2018

Predicting pavement performance utilizing artificial neural network (ANN) models

Fawaz Alharbi
Iowa State University

Predicting pavement performance utilizing artificial neural network (ANN) models

by

Fawaz Alharbi

A dissertation submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Civil Engineering (Transportation Engineering)

Program of Study Committee:
Omar Smadi, Major Professor
Shauna Hallmark
Peter Savolainen
Jennifer Shane
Guping Hu

The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this dissertation. The Graduate College will ensure this dissertation is globally accessible and will not permit alterations after a degree is conferred.

Iowa State University

Ames, Iowa

2018

DEDICATION

To my parents

To my wife

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to my committee chair and advisor, Dr. Omar Smadi, for his encouragement, guidance, and support. I am honored to have had the opportunity to be under his supervision. I must also thank all my committee members, Dr. Shauna Hallmark, Dr. Guiping Hu, Dr. Peter Savolainen, and Dr. Jennifer Shane for taking their valuable time to review my work.

Also, I would like to express my deep gratitude and thanks to my parents for their continued love and support. I am extremely grateful and thankful for all they provided me in the past and continue to provide me today. Additionally, I would like to send special thanks to my wife for her endless support, care, and love.

Finally, I would like to thank my country, Saudi Arabia, for giving me the opportunity to study abroad, and complete six years through my master and PhD programs in the United States. I would also like to thank Qassim University for supporting me financially to pursue my PhD program at Iowa State University.

ABSTRACT

Pavement management systems (PMS) play a significant role in cost-effective management of highway networks to optimize pavement performance over predicted service life of the pavements. Successful PMS implementation requires accurate performance prediction modeling to plan future maintenance and rehabilitation strategies.

The Iowa DOT manages three primary highway systems (i.e., Interstate, US, and Iowa highways) that represent 8% (approximately 9,000 miles) of the total roadway system in the state (114,000 miles), but these systems carry around 62% of the total vehicle miles traveled (VMT) and 92% of the total large truck VMT (ASCE, 2015). These highways play a major role in Iowa's economy because highways are important to several sectors (e.g., agriculture, manufacturing, and industry). According to the Bureau of Transportation Statistics, in 2012 around 263.36 billion tons of goods valued at $195.99 billion were transported on Iowa highways (BTS, 2012). PMSs that use robust pavement prediction models are needed to ensure continued optimum performance of Iowa highways. In the past, these models were developed from historical information about pavement condition data.

In this research, historical climate data was acquired from the Iowa Environmental Mesonet and integrated with pavement condition data to include all related variables in prediction modeling. An artificial neural network (ANN) model was used to predict the performance of ride, cracking, rutting, and faulting indices on different pavement types. The goodness of fit of the ANN prediction models was compared with multiple linear regression (MLR) models. The results show that ANN models were more accurate in predicting future conditions than MLR models. The contribution of input variables in prediction models were also determined and discussed.

The results indicated that weather factors directly influence highway pavement conditions, and that ANN model results can be used by decision makers and maintenance engineers to determine proper treatment actions and pavement designs to withstand harsh weather over the years. An ANN model that was used to estimate the correlation between the rutting depth and structural capacity of asphalt pavements suggests that rutting depth can be an indicator of structural capacity. As such, an ANN approach might be feasible for small transportation agencies (e.g., cities and counties) that cannot afford to collect structural information.

CHAPTER 1: INTRODUCTION

State highway agencies spend millions of dollars each year on maintenance and rehabilitation to meet legislative, agency, and public requirements. Effective pavement management requires a systematic approach that includes project planning, design, construction, maintenance, and rehabilitation. Pavement management systems (PMS) play a significant role in managing the condition of highway networks efficiently based on cost-effective strategies to be applied at a given time for maintaining that pavement condition at an acceptable level so the pavement can satisfy the demands of traffic and environment over its service life. In general, pavement conditions are characterized by cracking, surface deformation, roughness, surface friction (skid resistance), or faulting.

Individual PMSs operate on two administrative levels, the network and project management levels. At the network management level, a PMS predicts the overall pavement performance for determining budget allocation and treatment strategies. At the project management level, more detailed information and specific treatment options are required to determine when a particular pavement section may need maintenance or rehabilitation action.

Traffic loading and environmental factors result in pavement distress. The ability to trace that distress over time allows researchers and agency decision makers to develop performance prediction models. Predicting pavement performance requires historical data about pavement conditions, traffic loading, structural characteristics, and climate data. These data can be acquired from a single test road or from in-service pavements to obtain data for more practical prediction models. However, constructing and monitoring single test roads is expensive and unrealistic for small and local agencies. Developing accurate prediction models for pavements allows transportation agencies to effectively manage their highways in terms of budget allocation and scheduling maintenance and rehabilitation activities.

In this research, historical traffic loading and pavement condition data was obtained from the Iowa Department of Transportation (DOT), and climate data was acquired from the Iowa Environmental Mesonet (IEM) in order to include all related variables in the prediction models. The results of this research will improve pavement management strategies by predicting an accurate pavement distress, and evaluate the impact of Iowa weather conditions on predicting pavement performance.

Problem Statement

The Iowa DOT manages three primary highway systems (i.e., Interstate, US, and Iowa highways) that represent 8% (approximately 9,000 miles) of the total roadway system in the state (114,000 miles), but these systems carry around 62% of the total vehicle miles traveled (VMT) and 92% of the total large truck VMT (ASCE, 2015). These highways play a major role in Iowa's economy by connecting customers and supplies across the United States, and the roads are important to economic development in several sectors such as agriculture, manufacturing, and industry. According to the Bureau of Transportation Statistics, in 2012 around 263.36 billion tons of goods valued at $195.99 billion were transported on Iowa highways to other states (BTS, 2012).

Iowa faces critical challenges in providing a safe, efficient highway system, particularly in terms of balancing optimum highway conditions and available local, state, and federal funds. According to the American Society of Civil Engineers, 45% of major roads in Iowa were in fair condition, and large truck VMT, which directly affects pavement deterioration, will increase by 66% between 2015 and 2040 (2105). The Iowa DOT has allocated about $2.7 billion for highway construction and $1.2 billion for improving highway safety during fiscal years 2015 to 2019 (ASCE, 2015). Despite these allocations, Iowa DOT administration, maintenance and construction costs result in an estimated annual funding shortfall of over $215 million (Iowa DOT, 2016).

Current PMS models used by the Iowa DOT do not consider climate factors and as such, may not be accurate. Therefore, the Iowa DOT could benefit from better prediction of the future needs of pavements to ensure they serve as effectively as possible. Therefore, efforts have been made to acquire historical climate data from Iowa Environmental Mesonet (IEM) and integrate it with pavement condition data from Iowa DOT. Then pavement performance models could be developed for asphalt, concrete, and composite pavements.

In addition to pavement performance modeling, some transportation agencies (e.g., cities and counties) do not have the capability for conducting deflection tests on their roadways for structural evaluation because these tests generally require specialized equipment, experience, and knowledge. As a result, these agencies may rely primarily on functional condition data to assess the strength of their roadways. However artificial neural network (ANN) pavement prediction models have been developed that can account for both pavement conditions and climate data and can estimate the relationship between structural capacity and rutting depth in asphalt pavement at the network level.

Research Objectives

The goal of this research is to explore pavement performance prediction models that can help decision makers take appropriate actions by meeting the following objectives:

1. Developing and comparing traditional regression and artificial neural network models in predicting future pavement conditions for asphalt, concrete, and composite pavements and support pavement management decisions.
2. Determining the impact of various input variables on the deterioration of pavement conditions.
3. Utilizing an ANN model to estimate the correlation between structural capacity and rutting depth on asphalt pavements that will allow agencies to consider structural capacity in making investment decisions.

Dissertation Organization

Four chapters make up the rest of this dissertation. Chapter two presents information about pavement management systems and pavement condition evaluation and summarizes previous studies that have been done in modeling pavement performance. Chapter three describes the data and methodology used to predict pavement performance. Chapter four presents the results of developing prediction models, determining the relative importance of input variables, and estimating the correlation between rutting depth and structural capacity. Chapter five summarizes the research contributions with recommendations for future work.

CHAPTER 2: LITERATURE REVIEW

This chapter summarizes the literature about pavement management systems, assessment categories in evaluating pavements, pavement condition ratings, and pavement performance modeling.

Pavement Management Systems (PMS)

Management of large transportation assets requires tools for coordinating activities in an optimal manner, and a pavement management system (PMS) is an element of transportation infrastructure asset management that includes all transportation activities. A PMS is defined by the American Association of State Highway and Transportation Officials (AASHTO) as "a set of tools or methods that assist decision makers in finding optimum strategies for providing, evaluating, and maintaining pavements in a serviceable condition over a period of time" (AASHTO, 1993, p. I-31). The PMS concept began in the mid-1960s as support tools to help decision makers provide required rehabilitation and maintenance for highways with limited available funds (Kirbas, 2010).

In general, PMS activities include investment planning, design, construction, maintenance, and routine pavement evaluation (Falls et al., 2001). A PMS can improve the efficiency of decisions by reviewing the consequences of decisions made at different management levels (George, 2000). Moreover, by applying a PMS, the potential impact of limited funding can be reduced by optimizing budget allocation, prioritizing projects in a data-driven process, and using effective maintenance strategies (TAC, 1999).

A PMS provides highway agencies with the following capabilities (AASHTO, 2012):

- Evaluating current and future pavement conditions.

- Estimating the funds required for improving pavement condition up to a particular condition level.
- Identifying pavement treatments and preservation options based on available funds.
- Evaluating the long-term impact of changes in material properties, construction practices, or design procedures on pavement performance.

To develop a PMS, it is necessary to understand the PMS levels, PMS components, and available prediction models.

Pavement Management Levels

There are two administrative levels, the network and project management levels, in any pavement management and decision-making system (Mbwana, 2001). At the network level, decisions to achieve the agency's goals are identified and, at this level, prioritized reconstruction and rehabilitation activities and a schedule for maintenance activities are developed. Collecting specific data about an entire pavement network requires a significant investment, so agencies attempt to achieve a balance between the level of detail in data and available resources (AASHTO, 2012). The network level is typically used by directors of state-level transportation agencies or budget directors since they want to know the overall indices of pavement conditions, riding quality, or safety (Mbwana, 2001).

The project level, on the other hand, represents decisions that concentrate on individual portions of the network, and more detailed data collection methods, such as material testing to evaluate pavement conditions, are required at this level. Traffic loading, environmental factors, material properties, construction and maintenance work, and available funding are considered to be the inputs for project-level analysis (Dillon, 2003). These detailed data are utilized to predict pavement performance and establish optimal maintenance strategies. A comparison of the different criteria between project and network levels is shown in Table 1.

Table 1. Differences between PMS network and project levels (AASHTO, 2012)

Decision Level	Decision Makers	Type of Decisions	Range of Assets Considered	Level of Detail	Breadth of Decisions
Network	Asset manager Pavement management engineer District engineer	Treatment recommendations for a multi-year plan Funding needed to achieve performance targets Consequences of different investment strategies	Range of assets in a geographic area	Moderate	Moderate
Project	Design engineer Construction engineer Materials engineer Operations engineer	Maintenance activities for current funding year Pavement rehabilitation thickness design Material type selection Life cycle costing	Specific assets in a particular area	High	Focused

PMS Components

The components of PMSs vary based on available information and resources. AASHTO (2012) has determined the activities of pavement management systems to be the following:

- Inventorying pavement assets, including all information related to network pavements.
- Using models to analyze existing data to predict future pavement performance that supports appropriate decisions.
- Filing all related information about pavement networks to be used as feedback in generating standards or reports that can be used by other agencies to improve their PMS.

A PMS must at least contain inventories of physical pavement features, pavement conditions, traffic information, pavement performance analysis, and investment strategies for prioritizing projects for maintenance or rehabilitation activities for state highways and the national highway system (Cottrel et al., 1996). Modern PMSs should collect pavement condition data, analyze the data to determine maintenance and rehabilitation plans, and provide visualization of the analysis output to decision makers (Vines-Cavanaugh et al., 2016).

Assessment Categories in Evaluating Pavement Conditions

Evaluating pavement conditions is a fundamental component of the decision making process that is carried out to determine the current condition of pavement in terms of functional and structural adequacy. Accurate evaluation of pavement conditions requires good quality pavement distress data (e.g., accurately collected, collected often enough, and sufficient data for analysis). Haas et al. (1994) reported that pavement conditions can be determined by measuring roughness (as related to ride quality); surface distress, deflection (as related to structural adequacy); and surface friction (as related to safety). The following sections describe each assessment category.

Pavement Roughness

Pavement roughness is defined as pavement surface irregularities that can affect driver safety, vehicle operating costs, and ride quality (Islam and Buttlar, 2012). Pavement roughness is thus considered the most important pavement performance indicator because it is the primary characteristic that affects road users. Several factors have been found to affect pavement roughness, including traffic loading, climate factors, pavement type, drainage type, subgrade properties, and construction quality (Kargah-Ostadi et al., 2010). The International Roughness Index (IRI) is widely used by highway agencies to characterize pavement roughness as a ride quality indicator (Papagiannakis and Raveendran, 1998).

Pavement Surface Distress

The quantification of type, severity, and extent of surface distress is an effective approach to evaluate pavement conditions. There are different types of pavement materials (e.g., asphalt, concrete, and composite such as a concrete layer overlaid by an asphalt layer pavements), and for each pavement type, there are different types of distress that could impact pavement performance. In a 2003 AASHTO report, Miller and Bellinger identified fifteen distress types for asphalt pavements, sixteen for jointed concrete pavements, and fifteen for continuously reinforced concrete pavements. While distress types of composite and asphalt pavements are typically similar, composite pavements are exposed to reflection cracking, reflecting an asphalt layer joint or cracking deficiency (Huang, 1993). The causes and description of the major distresses are reported as follows.

Alligator cracking, also known as fatigue or map cracking, is one of the major distress types observed in asphalt pavements. Alligator cracking is defined as a series of interconnecting cracks that initiate from the bottom of the surface layer where the tensile stress is high (Castell, 2000). It is a load-related cracking caused by repeated traffic loading, and the severity of cracking depends on the stiffness modulus of the pavement material (El-Basyouny, 2005). Low strength of a pavement structure and improper drainage can also cause fatigue cracking (Dillon, 2003).

Longitudinal cracking occurs parallel to the pavement centerline. Chen and Won (2007) attribute the causes of longitudinal cracking in concrete pavement to delayed or shallow cutting of longitudinal joints and weak support under the concrete slab. In asphalt pavements, longitudinal cracking is caused by poor construction of joints between lanes or pavement shrinkage as a result of freeze-thaw cycles or low temperature, while in concrete pavement, the main causes of longitudinal cracking are repeated traffic loading and thermal gradient curling (Colorado DOT, 2004).

Transverse cracking occurs perpendicular to the pavement centerline and includes shrinkage cracking and reflective cracking, with the severity of transverse cracking dependent on pavement thickness and properties of base materials (Zhou, 2010). The differential movement of layers beneath the pavement surface and freeze-thaw cycles are the usual reasons for transverse cracking (Texas DOT, 2015).

Rutting is defined as a longitudinal deformation in the wheel-path of asphalt pavements, and rutting severity is affected by traffic loading or temperature variations that affect subgrade strength (Archilla and Madanat, 2000). Wang, Zhang, and Tan (2009) report that high temperature also has a significant effect on rutting propagation and that more attention should be paid to pavement design, material selection, and construction methods to mitigate the extent of rutting.

Faulting, a common type of distress in concrete pavements, results from vertical displacement between subsequent slabs across a joint or crack. Faulting is a concern because it can negatively affect ride quality (Bektas et. al., 2015). Faulting occurs at transverse joints as a result of inadequate load transfer, pumping action, and lack of base support (Jung et. al., 2008). According to the Ohio DOT, curling or warping of slabs due to temperature variation, settlement in subgrade soil, and pumping action of underlying fine soils are the main causes of faulting in concrete pavements (2006).

Structural Adequacy

Structural adequacy is described as the ability of pavement structures to carry expected traffic loads with acceptable levels of service. So evaluating structural capacity is an important consideration in pavement highway systems for optimizing network maintenance and agency fund allocation.

At least 14 state transportation agencies are beginning to incorporate structural evaluation by conducting deflection testing as a part of the routine evaluation of their highways (Rada et. al., 2016). Generally, structural assessment is conducted for a specific pavement section at the pavement management project level due to the detailed data, such as deflection, layer thickness, and laboratory results of material properties that are required to evaluate the structural strength of pavements (Haas et. al., 1994). Falling weight deflectometers (FWD), which have been commonly used in the United State since the 1980s, measure the deflection caused by an impact load at different distances from the load source as shown in Figure 1 (Rada et. al., 2016).

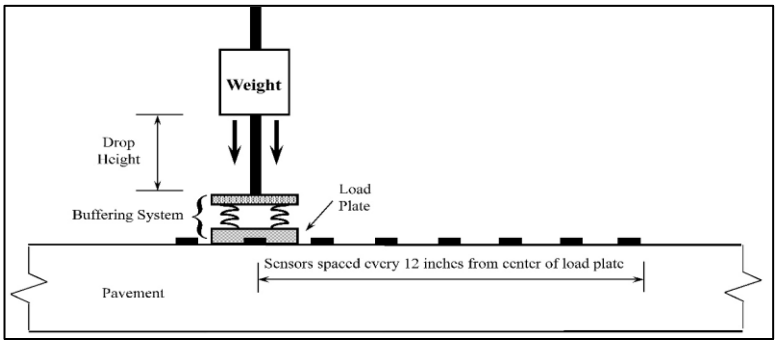

Figure 1. Schematic of FWD (Smith et al., 2017)

Rolling wheel deflectometers (RWD) have been developed to measure deflections at traffic speeds on in-service pavements for use in network-level pavement management and evaluation. An RWD impacts a vertical load to the pavement surface and measures the deflections by four spot laser mounted on a beam beneath the trailer (Smith et. al., 2017). RWDs provide several advantages over FWD testing because RWD testing does not disturb traffic flow or affect safety on the highway, and also it can be used at the network level management (Abdel-Khalek et. al., 2012). Iowa DOT compared the results of deflection values from FWD and RWD, and reported that FWD and RWD results were well correlated (Iowa DOT, 2006).

Surface Friction

Safety is an integral component of any PMS, and maintaining proper surface friction or skid resistance is an important parameter related to safety, especially in wet weather. Increasing the depth of the pavement surface texture from 0.3 mm to 1.5 mm can improve the surface friction that can decrease the crash rate by 50% (AASHTO, 2012). The equipment for measuring skid resistance has developed over the years, and all are mainly based on principles of friction between tires and the road surface (Flintsch et. al., 2012).

Pavement Condition Ratings

In the 1950s the American Association of State Highway Officials (AASHO) developed a pavement condition rating (PCR), also known as the present serviceability rating (PSR), that was based on subjective ratings of ride quality and rater experience (Attoh-Okine and Adarkwa, 2013). While the PSR is simple and convenient to use, it does not accurately evaluate pavement conditions because the factors are subjective (e.g., interaction of riding quality, rater's perception, and vehicle characteristics). The subjectivity of PSR led to the development of the pavement serviceability index (PSI), a more objective rating system. The PSI was developed in 1960 by Carey and Irick and was based mainly on panel ratings and measurements of roughness, rut depth, and cracking (Sun, 2001).

The main difference between the PSI and PSR is that PSI is derived by a formula for estimating the physical features of the pavement, and the PSR is mainly based on individual observations (Pierce et. al., 2013). Both the PSR and PSI have been widely used by highway agencies, but in the 1970s, the U.S. Army Corps of Engineers developed the Pavement Condition Index (PCI) based on types and severity of distress (Shahnazari et al., 2012). The PCI has been used since then by state DOTs for pavement evaluation.

In general, PCI ratings are single values that reflect the overall pavement condition based on the measurements of pavement roughness, surface distress, deflection, and surface friction. PCI values are on a numerical scale that can be used as a communication tool to provide a brief information about the pavement condition to senior administrators, elected officials, and the public (Haas et. al., 1994). Most importantly, the PCI values can be utilized by decision makers to assess the health of a pavement network, predict the time required for maintenance and rehabilitation actions, and estimate future funding needs (McNeil et. al., 1992).

Pavement Performance Modeling

Successful implementation of a pavement management system (PMS) requires an accurate performance prediction model for optimizing maintenance and rehabilitation strategies throughout the pavement service time. The pavement performance prediction model, described as an engine in a pavement management system, is defined as "a mathematical description of the expected values that a pavement attribute will take during a specified analysis period" (Hudson et. al., 1979, p. 8). Pavement performance is also defined in terms of how pavement changes its condition over time (Lytton, 1987). Prediction models help agency engineers to know when, where, and what maintenance actions should be taken (George, 2000). Figure 2 illustrates how an existing pavement section would behave in predicting its future performance.

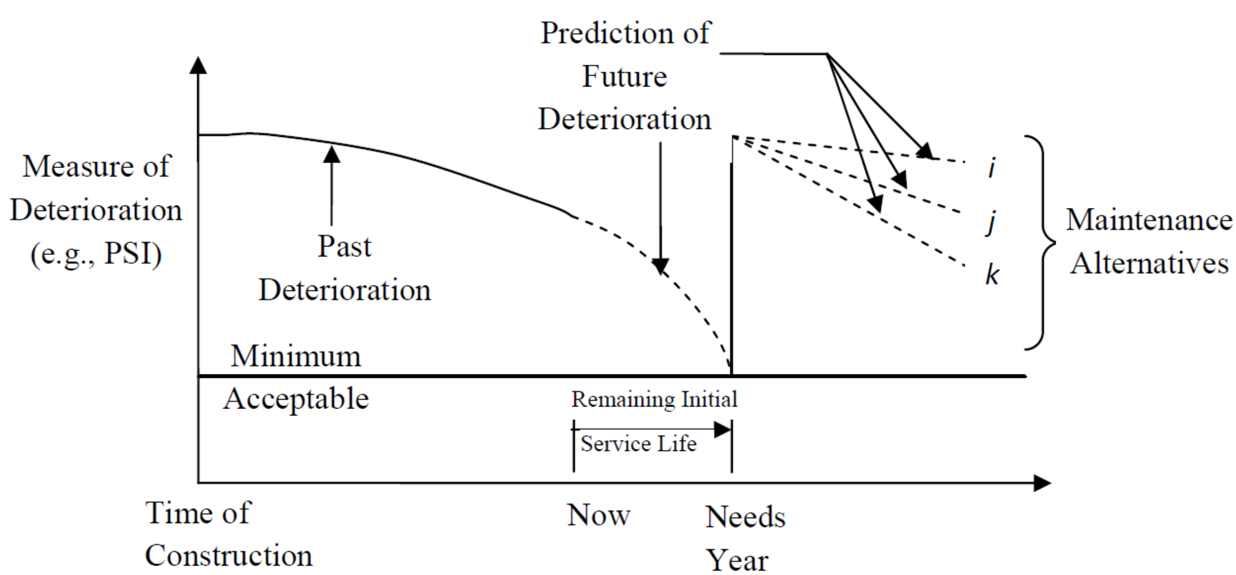

Figure 2. Illustration of pavement performance over time (Haas et al., 1994)

A prediction model can be employed at both the network and project management levels to determine maintenance and rehabilitation strategies. At the network level, the prediction model can predict the future condition of a pavement, the required budget, and project prioritization. The roles of pavement performance prediction models at the project level are to prioritize projects, to determine life cycle costs, and to determine maintenance and rehabilitation alternatives for each candidate project. Pavement performance is predicted based on structural properties, environmental factors, and traffic loading, enabling highway agencies to allocate budget and prioritize their projects (Hong and Prozzi, 2006).

Performance prediction models play a significant role in pavement management system with respect to the following activities:

- estimating future pavement conditions;
- identifying appropriate timing for pavement maintenance and rehabilitation actions;
- determining the most cost-effective treatment strategy in a pavement network;
- estimating funds required to meet agency objectives; and
- determining the impact of different pavement investment strategies (AASHTO, 2012).

Modeling pavement performance is also required to satisfy the requirements of the federal legislation called Moving Ahead for Progress in the 21st Century Act (MAP-21), which was introduced on July, 2012. MAP-21 requires each state to have a risk-based asset management plan and performance targets with respect to safety, improving infrastructure conditions, reducing congestion, system reliability, facilitate good movement and economic vitality, environmental sustainability, and project delivery (Corley-Lay, 2014). Evaluating pavement condition of highways is required by MAP-21 through its infrastructure conditions criteria.

The typical form of a performance model is to relate a pavement performance indicator to explanatory variables to establish a causal relationship between them and determine factors that influence pavement performance. The four requirements of a reliable performance prediction model are long term historical data of in-service pavements, including all variables that have a significant effect on response variables, an adequate model form that considers interaction and nonlinearity, and criteria to evaluate the accuracy of the model (Darter, 1980).

Various pavement performance models used in pavement management include: deterministic, probabilistic, expert or knowledge-based, and artificial neural network (ANN) models (Wolters and Zimmerman, 2010).

Deterministic Models

Deterministic models predict a single dependent value (e.g., PCI) from one or more independent variables (e.g., pavement age, traffic loading, environment, and structural parameters). Deterministic models, based mostly on regression analysis, can be broken down into three subcategories: empirical, mechanistic, and empirical-mechanistic models (Li, Xie and Haas, 1996).

Empirical models, widely used in pavement performance studies, require massive data for modeling. They estimate pavement response to variations in some input variables. Empirical models include S-shaped curves, polynomials, and logistic growth patterns. Several advantages and disadvantages of using empirical models have been reported by Silva et al. (2000):

- Advantages of using empirical models:
    - A simple mathematical method can be used to predict the pavement performance.
    - The relationships between actual and predicted coefficients can be easily described.
    - Empirical models can be updated using future analysis results.

- Disadvantages of using empirical models:
  - Accurate data is required to get a good regression model, and outliers may affect accuracy.
  - Maintenance or rehabilitation activity data may affect accuracy of model performance.
  - All significant variables must be to be included in the performance model.

