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Predicting creep deformation of asphalts modified with polymer using artificial neural networks

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Abstract. This study presents an application of the Artificial Neural Networks (ANN) for creep rate prediction of asphalt concrete modified with different rubber contents. Acrylonitrile butadiene rubbers (NBR) under powder form are used in this study. The polymer is an industrial waste produced by the Algerian Elastomer Company. The most appropriate model is the multilayer back propagation network. It is produced to implement the complexity of the non-linear between the data network and the product result. It is established by the incorporation of an important experimental database and by an appropriate choice of the architecture and of the learning process. We will show that the developed ANN model received rubber contents, test temperature, compactness and the loading stress as the input and provided the creep rate as the output has better capability to predict the final creep rate in a short time with low error. The model is further applied to evaluate the effect with different contents of polymer on creep rate of bituminous concrete modified. Obtained results show that creep rate is reduced at 2 % of polymer adding. However, an increase in percentage of additives over 2 % does not help to reduce permanent deformation of asphalt mixtures. ANN model introduced provided a more accurate tool for the design of bituminous concretes modified.

1. Introduction

Road pavement structures are exposed to very complex damaged effects among traffic and climate have a dominant influence on the behavior of pavement materials. In many countries like Canada, United States, France, etc..., pavements are subjected to high thermal amplitudes and the phenomenon of the thermal cracking. In Algeria, the phenomenon of permanent deformations (rutting) is largely observed [1]. Rutting due to permanent deformations is considered one among of the major distress mechanisms found in asphalt pavements. Rutting can be an issue in almost any climate conditions, especially in high-temperature regions that results in decreased pavement service life. It may be caused either by a deformation of the support soil or by a thinning by creep of the bituminous [2]. To reducing the extent of these deformations, researchers tried to improve pavement properties by reinforcing them with additives like polymers and crumb rubber. Modified binders are often used to progress the durability and hot mix asphalt (HMA) performance when pure binders can not meet specifics demands under severe conditions [3–11]. Although, many research studies have been developed to reduce asphalt concrete rutting, the formation of rutting mechanism is very complicated task in to interpret it mathematically [12, 13].

Life span of road pavement is an important topic in national economy, for similar reasons, it is very important to predict rutting in asphalt concrete in order to maintain the legitimate function of pavement and its maintenance. In this aspect, many researchers have used Modern acknowledgment techniques such as neural networks, genetic algorithms to predict the performance of asphalt mixtures considering different effective parameters [14, 15]. An important interest was observed for the artificial neural network method due to its advantages. ANN able to learning directly from examples and finding a relation between input and output variables [16].

ANN applications. Very detailed information about the applications of ANN in geotechnical and pavement engineering can be found in the literature. In a study published by Ritchie, Kaseko and Bavarian [17], an artificial neural network system is developed for automated pavement evaluation. In another work

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Kaseko and Ritchie [18], used neural networks in the detection of pavement cracks with image processing. Comparative analysis of two neural networks using pavement performance prediction as defined by the International Roughness Index, have been proposed by Roberts and al [19]. Kim and Kim [20], have been used the neural networks to predict layer modeling from falling weight deflect meter (FWD) and surface wave measurements. Mei et al [21], have developed a program with neural networks that allows real depths of cracks can be quickly assessed, surface cracks or fatigue cracks in bituminous pavements. Thodesen, Xiao, and Serji NA Mirkhanian [22], have been used the statistical regression and neural network (NN) approaches in predicting the viscosity values of crumb rubber modified binder at various temperatures. Tapkın, Çevik and Us [23], presents an application of ANN for the prediction of repeated creep test results for polypropylene modified asphalt mixtures. Terzi *et al.* [24], have be used the artificial neural networks for studying the asphalt concrete stability estimate from non-destructive test methods. Ghanizadeh and Ahadi [25], have published into their paper an application of Artificial Neural Networks for Analysis of Flexible Pavements under Static Loading of Standard Axle. Mirabdolazimi and Shafabakhsh [26], proposed ANN model for rutting depth of hot mix asphalts modified with forta fiber. Kamboozia, Ziari and Behbahani [27] have been used ANN approach to predicting rut depth of asphalt concrete by using of visco-elastic parameters. Alrashydah and Abo-Qudais [28] presents two predictive models, one with multiple regression analysis and the other with feed-forward ANN used to predict the HMA creep compliance behavior. Ziari et al [29] in his paper, presents multiple regression and artificial neural networks to modeling of creep compliance behavior in asphalt mixes.

