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The Fuzzy Logic Model for the Prediction of Marshall Stability of Lightweight Asphalt Concretes Fabricated using Expanded Clay Aggregate

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Keywords
Lightweight asphalt concretes
Expanded clay
Marshall Stability
Fuzzy logic.

Abstract: In the study, predictability of Marshall Stability (MS) of light asphalt concrete that fabricated using expanded clay and had varied mix properties with Fuzzy Logic (FL) were researched. With this aim, asphalt concrete samples that added expanded clay aggregate (EC) in accordance with gradation determined in Highway Technical Specification, had different percentage of bitumen (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/cm^3)) were prepared and determined Marshall stabilities with Marshall test.

After that Fuzzy Logic Model was conducted with the Marshall Stability results. In the model developed by FL method the amount of bitumen (%), transition speed of ultrasound (μs) and unit weight (gr/cm^3) were used as input variable and Marshall Stability (kg) parameters were used as output variable. In the study rules were written depending on the membership functions determined for input variables. In the defuzzification process center of gravity method was used. As a result, Marshall Stability of asphalt concrete fabricated using expanded clay aggregate, with FL method, can be determined in a short time easily, in a very low error rates and without an experimental study.

Genleştirilmiş Kil Agregası Kullanılarak Üretilmiş Hafif Asfalt Betonun Marshall Stabilite Tahmini İçin Bulanık Mantık Modeli

Anahtar Kelimeler
Hafif asfalt beton
Genleştirilmiş kil
Marshall Stabilitesi
Bulanık mantık.

Özet: Çalışmada, genleştirilmiş kil kullanılarak üretilen çeşitli karışım özelliklerine sahip hafif asphalt betonun Marshall stabilitesinin Bulanık Mantık yöntemiyle tahmin edilebilirliği araştırılmıştır. Bu amaçla, Karayolları Teknik Şartnamesine gore belirlenen gradasyon limitlerinde genleştirilmiş kil agregası eklenen asphalt betonu numuneleri farklı bitüm yüzdelerinde (4.5%, 5%, 5.5%, 6%, 6.5%, 7%, 7.5%, 8%, 8.5%, 9%, 9.5%, 10%, 10.5%) ve (1,75–1,87 (gr/cm^3) birim hacim ağırlıkta hazırlanmış ve Marshall Test yöntemiyle Marshall Stabiliteleri belirlenmiştir.

Bununla birlikte Marshall Stabilite sonuçlarıyla Bulanık Mantık Modeli kurulmuştur. Geliştirilen modelde bitüm miktarı (%), ultrases geçiş hızı (μs) ve birim hacim ağırlık (gr/ cm^3) girdi olarak, Marshall Stabilitesi (kg) parametreleri ise çıktı olarak kullanılmıştur. Çalışmada girdi değerleri için belirlenen üyelik fonksiyonlarına bağlı kural tabanı oluşturulmuştur. Durulaştırma işleminde ise ağırlık merkezi metodu kullanılmıştır. Sonuç olarak kısa sürede, kolaylıkla, düşük hata oranlarında ve deneysel çalışma gerektirmeden genleştirilmiş kil agregası kullanılarak üretilen asfalt numunelerinin Marshall Stabiliteleri Bulanık Mantık metoduyla belirlenebilmektedir.

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1. 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 (Cavaleri, Miraglia, & Papia, 2008).

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. At the same time, the increasing demand for road transportation has caused serious problems of noise pollution due to vehicular traffic, particularly in urban environments. These are only two of the problems resulting from the continuous increase in transport demand, which has prompted the international scientific community to search for innovative solutions to guarantee the environmental sustainability of infrastructures (Losa, Leandri, & Bacci, 2008a).

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 (Gündüz, Şapcı, & Bekar, 2006).

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 (Gündüz, Şapcı, & Bekar, 2006; Subaşı, 2009a).

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. Moreover, the expanded clay production process allows nondangerous waste materials to be reclaimed and thereby avoids the necessity to dispose of them in a landfill or dump this benefits the environment and also offers economic advantages (Losa, Leandri, & Bacci, 2008a).

