A Neuro-Fuzzy and Neural Network Approach for Rutting Potential Prediction of Asphalt Mixture Based on Creep Test

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Abstract

This study implements the soft computing techniques such as Artificial Neural Network (ANN) and an adaptive Neuro-Fuzzy (ANFIS) approach. Thus to model the rutting prediction with the aid of experimental uniaxial creep test results for asphalt mixtures. Marshall samples, having Maximum Nominal Size of 12.5 mm, have been selected from previous studies. These samples have been prepared and tested under different conditions. They were also subjected to different loading stress (0.034, 0.069, 0.103) MPa, and tested at various temperature (10, 20, 40, and 55) °C. The modeling analysis revealed that both approaches are powerful tools for modeling creep behavior of pavement mixture in terms of Root Mean Square Error and Correlation Coefficient. The best results are obtained with the ANFIS model.

Keywords: Asphalt Mixture, Creep Test, Neuro-Fuzzy Set, ANN, ANFIS.

1 Introduction

Rutting, a structural failure in asphalt pavement mixture, is a surface depression under wheel paths. It is an accumulation of permanent deformation in one of the pavement layers. It generally occurs due to consolidation or lateral movement of the paving materials by the traffic load [1]. In order to assess the rutting potential for flexible pavement mixtures, various types of creep tests are usually implemented to measure the accumulated strain. One of the available, simplest and easiest method is the uniaxial creep test. Which is conducted by applying a static load for a period of time to measure the resulting time-dependent strain [2]. This measured strain versus time can be presented in Figure (1). The strain initially begins as elastic deformation, then it changes gradually to elastoplastic deformation (partially elastic and partially plastic), and finally to plastic deformation. The viscoelastic and the viscoplastic phases are also common in the viscoelastic material such as asphalt mixtures. The deformation resulting from these phases is responsible for the rutting distress. The components of the total strain are expressed in Equation (1) [3].

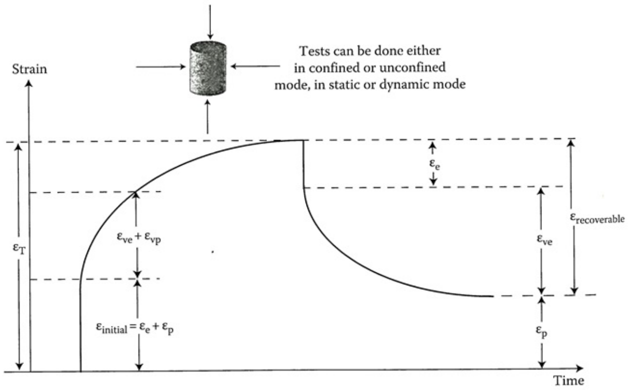


Figure 1: Strain Components for the Creep Test [4]

$$\varepsilon = \varepsilon_e + \varepsilon_p + \varepsilon_{ve} + \varepsilon_{vp} \quad \text{....................} \quad \text{Eq.(1)}$$

Where:

ε is the total strain
ε_e is a time-independent, recoverable elastic strain
ε_p is a time-independent, irrecoverable plastic strain
ε_{ve} is a time-dependent, recoverable viscoelastic strain
ε_{vp} is a time-dependent, irrecoverable viscoplastic strain

From this Figure and equation, the creep of the asphaltic material can be defined as a time-dependent deformation caused by applying a constant stress [5]. Accordingly, it is necessary to model the resulting strain as a function of its main influencing factors: stress level, loading time, and test temperature. Usually, these factors happen in non-ideal conditions. Therefore, it should be analyzed with the Soft Computing Techniques.

2 Background

Soft Computing Techniques differ from traditional or analytical technique due to thiers uncertainty, ambiguity, partial truth, and approximation [6]. The traditional technique deals with a robust solution that exists only in ideal conditions, where the real world cannot provide such conditions. This demonstrates the necessity to implement the soft computing to deal with these real-world problems like the human brain.

Actually, there are different modeling techniques that have been used in different engineering applications for the last two decades. Some of these methods are based on Artificial Neural Network (ANN) and Fuzzy Logic (FL) System or combination of them as in Adaptive Neuro-Fuzzy Inference System (ANFIS). The benefit of utilizing these modeling techniques is to model the material behavior based on series of experiments. These experiments contain the required information that been fed into these models for training. Consequently, these models will have the sufficient information for the material behavior. So, it would be capable not only to reproduce the results of the experiments but also to approximate the results of other experiments, based on the stored information.

Researchers in the pavement mixture field noticed that ANN is appropriate prediction tool, as stated by Abedali [7] during his study for prediction the complex shear modulus, as well as Serin et *al.* [8] once they used the fuzzy logic system to predict the Marshall Stability for the pavement mixture, besides Al-Mosawe [9] in his research, when he used the ANN and ANFIS tools to predict the paving mixture performance in terms of permanent deformation and stiffness modulus.

3 The Study Objective

The study aims to model the accumulated strain resulting from the uniaxial creep test by implementing ANN and ANFIS techniques. In order to achieve this objective, samples from a previous study [10] have been gathered to select the test results that specify the study objective. The detailed descriptions of the selected samples are explained in the experimental work section.