The main objective of this study was to evaluate the using of ANN approach to predict creep rate of modified and unmodified asphalt concrete, we interested to the incorporation of an acrylonitrile butadiene rubber (NBR) elastomer under powder form. The polymer is an industrial waste produced by the Algerian Elastomer Company (SAEL in Algeria). In the primary concern to preserve the environment against these waste we thought of exploited these waste in the asphalt pavement roads. ANN model with two hidden layers is developed to predict the effectiveness introduction of the polymer on creep rate of bituminous concrete. Training, testing, and validation stages of the model are performed using an experimental well-organized database. We show that this approach is also very advantageous because it takes account of the essential factors (the rubber contents, the temperature, the compactness and the loading stress). The concept of creep rate, [1] evaluated in a static creep test is applied as a measure of the performance of modified asphalt concrete compared to unmodified asphalt concrete.

2. Methods

Aggregates. The following (Table 1), presents the intrinsic characteristics of the aggregates used in this study. The various tests on aggregates show that the materials chosen have good intrinsic characteristics.

Table 1. Characteristics of aggregates.

tests	Granular class		
	0/3	3/8	8/15
Cleanliness (%)	–	2.33	1.57
Sand equivalent (%)	39		–
Los Angeles (%)	–	16	14
Micro Deval (%)	–	9	16
Specific density	2.58	2.70	2.70

In experimental investigations, 35/50 penetration grade bitumen, which properties described in (Table 2), has been used to prepare the modified bitumen.

Table 2. Asphalt properties.

Bitumen grade	35/50	Specification
Penetration at 25 °C (1/10 mm)	42	35 to 50
Softening point, ring and ball (°C)	51.6	50 to 58
Relative density (g/cm^3)	1.029	-
Ductility at 25 °C (mm)	> 1000	> 1000
Penetration index $_{LCPC}$	0.545	-

Additive. The polymer used as additive in this work, is a blackish industrial waste produced from the elastomer application company (SEAL in Algeria). It is used in powder form (Fig. 1). The powder is composed of grains smaller than 0.8 mm of diameter. The density is 1.22 measured compared with the ethanol density (0.79).

Figure 1. Waste in the powders form.

The static uniaxial creep test is considered as the simplest test used for evaluating the deformation behavior of viscoelastic materials such as asphalt mixtures. It was developed by the Shell organization in Amsterdam for testing bituminous mixtures in the 1970's. The test can be conducted either by applying a constant stress (creep test) or constant strain rate in tension or compression. The sample used for this test is usually cylindrical in shape and a friction reduction system between the specimen and loading plates is used. (Fig. 2) shows a typical test result for loading and unloading phases; the figure shows the initial strain which comprises elastic and plastic behavior which is known as time independent strain and occurs when the load is applied. This stage is followed by the time dependent strain which is also known as delayed elastic and viscous strain. Although, the creep test is used to estimate the performance properties of asphalt mixtures.

