

**ADDIS ABABA INSTITUTE OF TECHNOLOGY
SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING
DEPARTMENT OF GEOTECHNICAL ENGINEERING**



**CORRELATING CBR VALUES WITH BASIC SOIL
PARAMETERS
(USING NEUROXL PREDICTOR)**

A project submitted in partial fulfillment of the requirements for the
Degree of Master of Science in Civil Engineering

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January 2024 G.C

Declaration

I, Airmeyas Aychew, hereby declare that this research project entitled “**Correlating CBR values with basic soil parameters (by using Neuroxl Predictor)**” is my original work and has not been submitted in whole or in part for any other degree at this university or any other institution. All sources used in this thesis have been duly acknowledged.

I also declare that the content of this research project is the result of my own research and that it represents my personal views and findings. Where the contributions of others are involved, every effort has been made to indicate this and to give appropriate credit.

Airmeyas Aychew
January, 2024

ADDIS ABABA UNIVERSITY
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SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING
MASTER OF SCIENCE IN CIVIL ENGINEERING
(GEOTECHNICAL ENGINEERING)

Title: "Correlating CBR values with basic soil parameters
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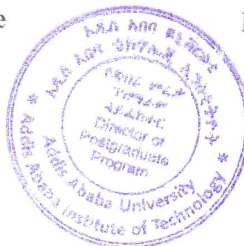
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ABSTRACT

The California bearing ratio (CBR) is an essential design parameter for soils and an indirect measure of soil strength. This is broadly used for the design of sub-grade, sub-base and base course materials for road, railway, and airfield projects. It is also used as a direct relationship to determine the response of the base or sub-base soil. This research studies the relationship between CBR values and other parameters of soil properties, although the samples include coarse and fine-grained soils, using advanced neural network programs to help us obtain an accurate predicted value. Most of the previous studies were conducted on fine-grained soil types and also used conventional multiple linear regression analysis methods.

To satisfy the objective of this study, one hundred and ninety-eight soil sample test results were collected. I participated as a material engineer in the testing and reporting process. Laboratory testing was performed in accordance with AASHTO standard test methods. Modified compaction, soak three-point modified CBR, wet sieve analysis, and Atterberg limit tests were performed on a total of one hundred and ninety-eight soil samples.

Statistical analyses were performed to validate the new model using 30 percent of the total sample size. Two types of analysis programs—Microsoft Excel software (ANOVA) for multiple non-linear regression relationships and the advanced NeuroXL predictive neural network program—were used to predict CBR values.

Independent soil property parameters were liquid limit, plastic limit, plastic index, amount of particle size less than 0.075 mm, amount of particle size less than 0.425 mm, amount of particle size less than 2.00 mm, amount of particle size less than 4.75 mm, optimum moisture content, and maximum dry density.

This study provided two alternative models. The first alternative model included compaction test parameters (OMC and MDD), particle size distribution parameters (4.75 mm PP, 2 mm PP, 0.425 mm PP, and 0.075 mm PP), and plasticity parameters (LL, PL, and PI). They were taken as independent parameters. The second alternative model excludes the compaction test parameters (OMC and MDD) as independent parameters when compared to the alternative one.

This study used two alternative analysis techniques: the first group of analysis techniques developed model equations for each classified data set (sub-grade, sub-base, and sub-base), and the second technique developed model equations for the unclassified data set group.

The predicted CBR values of both the NeuroXL prediction and multiple nonlinear ANOVA regression models were compared with the actual CBR values, which confirmed that there was an acceptable difference between the actual and predicted CBR values between both analysis methods.

Key words: CBR, neuroxl predictor, correlation, regression, ANOVA, AASHTO.

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LIST OF ABBREVIATIONS AND ACRONYMS

AASHTO: American Association of State Highway and Transportation

ASTM: American Society for Testing and Materials

CBR: California Bearing Ratio

USCS: Unified Soil Classification System

$P_{4.75}$: the percentage of soil that passes through a 4.75 mm sieve

P_2 : the percentage of soil that passes through a 2 mm sieve

$P_{0.425}$: the percentage of soil that passes through a 0.425 mm sieve

$P_{0.075}$: the percentage of soil that passes through a 0.075 mm sieve

W_L : Water content at liquid limit (LL)

W_p : Water content at plastic limit (PL)

I_p : Plasticity index (PI)

$\rho_{d \max}$: Maximum dry density (MDD)

W_{opt} : Optimum moisture content (OMC)

R : Regression coefficient

R^2 : Regression coefficient square

ANOVA: Analysis of variance

Abs: Absolute Value

1. INTRODUCTION

1.1 Background

The road network in Ethiopia plays an important role in the country's economy as it provides the main transportation services for goods and passengers. There are two types of road pavement: rigid and flexible. They are designed to limit the pressure generated at the sub-grade level by the traffic traveling on the pavement so that the sub-grade is not exposed to significant deformations. A pavement consists of a capping layer, a sub-base layer, a base course, and a wearing layer.

The selection and performance of pavement materials are based on laboratory and field tests, which are the CBR test, DCP, classification test (Atterberg limit and sieve analysis tests), and mechanical strength tests. In the pavement design stage and road construction stage, the CBR value is used as a critical input parameter. It is one factor in determining the thickness of pavement for airfield, highway, or railway projects.

The CBR value of a soil can depend on many factors, such as maximum dry density (MDD), optimum moisture content (OMC), liquid limit (LL), plastic limit (PL), plasticity index (PI), particle size distribution, soil type, permeability of the soil, etc. In addition, the soil condition, whether soaked or un-soaked, also affects the value. In the past, several investigators have attempted to correlate the soaked CBR with various soil properties. Most of the correlations were based on the soil parameters.

The CBR test is difficult and time-consuming. In addition, errors can occur during sampling, transportation, and testing of soil samples, which can lead to inaccurate results. To overcome these problems, an attempt was made to statistically correlate CBR value with liquid limit (LL), plastic limit (PL), plasticity index (PI), particle size distribution, maximum dry density (MDD), and optimal moisture content (OMC). This is because these tests are simple, completed in a short time, and also require a smaller soil sample compared to the CBR test.

In this research study, the relationship between California bearing ratio values and other soil properties was investigated on one hundred and ninety-eight soil samples using both analytical methods: ordinary ANOVA regression analysis and advanced neural network programming. This research includes both types of soil: coarse and fine grain sizes.

1.2 Statement of the Problem

The developed soil classification system and standard methods of soil testing, which are not based on the characteristics of soils in tropical climate regions, ensure the appropriateness of the system and methods.

Most of the previous researchers developed a model equation to predict CBR values of fine grain soils only; this new model can represent both granular and fine grain soil types.

Previous artificial neural networks required programming skills, but NeuroXL Predictor uses advanced neural network algorithms and does not require programming skills.

Previous researchers have suggested that the regression be improved by including more soil samples, because in this current research, one hundred and ninety-eight soilsamples are the main internal data.

1.3 Objective of the study

1.3.1 General objective

The main objective of this project is to determine the relationship between CBR values and soil property parameters for sub-grade, sub-base and base-course pavement construction materials using the NeuroXL Predictor program and ANOVA Excel analysismethods.

1.3.2 Specific objectives

To identify which soil parameters have the greatest influence on the CBR value.

To create a newmodel to estimate CBR values on pavement construction materials.

To introduce a new advanced neural network program (NeuroXL predictor) for geotechnical prediction and regression problems.

Comparison with a multivariable non-linear regression model to verify the suitability of the Neuroxl forecasting program for predicting soil parameters.

1.4 Scope of the study

- Research was done only on the condition of the California bearing ratio value of the soaked.
- This study is based on the primary data collected.
- Laboratory compaction and Three Point CBR tests under heavy load effort (modified compaction condition).

1.5 Significance of the study

- This research will lead to improved construction practices. Knowing the relationship between CBR and other soil properties will help engineers and construction professionals make better decisions about the preliminary design of roads, airports and other infrastructure.
- This study shows the importance of correlation between California bearing ratio (CBR) values and other soil properties in the civil engineering and construction industries using an artificial intelligence program (Neuroxl Predictor) analysis method.
- This research will help future researchers by suggesting alternative analysis techniques and methods.

1.6 Limitations of the study

- It was not possible to study the correlation of un-socked CBR values with soil properties due to the lack of data on un-socked CBR test results.
- Due to the high cost of the product, it was impossible to use the full version of the Neuroxl Predictor program.

2. LITERATURE REVIEW

2.1 General

Roads are necessary for transportation and the financial improvement of a country. Most of the road network in our country consists of flexible pavement. Flexible pavement consists of different layers such as sub-grade, sub-base, base course, and surface layer. [Ethiopian Roads Authority, (2013), ERA Pavement Design Manual Volume 1]

The California Bearing Ratio (CBR) is one of the methods to determine the sub-grade, sub-base and sub-base Soils strength. The design and performance of flexible pavement mainly depend on the strength of the construction material. The load from the pavement surface is ultimately transferred to the sub-grade. The sub-grade is designed such that the stress transferred should not exceed the elastic limit. [Ethiopian Roads Authority, (2013), ERA Pavement Design Manual Volume 1]

Hence, the suitability and stability of sub-grade material are evaluated before the construction of pavement. The California bearing ratio (CBR) value is considered a strength parameter in the design of pavement Structures. [Ethiopian Roads Authority, (2013), ERA Pavement Design Manual Volume 1]

Among the various methods of evaluating the sub-grade strength, a quick estimate of CBR is very important for a highway engineer, so a simple test that can be used as an index test was devised. Thus, the index test is an indirect measure of stiffness modulus, or shear strength. [Ethiopian Roads Authority,(2013), ERA Pavement Design Manual Volume 1]

The CBR value of a soil can depend on many factors, such as maximum dry density (MDD), optimum moisture content (OMC), liquid limit (LL), plastic limit (PL), plasticity index (PI), soil type, and permeability. Besides, the soaked or un-soaked condition of the soil also affects its value. Determining CBR is a long and time-consuming process. An attempt has been made to correlate soaked CBR values with MDD, OMC, LL, PL, and PI on soil samples collected from different locations. [Dr. Dilip Kumar T., (January 2014), A Study of Correlation between California Bearing Ratio (CBR) Value and Other Properties of Soil.]

The CBR value of fine grain soils (ML and MH) bears a significant correlation with PI, MDD, and OMC. The CBR value decreases with the increase in the plasticity index and optimum moisture content of soil but increases with the increase in the maximum dry density. There is a slight difference between the CBR value determined in the laboratory and the one computed by using multiple linear regression models involving LL, PL, PI, MDD, and OMC. [Dr. Dilip Kumar T. (January 2014), A Study of Correlation between California Bearing Ratio (CBR) Value and Other Properties of Soil.]

In the past, several investigators have attempted to correlate soaking CBR with different soil properties. Table 2.1 shows relationship of CBR tests with other soil parameters. As shown in this table. [Kleyn S. A., (1995), Possible developments in pavement foundation Design.]

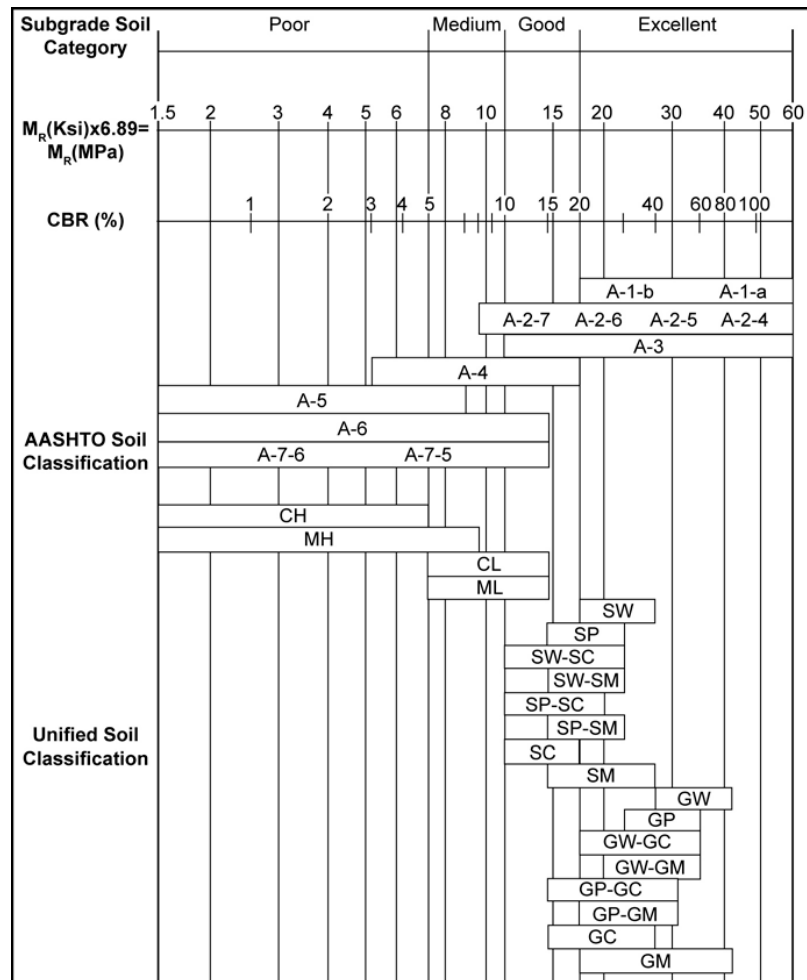
Table 2-1 Current correlations up to the 2000s (Recreated Table Source: [S. M. Lim, D. C. Wijeyesekera and I. Bakar, (2014), Correlations of soil classification and compaction parameters with soaked and Un-soaked CBR of soils.](Recreated table)

Reference	Correlation Equation	No.	Correlated parameters
Talukdar (2014)	$CBR(\text{soaked}) = 0.127LL + 0.00 PL - 0.16 PI + 1.405 MDD - 0.259 OMC + 4.618$	(1)	LL, PL, PI, MDD (gm/cc), OMC
Sabat (2013)	$CBR = 83.7 - 3.12 L + 0.540 QD + 0.44 CP - 5.08 MDD + 0.32 OMC$	(2)	L (lime) %, QD (Quarry dust) %, CP(curing period) days, MDD (kN/m ³), OMC
Patel & Patel (2013)	$CBR = 2.408 MDD - 1.283 \cdot 10^{-1} OMC - 39.345$	(3)	MDD, OMC
Nugroho, Hendri&Ningsih (2012)	$\Delta CBR = 25 + C1Clay + C2LL + C3IP + 3.5 OMC$	(4)	Clay, LL, IP, OMC
	$\Delta CBR = -25 + C1Clay - C2LL - C3IP + 3.5 OMC$	(5)	Clay, LL, IP, OMC
Patel & Patel (2012)	$CBR = 3.7533 MDD - 1.3669 E10 - 1 OMC + 1.5193 E10 - 1 W_{LM} - 70.10518931$	(6)	LL, PI, OMC, MDD
	$CBR = 3246.4 W_{LM} - 1.895$	(7)	$W_{LM} = LL(1 - C / 100)$
Yildirim & Guanaydin (2011) (Refer to Ramasubbarao & Siva, 2013)	$CBR = -0.1805F + 18.508$	(8)	F
	$CBR = 0.24G + 3.08$	(9)	G
	$CBR = 0.22G + 0.045S + 4.739 MDD + 0.122 OMC$	(10)	G, S, MDD(g/cc), OMC
	$CBR = 0.62 OMC + 58.9 MDD + 0.11 LL + 0.53 PL - 126$	(11)	OMC, MDD, LL, PL
Patel and Desai (2010)	$CBR(\text{soaked}) = 43.907 - 0.093(PI) - 18.78(MDD) - 0.3081(OMC)$	(12)	PI, MDD (gm/cc), OMC
	$CBR(\text{un-soaked}) = 17.009 - 0.0696(PI) - 0.296(MDD) - 0.0648(OMC)$	(13)	
Roy et al (2009)	$\text{Log}(CBR_{\text{soaked}}) = \text{Log}(\gamma_{d\text{max}} / \gamma_w) - \text{Log}(OMC)$	(14)	OMC, MDD (same unit)
Vinod& Cletus (2008)	$CBR = -0.889(W_{LM}) + 45.616$ where, $W_{LM} = LL(1 - C / 100)$	(15)	LL, Gradation
Gregory & Gross (2007)	$CBR = 0.09 Cu$	(16)	Cu
	$CBR = 100 q_{ult} / 6895$	(17)	q_{ult}

Liquid Limit (LL), Plastic Limit (PL), Plastic Index (PI) or (IP), Maximum Dry Density (MDD),

Optimum Moisture Content (OMC), Clay Percent (C), ($WLM = LL(1 - C/100)$), percent Fine (F), Percent Gravel (G), Percent Sand (S), Maximum dry unit weight of soil ($\gamma_d \text{ max}$), unit weight of water (γ_w), Un-drained vane shear strength of soil (C_u), Ultimate bearing capacity (qult).

Figure 2-1: CBR Values Correlations to Empirical Soil Properties and Classification Categories from NCHRP (2001).[Source: Ethiopian Road Authority, (2013), Geotechnical Design Manual]



Well-graded gravels (GW), poorly graded gravels (PG), Silty gravels (GM), Clayey gravels (GC), Well-graded sands (SW), poorly graded sands (SG), silty sands (SM), clayey sands (SC), Inorganic silts and very fine sands (ML), inorganic clays of low to medium plasticity (CL), Inorganic silts (MH), Inorganic clays of high plasticity (CH), (GW-GM) well-graded gravel with silt, (GW-GC) well-graded gravel with clay, (GP-GM) poorly graded gravel with silt (GP-GC) poorly graded gravel with clay, (SW-SM) well-graded sand with silt (SW-SC) well-graded sand with clay, (SP-SM) poorly graded sand with silt, (SP-SC) poorly graded sand with clay, resilient modulus value (M_R)

A-1-a through A-7-6 are AASHTO soil classification system group designation names.

Table 2-2: Typical CBR Value and Classification Categories(Source: Ethiopian Road authority, (2013), ERA flexible pavement design manual volume 1, Pages 3–8, (Recreated table)

Major Divisions		Symbol		Names	Value as Sub-grade	Typical Design CBR Values
COARSE GRAINED SOIL	GRAVEL AND GRAVELLY SOILS	GW		Well-graded gravels or gravel- sand mixtures, little or no fines	Excellent	40-80
		GP		Poorly graded gravels or gravel-sand mixtures, little or no fines	Good to excellent	30-60
		GM	d	Silty gravels, gravel-sand-silt mixtures	Good to excellent	40-60
			u		Good	20-30
		GC		Clayey gravels, gravel-sand-clay mixtures	Good	20-40
	SAND AND SANDY SOILS	SW		Well-graded sands or gravelly sands, little or no fines	Good	20-40
		SP		Poorly graded sands or gravelly sands, little or no fines	Fair to good	10-40
		SM	d	Silty sands, sand-silt mixtures	Fair to good	15-40
			u		Fair	10-20
		SC		Clayey sands, sand-clay mixtures	Poor to fair	5-20
FINE GRAINED SOILS	SILTS AND CLAYS LL IS LESS THAN 50	ML		Inorganic silts and very fine sands, rock Flour, siltyor clayey fine sands or clayey Silts with slight plasticity	Poor to fair	15 or less
		CL		Inorganic clays of low to medium plasticity, Gravelly clays, sandy clays, silty clays, Lean clays	Poor to fair	15 or less
		OL		Organic silts and organic silt-clays of low Plasticity	Poor	5 or less
	SILTS AND CLAYS LL IS GREATER THAN 50	MH		Inorganic silts, micaceous or diatomaceous fine sandy or silty soils, elastic silts	Poor	10 or less
		CH		Inorganic clays of high plasticity, fat clays	Poor to fair	15 or less
		OH		Organic clays of medium to high plasticity, Organic silts	Poor to very poor	5 or less
HIGHLY ORGANIC SOILS		Pt		Peat and other highly organic soils	Not suitable	

2.2 Soil Index Properties

Sieve analysis test: According to AASHTO T88, the particle size distribution of soil aggregates test provides information about the relative proportions of various sizes of particles in a given soil sample. The results of the sieve analysis can be used to classify the soil into different categories based on the grading requirements for various applications, such as road construction, foundation design, and drainage systems. The test also helps to identify the dominant particle size, which can be useful for predicting soil behavior under different conditions and for designing soil stabilization measures. [AASHTO, (1996), Standard Method of Test for Particle Size Analysis of Soils]

Atterberg limit test: According to AASHTO T89 and T90, it is the moisture content at which soil changes from a plastic state to a fluid state or from a semi-solid state to a plastic state. These tests can provide important information on the characteristics of a soil, such as its consistency, plasticity, and strength. The results are commonly used in engineering and construction projects to determine the stability of soils for various applications such as road construction, building foundations, and slope stability analysis. The data obtained from Atterberg limit tests can also be used to predict the behavior of soils under different environmental conditions and to develop appropriate soil management strategies. [AASHTO, (1996), Standard Method of Test for Determining the Liquid and Plastic Limit of Soils]

Compaction Tests: Determine two basic parameters according to AASHTO T180: the maximum dry density and maximum moisture content of a soil sample using a modified compaction test.

This information is important in designing and constructing various civil engineering structures such as highways, embankments, dams, and foundations. The maximum dry density and optimum moisture content provide critical information about the soil's ability to resist deformation and support loads. By determining these values, engineers can choose an appropriate soil type, calculate the necessary thickness and compaction requirements, and ensure that the soil meets the required standards for strength and stability. [AASHTO, (1996), Standard Method of Test for Determining the Liquid and Plastic Limit of Soils]

The California Bearing Ratio (CBR) is tested according to AASHTO T193 to determine the strength of sub-grade, sub-base, and base course materials for the design of pavement structures. The CBR test measures the ratio of the force required to penetrate a soil sample with a plunger to the force required to penetrate a standard material, typically crushed stone. This ratio provides an indication of the load-bearing capacity of the soil, which is critical for designing and constructing a durable and safe pavement structure. [AASHTO, (1996), Standard Method of Test for the CBR]

Moisture or Water Content of a soil: The ratio, expressed as a percentage, of the mass of water in a given mass of solid particles. Practical application is to determine the mass of water removed by drying the moist soil to a constant mass in a drying oven controlled at 110 °C and to

use this value as the mass of water in the given soil mass. The mass of soil remaining after oven drying is used as the mass of the solid particles. [AASHTO, (1996), Standard Method of Test for Laboratory Determining Moisture Content of Soils]

Soil classification, carried out according to AASHTO M145, is used to classify soils into different categories based on their physical and mechanical properties. This classification is important in determining the suitability of soils for construction purposes as well as for designing appropriate foundations, pavement structures, or embankments. The AASHTO M145 standard includes classification systems for both coarse-grained soils (such as gravels and sands) and fine-grained soils (such as silts and clays) and provides guidance on the tests that should be performed to determine the soil's classification. In general, soil classification testing is an important part of geotechnical engineering to ensure that structures are built on stable foundations with low potential.[AASHTO, (1996), Standard Method of Test for Classification of Soil and Soil-Aggregate Mixtures for Highway Construction Purposes]

Engineers and contractors can make informed decisions about how to design and build foundations, excavations, drainage systems, and other structures that will be stable and function properly over time.

2.3 Statistical Tools

The student t-test is a statistical test used to compare the mean values of two populations. In the context of comparing a predicted model with the actual value and another model, the student t-test can be used to assess whether there is a significant difference in the mean values of the predicted and actual outcomes, as well as between the predicted outcomes of two different models. This test allows us to determine if the differences between the models are statistically significant and can help us decide which model performs better in predicting outcomes. It is important to note that other statistical tests and techniques may also be used in conjunction with the student t-test to fully evaluate the model's performance. The student t-test can be used to validate a new model for experimental research. [Alfred Bartolucci, Karan P. Singh, and SejongBae, (2015), Introduction to Statistical Analysis of Laboratory Data]

Multiple non-linear regression analysis is a statistical technique used to examine the relationship between a dependent variable and two or more independent variables where the relationship is not linear. In non-linear regression analysis, the model used to describe the relationship between the variables is based on a curve rather than a straight line. The aim of this analysis is to estimate the parameters of a mathematical function that predicts the values of the dependent variable based on the values of the independent variables. This technique is used in many fields, including engineering, economics, social sciences, and natural sciences. [Alfred Bartolucci, Karan P. Singh, and SejongBae, (2015), Introduction to Statistical Analysis of Laboratory Data]

NeuroXL Predictor is a powerful neural network forecasting tool that is designed to help users accurately forecast and predict future events and trends based on historical data. This tool

enables users to quickly and easily create predictive models that can be used for a wide range of applications, including financial forecasting, sales forecasting, inventory management, or any other area where accurate predictions are needed. NeuroXL Predictor uses advanced neural network algorithms to automatically learn from past data and identify patterns and relationships that can be used to make accurate predictions about the future. The tool is easy to use and requires no programming skills, making it accessible to a wide range of users. The NeuroXL Predictor is a neural network add-in for Microsoft Excel. It has the following set of parameters:

- 2 **Input Data:** This represents the range of data cells that used as input to train the neural network.
- 3 **Output Data:** This represents the range of data cells that used as output to train the neural network.
- 4 **Learning Rate:** This parameter represents the rate at which the neural network learns from the training data. A higher learning rate will result in faster learning but may cause instability in the training process.
- 5 **Momentum:** This parameter represents the rate at which the neural network adapts its weights during the training process. A higher momentum value will enable the neural network to overcome local minima during the training process.
- 6 **Hidden Layers:** This parameter represents the number of hidden layers within the neural network, and each layer contains an arbitrary number of neurons.
- 7 **Activation Function:** This parameter represents the mathematical function that used to determine the output of each neuron in the neural network. Common activation functions include sigmoid, tanh, and ReLU.
- 8 **Training Algorithm:** This parameter represents the algorithm used to optimize the weights of the neural network during the training process. Common algorithms include backpropagation, resilient backpropagation, and conjugate gradients.
- 9 **Normalization:** This parameter represents the normalization method used to transform the input data into a comparable range. Common methods include Min-Max normalization and Z-score normalization. Overall, these parameters play a crucial role in determining the effectiveness of the neural network in predicting accurate outputs based on input data. [Analyzer XL LLC, (1998–2003), Unleashing the Power of Artificial Intelligence for Microsoft Excel Forecasting and Estimation a White Paper.]

3. RESEARCH METHODOLOGY

3.1 General

In this experimental study, the relationship between soil CBR values and soil property parameters was identified using both analytical methods: Microsoft Excel software (ANOVA) for multiple non-linear regression models and the neural prediction AI model (a zero-based log-sigmoid model). The data range of the collected sample test results covers the coarse and fine soils used for pavement materials. To determine the relationship between CBR value and soil property parameters, samples were collected from construction sites in the whole region of Ethiopia, and the sampling was in accordance with random sampling research methods. Statistical analyses were performed to generate and validate a new model.

