Viscosity Prediction Model for Reacted and Activated Rubber Modified Binders Utilizing Artificial Neural Networks

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ABSTRACT Crumb rubber surface activation and pretreatment are considered as one of the promising newly introduced methods for asphalt rubber production. Reacted and Activated Rubber (RAR) is an elastomeric asphalt extender produced by the hot blending and activation of crumb rubber with asphalt and Activated Mineral Binder Stabilizer (AMBS). Besides RAR's ability in enhancing the performance of asphaltic mixtures, its dry granulate industrial form enabled its addition directly into the mixture utilizing pugmill or the dryer drum with very minimal to no modification required on the plant level. This study aims to develop an Artificial Neural Network (ANN) viscosity prediction model for extracting a stand-alone viscosity prediction equation. Three different Performance Graded (PG) asphalt binders modified by ten dosages of RAR were tested and evaluated under this study. Sixty-six samples that generated more than three thousand viscosity data points were utilized in ANN modeling. The developed ANN model as well as the extracted stand-alone viscosity prediction equation had a high value of the coefficient of determination and were statistically valid. Both of them can predict the RAR modified binder viscosity as a function of binder grade, temperature, testing shearing rates, and RAR content.

KEYWORDS: Crumb rubber, surface activation, Reacted and Activated Rubber (RAR), binder viscosity, binder grade, viscosity testing, shearing rate, ANN modeling, viscosity prediction, A-VTS prediction.

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1. Introduction

Waste materials are considered a serious hazardous threat to the environment due to their accumulations as well as non-biodegradability. Millions of non-biodegradable rubber tires are being stockpiled yearly. Those rubber tires will end up eventually buried under the soil within landfill areas yielding a disturbance to the environment. One of the most common approaches to solve this issue is to recycle the non-biodegradable material into other forms of useful materials. Crumb Rubber (CR) is one of the main products of the rubber tire recycling industry that can be implemented into Hot Mix Asphalt (HMA) production.

Many researchers attempted the modification of crumb rubber to faster achieve its activation and to ease its addition to the HMA. One of the common methods for crumb rubber surface activation is the addition of an Activated Mineral Binder Stabilizer (AMBS). Reacted and Activated Rubber (RAR) is considered as a newly introduced elastomeric asphalt rubber extender that is mainly produced by the hot blending of AMBS, crumb rubber, and selected asphalt binder in specific percentages and procedures. The dry granular nature of RAR enabled its addition directly with minimal to no change required on the preexisting HMA plant and equipment.

This study aims to develop an Artificial Neural Network (ANN) viscosity prediction model for extracting a stand-alone RAR modified binder viscosity prediction equation.

2. Literature Review

2.1. Binder Viscosity

The viscosity is generally defined as the resistance of the substance to flow and is considered a very important property of asphaltic materials. This importance is driven by its ability to control the pumpability, the mixability, and the workability of the binder.

Different methods may be utilized for viscosity measurements such as 1) ford cup, 2) falling ball, and 3) capillary viscometer. However, most of them cannot add a temperature control device or are not applicable for non-Newtonian liquids. Therefore, the rotational viscosity (RV) is utilized for high-temperature viscosity measurement for the Superpave PG asphalt binder grading system [1].

The two main general properties that are needed for the characterization of any asphalt binder are physical and rheological. Since asphalt is a byproduct of petroleum crude oil, the source of crude oil, as well as its chemical composition, has a high effect on the resulted asphalt binder properties. Different crude oil sources will result in different binder properties. The effect of this difference is seen due to the fact that asphalt is a viscoelastic material, its performance is highly dependent on the temperature and the loading frequency. Considering all the variability resulting from the different chemical composition, loading rate, and temperature, asphalt properties are classified under two main broad categories: physical and rheological [2-4].

The newly developed Superpave testing protocols have resulted in enhancing the acceptance and utilization of rheological characterization for asphalt binders. Those properties include: 1) temperature susceptibility, 2) shear susceptibility, 3) rate of loading, and 4) stiffness. Dynamic Shear Rheometer (DSR), Bending Beam Rheometer (BBR), and Rotational Viscometer (RV) tests are utilized for binder classification. For example, the RV is utilized as a testing tool to determine the temperature susceptibility of the binder by subjecting it to a wide range of temperature values [5-6].

Bari and Witczak [3] have conducted a research study to develop a set of prediction models for asphalt binder viscosity as well as complex shear modulus. One of the major goals of this study was to enhance the pre-existing ASTM A-VTS prediction model by including the effect of loading frequency within the model factors. The original ASTM A-VTS equation is shown in Equation 1.

$$\log \log(\eta) = A + VTS \log TR \qquad (1)$$

Where,

η=viscosity (cP);
TR = temperature (degree Rankine);
A = regression intercept; and
VTS = regression slope (viscosity temperature susceptibility parameter).

As clearly demonstrated via Equation 1, once the values of A and VTS are known, it is possible to predict the asphalt viscosity values over a wide range of temperatures. However, the calculated viscosity will not account for different loading rates. The importance of enhancing Equation 1 is due to the fact that all the input levels of the Mechanistic-Empirical Pavement Design Guide (MEPDG) are utilizing the binder viscosity as the principle binder input parameter. Consequently, the binder design viscosity is calculated utilizing the ASTM A-VTS model (Equation 1).

