https://doi.org/10.36100/dorogimosti2024.30.157

UDC 625.7/.8

Ali Saleh[1], *https://orcid.org/0000-0002-6275-0297*
László Gáspár[2], *D.Sc., Prof., https://orcid.org/0000-0002-0574-4100*

[1]*Széchenyi István University, Faculty of Civil Engineering, Győr, Hungary*
[2]*KTI Institute for Transport Sciences Non-Profit Ltd., Budapest, Hungary*

MODELLING INDIRECT TENSILE STRENGTH OF WARM MIX ASPHALT WITH VARIABLE RECLAIMED ASPHALT PAVEMENT (RAP) CONTENT

Abstract

Introduction. There is a world-wide trend to also increase the sustainability of the road sector. The growing use of various industrial by-products, together with economical and eco-friendly construction and maintenance techniques can be observed in many countries.

Problem Statement. The utilization of warm mix asphalt and the use of relatively high share of reclaimed asphalt materials in new asphalt mixtures can have negative features, as well.

Purpose. Modelling indirect tensile strength of warm mix asphalt with variable reclaimed asphalt pavement (RAP) content was aimed at based on Hungarian laboratory test series.

Materials and Methods. Three models were developed for the prediction of indirect tensile strength, this important asphalt mechanical parameter of warm mix asphalt as a function of Foamed Bitumen Content (FBC) and the RAP share in the new asphalt mixture. Among others, linear regression analysis and support vector regression (SVR) models were applied.

Results. A comparison performed between Random Forest and Neural Network models illustrates and proves the versatility of machine learning techniques in predicting asphalt indirect tensile strength values both in wet and dry conditions. The research work enhances our understanding of the multifaceted dynamics influencing the performance of asphalt mixtures, offering valuable insights for optimizing pavement design and construction practices in diverse environmental conditions. The model developed successfully captures the relationship between the ITS (wet and dry) metric and its contributing factors, Foamed Bitumen Content (FBC) and RAP, with a high R-squared value.

Keywords: foamed bitumen; warm mix asphalt; Neural Network; support vector regression model; Machine learning.

Introduction

Ninety-six percent of the extensive road network, encompassing a substantial expanse of four million feet, is enveloped by asphalt, underscoring the pervasive integration of this material [1]. The vitality of pavement integrity is contingent upon the nuanced interplay of asphalt mixtures, wherein sophisticated design methodologies assume the role of orchestrators for achieving desirable engineering attributes. Taking centre stage in this milieu are the Superpave method, the Bailey method, the Coarse Aggregate Void Filling method (CVAF), Marshall method and the Balanced Mix method each distinguished as prominent methodologies that intricately contribute to the formulation of asphalt mixtures [2, 3].

The growing interest in warm mix asphalt (WMA) and its associated benefits has become more pronounced in recent years, driven by the potential for reduced costs in road projects, energy efficiency, and decreased fuel consumption. WMA's additional environmental advantages, particularly in emission reduction, contribute positively to both environmental conservation and the well-being of workers. Various technologies have emerged to address the need for lower temperatures in pavement construction, foaming asphalt (bitumen) standing out as an important key in the sustainable pavement construction [4].

The utilization of foam bitumen technology extends widely to the stabilization of base layers, offering a multitude of benefits. These include fortifying the base layer for increased strength, resulting in reduced pavement thickness requirements, enhanced resistance to water permeability, fewer construction-induced wet spots, and heightened resilience to adverse weather conditions. The inception of foaming bitumen dates back to 1956 when Professor Csanyi introduced the concept at Iowa State University [5]. Subsequent advancements by Mobil Oil, including the introduction of an expansion chamber, further refined the technology.

The mechanics of foam bitumen involve a meticulous blending of water, air, and bitumen within the expansion chamber. This orchestrated process entails injecting a small quantity of cold water into hot bitumen, causing it to expand to approximately fifteen times its original volume [6]. The characteristics of foam bitumen, such as the expansion ratio (ER) and half-life (HL), are intricately influenced by factors such as bitumen temperature, water percentage, air pressure, and bitumen quality. It's noteworthy that an increased water content amplifies the expansion ratio while concurrently diminishing the half-life a delicate balance in the intricate operation of sustainable pavement construction.

In addressing environmental sustainability concerns, there is a growing inclination towards optimizing the utilization of recycled asphalt materials (RAM), encompassing both reclaimed asphalt pavement (RAP) and recycled asphalt shingles (RAS). The amalgamation of RAM into novel asphalt mixtures not only serves to mitigate material costs but also contributes to the conservation of non-renewable resources. An investigation conducted by the National Asphalt Pavement Association (NAPA) in 2018 underscored a discernible trend, spotlighting a continuous increase in the nationwide average percentage of RAP in asphalt mixtures—from 15.6 % in 2009 to 21.1 % in 2018. Furthermore, the utilization of RAS experienced a notable upswing of 11.6 % between 2017 and 2018. Intriguingly, a significant 77 % of State Asphalt Paving Associations voiced the perspective that there remains untapped potential to further augment the assimilation of these recycled materials [7].

Studies have delved into the performance of foam bitumen mix (FBM) with varying reclaimed asphalt pavement (RAP) content, as explored by [8] and [9]. The examination of microstructures, particularly the effectiveness of mix coating, has been conducted using scanning electron microscope (SEM), as evidenced by studies such as those by [10] and [11]. The utilization of SEM and X-ray computed tomography has further been employed to scrutinize air void distribution in recycled mixtures, as reported in studies by [12] and [13].

To enhance the efficiency of laboratory experiments, researchers have employed modelling techniques such as artificial neural networks and design of experiments to identify the optimal bitumen content for various mixes. This approach has been exemplified in studies by [14]. Notably, it specifically evaluated the best binder content for warm recycled aggregate mixtures through the application of response surface methodology.

Background

Influence of binder

In a comprehensive exploration, Abreu et al. [15] delved into the influence of bitumen grade on foaming, particularly when combined with varying Reclaimed Asphalt Pavement (RAP) content in Foam Bitumen Mixtures (FBM). Their findings indicated that a softer grade of bitumen becomes imperative as the RAP content increases, leading to improved results in the foaming process. This insight emphasizes the nuanced relationship between bitumen characteristics and RAP content in optimizing foaming outcomes.

Arefin et al. [16] contributed to the body of knowledge by examining the short and long-term aging effects of Foam Bitumen Mixtures (FBM). Their research underscored the pivotal role of binder quality in influencing the aging process of the mixture. This conclusion accentuates the significance of considering the inherent properties of the binder in evaluating the durability and performance of foamed asphalt mixtures over time.

In a more recent investigation, Kar et al. [17] focused on understanding how the asphaltene and aromatic content of bitumen affect foaming characteristics. By scrutinizing these specific components, the study provided valuable insights into the intricate relationship between bitumen composition and the foaming process, contributing to the ongoing refinement of foamed asphalt technologies.

Notably, studies by Bairgi et al. [18] and Hasan et al. [19] challenged conventional notions by revealing that the elastic behaviour, as measured by elastic modulus, of the foamed binder does not exhibit a direct correlation with the foaming water content. This divergence from conventional expectations suggests that the complex interplay of factors influencing the foaming process extends beyond a straightforward relationship between elastic modulus and foaming water content.

Influence of RAP Content on FBM Performance

The impact of reclaimed asphalt pavement (RAP) content on the performance of Foam Bitumen Mix (FBM) has been subject to various investigations. Taziani et al. [20] conducted an assessment on FBM containing 100 % RAP and Portland cement as a filler. Their study involved the evaluation of dynamic creep and dynamic modulus, with comparisons drawn against the addition of fibres into the mix. The findings highlighted a notable positive influence on FBM performance attributed to the inclusion of fibers and cement.

Chomicz-Kowalska and Ramiączek [21] engaged in a comparative analysis between foam mix and emulsion mix. Their evaluation considered different laboratory compaction methods and varied percentages of RAP material. The results shed light on the impact of these factors on the properties of both mixes, emphasizing the significance of RAP content in influencing performance.