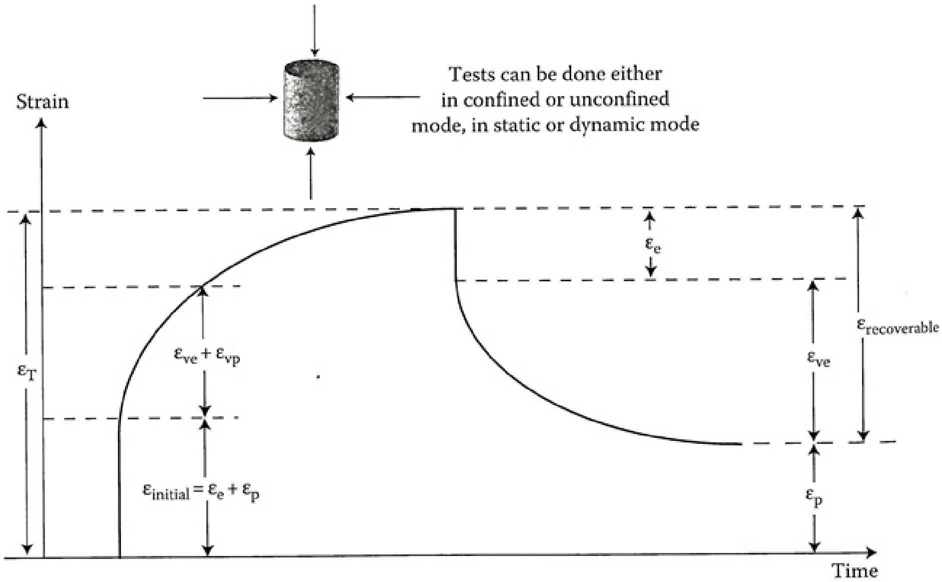

Figure 2. Typical Strain Results from Creep Testing:
where ε_T is total strain; ε_e is elastic strain; ε_p is plastic strain; ε_{ve} is viscoelastic strain;
ε_{vp} is viscoplastic strain.

The static creep test was conducted according to the methodology and specifications listed by Haddadi, Ghorbel and Laradi [1]. Table 3 summarizes the properties of all tested specimens (data base).

Table 3. Properties of the test specimens.

Properties of the test specimens	Data
Percentage of polymer (%)	0 %, –2 %, 3 % and 4 %
Temperature (°C)	25 °C, 40 °C and 60 °C
Stress (Mpa)	Min 0.010 Max 0.825
Compactness (%)	Min 65.41 % Max96.92 %
Experimental Creep rate %	Min 47.46 % Max 88.92 %

During the last decade, ANN were a primary center of interest for data-processing search and provide convenient solutions and often strongly precise to the problems of civil engineering. The artificial neural networks are considered among the biological metaphors used in our days for solving problems [30]. They are causing the attempts of a mathematical modeling of human brain functioning. The ANN (Fig. 2) is driven into him having a set of associated input-output databases on a learning rule. The learning process uses an algorithm, in which the ANN develops a function between inputs and outputs. Generally, in a learning process, neurons receive inputs ($E_1 \dots E_n$) and transmit them to the neurons in the hidden layer, which are responsible for simple mathematical calculations, involving connection weights ($W_{11}, \dots W_{1n}$), bias ($b_1, \dots b_n$) and the input value equation (1) [13].The result of these neurons is passed by a transfer function (F) equation (2) to each neuron that limits the output with the minimum and maximum authorized limits. The choice of the type of this function is a very essential element of ANN and often of the nonlinear functions will be needed [31], Once applied function, the final results are produced. After that, these results become the inputs to all the neurons in the next layer, and the calculation process is repeated. Through the layers to the output layer, the output values are produced in the output neurons (Y_k) equation (3). At this stage, an error value of output is calculated between the produced output and the desired output (target). Generally, the learning and iterative process stops when an acceptable gap is reached. On completion of the learning process, the network should be able to give the output solution for any data set.

$$I_k = \sum_{i=1}^{n} W_{ik} E_i + b_i \,, \tag{1}$$

$$F\left(I_k\right) = tansig\left(I_k\right) = \frac{2}{1 - exp^{-2I_k}} - 1, \tag{2}$$

$$Y_k = F\left(I_k\right) \tag{3}$$

Hyperbolic tangent transfer function equation (2) in the term of neural networks, is related to a bipolar *sigmoid*, which has an output in the range of -1 to +1. Mathematically equivalent to *tanh (n)*. It differs in that it runs faster than *tanh*, but the results can have very small numerical differences. This function is a good trade-off for neural networks, where speed is more important than the exact shape of the transfer function.