The newly developed equation introduced two new factors, c, and d, to account for the loading frequency in the original ASTM A-VTS equation as shown in Equation 2.

$$log\ log\left(\eta\right)_{fs,\ T} = c \times A + d \times VTS\ log\ T_R \qquad (2)$$

Where,

η fs, T = viscosity of asphalt binder as a function of loading frequency (fs) and temperature (T), (cP);
fs = loading frequency in dynamic shear mode as used in G*b testing;
TR = temperature (degree Rankine);
A = regression intercept from the ASTM Ai–VTSi equation (Equation 1);

VTS = slope from the ASTM Ai–VTSi equation (Equation 1);
c = frequency adjustment factor for A, function of loading frequency (fs); and
d = frequency adjustment factor for VTS, function of fs.

Equation 2 was developed and evaluated utilizing 8,940 data points collected from 41 different binders, 9 of which were modified binders. The database included 5 different aging conditions. The developed equation had a high level of accuracy and rationality over the full range of the database. Since the newly developed equation has a similar structure to the old equations utilized in the MEPDG, the paper recommended its implementation in the future versions of the software [3].

2.2. *Reacted and Activated Rubber*

The idea of activating the crumb rubber before utilizing is not new and has been used in other industries. There is a considerable amount of methods and technologies to modify the crumb rubber before adding it to the binder. In most of those methods, the surface modification for the crumb rubber is the ultimate goal to improve and strengthen its compatibility with the binder polymer matrix [7-8].

The new technology of Reacted and Activated Rubber is commercially available under the product name "RARX™" (hereinafter referred to as RAR), which is an elastomeric asphalt extender produced by the hot blending and activation of rubber with asphalt and AMBS. The new technology was a result of many experimental trials in which the AMBS was implemented in different mixtures of rubber and asphalt [9].

The main three components in RAR are asphalt, crumb rubber, and AMBS. Generally, the RAR blend would contain 62% crumb rubber, 22% soft bitumen, and 16% AMBS. Another 10% of AMBS is usually added for final coating during the mixing after the reaction of the first added 16% as an effort to prevent product re-coagulation9. A soft graded asphalt binder is utilized as the asphalt part of the RAR to produce the HMA in conventional mixing and laying temperature without sacrificing mixture workability [9].

2.3. *RAR Benefits and Performance Evaluation*

Having a dry granulate industrial form is one of the important enhancements introduced by the RAR technology to the Asphalt Rubber (AR) binder industry. Unlike regular AR binders, RAR is a dry granulated product; therefore, its handling and storage are easier. Furthermore, RAR could be added directly into the mixture utilizing a pugmill or the dryer drum of any asphalt mixing plant. Thus, RAR addition will require no or very minimal modification on the plant level.

RAR modifier is added to the asphalt mixture after mixing the aggregates, fillers, and binder at identical HMA mixing temperatures (usually 170°C to 180°C). RAR mixing cycle will take around 30s until an even distribution and absorption of RAR within the mixture is achieved. The addition of RAR will enhance the binder properties and the higher utilized RAR percent results in better performance. Typically, 15% of the binder content is considered as the step after which improvements in binder performance are seen [9].

Sousa et al. [10] have introduced, explained, and evaluated the binder modification process utilizing the newly developed RAR modification technology. Results of testing conducted during the Research and Development (R&D) stage of RAR technology were introduced and discussed. The testing included binder and mixture performance testing such as viscosity, penetration, ring and ball, resilience, Dynamic Shear Rheometer (DSR), Multi Stress Creep Recovery (MSCR), Marshall stability, drain down test, rutting deformation test, flexural fatigue test, and recovery tests. The utilized HMA mixtures in testing were prepared with different RAR proportions and included different mixture types such as dense, open, gap graded, and SMA mixtures. The study concluded that RAR-produced mixtures outperformed conventional, AR modified, and regular modified mixtures in all aspects. RAR modified binders had a higher positive and lower negative PG grades. In addition, it had better resilient and recovery properties. RAR modified HMA had better stability as well as fatigue and rutting resistance. The study pointed out that RAR-modified binders are much easier to produce, handle, store and transport to the project site compared to AR-modified binders due to their dry granulated nature. Furthermore, it was discussed that utilizing RAR modified binders will eliminate the need for the complicated wet production process of AR binders as well as the need for continuous agitation and reheating cycles at the plant or project site. Since RAR is replacing the conventional binder within the HMA mixture, it was discussed that RAR technology may be utilized to produce any AR mixture type given utilizing the correct RAR content. Finally, the study stated that RAR-modified mixtures are more cost-efficient compared to conventional and AR-modified mixtures [10].

2.4. Artificial Neural Network Modeling Background

Artificial Neural Networks (hereinafter referred to as ANN), are highly interconnected structures with strong computational and pattern recognition abilities utilizing simple processing units (artificial neurons) having the ability to perform parallel computation [11].

The smallest and simplest ANN is formed basically from three layers. An input layer, an output layer, and a single hidden layer in between. Each layer of those will include number of neurons. The number of hidden layers, as well as neurons, will determine the complexity and the ability of the network to deep-learning [12].

