

Journal of Materials and Engineering Structures

Research Paper

Machine Learning Approaches for Predicting Flexible Asphalt Pavement Elastic Modulus: ANN vs. Random Forest vs. XGBoost

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ARTICLE INFO

Article history :

Received 9 March 2025

Accepted 24 June 2025

Keywords:

Machine Learning

Elastic Modulus

Asphalt Pavement

Quanlity Control and Assurance

ABSTRACT

This study compared four predictive models—Linear Regression (LR), Artificial Neural Networks (ANN), Random Forest (RF), and Extreme Gradient Boosting (XGBoost)—for estimating the elastic modulus of flexible asphalt pavement. ANN demonstrated the highest predictive accuracy, with an optimized architecture featuring a single hidden layer with nine neurons. It achieved the best performance, with an R^2 value of 0.997, RMSE of 0.677, and MAE of 0.483. LR showed the weakest results, while RF and XGBoost performed better, with XGBoost slightly outperforming RF. However, neither model surpassed ANN. The findings highlight the importance of selecting appropriate predictive models for pavement modulus estimation, as ANN effectively captured complex nonlinear relationships. Due to limited data, the study evaluated models without splitting the dataset, which may have led to an overly optimistic assessment. Future research should incorporate larger datasets from diverse pavement structures and traffic conditions to improve model generalization. Additionally, exploring hybrid modeling approaches that combine multiple machine learning algorithms could further enhance predictive accuracy, offering more robust solutions for pavement design and quality assessment.

1 Introduction

Artificial Intelligence (AI) and Machine Learning (ML) have emerged as powerful tools in engineering, offering advanced computational capabilities to analyze complex relationships between variables. Among these, Artificial Neural Networks (ANNs) have demonstrated high efficiency in pattern recognition and predictive modeling. In pavement engineering, AI-based approaches have gained attention due to their ability to enhance decision-making, improve efficiency, and optimize quality control and assurance (QCA). Traditional pavement evaluation methods often rely on empirical equations and time-consuming laboratory tests, whereas AI-driven models can provide rapid and accurate estimations, ensuring timely interventions in construction and maintenance.

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e-ISSN: 2170-127X, (cc) BY-SA

RESEARCH REVIEW of Sciences and Technologies

Vietnam is experiencing rapid expansion of its expressway network, demanding rigorous quality control to ensure long-term durability and safety. Effective pavement performance evaluation requires continuous monitoring and accurate prediction of key mechanical properties, such as the elastic modulus of flexible asphalt pavements. The ability to predict the overall modulus of pavement structures based on material and structural properties of individual layers can significantly improve construction quality management and reduce costs associated with extensive testing.

This study aims to develop predictive models for estimating the overall elastic modulus of flexible pavement structures using various ML techniques, including ANN, Random Forest (RF), and Extreme Gradient Boosting (XGBoost). In addition, the traditional Linear Regression (LR) model is included as a baseline for comparison. A comparative analysis of these models will be conducted to evaluate their predictive accuracy, computational efficiency, and applicability in practical scenarios.

By integrating AI techniques into pavement analysis, this research contributes to the development of smarter, data-driven solutions for transportation infrastructure management. The findings are expected to support engineers and decision-makers in optimizing pavement design and maintenance strategies, ultimately improving road longevity and safety.

2 Machine Learning Applications in Flexible Pavement Engineering

ML techniques have been increasingly applied in pavement engineering due to their ability to model complex relationships between the various factors affecting pavement design, construction, and maintenance. Traditional methods rely on empirical equations and expert judgment, whereas these techniques offer a data-driven approach to improve accuracy and efficiency. In the following sections, this paper explores ML techniques, including the application of ANNs in various stages of pavement engineering: design, construction, and maintenance.

2.1 Applications for Flexible Pavement Design

Flexible pavement design entails the intricate relationship between materials, load distribution, and environmental factors. Traditionally, engineers rely on empirical methods and complex calculations. However, with the growing availability of data in pavement engineering, ML techniques have begun to revolutionize the design process. Researchers have started exploring ML as a powerful alternative, using it to refine and optimize design methods. A review of current literature has highlighted three primary areas of focus in asphalt pavement design: structural design, asphalt mixture performance prediction, and the estimation of the pavement's response to various load conditions.

2.1.1 Flexible Pavement Structure Design

A significant challenge in pavement structure design is accurately estimating the Equivalent Single Axle Load (ESAL), which quantifies traffic loading. Kwigizile et al. (2005) used a probabilistic neural network to classify vehicles based on axle count, spacing, and weight. Amorim et al. (2015) applied a Multi-Layer Perceptron Neural Network (MLPNN) to determine the influence coefficients for various axle configurations. Tiğdemir (2014) simplified ESAL estimation by using MLPNN to establish a direct relationship between design ESAL and pavement composition.

Pavement response analysis is another complex task, and MLPNN models have been proposed as alternatives to finite element (FE) analysis. Fakhri and Ghanizadeh (2014) predicted the 3D response pulse at the bottom of the asphalt layer using MLPNN, aiding in thickness and stiffness design. Ziyadi and Al-Qadi (2017) incorporated k-fold cross-validation to study the impact of wide-base tires on asphalt pavement responses.

To address flexible pavement design complexities, El-Ashwah et al. (2021) developed a simplified Mechanistic-Empirical (M-E) method implemented in the "ME-PAVE" software. This method uses two equivalent temperatures for rutting and fatigue cracking predictions, eliminating the need for hourly climatic data. Validated using FE analysis and Multi-layer Elastic Analysis (MLEA), the method demonstrated accuracy comparable to traditional practices.

ML techniques have also been widely applied in asphalt mix design and pavement performance prediction. Mallick (2003) developed an AI-based framework to accelerate mix design by integrating multiple tests that highlighted strong interrelations, optimizing the process. Similarly, Androjić and Dolaček-Alduk (2018) used MLPNN to examine the effects of asphalt mixture type, humidity, and production temperature on natural gas consumption in HMA production, identifying aggregate temperature as a key factor.

2.1.2 Asphalt Mixture Performance Prediction

ML techniques are increasingly applied to predict asphalt mixture performance, particularly for properties like dynamic modulus, rutting behavior, and fatigue performance. Several studies have employed MLPNN models to predict the dynamic modulus of asphalt mixtures. For instance, Seitllari et al. (2019) applied a single-hidden-layer MLPNN to estimate dynamic modulus changes in aged asphalt mixtures. Similarly, Kaya et al. (2018) utilized a single-hidden-layer MLPNN to predict the dynamic modulus of both hot mix asphalt (HMA) and warm mix asphalt (WMA), considering factors such as aggregate gradation and volumetric properties. Other researchers, including El-Badawy et al. (2018) and Barugahare et al. (2020), implemented MLPNN models with two hidden layers for HMA dynamic modulus prediction. Additionally, Moussa and Owais (2020) introduced a deep convolutional neural network (CNN) with multiple convolution blocks to predict dynamic modulus.

