GEORGIA DOT RESEARCH PROJECT 16-37

Final Report

DATA-DRIVEN PAVEMENT MAINTENANCE AND REHABILITATION STRATEGIES FOR GDOT'S NEW STATE ROUTE PRIORITIZATION POLICY

Georgia Department of Transportation

Office of Performance-based Management and Research
600 West Peachtree St. NW | Atlanta, GA 30308

<table>
<tr><td>1.Report No.:
FHWA-GA-19-1637</td><td>2. Government Accession No.: N/A</td><td colspan="2">3. Recipient's Catalog No.: N/A</td></tr>
<tr><td colspan="2" rowspan="2">4. Title and Subtitle:
Data-Driven Pavement Maintenance and Rehabilitation Strategies for GDOT’s New State Route Prioritization Policy</td><td colspan="2">5. Report Date: April 2019</td></tr>
<tr><td colspan="2">6. Performing Organization Code: N/A</td></tr>
<tr><td colspan="2">7. Author(s): Yichang (James) Tsai, Ph.D.; Zhaohua Wang, Ph.D.; Lauren Gardner; Ryan Salameh; Yi Jiao</td><td colspan="2">8. Performing Organ. Report No.: 16-37</td></tr>
<tr><td colspan="2" rowspan="2">9. Performing Organization Name and Address:
Georgia Institute of Technology
790 Atlantic Drive
Atlanta, GA 30332-0355</td><td colspan="2">10. Work Unit No.:</td></tr>
<tr><td colspan="2">11. Contract or Grant No.:
PI# 0015380</td></tr>
<tr><td colspan="2" rowspan="2">12. Sponsoring Agency Name and Address:
Georgia Department of Transportation
Office of Performance-based Management and Research
600 West Peachtree St. NW
Atlanta, GA, 30308</td><td colspan="2">13. Type of Report and Period Covered:
Final; December 2016 – April 2019</td></tr>
<tr><td colspan="2">14. Sponsoring Agency Code:</td></tr>
<tr><td colspan="4">15. Supplementary Notes:
Prepared in cooperation with the U.S. Department of Transportation, Federal Highway Administration.</td></tr>
<tr><td colspan="4">16. Abstract:
The Georgia Department of Transportation (GDOT) has used the models and application that were developed through the RP 05-19 to justify and forecast the network-level, long-term pavement performance, and Maintenance, Rehabilitation, and Reconstruction (MR&R) need to the legislature. However, the Markov-chain-based pavement deterioration transition probabilities have not been updated for more than 10 years and do not reflect the most recent pavement deterioration behaviors. In addition, GDOT has established a new policy that categorizes state highways into four priority categories according to their importance and utilization: critical, high, medium, and low. To improve the accuracy and reliability of forecasting network-level pavement performance and predicting future MR&R needs in light of the new state route priority categories, this research project studied pavement deterioration behavior at both project and network levels, updated the pavement deterioration transition probabilities using the recent COPACES data, analyzed the treatment unit cost and Annual Average Escalation Rate (AAER), and conducted comprehensive what-if analysis using the new software application, GDOT LP&S. Conclusions and recommendations for future research were offered.</td></tr>
<tr><td colspan="2">17. Key Words:
Asphalt pavement; deterioration; state route priority category; maintenance, rehabilitation and reconstruction; Markov transition probability; optimization; what-if analysis</td><td colspan="2">18. Distribution Statement: No Restriction</td></tr>
<tr><td>19. Security Classification (of this report): Unclassified</td><td>20. Security classification (of this page): Unclassified</td><td>21. Number of Pages: 180</td><td>22. Price: Free</td></tr>
</table>

Contract Research

GDOT Research Project No. 16-37

Final Report

DATA-DRIVEN PAVEMENT MAINTENANCE AND REHABILITATION STRATEGIES FOR GDOT'S NEW STATE ROUTE PRIORITIZATION POLICY

By

Yichang (James) Tsai, Ph.D., P.E.

Zhaohua Wang, Ph.D., P.E.

Lauren Gardner
Ryan Salameh
Yi Jiao

Georgia Institute of Technology

Contract with

Georgia Department of Transportation

In cooperation with

U.S. Department of Transportation

Federal Highway Administration

April 2019

SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003)

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACRONYMS AND ABBREVIATIONS

AADT	Annual Average Daily Traffic
AAER	Annual Average Escalation Rate
ESAL	Equivalent Single Axel Loads
GDOT	Georgia Department of Transportation
HMA	Hot Mix Asphalt
IRI	International Roughness Index
MCMC	Markov Chain Monte Carlo
MR&R	Maintenance, Rehabilitation, and Reconstruction
PACES	Pavement Condition Evaluation System
PCI	Pavement Condition Index
PSI	Present Serviceability Index
PSR	Pavement Serviceability Rating
TPM	Transition Probability Matrix

EXECUTIVE SUMMARY

The Georgia Department of Transportation (GDOT) has used the models and application that were developed through RP 05-19 to justify and forecast the network-level, long-term pavement performance, and Maintenance, Rehabilitation, and Reconstruction (MR&R) need to the legislature. However, the Markov-chain-based pavement deterioration transition probabilities have not been updated for more than 10 years and do not reflect the most recent pavement deterioration behavior. In addition, GDOT has established a new policy that categorizes state highways into four priority categories according to their importance and utilization: critical, high, medium, and low. To improve the accuracy and reliability of forecasting network-level pavement performance and predict future MR&R needs along with the new state route priority categories, this research project studied pavement deterioration behavior at both project and network levels, updated the pavement deterioration transition probabilities using the recent COPACES data in terms of the new state route priority categories, analyzed the treatment unit cost and Annual Average Escalation Rate (AAER), and conducted comprehensive what-if analysis using the new software application, GDOT LP&S. The following are the major research results and findings:

- GDOT has rated the statewide pavement conditions using PACES and has accumulated a wealth of historical data back to 1986. These data are invaluable for studying the pavement deterioration characteristics and determining suitable MR&R *strategies*.
- The Bayesian-based project-level deterioration model was explored in this project to incorporate the a priori knowledge on pavement deterioration behavior. The

objective was to improve the accuracy and reliability of pavement deterioration modeling at the project level. Though the models were not used for network-level what-if analysis, they have the potential to be applied in GDOT's pavement management system for selecting MR&R projects.

- In terms of 5 state route priority categories (critical roads are further divided into interstates and non-interstates) and 7 working districts, all state routes were grouped into 35 families. For each family, a TPM was created using historical COPACES data from FY 2010-2015.
- Pavement treatments were categorized as minor preventive maintenance, major preventive maintenance, or major rehab/reconstruction. Using the resurfacing database and local maintenance work orders, the unit costs for minor preventive maintenance and major preventive maintenance were calculated. The unit cost for the major rehab/reconstruction was estimated due to the lack of expenditure information.
- By comparing the calculated unit costs with the "2018 GDOT Reference Guide" cost estimations, the AAER was determined as 4.24%.
- The software application, GDOT LP&S, was re-developed by updating the four different optimization simulation strategies, "Optimization on All Families," "Optimization on Each Family," "Need Analysis," and "Need Analysis on Each Priority Type." Using this software application, the developed Markov TPMs were validated on non-interstate pavements and showed little variation between simulated results and historical condition data.
- A comprehensive what-if analysis was performed through case scenarios using the 4 optimization simulation strategies developed in GDOT LP&S. Assuming that the

current budget is kept constant for the next 10 years, the network composite rating is higher when using "Optimization on All Families" rather than "Optimization on Each Family." While considering the performance requirements to be a minimum network composite rating of 85 and a max percent of pavements in poor and bad condition states as 10%, the model shows a big maintenance backlog reflected by a budget of $1.14 billion in the first year. When the performance requirements are set as minimum composite ratings for each priority category, the need analysis shows a fluctuation in the budget, as the model aims to meet the pavement condition requirements for each category. Finally, a sensitivity analysis was performed by increasing and decreasing the current budget and analyzing the effect on performance while using both optimization simulation strategies.

The following are recommended for future research:

- The main limitation of the developed Bayesian-based pavement deterioration model lies in the computational complexity. It is better to incorporate the knowledge of experts to define the prior distribution.
- It is recommended other relevant factors be considered, e.g., environment, pavement design etc., in the Bayesian-based pavement deterioration model. In addition, for different types of distresses, different forecasting models are desirable. Thus, further pavement treatments can be better predicted.
- The reliability of the MR&R need analysis largely relies on the accuracy of treatment unit costs and AAER. Currently, very little treatment information and no-cost data were recorded in COPACES. Therefore, it is recommended the current COPACES data collection be enhanced by incorporating historical pavement treatment data.

CHAPTER 1. INTRODUCTION

RESEARCH BACKGROUND AND RESEARCH NEED

The Georgia Department of Transportation (GDOT) has justified and forecasted the "network-level, long-term pavement performance, and maintenance and rehabilitation (MR&R) need" to the legislature using the models and procedures that were developed by the Principal Investigators (PIs) at Georgia Tech in a previous research project (Research Project Number: 05-19). However, the pavement deterioration models have not been updated for more than 10 years and do not reflect the most recent pavement deterioration behaviors, and, therefore, they cannot predict MR&R needs accurately. In addition, GDOT has established a new policy that categorizes state highways into four priority categories according to their importance and utilization: critical, high, medium, and low. Because the critical highways consist of interstate and non-interstate highways, we actually used 5 categories for the analysis. This new policy has the advantage of maximizing the utilization of GDOT's resources for statewide pavement maintenance.

To address the above issues for network-level, long-term pavement performance forecasting and MR&R needs analysis, there is an urgent requirement to update the statewide pavement deterioration models using the most recent, historical pavement condition assessment data provided by COAPCES. To support GDOT's new route priority policy, different funding strategies and different performance goals need to be established and studied based on pavements' actual deterioration behaviors, predominant distresses (e.g. raveling in interstate highways), service levels, and traffic conditions.

The outcomes of this proposed study are essential to support GDOT's new policy for state route MR&R prioritization. The updated deterioration models will enhance the accuracy and reliability of GDOT's long-term pavement performance forecasting and M&R needs analysis, and, consequently, the updated models will establish a data-driven, transparent, and reliable process that can be used to more accurately and effectively justify funding needs to the legislature.

RESEARCH OBJECTIVES

The objectives of this study were 1) to improve the accuracy and reliability of the long-term pavement performance forecasting and MR&R need analysis using updated pavement deterioration models that will be derived from the most recent COPACES data, and 2) to conduct what-if analysis and sensitivity study to predict long-term, network-level pavement conditions with given annual budget, and forecast the MR&R needs in terms of different performance goals in different state route priority categories. Asphalt pavements are the focus of this proposed research project.

REPORT ORGANIZATION

This report is organized into the following chapters. CHAPTER 1 introduces the project background, need, and objectives. CHAPTER 2 presents a comprehensive literature review regarding pavement condition data collection and pavement deterioration modeling. CHAPTER 3 presents the study of a Bayesian-based project-level pavement deterioration regression in different State Route Priority Categories using the historical pavement COPACES data. CHAPTER 4 presents the updates on the Markov-chain-based network-level pavement deterioration model and validation. CHAPTER 5 presents the comprehensive what-if analysis on predicting network-level pavement performance and forecasting future MR&R needs. CHAPTER 6 summarizes research findings and offers recommendations for future research. Appendix I presents the user's guide for the software application, GDOT LP&S. Appendix II presents the Markov Transition Probability Matrices (TPMs) for all families. Finally, Appendix III presents the linear programming model formulations for different scenarios.

CHAPTER 2.   LITERATURE REVIEW

The Federal Highway-Aid Act of 1956 led the way for the construction of the federal highway system in place today. While the act provided federal dollars for the construction of the system, it was not until the Federal-Aid Highway Act of 1976 that the federal government took a larger role in the maintenance of the system created under President Eisenhower. The Federal Highway-Aid Act of 1976 provided a ninety percent federal share for "resurfacing, restoring, and rehabilitating" lanes in use for more than five years to reduce the $2.6 billion backlog of maintenance on the interstate system (Weingroff, 2017). While policy regarding federal and state funding for maintenance activities has changed throughout the course of history, the need to prioritize and program maintenance and rehabilitation activities that receive federal funding has remained constant. One key pavement management strategy that enables smarter prioritization and preservation of an entire network of pavements is the collection of pavement data for a Pavement Management System (PMS) database and subsequent organization of pavement data to reveal useful trends for future prediction. Both pavement condition assessments and project categorization are important tools to standardize information about roadway projects and adequately assess which projects need treatments and when. The focus of this chapter is to 1) provide a brief history of pavement data collection and assessment in the United States and, in particular, in Georgia and 2) describe how data collected for a pavement database can be organized to make meaningful predictions about a network of pavements.

PAVEMENT CONDITION DATA COLLECTION

The collection of data by state departments of transportation is an important first step in the creation of a pavement management database. While details collected at a state level within the United States are largely dependent on the resources available to the states, data collection for pavement management is often focused on the collection of pavement condition data. In this section, pavement condition assessment metrics in the United States and in Georgia, specifically, will be discussed.

Condition Assessment and Data Collection in the United States

In the early days of the Interstate Highway System (IHS), pavement performance metrics were widely unexplored. It was not until 1961 in Ottawa, Illinois, that pavement conditions began to be systematically assessed to understand the performance of a network of roadways. In the early study conducted by the American Association of State Highway Officials (AASHO), the Pavement Serviceability Rating (PSR) was utilized to establish a condition score for pavements. The initial metric, which relied on a panel of expert raters who surveyed roadway segments by driving over them, laid the groundwork for more qualitative performance metrics used to analyze pavements today (HRB, 1961). This subsection looks at the three major pavement performance metrics that the PSR gave way to the Present Serviceability Index (PSI), the Pavement Condition Index (PCI), and the International Roughness Index (IRI). The uses of these metrics for state-level pavement condition assessments are also discussed.

Present Serviceability Index

In 1962, the AASHO created the first and most generalizable rating system for pavement condition assessment. The metric created, known as the PSI, was formulated to indicate "the momentary ability of a pavement to serve traffic" (HRB, 1961). The rating was calculated using measurements of longitudinal profile variations and amounts of cracking, patching, and rutting. In 1993, the PSI was altered to reflect the effects traffic and environments have on the performance of the pavement (AASHTO, 1993). The metric in its existing form measures the ability of pavement to serve its users with a particular emphasis on roadway rideability or smoothness. The PSI utilizes a 0-5 rating system, where 0 indicates a pavement with bad serviceability and 5 represents a pavement with high serviceability (Christopher, Schwartz, & Boudreau, 2006). Today, the PSI is used for both flexible and rigid pavements and is a guiding metric for the design of new and rehabilitated roadway segments. Despite the generalizability of the metric, the PSI lacks detail in terms of the types of distresses occurring on a segment or project level. Detailed information about distresses helps make informed treatment selections and, therefore, the PSI's lack of detail led to the creation of other pavement assessment metrics.

Pavement Condition Index

While the PSI is still used today, the reliability of the index as a metric, given the limited number of factors used in rating condition, has been often disputed. Therefore, a new metric has resulted: PCI. PCI utilizes distress deducts for 1) alligator cracking, 2) bleeding, 3) block cracking, 4) bumps and sags, 5) corrugation, 6) depression, 7) edge cracking, 8) joint reflection cracking, 9) lane/shoulder drop-off, 10) longitudinal/transverse cracking, 11) patching and cut patching, 12) polished aggregate, 13) potholes, 14) railroad crossing, 15) rutting, 16) shoving, 17) slippage cracking, 18) swell, 19) raveling, and 20) weathering to characterize pavement condition (ASTM, 2011). The PCI, which was developed by the Army Corps of Engineers, uses a 0-100 rating scale, where 0 represents a pavement in poor condition and 100 represents a pavement that is newly constructed or in the best condition. The index is calculated by deducting points from the highest possible score (100) based on the severity or extent of distresses. While the PCI provides a thoroughness with the factors it considers, the process of determining the PCI is limited by the resources needed to properly conduct a survey of all 20 types of distresses.

International Roughness Index

The International Roughness Index (IRI) is a metric developed to understand pavement conditions in terms of rideability or roughness. The metric was developed in 1986 by the World Bank as a means to avoid empirical conversions between differing roughness indices around the world (Sayers, et al., 1986a). The IRI is measured at a vehicle speed of 80 km/hour and is the accumulated suspension motion of a vehicle divided by the distance traveled (mm/km or in/mi) (Sayers, et al., 1986b). Unlike the PSI or the PCI, the IRI does not consider the structural integrity of the pavement but focuses on the user experience on a roadway, as does the PSR. Despite the lack of detail provided by the IRI, the Federal Highway Administration (FHWA) mandated its use as a performance indicator on the National Highway System (NHS) to ensure acceptable ride quality.

Today, FHWA pushes for IRI on NHS roads to be 170 inches/mile or less (FHWA, 2017a).

Current Pavement Condition Assessment Practices

Presently in the United States, pavement condition assessment metrics still vary considerably. While the measurement of the IRI is required by states, most states use a combination of the PSR, PCI, and IRI to assess network conditions. In a comprehensive study done by the University of Texas, it was found that 29 states collect distress information similar to the PCI for assessment and 37 use the IRI data for pavement rating (Papagiannakis, et al., 2009). States, for the most part, were found to use the 0-100 rating of a PCI or 0-5 rating of a PSI with great variability in the sampling method and frequency of these surveys. Other state agencies, such as the Minnesota Department of Transportation (MnDOT), have created new indicators for condition assessment. The indicator used by the MnDOT combines the concept of ride quality (similar to the IRI) with surface cracking and distress information (MnDOT, 2011).

Pavement Condition Assessment and Data Collection in Georgia

In the 1980s, GDOT implemented the Pavement Condition Evaluation System (PACES), which utilizes distress surveys and an empirical deduct system to rate pavements throughout the state (GDOT, 2007). The PACES, which uses distress deduct values to calculate pavement ratings between 0 and 100, represents a balance between the simplicity of the PSI and the thoroughness of the PCI. The system, which has been utilized for yearly pavement surveys, has remained consistent for more than thirty years. The sections below give an overview of the details of the collection method for condition assessment data used by PACES and other data provided by Computerized PACES (COPACES).

Condition Collection Methods

As described previously, the main data source for the pavement condition of projects within the state is COPACES. The data in the system includes project-level and segment-level information about all interstate and state routes dating back to FY 1986. Just as in other rating systems, visual surveys are a vital aspect of determining the rating of the pavement and the overall condition of the state pavement system. Because visual inspections are both time-consuming and labor-intensive, GDOT conducts surveys for each mile of roadway by “selecting a sample section for cracking distresses representative of the pavement condition for that rating segment” (GDOT, 2007). These mile selections are considered “segments,” and the representative 100-foot samples are referred to as “sections.” The ratings of segments are averaged together to obtain a representative pavement condition for an entire project. Projects are, typically, lengths of roadway with common pavement features (such as mix design, year reconstructed, etc.) and logical termini. Therefore, survey data often includes variability, as the representative section chosen may vary from year to year. **Figure 2-1** provides an illustration to help distill the relationship between sections, segments, and projects.

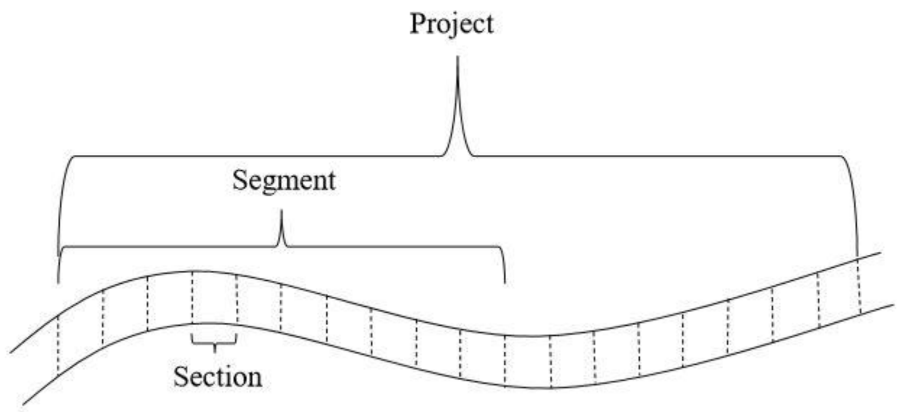


Figure 2-1. Illustration. PACES survey sampling terminology.

The ratings procured during section surveys consider ten distresses: rut depth, raveling (Levels 1-3), load cracking (Levels 1-4), edge distress (Levels 1-3), block cracking (Levels 1-3), bleeding/flushing (Levels 1-2), reflection cracking (Levels 1-3), corrugations/pushing (Levels 1-3), patched and potholes, and loss of section (Levels 1-3). The rater chooses the worst lane in a multilane section where divided highways are treated as separate sections. **Table 2-1** provides a summary of the characteristics needed to rate each distress. Ultimately, all of the deduct values from segments that fall within a project are averaged together to get project-level deduct values.

Table 2-1. PACES distress information.

Distress Type	Description of Measurement
Rutting	Pavement distance from flush grade on wheel paths (inches)
Raveling	Percentage of sample area with predominant raveling level observed (%)
Load cracking	Percentage of sample area with highest level of cracking observed (%)
Edge distress	Length of edge with predominant severity level (mile)
Block cracking	Percentage of sample area with highest level of cracking observed (%)
Bleeding/Flushing	Percentage of length of wheel paths that has bleeding or flushing in a segment (%)
Reflection cracking	Percentage of sample area with highest level of cracking observed (%)
Corrugations/pushing	Percentage of rated segment that has corrugations (%)
Patched and potholes	Number of spots for the entire rated segment
Loss of Section	Percentage of length of rated segment with loss of pavement section (%)

The deduct values calculated per project or segment are important, as they are ultimately used to summarize pavement condition. Pavement condition can be summarized by a Project Rating number that varies from 0-100. A Project Rating of 100 represents pavement with no visible distresses, whereas a Project Rating of 0 represents the worst condition a pavement can be in. Additionally, in the COPACES database, projects with a

Project Rating of 105 are the ones considered to be under construction. GDOT utilizes these ratings to analyze the system at the network level.

Other Information Collected in the COPACES

Historical COPACES data since FY 1986 is used to describe the trend in pavement condition deterioration for projects over time. As stated previously, COPACES data includes segment and project-level condition data, as well as distress information. However, the large data set that has been used for Georgia's PMS also includes fields such as district location, status of the project (if under construction), whether a project is on a divided highway, and other fields. These additional attributes help identify key characteristics of projects assessed during surveys.

OTHER DATA SOURCES FOR PAVEMENT MANAGEMENT DATABASES

In order to validate and calibrate deterioration models to fully understand condition trends for pavements, multiple data sources are required. Besides condition assessment data, two of the main data sources needed to fully understand a state's network of pavements are historical traffic data and treatment expenditure data. Below, each source is more thoroughly described in the context of the Georgia Asset Management System (GAMS).

Historical Traffic Data

Since the AASHO Road Test, conducted in the late 1950s and early 1960s, the effect of volume and mix of traffic on pavement deterioration has been incorporated into pavement modeling techniques. In a study by Alberto Garcia-Diaz, et al. (1984), the nonlinear relationship between pavement condition and traffic loading was confirmed. The study, which utilized test data from the Texas Department of Transportation (TxDOT), found that the relationship between pavement condition (PSI) and traffic (Equivalent Single Axle Loads (ESALs)) was sigmoidal in nature or that pavement conditions increasingly worsen with an increase in traffic loading (Garcia-Diaz & Riggins, 1984). Traffic data, in the form of Annual Average Daily Traffic (AADT), is, therefore, an important source for understanding and predicting future pavement condition, especially when categorizing pavement projects at a network level. Traffic data at the state level is provided by PACES data, as well as GDOT's geocounts system, which provides all annual traffic data from the state's permanent counter locations.

Treatment Expenditure Data

While treatment expenditure data does not play a great role in understanding existing pavement conditions within a state, these data are important in the context of general pavement management and expenditure forecasting. While the cost of materials and labor fluctuates each year due to inflation and industry demands, a predicted cost for future years can be deduced from a state's historical expenditure data. These costs are usually collected from the data provided by Georgia's GeoPI system, which contains resurfacing information, and the Work Order system, which contains expenditure data for preventative maintenance. However, this data may not be sufficient, especially in case only a few projects are performed each year (especially for the limited high-cost projects on interstates), thus affecting the accuracy of the prediction of treatment and rehabilitation costs within the state.

ORGANIZATION OF NETWORK-LEVEL PAVEMENT DATA

The collection of pavement condition, traffic, and expenditure data provides little value on its own. In order to thoroughly draw conclusions about pavement conditions within a network, the data must be properly organized in a way that enables conclusions to be drawn based on the characteristics of pavement projects. At the network level, GDOT does this by using Project Ratings. The Project Ratings gathered from COPACES data describe the five key conditions of pavement: Excellent, Good, Fair, Poor, and Bad. These condition states are used to indicate how a pavement is performing based on the distresses found through the survey process. The condition states and the associated ranges of Project Ratings for each are summarized below in **Table 2-2**.

Table 2-2. Project rating categories.

Category Name	Project Rating Range
Excellent	91-100
Good	81-90
Fair	71-80
Poor	55-70
Bad	0-54

These pavement condition categories enable GDOT to easily identify the existing conditions of asphalt pavements. For example, using processed 2015 COPACES data, a breakdown of the pavement condition in the state can be easily understood using these categories. The composite rating of the network of pavements, where the composite rating is defined as the project-length-weighted average of all the Project Ratings, was 80.40 out of 100.

Figure 2-2 represents the distribution of the pavements in the network for FY 2015 using state condition categories. From this figure, it can easily be distilled that less than 50% of pavements in Fiscal Year 2015 were in the "Good" or "Excellent" category, while more than half of pavements in the network ultimately require some form of minor treatment or major rehabilitation.

Figure 2-2. Chart. State of pavement network in Georgia for FY 2015.

While information about pavement condition states is a great tool for communicating pavement performance at the state level to policy-makers and, subsequently, setting performance goals, little can be gathered about the condition states of highly valued or highly utilized roadways versus underutilized roadways using these categories alone. At the network level, state-wide pavement condition states are often difficult to understand for decision-makers who determine where to invest in maintenance and rehabilitation given the variability in pavement rating, pavement location, and other attributes that affect pavement deterioration. When comparing projects, these additional factors play a large role in how fast and how detrimental deterioration of an asset will be. Therefore, project organization beyond condition states is necessary to adequately understand the future and existing conditions of the system and subsequent action that needs to be taken. By organizing projects by criteria other than Project Rating, the goal is to enable condition assessment to be more holistic, and, therefore, more comprehensive in terms of understanding how pavement groups work.

