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MODELING FLEXURAL STRENGTH OF EPS LIGHTWEIGHT CONCRETE USING REGRESSION, NEURAL NETWORK AND ANFIS

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ABSTRACT

Lightweight concrete (LWC) is a kind of concrete that made of lightweight aggregates or gas bubbles. These aggregates could be natural or artificial, and expanded polystyrene (EPS) lightweight concrete is the most interesting lightweight concrete and has good mechanical properties. Bulk density of this kind of concrete is between 300-2000 kg/m³. In this paper flexural strength of EPS is modeled using four regression models, nine neural network models and four adaptive Network-based Fuzzy Interface System model (ANFIS). Among these models, ANFIS model with Bell-shaped membership function has the best results and can predict the flexural strength of EPS lightweight concrete more accurately.

Keywords: EPS concrete; silica fume; flexural strength; modeling; regression; neural network, ANFIS.

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1. INTRODUCTION

Concrete is one of the most widely used materials in construction industry. The main reason that makes concrete one of the popular material in building construction is its mechanical properties and its low cost (Maslehuddin et al. 2018; Traore et al. 2018). Economically, the weight of concrete is one of the most factors. Normal weight concrete (NWC) has relatively high unit

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weight and has a bulk density ranging between 2200-2600 kg/m³. In order to reduce the unit weight of concrete, lightweight aggregates could be used, and the concrete which made of these kind of aggregates, called lightweight concrete (LWC). LWC has a bulk density ranging between 300-2000 kg/m³ (Maslehuddin et al. 2018; Aslam et al. 2017).

Lightweight concrete has been used for more than 80 years (Jafari and Mahini 2017). Because of its advantages, it is the most interesting field of researchers. These advantages including lower cost, better thermal performance, fire and frost resistance, cost-efficiency balance, sound absorption and etc. Because of lower density of LWC, lighter-weight structures could be produced (Aslam et al. 2017; Shafigh et al. 2018; Kwon and Mun 2018). Lightweight concrete has many applications including multi-storey buildings, concrete bridges, offshore oil platforms, and etc. (Jafari and Mahini 2017).

Lightweight concrete can be produced by:

i.Utilizing natural or artificial aggregates. Natural aggregate such as pumice, diatomite, volcanic cinders, scoria, tuff and artificial aggregate such as Oil-palm-boiler clinker (OPBC), clay, shale, slate, perlite. This type of LWCs are made in factories

ii.Using plastic granules instead of normal aggregates such as expanded polystyrene (EPS), polyurethane and etc.,

iii.Adding gas agent which produce gas in the alkaline environment of concrete such as aluminum powder or foaming agents (Maslehuddin et al. 2018; Aslam et al. 2017; Shafigh et al. 2018; Sadrmomtazi et al. 2012; Suseno et al. 2018).

Among these types of lightweight concrete, the one produced by expanded polystyrene with millimeter-size is more interesting than other types; because it is expected that structural elements fabricated on construction site. Also this kind of aggregate can be easily merged into concrete or mortar and create LWC (Bouvard et al. 2007; Liu and Chen 2014).

EPS lightweight concrete is a kind of new lightweight concrete that has good mechanical properties. First use of EPS was at 1973 by Cook (Liu and Chen 2014).

Strength properties, water absorption, shrinkage and electrical resistivity of EPS concrete containing silica fume and rice husk ash were experimentally studied by Sadrmomtazi et al. and the results showed a potential use of EPS beads for producing structural grade, moderate strength grade and insulating lightweight concrete [Sadrmomtazi et al. 2012]. Morover, in 2013, Sadrmomtazi et al., modeled the compressive strength of EPS lightweight concrete using regression, neural network and ANFIS.

Despite a number of research studies on the different properties of EPS concrete, it has rarely investigated modeling their flextural strenght properties. In this regard, the aim of this paper is to modeling the flexural strength of EPS lightweight concrete. Regression, neural network and ANFIS are the three methods used in this paper. Five regression, nine neural network and four ANFIS models were trained and tested. Before modeling, data were normalized to prevent the saturation problems. Finally, the results were compared to find the best model.