Rutting performance, another critical factor in asphalt mixture design, has also been examined using ML techniques. Studies by Shafabakhsh et al. (2015) and Hussan et al. (2019) applied MLPNNs to assess rutting potential, correlating it with variables such as asphalt content, aggregate gradation, and volumetric properties. Hafeez (2018) further explored the effects of load patterns, truck speeds, and pulse durations on rutting behavior using ML. Additionally, Moghaddam et al. (2015) developed an adaptive neuro-fuzzy network to predict rutting behavior in modified asphalt mixtures.

Fatigue performance, influenced by material properties, climate, and traffic loads, has also been the subject of ML applications. Tapkin (2014) experimented with MLPNNs featuring various hidden layers to predict the fatigue life of fly ash-modified dense asphalt mixtures. Moghaddam et al. (2016) used ML to predict the fatigue life of polyethylene terephthalate-modified asphalt mixtures. Moreover, Ahmed et al. (2017) developed ANN models for fatigue life prediction of HMA under strain-controlled and stress-controlled conditions, with the strain test model yielding more accurate results.

2.2 Applications for Pavement Construction, Inspection and Monitoring

Few studies have explored the use of ANNs in pavement construction, particularly in areas such as construction quality and material performance. For construction quality, Commuri & Zaman (2008) integrated ANNs into an asphalt compaction analyzer, enabling automated classification of compaction levels. Imran et al. (2018) developed an MLPNN model to estimate subgrade stiffness during compaction. Regarding material performance, ANN models are frequently used to predict resilient modulus (Saha et al., 2018; Khasawneh & Al-Jamal, 2019). To enhance prediction accuracy, some studies, including Nazzal & Tatari (2013), integrated MLPNN models with genetic algorithm (GA) optimization. Additionally, ANN models have been used to predict soil strength based on California Bearing Ratio (CBR) tests (see Ghorbani & Hasanzadehshooiili, 2018 as an example).

Regarding pavement inspection and monitoring, studies have focused on surface distress classification, localization, segmentation, and structural evaluation. ANNs have been widely applied using data from 2D/3D images, thermal images, ground-penetrating radar (GPR), and falling weight deflectometer (FWD).

Early pavement distress classification relied on MLPNN models with predefined feature extraction (Xu et al., 2008). With advancements in deep learning, NNs have improved accuracy through automated feature extraction (Park et al., 2019; Yang et al., 2020). The use of 3D images has further enhanced distress detection by reducing noise (Li et al., 2020; Zhou & Song, 2020).

To pinpoint distress locations, region-based CNNs (R-CNN, Fast R-CNN, Faster R-CNN) have been commonly used (Huyan et al., 2019), though they struggle with real-time processing (Ibragimov et al., 2020). YOLO-based methods provide faster detection while maintaining accuracy (Du et al., 2020; Dhiman & Klette, 2020), while SSD-based methods have been explored for mobile applications (Gupta et al., 2020).

Segmentation enables pixel-level distress detection. Fully Convolutional Networks (FCNs) have been applied to 2D images (Chen et al., 2020), while 3D imaging improves segmentation accuracy (Li et al., 2019). U-Net architecture reduces training data requirements (Huyan et al., 2020), and two-step segmentation frameworks enhance processing efficiency (Liu et al., 2020).

For pavement structural evaluation, MLPNN models have been applied to modulus back-calculation and pavement health assessment (Fakhri & Dezfoulian, 2019). CNN-based models have improved defect detection in GPR images, identifying subgrade defects and cracks (Gao et al., 2020). Mabrouk et al. (2022) proposed a method for backcalculating pavement layer

moduli based on deflections caused by vehicle speed, achieving high accuracy with an R^2 of 94.08% and low RMSE. Wang et al. (2019) combined ANN with GA to estimate layer moduli from FWD data, effectively modeling the degradation of asphalt and unbound materials. You et al. (2020) used ANN to predict the condition and moduli of intermediate pavement layers, showing results comparable to the PADAL model and multiple regression but with greater flexibility.

2.3 ANN Applications in Pavement Maintenance

ANNs have been widely used to assess pavement conditions by analyzing performance indicators. MLPNN models have been utilized to build the relationship between the International Roughness Index (IRI) and distress types like rutting and cracking (Chandra et al., 2013). Structural conditions also affect IRI, leading to the development of Takagi-Sugeno (T-S) Fuzzy Neural Networks (FNN) for damage estimation (Dong et al., 2019).

For comprehensive evaluation, researchers applied Radial Basis Function (RBF) neural networks for pavement health scores (Huang et al., 2012) and Self-Organizing Feature Map Neural Networks (SOMNNs) to integrate multiple factors (Hu et al., 2012). Ali et al. (2024) used ANN to predict IRI from U.S. and Canadian pavement data, achieving 99.1% R^2, surpassing Multiple Linear Regression (MLR). Chen et al. (2025) introduced the Physics-Guided Neural Network (PGNN), improving IRI prediction accuracy by 26.08% and reducing uncertainty by 22.15% over traditional ANN.

Pavement deterioration depends on traffic load, climate, and material properties. Static ANN models use current-year data for short-term predictions but struggle with long-term forecasting (Yao et al., 2019). Dynamic models, incorporating time-series data, improve accuracy. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have been applied to predict deterioration trends (Okuda et al., 2018). Feature selection methods, such as sensitivity analysis, help eliminate redundant variables (Yao et al., 2019).

Li et al. (2025) integrated ANN with Fuzzy Partial Differential Equations (FPDE) to predict pavement deterioration over ten years. The Physics-Informed Neural Network (PINN) improved accuracy by 20.9% over ANN. Deneko et al. (2024) used ANN to predict the Pavement Condition Index (PCI) based on traffic volume, land use, number of lanes, pavement age, etc. A two-hidden-layer ANN achieved the highest accuracy.

3 Theoretical Background of Predictive Models

As outlined earlier, this study evaluates four predictive models—LR, ANN, RF, and XGBoost—for estimating the elastic modulus of flexible asphalt pavement. Each model has distinct strengths and limitations, making it suitable for different types of data and problem structures.

