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Prediction of Modulus of Rupture from 7 Days Compressive Strength for Pavement Concrete Using A Fuzzy Logic Algorithm

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ABSTRACT

Concrete pavements (CP) have been widely used in many countries in the world as an alternative to other pavement techniques. Modulus of rupture is the most important parameter for CP design. However, compressive strength is widely used because it is easer to perform this test than the test for the modulus of rupture. In recent years, fuzzy logic approaches have been successfully used to solve some of the engineering problems. The main advantage of fuzzy models is their ability to describe knowledge in a descriptive human-like manner in the form of simple rules using linguistic variables only. A concrete pavement design requires 28 days modulus of rupture value. As known, modulus of rupture is proportional with compressive strength. The aim of the present work is to predict 28 days modulus of rupture of pavement concrete from the 7 days compressive strength using a fuzzy logic algorithm. The results show that the fuzzy logic algorithm used in this study can be used to predict 28 days modulus of rupture of pavement concrete for use in concrete pavement design.

Key Words: Concrete pavement, modulus of rupture, fuzzy logic.

INTRODUCTION

Since the first strip of concrete pavement was completed in 1893, concrete has been extensively used for paving highways and airports as well as business and residential streets. As time passes, the expected properties from a modern pavement have been increased with the development of the technology. Especially it is very important both to have adequate strength against the destructive traffic loads and to optimize the pavement structure from an economical point of view. Concrete pavements (CP) have been widely used in many countries in the world as an alternative to other pavement techniques.

Engineering design is usually based on concrete's compressive strength. Compressive strength refers to what concrete is capable of resisting from loads when they are pushing on the concrete. The approximate relationship between flexural strength (modulus of rupture, MR), tested in accordance with ASTM C 78, and compressive strength (f_c) of concrete is:

$$MR = k\sqrt{f_c} \tag{1}$$

Modulus of rupture is the most important parameter for CP design. However, compressive strength is widely used because it is easily obtained compared to the modulus of rupture. As known, modulus of rupture is proportional with compressive strength.

Concrete is well suited as a road paving material, both technically and financially, primarily on roads with a high traffic intensity and heavy loads. When used as a paving material, concrete provides a rigid covering with good load-distribution ability. Other properties include high load-bearing ability, good wear resistance, good durability, a bright surface and non-flammability [1].

In this study, the theory of fuzzy sets, especially fuzzy modeling is discussed to determine modulus of rupture of concrete pavement. A fuzzy logic algorithm has been devised for estimating modulus of rupture from 7 days compressive strength of concrete pavement.

FUZZY LOGIC

General

In 1965, L.A. Zadeh published his famous paper “Fuzzy sets” in Information and Control providing a new mathematical tool which enables us to describe and handle vague or ambiguous notions such as “a set of all real numbers which are much greater than 1”, “a set of beautiful women,” or “the set of tall men.” Since then, fuzzy set theory has been rapidly developed by Zadeh himself and numerous researchers, and an increasing number of successful real applications of this theory in a wide variety of unexpected fields have been appearing. The main idea of fuzzy set theory is quite intuitive and natural: Instead of determining the exact boundaries as in an ordinary set, a fuzzy set allows no sharply defined boundaries because of generalization of a characteristic function to a membership function [2].

The concept of fuzzy set was introduced by Zadeh [3], who pioneered the development of fuzzy logic instead of Aristotelian logic which has two possibilities only. Fuzzy logic concept provides a natural way of dealing with problems in which the source of imprecision is the absence of sharply defined criteria rather than the presence of random variables. Fuzzy approach considers cases where linguistic uncertainties play some role in the control mechanism of the phenomena concerned. Herein, uncertainties do not mean random, probabilistic and stochastic variations, all of which are based on the numerical data. Zadeh has motivated his work on fuzzy logic with the observation that the key elements in human thinking are not numbers but levels of fuzzy sets. Further he saw each linguistic word in a natural language as a summarized description of a fuzzy subset at a universe of discourse representing the meaning of this word. In consequence, he introduced linguistic variables as variables whose values are sentences in a natural or artificial language [4].

