Modeling of Resilient Modulus of Asphalt Concrete Containing Reclaimed Asphalt Pavement using Feed-Forward and Generalized Regression Neural Networks

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ABSTRACT
Reclaimed asphalt pavement (RAP) is one of the waste materials that highway agencies promote to use in new construction or rehabilitation of highways pavement. Since the use of RAP can affect the resilient modulus and other structural properties of flexible pavement layers, this paper aims to employ two different artificial neural network (ANN) models for modeling and evaluating the effects of different percentages of RAP on resilient modulus of hot-mix asphalt (HMA). To this end, 216 resilient modulus tests were conducted for establishing the experimental dataset. Input variables for predicting resilient modulus were temperature, penetration grade of asphalt binder, loading frequency, change of asphalt binder content compared to optimum asphalt binder content and percentage of RAP. Results of modeling using feed-forward neural network (FFNN) and generalized regression neural network (GRNN) model were compared with the measured resilient modulus using two statistical indicators. Results showed that for FFNN model, the coefficient of determination between observed and predicted values of resilient modulus for training and testing sets were 0.993 and 0.981, respectively. These two values were 0.999 and 0.967 in case of GRNN. So, according to comparison of R2 for testing set, the accuracy of FFNN method was superior to GRNN method. Tests results and artificial neural network analysis showed that the temperature was the most effective parameter on the resilient modulus of HMA containing RAP materials. In addition by increasing RAP content, the resilient modulus of HMA increased.
1. Introduction
Each year millions of tons of asphalt concrete are produced from damaged asphalt pavements in the world [1]. The disposal of this waste material in landfills has been a traditional solution, but the shortage of landfill areas, environmental regulations and related costs have prevented the safe disposal of these waste products. Investigations show that using RAP will result in technical, economical, and environmental benefits [1]. Recently, highway departments promote the use of RAP in asphalt pavement rehabilitations. The use of RAP has effect on some basic properties of hot-mix asphalt (HMA) such as resilient modulus. Resilient modulus as a measure of the stiffness of asphalt concrete mixture is one of the fundamental parameters that is used in evaluating of materials quality and as an input for asphalt pavement design. Colbert and You [2] evaluated the hot-mix asphalt containing 15, 35, and 50% RAP experimentally and indicated that the addition of RAP increased the resilient modulus by 52%. Sondag et al. [3] blended 0 to 50% RAP with virgin aggregates and based on resilient modulus and complex modulus tests results, recommended different percentages of RAP (10-50%) and the respective asphalt binder grades to yield the stiffness similar to a virgin mixture. Zaumanis and Mallick [4] investigated the approaches for increasing the amount of RAP in asphalt concrete mixtures above 40% and indicated that the stiffness of high content RAP asphalt concrete mixtures was higher than that of the virgin. However the increase in stiffness was not proportional to RAP content for all cases.

Nowadays, some asphalt laboratories generate a lot of resilient modulus data from their different asphalt concrete mixture tests. These data are saved in these laboratories databases. Since, artificial neural network (ANN) is a computational approach to solve new problems by applying the information gained from the past experiences, it seems that it is possible to use the previous resilient modulus test data for prediction of resilient modulus of asphalt concrete mixtures under other conditions (e.g. temperature, loading frequency, mix design, and …).

ANN technique has been widely applied in asphalt material studies. Tarefder et al. [5] used a four-layer feed-forward neural network to determine a mapping associating mix design and testing factors of asphalt concrete samples to predict their permeability. They observed an excellent agreement between simulation and laboratory data. Ozgan [6] applied an ANN based model for the results of Marshall stability tests. He concluded that experiment results and ANN model exhibit a good correlation. Xiao and Amirkhanian [7] used ANN approach for estimating stiffness behavior of rubberized asphalt concrete containing reclaimed asphalt pavement. Their results indicated that ANN techniques were more effective than traditional regression-based prediction models in predicting the fatigue life of the modified mixture. Zaghal [8] modeled creep compliance behavior of asphalt concretes using ANN technique. Results of ANN simulations showed the proposed model could effectively predict the creep compliance of asphalt concrete mixtures at different temperatures with different binders. ANN has been also used for prediction of resilient modules of asphalt concrete mixtures. They are shown in Table 1. Figure 1 shows the research framework.

