Prediction of California Bearing Ratio of Fine-grained Soil Stabilized with Admixtures

by

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Declaration

This is to certify that the thesis work entitled *"Prediction of California Bearing Ratio of Fine-grained Soil Stabilized with Admixtures"* has been carried out by *Animesh Chandra Roy* in the *Department of Civil Engineering*, Khulna University of Engineering & Technology, Khulna, Bangladesh. The above thesis work or any part of this work has not been submitted anywhere for the award of any degree or diploma.

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Affectionately dedicated

To

Parents, wife and bother

for their love, support and encouragement

and

Specially to my supervisor

for his unconditional support and inspiration,

without whom this research would not have been possible

Abstract

The main focus of this study was to predict California bearing ratio (CBR) of stabilized soils with quarry dust (QD) and lime as well as rice husk ash (RHA) and lime. In the laboratory, the stabilized soils were prepared at varying mixing proportions of QD as 0, 10, 20, 30, 40 and 50%; lime of 2, 4 and 6% with varying curing periods of 0, 7 and 28 days. Moreover, the admixtures of RHA with 0, 4, 8, 12 and 16%; lime of 0, 3, 4 and 5% was used to stabilize soil with RHA and lime. In this study, the soft computing systems like simple linear regression (SLR), multiple linear regressions (MLR), back propagation artificial neural network (ANN) with different algorithms like Levenberg-Marquardt neural network (LMNN), bayesian regularization neural network (BRNN) and scaled conjugate gradient neural network (SCGNN) was implemented for the prediction of CBR of stabilized soils. Moreover, support vector machine (SVM) with different kernel functions like linear SVM (SVM-L), quadratic SVM (SVM-Q) and cubic SVM (SVM-C) were also performed. The result of ANN reveals that QD, lime and OMC were the best independent variables for the stabilization of soil with QD, while, RHA, lime, CP, OMC and MDD for the stabilization of soil with RHA. In addition, SVM proved QD and lime as well as RHA, lime, CP, OMC and MDD were the best independent variables for the stabilization of soil with QD and RHA, respectively. To check the performance of various models of soft computing systems, the prediction parameters like root means square error (RMSE), overfitting ratio (OR), coeficient of determination (R^2) and mean absolute error (MAE) were considered.

Result reveals the values of OMC of stabilized soil with QD and lime decreases, while, OMC increases in case of stabilized soil with RHA and lime. In addition, MDD of stabilized soil with QD and lime increases, while, decreases in case of stabilized soil with RHA and lime. The optimum content of QD was found 40% and lime 4% at varying curing periods to get better CBR of stabilized soil with QD and lime. Moreover, the optimum content of RHA was also found 12% and lime 4% at varying curing periods to get better CBR of stabilized soil with RHA and lime. The maximum CBR of stabilized soil with QD was found than that of stabilized soil with RHA for every curing period. The observed CBR and selected independent variables can be expressed by a series of developed equations with reasonable degree of accuracy and judgement from SLR and MLR analysis. These developed equations may be proposed to predict CBR of stabilized soils by knowing others independents variables in same cases. The model ANN showed comparatively the better values of CBR with satisfactory limits of prediction parameters (RMSE, OR, R^2 and MAE) as compared to SLR, MLR and SVM for the prediction of CBR of stabilized soils. Therefore, the model ANN can be considered as the best fitted model in soft computing system for the prediction of CBR of stabilized soils. Finally, it might be concluded that the selected optimum content of admixtures and newly developed techniques of soft computing systems will further be used of other researchers to stabilize soil easily and then predict CBR of stabilized soils.

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Nomenclature

All the notation and symbols are defined where they first appear in the text or figures. For convenience, the more frequently used symbols and their meanings are listed below.

AASHTO	:	American Association of State Highway and Transportation Officials
ANN	:	Artificial Neural Network
ASTM	:	American Society for Testing and Materials
BRNN	:	Bayesian Regularization Neural Network
CBR	:	California Bearing Ratio
LMNN	:	Levenberg-Marquardt Neural Network
MAE	:	Mean Absolute Eroor
MDD	:	Maximum Dry Density
MLR	:	Multiple Linear Regression
MSE	:	Mean Square Error
NN	:	Neural Network
OMC	:	Optimum Moisture Content
OR	:	Overfitting Ratio
PSI	:	Pound per Square Inch
QD	:	Quarry Dust
R	:	Coefficient of Correlation
R^2	:	Coefficient of Determination
RHA	:	Rice Husk Ash
RMSE	:	Root Mean Square Error
SCGNN	:	Scaled Conjugate Gradient Neural Network
SLR	:	Simple Linear Regression
SVM	:	Support Vector Machine
SVM-C	:	Cubic Support Vector Machine
SVM-L	:	Linear Support Vector Machine
SVM-Q	:	Quadratic Support Vector Machine

Chapter 1

Introduction

1.1 Research Background

California Bearing Ratio (CBR) is an important parameter for the design and construction of subgrade layers of highway as well as foundation of civil infrastructures. The strength of an underlying soil to be used as a subgrade of highway and foundation is assessed from its CBR value (Venkatasubramanian and Dhinakaran, 2011). Moreover, geotechnical engineer needs to ensure bearing capacity of underlying soil for the subgrade of highway and the design of foundation for civil infrastructures. If the value of CBR in soil is low, the thickness of pavement is high, which will result in high cost of construction and vice-versa. To increase the CBR value of soil, soil improvement or stabilized techniques may be applied to existing soft soil. Soil stabilization may be defined as any process by which a soil material is improved and made more stable resulting in improved bearing capacity, increase in soil strength and durability under adverse moisture and stress conditions (Joel and Agbedi, 2010). Stabilization of soil using admixtures is one of the different methods to increase its CBR. The positive effects of soil stabilization using admixtures have been well documented in literature (Amu et al., 2005). The CBR of stabilized soil depends on different factors like percentage of admixtures, curing period, curing temperature, compaction properties of soil, Atterberg's limit of soil, particle sizes of soil, etc. The test of CBR is not only expensive but also time consuming.

There are different techniques for improving CBR of soil, one being stabilization using different admixtures like cement, lime, fly ash, rich husk ash (RHA), gypsum, baggage ash, quarry dust (QD), geotextile, etc.. The successful stabilization of soils has to depend on the proper selection of admixtures and amount of admixtures added (Hebib and Farrell, 1999). In this study, to stabilize soil, the admixtures such lime, RHA and QD at varying percentages were used. The QD is a byproduct of the crushing process which is a concentrated material to *use* as aggregates for concreting purpose, especially as fine aggregates. The QD may be utilized for the stabilization of soil along with a binder like lime to increase its CBR (Rajasekaran and Rao, 2000; Dash and Hussain, 2011). The lime is a calcium-containing inorganic mineral in which oxides, and hydroxides predominate. The lime usually used for the stabilization of soil is commercially available quick lime. RHA is a by-product from the burning of rice husk. Rice husk is extremely prevalent in East and South-East Asia because of the rice production in this area. The RHA is then used as a substitute or admixture in cement.

The soft computing systems such as artificial neural network (ANN) and support vector machine (SVM) can be used for the prediction of CBR of stabilized soils. CBR of soil has been predicted using ANN by a number of researchers (Taskiran, 2010; Kin, 2006). ANN is an effective tool for analyzing and predicting of CBR stabilized soil. ANNs are a form of artificial intelligence and mimics the nervous system of the human brain (Bhatt et al., 2014). The coefficient of regression (R^2), root means square error (RMSE) and over fitting ratio (OR) is mostly used for evaluating the performance of ANN models. The RMSE indicates the accuracy of approximation as overall, without indicating the individual data points. The OR is defined as the ratio of Root mean square error (RMSE) for testing and training data and its value close to 1.0 shows good generalization of the ANN model (Bhatt et al., 2014). In addition, SVM has also been applied for the prediction and analysis of geotechnical parameters of stabilized soils. SVM has been also applied for prediction of settlement of foundations on cohesionless soil, swelling pressure of expansive soil and compaction behavior of stabilized soil (Samui et al., 2011).

In this study, the soft computing systems such as simple linear regression (SLR) and multiple linear regressions (MLR) were performed to establish relationship between CBR and other independent variables of SLR and MLR techniques. In addition, the algorithms of Levenberg-Marquardt neural network (LMNN), Bayesian regularization neural network (BRNN) and scaled conjugate gradient neural network (SCGNN) of ANN's back propagation was performed for the prediction of CBR of stabilized soils. The values of CBR obtained as output (estimated) from ANN models were then compared with targeted values i.e. measured values from laboratory and R^2 were evaluated. Subsequently, the LMNN was performed for the computation of data and to determine the best fitted model for the prediction of CBR of stabilized soils. The SVM with different kernel functions like support vector machine-linear (SVM-L), support vector machine-quadratic (SVM-Q) and support vector machine-cubic (SVM-C) was performed to select a best fitted model of SVM. The best R^2 and MSE value among different kernel functions of SVM was carried out. The results of SCGNN model were then compared with the best R^2 and MSE value of different kernel functions of SVM to perform as a best fitted model for predicting CBR of stabilized soils. The optimum content of QD was found 40% with lime 4% at varying curing periods to get better CBR of stabilized soil with QD and lime. Moreover, the optimum content of

RHA was also found 12% with lime 4% at varying curing periods to get better CBR of stabilized soil with RHA and lime. The model ANN showed comparatively the better values of CBR with satisfactory limits of prediction parameters (RMSE, OR, R^2 and MAE) as compared to SLR, MLR and SVM for the prediction of CBR of stabilized soils. Therefore, the model ANN can be considered as the best fitted model in soft computing system for the prediction of CBR of stabilized soils. Finally, it can be concluded that the selected optimum content of admixtures and newly developed techniques of soft computing systems will further be used of other researchers to stabilize soil easily and then predict CBR of stabilized soils.

1.2 Objectives of the Study

The CBR is a penetration test for the evaluation of mechanical strength of natural ground, sub grades and base courses beneath new carriageway construction. The CBR rating was developed for measuring load-bearing capacity of soils used for building, roads etc. In this study, the admixtures like QD and RHA with lime at varying mixing proportions were used to stabilize soil. The main objectives of this study are as follows:

1. To analyze CBR of fine-grained soil stabilized with different admixtures.
2. To predict CBR of stabilized soil using soft computing systems.
3. To check the accuracy of the observed and predicted CBR of stabilized soil from soft computing systems.

1.3 Contribution to Knowledge

The quality and life of pavement is greatly affected by the type of sub grade, sub base and base course materials used for the construction of highways pavement. The durability and serviceability of pavement depends on the type and quality of sub grade soil. In Bangladesh, most of the flexible pavement is used to be constructed over weak and problematic sub grade. The CBR of these sub grade have very low, it need to be more thickness with more stabilized foundation for pavement. In this study, soil was stabilized with different admixtures and CBR was computed using SLR and MLR techniques through MS Excel conventionally. However, based on this study, it is also possible to predict the CBR of stabilized soil using ANN and SVM technique through MATLAB software that will be the most perfect CBR for the similar research all over the country.

1.4 Scope of the Work

In literature, many researchers used more independent variable, number of more input data, more admixtures and more different technique for the prediction of CBR of stabilized soil through soft computing system. However, in this study, maximum five independent variable, maximum total number of twenty input data and four techniques were used for the prediction of CBR of stabilized soil. The experiment was performed in two laboratories such as geotechnical Engineering and Transportation Engineering. Moreover, prediction of CBR of stabilized soil can be varied due to use of different version of MS Excel and MATLAB software as well as different independent variables, number of input and target data.

1.5 Structure of the Study

The study has been presented in five distinct chapters comprising different aspects of this study. The outline and relations among these five chapters as depicted in Figure 1.1.

Chapter 1 describes general knowledge on the background of soil, admixture such as quarry dust, rice husk ash and lime, California nearing ratio (CBR) of stabilized soil, soft computing system such as simple linear regression (SLR) and multiple linear regression (MLR) through Excel software as well as artificial neural network (ANN) and support vector machine through MATLAB software. In addition, to prediction of CBR of stabilized soil use this software, objectives of the present research and scope of the study respectively. This chapter also represents structures of chapter in this study.

Chapter 2 describes the different important technical terms whatever used in this study. This chapter deals with concept of soil stabilization, components of stabilization, factors affecting the stabilized soil, methods of stabilization, strength variation of different types of stabilizations and treatment of unsuitable sub grade material. The strength behavior of soil in terms of California bearing ratio (CBR) are presented and discussed in this chapter. The details description of soft computing system such as Simple Linear Regression (SLR) analysis, Multiple Linear Regression (MLR) analysis, Artificial Neural Network (ANN) and Support Vector Machine (SVM) are describe in this chapter.

Chapter 3 deals with the characterization of soil and admixture used in this study. The physical properties of the soil and admixture like quarry dust (QD), rice husk ash (RHA) are also highlighted in this chapter. The mixing proportions of admixtures and procedure for preparation of stabilized soils are also described in this chapter. To evaluate the various proportions of the admixture with soil and testing the California bearing ratio (CBR) of the sample were highlighted in this chapter. This chapter represents the soft computing system such as simple linear regression (SLR), multiple linear regressions (MLR), artificial neural network (ANN) and support vector machine (SVM)used in this study to predict CBR of stabilized soil.

Chapter 4 describes the characterization of stabilized soils prepared with quarry dust (QD) with lime as well as rice husk ash (RHA) with lime at varying mixing proportions. The computed values of optimum moisture content (OMC), maximum dry density (MDD) and California bearing ratio (CBR) of stabilized soils are also highlighted in this chapter. The results of OMC, MDD and CBR which was used in soft computing systems for further prediction of CBR are also highlighted in this chapter. This chapter also deals with simple linear regression (SLR), multiple linear regression (MLR) as well as artificial neural network (ANN) with different training algorithm like Levenberg-Marquardt neural network (LMNN), Bayesian regularization neural network (BRNN) and scaled conjugate gradient neural network (SCGNN). In addition, Support vector machine (SVM) with different kernel functions like linear support vector machine (SVM-L), quadratic support vector machine (SVM-Q) and cubic support vector machine (SVM-C) for prediction of CBR of stabilized soils are also highlighted and hence discussed.

Chapter 5 brings out major conclusions of the research. Recommendations for future research are also provided in this chapter.

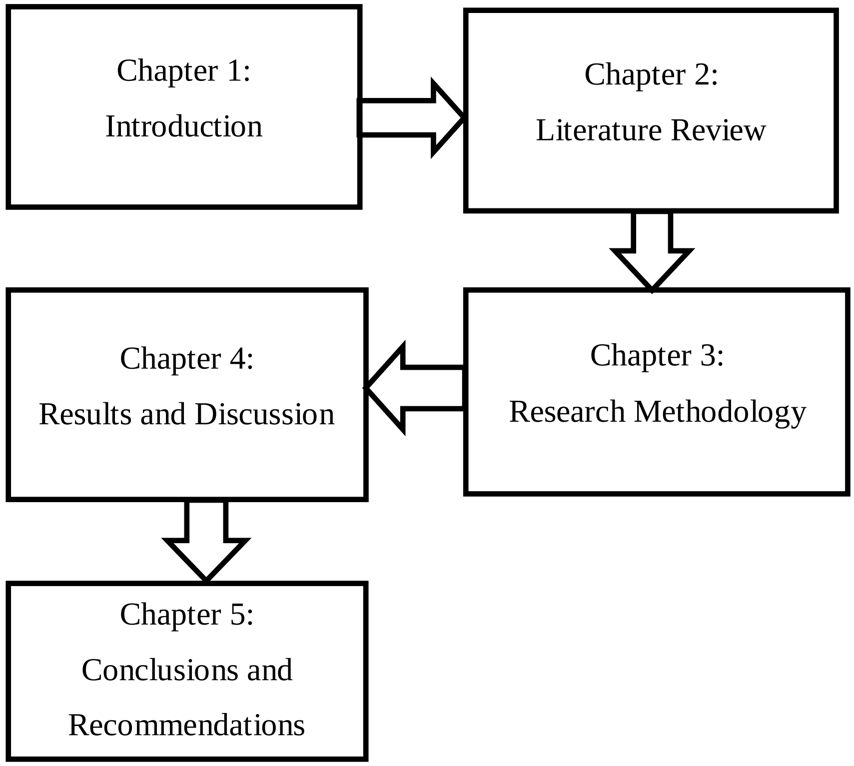

Figure1.1: Outline of chapters of this study.

Chapter 2

Literature Review

2.1 General

This chapter describes the different important technical terms whatever used in this study. This chapter also deals with the concept of soil stabilization, components of stabilization, factors affecting the stabilized soil, methods of stabilization, strength variation of different types of stabilizations and treatment of unsuitable sub grade material. The strength behavior of soil in terms of California bearing ratio (CBR) are presented and discussed in this chapter. The details description of soft computing system such as simple linear regression (SLR) analysis, multiple linear regression (MLR) analysis, artificial neural network (ANN) and support vector machine (SVM) are discussed in this chapter.

2.2 Concept of Soil Stabilization

There are different techniques for improving CBR of soil, one being stabilization. Soil stabilization may be defined as any process by which a soil material is improved and made more stable resulting in improved bearing capacity, increase in soil strength, and durability under adverse moisture and stress conditions (Joel and Agbede, 2010). It has been found that mixing two or more materials and compacting them for improving strength of the treated soil. This improvement technique is known as stabilization. Stabilization can increase the shear strength of a soil and/or control the shrink-swell properties of a soil, thus improving the load bearing capacity of a sub-grade to support pavements and foundations. Soil stabilization aims at improving soil strength and increasing resistance to softening by water through bonding the soil particles together, water proofing the particles or combination of the two (Sherwood, 1993).

Design and performance of flexible pavement mainly depends on the strength of sub-grade material. The load from the pavement surface is ultimately transferred from the sub-base to the sub-grade. The sub-grade is designed such that the stress transferred should not exceed elastic limit. Hence, the suitability and stability of sub-grade materials are evaluated before construction of pavement. The CBR is considered as strength parameter in design of sub-grade (Rakaraddi and Gomarsi, 2015). There are three purposes for soil stabilization have considered. The first one is strength improvement, to enhance its load-bearing capacity. The second purpose is for dust control by binding soil particles together, to eliminate or alleviate dust, generated by the operation of equipment and aircraft during dry weather or in arid climates. The third and final purpose is soil waterproofing, which is done to preserve the natural or constructed strength of a soil by preventing the entry of surface water (Mandeep and Soni, 2017).

The main objectives of soil stabilization are to increase bearing capacity of soil, its resistance to weathering process and soil permeability. The long-term performance of any construction project depends on the soundness of the underlying soils. The soil stabilization techniques are necessary to ensure the good stability of soil so that it can successfully sustain the load of the superstructure especially in case of soil which are highly active, also it saves a lot of time and millions of money when compared to the method of cutting out and replacing the unstable soil. Not all materials can be successfully stabilized, for example if cement is used as the stabilizer then a sandy soil is much more likely to yield satisfactory results than soft clay The material to be stabilized must be tested to ensure that it is compatible with the intended stabilizer–the subject of testing will be discussed later in this report. It is also recommended from experience that layers which are less than150mm thick should not be stabilized (Watson, 1994).

2.3 Techniques of Soil Stabilization

Civil engineering projects demand high-performance and high-quality of soils. Soil stabilization involves the alteration of one or more of the soil properties. The quality of soil is measured in terms of the size of its particles and as such is described as well-graded or poorly graded. The main purpose of undertaking the process is to prepare the land and build a strong foundation that can support the design loading. It is done to increase soil strength and durability as well as to suppress dust formation and prevent soil erosion. The methods used to improve the engineering properties of soil are broadly classified into two broad categories (https://www.globalroadtechnology.com, 2018) are (a) mechanical stabilization and (b) chemical stabilization.

2.3.1 Mechanical Stabilization

Mechanical stabilization involves the use of physical processes for soil stabilization shown in Figure 2.1. Unlike chemical stabilization, it changes only the physical properties of soil through compaction, soil blending (adding fibrous and non-biodegradable reinforcement) or placing a barrier on the soil (Afrin, 2017). In geo-technical engineering, soil compaction is a process wherein pressure is applied to soils by means of heavy machinery. It displaces air from the pores and causes soil densification. Regulating the amount of pressure when compacting is important as excess pressure disintegrates soil aggregates and causes them to lose their engineering properties. Soil reinforcement is another method employed in mechanical stabilization of soils. In this method, soils are reinforced by adding geo textiles and plastic mesh to arrest soil erosion and change features such as soil permeability. Besides this, graded aggregate materials are added to soils to decrease soil plasticity. Strategies for ground it are integral to Global Road Technology's services. It has developed a range of liquid soil stabilizers that bring in improvements such as enhanced strength, higher density, reduced water permeability and better bearing capacities. The products are designed to be environment friendly and are easily to apply for a number of applications.

Figure 2.1: Mechanical stabilization of soil (Source: Afrin, 2017).

2.3.2 Chemical Stabilization

Chemical stabilization alters the chemical properties of the soil through the use of admixtures. However, there are mechanical additives too that do not alter the chemical properties of the existing soil, but simply reinforce the natural properties of the parent soil. The chemical stabilization of soil is shown in Figure 2.2. This technique is more cost effective because treating the soil on site is less expensive that importing an aggregate. The main problem with chemical soil stabilization is that one needs to have a good sense of judgment. The stabilized soil materials have a higher strength, lower permeability and lower compressibility than the native soil (Keller, 2011). The type of soil, the right additive, the right amount to be used and the right application process are aspects to factor in when using this method of stabilizing soils. If either of them goes wrong, the end result can be opposite of the desired ones resulting in a total waste of time and higher monetary losses. The chief properties of soil which are of interest to engineers are volume stability, strength, compressibility, permeability and durability (Sherwood, 1993; Stab, 2002).

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Figure 2.2: Chemical stabilization of soil (Source: Stab, 2002).

2.4 Components of Soil Stabilization

Soil stabilization involves the use of stabilizing agents (binder materials) in weak soils to improve its geotechnical properties such as compressibility, strength, permeability and durability. The components of stabilization technology include soil sand or soil minerals and stabilizing agent or binders (cementations materials).

2.4.1 Soil

Most of stabilization has to be undertaken in soft soils (silty, clayey peat or organic soils) in order to achieve desirable engineering properties. According to Sherwood (1993) fine-grained granular materials are the easiest to stabilize due to their large surface area in relation to their particle diameter. Clay is the smallest particles amongst the other two types of soil. The particles in this soil are tightly packed together with each other with very little or no airspace. This soil has a very good water storage qualities and making hard for moisture and air to penetrate into it. It is very sticky to the touch when wet, but smooth when dried. Clay is the densest and heaviest types of soil which do not drains well or provides space for plant roots to flourish (https://byjus.com/biology/types-of-soil/, 2018). A clay soil compared to others has a large surface area due to flat and elongated particle shapes. Silt, which is known to have much smaller particles compared to the sandy soil and is made up of rock and other mineral particles which are smaller than sand and larger than clay. It is the smooth and quite fine quality of the soil that holds water better than sand. Silt is easily transported by moving currents and it is mainly found near the river, lake, and other water bodies. The slit soil is more fertile compared to the other three types of soil. Therefore it is also used in agricultural practices to improve soil fertility (https://byjus.com/biology/types-of-soil/, 2018). On the other hand, silty materials can be sensitive to small change in moisture and, therefore, may prove difficult during stabilization (Sherwood, 1993).

Figure 2.3: Three types of soils (Source: https://byjus.com/biology/types-of-soil/, 2018).

Sandy soil consists of small particles of weathered rock. Sandy soils are one of the poorest types of soil for growing plants because it has very low nutrients and poor in holding water, which makes it hard for the plant's roots to absorb water. This type of soil is very good for the drainage system. Three types of soil are shown in Figure 2.3. Sandy soil is usually formed by the breakdown or fragmentation of rocks like granite, limestone, and quartz. Peat and organic soils are rich in water content of up to about 2000%, high porosity and high organic content. The consistency of peat soil can vary from muddy to fibrous, and in most cases, the deposit is shallow, but in worst cases, it can extend to several meters below the surface (Pousetteet et al., 1999; Cortellazzo and Cola, 1999). Organic soils have high exchange capacity; it can hinder the hydration process by retaining the calcium ions liberated during the hydration of calcium silicate and calcium aluminates in the cement to satisfy the exchange capacity. In such soils, successful stabilization has to depend on the proper selection of binder and amount of binder added (Hebib and Farrell, 1999).

2.4.2 Stabilizing Admixture

The conventional admixtures can produce the desired strength for durable highway construction but are not economically viable. The thrust of this investigation therefore is to formulate a material composition which satisfies both strength requirement and cost considerations.

Lime Fly Ash Quarry Dust Rice Husk Ash

Figure 2.4: Commonly used some admixture for soil stabilization (Source: Rajasekaran and Rao, 2000).

The use of admixture modification is important and has increased over the years because of its economy and improved strength of composite materials. Recent trends in soil stabilization have evolved innovation techniques of utilizing locally available environmental and industrial wastes as materials for the modification and stabilization of this deficient soil. The commonly used admixtures are cement, lime; fly ash, quarry dust and rice husk ash shown in Figure 2.4.

2.4.2.1 Cement

Soil Stabilization is being used for a variety of engineering works, the most common application being in the construction of road and pavements, where the main objective is to increase the strength or stability of soil and to reduce the construction cost by making best use of the locally available materials. Over the cement as a main materials used for stabilizing soils. These materials have rapidly increased in price due to the sharp increase in the cost of energy.

Cement is the oldest binding agent since the invention of soil stabilization technology in 1960's. It may be considered as primary stabilizing agent or hydraulic binder because it can be used alone to bring about the stabilizing action required (Sherwood, 1993; Stab, 2002). Cement reaction is not dependent on soil minerals, and the key role is its reaction with water that may be available in any soil (Stab, 2002). This can be the reason why cement is used to stabilize a wide range of soils. Numerous types of cement are available in the market; these are ordinary Portland cement, blast furnace cement, sulphate resistant cement and high alumina cement.

The factors affects the soil cement mixtures of type of soil, quality of cement, quantity of water, mixing, compaction and curing as well as admixtures. The suitable materials must be pulverisable. They, in general, comprise granular materials with sufficient fines. Such material requires less cement. In materials, which contain deficiency in fines require more cement but they are also fall under suitable materials. The cement requirement depends upon the gradation of the soil. A well graded soil requires about 5 % cement, whereas a poorly graded, uniform soil may require about 9 % cement. Non-plastic silts require about 10 % cement, whereas plastic clays may need about 13 % cement. The actual quantity required shall have to be ascertained by carrying out laboratory tests (Engineering project, 2013)

2.4.2.2 Lime

Lime is a very fine material used in many construction applications is shown in Figure 2.4. Lime is produced by burning of calcium carbonate at elevated temperatures and is cooled up to obtain a homogeneous powder. There are many types of lime depending on its chemical composition and contents of calcium and magnesium. As the soil-lime reaction is time dependent (Bell,1996; Rajasekaran and Rao, 2000; Dash and Hussain, 2011). It is expected that this value will go on increasing with increase in the curing period. The effect can be brought by either quicklime, CaO or hydrated lime, Ca $(OH)_2$. Slurry lime also can be used in dry soils conditions where water may be required to achieve effective compaction (Hicks, 2002). Quicklime is the most commonly used lime; the followings are the advantages of quicklime over hydrated lime (Rogers and Glendinning, 1993).

a) Higher available free lime content per unit mass

b) Denser than hydrated lime (less storage space is required) and less dust

c) Generates heat which accelerate strength gain and large reduction in moisture content according to the reaction equation below

$$CaO+H_2O \text{ ->} Ca\ (OH)_2 + \textit{Heat(65 kJ/mol)}$$

Quicklime when mixed with wet soils, immediately takes up to 32% of its own weight of water from the surrounding soil to form hydrated lime; the generated heat accompanied by this reaction will further cause loss of water due to evaporation which in turn results into increased plastic limit of soil i.e. drying out and absorption (Stab, 2002; Sherwood,1993).

In lime stabilization the soil is stabilized by adding lime. By this method clayey soil is stabilized well. When lime is added to soil, it reacts with the soil and cations are exchanged in the diffused double layer. As a result plasticity is reduced significantly and the resulting material becomes more friable than the original clay. Consequently the material is therefore more suitable as sub grade. The amount of lime required for stabilization varies between 2 to 10 %. For a rough guide the following amount of lime may be used (Engineering project, 2013).

For clayey gravel having less than 50 % of silt-clay fraction 2 to 5 % of lime may be required. If the silt-clay fraction in soil exceeds more than 50 %, 5 to 10 % of lime may be used. For heavy clay the amount of lime required is about l0 %. The lime stabilization is not suitable for stabilization of sands (Engineering project, 2013).

2.4.2.3 Quarry Dust

Quarry dust is a rock particle. When huge rocks are broken in to small fragments it is used in construction as shown in Figure 2.4. It is as like as sand but mostly grey in colour. It is a mineral particle. The composition of quarry dust depends on the mineral composition of the parent rock. Quarry dust has been used for different activities in the construction industry such as road construction and manufacture of building materials such as light weight aggregates, bricks, and tile. It is a by-product of the crushing process which is a concentrated material to use as aggregates for concreting purpose, especially as fine aggregates. In quarrying activities, the rock has been crushed into various sizes; during the process the dust generated is called quarry dust and it is formed as waste (Mandeep and Soni, 2017).

There is no standard definition of quarry dust in the quarrying sector or construction industry. This leaves room for arbitrariness in description of the material. The terms quarry fines, dusts and wastes are used interchangeably, and are used to refer to materials which are of different particle size distribution; some of which are produced intentionally, and is thus not a waste material. According to the Commission of the European Communities (2007), if materials are not useable, does not meet the technical specifications required for its use or there is no specified market for it, then it remains a waste until a useful output has been identified. Finding uses for quarry dust will solve the problem of its disposal and resultant environmental pollution. It also yields some revenue (Eze-Uzomaka and Agbo, 2010). In addition, quarry dust is a solid waste produced from crusher units during crushing of large size rocks to obtain coarse aggregates, the disposal of which creates a lot of geoenvironmental problems. Quarry dust may be utilized for stabilization of soil along with a binder like lime to increase its CBR value (Sabat, 2013). Utilization of solid wastes like quarry dust not only protects the environment from degradation but also improves the engineering properties of the expansive soil (Sabat, 2012).

2.4.2.4 Fly Ash

Fly ash is a by-product of the pulverized coal combustion process. Fly ash has silica, alumina and various oxides and alkalies as its constituents. It is fine-grained and pozzolanic in nature shown in Figure 2.4. Fly ash is waste material imposing hazardous effect on environments and human health. Also, it cannot be disposed of properly and its disposal is not economically viable but if it is blended with other construction materials like clayey soil then it can be used best for various construction purposes like sub grade, foundation base and embankments. However, soil fly ash stabilization has the following limitations (White et al., 2005).

a) Soil to be stabilized shall have less moisture content; therefore, dewatering may be required.

b) Soil-fly ash mixture cured below 0 ^{0}C and then soaked in water is highly susceptible to slaking and strength loss.

c) Sulfur contents can form expansive minerals in soil-fly ash mixture, which reduces the long term strength and durability.

2.4.2.5 Rice Husk Ash

Rice husk is one of the most widely available agricultural wastes in many rice producing countries around the world. Globally, approximately 600 million tons of rice paddies are produced each year. On average 20% of the rice paddy is husk, giving an annual total production of 120 million tons of Rice husk ash (RHA) (Kumar et al., 2012). In Bangladesh there are a large number of rice mills which produce RHA as a result huge amount of waste. The use of agricultural waste (such as rice husk ash) will considerably reduce the cost of construction and as well reducing the environmental hazards the causes. Rice husk is an agricultural waste obtained from milling of rice shown in Figure 2.4. About 108 tons of rice husks are generated annually in the world. Hence, use of RHA for upgrading of soil should be encouraged. The previous Disposal of waste can be reduced using RHA as a soil stabilizer. The cost of stabilization may be minimized by replacing a good proportion of stabilizing agent using RHA. It will minimize the environmental hazards also. It found rice husk ash as best suitable to experiment with expansive soil for stabilization. The main reasons for choosing this material are (Gandhi, 2013) (a) its are economical as its are the waste products, (b) it do not have significant use in any productive work, (c) it have disposal problem, (d) its are locally available.

In addition, Rice husk ash is difficult to ignite and it does not burn easily with open flame unless air is blown through the husk. It is highly resistant to moisture penetration and fungal decomposition. Husk therefore makes a good insulation material. Rice husk ash has a high silica (SiO_2) contents which means that it decomposes slowly when brought back to the field. Handling of rice husk ash is difficult because it is bulky and dusty. It has angle of repose is about 40-45° which means that it's flow ability, e.g. in feed hoppers is very poor. Rice husk ash has low bulk density of only 70-110 kg/m³, 145 kg/m³ when vibrated or 180kg/m³ in form of brackets or pellets. It thus requires large volumes for storage and transport, which makes transport over long distances un-economical. Because of the high silica contents rice husk ash is very abrasive and wears conveying elements very quickly (Gandhi, 2013).

2.4.3 Factors Affecting the Strength of Stabilized Soil

Presence of organic matters, sulphates, compaction, moisture content, temperature Freeze-Thaw and Dry-Wet Effecting the stabilized soils may contribute to undesirable strength of stabilized materials (Sherwood, 1993).

2.4.3.1 Organic Matter

In many cases, the top layers of most soil constitute large amount of organic matters. However, in well drained soils organic matter may extend to a depth of 1.5 m (Sherwood, 1993). Soil organic matters react with hydration product e.g. calcium hydroxide $Ca(OH)_2$ resulting into low pH value. The resulting low pH value may retard the hydration process and affect the hardening of stabilized soils making it difficult or impossible to compact. In addition, the organic content in the soil can affect the stabilization process. For example, large amounts of organic matter can lower pH of the soil to be stabilized after reacting with the additives in the materials that are being used during the process. It is, therefore, necessary to determine the percentage of organic matter in the soil so that an allowance for the resultant reactions can be made when designing the soil stabilization process to be used. The organic matter is shown in Figure 2.5.

Figure 2.5: Organic matter in the soil (Source: Sherwood, 1993).

2.4.3.2 Sulphates

The use of calcium-based stabilizer in sulphate-rich soils causes the stabilized sulphate rich soil in the presence of excess moisture to react and form calcium sulphoaluminate (ettringite) and or thamausite, the product which occupy a greater volume than the combined volume of reactants. The acid sulphate soil is shown in Figure 2.6. However, excess water to one initially present during the time of mixing may be required to dissolve sulphate in order to allow the reaction to proceed (Sherwood, 1993).

Figure 2.6: Acid sulphate soil (Source: Sherwood, 1993).

2.4.3.3 Compaction

In practice, the effect of addition of binder in soil to the density of soil is of significant importance. Stabilized mixture has lower maximum dry density than that of unstabilized soil for a given degree of compaction is shown in Figure 2.7. The optimum moisture content increases with increasing binders (Sherwood, 1993). In cement stabilized soils, hydration process takes place immediately after cement comes into contact with water. This process involves hardening of soil mix which means that it is necessary to compact the soil mix as soon as possible. Any delay in compaction may result in hardening of stabilized soil mass and therefore extra compaction effort may be required to bring the same effect shown in Figure 2.7.

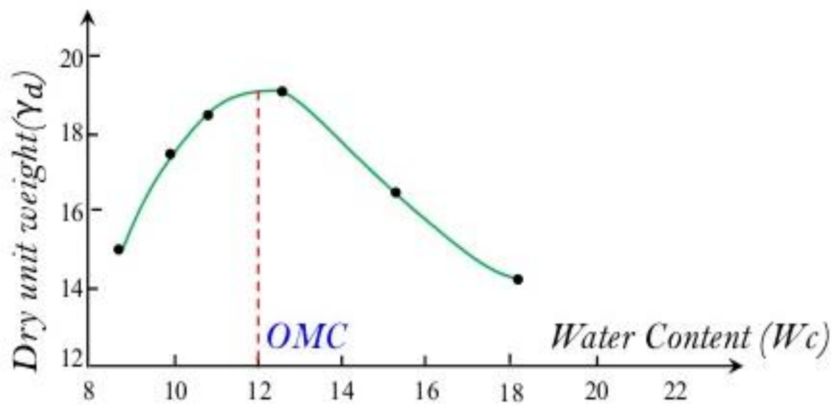


Figure 2.7: Factor affecting in compaction (Source: Sherwood, 1993).

In contrary, to cement, delay in compaction for lime-stabilized soils may have some advantages. Lime stabilized soil require mellowing period to allow lime to diffuse through the soil thus producing maximum effects on plasticity. After this period, lime stabilized soil may be remixed and given its final compaction resulting into remarkable strength than otherwise (Sherwood, 1993).

2.4.3.4 Moisture Content

In stabilized soils, enough moisture content is essential not only for hydration process to proceed but also for efficient compaction shown in Figure 2.8. Fully hydrated cement takes up about 20% of its own weight of water from the surrounding (Sherwood, 1993); on other hand, Quicklime (CaO) takes up about 32% of its own weight of water from the surrounding (Roger et al., 1996; Sherwood, 1993). Insufficient moisture content will cause binders to compete with soils in order to gain these amounts of moisture. For soils with great soil- water affinity (such as clay, peat and organic soils), the hydration process may be retarded due to insufficient moisture content, which will ultimately affect the final strength of soil.

It is also important to measure the moisture content of the soil before the soil stabilization process can begin. Different soil stabilization products, such as quicklime and cement, require varying amounts of moisture to produce the desired results. The level of moisture found may influence the choice of a product to use. Failure to do so can result in unsatisfactory results due to incomplete reactions between the soil and the products that have been used to stabilize that soil.

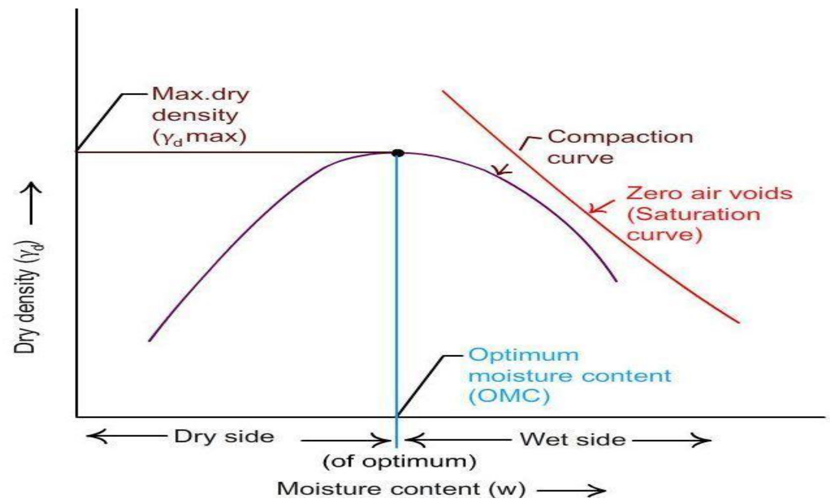


Figure 2.8: Factor affecting in moisture content (Source: Roger et al., 1996).

2.4.3.5 Temperature

Pozzolanic reaction is sensitive to changes in temperature. In the field, temperature varies continuously throughout the day. Pozzolanic reactions between binders and soil particles will slow down at low temperature and result into lower strength of the stabilized mass. In cold regions, it may be advisable to stabilize the soil during the warm season (Sherwood, 1993).The reactions between the soil and the binders used during the stabilization process have temperature requirements. For example, cement will take long to gain strength if it is applied to the soil when the temperature is below the optimum level. Conversely, the curing period will be accelerated if temperatures rise above the desired level. Rapid curing can result in lower strength. It is therefore prudent to select a time when the temperature will be just right for the products that are going to be used during the stabilization process.

2.4.3.6 Freeze-Thaw and Dry-Wet Effect

Stabilized soils cannot withstand freeze-thaw cycles. Therefore, in the field, it may be necessary to protect the stabilized soils against frost damage (Maher et al, 2004; Al- tabbaa and Evans, 2005). The affect of Freeze-Thaw in soil stabilization is shown in Figure 2.9.

Figure 2.9: Freeze-Thaw affect in soil stabilization (Source: Al- tabbaa and Evans, 2005).

Shrinkage forces in stabilized soil will depend on the chemical reactions of the binder. Cement stabilized soil are susceptible to frequent dry-wet cycles due to diurnal changes in temperature which may give rise to stresses within a stabilized soil and, therefore, should be protected from such effects (Sherwood, 1993; Maher et al., 2004). The effect of Dry-wet in soil stabilization is shown in Figure 2.10.

Figure 2.10: Dry-wet affect in soil stabilization (Source: Maher et al., 2004).

2.4.4 California Bearing Ratio

California Bearing Ratio (CBR) test is an important field/laboratory test in geotechnical engineering. It is performed to assess the resistance offered by sub grade layer of soil or in the foundation of a structure viz. earth dams, highway embankments, bridge abutments and retaining wall fills. The strength of soil can be considered to be indexed by its CBR (Bhatt et al., 2014)

CBR is defined as a ratio expressed in percentage of force per unit area required to penetrate a soil mass with a circular plunger of 50 mm diameter at the rate of 1.25 mm/min to that required for corresponding penetration in a standard material. The ratio is usually determined for penetration of 2.5 and 5 mm. Where the ratio at 5 mm is consistently higher than that at 2.5 mm, the ratio at 5 mm is used. The load value/corrected load value is taken from the load penetration curve and the CBR is calculated using following equation 2.1(IS: 2720-Part XVI-1987).

$$CBR = \frac{AppliedStressinExperiment\ (orLoad)}{StandardStress\ (orLoad)} X100 \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . (2.1)$$

The test can be performed in the laboratory on undisturbed or compacted remolded specimens in water soaked or unsoaked conditions, however CBR are highly dependent on the condition of the material at the time of testing. In the field, the test can be performed at ground surface or in a test pit, trench, on a level surface. The test on crushed stone is defined to have a CBR value of 100 percent and the corresponding load is called Standard Load (Bhatt et al., 2014). Standard unit load (pressure) for well graded crushed stone.

for 2.54 mm (0.1") penetration = 6.90 MPa (1000 psi).

for 5.08 mm (0.2") penetration = 10.30 MPa (1500 psi).

According to O’Flaherty (1974), the C.B.R. test is an empirical test and depends upon the condition of the soil at the time of testing. This requires that the soil must be tested in a condition that is critical to the designer. According to the state commission of roads and bridges (SCRB, 1999) specification the CBR must correspond to 95% of the maximum dry density of the modified AASHTO compaction.

To predict CBR value of soils, estimation models were developed by researchers and correlations were established relating various soil parameters. It stressed on the changes of the obtained experimental values, which were caused by changing in the geographical area all over the world (Linveh, 1989). For this he made to verify of correlations between a series of penetration tests and in situ California bearing ratio tests. It has done a study on the estimation of CBR by using conic penetrometer experiment (Al-Refeai and Al-Suhaibani, 1996). It calculated the CBR by correlating the soil index properties and measured CBR (Kin, 2006).

The sub grade provides a foundation for supporting the pavement structure. The sub grade whether in cut or fill should be well compacted to utilize its full strength and to economize thereby on the overall thickness of pavement required. For design, the sub grade strength is assessed in terms of the CBR of the sub grade soil in both fill and cut sections. For determining CBR value, the static penetration test procedure should be strictly adhered to. This is described in IS: 2720 (part 16) “Methods of test for soils laboratory determination of CBR”. The test must always be performed on molded samples of soils in the laboratory. CBR test is laborious and time consuming; but sometimes the results are not accurate due to the poor laboratory conditions. Further if the available soil is of poor quality, suitable additives are mixed with soil and the resulting strength of the soil will be assessed by CBR value, which is cumbersome (Venkatasubramanian and Dhinakaran, 2011). The strength of a soil to be used as a sub-grade in pavement is assessed from its CBR value. If the CBR value of soil is low, the thickness of pavement will be high, which will result in high cost of construction and vice versa (Sabat, 2013). There are different techniques of improving the CBR value of soil, one being stabilization.

Road transportation system is an important element in the physical development of a nation. In developing countries of the world, the road network is probably the most widely used of the several means of transportation, and it is an important index of the development that touches the lives of both rural and urban dwellers. In fact roads have been described as causes as well as consequences of civilization (O’Flaherty, 1974).

Road is necessary for transportation and economic development of a nation. Most of the road networks in a country consist of flexible pavement. Flexible pavement consists of different layers such as sub-grade, sub base, base course and surface layer. Sub-grade is the formation layer.

Design and performance of flexible pavement mainly depends on the strength of sub-grade material. The load from the pavement surface is ultimately transferred from the sub-base to sub-grade. The sub-grade is designed such that the stress transferred should not exceed elastic limit. Hence, the suitability and stability of sub-grade materials are evaluated before construction of pavement. The soaked CBR (in %) is considered as Strength parameter in design of sub-grade (Rakaraddi and Gomarsi, 2015). Of all the methods of pavement design, the CBR method has been found as the most reliable means for evaluating the strength of the sub grade (bearing capacity of the soil) and construction materials, and hence estimating the required thickness of pavement (Khanna, 1994). It is a penetration test meant for the evaluation of sub grade strength for roads and pavements.

2.4.5 Soft Computing Systems

In the literature, there are some techniques for the prediction of geotechnical; engineering peripheries in soil. In this study, the soft computing system like simple linear regression (SLR), multiple linear regression (MLR), artificial neural network (ANN) and support vector machine (SVM) were considered and discussed in the following articles.

2.4.5.1 Simple Linear Regression

The simple linear regression (SLR) analysis identifies the effect of independent variables on the dependent variable shown in Figure 2.11. All the test results consisting of various independent variables can be analyzed by statistical method of least regression.

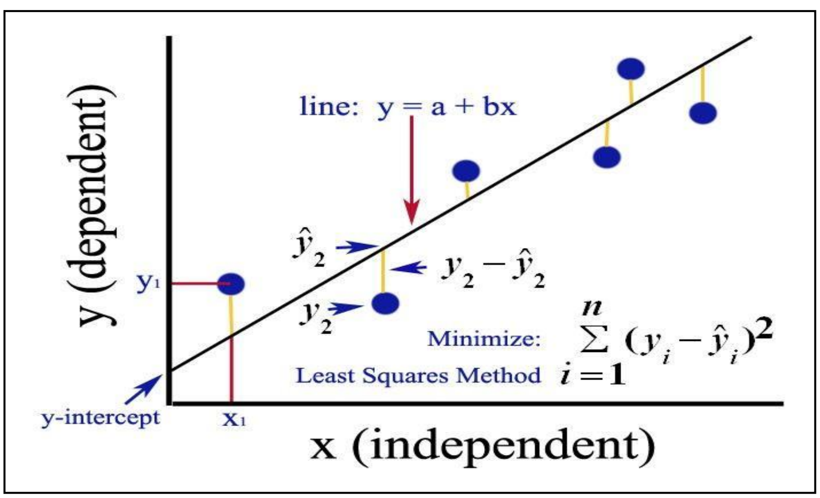


Figure 2.11: Simple linear regression (Source: Aderinola, 2007).

The best linear fitting approximation Equation 2.2 having maximum R^2 values is determined and are shown below (Bhatt et al., 2014).

$$y = a + bx \quad \ldots\ldots (2.2)$$

Where y = Dependent variable, x = Independent (Observed) variable. b is the slope of the line and a is the intercept, where the line cuts the y axis as well as a & b values have come as intercept and slope of the line in degree (°) value from the equation after analysis.

Correlation quantifies the degree to which dependent and independent variables are related. Linear regression quantifies goodness of fit with R^2 which measure how well future outcomes are likely to be predicted. Any correlation with R^2>0.80 considered as best fit (Aderinola, 2007).

2.4.5.2 Multiple Linear Regression

Multiple regression analysis (MRA) has been carried out by considering CBR as the dependent variable and the rest of soil properties as independent variables. With Genetic Algorithm each possible solution becomes an independent "organism" that can "breed" with other organisms. The spreadsheet model acts as an environment for the organisms, determining which are "fit" enough to survive based on their results.

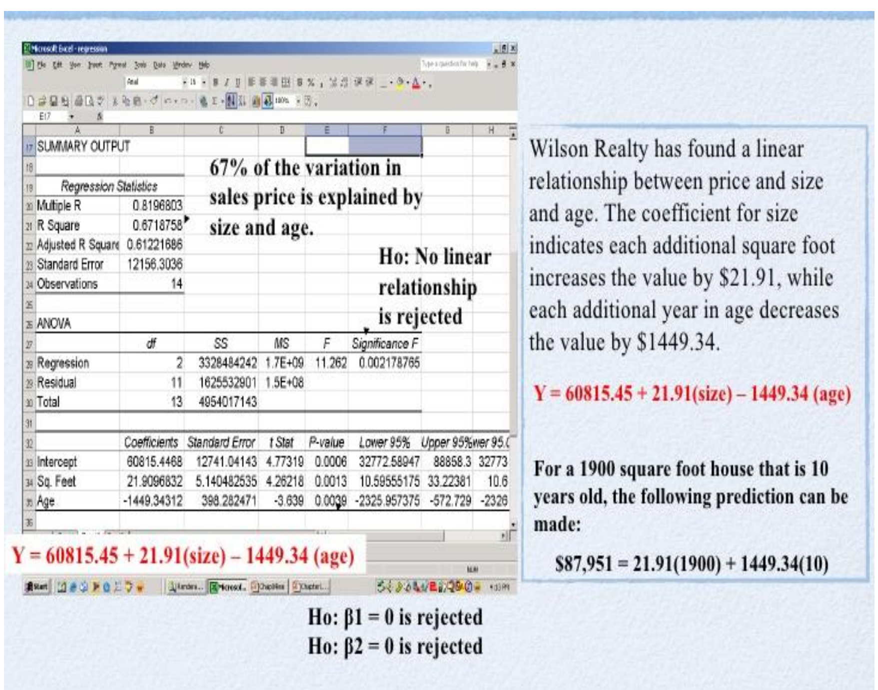


Figure 2.12: Multiple regression analysis (Source: Jyotis et al., 2013).

Moreover multiple linear regression analysis identifies the effect of two or more independent variables on one dependent variable like CBR (Bhatt et al., 2014). The expression of multiple linear regression analysis through is shown in Figure 2.12. MRA can be carried out using standard statistical software like Data Analysis Tool Bar of Microsoft Excel in order to derive the relationship statistically. The Objective Function for applying Genetic Algorithm in this research study will be formulated as follows. Y is directly proportional to the variables X1, X2, X3, X4, X5. So, the equation 2.3 created will be

$$Y = a + b1X1 + b2X2 + b3X3 + b4X4 + b5X5 + \cdots + bn\,xn \text{.............................. (2.3)}$$

Where, a is Y intercept point, Y = Dependent (Predicted) variable, b_1, b_2, ... , b_n are Slope of X_1, X_2, ... , X_n respectively, X1, X2, X3, X4, X5 are independent variable.

The values of above constants will be solved using the Multiple Regression Analysis in the Data Analysis Toolpak a built-in Add-In for Microsoft Excel. Correlation quantifies the degree to which dependent and independent variables are related. When R is 0.0, there is no relationship. When R is 1, there is a good relation. Any correlation with R^2 value equal to 0.80 or above will be viewed as a best fit (Aderinola, 2007). To test the significance of regressions, analysis of variance (ANOVA) was employed. In this test, a 95% level of confidence was chosen. If the calculated F value is greater than the tabulated F value, the null hypothesis is rejected and there is a real relation between dependent and independent variables (Jyotis et al., 2013; Taşkıran, 2010; Yildrim and Gunaydin, 2011). The comparative statistics of simple and multiple linear regressions stated by Bhatt et al. (2014) is provided in Table 2.1.

Table 2.1: Comparative statistics of simple and multiple linear regressions (After Bhatt et al., 2014)

Simple linear regression	Multiple linear regression
Equation, y=a+bx	Equation, y=a+b1x1+b2x2+b3x3+ - - - - - + bn xn
y is a dependent variable (Observed variable)	y is also dependent variable (Observed variable)
Have only one Independent variable (x)	Two or more independent variable (x1, x2, x3 …..xn)
a is intercept and b is slope of line , where the line cut y axis	a is intercept coefficient and b1, b2, b3….are the coefficient of independent variable successively.
Best predicted CBR depends on R^2	Best predicted CBR depends on R^2

2.4.5.3 Artificial Neural Network

Since early 1990s, artificial neural networks (ANN) have been in use in analyzing the geotechnical problems and demonstrated to be a superior predictive performance as compared to traditional methods. ANNs need no prior knowledge regarding the nature of the relationship between the input and output variables. This is one of the main benefits of ANN when compared with most empirical and statistical methods. ANN is a form of artificial intelligence and mimics the nervous system of the human brain. It consists of a series of processing elements (PEs) called nodes which are arranged in input, output and one or more hidden layers (Bhatt et al., 2014).

2.4.5.3.1 ANN Modeling

Feed forward neural network, with back propagation training algorithm, is use to develop the model. Where some numbers of inputs take, number of hidden layer taken is one and some numbers of neurons in the hidden layer. The neural networks “fitting app” of MATLAB is used for computations required for development of the model is shown in Figure 2.13 (Sabat, 2013).

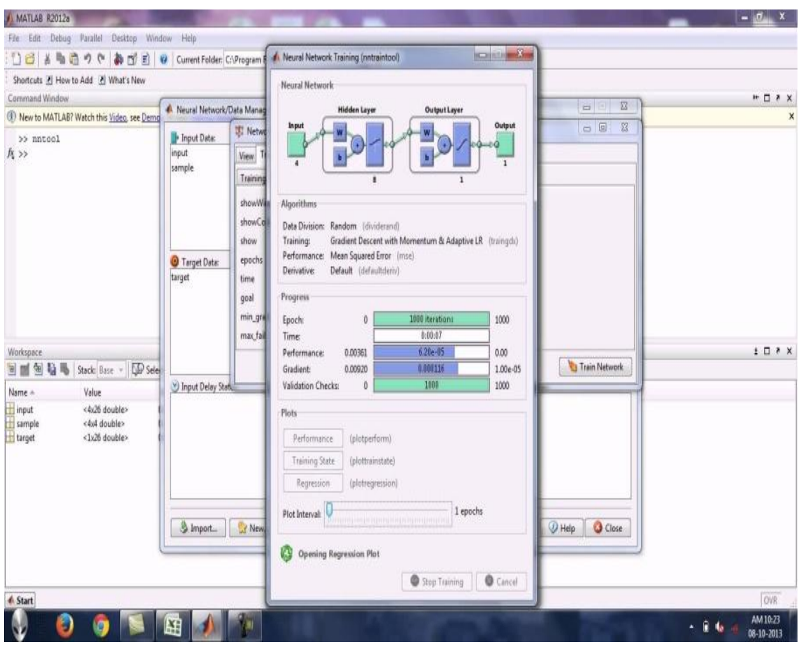


Figure 2.13: Modelling of ANN in MATLAB (Source: Sabat, 2013).

As the ANN is an alternate statistical method, the results should be compared in terms of statistical performance criteria. The correlation coefficient (R^2) and root means square error (RMSE) are mostly used for performance criteria evaluation of ANN models. The RMSE indicates the accuracy of approximation as overall, without indicating the individual data points

(Bhatt et al., 2014). The over fitting ratio (OR) is defined as the ratio of RMSE for testing and training data and its value close to 1.0 shows good generalization of the model (Das and Sabat, 2008). According to Smith (1986) if $R^2 \geq 0.64$, strong correlation exists two sets of variables. As the R^2-value is near about 1, hence the model is an efficient model for prediction of CBR. The number of hidden layers and number of neurons are varied to find the optimal structure with the goal to achieve convergence in the mean sum of squared errors and testing/training ratios of their MSE values near to one. The model having MSE ratio value one or near to one is good for generalization. Linear, tan-sigmoid, log sigmoid are the most commonly used transfer functions between the layers. (Bhatt et al., 2014).

Total number samples are prepared which generated total number of data sets. Out of total number of data sets, 70% data sets are use for training the model and 30% data sets for testing the model. The available data set is normalized prior to training to obtain better convergence. The data set has a wide range of values for inputs and targets and is scaled between 0 and 1 using the following Equation 2.4 (Kayadelen, 2008; Rafiq et al., 2001).

$$U_{normalized} = \frac{U_{actual} - U_{mean}}{U_{max} - U_{min}} \quad \text{..} \quad (2.4)$$

Where, $U_{normalized}$ is the normalized value of the observed variable, U_{actual} is the actual value of the observed variable, U_{max} is the maximum observation value of the data set and U_{min} is the minimum observation value of the data set. The normalized data set was then used to train neural networks to obtain the final weights and in the end of the analyses, the network outputs were post processed to convert the data back into non-normalized units. For analysis the optimum model the available experimental data is randomly divided into two separate data sets; the training data set and the testing data set (Bhatt et al., 2014). This network can be used as a general function approximate. The feed forward ANN with back propagation models through MATLAB was performed to predict the CBR of stabilized soils shown in Figure 2.14. (Ali et al., 2016)

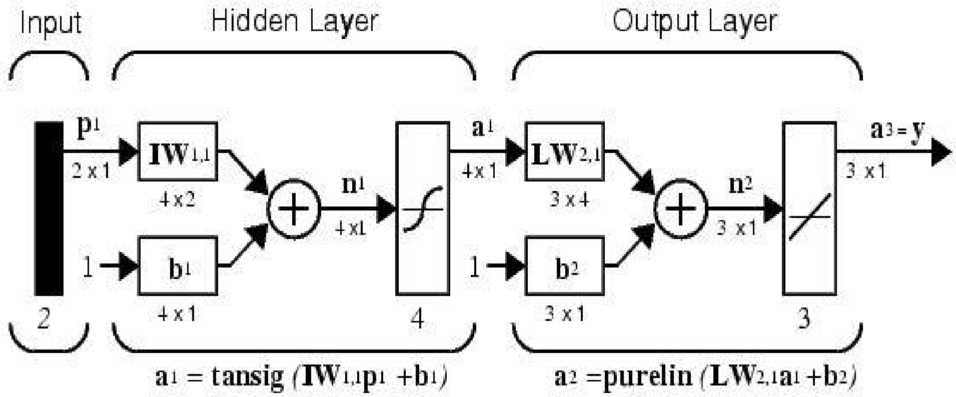


Figure 2.14: Feed forward network (Source: Ali et al., 2016).

