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ПРОГНОЗИРАНЕ НА РЕОЛОГИЧНИТЕ СВОЙСТВА НА БИТУМА ПРИ ПРОМЕНЛИВИ ТЕМПЕРАТУРНИ УСЛОВИЯ, БАЗИРАНО НА МАШИННО ОБУЧЕНИЕ

Мохамад Абди Афзали, Маниндер Сингх, Ражив Кумар

MACHINE LEARNING-BASED PREDICTION OF BITUMEN RHEOLOGICAL PROPERTIES UNDER VARYING TEMPERATURE CONDITIONS

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Abstract:

This study presents a machine learning-based approach to predict the rheological performance of bituminous binders at high temperatures and under different temperature conditions. Laboratory tests were performed on virgin, aged and rejuvenated RAP binders. The tests included penetration, softening point, viscosity and Dynamic Shear Rheometer (DSR) testing. Artificial Neural Network (ANN), Support Vector Machine (SVM) and Random Forest (RF) models were developed to predict rutting parameter ($G^*/\sin\delta$) with temperature and basic binder properties as inputs. The models showed good correlation between the predicted and experimental values and the best performance was observed for the SVM model with correlation coefficients of 0.9969 and 0.9949 for the training and testing datasets respectively. The proposed approach provides an efficient alternative to exhaustive DSR testing and demonstrates the potential of machine learning for data-driven characterisation of pavement materials.

Keywords:
Bitumen, Rheological Properties, Machine Learning, Dynamic Shear Rheometer.

1. INTRODUCTION

Bitumen operates as a critical thermo-viscoelastic binder within flexible pavement infrastructure, playing an indispensable role in maintaining the structural integrity of asphalt concrete under dynamic vehicular loading and fluctuating environmental conditions. The performance of this complex hydrocarbon mixture is intrinsically dependent upon temperature variations and loading rates (Ren et al., 2022). At elevated temperatures or under slow-moving traffic loads, bitumen behaves predominantly as a highly viscous, near Newtonian liquid, rendering the pavement susceptible to permanent shear deformation, commonly identified as

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rutting. Conversely, at intermediate to low temperatures, or under rapid loading frequencies, the material responds as an elastic solid, which, while resistant to rutting, introduces vulnerabilities to fatigue cracking and low temperature thermal fracture (Hassan et al., 2024).

Historically, the evaluation of properties of bitumen relied heavily upon empirical laboratory techniques, such as penetration depth, ring and ball softening point, and rotational or kinematic viscosity. While these conventional methods offer a foundational understanding of macroscopic consistency and temperature susceptibility, they lack the fundamental physical rigor required to accurately model the long term, stress strain response of the binder under complex field conditions (Loise et al., 2019). To address these profound limitations, the Strategic Highway Research Program (SHRP) pioneered the Superpave (Superior Performing Asphalt Pavements) framework, which mandated a shift toward mechanistic, rheological characterization (Shen & Ohne, 2002). Central to the Superpave methodology is the employment of the Dynamic Shear Rheometer (DSR) to quantify the dynamic linear viscoelastic properties of the binder at intermediate and high operating temperatures. The DSR applies an oscillatory shear stress to the material, partitioning its mechanical response into two fundamental parameters: the complex shear modulus (G*) and the phase angle ($\boldsymbol{\delta}$). The complex shear modulus (G*) signifies the absolute total resistance of the binder to cyclical deformation, encompassing both elastic rebound and viscous flow. The phase angle ($\boldsymbol{\delta}$) measures the temporal delay between the applied stress and the resulting strain, effectively delineating the ratio of viscous to elastic behavior (Sun et al., 2019).