2. MODELING METHODS

2.1 Regression modeling

Regression Modeling is a tool which analysis the relationship between a response parameter (dependent variable) and one or more input parameters (independent variables). There are two types of regression: Linear and Nonlinear. In linear regression modeling, the aim is to fit

a linear equation between parameters, and in nonlinear regression modeling, the aim is to fit a nonlinear equation. In this paper, the general form of regression is

$$y = f(\alpha_i \times x_i) \tag{1}$$

where f is the linear/nonlinear regression function, y is the dependent variable, x_i are the independent variables, and α_i are the constant coefficients of the model (Sobhani et al. 2010).

The main goal of regression modeling is to find a function (linear or nonlinear) which has the best fitting.

2.2 Artificial neural network model

Artificial Neural Network (ANN) is an artificial intelligence-based method that provides a nonlinear relationship between input and output variables (Manngård et al. 2018). Neural network is composed of simple elements. These elements are inspired by biological nervous system. ANN has a powerful ability in image process, regression, and etc. ANN consists of many processors which called processing elements (PE) or neurons, an input layer, one or more hidden layers (HLs) and one output layer. The layers between the input and output layer are called hidden layers and there is no direct link between input and output layers. The neurons receive the signals from input, process them through algorithms, biases and weights. The weights between the layers are selected randomly and during the processing, they didn't change. But in each cycle, they change to obtain the best performance. The efficiency of this model depends on the quality and quantity of data (Sobhani et al. 2010; Cao et al. 2018; Schmidhuber 2015; Heidari et al. 2018).

In order to use a neural network, it's necessary to specify some specifications, such as the number of layers, training algorithm, activation function, propagation rules and etc.

2.2.1 Training algorithm

Levenberg-Marquardt back-propagation algorithm is often the fastest back-propagation algorithm for training feed-forward neural networks. This algorithm is an approximation to Newton's method. Newton's method is faster and more accurate near an error minimum, so the aim is to shift toward Newton's method as quickly as possible (Hagan and Menhaj 1994; Mathworks (1) 2017).

2.2.2 Propagation rules

For a multilayer model the propagation rule is the weighted sum and it is defined as:

$$\sum_{i=1}^{n} w_{ij} x_i \tag{2}$$

where w_{ij} is the weight that connects PE *i* in the input layer to PE *j* in the hidden layer, x_i is the output from PE *i* in the input layer and *n* is the number of PEs. If there is bias in PE eq. 2 turned into (Villarrubia et al. 2018)

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$$\sum_{i=1}^{n} w_{ij} x_i + b \tag{3}$$

Fig. 1 shows the architecture of artificial neural networks. As shown in this figure, ANNs consist of Inputs, training algorithm, activation function, propagation rule and output.



Figure 1. Architecture of ANN

2.3 Adaptive network-based fuzzy interface system (ANFIS)

ANFIS is hybrid of neural network and fuzzy logic system for modeling the complex systems and it was first introduced by Jang. ANFIS uses a set of IF-THEN fuzzy rules to act like human reasoning style (Sobhani et al. 2010; Yuan et al. 2014). It has the benefits of both artificial neural network (ANN) and fuzzy systems. Particularly it has used in engineering applications, where classical methods fail or they are too complicated to be used (Vakhshouri and Nejadi 2017).

Type of membership functions and number of epochs are important factors in fuzzy logic system to create a model by minimum error size (Vakhshouri and Nejadi 2017). A membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1 (Mathworks (2) 2017).

The architecture of an ANFIS model with two input variables is shown in Fig. 2. For simplicity of illustration only two inputs (x, y) and one output f are considered in this figure.