Mechanistic models determine interaction between traffic loading and dynamic pavement responses (i.e., stress, strain, and deflection). Mechanistic models require extensive laboratory testing data or precise measurements as primary input factors that influence pavement performance (Mills et. al., 2012). In general, pavement engineers usually do not use primary response parameters because they deal mostly with more readily available distress data and pavement properties to predict pavement performance (Haas et al., 1994). As a result, they have not been able to accurately predict pavement performance. Further, pure mechanistic models are not considered to be prediction models (Shahin, 2005).

Mechanistic-empirical (ME) models, however, can be used for performance predictions because they address the complexity of interaction between stress, strain, and deflection with traffic loadings. ME models combine mechanistic and empirical models by using regression techniques. Also, they are more representative of pavement performance because they include new parameters such as material properties, traffic loading, and climate factors. However, according to Ayed (2016) there is a need to investigate the suitability of ME models at the network level.

Probabilistic Models

Probabilistic models are used to predict a range of values for dependent variables, such as probability of pavement condition changes from a given pavement condition to another condition. These models are used to capture the uncertainty in material properties, environmental conditions, and traffic loadings that can produce less accurate models. According to Golroo and Tighe (2012), the common types of probabilistic models are Markov models, Bayesian regression, survivor curves, and semi-Markov models. The primary Markov chain model involves an initial probability and a transition probability matrix, as shown in Equation 1, and the probability matrix shown in Figure 3 (Li et. al., 1996).

$$P_i = P_o(P)^i \quad (1)$$

where:
P_0 = the vector of initial probability;
P =probability transition matrix;
P_i = probability condition of ith duty cycle; and
i = duty cycle.

$$P = \begin{bmatrix} P_{11} & P_{12} & P_{13} & P_{14} & \cdots\cdots & P_{1n} \\ 0 & P_{22} & P_{23} & P_{24} & \cdots\cdots & P_{2n} \\ 0 & 0 & P_{33} & P_{34} & \cdots\cdots & P_{3n} \\ 0 & 0 & 0 & P_{44} & \cdots\cdots & P_{4n} \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ 0 & 0 & 0 & 0 & \cdots\cdots & P_{(n-1)n} \\ 0 & 0 & 0 & 0 & \cdots\cdots & 1 \end{bmatrix}$$

Figure 3. Markov Matrix

The major benefit of using probabilistic models is that the amount of data required for model development is less than the data needed for deterministic models (Jack and Chou, 2001).

According to Golroo and Tighe (2012), the benefits of utilizing probabilistic models for predicting pavement performance are as follows:

- probabilistic models, in conjunction with other tools, can capture uncertainty in a pavement performance-prediction model;
- the probabilistic approach is more realistic than the deterministic approach because it combines field observations and expert opinion; and
- expert knowledge can be incorporated in cases where the database is incomplete, of low quality, or imprecise.

Expert Models

Expert models are based on the collective experience and knowledge of agency engineers who are familiar with pavement deterioration patterns, and expert models can be used when there are no historical data available, there are missing data, or if a new design is produced (Wolters and Zimmerman, 2010). Hicks and Groeger (2011) summarized some states' practices in predicting pavement performance and reported that many agencies have used expert opinions. For example, the Connecticut DOT developed their performance curve based on expert panels, the Massachusetts DOT uses expert knowledge in predicting cracking, raveling, ride, and rutting performance, and the New Hampshire DOT predicts ride, cracking, and rutting indices based on expert knowledge.

Artificial Neural Network (ANN) Models

While various studies including factors that affect pavement performance have been conducted on pavement performance modeling, most of the models have faced challenges such as dealing with a large number of input variables, lack of availability of some variables, and correlation between the variables (Kargah-Ostadi and Stoffels, 2015). Recently, ANN models have been widely used to simulate the biological nervous systems in human brain. The biological nervous system contains billions of neuron cells, and each neuron receives inputs from other neurons, processes them by transfer function, and sends its own output to the next layer (Mehta et al., 2008).

ANN models use data to build prediction models and compute the relative importance of variables instead of the natural relationships among variables. An ANN can be defined as, “A computational mechanism with an ability to acquire, represent, and compute mapping from one multivariate space of information to another, given a set of data representing that mapping” (Rafiq et. al., 2001, p. 1542). ANN techniques can solve complex problems because of the capability of interconnecting neurons between layers to achieve computation of large data volumes (Basheer and Hajmeer, 2000).

Engineers often are faced with incomplete or noisy data, so ANN models may be the most appropriate models for recognizing meaningful relationships from data patterns to solve a particular problem (Rafiq et al. 2001). Zhang et al. (1998) reported that ANN models can predict nonlinear relationships between variables as well traditional models that are usually used to predict these relationships.

ANN models have been widely used in different civil engineering areas with good results because they are accurate and convenient (Karlaftis and Vlahogianni, 2011). Adeli (2001) conducted a review of the neural network model literature from 1989 to 2000, with a focus on structural engineering, construction engineering, and management, and reported that ANN models are suitable for modeling complex problems.

Other, more recent studies have shown the robustness of ANN models compared to regression models. For example, the comparison between ANN and autoregressive time series models for forecasting freeway speeds showed that neural networks provide more accurate predictions than classical statistical approaches (Vlahogianni and Karlaftis, 2013). Golshani et al. (2017) compared the prediction capabilities of traditional statistical models and neural network models for modeling two critical trip-related decisions related to travel mode and departure time. Their results show that the neural network models offered better performance with an easier and faster implementation process. ANN and multivariable regression models were also used to predict stress intensity factors in pavement cracking with results showing the advantage of utilizing ANN over multivariable regression models with respect to prediction accuracy (Wu et. al., 2014). In a 2004 study, Felker, Najjar, and Hossain reported that the ANN models provided a reasonably high R^2 in predicting roughness for jointed portland cement concrete pavements with $R^2 = 0.90$, while the statistical analysis approach yielded $R^2 = 0.73$ (2004). In a study by Kargah-Ostad, Stoffels, and Tabatabaee (2010), the ANN model also performed successfully in predicting IRI values using complex input variables. ANN models also have been used to predict cracking index for Florida's highways and were found to be more accurate than an autoregressive model (Lou et. al., 2001). Gencel, Kocabas, Gok, and Koksal developed ANN and linear regression models to determine the correlation between cement content, metal content, and traffic loading on rough wear of concrete, and the ANN models were superior to linear regression models in predicting the abrasive wear of concrete (2011).

Basheer and Hajmeer (2000) reported that ANN models have several capabilities to solve various problems from several categories such as:

- Pattern classification: ANN models can use supervised learning to deal with unknown input pattern and, unlike traditional statistics models, require no linearity assumption.
- Clustering: ANN models can use unsupervised learning to assign similar patterns to the

same cluster by finding similarities and differences between inputs.

- Modeling: training input and output data to find the relationship between them using multilinear ANN model.
- Optimization: ANN models were more efficient in solving optimization problems by maximizing or minimizing an objective function subject to a set of constraints.

Further, Attoh-Okine (1994) reported two benefits of using ANN over more traditional statistical prediction models: ANN models can handle unseen data and generalize results and they can solve complex problems because of their massive parallelism and strong interconnectivity.

Summary of Pavement Performance Models

The literature indicates that researchers have used ANN models to predict pavement performance since at least the 1990s and that ANN pavement performance models are powerful modeling tools. However, most of the existing studies in predicting pavement performance have focused on a specific pavement type at the project management level. Further, many models have not included all the parameters that might impact pavement performance because of lack of data, and many previous studies do not quantify the impact of input variables such as weather conditions on the ANN model predictions.

CHAPTER 3: METHODS

Decision makers rely on robust models to evaluate pavement performance and improve pavement asset management. Predicting pavement performance is often considered to be a difficult task because many factors must be considered. Consequently, accurate pavement performance models that include more pavement data are needed as the basis for pavement maintenance and rehabilitation strategies. There are many causes of pavement deterioration that potentially vary from one road section to the next, which makes the modeling of pavement performance a complex process. Therefore, developing pavement performance prediction models requires both obtaining relevant data (e.g., pavement conditions and climate data) and identifying robust performance prediction approaches. In this research, multiple linear regression (MLR) and artificial neural network (ANN) models were used to predict pavement performance and the results were compared. Also, this research analyzed the results of ANN models to determine the relative contribution of each variable on several distress indices. An ANN model was used to model a reliable relationship between structural strength numbers (SN) calculated from measuring deflections on roadways after impact and rutting depth at the network level for ACC pavements. The flowchart in Figure 4 describes the research steps.

Data are the main building blocks in performance modeling, so obtaining good quality data is essential to getting accurate results. In this study, two kinds of data were obtained. Pavement distress data was obtained from the Iowa DOT Pavement Management Information System (PMIS) and climate data was obtained from the Iowa Environmental Mesonet (IEM). Data used in this study are described in the following sections, followed by sections that discuss data integration, developing ANN and MLR pavement performance models, and developing an ANN model to correlate structural capacity and rutting.

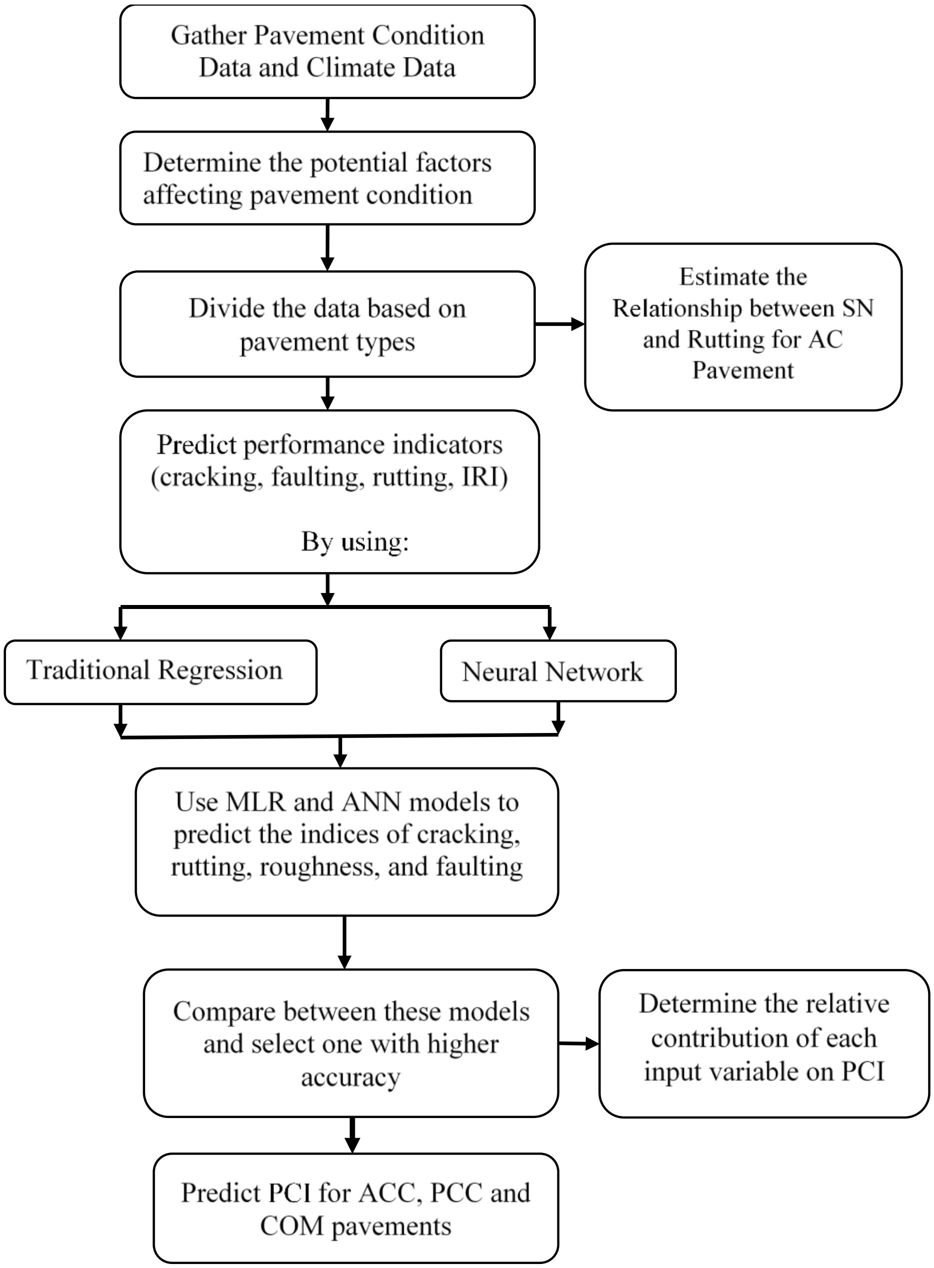

Figure 4. Research flowchart

Pavement Distress Data

The Iowa DOT PMIS database includes information about the highway system, including section identification, construction history, pavement type, maintenance history, traffic loading, structure parameters, and pavement distress. The Iowa DOT collects data about pavement surface distresses such as longitudinal cracking, transverse cracking, wheel-path cracking, alligator cracking, durability cracking, joint spalling, patching, and surface friction (skid resistance). These pavement distresses are assigned three severity levels: low, medium and high. The Iowa DOT also collects rutting depths for asphalt pavements and faulting for concrete pavements and measures pavement roughness, since it is used as one of the performance indicators (Bektas et. al., 2014).

The pavement condition data used in this study were collected on a two-year cycle. Pavement condition data for northwest Iowa were collected in even years (e.g., 2010, 2012, and 2014), while pavement condition data in southeast Iowa are collected in odd years (e.g., 2011, 2013, and 2015) as shown in Figure 5. The data collection process costs Iowa DOT around $1 million annually on contracts for collecting pavement condition data (Bektas, 2015).

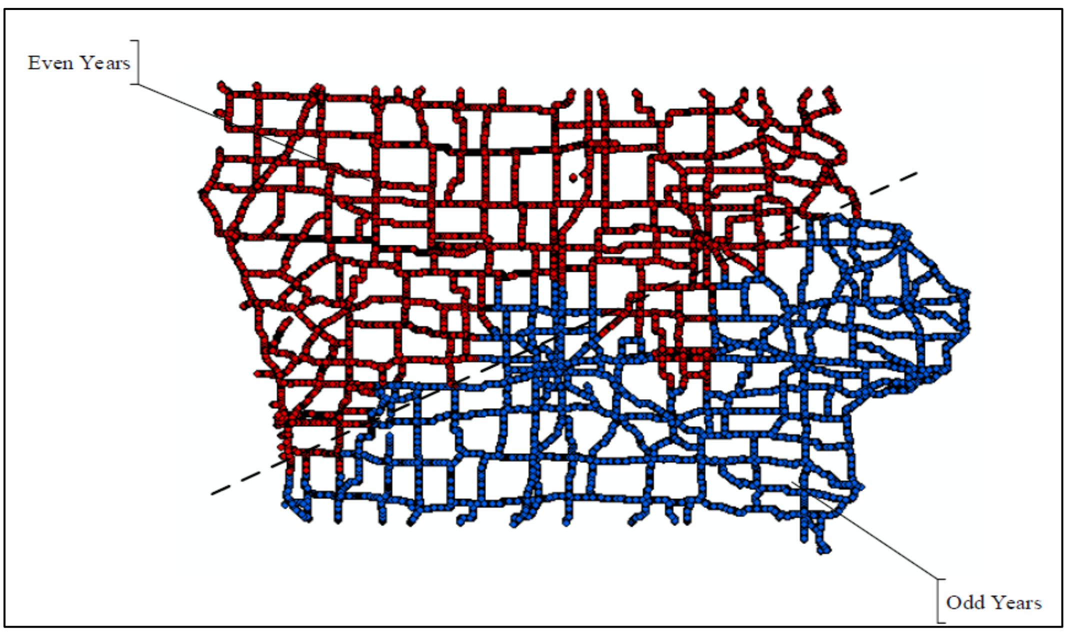

Figure 5. Data collection Practice (Jeong, Smadi and Abdelaty, 2016)

The collected pavement condition data are aggregated into the PMIS database by averaging the rutting and IRI values to represent the roughness and rutting of large pavement sections and by counting the lengths of cracks to represent the length of cracks per unit length. Each pavement section in the database includes IRI values, rutting depth, faulting values, and surface distresses. Each section in the PMIS is defined by the route number, the county, the highway system (Interstate, US, or Iowa highways), the direction, the district, and the beginning and ending mileposts, as shown in Figure 6. The PMIS also contains traffic, material, layer thicknesses, and pavement history information for each section. (Jeong et. al., 2016).

1	OBJECTID	ORIGKEY	PMISYR	SYSTEM	ROUTE	DIR	COUNTY	BPOST	EPOST	DISTRICT
2	1	02911094 86100 5043	2015	1	29	1	43	094 86	100 50	4
3	2	02911000 00008 9336	2015	1	29	1	36	000 00	008 93	4
4	3	02911053 25054 5678	2015	1	29	1	78	053 25	054 56	4
5	4	02911051 58052 1078	2015	1	29	1	78	051 58	052 10	4
6	14	02911033 45034 8665	2015	1	29	1	65	033 45	034 86	4
7	15	02911100 81101 1267	2015	1	29	1	67	100 81	101 12	3
8	16	02911133 75134 3297	2015	1	29	1	97	133 75	134 32	3
9	17	02911132 83133 7597	2015	1	29	1	97	132 83	133 75	3
10	18	02911149 11150 6797	2015	1	29	1	97	149 11	150 67	3

Figure 6. Screenshot from the PMIS database

Table 2 presents the total of directional miles for each of the seven pavement types in the PMIS database in 2015.

In this research, only asphalt concrete cement (ACC), portland concrete cement (PCC), and composite (COM) pavements were selected for developing performance prediction models because there were insufficient miles for the other pavement types. ACC and PCC pavements are described as flexible and rigid pavements, respectively.

Pavement condition data from 1998 through the end of 2015 was used in this research. Each pavement section in the study had the same features (i.e., pavement type, maintenance history, traffic loading, subgrade stiffness, layer thicknesses, and pavement distresses). Rutting, roughness, faulting, longitudinal cracking, longitudinal wheel-path cracking, transverse cracking, durability cracking, patching, and joint spalling were pavement distress features of the pavement sections.

Table 2. Pavement types in Iowa highways

Pavement Types		Directional Miles	% of Miles
ACC	Asphalt concrete cement	1798.21	16.17%
PCC	Portland concrete cement	3487.30	31.36%
COM	Composite with asphalt surface	5156.81	46.38%
CRC w/ATB	Continuous reinforcement concrete with asphalt treated base	4.83	0.04%
CRC w/GSB or CTB	Continuous reinforcement concrete with granular or cement treated base	0.97	0.01%
Composite w/JT PCC	Composite built on jointed concrete	262.23	2.36%
Composite w/CRC	Composite built on continuous reinforcement concrete	409.45	3.68%
Total		11119.80	100.00%

Iowa highways are classified into three systems: Interstate highways, US highways, and Iowa highways. The most recent PMIS data from 2015 shows totals of approximately 460 miles of interstate highway, 3544 miles of US highway, and 4567 miles of Iowa highway. The number of miles of ACC, PCC, and COM pavements in interstate, US, and Iowa highways are given in Table 3. The lengths and number of pavement segments at each pavement type based on 2015 data are given in Table 4.

Table 3. Center mile length of each pavement type (miles)

	Pavement Type			
	ACC	**PCC**	**COM**	**Total**
Interstate	57	364	39	460
Iowa	1366	752	2449	4567
US	221	1098	2225	3544
Total	1644	2214	4713	8571

Table 4. Descriptive statistics of pavement segments

	Number of Segments	Average Segment Length (miles)	Minimum Segment Length (miles)	Maximum Segment Length (miles)
ACC	464	3.88	0.16	18.61
PCC	1200	2.70	0.05	18.91
COM	1920	2.69	0.05	18.14

Pavement Condition Indices

Four indices have been developed to evaluate the pavement conditions of Iowa highways. These indices are on a 100-point scale to be consistent with the PCI scale that ranges from 0 to 100. Cracking and riding indices were developed for ACC, PCC, and COM pavements, rutting indices were developed for ACC and COM pavements, and a faulting index was developed for PCC pavements.

Cracking Index

Four types of cracking are evaluated by Iowa DOT for ACC pavements: transverse cracking (count/mile), longitudinal cracking (ft/mile), longitudinal-wheel-path cracking (ft/mile), and alligator cracking (ft^2/mile). For PCC pavements, transverse cracking (count/mile), longitudinal cracking (ft/mile), and longitudinal-wheel-path cracking (ft/mile) are evaluated.

The cracking index was developed based on a 100-point scale, with 0 indicating the worst condition and 100 indicating the best condition. The cracking index includes sub-indices for each type of crack. For instance, for ACC pavements, four sub-indices were developed for transverse, longitudinal, longitudinal-wheel-path, and alligator cracking. For PCC pavements, two sub-indices were developed for transverse and longitudinal cracking. Iowa DOT combines longitudinal and longitudinal-wheel-path into one index since these show similar behavior in PCC pavements.

These sub-indices are calculated based on deduction from 100 as shown in Equation 2,

$$Crack\ Sub\_index = 100 - \left(\frac{100 \times crack\ value}{treshold\ value}\right) \quad (2)$$

Iowa DOT has determined threshold values for calculating sub-indices for each pavement type in Iowa highways as shown in Table 5 (Mark Murphy, personal communication, December, 2017).

Table 5. Threshold for cracking indices

	Pavement Type		
Cracking Type	**ACC**	**PCC**	**COM**
Transverse (count/mile)	483	241	805
Longitudinal (ft/mile)	2640	1320	2640
Longitudinal-wheel-path (ft/mile)	2640	—	2640
Alligator (ft^2/mile)	6236	—	6236

A cracking index for each pavement type was calculated by summing the weighted coefficient values for ACC and COM and for PCC as shown in Equation 3 (for ACC and COM) and 4 (for PCC). The coefficient values of each sub-index were determined by Iowa DOT using equations 3 and 4.

$$Crack\ Index\ (ACC) = (0.2 \times Transverse) + (0.1 \times Longitudinal) + (0.3 \times LongitudinalWP) + (0.4 \times Alligator) \quad (3)$$

$$Crack\ Index\ (PCC) = (0.6 \times Transverse) + (0.4 \times Longitudinal) \quad (4)$$

Riding Index

The Iowa DOT calculates the riding index by converting the IRI values using Equation 5:

$$Riding\ Index = \left(\frac{IRI\ values - 253}{32 - 253}\right) \times 100 \quad (5)$$

The riding index is a 100 scale, with 0 being the worst and 100 being perfect. On the Iowa DOT ride index scale, all IRI values below 32 (in./mile) are considered to be 100, and all values above 253 (in./mile) are considered to be 0.

Rutting Index

Rutting depth is collected by Iowa DOT for ACC and COM pavements. Iowa DOT converts the rutting depth values into a 100-point scale rutting index ranging from 0 (worst) to 100 (perfect) using Equation 6.

$$Rutting\ Index = 100 - \left(\left(\frac{Rutting\ depth}{0.47}\right) \times 100\right) \tag{6}$$

Faulting Index

The faulting index is only calculated for PCC pavements (FI_{PCC}) based on the fault measurements from the PMIS database. The fault index also is a 100 scale where 100 indicates the perfect condition (no faulting) and 0 the worst. The fault threshold value is 0.47 in. so values equal to or greater than so 0.47 are rated as 0 on the faulting index. The Iowa DOT converts the fault values into an index by using Equation 7.

$$Faulting\ Index = 100 - \left(\left(\frac{Fault}{0.47}\right) \times 100\right) \tag{7}$$

Overall Pavement Condition Index

After calculating the individual indices, the overall pavement condition index (PCI) was calculated by combining the weighted individual indices. The weighing factors were determined by Iowa DOT. For PCC pavements, the PCI combines the cracking index, riding index, and faulting index by weighting factors based on Equation 8. For ACC and COM pavements, the PCI combines the cracking index, rutting index, and riding index as shown in Equation 9.

$$PCI_{PCC} = (0.4 \times Cracking\ Index) + (0.4 \times Riding\ Index) + (0.2 \times Faulting\ Index) \tag{8}$$

$$PCI_{COM\ \&\ ACC} = (0.4 \times Cracking\ Index) + (0.4 \times Riding\ Index) + (0.2 \times Rutting\ Index) \tag{9}$$

Pavement Age

Pavement age, calculated as the difference between the PMIS year (input date) and either the most recent resurfacing or construction year, affects pavement condition. In 2015, more than 60% of miles of Iowa highways were 40 years old or older, while more than 50% of interstate and US highway miles were less than 30 years (Figure 7).

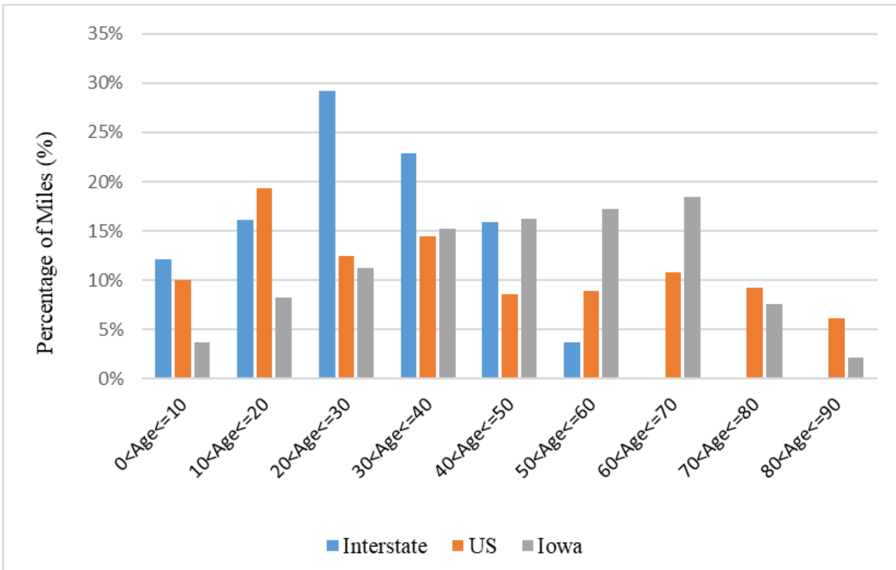

Figure 7. Distribution of pavement age of Iowa highway systems (2015)

Traffic Loading

Iowa highways carry heavy trucks, so traffic loading is a significant factor that might cause pavement deterioration. The traffic loading data in the PMIS database contains the average daily traffic (ADT); average daily truck traffic (Truck); and average equivalent single axle loads (ESAL) (18,000 lb). The ESAL converts all traffic loading with different magnitude and axle configuration into an equivalent number of 18,000 lb ESAL. Figure 8 shows the ESAL values for the Interstate, US, and Iowa systems in 2015 in Iowa. and Figure 9 shows changes in traffic loading over time.

