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Abstract

Asphalt endurance limit is a strain value if experienced by asphalt pavement layer, no accumulated damage will occur and is directly related to asphalt healing. Therefore, if the pavement experiences this value of strain, or lower, no fatigue damage would accumulate within that pavement section. Beam fatigue test data conducted under the NCHRP Project 9-44A were extracted and utilized to create an Artificial Neural Network predictive model (ANN) to determine the endurance limit strain values for conventional asphalt concrete pavements. The developed ANN model architecture as well as how to utilize it to predict the endurance limit were demonstrated and discussed in detail. Also, a stand-alone equation that is capable in the prediction of the endurance limit strain value, separate from the ANN model environment, was derived utilizing the eclectic extraction approach. The model training and validation data included 934 beam fatigue laboratory data points, as extracted from NCHRP Project 9-44A report. The developed model was able to determine the endurance limit strain value as a function of the stiffness ratio, number of cycles to failure, initial stiffness and rest period, and had a reasonable coefficient of determination (R^2) value, which indicates the reliability of both the developed ANN model and the stand-alone equation. Furthermore, a correlation between the endurance limit strain values, as predicted utilizing the generated regression model under the NCHRP project 944-A, and the endurance limit strain values predicted utilizing the stand-alone ANN derived equation was found with a high coefficient of determination (R^2) value.

Keywords: Endurance limit, healing, fatigue, artificial neural network, rest period.

1. Introduction

Fatigue cracking is one of the major challenges in the flexible pavement design. Fatigue cracking is defined as the longitudinal or interconnect cracks that propagates from the bottom to the top of the asphalt layers under repeated traffic loading cycles. Those cracks usually appear in the outer wheel path for thin Hot Mix Asphalt (HMA) layer and in the inner wheel path for the thick HMA layers (Abojaradeh 2003). The endurance limit is a strain value, below which no accumulated damage will occur to the pavement. Thus, a pavement with a design strain value at the bottom of the HMA layer that is equal to or lower than the endurance limit will never experience fatigue cracking, which classifies it as perpetual pavement (Newcomb 2001). Therefore, the endurance limit is directly related to asphalt healing. Asphalt healing is the ability of the HMA layer to regain its structural initial condition before the loading damage if given enough rest period time between two consecutive loading cycles (Peterson 1984).

Current mechanistic design approach assumes that there is an amount of damage associated to each loading cycle the HMA layer is subjected to, and that accumulated damage is consuming a portion of the total fatigue life of the pavement section. However, recent studies demonstrated that a well-constructed pavement section will not examine a fatigue cracking even if it was subjected to large numbers of loading cycles (Willis and Timm 2009; Thompson and Carpenter 2006; Prowell et al. 2010). The above statement drives the need to have a reliable prediction model for the endurance limit values for pavement design process consideration.

Growing number of researchers are utilizing the Artificial Neural Network (ANN) as a data mining approach due to its high classification and prediction accuracy. ANN is utilized to solve variety of problems such as pattern classification and function approximation (Setiono et al. 2002). Therefore, ANN modeling was utilized to create the endurance limit prediction model in this research paper.

2. Objective

The study aims to provide a reliable ANN model that has the ability to predict the fatigue endurance limit. To achieve the goal, the previously conducted beam fatigue tests under project NCHRP 944-A were utilized to create the desired model, which classifies strain value as the dependent variable, while the rest period, initial stiffness, number of cycles to failure, and the stiffness ratio are defined as the independent variables. The model was statistically validated and evaluated. Also, a stand-alone correlation equation was extracted via the eclectic extraction approach to be utilized outside the model environment.

3. Literature Review

3.1 Rest Period and Healing of HMA

Rest period is defined as the time between two consecutive loading cycles. The amount of the damage associated with testing during a rest period is lower than the amount of damage related to the continuous testing due to the healing that occurred during the rest period (Souliman 2012).

McElvane and Pell (1973) had conducted a research study utilizing the rotating bending fatigue testing technique. The testing was conducted utilizing multi-level loading and random duration of rest periods. The improvement occurred to the fatigue life was not quantified. However, it was concluded that the rest period will improve the fatigue life of the tested specimen.

Castro et al (2006) conducted a research study to examine the effect of the rest period on the fatigue life, which concluded that the introduction of 1-second rest period between two .1-

second loading times will increase the fatigue life of the tested specimen 10 times. This was completed in comparison to a test result of a specimen that was tested without a rest period.

The material self-recovery to its initial status and properties if given enough time to rest is defined as healing. This phenomenon was examined in the literature for many years and various engineering materials (metallic and nonmetallic) were found to have this ability (Suresh 1998; Souliman 2012).

The three-major mechanisms that prevent the growth of fatigue cracking and induce the crack healing for the non-metallic material such as cement concrete, asphalt concrete, and polymers can be summarized as follows: 1) Crack deflection, 2) Crack-bridging or trapping, and 3) Crack-shielding due to micro cracking or phase transformations (Suresh 1998).

Lytton (2000) has conducted a research study to evaluate the effect of the healing on the fatigue life and to explain the fracture and healing mechanisms. The fracture-healing mechanisms for the asphalt concrete were classified under two main categories, the surface energy storage and the surface energy release. It was concluded that the surface energy depends mainly on the chemical composition of the binder, while also concluding that the energy balance between the stored and released energy controls the fracture and healing mechanism of the asphalt aggregate mixture.

3.2 HMA Endurance Limit

Wöhler (1860) first introduced the concept of endurance limit in the literature for the metallic materials by the generation of the classical S/N curves. His findings also presented the fact that there is a load level below which the number of cycles to failure will remain constant and will not increase by decreasing the load. This load was defined as the Fatigue Endurance Limit (FEL) for metallic materials.

Although the endurance limit concept has been extensively addressed and examined for metallic and other materials, less work was done to study and understand this concept in viscoelastic material, such as asphalt (Souliman 2012).

Monismith and McLean (1972) had observed that the relationship between the strain and the loading cycles had converged at approximately 70 micro strains when the loading cycles were around 5 million cycles. Thus, a 70-micro strain was proposed by them as the endurance limit value for the asphalt pavements. Also, Maupin and Freeman (1976) had arrived to the same results and found that the 70-micro strain is the endurance limit for the asphalt pavements.

Carpenter (2006) demonstrated in his study that there is an endurance limit for the asphalt pavements and concluded that the endurance limit is dependent on the binder type and its values are limited between 70 to 100-micro strains in some cases. The drawn conclusion by this study matched the previous studies' conclusions in terms of endurance limits values.

