Statistics and Artificial Intelligence-Based Pavement Performance and Remaining Service Life Prediction Models for Flexible and Composite Pavement Systems

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Abstract
In their pavement management decision-making processes, U.S. state highway agencies are required to develop performance-based approaches by the Moving Ahead for Progress in the 21st Century (MAP-21) federal transportation legislation. One of the performance-based approaches to facilitate pavement management decision-making processes is the use of remaining service life (RSL) models. In this study, a detailed step-by-step methodology for the development of pavement performance and RSL prediction models for flexible and composite (asphalt concrete [AC] over jointed plain concrete pavement [JPCP]) pavement systems in Iowa is described. To develop such RSL models, pavement performance models based on statistics and artificial intelligence (AI) techniques were initially developed. While statistically defined pavement performance models were found to be accurate in predicting pavement performance at project level, AI-based pavement performance models were found to be successful in predicting pavement performance in network level analysis. Network level pavement performance models using both statistics and AI-based approaches were also developed to evaluate the relative success of these two models for network level pavement performance modeling. As part of this study, in the development of pavement RSL prediction models, automation tools for future pavement performance predictions were developed and used along with the threshold limits for various pavement performance indicators specified by the Federal Highway Administration. These RSL models will help engineers in decision-making processes at both network and project levels and for different types of pavement management business decisions.

Keywords
Artificial Intelligence, Remaining Service Life, Pavement Performance Prediction Models, Flexible Pavements, Composite Pavements, Neural Networks

Disciplines
Civil Engineering | Construction Engineering and Management | Transportation Engineering

Comments

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Statistics and Artificial Intelligence Based Pavement Performance and Remaining Service Life Prediction Models for Flexible and Composite Pavement Systems

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ABSTRACT
In their pavement management decision-making processes, state highway agencies (SHAs) are required to develop performance-based approaches based on The Moving Ahead for Progress in the 21st Century (MAP-21) Federal Transportation Legislation. One of the performance-based approaches to facilitate pavement management decision-making process is use of remaining service life (RSL) models. In this study, a detailed step-by-step methodology for the development of pavement performance and RSL prediction models for Iowa flexible and composite (Asphalt concrete (AC) over Jointed Plain Concrete Pavement (JPCP)) pavement systems is described. To develop such RSL models, pavement performance models based on statistics and artificial intelligence (AI) techniques were initially developed. While statistically defined pavement performance models were found to be accurate in predicting pavement performance at project level, AI based pavement performance models were found to be successful in predicting pavement performance in network level analysis. Network level pavement performance models using both statistics and AI based approaches were also developed to evaluate the relative success of these two models for network-level pavement-performance modeling. As part of this study, in development of pavement RSL prediction models, automation tools for future pavement performance predictions were developed and used along with Federal Highway Agency (FHWA)-specified threshold limits for various pavement performance indicators. These RSL models will help engineers in both network and project level decision-making processes and for different types of pavement-management business decisions.

Keywords: Artificial Intelligence, Remaining Service Life, Pavement Performance Prediction Models, Flexible Pavements, Composite Pavements, Neural Networks
INTRODUCTION
State highway agencies (SHAs) are required to develop performance-based approaches in their pavement management decision-making processes based on the Moving Ahead for Progress in the 21st Century (MAP-21) Federal Transportation Legislation. One such performance-based approach to facilitate the pavement management decision-making process is to use a remaining-service-life (RSL) model. A RSL for pavements can be defined as the time span between the present time and the time when a significant rehabilitation treatment or reconstruction should occur. Although application of a structural overlay or reconstruction would normally be regarded as a sign for termination of pavement service life, minor maintenance treatments or thin overlays are often not considered as such signs. RSL models for predicting the remaining life of pavements have been developed and are being used as part of the pavement management process.

