 - 0.213*PL + 43.392*G + 1.948*OMC + 70.462*MDD

Model 20: UCBR = - 532.593 - 0.259*PL + 69.889*G + 6.490*OMC + 155.467*MDD

Model 25: MDD = 2.5603 - 0.0435*G - 0.0423*OMC

Model 28: MDD = 2.516 - 0.0037*LL + 0.0057*G - 0.0413*OMC

Case 2: models having single variable terms, two way interactions or square of a variable are included in this case

Model 21: SCBR = - 39.9127 - 0.0169*(LL*OMC) + 10.689*(G*MDD)

Model 23: SCBR = - 40.3174 - 0.02914*(PL*OMC) + 10.941*(G*MDD).

A total of 17 MRA models are chosen on the basis of the less parameters used, with high values of R^2 and R^2 adj. Model 17 has high R^2 (0.917) and high adj R^2 (0.897) values for the soaked state, which indicates that the consequence of adding parameters is not as varied. For unsoaked condition, model 20 shows high R^2 (0.871) and R^2_{adj} (0.841) values (Table 4.7).

Model 25 and model 28 with R^2 values of 0.885 & 0.907 display the best parameter relationship with the MDD value, respectively, but because model 25 has only two parameters, it may take precedence to be the best-fit model equation (Table 4.7). The proposed MLR models with the standard of fit parameters are shown in Table 4.7.

Table 4.7 Summary of the Developed Model Using Multiple Regression Analysis

Model No.	Multiple Linear Regression Model	R	R^2	R^2_{adj}
1.	SCBR = - 152.704 + 1.013*OMC + 76.094 * MDD	0.870	0.757	0.732
2.	UCBR = - 351.245 + 4.887*OMC + 160.864 * MDD	0.830	0.683	0.649
3.	SCBR# = - 126.24 + 24.7502*G + 36.547*MDD	0.887	0.786	0.764
4.	UCBR = - 115.237 + 18.922*G +43.389*MDD	0.693	0.479	0.425
5.	SCBR = - 78.606 + 38.521*G - 0.861*OMC	0.817	0.669	0.634
6.	UCBR = - 135.406 +60.922*G + 0.122*OMC	0.600	0.360	0.293
7.	SCBR = - 282.737 + 41.989*G +2.512*OMC + 79.728*MDD	0.931	0.866	0.844
8.	UCBR = - 562.381 + 68.179*G + 7.177*OMC + 166.765*MDD	0.918	0.843	0.817
9.	SCBR = - 108.051 - 0.29054*LL + 0.4432 * OMC + 60.893*MDD	0.887	0.788	0.752
10.	SCBR# = - 155.88 + 0.572*PI + 0.998*OMC + 77.505*MDD	0.874	0.764	0.724

11.	SCBR = -111.5 - 0.213*LL - 0.063*PL + 0.4394 * OMC + 62.2*MDD	0.888	0.788	0.738
12.	UCBR = - 338.721 + 0.237*LL - 0.362*PL + 4.385 *OMC + 157.295*MDD	0.840	0.706	0.637
13.	SCBR = - 283.3 + 0.119*PI +41.458*G + 2.422 * OMC + 80.659*MDD	0.933	0.869	0.838
14.	UCBR = - 563.901 + 0.326*PI + 66.721*G + 6.931 *OMC + 169.319*MDD	0.925	0.856	0.823
15.	SCBR = - 137.734 + 0.223*PI + 24.908*G + 41.174*MDD	0.893	0.798	0.764
16.	UCBR = - 147.399 + 0.623*PI + 19.365*G + 56.336*MDD	0.726	0.528	0.449
17.	SCBR = - 237.461 - 0.379*LL+ 46.181*G + 1.794 *OMC + 60.259*MDD	0.957	0.917	0.897
18.	UCBR = - 520.554 - 0.3501*LL + 72.050*G + 6.514 *OMC+148.779*MDD	0.931	0.867	0.836
19.	SCBR = - 258.307 - 0.213*PL + 43.392*G + 1.948 *OMC + 70.462*MDD	0.949	0.900	0.876
20.	UCBR = - 532.593 - 0.259*PL + 69.889*G + 6.490 *OMC +155.467*MDD	0.933	0.871	0.841
21.	SCBR = - 39.9127 - 0.0169*(LL*OMC) + 10.689 * (G*MDD)	0.892	0.796	0.775
22.	UCBR = - 46.3419 - 0.0023*(LL*OMC) + 13.104 *(G*MDD)	0.688	0.474	0.419
23.	SCBR = - 40.3174 - 0.02914*(PL*OMC) + 10.941 *(G*MDD)	0.908	0.825	0.806
24.	UCBR = - 27.444 - 0.0384*(PL*OMC) + 10.692 * (G*MDD)	0.710	0.504	0.452
25.	MDD# = 2.5603 - 0.0435*G - 0.0423*OMC	0.941	0.885	0.872
26.	MDD = 2.543 - 0.0011*PI - 0.0381*G - 0.0411 * OMC	0.941	0.885	0.866
27.	MDD = - 0.243 - 0.0049*LL + 0.939*G	0.785	0.616	0.576
28.	MDD# = 2.516 - 0.0037*LL + 0.0057*G - 0.0413 * OMC	0.952	0.907	0.891
29.	MDD = - 0.26203 + 0.000271*PL + 0.898*G	0.759	0.577	0.533
30.	MDD = 2.5659 - 0.0017*PL - 0.0292*G - 0.0437 * OMC	0.945	0.893	0.875

 # Model selected for correlations

The p-values of the suggested models were less than 0.05 which fulfills the criteria of model selection. All the obtained models of MRA are also checked for multicollinearity. Model 1, 3, 10, 21, 23, 25, 28 are free from multicollinearity (Fig. 4.58). Results show that the variance inflation factor (VIF) values of the parameters in the model 7, 8, 9, 11, 13, 14, 17, 18, 19, 20 are greater than 10 which signifies multicollinearity as shown in Fig. 4.69 & Fig. 4.70.

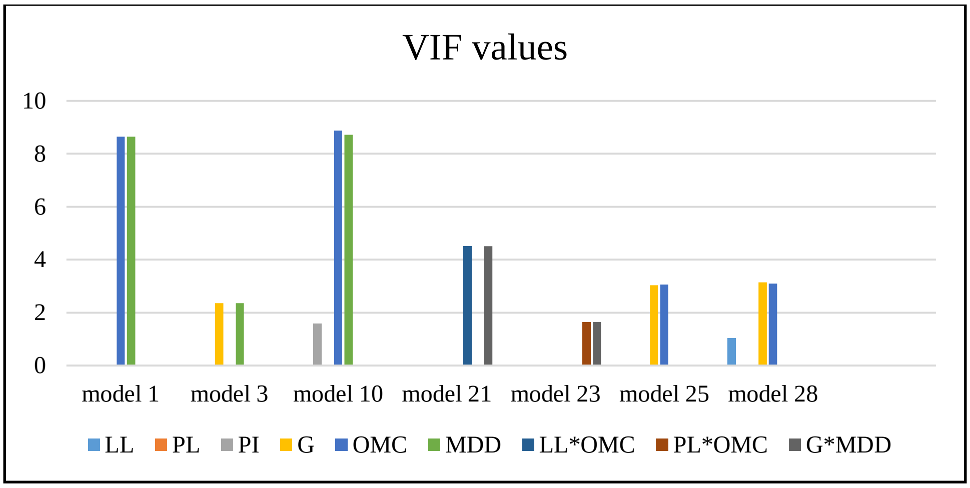


Fig. 4.58 Graphs of Different VIF Values of Different Parameters

Compaction parameters (OMC, MDD) and specific gravity (G) are found to be best for predicting the soaked and unsoaked CBR values. Model 7 and model 8 contain only 3 parameters with high R^2 value, which implies to be the best model equations if it free from multicollinearity. So, to remove multicollinearity from the models, Ridge regression methodology was applied to the models.

4.3.4 Ridge Regression

With the help of the *XREALSTATS* tool of M.S.Excel, results of ridge regression are carried out. With the help of cross-validation and ridge trace technique, a suitable value of λ (regularization parameter) is obtained. The figures 4.59 to 4.68 show the ridge traces of different models.