Hou et al. [22] delved into the study of RAP gradation's effect on the dynamic modulus of FBM under low temperatures (sub-zero area). Their research indicated that coarser gradations had a diminishing effect on the dynamic modulus of FBM at low temperatures. However, this influence was not significant at higher temperatures.

Guatimosim et al. [23] conducted a comprehensive assessment involving laboratory and field evaluations of cold recycled mix with foamed bitumen. Their results demonstrated early-stage damage in comparison to conventional mixtures. Over time, the deflection reduced with an increase in layer stiffness, emphasizing the evolving nature of FBM performance.

Impact of Mixing Temperature on FBM Performance

Foamed bitumen mixes are placed and compacted at ambient temperatures, often referred to as cold mixes, the role of mixing temperature becomes crucial. Several studies have underscored the significance of heating aggregates for improved coating and enhanced engineering properties [4]. Research indicates that the optimum mixing temperature for foamed asphalt mixes falls within the range of 13 °C to 23 °C, dependent on the aggregate type. Aggregates below this temperature range result in a lower quality foam asphalt mix [5].

Sánchez et al. [24] elevated aggregate temperatures up to 160 °C while preparing FBM samples with 60 % RAP content. Their findings indicated that exceeding an aggregate temperature increase of 90 °C resulted in the aging of RAP, subsequently reducing fatigue resistance. This underscores the importance of carefully controlling mixing temperatures to ensure optimal performance and longevity of foamed bitumen mixes.

Impact of foamed bitumen content

Foamed asphalt binders showcase diminished resistance to shear deformation when juxtaposed with their unfoamed counterparts. The foaming of asphalt, in turn, augments fatigue performance by mitigating asphalt stiffness. This amelioration is ascribed to the reduced temperatures required for mixing and compaction in foamed warm mixes, resulting in a decrease in aging effects. The inclusion of aged binder from reclaimed asphalt pavement (RAP) plays a pivotal role in compensating for the softer warm mix binder, thereby contributing to the mitigation of aging in asphalt binders within Foamed Warm Mix Asphalt (FWMA) containing RAP. Consequently, this intricate interplay underscores the potential advantages of asphalt foaming in optimizing fatigue resistance, particularly in scenarios involving the incorporation of recycled materials like RAP [25].

Methodology

Determination of aggregate gradation and optimum moisture content

Mixed operations involved the use of two gradations containing 100 % reclaimed asphalt pavement (RAP), two with 75 % RAP, two with 50 % RAP, two with 25 % RAP, and two consisting entirely of virgin aggregate all adhering to standard specifications (**Fig. 1**). The maximum specific gravity (Gmm) for these gradations were recorded as follows: 2.464, 2.471, 2.476, 2.468 and 2.474, respectively.

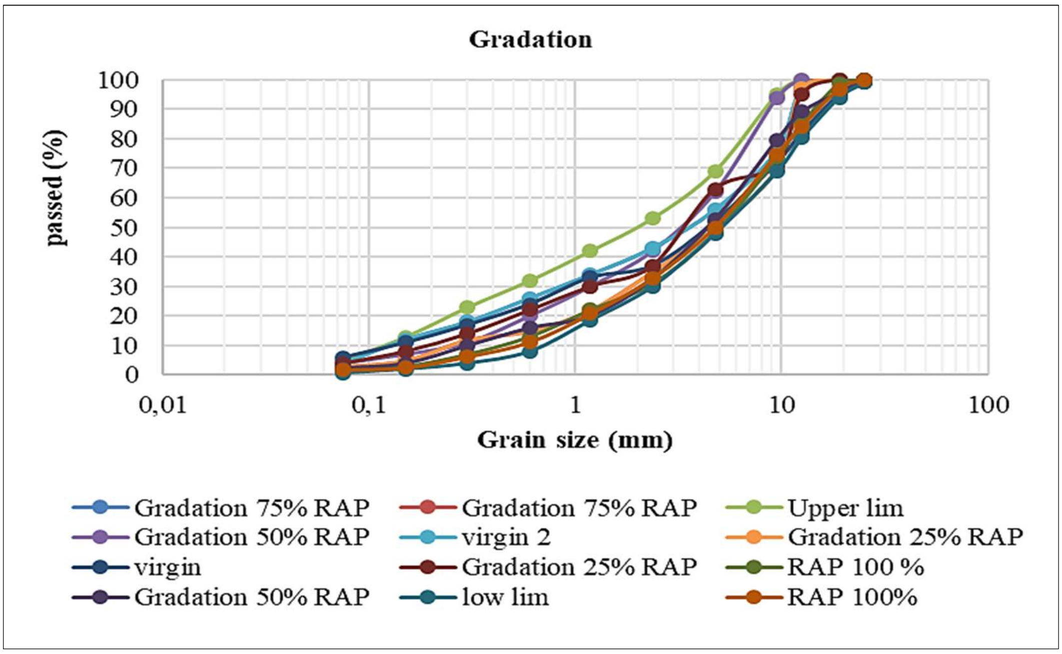

Figure 1 — Gradations selected

Determination of optimum moisture content

In our comprehensive testing series, the bitumen 70/100 was focused on, actually its compatibility with the specified standards. The results demonstrated that bitumen 70/100 met the prescribed criteria, further solidifying its suitability for effective aggregate stabilization in road construction applications. The culmination of these procedures yields optimal foamed bitumen characteristics, as evidenced by a half-life of 10.2 seconds and an expansion ratio of 12.6 times. These desirable properties are attained specifically with a 2 % water content at a bitumen temperature of 170 °C. Notably, these foam characteristics align with the prescribed standards, as articulated by the Wirtgen Group [6], demanding a minimum expansion ratio of 8 times the original volume and a half-life of 6 seconds for effective aggregate stabilization at temperatures exceeding 15 °C (**Figs. 2 – 4**).

