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Investigation of complex modulus of base and EVA modified bitumen with Adaptive-Network-Based Fuzzy Inference System

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A R T I C L E I N F O

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A B S T R A C T

This study aims to model the complex modulus of base and ethylene-vinyl-acetate (EVA) modified bitumen by using Adaptive-Network-Based Fuzzy Inference System (ANFIS). The complex modulus of base and EVA polymer modified bitumen (PMB) samples were determined using dynamic shear rheometer (DSR). PMB samples have been produced by mixing a 50/70 penetration grade base bitumen with EVA copolymer at five different polymer contents. In ANFIS modeling, the bitumen temperature, frequency and EVA content are the parameters for the input layer and the complex modulus is the parameter for the output layer. The hybrid learning algorithm related to the ANFIS has been used in this study. The variants of the algorithm used in the study are two input membership functions and three input membership functions for each of the all inputs. The input membership functions are triangular, gbell, gauss2, and gauss. The results showed that EVA polymer modified bitumens display reduced temperature susceptibility than base bitumens. In the light of analysis the Adaptive-Network-Based Fuzzy Inference System and statistical methods can be used for modeling the complex modulus of bitumen under varying temperature and frequency. The analysis indicated that the training accuracy is improved by decreasing the number of input membership functions and the utilization of the two gauss input membership functions appeared to be most optimal topology. Besides, it is realized that the predicted complex modulus is closely related with the measured (actual) complex modulus.

1. Introduction

Bitumens are complex mixtures of aliphatic, aromatic and naphtenic hydrocarbons, with smaller quantities of other organic and metallorganic compounds generally obtained from the vacuum residue of crude oil processing and mainly used as binder in road and airport pavements (Read & Whiteoak, 2003). Unfortunately, bitumen is a form of liquid at high temperature and becomes brittle at low temperatures, which can cause high temperature rutting, low temperature cracking of pavement and these functions limit its application (Yu, Zeng, Wu, Wang, & Liu, 2007). These deficiencies of bitumen can be decreased by the addition of polymers, which is closely connected with bitumen improved viscoelastic behavior (Yousefi, 2003). The rheological behavior of bitumen is a very complex phenomenon, varying from purely viscous to elastic, depending on loading time and temperature. A considerable increase in complex modulus at high temperature (low frequency) is obtained by the addition of several contents of polymer, and further increasing the polymer content results in increased complex modulus (Lu & Isacsson, 1999; Ruan, Davison, & Glover, 2003). Besides the increased stiffness at high temperatures, polymer also causes a decreased complex modulus (G^*) in bitumen at low service temperatures (high frequency).

EVA is one of the principal plastomers used in road construction in order to improve both the workability of the asphalt during construction and its deformation resistance in service (Haddadi, Ghorbel, & Laradi, 2008). Airey (2002) indicated that EVA provides the modification of bitumen throughout the crystallization of rigid three-dimensional networks within the bitumen resulting in considerable changes of the physical, chemical and morphological properties of the bitumen. The phase morphology of the polymer modified bitumens is the result of the mutual effects of polymer and bitumen and is influenced by polymer nature and its content. Sengoz, Topal, and Isikyakar (2009) concluded that phase inversion from a continuous bitumen phase to continuous polymer phase occurs when polymer content is around 5%.

At present fuzzy logic system has been utilized for modeling and predicting the mechanical properties of hot mix asphalt. Ozgan (2009) modeled the Marshall stability of asphalt concrete under varying temperature and exposure times using the fuzzy logic system. Kaur and Tekkedil (2000) developed an Expert System based

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on fuzzy logic to predict the rut depth of the asphalt pavements by the parameters of pavement construction materials such as pavement thickness, age of the road and total traffic count. A fuzzy logic algorithm has been devised by Tigdemir, Karasahin, and Sen (2002) for estimating the fatigue life of asphalt concrete through deformation measurements. Saltan, Saltan, and Sahiner (2007) indicated that the fuzzy logic approach can be used for modeling the deflection behavior against dynamic vehicle loading for flexible pavements instead of linear elastic theory and finite element method which require long times. To date no model has been presented for the prediction of complex modulus of bitumen with varied temperatures and frequency. This paper proposes an empirical model, which predicts the complex modulus of the base and EVA, modified bitumen under various temperature, frequency and EVA content.