Multiple advantages of RSL have been reported in the literature, with key positive RSL features that include the following:

- Provides the time, expressed in years, before rehabilitation is required for any given road section
- Easy to understand (especially for public)
- Can be a multi-conditional measure developed from any type of functional and/or structural data
- Allows agencies to distinguish between two road sections with the same current condition (i.e., the same current International roughness index (IRI))
- Provides deeper insight by converting “condition measures” into an “operational performance” measure that tells how well or long the road will continue serving the public
- Can be an ideal tool to address the transportation planning and performance management criteria requirements of the MAP-21 legislation

Performance curves or pavement performance models are used to evaluate how pavement’s performance changes over the time. They could be developed using various pavement performance indicators (International roughness index (IRI), distresses, and so on). Pavement performance models can be categorized into two groups, deterministic and probabilistic, based on their prediction results. Deterministic models estimate a single condition value for a given time during a pavement’s design life, while probabilistic models estimate the probability of a condition value for a given time. Most SHAs use deterministic models as part of their pavement management systems for various reasons: (1) ease in explaining such models to users and (2) ease in incorporating such models into pavement management systems (PMS)

RSL models are broadly categorized as mechanistic and empirical models. In mechanistic models, mechanistic-based pavement performance models are used (based on engineering principles); while, in empirical models, data from observed historical data and other parameters are analyzed mostly through statistical approaches. ANN-based pavement performance models were developed by some studies before mostly to model relationships between pavement performance data and several input parameters related to pavement structural design, traffic etc. However, there are not many studies found in the literature where network level ANN-based pavement performance models are developed to predict performance change of pavement sections over time in a quick and efficient way. Moreover, there is not any study found in the literature in which efficient network and project level RSL models are developed separately.
Threshold limits are determined performance indicator values at which a significant rehabilitation treatment or reconstruction is needed. Performance indicators and threshold limits are agency-specific parameters used for rehabilitation decision-making processes. Both performance models and threshold limits are components used in the development of RSL models.

OBJECTIVES
In this study, a detailed step-by-step methodology in the development of a framework for project and network level pavement performance and RSL prediction models for Iowa flexible and composite (Asphalt concrete (AC) over Jointed Plain Concrete Pavement (JPCP)) overlays is explained using real pavement performance data obtained from the Iowa Department of Transportation (DOT) pavement management information system (PMIS) database. Two approaches investigated for developing pavement performance models are a statistics approach in use of project level pavement management and an artificial intelligence (AI) based approach in use of network level pavement management. Using the developed statistics and AI based models, future pavement performance predictions are successfully calculated for each pavement section used in this study. Network level pavement performance models are also developed using statistically defined approach with the same input parameters used in ones developed using AI based approaches to evaluate the relative success of these approaches in network-level pavement-performance modeling.

Microsoft Excel based automation tools have been developed for both project and network level pavement performance modeling and analysis to facilitate pavement-performance and RSL model development, to make future pavement performance predictions, and to estimate RSL for any given pavement section. These tools, that make use of real pavement performance data to produce realistic future condition predictions, can be easily incorporated into pavement management processes and help engineers make better-informed performance-based pavement infrastructure planning decisions and optimize agency resource expenditures.

DESCRIPTIONS OF OVERALL APPROACHES AND DATA PREPARATION
Figure 1 depicts the pavement performance and RSL model development stages followed in this study. Initially, statistics and AI based approaches were investigated for developing pavement performance models in use of project level and network level pavement managements, respectively. Both project and network-level pavement performance models were developed for Iowa flexible and composite (AC over JPCP) pavement systems. Project-level pavement performance models were developed for each pavement section in each pavement type, while network-level pavement performance models were developed for each pavement performance indicator, or a condition matrix (i.e. distresses and IRI) for each pavement type.