This research focuses on the prediction of the resilient modulus of asphalt concrete...
mixtures containing different percentage of RAP. Two different ANN techniques including generalized regression neural network (GRNN) and feed-forward neural network (FFNN) were applied for prediction of resilient modulus and their accuracies have been compared to each other. The proposed model based on artificial neural networks helps designers and technicians to estimate the resilient modulus of asphalt concretes containing RAP materials with an appropriate accuracy.

Table 1. Application of ANN in prediction of resilient modulus

<table>
<thead>
<tr>
<th>Material</th>
<th>Inputs</th>
<th>Method</th>
<th>Main results</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Emulsified asphalt mixtures</td>
<td>Curing time, Cement content, Residual content</td>
<td>Back propagation NN</td>
<td>NN predicts the resilient modulus with high accuracy.</td>
<td>[9]</td>
</tr>
<tr>
<td>Rubberized mixtures containing RAP</td>
<td>Rubber content, RAP content, Binder rheology</td>
<td>ANN and regression models</td>
<td>ANN-based models are more effective than the regression models.</td>
<td>[10]</td>
</tr>
<tr>
<td>Fiber-reinforced asphalt concrete</td>
<td>Fiber content, Fiber length, Fiber type</td>
<td>Hybrid ANN-genetic algorithm model</td>
<td>The optimized ANN can predict the resilient modulus with high accuracy.</td>
<td>[11]</td>
</tr>
<tr>
<td>Asphalt treated permeable base</td>
<td>Asphalt contents, Aggregate gradations</td>
<td>Support vector machines and ANN</td>
<td>SVM model can gain higher precision than ANN approach.</td>
<td>[12]</td>
</tr>
</tbody>
</table>
2. Materials and Test Methods

2.1. Aggregate

The aggregate used in this research study obtained from an asphalt plant located in the west part of Tehran. The nominal maximum aggregate size was 19 mm. Tables 2 and 3 show the aggregate properties and aggregate gradation, respectively.

<table>
<thead>
<tr>
<th>Test</th>
<th>Test method</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Specific gravity</td>
<td>ASTM C-127</td>
<td>2.485</td>
</tr>
<tr>
<td>Los Angeles abrasion (%)</td>
<td>AASHTO T-96</td>
<td>16</td>
</tr>
<tr>
<td>Water absorption (Coarse aggregate) (%)</td>
<td>AASHTO T-85</td>
<td>2.6</td>
</tr>
<tr>
<td>Water absorption (Fine aggregate) (%)</td>
<td>AASHTO T-84</td>
<td>2.5</td>
</tr>
<tr>
<td>Percent fracture (one face) (%)</td>
<td>ASTM D5821</td>
<td>93</td>
</tr>
<tr>
<td>Percent fracture (two faces) (%)</td>
<td>ASTM D5821</td>
<td>81</td>
</tr>
<tr>
<td>Elongation index</td>
<td>BS 812</td>
<td>15</td>
</tr>
<tr>
<td>Flakiness index</td>
<td>BS 812</td>
<td>25</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sieve size (mm)</th>
<th>Percent passing</th>
</tr>
</thead>
<tbody>
<tr>
<td>25</td>
<td>100</td>
</tr>
<tr>
<td>19</td>
<td>92</td>
</tr>
<tr>
<td>9.5</td>
<td>70</td>
</tr>
<tr>
<td>4.75</td>
<td>50</td>
</tr>
<tr>
<td>2.36</td>
<td>36</td>
</tr>
<tr>
<td>0.3</td>
<td>11</td>
</tr>
<tr>
<td>0.075</td>
<td>5</td>
</tr>
</tbody>
</table>

2.2. Asphalt binders

The asphalt binders used in this study were of penetration 60/70 and 85/100 (Pen 60/70 and Pen 85/100). The properties of the asphalt binders used in this research are presented in Table 4.

