Modeling Marshall stability of lightweight asphalt concretes fabricated using expanded clay aggregate with anfis

SercanSerin[1], NihatMorova[2], ŞebnemSargın[3], SerdalTerzi[3], MehmetSaltan[3]

[1]Department of Civil Engineering, DUZCE University, Turkey
[2]Department of Manufacturing Engineering, SULEYMAN DEMIREL University, Turkey
[3]Department of Civil Engineering, SULEYMAN DEMIREL University, Turkey

Abstract

In this study, an Adaptive Neural Fuzzy Inference System (ANFIS) model for predicting the Marshall Stability (MS) of lightweight asphalt concrete containing expanded clay (EC) and has various mix proportions has been developed.

Experimental details were used to construct the model. The amount of bitumen (%), transition speed of ultrasound (µs) and unit weight (gr/cm^3) were used as input variables and Marshall Stability (kg) values were used as output variables. Statistical equations were used to evaluate the Developed ANFIS model.

Results showed that developed ANFIS model has strong potential to predict Marshall Stability of asphalt concrete using related inputs in a short time. Also the Marshall Stability of asphalt concrete containing expanded clay and has various mix proportions can be found without performing any experiments.

INTRODUCTION

Natural lightweight aggregate sources can be found in regions characterized by volcanic activity, where porous rocks (known as pumices) are available. Artificial lightweight aggregates (like the expanded clay obtained by thermal treatment of argillaceous materials) are produced in many countries, the raw materials being very common. They may exhibit higher resistance than natural lightweight aggregates, but this favorable result implies a greater production cost [1].

In the past few decades the demand for virgin natural aggregate, required for use in road construction, has increased considerably, resulting in environmental and hydrogeological disorders as well as landscape degradation [2].

Nowadays, Expanded Clay Aggregates (ECA) is an indispensable main raw material which especially used in the construction sector to produce lightweight building elements in Europe and the United States [3].

Clays has formed a mass full of with gas bubbles when it is heated and called “expanded clay”. It has the highest compressive strength among lightweight building materials. They express volume increase during heating process. They produced granules when heating process reached between 1000-1300°C and contain homogeneous, secret and little gaps called porous ceramic has sintered hard shell structures [3-4]. The use of artificial aggregates such as expanded clay in the production of asphalt concrete makes it possible to reduce both natural aggregate extraction and the use of nonrenewable raw resources, greatly benefiting the environment [2]. When literatures examined, it can be concluded that few works attempted on usability of expanded clay in the production of asphalt concrete [5-6-7-8-9-2-10].

Nowadays Artificial Intelligent methods have been extensively used in civil engineering applications [11-12]. One of the most popular artificial intelligence methods is ANFIS [13].Fuzzy logic and neural networks are the widely used artificial inference systems. Each approach has its merits and drawbacks. To take advantage of both approaches, integration of these systems has been proposed by many researchers in recent years[14]. Adaptive Neuro-Fuzzy Inference System (ANFIS) is fuzzy system that uses ANN's theory to determine its properties (fuzzy sets and fuzzy rules) [15]. A Neuro Fuzzy model brings together the linguistic representation of a fuzzy system with the learning ability of Artificial Neural Networks (ANNs) [16].

In this study, it has researched that predictability of MS of lightweight asphalt concrete fabricated using expanded clay and had varied mix properties with ANFIS. With this aim, asphalt concrete samples that added ECA in accordance with gradation determined in Highway Technical Specification (HTS), had different percentage of bituminous (POB) (4.5%, 5%, 5.5%, 6%, 6.5%, 7%, 7.5%, 8%, 8.5%, 9%, 9.5%, 10%, 10.5%) and unit weight (UW) (1,75–1,87 (gr/cm3)) were prepared and determined MS with Marshall test.

EXPERIMENTAL PROCEDURE

In the experimental part of this study, Crushed Stone Aggregates (CSA) obtained from the proximity of the province of Düzce and the ECA used in this study was supplied by Germany Liapor Company. The study not only the range of 0-2 mm ECA was included in the Hot Mix Asphalt (HMA).Within the framework of this study, first of all, material tests were carried out based on American Codes (ASTM), in order to obtain the physical and mechanical characteristics of the materials to be used in the mixtures. The physical and mechanical characteristics of the aggregates used in the mixtures are given in Table 1.