4 Experimental Work

4.1 Sample Preparation

Marshal specimens were prepared according to ASTM D1559 specification. The hot mix asphalt (HMA) is commonly a blend of various sizes of coarse aggregate, fine aggregate, and mineral filler. The gradation of the aggregate should be within the Iraqi's specification for Roads and Bridges (SORB, 2003) [11], as presented in Figure (2). These materials are generally heated till (200) °C for 2hr. and mixed at 160±5 °C with the pre-heated asphalt binder having a (170±20 centistokes) viscosity. Then it is placed in Marshal mold (2 in. (50.8 mm)) diameter and (4 in. (101.6 mm) height, and compacted with marshal hammer for 75 blows for each side, as recommended by (SORB, 2003) [11]. This to represent the field compaction of heavily traffic loaded pavement.

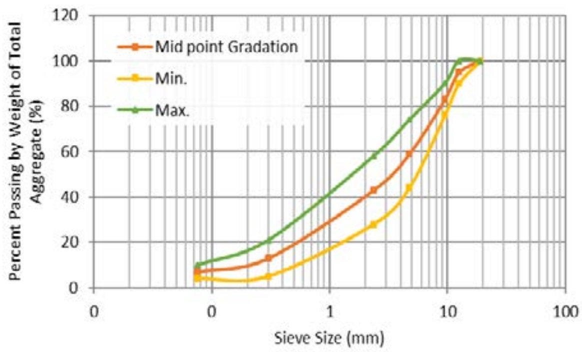


Figure 2: Selected Aggregate Gradation for Wearing Layer According to Iraqis specification.

The selection of the appropriate amount of the asphalt cement to cover all the aggregate particles is an iterative process. Therefore, it is usually performed until attaining maximum stability and bulk density, minimum flow, and accepted range of air voids, which is (3-5) % as stated in the Iraqi's specification for roads and bridges [11] for the wearing layer. The optimum asphalt content (OAC) that specifies these selected criteria is usually checked with the recommended criteria for the voids in mineral aggregate and voids filled with asphalt for verification.

For this study, the selected samples were made from crushed Al-Nibaee quarry aggregate, having a maximum nominal size of 12.5 mm, and a 7% (by weight of total aggregate) of Portland cement to act as a mineral filler. In addition, four samples with four percentages of asphalt cement (4 to 6.4 at 0.8 intervals) having (40-50) penetration grade were also used for binding and obtaining the OAC. the Marshal test results of the samples with optimum asphalt content, that had been found to be 4.6%) [10] is shown in Table (1).

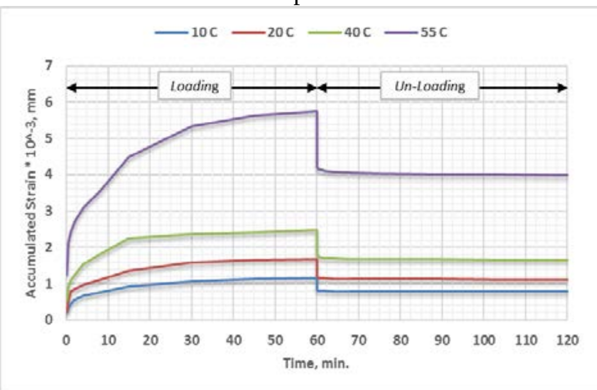
Table 1: HMA Properties with OAC

Property	Value	ASTM Testing	SORB Spec.
Bulk Density	2.338 gm/cm^3	D2726 [12]	Max.
Air Voids	4.24 %	D2041 [13]	3-5%
Stability	11.8 KN	D6927 [14]	8 KN Min.
Flow	2.9 mm		
Stiffness	4.069KN/mm	Stability/Flow	---

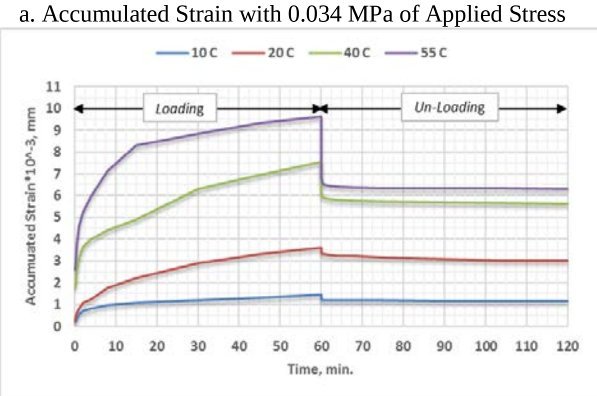
4.2 Uniaxial Creep Testing

Once the OAC had been specified, other Marshal specimens were prepared to be tested with the uniaxial creep test according to ASTM D1074 [15]. Actually, the uniaxial creep test, also known as unconfined or simple creep test, is generally conducted by applying a static load and recording strain values for one-hour duration, followed by removing the applied load and recording the accumulative strain for the consecutive second hour at a constant temperature.

