OKLAHOMA TRANSPORTATION CENTER

ECONOMIC ENHANCEMENT THROUGH INFRASTRUCTURE STEWARDSHIP

CALIBRATION OF CONTROLLING INPUT MODELS FOR PAVEMENT MANAGEMENT SYSTEM

M. PHIL LEWIS, PH.D., P.E.
DAVID H. JEONG, PH.D.
HOSSEIN KHALEGHIAN, PH.D. STUDENT

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Oklahoma Transportation Center
2601 Liberty Parkway, Suite 110
Midwest City, Oklahoma 73110

Phone: 405.732.6580
Fax: 405.732.6586
www.oktc.org

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<tr><td colspan="4">16. ABSTRACT
The Oklahoma Department of Transportation (ODOT) is currently using the Deighton Total Infrastructure Management System (dTIMS™) software for pavement management. This system is based on several input models which are computational backbones to develop maintenance and rehabilitation plans for pavements. Some of the major input models include the classification of pavement families, deterioration curves, and effectiveness of various treatment options. These major input models are currently in active use without any thorough validation using actual pavement condition assessment data.

Validation and calibration of existing input models for pavement management systems (PMS) has been one of the major technical goals by the pavement management unit of ODOT for many years. ODOT now has about 16 years of pavement condition assessment data, which provides a rich time series dataset. This research project will use the proven Knowledge Discovery in Database (KDD) approach to investigate pavement condition assessment data in a structured manner in order to evaluate the performance of current input models and if necessary, develop new models or calibrate the existing models for more accurate and reliable planning for pavement maintenance and rehabilitation activities. The performance of newly developed or calibrated input models will be compared with the performance of current input models.

The successful completion of this research project meets the immediate technical need of the pavement management unit. The data driven models developed in this project provides confidence to the pavement management team in developing short-term and long-term pavement management strategies and realistic pavement budget estimation and allocation. One of the primary outputs of this research project is a spreadsheet-based tool that assists pavement management engineers in updating the input models in the current PMS; thus, the output of this project will be immediately available to ODOT. The results of this project will also be able to answer skeptical questions about the returns on continuous pavement data collection investments of ODOT.</td></tr>
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SI (METRIC) CONVERSION FACTORS

Approximate Conversions to SI Units

Symbol	When you know	Multiply by	To Find	Symbol
		LENGTH		
in	inches	25.40	millimeters	mm
ft	feet	0.3048	meters	m
yd	yards	0.9144	meters	m
mi	miles	1.609	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm
ft^2	square feet	0.0929	square meters	m^2
yd^2	square yards	0.8361	square meters	m^2
ac	acres	0.4047	hectares	ha
mi^2	square miles	2.590	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.0283	cubic meters	m^3
yd^3	cubic yards	0.7645	cubic meters	m^3
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.4536	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams	Mg
		TEMPERATURE (exact)		
°F	degrees Fahrenheit	(°F-32)/1.8	degrees Celsius	°C
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.448	Newtons	N
lbf/in^2	poundforce per square inch	6.895	kilopascals	kPa

Approximate Conversions from SI Units

Symbol	When you know	Multiply by	To Find	Symbol
		LENGTH		
mm	millimeters	0.0394	inches	in
m	meters	3.281	feet	ft
m	meters	1.094	yards	yd
km	kilometers	0.6214	miles	mi
		AREA		
mm^2	square millimeters	0.00155	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.196	square yards	yd^2
ha	hectares	2.471	acres	ac
km^2	square kilometers	0.3861	square miles	mi^2
		VOLUME		
mL	milliliters	0.0338	fluid ounces	fl oz
L	liters	0.2642	gallons	gal
m^3	cubic meters	35.315	cubic feet	ft^3
m^3	cubic meters	1.308	cubic yards	yd^3
		MASS		
g	grams	0.0353	ounces	oz
kg	kilograms	2.205	pounds	lb
Mg	megagrams	1.1023	short tons (2000 lb)	T
		TEMPERATURE (exact)		
°C	degrees Celsius	9/5+32	degrees Fahrenheit	°F
		FORCE and PRESSURE or STRESS		
N	Newtons	0.2248	poundforce	lbf
kPa	kilopascals	0.1450	poundforce per square inch	lbf/in^2

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The authors would like to thank Mr. Matthew Swift and Mr. William Dickinson of the Oklahoma Department of Transportation (ODOT) Planning and Research Division for providing the data and access to the necessary ODOT databases that were needed to complete this research project.

CALIBRATION OF CONTROLLING INPUT MODELS FOR PAVEMENT MANAGEMENT SYSTEM

Final Report
July 31, 2013

M. Phil Lewis, Ph.D., P.E.
Assistant Professor
School of Civil and Environmental Engineering
Oklahoma State University
Stillwater, OK

David H. Jeong, Ph.D.
Associate Professor
Department of Civil, Construction, and Environmental Engineering
Iowa State University
Ames, IA

and

Hossein Khaleghian
Ph.D. Student
School of Civil and Environmental Engineering
Oklahoma State University
Stillwater, OK

Oklahoma Transportation Center
(Fiscal) 201 ATRC, Stillwater, OK 74078
(Technical) 2601 Liberty Parkway, Suite 110
Midwest City, OK 73110

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EXECUTIVE SUMMARY

The Oklahoma Department of Transportation (ODOT) is currently using the Deighton Total Infrastructure Management System (dTIMS™) software for pavement management. This system is based on several input models which are computational backbones to develop maintenance and rehabilitation plans for pavements. Some of the major input models include the classification of pavement families, deterioration curves, and effectiveness of various treatment options. These major input models are currently in active use without any thorough validation using actual pavement condition assessment data.

Validation and calibration of existing input models for pavement management systems (PMS) has been one of the major technical goals by the pavement management unit of ODOT for many years. ODOT now has about 16 years of pavement condition assessment data, which provides a rich time series dataset. This research project used the proven Knowledge Discovery in Database (KDD) approach to investigate pavement condition assessment data in a structured manner in order to evaluate the performance of current input models and develop new models for more accurate and reliable planning for pavement maintenance and rehabilitation activities. The performance of the newly developed input models were compared with the performance of current input models.

The successful completion of this research project meets the immediate technical need of the pavement management unit. Over 600 data driven models were developed in this project, which will provide confidence to the pavement management team in developing short-term and long-term pavement management strategies. The newly developed models were quantitatively similar with respect to precision but typically outperformed the current ODOT models with respect to accuracy and bias. One of the primary outputs of this research project is a spreadsheet-based tool that summarizes the newly developed models in a sortable format related to highway section, location, pavement family, and pavement index. This tool will assist pavement management engineers in updating the input models in the current PMS. The results of this project will also help to answer skeptical questions about the returns on continuous pavement data collection investments.

1.0 INTRODUCTION

The American Society of Civil Engineers (ASCE) estimates that $3.6 trillion is needed by 2020 to bring the nation's infrastructure to good condition (ASCE 2013a). Among the infrastructure systems that need capital investments, roads have been graded with a failure grade D. Pavement condition data for Oklahoma is also alarming – an estimated 70% of roads in the state are in poor or mediocre condition (ASCE 2013b). Driving on roads in need of repair costs Oklahoma motorists $978 million a year in extra vehicle repairs and operating costs – $425 per motorist. As the need for pavement rehabilitation is significantly growing, the importance of effective Pavement Management Systems (PMS) has also considerably increased.

A PMS is a systematic process that provides, analyzes, and summarizes pavement information for use in selecting and implementing cost-effective treatment strategies for a pavement network. The main goal of pavement management is to maintain pavements in good condition for the longest time at the lowest possible total cost (ODOT 2009). ODOT is currently using the Deighton Total Infrastructure Management System (dTIMS™) software for pavement management. This system operates based on several input models which are computational backbones to develop maintenance and rehabilitation plans for pavements including:

1) Classification of pavement families;
2) Deterioration curves; and
3) Effectiveness of various treatment options.

Currently, the Oklahoma Department of Transportation (ODOT) classifies pavement families based on the *ODOT Pavement Management Policy and Procedures Manual* developed in 2005. Current deterioration curves are regression models developed with a significantly limited number of data points developed by Applied Pavement Technologies, Inc. (APTech) in 2001. The effectiveness of various treatment options currently relies on engineering judgment and experience of pavement management engineers. These major input models are currently in active use without any thorough validation using actual pavement condition assessment data. Validation and calibration of existing input models for PMS has been one of the major technical goals by the pavement management unit of ODOT for many years.

1.1. Background

ODOT began its efforts to collect pavement condition data in 1994 as part of the PMS development. However, PMS development during the late 1980s and early 1990s was not successful because of the discontinuation of ODOT's maintenance contract for the PMS software, which created many technical problems. Because of this, a system-wide analysis was never performed. A new effort began in 2001 to establish a working PMS and since then, ODOT has been using dTIMS™ software as the main PMS. The dTIMS™ software determines short term and long term pavement management plans based upon several input models that are provided by the pavement management team.

Pavement management plans are typically developed for each pavement family. A pavement family is defined as a group of similar pavement sections that are expected to perform similarly and thus share a common performance or deterioration curve. The current ODOT classification of fourteen different pavement families is based on pavement type, traffic volume, and presence of "D" cracking (for JCP only) as shown in Table 1.1 (ODOT 2005).

Table 1.1 ODOT Pavement Family Classifications

ASPHALT PAVEMENTS	CONCRETE PAVEMENTS	COMPOSITE PAVEMENTS
1) AC Low Volume – AC with less than 2,000 AADT 2) AC Moderate Volume – AC with 2,000 – 10,000 AADT 3) AC High Volume – AC with 10,000 – 40,000 AADT 4) AC Very High Volume – AC with over 40,000 AADT	5) CRCP Low volume – CRCP with less than 10,000 AADT 6) CRCP High volume – CRCP with over 10,000 AADT 7) DJCP – Dowel Jointed Concrete Pavement 8) DMJCP – Mesh Dowel Jointed Concrete Pavement 9) Jointed Plain Concrete Pavement (JPCP) Low Volume – JPCP with less than 10,000 AADT 10) JPCP High Volume – with over 10,000 AADT 11) JPCP "D" – D cracked JPCP	12) Composite Low Volume – AC over PC with less than 10,000 AADT 13) Composite Moderate Volume – with 2,000-10,000 AADT 14) Composite High Volume – with 10,000 AADT

Deterioration curves are used to mimic the aging mechanism of pavements given a set of affecting parameters or attributes. Deterioration curves for each pavement family are one of the most important input models for PMS because the estimated aging pattern determines the timing of next treatment and provides the basis for pavement project budget estimation and allocations. The current deterioration curves used by ODOT were developed by APTech as part of the development of PMS (APTech 2002). For each type of pavement family, simple regression models were developed to predict the performance of the pavement type; however, the prediction models were developed with a very limited amount of data collected in 2001. The maximum sample size was 384 and the minimum size was 28. Consequently, the R^2 values of each prediction model are extremely low as can be seen in Table 1.2. These statistically imprecise deterioration curves have been continuously used in developing pavement management strategies and determining pavement investment plans for ODOT since 2002. In addition, the effectiveness of various treatment options as a function of extended life of pavement and required costs is also a very important parameter for developing optimal pavement rehabilitation plans; however, it has mostly been based on subjective decisions by pavement management engineers.

Table 1.2 Examples of Current ODOT Deterioration Curves

Pavement Type	Performance Index	Prediction Model	Median R^2 for 50th Percentile Curve	R^2 for Expert Curve
Asphalt, Hi Volume, Flexible	Ride	Ride = 100 – 0.214*Age-0.197*Age^2	0.377	0.192
Asphalt, Hi Volume, Flexible	Structural	Structural = 100-0.250*Age^2	0.033	0.193
Composite, Hi Volume	Rut	Rut=100-0.659*Age-0.134*Age^2	0.281	0.900
Plain, Hi Volume, No D Cracking	Ride	Ride = 100-3.116*Age-0.017*Age^2	0.183	0.835
Continuously Reinforced Concrete Pavement	Ride	Ride = 100-1.809*Age-0.004*Age^2	0.724	0.242

Currently, ODOT is collecting pavement conditions on the entire state highway system over a two-year cycle. Every year, half of the roadway conditions are collected. The major pavement condition data items collected are:

1) Sensor data;
2) Distress data;
3) Geometrics; and
4) Miscellaneous items.

The collected distress data are categorized in accordance with the ODOT pavement management distress-rating guide (ODOT 2005). Now with 16 years of pavement condition assessment data available, ODOT is ready to perform a full scale analysis to validate these controlling input models for PMS and, if necessary, develop new models or calibrate the current models for better pavement management.

1.2. Research Objectives

The successful completion of this research project meets the immediate technical need of the pavement management unit of having effective input models for their PMS. The data driven models developed in this project will provide confidence to the pavement management team in developing short-term and long-term pavement management strategies and realistic pavement budget estimation and allocation. The goal of this research project is to assess the performance of current input models for PMS. In order to achieve the overall goal, the following objectives must be accomplished:

1) Evaluate the current classification system of pavements;
2) Evaluate the performance of deterioration curves for different types of pavements;
3) Assess the effectiveness of various treatment options; and
4) Develop a decision support tool to help pavement management engineers.

2.0 LITERATURE REVIEW

A successful pavement management system requires an accurate pavement performance prediction model (Li *et al*. 2010). The roles of the model are to estimate future pavement conditions; identify the appropriate timing for pavement maintenance and rehabilitation actions; identify the most cost-effective treatment strategy for pavements in the network; estimate statewide pavement needs required to address agency-specified goals, objectives, and constraints; and demonstrate the consequences of different pavement investment strategies (APTech 2010). Many state departments of transportation (DOT) have undergone the development of pavement performance models, or are in the process of doing so.