2. Dynamic mechanical analysis

At present the most commonly used method of fundamental rheological testing of bitumen is by means of dynamic mechanical methods using oscillatory-type testing, generally conducted within the region of linear viscoelastic (LVE) response. The DSR operates on the principle that the performance of the bitumen is temperature and load duration dependent. The DSR function is based on sandwiching the bitumen between two plates, in which the lower plate is fixed and the top plate oscillates at a frequency shown in Fig. 1 (Roberts, Kandhal, Brown, Lee, & Kennedy, 1996). Complex modulus (G^*) contains elastic and viscous components, which are designated as the (shear) storage modulus (G') and (shear) loss modulus (G''). These two components are related to the complex (shear) modulus and to each other through the phase (or loss) angle (δ) which is the phase, or time, lag between the applied shear stress and shear strain responses during a test (Airey, 2003).

3. Sample preparation and experiment

The base bitumen with a 50/70 penetration grade was procured from Aliaga/Izmir Oil Terminal of the Turkish Petroleum Refinery Corporation. The EVA polymer used was Evatane® 2805 supplied in pellet form by the Arkema Company. Evatane® 2805, which contains vinyl acetate content of 27–29% is a highly flexible plastomer designed for bitumen modification and especially for road paving. In order to characterize the properties of the bitumen, conventional test methods, such as, penetration test, softening point test, and ductility test were performed. These tests were conducted in conformity with the relevant test methods that are presented in Table 1.

The EVA modified bitumen samples were prepared by means of a high shear laboratory type mixer rotating at 125 rpm. In preparation, the base bitumen was heated to fluid condition (180–185 °C), and has been poured into a 2000 ml spherical flask. The EVA polymer was then added slowly to the base bitumen. The concentrations of EVA in the base bitumen were chosen as 3–7% by an increase of 1% by weight. The temperature was kept constant at 185 °C, and the mixing process continued for 2 h.

The DSR test was performed on EVA PMB by using a Bohlin DSRII rheometer. The test was performed under controlled-stress loading conditions using frequency sweeps between 0.01 and 10 Hz and at temperatures between 10 and 80 °C. The test was carried out with 8 mm diameter, 2 mm gap parallel plate testing geometry between 10 and 30 °C, and with 25 mm diameter, 1 mm gap geometry between 30 and 80 °C. The stress amplitude for all the tests was confined within the linear viscoelastic response of the bitumen. The DSR test machine is seen in Fig. 2.

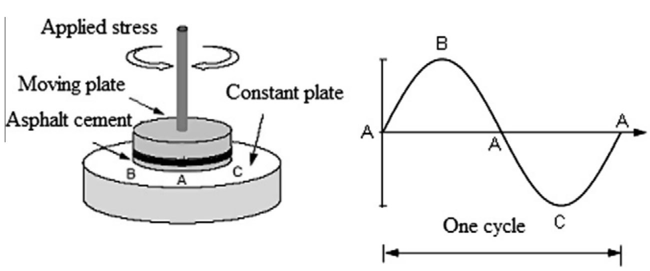

Fig. 1. Schematic representation of DSR.

Fig. 2. DSR test machine.

Table 1
Properties of the base and EVA modified bitumen.

Test	Specification	Specif. limits	Results					
			Base	EVA modified				
				3%	4%	5%	6%	7%
Penetration (25 °C; 0.1 mm)	ASTM D5 EN 1426	50–70	63	53	52	49	48	47
Softening point (°C)	ASTM D36 EN 1427	46–54	49	54	57	59	61	62
Viscosity at (135 °C) Pa s	ASTM D4402	–	0.51	−0.13	0.49	0.79	1.14	1.24
Thin film oven test (TFOT); (163 °C, 5 h)	ASTM D1754 EN 12607-1			0.04	0.06	0.05	0.07	0.06
Change of mass (%)		0.5 (max)	0.07	30	31	32	33	34
Retained penetration (%)	ASTM D5 EN 1426	50 (min)	51	6	6	5	4	5
Softening point after TFOT (°C)	ASTM D36 EN 1427	48 (min)	51	1	1	0	1	2
Ductility (25 °C), cm	ASTM D113	–	100	53	52	49	48	47
Specific gravity, gr/cm^3	ASTM D70	–	1.030	54	57	59	61	62
Flash point (°C)	ASTM D92 EN 22592	230 (min)	+260					