Figure 2. The architecture of ANFIS model

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The function of each layer are described as (Sobhani et al. 2010; Yuan et al. 2014):

Layer 1: The first layer is the fuzzy layer. Every node in this layer is an adaptive node with a node function of

$$O_i^1 = \mu_{A_i}(x) \tag{4}$$

where x is the input to node i, and A_i is the linguistic label 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

$$O_i^2 = w_i = \mu_{A_i}(x) \times \mu_{B_i}(x), \quad i = 1,2$$
(5)

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:

$$O_i^3 = \overline{w_i} = \frac{w_i}{\sum w_i}, \qquad i = 1,2 \tag{6}$$

Layer 4: Every node in this layer is an adaptive node with a node function:

$$O_i^4 = \overline{w_i} f_i, \qquad i = 1,2 \tag{7}$$

where $\overline{w_i}$ is the output of layer 3, and $f_i = p_i x + q_i y + r_i$ where $\{p_i, q_i, r_i\}$ is the parameter set.

Layer 5: The signal node in this layer is a circle node labeled \sum , that computes the overall output as the summation of all incoming signals

$$O_i^5 = \sum_i \overline{w_i} f_i = \sum_i w_i f_i / \sum_i w_i, \quad i = 1,2$$
(8)

There are five layers in this model: input, input membership function, rule, output membership function, and output.

3. MATERIALS AND MIXTURE DESIGN

3.1 Materials

The materials used to produce the lightweight concrete is described below:

3.1.1 Cementitious materials and fillers

In this study, the Portland cement (ASTM C150 (ASTM C150 2003)) as the main material and silica fume (SF) and rice hush ash (RHA) as the fillers were used. The chemical compositions and properties these materials are reported in Table 1.

	^		
Chemical composition	cement	silica fume (SF)	rice hush ash (RHA)
SiO ₂	21	91.1	91.62
Al_2O_3	4.6	1.55	0.49
Fe_2O_3	3.2	2.0	0.73
CaO	64.5	2.42	2.51
MgO	2.0	0.06	0.88
SO ₃	2.9	0.45	-
$Na_2O + 0.685K_2O$	1.0	-	2.39

Table 1: Chemical composition and properties of cement, silica fume and rice hush ash

3.1.2 Aggregates and EPS beads

The fine aggregate was natural siliceous river sand and the coarse aggregate was crushed limestone aggregate. The properties of these aggregates are reported in Table 2.

Table 2: Properties of stone aggregates

Aggregate type	specific gravity	absorption (%)	fineness modulus
Fine (0-4.75 mm)	2.51	3.40	2.82
Coarse (4.75-12 mm)	2.54	2.57	-

Properties	Description
morphology	Fibrillated or mono filament
Specific gravity (gr/cm ³)	0.95
Diameter (µm)	50
Modulus of elasticity (GPa)	5
Tensile strength (MPa)	450
Ultimate strain (%)	5 - 15
Elongation of fracture (%)	~ 20
Melting point (°C)	160
Bonding with cement	Good
Stability in cement	Good
Aspect ratio (L/d)	120

Table 3: Properties of PP fibers

3.1.3 Fibers and EPS beads

Moreover, the EPS beads were used as artificial lightweight aggregates in order to decrease the density of concrete. The size of 85% of EPS beads were about 3.5 mm.

In addition to the EPS beads, polypropylene (PP) fibers were used to improve the toughness of EPS lightweight concrete. The properties of PP fibers are presented in Table 3.

3.2 Mixture design

Twelve concrete mixtures were utilized with different composition of row materials and water to cementitious materials ratio as summarized in Table 4.

mixture	Cement (kg/m^3)	SF (%)	RHA	EPS	PP fibers	W/(C+	Aggregate size in mm, (kg/m^3)			
	(kg/m)		(%)	(kg/III)		CIVI)	0-3	3-6	6-12	
LWC-1	400	-	-	-		0.45	666	118	958	
LWC-2	400	-	-	15		0.43	541	95	777	
LWC-3	400	-	-	25		0.41	431	76	620	
LWC-4	400	-	-	40		0.40	294	52	423	
LWC-5	360	10	-	-	004 0 104	0.48	652	115	936	
LWC-6	360	10	-	15	0%, 0.1%, 0.1%	0.43	524	92	753	
LWC-7	360	10	-	25	0.5%, 0.5%, 1%	0.44	422	75	608	
LWC-8	360	10	-	40	by volume	0.43	282	50	406	
LWC-9	320	-	20	-		0.52	623	110	896	
LWC-10	320	-	20	15		0.56	469	83	674	
LWC-11	320	-	20	25		0.52	386	68	554	
LWC-12	320	-	20	40		0.51	245	43	352	

