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Data-driven Prediction of Dynamic Complex Modulus for Non-conventional Asphalt Mixtures

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The dynamic modulus (|E*|) of asphalt mixtures is one of the main material characteristics that governs the quality of asphalt pavements in their design and construction. While the |E*| values are traditionally obtained from intensive laboratory testing or statistical predictive equations, this research attempted to apply several machine learning (ML) techniques to predict |E*|, especially for non-conventional asphalt mixtures. The study used 3906 lab-measured |E*| data points from different types of non-standard asphalt mixtures, such as recycled asphalt pavement, recycled asphalt shingles, warm mix asphalt, asphalt rubber, air-blown asphalt, and polymer-modified asphalt. Mixture temperature, loading frequency, aggregate gradation, mixture volumetric, and asphalt binder information were included as variables used in the ML techniques. Relative comparisons were made to answer the following question: which ML technique would provide a more accurate prediction for |E*| when non-conventional asphalt mixtures are considered in the design and construction? It was found that, among the five ML techniques used in the study, decision trees and random forests showed the best prediction capability. Linear regression showed the least accurate prediction. It was also found that the |E*| measured for asphalt-rubber asphalt mixtures was best predicted by ML techniques.

Key Words: Asphalt Pavement, Asphalt Mixture, Dynamic Modulus, Machine Learning, Deep Learning

Introduction

The longevity of roadway pavements relies heavily on their structural design with sound material selection followed by proper construction. During the late 1990s and early 2000s, a new pavement design and evaluation procedure known as the Mechanistic-Empirical Pavement Design Guide (MEPDG) was developed under the National Cooperative Highway Research Program (NCHRP 01-37A, n.d.). The primary goal was to transition empirical-based pavement design practice towards a mechanistic-based approach that incorporates the mechanical responses of pavement mixtures and underlying layers. This effort has been continuing, and an advanced version of the MEPDG software,

AASHTOWare Pavement ME Design®, is currently being used or evaluated by numerous state highway agencies in the US (AASHTO, 2020).

One of the primary inputs for an asphalt pavement design and performance evaluation in the software is the dynamic modulus (|E*|), as this viscoelastic property dynamically determines the stiffness of asphalt mixture depending on a given pavement temperature and traffic loading frequencies. The software subsequently utilizes the |E*| values and other material characteristics to forecast the pavement's performance, specifically in relation to the accumulation of distresses such as rutting and cracking on asphalt pavement over its design life.

While the collection of laboratory-measured |E*| data is considered the most precise depiction of material response, it is not consistently undertaken by agency or consultant personnel who are involved in pavement design with the mechanistic-empirical approach. This is because not all laboratories have the necessary resources in terms of equipment, time, technician, and funding to conduct |E*| testing on a broad scale. Hence, the inclusion of |E*| prediction models within the software confers a practically significant advantage to those who would want to operate the software without the need for extensive laboratory measurements.

Machine learning (ML) is recently emerging as an alternative way that could replace the traditional statistical |E*| predictions. Various ML techniques have been used in previous research in civil and construction engineering. The literature review in the proceeding section provides several previous studies on research using ML techniques used in the discipline. Though much research has attempted to predict |E*| of asphalt mixture, limited study is found in using ML, particularly focusing on the prediction of |E*| for non-conventional asphalt mixtures. In this study, the authors employed several ML techniques to predict the |E*| of non-conventional asphalt mixtures and evaluated them to find the best predictive ML method.

Raw data included in this study come from 62 asphalt mixtures with a total of 3906 laboratory-measured |E*| data points (Mensching et al., 2018). The dataset contains six groups of non-conventional asphalt mixtures and one group of conventional mixture for comparison purposes. The non-conventional mixture groups are those mixed or modified with 1) Reclaimed Asphalt Pavement (RAP), 2) Recycled Asphalt Shingles (RAS), 3) Warm Mix Asphalt (WMA), 4) asphalt rubber, 5) air-blown asphalt, and 6) polymer modified. The ML predicted |E*| values are compared and evaluated with the laboratory-measured |E*| values based on four different metrics: mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and explained variance score (EVS).