Table 1Physical and mechanical characteristics of CSA to be used in HMA

	Sieve Diameters			
	2-4,75 mm	**4,75-9,5 mm**	**9,5-25 mm**	**Codes**
Water Absorption %	* (3,54)	1,63	0,81	ASTM C 127
Los Angeles %	*	*	23,804	ASTM C 131
Fine Material %	* (14,51)	1,27	0,45	ASTM C 117
Organic Material	Clear	Clear	Clear	ASTM C 40
Freeze-Thaw %	*	*	6,69	ASTM C 88
Peeling Strength. %	*	More than %50	More than %50	HTS Part 403 App-A
Average Density (gr/cm^3)	2,576	2,642	2,677	ASTM C 127
Loose specific gravity (g/cm^3)	1,61	1,40	1,41	ASTM C 29
Compact specific gravity (g/cm^3)	1,91	1,62	1,64	ASTM C 29

*Tests not required according to the technical specifications prepared by Highways Commission (Highways Technical Specifications-HTS)

Table 2 Physical characteristics of ECA to be used in HMA

Characteristics of ECA (0-2 mm)	
Test Name	**Average Values**
Apparentdensity (g/cm^3)	1.655
Loose specific gravity (g/cm^3)	0.82
Compact specific gravity (g/cm^3)	1.04
Water absorption (%)	15.25
Moisture content (%)	0.01

In the experimental part of this study, AC 60/70 asphalt cement (AC), which is produced in Izmir Refinery of TÜPRAŞ (Turkish Petroleum Refineries Corporation), was used. The physical characteristics of the binder are given in Table 3.

Table 3 Basic physical characteristics of bitumen

Characteristics of Bitumen	
Test Name	**Average Values**
Penetration (25 ºC)	60-70
Flash Point	180ºC
Fire Point	230 ºC
Softening Point	45,5°C
Ductility (5 cm/minute)	>100 cm
Specific Gravity	1,034

Aggregate mixtures were prepared in accordance with the technical specifications required by Highways Commission (Highways Technical Specifications-HTS). For this aim, first of all, a series of tests were carried out in order to determine the optimum bitumen percentage. Empirical calculation methods were used to determine the pre-optimum bitumen percentages. Then, these values were altered by ±1%, and a total of 13 (%4.5, %5, %5.5, %6, %6.5, %7, %7.5, %8, %8.5, %9, %9.5, %10, %10.5) bitumen percentages were determined. Three samples were prepared for each bitumen percentage value, therefore a total of 39 asphalt samples were prepared and used for Marshall Stability test in order to determine optimum bitumen percentage value for the aggregate sample to be used. So that, the prepared this samples' Marshall Stability (MS) and Flow rations were determined and then VMA, Vf, Vh, Dt, Dp and ultrasound values were determined too.

There is great adherence performance could be seen among HMA, aggregate and bitumen according to the CSA and ECA amounts. Hot asphalt mixtures were prepared which include 51% ECA and the remaining %49 CSA as aggregate for different percentage of bitumen gradation of aggregate according to the "Highways Technical Specification (HTS)". After mixture preparation, some physical and mechanical experiments were performed in laboratory condition.

ARCHITECTURE OF ANFIS

ANFIS incorporates the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model consisting of a set of IF–THEN fuzzy rules [17-18].

In ANFIS, both the learning capabilities of a neural network and reasoning capabilities of fuzzy logic were combined in order to give enhanced prediction capabilities, as compared to using a single methodology alone. The goal of ANFIS is to find a model or mapping that will correctly associate the input values with the target values. The fuzzy inference system (FIS) is a knowledge representation where each fuzzy rule describes a local behavior of the system. The network structure that implements FIS and employs hybrid-learning rules to train is called ANFIS [18].

Figure 1 (a) and (b) illustrates the architecture of an ANFIS model with two input variables and the fuzzy-reasoning mechanism, respectively. Suppose that the rule base of ANFIS contains two fuzzy IF–THEN rules of Takagi and Sugeno's type as follows [17-19-18]:

Rule 1: IF x is A_1 and y is B_1, THEN $f_1 = p_1x + q_1y + r_1$.

Rule 2: IF x is A_2 and y is B_2, THEN $f_2 = p_2x + q_2y + r_2$.