Table 4: Mixture proportion

4. DATA COLLECTION

The flexural strength of EPS lightweight concrete for four percentage of EPS, five percentage of PP, three weights of cement were reported in Table 4. Silica fume and rice hush ash were used 10 wt. % and 20 wt. %, respectively. EPS concrete specimens were prepared in the standard condition.

According to Table , cubic specimens of EPS concrete were produced and the database was created. These specimens were cured for 28 days. Then, according to ASTM C330 (ASTM C330 2003).

75 data records of EPS concrete Flexural strength at 28 days were gathered for database. 60 of these records were randomly utilized for training and the rest of them for testing the models. The structure of input-output of the modeler system was schematically shown in Fig. 3. In this Figure, the input parameters are (*i*) cement (C), (*ii*) silica fume (SF), (*iii*) water (W), (*iv*) fine aggregates (FA), (*v*) coarse aggregates (CA), (*vi*) expanded polystyrene beads (EPS), and (*vii*) Polypropylene fibers (PP) by weight per unit volume of concrete. Moreover, Table 5 summarizes the range of input and output of total data used for modeling purposes.



Figure 3. The structure of input-output of the modeler system

Variable	abbraviation	Range		
variable	abbieviation	min	max	
<u>Input</u>				
Cement (kg/m^3)	С	320	400	
Silica fume (kg/m^3)	SF	0	40	
Water (kg/m^3)	W	160	230	
Fine aggregates (kg/m ³)	FA	97	784	
Coarse aggregates (kg/m ³)	CA	118	958	
expanded polystyrene beads (kg/m ³)	EPS	0	55	
Polypropylene fibers (kg/m ³)	PP	0	9.1	
<u>Output</u>				
Flexural strength (MPa)	FS	0.8	7.4	

Table 5: Range of input and output variables

5. PREPROCESSING OF DATA

To prevent the saturation problem and consequently the low rate of the training [10], in neural network with log-sigmoid activation function it is important to normalize the data into a proper range. In this paper, the following function converts the real input data into the proportional values in the range of [0.1, 0.95]:

$$out = 0.1 + (0.95 - 0.1) * \frac{in - in_{min}}{in_{max} - in_{min}}$$
(9)

where out is the normalized value, in is the rough input, in_{max} and in_{min} are the maximum and minimum of rough input, respectively. Clearly, by inversing the eq. 9, the values of model results could be converted to the real range.

6. MODELING PERFORMANCE CRITERIONS

To evaluate the performance of models, root means square (RMS), correlation factor (CF) and non-dimensional error index (NDEI) should be calculated for all models and then compared to each other. The model which has the lower RMS and the higher CF, is the best model.

6.1 Root means square

Root Means square is calculated by the following equation:

$$RMS = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_{ri} - x_{pi})^2}$$
(10)

where *n* is the total number of samples, x_{ri} and x_{pi} are the real (experimental) and predicted values for the ith sample, respectively.

6.2 Correlation factor

Correlation Factor is calculated by the following equation:

$$CF(x_r, x_p) = \frac{cov(X_r, X_p)}{\sqrt{cov(X_r, X_r) * cov(X_p, X_p)}}$$
(11)

where

$$X_r = (x_{r1}, x_{r2}, \dots, x_{rn}), \quad X_p = (x_{p1}, x_{p2}, \dots, x_{pn})$$
(12)

and

$$cov(X_r, X_p) = E[(X_r - \mu_r).(X_p - \mu_p)]$$
⁽¹³⁾

where

$$\mu_r = E(X_r), \quad \mu_p = E(X_p) \tag{14}$$

where E is the mathematical expectation.