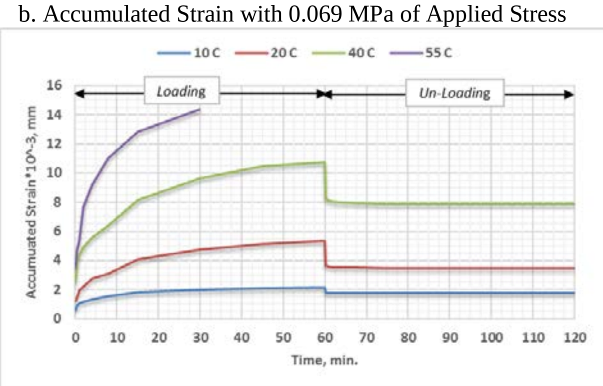
In fact, Brown et *al*., 2001 [2] stated that the temperature and the stress level have the most influencing effects on the accumulated strain, thereby rutting. So, this study aims to model the accumulated strain for the most influencing factors, which is temperature, stress levels, and loading time. Thus, the samples that have been selected for this purpose are the sample that had been tested at (0.034, 0.069, 0.103) MPa stress level. For each stress level, four samples had been tested at four different temperatures (10, 20, 40, and 55) °C. The experimental test results, presented in Figure (3), emphases that these variables have a significant impact on the strain values. Raising temperature or increasing the stress level would increase the strain values, especially at 55 °C, when the asphalt paving mixture cannot sustain the high applied stress of 0.103 MPa. That leads to premature failure.



a. Accumulated Strain with 0.034 MPa of Applied Stress



b. Accumulated Strain with 0.069 MPa of Applied Stress



c. Accumulated Strain with 0.103 MPa of Applied Stress

Figure 3: Experimental Test Results for the Proposed Models

5 Soft Computing Technique

5.1 Artificial Neural Network

An artificial neural network is a good intelligent tool that is utilized in the data training to build a model in various fields. Actually, the artificial neuron consists of five elements: inputs, weights, sum function, activation function, and outputs [16].

1. Inputs are the data enters the model or cells from the field or outside work.
2. Weights are values expressing the influence of input sets in the preceding layer at this process.
3. The Sum function is a function that computes effects of both inputs and weights on this process. This function computes the net input which feeds into a cell. The weighted sums of the $(net)_j$ are calculated by [17]:

$$(net)_j = \sum_{i=1}^{n} w_{ij} x_{ij} + b \qquad \text{.... Eq.(2)}$$

Where:
$(net)_j$: the weighted sum of the *j*. neuron for the input, received from the preceding layer with n neurons,
w_{ij} : the weight of the *j* neuron in the preceding layer,
x_i : the output of the *i* neuron in the preceding layer.
b : fix value as an internal addition.

4. The activation function is a function which process the net input that been gained from the sum function. This function determines the cell output. Generally, for multilayer perceptron models the sigmoid activation function is used for nonlinear systems.
5. The output $(out)_j$ of the j neuron is obtained as follows [17]:

$$(out)_j = f(net)_j = \frac{1}{1+e^{-\alpha(net)_j}} \qquad \text{.... Eq.(3)}$$

Where:
α: constant used for controlling the slope of the semi-linear zone.

However, the artificial neural network has some limitations. One of these is its incapability to clearly infer the relations established between independent (input) and dependent (output) variables. As a result, it is commonly referred as ‘‘black boxes’’ [18].

An ANN was implemented in this study to build a model that predicts the accumulated strain using MATLAB 2016b Software. Data represents the applied stress (0.034, 0.069, 0.103 MPa) test temperature (10, 20, 40, 55 °C), and the loading time (0-60 seconds) are fed into MATLAB ANN data fitting tool as inputs. Whereas, the accumulated strain as output. Thereby, the structure of the models, as presented in Figure (4), composed of one input layer with three nodes, one hidden layer of ten nodes, and one output layer which represents the strain.

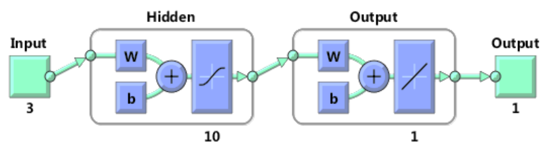


Figure 4: Structure of the Model

The purpose of the neurons in the hidden and the output layer are to estimate the weights and to build the activation function for the output processing. The accuracy and the precision of the ANN model depend on the structure of the network [19]. Actually, there is no specific rule for choosing the optimum number of hidden layers or number of neurons. So, several iteration runs were applied until the best network performance is obtained.

In this research, the data is divided into training, testing, and validation data for 70%, 15%, and 15% respectively of total data sets. The input data-set values used for training are fed into the network with the Levenberg-Marquardt training algorithm, as recommended by Beale et *al.* [19], then the weights are assigned to compute the output values. The predetermined database output value is compared with the calculated value to determine the error. This error is back-propagated to the network to adjust the weighting. The same process is iterated with the adjusted weight until the error reaches to a prescribed limit or failed to decrease for six consecutive iterations. This process is repeated with each input sets until it covers all the data sets. At the end, a checking data set is appeared to validate whether the prosed model can simulate the actual performance.

The error for the proposed model for this research is presented in Figure (5) with the model performance in Figure (6).

Figure (5) illustrates that most errors fall between -0.9 and 0.9 with training outlier at 1.05 and testing error at 1.77. However, this network can be considered good fitting, since the errors have a normal distribution around the zero value, and Mean Square Error MSE is small. In addition, the test and validation test errors having the same trends without overfitting.

The regression plots in Figure (6) display the proposed network outputs for training, validation, and test sets. It can be inferred that the model fit is soundly good for all datasets since the R values are approximately 0.99.

5.1.1 Model Building

Once the descriptive and the statistical parameters for the model is satisfactorily obtained. It would be necessary to simplify the synaptic weights connecting neurons. To comprehend this process clearly, it is explained in Figure (7). When input variables are represented with the (x_i) neurons, output (accumulated strain) is represented by (y) neuron. While the (n_{ij}) represents the neurons in the hidden layer.