Within Georgia, three additional categories are imposed to group similar pavement projects, two used in the previous studies on pavement management in Georgia and one recently defined and implemented in the state. The preexisting means of classifying roadway projects use the working district in which a project falls and the project's classification as interstate or non-interstate. The additional classification criteria imposed for data organization is a state prioritization. Each of the three components used for grouping similar projects is described in the subsections below.

Working District

In Georgia, there are 7 working districts determined by GDOT. These seven administrative areas encompass regions that share resources from the GDOT District offices. The boundaries correspond to county boundaries, which generally remain consistent from year to year (as seen in **Figure 2-3**).

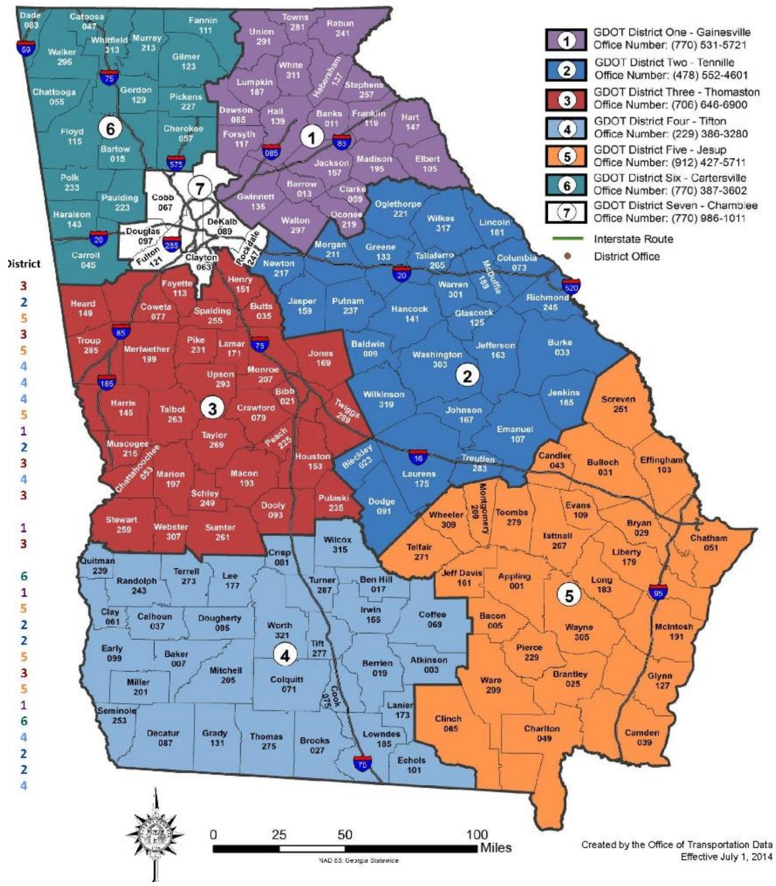


Figure 2-3. Map. GDOT working districts (GDOT, 2014b).

The use of the working district of a project as a geographical category enables projects with similar weather and soil conditions to be grouped together. In Georgia, this is particularly important, as the state's geography varies greatly above and below the Fall Line, depicted as Sand Hills in **Figure 2-4** below. The elevations tend to be greater, and the soils tend be classified as clays above the Fall Line. Below the Fall Line, the elevations tend decrease, and the soils tend to be classified as sands. While working districts do no capture the geographic differences between projects perfectly, they provide a good basis for differentiating pavements by location.

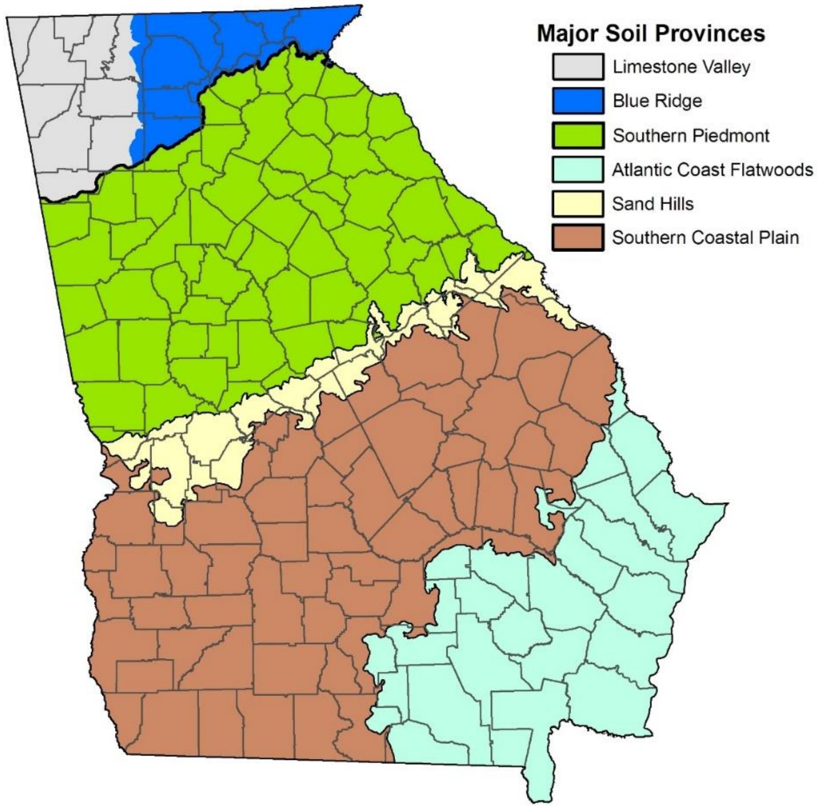


Figure 2-4. Map. Soil differences in the state of Georgia (UGA, 2017).

Interstate versus Non-interstate

Another category used to classify projects is interstate or non-interstate. An interstate highway is any roadway that is a part of the National Highway System and, therefore, serves as a major corridor for freight and connectivity within and between states. In Georgia, interstate roadways are all denoted by a state route number in the 400s such as SR 404 (I-16), SR 402 (I-20), and SR 409 (I-24). As of 2014, approximately 1,247 centerline miles can be classified as interstates within the state (GDOT, 2014a). Non-interstate roadways are those that are not necessarily a part of the NHS but are still maintained and operated by the state; in Georgia, such roadways are approximately fifteen times the centerline mileage of interstates. Splitting projects between these two road types helps account for differences in traffic, loading due to truck percentage, and pavement design type, which often varies greatly between interstate and non-interstate pavements. **Figure 2-5** shows interstate and non-interstate roadways in Georgia.

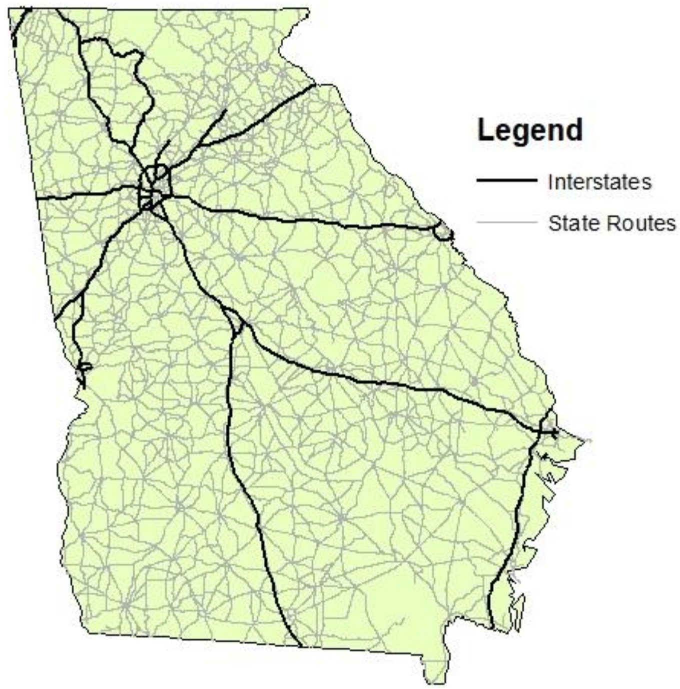


Figure 2-5. Map. Interstate versus non-interstate routes in Georgia.

State Route Prioritization

The final means of organizing pavement project data is through the use of state prioritization. In 2015, Wiegand et al. (2016) created a new means of categorizing roadways for maintenance prioritization and better performance measures. Four categories were created based on the importance of roadways for connectivity and access, as detailed in **Table 2-3** (Wiegand & Susten, 2016). The four categories (Critical, High, Medium, and Low) can be used to further group projects based on their importance in the pavement network. **Figure 2-6** depicts the classification of state route priority throughout the state roadway network.

Table 2-3. Characteristics of state route priority categories (Wiegand & Susten, 2016).

Category	Characteristics of Roadways
Critical	• National Freight Corridors • State Freight Corridors • Interstates • Intermodal Connectors
High	• STRAHNET/STRAHNET Connectors • NHS-Other Principal Arterials [Annual AADT>3000] • U.S. Routes • Sole Connections between County Seats • Georgia Emergency Management Agency Nuclear Power Plant Evacuation Routes
Medium	• Hurricane Evacuation Routes • NHS – Other Principal Arterial Routes Beginning or Ending at a Low Priority State Route • NHS- Other Principal Arterials (AADT <3,000) • All Other Routes that are not otherwise classified
Low	• Low AADT (Under 3,000) • Low-Speed Limit (Under 35 mph) • Low Connectivity (i.e. spans a single county, does not connect an urban area) • Short Length (Total Mileage<5 miles) that are not otherwise classified

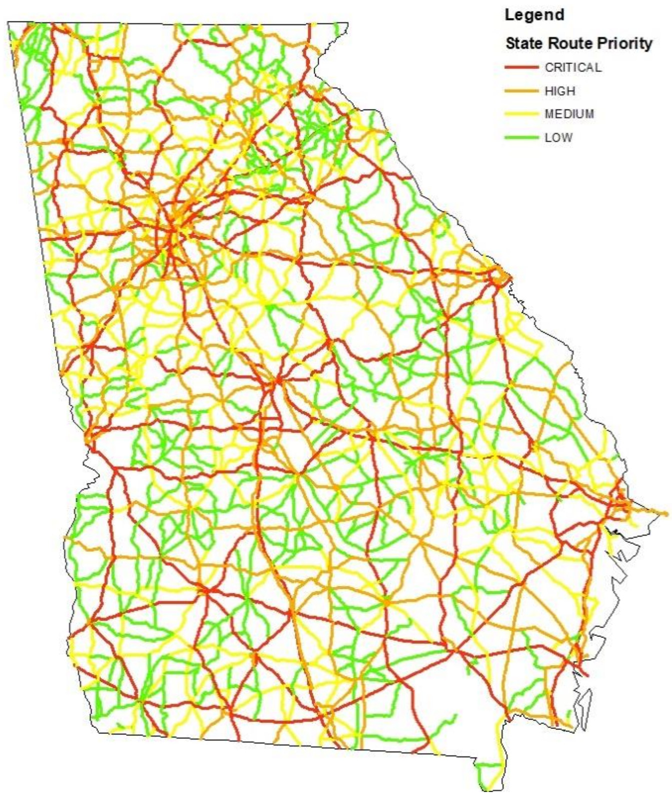


Figure 2-6. Map. State route prioritization categories.

PAVEMENT DETERIORATION MODELING

Pavement performance deterioration has been studied since the AASHO Road Test in the early 1960s. With advancements in computation speed and roadway data collection techniques, the study of pavement deterioration has also advanced. While new methods for understanding pavement performance over time are continuously being developed, the types of modeling used, especially within the United States, can largely be categorized into deterministic models or stochastic models. Deterministic modeling, which includes mechanistic models, empirical models, and mechanistic-empirical models, utilizes parameters or inputs that include no randomness and, therefore, result in stationary outputs. Stochastic or probabilistic modeling, conversely, utilizes random variables to estimate how probable outcomes may be in prediction. Examples of stochastic or probabilistic models include econometric, Markov Chain, and reliability models (Z. Li, 2005). In the following sections, the uses of deterministic modeling and probabilistic modeling for pavement performance are discussed.

Deterministic Modeling

As stated previously, the focus of deterministic models is to predict a precise or constant future value based on input values. In the context of pavement performance, this can mean that series of pavement performance indicators for a network are used to predict the exact performance of the pavement network in future years. Deterministic modeling is, therefore, commonly used by state DOTs, as it utilizes data already collected through condition assessments and is easily explained to decision-makers. However, these models do fall short in being able to comprehensively account for all the variables and randomness of variables affecting pavement condition or performance. The focus of this section is to more fully describe the use of deterministic modeling in the realm of pavement performance. Three subsets of deterministic models most often used by these entities are mechanistic modeling, empirical modeling, and mechanistic-empirical modeling. The uses of each model type in the context of pavement deterioration modeling are described below.

Mechanistic Models

Mechanistic models utilize mathematics and physics to evaluate a pavement's response. For pavements, mechanistic models are those that consider stress, strain, and deflection to better understand pavement structure (Rauhut, et al., 1984.   While mechanistic models are commonly used in pavement design, such as the models developed by Ontario, Canada's OPAC software (He, 1997), use of mechanistic models for modeling deterioration or performance has been scarcely studied. Hajek et. al. (1985) studied the difference in multiple performance models, including a mechanistic model utilizing the OPAC design formulas. By utilizing the relationship between deflection of subgrade and pavement roughness, the mechanistic model was able to adequately predict the PCI of a pavement over time. However, the mechanistic model was considered an overprediction of the actual PCI data collected in the state of Mississippi in this study (Hajek, et al., 1985). In addition to overprediction, mechanistic models are also limited by the factors they are able to model, the precision of the modeling, and the need to calibrate each model used usually with empirical data (AASHTO, 1993).

Empirical Models

Empirical performance models are widely used for the identification of pavement performance trends through the use of experimental data. Unlike mechanistic modeling, which often relies on lab tests, empirical modeling can make use of survey data and other easily collected parameters to predict performance over time. For that reason, empirical modeling has been used to understand the dependencies of ESALs (Garcia-Diaz & Rigginss, 1984; HRB, 1961), roughness (Al-Omari & Darter, 1994; Lin, et al., 2003), and varying distresses on pavement performance. Empirical modeling for pavement deterioration has taken both linear and non-linear forms, such as sigmoidal models (Chen & Mastin, 2015) and survivor curves. However, despite the practicality of using empirical data for prediction of pavement performance using condition or age, it is more common for state DOTs or research entities to use a combination of mechanistic and empirical data.

Mechanistic-Empirical Models

Mechanistic-empirical models incorporate both mechanistic data collected about material properties and empirical data collected through field evaluations. Most PMS utilizing mechanistic-empirical models focus on pavement serviceability through the use of a combination of variables, such as traffic loads, environmental factors, materials, subgrade strength, construction technique, and layer thickness (George, et al., 1989). In some cases, these factors are incorporated into the model directly, while for others, pavements are first grouped into like families based on similar characteristics such as structure, last resurfacing, and traffic volumes, before a model is developed (Chan, et al., 1997). The modeling is focused on combining these factors to best understand the characteristics of pavements through methods such as regression (Chan, et al., 1997), stepwise regression (Shahin, et al., 1987), multiple linear regression (Luo, 2014), and reliability models (Alsherri & George, 1988) among others. While mechanistic-empirical models are widely used due to their ability to consider a breadth of factors affecting pavement conditions, these models are still limited by their inability to account for errors deterministic models create by utilizing fixed inputs in the model.

Stochastic Modeling

Stochastic or probabilistic modeling utilizes non-discrete measures for prediction. Non-discrete measures can include random variables and probability distributions of variables and outcomes that encapsulate the randomness of an event, such as pavement deterioration. As alluded to previously, stochastic modeling often takes the form of econometric, Markov Chain, and reliability models; however, in pavement management, the Markov Chain is predominantly used. Despite the benefits of considering pavement data in a dynamic lens, probabilistic models are considerably more complex and, therefore, have only been used more recently as computation speeds have increased. The subsections to follow provide an overview of the Markov Chain in the context of network modeling, as well as other new probabilistic techniques being used by researchers and state DOTs.

Markov probabilistic modeling has been utilized for PMS since its introduction into the field by the Arizona DOT in 1982 (Golabi, et al., 1982). This stochastic or probabilistic model type utilizes historical data to predict the likelihood of a pavement deteriorating from one condition to the next. Markov models assume that all future states of a system depend only on the current state of conditions rather than events that occurred in the past as stated by the Markov property. However, the definition of a condition state and the likelihood of state changes differ for homogenous and nonhomogeneous Markov models.

Homogenous Markov modeling refers to Markov models that assume the transition probabilities of condition states to be constant or stationary over time. In the context of pavement management, homogenous models would assume that the likelihood of a pavement deteriorating from one condition to another each year would remain constant. For example, if pavement can be divided into two condition states, good and failing, then for a homogenous Markov model, the assumption is that the probability of pavement in the good category transitioning to the failing category would be the same from year to year. The Markov method was first deployed by the Arizona DOT, which utilized 120 condition states based on roughness, amount of cracking, change in cracking in previous years, and an index to the first crack and 17 maintenance activities to create transition probability matrices for network deterioration predictions (Golabi, et al., 1982). Butt et al. (1987) utilized a similar integration of homogenous modeling for a pavement network focused on 10 states of PCI and no maintenance activities, which provided better predictions of future conditions than a comparable least-squares model. In Butt's model, given no maintenance events were considered, the transition probability matrices (TPMs) for each family assumed a pavement could not improve its condition. Other studies have further refined models similar to ADOT's proposed in 1982 by assuming pavements can only deteriorate one condition per analysis period (Wang, et al., 1994) and further refining pavement "families" selection (Li, et al., 1996).

Nonhomogeneous Markov models do not assume or have supporting evidence that TPMs will be stationary over time. Therefore, nonhomogeneous models can be considered non-stationary. Typically, these models are created using time-based or state-based models. The former focuses on the time taken for a pavement to deteriorate from one condition to another, while the latter considers probabilities over a defined time period (Mishalani & Madanat, 2002). Non-homogenous state-based models include expected-value methods, simulation methods, and econometric methods, while timed-based models include parametric, semi-parametric, and non-parametric duration models (Li, et al., 1996). These advanced methods have been researched and implemented in recent years through the use of Poisson Hidden Markov models (Lethanh, et al., 2015) and Bayesian updating of Markov models (Hong & Prozzi, 2006; Tabatabaee & Ziyadi, 2013).

Markovian models are best used by states or agencies with unreliable or small historical datasets, as these methods can predict future performance given a finite amount of data. Therefore, using Markov processes requires less data collection and fewer resources than some of the empirical and mechanistic methods of modeling previously described. The data used to create a Markov model, while beneficial in terms of expenditure on data collection, means the model does not consider the causes of pavement deterioration directly. Therefore, Markov models are not appropriate for decision-making at a project level.

Other Modeling Techniques

Other modeling techniques discussed in pavement management literature include neural networks. Neural networks were introduced as computing systems advanced, and machine learning was introduced into the pavement management field. These systems, which consist of input values or neurons, hidden layers, and outputs, utilize collected data to output a network condition. In neural networks, inputs typically include factors that would be considered by deterministic modeling, including roughness, pavement age, climatic conditions, pavement structural properties, subgrade properties, drainage type, and MR&R treatments (Kargah-Ostadi & Stoffels, 2015). The uses of neural networks, compared to empirical or probabilistic methods alone, are mixed. Karagh-Ostadi et al. (2015) determined Bayesian Neural Networks resulted in good accuracy and generalization compared to other machine learning techniques, and Lou et al. (2001) similarly found the use of neural networks resulted in better accuracy (lower error) than comparable autoregressive models. Luo et al. (2014), however, found that the use of neural networks leads to higher levels of variability than the use of solely multiple linear regression models for pavement deterioration. Additionally, the forecasting error associated with neural networks was shown to increase more quickly with the number of years that needed to be predicted when compared to a Markov model (Yang, et al., 2006). This suggests that neural networks may not be appropriate for long-term pavement preservation planning.

SUMMARY

Although many rating systems are available to evaluate the condition of pavement and to identify its distresses, GDOT has used PACES, which is based on visual inspection of 10 different types of distresses, since the 1980s. Moreover, traffic data is collected for different purposes, including the priority categorization of roads, in addition to the treatment expenditure data, which is crucial for pavement management systems. Besides pavement condition ratings, projects are categorized by 7 working districts of similar weather and soil conditions in each, by interstate versus non-interstate roads accounting for differences in traffic, loading due to truck percentage, pavement design type, and, finally, by state route prioritization for maintenance resource allocation purposes.

CHAPTER 3. PROJECT-LEVEL DETERIORATION MODELING

Pavement deterioration modeling is the key to predicting pavement conditions over time and forecasting future pavement maintenance and rehabilitation needs. Though the objective of this research is to study the network-level pavement maintenance and rehabilitation needs, in which network-level pavement deterioration modeling is required, the project-level pavement deterioration is explored to reveal the characteristics of individual pavement deterioration. The research results could be valuable for determining the maintenance and rehabilitation treatment for each individual project.

INTRODUCTION

The forecasting of pavement deterioration is a crucial component of any pavement management system. An accurate pavement performance forecast helps a transportation agency make proper decisions about the right place and the right time to perform the necessary treatment and rehabilitation. Moreover, deterioration models help agencies set their long-term funding plans and are supported by good pavement performance estimations through the analyzed period. Over the years, efforts have been made to develop state-of-art models, both for network-level and project-level forecasting. Two major modeling approaches are deterministic and probabilistic (Luis & Donath, 2012). The deterministic approach includes empirical, mechanistic, and mechanistic-empirical methods, while the probabilistic approach mainly includes the Markov chain method.

The Markov chain model has proved to be more suitable for network-level pavement deterioration modeling than the project-level. This method has some drawbacks characterized by being memoryless, as it uses the assumption that the next state only depends on the current state; in addition, it only encompasses certain conditions (location, AADT, etc.) and, thus, requires calibration and modification to consider other conditions. On the other hand, the empirical method, which involves regression by fitting the observations to a linear or non-linear function, is considered to be a very primitive method, its main issue being overfitting (Garcia & Riggins, 1984). It also considers the function coefficients as having fixed but unknown values rather than random variables, which fails to accommodate the heterogeneity of different pavement segments. Mechanistic approaches, which build a sound relationship between observations and casual factors to establish the deterioration pattern of materials and relevant indexes, fail to consider the uncertainty in the observation (Rauhut, et al, 1984). Also, the calibration of model parameters can be difficult or even impossible because calibration requires a great amount of detailed information about the local area, like stress, strain, etc., and some of this information is not available.

Bayesian statistical approaches have proved to be promising in that context. Bayesian methods combine previous knowledge with observations while assuming that parameters are random variables in Bayesian statistics in order to accommodate the heterogeneity of pavement segments through the probability density function of the parameters. Rather than being a fixed value, the prediction derived from Bayesian model is the distribution of rates, which under most circumstances covers the real value. The prediction based on the Bayesian model can be achieved both on a project and network level. It is also easier to transplant the model to other conditions or locations.

Luis and Donath (2012) established a Bayesian regression forecasting model that correlated ESALs and rut depths; they have validated the method using AASHO Road Test data. Eun Sug et al. (2008) put forward a sigmoidal-function-based Bayesian model to improve the prediction method of Texas DOT. It is a time sequence model. This model is applied on a project level and has shown sound forecasting capability. Litao and Nasir (2014) studied the IRI deterioration pattern of pavements treated with thin Hot Mix Asphalt (HMA) overlays. Litao and Nasir combined two parts together: predicting the IRI value of the existing pavement (if no treatment was applied) and predicting the reduction in the IRI value owing to the application of the preservation treatment. They used the Bayesian model for the second part. Daeseok et al (2013) applied the Bayesian estimation with the Markov Chain Monte Carlo (MCMC) to improve the conventional the Markov Chain method. They also verified the method using time-series inspection data from the entire Korean National Highway network for 2007-2010. They studied the deterioration state of cracks, rutting, and IRI. Feng and Jorge (2005) also modeled the PSI using AASHO Road Test data. Feng and Jorge incorporated structural properties, environmental effects and traffic loading to provide a comprehensive model. They also used the difference equation instead of conventional sigmoidal function, making the integration of traffic loading to the model easier.

DATA PREPROCESSING

The data used for deriving the project-level deterioration model stems from the COPACES database. As noted in CHAPTER 1, the COPACES manual defined the specific deduction value for various types of distresses and their severity levels. The fiscal year (FY) data from COPACES, based on the time of the pavement project inspection, is used in our model.

To acquire a reasonable outcome, it is necessary to have COPACES data preprocessed. In that context, the model focuses solely on the asphalt pavement. Moreover, records with missing key attributes, such as FY and project ratings, were not used.

Another important step that requires care is the combination of segments into projects. This combination is based on the deteriorating situation of the pavement segment, such that segments with similar distress levels were combined into the same projects. Therefore, this project segmentation changes from year to year. In order to make sure that the same segments are being modeled, the common parts are extracted among different years and assigned a new project ID.

DEVELOPMENT OF BAYESIAN MODEL

Model Function

A commonly used equation for modeling project-level pavement deterioration is the sigmoid function (Park, et al., 2008), which is:

$$L_t = \alpha e^{-(\rho/AGE_t)^{\beta}} \tag{1}$$

where L_t represents the pavement project rating deduction value, α the maximum deduction value when AGE_t approaches infinity, ρ the prolongation factor that controls how long the pavement will last before significant increases in distress occur, and β is the slope factor that controls how steeply L_t changes in the middle of the curve.

In order to consider the variability of the pavement from year to year, a random variable χ_t that changes each year is introduced. Although raters have received proper training, there is still observational error. An observational error factor ε_t can be added to accommodate this.