All the input neurons are just connection joints with no processing occurring inside them. However, the neurons within the hidden as well as the output layer are formed from two main parts as shown in Figure 1. The first part is simply a summation (activation) function that will pass a single value resulting from the weighted inputs to the second part, which is a signal (transfer function) that is responsible for the wave signal flow within the network. Typical transfer function structure may be expressed as shown in Equation 3.

$$m = f(Wz + b) \tag{3}$$

Where,

m = output of the neuron;
W = weight vector;
b = bias;
z = input vector of the neuron;
and f = transfer function

2.5. Rule Extraction from Developed Artificial Neural Network Models

There is a growing use for ANN modeling techniques in business and engineering-related problems involving pattern recognition and regression analysis. The strength of ANN in this regard is that it does not require prior knowledge about the relations among modeling data. However, there is a desire to extract this knowledge from the trained networks, to provide the user with a better understanding of the results.

As an effort to open the ANN "black box" and generate rules from the results of the trained ANN models, the researchers discussed that one of the below listed three main approaches may be utilized in the rule extraction from the trained ANN network [13-14]:

- Decompositional: under this method, the network weights, bias, and activation function values are utilized to extract the rule while ignoring any possible relationships between input-output data into the network. The main focus here is to approximate the artificial neuron functions.
- Pedagogical: in this method, the focus is on the relationship between the input and output of the trained ANN network and its relation to the measured data. Those relations are studied to generate a rule that has the ability to replicate the results of the trained ANN network without the need for the exploration of the ANN network structure or approximating the activation and transfer functions within the artificial neuron.
- Eclectic: this method is considered a hybrid method of the two previous methods. in other words, the relationship between the input and output, the weights and bias values for the trained ANN network, and the approximation of the artificial neuron functions are utilized for the rule extraction.

3. **Study Objective**

The research aims to develop an Artificial Neural Network (ANN) model that can predict the binder viscosity as a function of the added RAR dose, temperature, testing shearing rate, and the binder grade, and then, use it to extract a stand-alone binder viscosity prediction equation that can predict the binder viscosity as an effort to generate ASTM A-VTS correlations for RAR modified binders.

4. **Materials, Design of Experiment, and Testing Procedure**

4.1. Materials

The binders utilized in this study were three different performance graded binders supplied by Valero Asphalt Terminal from Houston, Texas as follows:

- PG 64-22, hereinafter referred to as binder A.
- PG 70-22, hereinafter referred to as binder B.
- PG 76-22, hereinafter referred to as binder C.

The Reacted and Activated Rubber utilized in binder modification was supplied by Consulpav under product name RARX TM, hereinafter referred to as RAR. RAR was added to the virgin binder in ten different dosages, from 5 to 50% by the virgin binder weight in 5% step increments.

4.2. Experimental Design

The experiment was designed to evaluate the effect of three factors on the binder viscosity. The evaluated factors were binder grade, RAR content, and testing shearing rate. The full design of the experiment as shown in Figure 2 yielded a total of 66 samples including one replicate for each sample. The number of collected viscosity data points was 3,168 points [15].

4.3. Brookfield Rotational Viscosity Testing

This test has the ability to determine the binder viscosity at high temperatures; therefore, it is a tool by which mixing and compaction temperatures of HMA may be determined. Under this test, the binder viscosity is determined by measuring the amount of torque applied to rotate a standard spindle at a constant speed while being submerged in a standard testing chamber filled with a binder at a temperature of interest. For the purpose of this study, the test was conducted according to American Society for Testing and Materials (ASTM) standard D440216 and American Association of State Highway and Transportation Officials (AASHTO) standard T 316-1317. Spindle number 27 (SC4-27) had a sharing rate of 0.34 N and a sample volume of 10.5 ml was utilized to conduct the test. The testing setup was as shown in Figure 3. Four different testing shearing rates for each binder were utilized to evaluate the viscosity as shown in Figure 2. The testing shearing rates were calculated according to Equation 4 [18].

TSR= SR x N (4)

where,

TSR = Testing Shearing Rate (s-1);
SR = Spindle Shearing Rate (s-1);
N = Testing Speed in Revolutions per Minute (RPMs).

5. **Artificial Neural Network Modeling**

5.1. *Developed Model Architecture*

Three-layer feed-forward backpropagation neural network with a sigmoid activation function and one hidden layer is considered as one of the most common network structures utilized for data fitting and regression. Furthermore, a single hidden layer has the ability to solve the majority of non-linear problems without network overfitting [13].

Three-layer feed-forward neural network with a backpropagation-error calculation algorithm and two neurons in the hidden layer was utilized for the model development. The main components of the utilized model architecture are shown in Figure 4, and were as follows:

- Input layer (i): this layer had 4 input neurons. Each one of them was associated with an independent variable.
- Weight factors (Wih): those factors were the linking factors between the input layer (i) and the hidden layer (h). The extracted weight matrix had eight different values, one value from each input to each neuron.
- Hidden layer (h): the layer contained two hidden neurons with tan-sigmoid activation function as well as two biases values (b h1 and b h2).
- Weight factors (W'ho): those factors are the links between the hidden layer (h) and the output layer (o). The extracted matrix contained two values, one from each hidden neuron to the output neuron.
- Output layer (o): this layer had a single output neuron with a linear transfer function to the dependent variable and a single bias value (Bo).

