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# Artificial Neural Network for prediction of Shear Strength of Soil

Rahul R. Wankhade
*Department of Civil Engineering*
*Prof Ram Meghe College of Engineering and Management*
Amravati, India
rahul.r.wankhade@gmail.com

Dr. P. V. Durge
Departmet of Civil Engineering
Mauli College of Engineering,Shegao, India
pvdurge@gmail.com

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**Abstract**

Shear Strength determination demands extensive skilled experimental execution in addition to experienced judgment and sophisticated equipment's. Computational methods can be of great help and efficient in arriving at shear strength using relatively less demanding basic index properties of soil. The methods such as regression analysis, differential equations, probabilistic equations, analysis of variance, artificial and genetic neural networks are being extensively explored by researchers to develop prediction model for shear potency of earth. Exploring shear potency calculation effectiveness of synthetic neural network (ANNs) and multivariate deterioration (MR) is the key aim of this study. 2 Different ANNs counting multistoried perceptron (MLP) and spiral establishment reason (RBF) , and MR just as various variate against straight compounding (MNR) just as multivariate direct relapse (MLR) , contain is worn. Five not at all like ANN and MR models including a diversity of combination of soil corporeal properties, i.e.: sand content, silt content, clay content, smoothness file (PI) and compactness (ρ) contain too worn for assessment of forecast precision on together ANNs and ML steps. A comprehensive set of data obtained from sites across India. In count to association coefficient, origin denote square fault (RMSE), mean complete fault (MAE) and t-test are worn for assessment of forecast exactness on together ANNs with ML method. According to this analysis clay content and silt content are the most significant variables contributing in estimation of shear strength. The aftereffects of this examination demonstrated to MLP-ANN represents preferable execution slightly over RBF-ANN. These outcomes likewise demonstrated over the Liebenberg-Marquardt knowledge rule and sigmoid initiation work were seen as fitting for this issue. Moreover, MLR depicts better execution in forecast cut off quality characteristics than MNR models.

***Keywords:** Shear Strength, Multivariate Regression, Artificial Neural Network*

## I. INTRODUCTION

Skill of the Geotechnical Engineer lies in determining the ground condition at the site and modeling it to use for suitable design calculations. Thus involves planning, implementing and interpreting geotechnical investigation data. These demands high technicality and experienced Engineering judgment. One of the key functions is to decide shear power of soil as it governs stability and economic feasibility of the structures.

Shear strength is the inherent property of soil that can offers resistance against failure and sliding along a plane in the soil medium, It is generally considered to be dependent on the cohesion and inter-granular friction between the soil particles. Shear strength can be defined as "the internal resistance per unit area that the soil mass resist". The shear strength of soil is given by Coulomb's equation and its determination is considered to be most complex, particularly because of the difficulties in obtaining undisturbed soil sample and high skill requirements for laboratory determination by triaxial test. Thus encouraging use of alternative techniques, such as using correlation with basic index properties, relying on the experience and computational methods for modeling soil properties.



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More reliable models to predict shear strength as realistic as possible is highly preferable to avoid cumbersome and tedious laboratory work. Computational methods are being consistently adopted by researcher in many engineering specialization. The methods such as regression analysis, ANN, SVM are the commonly adopted in solving critical Geotechnical problems. Review of literature reveals that these methods are widely applicable for prediction of shear strength parameters, cohesion and angle of internal friction. Determination of shear strength in easy and economical ways will be of considerable advantage to Geotechnical Engineering. Computation methods have acknowledged substantial growth in current years, with a broad variety of application in the meadow of Geotechnics.

. Regression is one of the most popular statistical method used for empirical deterministic modeling. The most common is ordinary linear regression (with one or several variables) and non-linear regression modeling such as Polynomial, Exponential and Logistical. Advance developments includes generalized linear models, including Youngjo Lee and John Nelder's hierarchical generalized linear models [1]. D. E. Ewa J. G. Egbe and O.O.Tumenayo (2017) developed an multi-linear regression model that relates CBR to other soil parameters [2]. Andrea Delisio Jamal Rostami, Christian Moormann (2016) performed single and multiple regression analysis between TBM performance and geo mechanical parameters in data base for resolve of regression coefficients of association among unlike geographical and geo mechanical characteristics and field penetration index (FPI)[3]. Bindhu Lal Sushama Kiran (2016) performed linear and anti-linear least square regression (LLSR and NLSR) analysis on the dataset obtained from Bihar to test efficiency of an proposed ANNs model [4]. Mayorga Jaime Hossne Garcia and Fernan Andrdes (2012) developed regression equation between ideal compaction wetness (woptimal) and ideal shear quality ( optimal) and ideal mass thickness