Thus, the model is modified as follows:

$$L_t = \alpha e^{-\left(\frac{\chi_t \rho}{AGE_t}\right)^{\beta}} e^{\varepsilon_t} \qquad t = 1, 2, 3, 4 \ldots \qquad (2)$$

Figure 3-1 shows the rate deduction curve (Park, et al., 2008). The meanings of all the parameters can be demonstrated as follows:

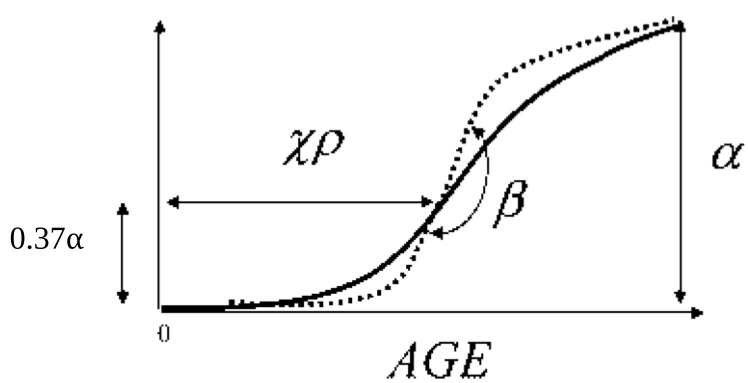


Figure 3-1. Graph. Rate deduction curve (Park et al., 2008).

Repetitive loads will also increase the rating deduction of the pavement. In order to consider the deterioration influence that traffic has on the pavement segment, we amplify the AGE_t by an AADT factor that is described as follows:

$$1 + \kappa \log\left(\mathrm{AADT}_t\right) \tag{3}$$

Generally, heavily loaded trucks will contribute more damage than cars of the same total loads. This implies that the truck percentage of the AADT may, also, affect the deterioration pattern. Thus, it is necessary to consider the impact of trucks in the same way as AADT is considered. An amplification factor is defined as follows:

$$1 + \eta \mathrm{PT}_t \tag{4}$$

where PT_t is the percentage of truck at year *t*.

In this way, the original AGE_t is multiplied by the two factors, which produces

$$AGE_t \times (1 + \kappa \log(\mathrm{AADT}_t)) \times (1 + \eta \mathrm{PT}_t) \tag{5}$$

$$L_t = \alpha e^{-\left(\frac{\chi_t \rho}{AGE_t(1+\kappa\, log(AADT_t))(1+\eta PT_t)}\right)^{\beta}} e^{\varepsilon_t} \qquad t = 1, 2, 3 \ldots \tag{6}$$

Apply logarithm to the both sides of equation (6):

$$\log(L_t) = \log(\alpha) - \left(\frac{\chi_t \rho}{AGE_t(1+\kappa \log(\mathrm{AADT}_t))(1+\eta \mathrm{PT}_t)}\right)^{\beta} e^{\varepsilon_t} \tag{7}$$

Apply logarithm to the equation (7) again:

$$\log(\log(\alpha) - \log(L_t)) = \beta \log(\rho) + \beta \log(\chi_t) - \beta[\log(AGE_t)$$

$$+ \log(1 + \kappa \log(\mathrm{AADT}_t)) + \log(1 + \eta \mathrm{PT}_t)] + \varepsilon_t \qquad (8)$$

We define:

$$Y_t = \log(\log(\alpha) - \log(L_t)) \qquad (9)$$

$$X_t = \log(AGE_t) + \log(1 + \kappa \log(\mathrm{AADT}_t)) + \log(1 + \eta \mathrm{PT}_t) \qquad (10)$$

$$\lambda_t = \log(\chi_t) \qquad (11)$$

The λ_t is modeled as a one-order autoregression process to apply the Kalman Filtering.

$$\lambda_t = \phi \lambda_{t-1} + \nu_t \qquad t = 2, 3, 4 \ldots \qquad (12)$$

$$\lambda_1 \sim N(0, M) \qquad (13)$$

$$M = V/(1 - \phi^2) \qquad (14)$$

Model Estimation through Bayesian Theorem

In our model, the parameters, $\alpha, \beta, \rho, \lambda_t, \phi, \nu_t, \varepsilon_t$, are regarded as random variables. We use the continuous Bayesian theorem to make inference and predictions, which is described below:

$$p(\Theta|Y) = \frac{p(Y|\Theta)p(\Theta)}{\int p(Y|\Theta)p(\Theta)d\Theta} \propto p(Y|\Theta)p(\Theta) \qquad (15)$$

where

Θ stands for a set of the parameters, including error parameters and regression parameters;

$p(\Theta|Y)$ denotes posterior distributions of parameters Θ given observations Y;

$p(Y|\Theta)$ represents the likelihood of the observations given the parameters Θ;

$p(\Theta)$ denotes the prior distribution of the parameters Θ;

The calculation of the denominator requires high-dimensional integration, which is impossible in this model. Thus, the MCMC (Markov Chain Monte Carlo) method is adopted to get the posterior summary of each parameter.

Prior Distribution

Traditionally, it can be assumed that the prior distributions are independent. Also, regression parameters like $\alpha, \beta, \rho, \kappa, \eta$ can be assumed to conform to truncated normal distribution. It is assumed that the prior distributions for $\alpha, \beta, \rho, \kappa, \eta$ are:

$$\alpha \sim \mathrm{N}(\alpha_0, \sigma_0^2) I_{\{\alpha_{min} < \alpha < \alpha_{max}\}} \tag{16}$$

$$\beta \sim \mathrm{N}(\beta_0, \sigma_1^2) I_{\{\beta_{min} < \beta < \beta_{max}\}} \tag{17}$$

$$\rho \sim \mathrm{N}(\rho_0, \sigma_2^2) I_{\{\rho_{min} < \rho < \rho_{max}\}} \tag{18}$$

$$\kappa \sim \mathrm{N}(\kappa_0, \sigma_\kappa^2) I_{\{\kappa_{min} < \kappa < \kappa_{max}\}} \tag{19}$$

$$\eta \sim \mathrm{N}(\eta_0, \sigma_\eta^2) I_{\{\eta_{min} < \eta < \eta_{max}\}} \tag{20}$$

Where

$$(\alpha_0, \sigma_0, \alpha_{min}, \alpha_{max}) = (90, 8, 70, 130) \quad (21)$$

$$(\beta_0, \sigma_1, \beta_{min}, \beta_{max}) = (1, 0.2, 0.2, 1.8) \quad (22)$$

$$(\rho_0, \sigma_2, \rho_{min}, \rho_{max}) = (14, 3, 0, 30) \quad (23)$$

$$(\kappa_0, \sigma_\kappa, \kappa_{min}, \kappa_{max}) = (0.05, 0.02, 0.01, 0.1) \quad (24)$$

$$(\eta_0, \sigma_\eta, \eta_{min}, \eta_{max}) = (0.4, 0.2, 0, 1) \quad (25)$$

The prior mean and standard deviation of $\alpha, \beta, \rho, \kappa, \eta$ can be given by relevant experts or engineers according to personal judgment. The prior distributions are subjective and may influence the posterior distribution. However, with more data available, the influence of prior distributions will get smaller.

For the autoregression factor ϕ, a uniform prior distribution, $p(\phi) = I_{\{0<\phi<1\}}$, is defined. As for the error parameters, ν_t, ε_t, it is assumed that they are independent and conform to normal distribution. But their precision, the reciprocal of variance, conform a gamma distribution as follows:

$$\nu_t \sim N(0, V), \qquad 1/V \sim Gamma(a_0, b_0) \quad (26)$$

$$\varepsilon_t \sim N(0, Q), \qquad 1/Q \sim Gamma(c_0, d_0) \quad (27)$$

There is limited information about the error parameter. So, the values of the gamma distribution shape parameters are set to be $a_0 = c_0 = 2$. Since the $1/V$ is gamma-distributed, the mean of $1/V$ is b_0/a_0. As the data size gets bigger, the shape value of posterior gamma distribution gets higher. To maintain a similar level of variance, the scale value also needs to be enlarged. It is critical to calibrate the prior value according to the trace plot of the parameter values. Empirically, the scale value is about one fiftieth of the data size. It is suggested the scale parameters be defined as follows:

$$b_0 = d_0 = \frac{n}{50} \tag{28}$$

If the b_0, d_0 is not defined properly, it will take longer for the Markov Chains to reach convergence, and autocorrelation level may be higher. Sometimes, this may lead to the failure of the MCMC algorithm.

Posterior Distribution Estimation

According to equation (15), the likelihood function $p(Y|\Theta)$ can be written as:

$$p(Y|\Theta) = \left(\frac{1}{2\pi Q}\right)^{\frac{n}{2}} \exp\left\{-\frac{1}{2Q}\sum_{k=1}^{n}(Y_k - \beta\log\rho + \beta X_k - \beta\lambda_k)^2\right\} \tag{29}$$

Since the regression parameters are independent, the prior joint density function is the product of each parameter density function, which is defined as follows:

$$p(\Theta) = p(\alpha)p(\beta)p(\rho)p(Q)p(V)p(\phi)p(\kappa)p(\eta)p(\lambda_1, \dots, \lambda_n|\phi, V) \tag{30}$$

Referring to equation (12), (13), (14), it is explicit that:

$$p(\lambda_1, \dots, \lambda_n|\phi, V) = \left(\frac{1}{2\pi M}\right)^{\frac{1}{2}} e^{-\frac{\lambda_1^2}{2M}} \left(\frac{1}{2\pi V}\right)^{\frac{n-1}{2}} \exp\left\{-\frac{1}{2V}\sum_{k=1}^{n}(\lambda_k - \phi\lambda_{k-1})^2\right\} \tag{31}$$

According to the assumption that parameters are independent, the joint prior distribution density function is the product of all the prior functions as follows:

$$p(\Theta) = \left(\frac{1}{2\pi\sigma_0^2}\right)^{\frac{1}{2}} e^{-\frac{(\alpha-\alpha_0)^2}{2\sigma_0^2}} I_{\{\alpha_{min}<\alpha<\alpha_{max}\}} \left(\frac{1}{2\pi\sigma_1^2}\right)^{\frac{1}{2}} e^{-\frac{(\beta-\beta_0)^2}{2\sigma_1^2}} I_{\{\beta_{min}<\beta<\beta_{max}\}} \left(\frac{1}{2\pi\sigma_2^2}\right)^{\frac{1}{2}}$$

$$e^{-\frac{(\rho-\rho_0)^2}{2\sigma_2^2}} I_{\{\rho_{min}<\rho<\rho_{max}\}} \frac{b_0^{a_0}}{\Gamma(a_0)} \left(\frac{1}{Q}\right)^{a_0+1} e^{-\frac{b_0}{Q}} \frac{d_0^{c_0}}{\Gamma(c_0)} \left(\frac{1}{V}\right)^{c_0+1} e^{-\frac{d_0}{V}} I_{\{0<\phi<1\}} \left(\frac{1}{2\pi\sigma_\kappa^2}\right)^{\frac{1}{2}}$$

$$e^{-\frac{(\kappa-\kappa_0)^2}{2\sigma_\kappa^2}} I_{\{\kappa_{min}<\kappa<\kappa_{max}\}} \left(\frac{1}{2\pi\sigma_\eta^2}\right)^{\frac{1}{2}} e^{-\frac{(\eta-\eta_0)^2}{2\sigma_\eta^2}} I_{\{\eta_{min}<\eta<\eta_{max}\}} I_{\{\kappa_{min}<\kappa<\kappa_{max}\}} \left(\frac{1}{2\pi\sigma_\eta^2}\right)^{\frac{1}{2}}$$

$$e^{-\frac{(\eta-\eta_0)^2}{2\sigma_\eta^2}} I_{\{\eta_{min}<\eta<\eta_{max}\}} \left(\frac{1}{2\pi M}\right)^{\frac{1}{2}} e^{-\frac{\lambda_1^2}{2M}} \left(\frac{1}{2\pi V}\right)^{\frac{n-1}{2}} \times \exp\left\{-\frac{1}{2V}\sum_{k=1}^{n}(\lambda_k-\phi\lambda_{k-1})^2\right\} \tag{32}$$

With the prior and likelihood functions, using equation (15), the posterior distribution is described as follows:

$$p(\Theta|Y) \propto p(Y|\Theta)p(\Theta) = \left(\frac{1}{2\pi Q}\right)^{\frac{n}{2}} \exp\left\{-\frac{1}{2Q}\sum_{k=1}^{n}(Y_k-\beta\log\rho+\beta X_k-\beta\lambda_k)^2\right\}$$

$$\left(\frac{1}{2\pi\sigma_0^2}\right)^{\frac{1}{2}} e^{-\frac{(\alpha-\alpha_0)^2}{2\sigma_0^2}} I_{\{\alpha_{min}<\alpha<\alpha_{max}\}} \left(\frac{1}{2\pi\sigma_1^2}\right)^{\frac{1}{2}} e^{-\frac{(\beta-\beta_0)^2}{2\sigma_1^2}}$$

$$I_{\{\beta_{min}<\beta<\beta_{max}\}} \left(\frac{1}{2\pi\sigma_2^2}\right)^{\frac{1}{2}} e^{-\frac{(\rho-\rho_0)^2}{2\sigma_2^2}} I_{\{\rho_{min}<\rho<\rho_{max}\}} \frac{b_0^{a_0}}{\Gamma(a_0)}$$

$$\left(\frac{1}{Q}\right)^{a_0+1} e^{-\frac{b_0}{Q}} \frac{d_0^{c_0}}{\Gamma(c_0)} \left(\frac{1}{V}\right)^{c_0+1} e^{-\frac{d_0}{V}} I_{\{0<\phi<1\}} \left(\frac{1}{2\pi\sigma_\kappa^2}\right)^{\frac{1}{2}} e^{-\frac{(\kappa-\kappa_0)^2}{2\sigma_\kappa^2}}$$

$$I_{\{\kappa_{min}<\kappa<\kappa_{max}\}} \left(\frac{1}{2\pi\sigma_\eta^2}\right)^{\frac{1}{2}} e^{-\frac{(\eta-\eta_0)^2}{2\sigma_\eta^2}} I_{\{\eta_{min}<\eta<\eta_{max}\}} \left(\frac{1}{2\pi M}\right)^{\frac{1}{2}}$$

$$e^{-\frac{\lambda_1^2}{2M}} \left(\frac{1}{2\pi V}\right)^{\frac{n-1}{2}} \exp\left\{-\frac{1}{2V}\sum_{k=1}^{n}(\lambda_k-\phi\lambda_{k-1})^2\right\} \tag{33}$$

Markov Chain Monte Carlo (MCMC) Method

The MCMC Method is a sampling method that builds specific multiple Markov Chains whose stationary distributions are the target posterior distribution. After the Markov Chain reaches convergence, we can start to sample from the Markov Chain as posterior samples. There are two widely used algorithms for the MCMC Method, the Metropolis-Hastings Sampling Algorithm and the Gibbs Sampling Algorithm. The Gibbs Sampling Algorithm is, in some ways, the same as the Metropolis-Hastings Sampling Algorithm, except the acceptance rate of the Gibbs Sampling Algorithm is exactly 1. In our model, an integrated algorithm that combines these two algorithms is applied. Because of the autoregression property of λ_k, we utilize Kalman Filtering to update λ_k in each iteration. For $\alpha, \beta, \rho, \phi, \kappa, \eta$, since the full conditional posterior distributions cannot be simplified into functional form and it is hard to draw candidate samples from their full conditional posterior distributions, it is apparent the Metropolis-Hastings Sampling is more feasible than Gibbs Sampling.

Since the full conditional posterior distributions of Q, V are inverse gamma distribution and it is handy to draw candidate sample from inverse gamma distribution, the application of Gibbs Sampling for Q and V is straightforward. One iteration of the MCMC algorithm includes 5 steps:

(a) Update Q, V;

(b) Update ϕ;

(c) Update α, κ, η;

(d) Update β, ρ;

(e) Update $\lambda_1, \ldots, \lambda_n$;

Pavement Deterioration Prediction

Using the MCMC Method, we can obtain the posterior distribution of family curve parameters $(\alpha, \beta, \rho, \kappa, \eta)$ and make predictions on a family level adopting the autoregression function:

$$\lambda_{n+1} = \phi\lambda_n + \nu_{n+1} \tag{34}$$

Also, we can make predictions on a project level by assuming that the posterior distribution of family curve parameters $(\alpha, \beta, \rho, \kappa, \eta)$ from the family level is the prior distribution on a project level. It is suggested the project level prediction be used as a future prediction instead of the family level prediction.

Initial Fiscal Year Determination

Knowing that some historical COPACES records do not contain the initial fiscal year of the project (that is, the year when the Project Rating is 100), a proper estimate is required. To achieve this, an extra step is added in each iteration of the MCMC algorithm:(f) Update δ : the year when a pavement distress appears.

Apart from this, the year AGE_t is substituted by $(AGE_t - \delta)$ in the previous steps (a, b, c, d, and e). Since the full conditional posterior distribution of δ cannot be simplified into a functional form, the Metropolis-Hastings Sampling is suitable for obtaining posterior summary of δ.

MODEL APPLICATION FOR USING COPACES DATA

The above model is applied to the COPACES data, mainly the Project Rating data from Georgia collected from FY 1986 to FY 2015. As noted in CHAPTER 2, GDOT has divided the whole state into 7 working districts, each with roughly similar weather and soil conditions, as well as classifying the pavement segments into 5 levels of priority, that form 35 families.

Methodology

Figure 3-2 is a flow chart showing the process of parameter estimation and rating prediction for each family. After finishing the data preprocessing, determining whether or not there is enough data for estimating family curve parameters is required. In case there are not enough records with an identified initial fiscal year (Rating=100) are available, it is recommended the data sample size be expanded by incorporating the data lacking an initial fiscal year, which is then estimated as demonstrated in the following section.

MCMC Algorithm

The MCMC algorithm for this model consists of three components: family level estimation, project-level estimation and prediction, and initial year estimation.

Family Level Estimation

(a) Update Q, V;

Q, *V* are inverse gamma-distributed. Using equation (33), the probability density function of *Q* is obtained as follows:

$$p(Q|Y) \propto p(\Theta|Y) \propto p(Y|\Theta)p(\Theta)$$

$$\propto \left(\frac{1}{2\pi Q}\right)^{\frac{n}{2}} \exp\left\{-\frac{1}{2Q}\sum\nolimits_{k=1}^{n}(Y_k - \beta\log\rho + \beta X_k - \beta\lambda_k)^2\right\}$$

$$\propto \left(\frac{1}{Q}\right)^{a_0+\frac{n}{2}+1} e^{-\frac{b_0}{Q}-\frac{\sum_{k=1}^{n}(Y_k-\beta\log\rho+\beta X_k-\beta\lambda_k)^2}{2Q}} \tag{35}$$

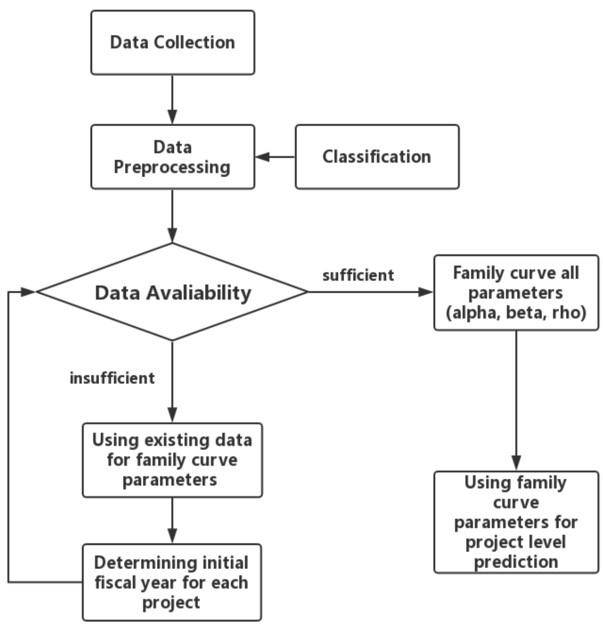


Figure 3-2. Chart. Data processing flow.

The probability density function of *Q* conforms the inverse gamma distribution. Similarly, *V* conforms to the inverse gamma distribution. Due to the ease of drawing samples from inverse the gamma distribution, Gibbs Sampling is used to update *Q*, *V*.

$$Q \sim \text{Gamma}\left(a_0 + \frac{n}{2}, b_0 + \frac{1}{2}\sum\nolimits_{k=1}^{n}(Y_k - \beta\log\rho + \beta X_k - \beta\lambda_k)^2\right) \tag{36}$$

$$V \sim \text{Gamma}\left(c_0 + \frac{n}{2}, d_0 + \frac{1}{2}(1-\phi^2)\lambda_1^2 + \frac{1}{2}\sum_{k=2}^{n}(\lambda_k - \phi\lambda_{k-1})^2\right) \tag{37}$$

(b) Update ϕ;

Using equation (33), the probability density function of ϕ is obtained as follows:

$$p(\phi|Y) \propto p(\Theta|Y) \propto p(Y|\Theta)p(\Theta)$$

$$\propto \left(\frac{1}{2\pi M}\right)^{\frac{1}{2}} e^{-\frac{\lambda_1^2}{2M}} I_{\{0<\phi<1\}} \left(\frac{1}{2\pi V}\right)^{\frac{n-1}{2}} \exp\left\{-\frac{1}{2V}\sum_{k=1}^{n}(\lambda_k - \phi\lambda_{k-1})^2\right\}$$

$$\propto \left(\frac{1}{M}\right)^{\frac{1}{2}} e^{-\frac{\lambda_1^2}{2M}} I_{\{0<\phi<1\}} \exp\left\{-\frac{1}{2V}\left[\left(\sum_{k=1}^{n}\lambda_k^2\right)\phi^2 - 2\left(\sum_{k=2}^{n}\lambda_k\,\lambda_{k-1}\right)\right]\right\}$$

$$\propto \left(\frac{1}{M}\right)^{\frac{1}{2}} e^{-\frac{\lambda_1^2}{2M}} I_{\{0<\phi<1\}} \exp\left\{-\frac{\left(\phi - \frac{\sum_{k=2}^{n}\lambda_k\lambda_{k-1}}{\sum_{k=1}^{n}\lambda_k^2}\right)^2}{2V\sum_{k=2}^{n}\lambda_k^2}\right\} \tag{38}$$

This equation cannot be simplified further. So, the Metropolis-Hastings Sampling is more practicable for updating ϕ. We use the truncated normal distribution, $I_{\{0<\phi<1\}} N\left(\frac{\sum_{k=2}^{n}\lambda_k\lambda_{k-1}}{\sum_{k=1}^{n}\lambda_k^2}, V\sum_{k=2}^{n}\lambda_k^2\right)$, as the proposal distribution of ϕ. And the acceptance rate is defined as $\min\{1, g(\phi^*)/g(\phi)\}$, where

$$g(\phi) = \left(\frac{1}{M}\right)^{\frac{1}{2}} e^{-\frac{\lambda_1^2}{2M}}, \quad M = \frac{V}{1-\phi^2} \tag{39}$$

(c) Update α, κ, η

Using equation (33), the probability density function of α is obtained as:

$$p(\alpha|Y) \propto p(\Theta|Y) \propto p(Y|\Theta)p(\Theta)$$

$$\propto \exp\left\{-\frac{1}{2Q}\sum_{k=1}^{n}(Y_k - \beta\log\rho + \beta X_k - \beta\lambda_k)^2\right\}\left(\frac{1}{2\pi\sigma_0^2}\right)^{\frac{1}{2}} e^{-\frac{(\alpha-\alpha_0)^2}{2\sigma_0^2}} I_{\{\alpha_{min}<\alpha<\alpha_{max}\}} \quad (40)$$

It is more feasible to apply Metropolis-Hastings Sampling. We use the truncated normal distribution, $I_{\{\alpha_{min}<\alpha<\alpha_{max}\}}N(\alpha_0, \sigma_0^2)$, as the proposal distribution of α. The acceptance rate is defined as $min\{1, f(\alpha^*)/f(\alpha)\}$, where

$$f(\alpha) = \exp\left\{-\frac{1}{2Q}\sum_{k=1}^{n}[Y_k^2 + 2Y_k(-\beta\log\rho + \beta X_k - \beta\lambda_k)]\right\} \quad (41)$$

Similarly, κ, η are updated in the same way.

(d) Update β, ρ

The method for updating β, ρ is also like that of updating α, κ, η. Using equation (33), the probability density function of β is obtained as follows:

$$p(\alpha|Y) \propto p(\Theta|Y) \propto p(Y|\Theta)p(\Theta)$$

$$\propto \exp\left\{-\frac{1}{2Q}\sum_{k=1}^{n}(Y_k - \beta\log\rho + \beta X_k - \beta\lambda_k)^2\right\}\left(\frac{1}{2\pi\sigma_1^2}\right)^{\frac{1}{2}} e^{-\frac{(\beta-\beta_0)^2}{2\sigma_1^2}} I_{\{\beta_{min}<\beta<\beta_{max}\}} \quad (42)$$

We use the truncated normal distribution, $I_{\{\beta_{min}<\beta<\beta_{max}\}}N(\beta_0, \sigma_1^2)$ as the proposal distribution of β. The acceptance rate is defined as $min\{1, j(\beta^*)/j(\beta)\}$, where

$$j(\beta) = \exp\left\{-\frac{1}{2Q}\sum_{k=1}^{n}[\beta^2(-\log\rho + X_k - \lambda_k)^2 + 2\beta Y_k(-\log\rho + X_k - \lambda_k)]\right\} \quad (43)$$

(e) Update $\lambda_1, \dots, \lambda_n$;

Using forward filtering and backward sampling to update $\lambda_1, \dots, \lambda_n$, we simulate as follows:

(1) Sample λ_n from $N(m_n, C_n)$ where m_n and C_n are obtained from the Kalman filtering recurrences:

$$m_t = a_t + e_t K_t \tag{44}$$

$$C_t = R_t - K_t^2 Q_t \tag{45}$$

$$a_t = m_{t-1}\phi \tag{46}$$

$$R_t = \phi^2 C_{t-1} + \mathrm{V} \tag{47}$$

$$f_t = a_t \beta \tag{48}$$

$$Q_t = \beta^2 R_t + Q \tag{49}$$

$$K_t = \frac{\beta R_t}{Q_t} \tag{50}$$

$$e_t = Y_t - \beta \log(\rho) + \beta X_t - f_t \tag{51}$$

(2) For each $t = n-1, n-2, \ldots, 1$, sample λ_t from $N(h_t, H_t)$ where $h_t = m_t + (\lambda_{t+1} - a_{t+1})B_t$, $H_t = C_t - B_t^2 R_{t+1}$, $B_t = \phi C_t / R_{t+1}$, and λ_{t+1} is the value just sampled.