3.1 Linear Regression (LR)

LR is one of the simplest and most widely used predictive models. It assumes a linear relationship between the independent variables and the dependent variable, estimating regression coefficients by minimizing the sum of squared residuals. The simplicity of LR allows for easy interpretation of variable significance and provides a baseline for model comparison. However, its performance can be limited when dealing with complex, nonlinear relationships. Additionally, LR is sensitive to multicollinearity, heteroscedasticity, and outliers, which can distort predictions.

3.2 Artificial Neural Networks (ANNs)

ANNs are inspired by the structure of the human brain and consist of interconnected neurons arranged in layers. The model learns by adjusting the weights of these connections using backpropagation and gradient descent. ANN is highly flexible and can capture complex, nonlinear relationships between variables, making it a powerful tool for predicting the elastic modulus of asphalt pavement. However, ANN models require careful tuning of hyperparameters (such as the number of hidden layers and neurons) and are prone to overfitting if not properly regularized. Additionally, they demand higher computational resources compared to simpler models like LR.

3.3 Random Forest (RF)

RF is an ensemble learning method that constructs multiple decision trees using bootstrap sampling. The final prediction is obtained by averaging (in regression) or majority voting (in classification) across all trees. This approach reduces overfitting, improves robustness, and performs well even with high-dimensional data. RF is also capable of handling missing values and provides feature importance rankings. However, its complexity increases with the number of trees, leading to longer training times and reduced interpretability compared to simpler models.

3.4 Extreme Gradient Boosting (XGBoost)

XGBoost is an optimized implementation of gradient boosting that sequentially builds decision trees to correct errors from previous trees. It is widely known for its high efficiency, scalability, and predictive accuracy. XGBoost incorporates regularization techniques (L1 and L2) to prevent overfitting and has built-in handling for missing values. However, like RF, XGBoost is computationally demanding and requires careful tuning of hyperparameters to achieve optimal performance.

3.5 Comparison of Models

The Table 1 below summarizes the key characteristics of each model. Each of these models offers unique advantages and challenges. While LR serves as a simple baseline, ANN is powerful for capturing nonlinearities, RF provides robustness through ensembling, and XGBoost delivers high accuracy with advanced optimization techniques. The comparative analysis of these models in this study aims to identify the most effective approach for predicting the elastic modulus of flexible asphalt pavement.

Table 1 – Coparision of LN, ANN, RF and XGBoost

Model	Strengths	Weaknesses
LR	Simple, interpretable, fast computation	Assumes linearity, sensitive to multicollinearity and outliers
ANN	Captures complex nonlinear patterns, flexible with large datasets	Computationally intensive, requires careful tuning to avoid overfitting
RF	Handles missing values, reduces overfitting, robust to noise	Slower for large datasets, less interpretable
XGBoost	High predictive accuracy, efficient, built-in regularization	Computationally demanding, requires hyperparameter tuning

4 Data Collection and Variable Selection

4.1 Data Collection

The data for this study was obtained from the quality inspection of the Bac Giang - Lang Son Expressway construction project, specifically from Km 45+100 to Km 108+500, covering a total length of 63.86 km. The roadway features a platform width of 25 m, comprising four main traffic lanes (4 × 3.75 m), two emergency stopping lanes (2 × 3 m), a safety buffer zone (2 × 0.75 m), a median strip (1.0 m), and unpaved shoulders (2 × 0.75 m).

As shown in Fig. 1, the pavement structure consists of three layers of Hot Mix Asphalt (HMA): a 6 cm thick Dense-Graded Asphalt Concrete 12.5 (DGAC12.5) layer, a 7 cm thick Dense-Graded Asphalt Concrete 19 (DGAC19) layer, and a 10 cm thick Open-Graded Asphalt Concrete 25 (OGAC25) layer. Beneath these asphalt layers, the subbase is composed of a 60 cm thick Type I Aggregate Base Course (ABC type I). Below the pavement structure is the compacted subgrade, which includes an upper layer of 30 cm with a required relative density (RD) of 98% and a lower layer with an RD of 95%.

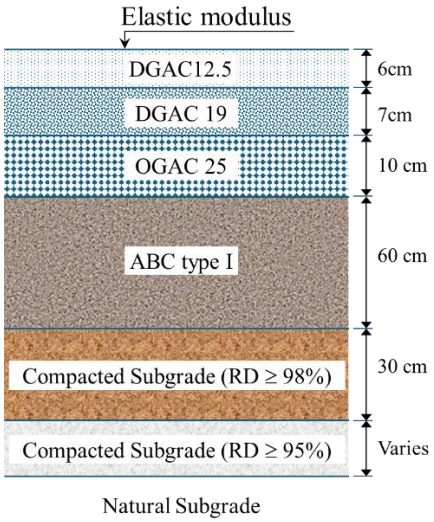


Fig. 1 - Pavement structure

Quality control assessments for the subgrade (RD95% and RD98%) encompass grain size distribution, Liquid Limit (LL), Plastic Limit (PL), Plasticity Index (PI), Maximum Dry Density (determined by the Proctor test), and the California Bearing Ratio (CBR). These tests were conducted in the field laboratory using soil from borrow pits. The compaction quality of the subgrade was evaluated based on RD, calculated as the ratio of field density to maximum dry density, with field density measured using the sand cone method. Similarly, quality control for the ABC type I includes grain size distribution, Maximum Dry Density (determined by the Proctor test), CBR, and RD, along with Flakiness Index and the Los Angeles (LA) Abrasion Test.

For HMA, quality control involves both laboratory and field core sampling for DGAC12.5, DGAC19, and OGAC25. Laboratory tests assess grain size distribution, asphalt binder content, specific gravity, air void content, maximum density, and Marshall Stability and Marshall Flow properties. Field core sampling includes thickness measurement, relative density evaluation, and additional Marshall Stability testing. These comprehensive evaluations ensure that each pavement layer meets the required design standards for durability and performance.

Upon completion of the final HMA layer (DGAC12.5), the Benkelman beam test was conducted to measure pavement surface deflections. Using the measured deflections, the elastic modulus of the pavement structure was back-calculated following the procedure outlined in TCVN 8867 (2011). In total, 69 samples, encompassing parameters from the subgrade to the pavement layers, as well as the elastic modulus, were collected and utilized in this study.

4.2 Preprocessing and Variable Selection

Before running the model, a systematic variable selection process was conducted to optimize predictive performance. First, a correlation analysis was performed using the correlation matrix to identify highly correlated independent variables ($|r| > 0.7$). Redundant variables were removed to reduce multicollinearity while retaining the most relevant features.

Next, Variance Inflation Factor (VIF) analysis was applied to detect multicollinearity among the remaining variables. A threshold of $VIF > 5$ was set, and variables exceeding this value were iteratively eliminated until all selected variables had acceptable VIF values.