In a circumstance where more than one autonomous factor (variable) influences the result of a procedure, a numerous relapse model is utilized. This is alluded to as various straight relapse model or multivariate least squares fitting. Despite the fact that adaptability is brought into the relapse investigation by the presence of different indicator factors, the multifaceted nature included by the utilization of various indicator factors makes this methodology generally appropriate for PC use. J. G. Egbe et al. (2017) applied Multi-Linear Regression Analysis (MLRA) model for predicting soil properties in Calabar South to offer a technical guide and solution in foundation designs problems in the area [2]. Baykan Hakan Ersoy and Robert L. Parsons (2013) performed analytical hierarchy process and multiple regression analysis on data groups got from soil tests on 41 examples in Tertiary volcanic regolith. While the chain of command model concentrated on deciding the most significant list properties influencing on quality parameters, relapse examination built up important connections between quality parameters and list properties [6]. MdEnayet Chowdhury and Nafeesa Khan (2018) conducted research to establish a mathematical relationship between three factors (edge of inside grinding, fines substance and greatest or least dry thickness) of cohesionless soil, in view of the Curve-Fitting instrument of MATLAB programming. Levenberg-Marquardt calculation is utilized for the fitting methodology. Among 120 reproductions, two conditions (created from polynomial surface fitting) of third-request polynomial are recommended (between a specific scope of fines content) toward the finish of the investigation [7]. Kok-KwangPhoon and JianyeChing demonstrated the practical construction of a multivariate probability distribution function using an actual soil database containing su(CIUC), OCR, and four piezocone parameters. Five hundred and thirty-five multivariate data points were compiled from 40



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clay sites around the world (Brazil, Canada, Hong Kong, Italy, Malaysia, Norway, Singapore, Sweden, UK, USA, and Venezuela)[8].Oluwapwlumi O. Ojuri(2013) carried out stepwise multiple regression to establish the best predictive models for the California Bearing Ratio (CBR) and undrained shear strength (Su) and reported an remarkable predictive model for undrained shear strength Su = - 547.713 + 0.381MDD-9.104GI with (F2 = 229.476, P < 0.005, adjusted R2 = 0.989, Std. Error = 7.5638) [9]

An network of mathematical models simulating formation and functionalities of human intelligence and anxious structure is referred to as Artificial neural network (ANNs). Building block of ANNs is Artificial Neuron, also called since dispensation rudiments or else nodes, which is simple mathematical model. This artificial neurons are arranged in layers: an input layer, an output layer and one or more hidden layers. Multiple Layers Perceptrons(MLPs) are class of ANNs using feedforward architecture. These networks are universal approximates because of their essential capability of approximating any continuous function to an arbitrary degree of accuracy. MLPs are usually applied to perform supervised learning tasks, which involve iterative training methods to adjust the connection weights within the network. They are usually trained with Back Propagation (BP) algorithm [10]. The most admired set of multilayer feed-forward system is multilayer observations in which each computational part utilize also the thresholding reason or the sigmoid capacity. Multilayer perceptrons can frame self-assertively complex choice limits and speak to any Boolean capacity. The extension of the back-proliferation training calculation for compelling loads in a multilayer perceptron has finished these system the almost all well known amongst researchers and user of neural networks[11].

Amit Prashant Dayakar Penumadu and David J. Forst (2004) used neural system dependent sand prototypes to replicate the tri-axial density reply for unreliable drainage, and beneath a series of analysis conditions[12]. Zijun Cao and Yu Wang (2014) developed Bayseian approach for facilitating the determination of characteristic values of geomaterial properties in geotechnical analysis and design when extensive testing cannot be performed, which is the case for majority of geotechnical projects, particularly those of a small or medium size[13].Hernán Eduardo Martínez-Carvajal, Márcio Muniz de Farias (2004) used artificial neural networks for modeling soil behavior directly from experimental data[14]. Dr. Sudhir Singh Bhadauria Rajeev Jain, Dr. Predeep Kumar Jain (2010) presented an artificial network technique to predict the shear strength parameters of medium compressible soil under unconsolidated undrained conditions [15]. PijushSamui and T. G. S(2010) worked out spot description model by Artificial Neural Network and large existing data from standard penetration test in three-dimensional subsurface of Bangalore, India [16]. Bindhu Lal Sushama Kiran and S. S. Tripathy (2016) applied Probabilistic Neural Network (PNN) for estimation of shear strength with variable input as water content (w), Plasticity Index (PI), Dry Density (ρ), Gravel Content, Sand content, Silt Content and Clay content [17]. Artificial neural network (ANN) models have been widely applied to various relevant civil engineering areas such as geotechnical engineering, water resources and coastal engineering[18]. Artificial Neural Networks (ANNs) has been applied in geo-engineering for the prediction of Over consolidation Ratio (OCR), determination of potential soil liquefaction, prediction of foundation settlement, evaluation of piles bearing capacity, prediction of compaction parameters for cohesive soils, compaction control of embankments built of cohesion less soils[19]. Neural networks are often employed as modern technological advents like neural networks, an offshoot of Artificial Intelligence, where the principle is to emulate a human brain to study the pattern and predict the outcome[20].