It may be noted that a back-propagation neural network with one (or more) sigmoid-type hidden layer(s) and a linear output layer can approximate any arbitrary (linear or nonlinear) function [30]. The number of hidden layers is normally chosen to be only one to reduce the network complexity and increase the computational efficiency [31]. In this way, a back-propagation neural network is selected for this prediction study, and it consists of four layers: one input layer (source nodes), two hidden layers with ten neurons in the first layer and five neurons in the second layer (with tangent hyperbolic sigmoid activation function), and one output layer with pure linear activation function (Fig. 3).

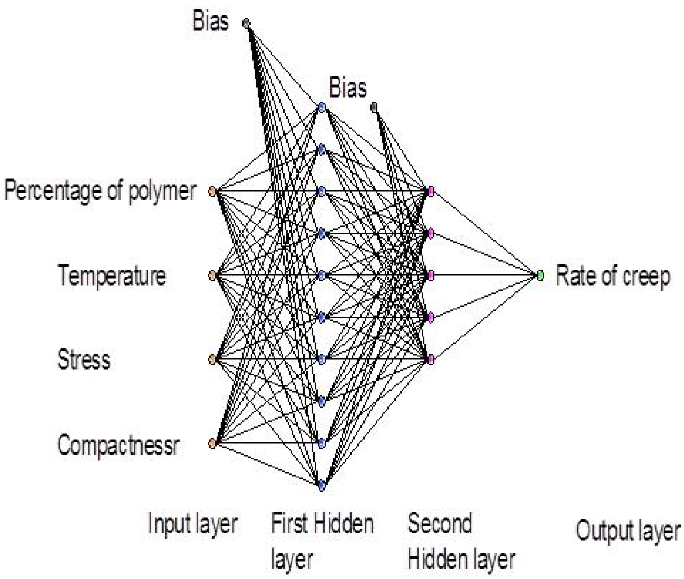

Figure 3. Neural network architecture.

The tangent hyperbolic sigmoid activation function *"tansig"* is more effective for nonlinear applications. In each of the two hidden layers, we use 10 and 5 neurons, respectively. Depending on to these neurons, we will adjust the matrix of the weights and will fix the weights of connections with bias to find results effective.

The Levenberg algorithm (trainlm) is used for the learning because it is more effective than other algorithms, as regards the use of time and memory in the execution [13]. The performance of the model is measured by the mean of square error function *(MSE)* equation (4), and “*R”* equation (5). Regression “*R”* values measured the correlation between predicted and measured values. *R* value equal 1; imply a precise relationship, 0 a random relationship. The superb performance of the model it has been ensured by the higher value of *R* and lower *MSE* value.

The input data have been divided randomly by the "dividerand" Matlab, in 70 %, 15 % and 15 % indicating the percentage of training or learning, the percentage of validation and the percentage of control or test, respectively.

$$\mathrm{MSE} = \frac{1}{N}\sum_{k=1}^{n}\left(y_k - \bar{y}_k\right)^2 \tag{4}$$

$$R = \frac{\sum_{k=1}^{n}\left(y_k - \bar{y}_k\right)\left(y^*_k - \bar{y}^*_k\right)}{\sqrt{\sum_{k=1}^{n}(y_k - \bar{y}_k)^2 \sum_{k=1}^{n}(y_k^* - \bar{y}^*_k)^2}}, \tag{5}$$

where y_k is the desired value;

$\overset{*}{y}_k$ is the estimated value;