5.2. *Model Development and Training Methodology*

Data collected during lab testing conducted according to the experimental design explained earlier was utilized in the model development. The utilized data included five different factors as follows: 1) Binder grade, 2) Testing shearing rate, 3) RAR content, 4) Temperature, and 5) Binder viscosity. The binder grade was changed from categorical variable to numerical variable by utilizing binder elastic modulus (stiffness) values obtained from the dynamic modulus (E*) test at 70℉ and 10 Hz. Since no dynamic modules testing was performed under this research study, the Artificial Neural Networks for Asphalt Concrete Dynamic Modulus Prediction (ANNACAP) program [19] recommended by the Long-Term Pavement Performance (LTPP) database for E* prediction was utilized in developing E* master curve for binder A, B, and C. The model was developed and trained to predict the binder viscosity as a function of the temperature, testing shearing rate, binder grade, and RAR content as shown within Equation 5.

$$Viscosity = f(Temperature, Testing\ Shearing\ Rate, Binder\ Grade, RAR\ Content) \quad (5)$$

MATLAB (MATLAB R2018a, The Math Works Inc.) was utilized to develop and train the model by feeding the data into the model layers. The total number of datasets utilized in training and developing the model was 3003 datasets. The logarithm of the binder grade (numerical value), testing shearing rate, RAR content, and the logarithm of the degree Rankine temperature were fed in the input layer, while the logarithm of the viscosity logarithm was fed in the output layer.

The model training was conducted utilizing the Levenberg-Marquardt backpropagation algorithm in MATLAB. This training algorithm divides the data into three sets. Under this algorithm, seventy percent of the data is utilized as model training data while the other thirty percent is divided equally towards model testing and model validation data. As an effort to keep the network generalization and avoid network overfitting, the model training was stopped when the validation data set error had stopped decreasing for six consecutive iterations [20] as shown in Figure 5.

The model performance was validated inside the MATLAB environment as shown in Figure 6. In addition, one-way ANOVA was conducted to evaluate the developed ANN model externally as shown in Table 1. As clearly shown within Figure 6 and Table 1, the model had a high value for the coefficient of correlation (R) as well as a high P-value at a 95% confidence level. The ANN-developed model significance, as well as statistical validity, were demonstrated by having an R-value of almost 1 and a P-value of 0.97. Therefore, the model was deemed suitable to be utilized in viscosity prediction as well as rule extraction of a stand-alone viscosity prediction equation.

5.3. Rule Extraction from the Developed Trained ANN Model

In an effort to open the black box and achieve a better understanding of the developed ANN models, many researchers attempted to generate rule extraction approaches [21,13,14]. The three main approaches to extract rules and develop a stand-alone equation from the trained ANN models were discussed in detail under the literature review. Out of those three approaches, the eclectic approach was utilized for rule extraction under this study. This approach is considered as a hybrid approach of decompositional and pedagogical approaches, in which the relationship between the input and output of the trained network as well as its structure inclusive of the weight factors and the biases are needed to generate the rule.

To extract the rule and generate a stand-alone viscosity prediction equation utilizing the developed ANN model architecture as shown in Figure 4, the following values were needed: 1) Weight values from the input to the hidden layer, 2) Bias values in the hidden layer, 3) Weight factors from the hidden layer to the output layer, and 4) Bias values in the output layer. Those values were extracted from MATLAB (MATLAB R2018a, The Math Works Inc.) after concluding the model training and were as shown below.

$$\mathbf{W_{ih}} = \begin{bmatrix} -0.0161 & -0.0191 & -0.140 & -.0035 \\ 0.5171 & 0.0832 & 0.1015 & -0.0883 \end{bmatrix}$$

$$\mathbf{W'_{ho}} = \begin{bmatrix} 10.5544 \\ -22.718 \end{bmatrix} \quad \mathbf{b_{hi}} = \begin{bmatrix} -2.6385 \\ -1.345 \end{bmatrix} \quad \mathbf{B_o} = [-9.2695]$$

The developed model structure, the weight values, the bias values, the relationship between the input and output data, and data normalization occurring inside the model environment, all along with statistical and mathematical analysis algorithms, were utilized to extract a stand-alone viscosity prediction equation from the trained and validated ANN model. The extracted equation was as shown in Equation 6.

$$\log\log(\eta) = 0.27443(\log PG) - 0.00033(TSR) - 2.32539(\log TR) + 0.48089(RAR) + 6.212 \quad (6)$$

Where,

η=viscosity (cP);
PG= binder grade (ksi), binder stiffness values obtained from the dynamic modulus (E*) test predicted by ANNACAP at 70 F and 10 Hz.
TSR= testing shearing rate (s-1) = testing spindle factor x rotation speed
TR = temperature (degree Rankine); and
RAR = percent of the added RAR from the virgin binder weight (fraction), for virgin binder only this value is zero.

The extracted stand-alone equation was evaluated utilizing the available 3003 datasets and founded to be reliable by having a high value of 0.97 as the coefficient of determination (R2) as shown in Figure 7. In addition, one-way ANOVA was conducted to further validate the developed equation. As shown in Table 2, the equation was statistically valid by having a P-value of almost 1 and an F-value that is much lower than the F critical value at a 95% confidence level. Therefore, the developed equation was deemed to be statistically valid and may be utilized in binder viscosity prediction outside the developed model environment as a stand-alone equation.