3.3 HMA Endurance Limit and Healing Concepts Developed Under NCHRP Project 944A

Souliman (2012) has developed a mathematical procedure to determine the value of the endurance limit based on the asphalt healing under the NCHRP project 944A. The asphalt healing index was defined as the difference in the stiffness ratio between the tests done with rest period and without rest period at the number of cycles to failure for test without rest period as shown in Figure 1.

A general stiffness ratio model was generated and utilized to determine the healing index values at different test combinations. The relationship between the healing index and the stiffness ratio at different temperatures is shown in Figure 2. From the endurance limit definition, it is clear that this limit occurs when no damage accumulation occurs in the pavement. Thus, it was defined as the strain value at the value of 0.5 HI. The value of 0.5 HI is equivalent to 0.5 stiffness ratio for tests without rest period, and 1 stiffness ratio for tests with rest period. Three different generations of SR prediction models were developed under this project. The third-generation model was utilized to predict the endurance limit by substituting a stiffness ratio value of 1 (no damage) and a number of cycles to failure of 20,000.

It was concluded by this project that the endurance limit is a function of the mixture initial stiffness (referring to the binder type, binder content, air voids, and mix temperature), rest periods between different loading cycles, stiffness ratio, and the number of loading cycles to failure. Furthermore, and due to the endurance limit being a function of all the previous variables, it was stated that there is no single value that represents the endurance limit. The developed models estimated the endurance limit values in a range of 22 to 223-micro strains.

4. The Design of the Experimental Study Done Under Project NCHRP 944-A

A factorial experiment was designed to study the effect of six factors on the endurance limit of the asphalt concrete: 1) Binder type, 2) Binder content, 3) Air voids, 4) N_f for a stress-controlled tests 5) Temperature, and 6) Rest periods.

The experiment conditions were as follows:

- Binder types: PG 58-28, PG 64-22, and PG 76-16.
- Binder content: optimum +5% and optimum - 5%.
- Air voids: 4.5% and 9.5%.
- Nf for a strain-controlled test: 2 levels L and H.
- Temperature: 40, 70, and 100 ^{o}F.
- Rest period: 0 and 5 sec.

The full factorial design, if used, would results in a total of 432 tests (3 binder types x 2 binder content x 2 air voids x 2 NF x 3 temperature x 2 rest periods x 3 replicates). Due to the huge number of tests required, the factorial design was reduced from 432 tests to 288 tests, utilizing a well-known design optimizing criteria named D-optimality.

Furthermore, at a later stage of the project, due to the need to check the relationship between the endurance limit, rest period, and strain level, an additional study was performed. This study introduced two new rest periods (5 and 10 sec.), and one new strain level (M level) to the previously used experiment conditions with a total number of 180 new tests.

Due to the extensive duration of the test, it was decided to run all tests with rest periods up to 20,000 cycles only. Extrapolation were utilized to find the values of SR for the tests with rest period at the number of cycles bigger than 20,000. The primary measurable variable for each test was the stiffness ratio (SR) at the end of the loading cycles.

5. Model Generation Utilizing Artificial Neural Network

5.1 Background

Neural networks are highly interconnected networks that have a very strong computational and pattern recognition capabilities. The strength of those networks is in the simulation of the brain working mechanism (Kustrin et al 2000). Figure 3 demonstrates the similarity between nerve neuron cell and an artificial neuron in a network.

Ceylan (2014) indicated that "neural networks are information processing computational tools in which highly interconnected neurals work in harmony to solve complex problems in a nontraditional manner. This power of NNs, emulating the biological nerves system, lies in the tremendous numbers of interconnections". The study concluded that there is a growing usage of the ANN in the engineering filed for traditional numerical and statistical methods such as regression analysis. The grown usage is due to its ability to provide engineers with a sophisticated real-time analysis and results without the need for complex analysis procedures for the input values nor to a large computational power similar to other analysis methods such as finite element solution techniques.

5.2 Utilized Model Architecture

A three-layer feed-forward backpropagation neural network with a sigmoid activation function and one hidden layer are the most common types of neural networks. Also, one hidden layer is typically sufficient for solving most of the non-linear problems without network overfitting (Chan and Chan 2016). For the purpose of this study, a three-layer feed-forward neural network, with a backpropagation-error calculation algorithm and two neurons in the hidden layer, was utilized.

Figure 4 demonstrates the utilized network architecture for the study, and its main components may be summarized as follows:

1) Input layer (i) with four input neurons, one neuron for each independent variable.
2) Weight factors (W_{ih}) between the input layer (i) and the hidden layer (h). The weight matrix contained eight different values, one value from each input to each neuron.
3) Hidden layer (h) with two hidden neurons having a tan-sigmoid activation function and two biases values (b_{h1} and b_{h2}).
4) Weight factors (W'_{ho}) between the hidden layer and the output layer. The weight matrix contained two values, one value from each hidden neuron to the output neuron.
5) Output layer (o) with one output neuron for the dependent variable having a linear transfer function and single bias value (B_o).

5.3 Model Training Methodology and Evaluation

Beam fatigue test data set as extracted from NCHRP project 944-A described above contained five different variables: 1) The stiffness ratio at cycle number, 2) Initial stiffness, 3) Rest period, 4) Cycles number, and 5) The applied strain. The model was developed and trained to predict the applied strain as a function of the stiffness ratio at cycle number, initial stiffness, rest period, and cycles number as shown in Equation 1.

$$\textit{Applied Strain} = f(\textit{Initial Stiffness, Rest Period, Stiffness Ratio, Cycles Number}) \quad (1)$$

The developed model was trained utilizing the extracted 934 data points in MATLAB (MATLAB R2015a, The Math Works Inc.) by feeding the logarithm of initial stiffness, tan hyperbolic of the rest period, stiffness ratio, and the logarithm of number of cycles to failure in the input layer. In addition, the logarithm value of the applied strain was assigned to the output layer. The training was conducted utilizing Levenberg-Marquardt backpropagation algorithm in MATLAB (MATLAB R2015a, The Math Works Inc.). This training algorithm divides the training data into three categories. The first 70% of the data was utilized for training the model, while the remaining 30% of the data was divided into model testing and validation data sets. As shown in Figure 5, as an effort to avoid overfitting and maintain network generalization, the training was stopped when the validation data set error had stopped decreasing (Elbagalati et al. 2017).

The model performance was evaluated by MATLAB as shown in Figure 6 internally and externally by utilizing Analysis of Variance (ANOVA) in Excel as shown in Table 1. Figure 6 demonstrates the ability of the model in the prediction of the strain for all data sets with a coefficient of determination (R^2) value of 0.93, indicating a high model reliability. in addition, as shown within Table 1, the model has a significance F-value of 0 and reasonable value of 32.54 as a standard error; therefore, this model is statistically valid.