A typical Neural Network contains a large number of artificial neurons called units arranged in a series of layers. In typical Artificial Neural Network, comprise different layers is shown in Figure 2.15. a) Input layer - It contains those units (Artificial Neurons) which receive input from the outside world on which network will learn, recognize about or otherwise process.

b) Output layer - It contains units that respond to the information about how it's learned any task.

c) Hidden layer - These units are in between input and output layers. The job of hidden layer is to transform the input into something that output unit can use in some way.

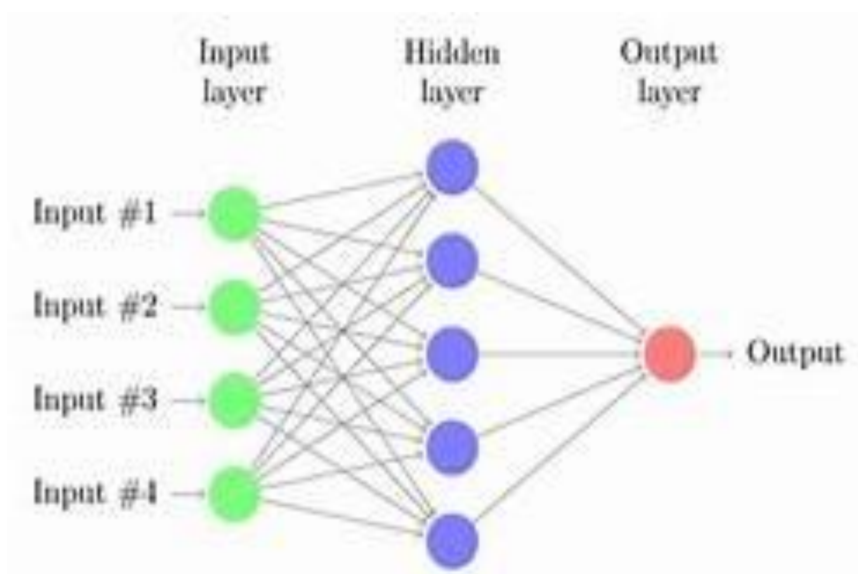


Figure 2.15: A neural network model (Source: Venkatasubramanian and Dhinakaran, 2011).

Most Neural Networks are fully connected that means to say each hidden neuron is fully linked to every neuron in its previous layer (input) and to the next layer (output) layer (Venkatasubramanian and Dhinakaran, 2011).

2.4.5.3.2 Training Algorithm of ANN Model

Levenberg-Marquardt Neural Network (LMNN), Bayesian Regularization Neural Network (BRNN), and Scaled Conjugate Gradient Neural Network (SCGNN) algorithms are used in training processes for analysis of ANN model called as LMNN model, BRNN model and SCGNN model respectively.

a) Levenberg- Marquardt neural network (LMNN)

This algorithm typically requires more memory but less time. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples (MATLAB R2017a). The problem of neural network learning can be seen as a function optimization problem, where it is trying to determine the best network parameters (weights and biases) in order to minimize network error. This said, several function optimization techniques from numerical linear algebra can be directly applied to network learning, one of these techniques being the Levenberg-Marquardt algorithm**.**

The Levenberg–Marquardt algorithm provides a numerical solution to the problem of minimizing a (generally nonlinear) function, over a space of parameters for the function. It is a popular alternative to the Gauss-Newton method of finding the minimum of a function. The Levenberg-Marquardt is very sensitive to the initial network weights. Also, it does not consider outliers in the data, what may lead to over fitting noise. To avoid those situations, it can use a technique known as regularization (https://www.codeproject.com/articles/55691/neural-network-x, 2018)

b) Bayesian regularization neural network (LMNN)

Bayesian regularization Neural Network (BRNN): This algorithm typically requires more time, but can result in good generalization for difficult, small or noisy datasets. Training stops according to adaptive weight minimization (regularization) (MATLAB R2017a). Trainb can train any network as long as its weight, net input, and transfer functions have derivative functions. Bayesian regularization minimizes a linear combination of squared errors and weights. It also modifies the linear combination so that at the end of training the resulting network has good generalization qualities. Moreover training stops when any of these conditions occurs that, he maximum number of epochs (repetitions) is reached, he maximum amount of time is exceeded, performance is minimized to the goal, the performance gradient falls below min grad or mu exceeds mu max (MacKay, 1992; Foresee and Hagan, 1997).

c) Scaled conjugate gradient neural network (LMNN)

Scaled Conjugate Gradient Neural Network (SCGNN): This algorithm requires less memory. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples (MATLAB R2017a). Trainscg can train any network as long as its weight, net input, and transfer functions have derivative functions. Back propagation is used to calculate derivatives of performance perf with respect to the weight and bias variables X.

The scaled conjugate gradient algorithm is based on conjugate directions, as in traincgp, traincgf, and traincgb, but this algorithm does not perform a line search at each iteration. Moreover raining stops when any of these conditions occurs that, the maximum number of epochs (repetitions) is reached, the maximum amount of time is exceeded, performance is minimized to the goal, the performance gradient falls below min_grad or validation performance has increase (Moller, 1993).

2.4.5.3.3 Performance Criteria of ANN Model

The number of hidden layer selected is one and the number of neurons in the hidden layer are variable (Sabat, 2015). At train network, train the network to fit input and target data. Training multiple times generates different result due to different initial condition and sampling. The results of the developed ANN model are evaluated by R^2 and MSE values from training and testing of the ANN model. Each layer basically contains a number of neurons working as an independent processing element and densely interconnected with each other. The train algorithms are (LMNN), (BRNN) and (SCGNN) of ANN were performed for the prediction of CBR at train network is shown in Table 2.2. According to Marry (2018) in ANN modeling has storing information on the entire network but the duration of the network is unknown. Moreover, Characterization of performance parameters for model analysis is shown in Table 2.3.

Table 2.2: Description with significance of LMNN, BRNN and SCGNN of ANN analysis

Neural network algorithm	Full meaning	Required memory or time	Stop of the training time
LMNN	Levenberg- Marquardt Neural Network	More memory and less time	Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples
BRNN	Bayesian regularization Neural Network	More time	Training stops according to adaptive weight minimization (regularization)
SCGNN	Scaled Conjugate Gradient Neural Network	Less memory	Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples

Table 2.3: Characterization of performance parameters for model analysis

Components	Full meaning	Definition	Equation	Certification value	Refference
R	Coefficient of corelation	Regression R Values measure the correlation between outputs and targets.	$R=\sqrt{(1-\frac{SSE}{SST})}$ Where, SSE=Sum of square regression error and SST= sum of squared total error	An R value of 1 means a close relationship, 0 a random relationship.	Bhatt et al., 2014
R^2	Coefficient of determination	Coefficient of determination mean the square value of R.	$R^2=1-\frac{SSE}{SST}$	An R^2 value of 1 means a close relationship, 0 a random relationship.	Bhatt et al., 2014
MSE	Mean square errore	Mean Squared Error is the average squared difference between outputs and targets.	$MSE=\frac{1}{N}\sum_{i=0}^{N}(ti-ai)^2$ ti=ith output ai=ith targer N=Number of output	Lower values are better. Zero means no error.	Sabat, 2013
RMSE	Root mean square error	Root mean square erroe is the root of MSE value	$RMSE=\sqrt{[\frac{1}{N}\sum_{i=0}^{N}(ti-ai)^2]}$	Lower values are better. Zero means no error.	Akshaya, 2013
OR	Overfitting Ratio	The over fitting ratio (OR) is defined as the ratio of RMSE for testing and training data	OR= (RMSE (Testing))/(RMSE (Training))	If its value close to 1. 0 shows good generalization of the model.	Akshaya, 2015
AE	Absulate error	It is the difference between the measured value and "true" value.	AE is (Δx) = xi – x Where xi is the measurement, x is the true value.	Lower values are better. Zero means no error.	Sabat, 2015
MAE	Mean absulate error	The Mean Absolute Error(MAE) is the average of all absolute errors.	$\text{MAE}=\frac{1}{n}\sum_{i=1}^{n}\lvert x_i-x\rvert$ Where, n = the number of errors, Σ = summation symbol (which means "add them all up"), |xi – x| = the absolute errors.	Lower values are better. Zero means no error.	Sabat, 2015

2.4.5.4 Support Vector Machine

A support vector machine (SVM) is machine learning algorithm that analyzes data for classification and regression analysis. SVM is a supervised learning method that looks at data and sorts it into one of two categories. An SVM outputs a map of the sorted data with the margins between the two as far apart as possible. SVMs are used in text categorization, image classification, handwriting recognition and in the sciences. A support vector machine is also known as a support vector network (SVN).

SVM analysis is a popular machine learning tool for classification and regression, first identified by Vladimir Vapnik and his colleagues in 1992 (Vapnik, 1995). SVM regression is considered a nonparametric technique because it relies on kernel functions. Statistics and Machine Learning Toolbox™ implements linear epsilon-insensitive SVM (ε-SVM) regression, which is also known as $L1$ loss. In ε-SVM regression, the set of training data includes predictor variables and observed response values. The goal is to find a function $f(x)$ that deviates from y_n by a value no greater than ε for each training point x, and at the same time is as flat as possible.

a) SVM classification

SVM Classifications are based on the idea of finding a hyper plane that best divides a dataset into predefined classes is shown in the Figure 2.16. The goal is to choose a hyper-plane with the greatest possible margin between the hyper-plane and any point within the training set, giving a greater chance of new data being classified correctly (Smarten, 2018).

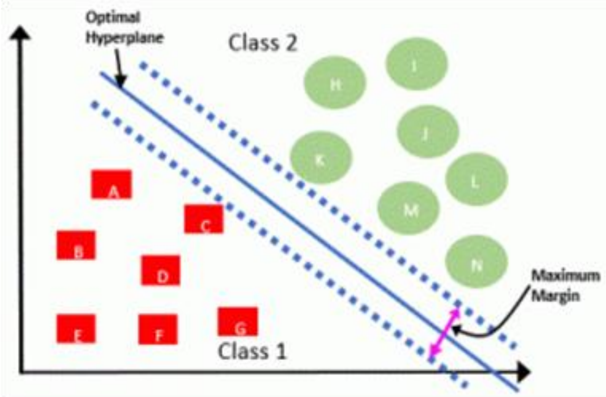


Figure 2.16: Selected optimal hyper-plane of SVM classification analysis (Source: Smarten, 2018).

The operation of the SVM algorithm is based on finding the hyper plane that gives the largest minimum distance to the training examples. Twice, this distance receives the important name of margin within SVM's theory. Therefore, the optimal separating hyper-plane maximizes the margin of the training data.

b) SVM regression

Support Vector Machines are very specific class of algorithms, characterized by usage of kernels, absence of local minima, sparseness of the solution and capacity control obtained by acting on the margin, or on number of support vectors, etc. They were invented by Vladimir Vapnik and his co-workers, and first introduced at the Computational Learning Theory (COLT) 1992 conference with the paper. All these nice features however were already present in machine learning since 1960's: large margin hyper planes usage of kernels, geometrical interpretation of kernels as inner products in a feature space. Usage of slack variables to overcome noise in the data and non - reparability was also introduced in 1960s.

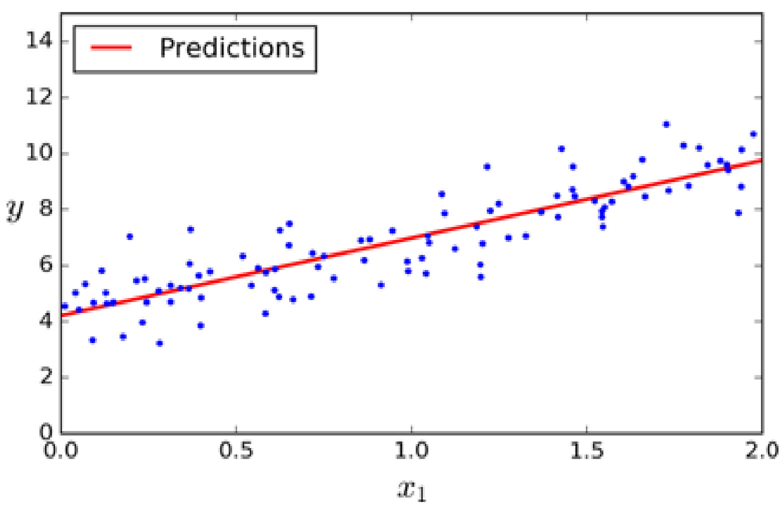


Figure 2.17: Regression analysis of SVM (Source: Chapelle and Vpnik, 1999).

However it was not until 1992 that all these features were put together to form the maximal margin classifier, the basic Support Vector Machine, and not until 1995 that the soft margin version was introduced (Chapelle and Vpnik, 1999). The regression analysis of support vector machine is shown in Figure 2.17. Support Vector Machine can be applied not only to classification problems but also to the case of regression. Still it contains all the main features that characterize maximum margin algorithm: a non-linear function is leaned by linear learning machine mapping into high dimensional kernel induced feature space. The capacity of the system is controlled by parameters that do not depend on the dimensionality of feature space.

2.4.5.4.1 Modeling of SVM

The basic aim of support vector machine is to give, as far as possible, a condensed (but systematic) presentation of a novel learning paradigm embodied in SVMs. Its focus will be on the constructive learning algorithms for the regression (function approximation) problems. The SVM is a supervised learning method that generates input-output mapping functions from a set of labelled training data. The model thus produced depends on only a subset of the training data near the class predicted boundaries line is shown in Figure 2.18. Similarly, the model produced by Support Vector Regression is close to the model of prediction line. SVM sare also said to belong to “kernel methods” (Wang, 2005).

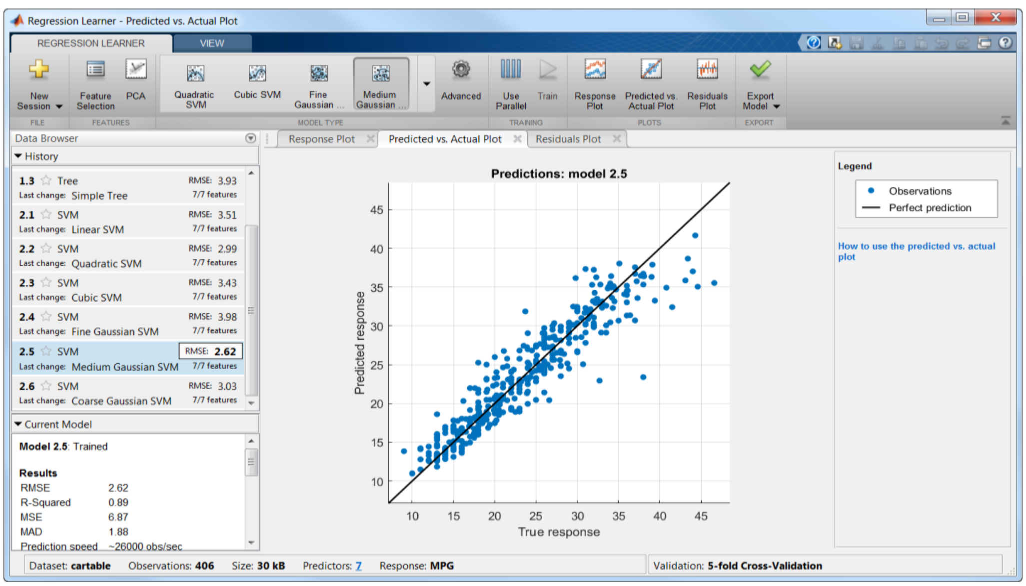


Figure 2.18: Train Regression model in MATLAB (Source: Wang, 2005).

In addition, to its solid mathematical foundation in statistical learning theory, SVM have demonstrated highly competitive performance in numerous real-world applications, such as bioinformatics, text mining, face recognition, and image processing, which has established SVM as one of the state-of- the-art tools for machine learning and data mining, along with other soft computing techniques, e.g., neural networks and fuzzy systems (Wang, 2005). Moreover in this modelling different Kernel functions can be specified for the decision function. But avoid over-fitting in choosing Kernel functions and regularization term is crucial. SVM do not directly provide probability estimates, these are calculated using an expensive five-fold cross-validation (Alex, 2004)

2.4.5.4.2 Application of SVM

SVM has also been applied for development of prediction models, in geotechnical engineering. SVM has been applied for prediction of, settlement of foundations on cohesionless soil (Samui, 2008), swelling pressure of expansive soil (Das et al., 2010), MDD and unconfined compressive strength of stabilized soil (Samui et al., 2011), liquefaction of soil (Lee and Chern, 2013) field hydraulic conductivity of clay liner (Samui et al., 2011), angle of shearing resistance of soil (Goyal et al., 2014), specific gravity and MDD of fly ash. Prediction of CBR of stabilized expansive soil, even non-stabilized any type of soil using SVM is limited in literature.

2.4.5.4.3 Kernel Function of SVM

The SVM with different kernel functions like linear support vector machine (SVM-L), quadratic support vector machine (SVM-Q) and cubic support vector machine (SVM-C) is used to prediction of CBR of stabilized soil using different admixture at varying proportion. From the MATLAB, it can get use of regression learner such as train regression models to make predictions using supervised machine learning (Regression Learner) statistics machine learning tool box 11.1. After predictor and response data, it have gotten the value of R, R^2, MAE, MSE & RMSE value to compare with each other of SVM-L, SVM-Q and SVM-C.

a) Linear support vector machine (SVM-L)

The learning of the hyperplane in linear SVM is done by transforming the problem using some linear algebra. This is where the kernel plays role. For linear kernel the equation for prediction for a new input using the dot product between the input (x) and each support vector (xi) is calculated as f(x) = B(0) + sum(ai * (x,xi)). This is an equation that involves calculating the inner products of a new input vector (x) with all support vectors in training data. The coefficients B0 and ai (for each input) must be estimated from the training data by the learning algorithm (https://medium.com/machine-learning-101, 2018).

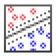
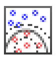
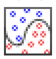
b) Quadratic support vector machine (SVM-Q)

A new quadratic kernel-free non-linear support vector machine (which is called QSVM) is introduced. The SVM optimization problem can be stated as follows: Maximize the geometrical margin subject to all the training data with a functional margin greater than a constant. The functional margin is equal to $W^T X + b$ which is the equation of the hyper-plane used for linear separation. The geometrical margin is equal to $1\|W\|$. And the constant in this case is equal to one. To separate the data non-linearly, a dual optimization form and the Kernel trick must be used. In this paper, a quadratic decision function that is capable of separating non-linearly the data is used. The geometrical margin is proved to be equal to the inverse of the norm of the gradient of the decision function. The functional margin is the equation of the quadratic function. QSVM is proved to be put in a quadratic optimization setting. This setting does not require the use of a dual form or the use of the Kernel trick (https://link.springer.com/article/10.100, 2018).

c) Cubic support vector machine

The Cubic SVM is a kernel function commonly used with support vector machines (SVM) and other kernel zed models, that represents the similarity of vectors (training samples) in a feature space over cubic of the original variables, allowing learning of non-linear models. Cubic SVM looks not only at the given features of input samples to determine their similarity, but also combinations of these. In the context of regression analysis, such combinations are known as interaction features. The (implicit) feature space of a cubic kernel is equivalent to that of cubic regression, but without the combinatorial blow up in the number of parameters to be learned (Chang et al., 2010). In addition, Characterization of different kernel functions of SVM is shown in Table 2.4.

Table 2.4: Characterization of different kernel functions of SVM (After: https://in.mathworks.com/help/stats/choose-a-classifier.html, 2018)

Classifier type	Prediction speed	Memory usage	Interpretability	Model flexibility	Sensitivity	Specificity	Accuracy
Linear SVM 	Binary: Fast Multiclass: Medium	Medium	Easy	Low Makes a simple linear separation between classes.	95.20%	100%	98%
Quadratic SVM 	Binary: Fast Multiclass: Slow	Binary: Medium Multiclass: Large	Hard	Medium	95.20%	100%	98%
Cubic SVM 	Binary: Fast Multiclass: Slow	Binary: Medium Multiclass: Large	Hard	Medium	95.20%	100%	98%

Chapter 3

Research Methodology

3.1 General

This chapter deals with the characterization of soil and admixtures used in this study. The physical properties of soil and admixtures like quarry dust (QD), rice husk ash (RHA) are also highlighted in this chapter. The mixing proportions of admixtures and procedure for preparation of stabilized soils are also described in this chapter. To evaluate the various proportions of admixtures with soil and its California bearing ratio (CBR) was also highlighted in this chapter. This chapter represents the soft computing systems such as simple linear regression (SLR), multiple linear regressions (MLR), artificial neural network (ANN) and support vector machine (SVM) used in this study to predict CBR of stabilized soil. The flow diagram for predicting of CBR values of stabilized soils using soft computing systems is shown in Figure 3.1.

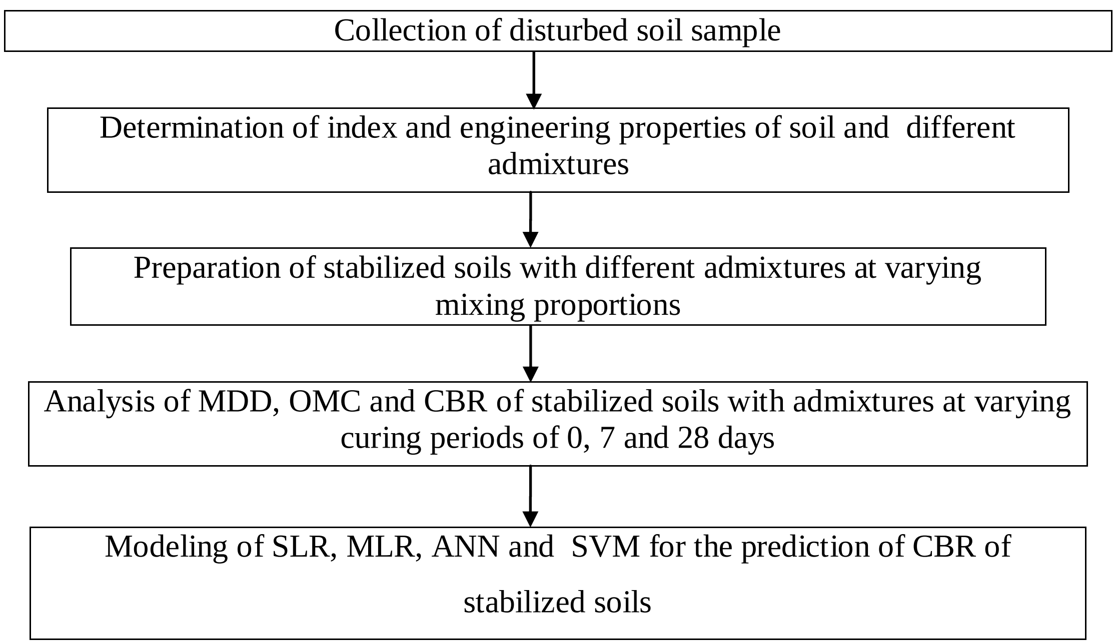


Figure 3.1: Overall flow chart of this study.

3.2 Characterization of Soil and Admixtures Used in This Study

In this study, disturbed soil sample was collected to determine the relevant properties of soil. In addition, the geotechnical properties of admixtures were also determined and hence described in the following articles.

3.2.1 Collection of Soil Sample

The soil sample used in this study was collected from KUET campus at a depth of 5 to 7 feet from the ground surface. Proper care was taken to remove any loose materials during collection of soil sample.

3.2.2 Physical Properties of Soil

The collected soil sample was air dried and then soil lumps were broken carefully with a wooden hammer to avoid breakage of soil particles. In the laboratory, the basic properties of soil sample were determined by adopting ASTM standard test procedures. The grain size distribution of soil used in this study is shown in Figure 3.2. The laboratory results of soil samples are provided in Table 3.1.

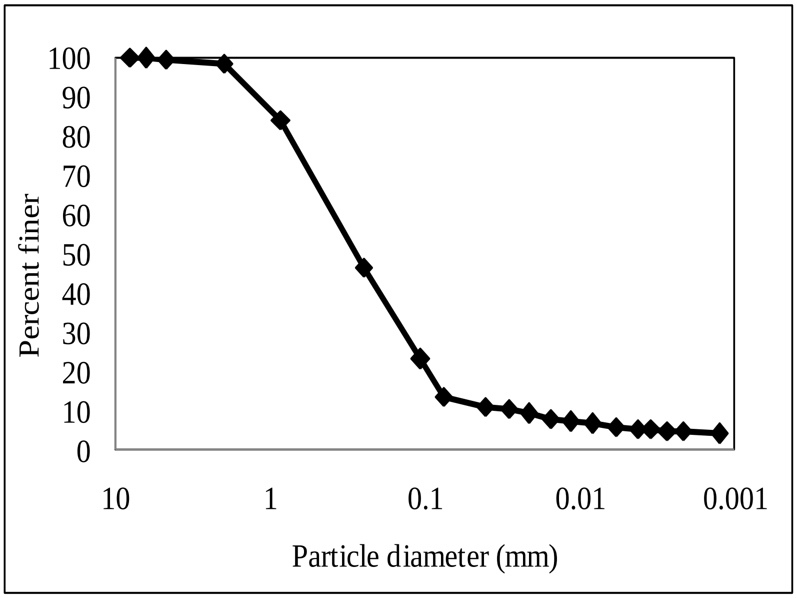


Figure 3.2: Grain size distribution of soil used in this statement.

Table 3.1: Physical properties of soil used in this study

Soil parameters	Unit	Value	Analytical method
Specific Gravity	--	2.70%	ASTM D 854
Initial Moisture Content	--	26%	ASTM D 2216
OMC	--	13.9%	ASTM D 1557 (Modified)
MDD	kN/m³	17.6	
LL	--	32%	ASTM D 4318
PL	--	22%	
PI	--	10%	
Soaked CBR	--	6.74%	AASHTO T 193
Gravel: Sand: Silt: Clay in %	--	0: 2.70: 73.2: 24.1	ASTM D 421 and D 422

3.2.3 Collection of Admixtures

The admixture of QD was collected from local stone crushing unit at Volagang, Sylhet, Bangladesh. In addition, RHA was also collected from local rice mill in Khulna city. Generally, No. 100 sieve has been used for preparing RHA by various researchers such as (Brooks, 2009). In this study, for preparing RHA to stabilize soil, #100 sieve was used to obtain required amount of RHA. Lime is a caustic material appears usually in white colour, it is normally obtained from lime stone. When lime combines through water it generates some heat and gains some reasonable strength characteristics (Sudipta et al., 2011). Quick lime was collected from local market in Khulna city. During collection these materials, it has been taken proper safety. In the laboratory, the geotechnical properties of QD was measured and mentioned in Table 3.2.

Table 3.2: Geotechnical properties of QD used in this study

Name	Unit	Value	Analytical method
Specific Gravity	--	2.65	ASTM D 854
Initial Moisture Content	--	2.4%	ASTM D 2216
OMC	--	10.02%	ASTM D 1557 (Modified)
MDD	kN/m³	19.8	
Gravel: Sand: Silt: Clay in %	--	0.38: 86.02: 9.03: 4.57	ASTM D 421 and D 422

3.2.4 Laboratory Scheme for CBR Test

In the laboratory, for preparing stabilized soils, the admixtures of QD with lime as well as RHA with lime were mixed at varying proportions mentioned in Table 3.3. The laboratory steps for CBR Test are discussed in the following articles.

Table 3.3: Mixing proportions of admixtures used in this study

Admixture (QD with lime)		Admixture (RHA with lime)	
QD (%)	lime (%)	RHA (%)	lime (%)
0	2	0	0
10	2	4	0
20	2	8	0
30	2	12	0
40	2	16	0
50	2	0	3
0	4	4	3
10	4	8	3
20	4	12	3
30	4	16	3
40	4	0	4
50	4	4	4
0	8	8	4
10	4	12	4
20	4	16	4
30	6	0	5
40	6	4	5
50	6	8	5
		12	5
		16	5

3.2.4.1 Mixing of the Soil Samples

The collected soil sample was first air and oven dried and then powdered manually. This powdered sample was then sieved through #4 sieve which were mixed with QD and lime as well as with RHA and lime at varying mixing proportions. Then the mixing samples were mixed with various percentage of water to get OMC and MDD of stabilized soil.

3.2.4.2 Preparation of Samples for CBR Test

For CBR test, samples were prepared by using 6 inch dia and 7 inch height compaction mold. In addition, a spacer disk height and collar height was considered as 60 and 40mm, respectively. The soil samples were prepared for mixing with QD and lime as well as RHA and lime except water. Thereafter, same quantity of OMC was added in soil prepared with QD and lime as well as in soil prepared with RHA and lime to make ready for blows shown in Figure 3.3.

Figure 3.3: Prepared sample for CBR test.

3.2.4.3 Compaction of Samples for CBR Test

The prepared soil samples were compacted using modified proctor test shown in Figure 3.4 (a). At first all the measurement and weight were taken before the compaction. The spacer disk was placed on the base plate and a filter paper kept on the spacer disk. Then the mold was placed over the spacer disk as well as a collar was fixed up on the mold. Later sample was poured in the mold of five layers and the compaction conducted per layer was 10, 30 and 65 blows, respectively. But the mold was clamped with base plate tightly during compaction. After compaction of five layers in each mold, it was level its top surface. Then the mold was removed from the base plate and spacer disk to take the weight of sample and mold. Further this sample was ready for curing periods of 0, 7 and 28 days as shown in Figure 3.4 (b).

(a) (b)

Figure 3.4: Laboratory procedure for (a) compaction of soil sample for CBR test and (b) ready samples for curing.

3.2.4.4 Curing of Samples for CBR Test

Total 54 samples for QD and lime as well as 60 samples for RHA and lime were curing for 0, 7 and 28 days. The samples were kept in water for curing shown in Figure 3.5. The water used in the curing was as the room temperature. The water temperature varies from 32 to 35°C.

Figure 3.5: Curing and cured sample for CBR test.

3.2.4.5 CBR Test of Samples

The curing samples were kept in open dry condition after removing the surcharge. When the molds become saturated dry, then the molds were untying its clamp for weighting of cured sample and mold. Later it was placed under the loading machine for CBR test as shown in Figure 3.6. CBR machine is a gradual loading machine which measures load with respect to deformation. Three molds were placed in the CBR testing machine to fix by wooden pieces for the tight hardly of sample. Then a collar and 4.70 kg of surcharge were placed on the mold. A deformation dial gauge was attached with the machine. By making the loading in dial gauge as zero, the load was gradually applied. The deformation was recorded for 0, 0.25, 0.50, 1.00, 1.25, 1.50, 2.00, 2.50, 3.00, 3.50, 3.75, 4.00, 4.50, 5.00, 6.00, 7.50, 10.00 and 12.50 mm, respectively and at the same time, the corresponding load was recorded. After the loading completed on sample, the mold was removed from the machine and the same procedure were repeated for the other samples.

Figure 3.6: CBR testing machine in the laboratory.

3.3 Soft Computing Systems

In this study, to predict CBR of stabilized soil with different admixtures at varying mixing proportions and curing period, the soft computing system like simple linear regression (SLR),

multiple linear regression (MLR), artificial neural network (ANN) with various algorithm as well as support vector machine (SVM) with different kernel functions, were performed and all these are discussed in the following articles.

3.3.1 Simple and Multiple Linear Regressions

In this study, SLR and MLR through MS Excel were performed to establish relationship between observed CBR as dependent variable and QD (%), RHA (%), lime (%), CP (days), OMC (%) or MDD (%) as independent variables. In SLR analysis, the following Equation 3.1 was developed based on observed CBR as dependent and QD, RHA. lime, CP, OMC or MDD as independent variables.

$$Y = a + bX \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.1)$$

Where *Y* is the dependent variable (observed CBR) and *X* is the independent variable like QD, RHA, lime, CP, OMC or MDD as shown in Table 3.1. Here, *b* is the slope of the line and *a* is the intercept, where the line cuts the y axis. The values of a and b were predicted from the equation after SLR analysis.

The developed Equation 3.1 was provided correlation between predicted CBR and independent variable like QD, RHA etc. for different stabilized soils at varying curing periods 0. 7 and 28 days. The obtained best correlation with R^2 0.798 between predicted CBR and QD as independent variable for curing periods of 28 days can be expressed by the following Equation 3.2 as an example. One can easily be obtained the almost perfect CBR of stabilized soil with QD and lime.

$$y = 0.584x+63.72\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3.2)$$

Where, y is the prediction value of CBR. Linear regression quantifies goodness of fit with R^2 provides a measure of how well future outcomes likely to be predicted by the model. A researcher Aderinola (2007) stated that any correlation with R^2 greater than 0.80 is considered as a best fitted model. In this study, to select the best fitted model, the statement published by Aderinola (2007) was considered. Dependent and independent variables in SLR analysis for different admixtures are depicted in Table 3.4.

Table 3.4: Dependent and independent variables in SLR analysis for different admixtures

Admixture (QD with lime)		Admixture (RHA with lime)	
Dependent variable	Independent variables	Dependent variable	Independent variables
0 days cured CBR (Observed)	QD (%)	0 days cured CBR (Observed)	RHA (%)
	lime (%)		lime (%)
	Curing period (days)		Curing period (days)
	OMC (%)		OMC (%)
	MDD (kN/m^3)		MDD (kN/m^3)
7 days cured CBR (Observed)	QD (%)	7 days cured CBR (Observed)	RHA (%)
	lime (%)		lime (%)
	Curing period (days)		Curing period (days)
	OMC (%)		OMC (%)
	MDD (kN/m^3)		MDD (kN/m^3)
28 days cured CBR (Observed)	QD (%)	28 days cured CBR (Observed)	RHA (%)
	lime (%)		lime (%)
	Curing period (days)		Curing period (days)
	OMC (%)		OMC (%)
	MDD (kN/m^3)		MDD (kN/m^3)

In MLR analysis, the following Equation 3.3 was developed based on observed CBR as dependent variable and two or more independent variables like QD, lime, RHA, CP, OMC and MDD.

$$Y = a + b1X1 + b2X2 + b3X3 + b4X4 + b5X5 \ldots\ldots\ldots\ldots\ldots\ldots(3.3)$$

Where Y is observed CBR (dependent variable), X1, X2, X3, X4, X5......Xn are QD, RHA, lime, CP, OMC and MDD independent variables as provided in Table 3.5. Here, *a* is the coefficient of intercept and b1, b2, b3, b4, b5........bn are coefficients of independent variables after MLR analysis.

The developed Equation 3.4 was provided correlation between predicted CBR and QD, RHA, lime, CP, OMC and MDD as independent variables for different stabilized soils at varying curing periods of 0, 7 and 28 days. Dependent and independent variables for MLR analysis are provided in Table 3.5.

Table 3.5: Dependent and independent variables for MLR analysis for different admixtures

Admixture (QD with lime)		Admixture (RHA with lime)	
Dependent Variable	Independent Variable	Dependent Variable	Independent Variable
0 days cured CBR (Observed)	QD, lime, CP, OMC, MDD	0 days cured CBR (Observed)	RHA, lime, CP, OMC, MDD
	QD, lime, OMC, MDD		RHA, lime, OMC, MDD
	lime, OMC, MDD		lime, OMC, MDD
	QD, OMC, MDD		RHA, OMC, MDD
	QD, lime, OMC		RHA, lime, OMC
	QD, lime, MDD		RHA, lime, MDD
	QD, lime		RHA , lime
	OMC, MDD		OMC, MDD
7 days cured CBR (Observed)	QD, lime, CP, OMC, MDD	7 days cured CBR (Observed)	RHA, lime, CP, OMC, MDD
	QD, lime, OMC, MDD		RHA, lime, OMC, MDD
	lime, OMC, MDD		lime, OMC, MDD
	QD, OMC, MDD		RHA, OMC, MDD
	QD, lime, OMC		RHA, lime, OMC
	QD, lime, MDD		RHA, lime, MDD
	QD, lime		RHA , lime
	OMC, MDD		OMC, MDD
28 days cured CBR (Observed)	QD, lime, CP, OMC, MDD	28 days cured CBR (Observed)	RHA, lime, CP, OMC, MDD
	QD, lime, OMC, MDD		RHA, lime, OMC, MDD
	lime, OMC, MDD		lime, OMC, MDD
	QD, OMC, MDD		RHA, OMC, MDD
	QD, lime, OMC		RHA, lime, OMC
	QD, lime, MDD		RHA, lime, MDD
	QD, lime		RHA , lime
	OMC, MDD		OMC, MDD

The obtained best correlation with R^2 0.87 between predicted CBR and QD, lime, CP, OMC and MDD as independent variables for curing period 28 days can be expressed by the following

Equation 3.4. One can easily be obtained the almost perfect CBR of stabilized soil with QD, lime, CP, OMC and MDD.

$$CBR = -262.723 + 2.332 * Lime - 0.033 * QD + 0 * CP - 0.214 * OMC + 18.839 * MDD \quad \ldots\ldots\ldots\ldots (3.4)$$

MLR quantifies goodness of fit with R^2 provides a measure of how well future outcomes are likely to be predicted by the model. A researcher Aderinola (2007) stated that any correlation with R^2 greater than 0.80 is considered as a best fitted model. In this study, to select the best fitted model, the statement published by Aderinola (2007) was considered.

3.3.2 Artificial Neural Network

In this study, feed forward artificial neural network (ANN) with back propagation was implemented to predict CBR of stabilized soils. ANN model have been analyzed to predict CBR of stabilized soils prepared from QD with lime as well as RHA with lime. In ANN model, QD (%), lime (%), CP (days), OMC (%) and MDD (kN/m^3) was considered as input to obtain CBR as output variable of stabilized soil with QD and lime. Moreover, from ANN model to predict CBR of stabilized soil with RHA and lime, the same input variables like RHA (%), lime (%), CP (days), OMC (%) and MDD (kN/m^3) were also considered.

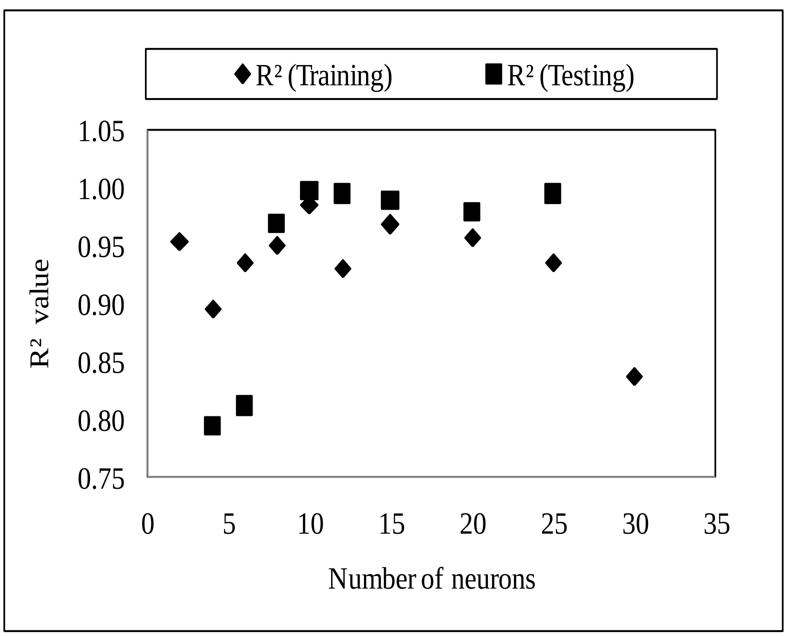
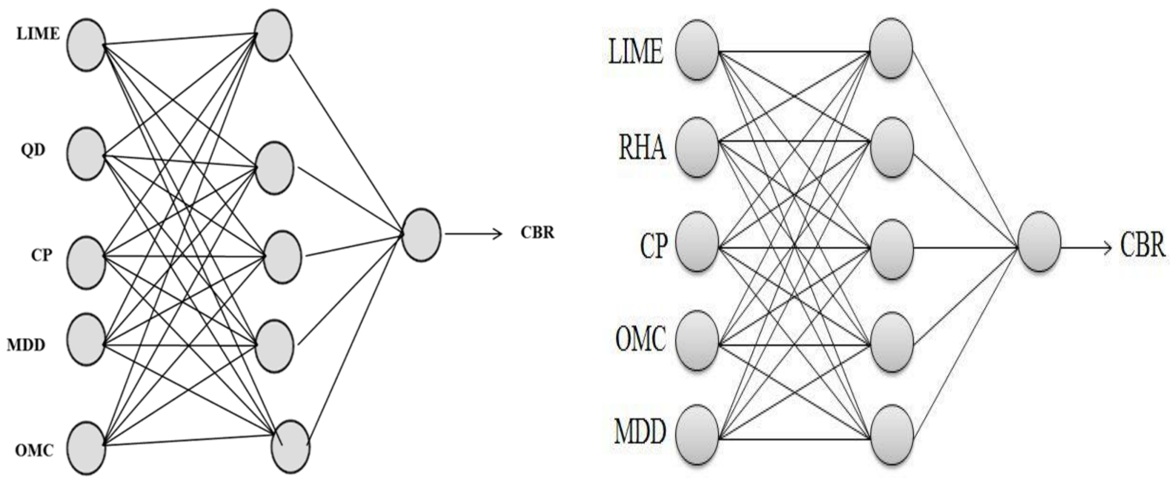


Figure 3.7: Effect of number of neuron in hidden layer.

To maximize the accuracy of model based on R^2, the ANN model has trained with different hidden neurons. In this study, the hidden neuron 10 showed the satisfactory values of R^2 which selected as the best neuron number for modeling of ANN shown in Figure 3.7. In modeling of ANN, maximum five numbers of input, one number of hidden layer and the selected 10 hidden neurons was considered shown in Figure 3.8.



(a) (b)

Figure 3.8: Architecture of the neural network model (a) stabilized soil with QD and lime (b) stabilized soil with RHA and lime.

The architecture of ANN model for the prediction of CBR of stabilized soil for both the admixtures of QD and RHA against different input variables is shown in Figure 3.8. In ANN analysis, total 38 (70% of 54) data sets for training and 16 (30% of 54) for testing were considered for the prediction of CBR of stabilized soil using QD and lime. In literature, several researcher such as Sabat (2015) was considered 70 and 30 % of total data for training and testing of ANN model, respectively. In this study, total 42 (70% of 60) data sets for training and 18 (30% of 60) for testing were considered for the prediction of CBR of stabilized soil using RHA and lime. The steps considered for ANN analysis are as follows.

a) Creating and adding data in MATLAB workspace

Firstly, in workspace of MATLAB, 18 data of five independent variables like QD (%), lime (%), CP (days), OMC (%) and MDD (%) at a curing period 0, 7 and 28 days was considered to get predicted CBR of stabilized soil with QD and lime as shown in Figure 3.9. Secondly, 18 data of four independent variable like QD (%), lime (%),OMC (%) and MDD (%) at a curing period 0, 7 and 28 days was considered to get predicted CBR of stabilized soil with QD and lime. Similarly, the predicted CBR of stabilized soil with QD and lime was obtained by reducing and internally rearranging of independent variables separately. In similar way, the analysis of stabilized soil with RHA and lime was performed to obtain predicted CBR.

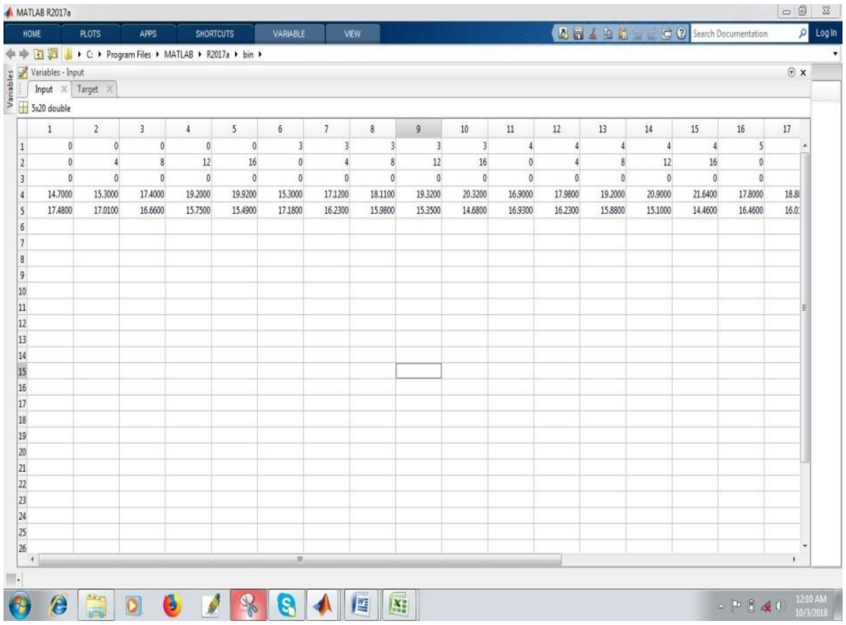


Figure 3.9: MATLAB workspace.

b) Use the command window and find out the fitting app

In this step, at first "nnstart" through command window then the first wizard function "fitting app" was performed for further analysis as shown in Figure 3.10.

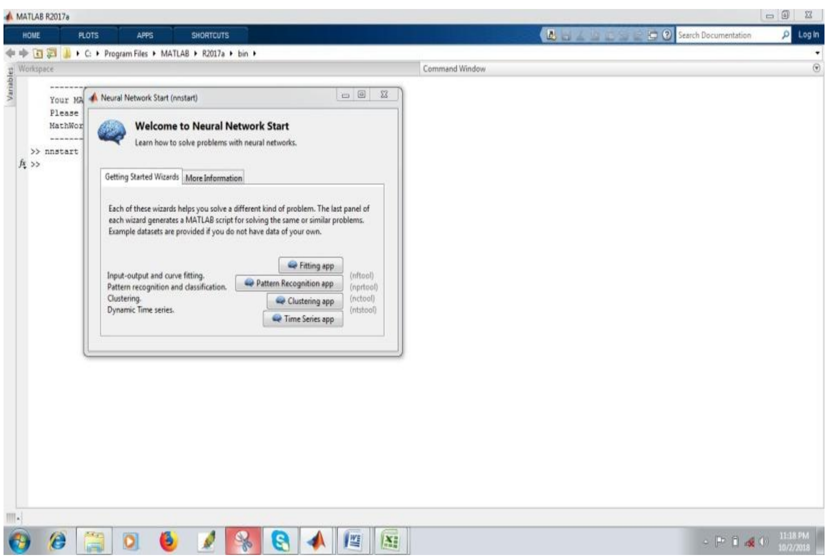


Figure 3.10: Command window.

c) Selection of neural fitting app

In this step, the Neural Fitting App was selected through fitting app to find out the architecture of ANN with input, output, hidden layers and hidden neurons etc. as shown in Figure 3.11.

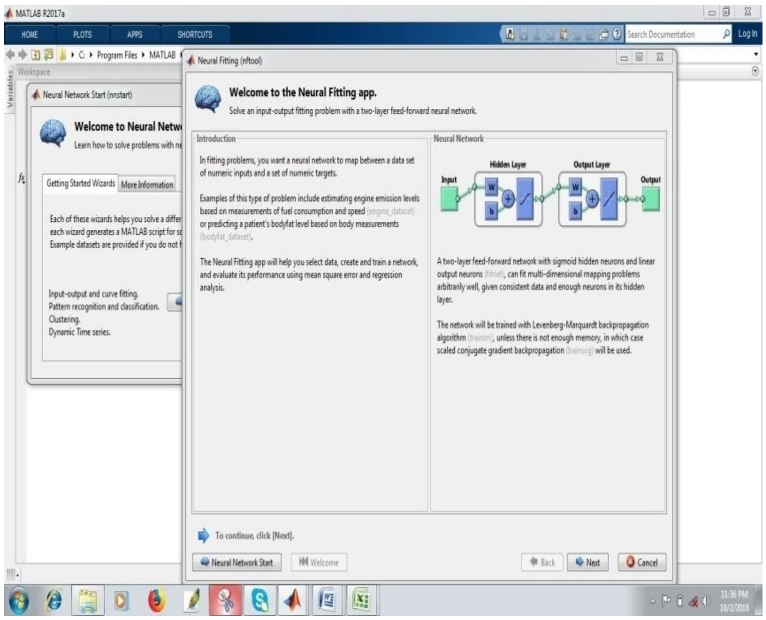


Figure 3.11: Neural fitting app.

d) Selected data for analysis

In this step, 5 independent variables (input) like QD (%), lime (%), CP (days), OMC (%) and MDD (%) and one dependent variable like observed CBR (target) was considered. In this analysis, dependent and each independent variable consists18 different test data sets. Therefore, the matrix was formed as 5x18 as input in this analysis. In addition, the observed CBR for a particular curing period 0 day with 18 different test data sets was considered as target representing as 1x18 matrix as shown in Figure 3.12. Similarly, 5 independent variables (input) like RHA (%), lime (%), CP (days), OMC (%) and MDD (%) and one dependent variable like observed CBR (target) was considered. In this analysis, dependent and each independent variable consists 20 different test data sets. Therefore, the matrix was formed as 5x20 as input in this analysis. In addition, the observed CBR for a particular curing period 0 day with 20 different test data sets was considered as target representing as 1x20 matrix.

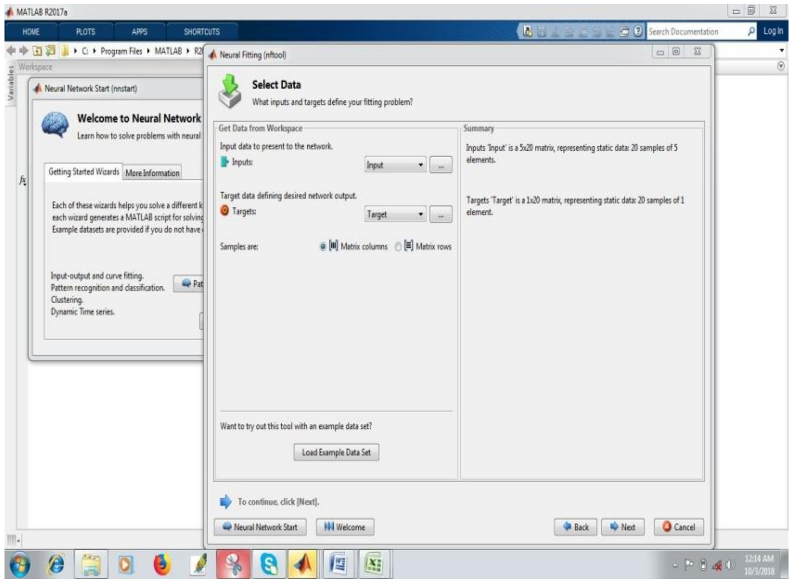


Figure 3.12: Data selection for input and target.

e) Set aside some sample for training and testing network

In this step, 70% data for training and 30% data for testing were considered. Firstly, for stabilized soil with QD and lime, 13 data (70% of 18) as well as 5 (30% of 18) for training and testing, respectively, for each independent variable at a particular curing period were considered. Secondly, this step was completed for stabilized soil with QD and lime with similar configuration of data sets for other independent variable. In addition, for stabilized soil with RHA and lime, 14 data (70% of 20) as well as 6 (30% of 20) for training and testing, respectively, for each independent variable at a particular curing period were considered as shown in Figure 3.13.

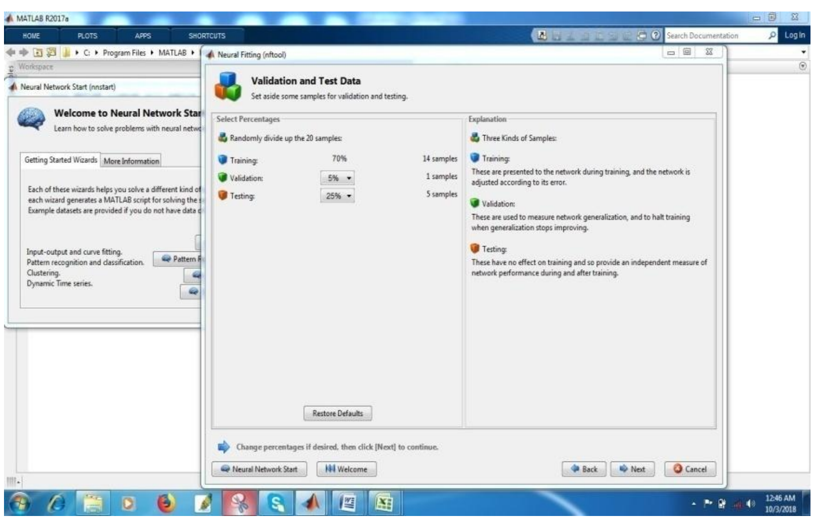


Figure 3.13: Data selection for training and testing network.

f) Selection of network architecture

The number of hidden layers and number of neuron are varied to find out the best structure of modeling. In order to compute the most appropriate ANN architecture for the modeling, the number of neurons in the hidden were tried to predict best CBR values as shown in Figure 3.14. To maximize the accuracy of model based on R^2, the ANN model has been run with different hidden neuron numbers. In this study, the hidden neuron number 10 reveals the satisfactory values of R^2 which selected as the best neuron number for modeling of ANN.

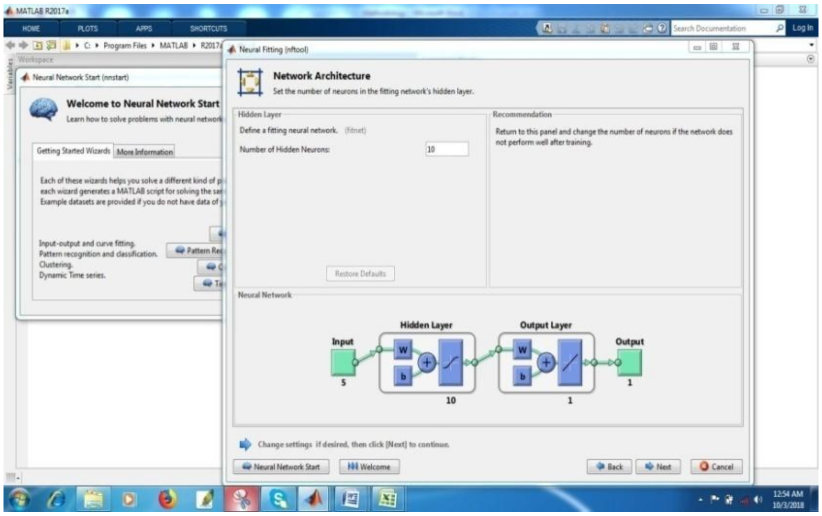


Figure 3.14: Neuron network architecture.

g) Selection of Algorithms through Train network

In this step, the training algorithms like LMNN, BRNN and SCGNN was found in this train network as shown in Figure 3.15. In train network, it has been trained with varying R^2 and MSE to select best model like LMNN, BRNN and SCGNN of ANN.

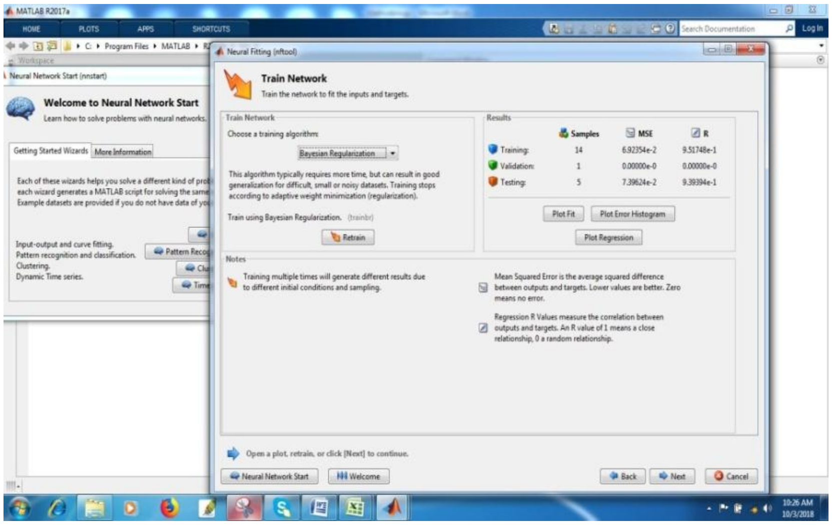


Figure 3.15: Training network.

3.3.3 Support Vector Machine

In this study, SVM model has been analyzed to predict CBR of stabilized soil using QD and lime as well as RHA and lime. The models has been analyzed by taking QD (%), lime (%), CP(days), OMC (%) and MDD (kN/m^3) as input as well as observed CBR (%) as output variable. In addition, for stabilized soil with RHA and lime; RHA (%), lime (%), CP (days), OMC (%) and MDD (kN/m^3) were considered as input variables and CBR (%) as output variable. The following steps were considered for the analysis of SVM.

a) Creating and adding data in MATLAB

From MATLAB, the regression learner has been selected to get new session for the selection of data table as shown in Figure 3.16. It started a new session by importing data from a file.