6.3 Non-dimensional error index

Non-dimensional error index can be calculated using:

$$NDEI = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_{ri} - x_{pi})^2}}{\sigma(x_r)}$$
(15)

where $\sigma(x_r)$ is the standard deviation (Sobhani and Najimi 2014).

7. RESULTS AND DISCUSSION

In this paper, three types of modeling include regression, neural network, and ANFIS were used. For implementing these models, Matlab software was used.

7.1 Linear and nonlinear regression modeling

Four regression models proposed. These models are presented in Table 6. The calculated coefficients (α_i) of these models are demonstrated in Table 7.

		Table 6: Proposed regression model
Model	Туре	Equation
R1	Linear	$FS = \alpha_0 + \alpha_1 C + \alpha_2 SF + \alpha_3 W + \alpha_4 FA + \alpha_5 CA + \alpha_6 EPS + \alpha_7 PP$
R2	Pure quadratic	$FS = \alpha_0 + \alpha_1 C + \alpha_2 SF + \alpha_3 W + \alpha_4 FA + \alpha_5 CA + \alpha_6 EPS + \alpha_7 PP + \alpha_8 C^2 + \alpha_9 SF^2 + \alpha_{10} W^2 + \alpha_{11} FA^2 + \alpha_{12} CA^2 + \alpha_{13} EPS^2 + \alpha_{14} PP^2$
R3	power	$FS = \alpha_0 + \alpha_1 C^{\alpha_2} + \alpha_3 SF^{\alpha_4} + \alpha_5 W^{\alpha_6} + \alpha_7 FA^{\alpha_8} + \alpha_9 CA^{\alpha_{10}} + \alpha_{11} EPS^{\alpha_{12}} + \alpha_{13} PP^{\alpha_{14}}$
R4	fractional	$\frac{1}{FS} = a_0 + \frac{a_1}{C} + \frac{a_2}{SF} + \frac{a_3}{W} + \frac{a_4}{FA} + \frac{a_5}{CA} + \frac{a_6}{EPS} + \frac{a_7}{PP}$
	,	Table 7: Evaluated coefficients of proposed models

Model	$lpha_0$	α ₁	α2	α ₃	$lpha_4$	α_5	α ₆	α ₇	<i>α</i> ₈	α ₉	α_{10}	<i>α</i> ₁₁	<i>α</i> ₁₂	<i>α</i> ₁₃	α_{14}
R1	.165	.082	.108	009	.733	122	140	041							
R2	.054	0	0	044	- 2.415	2.997	015	.220	.032	.092	014	4.394	-4.20	.017	245
R3	.327	165	13	.115	9.398	01	1.965	.334	1.291	.384	1.296	012	1.485	- .144	19.265
R4	1.137	.0012	.0183	.0503	- .5956	1.2961	050	- .0285							

The performance of these models (root mean square, correlation factor and non-dimensional error index) were calculated using the equations 10, 11 and 15 and demonstrated in Table 8. The prediction of regression models and experimental results are compared in Fig. 5.

Table 8: Performance of regression models												
	Trai	ning			Tes	ting		Check	Checking data			
Model	(Interpo	olation)			(Extrapolation)				ing auta			
	RMS	CF	NDEI		RMS CF NDEI		NDEI	RMS	CF	NDEI		
R1	0.4471	0.9668	0.2536		0.4272	0.9648	0.2869	0.4804	0.9523	0.2990		
R2	0.4150	0.9714	0.2354		0.4166	0.9649	0.2798	0.4082	0.9667	0.2541		
R3	0.4168	0.9712	0.2364		0.4344	0.9618	0.2917	0.4126	0.9650	0.2568		
R4	0.5895	0.9436	0.3344		0.4822	0.9445	0.3239	0.6420	0.9179	0.3996		

According to Fig. 4 and Table 8, model R2 is the best regression model, because it has the lowest RMS and highest CF. This model predicts the flexural strength of EPS concrete with RMS of 0.4150, 0.4166 and 0.4082 for training set, testing test and checking set, respectively. The CF values for training set, testing set and all data, according to model R2, are 0.9714, 0.9649 and 0.9667, respectively. The values of NDEI for training set, testing set and checking set and checking set in model R2 are 0.2354, 0.2796 and 0.2541, respectively.