The contemporary civil engineering landscape is increasingly driven by the imperative to cultivate sustainable, circular economies, primarily to mitigate the rapid depletion of virgin aggregates and the massive carbon footprint associated with refining raw petroleum binders. Consequently, the integration of Reclaimed Asphalt Pavement (RAP) material salvaged from the milling of end of life road infrastructure has become a foundational practice globally (Izaks et al., 2015). However, the incorporation of high volumetric percentages of RAP presents profound rheological and chemical challenges. During its prolonged service life, the bitumen matrix within the RAP undergoes severe oxidative aging, photochemical degradation, and the volatilization of its lighter molecular fractions. At a fundamental microstructural level, this aging process disrupts the colloidal stability of the binder, manifesting as a significant reduction in the maltene phase (resins and aromatics) and a corresponding agglomeration of the heavy asphaltene fraction (Mullapudi et al., 2019). This profound chemical transformation severely stiffens and embrittles the binder. While this extreme stiffness may inadvertently enhance high temperature rutting resistance, it critically compromises the binder's stress-relaxation capacity, leading to premature fatigue and catastrophic thermal cracking upon integration into new pavement mixtures.

To safely maximize RAP utilization without degrading long-term pavement performance, the deployment of chemical rejuvenating agents is strictly necessary (Devulapalli et al., 2019). Rejuvenators are specialized, low viscosity, maltene-rich additives formulated to diffuse into the oxidized RAP binder, replenish the depleted volatile fractions, separate the coagulated asphaltene micelles, and effectively restore the optimal viscoelastic balance of the material (Zaumanis et al., 2013). However, the rheological restoration process is highly sensitive to the precise dosing of the rejuvenator. Insufficient application fails to restore requisite flexibility, whereas over dosing excessively softens the composite binder, triggering immediate rutting failures under heavy traffic loads.

While the mechanistic insights provided by Dynamic Shear Rheometry are unparalleled, the physical acquisition of these parameters is burdened by substantial operational constraints. Conventional laboratory characterization of complex binder blends via the DSR is an exceptionally time consuming, resource intensive process. Frequency-temperature sweep tests demand sophisticated, high-capital equipment, meticulous sample preparation, and extended temporal windows to achieve precise thermodynamic equilibration before data acquisition can

commence (Meena et al., 2025). To transcend the physical and temporal limitations of traditional laboratory testing, Machine Learning (ML) techniques have emerged as transformative computational tools for modeling complex material behavior within civil engineering (Asi et al., 2024). ML algorithms possess the intrinsic capability to decipher highly non-linear, multidimensional interactions between input variables and output responses without relying upon rigid, predefined mathematical or physical equations. This ability has also been demonstrated in other engineering applications, where ML models are used to predict the hard-to-measure properties from the easily available input parameters, thus reducing the dependence on conventional testing (Wani et al., 2026). By training these algorithms on historical experimental datasets, ML models can effectively capture the underlying physics of material behavior, mapping basic, universally obtainable physical parameters to advanced mechanistic responses. As a result, the application of ML in predicting bitumen rheological properties has gained significant attention in recent years, allowing for the creation of "virtual rheometers" that drastically reduce experimental requirements (Sholevar et al., 2022). Similar applications of soft-computing techniques in asphalt materials have shown their ability to predict performance-related properties, reducing the time and effort required for conventional laboratory evaluation (Jalota & Suthar, 2023).

Recent studies, particularly post-2018, have systematically demonstrated the profound effectiveness of ML approaches within the domain of asphalt binder characterization. While early attempts often utilized simple linear regression methods or Response Surface Methodology (RSM), researchers quickly identified that these foundational statistical tools frequently failed to capture the exponential stiffening behaviors and phase angle asymptotes inherent to modified bitumens (Ayazi et al., 2024). The transition toward advanced algorithms has yielded remarkable predictive improvements. For instance, Dinesh et al. (2026) successfully developed highly robust ML models that mathematically linked Fourier Transform Infrared Spectroscopy (FTIR) derived chemical compositional data with specific rheological properties, achieving extraordinary prediction accuracy and significantly reducing the necessity for extensive physical testing (Meena et al., 2025). While highly accurate, the reliance on FTIR inputs presents accessibility challenges for standard quality control laboratories. Addressing this, Huang et al. (2024) pivoted toward ensemble machine learning techniques, rigorously evaluating Random Forest (RF) and Extreme Gradient Boosting (XGBoost) architectures (Huang & Qian, 2024). Their work reported excellent predictive performance, with coefficients of correlation (R2) approaching 0.99 for both the complex modulus and phase angle, demonstrating the superior capability of ensemble methods to reduce model variance and prevent overfitting. Additionally, numerous studies have emphasized the critical need for integrating empirical experimental data with advanced data-driven approaches. Goli and Sadeghpour Galooyak (2019) explored the precise architecture required to use Artificial Neural Networks for predicting the fundamental viscosity of polymer-modified binders, while Farooq et al. (2021) demonstrated comprehensive ML based predictions of macroscopic asphalt mixture performance. Xu et al. (2022) successfully applied ML models to predict the linear viscoelastic properties of asphalt binders, bypassing the need for physical master curve construction, and Wang et al. (2024) investigated the deep use of gradient boosting techniques to refine the accuracy of high temperature rheological predictions (Wang et al., 2024).