Project Level Estimation and Prediction

For the project level, the family curve parameters $\alpha, \beta, \rho, \kappa, \eta$ are considered as constants whose values are the mean of the posterior distributions. In this way, the MCMC algorithm is nearly the same as the previous one, except that it doesn't require updating $\alpha, \beta, \rho, \kappa, \eta$. One iteration of the MCMC algorithm consists of 5 steps:

(a) Update Q, V;

(b) Update ϕ;

(c) Update α, κ, η;

(d) Update β, ρ;

(e) Update $\lambda_1, \dots, \lambda_n$;

On the other hand, some records of the projects may not contain the initial year of the pavement segment, as mentioned previously. Thus, it is necessary to estimate the initial year (δ) to get a more accurate prediction. To achieve this, an extra step is added to update the initial year (δ), which will be introduced in more detail in the following section.

After sampling from the posterior distribution is finished, it is reasonable to make predictions based on the autoregression equation, $\lambda_{n+1} = \phi\lambda_n + \nu_{n+1}$. With the samples from the posterior distribution of λ_n, it is straightforward to simulate the posterior distribution of λ_{n+1}, which can be used to calculate the project deterioration curve of the next state as a project level prediction. After the posterior distribution of λ_{n+1} is simulated, the Monte Carlo simulation is applied to make predictions about the rate.

(a) Randomly draw a set of $\alpha, \beta, \rho, \kappa, \eta$ from the outcome samples of the MCMC algorithm

(b) Calculate the distress deduction use the following equation:

$$\chi_{n+1} = e^{\lambda_{n+1}} \tag{52}$$

$$L_{n+1} = \alpha e^{-\left(\frac{\chi_{n+1}\rho}{AGE_{n+1}(1+\kappa\, log(AADT_{n+1}))(1+\eta PT_{n+1})}\right)^{\beta}} \tag{53}$$

(c) Repeat the two steps above

(d) Use the samples of L_{n+1} obtained from the three steps above to calculate the distribution of L_{n+1}, including credible interval, mean, and median

Initial Year Estimation

In order to estimate the initial year (δ), AGE_k is substituted by $AGE_k - \delta$. The prior distribution of δ is set to be a uniform distribution, $\mathrm{U}(\theta_1, \theta_2)$.

Using equation (33), the probability density function of α is obtained as follows:

$$p(\delta|Y) \propto p(\Theta|Y) \propto p(Y|\Theta)p(\Theta)$$

$$\propto I_{\{\theta_1<\delta<\theta_2\}} \exp\left\{-\frac{1}{2Q}\sum_{k=1}^{n}(Y_k - \beta\log\rho + \beta X_k - \beta\lambda_k)^2\right\}$$

$$\propto I_{\{\theta_1<\delta<\theta_2\}} \exp\left\{-\tfrac{1}{2Q}\textstyle\sum_{k=1}^{n}[\beta^2 X_k^2 + 2\beta X_k(Y_k - \beta\log\rho - \beta\lambda_k)]\right\} \tag{54}$$

where $X_k = \log\,(AGE_k - \delta) + \log(1 + \kappa\log(\mathrm{AADT}_t)) + \log\,(1 + \eta\mathrm{PT}_t)$.

We use the truncated uniform distribution $\mathrm{U}(\theta_1, \theta_2)$ as the proposal distribution of δ. The acceptance rate is defined as $\min\{1, q(\delta^*)/q(\delta)\}$, where

$$q(\delta) = \exp\left\{-\tfrac{1}{2Q}\textstyle\sum_{k=1}^{n}[\beta^2 X_k^2 + 2\beta X_k(Y_k - \beta\log\rho - \beta\lambda_k)]\right\} \tag{55}$$

Case Study

The proposed model was applied to the COPACES data provided by GDOT. The family chosen was the District 5 (coastal area near Savannah) Low Priority Pavement Family.

Family Level

In this family, there are 141 valid records. Using the MCMC algorithm, it is possible to derive the family curve parameters posterior distributions. A burn-in period of 1,000,000 iterations was set. After the burn-in period, a posterior sample size of 2,000 was collected by sampling every 1,000 values, which is a total of 3,000,000 iterations.

Figure 3-3 **shows the relationship between the initial data and the estimated family deterioration curve. The curve was plotted using the mean value of the curve parameters $\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\rho}, \boldsymbol{\kappa}, \boldsymbol{\eta}$ (see Table** 3-1). The data was quite scattered, which suggests that the deterioration patterns of different projects vary greatly.

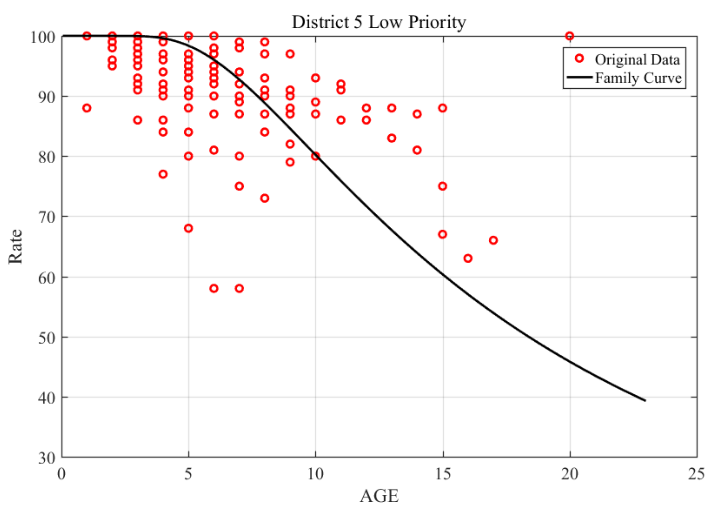


Figure 3-3. Graph. Data points and family deterioration curve.

Table 3-1. Summary of posterior distribution of α,β,ρ,κ,η.

	α	β	ρ	κ	η
Mean	107.0367	1.3130	14.8579	0.0274	0.4595
Median	106.7053	1.3236	14.7644	0.0240	0.4606
StD	7.2425	0.0704	1.5372	0.0130	0.1874
LL80%	97.5607	1.2171	12.9147	0.0128	0.2106
UL80%	116.4868	1.3984	16.8733	0.0462	0.6987

Note: StD represents Standard Deviation; LL80% stands for Lower Limit of 80% Credible Interval; LU80% stands for Upper Limit of 80% Credible Interval.

Since the MCMC method was applied, it was critical to check the convergence and the autocorrelation level:

(a) The convergence of the Markov Chain

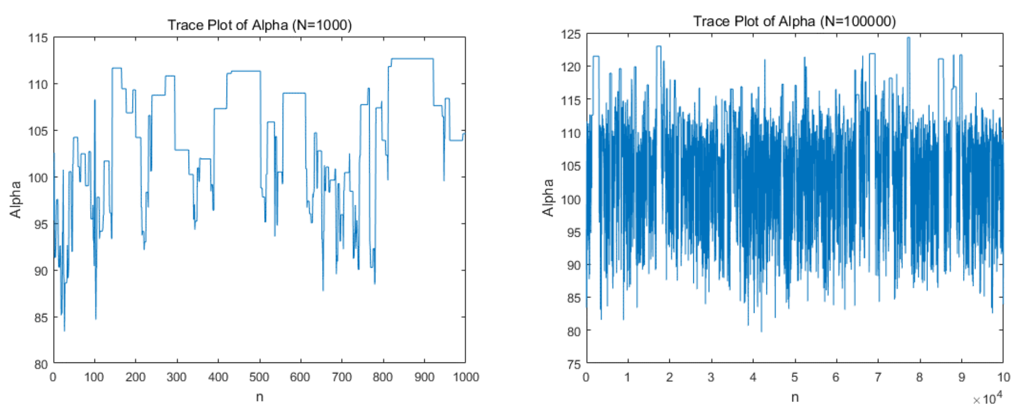


Figure 3-4. Graph. Trace plot of α at N=1000 and N=100,000.

As shown by **Figure 3-4**, the Markov Chain of α has converged, suggesting that the samples conform posterior distributions. Every parameter was checked, and all of them have converged. From the trace plot of β, we can see that although β converged after a burn-in period of 1,000,000 iterations, at certain intervals, the value of β remains the same over thousands of iterations.

We have also tried to expand the number of iterations to 10,000,000 to make sure that β converges after a burn-in period of 5,000,000 iterations, as shown in **Figure 3-5**.

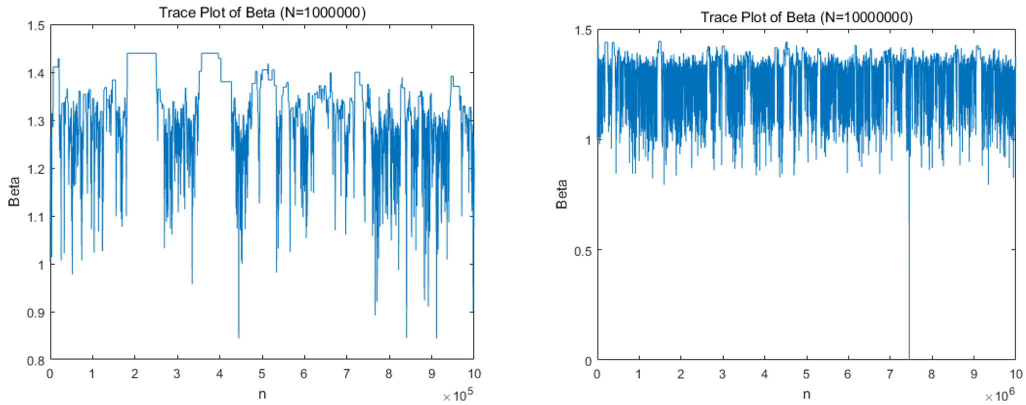


Figure 3-5. Graph. Trace plot of β at N=1,000,000 and N=10,000,000.

(b) The autocorrelation level of samples

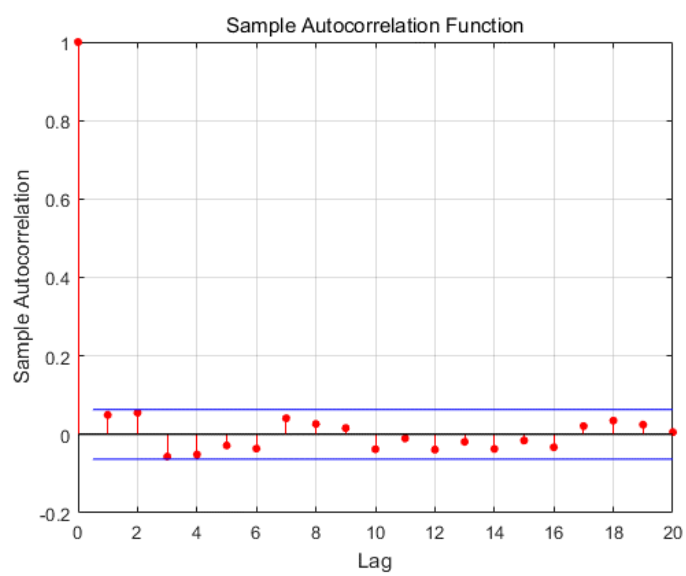


Figure 3-6. Graph. Autocorrelation plot of α.

As shown by **Figure 3-6**, the autocorrelation level of α is relatively small, and, thus, it was quicker to explore the posterior distribution with fewer samples. However, the autocorrelation level of β is relatively high, which was mainly caused by the low acceptance rate of β (as shown in **Figure 3-7**). The low acceptance rate of β forced the value of β to remain the same for thousands of iterations. A significant level of autocorrelation indicates that it will take more samples to explore the whole posterior distribution. This can be compensated for by having more iterations of the calculation and increasing the sampling interval.

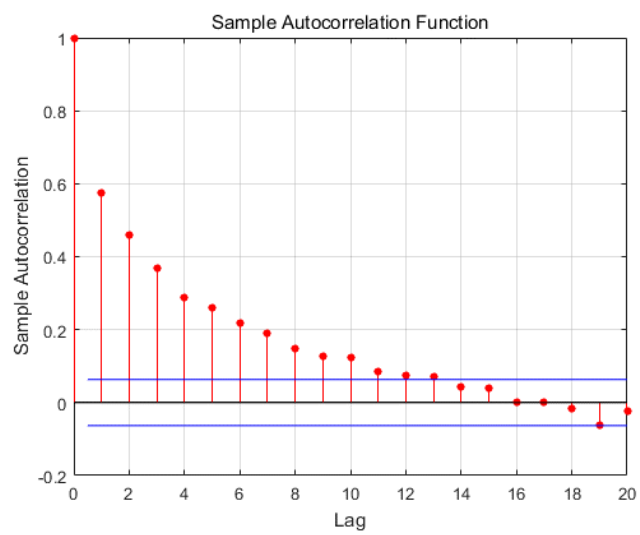


Figure 3-7. Graph. Autocorrelation plot of $\boldsymbol{\beta}$.

Project Level Forecasting and Model Validation

To assess the validity of the prediction based on the proposed model, the model was tested by comparing it to the project level prediction with the observed rates using projects without initial years. Project 001101210015.825.6 was selected. The data of the last year is deleted while estimating the parameters. **Table 3-2** records the data of Project 001101210015.825.6.

Using the proposed model, obtaining the posterior distribution of all the parameters and forecasting rates using MCMC is straightforward (see **Table 3-3**)

With all the samples from the MCMC methods, we can also plot the forecasting curve using the mean value of each parameter as shown in **Figure 3-8**. **Figure 3-9** shows the distribution of the forecasting rate of the next year (Year 1994). The 80% credible interval contains the actual observation of Year 1994. This indicates that this model is capable of accommodating each project by regarding the parameters as random variables. Also, it provides a sound prediction of the future pavement condition.

Table 3-2. COPACES data of 'Project 001101210015.825.6'.

Fiscal Year	Year	Rate	Deduction Value	AADT	Truck Percentage
1988	3	95	5	800	15.1%
1989	4	95	5	800	15.1%
1990	5	87	13	800	15.1%
1991	6	87	13	800	15.1%
1992	7	87	13	800	15.1%
1993	8	77	23	800	15.1%
1994	9	68	32	800	15.1%

Note: The Year is obtained by Fiscal Year minus Year 1985.

Table 3-3. Summary of posterior distribution of α,β,ρ,κ,η.

	α	β	ρ	κ	η	λ_{n+1}	$Rate$
Mean	108.1908	1.2606	13.8335	0.0370	0.4996	0.0373	70.8975
Median	107.9333	1.2717	13.7524	0.0363	0.5000	0.0307	71.0024
StD	7.3198	0.0931	1.2113	0.0149	0.1816	0.0740	2.9900
LL 80%	98.7705	1.1494	12.3595	0.0176	0.2648	-0.0417	67.2503
UL 80%	117.9508	1.3704	15.3416	0.0574	0.7291	0.1239	74.3854
LL 70%	100.4913	1.1743	12.6307	0.0204	0.3037	-0.0239	67.9683
UL 70%	115.8252	1.3546	15.0924	0.0531	0.6949	0.0988	73.7466

Note: StD represents Standard Deviation; LL 80% refers to Lower Limit of 80% Credible Interval, UL 80% refers to Upper Limit of 80% Credible Interval.

We tested several more projects and observed that this model can predict the future rates with a good rate of accuracy, which validated this model.

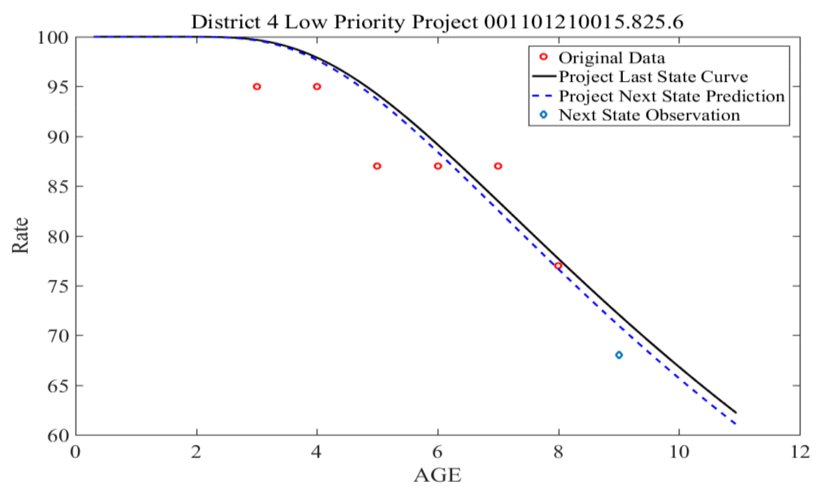


Figure 3-8. Graph. Forecasting of Project 001101210015.825.6.

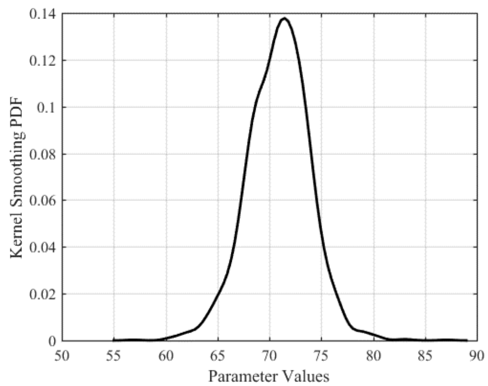
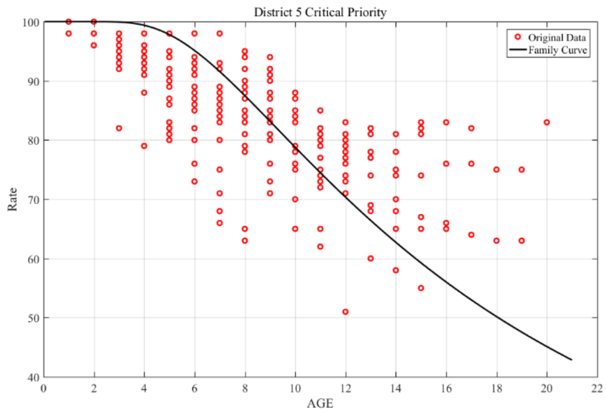


Figure 3-9. Graph. Kernel smoothing PDF of forecasting rate.

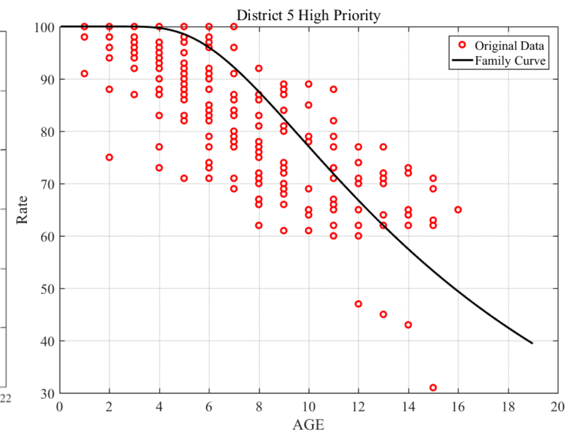
FAMILY-LEVEL DATA ANALYSIS

The model proposed in the previous section is based on the Bayesian statistics and MCMC method. This model can undergo an estimation and analysis both in a family level and project level. At the project level, it enables us to obtain the posterior estimation of the parameters and the rates. At the family level, it helps us to grasp general idea of the whole family in terms of deterioration characteristics. While it is vital to make forecasts to support decision-making in maintenance and rehabilitation, it is also critical to analyze the general deterioration pattern of each family to help a transportation agency allocate funding and make long-term plans.

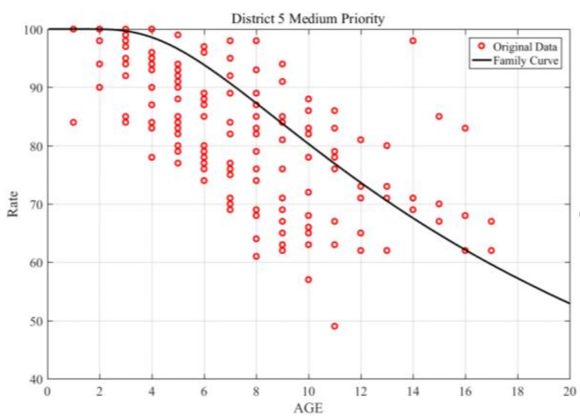
State Route Prioritization



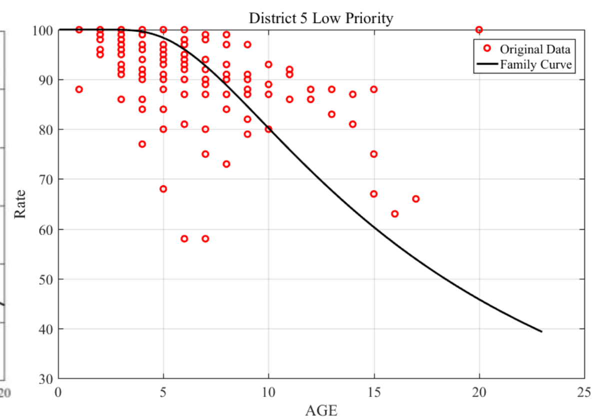
A. Critical Priority Family



B. High Priority Family



C. Medium Priority Family



D. Low Priority Family

Figure 3-10. Graphs. Pavement deterioration curve of District 5 families.

GDOT has prioritized all the pavements in Georgia into 5 categories based on the importance of the highways. We used the proposed model to analyze different families to see whether there is any relationship. However, interstate data is limited and several records were missing the initial fiscal year. Thus, only the four non-interstate families have been analyzed. **Table 3-4** summarizes the mean of each parameter from each priority level. Although there isn't any significant relationship between the family parameter and family priority level, the family level analysis still provides some useful information. **Figure 3-11** and **Figure 3-12** show the project-level deterioration curve for each family.

- As the priority level drops, the data points become more scattered, which implies a lower uniformity and higher heterogeneity among different projects.
- Generally, it will take 11 to 13 years before the rate drops below 70.
- The percentage of truck traffic will affect the deterioration rate greatly. With the same AADT, a 1% increase in the percentage of truck traffic results in an extra 0.4% deterioration.
- α/ρ represents the deterioration rate at the early stage, and β represents the middle stage deterioration rate. It can be seen that high priority pavement has the largest early stage and middle stage deterioration rates. Medium priority segments have the smallest deterioration rates.

Because this analysis is only based on a portion of all the data, validation is still needed in future research to ensure that the chosen sample is representative.

In order to have a direct opinion of different families, three projects after Year 2000 have been selected from each family.

Table 3-4. Summary of mean value of α,β,ρ,κ,η,α/ρ (District 5).

	α	β	ρ	κ	η	α/ρ
Critical (Non-interstate)	108.7861	1.2565	14.7855	0.0308	0.3697	7.3576
High	115.5819	1.4315	15.0013	0.0295	0.5884	7.7048
Medium	111.5461	1.0073	17.2860	0.0341	0.3498	6.4530
Low	107.0367	1.3130	14.8579	0.0274	0.4595	7.2040

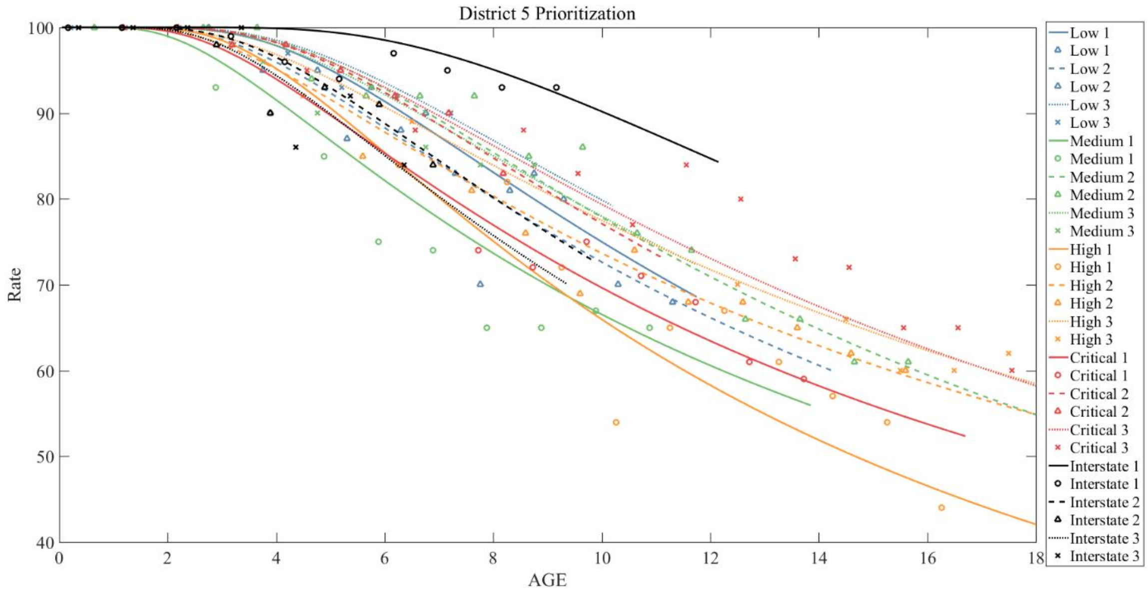


Figure 3-11. Graph. Project level prioritization (data and curve).