5.4. Viscosity Sensitivity Analysis Utilizing the Developed Stand-alone Equation

The sensitivity of the predicted viscosity utilizing the newly developed equation to the change in binder grade, binder temperature, and RAR content was evaluated in three different ways as follows: 1) ASTM A-VTS corrections for the tested binders were regenerated utilizing the newly developed equation, 2) ASTM A-VTS corrections for a new binder (PG 52-22), that was never part of the lab testing nor the ANN modeling data, were developed and evaluated, and 3) Virgin binder viscosity as predicted by the newly developed equation at different temperatures for the three tested binders as well as the forth newly introduced binder were evaluated and compared. The sensitivity analysis was conducted at four temperatures, ten different RAR content, and one shearing rate of 6.8s-1 (20 RPM).

As demonstrated via Figure 8, the newly developed equation had the ability to replicate the ASTM A-VTS corrections developed based on the lab testing. Furthermore, the equation was able to produce the ASTM A-VTS correlation for a new binder that was never part of the testing or the modeling data. As shown in Figure 9, the correlation followed the correct trend in which, the addition of RAR would decrease the correlation slope and consequently will decrease the binder temperature susceptibility. Finally, as observed in Figure 10, the equation had the ability to sense the change in the viscosity of the virgin binders at different temperatures. Also, the equation was able to sense the change of the viscosity at the same temperature for different binder grades. For example, PG 76-22 had the highest viscosity while PG 52-22 had the lowest at the same temperature.

6. **Conclusions**

Many researchers had attempted to modify the crumb rubber before adding it to the binder. The ultimate goal, in most cases, for those modifications is to modify the crumb rubber surface in an effort to improve and strengthen its compatibility with the polymer matrix existing within the binder. Activated Mineral Binder Stabilizer (AMBS) as a binder stabilizer prevents excessive bitumen drainage during haulage, storage, and placement and has helped improve the material performance since 2009. The new technology of Reacted and Activated Rubber (RAR), was a result of many experimental trials in which the AMBS was implemented in different mixtures of rubber and asphalt. The main three components in RAR are asphalt, crumb rubber, and AMBS. Compared to a regular AR binder, RAR is a dry granulated product; therefore, its handling and storage are easier. RAR's dry granulated nature will facilitate its addition to any existing asphalt production plant with minimum or no modification.

The goals of this study were to develop an ANN viscosity prediction model as an effort to generate a stand-alone viscosity prediction equation. Under the study, three different unaged binders modified by 10 different RAR dosages were utilized in ANN modeling.

Overall, the developed ANN model and the extracted stand-alone equation were statistically valid and had the ability to predict the ASTM A-VTS for RAR-modified binders. The specific conclusions of this study may be summarized as follows:

- The developed ANN model was statistically evaluated and founded to be valid by having an R-value of almost one and an F-value that is much lower than the F critical at a 95% confidence level. This model had the ability to predict the binder viscosity as a function of the binder grade, temperature, testing shearing rate, and RAR modification percentage.
- The developed ANN model, after being statistically validated, was utilized to extract a stand-alone viscosity prediction equation that may be utilized outside the model environment. The equation statistical validity was demonstrated by having a R2 value of 0.97 and F-value that is much lower than the F critical at a 95% confidence level.
- The importance of the newly developed viscosity prediction equation is its ability in developing the predicted full ASTM A-VTS corrections for RAR modified binders from which A and VTS may be calculated.
- Full sensitivity analysis for the newly developed equation was conducted utilizing the study binders as well as a newly introduced binder that was never utilized during the ANN modeling. The equation was sensitive to the change in RAR content, binder grade, and temperature following the trend found by the actual lab testing.
- The newly developed viscosity prediction equation was founded to be sensitive to the change in virgin binder viscosity by changing the binder grade.

For future research, it is recommended to further validate the developed viscosity prediction equation utilizing real viscosity testing results.

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Table 1: *Analysis of Variance for the Developed ANN Viscosity Model.*

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	1.32E-05	1	1.32E-05	0.002	0.968	3.843
Within Groups	49.779	6004	0.008			
Total	49.779	6005				

Table 2: *Analysis of Variance for the Predicted VS Measured Values of Viscosity for 3003 Datasets Utilizing the Generated Stand-alone Viscosity Prediction Equation.*

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	1.81E-05	1	1.81E-05	0.002	0.963	3.843
Within Groups	49.313	6004	0.008			
Total	49.313	6005				

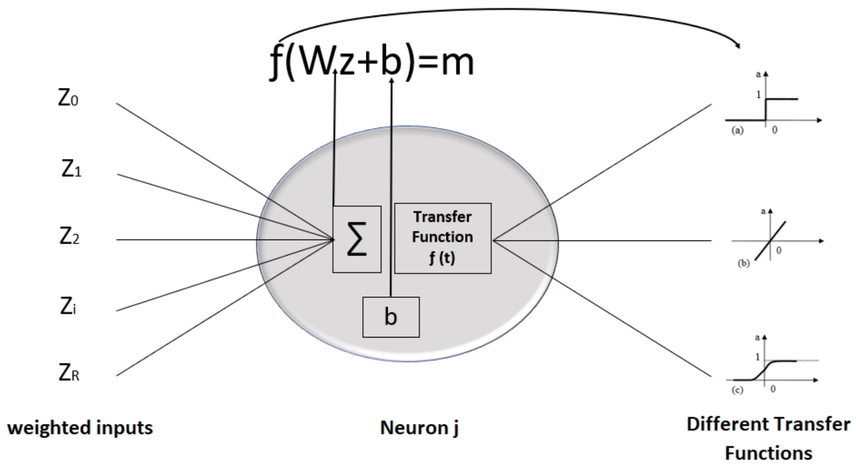

Figure 1. Artificial Neuron Model Architecture.