Despite significant advancements, existing studies often rely on complex machine learning models requiring large proprietary datasets or advanced chemical analyses such as FTIR and SARA, limiting their practical use in routine engineering. There is a clear need for simple, interpretable, and computationally efficient models based on easily measurable parameters like penetration, softening point, viscosity, and temperature. This study develops a machine learning-based framework to predict the high temperature rutting parameter ($G^*/\sin\boldsymbol{\delta}$) of bitumen. Three models Random Forest (RF), Artificial Neural Networks (ANN), and Support Vector Machines

(SVM) are developed and compared. The dataset includes VG-40, PAV-aged VG-40, and RAP binders with 4–10% rejuvenator. The novelty of this study is the development of a practical machine learning framework for the prediction of the high-temperature rutting parameter (G*/sinδ) of conventional, PAV-aged, and RAP-derived binders using readily measurable properties instead of advanced chemical characterization. It deals with RAP binders with 4-10% rejuvenator and compares three machine learning algorithms (Random Forest (RF), Artificial Neural Network (ANN) and Support Vector Machine (SVM)). The proposed framework is a low-cost and an efficient approach in reducing the need for extensive DSR testing and evaluating rejuvenated RAP binders using simple laboratory parameters such as penetration, softening point, viscosity, temperature and rejuvenator content.

2. METHODOLOGY

2.1 Materials

2.1.1 Bituminous binders

The study utilized viscosity-graded VG-40 bitumen, conforming to Bureau of Indian Standards (IS 73-2013), as the control virgin binder due to its high-temperature performance suitability. Its fundamental properties, including penetration, viscosity, and softening point, were determined using standard test methods to establish baseline input parameters for model development.

To simulate long-term field aging, the virgin binder underwent a two-stage accelerated aging process. Initially, short-term aging was conducted using the Rolling Thin Film Oven Test, followed by long-term oxidative aging in the Pressurized Aging Vessel. This produced PAV-aged VG-40, representing severely aged binder conditions.

Reclaimed Asphalt Pavement (RAP) was sourced from a 10-year-old highway section on Patiala Road, India. The aged binder was extracted using Trichloroethylene through centrifuge extraction, followed by filtration and recovery via a rotary evaporator in accordance with Rotary Evaporator Method. This ensured preservation of the binder’s original rheological properties prior to rejuvenation. The properties of bituminous binders presented in Table 1.

Table. 1 Basic physical properties of VG-40 virgin binder and aged RAP binder

Properties of Bitumen	Types of Bitumen		Test Method
	VG-40	Aged binder	
Viscosity (135°C, Poise)	450	3075	IS 1206
PG Grade (°C)	81.3	115	IS 1208
Softening point (°C)	50.1	91.65	IS 1205
Penetration (25°C, 0.1mm)	51	11	IS 1203

2.1.2 Rejuvenator

A commercially available, high-penetration chemical rejuvenator was utilized to restore the viscoelastic properties of the aged RAP binder and to generate a diverse dataset for machine learning modelling. The rejuvenator was incorporated into the recovered RAP binder at four controlled dosages of 4%, 6%, 8%, and 10% by total binder weight. Prior to blending, the RAP binder was heated to approximately 150°C to achieve a fluid state, after which the rejuvenator was gradually introduced under controlled conditions. The mixture was subjected to continuous low-shear mechanical mixing for 30 minutes to ensure complete homogenization and effective

diffusion of the rejuvenating agent while avoiding additional thermal aging or volatilization. These rejuvenated blends, along with the virgin VG-40 and PAV-aged binders, formed a comprehensive dataset representing varying degrees of binder stiffness and restoration levels for subsequent analysis and model development.