Success of the pavement performance prediction models in mimicking measured pavement performance indicators was quantified using a line-of-equality coefficient of correlation ($R^2$) (Equation 1), an absolute average error (AAE) (Equation 2) and a standard error of the estimates (SEE) (Equation 3). Higher $R^2$ and lower AAE and SEE values are signs of accurate model prediction.

$$R^2 = 1 - \frac{\sum_{j=1}^{n}(y_{\text{measured}} - y_{\text{predicted}})^2}{\sum_{j=1}^{n}(y_{\text{measured}} - y_{\text{mean}})^2}$$  (1)
\[ AAE = \frac{\sum_{j=1}^{n} |y_{j}^{measured} - y_{j}^{predicted}|}{n} \]  
\[ SEE = \sqrt{\frac{\sum_{j=1}^{n} (y_{j}^{measured} - y_{j}^{predicted})^2}{n}} \]

Where,
- \( n \) = Data set size
- \( j \) = Case number in the data set
- \( y_{j}^{measured} \) = Measured IRI or other pavement performance indicator measurements
- \( y_{j}^{predicted} \) = Model predictions for IRI or other pavement performance indicators

Once pavement performance models were developed for the two pavement types, remaining service lives for the pavement sections were calculated using threshold limits for various performance indicators. Based on the Federal Highway Administration (FHWA)’s Final Rule (effective February 17, 2017) regarding implementation of the performance management requirements of MAP-21 and the Fixing America’s Surface Transportation Act (1, 14), condition of the pavements is required to be determined based on the following metrics: IRI, percent cracking, rutting, and faulting (Table 1). IRI was used as a construction trigger for the rehabilitation decision-making process in project and network level RSL calculations. RSL is

**FIGURE 1 Schematic image of pavement performance and RSL model development stages.**
TABLE 1. Pavement Condition Rating Thresholds Determined by FHWA for Flexible and Composite Pavement Systems (14)

<table>
<thead>
<tr>
<th>Condition Metric</th>
<th>Performance Level</th>
<th>Threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>IRI (in/mile),</td>
<td>Good</td>
<td>&lt;95</td>
</tr>
<tr>
<td></td>
<td>Fair</td>
<td>95-170</td>
</tr>
<tr>
<td></td>
<td>Poor</td>
<td>&gt;170</td>
</tr>
<tr>
<td>Percent cracking</td>
<td>Good</td>
<td>&lt;5%</td>
</tr>
<tr>
<td></td>
<td>Fair</td>
<td>5-20%</td>
</tr>
<tr>
<td></td>
<td>Poor</td>
<td>&gt;20%</td>
</tr>
<tr>
<td>Rutting (in)</td>
<td>Good</td>
<td>&lt;0.20</td>
</tr>
<tr>
<td></td>
<td>Fair</td>
<td>0.20-0.40</td>
</tr>
<tr>
<td></td>
<td>Poor</td>
<td>&gt;0.40</td>
</tr>
</tbody>
</table>

The Iowa DOT has been collecting pavement condition data and storing them in its PMIS, and pavement structural design features and traffic volume information are also available as part of the PMIS. Iowa DOT’s PMIS database has been used as data source in this study. This database includes all information related to traffic, distress, and construction information related to the pavement sections.

The number of pavement sections and the total number of data points for each pavement type used in this study are as follows:
- 35 sections for flexible pavements (430 data points)
- 60 sections for composite (AC over JPCP) pavements (644 data points)

The pavement sections used in this study represent a variety of geographical locations across Iowa with various traffic levels, thicknesses, and ages. Distributions of locations, traffic levels, thicknesses, and ages for these pavement sections and other detailed information can be found in another study (15).

While analyzing pavement condition data points for each pavement section in PMIS database, it was realized that in some pavement sections, measured pavement condition values for some pavement performance indicators remained the same over some number of years, after which an increase in those pavement condition values was observed. Note that Iowa DOT has a pavement performance collection practice that pavement performance measurements for some sections are collected in even years while for some others they are collected in odd years. Because a pavement condition data was not collected or recorded every year for some sections, pavement condition measurements reported for previous years had been recorded as pavement condition measurements for upcoming years for these sections in PMIS. In such cases, a systematic data preparation methodology similar to one described in the literature for previous studies was developed (5, 16): A linear increase was achieved between the first year when pavement condition data points started to be the same over a number of years and the year when an increase in those pavement condition values was observed. Applying this data preparation methodology, more realistic pavement condition records can be obtained, and in turn, more accurate pavement performance models can be developed.
STATISTICS BASED PAVEMENT PERFORMANCE MODEL DEVELOPMENT AND ACCURACY EVALUATIONS