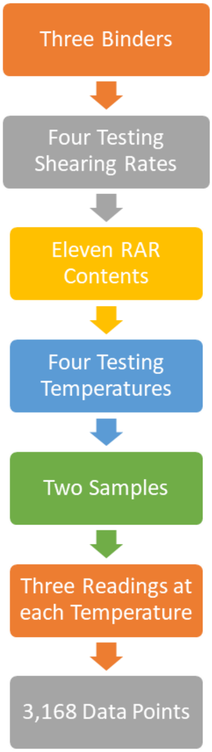

Figure 2. Three Factors Full Factorial Design Executed Under the Study.

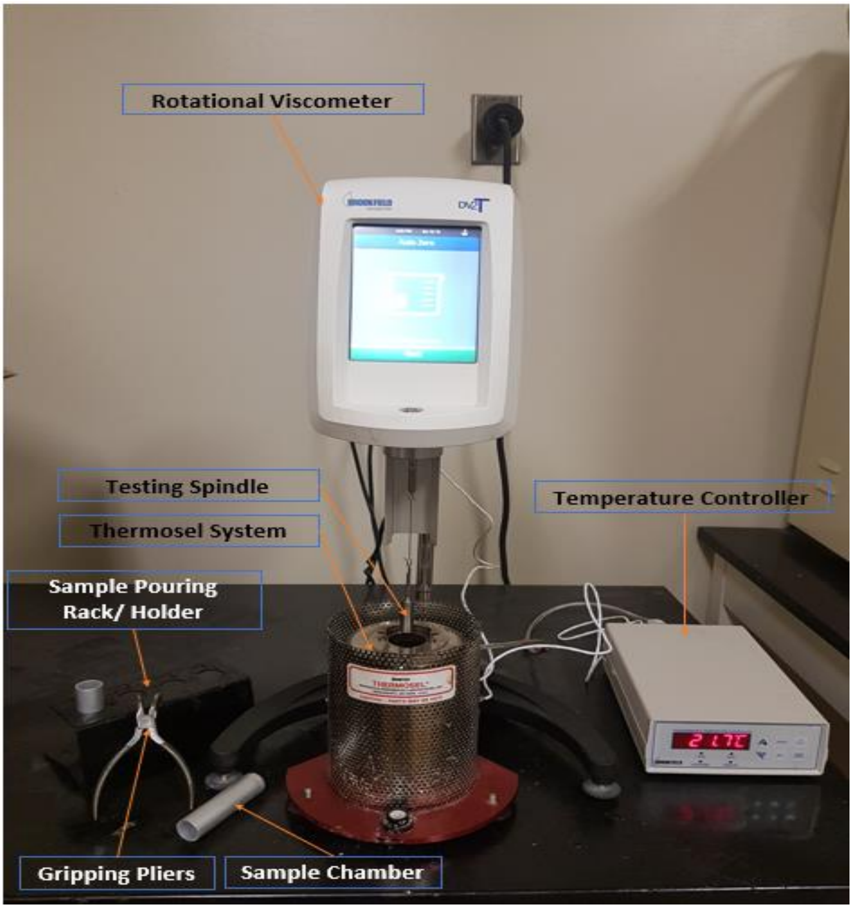

Figure 3. Rotational Viscometer Testing Setup.

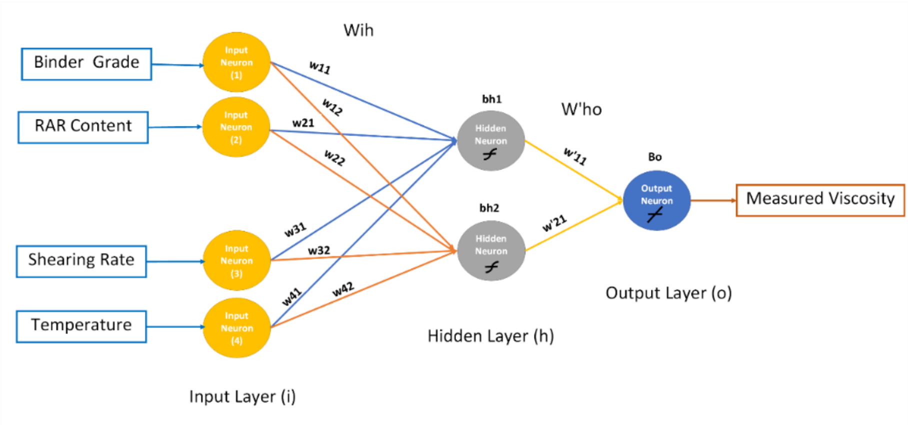

Figure 4. Developed ANN Model Architecture.

