Characterizing the Subgrade Soil Using Local Modifiers

I. Hafeez

Taxila Institute of Transportation Engineering, University of Engineering & Technology, Taxila
imran.hafeez@uettaxila.edu.pk

Abstract-Sub-grade layer perform important role in a pavement service life. Inadequate strength of subgrade soil may cause premature failure of pavement, especially if the pavement is subjected to heavy loading and the subgrade is under moist condition. Providing the thicker pavement over a weaker subgrade soil may increase per length cost. The study aims to improve the stiffness properties of three types of soils using the commonly available modifiers like lime, sand and marble (pulverized). Improvement in the soil with modifiers have been suggested based on triaxial and clegg impact hammer tests. Statistical analysis using the Local Linear Regression and Artificial Neural Networking techniques has been performed to ascertain the influence of modifiers on subgrade soil properties. The relationships developed were smooth and statistically efficient. It was evident from the test results that Local Linear Regression precisely assessed the relationship with significant values of statistical parameters as compared to other techniques. This study recommends using locally available modifiers to improve the soil properties and hence to reduce the overall pavement cost.

Keywords-Subgrade; Soil; Pavement; Stiffness; Clegg Impact Value

I. Introduction

A typical flexible pavement comprised of different layers of materials that transfers the wheel load to sub-grade layer through multi elastic layer system and derive support from the underlying sub-grade. Sub-grade layer supports the pavement as foundation [i]. The strength of sub-grade soil is defined as pavement ability to accommodate load induced compressive stresses and relatively lower compressive strains [ii]. However, in case of a weak sub-grade, soil properties may be improved. Soil stabilization techniques that may economize the highway projects by reducing the thicknesses of upper pavement layers. Pavement engineers considered increasing the strength and durability of pavement sub-grade soil by mixing a cementitious material during construction [iii]. Adding commonly available additives and modifiers is a common practice. Utilizing waste materials in soil stabilization save depleting landfill space [iv]. Stabilization of soils with conglomerate materials is another alternatives from economic point of view [v].

California Bearing Ratio (CBR) test was used in the past to estimate stiffness of pavement sub-grade soil. But with the advancement in research, the focus is shifted to more promising methods like using resilient modulus as it simulates with the in-situ conditions [vi]. The clegg impact value test has been used to augment the resilient modulus results in the research. In the past, extensive research was carried out to correlate CBR with MR; however, there has been a little work to establish relationship between the CIV and MR.

It has been established that CBR failed to assess actual dynamic loading on the pavement. Several research studies [vii-viii] presented similar findings. CBR has been used as a criterion for characterization of sub-grade for many years, but the advancement in research has shifted it towards the resilient modulus. Calculating the resilient modulus in the laboratory is a complex and time consuming procedure. Thus, many researcher studies have correlated the CBR and soil index properties to obtained resilient modulus. In this research, impact value and modified proctor test findings were correlated with the resilient modulus using linear and nonlinear regression techniques. Soil stabilization using different additives is a common practice in the world, which minimizes the wastage of the natural resources and contributes towards safer environment. Many researcher studies have suggested different materials like stone powder, lime, marble, marble slurry and Portland cement for improvement of soil. The effect of nontraditional additives on engineering characteristics of Laterite soil. Microstructural characteristics were also considered parallel in this study [ix].

Reference [x] suggested techniques to improve road subgrade soils using marble dust. The effect of modifier was studied red tropical soils. [xi] Proposed a method to improve sub grade for rural road soils using rice husk and lime. [xii] Further investigated the effect of marble dust and rice husk on strength and durability of expansive soil. [xiii] Utilized the stabilized dune sand in road engineering. [xiv] Studied the improvement of calcareous marl using lime and cement. The CBR and clegg Impact Hammer tests were performed for strength evaluation. According to this study cement modified soils yielded more strength and durability than lime treated soils. [xv] Stabilized the weak tropical organic soil by using cement sodium silicate grout. [xvi] Studied the utilization of marble slurry to enhance soil properties and protect environment. [xvii] Studied the effect of lime on the soil improvement and recommended an optimum percentage for soil improvement. [xviii] Improved the weak peat ground by using cement and silica fume treated columns. [xix] Reviewed the characterization of sub-grade material in ME-Design Guide 2002 and applied it to Minnesota fine-grained soils. [xx] Addressed calibration of laboratory resilient modulus measurements using field data of modulus of elasticity for sub-grade layer determined through plate load test. [xxi] Proposed resilient modulus of sub grade as an important parameter in the pavement design. [xxii] Studied the use of fly ash (FA) or ground granulated blast slag (GGBS) and reactive lime blends for cement-stabilized Nanjing clay, comparing them with Portland cement (PC) for enhanced technical performance. [xiii] Studied the effect of lime sludge on strength and compaction characteristics of soil. Several research studies in the past suggested different correlations among different soil properties. Table I shows a brief history of the models developed to correlate the resilient modulus with CBR, index properties and material properties. Table I discusses some of the earlier studies to predict resilient modulus from other parameters including soil index properties.