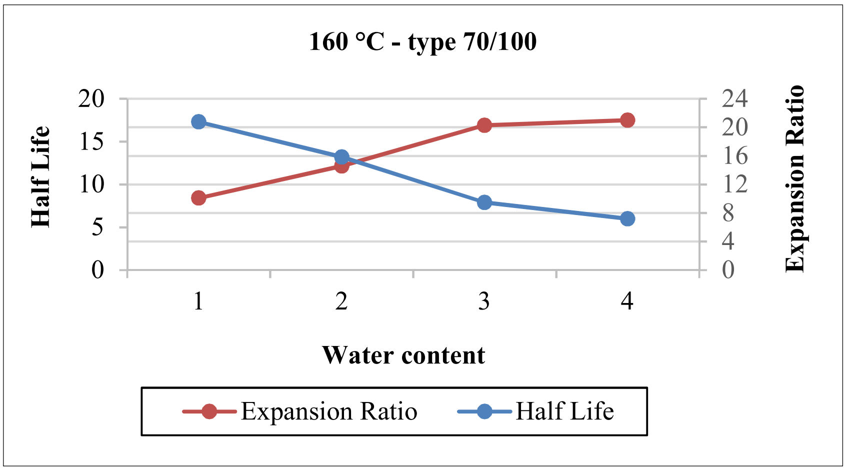

Figure 2 — Expansion Ratio & Half Life for bitumen 70/100 in 160 °C

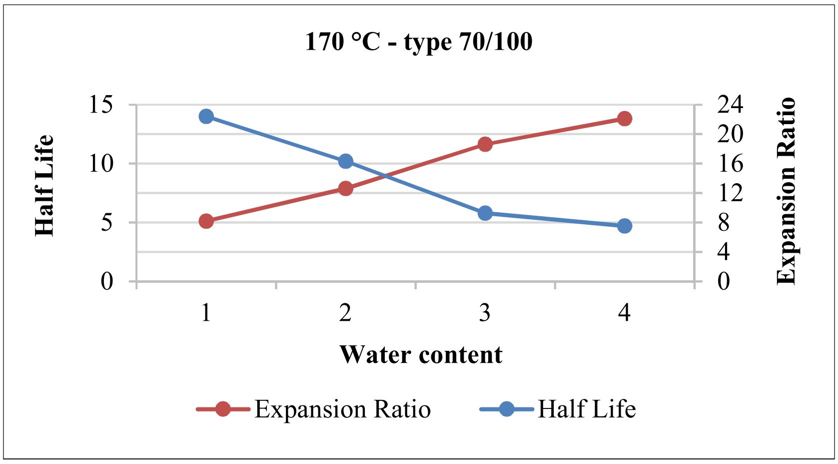

Figure 3 — Expansion Ratio & Half Life for bitumen 70/100 in 170 °C

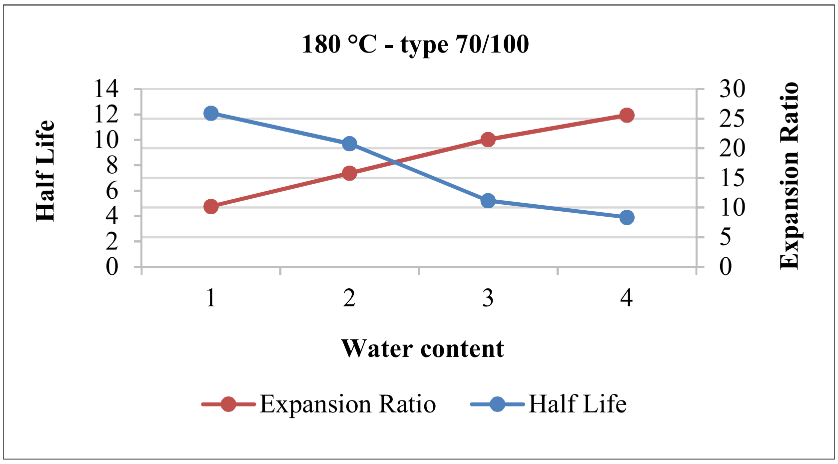

Figure 4 — Expansion Ratio & Half Life for bitumen 70/100 in 180 °C

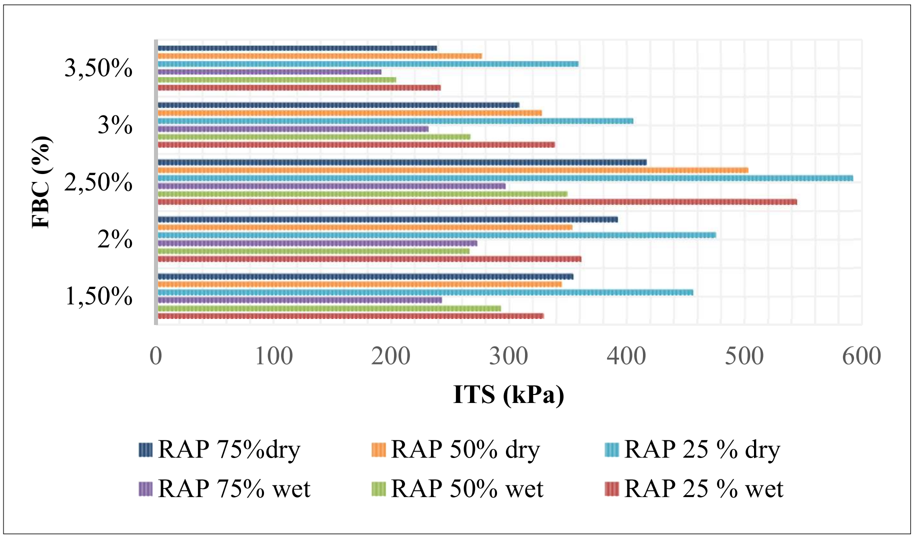

Figure 5 — ITS values as a function of FBC (%) and RAP (%)

Optimization of foam bitumen

The results in **Figure 5** illustrates the influence of both FBC and RAP percentages on the strength of the asphalt mixtures under different conditions. The data suggests that variations in these percentages can lead to significant differences in ITS, emphasizing the importance of carefully selecting FBC and RAP proportions for achieving desired performance characteristics in asphalt mixtures, particularly with respect to strength in wet and dry conditions.

TSR (Tensile Strength Ratio) in Indirect Tensile Strength (ITS) testing is a critical parameter for evaluating the thermal cracking resistance of asphalt mixtures. This testing method assesses the material's tensile strength under different temperature conditions. The TSR is calculated by comparing tensile strength at low and high temperatures. A high TSR indicates better resistance to cracking in cold weather, while a low TSR suggests susceptibility to thermal cracking. Overall, TSR in ITS testing helps in designing and selecting asphalt materials that can withstand diverse temperature conditions, ensuring the durability of asphalt pavements [26].

In **Figure 6**, the Tensile Strength Ratio (TSR) values are depicted for various combinations of Reclaimed Asphalt Pavement (RAP) and Foam Bitumen Content (FBC). All data points exhibit TSR values equal to or greater than 70, except for the specific case of (RAP 25 % with FBC 3.5 %), suggesting potential vulnerability to thermal cracking in this percentages.

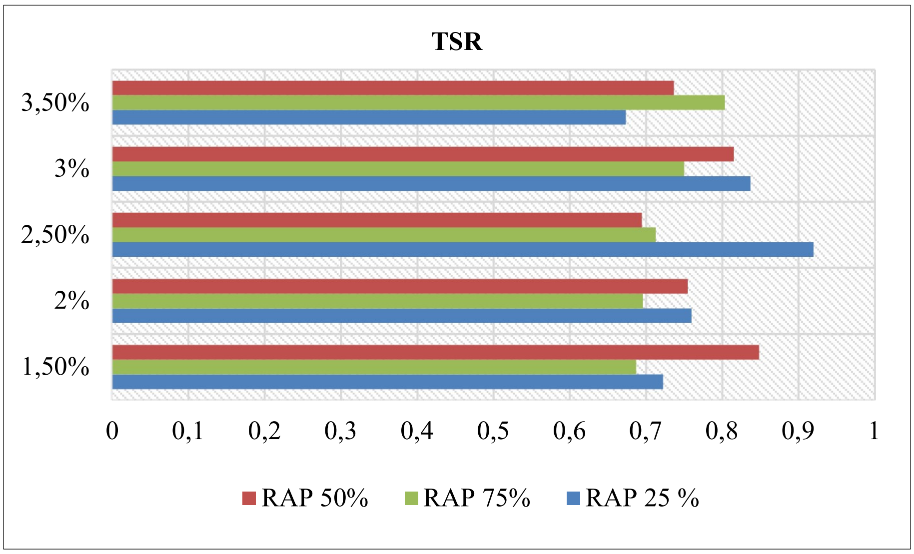

Figure 6 — Tensile Strength Ratio values as a function of FBC (%) and RAP (%)

Machine learning models

Support Vector regression (SVR)

The concept of Support Vector Machines for regression problems was initially introduced by Vapnik et al. [27] serving as a margin of tolerance (epsilon), is individually determined. Samples outside this region contribute to the calculation of the overall loss. The essence of SVR lies in fitting the target curve to minimize errors and customize the hyperplane for maximizing the margin.

The versatility of the SVR algorithm has been increasingly utilized for predicting various properties of asphalt mixtures in recent research. Notably, SVR has proven to be a precise model for predicting the dynamic modulus [28], [29] in predicting the dynamic modulus of Hot Mix Asphalt (HMA) [28]. Furthermore, SVR models have successfully predicted rut depth and indirect tensile strength of asphalt mixtures [30], [31]. Significantly, SVR models have also been developed for predicting pavement conditions with promising outcomes [32], [33]. This highlights the versatility and efficacy of SVR in diverse applications within the realm of asphalt research and pavement performance prediction.

Adam optimizer

The Adam optimizer is a popular optimization algorithm used in training neural networks. It stands for Adaptive Moment Estimation, and it combines techniques from two other optimization algorithms: Momentum optimization and RMSProp (Root Mean Square Propagation). Adam is known for its effectiveness in handling sparse gradients, noisy data, and non-stationary objective functions. Adam's adaptive learning rates for each parameter and its momentum-like behaviour make it well-suited for training deep neural networks. It combines the advantages of both momentum and RMSProp, providing robust and efficient optimization for a wide range of deep learning tasks [34].