Although the importance of the models in pavement management systems (PMS) have long been known, it has not always been easy to develop quality pavement performance models. For quality models, historical data is required but there is not always a reasonable approach to collect and save the necessary pavement data; thus, early models were developed based on a small number of sample data points, expert’s experience, or perhaps another state’s data. Even then, these models did not have a self-verification process.

Various efforts to evaluate and calibrate current pavement performance models began using historical databases. Li *et al.* (2010) tried to evaluate deterioration models based on the Mechanistic-Empirical Pavement Design Guide (MEPDG) incremental damage approach and the current Washington State Pavement Management System exponential models based on regression and a piecewise approach. The results showed that this approach was able to estimate accurately the year in which rehabilitation would be due and to predict performance trends. Ferreira *et al.* (2011) reviewed and compared various international pavement performance models including Highway Development and Management System, American Association of State Highway and Transportation Officials, Nevada Pavement Management System (PMS), Collop-Cebon whole-life pavement performance, Swedish PMS, and Spanish PMS. Bianchini and Bandini (2010) developed neuro-fuzzy reasoning models to predict and assess pavement performance. The results from this hybrid model were compared to results of multiple linear regression models (MLR). Chen and Zhang (2011) tried to compare studies about IRI-based pavement deterioration prediction models, which include the NCHRP model, Al-Omari-Darter model, Dubai model, and the New Mexico DOT model using the NMDOT's database. These studies also show that current models need to be revised using historical datasets when available.

When considering the development of pavement performance models for a pavement network, an agency may need to consider the types of model that are needed. Depending on the amount of data available for model development, as well as any recognized patterns in the data, the models may be classified as either an individual section or family based model, or as a deterministic, probabilistic, or expert/knowledge based model as shown in Figure 2.1.

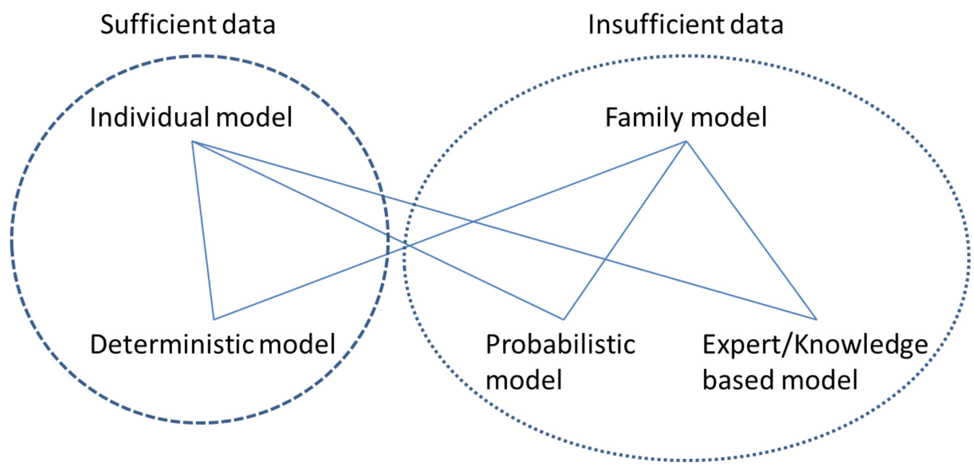


Figure 2.1 Types of Performance Models and Their Relationships

An individual model is based on the use of historical data from a particular pavement section. Individual models require a minimum of two data points to create a linear deterioration model but most agencies will not use an individual model unless they have three-to-five data points that show a reasonable deterioration trend; thus, at least three years of data is required. When insufficient data exist for an individual pavement section to allow it to be modeled based upon its own performance, its condition data can be combined with data from other pavement sections that have similar performance characteristics to develop a model. The resulting grouping is called a pavement family, which is defined in pavement management systems as a group of similar pavement sections that are expected to perform in a similar manner. A pavement family might be a group of pavements with the same surface type, underlying pavement layers, and traffic levels. Once the model type is determined as either individual or family, the performance model may be developed in terms of data patterns. Most deterministic pavement performance models are based on regression analysis, which uses two or more variables in a mathematical equation to predict the dependent variable (performance measure such as pavement index) as a function of the independent variables.

Deterministic models most often predict a single dependent value, such as the condition of a pavement, from one or more independent variables, such as the age of the pavement, past cumulative traffic, environment, and pavement construction characteristics. The simplest regression form is linear. The general form of the equation is shown in equation 1. In a linear regression model, the behavior of the independent variable is used to explain the behavior of a dependent variable.

$$y = b_0 + b_1 x \qquad \text{Equation 1}$$

where:

y = dependent variable

x = independent variable

b_0 and b_1 = coefficients

Oftentimes, deterioration curves are based on nonlinear regression equations. Higher order (polynomial) regressions yield curvilinear relationships between the independent and dependent variable and are represented by equation 2.

$$y = b_0 + b_1 x + ... + b_n x^n \qquad \text{Equation 2}$$

where:

y = dependent variable

x = independent variable

b_0, b_1 …b_n = coefficients

The primary difference between these two regression methods is the increased complexity of the form of the equation that the multiple variable regression models can have and the fact that the coefficients are no longer linear. Another nonlinear deterministic equation form used for pavement management is a power function. An example of the power form of the equation is shown in equation 3. Figure 2.2 shows the forms between the three types of regression models.

$$y = b_0 - b_1 x_1^{b_2}$$ Equation 3

where:

y = dependent variable

x_1 = independent variable

b_0, b_1, and b_2 = coefficients

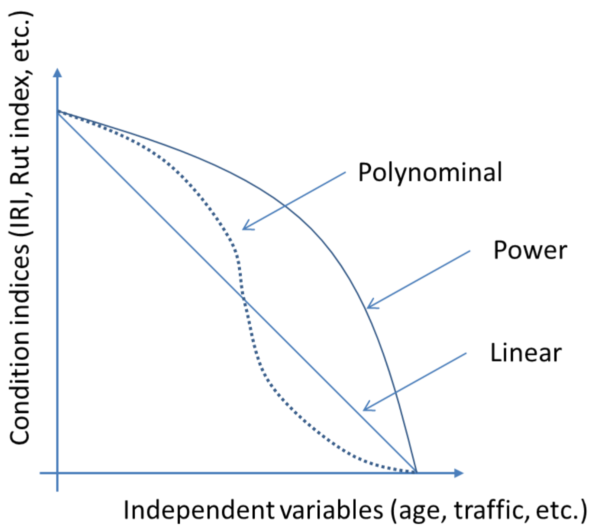


Figure 2.2 Three Types of Regression Models

In addition to the development of regression equations created from a single variable, some agencies consider the use of multiple variables. In a multiple regression model, the behaviors of several independent variables are used to estimate the performance of a dependent variable. The general form of the equation, which is an expanded version of the linear least-squared regression equation, is shown in equation 4.

$$y = b_0 + b_1 x_1 + b_2 x_2 + ... + b_n x_n$$ Equation 4

where:

y = dependent variable

$x_1, x_2, \ldots x_n$ = independent variables

$b_0, b_1, b_2, \ldots b_n$ = coefficients

The use of multiple variables (rather than a single variable) has the potential of better estimating the performance of an individual pavement section because of the number of variables specific to the section. If a single variable such as age is used, two sections from the same family will have the identical predicted performance if they have the same starting condition.

Another type of model, known as an expert or knowledge-based model, is developed based on the collective experience and knowledge of agency personnel. Expert models are typically used when historical data are not available, when there are gaps in the data, or when a new design is being used. Many agencies use expert models when they are first implementing a pavement management system or when they modify their approach to collecting pavement condition information.

ODOT first began its current pavement management efforts in 2000 when it was mandated by their legislature to implement a pavement management system. They quickly moved forward with the creation of the pavement management system (prior to any data collection and subsequent performance model development) and created performance curves based upon expert opinion. The original expert equations, which were developed based upon a family modeling approach for various individual indices, were utilized for the initial pavement management analysis. When the pavement condition data had been collected from around the state, the pavement performance models were updated to see how they compared to the expert curves.

The modeling approach using actual pavement condition data utilized the least squares curve fitting approach from a regression analysis to produce pavement performance models. A total of four functional modeling forms were evaluated: linear, cubic, quadratic, and the power model. For each model form, 25th, 50th, and 75th quartile curves are also defined to provide a more complete evaluation of the datasets. The three quartiles are defined as follows:

- The first quartile, the 25th quartile, is the median of all the values to the left of the median position for the whole set of data.
- The second quartile, the 50th quartile, is the median.
- The third quartile, the 75th quartile, is the median of all the values to the right of the median position for the whole data set.

A comparison example of the expert curve to the percentile curves is shown in Figure 2.3. The use of actual data resulted in performance curves that predicted significantly better performance compared to the expert curve.

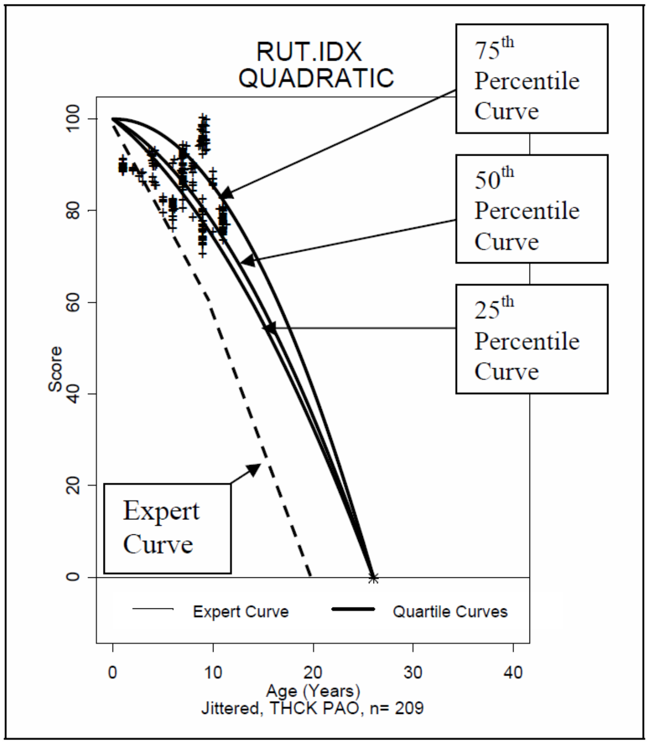


Figure 2.3 Comparison of Expert and Percentile Performance Curves

Currently, ODOT uses deterministic family performance models that are focused on predicting the index as a function of age. The performance models were created for a given pavement family by plotting the condition of the sections versus the age of each corresponding section. Regression techniques were then applied to predict the behavior of the condition index based on the age of the pavement. Tables 2.1 – 2.7 show all deterioration curves based on pavement families and each performance indices used in ODOT. These models are a part of dTIMS, the pavement management software used in ODOT.

The individual indices are then weighted and combined to form an overall indicator of the condition of each section called the Pavement Quality Index (PQI). The PQI is used in the ODOT PMS to measure the benefits of each treatment strategy. The weighting given each PQI component is intended to reflect the primary distresses found in each pavement type in Oklahoma. The weightings given each index in the PQI are as follows:

(1) AC PQI = 40%Ride + 30%Rut + 15%Functional + 15%Structural

(2) Composite PQI = 40% Ride + 15% Rut + 30% Functional +15% Structural

(3) JPCP (no D-cracking) PQI = 40% Ride + 30% Fault + 10% Joint + 20% Slab

(4) JPCP (with D-cranking) PQI = 40% Ride + 10% Fault + 40% Joint + 10% Slab

(5) DMJCP and DJCP PQI = 40% Ride + 10% Fault + 40% Joint + 10% Slab

(6) CRCP PQI = 40% Ride + 60% Structural

Table 2.1 Performance Models Currently Used in ODOT for AC

	AADT 40K – 70K	AADT 10K – 40K	AADT 0 – 10K
Ride	100-0.05(age)^2	100-0.05(age)^2	100-0.05(age)^2
Rut	100-2.0(age)	100-1.7(age)	100-1.3(age)
Functional	100-2.0(age)	100-2.0(age)	100-2.0(age)
Structural	100-0.06(age)^2	100-0.06(age)^2	100-0.04(age)^2

Table 2.2 Performance Models Currently Used in ODOT for COM

	AADT 10K – 70K	AADT 0 – 10K
Ride	100-0.08(age)^2	100-0.1(age)^2
Rut	100-1.7(age)	100-1.7(age)
Functional	100-2.3(age)	100-2.7(age)
Structural	100-0.05(age)^2	100-0.05(age)^2

Table 2.3 Performance Models Currently Used in ODOT for JPCP

	All AADT (0 – 70K)
Ride	100-0.08(age)^2
Fault	100-0.05(age)^2
Joint	100-0.03(age)^2
Slab	100-0.04(age)^2

Table 2.4 Performance Models Currently Used in ODOT for D-cracked JPCP

	All AADT (0 -70K)
Ride	100-0.08(age)^2
Fault	100-0.05(age)^2
Joint	100-0.0625(age)^2
Slab	100-0.04(age)^2

Table 2.5 Performance Models Currently Used in ODOT for DMJCP

	All AADT (0 – 70K)
Ride	100-0.024(age)^2
Fault	100-0.018(age)^2
Joint	100-0.05(age)^2
Slab	100-0.04(age)^2

Table 2.6 Performance Models Currently Used in ODOT for DJCP

	All AADT (0 –70K)
Ride	100-0.2(age)^2
Fault	100-0.018(age)^2
Joint	100-0.024(age)^2
Slab	100-0.028(age)^2

Table 2.7 Performance Models Currently Used in ODOT for CRCP

	All AADT (0 – 70K)
Ride	100-0.015(age)^2
Structural	100-0.028(age)^2

The first models developed by ODOT in 2000 did not reflect the pavement conditions of Oklahoma as a whole. Over the years, the models have been revised by engineers, but there is no evaluation based on historical databases. Individual sections-based models should be developed because ODOT now has sufficient data to develop such models. Current conditions differ greatly from the conditions used in the previous models. Furthermore, the origins of the family-based models come from insufficient datasets. These models might also show an identical result even if the real performance has different highway sections. The performance of each index developed in this research will be compared to the current family based index. From the comparative study, the research team can recommend better solution to ODOT engineers.