Following this, stepwise regression was performed using both the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The model began with an initial set of variables and sequentially added or removed predictors to minimize AIC and BIC values. This ensured that only the most statistically significant variables were retained while maintaining a balance between model complexity and prediction accuracy.

As a result of this selection process, 17 independent variables were chosen. Their characteristics are presented in

Table 2, while their final correlation matrix and VIF values are illustrated in Fig. 2.

Table 2 – Selected variables and their characteristics

No.	Variable Names	Notation	Mean	Std.dev
Dependent variable				
1	Pavement Elastic Modulus	*x50*	207.5	12.25
Independent variables				
Compacted Subgrage RD95%				
2	Liquid Limit (LL – RD95)	*x1*	41.61	1.05
3	California Bearing Ratio (CBR – RD95)	*x5*	14.49	1.56
4	Relative Density (RD95)	*x6*	95.8	1.12
Compacted Subgrage RD98%				
5	Liquid Limit (LL – RD98)	*x7*	41.06	1.00
6	California Bearing Ratio (CBR – RD98)	*x11*	16.18	1.27
7	Relative Density (RD98)	*x12*	98.26	1.21
Aggregate Base Course Type I (ABC type I)				
8	California Bearing Ratio (CBR – ABC type I)	*x16*	126.23	7.58
9	Relative Density (CBR – ABC type I)	*x17*	98.96	1.35
Hot Mix Asphalt				
10	Thickness (OGAC 25)	*x24*	101.51	5.33
11	Relative Density (OGAC 25)	*x25*	99.12	0.68
12	Marshall stability (OGAC 25)	*x26*	6.3	1.17
13	Thickness (DGAC 19)	*x34*	69.74	3.07
14	Relative Density (DGAC 19)	*x35*	99.04	0.42
15	Marshall stability (DGAC 19)	*x36*	8.08	1.24
16	Thickness (DGAC 12.5)	*x44*	50.8	3.44
17	Relative Density (DGAC 12.5)	*x45*	99.48	1.03
18	Marshall stability (DGAC 12.5)	*x46*	13.23	2.73

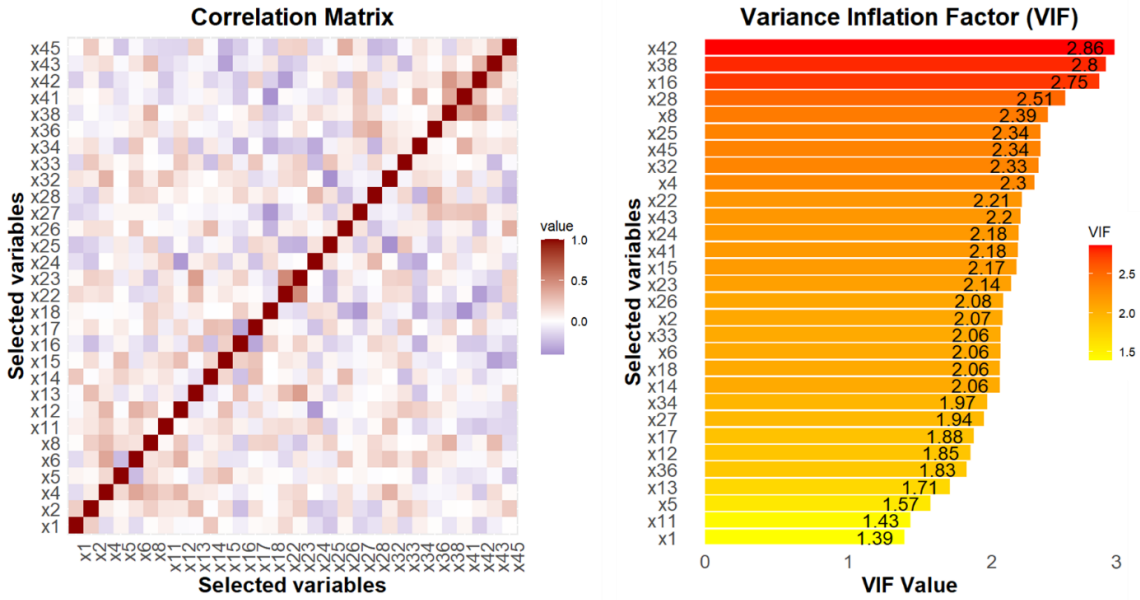


Fig. 2 - Correlation matrix and Variance Inflation Factor (VIF)

5 Model Dvelopment and Comparision:

As previously mentioned, this study first focused on optimizing the ANN model by testing 29 different hidden layer configurations to determine the best-performing architecture. These configurations included single-layer networks with 1 to 10 neurons and two-layer networks with equal or increasing neuron counts. Each model was evaluated based on R^2, RMSE, and MAE, as indicated in Fig. 3. The results showed that ANN 9, a single hidden-layer network with 9 neurons (see Fig. 4), achieved the highest performance ($R^2 = 0.997$, RMSE = 0.677, MAE = 0.483), confirming its strong predictive accuracy and minimal error. Consequently, ANN 9 was selected as the final ANN model for comparison with other approaches.