3.2 Data Collection

Primary data were collected for one hundred and ninety-eight soil sample test results, and tests were done in the Ethiopian Construction Design and Supervision Works Corporation, Central Material Laboratory. The author of this research also participated in the testing and reporting process as a material engineer. Laboratory testing was conducted in accordance with AASHTO standard test methods as per ERA guidelines. Modified compaction tests (AASHTO T180), soak three-point modified CBR tests (AASHTO T193), wet sieve analysis tests (AASHTO T88), and Atterberg limit tests (AASHTO T89 and T90) were performed on one hundred and ninety-eight soil samples. Statistical analyses were performed to validate the new model using 30 percent of the total sample size.

This study provided two alternative models. The first alternative model included compaction test parameters as independent parameters. The second alternative model excludes the compaction test parameters (OMC and MDD) as independent parameters.

This study used two alternative analysis techniques: the first group of analysis techniques developed model equations for each classified data set (sub-grade, sub-base and sub-base) and the second techniques developed model equations for the unclassified data set group (the whole data set).

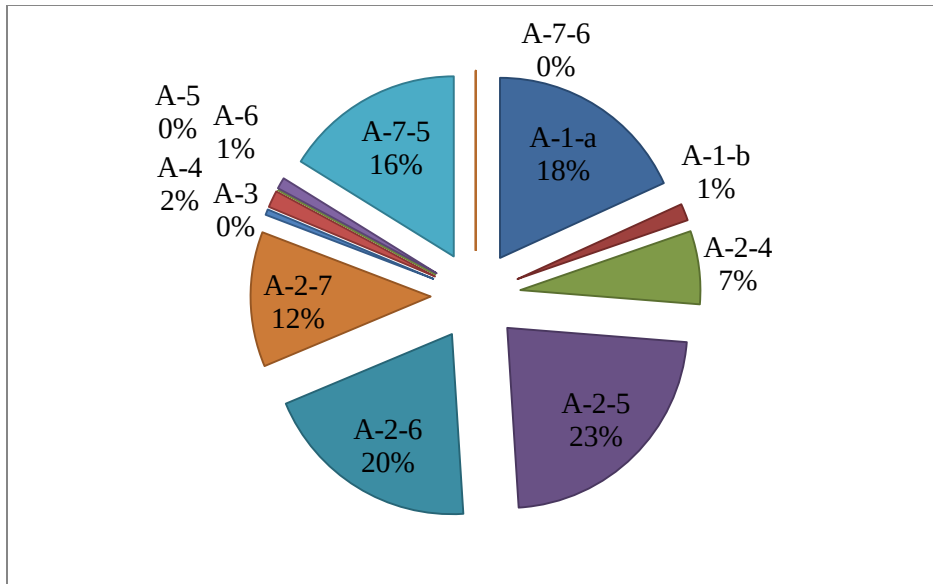


Figure 3-1 Distribution of soil types according to AASHTO soil class

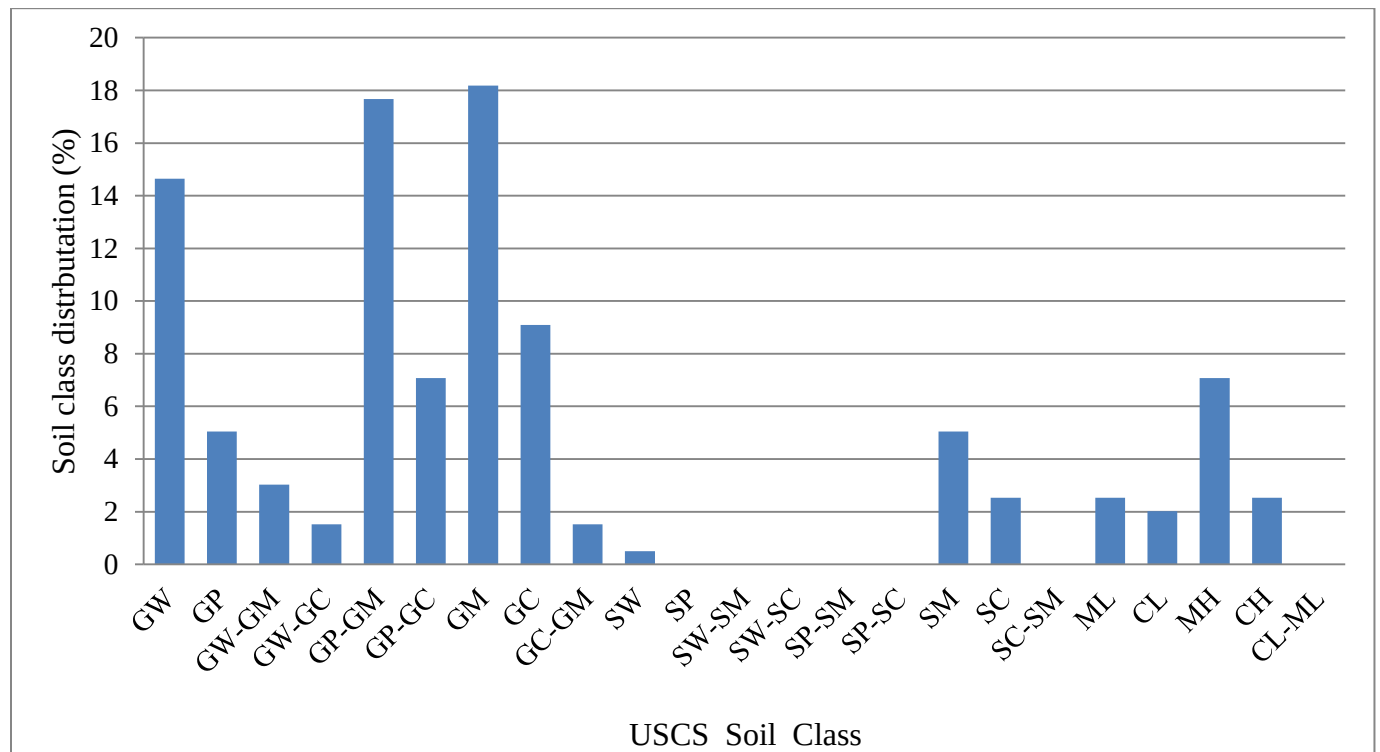


Figure 3-2 Distribution of soil types according to unified soil classification system

Plasticity Nature of Soil Samples for this Study

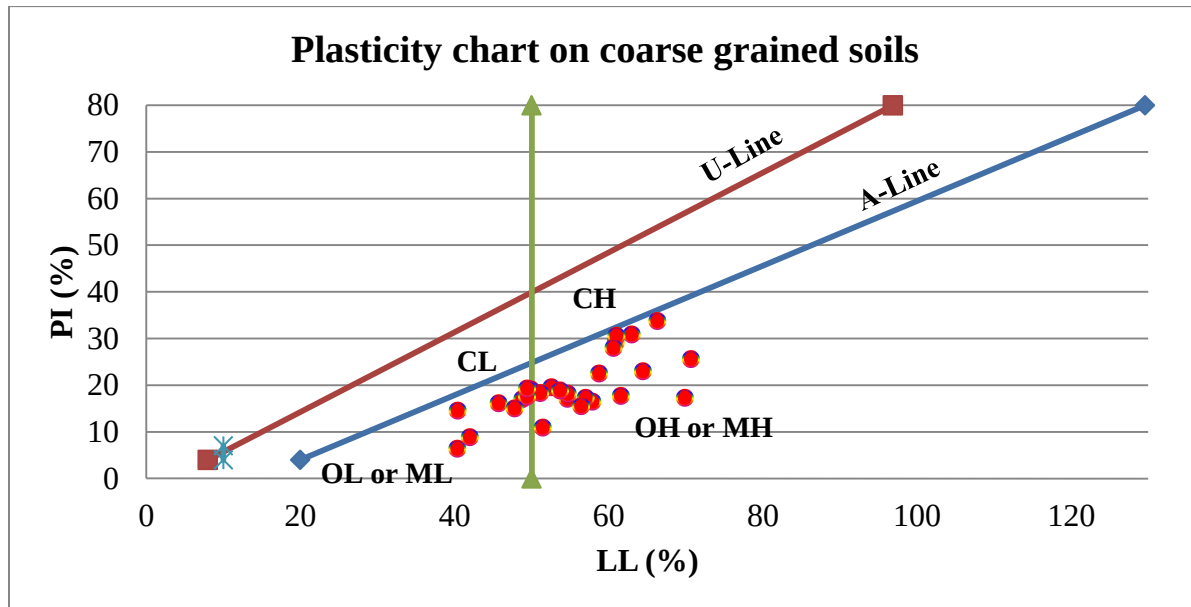


Figure 3-3 Plasticity chart on coarse-grained soil

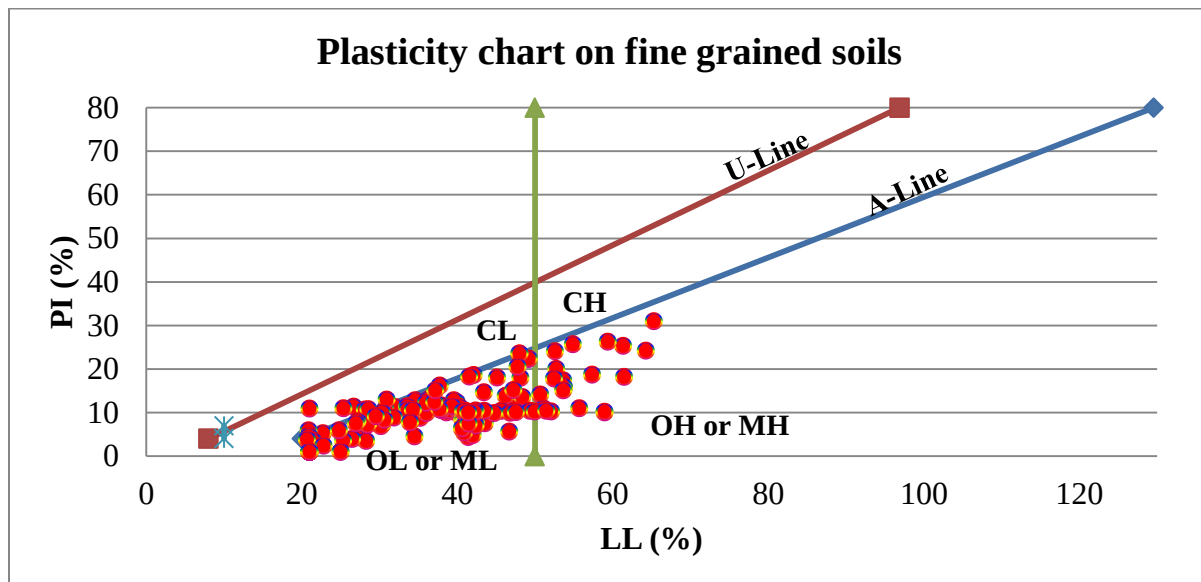


Figure 3-4 Plasticity chart on fine-grained soil

The plasticity chart classifies soil based on only its degree of plasticity. The plasticity chart in the above figures shows that out of one hundred and ninety-eight soil samples, most of the samples are ML (low plasticity inorganic silt). Some samples are MH (highly plastic inorganic silt), a small number of samples are CL (lowly plastic inorganic clay), and a very few samples are CH (high plastic inorganic clay).

4. DATA ANALYSIS AND DISCUSSION

The data were analyzed using multivariate non-linear analysis of variance (ANOVA) regression with Microsoft Excel software and the Neuroxl Predictor artificial intelligence program to find the model equation. The CBR value is the dependent variable, and other soil property parameters are the independent variables. Neuroxl's predictor works in conjunction with Microsoft's Excel AI program. A simple linear regression analysis was performed to determine the significance between a single independent parameter and the CBR value, and multiple nonlinear regression was performed by assuming CBR values as dependent parameters in the prediction model and then comparing the regression model with the Neuroxl prediction AI program.

4.1 Simple regression analysis

Simple regression analysis is a statistical method that measures the linear relationship between two variables, typically denoted as X and Y. The purpose of regression analysis is to find the best-fit line that describes the relationship between the variables.

In terms of correlation, a simple regression analysis can help us determine the strength of the relationship between the two variables. Specifically, the correlation coefficient (a measure of the strength and direction of the relationship) can be calculated using regression analysis. [Alfred Bartolucci, Karan P. Singh, and SejongBae, (2015), Introduction to Statistical Analysis of Laboratory Data]

4.1.1 Correlation analysis (from the entire soil sample data set, options 1 and 2)

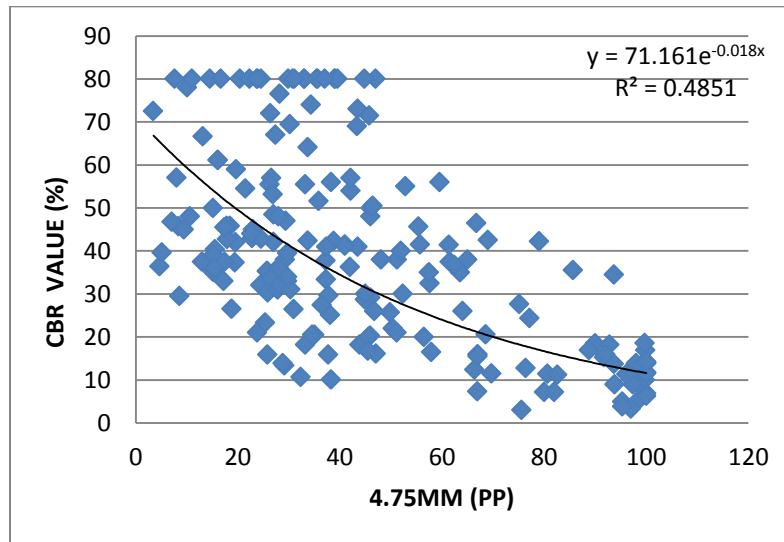


Fig. 4-1: Effect of particle size smaller than 4.75mm on soaked CBR value (from the entire soil sample data set, options 1 and 2)

As shown in the above figure, the CBR value of soil decreases as the percentage of particles smaller than 4.75mm increases.

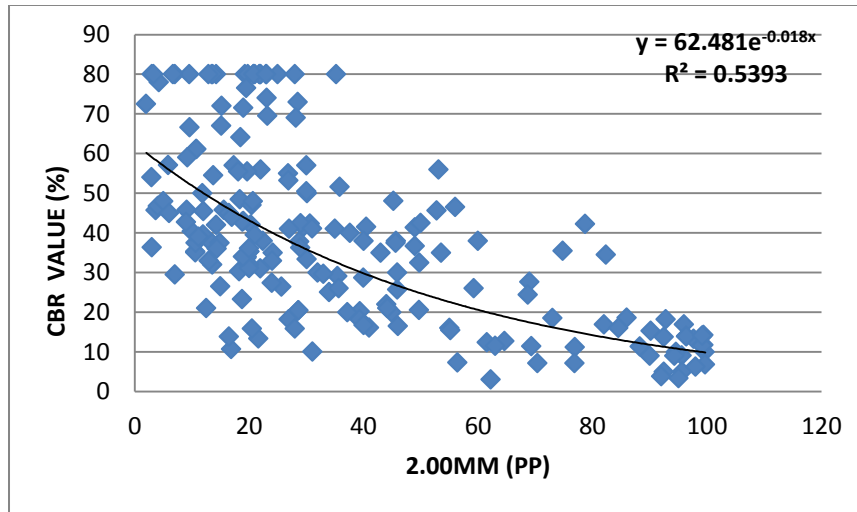


Fig. 4-2: Effect of particle size smaller than 2.00mm on soaked CBR value (from the entire soil sample data set, options 1 and 2)

As shown in the above figure, the CBR values of soil decrease with an increase in the percent pass of particles smaller than 2.00mm.

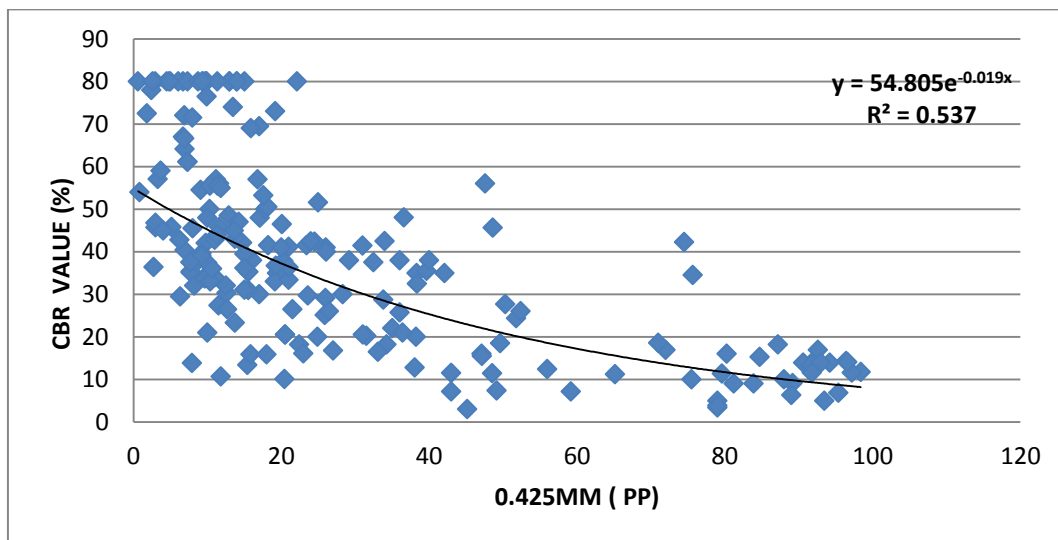


Fig. 4-3 Effect of a particle size smaller than 0.425mm on the soaked CBR value (from the entire soil sample data set, options 1 and 2)

As shown in the above figure, the CBR values of soil decrease with an increase in the percent pass of particles smaller than 0.425mm.

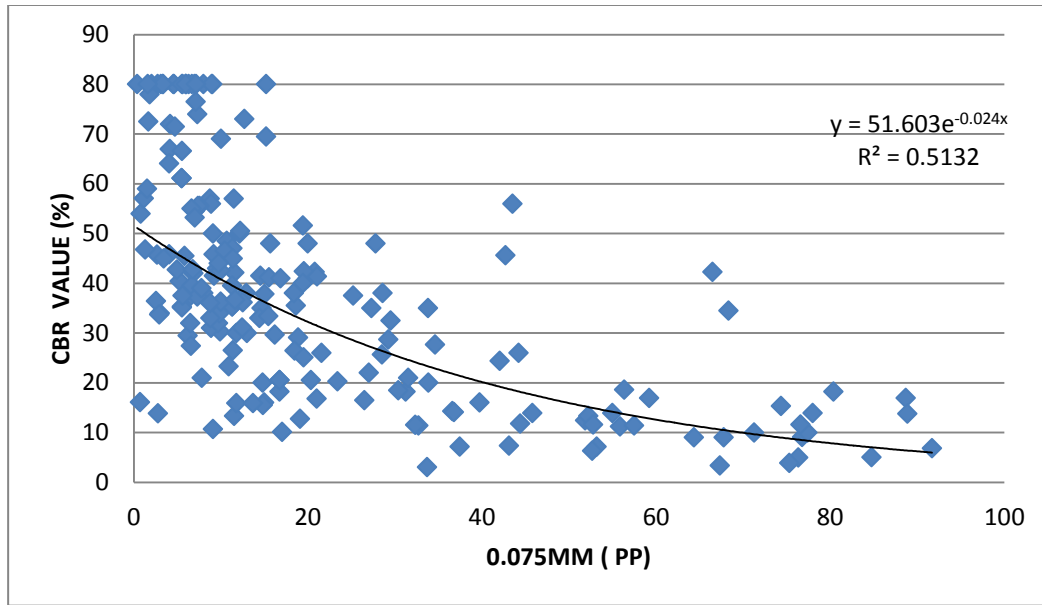


Fig. 4-4: Effect of particle size smaller than 0.075mm on soaked CBR value. (from the entire soil sample data set, options 1 and 2)

As shown in the above figure, the CBR values of soil decreases with an increase in the percent pass of particles smaller than 0.075mm.

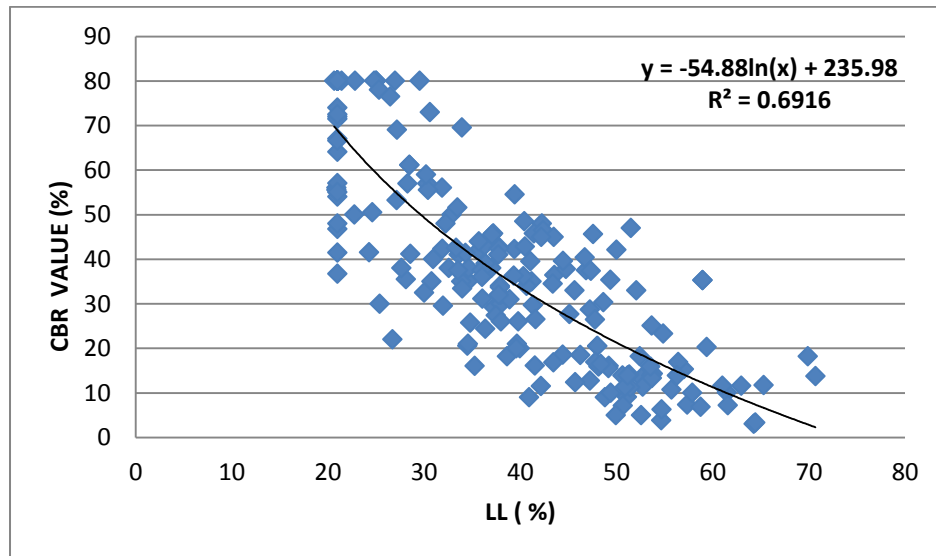


Fig. 4-5: Effect of liquid limit (LL) on soaked CBR value. (from the entire soil sample data set, options 1 and 2)

As shown in the above figure, the CBR value of soil decreases with the increase in the liquid limit consistency states value of soil.

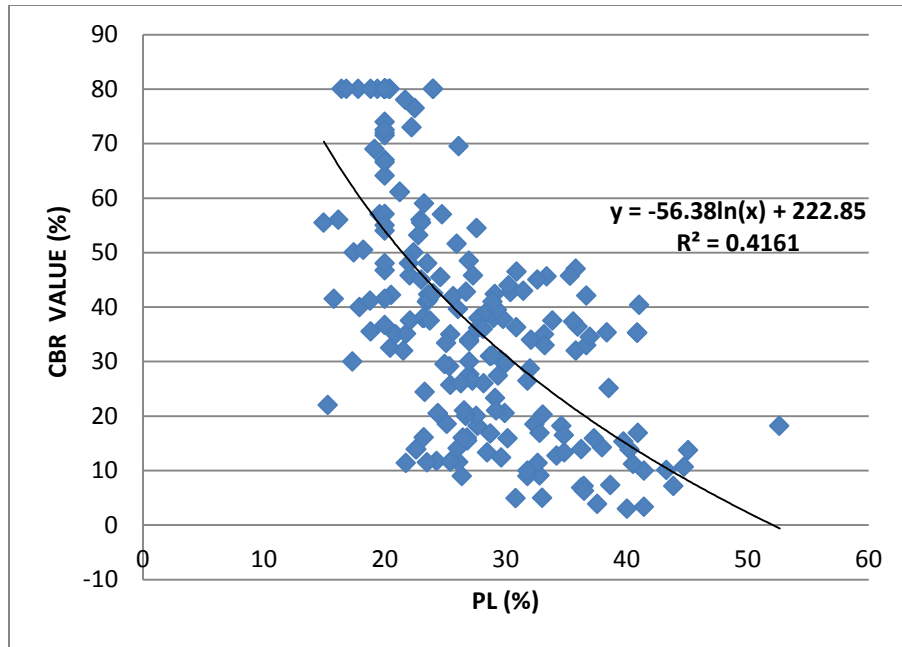


Fig. 4-6: Effect of Plastic Limit (PL) on Soaked CBR Value. (from the entire soil sample data set, options 1 and 2)

As shown in the above figure, the CBR value of soil decreases with the increase in the plastic limit consistency states value of soil.

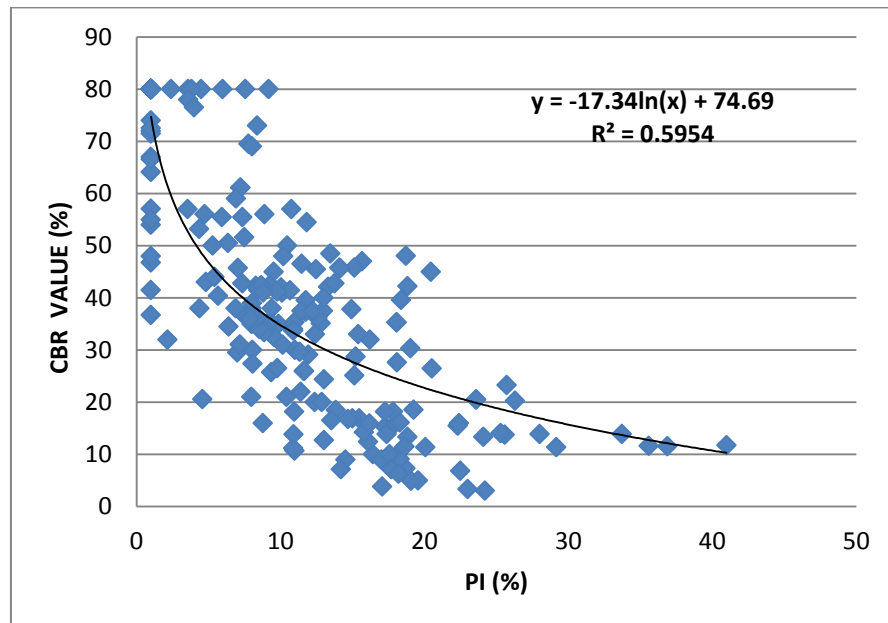


Fig. 4-7: Effect of plastic Index (PI) on soaked CBR value. (from the entire soil sample data set, options 1 and 2)

As shown in the above figure, the CBR value of soil decreases with the increase in the plastic Index consistency state value of soil.