Adaptive-network-based fuzz y in ference s ystem (ANFIS)

Adaptive neuro-fuzzy inference system (ANFIS) is a neuro-fuzzy system developed by Roger Jang [5-9]. It has a feed-forward neural network structure where each layer is a neuro-fuzzy system component (Fig. 1). ANFIS is used for the modeling of nonlinear or fuzzy input and output data, and for the prediction of output according to the input. It applies a combination of the least squares method and back-propagation gradient descent method for training fuzzy inference system membership function parameters to emulate a given training data set. Functionally, it is equivalent to the combination of neural network and fuzzy inference system. [10]

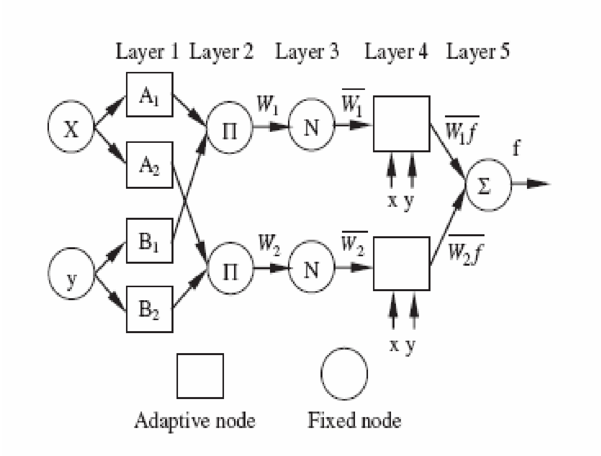

Fig. 1. The frameworks of ANFIS

ANFIS was first introduced by Jang in 1993 [6]. The model is based on Takagi–Sugeno inference model [11-12]. ANFIS uses a hybrid learning algorithm to identify consequent parameters of Sugeno-type fuzzy inference systems. In this paper, the Sugeno fuzzy model is assumed to have two inputs m and n and one output f. For a first-order Sugeno fuzzy model, a typical rule set with two fuzzy if–then rules can be expressed as:

• Rule 1: If (m is A_1) and (n is B_1) then

$$f_1 = p_1 m + q_1 n + r_1 \quad (2)$$

• Rule 2: If (m is A_2) and (n is B_2) then

$$f_2 = p_2 m + q_2 n + r_2 \quad (3)$$

Where p_1, p_2, q_1, q_2, r_1 and r_2 are linear parameters and A_1, A_2, B_1 and B_2 are nonlinear parameters.

The architecture of the ANFIS is shown in Fig. 1. The entire system consists of five layers, the fuzzy layer, product layer, normalized layer, de-fuzzy layer and total output layer. The relationship between input and output of each layer is discussed in the following sections. Layer 1 is the fuzzy layer, in which m and n are the input of nodes A_1, B_1 and A_2, B_2, respectively. A_1, A_2, B_1 and B_2 are the linguistic labels used in the fuzzy theory for dividing the membership functions. The membership relationship between the output and input functions of this layer can be expressed as below:

$$O_{1,i} = \mu_{Ai}(m), i = 1,2$$

$$O_{1,j} = \mu_{Bj}(m), j = 1,2$$

Where $O_{1,i}$ and $O_{1,j}$ denote the output functions and μ_{Ai} and μ_{Bi} denote the membership functions.

Layer 2 is the product layer that consists of two nodes labeled. The output W_1 and W_2 are the weight functions of the next layer. The output of this layer is the product of the input signal, which is defined as follows:

$$O_{2,i} = w_i = \mu_{Ai}(m)\mu_{Bi}(n), \qquad i = 1,2 \tag{5}$$

Where $O_{2,i}$ is the output of Layer 2.

The third layer is the normalized layer, whose nodes are labeled N. The function of this layer is to normalize the weight function in the following process:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, i = 1,2 \tag{6}$$

Where $O_{3,i}$ is the output of Layer 3.

The fourth layer is the defuzzification layer. The nodes in this layer are adaptive nodes. The relationship between the inputs and output of this layer can be defined as the following:

$$O_{4,i} = \overline{w}_i(p_i m + q_i n + r_i), i = 1,2 \tag{7}$$

Where $O_{4,i}$ is output of Layer 4. And p_i, q_i and r_i are the linear parameters of the node.