3.0 METHODOLOGY

In order to collect the data necessary to complete this study, the research team met with ODOT pavement management engineers. During the meetings, it was realized that no single dataset would fit the requirements of this study; therefore, four datasets were obtained from the Pavement Management Branch and were combined together to form a final dataset with a unique structure. The datasets that were used for the purpose of developing the final dataset for analysis were *Pavement Condition Assessment*, *Pavement Layers*, *Interstate Highway Structural Pavement History*, and *Annual Average Daily Traffic (AADT)*.

The *Pavement Condition Assessment* dataset includes data for approximately 16 years. ODOT began its efforts to collect pavement condition data in 1994 as part of the PMS development; however, PMS development during the late 1980s and early 1990s was not successful because of the discontinuation of ODOT's maintenance contract for the PMS software, which created many technical problems. A new effort began in 2001 to establish a working PMS and since then, ODOT has used dTIMS™ software as the main PMS. Currently, ODOT is collecting pavement conditions on the entire state highway system over a two-year cycle. Every year, half of the roadway conditions are collected. ODOT's Pavement Condition Indices were calculated from 2001 since Ride was the only index that could be obtained from previous collected data. *Pavement Condition Assessment* data is collected for 0.01 mile for all roads in Oklahoma. Since this dataset includes 1,506,726 rows of data, it was not practical for ODOT to calculate Pavement Condition Indices for all rows; thus, all the indices were calculated for 0.1 mile.

To assess the effects of the treatment history on pavement conditions, historical *Pavement Layers* data were collected for 0.1 mile. This dataset was used with the *Interstate Highway Structural Pavement History* to obtain accurate pavement layers history. In some cases, *Pavement Layers* data was not reliable due to systematic errors in the data collection process; thus, there were significant numbers of missing treatment activities. Therefore, the *Interstate Highway Structural Pavement History* dataset was used because it is regularly checked by the ODOT pavement management branch and field division engineers. Furthermore, ODOT prepared a new AADT record for increments of 0.1 mile based on the *Annual Average Daily Traffic* dataset. As a result, a new dataset was created by the research team that provided reliable pavement condition assessment, pavement layers, structural pavement history, and AADT data for the entire length of Interstate Highways of Oklahoma at 0.1 mile increments, including I-35, I-40, I-44, I-235, I-240, I-244, and I-444. Thus, this study was limited to interstate highways because pavement layering information was either unavailable or deemed invalid due to systematic errors in the data collection process. The new dataset was used as the basis of the analyses performed in order to complete the primary objectives of this study. Figure 3.1 shows the how the ODOT datasets were used for the construction of the final dataset.

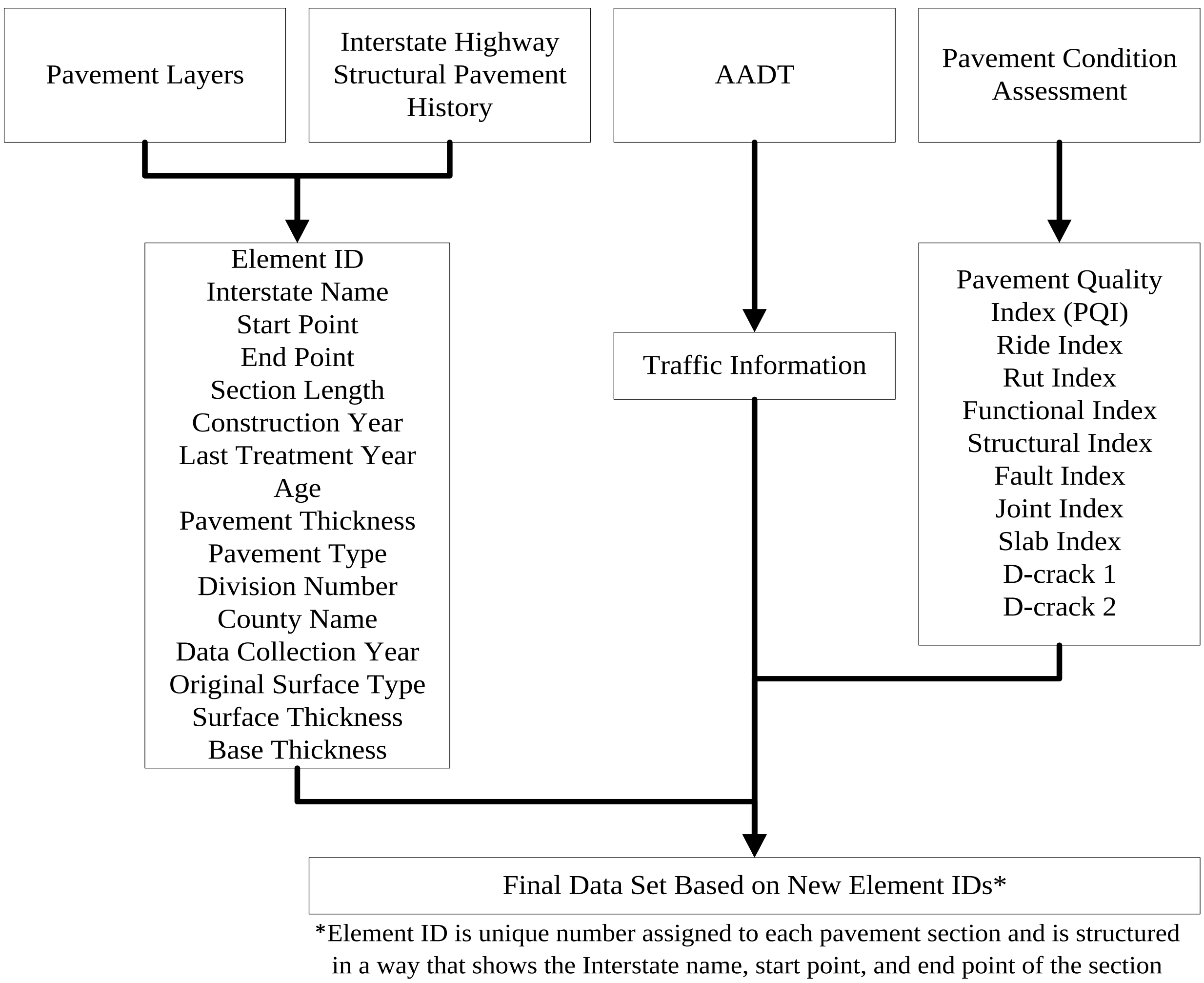


Figure 3.1 Construction of Final Dataset

The new dataset consists of homogeneous and continuous pavement sections with the same original construction year, treatment history, and structural layers. For instance, I-35 consists of 95 pavement sections for five data collection years, which results in 475 rows. There are 27 attributes in each data collection year. This information was used to develop the data for all the pavement sections in the final data set for all the data collection years separately including 2001, 2004, 2006, 2008, and 2010.

There were instances in which the pavement condition indices appeared to be invalid. In these situations the pavement sections were checked across other datasets to ensure the input values were accurate. For example, for asphalt pavement sections there should be no fault, joint, and slab indices. Typically, “-1” is placed in those locations where the data is non-existent; however, in some cases, asphalt pavement sections had values for fault, joint, and slab indices instead of “-1”. In these cases, the rows of invalid data were eliminated.

This research project used the proven Knowledge Discovery in Database (KDD) approach in data cleaning, data filtering, pattern extraction and prediction (Soibelman and Kim 2002). Using the KDD approach, the research team investigated pavement condition assessment data, maintenance and rehabilitation project records, and other pavement related data in a structured manner in order to evaluate the performance of current input models and, if necessary, develop new models or calibrate the existing models for more accurate and reliable planning for pavement maintenance and rehabilitation projects.

The KDD approach has mostly been used by data analysts and the management information system (MIS) communities. Even though this new data analysis process has not been actively employed in the engineering disciplines, the concept of finding hidden patterns from data is not new because many statistical analysis tools have been actively used to solve problems in the engineering domain. Typical statistical analyses start with an establishment of a hypothesis, then collect and analyze data to accept or annul the hypothesis. However, KDD starts with available data and then uses the data to solve a problem by selecting and using the most appropriate statistical or artificial intelligence-based prediction models. KDD is not a simple modeling and prediction process but is a framework for the whole problem solving process. It is a combination of many algorithms that is chosen based on available data and the problem.

A typical KDD approach involves five distinct but integrated stages as shown in Figure 3.2. In the problem understanding and data understanding stages, a clear and specific problem is defined. The data preparation phase covers all activities to construct the final dataset, which is then fed into the modeling tools from the initial raw data. This phase is a critical stage because performance of the developed models is highly dependent upon the quality of input data. In this stage, the collected data go through a data cleaning process to identify any possible mistakes or irregularity in the data and eliminate any outliers. The cleaned dataset then goes through the data construction stage in which the dataset is clustered. The key issue in the data construction stage is to discover the true dimensionality of the data. Not all variables are critical and some variables may be highly correlated each other. A data construction technique determines the possible number of uncorrelated clusters in the dataset which can explain most of the variability of the data. In the modeling phase, the actual search for knowledge in the data is performed. In the refinement phase, the most appropriate model can be selected through testing and evaluating all competing models.

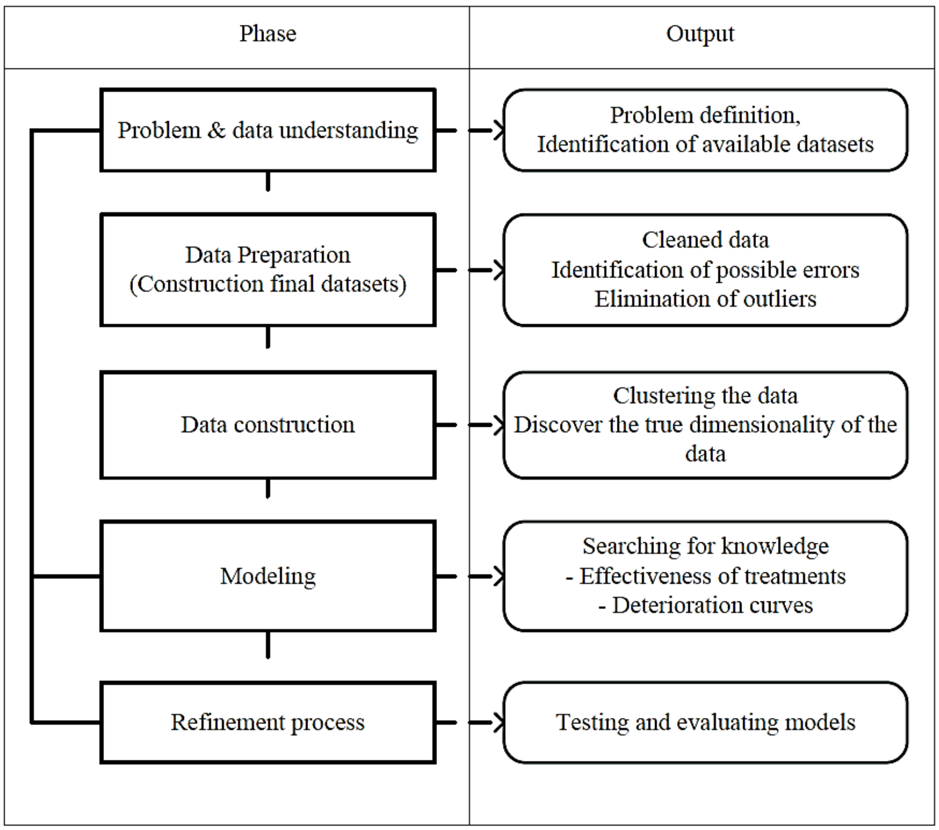


Figure 3.2 Main Processes of KDD Approach

KDD is the general framework that was used to perform the analyses required in this study. Each of the following sections addresses the specific methodologies that were used to accomplish the four primary objectives of the study.

3.1 Evaluate Current Classification System of Pavements

The current ODOT pavement families are classified into 14 different types based upon surface type, traffic volume, and presence of "D" cracking. For the purpose of evaluating the current classification of pavements, a clustering approach was used to evaluate whether or not the current classification system was similar to statistically determined clusters of pavements.

Cluster analysis is an exploratory data analysis tool which attempts to sort different objects into groups in a way that the degree of association between two objects is maximal if they belong to the same group and minimal otherwise. Figure 3.3 shows an example of how to cluster the data depending on various attributes. By using a clustering process, a number of clusters are identified based on prior knowledge including the type of pavement (such as asphalt, concrete, or composite), average daily traffic including vehicle types, weather factors, soil conditions, and operational conditions. Since each cluster contains only pavements with a maximum degree of association with each other, each cluster can be modeled differently.