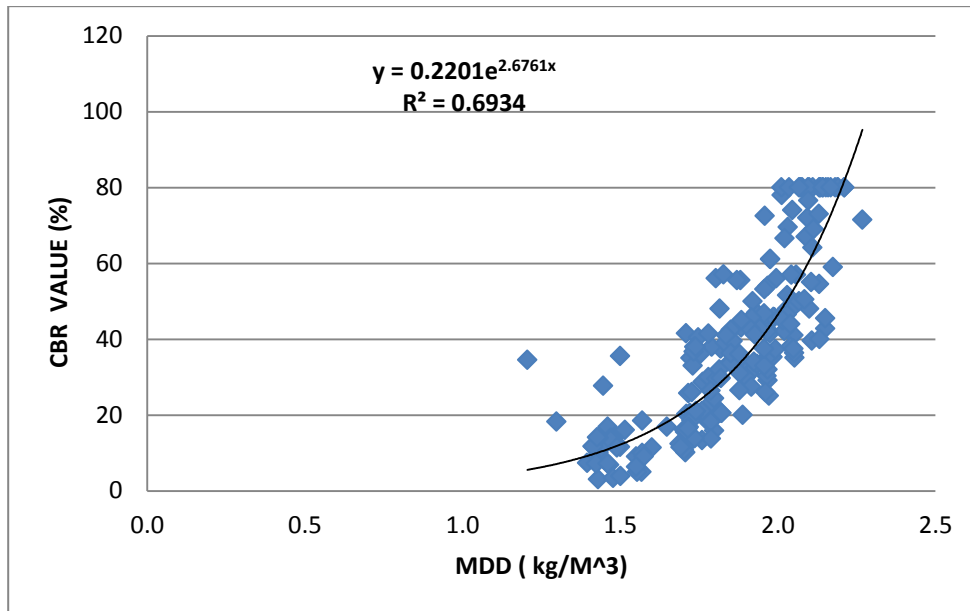


Fig. 4-8: Effect of maximum dry density (MDD) on soaked CBR value. (from the entire soil sample data set, options 1 and 2)

As shown in the above figure, the CBR value of soil increases with the increase in the maximum dry density value of soil.

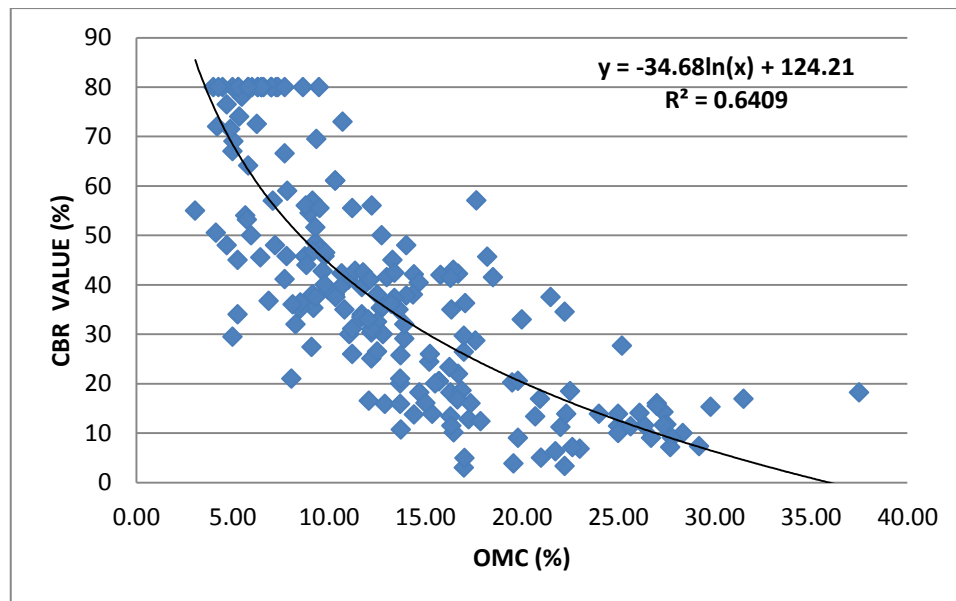


Fig. 4-9: Effect of Optimum Moisture Content (OMC) on Soaked CBR Value. (from the entire soil sample data set, options 1 and 2)

As shown in the above figure, the CBR value of soil increases with a decrease in its optimum moisture content.

4.1.2 Correlation analysis(sub-grade soils from a separated soil sample data set, Option 3)

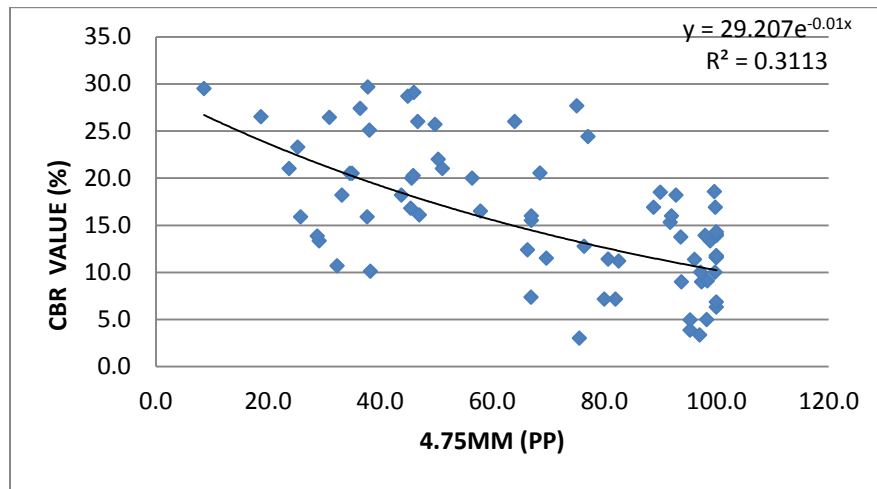


Fig. 4-10: Effect of particle size smaller than 4.75mm on soaked CBR value. (Sub-grade soils from a separated soil sample data set, Option 3)

As shown in the above figure, the CBR value of soil decreases as the percentage of particles smaller than 4.75mm increases.

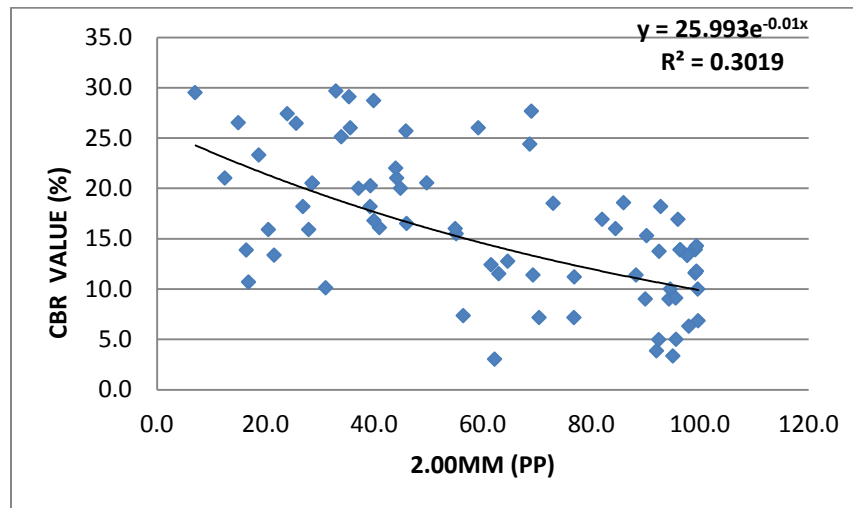


Fig. 4-11: Effect of particle size smaller than 2.00mm on soaked CBR value. (Sub-grade soils from a separated soil sample data set, Option 3)

As shown in the above figure, the CBR value of soil decreases with an increase in the percent pass of particles smaller than 2.00mm.

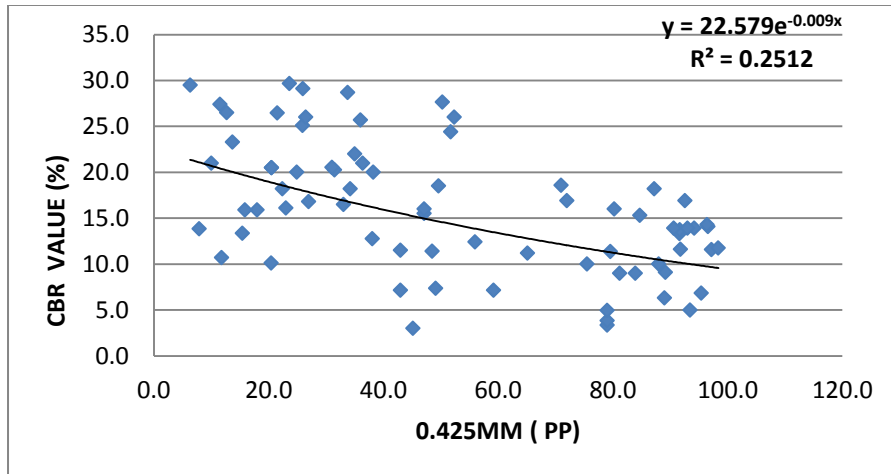


Fig. 4-12 Effect of a particle size smaller than 0.425mm on the soaked CBR value(Sub-grade soils from a separated soil sample data set, Option 3)

As shown in the above figure, the CBR value of soil decreases with an increase in the percent pass of particles smaller than 0.425mm.

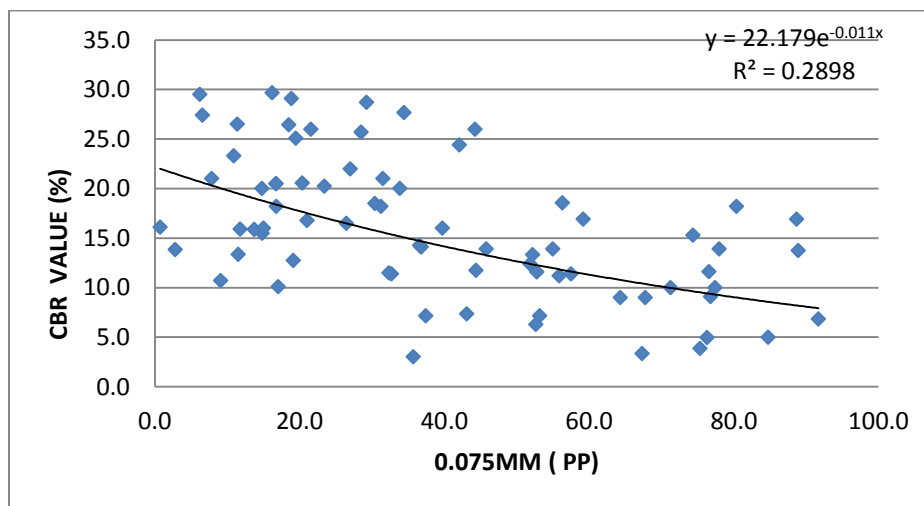


Fig. 4-13: Effect of particle size smaller than 0.075mm on soaked CBR value. (Sub-grade soils from a separated soil sample data set, Option 3)

As shown in the above figure, the CBR value of soil decreases with an increase in the percent pass of particles smaller than 0.075mm.

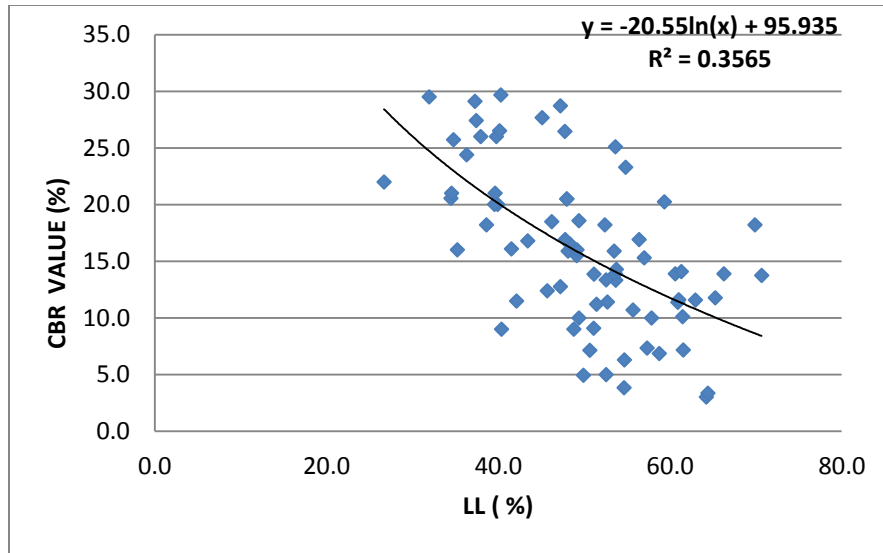


Fig. 4-14: Effect of liquid limit (LL) on soaked CBR value. (Sub-grade soils from a separated soil sample data set, Option 3)As shown in the above figure,the CBR value of soil decreases with the increase in the liquid limit consistency states value of soil.

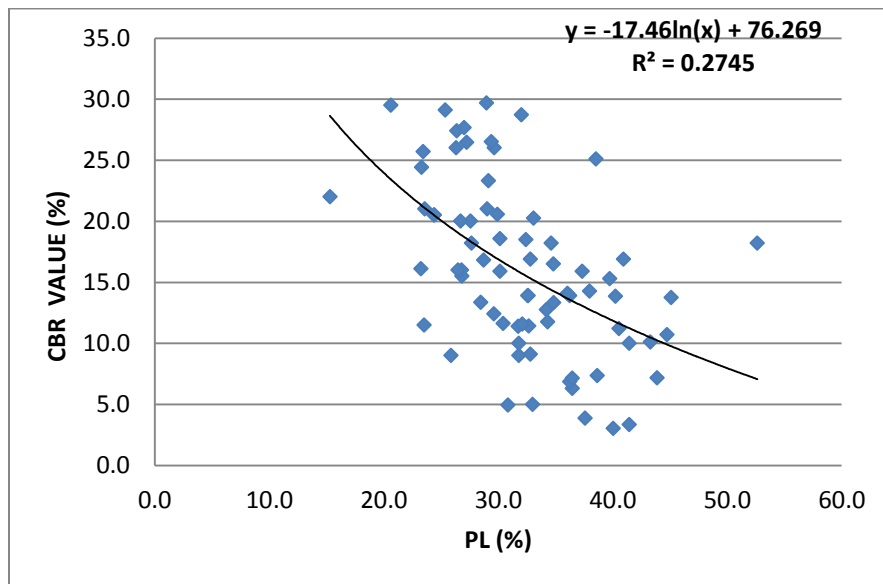


Fig. 4-15: Effect of Plastic Limit (PL) on Soaked CBR value(Sub-grade soils from a separated soil sample data set, Option 3)
As shown in the above figure, the CBR value of soil decreases with the increase in the plastic limit consistency states value of soil.

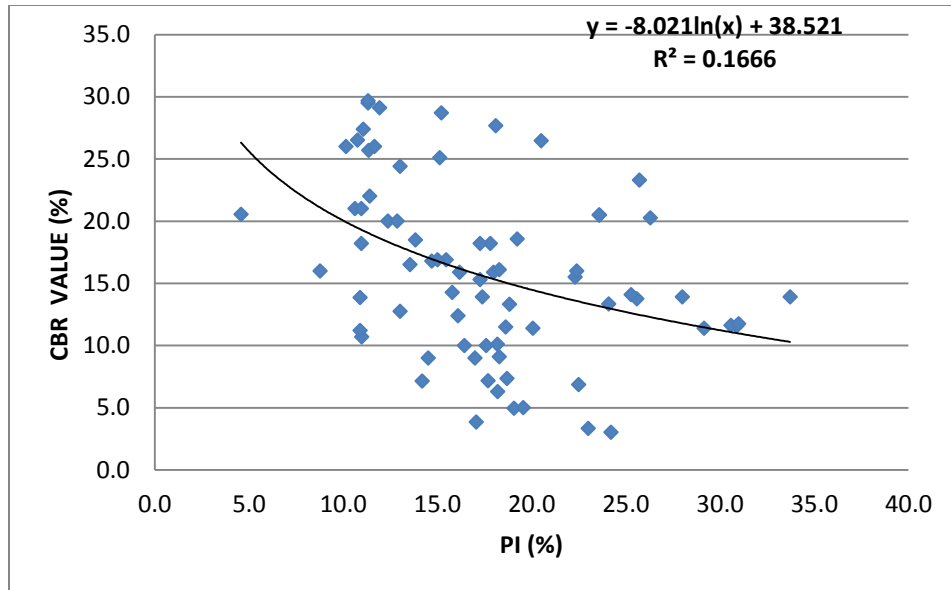


Fig. 4-16: Effect of plastic Index (PI) on soaked CBR values (Sub-grade soils from a separated soil sample data set, Option 3)

As shown in the above figure, the CBR value of soil decreases with the increase in the plastic Index consistency state value of soil.

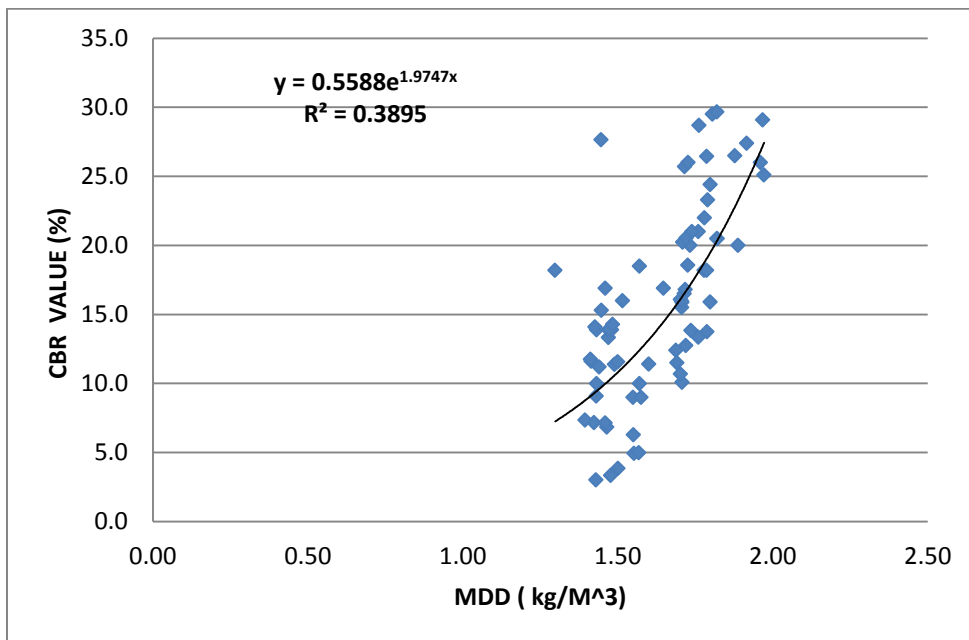


Fig. 4-17: Effect of maximum dry density (MDD) on soaked CBR value. (Sub-grade soils from a separated soil sample data set, Option 3)

As shown in the above figure, the CBR value of soil increases with the increase in the maximum dry density value of soil.

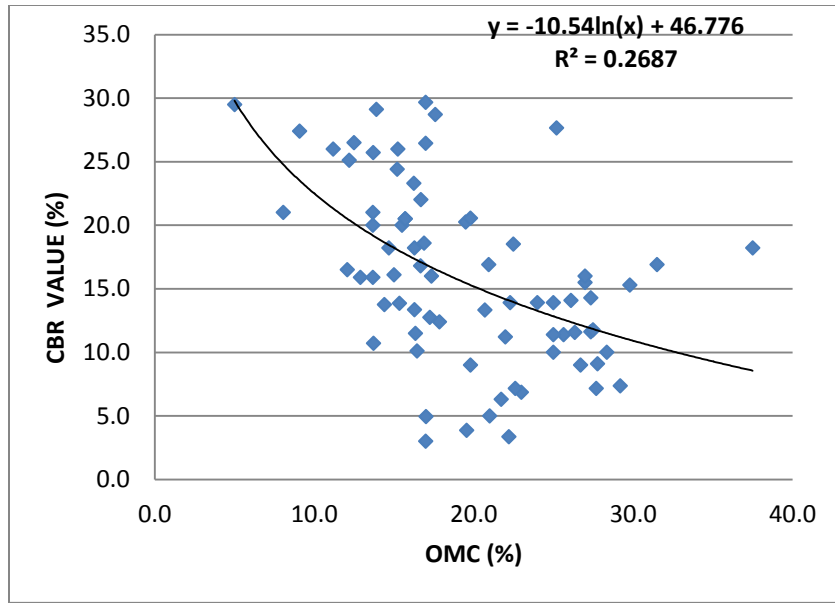


Fig. 4-18: Effect of Optimum Moisture Content (OMC) on Soaked CBR value. (Sub-grade soils from a separated soil sample data set, Option 3)

As shown in the above figure, the CBR value of soil increases with a decrease in its optimum moisture content.

4.1.3 Correlation analysis (sub-base soils from a separated soil sample data set, Option 4)

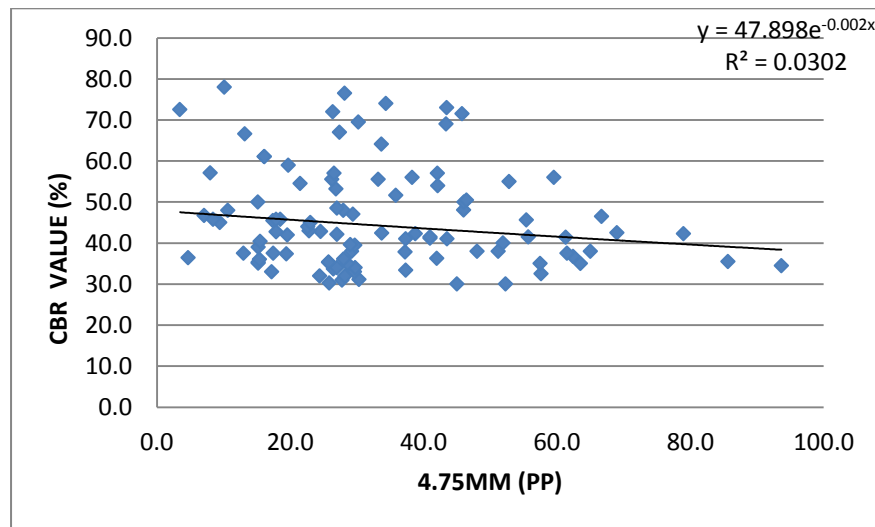


Fig. 4-19: Effect of particle size smaller than 4.75mm on soaked CBR values (Sub-base soils from a separated soils sample data set, Option 4)

As shown in the above figure, the CBR value of soil decreases as the percentage of particles smaller than 4.75mm increases.

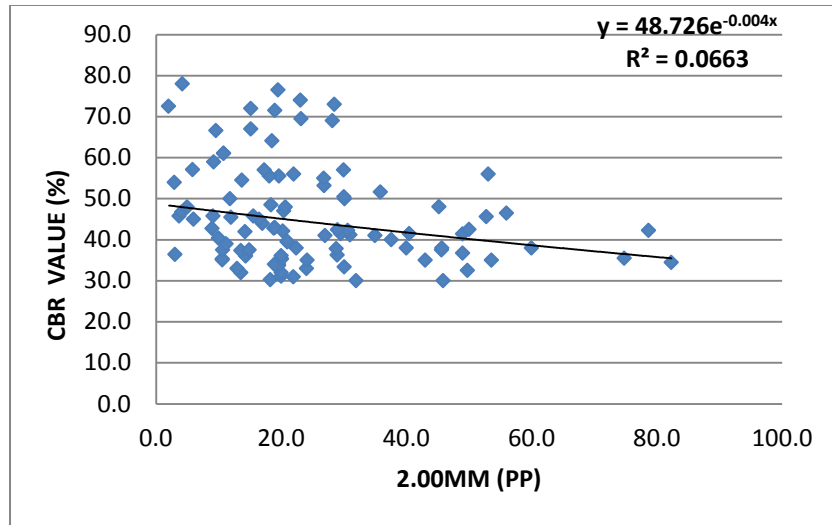


Fig. 4-20: Effect of particle size smaller than 4.75mm on soaked CBR values (Sub-base soils from a separated soils sample data set, Option 4)

As shown in the above figure, the CBR values of soil decreases with an increase in the percent pass of particles smaller than 2.00mm.

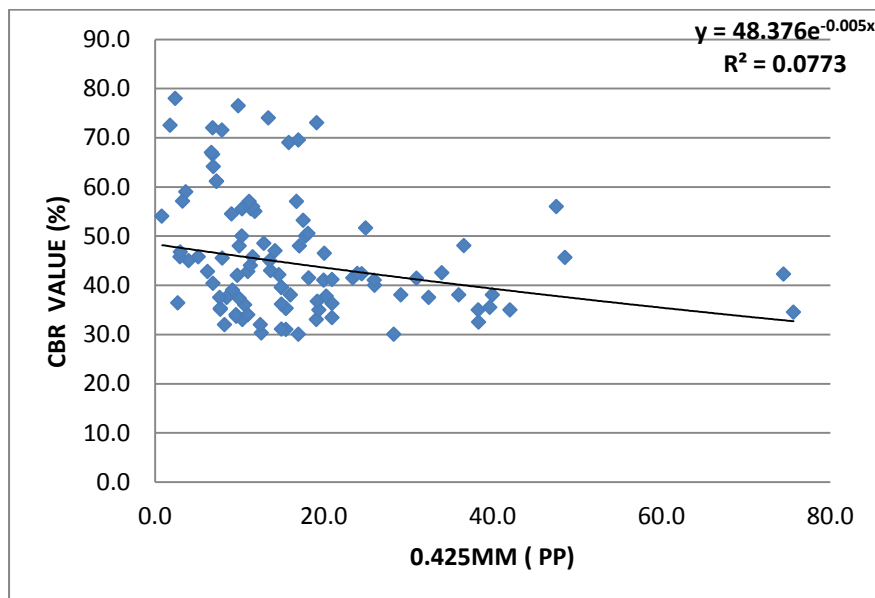


Fig. 4-21: Effect of a particle size smaller than 0.425mm on the soaked CBR values (Sub-base soils from a separated soils sample data set, Option 4)

As shown in the above figure, the CBR values of soil decreases with an increase in the percent pass of particles smaller than 0.425mm.

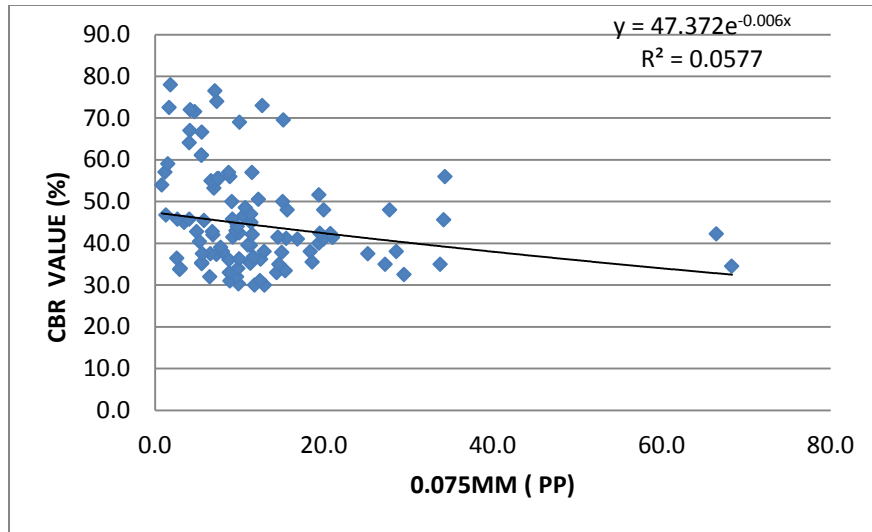


Fig. 4-22: Effect of particle size smaller than 0.075mm on soaked CBR values (Sub-base soils from a separated soils sample data set, Option 4)

As shown in the above figure, the CBR values of soil decreases with an increase in the percent pass of particles smaller than 0.075mm.