With this background, the objective of this study was to relatively evaluate the performance of ML techniques in predicting |E*| for non-conventional asphalt mixtures by answering the following question: which ML technique would provide a more accurate prediction for |E*| when non-conventional asphalt mixtures are considered in the design and construction? Five ML techniques including linear regression, support vector machines, decision trees, random forests, and deep learning were used to find the predicted |E*| values in this study.

Literature Review

Dao et al. (2020) investigated several ML algorithms to predict |E*| of warm mix asphalt containing high reclaimed asphalt pavement. The ML techniques that were used include the artificial neural network, SVM, Gaussian process regression, and ensemble boosted trees. The results showed the boosted algorithm was found the best predictor. Behnood and Golafshani (2021) applied an

innovative optimization algorithm called biogeography-based programming for predicting |E*| of both traditional and non-traditional asphalt mixtures and concluded the algorithm was successful. Gong et al. (2020) used the deep learning algorithm, specifically a feedforward neural network, to evaluate the |E*| predictions. The study found that the neural networks outperformed the traditional statistical predictions and other prediction methods. The algorithm used some volumetric information such as binder properties, mixture volumetrics, and aggregate gradation to create neural network to estimate the |E*|. Another example of a ML technique using neural network to predict |E*| is in Ceylan et al.'s research (Ceylan et al., 2009). In this study, the |E*| of conventional asphalt mixtures were predicted using the feedforward neural network with four layers and eight inputs. The research concluded that the |E*| values from their ML algorithm were significantly higher than those found from the statistically driven |E*| equations when the identical inputs were used. It was reported that a more accurate |E*| prediction could be found through artificial neural networks that minimize bias. Another study by Gong et al. (2018) focused on random forests to predict the international roughness index (IRI) of asphalt pavements. In the development and validation of their IRI prediction model, it was reported that the random forest regression outperformed the traditional linear regression model showing greater than 0.95 R^2 in both training and test datasets.

Methodology

Raw Data and Data Preprocessing

The raw data used in this study was retrieved from one of the previous studies (Mensching et al., 2018) that used non-conventional asphalt mixtures for comparing |E*| data between laboratory-measured and predicted with traditional statistically driven equations. The study collected a set of |E*| data measured in the laboratories at various test temperature-frequency conditions from 62 asphalt mixtures. A total of 3906 laboratory-measured |E*| data points were populated. Table 1 shows the breakdown of the data used in this study showing the material types and datapoints of each type. As indicated earlier, the non-conventional mixtures include RAP, RAS, WMA, Asphalt Rubber, Air-Blown Asphalt, and Polymer Modified. The RAP asphalt mixture type has the most data points (2358 data points) out of the seven asphalt mixture types. The WMA asphalt mixture has the second-highest number of data points (504 data points) which used several warm mix additives. Both the RAP and WMA include four different material types which result in a higher number of data points for that mixture. Polymer-modified mixture types include the materials styrene-butadiene-styrene (SBS) and terpolymer in the composite. This mixture type contains 270 data points. The RAS mixture type has 144 data points. This mixture is made of a combination of the composite and 6% RAS by weight. Asphalt rubber and air-blown asphalt modified mixtures have the least number of data points (90 data points each). In addition, a group of conventional asphalt mixtures was used as well for comparison purposes. This group of conventional materials includes 450 data points.

Prior to operating ML techniques, it was essential to sort out the raw data to efficiently use the dataset. Table 2 provides a list of the information that was used from the raw data and the selected variables of this study. It is worth noting that the variables were chosen based on the two traditional statistically driven predictive equations (Andrei et al., 1999 and Bari et al., 2006) that are currently used in the AASHTOWare software. A variable named "Log_E" in the dataset was treated as the dependent variable and all other variables were considered the independent variables. The unit of "Log E" is 10^5 psi following the traditional convention of |E*| prediction methodology.