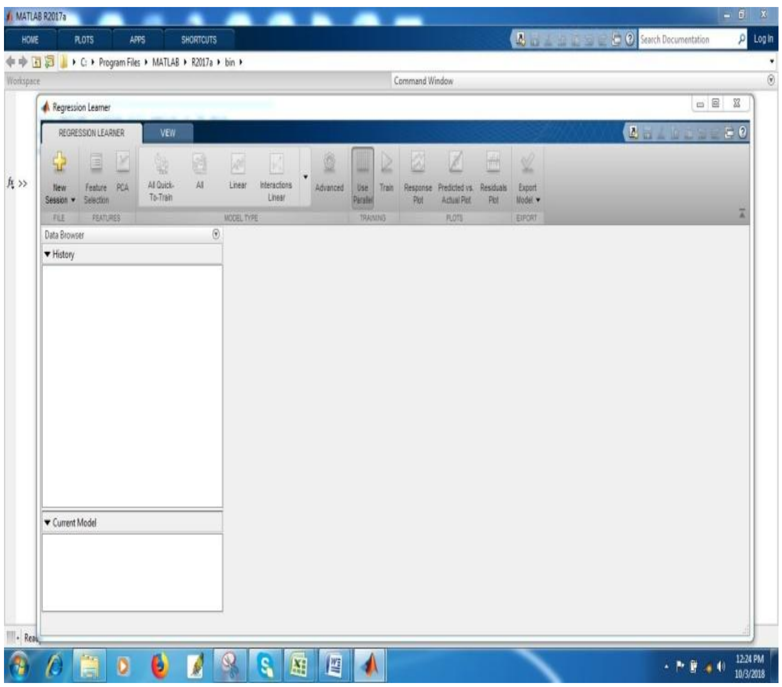


Figure 3.16: MATLAB regression learner.

b) Selected of new session

In this step, data table was selected from a file using new session. Thereafter, selected input data such as QD(%), lime (%), CP (days), OMC (%) and MDD (kN/m^3) as well as observed CBR (%) selected as target data. In addition, RHA(%), lime (%), CP (days), OMC (%) and MDD (kN/m^3) selected as input as well as observed CBR (%) as target as shown in Figure 3.17. Moreover cross-validation fold have taken as 5 folds as a constant value.

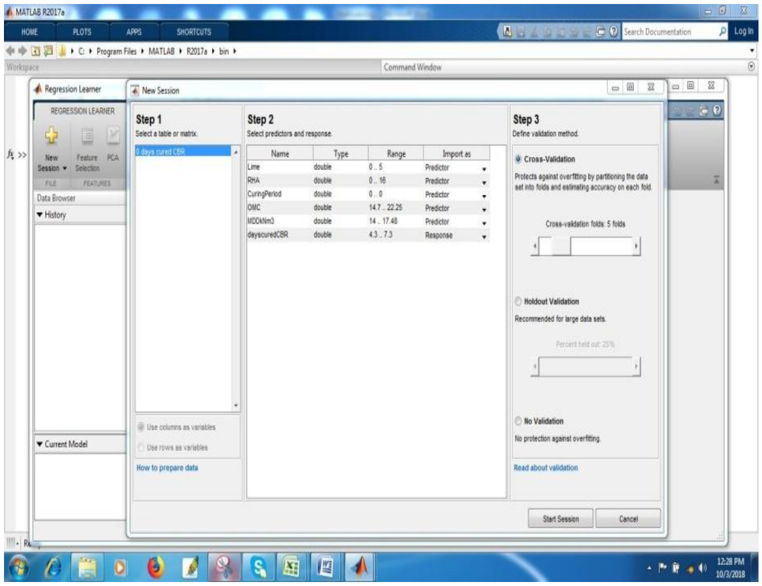
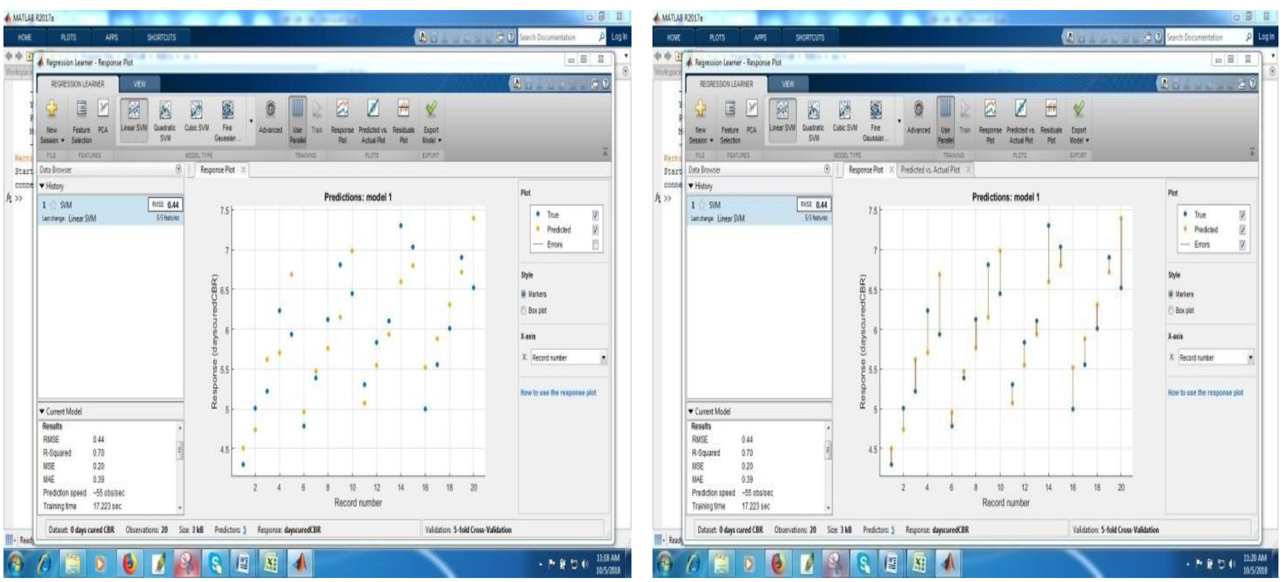


Figure 3.17: MATLAB new session.

c) Selected the regression learner-response plot

In this step, find out the Linear SVM (SVM-L), Quadratic SVM (SVM-Q) and Cubic SVM (SVM-C) from the SVM regression learner app. There after performing the train to get the prediction parameters of RMSE, R^2 and MAE. Moreover it observed that, blue point as true value and yellow point as predicted value by applying the response plot as shown in Figure 3.18.



(a) (b)

Figure 3.18: Regression learner-response plot. (a) Predicted and observed point of CBR (b) Error histogram between predicted and observed CBR.

d) Finally find out the plot of predicted CBR against observed CBR

In this step, the model was trained to obtain the best model like SVM-L, SVM-Q and SVM-C of SVM based on the satisfactory values of prediction parameters of R^2, RMSE and MAE. After retrained, obtained the best value of RMSE, R^2 and MAE were considered to select the best fitted models like SVM-L, SVM-Q and SVM-C of SVM for the prediction of perfect CBR of stabilized soil as shown in Figure 3.19.

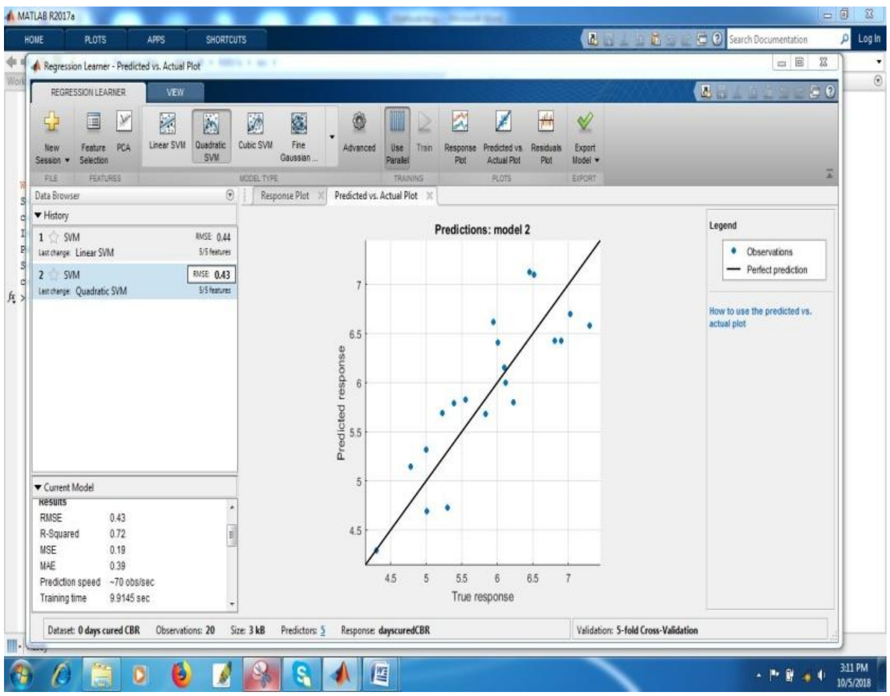


Figure 3.19: Plot for predicted CBR against observed CBR.

Chapter 4

Results and Discussion

4.1 General

This chapter describes the characterization of stabilized soils prepared by using quarry dust (QD) with lime as well as rice husk ash (RHA) with lime at varying mixing proportions. The computed values of optimum moisture content (OMC), maximum dry density (MDD) and California bearing ratio (CBR) of stabilized soils are also highlighted in this chapter. The results of OMC, MDD and CBR which was used in soft computing systems for further prediction of CBR are also highlighted in this chapter. This chapter also deals with simple linear regression (SLR), multiple linear regression (MLR) as well as artificial neural network (ANN) with different training algorithm like Levenberg-Marquardt neural network (LMNN), Bayesian regularization neural network (BRNN) and scaled conjugate gradient neural network (SCGNN). In addition, support vector machine (SVM) with different kernel functions like linear support vector machine (SVM-L), quadratic support vector machine (SVM-Q) and cubic support vector machine (SVM-C) for prediction of CBR of stabilized soils are also highlighted and hence discussed in the following articles.

4.2 Stabilized Soil with Admixtures

In the laboratory, stabilized soils were prepared with different admixtures like quarry dust (QD) and lime as well as rice husk ash (RHA) and lime at varying mixing proportions of QD, RHA and lime. For stabilization of soil with QD and lime, where QD as 0, 10, 20, 30, 40 and 50% as well as lime as 2, 4 and 6 % were used in soil. In addition, for stabilization of soil with RHA and lime, where RHA as 0, 4, 8, 12 and 16% as well as lime as 0, 3, 4 and 5% were also used in soil. The stabilized samples were then cured for 0, 7 and 28 days. In the laboratory, modified proctor test was performed to obtain compaction characteristics (OMC and MDD) and hence discussed in the following articles.

4.3 Compaction Characteristics of Stabilized Soils

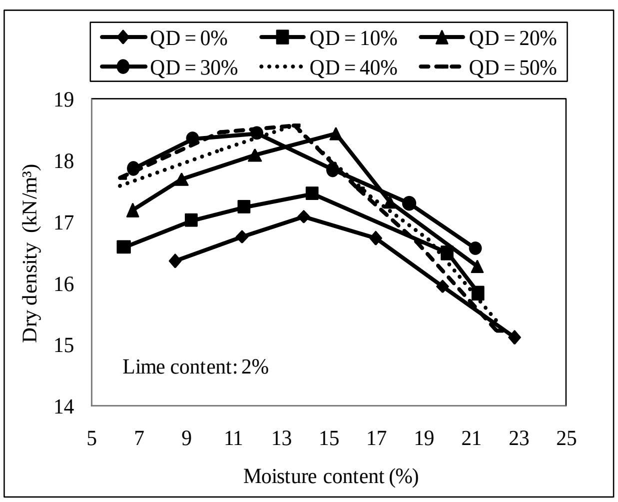
In the laboratory, modified proctor test was performed on prepared stabilized soils to obtain compaction characteristics like OMC and MDD. The relationships between dry density and moisture content of stabilized soil with QD and lime as well as RHA and lime are shown in Figure A.1 to A.8 as well as A.9 to A.16, respectively, in Annex-A. The results of compaction test are hence described in the following articles.

4.3.1 Compaction Curve

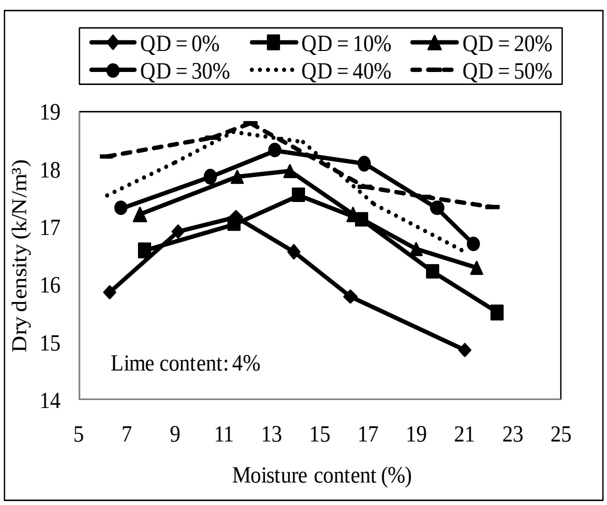
After performed compaction test on stabilized soil with QD and RHA, the compaction curves were exhibited and discussed in the following articles.

4.3.1.1 Stabilized Soil with QD and Lime

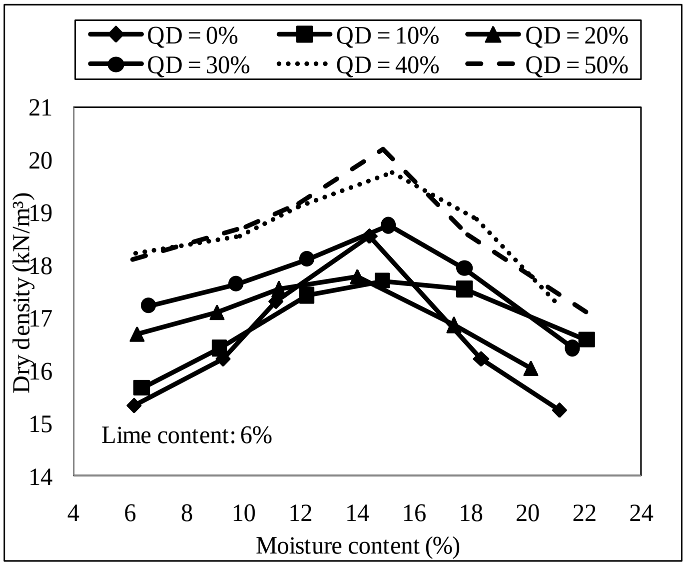
The variation of dry density in relation to the changing of moisture content of stabilized soil with QD and lime is shown in Figure 4.1. Figure 4.1 depicts that dry density increases with the increasing of QD and lime content in soil at a certain amount of moisture content. For a particular amount of QD like 50%, the stabilized soil with 6 % lime content showed comparatively the higher values of dry density due to more additive power of admixtures than that of stabilized soil with other less amount of QD content as shown in Figure 4.1(c). A research conducted by Al-Joulani (2012) and showed the variation of dry density with the changes of moisture contents for soil samples with different percentages of additives. The findings of this study are agreed well with the results postulated by Al-Joulani (2012).



(a)



(b)



(c)

Figure 4.1: Effect of QD content on compaction curve for (a) 2% lime content, (b) 4% lime content and (c) 6% lime content.

4.3.1.2 Stabilized Soil with RHA and Lime

The effect of RHA content with 3% lime on the compaction curve of stabilized soil with RHA and lime is shown in Figure 4.2.

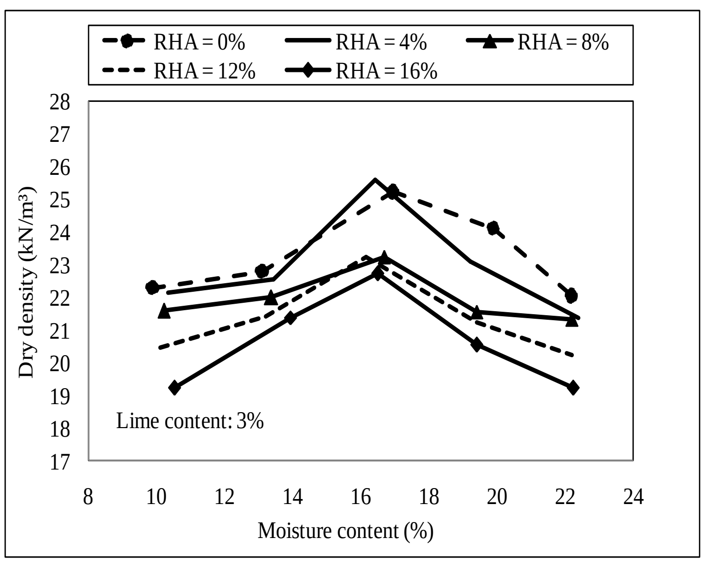


Figure 4.2: Effect of RHA content on dry density and moisture content.

Figure 4.2 reveals that dry density decreases for the increasing of RHA content with soil at certain amount of moisture content and then decreases. According to Al-Joulani (2012) the dry density values with moisture contents for soil samples with different percentage of additives are varied. The findings of this study are agreed well with the results by Al-Joulani (2012).

4.3.2 Optimum Moisture Content and Maximum Dry Density

The optimum moisture content (OMC) and maximum dry density (MDD) of stabilized soils at varying mixing proportions of QD with lime as well as RHA with lime were evaluated and hence discussed in the following articles.

4.3.2.1 Stabilized Soil with QD and Lime

The OMC and MDD of stabilized soil at varying mixing proportions of QD with lime are mentioned in Table 4.1. Table 4.1 depicts that the value of OMC decreases in the range of 14.32 to 11.29%, while, MDD increases in the range of 16.67 to 18.57 (kN/m^3) in relation to the increasing of mixing amount of QD from 0 to 50% and lime is 2 to 6%.

Table 4.1: Results of stabilized soil using QD and lime at varying mixing proportions

QD content (%)	Lime content (%)	Optimum moisture content, OMC (%)	Maximum dry density, MDD (kn/m^3)
0	2	13.72	16.95
10	2	12.89	17.42
20	2	12.67	18.08
30	2	12.10	18.17
40	2	11.54	18.40
50	2	11.29	18.57
0	4	14.12	16.86
10	4	13.47	17.33
20	4	13.16	17.88
30	4	12.58	18.00
40	4	12.07	18.38
50	4	11.78	18.47
0	6	14.32	16.67
10	6	13.89	17.21
20	6	13.12	17.67
30	6	12.76	17.78
40	6	12.34	18.15
50	6	11.92	18.36

The value of OMC decreases with the increasing of mixing proportions of QD due to less water absorption capacity of QD. Similarly, the values of MDD increase with the increase of mixing content of QD. A research conducted by Sabat (2013) stated that the values of OMC decreases, while MDD increases of stabilized soils with the increasing of QD and lime content. The findings of this study are agreed well with the results postulated by Sabat (2013).

Figure 4.3 shows the variation of MDD of stabilized soil with different percentages of QD and lime. MDD is an important parameter to calculate the CBR of stabilized soils. The MDD of stabilized soil decreases with the increasing of lime content as shown in Figure 4.3. In addition, MDD increases in relation to the increasing of QD content in soil. Figure 4.3 also shown that for a particular mixing content of QD (30%), the value of MDD decreases with the increasing of lime content. Moreover, for a particular amount of lime content (6%), the value of MDD increases in relation to the adding of QD in stabilized soil.

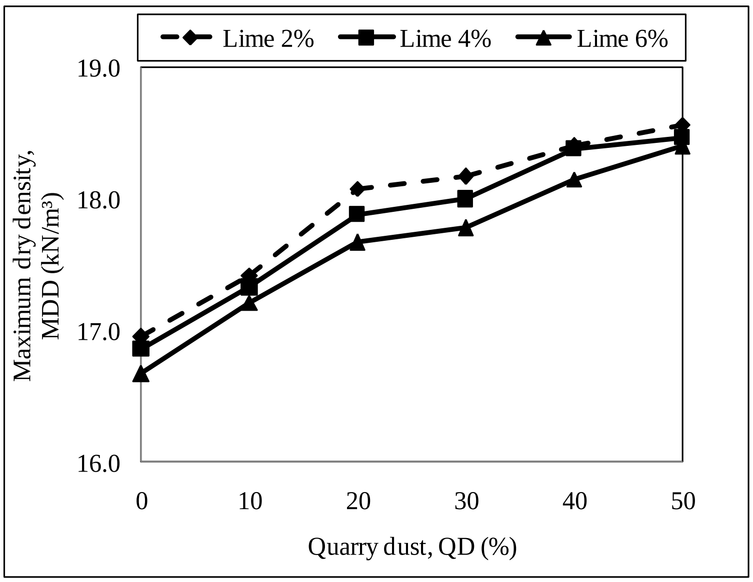


Figure 4.3: Variation of MDD with QD and lime.

In addition, Figure 4.4 shows the variation of OMC of stabilized soil with different percentages of QD and lime. OMC is an important parameter to determine the CBR of stabilized soils. The OMC of stabilized soil increases with the increasing of lime content as shown in Figure 4.4. In addition, OMC decreases in relation to the increasing of QD content in stabilized soil. Figure 4.4 also shown that for a particular mixing content of QD (30%), the value of OMC increases with the increasing of lime content. Moreover, for a particular mixing amount of lime content (6%), the value of OMC decreases in relation to the adding of QD in stabilized soil.

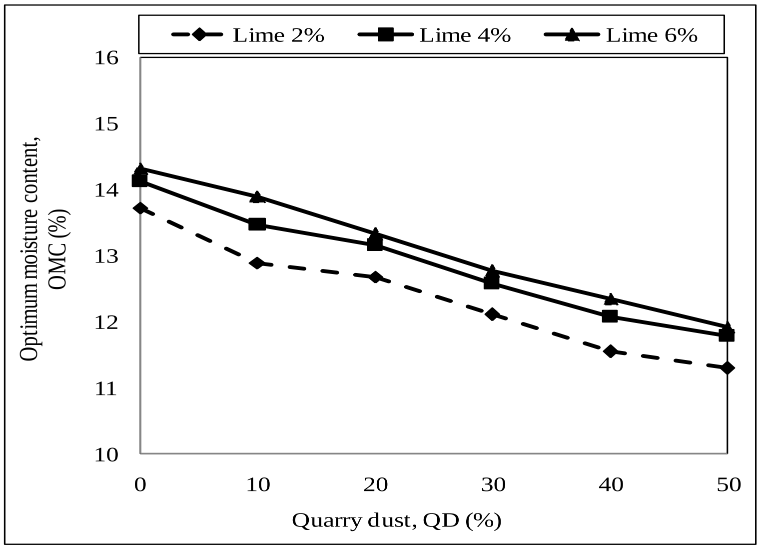


Figure 4.4: Variation of OMC with QD and lime.

The deviation of MDD and OMC in stabilized soil with QD (0 to 50%) and lime 2% is shown in Figure 4.5. The OMC decreases, while MDD increases with the increasing of QD content with a particular amount of lime (2%) as shown in Figure 4.5. A research conducted by Sarapu (2016) and stated that MDD decreases, while OMC increases with the increasing of admixture like RHA in soil. In this study, OMC and MDD of stabilized soil with QD showed the inverse behavior of stabilized soil with RHA due to the inherent properties of admixtures of QD and RHA. The findings in this study agreed well with the results postulated by Sarapu (2016).

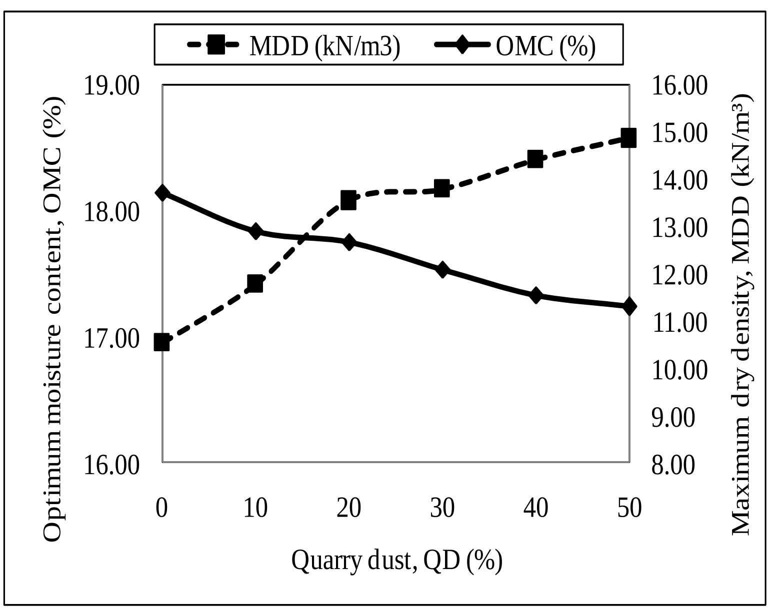


Figure 4.5: Variation of MDD and OMC with QD (%) and 2% lime.

4.3.2.2 Stabilized Soil with RHA and Lime

The OMC and MDD of stabilized soil at varying mixing proportions of RHA with lime were obtained and depicted in Table 4.2. Table 4.2 also depicts that the value of OMC increase in the range of 14.7 to 22.25%, while, MDD decreases in the range of 14.0 to 17.48 (kN/m^3) in relation to the increasing of mixing amount of RHA from 0 to 16% and lime is 0 to 5%.

Table 4.2: Results of stabilized soil using RHA and lime at varying mixing proportions

RHA content (%)	Lime content (%)	Optimum moisture content, OMC (%)	Maximum dry density, MDD (kN/m^3)
0	0	14.7	17.48
4	0	15.3	17.01
8	0	17.4	16.66
12	0	19.2	15.75
16	0	19.92	15.49
0	3	15.3	17.18
4	3	17.12	16.23
8	3	18.11	15.98
12	3	19.32	15.35
16	3	20.32	14.68
0	4	16.9	16.86
4	4	17.98	16.23
8	4	19.2	15.88
12	4	20.9	15.1
16	4	21.64	14.46
0	5	17.8	16.46
4	5	18.88	16.01
8	5	20.1	15.44
12	5	20.96	14.59
16	5	22.25	14

The value of OMC increases with the increasing mixing proportions of RHA due the more water absorption capacity of RHA. Similarly, the values of MDD decreases in relation to the increasing of the mixing content of RHA. A research conducted by Jay et al. (2017) stated that the value of OMC increases and MDD decreases of stabilized soils using RHA. The findings of this study are agreed well with the results postulated by Jay et al. (2017).

Figure 4.6 shows the variation of MDD of stabilized soil with different percentage of RHA and lime. MDD is an important parameter to calculate the CBR of stabilizes soils. The MDD of stabilized soil decreases with the increasing of lime content as shown in Figure 4.6. In addition, MDD decreases in relation to the increasing of RHA content in soil. Figure 4.6 also shows that for a particular mixing content of RHA (8%), the value of MDD decreases with the increasing of lime content. Moreover, for a particular mixing amount of lime content (5%), the value of MDD decreases in relation to the adding of RHA in stabilized soil. A research conducted by Chakraborty et al. (2014) stated that MDD decreases with the increasing of different percentage of RHA and lime content. So the findings of this study are agreed well about the topic with the result postulated by Chakraborty et al. (2014).

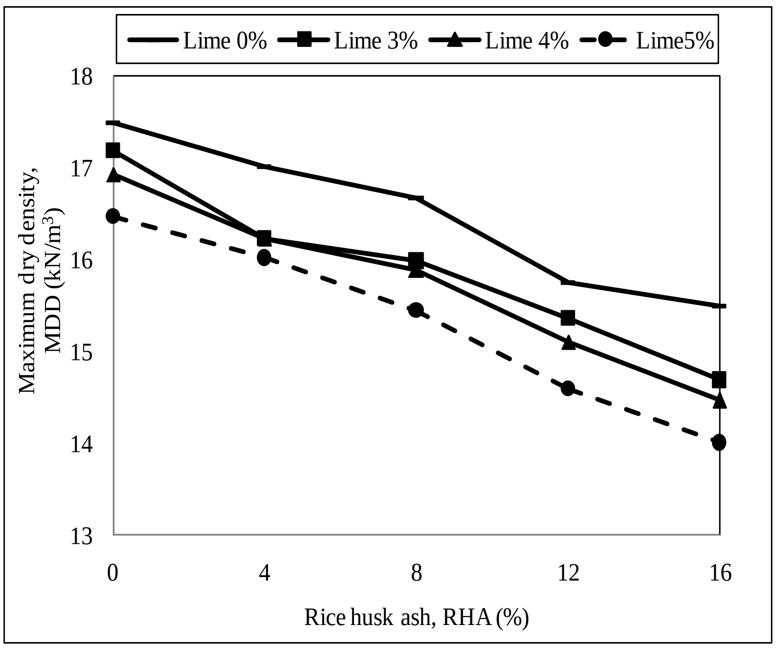


Figure 4.6: Variation of MDD with RHA and lime.

In addition, Figure 4.7 shows the variation of OMC of stabilized soil with different percentage of RHA and lime. OMC is an important parameter to calculate the CBR of stabilized soils. The OMC of stabilized soil increases with the increasing of lime content as shown in Figure 4.7. In addition, OMC increases in relation to the increasing of RHA content in stabilized soil. Figure 4.7 also shows that for a particular mixing content of OMC (8%), the value of OMC increases with the increasing of lime content. Moreover, for a particular mixing amount of lime content (5%), the value of OMC increases in relation to the adding of RHA in stabilized soil. A research conducted by Chakraborty et al. (2014) state that the OMC increases with increase in different percentage of RHA and lime. So the findings of this study are agreed well about the topic with the result postulated by Chakraborty et al. (2014).

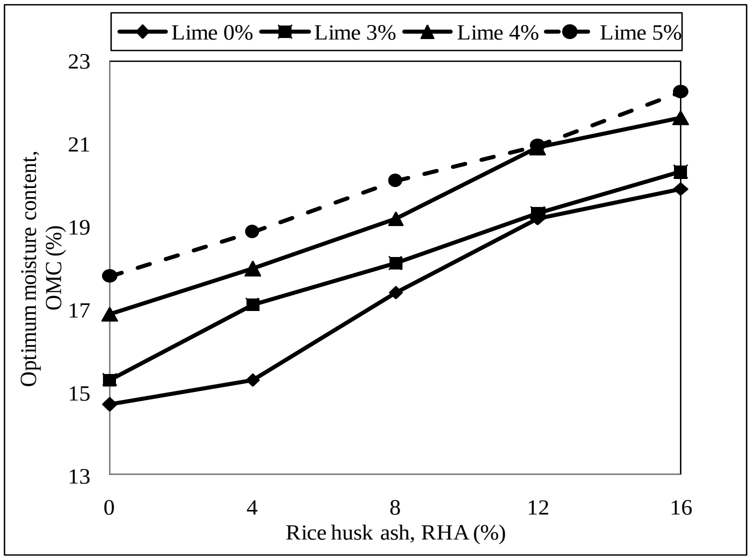


Figure 4.7: Variation of OMC with RHA and Lime.

Figure 4.8 illustrates the deviation of MDD and OMC in stabilized soil with RHA (0 to 16%) and lime of 4%. The MDD decreases while OMC increases with the increasing of RHA. A research by Sarapu (2016) showed MDD decreases while the OMC increases in the increase of RHA content in soil for stabilization. The findings of this study are agreed well with the results postulated by Sarapu (2016).

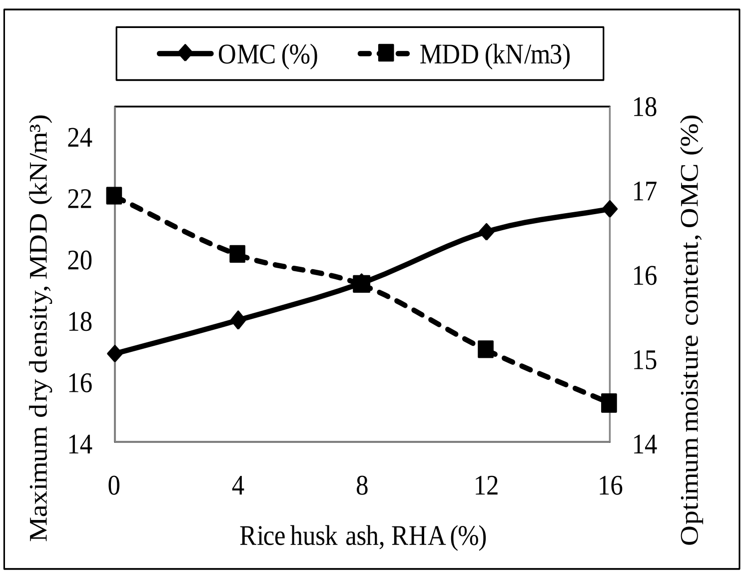


Figure 4.8: Variation of MDD and OMC with RHA (%) and 4% lime.

4.4 California Bearing Ratio

In the laboratory, stabilized soil with different admixtures like QD and RHA at varying mixing proportions and curing period was prepared. The CBR of stabilized soils was measured and the results of CBR of stabilized soils are hence discussed in the following articles.

4.4.1 Stabilized Soil with Quarry Dust and Lime

The results of CBR of stabilized soil with different mixing content of QD and lime at varying curing period of 0, 7 and 28 days is provided in Table 4.3 and discussed in the following article. In addition, OMC and MDD affected closely the CBR of stabilized soil. Moreover, the CBR of stabilized soil are greatly affected by the mixing amount of QD and lime in soil (Table 4.3).

Table 4.3: Results of CBR of stabilized soil with QD and lime at varying curing periods

QD content (%)	Lime content (%)	CBR (%) for different curing period (days)		
		0	7	28
0	2	28.70	33.34	57.66
10	2	32.92	40.21	69.30
20	2	35.17	45.32	73.20
30	2	38.86	51.31	78.65
40	2	42.82	61.10	87.25
50	2	40.36	56.64	81.89
0	4	29.03	44.67	62.12
10	4	30.12	46.21	73.55
20	4	39.80	53.78	79.00
30	4	53.68	62.32	87.81
40	4	77.54	83.27	98.26
50	4	66.35	74.50	91.22
0	6	28.87	39.80	59.89
10	6	31.52	41.14	71.50
20	6	37.48	44.77	76.22
30	6	46.27	59.55	83.50
40	6	60.18	74.19	91.75
50	6	53.35	69.13	87.21

4.4.1.1 Curing Period of 0 Days

Figure 4.9 shows the variation of CBR with different percentage of QD and lime at the curing period of 0 days. It is observed that CBR goes on increasing up to 4% of lime, further decreases with adding lime. For a particular amount of lime, CBR increases with the increasing of QD in soil. The CBR increases up to 40% of QD, further addition of QD decreases the values of CBR irrespective of the percentage of lime. The CBR increases to 77.54% from 28.70%, when the percentage of lime is 4%, QD is 40% and curing period is 0 days as shown in Figure 4.9. The decline in CBR after a peak value at 40% QD may be connected with the decrease in the clay proportions which plays the role of the bonding agent at the lower percentage of QD. A researcher Sabat (2013) stated that CBR increases in relation to the increasing of QD up to certain amount of QD (40%), further decreases CBR with increases of QD similarly at the curing period of 7and 28 days. The findings of this study are agreed well with researcher Sabat (2013).

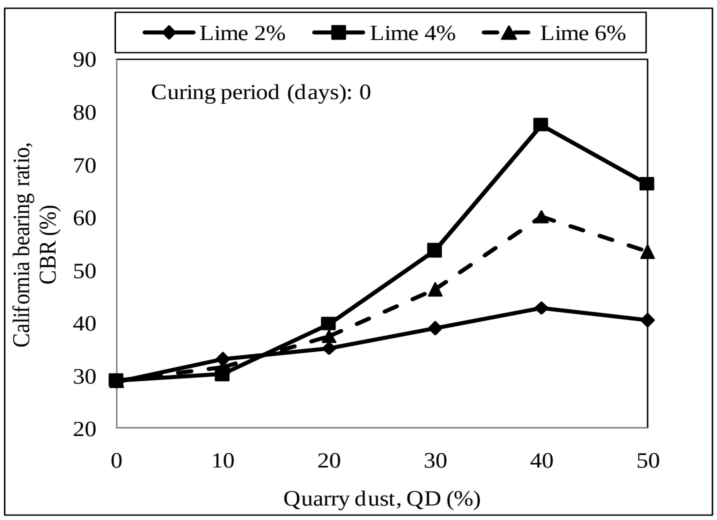


Figure 4.9: Variation of CBR of stabilized soil with QD and lime at curing period of 0 days.

4.4.1.2 Curing Period of 7 Days

Figure 4.10 shows the variation of CBR with different percentage of QD and lime at the curing period of 7 days. It is observed that CBR goes on increasing up to 4% of lime, further decreases with adding lime with soil. For a particular mixing amount of lime content, CBR increases with the increasing of QD content. The CBR increases up to 40% addition of QD, further addition of QD decreases the CBR values irrespective of the percentage of lime. The CBR increases to a value of 83.27% from 33.34%, when the percentage of lime is 4%, QD is 40% and curing period is 7 days as shown in Figure 4.10.

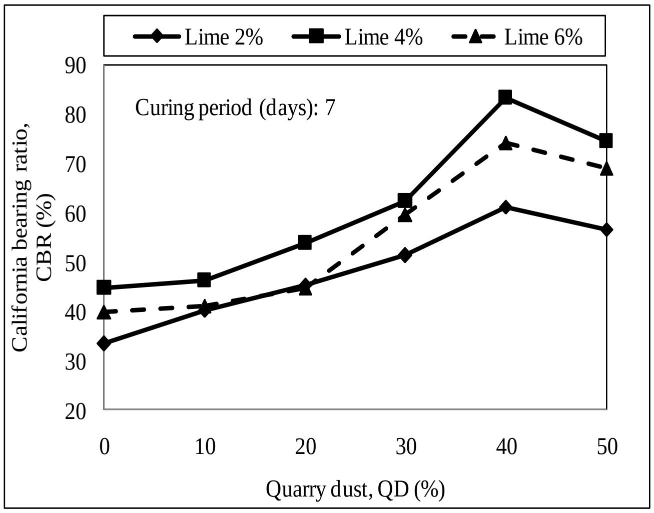


Figure 4.10: Variation of CBR of stabilized soil with QD and lime at curing period of 7 days.

4.4.1.3 Curing Period of 28 Days

Figure 4.11 shows the variation of CBR of stabilized soil with different percentage of QD and lime at the curing period of 28 days. It observed that CBR of stabilized soil goes on increasing up to 4% of lime, further decreases with adding lime with soil. For a particular mixing amount of lime content, CBR increases with the increasing of QD content in stabilized soil. The CBR increases up to 40% addition of QD, further addition of QD decreases the CBR values irrespective of the percentage of lime. The CBR increases to a value of 98.26% from 57.66%, when the percentage of lime is 4%, QD is 40% and curing period is 28 days as shown in Figure 4.11. The results of CBR of stabilized soil with QD and lime depicted that the optimum content of QD 40% was considered to get better CBR of stabilized soil for any curing period.

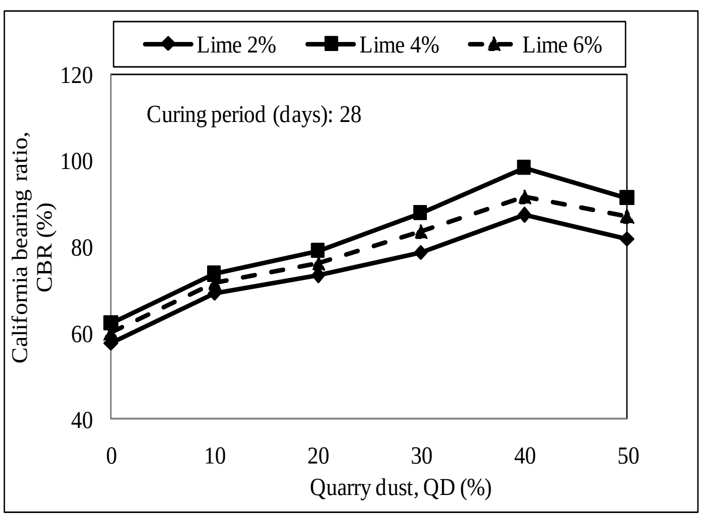


Figure 4.11: Variation of CBR of stabilized soil with QD and lime at curing period of 28 days.

4.4.2 Stabilized Soil with RHA and Lime

The results of CBR of stabilized soil with different mixing content of RHA and lime at varying curing period of 0, 7 and 28 days is provided in Table 4.4 and hence discussed in the following articles. In addition, OMC and MDD affect closely to CBR of stabilized soil. Moreover, the different percentage of RHA and lime keep more priority to find out the CBR of stabilized soil (Table 4.4). The values of CBR of stabilized soil are greatly affected by the mixing amount of QD and lime in soil (Table 4.4).

Table 4.4: Results of CBR in stabilized soil with RHA and lime at varying curing periods

RHA content (%)	Lime content (%)	CBR (%) for different curing period (days)		
		0	7	28
0	0	5.1	9.27	13.43
4	0	8.01	11.22	17.83
8	0	11.22	15.08	20.21
12	0	14.23	18.12	23.43
16	0	13.03	16.92	21.24
0	3	30.7	34.23	39.52
4	3	34.39	35.93	42.42
8	3	36.82	39.76	44.85
12	3	40.81	42.42	46.52
16	3	37.08	40.55	44.11
0	4	42.69	44.45	50.61
4	4	46.21	48.51	54.93
8	4	48.51	50.62	56.15
12	4	50.1	52.5	58.41
16	4	48.25	50.21	56.04
0	5	42.83	44.87	51.21
4	5	43.94	45.11	51.55
8	5	45.21	47.65	53.41
12	5	47.2	50.78	55.2
16	5	45.14	47.31	52.65

4.4.2.1 Curing Period of 0 Days

Figure 4.12 shows the variation of CBR of stabilized soil with different percentage of RHA and lime at the curing period of 0 days. It observed that CBR of stabilized soil goes on increasing up to 4% of lime, further decreases with adding lime with soil.

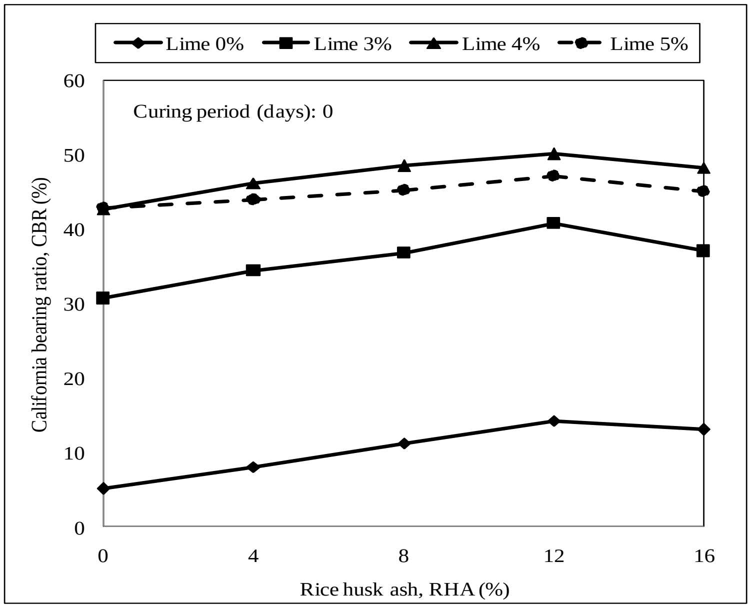


Figure 4.12: Variation of CBR of stabilized soil with RHA and lime at curing period of 0 days.

For a particular mixing amount of lime content, CBR increases with increasing of RHA content in soil. The CBR increases up to 12% addition of RHA, further addition of RHA decreases CBR irrespective the percentage of lime. The CBR increases to a value of 50.1% from 5.1%, when the percentage of lime is 4%, RHA is 12% and curing period is 0 days as shown in Figure 4.12. The reason for increment in CBR may be because of the gradual formation of lime compounds in the soil by the reaction between the RHA and some amounts of CaOH present in soil and lime present. The decrease in CBR at RHA content of 16% may be due to extra RHA that could not be mobilized for the reaction which consequently occupies spaces within the sample. A research conducted by Jai et al. (2017) stated that the CBR increases in relation to the increasing of RHA content in soil up. The result of this study agreed well with the researcher.

4.4.2.2 Curing Period of 7 Days

Figure 4.13 shows the variation of CBR of stabilized soil with different percentage of RHA and lime at the curing period of 7 days. It observed that CBR of stabilized soil goes on increasing up to 4% of lime, further decreases with adding lime with soil. For a particular mixing amount of lime content, CBR increases with the increasing of RHA content in stabilized soil. The CBR increases up to 12% addition of RHA, further addition of RHA decreases the CBR values irrespective of the percentage of lime. The CBR increases to a value of 52.5% from 9.27%, when the percentage of lime is 4%, RHA is 12% and curing period is 7 days as shown in Figure 4.13. Chakraborty et al. (2014) stated that, the CBR increases in relation to the increasing of lime content in soil up to certain amount of lime (6%) with different percentage of RHA, further decreases the CBR with increases of lime content. The result of this study were agreed well with the researcher who conducted by Chakraborty et al. (2014).

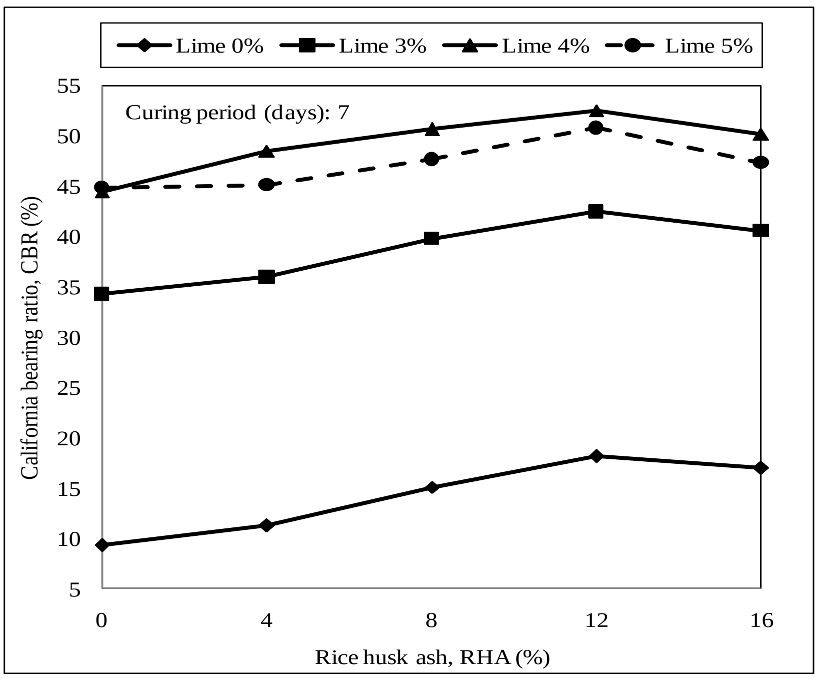


Figure 4.13: Variation of CBR of stabilized soil with RHA and lime at curing period of 7 days.

4.4.2.3 Curing Period of 28 Days

Figure 4.14 shows the variation of CBR of stabilized soil with different percentage of RHA and lime at the curing period of 28 days. It observed that CBR of stabilized soil goes on increasing up to 4% of lime, further decreases with adding lime with soil. For a particular mixing amount of lime content, CBR increases with the increasing of RHA content in stabilized soil. The CBR increases up to 12% addition of RHA, further addition of RHA decreases the CBR values irrespective of the percentage of lime. The CBR increases to a value of 58.41% from 13.43%, when the percentage of lime is 4%, RHA is 12% and curing period is 28 days as shown in Figure 4.14. The results of CBR of stabilized soil with RHA and lime depicted that the optimum content of RHA 12% was considered to get better CBR of stabilized soil for any curing period.

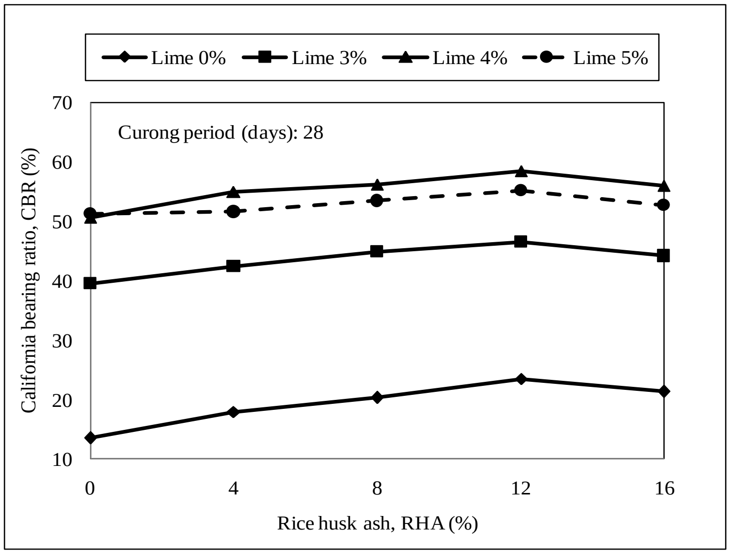


Figure 4.14: Variation of CBR of stabilized soil with RHA and lime at curing period of 28 days.

4.5 Soft Computing Systems

In this study, to predict CBR of stabilized soil, the soft computing systems such as simple linear regression (SLR), multiple linear regression (MLR) through MS excel was performed. In addition, artificial neural network (ANN) with the different training algorithm like Levenberg-Marquardt neural network (LMNN), Bayesian regularization (BRNN) and Scale conjugate gradient neural network (SCGNN) through MATLAB was implemented. Moreover, the support vector machine (SVM) with the different kernel functions like Linear SVM (SVM-L), Quadratic SVM (SVM-Q) and Cubic SVM (SVM-C) was also performed and hence discussed in the following articles.

4.5.1 Simple Linear Regression

In simple linear regression (SLR) analysis, QD (%), lime (%), CP (days), OMC (%) or MDD (kN/m³) as well as observed CBR considered as independent and dependent variables, respectively, of stabilized soil with QD and lime at different curing period of 0, 7 and 28 days. Moreover, RHA (%), lime (%), CP (days), OMC (%) or MDD (kN/m³) as well as observed CBR considered as independent and dependent variables, respectively of stabilized soil with RHA and lime at different curing period of 0, 7 and 28 days. The relationships between predicted CBR and independent variables of stabilized soil with QD and lime as well as RHA and lime is shown in Figure B.1 to B.12 as well as B.12 to B.24, respectively, in Annex-B. The analysis of SLR for stabilized soils is described in the following articles.

4.5.1.1 Stabilized Soil with QD and Lime

In SLR analysis, QD (%), lime (%), CP (days), OMC (%) or MDD (kN/m³) as well as observed CBR considered as independent and dependent variables, respectively, at different curing period of 0, 7 and 28 days. After analysis, the value of R^2 was found at different curing periods depicted in Table 4.5. In Table 4.5, it is observed the best R^2 of 0.596 when independent variable of QD (%) and dependent variable as observed CBR (%) for curing period of 0 days, The best R^2 was found to be 0.722 when independent variable was QD (%) and dependent variable as observed CBR (%) for curing period 7 days. Similarly, for curing period 28 days, the best R^2 was found to be 0.798 with independent variable QD (%) and dependent variable as observed CBR (%).

Table 4.5: Performance analysis of SLR for stabilized soil with QD and lime at various curing period

Group	Dependent variable	Independent variables	R^2 at varying curing period (days)		
			0	7	28
A	Observed CBR	lime (%)	0.037	0.04	0.018
B		QD (%)	0.596	0.722	0.798
C		OMC (%)	0.411	0.505	0.64
D		MDD (kN/m³)	0.507	0.602	0.768

The predicted CBR of stabilized soil was correlated with all the variables independently and it was observed that CBR increases in relation to the increasing of QD (%) shown in Figure 4.15. The SLR analysis provided the best R^2 was 0.798 (shown in Group B) for curing period 28 days when QD (%) have taken as an independent variable. A researcher Bhatt et al. (2014) stated that all the test results consisting of gravel, sand, fine grained, liquid limit, plastic limit, OMC or MDD as independent variable and CBR is dependent variable that’s analyzed by statistical method of least regression. The best linear fitting approximation equations having maximum R^2

values are determined. Where independent variable used as FG, G and MDD separately on one dependent variable is CBR for different equations and plots. The findings of this study are agreed well with the results published by researcher Bhatt et al. (2014).

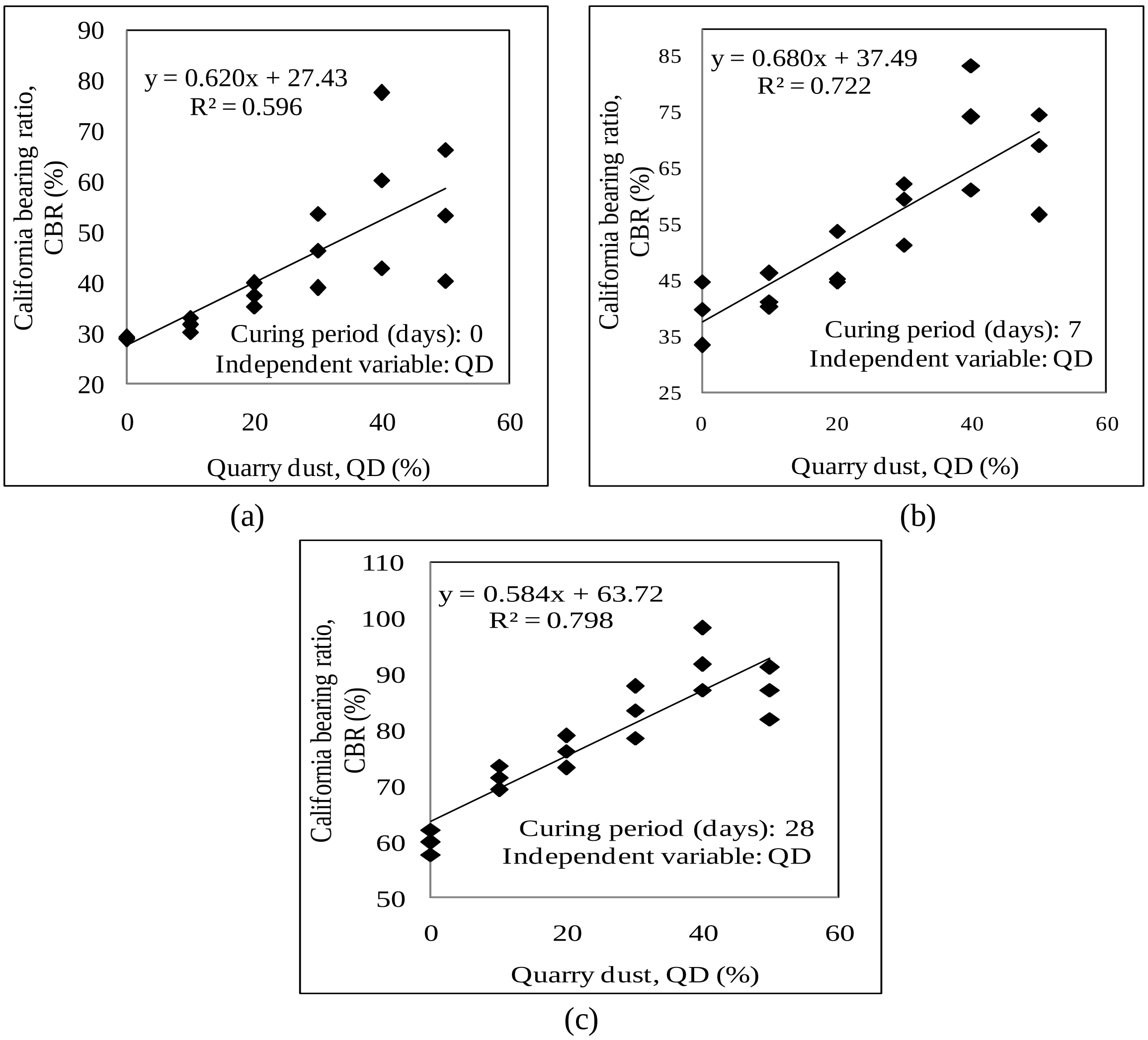


Figure 4.15 Changes of CBR with the variation of QD in stabilized soils.

In SLR analysis, the best linear fitting approximation equations having maximum value of R^2 were determined from the curing periods of 0, 7 and 28 days and can be expressed in Equations 4.1, 4.2 and 4.3, respectively. After analysis of SLR, the developed equations were selected as best based on R^2 for predicting CBR of stabilized soil with QD at varying curing periods provided in Table 4.6. From Table 4.6, it is clear that since best R^2 was found to be 0.798 by

SLR analysis, therefore the best prediction of CBR at 28 days curing period can be determined by the Equation 4.3 where QD (%) has taken as an independent variable.

Table 4.6: Developed equations for predicting CBR of stabilized soils with QD and lime at varying curing periods

Correlation of predicted CBR	Equation No.	R^2	Curing period (days)	Figure No. (Chapter 4)
$CBR = 0.62\ QD + 27.43$	4.1	0596	0	Figure 4.15 (a)
$CBR = 0.68\ QD + 37.49$	4.2	0.722	7	Figure 4.15 (b)
$CBR = 0.584\ QD + 63.72$	4.3	0.798	28	Figure 4.15 (c)

4.5.1.2 Stabilized Soil with RHA and Lime

In SLR analysis, RHA (%), lime (%), CP (days), OMC (%) or MDD (kN/m³) as well as observed CBR considered as independent and dependent variables, respectively at different curing period 0, 7 and 28 days. After analysis, the value of R^2 was found at different curing periods shown in Table 4.7. From Table 4.7 it is observed that for 0 days curing the best R^2 is found to be 0.905 when independent variable is Lime (%) and dependent variable as observed CBR (%). For curing period of 7 days, the best R^2 was found to be 0.901 when independent variable is Lime (%) and dependent variable as observed CBR (%).