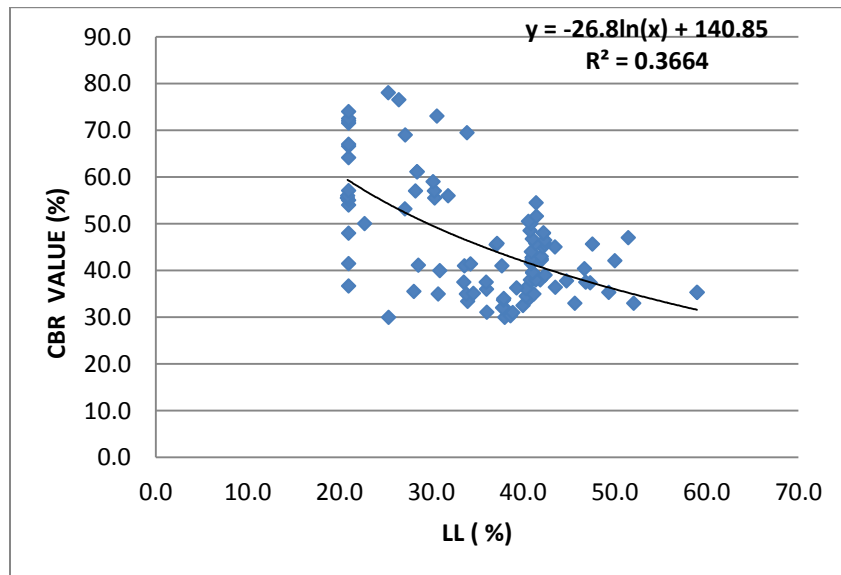


Fig. 4-23: Effect of liquid limit (LL) on soaked CBR value. (Sub-base soils from a separated soils sample data set, Option 4)

As shown in the above figure, the CBR value of soil decreases with the increase in the liquid limit consistency states value of soil.

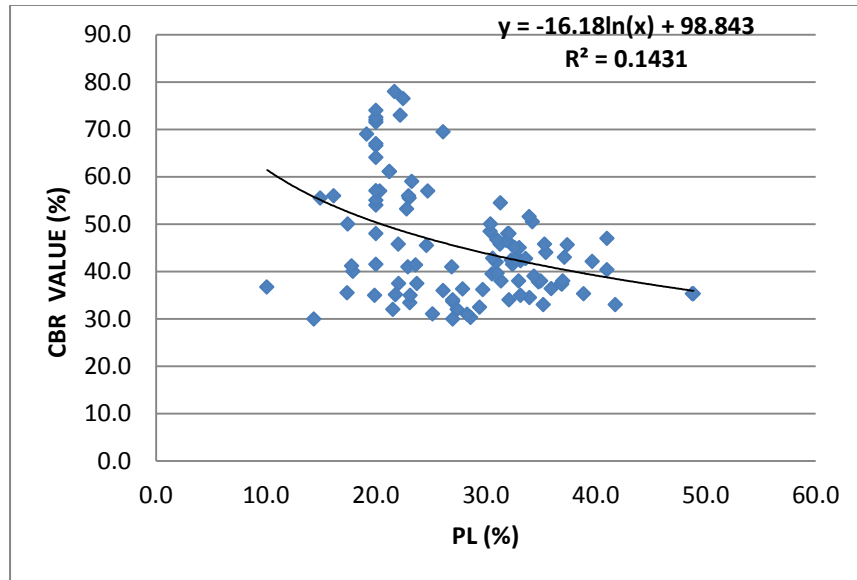


Fig. 4-24: Effect of Plastic Limit (PL) on Soaked CBR Value. (Sub-base soils from a separated soils sample data set, Option 4)

As shown in the above figure, the CBR value of soil decreases with the increase in the plastic limit consistency states value of soil.

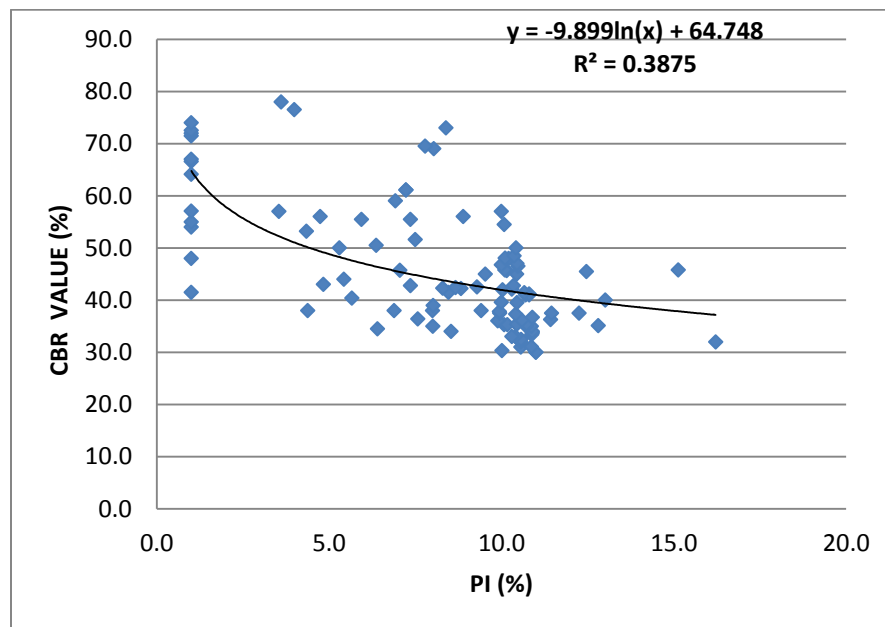


Fig. 4-25: Effect of plastic Index (PI) on soaked CBR value. (Sub-base soils from a separated soils sample data set, Option 4)

As shown in the above figure, the CBR value of soil decreases with the increase in the plastic Index consistency state value of soil.

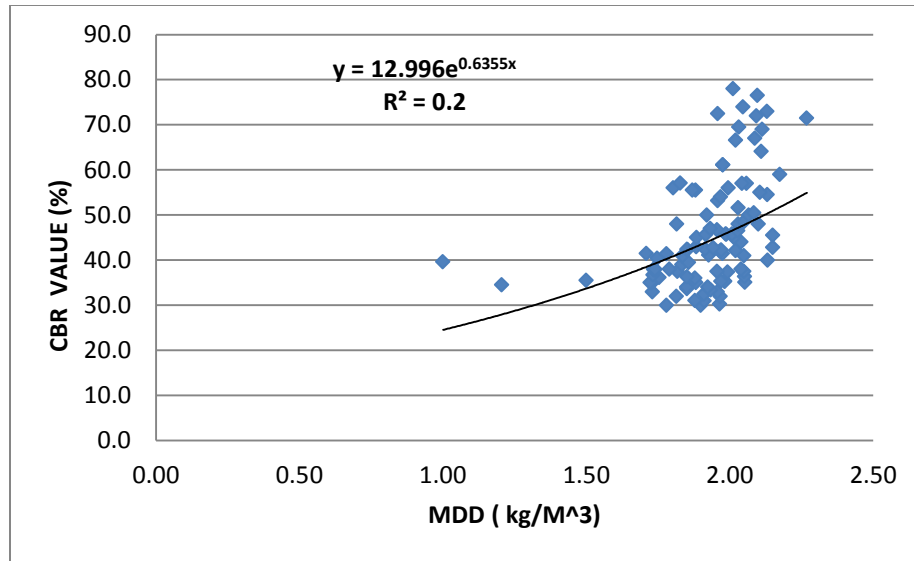


Fig. 4-26: Effect of maximum dry density (MDD) on soaked CBR value. (Sub-base soil from a separated soil sample data set, Option 4)

As shown in the above figure, the CBR value of soil increases with the increase in the maximum dry density value of soil.

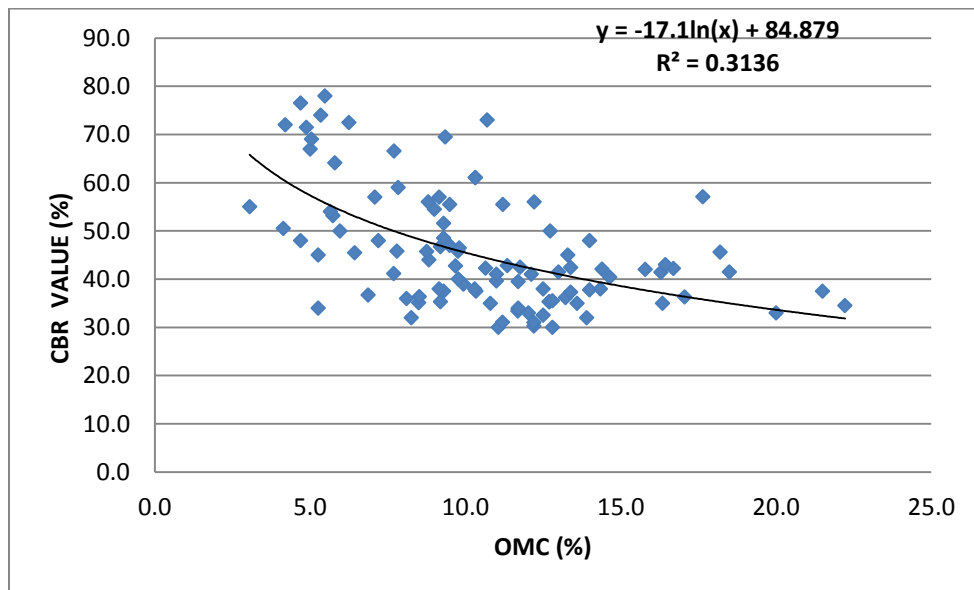


Fig. 4-27: Effect of Optimum Moisture Content (OMC) on Soaked CBR Value. (Sub-base soil from a separated soil sample data set, Option 4)

As shown in the above figure, the CBR value of soil increases with a decrease in its optimum moisture content.

4.1.4 Correlation analysis(from a separated soil sample data set on Base Course Soil Option 5)

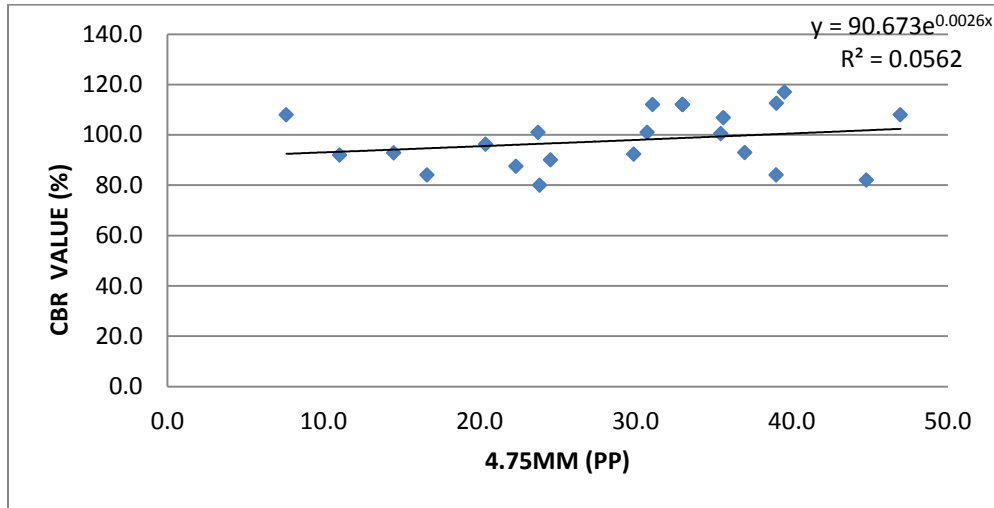


Fig. 4-28: Effect of particle size smaller than 4.75mm on soaked CBR value(base-course soils from a separated soil sample data set, Option 5)

As shown in the above figure, the CBR values of soil slightly increase with the increase in the percent pass of particles smaller than 4.75mm. The correlation coefficient (R^2) is very low due to the limited sample size of the analysis.

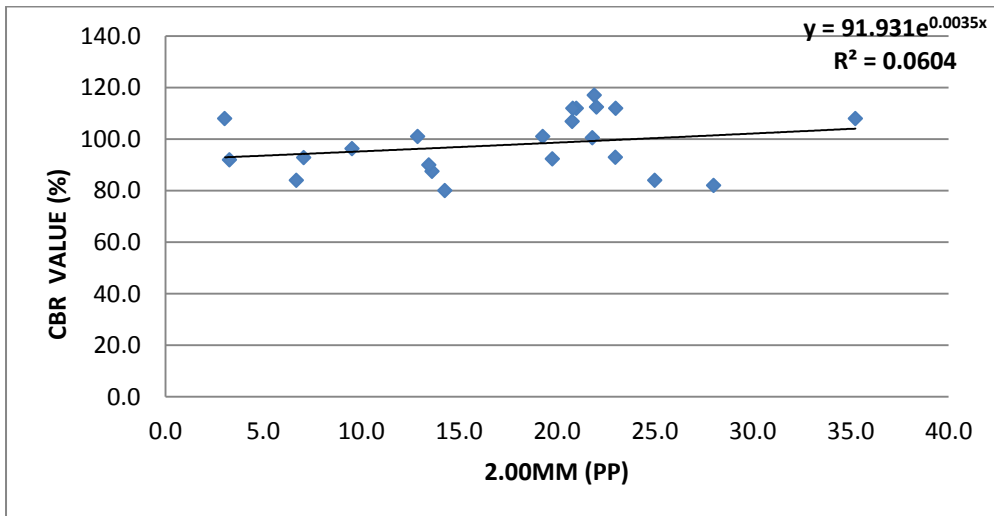


Fig. 4-29: Effect of particle size smaller than 2.00mm on soaked CBR value(base-course soils from a separated soil sample data set, Option 5)

As shown in the above figure, the CBR values of soil slightly increase with the increase in the percent pass of particles smaller than 2.00mm. The correlation coefficient (R^2) is very low due to the limited sample size of the analysis.

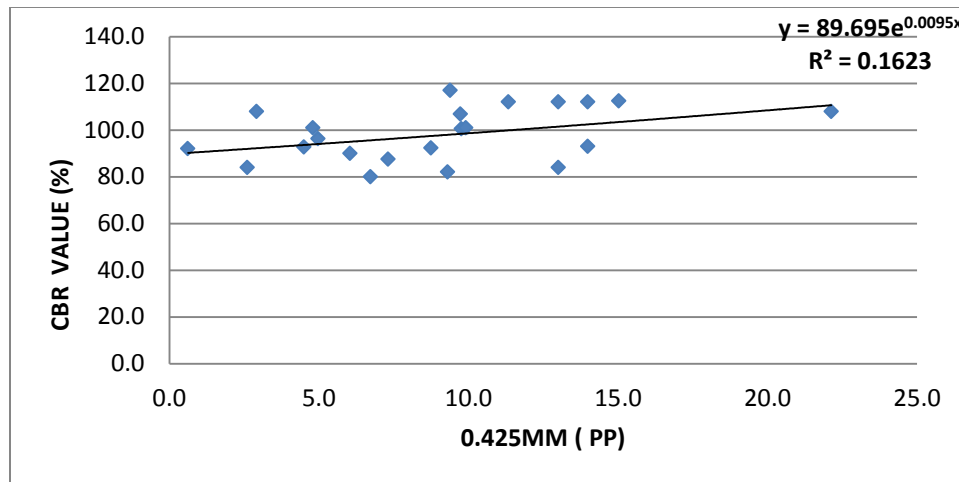


Fig. 4-30: Effect of a particle size smaller than 0.425mm on the soaked CBR value(base-course soils from a separated soil sample data set, Option 5)

As shown in the above figure, the CBR values of soil slightly increase with the increase in the percent pass of particles smaller than 0.425mm. The correlation coefficient (R^2) is low due to the limited sample size of the analysis.

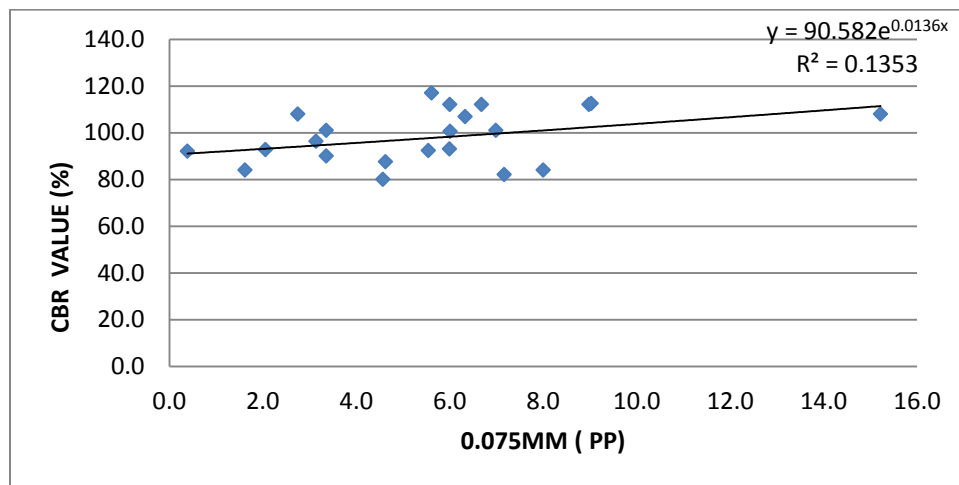


Fig. 4-31: Effect of particle size smaller than 0.075mm on soaked CBR value. (Base-course soils from a separated soil sample data set, Option 5)

As shown in the above figure, the CBR values of soil slightly increase with the increase in the percent pass of particles smaller than 0.075mm. The correlation coefficient (R^2) is very low due to the limited sample size of the analysis.

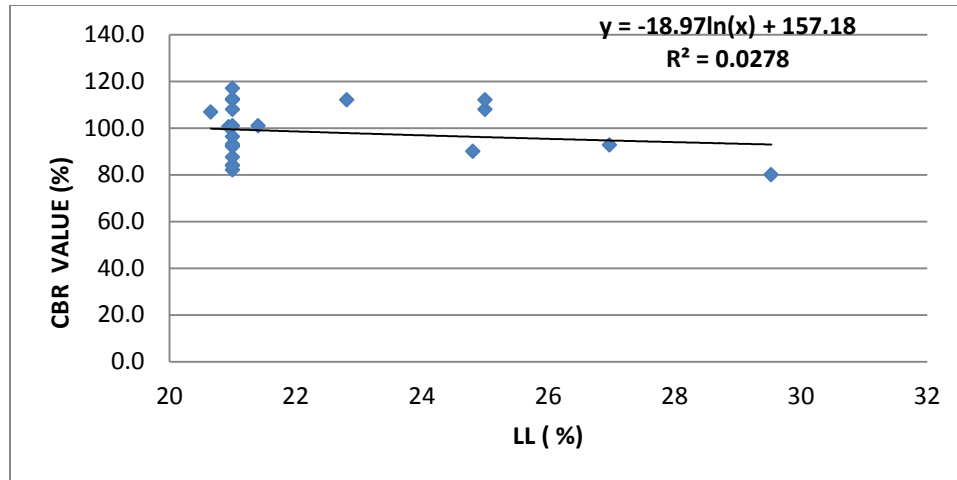


Fig. 4-32: Effect of liquid limit (LL) on soaked CBR value. (Base-course soils from a separated soil sample data set, Option 5)

As shown in the above figure, the CBR value of soil slightly decreases with the increase in the liquid limit consistency state value of soil. The correlation coefficient (R^2) is very low due to the limited sample size of the analysis.

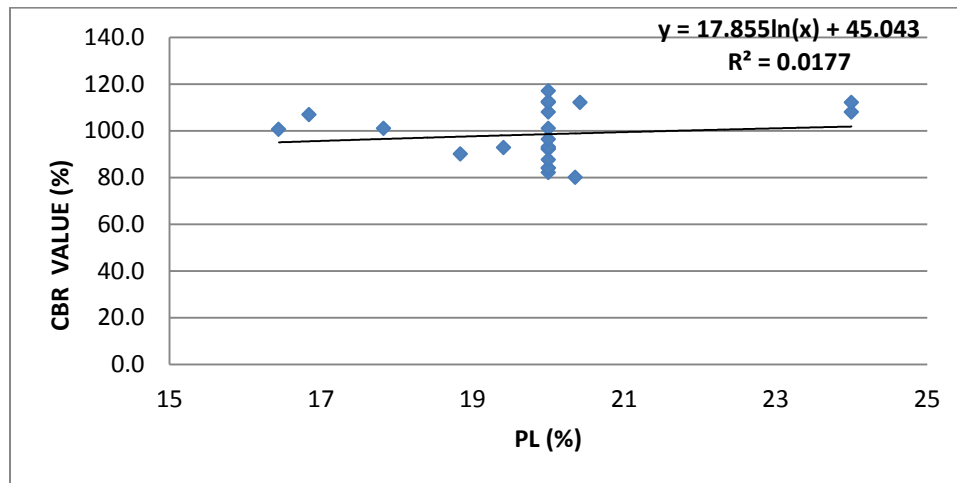


Fig. 4-33: Effect of Plastic Limit (PL) on Soaked CBR values (base-course soils from a separated soil sample data set, Option 5)

As shown in the figure above, the soil CBR Values for the plastic limit values are constant and show a very low correlation coefficient (R^2). This is due to the limitation of sample size of the analysis.

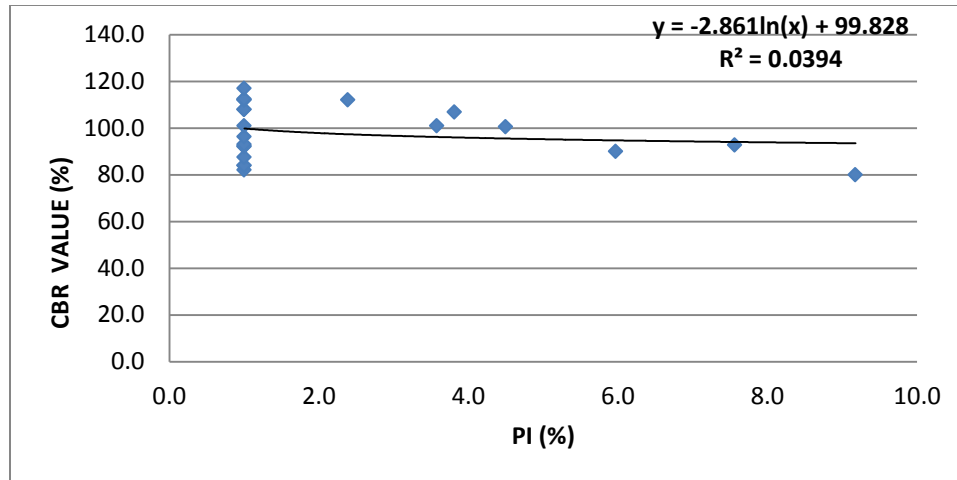


Fig. 4-34: Effect of plastic index (PI) on soaked CBR values (base-course soils from a separated soil sample data set, Option 5)

As shown in the above figure, the CBR value of soil slightly decreases with the increase in the plastic index consistency state value of soil. The correlation coefficient (R^2) is very low due to the limited sample size of the analysis.

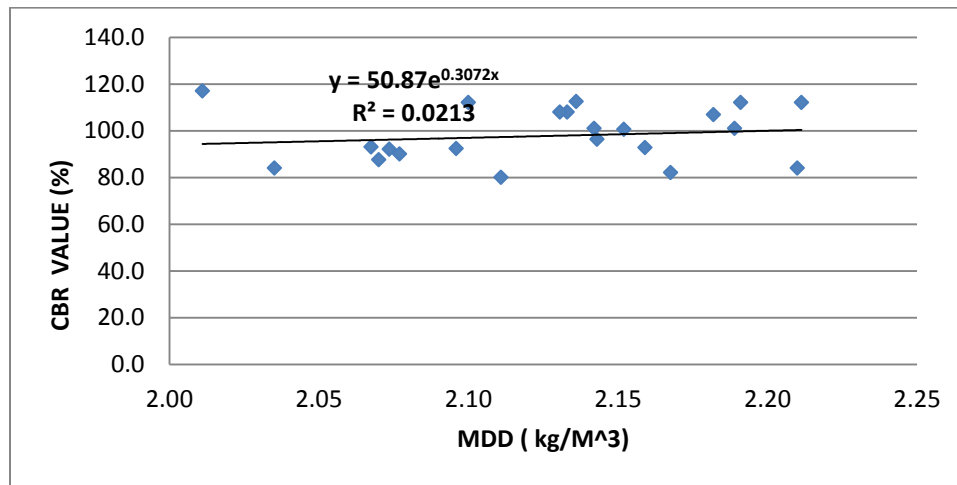


Fig. 4-35: Effect of maximum dry density (MDD) on soaked CBR values (base-course soils from a separated soil sample data set, Option 5)

As shown in the above figure, the CBR values of soil slightly increase with the increase in the maximum dry density values of soil. The correlation coefficient (R^2) is very low due to the limited sample size of the analysis.