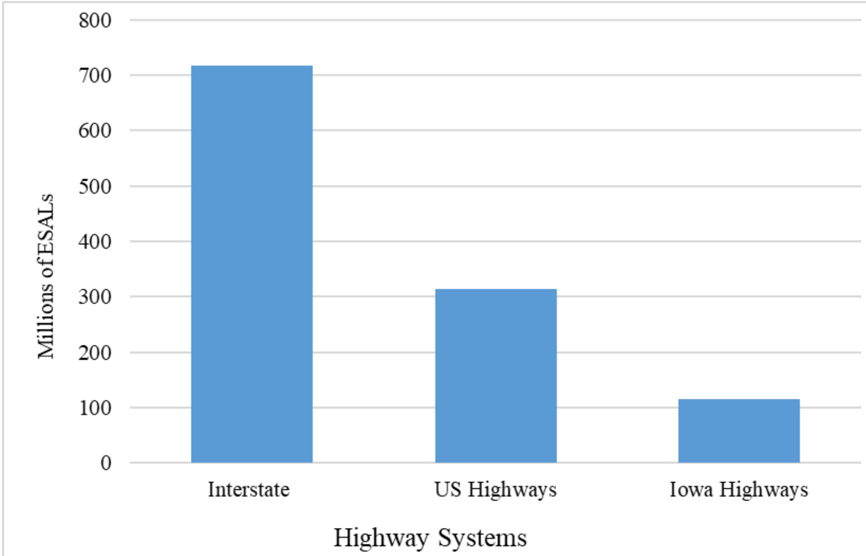

Figure 8. Traffic loading distribution of Iowa highways (2015)

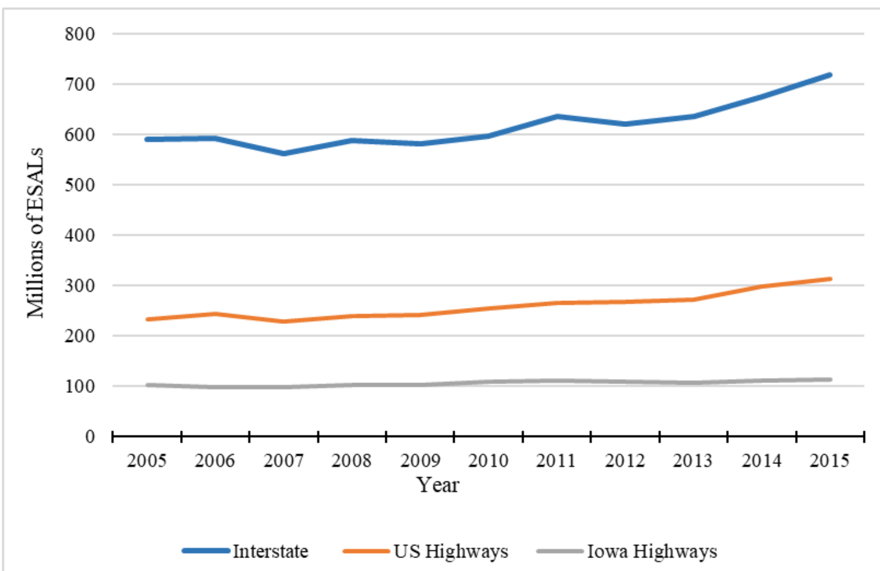

Figure 9. Changes in traffic loading on highways in Iowa

Climate Data

Weather conditions, such as temperature variation and moisture change, affect the material properties of both pavement surfaces and sublayers (Žiliūtė et. al., 2016). Further, when saturated pavement material is subjected to frost heave during freeze-thaw cycles freezing causes tensile stresses that increase deterioration process (Smith et. al., 2006). Later thawing leaves voids that can also contribute to pavement deterioration (Adkins et. al., 1989). The state of Iowa is located in a wet-freeze climate zone and is exposed to severe weather, especially in the winter, so it is important to investigate the effects of environmental factors on pavement condition, particularly since weather factors have not previously been considered in pavement performance modeling at the network level.

The climate data for this study was obtained from the Iowa Environmental Mesonet (IEM). The IEM is a data collection project developed by the Department of Agronomy at Iowa State University (ISU). The climate data in the IEM is based on observational data collected from the National Weather Service (NWS) by manual and automated sensors in each county across the state (Breakah et. al., 2010). The NWS is an agency in the United States that collects all related information about weather conditions. In Iowa, there are 111 weather stations as of 2015 (Figure 10).

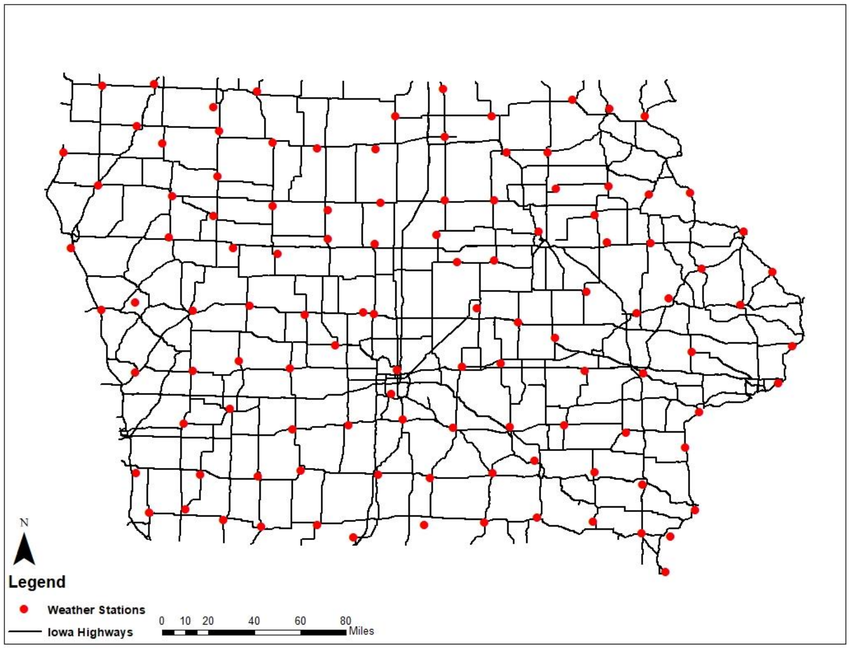

Figure 10. NWS climate stations in Iowa

The weather data that were used in the analysis were average annual temperature, average annual rainfall, average annual snowfall, and the number of freeze-thaw cycles. Figure 11 shows the format of the weather database that was obtained from the IEM at Iowa State University that contains weather data from 1951 to the present.

FID	Shape	station	year	avg_temp	tot_precip	tot_snow	cycles
0	Point	IA6389	2014	47.80137	44.0457	37.603	64
1	Point	IA0241	2014	45.932877	46.0541	28.3026	70
2	Point	IA7664	2014	42.332877	28.0511	39.3015	68
3	Point	IA0133	2014	43.079452	39.2249	54.6029	63
4	Point	IA1635	2014	47.727397	35.8825	37.2015	53
5	Point	IA7613	2014	49.745205	37.8142	11.2026	79
6	Point	IA7312	2014	44.168493	37.8817	31.1014	76
7	Point	IA0112	2014	47.186301	35.8511	30.9004	71
8	Point	IA2724	2014	42.289041	25.9336	38.2023	62
9	Point	IA5086	2014	43.156164	34.4567	37.2024	67
10	Point	IA4502	2014	47.426027	46.8142	31.8021	68
11	Point	IA1233	2014	45.635616	38.9146	26.003	74
12	Point	IA2110	2014	44.449315	35.7631	40.8018	58
13	Point	IA6800	2014	46.168493	31.712	42.1016	64
14	Point	IA0608	2014	45.365753	36.3907	40.5006	59
15	Point	IA4705	2014	47.4	37.0611	44.1011	58

Figure 11. Screenshot of the IEM weather database

Freeze-thaw cycles were defined by counting the number of times the temperature changes from freezing to thawed states. In this research, the freeze-thaw cycle was considered when the temperature fell below a freeze point (to be more conservative, 30°F was considered the freeze point), and followed by the temperature rising above 32°F.

In some areas in Iowa, the number of freeze-thaw cycles was low because the temperature stayed below 30°F all winter. For example, Figure 12 shows that the area in northern Iowa had the fewest freeze-thaw cycles in 2014. Most freeze-thaw cycles happen during spring and fall months when temperatures can be expected to change during a day.

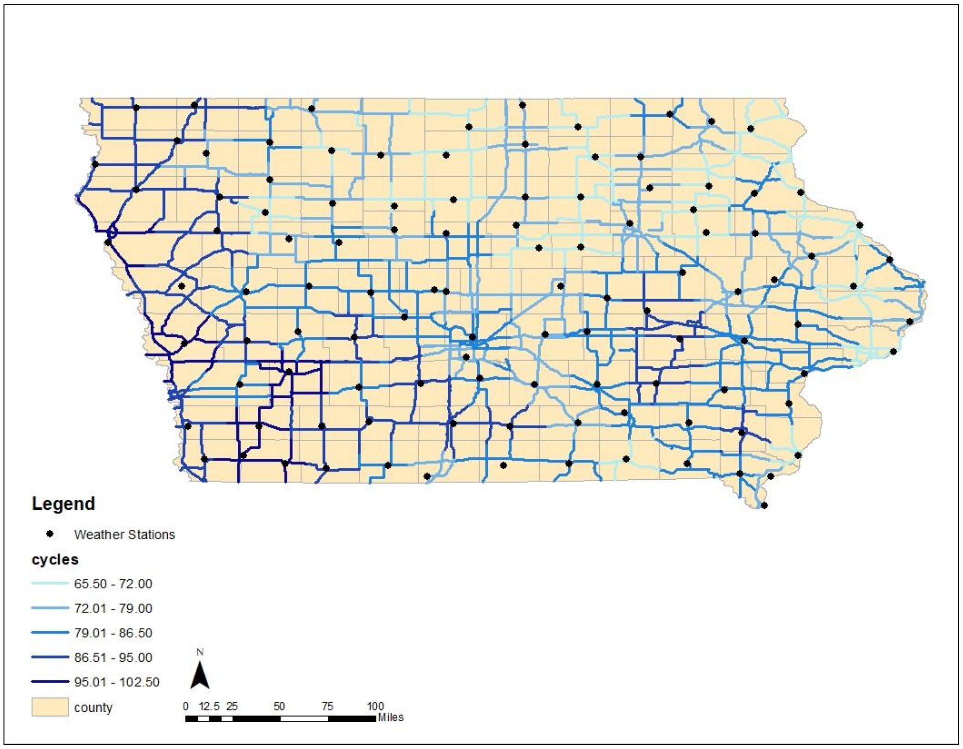

Figure 12. Average annual freeze-thaw cycles for 2014

Data Integration

Geographic information system (GIS) software was used to integrate the PMIS road condition data and the IEM climate data according to locations. The GIS spatial integration process provided accurate overlays of the weather stations over Iowa highways. The GIS also was used to display weather conditions as colored maps. To ensure that the climate data and locations of each pavement section were associated, each pavement section was assigned to the closest weather station. For example, Figure 13 shows the 32 pavement sections that were closest to weather station IA0133.

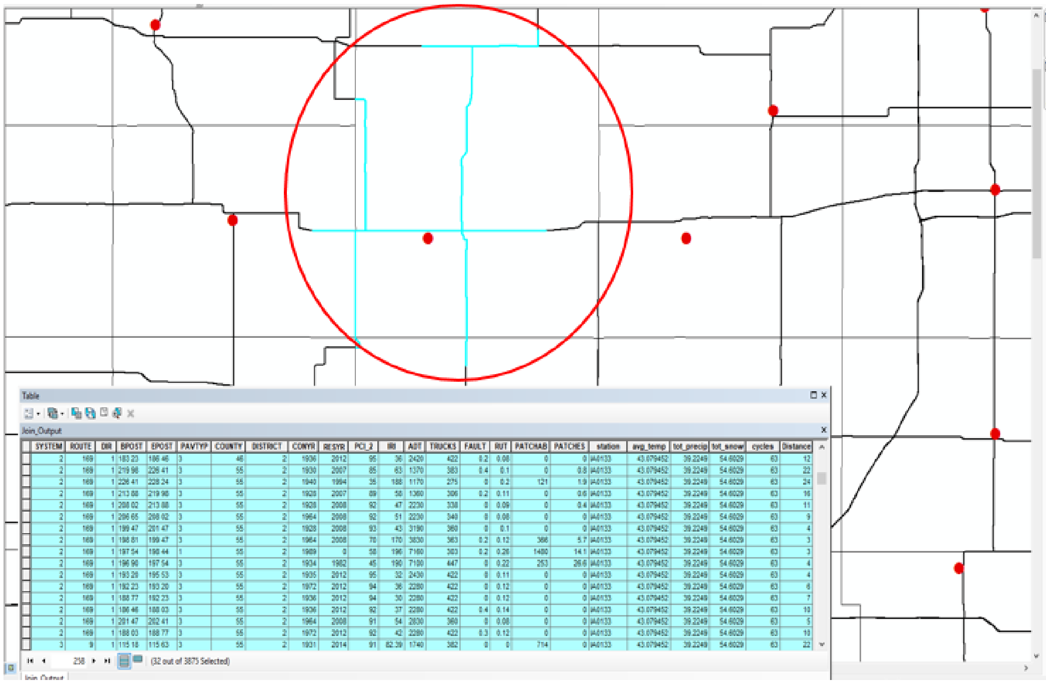

Figure 13. Pavement sections associated with the closest weather station

The distances between the weather stations and their related pavement sections ranged from 0 to 24 miles with an average distance of around 7 miles, while most pavement sections are located between 0 and 5 miles from the weather station. Figure 14 shows the distribution of the distances between pavement sections and their weather stations.

GIS software integrated the PMIS attribute table and weather station attribute table based on their spatial locations to create the final dataset (Figure 15). In that dataset, that each pavement section record contains the section location, pavement distresses, traffic loading, and structural characteristics. Each pavement record also includes the average annual temperature, snowfall and rainfall amount, the number of freeze-thaw cycles for the nearest weather station, and the distance between each pavement segment and its closest weather station.

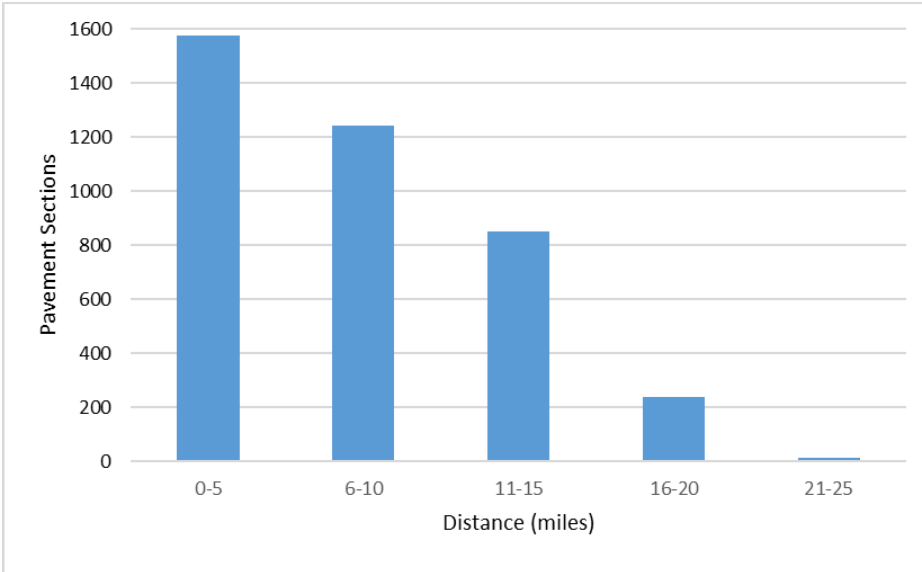

Figure 14. Distribution of the distances from pavement sections to the closest weather station

SYSTEM	ROUTE	BPOST	EPOST	PAVTYP	COUNTY	DISTRICT	RESYR	PCI_2	IRI	ADT	TRUCKS	FAULT	RUT	PATCHAB	station	avg_temp	tot_precip	tot_snow	cycles	Distance
2	34	191 77	193 79	1	90	5	0	77	111	8650	1179	0.2	0.1	0	IA6389	47.80137	44.0457	37.603	64	7
2	34	193 79	200 24	1	90	5	0	78	91	8180	1166	0.2	0.13	0	IA6389	47.80137	44.0457	37.603	64	9
2	34	189 74	191 10	3	90	5	1995	76	121.33	6550	633	0.3	0.1	17	IA6389	47.80137	44.0457	37.603	64	8
2	34	191 10	191 77	1	90	5	0	71	120	7380	882	0.2	0.16	0	IA6389	47.80137	44.0457	37.603	64	7
2	34	187 37	188 79	1	90	5	0	54	211	14300	702	0.2	0.12	187	IA6389	47.80137	44.0457	37.603	64	6
2	34	186 54	187 37	3	90	5	1990	68	122	8820	529	0.2	0.26	0	IA6389	47.80137	44.0457	37.603	64	6
2	34	181 49	186 54	3	90	5	2013	69	149	4970	496	0.2	0.24	0	IA6389	47.80137	44.0457	37.603	64	6
2	34	188 79	189 74	1	90	5	0	47	174.17	5870	380	0.2	0.1	0	IA6389	47.80137	44.0457	37.603	64	7
2	34	187 27	188 79	1	90	5	0	57	194	13150	706	0.2	0.1	0	IA6389	47.80137	44.0457	37.603	64	6
2	34	193 79	200 61	1	90	5	0	77	92	8760	1218	0.2	0.13	0	IA6389	47.80137	44.0457	37.603	64	9
2	34	191 77	193 79	1	90	5	0	69	101	5130	617	0.3	0.14	238	IA6389	47.80137	44.0457	37.603	64	7
2	34	191 10	191 77	1	90	5	0	60	139	7300	871	0.2	0.16	0	IA6389	47.80137	44.0457	37.603	64	7
2	34	189 85	191 10	3	90	5	1995	71	123	8810	934	0	0.18	0	IA6389	47.80137	44.0457	37.603	64	8
2	34	188 79	189 85	1	90	5	0	58	185	8230	620	0.2	0.16	0	IA6389	47.80137	44.0457	37.603	64	7
2	63	052 20	053 96	1	90	5	0	81	90	7130	1090	0.2	0.13	0	IA6389	47.80137	44.0457	37.603	64	9
2	63	046 10	052 20	4	90	5	1989	90	60	8460	1498	0.2	0.1	0	IA6389	47.80137	44.0457	37.603	64	4
2	63	033 02	033 82	3	90	5	2007	85	74	7480	548	0.2	0.11	0	IA6389	47.80137	44.0457	37.603	64	8
2	63	026 72	031 33	3	90	5	2007	89	58	6020	546	0.2	0.1	0	IA6389	47.80137	44.0457	37.603	64	10
2	63	041 00	046 10	1	90	5	0	78	102	7200	1299	0.2	0.09	355	IA6389	47.80137	44.0457	37.603	64	1
2	63	034 14	041 00	1	90	5	0	80	83	5430	1081	0.2	0.11	0	IA6389	47.80137	44.0457	37.603	64	2
2	63	031 33	033 02	3	90	5	2007	86	61	5580	554	0	0.12	0	IA6389	47.80137	44.0457	37.603	64	8
2	63	034 14	041 00	1	90	5	0	80	88	5990	1159	0.2	0.12	0	IA6389	47.80137	44.0457	37.603	64	2
2	63	052 20	053 96	1	90	5	0	55	118	8010	1642	0.2	0.14	0	IA6389	47.80137	44.0457	37.603	64	9
2	63	033 45	033 82	1	90	5	0	45	127	5900	483	0.3	0.12	0	IA6389	47.80137	44.0457	37.603	64	8
2	63	046 10	052 20	1	90	5	0	78	100	8260	1498	0.2	0.1	0	IA6389	47.80137	44.0457	37.603	64	4
2	63	041 00	046 10	1	90	5	0	76	112	6770	1145	0.2	0.09	303	IA6389	47.80137	44.0457	37.603	64	1
3	16	002 55	002 88	4	90	5	2009	89	50	2640	235	0	0.12	0	IA6389	47.80137	44.0457	37.603	64	15
3	16	000 00	000 84	4	90	5	2009	86	73	2190	207	0.2	0.13	0	IA6389	47.80137	44.0457	37.603	64	13
3	16	000 84	002 55	3	90	5	2009	90	48	2640	235	0	0.13	0	IA6389	47.80137	44.0457	37.603	64	14
3	16	002 88	005 51	4	90	5	2009	87	63	2310	235	0	0.12	0	IA6389	47.80137	44.0457	37.603	64	15
3	23	000 00	000 59	3	54	5	1994	51	163	1600	272	0	0.12	0	IA6389	47.80137	44.0457	37.603	64	5
3	23	000 59	001 89	3	54	5	1994	64	127	1600	272	0	0.13	0	IA6389	47.80137	44.0457	37.603	64	6
3	137	013 66	014 43	4	90	5	1965	75	149	5100	1594	0.3	0.09	0	IA6389	47.80137	44.0457	37.603	64	10
3	149	004 21	005 23	3	90	5	2003	74	109	6530	449	0.3	0.12	54	IA6389	47.80137	44.0457	37.603	64	2
3	149	011 69	012 08	3	54	5	1994	45	206	3490	433	0	0.13	0	IA6389	47.80137	44.0457	37.603	64	5
3	149	006 71	010 26	3	90	5	1995	67	94	3490	433	0.2	0.27	0	IA6389	47.80137	44.0457	37.603	64	2
3	149	006 13	006 71	3	90	5	2003	76	70	3490	433	0	0.12	0	IA6389	47.80137	44.0457	37.603	64	2
3	149	012 08	016 96	4	54	5	1991	58	140	2640	285	0	0.25	0	IA6389	47.80137	44.0457	37.603	64	5
3	149	005 23	006 13	3	90	5	2003	74	76	5800	486	0.3	0.14	0	IA6389	47.80137	44.0457	37.603	64	2
3	149	017 67	020 09	4	54	5	1991	61	131	1980	214	0	0.19	0	IA6389	47.80137	44.0457	37.603	64	9

Figure 15. Final dataset format after integration of PMIS and IEM data

After integrating the data for years from 1998 through 2015, the climate data (i.e., temperature, snowfall, rainfall, and freeze-thaw cycles) were represented by GIS maps to illustrate which pavement segments had experienced more extreme conditions. Figure16 shows the average annual temperature for the entire highway network in 2015, when the lowest average was recorded in Worth County in northern Iowa. The highest average temperature in 2015 was recorded in Polk County in the middle of the state around Des Moines.

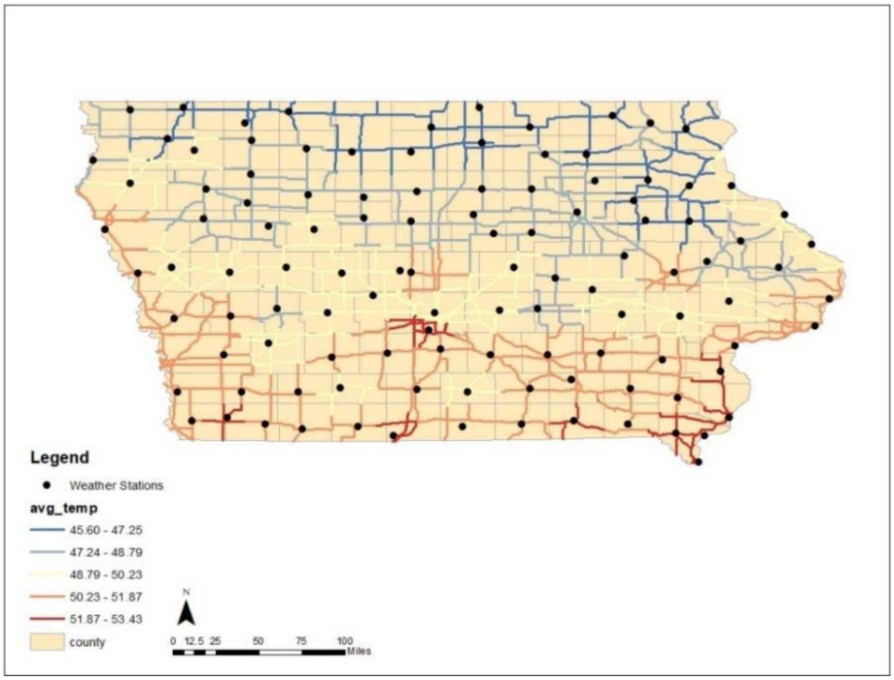

Figure 16. Iowa average temperatures (2015)

The statewide average annual rainfall was higher in the southern part of the state (Figure 17) in 2015 when he largest amount of rain fell on Taylor County in southern Iowa. The statewide average annual snowfall in 2015 was highest in northern Iowa.