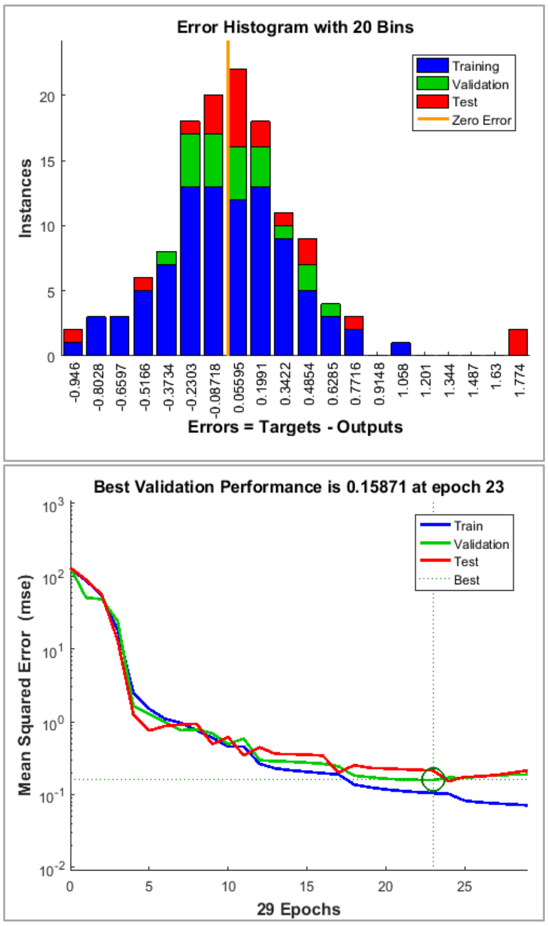


Figure 5: Training, Validation and Testing Errors

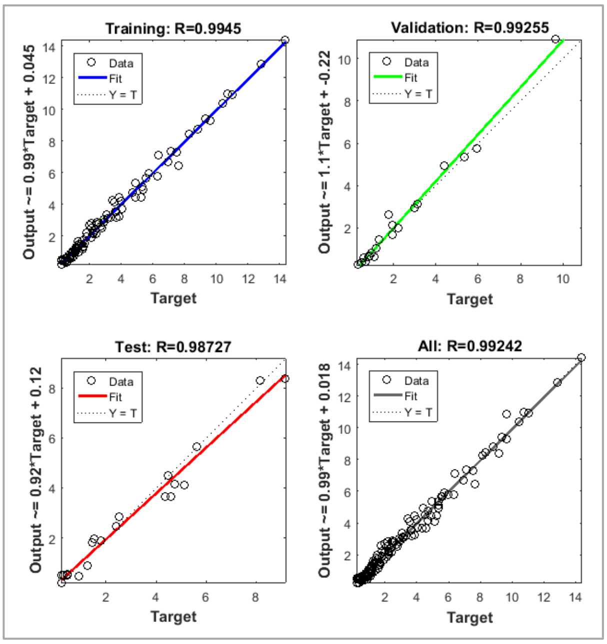


Figure 6: The Proposed ANN Creep Model Performance

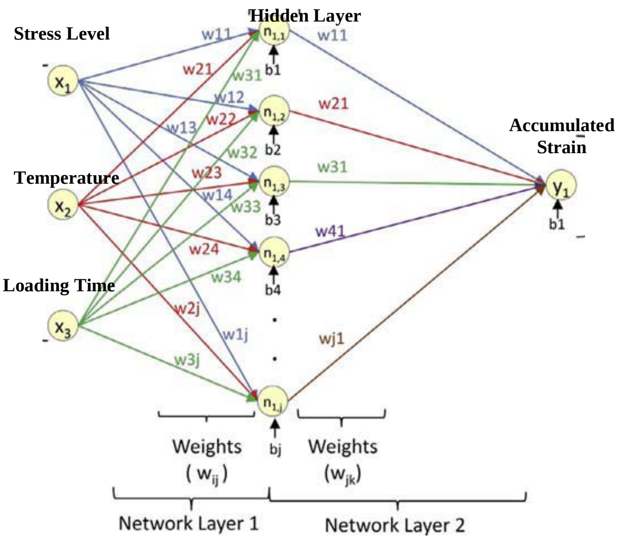


Figure 7: Description of the ANN Structure

For the current ANN Creep model, the number of input data sets is three (Stress Level, Temperature, and loading Time). The number of hidden layer's neurons is (10), whereas it is only one output which is the accumulated strain. The Figure (5) also exhibit that the number of the interlayers is two.

By implementing Eq.2 and 3 for each layer, the following model can be obtained:

$\varepsilon = f(S.T.t)$………… Eq.(3)

$$\varepsilon = \varphi_2\left(\sum_{j=1}^{10} w_{j1}\varphi_1\left(\sum_{j=1}^{3} w_{ij}x_i + b_j\right) + b_1\right)$$

ε : accumulated strains $*10^{-3}$ mm/mm.
S: Stress Level, MPa.
T: Test Temperature
t: Loading Time, seconds.
φ_i: activation function.
w_{j1}: weight values, connecting neurons in the (*jth*) hidden layer to the output neuron.
w_{ij}: weight values, connecting neurons in the (*ith*) input layer to the (*jth*) neuron in the hidden layer.
bj: bias of the hidden layer.
b_1: bias of the output layer.