A statistically defined sigmoid pavement-deterioration curve-based approach was used for project level pavement performance model development in this study. Sigmoidal equations have been particularly used in statistics model development because: (1) they have a low initial slope and an increasing slope with time and (2) they follow a trend in which pavement condition always gets worse and damage is irreversible, and both these features of sigmoidal models cause these models to mimic pavement deterioration behavior observed in project level studies (5, 17, 18). Since sigmoidal equations have been found to successfully model pavement deterioration when there is single pavement deterioration trend (project-level), a sigmoidal equation for each pavement section in each pavement type was optimized, with each equation having different coefficients. IRI was used as a performance indicator in project-level pavement performance models.

Equation 4 is the generalized sigmoidal equation used for IRI calculation.

\[
IRI = C_1 + \frac{C_2}{1 + e^{(C_3 + C_4 \times \text{age})}}
\]  

(4)

where \( C_1, C_2, C_3 \) and \( C_4 \) are coefficients that represent contributions of different input parameters.

Sigmoidal curves were fitted to measured IRI values by minimizing the square of differences value between measured and predicted IRI values. The fitting process was carried out by manipulating prediction coefficients (Equation 4) to produce minimum error.

Figure 2 shows examples of IRI prediction models for flexible, and composite (AC over JPCP) pavement types. Using these models, future IRI predictions can be calculated for these pavement types.

As part of this study, a Microsoft Excel Macro-based automation tool was developed, automatically updating and improving pavement performance prediction models as more data were added into the model development dataset. The benefit of this tool is that, as engineers add more data into the model development dataset, they will be able to automatically refine performance prediction models and make decisions using the most recent and more accurate pavement performance models. Another benefit of using this tool is that pavement performance prediction models can be developed using very few data points.
FIGURE 2 IRI prediction model result and equation examples for (a) a new flexible pavement section (US 61, MP 167.95 to 174.74, N, Traffic (AADTT): 1,154, Construction year: 1999) and (b) a composite (AC over JPCP) pavement section (US 30, MP 310.08 to 318.84, W, Traffic (AADTT): 1,264, Restoration year: 2000).
Once pavement performance model has been developed for each pavement section, as explained in the previous section, the remaining service lives for each pavement section can be calculated using threshold limits for the pavement performance indicators. In this study, IRI was used as a performance indicator for project level RSL calculations because: (1) it quantifies functional performance of pavement systems, the aspect most road users care about, (2) it has also been adopted as a standard for the Federal Highway Performance Monitoring System (19), and (3) it is also one of the condition metrics identified for use by FHWA (14). The same threshold level recommended by FHWA for poor pavement condition (i.e., an IRI value of 170 in/mile) was selected as the threshold value in this study for project-level RSL calculations (14).

The RSL for each pavement section was calculated by the following steps:

1. Statistically defined pavement performance models were developed for each pavement section in each pavement type (i.e., flexible and composite).
2. Using the developed pavement performance models, future IRI predictions were calculated for each pavement section.
3. Whether future IRI predictions reached the threshold limit (170 in/mi) was checked.
   a. If yes, the RSL value for each pavement section was calculated by subtracting the present year from the year when IRI predictions first reached the threshold limit.
   b. If no, meaning that, based on available measured IRI data, future IRI predictions had not reached 170 in/mile over a long period of analysis time (i.e. 40 years). In other words, these pavement sections performed very well in terms of smoothness criteria. Adding more data points (i.e., future performance measurements) would change the model and increase its accuracy. In these cases, RSL value for each pavement section was calculated by subtracting the current age of pavement from 40 years.

Figure 3 shows the distribution of RSL for flexible and composite (AC over JPCP) pavement sections investigated in this study, respectively.
Flexible pavements
FIGURE 3 RSL distribution for flexible (a) based on pavement section ID and (b) based on pavement length) and composite (AC over JPCP) pavement sections ((c) based on pavement section ID and (d) based on pavement length).