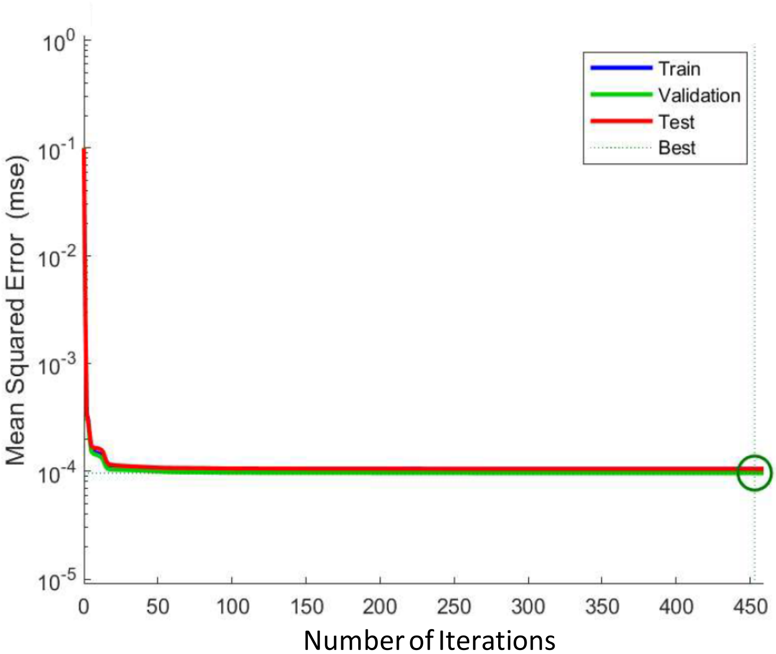

Figure 5. Number of Iterations/ Epochs Required for Model Training (MATLAB R2018a, The Math Works Inc.).

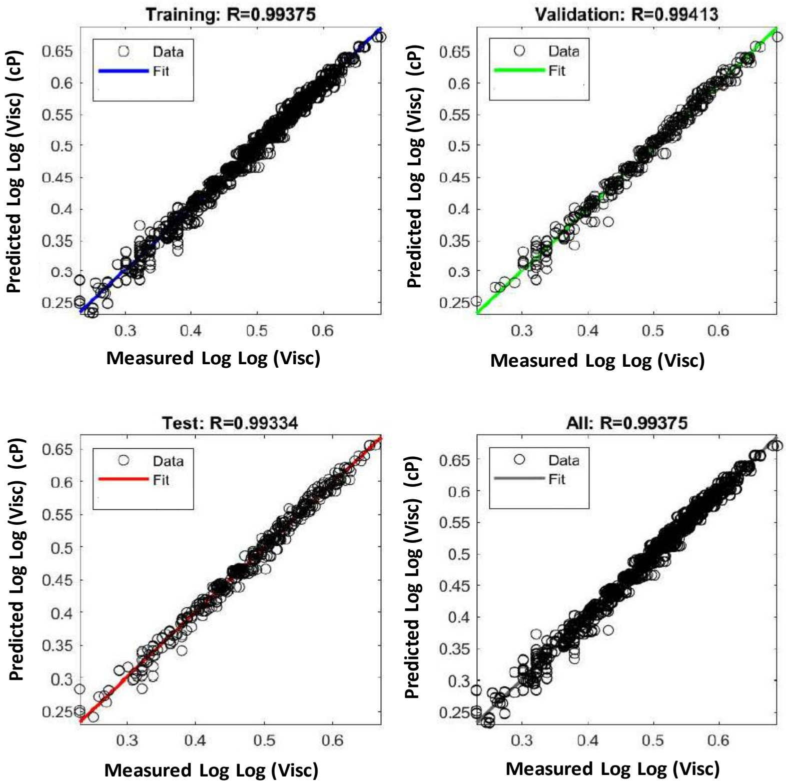

Figure 6. Regression Plots for Training, Validation, Testing, and Overall data (MATLAB R2018a, The Math Works Inc.).

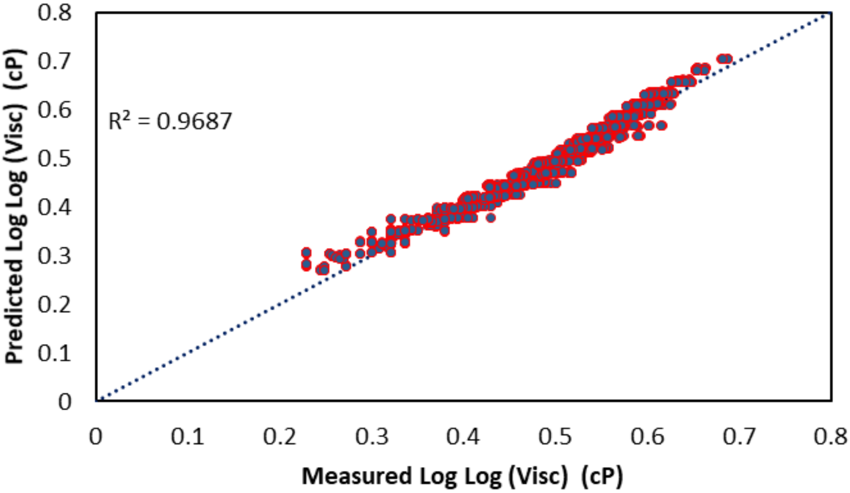

Figure 7. Predicted VS Measured Values of Viscosity for 3003 Datasets Utilizing the Generated Stand-alone Viscosity Prediction Equation.

