Indexed in
Scopus Compendex and Geobase Elsevier,
Geo-Ref Information Services-USA, List B of Scientific
Journals, Poland, Directory of Research Journals

International Journal
of Earth Sciences
and Engineering

www.cafetinnova.org

ISSN 0974-5904, Volume 09, No. 01

February 2016, P.P. 81-86

Artificial Neural Network Modelling and Economic Analysis of Black Cotton Soil Subgrade Stabilized with Flyash and Geotextile

VINODHKUMAR S AND BALAJI S
Department of Civil Engineering, Kongu Engineering College, Perundurai – 638052, INDIA
Email: *ervinodhkumars@gmail.com,* er.shbalaji@gmail.com

Abstract: For roads on black cotton soils, stabilization process is indispensable to subdue swell-shrink problems and also to improve CBR value. The aim of this research is to contrive an Artificial Neural Network model which can be used to predict values of CBR of sub-grade soil with the addition of flyash and geotextile. The input values for this research includes Atterberg's limits, Optimum Moisture Content & Fraction of Fly Ash added and number of geotextile layers which can affect the CBR values. The effects of number of neurons in hidden layer with different algorithms are scrutinized. Levenberg-Marquardt back propagation shows maximum R value of 0.98695 and minimum MSE value of 8.0242e-11. Economic beneficial are reconnoitered according to schedule of rates of materials as well.

Keywords: *Black Cotton soil, Flyash, Geotextile, Artificial Neural Networks, Economic analysis*

1. Introduction:

Black cotton soil is one of the major soil deposits of India which encompasses central part of India, Decan pleatu and some part of south India. Black cotton soil occupies an area of 300,000 sq.km. The major problem with black cotton soil is volumetric changes. It causes severe damages to structures built over it particularly the light weight structures [3]. Due to high swell pressure and high volume change characteristics of black cotton soil pipe lines, pavement, foot path, and temporary light weight structures are prone to be damaged. This necessitates the stabilization process for black cotton soils. The commonly used materials are lime [1], [4], cement [8] and flyash [2], [10], [11]. Since the costs of materials are increasing, many new reliable and alternate materials are emerging day by day. These materials will not only reduce the cost but also increase the life time. One such kind of material is geotextile. Geotextiles are made from polymeric materials like polyethylene, polypropylene, etc.

2. Materials:

Soil for this research work is acquired from Peelamedu, Coimbatore. The soil has 4 % of Gravel, 18.5 % of sand, 34.5 % of Silt and 43 % of Clay. The soil falls under clay of intermediate compressibility as per BIS 1498. The properties of Geotextile are in Table 1.

3. Methodology:

Methodology chiefly consists of three parts. Part 1 includes determination of Optimum Moisture Content (OMC), Maximum Dry Density (MDD), soaked CBR and Unsoaked CBR for soil with 10 %, 20 %, 30 %, 40 % and 50 % of flyash addition while part 2 is allotted for analysis of OMC, MDD, soaked CBR for soil with 10 %, 20 %, 30 %, 40 % and 50 % of flyash addition along with single and double layer of geotextile. Part 3 is principally engrossed on ANN modelling and economic analysis.

Table 1: *Properties of geotextile*

Property	Values
Tensile Strength (MD) kN/m	28.5
Tensile Strength (CD) kN/m	26.5
Elongation (MD) %	30
Elongation (CD) %	27
Trapezoid Strength (MD) N	320
Trapezoid Strength (CD) N	320
Puncture Strength (N)	370
Apparent Opening Size (mm)	0.075
Water Permeability	9.5 $l/m^2/s$
Mass Per unit Area (gsm)	140

4. Testing techniques:

To ascertain the plasticity characteristics of soil, liquid limit and plastic limit tests are done. Moisture-Density relationship, Strength of subgrade and Swelling behavior are obtained from standard Proctor's test, CBR (soaked and unsoaked), and differential free swell test respectively and the tests are strictly adhered to Indian standard testing methods (IS 2720 - Part 5, 1985, IS 2720 - Part 16, 1987, IS 2720 - Part 40, 1977). Summary of results are given in Table 2.

5. Discussion on results:

5.1. Variation of Atterberg's limits with addition of flyash:

It can be observed from Figures 1, 2 and 3 that liquid limit, plastic limit, and plasticity index are decreasing with the addition of flyash which is stimulated by decrease in diffused double layer thickness and clay undertakes flocculated structure with the addition of flyash [16].