When literatures examined, it can be concluded that few works attempted on usability of expanded clay in the production of asphalt concrete (Lehmann, & Adam, 1956; Area, 1969; Aams, & Shah, 1974; Jansen, Kiggins, Swan, Malloy, Kashi, Chan, Javdekar, Siegal, & Weingram, 2001; Agostinacchio, & Olita, 2004; Canestrari, Bocci, Ferrotti, & Pasquini, 2007; Losa, Leandri, & Bacci, 2008a; Losa, Bacci, Leandri, Alfinito, & Cerchiai, 2008b).

Nowadays Artificial Intelligent methods have been extensively used in civil engineering applications (Emiroğlu, Kişi, & Bilhan, 2010; Mashrei, Abdulrazzag, Abdalla, & Rahman, 2010).

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 (Kucuk, Aksoy, Basarir, Onargan, Genis, & Ozacar, 2011).

Designers utilize principles of science and mathematics to develop specific technologies. These technologies are then used to create engineered tools such as products, structures, machines, processes or entire systems. It has already been seen that different tasks in engineering problem solving require different analysis (Emiroğlu, Beycioğlu & Yildiz, 2012). Recently, artificial intelligence and statistical analysis have been extensively using in the fields of civil engineering applications such as construction management, building materials, hydraulic, geotechnical and transportation engineering etc. (Tutumluer & Meier, 1996; Terzi, 2007; Ayata, Çam, & Yıldız, 2007; Saltan & Terzi, 2008; Taşdemir, 2009; Topçu & Sarıdemir, 2008; Alasha'ary, Moghtaderi, Page, & Sugo, 2009; Subaşı, 2009; Saffarzadeh & Heidaripanah, 2009; Özgan, 2011; Yilmaz, Kok, Şengöz, Şengür, & Avcı, 2011; Mirzahosseini, Aghaeifar, Alavi, Gandomi, & Seyednour, 2011; Moazami, Behbahani, & Muniandy, 2011; Tapkın, Çevik, & Uşar, 2010).

In this study, it has researched that predictability of MS of lightweight asphalt concrete fabricated using expanded clay and had varied mix properties with FL. 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.

2. Stability of Flexible Pavements

Stability of asphalt concrete determines the performance of the highway pavement. Low stability in asphalt concrete may lead to various types of distress in asphalt pavements (Kalyoncuoğlu & Tığdemir, 2004; Tığdemir, Karaşahin, & Şen, 2002). Cracking, especially fatigue cracking, due to repeated loading has been recognized as an important distress problem in asphalt concrete pavements. The stability of asphalt concrete pavements depends on the stiffness of the mix, bitumen content, softening point of bitumen, viscosity of bitumen, grading of aggregate, construction practice, traffic, and climate conditions (Özgan, 2010).

The Marshall mix design method and criteria were originally developed for airfield pavements, but were later also adopted for use in highway pavements. Due to its simplicity, the Marshall method of mix design was the most commonly used mix design method in the U.S. before the introduction of the Superpave design system, and it is still the most commonly-used mix design method throughout the world (Chen & Liew, 2003).

The Marshall stability is the maximum load the specimen can withstand before failure when tested in the Marshall stability test. The configuration of the Marshall stability test is close to that of the indirect tensile strength test, except for the confinement of the Marshall specimen imposed by the Marshall testing head. Thus, the Marshall stability is related to the tensile strength of the asphalt mixture (Chen & Liew, 2003).

The use of cores has several significant limitations, the technique is destructive, and although patching core holes is a quick and simple process, they become localized points of weakness in a pavement. Determining the density of cores takes time. The mat must be allowed to cool before cores can be drilled efficiently. This time lag alone means that the mat cannot be compacted further if the indicated density is below target values. Once cores are secured, they must be transported to a field or central laboratory for testing (Sanders, Rath & Parker, 1994).

3. 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 standards (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 1. Physical 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**	**Standard**
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**
Apparent density (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
Specific Gravity	1,034

Aggregate mixtures were prepared in accordance with the technical specifications required by Highways Commission (Highways Technical Specifications-HTS). The upper and lower limits required for the mixture grading and HTS binder layer are shown in the gradation curve given in Figure 1.