5.4 Rule Extraction from the Generated ANN Model - ANN Equation

Despite the fact that ANN is a reliable tool for analysis and data classification, many of the researchers considered it as a black box due to their inability to have a clear understanding for what is happening inside the model.

Recently, researchers had attempted to open this black box and generate rules from the results of the trained ANN models (Augasta and Kathirvalavakumar 2012; Chan and Chan 2016). There are three main approaches for ANN rule extraction as follows: 1) decompositional, 2) Pedagogical, and 3) Eclectic. Decompositional is referring to when the network weights, bias, and activation function values are utilized to extract the rule. Pedagogical is when the relationship between the input and output of the trained ANN network is studied to generate a rule that has the ability to replicate the results of the trained ANN network without the need of the exploration of the ANN network structure. Finally, eclectic, which is considered as a hybrid approach of the two previous approaches, is when the relationship between the input and output as well as the weights and bias values for the trained ANN network are utilized for rule extraction (Augasta and Kathirvalavakumar 2012; Chan and Chan 2016). For the purpose of rule extraction in this paper, the eclectic approach was utilized.

From the utilized ANN structure, as shown in Figure 4, it can be concluded that the weights from the input layer to the hidden layer, the bias values in the hidden layer, the weights from the hidden layer to the output layer, and the bias values in the output layer are needed to extract the rule form the trained ANN network. The values of the weights and biases are emphasized below as extracted from MATLAB (MATLAB R2015a, The Math Works Inc.).

$\mathbf{W_{ih}}= \begin{bmatrix} -1.1609 & 0.3925 & 0.0476 & -0.3193 \\ 0.1329 & 0.0318 & 0.0318 & -0.2113 \end{bmatrix}$ $\mathbf{W'_{ho}}= \begin{bmatrix} -0.9741 \\ -0.5039 \end{bmatrix}$

$\mathbf{b_{hi}}= \begin{bmatrix} 1.9361 \\ 0.0575 \end{bmatrix}$ $\mathbf{B_o}= [2.5883]$

The extracted weights, the network structure, and the relationship between the input and the output of the ANN network were utilized, along with statistical analysis techniques to extract the rule and generate a stand-alone equation from the trained ANN model. The extracted equation was as shown in Equation 2.

$$\mathcal{E} = 10^{(-0.28256Log(E_o)+0.1058\tanh(RP)-0.06934Log(Nf)-0.11089(SR)+3.40365)} \quad (2)$$

where,

ε = applied strain (microstrain)

E_o = initial stiffness (ksi)

RP = rest period (seconds)

N_f = number of cycles to failure

SR = stiffness ratio

The generated stand-alone equation was tested utilizing all of the modeling data (934 data sets) and it was found to have an acceptable coefficient of determination (R^2) value of 0.74 as shown in Figure 7. In addition, the statistical analysis results for the developed equation as shown in Table 2 clearly demonstrates that it is statistically valid since that the model has a significance F-value much lower than 0.05.

5.5 Simplified ANN Endurance Limit Stand-Alone Equation

The extracted equation as well as the generated ANN model may be utilized to calculate the endurance limit value for the HMA by the interpretation of endurance limit definition into numbers. As discussed under the literature review part, the endurance limit is the strain level at which no damage accumulation will occur in the HMA layer. Simply, this strain level maybe calculated by substituting a stiffness ratio value of 1 and number of cycles to failure of 20,000 in the equation or the developed ANN model. In other words, the calculated strain value when the final stiffness is equal to the initial stiffness is the endurance limit.

Equation 3 was generated by substituting a stiffness ratio value of 1 and the numbers of cycles to failure value of 20,000 in Equation 2 to calculate the endurance limit directly for different initial stiffness and rest period values.

$$EL = 10^{(-0.28256Log(E_o)+0.1058\tanh(RP)+2.99452658)} \tag{3}$$

where,

EL = endurance limit strain (microstrain)

$E_{o=}$ initial flexural stiffness (ksi)

RP = rest period (seconds), ≠ zero

The ability of this equation to replicate the value of endurance limit as predicted by the generated ANN model was graphically evaluated as shown in Figure 8 and found to have a high coefficient of determination (R^2) value of 0.98. Having this high coefficient of determination

(R^2) value clearly demonstrates that the equation has a great ability to replicate the endurance limit values as calculated by the ANN model and may be utilized for endurance limit calculations.

5.6 Endurance Limit Values Comparison

The EL values as calculated utilizing the stand-alone equation were compared to the EL values as calculated utilizing the NCHRP 944-A generated equation:

$$\mathrm{SR} = 2.0844 - 0.1386 \times \log(\mathrm{Eo}) - 0.4846 \times \log(\varepsilon) - 0.2012 \times \log(\mathrm{N}) + 1.4103 \times \tanh(0.8471 \times \mathrm{RP}) + 0.0320 \times \log(\mathrm{Eo}) \times \log(\varepsilon) - 0.0954 \times \log(\mathrm{Eo}) \times \tanh(0.7154 \times \mathrm{RP}) - 0.4746 \times \log(\varepsilon) \times \tanh(0.6574 \times \mathrm{RP}) + 0.0041 \times \log(\mathrm{N}) \times \log(\mathrm{Eo}) + 0.0557 \times \log(\mathrm{N}) \times \log(\varepsilon) + 0.0689 \times \log(\mathrm{N}) \times \tanh(0.259 \times \mathrm{RP}) \quad (4)$$

where,

ε = strain (microstrain)

E_{o} = initial flexural stiffness (ksi)

RP = rest period (seconds)

N = number of cycles

The EL values were calculated as the strain values when the stiffness ratio is 1 and the number of cycles to failure is 20,000 cycles utilizing equation 4. However, strain values related to zero rest period tests were excluded from the comparison since that when the rest period is zero there will be no healing for the asphalt; therefore, there will be no EL strain values.

Good correlation between both EL values was found with a coefficient of determination (R^2) value of 0.8 as shown in Figure 9. However, there are considerable differences between both values, which is demonstrated by Figure 9 and Table 3, which shows the standard error value.