5.2. Variations in OMC and MDD:

A decrease in OMC is encountered as a result of reduction in double layer thickness with the addition of flyash while the trend of MDD is also subsiding since the flyash has lower specific gravity than soil. The geotextile is chemically inert and possess low specific gravity than soil and flyash mixtures. Thus inclusion of geotextile does not cause any change in OMC but MDD is decreasing when compared with soil-flyash mixture. Figures 4, 5 and 6 depict this trend.

5.3. Variations in CBR:

The CBR of soil blended with flyash climbs up to 20% flyash mix, later on it decreases with further addition of flyash and 20% is the optimum content of flyash. The inclusion of flyash upto 20% by weight promotes cementitious reactions and flyash in excess of 20% may be surplus as well as they remain dormant particles and exhibits null cohesive strength hence CBR has diminished. Figure 7 and 8 reports the variation in CBR values with the addition of flyash.

Table 2: *Summary of results*

Property	Flyash content % by weight					
	0%	10%	20%	30%	40%	50%
Liquid limit (%)	47	40	31	26	23	21
Plastic limit (%)	17	13	11	9.2	8	7.1
Differential free swell index (%)	40	36	31	27	24	22
Optimum moisture content (OMC) at standard proctor density (%)	15	14.93	13.45	12.2	10.76	9.7
Maximum dry density at standard proctor density (g/cc)	1.658	1.678	1.642	1.628	1.611	1.593
Soaked CBR (%)	2.68	3.22	4.29	3.57	2.86	2.68
Unsoaked CBR (%)	12.88	16.1	17.17	16.46	15.38	14.31
Optimum moisture content with single layer of geotextile (%)	14.41	14.11	13.09	12	10.4	9.26
Maximum dry density single layer of geotextile (g/cc)	1.649	1.669	1.630	1.617	1.603	1.580
Optimum moisture content with single layer of geotextile (%)	14.36	14.08	13	12.17	10.28	8.967
Maximum dry density single layer of geotextile (g/cc)	1.621	1.657	1.618	1.612	1.584	1.564
Soaked CBR with single layer of geotextile (%)	3.57	3.75	6.08	4.83	3.93	3.22
Soaked CBR with double layer of geotextile (%)	6.44	6.8	10.73	7.87	5.72	5.37