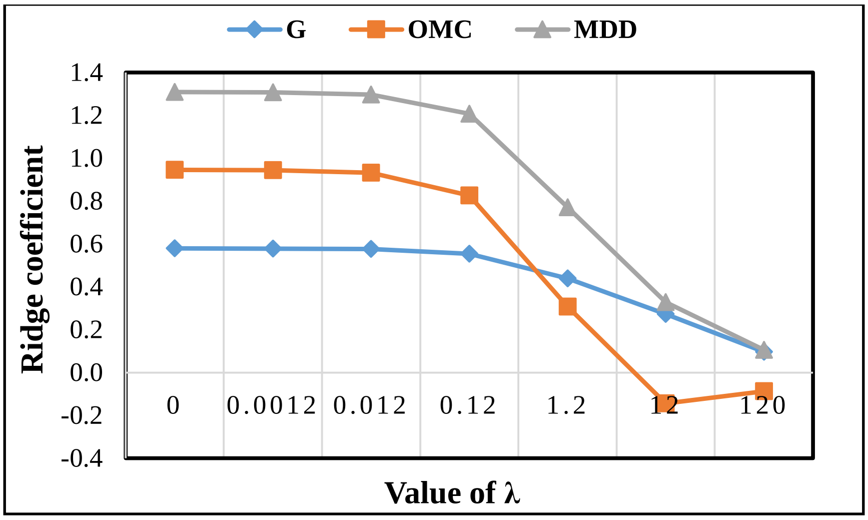


Fig. 4.59 Ridge Trace of Model 7

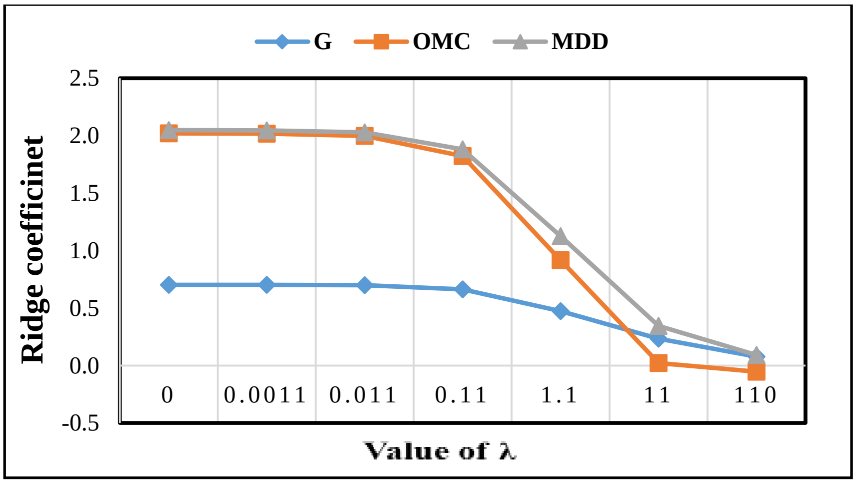


Fig. 4.60 Ridge Trace of Model 8

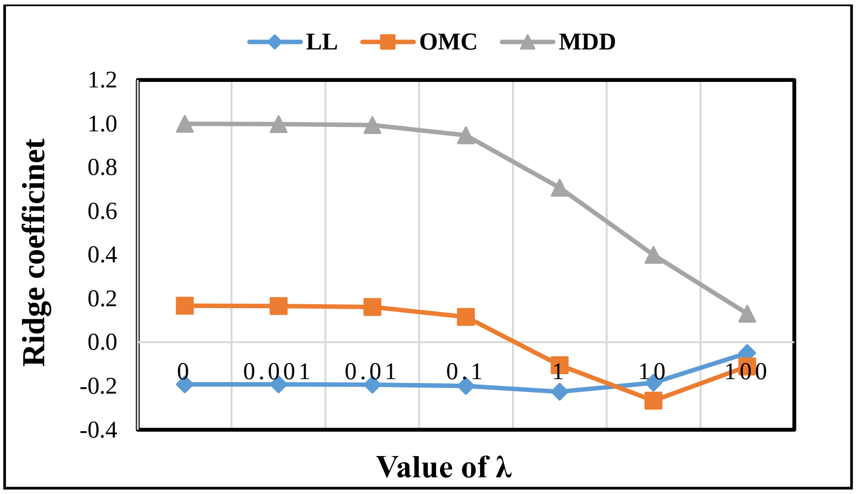


Fig. 4.61 Ridge Trace of Model 9

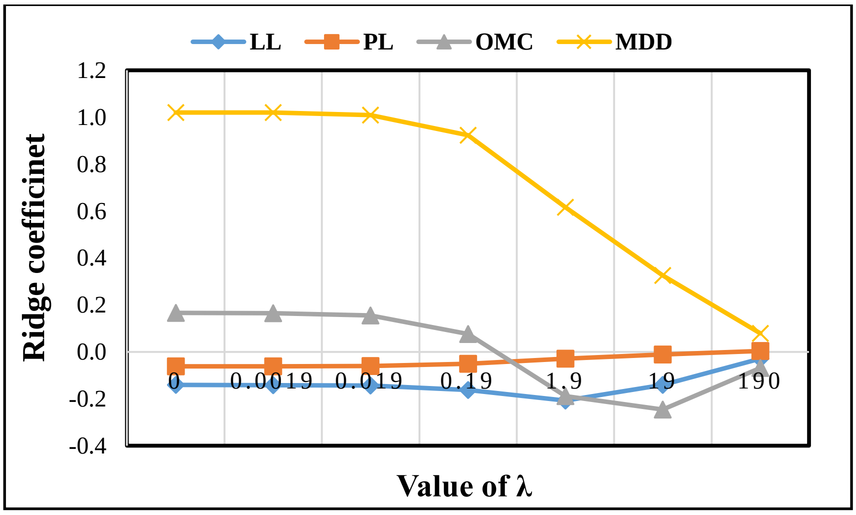


Fig. 4.62 Ridge Trace of Model 11

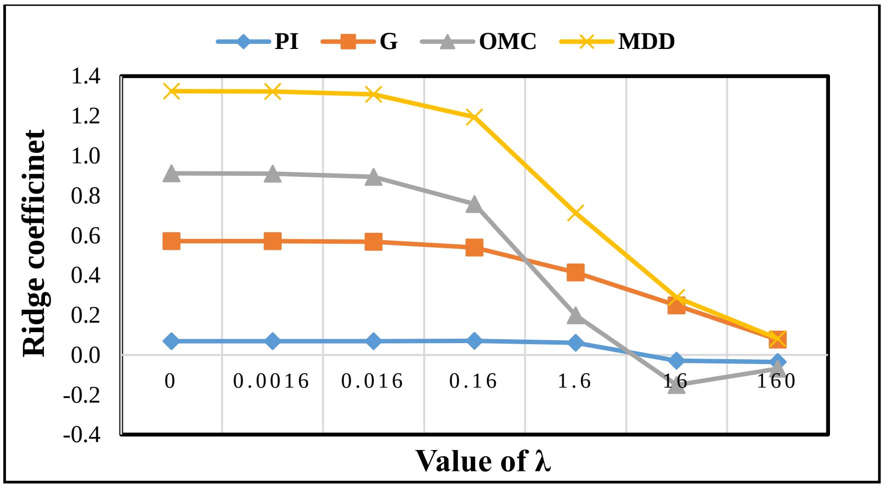


Fig. 4.63 Ridge Trace of Model 13

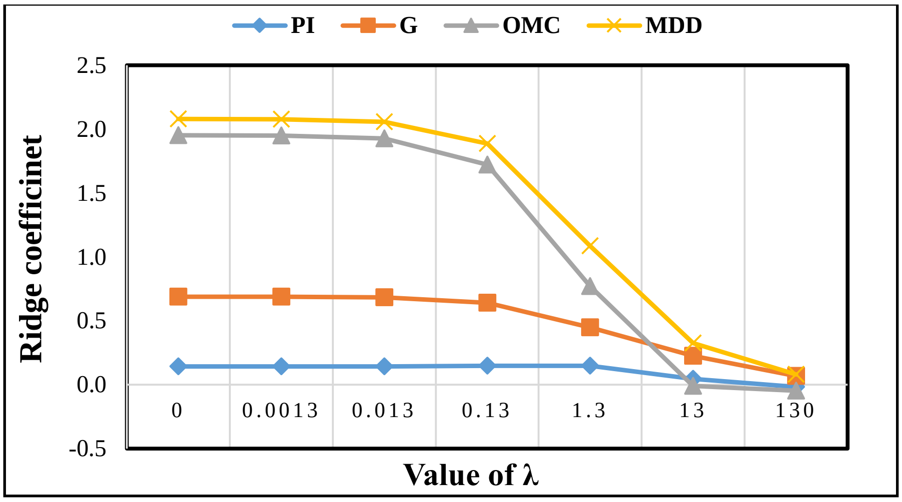


Fig. 4.64 Ridge Trace of Model 14

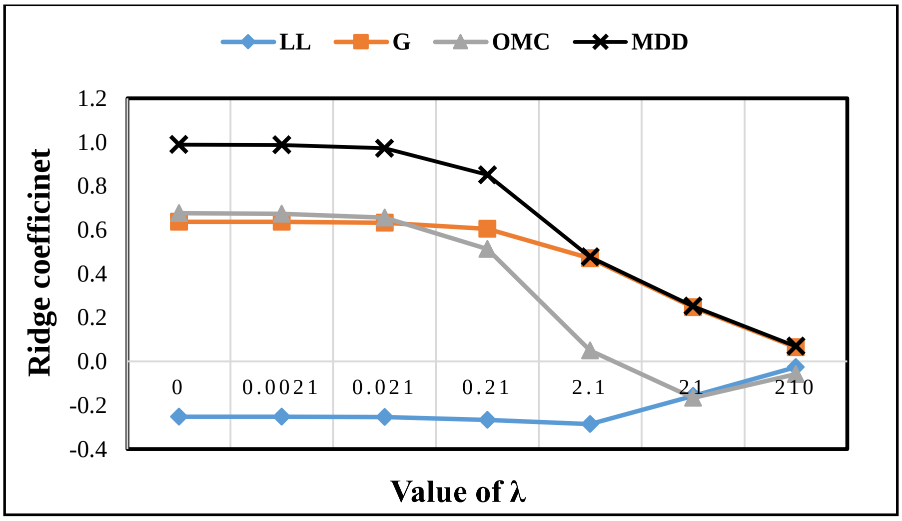


Fig. 4.65 Ridge Trace of Model 17

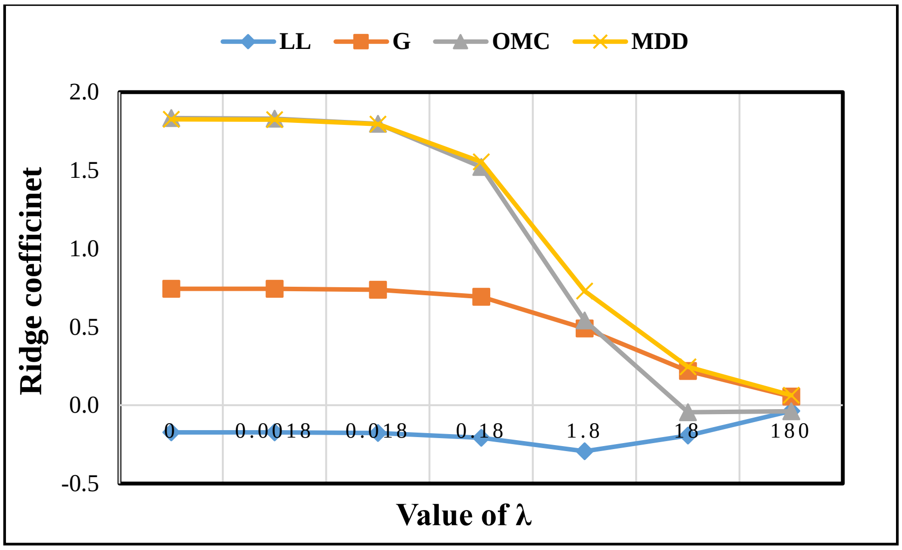


Fig. 4.66 Ridge Trace of Model 18

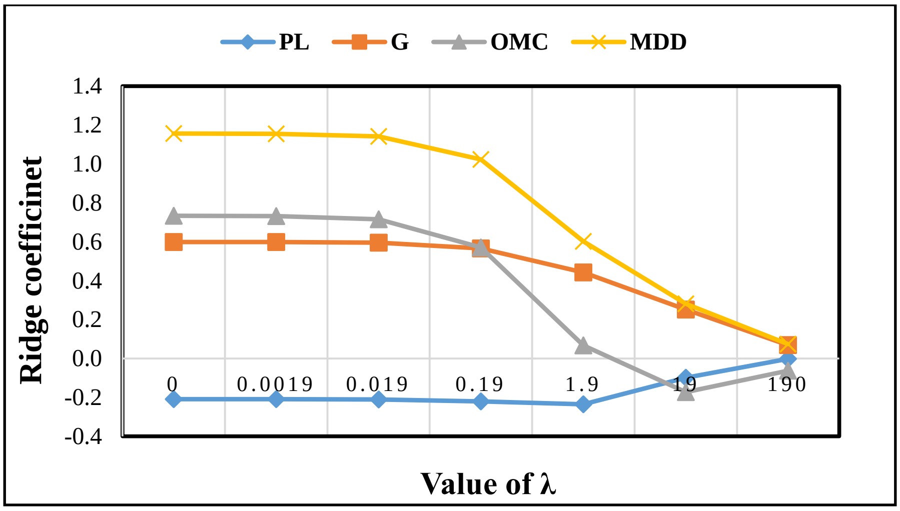


Fig. 4.67 Ridge Trace of Model 19

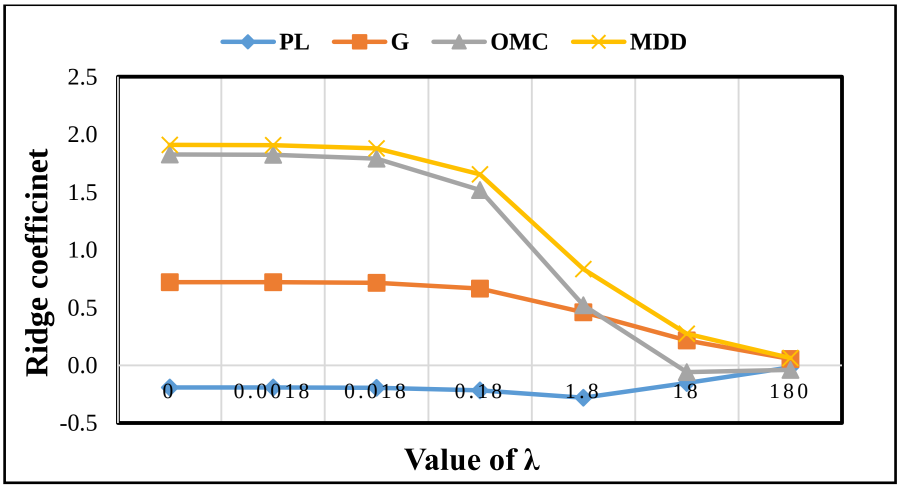


Fig. 4.68 Ridge Trace of Model 20

The values of *Lambda* (λ) obtained from the figures 4.59 to 4.68 are within the range of 0.1-0.21. These values of λ minimise the mean squared error of the equation (MSE) and also correct the variance inflation factor (VIF) values of the parameters. Table 4.8 & 4.9 gives the corrected values and corrected models equations after applying ridge regression by lowering the error value and reducing constant of coefficients.

Table 4.8 Value of λ with the Corrected Correlation Parameters

Model No.	Value of λ	Previous values			Values after correction			% red. b/w R^2& R^2_{adj}
		R	R^2	R^2_{adj}	R	R^2	R^2_{adj}	
Model 7	0.12	0.931	0.866	0.844	0.922	0.851	0.828	2.7
Model 8	0.11	0.918	0.843	0.817	0.896	0.803	0.772	3.86
Model 9	0.10	0.887	0.788	0.752	0.885	0.783	0.749	4.34
Model 11	0.19	0.888	0.788	0.738	0.883	0.800	0.730	8.75
Model 13	0.16	0.933	0.869	0.838	0.922	0.849	0.816	3.89
Model 14	0.13	0.925	0.856	0.823	0.899	0.808	0.766	5.19
Model 17	0.21	0.957	0.917	0.897	0.949	0.900	0.878	2.44
Model 18	0.18	0.931	0.867	0.836	0.903	0.815	0.773	5.15
Model 19	0.19	0.949	0.900	0.876	0.939	0.882	0.856	2.95
Model 20	0.18	0.933	0.871	0.841	0.903	0.816	0.775	5.02

Table 4.9 Details of the Corrected Models Equations (Ridge Regression)

Model No.	Ridge Regression Model
Model 7#	SCBR = - 262.446 + 40.159*G + 2.1933*OMC + 73.6*MDD
Model 8#	UCBR = - 519.148 + 64.362*G + 6.491*OMC + 153.629*MDD
Model 9#	SCBR = - 99.993 - 0.3009*LL + 0.309*OMC + 57.699*MDD
Model 11#	SCBR = -99.4861 - 0.2447*LL - 0.0523*PL + 0.201*OMC + 56.25 * MDD
Model 13#	SCBR = - 257.406 + 0.121*PI + 39.141*G + 2.014*OMC + 72.821*MDD
Model 14#	UCBR = - 512.673 + 0.3341*PI + 62.227*G + 6.111*OMC + 153.722*MDD
Model 17#	SCBR = - 209.474 - 0.4023*LL+ 43.845*G + 1.362*OMC + 51.824*MDD
Model 18#	UCBR = - 450.145 - 0.421*LL + 67.085*G + 5.403*OMC + 126.647 *MDD
Model 19	SCBR = - 231.22 - 0.2254*PL + 41.063*G + 1.516*OMC + 62.282*MDD
Model 20#	UCBR = - 465.068 - 0.2969*PL + 64.44*G + 5.391*OMC +134.755*MDD

 # Model selected for correlation

Based on the obtained results, model 3 & 10 of Multiple Regression Analysis and model 7, 9, 11, 13 and 17 of Ridge Analysis are chosen for predicting soaked CBR values, Also, model 8, 14, 18 and 20 (ridge) and Model 25 and 28 (multiple regression) are chosen for unsoaked CBR values and MDD values respectively. All these models are selected on the basis of high R^2, high R^2 adj, low percentage reduction between the difference of R^2 & R^2 adj, and multicollinearity free models. Figures 4.69 and 4.70 shows the VIF values of multiple and ridge regression models.

