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Pavement Sections' Reliability Based on Deterioration Model Using Artificial Neural Network (ANN)

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ABSTRACT

Pavement distresses, such as cracks and ruts, reduce pavements' effectiveness and serviceability and can lead to failure. This underlines the importance of predicting pavements' deterioration in pavement management systems (PMSs) for effective maintenance and rehabilitation (M&R) strategies. Consequently, it is essential to understand the concept of service life, which represents how long a pavement will remain in service based on how reliable it is. This study introduces a pavement deterioration model using data from the Long-Term Pavement Performance program for the international roughness index (IRI) and other factors. Different machine learning methods were utilized in developing the model to incorporate eight factors that significantly affect pavement roughness; these methods are: linear regression, regression tree, Gaussian Process Regression (GPR), Support Vector Machine (SVM), Ensemble Trees, and Artificial Neural Network (ANN). For comparison, the models' performances were evaluated using Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and R squared (R^2). The weights and biases of the best model and the Federal Highway Administration (FHWA) recommended IRI ranges were utilized to create the limit state function. A reliability analysis using Monte Carlo Simulation (MCS) was determined to calculate the sections' probability of failure. This study concluded that pavement sections in the US and Canada are reliable and that the mean yearly Kilo Equivalent Single Axle Load (KESAL) significantly contributes to pavement failure.

Keywords: Pavement deterioration, IRI, Machine learning, Neural network, Pavement reliability, Probability of failure.

INTRODUCTION

Infrastructure facilities provide services essential to society, including airports, bridges, highways, telecommunications, and water networks. Infrastructure agencies monitor and develop these facilities to increase the country's economic strength (Morcous, 2000). Transportation infrastructures draw researchers' attention because of their importance, and their deterioration can lead to severe problems. In the transportation infrastructure, pavements are crucial to vehicle movement, driver safety, and serviceability. Pavement performance pertains to a road's surface and structural characteristics in meeting design criteria during its service life. Numerous factors affect the performance of asphalt pavements, including the durability of the surface layer, traffic, environment, sub-grade quality, and construction quality (Zeiada et al., 2020).

The integrity of pavement structures is fundamental to transportation systems worldwide. Pavement deterioration is an inherent, unpredictable process that compromises infrastructure's structural integrity and functionality over time. Accurately modeling this deterioration is crucial for effective infrastructure management and maintenance. Deterioration models are generally categorized into deterministic, stochastic, and artificial intelligence (AI) models. Deterministic models utilize mathematical or statistical techniques to predict the condition of pavement sections based on non-random, fixed variables, typically representing the average expected outcome. For instance, Xu et al. (2014) evaluated pavement-deterioration modeling and prediction for Kentucky's highways using the Multiple Linear Regression (MLR) model and compared it with the Artificial Neural Network (ANN) model. The study concluded that MLR and ANN can predict wheel-path cracking accurately, but ANN is more robust. In another instance, Al-Khateeb et al. (2011) developed a two-dimensional finite-element model to investigate the impact of static repeated wheel loads on rutting formation and pavement response. The finite-element method, known for its deterministic approach, provides a structured framework for modeling complex systems with defined parameters and boundary conditions. The study conducted a sensitivity analysis and indicated that the rut depth increases with the increase in temperature and tire pressure and with the decrease in sub-grade strength.

Stochastic models incorporate randomness and uncertainty in variable inputs, thus allowing the prediction of a range of possible outcomes rather than a single deterministic value. Among stochastic models, the Markov chain method is the most commonly used method to predict deterioration, such as in Kobayashi et al. (2010), Morcous et al. (2003), and Shakya et al. (2023) studies that explored the use of Markov deterioration models to forecast pavement conditions. Lastly, AI models use advanced computational techniques to perform tasks requiring human cognition. They are adept at handling complex, non-linear interactions within large datasets, making them particularly suited for predicting infrastructure deterioration where conventional models might falter. As an example, Amir and Henry (2023) compared the effectiveness of ANN and K-Nearest Neighbors (KNNs) methods in predicting pavement deterioration, finding that ANN outperforms KNN in managing maintenance. As another example, Thube (2012) utilized ANN to predict pavement distress on low-volume roads in India and compared the outcomes against the HDM-4 models. The study confirmed that ANNs can accurately forecast pavement conditions when trained with sufficient data and appropriate algorithms. Moreover, Madeh Piryonesi and El-Diraby (2021) demonstrated the use of machine learning algorithms, including Random Forest and Gradient-boosted trees, to predict the Pavement Condition Index (PCI) and International Roughness Index (IRI) from a long-term performance database. The study concluded that complex algorithms, such as ensemble learning, improve the prediction. Lastly, Al-Khateeb and Khadour (2020) developed an experimental Pavement Serviceability Index (PSI) model based on regression analysis to predict pavement performance. The study involved thirty-five asphalt pavement sections. It was determined that the most significant factor affecting the PSI was the rut depth.