In this comparison, there are some important points to consider, such as what was done is comparing predicted to predicted values. All the compared values were predicted values, not measured. Second, in the NCHRP 944-A project, no beam was tested on its endurance limit; therefore, there is no measured value of the EL strain. Third, when predicting the EL value utilizing the strain model developed under the NCHRP 944-A project, the relationship line between the stiffness ratio and the strain was extended linearly until reaching a SR of 1. In other words, a linear relationship (on the log scale) between the strain and the SR was assumed without having any data point in this area as shown in Figure 10. In fact, the newly developed Artificial Neural Network Model (ANN) maybe stronger in prediction when it comes to this point since that it drives the relationship between the data based on the nature and correlation existed within it, in a way to simulate the brain working mechanism.

The newly developed ANN model had a higher value of the coefficient of determination (R^2) when compared to the model developed under the NCHRP project 944-A, and that gives an indication about the ability of the model in the strain prediction, thus; it may be used for EL strain prediction.

6. Summary and Conclusions

The asphalt healing is directly related to the endurance limit; therefore, the endurance limit is not a single value. The importance of the endurance limit is in the design of the perpetual pavements, since that, if a pavement layer is experiencing a tensile strain equivalent to the endurance limit stain or lower, no damage will accumulate in the pavement layer and it will never fail under repeated loading cycles due to fatigue cracking.

This paper amid to utilize ANN modeling to create a prediction model for the endurance limit and extract the rule (stand-alone equation) from it. The developed model was generated utilizing 934 beam fatigue test data points as extracted from NCHRP project 944-A and had a good prediction accuracy with a coefficient of determination value (R^2) value of 0.93. Eclectic extraction approach was utilized along with statistical analysis techniques to extract the rule from the generated ANN model and create a stand-alone equation that maybe utilized outside the MATLAB model environment. The extracted stand-alone equation had a reasonable prediction accuracy with a coefficient of determination value (R^2) value of 0.74. In addition, the ANN model utilized architecture as well as the training techniques, utilized activation, and transfer functions were discussed in detail to provide a clear procedure that maybe utilized to model any other specific beam fatigue test data and create an ANN prediction model.

The developed simplified endurance limit equation (Equation 3) was able to replicate the ANN model calculated endurance limit values with a high coefficient of determination value (R^2) value of 0.97. Having the coefficient of determination value (R^2) value indicates the reliability of the endurance limit derived equation and envision its high ability to simulate the endurance limit calculation utilizing the ANN model in MATLAB environment.

The EL values as calculated utilizing the stand-alone equation were compared to the EL values as calculated utilizing the NCHRP 944-A generated equation. Both EL values founded to be well correlated with a coefficient of determination value (R^2) of 0.8. However, there are considerable differences between both EL predicted values. The differences in the predicted values of the EL strain maybe due the nonlinearity of the relationships created within the ANN model to simulate the brain working mechanism. The strength of those relationships is that they were created for the given input output data (custom made based on the nature of the data); therefore, the ANN model is stronger in the prediction when compared to the regular regression models presented under the NCHRP 944-A project.

Further testing is required to create a new ANN predicting model and equations for non-conventional asphalt mixtures. In addition, further field verification utilizing an actual pavement section for the developed model as well as the equation is highly recommended.

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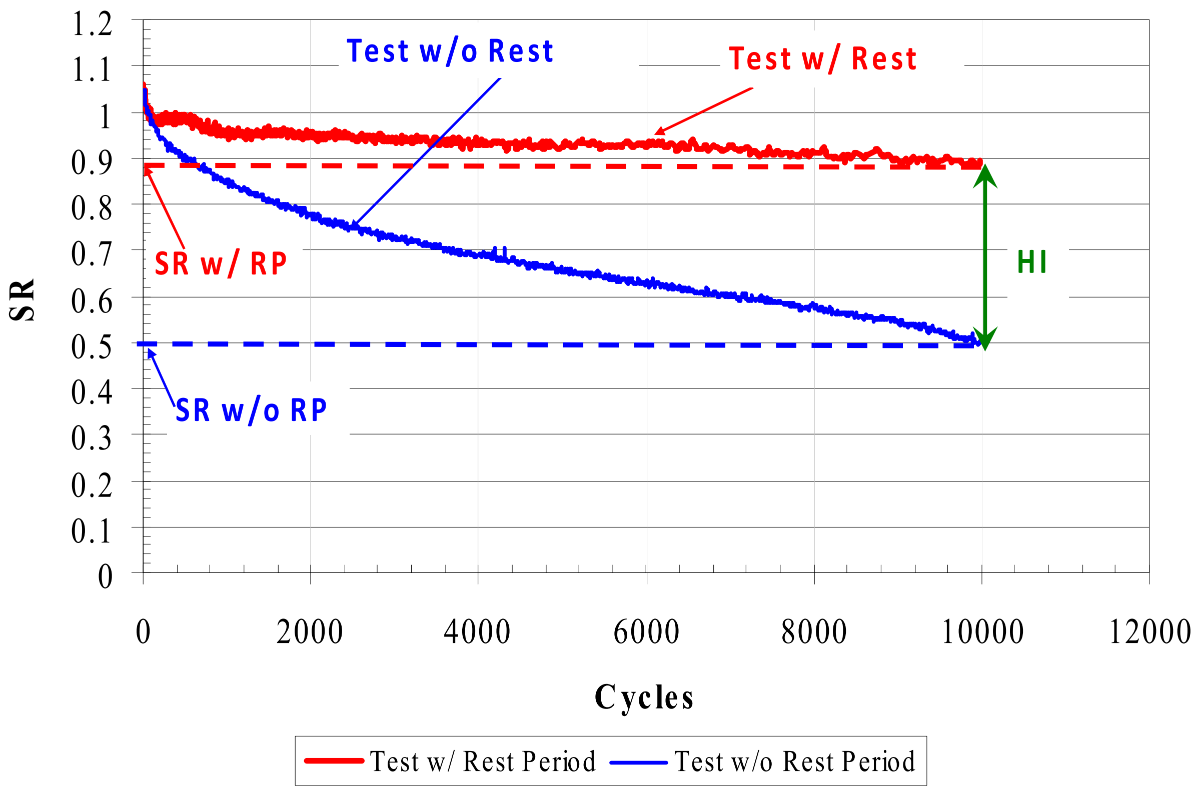
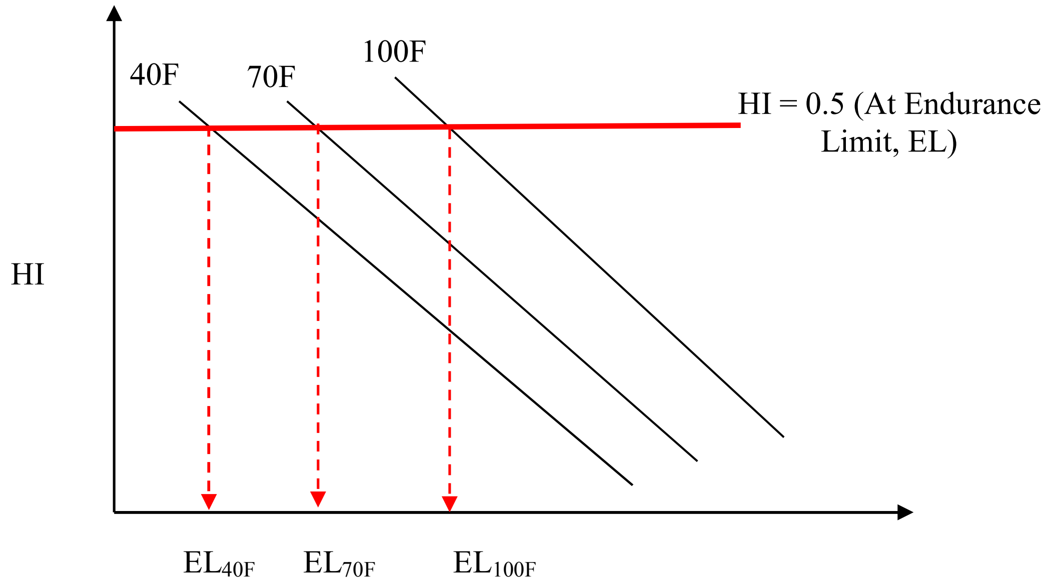