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Figure 4. Comparison of regression models with experimental results: (A) training set, (B) testing set, (C) checking set

7.2 Artificial neural networks models

The schematic structure and general properties of used ANN are shown in Fig. 5 and Table 9, respectively.

	Table	9: General prop	erties of NNM			
Туре	Training method/ algorithm	Activation function in HLs	Activation function in output layer	No. of PE in HL	Layers number	HLs number
Feed-forward back-propagation network	Supervised/ Levenberg- Marquardt BP	Log-sigmoid	Linear transfer function	variable	4	2

The neural network models were trained by 60 data and tested by 15 data. Matlab software and its neural network tools were used to train the NN models.



Figure 5. The schematic structure of ANN model

The architectures and performance of neural network models are summarized in Table 10. First number in model name indicates the number of processing elements in hidden layer 1 and second number indicates the number of processing elements in hidden layer 2. According to Table 10, NNM34 has the best performance (lower RMS, lower NDEI highest CF). RMS values of this model are 0.1317, 0.2138 and 0.0842 for training set, testing set and checking data, respectively. CF values of this model are 0.9972, 0.9899 and 0.9987 for training set, testing set and checking data, respectively. The values of NDEI are 0.0747, 0.1436 and 0.0524 for training data, testing data and checking data, respectively.

Model	No. o i	of PE n	Traini	Training set		Testing set					Check data				
name	HL1	HL2	RMS	CF	NDEI	_	RMS	CF	NDEI		RMS	CF	NDEI		
NNM11	1	1	0.3965	0.9770	0.2249		0.3934	0.9673	0.2642		0.3913	0.9684	0.2436		
NNM22	2	2	0.2140	0.9927	0.1214		0.2756	0.9844	0.1851		0.2055	0.9921	0.1279		
NNM33	3	3	0.1643	0.9956	0.0932		0.2463	0.9879	0.1654		0.2168	0.9913	0.1349		
NNM34	3	4	0.1317	0.9972	0.0747		0.2138	0.9899	0.1436		0.0842	0.9987	0.0524		
NNM43	4	3	0.1421	0.9968	0.0806		0.3148	0.9882	0.2114		0.1815	0.9936	0.1129		
NNM44	4	4	0.1423	0.9970	0.0807		0.2673	0.9871	0.1795		0.2627	0.9914	0.1635		
NNM45	4	5	0.1089	0.9981	0.0618		0.3776	0.9693	0.2536		0.2976	0.9850	0.1852		
NNM54	5	4	0.1120	0.9980	0.0635		0.4415	0.9576	0.2965		0.4156	0.9659	0.2587		
NNM55	5	5	0.1338	0.9971	0.0759		0.5940	0.9487	0.3989		0.4104	0.9735	0.2554		

Table 10: Architecture and performance of NNMs

As mentioned before NNM34 is the best model for neural network modeling, so experimental results versus modeling results for NNM34 is shown in Fig. 6. The horizontal and vertical axis represents the modeling results and experimental results, respectively. Accumulating more points near the diagonal line, represents better performance for the model.



Figure 6. Compression of experimental results and modeling result for (a) training data (b) testing data, (c) checking data

7.3 ANFIS model

Similar to neural network, the ANFIS model use 7 inputs (i.e. C, SF, W, FA, CA, EPS and PP) and one output (i.e. FS). In this paper four types of membership function (MF) were used. These membership functions are Triangular, Trapezoidal, Bell-shaped and Gaussian. The formula and graphs of these MFs are shown in Table 11.