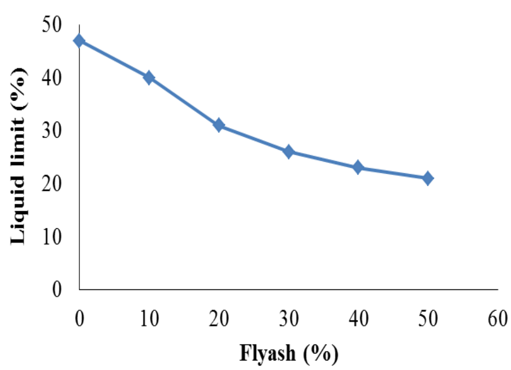

Figure 1: *Variation in liquid limit*

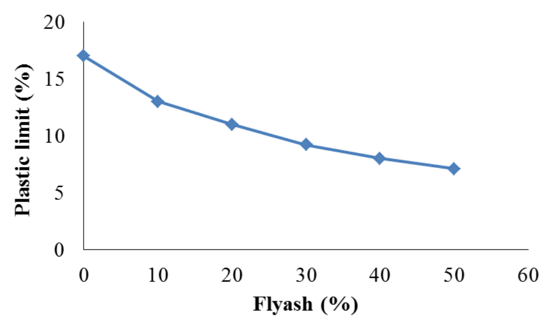

Figure 2: *Variation in plastic limit*

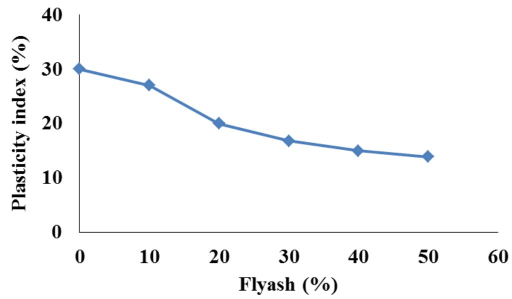

Figure 3: *Variation in plasticity index*

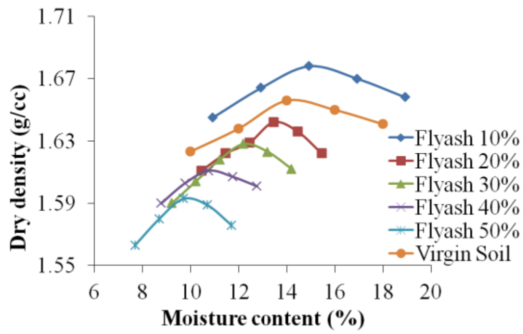

Figure 4: *Variation of OMC & MDD with addition of flyash*

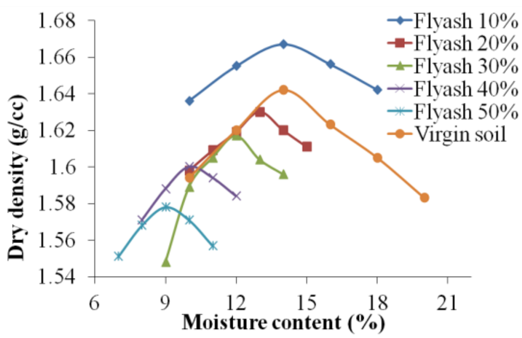

Figure 5: *Variation of OMC & MDD with addition of flyash and single layer of geotextile*

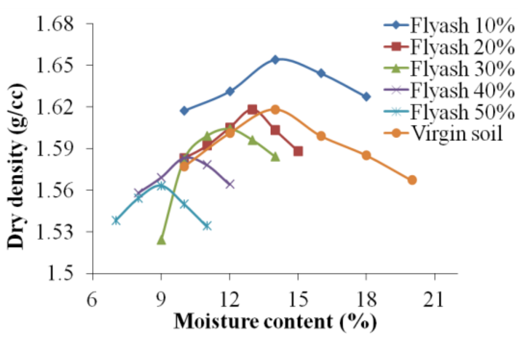

Figure 6: *Variation of OMC & MDD with addition of flyash and double layer of geotextile*

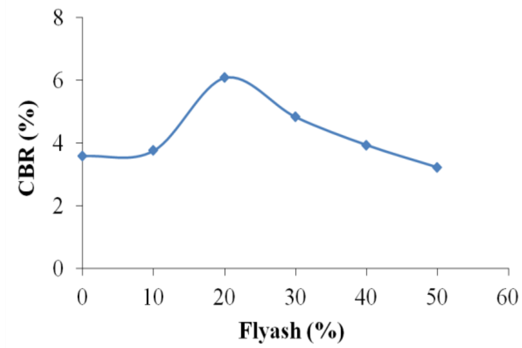

Figure 7:*Variations in CBR with the addition of flyash and single layer of geotextile*

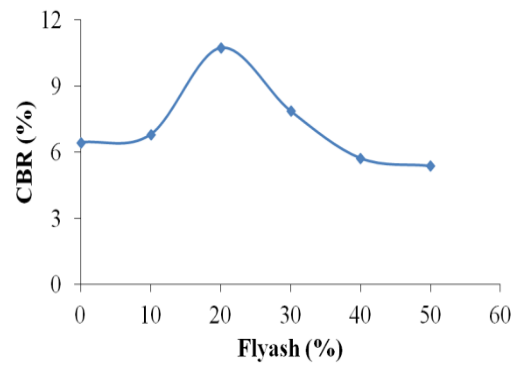

Figure 8:*Variations in CBR with the addition of flyash and double layer of geotextile*

6. Introduction to ANN modelling:

Artificial Neural Networks (ANN) is a kind of artificial intelligence computational tool, which mimics the human neural system. ANN processes the raw data based on experience not from a coded programme. Numerous types of ANN are available based on manipulation of data, methods to classify data, and data filtering etc. In general, an ANN consists of three layers such as input, hidden, and output layer. The hidden layer consists of neurons in which computational works are done on the input datum. The concepts based on which ANN develops relationship among variables is called learning algorithms [22]. Out of number of algorithms available, algorithms based on back-propagation theory are most popular since the target values are compared with original output and error is fed back to network so as to adjust weights assigned to each neurons and the process is repeated until minimum error is achieved. ANN is a powerful tool to establish a relationship among several variables where the phenomena behind the mechanism are not clearly understood. The complexity with ANN modelling is fixing the number of neurons in hidden layers and number of hidden layers to get an optimal ANN model which may be overcome by trial and error process.