Figure 1. Healing index definition (Souliman 2012)



431
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433 **Figure 2. Endurance limit determination at each temperature based on HI**
434 **(Souliman 2012)**
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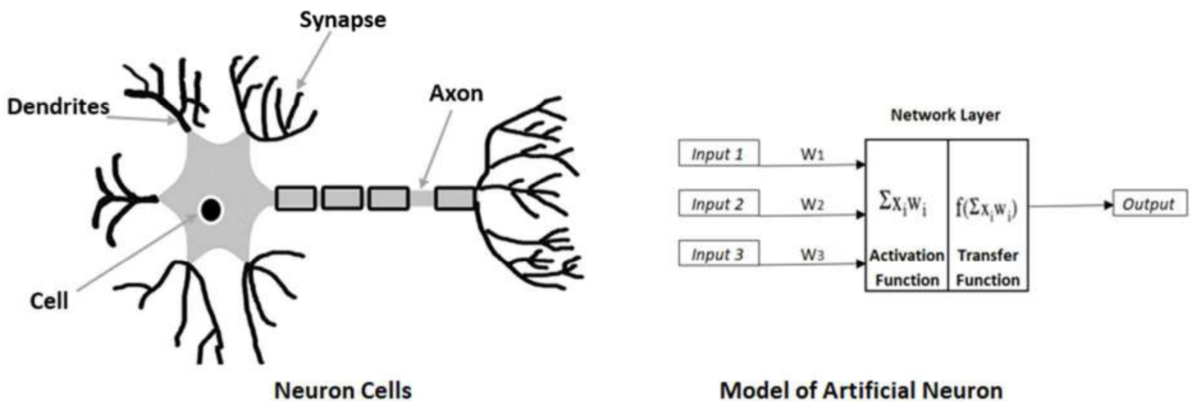