Composite pavements
ARTIFICIAL INTELLIGENCE BASED PAVEMENT PERFORMANCE MODEL DEVELOPMENT AND ACCURACY EVALUATIONS

AI based approach was investigated for developing pavement performance models in use of network level pavement management. AI techniques, such as artificial neural networks (ANNs), have been widely used to model complex pavement engineering problems (20, 21). ANN-based models are very useful tools for modeling pavement deterioration when considering many pavement sections with various traffic, thickness (network-level) or deterioration trends. They are also very fast tools with which thousands of pavement scenarios for which various traffic, thickness, and conditions can be solved in seconds. Both these features of ANN models make them useful tools to be used in the development of network-level pavement-performance modeling. In this study, an ANN-based pavement-performance model was developed for each pavement-performance indicator (i.e. distress, IRI) and for each pavement type: flexible, and composite (AC over JPCP). 80% of all data points in each pavement type was used in the model development, and out of this set of data points, 48%, 8% and 24%, respectively, were used as training, testing, and validation datasets. The remaining 20% of all data points were not used in model development but rather were used as an independent testing dataset. ANN models must have the following capabilities:

- High accuracy: they must successfully produce results very similar to those from measured distresses
- Physically meaningful future distress predictions: distress predictions must increase in the future unless a maintenance or repair activity occurs

A Microsoft Excel Macro based network-level pavement performance prediction automation tool was developed that predicts future pavement performance for each pavement section using developed ANN models. This tool calculates future pavement performance predictions for any pavement performance indicator (i.e., IRI, each distress) of any pavement section.

The following steps were used in the development of this tool:
1. ANN models were developed in the MATLAB® environment using six training algorithms and a variable number of hidden neurons (from 5 to 60).
2. The ANN model producing highest accuracy was selected as the final model for the given pavement performance indicator.
3. Weights and biases for the final ANN model were extracted into the automation tool.
4. Using these extracted weights and biases, through matrix multiplications, future distress predictions were calculated for the given thickness, accumulated equivalent single axle load (ESAL) traffic, age, and previous two years’ pavement performance records for any pavement performance indicator. 1% compound truck traffic growth was assumed in calculating future traffic.

As part of this study, an ANN model for each pavement type was developed for rutting, longitudinal cracking, transverse cracking, and IRI predictions. 35 flexible pavement sections with 360 data points of each pavement performance indicator were used in model development and independent testing. 172, 30, 86 and 72 data points, respectively, were used as training, testing, validation, and independent testing datasets. 60 composite pavement sections with 524 data points of each pavement performance indicator were used in model development and independent testing. 251, 42, 126 and 105 data points, respectively, were used as training, testing, validation, and independent testing datasets. Table 2 summarizes input and output parameters used in the five ANN models developed for flexible and composite pavements. As
can be seen in Table 2, AC thickness, traffic (accumulated ESALs), age, and previous two years’ pavement performance records were used in rutting, longitudinal cracking, transverse cracking, and IRI (approach 1) model development. On the other hand, in approach 2, IRI model was developed using age, measured distress values (rutting, longitudinal cracking and transverse cracking in this case), and previous two years’ measured IRI data. In approach 2, ANN-model-predicted rutting and longitudinal and transverse cracking values, along with other input parameters, were used as inputs to predict future IRI.

**TABLE 2. Summary of Input and Output Parameters Used in Five ANN Models Development for Flexible and Composite Pavements**

<table>
<thead>
<tr>
<th>Model Name</th>
<th>Input Parameters</th>
<th>Output Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rutting</td>
<td>AC thickness, traffic (accumulated ESALs), age, rut (i-2) year, rut (i-1) year</td>
<td>Rut (i) year</td>
</tr>
<tr>
<td>Longitudinal Cracking</td>
<td>AC thickness, traffic (accumulated ESALs), age, longitudinal cracking (i-2) year, longitudinal cracking (i-1) year</td>
<td>Longitudinal cracking (i) year</td>
</tr>
<tr>
<td>Transverse Cracking</td>
<td>AC thickness, traffic (accumulated ESALs), age, transverse cracking (i-2) year, transverse cracking (i-1) year</td>
<td>Transverse cracking (i) year</td>
</tr>
<tr>
<td>IRI (Approach 1)</td>
<td>AC thickness, traffic (accumulated ESALs), age, IRI (i-2) year, IRI (i-1) year</td>
<td>IRI (i) year</td>
</tr>
<tr>
<td>IRI (Approach 2)</td>
<td>Age, rut (i) year, longitudinal cracking (i) year, transverse cracking (i) year, IRI (i-2) year, IRI (i-1) year</td>
<td>IRI (i) year</td>
</tr>
</tbody>
</table>