N is the number of neurons in the output layer;

n is the number of vectors presented to the network;

$\bar{y}_k = \frac{1}{n}\sum_n y_k$; $\bar{y}^*_k = \frac{1}{n}\sum_n \overset{*}{y}_k$

The database is divided into three parts: Learning (70 %), Testing (15 %) and validation (15 %). A set of training data was used to train the ANN model. The set of validation data was used to stop the learning process, and the set of test data was used to evaluate the ANN model performance. After completion of the learning process. Each set of data consists of vectors of the influencing parameters, and corresponding creep rate. After distributing the data will be normalized between -1 and +1. Before the submission to the ANN for them to be in agreement with the bounds of the Tangent sigmoid transfer function used in the hidden layers and the linear sigmoid function of the output layer.

The architecture of the developed ANN model is first described, followed by the determination of its learning parameters and performance. The model was trained and tested with a set of learning data, testing, and validation using the back-propagation algorithm. Implementation and simulation were performed using MATLAB software. Initially, the optimal number of neurons in the hidden layer was determined (Fig. 2).

3. Results and Discussion

ANN model analysis. The precision of the artificial neuron network depends principally on the chosen architecture of the neuron network. The number of hidden layers and neurons in each layer do not obey any rule of selection. The optimal network architecture was determined using the error correction approach.

The creep rate values predicted with ANN and the experimental values of the different mixtures studied are shown in (Fig. 4). It can be concluded that the proposed ANN could learn the relationship between the different input parameters (temperature, rubber contents, loading stress and compactness) and the output parameter (creep rate). We remark, that the values of the creep rate predicted with ANN are close to the measured experimental values. This means that ANN is able to generalize the input and output variables with a good precision. The error percentage between the predicted and measured creep rate is also shown in this (Fig. 4), easily we can see the error is very low between these two values.

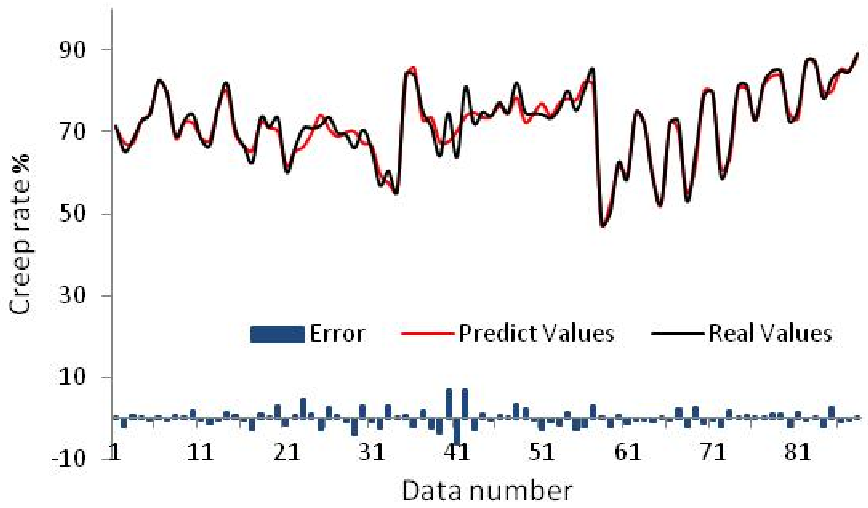

Figure 4. Comparison of real values and predicted values.

The relationship between the predicted creep rate and the experimentally measured creep rate is shown in the (Fig. 5). We can observe the creep rate predicted values are very close to experimental values creep rate. This demonstrates a good correlation between the input and output parameters of the ANN model developed. Also, in this (Fig. 5), the correlation coefficient R values in training, validation and testing the data set are 0.9839; 0.9838; 0.9922 and 0.9858, respectively. This result implies that; the developed model has considerable accuracy for predicting.