Reliability quantification in pavement design assesses the likelihood of pavement performance meeting expected traffic loads without failure. Historical analyses have highlighted the use of reliability to overcome the limitations inherent in traditional safety factors. Seminal works by Lemer and Moavenzadeh (1971) and subsequent studies by researchers such as George and Nair (1982) and Moavenzadeh and Bradameyer (1977) underscored this point. The integration of reliability into pavement design was notably included in the 1993 AASHTO guide and its subsequent enhancements, as documented by Suherman (2009). Schlotjes et al. (2015) significantly contributed to this field by combining expert knowledge and computational techniques, specifically support vector machines (SVMs), to evaluate the failure probabilities of individual road sections. Their research utilized a dataset from a New Zealand pavement performance study to uncover prevalent failure types, contributing factors, and risk profiles of the road network, culminating in recommendations for project- and network-level pavement maintenance strategies. This approach emphasized the critical role of integrating strength-related parameters into failure predictions. More recently, Tabesh et al. (2023) developed statistical models using Bayesian regression techniques for designing asphalt concrete pavements resistant to transverse cracking. Their study further explored applying structural reliability methods, including Monte Carlo simulation, to enhance pavement design analysis.

Building on the insights garnered from the literature, the current study stands out by conducting a comparative analysis of multiple machine learning algorithms to develop models for predicting pavement deterioration, subsequently selecting the most effective model based on metrics such as mean squared error (MSE), root means squared error (RMSE), and R-squared (R^2). The chosen model is then utilized to perform a reliability analysis using Monte Carlo Simulation (MCS), bridging the gap between predictive modeling and practical application. This approach enhances the understanding of pavement failure probabilities. It ensures that the predictive outcomes align with the Federal Highway Administration (FHWA) recommended ranges (Table 1) for the IRI, facilitating the creation of a limit state function. This methodology underscores the study's novelty, offering a robust framework that combines scientific rigor with practical relevance for real-world implementation in pavement management systems. Therefore, this study aims to develop and compare multiple regression and machine learning models to accurately predict the IRI and then identify the most optimal model for determining the probability of failure by calculating the limit state function. The specific objectives of this study are to:

1. Recognize and select the best prediction model with the highest performance.
2. Obtain the limit state function based on the best model's results.
3. Determine the probability of failure of the pavement sections.
4. Analyze the impact of controllable factors on the probability of failure.

Table 1. IRI ranges specified by FHWA (Mannering, 2014)

Condition	IRI (m/km)	Ride Quality
Very good	< 0.95	Acceptable: 0 - 2.68
Good	0.95 - 1.48	
Fair	1.50 - 1.88	
Mediocre	1.89 - 2.68	
Poor	> 2.68	Less Than Acceptable: > 2.68

MATERIALS AND METHODS

Research Methodology

In this study, the following stages, represented in Figure (1) were followed. First, the roughness data and other factors were extracted from the Long-Term Pavement Performance (LTPP) database. The raw data was then processed, cleaned, and prepared for use. Next, the data was analyzed using statistical analysis, and the correlations between the factors were calculated. Then, multiple prediction models were developed, and the performance of each model was computed. The 5-fold cross-validation method was then used to evaluate the developed models. The model with the best performance was chosen, and the limit state function was generated by extracting the model's outcomes. The established limit state function determined the pavement failure probability and reliability index. Finally, the sensitivity analysis of the controllable factors was assessed based on the probability of failure.