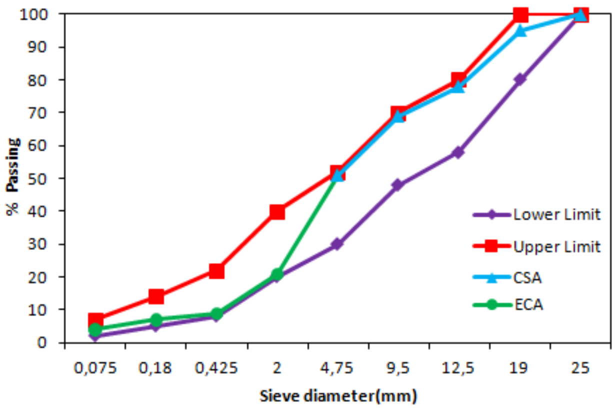

Figure 1. Gradation curve of the aggregates used in mixture

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.

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.

4. Theory of Fuzzy Logic

Fuzzy set theory was developed by Lotfi Zadeh in 1965 to deal with the imprecision and uncertainty that is often present in real-world applications (Zadeh, 1965). In 1974 Mamdani (Mamdani, 1976), by applying Zadeh's theories of linguistic approach and fuzzy inference, successfully used the 'IF-THEN' rule on the automatic operating control of steam generator. It needs only to set a simple controlling method based on engineering experience. Therefore, it is particularly useful in complicated structural systems. Fuzzy logic has been developing since 1965 and become most successful in application. (Tanyildizi, 2009).

In recent years, the number and variety of applications of fuzzy logic have increased significantly. The applications range from consumer products such as cameras, camcorders, washing machines, and microwave ovens to industrial process control, medical instrumentation, decision-support systems, and portfolio selection (Işık & Arslan, 2011).

Fuzzy inference is the real process of mapping from a given set of input variables to an output relied upon a set of fuzzy rules. The main process of a general fuzzy inference system (FIS) includes four activities called as fuzzification, fuzzy rule base, fuzzy inference engine and defuzzification (Kuşan, Aytekin & Özdemir, 2010). (Figure 2).

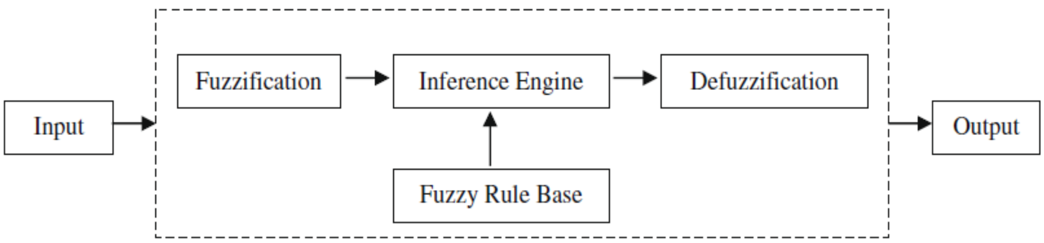

Figure 2. Basic elements of FL

These parts are detailed below.

- Fuzzification: It converts each input data to degrees of membership by a lookup in one or more of several membership functions.
- Fuzzy rule base: This contains rules that include all possible fuzzy relationship between input and outputs using IF-THEN format.
- Fuzzy Interference Engine: Collects all fuzzy rules in the fuzzy rule base and learns how to transform a set of inputs to related outputs.
- Defuzzification: This converts the resulting fuzzy outputs from fuzzy interference engine to a number (Akkurt, Başyigit, Kilincarslan & Beycioglu, 2010).

There are two types of FIS that can be implemented in the MATLAB's FIS toolbox: Mamdani-type and Sugeno-type. Mamdani's method is the most commonly seen fuzzy methodology and it expects the output MFs to be fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification (Omid, 2011).

In this study Mamdani type fuzzy logic modeling studied for the prediction of Marshall Stability of asphaltic concrete.

5. Fuzzy Modeling Details

In this paper, a fuzzy logic model was developed to predict Marshall Stability of asphalt concrete using experimental variables. The model has three inputs and an output. Inputs were amount of bitumen (%), transition speed of ultrasound (µs), and unit weight (gr/cm^3) and output was the Marshall stability of asphalt concrete. Flow diagram for study is given below (Fig.3).