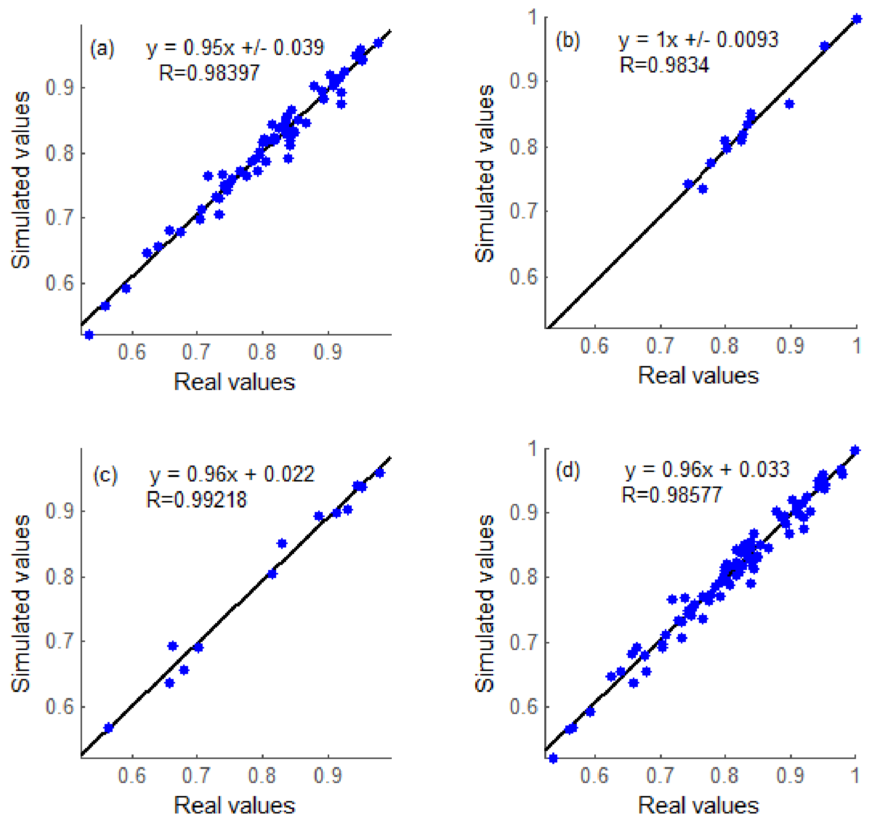

Figure 5. Relationship between the Real and ANN predicted values for (a) training data, (b) validation data, (c) testing data, and (d) all data.

Influence of polymer content on creep rate. The ANN model developed depending on four input constants, it is very precious to appreciate the influence of each constant on creep rate. For this purpose, the ANN model is applied to simulate the effect of additive content and temperature on creep rate.

Fig. 6 shows the variation of creep rate with polymer content (Temperature was kept constant at 25 °C, and 60 °C, the stress was kept at 0.14 MPa). It can be seen that at 2 % additive contents in both cases of temperature, the creep rate is reduced compared with others percent additive contents.

The critical observation is that the creep rate predicted values is very close to the experimental measured values on both cases. It can be concluded that the ANN developed model has important accuracy for predicting.

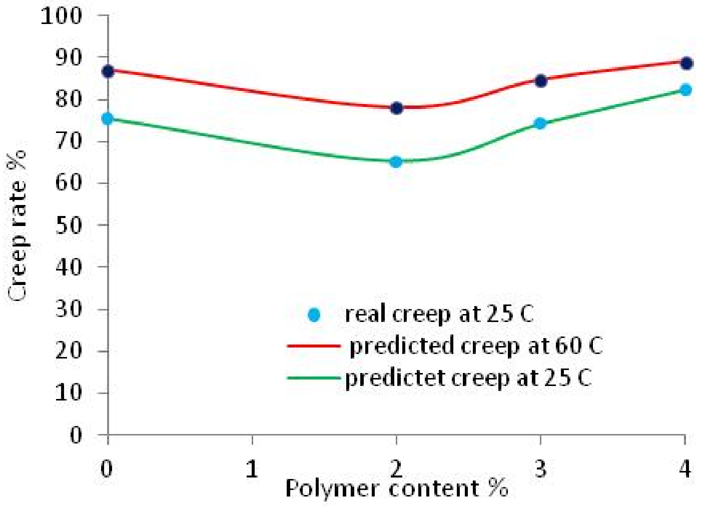

Figure 6. Effect of polymer content on final creep rate at 25 °C and 60 °C.