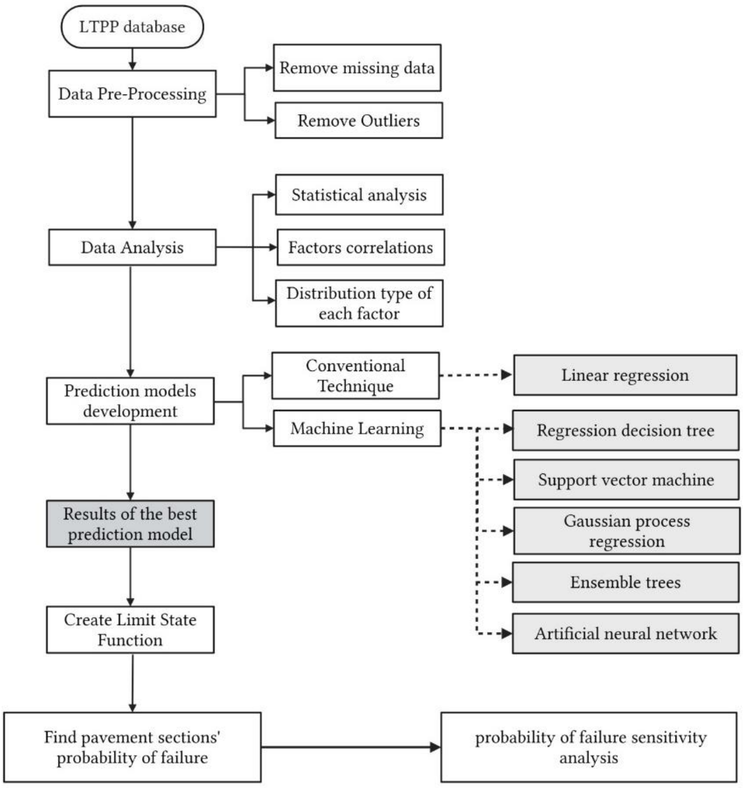

Figure (1): Methodology framework

Data Collection

This study utilizes pavement roughness data collected from the LTPP database. The most extensive pavement study ever conducted was in the United States (US) and Canada. Over 2500 test sections collected over 20 years are included in the database. This information includes inventory details, material testing, pavement performance measures, climatic data, traffic, maintenance, and rehabilitation (LTPP InfoPave). Asphalt pavement portions without maintenance or rehabilitation were chosen for this study. It was found that 194 sections fulfilled the previously mentioned criteria. Each year's condition represents one data point. In the LTPP database, numerous variables potentially influencing pavement roughness have been compiled and categorized into four primary groups: structure, climate, traffic, and performance. These factors serve as the input for the model, with the IRI representing the output. Moreover, attributes, including the pavement's age, the roadway's functional class, among others, were gathered for each section. Selected variables from each category are presented in Table 2.

Table 2. Retrieved factors

Data type	Data attribute
Characteristics	Age (years)
Structure	Total asphalt concrete thicknes (mm)
Climate	Precipitation (mm)
	Temperature (ºC)
	Freezing Index (ºC)
	Minimum “Annual Average Humidity” (AAH) (%)
	Maximum “Annual Average Humidity” (AAH)(%)
Traffic	KESAL (18 - kip)
Performance	IRI (m/km)

Data Pre-processing

A complete dataset was obtained at this stage. Some pre-processing and analysis were performed to prepare and understand the data. First, missing data and outliers were removed, resulting in 829 data points. According to the data used in this study, IRI ranges between 0.56 and 2.2 (m/km). Next, the correlation, which illustrates a varied relationship between different factors, was performed between IRI and other factors, as presented in Figure(2), with the color intensity indicating the strength and direction of the correlation. Values close to 0 indicate weak or no linear correlation, while values closer to -1 or 1 indicate strong negative or positive correlation. The goal was to find the correlation and independent variables of IRI, but the matrix also suggests some level of correlation between other factors. According to the correlation results, a strong positive correlation exists between annual average humidity and freezing index and between annual average humidity and precipitation, as indicated by the values of 0.371 and 0.417, respectively.

	Age	Total Asphalt concrete thickness	Precipitation	Temperature	Freezing Index	Annual Average Humidity (min)	Annual Average Humidity (max)	KESAL	IRI
Age	1								
Total Asphalt concrete thickness	-0.01	1							
Precipitation	-0.06	-0.18	1						
Temperature	0.189	-0.19	0.277	1					
Freezing Index	-0.27	0.098	-0.19	-0.89	1				
Annual Average Humidity (min)	-0.27	-0.07	0.371	-0.47	0.417	1			
Annual Average Humidity (max)	-0.1	0.035	0.056	0.01	0.121	-0.11	1		
KESAL	-0.21	0.16	0.117	-0.06	0.214	-0.01	0.189	1	
IRI	0.274	-0.12	-0.01	0.055	-0.13	-0.04	-0.03	-0.34	1

Figure (2): The correlations between the factors

Conversely, the strongest negative correlation is -0.89, meaning that the temperature decreases as the freezing index increases. Therefore, the most significant factors that affect the IRI are age, total asphalt thickness, freezing index, and Kilo Equivalent Single Axle Load (KESAL). Subsequently, some descriptive analysis was performed, and the results are shown in Table 3. This analysis allows for a quick assessment of the variability of each factor. Focusing on the roughness, the IRI has a mean value of 1.13 with a standard deviation of 0.37, suggesting moderate variability in pavement roughness across the samples. Additionally, the wide range indicated by the mean, minimum, and maximum of the climate factors, such as Precipitation, Temperature, and Freezing Index, shows that the data collected includes samples from different climate regions.