<table>
<thead>
<tr>
<th>Test</th>
<th>Test method</th>
<th>60/70</th>
<th>85/100</th>
</tr>
</thead>
<tbody>
<tr>
<td>Specific gravity (25°C)</td>
<td>ASTM D70</td>
<td>1.016</td>
<td>1.000</td>
</tr>
<tr>
<td>Flash point (Cleveland)(°C)</td>
<td>ASTM D92</td>
<td>310</td>
<td>298</td>
</tr>
<tr>
<td>Penetration (25°C)(0.1 mm)</td>
<td>ASTM D5</td>
<td>69</td>
<td>85</td>
</tr>
<tr>
<td>Ductility (25°C) (cm)</td>
<td>ASTM D113</td>
<td>&gt;100</td>
<td>&gt;100</td>
</tr>
<tr>
<td>Softening point (°C)</td>
<td>ASTM D36</td>
<td>49</td>
<td>48</td>
</tr>
<tr>
<td>Kinematic viscosity @ 120 ° C (Centistokes)</td>
<td>ASTM D2170</td>
<td>832</td>
<td>797</td>
</tr>
<tr>
<td>Kinematic viscosity @ 135 ° C (Centistokes)</td>
<td>ASTM D2170</td>
<td>440</td>
<td>372</td>
</tr>
<tr>
<td>Kinematic viscosity @ 150 ° C (Centistokes)</td>
<td>ASTM D2170</td>
<td>137</td>
<td>133</td>
</tr>
</tbody>
</table>
2.3. Reclaimed asphalt

Reclaimed asphalt in this research was prepared from an asphalt pavement in Tehran. Tables 5, 6 and 7 show the properties of aggregate, aggregate gradation and asphalt binder extracted from reclaimed asphalt, respectively.

| Table 5. Properties of reclaimed asphalt aggregate |
|---------------------------------|-----------------|------------|
| Test                             | Test Method     | Result     |
| Asphalt binder content (%)       | ASTM D2172      | 5.4        |
| Water absorption (Coarse aggregate) (%) | ASTM C127 | 2.1        |
| Water absorption (Fine aggregate) (%) | ASTM C128 | 2.51       |
| Specific gravity (Coarse aggregate) | ASTM C127 | 2.495      |
| Specific gravity (Fine aggregate) | ASTM C128      | 2.502      |

| Table 6. Aggregate gradation of reclaimed asphalt |
|---------------------------------|-----------------|
| Sieve size (mm) | Percent passing |
| 19          | 100             |
| 9.5         | 98              |
| 4.75        | 78              |
| 2.36        | 52              |
| 0.3         | 17              |
| 0.075       | 9               |

| Table 7. Properties of extracted asphalt binder |
|---------------------------------|-----------------|------------|
| Test                             | Test method     | result     |
| Penetration (25 °C)(0.1 mm)     | ASTM D5         | 20         |
| Softening point (°C)            | ASTM D36        | 72         |
| Kinematic viscosity @ 135 °C (Centistokes) | ASTM D2170 | 1977       |

2.4. Mix design and fabrication of specimens

The optimum asphalt binder contents of the control mixtures were determined using Marshall mix design method (ASTM D1559) with 75 blows on each side. The optimum asphalt binder contents were obtained 5.5% and 4.9% for asphalt containing asphalt binders of Pen 60/70 and Pen 85/100, respectively. The asphalt concrete mixtures containing different percentages of RAP (25, 50 and 75 wt.% of the total mix) were made by the same optimum asphalt binder content, so that the amount of asphalt binder would not confound the analysis of the test results.

2.5 Resilient Modulus Test

When a material is subjected to a stress, the induced strain will depend on the properties of the material. In general, the total strain may be divided to recoverable and non-recoverable strains. The recoverable part of strain is called resilient strain and the non-recoverable is called plastic strain. The Resilient Modulus ($M_R$) is defined as the ratio of applied deviator stress to the recoverable strain (Eq.1) [13].
\[ M_R = \frac{\sigma_d}{\epsilon_r} \]  
(1)

Where \( \epsilon_r \) is resilient or recoverable strain and \( \sigma_d \) is the deviator stress.