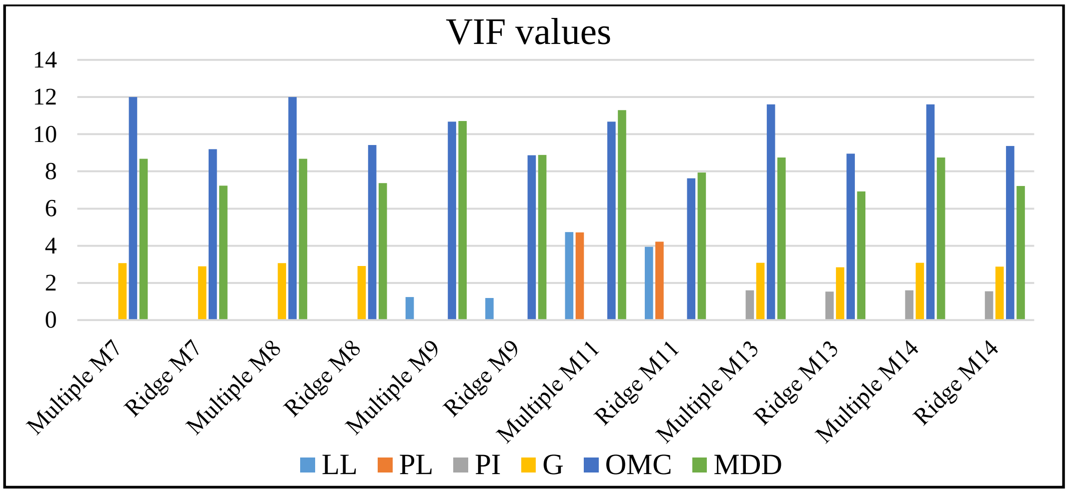


Fig. 4.69 Graphs of Different VIF Values of Multiple and Ridge Models

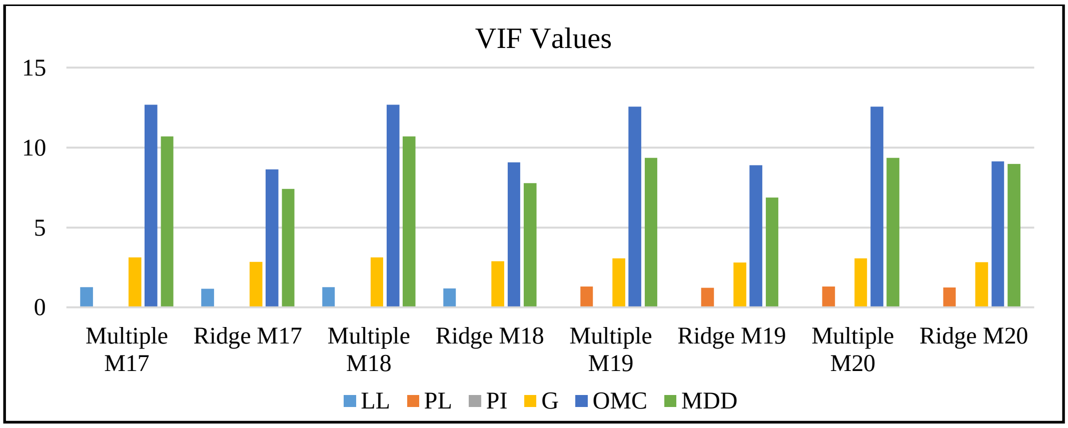


Fig. 4.70 Graphs of Different VIF Values of Multiple and Ridge Models

Figures 4.69 and 4.70 show the presence of multicollinearity in multiple regression models but these models are free from multicollinearity after applying ridge regression by lowering the VIF value below 10.

➢ After finalising the models for soaked CBR, unsoaked CBR and MDD, measured data are compared with predicted data which shows the consistency and precision of predicted equation. All the comparable results of measured value vs predicted value are as shown in Fig 4.71 to Fig. 4.88.

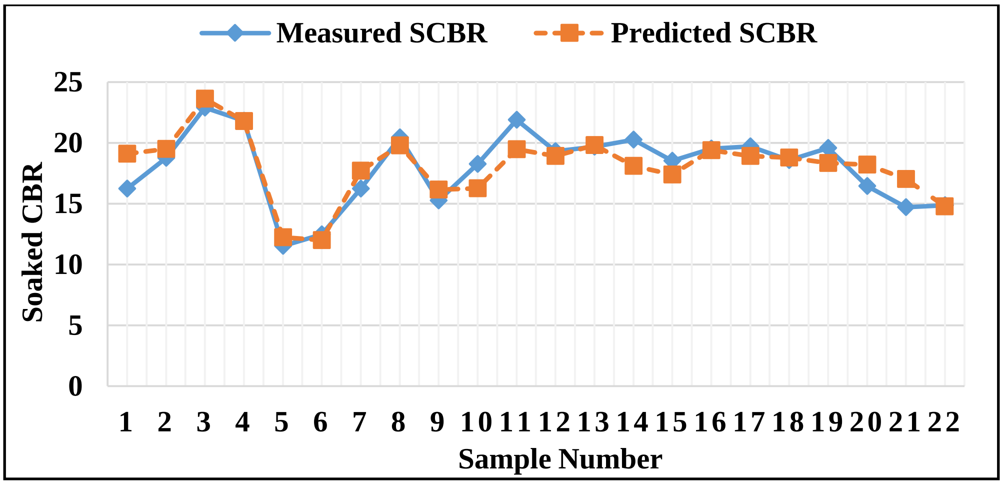


Fig. 4.71 Plot of Series of Model 3

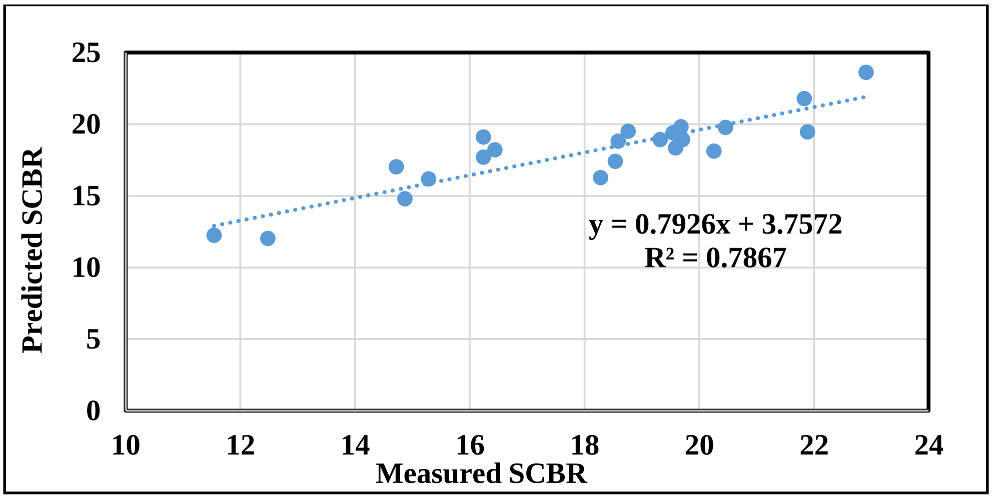


Fig. 4.72 Measured Vs Predicted Soaked CBR (Model 3)

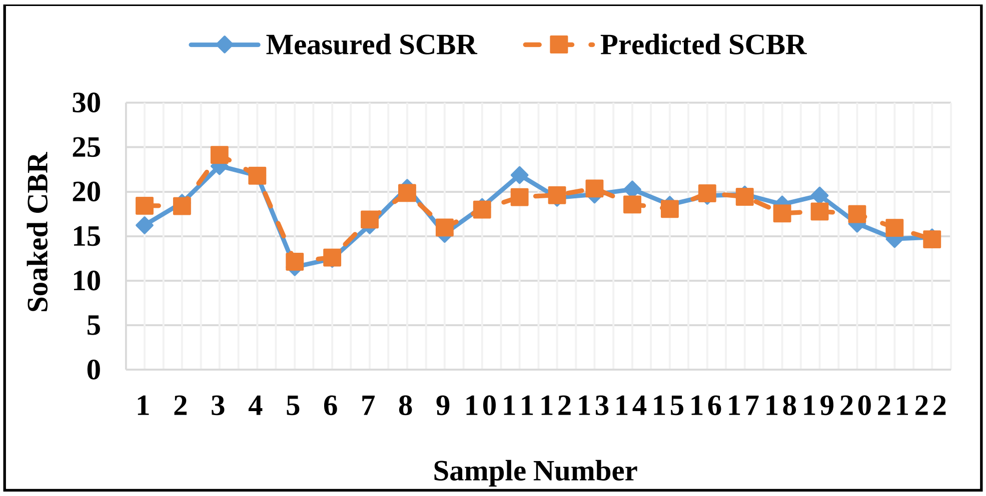


Fig. 4.73 Plot of Series of Model 7 (Ridge)

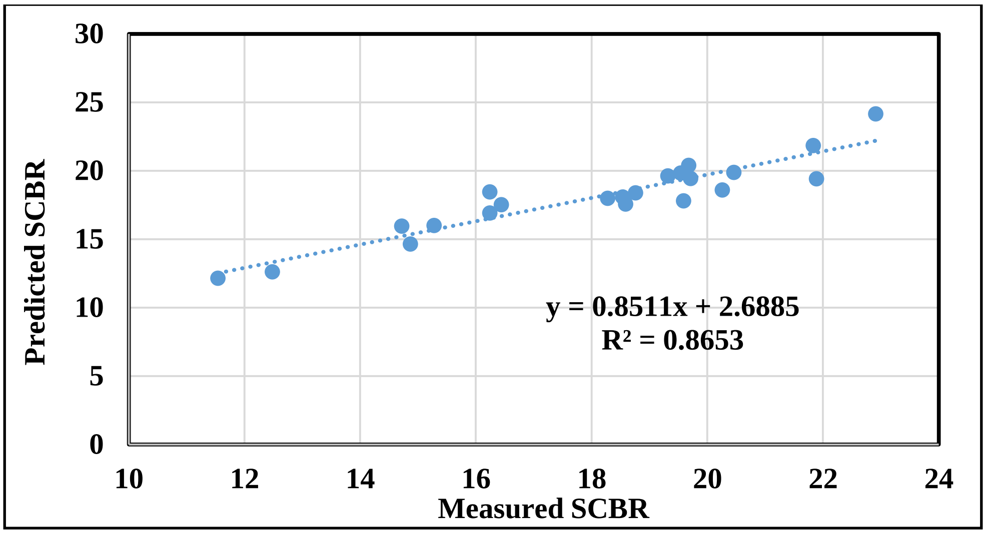


Fig. 4.74 Measured Vs Predicted Soaked CBR (Model 7, Ridge)

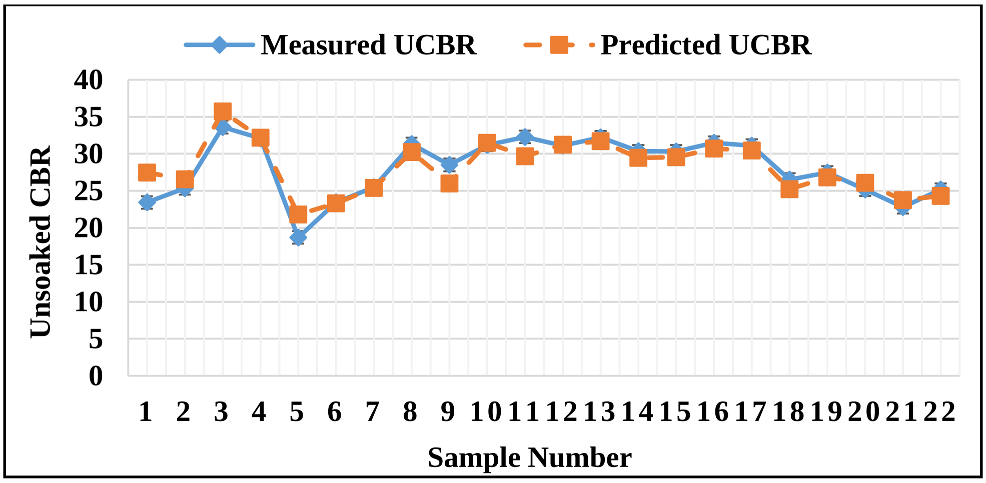


Fig. 4.75 Plot of Series of Model 8 (Ridge)