2.2 Experimental Methods

A comprehensive experimental program was conducted to simulate field aging, recover RAP binder, prepare rejuvenated blends, and evaluate rheological properties for machine learning modelling. The virgin VG-40 binder was first subjected to a two-stage aging protocol using the Rolling Thin Film Oven Test and Pressurized Aging Vessel to replicate short- and long-term oxidative aging. RAP material was collected from a field pavement and processed through centrifuge extraction using Trichloroethylene, followed by recovery via rotary evaporation in accordance with Rotary Evaporator Method. Rejuvenated binders were then prepared by blending RAP with rejuvenator at controlled dosages (4–10%) under standardized thermal and mechanical conditions.

Subsequently, key empirical properties- including penetration (IS 1203), softening point (IS 1205), and kinematic viscosity at 135°C (IS 1206) (IS:1201-1220, 1978)-were determined to serve as model input parameters, while Performance Grade (PG) classification (AASHTO M320) was also recorded. The primary output parameter, $G^*/\sin\boldsymbol{\delta}$, representing rutting resistance, was measured using a Dynamic Shear Rheometer in accordance with Dynamic Shear Rheometer Test under controlled temperature and loading conditions. The resulting dataset, encompassing virgin, aged, and rejuvenated binders, was used for training and validating the machine learning models. Adopted methodology for this study is presented in Figure 1.

2.3 Machine Learning Framework

A comprehensive experimental program was conducted to simulate field aging, recover RAP binder, prepare rejuvenated blends, and evaluate rheological properties for machine learning modelling. The virgin VG-40 binder was first subjected to a two-stage aging protocol using the Rolling Thin Film Oven Test and Pressurized Aging Vessel to replicate short- and long-term oxidative aging. RAP material was collected from a field pavement and processed through centrifuge extraction using Trichloroethylene, followed by recovery via rotary evaporation in accordance with Rotary Evaporator Method. Rejuvenated binders were then prepared by blending RAP with rejuvenator at controlled dosages (4–10%) under standardized thermal and mechanical conditions.

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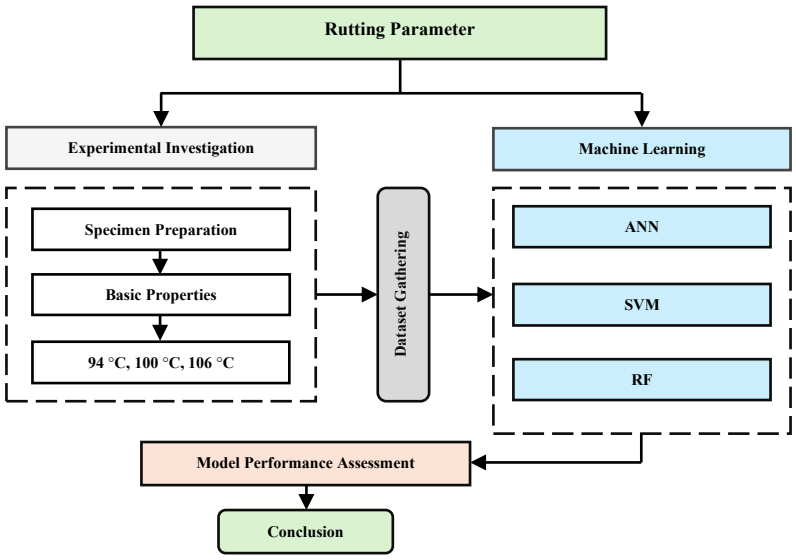

Figure 1. Implemented methodology flow chart

Table. 2 User defined parameters for used models

Models	SVM		ANN		RF	
Parameters	C	1	N	500	Max depth	0
	N	0	L	0.3	Seeds	1
	Num	2	M	0.2	Num DP	2
	Omega	1	Num DP	5	-	-
	Sigma	1	-	-	-	-