4. Adaptive-Network-Based Fuzzy Inference System

Both artificial neural network and fuzzy logic are used in ANFIS's architecture (Avcı & Akpolat, 2006). ANFIS, which is used learning algorithms of neural network, is consisted of if-then rules and couples of input–output. In this study the fuzzy inference involving two inputs (x and y) and one output (z) is taken into consideration. For a first order Sugeno fuzzy model, a typical rule set with base fuzzy if-then rules can be expressed as:

$$\text{If } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f_1 = p_1x + q_1y + r_1 \quad (1)$$

where p, r, and q are linear output parameters. The ANFIS's architecture which involves two inputs and one output is presented in Fig. 3.

This architecture is formed by using five layers and nine if-then rules:

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

$$O_{1,i} = \mu_{Ai}(x), \text{ for } i = 1,2,3, \quad O_{1,i} = \mu_{Bi-3}(y), \text{ for } i = 4,5,6 \quad (2)$$

where x and y are inputs to node i, and A_i, B_i are linguistic label associated with this node function. In order words, $O_{1,i}$ is the membership function of A_i and B_i. Usually $\mu_{Ai}(x)$ and $\mu_{Bi}(y)$ are chosen to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as

$$\mu_{Ai}(x),\ \mu_{Bi-3}(y) = \exp((-(x_i - c_i)/(a_i))^2) \quad (3)$$

where a_i, c_i are the parameter sets. These parameters in this layer are referred to as premise parameters.

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

$$O_{2,i} = w_i = \mu_{Ai}(x) \cdot \mu_{Bi-3}(y), \quad i = 1,2,3,\ldots,9 \quad (4)$$

Each node output represents the firing strength of a rule. (In fact, other T-norm operator that performs generalized AND can be used as the node function in this layer.)

Layer-3: Every node in this layer is a circle node labelled N. The ith node calculates the ratio of the ith rules firing strength to the sum of all rule's firing strengths:

$$O_{3,i} = \bar{w}_i = w_i/(w_1 + w_2 + \cdots + w_9), \quad i = 1,2,3,\ldots,9 \quad (5)$$

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

$$O_{4,i} = \bar{w}_i \cdot fi = w_i \cdot (p_ix + q_iy + r_i), \quad i = 1,2,3,\ldots,9 \quad (6)$$

where w_i is the output of layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer will be referred to as consequent parameters.

Layer-5: The single node in this layer is a circle node labelled Σ that computes the overall output as the summation of all incoming signals:

$$O_{5,i} = \text{overall output} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (7)$$

4.1. System modeling by ANFIS

The aim of system modeling is that it can be used in computer simulations compared to physical systems which are used in real applications. In this way, practical applications can be realized simply. Fig. 4a and b presents the forward and reverse modeling of a system by using ANFIS respectively (Avcı, 2008).

4.2. Modeling of base and EVA modified bitumens using ANFIS

In this study, the temperature of the bitumen (T), frequency (F) and EVA content are the parameters chosen as the input layer and