The functions of each layer are described subsequently:

Layer 1 – Every node i in this layer is a square node with a node function:

$$O_i^1 = \mu_{Ai}(x) \tag{1}$$

where x is the input to node i and Ai is the linguistic label (fuzzy sets: small, large, etc.) associated with this node function.

Layer 2 – Every node in this layer is a circle node labeled Π which multiplies the incoming signals and sends the product out. For instance,

$$W_i = \mu_{Ai}(x) \times \mu_{Bi}(y), \quad i = 1,2 \tag{2}$$

each node output represents the firing weight of a rule.

Layer 3 – Every node in this layer is a circle node labeled N. The ith node calculates the ratio of the ith rule's firing weight to the sum of all rule's firing weights:

$$W_i = W_i /\left(\frac{W_1}{W_2}\right) \quad i = 1,2 \tag{3}$$

Layer 4 – Every node in this layer is a square node with a node function:

$$O_i^4 = \overline{W_i} f_i = W_i(p_i x + q_i y + r_i), \quad i = 1,2 \tag{4}$$

Where $\overline{W_i}$ is the output of layer 3, and { p_i, q_i,r_i} is the parameter set.

Layer 5 – The signal node in this layer is a circle node labeled ∑ that computes the overall output as the summation of all incoming signals, i.e.

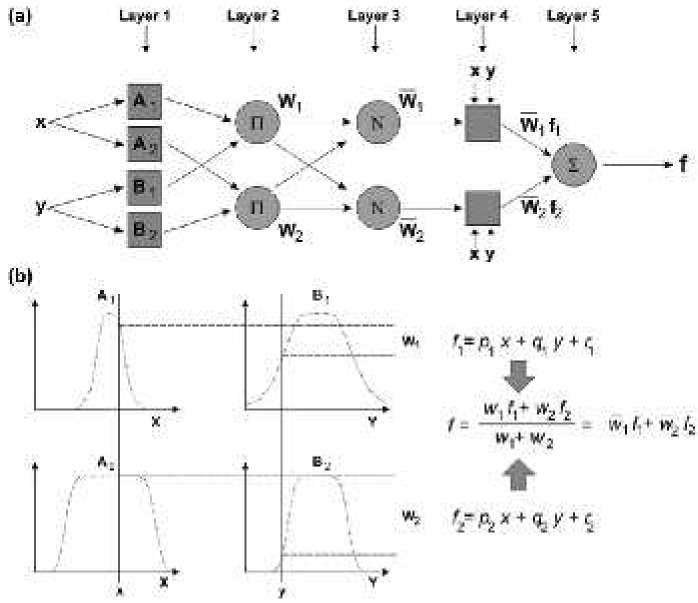

Figure 1 (a) Architecture of ANFIS and (b) Fuzzy-reasoning scheme of ANFIS [17-20-18]

$$O_i^5 = \sum_i W f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{5}$$

The basic learning rule of ANFIS is the back-propagation gradient descent, which calculates error signals recursively from the output layer backward to the input nodes. This learning rule is exactly the same as the back-propagation learning rule used in the common feed-forward neural networks. Recently, ANFIS adopted a rapid learning method named as hybrid-learning method, which utilizes the gradient descent and the least-squares method to find a feasible set of antecedent and consequent parameters [17-21-19-18].This latter method has been employed in the present study for developing the ANFIS model. MATLAB version 7.11.0 (R2010b) with using Fuzzy Logic Toolbox was employed for this method.

In this paper, an ANFIS model was developed to predict Marshall Stability (MS) of asphalt concrete using experimental variables. The model has three inputs and an output. Inputs were bitumen (%), ultrasound (μs)and unit weight (gr/cm^3) and output was the Marshall stability (kg) of asphalt concrete.

While developing the model 32 (80% of all samples) experimental data used for training and 7 (about 20% of all samples) experimental data used for testing. After experimenting different learning algorithms with different epochs, best correlations was found through hybrid learning algorithm and 1000 epochs.

The general structure of model and membership functions for input and output parameters used for ANFIS modeling are given in Figure 2 as a diagram.