Figure 3. Similarity between nerve neuron cell and an artificial neuron

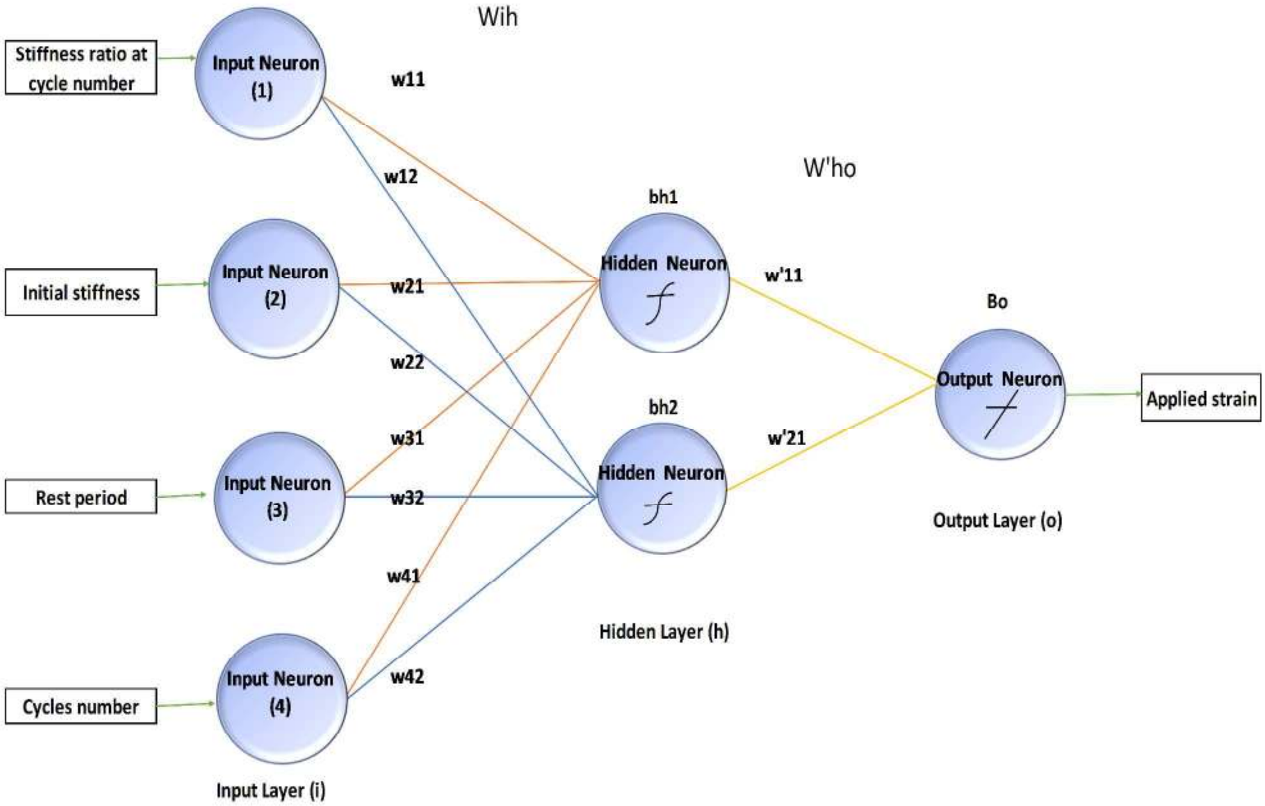

Figure 4. ANN utilized model architecture

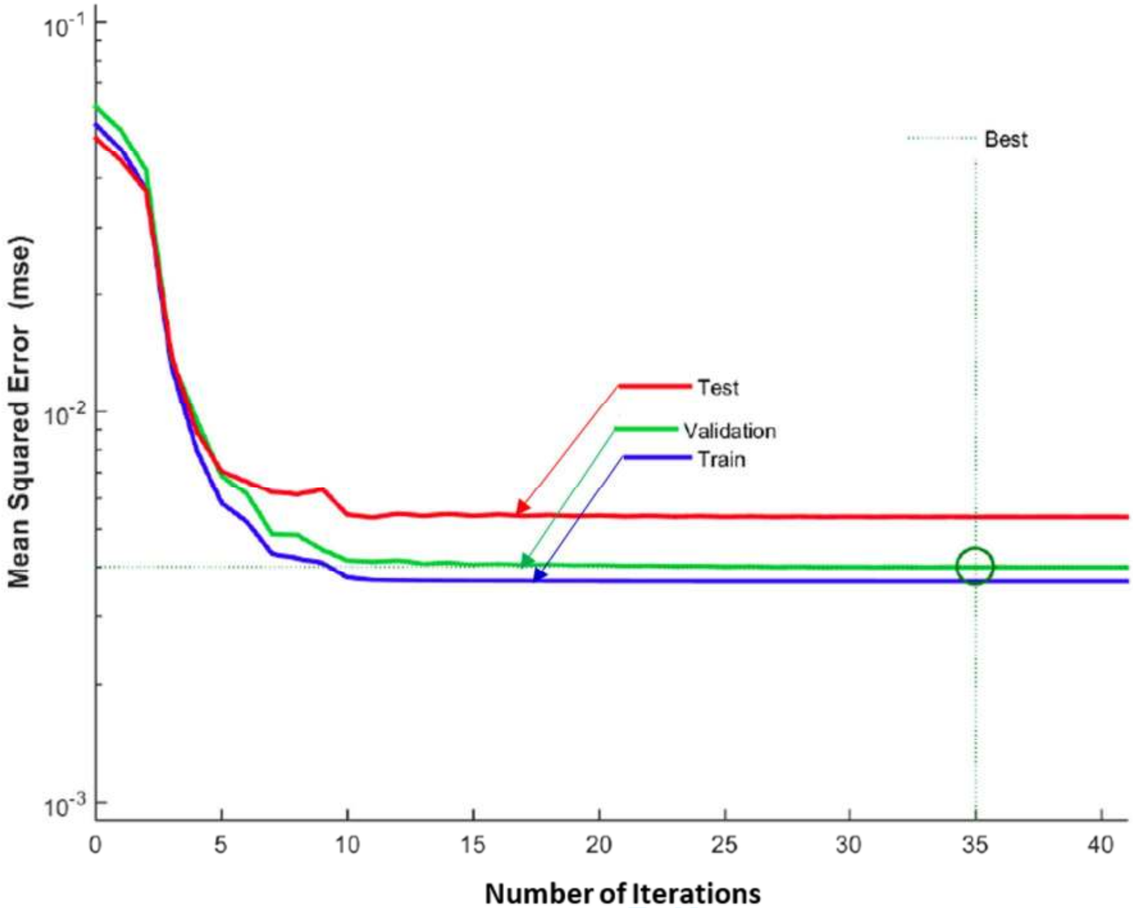

Figure 5. Number of iterations/ epochs required for model training (MATLAB R2015a, The Math Works Inc.)

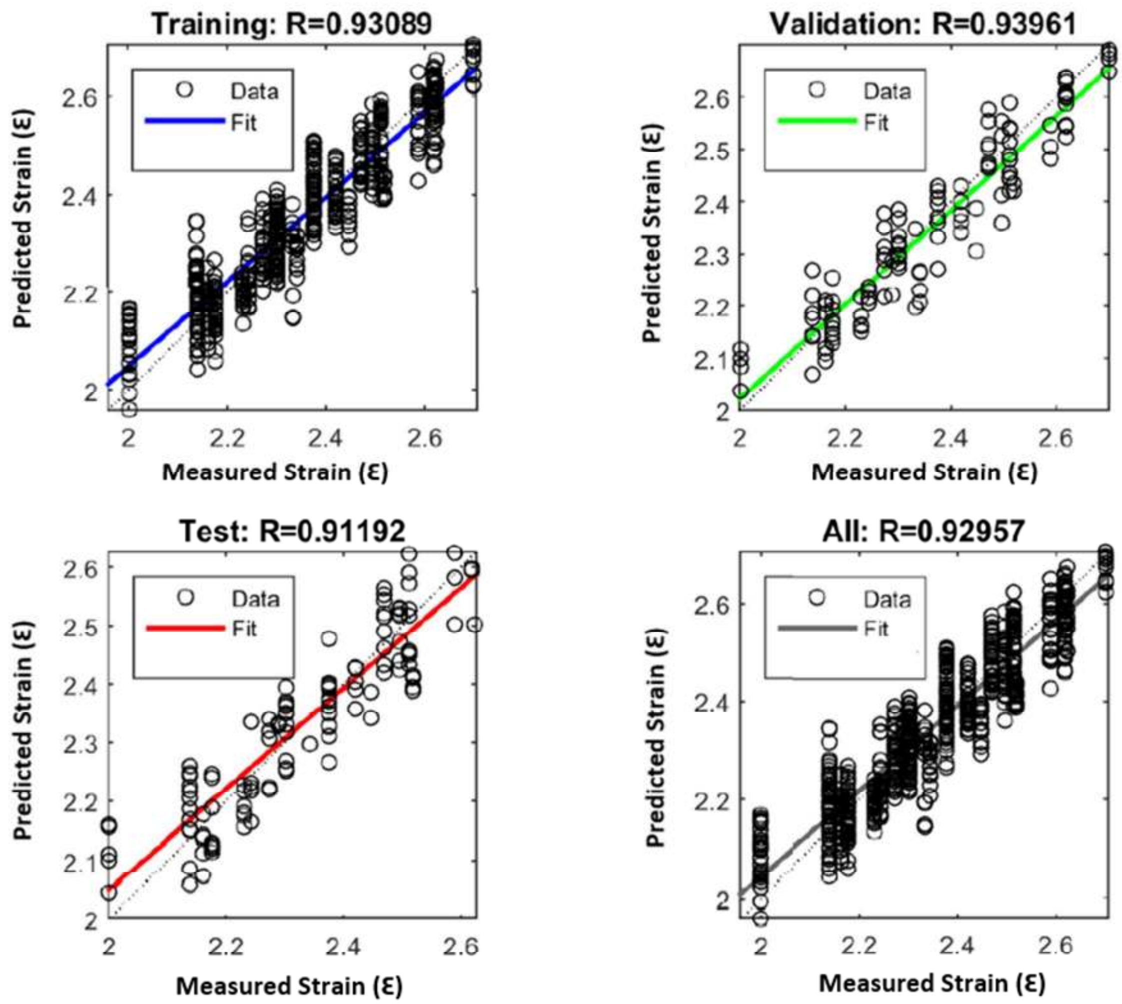

Figure 6. Regression plots for training, validation, testing, and overall data (MATLAB R2015a, The Math Works Inc.)