Additionally, the importance of each predictor for generating the neural network, for both training and testing samples, is also checked and presented in Figure (8).

Obviously, the test temperature has the most importance among other predictors, followed by the loading time. The stress level has the lowest effect. However, it still has a high impact since its normalized importance is relatively high. In other words, all the selected predictors are important.

5.2 Adaptive Neuro-Fuzzy Inference System

The adaptive neuro-fuzzy, Sugeno-Style, inference system (ANFIS) is a powerful tool for modeling the complex non-linear trend with the aid of linguistic rules for the fuzzy logic. This system is based on the fuzzy set theory. It was first introduced in 1975 by Ebrahim Mamdani. His style presents the output results as a fuzzy set of crisp value. Whereas, the Sugeno-type was proposed by Takagi-Sugeno in 1985 [17].

A typical Fuzzy Inference System components are Fuzzification, Fuzzy Rules, Inference Engine, and Defuzzification Process, as presented in Figure (9).

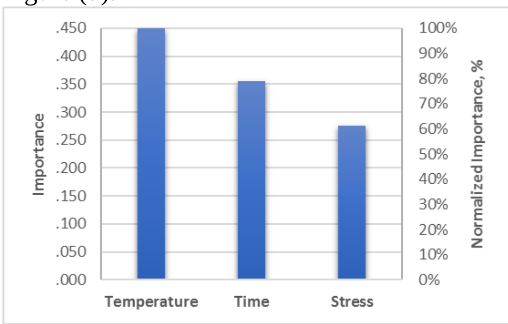


Figure 8: Importance of Explanatory Variables

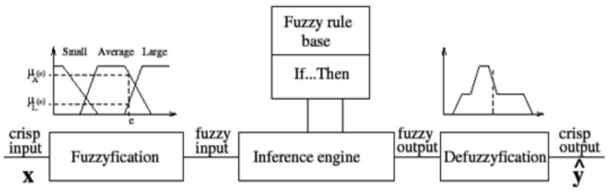
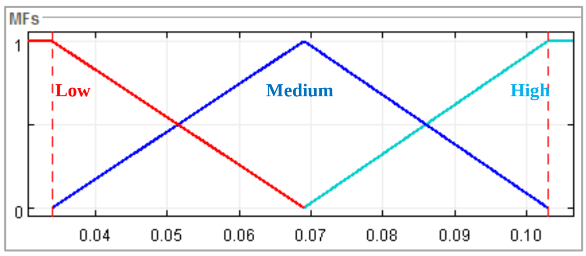
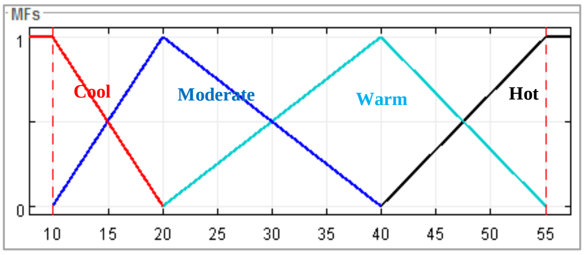


Figure 9: Fuzzy Inference System Components [20]

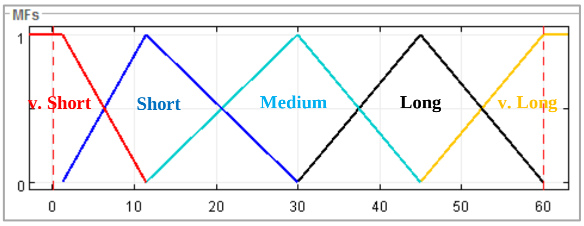
1. Fuzzification Process converts the numerical input values to linguistic variables by membership degrees [21]. Actually, there are several membership functions embedded in MATLAB Neuro-Fuzzy Designer Toolbox. Selecting the most appropriate one depends on the data trends. Thus, several runs with different membership function shapes were applied until the best model fit that satisfies a minimum Root Mean Square Error (RMSE) is obtained. The appropriate shape and numbers of the membership function for the input variables are obtained and presented in Figure (10) and Table (2) with details.



a. Stress Level (MPa)



b. Temperature (°C)



c. Loading Time (minutes)

Figure 10: Shapes of Membership Functions for the Input Variables

The Figure (10) shows a triangular and trapezoidal membership function for all the implemented fuzzy sets. Three clusters (Low, Medium and High) for the Stress Level, four clusters (Cool, Moderate, Warm and Hot) for the temperature, and five clusters (Very Short, Short, Medium, Long and Very Long) for the loading duration were applied for the proposed ANFIS Creep Model.

2. Fuzzy Rules covers all possible relations concerning inputs with the corresponding outputs data sets. A typical rule is expressed in the form of *IF-THEN* rules:
   If [Input 1 is x] and [Input 2 is y], then Output is [z = ax + by + c]

Where, *a* and *b* are constants for the first order model. For a zero-order, the output *z* is constant, and (*a* = *b* = 0).