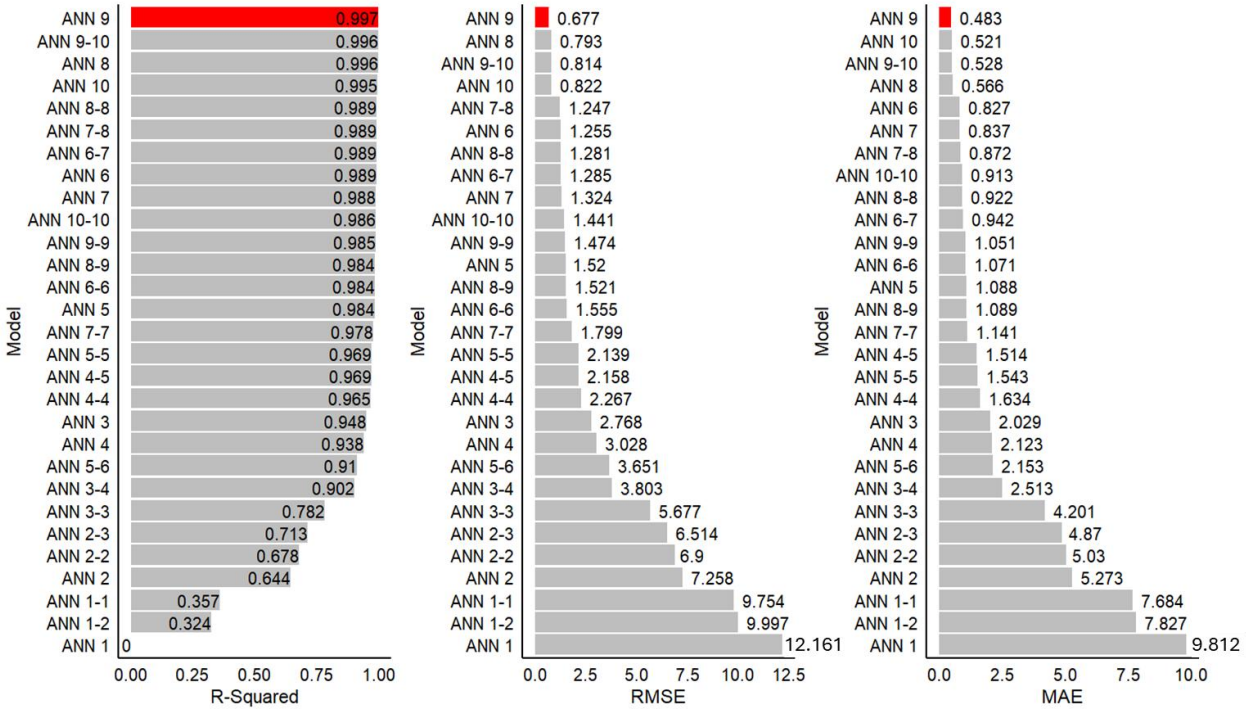


Fig. 3 - Comparison of ANN with 29 different hidden layer configurations

To comprehensively evaluate predictive capabilities, this study also implemented RF, XGBoost, and LR models using the same refined predictor set. The RF model was trained with optimized hyperparameters, including the number of trees and tree depth, while the XGBoost model was tuned using learning rate, maximum depth, and the number of boosting rounds. LR was used as a baseline to assess how well non-linear models like ANN, RF, and XGBoost outperformed a traditional statistical approach.

The performance comparison of the four models, as presented in Fig. 5, highlights ANN's superior predictive accuracy. ANN 9 achieved the highest R^2 (0.997) and the lowest RMSE (0.677) and MAE (0.483), indicating minimal prediction errors. In contrast, LR exhibited the weakest performance, with a significantly lower R^2 (0.290) and much higher RMSE and MAE values. RF and XGBoost both outperformed LR, with XGBoost achieving better predictive accuracy than RF.

Between ANN and the other ML models, ANN demonstrated the best overall performance, surpassing RF and XGBoost in accuracy and error minimization. While XGBoost showed strong predictive capability, it still fell short of ANN's performance.

In conclusion, LR was unsuitable due to its poor predictive accuracy, while RF and XGBoost provided better results, with XGBoost performing slightly better than RF. However, ANN remained the most effective model, exhibiting the highest accuracy and the lowest prediction errors. Its ability to capture complex relationships while maintaining minimal error makes it the best choice for predicting the elastic modulus of flexible asphalt pavement.

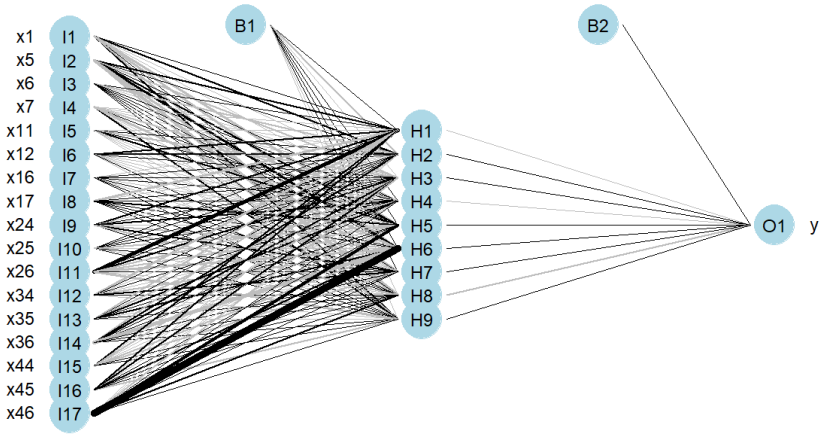


Fig. 4 - Structure of ANN with 1 hidden layer and 9 neurons

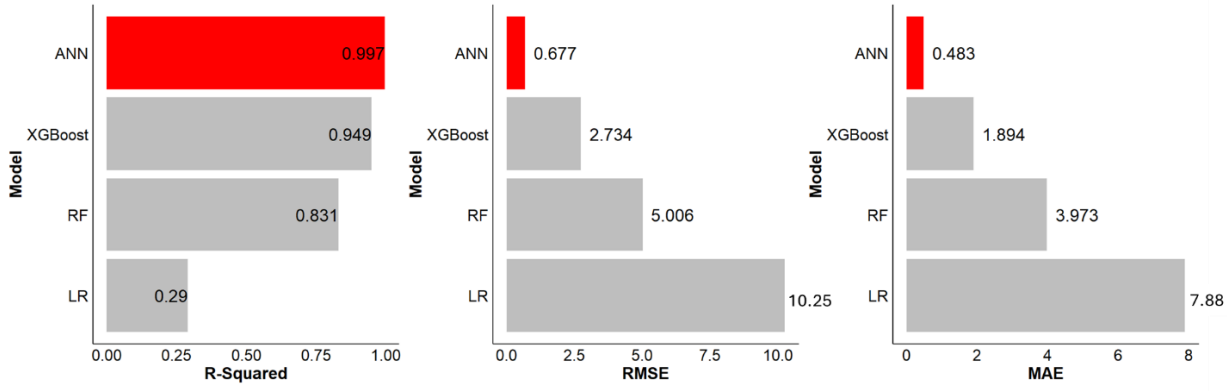


Fig. 5 - Performance comparison of ANN, Random Forest, XGBoost, and Linear Regression

Moreover, the scatter plots of predicted vs. actual values presented in Fig. 6 confirm the model performance differences. The ANN model (top-left) shows a near-perfect alignment along the 1:1 line, indicating highly accurate predictions. XGBoost (top-right) also demonstrates strong predictive ability but with slightly more deviation. RF (bottom-left) exhibits noticeable dispersion, reflecting reduced accuracy. In contrast, the LR model (bottom-right) shows the widest spread, confirming its

lower predictive capability. These visual representations reinforce the quantitative evaluation results, highlighting ANN as the most effective model for this dataset.