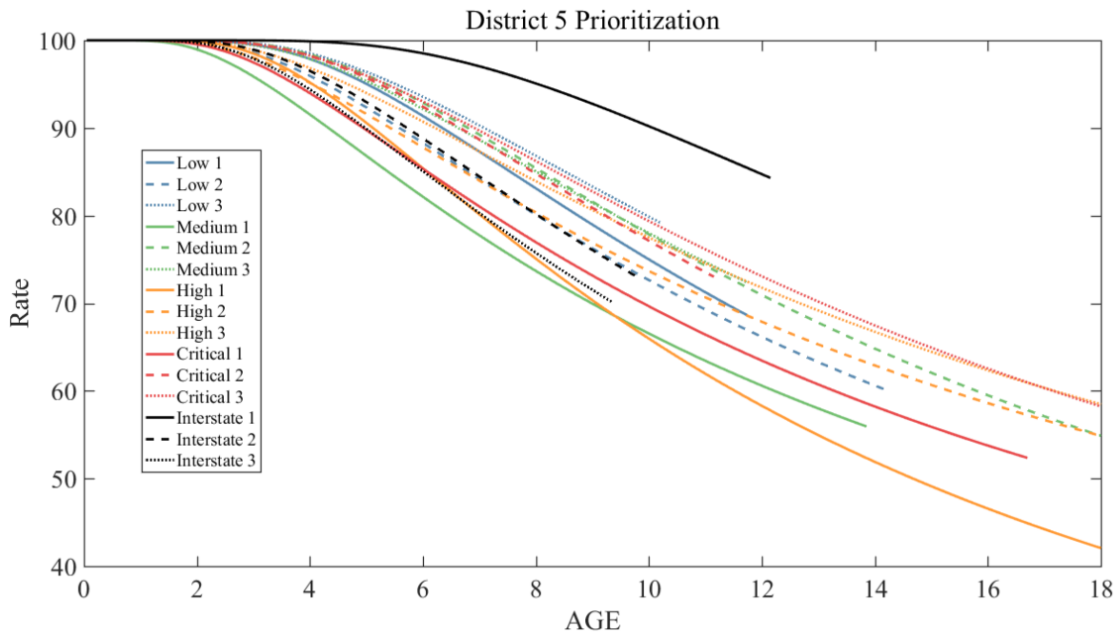
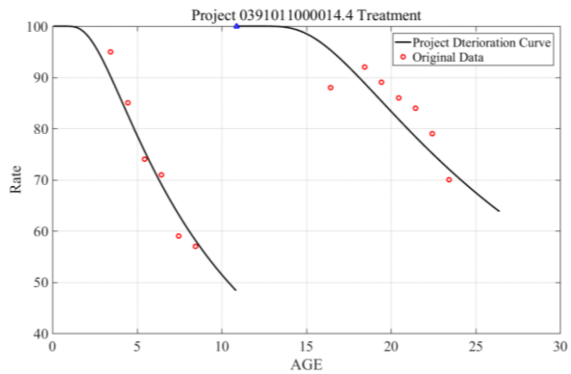
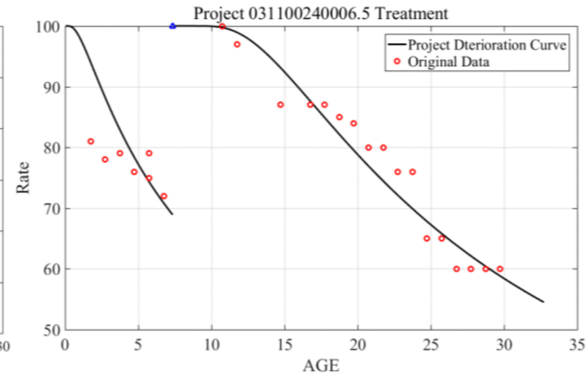


Figure 3-12. Graph. Project level prioritization (curve only).

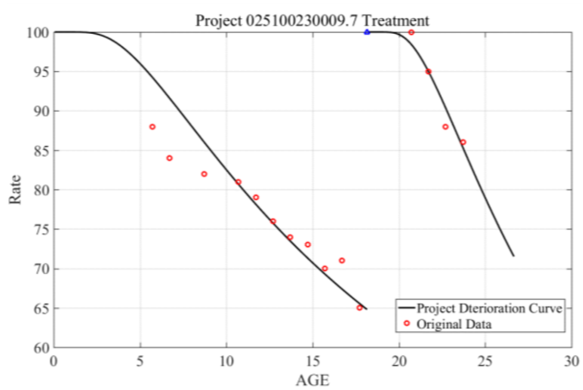
Pavement Life Cycle



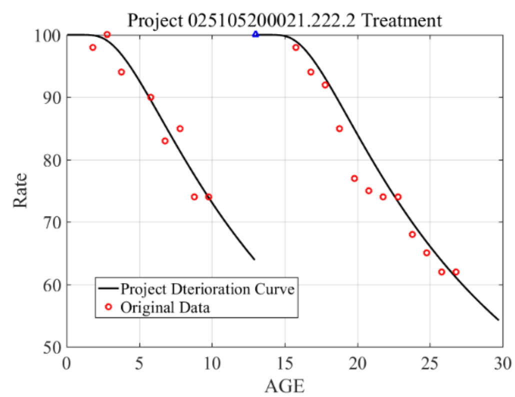
A. Low Priority Family



B. Medium Priority Family



C. High Priority Family



D. Critical Priority Family

Figure 3-13. Graphs. Pavement life cycle of the selected projects in each family.

According to the conventional engineering knowledge, the life span of a pavement will become shorter and shorter after each resurfacing over time. From **Figure 3-13**, we can see that for low and medium priority level projects, the life span gets longer after rehabilitation, and the overall deterioration rate has decreased. Most likely, this is related to changes in design during rehabilitation. For high and critical priority projects, the life span after treatment is shortened. For instance, a high priority project initially takes about

15 years after construction before its rate drops to 70; yet, after treatment, it only takes 9 years. Similarly, for a critical project, the life span decreases from 11 years to 10 years after rehabilitation. Note that since only one randomly picked project from each priority level was analyzed, it cannot represent the whole family.

SUMMARY

A project-level Bayesian model for forecasting the rating of pavement was developed to be applied to all the projects and transplanted to any location and condition after proper calibration. Several tests were performed to validate the model. This Bayesian method is also used to do some general family level research to obtain an overall idea of each family. The following are the major findings:

- As the priority level gets lower, the data points get more scattered.
- Generally, projects of higher priority level tend to have a lower deterioration rate, but low-priority level projects have a higher deterioration rate, which is probably due to the low AADT and percentage of trucks.
- Generally, it will take 11 to 13 years before the rate drops below 70.
- The percentage of truck traffic will greatly affect the deterioration rate. With the same AADT, a 1% increase in the percentage of truck traffic results in an extra 0.4% deterioration.
- High priority pavements have the largest early stage and middle stage deterioration rates. On the other hand, medium priority pavements have the lowest deterioration rates.

- The data availability and quality are crucial for the family-level analysis, especially the detailed information about treatment method and time.

CHAPTER 4. NETWORK-LEVEL PAVEMENT DETERIORATION MODELING AND VALIDATION

Proper prediction of pavement deterioration at the network-level requires detailed data sources, the right type of prediction model, and proper assumptions about the network considered. In this chapter, pavement deterioration modeling in general and for GDOT in particular are considered. In the chapter, the selection and updating of a Markovian probabilistic model for Georgia are described.

DEVELOPMENT OF A NETWORK-LEVEL PMS MODEL FOR GEORGIA

Based on the literature review conducted and an analysis of the function of the existing PMS model developed by Georgia Tech and used by GDOT, the continued use of a Markovian-based model for GDOT's PMS seemed to be the best choice for understanding pavement deterioration within the state. While the existing model developed under Research Project 05-19 has proven to be adequate for high-level management, the model needed to be updated using the most current data about state network conditions in order to meet the GDOT's needs.

In this section, the full procedure for updating the existing probabilistic model used by GDOT is described. This includes the data processing procedure for network-level data, the pavement families created for better studying pavement deterioration, the newly updated Markovian Transition Probability Matrices (TPMs) based on current COPACES data, the updated expenditure data required to accurately predict pavement MR&R costs, and, finally, a summary of how the existing model uses these updated components to create expenditure and condition predictions.

Data Description

As discussed in CHAPTER 2, one of the main sources of data at the network level is COPACES data. The data provided by the database enables a closer look at the geographical location of projects and project ratings for the entire state network. For the purposes of this study, project information was primary source of data used to understand the Georgia pavement network. Project location information was used to identify trends in pavement deterioration over time, and project ratings were used as the metric for deterioration. While COPACES contains data from FY 1986 to the present, due to the nature of the model chosen, which more accurately predicts pavement deterioration using the most recent data available, only the most recent five years of data available were used to update the PMS model. Therefore, information about the network was limited to FY 2010- FY 2015 for the purposes of the study. Despite limiting the data to a five-year period, the volume of data and the need to further process the data remained. The next section describes in detail the procedure for assuring data veracity.

Data Processing

While the process of data collection and surveying by GDOT is done by trained personnel, the quality of data in COPACES remains variable. For the most part, errors in the system result from differences in rater opinions and data entry . While these issues can be minimized through training and safe locks on the data collection entry tools, the errors cannot be completely eliminated. Therefore, the importance of processing data, even at a network level, is crucial to maintaining data veracity.

The COPACES condition survey projects from 2010 to 2015 were processed for the purposes of model development. The following are the steps used to process the data at the network level:

1) Filtering out the projects with missing critical information, such as Project Rating.
2) Filtering out the projects that are not surveyed by AO, which represents projects surveyed at the local level rather than a district or state level, for data consistency.
3) Filtering out the non-asphalt surface type projects.
4) Eliminating the projects with under-construction status.
5) Assigning each project a Project ID. Project IDs are created by concatenating the County Code, Route Type, Route Number, and Route Suffix (known collectively as an RCLink) with the milepost to and from fields for each project. Filtering out the duplicated projects.
6) Eliminating the projects with irrational deterioration trends, such as when a Project Rating is improved without rehabilitation for a particular Project ID.

Appendix II provides a more in-depth explanation of some of these processes. Overall, these steps improve the quality of data for further analysis at the network level.

Pavement Families

After data processing, data was grouped to create more concise and related pavement "families," as discussed in CHAPTER 2. In the previous model, 14 pavement families were developed. The families were created using the 7 working districts and interstate and non-interstate categorization. While the results of these groupings were adequate, additional information about pavement projects was used to further group the projects and create new project families. In the updated model, 35 pavement families were created. These 35 families were created based on the 7 working districts, interstate versus non-interstate distinction, and, finally, the state route priority category. **Figure 4-1** more clearly depicts the division of the pavement projects into families with a detailed look at the division of projects in District 1.

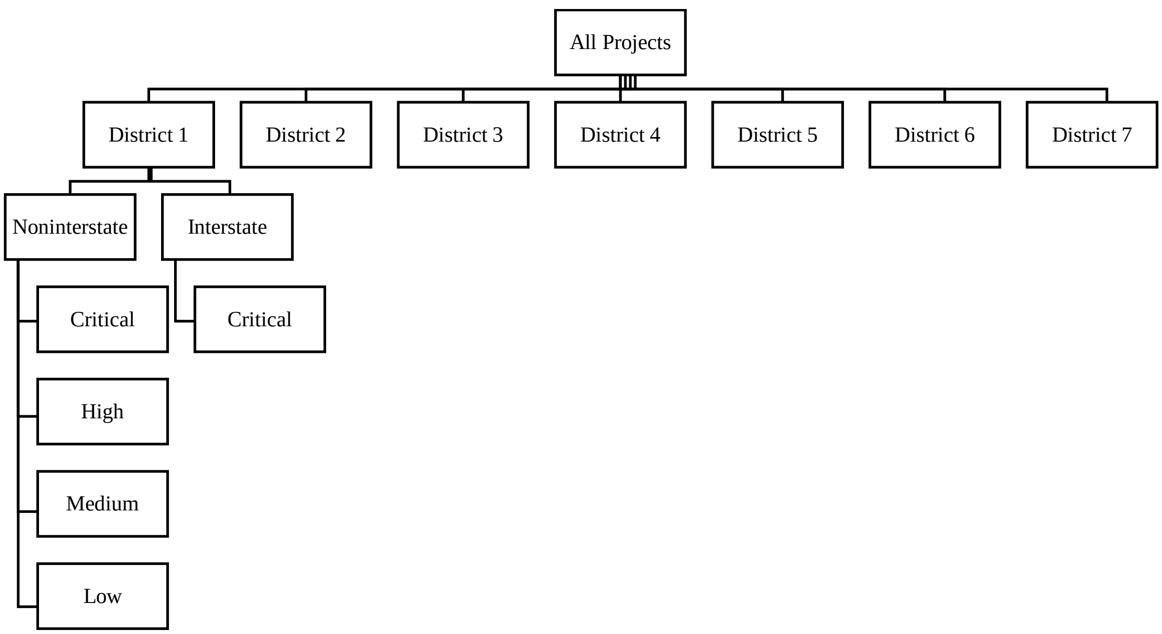


Figure 4-1. Graph. Pavement family example for the updated model.

Pavement Condition States

As discussed in CHAPTER 2, the Georgia Department of Transportation currently uses five condition states to describe pavement. The conditions states include “Excellent,” “Good,” “Fair,” “Poor,” and “Bad.” These conditions are used to define homogenous Markovian states and to create subsequent Transition Probability Matrices. **Table 4-1** and

Table 4-2 provide an overview of the condition states of non-interstates and interstates within the GDOT system between FY 2010 and FY 2015.

Table 4-1. Non-interstate highway pavement condition from FY2010 – FY 2015.

Year	Bad	Poor	Fair	Good	Excellent	Composite Rating
2010	1.86%	23.13%	26.71%	19.02%	29.28%	80.81
2011	2.57%	24.98%	26.65%	18.82%	26.98%	79.90
2012	2.83%	26.40%	28.51%	18.12%	24.14%	78.93
2013	3.26%	27.97%	26.88%	18.69%	23.19%	78.37
2014	3.68%	24.90%	25.92%	21.11%	24.40%	79.12
2015	0.03%	22.07%	23.56%	26.32%	24.76%	79.95

Table 4-2. Interstate highway pavement condition from FY2010 – FY 2015.

Year	Bad	Poor	Fair	Good	Excellent	Composite Rating
2010	0.98%	17.76%	15.16%	24.02%	42.08%	85.22
2011	1.16%	16.96%	22.15%	15.28%	44.44%	84.30
2012	3.72%	11.07%	30.27%	17.02%	37.93%	83.92
2013	1.96%	6.68%	30.97%	15.46%	44.94%	86.54
2014	0.47%	21.29%	21.21%	12.97%	44.05%	84.25
2015	0.00%	11.40%	22.54%	20.03%	46.03%	86.06

Markov TPMs

The Markov TPMs for each family depict the pavement deterioration trends for each group. The TPMs created represent the probability of a pavement deteriorating from one condition to the next over a year's span. The probability of a pavement's state change is represented by pij where i is the condition of the pavement in the first year and j represents the condition of the pavement in the second year. **Table 4-3** depicts the general notation for a Markov TPM. As described by the table, it is assumed that a pavement can 1) only deteriorate (cannot improve) over the span of a year without treatment and 2) pavements are constrained to deteriorating to the next lowest condition state over the span of a year. These assumptions are supported by both previous literature and engineering judgment.

Table 4-3. Notation of markov TPM.

States j i	Excellent	Good	Fair	Poor	Bad
Excellent	p_{11}	p_{12}	0	0	0
Good	0	p_{22}	p_{23}	0	0
Fair	0	0	p_{33}	p_{34}	0
Poor	0	0	0	p_{44}	p_{45}
Bad	0	0	0	0	*1.0*

For the purpose of this analysis, p_{ij} is the percent of all pavements in a family that have deteriorated from condition state i to condition state j over the one-year analysis period. This calculation is computed using historical data in each family. To calculate the probability of p_{ij}, the sum of all the mileage of pavements that transition from state i to state j in a year's time is divided by all the total mileage of pavements within a family that were in condition state i at the start of the analysis. Using the general notation and definition described, the matrices follow three rules:

1) The probability p_{ij} should be a number between 0 and 1.
2) The sum of p_{ii} and p_{ij} should be equal to 1.
3) All other items in the matrix should be equal to 0.

As alluded to previously, one TPM was created for each of the 35 families specified to account for differences in deterioration that may occur in like groups. TPMs were created using historical COPACES survey data from FY 2010-2015 that were processed and cleaned. In instances where pavements did not adhere to the assumption of only one condition state drop per year, pavement projects were not considered in the creation of TPMs. However, the number of projects dropping more than one condition state in a year was less than five percent of the total mileage in the group analyzed. Additionally, adjustments had to be made for all families' transition probabilities from Fair to Fair, Fair to Poor, Poor to Poor, and Poor to Bad. Due to the low mileage used to initially calculate these probabilities for each of the families, the same probability was used for each family for the described transitions. A probability of 0.4, 0.6, 0.95, and 0.05 was used for the transition from Fair to Fair, Fair to Poor, Poor to Poor, and Poor to Bad respectively. These probabilities were chosen as they minimized the difference between the model results and historical results for expenditure. **Table 4-4** shows an example of the TPMs created for the Critical, Non-interstate families for all 7 working districts. TPMs for all families are included in Appendix III.

Table 4-4. TPM for critical, non-interstate families for seven working districts.

District 1					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.7034	0.2966	0	0	0
Good	0	0.5501	0.4499	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 2					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.7867	0.2133	0	0	0
Good	0	0.8082	0.1918	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 3					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.6704	0.3296	0	0	0
Good	0	0.7318	0.2682	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 4					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.8225	0.1775	0	0	0
Good	0	0.7008	0.2992	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 5					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.7821	0.2179	0	0	0
Good	0	0.7046	0.2954	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 6					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.5995	0.4005	0	0	0
Good	0	0.6834	0.3166	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1

District 7					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.4161	0.5839	0	0	0
Good	0	0.95	0.05	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1

Treatments and Performance

As the detailed information on expenditures of specific MR&R activities is not easily obtained due to lack of integration of pavement management tools under Georgia's current system, three treatment categories were defined for the purpose of this model: Minor Preventative Maintenance, Major Preventative Maintenance, and Major Rehabilitation/Reconstruction. These MR&R categories are used as associated treatments for varying pavement conditions within the model. An overview of when these activities are to be applied is depicted in **Table 4-5**.

Table 4-5. Treatment for each condition state.

State	**MR&R Activities**
Excellent	Do Nothing
Good	Do Nothing
Fair	Do Nothing, Minor Preventative Maintenance
Poor	Do Nothing, Major Preventative Maintenance
Bad	Do Nothing, Major Rehab/Reconstruction

Using the above decision criteria for treatment application in the model, the unit costs for each treatment type had to be calculated, as well as the Annual Average Escalating Rate (AAER) for all treatments, in order to properly track increases in the unit costs over time. The following subsections describe the procedure for calculating the unit costs and AAER necessary for the model.

Unit Cost Calculation

Unit costs for the different treatment types are calculated from historical expense data or are estimated in case that data was not available. For major preventative maintenance, GDOT's resurfacing database is used to compute the unit cost for interstates and non-interstates by considering milling, inlay, and overlay projects between FY 2010 and FY 2016. After calculating the project's unit cost per linear mile, values showed variability, since the number of lanes is not constant for each project. Therefore, knowing that the database only provides the project's cost and centerline mileage, the number of lanes is obtained for each project after locating it using GDOT's GeoPI system and finding its corresponding satellite image on Google Maps. Note that the road layout changes along each project, whether it is the number of lanes or the median presence (divided/undivided). The most dominant or average number of lanes along the length of each project is determined visually. Moreover, although pavement condition is assessed in each direction (in case the road is divided), the unit cost analysis shows that these roads are usually resurfaced in both directions within one project. Cost per lane-mile is calculated for each project and then averaged for each fiscal year.

Figure 4-2 shows the limited variation in the unit costs of the sample non-interstate major preventative maintenance projects in FY 2010 – FY 2016. **Table 4-6** shows the average unit cost of major preventative treatment for interstates and non-interstates. Note that the sample projects used to determine the unit cost for interstates are very limited for each fiscal year and explained by their relatively significant costs, which results in the variation observed.

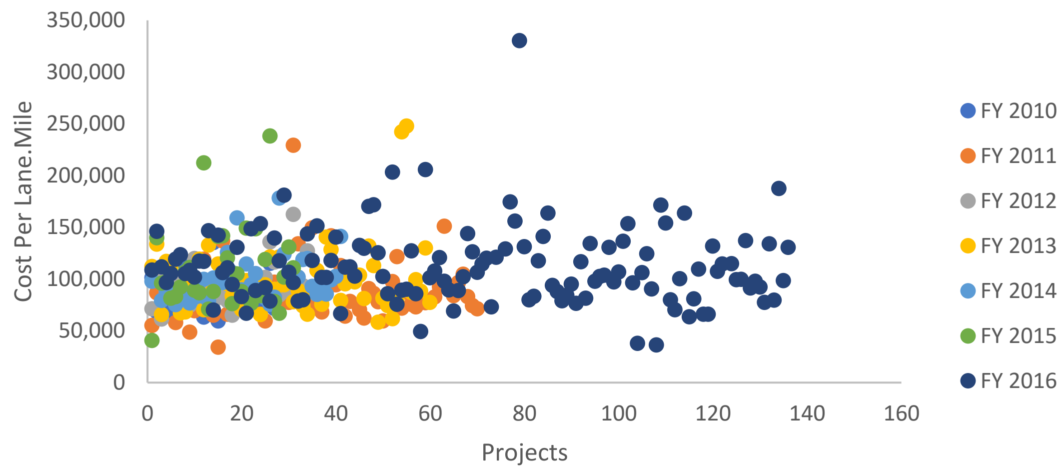


Figure 4-2. Graph. Non-interstate major preventative cost per lane mile.

Table 4-6. Major preventative maintenance unit cost.

Major Preventative	Unit Cost per Lane-mile	
	Non-Interstate	Interstate
FY 2010	$ 87,981.85	$ 201,163.19
FY 2011	$ 87,276.00	$ 341,975.27
FY 2012	$ 92,823.40	$ 211,499.89
FY 2013	$ 99,981.53	$ 276,737.58
FY 2014	$ 100,197.74	$ 222,941.37
FY 2015	$ 108,866.82	$ 268,299.99
FY 2016	$ 112,498.61	$ 213,485.30

Because the developed model calculates the initial condition state vector using survey miles rather than lane-miles, the average number of lanes of all projects in each district is obtained from the COPACES database for interstates and non-interstates as shown in **Table 4-7**. As a result, the average number of survey lanes for non-interstates is 2.51, whereas for interstates it is 3.23. These values are used in the next section to determine the final unit cost values to be used in our model after adjusting it by the Average Annual Escalating Rate (AAER).

Table 4-7. Average number of COPACES project survey miles.

District	Average Number of Survey Lanes	
	Non-interstate	Interstate
D1	2.28	3.79
D2	2.34	2.55
D3	2.39	2.84
D4	2.33	2.87
D5	2.51	2.62
D6	2.4	2.79
D7	3.3	5.15
Average	**2.51**	**3.23**

As for minor preventative maintenance, a localized database with county work order information is used, including expenditure data for crack sealing, crack filling, strip sealing, and chip sealing. Using the provided information, unit costs are calculated by dividing the total expenditure by the total centerline mileage for each fiscal year because the number of lanes and project location information is not available. Nonetheless, the obtained values are divided by the average number of lanes calculated above in order to compare it to the other treatment types' costs. **Table 4-8** shows the resulting unit cost values per lane-mile. Note that, due to the lack of data, the average cost ratio for major preventative treatment of interstates over non-interstates was used to estimate the minor preventative unit cost for interstates. Expenditure data for major rehabilitation and reconstruction is not available, mainly because of its high cost, which is preventing GDOT from applying it on full-scale projects. For the purpose of the model, its unit cost is estimated to be 2.5 times the cost major preventative maintenance.

Table 4-8. Minor preventative maintenance unit cost.

Minor Preventative	Unit Cost per Lane-mile	
	Non-Interstate	**Interstate**
FY 2010	$ 914.99	$ 2,699.21
FY 2011	$ 1,059.77	$ 3,126.33
FY 2012	$ 1,009.91	$ 2,979.25
FY 2013	$ 970.43	$ 2,862.76
FY 2014	$ 1,080.51	$ 3,187.51
FY 2015	$ 1,102.85	$ 3,253.40
FY 2016	$ 1,030.66	$ 3,040.43

AAER Determination

AAER is calculated for each treatment as the average of the escalating rates for each year from FY 2010 till FY 2016, which, in turn, are calculated as the percent change in cost from t to $t+1$. As a result, using the unit costs calculated from the given expenditure data, the AAER for major preventative maintenance of non-interstates and interstates and the minor preventative maintenance of non-interstates was found to be 4.24%, 3.29%, and 2.35%, respectively. In order to determine which AAER value to use for our model, the major preventative treatment unit cost per lane-mile was projected to the FY 2018 using the 3 options. After that, the resulting projected unit costs are compared to “GDOT Reference Guide 2018,” which estimates resurfacing cost per lane mile to be $125,000 for non-interstates and $300,000 for interstates. An AAER of 4.24% provides the closest cost estimate and was, therefore, chosen for the model. **Figure 4-3** shows the major preventative maintenance historical unit costs per lane-mile and the adjusted costs for non-interstates and interstates using the chosen AAER, as well as the non-interstate minor preventative maintenance.

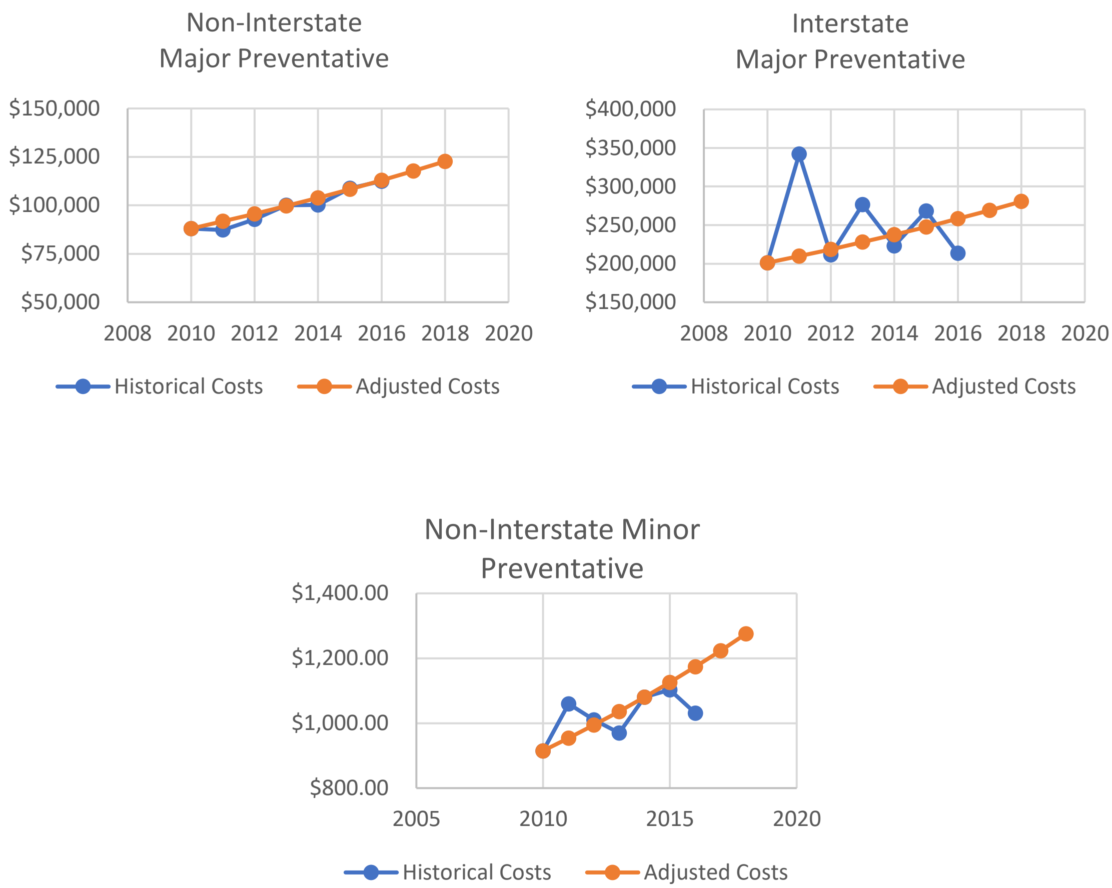


Figure 4-3. Graphs. Historical versus adjusted costs for major and minor preventative treatments.