The fifth layer is the output layer, whose node is labeled as ∑. The output of this layer is composed of all the ingredients of the inputs, which represents the results of cleaning rates. The output can be expressed as below:

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, i = 1,2 \tag{8}$$

Where $O_{5,i}$ is the output of Layer 5.

2.3. Fuzzy Logic Example

Many textbooks provide basic information on the concepts and operational fuzzy algorithms [13-17]. In several research, fuzzy approach has been used [18,19]. The key idea in fuzzy logic is allowance of partial belongings of any object to different subsets of the universal set instead of belonging to a single set completely. Partial belonging to a set can be described numerically by a membership function which assumes values between 0 and 1 inclusive. For instance Fig.2 shows a typical membership function for small, medium and large class size in universe, U. Hence, these verbal assignments are fuzzy subsets of the universal set. In this figure, set values less than 2 are definitely “small”; those between 4 and 6 are certainly “medium; while values larger than 8 are definitely “large”. However, intermediate values such as 2.2 partially belong to the subsets “small” and “medium”. In fuzzy terminology 2.2 has a membership value of 0.9 in “small” and 0.1 in “medium”, but 0.0 in “large” subsets [20]. The literature is rich with references concerning the ways to assign membership values or functions to fuzzy variables. Among these ways are intuition, inference rank ordering, angular fuzzy sets, neural networks, genetic algorithms, inductive reasoning, etc. [16]. Especially, the intuitive approach is used rather commonly because it is simply derived from capacity of humans to develop membership functions through their own innate intelligence and understanding. Intuition involves contextual and semantic knowledge about an issue; it can be also involve linguistic truth values about this knowledge [15].

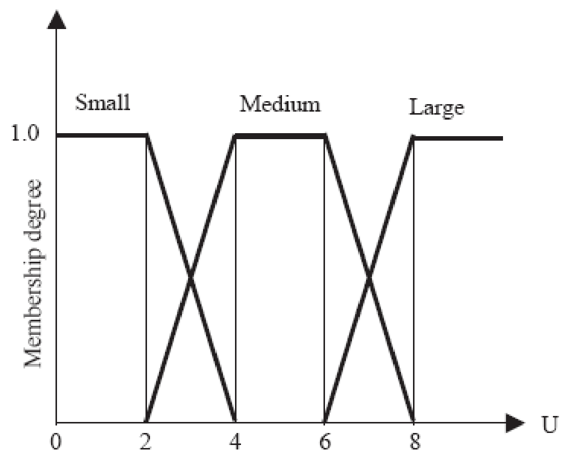

Fig.2. Fuzzy subsets

Even if the measurements are carefully carried out as crisp quantities they can be fuzzified. Furthermore, if the form of uncertainty happens to arise because of imprecision, ambiguity or vagueness, then the variable is fuzzy and can be represented by a membership function. Unlike the usual constraint where, say, the variable in Fig. 2 must not exceed 2, a fuzzy constraint takes the form as saying that the same variable should preferably be less than 2 and certainly should not exceed 4.

This is tantamount in fuzzy sets terms that values less than 2 have membership of 1 but values greater than 4 have membership of 0 and values between 2 and 4 would have membership between 1 and 0. In order to simplify the calculations, usually the membership function is adopted as linear in practical applications. The objective then can be formulated as maximizing the minimum membership value, which has the effect of balancing the degree to which the objective is attained with degrees to which the constraints have to be relaxed from their optimal values [4].

EXPERIMENTS A ND COMPUTATIONAL PROCEDURE

MATERIALS

ASTM Type I, Portland cement (PC), from Set cement factory in Ankara, Turkey, was used in this study. SF (Silica Fume), FA (Fly Ash), superplasticiser, limestone and natural sand were obtained from Antalya Electro Metallurgy Enterprise, Çayırhan Thermal Power Plant, Aşkale and Serçeme River in Erzurum in Turkey, respectively. The chemical composition and physical properties of PC, FA and SF used in this study are summarized in Table 1.