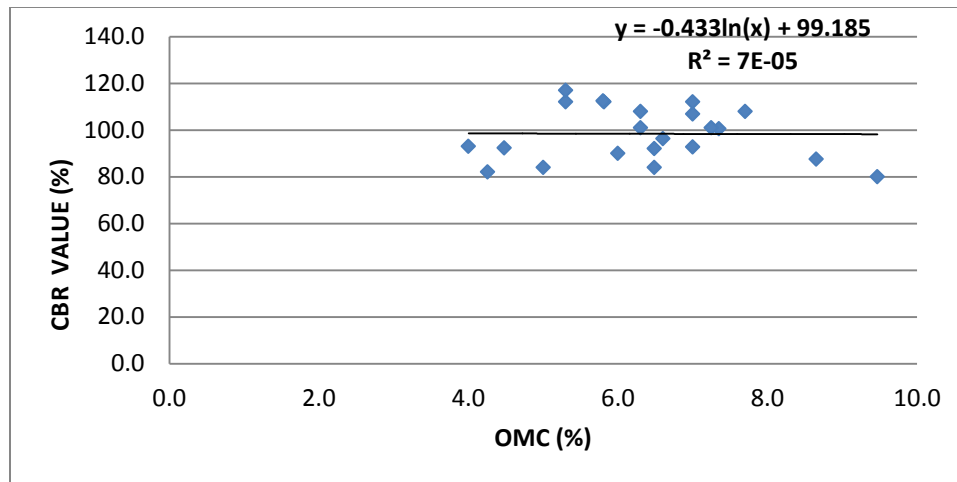


Fig. 4-36: Effect of optimum moisture content (OMC) on Soaked CBR Values (Base-course soils from a separated soil sample data set, Option 5)

As shown in the figure above, the soil CBR values for the optimum moisture content values are constant and show a very low correlation coefficient (R^2). This is due to the limitation of the sample size of the analysis.

Summary of Simple Regression Analysis

The coefficient of determination, known as R-squared, is a statistical measure used to explain the variance of the dependent variable based on the variance of one or more independent variables in a regression model. It ranges from 0 to 1, where 0 indicates that the model does not explain any variability, and 1 indicates that the model explains the variability correctly. An acceptable value for R-squared depends on the context and the purpose of the regression model. In general, a higher R-squared value indicates a better fit of the model to the data, but a higher value does not always mean that the model is better. [Alfred Bartolucci, Karan P. Singh, and SejongBae, (2015), Introduction to Statistical Analysis of Laboratory Data]

Table 4-1 Models developed from simple regression analysis for soaked CBR values

Simple linear regression analysis model Equations			
Include the entire sample	Sub-Grade group	Sub-base group	Base-course group
$\text{CBR} = 71.16e^{-0.018 (P_{4.75})}$ $R^2 = 0.49$	$\text{CBR} = 29.21e^{-0.01(P_{4.75})}$ $R^2 = 0.31$	$\text{CBR} = 47.9e^{-0.002 (P_{4.75})}$ $R^2 = 0.03$	$\text{CBR} = 90.67e^{0.0026 (P_{4.75})}$ $R^2 = 0.06$
$\text{CBR} = 62.48e^{-0.018 (P_2)}$ $R^2 = 0.54$	$\text{CBR} = 25.99e^{-0.01 (P_2)}$ $R^2 = 0.30$	$\text{CBR} = 48.73e^{-0.004 (P_2)}$ $R^2 = 0.07$	$\text{CBR} = 91.93e^{0.0035 (P_2)}$ $R^2 = 0.06$
$\text{CBR} = 54.81e^{-0.019 (P_{0.425})}$ $R^2 = 0.54$	$\text{CBR} = 22.58e^{-0.009 (P_{0.425})}$ $R^2 = 0.25$	$\text{CBR} = 48.38e^{-0.005 (P_{0.425})}$ $R^2 = 0.08$	$\text{CBR} = 89.70e^{0.0095 (P_{0.425})}$ $R^2 = 0.16$
$\text{CBR} = 51.60e^{-0.024 (P_{0.075})}$ $R^2 = 0.51$	$\text{CBR} = 22.18e^{-0.011 (P_{0.075})}$ $R^2 = 0.29$	$\text{CBR} = 47.37e^{-0.006 (P_{0.075})}$ $R^2 = 0.06$	$\text{CBR} = 90.58e^{0.0136 (P_{0.075})}$ $R^2 = 0.14$
$\text{CBR} = -54.88\ln(w_L) + 236$ $R^2 = 0.69$	$\text{CBR} = -21\ln(w_L) + 96$ $R^2 = 0.36$	$\text{CBR} = -26.8\ln(w_L) + 141$ $R^2 = 0.37$	$\text{CBR} = -19\ln(w_L) + 157$ $R^2 = 0.03$
$\text{CBR} = -56.38\ln(w_p) + 223$ $R^2 = 0.42$	$\text{CBR} = -17\ln(w_p) + 76$ $R^2 = 0.27$	$\text{CBR} = -16.18\ln(w_p) + 99$ $R^2 = 0.14$	$\text{CBR} = 18\ln(w_p) + 45$ $R^2 = 0.02$
$\text{CBR} = -17.34\ln(I_p) + 75$ $R^2 = 0.60$	$\text{CBR} = -8\ln(I_p) + 39$ $R^2 = 0.17$	$\text{CBR} = -9.90\ln(I_p) + 65$ $R^2 = 0.39$	$\text{CBR} = -3\ln(I_p) + 100$ $R^2 = 0.04$
$\text{CBR} = 0.22e^{2.6761 (\rho_{d\max})}$ $R^2 = 0.69$	$\text{CBR} = 0.56e^{1.9747 (\rho_{d\max})}$ $R^2 = 0.39$	$\text{CBR} = 12.99e^{0.6355 (\rho_{d\max})}$ $R^2 = 0.2$	$\text{CBR} = 50.87e^{0.3072 (\rho_{d\max})}$ $R^2 = 0.02$
$\text{CBR} = -34.68\ln(w_{\text{opt}}) + 124$ $R^2 = 0.64$	$\text{CBR} = -10\ln(w_{\text{opt}}) + 47$ $R^2 = 0.27$	$\text{CBR} = -17.1\ln(w_{\text{opt}}) + 85$ $R^2 = 0.31$	$\text{CBR} = -0.4\ln(w_{\text{opt}}) + 99$ $R^2 = 7E-05$

$P_{4.75}$, the percentage of soil that passes through a 4.75 mm sieve

P_2 , the percentage of soil that passes through a 2 mm sieve

$P_{0.425}$, the percentage of soil that passes through a 0.425 mm sieve

$P_{0.075}$, the percentage of soil that passes through a 0.075 mm sieve

W_L , water content at the liquid limit

W_p , water content at the plastic limit

I_p , plasticity index

$\rho_{d\max}$, maximum dry density

W_{opt} , Optimum moisture content

4.2 Multiple non-linear ANOVA regression analysis of the total data set

4.2.1 Multiple non-linear regression analysis (Option 1)

Multiple non-linear regression analysis is a statistical technique used to examine the relationship between a dependent variable and two or more independent variables.

In this analysis, the plastic properties of the soil are represented by liquid limit, plastic limit and plastic index (W_L , W_P and I_P), the distribution of the soil particle size ($P_{4.75}$, P_2 , $P_{0.425}$ and $P_{0.075}$), and compaction properties are represented by (ρ_{dmax} and W_{opt}) as independent variables. ANOVA (Analysis of Variance) is a statistical technique used to compare the means of more than two groups. In Excel, an ANOVA can be performed using the Data Analysis Tool Pack.

Model Equation (Option 1): This formula is used when compaction, Atterberg limit, and grain size distribution test parameter data are available. This equation can apply to entire construction materials, such as sub-grade, sub-base, and base course soil. (ANOVA, multivariate non-linear regression analysis).

$$\text{CBR Value (\%)} = 308 - 0.36(P_{4.75}) + 0.33(P_2) - 0.01(P_{0.425}) - 0.03(P_{0.075}) + 0.01(w_L^2) - 0.02(w_P^2) - 4.27(I_P) + 0.05(I_P^2) - 330(\rho_{dmax}) + 110(\rho_{dmax}^2) - 0.22(w_{opt}) + 0.01(w_{opt}^2) \quad (1)$$

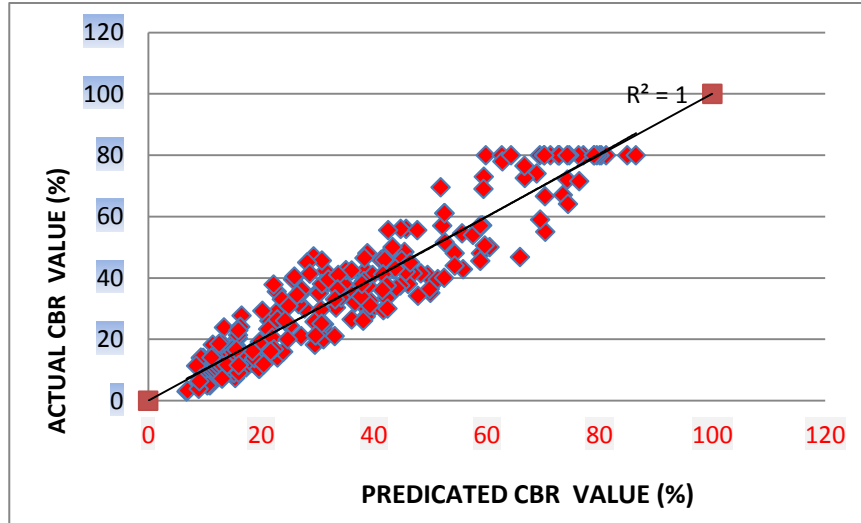


Figure 4.37: Scatter plot of predicted CBR and experimental values of CBR

As can be seen from the above figure, the proximity of the data points to the line of R-squared equal to one indicates a strong linear relationship between the predicted and experimental CBR values. This suggests that the model or method used was reliable and can be utilized with confidence in future prediction analyses related to CBR.

4.2.2 Multiple non-linear regression analysis of the total data set (Option 2)

Option two followed the same procedure with multiple non-linear regression analyses (option 1). However, it excludes the compaction behavior of soil parameters (OMC and MDD) as an independent parameter during analysis.

Model Equation (Option 2): This formula is used when test parameter data for Atterberg's limit, natural moisture content, and soil grain size distribution test parameters are available but the compaction test parameter is unavailable. This equation can apply to entire construction materials, such as sub-grade, sub-base and base course soils. (ANOVA, multivariate non-linear regression analysis)

$$\text{CBR Value (\%)} = 106 - 0.28(P_{4.75}) + 0.03(P_2) + 0.03(P_{0.425}) + 0.01(P_{0.075}) + 0.02(w_L^2) - 0.04(w_p^2) - 6.49(I_p) + 0.08(I_p^2) \quad (2)$$

4.2.3 Multiple non-linear regression analysis on sub-grade soils (Option 3)

Classification of sub-grade, sub- base, and base-course pavement materials helps engineers and contractors make informed decisions about the selection, placement, and treatment of each pavement layer, ensuring a strong and durable foundation for the proposed structure or road.

The separation of data sets allows the performance and suitability of each layer to be analyzed independently and allows engineers to use specifications and requirements for each layer based on individual CBR values. In this part of the study, a regression analysis was conducted by classifying the total soil data sets into sub-grade, sub-base and base course soils.

According to the Ethiopian Roads Authority Rigid and Flexible Pavement Design Manual (2013), the design level strength was assigned to six strength classes, and the thickness design reflects the sensitivity of the soil strength to the class.

The manual advises that special treatment is required for sub-grades with a CBR of less than 2 percent.

Table 4.2: Sub-grade Strength Classes

Class	S-1	S-2	S-3	S-4	S-5	S-6
CBR Range (%)	<3	3,4	5,6,7	8-14	15 - 30	>30

ERA Manual 2013 states that minimum CBR values for sub-base materials should be greater than 30 percent. The manual further states that CBR values for natural base course materials should be more than 80% and CBR values for crushed base course should be more than 100%. In this option 3, the data set of pavement construction materials is analyzed in three different categories and listed in the table below.

Table 4.3: ERA manual general requirements for pavement construction materials

Pavement construction material type	CBR Value Range (%)	Plasticity Index (%)	Total No. of Samples for analysis
Sub-grade	<30	-	74
Sub-base	30-80	<25	102
Base course	> 80	≤6	22

Model Equation (Option 3): This formula is used when compaction, Atterberg limit, and grain size distribution test parameter data are available. This equation is valid only for Sub-grade soils with a CBR value below 30%. (ANOVA, multivariate non-linear regression analysis)

$$\begin{aligned} \text{CBR Value (\%)} = & 112 - 0.26(P_{4.75}) + 0.19(P_2) + 0.01(P_{0.425}) - 0.02(P_{0.075}) - 0.01(w_p^2) \\ & - 1.74(I_p) + 0.01(I_p^2) - 110(\rho_{dmax}) + 41(\rho_{dmax}^2) - 0.53(w_{opt}) + 0.02(w_{opt}^2) \end{aligned} \quad (3)$$

4.2.4 Multiple non-linear regression analysis on sub-base soils (Option 4)

Model Equation (Option 4): This formula is used when compaction, Atterberg limit, and grain size distribution test parameter data are available. This equation is only valid for sub-base soils with CBR values between 30 and 80%. (ANOVA, multivariate non-linear regression analysis).

$$\begin{aligned} \text{CBR Value (\%)} = & 183 - 0.29(P_{4.75}) + 0.18(P_2) - 0.09(P_{0.425}) + 0.11(P_{0.075}) + 0.01(w_L^2) - 0.02(w_p^2) \\ & - 0.62(I_p) - 0.14(I_p^2) - 170(\rho_{dmax}) + 58(\rho_{dmax}^2) - 0.75(w_{opt}) + 0.04(w_{opt}^2) \end{aligned} \quad (4)$$

4.2.5 Multiple non-linear regression analysis on base-course soils (Option 5)

Model Equation (Option 5): This formula is used when compaction, Atterberg limit, and grain size distribution test parameter data are available. This equation is valid only for base course soils with an above 80% CBR value. (ANOVA, multivariate non-linear regression analysis)

$$\begin{aligned} \text{CBR Value (\%)} = & -7200 - 0.57(P_{4.75}) + 0.02(P_2) + 3.3(P_{0.425}) - 2.7(P_{0.075}) + \\ & 0.82(I_p) - 0.25(I_p^2) + 6742(\rho_{dmax}) - 1571(\rho_{dmax}^2) + 20(w_{opt}) - 1.45(w_{opt}^2) \end{aligned} \quad (5)$$

4.3 NeuroXL Predictor Zero-based Log-Sigmoid Analyses

In this analysis, the plastic properties of the soil are represented by liquid limit, plastic limit and plastic index (W_L , W_P and I_p), the distribution of the soil particle size ($P_{4.75}$, P_2 , $P_{0.425}$ and $P_{0.075}$), and compaction properties are represented by (ρ_{dmax} and W_{opt}) as independent variables.

After downloading the free trial version of Neuroxl Predictor from <https://www.neuroxl.com/>, open Excel with dependent and independent parameters in the column direction, then activate the NeuroxlPredictor tool from the Quick Access Toolbar in Add-Ins. The full steps of the Neuroxl predictor program analysis steps are available in <https://www.neuroxl.com/>.

4.3.1 NeuroXL Predictor (Option 1): The prediction process includes compaction, Atterberg limit, and grain size distribution test parameters on the entire construction materials, such as sub-grade, sub-base, and base course soil.

Table 4.4: Comparing actual CBR value with neuroxl predicted CBR value (option 1)

Model Options No.	Actual CBR Value	Neuroxl predictor predicted CBR value
	Standard Deviation	
1	26.5	32

4.3.2 NeuroXL Predictor Result (Option 2): The prediction process includes only the classification test parameters of the Atterberg limit and grain size distribution test on the entire construction materials, such as sub-grade, sub-base, and base course soil.

Table 4.5: Comparing Actual CBR value with neuroxl predicted CBR value (option 2)

Model Options No.	Actual CBR Value	Neuroxl predictor predicted CBR value
	Standard Deviation	
2	26.5	37

4.3.3 NeuroXL Predictor Result (Option 3): The prediction process includes compaction, Atterberg limit, and grain size distribution test parameters on sub grade soils with a CBR value below 30%.

Table 4.6: Comparing Actual CBR value with neuroxl predicted CBR value (option 3)

Model Options No.	Actual CBR Value	Neuroxl predictor predicted CBR value
	Standard Deviation	
3	7.5	7

4.3.4 NeuroXL Predictor Result (Option 4): The prediction process includes experimental measurements of compaction, Atterberg limit, and grain size distribution on subbase soils at CBR values between 30 and 80%.

Table 4.7: Comparing Actual CBR value with neuroxl predicted CBR value (option 4)

Model Options No.	Actual CBR Value	Neuroxl predictor predicted CBR value
	Standard Deviation	
4	11	18

4.3.5 NeuroXL Predictor Result (Option 5):The prediction process includes compaction, Atterberg limit, and grain size distribution test parameters on base-course soils with an above-80% CBR value.

Table 4.8: Comparing Actual CBR value with neuroxl predicted CBR value (option 5)

Model Options No.	Actual CBR Value	Neuroxl predictor predicted CBR value
	Standard Deviation	
5	10.4	15

4.4 Comparing Multiple non-linear regression and neuroxl predictor analyses

Higher adjusted R-squared values are generally desirable as they indicate that the model is more effective at capturing and explaining the relationships between the independent and dependent variables.

The standard error is a measure of the accuracy with which a sample statistic estimates a population parameter. A lower standard error of the regression indicates that the data points are closer to the regression line and that the model's predictions are more accurate. As seen in the above table, there are five multiple non-linear regression analysis options Adjusted R square values decreased with the decrease in sample size.

Standard deviation used to compare actual CBR values with other predicted models. A smaller standard deviation indicates that the model's predictions are more consistent and have less variability.

Table 4.9: Comparing ANOVA regression statistical analyses result parameters

Comparing Multiple Non-Linear Regression Analysis Outputs					
Over the entire sample			Over-separated samples		
	Option 1	Option 2	Option 3 (Sub- grade)	Option 4 (Sub-Base)	Option 5 (Base Course)
Multiple R	0.95	0.88	0.82	0.86	0.9
R Square	0.91	0.77	0.68	0.74	0.81
Adjusted R Square	0.9	0.76	0.58	0.68	0.56
Standard Error	9.21	14	4.47	6.92	6.87
Observations	138	138	52	64	22

Table 4.10: Comparing the two optional analysis methods standards deviation

Model Options No.	Actual CBR Value	This study predicted values	
		(A) ANOVA, regression predicted CBR value	(B) Neuroxl predictor predicted CBR value
		Standard Deviation	
1	26.5	29.2	32
2	26.5	30.2	37
3	7.5	5.7	7
4	11.0	16.1	18
5	10.4	8.4	15

5. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The main objective of this project is to determine the relationship between CBR values and soil property parameters for sub-grade, sub-base and base-course pavement construction materials using the NeuroXL Predictor program and ANOVA Excel analysis methods. Based on the results of this study, the following conclusions were drawn:

1. California bearing ratio values are highly correlated with soil plasticity parameters, compaction parameters, and grain size distribution parameters of the soil.
2. The correlation of the California bearing ratio value increases with increasing values of soil property parameters in the maximum dry density and particle size distribution parameters.
3. The correlation of the California bearing ratio decreases with increasing values of the soil plasticity parameters and the soil compaction parameter of optimum moisture content.
4. The correlation coefficient squared (R^2) of the base course soil model (Option 5) is very small due to the limited sample size.
5. A regression model (option 1) that includes soil compaction parameters provides better predictions than a regression model (option 2) without compaction test parameters.
6. Multiple non-linear regression analysis provides better predictive values than linear regression and Neuroxl predictor artificial intelligence program analysis.
7. Both alternative analysis options—multiple non-linear regression analysis and Neuroxl's advanced neural network prediction program—predicted results that were very close to the actual CBR value.
8. The classified data set (sub-grade, sub-base, and base-course materials) analysis technique requires a large sample size for each group to get a better prediction.
9. The unclassified analysis technique gives the best predicted California bearing ratio values compared to the classified data set (sub-base, sub-base, and base-course) analysis technique.
10. Neuroxl's advanced artificial intelligence software analysis method provides higher standard deviations than multiple non-linear regression analysis methods. This is because the free trial version of the AI program is limited.
11. It is recommended to use alternate equations to get a more approximate predicted CBR value.

5.2 Recommendation

- In future research, other studies should be carried out by including more clay soil and base course samples.
- In order to obtain better predictive results, further studies should be conducted using the full version of Neuroxl predictive tools.
- The developed equations may need further improvement by increasing the number of soil samples and including different soil types.

REFERENCE

- [1] Ethiopian Roads Authority, (2013), ERA Pavement Design Manual Volume 1
- [2] Dr. Dilip Kumar T., (January 2014), A Study of Correlation between California bearing ratio (CBR) Value and Other Properties of Soil.
- [3] S. M. Lim, D. C. Wijeyesekera, and I. Bakar (2014), Correlations of soil classification and compaction parameters with soaked and Un-soaked CBR of soils.
- [4] Ethiopian Road Authority, (2013), Geotechnical Design Manual
- [5] Kley S. A., (1995), possible developments in pavement foundation Design.
- [6] American Association of State Highway and Transport Officials, (1996), Standard Method of Test for Particle Size Analysis of Soils (AASHTO designation T 88–95)
- [7] American Association of State Highway and Transport Officials, (1996), Standard Method of Test for Determining the Liquid Limit of Soils (AASHTO designation T 89–95)
- [8] American Association of State Highway and Transport Officials, (1996), Standard Method of Test for Plastic Limit and Plasticity Index (AASHTO designation T 90–95)
- [9] American Association of State Highway and Transport Officials, (1996), Standard Method of Test for Moisture-density Relation of Soil (AASHTO designation T 180-95)
- [10] American Association of State Highway and Transport Officials, (1996), Standard Method of Test for the CBR (AASHTO designation T 193-95)
- [11] American Association of State Highway and Transport Officials, (1996), Standard Method of Test for Laboratory Determining Moisture Content of Soils (AASHTO designation T 265)
- [12] American Association of State Highway and Transport Officials, (1996), Standard Method of Test for Classification of Soil and Soil-Aggregate Mixtures for Highway Construction Purposes (AASHTO designation M-145)
- [13] American society for testing and materials, (2000). Standard practice for classification of Soils for engineering purposes (ASTM designation D 2487).
- [14] Alfred Bartolucci, Karan P. Singh, and Sejong Bae, (2015), Introduction to the statistical analysis of Laboratory Data.
- [15] Analyzer XL LLC, (1998–2003), Unleashing the Power of Artificial Intelligence for Microsoft Excel Forecasting and Estimation a White Paper.

[16] Abyinur Solomon, (2021), "Developing Correlation between Index Properties and California Bearing Ratio, CBR of Soils: A Case Study on Gedo-Mena-begna Road Upgrading Project; on the Way from Gedo to Fincha"

[17] Roy, T. K., Chattopadhyay, B.C., and Roy, S. K., (2009), Prediction of CBR from Compaction Characteristics of Cohesive Soil, Highway Research Journal, July–Dec., 77–88

[18] Leliso Y., (2013), Correlation of CBR value with soil index properties for Addis Ababa, M.Sc. thesis, AAU, AAiT

[19] Dereje Bogale, (2019), Prediction of Soaked CBR value from Index properties and compaction characteristics of sub-grade soil for the case of Jinka-Mendir Design and Build Road project, MSc thesis, AAU, AAiT

Appendix A. Table A. Summary of soil samples test results to train model analysis

No.	ACTUAL CBR (%)	Particle size distribution Parameters				Atterberg limit Parameters			Compaction Parameters		Soil Classification	
		4.75 mm PP	2 mm PP	0.425 mm PP	0.075 mmPP	LL (%)	PL (%)	PI (%)	MDD KG/M ³	OMC (%)	AASHTO SOIL CLASS	USCS SOIL CLASS
1	3.0	75.6	62.2	45.1	35.7	64.3	40.0	24.2	1.4	17.0	A-7-5	SM
2	3.4	97.0	95.0	79.0	67.3	64.4	41.4	23.0	1.5	22.2	A-7-5	MH
3	5.0	95.3	92.5	79.0	76.3	49.9	30.8	19.1	1.6	17.0	A-7-5	CL
4	6.3	100.0	98.0	89.0	52.7	54.7	36.5	18.2	1.6	21.7	A-7-5	MH
5	6.9	100.0	99.7	95.4	91.7	58.8	36.3	22.5	1.5	23.0	A-7-5	MH
6	7.2	82.0	76.9	43.0	37.5	50.7	36.5	14.2	1.5	22.6	A-7-5	SM
7	7.4	66.9	56.4	49.1	43.1	57.4	38.7	18.7	1.4	29.2	A-7-5	SM
8	9.0	97.4	94.3	83.9	64.3	40.4	25.9	14.5	1.6	19.8	A-6	CL
9	10.0	99.8	99.6	75.5	71.3	57.9	41.4	16.4	1.4	28.4	A-7-5	MH
10	10.0	97.2	94.6	88.0	77.4	49.4	31.8	17.6	1.6	25.0	A-7-5	ML
11	10.7	32.3	16.9	11.8	9.1	55.7	44.7	11.0	1.7	13.7	A-2-7	GP-GM
12	11.4	96.1	88.3	79.6	57.5	60.9	31.8	29.2	1.5	25.7	A-7-5	CH
13	11.5	69.7	63.0	43.0	32.3	42.1	23.5	18.6	1.7	16.3	A-2-7	SC
14	11.6	100.0	99.2	91.8	76.6	61.0	30.4	30.6	1.4	27.4	A-7-5	CH
15	11.8	100.0	99.4	98.4	44.4	65.3	34.3	31.0	1.4	27.5	A-7-5	SC
16	12.8	76.4	64.6	38.1	19.1	47.2	34.2	13.0	1.7	17.3	A-2-7	GM
17	13.3	98.9	97.7	91.7	52.2	53.7	34.8	18.8	1.5	20.7	A-7-5	MH
18	13.4	29.1	21.6	15.4	11.5	52.6	28.5	24.1	1.8	16.3	A-2-7	GP-GC
19	13.8	93.7	92.5	91.7	88.9	70.7	45.1	25.6	1.8	14.4	A-7-5	MH
20	13.9	28.8	16.5	7.9	2.8	51.1	40.2	10.9	1.7	15.4	A-2-7	GW
21	13.9	98.0	96.4	90.6	55.0	60.6	32.6	28.0	1.5	25.0	A-7-5	CH
22	13.9	100.0	96.4	93.0	78.0	66.3	32.6	33.7	1.4	24.0	A-7-5	CH
23	14.3	100.0	99.4	96.4	36.6	53.8	38.0	15.8	1.5	27.4	A-7-5	SM
24	15.3	91.8	90.2	84.7	74.4	57.0	39.8	17.3	1.5	29.8	A-7-5	MH
25	15.5	67.0	55.2	47.1	14.8	49.2	26.8	22.3	1.7	27.0	A-2-7	GC
26	15.9	25.8	20.5	15.9	11.8	48.1	30.2	18.0	1.8	12.9	A-2-7	GP-GM
27	16.0	67.0	55.0	47.1	15.0	49.2	26.8	22.4	1.7	27.0	A-2-7	GC
28	16.0	92.0	84.5	80.3	39.7	35.3	26.5	8.8	1.5	17.3	A-4	SM
29	16.1	47.0	41.0	23.0	0.7	41.5	23.2	18.3	1.7	15.0	A-2-7	GP
30	16.8	45.5	40.0	27.0	21.0	43.4	28.7	14.7	1.7	16.7	A-2-7	GM