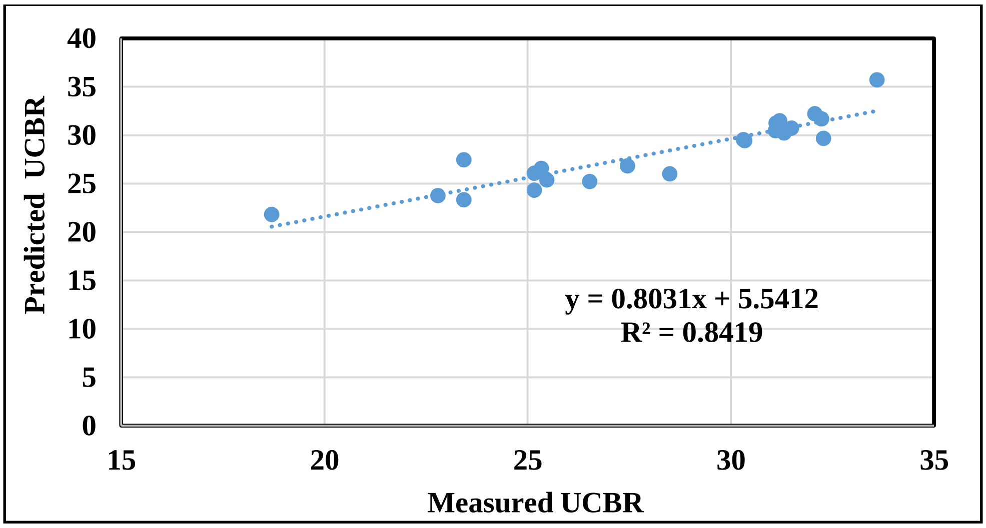


Fig. 4.76 Measured Vs Predicted Unsoaked CBR (Model 8, Ridge)

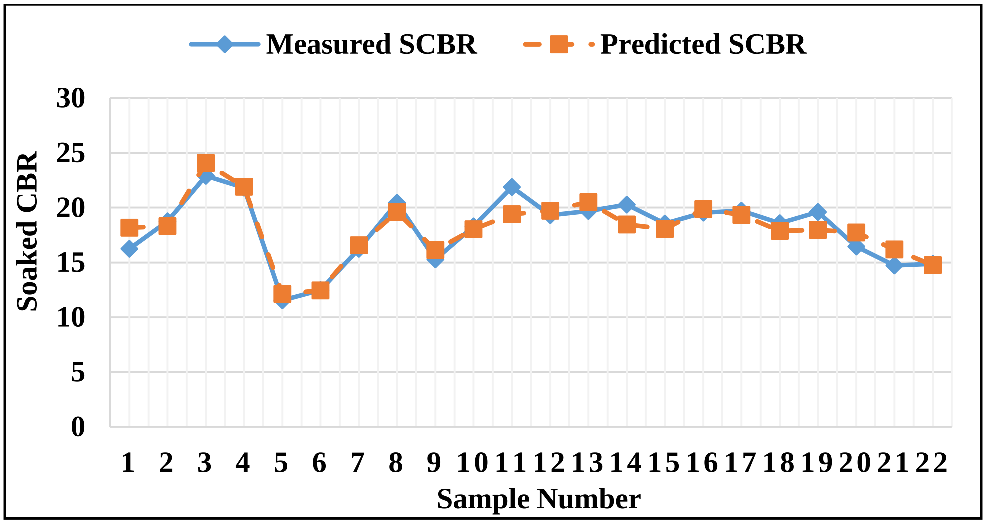


Fig. 4.77 Plot of Series of Model 13 (Ridge)

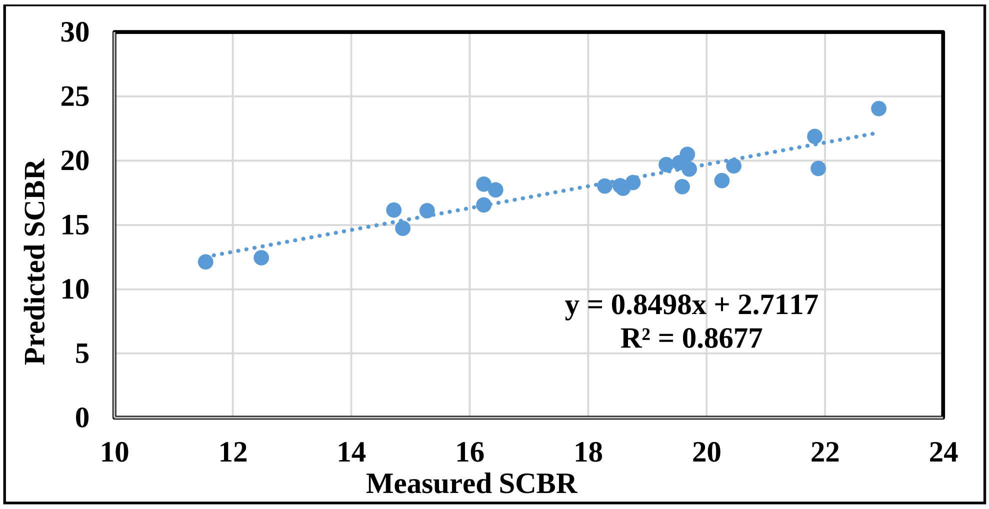


Fig. 4.78 Measured Vs Predicted Soaked CBR (Model 13, Ridge)

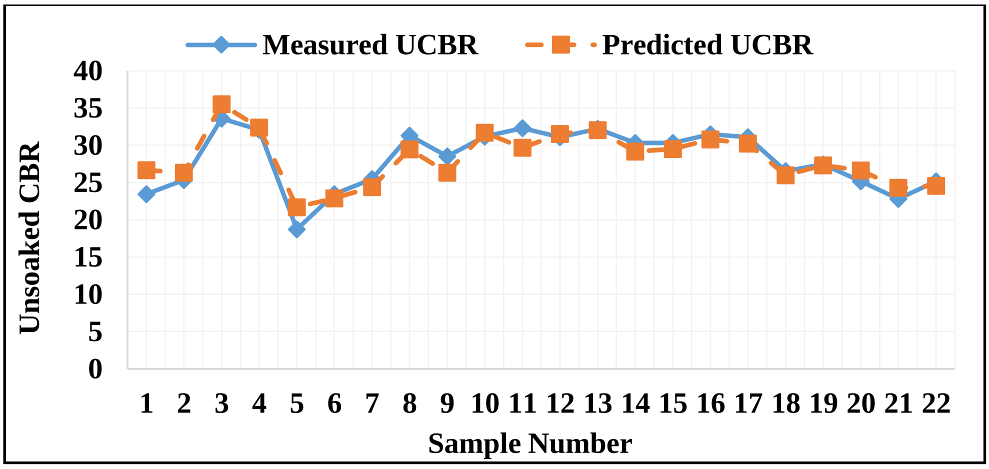


Fig. 4.79 Plot of Series of Model 14 (Ridge)

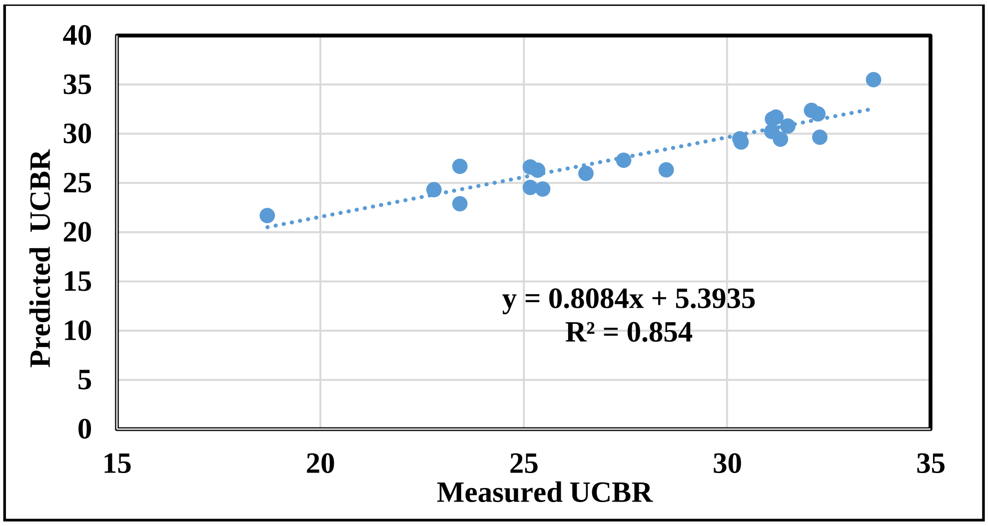


Fig. 4.80 Measured Vs Predicted Unsoaked CBR (Model 14, Ridge)

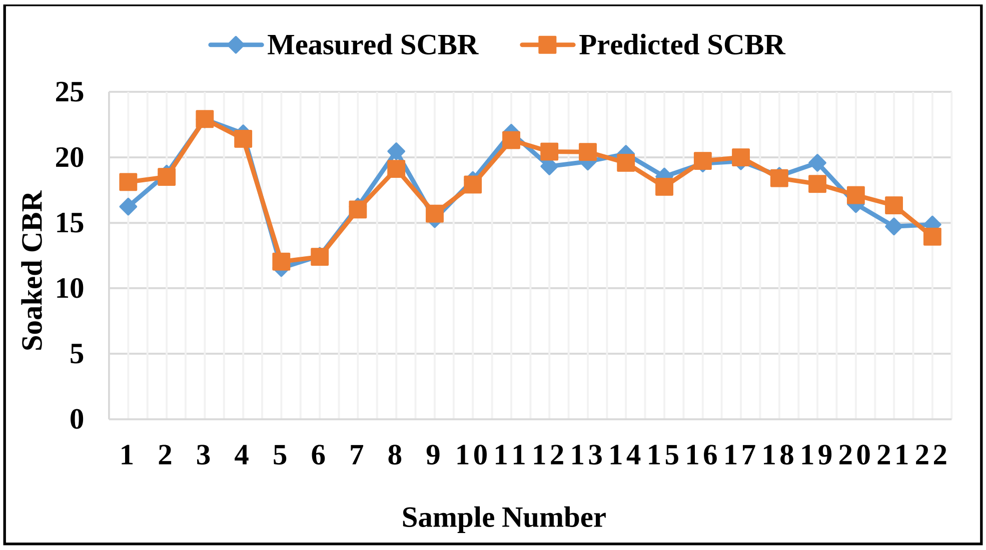


Fig. 4.81 Plot of Series of Model 17 (Ridge)

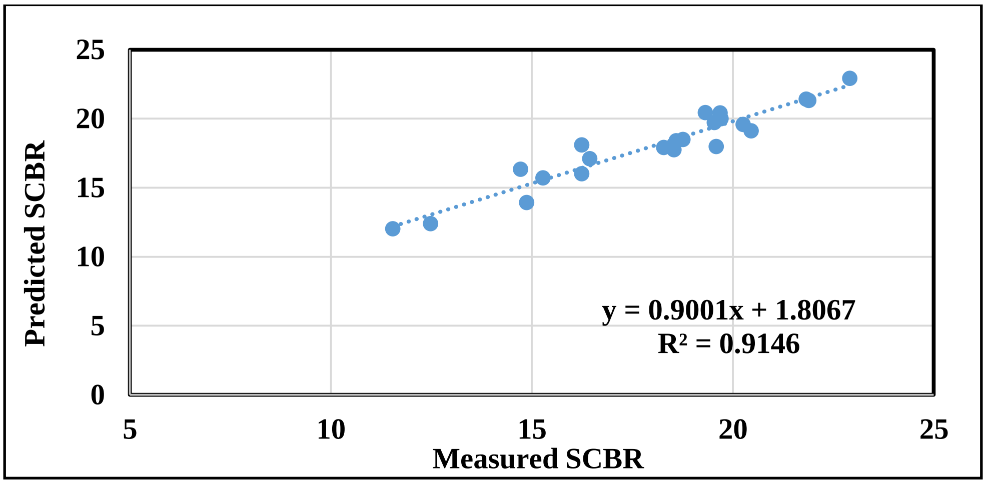


Fig. 4.82 Measured Vs Predicted Unsoaked CBR (Model 17, Ridge)