Final Unit Cost Values

Table 4-9 shows the final unit costs to be used in our model, whether for validation of the Markov TPM using the historical data between FY 2010 and FY 2015 or for multiyear analysis that uses the initial conditions state vector of FY 2015 to represent those of FY 2018 for the purpose of the analysis.

Table 4-9. Final unit costs for model.

		Unit Costs per Survey Mile				
		Minor Preventative	**Major Preventative**	**Major Rehab/ Reconstruction**	**Average Nb of Lanes**	**AAER**
Non-Interstate	**FY 2010**	$2,294.00	$220,583.07	$551,457.68	2.51	4.24%
	FY 2018	$3,197.93	$307,618.30	$769,045.75		
Interstate	**FY 2010**	$6,757.29	$649,757.11	$1,624,392.79	3.23	
	FY 2018	$9,419.93	$906,131.09	$2,265,327.73		

Integration of Cost into Model

Using the calculated unit costs and AAER, the cost of network maintenance can be predicted. For each year of prediction, the corresponding mileage that falls into the "Fair," "Poor," and "Bad" condition states can be calculated using the developed TPMs; subsequently, the model can choose to treat some or all of the projects in these categories. If a project is treated, the costs for that year are calculated using the single-payment compounding equation where Year 0 is FY 2018. Additionally, the performance of the pavement for subsequent years will follow the rules in **Table 4-10**.

Table 4-10. Treatment effect on pavement condition.

Treatment	Performance
Major Rehabilitation	Pavement condition will increase to Excellent.
Major Preventative Maintenance	Pavement condition will increase to Excellent.
Minor Preventative Maintenance	Pavement condition will stay the same.

Model Optimization Simulation Strategies

Using the newly updated TPMs, unit costs, and AAER and introducing additional families that incorporate the state route priority, the Markovian model introduced in Research Project 05-19 was able to be updated and improved. The model is able to run a total of four strategies using the PMS model, which includes Optimization on Each Family, Optimization on All Families, Need Analysis, and Need Analysis on Each Priority Type; this will be summarized in subsequent subsections. Details about the linear programming formulations are found in Appendix IV.

Optimization on Each Family

Optimization on Each Family is a simulation strategy used to identify the optimal or maximum composite rating for each family in the network given an annual budget. Linear programming is used to optimize the condition rating of each of the 35 families created. Optimization for Each Family is an important simulation strategy, as it allows each family to receive a specific amount of funding. Enabling funding to differ for families allows for optimal MR&R strategies to be created across different state route priority categories and for interstates and non-interstates.

Optimization on All Families

Optimization on All Families, similar to the first simulation strategy, utilizes a given annual total budget to maximize the composite rating of the entire network. Unlike the first strategy, linear programming is used to achieve optimization over the entire system rather than over 35 families. Optimization on All Families is useful for long-term pavement performance predictions.

Need Analysis

Need Analysis refers to a simulation strategy for which a minimum performance standard can be set for the entire network of pavements. Using Need Analysis, the system can be restrained by a network composite rating and the percent of pavements in Poor or Bad condition. The default settings of this strategy are to constrain the network composite rating to 85 or greater and to restrict the percentage of pavements in Poor or Bad conditions to 10% of the network. In using this strategy, linear programming outputs the minimum budgets needed to achieve these system or network requirements. The Need Analysis strategy is recommended for determining short-term budgets or supporting legislation to increase spending on MR&R activities.

Need Analysis on Each Priority Type

The Need Analysis on Each Priority Type simulation strategy is similar to the Need Analysis on the entire network. Using this approach, the user can determine the minimum composite rating required for each state route priority category for interstates and non-interstates. In total, five separate composite ratings are needed for the purpose of the simulation (Non-interstate Critical, High, Medium, and Low and Interstate Critical). Through the use of the Need Analysis on Each Type, the goal is to determine the minimum funding required to achieve these differing composite scores. The strategy enables more freedom in determining performance goals on pavements with differing priority levels.

Model Validation

The model described throughout this chapter was utilized to create a program that easily predicts budgets or performance based on the strategies previously described. The program, which was modified from the existing GDOT LP&S program from Project 05-19, was utilized to assess the validity of the Markovian strategies implemented throughout the chapter. Model validation was based on the comparison of historical pavement condition data in **Table 4-1** and **Table 4-2** to that output by the model. While data for both non-interstates and interstates exist, only non-interstate data was used for the validation of the model as interstate data is both too small in mileage, therefore limiting accuracy, and too variable in terms of expenditure.

To properly compare the historical data to the outputs of the developed model, the model was run to predict pavement conditions from FY 2010─FY 2015. In terms of the scenario run to achieve a prediction similar to the historical performance, Optimization on All Families was performed using an annual budget of $190 million dollars and unit costs from FY 2010. These inputs were based on historical expenditure data and engineering judgment. The scenario was run for multiple TPMs in order to find the best transition probabilities for the Fair and Poor pavement conditions.

As depicted in **Table 4-11**, **Figure 4-4**, and **Figure 4-5**, the developed model is consistent with the historical pavement performance based on both condition states and composite rating. The mean difference between the simulated results and historical data ranged from 0.94 to 3.67 with the greatest difference between the model and historical data corresponding to the percent of the network in the Poor category. The variance in the average difference for the six years of data was minute, and all variances were less than 1. When comparing the average composite rating, the mean difference between the model and the historical data was 0.84, and the variance was 0.35. The results of the comparison validate the use of the model within a certain level of error.

Table 4-11. Difference between model simulated results and historical condition.

	Mean	Variance	Maximum
Excellent (%)	1.42	1.6 E-4	3.39
Good (%)	3.66	3.64 E-4	5.56
Fair (%)	0.94	2.35 E-5	1.64
Poor (%)	3.67	3.2 E-4	5.34
Bad (%)	1.49	9.7 E-5	3.41
Composite Rating	0.84	0.35	1.99

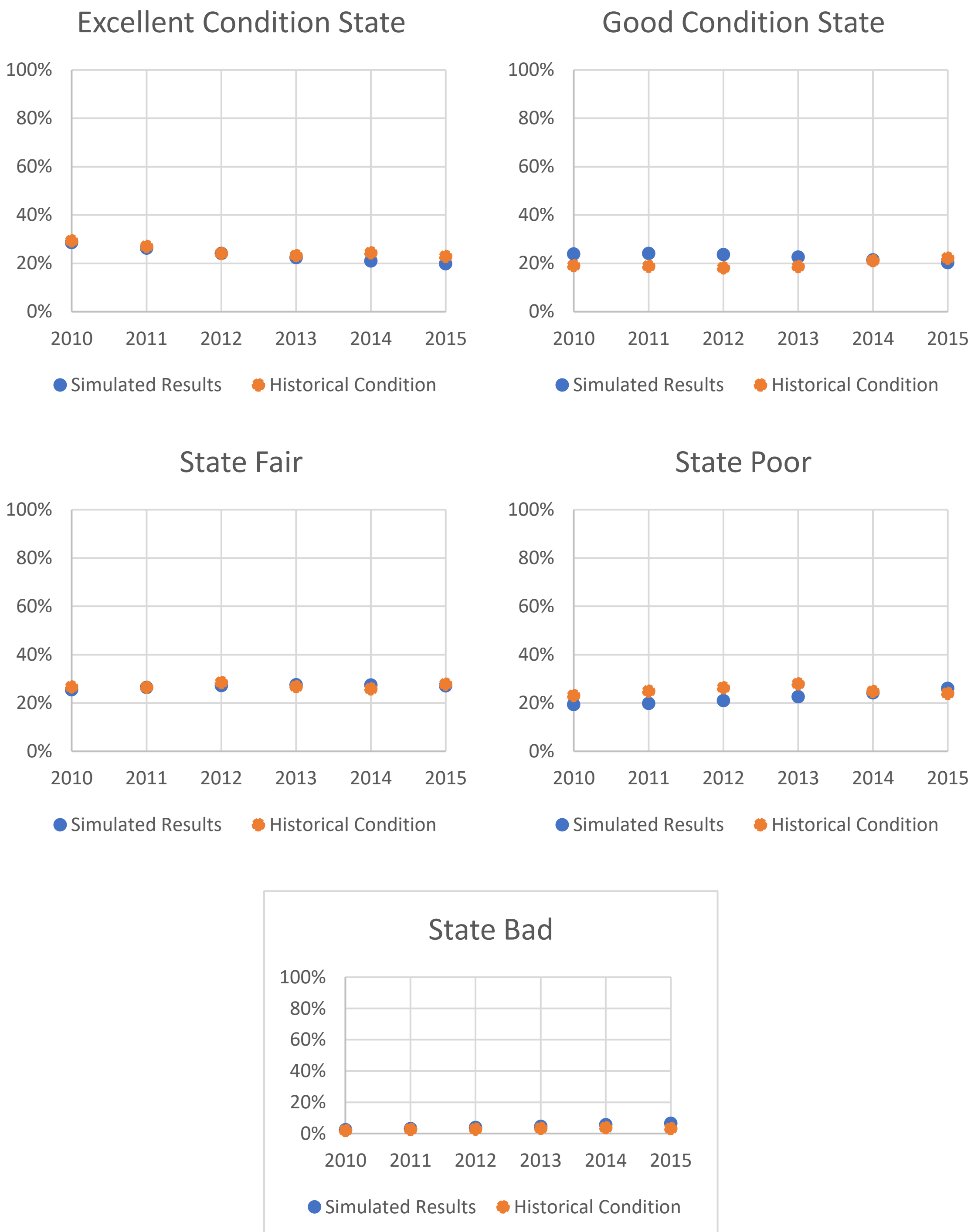


Figure 4-4. Graphs. Comparison of model simulation vs historical state condition.

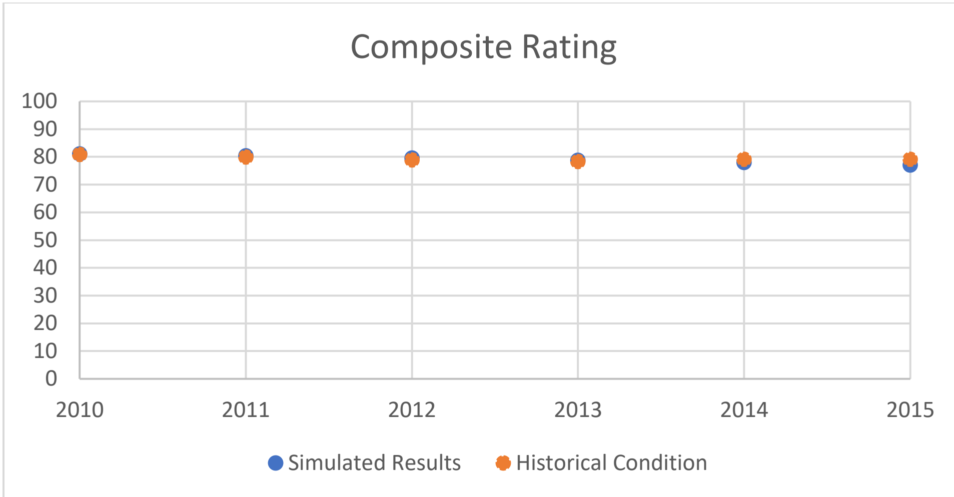


Figure 4-5. Graph. Comparison of model simulation vs historical composite rating.

SUMMARY

Although many pavement deterioration models were explored using several deterministic, stochastic, and other modeling methods, the Markov Chain model is still the best choice for Georgia's network-level pavement management system. However, as the existing model was developed under Research Project 05-19 in 2008, it needs to be updated using the most current data about state network conditions and incorporating the new state route prioritization concept. After obtaining the most recent pavement condition data from FY 2010 to FY 2015, the necessary processing was performed to filter all data errors and incompleteness. Then, pavements were grouped into 35 families based on the 5 priority categories that take into consideration interstate and non-interstate distinctions and the 7 working districts. Condition state distribution was established for each family and each year to be used in developing the 35 Markov Transition Probability Matrices (TPMs). For pavement management system purposes, minor and major preventative treatment costs were obtained for interstates and non-interstates using the resurfacing database and local maintenance work orders; major rehabilitation and reconstruction costs were estimated due to lack of expenditure information. Using this cost data, the AAER was chosen as 4.24% by comparing the calculated unit costs with the ”2018 GDOT Reference Guide” cost estimations. Next, the four different optimization simulation strategies that were introduced in the previous project were updated and improved to better fit the current model. These strategies include: “Optimization on All Families”, “Optimization on Each Family”, “Need Analysis,” and “Need Analysis on Each Priority Type”. Finally, model validation was performed on non-interstates, which showed little variation between simulated results and historical condition data.

CHAPTER 5. MULTI-YEAR PAVEMENT PERFORMANCE AND MR&R NEEDS

The balance between meeting federal and state performance guidelines and keeping the pavement MR&R budget to a level that is accepted by the state legislature is a difficult process. Often, the balance is unachievable, as the cost to keep pavement performing at even the minimum performance standard is unable to be met by the funding provided by the state and federal government. Such a restriction can result in poor pavement MR&R planning, which focuses on a "worst-first" approach rather than a more sustainable method. The goal of this chapter is to focus on the underlying system of funding and performance metrics in the state of Georgia, how the developed pavement forecasting model can be used as a tool to advocate for funding levels or to understand the predicted network performance when that funding cannot be met, and provide suggestions on how the tool can be used to implement further funding and policy strategies that are the best for the network. In doing so, the hope is to provide higher-level management within DOT evidence and support for decision-making for pavement management activities.

FEDERAL-LEVEL FUNDING AND PERFORMANCE CRITERIA FOR MR&R

Federal funding and governance for MR&R and transportation in general are provided through a combination of federal entities (such as the Federal Highway Administration) and the United States Congress. These two players are key to developing state apportionments and federal guidelines to ensure roadways in the NHS are appropriately improved and maintained as the system ages. In terms of pavement maintenance, the federal government's emphasis is on the regulation of the performance goals rather than providing all necessary funding. The following sections will provide detail on the method and means for funding provided to the states from the federal government, as well as the performance measures required at a state level to receive any funding.

Funding

Funding streams from the federal government are dictated by 23 U.S. Code § 104 or the MAP-21 Act, which lays out the rules of apportionment. Since 2012, apportionment has utilized a formula-based approach to provide funding for state DOTs. Under 23 U.S. Code § 104, apportionment to states must fall under a) the National Highway Performance Program (NHHP), b) the Surface Transportation Block Grant Program (STBG), c) the Highway Safety Improvement Program (HSIP), d) the Congestion Mitigation and Air Quality Improvement Program (CMAQ), e) Metropolitan Planning, or f) the National Highway Freight Program (NHFP). In the case of routine and capital maintenance, funding streams from a federal level fall under the NHHP which enables "construction, reconstruction, resurfacing, restoration, rehabilitation, preservation, or operational improvement of segments of the National Highway System" (23 U.S.C 104, 2012). Under this Code, states receive funding that is equivalent to the national amount for the program for a fiscal year multiplied by the ratio of the state's base apportionment for the fiscal year (which is the same as the previous year) over the total national base apportionment. The total state funding is subdivided into the six programs previously described. Of the total apportionment, a 63.7 percent deduct funding for freight and congestion programs is assigned to the NHHP and, consequently, can be used by the state (23 U.S.C 104, 2012). In the state of Georgia, under these provisions, the DOT received a total of $1,593,146,310 from the federal government of which only $285,486,452 was used on MR&R in FY 2017 (Deal & MacCartney, 2017).

Policy on Minimum Performance

Under MAP-21, funding is to be dispersed to state agencies upon satisfaction of minimum performance and condition requirements. When specifically looking at pavements, states are required to develop risk-based asset management plans that summarize the assets and their conditions, inform the FHWA of the objectives and measures used by the state, identify any performance gaps, report life-cycle cost and risk analyses, determine a financial plan, and disclose investment strategies (23 U.S.C 119, 2012). The policy requires that the state maintain highway infrastructure in a state of good repair by measuring the condition and performance of the interstate systems that fall within a state, as well as the condition and performance of non-interstate roadways in the NHS (23 U.S.C 150, 2012). Both MAP-21 and the FAST Act determine that failure to meet these goals alters the funding received by the state. According to Section 119, states that fail to comply are forced to match federal apportionment from the previous year and utilize at least ten percent of the federal funds' apportionment for the current Fiscal Year for the purpose of maintenance. Compliance with the minimum standards is to occur every two years under the FAST Act and is evaluated by the Secretary of Transportation. Under Federal Register 490.307, the measures used in the decision are the percent of pavements in good condition on the interstate system, the percent of pavements in poor condition on the interstate system, the percent of pavements in the NHS that are not interstates in good condition, and the percent of pavements in the NHS that are not interstates in poor condition (23 U.S.C 490, 2016). While the condition states of good and poor are left to the states to decide, each state is additionally required to report conditions in terms of IRI, PSR, rutting, crack percentage, and thickness flexibility (FHWA, 2016).

STATE-LEVEL FUNDING AND PERFORMANCE CRITERIA FOR MR&R

Whereas the federal level of government provides extensive policy on performance criteria for pavement networks, the state-level government is important in funding MR&R on state and federally owned roadways. Funding at a state level is dictated by the state legislature, while additional performance objectives for pavements are created by the state DOT. In this section, the funding and performance policies for pavement management are more thoroughly explored for the state of Georgia.

Funding

In the state of Georgia, routine maintenance is largely funded using a combination of motor fuel tax, hotel fees, electric vehicle fees, heavy vehicle fees, bridge bonds, and other fees imposed by the state. These taxes and fees, which are collected at a local level, are utilized to create a budget for GDOT that is created and voted on by the Governor and the Georgia General Assembly each fiscal year. In FY 2017, state funding allotted $2.06 billion dollars to the state DOT, approximately 25% more funding than that provided by the federal government. Of the $2.06 billion dollars, it is estimated that approximately $402 million of that was used for interstate maintenance and resurfacing and state route resurfacing in FY 2017 (GDOT, 2017a). The difference between the total budget of the GDOT and that received for MR&R specifically leaves room for further budget allocation to MR&R. Through better forecasting of pavement performance, the aim is to better emphasize the role additional funding plays on the pavement network.

Policy on Minimum Performance

While compliance with federal performance standards is the primary state goal, GDOT sets separate performance goals to conform to its strategic goal of taking care of existing assets. For pavement, the goal for minimum performance for non-interstate roads is to maintain 90% or more of roadways at a COPACES value of 71 or higher. Similarly, GDOT also sets the same goal for interstate pavements. In FY 2017, 74% of the GDOT maintained interstates and 71% of the GDOT maintained non-interstates met the target COPACES value (GDOT, 2017b). While existing goals for performance are set based on network conditions, in the future, pavement performance goals will incorporate pavement route priority. Through this approach, Critical, High, Medium, and Low priority routes can have separate performance goals based on their importance. Implications of this strategy are discussed in the next section.

ANALYSIS OF PERFORMANCE FORECASTING AND FUNDING NEEDS

In this section, the newly updated model described in CHAPTER 4 will be utilized for a series of analyses focused on forecasting pavement performance and MR&R needs in the long-term (10 years). The model, which enables both customization and optimization, will be implemented in understanding two scenarios: network-level performance with a fixed funding stream and network-level funding with fixed performance goals. Moreover, a sensitivity analysis is performed to check the effect of budget changes on network performance. The developed model can be utilized to support decision-making and legislative funding recommendations for MR&R activities within Georgia. In doing so, the hope is to enable more efficient expenditure while complying with state and federal performance measures.

Network-level Performance Forecasting with Existing Funding Levels

The first simulation explored is focused on understanding what the pavement condition in the network would look like if funding levels remained the same. The analysis period is set to be 10 years. In this case, the funding level from FY 2018 of $447 million, the most recently reported year of funding, was used as the funding level for each year in the analysis. It is assumed that the $447 million is split evenly between the Critical, High, Medium, and Low categories for interstate and non-interstates (5 categories total), resulting in each category receiving $89.4 million annually. This budget can be distributed equally by either mileage or by working district. For the purpose of both performance scenarios, budget per Critical, High, Medium, and Low categories are evenly distributed by mileage rather than district as the network-level performance using distribution by mileage rather than distribution by district is slightly better. For this simulation, two optimization strategies were considered: “Optimization on all Families” and “Optimization on Each Family.”

Optimization on all Families

“Optimization on All Families” refers to optimization on the entire network rather than on individual families or priority categories. The results of this analysis are presented in **Figure 5-1** to **Figure 5-4**. In this scenario, the network composite rating remains stable close to the initial composite rating of 80.40, peaking at 81.16 in 2021 and slightly dropping to reach 79.12 at the end of the analysis period. Moreover, the percent of pavements in Poor and Bad condition states drops from an initial 24.34% to 18.72% in 2023 and increases back again until it reaches 22.63% in 2028. On the other hand, as shown in **Figure 5-4**, this budget allocation affects the composite rating of each priority category differently. The critical interstate category rating drops significantly from 86.06 in FY 2018 to 72.68 in FY 2028, whereas that of the non-interstate priority categories either slightly drops or increases as shown in the figure below. This can be explained by the higher treatment costs for interstates, which forces the optimization process to choose to maintain non-interstates with lower costs resulting in higher benefit on the network composite rating.

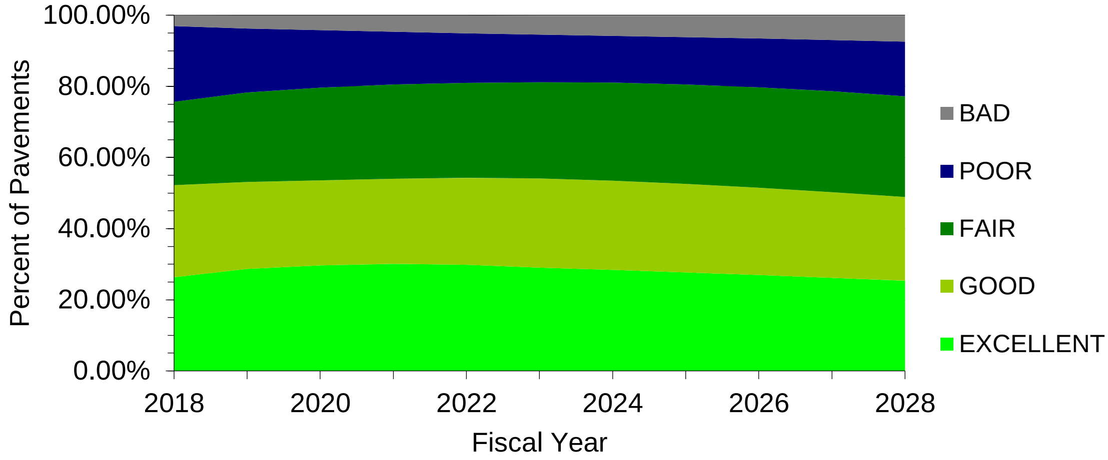


Figure 5-1. Graph. Yearly network condition distribution for 'Optimization on all Families'.

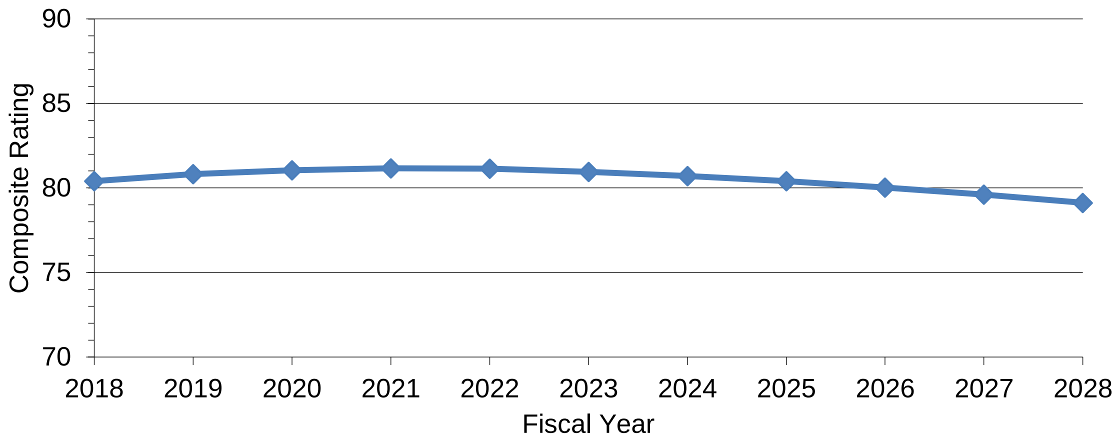


Figure 5-2. Graph. Network composite rating for 'Optimization on All Families'.