2.3.1 Artificial Neural Networks (ANN)

A Multilayer Perceptron (MLP)-based Artificial Neural Network was developed to model the highly non-linear relationship between input parameters and the rheological rutting response (G*/sin$\boldsymbol{\delta}$). The network architecture consisted of an input layer with five features, multiple dense hidden layers, and a single-node output layer for continuous prediction. To effectively capture complex non-linear interactions arising from temperature variations, aging, and rejuvenator dosage, the Rectified Linear Unit activation function was employed in hidden layers, while a linear activation was used in the output layer. Model optimization was performed using the Adam optimizer, with Mean Squared Error (MSE) as the loss function. Prior to training, input features were standardized to ensure numerical stability. The model was trained iteratively through backpropagation, where weights and biases were adjusted to minimize prediction error. Hyperparameters, including the number of hidden layers, neurons, learning rate, and batch size, were systematically tuned to achieve optimal performance while preventing overfitting and ensuring robust generalization across varying binder conditions.

2.3.2 Support Vector Machines (SVM)

Support Vector Regression (SVR), a variant of Support Vector Machines, was employed as a robust predictive model for estimating the continuous rheological parameter (G*/sin$\boldsymbol{\delta}$). Unlike conventional regression techniques, SVR is based on the principle of structural risk minimization, aiming to fit an optimal hyperplane that maximizes the margin while keeping prediction errors within a predefined tolerance. To address the strong non-linearity between input features and binder behavior, the Radial Basis Function (RBF) kernel was utilized to transform the input space into a higher-dimensional feature space, enabling effective separation of complex data patterns. Key hyperparameters, including the regularization parameter (C) and kernel

coefficient (gamma), were optimized using grid search with cross-validation to balance model accuracy and generalization. The resulting SVM model provided a stable and reliable benchmark for comparison with other machine learning approaches.

2.3.3 Random Forest (RF)

The Random Forest (RF) algorithm was implemented as an ensemble-based learning approach to enhance predictive accuracy and mitigate overfitting associated with single decision tree models. RF constructs a large number of independent decision trees using bootstrap aggregation (bagging), where each tree is trained on a randomly sampled subset of the dataset with replacement. Additionally, feature bagging was employed at each node split, allowing only a random subset of input features to be considered, thereby increasing model diversity and reducing correlation among trees. For prediction, each tree independently estimates the target parameter (G*/sin$\boldsymbol{\delta}$), and the final output is obtained by averaging all individual predictions, ensuring improved stability and generalization. Hyperparameters such as the number of trees, maximum tree depth, and minimum samples per split were optimized to achieve optimal performance. Furthermore, the RF model enabled feature importance analysis, providing valuable insights into the relative influence of input variables on binder rheological behavior.

2.3.4 Model Evaluation Metrics

To ensure the predictive reliability and robustness of the ANN, SVM, and RF models, the dataset was divided into training and testing subsets, and model performance was evaluated using a comprehensive set of statistical indicators. Unlike cross-validation approaches, a direct train–test evaluation strategy was adopted to assess the generalization capability of the developed models on unseen data.

The predictive accuracy of the models was quantified using several complementary statistical metrics, including the Correlation Coefficient (R), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Relative Absolute Error (RAE), Root Relative Squared Error (RRSE), Willmott Index (d), and Nash–Sutcliffe Efficiency (NSE). The correlation coefficient (R) was used to measure the strength of the linear relationship between predicted and experimental values, with values closer to 1 indicating strong agreement. MAE and RMSE were employed to quantify the average magnitude of prediction errors, where RMSE provides greater sensitivity to larger deviations.

Additionally, RAE and RRSE were used to evaluate model performance relative to a baseline predictor, while the Willmott Index (d) and NSE offered normalized measures of agreement and predictive efficiency, respectively. Collectively, these metrics provided a robust and multi-dimensional assessment of model accuracy, consistency, and generalization in predicting the rheological parameter (G*/sin$\boldsymbol{\delta}$).