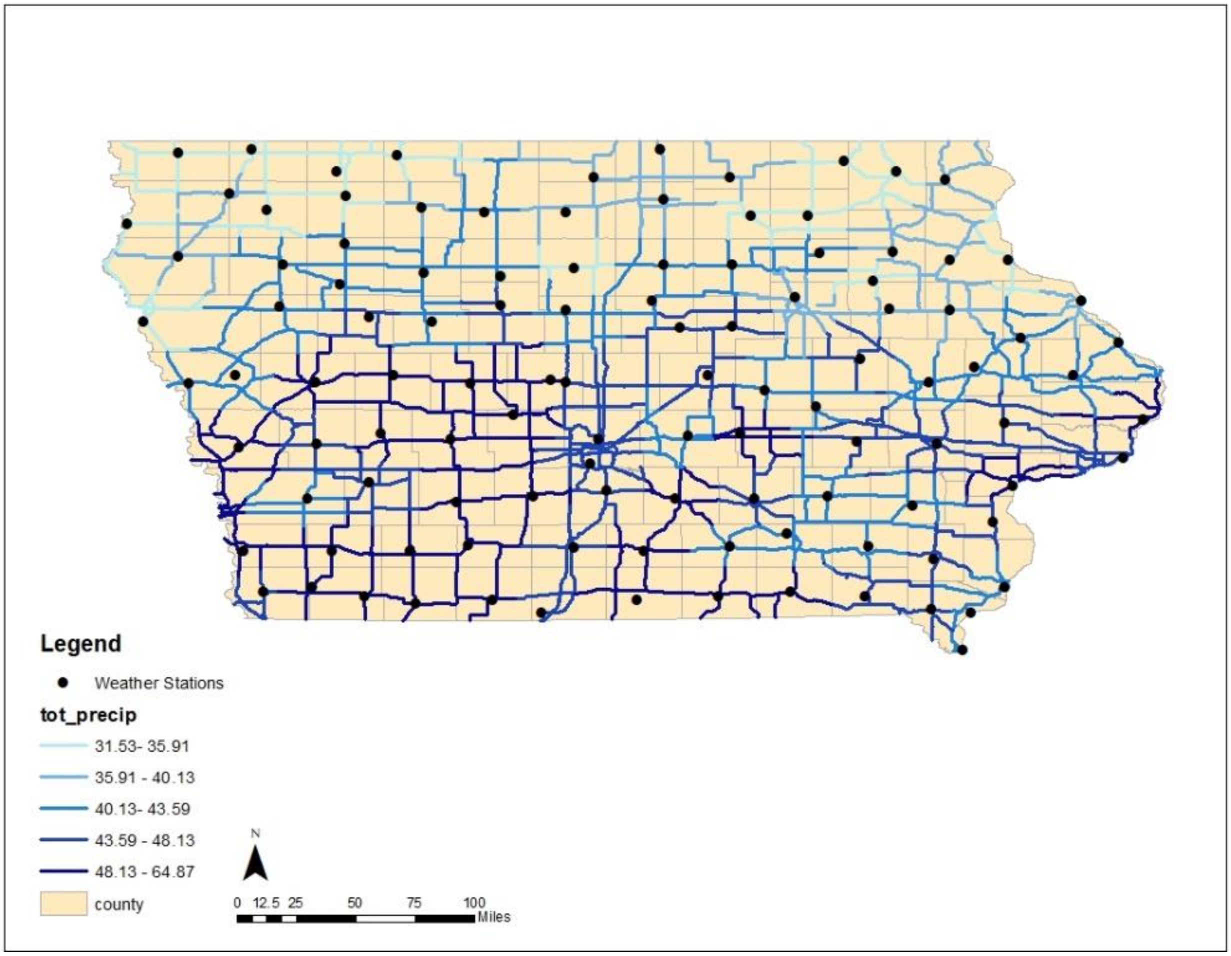

Figure 17. Average rainfall amount (in.) on Iowa highways (2015)

Figure 18 shows the higher amount of snow was in Clayton County in the northwest part of the state. Figure 19 illustrates the number of freeze-thaw cycles over the state when temperatures fluctuated above and below freezing. In 2015, the most freeze-thaw cycles occurred in the southern and western parts of the state.

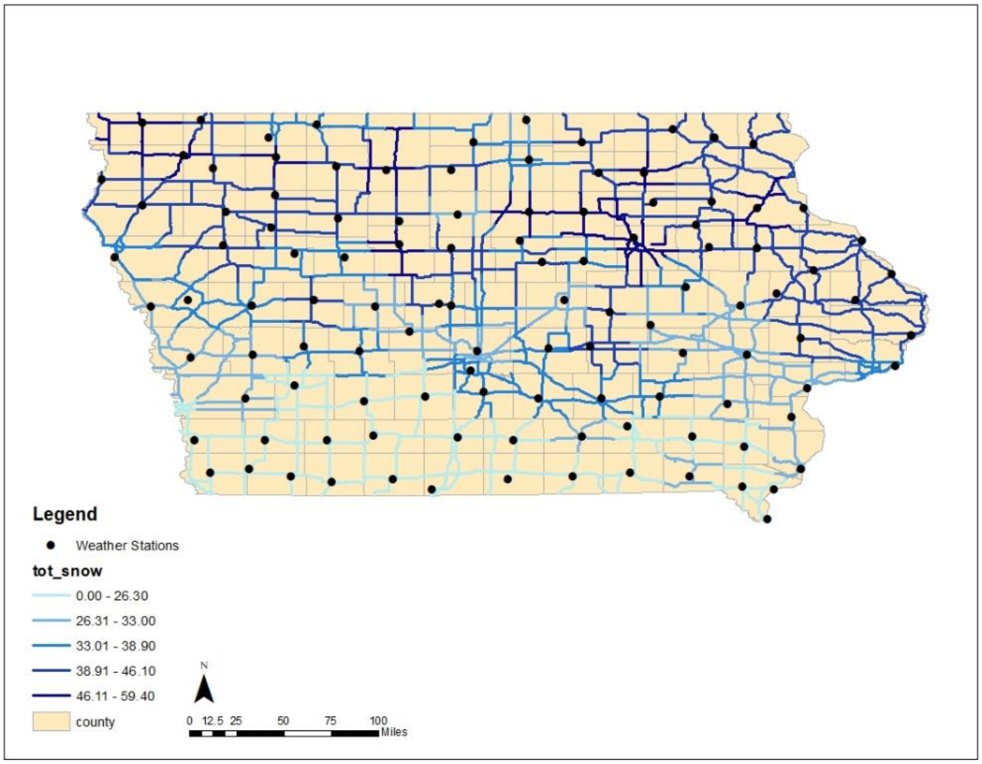

Figure 18. Average snowfall amount (in.) on Iowa highways (2015)

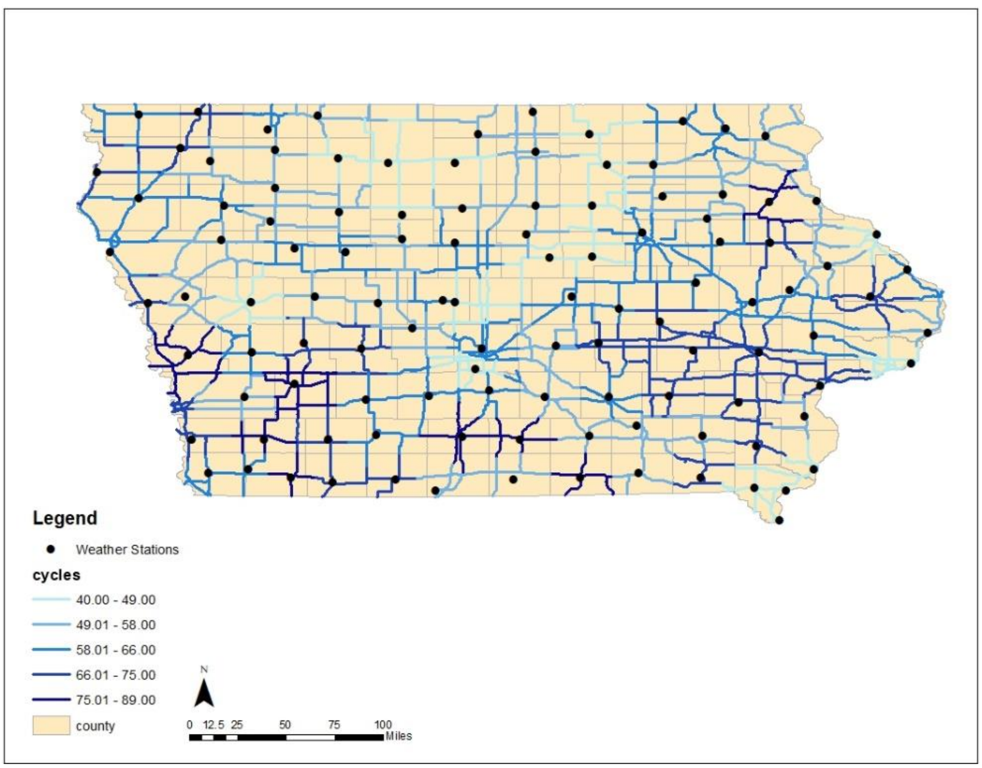

Figure 19. Number of freeze-thaw cycles of Iowa highways (2015)

Performance Indicators

The Iowa DOT uses two pavement performance indicators to assess pavement conditions, the Pavement Condition Index (PCI) and the International Roughness Index (IRI). The PCI uses an objective scale ranging from 0 to 100 to quantify pavement conditions. PCI ratings fall into five categories very poor (0-20); poor (21-40); fair (41-60); good (61-80); and excellent (81-100). In 2015, more than 41.56% of miles in Iowa were in an excellent condition, 35.12% were in good condition, 18.83% were in fair condition, and the remaining were in poor or very poor condition (Figure 20). Figure 21 shows a GIS map of Iowa with the PCI for all Iowa highways.

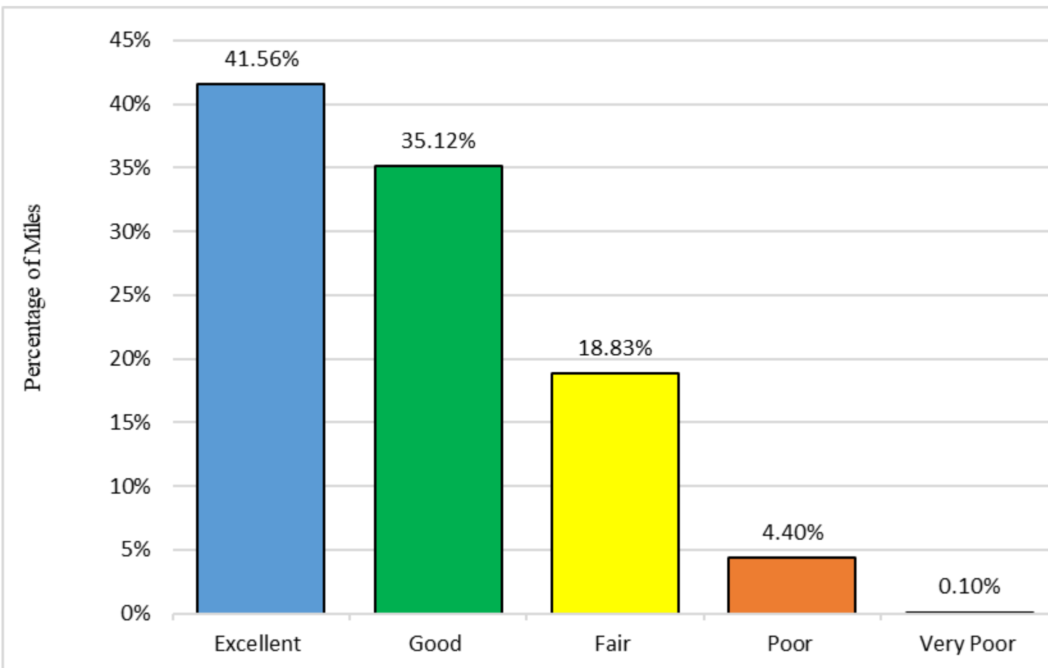

Figure 20. PCI rating distribution of Iowa highways (2015)

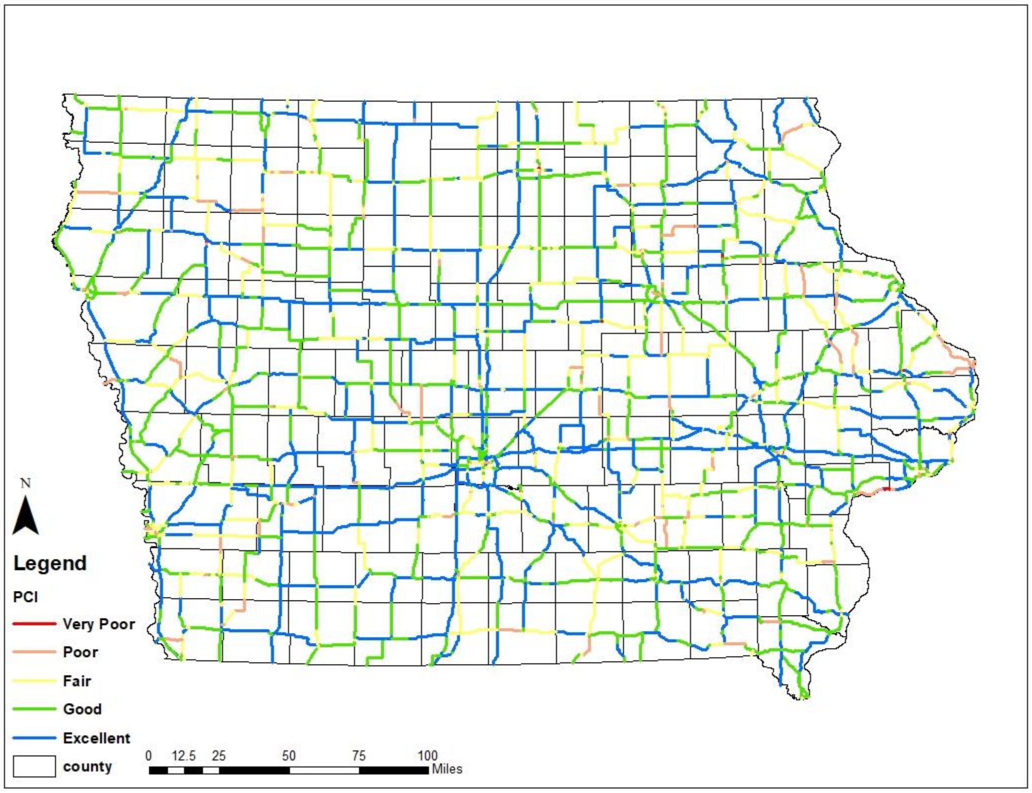

Figure 21. PCI map of Iowa highways (2015)

The International Roughness Index (IRI) is obtained by measuring the longitudinal profile of a pavement. Pavements are classified as good (95 in./mile); fair (95–170 in./mile); or poor (>170 in./mile) condition. In 2015 in Iowa, 52.66% of highway miles were in good condition, 39% were in fair condition, and 8.31 % were in poor condition (Figure 22). Figure 23 is a map of the IRI measurements of Iowa highways in 2015.

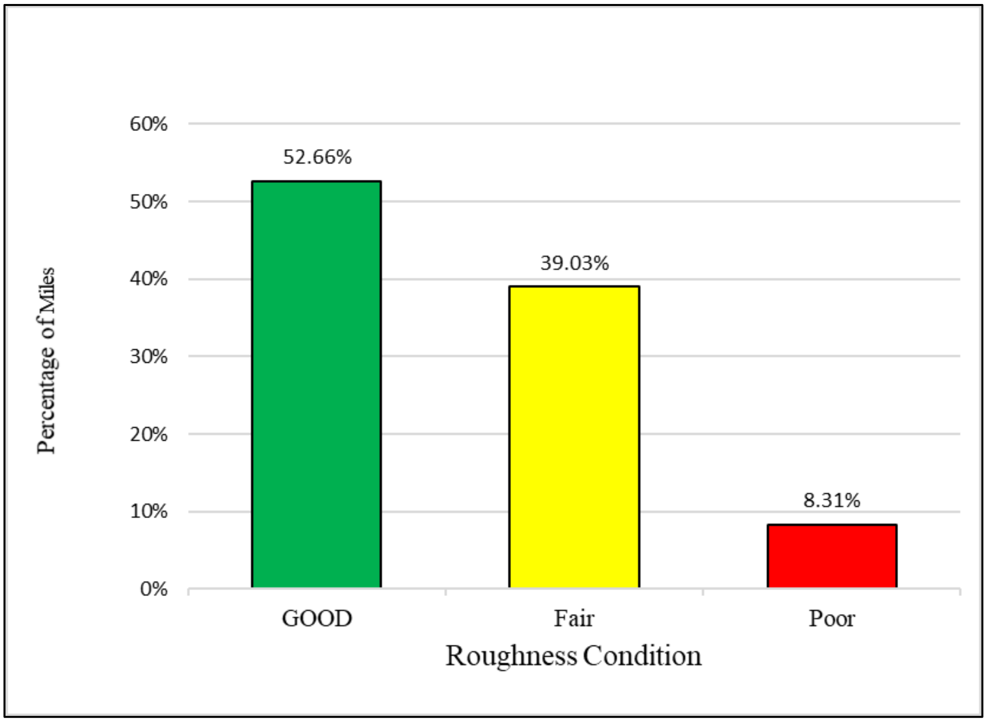

Figure 22. Pavement roughness distribution of Iowa highways (2015)

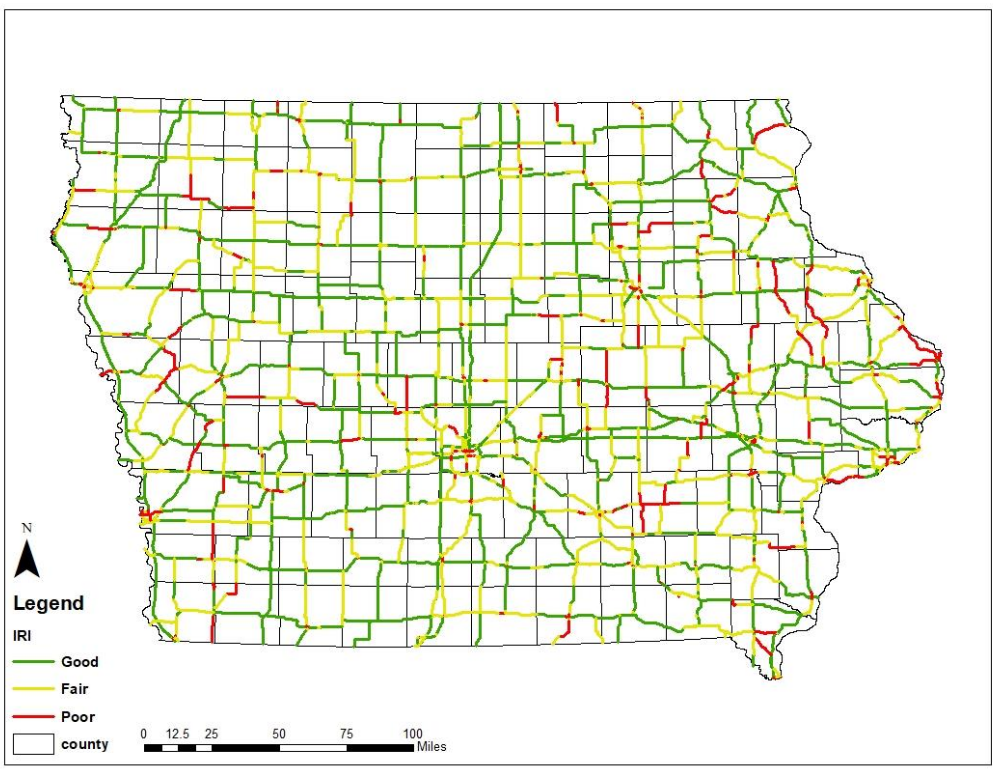

Figure 23. IRI map of Iowa highways (2015)

Developing Pavement Performance Models

Two kinds of pavement performance models, traditional multiple linear regression (MLR) and artificial neural network (ANN) models were developed to study three pavement types with different pavement properties and different material properties. Goodness of fit is a common measure for evaluating model performance. Therefore, the coefficient of determination (R^2) and root mean square error (RMSE) were utilized to measure and compare the performance of the models. Good prediction models should have a high R^2 and a low RMSE. R^2 values represent the correlation between the actual and predicted values to determine the accuracy of the model (Rahman and Tardfer, 2017). R^2 values range between 0 and 1 where 1 indicates that the actual and predicted values are in agreement and 0 indicates there is no relationship between them. RMSE values represent used measure the differences between predicted and actual values. R^2 and RMSE values were determined using Equation 10 and Equation 11 respectively

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \right] \tag{10}$$

$$RMSE = \sqrt{\frac{\sum_{i}^{n} (y_i - \hat{y}_i)^2}{n}} \tag{11}$$

where
y_i = actual value observation i;
$\hat{y}$ = predicted value of observation i;
$\bar{y}$ = average value of observation i; and
n = number of observations.

Historical data was used on in both ANN and MLR models to predict individual distresses for three pavement types, ACC, PCC, and COM pavements. These individual distresses were predicted based on weather factors (i.e., temperature, precipitation, and freeze-thaw cycles), traffic loading, pavement age, SN, layer thicknesses, and subgrade stiffness. By predicting individual distresses, decision makers can evaluate the individual distress for each pavement section, and determine which distress has more effect on the overall pavement condition.

These models were used to predict the individual distresses in ACC, PCC, and COM pavements. For ACC and COM pavements, three models were developed for predicting roughness, cracking, and rutting, and for PCC pavements, three models were developed for predicting roughness, cracking, and faulting. These predicted distresses were combined to calculate the PCI values based on Equations 8 and 9 in order to represent the overall PCI over the years. The flowchart in Figure 24 illustrates the modeling process. To determine the reliability of ANN models, the results obtained from the ANN models were compared with the results from MLR models.

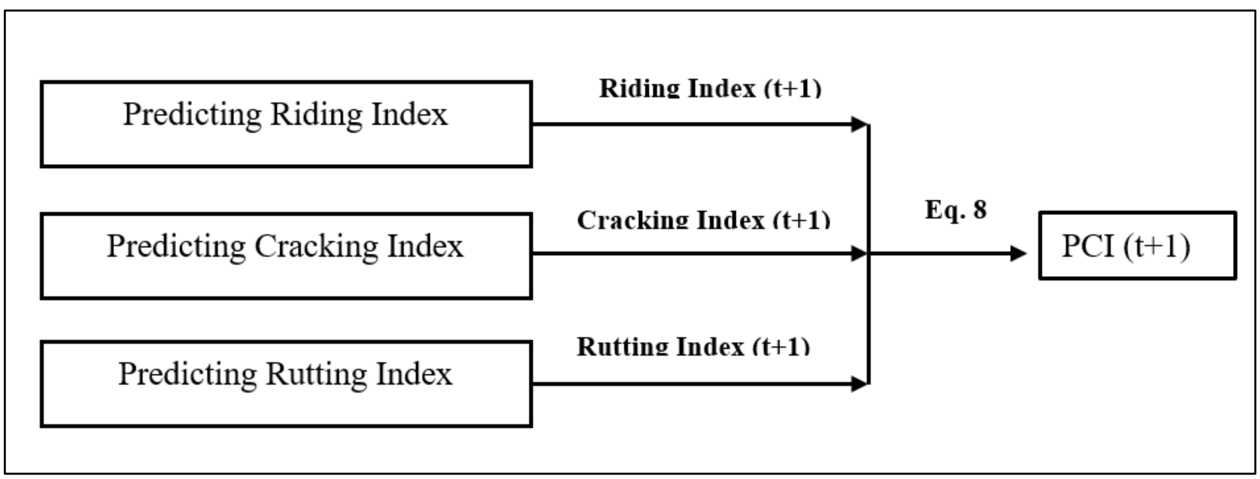

Figure 24. Flowchart of predicting PCI for ACC pavements

Stepwise analysis was used to determine factors that affect pavement conditions to remove any correlation between input variables by using JMP software. Stepwise analysis is the best approach for selecting candidate variables and removing insignificant variables (Nunez, et. al., 1986). In general, the factors that affect pavement conditions are climate factors (i.e., temperature, rainfall, snowfall, and freeze-thaw cycles), traffic loading, pavement thickness, structure number, and initial measurement values of pavement conditions.

The initial values of pavement conditions have been used by researchers as input factors to predict pavement conditions. Wang and Li (2011) predicted pavement roughness based on the initial roughness values, and Evangelista et. al., (2012) reported that initial crack size and pavement thickness have a significant impact on increasing the crack growth rate in concrete pavements. Smith et. al. (2002) reported that predicting the riding index will be improved significantly when initial roughness is considered. However, for this study, at the network level, the initial conditions of pavement sections were not available in the PMIS database. Iowa DOT collects pavement condition data in two year cycles, and the most recent measurement values are used as initial values in this study. This approach of using previous pavement condition values has been used by Kargah-Ostadi et. al. (2014) who considered the most recent IRI value instead of the initial, constructed IRI value to predict pavement roughness. Also, Meegoda and Gao (2014) reported that IRI data from previous years can be used as an initial IRI value when initial, constructed roughness data is not available. The input variables used in this study to predict the riding, cracking, and rutting indices for ACC, COM, PCC pavements are listed in Tables 6, 7, and 8, respectively.

Table 6. Input variables for modeling ACC pavements

Riding Index (RI)	Cracking Index (CI)	Rutting Index (RuI)
Pavement age Previous RI value Pavement thickness Subgrade stiffness Average rainfall Average temperature	Pavement age Previous CI value Average temperature Structure number	Pavement age Previous RuI value Pavement thickness Average temperature

Table 7. Input variables for modeling COM pavements

Riding Index (RI)	Cracking Index (CI)	Rutting Index (RuI)
Pavement age Previous RI value PCC thickness Pavement thickness Subgrade stiffness AADT Average temperature Average rainfall Freeze-thaw cycles	Pavement age Previous CI value ACC thickness PCC thickness Subgrade stiffness Trucks Average temperature	Pavement age Previous RI value PCC thickness Pavement thickness Subgrade stiffness AADT Structure Number Average temperature Average snowfall Average rainfall Freeze-thaw cycles

Table 8. Input variables for modeling PCC pavements

Riding Index (RI)	Cracking Index (CI)	Faulting Index (FI)
Pavement age Previous RI value Average rainfall Freeze-thaw cycles	Pavement age Previous CI value Trucks Pavement thickness	Pavement age Previous FI value AADT Average rainfall Freeze-thaw cycles

Before analyzing the data, JMP software was used to randomly divide the dataset into a training dataset (70%) and a validation dataset (30%) to explain how well the model performed. The performance of the prediction models was evaluated using two approaches: root mean square error (RMSE) and coefficient of determination (R^2).

Developing Artificial Neural Network (ANN) Models

Three main components are used to develop ANN models: the structure of connection between input and output layers (architecture); the method of adjusting the connection weight (learning method); and the neuron activation function.

ANN architecture plays a major role in developing an optimum ANN model, and efforts are required to determine the optimum architecture. The ANN model architecture used in this study consists of three layers: input layer, hidden layer, and output layer as shown in Figure 25.