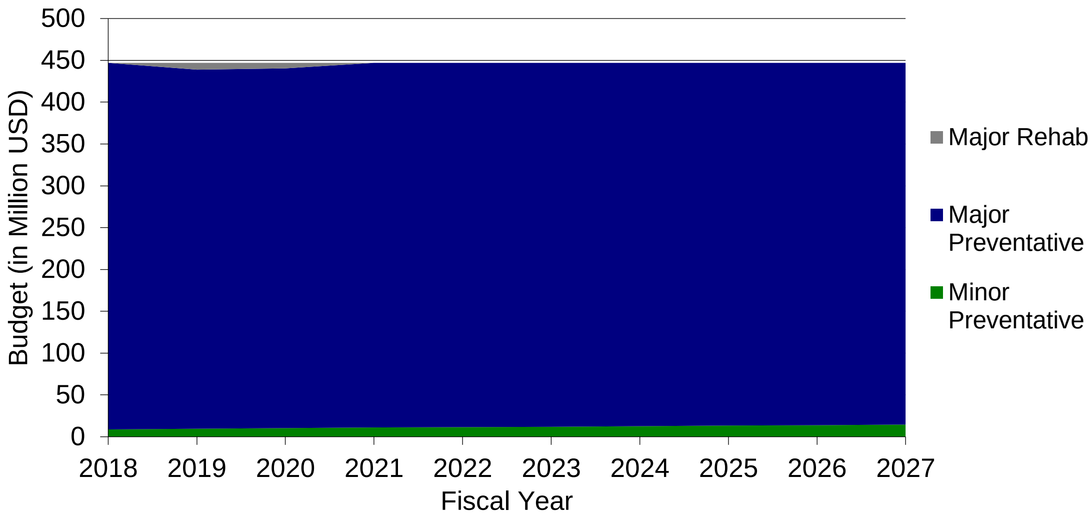


Figure 5-3. Graph. Detailed network cost distribution for 'Optimization on All Families'.

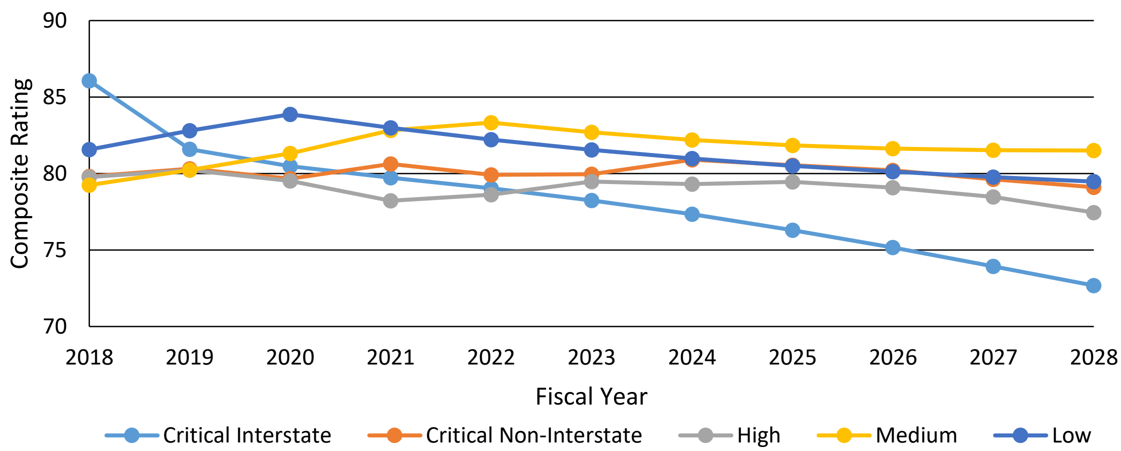


Figure 5-4. Graph. Priority Categories Composite Rating for 'Optimization on All Families'.

Optimization on Each Family

"Optimization on Each Family" simulation strategy uses optimization to maximize performance for each of the 35 created families discussed in previous sections. The results of this analysis are presented in **Figure 5-5** to **Figure 5-8**. Compared to the previous "Optimization on all Families" strategy, the network composite rating only decreases from its initial value until it reaches a rating of 77.12 at the end of the 10-year analysis period compared to 79.12 in the previous scenario. Moreover, the percent of pavements in Poor or Bad condition states goes up to 30.97%, as opposed to a lower value of 22.63% when optimizing on all families. When analyzing the performance of the five priority categories, we notice a higher composite rating for critical interstates of 81.60 compared to 72.68 in the previous scenario, due to the optimization that takes place on every family to maximize its performance rather than that of the whole network at once. However, that increase in interstate conditions is reflected with a decrease in the conditions of the medium and high priority non-interstate categories, as shown in **Figure 5-8**. As a conclusion, this shows that there is a trade-off between the two optimization simulation strategies, as the decision-maker should choose between a higher overall composite rating for the whole network or a higher and more even composite rating among all families and, hence, the priority categories. Moreover, this strategy does not utilize all the allocated budget of $447 million as shown in **Figure 5-5**, making it less efficient.

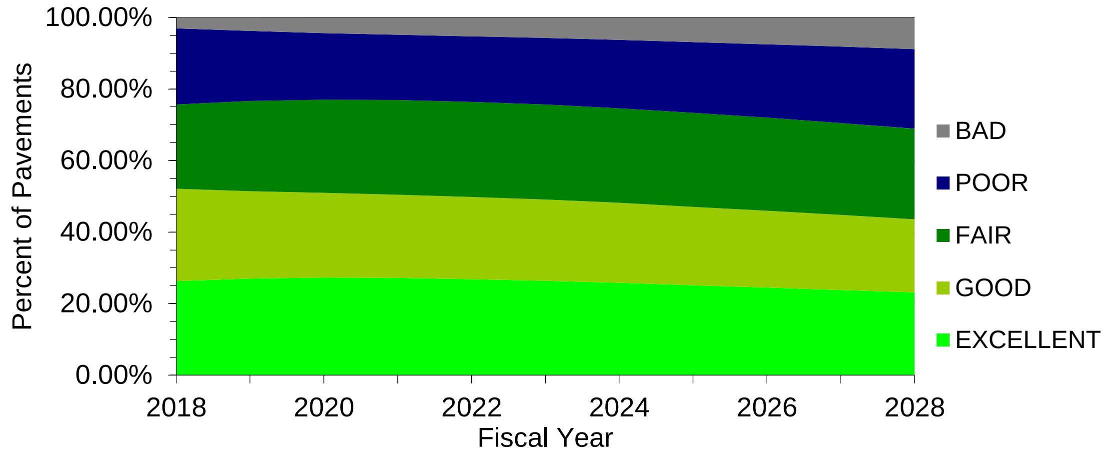


Figure 5-5. Graph. Yearly network condition distribution for 'Optimization on Each Family'.

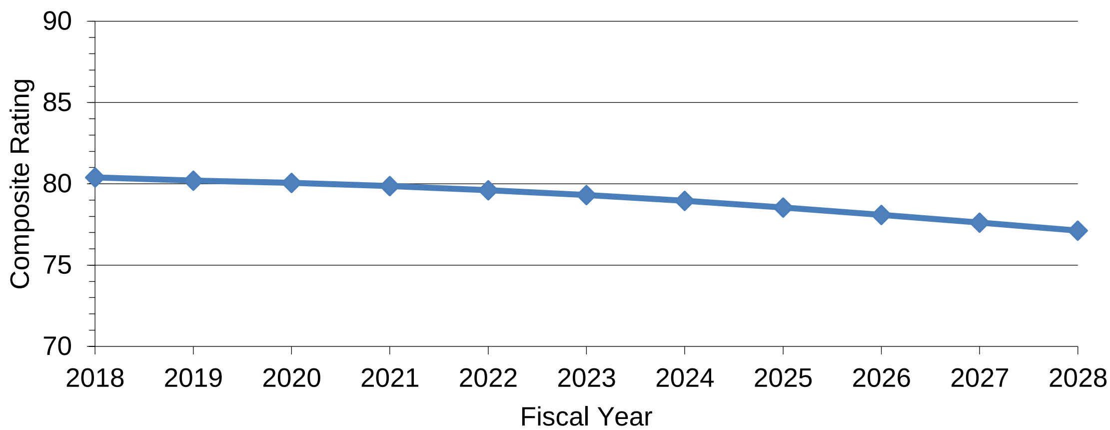


Figure 5-6. Graph. Network composite rating for 'Optimization on Each Family'.

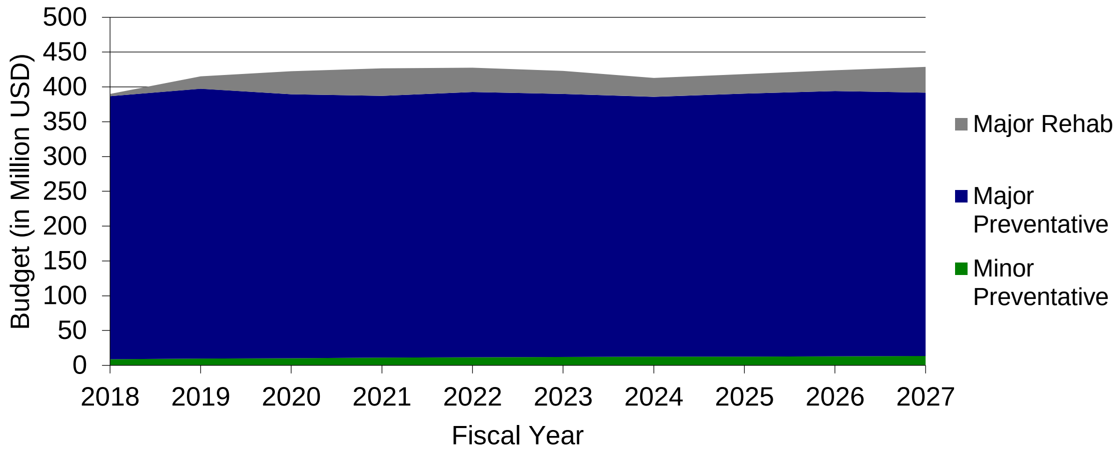


Figure 5-7. Graph. Detailed network cost distribution for 'Optimization on Each Family'.

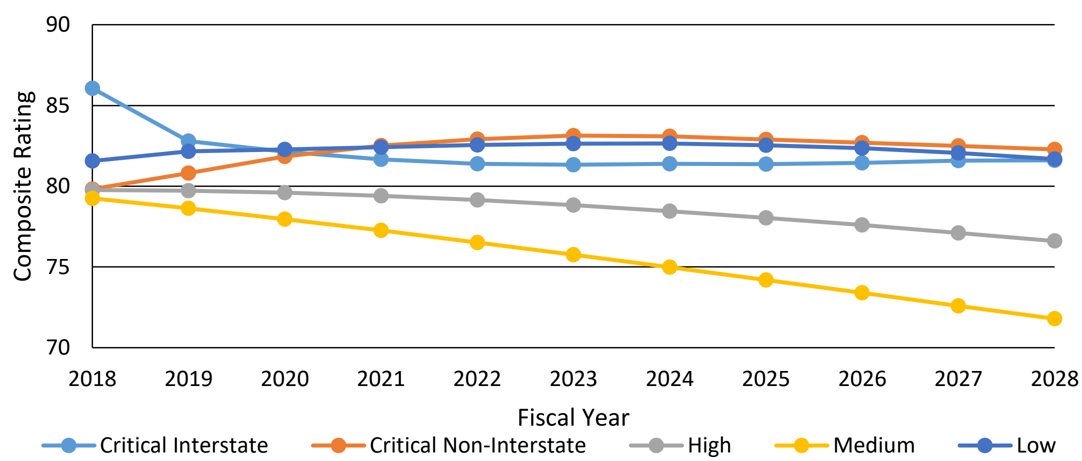


Figure 5-8. Graph. Priority categories composite rating for 'Optimization on Each Family'.

Network-level Funding Needs with Pre-defined Performance Goals

This analysis is focused on determining the amount of funding necessary for achieving minimum performance goals either for the whole network or for each state route priority category. Two scenarios will be explored in this section. The first scenario uses a need analysis for the network with performance goals set to match the state policy. The second scenario uses the need analysis for state priority categories while defining a minimum composite rating for each using engineering judgment. Both scenarios are analyzed, and their results are compared to determine the difference in the funding needed to satisfy the requirements of each.

Need Analysis for Entire Network

The scenario analyzed uses the suggested state performance standards to define the need over a ten-year period. The suggested policy is focused on achieving a composite rating of 85 or greater with less than 10 percent of total pavements in Poor or Bad condition. The analysis resulted in substantial spending initially to meet these performance constraints. **Figure 5-9** to **Figure 5-12** show the results of the analysis. For the first year of the analysis, $1.15 billion is required to achieve the performance goal, pointing to a huge maintenance backlog. However, subsequent years require significantly less investment in MR&R with an average budget of $508 million per year, a 13.65% increase in the current budget. As a result, the percent of total pavements in Poor and Bad condition drops as expected from an initial 24.34% to less than 10% for the following three years until it reaches a stable 10% from FY 2023 onwards, as shown in **Figure 5-9**. Moreover, the network composite rating increases go from 80.40 in FY 2018 to 85 with higher values after FY 2022, as shown in **Figure 5-10**. However, as discussed in the previous sections, a drawback of analyzing the network as a whole is the lack of control on the performance of the priority categories or the families due to the difference in treatment costs coupled with an equal benefit. This is shown in **Figure 5-12** as the composite rating of the “Critical Interstates” priority category drops greatly from its initial value of 86.06 to reach 71.51 after 10 years.

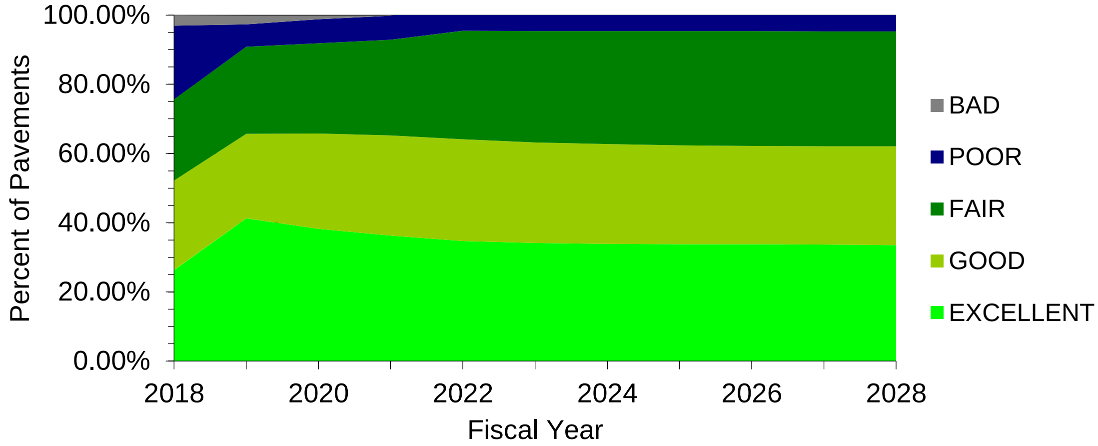


Figure 5-9. Graph. Yearly network condition distribution for ‘Need Analysis’.

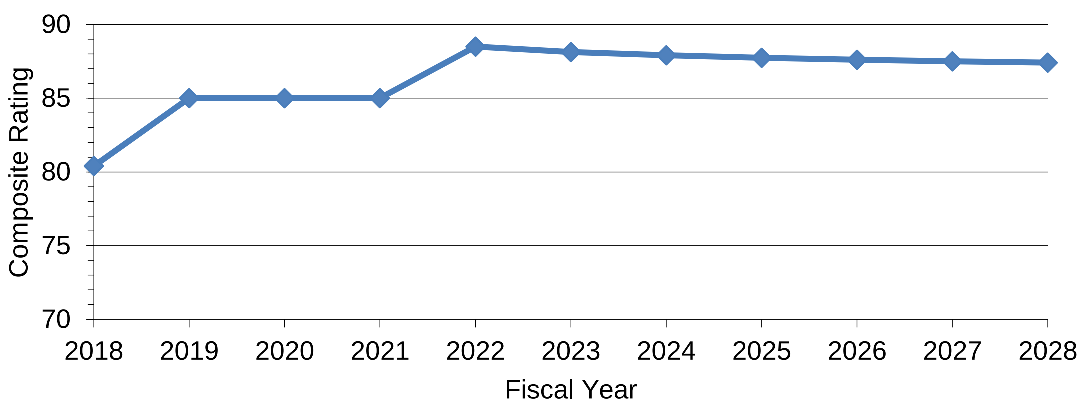


Figure 5-10. Graph. Network composite rating for ‘Need Analysis’.

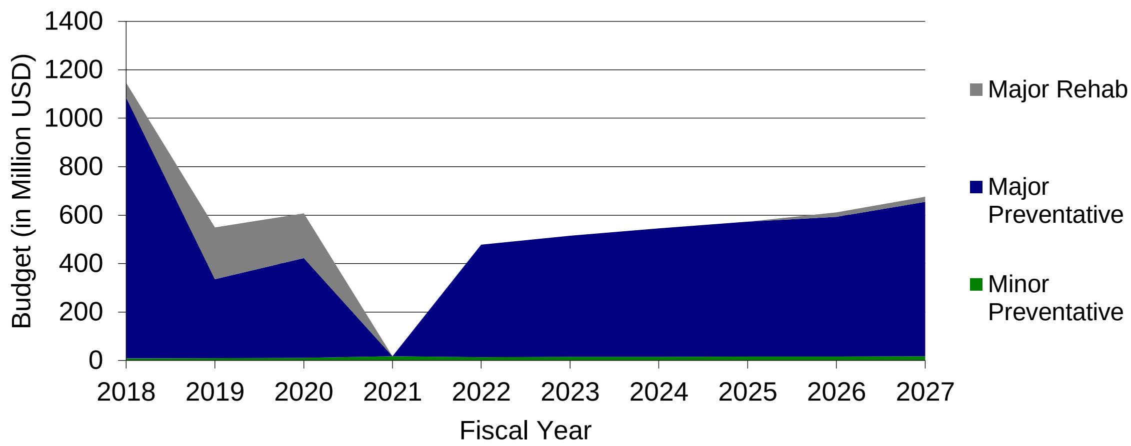


Figure 5-11. Graph. Detailed network cost distribution for 'Need Analysis'.

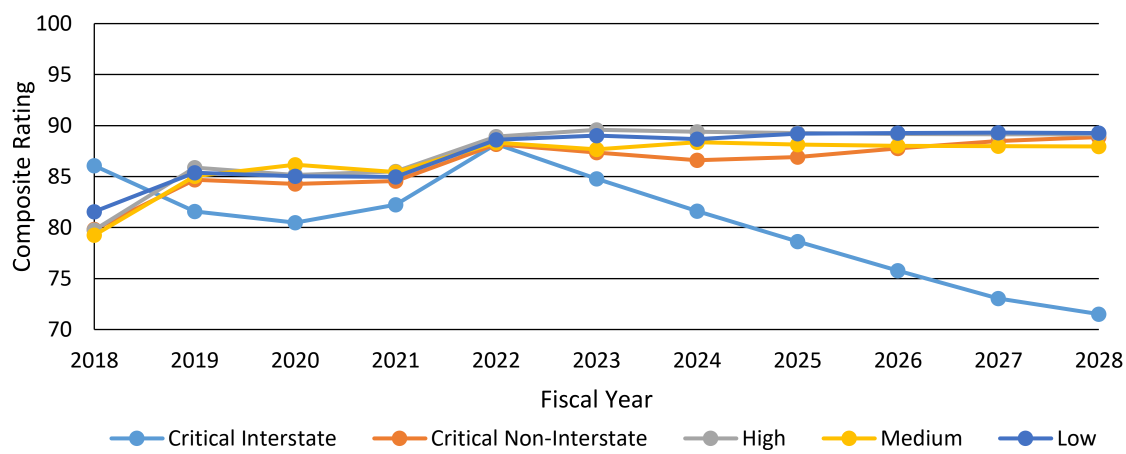


Figure 5-12. Graph. Priority categories composite rating for 'Need Analysis'.

Need Analysis for Priority Categories

This scenario is focused on achieving determined composite scores based on the state route priority of the roadways. While there is no set policy as to how the pavements in each category must be performing, using engineering judgement, composite ratings for each category were selected as depicted in **Table 5-1** based on our discussion with GDOT's engineers. The logic behind the values chosen is that higher priority state routes would require higher performance as these groups of roadways represent sources of economic benefit. While these roadways require higher performance, the lower priority roadways are not neglected in this scenario, with the lowest value used being a composite rating of 68.

Table 5-1. Minimum composite score criteria for priority categories.

Priority Category	Non-interstate Minimum Composite Score	Interstate Minimum Composite Score
Critical	85	85
High	82	N/A
Medium	72	N/A
Low	68	N/A

Using these inputs, the model is able to output the funding required to maintain the system in the conditions described. The results of the analysis over a ten-year period are depicted in **Figure 5-13** to **Figure 5-16**. Notice that since there is no requirement on the network composite rating, the score peaks at 90.37 for the network and ends at a composite rating of 77.21. The low composite rating for the network in the long-term suggests that alternative performance goals that are higher for each category of pavements shall be considered. On the other hand, the composite ratings of the different priority categories satisfy the performance requirements, which in the case of "Medium" and "Low" priority categories are less than the initial conditions. From **Figure 5-15**, it is evident that the cost fluctuates depending on whether the conditions of each priority category meet the requirements for each year. Therefore, this budget ranges between a maximum of $620 million and a low budget of $19 million with an average of $277 million over the whole analysis period.

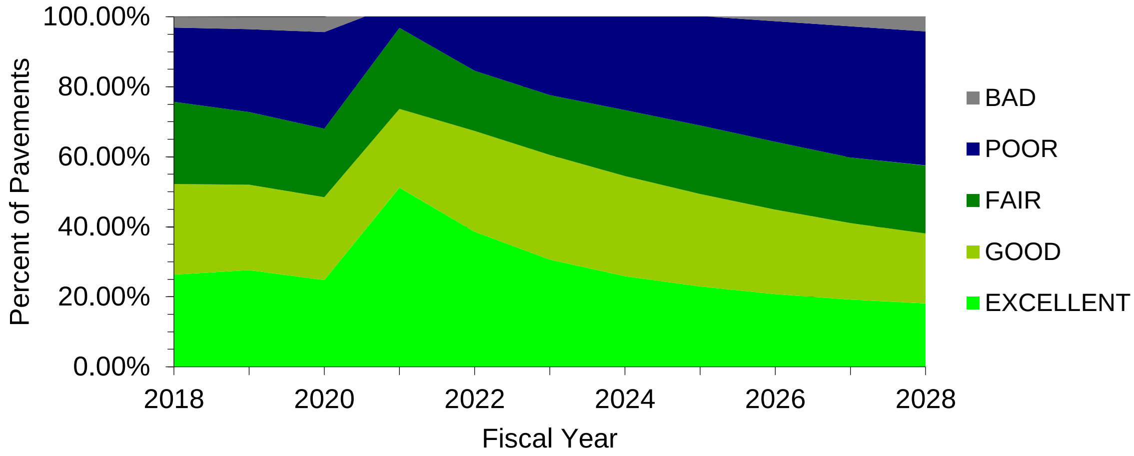


Figure 5-13. Graph. Yearly network condition distribution for 'Need Analysis for Priority Categories'.

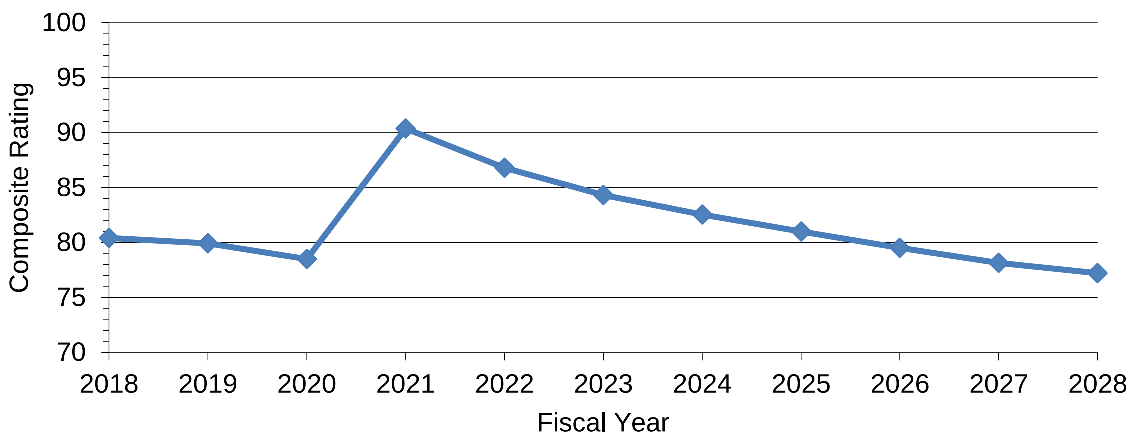


Figure 5-14. Graph. Network composite rating for 'Need Analysis for Priority Categories'.

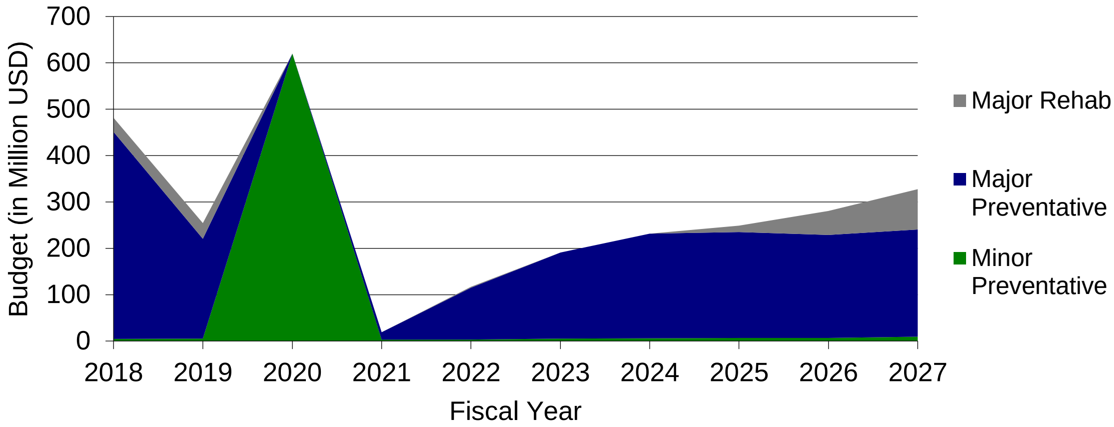


Figure 5-15. Graph. Detailed network cost distribution for 'Need Analysis for Priority Categories'.