Random Forest (RF)

Ensemble approaches leverage the synergy of multiple learning algorithms to enhance predictive performance beyond the capabilities of individual algorithms [35]. Bagging (Bootstrap Aggregating) is a prominent method within ensemble learning, and Random Forest emerges as an advanced iteration, building on the principles of bootstrap aggregation. This technique aggregates predictions from a series of decision trees [36].

Random Forest distinguishes itself from bagging by introducing a unique advantage it can selectively choose a subset of features for splitting when constructing each decision tree. This feature significantly reduces the model's variance without introducing undue prediction bias. In the Random Forest algorithm, the final output is determined through a majority voting mechanism, especially in regression scenarios.

Random Forest has demonstrated effectiveness in predicting critical characteristics such as dynamic modulus [9], rut depth [37], International Roughness Index (IRI) [37], alligator cracking [38], and pavement friction [39]. Its flexibility and robustness position Random Forest as a valuable tool in asphalt research, contributing to precise predictions and informed decision-making in the evaluation of pavement properties and performance.

Bitumen foaming model

Three models were built, the first model is a regression task in machine learning, specifically using a neural network to predict the 'ITS' based on input features 'FBC' and 'RAP'. The model utilizes a training loop that refines the model iteratively until the model be able to simulate and study a lot of new values with different conditions.

The second model was built based on the previous one, it conducts linear regression analysis on a dataset comprising four columns: 'FBC', 'RAP', 'ITS_Dry', and 'ITS_Wet'.

The third model was utilizing Support Vector Regression (SVR) to predict Indirect Tensile Strength (ITS) under wet and dry conditions was used.

After that, RF model was built to check the previous models, two separate instances are trained for wet and dry conditions. Following training, the models are evaluated on the test set, and the mean squared error is calculated to quantify their predictive performance.

Results

Relationship between input and ITS

Foamed Bitumen Content (FBC) Impact on ITS

Mechanical Properties: The foamed bitumen content increases the stiffness and flexibility of the asphalt mixture.

Enhanced Performance: Properly controlled FBC can lead to improved adhesion between aggregates and the bitumen binder. This enhanced adhesion can contribute to higher indirect tensile strength (ITS), indicating better resistance to cracking and improved overall performance of the pavement.

Reclaimed Asphalt Pavement (RAP) Influence on Mechanical Properties

Sustainability: The use of RAP in asphalt mixes is a sustainable practice as it reduces the demand for virgin materials and minimizes the environmental impact associated with asphalt production.

ITS and Durability: The balanced use of RAP contributes to a mix of good durability and resistance to distress, enhancing the long-term performance of the pavement.

Customization: The combined use of FBC and RAP allows to customize asphalt mix designs to meet specific project requirements, considering factors such as climate, traffic loads, and pavement structure.

Performance of ML models

The first model in this machine learning regression task utilizes a neural network to predict the Indirect Tensile Strength ('ITS') based on input features 'FBC' and 'RAP.' The model undergoes a training loop, refining itself iteratively to simulate and study a wide range of new values under different conditions. In the data preparation step, input features are consolidated into a NumPy array `X`, and the target variable 'ITS' is stored in an array `y`. The training loop involves splitting the data into training and testing sets, standardizing features using `StandardScaler`, and constructing a neural network with specific architecture using the Keras API.

The neural network comprises an input layer with 2 neurons, a hidden layer with 64 neurons and 'relu' activation, another hidden layer with 32 neurons and 'relu' activation, and an output layer with 1 neuron for regression. The model is compiled using the Adam optimizer and mean squared error loss. It is then trained on standardized data for 200 epochs. The Mean Squared Error on the test data and R-squared are calculated, and the training history, including plots of loss, validation loss, and $R2$, is visualized in **Figure 7**.

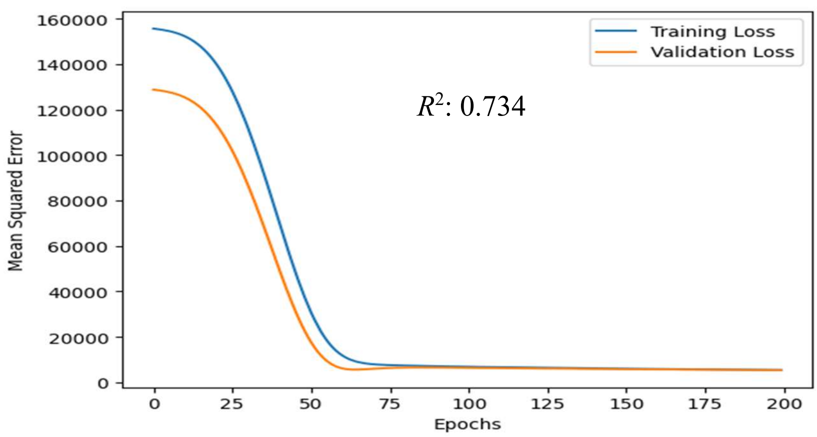

Figure 7 — Training and Validation Loss histories (model 1)

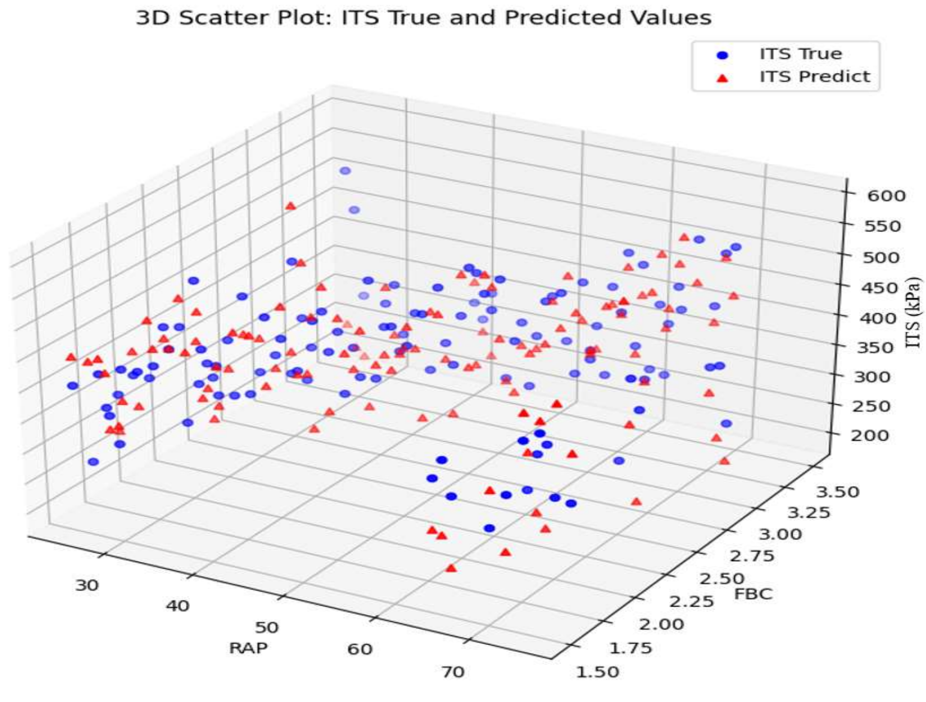

Figure 8 — 3D scatter plot of ITS values as a function of FBC (%) and RAP (%)

Figure 8 displays 3D scatter plots that result from the trained model, offering a visual representation of the relationship between true and predicted 'ITS' values. These plots provide insights into how well the model aligns with the actual data. Additionally, **Figure 9** shows 2D scatter plots captured during the training process, allowing observation of the evolution and adjustments in the model's predictions over time.

A correlation analysis between the variables investigated was performed, as shown in **Figure 10**.