At the input layer, the independent variables that relate to the output layer are entered, and each independent variable is assigned to an individual neuron. The challenge is to decide how many neurons should be in the hidden layer because that choice impacts model performance. For example, using too many neurons in a hidden layer might make the model more complex (Rafiq et. al., 2001).

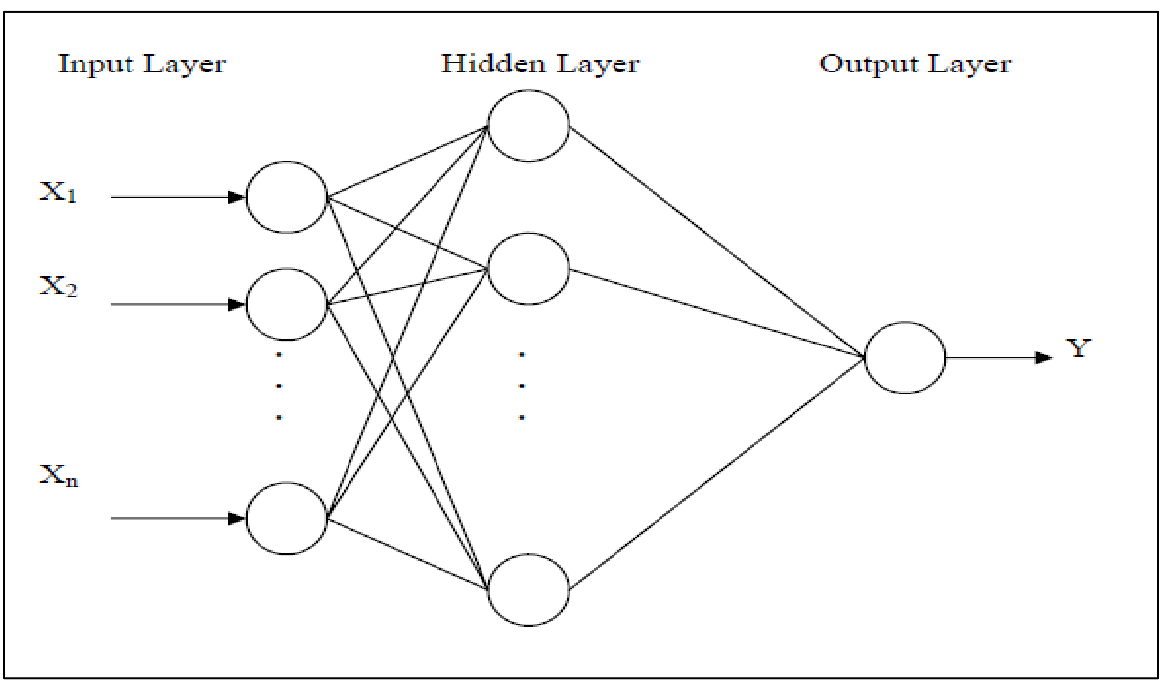

Figure 25. Neural network architecture (Yang, Lu, and Gunaratne, 2003)

There is no standard method for selecting the appropriate number of neurons, so training the ANN model with sequential number of hidden neurons and then selecting the number of neurons that achieve minimum RMSE was employed. Figure 26 shows the performance of an ANN model for determining the number of neurons in the hidden layer for predicting cracking index in composite pavement where the lowest RMSE value was achieved at 12 hidden neurons. The final layer in the structure of ANN model is the output layer that produces the result from processing provided by the hidden layer.

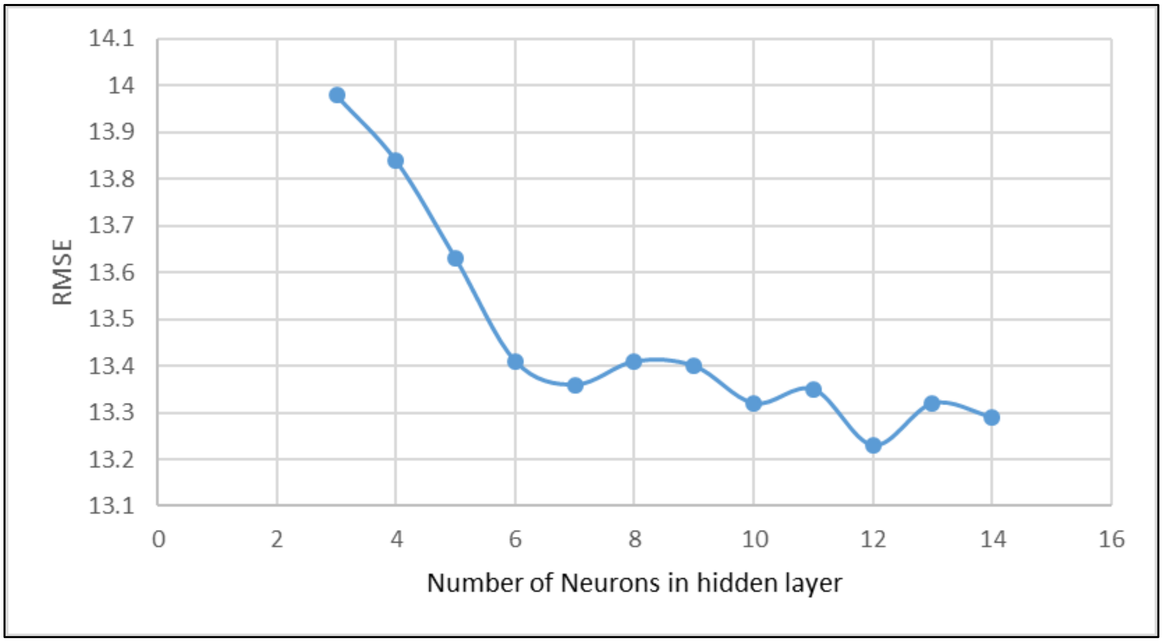

Figure 26. RMSE values to determine the number of neurons for training a COM pavement model

ANN learning process

After determining the architecture of an ANN model, software (e.g., JMP) is used to randomly divide the database is into training (70%) and validation (30%) datasets to train the neural networks. The training data set is used to develop the model, while the validation data is used to assess the accuracy of the ANN model and avoid overfitting in the model (Ling et. al., 2017). The results of the training process produce the weight matrices that are stored in links between layers and that can also be used to extract information about the contribution of each input in the model output. In the training process, the connection weights between the layers is adjusted, thereby, minimize the overall mean error by using back-propagation algorithm.

In general, the ANN learning process is usually classified into supervised and unsupervised processes (Shahin et. al., 2008). The supervised learning process utilizes historical data both for network inputs and desired outputs. The predicted output is compared to measured values to calculate an error that can then be used to adjust the connection weights between the model inputs and outputs. In the unsupervised learning process, the connection weight is adjusted based on stimuli inputs with no desired output provided in order to cluster the input values to similar features.

The back-propagation algorithm is considered as a supervised learning process, and it has been adopted by most researchers (Zhang et. al., 1998). In back-propagation algorithm, the input data propagated to the neurons in the hidden layer for processing, after which, the resulting data are propagated to the output layer. The results from the output layer are compared to the actual data for calculating the resulted error, following which the weights are adjusted after the calculated error is propagated back, with the process repeated until the model produces a lower error value.

Neuron activation function

The basic unit of an ANN model is a neuron that combines inputs and produces an output as shown in Figure 27. The neurons are not individually powerful in terms of computational power, but their interconnection with neurons in different layers produces the desired relationship among variables and demonstrates the processing capabilities of the neurons (Attoh-Okine, 1994).

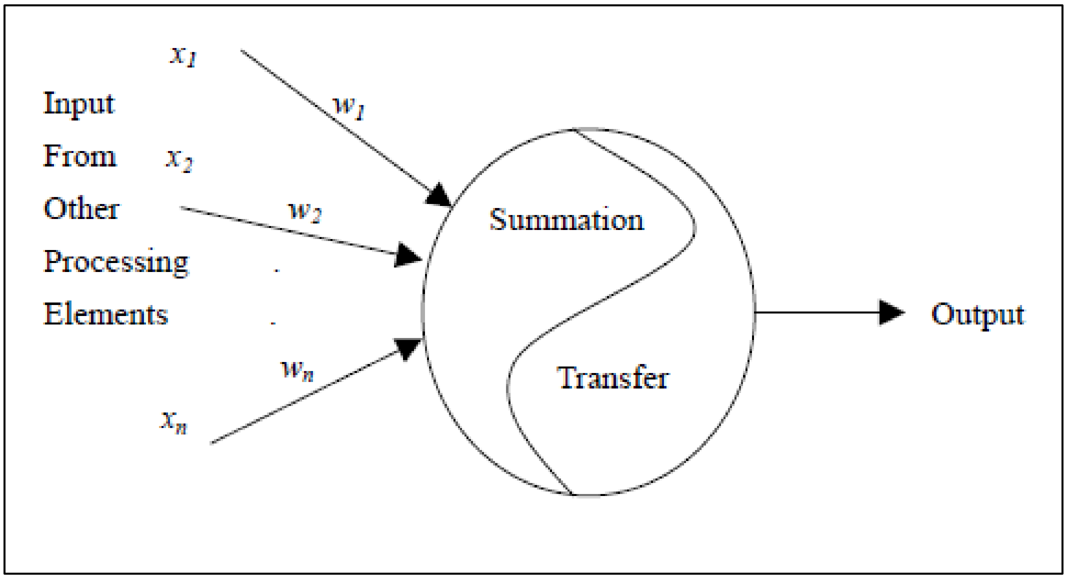

Figure 27. Diagram of an artificial neuron (Liu, 2013)

Each neuron in the hidden layer has its own summation and transfer functions with respect to the input and output values. The activation function determines the relationship between inputs and output layers. The output of the summation function is given by Equation 11,

$$y = O_j = f\left(\sum_{i=1}^{n} x_i w_i\right) \tag{11}$$

where:
O_j = output of hidden neuron j^{th};
f = transfer function
x_i = i^{th} input; and
w_i: connection weight between input i^{th} and output j^{th}.

Five transfer functions: linear, linear threshold, step, sigmoid and Gaussian functions have been used in a number of studies depending on the characteristics of the problem under investigation (Liu, 2013). The sigmoid function has been used in this research as the neuron activation function because of its support of nonlinearity and capability for avoiding excessively large values. The sigmoid transfer function is presented in Equation 12,

$$f(y) = \frac{1}{1+e^{-a(y)}} \tag{12}$$

where
y = input to the transfer function; and
a = coefficient of sigmoid function.

Relative contribution of input variables

Despite the vast capability of ANN in prediction modeling, such models are often criticized as “black box” models, because of the difficulty in interpreting the contribution of each variable to the response variable making it hard to gain an understanding of the relationships among variables, which is considered a weakness when compared to traditional statistical models (Olden and Jackson, 2002).

In ANN models, the values of weights links between input, hidden, and output layers play a significant role in determining the relative contribution of independent variables. Shekharan (1999) reported that a number of researchers have attempted to extract the knowledge of an ANN model by utilizing the connection weights to estimate the relative importance of each variable from information stored in the weights. The common approach for estimating the relative importance of different input variables in pavement performance prediction models is called Garson’s algorithm. Garson’s algorithm has been found to produce more reliable results in the case of nonlinear relations (Fischer, 2015)**.** In Garson’s algorithm, the output layer connection weight is partitioned into each input neuron using the absolute value of connection weights (Olden and Jackson 2002). Shekharan (1999) presented the equation that has been utilized to calculate the relative contribution of each independent variable in ANN models (Equation 13),

$$RC = \frac{\sum_{j}^{h}\left(\frac{w_{ij}O_j}{\sum_{i}^{v} w_{ij}}\right)}{\sum_{i}^{v}\left[\sum_{j}^{h}\left(\frac{w_{ij}O_j}{\sum_{i}^{v} w_{ij}}\right)\right]} \tag{13}$$

where:
h = number of hidden neurons
v = number of input variables
O_j = connection weight between (*j*) hidden neurons and the output neuron
w_{ij} = connection weight values between inputs (*i*) and (*j*) hidden neurons

Garson’s algorithm was utilized to calculate the relative contribution (RC) of independent variables. RC values range between 0 and 100 percent, where the larger RC of a specific factor indicates that it has a greater effect on the pavement condition. RC values were calculated for the effects of variables on riding, cracking, rutting, and faulting for ACC, PCC, and COM pavements.

Developing Multiple Linear Regression (MLR) Models

Regression analysis is a powerful method that requires historical data to predict a dependent variable based on one or more independent variables. In this research, multiple linear regression (MLR) models were used to predict values of pavement conditions (ride, cracking, rutting, and faulting) and those results were compared with prediction results from ANN modeling. MLR modeling has been widely used by highway agencies to predict pavement performance because of its simplicity and ease of implementation. MLR has also been used by researchers in predicting pavement deterioration rates (Xu et. al., 2015). Knapp et. al. (2000) developed an MLR model to investigate the effect of winter weather on traffic volume and safety in roads.

Some regression assumptions must be considered in developing regression models. For example, Sousa et. al. (2007) reported that error values are assumed to be independent across observations because collinearity between variables can lead to incorrect predictions. Smith et. al., (1999) reported that the distribution of the error term is a normal distribution $N(0, \sigma^2)$ and that the relationship between response variable (y_i) and the explanatory variables is linear (Equation 14),

$$Y = \beta_0 + \beta X + e \tag{14}$$

where
Y = dependent (response) variable;
β_o = constant term;
β = regression coefficient;
X = independent variable; and
e = error term.

An ANN Model for Correlating Structural Capacity and Rutting

Several factors such as climate factors, thickness, and traffic loading cause rutting in ACC pavements (Mirzapour Mounes et. al., 2014). An ANN model was developed for this study to estimate the correlation between structural capacity and rutting. Traffic loading, pavement age, subgrade stiffness, layer thickness, average annual number of snowfall, average annual of rainfall, average annual temperature, freeze-thaw cycles, and rutting were utilized as independent variables to predict the structure number (SN). SN represents the pavement structural capacity and was used as the dependent variable.

The analysis process focused on ACC pavements on Iowa highways. The other pavement types were not included in this analysis because there was insufficient structural data for those cases. Also, the analysis focused on ACC pavement sections that have not been exposed to any maintenance or rehabilitation activities. So the obtained data includes all section data until the year of applying any maintenance or rehabilitation operations.

A total of 1144 data points from Iowa highways for years from 1998 to 2015 were trained by using the back-propagation algorithm ANN model. Before training the ANN model, JMP software divided the dataset randomly into 70% for training process and 30% for the validation process. The performance of the ANN model was evaluated by coefficient of determination (R^2) and root mean square error (RMSE).

CHAPTER 4: RESULTS AND DISCUSSION

Understanding pavement performance during its service life has an impact on managing the roads in an effective manner and optimizing maintenance and rehabilitation strategies. This chapter presents the results of utilizing ANN and MLR models with both pavement condition and weather variables to predict pavement performance conditions. Future pavement conditions of Iowa highways were predicted more accurately by ANN models than MLR models. The ANN model demonstrated the capability for predicting pavement conditions based on several variables and for estimating the relationship between SN and rutting in asphalt pavements at the network management level.

Comparison of ANN and MLR Models

The performance of the ANN models was compared with the performance of the MLR models to assess the accuracy of the models in predicting pavement performance as calculated by riding, rutting, cracking, and faulting indices. R^2 and RMSE values were used to measure and compare the performance of the models. Good prediction models should have a high R^2 and a low RMSE.

Historical data was used on both ANN and MLR models to predict individual distresses for three pavement types, ACC, PCC, and COM pavements. These individual distresses were predicted based on weather factors (i.e., temperature, precipitation, and freeze-thaw cycles), traffic loading, pavement age, SN, layer thicknesses, and subgrade stiffness. By predicting individual distresses, decision makers can evaluate the individual distress for each pavement section, and determine which distress has more effect on the overall pavement condition.

After determining the architecture of each ANN model, the database for the period from 1998 to 2015 was randomly divided by JMP software into training (70%) and validation (30%)

datasets. JMP software was also used for training the neural networks. The training data set was used to develop the model whereas the validation data was used to assess the accuracy of the ANN model and avoid overfitting in the model (Ling et. al., 2017). The results of the training process produced the weight matrices that are stored in links between layers and that can also be used to extract information about the contribution of each input in the model output. The analysis showed that the ANN models yield reasonably accurate models compared to the results of MLR models as shown in Tables 9, 10, and11.

For ACC pavements**,** the ANN models yielded more accurate predictions than the MLR models in riding, cracking, and rutting indices as shown in Table 9. The R^2 values indicate there are good correlations between actual and predicted indices for each index. The R^2 values from the ANN models are higher than the R^2 values of the MLR models by 61.40%, 48.15%, and 48.15% for riding, cracking, and rutting index, respectively.

Table 9. Comparison of MLR and ANN for ACC pavements

Pavement Index	MLR		ANN		% of R^2 Improvement
	R^2	RMSE	R^2	RMSE	
Riding Index	0.57	12.97	0.92	8.42	61.40%
Cracking Index	0.54	16.62	0.80	14.31	48.15%
Rutting Index	0.41	12.10	0.72	9.16	75.61%

For PCC pavements, as can be seen in Table 10, the ANN models achieve better accuracy models with improvement in R^2 by 23.00%, 26.93%, and 80.00% than MLR models in predicting riding, crack, and fault indices, respectively, compared with MLR models.

Table 10. Comparison of MLR and ANN for PCC pavements

Pavement Index	MLR		ANN		% of R^2 Improvement
	R^2	RMSE	R^2	RMSE	
Riding Index	0.74	11.84	0.91	10.60	23.00%
Cracking Index	0.54	18.61	0.68	15.23	26.93%
Faulting Index	0.35	15.00	0.63	12.96	80.00%

For COM pavements, the comparison of the results produced by ANN and MLR models showed that the ANN model performed better accurate models than MLR models as shown in Table 11. The R^2 values from the ANN models indicate that the ANN models are more accurate than MLR models.

Table 11. Comparison of MLR and ANN for composite pavements

Pavement Index	MLR		ANN		% of R^2 Improvement
	R^2	RMSE	R^2	RMSE	
Riding Index	0.54	15.68	0.88	11.72	62.96%
Cracking Index	0.65	14.00	0.88	13.50	35.38%
Faulting Index	0.44	12.57	0.75	9.78	70.45%

These analyses show that the ANN model is more accurate than the MLR model. This conclusion is consistent with conclusions reported in previous studies. For example, Chandra, et. al. (2012) compared between the performance of ANN and MLR models in predicting pavement roughness from different kinds of distress and reported that the ANN model has significantly better accuracy than MLR model with mean square error 18% less than that for the MLR. These findings are consistent with Thube (2012) who developed ANN models to predict cracking, raveling, rutting and roughness and reported good R^2 values. Saghafi et. al. (2009) also reported that the ANN models predicted faulting in concrete pavement with higher accuracy than an MLR model. In this research, both the ANN and MLR models included the weather factors that influence pavement conditions.

Validation of Prediction Models

For the ANN models, the process of developing the neural network of a validation dataset is similar to the training process, except no weight matrices are produced from the validation process. If the accuracy of models from the validation process is higher that indicates the prediction model perform well (Ling et. al., 2017). Otherwise, the model needs to be run with different architecture until it gets similar error values for training and validation datasets. In this study, the R^2 values from the validation process of the ANN models ranged from 0.60 to 0.91, while RMSE values ranged from 19.22 to 8.69 (Table 12).

Table 12. Goodness of fit of ANN models of validation dataset

Pavement Type	Pavement Index	R^2	RMSE
ACC	Riding Index	0.91	8.69
	Cracking Index	0.78	14.68
	Rutting Index	0.70	9.67
PCC	Riding Index	0.90	11.73
	Cracking Index	0.67	19.22
	Faulting Index	0.60	13.53
COM	Riding Index	0.87	12.06
	Cracking Index	0.81	14.00
	Rutting Index	0.74	9.97

For the MLR models, residual plots were used to assess the performance of the MLR model. The residual is the difference between predicted and measured values and is calculated by Equation 15.

$$e_i = \text{actual } i - \text{predicted } i \tag{15}$$

The analysis of residual distribution plots is the most common technique used to verify that regression assumptions were met (Rajagopal, 2006). The residual plots for the MLR models were approximately randomly distributed around the centerline at 0 with no certain pattern. This indicates that the MLR models successfully predicted the dependent variables and that the constant variance assumption was verified. Figures 28, 29 and 30 show the residual plots of the performance prediction models of cracking, riding, and rutting indices in ACC pavements, respectively.

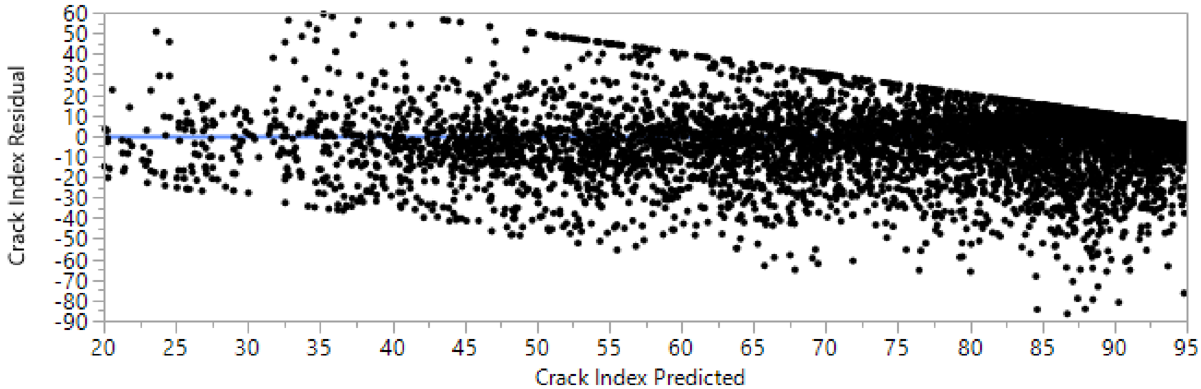

Figure 28. Residual plot for the cracking model in ACC pavements

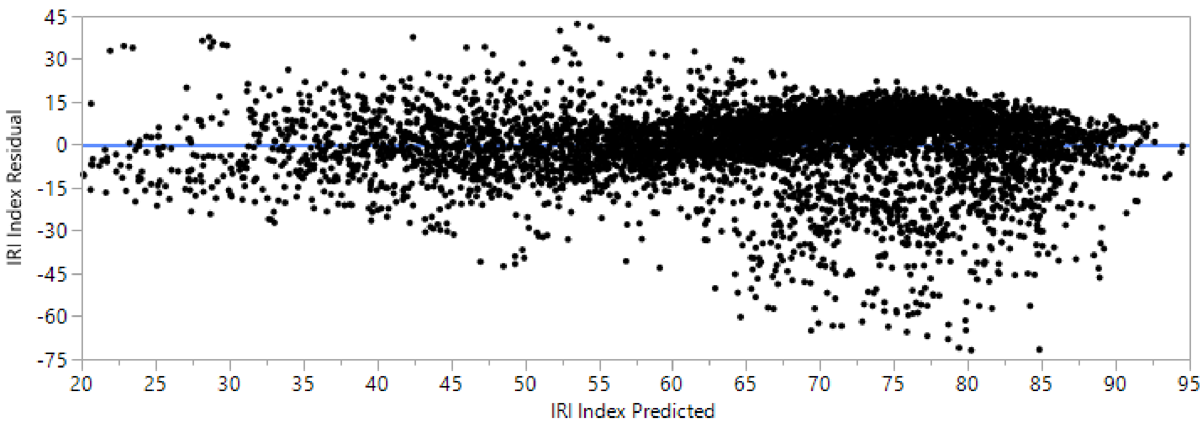

Figure 29. Residual plot for the riding model in ACC pavements

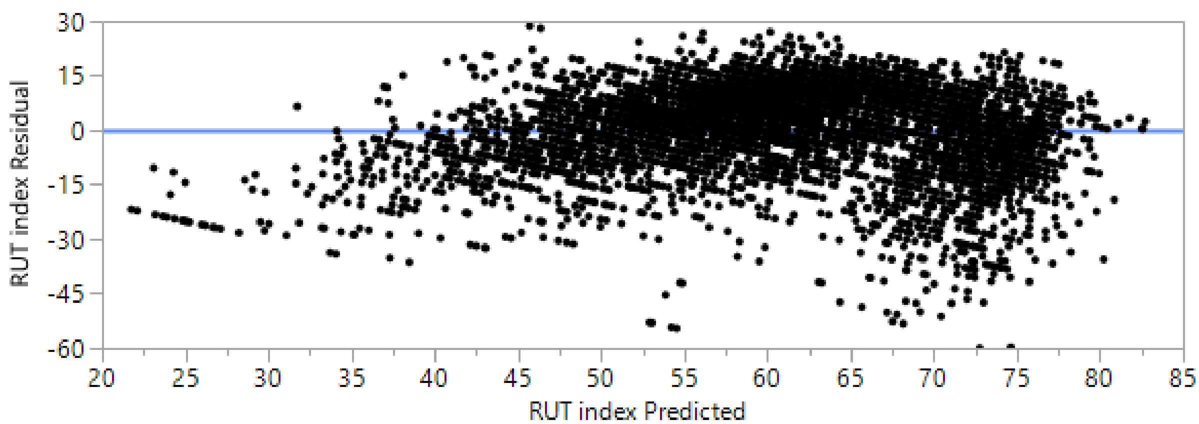

Figure 30. Residual plot for the rutting model in ACC pavements

ANN Predictions of Future Pavement Performance

After predicting the pavement condition indices, the weights and biases matrices from ANN layers were used to predict the future performance of riding, cracking, rutting, and faulting indices assuming no future treatment will be applied. The adjusted weights were developed by a back-propagation algorithm during the training process in order to make the predicted values close to the actual values. The weights and biases matrices were stored by JMP software. Predicting the future pavement conditions was predicted incrementally; for instance, the first predicted value for pavement condition in age (t+1) was used to predict the second year pavement condition (t+2) as the input of the previous pavement condition and so on. The ANN models were based on the average of weather factors and traffic loading, structure parameters, and initial pavement condition. Thereafter, these values from each distress index were combined together to present PCI values calculated using Equation 8 (for ACC and COM) and Equation 9 (for PCC) pavements. These PCI values provide performance predictions for the three kinds of pavement.