Figure 4 compares measured pavement condition records and ANN model predictions for flexible and composite (AC over JPCP) pavements using a) rutting, b) longitudinal cracking, c) transverse cracking, d) IRI (approach 1), and e) IRI (approach 2) ANN models, respectively. While the ANN models accurately predicted corresponding pavement performance indicators, the IRI models produced more accurate predictions compared to the rutting, longitudinal cracking, and transverse cracking models because of their higher R² and lower AAE and SEE values. The IRI models developed using approach 1 and approach 2 produced similar accuracies. In all cases investigated, high R² and low AAE and SEE values were obtained for all training, testing, validation and independent testing datasets.
Flexible pavements
Composite pavements

FIGURE 4 Comp. between measured pavement cond. records and ANN model predictions using (a) & (f) rutting, (b) & (g) longitudinal cracking, (c) & (h) transverse cracking, (d) & (i) IRI (approach 1), and (e) & (j) IRI (approach 2) ANN models for flexible and composite pavements, respectively.
ARTIFICIAL INTELLIGENCE BASED PAVEMENT RSL MODEL DEVELOPMENT AND RESULTS

Once AI based network level pavement performance models were developed for each pavement performance indicator or condition metric, as explained in the previous section, the remaining service life for each pavement section in a road network could be calculated using these performance models and corresponding threshold limits for the pavement performance indicators. In this study, IRI was used as the performance indicator for network level RSL calculations because, as stated earlier, this condition metric was determined by FHWA (1, 14) (Table 1). RSL is determined based on the year when future performance predictions reach the poor condition threshold.

The RSL value for each pavement section in a road network was calculated based on the following steps:

1. Using developed AI based pavement performance models, future pavement condition predictions were calculated for each pavement section.
2. Whether future pavement condition predictions reached threshold limits was checked for each corresponding condition metric.
   a. If yes, RSL value for each pavement section was calculated by subtracting the present year from the year when pavement condition predictions first reached the threshold limit.
   b. If no, based on available pavement condition data, this means that future pavement condition predictions do not reach corresponding condition metric threshold over a long period of analysis time (i.e., 40 years). In other words, this means that these pavement sections perform very well in terms of the corresponding condition metric, although adding more data points (i.e., future performance measurements) would increase accuracy of the predictions. In these cases, RSL value for each pavement section was calculated by subtracting the current age of pavement from 40 years.

Figure 5 shows the distribution of RSL for 35 flexible and 60 composite (AC over JPCP) pavement sections when: (1) an IRI threshold limit of 170 in/mile was used as the threshold limit and (2) an ANN-based network-level IRI model (approach 1) was used as the pavement performance model in calculation of RSL values.
Flexible pavements
FIGURE 5 RSL distribution for flexible pavement sections ((a) based on pavement section ID and (b) based on pavement length, when IRI model (approach 1) and for composite pavement sections ((c) based on pavement section ID and (d) based on pavement length, when IRI model (approach 1) threshold limit of 170 in/mile were used.
COMPARISONS BETWEEN STATISTICS AND AI BASED NETWORK LEVEL PAVEMENT PERFORMANCE MODELS

Network level IRI performance models were developed using statistically defined approach for both flexible and composite (AC over JPCP) pavement types to evaluate their relative success in network-level pavement-performance modeling in comparisons to ones developed using ANN-based approaches. The input parameters used for developing statistics-based network-level IRI models for both pavement types were same as ANN-based network-level IRI (approach 1) models:

- Input parameters: AC thickness, traffic (accumulated ESALs), age, IRI (i-2) year, IRI (i-1) year
- Output parameter: IRI (i) year

The same generalized sigmoidal equation (Equation 4) was also used in the development of network-level statistical models, and the same methodology, error minimization, was used in the optimization of network-level statistical models.