There are several methods for determining the resilient modulus of asphalt concrete mixtures. In this research study the resilient modulus test was conducted in the indirect tensile mode and in accordance with ASTM D4123 [14]. Figure 2 shows the machine used for determining the resilient modulus of the asphalt concrete mixtures. The loading waveform was haversine. In addition the loading frequencies were 0.33, 0.5 and 1 Hz. The test was conducted at 5, 25 and 40°C and then resilient modulus was computed using the Eq. 2. The specimens remained in the controlled-temperature chamber at each temperature for about 24 h prior to testing. Each specimen was precondition by applying 100 repeated haversine waveform load to obtain uniform deformation readout. In accordance with ASTM D4123 a minimum of 50 to 200 load repetitions is typical. The magnitudes of loads were 1000 N for tests at 5°C and 500 N for tests at 25°C and 40°C. In accordance with ASTM D4123 the load range should be that to induce 10 to 50% of the tensile strength.

\[ M_R = \frac{P(\nu + 0.27)}{t\Delta H} \]  
(2)

Where \( M_R \) is resilient modulus (MPa), \( P \) is the magnitude of the dynamic load (N), \( \nu \) is Poisson ratio, \( \Delta H \) is the total recoverable horizontal deformation (mm) and \( t \) is the specimen thickness (mm). The height (thickness) and diameter of the specimens were about 70 mm and 102 mm, respectively. The Poisson ratio (\( \nu \)) may be computed from Eq. 3 [15].

\[ \nu = 0.15 + \frac{0.35}{1 + e^{(3.1849 - 0.04233t)0.35}} \]  
(3)

Where \( e \) is the base of the natural logarithm (2.7183) and \( t \) is the test temperature and is expressed in degrees Fahrenheit.

![Figure 2. Machine for measuring the resilient modulus of asphalt concrete mixtures](image-url)
3. Establishment of dataset

The final dataset was established based on the results of 214 experimental resilient modulus tests. Input variables (or predictors) were considered as temperature (5, 25, and 40 °C), penetration grade of asphalt binder (60/70 and 85/100), loading frequency (0.33, 0.5, and 1 Hz), change of asphalt binder content compared to the optimum asphalt binder content (-1, 0, and 1%), and percentage of RAP (0, 25, 50, and 75%). Output (or dependent variable) was assumed as resilient modulus of asphalt concrete mixtures in MPa. Statistical properties of different fields of experimental dataset are given in Table 8.

<table>
<thead>
<tr>
<th>Statistical Parameter</th>
<th>Temperature (°C)</th>
<th>PGC\textsuperscript{a}</th>
<th>Frequency (Hz)</th>
<th>CBC\textsuperscript{b}</th>
<th>RAP (%)</th>
<th>M\textsubscript{R} (MPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum</td>
<td>5</td>
<td>0</td>
<td>0.33</td>
<td>-1</td>
<td>0</td>
<td>539</td>
</tr>
<tr>
<td>Maximum</td>
<td>40</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>75</td>
<td>20883</td>
</tr>
<tr>
<td>Mean</td>
<td>23.18</td>
<td>0.50</td>
<td>0.61</td>
<td>0.00</td>
<td>37.85</td>
<td>7836.71</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>14.35</td>
<td>0.50</td>
<td>0.29</td>
<td>0.82</td>
<td>27.91</td>
<td>6074.23</td>
</tr>
</tbody>
</table>

\textsuperscript{a}PGC: Penetration grade code (0 for 60/70 asphalt binder and 1 for 85/100 asphalt binder)
\textsuperscript{b}CBC: change of asphalt binder content compared to optimum asphalt binder content

4. Modeling using Artificial Neural Network (ANN)

The mathematical theory of neural networks states that every continuous function that maps intervals of real numbers to some output interval of real numbers can be approximated arbitrarily closely by a feed-forward neural networks with just one hidden layer [16]. Therefore, in this study artificial neural network models were developed for predicting resilient modulus of asphalt concrete mixtures containing RAP with respect to different mix parameters, loading time and temperature.

In order to modeling resilient modulus, two famous architectures including feed-forward neural networks (FFNN) and generalized regression neural networks (GRNN) were employed. These two architectures of neural network will be described in the next sections.