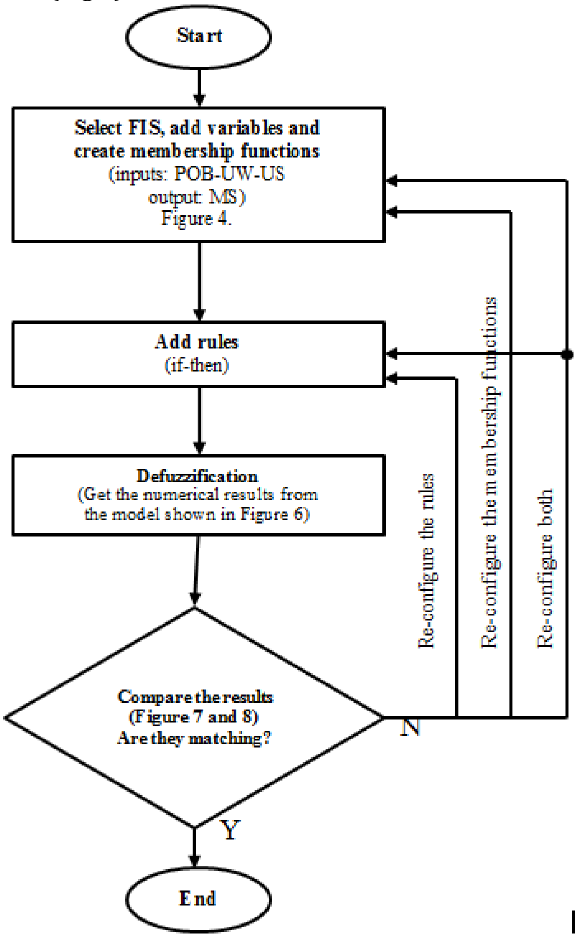

Figure 3. Flow diagram

While modeling, the membership functions for bitumen (%), ultrasound (µs), unit weight, Marshall Stability of asphalt concrete were selected 8, 4, 7, 11 respectively. The general structure of the model and membership functions for input and output parameters used for fuzzy logic modeling are given in Figure 4. as a diagram. Also the membership functions are detailed as below.

```
Name='POB'
Range=[4.5 10.5]
NumMFs=8
MF1='POB1':'trimf',[4.5 4.5 5]
MF2='POB2':'trimf',[4.5 5 6]
MF3='POB3':'trimf',[5 6 7]
MF4='POB4':'trimf',[6.02 7.03174603174603 7.92]
MF5='POB5':'trimf',[6.99 8.06349206349206 8.98]
MF6='POB7':'trimf',[9.02 9.64 10.5396825396825]
MF7='POB8':'trimf',[9.96825396825397 10.5 10.5]
MF8='POB6':'trimf',[8.05 9.07 9.98412698412698]
Name='UW'
Range=[1.78 1.84]
NumMFs=7
MF1='uw1':'trimf',[1.78 1.78 1.78992063492063]
MF2='uw2':'trimf',[1.78031746031746
1.79031746031746 1.80031746031746]
MF3='uw3':'trimf',[1.79 1.80134920634921 1.81]
MF4='UW4':'trimf',[1.80047619047619
1.81047619047619 1.82047619047619]
MF5='UW5':'trimf',[1.81 1.82 1.83]
MF6='UW6':'trimf',[1.81984126984127
1.82984126984127 1.83984126984127]
MF7='UW7':'trimf',[1.83 1.84 1.84]
Name='US'
Range=[2.5 4]
NumMFs=4
MF1='US1':'trimf',[2.5 2.5 3]
MF2='US2':'trimf',[2.5 3 3.5]
MF3='US3':'trimf',[3 3.5 4]
MF4='US4':'trimf',[3.5 4 4]
Name='MS'
Range=[180 385]
NumMFs=11
MF1='MS1':'trimf',[180 180 199.794973544974]
MF2='MS2':'trimf',[180 199.794973544974 220]
MF3='MS4':'trimf',[219 242.09656084656l 260]
MF4='MS5':'trimf',[240 257 280.601851851852]
MF5='MS6':'trimf',[259 278.43253968254 301]
MF6='MS7':'trimf',[281 301.210317460317 320]
MF7='MS8':'trimf',[301 320.734126984127 340]
MF8='MS9':'trimf',[321 340.800264550265 360]
MF9='MS3':'trimf',[199 220.945767195767 240]
MF10='MS10':'trimf',[339.715608465609 361 384]
MF11='MS11':'trimf',[359 384 384]
```