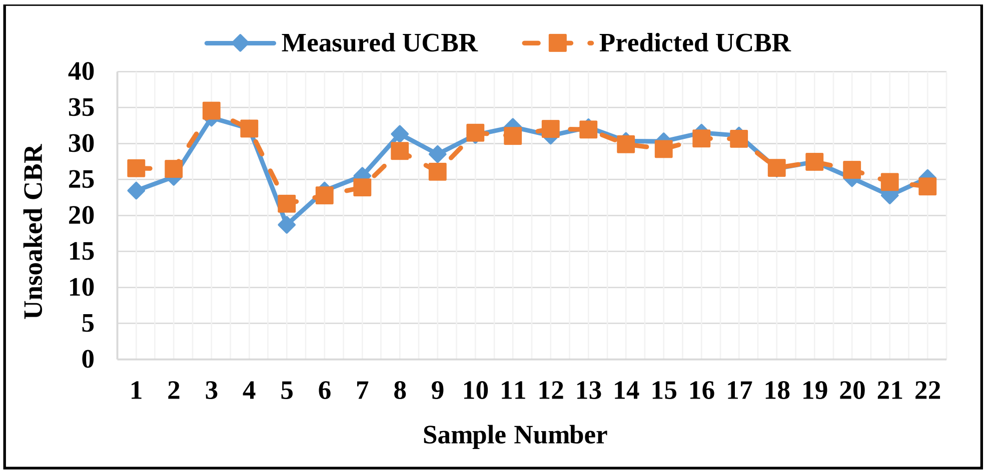


Fig. 4.83 Plot of Series of Model 20 (Ridge)

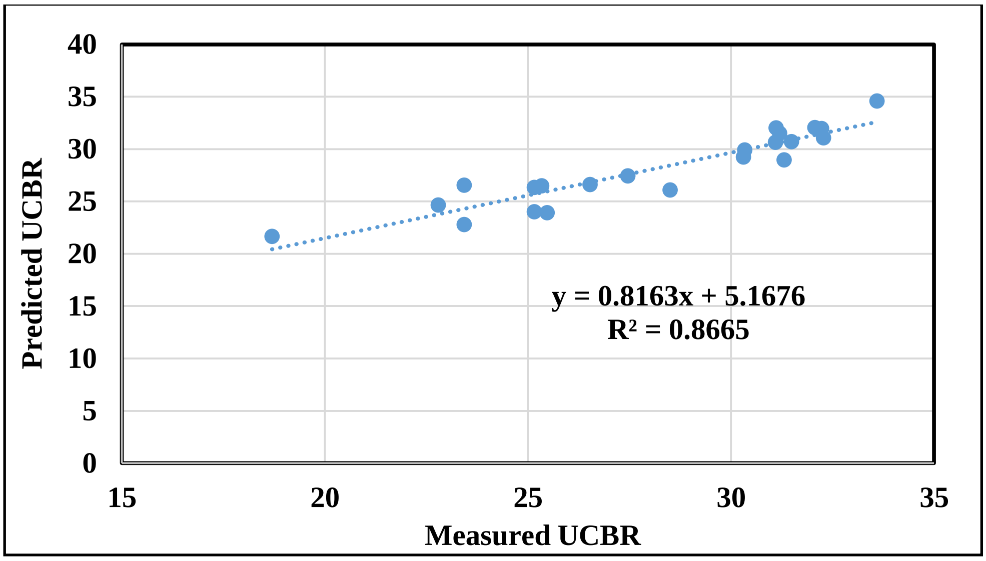


Fig. 4.84 Measured Vs Predicted Unsoaked CBR (Model 20, Ridge)

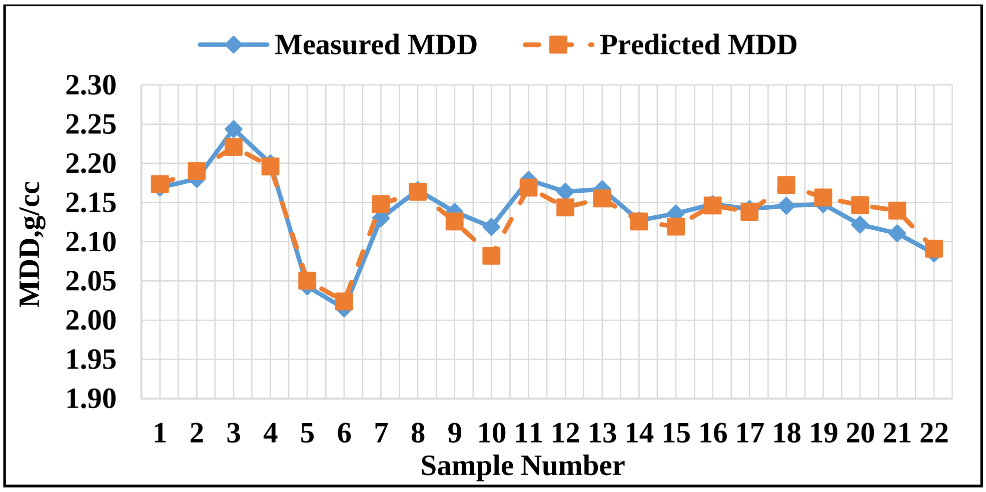


Fig. 4.85 Plot of Series of Model 25 (MRA)

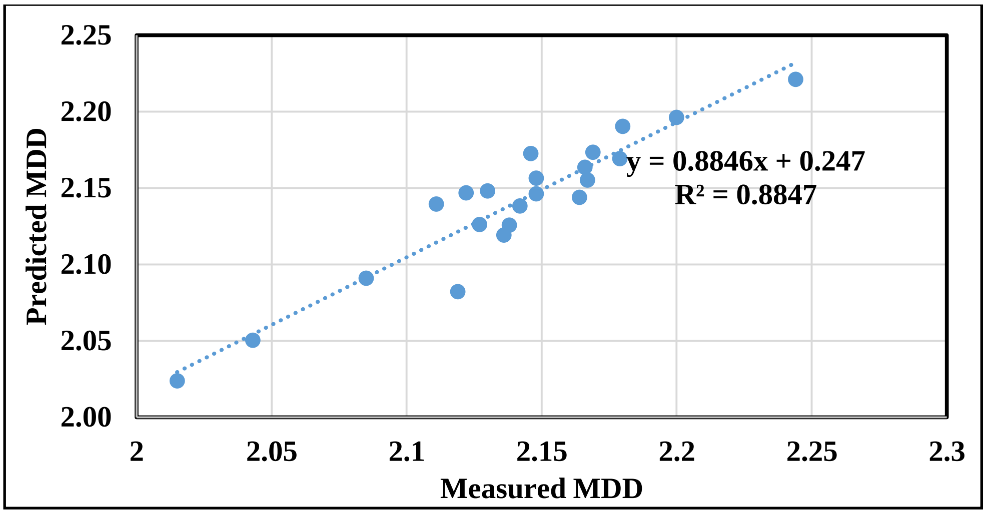


Fig. 4.86 Measured Vs Predicted MDD (Model 25, MRA)

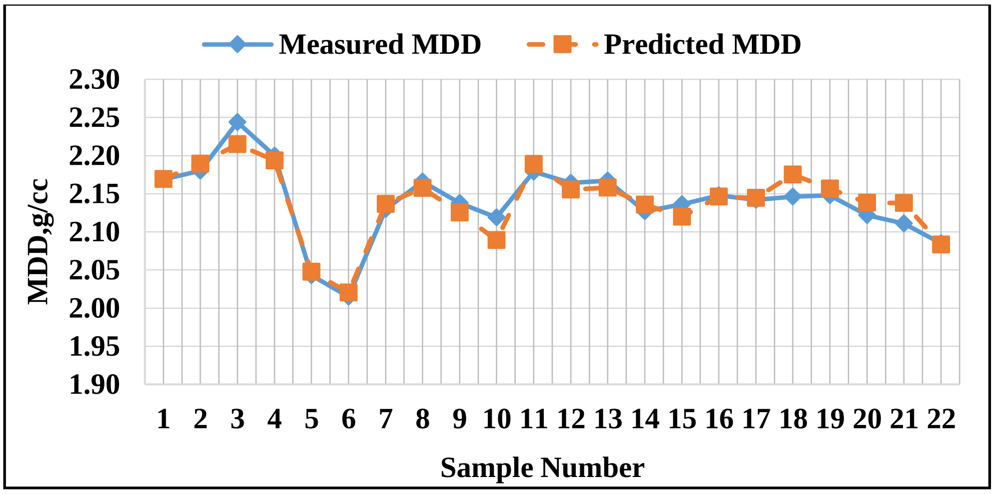


Fig. 4.87 Plot of Series of Model 28 (MRA)

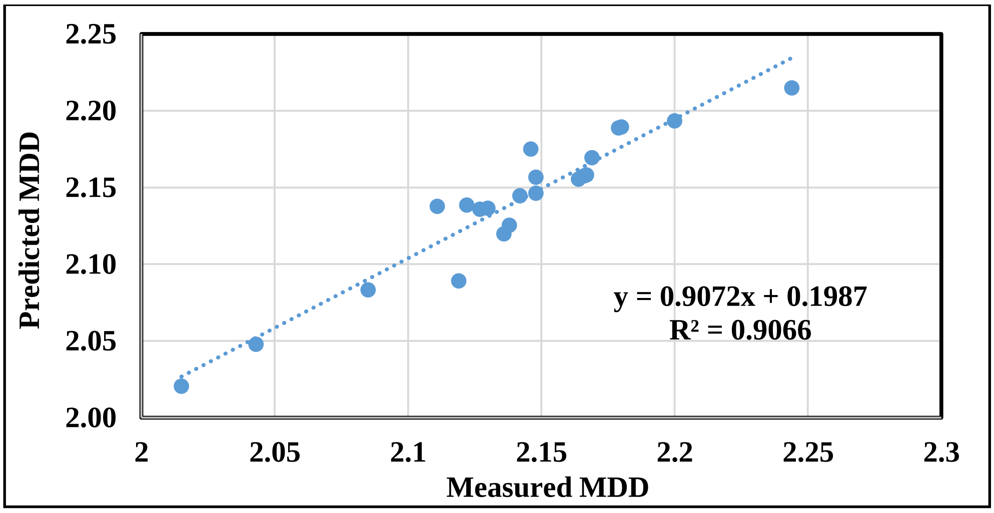


Fig. 4.88 Measured Vs Predicted MDD (Model 28, MRA)

From Figures 4.71 to 4.88, it is found that selected models are well correlated with their measured values. Series plot of measured vs predicted values indicate that the prediction results are very near to the measured values which shows the effectiveness of the prediction equation.

It is observed from the Fig. 4.74 that model 7 includes only three parameters (G, OMC & MDD) and gives an excellent relationship with the soaked CBR (R^2 = 0.87). Figure 4.81 shows the excellent results of the prediction model (model 17) of soaked CBR as it has a high R^2 value (0.91) of the predicted model. Model 7 (3 variables) and model 17 (4 variables) of soaked CBR have been selected as the best regression equations among all other soaked CBR model's equations. Fig. 4.89 shows the graphs of performance parameters of different models on the basis of which the best fit equation is selected for soaked CBR.