FFNN which is known also as multilayer perceptron (MLP) is the simplest type of artificial neural network architecture. In this network, the information only moves in one direction from the input layer through the hidden layers and to the output layer [17].

Analogous to the human brain, a FFNN uses many simple computational elements, named artificial neurons, connected by variable weights [18]. A typical artificial neuron is illustrated in Figure 3. A FFNN can be trained to predict a particular function by adjusting the values of the connections (weights) between the elements. Neural networks are trained so that a particular input leads to a specific target output. The network is adjusted based on a comparison of the output and the target until the network output matches the target. Typically many such input/target output pairs are used to train a network.
4.1. Feed-Forward Neural Network (FFNN)

The training of a FFNN using the back propagation algorithm involves two phases [19,20]:

Forward Phase. During this phase, the free parameters of the network are fixed, and the input signal is propagated through the network from input layer to hidden layer and then to output layer. The forward phase ends with the computation of an error signal.

\[ e_i = d_i - y_i \]  

where \( d_i \) is the desired response, and \( y_i \) is the predicted output by the network in response to the input \( x_i \).

Backward Phase. In this phase, the error signal \( e \) is propagated through the network in the backward direction. In fact in this phase, adjustments are applied to the free parameters of the network so as to minimize the error \( e \) in a statistical sense.

In this research, the back propagation training algorithm of Levenberg - Marquardt was employed. The architecture of a feed-forward back propagation neural network has been presented in Figure 4.
4.2. General Regression Neural Network (GRNN)

Generalized Regression Neural Network (GRNN) was proposed by Specht [22]. GRNN is a type of ANN which uses a brain synapse-like structure to handle the information. The GRNN has good approximation ability and learning speed especially for large sample data. The GRNN also has good forecasting result in case of small datasets [23]. The main aim of the GRNN is to estimate the output vector \( Y = [y_1, y_2, \ldots, y_k]^T \) based on the input vector \( X = [x_1, x_2, \ldots, x_n]^T \) by a non-linear or linear regression surface. The procedure of the GRNN model can be expressed as

\[
E[Y | X] = \frac{\int_{-\infty}^{\infty} Y f(Y, X) dX}{\int_{-\infty}^{\infty} f(Y, X) dX}
\]

(5)

where \( X \) is the input vector with a dimension of \( n \), \( Y \) is the predicted value by GRNN model, \( E[Y | X] \) is the expected value of the output \( Y \), given the input vector \( X \) and \( f(Y, X) \) is the joint probability density function of \( X \) and \( Y \).

The GRNN is organized using four layers including input layer, pattern layer, summation layer, and output layer (Figure 5). The input layer receives input parameters and stores them to an input vector \( X \). Number of neurons in input layer is equal to the dimension of input vector. Then, the data from input layer are fed to the pattern layer. The pattern layer implements a non-linear transformation from the input space to the pattern space. The neurons in the pattern layer can memorize the relationship between the input neuron and the proper response of pattern layer. The number of neurons in hidden layer is equal to the number of input variables. The pattern Gaussian function of \( p_i \) is as follows:

\[
p_i = \exp \left[ -\frac{(X-X_i)^T (X-X_i)}{2\sigma^2} \right] \quad (i=1,2,\ldots,n)
\]

(6)

Where \( \sigma \) is the smoothing parameter, \( X \) is the input variable and \( X_i \) is a specific training vector of the neuron \( i \) in the pattern layer. The summation layer has two summations which are \( S_s \) and \( S_w \). The simple summation \( S_s \) computes the arithmetic sum of the pattern layer outputs, and the interconnection weight is equal to ‘1’. The weighted summation \( S_w \) computes the weighted sum of the pattern layer outputs, and the interconnection weight is \( w \). These two parameters can be represented as Eqs. (7) and (8), respectively:

\[
S_s = \sum_{i=1}^{p} p_i
\]

(7)

\[
S_w = \sum_{i=1}^{p} w_i p_i
\]

(8)

Where \( w_i \) is the weight of pattern neuron \( i \) connected to the summation layer.