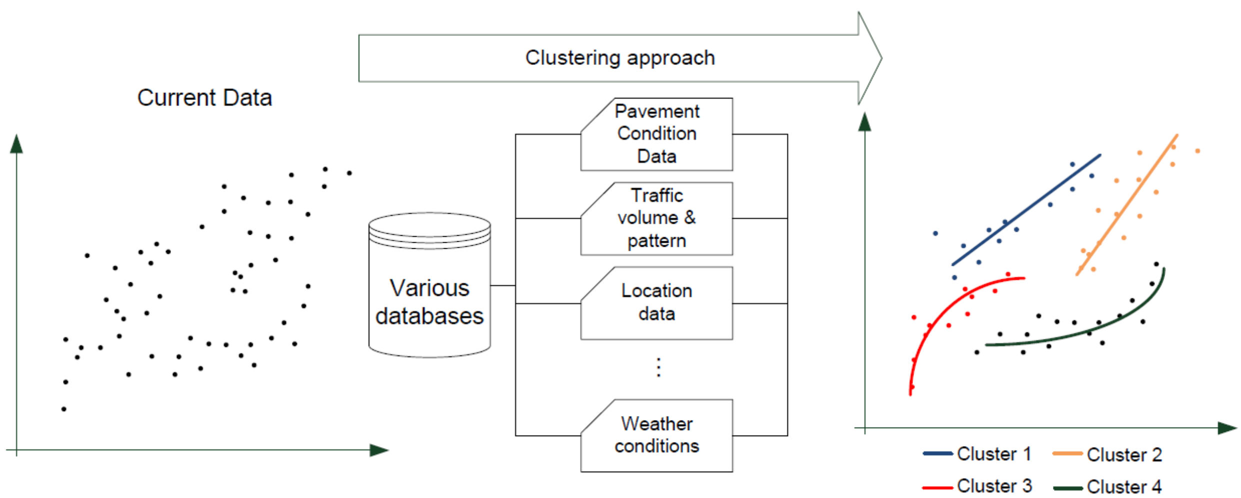


Figure 3.3 Clustering Approach for Classifying Pavements

In addition to this clustering approach, the final dataset was further subdivided into categories related to road type and location. All data related to each interstate highway in the ODOT system and the ODOT Field Division in which the highway section is located was grouped together. This permitted models to be developed based on pavement family, road type, and location which allows a higher resolution analysis of ODOT highways.

3.2 Evaluate Performance of Deterioration Curves

For this objective, deterministic performance models were created based on the newly developed dataset. The purpose of these models is to predict the various pavement condition indices as a function of age. Furthermore, pavement base thickness and surface thickness were considered in order to assess the effectiveness of various treatment options. The data were divided into pavement families, ODOT field division, and interstate highway in order to assist in the evaluation of the results on a higher resolution scale.

With regard to multiple linear regression modeling, normality tests were performed for all interstate highways sections to determine whether or not the data reflected a normal distribution. Stepwise regression was utilized to find effective equations to predict each of the pavement condition indexes as a function of age, surface thickness, and base thickness. The goodness-of-fit of the model (R^2) is an effective measure of how well the equation accounts for the variability in the data; thus, an R^2 value close to 1.0 indicates that the equation addresses most of the variability. The resulting equations based only on age were in the form of $y = mx_1 + b$, where y = the specified pavement condition index, m = the slope coefficient of the regression line, x_1 = age, and b = y-intercept. Higher order quadratic equations were also considered in order to determine if they were better predictors; these equations were in the form of $y = ax^2+bx+c$, where x = age and a, b, and c are coefficients. For the models that utilized either or both base thickness and surface thickness, the equations were in the form of $y = ax_1+bx_2+cx_3+k$, where x_1 = age, x_2 = base thickness, x_3 = surface thickness, and a, b, c, and k are coefficients.

In order to validate and assess the effectiveness of the models, the predicted pavement condition index results based on the models were plotted versus the actual pavement condition index results from the ODOT data. A trend line (in the form of $y = mx + b$) was fitted to the data and the equation and R^2 value of the trend line was determined. Based on these values, it was possible to assess the effectiveness of the model. For example, the R^2 value represents the precision of the model, the slope component (m) of the trend line represents the accuracy of the model, and the y-intercept (b) of the trend line represents the bias of the model.

In order to compare the effectiveness of the newly developed models by the OSU research team to the models currently used by ODOT (see Table 2.1), the predicted values for the current ODOT models were compared to the actual values from the ODOT data in a similar manner used to validate the OSU models. The precision (R^2), accuracy (m), and bias (b) of both sets of models were compared to determine their effectiveness and whether or not the new OSU models are viable candidates to replace the current models used by ODOT.

3.3 Assess Effectiveness of Various Treatment Options

For this objective, the research team used the newly developed dataset to determine the effectiveness of different treatment options. The same approach used to develop the new deterioration curves (described in the previous section) was used for this objective. The research team developed multiple linear regression models to predict pavement indexes based on input variables such as age, base thickness, and surface thickness; thus, pavement index prediction models are available for full-depth highway sections and also those sections that have received one of the various treatment options. These models permit pavement management decision makers to assess the effectiveness of a given treatment option based on the various pavement indexes.

To date, engineering judgments and expert opinions are the only sources to determine the effectiveness of various treatment options since there have been no statistically proven methods introduced to ODOT. When the condition for a particular pavement section falls below a certain threshold value, various treatment options are considered and one of them is selected and applied to the pavement. For example, for asphalt and composite pavements, different levels of structural, rut, and functional indexes, in addition to traffic volume, are currently considered to select the most appropriate treatment method. Concrete pavements require information on traffic volume, structural index or slab index, ride index, joint index, and presence of “D” cracking (for Jointed Plain Concrete Pavements only) in determining the most proper treatment method.

3.4 Develop a Spreadsheet-based Pavement Management Tool

For this objective, the results of the pavement deterioration curves were summarized in a spreadsheet that may be used as a decision-support tool by ODOT personnel. The spreadsheet summarizes the results in a database format that may be sorted and filtered by Interstate number, ODOT field division number, AADT category, pavement family, and pavement index. Two equations are presented – one for the multiple linear regression results (MLR) and also the age-based equation. The R^2 values are provided for each deterioration model.

4.0 RESULTS

The results of this project are immediately available for use by ODOT pavement management decision-makers. Development and validation of new input models for the ODOT PMS, as well as evaluation of the current input models, has long been a need of ODOT. The completion of this research project meets this need and provides the pavement management team with the most updated input models, which are based on and validated with actual pavement condition assessment data that ODOT has collected since 1994. The results of this research may help answer skeptical questions regarding the returns on continuous pavement data collection investments of ODOT. The data driven and validated models developed in this project will provide confidence to the pavement management team in developing short-term and long-term pavement management strategies. Reliable and informed decisions on maintenance and rehabilitation projects will translate into more accurate decision making of pavement project investments. It will also allow ODOT to develop more realistic pavement budget estimations and allocations over time. This section addresses the key findings for each of the primary objectives of the project.

4.1 Evaluate Current Classification System of Pavements

The clustering analysis failed to produce any new meaningful pavement families for analysis; thus, the current pavement families, upon which ODOT bases its current analyses, were kept intact for this analysis. However, the current pavement families were further subdivided based on the interstate that the highway section belonged to and also the ODOT field division where the highway section is located. This additional segregation of the pavement condition data and resulting models allows pavement management decision-makers to compare the differences between the input models based on pavement family, highway, and location.

Since the newly developed dataset was limited to interstate highways, only eight of the 14 pavement families were able to be analyzed (as defined by Table 1.1); there was not sufficient data for analysis for the remaining six pavement families because the pavement layers data was not available for these pavement families. Furthermore, of these eight pavement families, six of the eight ODOT field divisions were represented. Table 4.1 summarizes the pavement families and locations of the interstate highway section which were analyzed. For example, pavement family 3-AC High Volume, was analyzed based on interstate highway sections located in ODOT field divisions 1, 3, 4, and 5. Of the eight field divisions in Oklahoma, only Divisions 2 and 6 did not have available highway sections for analysis.

Table 4.1 Location of Pavement Family Analyses

	ODOT Field Division							
Pavement Family	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
3-AC High Volume	✓		✓	✓	✓			
4-AC Very High Volume			✓	✓				✓
6-CRCP High Volume	✓		✓	✓	✓			✓
7-DJCP	✓			✓			✓	
8-DMJCP	✓		✓					
9-JPCP Low Volume							✓	
10-JPCP High Volume				✓			✓	✓
14-COMP High Volume	✓		✓	✓			✓	✓

4.2 Evaluate Performance of Deterioration Curves

This section presents the results of the pavement deterioration curves for the eight pavement families. Two sets of equations are presented – one for the best fitted multiple linear regression (MLR) models based on age, base thickness (BT), and surface thickness (ST) and one set of models based on age only. The deterioration models are categorized by pavement family and equation type (MLR or age-based). Each pavement family is further classified by interstate highway section and ODOT field division location and a summary equation for all highway sections in that pavement family is provided. Furthermore, "n" represents the number of individual pavement sections that were used to construct that particular model. The results are summarized in Tables 4.2 – 4.75.

PAVEMENT FAMILY 3 – AC HIGH VOLUME

Table 4.2 Pavement Family 3 – AC High Volume – PQI (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	3	44	61.6 - 1.37 Age + 3.46 BT	65.00%
I-35	4	44	88.2 - 1.82 Age + 1.12 ST	82.50%
I-40	1	50	89.3 - 1.23 Age + 1.60 ST - 0.369 BT	34.00%
I-40	3	57	98.5 - 1.11 Age	53.50%
I-40	4	24	71.7 - 0.990 Age + 2.73 ST + 0.531 BT	85.20%
I-40	5	190	96.1 - 1.16 Age + 0.594 ST - 0.179 BT	68.80%
All	---	419	100 - 1.26 Age + 0.266 ST - 0.272 BT	54.50%

Table 4.3 Pavement Family 3 - AC High Volume – PQI (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	3	44	$94.65 + 0.9318\ Age - 0.1256\ Age^2$	48.70%
I-35	4	44	99.37 - 2.011 Age	74.60%
I-40	1	50	97.93 - 1.281 Age	23.00%
I-40	3	57	98.54 - 1.114 Age	53.50%
I-40	4	24	$98.86 + 0.1625\ Age - 0.1161\ Age^2$	66.90%
I-40	5	190	100.4 - 1.350 Age	67.00%
All	---	419	99.53 - 1.299 Age	52.00%

Table 4.4 Pavement Family 3 – AC High Volume – Ride Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	3	44	87.1 - 0.737 Age + 0.993 BT	40.90%
I-35	4	44	89.2 - 1.23 Age + 0.958 ST	65.40%
I-40	1	50	87.9 - 1.01 Age + 1.06 ST	28.00%
I-40	3	57	93.3 - 0.714 Age + 0.371 BT	54.40%
I-40	4	24	69.0 - 0.258 Age + 2.37 ST + 0.852 BT	65.40%
I-40	5	190	101 - 0.961 Age	45.00%
All	---	419	100 - 0.879 Age + 0.284 ST - 0.234 BT	39.40%

Table 4.5 Pavement Family 3 – AC High Volume – Ride Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	3	44	$96.03 + 0.1295\ Age - 0.04919\ Age^2$	39.40%
I-35	4	44	98.69 - 1.390 Age	56.30%
I-40	1	50	98.22 - 1.184 Age	22.80%
I-40	3	57	99.11 - 0.8859 Age	50.30%
I-40	4	24	$97.76 + 0.8412\ Age - 0.1158\ Age^2$	33.20%
I-40	5	190	101.3 - 0.9606 Age	45.00%
All	---	419	99.84 - 0.9283 Age	36.70%

Table 4.6 Pavement Family 3 - AC High Volume – Rut Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	3	44	- 2.8 - 2.40 Age + 9.27 BT	54.00%
I-35	4	44	31.6 - 1.38 Age + 1.69 ST + 2.40 BT	41.90%
I-40	1	50	68.0 - 0.868 Age + 2.87 ST	32.40%
I-40	3	57	87.8 - 1.57 Age + 0.907 ST	45.80%
I-40	4	24	25.0 - 1.38 Age + 7.56 ST + 1.04 BT	84.70%
I-40	5	190	85.1 - 1.64 Age + 1.21 ST	45.70%
All	---	419	93.2 - 1.74 Age + 0.457 ST	34.50%

Table 4.7 Pavement Family 3 - AC High Volume– Rut Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	3	44	91.49 + 1.276 Age - 0.1794 Age^2	20.50%
I-35	4	44	95.40 - 1.693 Age	27.30%
I-40	1	50	95.88 - 1.344 Age	14.20%
I-40	3	57	98.04 - 1.852 Age	43.30%
I-40	4	24	97.71 + 0.185 Age - 0.1850 Age^2	44.30%
I-40	5	190	97.89 - 1.992 Age	43.10%
All	---	419	98.00 - 1.851 Age	34.10%

Table 4.8 Pavement Family 3 – AC High Volume – Functional Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	3	44	94.03 + 2.128 Age - 0.2290 Age^2	54.30%
I-35	4	44	201 - 4.41 Age - 4.91 BT	64.50%
I-40	1	50	115 - 1.94 Age - 0.754 BT	30.40%
I-40	3	57	125 - 1.78 Age - 1.86 BT	22.40%
I-40	4	24	132 - 2.30 Age - 3.38 ST	53.20%
I-40	5	190	95.7 - 1.68 Age + 0.562 ST	45.50%
All	---	419	111 - 1.87 Age - 0.745 BT	34.80%