Table 1

Summary of Dynamic Modulus Dataset

Type of Asphalt Mixture	Data Points	Note
Conventional	450	
RAP	2358	20%, 22%, 30%, 44%, RAP by weight
RAS	144	6% RAS by weight
WMA	504	Foamed, Advera®, Evotherm®, Sasobit®
Asphalt Rubber	90	6% Tire Scraps by weight
Air-blown Asphalt	90	
Polymer Modified	270	SBS, Terpolymer
Total Data Points	3906	

Table 2

Variables used in the ML operation

Variable Abbreviation	Variable Description
temp	Temperature (ºF)
f	Frequency (Hz)
p_{34}	The cumulative percent retained in 3/4” sieve
p_{38}	The cumulative percent retained in 3/8" sieve
p_4	The cumulative percent retained in # 4 sieve
p_{200}	The percent passing # 200 sieve
V_a	Percent of air voids
V_{beff}	Percent of effective binder content by volume
Vis	Viscosity of the binder (10^6 poise)
Log_E	Log E (10^5 psi)

Machine Learning

The five ML techniques were run in Python using the Jupyter notebook. A total of seven notebooks for each of the five mixture types were created for the coding process for the seven mixture types presented in Table 1. Figure 1 shows a flow chart of the steps used in programming the ML techniques. The coding process of each ML technique was similar until the data was split into the training and testing sets (80% and 20%, respectively). After this split in the data, the code was specific to each ML technique.

As indicated earlier, the evaluation metrics used in this study include MAE, MSE, RMSE, and EVS. MAE, defined as $\frac{1}{n}\sum_i^n|y_i - \hat{y}_i|$, is a common evaluation metric for regression that does not punish larger errors, and measures the absolute value of the mean of the distance between the targeted value and the predicted value. MSE is the mean of the squared errors and is defined by $\frac{1}{n}\sum_i^n(|y_i - \hat{y}_i|)^2$. This evaluation metric is sometimes used over MAE because larger errors are noted. The MSE measures how close a regression line is to the data points. RMSE is the square root of the MSE to normalize the unit of the MSE. The EVS is used to provide how much variance exists in the model as

defined by $\text{EVS} = 1 - \frac{\text{Error of Sum Squared}}{\text{Total Corrected Sum of Squares}}$. The error of the sum squared, and the total corrected sum of squares are two components of the equation to find the explained variance. It should be recognized that it is ideal for the EVS score to be closer to 1.0, however for MAE, MSE, and RMSE the goal is to have a value closer to 0.