The generated ANFIS Rules for the proposed creep model is presented in Figure (11) and Table (3)

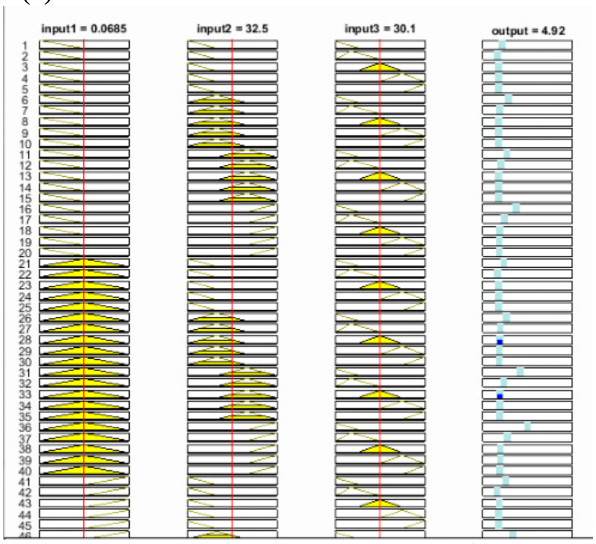


Figure 11: The ANFIS Rule Viewer of the Proposed Creep Model

This Figure illustrates an example of the model application.

If the [(*Stress Level*) is (*0.0685*) MPa and (*Temperature*) is (*32.5*) °C and (*Loading Time*) is (*30.1*) seconds] Then [the (*accumulated Strain*) is (*4.92*10-3*)mm/mm].

Table 2: Details of Membership Function Parameters

Predictive Variable	No. of MF	Linguistic Variables	MF Type	MF Parameters
Stress	3	Low	Semi-Trapezoidal	[0.034 0.034 0.069]
		Medium	Triangular	[0.034 0.069 0.103]
		High	Semi-Trapezoidal	[0.069 0.103 0.103]
Temperature	4	Cool	Semi-Trapezoidal	[10 10 20]
		Moderate	Triangular	[10 20 40]
		Warm	Triangular	[20 40 55]
		Hot	Semi-Trapezoidal	[40 55 55]
Loading Time	5	v. short	Semi-Trapezoidal	[0.1 1.31 11.5]
		Short	Triangular	[1.31 11.5 30]
		Medium	Triangular	[11.5 30 45]
		Long	Triangular	[30 45 60]
		v.Long	Semi-Trapezoidal	[45 60 60]

Table 3: ANFIS Rules for the Proposed Creep Model

Rule No.	If *Stress* is	And *Temperature* is	And *Time* is	Then *Strain**10^{-3} is	Rule No.	If *Stress* is	And *Temperature* is	And *Time* is	Then **Strain***10^{-3} is
1	Low	Cool	V. Short	0.434	30	Medium	Moderate	V. Long	3.611
2	Low	Cool	Short	0.921	31	Medium	Warm	V. Short	3.126
3	Low	Cool	Moderate	1.067	32	Medium	Warm	Short	4.914
4	Low	Cool	Long	1.134	33	Medium	Warm	Moderate	6.309
5	Low	Cool	V. Long	1.155	34	Medium	Warm	Long	6.955

Rule No.	If *Stress* is	And *Temperature* is	And *Time* is	Then *Strain**10^{-3} is
6	Low	Moderate	V. Short	0.790
7	Low	Moderate	Short	1.351
8	Low	Moderate	Moderate	1.576
9	Low	Moderate	Long	1.656
10	Low	Moderate	V. Long	1.685
11	Low	Warm	V. Short	1.084
12	Low	Warm	Short	2.252
13	Low	Warm	Moderate	2.367
14	Low	Warm	Long	2.419
15	Low	Warm	V. Long	2.474
16	Low	Hot	V. Short	2.402
17	Low	Hot	Short	4.492
18	Low	Hot	Moderate	5.342
19	Low	Hot	Long	5.622
20	Low	Hot	V. Long	5.753
21	Medium	Cool	V. Short	0.534
22	Medium	Cool	Short	1.065
23	Medium	Cool	Moderate	1.208
24	Medium	Cool	Long	1.321
25	Medium	Cool	V. Long	1.458
26	Medium	Moderate	V. Short	0.81
27	Medium	Moderate	Short	2.228
28	Medium	Moderate	Moderate	2.895
29	Medium	Moderate	Long	3.315
35	Medium	Warm	V. Long	7.532
36	Medium	Hot	V. Short	4.585
37	Medium	Hot	Short	8.316
38	Medium	Hot	Moderate	8.835
39	Medium	Hot	Long	9.324
40	Medium	Hot	V. Long	9.633
41	High	Cool	V. Short	1.035
42	High	Cool	Short	1.804
43	High	Cool	Moderate	1.975
44	High	Cool	Long	2.084
45	High	Cool	V. Long	2.135
46	High	Moderate	V. Short	1.951
47	High	Moderate	Short	4.052
48	High	Moderate	Moderate	4.728
49	High	Moderate	Long	5.128
50	High	Moderate	V. Long	5.365
51	High	Warm	V. Short	4.361
52	High	Warm	Short	8.139
53	High	Warm	Moderate	9.635
54	High	Warm	Long	10.437
55	High	Warm	V. Long	10.735
56	High	Hot	V. Short	5.365
57	High	Hot	Short	12.849
58	High	Hot	Moderate	12.849

3. Fuzzy inference engine considers all rules combinations in the fuzzy rule base and modifies it with a backpropagation algorithm [17]. This enables the fuzzy systems to learn how to convert input sets to equivalent outcomes. The product inference operator for three inputs (Stress Level, Test Temperature, and the Loading Time) and one output (the accumulated Strain) has been applied for the proposed ANFIS Model as presented in Figure (12).