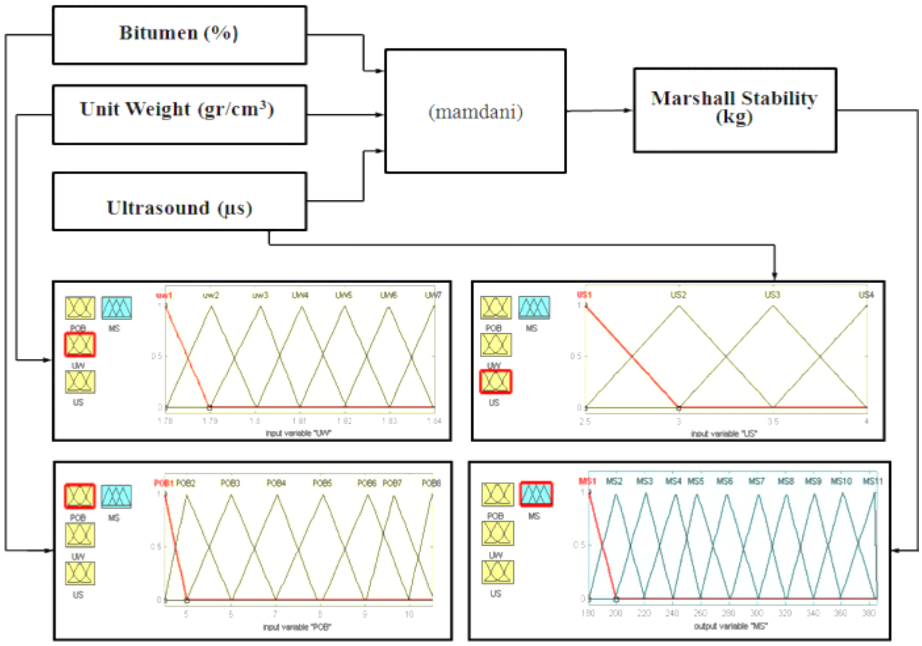

Figure 4. General structure and membership functions of the model

In the rule base 244 rules formed using experimental results and experiences. Some of formed rules are given Table 1. After determining membership functions and forming rules (244), the FL model results obtained using defuzzification monitor. The Marshall stability from developed FL model as a function of inputs is seen in Figure 5. Centroid was used as defuzzification method. The models defuzzification monitor is shown in Fig. 6.