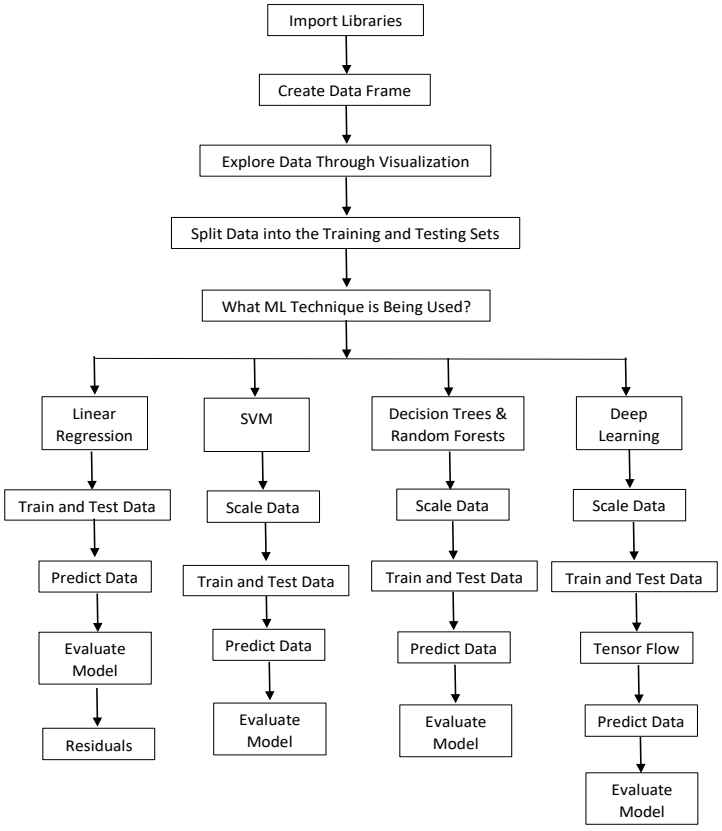

Figure 1. Coding Steps for Each Machine Learning Technique

Results and Discussion

Several bar charts from Figures 2 to 5 were created to compare the results of each evaluation metric. Figure 2 compares the MAE of all five ML techniques. For each ML technique, the MAE is provided for the individual asphalt mixture type along with the MAE of all combined data. Similar figures are created for MSE, RMSE, and EVS as shown in Figures 3, 4, and 5, respectively. It should be recalled that the goals of MAE, MSE, and RMSE are to have results closer to zero for an effective prediction of |E*|, while the goal of EVS is to have results closer to 1.

In Figure 2, it was evident that decision trees and random forests provided the relatively lower MAEs regardless of the mixture type. This clearly indicates that the two techniques have the better ability to predict |E*| than the other three methods. It was also noticed that linear regression showed the poorest results indicating an inferior ability of |E*| prediction followed by SVM. Deep learning is placed in the third place.

Within each ML group, the air-blown and asphalt rubber materials stand out except for the deep learning group where the |E*| predictions of asphalt rubber mixtures are not close to each other. The best prediction combination (material and ML method) was found to be asphalt rubber with decision trees followed by asphalt rubber with random forests. This trend is consistently found with the other two evaluation metrics: MSE and RMSE. The decision trees and random forests showed exceptional prediction capabilities compared to the other three for all mixture types.