The number of neurons in the output layer is equal to the dimension \( k \) of the output vector \( Y \). After commutating the summations of neurons in the summation layer, they are fed into the output layer. The output \( Y \) of the GRNN model can be determined as follows:

\[
Y = \frac{S_s}{S_w}
\]

(9)

As can be seen, the GRNN model has only one parameter \( \sigma \) that needs to be determined. The parameter \( \sigma \) determines the generalization capability of the GRNN.
4.3. Evaluation of models performance

In the present study, the performances of FFNN and GRNN were evaluated according to the following statistical indicators (Eqs. 10 and 11) [25], [26]:

Root Mean Square Error (RMSE):

\[ RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - x_i)^2} \]  \hspace{1cm} (10)

Coefficient of determination \((R^2)\):

\[ R^2 = \frac{1}{N} \left[ \frac{\sum_{i=1}^{N} (x_i - \bar{x})(y_i - \bar{y})}{\sigma_x \sigma_y} \right]^2 \] \hspace{1cm} (11)

where \(N\) is the size of observations vector, \(x_i\) is the x value for observation \(i\), \(y_i\) is the y value for prediction \(i\), \(\bar{x}\) is the mean x value, \(\bar{y}\) is the mean y value, \(\sigma_x\) is the standard deviation of \(x\), and \(\sigma_y\) is the standard deviation of \(y\).

5. Optimum Architecture and Performance of ANN Models

5.1. Optimum Architecture of FFNN

The performance of a FFNN model mainly depends on the network architecture and setting of parameters. One of the most difficult tasks in FFNN studies is to find this optimal network architecture which is based on the determination of numbers of optimal layers and neurons in the hidden layers by trial and error approach. The assignment of initial weights and other related parameters may also influences the performance of the FFNN in a great extent. However, there is no well defined rule or procedure to determine optimal network architecture and parameter settings where trial and error method still remains valid.

In this study, Matlab ANN toolbox was used for implementation of FFNN. Matlab ANN toolbox randomly assigns the initial weights for each run each time which considerably changes the performance of the trained ANN even if all the parameters and ANN architecture are kept constant. This leads to extra difficulties in the selection of the optimal network architecture and parameter settings. To overcome this difficulty, a program has been developed in Matlab which handles the trial and error process automatically. The program tries various numbers of the neurons in the hidden layer for several times and selects the best ANN architecture with the minimum RMSE (Root Mean Squared Error) for overall dataset. The
testing (20%), cross validating (10%) and training (70%) sets for ANN training procedure were selected randomly from the established database. The optimal ANN architecture was found to be 5-14-1 (one hidden layer with 20 neurons). Hyperbolic tangent sigmoid and linear transfer functions were used for the hidden layers and output layer, respectively. More details are presented in appendix A.

5.2. Optimum Architecture of GRNN

Matlab ANN toolbox was employed in this research study for training and testing of GRNN model. The smoothing parameter of $\sigma$ affects the generalization capability of the GRNN and should be set to an appropriate value for optimal performance of GRNN. In order to determine the optimum value of smoothing parameter, a program was developed in Matlab. This program was able to train GRNN according to different values of spread parameter. In case of each value of smoothing parameter ($\sigma$ could varies from 0.001 to 1 with increment of 0.001), the value of RMSE for testing set was determined and the value that results in minimum value of RMSE was selected as optimum value of smoothing parameter. 80% of dataset records were selected as training set and remaining 20% were considered as testing set. Training set in case of GRNN was the union of training and cross validation sets of FFNN and testing set was the same for both neural network models. Variation of RMSE versus spread parameters for both training and testing sets is demonstrated in Figure 6. According to the Figure 6, by increasing the smoothing parameter, the RMSE of training set increases, but the minimum RMSE of testing set is achieved when the value of smoothing parameters is equal to 0.157.

![Figure 6. RMSE versus smoothing parameter.](image)

5.3. Performances of FFNN and GRNN

The performances of FFNN and GRNN for predicting resilient modulus using training and testing sets are demonstrated in Figures 7 to 10. Also, the RMSE and $R^2$ values for each model are given in Table 9.
Figure 7. Performance of FFNN model (training set).

Figure 8. Performance of FFNN model (testing set).