Table 4.9 Pavement Family 3 - AC High Volume – Functional Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	3	44	94.03 + 2.128 Age - 0.2290 Age^2	54.30%
I-35	4	44	104.7 - 4.347 Age	55.40%
I-40	1	50	100.6 - 1.500 Age	15.30%
I-40	3	57	95.75 - 0.9215 Age	7.80%
I-40	4	24	103.5 - 2.068 Age	42.00%
I-40	5	190	101.7 - 1.838 Age	44.80%
All	---	419	100.5 - 1.807 Age	29.60%

Table 4.10 Pavement Family3 - AC High Volume – Structural Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	3	44	$98.54 + 0.7810\ Age - 0.08522\ Age^2$	33.60%
I-35	4	44	148 - 2.19 Age - 2.24 BT	63.10%
I-40	1	50	101 - 1.53 Age + 1.72 ST - 1.01 BT	38.70%
I-40	3	57	100 - 0.447 Age	29.70%
I-40	4	24	$99.20 + 0.6599\ Age - 0.1048\ Age^2$	75.40%
I-40	5	190	109 - 0.714 Age - 0.419 ST - 0.250 BT	29.90%
All	---	419	109 - 0.731 Age - 0.644 BT	30.80%

Table 4.11 Pavement Family 3 - AC High Volume – Structural Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	3	44	$98.54 + 0.7810\ Age - 0.08522\ Age^2$	33.60%
I-35	4	44	104.5 - 2.159 Age	55.40%
I-40	1	50	98.76 - 1.230 Age	11.80%
I-40	3	57	99.97 - 0.4474 Age	29.70%
I-40	4	24	$99.20 + 0.6599\ Age - 0.1048\ Age^2$	75.40%
I-40	5	190	101.7 - 0.6147 Age	23.80%
All	---	419	100.6 - 0.6769 Age	16.00%

PAVEMENT FAMILY 4 - AC VERY HIGH VOLUME

Table 4.12 Pavement Family 4 – AC Very High Volume – PQI (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	3	36	100 - 1.59 Age	77.60%
I-35	4	10	96.10 + 0.0620 Age - 0.1411 Age^2	92.40%
I-40	4	41	100 - 2.03 Age	87.00%
I-44	3	11	81.4 + 1.8 ST	73.60%
I-44	8	43	93.1 - 1.49 Age	43.90%
I-240	4	9	92.6 - 0.579 Age	59.90%
All	---	156	92.9 - 1.10 Age - 0.315 ST + 0.467 BT	49.20%

Table 4.13 Pavement Family 4 – AC Very High Volume – PQI (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	3	36	100.5 - 1.590 Age	77.60%
I-35	4	10	96.10 + 0.0620 Age - 0.1411 Age^2	92.40%
I-40	4	41	100.4 - 2.029 Age	87.00%
I-44	3	11	98.46 - 0.6278 Age	69.40%
I-44	8	43	93.12 - 1.487 Age	43.90%
I-240	4	9	92.56 - 0.5788 Age	59.90%
All	---	156	95.44 - 1.071 Age	43.90%

Table 4.14 Pavement Family 4 - AC Very High Volume– Ride Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	3	36	94.4 - 0.527 Age + 0.390 BT	43.40%
I-35	4	10	86.91 + 3.544 Age - 0.3174 Age^2	77.60%
I-40	4	41	101 - 0.455 Age - 0.192 BT	20.50%
I-44	3	11	99.12 + 0.0648 Age - 0.01974 Age^2	50.00%
I-44	8	43	97.6 - 1.67 Age	46.30%
I-240	4	9	113 - 3.86 ST	57.80%
All	---	156	95.4 - 0.640 Age - 0.381 ST + 0.400 BT	24.50%

Table 4.15 Pavement Family 4 - AC Very High Volume – Ride Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	3	36	98.76 - 0.5306 Age	33.70%
I-35	4	10	86.91 + 3.544 Age - 0.3174 Age^2	77.60%
I-40	4	41	98.13 - 0.4553 Age	13.70%
I-44	3	11	99.12 + 0.0648 Age - 0.01974 Age^2	50.00%
I-44	8	43	97.57 - 1.671 Age	46.30%
I-240	4	9	92.37 - 0.3354 Age	32.30%
All	---	156	96.60 - 0.6085 Age	18.80%

Table 4.16 Pavement Family 4 – AC Very High Volume – Rut Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	3	36	103 - 3.83 Age	75.50%
I-35	4	10	99.1 - 1.77 Age	76.20%
I-40	4	41	91.5 - 3.64 Age + 1.14 ST	74.60%
I-44	3	11	79.2 + 1.88 ST	39.50%
I-44	8	43	75.4 - 1.35 Age + 0.992 BT	28.70%
I-240	4	9	90.2 - 0.942 Age	53.70%
All	---	156	85.0 - 1.78 Age - 0.626 ST + 1.07 BT	41.00%

Table 4.17 Pavement Family 4 – AC Very High Volume – Rut Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	3	36	102.5 - 3.828 Age	75.50%
I-35	4	10	99.09 - 1.772 Age	76.20%
I-40	4	41	99.68 - 3.668 Age	71.40%
I-44	3	11	96.70 - 0.6193 Age	33.60%
I-44	8	43	84.25 - 1.478 Age	22.90%
I-240	4	9	90.24 - 0.9417 Age	53.70%
All	---	156	91.56 - 1.711 Age	33.10%

Table 4.18 Pavement Family 4 - AC Very High Volume– Functional Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	3	36	94.8 - 1.17 Age + 0.707 ST	41.70%
I-35	4	10	107 - 4.31 Age	61.00%
I-40	4	41	98.14 + 1.077 Age - 0.5183 Age^2	61.30%
I-44	3	11	44.1 + 5.74 ST	73.30%
I-44	8	43	108 - 2.07 Age - 1.59 BT	22.10%
I-240	4	9	25.6 - 1.05 Age + 5.02 BT	54.20%
All	---	156	96.0 - 1.58 Age	24.00%

Table 4.19 Pavement Family 4- AC Very High Volume– Functional Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	3	36	101.4 - 1.178 Age	36.00%
I-35	4	10	106.5 - 4.306 Age	61.00%
I-40	4	41	98.14 + 1.077 Age - 0.5183 Age^2	61.30%
I-44	3	11	98.38 - 1.996 Age	69.50%
I-44	8	43	93.52 - 1.859 Age	15.60%
I-240	4	9	90.65 - 0.7191 Age	27.70%
All	---	156	95.99 - 1.582 Age	24.00%

Table 4.20 Pavement Family 4 – AC Very High Volume– Structural Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	3	36	96.9 - 0.351 Age + 0.332 ST	20.00%
I-35	4	10	98.61 + 1.368 Age - 0.2937 Age^2	86.70%
I-40	4	41	100 - 0.403 Age	19.30%
I-44	3	11	81.3 + 0.157 Age + 1.94 ST	15.60%
I-44	8	43	99.1 - 0.696 Age	16.20%
I-240	4	9	99.6 - 0.362 Age	64.60%
All	---	156	99.6 - 0.523 Age	18.30%

Table 4.21 Pavement Family - 4 AC Very High Volume – Structural Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	3	36	99.95 - 0.3542 Age	14.40%
I-35	4	10	98.61 + 1.368 Age - 0.2937 Age^2	86.70%
I-40	4	41	100.2 - 0.4031 Age	19.30%
I-44	3	11	99.18 - 0.4449 Age	9.70%
I-44	8	43	99.10 - 0.6961 Age	16.20%
I-240	4	9	99.62 - 0.3619 Age	64.60%
All	---	156	99.60 - 0.5232 Age	18.30%

PAVEMENT FAMILY 6 - CRCP HIGH VOLUME

Table 4.22 Pavement Family 6 - CRCP High Volume– PQI (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	3	8	92.7 - 0.250 Age	3.30%
I-35	4	62	112 - 0.482 Age - 0.925 BT	18.20%
I-40	1	33	$94.59 + 0.6040\ Age - 0.04415\ Age^2$	89.40%
I-40	5	10	99.8 - 0.228 Age	25.60%
I-44	8	31	102 - 0.198 Age - 0.370 BT	62.20%
I-444	8	15	114 - 1.36 Age	9.80%
All	---	173	$94.28 + 0.3213\ Age - 0.03238\ Age^2$	66.50%

Table 4.23 Pavement Family 6 - CRCP High Volume – PQI (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	3	8	92.68 - 0.2503 Age	3.30%
I-35	4	62	96.84 - 0.3598 Age	11.90%
I-40	1	33	$94.59 + 0.6040\ Age - 0.04415\ Age^2$	89.40%
I-40	5	10	99.83 - 0.2281 Age	25.60%
I-44	8	31	95.36 - 0.3263 Age	28.90%
I-444	8	15	113.6 - 1.362 Age	9.80%
All	---	173	$94.28 + 0.3213\ Age - 0.03238\ Age^2$	66.50%

Table 4.24 Pavement Family 6 - CRCP High Volume – Ride Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	3	8	83.5 - 0.471 Age	3.70%
I-35	4	62	116 - 0.866 Age - 1.36 BT	27.00%
I-40	1	33	$96.68 - 0.4579\ Age - 0.01523\ Age^2$	84.40%
I-40	5	10	98.6 - 0.203 Age	65.70%
I-44	8	31	98.1 - 0.236 Age - 0.630 BT	50.50%
I-444	8	15	109 - 1.65 Age	22.00%
All	---	173	$89.45 + 0.1727\ Age - 0.03342\ Age^2$	62.00%

Table 4.25 Pavement Family 6 – CRCP High Volume – Ride Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	3	8	83.48 - 0.4711 Age	3.70%
I-35	4	62	93.80 - 0.6864 Age	20.60%
I-40	1	33	$96.68 - 0.4579\ Age - 0.01523\ Age^2$	84.40%
I-40	5	10	98.61 - 0.2031 Age	65.70%
I-44	8	31	86.96 - 0.4546 Age	18.60%
I-444	8	15	109.1 - 1.649 Age	22.00%
All	---	173	$89.45 + 0.1727\ Age - 0.03342\ Age^2$	62.00%

Table 4.26 Pavement Family 6 – CRCP High Volume – Structural Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	3	8	99.2 - 0.161 Age	2.10%
I-35	4	62	103 - 0.094 Age - 0.285 BT	1.00%
I-40	1	33	92.34 + 1.322 Age - 0.06214 Age^2	80.60%
I-40	5	10	101 - 0.245 Age	11.50%
I-44	8	31	120 - 0.300 Age - 1.46 ST - 0.0555 BT	51.50%
I-444	8	15	113 - 1.05 Age	2.20%
All	---	173	97.62 + 0.3930 Age - 0.03056 Age^2	42.10%

Table 4.27 Pavement Family 6 - CRCP High Volume – Structural Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	3	8	99.15 - 0.1612 Age	2.10%
I-35	4	62	98.71 - 0.0563 Age	0.30%
I-40	1	33	92.34 + 1.322 Age - 0.06214 Age^2	80.60%
I-40	5	10	100.6 - 0.2448 Age	11.50%
I-44	8	31	100.9 - 0.2305 Age	24.60%
I-444	8	15	113.1 - 1.054 Age	2.20%
All	---	173	97.62 + 0.3930 Age - 0.03056 Age^2	42.10%

PAVEMENT FAMILY 7 - DJCP

Table 4.28 Pavement Family 7 - DJCP – PQI (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	4	26	93.8 + 0.387 ST	12.60%
I-35	7	23	93.6 + 0.216 ST	21.20%
I-40	1	13	32.5 + 5.07 ST + 0.661 BT	50.70%
I-40	4	10	128 - 1.60 BT	36.00%
All	---	91	80.8 - 0.184 Age + 0.688 ST + 0.491 BT	45.30%

Table 4.29 Pavement Family 7 - DJCP – PQI (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	4	26	97.88 - 0.0776 Age	0.70%
I-35	7	23	97.91 + 0.0652 Age	1.30%
I-40	1	13	96.09 + 1.004 Age - 0.1244 Age^2	19.50%
I-40	4	10	93.95 + 1.559 Age - 0.1908 Age^2	10.00%
All	---	91	97.37 - 0.2983 Age	4.60%

Table 4.30 Pavement Family 7 - DJCP – Ride Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	4	26	84.6 + 0.989 ST	13.30%
I-35	7	23	84.6 + 0.531 ST	21.40%
I-40	1	13	- 2.6 + 7.76 ST + 0.971 BT	66.50%
I-40	4	10	111 + 0.095 Age + 2.97 ST - 2.59 BT	42.80%
All	---	91	70.5 - 0.303 Age + 1.03 ST + 0.696 BT	37.40%

Table 4.31 Pavement Family 7 - DJCP – Ride Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	4	26	95.05 - 0.1825 Age	0.60%
I-35	7	23	95.01 + 0.2065 Age	2.10%
I-40	1	13	94.52 + 0.882 Age - 0.1172 Age^2	12.80%
I-40	4	10	89.58 + 2.753 Age - 0.3827 Age^2	17.30%
All	---	91	94.70 - 0.4680 Age	4.40%

Table 4.32 Pavement Family 7 - DJCP – Fault Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	4	26	98.9 + 0.0404 BT	11.90%
I-35	7	23	99.3 + 0.0531 BT	10.10%
I-40	1	13	8.3 + 0.190 Age + 7.66 ST + 0.558 BT	47.30%
I-40	4	10	136 - 1.91 BT	34.60%
All	---	91	88.0 + 0.430 ST + 0.340 BT	32.70%