Table 1. Chemical analysis and physical properties of PC, SF and FA,

Component	PC (%)	SF (%)	FA (%)
SiO_2	19.80	88.95	47.5
Fe_2O_3	3.42	0.5 – 1	16.3
Al_2O_3	5.61	1 – 3	15.95
CaO	62.97	0.8 – 1.2	6.6
MgO	1.76	1.0 – 2.0	4.65
SO_3	2.95	–	–
K_2O	0.3	–	–
TiO_2	0.2	–	–
Sulphide (S^{2-})	0.17	0.1–0.3	–
Chloride (Cl^-)	0.04	–	–
Undetermined	0.30	–	–
Free CaO	0.71	–	11.5
LOI	0.36	0.5–1.0	2.4
Specific gravity	3.15	2.18	2.4
Specific surface (cm^2/g)	3410	–	–
Remainder on 200-mm sieve (%)	0.1	–	–
Remainder on 90-mm sieve (%)	3.1	–	–
Compressive strength (MPa)			
2 days,	24.5	–	–
7 days	42.0	–	–
28 days	44.4	–	–

ASTM Type I PC was added as the basic cementations material. The dosage was 350 kg/m^3. SF and FA was added as a partial replacement of the cement at levels of 0, 10, 20, and 30% based on some previous studies and 0, 5, 10 and 15% by weight of the total cementations materials, respectively. The w/c ratios were 0.30, 0.35, 0.40 and 0.45. The dosage level of superplasticiser was slightly adjusted for some mixes to maintain approximately the same workability. The coarse aggregate was crushed limestone with maximum size of 32 mm and natural sand with a fineness modulus of 2.66 was used for making concrete mixtures. The four different types of gradations used in this study are shown in Table 2. Parameters and their values are given in Table 3.

Table 2. Gradations as cumulative retained (%)

Sieve sizes (mm)	Gradation Type			
	I	II	III	IV
16 – 32	38	20	27	33
8 – 16	62	38	46	53
4 – 8	77	53	62	70
0 – 4	100	100	100	100

Table 3. Parameters and their values corresponding to their levels to be studied

Factors	Levels			
	1	2	3	4
A (water/cementitious ratio)	0.30	0.35	0.40	0.45
B (gradation type)	I	II	III	IV
C (fly ash content) (%)	0	5	10	15
D (silica fume content) (%)	0	10	20	30

Three 100*200 mm cylinders specimens were cast for each mix. The specimens were demoulded after 24 hours and stored in a water tank at 21 ± 1^{o}C until tested at 7 days. Compressive strength of each specimen was determined in accordance with ASTM C 109.

28-day flexural strength (modulus of rupture) test was conducted in accordance with ASTM C78-94 using a simple beam with three-point loading at a loading rate of 0.2 kN/s.

METHOD

In this study, the experiments were designed based on the Taguchi method. In the orthogonal array technique, the minimum required number of experiments for four factors at four levels is 16. It is, therefore, designed in $L_{16}(4^4)$ and results were obtained from 7 days compressive strength and 28 days modulus of rupture tests. 16 experimental results were used for the prediction of the other 240 experimental results. 112 results of total 256 (240+16) results were used as training data, other 112 results as testing data and the others as checking data. According to the obtained results, the correlation matrix was formed and the effect of mixing parameters on compressive strength and modulus of rupture of pavement concrete and their interactions was observed.

In the traditional approach of experimentation, while one factor is kept varying, all the other factors are kept constant. The optimum conditions arrived in the conventional approach may not be a true optimum if interactions between the factors are present. To study the factors and its interactions, factorial experiments and response surface designs are available. In the case of a full factorial design, the number of experiments is numerous, and it is practically not possible to carry out the experiments in most of the cases. So the fractional factorial experiments using orthogonal array was investigated by Taguchi [21,22], which can substantially decrease the number of experiments and is feasible to study the effect of factors and its interactions. The linear graph developed by Taguchi [21] is useful to scientists and engineers to design and analyze the experimental data without having basic knowledge of factorial design. The test data used in this study were taken from Hınıslıoglu and Bayrak [23].

Compressive strength and modulus of rupture of pavement concrete test results were predicted with Taguchi method for using in ANFIS and these data were used for training and testing as given in Fig. 3, Fig. 4 and as Table in an Appendix. In these graphs, there are many irregularities. Because we have a lot of experimental results and we must use all of these data to estimate more correctly.

