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Kernel machines and firefly algorithm based dynamic modulus prediction model for asphalt mixes considering aggregate morphology

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HIGHLIGHTS

- SVR proved successful in outperforming Witczak and ANN models for estimation of dynamic modulus of asphalt mixes.
- Aggregate shape parameters are considered in estimation of dynamic modulus.
- An approach for formulation of SVR-FA model equations for direct prediction of HMA stiffness is also discussed.
- SVR-FA algorithm is capable of successfully predicting dynamic modulus values using the aggregate shape parameters.

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ABSTRACT

Artificial Intelligence algorithm support vector regression (SVR) has proved successful in outperforming conventional Witczak and ANN models for estimation of dynamic modulus (E^*) of asphalt mixes. However, there were two issues related to the development of E^* prediction models that the present study addresses. Firstly, since aggregates occupy almost 95% by weight of HMA, it is quite possible that the morphology of these aggregates play an important role in influencing the E^* values. To address this issue, aggregate shape parameters, namely, angularity, sphericity, texture and form were used with aggregate gradation for stiffness estimation. Secondly, to fine tune the hyper-parameters firefly algorithm (FA) was coupled with SVR. E^* tests of 20 HMA mixes having different sources, sizes of aggregates, and volumetric properties were conducted at 4 temperatures and 6 frequencies. Aggregate shape parameters were measured using the automated aggregate image measurement system (AIMS). SVR-FA models were developed that predicted the E^* with an R^2 of 0.98. SVR-FA models were compared with SVR and ANN models for E^* prediction. Further, a sensitivity analysis was conducted to identify the important input parameters. Lastly, an approach for formulation of SVR-FA model equations for direct prediction of HMA stiffness is also discussed. FA proved instrumental in improving the efficiency of SVR by optimizing the hyper-parameters with lesser manual effort. Finally, it was concluded that SVR-FA algorithm is capable of successfully predicting the E^* values using the aggregate shape parameters.

1. Introduction

Dynamic Modulus (E^*) is a fundamental property of asphalt mixes that has a significant effect on the major pavement distresses such as, fatigue, rutting, and low temperature cracking [1]. Also, as per the Mechanical Empirical Pavement Design Guide [2], E^* is an important parameter required for the calculation of damage accumulation over the life cycle of a flexible pavement. E^* of a mix can be directly measured through laboratory tests prescribed by AASHTO TP62-06 [3]. However, the laboratory tests can be expensive, time-consuming and depend on the sensitivity of the instrument [4]. Hence, to simplify the situation many researchers used predictive models namely, Witczak models [5,6], Al-Khateeb model [7] and Hirsch model [8] to estimate E^*, based on aggregate gradation, volumetric properties of compacted mix and asphalt binder properties. Due to the regression relationship between E^* and independent variables, prediction accuracy of these models vary with the test temperature, type of mix and aggregate gradation [9–12]. To enhance the prediction capability of the models,

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Far et al. [12] and Ceylan et al. [10,11,13] developed Artificial Neural Network (ANN) models for E* prediction, which resulted in significant improvement in accuracy as compared to the multi-regression models. Recently, another efficient machine learning algorithm called Support Vector Regression (SVR) was proposed for the prediction of E* [14,15]. The results showed that SVR could outperform ANN and multi-regression models in terms of prediction accuracy.

SVR works on the principle of structural risk minimization, unlike ANN which is based on empirical risk minimization. Hence, SVR can give predictive models with greater generalization capability [16]. Also, SVR results in unique solutions unlike conventional ANN, which suffers from risk of encountering local minima. The motivation behind the application of SVR includes, (1) capability of modeling non-linear behavior using appropriate kernels, (2) ability to generalize better due to a bound on overall risk along with the minimization of training error, (3) using necessary data points known as support vectors to solve the optimization problem and (4) requirement of lesser training data. However, one of the drawbacks of using SVR is that there is no straight-forward method for optimization of its hyper-parameters. Gopalakrishnan and Kim [13] mentioned the need of further fine tuning of SVR control parameters to achieve better prediction accuracy. To address this issue, recently, researchers have explored the application of Firefly algorithm (FA) with SVR to enhance the accuracy of a prediction model and concluded that SVR-FA outperformed algorithms like ANN, SVR and genetic programming [17,18].

Although all the above approaches utilized aggregate gradations, but none of them considered aggregate shape parameters as potential input variables for E* estimation. Due to the presence of 95% of aggregate (by weight) in asphalt mixes, their shape properties, namely, angularity, sphericity, texture and form (2-D) are expected to have a direct effect on performance and serviceability [19–22]. Bari and Witczak [6] mentioned that mixes with similar volumetric properties and aggregate gradation may result in different values of E*. Therefore, it is important to emphasize the importance of aggregate shape properties in estimation of E*.