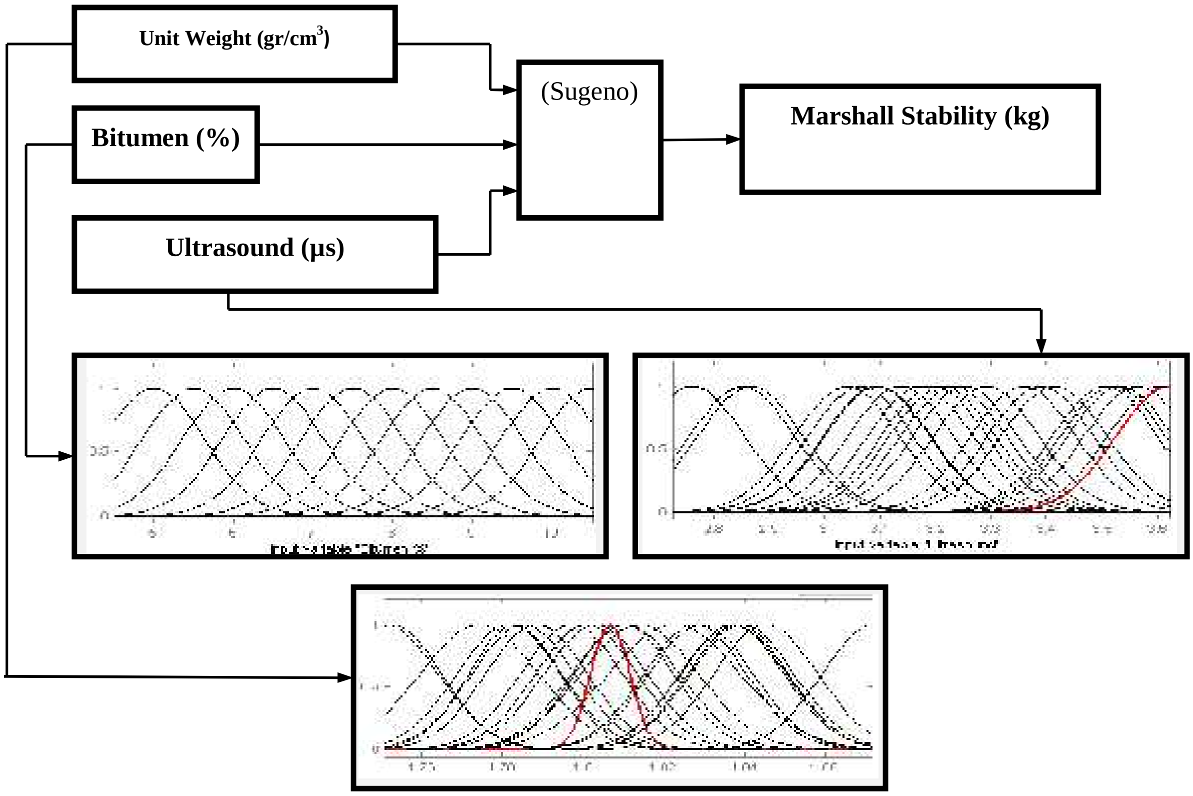

Figure 2 General structure and membership functions of the model

Using SPSS program, the descriptive statistics for the training set of randomly selected 32 data are given in Table 4.

Table 4 Descriptive statistics of selected data as training set

Physical prop.	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
Bitumen percentage (%)	32	6,00	4,50	10,50	7,7031	1,85724	3,449
Ultrasound (µs)	32	,89	2,73	3,62	3,2472	,25085	,063
Unit Weight (gr/cm^3)	32	,12	1,75	1,87	1,8094	,02906	,001
Marshall Stability (kg)	32	199,00	182,00	381,00	2,8003E2	54,01582	2,918E3

In the model 23sinusoidal “gaussmf” membership functions were selected for percentage of bitumen (POB), 23sinusoidal “gaussmf” membership functions were selected for ultrasound (US) and 23sinusoidal “gaussmf” membership functions were selected for unit weight (UW). All membership functions ranges were used for POB (% 4,5 - % 10,5), for US (2,51- 3,62) and for UW (1,75 - 1,87) respectively.

In the model 23 rules define the relationship between inputs and output. Table 5 shows that detailed structural properties of model. After training, the model was tested only using test input data by Defuzzification monitor. Also Figures 3 (a)and (b) shows matching figure of the measured results with the results obtained from developed ANFIS model for training and testing stage.