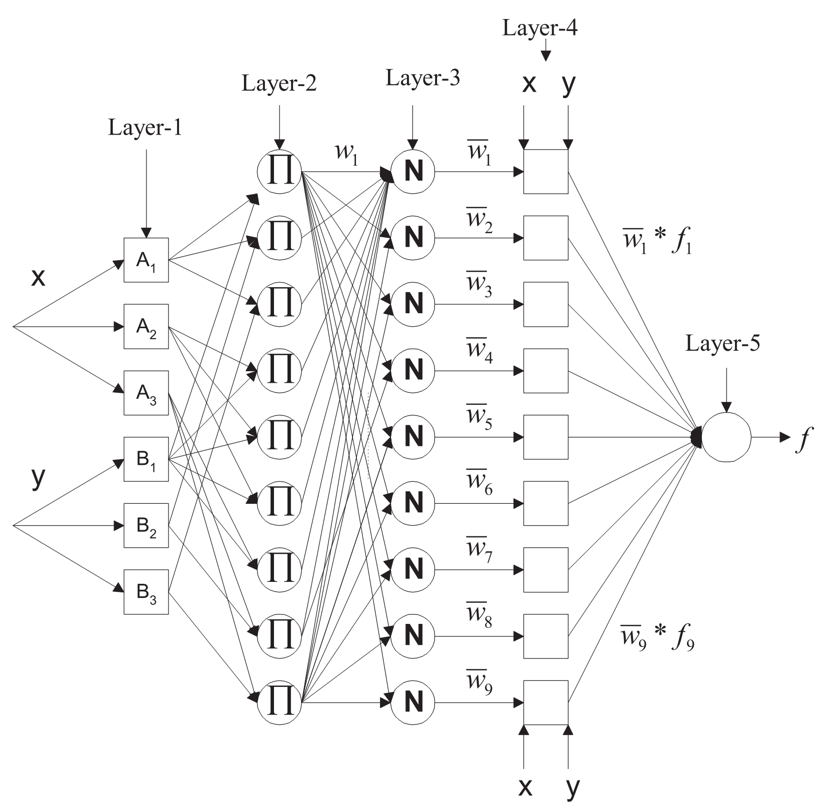

Fig. 3. ANFIS architecture of 2-inputs and 9-rules.

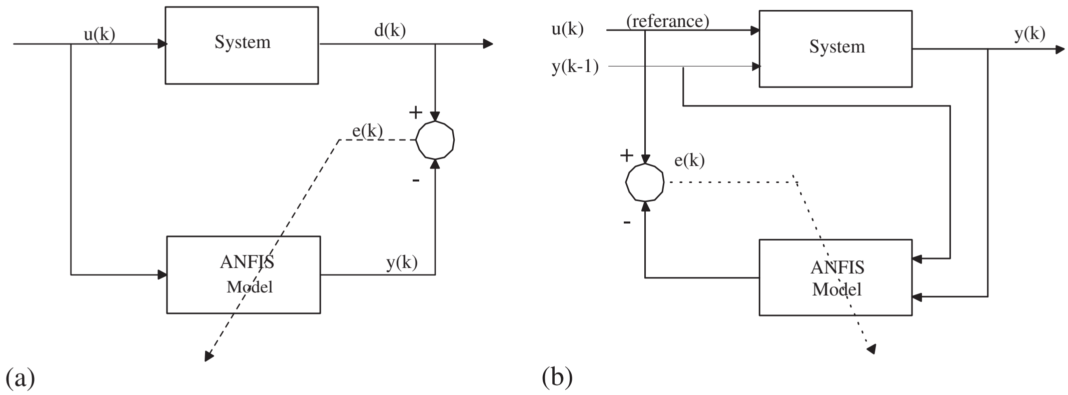

Fig. 4. (a) Forward modeling of system. (b) Reverse modeling of system.

the complex modulus of the bitumen (G^*) as the output layer. The related illustration is given in Fig. 5.

The hybrid learning algorithm for ANFIS has been used in this study. The variants of the algorithm used in the study are two input membership functions and three input membership functions for each of all inputs respectively. These input membership functions are triangular, gbell, gauss2, and gauss.

In the training, two kinds of input membership function were applied (2) and (3). The dataset for the G^* of system available included 192 data patterns. The efficiency of the proposed method was demonstrated by using the 4-fold cross-validation test. In 4-fold cross-validation dataset is randomly split into four exclusive subsets ($X_1, \ldots, X_4$) of approximately equal size and the holdout method is repeated 4 times. Three folds contain 50 samples and the last fold contains 42 samples. At each time, two of the four subsets is used as the test set and the other two subsets are put together to form a training set. The advantage of this method is that it is not important how the data is divided. Every data point appears in a test set only once, and appears in a training set two times. Therefore, the verification of the efficiency of the proposed method against to the over-learning problem should be demonstrated.