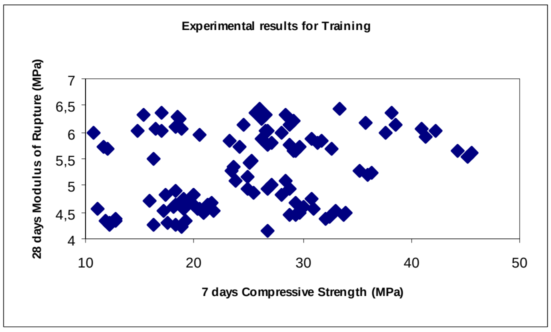

Fig. 3. Experimental results for Training

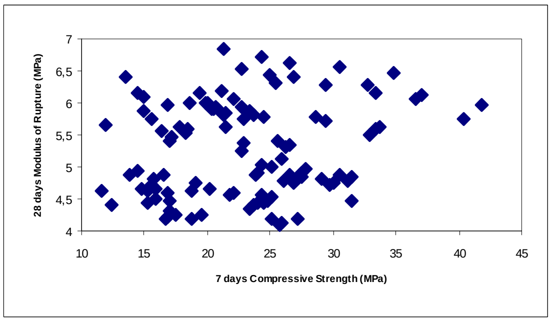

Fig. 4. Experimental results for Testing

The computation of the data for ANFIS was conducted using the software Matlab. Because the ANFIS training includes the gradient descent method and the least squares method, it is very complex to program routine for direct computation and hard to apply. However, the ANFIS training algorithms was embedded in the software Matlab's fuzzy inference toolbox, which makes it easy to process the data just by using the training and predicting functions. The main computation procedure includes four steps. The first step is data input. The experimental data are divided into input data and output data. Input data are the cleaning parameters, while output data is the cleaning width. The input of the experimental data includes the input data and output data in the form of data array to the system. The second step is assigning fuzzy sets. For the data input, several fuzzy sets should be assigned to each kind of input and output data. The system will set membership functions for them according to the fuzzy sets and range of data automatically in the data processing process. The third step is using the ANFIS training function in the toolbox for the training of the input data. The training of the data will be performed automatically in the system and an array of training errors will be obtained. The last step is the output prediction. After training, an ANFIS model of the cleaning system will be obtained for output prediction. The prediction result is easy to obtain just by inputting the cleaning parameters and using the predicting function.

In ANFIS study, the data set of both groups is divided randomly into two equal parts as: ‘‘training’’ and ‘‘test’’ data [24]. Sub-clustering is used to generate the ANFIS structure automatically. The training phase involves an iterative procedure, which seeks to calculate optimum values of the system parameters by minimizing the sum of squared differences between model predictions and training data values. The hybrid method is preferred for the training phase. The algorithm of ANFIS is shown schematically in Fig. 5.

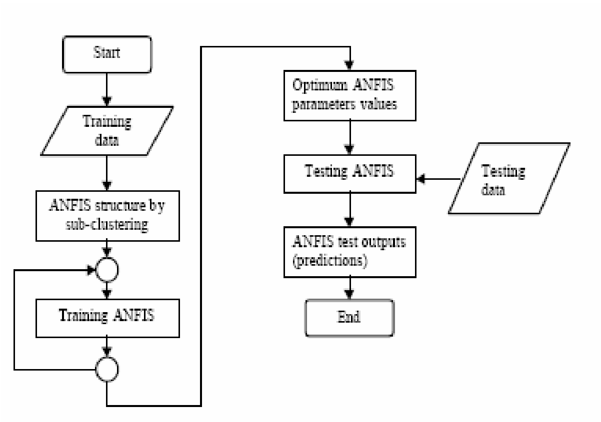

Fig. 5. The flowchart of the ANFIS

In the first step in ANFIS, it is required to fuzzify the input parameters using an appropriate partitioning technique. In this context, utilizing grid partitioning technique and Gaussian membership functions, input variables were fuzzified.

In the second step, the first-order Sugeno FIS with linear output function was selected as the inference system. Later, ANFIS structure was completed by the selection of hybrid learning algorithm. Since grid partitioning was selected, fuzzy rules were established for the inference system. In the rule-base, fuzzy variables were connected with T-norm (fuzzy AND) operators and rules were associated using max-min decomposition technique. Furthermore, training continued for epochs and process terminated by the observation of the stability in error decrement. The detailed information about ANFIS algorithm can be taken from the literature. For example, from the references listed.