Fig. 7 hosts the variation of creep rate with temperature (Polymer content was kept constant at 2 % and the stress was kept at 0.14 MPa).

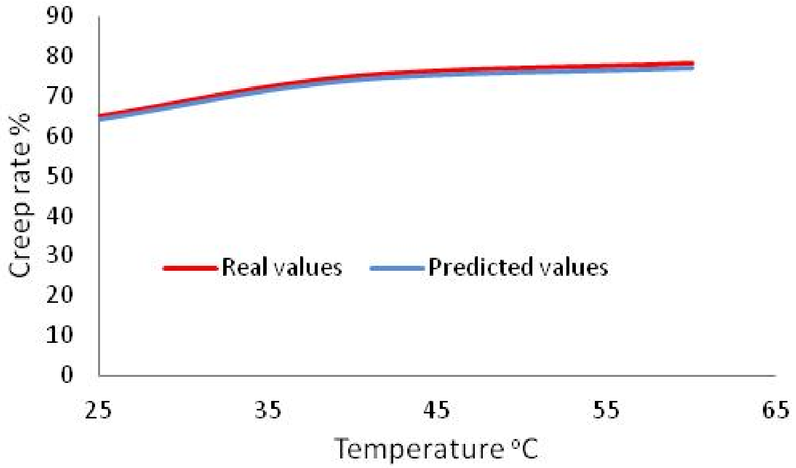

Figure 7. Effect of temperature on final creep rate.

It can be seen that the creep rate is influenced by temperature, the creep rate decreases at low temperature 25 °C and the increase in high temperature 60 °C. The critical observation is the two curves are superposed. It can be concluded that the ANN developed model can be used to predict the effect of temperature on creep deformation.

According to the results it should be noted that the use of polymers improves the creep behavior of bituminous concretes. As it was proved earlier [23], [28], artificial neural network proposed model found to be an effective tool to predict asphalt concrete creep deformation.

The reader must not forget that the obtained results at the end of this study is valid only for a specific type of aggregate, bitumen, polymer, modification technique, static creep test [1] and laboratory conditions

4. Conclusion

In this study, the ANN model was proposed to achieve a high degree of precision in the prediction of modified asphalt concrete creep rate. Based on the results of this study, the following outcomes were achieved:

1. Rubber contents, testing temperatures, compactness, and stress condition have a significant impact on creep rate. Back-propagation neural networks algorithms are used for the process.

2. The experimental creep rate values versus the predicted values by ANN compared using correlation coefficient R. The performance of the model is measured by the mean square error function (MSE). The correlation coefficient R is greater than 0.98 %. It is clearly shown that the ANN model proposed has better capability to predict the final creep rate in a short time with low error. It has indicated good agreement between ANN predicted values and experimental ones.

3. In addition, the ANN is applied to observe the effect of additive content and the temperature on creep rate. The results indicate that the creep rate of asphalt concrete can be improved through incorporating 2 % of the polymer in the powder form into the mixtures. That means the polymers reduce the creep rate. The increase in additive contents over 2 % (3 % and 4 %) does not reduce significantly the creep rate. So, the creep rate is also influenced by variation of temperature, the results indicate that the creep rate increases with temperature.

4. The ANN proposed in this work can be useful in the design of future studies on this topic for making a primary decision about the use of different variables in the modified or unmodified asphalt mixtures.

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