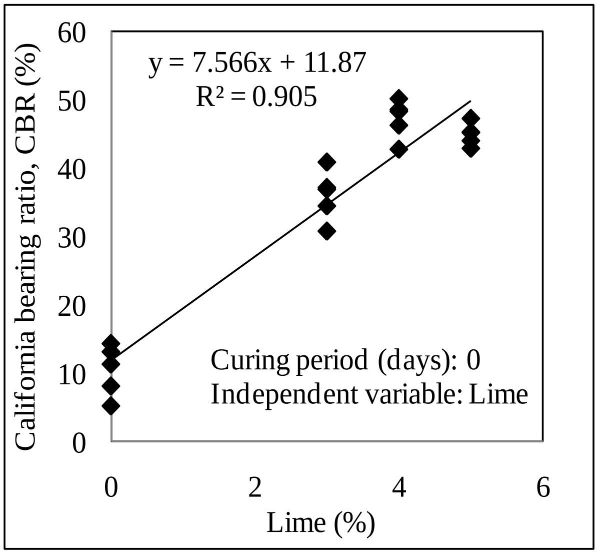
Table 4.7: Performance analysis of SLR for stabilized soil with RHA and lime at various curing period

Group	Dependent variable	Independent variable	R^2 at varying curing period (days)		
			0	7	28
A	Observed CBR	lime (%)	0.905	0.901	0.908
B		RHA (%)	0.023	0.028	0.018
C		OMC (%)	0.33	0.343	0.319
D		MDD (kN/m³)	0.284	0.297	0.269

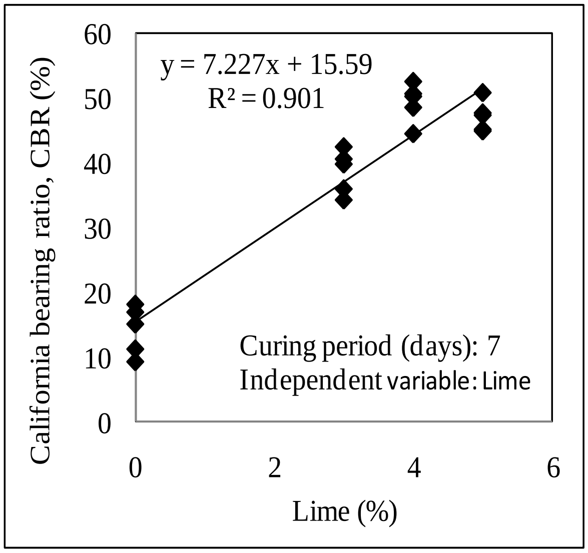
For curing period of 28 days, the best R^2 was found to be 0.908 when independent variable is also Lime (%) and dependent variable as observed CBR (%). Moreover it has been found out the R^2 value basis on the equation is

$$y = c + dx \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.4)$$

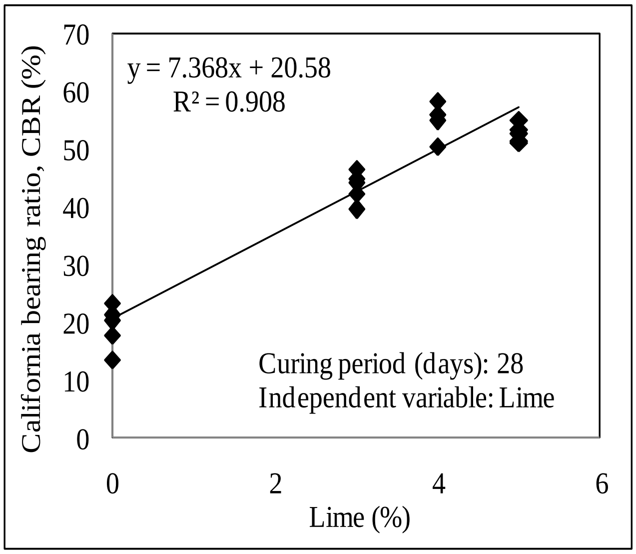
Figure 4.16 shown that, the y is predicted CBR, x is independent variable (Lime), d is the slope of the line and c is the intercept, where the line cuts the y axis.



(a)



(b)



(c)

Figure 4.16: Changes of CBR with the variation of Lime (%) in stabilized soils.

The predicted CBR of stabilized soil was correlated with all the variables independently and it was observed that, the CBR increases in relation to the increasing of Lime (%) shown in Figure

4.16. The SLR analysis gives the best R^2 value is 0.908 (shown in group A) for the curing period of 28 days when lime (%) have taken as an independent variable.

In this study, in SLR analysis the best linear fitting approximation equations having maximum value of R^2 were determined from the curing periods of 0, 7 and 28 days and can be expressed in Equations 4.5, 4.6 and 4.7 respectively. After analysis of SLR, the developed equations were selected as best based on R^2 for predicting CBR of stabilized soil with RHA at varying curing periods provided in Table 4.8.

Table 4.8: Developed equations for predicting CBR of stabilized soils with RHA and lime at varying curing periods.

Correlation of predicted CBR	Equation No.	R^2	Curing period (days)	Figure No. (Chapter 4)
$CBR = 7.566\ Lime + 11.87$	4.5	0.905	0	Figure 4.16 (a)
$CBR = 7.227\ Lime + 15.59$	4.6	0.901	7	Figure 4.16 (b)
$CBR = 7.368\ Lime + 20.58$	4.7	0.908	28	Figure 4.16 (c)

From above equations in the Table 4.8 it is clear that, since best R^2 value is 0.908 by SLR analysis, therefore the best prediction value of CBR at 28 days curing period can be determined by using the Equation 4.8 where lime (%) act as an independent variable.

4.5.2 Multiple Linear Regressions

In multiple linear regression (MLR) analysis, QD (%), lime (%), CP (days), OMC (%) and MDD (kN/m^3) as well as observed CBR considered as independent and dependent variables, respectively of stabilized soil with QD and lime at different curing period of 0, 7 and 28 days. Moreover, RHA (%), lime (%), CP (days), OMC (%) and MDD (kN/m^3) as well as observed CBR considered as independent and dependent variables, respectively of stabilized soil with RHA and lime at different curing period of 0, 7 and 28 days. The relationships between Predicted CBR and independent variables of stabilized soil with QD and lime as well as RHA and lime is shown in Figure C.1 to C.24 as well as C.25 to C.48, respectively, in the Annex-C. The analysis of MLR for stabilized soils is described in the following articles.

4.5.2.1 Stabilized Soil with QD and Lime

In MLR analysis, QD (%), lime (%), CP (days), OMC (%) and MDD (kN/m³) as well as observed CBR considered as independent and dependent variables, respectively at different curing period of 0, 7 and 28 days. The results of R^2 by MLR analysis are provided at different curing period in Table 4.9. The values of 0.663, 0.787 and 0.872 were found for R^2 at curing period of 0, 7 and 28 days for the independent variables in group A (QD, lime, CP, OMC, MDD). After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as group B, C, D, E, F, G and H to get best R^2 of stabilized soils with QD and lime (Table 4.9). A research conducted by Bhatt et al. (2014) stated that, MLR analysis identifies the effect of two or more independent variables on dependent variable. The MLR analysis was carried out by taking all the independent variables in consideration at first and thereafter eliminating one or more forming various combinations to get the best R^2. The findings of this study are agreed well with the results postulated by Bhatt et al. (2014).

Table 4.9: Performance analysis of MLR for stabilized soil with QD and lime at various curing period

Group	Dependent variable	Independent variables	R^2 at varying curing period (days)		
			0	7	28
A	Observed CBR	QD, lime, CP, OMC, MDD	0.663	0.787	0.872
B		QD, lime, OMC, MDD	0.663	0.787	0.871
C		Lime, OMC, MDD	0.628	0.741	0.870
D		QD, OMC, MDD	0.663	0.786	0.853
E		QD, lime, OMC	0.651	0.781	0.82
F		QD, lime, MDD	0.640	0.766	0.863
G		QD, lime,	0.633	0.763	0.817
H		OMC, MDD	0.533	0.619	0.792

From Table 4.9, the selected best R^2 was 0.872 at curing period of 28 days in group A (QD, lime, CP, OMC, MDD) as compared to other groups of B, C, D, E, F, G and H. In addition, the predicted model for CBR containing the five variables and giving significant value of R^2 derived by MLR analysis is given by Equation (4.8), where MDD is in (kN/m³) and all other parameters are in %.

$$CBR = -262.723 + 2.332 * Lime - 0.033 * QD + 0 * CP - 0.214 * OMC + 18.839 * MDD$$

$$\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.8) \quad when\ R^2\ is\ 0.872$$

Equation (4.8) can be taken as satisfactory for the prediction of CBR and more reliable equations need to be evolved for better values of R^2. Moreover, the best prediction of CBR at curing period of 28 days can be determined by use this equation.

4.5.2.2 Stabilized Soil with RHA and Lime

In MLR analysis, RHA (%), lime (%), CP (days), OMC (%) and MDD (kN/m³) as well as observed CBR considered as independent and dependent variables, respectively at different curing period of 0, 7 and 28 days. The results of R^2 by MLR analysis are provided at different curing period in Table 4.10. The values of 0.949, 0.950 and 0.946 were found for R^2 at curing period of 0, 7 and 28 days for the independent variable in group A (RHA, lime, CP, OMC, MDD). After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as group B, C, D, E, F, G and H to get best R^2 of stabilized soils with RHA and lime (Table 4.10).

Table 4.10: Performance analysis of MLR for stabilized soil with RHA and lime at various curing period

Group	Dependent variable	Independent variables	R^2 at varying curing period (days)		
			0	7	28
A	Observed CBR	RHA, lime, CP, OMC, MDD	0.949	0.950	0.946
B		RHA, lime, OMC, MDD	0.949	0.949	0.946
C		lime, OMC, MDD	0.925	0.925	0.926
D		RHA, OMC, MDD	0.79	0.79	0.795
E		RHA, lime, OMC	0.93	0.931	0.927
F		RHA, lime, MDD	0.947	0.948	0.946
C		RHA, lime	0.928	0.929	0.927
D		OMC, MDD	0.34	0.351	0.331

From table 4.10 the selected the best R^2 is 0.95 for curing period of 7 days shows as group A (RHA, lime, CP, OMC, MDD) as compared to other B, C, D, E, F, G and H. In addition, the predicted model for CBR containing five variables and giving significant value of R^2 derived by MLR is given by Equations (4.9), where MDD is in (kN/m³) and all other parameters are in %.

$$\mathrm{CBR} = -228.643 + 10.516 * \mathrm{lime} + 2.582 * \mathrm{RHA} + 0 * \mathrm{CP} - 0.366 * \mathrm{OMC} + 13.918 * \mathrm{MDD}$$

.... (4.9) when R^2 is 0.95

Equation (4.9) can be taken as satisfactory for the prediction of CBR and more reliable equations need to be evolved for better values of R^2. Moreover, the best prediction of CBR at curing period of 7 days can be determined by use this equation.

4.5.2.3 Selection of Variables from SLR and MLR

The selected groups containing various independent variables based on R^2 from SLR and MLR analysis is provided in Table 4.11. The result of SLR depicts that the independent variable such as QD has greatly influenced the predicted CBR of stabilized soil with QD and lime. In addition, lime has greatly influenced the predicted CBR of stabilized soil with RHA and lime. Moreover, The results of MLR reveals that the independent variables like QD, Lime, CP, OMC and MDD as well as RHA, lime, CP, OMC and MDD has greatly influenced the predicted CBR of stabilized soil with QD as well as RHA with lime, respectively. The observed CBR and selected independent variables can be expressed by a series of developed equation of reasonable degree of accuracy and judgement from SLR and MLR analysis. These developed equations may be proposed to predict CBR of stabilized soils by knowing others independents variables.

Table 4.11: Selected groups from SLR and MLR

Stabilization of soil with	Selected independent variables		R^2 for selected independent variables /Models	
	SLR	MLR	SLR	MLR
QD and lime	QD	QD, lime, CP, OMC and MDD	0.798	0.872
RHA and lime	lime	RHA, lime, CP, OMC and MDD	0.908	0.95

4.5.3 Artificial Neural Network

In this study, ANN was performed on stabilized soil with different admixtures at varying curing periods. The ANN was implemented to select the best fitted model such as Levenberg-Marquardt neural network (LMNN), Bayesian regularization neural network (BRNN) and scaled conjugate gradient neural network (SCGNN). The number of hidden layers and neurons were varied to find out the best structure of ANN modeling. In order to compute the most appropriate ANN architecture for modeling, the number of neurons in the hidden were tried to predict the best

CBR of stabilized soils. The number of hidden neurons in hidden layer was varied as 2, 4, 6, 8, 10, 12, 15, 20, 25 and 30. In this study, the hidden layer ranges from 2 to 30 provided the good results of R^2. Moreover, when increased the number of neurons in hidden layer from 2 to 10 in interval 2, then increase R^2 consequently. Thereafter, R^2 decreases with increases number of neuron as 12, 15, 20, 25, and 30, respectively, shown in Figure 4.17.

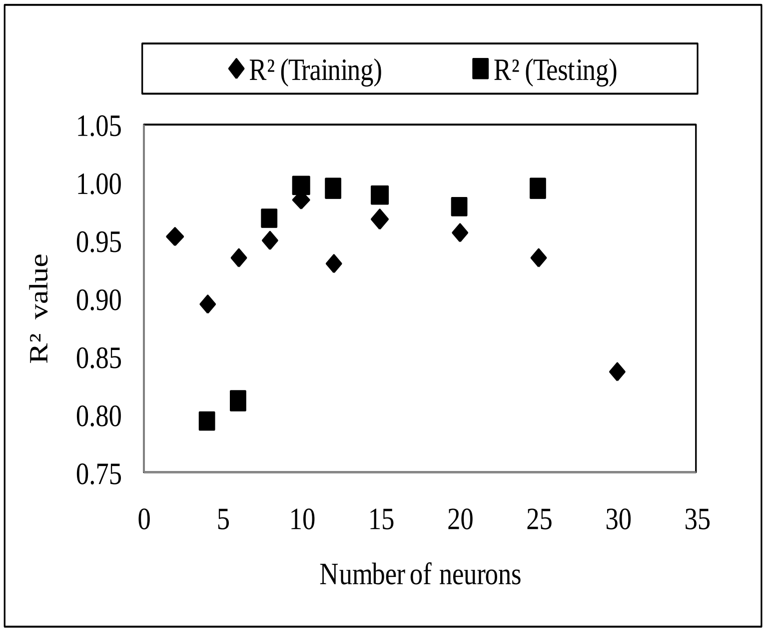


Figure 4.17: Effect of number of neuron in hidden layer of ANN modelling.

Figure 4.17 depicts R^2 is higher for training and testing than that of other R^2 when neuron number used as 10 for LMNN at the curing period of 0 day. Therefore, in this study, in order to compute most appropriate ANN architecture for modeling of different algorithm like LMNN, BRNN and SCGNN, the number of neurons 10 was used to predict best CBR of stabilized soil. A research conducted by Rajkumar and Meenambal (2017) stated that numbers of neurons in hidden layer varies from 2, 4, 6, 8, 10, 15, 20, 25 and 30, respectively. It has been performed the best number of R^2 around 10 by relationship between number of neuron and R^2 value. So the findings of this study have most consistency with researcher and agreed well with the results postulated by Rajkumar and Meenambal (2017). Further, the different algorithms like LMNN, BRNN and SCGNN of ANN was performed with the selected number of 10 hidden neurons and hence discussed in the following articles.

4.5.3.1 Stabilized Soil with QD and Lime

In this study, the algorithms of LMNN, BRNN and SCGNN through ANN model has been evaluated based on R^2 and OR to predict the CBR of stabilized soil with QD and lime. In ANN analysis, QD (%), lime (%), CP (days), OMC (%) and MDD (kN/m^3) as well as CBR (%) were considered as independent and dependent variable, respectively. To get the best performance of LMNN, BRNN and SCGNN, it has been eliminated one or more independently and rearranged at various combinations. According to Bhatt et al. (2014) in ANN analysis, the number of input (independent variable) such as Gravel, sand, fine grained, LL, PL, OMC and MDD, changes from seven to two and the target (dependent variable) as observed CBR. The findings of this study agreed well with the results postulated by Bhatt et al. (2014).

4.5.3.1.1 Analysis of LMNN

The results of OR and R^2 of LMNN analysis are provided in Table 4.12. The values of 1.231 and 0.987 were found for OR and R^2, respectively, for the independent variable in group A (QD, lime, CP, OMC, MDD). In addition, the values of 0.769 and 0.966 were found for OR and R^2 respectively, for the independent variables in group B (QD, lime, OMC and MDD). After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as group C, D, E, F, G and H to get best R^2 of stabilized soils with QD and lime (Table 4.12).

Table 4.12: Performance of LMNN for stabilized soil with QD and lime

Group	Dependent variable	Independent variables	Mean square error (MSE)		Over fitting ratio (OR)	Determination coefficient (R^2)
			Training	Testing		
A	Observed CBR	QD, lime, CP, OMC, MDD	8.415	12.750	1.231	0.987
B		QD, lime, OMC, MDD	5.937	3.510	0.769	0.966
C		lime, OMC, MDD	4.218	3.293	0.884	0.945
D		QD, OMC, MDD	5.972	3.612	0.778	0.984
E		QD, lime, OMC	2.198	2.882	1.145	0.992
F		QD, lime, MDD	1.857	2.566	1.175	0.987
G		QD, lime	12.937	4.681	0.602	0.961
H		OMC, MDD	10.091	27.968	1.665	0.840

From Table 4.12, it can be observed that the group E (QD, lime and OMC) showed the best R^2 with 0.992 which is almost close to 1 with its best OR 1.145 (also close to 1). Therefore, group E (QD, lime and OMC) was considered as best of LMNN as compared to other groups of A, B, C, D, F, G and H. A research conducted by Bhatt et al. (2014) stated that in the five different models the number of input as independent variables changes from seven to two and the target (dependent variable) was CBR as observed CBR. As well as the best model select depend on its OR and R^2. The findings of this study are agreed well with the results postulated by Bhatt et al. (2014).

4.5.3.1.2 Analysis of BRNN

The results of OR and R^2 of BRNN analysis are provided in Table 4.13. The values of 1.386 and 0.941were found for OR and R^2, respectively, for the independent variable in group A (QD, lime, CP, OMC, MDD). After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as group B, C, D, E, F, G and H to get best R^2 of stabilized soils with QD and lime (Table 4.13). From Table 4.13, it can be observed that the group D (QD, OMC and MDD) showed the best R^2 with 0.987 which is almost close to 1 with its best OR 1.282 (also close to 1). Therefore, group D (QD, OMC and MDD) is considered as best of BRNN as compared to A, B, C, E, F, G and H.

Table 4.13: Performance of BRNN for stabilized soil with QD and lime

Group	Dependent variable	Independent variables	Mean square error (MSE)		Over fitting ratio (OR)	Determination coefficient (R^2)
			Training	Testing		
A	Observed CBR	QD, lime, CP, OMC, MDD	10.831	20.804	1.386	0.941
B		QD, lime, OMC, MDD	11.893	4.905	0.642	0.937
C		lime, OMC, MDD	15.043	4.377	0.539	0.930
D		QD, OMC, MDD	3.553	5.839	1.282	0.987
E		QD, lime, OMC	8.619	15.555	1.343	0.940
F		QD, lime, MDD	16.056	30.945	1.388	0.870
G		QD, lime	8.485	16.002	1.373	0.933
H		OMC, MDD	13.933	33.257	1.545	0.871

4.5.3.1.3 Analysis of SCGNN

The results of OR and R^2 of SCGNN analysis are provided in Table 4.14. The values of 1.254 and 0.960 were found for OR and R^2, respectively, for the independent variable in group A (QD, lime, CP, OMC, MDD). After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as group B, C, D, E, F, G and H to get best R^2 of stabilized soils with QD and lime (Table 4.14). From Table 4.13, it can be observed that the group E (QD, lime and OMC) showed the best R^2 with 0.995 which is almost close to 1 with its best OR 0.924 (also close to 1). Therefore, group E (QD, lime and OMC) is considered as best of SCGNN as compared to A, B, C, D, F, G and H.

Table 4.14: Performance of SCGNN for stabilized soil with QD and lime

Group	Dependent variable	Independent variables	Mean square error (MSE)		Over fitting ratio (OR)	Determination coefficient (R^2)
			Training	Testing		
A	Observed CBR	QD, lime, CP, OMC, MDD	3.459	5.436	1.254	0.960
B		QD, lime, OMC, MDD	2.768	4.792	1.316	0.975
C		lime, OMC, MDD	9.421	12.707	1.161	0.932
D		QD, OMC, MDD	5.755	7.978	1.177	0.942
E		QD, lime, OMC	5.929	5.056	0.924	0.995
F		QD, lime, MDD	7.06	5.359	0.871	0.991
G		QD, lime	4.993	8.922	1.337	0.959
H		OMC, MDD	8.599	12.783	1.219	0.842

4.5.3.1.4 Modelling ANN for Curing Period of 0 Days

The results of OR and R^2 from ANN analysis at curing period of 0 days are provided in Table 4.15. The values of 1.275 and 0.948 were found for OR and R^2, respectively, for the independent variables in group A (QD, lime, CP, OMC, MDD). After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as group B, C, D, E, F, G and H to get best R^2 of stabilized soils with QD and lime (Table 4.15). From Table 4.15, it can be observed that the group E (QD, lime and OMC) showed the best R^2 with 0.992 which is almost close to 1 with its best OR 1.145 (also close to 1) at curing period of 0 days. Therefore, group E (QD, lime and OMC) is considered as best of LMNN as compared to A, B, C, D, F, G and H.

Table 4.15: Performance of different algorithms through ANN at curing period of 0 days

Group	Dependent variable	Independent variables	Neural network	Mean square error (MSE)		Over fitting ratio (OR)	Determination coefficient (R^2)
				Training	Testing		
A	Observed CBR	QD, lime, CP, OMC, MDD	LMNN	7.117	11.568	1.275	0.948
B		QD, lime, OMC, MDD	LMNN	3.626	6.922	1.382	0.951
C		lime, OMC, MDD	SCGNN	7.421	10.707	1.201	0.932
D		QD, OMC, MDD	BRNN	3.553	5.139	1.203	0.987
E		QD, lime, OMC	LMNN	2.198	2.882	1.145	0.992
F		QD, lime, MDD	SCGNN	7.06	4.359	0.786	0.991
G		QD, lime	SCGNN	4.993	8.922	1.337	0.959
H		OMC, MDD	BRNN	41.624	13.706	0.574	0.816

4.5.3.1.5 Modeling ANN for Curing Period of 7 Days

Table 4.16: Performance of different algorithms through ANN at curing period of 7 days

Group	Dependent variable	Independent variables	Neural network	Mean square error (MSE)		Over fitting ratio (OR)	Determination coefficient (R^2)
				Training	Testing		
A	Observed CBR	QD, lime, CP, OMC, MDD	LMNN	6.414	8.750	1.168	0.987
B		QD, lime, OMC, MDD	SCGNN	5.768	3.792	0.811	0.975
C		lime, OMC, MDD	BRNN	11.043	4.377	0.63	0.93
D		QD, OMC, MDD	LMNN	5.079	9.608	1.375	0.966
E		QD, lime, OMC	SCGNN	5.929	5.056	0.924	0.995
F		QD, lime, MDD	LMNN	2.657	3.866	1.206	0.987
G		QD, lime	LMNN	8.937	4.681	0.724	0.961
H		OMC, MDD	LMNN	8.091	17.968	1.490	0.84

The results of OR and R^2 from ANN analysis at curing period of 7 days are provided in Table 4.16. The values of 1.168 and 0.987 were found for OR and R^2, respectively, for the independent variables in group A (QD, lime, CP, OMC, MDD). After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as group B, C, D, E, F, G and H to get best R^2 of stabilized soils with QD and lime (Table 4.16). From Table 4.16, it can be observed that the group E (QD, lime and OMC) showed the best R^2 with 0.995 which is almost close to 1 with its best OR 0.924 (also close to 1) at curing period of 7 days. Therefore, group E (QD, lime and OMC) is considered as best of SCGNN as compared to A, B, C, D, F, G and H.

4.5.3.1.6 Modeling ANN for Curing Period of 28 Days

The results of OR and R^2 from ANN analysis at curing period of 28 days are provided in Table 4.17. The values of 1.382 and 0.978 were found for OR and R^2, respectively, for the independent variables in group A (QD, lime, CP, OMC, MDD).

Table 4.17: Performance of different algorithms through ANN at curing period of 28 days

Group	Dependent variable	Independent variables	Neural network	Mean square error (MSE)		Over fitting ratio (OR)	Determination coefficient (R^2)
				Training	Testing		
A	Observed CBR	QD, lime, CP, OMC, MDD	LMNN	2.532	4.833	1.382	0.978
B		QD, lime, OMC, MDD	LMNN	5.937	3.510	0.769	0.966
C		lime, OMC, MDD	LMNN	4.8176	2.293	0.69	0.945
D		QD, OMC, MDD	LMNN	5.992	3.112	0.721	0.984
E		QD, lime, OMC	LMNN	3.784	6.446	1.305	0.963
F		QD, lime, MDD	LMNN	1.736	2.755	1.26	0.987
G		QD, lime	LMNN	4.476	8.533	1.381	0.957
H		OMC, MDD	BRNN	13.933	33.257	1.545	0.871

After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as group B, C, D, E, F, G and H to get best R^2 of stabilized soils with QD and lime (Table 4.17). From Table 4.17, it can be observed that the group F (QD, lime and MDD) showed the best R^2 with 0.987 which is almost close to 1 with its best OR 1.26 (also close to 1) at curing period of 28 days. Therefore, group F (QD, lime and MDD) is considered as best of LMNN as compared to A, B, C, D, E, G and H.

4.5.3.2 Stabilized Soil with RHA and Lime

In this analysis, the algorithms of LMNN, BRNN and SCGNN through ANN model has been evaluated based on R^2 and OR to predict the CBR of stabilized soil with RHA and lime. In ANN analysis, RHA (%), lime (%), CP (days), OMC (%) and MDD (kN/m^3) as well as CBR (%) were considered as independent and dependent variable, respectively. To get the best performance of LMNN, BRNN and SCGNN, it has been eliminated one or more independently variable and rearranged at various combinations. According to Bhatt et al. (2014) in ANN analysis, the number of input (independent variable) such as Gravel, sand, fine grained, LL, PL, OMC and MDD, changes from seven to two and the target (dependent variable) as observed CBR. The findings of this study have consistency with the researcher and agreed well with the results postulated by Bhatt et al. (2014).

4.5.3.2.1 Analysis of LMNN

The results of OR and R^2 of LMNN analysis are provided in Table 4.18. The values of 1.371 and 0.988 were found for OR and R^2, respectively, for the independent variable in group A (RHA, lime, CP, OMC, MDD). In addition, the values of 0.789 and 0.981 were found for OR and R^2 respectively, for the independent variables in group B (RHA, lime, OMC, MDD). After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as group C, D, E, F, G and H to get best R^2 of stabilized soils with RHA and lime (Table 4.18). From Table 4.18, it can be observed that the group C (lime, OMC and MDD) showed the best R^2 with 0.995 which is almost close to 1 with its best OR 1.171 (also close to 1). Therefore, group C (lime, OMC and MDD) is considered as best of LMNN as compared to A, B, D, E, F, G and H. A research conducted by Bhatt et al. (2014) stated that in the five different models the number of input as independent variables change from seven to two and the target (dependent variable) is CBR as observed CBR. As well as the best model select depend on their OR and R^2. The findings of this study are agreed well with the results postulated by Bhatt et al. (2014).

Table 4.18: Performance of LMNN for stabilized soil with RHA and lime

Group	Dependent variable	Independent variables	Mean square error (MSE)		Over fitting ratio (OR)	Determination coefficient (R^2)
			Training	Testing		
A	Observed CBR	RHA, lime, CP, OMC, MDD	2.263	4.251	1.371	0.988
B		RHA, lime, OMC, MDD	6.826	4.247	0.789	0.981
C		lime, OMC, MDD	3.381	4.635	1.171	0.995
D		RHA, OMC, MDD	5.956	1.79	0.548	0.973
E		RHA, lime, OMC	4.859	2.875	0.77	0.978
F		RHA, lime, MDD	2.025	2.918	1.20	0.992
G		RHA, lime	3.979	2.232	0.749	0.988
H		OMC, MDD	72.367	232.129	1.791	0.634

4.5.3.2.2 Analysis of BRNN

The results of OR and R^2 of BRNN analysis are provided in Table 4.19. The values of 1.103 and 0.998 were found for OR and R^2, respectively, for the independent variable in group A (RHA, lime, CP, OMC, MDD). After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as group B, C, D, E, F, G and H to get best R^2 of stabilized soils with RHA and lime (Table 4.19). From Table 4.19, it can be observed that the group A (RHA, lime, CP, OMC, MDD) showed the best R^2 with 0.998 which is almost close to 1 with its best OR 1.103 (also close to 1). Therefore, group A (RHA, lime, CP, OMC, MDD) is considered as best of LMNN as compared to B, C, D, E, F, G and H.

Table 4.19: Performance of BRNN for stabilized soil with RHA and lime

Group	Dependent variable	Independent variables	Mean square error (MSE)		Over fitting ratio (OR)	Determination coefficient (R^2)
			Training	Testing		
A	Observed CBR	RHA, lime, CP, OMC, MDD	2.32	2.823	1.103	0.998
B		RHA, lime, OMC, MDD	4.564	3.441	0.868	0.996
C		lime, OMC, MDD	1.849	2.83	1.237	0.992
D		RHA, OMC, MDD	12.398	6.847	0.743	0.948
E		RHA, lime, OMC	7.458	5.160	0.832	0.997
F		RHA, lime, MDD	7.117	4.268	0.774	0.969
G		RHA, lime	7.4	4.174	0.751	0.969
H		OMC, MDD	1110.034	144.226	0.360	0.444

4.5.3.2.3 Analysis of SCGNN

The results of OR and R^2 of BRNN analysis are provided in Table 4.20. The values of 1.304 and 0.983 were found for OR and R^2, respectively, for the independent variable in group A (RHA, lime, CP, OMC, MDD). After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as group B, C, D, E, F, G and H to get best R^2 of stabilized soils with RHA and lime (Table 4.20). From Table 4.20, it can be observed that the group G (RHA and lime) showed the best R^2 with 0.992 which is almost close to 1 with its best OR 1.261 (also close to 1). Therefore, group G (RHA and lime) is considered as best of SCGNN as compared to A, B, C, D, E, F and H.

Table 4.20: Performance of SCGNN for stabilized soil with RHA and lime

Group	Dependent variable	Independent variables	Mean square error (MSE)		Over fitting ratio (OR)	Determination coefficient (R^2)
			Training	Testing		
A	Observed CBR	RHA, lime, CP, OMC, MDD	3.683	6.263	1.304	0.983
B		RHA, lime, OMC, MDD	4.537	8.314	1.354	0.980
C		lime, OMC, MDD	7.993	3.74	0.684	0.987
D		RHA, OMC, MDD	16.29	8.229	0.711	0.937
E		RHA, lime, OMC	1.469	2.684	1.352	0.991
F		RHA, lime, MDD	2.736	5.063	1.360	0.974
G		RHA, lime	1.307	2.079	1.261	0.992
H		OMC, MDD	89.892	37.609	0.647	0.465

4.5.3.2.4 Modeling ANN for Curing Period of 0 Days

The results of OR and R^2 from ANN analysis at curing period of 0 days are provided in Table 4.21. The values of 1.103 and 0.998 were found for OR and R^2, respectively, for the independent variables in group A (RHA, lime, CP, OMC, MDD). After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as group B, C, D, E, F, G and H to get best R^2 of stabilized soils with RHA and lime (Table 4.21). From Table 4.21, it can be observed that the group A (RHA, lime, CP, OMC, MDD) showed the best R^2 with 0.998 which is almost close to 1 with its best OR 1.103 (also close to 1) at curing period of 0 days. Therefore, group A (RHA, lime, CP, OMC, MDD) was considered as best for BRNN as compared to other groups of B, C, D, E, F, G and H.

Table 4.21: Performance of different algorithms through ANN at curing period of 0 days

Group	Dependent variable	Independent variables	Neural network	Mean square error (MSE)		Over fitting ratio (OR)	Determination coefficient (R^2)
				Training	Testing		
A	Observed CBR	RHA, lime, CP, OMC, MDD	BRNN	2.32	2.824	1.103	0.998
B		RHA, lime, OMC, MDD	BRNN	1.13	1.57	1.179	0.994
C		lime, OMC, MDD	LMNN	1.233	1.791	1.205	0.994
D		RHA, OMC, MDD	LMNN	11.373	7.802	0.828	0.95
E		RHA, lime, OMC	BRNN	7.458	5.76	0.879	0.997
F		RHA, lime, MDD	LMNN	3.944	5.824	1.215	0.984
G		RHA, lime	SCGNN	1.307	2.179	1.291	0.992
H		OMC, MDD	LMNN	42.519	98.119	1.519	0.497

4.5.3.2.5 Modeling ANN for Curing Period of 7 Days

The results of OR and R^2 from ANN analysis at curing period of 7 days are provided in Table 4.22. The values of 1.177 and 0.997 were found for OR and R^2, respectively, for the independent variables in group A (RHA, lime, CP, OMC, MDD). After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as group B, C, D, E, F, G and H to get best R^2 of stabilized soils with RHA and lime (Table 4.22). From Table 4.22, it can be observed that the group A (RHA, lime, CP, OMC, MDD) showed the best R^2 with 0.997 which is almost close to 1 with its best OR 1.177 (also close to 1) at curing period of 7 days. Therefore, group A (RHA, lime, CP, OMC, MDD) is considered as best of BRNN as compared to B, C, D, E, F, G and H.

Table 4.22: Performance of different algorithms through ANN at curing period of 7 days

Group	Dependent variable	Independent variables	Neural network	Mean square error (MSE)		Over fitting ratio (OR)	Determination coefficient (R^2)
				Training	Testing		
A	Observed CBR	RHA, lime, CP, OMC, MDD	BRNN	2.543	3.526	1.177	0.997
B		RHA, lime, OMC, MDD	BRNN	4.564	3.041	0.816	0.996
C		lime, OMC, MDD	BRNN	1.680	1.108	0.812	0.992
D		RHA, OMC, MDD	LMNN	5.956	1.99	0.578	0.973
E		RHA, lime, OMC	BRNN	2.285	4.28	1.369	0.988
F		RHA, lime, MDD	LMNN	2.91	1.725	0.770	0.986
G		RHA, lime	LMNN	2.943	5.012	1.305	0.985
H		OMC, MDD	SCGNN	76.114	188.456	1.574	0.40

4.5.3.2.6 Modeling ANN for Curing Period of 28 Days

The results of OR and R^2 from ANN analysis at curing period of 28 days are provided in Table 4.23. The values of 1.214 and 0.996 were found for OR and R^2, respectively, for the independent variables in group A (RHA, lime, CP, OMC, MDD). After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as groups B, C, D, E, F, G and H to get best R^2 of stabilized soils with RHA and lime (Table 4.23). From Table 4.23, it can be observed that the group A (RHA, lime, CP, OMC, MDD) showed the best R^2 with 0.996 which is almost close to 1 with its best OR 1.214 (also close to 1) at curing period of 0 days. Therefore, group A (RHA, lime, CP, OMC, MDD) is considered as best of BRNN as compared to B, C, D, E, F, G and H.

Table 4.23: Performance of different algorithms through ANN at curing period of 28 days

Group	Dependent variable	Independent variables	Neural network	Mean square error (MSE)		Over fitting ratio (OR)	Determination coefficient (R^2)
				Training	Testing		
A	Observed CBR	RHA, lime, CP, OMC, MDD	BRNN	2.666	3.932	1.214	0.996
B		RHA, lime, OMC, MDD	BRNN	1.855	2.922	1.255	0.991
C		lime, OMC, MDD	LMNN	3.381	5.635	1.291	0.995
D		RHA, OMC, MDD	BRNN	10.263	21.877	1.46	0.946
E		RHA, lime, OMC	BRNN	1.554	3.663	1.535	0.986
F		RHA, lime, MDD	LMNN	3.025	4.938	1.278	0.992
G		RHA, lime	LMNN	2.179	1.132	0.721	0.988
H		OMC, MDD	LMNN	72.368	232.13	1.791	0.634

4.5.3.3 Selection of Model from ANN

In this study, the models of ANN were selected based on different algorithms like LMNN, BRNN and SCGNN as well as varying curing periods 0, 7 and 28 days for predicting CBR of stabilized soils and hence discussed in the following articles.

4.5.3.3.1 Based on Model

The results of MSE, OR and R^2 for algorithms of ANN for the prediction of CBR of stabilized soil with QD and lime is provided in Table 4.24. In this analysis, the model for stabilized soil with QD and lime for various curing periods was selected based on R^2 shown in Figure 4.18.

Table 4.24: Performance analysis of different models of ANN for stabilized soil with QD and lime

Selected group	Dependent variable	Independent variables	Selected model	Mean square error (MSE)		Over fitting ratio (OR)	Determination coefficient (R^2)
				Training	Testing		
E	Observed CBR	QD, lime, OMC	LMNN	2.198	2.882	1.145	0.992
D		QD, OMC, MDD	BRNN	3.553	5.839	1.282	0.987
E		QD, lime, OMC	SCGNN	5.929	5.056	0.924	0.995

The model SCGNN showed comparatively the higher value of R^2 with 0.995 as well as OR with 0.924 (both tends to 1) than that of LMNN and BRNN models. Therefore, the model SCGNN (Group E; QD, lime and OMC) was selected the best fitted model as compared to LMNN and BRNN for the prediction of CBR of stabilized soil with QD and lime.

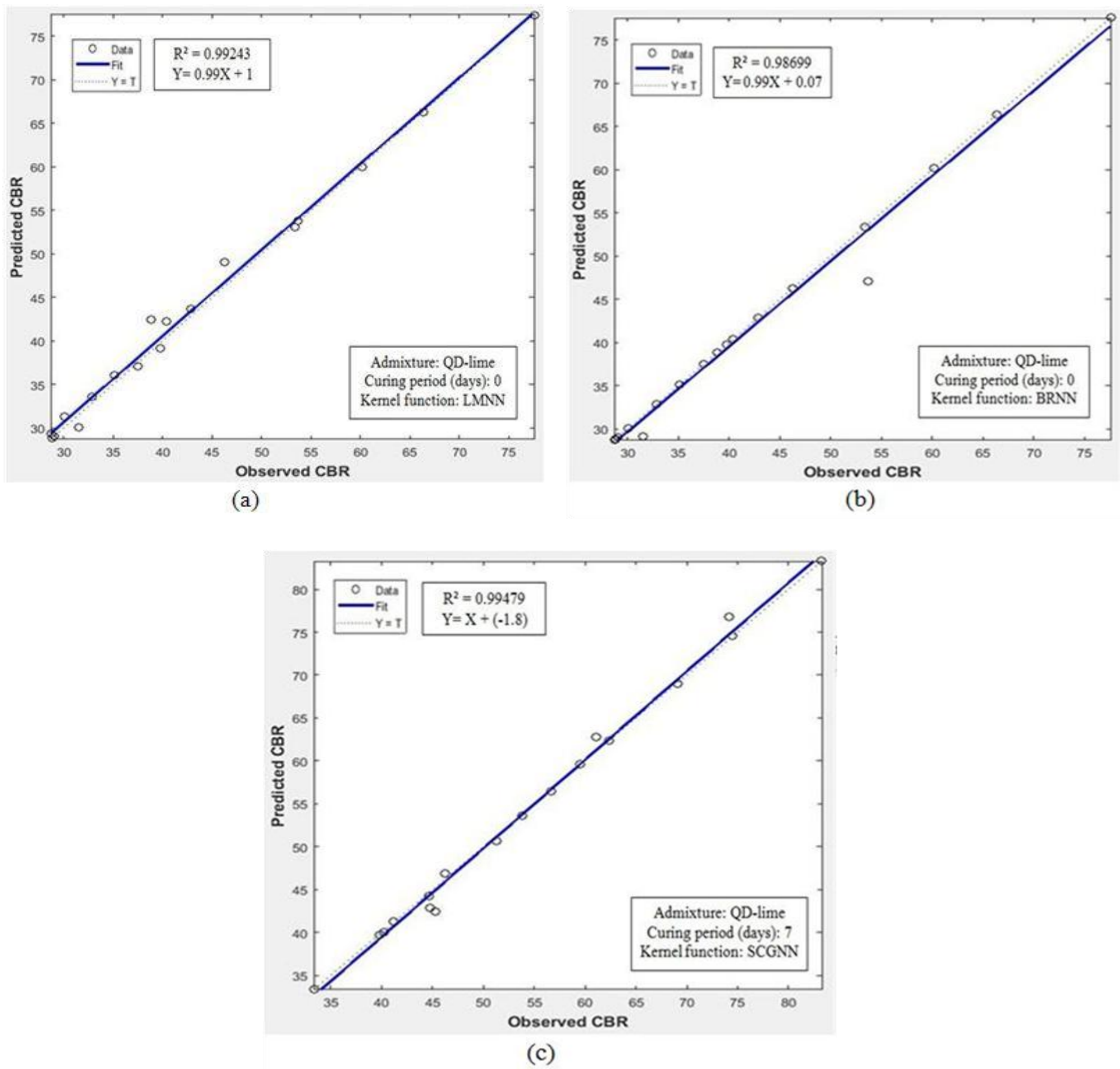


Figure 4.18: Correlation between observed and predicted CBR of (a) LMNN (b) BRNN and (c) SCGNN.

In this analysis, The R^2 value is close to 1 indicates a close relationship between observed and Predicted CBR for LMNN, BRNN and SCGNN model is shown in Figure 4.18. Also Figure 4.18

shows that, the best R^2 was 0.995 obtain from SCGNN analysis and it means of all data are very close to the fitted line due to the best value of R^2 after modeling of SCGNN.

In contrast, the results of MSE, OR and R^2 for models LMNN, BRNN and SCGNN from ANN analysis for the prediction of CBR of stabilized soil with RHA and lime is provided in Table 4.25. In this analysis, the R^2 value is close to 1 indicates a close relationship between observed and predicted CBR for LMNN, BRNN and SCGNN model is shown in Figure D.1 in Annex D. The best R^2 with 0.998 was obtained from BRNN analysis and it means of all data are very close to the fitted line due to the best value of R^2 after modeling of BRNN shown in Figure D.2 in Annex D. The model BRNN showed comparatively the higher value of R^2 with 0.998 as well as OR with 1.103 (both tends to 1) than that of LMNN and SCGNN (Table 4.25). Therefore, BRNN (Group B; RHA, lime, CP, OMC and MDD) was selected the best fitted model as compared to LMNN and SCGNN for the prediction of CBR of stabilized soil with RHA and lime.

Table 4.25: Performance analysis of different models of ANN for stabilized soil with RHA and lime

Selected group	Dependent variable	Independent variables	Selected model	Mean square error (MSE)		Over fitting ratio (OR)	Determination coefficient (R^2)
				Training	Testing		
C	Observed CBR	lime, OMC, MDD	LMNN	3.381	4.635	1.171	0.995
A		RHA, lime, CP, OMC, MDD	BRNN	2.32	2.823	1.103	0.998
G		RHA, lime	SCGNN	1.307	2.079	1.261	0.992

4.5.3.3.2 Based on Curing Period

The results of MSE, OR and R^2 for selected models of ANN for the prediction of CBR of stabilized soil with QD and lime at curing periods 0, 7 and 28 days is provided in Table 4.26. The results of ANN depicts that LMNN, SCGNN and LMNN were the selected models for curing periods 0, 7 and 28 days, respectively for stabilized soil with QD and lime (Table 4.26). The model SCGNN showed the highest R^2 with 0.995 as well as OR with 0.924 (both tends to 1) at curing period 7 days for the prediction of CBR of stabilized soil (Table 4.26). In addition, the model SCGNN (group E; QD, lime and OMC) was selected as the best fitted model for curing period 7 days as compared to both of LMNN for the prediction of CBR of stabilized soil with

QD and lime. Moreover, the R^2 of the best selected model SCGNN of ANN for stabilized soil with QD and lime at curing period 7 days is shown in Figure 4.19. Therefore, Figure 4.19 reveals that the R^2 value of 0.99972, 0.99417, 0.99922 and 0.99479 for training, validation, testing and the all data set, respectively.

Table 4.26: Performance analysis of different models of ANN for stabilized soil with QD and lime

Selected group	Dependent variable	Independent variables	Selected model	Curing period (days)	Mean square error (MSE)		Over fitting ratio (OR)	Determination coefficient (R^2)
					Training	Testing		
E	Observed CBR	QD, lime, OMC	LMNN	0	2.198	2.882	1.1452	0.992
E		QD, lime, OMC	SCGNN	7	5.929	5.056	0.924	0.995
F		QD, lime, MDD	LMNN	28	1.736	2.755	1.26	0.987

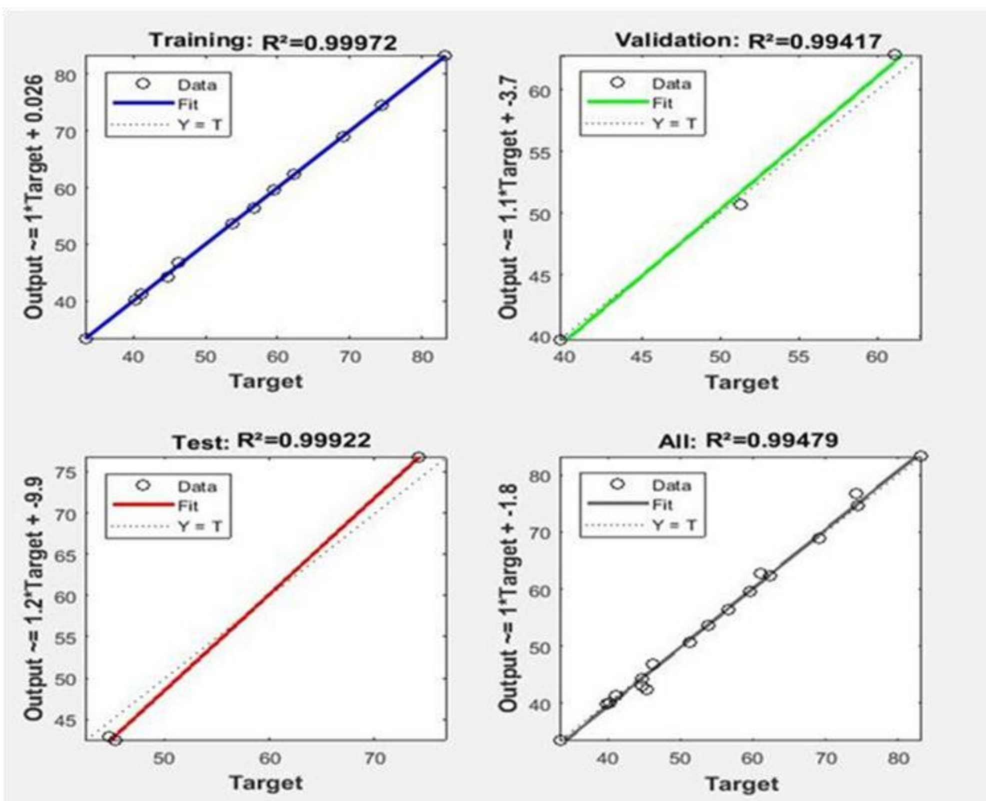


Figure 4.19: Regression coefficient of SCGNN from ANN of sstabilized soil with QD and lime.

The correlations between observed and predicted CBR of stabilized soil with QD and lime for the selected best models LMNN, SCGNN and LMNN of ANN at varying curing periods 0, 7 and 28 days, respectively, shown in Figure 4.20. From Figure 4.20, the best R^2 was obtained 0.995 after SCGNN analysis (Figure 4.20b) at curing period 7 days as compared to other curing periods 0 and 28 days. It means almost all the data are very close to fitted line in case of SCGNN model at curing period 7 days. The R^2 value is close to 1 indicating a close relationship by best fitted line between observed and predicted CBR.

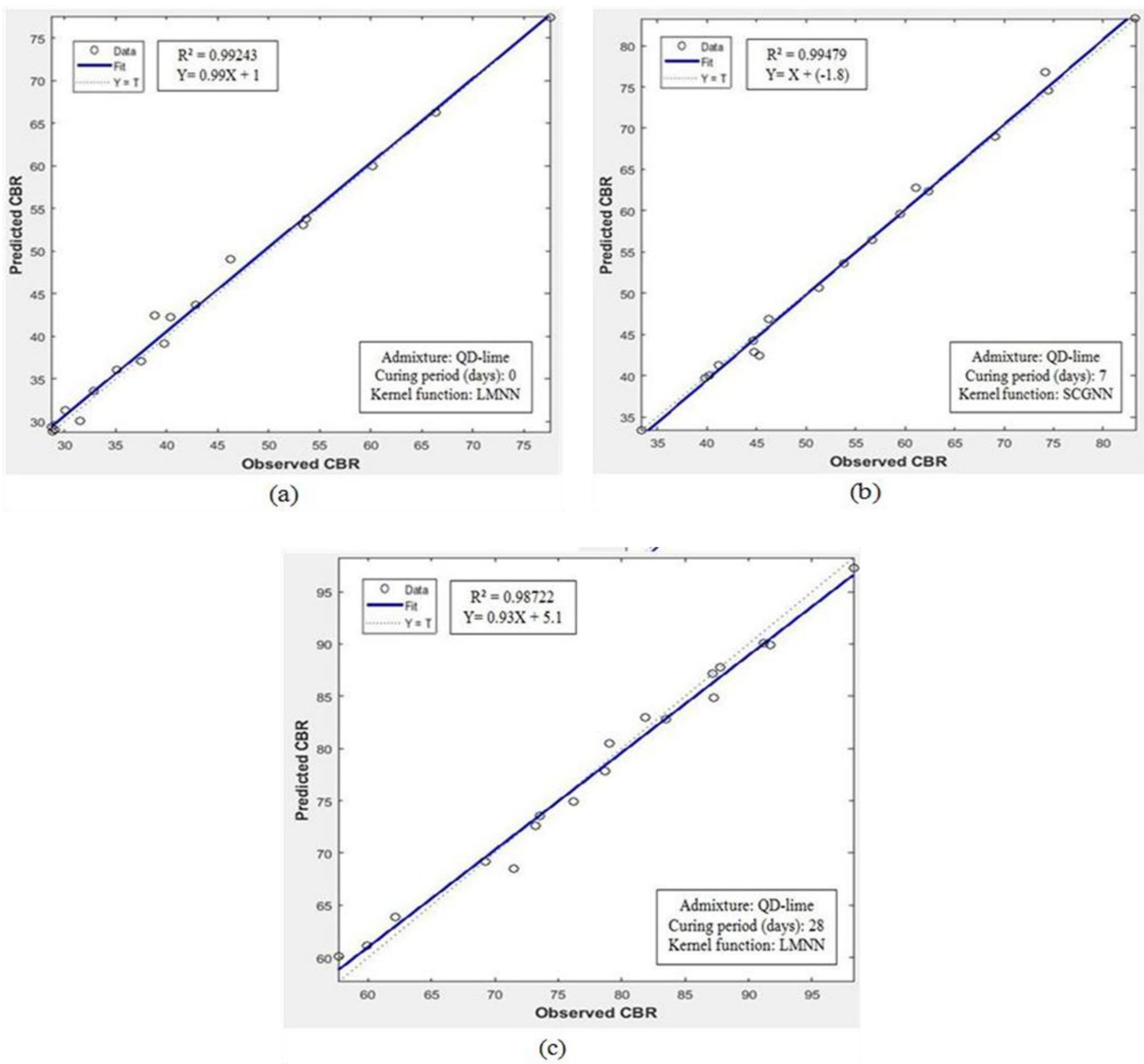


Figure 4.20: Correlation between observed and predicted CBR of stabilized soil with QD and lime for selected models of ANN at curing period (a) 0 (b) 7 and (c) 28 days.

Table 4.27: Performance analysis of ANN models based on curing periods for stabilized soil with RHA and lime

Selected group	Dependent variable	Independent variable	Neural network	Curing Period (days)	Mean square error (MSE)		Over fitting ratio (OR)	R^2
					Training	Testing		
A	Observed CBR	RHA, lime, CP, OMC, MDD	BRNN	0	2.32	2.823	1.103	0.998
A		RHA, lime, CP, OMC, MDD	BRNN	7	2.543	3.526	1.177	0.997
A		RHA, lime, CP, OMC, MDD	BRNN	28	2.666	3.932	1.214	0.996

The values of performance parameter like MSE, OR and R^2 for selected models of ANN for the prediction of CBR of stabilized soil with RHA and lime at curing periods 0, 7 and 28 days is provided in Table 4.27. In Table 4.27, the model BRNN showed comparatively the higher value of R^2 with 0.998 and OR with 1.103 (both tends to 1) at curing period of 0 days than that of BRNN (at the curing period of 7 and 28 days). Therefore, BRNN (group A; RHA, lime, CP, OMC and MDD) was selected the best fitted model at curing period 0 days as compared to BRNN (at curing period of 7 and 28 days) for the prediction of CBR of stabilized soil with RHA and lime.

The correlations between observed and predicted CBR of stabilized soil with RHA and lime for the selected best model BRNN of ANN for all curing period shown in Figure D.3 in Annex-D. From this analysis, the best R^2 (0.998) was observed after BRNN analysis at 0 days curing period as compared to other curing period of 7 and 28 days. It means the almost all data are very close to fitted line after modeling of BRNN at the curing period of 0 days.

The selected best fitted models from ANN analysis for the perfect prediction of CBR in stabilized soils are provided in Table 4.28. In this analysis, for selecting best models, the analysis was performed based different algorithm and curing periods separately. The results of ANN analysis for both criteria (models and curing periods) shows the model SCGNN was the best fitted for predicting CBR of stabilized soil with QD and lime. In addition, the results of ANN analysis for both criteria (models and curing periods) shows the model BRNN was the best fitted for predicting CBR of stabilized soil with RHA and lime (Table 4.28).

Table 4.28: Selected Models from ANN analysis

Criteria	Best Model from analysis		R^2	
	Stabilized soil with			
	QD and lime	RHA and lime	QD and lime	RHA and lime
Models	SCGNN	BRNN	0.995	0.998
Curing period	SCGNN	BRNN	0.995	0.998

4.5.4 Support Vector Machine

The support vector machine (SVM) analysis is also an important part for the prediction of CBR of stabilized soil using two or more independent variable such as QD (%), lime (%), CP (days), OMC (%) and MDD (kN/m³) at different curing period of 0, 7 and 28 days. Other independent variable such as RHA (%), lime (%), CP (days), OMC (%) and MDD (kN/m³) as well as dependent variable CBR (%) (as observed CBR) at different curing period of 0, 7 and 28 days were also considered in SVM analysis. The SVM modeling was implemented to select the best fitted like Linear support vector machine (SVM-L), Quadratic support vector machine (SVM-Q) Cubic support vector machine (SVM-C). The analysis of SVM is discussed in the following articles.

4.5.4.1 Stabilized Soil with QD and Lime

In this study, the performance of different kernel functions like SVM-L, SVM-Q and SVM-C through SVM model has been evaluated based on RMSE, R^2 and MAE. In SVM analysis, QD (%), lime (%), CP (days), OMC (%) and MDD (kN/m³) as well as CBR (%) were considered as independent and dependent variables (as observed CBR), respectively. To get the best performance of SVM-L, SVM-Q and SVM-C, it has been eliminated one or more independent variables and rearranged at various combination and discussed in the following articles.

4.5.4.1.1 Analysis of SVM-L

The results of RMSE, R^2 and MAE of SVM-L analysis are provided in Table 4.29. The values for RMSE, R^2 and MAE were found as 5.38, 0.77 and 4.53, respectively, for the independent variables in group A (QD, lime, CP, OMC, MDD). In addition, the values of 5.34, 0.77 and 4.48 were found for RMSE, R^2 and MAE, respectively, for the independent variables in group B (QD, lime, OMC and MDD).

Table 4.29: Performance of SVM-L for stabilized soil with QD and lime

Group	Dependent variable	Independent variables	RMSE	R^2	MAE
A	Observed CBR	QD, lime, CP, OMC, MDD	5.38	0.77	4.53
B		QD, lime, OMC, MDD	5.34	0.77	4.48
C		lime, OMC, MDD	5.25	0.78	4.32
D		QD, OMC, MDD	5.57	0.75	4.51
E		QD, lime, MDD	5.19	0.79	4.24
F		QD, lime, OMC	5.28	0.78	4.36
G		QD, lime	5.96	0.72	4.85
H		OMC, MDD	5.86	0.73	4.73

After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as groups C, D, E, F, G and H to get best R^2 of stabilized soils with QD and lime (Table 4.29). From Table 4.29, it can be observed that the group E (QD, lime and MDD) showed the best R^2 with 0.79 which is almost close to 1 with its best RMSE 5.19 (lowest value) and MAE 4.24 (lowest value). Therefore, group E (QD, lime and MDD) was considered as best of SVM-L as compared to other groups of A, B, C, D, F, G and H.

4.5.4.1.2 Analysis of SVM-Q

Table 4.30 depicts the results of RMSE, R^2 and MAE of SVM-Q through SVM analysis. The values of 4.45, 0.84 and 3.64 were found for RMSE, R^2 and MAE, respectively, for the independent variable in group A (QD, lime, CP, OMC, MDD). After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as groups B, C, D, E, F, G and H to get best R^2 of stabilized soils with QD and lime (Table 4.30). From Table 4.30, it can be observed that the group G (QD and lime) showed the best R^2 with 0.90 which is almost close to 1 with its best RMSE 3.61 (lowest value) and MAE 2.71 (lowest value). Therefore, group G (QD and lime) is considered as best of SVM-Q as compared to other groups A, B, C, D, E, F and H.

Table 4.30: Performance of SVM-Q for stabilized soil with QD and lime

Group	Dependent variable	Independent variables	RMSE	R^2	MAE
A	Observed CBR	QD, lime, CP, OMC, MDD	4.45	0.84	3.64
B		QD, lime, OMC, MDD	4.61	0.83	3.76
C		lime, OMC, MDD	4.44	0.84	3.38
D		QD, OMC, MDD	4.57	0.83	3.73
E		QD, lime, MDD	4.36	0.85	3.34
F		QD, lime, OMC	4.47	0.84	3.71
G		QD, lime	3.61	0.90	2.71
H		OMC, MDD	6.29	0.69	5.28

4.5.4.1.3 Analysis of SVM-C

The results of RMSE, R^2 and MAE of SVM-Q analysis are provided in Table 4.31. The values of 4.85, 0.81 and 3.89 were found for RMSE, R^2 and MAE, respectively, for the independent variables in group A (QD, lime, CP, OMC, MDD).