In the present study, E* tests were conducted for 20 different mixes at 4 temperatures and 6 frequencies. The aggregates of each mix were divided into different sizes of coarse and fine aggregates. Shape parameters, namely, angularity, sphericity, form and texture for these aggregates were measured using Aggregate Image Measurement System (AIMS). SVR-FA algorithm was used to develop E* predictive model using cumulative shape index factors, volumetric properties of mix, viscosity of binder and frequency. Cumulative shape factors considered the combined effect of aggregate gradation and particle morphology. FA was utilized to fine-tune the SVR hyper-parameters to enhance the accuracy of prediction. Regression coefficient, mean average relative error and overfitting ratio were calculated to evaluate the accuracy of prediction. SVR-FA model is further compared with ANN and SVR models for E* prediction. A sensitivity analysis to quantify important parameters for E* estimation was done. Lastly, an approach for formulation of model equations using SVR-FA algorithm to predict *E** directly is also discussed.

2. Objective of the study

- Development of SVR-FA models for evaluating E* using cumulative shape factor indices of aggregates.
- Comparison of the developed SVR-FA model with artificial neural networks (ANN) and support vector machine regression (SVR) models.
- Development of SVR-FA model equations for direct prediction of E*.
- Study sensitivity analysis of input parameters for estimation of E*.

3. Background on Support Vector Regression

Support Vector Machine Regression (SVR) is a machine learning algorithm based on statistical learning theory, introduced by Vapnik [23,24]. SVR aims at finding an optimal regression function that has at most ε deviation from the original targets y, and is also as flat as possible. Such a function, $f(x)$ is represented in Eq. (1).

$$f(x) = < w, x > + b; w \in X,\ b \in R \tag{1}$$

where <·,·> denotes the dot product in X. One way to ensure the flatness of the function is to minimize the norm of parameter w. Though it is required that optimal regression function always predict the targets y with a precision ε, but in reality, this may result in infeasible constraints while solving the optimization problem. Hence, to deal with this infeasibility, slack variables ξ_i^*, ξ_i (upper and lower bound on training error, respectively) are introduced. Hence, the optimization problem of SVR can be expressed as shown in Eq. (2).

$$\begin{aligned} &\bullet\ \text{minimize } 1/2 * \|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) \\ &\bullet\ \text{subject to } \{ y_i - < w, x_i > - b \leqslant \varepsilon + \xi_i \\ &\qquad \{ < w, x_i > + b - y_i \leqslant \varepsilon + \xi_i^* \\ &\qquad \xi_i, \xi_i^* \geqslant 0 \end{aligned} \tag{2}$$

The hyper-parameter C in Eq. (2) is the trade-off between flatness of the function and amount up to which the deviations greater than ε are allowed [25]. Very large values of C may end up in over-penalizing the error bounds, hence can result in over-fitting. On the contrary, smaller values of C may lead to under-fitting. The hyper-parameter ε denotes the width to fit the training data. It represents the trade-off between the sparseness and closeness in the representation of the data [14]. The data points that lie outside the 'ε-tube' are dealt with the cost function shown in Eq. (3), known as ε-insensitivity loss function. Fig. 1 depicts the ε-insensitivity loss function graphically.

$$L_\varepsilon(y) := \left\{ \begin{array}{ll} 0 & if\ |\xi| \leqslant \varepsilon \\ |\xi| - \varepsilon & otherwise \end{array} \right\} \tag{3}$$

where $|\xi| = |y - f(x)|$.

The above formulated optimization problem is solved using the Lagrange multiplier approach and the solution of the optimal regression function is expressed as Eq. (4).

$$f(x) = \sum_{i=1}^{l}((\alpha_i - \alpha_i^*) < x_i, x > + b), \quad \text{where } 0 < \alpha_i, \alpha_i^* < C \tag{4}$$

α_i, α_i^* are the Lagrangian multipliers and are equal to zero for the data set that lie within the ε-tube as per the Karush-Kuhn-Tucker (KKT) conditions. In other words, only the points that lie outside the ε-tube (i.e. the region between the dashed lines in Fig. 1) have non-zero α_i, and α_i^*, which are known as Support Vectors. Only support vectors are used to determine the optimal regression function, as only for these points α_i, α_i^* are non-zero.

In the case of non-linear relationship, instead of trying to fit a non-linear model, the training data x_i are transformed to a high dimensional space R^D by mapping φ: $R^d \rightarrow R^D$ by using kernel functions. Hence, the dot product $< x_i, x >$ in the linear space becomes $< \varphi(x_i), \varphi(x_j) >$ in the high-dimensional space. Thus, the optimal regression function for the non-linear problem is given in Eq. (5).