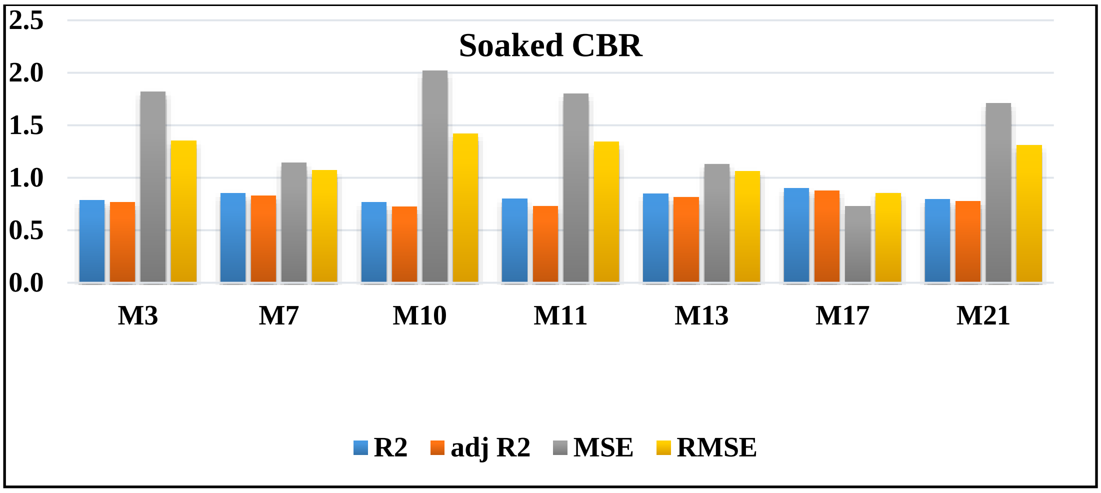
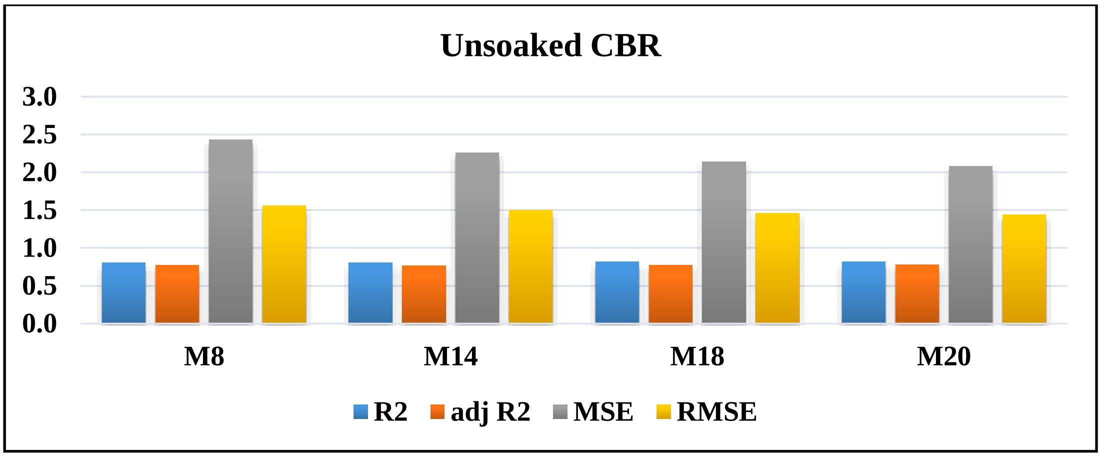


Fig .4.89 Performance Parameters of Models (Soaked CBR)

**M = model*

Figure 4.77, 4.85 reveals that for the unsoaked CBR, Model 8 (3 variables) and model 20 (4 variables) are the best because their results are better than all the other models. The percentage reduction between R^2 and R^2_{adj} are varied in the range of 2 - 5 % except for model 11. Also, models 7, 17, 18, 20 have a low percentage reduction which signifies that including parameters shows a good relationship with dependent variables i.e. SCBR &UCBR (Table 4.8). Fig. 4.90 shows the performance parameters of unsoaked CBR of finalise models for choosing the best models among them.

Both the prediction models of the MDD (model 25 & model 28) shows a very less percentage of reduction between R^2 and R^2_{adj} (about 1.5 %). As most of the study is done on soil having more gravel portion with little fines, it is better to fit the MDD values from model 25 which contains G and OMC as their parameters.



**M = model*

Fig .4.90 Performance Parameters of Models (Unsoaked CBR)

4.3.5 ANOVA Test

For adequacy, models are checked by the Analysis of Variance (ANOVA) test. The test is based on the null hypothesis which tells that those dependent variables (CBR, MDD) are not related to independent variables (LL, PL, PI, G, OMC, MDD) while the alternate hypothesis tells that those dependent parameters are related to independent parameters. The null hypothesis is rejected for all the proposed models of equations because the p-value is less than the significance value (α=0.05). In other words, the proposed models show a very good relation between the CBR and MDD. Table 4.10 shows the ANOVA results.

Table 4.10 ANOVA Results (α=0.05)

Model 7	*df*	*SS*	*MS*	*F*	*p-value*	*sig*
Regression	3	17.87315	5.957718	36.20154	4.67E-08	yes
Residual	19	3.126846	0.164571			
Total	22	21				
Model 8	*df*	*SS*	*MS*	*F*	*p-value*	*sig*
Regression	3	16.8643	5.621433	25.82566	6.48E-07	yes
Residual	19	4.135702	0.217669			
Total	22	21				
Model10	*df*	*SS*	*MS*	*F*	*p-value*	*sig*
Regression	3	143.2166	47.73885	19.41555	7.12E-06	yes
Residual	18	44.25831	2.458795			
Total	21	187.4749				

Model 13	*df*	*SS*	*MS*	*F*	*p-value*	*sig*
Regression	4	17.84519	4.461299	25.4543	3.37E-07	yes
Residual	18	3.154806	0.175267			
Total	22	21				
Model 14	*df*	*SS*	*MS*	*F*	*p-value*	*sig*
Regression	4	16.97779	4.244448	18.99455	2.87E-06	yes
Residual	18	4.022209	0.223456			
Total	22	21				
Model 17	*df*	*SS*	*MS*	*F*	*p-value*	*sig*
Regression	4	18.90292	4.725729	40.56261	8.99E-09	yes
Residual	18	2.097082	0.116505			
Total	22	21				
Model 20	*df*	*SS*	*MS*	*F*	*p-value*	*sig*
Regression	4	17.14023	4.285057	19.9833	2E-06	yes
Residual	18	3.859774	0.214432			
Total	22	21				
Model 25	*df*	*SS*	*MS*	*F*	*p-value*	*sig*
Regression	2	0.04466	0.02233	72.88732	1.22E-09	yes
Residual	19	0.005821	0.000306			
Total	21	0.050481				

4.3.6 Hypothesis Test

To check the significance and performance of the selected models statistically, a hypothesis test was performed by using a T-Test (sample size < 30) in the M.S.Excel. The significance level (α =0.05) of 95 % was used in this test. Two hypotheses were given:

- Null hypothesis (H_0):- Mean Measured CBR value = Mean Predicted CBR from proposed MRA model
- The alternative hypothesis (H_1):- Mean Measured CBR value ≠ Mean Predicted CBR from proposed MRA model

For this test, if the p-value is less than 0.05, the null hypothesis is rejected otherwise accept the alternative hypothesis. Table 4.11 shows the results of the T-Test. The results of the T-test from M.S.Excel shows that the p-value of all the predicted models is greater than the significance value i.e. 0.05 which accept the null hypothesis and predict that both the values of measured and predicted are related to each other,

Table 4.11 T-Test: Paired Two Sample for Means

	Model 3		Model 7		Model 8		Model 9		Model 10		Model 11	
	MSCBR	PSCBR	MSCBR	PSCBR	*MUCBR*	*PUCBR*	*MSCBR*	PSCBR	*MSCBR*	*PSCBR*	*MSCBR*	*PSCBR*
Mean	18.053	17.351	18.053	18.054	28.136	28.137	18.053	18.054	18.053	17.986	18.053	18.075
Variance	8.927	7.128	8.927	7.473	15.948	12.216	8.927	7.473	8.927	6.868	8.927	7.039
Observations	22.000	22.000	22.000	22.000	22.000	22.000	22.000	22.000	22.000	22.000	22.000	22.000
Pearson Correlation	0.887	–	0.930	–	0.917	–	0.887	–	0.874	–	0.888	–
Hypothesized Mean Difference	0.000	–	0.000	–	0.000	–	0.000	–	0.000	–	0.000	–
df	21.000	–	21.000	–	21.000	–	21.000	–	21.000	–	21	–
t Stat	2.385	–	-0.0019	–	7.24E-05	–	0.00033	–	0.215	–	-0.0763	–
P(T<=t) one-tail	0.013	–	0.499	–	0.499	–	0.499	–	0.416	–	0.469	–
t Critical one-tail	1.721	–	1.721	–	1.721	–	1.721	–	1.721	–	1.721	–
P(T<=t) two-tail	0.026	–	0.998	–	0.999	–	0.999	–	0.831	–	0.939	–
t Critical two-tail	2.080	–	2.079	–	2.079	–	2.079	–	2.079	–	2.079	–

Contd...

Model 13			Model 14		Model 17		Model 18		Model 20	
	MSCBR	*PSCBR*	*MUCBR*	*PUCBR*	*MSCBR*	*PSCBR*	*MUCBR*	*PUCBR*	*MUCBR*	*PUCBR*
Mean	18.053	18.053	28.137	28.139	18.053	18.055	28.137	28.134	28.137	28.135
Variance	8.927	7.430	15.948	12.204	8.927	7.908	15.948	12.272	15.948	12.263
Observations	22.000	22.000	22.000	22.000	22.000	22.000	22.000	22.000	22.000	22.000
Pearson Correlation	0.931	–	0.924	–	0.956	–	0.928	–	0.931	–
Hypothesized Mean Difference	0.000	–	0.000	–	0.000	–	0.000	–	0	–
df	21	–	21	–	21	–	21	–	21	–
t Stat	0.000564	–	-0.00782	–	-0.01457	–	0.00832	–	0.007031	–
P(T<=t) one-tail	0.499	–	0.497	–	0.494	–	0.497	–	0.497	–
t Critical one-tail	1.721	–	1.721	–	1.721	–	1.721	–	1.721	–
P(T<=t) two-tail	0.999	–	0.994	–	0.988	–	0.993	–	0.994	–
t Critical two-tail	2.079	–	2.079	–	2.079	–	2.079	–	2.079	–

Contd...

	Model 25			Model 28	
	MDD	*PMDD*		*MDD*	*PMDD*
Mean	2.139	2.139		2.139	2.140
Variance	0.00240	0.00213		0.0024	0.0022
Observations	22	22		22	22
Pearson Correlation	0.941	–		0.952	–
Hypothesized Mean Difference	0	–		0	–
df	21	–		21	–
t Stat	-0.00704	–		-0.0507	–
P(T<=t) one-tail	0.497	–		0.480	–
t Critical one-tail	1.721	–		1.721	–
P(T<=t) two-tail	0.994	–		0.960	–
t Critical two-tail	2.079	–		2.079	–

It means that the predicted model is well enough to find the values nearer to measured values.

Table 4.12 shows the model evaluation parameters which also signifies the criteria of selecting the equations and their parameters

Table 4.12 Model Performance Evaluation

Model No.	**Model relations with parameters**	**R^2**	**R^2_{adj}**	**MSE**	**RMSE**	**SE**
Simple Regression Analysis (SRA), Soaked CBR						
3A	SCBR s PI (Lin)	0.183	0.143	2.86	1.69	2.77
4A	SCBR vs G (Lin)	0.635	0.62	3.11	1.76	1.85
4C	SCBR vs G (Expo)	0.639	-	3.49	1.87	-
5A	SCBR vs OMC (Lin)	0.577	0.56	3.6	1.89	1.99
5C	SCBR vs OMC (Expo)	0.595	-	3.68	1.92	-
6A	SCBR vs MDD (Lin)	0.74	0.724	2.24	1.49	1.57
6C	SCBR vs MDD (Expo)	0.75	-	2.41	1.55	-
S10	SCBR vs (UCBR/OMC) (Lin)	0.875	0.868	1.09	1.03	0.354
Simple Regression Analysis (SRA), Unsoaked CBR & MDD						
3A	UCBR vs PI (Lin)	0.05	0.005	4.48	2.12	3.98
4A	UCBR vs G (Lin)	0.36	0.33	9.74	3.12	3.27
4B	UCBR vs G (Poly)	0.45	-	37.67	6.14	-
6A	UCBR vs MDD (Lin)	0.46	0.44	8.16	2.86	2.99
S7	MDD vs OMC (Lin)	0.88	0.878	0.00027	0.0163	0.017

Multiple Regression Analysis (MRA), Soaked CBR						
3	SCBR vs G,MDD	0.786	0.764	2.32	1.52	1.45
7	SCBR vs G,OMC,MDD	0.851	0.828	1.14	1.07	0.41
10	SCBR vs PI,OMC,MDD	0.764	0.724	2.02	1.42	1.57
11	SCBR vs LL,PL,OMC,MDD	0.8	0.73	1.80	1.34	0.51
13	SCBR vs PI,G,OMC,MDD	0.849	0.816	1.13	1.06	0.42
17	SCBR vs LL,G,OMC,MDD	0.9	0.878	0.729	0.854	0.34
21	SCBR vs (LL*OMC), (G*MDD)	0.796	0.775	1.71	1.31	1.4
Multiple Regression Analysis (MRA), Unsoaked CBR & MDD						
8	UCBR vs G,OMC,MDD	0.803	0.772	2.43	1.56	0.48
14	UCBR vs PI,G,OMC,MDD	0.808	0.766	2.26	1.5	0.47
18	UCBR vs LL,G,OMC,MDD	0.815	0.773	2.14	1.46	0.46
20	UCBR vs PL,G,OMC,MDD	0.816	0.775	2.08	1.44	0.46
25	MDD vs G,OMC	0.885	0.872	0.00026	0.016	0.017
28	MDD vs LL,G,OMC	0.907	0.891	0.00021	0.014	0.016

Summary and Conclusion

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Chapter 5 SUMMARY AND CONCLUSIONS

5.1 General

This chapter summarizes the results of the different tests i.e. liquid limit, plastic limit, specific gravity, proctor test & CBR value test performed. A summary of model equations obtained from the different statistical approach is also in this chapter. The details of simple, non-linear, multiple regression model performance which are checked by the coefficient of determination (R^2), correlation coefficient (R), and RMSE value are also highlighted. Details about the independent variables that may affect the relation have also been discussed. Conclusions about the parameters selection and their behaviour with CBR and MDD values were derived from the obtained results of models.