6.1. Model architecture:

The ambition of this research is to develop an ANN model to predict CBR value and also to study the effect of number of neurons in hidden layer with different algorithms such as Quasi-Newton back propagation, Bayesian regulation back propagation, Conjugate gradient back propagation with Powell-Beale restarts, Conjugate gradient back propagation with Fletcher-Reeves updates, Conjugate gradient back propagation with Polak-Ribiére updates, Gradient descent back propagation, Levenberg-Marquardt back propagation, One-step secant back propagation, Resilient back propagation, Scaled conjugate gradient back propagation. The ANN models have been developed by taking, Atterberg's limits, % of flyash added, OMC (%) and MDD (kN/m^3), number of geotextile layers as input variables and soaked CBR (%) as output variable [21]. Each datum set is trained with different algorithms [23]. The numbers of neurons in hidden layer are varied as 2, 4, 6, 8, 10, 15, 20, 25, and 30. At the end of training a datum set with an algorithm and neuron, errors are computed.

6.1.2. Evaluation of ANN model:

An ANN model can be evaluated from Mean Squared Error (MSE) and Regression R value. Mean Squared Error is the average squared difference between outputs and targets. Lower values are better. Zero means no error. Regression R Values measure the correlation between outputs and targets. An R value of 1 means a close relationship, 0 a random relationship.

6.1.3. Effect of training algorithm:

As stated earlier, at the end of training a set MSE and R values are obtained. This process is repeated until the maximum R value and minimum MSE has reached for the particular algorithm [19]. The values are tabulated in Table 3. Measurement of R value can be seen from Figure 9. From the results we can infer that Levenberg-Marquardt back propagation shows maximum R value of 0.98695 and minimum MSE value of 8.0242e^{-11} and hence Levenberg-Marquardt back propagation can be used although it consumes higher memory usage compared to any other algorithm. When there is a constraint to memory usage Scaled conjugate gradient back propagation can be employed.

6.1.4. Effect on number of neurons in hidden layer:

Keeping the percentage of data allotted for training and testing as constant, numbers of neurons are varied and R value is noted. Randomness is observed between R value and numbers of neurons [23]. Relationship between number of neurons and R values for Levenberg-Marquardt back propagation are shown in Table 4.

***Table 3:** Effect of training algorithm*

S. No	Algorithm	R Value	MSE
1	Quasi-Newton back propagation	0.88712	$1.083\text{x}10^{-4}$
2	Bayesian regulation back propagation	0.85190	$4.983\text{x}10^{-5}$
3	Conjugate gradient back propagation with Powell-Beale restarts	0.94122	$3.776\text{x}10^{-7}$
4	Conjugate gradient back propagation with Fletcher-Reeves updates	0.81167	$7.339\text{x}10^{-6}$
5	Conjugate gradient back propagation with Polak-Ribiére updates	0.85819	$2.964\text{x}10^{-9}$
6	Gradient descent back propagation	0.94862	$9.985\text{x}10^{-9}$
7	Levenberg-Marquardt back propagation	0.98695	$8.0242\text{x}10^{-11}$
8	One-step secant back propagation	0.92335	$1.388\text{x}10^{10}$
9	Scaled conjugate gradient back propagation	0.96904	$1.946\text{x}10^{-6}$