Flexible Pavement Case

A globally-optimized sigmoid equation (Equation 5) was developed by correlating the coefficients of the sigmoidal equation \( C_1, C_2, C_3, \) and \( C_4 \) with the input parameters for the whole dataset of model development (35 flexible pavement sections (360 data points))

\[
IRI = C_1 + \frac{C_2}{1 + e^{-1(17.57+0.93\times age)}}
\]

Where

- \( C_1 = 7.52E-7 \times \text{ACC Traffic} - 2.11 \times \text{AC Thickness} + 1.04 \times \text{IRI (i-2) year} + 0.32 \times \text{IRI (i-1) year} \)
- \( C_2 = -0.04 \times \text{ACC Traffic} - 2.00 \times \text{AC Thickness} + 2.94 \times \text{IRI (i-2) year} + 3.90 \times \text{IRI (i-1) year} \)

A model with the model architecture of 5 - 5 - 1 (number of inputs - number of hidden neurons - number of outputs) was used as the network-level ANN model.

Figure 6a compares the accuracies of statistics and ANN-based network-level IRI models for flexible pavements. As can be seen in the figure, the ANN model produced greater accuracy with higher \( R^2 \) and lower AAE and SEE values than the statistics model.

Composite (AC over JPCP) Pavement Case

A globally-optimized sigmoid equation (Equation 6) was developed by correlating the coefficients of the sigmoidal equation \( C_1, C_2, C_3, \) and \( C_4 \) with the input parameters for the entire dataset of model development (60 composite pavement sections (524 data points))

\[
IRI = C_1 + \frac{C_2}{1 + e^{-1(17.57+0.93\times age)}}
\]

Where

- \( C_1 = 1.37E-7 \times \text{ACC Traffic} - 2.12 \times \text{AC Thickness} + 0.82 \times \text{IRI (i-2) year} + 0.30 \times \text{IRI (i-1) year} \)
- \( C_2 = -0.04 \times \text{ACC Traffic} - 2.00 \times \text{AC Thickness} + 2.94 \times \text{IRI (i-2) year} + 3.90 \times \text{IRI (i-1) year} \)

A model with the model architecture of 5 - 5 - 1 was used as the network-level ANN model.

Figure 6b compares the accuracies of the statistics and ANN-based network-level IRI models for composite pavements. As can be seen in the figure, the ANN model produced more accuracy with higher \( R^2 \) and lower AAE and SEE values than the statistical model.
FIGURE 6 Accuracy comparisons between statistics and ANN based network level IRI models for (a) flexible and (b) composite pavements.

CONCLUSIONS AND RECOMMENDATIONS

Overall Conclusions
In this study, a detailed step-by-step methodology for development of a framework for pavement performance and RSL prediction models was established and explained using real pavement performance data obtained from the Iowa DOT PMIS database. To develop RSL models, project and network-level pavement performance models were initially developed using two approaches: a statistically defined approach for project-level model development and an AI based approach for network-level model development. Then, using threshold limits for various pavement-performance indicators (IRI for project-level and network-level models) and FHWA-specified
threshold limits for pavement performance indicators, RSL models were developed for flexible, and composite (AC over JPCP) pavements.

A statistically defined sigmoid pavement deterioration curve-based approach was used for project-level pavement-performance model development. Sigmoidal equations have been particularly used in the statistics model development because: (1) they have a low initial slope that increases with time, and (2) they follow a trend in which pavement condition always gets worse and damage is irreversible, and both these features make these models mimic the pavement deterioration behavior observed in field studies. Sigmoidal equations were found to successfully model pavement deterioration when there is a single pavement deterioration trend (project-level). One of the benefits of project-level pavement performance models is that they can be developed using very few data. Therefore, they can be extensively used when only a few pavement condition or structural and traffic data are available for pavement sections.