Table 4.33 Pavement Family 7 - DJCP – Fault Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	4	26	$99.39 + 0.3753\ \text{Age} - 0.06301\ \text{Age}^2$	7.10%
I-35	7	23	99.76 - 0.01186 Age	0.20%
I-40	1	13	98.26 - 0.0934 Age	1.00%
I-40	4	10	$95.16 + 1.825\ \text{Age} - 0.1763\ \text{Age}^2$	17.60%
All	---	91	98.94 - 0.0916 Age	0.80%

Table 4.34 Pavement Family 7 - DJCP – Joint Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	4	26	98.0 + 0.0368 Age + 0.064 ST + 0.0467 BT	9.30%
I-35	7	23	98.7 + 0.0911 BT	17.60%
I-40	1	13	89.9 + 0.425 BT	61.70%
I-40	4	10	105 - 0.242 Age - 1.12 ST + 0.350 BT	45.60%
All	---	91	77.3 + 0.799 ST + 0.691 BT	46.20%

Table 4.35 Pavement Family 7 - DJCP – Joint Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	4	26	$99.36 + 0.3140\ \text{Age} - 0.04932\ \text{Age}^2$	4.80%
I-35	7	23	99.51 - 0.04060 Age	1.10%
I-40	1	13	97.17 + 0.1178 Age	3.00%
I-40	4	10	99.75 - 0.1593 Age	7.80%
All	---	91	98.46 - 0.1695 Age	0.90%

PAVEMENT FAMILY 8 – DMJCP

Table 4.36 Pavement Family 8 - DMJCP – PQI (MLR Equation)

Interstate	Division	n	Equation	R^2
I-40	1	29	105 - 1.08 Age	78.90%
I-40	3	13	- 424.6 + 25.58 Age - 0.3325 Age^2	44.50%
All	---	49	104 - 1.05 Age	81.70%

Table 4.37 Pavement Family 8 -DMJCP – PQI (Age Equation)

Interstate	Division	n	Equation	R^2
I-40	1	29	105 - 1.08 Age	78.90%
I-40	3	13	- 424.6 + 25.58 Age - 0.3325 Age^2	44.50%
All	---	49	104 - 1.05 Age	81.70%

Table 4.38 Pavement Family 8 - DMJCP – Ride Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-40	1	29	98.48 - 0.7033 Age	57.70%
I-40	3	13	12.04 + 1.495 Age	49.70%
All	---	49	98.40 - 0.7053 Age	60.60%

Table 4.39 Pavement Family 8 - DMJCP – Ride Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-40	1	29	98.48 - 0.7033 Age	57.70%
I-40	3	13	12.04 + 1.495 Age	49.70%
All	---	49	98.40 - 0.7053 Age	60.60%

Table 4.40 Pavement Family 8 - DMJCP – Fault Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-40	1	29	105 - 0.579 Age	57.90%
I-40	3	13	- 312.1 + 20.04 Age - 0.2577 Age^2	14.80%
All	---	49	101.0 - 0.0561 Age - 0.01304 Age^2	60.60%

Table 4.41 Pavement Family 8 - DMJCP – Fault Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-40	1	29	105 - 0.579 Age	57.90%
I-40	3	13	- 312.1 + 20.04 Age - 0.2577 Age^2	14.80%
All	---	49	101.0 - 0.0561 Age - 0.01304 Age^2	60.60%

Table 4.42 Pavement Family 8 - DMJCP – Joint Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-40	1	29	111 - 1.72 Age	68.70%
I-40	3	13	- 367.7 + 24.98 Age - 0.3600 Age^2	75.00%
All	---	49	109 - 1.60 Age	71.20%

Table 4.43 Pavement Family 8 - DMJCP – Joint Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-40	1	29	111 - 1.72 Age	68.70%
I-40	3	13	- 367.7 + 24.98 Age - 0.3600 Age^2	75.00%
All	---	49	109 - 1.60 Age	71.20%

Table 4.44 Pavement Family 8 - DMJCP – Slab Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-40	1	29	102 - 0.525 Age	30.20%
I-40	3	13	37.9 + 0.64 Age	1.60%
All	---	49	164 - 0.880 Age - 6.08 ST	28.40%

Table 4.45 Pavement Family 8 - DMJCP – Slab Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-40	1	29	102 - 0.525 Age	30.20%
I-40	3	13	37.9 + 0.64 Age	1.60%
All	---	49	93.50 + 0.0543 Age - 0.01330 Age^2	25.20%

PAVEMENT FAMILY 9 - JPCP LOW VOLUME

Table 4.46 Pavement Family 9 - JPCP Low Volume– PQI (MLR Equation)

Interstate	Division	n	Equation	R^2
I-44	1	14	93.3 - 0.378 Age	35.10%

Table 4.47 Pavement Family 9 – JPCP Low Volume – PQI (Age Equation)

Interstate	Division	n	Equation	R^2
I-44	1	14	93.3 - 0.378 Age	35.10%

Table 4.48 Pavement Family 9 – JPCP Low Volume – Ride Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-44	1	14	93.1 - 0.754 Age	58.30%

Table 4.49 Pavement Family 9 - JPCP – Ride Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-44	1	14	93.1 - 0.754 Age	58.30%

Table 4.50 Pavement Family 9 - JPCP Low Volume– Fault Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-44	1	14	97.6 - 0.266 Age	10.30%

Table 4.51 Pavement Family 9 – JPCP Low volume – Fault Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-44	1	14	97.6 - 0.266 Age	10.30%

Table 4.52 Pavement Family 9 – JPCP Low Volume – Joint Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-44	1	14	93.5 - 0.104 Age	1.10%

Table 4.53 Pavement Family 9 – JPCP Low Volume – Joint Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-44	1	14	93.5 - 0.104 Age	1.10%

Table 4.54 Pavement Family 9 - JPCP Low Volume– Slab Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-44	1	14	61.4 + 0.226 Age + 2.06 BT	58.80%

Table 4.55 Pavement Family 9 – JPCP Low Volume – Slab Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-44	1	14	86.80 + 0.0825 Age	2.40%

PAVEMENT FAMILY 10 – JPCP HIGH VOLUME

Table 4.56 Pavement Family 10 – JPCP High Volume – PQI (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	4	43	100 - 2.44 Age	82.60%
I-40	4	45	79.5 - 0.960 Age	64.80%
I-44	4	75	90.4 - 0.852 Age	43.10%
I-44	7	12	82.3 - 0.526 Base Thickness	28.10%
I-235	4	37	88.3 - 0.671 Age	41.60%
I-240	4	13	97.4 - 0.709 Age - 2.66 Base Th.	90.70%
All	---	248	88.42 - 0.8956 Age	44.20%

Table 4.57 Pavement Family 10 - JPCP High Volume – PQI (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	4	43	100.5 - 2.444 Age	82.60%
I-40	4	45	79.47 - 0.9598 Age	64.80%
I-44	4	75	90.40 - 0.8523 Age	43.10%
I-44	7	12	56.83 + 0.4676 Age	23.30%
I-235	4	37	88.32 - 0.6710 Age	41.60%
I-240	4	13	90.49 - 1.274 Age	83.60%
All	---	248	88.42 - 0.8956 Age	44.20%

Table 4.58 Pavement Family 10 – JPCP High Volume – Ride Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	4	43	101 - 3.58 Age	81.10%
I-40	4	45	54.9 - 1.32 Age + 2.25 Base Th.	74.80%
I-44	4	75	84.8 - 1.43 Age	50.70%
I-44	7	12	78.6 - 1.69 Base Thickness	65.90%
I-235	4	37	73.7 - 1.14 Age	39.40%
I-240	4	13	76.4 - 1.34 Age	88.40%
All	---	248	81.81 - 1.417 Age	51.00%

Table 4.59 Pavement Family 10 – JPCP High Volume – Ride Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	4	43	100.6 - 3.576 Age	81.10%
I-40	4	45	75.39 - 1.418 Age	70.10%
I-44	4	75	84.83 - 1.426 Age	50.70%
I-44	7	12	- 6.08 + 1.589 Age	61.50%
I-235	4	37	73.73 - 1.140 Age	39.40%
I-240	4	13	76.37 - 1.336 Age	88.40%
All	---	248	81.81 - 1.417 Age	51.00%

Table 4.60 Pavement Family 10 - JPCP High Volume– Fault Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	4	43	106 - 4.74 Age + 1.22 Base Th.	84.50%
I-40	4	45	84.0 - 0.815 Age	37.10%
I-44	4	75	92.8 - 0.903 Age	24.80%
I-44	7	12	93.1 - 0.162 Age	1.80%
I-235	4	37	90.6 - 0.053 Age	0.20%
I-240	4	13	129 - 1.07 Age - 7.40 Base Th.	90.20%
All	---	248	83.2 - 0.860 Age + 0.891 Base Th.	19.80%

Table 4.61 Pavement Family 10 - JPCP High Volume – Fault Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	4	43	109.1 - 4.300 Age	83.10%
I-40	4	45	84.00 - 0.8153 Age	37.10%
I-44	4	75	92.76 - 0.9027 Age	24.80%
I-44	7	12	93.06 - 0.1616 Age	1.80%
I-235	4	37	90.61 - 0.0527 Age	0.20%
I-240	4	13	110.2 - 2.636 Age	78.30%
All	---	248	90.47 - 0.7700 Age	16.70%

Table 4.62 Pavement Family 10 JPCP – Joint Index (Best Fitted Equation)

Interstate	Division	n	Equation	R^2
I-35	4	43	98.71 - 0.1544 Age	7.20%
I-40	4	45	96.8 - 0.156 Age	6.70%
I-44	4	75	97.8 + 0.0154 Age	0.50%
I-44	7	12	60.79 + 2.646 Age - 0.05080 Age^2	28.90%
I-235	4	37	98.7 - 0.158 Age	10.60%
I-240	4	13	96.3 - 0.131 Age + 0.356 Base Th.	3.20%
All	---	248	80.4 - 0.136 Age + 1.90 Surface Th.	6.20%

Table 4.63 Pavement Family 10 - JPCP High Volume– Joint Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	4	43	98.71 - 0.1544 Age	7.20%
I-40	4	45	96.80 - 0.1564 Age	6.70%
I-44	4	75	97.78 + 0.01541 Age	0.50%
I-44	7	12	60.79 + 2.646 Age - 0.05080 Age^2	28.90%
I-235	4	37	98.70 - 0.1575 Age	10.60%
I-240	4	13	97.20 - 0.0553 Age	1.80%
All	---	248	97.74 - 0.1461 Age	5.00%

Table 4.64 Pavement Family 10 - JPCP High Volume– Slab Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	4	43	96.7 - 0.837 Base Thickness	12.90%
I-40	4	45	72.8 - 0.891 Age	29.60%
I-44	4	75	94.5 - 0.101 Age	2.50%
I-44	7	12	107 - 0.527 Age	15.20%
I-235	4	37	96.72 + 0.5734 Age - 0.02909 Age^2	84.60%
I-240	4	13	85.0 + 0.314 Age	68.60%
All	---	248	85.6 - 0.586 Age + 0.966 Base Th.	15.40%

Table 4.65 Pavement Family 10 - JPCP High Volume – Slab Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	4	43	94.82 - 0.3495 Age	6.60%
I-40	4	45	72.85 - 0.8912 Age	29.60%
I-44	4	75	94.52 - 0.1010 Age	2.50%
I-44	7	12	107.0 - 0.5267 Age	15.20%
I-235	4	37	96.72 + 0.5734 Age - 0.02909 Age^2	84.60%
I-240	4	13	85.04 + 0.3138 Age	68.60%
All	---	248	93.45 - 0.4887 Age	10.00%

PAVEMENT FAMILY 14 - COMP HIGH VOLUME

Table 4.66 Pavement Family 14 - COMP High Volume– PQI (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	3	27	- 16.1 - 2.43 Age + 9.58 Sur. Th. + 0.217 Base Th.	81.10%
I-35	4	68	94.2 - 1.50 Age	52.80%
I-35	7	42	96.22 + 0.217 Age - 0.1402 Age^2	52.10%
I-40	1	10	95.3 - 3.02 Age	84.60%
I-44	7	12	95.7 - 1.29 Age	53.40%
I-244	8	35	93.8 - 2.77 Age	55.20%
All	---	199	91.1 - 1.85 Age + 0.472 Base Th.	48.00%

Table 4.67 Pavement Family 14 - COMP High Volume – PQI (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	3	27	111.5 - 2.740 Age	67.00%
I-35	4	68	94.21 - 1.499 Age	52.80%
I-35	7	42	96.22 + 0.217 Age - 0.1402 Age^2	52.10%
I-40	1	10	95.30 - 3.016 Age	84.60%
I-44	7	12	95.71 - 1.291 Age	53.40%
I-244	8	35	93.75 - 2.769 Age	55.20%
All	---	199	95.18 - 1.686 Age	42.80%

Table 4.68 Pavement Family 14 - COMP High Volume – Ride Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	3	27	- 71.1 - 2.21 Age + 13.5 Sur. Th. + 0.536 Base Th.	78.50%
I-35	4	68	56.8 - 0.598 Age + 2.69 Sur. Th.	8.70%
I-35	7	42	93.40 + 1.921 Age - 0.2377 Age^2	45.30%
I-40	1	10	86.4 - 2.07 Age	39.80%
I-44	7	12	87.48 + 0.935 Age - 0.0932 Age^2	19.10%
I-244	8	35	95.8 - 2.35 Age - 0.906 Base Th.	59.20%
All	---	199	86.4 - 1.35 Age + 0.599 Base Th.	24.00%