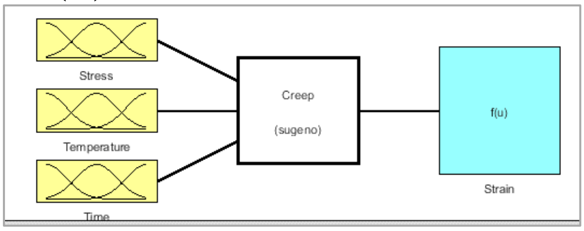


Figure 12: The Proposed ANFIS Creep Model Inference Engine

4. Defuzzification Process transforms the resulting fuzzy outputs obtained from the Fuzzy Inference Engine to a real number [20]. The weighted average defuzzification method was adopted for the proposed model.

Hence, the selected data points for the model building was fed into Fuzzy Logic Toolbox embedded in MATLAB 2016b software. The data composed of three input sets with their membership function (Stress Level (Low, Medium, High), Test Temperature (Cool, Moderate, Warm, Hot), and the Loading Time (Very Short, Short, Moderate, Long, and Very Long)) with the corresponding output (the accumulated Strain) and (58) rules to form the network presented in Figure (13).

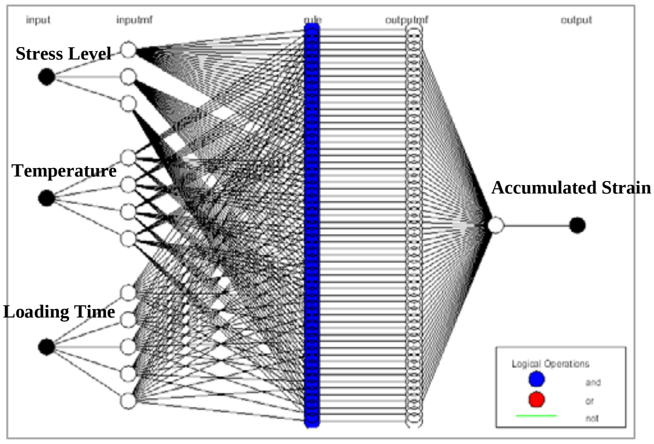


Figure 13: Network Structure for the Proposed ANFIS Creep Model

The structure of the network simplifies the calculation of the gradient vector for factors in the FIS. when the gradient vector is achieved, a number of optimization procedures to reduce an error measure (Sum of the squared difference between observed and inferred outputs) can be applied. This is the same learning process conducted in the neural network [17].

Results of the prediction run for the proposed ANFIS creep model are presented in Figure (14). This Figure shows the impact of the three factors on the accumulated strain. It reveals that the test temperature has the most significant influence on the accumulated strain for the asphalt pavement mixture. Increasing the test temperature, stress level, or the stress duration would increase the resulting strain. This increase would be higher for the high range of the aforementioned three variables.

This trend supports the previous discussion for the ANN Creep model, when comparing the predictive variables, in Figure (8), to notice that the test temperature has the most normalized importance.

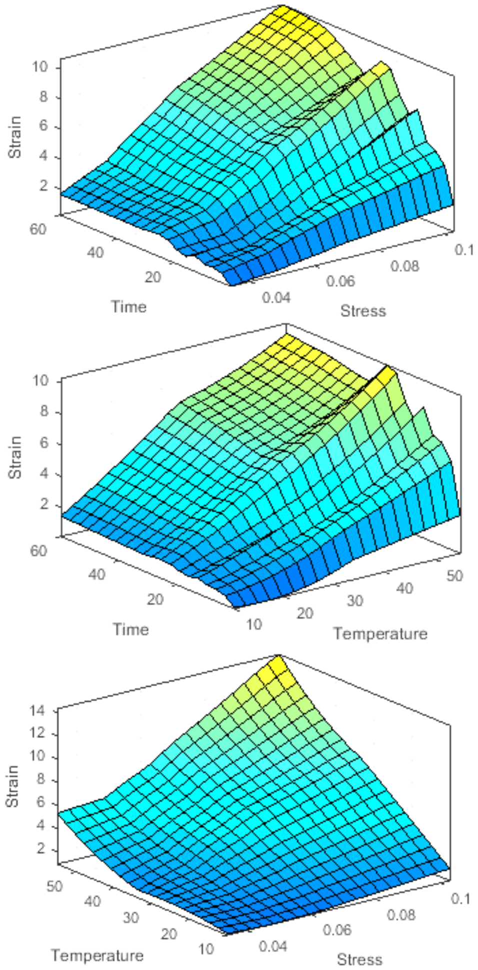


Figure 14: The System Response for the Proposed ANFIS Creep Model

6 Test Results

The performance and the accuracy of the proposed two selected techniques are observed to be quite satisfactory and computationally efficient. However, the ANFIS model predicts the accumulated strain very close to the experimental strain values. A comparison of the observed experimental results with the results obtained from the selected two models are presented in Figure (15). The outputs of the proposed models are plotted versus the experimental results and presented in Figure (16).

This Figure shows the output of the two models with the experimental results for each data set. The predicted outputs for the two models are presented in dashed lines. Whereas, the observed experimental is shown in solid line. However, it is hard to differentiate between the ANFIS model output line and the observed (target) line, because of their high fitness. Although, the ANFIS model is more precise than ANN model. The ANN model is also considered a good predictor model.