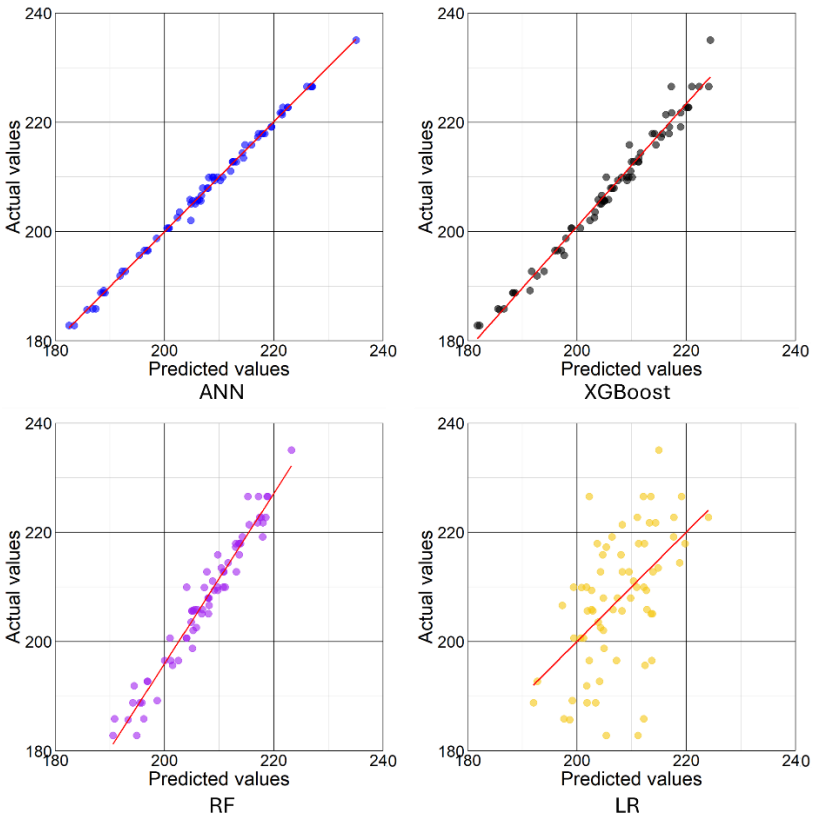


Fig. 6 - Comparison of predicted vs. actual values for ANN, Random Forest, XGBoost, and Linear Regression models

6 Conclusion

This study evaluated and compared four predictive models—Linear Regression (LR), Artificial Neural Networks (ANN), Random Forest (RF), and Extreme Gradient Boosting (XGBoost)—for estimating the elastic modulus of flexible asphalt pavement. Through a comprehensive analysis, ANN emerged as the most effective model, demonstrating superior predictive accuracy with the highest R^2 value (0.997) and the lowest RMSE (0.677) and MAE (0.483). The optimized ANN architecture, featuring a single hidden layer with nine neurons, successfully captured the nonlinear relationships inherent in the dataset, leading to precise and reliable predictions.

In contrast, LR exhibited the weakest performance, with significantly lower predictive accuracy and higher error rates, confirming its limitations in modeling complex, nonlinear relationships. RF and XGBoost outperformed LR, with XGBoost demonstrating slightly better predictive accuracy than RF due to its advanced gradient boosting optimization techniques. However, neither model surpassed the ANN in terms of accuracy and error minimization.

The findings of this study highlight the importance of selecting appropriate predictive models for estimating pavement elastic modulus. ANN's ability to capture intricate patterns within the data makes it the most suitable choice for this application. The results provide valuable insights for engineers and researchers in pavement design and quality assessment, reinforcing the potential of ANN-based models for improving predictive performance in transportation infrastructure analysis.

It is noteworthy that, in this study, the model was evaluated on the entire dataset without splitting it into training and testing sets due to the limited data available. This approach may result in higher model accuracy compared to when data is divided, but it can also lead to an overly optimistic assessment of model performance. If the model is applied to new data, its actual performance may be lower than the results obtained in this study. Therefore, incorporating larger datasets from diverse pavement structures and traffic conditions could improve model generalization and applicability across various roadway

networks. Additionally, future research could explore hybrid modeling approaches that combine the strengths of different machine learning algorithms to further enhance prediction accuracy.

Acknowledgment

This research was funded by the Ministry of Education and Training (MoET) under Grant No. B2024-GHA-07. The authors sincerely thank VNC Construction Joint Stock Company for providing the data used in this study. Their support was instrumental to the successful completion of this research.

REFERENCES

[1]- V. Kwigizile, R. N. Mussa, M. Selekwa, Connectionist approach to improving highway vehicle classification schemes: The Florida case. Transp. Res. Rec. 1917(1) (2005) 182-189.

[2]- S. I. Amorim, J. C. Pais, A. C. Vale, M. J. Minhoto, A model for equivalent axle load factors. Int. J. Pavement Eng. 16(10) (2015) 881-893. https://doi.org/10.1080/10298436.2014.968570

[3]- M. Tiğdemir, Re-evaluation of the AASHTO-flexible pavement design equation with neural network modeling. PLoS One 9(11) (2014) e113226. https://doi.org/10.1371/journal.pone.0113226

[4]- M. Fakhri, A. R. Ghanizadeh, Modelling of 3D response pulse at the bottom of asphalt layer using a novel function and artificial neural network. Int. J. Pavement Eng. 15(8) (2014) 671-688. https://doi.org/10.1080/10298436.2013.851791

[5]- M. Ziyadi, I. L. Al-Qadi, Efficient surrogate method for predicting pavement response to various tire configurations. Neural Comput. Appl. 28 (2017) 1355-1367. https://doi.org/10.1007/s00521-016-2442-1

[6]- A. S. El-Ashwah, S. M. El-Badawy, A. R. Gabr, A simplified mechanistic-empirical flexible pavement design method for moderate to hot climate regions. Sustainability 13(19) (2021) 10760. https://doi.org/10.3390/su131910760

[7]- R. B. Mallick, M. K. Nivedya, R. Veeraragavan, Artificial Intelligence Based Mix Design of Pavement Mixes. In: Int. Airfield Highw. Pavements Conf. 2019, Reston, VA, 2019, pp. 19-30.

[8]- I. Androjić, Z. Dolaček-Alduk, Artificial neural network model for forecasting energy consumption in hot mix asphalt (HMA) production. Constr. Build. Mater. 170 (2018) 424-432. https://doi.org/10.1016/j.conbuildmat.2018.03.086

[9]- A. Seitllari, Y. S. Kumbargeri, K. P. Biligiri, I. Boz, A soft computing approach to predict and evaluate asphalt mixture aging characteristics using asphaltene as a performance indicator. Mater. Struct. 52(5) (2019) 100. https://doi.org/10.1617/s11527-019-1402-5

[10]- O. Kaya, N. Garg, H. Ceylan, S. Kim, Development of artificial neural networks based predictive models for dynamic modulus of airfield pavement asphalt mixtures. In: Int. Conf. Transp. Dev. 2018, Reston, VA, 2018, pp. 1-7.