Figure 9. Performance of GRNN model (training set).
According to Table 9, in case of FFNN, the coefficient of determination ($R^2$) between observed and predicted values of resilient modulus for training and testing sets is 0.993 and 0.981, respectively. These two values are 0.999 and 0.971 for GRNN. It is evidence that the accuracy of FFNN model is superior to GRNN. In this case, the FFNN model is capable to predict resilient modulus of asphalt concrete with $R^2$ more than 0.98.

## 6. Parametric Analysis

In order to investigate the effect of various factors such as the temperature, penetration grade of asphalt binder, loading frequency, change of asphalt binder content compared to optimum asphalt binder content, and percentage of RAP on the resilient modulus of asphalt concrete mixtures, one asphalt concrete mixture under standard conditions was assumed. The assumed asphalt concrete mixture with standard conditions is given in Table 10.

<table>
<thead>
<tr>
<th>Temp.(°C)</th>
<th>PGC$^a$</th>
<th>Frequency (Hz)</th>
<th>CBC$^b$ (%)</th>
<th>RAP (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>25</td>
<td>0</td>
<td>0.5</td>
<td>0</td>
<td>25</td>
</tr>
</tbody>
</table>

$^a$PGC: Penetration grade code (0 for 60/70 asphalt binder and 1 for 85/100 asphalt binder)

$^b$CBC: change of asphalt binder content compared to optimum asphalt binder content

To study the effect of different parameters, on the resilient modulus, the trained FFNN was used and by changing the desired parameters, the resilient modulus was computed. The results of the parametric analysis are presented in Figures 11 to 15.
Figure 11. Effect of temperature on the resilient modulus of asphalt concrete mixture.

Figure 12. Effect of penetration grade of asphalt binder on the resilient modulus of asphalt concrete mixture.

Figure 13. Effect of loading frequency on the resilient modulus of asphalt mixture.
According to Figures 11 to 15, the effect of different parameters on the resilient modulus of asphalt concrete mixtures can be stated as follows:

Temperature: by increasing the temperature, the resilient modulus of asphalt mixes decreases and vice versa. Due to visoelastic behavior of asphalt materials, by increasing temperature, the viscosity of asphalt binder decreases and thus the stiffness of asphalt concrete decreases.

Change of asphalt binder content compared to optimum asphalt binder content: by increasing asphalt binder content compared to optimum asphalt binder content, resilient modulus increases. Also by decreasing asphalt binder content compared to optimum asphalt binder content, resilient modulus decreases. As the asphalt binder content increases, the adhesion and tensile strength in the mixture structure improves. This leads to decrease in the horizontal deformation in the resilient modulus test, so in according to equation 2, the resilient modulus of asphalt concrete mixtures increases. However it should be noted that if the asphalt binder...
content increases so much, the excess asphalt binder will weak the interlocking the aggregate and so the resilient modulus of asphalt concrete mixture will decrease.

Penetration grade of asphalt binder: by increasing the Penetration grade, the resilient modulus of asphalt mixes decreases and vice versa. Asphalt binder with higher penetration grade has lower viscosity and this decreases the stiffness and resilient modulus of the asphalt concrete mixtures.

Loading frequency: by changing loading frequency between 0.5 to 0.9 Hz, no distinctive change is observed for resilient modulus. This can be explained by narrow range of frequency change.

In fact for exploring the effect of frequency on the resilient modulus of asphalt concrete, the frequency should be changed in a wide range specially for moderate and low temperatures. For further research, it is recommended that a wide range of frequencies (from 0.1 to 10) to be used for experimental program.

RAP content: By Increasing RAP content, the resilient modulus of asphalt mixes increases, significantly. Since, RAP contains aged asphalt binder, so the addition of RAP makes the mixture stiffer and increases the resilient modulus. It should be noted that although the increasing of resilient modulus may considered as a positive parameter for pavement design, but the other properties such as fatigue and rutting resistance of asphalt concrete mixture containing RAP should be evaluated.