Model validation is the utilization of the test data in trained network to see the prediction capability by comparing the output and target pairs. The statistical parameters, such as the root-mean squared (RMS), the coefficient of multiple determinations (R^2) and the coefficient of variation (cov) may be used to compare predicted and measured (target) values for model validation.

The error estimated by the RMS is defined by the following equation,

$$\mathrm{RMS} = \sqrt{\frac{\sum_{m=1}^{n}(y_{\mathrm{pre},m} - t_{\mathrm{mea},m})^2}{n}} \tag{8}$$

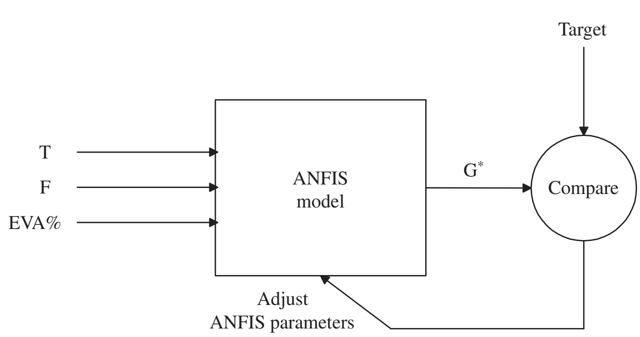

Fig. 5. Proposed model block diagram.

In addition, the coefficient of multiple determinations (R^2) and the coefficient of variation (cov) in percent are defined as follows:

$$R^2 = 1 - \frac{\sum_{m=1}^{n}(y_{\mathrm{pre},m} - t_{\mathrm{mea},m})^2}{\sum_{m=1}^{n}(t_{\mathrm{mea},m})^2} \tag{9}$$

$$\mathrm{cov} = \frac{\mathrm{RMS}}{|\bar{t}_{\mathrm{mea},m}|}100 \tag{10}$$

where n is the number of data patterns in the independent data set, $y_{\mathrm{pre},m}$ indicates the predicted, $t_{\mathrm{mea},m}$ is the measured value of one data point m, and $\bar{t}_{\mathrm{mea},m}$ is the mean value of all measured data points.

5. Results and discussions

5.1. Dynamic mechanical analysis test results

In order to evaluate the efficiency of EVA polymer, the modification index was determined by the ratio of complex modulus of modified bitumen to the complex modulus of the base bitumen. The effect of EVA content and temperature on modification index at low (0.01 Hz) and high (1 Hz) frequency is presented in Fig. 6 and 7 respectively. As seen in Fig. 6 for all contents of EVA modified bitumens, the modification index increases with increasing temperature, the index reaches a peak at 50 °C then decreases gradually. The complex modulus tends to be similar at low temperatures and there is not a significant difference in the increment of complex modulus on reaching high temperatures (80 °C). Among the modification index values at 50 °C, as the EVA content increases, modification index increases as well. This indicates that the PMB containing high proportion (7%) of EVA exhibits decreased

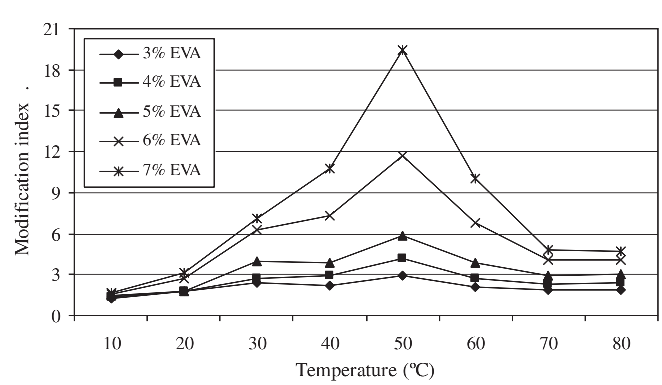

Fig. 6. Modification index temperature relationship for base and EVA PMB at 0.01 Hz.