Table 5Details of ANFIS model

Parameter types of ANFIS Value	
Number of nodes	190
Number of linear parameters	92
Number of nonlinear parameters	138
Total number of parameters	230
Number of training data pairs	32
Number of checking data pairs	0
Number of fuzzy rules	23
Number of layers	3
Input	3
output	1
Type of input member function	Bell-shaped Gauss function
Range of influence	.2
Squash factor	1.25
Accept ratio	.5
Reject ratio	.15

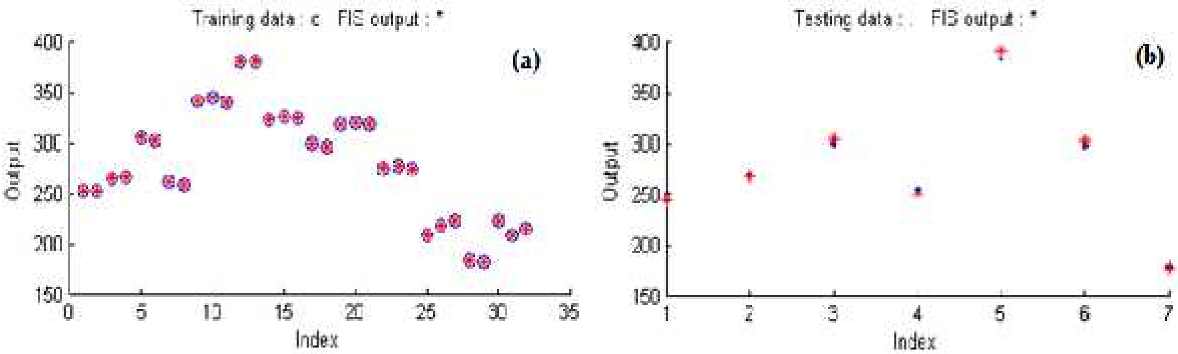

Figure3 (a) Matching figure of results for training (ANFIS-exp) (b) Matching figure of results for testing (ANFIS-exp)

The MS from developed ANFIS model as a function of Bitumen, Ultrasound and Unit Weight is shown in Figure 4 a-b-c-d-e and f.