TABLE I
HISTORY OF MODEL DEVELOPMENT ON RESILIENT MODULUS

Author	Equation	Variables
Uzan (1985)	$M_R = a(3p_{max})^b$	a, b= parameter showing material properties P_{max}= maximum atm. pressure
Elhannani (1991)	$\varepsilon_v = pa^{(1-b)}p^b[(1/a)-((1-b)/6c)*(q/p)2 - (b/d)(q/p)]$ $\varepsilon_s = pa^{(1-b)}p^b [(1/3c)*(q/p) - 1/d]$	Where a, c, d are the constant parameters with stress units
Boateng-Poku and Drumm (1990)	$M_R = (A + B*\sigma_d) / \sigma_d$	A, B= material constants
Uzan (1992)	$M_R = k_1 P_a (\theta/P_a)^{k2} * (\sigma_d / P_a)^{k3}$	k_1, k_2, k_3 are considered as parameters showing material properties
Matthew Witczak (2003)	$M_R = k_1 P_a \left(\frac{\sigma_b}{P_a}\right)^{k_2} \left(\frac{\tau_{oct}}{P_a}+1\right)^{k_3}$	Where, σ_b is the bulk stress and τ_{oct} is the octahedral stress on sample

Providing a thicker pavement structure over a weaker subgrade soil may leads premature pavement failure, especially when the soil comes in contact with water. Also, it may increase the unit length cost of the pavement. It would be more viable way to improve weaker subgrade soils and provide relatively thinner pavement section. Present study focused on sub-grade soil improvement using different modifiers.

The results of the improved soil were then compared with the stiffness of the granular (A-2-4) and silt clayey (A-4) soil, which are generally considered appropriate for the sub-grade layer of a pavement. A weaker soil (A-6 soil as per AASHTO Soil Classification System) was chosen in this study, which is commonly available in most of part of the country. Commonly available cheap modifiers including marble waste, lime and sand in six different percentages each for improving the stiffness properties of the soil have been used.

The improvement in sub-grade strength were evaluated by different methods including CBR and M_R value. Triaxial test and clegg Impact Hammer test have been conducted to determine resilient modulus (M_R) and clegg impact value (CIV), respectively. Also, relationship has been developed between the laboratory and field data. Resilient modulus of sub-grade soil is an important parameter that has been used in the mechanistic-empirical pavement design methodology. It characterizes stress-strain behavior of sub-grades subjected to repeated traffic loadings [ii, iv]. Highway design agencies suggested relatively better soil in the pavement design methodology for sub-grade layers. Present study predicts resilient modulus from Triaxial and clegg impact testing data. Such relationship has been statistically analyzed using different techniques.

II. OBJECTIVES AND RESEARCH METHODOLOGY

Followings are the objectives of this research study; to improve the stiffness properties of weak sub grade soil by using different modifiers by optimizing percentage of each modifier in the soils. Evaluating the effect of modification on the resilient modulus and clegg impact values of soil and proposing a regression model within an acceptable significance level. To correlate resilient modulus with clegg impact value and assessing the sensitivity of relationship using different approaches artificial neural networking techniques.

A two phase study was planned to accomplish the study objectives. Phase I comprised of laboratory testing using the soil classification. Modified proctor test was run to determine the optimum moisture content and maximum dry density of different soils and their mixtures with different types of modifiers. Triaxial test for resilient modulus of weak sub-grade soil and clegg impact value to evaluate the stiffness behavior of the soil were utilized.

Phase II involved statistical analysis to predict the resilient modulus from different test results primarily; optimum moisture content, maximum dry density and clegg impact value. Local linear regression and artificial neural networking techniques were used for statistical analysis. Fig. 1 illustrates the methodology adopted for the research study.

Three soil types were selected in this research study including granular, silty and clayey soils. These soils covers the major area of the whole country and true representative of typical available soil for subgrade formation. Soil and modifiers samples were collected from the local areas near the testing laboratory. Classification of different soils was performed at initial.

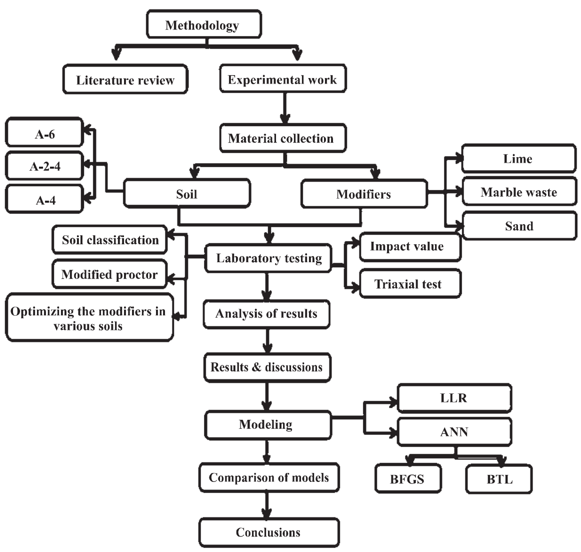

Fig. 1. Scope and methodology of the work

Soil index properties like liquid limit, plastic limit, difference of liquid and plastic limit (Plasticity index) and grain size distribution through sieve analysis and hydrometer analysis were determined. Specific gravity test were also performed on all soil samples. The test result for soil index properties have been shown in Table II.