No.	ACTUAL CBR (%)	Particle size distribution Parameters				Atterberg limit Parameters			Compaction Parameters		Soil Classification	
		4.75 mm PP	2 mm PP	0.425 mm PP	0.075 mmPP	LL (%)	PL (%)	PI (%)	MDD KG/M ³	OMC (%)	AASHTO SOIL CLASS	USCS SOIL CLASS
31	16.9	88.8	82.0	72.0	59.2	47.8	32.8	15.0	1.7	21.0	A-7-5	ML
32	18.2	43.8	39.3	34.2	31.2	38.6	27.7	11.0	1.8	14.7	A-2-6	GM
33	18.2	33.2	26.9	22.4	16.8	52.4	34.6	17.8	1.8	16.3	A-2-7	GM
34	18.2	92.8	92.8	87.2	80.4	69.9	52.6	17.3	1.3	37.5	A-7-5	MH
35	18.5	90.0	73.0	49.6	30.4	46.2	32.4	13.8	1.6	22.5	A-2-7	SM
36	18.6	99.7	86.0	71.0	56.3	49.4	30.2	19.2	1.7	16.9	A-7-5	CL
37	20.0	56.5	44.9	38.2	33.8	40.0	27.6	12.4	1.9	13.7	A-2-6	GM
38	20.0	45.6	37.2	24.9	14.8	39.6	26.7	12.9	1.7	15.5	A-2-6	GM
39	20.3	45.9	39.4	31.5	23.4	59.4	33.1	26.3	1.7	19.5	A-2-7	GM
40	20.5	34.6	28.6	20.5	16.7	48.0	24.4	23.6	1.8	15.7	A-2-7	GC
41	20.6	68.6	49.7	31.1	20.3	34.5	29.9	4.6	1.7	19.8	A-1-b	GM
42	21.0	23.8	12.5	10.0	7.8	34.6	23.6	11.0	1.7	8.1	A-2-6	GP-GM
43	22.0	50.4	44.0	35.0	27.0	26.7	15.3	11.4	1.8	16.7	A-2-6	GC
44	23.3	25.3	18.8	13.7	10.9	54.9	29.1	25.7	1.8	16.3	A-2-7	GP-GM
45	25.7	49.8	45.9	36.0	28.5	34.8	23.4	11.3	1.7	13.7	A-2-6	GM
46	26.0	64.0	59.2	52.4	44.2	39.8	29.6	10.1	1.7	15.2	A-4	SM
47	26.5	31.0	25.7	21.5	18.5	47.8	27.2	20.5	1.8	17.0	A-2-7	GC
48	27.4	36.5	24.0	11.5	6.6	37.4	26.4	11.1	1.9	9.1	A-2-6	GP-GM
49	27.7	75.1	69.0	50.3	34.4	45.1	27.0	18.1	1.5	25.2	A-2-7	SC
50	29.1	46.0	35.4	26.0	18.9	37.3	25.4	11.9	2.0	13.9	A-2-6	GM
51	29.5	8.6	7.1	6.3	6.2	32.0	20.6	11.3	1.8	5.0	A-2-4	GP-GM
52	29.7	37.8	33.0	23.6	16.2	40.3	29.0	11.3	1.8	17.0	A-2-6	GM
53	30.0	52.3	45.9	28.3	11.8	25.4	14.4	11.0	1.9	11.1	A-2-6	GP-GC
54	31.1	30.3	20.0	15.0	12.5	36.0	25.2	10.9	1.9	11.2	A-2-6	GM
55	32.0	28.2	20.0	12.5	9.7	37.8	21.5	16.2	2.0	8.3	A-2-6	GP-GC
56	32.5	57.6	49.7	38.3	29.5	40.0	29.4	10.6	1.9	12.5	A-2-6	GC
57	33.0	17.2	12.9	10.4	8.8	52.1	41.8	10.3	2.0	12.0	A-2-5	GP-GM
58	33.4	37.3	30.1	21.0	15.5	34.0	23.1	10.9	1.9	11.7	A-2-6	GM
59	33.7	26.5	19.6	9.6	2.9	37.9	27.0	10.9	1.9	11.7	A-2-6	GP
60	34.0	29.7	19.0	11.0	9.8	40.6	32.1	8.5	1.9	5.3	A-2-5	GP-GM
62	35.0	28.6	24.2	19.4	14.7	41.2	33.2	8.0	1.7	10.8	A-2-5	GM

No.	ACTUAL CBR (%)	Particle size distribution Parameters				Atterberg limit Parameters			Compaction Parameters		Soil Classification	
		4.75 mm PP	2 mm PP	0.425 mm PP	0.075 mm PP	LL (%)	PL (%)	PI (%)	MDD KG/M ³	OMC (%)	AASHTO SOIL CLASS	USCS SOIL CLASS
61	34.5	93.7	82.3	75.7	68.3	40.4	34.0	6.4	1.2	22.2	A-4	ML
63	35.0	57.5	53.6	42.1	33.8	33.8	23.1	10.7	1.7	13.6	A-2-6	GM
64	35.3	25.7	20.0	15.5	11.3	59.0	48.8	10.2	2.0	12.7	A-2-5	GM
65	35.3	15.2	10.6	7.7	5.5	49.4	38.9	10.4	2.0	9.2	A-2-5	GW-GM
66	35.5	85.7	74.8	39.7	18.6	28.1	17.4	10.7	1.5	12.8	A-2-6	SM
67	36.0	15.4	14.3	10.6	8.8	36.0	26.1	9.9	1.9	8.1	A-2-5	GP-GM
68	36.3	42.0	29.0	21.0	10.0	39.3	27.9	11.4	1.9	17.1	A-2-6	GP-GM
69	37.5	61.5	45.6	32.4	25.2	33.5	22.1	11.5	2.1	9.3	A-2-6	GC
70	37.5	17.4	14.9	7.7	5.6	36.0	23.7	12.3	2.0	10.3	A-2-6	GW-GC
71	38.0	65.0	60.0	40.0	8.0	41.0	33.0	8.0	2.0	10.3	A-2-5	GP-GM
72	38.0	29.2	22.4	16.1	13.0	40.8	31.4	9.4	1.8	9.2	A-2-5	GC
73	38.0	51.2	45.7	36.0	28.6	41.9	35.0	6.9	1.7	14.4	A-2-5	GM
74	38.0	48.0	40.0	29.2	18.4	41.4	37.0	4.4	1.7	12.5	A-2-5	GC-GM
75	39.0	15.2	11.2	9.2	7.8	42.4	34.4	8.0	1.8	9.9	A-2-5	GP-GM
76	39.6	29.0	21.0	15.0	11.0	41.0	31.0	10.0	1.0	11.0	A-2-5	GP-GM
77	40.4	15.5	10.0	6.9	5.3	46.7	41.0	5.7	1.8	14.7	A-2-5	GW
78	41.0	43.5	35.0	26.0	20.0	33.6	22.9	10.7	2.1	11.0	A-2-6	GC
79	41.2	41.0	31.0	21.0	15.5	28.6	17.8	10.8	1.9	7.7	A-2-6	GC
80	41.4	61.3	49.0	31.0	21.0	34.3	23.6	10.7	1.8	16.3	A-2-6	GC
81	41.5	55.7	40.4	23.4	14.6	21.0	20.0	1.0	1.7	18.5	A-3	GM
82	41.5	41.0	29.5	18.2	9.2	40.9	32.4	8.5	2.0	13.0	A-2-5	GW-GC
83	42.1	27.0	20.3	14.7	11.6	50.0	39.7	10.3	2.0	14.4	A-2-5	GP-GM
84	42.2	79.0	78.7	74.5	66.5	42.0	33.2	8.8	2.0	16.7	A-2-5	CL
85	42.4	33.7	29.0	24.0	19.5	41.0	32.3	8.7	1.9	13.4	A-2-5	GM
86	42.8	17.9	9.0	6.2	5.0	41.0	33.6	7.4	1.9	9.7	A-2-5	GP-GM
87	44.0	22.7	17.0	11.3	9.8	40.9	35.5	5.4	2.0	8.8	A-2-5	GP-GM
88	45.0	23.0	16.5	13.6	11.4	43.5	33.0	10.4	1.9	13.3	A-2-5	GP-GC
89	45.5	17.4	12.0	8.0	5.8	37.1	24.6	12.5	2.2	6.4	A-2-6	GP-GM
90	45.6	55.4	52.8	48.6	34.2	47.6	37.4	10.2	1.9	18.2	A-2-5	GM
91	45.8	18.5	15.6	11.6	9.2	37.2	22.1	15.1	2.0	9.8	A-2-6	GP-GC
92	45.8	17.9	9.1	5.1	4.1	41.4	31.3	10.1	2.0	7.8	A-2-5	GW

No.	ACTUAL CBR (%)	Particle size distribution Parameters				Atterberg limit Parameters			Compaction Parameters		Soil Classification	
		4.75 mm PP	2 mm PP	0.425 mm PP	0.075 mmPP	LL (%)	PL (%)	PI (%)	MDD KG/M ³	OMC (%)	AASHTO SOIL CLASS	USCS SOIL CLASS
93	46.8	7.1	4.1	3.0	1.3	41.0	31.0	10.0	2.0	9.2	A-2-5	GP
94	47.0	29.4	20.4	14.2	11.3	51.5	41.0	10.4	1.9	9.5	A-2-5	GP-GM
95	48.0	28.0	20.7	17.1	15.7	21.0	20.0	1.0	1.8	4.7	A-1-b	GM
96	48.0	46.0	45.2	36.6	27.8	42.2	32.1	10.1	2.0	14.0	A-2-5	GC
97	48.5	27.0	18.4	12.9	10.7	40.8	30.4	10.4	2.1	9.3	A-2-5	GP-GM
98	50.0	15.1	11.8	10.3	9.1	40.9	30.4	10.4	1.9	12.7	A-2-5	GP-GC
99	50.5	46.5	30.0	18.1	12.3	40.6	34.2	6.4	2.1	4.1	A-2-5	GC-GM
100	51.6	35.8	35.8	25.0	19.4	41.5	34.0	7.5	2.0	9.3	A-2-5	GM
101	54.0	42.1	2.9	0.8	0.8	21.0	20.0	1.0	2.0	5.7	A-1-a	GW-GM
102	54.5	21.5	13.8	9.1	7.0	41.4	31.3	10.1	2.1	9.0	A-2-4	GP-GM
103	55.5	26.2	18.1	11.4	7.4	30.4	23.0	7.4	1.9	9.5	A-2-4	GP-GC
104	56.0	59.5	53.1	47.6	34.4	31.9	23.0	8.9	2.0	8.8	A-2-4	GM
105	57.0	26.6	17.3	11.2	8.7	30.3	20.3	10.0	2.1	9.2	A-2-4	GP-GC
106	57.0	42.1	30.0	16.8	11.5	28.3	24.7	3.5	2.0	7.1	A-1-a	GP-GM
107	57.1	8.0	5.9	3.3	1.2	21.0	20.0	1.0	1.8	17.6	A-1-a	GP
108	61.1	16.1	10.8	7.3	5.5	28.5	21.2	7.2	2.0	10.3	A-2-4	GP-GC
109	61.1	16.1	10.8	7.3	5.5	28.5	21.2	7.2	2.0	10.3	A-2-4	GP-GC
110	66.6	13.2	9.6	6.9	5.5	21.0	20.0	1.0	2.0	7.7	A-1-a	GW-GM
111	69.0	43.4	28.2	15.9	10.0	27.2	19.2	8.0	2.1	5.0	A-2-4	GP-GC
112	72.0	26.4	15.2	6.9	4.2	21.0	20.0	1.0	2.1	4.2	A-1-a	GW
113	72.5	3.4	2.0	1.8	1.7	21.0	20.0	1.0	2.0	6.3	A-1-a	GP
114	73.0	43.5	28.5	19.2	12.7	30.6	22.2	8.4	2.1	10.7	A-2-4	GC
115	76.5	28.2	19.5	9.9	7.1	26.5	22.5	4.0	2.1	4.7	A-1-a	GP-GC
116	78.0	10.1	4.2	2.4	1.9	25.3	21.7	3.6	2.0	5.5	A-1-a	GP
117	80.0	23.9	14.3	6.7	4.6	29.5	20.4	9.2	2.1	9.5	A-2-4	GW
118	82.0	44.8	28.0	9.3	7.2	21.0	20.0	1.0	2.2	4.3	A-1-a	GW
119	84.0	39.0	25.0	13.0	8.0	24.8	18.8	1.0	2.2	5.0	A-1-a	GW
120	84.0	16.6	6.7	2.6	1.6	21.0	20.0	1.0	2.0	6.5	A-1-a	GW
121	84.6	13.4	5.8	3.1	2.2	21.0	20.0	2.0	2.2	4.6	A-1-a	GW
122	87.5	22.3	13.6	7.3	4.6	27.0	19.4	1.0	2.1	8.7	A-1-a	GW
123	90.0	24.5	13.5	6.0	3.4	21.0	20.0	6.0	2.1	6.0	A-1-a	GW

No.	ACTUAL CBR (%)	Particle size distribution Parameters				Atterberg limit Parameters			Compaction Parameters		Soil Classification	
		4.75 mm PP	2 mm PP	0.425 mm PP	0.075 mmPP	LL (%)	PL (%)	PI (%)	MDD KG/M ³	OMC (%)	AASHTO SOIL CLASS	USCS SOIL CLASS
124	92.0	11.0	3.3	0.6	0.4	21.0	20.0	1.0	2.1	6.5	A-1-a	GW
125	92.3	29.9	19.8	8.7	5.5	20.9	16.4	1.0	2.1	4.5	A-1-a	GW
126	92.8	14.5	7.1	4.5	2.1	21.4	17.8	7.6	2.2	7.0	A-2-4	GW
127	93.0	37.0	23.0	14.0	6.0	21.0	20.0	1.0	2.1	4.0	A-1-a	GW
128	93.0	37.0	23.0	14.0	6.0	20.7	16.8	5.1	2.1	4.0	A-1-a	GP-GC
129	96.3	20.4	9.5	5.0	3.1	25.0	24.0	1.0	2.1	6.6	A-1-a	GW
130	100.5	35.5	21.8	9.8	6.0	21.0	20.0	4.5	2.2	7.4	A-1-a	GW
131	101.0	30.7	19.3	9.9	7.0	25.0	24.0	3.6	2.2	7.3	A-1-a	GW
132	101.0	23.8	12.9	4.8	3.4	22.8	20.4	1.0	2.1	6.3	A-1-a	GW
133	105.8	31.0	21.8	11.5	7.2	21.0	20.0	1.0	2.2	5.7	A-1-a	GW-GM
134	108.0	47.0	35.2	22.1	15.2	21.0	20.0	1.0	2.1	6.3	A-1-a	GW
135	108.0	7.6	3.0	2.9	2.8	36.3	26.6	1.0	2.1	7.7	A-1-a	GW
136	112.0	33.0	23.0	13.0	6.0	35.3	25.6	1.0	2.1	7.0	A-1-a	GW
137	112.0	31.1	20.8	11.3	6.7	23.0	21.0	1.0	2.2	5.8	A-1-a	GW
138	112.5	39.0	22.0	15.0	9.0	18.0	12.9	1.0	2.1	5.8	A-1-a	GW

” 4.75 mm pp” (Particle size percentile less than 4.75 mm), “2 mm pp” (Particle size percentile less than 2 mm), “0.425 mm pp”(Particle size percentile less than 4.75 mm) and “0.075 mm pp” (Particle size percentile less than 0.075 mm).

Appendix A. Table B. Summary of soil samples test results for Testing of Model Analysis

No.	ACTUAL CBR (%)	Particle size distribution Parameters				Atterberg limit Parameters			Compaction Parameters		Soil Classification	
		4.75 mm PP	2 mm PP	0.425 mm PP	0.075 mm PP	LL (%)	PL (%)	PI (%)	MDD KG/M ³	OMC (%)	AASHTO SOIL CLASS	USCS SOIL CLASS
1	3.0	59.0	52.0	45.0	41.0	53.0	32.0	21.0	1.8	15.8	A-7-5	SM
2	6.1	42.1	39.0	38.0	36.9	56.5	24.5	32.1	1.9	9.4	A-7-6	GC
3	8.2	82.2	75.4	66.5	53.7	48.0	32.9	15.1	1.5	24.5	A-7-5	SM
4	9.0	93.8	90.0	81.2	67.8	45.0	29.0	16.0	1.6	26.7	A-7-5	ML
5	9.1	98.4	95.6	89.2	76.8	44.0	27.0	17.0	1.4	27.8	A-7-5	MH
6	11.2	82.6	76.9	65.1	55.9	53.0	39.6	13.4	1.4	22.0	A-7-5	MH
7	11.6	99.8	74.5	61.0	57.7	40.0	24.8	15.2	1.8	16.9	A-6	ML
8	11.9	24.0	31.1	20.4	17.1	45.0	24.0	21.0	1.7	16.5	A-2-7	GC
9	12.4	66.3	61.6	56.0	51.8	44.0	29.6	14.4	1.7	17.9	A-7-5	ML
10	12.6	54.5	46.9	37.6	16.2	44.0	35.3	8.7	1.5	13.8	A-2-7	GM
11	13.1	87.7	81.2	64.9	35.7	48.0	34.5	13.5	1.6	19.0	A-2-7	GM
12	13.4	36.4	16.9	11.8	10.5	40.0	26.7	13.3	1.7	13.7	A-2-7	GP-GM
13	16.5	57.9	46.0	33.1	26.5	55.0	49.6	5.4	1.7	12.1	A-2-7	GM
14	18.4	91.4	82.9	68.4	55.4	54.0	43.7	10.3	1.4	30.0	A-7-5	MH
15	21.0	51.1	44.2	36.4	31.5	43.0	28.0	15.0	1.8	13.7	A-2-6	GM
16	21.5	37.1	28.3	22.5	17.4	40.0	25.0	15.0	1.8	12.4	A-2-6	GP-GM
17	24.4	77.1	68.7	51.8	42.1	59.0	40.0	19.0	1.8	15.2	A-6	SC
18	25.1	38.1	34.0	25.9	19.5	49.6	29.0	20.6	2.0	12.2	A-2-7	GM
19	26.0	46.7	35.7	26.5	21.6	49.6	27.0	22.6	2.0	11.2	A-2-6	GM
20	26.5	18.8	15.0	12.7	11.4	49.6	30.0	19.6	1.9	12.5	A-2-6	GP-GM
21	29.6	23.2	20.1	15.0	11.2	39.0	25.2	13.8	1.8	11.0	A-2-4	GP-GM
22	30.0	45.0	32.0	17.0	13.0	49.6	49.6	11.0	1.8	12.8	A-2-6	GM
23	31.0	27.8	22.0	15.5	8.9	49.6	49.6	10.6	1.9	12.2	A-2-6	GP-GM
24	32.0	24.4	13.6	8.2	6.5	49.6	49.6	10.6	1.8	13.9	A-2-6	GW-GM
25	33.0	29.7	24.1	19.1	14.4	49.6	49.6	10.4	1.7	20.0	A-2-5	GM
26	33.9	28.1	19.3	10.3	6.4	39.3	29.7	9.7	1.9	8.5	A-2-6	GP
27	34.0	27.0	19.6	9.6	3.0	49.6	49.6	10.9	1.9	11.7	A-2-6	GP
28	34.8	61.2	53.3	47.6	41.5	49.6	49.6	7.2	1.5	16.5	A-2-5	GM
29	35.0	63.5	43.0	38.3	27.3	49.6	49.6	10.9	1.9	16.4	A-2-6	GC
30	35.3	25.7	20.0	15.5	11.3	49.6	49.6	10.1	2.0	12.7	A-2-5	GP-GM
31	36.2	28.0	20.0	15.0	12.5	49.6	49.6	10.6	1.8	13.2	A-2-6	GM

No.	ACTUAL CBR (%)	Particle size distribution Parameters				Atterberg limit Parameters			Compaction Parameters		Soil Classification	
		4.75 mm PP	2 mm PP	0.425 mm PP	0.075 mm PP	LL (%)	PL (%)	PI (%)	MDD KG/M ³	OMC (%)	AASHTO SOIL CLASS	USCS SOIL CLASS
32	37.0	33.1	24.3	17.6	13.9	38.8	29.9	9.6	2.1	8.9	A-2-5	GP
33	37.3	19.4	13.6	10.0	7.3	49.6	49.6	10.4	2.0	13.4	A-2-5	GP-GM
34	37.5	13.0	10.7	8.5	6.6	49.6	49.6	10.0	1.8	21.5	A-2-5	GP-GM
35	38.5	31.6	25.6	19.2	13.1	41.9	35.7	6.2	1.8	11.2	A-2-5	GC-GM
36	39.5	29.7	21.0	15.0	11.3	49.6	49.6	10.4	1.9	11.7	A-2-5	GP-GM
37	42.3	38.8	30.7	24.5	20.8	49.6	49.6	8.3	1.9	10.7	A-2-5	GC
38	42.5	69.0	50.0	34.0	10.0	49.6	49.6	9.3	1.9	11.8	A-2-5	GP-GM
39	43.0	22.8	19.0	13.7	9.6	49.6	49.6	4.8	1.9	16.4	A-2-5	GP-GM
40	43.4	23.7	18.0	11.2	8.3	41.0	33.1	7.9	2.1	10.1	A-2-5	GP-GM
41	45.0	9.4	6.0	4.0	3.5	49.6	49.6	9.5	2.0	5.3	A-2-5	GW
42	45.8	8.4	3.7	3.0	2.7	49.6	49.6	7.0	2.0	8.8	A-2-5	GP
43	46.5	66.7	56.0	20.1	10.5	49.6	49.6	10.5	2.0	9.8	A-2-5	GP-GM
44	48.0	10.6	5.0	10.0	20.0	49.6	49.6	10.2	2.1	7.2	A-2-5	GC
45	50.0	46.1	30.1	17.9	15.2	49.6	49.6	5.3	2.1	6.0	A-1-b	GC-GM
46	52.8	39.0	19.4	12.9	10.1	32.9	27.9	4.3	2.0	7.5	A-2-5	GM
47	53.2	26.9	26.9	17.6	7.0	49.6	49.6	4.3	2.0	5.7	A-1-a	GW-GM
48	55.5	33.2	19.7	10.3	7.6	49.6	49.6	5.9	1.9	11.2	A-1-a	GP-GC
49	56.0	38.3	22.0	11.6	8.9	49.6	49.6	4.7	1.8	12.2	A-1-a	GP-GC
50	59.0	19.7	9.2	3.7	1.5	49.6	49.6	6.9	2.2	7.8	A-2-4	GW
51	63.9	14.7	10.2	7.1	5.5	25.0	20.6	4.1	2.0	9.0	A-2-4	GP-GC
52	70.8	28.3	19.2	12.0	9.7	28.2	23.3	4.4	2.1	6.8	A-2-4	GM
53	74.0	34.3	23.1	13.4	7.3	49.6	49.6	1.0	2.1	5.3	A-1-a	GP-GM
54	81.0	17.0	9.3	4.6	3.3	27.5	21.1	6.4	2.1	7.5	A-1-a	GW
55	83.0	41.9	26.5	11.2	7.6	23.0	19.4	1.0	2.2	4.7	A-1-a	GW
56	86.0	17.8	9.7	5.2	3.4	24.2	19.7	1.5	2.1	6.7	A-1-a	GW
57	91.0	17.8	8.4	3.3	1.9	21.0	20.0	3.5	2.1	6.3	A-1-a	GW
58	92.9	25.8	15.1	9.3	4.1	21.2	18.9	4.3	2.1	5.5	A-2-4	GW
59	94.7	28.7	16.2	9.5	4.5	23.0	20.7	3.1	2.1	5.3	A-1-a	GW
60	99.8	32.5	21.2	10.6	6.5	21.0	20.0	4.5	2.2	8.2	A-1-a	GP-GM
61	106.9	39.0	28.5	16.8	11.2	21.0	20.0	1.0	2.1	6.0	A-1-a	GW
62	111.2	35.1	24.1	13.0	9.0	23.0	21.0	1.0	2.1	5.9	A-1-a	GP-GM

Appendix B. NeuroXL Predictor Zero-based Log-sigmoid model Analysis Steps (Option I)

In this analysis, the plasticity characteristic of soil is represented by (LL, PL, PI), the soil particle size distribution is represented by (4.75 mm PP, 2 mm PP, 0.425 mm PP, 0.075 mm PP), and the compaction characteristics of the soil are also represented by (OMC and MDD) as independent variables.

After downloading the free trial version of Neuroxl Predictor from <https://www.neuroxl.com/>, open Excel with Dependent and Independent parameters in column direction, then activate the neuroxlpredictor tool from the Quick Access Toolbar in Add-Ins.

The screenshot displays the NeuroXL Predictor Excel add-in interface. The main window shows a data table with columns for independent variables (LL, PL, PI, PP, MDD, OMC) and dependent variables (CBR). A dialog box is displayed in the center, stating "This is trial version Days remaining: 10" with an "OK" button. The Excel ribbon at the top includes "File", "Home", "Insert", "Page Layout", "Formulas", "Data", "Review", "View", "Add-ins", "Help", and "Tell me what you want to do". The "Add-ins" tab is active, showing "NeuroXL Predictor" and "NeuroXL CBR %".