Table 4.69 Pavement Family 14 - COMP High Volume– Ride Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	3	27	115.4 - 2.804 Age	45.80%
I-35	4	68	84.89 - 0.4571 Age	3.80%
I-35	7	42	93.40 + 1.921 Age - 0.2377 Age^2	45.30%
I-40	1	10	86.37 - 2.066 Age	39.80%
I-44	7	12	87.48 + 0.935 Age - 0.0932 Age^2	19.10%
I-244	8	35	92.47 - 2.864 Age	54.30%
All	---	199	91.67 - 1.137 Age	16.80%

Table 4.70 Pavement Family 14 - COMP High Volume – Rut Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	3	27	90.8 - 2.52 Age + 0.535 Base Th.	52.40%
I-35	4	68	165 - 0.484 Age - 6.78 Sur. Th.	40.90%
I-35	7	42	94.51 + 0.240 Age - 0.2097 Age^2	45.60%
I-40	1	10	97.5 - 0.413 Age	7.00%
I-44	7	12	94.2 + 0.192 Age	3.10%
I-244	8	35	88.23 - 0.836 Age	1.90%
All	---	199	95.6 - 1.50 Age	16.20%

Table 4.71 Pavement Family 14 - COMP High Volume– Rut Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	3	27	105.4 - 2.898 Age	41.20%
I-35	4	68	94.81 - 0.8383 Age	11.80%
I-35	7	42	94.51 + 0.240 Age - 0.2097 Age^2	45.60%
I-40	1	10	97.47 - 0.4130 Age	7.00%
I-44	7	12	94.23 + 0.1920 Age	3.10%
I-244	8	35	88.23 - 0.836 Age	1.90%
All	---	199	95.57 - 1.496 Age	16.20%

Table 4.72 Pavement Family 14– COMP High Volume – Functional Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	3	27	116 - 3.89 Age	50.50%
I-35	4	68	64.8 - 3.46 Age + 3.45 Sur. Th.	56.90%
I-35	7	42	101 - 2.56 Age	45.70%
I-40	1	10	95.9 - 6.12 Age	76.30%
I-44	7	12	102 - 3.71 Age	50.20%
I-244	8	35	95.1 - 4.82 Age	45.80%
All	---	199	91.8 - 3.18 Age + 0.551 Base Th.	41.50%

Table 4.73 Pavement Family14 – COMP High Volume – Functional Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	3	27	116.3 - 3.887 Age	50.50%
I-35	4	68	100.7 - 3.278 Age	54.60%
I-35	7	42	101 - 2.56 Age	45.70%
I-40	1	10	95.94 - 6.124 Age	76.30%
I-44	7	12	101.6 - 3.711 Age	50.20%
I-244	8	35	95.12 - 4.824 Age	45.80%
All	---	199	96.65 - 2.986 Age	39.40%

Table 4.74 Pavement Family14 - COMP High Volume – Structural Index (MLR Equation)

Interstate	Division	n	Equation	R^2
I-35	3	27	- 51.5 + 11.8 Surface Thickness	28.00%
I-35	4	68	138 - 1.28 Age - 3.21 Sur. Th.	35.20%
I-35	7	42	96.2 - 0.244 Age - 0.00109 Sur. Th. + 0.210 Base Th.	7.90%
I-40	1	10	66.86 + 8.201 Age - 0.4779 Age^2	83.90%
I-44	7	12	92.46 + 3.071 Age - 0.3055 Age^2	63.00%
I-244	8	35	118 - 1.86 Surface Thickness	30.80%
All	---	199	99.5 - 0.894 Age + 0.228 Base Th.	20.50%

Table 4.75 Pavement Family 14 - COMP High Volume – Structural Index (Age Equation)

Interstate	Division	n	Equation	R^2
I-35	3	27	97.53 - 0.1173 Age	0.40%
I-35	4	68	104.6 - 1.447 Age	29.70%
I-35	7	42	98.43 - 0.2316 Age	3.40%
I-40	1	10	66.86 + 8.201 Age - 0.4779 Age^2	83.90%
I-44	7	12	92.46 + 3.071 Age - 0.3055 Age^2	63.00%
I-244	8	35	99.98 - 0.3413 Age	12.90%
All	---	199	101.4 - 0.8141 Age	18.30%

In order to validate and assess the effectiveness of both the current ODOT and newly developed OSU models, the predicted pavement condition index results based on the models were plotted versus the actual pavement condition index results from the ODOT data. A trend line (in the form of $y = mx + b$) was fitted to the data and the equation and R^2 value of the trend line was determined. Based on these values, it was possible to assess the effectiveness of the model. For example, the R^2 value represents the precision of the model, the slope component (m) of the trend line represents the accuracy of the model, and the y-intercept (b) of the trend line represents the bias of the model.

In order to compare the effectiveness of the newly developed models by the OSU research team to the models currently used by ODOT, the predicted values for the current ODOT models were compared to the actual values from the ODOT data in a similar manner used to validate the OSU models. The precision (R^2), accuracy (m), and bias (b) of both sets of models were compared to determine their effectiveness and whether or not the new OSU models are viable candidates to replace the current models used by ODOT. Tables 4.76 – 4.83 provide the validation summaries for each pavement family with respect to precision, accuracy and bias. The results of the OSU models are compared to the results of the models currently in use by ODOT. In most cases, both sets of models performed similarly with respect to precision but the OSU models typically had higher accuracy and lower bias components than the ODOT models.

Table 4.76 Pavement Family 3 – AC High Volume – Validation Summary

Index	Precision (R^2)		Accuracy (m)		Bias (b)	
	OSU	ODOT	OSU	ODOT	OSU	ODOT
PQI	0.52	0.52	0.80	0.51	13.54	46.42
Ride	0.37	0.37	0.57	0.32	39.44	66.32
Rut	0.33	0.34	0.55	0.31	41.18	61.99
Functional	0.30	0.30	0.71	0.33	8.35	57.83
Structural	0.14	0.14	0.38	0.22	56.52	75.11

Table 4.77 Pavement Family 4 – AC Very High Volume – Validation Summary

Index	Precision (R^2)		Accuracy (m)		Bias (b)	
	OSU	ODOT	OSU	ODOT	OSU	ODOT
PQI	0.45	0.50	0.63	0.43	37.47	55.54
Ride	0.18	0.18	1.03	0.16	-10.42	82.60
Rut	0.36	0.36	0.27	0.31	67.61	63.44
Functional	0.36	0.36	0.27	0.27	65.22	65.15
Structural	0.17	0.17	1.05	0.21	-14.98	76.51

Table 4.78 Pavement Family 6 – CRCP High Volume – Validation Summary

Index	Precision (R^2)		Accuracy (m)		Bias (b)	
	OSU	ODOT	OSU	ODOT	OSU	ODOT
PQI	0.66	0.69	1.21	0.62	-20.11	37.97
Ride	0.62	0.62	0.33	0.32	68.98	69.45
Structural	0.41	0.41	1.25	0.56	-34.91	39.21

Table 4.79 Pavement Family 7 - DJCP – Validation Summary

Index	Precision (R^2)		Accuracy (m)		Bias (b)	
	OSU	ODOT	OSU	ODOT	OSU	ODOT
PQI	0.05	0.04	0.06	0.19	92.53	79.69
Ride	0.04	0.04	0.07	0.22	91.00	74.48
Fault	0.002	0.002	0.10	0.01	86.03	98.57
Joint	0.01	0.01	0.09	0.02	88.92	97.69
Slab	0.17	0.17	0.21	0.21	78.69	78.84

Table 4.80 Pavement Family 8 – DMJCP – Validation Summary

Index	Precision (R^2)		Accuracy (m)		Bias (b)	
	OSU	ODOT	OSU	ODOT	OSU	ODOT
PQI	0.82	0.81	0.82	1.37	9.44	-37.91
Ride	0.61	0.53	0.61	0.97	31.77	-1.79
Fault	0.61	0.61	0.56	0.77	37.91	14.29
Joint	0.73	0.73	0.53	1.13	41.77	-24.54
Slab	0.25	0.25	0.20	0.82	73.06	-11.55

Table 4.81 Pavement Family 9 – JPCP Low Volume – Validation Summary

Index	Precision (R^2)		Accuracy (m)		Bias (b)	
	OSU	ODOT	OSU	ODOT	OSU	ODOT
PQI	0.35	0.32	0.35	2.36	58.61	-173.08
Ride	0.58	0.58	0.58	2.85	34.59	-205.58
Fault	0.10	0.08	0.10	0.80	81.49	-43.26
Joint	0.01	0.002	0.01	0.07	95.32	49.81
Slab	0.02	0.04	0.02	-0.69	100.75	103.61

Table 4.82 Pavement Family 10 – JPCP High Volume – Validation Summary

Index	Precision (R^2)		Accuracy (m)		Bias (b)	
	OSU	ODOT	OSU	ODOT	OSU	ODOT
PQI	0.44	0.32	0.63	0.98	31.29	0.76
Ride	0.51	0.35	0.48	0.97	48.64	6.46
Fault	0.17	0.09	0.94	0.33	-50.83	50.41
Joint	0.07	0.07	0.82	0.48	-2.82	39.28
Slab	0.13	0.13	0.27	0.37	62.42	48.32

Table 4.83 Pavement Family 14 – COMP High Volume – Validation Summary

Index	Precision (R^2)		Accuracy (m)		Bias (b)	
	OSU	ODOT	OSU	ODOT	OSU	ODOT
PQI	0.43	0.43	0.86	0.41	1.63	55.50
Ride	0.17	0.17	0.39	0.20	45.67	76.00
Rut	0.16	0.16	0.39	0.18	48.51	70.48
Functional	0.39	0.39	0.90	0.30	-21.40	58.97
Structural	0.19	.19	1.87	0.19	-120.7	76.91

4.3 Assess Effectiveness of Various Treatment Options

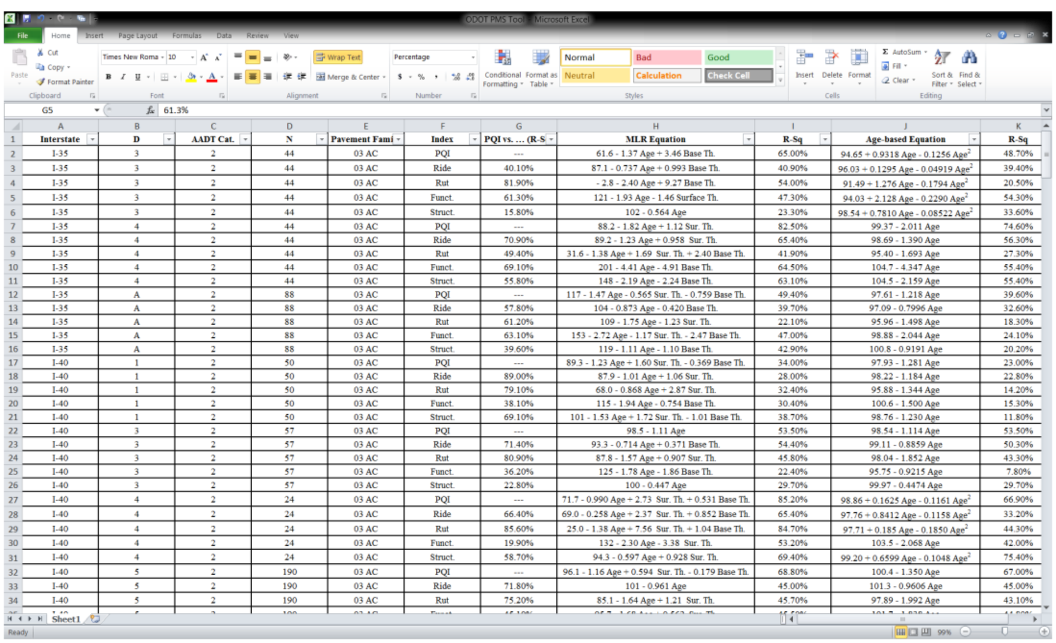
For this objective, the research team used the newly developed dataset to determine the effectiveness of different treatment options. The research team developed multiple linear regression models to predict pavement indexes based on input variables such as age, base thickness, and surface thickness; thus, pavement index prediction models are available for full-depth highway sections and also those sections that have received various treatment options. These models permit pavement management decision makers to assess the effectiveness of a given treatment option based on the various pavement indexes.

By segregating the data and the resulting models into many subcategories, pavement management decision-makers are able to assess the various pavement condition indexes for a very specific highways section. This is valuable because the deterioration curves for one highway section may not perform the same as another highway section with similar characteristics, even if it is in the same pavement family classification. For example, consider the MLR equations for I-35 Pavement Family 3 – AC High Volume – PQI shown in Table 4.2. Even though the same interstate is under consideration, and coincidentally, the models were developed with the same number of data observations, the resulting deterioration curves for the highway sections located in ODOT Field Divisions 3 and 4 use different variables - Division 3 uses and age and base thickness whereas Division 4 uses age and surface thickness. Even the age-based equations for the same pavement family shown in Table 4.3 have different forms of equations – Division 3 is quadratic whereas Division 4 is linear. By having this type of high-resolution analysis, pavement management decision-makers are able to assess treatment options for specific highway sections in specific locations.