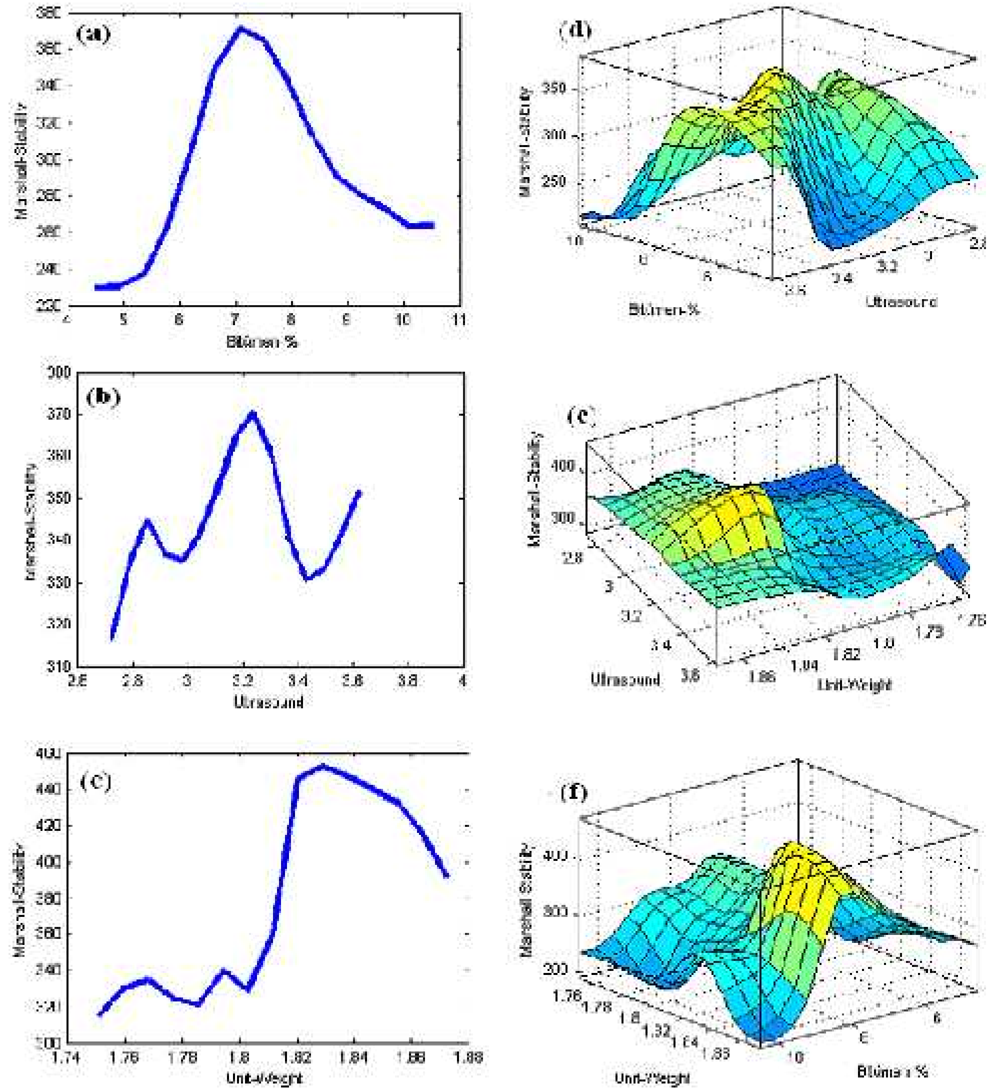

Figure 4 (a), (b), (c), (d), (e), (f)Relationship between inputs and outputs

RESULTS AND DISCUSSIONS

The adequacy of the developed ANFIS model were evaluated by considering the coefficient of determination (R^2) Eq. (6), root mean squared error (RMSE) Eq. (7) and Standard Error of the Estimate (SEE) Eq. (8).

$$R^2 = 1 - \{[\sum_{i=1}^{n}(Y_{i(observed)} - Y_{i(model)})^2]/[\sum_{i=1}^{n}(Y_{i(observed)} - Y_{i(mean)})^2]\} \quad (6)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Y_{i(observed)} - Y_{i(predicted)}\right)^2} \quad (7)$$

$$SEE = \sum_{i=1}^{n}(Y_{i(observed)} - Y_{i(model)})^2 \quad (8)$$

Where;

n= Total number of data

$Y_{i(observed)}$= Measured (experimental)
$Y_{i(model)}$= Developed model result

Table 6 represent calculated R^2, RMSE, SSE and SEE values for training and test groups of developed ANFIS model.

Table 6 Statistics of Marshall stability estimation using ANFIS

Statistics	R-square	Adjusted R-square	SEE	RMSE
Training Set	0.9919	0.9916	735	4.95
Testing Set	0.9948	0.9937	119.8	4.896

Fig. 11 (a) and (b) show the model performances of the ANFIS modeling based on the 95% prediction bounds illustrated on the figures and linear curve fitting statistics summarized in Table 6also matching figure of the values of experimental and ANFIS model for training and testing set is given in Figure 11 (c) and (d), respectively.

According to the comparison of the curve fitting statistics, as can be seen from Table 6 and Figure 5 (a-b-c-d), the smallest prediction errors are observed in ANFIS model according to the curve fitting statistics. The RMSE values of the ANFIS model at the training stage is 4,95. Besides, the RMSE values of the ANFIS model at the testing stage is 4,896. All of the statistical values in Table 6 show that the ANFIS model is suitable and predicted the Marshall Stability values very close to the experimental values.