Performance curves were drawn between PCI and pavement age. The ultimate goal of the performance curves is to effectively assist decision makers in knowing when, where, and what maintenance action should be taken for a given pavement section based on PCI values. The PCI scale is divided into very poor, poor, fair, good, and excellent conditions based on threshold values on a scale that ranges from 0 to 100 (Table 13).

Table 13. Threshold values of PCI from Iowa DOT

PCI	Interstate highway
Very Poor	0–20
Poor	21–40
Fair	41–60
Good	61–80
Excellent	81–100

ANN models were used to predict the pavement performance of ACC, PCC, and COM pavements during their design life period. For this analysis, three pavement sections, one each of ACC, PCC, and COM pavements, were selected to analyze their performance over the years and predict future performance. The curves for each pavement section begin at the year of construction, and it is assumed that no maintenance has been or will be done on the section. These curves are shown in Figures 31, 32, and 33.

ACC pavements represent about 16% of Iowa highways. The performance curve for an ACC pavement section from I-35 is shown in Figure 31. The performance curve shows that the pavement section was in poor condition, (i.e., the PCI value is lower than 41) 11 years after construction.

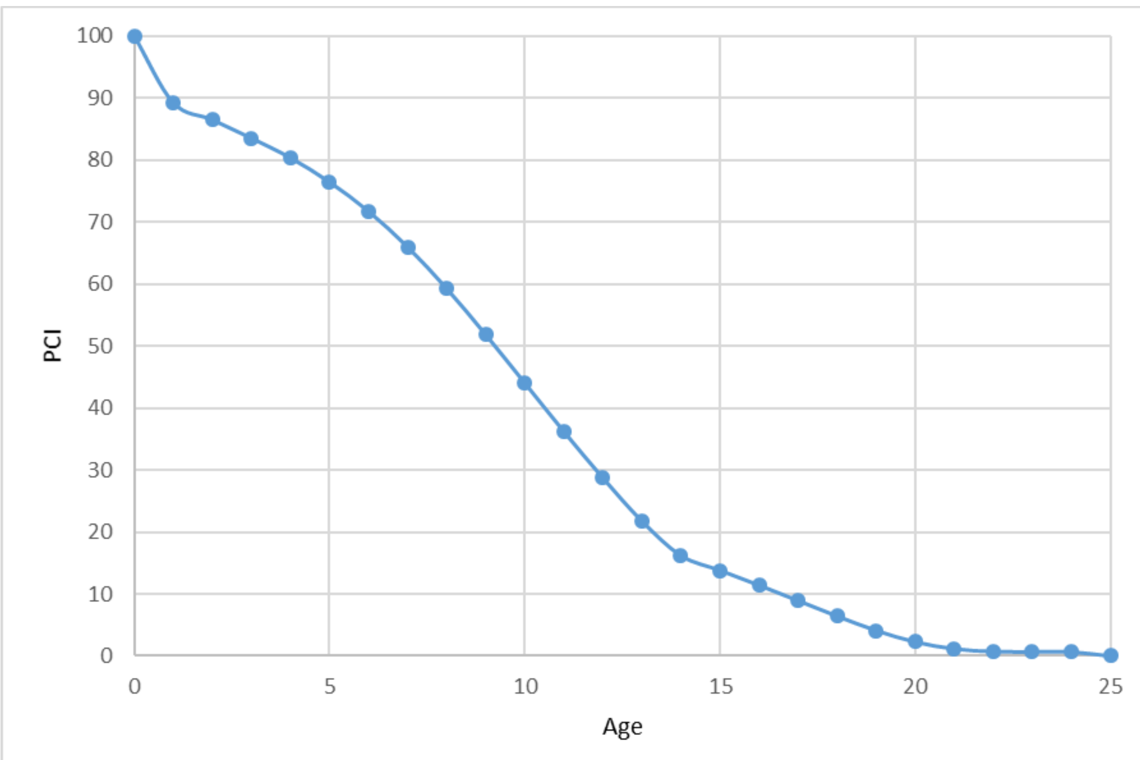

Figure 31. Pavement performance curve for I-35 section (ACC pavement)

Figure 32 shows the performance curve of a pavement section of US-30 in Story County. The pavement type of this section is a composite pavement with PCC overlaid by ACC pavement. Composite pavement is widely used in Iowa, with around 46% of the total highway. The composite pavements typically last longer than ACC pavement because the concrete base layer makes it a stronger structure. The US-30 pavement section can serve in good or fair condition up to approximately 20 years, which is better performance than the ACC pavement section.

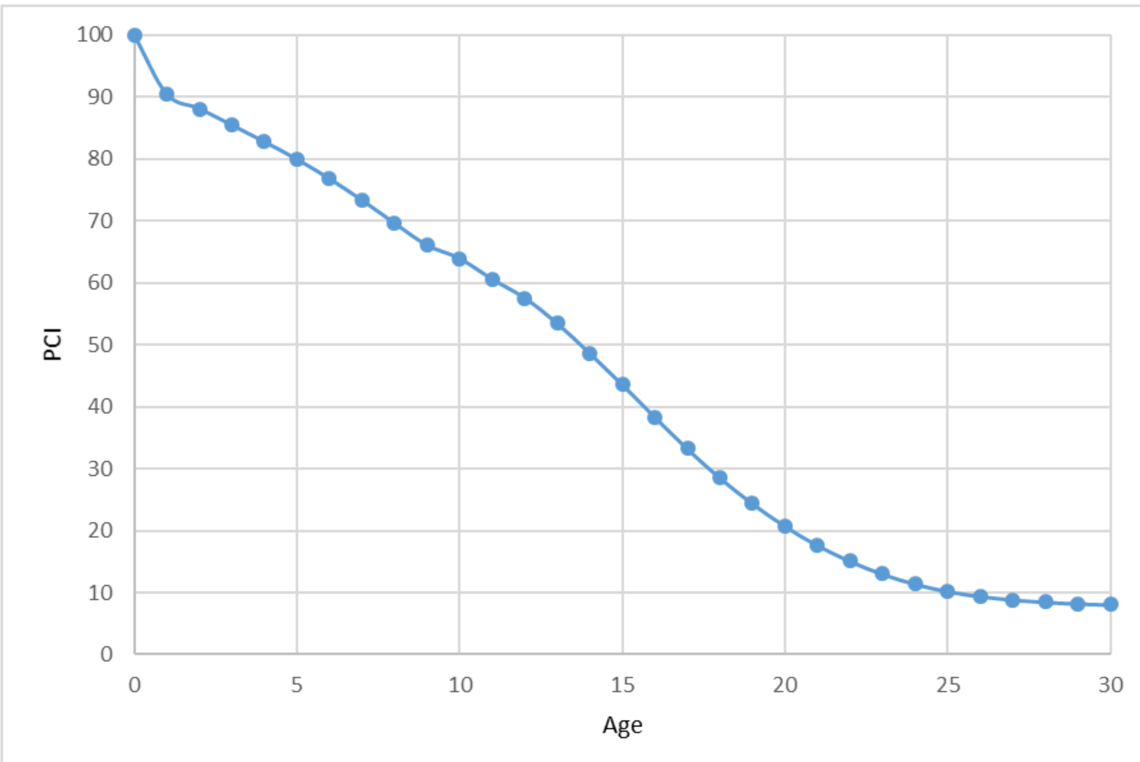

Figure 32. Pavement performance curve for US-30 section (COM pavement)

Figure 33 shows the performance curve of a PCC pavement section of Iowa highway 1. This performance curve indicates that PCC pavement lasts longer than both ACC and COM pavements and that PCC deteriorates at a lower rate early age. The curve indicates that this pavement section should be in good or fair condition for almost 40 years.

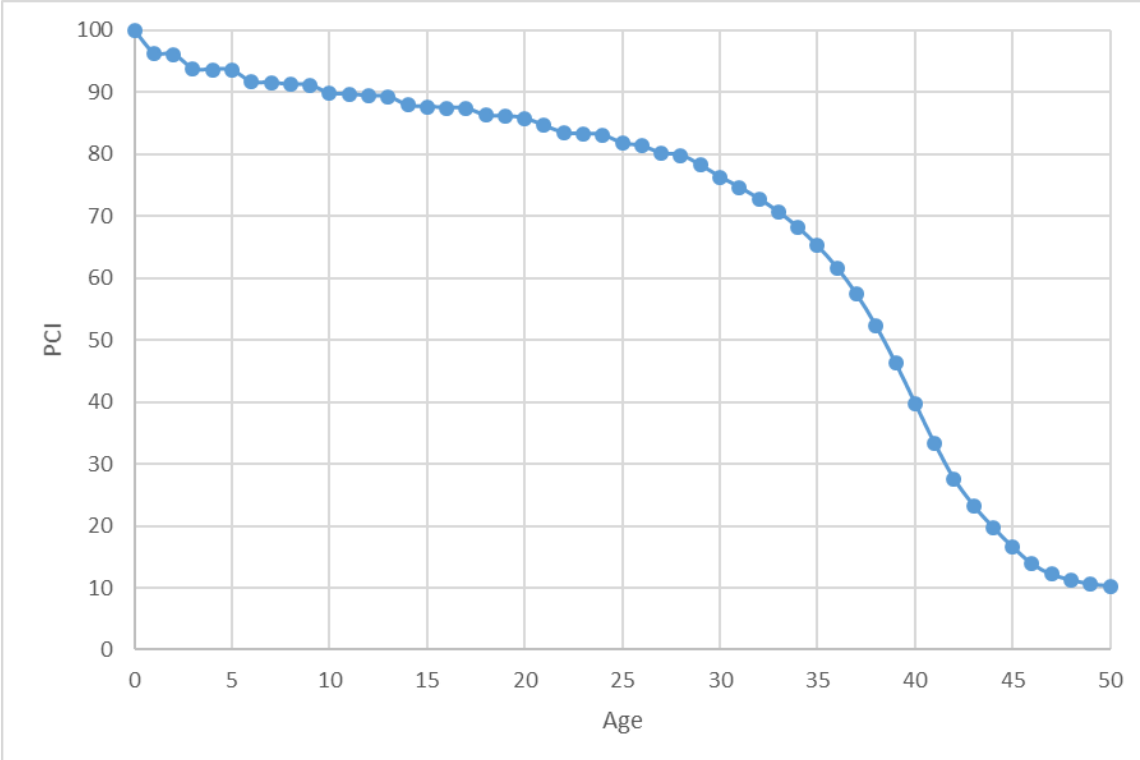

Figure 33. Performance curve for the Iowa-1 pavement section (PCC pavement)

Relative Contribution of Input Variables

An effort has been made in this study to estimate the relative importance of each input variable in predicting the individual distress values for each pavement type. By knowing the relative contribution of each variable in the ANN models, the image of ANN as black box model can be changed. Garson's algorithm (Equation 13) utilizes connection weights in links between ANN layers to calculate the relative contributions (RC) of input variables (e.g., temperature or traffic loading) on output variables (e.g., rutting or cracking). The RC of each input variable is reported as a percentage, with the total RC equal to 100%. Because pavement types are not necessarily influenced by every input variable, only the variables that influence the indices related to each pavement type are shown.

Variables that Influence ACC Pavements

Figures 34 through 36 show the relative contribution of input variables on the riding, cracking, and rutting indices values for ACC pavements. The pavement age was the most significant factor affecting the riding index. The significance of age in predicting riding indices in ACC, PCC, and COM pavements was expected because increasing pavement age means increased exposure to weather factors and traffic loads. Also, pavement age is considered the best predictor because it can be determined accurately. The average annual temperature has a large influence on riding, cracking, and rutting indices, which is consistent with previous studies. The cracking and rutting and indices were significantly affected by weather temperature (Figures 34 and 35).

These results are consistent with previous research, such as a study done in Michigan that reported that the performance of flexible pavements is most sensitive to temperature and precipitation (Yang et al., 2017). Also, Breakah et al. reported that for ACC pavement, high temperature affects the resilient modulus of pavements, cold weather increases pavement stiffness, which can cause shrinkage cracking, and precipitation possibly affects the strength of the subgrade by infiltration through layers (2010). Temperature variation can reduce the strength of asphalt surface layers and cause rutting, which means the pavement structure cannot carry the expected traffic loads (Johanneck and Khazanovich, 2010).

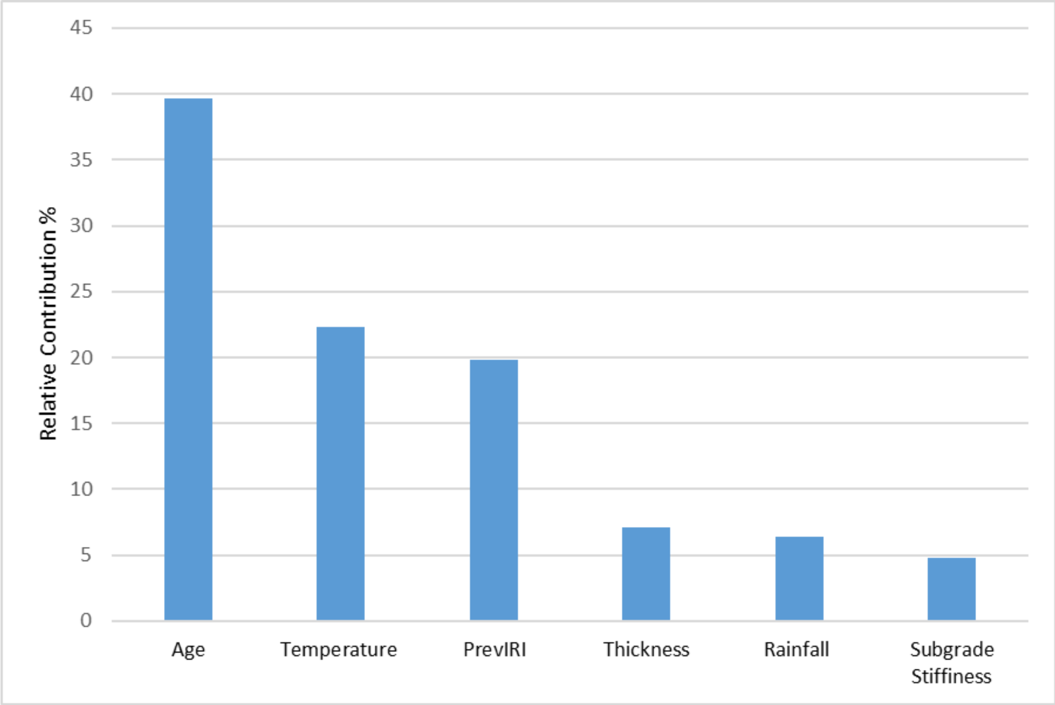

Figure 34. Relative contribution of inputs on Riding Index (ACC Pavement)

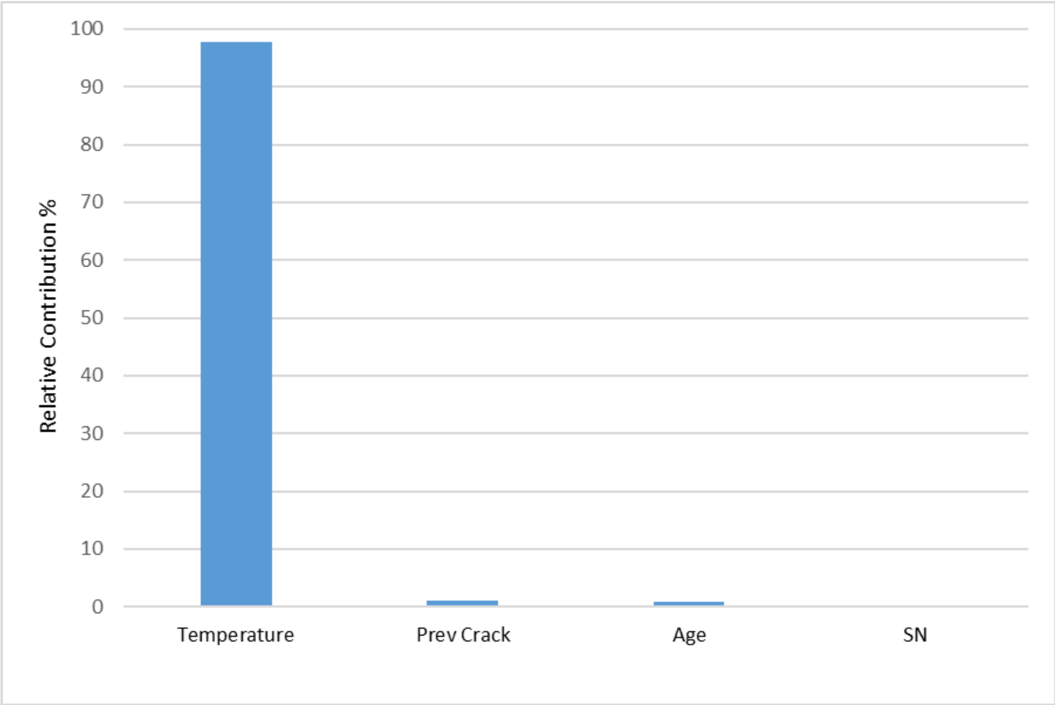

Figure 35. Relative contribution of inputs on Cracking Index (ACC Pavement)

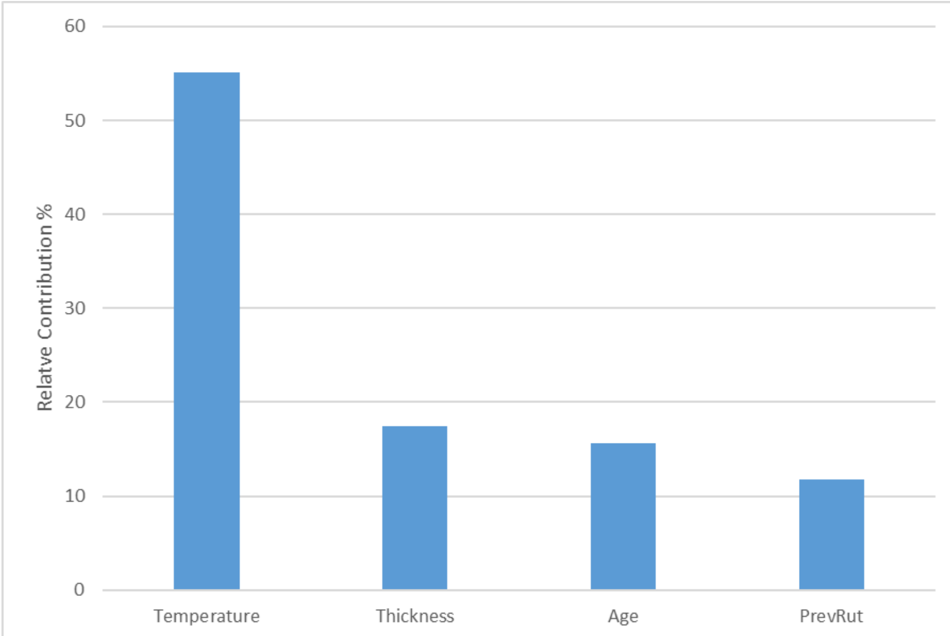

Figure 36. Relative contribution of inputs on Rutting Index (ACC Pavement)

Variables that Influence PCC Pavements

For PCC pavement, as shown in Figure 37, the riding index is greatly affected by the previous roughness value, and this finding was shown in literature reviews. According to a study done in Wisconsin, the previous roughness value has a large impact on predicting pavement roughness in concrete pavements (Wen and Chen, 2007). Also, pavement age affects both riding and cracking indices of PCC pavements because as pavement age increases, the ability of a concrete slab to withstand repeated traffic loadings and weather factors decreases.

The relative contributions of rainfall and freeze-thaw cycles were of secondary importance after previous values of IRI and pavement age, but collectively their contributions reach 20% (Figure 37). However, weather factors have a higher influence on predicting the faulting index. The largest effect on the faulting index comes from temperature with a relative contribution around 50% (Figure 38). The effect of temperature on concrete pavement has been found in previous research. For example, curling and warping of concrete pavement slab are caused by temperature variation (Johanneck and Khazanovich, 2010). Truck loadings on PCC pavements also contribute nearly 60% to predicting the cracking index (Figure 39).

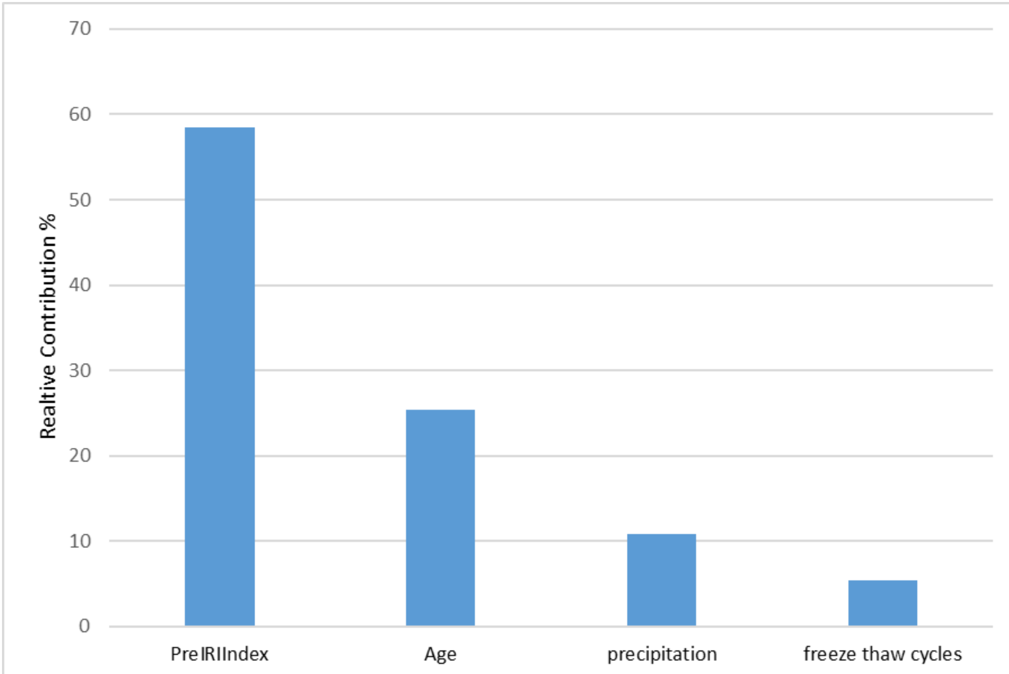

Figure 37. Relative contribution of inputs on Riding Index (PCC Pavement)

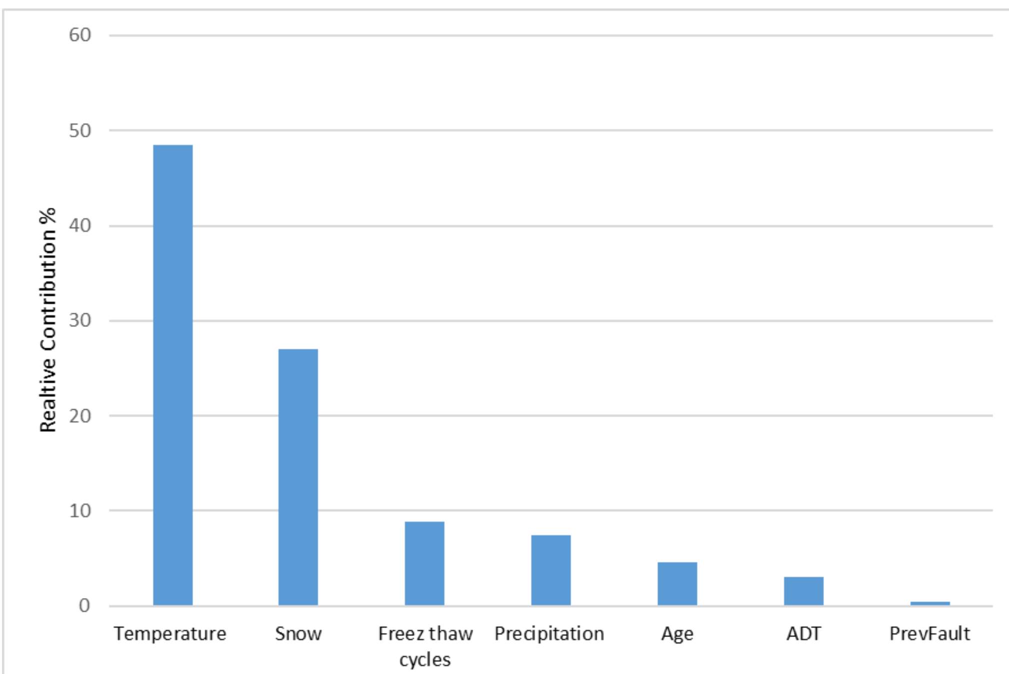

Figure 38. Relative contribution of inputs on Faulting Index (PCC Pavement)

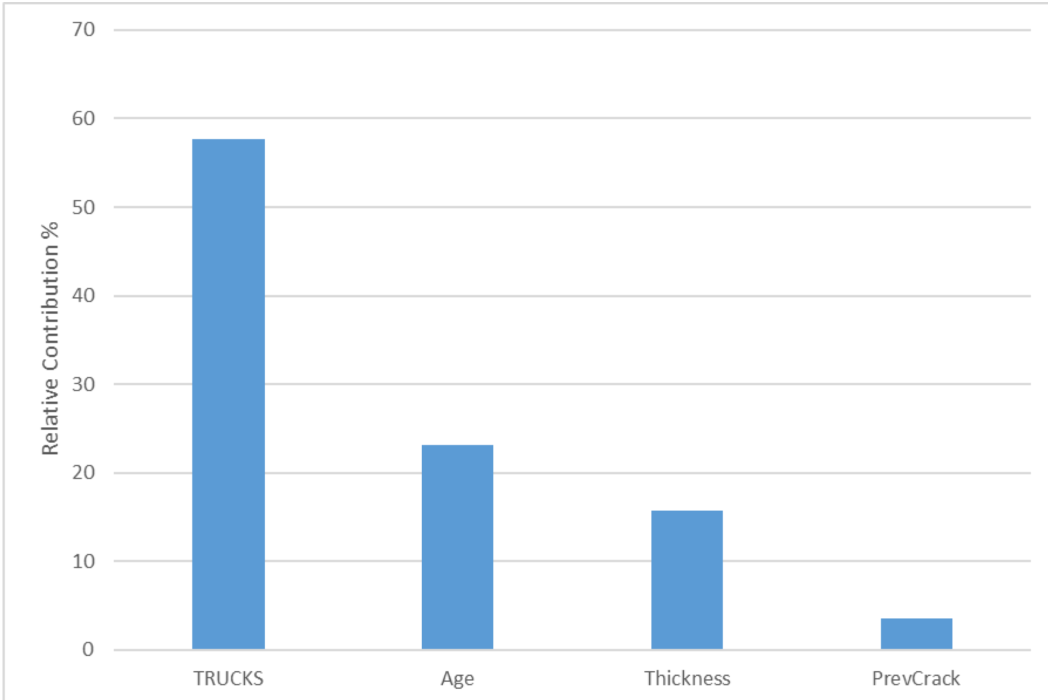

Figure 39. Relative contribution of inputs on Cracking Index (PCC Pavement)

Variables that Influence Composite Pavements

For COM pavement, Figure 40 shows the factors that have an effect on riding index values. Since COM pavements are constructed with a PCC base layer under an ACC, factors that affect riding index in ACC and PCC pavements were found to have significant influence on the riding index of COM pavement. The riding index was most affected by freeze-thaw cycles whereas the cracking index was affected by average annual temperatures as shown in Figures 40 and 41. According to Chen et. al. (2015), freeze-thaw cycles can cause cracking, especially reflective cracking in the PCC layer by movements at slab joints. The average number of freeze-thaw cycles, the average annual temperature, and the average annual snowfall amount were found to have a large impact on the rutting index (Figure 42). The results show that COM pavements were less sensitive to traffic loading because combining PCC and ACC results in good structural capacity.