3. RESULTS AND DISCUSSION

3.1 Artificial Neural Networks (ANN)

The predictive performance of the Artificial Neural Network (ANN) model demonstrated a high degree of accuracy and generalization capability in estimating the rutting parameter (G*/sin$\boldsymbol{\delta}$ in) . The strong correlation between predicted and experimental values is evident from the high correlation coefficients obtained for both training (R = 0.9798) and testing (R = 0.9872), indicating excellent model reliability and consistency. The low error values, with MAE of 1.3064 (training) and 0.931 (testing), along with RMSE values of 1.723 and 1.0548 respectively, confirm the model’s ability to minimize prediction deviations across a wide range of binder conditions.

Furthermore, the relatively low RAE (≈0.20–0.23) and RRSE (≈0.19–0.21) values indicate that the ANN model significantly outperforms baseline prediction approaches. The Willmott Index (d

> 0.98) and Nash–Sutcliffe Efficiency (NSE > 0.95) further validate the model’s strong agreement with experimental observations and its high predictive efficiency. Notably, the testing performance is slightly superior to the training results, suggesting the absence of overfitting and confirming the robustness of the trained network.

The predicted versus actual plot also reveals that the majority of data points fall within the ±10% error bounds as presented in Figure 2, highlighting the ANN model’s capability to accurately capture the highly non-linear and temperature-dependent rheological behavior of virgin, aged, and rejuvenated binders. Overall, the ANN model proves to be a highly effective and reliable tool for predicting bitumen rheological properties, offering a practical alternative to extensive laboratory testing.

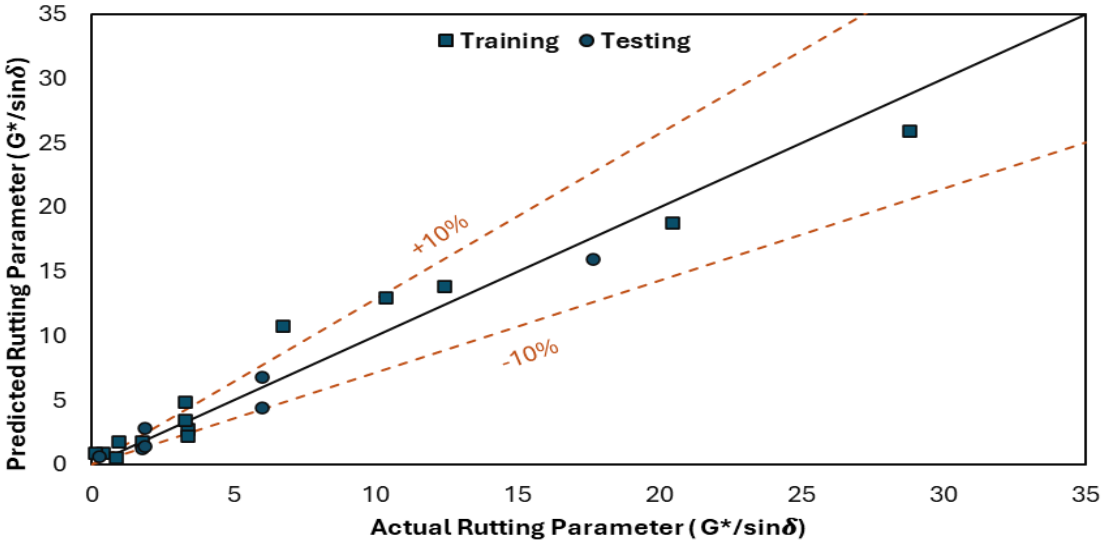

Figure. 2 Actual versus predicted SARA fractions using the ANN model

3.2 Support Vector Machines (SVM)

The Support Vector Machine (SVM) model exhibited excellent predictive capability in estimating the rutting parameter (G*/sin$\boldsymbol{\delta}$), as reflected by the very high correlation coefficients for both training (R = 0.9969) and testing (R = 0.9949) as presented in Figure 3. These values indicate a near-perfect agreement between predicted and experimental results, demonstrating the effectiveness of the SVR framework with the RBF kernel in capturing complex non-linear relationships. The training phase showed very low error values (MAE = 0.4817, RMSE = 0.8584), confirming precise model fitting, while slightly higher testing errors (MAE = 1.0357, RMSE = 1.3061) suggest minor generalization loss, yet still within acceptable limits for engineering applications.