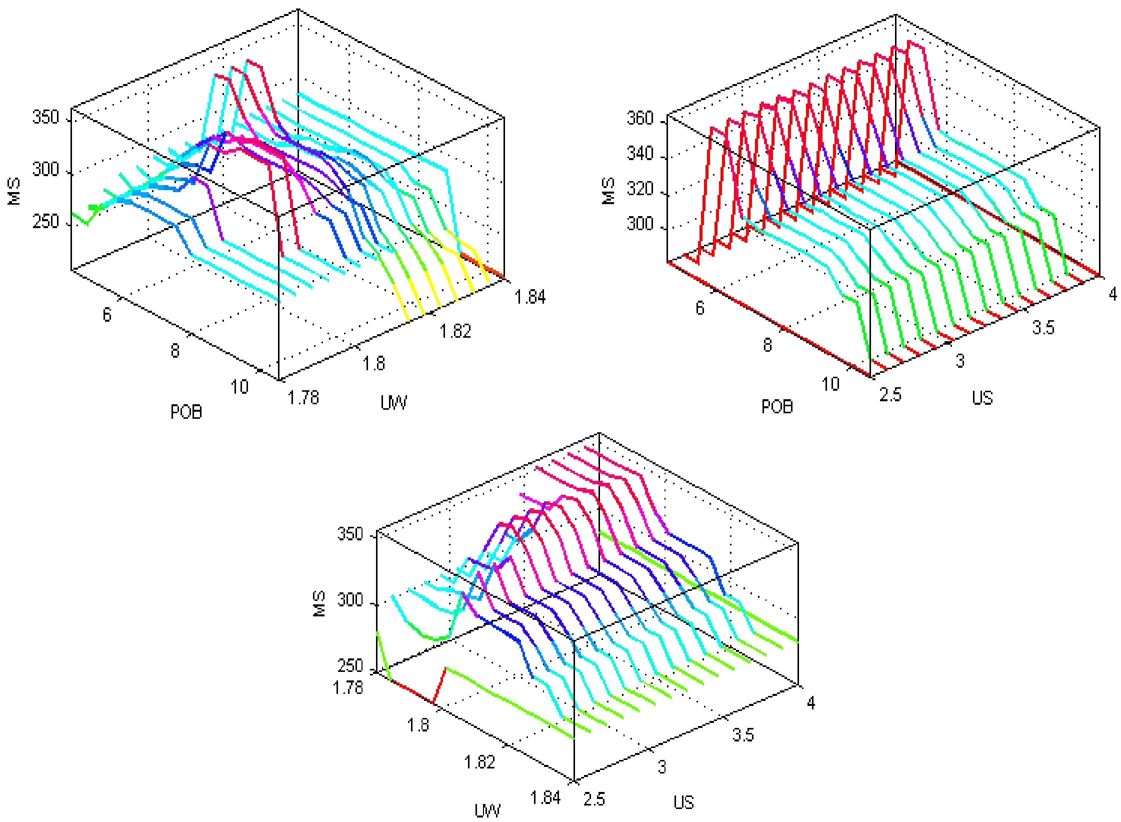

Figure 5. Relationship between inputs and output of the model

Table 4. Some of examples rules.

Fuzzy rules
1. If (POB is POB1) and (UW is uw1) and (US is US1) then (MS is MS5) (1)
2. If (POB is POB1) and (UW is uw1) and (US is US1) then (MS is MS6) (1)
3. If (POB is POB1) and (UW is uw1) and (US is US1) then (MS is MS7) (1)
4. If (POB is POB1) and (UW is uw1) and (US is US2) then (MS is MS5) (1)
5. If (POB is POB1) and (UW is uw1) and (US is US2) then (MS is MS6) (1)
6. If (POB is POB1) and (UW is uw1) and (US is US2) then (MS is MS7) (1)
7. If (POB is POB1) and (UW is uw2) and (US is US2) then (MS is MS5) (1)
8. If (POB is POB1) and (UW is uw2) and (US is US2) then (MS is MS6) (1)
9. If (POB is POB1) and (UW is uw2) and (US is US2) then (MS is MS7) (1)
10. If (POB is POB2) and (UW is uw2) and (US is US2) then (MS is MS5) (1)