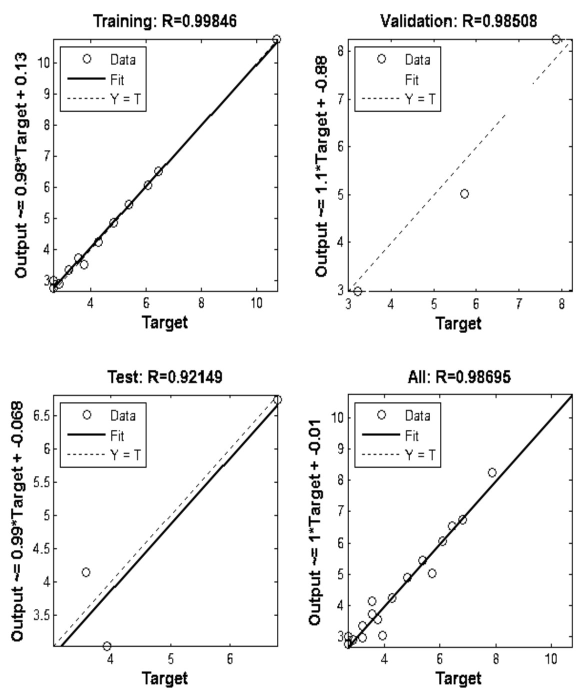

***Figure 9**: Measurement of R value*

Table 4: *Relationship between number of neurons and R values*

Number of neurons	Percentage of data allotted and R value		
	10%-10%	15%-15%	20%-20%
2	0.9334	0.9736	0.8340
4	0.7812	0.8712	0.6725
6	0.8573	0.6698	0.9745
8	0.9223	0.7845	0.9421
10	0.8125	0.9869	0.7967
15	0.8823	0.4356	0.5698
20	0.9461	0.5739	0.8883
25	0.9388	0.7866	0.8934
30	0.7174	0.4358	0.8352

7. Economic analysis of pavements:

For any Civil Engineering project, cost is a prime factor. Everyone is in the eager of finding economic as well as reliable alternatives against the high cost traditional methods. Geotextiles have been used in pavements either to extend the service life of the pavement or to reduce the total thickness of the pavement system. In order to quantify the cost-effectiveness of using geotextiles in pavement, four pavements such as natural subgrade pavement (P1), pavement stabilized with flyash (P2), pavement stabilized with flyash along with single layer of geotextile (P3), pavement stabilized with flyash along with double layer of geotextile (P4) have been designed based on their CBR value for a stretch of 1km and a width of 7.5m. Material required for each layer of the pavement as per Ministry of Road Transportation and Highways (MORTH) specifications are then computed. Costs of these materials are estimated as per schedule of rates of Tamilnadu Highways Department and National Highways Authority of India (NHAI). Designs of pavements are made using the software TNHD_PAVE. The economic analysis of pavement sections is shown in Table 5. From the table, it is evident that pavement stabilized with flyash along with double layer of geotextile is more economical.

Table 5*: Pavement sections*

Layer Details	P1 section (mm)	Cost of P1 in Rupees	P2 section (mm)	Cost of P2 in Rupees	P3 section (mm)	Cost of P3 in Rupees	P4 section (mm)	Cost of P4 in Rupees
BC	20	1030100	20	1030100	20	1030100	20	1030100
DBC	180	8025750	170	7579875	160	7134000	140	6242250
WMM	370	2270103	250	1533854	220	1533854	200	1227083
GSBC	385	1558455	330	1335819	280	1133422	220	890546
SUB GRADE	500	0	500	40040	500	99122	500	158204
TOTAL	1455	12884408	1270	11519688	1180	10930498	1080	9548183
% Savings	0	0	12.7	11.84	18.9	17.87	25.7	34.9

8. Conclusion:

Based on the laboratory investigations, computational modelling, and economic analysis following conclusions can be drawn.

1. The decrease in OMC and MDD with the addition of flyash is mainly due to reduction in CEC and thickness of double layer.
2. The addition of geotextile layers reduces the MDD but OMC remains almost unchanged.
3. Maximum unsoaked CBR of 17.17% and Maximum soaked CBR of 4.29% are obtained at flyash content of 20% by weight. Hence 20 % of flyash content is optimum for stabilization purposes.
4. Soaked CBR of subgrade soil is further increased with inclusion of geotextile layers. Soaked CBR value has increased to 6.08% with single layer of geotextile while 10.73% of soaked CBR has obtained for two layers of geotextile.
5. ANN showed R^2 value of 0.9869. This model is applicable for CI category of clays and properties of reinforcement remains the same.
6. Pavement stabilized with flyash along with double layer of geotextile proves to be economical one which saves the money about 35% compared to natural subgrade pavement.
7. Pavement stabilized with flyash along with single layer of geotextile has material savings of 18.9% while pavement stabilized with flyash along with double layer of geotextile has material savings of 25.7%.

References:

[1] Bell, F.G, “Lime stabilization of clay minerals and soils”, Engineering Geology, Vol. 42, No. 4, pp. 223-237, 1996.

[2] Bhuvaneshwari, S, Robinson, R.G and Gandhi, S.R, “Stabilization of expansive soils using fly

ash", Fly Ash Utilization Programme (FAUP), Technology Information Forecasting & Assessment Council (TIFAC), Department of Science and Technology (DST), New Delhi, India, 2005.