[11]- S. El-Badawy, R. Abd El-Hakim, A. Awed, Comparing artificial neural networks with regression models for hot-mix asphalt dynamic modulus prediction. J. Mater. Civ. Eng. 30(7) (2018) 04018128. https://doi.org/10.1061/(ASCE)MT.1943-5533.0002282

[12]- J. Barugahare, A. N. Amirkhanian, F. Xiao, S. N. Amirkhanian, ANN-based dynamic modulus models of asphalt mixtures with similar input variables as Hirsch and Witczak models. Int. J. Pavement Eng. 23(5) (2022) 1328-1338. https://doi.org/10.1080/10298436.2020.1799209

[13]- G. S. Moussa, M. Owais, Pre-trained deep learning for hot-mix asphalt dynamic modulus prediction with laboratory effort reduction. Constr. Build. Mater. 265 (2020) 120239. https://doi.org/10.1016/j.conbuildmat.2020.120239

[14]- G. H. Shafabakhsh, O. J. Ani, M. Talebsafa, Artificial neural network modeling (ANN) for predicting rutting performance of nano-modified hot-mix asphalt mixtures containing steel slag aggregates. Constr. Build. Mater. 85 (2015) 136-143. https://doi.org/10.1016/j.conbuildmat.2015.03.060

[15]- S. Hussan, M. A. Kamal, I. Hafeez, N. Ahmad, Evaluation and modelling of permanent deformation behaviour of asphalt mixtures using dynamic creep test in uniaxial mode. Int. J. Pavement Eng. 20(9) (2019) 1026-1043. https://doi.org/10.1080/10298436.2017.1380805

[16]- I. Hafeez, Investigating the creep response of asphalt mixtures under waveform loading. Road Mater. Pavement Des. 19(4) (2018) 819-836. https://doi.org/10.1080/14680629.2017.1279071

[17]- T. B. Moghaddam, M. Soltani, M. R. Karim, S. Shamshirband, D. Petković, H. Baaj, Estimation of the rutting

performance of Polyethylene Terephthalate modified asphalt mixtures by adaptive neuro-fuzzy methodology. Constr. Build. Mater. 96 (2015) 550-555. https://doi.org/10.1016/j.conbuildmat.2015.08.043

[18]- S. Tapkin, Estimation of fatigue lives of fly ash modified dense bituminous mixtures based on artificial neural networks. Mater. Res. 17 (2014) 316-325. https://doi.org/10.1590/S1516-14392014005000040

[19]- T. B. Moghaddam, M. Soltani, H. S. Shahraki, S. Shamshirband, N. B. M. Noor, M. R. Karim, The use of SVM-FFA in estimating fatigue life of polyethylene terephthalate modified asphalt mixtures. Measurement 90 (2016) 526-533. https://doi.org/10.1016/j.measurement.2016.05.004

[20]- T. M. Ahmed, P. L. Green, H. A. Khalid, Predicting fatigue performance of hot mix asphalt using artificial neural networks. Road Mater. Pavement Des. 18(sup2) (2017) 141-154. https://doi.org/10.1080/14680629.2017.1306928

[21]- S. Commuri, M. Zaman, A novel neural network-based asphalt compaction analyzer. Int. J. Pavement Eng. 9(3) (2008) 177-188. https://doi.org/10.1080/10298430701232018

[22]- S. Asif Imran, M. Barman, S. Commuri, M. Zaman, M. Nazari, Artificial neural network-based intelligent compaction analyzer for real-time estimation of subgrade quality. Int. J. Geomech. 18(6) (2018) 04018048. https://doi.org/10.1061/(ASCE)GM.1943-5622.0001089

[23]- S. Saha, F. Gu, X. Luo, R. L. Lytton, Use of an artificial neural network approach for the prediction of resilient modulus for unbound granular material. Transp. Res. Rec. 2672(52) (2018) 23-33. https://doi.org/10.1177/0361198118756881

[24]- M. A. Khasawneh, N. F. Al-jamal, Modeling resilient modulus of fine-grained materials using different statistical techniques. Transp. Geotech. 21 (2019) 100263. https://doi.org/10.1016/j.trgeo.2019.100263

[25]- M. D. Nazzal, O. Tatari, Evaluating the use of neural networks and genetic algorithms for prediction of subgrade resilient modulus. Int. J. Pavement Eng. 14(4) (2013) 364-373. https://doi.org/10.1080/10298436.2012.671944

[26]- A. Ghorbani, H. Hasanzadehshooiili, Prediction of UCS and CBR of microsilica-lime stabilized sulfate silty sand using ANN and EPR models; application to the deep soil mixing. Soils Found. 58(1) (2018) 34-49. https://doi.org/10.1016/j.sandf.2017.11.002

[27]- G. Xu, J. Ma, F. Liu, X. Niu, Automatic recognition of pavement surface crack based on BP neural network. In: Proc. Int. Conf. Comput. Electr. Eng., IEEE, 2008, pp. 19-22. https://doi.org/10.1109/ICCEE.2008.96

[28]- S. Park, S. Bang, H. Kim, H. Kim, Patch-based crack detection in black box images using convolutional neural networks. J. Comput. Civ. Eng. 33(3) (2019) 04019017. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000831

[29]- Q. Yang, W. Shi, J. Chen, W. Lin, Deep convolution neural network-based transfer learning method for civil infrastructure crack detection. Autom. Constr. 116 (2020) 103199. https://doi.org/10.1016/j.autcon.2020.103199

[30]- B. Li, K. C. Wang, A. Zhang, E. Yang, G. Wang, Automatic classification of pavement crack using deep convolutional neural network. Int. J. Pavement Eng. 21(4) (2020) 457-463. https://doi.org/10.1080/10298436.2018.1485917

[31]- S. Zhou, W. Song, Deep learning-based roadway crack classification using laser-scanned range images: A comparative study on hyperparameter selection. Autom. Constr. 114 (2020) 103171. https://doi.org/10.1016/j.autcon.2020.103171

[32]- J. Huyan, W. Li, S. Tighe, J. Zhai, Z. Xu, Y. Chen, Detection of sealed and unsealed cracks with complex backgrounds using deep convolutional neural network. Autom. Constr. 107 (2019) 102946. https://doi.org/10.1016/j.autcon.2019.102946