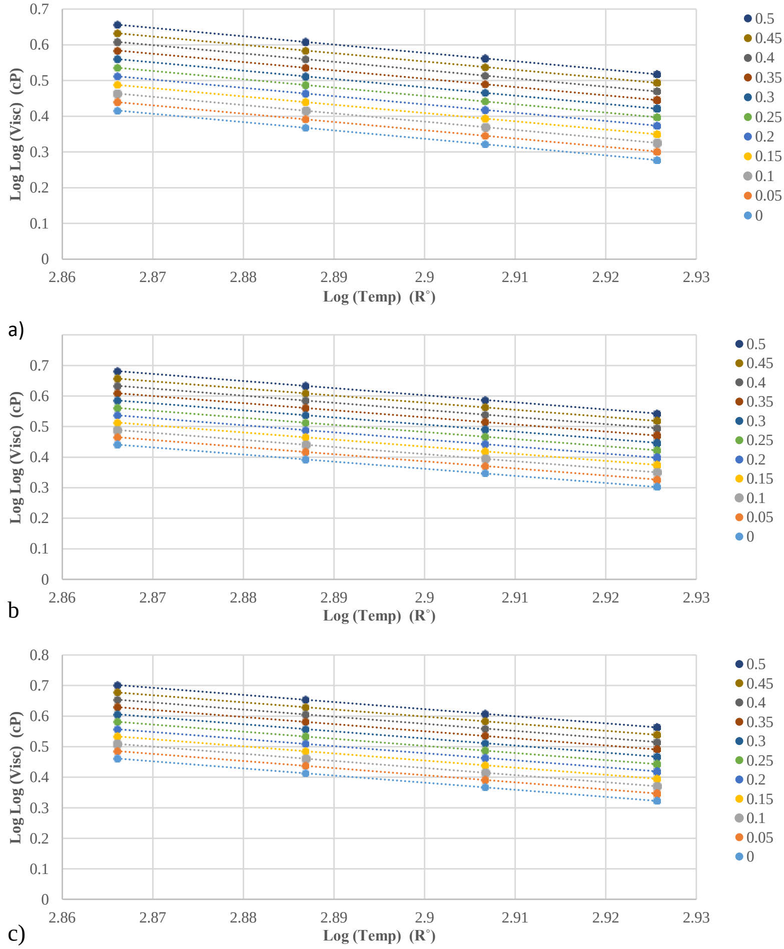

Figure 8. ASTM A-VTS Correlations Generated Utilizing the Newly Developed Prediction Equation for: a) Binder A, b) Binder B, and c) Binder C.

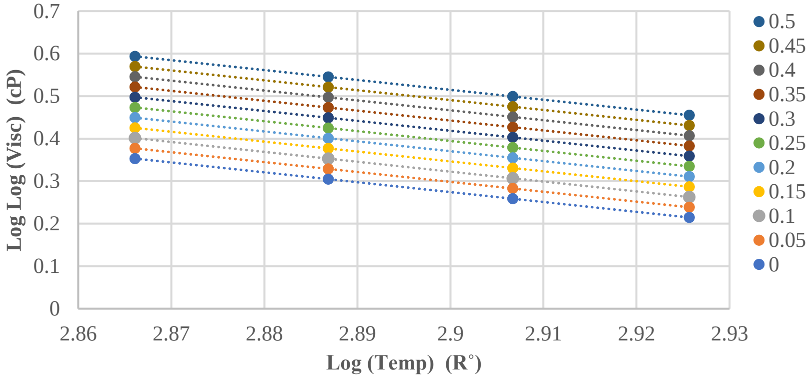

Figure 9. ASTM A-VTS Correlations Generated Utilizing the Newly Developed Prediction Equation for the New Binder PG 52-22.

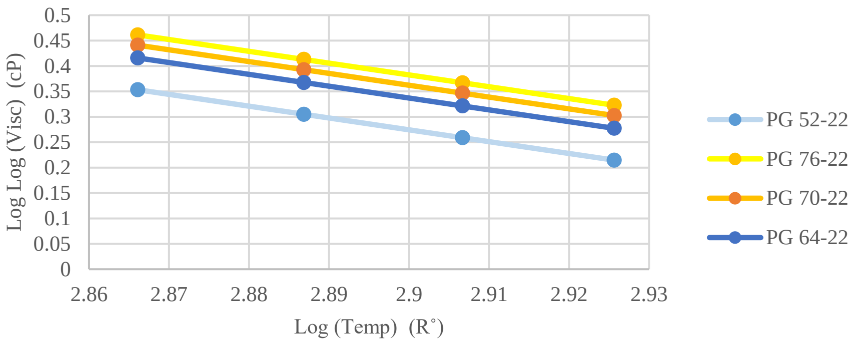

Figure 10. ASTM A-VTS Correlations Generated Utilizing the Newly Developed Prediction Equation for the Four Different Evaluated Virgin Binders.