4.4 Develop a Spreadsheet-based Pavement Management Tool

For this objective, the results of the pavement deterioration curves were summarized in a spreadsheet that may be used as a decision-support tool by ODOT personnel. The spreadsheet summarizes the results in a database format that may be sorted and filtered by Interstate number, ODOT field division number, AADT category, pavement family, and pavement index. Two equations are presented – one for the multiple linear regression results (MLR) and another for the age-based equation. The R^2 values are provided for each deterioration model to indicate the amount of variability accounted for in the data. Figure 4.1 shows a screenshot of the spreadsheet-based pavement management tool.

The pavement management tool includes deterioration curves for I-35, I-235, I-40, I-240, I-44, I-244, I-444, and all Interstates. Of these highway sections, ODOT Field Division 1, 3, 4, 5, 7, and 8 are represented, as well as, eight of the 14 pavement families currently used by ODOT. The tool provides multiple linear regression equations (MLR) based on age, base thickness, and surface thickness and it also provides age-only equations for predicting deterioration behavior of pavements based on Pavement Quality Index (PQI), Ride Index, Rut Index, Structural Index, Functional Index, Fault Index, Joint Index, and Slab Index, as appropriate. Altogether, there are 630 equations in the pavement management tool – 315 MLR equations and 315 age-based equations.



Interstate	D	AADT Cat.	N	Pavement Fami	Index	PQI vs. … (R-S	MLR Equation	R-Sq	Age-based Equation	R-Sq
I-35	3	2	44	03 AC	PQI	---	61.6 - 1.37 Age + 3.46 Base Th.	65.00%	94.65 + 0.9318 Age - 0.1256 Age^2	48.70%
I-35	3	2	44	03 AC	Ride	40.10%	87.1 - 0.737 Age + 0.993 Base Th.	40.90%	96.03 + 0.1295 Age - 0.04919 Age^2	39.40%
I-35	3	2	44	03 AC	Rut	81.90%	- 2.8 - 2.40 Age + 9.27 Base Th.	54.00%	91.49 + 1.276 Age - 0.1794 Age^2	20.50%
I-35	3	2	44	03 AC	Funct.	61.30%	121 - 1.93 Age - 1.46 Surface Th.	47.30%	94.03 + 2.128 Age - 0.2290 Age^2	54.30%
I-35	3	2	44	03 AC	Struct.	15.80%	102 - 0.564 Age	23.30%	98.54 + 0.7810 Age - 0.08522 Age^2	33.60%
I-35	4	2	44	03 AC	PQI	---	88.2 - 1.82 Age + 1.12 Sur. Th.	82.50%	99.37 - 2.011 Age	74.60%
I-35	4	2	44	03 AC	Ride	70.90%	89.2 - 1.23 Age + 0.958 Sur. Th.	65.40%	98.69 - 1.390 Age	56.30%
I-35	4	2	44	03 AC	Rut	49.40%	31.6 - 1.38 Age + 1.69 Sur. Th. + 2.40 Base Th.	41.90%	95.40 - 1.693 Age	27.30%
I-35	4	2	44	03 AC	Funct.	69.10%	201 - 4.41 Age - 4.91 Base Th.	64.50%	104.7 - 4.347 Age	55.40%
I-35	4	2	44	03 AC	Struct.	55.80%	148 - 2.19 Age - 2.24 Base Th.	63.10%	104.5 - 2.159 Age	55.40%
I-35	A	2	88	03 AC	PQI	---	117 - 1.47 Age - 0.565 Sur. Th. - 0.759 Base Th.	49.40%	97.61 - 1.218 Age	39.60%
I-35	A	2	88	03 AC	Ride	57.80%	104 - 0.873 Age - 0.420 Base Th.	39.70%	97.09 - 0.7996 Age	32.60%
I-35	A	2	88	03 AC	Rut	61.20%	109 - 1.75 Age - 1.23 Sur. Th.	22.10%	95.96 - 1.498 Age	18.30%
I-35	A	2	88	03 AC	Funct.	63.10%	153 - 2.72 Age - 1.17 Sur. Th. - 2.47 Base Th.	47.00%	98.88 - 2.044 Age	24.10%
I-35	A	2	88	03 AC	Struct.	39.60%	119 - 1.11 Age - 1.10 Base Th.	42.90%	100.8 - 0.9191 Age	20.20%
I-40	1	2	50	03 AC	PQI	---	89.3 - 1.23 Age + 1.60 Sur. Th. - 0.369 Base Th.	34.00%	97.93 - 1.281 Age	23.00%
I-40	1	2	50	03 AC	Ride	89.00%	87.9 - 1.01 Age + 1.06 Sur. Th.	28.00%	98.22 - 1.184 Age	22.80%
I-40	1	2	50	03 AC	Rut	79.10%	68.0 - 0.868 Age + 2.87 Sur. Th.	32.40%	95.88 - 1.344 Age	14.20%
I-40	1	2	50	03 AC	Funct.	38.10%	115 - 1.94 Age - 0.754 Base Th.	30.40%	100.6 - 1.500 Age	15.30%
I-40	1	2	50	03 AC	Struct.	69.10%	101 - 1.53 Age + 1.72 Sur. Th. - 1.01 Base Th.	38.70%	98.76 - 1.230 Age	11.80%
I-40	3	2	57	03 AC	PQI	---	98.5 - 1.11 Age	53.50%	98.54 - 1.114 Age	53.50%
I-40	3	2	57	03 AC	Ride	71.40%	93.3 - 0.714 Age + 0.371 Base Th.	54.40%	99.11 - 0.8859 Age	50.30%
I-40	3	2	57	03 AC	Rut	80.90%	87.8 - 1.57 Age + 0.907 Sur. Th.	45.80%	98.04 - 1.852 Age	43.30%
I-40	3	2	57	03 AC	Funct.	36.20%	125 - 1.78 Age - 1.86 Base Th.	22.40%	95.75 - 0.9215 Age	7.80%
I-40	3	2	57	03 AC	Struct.	22.80%	100 - 0.447 Age	29.70%	99.97 - 0.4474 Age	29.70%
I-40	4	2	24	03 AC	PQI	---	71.7 - 0.990 Age + 2.73 Sur. Th. + 0.531 Base Th.	85.20%	98.86 + 0.1625 Age - 0.1161 Age^2	66.90%
I-40	4	2	24	03 AC	Ride	66.40%	69.0 - 0.258 Age + 2.37 Sur. Th. + 0.852 Base Th.	65.40%	97.76 + 0.8412 Age - 0.1158 Age^2	33.20%
I-40	4	2	24	03 AC	Rut	85.60%	25.0 - 1.38 Age + 7.56 Sur. Th. + 1.04 Base Th.	84.70%	97.71 + 0.185 Age - 0.1850 Age^2	44.30%
I-40	4	2	24	03 AC	Funct.	19.90%	132 - 2.30 Age - 3.38 Sur. Th.	53.20%	103.5 - 2.068 Age	42.00%
I-40	4	2	24	03 AC	Struct.	58.70%	94.3 - 0.597 Age + 0.928 Sur. Th.	69.40%	99.20 + 0.6599 Age - 0.1048 Age^2	75.40%
I-40	5	2	190	03 AC	PQI	---	96.1 - 1.16 Age + 0.594 Sur. Th. - 0.179 Base Th.	68.80%	100.4 - 1.350 Age	67.00%
I-40	5	2	190	03 AC	Ride	71.80%	101 - 0.961 Age	45.00%	101.3 - 0.9606 Age	45.00%
I-40	5	2	190	03 AC	Rut	75.20%	85.1 - 1.64 Age + 1.21 Sur. Th.	45.70%	97.89 - 1.992 Age	43.10%

Figure 4.1 Screenshot of Pavement Management Decision-Support Tool

5.0 CONCLUSIONS AND RECOMMENDATIONS

This section summarizes the key findings of the research project and also offers suggestions for advancing the study beyond what has already been accomplished.

5.1 Evaluate Current Classification System of Pavements

The clustering approach did not yield any new groups of data to categorize as pavement families that the researchers deemed to be useful to ODOT. Furthermore, in order to compare the newly developed highway deterioration curves to the currently used models, a common classification system was necessary; thus, the current ODOT pavement family classifications were used. The current pavement family classifications, however, were subcategorized into smaller subsets of data that yielded pavement deterioration models for each applicable pavement condition index. These subsets will prove useful to ODOT pavement management personnel that wish to predict pavement indexes for specific interstates in specific locations. If ODOT wishes to pursue a new classification system of pavements, it is recommended that the clustering approach be used on the subsets of data that were developed in this study.

Due to a lack of pavement layering data for all highway types (only interstate layering data were available from ODOT), only interstates were analyzed in this study. As result, eight of the 14 ODOT pavement families are represented with deterioration models. These models do represent, however, all interstates found in Oklahoma and in six of the eight ODOT field divisions. If pavement layering data is available for other highway sections found in the remaining six pavement families, then pavement deterioration curves may be developed for these pavement families as well. If, however, that data is not available, it will be somewhat difficult to assess the true impact of treatment options on the pavement condition indexes. It is recommended that the deterioration curves for the remaining pavement families be developed if the necessary pavement layering data is available.

5.2 Evaluate Performance of Deterioration Curves

As a result of this study, 630 pavement deterioration curves were developed based on real-world, ODOT provided pavement conditions assessment data. These curves predict the appropriate pavement condition indexes for eight pavement families. Half of these curves (315) are based on best fitting models using multiple linear regression and age, base thickness, and surface thickness as predictor variables. The other half of these models are based on age only, but some are in the quadratic form and others are in the linear form. ODOT, therefore, may choose to use the set of models that they prefer. When comparing the newly developed models to the models currently in use by ODOT, both the new and current models perform similarly with respect to precision but the new models perform better in most cases with respect to accuracy and bias. It is recommended that ODOT strongly consider using these models to update the models that they are currently using in their pavement management system.

5.3 Assess Effectiveness of Various Treatment Options

The research team developed multiple linear regression models to predict pavement indexes based on input variables such as age, base thickness, and surface thickness; thus, pavement index prediction models are available for full-depth highway sections and also those sections that have received various treatment options. These models permit pavement management decision makers to assess the effectiveness of a given treatment option based on the various pavement indexes. By segregating the data and the resulting models into many subcategories, pavement management decision-makers are able to assess the various pavement condition indexes for very specific highways section. This is valuable because the deterioration curves for one highway section may not perform the same as another highway section with similar characteristics, even if it is in the same pavement family classification. It is recommended that, if the required pavement layering data is available for the pavement families that were not analyzed in this study, pavement condition index models be developed for these highway sections as well in order for ODOT to have a complete and thorough set of pavement deterioration curves for their pavement management system.

5.4 Develop a Spreadsheet-based Pavement Management Tool

The 630 pavement deterioration curves were summarized in a spreadsheet based on the best fitting MLR models and age-based models. These models are subcategorized according to interstate name and location; a model for each appropriate pavement index is provided. This spreadsheet includes filters that allow it to be searched based on interstate, ODOT field division, average annual daily traffic (AADT), pavement family, and pavement index. This pavement management tool provides a quick and easy methodology for finding the desired pavement deterioration model. It is recommended that this tool be updated as additional pavement deterioration models are developed.

5.5 Technology Transfer

The work performed in this research project was completed using ODOT pavement data and therefore is most applicable to the ODOT Pavement Management Branch. The research team will meet with ODOT representatives to discuss the findings and relative details of the research. It should be noted, however, that the methodologies presented here may be applicable to any state department of transportation or pavement management organization; thus, this research has broad appeal across the pavement management realm.

6.0 REFERENCES

American Society of Civil Engineers (2013a), "2013 Report Card for America's Infrastructure," www.infrastructurereportcard.org. Accessed August 8, 2013.

American Society of Civil Engineers (2013b), "2013 Report Card for America's Infrastructure: Oklahoma," www.infrastructurereportcard.org/oklahoma/oklahoma-overview. Accessed August 8, 2013.

Applied Pavement Technology (2002). *Oklahoma Technical Assistance: Performance Model Development*. Champaign, IL.

Applied Pavement Technology, Inc. (2010). *Current Practices in Pavement Performance Modeling*, Project Report 08-03 (C07), Urbana, IL.

Bianchini, A., and Bandini, P. (2010). "Prediction of Pavement Performance through Neuro-Fuzzy Reasoning," *Computer-Aided Civil and Infrastructure Engineering*, 25, 39-54.

Chen, C. and Zhang, J. (2011). "Comparisons of IRI-Based Pavement Deterioration Prediction Models Using New Mexico Pavement Data," American Society of Civil Engineers, *Proceedings of the Geo-Frontiers 2011 Conference: Advances in Geotechnical Engineering*, Dallas, TX.

Ferreira, A., de Picado-Santos, L., Wu, Z., and Flintsch, G. (2011). "Selection of Pavement Performance Models for Use in the Portuguese PMS," *International Journal of Pavement Engineering*, 12(1), 87-97.

Li, J., Luhr, D., and Uhlmeyer, J. (2010). "Pavement Performance Modeling Using Piecewise Approximation," *Transportation Research Record: Journal of the Transportation Research Board*, 2153, 24-29.

ODOT (2005). *Pavement Management Policy and Procedures Manual*, Internal Report: Oklahoma Department of Transportation, Planning and Research Division, Pavement Management Branch, Oklahoma City, OK.

ODOT (2009). *2009 Oklahoma Interstate Highway System Pavement Management Report*, Internal Report: Oklahoma Department of Transportation, Planning and Research Division, Pavement Management Branch, Oklahoma City, OK.

Soibelman, L., & Kim, H. (2002). "Data Preparation Process for Construction Knowledge Generation through Knowledge Discovery in Databases," *Journal of Computing in Civil Engineering*, 16(1), 39-48.