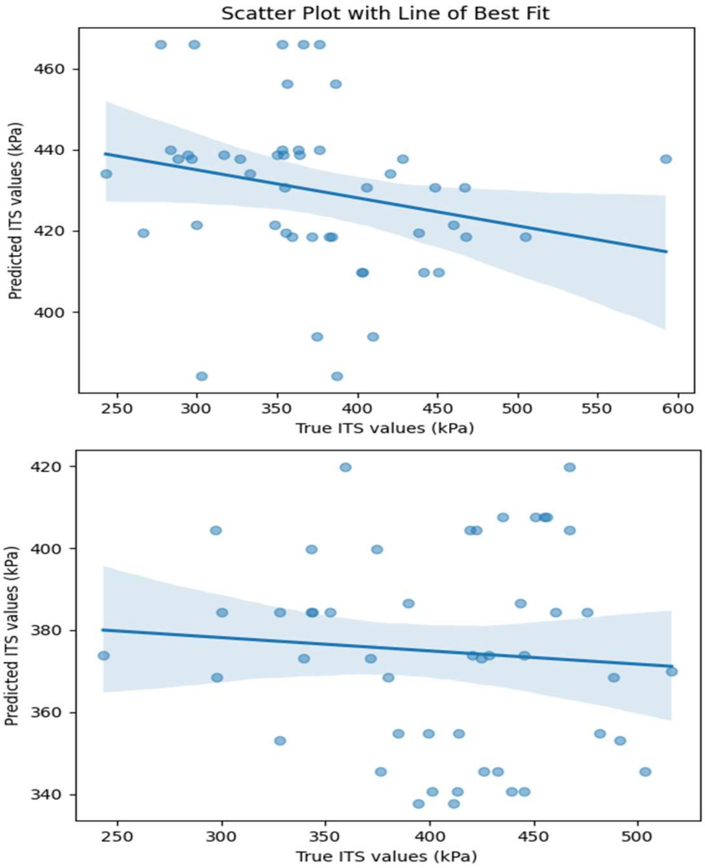

Figure 9 — 2D scatter plots of ITS values during training process

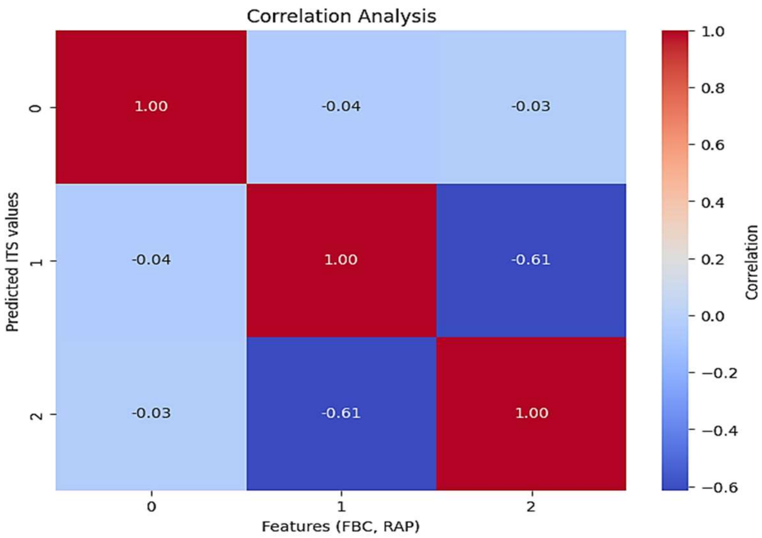

Figure 10 — Correlation analysis (model 1)

The final equation of the model is expressed as:

$$ITS = 0.294 \cdot FBC + 13.57 \cdot RAP + 387.49. \quad (1)$$

This equation captures the relationship learned by the neural network between the input features and the predicted 'ITS' values.

The training process involves the use of the mean squared error (MSE) loss function and the Adam optimizer. The key equations associated with the learning process include:

(1) MSE Loss Function:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2. \quad (2)$$

The Mean Squared Error is employed as the loss function, where n is the number of data points, y_i is the true 'ITS' value, and $\hat{y}_i$ is the predicted 'ITS' value.

(2) Adam Optimization:

The Adam optimizer updates the model weights using the following equations:
update rules at each time step (t):

$$t = t + 1, \quad (3)$$

compute gradient at time step t:

$$g_t = \nabla_\theta \cdot J\,(\theta_t)\,, \quad (4)$$

update first moment estimate:

$$m_t = \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t\,, \quad (5)$$

update second moment estimate:

$$m_t = \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t, \quad (6)$$

bias-corrected first moment estimate:

$$\widehat{m}_t = \frac{m_t}{1 - \beta_1^t}\,, \quad (7)$$

bias-corrected second moment estimate:

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t}\,, \quad (8)$$

update parameters:

$$\theta_{t+1} = \theta_t - \alpha \cdot \frac{\widehat{m}_t}{\sqrt{\hat{v}_t} + \varepsilon}\,. \quad (9)$$

Here, $J\,(\theta_t)$ represents the objective function with respect to the parameters θ_t, $\nabla_\theta \cdot J\,(\theta_t)$ is the gradient of the objective function, and ε is a small constant (e.g., (1e-8) added to avoid division by zero.

These equations play a crucial role in adjusting the model parameters during training, aiming to minimize the MSE loss and enhance the predictive accuracy of the 'ITS' values.

The second model performs linear regression analysis on a dataset containing four columns: 'FBC', 'RAP', 'ITS_Dry', and 'ITS_Wet.' The data is loaded into a Pandas DataFrame and then divided into features (X) and target variables (y). The dataset undergoes further partitioning into training (80 %) and testing (20 %) sets using `train_test_split`. To maintain consistent scales across features, feature scaling is applied using `StandardScaler`.

The linear regression model is trained on the training data utilizing the `LinearRegression` class from scikit-learn. Predictions are generated on the scaled test set. Notably, this model considers both 'ITS_Dry' and 'ITS_Wet' as distinct outputs. Visual assessment of the model's performance is conducted through the creation of two scatter plots (**Fig. 11**). The first subplot presents a scatter plot with the line of best fit for 'ITS_Dry,' while the second subplot does the same for 'ITS_Wet.'

The correlation analysis was performed as shown in **Figure 12**.

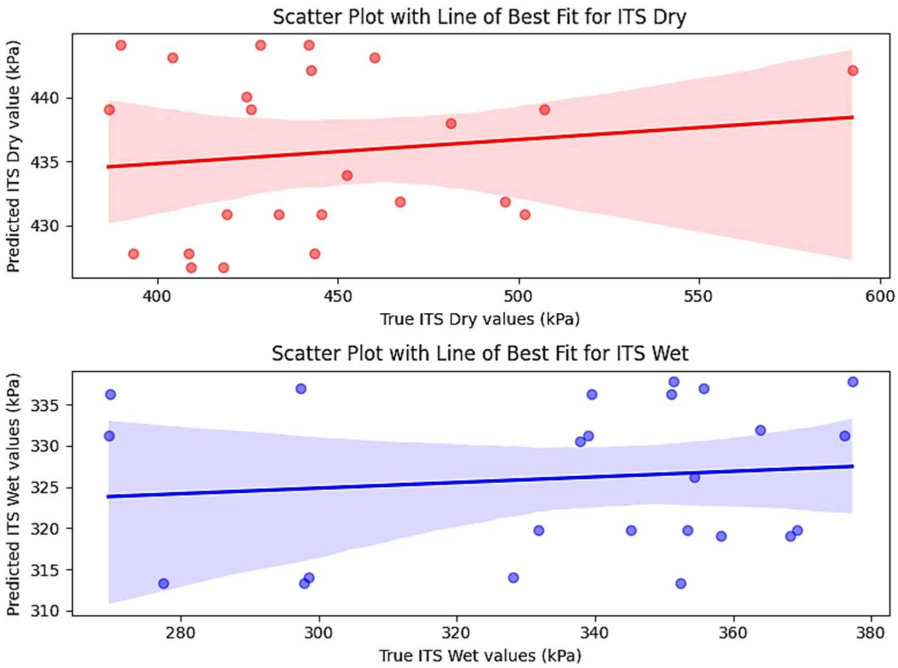

Figure 11 — Scatter Plot with Line of Best Fit for ITS Dry and ITS wet (model 2)