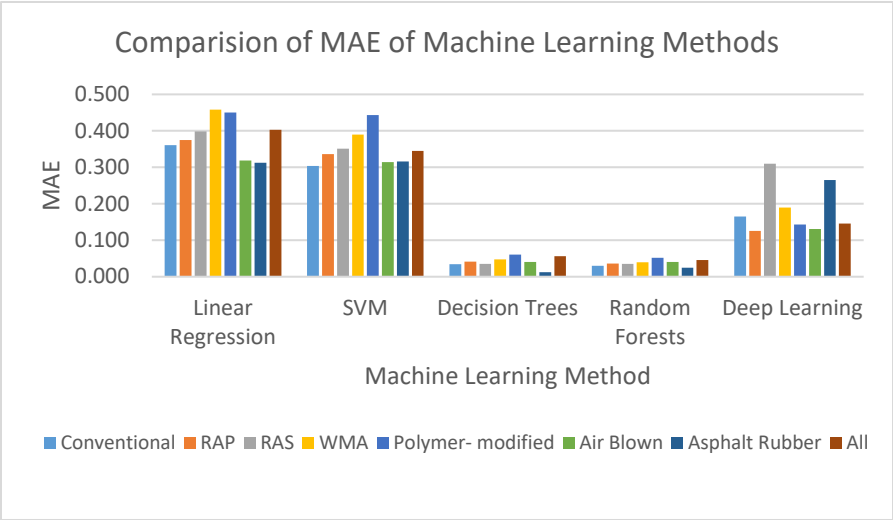

Figure 2. Comparison of MAE of All ML Techniques

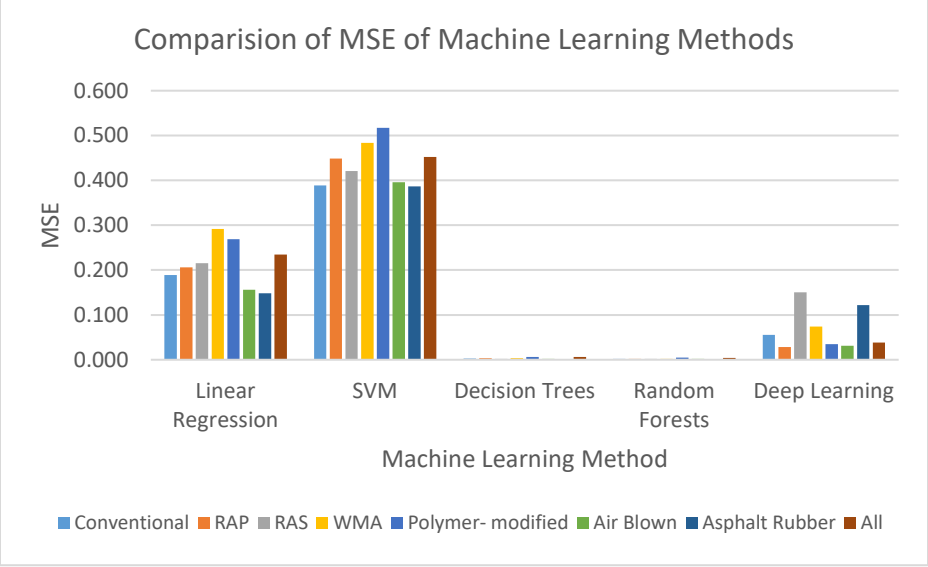

Figure 3. Comparison of MSE of All ML Techniques

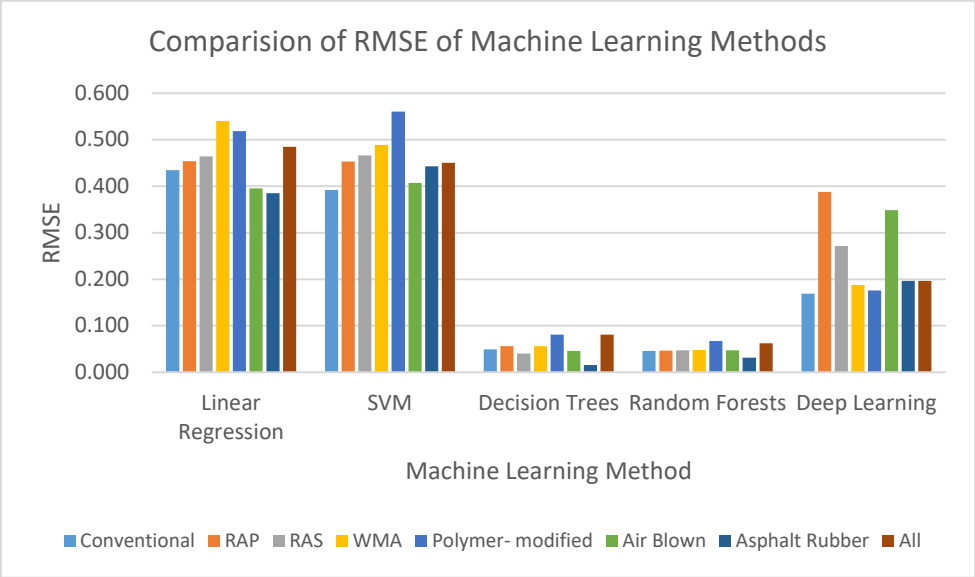

Figure 4. Comparison of RMSE of All ML Techniques

Figure 5 presents a comparative analysis of the EVS for the five ML methodologies. The analysis revealed that both the SVM and linear regression models exhibited suboptimal performance, aligning with the findings obtained from the MAE, MSE, and RMSE metrics. The approaches exhibited low expected value of EVS for all non-conventional mixing types, along with high MAE, MSE, and RMSE, as previously demonstrated. This observation suggests that the methods were not successful in accurately predicting the value of |E*|. The deep learning approach exhibited superior performance compared to SVM and linear regression, while falling short of the performance achieved by decision trees and random forests. The findings are consistent with a prior study (Gong et al., 2018) that demonstrated the superior performance of neural networks, a component of deep learning, compared to linear regression. The performance of decision trees and random forests surpassed that of conventional machine learning algorithms, yielding outstanding results. These methods provide the highest levels of accuracy. Both methods yielded EVS values that were more than or equal to 0.99.

The outcomes between the two methods exhibit a high degree of similarity, with random forests demonstrating a modest superiority in performance. Upon examining the data visually presented in the figure for all types of mixtures, it can be observed that random forests exhibit a superior EVS value. As previously stated, the EVS demonstrates the efficacy of the method in accurately forecasting the value of |E*|. In general, decision trees and random forests provide outstanding performance compared to the other five ML algorithms.