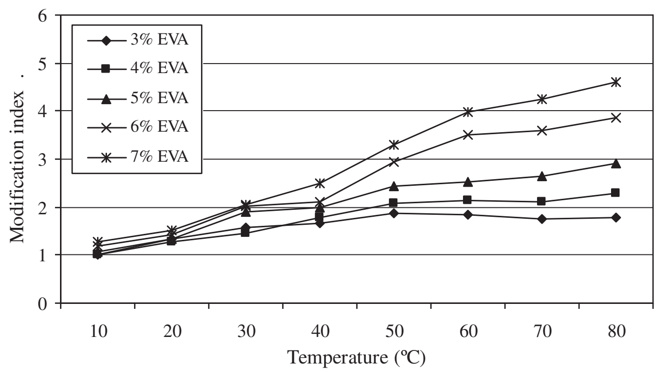

Fig. 7. Modification index temperature relationship for base and EVA PMB at 1 Hz.

thermal susceptibility compared to base bitumen at low frequency and especially at 50 °C.

As seen in Fig. 7, the modification index increases regularly between 10 and 80 °C. Besides, the improvement effect of EVA at high frequency is not as high as it is at low frequency when considering the intermediate temperatures such as 50 °C. Utilization of 6% and 7% EVA, increases the complex modulus approximately 4 and 5 times than those of the base bitumen at 80 °C for both 0.01 and 1 Hz. Therefore, it can be concluded that the frequency has not a profound effect on the complex modulus at high temperatures.

5.2. Adaptive-Network-Based Fuzzy Inference System results

The computer program was performed on MATLAB (version 5.3. The MathWorks Inc., USA) environment by using the fuzzy toolbox. At first the dataset is normalized within the range [0, 1] through the following transformation formula:

$$u_{nar} = \frac{u}{\vec{1}_N\left(\sqrt{diag(u^T u)}\right)^T} \tag{11}$$

where u are the input or output data set. $\vec{1}_N = [111\cdots1]^T$ is an N-dimensional vector N represents number of patterns in the input or output set. *diag* is diagonal values of the square matrix $(u^T u)$.

ANFIS topologies with various input membership functions and number of input membership functions are trained. Fig. 8 presents the comparison of calculated and ANFIS predicted G^* values of modeling system for two Gauss input membership functions. The related test results (RMS, cov and R^2) are represented in Table 2.

As seen in Table 2, training accuracy improves by decreasing the number of input membership functions as indicated by the smaller RMS and cov values and R^2-values approaching 1. On the other hand, beyond a certain point the errors obtained begin to increase

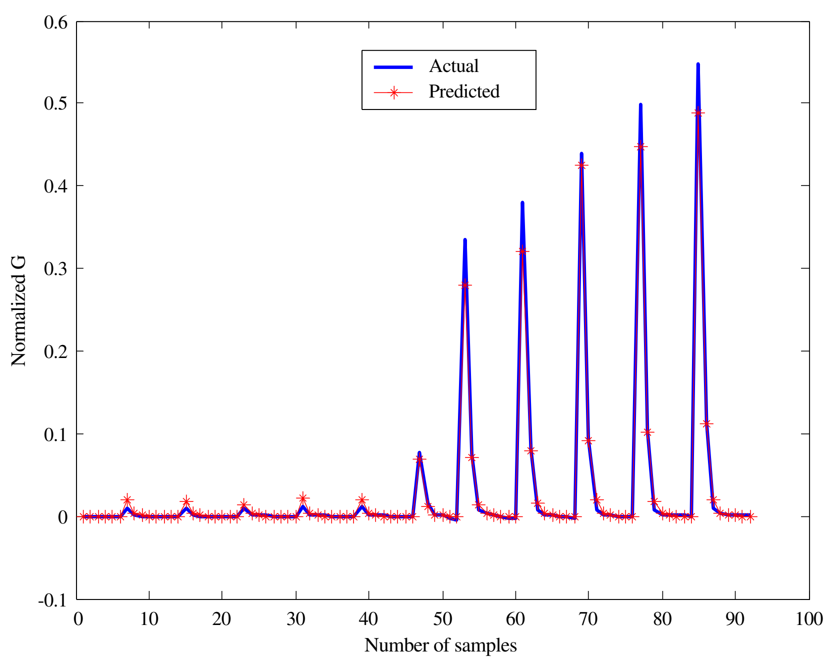

Fig. 8. The comparison of actual and ANFIS predicted G^* for two Gauss input membership functions.