[33]- E. Ibragimov, H. J. Lee, J. J. Lee, N. Kim, Automated pavement distress detection using region-based convolutional neural networks. Int. J. Pavement Eng. 23(6) (2022) 1981-1992. https://doi.org/10.1080/10298436.2020.1833204

[34]- Y. Du, N. Pan, Z. Xu, F. Deng, Y. Shen, H. Kang, Pavement distress detection and classification based on YOLO network. Int. J. Pavement Eng. 22(13) (2021) 1659-1672. https://doi.org/10.1080/10298436.2020.1714047

[35]- A. Dhiman, R. Klette, Pothole detection using computer vision and learning. IEEE Trans. Intell. Transp. Syst. 21(8) (2019) 3536-3550. https://doi.org/10.1109/TITS.2019.2931297

[36]- S. Gupta, P. Sharma, D. Sharma, V. Gupta, N. Sambyal, Detection and localization of potholes in thermal images using deep neural networks. Multimed. Tools Appl. 79 (2020) 26265-26284. https://doi.org/10.1007/s11042-020-09293-8

[37]- T. Chen, Z. Cai, X. Zhao, C. Chen, X. Liang, T. Zou, P. Wang, Pavement crack detection and recognition using the architecture of segNet. J. Ind. Inf. Integr. 18 (2020) 100144. https://doi.org/10.1016/j.jii.2020.100144

[38]- B. Li, K. C. Wang, A. Zhang, Y. Fei, G. Sollazzo, Automatic segmentation and enhancement of pavement cracks based on 3D pavement images. J. Adv. Transp. 2019(1) (2019) 1813763. https://doi.org/10.1155/2019/1813763

[39]- J. Huyan, W. Li, S. Tighe, Z. Xu, J. Zhai, CrackU-net: A novel deep convolutional neural network for pixelwise pavement crack detection. Struct. Control Health Monit. 27(8) (2020) e2551. https://doi.org/10.1002/stc.2551

[40]- J. Liu, X. Yang, S. Lau, X. Wang, S. Luo, V. C. S. Lee, L. Ding, Automated pavement crack detection and segmentation based on two-step convolutional neural network. Comput.-Aided Civ. Infrastruct. Eng. 35(11) (2020) 1291-1305. https://doi.org/10.1111/mice.12622

[41]- M. Fakhri, R. S. Dezfoulian, Pavement structural evaluation based on roughness and surface distress survey using neural network model. Constr. Build. Mater. 204 (2019) 768-780. https://doi.org/10.1016/j.conbuildmat.2019.01.142

[42]- J. Gao, D. Yuan, Z. Tong, J. Yang, D. Yu, Autonomous pavement distress detection using ground penetrating radar and region-based deep learning. Measurement 164 (2020) 108077. https://doi.org/10.1016/j.measurement.2020.108077

[43]- G. M. Mabrouk, O. S. Elbagalati, S. Dessouky, L. Fuentes, L. F. Walubita, Using ANN modeling for pavement layer moduli backcalculation as a function of traffic speed deflections. Constr. Build. Mater. 315 (2022) 125736. https://doi.org/10.1016/j.conbuildmat.2021.125736

[44]- H. Wang, M. Li, P. Szary, X. Hu, Structural assessment of asphalt pavement condition using backcalculated modulus and field data. Constr. Build. Mater. 211 (2019) 943-951. https://doi.org/10.1016/j.conbuildmat.2019.03.250

[45]- L. You, K. Yan, N. Liu, Assessing artificial neural network performance for predicting interlayer conditions and layer modulus of multi-layered flexible pavement. Front. Struct. Civ. Eng. 14(2) (2020) 487-500. https://doi.org/10.1007/s11709-020-0609-4

[46]- S. Chandra, C. R. Sekhar, A. K. Bharti, B. Kangadurai, Relationship between pavement roughness and distress parameters for Indian highways. J. Transp. Eng. 139(5) (2013) 467-475. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000512

[47]- S. Dong, P. Hao, S. L. Tighe, A diagnostic method for evaluating the condition index of cement-stabilized base using TS fuzzy neural network. Int. J. Pavement Eng. 20(10) (2019) 1140-1153. https://doi.org/10.1080/10298436.2017.1394097

[48]- Y. X. Huang, F. Shao, Y. W. Liu, Damage condition assessment of expressway asphalt pavement based on RBF neural network. Adv. Mater. Res. 446 (2012) 2548-2553. https://doi.org/10.4028/www.scientific.net/AMR.446-449.2548

[49]- [18]- T. Okuda, K. Suzuki, N. Kohtake, Non-parametric prediction interval estimate for uncertainty quantification of the prediction of road pavement deterioration. In: Proc. Int. Conf. Intell. Transp. Syst. (ITSC), (2018) 824-830. https://doi.org/10.1109/ITSC.2018.8569337

[50]- M. J. Hu, R. H. Ge, Q. F. Qiu, Q. Jin, Asphalt pavement performance evaluation based on SOM neural network. Appl. Mech. Mater. 188 (2012) 219-225. https://doi.org/10.4028/www.scientific.net/AMM.188.219

[51]- A. A. Ali, U. Heneash, A. Hussein, S. Khan, Application of artificial neural network technique for prediction of pavement roughness as a performance indicator. J. King Saud Univ.-Eng. Sci. 36(2) (2024) 128-139. https://www.sciencedirect.com/science/article/pii/S1018363923000016

[52]- K. Chen, M. E. Torbaghan, N. Thom, A. Faramarzi, Physics-guided neural network for predicting international roughness index on flexible pavements considering accuracy, uncertainty, and stability. Eng. Appl. Artif. Intell. 142 (2025) 109922. https://doi.org/10.1016/j.engappai.2024.109922

[53]- L. Yao, Q. Dong, J. Jiang, F. Ni, Establishment of prediction models of asphalt pavement performance based on a novel data calibration method and neural network. Transp. Res. Rec. 2673(1) (2019) 66-82. https://doi.org/10.1177/0361198118822501

[54]- J. Li, S. Zhang, X. Wang, Physics-informed neural network with fuzzy partial differential equation for pavement performance prediction. Autom. Constr. 171 (2025) 105983. https://doi.org/10.1016/j.autcon.2025.105983

[55]- E. Deneko, E. Filaj, M. Gheibi, R. Moezzi, Predicting pavement surface conditions through artificial neural networks. In: Proc. Inst. Civ. Eng. - Munic. Eng. 177(3) (2024) 99-110. https://doi.org/10.1680/jmuen.23.00054