TABLE II
SOIL INDEX PROPERTIES

Liquid Limit (%)	Plasticity Index (%)	Passing # 200 sieve	Passing # 40 sieve	Clay content (%)	Silt Content (%)	AASHTO Classification
20.5	1.0	28.0	N/A	3.2	25.4	A-2-4
24.4	4.9	42.0	N/A	9.0	33.1	A-4
37.2	13.1	96.0	99	19.3	78.7	A-6

Different percentages of modifiers like lime; marble (pulverized) and sand were mixed in the soil to improve the physical and mechanical properties. The modified proctor test was performed on all soil samples mixed with six different percentages of each of the three modifiers to get the maximum dry density and optimum moisture content. A total of 54 modified proctor test were performed on the selected soil samples.

An optimized value of different modifiers for different soils were determined using the typical plots between the moisture-density relationships. It was observed that maximum dry density of soil samples decreases with an increase in lime and marble percentages while, it increases with an increase in sand percentage. Similarly, it was also observed that the moisture content decreases with an increase in sand and marble percentage, while it increases when lime percentage increased.

Triaxial test was performed using NU-14 in replicates on soil samples in accordance with AASHTO T 307 [xiv]. The specimens of 100 mm diameter and 200 mm height were fabricated using the superpave gyratory molds at an optimum moisture content. The loading sequence involved 500 conditioning repetitions and 1500 load repetitions at different stress levels. A load stress with a rest period of 0.9 sec and load period of 0.1 sec was applied and the results were recorded using two linear variable differential transformers (LVDTs). The clegg impact test was performed using clegg impact hammer in accordance with ASTM D 5874 [xv]. The molds for impact value test were prepared in a CBR mold having 200mmdiameter. Tests were performed in replicates and the data obtained from different test was screened and results with higher standard deviation were discarded.

III. RESULTS AND DISCUSSION

Soil samples prepared at an optimum moisture content at each modifier percentage were tested at both triaxial machine and clegg impact tester. Results obtained from a triaxial test have been shown in Fig. 2.

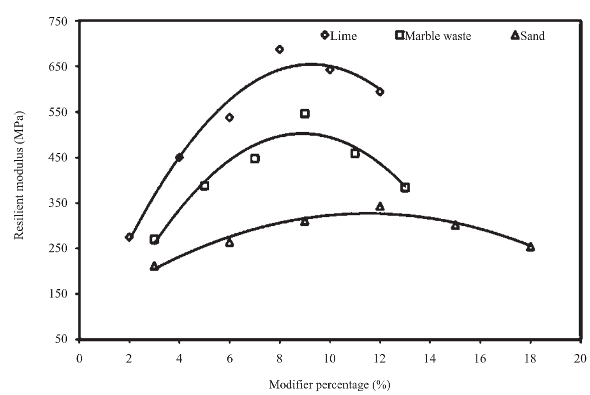

Fig. 2. Influence of modifier percentage on M_R Value

It may be noted from the Fig. II that resilient modulus value increases with an increase in the modifier percentage, but up to a certain limit. A further increase in modifiers percentage decreases the resilient modulus value. The peak value yields an optimum percentage of a modifier against for different soil types. Fig. 3 shows the results obtained from a clegg impact test.

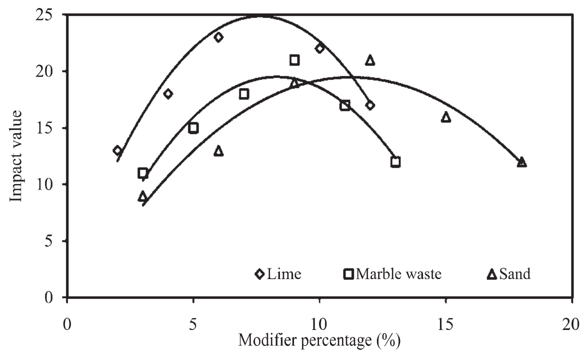

Fig. 3. Influence of modifier percentage on clegg impact value

The trends obtained from a clegg impact test were in line with the resilient modulus test. Fig. 4 shows optimum values of both moisture content and modifier percentages. Statistical modeling was then performed on the testing data for augmenting the test results.

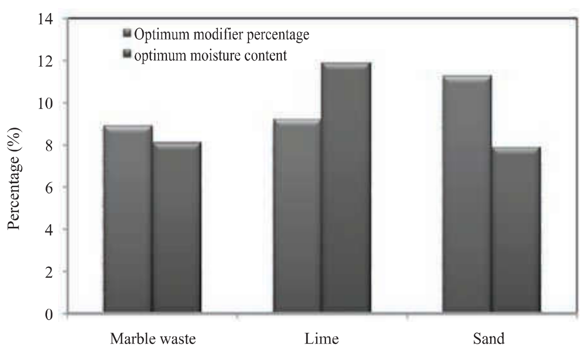

Fig. 4. Optimum modifier and moisture content values

Local linear regression and Artificial Neural Networking (ANN) techniques were adopted for modeling the test results. Both triaxial and clegg impact tests data was iterated using the statistical package and Following relationship was found between the clegg impact value and resilient modulus test values.

$$M_R = 0.62(CIV) + 182.37 \quad (1)$$

A coefficient of determination (R^2) of 0.70 was found for the equation I. The frequency distribution curves indicates that about 70% of the model computed values remains near to the estimated median value.

B. Artificial Neural Networks (ANN)

Artificial Neural Network is a computational technique to analyze the test data like neuron system in the brain. It processes the data using testing and training algorithms and develops a link between past and future events [xxvi]. The training part, also called as learning part comprises of supervised and unsupervised. In the artificial neuron model, *n* input signals $_iX$ are being sent through links, which are further multiplied with their corresponding synoptic weights, $_iW$, *i = 1, 2, 3, ..., n.* A linear combiner added up all the signals through this link like a junction. This combiner is therefore called as activation function *f (.)*. In this algorithm, the main purpose of combined is to limit the amplitude of the output and gives its nonlinearity. Mathematically; this function can be shown as [xxvii].

$$\sigma = \sum_{i-1}^{n} X_i W_i \quad (2)$$

There are several techniques to interlink different neurons for the performance of a specific task. A single neuron cannot complete a task, rather interlinked neurons, mostly in shape of layers work together to complete a computational task. Such layers are usually called as input layer, intermediate layer and output layer [xxviii]. An important aspect of model development using ANNs is training (learning) phase.

Typical ANN algorithms are Back propagation (BP), conjugate gradient (CG), Broyden Fletcher Goldfarb Shanno (BFGS), quasi Newton and Levenberg-Marquardt (LM). The suitability of each algorithm to fit the testing data depends purely on the nature of data. The conjugate gradient algorithm works on the concept of conjugate directions using the following relationship;

$$g_{j+1} = \nabla E(w_j + a_j d_j) = 0 \quad (3)$$

Where α_j is calculated using a line search algorithm technique, H = Hessian matrix evaluated at point w_{j+1}, d_{j+1} = new direction, d_j = Existing search direction. Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm is a quasi-newton method that is used to find out either zeroes or local maxima and minima of a function using the following relationship;

$$w_{j+1} = w_j - \alpha_j G_j g_j \quad (4)$$

Where α_j = line search constant, G_j = inverse Hessian matrix, g_j = gradient vectors, w_j = estimated weight, w_{j+1} = upgraded weight.

Present study aims at predicting the resilient modulus of soil from engineering characteristics of soil using different ANN techniques. Data was trained in two hidden layers and simple trial and error method was used to define number of nodes per each layer. The basic aim of selecting double hidden layer process was to avoid complexity in the results. Under such situation, ANN model might be unable to predict the desired results for a complex nonlinear conditions [xxix]. A local linear regression has also been utilized to confirm the results and to assess the variability in the computed results.

C. ANN based modeling

The normalization process, by scaling between 0 and 1, has been adopted in order to make all the variables dimensionless. The calculation of normalized values was performed using following standard formula:

$$(Normalized)\ P_i = \frac{P_i - P_{min}}{P_{max} - P_{min}} \quad (5)$$

Where;

P_i = ith value of variable P

P_{min} = the minimum value for variable P

P_{max} = the maximum value for variable P

Then, Gamma test was adopted to determine the best input combinations. Gamma test is a novel mathematical tool which is performed to check the noise in the data and also to choose the best combinations between the input parameters. The best combination of input parameters is prerequisite for a smooth and efficient model. The test is capable of calculating the variance of noise, Gamma Statistics or Best Mean Square Error, on our desired output.

Gamma test separates x/y relationship into smooth and noisy. Such process is known as disintegration the relationship between x and y, while the initial data set. $\{(x_i, y_i), 1 \leq i \leq M\}$ defines the relationship between both the variables. Following relationship shows *f* as a part of smooth and *r* as a part of noise [xxvii].

$$Y = f(x) + r \quad (6)$$

The function *f* is known as unknown function and can be shown with a constant bias in case of zero noise (*r*) value. Even with an unknown value, noise can be calculated using this tool. With an increase in the test data size, the variance of a noise also increases and a stage reached when the gamma value becomes equal to an asymptotic value.

Table III describes the variables which are involved in model development. Tests to find out these variables and observation lengths are also mentioned. Output and input variables were selected for model development.

TABLE III
VARIABLES INVOLVED IN STATISTICAL MODELING

Dataset	Test performed	Status	Observation Length
Resilient modulus	Triaxial	Output	18
Impact value	Impact value test	Input	
Optimum moisture content	Modified proctor		
Maximum dry density			

Table IV explains the different experiments carried out to find gamma statistic by performing Gamma test in Win Gamma environment.

TABLE IV
SELECTION OF THE BEST SUITED EXPERIMENTS FOR MODEL FORMATION

Experiment No.	Mask	Gamma Statistics	Training Length	Testing Length
1	111	0.0179	10	8
2	011	0.0092	10	8
3	101	0.0201	10	8
4	110	0.0199	10	8
5	100	0.0269	10	8
6	010	0.0161	10	8
7	001	0.0184	10	8

It is obvious from the values that experiment no. 2 (mask 011) outperformed the other experiments with a higher degree of accuracy. Experiments 6 and 1 were also selected due to their higher accuracy as compared to the rest of the combinations for model development. Hit and trial method was used for choosing the best possible combination of training and testing lengths.

Table V explains the statistical parameters like R^2, mean bias error (MBE) and root mean square error (RMSE) calculated during the modeling for evaluation of the models developed. The bold values in the table represent the best values in each column e.g. BFGS model 3 would be considered the best of all the above models with respect to RMSE in training phase with the least value of 26.899. The best model for each technique is declared based on the more accurate statistical parameters.

TABLE V
STATISTICAL PARAMETERS FOR THE DEVELOPED MODELS

Technique	Model No	R-square	MBE	RMSE	R-square	MBE	RMSE
LLR	1	0.921	0	40.09	0.965	-91.09	94.87
	2	0.641	0	85.18	0.657	-63.93	117.9
	3	0.923	0	39.35	0.904	-96.1	103.1
BFGS	1	0.961	1.42	28.26	0.893	-94.7	102.6
	2	0.729	-2.29	75.28	0.631	-65.06	120.96
	3	0.965	4.02	26.90	0.747	-90.42	117.62
BTL	1	0.910	-1.81	42.65	0.841	-124.7	134.8
	2	0.824	-1.71	59.86	0.599	-51.86	141.9
	3	0.960	-0.49	28.38	0.643	-106.3	130.6

D. Broyden Fletcher Goldfrab Shanno Neural Networking

The prediction of resilient modulus based on BFGS models was also satisfactory with the second model being the least accurate based on parameters. Of the other two, model one was selected as the best model as it had the least mean bias error (1.422) in training and negative MBE in testing phase. R-square was highest (0.893) in testing phase and almost equal to highest (0.961) in training. RMSE value was least in training as compared to a bit high value in testing. Fig. 5 and 6 represents the predicted resilient modulus using BFGS technique and the difference between the actual and predicted values for the observation length.

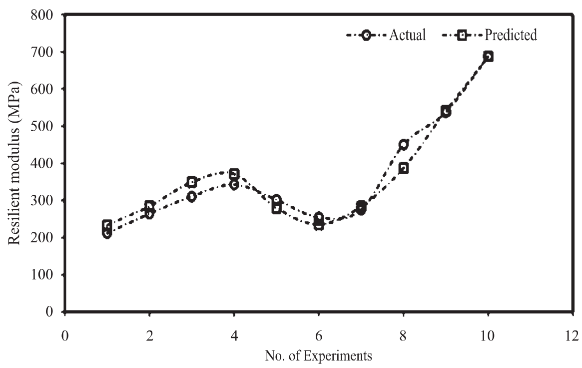

Fig. 5. Scatter and time series plots for training series data for BFGS

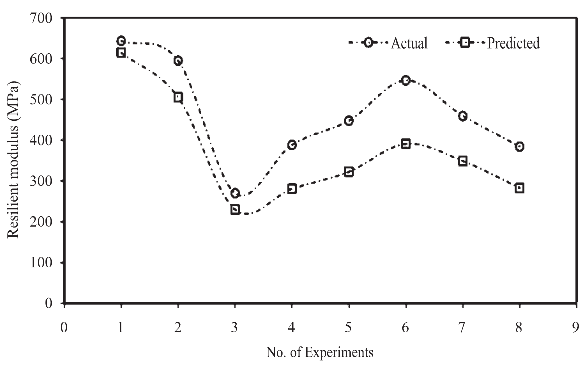

Fig. 6. Scatter and time series plots for testin series for BFGS

E. Backpropagation Two Layer Neural Networking

The third technique used in model development was back propagation two layer neural network. Similar to first two techniques, three models were developed for three combinations of inputs already specified. Of these three, most suitable model (R^2 of 0.96) was selected and drawn here based on statistical parameters. Other parameters like MBE and RMSE among different models were also compared. The model yielding higher R^2 value and lower RMSE and MBE was selected for BTL techniques. Fig. 7 and 8 show the scatter plot relationship between actual and predicted resilient modulus values for first model of BTL.

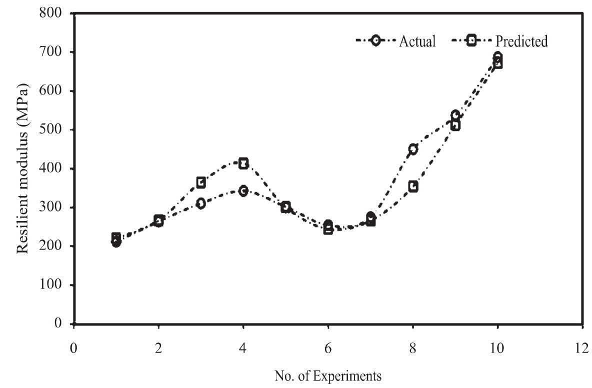

Fig. 7. Scatter and time series plots for training series data for BTL

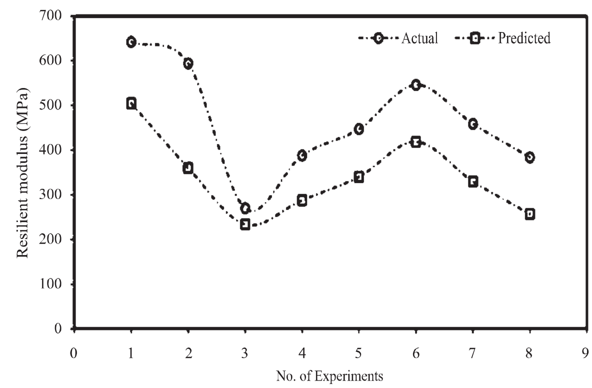

Fig. 8. scatter and time series plots for testing series data for BTL

This model also shows the relation between the actual and predicted values of resilient modulus for the observation lengths. It is obvious from the above discussion and statistical data that Local Linear Regression was more precise as compared BFGS and BTL Neural Networking techniques. The models developed using LLR technique for resilient modulus prediction are statistically more reliable and predicted values are more accurate as compared the models developed by using the other techniques.

E. Local Linear Regression (LLR)

Local linear regression is one of the reliable techniques that assess the relationship among different factors with relatively higher degree of accuracy. That is why this technique has widely been used for low dimensional forecasting. Solution of a linear matrix as basic requirement of the model can be obtained using p_{max} points under the influence of statistics. For a given neighborhood, following relationship is commonly used to solve a linear matrix;

$$Xm = y \qquad (7)$$

Where, X, m and y are *d* matrix, column vector of parameters and column vector of length p_{max}, respectively. The X is always in d dimension and is a d matrix of p_{max} input points, and $xi(1 \leq i \leq pmax)$ are the nearest neighbor points. These parameters are determined to provide the optimal mapping from X to y so that:

$$\begin{bmatrix} x_{11} & x_{12} & x_{13} & \cdots & x_{1d} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2d} \\ x_{31} & x_{32} & x_{33} & \cdots & x_{3d} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{xpmax1} & x_{xpmax2} & x_{xpmax3} & \cdots & x_{xpmaxd} \end{bmatrix} \begin{bmatrix} m_1 \\ m_2 \\ m_3 \\ \vdots \\ m_d \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_{max} \end{bmatrix} \quad (6)$$

The rank r of a matrix X shows its number of linearly independent rows. This number of rank is representative of existence or uniqueness of the solution for m. Assuming that matrix X is a nonsingular square matrix, following relationship works for the solution;

$$m = X^{-1}y \quad (8)$$

in case of non-square and non-singular X value, following relationship can be used to find a vector m;

$$|Xm - y|2 \quad (9)$$

It may be observed from Table V that the first model by using LLR techniques is the most reliable based on the statistical parameters out of three models. Mean biased error was zero in testing for all the models of LLR, which clearly shows the zero systematic error; whereas it was negative (-91.091) for testing, showing the under estimation of trends of the model. Standard efficiency, R^2 value was also highest for first model in testing (0.97) and it was almost equal to the highest in training phase (0.92) of the same model. First model also has the least value of RMSE in testing and almost equal to the lowest in training. From the above discussion, it was crystal clear that for local linear regression, first model was the most smooth and efficient one. Fig. 9 and 10 show the comparison between the actual and predicted resilient modulus by the first model in both training as well as testing.

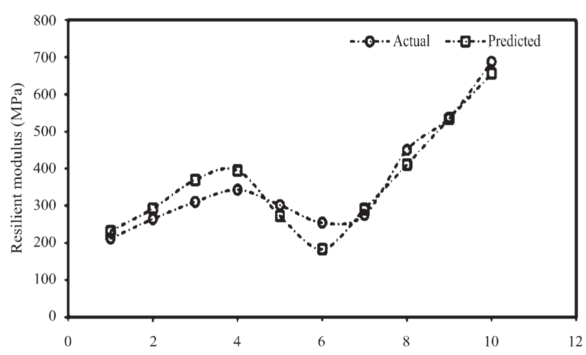

Fig. 9. Scatter and time series plots for training series data for LLR

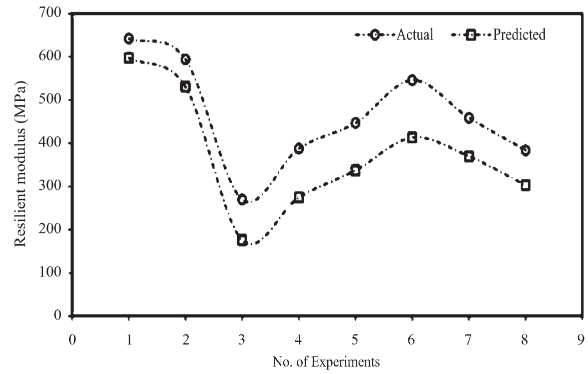

Fig. 10. Scatter and time series plots for testing series data for LLR

The study thus recommends utilizing the local available modifiers in the weak subgrade soil to improve the stiffness properties and to adopt statistical methods and artificial neural network approach for the selection of appropriate relationship. The effect of modifiers was significant in case of clayey soils rather granular soils. The study thus recommends utilizing the modifiers for the improvement of clayey soils. An improved subgrade can reduce the pavement structural thickness for the same traffic load and hence the construction cost

IV. ACKNOWLEDGMENT

Author gratefully acknowledged the support of Taxila Institute of Transportation Engineering, University of Engineering and Technology, Taxila in the provision of financial assistance and laboratory testing facilities. Author also acknowledged the technical assistantship of Engineer Imtiaz Ahmad.

V. CONCLUSION

This research study was initiated with an objective of improving the weak sub-grade soil by adding different modifiers like lime, marble and sand. The modifiers were used in six different percentages of each. Soil classification, modified proctor, triaxial and clegg impact value tests were performed to achieve the study objectives. Further, statistical analysis was performed to predict the resilient modulus from dry density, moisture content and impact value using local linear regression and artificial neural networking techniques. The following outcomes were achieved by the research study;

A significant improvement in stiffness properties in all the soils was observed during the study. All the three modifiers improved the stiffness of the soils. But it was observed that the lime had the most significant effect to improve the stiffness of the soil samples. It was also observed that the clayey soil showed improvement in stiffness properties than the other soils used in the study.

It has been observed that an increase in lime and marble waste percentage causes a decrease in the dry density of the soil samples, where as an increase in percentage of sand has improved the dry density of the soils. Similarly, percentage increment in lime has increased the optimum moisture content of the samples; whereas increments in percentage of sand and marble waste has decreased the optimum moisture content. The basic reason behind this increase in moisture content for lime is attributed to its fineness.

The significant relationships were developed to predict the resilient modulus by dry density, moisture content and impact value by using local linear regression and artificial neural networking techniques including BFGS and BTL techniques.

All the prediction techniques predict the resilient modulus from other test parameters with a reasonable accuracy, but Local linear regression (LLR) better predict the results.

REFERENCES

[I] C. Zhou., B. Haung, E. Drumm, X. Shu, Q. Dong, and S. Udeh, 2013. Seasonal Resilient Modulus Inputs for Tennessee Soils and Their Effects on Asphalt Pavement Performance. Transportation Research Board, Washington, D. C. TRB record NO. 13-4351. 2013.

[ii] D. Kim, J.R. Kim, Resilient Behavior of Compacted Sub-Grade Soils under the Repeated Triaxial Test. Construction and Building Materials. 21(7):1470–1479, 2007.

[iii] J. S. Trivedia, S. Nair, and C. Iyyunni, Optimum Utilization of Fly Ash for Stabilization of Sub-grade Soil using Genetic Algorithm. Procedia Engg. 2013, 51:250–258, doi: 10.1016/j.proeng. 2013.01.034

[iv] A. Fauzia, W.M.N.W Abdul Rahman, and Z. Jauhari, Utilization Waste Material as Stabilizer on Kuantan Clayey Soil Stabilization, Procedia Engg. 53:42–47, 2013.

[v] D. C. Fresno, D.M. Quesada, A. V. Zamanillo, and M. A. Calzada-Pérez, Lime Stabilization of bentonite sludge from tunnel boring. App Clay Sci. 51(3):250–257, 2011.

[vi] P. Solanki, M. Zaman, K. K. Muraleetharan, and D. Timm, Evaluation of Resilient Moduli Of Pavement Layers at an Instrumented Section on I-35 in Oklahoma. Journal of Road Material and Pavement Design. Special Issue on ICAM, 167–188, 2009.

[vii] N. Al-Joulani,. Effect of stone powder and lime on strength, compaction and cbr properties of fine soils. Jordan Journal of Civil Engg. 6(1), 2012.

[viii] V. Agrawal, M. Gupta, Expansive Soil Stabilization Using Marble Dust. International Journal of Earth Science and Engg. 4(6):59–62, 2011.

[ix] H. Moayedi, K. A. Kassim, S. Kazemian, M. Raftari, and M. Mokhberi, Improvement of Peat Using Portland Cement and Electrokinetic Injection Technique. Arabian Journal of Sciences and Engg., 39:6851–6862, 2014.

[x] A. Marto, N. Latifi, A. Eisazadeh,. Effect of Non-Traditional Additives on Engineering and Microstructural Characteristics of Laterite Soil. Arabian Journal of Sciences and Engg., 39(1):6949–6958, 2014.

[xi] C. O. Okagbue, and T. U. S. Onyeobi, Potential of marble dust to stabilize red tropical soils for road construction. Engineering Geology. 53 (4):371–380, 1999.

[xii] S. Biswas, A. Biswas, and A. Dighade, Utilization of Rice Husk with Lime in Sub-grade Soil for a Rural Road. IJCA Proceedings on International Conference on Emerging Frontiers in Technology for Rural Area. (4):1-3, 2012.

[xiii] A. K. Sabat, and R. P. Nanda, Effect of Marble Dust on Strength and Durability of Rice husk ash stabilised expansive soil. International Journal of Civil and Structural Engg. 1(4):939–948, 2011.

[xiv] AASHTO T307: "Standard method of test for determing the resilient modulus of soils and aggregate materials." American Association of State Highway and Transportation Officials, Washington, D.C, (2009)

[xv] ASTM D5874 Standard test methods for determination of the impact value (IV) of a soil." American Society for Testing Materials. Washington, D. C, (2009)

[xvi] A. Ghrieb, R. Mitiche-Kettab, A. Bali, Stabilization and Utilization of Dune Sand in Road Engineering. Arabian Journal of Sciences and Engg., 39:1517–1529, 2014.

[xvii] O. S. B. Al-Amoudi, K. Khan, N.S. Al-Kahtani, Stabilization of a Saudi Calcareous Marl Soil. Construction and Building Materials. 24(10):1848-1854, 2010.

[xviii] B. Kalantari, A. Prasad, B. B. K. Huat, Cement and Silica Fume Treated Columns to Improve Peat Ground. Arabian Journal of Sciences and Engg., 38:805–816, 2013.

[xix] V. Amit, and R. R. Singh, Utilization of Marble Slurry to Enhance Soil Properties and Protect Environment. Journal of Environment and Research Development 7(4A):1479–1483, 2013.

[xx] J. Singh, A. Kumar, R. Jain, N. K Khullar, Effect of Lime on Properties of Soil. 12th International Conference of International Association for Computer Methods and Advances in Geomechanics (IACMAG), Goa, India 1-6 October, 2008.

[xxi] S. Kazemian, A. Prasad, B. B. K. Huat, V. Ghiasi, and S. Ghareh, Effects of cement–sodium silicate system grout on tropical organic soils. Arabian Journal of Sciences and Engg., 37:2137–2148, 2012.

[xxii] L. Khazanvoich, C. Celauro, B. Chadbourn, J. Zollars, and S. Dai, Evaluation of sub-grade resilient modulus predictive model for use in mechanistic-empirical pavement design guide. J Trans Research Board, Washington D.C., TRR No. 1947, 155-166, 2006.

[xxiii] W. V. Ping, L. Ge, Field verification of laboratory resilient modulus measurements on sub-grade soils. Journal of Transportation Research Board. 1577: 53-61, 1997.

[xxiv] A. M. Rahim, Sub-grade soil index properties to estimate Resilient Modulus for pavement design. International Journal of Pavement Engg. 6(3):163–169, 2005.

[xxv] Y. Chao, L. Songyu, and D. Yongfeng, Experimental research for the application of mining waste in the trench cutting remixing deep wall method. Advances in Materials Science and Engineering.doi.org/10.1155/2015/202848, 2015.

[xxvi] N. R. Chandak, and A. Babu, Effect of Lime Sludge on Strength and Compaction of Soil. Journal of Civil Engg. Research, 2015. 5(1):18–20, DOI:10.5923/J.JCE.20150501.03

[xxvii] M. A. Shamim, R. Remesan, D. Han, and A. R. Ghumman, Solar Radiation Estimation in ungauged Catchments. Proc ICE-Water Management. 163:349–359, 2010.

[xxviii] S. Agalbjorn, N. Koncar, and A. J. Jones, A note on the gamma test. Neural Computing and Applications. 5: 131–133, 1997.

[xxix] R. Remesan, M. A. Shamim, and D. Han, Model data selection using gamma test for daily solar radiation estimation. Hydrological processes 22:4301–4309, 2008.

[xxx] A. J. Jones, New tools in non-linear modelling and prediction" Computational Management Science 1:109–149, 2004.