Table 2
Statistical values of ANFIS model.

Algorithm- input membership functions	RMS				cov				R^2				Mean values		
	1	2	3	4	1	2	3	4	1	2	3	4	RMS	cov	R^2
Two triangular	0.0192	0.0186	0.0171	0.0131	70.56	64.13	59.33	36.62	0.965	0.975	0.976	0.989	0.0170	57.66	0.9686
Three triangular	0.0909	0.0944	0.0960	0.1023	284.15	305.17	340.56	366.92	0.0075	0.0072	0.0067	0.0046	0.0959	324.20	0.0065
Two gbell	0.0514	0.0519	0.0620	0.0419	181.13	184.24	190.01	145.06	0.6998	0.7287	0.7417	0.6702	0.0518	175.11	0.7102
Three gbell	0.0913	0.0956	0.0941	0.0950	304.63	335.62	306.56	324.23	0.0437	0.0489	0.0444	0.0455	0.0940	317.76	0.0456
Two gauss	0.0120	0.0128	0.0119	0.0125	39.06	47.14	38.07	39.73	0.9866	0.9777	0.9876	0.9813	0.0124	42.00	0.9833
Three gauss	0.0940	0.0962	0.0949	0.0977	320.14	326.76	319.62	328.08	0.0094	0.0105	0.0090	0.0106	0.0957	323.65	0.0099
Two gauss2	0.0249	0.0251	0.0265	0.0275	84.55	85.86	89.585	89.96	0.9330	0.9304	0.9224	0.9222	0.0260	87.89	0.9270
Three gauss2	0.998	0.999	0.1001	0.1010	323.86	327.49	350.24	353.49	0.0912	0.0846	0.0833	0.0801	0.1002	338.77	0.0848

together with the complexity of the ANFIS as the larger the number of input membership functions the more complex the network is. Besides, the convergence to the target error rate takes more iteration. This situation is very time consuming.

Based on the statistical data presented in Tables 2, for G^* values of algorithm by using two gauss input membership functions appeared to be most optimal topology. This topology gained 0.0124 mean RMS value, 42.00 mean cov value and, 0.9833 mean R^2 value, respectively.

6. Conclusion

One of the key material properties of bitumen is the complex modulus. This property is related to major distress modes such as traffic induced permanent deformation and rutting, as well as fatigue and low temperature cracking. The complex modulus is dependent upon temperature and loading frequency. The study indicated that the modification index increases with increasing temperature. EVA polymer modified bitumens display reduced temperature susceptibility than base bitumens. In the light of the findings it is concluded that the improvement effect of EVA polymer at high frequency is not as high as it is at low frequency when considering the intermediate temperatures such as 50 °C.

The hybrid learning algorithm was used related to ANFIS and triangular, gbell, gauss2, and gauss were used as input membership functions. The efficiency of the proposed method was demonstrated by using the 4-fold cross-validation test. ANFIS topologies with various input membership functions and number of input membership functions are trained. The analysis showed that the training accuracy improved by decreasing the number of input membership functions and the utilization of the two gauss input membership functions appeared to be most optimal topology among the other algorithms.

Based on the results of the study, it can be concluded that both the Adaptive-Network-Based Fuzzy Inference System and statistical methods can be used for modeling and predicting of the complex modulus of bitumen under varying temperature and frequency. It is also demonstrated that ANFIS is an excellent method that can reduce the time consumed and can be used as an important tool in evaluating the factors affecting complex modulus of asphalt mixture at the design stage.

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