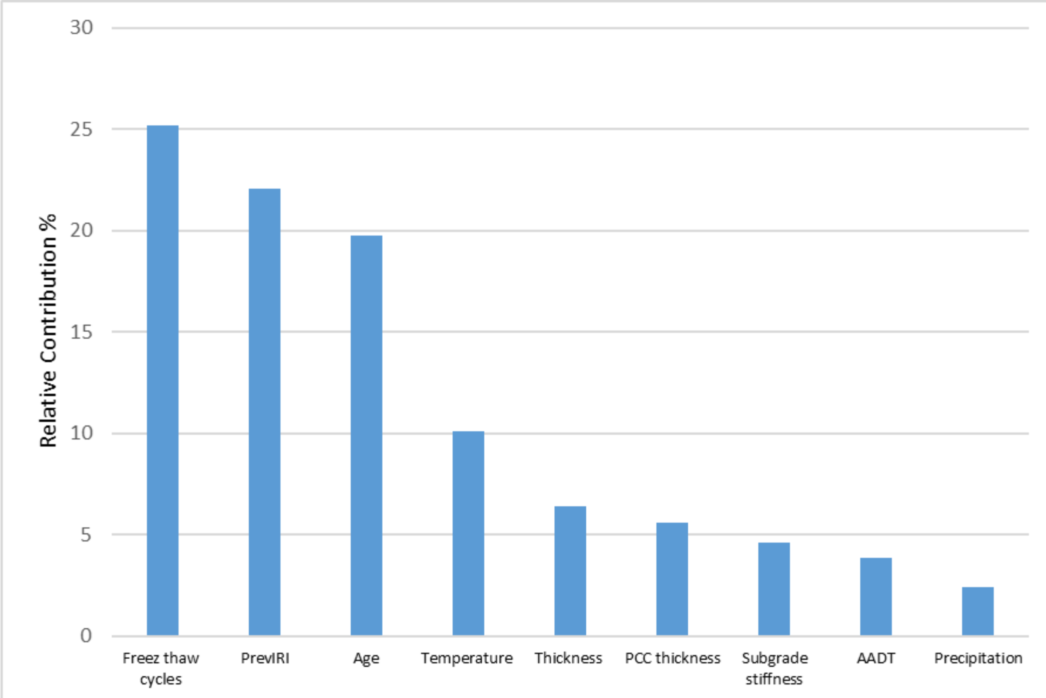

Figure 40. Relative contribution of inputs on Riding Index (COM Pavement)

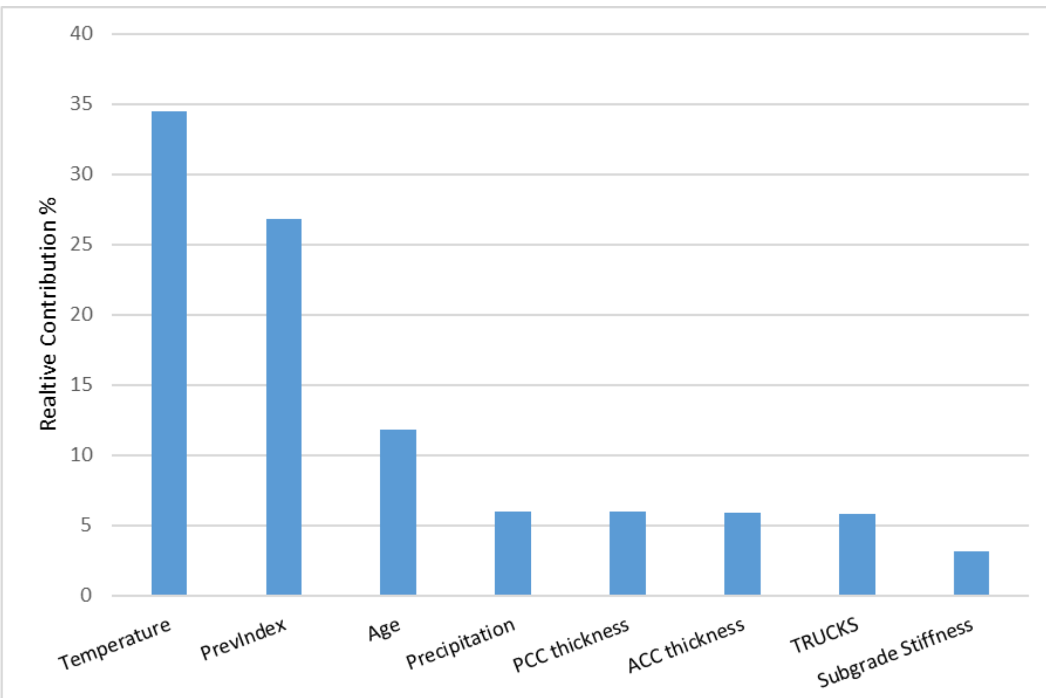

Figure 41. Relative contribution of inputs on Cracking Index (COM Pavement)

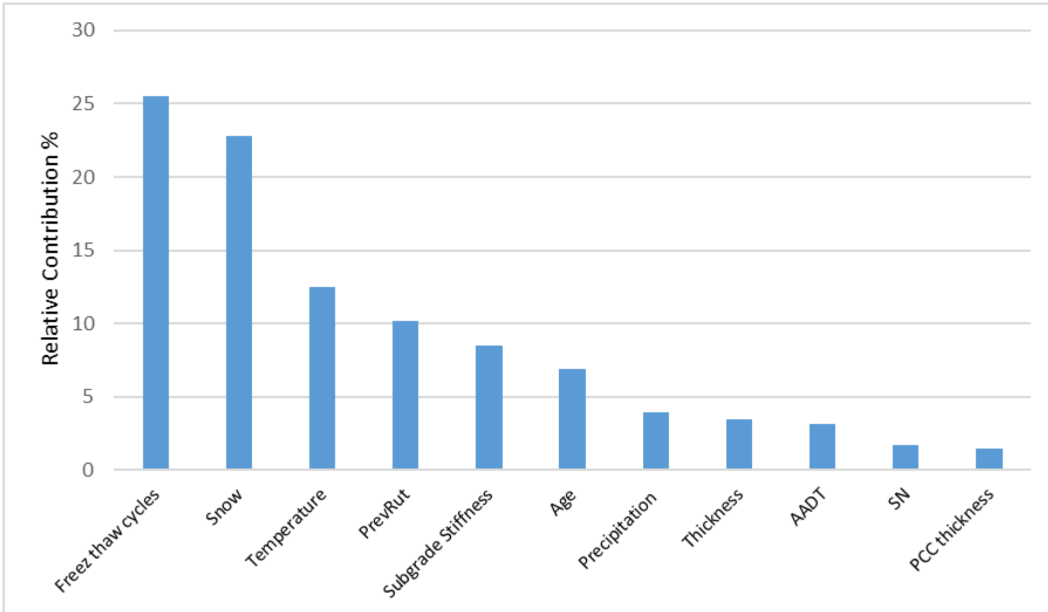

Figure 42. Relative contribution of inputs on Rutting Index (COM Pavement)

The main contribution of this research is to evaluate and quantify the impact of weather factors on pavement conditions of ACC, PCC, and COM pavements. Considering weather factors is important in modeling pavement performance, because pavement deterioration rates in Iowa are definitely affected by freeze-thaw cycles, temperatures, and precipitation. These results can be used by decision makers and maintenance engineers to determine proper treatment actions and improve pavement design to withstand harsh weather over the years.

ANN Models for Correlating Structural Capacity and Rutting

Before training the ANN model to investigate the relationship between the SN and rutting depth, the two were plotted to determine any relationship between them. Figure 43 shows that there is no strong relationship between the actual rutting depth and the actual SN.

Different combinations of neural network architecture were examined to develop the best ANN model for correlating SN and rutting depth in ACC pavements in Iowa. Applying an ANN model with pavement thickness, subgrade stiffness, traffic loading, pavement age, temperature, rainfall, snowfall, and freeze-thaw cycles variables revealed a correlation between the SN and rutting. The ANN architecture of this ANN model included 10 hidden neurons. After training the model, the model estimated the correlation an R^2 value of 0.90 and an RMSE of 12.6. The fitted line between predicted and actual SN is shown in Figure 44.

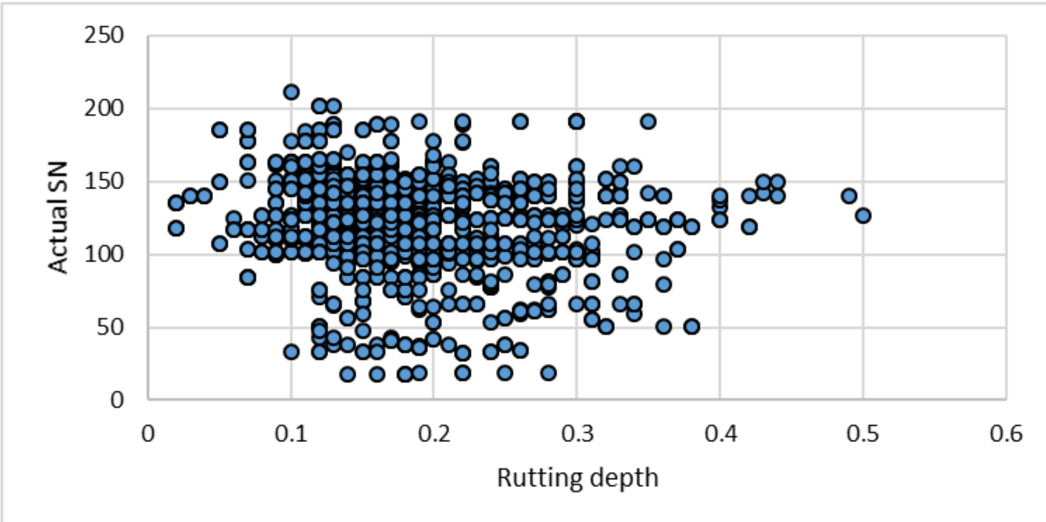

Figure 43. Scatter plots of actual SN vs actual rutting depth

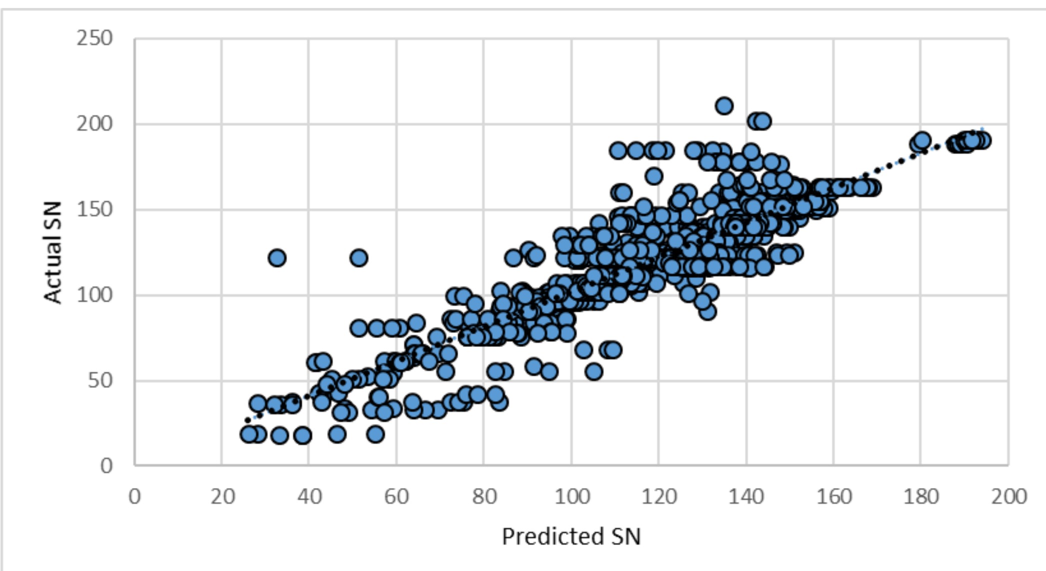

Figure 44. Fitted line between actual and predicted SN for ACC pavements

These results demonstrate that ANN modeling can use rutting data to estimate the structural capacity of an ACC pavement. In general, structural evaluation tests (e.g., deflection testing) should be used to directly assess pavement structures. However, when there is no structural data available, rutting data can analyzed to provide an estimation of SN.

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

Predicting future pavement performance is essential for allocating available funding for maintenance and rehabilitation activities at the network level as well as for determining the most cost-effective strategies at the project management level. The objectives of this study were to use ANN models to accurately predict pavement performance of ACC, PCC, and COM pavements in Iowa and to estimate the correlation between structural capacity (SN) and rutting depth on ACC pavements.

The models in this study were developed to include climate data in addition to historical pavement condition data. This research included weather factors as inputs in both ANN and MLR prediction models. Results of the ANN models were more accurate than the MLR models, perhaps because ANN models can deal with larger, more complex data sets. It is important to determine the relative contribution of each factor to consider them in future design adjustments and selecting appropriate treatments. Also, by identifying factors affecting pavement performance, the idea about a neural network model as a black box model can be changed. Four weather factors were included: average annual temperature, average annual snowfall, average annual rainfall, and freeze-thaw cycles. The average annual temperature influenced the performance of ACC pavements. Cracking, riding, and rutting distresses in ACC pavements were impacted by temperature. Furthermore, the average annual temperature, freeze-thaw cycles, and precipitations affected distress in COM pavements. The PCC pavements were most sensitive to temperature, snowfall, and freeze-thaw cycles on the faulting index whereas the cracking index was affected by truck loadings and pavement age. The riding index in PCC pavements was mostly impacted by previous riding index values and pavement age.

ANN modeling of ACC pavements based on historical data that included structural characteristics, traffic, weather, and pavement age also provided clear evidence of the relationship between rutting and structural capacity. The model accurately estimated the correlation between structural performance using rutting data for ACC at the network level. Because conducting deflection tests to determine structural capacity is expensive and extensive experience and knowledge is required to deal with the resulting data, this research suggests that an ANN approach might be feasible for small transportation agencies (cities and counties) to assess the strength of asphalt pavements.

This research developed models that accurately predicted future pavement conditions, predictions that can support decisions for pavement maintenance activities and resource allocation in pavement management systems.

This research recommends to determine the impact of the changes in pavement deterioration resulting from weather data on the decision support tools used by Iowa DOT such as allocating available fund, and that the Iowa DOT would improve the pavement management system. Further, it is recommended that Iowa DOT consider adopting ANN pavement performance modeling that includes pavement condition and weather variables to support decisions at both the network and project management levels. Further research effort can also focused on calibrating the mechanistic empirical pavement design guide performance models based on the ANN results

This research had some limitations related to pavement distress data and climate data. Over 40% of the Iowa DOT pavement are composite and the cracking data did not address reflective cracking. Adding reflective cracking could help further refine the accuracy of the performance models.

Regarding weather data, in some cases, weather stations were 24 miles and that might not have been reflective of the local conditions.

REFERENCES

AASHTO. (1993). AAS*HTO guide for design of pavement structures*. 1993 (Vol. 1). AASHTO.

AASHTO. (2012). *Pavement management guide*. 2012. (2nd ed.). AASHTO.

Abdel-Khalek, A. M., M. A. Elseifi, K. Gaspard, Z. Zhang, & K. Dasari. (2012). Model to Estimate Pavement Structural Number at Network Level with Rolling Wheel Deflectometer Data. *Transportation Research Record: Journal of the Transportation Research Board*, (2304), 142-149.

Adeli, H. (2001). Neural networks in civil engineering: 1989–2000. *Computer-Aided Civil and Infrastructure Engineering*, *16*(2), 126-142.

Adkins, D. F., & V. T. Christiansen. (1989). Freeze-thaw deterioration of concrete pavements. *Journal of Materials in Civil Engineering*, *1*(2), 97-104.

Archilla, A. R., & S. Madanat. (2000). Development of a pavement rutting model from experimental data. Journal of Transportation engineering, *126*(4), 291-299.

ASCE. (2015). *Iowa infrastructure 2015 report card*. American Society of Civil Engineers.

Attoh-Okine, N. (1994). Predicting roughness progression in flexible pavements using artificial neural networks. *Transportation Research Board Conference Proceedings*, (Vol. 1, No. 1).

Attoh-Okine, N., & O. Adarkwa. (2013). *Pavement condition surveys—Overview of current practices*. Delaware Center for Transportation, University of Delaware: Newark, DE, USA.

Ayed, A. (2016). Development of empirical and mechanistic empirical performance models at project and network levels. (Doctoral thesis, University of Waterloo, Waterloo, Ontario, Canada). Retrieved from https://uwspace.uwaterloo.ca/handle/10012/10606.

Basheer, I. A., & M. Hajmeer. (2000). Artificial neural networks: Fundamentals, computing, design, and application. *Journal of Microbiological Methods*, *43*(1), 3-31.

Bektas, F., O. Smadi, & M. AL-Zoubi. (2014). *Pavement management performance modeling: Evaluating the existing PCI equations*. Iowa State University, Institute of Transportation.

Bektas, F., O. Smadi, & I. Nlenanya. (2015). Pavement condition: New approach for Iowa Department of Transportation. *Transportation Research Record: Journal of the Transportation Research Board*, (2523), 40-46. https://doi.org/10.3141/2523-05

Breakah, T., R. C. Williams, D. E. Herzamann, & E. S. Takle. (2010). Effects of using accurate climatic conditions for mechanistic-empirical pavement design. *Journal of Transportation Engineering*, *137*(1), 84-90.

BTS. (2012). U.S. Department of Transportation. 2012 Commodity Flow Survey, State Summaries. Bureau of Transportation Statistics (BTS).

Castell, M. A., A. R. Ingraffea, & L. H. Irwin. (2000). Fatigue crack growth in pavements. *Journal of Transportation Engineering*, *126*(4), 283-290.

Chandra, S., Sekhar, C. R., Bharti, A. K., & Kangadurai, B. (2012). Relationship between pavement roughness and distress parameters for Indian highways. *Journal of Transportation Engineering*, *139*(5), 467-475.

Chen, C., C. Williams, M. Marasinghe, J. Ashlock, O. Smadi, S. Scharm, & A. Buss. (2015). Assessment of composite pavement performance by survival analysis. J*ournal of Transportation Engineering*, 141(9), DOI: 10.1061/(ASCE)TE.1943-5436 .0000784.

Chen, D. H., & M. Won. (2007). Field investigations of cracking on concrete pavements. *Journal of Performance of Constructed Facilities*, *21*(6), 450-458.

Colorado DOT. (2004). *Colorado DOT distress manual for HMA and PCC pavements*. The National Center for Pavement Preservation.

Corley-Lay, J. (2014). Pavement performance measures: How states see good, fair, and poor. *Transportation Research Record: Journal of the Transportation Research Board*, (2431), 1-5.

Cottrel, W., H. Lee, J. Nepstad, & M. Crandall. (1996). Efforts toward developing a regional pavement management system in Utah. 48-57 *Transportation Research Record: Journal of the Transportation Research Board* (1524), 48-57.

Darter, M. (1980). Requirements for reliable predictive pavement models. *Transportation Research Record: Journal of the Transportation Research Board*, (766) 25-31.

Dillon, B. (2003). State of the art and practice of site pavement management systems: recommendations for Union Pacific's site pavement management system. (Masters Thesis, College of Engineering and Technology, Brigham Young University, Provo, UT.).

El-Basyouny, M., & M. Witczak. (2005). Part 2: Flexible pavements: Calibration of alligator fatigue cracking model for 2002 design guide. *Transportation Research Record: Journal of the Transportation Research Board*, (1919), 76-86.

Evangelista Jr, F., J. Roesler, & C. Duarte. (2012). Prediction of potential cracking failure modes in three-dimensional airfield rigid pavements with existing cracks and flaws. *Transportation Research Record: Journal of the Transportation Research Board*, (2266), 11-19.

Falls, L., R. Haas, S. McNeil, & S. Tighe. (2001). Asset management and pavement management: Using common elements to maximize overall benefits. *Transportation Research Record: Journal of the Transportation Research Board*, (1769), 1-9.

Felker, V., Y. M. Najjar, & M. Hossain. (2004). *Modeling the roughness progression on Kansas portland cement concrete (PCC) pavements* (No. K-TRAN:KSU-00-6). Kansas Department of Transportation.

Fischer, A. (2015). How to determine the unique contributions of input-variables to the nonlinear regression function of a multiplayer perception. *Ecological Modelling*, (309), 60-63.

Flintsch, G., K. K. McGhee, E. Izepp, & S. Najafi. (2012). *The little book of tire pavement friction*. Pavement Surface Properties Consortium.

Hicks, R. G., & J. Groeger. (2011). *Pavement management practices in state highway agencies: Newington, Connecticut peer exchange results*. Federal Highway Administration. FHWA-HIF-11-036.

Gencel, O., F. Kocabas, M. S. Gok, & F. Koksal. (2011). Comparison of artificial neural networks and general linear model approaches for the analysis of abrasive wear of concrete. *Construction and Building Materials*. *25*(8), 3486-3494.

George, K. P. (2000). *MDOT pavement management System: Prediction models and feedback system*. Mississippi Department of Transportation.

Golroo, A., & S. Tighe. 2012. Development of pervious concrete pavement performance models using expert opinion. *Journal of Transportation Engineering*, *138*(5), 634-648.

Golshani, N., R. Shabanpour, S. Mahmoudifard, S. Derriblr, & A. Mohammadian. (2017). Comparison of artificial neural networks and statistical copula-based joint models (No. 17-01202).

Haas, R., W. R. Hudson, & J. Zaniewaski. (1994). *Modern pavement management*. Malabar, FL: Krieger.

Hong, F., & J. A. Prozzi. (2006). Estimation of pavement performance deterioration using Bayesian approach. *Journal of infrastructure systems*, *12*(2), 77-86.

Huang, Y. H. (1993). *Pavement analysis and design* (2nd ed.). Pearson Education: Englewood Cliffs, NJ.

Hudson, W. R., R. Haas, & R. D. Pedigo. (1979). *Pavement management system development*. NCHRP report, (215).

Iowa DOT. (2006). Rolling wheel deflectometer (RWD) demonstration for the Iowa Department of Transportation (Iowa DOT). Champaign, IL: Applied Research Associates, Inc.

Iowa DOT. (2016). *2016 road use tax fund (RUTF) study*. Iowa Department of Transportation.

Islam, S., & W. G. Buttlar. (2012). Effect of pavement roughness on user costs. *Transportation Research Record: Journal of the Transportation Research Board*, (2285), 47–55.

Jack, J., & Y. Chou. (2001). Pavement performance analysis applying probabilistic deterioration methods. *Transportation Research Record: Journal of the Transportation Research Board*, (1769) 20-27.

Jeong, H. D., O. Smadi, & A. Abdelaty. (2016). *Historical performance evaluation of Iowa pavement treatments using data analytics*. Ames, IA: Midwest Transportation Center.

Johanneck, L., & L. Khazanovich. (2010). Comprehensive evaluation of effect of climate in mechanistic-empirical pavement design guide predictions. *Transportation Research Record: Journal of the Transportation Research Board*, (2170), 45-55.

Jung, Y. S., T. J. Freeman, & D. G. Zollinger. (2008). *Guidelines for routine maintenance of concrete pavement*. Texas Department of Transportation (No. FHWA/TX-08/0-5821-1).

Kargah-Ostadi, N. (2014). Comparison of machine learning techniques for developing performance prediction models. *Computing in Civil and Building Engineering (2014)*, 1222-1229.

Kargah-Ostadi, N., & S. M. Stoffels. (2015). Framework for development and comprehensive comparison of empirical pavement performance models. *Journal of Transportation Engineering*, *141*(8), DOI: 10.1061/(ASCE)TE.1943-5436.0000779.

Kargah-Ostadi, N., S. Stoffels, & N. Tabatabaee. (2010). Network-level pavement roughness prediction model for rehabilitation recommendations. *Transportation Research Board: Journal of the Transportation Research Board*, (2155), 124-133.

Karlaftis, M. G., & E. I. Vlahogianni. (2011). Statistical methods versus neural networks in transportation research: Differences, similarities and some insights. *Transportation Research Part C*: *19*(3), 387-399.

Kirbas, U., & M. Gursoy. (2010). Developing the basics of pavement management system in Besiktas district and evaluation of the selected sections. *Scientific Research and Essays*, *5*(8), 806-812.

Knapp, K. K., L. D. Smithson, & A. J. Khattak. (2000). The mobility and safety impacts of winter storm events in a freeway environment, In *Mid-continent Transportation Symposium 2000 proceedings*. Ames, IA.

Li, N., W.-C. Xie, & R. Haas. (1996). Reliability based processing of Markov chains for modeling pavement network deterioration. *Transportation Research Record: Journal of the Transportation Board*, (1524), 203-213.

Ling, M., X. Luo, S. Hu, F. Gu, & R. L. Lytton. (2017). Numerical modeling and artificial neural network for predicting J-integral of top-down cracking in asphalt concrete pavement. In *Transportation Research Board 96th Annual Meeting* (No. 17-05318).

Liu, L. (2013). A methodology for developing performance-related specifications for pavement preservation treatments. (Doctoral dissertation, Texas A&M University, College Station, TX).

Lou, Z., M. Gunaratne, J. J. Lu, & B. Dietrich. (2001). Application of neural network model to forecast short-term pavement crack condition: Florida case study. *Journal of Infrastructure Systems*, *7*(4)166-171.

Lytton, R. L. (1987). Concepts of pavement performance prediction and modeling. In Proc., *2nd North American Conference on Managing Pavements*. (Vol. 2).

Mbwana, J. (2001). A framework for developing stochastic multi-objective pavement management systems. In *First Road Transportation Technology Transfer Conference in Africa 2001* (pp. 350-363).

McNeil, S., M. Markow, L. Neumann, J. Ordway, & D. Uzarski. (1992). Emerging issues in transportation facilities management. *Journal of Transportation Engineering*, *118*(4), 477-495.

Meegoda, J. N., & S. Gao. (2014). Roughness progression model for asphalt pavements using long-term pavement performance data. *Journal of Transportation Engineering*, *140*(8), DOI: 10.1061/(ASCE)TE.1943-5436.0000682.

Mehta, A., H. Mehta, T. C. Manjunath, & C. Ardil. (2008). A multi-layer artificial neural network architecture design for load forecasting in power systems. *International Journal of Applied Mathematics and Computer Sciences*, *4*(4), 227-240.

Mezhoud, S., P. Clastres, H. Houari, & M. Belachia. (2016). Forensic Investigation of causes of premature longitudinal cracking in a newly constructed highway with a composite pavement system. *Journal of Performance of Constructed Facilities*, *31*(2), 04016095.

Miller, J. S., & W. Y. Bellinger. (2003). *Distress identification manual for the long-term pavement performance program*. (No. FHWA-RD-03-031).

Mills, L., N. Attoh-Okine, & S. McNeil. (2012). Developing pavement performance models for Delaware. *Transportation Research Record: Journal of the Transportation Research Board*, (2304), 97-103.

Mirzapour Mounes, S., Karim, M. R., Khodaii, A., & Almasi, M. H. (2014). Improving rutting resistance of pavement structures using geosynthetics: An overview. *The Scientific World Journal*, 2014.

Nunez, M. M., & M. Y. Shahin. (1986). Pavement condition data analysis and modeling. *Transportation Research Record: Journal of the Transportation Research Board*, (1070), 125-132.

Ohio DOT. (2006). *Pavement condition rating*. The Ohio Department of Transportation.

Olden, J. D., & D. A. Jackson. (2002). Illuminating the "black box": A randomization approach for understanding variable contributions in artificial neural networks. *Ecological modelling*, *154*(1), 135-150.

Papagiannakis, A., & B. Raveendran. (1998). International standards organization-compatible index for pavement roughness. *Transportation Research Record: Journal of the Transportation Research Board*, (1643), 110-115.

Pierce, L., G. McGovern, & K. Zimmerman. (2013). Practical Guide for Quality Management of Pavement Condition Data Collection. Federal Highway Administration.

Rada, G. R., S. Nazarian, B. A. Visintine, R. Siddharthan, & S. Thyagarajan. (2016). *Pavement structural evaluation at the network level* (No. FHWA-HRT-15-074).

Rafiq, M. Y., G. Bugmann, & D. J. Easterbrook. (2001). Neural Network Design for Engineering Applications. *Computers & Structures*, *79*(17), 1541-1552.

Rahman, A. A., & R. A. Tarefder. (2017, November). Dynamic modulus predictive model based on artificial neural network for the superpave asphalt mixtures of New Mexico. In *ASME 2017 International Mechanical Engineering Congress and Exposition* (pp. V014T11A046-V014T11A046). American Society of Mechanical Engineers

Rajagopal, A. (2006). *Developing pavement performance prediction models and decision trees for the city of Cincinnati* (No. FHWA/OH-2006/14).

Shahin, M. A., M. B. Jaksa, & H. R. Maier. (2008). State of the art of artificial neural network in geotechnical engineering. *Electronic Journal of Geotechnical Engineering*, 8, 1-26.

Shahin, M. Y. (2005). *Pavement management for airports, roads, and parking lots*. (Vol. 501). New York: Springer.

Shahnazari, H., M. A. Tutunchian, M. Mashayekhi, & A. A. Amini. (2012). Application of soft computing for prediction of pavement condition index. *Journal of Transportation Engineering*, *138*(12),1495-1506.

Shekharan, A. (1999). Assessment of relative contribution of input variables to pavement performance prediction by artificial neural networks. *Transportation Research Record: Journal of the Transportation Research Board*, (1655), 35-41.

Silva, F., T. Van Dam, W. Bulleit, & R. Ylitalo. (2000). Proposed pavement performance models for local government agencies in Michigan. *Transportation Research Record: Journal of the Transportation Research Board*, (1699), 81-86.

Smith, B. S. (2006). *Design and construction of pavements in cold regions: State of the practice*. PhD thesis, Brigham Young University, Provo, UT.

Smith, S. D. (1999). Earthmoving productivity estimation using linear regression techniques. *Journal of Construction Engineering and Management*, *125*(3), 133-141.

Smith, K. D., J. E. Bruinsma, M. J. Wade, K. Chatti, J. M. Vandenbossche, & H. T. Yu. (2017). *Using falling weight deflectometer data with mechanisitc-empirical design and analysis*, Volume I (No. FHWA-HRT-16-009).

Smith, K. L., L. Titus-Glover, & L.D. Evans. (2002). *Pavement smoothness index relationships* (No. FHWA-RD-02-057).

Sousa, S. I. V., F. G. Martins, M. C. M. Alvim-Ferraz, & M. C. Pereira. (2007). Multiple linear regression and artificial neural networks based on principal components to predict ozone concentrations. *Environmental Modelling and Software*, *22*(1), 97-103.

Sun, L. (2001). Developing spectrum-based models for international roughness index and present serviceability index. *Journal of Transportation Engineering*, *127*(6), 463-470.

TAC. (1999). *Highway asset management systems*. Transportation Association of Canda.

Texas DOT. (2015). *Pavement management information system rater's manual*. Texas Department of Transportation.

Thube, D. T. (2012). Artificial neural network (ANN) based pavement deterioration models for low volume roads in India. *International Journal of Pavement Research and Technology*, 5(2), 115-120.

Vines-Cavanaugh, D., S. Shamsabadi, Y. Zhao, G. Huang, S. Wadia-Fascetti, G. Schirner, R. Briken, & M. Wang. (2016). City-wide application of the affordable and rapid streetscan pavement-management system. *Journal of Infrastructure Systems*, *23*(2), DOI: 10.1061/(ASCE)IS.1943- 555X.0000333.

Vlahogianni, E. I., & M. G. Karlaftis. (2013). Testing and comparing neural network and statistical approaches for predicting transportation time series. *Transportation Research Record: Journal of the Transportation Research Board*, (2399), 9-22.

Xu, G., L Bai, Z. Sun, T. Nowaczyk, C. Shive, & J.Wilcoxson. (2015, May). Pavement Deterioration Prediction Model and Project Selection for Kentucky Highways. In *9th International Conference on Managing Pavement Assets*.

Wang, H., Q. Zhang, & J. Tan. (2009). Investigation of layer contributions to asphalt pavement rutting. *Journal of Materials in Civil Engineering*, *21*(4), 181-185.

Wang, K. C., & Q. Li (2011). Pavement smoothness prediction based on fuzzy and gray theories. *Computer-Aided Civil and Infrastructure Engineering*, *26*(1), 69-76.

Wen, H., & C. Chen. (2007). Factors affecting initial roughness of concrete pavement. *Journal of Performance of Constructed Facilities*, *21*(6), 459-464.

Wolters, A., & K. Zimmerman. (2010). Research of Current Practices in Pavement Performance Modeling. (No. FHWA-PA-2010-007-080307).

Wu, Z., F. Zhou, & S. Hu. (2014). Prediction of stress intensity factors in pavement cracking with neural networks based on semi-analytical FEA. *Expert Systems with Applications*, *41*(4), 1021-1030.

Yang, J., J. J. Lu, & M. Gunaratne. (2003). *Application of neural network models for forecasting of pavement crack index and pavement condition rating*. Report submitted to the Florida Department of Transportation.

Yang, X., Z. You, J. Hiller, & D. Watkins. (2017). Sensitivity of flexible pavement design to Michigan's climate inputs using pavement ME design. *International Journal of Pavement Engineering*, *18*(7), 622-632.

Zhang, G., B. E. Patuwo, & M. Y. Hu. (1998). Forecasting with artificial neural networks: The state of the art. *International Journal of Forecasting*, *14*(1), 35-62.

Zhou, L., F. Ni, & Y. Zhao. (2010). Evaluation method for transverse cracking in asphalt pavements on freeways. *Transportation Research Record: Journal of the Transportation Research Board*, (2153), 97-105.

Žiliūtė, L., Motiejūnas, A., Kleizienė, R., Gribulis, G., & Kravcovas, I. (2016). Temperature and moisture variation in pavement structures of the test road. *Transportation Research Procedia*, *14*, 778-786.

APPENDIX A. WEIGHT MATRICES

1. Weight matrix for calculating the relative contribution of each input variable in predicting riding index in asphalt pavements.

Parameter	H 1	H2	H 3	H 4	H 5	H 6	H 7	H 8	H 9	H 10
PrevIRI	0.16	0.02	1.23	-0.97	0.73	-0.56	0.70	-0.03	0.68	0.19
Age	-1.39	-1.51	0.07	-3.17	0.08	-1.56	1.71	-4.54	5.34	4.32
PAVTHICK	0.08	-2.95	0.00	-0.08	-0.17	0.19	-0.07	1.88	-0.53	-0.22
AVEK	0.31	0.51	0.03	-0.02	-0.01	0.21	-1.20	-0.47	-0.21	-0.30
avg_temp	0.55	5.29	0.21	-0.02	0.23	0.13	-7.88	8.01	0.43	0.30
tot_precip	-0.13	-2.43	-0.05	-0.21	0.15	-0.06	-0.88	-1.01	0.35	0.05
Output	11.66	-0.74	37.37	-7.46	-30.76	-20.21	-1.08	0.51	-10.59	-7.58

2. Weight matrix for calculating the relative contribution of each input variable in predicting cracking index in asphalt pavements.

Parameter	H 1	H 2	H 3	H 4	H 5	H 6	H 7	H 8	H 9	H 10	H 11	H 12
PrevCrack	-1.04	-0.37	-0.11	-0.24	0.68	-0.30	-0.50	0.29	0.10	0.32	-0.37	-0.48
Age	-0.10	-0.55	-0.17	-3.10	-0.01	2.11	0.55	-0.17	-0.94	1.85	-0.60	-3.13
avg_temp	-20.88	85.93	-24.97	-274.67	11.05	-85.65	-151.23	-160.10	55.47	274.14	105.63	-152.06
SN	0.00	0.22	-0.08	0.69	0.00	0.12	-0.31	-0.28	0.01	0.41	0.19	0.80
Output	36.01	16.12	59.67	-5.82	102.50	13.91	2.91	-13.70	19.75	-2.73	-19.08	6.83

3. Weight matrix for calculating the relative contribution of each input variable in predicting rutting index in asphalt pavements.

Parameter	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11	H12
PrevRut	-1.22	0.39	-0.53	1.31	1.78	-1.01	-1.14	-0.03	1.35	-0.82	-0.20	0.14
Age	-0.14	0.09	5.80	1.27	2.06	-2.59	-0.18	-0.60	-0.91	-2.14	-1.46	-4.04
PAVTHICK	-6.44	-0.53	0.69	-1.77	-3.97	2.15	0.20	-0.85	0.64	-6.79	0.63	-0.39
avg_temp	-9.93	1.45	17.61	2.82	-11.39	-1.63	-0.75	-7.14	-5.42	7.31	-15.14	-3.54
Output	2.71	-65.86	4.28	22.63	2.87	11.30	-82.32	-5.26	-9.90	1.89	2.18	7.95

4. Weight matrix for calculating the relative contribution of each input variable in predicting riding index in concrete pavements.

Parameter	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10
PreIRIIndex	-1.71	11.15	6.18	9.37	-5.12	15.75	-3.27	-15.41	-30.17	20.82
tot_precip	5.19	-0.49	2.19	-0.49	0.42	1.12	1.77	0.14	2.94	3.31
cycles	-0.44	0.10	2.23	-0.20	1.05	0.81	1.12	0.32	0.74	3.09
Age	-3.90	-0.94	-9.13	-2.73	-3.61	1.00	4.49	1.29	11.87	-10.44
Output	0.10	21.86	1.54	23.57	-8.97	13.11	6.46	-6.19	3.81	-2.78

5. Weight matrix for calculating the relative contribution of each input variable in predicting cracking index in concrete pavements.

Parameter	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10
PrevCrack	0.02	-0.06	0.08	-0.06	0.02	-0.04	-0.05	-0.03	0.04	-0.04
Age	-0.11	1.05	0.41	-0.20	-0.26	-0.29	-0.04	-0.05	0.04	-0.66
TRUCKS	0.47	0.11	-1.45	0.63	2.20	0.97	0.71	0.44	-0.68	0.33
PAVTHICK	-0.02	0.26	0.07	-0.12	0.11	-0.08	0.50	-0.51	-0.13	0.11
Output	47.55	-0.12	-2.06	-22.92	3.32	-6.42	-2.93	-3.10	16.31	-0.33

6. Weight matrix for calculating the relative contribution of each input variable in predicting cracking index in concrete pavements.

Parameter	H1	H2	H3	H4	H5	H6	H7	H8	H9
avg_temp	0.70	4.35	-1.63	-2.99	1.81	-0.44	-2.67	0.17	-1.77
tot_precip	-0.04	0.68	-0.44	-0.68	0.03	-0.09	-0.27	0.11	-0.12
tot_snow	0.00	2.25	-1.55	-2.04	1.10	0.37	-0.47	0.30	0.95
cycles	0.08	-1.16	0.54	1.08	-0.20	-0.08	0.58	0.02	-0.10
PrevFault	0.01	0.00	-0.05	-0.08	0.01	0.00	-0.01	0.00	0.00
Age	0.10	-0.32	-0.03	0.27	0.10	-0.03	0.30	0.05	-0.09
ADT	-0.06	-0.20	0.20	0.19	0.10	0.06	0.05	0.00	-0.08
Output	-12.11	-19.27	-0.20	-28.89	21.71	-47.67	-10.69	-19.44	15.55

7. Weight matrix for calculating the relative contribution of each input variable in predicting riding index in composite pavements.

Parameter	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11	H12
PrevIRI	-11.79	-1.52	-1.71	0.57	0.57	0.30	-3.28	4.06	-0.50	-0.20	-1.76	-1.63
Age	-6.62	-0.31	0.61	3.42	-1.07	0.84	0.71	1.74	0.44	-5.35	1.82	6.73
TPCCDPTH	0.15	0.04	2.20	0.01	-1.78	-0.08	-0.23	0.53	0.00	-0.60	0.07	-2.01
PAVTHICK	-0.41	0.09	-0.31	-1.40	-0.47	0.19	-1.10	-0.59	-0.35	-1.36	-0.73	0.35
AVEK	-0.54	0.01	-0.11	-1.14	-0.38	-0.44	0.17	-1.09	-0.21	-1.37	-0.57	-0.37
ADT	0.98	-0.01	0.28	0.34	0.26	-0.19	-0.02	0.44	0.17	2.40	0.32	0.18
tot_precip	0.50	0.02	-0.22	0.27	-0.16	-0.23	-0.36	0.40	0.07	0.57	0.21	0.21
avg_temp	2.62	-0.09	0.25	1.45	-4.63	0.72	0.88	4.33	0.40	0.93	0.49	-0.41
cycles	5.44	-0.27	1.52	3.77	-19.12	-14.62	1.24	0.41	1.16	-0.27	-0.34	1.18
Output	-1.01	-30.62	-8.29	1.65	-0.71	1.36	15.79	-16.58	-12.73	1.30	-16.15	-8.81

8. Weight matrix for calculating the relative contribution of each input variable in predicting cracking index in composite pavements.

Parameter	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10
PrevIndex	-107.27	0.24	-3.50	-2.10	4.12	-0.77	0.50	0.47	0.83	3.28
Age	-1.08	9.05	-1.09	6.29	1.04	0.00	6.31	-0.65	5.73	-3.90
TACCDPTH	-0.05	-2.00	0.99	-3.94	0.24	0.02	-3.29	-0.91	-0.68	-0.01
TPCCDPTH	-0.20	-0.23	2.45	-4.14	0.67	-0.05	-1.94	-0.50	-0.21	-0.76
AVEK	-0.19	0.82	0.24	0.15	0.06	-0.09	-0.51	-0.38	0.70	-2.80
TRUCKS	2.97	-2.54	0.67	1.66	-0.31	-0.05	-5.96	0.20	-1.40	0.53
tot_precip	0.33	3.91	0.46	1.61	0.43	-0.02	0.28	-0.67	0.32	9.04
avg_temp	-7.71	-23.09	-5.44	-35.12	-0.73	-0.03	6.55	-0.69	-27.46	25.15
Output	1.82	4.40	12.41	-1.58	7.56	-49.72	-2.99	14.16	-4.41	3.02

9. Weight matrix of calculating the relative contribution of each inputs in predicting rutting index in composite pavements.

Parameter	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10
PrevRut	-1.86	0.37	-0.54	0.86	0.67	0.23	1.61	0.42	-1.12	-0.43
Age	2.48	-0.59	-0.12	0.16	-1.67	-0.07	-0.18	-0.15	-0.19	-0.42
TPCCDPTH	0.08	-0.15	-0.49	-0.42	0.04	-0.09	-0.07	0.11	-0.02	0.43
PAVTHICK	-1.03	-0.06	0.45	-0.29	0.62	-0.57	-0.09	0.40	-0.05	-0.31
STRUCTNO	0.04	0.18	-0.50	0.24	-0.19	0.08	0.19	-0.03	0.01	1.21
AVEK	-2.56	0.15	-2.10	0.18	1.17	0.85	0.72	-1.20	-0.10	1.27
ADT	0.03	-0.37	-0.09	-0.54	0.29	0.54	0.41	-0.83	0.10	0.51
avg_temp	-0.52	-0.94	-2.61	-2.84	1.31	1.40	1.42	-2.32	0.13	-1.37
tot_precip	0.39	-0.48	-0.62	-0.48	-0.29	0.87	-0.27	0.36	0.07	-1.31
tot_snow	0.85	0.56	2.57	1.95	0.37	-5.71	-4.35	-1.35	-0.57	22.72
cycles	0.19	-4.04	5.83	1.49	0.39	-4.48	-1.76	12.81	-0.70	-3.57
Output	6.47	13.78	5.88	-10.04	11.04	11.27	-15.96	5.86	-46.79	2.73

APPENDIX B. MODEL OUTPUTS

Multiple linear regression model outputs of predicting pavement distress for asphalt, concrete, and composite pavements.

1. Multiple linear regression model results for predicting riding index in asphalt pavements.

Summary of Fit	
R Square	0.57
R Square adj.	0.57
RMSE	12.97
Mean of Response	65.98
Observations	6222

Parameters of Estimates				
Term	Estimate	Std Error	t Ratio	Prob > |t|
Intercept	52.03	3.69	14.08	<0.0001*
PrevIRI	0.56	0.01	60.29	<0.0001*
Age	-0.52	0.02	-29.33	<0.0001*
Pave. Thick	0.02	0.00	11.68	<0.0001*
AVEK	0.08	0.01	14.59	<0.0001*
Ave_temp	-0.54	0.07	-7.55	<0.0001*
Tot_precip	-0.09	0.02	-4.28	<0.0001*

2. Multiple linear regression model results for predicting cracking index in asphalt pavements.

Summary of Fit	
R Square	0.54
R Square adj.	0.54
RMSE	16.62
Mean of Response	77.85
Observations	8295

Parameters of Estimates				
Term	**Estimate**	**Std Error**	**t Ratio**	**Prob > |t|**
Intercept	7.49	4.48	1.67	0.0949
PrevCrack	0.69	0.00	85.90	<0.0001*
Age	-0.34	0.016	-20.74	<0.0001*
SN	-0.02	0.00	-6.87	<0.0001*
Ave_temp	0.54	0.09	6.25	<0.0001*
Tot_precip	-0.09	0.02	-3.94	<0.0001*
Tot_snow	-0.07	0.016	-4.48	<0.0001*

3. Multiple linear regression model results for predicting rutting index in asphalt pavements.

Summary of Fit	
R Square	0.41
R Square adj.	0.41
RMSE	12.10
Mean of Response	60.86
Observations	5505

Parameters of Estimates				
Term	**Estimate**	**Std Error**	**t Ratio**	**Prob > |t|**
Intercept	69.45	3.29	21.12	<0.0001*
PrevRut	0.49	0.01	54.94	<0.0001*
Age	-0.19	0.015	-12.68	<0.0001*
Pave. Thick	0.01	0.00	4.72	<0.0001*
Ave_temp	-0.92	0.07	-13.24	<0.0001*

4. Multiple linear regression model results for predicting riding index in concrete pavements.

Summary of Fit	
R Square	0.74
R Square adj.	0.74
RMSE	10.85
Mean of Response	35.44
Observations	835

Parameters of Estimates				
Term	**Estimate**	**Std Error**	**t Ratio**	**Prob > |t|**
Intercept	-13.6	3.47	-3.92	<0.0001*
PrevIRI	0.91	0.02	42.40	<0.0001*
Tot_precip.	0.18	0.06	3.06	<0.0001*
Cycles	0.09	0.03	3.13	<0.0001*
Age	-0.02	0.03	-0.78	0.44

5. Multiple linear regression model results for predicting cracking index in concrete pavements.

Summary of Fit	
R Square	0.49
R Square adj.	0.49
RMSE	15.39
Mean of Response	82.83
Observations	15298

Parameters of Estimates				
Term	**Estimate**	**Std Error**	**t Ratio**	**Prob > |t|**
Intercept	27.46	2.99	9.18	<0.0001*
PrevCrack	0.65	0.01	101.85	<0.0001*
Age	-0.20	0.01	-23.60	<0.0001*
Pave. Thick.	-0.005	0.00	-6.10	<0.0001*
Trucks	0.001	0.00	9.96	<0.0001*
Avg_Temp	0.14	0.06	2.39	<0.0001*
Tot_snow	-0.05	0.01	-4.84	<0.0001*

6. Multiple linear regression model results for predicting faulting index in concrete pavements.

Summary of Fit	
R Square	0.39
R Square adj.	0.38
RMSE	14.51
Mean of Response	67.78
Observations	571

Parameters of Estimates				
Term	**Estimate**	**Std Error**	**t Ratio**	**Prob > |t|**
Intercept	45.67	5.58	8.18	<0.0001*
PrevFault	0.39	0.03	13.05	<0.0001*
Age	-0.16	0.03	-4.47	<0.0001*
Pave. Thick.	0.046	0.01	4.33	<0.0001*
Tot_snow	0.13	0.05	2.58	<0.0001*
Cycles	-0.21	0.04	-5.20	<0.0001*

7. Multiple linear regression model results for predicting riding index in composite pavements.

Summary of Fit	
R Square	0.54
R Square adj.	0.54
RMSE	15.68
Mean of Response	56.04
Observations	12923

Parameters of Estimates				
Term	**Estimate**	**Std Error**	**t Ratio**	**Prob > |t|**
Intercept	42.16	3.20	13.17	<0.0001*
PrevIRI	0.48	0.01	76.84	<0.0001*
Age	-0.46	0.02	-27.42	<0.0001*
TPCCDPTH	-1.22	0.15	-8.24	<0.0001*
PaveThick	0.05	0.00	25.36	<0.0001*
AVEK	0.21	0.01	37.40	<0.0001*
ADT	-0.01	0.00	-8.73	<0.0001*
Avg_temp	-0.73	0.06	-12.44	<0.0001*
Tot_precip	-0.07	0.02	-3.71	0.0002
cycles	0.03	0.01	3.56	0.0004

8. Multiple linear regression model results for predicting cracking index in composite pavements.

Summary of Fit	
R Square	0.65
R Square adj.	0.65
RMSE	13.88
Mean of Response	75.98
Observations	13951

Parameters of Estimates				
Term	**Estimate**	**Std Error**	**t Ratio**	**Prob > |t|**
Intercept	-48.92	2.49	-19.66	<0.0001*
PrevCrack	0.99	0.00	140.21	<0.0001*
Age	0.18	0.01	-14.07	<0.0001*
TACCDPTH	-0.57	0.12	-4.74	<0.0001*
TPCCDEPTH	0.58	0.11	4.99	<0.0001*
AVEK	-0.01	0.00	-2.53	<0.0113
Tot_Precip.	0.08	0.01	5.32	<0.0001*
Avg_temp	0.78	0.05	15.38	<0.0001*

9. Multiple linear regression model results for predicting rutting index in composite pavements.

Summary of Fit	
R Square	0.44
R Square adj.	0.44
RMSE	12.57
Mean of Response	622.51
Observations	19326

Parameters of Estimates				
Term	**Estimate**	**Std Error**	**t Ratio**	**Prob > |t|**
Intercept	35.98	2.50	14.37	<0.0001[*]
PrevRUT	0.47	0.00	85.23	<0.0001[*]
Age	-0.39	0.01	-36.89	<0.0001[*]
TPCCDPTH	0.47	0.08	5.99	<0.0001[*]
TACCDPTH	-0.17	0.07	-2.25	<0.0243
Pav.Thick	-0.02	0.00	-15.06	<0.0001[*]
AVEK	0.02	0.00	14.89	<0.0001[*]
ADT	-0.01	0.00	-7.25	<0.00022
Avg_temp	-0.36	0.04	3.75	<0.0001[*]
Tot_precip.	0.09	0.01	-7.25	<0.0001[*]
Tot_snow	0.12	0.01	13.65	<0.0001[*]
Cycles	0.02	0.01	3.17	0.0015