No.	ACTUAL CBR (%)	4.75mm PP	2mm PP	0.425mm PP	0.075mm PP	LL-2 (%)	PL-2 (%)	PI-2 (%)	MDD (%)	MOD (%)	OMC (%)	OMC-2 (%)	NeuroXL CBR %
1	20.5	35.0	28.6	20.5	16.7	2304.0	695.4	23.6	557.0	1.82	3.3	15.7	216.5
2	48.0	46.0	46.2	36.6	27.8	1784.2	553.7	18.7	350.1	2.03	4.1	14.0	196.0
3	42.2	79.0	78.7	74.5	66.5	1550.8	423.3	18.8	354.6	1.97	3.9	16.7	278.9
4	48.5	27.0	18.4	12.9	10.7	1634.6	756.8	13.5	181.4	2.05	4.2	9.1	86.5
5	39.0	33.0	32.0	33.0	6.0	625.0	576.0	1.0	1.0	1.0	1.0	1.0	49.0
6	24.0	27.0	19.6	9.6	3.0	1438.4	729.0	10.9	118.8	1.98	3.4	11.7	136.9
7	16.0	67.0	65.0	47.1	15.0	2420.6	718.2	22.4	501.8	1.71	2.9	27.0	729.0
8	22.0	59.4	44.0	35.0	27.0	712.9	234.1	11.4	130.0	1.78	3.2	16.7	278.9
9	41.0	43.5	35.0	26.0	20.0	1125.6	552.3	10.1	102.2	2.05	4.2	11.0	121.0
10	20.3	45.9	39.4	31.5	23.4	3525.2	1093.8	26.3	691.8	1.71	2.9	19.5	380.3
11	41.5	41.0	29.5	18.2	9.1	589.4	250.0	8.5	71.7	1.98	3.9	13.0	160.0
12	57.0	36.6	17.3	11.2	8.7	921.0	384.0	10.8	115.6	2.06	4.2	9.1	83.7
13	35.3	25.7	20.0	15.5	11.3	5476.4	1671.6	18.1	326.7	1.98	3.9	12.7	161.2
14	80.0	47.0	35.2	22.1	15.2	625.0	576.0	1.0	1.0	2.13	4.5	6.3	39.7
15	35.3	25.7	20.0	15.5	11.3	3476.4	1671.6	18.1	326.7	1.98	3.9	12.7	161.2
16	80.0	30.7	19.3	9.9	7.0	458.1	317.8	3.6	12.8	2.19	4.8	7.3	52.6
17	80.0	35.5	21.8	9.8	6.0	438.4	270.3	4.5	20.2	2.15	4.6	7.4	54.0
18	80.0	35.6	20.8	9.7	6.3	426.6	283.7	3.8	14.5	2.18	4.8	7.0	49.0
19	29.1	46.0	35.4	26.0	18.9	1390.8	643.1	11.9	145.4	1.97	3.9	13.9	193.2
20	24.5	21.5	13.8	9.1	7.0	1554.0	762.0	11.8	139.6	2.11	4.5	9.0	81.0
21	25.0	62.5	43.0	38.3	27.3	947.0	437.1	9.9	97.4	1.98	3.5	16.4	267.5
22	7.4	66.9	56.4	49.1	43.1	3290.4	1494.6	18.7	340.8	1.40	1.9	29.2	853.6
23	12.8	76.4	64.6	38.1	19.1	2231.5	1170.5	13.0	169.7	1.72	3.0	17.3	297.6
24	13.4	29.1	21.6	15.4	11.5	2764.7	811.1	24.1	580.8	1.76	3.1	16.3	265.7
25	23.3	25.3	18.8	13.7	10.9	3009.6	849.1	25.7	661.5	1.79	3.2	16.3	264.1
26	15.3	91.8	90.2	84.7	74.4	3250.9	1550.1	17.3	298.1	1.45	2.1	29.8	888.0
27	10.0	99.8	99.6	75.5	71.1	3349.6	1717.9	16.4	269.9	1.43	2.1	28.8	803.7
28	25.2	25.7	7.9	39.7	18.6	790.4	385.0	9.3	80.0	1.40	2.3	12.8	165.8
29	20.6	68.6	49.7	31.1	20.3	1190.2	895.6	4.6	20.9	1.72	3.0	19.8	392.0
30	3.0	75.6	62.2	45.1	33.7	1128.9	1603.2	24.2	586.4	1.43	2.0	17.0	289.0
31	42.1	27.0	20.3	14.7	11.6	2499.1	1346.8	13.3	177.1	2.02	4.1	14.4	207.4
32	35.3	15.2	10.6	7.7	5.5	2438.0	1471.9	11.0	120.8	1.97	3.9	9.1	84.6
33	41.5	55.7	40.4	23.4	14.6	441.0	400.0	1.0	1.0	1.71	2.9	18.5	343.3

1. In the upper left corner of the NeuroXL prediction window, there are three tabs: neural network, parameters, and configuration options.

In the Neural Network tab, it is used to input dependent and independent parameters for both training levels and predictions. We can also observe the learning process by plotting.

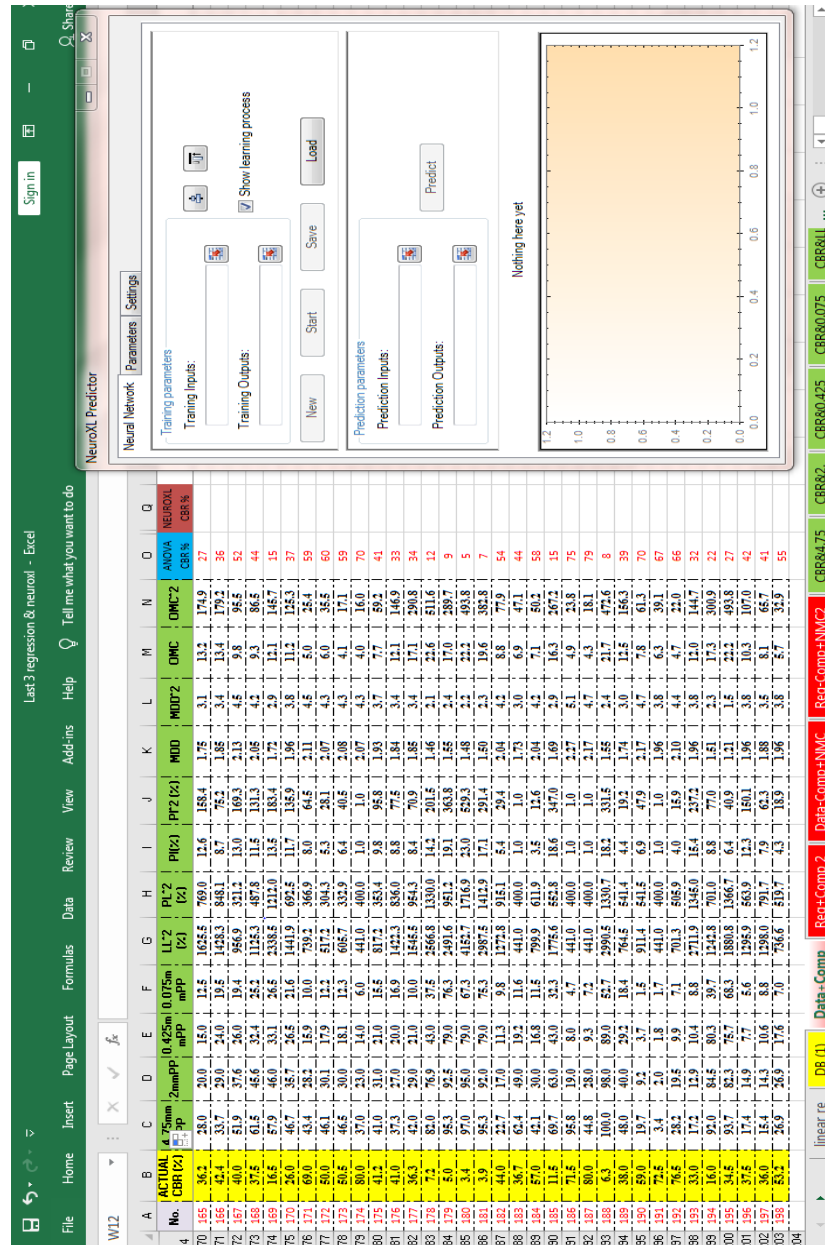
"New" is used to continue the training process.

Enter the parameters and press the "Start" button to start training the Neuroxl prediction.

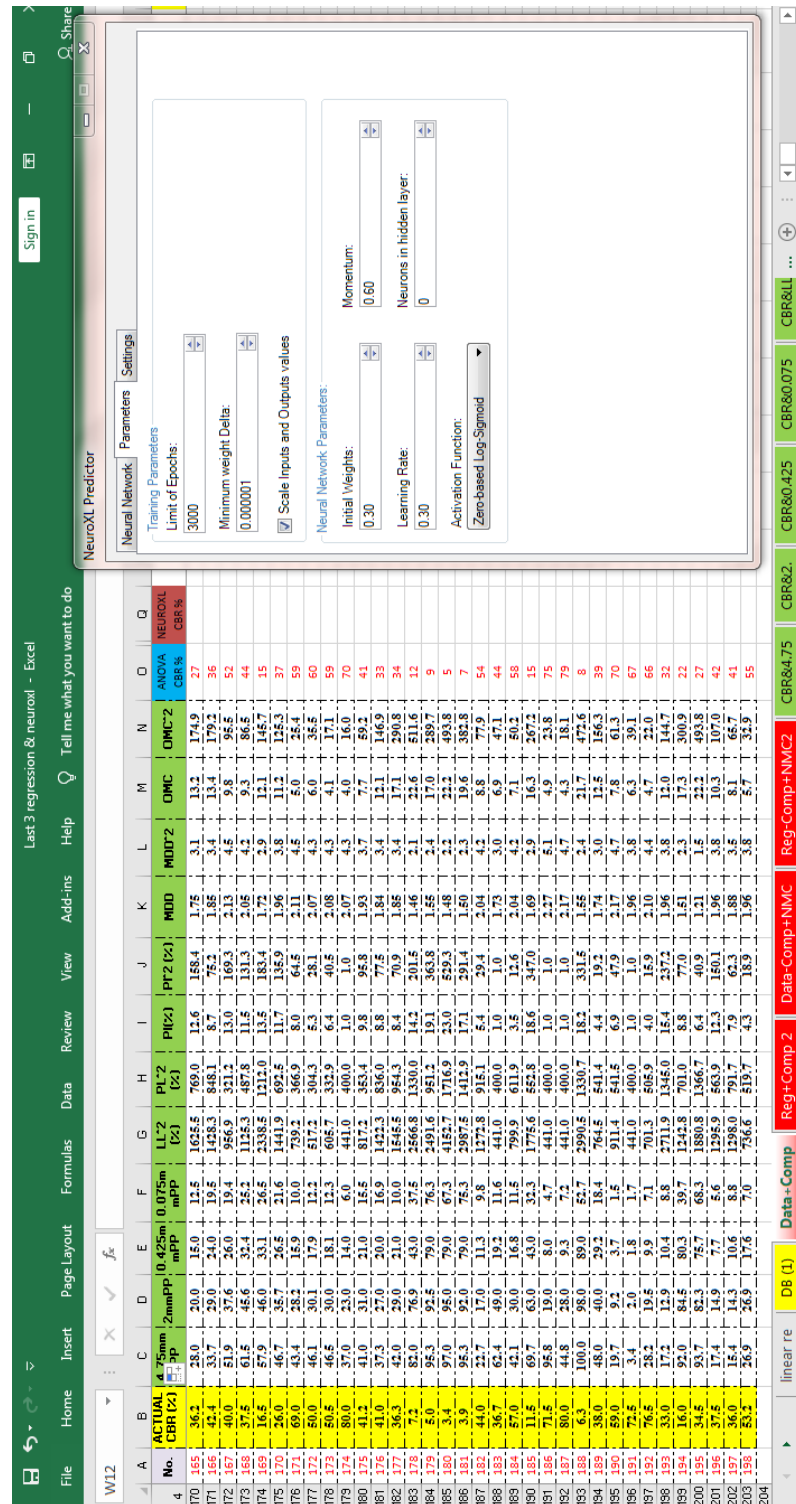
"Save" command key to save the total predicted result.

"Load" button to load the previously saved predicted result.

The "predict" button commands Neuroxl Prediction to start making predictions using the trained data.



- "Parameters" tabs contain two parts: training parameters and neural network parameters. It has an activation function. As we see in the figure below, the default value for this research the activation function was a "Zero-based Log-sigmoid model".



3. The "Settings" tab, as we see in the figure below, applies the default settings for this research.

NeuroXL Predictor

Neural Network Parameters Settings

☒ Save Settings

☒ Save recent range values

Default settings

Chart update period: 10

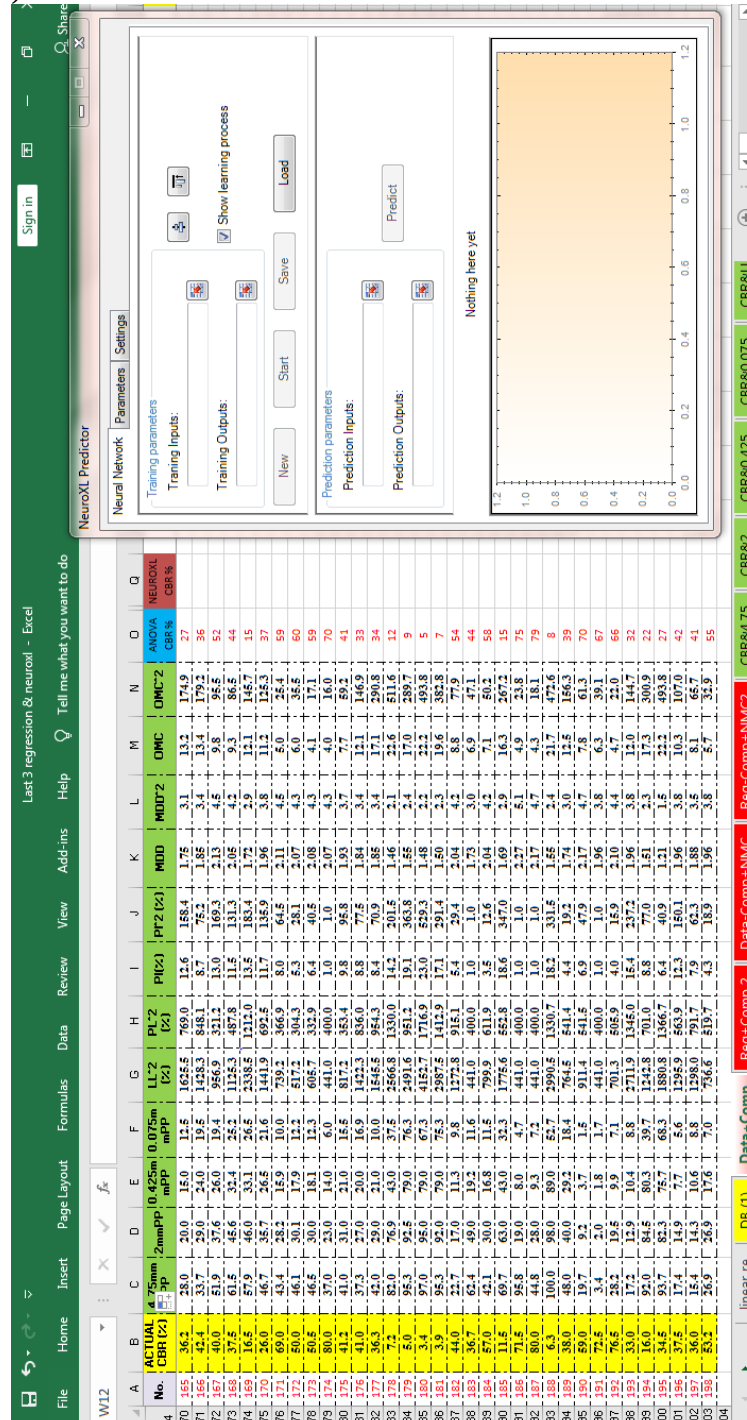
Prediction Decimal places: 3

W12	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	Q
	No.	ACTUAL CBR (%)	0.75mm 2mmPP	0.425mm 0.075mm mPP	LL-2 (%)	PL-2 (%)	PL-2 (%)	PL-2 (%)	PL-2 (%)	PL-2 (%)	MOD	MOD ²	OMC	OMC ²	ANNOVA CBR %	NEUROXL CBR %
170	165	36.2	28.0	20.0	15.0	12.5	1625.5	769.0	12.6	158.4	1.75	3.1	13.2	174.9	27	
171	166	42.4	33.7	29.0	24.0	19.5	1458.3	848.1	8.7	75.3	1.85	3.4	13.4	179.2	36	
172	167	40.0	31.9	37.0	26.0	19.1	926.0	321.2	13.0	169.3	2.13	4.5	9.8	96.2	52	
173	168	37.5	31.5	45.6	32.4	25.2	1125.3	487.8	11.5	131.3	2.05	4.2	9.5	96.5	44	
174	169	16.5	57.9	46.0	33.1	26.5	2388.5	1215.0	13.5	183.4	1.72	2.9	11.1	146.7	15	
175	170	26.0	46.7	35.7	26.5	21.6	1441.9	692.5	11.7	135.9	1.96	3.8	11.2	125.3	37	
176	171	69.0	43.4	28.2	16.9	10.0	739.2	366.9	8.0	64.5	2.11	4.5	6.0	25.4	59	
177	172	50.0	46.1	30.1	17.9	12.2	517.2	304.3	5.3	28.1	2.07	4.3	6.0	35.5	60	
178	173	50.5	46.5	30.0	18.1	12.3	605.7	332.9	6.4	40.5	2.08	4.3	4.1	17.1	59	
179	174	80.0	37.0	23.0	14.0	6.0	441.0	400.0	1.0	1.0	2.07	4.3	4.0	16.0	70	
180	175	41.2	41.0	31.0	21.0	15.5	817.2	353.4	9.8	95.8	1.93	3.7	7.7	59.2	41	
181	176	41.0	37.3	27.0	20.0	16.9	1422.3	836.0	8.8	77.5	1.84	3.4	12.1	146.9	32	
182	177	36.3	42.0	22.0	21.0	10.0	1245.2	551.3	8.4	70.9	1.85	3.4	12.1	206.2	34	
183	178	7.2	82.0	76.9	43.0	27.5	2566.8	1350.0	14.2	201.5	1.46	2.1	22.5	511.6	12	
184	179	5.0	95.3	92.5	79.0	76.3	2491.6	951.2	19.1	363.8	1.55	2.4	17.0	289.7	9	
185	180	3.4	97.0	95.0	79.0	67.3	4152.7	1716.9	23.0	529.3	1.48	2.2	22.2	493.8	5	
186	181	3.9	95.3	92.0	79.0	75.3	2987.5	1412.9	17.1	291.4	1.50	2.3	19.6	382.8	7	
187	182	44.0	22.7	17.0	11.3	9.8	1272.8	915.1	5.4	29.4	2.04	4.2	8.8	77.9	54	
188	183	36.7	62.4	49.0	19.2	11.6	441.0	400.0	1.0	1.0	1.73	3.0	6.9	47.1	44	
189	184	57.0	42.1	30.0	16.8	11.5	799.9	611.9	3.5	12.6	2.04	4.2	7.1	50.2	58	
190	185	11.5	69.7	63.0	43.0	32.3	1775.6	852.8	18.6	347.0	1.69	2.9	16.3	267.2	15	
191	186	71.5	95.8	129.0	8.0	7.7	441.0	400.0	1.0	1.0	2.27	5.1	4.9	23.8	75	
192	187	80.0	44.5	23.0	9.5	7.2	441.0	400.0	1.0	1.0	2.17	4.7	4.2	18.1	79	
193	188	6.3	100.0	98.0	89.0	52.7	2990.5	1350.7	18.2	331.5	1.55	2.4	21.7	472.6	8	
194	189	38.0	48.0	40.0	29.2	18.4	764.5	541.4	4.4	19.2	1.74	3.0	12.5	156.3	39	
195	190	59.0	19.7	9.2	3.7	1.5	911.4	541.5	6.9	47.9	2.17	4.7	7.8	61.3	70	
196	191	72.5	3.4	2.0	1.8	1.7	441.0	400.0	1.0	1.0	1.96	3.8	6.3	39.1	67	
197	192	76.5	28.2	19.5	9.9	7.1	701.3	505.9	4.0	15.9	2.10	4.4	4.7	22.0	66	
198	193	33.0	17.2	12.9	10.4	5.8	2711.9	1345.0	15.4	237.2	1.96	3.8	12.0	144.7	32	
199	194	16.0	92.0	84.5	80.3	39.7	1242.8	701.0	8.8	77.0	1.51	2.3	17.3	300.9	22	
200	195	34.5	93.7	82.3	75.7	68.3	1880.8	1366.7	6.4	40.9	1.21	1.5	22.2	493.8	37	
201	196	27.5	17.4	14.5	7.7	5.6	1295.9	563.9	12.3	150.1	1.96	3.8	10.2	107.0	42	
202	197	36.0	15.4	10.6	8.8	4.3	1298.0	791.7	7.9	62.3	1.88	3.6	8.1	65.4	41	
203	198	53.2	26.9	26.9	17.6	7.0	726.6	519.7	4.3	18.9	1.96	3.8	5.7	32.9	55	

Reg+Comp+NNMC2 Reg+Comp+NNMC Data+Comp+2 Reg+Comp Data+Comp D8 (1) linear re

CBR&0.075 CBR&0.425 CBR&2 CBR&4.75 CBR&7.75 CBR&11

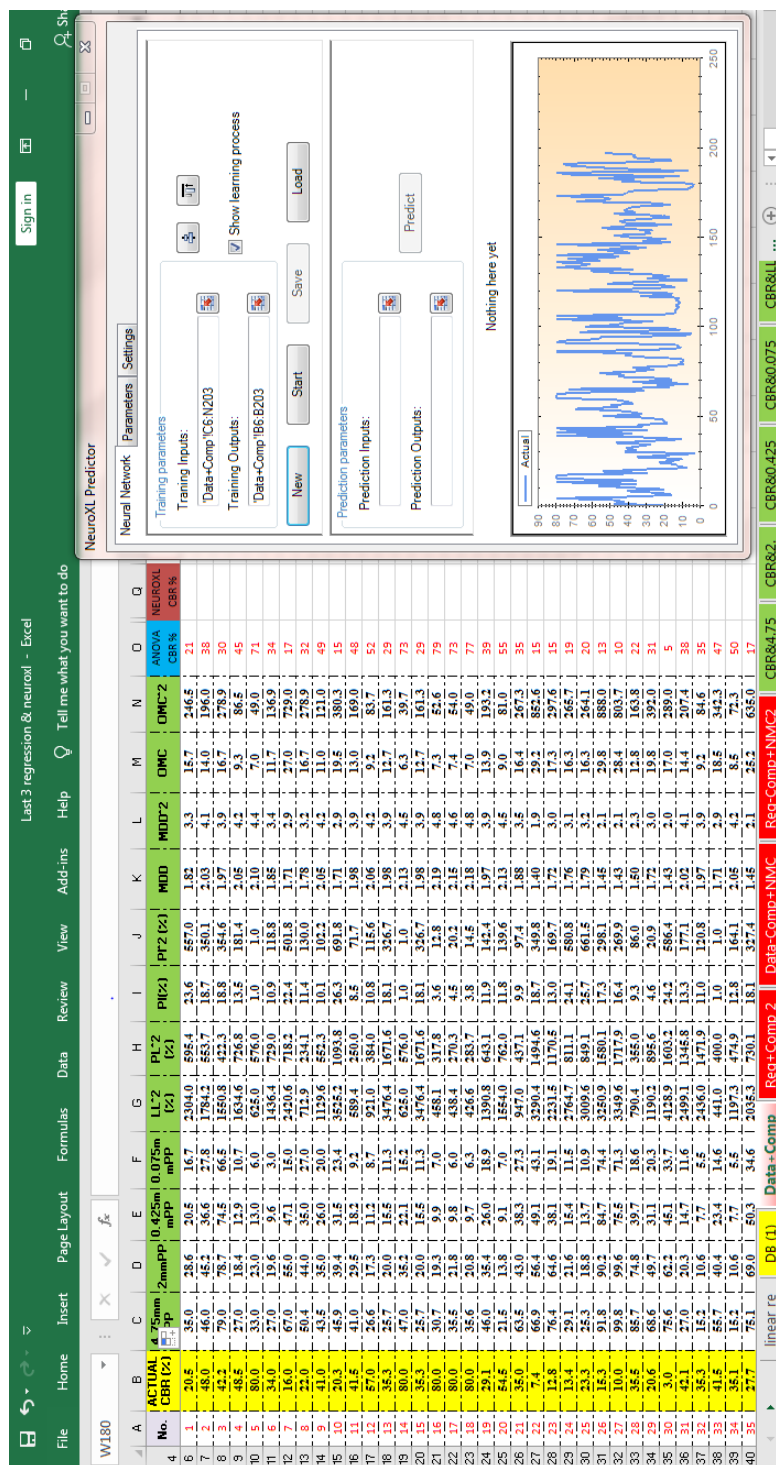
- The first step is to go to the "neural network" tab, then click on the red arrow sign below "training inputs".(option 1)



- [illegible]