5.2 Summary

5.2.1 Test Summary

Results show that soil has a low plasticity index but it has been used as a parameter in the prediction equation for checking the impact of the presence of some fine content in CBR values. The results of all the tests are shown in Table 5.1.

Table 5.1 Summary of Laboratory Tests

Sample No.	LL (%)	PL (%)	PI (%)	G	OMC (%)	MDD (g/cc)	CBR (%)	
							Unsoaked	Soaked
BA1	26.35	24.35	2.00	2.67	6.4	2.169	23.43	16.24
BA2	25.45	22.3	3.15	2.67	6.0	2.18	25.34	18.76
BA3	27.60	24.8	2.80	2.74	5.2	2.244	33.60	22.91
BA4	26.65	22.00	4.65	2.73	5.8	2.200	32.07	21.83
DA1	25.60	18.65	6.95	2.58	9.4	2.043	18.70	11.54
DA2	26.34	19.46	6.88	2.61	10	2.015	23.43	12.48
GA1	28.56	26.47	2.09	2.67	7.0	2.13	25.47	16.24
GA2	27.42	25.00	2.42	2.70	6.6	2.166	31.31	20.46
GI1	24.76	18.46	6.30	2.60	7.6	2.138	28.50	15.28
GI2	23.46	16.24	7.22	2.63	8.6	2.119	31.20	18.28
HA1	20.00	15.53	4.47	2.67	6.5	2.179	32.28	21.89
HA2	22.31	16.35	5.96	2.67	7.1	2.164	31.11	19.32
HA3	25.00	19.00	6.00	2.70	6.8	2.167	32.23	19.68
HA4	23.21	18.34	4.87	2.69	7.5	2.127	30.34	20.26
HA5	25.23	19.65	5.58	2.65	7.7	2.136	30.31	18.54
HA6	26.00	20.45	5.55	2.71	7.0	2.148	31.49	19.54
HA7	24.18	19.36	4.82	2.70	7.2	2.142	31.10	19.71
KA1	24.85	18.05	6.80	2.69	6.4	2.146	26.53	18.59
KA2	25.34	19.09	6.25	2.67	6.8	2.148	27.46	19.59
KA3	28.08	21.14	6.94	2.70	7.0	2.122	25.16	16.44
KA4	26.00	19.00	7.00	2.67	7.2	2.111	22.79	14.72
KA5	27.23	20.21	7.02	2.62	8.4	2.085	25.16	14.87

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5.2.2 Model Analysis

A stochastic approach is used for the development of different correlations between different engineering properties of soil. The use of such approaches allows decision-makers to achieve the soil properties of non-visited locations by applying these models equations. These equations have a limited number of soil parameters that can be tested easily in the laboratory. The regression approach is applied to the CBR (soaked & unsoaked) and MDD values. In this study, the soil samples tested in the laboratory are cohesionless (some fines). Parameter MDD has been selected for two cases i.e. in 1 case it is selected as the independent variable for CBR value analysis but in 2 case, a distinct relationship has also been obtained for MDD values (dependent) with other soil parameters. Table 5.2, 5.3, 5.4 shows the models summary

5.2.3 Simple Regression Analysis

- The plastic limit has almost zero correlation with CBR because of the very low percentage of fines.
- The relation of PI and CBR shows a negative poor correlation.
- Parameter OMC shows a negative correlation with soaked CBR values which signifies that with an increase in OMC values, CBR decreases. A good correlation value was observed between CBR and OMC ($R = -0.76$).

  SCBR = - 2.0183*OMC + 32.567

- Linear and non-linear (polynomial, exponential, & logarithmic) analysis of MDD values shows that with the increase in MDD, there is an increase in CBR values. Soaked CBR shows a high correlation ($R = 0.859$) with MDD.
- A low mean square error (MSE) value is observed for the linear model (model 6A) of soaked CBR (Vs MDD) as compared with the exponential model (model 6C) equation. Hence this will be an effective model for predicting soaked CBR value.
- OMC proved to be an effective parameter for the correlation purpose as it gives very good negative correlation with MDD values ($R^2 = 0.88$).
  MDD = - 0.041*OMC + 2.4348

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Table 5.2 Predicted Values and Percentage Error of Soaked CBR Models

Sample No.	MSCBR	Model1		Model3		Model7		Model9		Model10		Model11	
		PSCBR	%Error	PSCBR	%error	PSCBR	%Error	PSCBR	%Error	PSCBR	%Error	PSCBR	%Error
BA1	16.24	19.39	-19.41	19.11	-17.66	18.46	-13.65	19.21	-18.29	18.90	-16.35	19.08	-17.47
BA2	18.76	19.79	-5.48	19.50	-3.96	18.39	1.98	19.99	-6.56	19.55	-4.21	19.91	-6.11
BA3	22.91	23.78	-3.79	23.63	-3.13	24.16	-5.44	22.79	0.53	23.66	-3.28	22.92	-0.05
BA4	21.83	21.09	3.39	21.79	0.20	21.83	-0.01	20.72	5.07	21.16	3.06	20.83	4.60
DA1	11.54	13.11	-13.59	12.24	-6.03	12.15	-5.27	13.09	-13.46	12.95	-12.18	13.08	-13.32
DA2	12.48	11.64	6.74	12.01	3.74	12.61	-1.03	11.44	8.32	11.36	9.01	11.39	8.73
GA1	16.24	17.09	-5.21	17.71	-9.04	16.90	-4.08	16.48	-1.48	16.48	-1.48	16.31	-0.44
GA2	20.46	19.38	5.26	19.78	3.31	19.88	2.84	18.78	8.23	18.93	7.46	18.71	8.55
GI1	15.28	18.35	-20.12	16.17	-5.81	16.00	-4.68	18.27	-19.57	18.42	-20.54	18.39	-20.33
GI2	18.28	18.01	1.48	16.27	11.00	18.00	1.56	17.88	2.21	18.09	1.03	18.06	1.20
HA1	21.89	20.26	7.43	19.47	11.07	19.41	11.32	21.73	0.74	20.19	7.75	21.65	1.09
HA2	19.32	19.78	-2.39	18.93	2.03	19.62	-1.57	20.35	-5.35	19.88	-2.90	20.44	-5.79
HA3	19.68	19.68	0.00	19.82	-0.71	20.39	-3.62	19.62	0.28	19.82	-0.73	19.75	-0.37
HA4	20.26	17.41	14.08	18.12	10.55	18.58	8.29	18.07	10.80	17.22	15.00	18.00	11.18
HA5	18.54	18.31	1.23	17.40	6.14	18.08	2.50	18.04	2.67	18.24	1.63	18.13	2.21
HA6	19.54	18.46	5.55	19.40	0.73	19.83	-1.50	18.29	6.40	18.47	5.47	18.36	6.06
HA7	19.71	18.22	7.57	18.92	4.00	19.43	1.43	18.55	5.87	18.08	8.28	18.53	6.01
KA1	18.59	17.64	5.10	18.80	-1.15	17.57	5.50	18.33	1.38	17.94	3.50	18.36	1.22
KA2	19.59	18.23	6.92	18.35	6.31	17.79	9.20	18.43	5.94	18.39	6.10	18.49	5.60
KA3	16.44	16.48	-0.22	18.20	-10.73	17.52	-6.56	16.16	1.69	16.70	-1.55	16.25	1.15
KA4	14.72	15.86	-7.74	17.03	-15.66	15.94	-8.31	16.22	-10.16	16.05	-9.04	16.23	-10.28
KA5	14.87	15.20	-2.24	14.79	0.56	14.65	1.46	14.72	1.03	15.22	-2.38	14.80	0.44

Sample No.	MSCBR	Model13		Model17		Model 19		Model 21		Model 23	
		PSCBR	%Error	PSCBR	%Error	PSCBR	%Error	PSCBR	%Error	PSCBR	%Error
BA1	16.24	18.18	-11.95	18.12	-11.56	17.72	-9.12	19.14	-17.86	18.50	-13.94
BA2	18.76	18.32	2.37	18.50	1.36	18.26	2.65	19.72	-5.13	19.47	-3.77
BA3	22.91	24.06	-5.03	22.94	-0.11	23.35	-1.91	23.38	-2.07	23.20	-1.25
BA4	21.83	21.90	-0.32	21.42	1.90	21.74	0.43	21.67	0.72	21.68	0.71
DA1	11.54	12.12	-5.06	12.03	-4.23	12.01	-4.08	12.36	-7.12	12.24	-6.10
DA2	12.48	12.46	0.17	12.41	0.54	12.23	2.03	11.85	5.04	11.55	7.43
GA1	16.24	16.56	-1.97	16.02	1.33	15.72	3.17	17.50	-7.75	16.51	-1.64
GA2	20.46	19.59	4.25	19.12	6.56	18.92	7.51	19.54	4.50	18.86	7.82
GI1	15.28	16.12	-5.50	15.72	-2.85	16.06	-5.13	16.33	-6.84	16.41	-7.42
GI2	18.28	18.04	1.33	17.93	1.91	18.13	0.83	16.25	11.12	16.59	9.26
HA1	21.89	19.41	11.33	21.33	2.58	20.48	6.42	20.08	8.28	20.40	6.83
HA2	19.32	19.71	-2.00	20.44	-5.78	20.27	-4.94	19.17	0.78	19.52	-1.01
HA3	19.68	20.50	-4.16	20.42	-3.74	20.64	-4.89	19.75	-0.38	19.93	-1.28
HA4	20.26	18.47	8.85	19.58	3.36	18.95	6.47	18.30	9.65	18.27	9.80
HA5	18.54	18.05	2.66	17.75	4.26	17.88	3.58	17.31	6.64	17.20	7.21
HA6	19.54	19.86	-1.61	19.74	-1.02	19.85	-1.56	19.23	1.57	19.20	1.74
HA7	19.71	19.34	1.87	20.00	-1.45	19.61	0.51	18.96	3.79	18.90	4.13
KA1	18.59	17.87	3.88	18.41	0.99	18.53	0.32	19.10	-2.77	19.48	-4.77
KA2	19.59	17.97	8.26	17.98	8.22	18.21	7.07	18.48	5.67	18.65	4.81
KA3	16.44	17.74	-7.90	17.12	-4.12	17.66	-7.42	18.01	-9.53	18.06	-9.83
KA4	14.72	16.17	-9.87	16.34	-11.01	16.53	-12.28	17.17	-16.65	17.36	-17.96
KA5	14.87	14.74	0.86	13.94	6.25	14.40	3.15	14.61	1.73	14.50	2.47

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Table 5.3 Predicted Values and Percentage Error of Unsoaked CBR Model

S.No.	MUCBR	Model 8		Model 14		Mode18		Model 20	
		PUCBR	% Error	PUCBR	% Error	PUCBR	% Error	PUCBR	% Error
BA1	23.43	27.46	-17.22	26.68	-13.88	27.16	-15.90	26.55	-13.30
BA2	25.34	26.56	-4.81	26.31	-3.83	26.77	-5.63	26.48	-4.50
BA3	33.6	35.70	-6.26	35.50	-5.65	34.34	-2.20	34.56	-2.86
BA4	32.07	32.19	-0.39	32.40	-1.02	31.74	1.03	32.05	0.05
DA1	18.7	21.79	-16.52	21.70	-16.05	21.68	-15.96	21.63	-15.68
DA2	23.43	23.31	0.50	22.91	2.23	23.08	1.49	22.79	2.75
GA1	25.47	25.37	0.40	24.38	4.27	24.53	3.70	23.90	6.18
GA2	31.31	30.23	3.44	29.45	5.94	29.42	6.04	28.96	7.51
GI1	28.5	25.99	8.82	26.33	7.61	25.69	9.87	26.08	8.51
GI2	31.2	31.49	-0.93	31.70	-1.59	31.24	-0.14	31.50	-0.96
HA1	32.28	29.65	8.15	29.65	8.13	31.64	2.00	31.05	3.81
HA2	31.11	31.24	-0.42	31.51	-1.30	32.00	-2.88	32.02	-2.93
HA3	32.23	31.69	1.69	32.02	0.65	31.64	1.82	31.95	0.85
HA4	30.34	29.44	2.97	29.15	3.92	30.44	-0.34	29.89	1.48
HA5	30.31	29.55	2.52	29.51	2.65	29.13	3.89	29.21	3.62
HA6	31.49	30.71	2.48	30.80	2.21	30.57	2.93	30.69	2.55
HA7	31.1	30.44	2.12	30.23	2.80	30.98	0.37	30.64	1.49
KA1	26.53	25.22	4.94	25.99	2.02	26.22	1.19	26.61	-0.29
KA2	27.46	26.84	2.27	27.32	0.52	27.08	1.38	27.43	0.09
KA3	25.16	26.07	-3.62	26.64	-5.88	25.73	-2.26	26.33	-4.66
KA4	22.79	23.75	-4.20	24.33	-6.74	24.28	-6.54	24.63	-8.08
KA5	25.16	24.32	3.32	24.56	2.39	23.60	6.21	24.02	4.55