The low RAE (0.0757 for training and 0.2506 for testing) and RRSE (0.1046 and 0.2358) further confirm that the SVM model significantly outperforms baseline predictions. Additionally, the high Willmott Index (d = 0.9971 for training and 0.9843 for testing) and Nash–Sutcliffe Efficiency (NSE = 0.9891 and 0.9444) indicate strong agreement and high predictive efficiency.

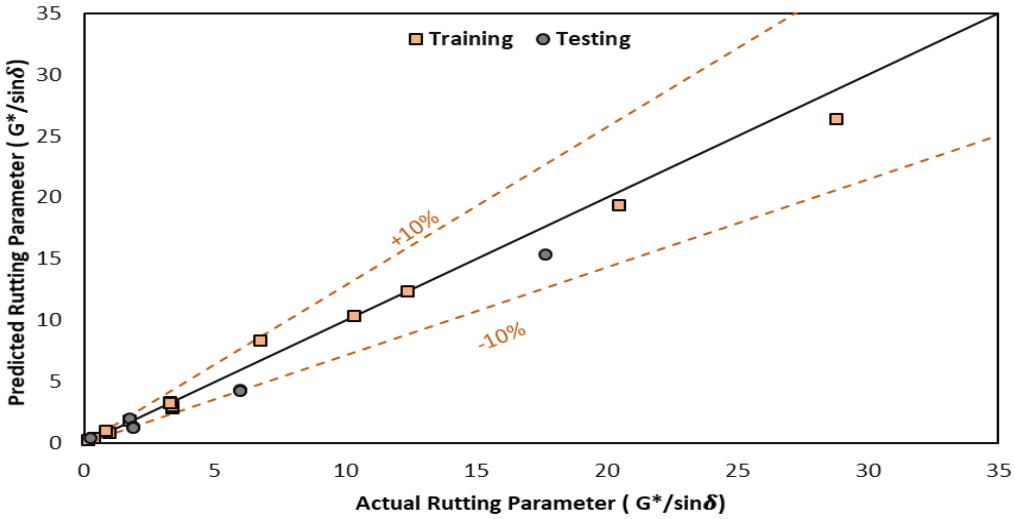

Figure. 3 Actual versus predicted rutting parameters using the SVM model

3.3 Random Forest (RF)

The Random Forest (RF) model demonstrated reliable and stable predictive performance in estimating the rutting parameter (G*/sin$\boldsymbol{\delta}$) as presented in Figure 4, with consistent results across both training and testing datasets. The correlation coefficients obtained for training (R = 0.9734) and testing (R = 0.9735) indicate a strong linear agreement between predicted and experimental values, reflecting good model generalization. The error metrics further support this observation, with MAE values of 1.3753 (training) and 0.9491 (testing), and RMSE values of 1.9225 and 1.2902, respectively. Although these errors are slightly higher compared to ANN and SVM models, they remain within acceptable limits for practical engineering applications.

The RAE and RRSE values (≈0.21–0.23) suggest that the RF model performs significantly better than baseline predictions, while the high Willmott Index (d ≈ 0.985) and Nash–Sutcliffe Efficiency (NSE ≈ 0.945) indicate strong agreement and predictive efficiency. Notably, the similarity between training and testing results highlights the model’s robustness and its resistance to overfitting, a key advantage of ensemble-based methods.