Table 4.31: Performance of SVM-C for stabilized soil with QD and lime

Group	Dependent variable	Independent variables	RMSE	R^2	MAE
A	Observed CBR	QD, lime, CP, OMC, MDD	4.85	0.81	3.89
B		QD, lime, OMC, MDD	4.39	0.85	3.65
C		Lime, OMC, MDD	5.01	0.8	4.04
D		QD, OMC, MDD	4.82	0.82	3.67
E		QD, lime, MDD	4.88	0.81	3.88
F		QD, lime, OMC	4.28	0.86	3.28
G		QD, lime	6.03	0.81	4.86
H		OMC, MDD	5.73	0.74	4.43

The independent variables were eliminated one or more and rearranged successively at various combination of variables designated as group B, C, D, E, F, G and H to get best R^2 of stabilized soils with QD and lime (Table 4.31). From Table 4.31, it can be observed that the group F (QD, lime and OMC) showed the best R^2 with 0.86 which is almost close to 1 with its best RMSE 4.28 (lowest value) and MAE 3.28 (lowest value). Therefore, group F (QD, lime and OMC) is considered as best of SVM-C as compared to A, B, C, D, E, G and H.

4.5.4.1.4 Modeling SVM for Curing Period of 0 days

The results of RMSE, R^2 and MAE from SVM analysis at curing period of 0 days are provided in Table 4.32. The values for RMSE, R^2 and MAE were found 8.26, 0.65 and 6.21, respectively, for the independent variables in group A (QD, lime, CP, OMC, MDD). After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as group B, C, D, E, F, G and H to get best R^2 of stabilized soils with QD and lime (Table 4.32). From Table 4.32, it can be observed that the group G (QD and lime) showed the best R^2 with 0.80 which is almost close to 1 with its best RMSE 6.15 (lowest value) and MAE 4.42 (lowest value) at curing period of 0 days. Therefore, group G (QD and lime) is considered as best of SVM-C as compared to A, B, C, D, E, F and H.

Table 4.32: Performance of different kernel functions through SVM at curing period of 0 days

Group	Dependent variable	Curing Period (days)	Independent variables	Kernel function	RMSE	R^2	MAE
A	Observed CBR	0	QD, lime, CP, OMC, MDD	SVM-C	8.26	0.65	6.21
B			QD, lime, OMC, MDD	SVM-C	8.35	0.64	6.33
C			lime, OMC, MDD	SVM-C	8.33	0.64	6.63
D			QD, OMC, MDD	SVM-C	7.48	0.71	5.31
E			QD, lime, MDD	SVM-C	9.09	0.57	6.69
F			QD, lime, OMC	SVM-C	7.54	0.71	5.31
G			QD, lime	SVM-C	6.15	0.80	4.42
H			OMC, MDD	SVM-C	9.10	0.57	5.96

4.5.4.1.5 Modeling SVM for Curing Period of 7 days

Table 4.33 depicts the results of RMSE, R^2 and MAE from SVM analysis at curing period of 7 days. From this analysis, the values of 6.87, 0.75 and 5.40 were found for RMSE, R^2 and MAE, respectively, for the independent variable in group A (QD, lime, CP, OMC, MDD). The independent variables were eliminated one or more and rearranged successively at various combination of variables designated as groups B, C, D, E, F, G and H to get best R^2 of stabilized soils with QD and lime (Table 4.33). From Table 4.33, it can be observed that the group G (QD and lime) showed the best R^2 with 0.81 which is almost close to 1 with its best RMSE 6.03 (lowest value) and MAE 4.86 (lowest value) at curing period of 7 days. Therefore, group G (QD and lime) is considered as best of SVM-C as compared to A, B, C, D, E, F and H.

Table 4.33: Performance of different kernel function through SVM at curing period of 7 days

Group	Dependent variable	Curing Period (days)	Independent variables	Kernel function	RMSE	R^2	MAE
A	Observed CBR	7	QD, lime, CP, OMC, MDD	SVM-Q	6.87	0.75	5.4
B			QD, lime, OMC, MDD	SVM-Q	6.73	0.76	5.57
C			lime, OMC, MDD	SVM-C	6.51	0.78	4.97
D			QD, OMC, MDD	SVM-Q	7.53	0.7	6.84
E			QD, lime, MDD	SVM-Q	6.44	0.78	5.06
F			QD, lime, OMC	SVM-C	6.65	0.77	5.12
G			QD, lime	SVM-C	6.03	0.81	4.86
H			OMC, MDD	SVM-C	7.85	0.68	6.61

4.5.4.1.6 Modeling SVM for Curing Period of 28 days

The results of RMSE, R^2 and MAE from SVM analysis at curing period of 28 days are provided in Table 4.34. The values of 4.45, 0.84 and 3.64 were found for RMSE, R^2 and MAE, respectively, for the independent variable in group A (QD, lime, CP, OMC, MDD).

Table 4.34: Performance of different kernel function through SVM at curing period of 28 days

Group	Dependent variable	Curing Period (days)	Independent variables	Kernel function	RMSE	R^2	MAE
A	Observed CBR	28	QD, lime, CP, OMC, MDD	SVM-Q	4.45	0.84	3.64
B			QD, lime, OMC, MDD	SVM-C	4.39	0.85	3.65
C			lime, OMC, MDD	SVM-Q	4.44	0.84	3.38
D			QD, OMC, MDD	SVM-Q	4.57	0.83	3.73
E			QD, lime, MDD	SVM-Q	4.36	0.85	3.34
F			QD, lime, OMC	SVM-C	4.28	0.86	3.28
G			QD, lime	SVM-Q	3.61	0.90	2.71
H			OMC, MDD	SVM-C	5.73	0.74	4.43

After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as group B, C, D, E, F, G and H to get best R^2 of stabilized soils with QD and lime (Table 4.34). From Table 4.34, it can be observed that the group G (QD and lime) showed the best R^2 with 0.90 which is almost close to 1 with its best RMSE 3.61 (lowest value) and MAE 2.71 (lowest value) at curing period of 28 days. Therefore, group G (QD and lime) is considered as best of SVM-C as compared to A, B, C, D, E, F and H.

4.5.4.2 Analysis of SVM for stabilized Soil with RHA and Lime

In this study, the kernel functions of SVM-L, SVM-Q and SVM-C through SVM model has been evaluated based on RMSE, R^2 and MAE to predict the CBR of stabilized soil with RHA and lime. In SVM analysis, RHA (%), lime (%), CP (days), OMC (%) and MDD (kN/m^3) as well as CBR (%) were considered as independent and dependent variable, respectively. To get the best performance of SVM-L, SVM-Q and SVM-C, it has been eliminated one or more independent variable and arrange at various combination.

4.5.4.2.1 Analysis of SVM-L

The results of RMSE, R^2 and MAE of SVM-L analysis are provided in Table 4.35. The values of 5.27, 0.87 and 4.54 were found for RMSE, R^2 and MAE, respectively, for the independent variables in group A (RHA, lime, CP, OMC, MDD).

Table 4.35: Performance of SVM-L for stabilized soil with RHA and lime

Group	Dependent variable	Independent variables	RMSE	R^2	MAE
A	Observed CBR	RHA, lime, CP, OMC, MDD	5.27	0.87	4.54
B		RHA, lime, OMC, MDD	5.17	0.87	4.5
C		lime, OMC, MDD	5.21	0.88	4.48
D		RHA, OMC, MDD	9.52	0.6	7.75
E		RHA, lime, OMC	5.34	0.87	4.64
F		RHA, lime, MDD	4.99	0.88	4.07
G		RHA, lime	3.64	0.94	2.92
H		OMC, MDD	13.33	0.16	8.67

After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as groups B, C, D, E, F, G and H, to get the best R^2 of stabilized soils with RHA and lime (Table 4.35). From Table 4.35, it can be observed that the group G (RHA and lime) showed the best R^2 with 0.94 which is almost close to 1 with its best RMSE 3.64 (lowest value) and MAE 2.92 (lowest value). Therefore, group G (RHA and lime) is considered as best of SVM-L as compared to A, B, C, D, E, F and H.

4.5.4.2.2 Analysis of SVM-Q

The results of RMSE, R^2 and MAE of SVM-Q analysis are provided in Table 4.36. The values of 3.00, 0.96 and 2.60 were found for RMSE, R^2 and MAE, respectively, for the independent variable in group A (RHA, lime, CP, OMC, MDD). After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as group B, C, D, E, F, G and H to get best R^2 of stabilized soils with RHA and lime (Table 4.36). From Table 4.36, it can be observed that the group C (lime, OMC and MDD) showed the best R^2 with 0.96 which is almost close to 1 with its best RMSE 2.95 (lowest value) and MAE 2.51 (lowest value). Therefore, group C (lime, OMC and MDD) is considered as best of SVM-Q as compared to A, B, D, E, F, G and H.

Table 4.36: Performance of SVM-Q for stabilized soil with RHA and lime

Group	Dependent variable	Independent variables	RMSE	R^2	MAE
A	Observed CBR	RHA, lime, CP, OMC, MDD	3.0	0.96	2.60
B		RHA, lime, OMC, MDD	3.46	0.95	3.05
C		lime, OMC, MDD	2.95	0.96	2.51
D		RHA, OMC, MDD	8.73	0.64	7.35
E		RHA, lime, OMC	3.09	0.95	2.57
F		RHA, lime, MDD	3.49	0.94	2.81
G		RHA, lime	3.49	0.94	2.73
H		OMC, MDD	14.27	0.01	9.69

4.5.4.2.3 Analysis of SVM-C

The results of RMSE, R^2 and MAE of SVM-C analysis are provided in Table 4.37. The values of 2.37, 0.97 and 2.00 were found for RMSE, R^2 and MAE, respectively, for the independent variable in group A (RHA, lime, CP, OMC, MDD). After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as group B, C, D, E, F, G and H to get best R^2 of stabilized soils with RHA and lime (Table 4.37). From Table 4.37, it can be observed that the group A (RHA, lime, CP, OMC, MDD) showed the best R^2 with 0.97 which is almost close to 1 with its best RMSE 2.37 (lowest value) and MAE 2.00 (lowest value). Therefore, group A (RHA, lime, CP, OMC, MDD) is considered as best of SVM-Q as compared to B, C, D, E, F, G and H.

Table 4.37: Performance of SVM-C for stabilized soil with RHA and lime

Group	Dependent variable	Independent variables	RMSE	R^2	MAE
A	Observed CBR	RHA, lime, CP, OMC, MDD	2.37	0.97	2.0
B		RHA, lime, OMC, MDD	2.64	0.97	2.23
C		lime, OMC, MDD	2.41	0.97	2.17
D		RHA, OMC, MDD	8.93	0.62	7.42
E		RHA, lime, OMC	3.01	0.96	2.58
F		RHA, lime, MDD	2.94	0.96	2.32
G		RHA, lime	2.94	0.96	2.32
H		OMC, MDD	15.01	-0.07	10.65

4.5.4.2.4 Modeling SVM for Curing Period of 0 Days

Table 4.38 depicts the results of RMSE, R^2 and MAE from SVM analysis at curing period of 0 days. The values of 3.08, 0.96 and 2.65 were found for RMSE, R^2 and MAE, respectively, for the independent variable in group A (RHA, lime, CP, OMC, MDD). The independent variables were eliminated one or more and rearranged successively at various combination of variables designated as group B, C, D, E, F, G and H to get best R^2 of stabilized soils with RHA and lime (Table 4.38). From Table 4.38, it can be observed that the group C (lime, OMC and MDD) showed the best R^2 with 0.96 which is almost close to 1 with its best RMSE 2.95 (lowest value) and MAE 2.51 (lowest value) at curing period of 0 days. Therefore, group C (RHA, lime and OMC) is considered as best of SVM-Q as compared to A, B, D, E, F, G and H.

Table 4.38: Performance of different kernel function through SVM at curing period of 0 days

Group	Dependent variable	Curing Period (days)	Independent variables	Kernel function	RMSE	R^2	MAE
A	Observed CBR	0	RHA, lime, CP, OMC, MDD	SVM-C	3.08	0.96	2.65
B			RHA, lime, OMC, MDD	SVM-Q	3.46	0.95	3.05
C			lime, OMC, MDD	SVM-Q	2.95	0.96	2.51
D			RHA, OMC, MDD	SVM-L	9.52	0.6	7.75
E			RHA, lime, OMC	SVM-C	3.01	0.96	2.58
F			RHA, lime, MDD	SVM-C	3.86	0.93	3.2
G			RHA, lime	SVM-L	3.64	0.94	2.92
H			OMC, MDD	SVM-L	13.8	0.15	9.05

4.5.4.2.5 Modeling SVM for Curing Period of 7 Days

The results of RMSE, R^2 and MAE from SVM analysis at curing period of 7 days are provided in Table 4.39. The values of 2.37, 0.97 and 2.00 were found for RMSE, R^2 and MAE, respectively, for the independent variable in group A (RHA, lime, CP, OMC, MDD).

Table 4.39: Performance of different kernel function through SVM at curing period of 7 days

Group	Dependent variable	Curing Period (days)	Independent variables	Kernel function	RMSE	R^2	MAE
A	Observed CBR	7	RHA, lime, CP, OMC, MDD	SVM-C	2.37	0.97	2.0
B			RHA, lime, OMC, MDD	SVM-C	2.64	0.97	2.23
C			lime, OMC, MDD	SVM-C	2.41	0.97	2.11
D			RHA, OMC, MDD	SVM-C	9.2	0.59	7.53
E			RHA, lime, OMC	SVM-C	3.04	0.96	2.24
F			RHA, lime, MDD	SVM-C	3.57	0.94	2.89
G			RHA, lime	SVM-C	3.44	0.95	2.88
H			OMC, MDD	SVM-Q	14.27	0.01	9.69

After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as group B, C, D, E, F, G and H to get best R^2 of stabilized soils with RHA and lime (Table 4.39). From Table 4.39, it can be observed that the group A (RHA, lime, CP, OMC, MDD) showed the best R^2 with 0.97 which is almost close to 1 with its best RMSE 2.37 (lowest value) and MAE 2.00 (lowest value) at curing period of 7 days. Therefore, group A (RHA, lime, CP, OMC, MDD) is considered as best of SVM-C as compared to B, C, D, E, F, G and H.

4.5.4.2.6 Modeling SVM for Curing Period of 28 Days

The results of RMSE, R^2 and MAE from SVM analysis at curing period of 28 days are provided in Table 4.40. The values of 3.00, 0.96 and 2.60 were found for RMSE, R^2 and MAE, respectively, for the independent variable in group A (RHA, lime, CP, OMC, MDD). After that the independent variables were eliminated one or more and rearranged successively at various combination of variables designated as group B, C, D, E, F, G and H to get best R^2 of stabilized soils with RHA and lime (Table 4.40). From Table 4.40, it can be observed that the group C (lime, OMC and MDD) showed the best R^2 with 0.96 which is almost close to 1 with its best RMSE 2.90 (lowest value) and MAE 2.38 (lowest value) at curing period of 28 days. Therefore, group C (lime, OMC and MDD) is considered as best of SVM-C as compared to A, B, C D, E, F, G and H.

Table 4.40: Performance of different kernel function through SVM at curing period of 28 days

Group	Dependent variable	Curing Period (days)	Independent variables	Kernel function	RMSE	R^2	MAE
A	Observed CBR	28	RHA, lime, CP, OMC, MDD	SVM-Q	3.0	0.96	2.60
B			RHA, lime, OMC, MDD	SVM-L	5.17	0.87	4.50
C			lime, OMC, MDD	SVM-C	2.90	0.96	2.38
D			RHA, OMC, MDD	SVM-Q	8.73	0.64	7.35
E			RHA, lime, OMC	SVM-Q	3.09	0.95	2.57
F			RHA, lime, MDD	SVM-Q	3.49	0.94	2.81
G			RHA, lime	SVM-C	2.94	0.96	2.39
H			OMC, MDD	AVM-L	13.33	0.16	8.67

4.5.4.3 Selection of Model from SVM

In this study, the models of SVM were selected based on different kernel functions like SVM-L, SVM-Q and SVM-C as well as varying curing periods 0, 7 and 28 days for predicting CBR of stabilized soils and hence discussed in the following articles.

4.5.4.3.1 Based on Model

The performance analysis of different models of SVM for stabilized soil with QD and lime is provided in Table 4.41. From Table 4.41, it was observed that SVM-Q showed the lower value of RMSE with 3.61 than that of 5.19 (SVM-L) and 4.28 (SVM-C). Comparatively the higher value of R^2 (0.90) was found for SVM-Q as compared to 0.79 (SVM-L) and 0.86 (SVM-C). Moreover, the lower value of MAE (2.71) was found for SVM-Q as compared to 4.24 (SVM-L) and 3.28 (SVM-C).

Table 4.41: Performance analysis of different models of SVM for stabilized soil with QD and lime

Selected group	Dependent variable	Independent variables	Selected model	RMSE	R^2	MAE
E	Observed CBR	QD, lime, MDD	SVM-L	5.19	0.79	4.24
G		QD, Lime	SVM-Q	3.61	0.90	2.71
F		QD, lime, OMC	SVM-C	4.28	0.86	3.28

The relationship between predicted and observed CBR of stabilized soil from different kernel functions with R^2 shown in Figure 4.21. Therefore, it has been also observed that SVM-Q (Group G; QD and lime) was the best model as compared to SVM-L and SVM-C for stabilized with the satisfactory values of prediction parameters. Moreover, R^2 value (0.90) is close to 1 indicated a very good corelationship between predicted and observed CBR (Figure 4.21). Figure 4.21 also depicts that for SVM-Q (Figure b) with R^2 of 0.90 and all observation points are so close to the perfect prediction line as compared to SVM-L and SVM-C. Therefore, the accuracy of the prediction of CBR from SVM-Q was more precise. A research conducted by Wang (2005) stated that the best SVM model produced depends on only a subset of the training data near the class of perfect prediction boundaries line. Similarly, the model produced by SVM is close to the model of prediction line. So the findings of the study comply the concept postulated by Wang, (2015).

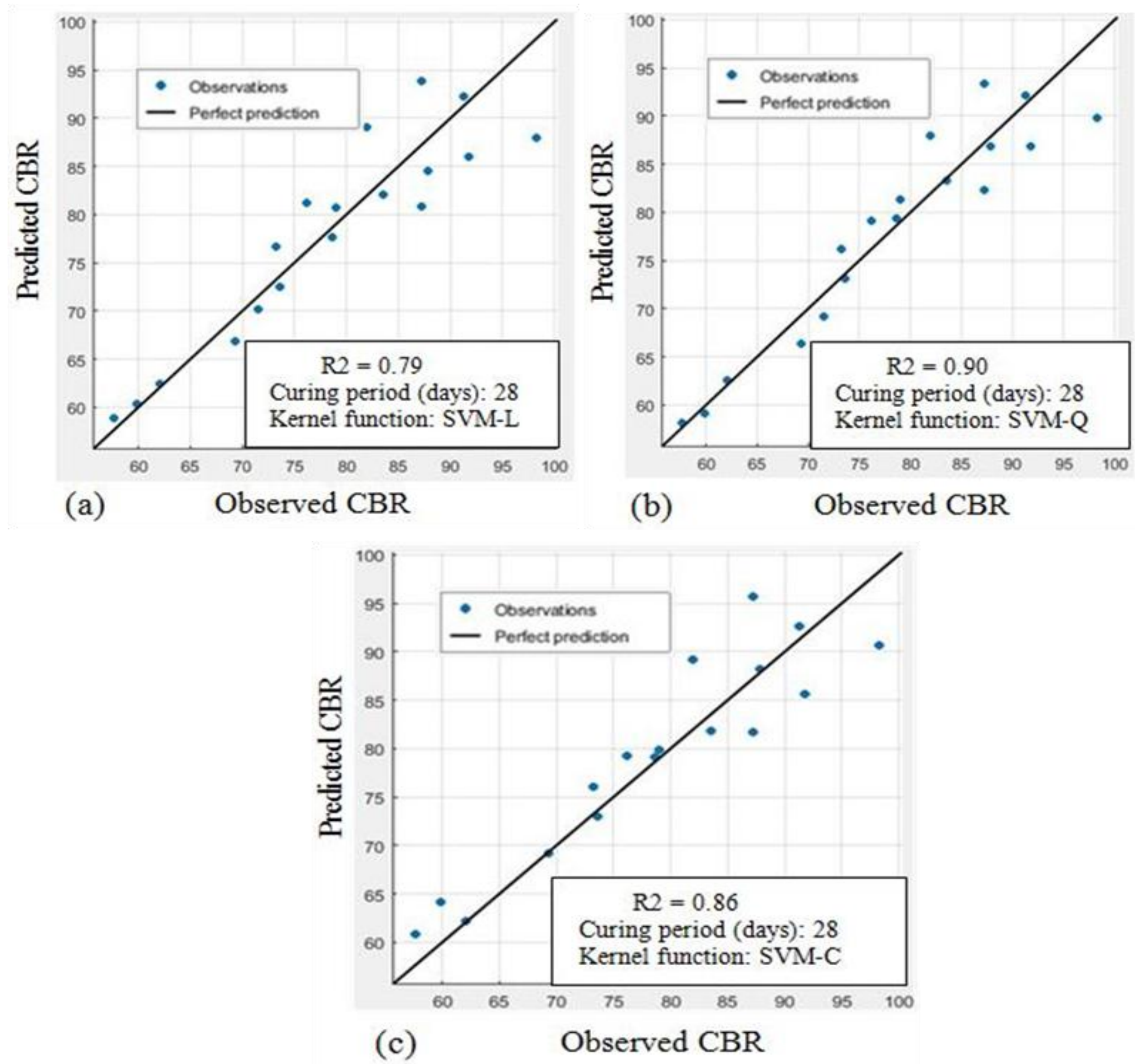


Figure 4.21: Correlation of predicted with observed CBR of stabilized soil with QD and lime for (a) SVM-L (b) SVM-Q and (c) SVM-C.

The performance analysis of different models of SVM for stabilized soil with RHA and lime is provided in Table 4.42. From Table 4.42, it was observed that SVM-C showed the lower value of RMSE with 2.37 than that of 3.64 (SVM-L) and 2.95 (SVM-Q). Comparatively the higher value of R^2 (0.97) was found for SVM-C as compared to 0.94 (SVM-L) and 0.96 (SVM-Q). Moreover, the lower value of MAE (2.0) was found for SVM-C as compared to 2.92 (SVM-L) and 2.51 (SVM-Q).

Table 4.42: Performance analysis of different models of SVM for stabilized soil with RHA and lime

Selected group	Dependent variable	Independent variables	Selected model	RMSE	R^2	MAE
G	Observed CBR	RHA, lime	SVM-L	3.64	0.94	2.92
C		lime, OMC and MDD	SVM-Q	2.95	0.96	2.51
A		RHA, lime, CP, OMC, MDD	SVM-C	2.37	0.97	2.0

Moreover, R^2 value (0.97) is close to 1 indicated a very good correlation between predicted and observed CBR in Figure D.4 in Annex D. In this analysis, the model SVM-C showed the best R^2 of 0.97 (Table 4.42) and all observation points are so close to the perfect prediction line as compared to SVM-L and SVM-Q. Therefore, the accuracy of the prediction of CBR from SVM-C was more precise.

4.5.4.3.2 Based on Curing Period

The results of RMSE, R^2 and MAE for selected models of SVM for the prediction of CBR of stabilized soil with QD and lime at curing periods 0, 7 and 28 days is provided in Table 4.43. Based on results SVM-C for curing periods 0, 7 as well as SVM-Q for 28 days were selected as good predictor for the prediction of CBR (Table 4.43). The model SVM-Q showed the highest R^2 with 0.90 as well as RMSE and MAE with 3.61 and 2.71 (both lowest value) at curing period 28 days for the prediction of CBR of stabilized soil (Table 4.43). Therefore, the model SVM-Q was selected as best fitted for the prediction of CBR in stabilized soil with QD and lime.

Table 4.43: Performance analysis of different models of SVM for stabilized soil with QD and lime

Selected group	Dependent variable	Independent variables	Curing period (days)	Selected model	RMSE	R^2	MAE
G	Observed CBR	QD, lime	0	SVM-C	6.15	0.80	4.42
G		QD, lime	7	SVM-C	6.03	0.81	4.86
G		QD, lime	28	SVM-Q	3.61	0.90	2.71

Therefore, the model SVM-Q (group G; QD and lime) was selected as the best fitted model for curing period 28 days as compared to both of SVM-C at curing period of 0 and 7 days for the prediction of CBR of stabilized soil with QD and lime. Moreover, the error histogram of CBR in stabilized soil with QD and lime at varying curing periods after performing different kernel functions of SVM is shown in Figure 4.22.

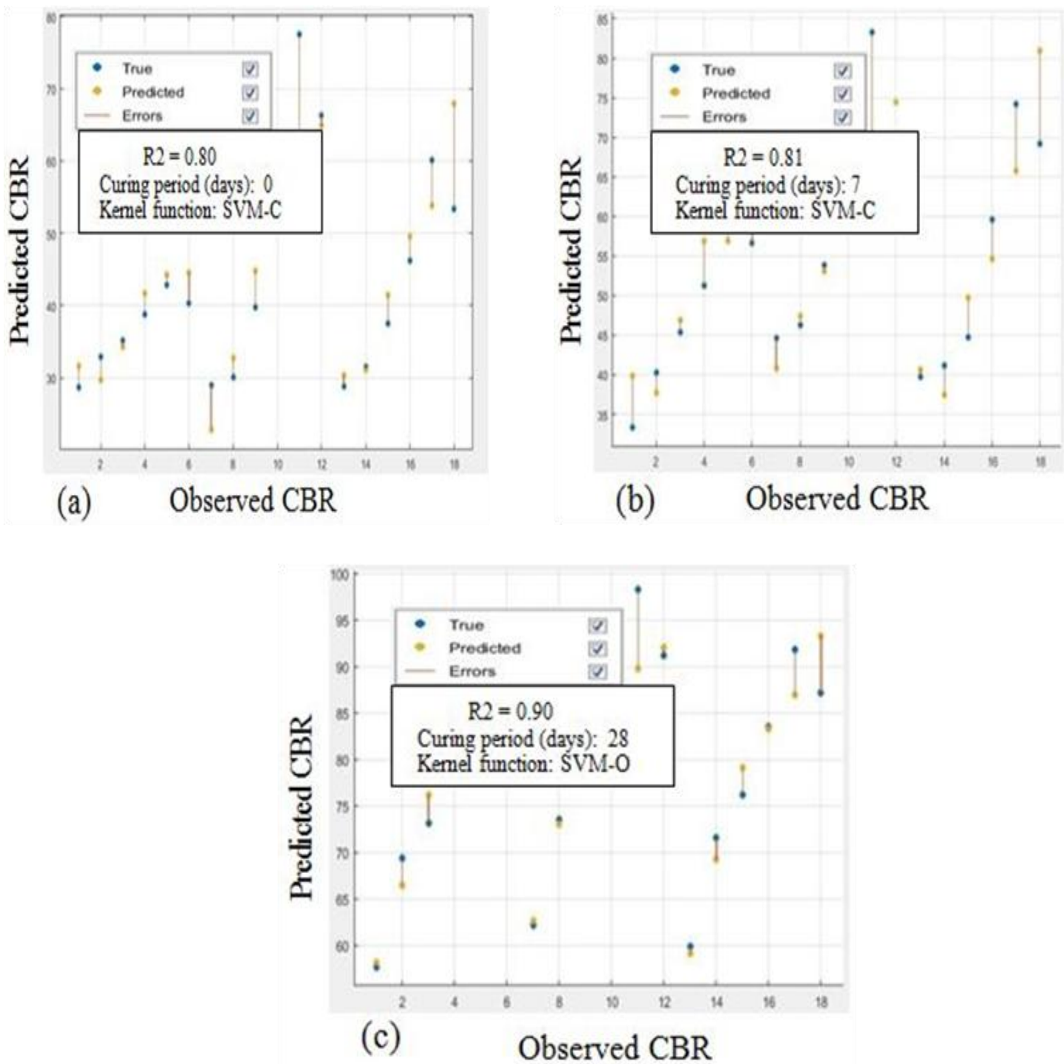


Figure 4.22: Error histogram of CBR in stabilized soil with QD and lime for selected model of SVM at curing period of (a) 0 (b) 7 (c) 28 days.

From Figure 4.22, it is clear that the error represents the differences or how much the predicted CBR far from observed CBR in the laboratory. In addition, more error (less R^2) indicates the predicted CBR from SVM was so far from observed CBR in the laboratory as well as vice-versa.

Figure 4.22 depicts the model SVM-Q with higher R^2 (0.90) or less error (Figure 4.22c), i. e. the predicted and observed CBR from SVM-Q was more accurate for curing period 28 days in compare with SVM-C for 0 and 7 days (Figure 4.22a and Figure 4.22b). Therefore, the model SVM-Q with less error (more R^2) was selected as best fitted for the prediction of CBR in stabilized soil with QD and lime.

In addition, the results of RMSE, R^2 and MAE for selected models of SVM for the prediction of CBR of stabilized soil with RHA and lime at varying curing periods are provided in Table 4.44. From SVM analysis for stabilized soil with RHA and lime, SVM-Q for curing period 0 days as well as SVM-C for 7 and 28 days were obtained as good predictor for the prediction of CBR (Table 4.44). Therefore, with highest R^2 (0.97) as well as lowest values of RMSE (2.37) and MAE (2.0) at curing period 7 days, the model SVM-C was selected as the best fitted for the prediction of CBR of stabilized soil with RHA and lime (Table 4.44).

Table 4.44: Performance analysis of different models of SVM for stabilized soil with RHA and lime

Selected group	Dependent variable	Independent Variables	Selected model	Curing period (days)	RMSE	R^2	MAE
C	Observed CBR	lime, OMC, MDD	SVM-Q	0	2.95	0.96	2.51
A		RHA, lime, CP, OMC, MDD	SVM-C	7	2.37	0.97	2.0
C		lime, OMC, MDD	SVM-C	28	2.90	0.96	2.38

In addition, the model SVM-C (group A; RHA, lime, CP, OMC and MDD) was selected as the best fitted model for curing period 7 days as compared to SVM-Q and SVM-C (group C) at curing period of 0 and 28 days for the prediction of CBR.

Moreover, R^2 (0.97) for SVM-C is close to 1 indicated a good correlation between predicted and observed CBR shown in Figure D.5 in Annex D. In this analysis, the model SVM-C shows that best R^2 of 0.97 (Table 4.44) and all observation points are so close to the perfect prediction line as compared to SVM-Q and SVM-C (group C). Therefore, the accuracy of the prediction of CBR from SVM-C was more precise.

The selected best fitted models from SVM analysis for the perfect prediction of CBR in stabilized soils are provided in Table 4.45. In this analysis, for selecting best models, the analysis was performed based different kernel functions and curing periods separately. The results of SVM analysis for both criteria (models and curing periods) shows the model SVM-Q was the best fitted for predicting CBR of stabilized soil with QD and lime. In addition, the results of SVM analysis for both criteria (models and curing periods) shows the model SVM-C was the best fitted for predicting CBR of stabilized soil with RHA and lime (Table 4.45).

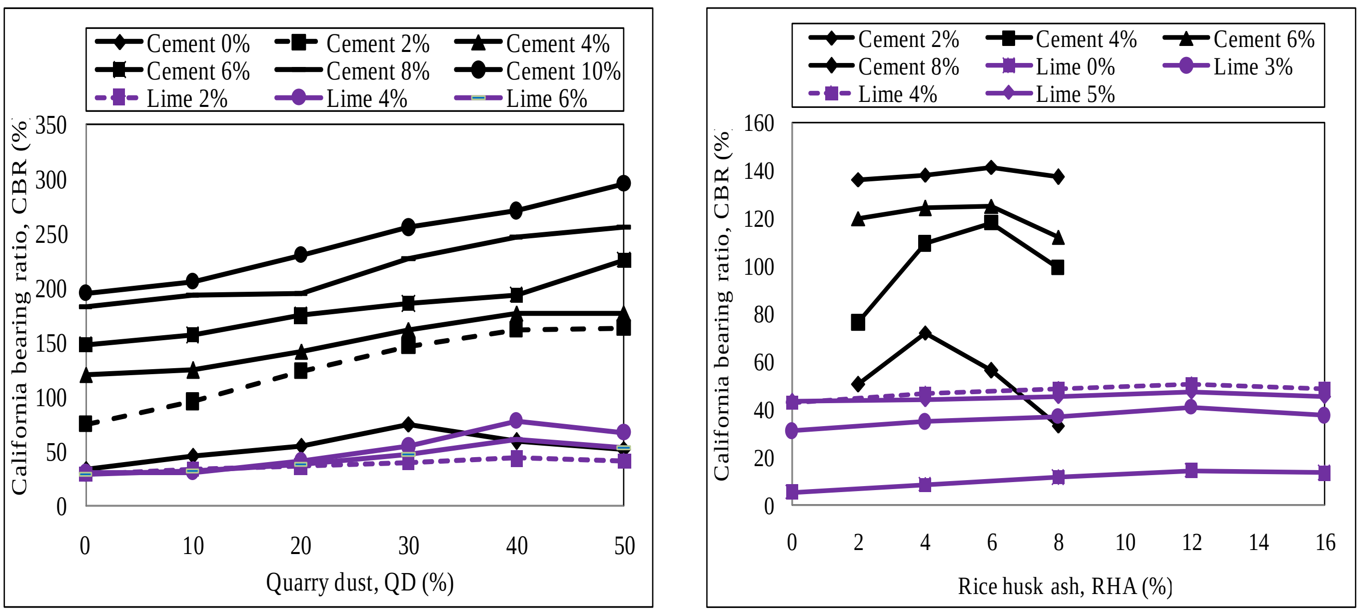
Table 4.45: Selected models from SVM analysis

Criteria	Best model from analysis		R^2	
	Stabilized soil with			
	QD and lime	RHA and lime	QD and lime	RHA and lime
Models	SVM-Q	SVM-C	0.90	0.97
Curing period	SVM-Q	SVM-C	0.90	0.97

4.6 Comparison of CBR of Stabilized Soil with Other Researcher

In the literature, the researchers of Eze-Uzomaka et al. (2010) investigated the effect of QD with lime in laterite soil for base course material. It was stabilized with 10, 20, 30, 40 and 50% of QD as well as 0, 2, 4, 6, 8 and 10% of cement and by weight of dry soil. Soil samples were subjected to CBR test (Eze-Uzomaka et al., 2010). In literature CBR is maximum when QD is 50% and lime is 10% as shown in Figure 4.23 (a). But in the present study, CBR was maximum when QD is 40% and lime is 4%. Further the CBR value decreases for QD content of 50%. The decline in CBR value after a peak value at 40% quarry dust may be connected with the decrease in the clay proportions which plays the role of the bonding agent at the lower percentage of QD. Addition of QD to fine-grained lime mixtures give rise to increase in CBR for all the different combination of QD and lime. As the clay fraction in the mixture is decreased due to increase in QD content, lime takes over the liming work which earlier on was done by the clay fraction at lower percentage of quarry dust in the fine-grained-QD mixtures. The granite in the QD adds strength and rigidity to the mixture the quantity of the quarry dust increases.

In addition, the effect of RHA on the soil was investigated with CBR. It was stabilized with 2, 4, 6 and 8% of RHA as well as 2, 4, 6 and 8% of cement with soil (Alhassan and Mustafa, 2007). In literature the CBR is maximum when RHA is 6% and lime is 8% as shown in Figure 4.23 (b). But in this study CBR is maximum when RHA is 12% and lime is 4%. Further the CBR value decreased for RHA content of 16%. The reason for increment in CBR may be because of the gradual formation of lime compounds in the soil by the reaction between the RHA and some amounts of CaOH present in the soil and lime present. The decrease in CBR at RHA content of 16% may be due to extra RHA that could not be mobilized for the reaction which consequently occupies spaces within the sample. This reduced the bond in the soil-RHA mixture. So the findings of the literature are higher than this study due to used of laterite soil.



(a) (b)

Figure 4.23 Comparison of CBR of (a) QD with lime and QD with cement (b) RHA with lime and RHA with cement stabilized soil.

4.7 Final Evaluation Based on Findings of this Study

In this analysis, the optimum content of different admixtures used in this study for the stabilization of soil was evaluated based on the better results of CBR. In addition, the best models from SLR, MLR, ANN and SVM were also evaluated with the satisfactory values of prediction parameters (R^2, RMSE, MSE and MAE) to predict the perfect CBR of stabilized soils.

The predicted CBR of stabilized soils from SLR, MLR, ANN and SVM are provided in Table E.1 to Table E.7 shown in Annex E. The selected optimum content of admixtures and newly developed techniques of soft computing systems (best model) will further be used of other researchers to stabilize soil easily and then predict CBR of stabilized soils. In this study, the optimum content of admixtures like QD, RHA and lime was evaluated of stabilized soils with QD and RHA. In addition, the best performance of models from SLR, MLR, ANN and SVM were also evaluated and hence discussed in followings.

4.7.1 Optimum Content of Admixtures

In this study, the stabilized soils were prepared using QD with lime and RHA with lime. The values of maximum CBR for stabilized soil with QD (40%) and lime (4%) were obtained as 77.54, 83.27 and 98.26% at curing period of 0, 7 and 28 days respectively, provided in Table 4.46. Moreover, the values of maximum CBR were obtained of 50.1, 52.5 and 58.41% for stabilized soil with RHA (12%) and lime (4%) at curing period of 0, 7 and 28 days, respectively. The maximum CBR (98.26%) was found for stabilized soil with QD and lime at curing period 28 days than other mixing content and curing periods used in this study. Therefore, the higher CBR was found for stabilized soil with QD and lime than that of stabilized soil with RHA and lime.

Table 4.46: Obtained results of CBR of stabilized soil with QD and RHA

Stabilized soils with	Optimum content of admixtures		CBR (%) at varying curing period (days)		
			0	7	28
QD and lime	QD (40 %)	Lime (4 %)	77.54	83.27	98.26
RHA and lime	RHA (12 %)	Lime (4 %)	50.1	52.5	58.41

In the laboratory, the stabilized soil samples were prepared at varying mixing proportions of QD as 0, 10, 20, 30, 40 and 50% with lime of 2, 4 and 6%. The mixing and optimum content of admixtures used in this study are presented in Table 4.47. A research conducted by Sabat (2013) on stabilized soil prepared at varying mixing proportions of QD with 0, 10, 20, 30, 40 and 50%; lime with 2, 3, 4, 5 and 6% (Table 4.47). Thereafter, CBR increases up to 40% of QD, further addition of QD, CBR decreases irrespective the percentage of lime content. That means, CBR was found to be maximum for QD with 40% and lime as 4% for the stabilization of soil. A researcher shown in the literature, CBR was found to be maximum when QD and lime used as 40 and 4%, respectively, for the stabilization of soil (Table 4.47). It indicated that in this study, the CBR test procedure comply the procedure of the research that is postulated by Sabat (2013).

In addition, stabilized soil samples were prepared at varying mixing proportions of RHA of 0, 4, 8, 12 and 16% with lime of 0, 3, 4 and 5%. A research conducted by Chakraborty et al. (2014), stabilized soils were prepared at varying mixing proportions of RHA with 0, 3, 6, 9 and 12 %; lime with 0, 2, 4, 6, 8 and 10%. Thereafter, in the present study, CBR increases up to 12% of RHA, further addition of RHA CBR decreases irrespective the percentages of lime. That means, CBR is maximum when RHA and lime used as 12 and 4%, respectively, for the stabilization of soil. The researcher also shown in literature, CBR was maximum when RHA and lime used as 9 and 6%, respectively, for the stabilization of soil. It indicated that in this study, the CBR test procedure comply the procedure of the research that is postulated by Chakraborty et al. (2014).

Table 4.47: Optimum content of admixtures in this study

Admixtures		Mixing content (%)		Optimum content (%)		Reference of literature
Present study	Literature	Present study	Literature	Present study	Literature	
QD with lime	QD with lime	QD of 0, 10, 20, 30, 40 and 50; lime of 2, 4 and 6	QD of 0, 10, 20, 30, 40 and 50; lime is 2, 3, 4, 5 and 6	CBR is maximum when QD is 40 and lime is 4	CBR is maximum when QD is 40 and lime is 4	Sabat, 2013
RHA with lime	RHA with lime	RHA of 0, 4, 8, 12 and 16; lime of 0, 3,4 and 5	RHA of 0, 3, 6, 9 and 12; lime of 0, 2, 4, 6, 8 and 10	CBR is maximum when RHA is 12 and lime is 4	CBR is maximum when RHA and lime used as 9 and 6	Chakraborty et al., 2014

Table 4.48: Final models for analysis of stabilized soil with admixtures

Admixture	R^2 of SLR		R^2 of MLR		R^2 of ANN		R^2 of SVM		Selected model	
	Present study	Literature	Present study	Literature	Present study	Literature	Present study	Literature	Present study	Literature
QD and lime	0.798	--	0.872	0.933	0.995	0.981	0.90	0.98	ANN	ANN
RHA and lime	0.908	0.624	0.95	0.882	0.998	0.985	0.97	--	ANN	ANN
Reference of literature	--	Bhatt et al., 2014	--	(Sabat, 2013) and (Bhatt et al., 2014)	--	(Sabat, 2013) and (Ali et al., 2016)	--	Sabat, 2015	--	Sabat, 2013

4.7.2 Final Selection of Model of this Analysis

In SLR analysis, R^2 was found 0.798 when QD considered as independent variable of stabilized soil with QD and lime (Table 4.48). Moreover, the R^2 was found 0.908 when lime considered as independent variable for the stabilization of soil with RHA and lime. A research conducted by Bhatt et al. (2014) reveals the R^2 was 0.624 for SLR analysis, considering MDD and CBR as independent and dependent variable, respectively, for the stabilization of soil. It indicated that, in this study after SLR analysis the R^2 values (0.798 and 0.908) was better than the findings postulated by Bhatt et al. (2014).

In addition, the R^2 was found 0.872 from MLR analysis of stabilized soil with QD and lime. This value (0.872) was near about the R^2 (0.933) that was found other researcher Sabat (2013). Moreover, the R^2 was found 0.95 when RHA, lime, CP, OMC and MDD considered as independent variable of stabilized soil using RHA and lime (Table 4.48). A research conducted by Bhatt et al. (2014) and the value of R^2 was found 0.882 after MLR analysis considering gravel (G), sand (S), fine grained (FG), OMC and MDD as independent and CBR as dependent variable of stabilized soil. Therefore, the findings of this study were agreed well with the results postulated by Sabat (2013) and Bhatt et al. (2014).

The R^2 was found 0.995 from ANN analysis for stabilized soil with QD and lime. This value (0.995) was higher than R^2 (0.981) which was found from a research conducted by Sabat (2013). Moreover, the R^2 was found 0.998 of stabilized soil using RHA and lime. This value (0.998) is higher than R^2 of 0.985 which found from a research conducted by Ali et al. (2013). Therefore, the findings of this study are agreed well with the results postulated by Sabat (2013) and Ali et al. (2016). In addition, from SVM analysis, the R^2 was found 0.90 and 0.97 for stabilized soil with QD and lime as well as RHA and lime, respectively. A research conducted by Sabat (2015) reveals that the R^2 was found 0.98 after SVM analysis. It indicated that, after SVM analysis the R^2 value (0.90 and 0.97) is near about the research that is postulated by Sabat (2015). Therefore, the findings of this study were agreed well with the results postulated by Sabat. (2016).

The values of R^2 were found as 0.798, 0.872, 0.995 and 0.90 for SLR, MLR, ANN and SVM, respectively, for prediction of CBR of stabilized soil with QD and lime (Table 4.48). Moreover, the values of R^2 were found as 0.908, 0.95, 0.998 and 0.97 for LR, MLR, ANN and SVM, respectively, for prediction of CBR of stabilized soil with RHA and lime. From stabilized soil with QD and lime, the best R^2 was found 0.995 from ANN analysis as compared to SLR, MLR and SVM analysis. Moreover, from stabilized soil with RHA and lime, the best R^2 was found 0.998 by ANN as compared to SLR, MLR and SVM analysis. Therefore, ANN modeling get its superior priority as the best performer to predict CBR of stabilized soil using QD and lime as well as RHA and lime. A research conducted by Sabat (2013) and Ali et al. (2016) and found the best model of ANN as compared to SLR, MLR and SVM. That means, the findings of this study was near about the findings of both researchers. Finally the findings of this research are clearly agreed with these research that conducted by at (2013) and Ali et al. (2016).

4.8 Concluding Remarks

The main focus of this study was to predict CBR of stabilized soil using QD and lime as well as RHA and lime at different curing period of 0, 7 and 28 days. In this study, the soft computing systems like SLR and MLR through MS Excel as well as ANN and SVM through MATLAB were implemented for the prediction of CBR of stabilized soils. For the stabilization of soil with QD and lime; QD as 0, 10, 20, 30, 40 and 50% as well as lime 2, 4 and 6 % in soil was used. The value of OMC decreases in the range of 14.32 to 11.29%, while, MDD increases in the range of 16.67 to 18.57 (kN/m^3) in relation to the increasing of mixing amount of QD from 0 to 50% and lime is 2 to 6%. In addition, for the stabilization of soil with RHA and lime; RHA as 0, 4, 8, 12 and 16% as well as lime of 0, 3, 4 and 5% in soil was also used. The value of OMC increase in the range of 14.7 to 22.25%, while, MDD decreases in the range of 14.0 to 17.48 (kN/m^3) in relation to the increasing of mixing amount of RHA from 0 to 16% and lime is 0 to 5%.

The CBR of stabilized soil with QD and RHA increases with the increasing of curing period of 0, 7 and 28 days. However, CBR of stabilized soil goes on increasing up to 4% of lime, further decreases with adding of lime in soil. For a particular mixing amount of lime, CBR increases with the increasing of QD in soil. The CBR increases up to 40% of QD, further addition of QD, CBR decreases, irrespective the percentage of lime for curing period of 0, 7 and 28 days. Moreover, CBR of stabilized soil goes on increasing up to 4% of lime, further decreases with adding of lime in soil. For a particular mixing amount of lime content, CBR increases with the increasing of RHA in soil. The CBR increases up to 12% of RHA, further addition of RHA, CBR decreases, irrespective the percentage of lime at curing period of 0, 7 and 28 days.

In SLR analysis, the predicted CBR of stabilized soil with QD and lime was correlated with all the variables independently and it was observed that CBR increases in relation to the increasing of QD content. The SLR analysis provided the best R^2 of 0.798 for curing period 28 days when QD have taken as an independent variable. In addition, the predicted CBR with RHA and lime was also correlated with all the variables independently and it was observed that, the CBR increases in relation to the increasing of lime content in soil. The SLR analysis provided the best R^2 of 0.908 for the curing period of 28 days when lime has taken as independent variable. In addition, in MLR analysis, it was observed that the independent variables of QD, RHA, lime, CP, OMC and MDD were greatly influenced on the predicted values of CBR of stabilized soil prepared with QD and lime as well as RHA and lime. The optimum content 40% and 4% was found for QD and lime, respectively, at varying curing periods to get better CBR of stabilized soil with QD and lime. Moreover, the optimum content 12% and 4% was found for RHA and lime at varying curing periods to get better CBR of stabilized soil with RHA and lime. The maximum CBR of stabilized soil with QD was found than that of stabilized soil with RHA for every curing period. The observed CBR and selected independent variables can be expressed by a series of developed equation of reasonable degree of accuracy and judgement from SLR and MLR analysis. These developed equations may be proposed to predict CBR of stabilized soils by knowing others independents variables.

From ANN analysis, for stabilized soil with QD and lime the best R^2 were found 0.992, 0.987 and 0.995 for LMNN, BRNN and SCGNN, respectively. Moreover, the best R^2 were found 0.992 (LMNN), 0.995 (SCGNN) and 0.987 (LMNN) for 0, 7 and 28 days, respectively, for stabilized soil with QD and lime. Therefore, the best R^2 were found 0.995 of SCGNN model at curing period of 7 days with the independent variables QD, lime and OMC. In addition, for stabilized soil with RHA and lime, best R^2 were found as 0.995, 0.998 and 0.992 for LMNN, BRNN and SCGNN, respectively. Moreover, the best R^2 were found as 0.998 (BRNN), 0.997 (BRNN) and 0.996 (BRNN) for 0, 7 and 28 days, respectively. Therefore, the best R^2 were found 0.998 of BRNN through ANN model at curing period of 28 days with RHA, lime, CP, OMC and MDD as independent variables. In SVM analysis, for stabilized soil with QD and lime, the best R^2 were found as 0.79, 0.90 and 0.86 for SVM-L, SVM-Q and SVM-C, respectively. Moreover, the best R^2 were found as 0.80 (SVM-C), 0.81 (SVM-C) and 0.90 (SVM-Q) for 0, 7 and 28 days respectively. Therefore, the best R^2 were found 0.90 of SVM-Q through SVM model at curing period of 28 days with QD and lime as independent variable. In addition, for stabilized soil with RHA and lime, best R^2 were found as 0.94, 0.96 and 0.97 for SVM-L, SVM-Q and SVM-C, respectively. Moreover the best R^2 were found as 0.96 (SVM-Q), 0.97 (SVM-C) and 0.96 (SVM-C) for 0, 7 and 28 days, respectively. Therefore the best R^2 were found 0.97 of SVM-C through SVM at curing period of 7 days with RHA, lime, CP, OMC and MDD as independent variable. The model ANN showed comparatively the better values of CBR with satisfactory limits of prediction parameters (RMSE, OR, R^2 and MAE) as compared to SLR, MLR and SVM for the prediction of CBR of stabilized soils. Therefore, the model ANN can be considered as the best fitted model in soft computing system for the prediction of CBR of stabilized soils. Finally, it can be concluded that the selected optimum content of admixtures and newly developed techniques of soft computing systems will further be used of other researchers to stabilize soil easily and then predict CBR of stabilized soils.

Chapter 5
Conclusions and Recommendations

5.1 Conclusions

The main focus of this study was to predict CBR of stabilized soils with QD and lime as well as RHA and lime at varying curing periods. The soft computing systems such as SLR, MLR, ANN and SVM were implemented to predict CBR of stabilized soil. The accurate prediction of CBR plays important rules for the design and construction of pavement for roads and highways. Moreover, if CBR value is low, the thickness of pavement will be high. On the basis of this concept, the present study executed some analysis through soft computing systems to predict CBR of stabilized soil with admixtures. Based on the findings of this study, the following conclusions were to be drawn:

1. The values of OMC of stabilized soil with QD and lime decreases, while, OMC increases in case of stabilized soil with RHA and lime.
2. The values of MDD of stabilized soil with QD and lime increases, while, MDD decreases in case of stabilized soil with RHA and lime.
3. The optimum content 40% and 4% was found for QD and lime, respectively, at varying curing periods to obtain better CBR of stabilized soil with QD and lime. Moreover, the optimum content of RHA was found 12% and lime of 4% at varying curing periods to obtain better CBR of stabilized soil with RHA and lime.
4. The maximum CBR of stabilized soil with QD was found than that of stabilized soil with RHA for every curing period.
5. The maximum CBR of stabilized soil with QD and lime at curing period of 28 days was found than that of other mixing content and curing periods.
6. The result of ANN analysis reveals that QD, lime and OMC were the best independent variables for the stabilization of soil with QD, while, RHA, lime, CP, OMC and MDD for stabilized soil with RHA. In addition, SVM proved QD and lime as well as RHA, lime, CP, OMC and MDD were the best independent variables for the stabilization of soil with QD and RHA, respectively.

7. The observed CBR and selected independent variables can be expressed by a series of developed equation of reasonable degree of accuracy and judgement from SLR and MLR analysis. These developed equations may be proposed to predict CBR of stabilized soils by knowing others independents variables in same cases.
8. The model ANN showed comparatively the better values of CBR with satisfactory values of prediction parameters as compared to SLR, MLR and SVM for the prediction of CBR of stabilized soils.

Finally, it can be concluded that the selected optimum content of admixtures and newly developed techniques of soft computing systems will further be used of other researchers to stabilize soil easily and then predict CBR of stabilized soils

5.2 Recommendations for Further Studies

The following recommendations are required for further studies:

1. Other suitable aggregate materials can be used as admixtures when this study will be performed in future.
2. Other input parameters such as plastic limit, liquid limit, shrinkage limit, and swelling of soil and stabilized soil can be used to predict the CBR of stabilized soil.
3. The independent variables can be used more than five to predict the CBR of stabilized soil.
4. The procedure of this study can be followed for further researchers to get the best CBR value of stabilized soil.
5. The update version of software's can be used to predict the CBR of stabilized soil to get better results.

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Annex-A

Compaction Curves of Stabilized Soil using Admixtures

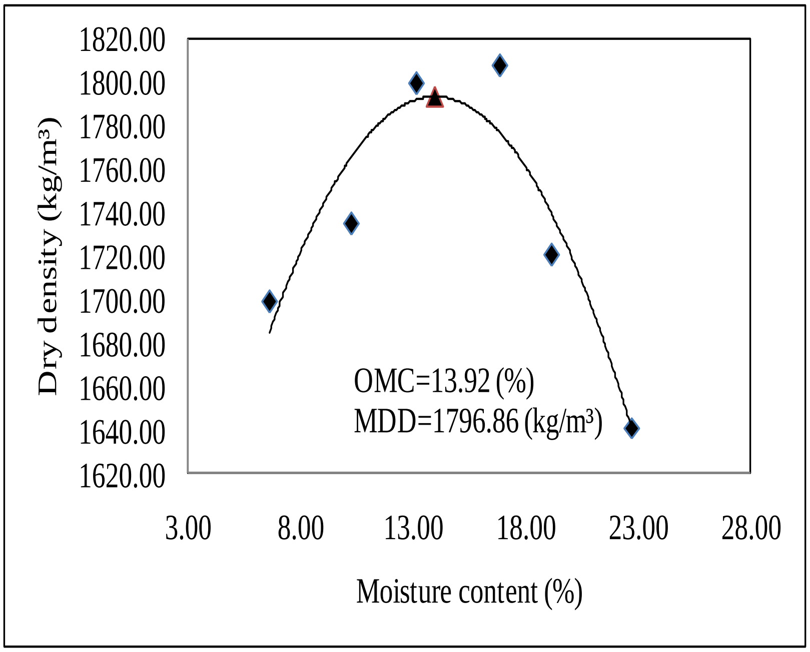


Figure A.1: Compaction curve of stabilized soils (QD 0% and lime 0%).

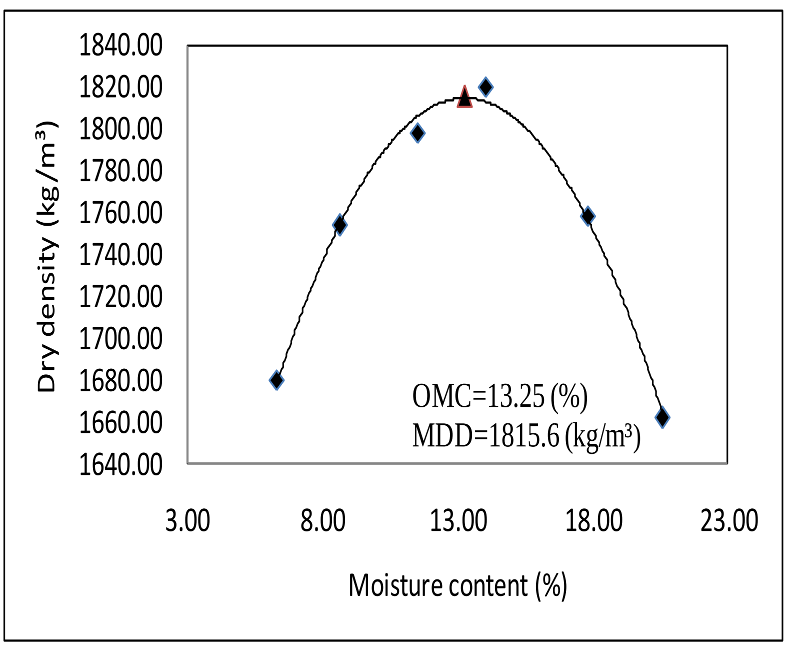


Figure A.2: Compaction curve of stabilized soils (QD 10% and lime 3%).

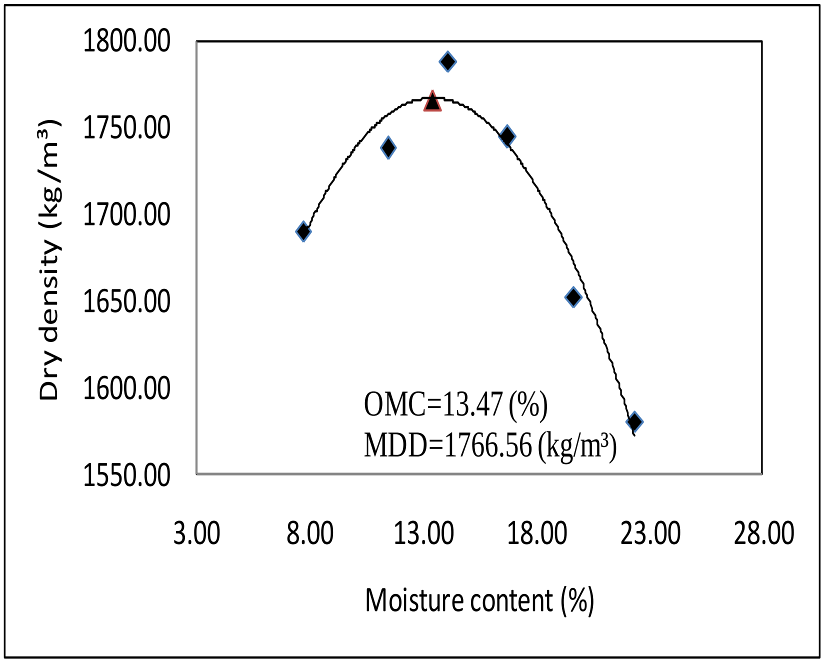


Figure A.3: Compaction curve of stabilized soils (QD 10% and lime 4%).