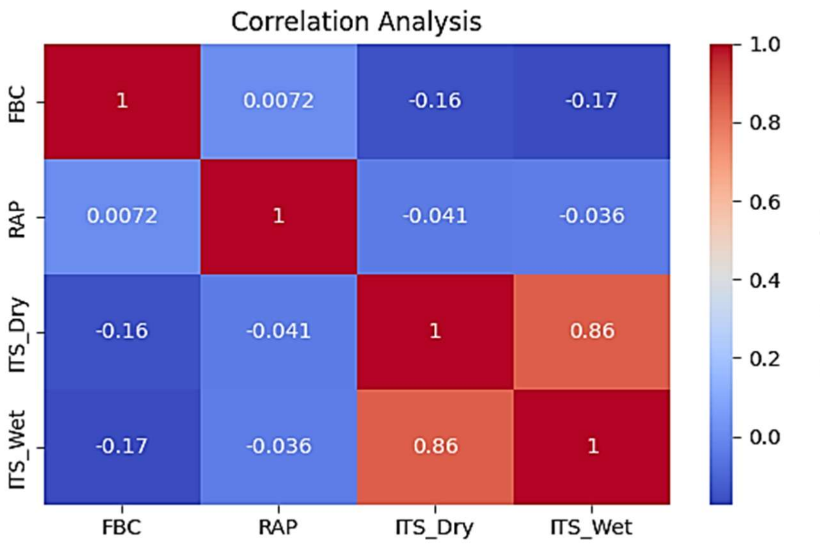

Figure 12 — Correlation analysis (model 2)

The Neural Network models are designed with two hidden layers, comprising 256 and 128 neurons, and ReLU activation functions. These models are compiled using the Adam optimizer with a learning rate of 0.001 and mean squared error loss. The features are standardized using `StandardScaler`, and the Neural Network models are then trained for 300 epochs as shown in **Figure 13**.

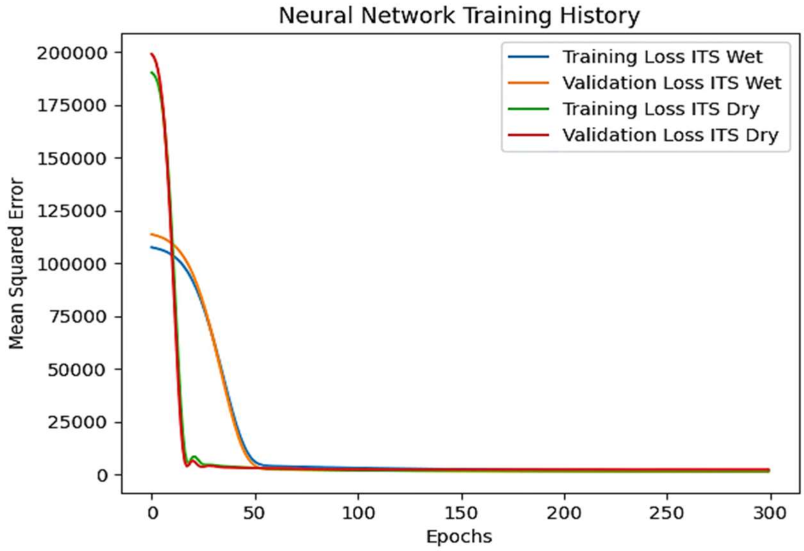

Figure 13 — Neural network training history (model 3)

The third model utilizes Support Vector Regression (SVR) to predict Indirect Tensile Strength (ITS) under wet and dry conditions was used. The dataset is structured with features ('FBC' and 'RAP') and corresponding target variables ('ITS_wet' and 'ITS_dry'). The dataset is then split into training and testing sets for both wet and dry conditions. To ensure consistent scaling, feature standardization is performed using `StandardScaler`. Two SVR models are trained separately for wet and dry conditions, employing a linear kernel.

Following training, predictions are made on the test set, and model performance is evaluated using key metrics such as *R*-squared and correlation coefficients for both wet and dry conditions. The dataset is split into training and testing sets, and feature standardization is performed using `StandardScaler`. The model is trained for 300 epochs with a batch size of 32, and the training history (**Fig. 14**), including loss and validation loss.

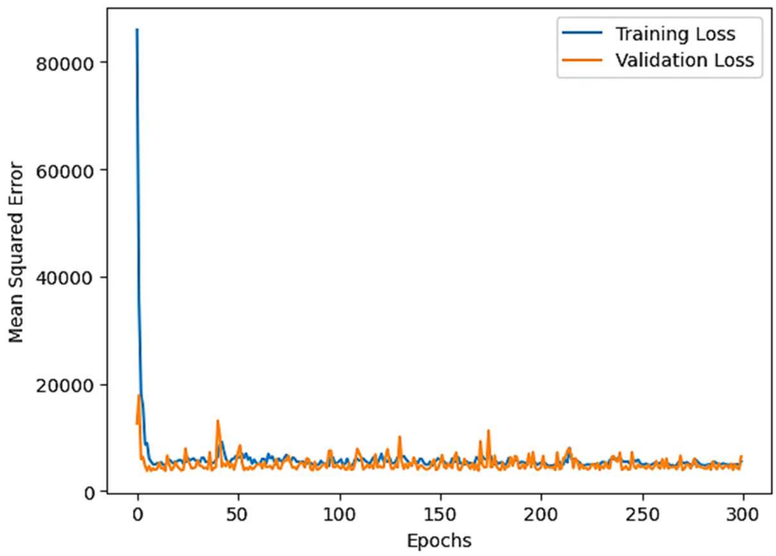

Figure 14 —Training and Validation Loss histories (model 3)

The ITS metric performance is:
For ITS wet: R-squared: 0.7125; correlation: – 0.025.
For ITS dry: R-squared: 0.7801; correlation: – 0.023.

The ITS metric performance is:
For ITS wet: R-squared: 0.7125; correlation: – 0.025.
For ITS dry: R-squared: 0.7801; correlation: – 0.023.

The resulted equations for this model were:

$$\text{ITS wet} = 341.33 + - 1.44 \cdot \text{FBC} + 2.81 \cdot \text{RAP}\,, \tag{10}$$

$$\text{ITS dry} = 412.30 + - 1.48 \cdot \text{FBC} + 2.77 \cdot \text{RAP}. \tag{11}$$

In the checking model (using Random Forest) scatter plots are generated to provide a visual representation of the predictions made by both Random Forest and Neural Network models against the true 'ITS' values for both wet and dry conditions (**Fig. 15**).

Furthermore, a correlation analysis is conducted to determine the correlation coefficients between thetrue and predicted 'ITS' values for both Random Forest and Neural Network models in wet and dry conditions (**Fig. 16**).

The model evaluates two predictive models, namely Random Forest and Neural Network, for estimating 'ITS' values in both wet and dry conditions based on the features 'FBC' and 'RAP'. The Random Forest models are constructed using the `Random Forest Regressor` from scikit-learn with 100 estimators, while the Neural Network models are built using Keras with a consistent architecture for wet and dry conditions.