Table 3. Descriptive statistics of the factors

	Age	Total asphalt concrete thickness	Precipitation	Temperature	Freezing Index	Annual Average Humidity (min.)	Annual Average Humidity (max.)	KESAL	IRI
N sample	829	829	829	829	829	829	829	829	829
Mean	10.04	5.81	1061.79	11.92	345.35	19.67	115.80	195.55	1.13
STD DEV	7.93	2.70	386.02	5.04	423.46	9.65	5.25	172.59	0.37
COV	79.0%	46.5%	36.4%	42.3%	122.6%	49.0%	4.5%	88.3%	32.8%
Minimum	0	0.9	106.4	1.9	0	2	100	0	0.561
Maximum	46	13.4	2161.4	20.9	1681	50	133	1253	2.204

IRI Modeling

In this study, IRI was utilized as a metric for pavement performance. The aim was to develop models for predicting pavement performance. The computation involved two types of methods: conventional techniques, such as Linear Regression and Machine Learning (ML) methods, including numerous methods of Regression Tree, Support Vector Machine (SVM), Gaussian Process Regression (GPR), Ensemble Trees, and Artificial Neural Network (ANN). Before implementing the models, the data was split into three sub-sets: 70% training, 15% Vvalidation, and 15% testing. Below is a brief description of each method used.

Linear Regression

As a predictive model, a regression model explains the connection between a dependent variable and multiple independent variables. In this regression model, linearity is a measure of the linear coefficients of the parameters. In this study, only one type of this approach was investigated: linear regression. Equation (1) explains the basis of the regression model:

$$Y = a + b_1X_1 + b_2X_2 + \cdots + b_iX_i \mp e \qquad (1)$$

where Y is a dependent variable, a is a constant, b_i is the estimated coefficient from the regression, and X_i is the independent variable.

Regression Decision Tree

A regression decision tree is a hierarchical model that builds regression or classification models through simple decision rules. This tree is incrementally formed by dividing a dataset into progressively smaller sub-sets through multiple splits to enhance prediction accuracy. Typically comprising root, branch, and leaf nodes, decision trees classify data points starting from the root upwards. Each branch node conducts a conditional test to assess data adherence to set criteria, often based on factors like the sum of square errors in regression problems. The fundamental aim is to minimize deviations from the mean, thereby reducing variance in the output features (Zeiada et al., 2020). Equation (2) shows how deviation reduction is expressed:

$$D_{Total} = \sum (Y_i - \bar{Y})^2 \qquad (2)$$

where Y_i is the target feature, and $\bar{Y}$ is the mean of the output features.

Support Vector Machine (SVM)

SVM uses kernel functions to create high-dimensional feature spaces from input data, enabling the application of linear methods to handle complex non-linear relationships. It relies primarily on calculating a linear regression function based on the non-linear mapping of SVM input data, which is pattern recognition. This study employed various SVM variants, including Linear, Quadratic, Cubic, and Gaussian SVMs (fine, medium, and coarse). Equation (3) depicts the function used in the SVM models, called the kernel.

$$k(x, y) = \big(1 + (x, y)\big)^p \qquad (3)$$

where p is a user-specified and tuneable parameter that determines whether the kernel is linear, quadratic, or cubic. Based on the kernel scale, SVM will be classified as fine, medium, and coarse Gaussian models (Zeiada et al., 2020).

Gaussian Process Regression (GPR)

The GPR model complements the other machine learning models due to its flexible, non-parametric approach. GPR models excel in estimating uncertainty and analyzing noise and smoothness in training data using a Gaussian distribution for random variables. Compared to other kernel-dependent regression models, the GPR model, which also defines a stochastic process, provides a reliable response. Gaussian processes have been employed in various functions, including squared exponential GPR, Marten 5/2 GPR, and exponential GPR. As illustrated below, the differences between these specifications are due to the types of kernel functions that they use (Zeiada et al., 2020).

Squared exponential kernel equation:

$$K_{SE}\left(x,\underline{x}\right)=\sigma^2\,exp\,exp\left(\frac{\left(x-\underline{x}\right)^2}{2l^2}\right)\qquad(4)$$

where parameter l defines the characteristic length scale, and σ is a constant.

Matern kernel equation:

$$K_m=\frac{1}{2^{v-1}T(v)}\left(\frac{\sqrt{2v}}{1}r\right)^v k_v\left(\frac{\sqrt{2v}}{1}r\right)\qquad(5)$$

where v depends on input distance, kv is a modified Bessel function, and T and r are defined as follows:

$$T=l^{-2}\qquad(6)$$

$$r=|(x-x')|\qquad(7)$$

Exponential kernel equation:

$$K_E=exp\,exp\left(\left(-\frac{r}{l}\right)^y\right)\qquad(8)$$

where $0<\gamma\leq 2$.

Rational quadratic kernel equation:

$$K_{RQ}\left(x,\underline{x}\right)=\left(1+\frac{\left(x-\underline{x}\right)^2}{2.\alpha.l^2}\right)^{-\alpha}\qquad(9)$$

where α depends on input distance.

Ensemble Trees

Ensemble methods, generally, combine multiple weak models to create a more robust and accurate model. These methods can combine algorithms similar to or different from those used in individual models. Bagged trees and boosted trees are the two types of modules that make up ensemble decision trees. The ensemble achieves diversity through bagged trees, as different bootstraps are constructed for each tree and then integrated into the decision tree. The final decision is formulated by rounding all the trees' final decisions.

On the other hand, boosted trees work in two steps: First, they generate an averagely-performing model using sub-sets of the original database. Then, they enhance the model's performance by combining these sub-sets with a specific cost function. Equation (10) provides the mathematical basis for ensemble trees (Zeiada et al., 2020).

$$\hat{y}_{bag}=\frac{1}{B}\sum_{b=1}^{B}\hat{Y}b(x)\qquad(10)$$

Artificial Neural Network

Artificial neural networks (ANNs) approach provides a practical method for solving successfully all kinds of problems. The neuronal network simulates the way in which the human brain analyzes and processes information. An ANN comprises several simple units linked together *via* a network. Several study factors are represented in the input pattern, and their relationship to the output pattern is learned from that. It involves a training process in which a network stores patterns and predicts knowledge for new problems despite missing data. The model can then be used to predict/classify a modeled system once the training network has been completed using the appropriate representative training set. This model is advantageous, because it can be used with various input patterns. The ANN consists of layers containing the layouts of several sets of units logically. It consists of three layers: an input layer, a hidden layer, and an output layer. The particular layer, which is the hidden layer, is between the input buffer and the output layer. After developing the network, the ANN equation can be generated using the weights and biases. Equation (11) is designed for two hidden layers (Wenqi et al., 2017).

$$Y=b_3+LW_2.f\left(b_2+LW_1.f(b_1+IW.X_n)\right)\qquad(11)$$

where b_1, b_2, and b_3 are biases, LW_n are weights between layers, IW is the weight coming from the input layer, f stands for the activation functions, and X_n represents the input values.

5-Fold Cross-validation

A validation procedure was executed to evaluate the ML models' relevance and verify their efficacy. It is an important step that prevents overfitting and tunes the model's hyperparameters. The dataset employed in this research was limited, with 15% withheld to assess the model's performance. The k-fold cross-validation method was selected for validation due to its simplicity and reduced bias in estimating model performance compared to alternative approaches. This method involves a single parameter that specifies the number of sub-sets into which the data is segmented.

The steps of the k-fold cross-validation process are as follows:

1. Divide the dataset randomly into k sub-sets.
2. For each group:
   - 2.1 Employ one sub-set as the test set.
   - 2.2 Use the remaining sub-sets as the training set.
   - 2.3 Construct the model using the training data and then use the test data to evaluate the model's accuracy.
   - 2.4 Record the performance metrics, and then discard that iteration of the model.
3. Repeat steps 2.1 to 2.4 for each fold.

Performance Criteria

While validation focuses on model selection and tuning, testing or assessment provides a measure of the model's effectiveness and reliability. Models can be validated and assessed based on performance criteria. Performance criteria are quantitative matrices that are used to measure and assess the model's accuracy. Therefore, the model's performance criteria involve measuring and interpreting the accuracy and effectiveness as a result of the validation or testing step in the model development. Models' assessment involves testing the finalized model on a separate new dataset, which is a testing set, providing an unbiased estimate of its performance. The developed models were compared in this study utilizing MSE, RMSE, and R^2. MSE represents the average of the squares of the prediction errors that serves as a measure of the model's accuracy, with lower values indicating better performance. RMSE is the average magnitude of the prediction errors, indicating how accurately the model predicts the outcome variable, with lower values indicating better model performance. R^2 quantifies the proportion of the variance in the dependent variable that is predictable from the independent variables, with values closer to 1 indicating better models. The performance measures are represented quantitatively in Equations (12, 13, and 14).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y}_i)^2 \quad (12)$$

$$RSME = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad (13)$$

$$R^2 = 1 - \frac{SS_{RES}}{SS_{TOT}} = 1 - \frac{\sum(y_i - \bar{y}_i)^2}{\sum(y_i - \mu)^2} \quad (14)$$

where n is the number of observations, y_i represents the observations (Actual), $\bar{y}_i$ stands for the predicted values, and μ is the mean value of the samples.

Lower values of MSE and RMSE indicate a lower error for predicted values, while a higher R-squared value indicates a better model performance.

Monte Carlo Simulation (MCS)

The reliability (R) of pavement sections involves assessing the pavement's surface roughness and its impact on ride quality, safety, and structural performance. The probability of success (P_s) refers to the likelihood that a system will operate as intended without failure. In this context, reliability represents the probability of success, ensuring that the pavement section continues functioning as required over a specific period and under certain conditions. P_s is the complement of the probability of failure (P_f). Therefore, R is expressed by Equation (15).

$$Reliability\ (R) = P_s = 1 - P_f \quad (15)$$

The reliability index β is a statistical measure derived from the safety margin. It quantifies the probability of failure by considering the uncertainties in both resistance and load. The relationship between β and P_f is given by Equation (16).

$$P_f = \Phi(-\beta) \quad (16)$$

where Φ is the cumulative distribution function of the standard normal distribution.

In this study, IRI was used to measure the roughness of the pavement. Using the IRI ranges recommended by FHWA, the pavement section is at failure when the IRI exceeds 2.68. Therefore, the success (S) in predicting pavement failure is estimated as in Equation (17).

$$S = IRI_{Predicted} - IRI_f = IRI_{Predicted} - 2.68. \quad (17)$$

The $IRI_{Predicted}$ is computed using the machine learning method. However, the solution of the ML model is very complicated to be represented as one number; thus, the model's parameters were used to create the limit state function that will be used directly in the MCS method to estimate P_f. MCS is used to determine the outcomes' probability in systems with a high degree of randomness, making perfect prediction difficult. In these simulations, random samples are repeatedly generated to achieve specific results. Specifically, the MCS involves assigning random values to uncertain variables, running the model, and recording the resulting outcomes. This process is repeated multiple times with different values assigned to the variable. An estimate is generated using the averaged results from these simulations. This study used the MCS to calculate the probability of failure, which forms the basis for determining reliability.

RESULTS AND DISCUSSION

After comparing the 28 developed models (Table 4), the results revealed that the optimal model is the ANN model with two hidden layers, each containing 25 neurons. This model achieved an MSE of 0.2172, an RMSE of 0.0115, and an R-squared value of 0.82. The weights and biases of the chosen ANN model were retrieved to generate the limit state function, denoted by g(x) and represented in Equation (18), based on the model matrices.

$$g(x) = abs\ (b_3 + LW_2.tanh\big(b_2 + LW_1.tanh(b_1 + IW.X_n)\big) - 2.68 \quad (18)$$

where b1, b2, and b3 are biases, LWn are weights between layers, IW is the weight coming from the input layer, tanh stands for the activation functions, and X_n represents the input values. All these parameters are matrices with dimensions equal to 25 in rows or columns because of the number of neurons. Using the provided limit state function, MCS was conducted, and the results are presented in Figure (3), which provides a visual representation. Figure (3a) summarizes the MCS results, where P_f indicates the probability of failure, and β represents the reliability index, as mentioned before. As indicated by the value of P_f, there is a relatively low probability that the pavement sections will fail and will not meet their performance expectations. On the other hand, a β of 2.1038 denotes a satisfactory safety level, since it is within the range from 2 to 3, indicating an acceptably low probability of failure for many civil engineering structures.

Table 4. Comparisons of the models

Model type	Model name	Performance		
		RMSE	MSE	R-Squared
Regression	Linear	0.33498	0.112210	0.18
Regression decision tree	Fine	0.28239	0.079747	0.41
	Medium	0.28381	0.080547	0.41
	Coarse	0.29307	0.858920	0.37
Support vector machine	Linear	0.35005	0.122540	0.10
	Quadratic	0.27915	0.077925	0.43
	Cubic	0.26609	0.070806	0.48
	Fine Gaussian	0.26167	0.068470	0.50
	Medium Gaussian	0.25479	0.064920	0.52
	Coarse Gaussian	0.32991	0.108840	0.20

Gaussian process regression	Rational Quadratic	0.23290	0.169640	0.60
	Squared Exponential	0.23563	0.055520	0.59
	Matern 5/2	0.23372	0.054627	0.60
	Exponential	0.23651	0.055938	0.59
Ensemble trees	Boosted	0.25192	0.063465	0.53
	Bagged	0.23825	0.056765	0.58
Artificial neural network (One hidden layer)	5	0.3173	0.0597	0.43
	10	0.307	0.0401	0.62
	15	0.2821	0.0382	0.63
	20	0.2558	0.0344	0.65
	25	0.2324	0.0304	0.70
	30	0.2635	0.0327	0.64
Artificial neural network (Two hidden layers)	5 - 5	0.3089	0.0578	0.44
	10 - 10	0.3038	0.0291	0.63
	15 - 15	0.2621	0.023	0.68
	20 - 20	0.2495	0.0125	0.78
	25 - 25	0.2172	0.0115	0.82
	30 - 30	0.2552	0.0134	0.69

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-------------------------------------------
Monte Carlo simulation
-------------------------------------------
Pf                1.7700e-02
Beta              2.1038
CoV               0.0745
ModelEvaluations  10000
PfCI              [1.5116e-02 2.0284e-02]
BetaCI            [2.0479e+00 2.1670e+00]
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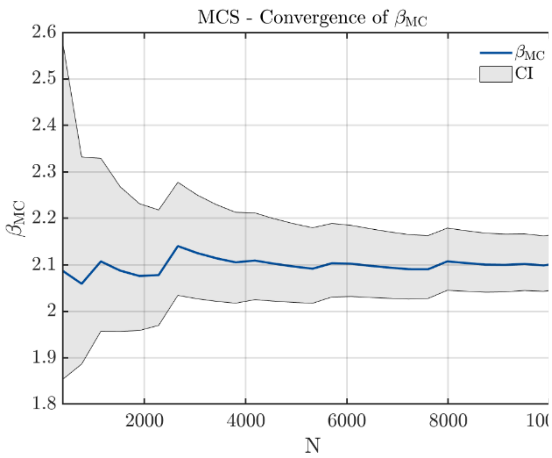
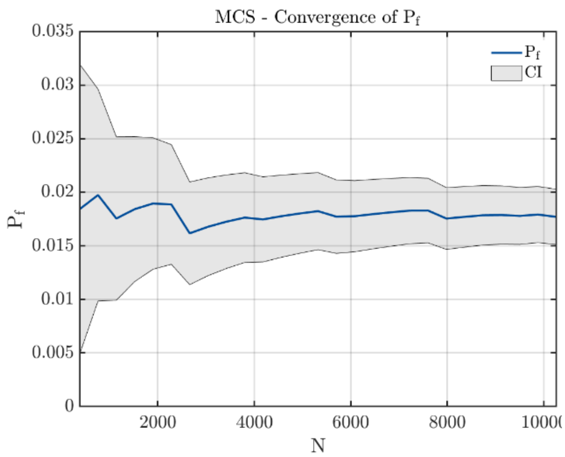
(a)





(b) (c)

Figure (3): MATLAB results (a) MCS results, (b) Reliability index, and (c) Probability of failure

Figure (3b) represents graphically the convergence of β over the number of simulations. The solid line delineates the estimated reliability index, while the shaded area depicts its 95% confidence interval. The trend indicates that as the number of simulations increases, the estimation of the reliability index stabilizes. Figure (3c) illustrates the same idea as the previous one, while Figure (3b) represents the convergence over the number of simulations for P_f instead of β. It confirms that the probability of failure stabilizes as the number of simulations increases. The outputs denoted that the MCS has provided a stable and reliable probability estimation that provides a comprehensive understanding of the risk associated with pavement deterioration. These results are essential for effective pavement management, as they help decision-makers prioritize maintenance and rehabilitation (M&R) planning. This prioritization helps in targeting the resources effectively, ensuring that critical sections receive attention before they deteriorate to unacceptable levels, thereby preventing costly emergency repairs. Additionally, efficient resource allocation ensures that budget constraints do not compromise the quality of pavement infrastructure, as resources are directed towards sections that will benefit most from intervention. Generally, ensuring that pavements remain within the desired reliability range minimizes the risk of unexpected failures, thus enhancing road safety for users. The findings from the reliability analysis provide a robust framework for improving pavement management and maintenance planning. By integrating these probabilistic assessments into decision-making processes, transportation agencies can enhance pavement infrastructure management's sustainability, safety, and cost-effectiveness.

Lastly, sensitivity analysis was performed for the controlled factor KESAL, highlighting its critical impact on P_f of pavement sections. Other factors are affecting the pavement structure, but they are uncontrollable. Therefore, it cannot be determined practically. The results represented in Table 5 demonstrate a clear positive relationship between KESAL and P_f. As the KESAL values increase, indicating higher traffic loads, P_f also increases. It can be seen that this relationship increases incrementally, with P_f of 0.0012 for 0 KESAL rising to 0.3823 for 1100 KESAL. Plotting these results, as represented in Figure (4)shows that they indicate a non-linear relationship. This non-linear increase in P_f with respect to KESAL suggests that as traffic loading increases, the pavement's risk of failure grows disproportionately. This sensitivity analysis reveals the significance of KESAL for the probability of failure, confirming that it is a contributing factor to pavement performance.

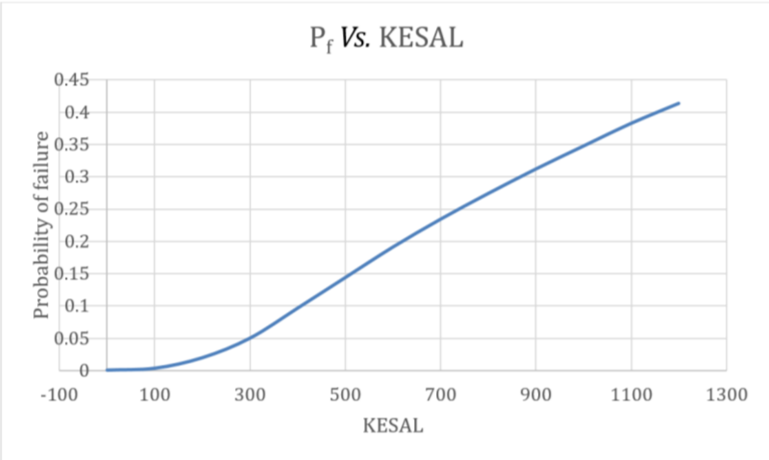


Figure (4): Probability of failure *versus* KESAL

Table 5. Probability of failure when changing KESAL mean

KESAL	P_f
0	0.0012
100	0.0041
200	0.0204
300	0.0506
400	0.097
500	0.1442
600	0.1913
700	0.2343
800	0.274
900	0.3118
1000	0.3473
1100	0.3823

In practical terms, the findings suggest that managing traffic loads, perhaps through load restrictions or improved design standards for roads expected to carry heavy traffic, could mitigate the risk of pavement failure. Moreover, incorporating KESAL into predictive models for pavement performance can enhance their accuracy, leading to more effective maintenance strategies.

CONCLUSION

To conclude, pavement deterioration is a complex process influenced by many factors, including material quality, traffic loads, and environmental conditions, reducing pavement performance and serviceability over time. This study aims to develop and validate a predictive model for pavement deterioration using machine learning techniques to measure pavement sections' reliability. Therefore, data on pavement conditions and influencing factors was collected from the LTPP database, followed by data cleaning to remove missing values and outliers. Various models for predicting pavement wear were created using traditional and machine learning methods, including linear regression, regression tree, SVM, GPR, Ensemble Trees, and ANN. These models were validated through a 5-fold cross-validation process and were assessed using MSE, RMSE, and R^2. The ANN model, with two hidden layers and 25 neurons each, emerged as the most accurate model, achieving an R^2 of 0.82. This model's parameters, specifically weight and biases obtained from the ANN, were used in formulating the limit-state equation. This equation was used to compute the probability of failure, employing FHWA's IRI recommended ranges, and was then utilized to assess the overall reliability of the pavement sections. The analysis showed a 98% reliability rate for pavements without M&R interventions, with significant sensitivity to changes in the yearly load per KESAL and total asphalt concrete thickness. The ANN model proved effective in accurately predicting pavement conditions. Future research could extend this model to include pavements that have undergone M&R, as well as to investigate the impact of such interventions on pavement deterioration. In addition, the same model can be developed using different performance indicators, and comparisons can be made. Moreover, developing models specific to climate regions could offer insights into how environmental factors affect pavement performance, with reliability analyses tailored for each model. Lastly, it is recommended to explore the integration of the model findings with the Mechanistic-Empirical Pavement Design Guide (MEPDG) using AASHTOWare ME Design tools. This integration could comprehensively validate the developed model and enhance its practical applicability in pavement -design and- maintenance planning.

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