- | Last 3 regression & neurol - Excel | | | | | | | | | | | | | | Sign in | |
|---|---------|--------|---------|---------|------|------|--------|--------|------|-------|-------|------|-------|---------|----------|
| Tell me what you want to do | | | | | | | | | | | | | | | |
| File Home Insert Page Layout Formulas Data Review View Add-ins Help | | | | | | | | | | | | | | | |
| B6 | | | | | | | | | | | | | | | |
| | | | | | | | | | | | | | | | |
| A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P |
| | ACTUAL | 4.75mm | 0.425mm | 0.075mm | | LL*2 | PL*2 | PI*2 | PT*2 | MOD | MOD*2 | OMC | OMC*2 | ANOVA | NEUROXAL |
| | CBR (%) | PP | 2mmPP | mPP | mPP | (%) | (%) | (%) | (%) | | | | | CBR % | CBR % |
| 4 | | | | | | | | | | | | | | | |
| 6 | 1 | 20.5 | 35.0 | 28.6 | 20.5 | 16.7 | 2304.0 | 595.4 | 23.6 | 557.0 | 3.3 | 15.7 | 246.5 | 21 | |
| 7 | 2 | 48.0 | 46.0 | 45.2 | 36.6 | 27.8 | 1784.2 | 553.7 | 18.7 | 350.1 | 2.03 | 4.1 | 14.0 | 38 | |
| 8 | 3 | 42.2 | 79.0 | 78.7 | 74.5 | 66.5 | 1550.8 | 422.3 | 16.8 | 354.6 | 1.97 | 3.9 | 16.7 | 30 | |
| 9 | 4 | 48.5 | 27.0 | 18.4 | 12.9 | 10.7 | 1634.6 | 756.8 | 13.5 | 181.4 | 2.05 | 4.2 | 9.3 | 45 | |
| 10 | 5 | 80.0 | 33.0 | 23.0 | 13.0 | 6.0 | 625.0 | 576.0 | 1.0 | 1.0 | 1.0 | 7.0 | 49.0 | 71 | |
| 11 | 6 | 34.0 | 27.0 | 22.6 | 9.6 | 3.0 | 1486.4 | 230.0 | 10.9 | 118.8 | 1.85 | 3.4 | 11.7 | 34 | |
| 12 | 7 | 16.0 | 67.0 | 55.0 | 47.1 | 35.0 | 2420.6 | 718.2 | 22.4 | 501.8 | 1.71 | 2.9 | 27.0 | 17 | |
| 13 | 8 | 22.0 | 50.4 | 44.0 | 35.0 | 27.0 | 712.9 | 234.1 | 11.4 | 130.0 | 1.78 | 3.2 | 16.7 | 32 | |
| 14 | 9 | 41.0 | 43.5 | 35.0 | 26.0 | 20.0 | 1129.6 | 552.3 | 10.1 | 102.2 | 2.05 | 4.2 | 11.0 | 49 | |
| 15 | 10 | 20.3 | 46.9 | 39.4 | 33.5 | 23.4 | 3252.2 | 1093.8 | 26.3 | 691.8 | 1.71 | 2.9 | 19.5 | 15 | |
| 16 | 11 | 41.5 | 41.0 | 29.5 | 18.2 | 9.2 | 589.4 | 250.0 | 8.5 | 71.7 | 1.98 | 3.9 | 13.0 | 48 | |
| 17 | 12 | 57.0 | 26.6 | 17.3 | 11.2 | 8.7 | 921.0 | 384.0 | 10.8 | 115.6 | 2.06 | 4.2 | 9.2 | 52 | |
| 18 | 13 | 35.3 | 25.7 | 20.0 | 15.5 | 11.3 | 3476.4 | 1671.6 | 18.1 | 326.7 | 1.98 | 3.9 | 12.7 | 29 | |
| 19 | 14 | 80.0 | 47.0 | 35.2 | 21.1 | 15.2 | 625.0 | 576.0 | 1.0 | 1.0 | 2.13 | 4.5 | 6.3 | 73 | |
| 20 | 15 | 35.3 | 25.7 | 20.0 | 15.5 | 11.3 | 3476.4 | 1671.6 | 18.1 | 326.7 | 1.98 | 3.9 | 12.7 | 29 | |
| 21 | 16 | 80.0 | 30.7 | 19.3 | 9.9 | 7.0 | 688.1 | 317.8 | 3.6 | 12.8 | 2.19 | 4.8 | 7.1 | 79 | |
| 22 | 17 | 80.0 | 35.5 | 21.8 | 9.6 | 6.0 | 438.1 | 270.3 | 4.5 | 20.2 | 2.15 | 4.6 | 7.4 | 73 | |
| 23 | 18 | 80.0 | 35.6 | 20.8 | 9.7 | 6.3 | 426.6 | 283.7 | 3.8 | 14.5 | 2.18 | 4.8 | 7.0 | 77 | |
| 24 | 19 | 25.1 | 46.0 | 35.4 | 26.0 | 18.9 | 1990.8 | 643.1 | 11.9 | 142.4 | 1.97 | 3.9 | 13.9 | 39 | |
| 25 | 20 | 54.5 | 21.5 | 13.8 | 9.1 | 7.0 | 1554.0 | 762.0 | 11.8 | 135.6 | 2.13 | 4.5 | 9.0 | 55 | |
| 26 | 21 | 35.0 | 63.5 | 43.0 | 38.3 | 27.3 | 3470.0 | 437.1 | 9.9 | 97.4 | 1.88 | 3.5 | 16.4 | 35 | |
| 27 | 22 | 7.4 | 66.9 | 56.4 | 49.1 | | | | | | | | | | |

- Fourth step: After selecting training inputs and training output parameters, click on the "New" button. As we see in the plot, the actual CBR value is ready for analysis.(Option 1)



- NeuroXL Predictor

Neural Network Parameters Settings

Training parameters

Training Inputs:

Data-Comp/CS6 N203

Training Outputs:

Data-Comp/IB6 B203

Show learning process

Stop Load New Save Predict

Prediction parameters

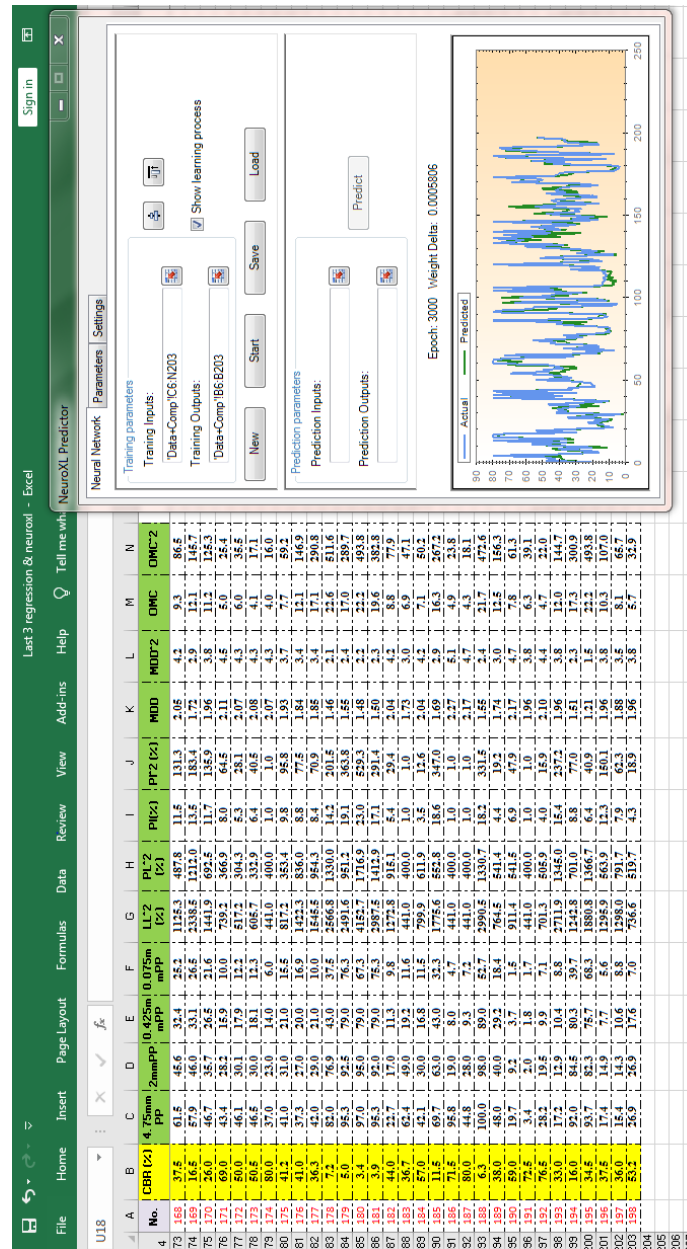
Prediction Inputs:

Prediction Outputs:

Epoch: 281 Weight Delta: 0.0033013

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	Q
	No.	ACTUAL	4 75mm	2mmPP	(0.425mm	0.075mm	LL'2	PL'2	PI'2 (%)	PI'2 (%)	MID	MID'2	OMC	OMC'2	ANOVA	NEUROXL
		CBR (%)	mmPP	mPP	mPP	mPP	(%)	(%)							CAS%	CAS %
4	6	1	20.5	35.0	28.6	20.5	16.7	2304.0	295.4	23.6	457.0	1.82	3.3	15.7	246.5	21
7	1	18.0	46.0	42.2	36.6	27.8	1784.2	443.7	18.7	350.1	1.03	4.1	1.0	19.0	19.0	38
8	2	18.0	46.0	42.2	36.6	27.8	1784.2	443.7	18.7	350.1	1.03	4.1	1.0	19.0	19.0	38
9	1	48.5	79.0	78.7	74.5	66.5	1590.3	322.3	18.6	356.6	1.07	3.9	16.7	278.9	30	
3	1	48.5	79.0	78.7	74.5	66.5	1590.3	322.3	18.6	356.6	1.07	3.9	16.7	278.9	30	
5	1	48.5	79.0	78.7	74.5	66.5	1590.3	322.3	18.6	356.6	1.07	3.9	16.7	278.9	30	
10	5	80.0	33.0	33.0	33.0	6.0	625.0	575.0	1.0	1.0	2.10	4.4	7.0	49.0	71	
11	5	34.0	27.0	19.6	9.6	3.0	1436.4	729.0	10.9	118.8	1.85	3.4	11.7	136.9	34	
12	7	16.0	67.0	85.0	47.1	15.0	2420.6	718.2	22.5	401.8	1.71	2.9	27.0	729.9	37	
13	8	22.0	50.4	44.0	35.0	27.0	712.9	1304.1	11.4	130.0	1.78	3.2	16.7	278.9	32	
14	9	41.0	43.5	35.0	26.0	20.0	1129.6	552.3	10.1	102.2	2.05	4.2	11.0	121.0	49	
15	10	20.3	45.9	39.4	31.5	23.4	3525.2	1093.8	26.3	691.8	1.71	2.9	19.5	380.2	15	
16	11	41.5	41.0	29.5	18.2	9.2	599.4	350.0	8.5	71.7	1.98	3.9	13.0	169.0	48	
17	12	57.0	26.6	17.3	11.2	8.7	921.0	884.0	10.8	115.6	2.06	4.2	9.2	83.7	52	
18	13	35.3	25.7	20.0	15.5	11.3	3476.4	1671.6	18.1	326.7	1.98	3.9	12.7	161.3	39	
19	14	80.0	47.0	35.2	21.1	15.2	625.0	575.0	1.0	1.0	2.13	4.5	6.3	39.7	73	
20	15	35.3	25.7	20.0	15.5	11.3	3476.4	1671.6	18.1	326.7	1.98	3.9	11.7	161.3	29	
21	16	80.0	30.7	19.3	9.9	7.0	488.1	317.6	3.6	12.8	2.19	4.8	7.3	52.6	79	
22	17	80.0	35.5	21.8	9.8	6.0	438.4	370.3	4.5	20.2	2.15	4.6	7.4	54.0	73	
23	18	80.0	35.5	21.8	9.8	6.0	438.4	370.3	4.5	20.2	2.15	4.6	7.4	54.0	73	
24	19	54.1	46.0	35.4	24.0	18.9	1390.8	643.1	11.9	145.4	1.97	3.9	13.9	193.2	39	
25	20	54.1	46.0	35.4	24.0	18.9	1390.8	643.1	11.9	145.4	1.97	3.9	13.9	193.2	39	
26	21	35.0	63.5	43.0	33.3	27.3	947.0	437.1	9.9	97.4	1.88	3.5	16.4	267.3	35	
27	22	7.4	66.9	56.4	49.1	43.1	3290.4	1494.6	18.7	348.8	1.05</					

- Sixth Step: After completion of the training process, the plot is paused. Now that Neuroxl is ready for prediction, click predicate. (Option 1)



10. In the seventh step, after completion of the training process, select 12 independent parameters of CBR for 60 soil samples to test result parameters for prediction inputs (60X12 arrays).(Option 1) (with the same procedure as step 2, but use different samples data for prediction inputs).

Excel - Last 3 regression & neural - Tell me what you want to do

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C6

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	T
		CBR (%)	4.75mm PP	2mmpp	0.425mm mpp	0.075mm mpp	LL-2 (%)	PL-2 (%)	PI(%)	PI-2 (%)	MDD	MDD-2	OMC	OMC-2	CBR Value	CBR Value	
6	1	20.5	35.0	28.6	20.5	16.7	2304.0	593.4	23.6	557.0	1.82	3.3	15.7	246.5	21		
7	2	48.0	46.0	45.2	36.6	27.8	1784.2	553.7	18.7	380.1	2.03	4.1	14.0	196.0	38		
8	3	42.2	79.0	78.7	74.5	66.5	1850.8	423.3	18.8	354.6	1.97	3.9	16.7	278.9	30		
9	4	48.5	27.0	18.4	12.9	10.7	1634.6	725.8	13.5	181.4	2.05	4.2	9.3	86.5	45		
10	5	80.0	33.0	23.0	13.0	6.0	625.0	576.0	1.0	1.0	2.10	4.4	7.0	49.0	71		
11	6	34.0	27.0	19.6	9.6	3.0	1436.4	725.0	10.9	118.8	1.85	3.4	11.7	136.9	34		
12	7	16.0	67.0	55.0	47.1	15.0	2420.6	718.2	22.4	501.8	1.71	2.9	27.0	729.0	17		
13	8	22.0	50.4	44.0	35.0	27.0	712.9	334.1	11.4	130.0	1.78	3.2	16.7	278.9	32		
14	9	41.0	43.5	35.0	26.0	20.0	1129.6	552.3	10.1	102.2	2.05	4.2	11.0	121.0	49		
15	10	20.3	45.9	39.4	31.5	23.4	3525.2	1093.8	26.3	691.8	1.71	2.9	19.5	380.3	15		
16	11	41.5	41.0	29.5	18.2	9.2	589.4	550.0	8.5	71.7	1.98	3.9	13.0	169.0	48		
17	12	57.0	26.6	17.3	11.2	8.7	921.0	384.0	10.8	115.6	2.06	4.2	9.2	83.7	52		
18	13	35.3	25.7	20.0	15.5	11.3	3476.4	671.6	18.1	356.7	1.98	3.9	12.7	161.3	29		
19	14	80.0	47.0	35.2	22.1	15.2	625.0	576.0	1.0	1.0	2.13	4.5	6.3	39.7	73		
20	15	35.3	25.7	20.0	15.5	11.3	3476.4	671.6	18.1	356.7	1.98	3.9	12.7	161.3	29		
21	16	80.0	30.7	19.3	9.9	7.0	458.1	317.8	3.6	12.8	2.19	4.8	7.3	52.6	79		
22	17	80.0	35.5	21.8	9.8	6.0	438.4	270.3	4.5	20.2	2.15	4.6	7.4	54.0	73		
23	18	80.0	35.6	20.8	9.7	6.3	426.6	383.7	3.8	14.5	2.18	4.8	7.0	49.0	77		
24	19	29.1	46.0	35.4	26.0	18.9	1390.8	645.1	11.9	142.4	1.97	3.9	13.9	193.2	39		
25	20	54.5	21.5	13.8	9.1	7.0	1854.0	762.0	11.8	139.6	2.13	4.5	9.0	81.0	55		
26	21	35.0	63.5	43.0	38.3	27.3	947.0	437.1	9.9	97.4	1.88	3.5	16.4	267.3	35		
27	22	7.4	66.9	56.4	49.1	43.1	3290.4	1494.6	18.7	349.8	1.40	1.9	29.2	852.6	15		
28	23	13.8	76.4	64.6	38.1	19.1	2312.5	1705.5	13.0	169.7	1.72	3.0	77.2	297.5	15		
29	24	13.4	29.1	21.6	15.4	11.5	2764.7	811.1	24.1	580.8	1.76	3.1	16.3	265.7	19		
30	25	23.3	25.3	18.8	13.7	10.9	3009.6	849.1	25.7	661.5	1.79	3.2	16.3	264.1	20		
31	26	15.3	91.8	90.2	84.7	74.4	3250.9	1580.1	17.3	298.1	1.45	2.1	29.8	888.0	13		
32	27	10.0	99.8	99.6	75.2	71.3	3349.6	1717.9	16.4	269.9	1.43	2.1	28.4	803.7	17		
33	28	35.5	85.7	74.8	39.7	18.6	790.4	355.0	9.3	86.0	1.50	2.3	12.8	163.8	17		
34	29	20.6	68.6	49.7	31.1	20.3	1190.2	595.6	4.6	20.9	1.72	3.0	19.8	392.0	17		
35	30	3.0	75.6	62.2	45.1	33.7	4128.9	1603.2	24.2	586.4	1.43	2.0	17.0	289.0	17		
36	31	45.1	27.0	20.3	14.7	11.6	2499.1	345.8	13.3	177.1	2.02	4.1	14.4	207.4	17		
37	32	35.3	15.2	10.6	7.7	5.5	2436.0	1471.9	11.0	120.8	1.97	2.9	9.2	84.6	17		
38	33	41.5	55.7	40.4	23.4	14.6	441.0	400.0	1.0	1.0	1.71	2.9	18.5	342.3	17		
39	34	35.1	15.2	10.6	7.7	5.5	1197.3	474.9	12.8	164.1	2.05	4.2	8.5	71.3	17		
40	35	27.7	75.1	69.0	50.3	34.6	2035.3	730.1	18.1	374.4	1.45	2.1	25.2	635.0	17		

linear re DB (1) Data+Comp Reg+Comp 2 Data+Comp+NMIC Reg-Comp+NMIC2 CBR&4.75 CBR&2. CBR&0.425 CBR&0.075

Select Range
Select the Range
[C66:\$N\$203]
OK Cancel

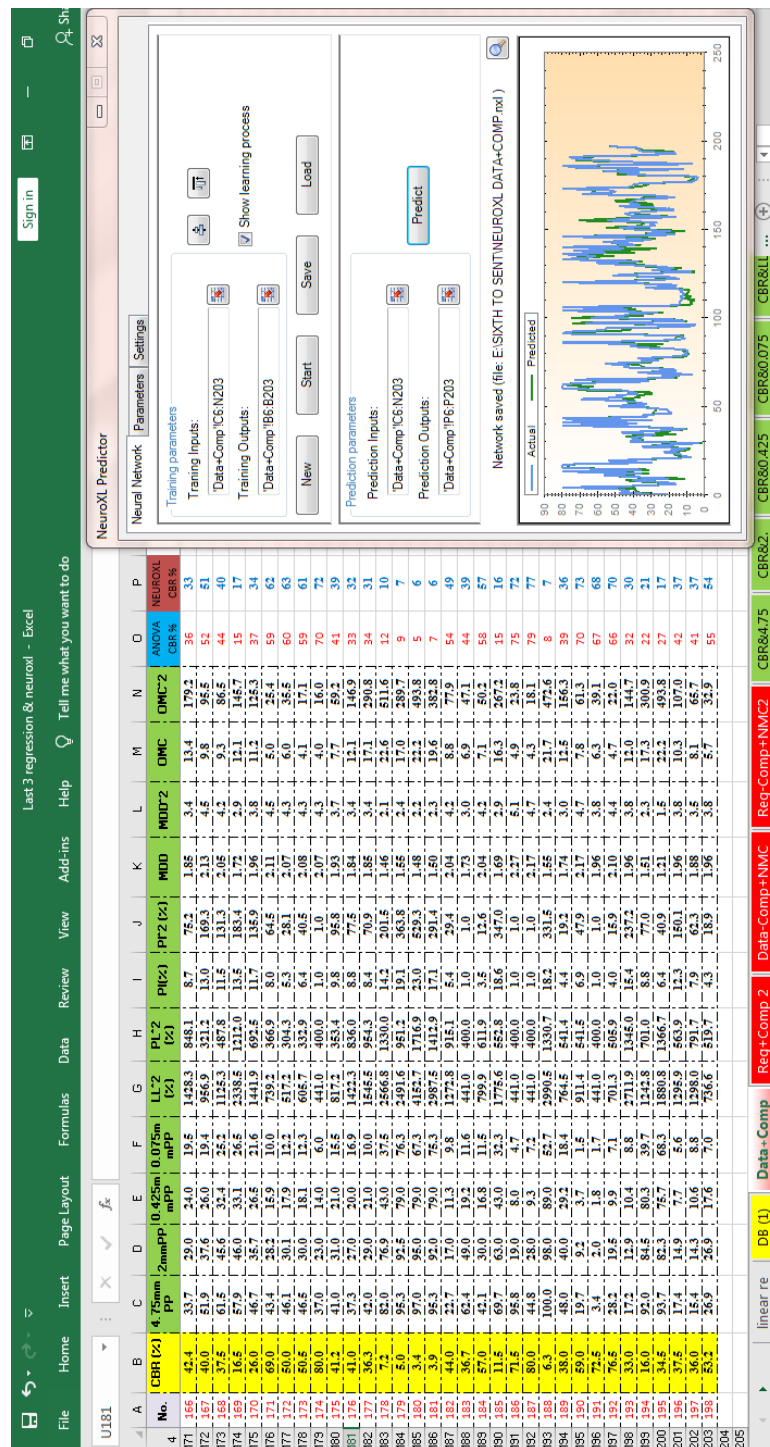
11. Eighth Step: Next, select an empty 60 rows cell in Excel for the predicted result CBR value "neuroxl Predictor CBR value" (60X1 arrays).(Option 1)

The screenshot shows an Excel spreadsheet with a data table. The columns are labeled as follows: CBR, No., 4.75mm, 0.425mm, 0.075mm, mPP, 2mmPP, LL, PI, PL, LL, PI, PL, LL, PI, PL, LL, PI, PL. The rows are numbered 1 to 40. A 'Select Range' dialog box is open, showing the range 'SP56:SP5203'. The dialog box has 'OK' and 'Cancel' buttons.

CBR	No.	4.75mm	0.425mm	0.075mm	mPP	2mmPP	LL	PI	PL	LL	PI	PL	LL	PI	PL	LL	PI	PL
1	20.5	35.0	28.6	20.5	16.7	200.0	595.4	23.6	557.0	182	3.3	157	246.5	21				
2	48.0	46.0	45.2	36.6	27.8	178.2	553.7	18.7	350.1	203	4.1	140	196.0	38				
3	42.2	79.0	78.7	74.5	66.5	1550.8	422.3	18.8	354.6	197	3.9	16.7	278.9	30				
4	48.5	27.0	18.4	12.9	10.7	163.6	726.8	13.5	181.4	205	4.2	9.3	86.5	45				
5	80.0	33.0	23.0	13.0	6.0	625.0	576.0	1.0	1.0	2.10	4.4	7.0	49.0	71				
6	34.0	27.0	19.6	9.6	3.0	1436.4	719.0	10.9	118.8	185	3.4	11.7	136.9	34				
7	16.0	67.0	52.0	47.1	15.0	240.6	718.2	2.1	501.8	172	2.9	24.0	229.0	17				
8	22.0	80.4	44.0	35.0	27.0	712.9	234.1	11.4	130.0	178	3.2	16.7	278.9	32				
9	41.0	43.5	35.0	26.0	20.0	1129.6	552.3	10.1	102.2	205	4.2	11.0	121.0	49				
10	20.3	45.9	39.4	31.5	23.4	3252.2	1093.8	26.3	691.8	171	2.9	19.5	380.3	15				
11	41.5	41.0	29.5	18.2	9.2	589.4	250.0	8.5	71.7	198	3.9	13.0	169.0	48				
12	57.0	26.6	17.3	11.2	8.7	921.0	384.0	10.8	115.6	206	4.2	9.2	83.7	52				
13	35.5	25.7	20.0	15.5	11.3	3476.4	1671.6	18.1	356.7	198	3.9	12.7	161.3	29				
14	80.0	27.0	32.2	22.1	15.2	625.0	576.0	1.0	1.0	2.13	4.5	6.3	39.7	73				
15	55.3	25.7	20.0	15.5	11.3	3476.4	1671.6	18.1	356.7	198	3.9	12.7	161.3	29				
16	80.0	30.7	19.3	9.9	7.0	458.1	317.8	3.6	12.8	219	4.8	7.3	52.6	79				
17	80.0	35.5	21.8	9.8	6.0	438.4	270.3	4.5	20.2	215	4.6	7.4	54.0	73				
18	80.0	35.6	20.8	9.7	6.3	426.6	283.7	3.8	14.5	218	4.8	7.0	49.0	77				
19	29.1	46.0	35.4	26.0	18.9	1390.8	643.1	11.9	142.4	197	3.9	13.9	193.2	39				
20	54.5	21.5	13.8	9.1	7.0	1554.0	763.0	11.8	139.6	213	4.5	9.0	81.0	55				
21	55.0	63.5	43.0	38.3	27.3	947.0	437.1	9.9	97.4	188	3.5	16.4	257.5	35				
22	74	66.9	56.4	49.1	43.1	3290.4	1494.6	18.7	349.8	140	1.9	29.2	852.6	15				
23	12.8	76.4	64.6	38.1	19.1	2231.5	1170.5	13.0	169.7	172	3.0	17.3	297.6	15				
24	13.4	29.1	21.6	15.4	11.5	2764.7	811.1	24.1	580.8	176	3.1	16.3	265.7	19				
25	23.3	25.3	18.8	13.7	10.9	3009.6	849.1	25.7	661.5	179	3.2	16.3	264.1	20				
26	15.3	91.8	90.2	84.7	74.4	3250.9	1580.1	17.3	298.1	145	2.1	29.8	888.0	13				
27	10.0	99.8	99.6	75.5	71.3	3349.6	1717.9	16.4	269.9	143	2.1	28.8	803.7	10				
28	25.5	85.7	74.8	39.7	18.6	790.4	355.0	9.5	86.0	150	2.5	14.8	163.8	22				
29	20.6	68.6	49.7	31.1	20.3	1190.2	895.6	4.6	20.9	172	3.0	19.8	592.0	31				
30	3.0	75.6	62.2	45.1	33.7	4128.9	1603.2	24.2	586.4	143	2.0	17.0	289.0	5				
31	42.1	27.0	20.3	14.7	11.6	2499.1	1345.8	13.3	177.1	202	4.1	14.4	207.4	38				
32	35.3	15.2	10.6	7.7	5.5	2436.0	1471.9	11.0	120.8	197	3.9	9.2	84.6	35				
33	41.5	55.7	40.4	23.4	14.6	441.0	400.0	1.0	1.0	1.71	2.9	18.5	342.3	47				
34	34.1	15.2	10.6	7.7	5.5	1197.3	474.9	14.8	164.1	205	4.2	8.5	71.1	50				
35	27.7	75.1	69.0	50.3	34.6	2035.3	730.1	18.1	377.4	145	2.1	25.2	635.0	17				

- [illegible]

13. Tenth Step: Save the whole neuroxl predictor process by clicking the "Save", command button.(Option 1)



For more information on NeuroXL Predictor, please visit the Website www.neuroxl.com



Appendix C. Table B. ANOVA multiple non-Linear regression analysis result (Option 1)

SUMMARY OUTPUT			
Regression Statistics			
Multiple R	0.92		
R Square	0.85		
Adjusted R Square	0.84		
Standard Error	7.31		
Observations	177		
ANOVA			
	Degree of Freedom	SS	MS
Regression	12	49542	4129
Residual	164	8767	53
Total	176	58309	
	Coefficients	Standard Error	P- value
Intercept	308.81	36.57	7E-14
$P_{4.75}$	-0.37	0.18	4E-02
P_2	0.34	0.27	2E-01
$P_{0.425}$	-0.01	0.19	1E+00
$P_{0.075}$	-0.03	0.11	8E-01
W_L^2	0.01	0.01	8E-02
W_P^2	-0.03	0.01	2E-02
I_p	-4.27	0.45	2E-16
I_p^2	0.06	0.02	5E-03
$\rho_{d \max}$	-329.99	44.24	1E-11
$\rho_{d \max}^2$	110.46	12.92	4E-14
W_{opt}	-0.23	0.63	7E-01
W_{opt}^2	0.02	0.02	2E-01

“ANOVA” represents Analysis of Variance, “SS” stands for Analysis of Variance Sum of Squares,

“MS” represents Analysis of Variance Mean Squares, $w_L^2 = w_L * w_L$, $w_P^2 = w_P * w_P$,

$\rho_{d \max}^2 = \rho_{d \max} * \rho_{d \max}$ and $W_{opt}^2 = W_{opt} * W_{opt}$.