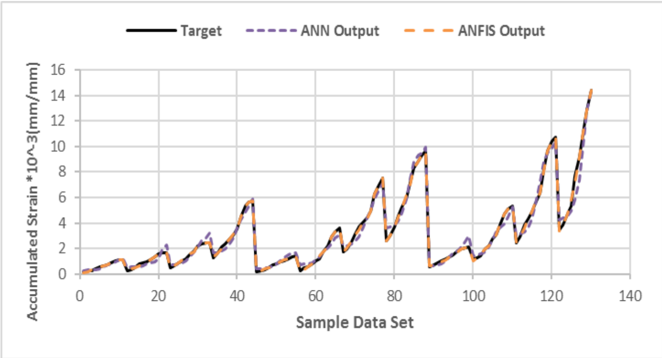


Figure 15: Comparison among Experimental, ANN, and ANFIS Creep Models

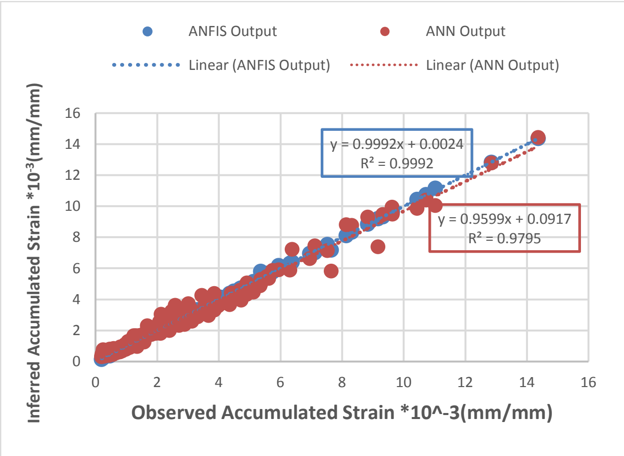


Figure 16: Inferred Versus Observed Strain Values

It is clear to notice from this Figure that both models are well in predicting the strain. The ANFIS model is found to be closer to the 45°-degree line (y=x). In addition, Correlation coefficient (R) is also higher than in ANN model. However, R-value for both models is close to unity.

The error for the models is expressed in terms of the Root Mean Square Error RMSE which is the average squared error between the proposed network outputs (*O*) and the target (predefined or observed) outputs (*t*) as presented in Equation (4) [16]. Besides, the Correlation Coefficient (*R*) for each model is calculated by Equation (5).

$$RMSE = \sqrt{\frac{\sum_i |t_i - o_i|^2}{n}} \qquad \text{......... Eq.(4)}$$

$$R^2 = 1 - \left(\frac{\sum_i (t_i - o_i)^2}{\sum_i (o_i)^2}\right) \qquad \text{......... Eq.(5)}$$

Where:

RMSE: Root Mean Square Error,

t : the Target (experimental results) output,

o : the calculated (inferred) output,
n: number of data sets

These statistical parameters are calculated and presented in Table (4) to comprehend the models' performance. The results in this table reveal that both models are performing well. The most suitable model for predicting strain values from the creep test is the ANFIS model. Since it provides less RMSE and higher R-value.

Table 4: Statistical Parameters of Proposed ANN and ANFIS Models

Statistical parameters	ANN		ANFIS	
	Training	Testing	Training	Testing
RMSE	0.1048	0.2140	0.0811	0.0740
R	0.9944	0.9872	0.9987	0.9991

7 Conclusion

In order to develop a model which is able to predict the rutting potential for the asphalt paving mixture, samples from uniaxial creep test results obtained from previous work have been selected to be analyzed. The soft computing techniques, ANN and ANFIS models, were implemented for the analyzing purpose. The main conclusions that can be drawn from this analysis are:

1. Both the selected techniques (ANN and ANFIS) are found to be good predicting tools for accumulated strain measurement.
2. The artificial neural network model can well predict the strain with a 0.21 error.
3. The adaptive neuro-fuzzy inference system is able to predict the strain effectively with a 0.074 error.
4. ANFIS model is more computationally efficient when compared with the ANN model, due it's lower RMSE and higher R-value

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النهج العصبي الضبابي والشبكات العصبية للتنبؤ بالتخدد للخلطات الاسفلتية إعتماداً على نتائج اختبار الزحف

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الخلاصة

هذه الدراسة تبحث في تطبيق تقنيات الحوسبة الناعمة مثل الشبكة العصبية الاصطناعية (ANN) والنهج العصبي الضبابي التكيفي (ANFIS) لنمذجة التنبؤ بالتخدد بمساعدة نتائج اختبار زحف أحادي المحور لعينات مختارة من خلطات الخرسانة الإسفلتية. وقد تم اختيار عينات مارشال (ذات مقاس أقصى للركام 12.5 ملم) من الدراسات السابقة. حيث تم إعداد هذه العينات واختبارها في ظل ظروف مختلفة. كما خضعت لأحمال مختلفة (0.034، 0.069، 0.103) ميكا باسكال، وتم اختبارها في ظروف درجات حرارة ايضاً مختلفة (10،20،40،55) درجة مئوية. وكشف تحليل النمذجة أن كلا النهجين هي أدوات قوية لنمذجة سلوك زحف خلطات التبليط الاسفلتي من حيث جذر مربع الخطأ ومعامل الارتباط. أفضل النتائج مع أقوى أداء تم الحصول عليه في موديل ANFIS.