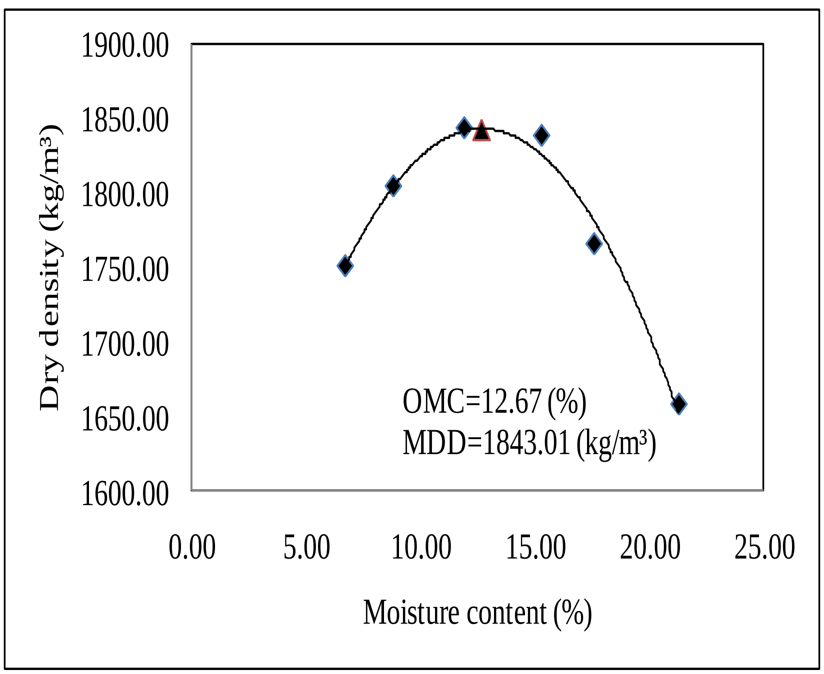


Figure A.4: Compaction curve of stabilized soils (QD 20% and lime 2%)

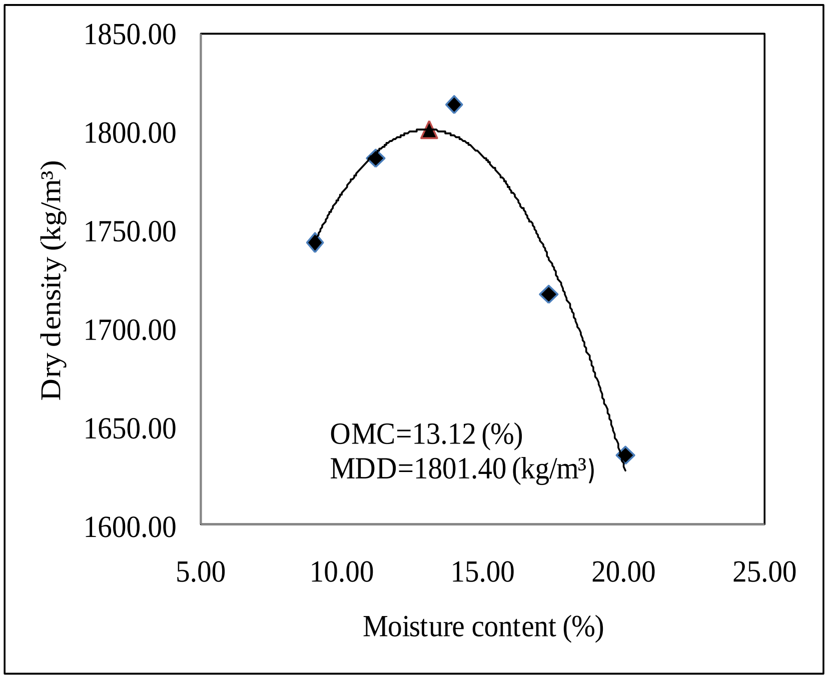


Figure A.5: Compaction curve of stabilized soils (QD 20% and lime 6%).

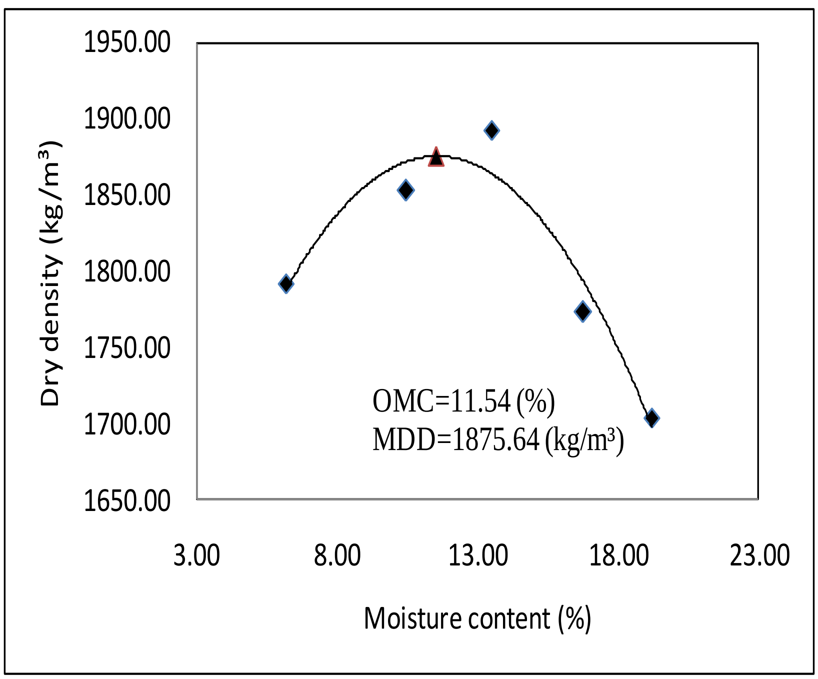


Figure A.6: Compaction curve of stabilized soils (QD 40% and lime 2%).

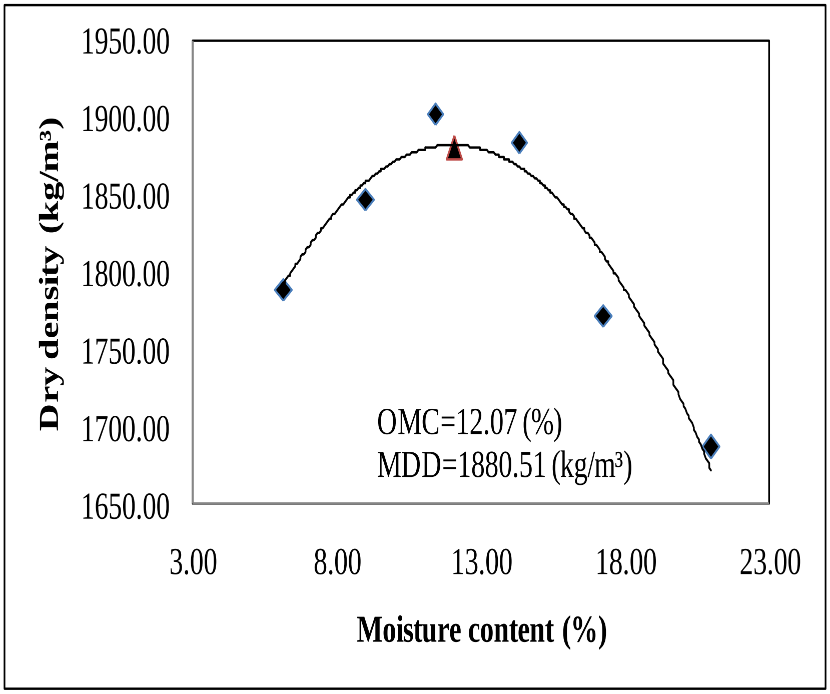


Figure A.7: Compaction curve of stabilized soils (QD 40% and lime 4%).

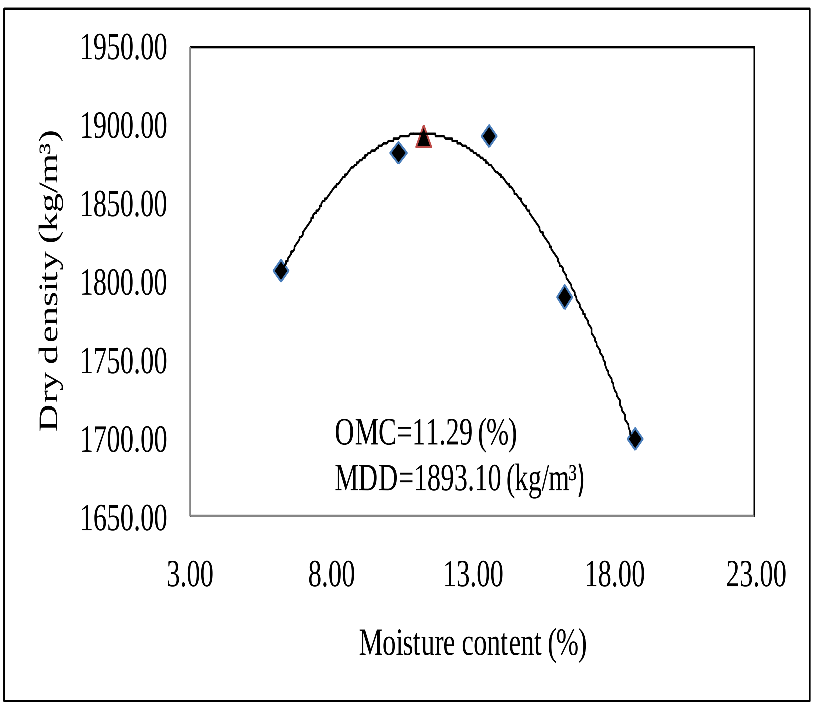


Figure A.8: Compaction curve of stabilized soils (QD 50% and lime 2%).

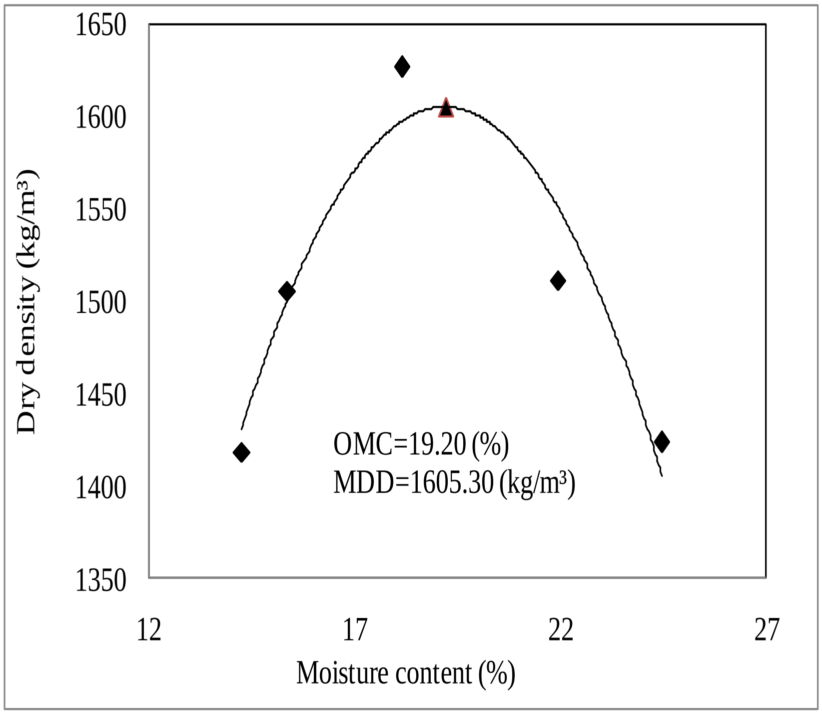


Figure A.9: Compaction curve of stabilized soils (RHA 12% and lime 0%).

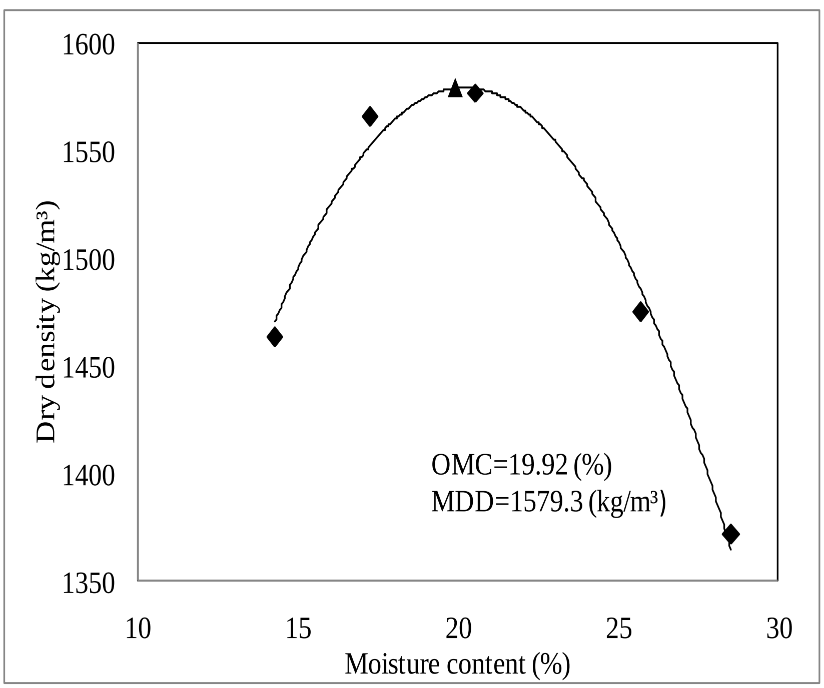


Figure A.10: Compaction curve of stabilized soils (RHA 16% and lime 0%).

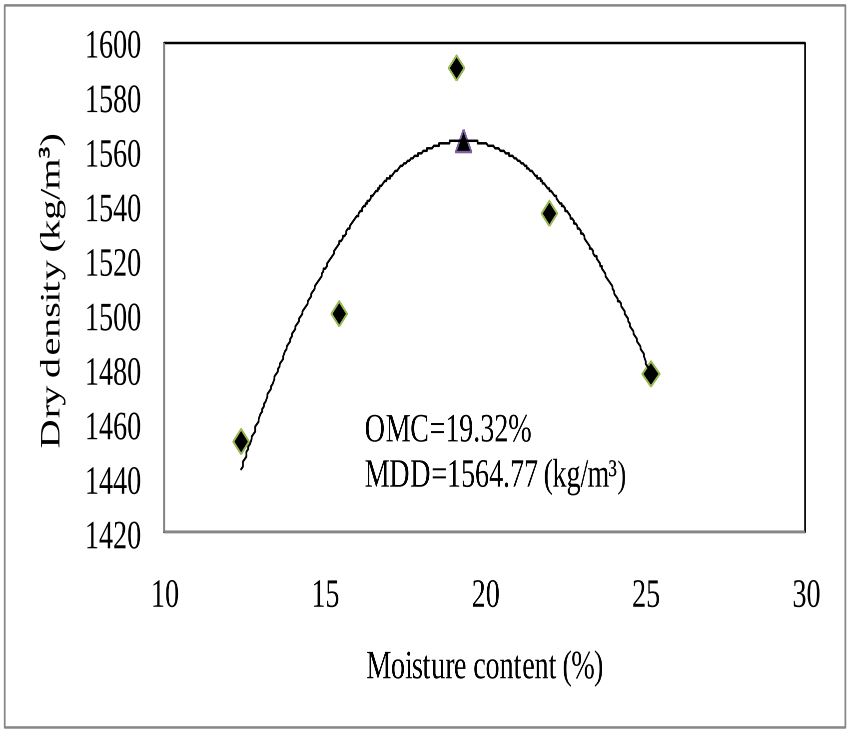


Figure A.11: Compaction curve of stabilized soils (RHA 12% and lime 3%).

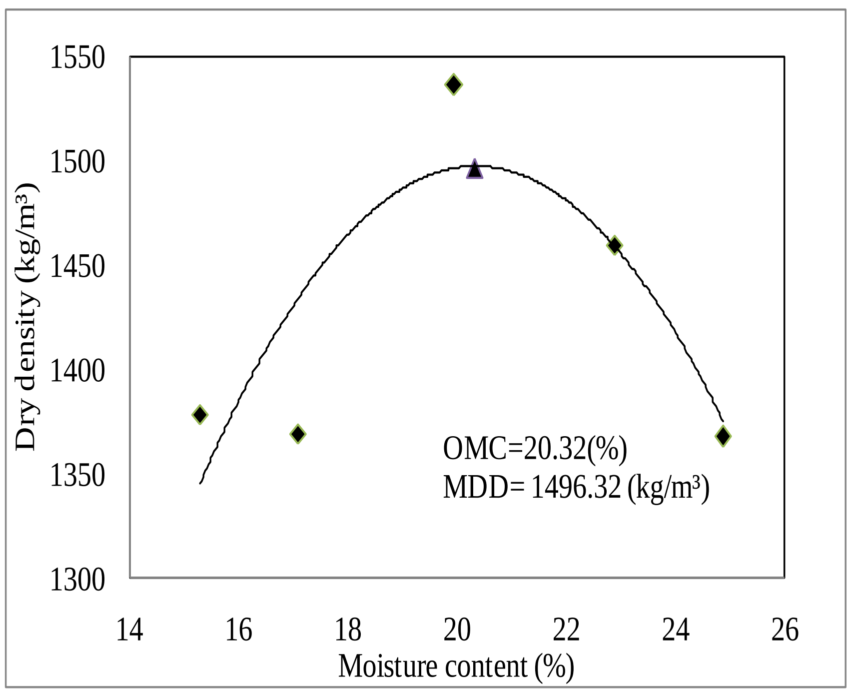


Figure A.12: Compaction curve of stabilized soils (RHA 16% and lime 3%).

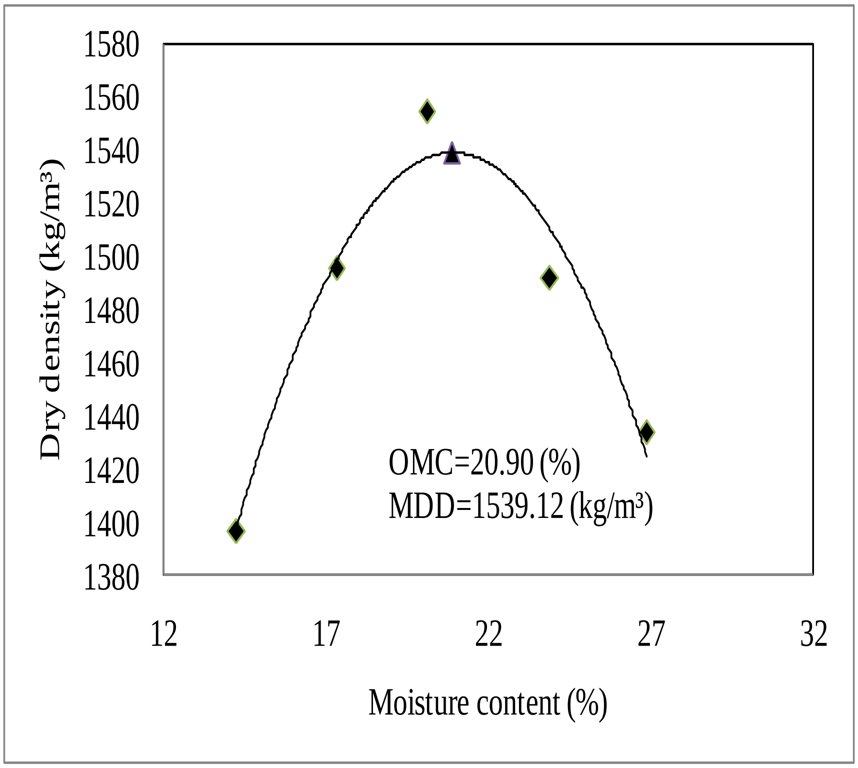


Figure A.13: Compaction curve of stabilized soils (RHA 12% and lime 4%).

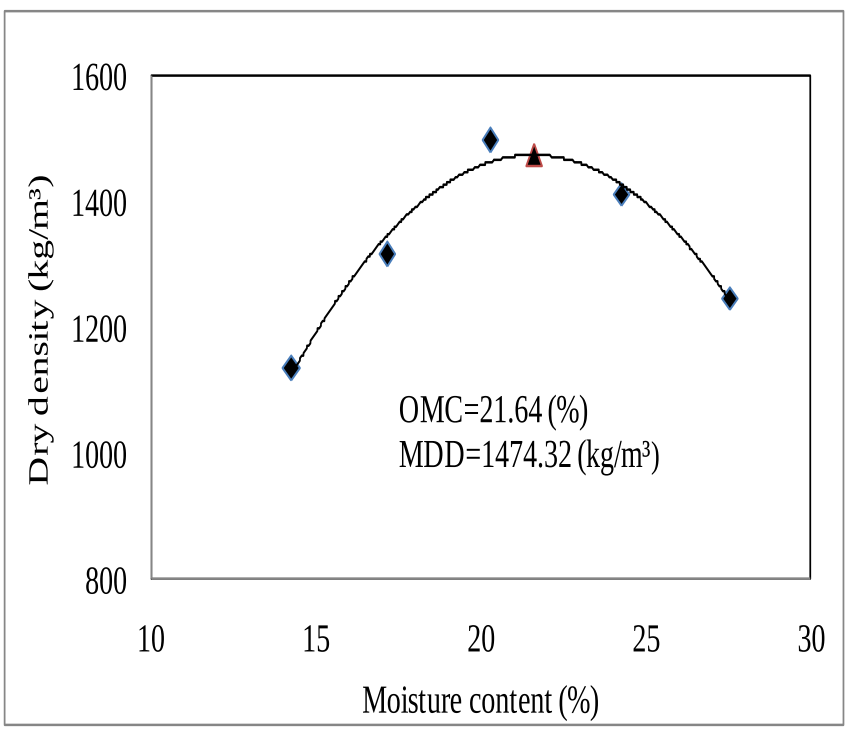


Figure A.14: Compaction curve of stabilized soils (RHA 16% and lime 4%).

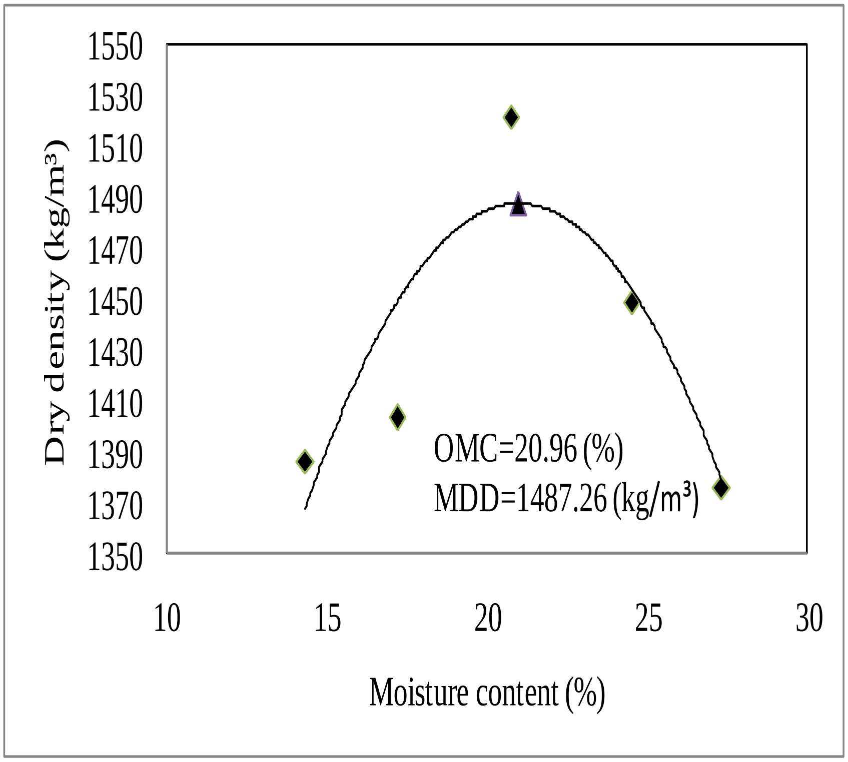


Figure A.15: Compaction curve of stabilized soils (RHA 12% and lime 5%.

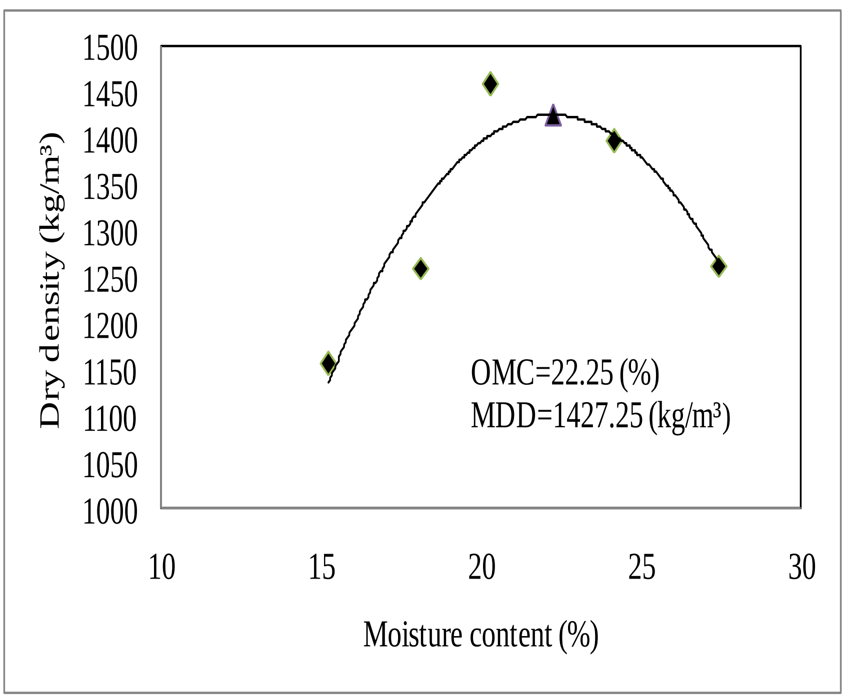


Figure A.16: Compaction curve of stabilized soils (RHA 16% and lime 5%).

Annex-B

Simple Linear Regression Analysis of Stabilized Soil using Admixture

Lime (%)	CBR) 0 day curing)
2	28.7
2	32.92
2	35.17
2	38.86
2	42.82
2	40.36
4	29.03
4	30.12
4	39.8
4	53.68
4	77.54
4	66.35
6	28.87
6	31.52
6	37.48
6	46.27
6	60.18
6	53.35

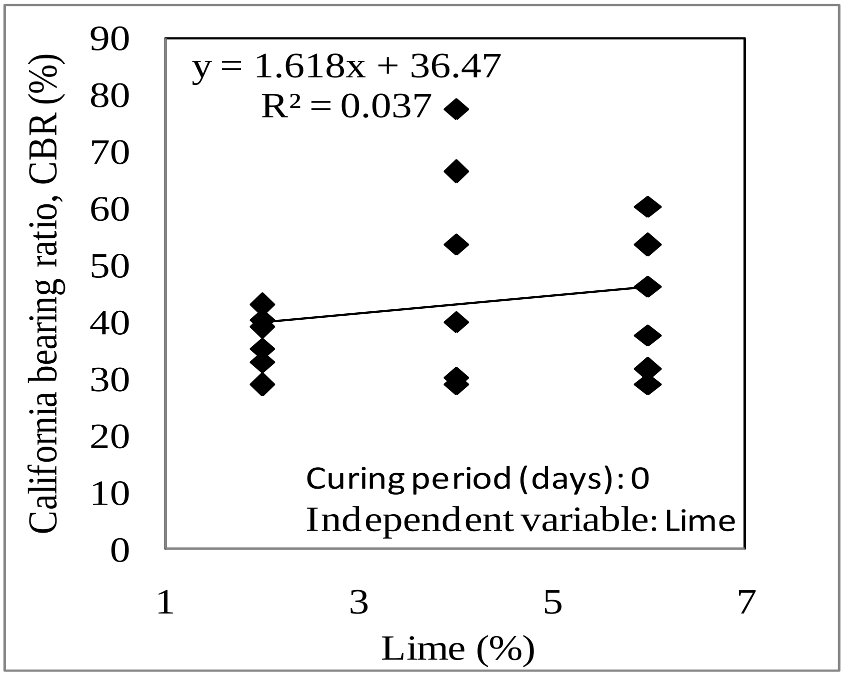


Figure B.1: Correlation of CBR and lime content at curing period of 0 days.

Lime (%)	CBR (7 days curing)
2	33.34
2	40.21
2	45.32
2	51.31
2	61.1
2	56.64
4	44.67
4	46.21
4	53.78
4	62.32
4	83.27
4	74.5
6	39.8
6	41.14
6	44.77
6	59.55
6	74.19
6	69.13

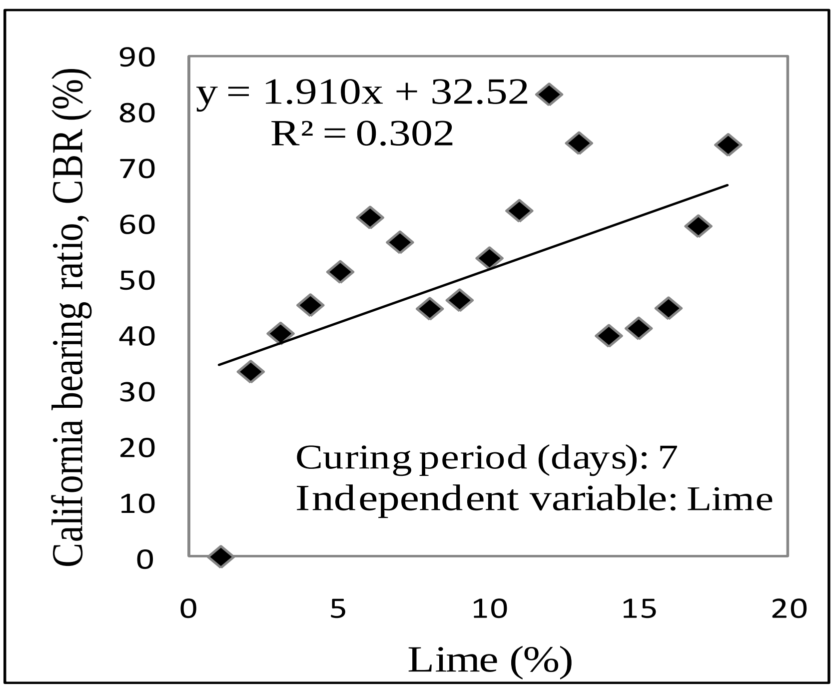


Figure B.2: Correlation of CBR and lime content at curing period of 7 days.

Lime (%)	CBR (28 days curing)
2	57.66
2	69.3
2	73.2
2	78.65
2	87.25
2	81.89
4	62.12
4	73.55
4	79
4	87.81
4	98.26
4	91.22
6	59.89
6	71.5
6	76.22
6	83.5
6	91.75
6	87.21

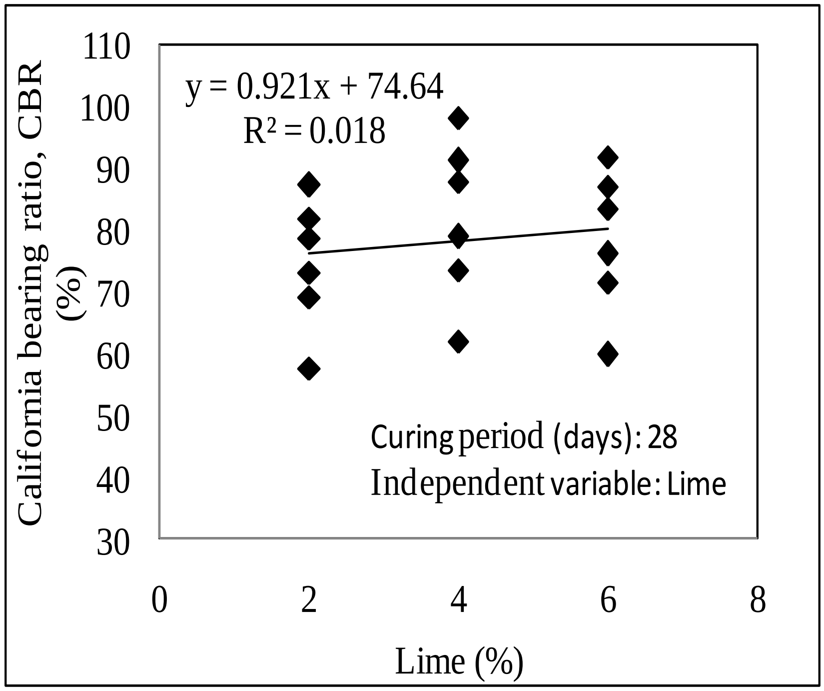


Figure B.3: Correlation of CBR and Lime content at curing period of 28 days.

QD (%)	CBR) 0 day curing)
0	28.7
10	32.92
20	35.17
30	38.86
40	42.82
50	40.36
0	29.03
10	30.12
20	39.8
30	53.68
40	77.54
50	66.35
0	28.87
10	31.52
20	37.48
30	46.27
40	60.18
50	53.35

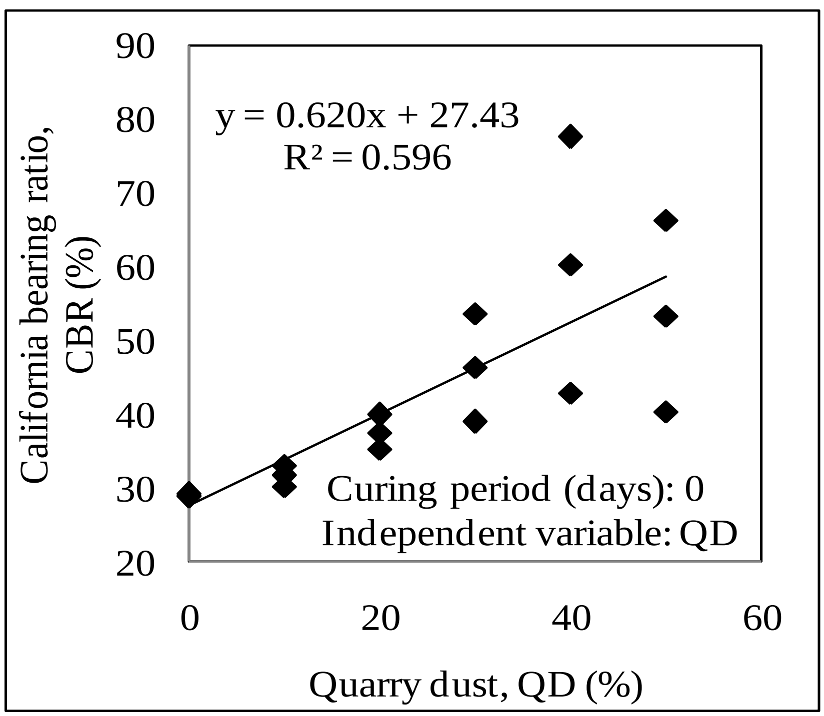


Figure B.4: Correlation of CBR and QD at curing period of 0 days.

QD (%)	CBR (7 days curing)
0	33.34
10	40.21
20	45.32
30	51.31
40	61.1
50	56.64
0	44.67
10	46.21
20	53.78
30	62.32
40	83.27
50	74.5
0	39.8
10	41.14
20	44.77
30	59.55
40	74.19
50	69.13

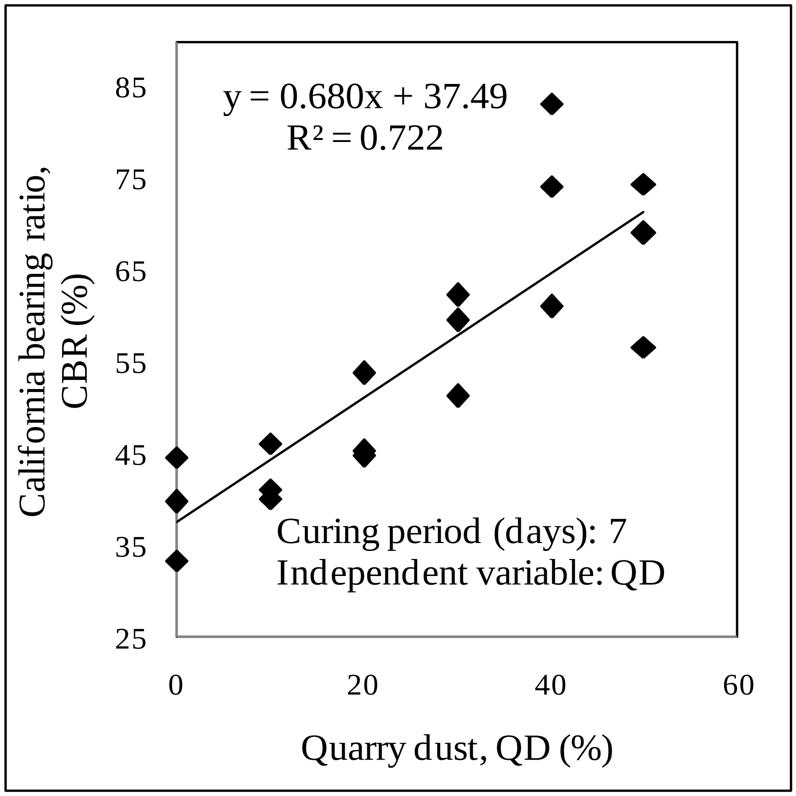


Figure B.5: Correlation of CBR and QD by SLR at curing period of 7 days.

QD (%)	CBR (28 days curing)
0	57.66
10	69.3
20	73.2
30	78.65
40	87.25
50	81.89
0	62.12
10	73.55
20	79
30	87.81
40	98.26
50	91.22
0	59.89
10	71.5
20	76.22
30	83.5
40	91.75
50	87.21

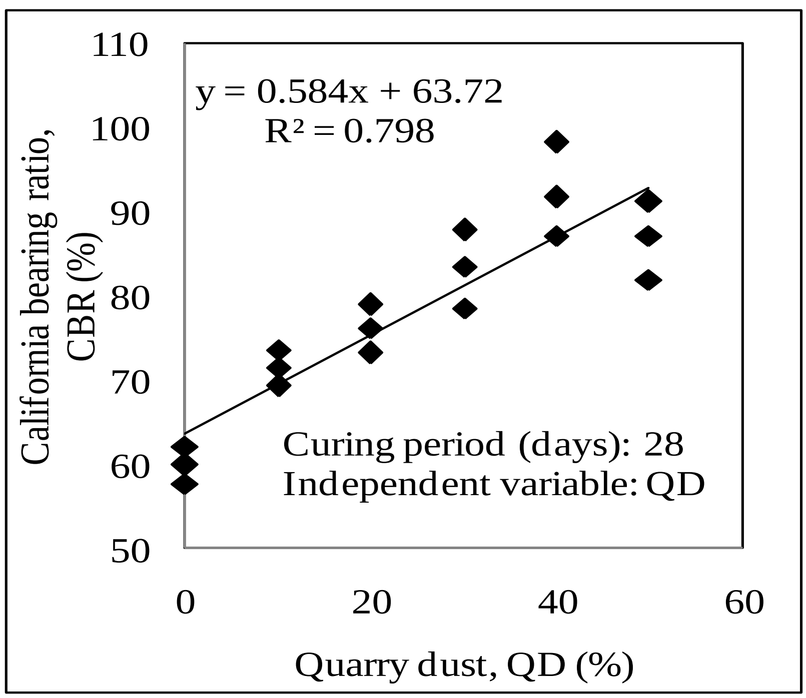


Figure B.6: Correlation of CBR and QD by SLR at curing period of 28 days.

OMC (%)	CBR) 0 day curing)
13.72	28.7
12.89	32.92
12.67	35.17
12.10	38.86
11.54	42.82
11.29	40.36
14.12	29.03
13.47	30.12
13.16	39.8
12.58	53.68
12.07	77.54
11.78	66.35
14.32	28.87
13.89	31.52
13.12	37.48
12.76	46.27
12.34	60.18
11.92	53.35

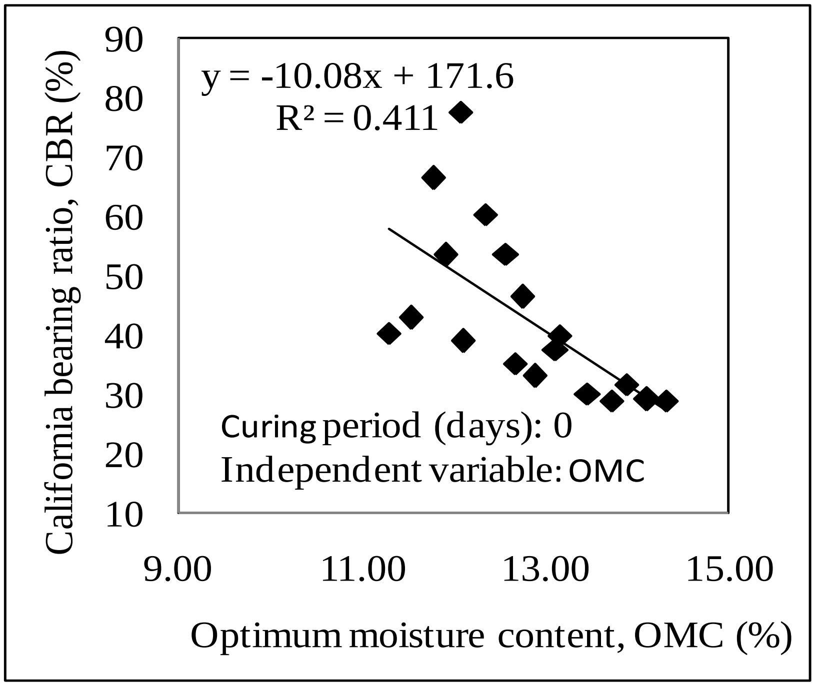


Figure B.7: Correlation of CBR and OMC at curing period of 0 days.

OMC (%)	CBR (7 days curing)
13.72	33.34
12.89	40.21
12.67	45.32
12.10	51.31
11.54	61.1
11.29	56.64
14.12	44.67
13.47	46.21
13.16	53.78
12.58	62.32
12.07	83.27
11.78	74.5
14.32	39.8
13.89	41.14
13.12	44.77
12.76	59.55
12.34	74.19
11.92	69.13

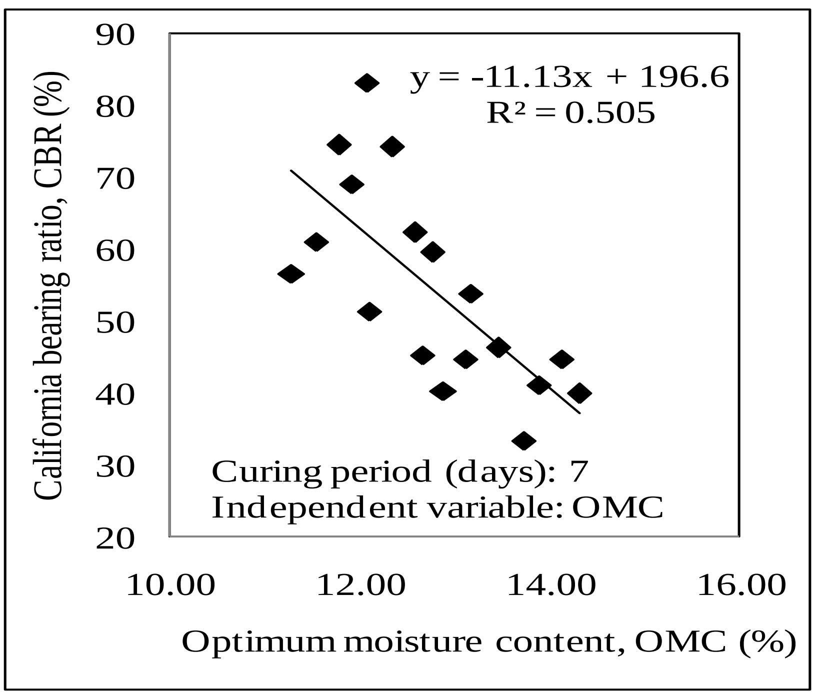


Figure B.8: Correlation of CBR and OMC by SLR at curing period of 7 days.

OMC (%)	CBR (28 days curing)
13.72	57.66
12.89	69.3
12.67	73.2
12.10	78.65
11.54	87.25
11.29	81.89
14.12	62.12
13.47	73.55
13.16	79
12.58	87.81
12.07	98.26
11.78	91.22
14.32	59.89
13.89	71.5
13.12	76.22
12.76	83.5
12.34	91.75
11.92	87.21

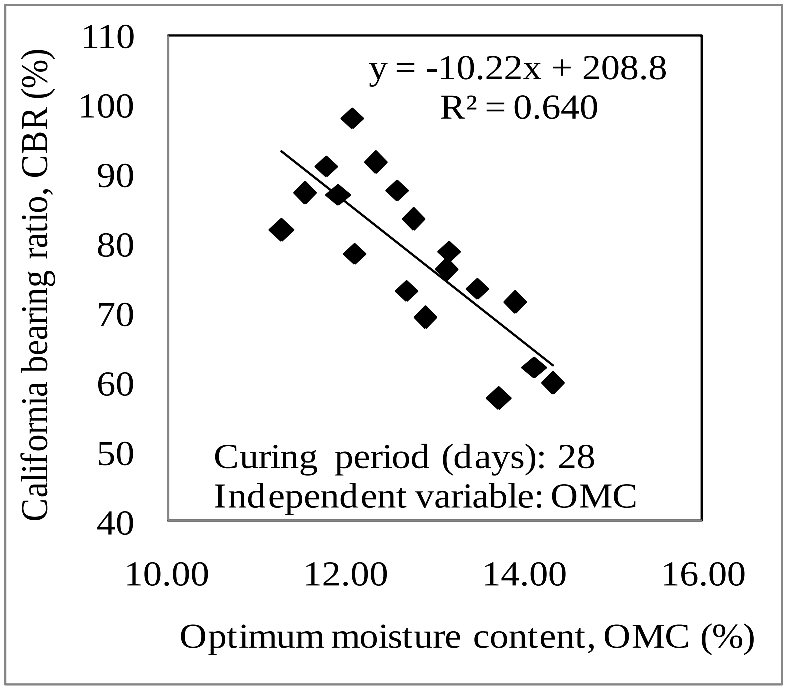


Figure B.9: Correlation of CBR and OMC at curing period of 28 days.

MDD (kN/m^3)	CBR) 0 day curing)
16.95	28.7
17.42	32.92
18.08	35.17
18.17	38.86
18.40	42.82
18.57	40.36
16.86	29.03
17.33	30.12
17.88	39.8
18.00	53.68
18.38	77.54
18.47	66.35
16.67	28.87
17.21	31.52
17.67	37.48
17.78	46.27
18.15	60.18
18.36	53.35

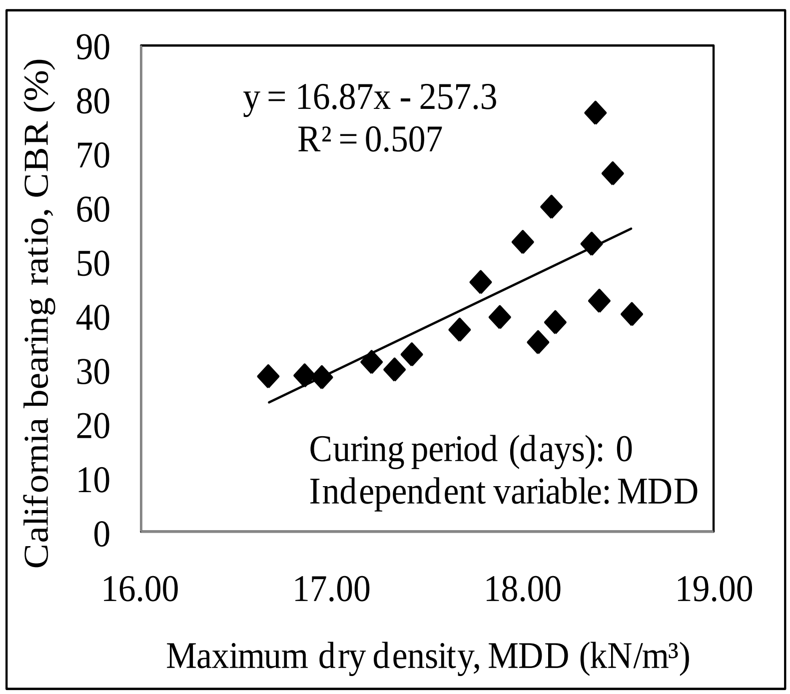


Figure B.10: Correlation of CBR and MDD at curing period of 0 days.

MDD (kN/m^3)	CBR (7 days curing)
16.95	33.34
17.42	40.21
18.08	45.32
18.17	51.31
18.40	61.1
18.57	56.64
16.86	44.67
17.33	46.21
17.88	53.78
18.00	62.32
18.38	83.27
18.47	74.5
16.67	39.8
17.21	41.14
17.67	44.77
17.78	59.55
18.15	74.19
18.36	69.13

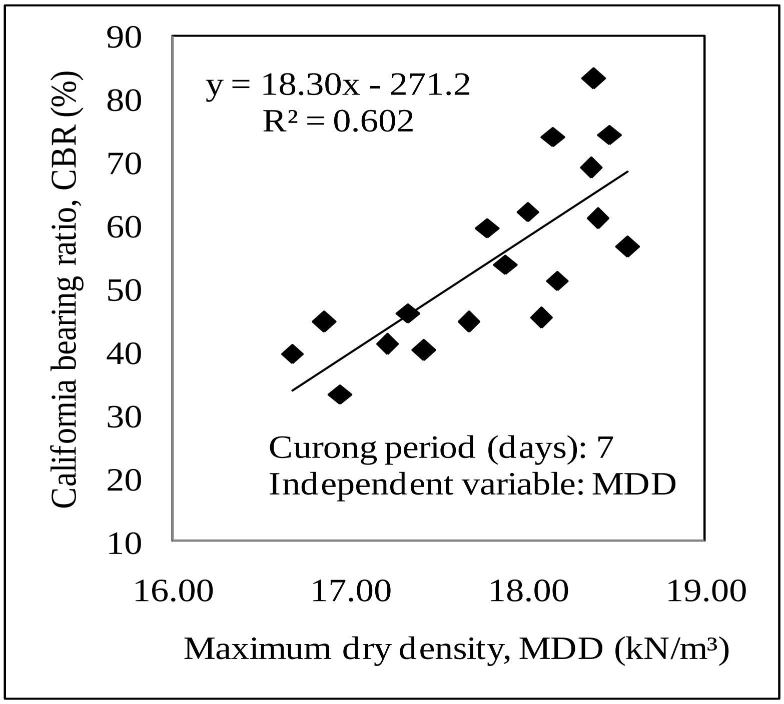


Figure B.11: Correlation of CBR and MDD at curing period of 7 days.

MDD (kN/m^3)	CBR (28 days curing)
16.95	57.66
17.42	69.3
18.08	73.2
18.17	78.65
18.40	87.25
18.57	81.89
16.86	62.12
17.33	73.55
17.88	79
18.00	87.81
18.38	98.26
18.47	91.22
16.67	59.89
17.21	71.5
17.67	76.22
17.78	83.5
18.15	91.75
18.36	87.21

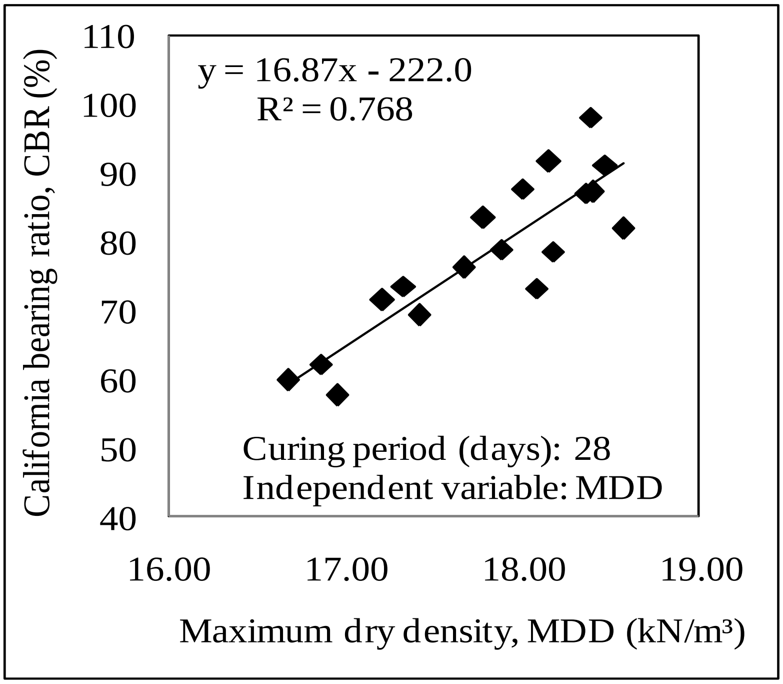


Figure B.12: Correlation of CBR and MDD at curing period of 28 days.

Lime (%)	CBR (0 day curing)
0	5.1
0	8.01
0	11.22
0	14.23
0	13.03
3	30.7
3	34.39
3	36.82
3	40.81
3	37.08
4	42.69
4	46.21
4	48.51
4	50.1
4	48.25
5	42.83
5	43.94
5	45.21
5	47.2
5	45.14

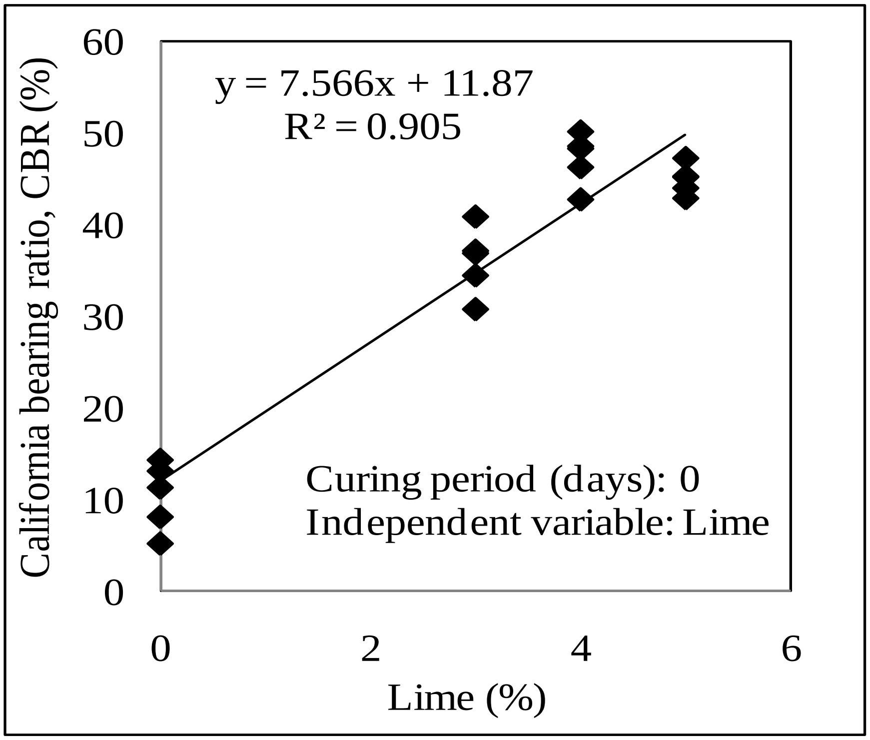


Figure B.13: Correlation of CBR and Lime content at curing period of 0 days.

Lime (%)	CBR (7 days curing)
0	9.27
0	11.22
0	15.08
0	18.12
0	16.92
3	34.23
3	35.93
3	39.76
3	42.42
3	40.55
4	44.45
4	48.51
4	50.62
4	52.5
4	50.21
5	44.87
5	45.11
5	47.65
5	50.78
5	47.31

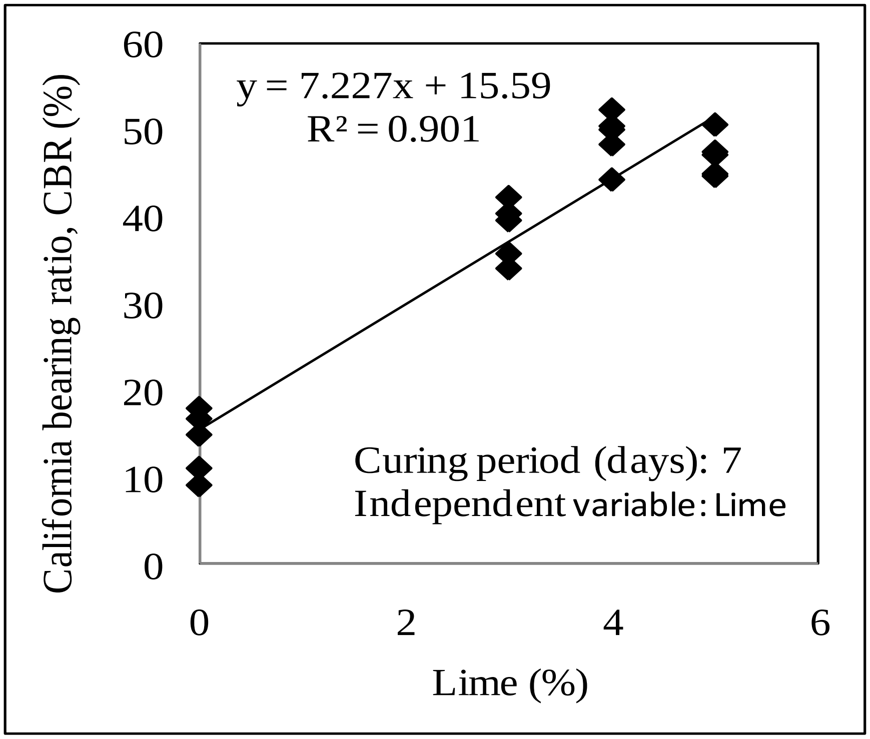


Figure B.14: Correlation of CBR and Lime content at curing period of 7 days.