7. Conclusion

In this study, two different versions of artificial neural networks including FFNN and GRNN, were employed for modeling of the resilient modulus of asphalt concrete mixtures containing reclaimed asphalt pavement. In ANN architecture, temperature (°C), penetration grade code (0 for 60/70 asphalt binder and 1 for 85/100 asphalt binder), loading frequency (Hz), change of asphalt binder content compared to optimum asphalt binder content (%), and RAP content (%) were chosen as the input parameters and the resilient modulus (MPa) of asphalt concrete mixtures was assumed as the output parameter.

According to the results of this study the following statements can be concluded:
- The optimum architecture of FFNN for predicting resilient modulus was determined as 5-14-1 (one hidden layer) with hyperbolic tangent sigmoid and linear transfer functions for the hidden layer and output layer, respectively. $R^2$ and RMSE for predicted values of resilient modulus using FFNN was determined as 0.981 and 827.20 for testing set, while these values are 0.971 and 1017.46 in case of GRNN. Thus, the accuracy of FFNN model was superior to GRNN model for predicting resilient modulus of asphalt concrete mixtures containing RAP materials.
- The most effective parameter on the resilient modulus of asphalt concrete mixtures containing RAP materials was temperature.
- The resilient modulus of asphalt concrete mixtures increased when the RAP content increases or stiffer asphalt binder is employed.
- Results of this study also showed that by decreasing temperature and increasing asphalt binder content compared to optimum asphalt binder content, resilient modulus increases.
References


Simple Performance Test for Superpave Mix Design (Vol. 465), TRB, National Research Council, Washington, DC, USA.


Appendix A. Weights and biases of Artificial Neural Network (ANN)

This Appendix is assigned to input vector, output vector, weight factors, and bias factors of the back propagation neural network which was discussed in section 4.5. The optimum architecture of back propagation neural network is 5-14-1 with sigmoid transfer function in the hidden layer and linear transfer function in the output layer. The order of normalized predictors in the input vector is as follows:

I=\{T,PGC,Frequency,CBC,RAP\}_{1x5} \quad (12)

The order of normalized output parameters in the output vector is as follows:

O=\{Mr\}_{1x1} \quad (13)

Equation (14) may be used for simulation of ANN and prediction of resilient modulus based on given input vector.

\{Out\} = tansig (\{Inp\} \times \{W_h\}^T + \{\theta_h\}^T) \times \{W_o\}^T + \{\theta_o\}^T \quad (14)

Where tansig (x) can be obtained as follows:

\text{tansig}(x) = \frac{2}{1+e^{-2x}} - 1 \quad (15)

Weight matrix for hidden and output layers are given in Table 11 and Table 12, respectively. Bias vector for hidden and
output layer are given in Table 13 and Table 14, respectively.

Table 11. Weight matrix of hidden layer \((W_h)_{14 \times 5}\)

<table>
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<th>0.331131154</th>
<th>-0.150468515</th>
<th>3.894341144</th>
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<td>1.775558134</td>
<td>1.225965169</td>
</tr>
</tbody>
</table>

Table 12. Weight matrix of output layer \((W_o)_{14 \times 1}\)

| -0.295478876 | -0.017525849 |
| -0.204809027 |           |
| 0.083193339 |            |
| 0.397573892 | -2.188464110 |
| 0.024329070 | 1.336729674  |
| 0.064349455 | 1.370637157  |
| -0.060940316 | 0.275829938  |
| 0.289739736 | -2.188464110 |
| 0.077479325 | 1.655692989  |
| -0.104030104 | -1.621861283 |
| 0.057266017 | 2.530472150  |
| 0.105736230 | -4.183043913 |
| 0.175164928 | -2.608443726 |
| 0.022502847 |           |

Table 13. Bias vector of hidden layer \((\theta^h)\)

| -4.765303345 |
| -3.153745569 |
| -2.332963106 |
| -0.607005988 |
| -1.178814078 |
| 1.336729674  |
| 1.370637157  |
| 0.275829938  |
| -2.188464110 |
| 1.655692989  |
| -1.621861283 |
| 2.530472150  |
| -4.183043913 |
| -2.608443726 |

Table 14. Bias vector of output layer \((\theta^o)\)

| -0.017525849 |

Bias vector for hidden and output layer are given in Table 13 and Table 14, respectively: