MDOT State Study 12019-00(004)/ 107895-101000— Use of Artificial Neural Networks (ANNs) to Predict Pavement Management Data Attributes

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<tr><td colspan="3">16. Abstract: The continuous investigation into the mechanical properties and rehabilitation management of existing pavements is vital for the sustainability and efficiency of transportation systems. The Mississippi Department of Transportation (MDOT) database, containing over 40 million records, necessitates modernized decision-making models that align with current design methods and materials. In collaboration with the University of Mississippi, MDOT's pavement management program aimed to update outdated Markov transition matrices with advanced Artificial Neural Networks (ANNs). This four-year project focuses on dynamic sequential ANNs to develop performance prediction models for flexible, rigid, and composite pavements, utilizing extensive distress data. Initial results for flexible pavements showed promising outcomes, with robust statistical accuracy measures for rigid pavements (JCP and CRCP) and composite pavements, although further data and calibration are recommended. The developed models, accessible through a user-friendly interface, are expected to improve the prioritization of maintenance and rehabilitation resources, achieving significant time and cost savings while enhancing the overall efficiency of MDOT's pavement management practices.</td></tr>
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The Research Division

MDOT Research Division supports MDOT's mission by administering Mississippi's State Planning and Research (SP&R) Part II funds in an innovative, ethical, accountable, and efficient manner, including selecting and monitoring research projects that solve agency problems, move MDOT forward, and improve the network for the traveling public.

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List of Abbreviations

AASHTO	American Association of State Highway and Transportation Officials
ANN	Artificial Neural Network
ASE	Average Square Error
CESAL	Equivalent Single Axle Load
CN	Construction Number
CRCP	Continuously Reinforced Concrete Pavement
CRCP	Continuously Reinforced Concrete Pavement
CS&O	Concrete Slab Treated with Crack, Seat, and Overlay
ESAL	Equivalent Single Axle Load
FHWA	U.S. Department of Transportation's Federal Highway Administration
GPS	General Pavement Studies
GUI	Graphical User Interface
HMA	Hot Mix Asphalt
IMS	Information Management System
IRI	International Roughness Index
IRI_{Left}	Left (inside) Wheel Path International Roughness Index
IRI_{Mean}	Mean International Roughness Index
IRI_{Right}	Right (outside) Wheel Path International Roughness Index
IRRE	International Road Roughness Experiment
JCP	Jointed Concrete Pavement
JPCP	Jointed Plain Concrete Pavement
JRCP	Jointed Reinforced Concrete Pavement
LOGSIG	Log Sigmoid
LTPP	Long-Term Pavement Performance

M&R	Maintenance and Rehabilitation
MAR	Mean Absolute Relative Error
MDOT	Mississippi Department of Transportation
MEPDG	Mechanistic-Empirical Pavement Design Guide
ML	Machine Learning
MLR	Multiple Linear Regression
NCHRP	National Cooperative Highway Research Program
NMDOT	New Mexico Department of Transportation
PCC	Portland Cement Concrete
PCI	Pavement Condition Index
PCR	Pavement Condition Rating
PMS	Pavement Management Systems
PSI	Present Serviceability Index
PSR	Present Serviceability Rating
R	Coefficient of Correlation
R^2	Coefficient of Determination
RF	Random Forest
SF	Site Factor
SHRP	Strategic Highway Research Program
SN	Structural Number
SPS	Specific Pavement Study
SVM	Support Vector Machine
USDOT	United States Department of Transportation

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Executive Summary

The continuous investigation into the mechanical properties and rehabilitation management of existing pavements is crucial for the sustainability and efficiency of transportation systems. The evolving landscape of transportation technology demands a proactive approach to address challenges in pavement systems. With over 40 million records in the Mississippi Department of Transportation (MDOT) database, efficient utilization of this extensive data requires modernized decision-making processes and models aligned with contemporary design methods and materials. MDOT's pavement management program, initiated in collaboration with the University of Mississippi, set the foundation for decision-making models. However, the existing Markov transition matrices, developed over three decades ago, no longer align with recent advancements in material science and pavement design. This research aims to update and enhance these models to accurately reflect the current state of transportation infrastructure, considering the voluminous and diverse data collected annually. The research methodology employs Artificial Neural Networks (ANNs), cutting-edge computational tools inspired by biological neural systems. The proposed four-year project involves investigating existing MDOT models, conducting a literature review on pavement management system (PMS) performance and modeling, and building a comprehensive database. The study focuses on dynamic sequential ANNs to develop performance prediction models for flexible, rigid, and composite pavements, utilizing distress data from Mississippi pavement sections. For flexible pavement, significant efforts led to a robust database with over 40,000 entries. The developed model shows promising outcomes, effectively capturing the dynamic nature of pavement deterioration. Recommendations include further study on significant changes and separate models for distinct deterioration patterns. In rigid pavements (JCP and CRCP), despite smaller datasets, both models exhibit robust statistical accuracy measures. They highlight their effectiveness in capturing pavement behavior. However, the study recommends incorporating more data spanning the entire lifespan of CRCP and JCP for comprehensive insights into long-term performance. The composite pavement model displays promising statistical accuracy measures but reveals inconsistencies in minor rehabilitation efforts. Careful examination and consideration of minor rehabilitation responses are advised. Despite utilizing a significant amount of data, further calibration trials and the inclusion of composite pavement characteristics in the database are recommended for improved model performance.

In summary, the developed models proficiently depict pavement responses. Accessible through a user-friendly interface, these models are poised to achieve heightened accuracy through additional surveys and ongoing calibration efforts. The study strongly promotes the seamless integration of advanced computational tools and methodologies into MDOT's pavement management system. This integration is anticipated to streamline the prioritization of resources, enabling optimized planning for maintenance and rehabilitation actions. The ultimate goal is to achieve time and cost savings while enhancing the overall efficiency of MDOT's pavement management practices.

Project Background

Introduction

Ongoing investigations of the mechanical properties of existing pavements and their rehabilitation management have been crucial for the continuation of an uninterrupted transportation system. Such investigations require well-coordinated field measurements and a comprehensive decision-making process to overcome some of the upcoming issues in pavement systems. As the equipment to collect data in transportation systems has been constantly improved and updated, more data with higher resolution is collected and thousands of datasets are available. During a typical one-year survey, approximately 27,250 miles of survey data are collected from state, interstate, and non-interstate highways, as well as freeway expressways or other principal arterial routes. Currently, there are over 40 million records in the Mississippi Department of Transportation (MDOT) database system. The data that is collected includes condition, distress, friction, curve and grade, mean roughness index, global positioning system (GPS) location, 360-degree images, and roadway images.

Mississippi Department of Transportation (MDOT) began a pavement management program in the late 1980s through a research collaboration with the University of Mississippi. The early work in this program resulted in sets of models that were utilized for decision-making. Later on, Markov transition matrices were developed to estimate the probability of a pavement section moving from one state of distress to a state of more severe distress within one year given a specific pavement preservation action. Among all different pavement condition indices used to assess pavement surface conditions, MDOT utilizes the Pavement Condition Rating (PCR) and International Roughness Index (IRI), which are the most widely used and well-recognized pavement performance indicators to make a timely decision and maintenance schedule. However, existing models were developed over 30 years ago. Since that time, the design methods, materials, and construction practices have been updated to the latest technology based on cutting-edge research in material science and pavement design. Previously developed models are no longer valid for the new design methods and material changes.

Decision support systems in transportation applications must work rapidly to ensure maintenance without delay and reduce serious issues regarding traffic operations. MDOT Planning Division relies on prediction models to estimate the performance of the pavement systems for upcoming maintenance and rehabilitation actions. Timely actions will result in efficiently planned maintenance and rehabilitation schedules, which will save MDOT money and time. Therefore, the development of more advanced pavement performance models using modeling techniques that are more intelligent, inclusive, reliable, and accurate when estimating future pavement conditions, identifying rehabilitation needs, and analyzing rehabilitation impacts. Advanced modeling techniques utilizing machine learning techniques showed promising results in predicting pavement deterioration, offering significant improvements over traditional techniques by processing large volumes of data with a higher degree of accuracy (Barros 2021; Barros et al. 2022d, c, f; a; Bashar and Torres-Machi 2021).

The Artificial Neural Networks (ANNs) approach is a very powerful computational tool that emulates the biological neural system. It consists of three or more layers: input, hidden, and output, and each layer is made of neurons located in multiple interconnected layers where the computations are performed. ANNs learn by providing sample observations of the phenomenon to be modeled. ANNs are highly capable learning systems that allow the exploration of complex relationships and have been used by researchers, government agencies, and companies because they can be integrated into a decision-support system. The number of data used for training ANNs plays an important role in the accuracy of the prediction models. The available historical data can be used for training, testing, and cross-validation for reliable prediction models using the ANN approach. The developed ANNs models can be used for sensitivity analysis, which is performed to explore the projected future estimates as well as the historic development of the predictions. ANNs models need to be trained on large datasets to minimize the error when generalizing physical phenomena and patterns to ultimately develop an effective decision-making system. Also, by integrating additional parameters into the ANN models they can be optimized for improved reliability.

Pavement management systems (PMS) data has been continuously collected by MDOT and needs to be utilized for better characterization of the PMS performance. Artificial Neural Networks (ANNs) methodology has been widely used in many applications and is an attractive alternative approach for developing accurate prediction models because it can produce meaningful and cost-effective solutions even when input data are incomplete, contain errors, or have trend inconsistencies. The rate of deterioration of the pavement and its condition needs to be predicted so that the type, cost, and timing of the maintenance can be estimated.

Combined with a review of the independent variables to be included and a new data set including the inconsistent deflection data, the ANNs approach is a very suitable method for developing new PMS models. The proposed research project will explore the application of neural network technology to develop PMS performance prediction models for use in the MDOT pavement management system.

Research Objectives

To address the needs described in the previous section, this research has the following objectives:

- Investigate the existing MDOT models and their significance to current field practices.
- Conduct a literature review on PMS performance and modeling
- Build a database from previously collected data
- Perform analysis to identify the significance of variable to desired outputs
- Establish meaningful goodness of fit metrics
- Establish the data sets to be utilized in model development
- Develop a methodology for utilizing the inconsistent deflection data
- Establish neural network-based PMS performance models
- Develop a user-friendly interface to be easily utilized by MDOT personnel and provide help integrating the models into the MDOT PMS system
- Perform sensitivity analysis for future and past projections

Research Plan

A research plan was developed to describe the activities that were conducted to accomplish the research objectives. The tasks are explained, as follows: (Note that C stands for PIs/Consultant’s Task and M implies MDOT’s Task)

Task 1M: MDOT will provide the existing models. MDOT will compile the existing Markov transition models from MDOT's PMS network and provide them to PIs. All the necessary information that is included in the models will be explained to PIs.

Task 1C: PIs will evaluate existing Markov transition models based on MDOT's description. The models will be studied in order to evaluate their strength and weaknesses.

Task 2C: Review literature on related existing research on pavement management systems that are based on Markov transition models and Artificial Neural Networks.

Task 3C: PIs will clean, organize, and cluster the raw data provided by MDOT personnel for ANNs modeling purposes. PIs will conduct statistical analysis to understand the significance and the relationship between the database variables. In this task, the number of prediction models for each pavement type will be determined. Variability in the models will carefully be considered for broader solution space.

Task 2M: MDOT will look at the organized data and provides feedback. Based on the statistical analysis and performance-based considerations, database components are reorganized and clustered for each pavement type based on MDOT's decision support system needs.

Task 4C: PMS performance prediction model is utilized for Artificial Neural Networks Modeling for Asphalt Pavement – Flexible pavement (flex) systems on state, interstate, non-interstate highways, and other highways. PIs will have weekly meetings to discuss the progress of the ongoing model development stages and determine the necessary modifications for the upcoming meeting.

Task 3M: The model for Asphalt Pavement – Flex Systems is presented to MDOT. The progress on the developed models will be presented to MDOT personnel to collect feedback for making necessary adjustments in the models. The integration of these models into the hybrid decision support system is carried out along with the next task.

Task 5C: Artificial Neural Networks Modeling approach for Composite Pavement – JCP data analysis will be performed on state, interstate, non-interstate highways, and other highways. Similarly, the organized database for composite pavement in Task 3C is utilized for ANNs modeling. Weekly meetings with graduate and undergraduate students are held to discuss the progress on the performance of the prediction models and their significance.

Task 4M: The developed Composite Pavement- JCP model will be presented to MDOT personnel and feedback on state, interstate, non-interstate highways, and other highways will be collected. The necessary adjustments and modifications to models are noted. ANN models are retrained with the modified parameters, if needed, for the finalized prediction model.

Task 6C: Jointed Concrete Pavement Systems database on state, interstate, non-interstate highways, and other highways will be explored for ANNs modeling. Training ANN models over the weeks is performed by the students. The statistical accuracy measures are discussed in weekly meetings and recommended adjustments are made for reaching the ultimate performance of ANNs modeling technique.

Task 5M: Jointed Concrete system prediction models are presented to MDOT on various applications throughout the Mississippi pavement sections. Recommended changes to improve the models are highlighted by the MDOT personnel. The developed models are retrained for the final version of the prediction models.

Task 7C: The last ANNs model for Continuously Reinforced Concrete Pavement Systems on state, interstate, non-interstate highways, and other highways will be developed for the PMS prediction model. Trained models are discussed weekly and their statistical accuracy performances are compared to other developed models to consider the outstanding model for the decision support system. Along with the last ANN model for Continuously Reinforced Concrete Pavement Systems, the Hybrid Decision Making System (HDMS) is developed by integrating all the models into one system. This integrated system will also include MDOT decision support trees to enhance quick rehabilitation decisions in one system.

Task 6M: PIs will present all the models to MDOT personnel along with the sensitivity analysis for the projected prediction capability of the models. HDMS tool is fully explained and MDOT personnel is trained on how to utilize the HDMS system and the integrated models in the system. If necessary, PIs help programming these models into the MDOT decision system.

Task 8C: Based on the feedback from MDOT personnel, changes to improve the final models will be performed. The finalized models are delivered to MDOT. PIs write a final report including all the model specifications and the results.

Literature Review

Machine Learning

Overview of Machine Learning

Machine Learning (ML) is the science of making computers learn and act intelligently and improving their learning over time by feeding them data and information with observations and real-world interactions. The fundamental goal of the ML algorithms is to generalize beyond the training samples to successfully interpret data that it has never seen before (Faggella 2020). Several types of machine learning algorithms (i.e., K-nearest neighbor, support vector machines, naive Bayes, logistic regression, decision trees, artificial neural networks, Bayesian networks, conditional random fields, etc.) have been developed and used to process large volumes of data with high degrees of accuracy, handle noisy and complex data, solve non-linear problems, and once trained, make predictions and generalizations at any time (Bashar and Torres-Machi 2021; Darko et al. 2020).

The machine learning techniques hold significant potential for building a modern and robust pavement system management due to the excellence in automation and pattern recognition (Bashar and Torres-Machi 2021). The literature review shows that artificial neural networks are not only one of the first machine learning techniques to be used but also the most used technique in civil and pavement engineering (Adeli 2001; Ceylan et al. 2014). Because ML has a data-driven approach, IRI appears as a suitable indicator for modeling, since it is widely available in pavement databases (e.g., LTPP database), measured by objective means (e.g., laser profilometer), and known as one of the most common indicators for pavement performance evaluation (Marcelino et al. 2021). In this project, an artificial neural network technique was used for the development of pavement performance prediction models for flexible, rigid, and composite pavements.

Artificial Neural Networks

Overview of ANN

An artificial neural network is an information-processing system based on mathematical models that use the concept of human cognition and neural biology (Najjar and Huang 2007). The ANN method attempts to emulate the structure and/or functional aspects of biological neural networks (Yasarer 2010). It consists of several simple processing elements called neurons (or nodes) and connecting links between them. When the information is processed, the connection links are used to transfer signals between neurons (Najjar and Huang 2007). Each neuron evaluates its input signals to determine its output signal and transmits it to all neurons that are on the receiving side of the connection links originating in the transmitting neuron. Each connection has an associated weight that multiplies the signal transmitted (Najjar and Huang 2007). Complex relationships that are difficult to reproduce using traditional sequential, logic-based modeling and computation technics can be successfully represented by neural networks. However, the accuracy of ANN models is highly dependent on the accuracy of the database used to train the neural network. For this reason, the database cannot contain a significant amount of erroneous data or be too small, otherwise, the ANN model will generate significantly inaccurate or wrong predictions (Yasarer 2010). There are many types of neural networks characterized by their architecture, training algorithm, and activation function (Fausett 2005) as explained in the next sections.

ANN Elements and Architecture

The most simple and essential element of a neural network is called a neuron, which imitates the biological neurons from the nervous system. These neurons are a part of the ANN architecture that also consists of four main elements: input layer, hidden layer(s), an output layer, and connection weights (Tennant Duckworth 2020). Figure 1 shows an example of a typical ANN architecture.

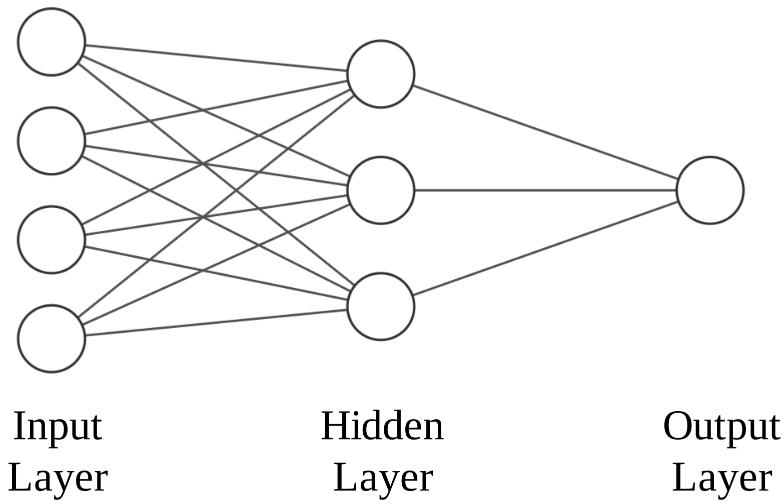


Figure 1. Example of Typical ANN Architecture

The layers presented in Figure 1 are described as follows (Sultana 2021; Yasarer 2013):

- Input Layer: It consists of independent variables that are used in the model.
- Hidden Layer(s): The hidden layer(s) can consist of one or more layers, and each layer can contain a different number of hidden nodes.
- Output Layer: It consists of the dependent variable used in the model. It can contain one or more output nodes.

Feed-Forward Network and Error Backpropagation Learning Algorithm

In this research, a feed-forward neural network with a back-propagation training algorithm was used for the development of pavement prediction models for asphalt, concrete, and composite pavements. The neural network gains its knowledge through a trained feed-forward network that uses a set of training data consisting of inputs (independent variables) and output(s) (dependent variable(s)). The resulted output is compared to the target values and the back-propagation process adjusts the connection weight to reduce the error between actual and target values (Jaafar 2019). After training, the network provides an approximate functional mapping of any input pattern onto its corresponding output pattern. Then, the validation process was carried out using datasets that were excluded from the model database (Jaafar 2019). After the validation process, it is necessary to retrain the best-performing network using all experimental data to increase the prediction accuracy and account for all patterns in the database (Yasarer 2010).

This project used different databases that contain both categorical and continuous variables. For this reason, the model development considered only one hidden layer. The use of more than one hidden layer combined with an insufficient number of databases may cause the network to memorize the data in the training phase. Therefore, the developed model used only one hidden layer to maintain the generalization capability of the network (Yasarer 2013).

Learning Algorithm

Nodal Input Values

The nodes from the input layer are connected to the hidden layer nodes and subsequently to the output layer nodes as shown in Figure 1. Node values are multiplied by the specific connection weights added to calculate a total sum of weights that will be transferred to the next node. A bias is also added as an additional set of weights and carried in the calculation. The sum of weights along with a bias is used to adjust the output of the hidden node, which will be the new feedforwarded value for the next node (Sultana 2021). Sultana exemplified the calculation of an arbitrary node "A" at a hidden layer; the node value is the sum of the value of the weights from the input layer. Equation 1 expresses the input value for a node "A" (Tennant Duckworth 2020; Yasarer 2010):

$$Node_A = \sum_{i=1}^{n}[(Input\ Node\ value)_i \times (connection\ weight)_i] + bias \qquad Eq.1$$

Activation Function: Sigmoidal Function

Many activation functions can be used to introduce non-linearity in artificial neural networks. The use of non-linear functions allows the model to learn complex relationships from the database and turn the model into a universal approximator. Bipolar sigmoidal, logistic sigmoidal, and binary steps are an example of some available functions. Specific applications might require the use of specific functions with different ranges and properties. However, the activation function must be continuous, differentiable, and monotonically non-decreasing to be applied in the backpropagation neural network (Al-masaeid 2019; Sultana 2021).

The feed forwarded information at the nodes in the hidden layer(s) and output layer need to pass through the activation function to introduce the nonlinearity into the network. Nonlinear transformations that occur in all nodes of the hidden and output layer(s) can be simplified using Equation 2 for an arbitrary node "A" (Al-masaeid 2019; Sultana 2021; Yasarer 2010):

$$Out_A = f(Net_j^L)_A \qquad Eq.2$$

Where:

- f: activation function
- $(input)_A$: input for node A, computed using Equation 3.

A sigmoidal function was used as the activation function in this project. The sigmoidal function is especially advantageous for use in backpropagation networks because the simple relationship between the value of the function at a point and the value of the derivative at that point reduce the computational load during the training phase (Fausett 2005). An output value with a specific interval between 0 and 1 is expected for this function (Yasarer 2010). Figure 2 shows the graphical representation of the sigmoidal activation function that can be mathematically expressed using Equation 3.

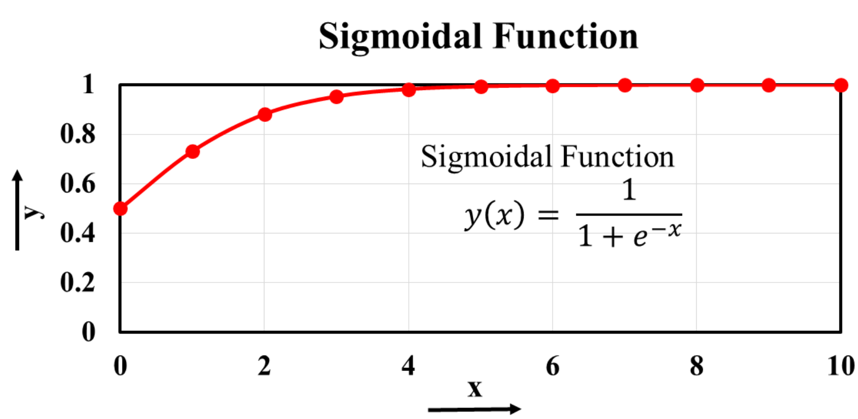


Figure 2. Sigmoidal Function

$$y(x) = \frac{1}{1+e^{-x}} \qquad Eq. 3$$

Weight Adjustment

The predicted values resulting from the output node are compared to the actual (targeted) value and the error calculated from this comparison is used to adjust the connection weights. Different propagating error methods can be used to adjust the connection weights. The most common are Levenberg-Marquardt, Perceptron's, and Gradient Descent (Qatu 2019; Sultana 2021). In this study, the gradient descent method was used due to its simplicity, stability, and effectiveness. The gradient descent method propagates the error from the output layer to the preceding layers using the derivatives of the activation function (Sultana 2021; Tennant Duckworth 2020). The weight's incremental adjustments can be calculated using Equation 4 (Yasarer 2010).

$$\Delta w_{ji}^{L} = w_{ji}^{L(new)} - w_{ji}^{L(old)} \qquad Eq. 4$$

Where:

- New: current iteration
- Old: previous iteration

Gasteiger and Zupan used the Delta rule to calculate the backpropagation neural network algorithm's incremental change (Equation 5).

$$\Delta w_{ji}^{L} = n\delta_j^L Out_i^{L-1} \qquad Eq. 5$$

Where (Gasteiger and Zupan 1993):

- n: learning rate
- δ: represents the weighted error of the connection ji
- Out_i^{L-1}: outcome from the i^{th} neuron in the $(L\text{-}1)^{th}$ layer

Learning Process

The learning process can be summarized in six steps (Yasarer 2010):

1. Input vectors are identified as $X_1, X_2, X_3, \ldots, X_n$, where n indicates the total number of variables
2. Propagate the input vectors, $X_1, X_2, X_3, \ldots, X_n$ via the connection weights to generate the output vectors.
3. Itemize the initial weights and update the connection weights on the output layer.
4. Update all weights in the hidden layer(s).
5. Repeat steps 1 through 4 for each training dataset.
6. Repeat steps 1 through 5 until the predicted output meets the corresponding target output within a predetermined tolerance or the training iterations reach the maximum limit.

Number of Hidden Nodes

The user is responsible to specify the number of initial and maximum hidden nodes in the ANN model development. The ANN process begins with the user-specified initial hidden node and goes up to the maximum allowed number predetermined. At the end of this process, the ANN structures with the least number of hidden nodes and the best statistical accuracy errors are selected to be re-evaluated in terms of statistical accuracy measures as well as graphical accuracy measures. Equation 6 can be used to calculate the maximum number of hidden nodes (Yasarer 2010).

$$Max.\,Number\ of\ Hidden\ Nodes \leq \frac{(number\ of\ training\ datasets) - (number\ of\ output\ variables)}{(number\ of\ input\ variables) + (number\ of\ output\ variables) + 1} \quad Eq.6$$

Yasarer pointed out that choosing too many hidden nodes may lead to an overtraining situation. On the other hand, a few numbers of hidden nodes may not be sufficient to capture the behavior of complex phenomena. To utilize the generalization capability of the neural network approach, this study uses networks with one hidden layer (Yasarer 2010).

Model Selection Criteria

Three statistical accuracy measures were used to compare the performance of the developed networks and to select the best performing network. The three measures are the Average Square Error (ASE), the Mean Absolute Relative Error (MARE), and the Coefficient of Determination (R^2). During the evaluation process, the training, testing, validation, and overall performance statistics need to be considered. The best-performing model is chosen based on the lowest ASE, lowest MARE, and highest R^2, which indicates the level of agreement between predicted and actual output values. Equation 7 shows the ASE calculation (Yasarer et al. 2020a).

$$ASE = \frac{\sum_{i=1}^{N}\sum_{j=1}^{n}\left(Y_{ij}^{P} - Y_{ij}^{o}\right)^2}{N.n} \quad Eq.7$$

Equation 8 expresses the MARE calculation (Yasarer et al. 2020a).

$$MARE = \frac{\sum_{i=1}^{N}\sum_{j=1}^{n}\left|\frac{Y_{ij}^{P} - Y_{ij}^{o}}{Y_{ij}^{O}}\right|}{N.n} \quad Eq.8$$

Where:

- Y_{ij}^{P} = Predicted output
- Y_{ij}^{O} = Actual output
- N = Number of datasets
- n = Number of outputs

Normalization of the input values is performed to prevent the ANN models from being biased towards a specific input. Equations 9 and 10 show the data normalization formula for input variables, while Equations 11 and 12 show the output variables (Sultana 2021).

$$\frac{X_{Max} - ANN_{XMin}}{ANN_{XMax} - ANN_{XMin}} = 0.8 \quad \text{Eq. 9}$$

$$\frac{X_{Min} - ANN_{XMin}}{ANN_{XMax} - ANN_{XMin}} = 0.2 \quad \text{Eq. 10}$$

$$\frac{Y_{Max} - ANN_{YMin}}{ANN_{YMax} - ANN_{YMin}} = 0.9 \quad \text{Eq. 11}$$

$$\frac{Y_{Min} - ANN_{YMin}}{ANN_{YMax} - ANN_{YMin}} = 0.1 \quad \text{Eq. 12}$$

Where:

- X = Value of each independent variable
- X_{max} = Maximum value of X independent variable
- X_{min} = Minimum value of X independent variable
- Y = Value of dependent variable
- Y_{max} = Maximum value of Y dependent variable
- Y_{min} = Minimum value of Y dependent variable
- ANN_{xmax} = Maximum X value normalized with respect to the value on the right side of the equation
- ANN_{xmin} = Minimum X value normalized with respect to the value on the right side of the equation
- ANN_{Ymax} = Maximum Y value normalized with respect to the value on the right side of the equation
- ANN_{Ymin} = Minimum Y value normalized with respect to the value on the right side of the equation

Summary of ANN Model Development Stages

The ANN model development and the desired criteria to choose the optimal network structures can be described in four successive stages (Yasarer and Najjar 2011), as follows:

- Stage 1: Determine the ANN architecture. Decide input and output categories based on problem characteristics and ANN knowledge. Classify the datasets as training, testing, and validation sets.
- Stage 2: Train and test the network on the experimental data to obtain the optimum number of hidden nodes and iterations for the ANN architecture defined in the previous stage. Determine the best-performing networks based on the lowest ASE, lowest MARE, and highest R^2 values.
- Stage 3: Validate the best-performing network from the second stage using the validation database. Check if the accuracy results from the training, testing, and validation database are comparable. If they are, then stage four may be not necessary.
- Stage 4: Retrain the best-performing network from Stage 2 using all experimental data to increase prediction accuracy and account for all patterns in the database.

Typically, retraining the selected final network with all experimental data is expected to provide reliable predictions and overall better accuracy measures since all the knowledge in the database is incorporated into the final network (Yasarer and Najjar 2011). Research studies by Najjar and co-workers (Najjar and Basheer 1996; Najjar and Huang 2007; Yasarer and Najjar 2011, 2014a; b) recommend that stage four is necessary to arrive at a better-performing network model. In this study, the TR-SEQ1 computer program (Najjar 1999) was used to develop the ANN models.

Dynamic-Sequential ANN Modeling

A dynamic-sequential ANN modeling technique was also used in this study to develop pavement performance models. The dynamic ANN-based training technique adopted by Najjar (Najjar 1999) and Yasarer (Yasarer 2013) is used to model the time-dependent pavement roughness performance. The dynamic-sequential technique uses the framework of the conventional feed-forward error-backpropagation neural network approach (Najjar and Felker 2006; Yasarer 2013). According to the feedback approach, the futuristic (i.e., year (n+1)) roughness value (i.e., $(IRI)^{n+1}$) is determined from some predetermined input parameters. This logic is mathematically represented by Equation 13 (Najjar and Felker 2006).

$$\{(IRI)^{n+1}\} = ANN_{(m+1)-k-1}\{x_1, x_2, \ldots, x_m(IRI)^n\} \qquad Eq. 13$$

Where ANN denotes the neural network model that best relates a given number of inputs (m+1) [i.e., x_1, x_2, ..., x_m, $(IRI)^n$] to the desired output [i.e., $(IRI)^{n+1}$]. Note that $\{x_1, x_2, ..., x_m\}$ is a vector of *(m)* parameters used to represent all static input parameters that might affect the desired output. The *(m+1)-k-1* notation represents the architecture of the selected network. In this case, *(m+1)* represents the *(m)* static inputs, and the one additional feedback parameter, *k* is the optimal number of hidden nodes, which needs to be determined through the training and testing processes, and (*1*) is the desired number of outputs, namely, the futuristic roughness IRI value [i.e., $(IRI)^{n+1}$] (Najjar and Felker 2006). An important component of dynamic-sequential modeling is that the datasets must be in sequential order and equal time steps. For the dynamic procedure is assumed that each data is recorded at the same intervals (Tennant Duckworth 2020). Figure 3 shows an example of dynamic network architecture with one output.

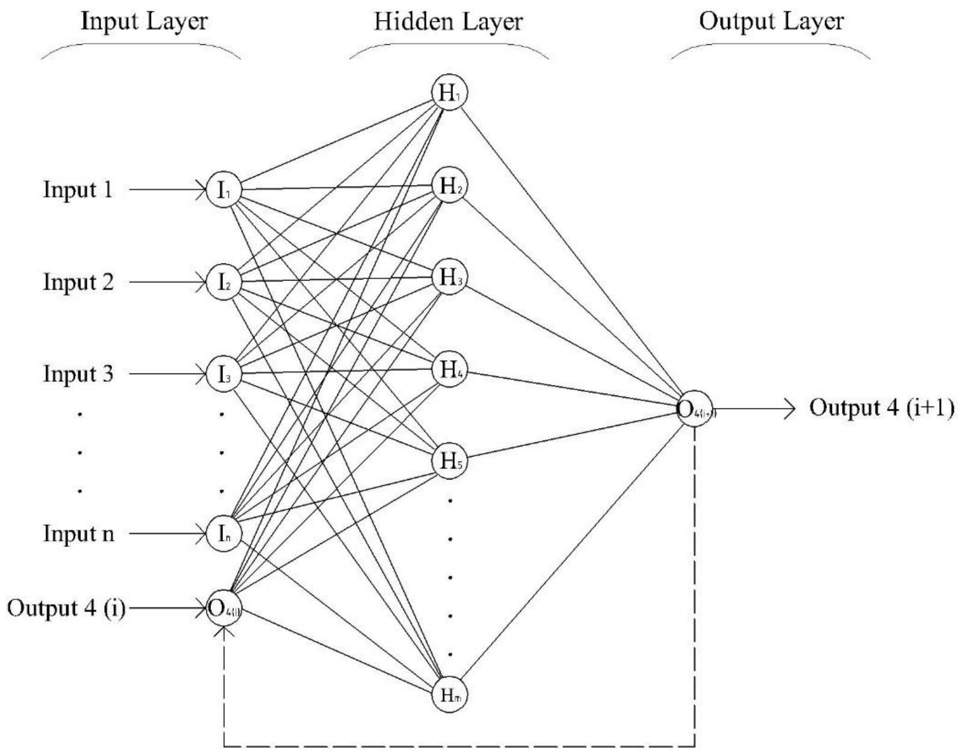


Figure 3. Dynamic-Sequential Network Structure (Yasarer 2013)

Overview of Pavement Performance Indicators

Among the most important measures of pavement performance, roughness is an indicator of road conditions and is used for making objective decisions related to the management of road networks (Sayers et al. 1986). Pavement roughness describes the irregularities in the pavement surfaces that affect the ride quality experienced by daily road users (Jaafar 2019). From several pavement condition indices used to assess pavement surface conditions, the PCR and IRI are the most used and well-recognized pavement performance indicators.

The PCR is a rating method based on visual inspection of pavement distress. Although the relationship between pavement distress and performance is hard to be understood, there is evidence that the ability of pavement to sustain traffic loads safely and smoothly is adversely affected by the incidence of observable distress. The PCR method provides a procedure for uniformly identifying and describing, in terms of severity and extent, pavement distress. The mathematical expression for PCR gives an index reflecting the composite effects of varying distress types, severity, and extent upon the overall condition of the pavement. The PCR calculation is based upon the summation of deducting points for each observable kind of distress. Deduct values are a function of distress type, severity, and extent (Ohio Department of Transportation 2006). The weights of distresses, severity, and extent are multiplied to find the deduction for each distress type. Equation 14 shows the PCR mathematical expression (Tennant Duckworth 2020).

$$PCR = 100 - \sum_{1}^{n} Deduct_i \qquad Eq. 14$$

Where:

- PCR = Pavement Condition Rating
- n = number of observable distresses
- $Deduct_i$ = multiplication of the weight of distress, weight of severity, and weight of extent for distress i.

The Ohio Department of Transportation developed a PCR scale to describe the pavement condition using the PCR numbers calculated from Equation 14. This scale has a range from 0 to 100; a perfect pavement with no observable distress has a PCR of 100 and pavement with all distress present at their "High" levels of severity and "Extensive" levels of extent have a PCR of 0. Figure 4 illustrates the PCR Scale and the explanatory condition of a pavement associated with the various ranges of the PCR values.

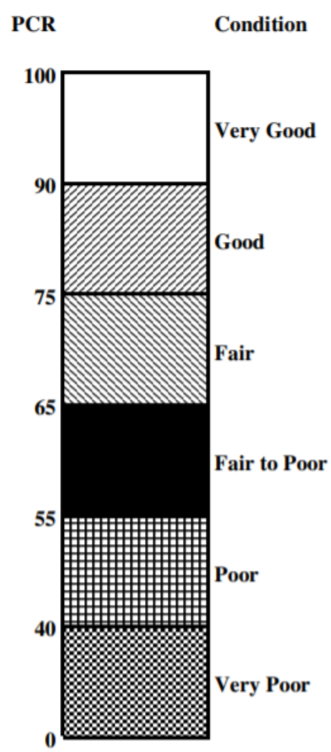


Figure 4. Pavement Condition Rating (PCR) Scale (Ohio Department of Transportation 2006)

Several methods were created to measure pavement roughness which turned difficult the use of roughness data since they were obtained by different methods. For this reason, there was a need to establish a standard roughness index to eliminate possible problems caused by using different roughness indices, methods, and data collection (Sayers et al. 1986). In 1982, the World Bank and the government of Brazil proposed the International Road Roughness Experiment (IRRE) to find a standard roughness index appropriate for the many types of roughness to provide a basis for comparing roughness measures obtained by different procedures. Forty-nine road test sites were measured using different test equipment and measurement conditions. A full roughness range of asphaltic concrete, surface treatment, gravel, and earth roads was included in the study. The results from the IRRE showed that a standard roughness index was practical, and an index was proposed that is measurable by most of the equipment, including road meters and profilometers. This selected measure has been denoted as IRI. The IRI is based on the quarter-car analysis method, a mathematical model of a vehicle that represents a body and a single wheel (Sayers 1989), with standardized parameter values and a reference simulation speed of 80 km/h (Sayers et al. 1986).

The IRI measurement can be expressed in two types of units, in/mile or m/km. A higher IRI value indicates a rough pavement profile, which affects the ride quality experienced by road users. A lower IRI value indicates a smooth pavement profile, causing a better ride quality for road users. Using high-speed vans equipped with laser equipment, accelerometers, and a computer, the pavement profile is measured generating the IRI values. The surface profiles are measured at traffic speed and the onboard accelerometer provides the data to calculate the changes in the vertical position. The distance between the vehicle and the surface of the road is measured by laser and the collected data is stored in the computer periodically. Since the change in longitudinal pavement profile over time is directly related to the change in roughness with time, it becomes an important indicator of pavement performance. The MEPDG (AASHTO 2008) designed to update the 1993 AASHTO (AASHTO 1993) uses the IRI measurements of longitudinal roughness to indicate pavement smoothness. The IRI measurements are stable, easy to be reproduced from longitudinal profile elevation, highly correlated with other roughness measuring devices, and provide good correlations with important user serviceability ratings, like present serviceability rating (Barros 2021).

Pavement Performance Models

The role of pavement performance models in the road network system has pointed transportation agencies to advanced modeling techniques that are intelligent and efficient. Advanced modeling techniques using machine learning appear as a promising tool for predicting pavement deterioration, offering significant improvements over traditional techniques (Barros 2021). Several studies have been exploring the use of ANN for predicting pavement performance in asphalt, concrete, and composite pavements. The main difference between the performance model and the prediction model is that the performance model relies on the mechanistic response of a phenomenon rather than the statistical accuracy. In this sense, logical response is the main goal to achieve. Therefore, the sensitivity analysis plays an important role. This section reviews the pavement performance models utilizing machine learning for different pavement types.

Flexible Pavement Performance Models

Attoh-Okine (Attoh-Okine 1994) used a backpropagation neural network algorithm to develop an IRI prediction model for flexible pavements using data from the LTPP database and applied a sensitivity analysis to find the relative significance of the material and construction variables on the roughness. Asphalt content, asphalt layer thickness, cumulative equivalent single axle load, structural number (SN), and the percentage of fines passing through the No. 200 sieve were used as independent variables. The study concluded that the ANN technique was feasible when a large database on pavement conditions was available. This technique could form the basis for developing a generic intelligent pavement deterioration process. However, it is also important to explore different preprocessing of input data, learning rules, and transfer functions to perform more successful predictions.

Kargah-Ostadi et al. (Kargah-Ostadi et al. 2010) developed an ANN model for flexible pavements using a specific pavement study (SPS-5) from the LTPP database. The objective of the study was to predict and compare pavement roughness variation trends after various rehabilitation alternatives. The optimum ANN structure had eight input variables, five hidden nodes within one hidden layer, and one output. The ANN model performed successfully in predicting IRI trends following each kind of treatment in the SPS-5 experiment.

Hossain et al. (Hossain et al. 2019) developed an ANN prediction model for flexible pavements using climate and traffic data collected from the LTPP database. The study compared the ANN-predicted IRI and measured IRI for flexible pavements under specific climatic zones (wet freeze) with a two hidden-layered ANN structure with seven independent variables, nine hidden nodes for the first and second hidden layers, and one output (7-9-9-1), using a nonlinear transfer function. An RMSE of 0.027 was found for the flexible ANN model, indicating that the IRI prediction was reasonable for both short-term and long-term predictions using only climate and traffic data.

Jaafar (Jaafar 2019) developed prediction models using ANN and MLR techniques for predicting IRI, rutting, and cracking for asphalt pavements using the LTPP database. For the IRI modeling, the ANN architecture used seven independent variables, five hidden nodes within a single hidden layer, and one output (i.e., 7-5-1 ANN structure). A coefficient of determination (R^2) of 0.52 and 0.40 was found for the ANN and MLR models, respectively. The results show that both models were reasonably accurate for IRI prediction in asphalt pavements, but the ANN model outperformed the MLR with higher accuracy. Sollazzo et al. (Sollazzo et al. 2017) also developed an ANN model and compared with linear regression, obtaining better accuracy when using the ANN model compared to the MLR model.

Choi (Choi et al. 2004) developed an ANN prediction model for flexible pavements on a granular base from three states: Texas, New Mexico, and Arizona. The results show that the ANN model could provide a reasonable explanation for their predictive behavior and model the relationship between input variables and pavement performance.

Duckworth (Tennant Duckworth 2020) and Duckworth et al. (Duckworth et al. 2022) developed pavement performance prediction models using the ANNs approach for flexible pavements based on the MDOT database. A two-output model for predicting PCR and IRI was found to be the most promising. The ANN model successfully characterized the deterioration behavior with statistical measures in a suitable range.

Yamany (Yamany et al. 2020) developed pavement performance models for flexible pavements using data from eight Midwestern states, and Zeiada (Zeiada et al. 2020), developed prediction models for warm climate regions in the LTPP database. Both studies found that by specifying these characteristics their prediction models performed better since the data gathered the same characteristics and helped the model to understand the variability of the datasets.

Barros et al. (Barros et al. 2022c) developed ANN performance models for flexible pavements considering traffic and climate loads, pavement age, initial roughness condition, and M&R interventions using the LTPP database. The developed models efficiently characterized the deterioration behavior of asphalt pavements over time and effectively captured the effect of M&R interventions. The predicted IRI values were in good agreement with observed values and the developed models (R^2=0.61 and R^2=0.67 for Model 1 and Model 2, respectively). Barros highlights that even though the development of the ANN model requires a good understanding of the roughness phenomena, the developed models are simple, fast, and do not require the user to have any prior knowledge of IRI or ANN.

Rigid Pavement Performance Prediction Models (JCP and CRCP)

Compared to flexible pavements, relatively few studies have been conducted in recent years to predict concrete pavements' roughness. Hossain et al. (Hossain et al. 2020) developed a prediction model for IRI for rigid pavement using climate and traffic data by employing Artificial Neural Network (ANN) modeling. The climate and traffic data are collected from the LTPP database. The ANN model is trained using 70% of climate, traffic, and IRI data, 15% data is used to test the model, and the rest 15% data is employed to validate the model. The trained model and the validated model are compared by calculating the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) of ANN-predicted IRI and measured IRI. The study developed a model for rigid pavement located at the wet no-freeze climatic zone, employing 7-9-9-1 ANN structure and using hyperbolic tangent sigmoidal transfer function, the RMSE value and MAPE value generated is 0.01 and 0.01 (1% error) respectively.

Andrews et al. (Yasarer et al. 2021) developed a new set of ANN models that contain daily traffic volume, IRI, soil condition, pavement thickness, and mean roughness index (MRI) for the Jointed Concrete Pavements (JCP) in Mississippi. The best-performing ANN model had an R^2 of 0.93 and was integrated into a Microsoft Excel spreadsheet to generate an application that is simple, user- friendly, and allows the user to visualize the future projections of the pavement section. The authors recommended that MDOT personnel can employ this application to predict the condition of the JCP and prioritize the maintenance and rehabilitation schedule.

Yasarer et al. (Yasarer et al. 2020b) developed a performance model for CRCP pavement using the ANN modeling technique for Mississippi. This study used maintenance and rehabilitation actions as an input in the model. The database used in this study contained 69 CRCP pavement sections that resulted in 212 datasets from 2010 to 2018. The ANN model was trained using 25% data, then tested with 25% data, and the other 25% of data was employed to validate the model by comparing ANN-predicted IRI and measured IRI. The study developed a model employing an 11-18-1 ANN structure with an accuracy of 0.0012 ASE, 5.923 MARE, and 0.872 R^2 statistical measures.

Sultana (Sultana 2021) developed performance models for Jointed Plain Concrete Pavement (JPCP), Jointed Reinforced Concrete Pavement (JRCP), and Continuously Reinforced Concrete Pavement (CRCP) using MLR and ANN techniques considering the effects of M&R history in the model development. The input and output variables were similar for all the models and retrieved from the LTPP database. The ANN models showed better accuracy in predicting pavement performance compared to the multiple regression models for all types of concrete pavements. A high R^2 of 0.94, 0.95, and 0.95 were obtained for the JPCP, JRCP, and CRCP, respectively, presenting a significant improvement over models that currently use mechanistic-empirical pavement design.

Sultana et al. (Sultana et al. 2022a) developed an ANN pavement deterioration model for jointed plain concrete pavement (JPCP). The models were developed using LTPP data for the wet, freeze climatic region. The input variables were initial pavement condition (i. e., initial IRI), pavement structural and mechanical properties (i.e., age, concrete pavement thickness, base/subbase thickness, average contraction spacing, base/subbase materials type), traffic (Cumulative ESAL (CESAL)), and climate attributes (i.e., average annual air temperature, total annual precipitation, annual freezing index, annual freeze-thaw), and IRI as the output variable. The developed ANN model had an R^2 of 0.92, an ASE, and a MARE value of 0.00103 and 9.93, respectively. The total data points used to develop the ANN model were 636 and the final model structure was 13-19-1, where 13 is the number of input variables, 19 hidden nodes, and 1 output variable.

The best model was used to simulate extreme climate conditions by developing a Graphical User Interface (GUI). IRI values gradually increased, and pavement conditions deteriorated over time when climate conditions change to the extreme. The study addressed a few gaps in the literature including the scarcity of studies on long-term IRI prediction using LTPP data and studies on the effect of climate attributes in pavement deterioration.

Sultana et al. (Sultana et al. 2022b) exhibited a methodology to determine pavement performance incorporating maintenance and rehabilitation history using the LTPP database and ANN modeling approach. The study incopored the M&R history as construction number (CN) in the LTPP database and the hypothesis testing demonstrated M&R treatment has a significant effect on pavement performance. Several ANN models were attempted to evaluate the best way to include M&R history and resulted in more realistic prediction of pavement condition A continuous CN approach resulted in an R^2 of 0.901 compared to the categorical CN approach of R^2 of 0.878.

Sultana et al. (Sultana et al. 2021a, 2022c) utilized Construction Number (CN) variable for developing IRI prediction models for Jointed Plain Concrete Pavements (JPCP). Three ANN models were developed using variables such as initial IRI, pavement age, concrete pavement thickness, ESAL, climatic region, and CN. The best model had an R^2 of 0.87 and successfully estimated the increase of IRI values with time and decrease of IRI value after maintenance and rehabilitation.

Sultana et al. (Sultana et al. 2021b) studied climate attributes such as precipitation, extreme temperature, and freeze-thaw cycles along with traffic loads that cause pavement distresses. Sultana developed IRI models that successfully estimated the IRI values for Jointed Plain Concrete Pavement (JPCP) considering the M&R history of the pavements using the ANN approach. The variables used for the ANN model development are initial IRI, pavement age, concrete pavement thickness, equivalent single axle load (ESAL), climatic region (wet-freeze, wet non-freeze, dry-freeze, dry non-freeze), CN, and several climatological data. The best performing ANN model resulted in promising statistical measures (i.e. R^2= 0.87).

Abd El-Hakim and El-Badawy (Abd El-Hakim and El-Badawy 2013) developed an ANN model to predict IRI values for Jointed Plain Concrete Pavement (JPCP) sections using the LTPP database. The model inputs were initial IRI value, pavement age, transverse cracking, percent joints spalled, flexible and rigid patching areas, total joint faulting, freezing index, and percent subgrade passing No. 200 U.S. sieve. The data included a total of 184 IRI measurements and the results show that the ANN model yielded a higher prediction accuracy (R^2 of 0.83, and ratio of standard error of estimate (predicted) to standard deviation of the measured IRI values: Se/Sy =0.414) compared to the MEPDG model (R^2 of 0.584, Se/Sy =0.643). In addition, the bias in the predicted IRI values using the ANN model was significantly lower compared to the MEPDG regression model.

Composite Pavement Performance Prediction Models

Literature review to date shows that ANN models performed successfully in predicting IRI values for asphalt and concrete pavements. However, performance prediction models for composite pavements have not been well investigated. A few studies are available using composite pavements data and fewer studies utilized M&R history in the model development. These studies are summarized in this section.

Kaya et al. (Kaya et al. 2020) developed pavement performance models for flexible and composite (asphalt concrete over the jointed plain concrete pavement) pavement systems in Iowa. ANN-based models were found to be good tools for modeling pavement deterioration when there were many pavement sections with various traffic, thickness, and other various deterioration trends.

Abdelaziz et al. (Abdelaziz et al. 2020) develop an IRI prediction model for both original and overlaid flexible pavements using general pavement studies (GPS-1, GPS-2, and GPS-6) and the specific pavement studies (SPS-1, SPS-3, and SPS-5) of the LTPP database. Multiple linear regression (MLR) and ANN techniques predict IRI as a function of pavement age, initial IRI, transverse cracks, alligator cracks, and standard deviation of the rut depth. The ANN model resulted in better results compared to the regression model, $R^2 = 0.75$ and $R^2 = 0.57$, respectively. The network consisted of five inputs, three hidden layers with ten nodes each, and one output, 5-10-10-10-1 with a Logarithmic-Sigmoidal (LOGSIG) as the transfer function.

Barros et al. (Barros et al. 2021a; b) developed pavement roughness models for composite pavements using the LTPP database and the feed-forward ANN approach. A total of 592 data points from 52 pavement sections were analyzed. Five models were developed and the best performing model had an ASE of 0.002, a MARE of 12.936, and an R^2 of 0.88. It utilized 14 input variables (i.e. Initial IRIMean, Age, Wet-Freeze, Wet Non-Freeze, Dry-Freeze, Dry Non-Freeze, Asphalt Thickness, Concrete Thickness, CN Code, ESAL, Annual Air Temperature, Freeze Index, Freeze-Thaw, and Precipitation) and one output variable (IRIMean).

Barros et al. (Barros et al. 2022b) analyzed roughness data for composite pavements (asphalt overlay on concrete) in the wet non-freeze climate zone of the Long-Term Performance Pavement (LTPP) database and developed pavement roughness prediction models using ANN and Multiple Linear Regression (MLR) approaches to evaluate the accuracy of developed models and identify the best performance model. A total of 49 sections with 353 data points were used for the analysis. The ANN and MLR models included 11 input variables and 1 output variable. The results indicated the ANN model outperformed the MLR model with a MARE (13.14) 53% lower and an ASE (0.00182) 99% lower, compared to the MLR model. The R^2 value improved from 0.37, obtained by the MLR model, to 0.86, obtained by the ANN model. This translates into 132% better prediction accuracy by using the ANN-based model. The use of a specific climate region helped the model to capture almost 90% of the variability, which may be not viable when using data from all climate zones together. Furthermore, the developed models did not use any distress data for input variables, which can help transportation agencies save time and money from data collection and processing.

Barros et al. (Barros et al. 2022e) developed three ANN models using different M&R variables to identify which approach would give the most accurate roughness prediction. Results show that Model 1 outperformed all other models with an ASE of 0.0011, a MARE of 10.45, and a high R^2 of 0.90. The network structure of the best model includes 9 input variables, 1 hidden layer with 19 hidden nodes, 20,000 iterations, and 1 output.

The literature review indicates that the M&R history was not considered in many pavement performance prediction models. Therefore, this research considers several input variables, including M&R history for developing performance models for flexible, concrete, and composite pavements in Mississippi. The performance models will predict IRI and PCR values using easily available variables that will help MDOT to prepare M&R programs and budgets without estimating distress in future years.

Methodology

The pavement performance modeling methodology flowchart used in this research is shown in Figure 5.

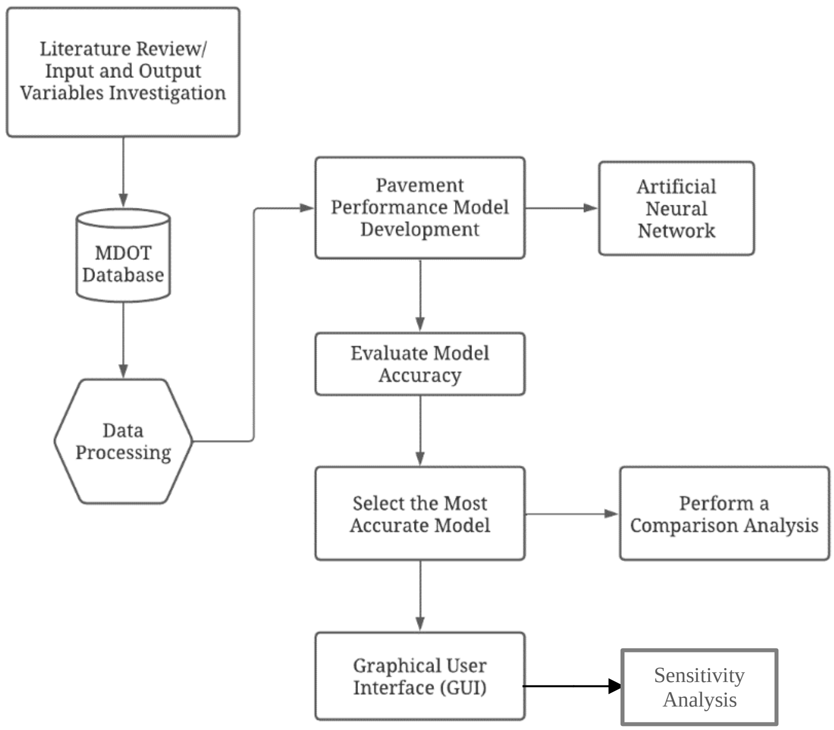


Figure 5. Pavement Performance Modeling Methodology

The model development methodology is described, as follows:

- Conduct an extensive literature review to identify key input and output variables.
- Compile databases for flexible, rigid (JCP and CRCP), and composite pavements from the MDOT database, including variables that affect pavement performance.
- Assess the quality of databases and identify missing/erroneous data items.
- Develop pavement performance models for all pavement types using the ANN modeling technique.
- Evaluate the accuracy of the developed performance prediction models.
- Select the best-performing model based on statistical measures and verify the prediction behavior.
- Implement the selected performance models via Graphical User Interface (GUI).
- Evaluate the selected model using GUI for the enhancement of pavement asset management.

Data Description and Collection

The pavement database utilized in this research is a part of Mississippi's pavement survey performed by the MDOT. Every two years, MDOT collects data to monitor the current pavement conditions and predict M&R for the Mississippi road network. Four different pavement types are found in the database: flexible, JCP, CRCP, and composite pavements. All pavement types were utilized in this study to develop performance prediction models. MDOT operates a pavement management system that includes PCR, IRI, and distress data (Barros et al. 2022d). Due to the new methods in the data collection system, only recorded datasets from 2010 to 2020 were utilized, which resulted in 6 usable years of data. To characterize the behavior of pavement deterioration in a one-year time increment, a continuous database was needed to be used for developing reliable models. Since MDOT collects data every even year, to develop prediction models that are applicable for a 1-year increment, the odd-year data were generated by averaging consecutive years from 2010 to 2020. This approach was successfully utilized for the MDOT database in previous studies (Barros et al. 2022a; d; Duckworth et al. 2022; Tennant Duckworth 2020; Yasarer et al. 2020b, 2021).

By assessing the quality of databases, sections with missing or illogical data have been excluded as the ANN model development process needs a complete dataset. This includes instances of negative IRI and the sections without the recorded length. After the data processing procedure, the flexible pavement database consisted of 35,712 data points for 3,968 sections. The JCP database comprised 909 data points for 101 sections while the CRCP database had 396 data points for 44 sections. The composite pavement database consisted of 10,305 data points for 1,145 sections. The data processing procedure utilized in this research is explained in the following sections.

Data Processing

The database for the development of performance prediction models is obtained after cleansing and reorganizing the raw data files. The purpose of developing an ANN pavement performance model is to predict when M&R actions are needed and how it affect the roadway. It is known that not all rehabilitation actions were properly recorded in the MDOT's pavement survey and for this reason, a different approach for assigning rehabilitation actions was proposed based on the discussions with the state agency.

Rehabilitation Actions

When data processing the database, numerous pavement sections were noticed to have vast improvements in terms of PCR and/or IRI without any recorded rehabilitations. Improvement of PCR and IRI values without any recorded rehabilitation was found to be irrational. Some uncertainty due to the calibration of the profilometer, systematic errors, and the environmental conditions on the day of the survey may have resulted in some of the irrational condition measures (Yasarer et al. 2020b). To incorporate the effect of the rehabilitation on PCR and IRI a new approach to classify rehabilitation actions was needed. Two separate artificial rehabilitation actions based on significant changes in PCR and IRI have been assigned to the database. Threshold values for PCR and IRI were assigned based on the evaluation of data history, consultation with experts in pavements, transportation, and ANN, and verified by MDOT. Several threshold values were studied (Duckworth et al. 2022; Tennant Duckworth 2020; Yasarer et al. 2020b; Yasarer and Andrews 2021) and optimum threshold values were found.

A preliminary study was performed and through the examination, a rehabilitation action was assigned to flexible sections when PCR values increased by more than 2.5 or IRI decreased by more than 0.2 mm/m (Duckworth et al. 2022), for JCP sections when PCR increased more than 2.5 and IRI decreased by 0.05 mm/m(Yasarer et al. 2021), and for CRCP sections when PCR values increased by more than 2.5 or IRI decreased by more than 0.06 (Yasarer et al. 2020b). These artificial rehabilitations were known as PCR or IRI rehabilitation based on their changes. In the initial database, a rehabilitation action was assigned "1" if it occurred and assigned "0" if it did not occur. However, after further study, another approach was found to be more realistic and accurate. The new approach was based on PCR and IRI percentage changes. If PCR increased 8% to 12% and IRI decreased 5% to 16% in a year compared to the previous measurement, a minor rehabilitation was assumed to take place in that year. If PCR increased above 12% and IRI decreased more than 16%, a major rehabilitation was assumed. If none of these situations occurred, it was assumed no rehabilitation (Barros et al. 2022d; a; Tennant Duckworth 2020).

Input and Output Variables

For the pavement performance prediction modeling, several input variables were selected after an extensive literature review and consultation with MDOT personnel to identify what parameters were significant to the agency and retrieved from the MDOT database. Different inputs were tried using a trial-and-error method to select the most significant variables considering the practical point of view and these variables are described in the following sections.

Output Variables

Among the most important measures of pavement performance, the IRI and PCR are the most used and well-recognized pavement performance indicators (Barros et al. 2022d). These indicators are considered the most significant in determining the condition of the pavement and, therefore, were utilized in this research. It is known that PCR and IRI usually change inversely over time, when PCR increases, IRI decreases. However, to achieve better results in the modeling process both output variables must be directly proportional. Therefore, a new variable named complementary PCR (i.e., 100-PCR) was developed. The complementary PCR is calculated by subtracting 100 – PCR, which resulted in a directly proportional relationship with the IRI variable. The utilization of complementary PCR and IRI helped the network to optimize the model with higher accuracy and to establish a better correlation between actual and predicted outputs (Yasarer et al. 2020b). The output variables utilized in this research are described, as follows:

- IRI: International Roughness Index measured in that specific year in mm/m or m/km.
- PCR: Pavement Condition Rating calculated in that specific year
- Complementary PCR: this variable is calculated by subtracting PCR from 100 (i.e., 100-PCR).

Input Variables

For the pavement modeling database, several input variables were tried using a trial-and-error method to select the most significant variables considering the practical point of view and identifying the optimum modeling structure. The input variables utilized in this research for flexible, rigid (JCP and CRCP), and composite pavements, are explained as follows:

- Beginning Latitude: latitude coordinates to indicate the initial location of the roadway section
- Beginning Longitude: longitude coordinates to indicate the initial location of the roadway section
- Ending Latitude: latitude coordinates to indicate the end of the roadway section
- Ending Longitude: longitude coordinates to indicate the end of the roadway section
- Structural Number (SN): number used to indicate the strength of the roadway when factoring material properties, thickness, and drainage in each layer of flexible pavement. This variable is only used in the flexible pavement database.
- Pavement Top Layer Thickness: indicates the asphalt overlay concrete thickness in the pavement section in millimeters. This variable is only used in the composite pavement database.
- Concrete Pavement Thickness: indicates the concrete thickness in the pavement section in millimeters. This variable is only used in the rigid (JCP and CRCP) pavement database.
- Section Length: length of the section recorded in miles

- Pavement Age in 2010: shows the pavement section’s age since the earliest available pavement measurement was recorded.
- PCR in 2010: shows the initial PCR value in 2010 to indicate the base starting value.
- IRI in 2010: shows the initial IRI in 2010 to indicate the baseline value to represent the pavement's initial condition.
- Time since 2010: represents the time since 2010 to the desired prediction year. This value is associated with the effects of pavement aging.
- Drainage: categorical variable that indicates the presence of drainage components in the section. A value of “0” indicates no drainage while a value of “1” indicates the existence of drainage.
- Accumulated Rainfall (mm): accumulated annual rainfall to determine how much rainfall affects a roadway section throughout the modeling years. This was accomplished for each year by summing current and previous years’ rainfall data.
- IRI Rehabilitation: categorical variable to represent rehabilitation actions based on IRI changes
- PCR Rehabilitation: categorical variable to represent rehabilitation actions based on PCR changes
- PCR and IRI Minor Rehabilitation: categorical variable to represent minor rehabilitation. Use “1” if PCR increased 8% to 12% and IRI decreased 5% to 16% in a year compared to the previous measurement. If not, use “0”.
- PCR and IRI Major Rehabilitation: categorical variable to represent major rehabilitation. Use “1” if PCR increased above 12% and IRI decreased more than 16%. If not, use “0”.
- Equivalent Single Axle Load (ESAL): traffic variable to indicate the ESAL value in that specific year.
- Cumulative Equivalent Single Axle Load (CESAL): traffic variable to indicate the CESAL in that specific year.
- Two Lane Road: categorical variable to indicate the type of road for a specific section. Use “1” if this section has a two-lane road. If not, use “0”.
- Four Lane Road: categorical variable to indicate the type of road for a specific section. Use “1” if this section has a four-lane road. If not, use “0”.
- Interstate: categorical variable to indicate the type of road for a specific section. Use “1” if this section is an interstate. If not, use “0”.
- PRE PCR: variable used for dynamic ANN models to indicate the PCR from the previous years that will be used to predict the actual year.
- PRE IRI: variable used for dynamic ANN models to indicate the IRI from the previous years that will be used to predict the actual year.

Summary of Input and Output Variables

A summary of all input and output variables utilized in the pavement performance modeling study is shown in Table 1.

Table 1. Summary of Input and Output Variables for All Pavement Types

Pavement Type	**Flexible**	**Rigid (JCP and CRCP)**	**Composite**
Input Variables	Begin Latitude	Begin Latitude	Begin Latitude
	Begin Longitude	Begin Longitude	Begin Longitude
	End Latitude	End Latitude	End Latitude
	End Longitude	End Longitude	End Longitude
	Structural Number (SN)	Section Length	Section Length
	Section Length	Pavement Age in 2010	Pavement Age in 2010
	Pavement Age in 2010	Concrete Thickness	Pavement Top Layer Thickness
	PCR @ 2010	PCR @ 2010	PCR @ 2010
	IRI @ 2010	IRI @ 2010	IRI @ 2010
	Time (t)	Time (t)	Time (t)
	Drainage	Drainage	Drainage
	Accumulated Rainfall (mm)	Accumulated Rainfall (mm)	Accumulated Rainfall (mm)
	IRI Rehabilitation	IRI Rehabilitation	IRI Rehabilitation
	PCR Rehabilitation	PCR Rehabilitation	PCR Rehabilitation
	PCR and IRI Minor Rehabilitation	PCR and IRI Minor Rehabilitation	PCR and IRI Minor Rehabilitation
	PCR and IRI Major Rehabilitation	PCR and IRI Major Rehabilitation	PCR and IRI Major Rehabilitation
	ESAL	ESAL	ESAL
	CESAL	CESAL	CESAL
	Two Lane Road	Two Lane Road	Two Lane Road
	Four Lane Road	Four Lane Road	Four Lane Road
	Interstate	Interstate	Interstate
	Pre PCR	Pre PCR	Pre PCR
	Pre IRI	Pre IRI	Pre IRI
Output Variables	PCR	PCR	PCR
	IRI	IRI	IRI
	Complementary PCR	Complementary PCR	Complementary PCR
	IRI and Complementary PCR	IRI and Complementary PCR	IRI and Complementary PCR

Development of Performance Models

ANN Model Development

The ANN pavement performance models were developed in four stages, as explained in the "Summary of ANN Model Development Stages" section. Stage one comprises the selection of input and output variables and the classification of the datasets in training (50%), testing (25%), and validation (25%). In stage two datasets are trained and tested to obtain the optimum number of hidden nodes and iterations to determine the best-performing networks. In stage three, the best networks from stage 2 are tested with the validation datasets. In the fourth stage, the best-performing network from stage 2 is retrained using all experimental data to increase prediction accuracy and account for all patterns in the database (Yasarer 2013).

A feedforward neural network with a back-propagation training algorithm was used for the development of performance prediction models in this study. A one-hidden-layer network was considered in the model development since the use of more than one hidden layer may cause the network to memorize the data in the training phase (Yasarer 2010). A sigmoidal function was used for data generalization purposes and the TR-SEQ1 computer program (Najjar 1999) was used to develop the ANN models.

ANN Model Selection

The best ANN models for each pavement type were selected based on the lowest Average Square Error (ASE), Mean Absolute Relative Error (MARE), and highest Coefficient of Determination (R^2). The maximum and minimum values of each independent variable were included in the training phase for the network to represent the characteristics of the response. The maximum and minimum ranges of each input/output variable for ANN model development were chosen on purpose to be wider than their actual ranges for better mathematical mapping (Yasarer 2010).

ANN Model Structure

Different models were developed varying the numbers of independent and dependent variables using a trial-and-error method to select the most significant variables considering the practical point of view and identify the optimum modeling structure (Barros et al. 2022d). The developed models and variables used in this research for each pavement type are presented in the following sections

Flexible Pavements

A total of 7 models were developed in this study to select the most accurate and practical model for MDOT utilization. Models utilized 15 to 19 independent variables and one or two dependent variables in their structure. Various trials with different independent variable combinations were carried out. As more survey data became available over the years, the models and trials were expanded to improve the prediction capability of the models. Some of the significant features of the trial runs are listed below.

- 2020 Without ESAL
- 2020 With ESAL
- 2020 With ESAL Complementary PCR
- 2020 With CESAL
- 2020 With CESAL IRI <= 5 m/km
- 2020 CESAL IRI <= 5 m/km With Lanes

- 2020 ESAL IRI <= 5 m/km With Lanes
- **2022 CESAL IRI <=5m/km With Lanes**

A summary of all developed models for flexible pavements and their structure is presented in Table 2.

Table 2. Flexible Pavement Models Structure

Flexible Pavement	2020 Without ESAL	2020 With ESAL IRI	2020 With ESAL Complementary PCR	2020 With CESAL	2020 With CESAL IRI <= 5 m/km	2020 CESAL IRI <= 5 m/km With Lanes	2020/2022 ESAL IRI <= 5 m/km With Lanes
Independent Variables	Begin Latitude	Begin Latitude	Begin Latitude	Begin Latitude	Begin Latitude	Begin Latitude	Begin Latitude
	Begin Longitude	Begin Longitude	Begin Longitude	Begin Longitude	Begin Longitude	Begin Longitude	Begin Longitude
	End Latitude	End Latitude	End Latitude	End Latitude	End Latitude	End Latitude	End Latitude
	End Longitude	End Longitude	End Longitude	End Longitude	End Longitude	End Longitude	End Longitude
	SN	SN	SN	SN	SN	SN	SN
	Section Length	Section Length	Section Length	Section Length	Section Length	Section Length	Section Length
	Pavement Age in 2010	Pavement Age in 2010	Pavement Age in 2010	Pavement Age in 2010	Pavement Age in 2010	Pavement Age in 2010	Pavement Age in 2010
	PCR @ 2010	PCR @ 2010	PCR @ 2010	PCR @ 2010	PCR @ 2010	PCR @ 2010	PCR @ 2010
	IRI @ 2010	IRI @ 2010	IRI @ 2010	IRI @ 2010	IRI @ 2010	IRI @ 2010	IRI @ 2010
	Time (t)	Time (t)	Time (t)	Time (t)	Time (t)	Time (t)	Time (t)
	Drainage	Drainage	Drainage	Drainage	Drainage	Drainage	Drainage
	PCR/IRI Minor Rehab.	PCR/IRI Minor Rehab.	PCR/IRI Minor Rehab.	PCR/IRI Minor Rehab.	PCR/IRI Minor Rehab.	PCR/IRI Minor Rehab.	PCR/IRI Minor Rehab.
	PCR/IRI Major Rehab.	PCR/IRI Major Rehab.	PCR/IRI Major Rehab.	PCR/IRI Major Rehab.	PCR/IRI Major Rehab.	PCR/IRI Major Rehab.	PCR/IRI Major Rehab.
		ESAL		CESAL	CESAL	CESAL	ESAL
						Two Lane Road	Two Lane Road
						Four Lane Road	Four Lane Road
						Interstate	Interstate
	Pre PCR		Pre PCR	Pre PCR	Pre PCR	Pre PCR	Pre PCR
	Pre IRI	Pre IRI		Pre IRI	Pre IRI	Pre IRI	Pre IRI
Dependent Variables	Complementary PCR		Complementary PCR	Complementary PCR	Complementary PCR	Complementary PCR	Complementary PCR
	IRI	IRI		IRI	IRI	IRI	IRI

Rigid Pavements

A total of six models were considered among many models for rigid pavements. Four models for JCP and four models for CRCP. Both JCP and CRCP models used 15 to 18 independent and 2 output variables in their structure.

Jointed Concrete Pavements (JCP)

This section describes the model structure for JCP pavements. A summary of promising models for JCP pavements and their model structure is presented in Table 3.

Table 3. JCP Pavement Models Structure

JCP Pavement	2020 ESAL	2020 CESAL	2020 ESAL With Lanes	2022 CESAL
Independent Variables	Begin Latitude	Begin Latitude	Begin Latitude	Begin Latitude
	Begin Longitude	Begin Longitude	Begin Longitude	Begin Longitude
	End Latitude	End Latitude	End Latitude	End Latitude
	End Longitude	End Longitude	End Longitude	End Longitude
	Concrete Thickness	Concrete Thickness	Concrete Thickness	Concrete Thickness
	Section Length	Section Length	Section Length	Section Length
	Pavement Age in 2010	Pavement Age in 2010	Pavement Age in 2010	Pavement Age in 2010
	PCR @ 2010	PCR @ 2010	PCR @ 2010	PCR @ 2010
	IRI @ 2010	IRI @ 2010	IRI @ 2010	IRI @ 2010
	Time (t)	Time (t)	Time (t)	Time (t)
	PCR/IRI Minor Rehab.	PCR/IRI Minor Rehab.	PCR/IRI Minor Rehab.	PCR/IRI Minor Rehab.
	PCR/IRI Major Rehab.	PCR/IRI Major Rehab.	PCR/IRI Major Rehab.	PCR/IRI Major Rehab.
	ESAL	CESAL	ESAL	ESAL
			Two Lane Road	
			Four Lane Road	
			Interstate	
	Pre PCR	Pre PCR	Pre PCR	Pre PCR
	Pre IRI	Pre IRI	Pre IRI	Pre IRI
Dependent Variables	Complementary PCR	Complementary PCR	Complementary PCR	Complementary PCR
	IRI	IRI	IRI	IRI

Continuously Reinforced Concrete Pavement (CRCP)

This section describes the model structure for CRCP pavements. A summary of promising models for CRCP pavements and their structure is presented in Table 4. The trials with different data configurations were presented in the table. Most of the variables are common except ESAL, cumulative ESAL, Lane category, and updated database with cumulative ESAL.

Table 4. CRCP Models Structure

CRCP Pavement	2020 ESAL	2020 CESAL	2020 ESAL With Lanes	2022 CESAL
Independent Variables	Begin Latitude	Begin Latitude	Begin Latitude	Begin Latitude
	Begin Longitude	Begin Longitude	Begin Longitude	Begin Longitude
	End Latitude	End Latitude	End Latitude	End Latitude
	End Longitude	End Longitude	End Longitude	End Longitude
	Concrete Thickness	Concrete Thickness	Concrete Thickness	Concrete Thickness
	Section Length	Section Length	Section Length	Section Length
	Pavement Age in 2010	Pavement Age in 2010	Pavement Age in 2010	Pavement Age in 2010
	PCR @ 2010	PCR @ 2010	PCR @ 2010	PCR @ 2010
	IRI @ 2010	IRI @ 2010	IRI @ 2010	IRI @ 2010
	Time (t)	Time (t)	Time (t)	Time (t)
	PCR/IRI Minor Rehab.	PCR/IRI Minor Rehab.	PCR/IRI Minor Rehab.	PCR/IRI Minor Rehab.
	PCR/IRI Major Rehab.	PCR/IRI Major Rehab.	PCR/IRI Major Rehab.	PCR/IRI Major Rehab.
	ESAL	CESAL	ESAL	CESAL
			Two Lane Road	
			Four Lane Road	
			Interstate	
	Pre PCR	Pre PCR	Pre PCR	Pre PCR
	Pre IRI	Pre IRI	Pre IRI	Pre IRI
Dependent Variables	Complementary PCR	Complementary PCR	Complementary PCR	Complementary PCR
	IRI	IRI	IRI	IRI

Composite Pavements

A total of 7 models were selected among many developed models in this study to select the most accurate and practical model for MDOT utilization. Models utilized 15 to 19 independent variables and two dependent variables in their structure. A summary of promising models for composite pavements and their structure is presented in Table 5.

Table 5. Composite Pavement Models Structure

Composite Pavement	**2020 Without ESAL**	**2020 With ESAL**	**2020 With CESAL**	**2020 With CESAL No Outliers**	**2020 With ESAL No Outliers**	**2020 ESAL with Lanes**	**2022 With ESAL No Outliers**
Independent Variables	Begin Latitude	Begin Latitude	Begin Latitude	Begin Latitude	Begin Latitude	Begin Latitude	Begin Latitude
	Begin Longitude	Begin Longitude	Begin Longitude	Begin Longitude	Begin Longitude	Begin Longitude	Begin Longitude
	End Latitude	End Latitude	End Latitude	End Latitude	End Latitude	End Latitude	End Latitude
	End Longitude	End Longitude	End Longitude	End Longitude	End Longitude	End Longitude	End Longitude
	Top Layer Thickness	Top Layer Thickness	Top Layer Thickness	Top Layer Thickness	Top Layer Thickness	Top Layer Thickness	Top Layer Thickness
	Section Length	Section Length	Section Length	Section Length	Section Length	Section Length	Section Length
	Pavement Age in 2010	Pavement Age in 2010	Pavement Age in 2010	Pavement Age in 2010	Pavement Age in 2010	Pavement Age in 2010	Pavement Age in 2010
	PCR @ 2010	PCR @ 2010	PCR @ 2010	PCR @ 2010	PCR @ 2010	PCR @ 2010	PCR @ 2010
	IRI @ 2010	IRI @ 2010	IRI @ 2010	IRI @ 2010	IRI @ 2010	IRI @ 2010	IRI @ 2010
	Time (t)	Time (t)	Time (t)	Time (t)	Time (t)	Time (t)	Time (t)
	PCR/IRI Minor Rehab.	PCR/IRI Minor Rehab.	PCR/IRI Minor Rehab.	PCR/IRI Minor Rehab.	PCR/IRI Minor Rehab.	PCR/IRI Minor Rehab.	PCR/IRI Minor Rehab.
	PCR/IRI Major Rehab.	PCR/IRI Major Rehab.	PCR/IRI Major Rehab.	PCR/IRI Major Rehab.	PCR/IRI Major Rehab.	PCR/IRI Major Rehab.	PCR/IRI Major Rehab.
		ESAL	CESAL	CESAL	ESAL	ESAL	ESAL
						Two Lane Road	
						Four Lane Road	
						Interstate	
	Pre PCR	Pre PCR	Pre PCR	Pre PCR	Pre PCR	Pre PCR	Pre PCR
	Pre IRI	Pre IRI	Pre IRI	Pre IRI	Pre IRI	Pre IRI	Pre IRI
Dependent Variables	Complementary PCR	Complementary PCR	Complementary PCR	Complementary PCR	Complementary PCR	Complementary PCR	Complementary PCR
	IRI	IRI	IRI	IRI	IRI	IRI	IRI

Research Findings and Applications

In this section, the results of the best-performing models for flexible and rigid pavements are presented. This research study explored thousands of model structures, input-output combinations, and different modeling strategies, such as static and dynamic machine learning modeling techniques, to find out/explore the best way to model a very complicated phenomenon that contains so many levels of uncertainties and errors. It would be impossible to present all the trials in these documents. Accordingly, in this section, the final model that is used for the graphical user interface is presented to keep the documentation simple and easy to understand.

Flexible Pavements

A flexible pavement consists of a surface course made of bituminous material and underlying base and subbase courses. Typically, asphalt, known for its viscous properties allowing significant plastic deformation, is used as the bituminous material. While most asphalt surfaces are constructed on a gravel base, some "full depth" asphalt surfaces are directly laid on the subgrade. One notable advantage of flexible pavement is its initially low installation cost, making it a widespread choice globally. However, regular maintenance and repairs are essential every few years. Additionally, flexible pavement deteriorates relatively quickly, with the likelihood of cracks and potholes due to factors such as poor drainage and heavy vehicular traffic. For this reason, it is very important to predict the condition of a flexible pavement section and integrate the maintenance activity into the management system. A total of 46,830 datasets were used for flexible model development. About 50% of the database is used for training and 50% were used for testing and validation purposes. After 4 four-stage model development process was followed, the statistical accuracy measures of the training, testing, validation, and all data were obtained. After going through hundreds of model trials with updated survey results and independent variable combinations, the selection of the best-performing models was done based on sensitivity analysis rather than statistical accuracy measures because it was found that the models with the best statistical measures did not provide the logical and realistic pavement response. Accordingly, the best-performing models were selected based on their prediction consistency and M&R actions even though their accuracy measures may seem to be insufficient. Figures 6 and 7 depict the statistical accuracy measures of the selected models for the two outputs: IRI and complimentary PCR. The plots indicate various outlier areas where IRI values are very high. It should be noted that the deterioration mechanism changes as the pavement section's condition depreciates. Accordingly, it can be difficult for a prediction model to generalize all the deterioration mechanisms from poor to good ranking. The statistical measures can be considered sufficient enough to be used, especially with consideration of the complexity depreciation mechanism. One of the unique contributions of this study is the M&R integration into the prediction models. There is no comprehensive study in the literature, which involves M&R actions along with simple pavement section characteristics for the determination of the pavement performance prediction.

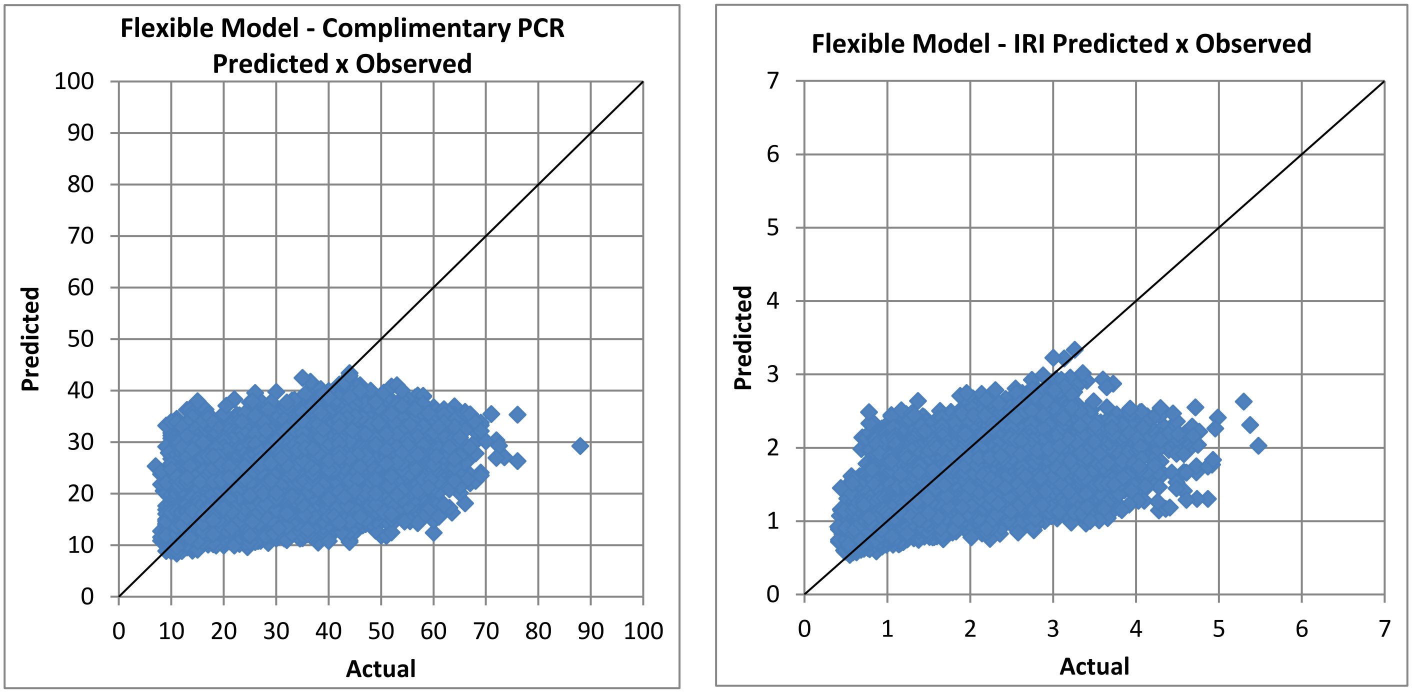


Figure 6. Observed vs. predicted IRI (right) and PCR (left) for 2022 CESAL

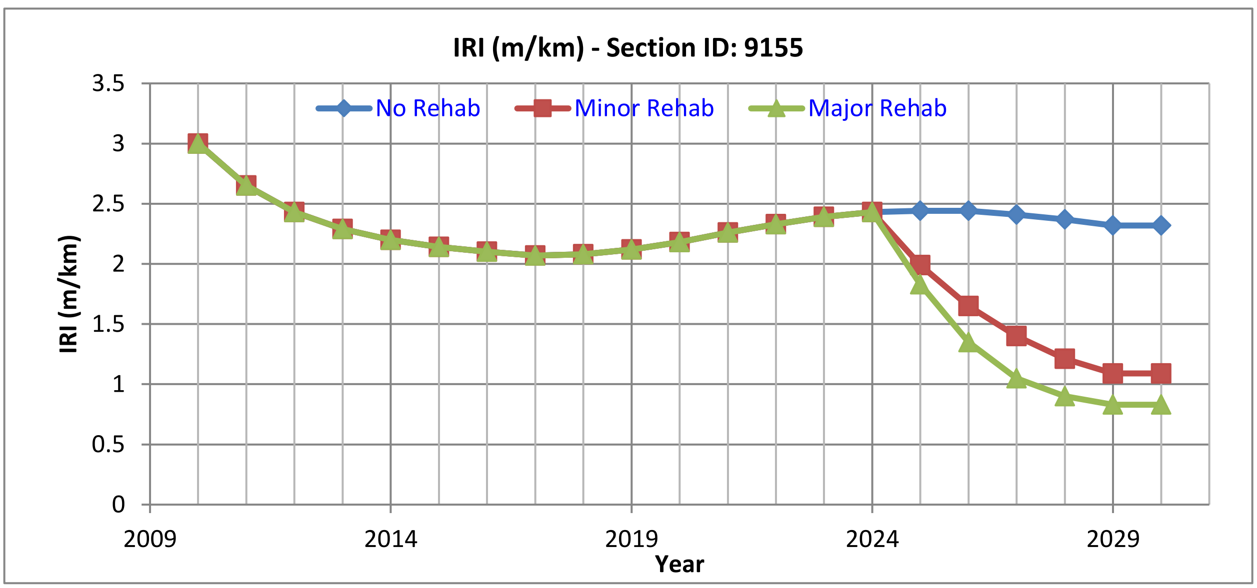


Figure 7. IRI projection for section ID 9155 with M&R applied in the year 2024

As illustrated in Figure 7, the depiction of flexible pavement reveals a progressive deterioration trend over time, culminating in the implementation of Maintenance and Rehabilitation (M&R) actions in the year 2024. This simulation of pavement response is derived through the utilization of a user-friendly Graphical User Interface (GUI) designed for flexible pavement analysis. Within this interface, users have the flexibility to choose both the projection timeline and the specific years for Maintenance and Rehabilitation activities. The graphical representation in Figure 7 visually captures the evolving condition of the flexible pavement, highlighting its susceptibility to wear and tear over the considered period. The deterioration trajectory underscores the importance of timely intervention through M&R strategies in 2024, serving as a pivotal point in the lifecycle of the pavement system. The interactive nature of the GUI empowers users to customize their analysis by selecting the desired projection period and pinpointing the years for scheduled Maintenance and Rehabilitation actions. This feature enhances the adaptability of the simulation tool, allowing stakeholders to make informed decisions based on the anticipated performance and longevity of the flexible pavement infrastructure.

As can be seen from Figure 7, flexible pavement indicates deterioration over time until the M&R actions take place in the year 2024. This pavement response simulation is generated by the Graphical User Interface (GUI) for flexible pavement where the user can select the projection and the M&R years.

Table 6. Flexible Model Statistics for 2022 CESAL IRI <=5m/km Model

Model		**IRI (m/km)**	**Complimentary PCR**
Model Structure		19 – 6 – 9 - 20000 - 2	
Training	MARE	25.74	24.37
	R^2	0.31	0.25
	ASE	0.00003	0.01050
Testing	MARE	25.56	24.97
	R^2	0.30	0.23
	ASE	0.00003	0.01117
Validation	MARE	25.50	25.03
	R^2	0.30	0.24
	ASE	0.00003	0.01133
All data	MARE	20.81	20.81
	R^2	0.43	0.36
	ASE	0.00003	0.00812

Table 6 shows the statistical accuracy measures of the selected models. The model statistics for training, testing, and validation have shown a very consistent trend, which indicates that the data distribution for the model processing was done systematically. The model structure is presented with 19 inputs, 6 initial hidden nodes, 9 final hidden nodes, 20000 iterations, and two outputs. Once the model structure was selected based on the model testing and validation performance, all data was combined the trained on every single dataset in the database. In this step, the model extracts all the knowledge from each dataset and generates reliable predictions based on the history of the data and knowledge gained from this process.

User Interface for Flexible Database

Once the best-performing model was selected, all the modeling parameters from the machine learning platform were extracted into an Excel Spreadsheet. Using the development toolboxes and Visual Basic Programming language, the Graphical User Interface (GUI) was generated shown in Figure 8. For easy use, all of the independent parameters required from the user regarding the pavement section were integrated into the spreadsheet. Using the dropdown menu next to Section ID, the user can select the section number of the flexible pavement, and the spreadsheet is automatically updated with the associated section characteristics. The user also has the option to fill in this information manually. The other section where the user required the provide information is the projection year and the rehabilitation year. All the information required from the user is highlighted with orange color text. As the user clicks on the “PROJECTIONS" button, another menu pops up to ask about the estimated ESAL increase in percent for the projected years. Once this form is submitted, the predictions for the desired years will be generated in a table and the plots for PCR and IRI will be shown below the generated table.

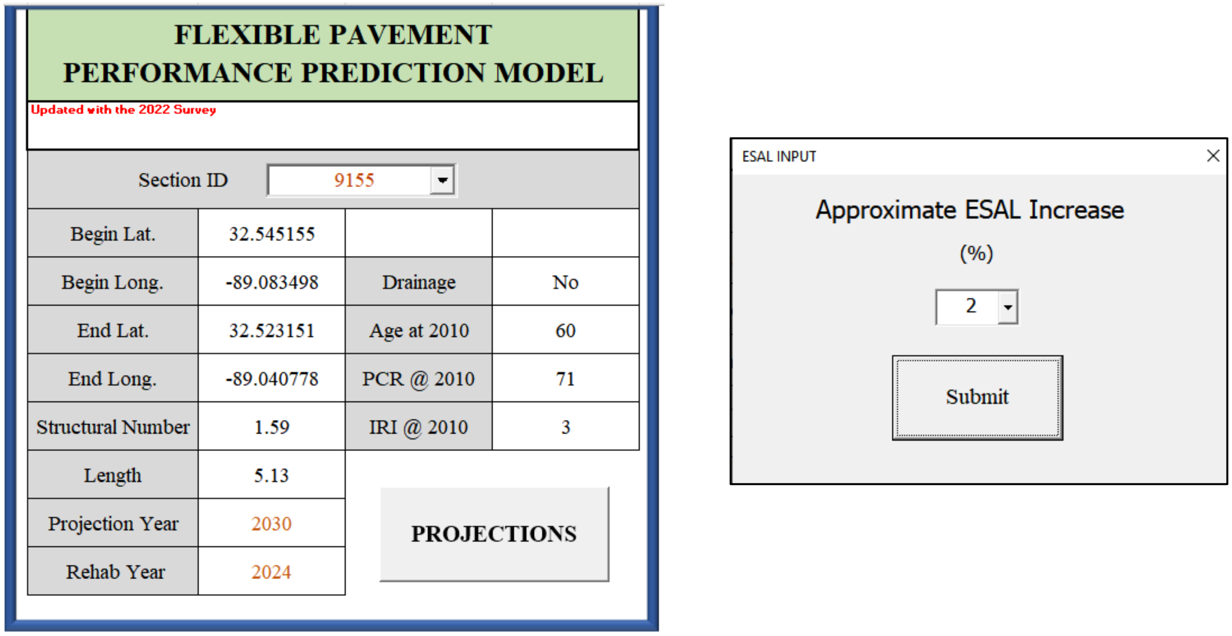


Figure 8. Graphical User Interface for Flexible Pavement

Rigid Pavements

Rigid pavement is constructed using either cement concrete or reinforced concrete slabs, with grouted concrete roads falling within the semi-rigid pavement category. The design philosophy behind rigid pavement centers on creating a structurally robust cement concrete slab capable of withstanding traffic-induced loads. This type of pavement exhibits high rigidity and a substantial modulus of elasticity, effectively distributing the load over a relatively broad area of the underlying soil. Unlike flexible pavements, minor fluctuations in subgrade strength exert minimal influence on the structural capacity of rigid pavement. In the design process, the flexural strength of the concrete slab takes precedence over the strength of the subgrade. This distinctive property enables the rigid pavement to bridge over localized failures and areas of insufficient subgrade support when the subgrade undergoes deflection beneath the pavement. This resilience is attributed to the slab action, emphasizing the robust and load-distributing characteristics inherent to rigid pavement designs. Rigid pavements in this study are considered into two categories: jointed concrete pavements (JCP) and continuously reinforced concrete pavements (CRCP). Accordingly, two separate models and GUIs were developed. In the following sections, the model statistics and GUIs are presented in detail. It should be noted that the average life span of a rigid pavement is about 30 years. The models developed in this study utilized 12 years of data history which does not fully cover the life span of a rigid pavement.

Jointed Concrete Pavements (JCP)

Utilizing contraction joints to mitigate random cracking, Jointed Concrete Pavement (JCP) stands out as a widely adopted paving method. This pavement system, extensively employed by both Departments of Transportation (DOTs) and municipalities, strategically incorporates a sufficient number of joints to govern the location of anticipated natural cracks. All intentional cracking is directed to occur precisely at these joints, minimizing the occurrence of cracks elsewhere in the slabs. Notably, JCP does not incorporate any steel reinforcement. Concrete pavement joints fall into distinct categories, each serving a specific function to ensure optimal performance under traffic for pavements, highways, or airfields. Up to date, there are 101

JCP sections in Mississippi. To develop a JCP performance prediction model, a total of 1080 datasets were utilized. The database included 2022 Survey results for the sections. The final model structure was determined after hundreds of trials performed. 15 inputs were utilized to predict 2 outputs: IRI and PCR. The initial and final hidden nodes were found to be 3 and 6, respectively, after many trials with 20,000 iterations. The statistical accuracy measures were presented in Table 7 for the two outputs. Graphical representations of the model for the predicted IRI and complementary PCR versus observed are shown in Figure 9. Randomly selected section simulation with M&R events is depicted in Figure 10. The statistical accuracy measures of the best-performing model for ANN model development stages: training, testing, validation, and all data are shown in Table 7.

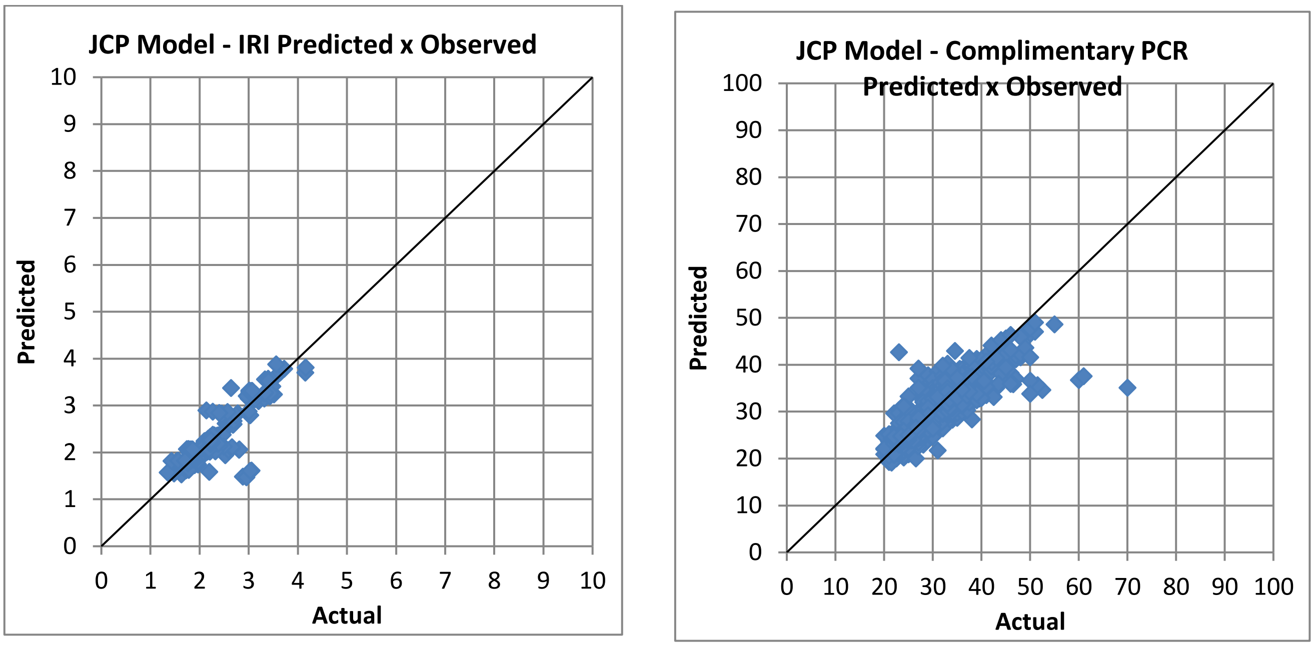


Figure 9. Observed vs. predicted PCR (left) and IRI (right) for JCP 2022

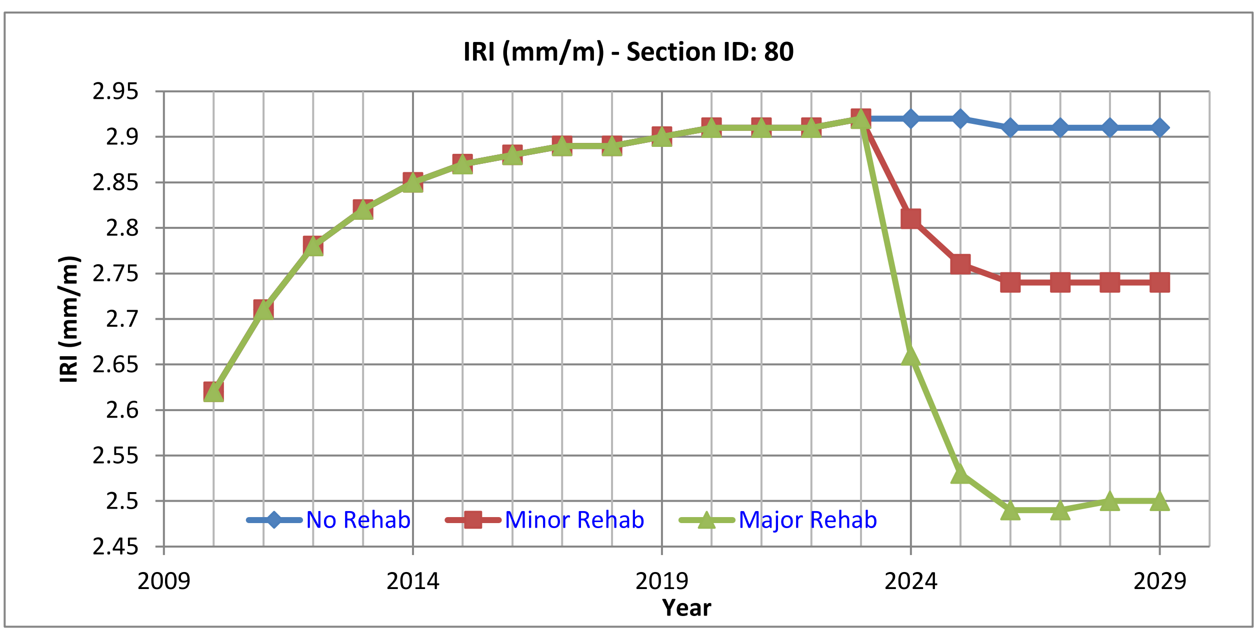


Figure 10. IRI projection for section ID 80 with M&R applied in the year 2023

As depicted in Figure 10, the response of JCP reveals a gradual decline over time, reaching a point necessitating Maintenance and Rehabilitation (M&R) actions in 2023. This pavement response simulation utilizes a user-friendly Graphical User Interface (GUI) designed for JCP performance analysis, offering users the flexibility to choose the projection timeline and specific Maintenance and Rehabilitation years. The graphical representation visually captures the evolving state of the JCP, emphasizing its susceptibility to wear and tear. The trajectory of deterioration underscores the significance of timely M&R strategies in 2023, marking a pivotal phase in the pavement system's lifecycle. The interactive GUI empowers users to customize their analysis, selecting the desired projection period and pinpointing years for scheduled Maintenance and Rehabilitation actions, enhancing the tool's adaptability for informed decision-making. As evident in Figure 10, JCP exhibits a deterioration trend until M&R actions are undertaken in 2023. This simulation, facilitated by the Graphical User Interface (GUI) for JCP, allows users to choose the projection and M&R years.

Table 7. JCP Models Statistics for Complementary PCR and IRI

		IRI	**PCR**
Model Structure		15 – 3 – 6 – 20000 – 2	
Training	MARE	6.23	7.72
	R^2	0.95	0.75
	ASE	0.000003	0.00130
Testing	MARE	8.44	11.35
	R^2	0.69	0.52
	ASE	0.000012	0.00227
Validation	MARE	12.28	7.76
	R^2	0.74	0.73
	ASE	0.000013	0.00087
All data	MARE	6.31	6.78
	R^2	0.93	0.74
	ASE	0.000004	0.00104

Table 7 displays the statistical accuracy measures of the chosen models. The model statistics for training, testing, and validation exhibit a remarkably consistent trend, underscoring the systematic approach employed in processing the model data distribution. The model structure comprises 15 inputs, 3 initial hidden nodes, 6 final hidden nodes, 20,000 iterations, and two outputs. After finalizing the model structure based on testing and validation performance, all data was combined and trained on every dataset in the database. During this step, the model embraces knowledge from each dataset, generating reliable predictions rooted in the historical data and insights gained from this process.

User Interface for Jointed Concrete Pavement

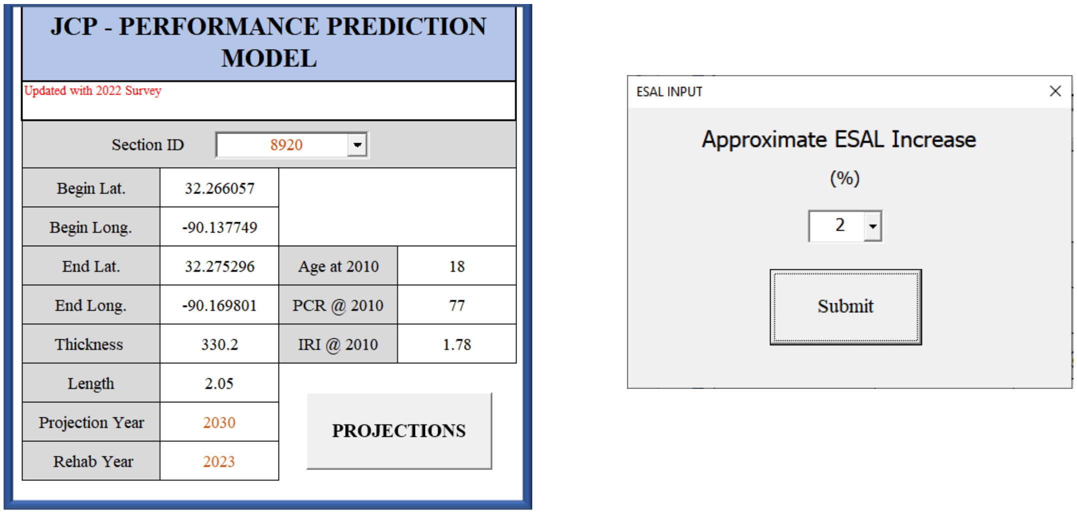


Figure 11. Graphical User Interface for Jointed Concrete Pavement

After the identification of the best-performing model, all modeling parameters from the machine learning platform were transferred to an Excel Spreadsheet. Employing development toolboxes and the Visual Basic Programming language, a user-friendly Graphical User Interface (GUI) shown in Figure 11 was precisely designed and generated. To enhance user convenience, the spreadsheet seamlessly incorporates all independent parameters related to the pavement section. Within the spreadsheet, users can effortlessly select the section number of the flexible pavement from a dropdown menu next to Section ID. Consequently, the spreadsheet dynamically updates the pertinent characteristics associated with the chosen section. Alternatively, users have the flexibility to manually input this information. The critical information required from the user, including the projection year and rehabilitation year, is highlighted in orange text for easy identification. Upon clicking the "PROJECTIONS" button, a supplementary menu emerges, prompting the user to input the estimated Equivalent Single Axle Load (ESAL) increase percentage for the projected years. Upon submission of this form, the model generates predictions for the specified years, presenting the results in a comprehensive table. Additionally, accompanying plots for Pavement Condition Rating (PCR) and International Roughness Index (IRI) are displayed below the generated table. This user-centric approach ensures a seamless and efficient interaction with the predictive modeling tool.

Continuously Reinforced Concrete Pavement (CRCP)

Continuously Reinforced Concrete Pavements (CRCP) represent a distinctive type of concrete pavement distinguished by the absence of transverse contraction joints. In this design, transverse cracks are anticipated within the slab at intervals typically ranging from 1.5 to 6 feet (0.5 to 1.8 meters). The key feature of CRCP lies in the substantial inclusion of embedded reinforcing steel, constituting approximately 0.6-0.7% of the cross-sectional area, ensuring a tight cohesion of cracks. The determination of an optimal spacing between these cracks is an integral part of the pavement design process. While CRCP designs tend to incur higher initial costs compared to Jointed Plain Concrete Pavement (JPCP) or Jointed Reinforced Concrete Pavement (JRCP) designs due to increased quantities of steel, they often exhibit superior long-term performance. Typically boasting design service lives of 30-40 years, CRCP demonstrates a compelling cost-effectiveness over time. Many state highway agencies opt for CRCP designs, particularly in heavily trafficked urban corridors where the pavement is subjected to tens of millions of equivalent load repetitions over its service life. Moreover, CRCP's tight crack widths and minimal vertical movement between adjacent joints, attributed to the restraint provided by the embedded steel, make it an excellent candidate for resurfacing with asphalt concrete. This characteristic reduces the frequency and severity of reflective cracking, enhancing the overall durability and resilience of the pavement. in Mississippi, there are 44 sections of CRCP with 512 associated datasets.

To construct a performance prediction model for CRCP, a comprehensive dataset comprising 512 entries was employed, encompassing results from the 2022 survey of various sections. The final model architecture emerged after rigorous experimentation involving numerous trials. Fifteen input parameters were strategically chosen to forecast two key outputs: the International Roughness Index (IRI) and Pavement Condition Rating (PCR). Through an iterative process involving 6,100 iterations, the optimal configuration for the model was determined, with the initial and final hidden nodes set at 5 and 8, respectively. Table 8 presents the statistical accuracy measures for the two predicted outputs, IRI and PCR. Additionally, Figure 12. Observed vs. predicted IRI (right) and PCR (left) for CRCP 2022provides graphical representations of the model, juxtaposing predicted IRI and complementary PCR against observed values.

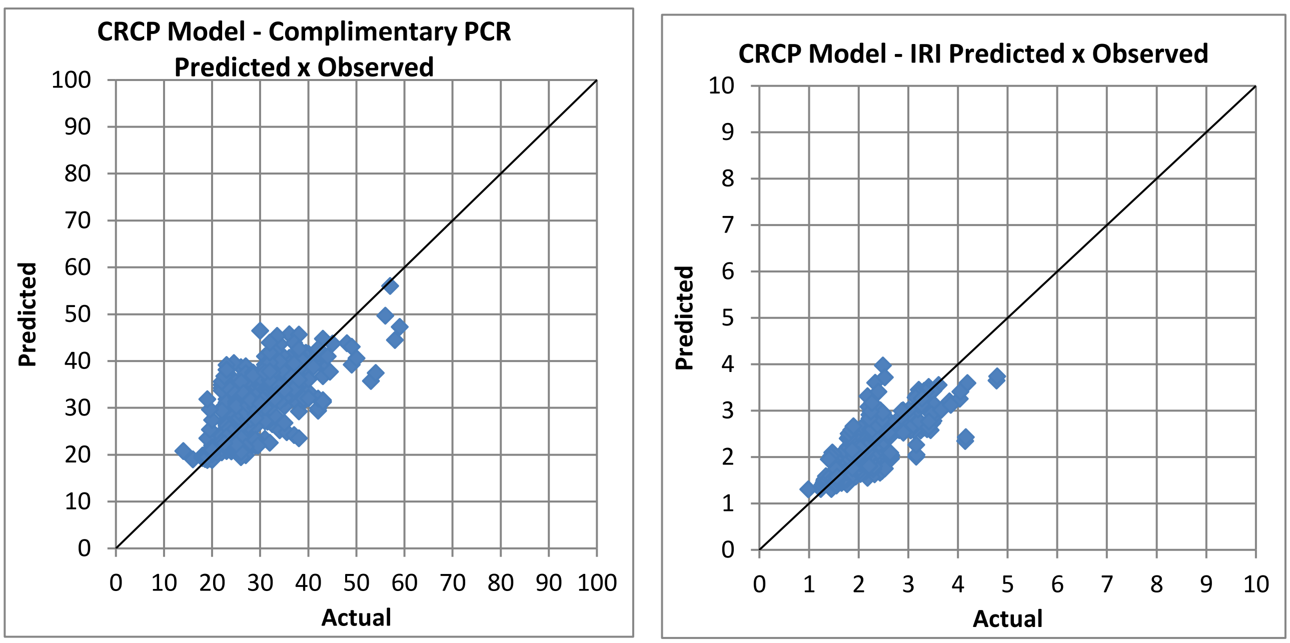


Figure 12. Observed vs. predicted IRI (right) and PCR (left) for CRCP 2022

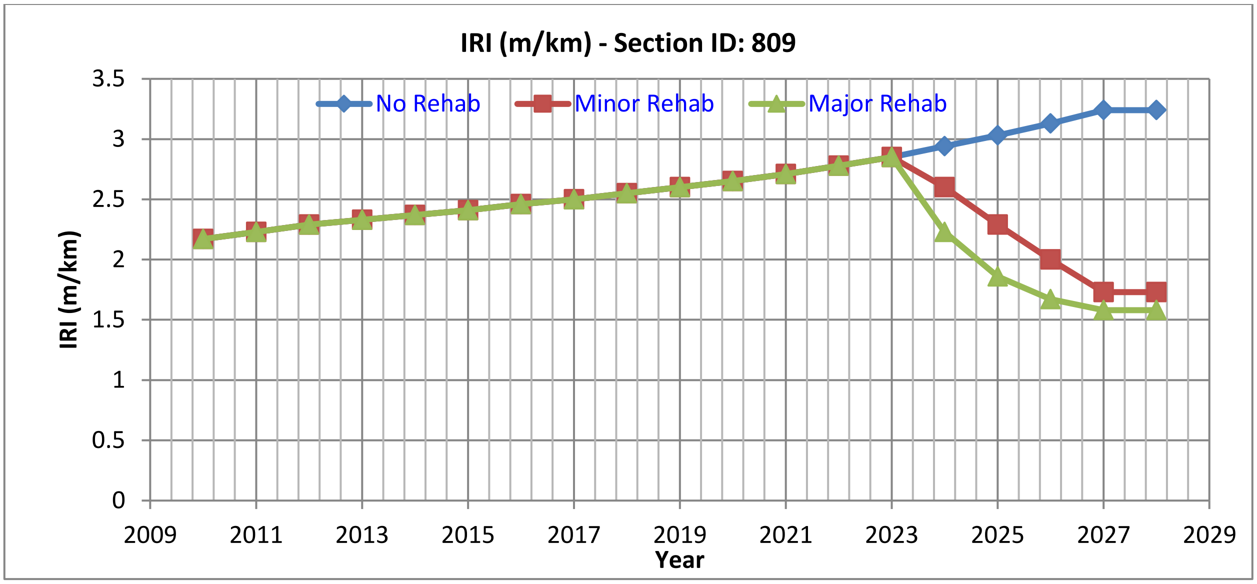


Figure 13. IRI projection for section ID 809 with M&R applied in the year 2023

Figure 13 offers a simulation of randomly selected sections with Maintenance and Rehabilitation (M&R) events. Table 8 further details the statistical accuracy measures for the best-performing model across various stages of artificial neural network (ANN) development, including training, testing, validation, and the entire dataset. This multifaceted approach ensures a robust and reliable JCP performance prediction model.

Table 8. CRCP Models Statistics for Complementary PCR and IRI

Model		**IRI**	**Complementary PCR**
Model Structure		15 – 5 – 8 – 6100 - 2	
Training	MARE	8.11	17.19
	R^2	0.81	0.50
	ASE	0.000008	0.00415
Testing	MARE	9.84	26.98
	R^2	0.59	0.11
	ASE	0.000008	0.00840
Validation	MARE	16.44	26.17
	R^2	0.03	0.13
	ASE	0.000023	0.00744
All data	MARE	9.88	12.75
	R^2	0.65	0.56
	ASE	0.000011	0.00255

The good agreement between the observed and predicted outputs can be inferred from Table 8. Training, testing, validation, and all data statistics are significant and can be considered in the good range. It can be noted that IRI prediction error is less than Complimentary PCR prediction errors. Both IRI and complimentary PCR prediction errors are acceptable to be considered as performance models.

Graphical User Interface for Continuously Reinforced Concrete Pavement (CRCP)

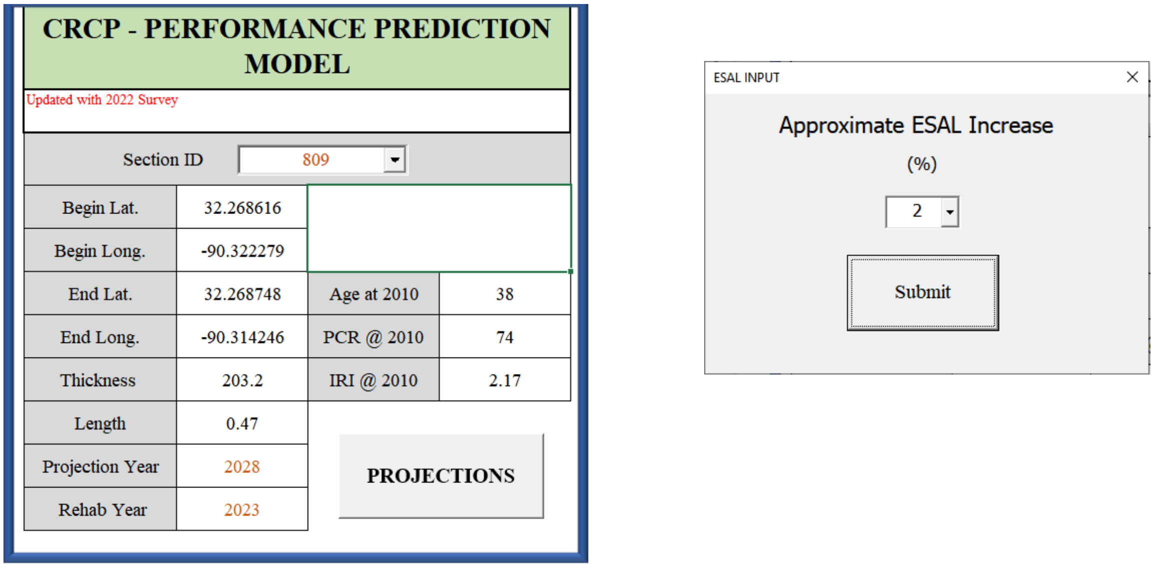
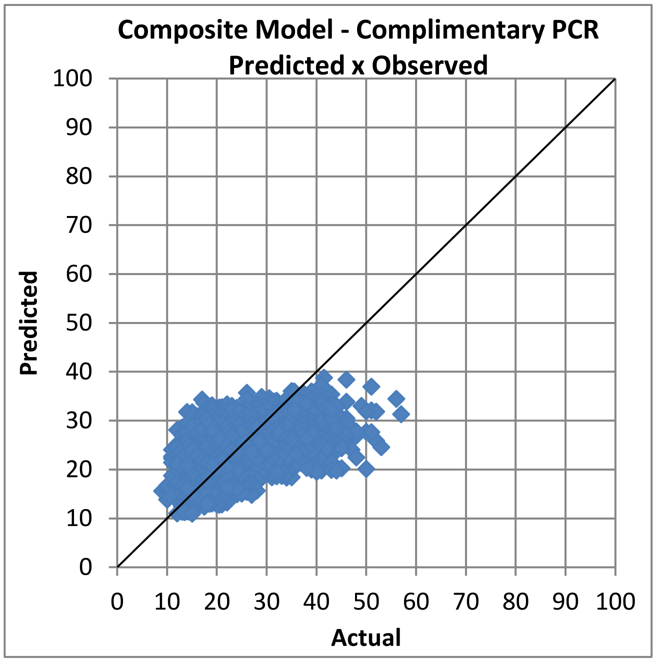


Figure 14. Graphical User Interface for Continuously Reinforced Pavement

Following the selection of the best-performing model, its parameters were transferred to an Excel Spreadsheet. Utilizing development toolboxes and Visual Basic Programming, a user-friendly Graphical User Interface (GUI) was crafted and illustrated in Figure 14. The spreadsheet integrates all independent parameters related to the pavement section for user convenience. Users can effortlessly choose the flexible pavement section number from a dropdown menu next to Section ID, dynamically updating associated characteristics. Alternatively, users can manually input information. Key user inputs, such as projection and rehabilitation years, are highlighted in orange for easy identification. Upon clicking the "projections" button, a supplementary menu prompts users to input the estimated ESAL increase percentage for projected years. Upon form submission, the model generates predictions, presenting results in a comprehensive table with accompanying PCR and IRI plots.

Composite Pavements

Composite pavement, a sophisticated hybrid construction, seamlessly integrates the strengths of both asphalt and concrete to create a robust and resilient road surface. This innovative pavement structure typically comprises a foundational layer of concrete and a top layer of asphalt. The concrete layer serves as the structural backbone, imparting superior load-bearing capacity and stability to the pavement, while the asphalt overlay functions as the protective and durable surface. The inherent synergy between the two materials allows composite pavements to deliver exceptional performance in diverse roadway applications. One of the primary advantages of composite pavements lies in their ability to rehabilitate existing roadways effectively. By leveraging the structural integrity of concrete and the smooth, wear-resistant properties of asphalt, these pavements can breathe new life into aging infrastructure. In the realm of pavement maintenance and enhancement, asphalt overlays play a pivotal role in renewing distressed concrete surfaces. This approach involves applying a fresh layer of asphalt over worn or damaged concrete, effectively renewing the pavement's appearance and functionality. The asphalt overlay acts as a protective shield, shielding the underlying concrete from further deterioration while providing a smooth and skid-resistant driving surface. The significance of composite pavements extends beyond their physical composition; it is also rooted in data-driven insights and predictive modeling. As of 2022, the MDOT database stands as a testament to the extensive utilization and monitoring of composite pavements. Within this database, a



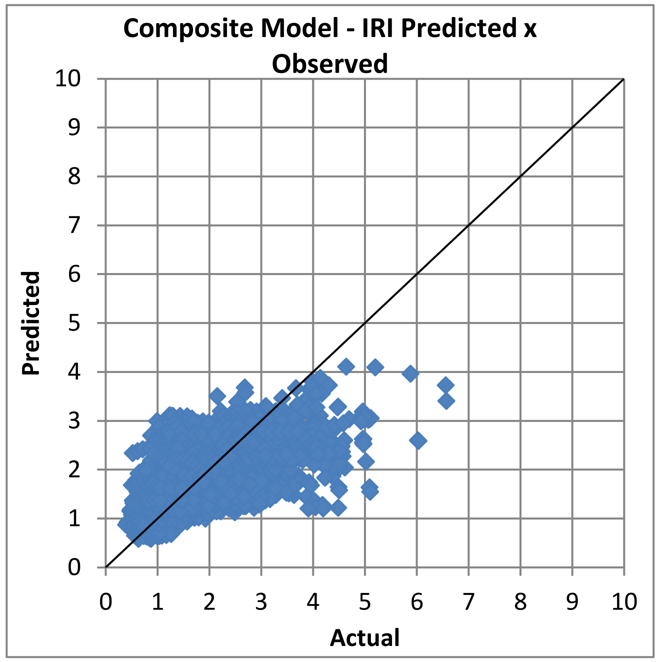


Figure 15. Observed vs. predicted PCR (left) and IRI (right) for composite pavement

remarkable 1141 composite pavement sections have been meticulously documented, accompanied by a comprehensive set of 12406 historical pavement distress data points. This wealth of data serves as a valuable resource for the development of predictive models that enhance our understanding of composite pavement behavior over time. By analyzing the historical distress data, patterns, trends, and key indicators that contribute to the formulation of effective maintenance strategies and future pavement design improvements can be observed. Its application in rehabilitating existing roadways and the integration of predictive modeling based on extensive data collection underscore its importance in the ongoing evolution of sustainable and resilient infrastructure.

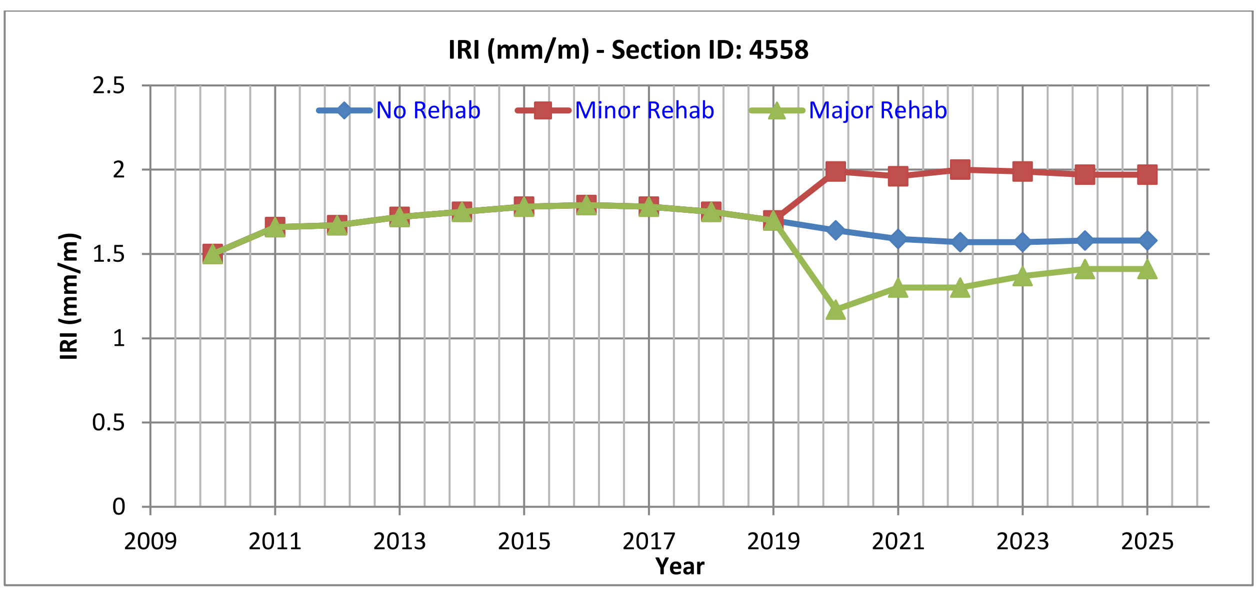


Figure 16. IRI projection for section ID 4558 with M&R applied in the year 2019

Table 9. Composite Pavement Models Statistics for Complementary PCR and IRI

Model		IRI	PCR
Model Structure		15- 3 - 4 – 20000 - 2	
Training	MARE	21.54	17.00
	R^2	0.50	0.39
	ASE	0.00002	0.00278
Testing	MARE	24.05	18.74
	R^2	0.41	0.30
	ASE	0.00003	0.00314
Validation	MARE	22.17	17.43
	R^2	0.48	0.34
	ASE	0.00003	0.00294
All data	MARE	22.14	17.30
	R^2	0.48	0.37
	ASE	0.00002	0.00288

Examining Table 9 reveals encouraging statistical accuracy measures for composite pavement. While the overall data statistics may be deemed low, it's noteworthy that error statistics fall within a favorable range. Additionally, Figure 15 clearly illustrates that the model effectively captures the observed trend in the pavement response. The combination of the insightful plots and the robust statistical quantities suggests that this model can be regarded as effective in representing the complex dynamics of composite pavement behavior. Despite these positive indicators, a closer look at the sensitivity analysis in Figure 16 reveals certain inconsistencies. Notably, it suggests that minor rehabilitation efforts may paradoxically worsen the pavement condition, a scenario that contradicts mechanical expectations. This anomaly calls for a careful reassessment of the model's sensitivity to rehabilitation actions, emphasizing the need for further refinement and calibration. To enhance the model's reliability, future iterations could involve a more comprehensive calibration process and a thorough examination of the specific mechanisms influencing the pavement's response to rehabilitation efforts. Additionally, ongoing data collection and integration of historical records could contribute to a more nuanced understanding, refining the model for more accurate predictions and insights into the performance of composite pavements over time.

Graphical User Interface for Composite Pavement (CRCP)

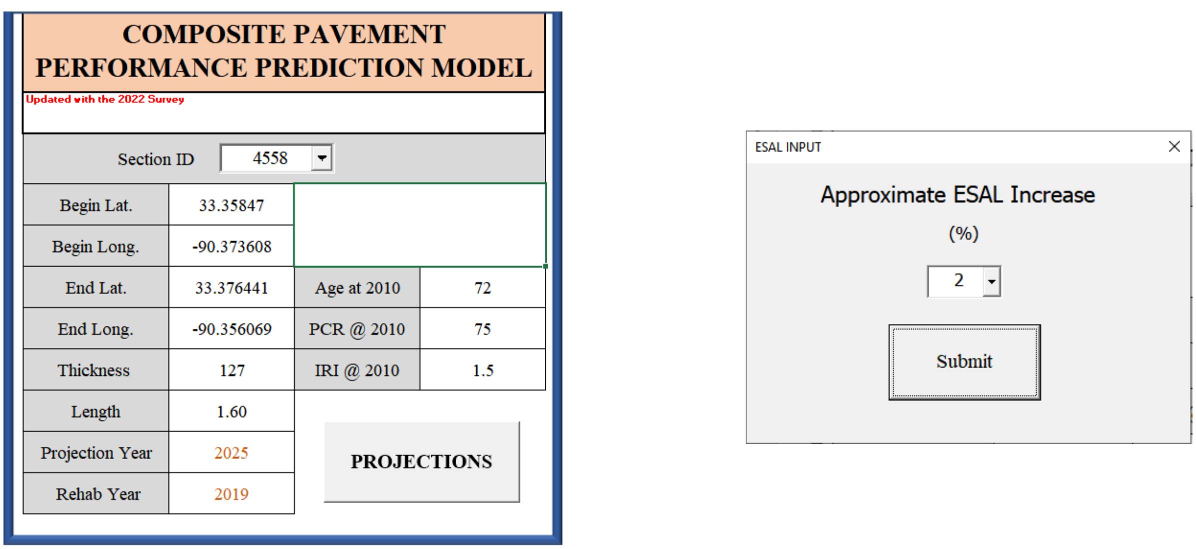


Figure 17. Graphical User Interface for Continuously Reinforced Pavement

After selecting the top-performing model, its parameters were transferred to an Excel Spreadsheet. Utilizing development toolboxes and Visual Basic Programming, a user-friendly Graphical User Interface (GUI) was designed (see Figure 17). The spreadsheet consolidates all independent parameters related to the pavement section for user convenience. Users can easily select the flexible pavement section number from a dropdown menu next to Section ID, dynamically updating associated characteristics. Alternatively, users have the flexibility to manually input information. Crucial user inputs, like projection and rehabilitation years, are highlighted in orange for quick identification. Clicking the "projections" button triggers a supplementary menu, prompting users to input the estimated ESAL increase percentage for projected years. Upon form submission, the model generates predictions, presenting results in a comprehensive table with accompanying PCR and IRI plots.

Conclusions

In this study, the distress data from pavement sections in Mississippi was used to develop the performance prediction models using the dynamic sequential Artificial Neural Networks (ANNs) approach with a backpropagation algorithm. It is a known fact that the pavement condition in the current year is highly dependent on the previous year's condition. Accordingly, the dynamic sequential ANNs modeling approach is the most suitable approach for the pavement performance models. The pavement sections were categorized into flexible, rigid, and composite. IRI and PCR are the common outputs to evaluate the condition of the pavement sections and are accordingly utilized for all the developed models. Rehabilitation actions were assigned based on IRI and PCR measurements. All the models with common and varying input(s) and output(s) are represented in Table 2. All the future predictions, up to 12 years of data history, are based on the survey data collected in 2010. All the developed models have significant model statistics, which makes them useable to assess the condition of the particular type of pavement.

Flexible Pavement

A substantial amount of effort was dedicated to establishing a robust and coherent database for flexible pavement, encompassing over 40,000 data entries. Through numerous iterations, the optimal variable combinations were meticulously identified, marking the finalization of model trials. The performance of the flexible pavement model is detailed in Table 6, and the graphical accuracy plot in Figure 6 showcases promising outcomes. While conventional statistical measures might not overtly suggest high accuracy, a closer examination of the sensitivity analysis, as depicted in Figure 7, reveals a logical pavement response within the developed model. Notably, most prediction errors are concentrated in higher International Roughness Index (IRI) values, affirming the dynamic nature of the deterioration mechanism as the pavement degrades over time. An insightful recommendation arising from these findings is to conduct an additional study to pinpoint significant changes and propose separate models for distinct deterioration patterns. Recognizing the inherent challenges in characterizing all pavement sections with a single model due to unquantifiable uncertainties, the study underscores the success of the flexible performance model in effectively characterizing the behavior of flexible pavement response. This achievement underscores the model's robustness in capturing the nuanced dynamics of flexible pavement, laying the groundwork for further refinement and specialized modeling to enhance predictive accuracy in specific degradation scenarios.

Rigid Pavement (JCP and CRCP)

While the quantity of rigid pavements is notably less compared to flexible pavements, the datasets used for modeling are proportionately smaller. Despite this, both JCP and CRCP performance prediction models exhibit remarkably robust statistical accuracy measures, as evident in Tables 9 and 10. Comprehensive graphical accuracy comparisons for these two pavement types are depicted in Figures 9 and 12, showcasing the models' effectiveness in capturing pavement behavior. The sensitivity analysis results for JCP and CRCP, presented in Figures 10 and 13, further underscore the models' success in characterizing pavement behavior, as reflected in both statistical measures and performance indicators. However, it's crucial to note that the data collection period employed in this study is relatively small when considering the extensive lifespan of CRCP and JCP pavements. To ensure a comprehensive understanding and proper capture of the response to Pavement Condition Rating (PCR) and International Roughness Index (IRI) rehabilitation actions, it is recommended to incorporate more data spanning the entire lifespan of CRCP and JCP. This expansion in data coverage would enhance the models' capacity to provide accurate predictions and insights into the long-term performance and deterioration patterns of rigid pavements.

Composite Pavement

The statistical accuracy measures for the composite pavement performance model are presented in Table 13 and the graphical accuracy plots for IRI and PCR are shown in Figure 15. Examining Table 13 reveals promising statistical accuracy measures for composite pavement. While all data statistics are generally low, it's important to note that error statistics fall within a favorable range. Additionally, Figure 15 illustrates that the model successfully captures the observed trend. Combining both the plots and statistical quantities, this model can be deemed reliable. Nevertheless, the sensitivity analysis in Figure 16 presents some inconsistencies, such as the counterintuitive notion that minor rehabilitation efforts worsen the pavement condition, which contradicts mechanical expectations. For this reason, minor rehabilitation responses should be carefully examined and considered in between no rehabilitation and major rehabilitation actions. Even though a significant amount of data (i.e. 12406 datasets from 1141 sections) was utilized, the performance of the model is not as desirable. This could be due to multiple reasons: 1- the model needs more calibration trials, and 2- the lack of composite pavement characteristics missing from the database. It is believed that further calibration trials and more data inclusion in the model training can solve this problem as it’s known that composite pavement has a sophisticated mechanistic behavior.

Overall

The developed models effectively characterize the pavement response across various significance levels. Users can access all the models through the provided graphical user interface. Enhanced accuracy is anticipated with additional surveys as more historical data is incorporated into the model training process. Further calibration is necessary for composite pavement performance models to achieve a more logical rehabilitation response. Integration of these models into MDOT's decision trees is feasible. However, caution is advised in the utilization of the generated results.

Implementation Plan/Recommendations

MDOT can utilize all the developed performance models via the developed GUIs for each pavement type. They were designed and implemented to be user-friendly and they can be used by anybody without the knowledge of modeling techniques. Plots and tables are generated automatically as the simulation is started. It is recommended that the generated predictions have errors and should be considered as guidance even though some models have pretty good accuracy. It would be beneficial to compare the future survey results with the predictions from these models. It is also highly recommended that these models should be updated with the new survey results. The more data the models are trained with, the better accuracy will be achieved over the years. The pavement response will improve with more and more data.

Products

There are four products from this study:

1- Flexible Pavement Performance Model: This model can be used via the graphical user interface developed in Microsoft Excel, labeled as “GUI_FLEX”

2- Jointed Concrete Pavement Performance Model: This model can be utilized via the graphical user interface developed in Microsoft Excel, labeled as “GUI_JCP”

3- Continuously Reinforced Concrete Pavement Performance Model: This model can be utilized via the graphical user interface developed in Microsoft Excel, labeled as “GUI_CRCP”

4- Composite Pavement Performance Model: This model can be utilized via the graphical user interface developed in Microsoft Excel, labeled as “GUI_Composite”

Three students were funded from this study who are listed below:

1- Will Andrews, Master’s Degree in Engineering Science, 2020, employed by MDOT in Jackson, MS.

2- Tennant Duckworth, Master’s Degree in Engineering Science, 2020, employed by Eustis Engineering LLC in New Orleans, LA.

3- Rulian Ferreira De Almeida Barros, Doctor of Philosophy in Engineering Science, 2022, Employed by Crawford, Murphy & Tilly in Indianapolis, IN.

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