Lime (%)	CBR (28 days curing)
0	13.43
0	17.83
0	20.21
0	23.43
0	21.24
3	39.52
3	42.42
3	44.85
3	46.52
3	44.11
4	50.61
4	54.93
4	56.15
4	58.41
4	56.04
5	51.21
5	51.55
5	53.41
5	55.2
5	52.65

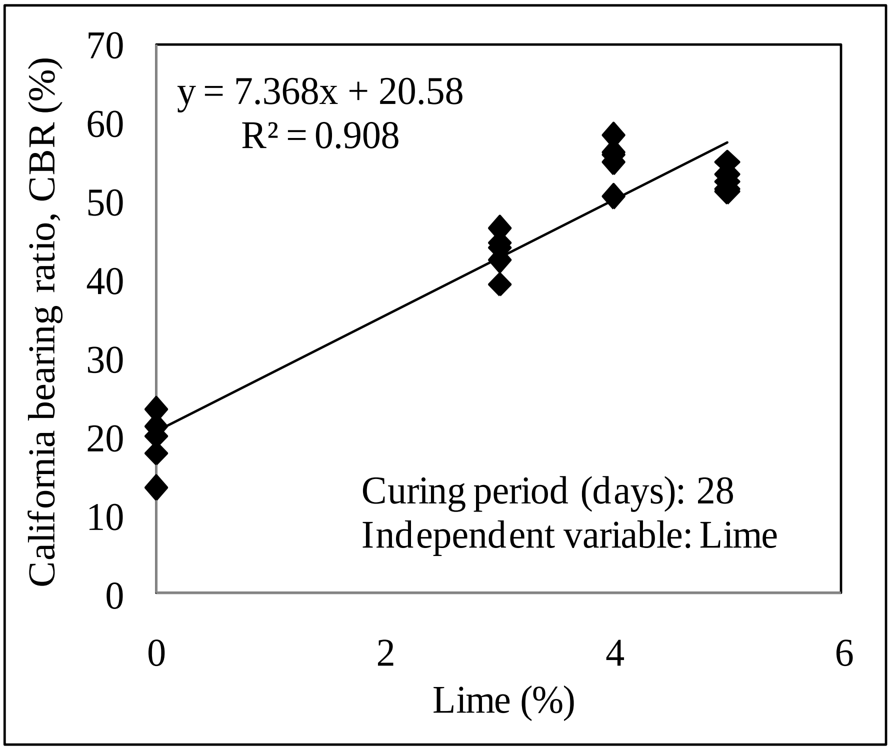


Figure B.15: Correlation of CBR and Lime content at curing period of 28 days.

RHA (%)	CBR (0 day curing)
10	5.1
4	8.01
8	11.22
12	14.23
16	13.03
0	30.7
4	34.39
8	36.82
12	40.81
16	37.08
0	42.69
4	46.21
8	48.51
12	50.1
16	48.25
0	42.83
4	43.94
8	45.21
12	47.2
16	45.14

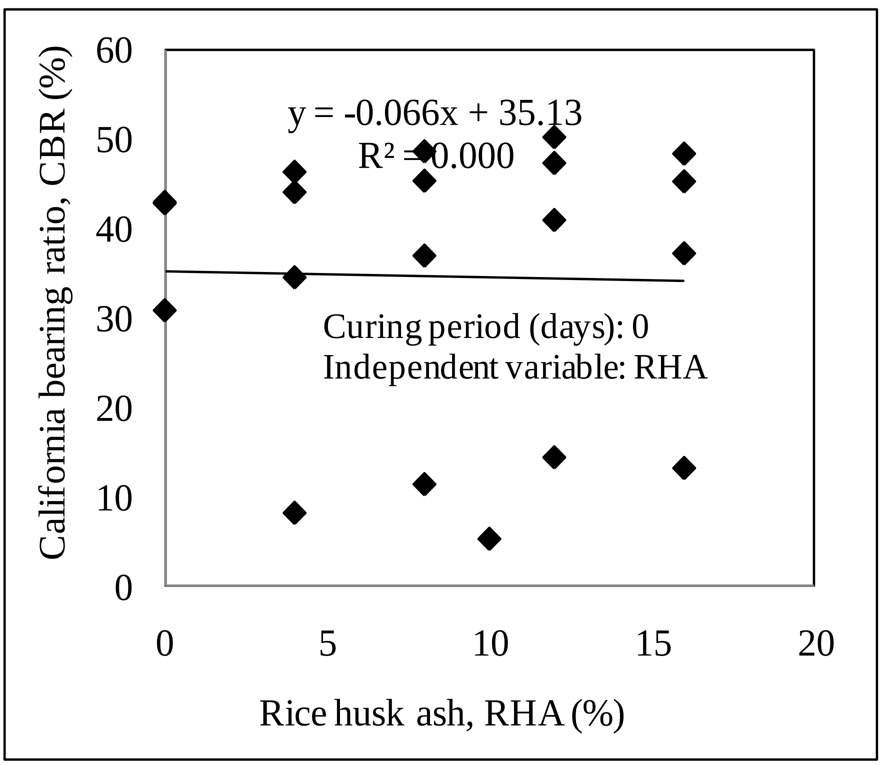


Figure B.16: Correlation of CBR and RHA content at curing period of 0 days.

RHA (%)	CBR (7 days curing)
0	9.27
4	11.22
8	15.08
12	18.12
16	16.92
0	34.23
4	35.93
8	39.76
12	42.42
16	40.55
0	44.45
4	48.51
8	50.62
12	52.5
16	50.21
0	44.87
4	45.11
8	47.65
12	50.78
16	47.31

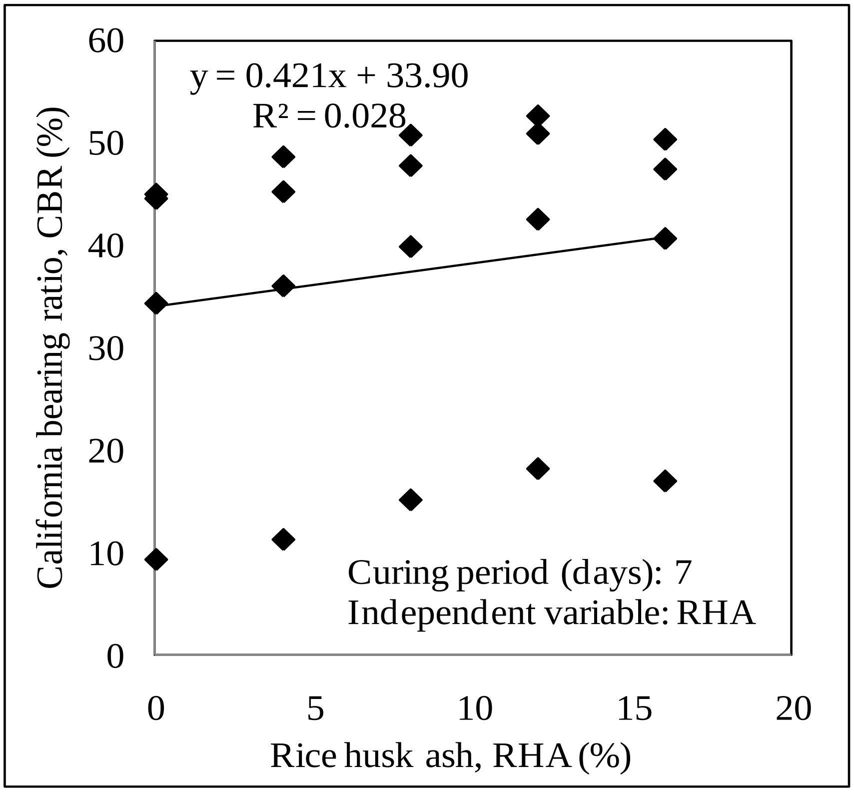


Figure B.17: Correlation of CBR and RHA content at curing period of 7 days.

RHA (%)	CBR (28 days curing)
0	13.43
4	17.83
8	20.21
12	23.43
16	21.24
0	39.52
4	42.42
8	44.85
12	46.52
16	44.11
0	50.61
4	54.93
8	56.15
12	58.41
16	56.04
0	51.21
4	51.55
8	53.41
12	55.2
16	52.65

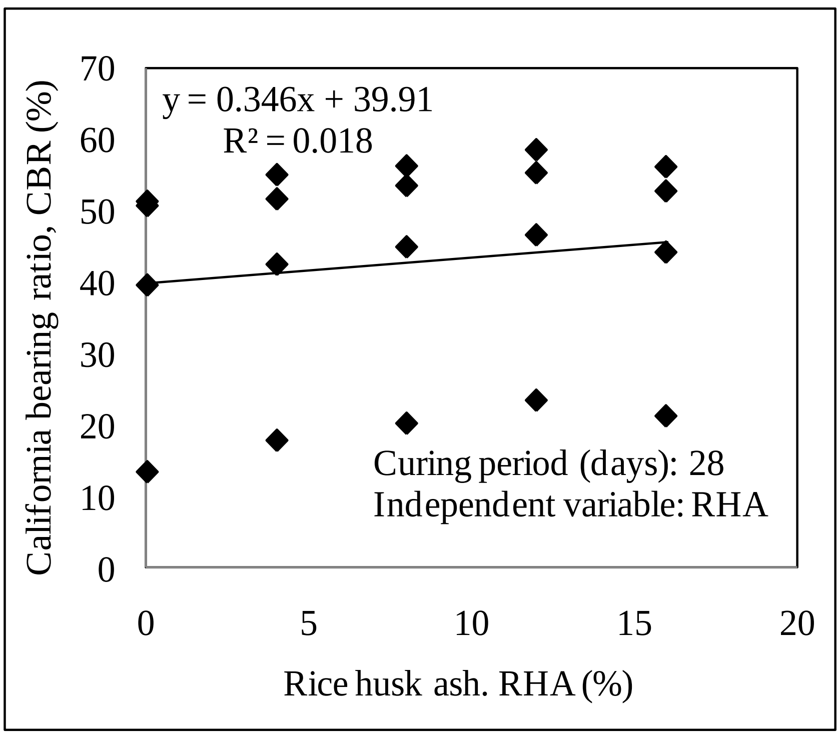


Figure B.18: Correlation of CBR and RHA content at curing period of 28 days.

OMC (%)	CBR (0 day curing)
14.7	5.1
15.3	8.01
17.4	11.22
19.2	14.23
19.92	13.03
15.3	30.7
17.12	34.39
18.11	36.82
19.32	40.81
20.32	37.08
16.9	42.69
17.98	46.21
19.2	48.51
20.9	50.1
21.64	48.25
17.8	42.83
18.88	43.94
20.1	45.21
20.96	47.2
22.25	45.14

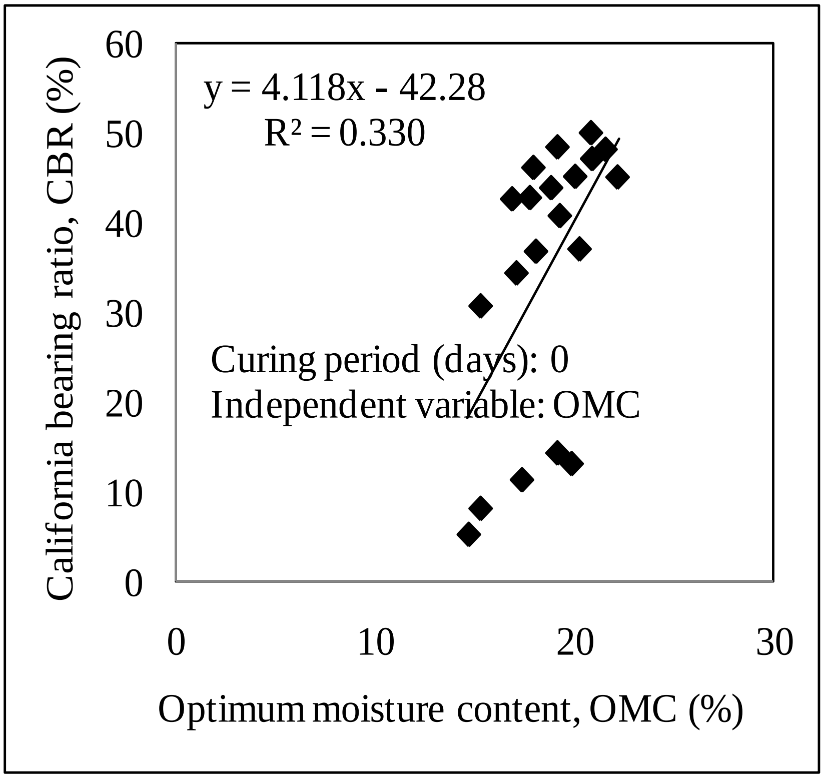


Figure B.19: Correlation of CBR and OMC content at curing period of 0 days.

OMC (%)	CBR (7 days curing)
14.7	9.27
15.3	11.22
17.4	15.08
19.2	18.12
19.92	16.92
15.3	34.23
17.12	35.93
18.11	39.76
19.32	42.42
20.32	40.55
16.9	44.45
17.98	48.51
19.2	50.62
20.9	52.5
21.64	50.21
17.8	44.87
18.88	45.11
20.1	47.65
20.96	50.78
22.25	47.31

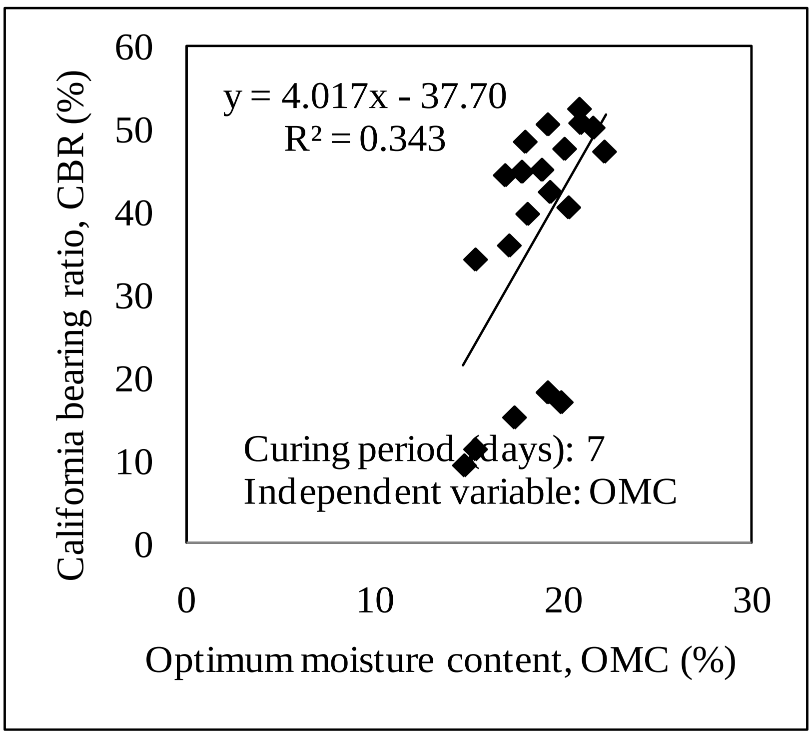


Figure B.20: Correlation of CBR and OMC content at curing period of 7 days.

OMC (%)	CBR (28 days curing)
14.7	13.43
15.3	17.83
17.4	20.21
19.2	23.43
19.92	21.24
15.3	39.52
17.12	42.42
18.11	44.85
19.32	46.52
20.32	44.11
16.9	50.61
17.98	54.93
19.2	56.15
20.9	58.41
21.64	56.04
17.8	51.21
18.88	51.55
20.1	53.41
20.96	55.2
22.25	52.65

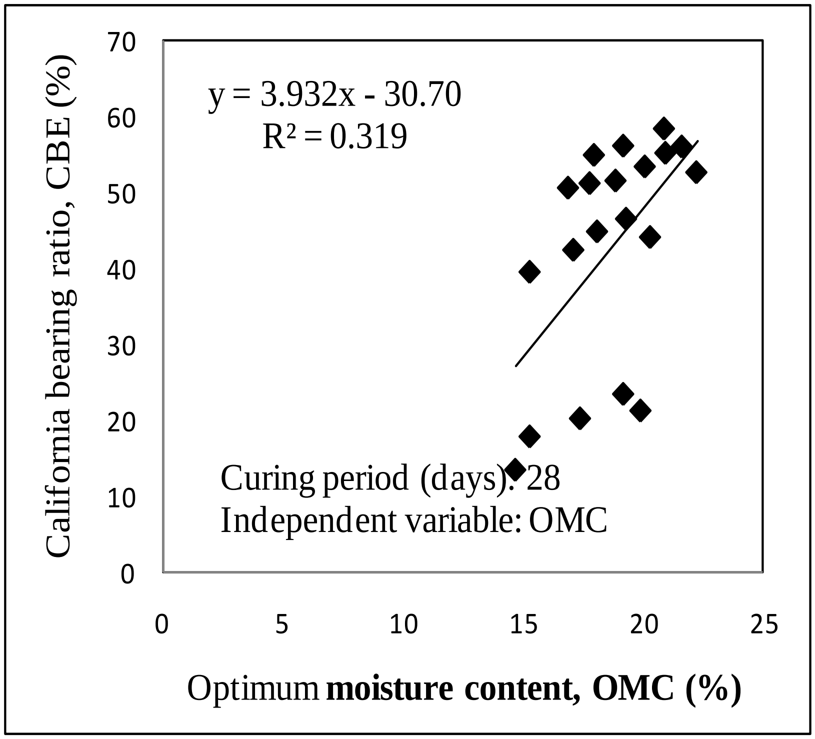


Figure B.21: Correlation of CBR and OMC content at curing period of 28 days.

MDD (kN/m^3)	CBR (0 day curing)
17.48	5.1
17.01	8.01
16.66	11.22
15.75	14.23
15.49	13.03
17.18	30.7
16.23	34.39
15.98	36.82
15.35	40.81
14.68	37.08
16.86	42.69
16.23	46.21
15.88	48.51
15.1	50.1
14.46	48.25
16.46	42.83
16.01	43.94
15.44	45.21
14.59	47.2
14	45.14

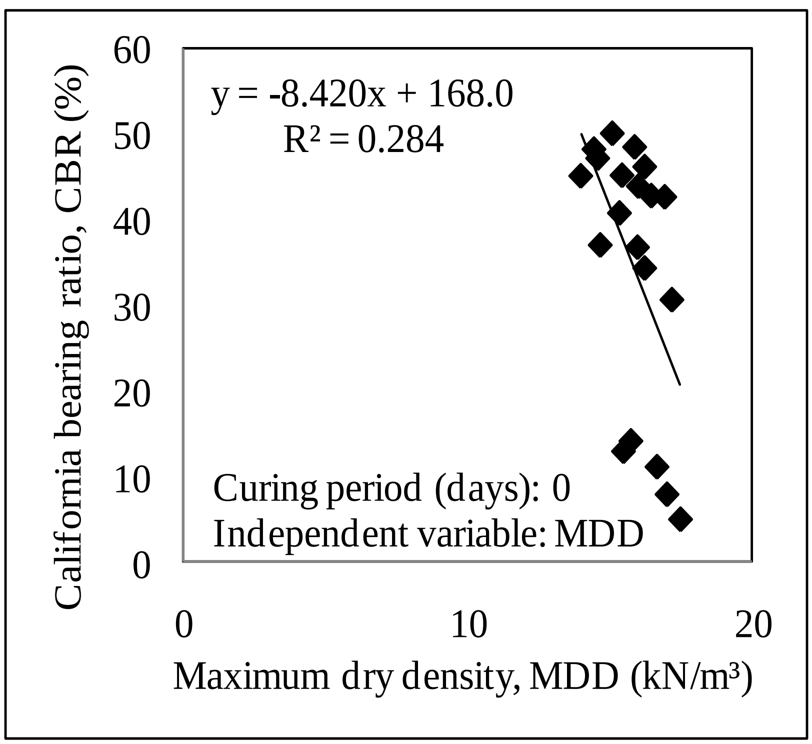


Figure B.22: Correlation of CBR and MDD content at curing period of 0 days.

MDD (kN/m^3)	CBR (7 days curing)
17.48	9.27
17.01	11.22
16.66	15.08
15.75	18.12
15.49	16.92
17.18	34.23
16.23	35.93
15.98	39.76
15.35	42.42
14.68	40.55
16.86	44.45
16.23	48.51
15.88	50.62
15.1	52.5
14.46	50.21
16.46	44.87
16.01	45.11
15.44	47.65
14.59	50.78
14	47.31

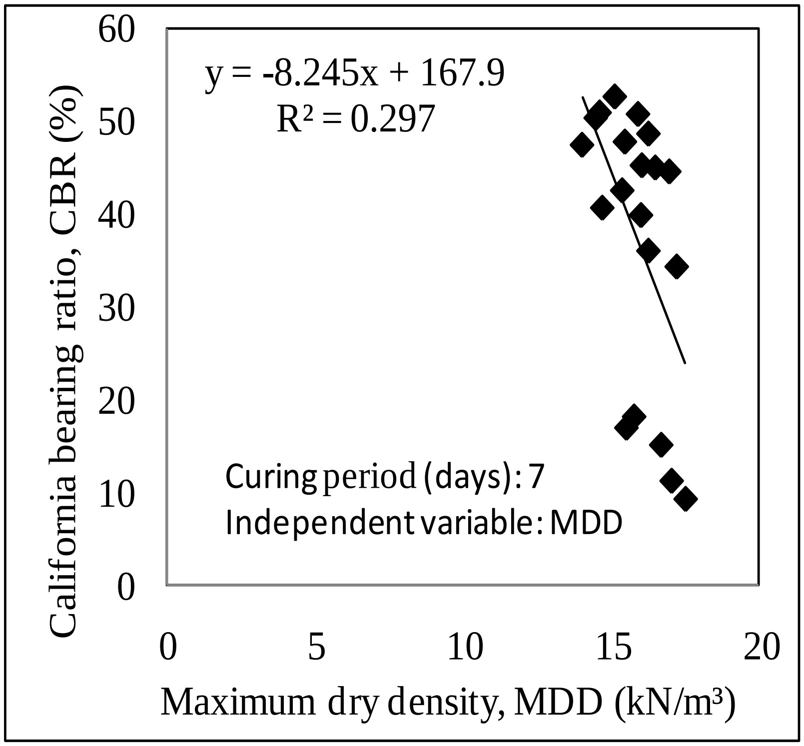


Figure B.23: Correlation of CBR and MDD content at curing period of 7 days.

MDD (kN/m^3)	CBR (28 days curing)
17.48	13.43
17.01	17.83
16.66	20.21
15.75	23.43
15.49	21.24
17.18	39.52
16.23	42.42
15.98	44.85
15.35	46.52
14.68	44.11
16.86	50.61
16.23	54.93
15.88	56.15
15.1	58.41
14.46	56.04
16.46	51.21
16.01	51.55
15.44	53.41
14.59	55.2
14	52.65

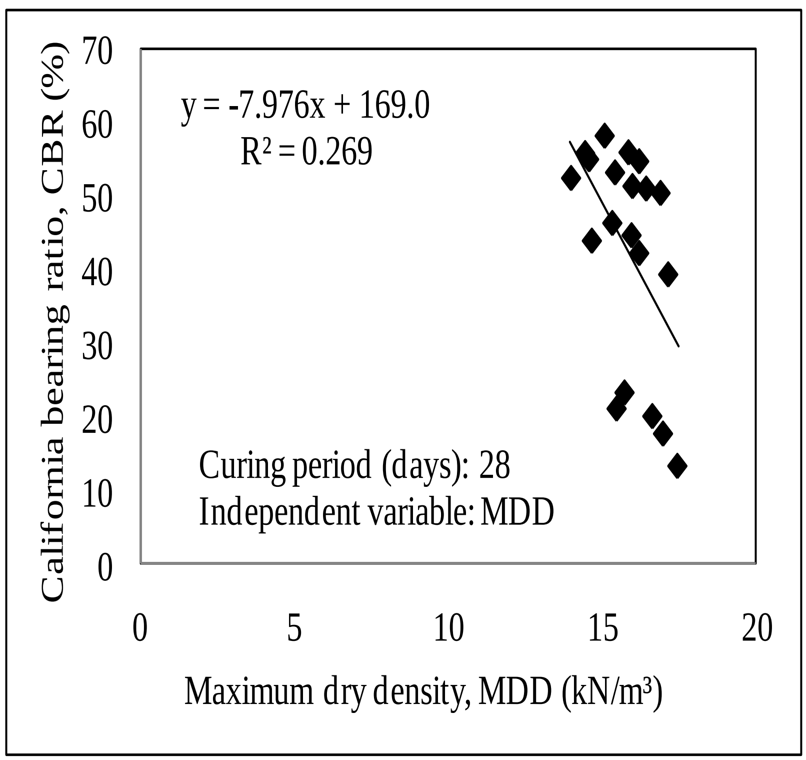


Figure B.24: Correlation of CBR and MDD content at curing period of 28 days.

Annex-C

Multiple Linear Regression Analysis of Stabilized Soil using Admixtures

Table C.1: MLR analysis with all independent variables

Lime (%)	QD (%)	CP (days)	OMC (%)	MDD (kN/m^3)	CBR (0 day curing)
2	0	0	13.72	16.95	28.70
2	10	0	12.89	17.42	32.92
2	20	0	12.67	18.08	35.17
2	30	0	12.10	18.17	38.86
2	40	0	11.54	18.40	42.82
2	50	0	11.29	18.57	40.36
4	0	0	14.12	16.86	29.03
4	10	0	13.47	17.33	30.12
4	20	0	13.16	17.88	39.80
4	30	0	12.58	18.00	53.68
4	40	0	12.07	18.38	77.54
4	50	0	11.78	18.47	66.35
6	0	0	14.32	16.67	28.87
6	10	0	13.89	17.21	31.52
6	20	0	13.12	17.67	37.48
6	30	0	12.76	17.78	46.27
6	40	0	12.34	18.15	60.18
6	50	0	11.92	18.36	53.35

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.814
R Square	0.663
Adjusted R Square	0.483
Standard Error	9.369
Observations	18.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	5	2248.816	449.763	6.405	0.004
Residual	13	1141.154	87.781		
Total	18	3389.971			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-402.060	407.407	-0.987	0.342	-1282.209	478.089	-1282.209	478.089
Lime (%)	-0.535	3.389	-0.158	0.877	-7.857	6.786	-7.857	6.786
QD (%)	1.083	0.926	1.171	0.263	-0.916	3.083	-0.916	3.083
CP (days)	0.000	0.000	65535.000	#NUM!	0.000	0.000	0.000	0.000
OMC (%)	17.237	18.144	0.950	0.359	-21.961	56.435	-21.961	56.435
MDD (kN/m3)	11.241	16.323	0.689	0.503	-24.022	46.504	-24.022	46.504

Table C.2: MLR analysis with all independent variables

Lime (%)	QD (%)	CP (days)	OMC (%)	MDD (kN/m^3)	CBR (7 day curing)
2	0	7	13.72	16.95	33.34
2	10	7	12.89	17.42	40.21
2	20	7	12.67	18.08	45.32
2	30	7	12.10	18.17	51.31
2	40	7	11.54	18.40	61.10
2	50	7	11.29	18.57	56.64
4	0	7	14.12	16.86	44.67
4	10	7	13.47	17.33	46.21
4	20	7	13.16	17.88	53.78
4	30	7	12.58	18.00	62.32
4	40	7	12.07	18.38	83.27
4	50	7	11.78	18.47	74.50
6	0	7	14.32	16.67	39.80
6	10	7	13.89	17.21	41.14
6	20	7	13.12	17.67	44.77
6	30	7	12.76	17.78	59.55
6	40	7	12.34	18.15	74.19
6	50	7	11.92	18.36	69.13

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.887
R Square	0.787
Adjusted R Square	0.644
Standard Error	7.431
Observations	18.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	5	2647.952	529.590	11.989	0.000
Residual	13	717.807	55.216		
Total	18	3365.759			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-317.591	323.117	-0.983	0.344	-1015.644	380.461	-1015.644	380.461
Lime (%)	-0.576	2.688	-0.214	0.834	-6.382	5.231	-6.382	5.231
QD (%)	1.220	0.734	1.661	0.121	-0.366	2.805	-0.366	2.805
CP (days)	0.000	0.000	65535.000	#NUM!	0.000	0.000	0.000	0.000
OMC (%)	16.366	14.390	1.137	0.276	-14.722	47.454	-14.722	47.454
MDD (kN/m3)	7.587	12.946	0.586	0.568	-20.380	35.555	-20.380	35.555

Table C.3: MLR analysis with all independent variables

Lime (%)	QD (%)	CP (days)	OMC (%)	MDD (kN/m^3)	CBR (28 day curing)
2	0	28	13.72	16.95	57.66
2	10	28	12.89	17.42	69.30
2	20	28	12.67	18.08	73.20
2	30	28	12.10	18.17	78.65
2	40	28	11.54	18.40	87.25
2	50	28	11.29	18.57	81.89
4	0	28	14.12	16.86	62.12
4	10	28	13.47	17.33	73.55
4	20	28	13.16	17.88	79.00
4	30	28	12.58	18.00	87.81
4	40	28	12.07	18.38	98.26
4	50	28	11.78	18.47	91.22
6	0	28	14.32	16.67	59.89
6	10	28	13.89	17.21	71.50
6	20	28	13.12	17.67	76.22
6	30	28	12.76	17.78	83.50
6	40	28	12.34	18.15	91.75
6	50	28	11.92	18.36	87.21

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.934
R Square	0.872
Adjusted R Square	0.755
Standard Error	4.703
Observations	18.000

ANOVA

	df	*SS*	*MS*	*Significance F*
Regression	5	1955.984	391.197	0.000
Residual	13	287.568	22.121	
Total	18	2243.552		

	Coefficients	*Standard Error*	*t Stat*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-262.723	204.516	-1.285	-704.552	179.106	-704.552	179.106
Lime (%)	2.332	1.701	1.371	-1.343	6.008	-1.343	6.008
QD (%)	-0.033	0.465	-0.071	-1.037	0.971	-1.037	0.971
CP (days)	0.000	0.000	65535.000	0.000	0.000	0.000	0.000
OMC (%)	-0.214	9.108	-0.023	-19.891	19.463	-19.891	19.463
MDD (kN/m3)	18.839	8.194	2.299	1.137	36.541	1.137	36.541

Table C.4: MLR analysis with all independent variables except CP

Lime (%)	QD (%)	OMC (%)	MDD (kN/m^3)	CBR (0 day curing)
2	0	13.72	16.95	28.70
2	10	12.89	17.42	32.92
2	20	12.67	18.08	35.17
2	30	12.10	18.17	38.86
2	40	11.54	18.40	42.82
2	50	11.29	18.57	40.36
4	0	14.12	16.86	29.03
4	10	13.47	17.33	30.12
4	20	13.16	17.88	39.80
4	30	12.58	18.00	53.68
4	40	12.07	18.38	77.54
4	50	11.78	18.47	66.35
6	0	14.32	16.67	28.87
6	10	13.89	17.21	31.52
6	20	13.12	17.67	37.48
6	30	12.76	17.78	46.27
6	40	12.34	18.15	60.18
6	50	11.92	18.36	53.35

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.814
R Square	0.663
Adjusted R Square	0.560
Standard Error	9.369
Observations	18.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	2248.816	562.204	6.405	0.004
Residual	13	1141.154	87.781		
Total	17	3389.971			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-402.060	407.407	-0.987	0.342	-1282.209	478.089	-1282.209	478.089
Lime (%)	-0.535	3.389	-0.158	0.877	-7.857	6.786	-7.857	6.786
QD (%)	1.083	0.926	1.171	0.263	-0.916	3.083	-0.916	3.083
OMC (%)	17.237	18.144	0.950	0.359	-21.961	56.435	-21.961	56.435
MDD (kN/m3)	11.241	16.323	0.689	0.503	-24.022	46.504	-24.022	46.504

Table C.5: MLR analysis with all independent variables except CP

Lime (%)	QD (%)	OMC (%)	MDD (kN/m^3)	CBR (7 day curing)
2	0	13.72	16.95	33.34
2	10	12.89	17.42	40.21
2	20	12.67	18.08	45.32
2	30	12.10	18.17	51.31
2	40	11.54	18.40	61.10
2	50	11.29	18.57	56.64
4	0	14.12	16.86	44.67
4	10	13.47	17.33	46.21
4	20	13.16	17.88	53.78
4	30	12.58	18.00	62.32
4	40	12.07	18.38	83.27
4	50	11.78	18.47	74.50
6	0	14.32	16.67	39.80
6	10	13.89	17.21	41.14
6	20	13.12	17.67	44.77
6	30	12.76	17.78	59.55
6	40	12.34	18.15	74.19
6	50	11.92	18.36	69.13

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.887
R Square	0.787
Adjusted R Square	0.721
Standard Error	7.431
Observations	18.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	2647.952	661.988	11.989	0.000
Residual	13	717.807	55.216		
Total	17	3365.759			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-317.591	323.117	-0.983	0.344	-1015.644	380.461	-1015.644	380.461
Lime (%)	-0.576	2.688	-0.214	0.834	-6.382	5.231	-6.382	5.231
QD (%)	1.220	0.734	1.661	0.121	-0.366	2.805	-0.366	2.805
OMC (%)	16.366	14.390	1.137	0.276	-14.722	47.454	-14.722	47.454
MDD (kN/m3)	7.587	12.946	0.586	0.568	-20.380	35.555	-20.380	35.555

Table C.6: MLR analysis with all independent variables except CP

Lime (%)	QD (%)	OMC (%)	MDD (kN/m^3)	CBR (28 day curing)
2	0	13.72	16.95	57.66
2	10	12.89	17.42	69.30
2	20	12.67	18.08	73.20
2	30	12.10	18.17	78.65
2	40	11.54	18.40	87.25
2	50	11.29	18.57	81.89
4	0	14.12	16.86	62.12
4	10	13.47	17.33	73.55
4	20	13.16	17.88	79.00
4	30	12.58	18.00	87.81
4	40	12.07	18.38	98.26
4	50	11.78	18.47	91.22
6	0	14.32	16.67	59.89
6	10	13.89	17.21	71.50
6	20	13.12	17.67	76.22
6	30	12.76	17.78	83.50
6	40	12.34	18.15	91.75
6	50	11.92	18.36	87.21

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.934
R Square	0.871
Adjusted R Square	0.832
Standard Error	4.703
Observations	18.000

ANOVA

	df	*SS*	*MS*	*Significance F*
Regression	4	1955.984	488.996	0.000
Residual	13	287.568	22.121	
Total	17	2243.552		

	Coefficients	*Standard Error*	*t Stat*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-262.723	204.516	-1.285	-704.552	179.106	-704.552	179.106
Lime (%)	2.332	1.701	1.371	-1.343	6.008	-1.343	6.008
QD (%)	-0.033	0.465	-0.071	-1.037	0.971	-1.037	0.971
OMC (%)	-0.214	9.108	-0.023	-19.891	19.463	-19.891	19.463
MDD (kN/m3)	18.839	8.194	2.299	1.137	36.541	1.137	36.541

Table C.7: MLR analysis with independent variables except QD and CP

Lime (%)	OMC (%)	MDD (kN/m^3)	CBR (0 day curing)
2	13.72	16.95	28.70
2	12.89	17.42	32.92
2	12.67	18.08	35.17
2	12.10	18.17	38.86
2	11.54	18.40	42.82
2	11.29	18.57	40.36
4	14.12	16.86	29.03
4	13.47	17.33	30.12
4	13.16	17.88	39.80
4	12.58	18.00	53.68
4	12.07	18.38	77.54
4	11.78	18.47	66.35
6	14.32	16.67	28.87
6	13.89	17.21	31.52
6	13.12	17.67	37.48
6	12.76	17.78	46.27
6	12.34	18.15	60.18
6	11.92	18.36	53.35

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.792
R Square	0.628
Adjusted R Square	0.548
Standard Error	9.492
Observations	18.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	2128.538	709.513	7.875	0.003
Residual	14	1261.433	90.102		
Total	17	3389.971			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-293.435	401.908	-0.730	0.477	-1155.443	568.573	-1155.443	568.573
Lime (%)	2.986	1.581	1.888	0.080	-0.405	6.377	-0.405	6.377
OMC (%)	-0.170	10.532	-0.016	0.987	-22.759	22.418	-22.759	22.418
MDD (kN/m3)	18.352	15.349	1.196	0.252	-14.569	51.272	-14.569	51.272

Table C.8: MLR analysis with independent variables except QD and CP

Lime (%)	OMC (%)	MDD (kN/m^3)	CBR (7 day curing)
2	13.72	16.95	33.34
2	12.89	17.42	40.21
2	12.67	18.08	45.32
2	12.10	18.17	51.31
2	11.54	18.40	61.10
2	11.29	18.57	56.64
4	14.12	16.86	44.67
4	13.47	17.33	46.21
4	13.16	17.88	53.78
4	12.58	18.00	62.32
4	12.07	18.38	83.27
4	11.78	18.47	74.50
6	14.32	16.67	39.80
6	13.89	17.21	41.14
6	13.12	17.67	44.77
6	12.76	17.78	59.55
6	12.34	18.15	74.19
6	11.92	18.36	69.13

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.861
R Square	0.741
Adjusted R Square	0.686
Standard Error	7.884
Observations	18.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	2495.581	831.860	13.384	0.000
Residual	14	870.178	62.156		
Total	17	3365.759			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-195.330	333.810	-0.585	0.568	-911.282	520.621	-911.282	520.621
Lime (%)	3.388	1.313	2.580	0.022	0.571	6.204	0.571	6.204
OMC (%)	-3.227	8.747	-0.369	0.718	-21.988	15.534	-21.988	15.534
MDD (kN/m3)	15.591	12.748	1.223	0.242	-11.752	42.934	-11.752	42.934

Table C.9: MLR analysis with independent variables except QD and CP

Lime (%)	OMC (%)	MDD (kN/m^3)	CBR (28 day curing)
2	13.72	16.95	57.66
2	12.89	17.42	69.30
2	12.67	18.08	73.20
2	12.10	18.17	78.65
2	11.54	18.40	87.25
2	11.29	18.57	81.89
4	14.12	16.86	62.12
4	13.47	17.33	73.55
4	13.16	17.88	79.00
4	12.58	18.00	87.81
4	12.07	18.38	98.26
4	11.78	18.47	91.22
6	14.32	16.67	59.89
6	13.89	17.21	71.50
6	13.12	17.67	76.22
6	12.76	17.78	83.50
6	12.34	18.15	91.75
6	11.92	18.36	87.21

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.934
R Square	0.870
Adjusted R Square	0.844
Standard Error	4.533
Observations	18.000

ANOVA

	df	*SS*	*MS*	*Significance F*
Regression	3	1955.874	651.958	0.000
Residual	14	287.679	20.548	
Total	17	2243.552		

	Coefficients	*Standard Error*	*t Stat*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-266.021	191.933	-1.386	-677.675	145.634	-677.675	145.634
Lime (%)	2.225	0.755	2.947	0.606	3.845	0.606	3.845
OMC (%)	0.315	5.029	0.063	-10.472	11.102	-10.472	11.102
MDD (kN/m3)	18.623	7.330	2.541	2.901	34.344	2.901	34.344

Table C.10: MLR analysis with independent variables except Lime and CP

QD (%)	OMC (%)	MDD (kN/m^3)	CBR (0 day curing)
0	13.72	16.95	28.70
10	12.89	17.42	32.92
20	12.67	18.08	35.17
30	12.10	18.17	38.86
40	11.54	18.40	42.82
50	11.29	18.57	40.36
0	14.12	16.86	29.03
10	13.47	17.33	30.12
20	13.16	17.88	39.80
30	12.58	18.00	53.68
40	12.07	18.38	77.54
50	11.78	18.47	66.35
0	14.32	16.67	28.87
10	13.89	17.21	31.52
20	13.12	17.67	37.48
30	12.76	17.78	46.27
40	12.34	18.15	60.18
50	11.92	18.36	53.35

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.814
R Square	0.663
Adjusted R Square	0.590
Standard Error	9.037
Observations	18.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	2246.625	748.875	9.170	0.001
Residual	14	1143.346	81.668		
Total	17	3389.971			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-377.114	362.254	-1.041	0.316	-1154.072	399.844	-1154.072	399.844
QD (%)	0.954	0.411	2.320	0.036	0.072	1.836	0.072	1.836
OMC (%)	14.800	9.214	1.606	0.131	-4.962	34.562	-4.962	34.562
MDD (kN/m3)	11.649	15.546	0.749	0.466	-21.693	44.991	-21.693	44.991

Table C.11: MLR analysis with independent variables except Lime and CP

QD (%)	OMC (%)	MDD (kN/m^3)	CBR (7 day curing)
0	13.72	16.95	33.34
10	12.89	17.42	40.21
20	12.67	18.08	45.32
30	12.10	18.17	51.31
40	11.54	18.40	61.10
50	11.29	18.57	56.64
0	14.12	16.86	44.67
10	13.47	17.33	46.21
20	13.16	17.88	53.78
30	12.58	18.00	62.32
40	12.07	18.38	83.27
50	11.78	18.47	74.50
0	14.32	16.67	39.80
10	13.89	17.21	41.14
20	13.12	17.67	44.77
30	12.76	17.78	59.55
40	12.34	18.15	74.19
50	11.92	18.36	69.13

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.887
R Square	0.786
Adjusted R Square	0.740
Standard Error	7.173
Observations	18.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	2645.419	881.806	17.138	0.000
Residual	14	720.340	51.453		
Total	17	3365.759			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-290.769	287.537	-1.011	0.329	-907.475	325.936	-907.475	325.936
QD (%)	1.080	0.326	3.309	0.005	0.380	1.780	0.380	1.780
OMC (%)	13.745	7.314	1.879	0.081	-1.941	29.431	-1.941	29.431
MDD (kN/m3)	8.026	12.339	0.650	0.526	-18.439	34.491	-18.439	34.491

Table C.12: MLR analysis with independent variables except Lime and CP

QD (%)	OMC (%)	MDD (kN/m^3)	CBR (28 day curing)
0	13.72	16.95	57.66
10	12.89	17.42	69.30
20	12.67	18.08	73.20
30	12.10	18.17	78.65
40	11.54	18.40	87.25
50	11.29	18.57	81.89
0	14.12	16.86	62.12
10	13.47	17.33	73.55
20	13.16	17.88	79.00
30	12.58	18.00	87.81
40	12.07	18.38	98.26
50	11.78	18.47	91.22
0	14.32	16.67	59.89
10	13.89	17.21	71.50
20	13.12	17.67	76.22
30	12.76	17.78	83.50
40	12.34	18.15	91.75
50	11.92	18.36	87.21

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.924
R Square	0.853
Adjusted R Square	0.822
Standard Error	4.849
Observations	18.000

ANOVA

	df	*SS*	*MS*	*Significance F*
Regression	3	1914.413	638.138	0.000
Residual	14	329.139	23.510	
Total	17	2243.552		

	Coefficients	*Standard Error*	*t Stat*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-371.378	194.363	-1.911	-788.245	45.490	-788.245	45.490
QD (%)	0.533	0.221	2.414	0.059	1.006	0.059	1.006
OMC (%)	10.402	4.944	2.104	-0.201	21.005	-0.201	21.005
MDD (kN/m3)	17.061	8.341	2.045	-0.829	34.950	-0.829	34.950

Table C.13: MLR analysis with independent variables except CP and MDD

Lime (%)	QD (%)	OMC (%)	CBR (0 day curing)
2	0	13.72	28.70
2	10	12.89	32.92
2	20	12.67	35.17
2	30	12.10	38.86
2	40	11.54	42.82
2	50	11.29	40.36
4	0	14.12	29.03
4	10	13.47	30.12
4	20	13.16	39.80
4	30	12.58	53.68
4	40	12.07	77.54
4	50	11.78	66.35
6	0	14.32	28.87
6	10	13.89	31.52
6	20	13.12	37.48
6	30	12.76	46.27
6	40	12.34	60.18
6	50	11.92	53.35

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.807
R Square	0.651
Adjusted R Square	0.576
Standard Error	9.192
Observations	18.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	2207.186	735.729	8.708	0.002
Residual	14	1182.785	84.485		
Total	17	3389.971			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-173.145	231.091	-0.749	0.466	-668.786	322.495	-668.786	322.495
Lime (%)	-0.905	3.283	-0.276	0.787	-7.946	6.136	-7.946	6.136
QD (%)	1.321	0.843	1.567	0.139	-0.487	3.128	-0.487	3.128
OMC (%)	14.627	17.408	0.840	0.415	-22.708	51.963	-22.708	51.963

Table C.14: MLR analysis with independent variables except CP and MDD

Lime (%)	QD (%)	OMC (%)	CBR (7 day curing)
2	0	13.72	33.34
2	10	12.89	40.21
2	20	12.67	45.32
2	30	12.10	51.31
2	40	11.54	61.10
2	50	11.29	56.64
4	0	14.12	44.67
4	10	13.47	46.21
4	20	13.16	53.78
4	30	12.58	62.32
4	40	12.07	83.27
4	50	11.78	74.50
6	0	14.32	39.80
6	10	13.89	41.14
6	20	13.12	44.77
6	30	12.76	59.55
6	40	12.34	74.19
6	50	11.92	69.13

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.884
R Square	0.781
Adjusted R Square	0.734
Standard Error	7.254
Observations	18.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	2628.984	876.328	16.652	0.000
Residual	14	736.775	52.627		
Total	17	3365.759			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-163.076	182.388	-0.894	0.386	-554.260	228.109	-554.260	228.109
Lime (%)	-0.825	2.591	-0.318	0.755	-6.382	4.732	-6.382	4.732
QD (%)	1.380	0.665	2.074	0.057	-0.047	2.806	-0.047	2.806
OMC (%)	14.604	13.739	1.063	0.306	-14.863	44.071	-14.863	44.071

Table C.15: MLR analysis with independent variables except CP and MDD

Lime (%)	QD (%)	OMC (%)	CBR (28 day curing)
2	0	13.72	57.66
2	10	12.89	69.30
2	20	12.67	73.20
2	30	12.10	78.65
2	40	11.54	87.25
2	50	11.29	81.89
4	0	14.12	62.12
4	10	13.47	73.55
4	20	13.16	79.00
4	30	12.58	87.81
4	40	12.07	98.26
4	50	11.78	91.22
6	0	14.32	59.89
6	10	13.89	71.50
6	20	13.12	76.22
6	30	12.76	83.50
6	40	12.34	91.75
6	50	11.92	87.21

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.905
R Square	0.820
Adjusted R Square	0.781
Standard Error	5.375
Observations	18.000

ANOVA

	df	*SS*	*MS*	*Significance F*
Regression	3	1839.056	613.019	0.000
Residual	14	404.496	28.893	
Total	17	2243.552		

	Coefficients	*Standard Error*	*t Stat*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	120.920	135.141	0.895	-168.929	410.768	-168.929	410.768
Lime (%)	1.713	1.920	0.892	-2.404	5.831	-2.404	5.831
QD (%)	0.365	0.493	0.740	-0.692	1.422	-0.692	1.422
OMC (%)	-4.588	10.180	-0.451	-26.422	17.246	-26.422	17.246

Table C.16: MLR analysis with independent variables except CP and OMC

Lime (%)	QD (%)	MDD (kN/m^3)	CBR (0 day curing)
2	0	16.95	28.70
2	10	17.42	32.92
2	20	18.08	35.17
2	30	18.17	38.86
2	40	18.40	42.82
2	50	18.57	40.36
4	0	16.86	29.03
4	10	17.33	30.12
4	20	17.88	39.80
4	30	18.00	53.68
4	40	18.38	77.54
4	50	18.47	66.35
6	0	16.67	28.87
6	10	17.21	31.52
6	20	17.67	37.48
6	30	17.78	46.27
6	40	18.15	60.18
6	50	18.36	53.35

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.800
R Square	0.640
Adjusted R Square	0.563
Standard Error	9.336
Observations	18.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	2169.591	723.197	8.296	0.002
Residual	14	1220.380	87.170		
Total	17	3389.971			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-117.338	275.008	-0.427	0.676	-707.171	472.495	-707.171	472.495
Lime (%)	2.202	1.778	1.238	0.236	-1.612	6.015	-1.612	6.015
QD (%)	0.363	0.528	0.686	0.504	-0.771	1.496	-0.771	1.496
MDD (kN/m3)	8.002	15.907	0.503	0.623	-26.115	42.119	-26.115	42.119

Table C.17: MLR analysis with independent variables except CP and OMC

Lime (%)	QD (%)	MDD (kN/m^3)	CBR (7 day curing)
2	0	16.95	33.34
2	10	17.42	40.21
2	20	18.08	45.32
2	30	18.17	51.31
2	40	18.40	61.10
2	50	18.57	56.64
4	0	16.86	44.67
4	10	17.33	46.21
4	20	17.88	53.78
4	30	18.00	62.32
4	40	18.38	83.27
4	50	18.47	74.50
6	0	16.67	39.80
6	10	17.21	41.14
6	20	17.67	44.77
6	30	17.78	59.55
6	40	18.15	74.19
6	50	18.36	69.13

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.875
R Square	0.766
Adjusted R Square	0.715
Standard Error	7.508
Observations	18.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	2576.533	858.844	15.235	0.000
Residual	14	789.226	56.373		
Total	17	3365.759			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-47.261	221.156	-0.214	0.834	-521.593	427.071	-521.593	427.071
Lime (%)	2.023	1.430	1.415	0.179	-1.044	5.090	-1.044	5.090
QD (%)	0.535	0.425	1.259	0.228	-0.376	1.447	-0.376	1.447
MDD (kN/m3)	4.512	12.792	0.353	0.730	-22.924	31.948	-22.924	31.948

Table C.18: MLR analysis with independent variables except CP and OMC

Lime (%)	QD (%)	MDD (kN/m^3)	CBR (28 day curing)
2	0	16.95	57.66
2	10	17.42	69.30
2	20	18.08	73.20
2	30	18.17	78.65
2	40	18.40	87.25
2	50	18.57	81.89
4	0	16.86	62.12
4	10	17.33	73.55
4	20	17.88	79.00
4	30	18.00	87.81
4	40	18.38	98.26
4	50	18.47	91.22
6	0	16.67	59.89
6	10	17.21	71.50
6	20	17.67	76.22
6	30	17.78	83.50
6	40	18.15	91.75
6	50	18.36	87.21

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.934
R Square	0.863
Adjusted R Square	0.844
Standard Error	4.532
Observations	18.000

ANOVA

	df	*SS*	*MS*	*Significance F*
Regression	3	1955.972	651.991	0.000
Residual	14	287.580	20.541	
Total	17	2243.552		

	Coefficients	*Standard Error*	*t Stat*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-266.254	133.499	-1.994	-552.580	20.072	-552.580	20.072
Lime (%)	2.298	0.863	2.663	0.447	4.149	0.447	4.149
QD (%)	-0.024	0.257	-0.093	-0.574	0.526	-0.574	0.526
MDD (kN/m3)	18.879	7.722	2.445	2.317	35.441	2.317	35.441

Table C.19: MLR analysis with independent variables except CP, OMC and MDD

Lime (%)	QD (%)	CBR (0 day curing)
2	0	28.70
2	10	32.92
2	20	35.17
2	30	38.86
2	40	42.82
2	50	40.36
4	0	29.03
4	10	30.12
4	20	39.80
4	30	53.68
4	40	77.54
4	50	66.35
6	0	28.87
6	10	31.52
6	20	37.48
6	30	46.27
6	40	60.18
6	50	53.35

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.796
R Square	0.633
Adjusted R Square	0.585
Standard Error	9.101
Observations	18.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	2147.534	1073.767	12.964	0.001
Residual	15	1242.437	82.829		
Total	17	3389.971			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	20.958	6.486	3.231	0.006	7.133	34.783	7.133	34.783
Lime (%)	1.618	1.314	1.232	0.237	-1.182	4.418	-1.182	4.418
QD (%)	0.621	0.126	4.941	0.000	0.353	0.888	0.353	0.888

Table C.20: MLR analysis with independent variables except CP, OMC and MDD

Lime (%)	QD (%)	CBR (7 day curing)
2	0	33.34
2	10	40.21
2	20	45.32
2	30	51.31
2	40	61.10
2	50	56.64
4	0	44.67
4	10	46.21
4	20	53.78
4	30	62.32
4	40	83.27
4	50	74.50
6	0	39.80
6	10	41.14
6	20	44.77
6	30	59.55
6	40	74.19
6	50	69.13

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.874
R Square	0.763
Adjusted R Square	0.732
Standard Error	7.286
Observations	18.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	2569.519	1284.760	24.203	0.000
Residual	15	796.240	53.083		
Total	17	3365.759			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	30.723	5.193	5.917	0.000	19.655	41.790	19.655	41.790
Lime (%)	1.694	1.052	1.611	0.128	-0.547	3.936	-0.547	3.936
QD (%)	0.681	0.101	6.768	0.000	0.466	0.895	0.466	0.895

Table C.21: MLR analysis with independent variables except CP, OMC and MDD

Lime (%)	QD (%)	CBR (28 day curing)
2	0	57.66
2	10	69.30
2	20	73.20
2	30	78.65
2	40	87.25
2	50	81.89
4	0	62.12
4	10	73.55
4	20	79.00
4	30	87.81
4	40	98.26
4	50	91.22
6	0	59.89
6	10	71.50
6	20	76.22
6	30	83.50
6	40	91.75
6	50	87.21

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.904
R Square	0.817
Adjusted R Square	0.793
Standard Error	5.230
Observations	18.000

ANOVA

	df	*SS*	*MS*	*Significance F*
Regression	2	1833.188	916.594	0.000
Residual	15	410.364	27.358	
Total	17	2243.552		

	Coefficients	*Standard Error*	*t Stat*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	60.038	3.728	16.106	52.092	67.983	52.092	67.983
Lime (%)	0.922	0.755	1.221	-0.687	2.531	-0.687	2.531
QD (%)	0.584	0.072	8.094	0.430	0.738	0.430	0.738

Table C.22: MLR analysis with independent variables except CP, Lime and QD

OMC (%)	MDD (kN/m^3)	CBR (0 day curing)
13.72	16.95	28.70
12.89	17.42	32.92
12.67	18.08	35.17
12.10	18.17	38.86
11.54	18.40	42.82
11.29	18.57	40.36
14.12	16.86	29.03
13.47	17.33	30.12
13.16	17.88	39.80
12.58	18.00	53.68
12.07	18.38	77.54
11.78	18.47	66.35
14.32	16.67	28.87
13.89	17.21	31.52
13.12	17.67	37.48
12.76	17.78	46.27
12.34	18.15	60.18
11.92	18.36	53.35

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.730
R Square	0.533
Adjusted R Square	0.471
Standard Error	10.272
Observations	18.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	1807.240	903.620	8.564	0.003
Residual	15	1582.731	105.515		
Total	17	3389.971			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-607.160	396.029	-1.533	0.146	-1451.277	236.956	-1451.277	236.956
OMC (%)	9.075	10.091	0.899	0.383	-12.432	30.583	-12.432	30.583
MDD (kN/m3)	30.020	15.205	1.974	0.067	-2.388	62.428	-2.388	62.428

Table C.23: MLR analysis with independent variables except CP, Lime and QD

OMC (%)	MDD (kN/m^3)	CBR (7 day curing)
13.72	16.95	33.34
12.89	17.42	40.21
12.67	18.08	45.32
12.10	18.17	51.31
11.54	18.40	61.10
11.29	18.57	56.64
14.12	16.86	44.67
13.47	17.33	46.21
13.16	17.88	53.78
12.58	18.00	62.32
12.07	18.38	83.27
11.78	18.47	74.50
14.32	16.67	39.80
13.89	17.21	41.14
13.12	17.67	44.77
12.76	17.78	59.55
12.34	18.15	74.19
11.92	18.36	69.13

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.786
R Square	0.619
Adjusted R Square	0.568
Standard Error	9.251
Observations	18.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	2081.999	1040.999	12.163	0.001
Residual	15	1283.760	85.584		
Total	17	3365.759			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-551.270	356.669	-1.546	0.143	-1311.493	208.953	-1311.493	208.953
OMC (%)	7.263	9.088	0.799	0.437	-12.107	26.633	-12.107	26.633
MDD (kN/m3)	28.829	13.694	2.105	0.053	-0.358	58.017	-0.358	58.017

Table C.24: MLR analysis with independent variables except CP, Lime and QD

OMC (%)	MDD (kN/m^3)	CBR (28 day curing)
13.72	16.95	57.66
12.89	17.42	69.30
12.67	18.08	73.20
12.10	18.17	78.65
11.54	18.40	87.25
11.29	18.57	81.89
14.12	16.86	62.12
13.47	17.33	73.55
13.16	17.88	79.00
12.58	18.00	87.81
12.07	18.38	98.26
11.78	18.47	91.22
14.32	16.67	59.89
13.89	17.21	71.50
13.12	17.67	76.22
12.76	17.78	83.50
12.34	18.15	91.75
11.92	18.36	87.21

SUMMARY OUTPUT

Regression Statistics	
Multiple F	0.890
R Square	0.792
Adjusted I	0.765
Standard	5.575
Observati	18.000

ANOVA

	df	*SS*	*MS*	*F*
Regressio	2	1777.411	888.706	28.598
Residual	15	466.141	31.076	
Total	17	2243.552		

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-499.834	214.923	-2.326	0.034	-41.737	-957.931	-41.737
OMC (%)	7.205	5.476	1.316	0.208	18.877	-4.467	18.877
MDD (kN/	27.319	8.252	3.311	0.005	44.907	9.731	44.907

Table C.25: MLR analysis with all independent variables

Lime (%)	RHA (%)	Curing period (days)	OMC (%)	MDD (kN/m^3)	CBR (0 day curing)
0	0	0	14.7	17.48	5.1
0	4	0	15.3	17.01	8.01
0	8	0	17.4	16.66	11.22
0	12	0	19.2	15.75	14.23
0	16	0	19.92	15.49	13.03
3	0	0	15.3	17.18	30.7
3	4	0	17.12	16.86	34.39
3	8	0	18.11	15.98	36.82
3	12	0	19.32	15.35	40.81
3	16	0	20.32	14.68	37.08
4	0	0	16.9	16.93	42.69
4	4	0	17.98	16.23	46.21
4	8	0	19.2	15.88	48.51
4	12	0	20.9	15.1	50.1
4	16	0	21.64	14.46	48.25
5	0	0	17.8	16.46	42.83
5	4	0	18.88	16.01	43.94
5	8	0	20.1	15.44	45.21
5	12	0	20.96	14.59	47.2
5	16	0	22.25	14	45.14