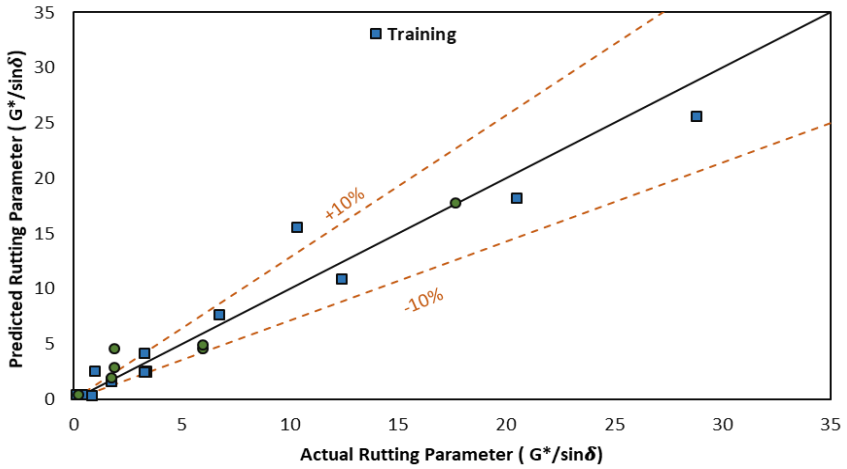

Figure. 4 Actual versus predicted rutting parameters using the RF model

3.5 Best Model Prediction

A comparative evaluation of the three machine learning models—ANN, SVM, and RF—clearly indicates that the Support Vector Machine (SVM) model outperformed the other approaches in predicting the rutting parameter (G*/sin$\boldsymbol{\delta}$). The SVM model achieved the highest correlation coefficients (R = 0.9969 for training and 0.9949 for testing) along with the lowest

error metrics during training, demonstrating superior fitting capability and strong non-linear mapping efficiency. Although the ANN model showed slightly better generalization in terms of lower testing error (RMSE = 1.0548), the SVM maintained consistently high accuracy with minimal deviation, indicating a well-balanced bias–variance trade-off. In contrast, the RF model, while robust and resistant to overfitting, exhibited comparatively higher error values and lower correlation coefficients.

Furthermore, the superior performance of SVM is attributed to its effective use of the RBF kernel, which enables accurate modelling of complex rheological behavior under varying temperature and rejuvenation conditions. Therefore, based on overall statistical performance, predictive accuracy, and consistency, the SVM model is identified as the most optimal and reliable predictive tool for estimating ($G^*/\sin\boldsymbol{\delta}$), offering significant potential for practical implementation in pavement material design and analysis.

Table. 3 Comparison Graph

Metric	Phase	Random Forest (RF)	Artificial Neural Network (ANN)	Support Vector Machine (SVM)
Correlation Coefficient (R)	Training	0.9734	0.9798	0.9969
	Testing	0.9735	**0.9872**	0.9949
Mean Absolute Error (MAE)	Training	1.3753	1.3064	0.4817
	Testing	0.9491	**0.931**	1.0357
Root Mean Squared Error (RMSE)	Training	1.9225	1.723	0.8584
	Testing	1.2902	**1.0548**	1.3061
Relative Absolute Error (RAE)	Training	0.2161	0.2053	0.0757
	Testing	0.2297	**0.2253**	0.2506
Root Relative Squared Error (RRSE)	Training	0.2342	0.2099	0.1046
	Testing	0.233	**0.1905**	0.2358
Willmott Index (d)	Training	0.985	0.9881	0.9971
	Testing	0.9857	**0.9899**	0.9843
Nash–Sutcliffe Efficiency (NSE)	Training	0.9452	0.956	0.9891
	Testing	0.9457	**0.9637**	0.9444

4. CONCLUSION

A comprehensive machine learning framework was successfully developed to predict the high temperature rheological parameter ($G^*/\sin\delta$) of bitumen by using simple and widely accessible empirical inputs which diminishes the need for advanced and costly laboratory testing. The results showed that basic properties like penetration, softening point, temperature, kinematic viscosity and PG grade can be used to describe complex rheological behaviour when integrated with data-driven models. Among the three models considered, the Support Vector Machine (SVM) model showed the best predictive accuracy, with the strongest correlation and lowest prediction error. The Artificial Neural Network (ANN) also showed good predictive and generalisation abilities. The Random Forest (RF) model provided stable and robust predictions

with good resistance to overfitting. The predicted vs. actual values analysis also demonstrated that the majority of the predictions fell within the permissible range of ±10% of error, confirming the universality of the developed models across different ageing and rejuvenation conditions.

The proposed approach offers a quick, inexpensive, and scalable alternative to extensive Dynamic Shear Rheometer (DSR) testing and associated experimental requirements. The proposed framework can aid in the data-driven characterisation of pavement materials and promote the sustainable utilisation of RAP thru the optimisation of rejuvenator dosages. In addition, the methodology shows promise for practical application in pavement engineering thru the provision of a rapid assessment and prediction of binder performance under various conditions.

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