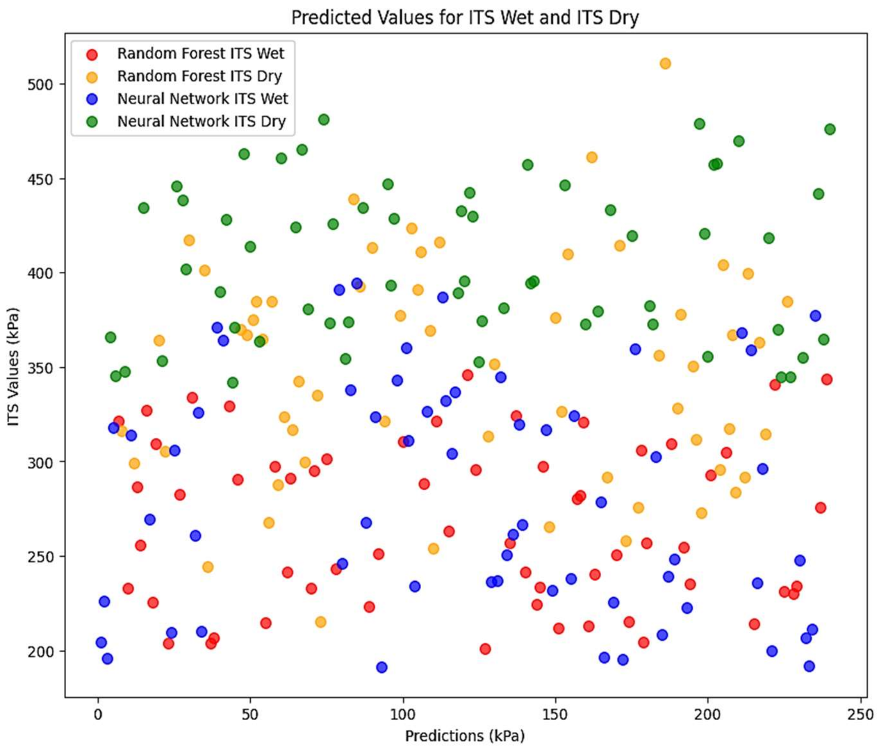

Figure 15 — Scatter plot of ITS Wet and Dry values predicted by Random Forest and Neural Network models (model 3)

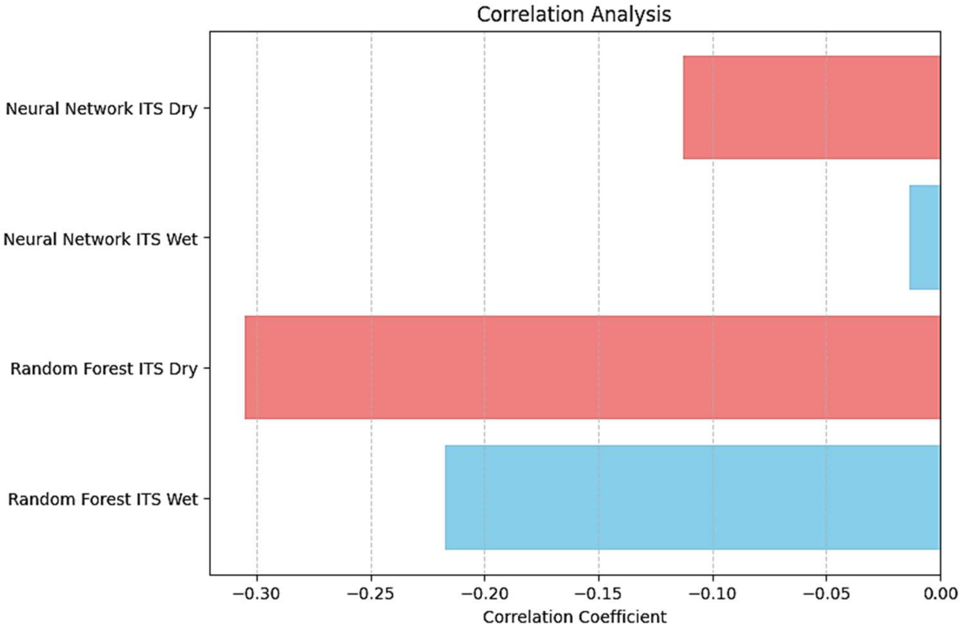

Figure 16 — Correlation analysis with correlation coefficients (model 3)

Conclusions

In conclusion, the comprehensive analysis undertaken in this study sheds light on the intricate relationships between foamed bitumen content (FBC), reclaimed asphalt pavement (RAP), and the indirect tensile strength (ITS) of asphalt mixtures. The impact of FBC on mechanical properties and enhanced performance, coupled with the sustainable practices associated with RAP, collectively contribute to the overall durability and resistance to distress of asphalt pavements.

The developed model successfully captures the relationship between ITS metric and its contributing factors, FBC and RAP. The model demonstrates a reasonably high $R2$-value of 0.734, indicating a good fit to the data.

Further analysis of the model's performance in different conditions reveals that the ITS metric exhibits distinct behaviour in wet and dry conditions. For ITS wet, the $R2$-value of 0.712 and a low correlation of — 0.025 suggest a moderate fit to the data. In contrast, ITS dry demonstrates a higher $R2$-value of 0.780 and a similarly low correlation of — 0.02, indicating a slightly better fit in dry conditions.

Linear regression analysis and support vector regression (SVR) models are also explored, each providing valuable insights into the prediction of ITS under different conditions. The models' evaluation, including scatter plots, correlation analyses, and $R2$-metrics, demonstrates the effectiveness of these approaches in capturing the inherent complexities of the asphalt mixture.

Furthermore, the comparison between Random Forest and Neural Network models proves the versatility of ML techniques in predicting asphalt ITS values for both wet and dry conditions.

References

1. Roberts, F. L., Mohammad, L. N.,Wang, L. B. History of Hot Mix Asphalt Mixture Design in the United States. 2011 [in English].

2. Cooper, S. B. et al. Balanced asphalt mixture design through specification modification: Louisiana's experience, Transportation Research Record. 247 (1), 2014. DOI: https://doi.org/10.3141/2447-10 [in English].

3. Baghaee M. T., Baaj, H. Application of compressible packing model for optimization of asphalt concrete mix design. *Construction and Building Materials.* 159, 2018. P. 530–539 [in English].

4. Kar, S. S. et al. Impact of low viscosity grade bitumen on foaming characteristics. *Journal of the South African Institution of Civil Engineering*. 60 (2), 2018. P. 40–52 [in English].

5. Csanyi, L. H. Foamed asphalt in bituminous paving mixtures. *Highway Research Board Bulletin*, 160, 1957. P. 108–122 [in English].

6. Wirtgen, G. Wirtgen cold recycling technology. 2012 [in English].

7. Williams, B. A., Copeland, A., Ross, T. C. Asphalt pavement industry survey on recycled materials and warm-mix asphalt usage: 2017. 2018 [in English].

8. Iwanski, M. M., Chomicz-Kowalska, A., Maciejewski, K. Resistance to moisture-induced damage of half-warm-mix asphalt concrete with foamed bitumen. *Materials*. 13 (3), 2020, 654. DOI: http://doi.org/ma13030654 [in English].

9. Kar, S. S. et al. Impact of binder on properties of foamed bituminous mixtures. *Proceedings of Institution of Civil Engineers: Construction Materials*. 170 (4), 2017. P. 194–204 [in English].

10. Hoy, M., Horpibulsuk, S., Arulrajah, A. Strength development of Recycled Asphalt Pavement - Fly ash geopolymer as a road construction material. *Construction and Building Materials*, 117, 2016. P. 209–219 [in English].

11. Dong, F. et al. Comparison of high temperature performance and microstructure for foamed WMA and HMA with RAP binder. *Construction and Building Materials*, 134, 2017. P. 594–601 [in English].

12. Li, J., Fu, W., Zang, H. Design Method for Proportion of Cement-Foamed Asphalt Cold Recycled Mixture. MATEC Web of Conferences, 142, 2018, 02002 [in English].

13. Li, Z. et al. Effect of cement on the strength and microcosmic characteristics of cold recycled mixtures using foamed asphalt. *Journal of Cleaner Production*, 230, 2019, P. 956–965 [in English].

14. Bala, N., Napiah, M., Kamaruddin, I. Nanosilica composite asphalt mixtures performance-based design and optimisation using response surface methodology. *International Journal of Pavement Engineering*. 21 (1), 2020. P. 29–40 [in English].

15. Abreu, L. P. F. et al. Suitability of different foamed bitumens for warm mix asphalts with increasing recycling rates. *Construction and Building Materials*, 142, 2017. P. 342–353 [in English].

16. Arefin, M. S. et al. Effect of short-term and long-term ageing on dynamic modulus of foamed warm mix asphalt. International *Journal of Pavement Engineering*. 21 (4), 2020. P. 524–536 [in English].