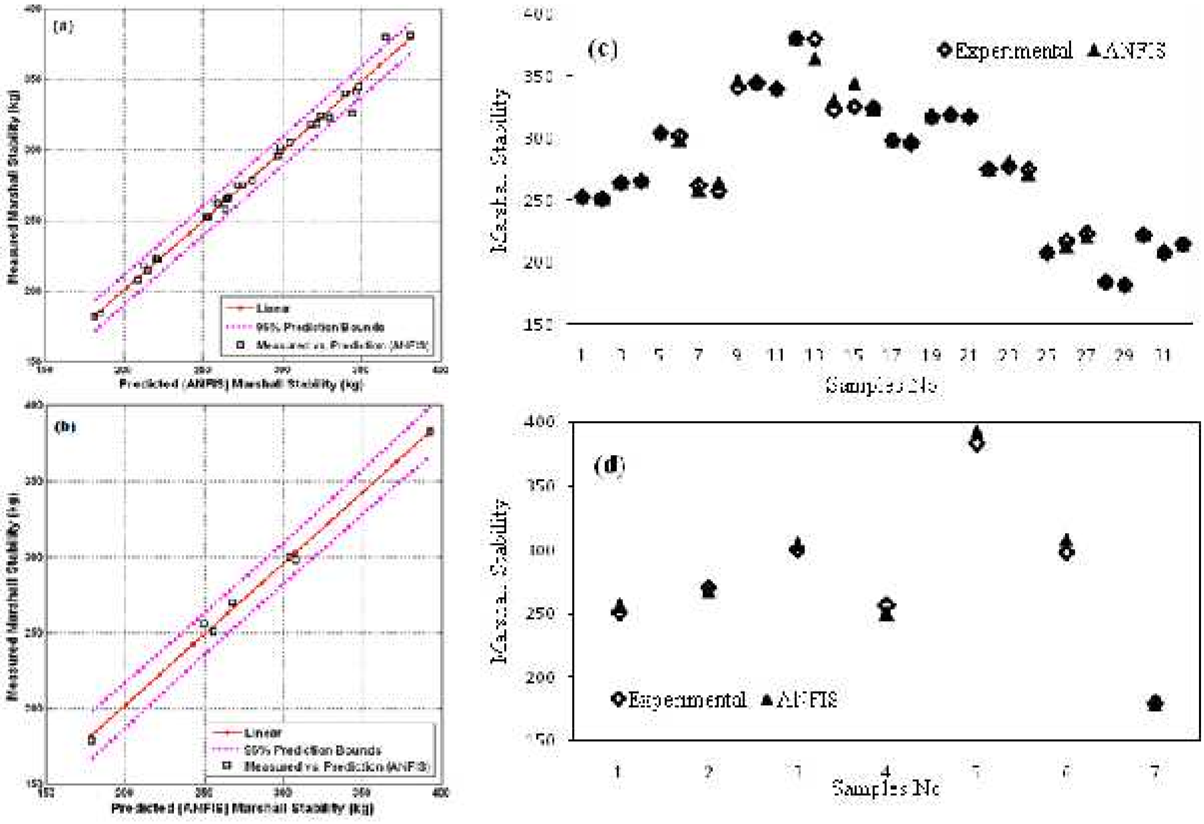

Figure 5 Comparison of experimental Marshall Stability values with the predicted values. (a) Training stage of ANFIS, (b) Testing stage of ANFIS, (c) matching figure for

training set between experimental and ANFIS, (d) matching figure for testing set between experimental and ANFIS

CONCLUSIONS

In this study, an ANFIS model for predicting the Marshall Stability (MS) of lightweight asphalt concrete containing expanded clay and has various mix proportions has been developed.

While developing the ANFIS model, 32 randomly selected experimental data were used as training data and 7 data (residual) were used as testing data. Different approaches (learning algorithm) and iteration numbers were attempted while developing the model.The best correlation was found with hybrid learning algorithm and 1000 epochs. After finding the best closely ANFIS model with experimental, the results of ANFIS model were compared with the experimental results. For comparing the results, coefficient of determination (R^2), Root mean square error (RMSE) and Standard Error of estimation (SEE) were used as comparison criteria.When predicted and measured MS values compared in the training set, RMSE and R^2 were found as 4.95 and 0.9916 respectively. When similar comparison was done for testing set, these values were found as 4.896 and 0,9948 respectively.

As a result, stability values of lightweight asphalt concrete containing expanded clay and have various mix proportions can be predicted using the ANFIS model without any experiments. ANFIS is a useful artificial intelligent method for engineering applications.

REFERENCES

[1] Cavaleri L, Miraglia N, Papia M (2008). Pumice concrete for structural wall panels. Engineering Structures. 25: 115-125.

[2] Losa, M. Leandri, P. and Bacci, R. (2008a). Mechanical and Performance-Related Properties of Asphalt Mixes Containing Expanded Clay Aggregate, Transportation Research Record: Journal of the Transportation Research Board, No. 2051, Transportation Research Board of the National Academies, Washington, D.C., pp. 23–30.

[3] Gündüz L, Şapcı N, Bekar M (2006). Utilization of Expanded Clay As Lightweight Aggregate, J. Clay Sci. Technol. Kibited 1(2): 43-49.

[4] Subaşı S. (2009a). The Effects of Using Fly Ash on High Strength Lightweight Concrete Produced with Expanded Clay Aggregate, Scientific Research and Essay Vol. 4 (4) pp. 275-288.