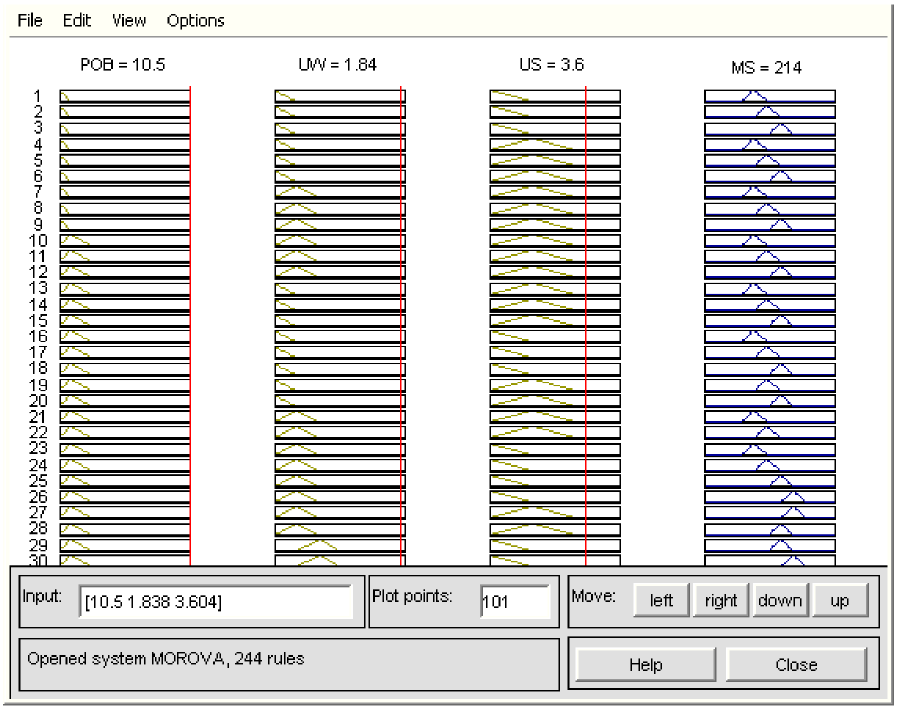

Figure 6. Defuzzification monitor of the model

6. Results and Discussions

In this study, the predictability of the developed FL model evaluated by using some statistical equations. Eq. (1) is the Root Mean Squared Error (RMSE) and Eq. (2) is the coefficient of simulation efficiency (COE).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Y_{i(m)} - Y_{i(p)}\right)^2} \qquad (1)$$

$$COE = 1 - \frac{\sum_{i=1}^{n}[(x_m)_i - (x_p)_i]^2}{\sum_{i=1}^{n}[(x_m)_i - (\bar{X})]^2} \qquad (2)$$

In equation 1 and 2 subscripts m, p, N and $\bar{X}$ indicate measured, predicted, pattern and average measured data respectively.

Also experimental studies and FL model results comparison graphics are illustrated in Figure 7 and 8.

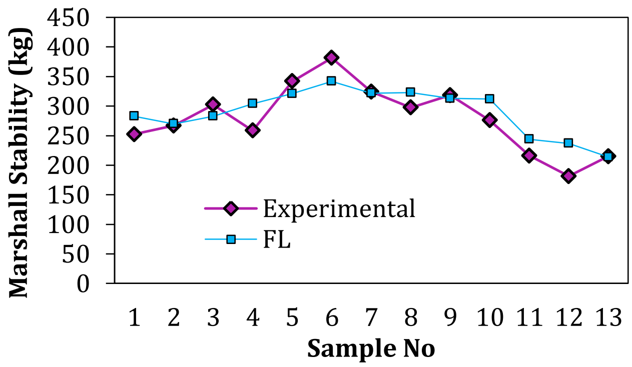

Figure 7. Matching figure of the values of experimental and fuzzy logic model

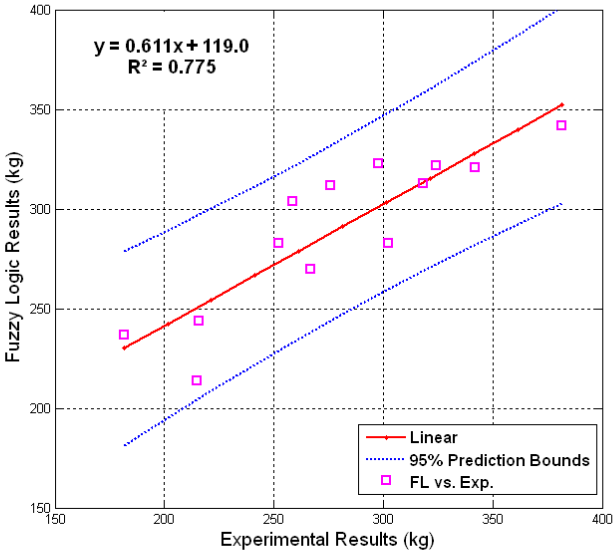

Figure 8. Comparison of experimental and fuzzy logic results

As shown in Fig. 7 and 8, the results obtained FL model is very close to the experimental results. This situation is demonstrated clearly by the statistical parameters shown in Table 5 (COE and RMSE).

Table 5. Statistics of Marshall stability prediction using FL Statistics

Statistics	
COE	**RMSE**
0.7758	19.25

7. Conclusions

In this study, a model was developed by fuzzy logic method and it's usability for predicting the Marshall Stability of lightweight asphalt concrete fabricated using expanded clay was investigated. While modeling 13 experimental results were used to develop the model. Coefficient of determination (R^2) and Total Root Mean Square Error (RMSE) criteria were used for comparison of experimental results with the results predicted by the model of FL. When the results were compared, RMSE and R^2 values were found as 19.25 and 0.7758 respectively. As a result, Marshall Stability values of lightweight asphalt concrete fabricated using expanded clay could be predicted practically with very low error rates in a very short time without performing any experiments.

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