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The Radial Basis Function (RBF) network, which has two layers, is a special class of multilayer feed-forward net-works. Each unit in the hidden layer employs a radial basis function, such as a Gaussian kernel, as the activation function. The radial basis function (or kernel function) is centered at the point specified by the weight vector associated with the unit. Both the positions and the widths of these kernels must be learned from training patterns. There are usually many fewer kernels in the RBF network than there are training patterns. Each output unit implements a linear combination of these radial basis functions. From the point of view of function approximation, the hidden units provide a set of functions that constitute a basis set for representing input patterns in the space spanned by the hidden units[11].

## II. Materials and Methods

### A. *Sampling and Data Analysis*

In this study, the database is obtained from Geotechnical Investigation reports of 26 sites across India. The Geotechnical Investigations are in accordance with the guidlines of Indian standards. Total of 321 bore hole were studied depthwise for diffrent soil properties. These soil properties include Liquid Limit (LL), Plastic Limit (PL) , Field Moisture content (w), sand content (S), silt content (M), clay content (C) , density(ρ), field SPT (N), angle of internal friction (ϕ) and cohesion (c), all determined in accordance with IS:2720. The soil database demonstrates that the soils are predominantly Sandy Silt according to IS Classification.

The most important factors representing the shear strength behavior were identified based on the literature review. The ratio of undrained shear strength of clay to overburden stress have been correlated to Atterberg limits, plasticity index has been reported by many researchers. Power equation for correlation between undrained shear strength to plasticity index and linear equation for correlation for undrained shear strength and liquid limit are reported in literature [21]. KamilKayabali (2011) observed that if the shear strength at plastic limit and liquid limit are set properly, the undrained shear strength of remolded soils at any water content between PL and LL can be determined easily by reappraising a large body of shear strength and soil consistency data[22]. B. Voight (1973) in his study concluded with the intention of smoothness file appears to be a functional pasture guide to the important engineering property of outstanding potency of natural soils. A similar, although less distinctive, correlation was obtained with a plot of water content at residual strength against residual strength coefficient[23].

TABLE I. FUNDAMENTAL EXPLANATORY STATISTICS FOR THE ORIGINAL STATISTICS SET.

| **Statistics** | **Depth (m)** | **Plasticity Index (%)** | **Water Content (%)** | **Sand Content (%)** | **Silt Content (%)** | **Clay Content (%)** | **Bulk Density (gm/cc)** | **SPT Value (no's)** | **Cohesion (kg/cm2)** | **Angle Friction (Degree)** | **Shear Strength (kg/cm2)** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Count | 322 | 322 | 322 | 322 | 322 | 322 | 322 | 322 | 322 | 322 | 322 |
| Mean | 11.02 | 24.40 | 27.49 | 14.44 | 58.46 | 25.94 | 1.88 | 18.72 | 0.49 | 10.34 | 52.59 |
| Std Dev. | 9.90 | 16.58 | 14.23 | 13.60 | 17.38 | 16.42 | 0.17 | 15.84 | 0.35 | 7.08 | 36.41 |
| Minimum | 1 | 5 | 0.3 | 0.00 | 13 | 0.00 | 1.41 | 0.00 | 0.01 | 1.00 | 1.60 |


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|---|---|---|---|---|---|---|---|---|---|---|---|
| Maximum | 41 | 120 | 88 | 74 | 99 | 79 | 2.37 | 100 | 1.73 | 32 | 176.61 |
| Median | 7.50 | 20.00 | 22.33 | 11.00 | 61.00 | 22.00 | 1.91 | 15.00 | 0.35 | 9.00 | 40.12 |

numerical images of examine parameter are specified in Table 1. All parameters appropriation of mean and normal qualities is near one another. This shows factual conveyance of this parameter for tested examples are almost ordinary. As appeared in Table 1, the deliberate estimation of contact point from a lesser estimation of 10.2* degrees to a superior estimation of 32.17* degrees. Their mean and middle estimations contact point are 22.37*, and 23.32* degrees, separately. The attachment esteems goes from 0.01 to 0.34 (kg/cm2), through a mean estimation of 0.11 (kg/cm2), and a middle estimation of 0.1 (kg/cm2). flanked by analyzed parameters, thickness have the fewer spatial variety. What's more, experiment results are displayed by recurrence histograms so as to signify thickness of tests in each test (Fig. 1)

TABLE II. CORRELATION MEDIUM FOR UNIQUE DATA SET.