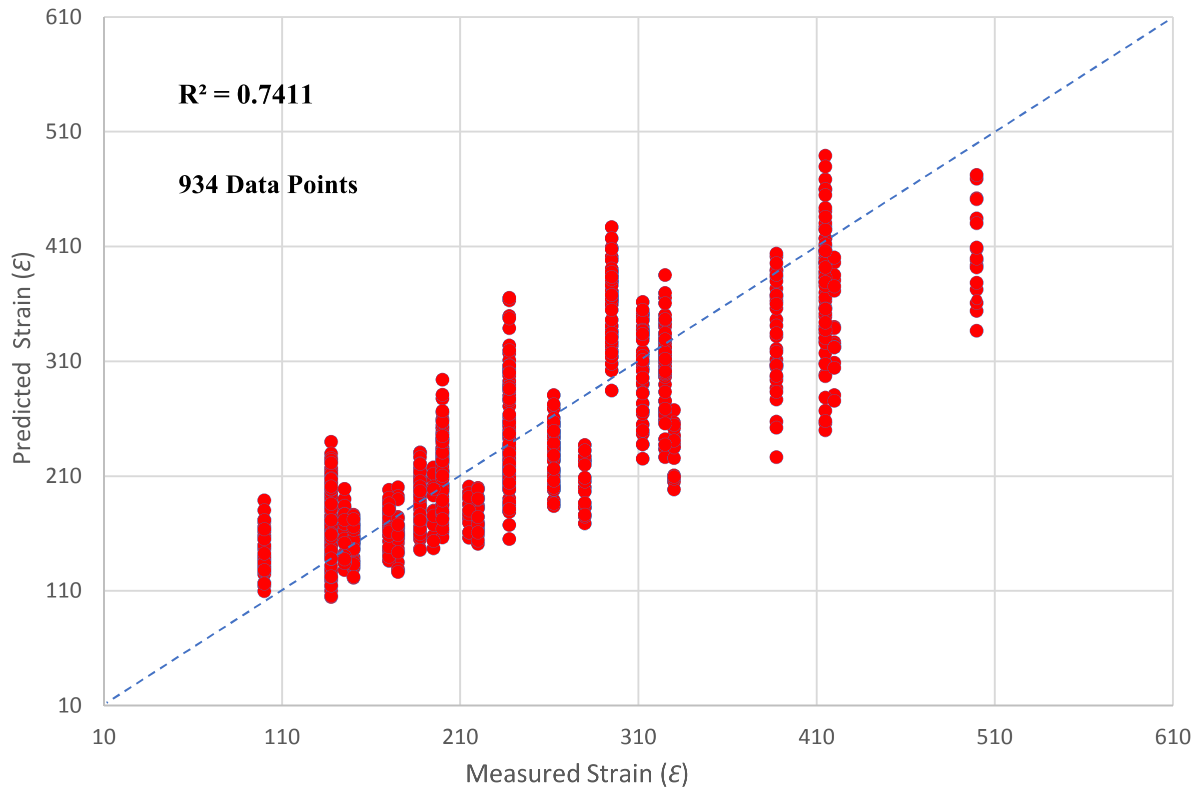

Figure 7. Predicted VS measured values of strain for 934 data sets utilizing the generated ANN equation (Equation 2).

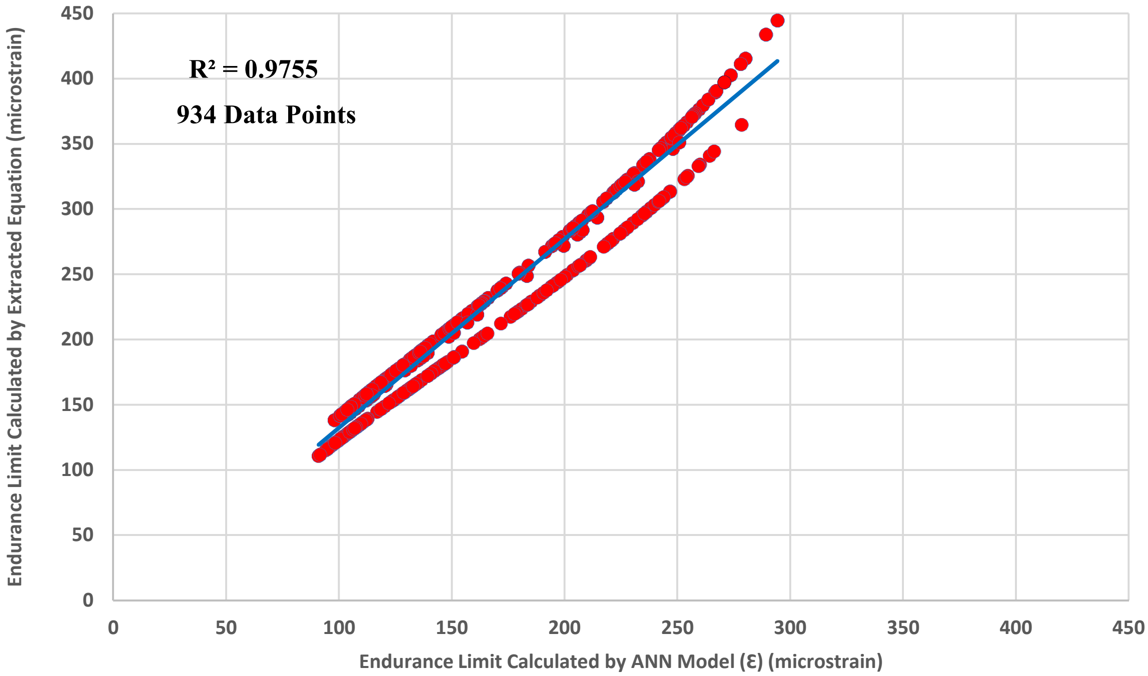

Figure 8. Endurance limit values calculated utilizing the ANN model VS simplified Equation (3) calculated values.