Artificial intelligence (AI)-based pavement-performance models were used for network-level pavement performance model development in this study. AI techniques such as artificial neural network (ANN)-based models have been found to be great tools for modeling pavement deterioration when there are many pavement sections with various traffic, thickness, and other various deterioration trends (network-level). They are also very fast tools that can solve thousands of pavement scenarios with various traffic, thickness, and conditions in seconds (near real time). Both these features of ANN models make them great tools for use in development of network-level pavement-performance modeling.

As part of this study, network-level pavement performance models were also developed using statistics and ANN-based approaches, with identical input parameters used in both approaches to evaluate their relative success for network-level pavement-performance modeling. It was found that network-level ANN based pavement performance models produced greater accuracy with higher $R^2$ and lower AAE and SEE values compared to network-level statistical models.

As part of this study, Microsoft Excel based automation tools were developed for both project and network-level pavement performance modeling and analysis:

- The project-level pavement-performance modeling and RSL calculation tool is capable of developing project-based statistical models for predicting future pavement performance as well as calculating RSL values based on user-defined threshold limits. It is also capable of automatically updating and improving pavement-performance prediction models because it allows more data to be added into the model development dataset. The benefit of this tool is that, as engineers add more data into the model development dataset, they will be able to automatically refine performance prediction models and make decisions using more recent and more accurate pavement performance models.

- The network-level pavement performance modeling tool is capable of making pavement-performance predictions based on pre-developed ANN-based pavement-performance models. While having only thickness, traffic, age, and previous two years’ pavement performance records for any pavement performance indicator, it can make future pavement-performance calculations in less than a second for any pavement section. It is also capable of producing pavement-performance predictions for thousands of pavement scenarios under various traffic, thickness, and other conditions in seconds. The network-level pavement performance modeling tool is also capable of (1) making future pavement-performance predictions for some distresses (i.e., transverse cracking, rutting, and longitudinal cracking), then (2) using these predicted distress values as inputs in making future IRI predictions.
The pavement performance modeling and prediction models developed and explained in this study are very powerful and versatile tools that can easily be adopted by the Federal and State Highway Agencies, County Engineer Offices, and so on for predicting the future performance of their transportation infrastructure systems and can easily be used as a decision making tool in managing their transportation infrastructure assets.

Recommendations
This study can be further expanded by: (1) including other pavement performance indicators (i.e., faulting for rigid pavements, material-related distresses, etc.), (2) defining other agency-specific threshold limits, and (3) prioritizing some pavement performance indicators over others, and so on, as part of RSL model development. Some SHAs use decision trees to determine when a major rehabilitation or reconstruction is needed. Multi-objective RSL models can be developed considering various pavement performance indicators with different priorities. RSL results will allow agencies to distinguish between two pavement sections with the same current condition (i.e., the same current IRI) but having different performance behaviors with times. This can be an ideal approach to addressing the transportation planning and performance management criteria requirements of the MAP-21 legislation.

Note that RSL models are only to help engineers in their decision-making process. They consider only a limited number of condition metrics (IRI, some distresses, etc.) but may fail to consider other important parameters such as structural capacity and integrity of pavement systems. Engineers should consider various parameters as well as RSL model results, combined with their engineering judgment to determine when a pavement section will fail and need major rehabilitation or reconstruction. Note that calculated RSL results in this study are based on a limited number of dataset elements, developed pavement performance models and FHWA-specified threshold limits. Adding more data points (i.e., future performance measurements) would change the pavement performance models as well as the calculated RSL results.

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AUTHOR CONTRIBUTION STATEMENT
The authors confirm contribution to the paper as follows: study conception and design: Halil Ceylan, Orhan Kaya, Sunghwan Kim, Danny Waid, and Brian P. Moore; data collection: Orhan Kaya and Sunghwan Kim; analysis and interpretation of results: Orhan Kaya, Halil Ceylan, Sunghwan Kim, Danny Waid, and Brian P. Moore; draft manuscript preparation: Orhan Kaya, Halil Ceylan, and Sunghwan Kim. All authors reviewed the results and approved the final version of the manuscript.
REFERENCES