Summary and Conclusions

In this study, ML techniques were applied to predict |E*| of non-conventional asphalt mixtures. The goal of using ML techniques was to relatively evaluate the accuracy and effectiveness of ML in predicting |E*| within different ML methods. The ML techniques selected in this study include linear regression, SVM, decision trees, random forest, and deep learning. These ML techniques were applied

to seven non-conventional asphalt mixture groups and one conventional mixture group. The following performance metrics MAE, MSE, RMSE, and EVS were used as evaluation guidance.

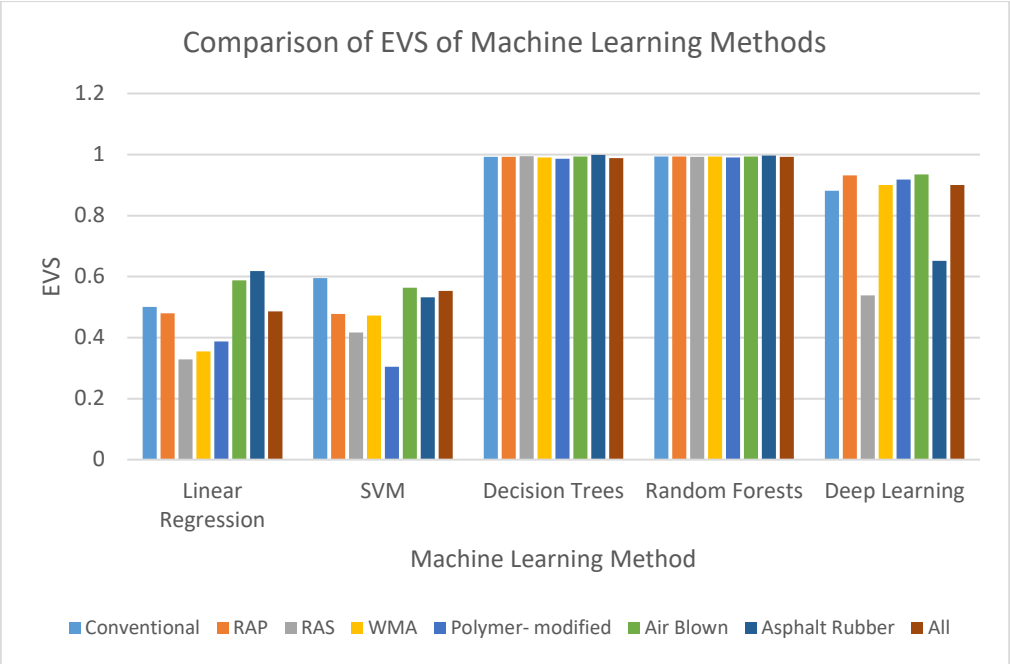

Figure 5. Comparison of EVS of All ML Techniques

When all the methods are compared using the metrics, decision trees and random forests provided the best results which consisted of all excellent accuracies for all non-conventional material types as well as conventional mixture group. Random forests had slightly better results than decision trees. However, both methods had excellent results and outperformed the other ML techniques. The results of deep learning were not as good as the results from decision trees and random forests. Overall linear regression and SVM did not perform well. SVM had slightly better results than linear regression.

In conclusion, the present study determined that certain ML techniques yielded superior outcomes compared to others when applied to the |E*| dataset of non-conventional asphalt mixtures. In general, decision trees and random forests are two methodologies that exhibit higher predictive accuracy in estimating the value of |E*|, irrespective of the types of mixtures involved. The asphalt rubber asphalt mixtures are well orchestrated with all ML methods. Nevertheless, it is important to exercise caution when interpreting this result as the study in question possesses certain limitations. One of the disadvantages of this study is the unequal distribution of data points among different types of asphalt mixtures. As depicted in Table 1, the data utilized in the study exhibits a distribution, wherein certain asphalt mixture types have a greater abundance of data in comparison to others. For example, the dataset for RAS has 2,358 data points, while the dataset for asphalt rubber consists of only 90 data points. The variation in data quantity and data variety might have an impact on the outcomes and predictive accuracy of |E*|. This was not addressed within the scope of this study; however, it merits consideration for future investigations.

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