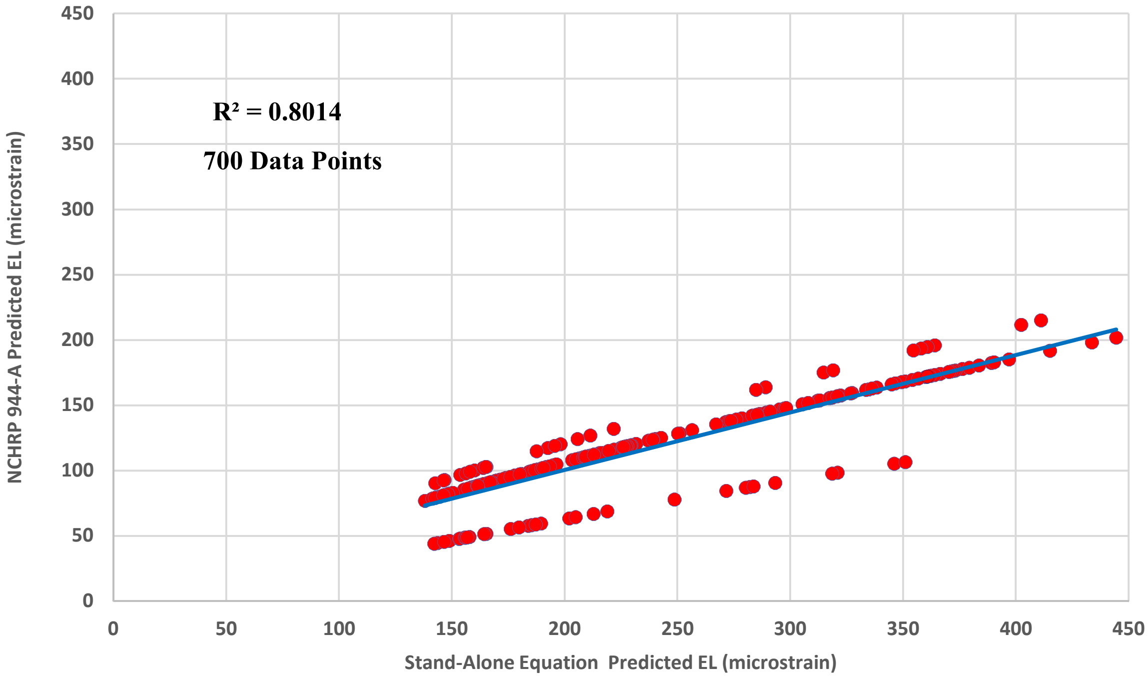

Figure 9. Endurance limit values calculated utilizing the simplified Equation (3) vs NCHRP 944-A generated equation values.

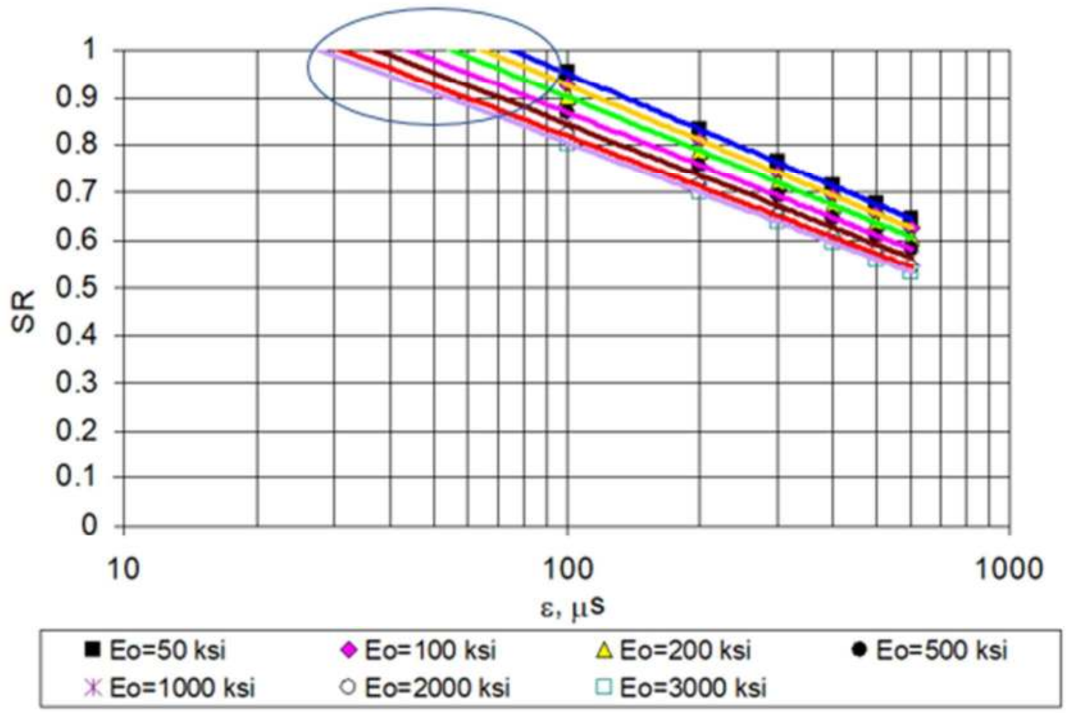

Figure 10. SR vs strain for several initial stiffness values and 1 second rest period. (Souliman 2012)

Table 1. Analysis of variance for predicted VS measured values of strain for 934 data sets utilizing the developed ANN model.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.932172173
R Square	0.868944959
Adjusted R Square	0.868804342
Standard Error	32.53500727
Observations	934

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	6541183	6541183	6179.516	0
Residual	932	986546.9	1058.527		
Total	933	7527729			

Table 2. Analysis of variance for predicted VS measured values of strain for 934 data sets utilizing the generated ANN equation (Equation 2).

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.85794261
R Square	0.736065522
Adjusted R Square	0.735782331
Standard Error	0.076153751
Observations	934

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	15.07366	15.07366	2599.179	7.9558E-272
Residual	932	5.405035	0.005799		
Total	933	20.4787			

Table 3. Analysis of variance for endurance limit values calculated utilizing the simplified Equation (3) vs NCHRP 944-A generated equation values for 700 data sets.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.895184
R Square	0.801355
Adjusted R Square	0.80107
Standard Error	34.74031
Observations	700

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	3398362.431	3398362	2815.803	3.6058E-247
Residual	698	842408.578	1206.889		
Total	699	4240771.009			