| **Parameters** | **Depth** | **Plasticity Index** | **Water Content** | **Sand Content** | **Silt Content** | **Clay Content** | **Bulk Density** | **SPT Value** | **Cohesion** | **Angle Friction** | **Shear Strength** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Depth | 1 | -0.094 | -0.099 | -0.047 | -0.006 | 0.003 | 0.266 | 0.498 | 0.466 | -0.181 | 0.517 |
| Plasticity Index | | 1 | 0.738 | -0.262 | -0.313 | 0.556 | -0.402 | -0.297 | -0.099 | -0.260 | -0.127 |
| Water Content | | | 1 | -0.273 | -0.160 | 0.398 | -0.546 | -0.35 | -0.226 | -0.296 | -0.247 |
| Sand Content | | | | 1 | -0.473 | -0.259 | 0.0097 | 0.218 | -0.086 | 0.377 | -0.066 |
| Silt Content | | | | | 1 | -0.676 | 0.0708 | 0.012 | -0.015 | -0.129 | -0.011 |
| Clay Content | | | | | | 1 | -0.121 | -0.23 | 0.081 | -0.189 | 0.056 |
| Bulk Density | | | | | | | 1 | 0.296 | 0.319 | 0.164 | 0.346 |
| SPT Value | | | | | | | | 1 | 0.257 | 0.273 | 0.308 |
| Cohesion | | | | | | | | | 1 | -0.315 | 0.996 |
| Angle of Friction | | | | | | | | | | 1 | -0.279 |
| Shear Strength | | | | | | | | | | | 1 |

The linear relationships between the variables are investigated by obtaining correlation matrix as shown in Table 2. The relationship strength is depicted by correlation coefficient (r-value). According to Bivariate correlation analysis their exist an relation between dependent variable shear strength and the independent variable depth, Plasticity Index, Water Content, Bulk density & SPT value. The strongest correlation is represented by correlation coefficient 0.517 between shear strength & depth. Moderate correlation is indicated between bulk density, SPT value, water content & Plasticity Index and dependent variable shear strength with correlation coefficient 0.346, 0.308, 0.247 & 0.127 respectively. Whereas, the other variables such as Sand content, Silt Content, Clay content with low correlation coefficient values comparatively indicates insignificant influence on the shear strength.



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### B. *Multivariate Linear Regression*

Regression is one of the most popular statistical method used for empirical deterministic modeling. The most common is ordinary linear regression (with one or several variables) and non-linear regression modeling such as Polynomial, Exponential \& Logistical. Advance developments includes generalized linear models, including Youngjo Lee and John Nelder's hierarchical generalized linear models [1].

Regression Analysis summarizes the pragmatic associations in a meticulous position of data, with no curiosity in the purposeful appearance of the model per se or in predictions to other sets of data or situations. When used for prediction, such as for shear strength parameters, it is beneficial to incorporate fundamental governing soil characteristics to develop more realistic model and provide occasion to check and inform the theories. Extrapolated prediction using deterioration models beyond the sample space are to be avoided. More realistic modeling requires finding the common shape the reply arc, restricting negative values for response variable, identifying response variable approaching asymptote in favor of high or low value of self-governing variables. finding these behavior prompts to adopt nonlinear models instead of linear regression models. In some instance, an response curve requiring numerous conditions of a polynomial model to able-bodied the plateau might be described very well with a two-parameter exponential model. Including minute details, such as interaction between several different components to produce final result leads to complexity and cannot be modeled as single functional model [1].

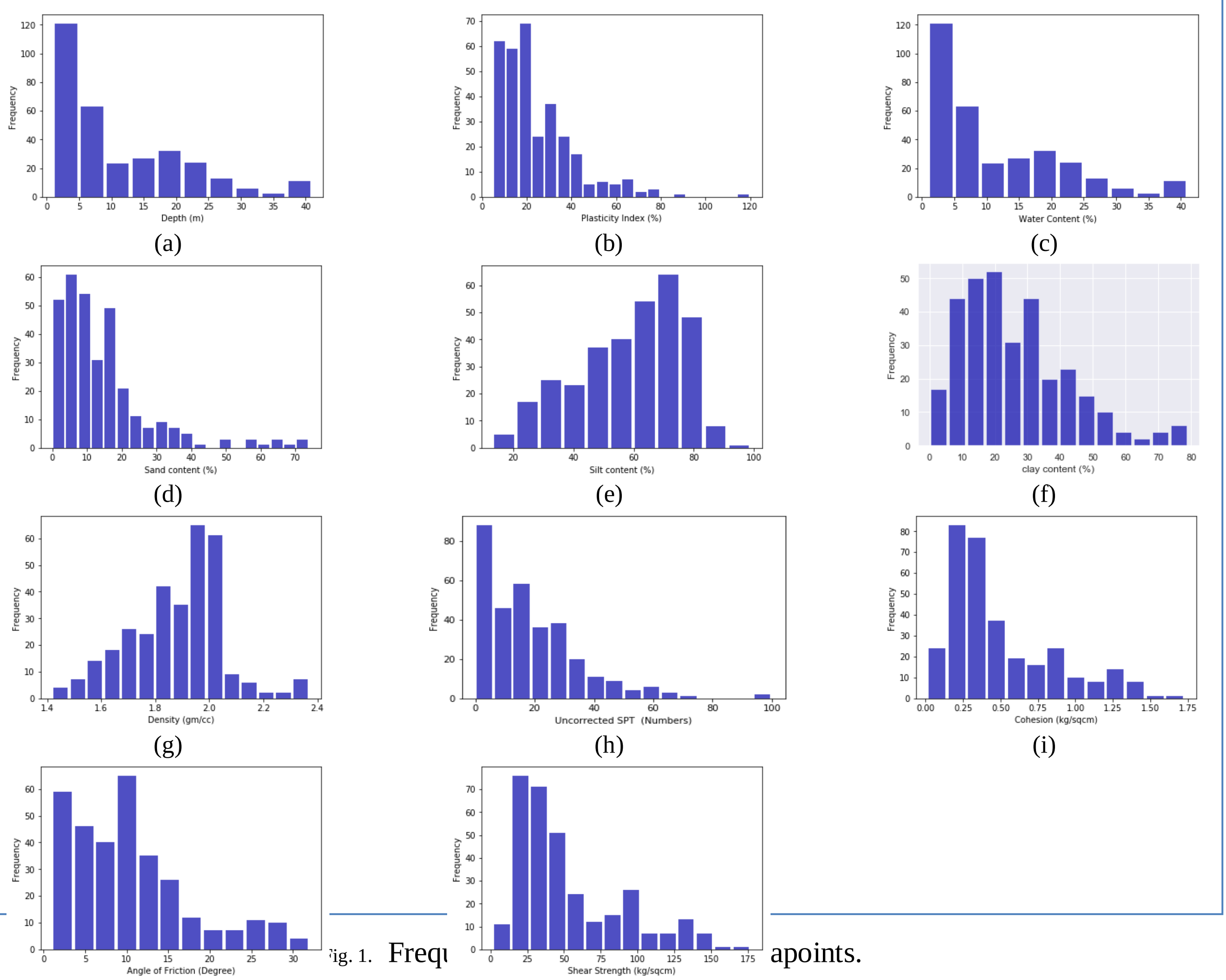


Fig. 1. Frequ apoints.



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Regression is popular modeling method comprising of linear and nonlinear models with generalized linear models for analyzing better counts and proportions as with more usual numeric variables. Recent developments in generalized linear models, includes Youngjo Lee and John Nelder's hierarchical generalized linear models with the range of possibilities. Some of the regression techniques are discussed in the forthcoming sections.

Simple linear deterioration- The shortest linear replica consists only self-determining changeable and states that the precise demonstrate of the destitute variable changes at a steady rate as the estimation of the autonomous variable increments or diminishes. Therefore, the utilitarian connection between the genuine mean of Yi, meant by □ □ (Yi), and Xi is the condition of a straight line

$$\varepsilon(Y_i) = \beta_0 + \beta_1 X_i (1)$$

β0 = intercept, i.e value of ε(Yi) when X = 0

β1 = slope of the line, the rate of vary in ε(Yi) per unit change in X

The random errors εi have zero mean and are assumed to have common variance σ2 and to be pairwise independent. The random error assumptions are frequently stated as εi ~NID(0, σ2). Where NID stands for "normally and independently distributed." The quantities in parentheses denote the mean and the variance, respectively, of the normal distribution.

Multiple linear regression-Most models will use more than one independent variable to explain the behavior of the dependent variable. The linear additive model can be extended to include any number of independent variables:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_1 X_{i1} + \beta_1 X_{i1} + - - - + \beta_1 X_{i1} + \varepsilon_I (2)$$

The subscript documentation has been reached out to remember a number for every X and □ to distinguish every free factor and its relapse coefficient. There are p free factors and, including □ 0, p' = p+1 parameters to be assessed. The typical least squares presumptions apply. The □ i is thought to be autonomous and to have normal change σ2. The independent variables are assumed to be measured without error. The least squares method of estimation applied to this model requires that estimates of the p + 1 parameters be found such that

$$SS(Res) = \Sigma(Y_i - Y_i)^2 = \Sigma(Y_i - \beta_1 X_{i1} - \beta_2 X_{i2} - ---- \beta_2 X_{i2})^2 (3)$$

### C. *Artificial Neural Network*

An network of mathematical models simulating structure and functionalities human brain and nervous system is refered to as Artificial neural network (ANNs). Building block of ANNs is Artificial Neuron, also called as meting out rudiments or nodes, which is simple mathematical model. This artificial neurons are arranged in layers: an input layer, an output layer and one or more hidden layers.

Input layer: Data, information, signals, features or measurements from the external system are received by this layer and normalize inside the boundary value produced by commencement function. concealed, in-between, or imperceptible layers: The layer extracts the pattern connected with the course or organization life form analyzed. Output layer: Produces and presents the final outputs.

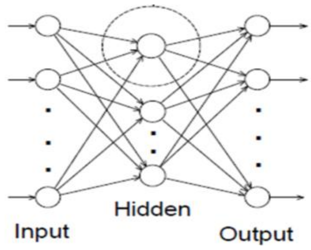


Fig. 2. Typical Artificial Neural Network

Input value from each artificial neuron in the preceding layer (xi) be adjusted by multiplying it with load (wji). The weighted values are bind together and a threshold value (θj) is added, to get joint input (Ij). This joint participation (Ij) is after that conceded through a non-linear transfer function(f()) to produce the output yj., which then acts as input for next artificial neuron. This process is summarized in equation 1 and 2 and illustrated in Fig. 3.

$$I_j = \sum w_{ji} + \theta_j \quad (4)$$

$$y_j = f(I_j) \quad (5)$$



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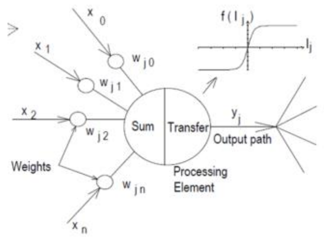


Fig. 3. Typical Artificial Neural Network

Where, Ij = the activation level of node j;

wji = the connection weight between nodes j and i;

xi = the input from node i, i = 0, 1, …, n;

θj = the bias or threshold for node j;

yj = the output of node j; and

f(.) = the transfer function.

Modeling with ANN involves finding right set of weights (wji) that produce input /output mapping with smallest possible error. The ANN modeling philosophy is similar to conventional statistical models the objective is to locate the obscure capacity f, which relates the information variable x to the yield variable y. In a direct relapse model, the capacity f can be acquired by changing the incline and y catch of the straight line, with the goal that the mistake between the real yields and yields of the straight line is limited. A similar standard is utilized in ANN models. ANNs can frame the basic straight relapse model by having one info, one yield, no concealed layer hubs and a direct exchange work. The association weight w in the ANN model is proportionate to the slant tan□ and the edge □ is equal to the catch â, in the direct relapse model. ANNs modify their loads by over and again showing instances of the model information sources and yields so as to limit a blunder work between the verifiable yields and the yields anticipated by the ANN model [20].

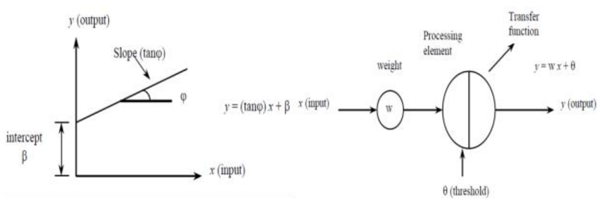


Fig. 4. Representation of Artificial Neural Network Model

Degree of non-linearity is achieved by changing transfer function and number of hidden layer nodes and can be upgraded from univariate to multivariate by increasing the number of input nodes[20].

Activation functions can be divided into two groups, the first based on dot products and the second based on distance measures. Activation based on the dot product is the weighted sum of inputs expressed as $z_i(x, w_i) = \sum_{j=1}^{n} w_{ij}\, x_j zi$. With n equals number of input neurons, activation function $z_i(x, w_i) = \sum_{j=1}^{n} w_{ij}\, x_j = 0$ represents an (n-1)-dimensional hyperplan passing through the origin of coordinate system, whereas activation function $z_i(x, w_i) = \sum_{j=1}^{n} w_{ij}\, x_j - \theta_i = 0$ represents an (n-1)-dimensional hyperplan with an threshold θ (not passing through the origin of coordinate system). The activation function zi(x,wi) = 0 is zero, when an input x is located on a hyperplane, which is spanned by the weights wi and wn. Activation increases (or decreases) with increasing distance from the plane. The sign of activation indicates on which of the plane the input x is. Thus, the sign separates the input space into two direction. For an network with n-input neurons, 3-trainable weights and 1-output neuron, n-dimensional input space is separated by (n-1) dimensional hyperplanes as determined by hidden neurons. With each hidden neuron separating input into two classes, an complex class separator is defined by hidden neurons, which allows a connection between subspaces of the input space. Activation functions based on dot products should be combined with the output functions that account for the sign, because otherwise the discrimination of subspaces separated by hyperplanes is not possible[24].

### *D. Criteria for evaluation*

Model performance have been accessed using standard statistical measures such as, association coefficient(r) , origin signify quadrangle fault



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(RMSE), denote utter fault (MAE) and t-test. The standard statistical measures were worked out as following:

The learning and testing data sets are evaluated separately on the basis of the analysis of the following error measures[19]:

*a) Root Mean Squared Error (RMSE):*

$$RMSE_i = \sqrt{\frac{1}{P}\sum_{i=p}^{P}(t_i^p - y_i^p)^2} \quad (6)$$

*b) Mean Absolute Error (MAE):*

$$MAE_i = \sum_{p=1}^{P}(t_i^p - y_i^p)^2 \quad (7)$$

*c) Correlation Coefficient (r):*

$$r = \frac{\sum_{i=1}^{p}(t_i - \bar{t})\, X\, (y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(t_i - \bar{t})^2 X\, (y_i - \bar{y})^2}} \quad (8)$$

*d) t-value:*

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} \quad (9)$$

where ,$t_i^p$ &$y_i^p$ are target and neurally computed i-th outputs (i=1,2,.......M) for p-th pattern (p=1,2......,P)

## III. Results and Discussion

### A. *outcome of MLR*

numerical presentation assessment criterion of MLR for shear strength are presented in Table 3. The increasing numbers of geotechnical parameters improves the ability of the model prediction. The accuracy of the MRL model is evaluated using t-test. The outcome of this analysis with 95% likelihood in five models is shown in Table 4. Mostly all model are having high t-value in comparison with the tabulated value hence suggests the practical usability of the Models for shear strength predictions. As per t-test consequences, most outstanding replica for forecast is the replica (v) with most of the t-values greater than the tabulated value, hence suggesting stronger correlation amongst the parameters. The evaluation of the shear strength expected by MLR and target value from the database has been accessible in Figs 5 and 6 correspondingly. The MLR representation equation for the calculation of shear strength is given below:

$$Predicted_{SS} = -20.908 + 1.730\, D + 0.312\, PI - 0.566\, w + 33.38\, BD - 0.019\, SPT \quad (10)$$

TABLE III. NUMERICAL PRESENTATION ASSESSMENT CRITERIA FOR THE MLR MODEL IN FORECAST OF SHEAR STRENGTH.

| Index Parameter | r | RMSE (degree) | MAE (degree) |
|---|---|---|---|
| (i) Depth | 0.268 | 31.112 | 25.07 |
| (ii) Depth and PI | 0.274 | 30.980 | 24.83 |
| (iii) Depth, PI and w | 0.316 | 30.070 | 23.68 |
| (iv) Depth, PI, w and BD | 0.330 | 29.700 | 23.56 |
| (v) Depth, PI, w, BD and SPT | 0.330 | 29.700 | 23.57 |
| | | | |

### B. *Results of ANN*

The artificial neural network model used for the prediction of shear strength is Multiple Layer Perceptron type.RMSE, MAE with r values for the ANN copy are given in Table 5. Model (v) having inputs as depth, PI, w BD and SPT has the smallest MAE (22.920), RMSE (27.920) and the highest r (0.698). With r value at 0.698 ie less than 0.8 the Model (v) do not suggest strong correlation between observed shear strength values and the predicted values. The model have been developed with WEKA 3.8 with optimized architectural parameters, a number of score include executed by unlike architectural settings.

TABLE IV. CALCULATED T-NUMBERS OF ALL PROPERTIES WITH 95 % PROBABILITY FOR SHEAR STRENGTH

| Parameter | Calculated Value (CL = 95%) | Model (i) | Model (ii) | Model (iii) | Model (iv) | Model (v) |
|---|---|---|---|---|---|---|
| Constant | 1.98 | 12.143 | 9.553 | 10.699 | -0.877 | -0.857 |
| D | 1.98 | 10.820 | 10.644 | 10.744 | 9.785 | 8.628 |
| PI | 1.98 | | -1.646 | 2.107 | 2.099 | 2.085 |



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| | | | | | | |
|---|---|---|---|---|---|---|
| w | 1.98 | | | -4.419 | -2.938 | -2.910 |
| BD | 1.98 | | | | 2.815 | 2.812 |
| SPT | 1.98 | | | | | -0.153 |

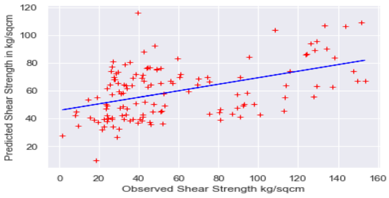


Fig. 5. Correlation figure of observed and expected values of Shear Strength of MLR Model

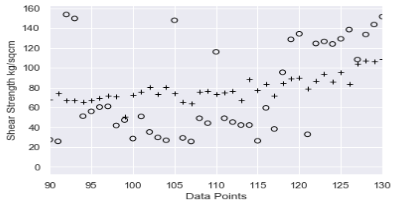


Fig. 6. fault allocation in favor of 40 individual data of shear strength in MLR Model

The top system was projected based on sigmoid commencement purpose with 5-3-1 construction of neurons for unseen sheet (Fig. 7). A assessment of the calculated shear strength by ANN Model (v) and the observed value from the Geotechnical Investigation database for the testing phase is shown in Fig. 8. Error between the observed shear strength value and the predicted value for individual 40 data sets has been also shown in Fig.8.