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.974
R Square	0.949
Adjusted R Square	0.869
Standard Error	3.867
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	5	4202.418	840.484	70.271	0.000
Residual	15	224.262	14.951		
Total	20	4426.680			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-244.817	114.520	-2.138	0.049	-488.909	-0.724	-488.909	-0.724
Lime (%)	10.955	1.593	6.878	0.000	7.560	14.350	7.560	14.350
RHA (%)	2.631	0.986	2.667	0.018	0.529	4.733	0.529	4.733
Curing period (days)	0.000	0.000	65535.000	#NUM!	0.000	0.000	0.000	0.000
OMC (%)	-0.283	1.875	-0.151	0.882	-4.279	3.714	-4.279	3.714
MDD (kN/m3)	14.563	6.025	2.417	0.029	1.720	27.406	1.720	27.406

Table C.26: MLR analysis with all independent variables

Lime (%)	RHA (%)	Curing period (days)	OMC (%)	MDD (kN/m^3)	CBR (7 days curing)
0	0	7	14.7	17.48	9.27
0	4	7	15.3	17.01	11.22
0	8	7	17.4	16.66	15.08
0	12	7	19.2	15.75	18.12
0	16	7	19.92	15.49	16.92
3	0	7	15.3	17.18	34.23
3	4	7	17.12	16.23	35.93
3	8	7	18.11	15.98	39.76
3	12	7	19.32	15.35	42.42
3	16	7	20.32	14.68	40.55
4	0	7	16.9	16.86	44.45
4	4	7	17.98	16.23	48.51
4	8	7	19.2	15.88	50.62
4	12	7	20.9	15.1	52.5
4	16	7	21.64	14.46	50.21
5	0	7	17.8	16.46	44.87
5	4	7	18.88	16.01	45.11
5	8	7	20.1	15.44	47.65
5	12	7	20.96	14.59	50.78
5	16	7	22.25	14	47.31

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.975
R Square	0.950
Adjusted R Square	0.870
Standard Error	3.663
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	5	3854.926	770.985	71.836	0.000
Residual	15	201.236	13.416		
Total	20	4056.162			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-228.643	108.481	-2.108	0.052	-459.866	2.579	-459.866	2.579
Lime (%)	10.516	1.509	6.971	0.000	7.301	13.732	7.301	13.732
RHA (%)	2.582	0.934	2.764	0.014	0.591	4.574	0.591	4.574
Curing period (days)	0.000	0.000	65535.000	#NUM!	0.000	0.000	0.000	0.000
OMC (%)	-0.366	1.776	-0.206	0.840	-4.152	3.420	-4.152	3.420
MDD (kN/m3)	13.918	5.708	2.438	0.028	1.752	26.084	1.752	26.084

Table C.27: MLR analysis with all independent variables

Lime (%)	RHA (%)	Curing period (days)	OMC (%)	MDD (kN/m^3)	CBR (28 days curing)
0	0	28	14.7	17.48	13.43
0	4	28	15.3	17.01	17.83
0	8	28	17.4	16.66	20.21
0	12	28	19.2	15.75	23.43
0	16	28	19.92	15.49	21.24
3	0	28	15.3	17.18	39.52
3	4	28	17.12	16.23	42.42
3	8	28	18.11	15.98	44.85
3	12	28	19.32	15.35	46.52
3	16	28	20.32	14.68	44.11
4	0	28	16.9	16.86	50.61
4	4	28	17.98	16.23	54.93
4	8	28	19.2	15.88	56.15
4	12	28	20.9	15.1	58.41
4	16	28	21.64	14.46	56.04
5	0	28	17.8	16.46	51.21
5	4	28	18.88	16.01	51.55
5	8	28	20.1	15.44	53.41
5	12	28	20.96	14.59	55.2
5	16	28	22.25	14	52.65

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.973
R Square	0.946
Adjusted R Square	0.865
Standard Error	3.868
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	5	3958.331	791.666	66.126	0.000
Residual	15	224.476	14.965		
Total	20	4182.807			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-231.954	114.574	-2.024	0.061	-476.163	12.255	-476.163	12.255
Lime (%)	10.369	1.593	6.507	0.000	6.973	13.765	6.973	13.765
RHA (%)	2.338	0.987	2.369	0.032	0.234	4.441	0.234	4.441
Curing period (days)	0.000	0.000	65535.000	#NUM!	0.000	0.000	0.000	0.000
OMC (%)	0.196	1.876	0.104	0.918	-3.803	4.194	-3.803	4.194
MDD (kN/m3)	13.958	6.028	2.315	0.035	1.109	26.807	1.109	26.807

Table C.28: MLR analysis with all independent variables except CP

Lime (%)	RHA (%)	OMC (%)	MDD (kN/m^3)	CBR (0 day curing)
0	0	14.7	17.48	5.1
0	4	15.3	17.01	8.01
0	8	17.4	16.66	11.22
0	12	19.2	15.75	14.23
0	16	19.92	15.49	13.03
3	0	15.3	17.18	30.7
3	4	17.12	16.86	34.39
3	8	18.11	15.98	36.82
3	12	19.32	15.35	40.81
3	16	20.32	14.68	37.08
4	0	16.9	16.93	42.69
4	4	17.98	16.23	46.21
4	8	19.2	15.88	48.51
4	12	20.9	15.1	50.1
4	16	21.64	14.46	48.25
5	0	17.8	16.46	42.83
5	4	18.88	16.01	43.94
5	8	20.1	15.44	45.21
5	12	20.96	14.59	47.2
5	16	22.25	14	45.14

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.974
R Square	0.949
Adjusted R Square	0.936
Standard Error	3.867
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	4202.418	1050.605	70.271	0.000
Residual	15	224.262	14.951		
Total	19	4426.680			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-244.817	114.520	-2.138	0.049	-488.909	-0.724	-488.909	-0.724
Lime (%)	10.955	1.593	6.878	0.000	7.560	14.350	7.560	14.350
RHA (%)	2.631	0.986	2.667	0.018	0.529	4.733	0.529	4.733
OMC (%)	-0.283	1.875	-0.151	0.882	-4.279	3.714	-4.279	3.714
MDD (kN/m3)	14.563	6.025	2.417	0.029	1.720	27.406	1.720	27.406

Table C.29: MLR analysis with all independent variables except CP

Lime (%)	RHA (%)	OMC (%)	MDD (kN/m^3)	CBR (7 days curing)
0	0	14.7	17.48	9.27
0	4	15.3	17.01	11.22
0	8	17.4	16.66	15.08
0	12	19.2	15.75	18.12
0	16	19.92	15.49	16.92
3	0	15.3	17.18	34.23
3	4	17.12	16.23	35.93
3	8	18.11	15.98	39.76
3	12	19.32	15.35	42.42
3	16	20.32	14.68	40.55
4	0	16.9	16.86	44.45
4	4	17.98	16.23	48.51
4	8	19.2	15.88	50.62
4	12	20.9	15.1	52.5
4	16	21.64	14.46	50.21
5	0	17.8	16.46	44.87
5	4	18.88	16.01	45.11
5	8	20.1	15.44	47.65
5	12	20.96	14.59	50.78
5	16	22.25	14	47.31

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.974
R Square	0.949
Adjusted R Square	0.936
Standard Error	3.867
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	4202.418	1050.605	70.271	0.000
Residual	15	224.262	14.951		
Total	19	4426.680			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-244.817	114.520	-2.138	0.049	-488.909	-0.724	-488.909	-0.724
Lime (%)	10.955	1.593	6.878	0.000	7.560	14.350	7.560	14.350
RHA (%)	2.631	0.986	2.667	0.018	0.529	4.733	0.529	4.733
OMC (%)	-0.283	1.875	-0.151	0.882	-4.279	3.714	-4.279	3.714
MDD (kN/m3)	14.563	6.025	2.417	0.029	1.720	27.406	1.720	27.406

Table C.30: MLR analysis with all independent variables except CP

Lime (%)	RHA (%)	OMC (%)	MDD (kN/m^3)	CBR (28 days curing)
0	0	14.7	17.48	13.43
0	4	15.3	17.01	17.83
0	8	17.4	16.66	20.21
0	12	19.2	15.75	23.43
0	16	19.92	15.49	21.24
3	0	15.3	17.18	39.52
3	4	17.12	16.23	42.42
3	8	18.11	15.98	44.85
3	12	19.32	15.35	46.52
3	16	20.32	14.68	44.11
4	0	16.9	16.86	50.61
4	4	17.98	16.23	54.93
4	8	19.2	15.88	56.15
4	12	20.9	15.1	58.41
4	16	21.64	14.46	56.04
5	0	17.8	16.46	51.21
5	4	18.88	16.01	51.55
5	8	20.1	15.44	53.41
5	12	20.96	14.59	55.2
5	16	22.25	14	52.65

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.973
R Square	0.946
Adjusted R Square	0.932
Standard Error	3.868
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	3958.331	989.583	66.126	0.000
Residual	15	224.476	14.965		
Total	19	4182.807			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-231.954	114.574	-2.024	0.061	-476.163	12.255	-476.163	12.255
Lime (%)	10.369	1.593	6.507	0.000	6.973	13.765	6.973	13.765
RHA (%)	2.338	0.987	2.369	0.032	0.234	4.441	0.234	4.441
OMC (%)	0.196	1.876	0.104	0.918	-3.803	4.194	-3.803	4.194
MDD (kN/m3)	13.958	6.028	2.315	0.035	1.109	26.807	1.109	26.807

Table C.31: MLR analysis with independent variables except RHA and CP

Lime (%)	OMC (%)	MDD (kN/m^3)	CBR (0 day curing)
0	14.7	17.48	5.1
0	15.3	17.01	8.01
0	17.4	16.66	11.22
0	19.2	15.75	14.23
0	19.92	15.49	13.03
3	15.3	17.18	30.7
3	17.12	16.23	34.39
3	18.11	15.98	36.82
3	19.32	15.35	40.81
3	20.32	14.68	37.08
4	16.9	16.86	42.69
4	17.98	16.23	46.21
4	19.2	15.88	48.51
4	20.9	15.1	50.1
4	21.64	14.46	48.25
5	17.8	16.46	42.83
5	18.88	16.01	43.94
5	20.1	15.44	45.21
5	20.96	14.59	47.2
5	22.25	14	45.14

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.962
R Square	0.925
Adjusted R Square	0.911
Standard Error	4.546
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	4096.042	1365.347	66.071	0.000
Residual	16	330.638	20.665		
Total	19	4426.68			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-49.936	103.679	-0.482	0.637	-269.726	169.853	-269.726	169.853
Lime (%)	6.946	0.620	11.201	0.000	5.632	8.261	5.632	8.261
OMC (%)	1.913	1.981	0.966	0.349	-2.286	6.112	-2.286	6.112
MDD (kN/m3)	1.765	4.285	0.412	0.686	-7.320	10.849	-7.320	10.849

Table C.32: MLR analysis with independent variables except RHA and CP

Lime (%)	OMC (%)	MDD (kN/m^3)	CBR (7 days curing)
0	14.7	17.48	9.27
0	15.3	17.01	11.22
0	17.4	16.66	15.08
0	19.2	15.75	18.12
0	19.92	15.49	16.92
3	15.3	17.18	34.23
3	17.12	16.23	35.93
3	18.11	15.98	39.76
3	19.32	15.35	42.42
3	20.32	14.68	40.55
4	16.9	16.86	44.45
4	17.98	16.23	48.51
4	19.2	15.88	50.62
4	20.9	15.1	52.5
4	21.64	14.46	50.21
5	17.8	16.46	44.87
5	18.88	16.01	45.11
5	20.1	15.44	47.65
5	20.96	14.59	50.78
5	22.25	14	47.31

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.962
R Square	0.925
Adjusted R Square	0.911
Standard Error	4.357
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	3752.452	1250.817	65.895	0.000
Residual	16	303.710	18.982		
Total	19	4056.162			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-37.371	99.367	-0.376	0.712	-248.021	173.278	-248.021	173.278
Lime (%)	6.582	0.594	11.074	0.000	5.322	7.842	5.322	7.842
OMC (%)	1.789	1.898	0.943	0.360	-2.235	5.814	-2.235	5.814
MDD (kN/m3)	1.357	4.107	0.330	0.745	-7.350	10.064	-7.350	10.064

Table C.33: MLR analysis with independent variables except RHA and CP

Lime (%)	OMC (%)	MDD (kN/m^3)	CBR (28 days curing)
0	14.7	17.48	13.43
0	15.3	17.01	17.83
0	17.4	16.66	20.21
0	19.2	15.75	23.43
0	19.92	15.49	21.24
3	15.3	17.18	39.52
3	17.12	16.23	42.42
3	18.11	15.98	44.85
3	19.32	15.35	46.52
3	20.32	14.68	44.11
4	16.9	16.86	50.61
4	17.98	16.23	54.93
4	19.2	15.88	56.15
4	20.9	15.1	58.41
4	21.64	14.46	56.04
5	17.8	16.46	51.21
5	18.88	16.01	51.55
5	20.1	15.44	53.41
5	20.96	14.59	55.2
5	22.25	14	52.65

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.962
R Square	0.926
Adjusted R Square	0.912
Standard Error	4.391
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	3874.348	1291.449	66.989	0.000
Residual	16	308.458	19.279		
Total	19	4182.807			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-58.797	100.141	-0.587	0.565	-271.087	153.493	-271.087	153.493
Lime (%)	6.807	0.599	11.364	0.000	5.538	8.077	5.538	8.077
OMC (%)	2.147	1.913	1.122	0.278	-1.909	6.202	-1.909	6.202
MDD (kN/m3)	2.587	4.139	0.625	0.541	-6.188	11.361	-6.188	11.361

Table C.34: MLR analysis with independent variables except Lime and CP

RHA (%)	OMC (%)	MDD (kN/m^3)	CBR (0 day curing)
0	14.7	17.48	5.1
4	15.3	17.01	8.01
8	17.4	16.66	11.22
12	19.2	15.75	14.23
16	19.92	15.49	13.03
0	15.3	17.18	30.7
4	17.12	16.23	34.39
8	18.11	15.98	36.82
12	19.32	15.35	40.81
16	20.32	14.68	37.08
0	16.9	16.86	42.69
4	17.98	16.23	46.21
8	19.2	15.88	48.51
12	20.9	15.1	50.1
16	21.64	14.46	48.25
0	17.8	16.46	42.83
4	18.88	16.01	43.94
8	20.1	15.44	45.21
12	20.96	14.59	47.2
16	22.25	14	45.14

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.889
R Square	0.790
Adjusted R Square	0.750
Standard Error	7.631
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	3495.068	1165.023	20.009	0.000
Residual	16	931.612	58.226		
Total	19	4426.68			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	206.392	185.248	1.114	0.282	-186.316	599.099	-186.316	599.099
RHA (%)	-3.770	0.645	-5.848	0.000	-5.137	-2.404	-5.137	-2.404
OMC (%)	5.884	3.250	1.811	0.089	-1.005	12.774	-1.005	12.774
MDD (kN/m3)	-15.871	8.072	-1.966	0.067	-32.982	1.240	-32.982	1.240

Table C.35: MLR analysis with independent variables except Lime and CP

RHA (%)	OMC (%)	MDD (kN/m^3)	CBR (7 days curing)
0	14.7	17.48	9.27
4	15.3	17.01	11.22
8	17.4	16.66	15.08
12	19.2	15.75	18.12
16	19.92	15.49	16.92
0	15.3	17.18	34.23
4	17.12	16.23	35.93
8	18.11	15.98	39.76
12	19.32	15.35	42.42
16	20.32	14.68	40.55
0	16.9	16.86	44.45
4	17.98	16.23	48.51
8	19.2	15.88	50.62
12	20.9	15.1	52.5
16	21.64	14.46	50.21
0	17.8	16.46	44.87
4	18.88	16.01	45.11
8	20.1	15.44	47.65
12	20.96	14.59	50.78
16	22.25	14	47.31

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.889
R Square	0.790
Adjusted R Square	0.750
Standard Error	7.631
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	3495.068	1165.023	20.009	0.000
Residual	16	931.612	58.226		
Total	19	4426.68			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	206.392	185.248	1.114	0.282	-186.316	599.099	-186.316	599.099
RHA (%)	-3.770	0.645	-5.848	0.000	-5.137	-2.404	-5.137	-2.404
OMC (%)	5.884	3.250	1.811	0.089	-1.005	12.774	-1.005	12.774
MDD (kN/m3)	-15.871	8.072	-1.966	0.067	-32.982	1.240	-32.982	1.240

Table C.36: MLR analysis with independent variables except Lime and CP

RHA (%)	OMC (%)	MDD (kN/m^3)	CBR (28 days curing)
0	14.7	17.48	13.43
4	15.3	17.01	17.83
8	17.4	16.66	20.21
12	19.2	15.75	23.43
16	19.92	15.49	21.24
0	15.3	17.18	39.52
4	17.12	16.23	42.42
8	18.11	15.98	44.85
12	19.32	15.35	46.52
16	20.32	14.68	44.11
0	16.9	16.86	50.61
4	17.98	16.23	54.93
8	19.2	15.88	56.15
12	20.9	15.1	58.41
16	21.64	14.46	56.04
0	17.8	16.46	51.21
4	18.88	16.01	51.55
8	20.1	15.44	53.41
12	20.96	14.59	55.2
16	22.25	14	52.65

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.892
R Square	0.795
Adjusted R Square	0.756
Standard Error	7.324
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	3324.622	1108.207	20.661	0.000
Residual	16	858.185	53.637		
Total	19	4182.807			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	195.121	177.798	1.097	0.289	-181.793	572.035	-181.793	572.035
RHA (%)	-3.721	0.619	-6.014	0.000	-5.033	-2.410	-5.033	-2.410
OMC (%)	6.033	3.119	1.934	0.071	-0.579	12.645	-0.579	12.645
MDD (kN/m3)	-14.848	7.747	-1.917	0.073	-31.271	1.575	-31.271	1.575

Table C.37: MLR analysis with independent variables except CP and MDD

Lime (%)	RHA (%)	OMC (%)	CBR (0 day curing)
0	0	14.7	5.1
0	4	15.3	8.01
0	8	17.4	11.22
0	12	19.2	14.23
0	16	19.92	13.03
3	0	15.3	30.7
3	4	17.12	34.39
3	8	18.11	36.82
3	12	19.32	40.81
3	16	20.32	37.08
4	0	16.9	42.69
4	4	17.98	46.21
4	8	19.2	48.51
4	12	20.9	50.1
4	16	21.64	48.25
5	0	17.8	42.83
5	4	18.88	43.94
5	8	20.1	45.21
5	12	20.96	47.2
5	16	22.25	45.14

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.964
R Square	0.930
Adjusted R Square	0.916
Standard Error	4.413
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	4115.085	1371.695	70.435	0.000
Residual	16	311.596	19.475		
Total	19	4426.680			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	24.159	30.823	0.784	0.445	-41.183	89.502	-41.183	89.502
Lime (%)	8.128	1.234	6.588	0.000	5.513	10.744	5.513	10.744
RHA (%)	0.733	0.681	1.076	0.298	-0.711	2.176	-0.711	2.176
OMC (%)	-1.063	2.108	-0.504	0.621	-5.532	3.406	-5.532	3.406

Table C.38: MLR analysis with independent variables except CP and MDD

Lime (%)	RHA (%)	OMC (%)	CBR (7 days curing)
0	0	14.7	9.27
0	4	15.3	11.22
0	8	17.4	15.08
0	12	19.2	18.12
0	16	19.92	16.92
3	0	15.3	34.23
3	4	17.12	35.93
3	8	18.11	39.76
3	12	19.32	42.42
3	16	20.32	40.55
4	0	16.9	44.45
4	4	17.98	48.51
4	8	19.2	50.62
4	12	20.9	52.5
4	16	21.64	50.21
5	0	17.8	44.87
5	4	18.88	45.11
5	8	20.1	47.65
5	12	20.96	50.78
5	16	22.25	47.31

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.965
R Square	0.931
Adjusted R Square	0.918
Standard Error	4.191
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	3775.155	1258.385	71.650	0.000
Residual	16	281.007	17.563		
Total	19	4056.162			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	28.421	29.271	0.971	0.346	-33.631	90.474	-33.631	90.474
Lime (%)	7.815	1.172	6.669	0.000	5.331	10.299	5.331	10.299
RHA (%)	0.768	0.647	1.188	0.252	-0.603	2.139	-0.603	2.139
OMC (%)	-1.111	2.002	-0.555	0.587	-5.355	3.133	-5.355	3.133

Table C.39: MLR analysis with independent variables except CP and MDD

Lime (%)	RHA (%)	OMC (%)	CBR (28 days curing)
0	0	14.7	13.43
0	4	15.3	17.83
0	8	17.4	20.21
0	12	19.2	23.43
0	16	19.92	21.24
3	0	15.3	39.52
3	4	17.12	42.42
3	8	18.11	44.85
3	12	19.32	46.52
3	16	20.32	44.11
4	0	16.9	50.61
4	4	17.98	54.93
4	8	19.2	56.15
4	12	20.9	58.41
4	16	21.64	56.04
5	0	17.8	51.21
5	4	18.88	51.55
5	8	20.1	53.41
5	12	20.96	55.2
5	16	22.25	52.65

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.963
R Square	0.927
Adjusted R Square	0.913
Standard Error	4.364
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	3878.099	1292.700	67.879	0.000
Residual	16	304.708	19.044		
Total	19	4182.807			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	25.854	30.481	0.848	0.409	-38.762	90.470	-38.762	90.470
Lime (%)	7.660	1.220	6.278	0.000	5.073	10.247	5.073	10.247
RHA (%)	0.518	0.673	0.770	0.453	-0.909	1.946	-0.909	1.946
OMC (%)	-0.552	2.085	-0.265	0.795	-4.971	3.868	-4.971	3.868

Table C.40: MLR analysis with independent variables except CP and OMC

Lime (%)	RHA (%)	MDD (kN/m^3)	CBR (0 day curing)
0	0	17.48	5.1
0	4	17.01	8.01
0	8	16.66	11.22
0	12	15.75	14.23
0	16	15.49	13.03
3	0	17.18	30.7
3	4	16.23	34.39
3	8	15.98	36.82
3	12	15.35	40.81
3	16	14.68	37.08
4	0	16.86	42.69
4	4	16.23	46.21
4	8	15.88	48.51
4	12	15.1	50.1
4	16	14.46	48.25
5	0	16.46	42.83
5	4	16.01	43.94
5	8	15.44	45.21
5	12	14.59	47.2
5	16	14	45.14

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.974
R Square	0.947
Adjusted R Square	0.940
Standard Error	3.747
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	4202.078	1400.693	99.781	0.000
Residual	16	224.602	14.038		
Total	19	4426.680			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-251.71	101.759	-2.474	0.025	-467.426	-35.988	-467.426	-35.988
Lime (%)	10.84	1.355	7.998	0.000	7.967	13.713	7.967	13.713
RHA (%)	2.57	0.859	2.988	0.009	0.745	4.386	0.745	4.386
MDD (kN/m3)	14.72	5.751	2.559	0.021	2.527	26.912	2.527	26.912

Table C.41: MLR analysis with independent variables except CP and OMC

Lime (%)	RHA (%)	MDD (kN/m^3)	CBR (7 days curing)
0	0	17.48	9.27
0	4	17.01	11.22
0	8	16.66	15.08
0	12	15.75	18.12
0	16	15.49	16.92
3	0	17.18	34.23
3	4	16.23	35.93
3	8	15.98	39.76
3	12	15.35	42.42
3	16	14.68	40.55
4	0	16.86	44.45
4	4	16.23	48.51
4	8	15.88	50.62
4	12	15.1	52.5
4	16	14.46	50.21
5	0	16.46	44.87
5	4	16.01	45.11
5	8	15.44	47.65
5	12	14.59	50.78
5	16	14	47.31

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.975
R Square	0.948
Adjusted R Square	0.941
Standard Error	3.551
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	3854.357	1284.786	101.863	0.000
Residual	16	201.805	12.613		
Total	19	4056.162			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-237.553	96.456	-2.463	0.026	-442.032	-33.074	-442.032	-33.074
Lime (%)	10.368	1.285	8.070	0.000	7.644	13.092	7.644	13.092
RHA (%)	2.498	0.814	3.069	0.007	0.772	4.223	0.772	4.223
MDD (kN/m3)	14.120	5.452	2.590	0.020	2.563	25.678	2.563	25.678

Table C.42: MLR analysis with independent variables except CP and OMC

Lime (%)	RHA (%)	MDD (kN/m^3)	CBR (28 days curing)
0	0	17.48	13.43
0	4	17.01	17.83
0	8	16.66	20.21
0	12	15.75	23.43
0	16	15.49	21.24
3	0	17.18	39.52
3	4	16.23	42.42
3	8	15.98	44.85
3	12	15.35	46.52
3	16	14.68	44.11
4	0	16.86	50.61
4	4	16.23	54.93
4	8	15.88	56.15
4	12	15.1	58.41
4	16	14.46	56.04
5	0	16.46	51.21
5	4	16.01	51.55
5	8	15.44	53.41
5	12	14.59	55.2
5	16	14	52.65

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.973
R Square	0.946
Adjusted R Square	0.936
Standard Error	3.747
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	3958.168	1319.389	93.974	0.000
Residual	16	224.639	14.040		
Total	19	4182.807			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-227.184	101.767	-2.232	0.040	-442.921	-11.447	-442.921	-11.447
Lime (%)	10.449	1.356	7.708	0.000	7.575	13.322	7.575	13.322
RHA (%)	2.383	0.859	2.775	0.014	0.562	4.203	0.562	4.203
MDD (kN/m3)	13.850	5.752	2.408	0.028	1.656	26.044	1.656	26.044

Table C.43: MLR analysis with independent variables except CP, OMC and MDD

Lime (%)	RHA (%)	CBR (0 day curing)
0	0	5.1
0	4	8.01
0	8	11.22
0	12	14.23
0	16	13.03
3	0	30.7
3	4	34.39
3	8	36.82
3	12	40.81
3	16	37.08
4	0	42.69
4	4	46.21
4	8	48.51
4	12	50.1
4	16	48.25
5	0	42.83
5	4	43.94
5	8	45.21
5	12	47.2
5	16	45.14

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.964
R Square	0.928
Adjusted R Square	0.920
Standard Error	4.315
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	4110.137	2055.068	110.368	0.000
Residual	17	316.543	18.620		
Total	19	4426.680			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	8.668	2.278	3.806	0.001	3.862	13.473	3.862	13.473
Lime (%)	7.566	0.516	14.670	0.000	6.478	8.654	6.478	8.654
RHA (%)	0.401	0.171	2.351	0.031	0.041	0.761	0.041	0.761

Table C.44: MLR analysis with independent variables except CP, OMC and MDD

Lime (%)	RHA (%)	CBR (7 days curing)
0	0	9.27
0	4	11.22
0	8	15.08
0	12	18.12
0	16	16.92
3	0	34.23
3	4	35.93
3	8	39.76
3	12	42.42
3	16	40.55
4	0	44.45
4	4	48.51
4	8	50.62
4	12	52.5
4	16	50.21
5	0	44.87
5	4	45.11
5	8	47.65
5	12	50.78
5	16	47.31

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.964
R Square	0.929
Adjusted R Square	0.921
Standard Error	4.105
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	3769.747	1884.873	111.876	0.000
Residual	17	286.415	16.848		
Total	19	4056.162			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	12.225	2.166	5.643	0.000	7.654	16.795	7.654	16.795
Lime (%)	7.227	0.491	14.731	0.000	6.192	8.262	6.192	8.262
RHA (%)	0.421	0.162	2.596	0.019	0.079	0.764	0.079	0.764

Table C.45: MLR analysis with independent variables except CP, OMC and MDD

Lime (%)	RHA (%)	CBR (28 days curing)
0	0	13.43
0	4	17.83
0	8	20.21
0	12	23.43
0	16	21.24
3	0	39.52
3	4	42.42
3	8	44.85
3	12	46.52
3	16	44.11
4	0	50.61
4	4	54.93
4	8	56.15
4	12	58.41
4	16	56.04
5	0	51.21
5	4	51.55
5	8	53.41
5	12	55.2
5	16	52.65

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.963
R Square	0.927
Adjusted R Square	0.918
Standard Error	4.243
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	3876.766	1938.383	107.673	0.000
Residual	17	306.041	18.002		
Total	19	4182.807			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	17.814	2.239	7.955	0.000	13.089	22.538	13.089	22.538
Lime (%)	7.368	0.507	14.529	0.000	6.298	8.438	6.298	8.438
RHA (%)	0.346	0.168	2.063	0.055	-0.008	0.700	-0.008	0.700

Table C.46: MLR analysis with independent variables except CP, Lime and RHA

OMC (%)	MDD (kN/m^3)	CBR (0 day curing)
14.7	17.48	5.1
15.3	17.01	8.01
17.4	16.66	11.22
19.2	15.75	14.23
19.92	15.49	13.03
15.3	17.18	30.7
17.12	16.23	34.39
18.11	15.98	36.82
19.32	15.35	40.81
20.32	14.68	37.08
16.9	16.93	42.69
17.98	16.23	46.21
19.2	15.88	48.51
20.9	15.1	50.1
21.64	14.46	48.25
17.8	16.46	42.83
18.88	16.01	43.94
20.1	15.44	45.21
20.96	14.59	47.2
22.25	14	45.14

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.583
R Square	0.340
Adjusted R Square	0.262
Standard Error	13.113
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	1503.506	751.753	4.372	0.029
Residual	17	2923.175	171.951		
Total	19	4426.680			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-182.637	297.114	-0.615	0.547	-809.493	444.219	-809.493	444.219
OMC (%)	6.678	5.580	1.197	0.248	-5.094	18.451	-5.094	18.451
MDD (kN/m3)	5.841	12.317	0.474	0.641	-20.145	31.827	-20.145	31.827

Table C.47: MLR analysis with independent variables except CP, Lime and RHA

OMC (%)	MDD (kN/m^3)	CBR (7 days curing)
14.7	17.48	9.27
15.3	17.01	11.22
17.4	16.66	15.08
19.2	15.75	18.12
19.92	15.49	16.92
15.3	17.18	34.23
17.12	16.23	35.93
18.11	15.98	39.76
19.32	15.35	42.42
20.32	14.68	40.55
16.9	16.93	44.45
17.98	16.23	48.51
19.2	15.88	50.62
20.9	15.1	52.5
21.64	14.46	50.21
17.8	16.46	44.87
18.88	16.01	45.11
20.1	15.44	47.65
20.96	14.59	50.78
22.25	14	47.31

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.593
R Square	0.351
Adjusted R Square	0.275
Standard Error	12.441
Observations	20.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	1424.760	712.380	4.602	0.025
Residual	17	2631.402	154.788		
Total	19	4056.162			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-163.111	281.896	-0.579	0.570	-757.860	431.638	-757.860	431.638
OMC (%)	6.305	5.294	1.191	0.250	-4.865	17.474	-4.865	17.474
MDD (kN/m3)	5.220	11.686	0.447	0.661	-19.436	29.875	-19.436	29.875

Table C.48: MLR analysis with independent variables except CP, Lime and RHA

OMC (%)	MDD (kN/m^3)	CBR (28 days curing)
14.7	17.48	13.43
15.3	17.01	17.83
17.4	16.66	20.21
19.2	15.75	23.43
19.92	15.49	21.24
15.3	17.18	39.52
17.12	16.23	42.42
18.11	15.98	44.85
19.32	15.35	46.52
20.32	14.68	44.11
16.9	16.93	50.61
17.98	16.23	54.93
19.2	15.88	56.15
20.9	15.1	58.41
21.64	14.46	56.04
17.8	16.46	51.21
18.88	16.01	51.55
20.1	15.44	53.41
20.96	14.59	55.2
22.25	14	52.65

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.575
R Square	0.331
Adjusted R Square	0.252
Standard Error	12.830
Observations	20.000

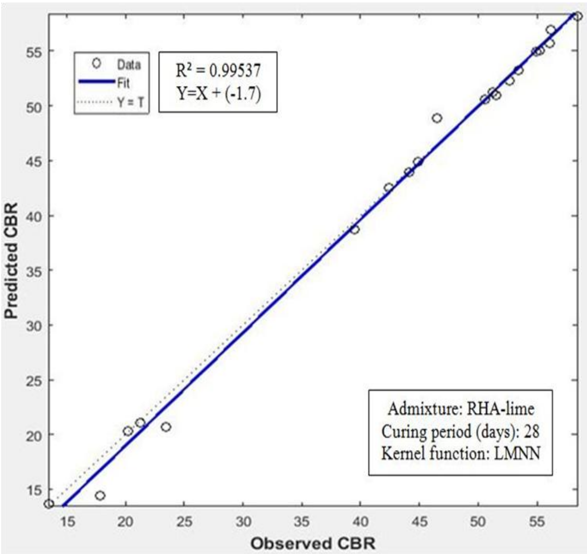
ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	1384.601	692.301	4.206	0.033
Residual	17	2798.206	164.600		
Total	19	4182.807			

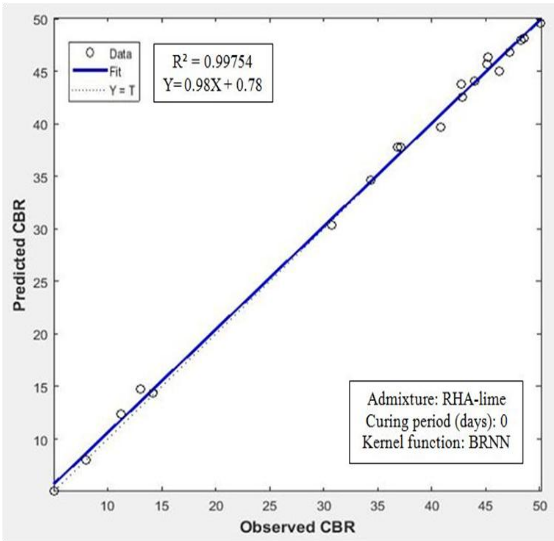
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-188.840	290.694	-0.650	0.525	-802.150	424.470	-802.150	424.470
OMC (%)	6.817	5.459	1.249	0.229	-4.701	18.335	-4.701	18.335
MDD (kN/m3)	6.582	12.051	0.546	0.592	-18.843	32.006	-18.843	32.006

Annex-D

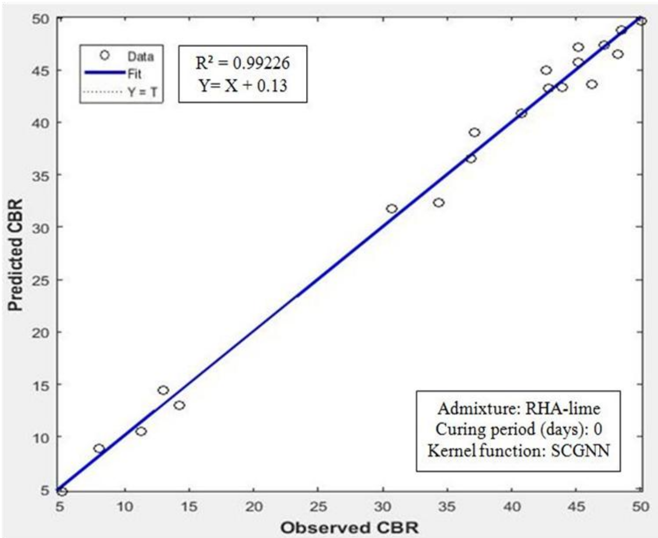
Results from ANN and SVM Analysis



(a)



(b)



(c)

Figure D.1: Correlation between observed and predicted CBR of stabilized soil with RHA and lime (a) LMNN (b) BRNN and (c) SCGNN.

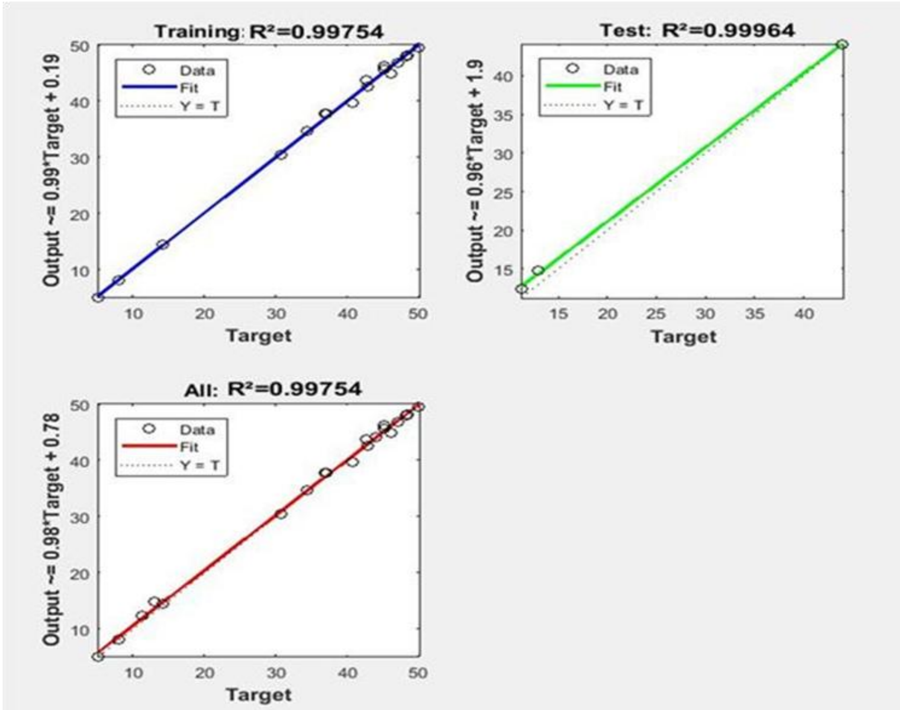
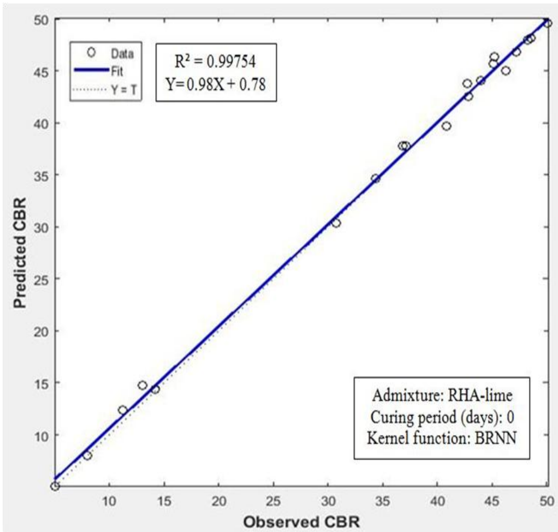
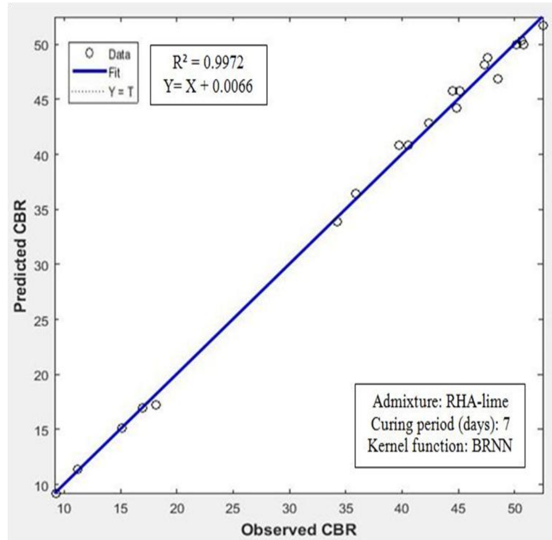


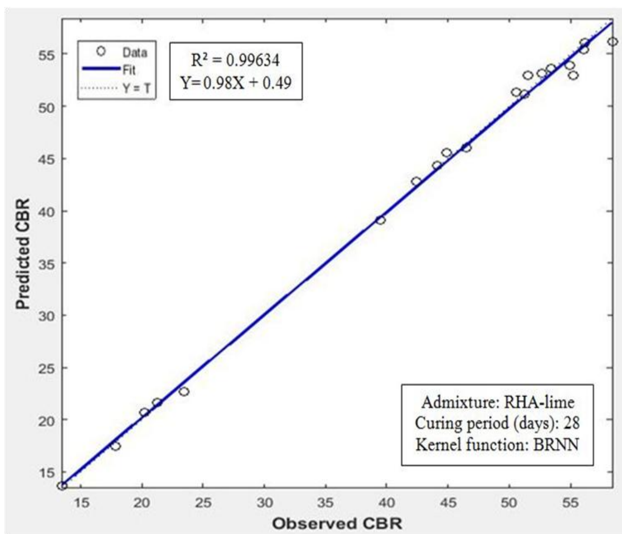
Figure D.2: Regression coefficient of BRNN through ANN model for stabilized soil with RHA and lime.



(a)



(b)



(c)

Figure D.3: Correlation between observed and predicted CBR of stabilized soil with RHA and lime for ANN at curing period of (a) 0 (b) 7 and (c) 28 days.

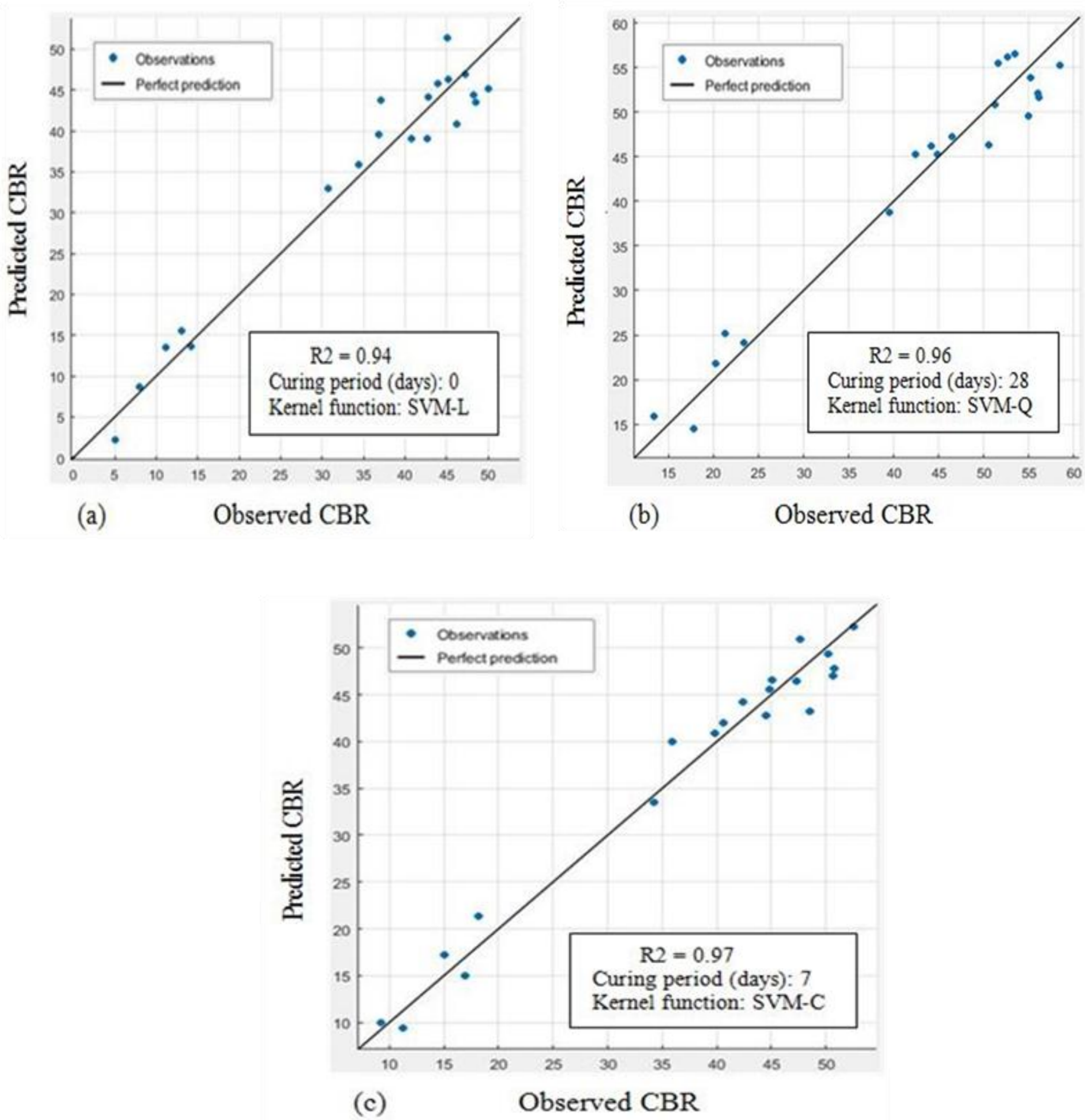


Figure D.4: Correlation between observed and predicted CBR of stabilized soil with RHA and lime (a) SVM-L (b) SVM-Q and (c) SVM-C.

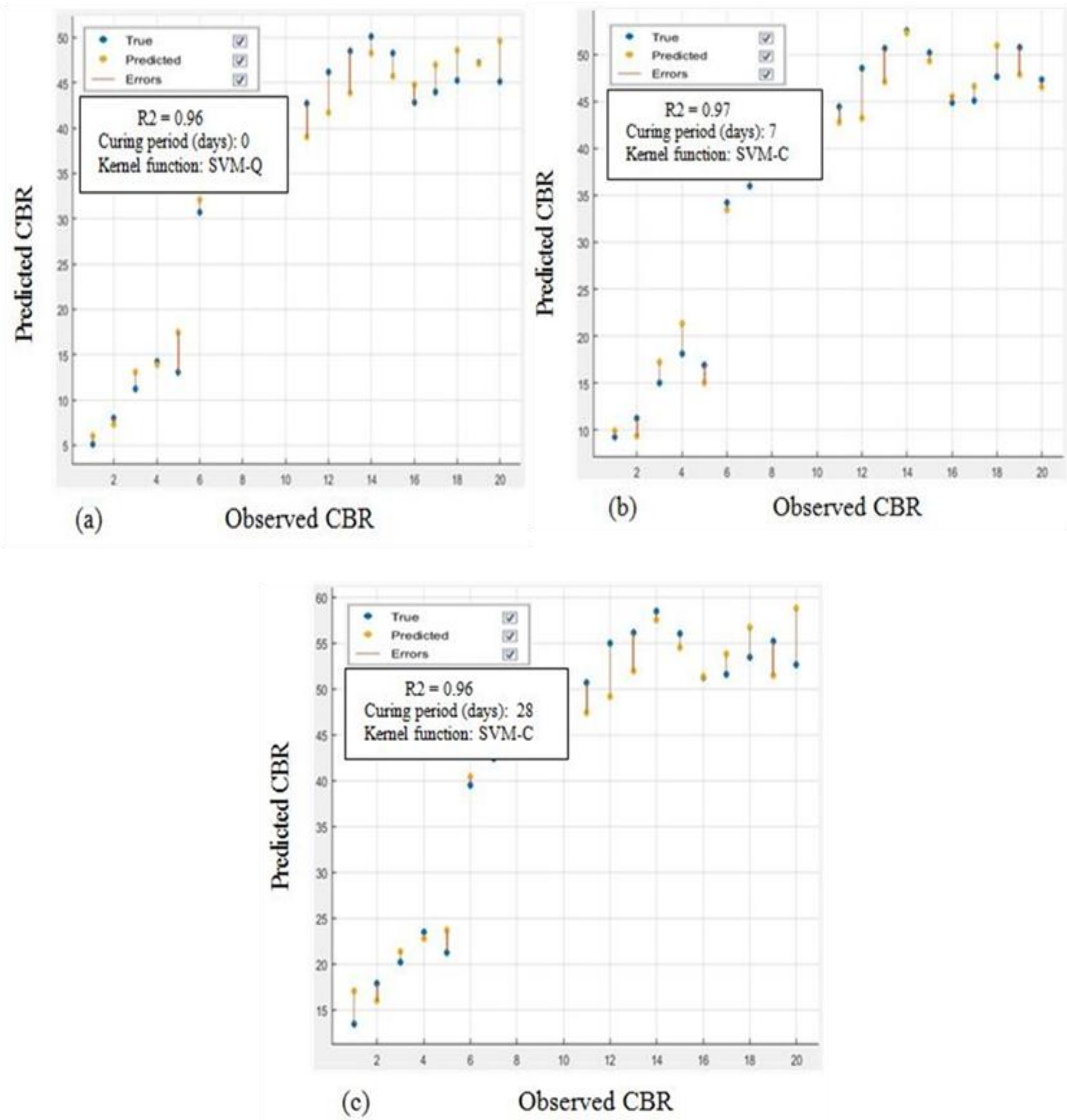


Figure D.5: Error histogram of CBR in stabilized soil with QD and lime for SVM at curing Period of (a) 0 (b) 7 and (c) 28 days.

Annex-E

Predicted CBR of Stabilized Soils

Table E.1: Predicted CBR of stabilized soils from SLR analysis

SLR (R^2=0.798 from Equation: 4.3), curing period (days): 28		
Independent variable	Stabilized soil with QD (%) and lime (%)	
QD (%)	Observed CBR	Predicted CBR
0	57.66	63.72
10	69.3	69.56
20	73.2	75.4
30	78.65	81.24
40	87.25	87.08
50	81.89	92.92
0	62.12	63.72
10	73.55	69.56
20	79	75.4
30	87.81	81.24
40	98.26	87.08
50	91.22	92.92
0	59.89	63.72
10	71.5	69.56
20	76.22	75.4
30	83.5	81.24
40	91.75	87.08
50	87.21	92.92

SLR (R^2=0.908 from Equation: 4.7), curing period (days): 28		
Independent variable	Stabilized soil with RHA (%) and lime (%)	
Lime (%)	Observed CBR	Predicted CBR
0	13.43	20.58
0	17.83	20.58
0	20.21	20.58
0	23.43	20.58
0	21.24	20.58
3	39.52	42.68
3	42.42	42.68
3	44.85	42.68
3	46.52	42.68
3	44.11	42.68
4	50.61	50.05
4	54.93	50.05
4	56.15	50.05
4	58.41	50.05
4	56.04	50.05
5	51.21	57.42
5	51.55	57.42
5	53.41	57.42
5	55.2	57.42
5	52.65	57.42

Table E.2: Predicted CBR of stabilized soil with QD and lime from MLR analysis

MLR (R^2=0.872 from Equation: 4.8), curing period (days): 28						
Independent variables					Stabilized soil with QD (%) and lime (%)	
QD (%)	Lime (%)	CP (days)	OMC (%)	MDD (kN/m^3)	Observed CBR	Predicted CBR
0	2	28	13.72	16.95	57.66	58.33
10	2	28	12.89	17.42	69.3	67.03
20	2	28	12.67	18.08	73.2	79.18
30	2	28	12.10	18.17	78.65	80.67
40	2	28	11.54	18.40	87.25	84.79
50	2	28	11.29	18.57	81.89	87.72
0	4	28	14.12	16.86	62.12	61.21
10	4	28	13.47	17.33	73.55	69.87
20	4	28	13.16	17.88	79	79.97
30	4	28	12.58	18.00	87.81	82.02
40	4	28	12.07	18.38	98.26	88.96
50	4	28	11.78	18.47	91.22	90.39
0	6	28	14.32	16.67	59.89	62.25
10	6	28	13.89	17.21	71.5	72.19
20	6	28	13.12	17.67	76.22	80.69
30	6	28	12.76	17.78	83.5	82.51
40	6	28	12.34	18.15	91.75	89.24
50	6	28	11.92	18.36	87.21	92.95

Table E.3: Predicted CBR of stabilized soil with RHA and lime from MLR analysis

MLR (R^2=0.950 from Equation: 4.9), curing period (days): 7						
Independent variables					Stabilized soil with RHA (%) and lime (%)	
RHA (%)	Lime (%)	CP (days)	OMC (%)	MDD (kN/m^3)	Observed CBR	Predicted CBR
0	0	7	14.7	17.48	9.27	9.26
4	0	7	15.3	17.01	11.22	12.83
8	0	7	17.4	16.66	15.08	17.52
12	0	7	19.2	15.75	18.12	14.52
16	0	7	19.92	15.49	16.92	20.97
0	3	7	15.3	17.18	34.23	36.42
4	3	7	17.12	16.23	35.93	32.86
8	3	7	18.11	15.98	39.76	39.34
12	3	7	19.32	15.35	42.42	40.46
16	3	7	20.32	14.68	40.55	41.10
0	4	7	16.9	16.86	44.45	41.89
4	4	7	17.98	16.23	48.51	43.06
8	4	7	19.2	15.88	50.62	48.07
12	4	7	20.9	15.1	52.5	46.92
16	4	7	21.64	14.46	50.21	48.07
0	5	7	17.8	16.46	44.87	46.51
4	5	7	18.88	16.01	45.11	50.18
8	5	7	20.1	15.44	47.65	52.13
12	5	7	20.96	14.59	50.78	50.31
16	5	7	22.25	14	47.31	51.96

Table E.4: Predicted CBR of stabilized soil with QD and lime from ANN analysis

ANN (SCGNN, R^2=0.995), curing period (days): 7				
Independent variables			Stabilized soil with QD (%) and lime (%)	
QD (%)	Lime (%)	OMC (%)	Observed CBR	Predicted CBR
0	2	13.72	33.34	31.54
10	2	12.89	40.21	38.41
20	2	12.67	45.32	43.52
30	2	12.10	51.31	49.51
40	2	11.54	61.10	59.30
50	2	11.29	56.64	54.84
0	4	14.12	44.67	42.87
10	4	13.47	46.21	44.41
20	4	13.16	53.78	51.98
30	4	12.58	62.32	60.52
40	4	12.07	83.27	81.47
50	4	11.78	74.50	72.70
0	6	14.32	39.80	38.00
10	6	13.89	41.14	39.34
20	6	13.12	44.77	42.97
30	6	12.76	59.55	57.75
40	6	12.34	74.19	72.39
50	6	11.92	69.13	67.33

Table E.5: Predicted CBR of stabilized soil with RHA and lime from ANN analysis

ANN (BRNN, R^2=0.998), curing period (days): 0						
Independent variables					Stabilized soil with RHA (%) and lime (%)	
RHA (%)	Lime (%)	Curing period (days)	OMC (%)	MDD (kN/m^3)	Observed CBR	Predicted CBR
0	0	0	14.7	17.48	5.1	5.78
4	0	0	15.3	17.01	8.01	8.63
8	0	0	17.4	16.66	11.22	11.78
12	0	0	19.2	15.75	14.23	14.73
16	0	0	19.92	15.49	13.03	13.55
0	3	0	15.3	17.18	30.7	30.87
4	3	0	17.12	16.23	34.39	34.48
8	3	0	18.11	15.98	36.82	36.86
12	3	0	19.32	15.35	40.81	40.77
16	3	0	20.32	14.68	37.08	37.12
0	4	0	16.9	16.93	42.69	42.62
4	4	0	17.98	16.23	46.21	46.07
8	4	0	19.2	15.88	48.51	48.32
12	4	0	20.9	15.1	50.1	49.88
16	4	0	21.64	14.46	48.25	48.07
0	5	0	17.8	16.46	42.83	42.75
4	5	0	18.88	16.01	43.94	43.84
8	5	0	20.1	15.44	45.21	45.09
12	5	0	20.96	14.59	47.2	47.04
16	5	0	22.25	14	45.14	45.02

Table E.6: Predicted CBR of stabilized soil with QD and lime from SVM analysis

SVM (SVM-Q, R^2=0.90), curing period (days): 28			
Independent variables		Stabilized soil with QD (%) and lime (%)	
QD (%)	Lime (%)	Observed CBR	Predicted CBR
0	2	57.66	57.82
10	2	69.30	67.44
20	2	73.20	74.77
30	2	78.65	79.82
40	2	87.25	82.58
50	2	81.89	83.06
0	4	62.12	63.29
10	4	73.55	73.21
20	4	79.00	80.84
30	4	87.81	86.19
40	4	98.26	89.26
50	4	91.22	90.04
0	6	59.89	60.11
10	6	71.50	70.33
20	6	76.22	78.27
30	6	83.50	83.92
40	6	91.75	87.29
50	6	87.21	88.38

Table E.7: Predicted CBR of stabilized soil with RHA and lime from SVM analysis

SVM (SVM-C, R^2=0.97), curing period (days): 7						
Independent variables					Stabilized soil with RHA (%) and lime (%)	
RHA (%)	Lime (%)	Curing period (days)	OMC (%)	MDD (kN/m^3)	Observed CBR	Predicted CBR
0	0	7	14.7	17.48	9.27	7.76
4	0	7	15.3	17.01	11.22	9.60
8	0	7	17.4	16.66	15.08	16.71
12	0	7	19.2	15.75	18.12	19.74
16	0	7	19.92	15.49	16.92	15.67
0	3	7	15.3	17.18	34.23	32.61
4	3	7	17.12	16.23	35.93	37.55
8	3	7	18.11	15.98	39.76	41.38
12	3	7	19.32	15.35	42.42	43.82
16	3	7	20.32	14.68	40.55	42.18
0	4	7	16.9	16.93	44.45	43.21
4	4	7	17.98	16.23	48.51	44.30
8	4	7	19.2	15.88	50.62	48.20
12	4	7	20.9	15.1	52.5	50.88
16	4	7	21.64	14.46	50.21	48.74
0	5	7	17.8	16.46	44.87	44.66
4	5	7	18.88	16.01	45.11	46.73
8	5	7	20.1	15.44	47.65	49.27
12	5	7	20.96	14.59	50.78	49.16
16	5	7	22.25	14	47.31	47.71