The ANFIS models were trained by 60 data and tested by 15 data. 100 epochs were specified for training process to assure that minimum error was gained. Also 15 data were chosen randomly among training and testing data as checking data.

The results of these ANFIS models were shown in Table 12. According to this table, all models have good performance, but the model with Bell-shaped membership function has the best performance for testing and checking data, so ANF-Bell is the best model. The RMS values of this model are 2.48e-4, 0.4494 and 0.2192 for training data, testing data and checking data, respectively. The values of CF of this model for training data, testing data and checking data are 1.0000, 0.9727 and 0.9915, respectively. Also the values of NDEI are 1.41e-4, 0.3018 and 0.1364 for training data, testing data and checking data, respectively.

Comparison of experimental results and ANF-Bell model is shown in Fig. 7.

Туре	Formula		Graph
Triangular	$f(x; a, b, c) = \begin{cases} \frac{0}{b-a} \\ \frac{c-x}{c-b} \\ 0 \end{cases}$	$ x \le a \\ a \le x \le b \\ b \le x \le c \\ c \le x $	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$
Trapezoidal	$f(x; a, b, c, d) = \begin{cases} \frac{0}{x - a} \\ \frac{1}{1} \\ \frac{d - x}{d - c} \\ 0 \end{cases}$	$ x \le a \\ a \le x \le b \\ b \le x \le c \\ c \le x \le d \\ d \le x $	$\begin{array}{cccccccccccccccccccccccccccccccccccc$
Bell-shaped	$f(x; a, b, c) = \frac{1}{1 + \left \frac{x - c}{a}\right ^{2b}}$		$ \begin{array}{cccccccccccccccccccccccccccccccccccc$
Gaussian	$f(x;c,\sigma) = e^{\frac{-(x-c)^2}{2\sigma^2}}$		0.9 0.8 0.7 0.6 0.5 0.4 0.3 0.2 0.1 0 0 1 2 3 4 5 6 7 8 9 10

Table 11: Types of member function

Table 1	2. The	results	of A	NFIS	models
I dole l	2. Inc	results	01 1	11110	modells

Model	ME	Т	Training data		_	Testing data			C	Checking data		
name	MIF	RMS	CF	NDEI		RMS	CF	NDEI	RMS	CF	NDEI	
ANF-Tri	Triangular	0.0011	1.0000	6.46e-4	-	0.7273	0.9551	0.4885	0.3464	0.9815	0.2157	
ANF-Trap	Trapezoidal	0.0399	0.9997	0.0226		0.8414	0.9067	0.5651	0.3883	0.9694	0.2417	
ANF-Bell	Bell-shaped	2.48e-4	1.0000	1.41e-4		0.4494	0.9727	0.3018	0.2192	0.9915	0.1364	
ANF-Gauss	Gaussian	8.59e-5	1.0000	4.87e-5		0.6133	0.9469	0.4119	0.3517	0.9799	0.2189	



Figure 7. Comparison of experimental and modeling (ANF-Bell model) results for: (a) training set, (b) testing set, (c) checking set

8. CONCLUSION

In this paper, flexural strength of EPS lightweight concrete were modeled using regression, artificial neural network and ANFIS model. 75 data were made experimentally and among these data, 60 data were randomly selected to train the models and 15 data were used to test the proposed models. Four regression models, five neural network models and four ANFIS model were trained and the following results were obtained as follows:

• Among the four regression models (e.g. linear, pure quadratic, power and fractional) pure quadratic model has the best performance with lower RMS and higher CF.

- For neural network models, the optimal number of PEs in HLs should be found. Among the nine neural network models, NNM34 has the best result, so the optimal number of PEs in HL1 is 3 and in HL2 is 4.
- For ANFIS models several membership function were trained and among these MFs, Bell-Shaped MFs has the best results.
- Among all regression, neural network and ANFIS models, Bell-shaped membership function of ANFIS model has best performance and could predict the Flexural Strength of EPS lightweight concrete better than other models.

On behalf of all authors, the corresponding author states that there is no conflict of interest

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