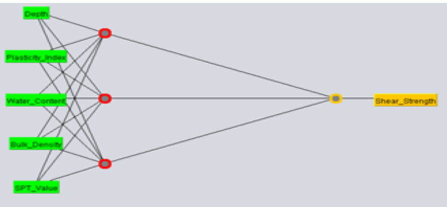


Fig. 7. structural design for NN Model (v) for forecast of Shear power

In all the models r-value for training set is more than that of the testing sets , which is in general agreement with the observed trend in many research work. The best ANN model proposed is having an 5-3-1 architecture with sigmoidal activation functions. The assessment of calculated and observed values of the finest model is revealed in Fig. 8. in addition, the experiential and predicted consistency standards consequences intended for 40 individual tests statistics contain also been revealed in Fig. 9.


Fig. 8. association figure of observed with predicted values of Shear Strength of MLP Model

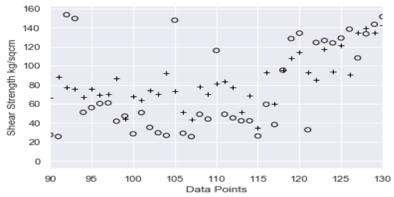


Fig. 9. fault allocation of 40 individual data for shear strength in MLP Model

Fig. 10.

TABLE V. STATISTICAL PERFORMANCE OF THE ANN MULTILAYER PERCEPTRON MODEL

| **Index Parameter** | **r** | | **RMSE (degree)** | | **MAE (degree)** | | **t-value** | |
|---|---|---|---|---|---|---|---|---|
| | ***preparation*** | ***test*** | ***preparation*** | ***test*** | ***preparation*** | ***test*** | ***preparation*** | ***test*** |
| (i) Depth | 0.50 | 0.43 | 31.87 | 35.06 | 26.63 | 30.15 | 10.40 | 5.53 |
| (ii) Depth and PI | 0.50 | 0.43 | 31.96 | 35.20 | 26.76 | 30.46 | 10.54 | 5.58 |
| (iii) Depth, PI and w | 0.56 | 0.46 | 32.81 | 36.61 | 28.28 | 32.24 | 12.40 | 6.08 |
| (iv) Depth, PI, w and BD | 0.67 | 0.56 | 28.16 | 33.45 | 23.25 | 28.00 | 16.53 | 7.90 |
| (v) Depth, PI, w, BD and SPT | 0.69 | 0.60 | 27.92 | 32.14 | 22.92 | 27.05 | 17.46 | 8.69 |



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## IV. CONCLUSION

This research focused on development of Multivariate Linear Regression and Multi-layer Perceptron replica intended for the forecast of shear power. The geotechnical parameters depth, plasticity index, water content , bulk density and SPT values are taken from the database developed using various geotechnical investigation reports from across the country. The shear strength has been worked out using measured cohesion, friction angle and major stress. The model so developed is evaluated using r, RMSE, MAE and t-test. Neural network based model suggest better predictability with r value of 0.689 in comparison with -0.33for Multivariate linear model. However, neural network based MLP model fall short of indicting stronger relationship amongst the geotechnical parameter. The contributing factor for lesser predictibity could be due to large variation in location of datapoints, use of uncorrected SPT value and deduced shear strength values. The model with highest predictability is the one with depth, Plasticity Index, water content, bulk density and Multivariate linear regression shows less promising results with the highest correlation coefficient of 0.33 deterioration has been accepted away by five models together C and φ. The acquired consequences demonstrated the finest models for assessment through C and φ be analogous which picked implied intended for ANN models. Result of selected MLR replica for estimation of φ explain 2.40, 0.88 with 1.96 qualities for RMSE, r with MAE, separately. What's more, the outcomes for forecast of C be 0.039, 0.81 with 0.030 (kg/cm2), individually. Examinations among ANN with MLR models presentation for judgment of φ set up that three MLR models (I, ii and v) performed improved by indistinguishable models in ANN. The replica contain comparable daily schedule in collaboration ANN and MLR steps yet the ANN replica iv has preferable result over the indistinguishable model in MLR. This evaluation for conviction of C showed that the all of models in ANN have improved introduction through MLR Models. Furthermore, an evaluation of the best model daily practice among ANN and MLR models showed that ANN was extra fitting to appraise consistency, however meant for assessment of obstruction point utilization of ANN with MLR strategies have agreeable capacity. beginning a realistic top of vision, in light of straightforwardness estimation contribution parameters, by methods for these models is SPT as contribution with r, RMSE, MAE values 0.689, 27.92 and 22.92 individually. This model engineering is sigmoidal enactment work with 5-3-1 neurons for various layers..

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