RESULTS AND DISCUSSION

The prediction of cleaning width in ANFIS was achieved using the evalfis function of Matlab software. The prediction was performed according to the input parameters, and the predicting results and errors are listed in Table 5. It can be seen from the table that the prediction values were very close to the experimental values of the cleaning width. The hybrid train algorithm was selected in computational procedure. Learning rate, training error, epoch and rules for each input are 0.01, 0.5085, 80 and 24, respectively. The prediction errors ranged from 0.01 to 0.14, and the average prediction error was 0.08.

According to ANFIS results, the relationship between input and output parameters is shown in Fig. 6 and sample predict of model is given in Fig. 7. It is seen upward and downward peak values in Fig. 6. Because the values were selected randomly from the total data series, except from the orderly data series. If all data were taken into consideration, it could be seen regular tendency in the Fig. 6.

In Figure 7, it was seen a ANFIS prediction window which is formed according to rule base of ANFIS algorithm. In these figure, there is a prediction of modulus of rupture as depend on compressive strength. Detailed information about this prediction results was shown in Table 4.

In this study, ANFIS algorithm was established by taking into consideration that these results include errors. But most of the errors are negligible level. There is a good agreement between the results as seen in Table 4.

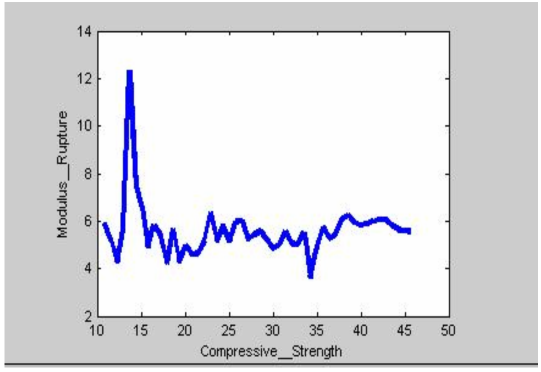

Fig. 6. The relationship between input and output parameters

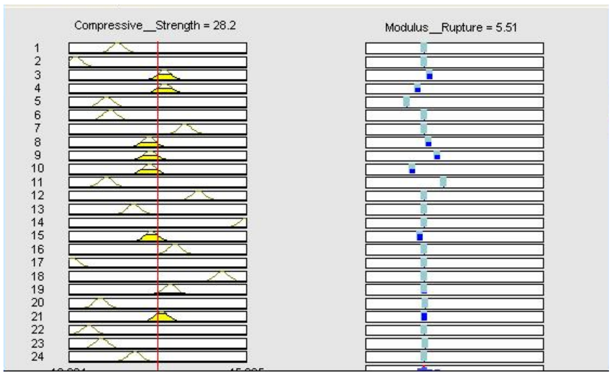

Fig. 7. Sample predict of model

Table 4. Comparision of experimental and predicted ANFIS results

Test No	7 Days Compressive Strength (Mpa)	Modulus of Rupture (Mpa)		
		Experimental	Predicted	Error
1	28.734	5.888	5.58	0.05
2	23.278	6.430	5.61	0.13
3	29.000	5.942	5.49	0.08
4	24.530	5.504	5.84	0.06
5	15.933	5.614	6.4	0.14
6	41.305	5.649	5.98	0.06
7	38.190	6.079	6.27	0.03
8	41.687	5.700	6.02	0.06
9	37.359	6.187	5.63	0.09
10	30.775	4.533	5.04	0.11
11	28.454	4.878	5.55	0.14
12	19.731	4.299	4.47	0.04
13	21.958	4.589	4.68	0.02
14	17.683	4.666	4.03	0.14
15	17.848	4.526	4.09	0.10
16	27.202	4.803	5.21	0.08
17	17.440	4.556	4.53	0.01
18	23.316	4.960	5.53	0.11
19	24.834	5.104	5.41	0.06
20	21.760	5.179	4.57	0.12

CONCLUSIONS

In this study, ANFIS methodology was employed to simulate the relationship between 7 days compressive strength and 28 days modulus of rupture. Results denoted that ANFIS methodology produced very successful results and was able to predict 28 days modulus of rupture form 7 days compressive strength. There is a good agreement between the results. In further researches, ANFIS methodology can be used in similar studies. Thus, it will be gained as cost and time in the experimental study.

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