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Table 5.4 Predicted values and Percentage Error of MDD Models

Sample No.	MDD	Model 25		Model 28	
		PMDD	% Error	PMDD	% Error
BA1	2.169	2.173435	-0.20447	2.169404	-0.01863
BA2	2.180	2.190355	-0.475	2.189254	-0.4245
BA3	2.244	2.22115	1.018271	2.214738	1.304011
BA4	2.20	2.196205	0.1725	2.193416	0.299273
DA1	2.043	2.05045	-0.36466	2.047766	-0.23328
DA2	2.015	2.023765	-0.43499	2.020419	-0.26893
GA1	2.130	2.148055	-0.84765	2.136447	-0.30268
GA2	2.166	2.16367	0.107572	2.157356	0.399077
GI1	2.138	2.12572	0.574369	2.125328	0.592703
GI2	2.119	2.082115	1.74068	2.089009	1.415337
HA1	2.179	2.169205	0.449518	2.188769	-0.44832
HA2	2.164	2.143825	0.932301	2.155442	0.395471
HA3	2.167	2.15521	0.54407	2.15805	0.413013
HA4	2.127	2.126035	0.045369	2.135706	-0.40931
HA5	2.136	2.119315	0.781133	2.119744	0.761049
HA6	2.148	2.146315	0.078445	2.146147	0.086266
HA7	2.142	2.13829	0.173203	2.144564	-0.1197
KA1	2.146	2.172565	-1.23788	2.175068	-1.35452
KA2	2.148	2.156515	-0.39642	2.156621	-0.40135
KA3	2.122	2.14675	-1.16635	2.138394	-0.77257
KA4	2.111	2.139595	-1.35457	2.137659	-1.26286
KA5	2.085	2.09101	-0.28825	2.083263	0.083309

- Ratio UCBR/OMC proved to be effective for predicting soaked CBR value as it has a high correlation coefficient (R= 0.94). The MSE and RMSE value of the predicted model was found to be 1.06 and 1.03 respectively.

SCBR =2.858 *(UCBR/OMC) + 6.519 **R^2 = 0.87**

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5.2.4 Multiple and Ridge Regression Analysis

- It was observed that as compared to simple regression analysis, the multiple regression approach gives better results for model prediction of coarse-grained soil.
- Regression models 7 and 8 which correlate soaked and unsoaked CBR with G, OMC, & MDD respectively are found to be a best-fit model as it has only 3 parameters.

  SCBR = - 262.446 + 40.159*G + 2.1933*OMC + 73.6*MDD

  UCBR = - 519.148 + 64.362*G + 6.491*OMC + 153.629*MDD
- The percentage reduction of R^2 and R^2_{adj} for model 7 is low i.e. 2.7 %. Also, this relation has low MSE (1.14) and RMSE (1.07) values which shows that the equation predicts the value with the least error.
- Also, the ridge regression model 17 and model 20 of the soaked CBR and unsoaked CBR, respectively proved to be an effective model for the prediction of the values as it has the low MSE and the high correlation of determination value.

  SCBR = - 209.474 - 0.4023*LL+ 43.845*G + 1.362*OMC + 51.824*MDD

  UCBR = - 465.068 - 0.2969*PL + 64.44*G + 5.391*OMC +134.755*MDD
- All results of model 25 based on ANOVA results, MSE (0.00026), RMSE (0.016), % reduction of R^2 and adjusted R^2 (1.5%) shows that the combination of G and OMC parameters was found to be well correlated with MDD.

  MDD= 2.5603 - 0.0435*G - 0.0423*OMC
- The obtained value of the regularization parameter (λ) was in between 0.1 - 0.21 which is effective in reducing the VIF (less than 10) values of independent variables.
- The obtained models of three independent variables show a very good relation with measured CBR and signify that these models are well enough to predict the output values.

  Predicted SCBR = 0.8511*Measured SCBR + 2.6885 R^2 = 0.86, (model 7)

  Predicted UCBR = 0.8031*Measured UCBR + 5.5412 R^2 = 0.84, (model 8)

  Predicted MDD = 0.8846*Measured MDD + 0.247 R^2 = 0.88, (model 25)

5.3 Conclusions

From the above findings, the following conclusions can be drawn

- The simple regression models of the study concluded that the CBR value has mostly effected by MDD followed by OMC, PI, LL, and PL in decreasing order.

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- MRA results conclude that as a comparison with the individual soil property, the combination of soil properties (compaction parameter, Atterberg's limit) give a better correlation.
- Nonlinear analysis (polynomial) may also give better results of coarse-grained soil but before the selection of that model, the problem of overfitting and multicollinearity of the equation has to be checked.
- The findings of this research work show that compaction parameters are important for coarse-grained soil as their correlation with strength characteristics of soil i.e. CBR is very high.
- In this analysis, high accuracy and low bias models are obtained, indicating that the closest the expected values are to their corresponding observed values. In the research areas, this would aid in estimating or projecting the CBR values.
- This study concludes that multiple regression analysis gives better results than simple regression. The study shows the impact of *ridge regression* in data analysis methods while checking multicollinearity between the parameters.
- All the results and equations obtained work only for selected areas of the district of Bageshwar. The equations obtained are true only for soils that have much of the gravel and sand percentage with little to medium fines of 2 % - 10 %.

5.4 Scope of Further Study

- The Artificial Neural Network (ANN) approach gives the results with more precision & least error as compared to other methods of regression. Hence for modelling the soil behaviour, **ANN** approach should be used in future studies.
- Ridge regression can be an alternative to the methods of least squares. To select meaningful estimates of model coefficients, it offers a sensitivity analysis of regression models (low biased).
- The present study can be extended by testing more sample sizes and correlating the strength parameters like cohesion and angle of friction with other engineering properties of soil.
- With the help of optimization techniques, research work may be further expanded. It aids in obtaining a low biased model which has the best efficiency for predicting the results.

Literature Cited

LITERATURE CITED

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VITA

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ABSTRACT

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All infrastructural projects such as houses, bridges, dams, railways, etc. should be safe and efficient to prevent settlement and failure. Therefore, to know the strength, behaviour, and design requirements of the structures before construction on any site, the soil should be properly examined. Soil properties, such as index properties, are used to assess and identify soil. These characteristics are defined by the liquid limit (LL), plastic limit (PL), and shrinkage limit. Also, the strength characteristics are determined by the direct shear test, triaxial test, unconfined compressive strength test (UCS), etc. Laboratory experiments, such as California bearing ratio (CBR) Test, standard proctor test, UCS, etc. prove to be laborious and time-consuming when different conditions and data are required. Many researchers tried to overcome this problem by correlating soil strength parameters and different soil index properties.

An attempt has been made in this research work to investigate the engineering properties (CBR, MDD) of soil by correlating them with various parameters such as LL, PL, plasticity index (PI), specific gravity (G),optimum moisture content (OMC) & maximum dry density (MDD). A total of 22 soil samples from the Bageshwar district were examined in the laboratory. Regression analysis is a computational, analytical, and simulation method that has been used to derive interrelationships between different variables (dependent and independent). To solve and obtain static data, simple and multiple regression methods were used. Best-fit equations were obtained based on high coefficient of determination (R^2) and adjusted R^2 value, variance inflation factor (VIF) parameters, low mean square error (MSE) and root mean square error (RMSE) value, analysis of variance (ANOVA) test, hypothesis test (T-test). Ridge regression was applied to the model equation to reduce the problem of multicollinearity. This was done by selecting an appropriate regularization parameter (λ) value. Correlation and regression analyses were performed in M.S. Excel.

The findings indicate that CBR and MDD do not correlate with LL and PL. Instead of LL and PL, PI was used as a parameter for correlation. The efficient parameters giving the best fit CBR value equation were G, OMC, and MDD. Results from multiple regression analysis suggest that the combination of soil properties (compaction parameters, Atterberg's limit) provides a strong association in contrast to the individual soil properties. In the analysis, a strong R^2 value (0.86) of the projected model for soaked CBR was obtained. The data obtained from the empirical equations were compared with the measured data and it was found that the present study gives better correlation equations with the least errors.

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सभी ढांचागत परियोजनाएं जैसे घर, पुल, बांध, रेलवे, आदि को सुरक्षित और कुशल होना चाहिए ताकि धंसना और विफलता को रोका जा सके। इसलिए, किसी भी निर्माण-स्थान पर निर्माण से पहले संरचनाओं की ताकत, व्यवहार और प्रारंभिक रेखा-चित्र की आवश्यकताओं को जानने के लिए मिट्टी की ठीक से जांच की जानी चाहिए। मिट्टी के गुण, जैसे कि सूचकांक गुण, का उपयोग मिट्टी के आकलन और पहचान करने के लिए किया जाता है। इन विशेषताओं को लिक्विड लिमिट (एलएल), प्लास्टिक लिमिट (पीएल) और सून्केज लिमिट से परिभाषित किया जाता है। इसके अलावा, ताकत की विशेषताओं को प्रत्यक्ष कतरनी परीक्षण, त्रिअक्षीय परीक्षण, अपुष्ट संपीड़न परीक्षण (यूसीएस) आदि द्वारा निर्धारित किया जाता है। प्रयोगशाला प्रयोग जैसे कैलिफोर्निया असर अनुपात परीक्षण (सीबीआर) , मानक प्रॉक्टर परीक्षण, यूसीएस, आदि विभिन्न परिस्थितियों और आँकड़ों की आवश्यकता के आधार पर श्रमसाध्य और समय लेने वाले साबित होते हैं। कई शोधकर्ताओं ने मिट्टी की ताकत मापदंडों और विभिन्न मिट्टी सूचकांक गुणों को सहसंबंधित करके इस समस्या को दूर करने का प्रयास किया।

इस शोध कार्य में एलएल, पीएल, ढलनशीलता सूचकांक (पीआई), विशिष्ट गुरुत्व (जी), इष्टतम नमीं मान(ओएमसी) और अधिकतम सूखा घनत्व(एमडीडी) जैसे विभिन्न मापदंडों के साथ मिट्टी के व्यवहारिक गुणों (सीबीआर, एमडीडी) की जांच करने का प्रयास किया गया है। बागेश्वर जिले से कुल 22 मिट्टी के नमूनों की प्रयोगशाला में जांच की गई। प्रतिगमन विश्लेषण एक अभिकलनात्मक, विश्लेषणात्मक और अनुकार विधि है जिसका उपयोग विभिन्न चर (निर्भर और स्वतंत्र) के बीच अंतर्संबंधों को प्राप्त करने के लिए किया गया है। स्थिर आँकड़ों को हल करने और प्राप्त करने के लिए बुनियादी और कई प्रतिगमन विधियों का उपयोग किया गया। निर्धारण के उच्च गुणांक (R^2) और समायोजित R^2 मूल्य, विचरण मुद्रास्फीति कारक (वीआईएफ) मापदंड, कम माध्य मूल मान त्रुटि (एमएसई) और वर्ग माध्य मूल मान त्रुटि (आरएमएसई), भिन्नता का विश्लेषण (एनोवा) परीक्षण और परिकल्पना परीक्षण (टी-परीक्षण) के आधार पर सर्वश्रेष्ठ उपयुक्त समीकरण प्राप्त किए गए। बहुसंरेखता की समस्या को कम करने के लिए प्रतिमान समीकरण में रिज प्रतिगमन लागू किया गया। यह एक उपयुक्त नियमितीकरण मापदण्ड (λ) मान का चयन करके किया गया। सहसंबंध और प्रतिगमन विश्लेषण एम. एस. एक्सेल में किए गए।

निष्कर्ष बताते हैं कि सीबीआर और एमडीडी का एलएल और पीएल के साथ कोई संबंध नहीं है। एलएल और पीएल के स्थान पर, पिआई को सहसंबंध के लिए एक मापदण्ड के रूप में इस्तेमाल किया गया। सबसे अच्छा सीबीआर मूल्य समीकरण देने वाले कुशल मापदण्ड जी, ओएमसी और एमडीडी थे। एकाधिक प्रतिगमन विश्लेषण के परिणाम बताते हैं कि मिट्टी के गुणों (संघनन मापदंडों, एटरबर्ग की सीमा) का संयोजन, मिट्टी के व्यक्तिगत गुणों के तुलनात्मक एक मजबूत संघ प्रदान करता है। लथपथ सीबीआर के लिए विश्लेषण में अनुमानित प्रतिमान का एक मजबूत R^2 मान (0.86) प्राप्त किया गया।

अनुभवजन्य समीकरणों से प्राप्त आंकड़ों की तुलना मापे हुए आंकड़ों से की गई और यह पाया गया कि वर्तमान अध्ययन कम से कम त्रुटियों के साथ बेहतर सहसंबंध समीकरण देता है।

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