17. Kar, S. S. et al. Impact of Chemical Composition on Foaming Characteristics of Asphalt Binder. *Journal of Transportation Engineering, Part B: Pavements*. 146 (3), 2020, 04020045 [in English].

18. Bairgi, B. K., Mannan, U. A., Tarefder, R. A. Influence of foaming on tribological and rheological characteristics of foamed asphalt. *Construction and Building Materials*. 205, 2019. P. 186–195 [in English].

19. Hasan M. R. et al. Characterizations of foamed asphalt binders prepared using combinations of physical and chemical foaming agents. *Construction and Building Materials.* 204, 2019. P. 94–104 [in English].

20. Taziani, E. A. et al. Investigation on the combined effect of fibers and cement on the mechanical performance of foamed bitumen mixtures containing 100 % RAP. Advances in Materials Science and Engineering, 2016 [in English].

21. Chomicz-Kowalska, A., Ramiaczek, P. Comparative Evaluation and Modification of Laboratory Compaction Methods of Road Base Mixtures Manufactured in Low-emission CIR Technology with Foamed Bitumen and Bitumen Emulsion. In: Procedia Engineering. Elsevier Ltd. 2017. P. 560–569 [in English].

22. Hou, Y. et al. Dynamic Characteristics of Warm Mix Foamed Asphalt Mixture in Seasonal Frozen Area. Advances in Materials Science and Engineering, 1825643, 2019 DOI: https://doi.org/10.1155/20191825643 [in English].

23. Guatimosim, F. V. et al. Laboratory and field evaluation of cold recycling mixture with foamed asphalt. *Road Materials and Pavement Design*, 19 (2), 2018. P. 385–399 [in English].

24. Sánchez, D. B., Airey, G., Caro, S., Grenfell, J. Effect of foaming technique and mixing temperature on the rheological characteristics of fine RAP-foamed bitumen mixtures. *Road Materials and Pavement Design*, 21 (8) 2020, 2143–2159. DOI: https://doi.org/10.1080/14680629. 2019. 159322 [in English].

25. Gandhi, T., Rogers, W., Amirkhanian, S. Laboratory evaluation of warm mix asphalt ageing characteristics. *International Journal of Pavement Engineering*, 11 (2), 2010. P. 133–142 [in English].

26. Kamran, F. et al. Performance evaluation of stabilized base course using asphalt emulsion and asphaltenes derived from Alberta oil sands. In *Transportation Research Record. SAGE Publications Ltd*. 2675 (10), 2021. P. 764–775. DOI: https://doi.org/10.1177/03611981211012692 [in English].

27. Vapnik, V. The nature of statistical learning theory. Springer Science & Business Media. 1999 [in English].

28. Gopalakrishnan, A., Kim, S. Support Vector Machines Approach to HMA Stiffness Prediction. *Journal of Engineering Mechanics*, 137 (2), 2010. P. 324–335. DOI: https://doi.org/10.1061/(ASCE)EM. 1943-7889. 0000214 [in English].

29. Maalouf, M., Khoury, N., Trafalis, T. B. Support vector regression to predict asphalt mix performance. *International Journal for Numerical and Analytical Methods in Geomechanics*, 32 (16), 2008. P. 1989–1996 [in English].

30. Nazemi, M., Heidaripanah, A. Support vector machine to predict the indirect tensile strength of foamed bitumen-stabilised base course materials. *Road Materials and Pavement Design*, 17 (3), 2016. P. 768–778 [in English].

31. Zhao, Y. et al. Prediction of air voids of asphalt layers by intelligent algorithm. *Construction and Building Materials*, 317, 2022. 125908 [in English].

32. Ziari, H. et al.: Prediction of pavement performance: Application of support vector regression with different kernels. *Transportation Research Record*, 2589, 2016. P. 135–145 [in English].

33. Karballaeezadeh, N. et al. Prediction of remaining service life of pavement using an optimized support vector machine (case study of Semnan–Firuzkuh road). *Engineering Applications of Computational Fluid Mechanics*, 13 (1), 2019. P. 188–198.

34. Huang, Y., Li, J., Fu, J. Review on application of artificial intelligence in civil engineering, CMES - *Computer Modeling in Engineering and Sciences*, 121 (3), Tech Science Press, 2019. P. 845–875. DOI: https://doi.org/10.32604/cmes.2019.07653 [in English].

35. Gong, H. et al. Use of random forests regression for predicting IRI of asphalt pavements. *Construction and Building Materials*, 189, 2018. P. 890–897 [in English].

36. Fathi, A. et al. Parametric Study of Pavement Deterioration Using Machine Learning Algorithms. Proceedings of International Airfield and Highway Pavements Conference, 2019. P. 12. DOI: http://dx.doi.org/10.1061/9780784482476.004 [in English].

37. Gong, H. et al. Investigating impacts of asphalt mixture properties on pavement performance using LTPP data through random forests. *Construction and Building Materials*, 204, 2019. P. 203–212 [in English].

38. Zhan, Y. et al. Effect of aggregate properties on asphalt pavement friction based on random forest analysis. *Construction and Building Materials*, 292. 2021 [in English].

39. Daneshvar, D., Behnood, A. Estimation of the dynamic modulus of asphalt concretes using random forests algorithm. *International Journal of Pavement Engineering*, 23 (2), 2022. P. 250–260 [in English].

Салех Алі[1], https://orcid.org/0000-0002-6275-0297
Ласло Гаспар[2], *д-р техн. наук, проф.*, https://orcid.org/0000-0002-0574-4100

[1]*Університет Іштвана Сечені, Факультет будівництва, Дьєр, Угорщина*
[2]*Інститут транспортних наук KTI, Некомерційна ТОВ, Будапешт, Угорщина*

МОДЕЛЮВАННЯ НЕПРЯМОЇ МІЦНОСТІ НА РОЗТЯГ ТЕПЛИХ АСФАЛЬТОБЕТОННИХ СУМІШЕЙ ЗІ ЗМІННИМ ВМІСТОМ РЕГЕНЕРОВАНОГО АСФАЛЬТОБЕТОННОГО ПОКРИТТЯ (RAP)

Анотація

Вступ. Сьогодні існує світова тенденція підвищення стійкості дорожнього сектора. У багатьох країнах спостерігається зростання використання різних промислових відходів, а також економічних та екологічних методів будівництва і технічного обслуговування.

Постановка проблеми. Використання теплих асфальтобетонних сумішей та застосування відносно високого вмісту регенерованих асфальтобетонних матеріалів у нових асфальтобетонних сумішах також може мати негативні наслідки.

Мета. Метою дослідження було моделювання непрямої міцності на розтяг теплих асфальтобетонних сумішей зі змінним вмістом регенерованого асфальтобетонного покриття (RAP) на основі серії угорських лабораторних тестів.

Матеріали та методи. Було розроблено три моделі для прогнозування непрямої міцності на розтяг, цього важливого механічного параметра теплих асфальтобетонних сумішей, як функції вмісту спіненого бітуму (FBC) та частки RAP у новій асфальтобетонній суміші. Зокрема, було застосовано методи лінійного регресійного аналізу та підтримуючих векторних регресійних моделей (SVR).

Результати. Порівняння, проведене між моделями випадкового лісу та нейронної мережі, ілюструє та доводить універсальність методів машинного навчання у прогнозуванні значень непрямої міцності асфальтобетону як у вологих, так і в сухих умовах. Це дослідження покращує наше розуміння багатогранної динаміки, що впливає на ефективність асфальтобетонних сумішей, та надає цінні знання для оптимізації проектування та будівельних практик дорожнього покриття в різних умовах навколишнього середовища. Розроблена модель успішно відображає взаємозв’язок між показником ITS (вологий і сухий) та його чинниками, такими як вміст спіненого бітуму (FBC) і RAP, з високим значенням коефіцієнта детермінації R^2.

Ключові слова**:** машинне навчання, модель підтримуючих векторів регресії, нейронна мережа, спінений бітум, теплий асфальтобетон.