[3] Chen, F.H, "Foundations on expansive soils", Elsevier Scientific Publishing Company, New York, 1975.

[4] Dash, S.K and Hussain, M, "Lime stabilization of soils: Reappraisal", Journal of Materials in Civil Engineering, Vol.24, No.6, pp.707-714, 2012.

[5] Edil, T.B, Berthoueux, P.M and Vesperman, K.D, "Fly ash as a potential waste liner", Proceedings of the Geotechnical Practice for Waste Disposal, ASCE, R. D. Woods, New York, pp 447–461, 1987.

[6] Garson, G.D, "Interpreting Neural Network connection weights" AI Expert, Vol.6, No.7, pp.47-51, 1991.

[7] IRC 37 - 2012, "Guidelines for the Design of Flexible Pavements", Third Revision.

[8] IS 2720 - Part 5, 1985, "Methods of test for soils", Bureau of Indian Standards, New Delhi, India.

[9] IS 2720 - Part 16, 1987, "Methods of test for soils", Bureau of Indian Standards, New Delhi, India.,

[10] IS 2720 - Part 40, 1977, "Methods of test for soils", Bureau of Indian Standards, New Delhi, India.

[11] Joel, M and Agbedi, I, "Mechanical-Cement stabilization of laterite for use as flexible pavement material", Journal of Material in Civil Engineering, Vol.23, No.2, pp.146-152, 2011.

[12] Kaur, S, Ubboveja, V.S and Agarwal, A, "Artificial Neural Network modelling for prediction of CBR", Indian Highways, Vol.39, No.1, pp.31-37, 2011.

[13] Pandian, N.S, "Fly ash characterization with reference to geotechnical applications", Journal of IISc, Vol. 84, pp. 189–216, 2004.

[14] Phani Kumar, S.R and Sharma, R.S, "Effect of fly ash on engineering properties of expansive soils", Journal of Geotechnical and Geoenvironmental Engineering, Vol. 130, No. 7, pp. 764–767, 2004.

[15] Ramakrishna, A.N, Pradeep Kumar, A.V and Gowda, K, "Complex CBR (of BC Soil-RHA-Cement Mix) Estimation: Made Easy by ANN Approach [A Soft Computing Technique]", Advanced Materials Research, Vol. 261-263, pp. 675-679, 2011.

[16] Rao, K.D, "The efficacy of reinforcement technique on the fly ash stabilized expansive soil as a sub grade embankment for highways", International Journal of Engineering Science and Technology, Vol. 3, No. 2, pp. 772–782, 2011.

[17] Rao, A.D and Rao, M.R, "Swell—Shrink behaviour of expansive soils under stabilized fly ash cushions", 12th International Conference on International Association for Computer Methods and Advances in Geomechanics (IACMAG), Goa, India, 2008.

[18] Sabat, A.K, "Statistical models for prediction of swelling pressure of a stabilized expansive soil", Electronic Journal of Geotechnical Engineering, Vol.17, pp 837-846, 2012.

[19] Sivapullaiah, P.V, Prashanth, J.P and Sridharan, A, "Effect of fly ash on index properties of black cotton soil", Soils and Foundations, Vol. 36, No.1, pp. 97–103, 1996.

[20] Schedule of Rates, TNHD, 2013-2014.

[21] Schedule of Rates, TNPWD, 2013-2014.

[22] Martinez, H.P, Yannakakis, G.N and Hallam, J, "Don't Classify Ratings of Affect; Rank them", IEEE Transactions on Affective Computing, pp.1-13, 2014.

[23] Nitish Srivastava, Georey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov, "Dropout: A Simple Way to Prevent Neural Networks from Overtting", Journal of Machine Learning Research, Vol. 15, pp. 1929-1958, 2014.

[24] Taşkıran, T, "Prediction of California bearing ratio (CBR) of fine grained soils by AI methods", Advances in Engineering Software, Vol.41, pp.886-892, 2010.

[25] Tomas Olsson, Daniel Gillblad, Peter Funk, and Ning Xiong, "Case-Based Reasoning for Explaining Probabilistic Machine Learning", International Journal of Computer Science & Information Technology (IJCSIT), Vol 6, No 2, 2014.

[26] Yildirım, B and Gunaydin, O, "Estimation of California bearing ratio by using soft computing systems", Expert Systems with Applications, Vol.38, pp: 6381- 639, 2011.