[5] Lehmann, H. L., and V. Adam. (1956). Use of Expanded Clay Aggregate in Bituminous Construction. Highway Research Board Proceeding. Vol.38, pp. 398-407

[6] Aams, V., and S. C. Shah. (1974). Evaluation of Open-Graded Plan-Mix Seal Surfaces for Correction of Slippery Pavement. In Trasportation Research Record 523, TRB, National Research Council, Washington, D.C., pp.88-96.

[7] Jansen, D.C., M.L. Kiggins, C. W. Swan, R. A. Malloy, M. G. Kashi, R. A. Chan, C. Javdekar, C. Siegal, and J. Weingram. (2001). Lightweight Fly Ash-Plastic Aggregates in Concrete. In Trasportation Research Record: Journal of the Transportation Research Board, No. 1775, TRB, National Research Council, Washington, D.C., pp.44-52.

[8] Agostinacchio, M. Olita, S. (2004). Use Of Expanded Clay For High Grip Bituminous Wearing Courses - II° International Congress SIIV 2004, Florence, Italy.

[9] Canestrari, F., M. Bocci, G. Ferrotti, and E. Pasquini, (2007). Mechanical Characterization of Environmentally Friendly Mixtures.International Conference on Advanced Characterisation of Pavement and Soil Engineering Materials, Athens, Greece.

[10] Losa, M. Bacci, R. Leandri, P. Alfinito, L. Cerchiai, M. (2008b). Surface Characteristics of Asphalt Pavements with Synthetic Lightweight Aggregate, 6th Symposium on Pavement Surface Characteristics SURF 2008, Portoroz, Slovenia.

[11] Emiroglu, M. E., Kisi, O., &Bilhan, O. (2010). Predicting discharge capacity of triangular labyrinth side weir located on a straight channel by using an adaptive neuro-fuzzy technique. Advances in Engineering Software, 41 (2), pp. 154-160,

[12] Mashrei, M. A., Abdulrazzaq, N., Abdalla, T. Y., &Rahman, M. S. (2010). Neural networks model and adaptive neuro-fuzzy inference system for predicting the moment capacity of ferrocement members. Engineering Structures, Volume 32, Issue 6, pp. 1723-1734.

[13] Emiroğlu, M., Beycioğlu, A., &Yildiz, S. (2012). ANFIS and statistical based approach to prediction the peak pressure load of concrete pipes including glass fiber. Expert Systems with Applications, Volume 39, Issue 3, 15 February 2012, Pages 2877-2883.

[14] Kucuk, K., Aksoy, C.O., Basarir, H., Onargan, T., Genis, M., &Ozacar, V. (2011). Prediction of the performance of impact hammers by adaptive neuro-fuzzy inference system modeling. Tunnelling and Underground Space Technology, 26, 38–45.

[15] Faisal, T., Taib, M.N., & Ibrahim, F. (2012). Adaptive Neuro-Fuzzy Inference System for diagnosis risk in dengue patients. Expert Systems with Applications, 39, 4483–4495.

[16] Cabalar, A. F., Cevik, A., Gokceoglu, C. (2012). Some applications of Adaptive Neuro-Fuzzy Inference System (ANFIS) in geotechnical engineering. Computers and Geotechnics, 40, 14–33.

[17] Jang, J.S.R. (1993). ANFIS: adaptive-network-based fuzzy inference system, IEEE Transactions on Systems, Man, and Cybernetics 23(3), 665–685.

[18] Madandoust, R., Bungey, J.H., &Ghavidel, R. (2012). Prediction of the concrete compressive strength by means of core testing using GMDH-type neural network and ANFIS models. Computational Materials Science, 51, 261–272.

[19] Nazari, A., Milani, A.A., &Khalaj, G. (2011). Modeling ductile to brittle transition temperature of functionally graded steels by ANFIS.Applied Mathematical Modelling, journal homepage: www.elsevier.com/locate/apm, in Press.

[20] Yılmaz, I., &Kaynar, O., (2011). Multiple regression, ANN (RBF, MLP) and ANFIS models for prediction of swell potential of clayey soils. Expert Systems with Applications, 38, 5958–5966.

[21] Topçu I.B., Sarıdemir, M., (2008).Prediction of rubberized concrete properties using artificial neural network and fuzzy logic. Construction and Building Materials, 22, 532–540.