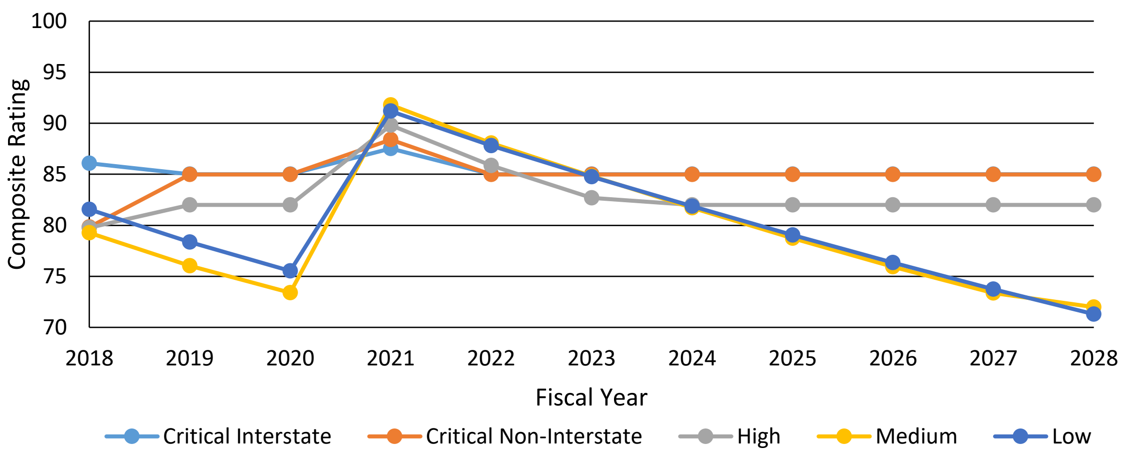


Figure 5-16. Graph. Priority categories rating for 'Need Analysis for Priority Categories'.

Sensitivity Analysis

The third scenario conducts a sensitivity analysis using both the "Optimization on All Families" and "Optimize on Each Family" simulation strategy by increasing and decreasing the annual budget 10%, 20%, and 30% of the current budget of $447 million as shown in **Table 5-2**. The analysis period is also set to be 10 years, and the budget is distributed equally among priority categories and evenly by mileage among districts. As shown in **Figure 5-17**, by using the current budget, the network composite rating will be slightly higher than the initial value in the short term, and increasing that budget will further affect the rating positively, also making it higher in the long term. A decrease in only 10% in the budget will result in a lower network rating than the initial one in both the short and the long term. Therefore, a decrease in the budget by 10, 20, and 30 percent result in network composite rating to be 77.65, 76.22, 74.59, respectively, after 10 years instead of 79.12 if the current budget is adopted. Comparing these results with the "Optimization on Each Family" simulation strategy, knowing the current budget results in a lower network rating in five and ten years, decreasing the budget will definitely worsen the situation, as shown in **Figure 5-18**. Moreover, a 20% or more increase in the budget is needed to make the network composite rating higher than the initial rating after 5 years, while increasing the budget to 30% is still short in the long term.

Table 5-2. Sensitivity study budget variation.

	Current	**+10%**	**+20%**	**+30%**	**-10%**	**-20%**	**-30%**
Budget (in Million USD)	447	491.7	536.4	581.1	402.3	357.6	312.9

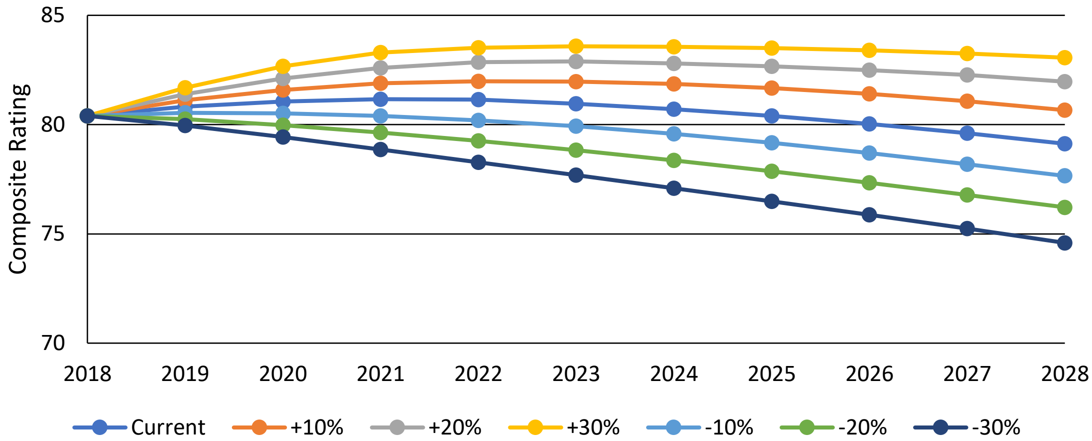


Figure 5-17. Graph. Sensitivity analysis of network composite rating for 'Optimization on All Families'.

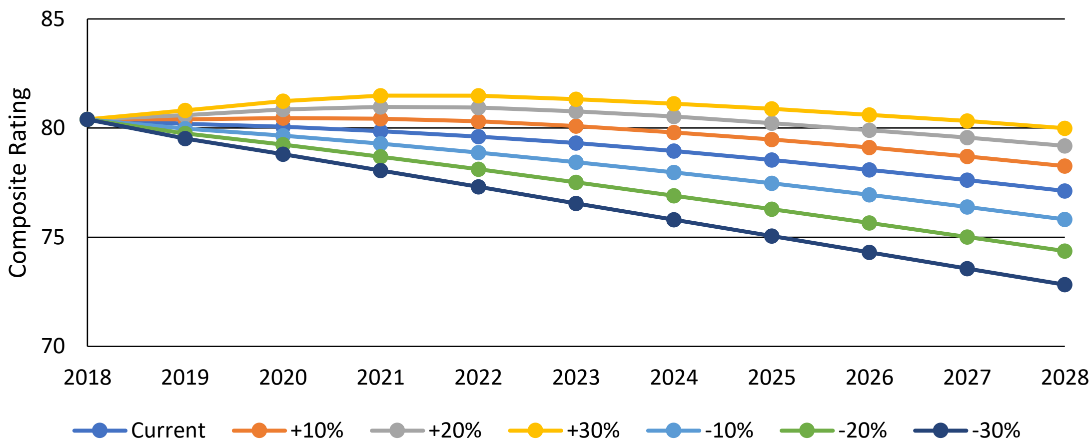


Figure 5-18. Graph. Sensitivity analysis of network composite rating for 'Optimization on Each Family'.

To further explore the effect of the budget change on the pavement condition, **Figure 5-19** to **Figure 5-22** show the performance of interstates and non-interstates for both simulation strategies. When optimizing on all families, the interstate composite rating decreases significantly, even with a 30 percent budget increase, as opposed to non-interstates, whose rating increases in the short term and in the long term if the increase is 10% or higher. Notice, also, the overlap of the different scenarios for interstates, proving that due to the higher maintenance costs, some years don't have budgets for interstates, as the major goal is to improve the network condition, which is accomplished with non-interstate maintenance at a lower cost. As for optimization on each family, the overall interstate rating is higher than the other strategy, whereas the non-interstates are lower. This explains how in this scenario funds that were previously budgeted for non-interstates are transferred to interstates to achieve a better rating for each family.

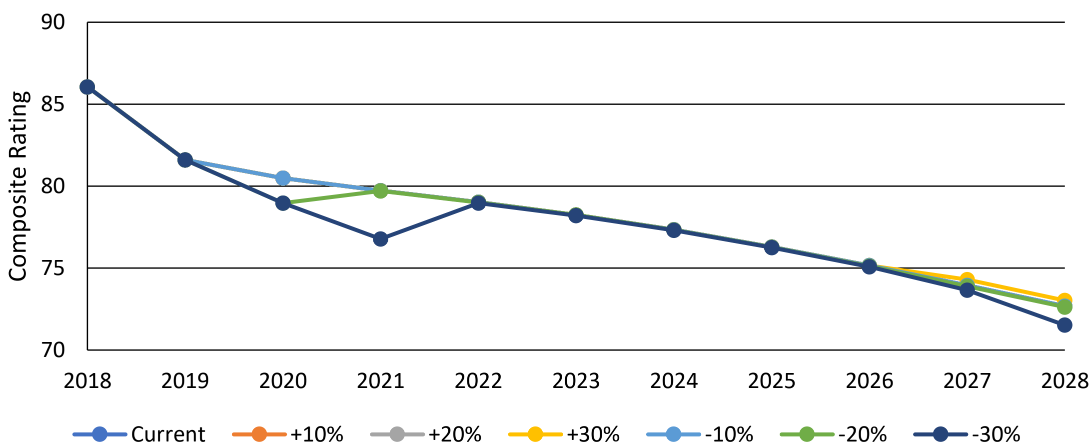


Figure 5-19. Graph. Sensitivity analysis of interstate composite rating for 'Optimization on All Families'.

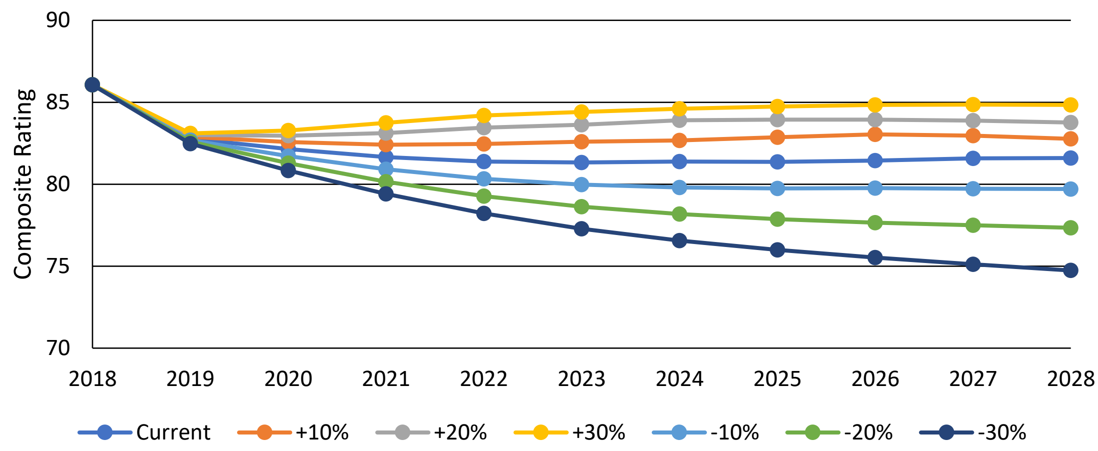


Figure 5-20. Graph. Sensitivity analysis of interstate composite rating for 'Optimization on Each Family'.

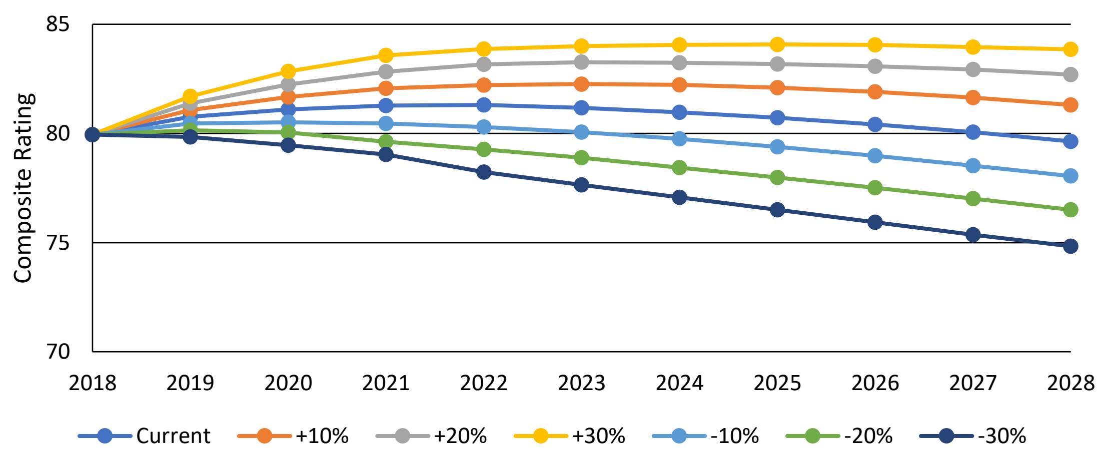


Figure 5-21. Graph. Sensitivity analysis of non-interstate composite rating for 'Optimization on All Families'.

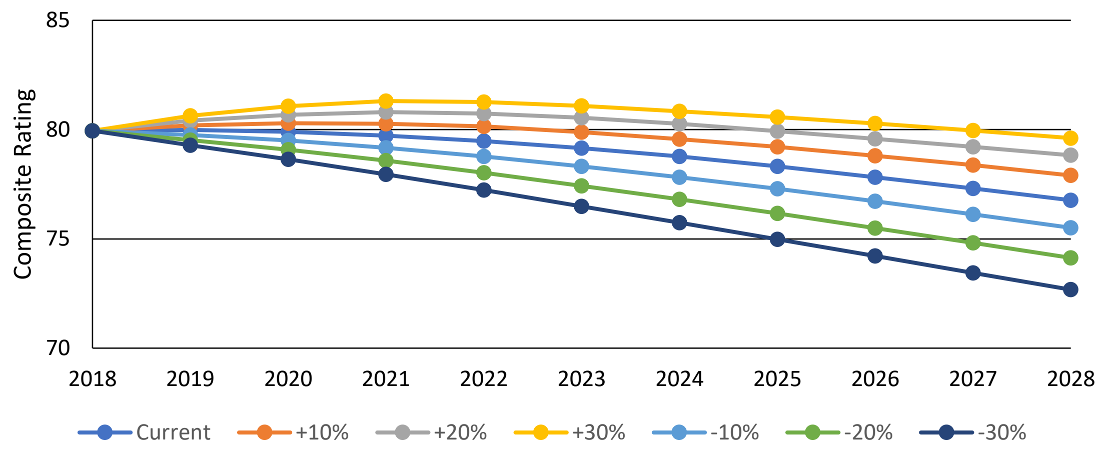


Figure 5-22. Graph. Sensitivity analysis of non-interstate composite rating for 'Optimization on Each Family'.

SUMMARY

Funding received by state DOTs is usually tied up with certain performance requirements. For instance, federal funding falling under different programs requires the development of a risk-based asset management plan that includes an overview of the assets and their conditions by reporting the percent of NHS pavements in good and poor condition, proving that the network is in a state of good repair. As for state-level funding, the performance requirements state that 90% or more of roadways must be maintained at a COPACES value of 71 or higher. After exploring the funding sources and their requirements, pavement performance was analyzed through case scenarios using the 4 optimization simulation strategies developed in the model above. Assuming that the current budget is kept constant for the next 10 years, the network composite rating is higher when using "Optimization on All Families" rather than "Optimization on Each Family," yet the condition of each family cannot be controlled. Therefore, since the treatment cost of non-interstates is lower than that of interstates with similar benefits on the composite rating, the model tends to maintain the first, resulting in a better performance for non-interstates when considering the network as a whole. However, when optimizing each family, the non-interstate rating drops in favor of treating interstate families, which negatively affects the network composite rating.

A similar logic is involved when performing the need analysis for the network versus that for each priority category. While considering the performance requirements to be a minimum network composite rating of 85 and a max percent of pavements in poor and bad condition states as 10%, the model shows a huge maintenance backlog reflected by a budget of $1.15 billion in the first year. When the performance requirements are set as minimum composite ratings for each priority category, the need analysis shows a fluctuation in the budget as the model aims to meet the pavement condition requirements for each category. Finally, a sensitivity analysis was performed by increasing and decreasing the current budget and analyzing its effect on performance while using both optimization simulation strategies.

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

GDOT has used the models and application that were developed through the RP 05-19 to justify and forecast the network-level, long-term pavement performance, and MR&R need to the legislature. However, the Markov-chain-based pavement deterioration transition probabilities have not been updated for more than 10 years and do not reflect the most recent pavement deterioration behavior. In addition, GDOT has established a new policy that categorizes state highways into four priority categories according to their importance and utilization: critical, high, medium, and low. To improve the accuracy and reliability of forecasting network-level pavement performance and predicting future MR&R needs along with the new state route priority categories, this research project studied pavement deterioration behavior at both project and network levels, updated the pavement deterioration transition probabilities using the recent COPACES data in terms of the new state route priority categories, analyzed the treatment unit cost and AAER, and conducted comprehensive what-if analysis using the new software application, GDOT LP&S. The following summarizes the major research results and findings:

- GDOT has rated the statewide pavement conditions using its PACES and has accumulated a wealth of historical data back to 1986. These data are invaluable for studying the pavement deterioration characteristics and determining suitable MR&R strategy.
- The Bayesian-based project-level deterioration model was explored in this project to incorporate a priori knowledge on pavement deterioration behavior. The objective

was to improve the accuracy and reliability of pavement deterioration modeling at the project level. Though the models were not used for network-level what-if analysis, they have the potential to be applied in GDOT's pavement management system for selecting MR&R projects.

- In terms of the 5 state route priority categories and 7 working districts, the entire state routes were grouped into 35 families. For each family, TPM was created using historical COPACES data from FY 2010-2015.
- Pavement treatments are categorized as minor preventive maintenance, major preventive maintenance, and major rehab/reconstruction. Using the resurfacing database and local maintenance work orders, the unit costs for minor preventive maintenance and major preventive maintenance were calculated. The unit cost for the major rehab/reconstruction was estimated due to the lack of expenditure information.
- By comparing the calculated unit costs with the "2018 GDOT Reference Guide" cost estimations, the AAER was determined as 4.24%.
- The software application, GDOT LP&S, was re-developed by updating the four different optimization simulation strategies, "Optimization on All Families," "Optimization on Each Family," "Need Analysis," and "Need Analysis on Each Priority Type." Using this software application, the developed Markov TPMs were validated on non-interstate pavements, showing little variation between simulated results and historical condition data.
- A comprehensive what-if analysis was performed through case scenarios using the 4 optimization simulation strategies developed in GDOT LP&S. Assuming that the current budget is kept constant for the next 10 years, the network composite rating is

higher when using “Optimization on All Families” rather than “Optimization on Each Family.” While considering the performance requirements to be a minimum network composite rating of 85 and a max percent of pavements in poor and bad condition states as 10%, the model shows a big maintenance backlog reflected by a budget of $1.14 billion in the first year. When the performance requirements are set as minimum composite ratings for each priority category, the need analysis shows a fluctuation in the budget as the model aims to meet the pavement condition requirements for each category. Finally, a sensitivity analysis was performed by increasing and decreasing the current budget and analyzing its effect on performance while using both optimization simulation strategies.

The following are recommended for future research:

- The main limitation of the developed Bayesian-based pavement deterioration model lies in computational complexity. It is better to incorporate the knowledge of experts to define the prior distribution.
- It is recommended other relevant factors, e.g., environment, pavement design etc., in the Bayesian-based pavement deterioration model be considered. In addition, for different types of distresses, different forecasting models are desired. Thus, further pavement treatments can be better predicted.
- The reliability of the MR&R need analysis largely relies on the accuracy of treatment unit costs and AAER. Currently, very little treatment information and no-cost data were recorded in COPACES. Thus, it is recommended the current COPACES data collection be enhanced by incorporating the historical pavement treatment data.

ACKNOWLEDGMENTS

The work described in this final report was supported by the Georgia Department of Transportation (GDOT) Research Project 16-37. We would like to thank Mr. Andy Doyle (Jesse) and Ms. Ernay Robinson from the Office of Maintenance; Mr. David Jared, Mr. Binh Bui, and Mr. Brennan Roney from the Office of Performance-Based Management and Research for their strong support and heavy involvement in this project. We would like to thank other members of the research team (Yifei Fan, Mingshu Li, and Georgene Geary) for their diligent work at the Georgia Institute of Technology.

REFERENCES

AASHTO (1993). *Guide for Design of Pavement Structures*, American Association State Highway and Transportation Officials, Washington, D.C.

Alsherri, A., and George, K. P. (1988). “Reliability Model for Pavement Performance.”, *Journal of Transportation Engineering*, 114(3), pp. 294-306.

ASTM (2011). *Standard Practice for Roads and Parking Lots Pavement Condition Index Surveys*, D6433-11, American Society for Testing and Materials, West Conshohocken, PA.

Chan, P., M. Opperman, and Wu, S. (1997). “North Carolina’s Experience in Development of Pavement Performance Prediction and Modeling.*”, Transportation Research Record: Journal of the Transportation Research Board*, 1592, pp. 80-88.

Chen, D. and Mastin, N. (2015). “Sigmoidal Models for Predicting Pavement Performance Conditions.”, *Journal of Performance Constructed Facilities*, 30(4).

Christopher, B., Schwartz, C. and Boudreau, R. (2006). *Geotechnical Aspects of Pavements*, FHWA NHI-05-037, Federal Highway Administration, U.S. Department of Transportation, Washington, D.C.

Deal, N. and MacCartney, T. (2017). *Budget in Brief. Atlanta, GA: Governor's Office of Planning and Budget*.

US Code (2012), United States Code § 104, 2012, Available online: https://law.justia.com/codes/us/2012/title-23/chapter-1/section-104/

FHWA (2016). *Highway Performance Monitoring System Field Manual*, Federal Highway Administration. Available online: https://www.fhwa.dot.gov/policyinformation/hpms/fieldmanual/

FHWA (2017a). *Smoothness. Surface Characteristics*, Federal Highway Administration. Available online: https://www.fhwa.dot.gov/pavement/smoothness/index.cfm/.

FHWA (2017b). *Pavement Performance Measures*, Federal Highway Administration. Available online: https://www.fhwa.dot.gov/tpm/pubs/PM2PavementFactSheet.pdf/

Garcia-Diaz, A. and Riggins, M. (1984). “Serviceability and Distress Methodology for Predicting Pavement Performance.”, *Transportation Research Record: Journal of the Transportation Research Board*, 227, 1984, pp. 56-61.

GDOT (2007). *Pavement Condition Evaluation System*, Georgia Department of Transportation.

GDOT (2014a). *Mileage by Route and Road System*, Report 445, Georgia Department of Transportation. Available online: http://www.dot.ga.gov/DriveSmart/Data/Documents/400%20Series/445/DPP445_2014.pdf/.

GDOT (2014b). *Georgia Counties and GDOT Field Districts*, Georgia Department of Transportation.

GDOT (2017a). *Accountability and Investment Report*, Georgia Department of Transportation. Available online: http://www.dot.ga.gov/PartnerSmart/Public/Documents/publications/Investment%20Report/2017InvestmentReport.pdf/.

GDOT (2017b). *Performance Management Dashboard,* Georgia Department of Transportation. Available online: http://www.dot.ga.gov/AboutGDOT/Performance/.

GDOT (2018). *2018 Reference Guide,* Georgia Department of Transportation, Available online: http://www.dot.ga.gov/PartnerSmart/Public/Documents/publications/ReferenceGuide/RefGuide2018.pdf/.

George, K. P., Frajagopal, A.S., and Lim, L.K. (1989). "Models for Predicting Pavement Deterioration.", *Transportation Research Record: Journal of the Transportation Research Board*, 1215, pp.1-7.

Golabi, K., Kulkarni, R., and Way, G. (1982). "A Statewide Pavement Management System Interfaces.", *Informs Journal on Applied Analytics*, 12(6), pp. 5-21.

Hajek, J., Phang,W., Prakash, A., and Wrong, G. (1985). "Performance Prediction for Pavement Management.", *Paper presented at the 1st North American Pavement Management Conference*, Toronto, Canada.

Han, D., Kaito, K. and Kobayashi, K. (2014). "Application of Bayesian estimation method with Markov hazard model to improve deterioration forecasts for infrastructure asset management." *KSCE Journal of Civil Engineering*, 18, pp. 2107-2119.

Hong, F. and Prozzi, J.A. (2005). "Updating pavement deterioration models using the Bayesian principles and simulation techniques.", *First Annual Inter-University Symposium on Infrastructure Management (AISIM)*, University of Waterloo, Ontario, Canada.

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

Highway Research Board (1961). *The AASHO Road Test Report 7*, National Academy of Sciences-National Research Council, Washington, D.C.

Jiménez, L.A. and Mrawira, D. (2012). "Bayesian regression in pavement deterioration modeling: revisiting the AASHO road test rut depth model.", *Infraestructura Vial*, pp.28-35.

Kargah-Ostadi, N., and Stoffels, S. (2015). "Framework for Development and Comprehensive Comparison of Empirical Pavement Performance Models.", *Journal of Transportation Engineering*, 141(8).

Lethanh, N., Kaito,K., and Kobayashi, K. (2015). "Infrastructure Deterioration Prediction with a Poisson Hidden Markov Model on Time Series Data.", *Journal of Infrastructure Systems*, 21(3).

Li, N., Xie, W.C., and Haas, R. (1996). "Reliability-Based Processing of Markov Chains for Modeling Pavement Network Deterioration.", *Transportation Research Record: Journal of the Transportation Research Board*, 1524, pp. 203-213.

Li, Z (2005). *A Probabilistic and Adaptive Approach to Modeling Performance of Pavement Infrastructure*, Dissertation, University of Texas at Austin.

Liu, L. and Gharaibeh, N. (2014). "Bayesian model for predicting the performance of pavements treated with thin hot-mix asphalt overlays.", *Transportation Research Record: Journal of the Transportation Research Board*, 2431 (2014): 33-41.

Luo, C. (2014). *Pavement deterioration modeling and design of a composite pavement distress index for Kentucky interstate highways and parkways*, University of Louisville, Louisville, Kentucky.

Mishalani, R. and Madanat, S. (2002). “Computation of Infrastructure Transition Probabilities Using Stochastic Duration Model.”, *Journal of Infrastructure Systems*, 8(4), pp. 139-148.

MNDOT (2011). *Mn/DOT Pavement Distress Identification Manual*, Minnesota Department of Transportation, Maplewood, MN.

Moving Ahead for Progress in the 21st Century, HR 4348, House of Representatives 119, 134-135, 148-150 § 1106, 1112-1113, 1201-1203, 2012.

National Performance Management Measures, House of Representatives § 490, 2016.

Ortiz-García, J.J., Costello,S.B. and Snaith, S.S. (2006). "Derivation of transition probability matrices for pavement deterioration modeling." *Journal of Transportation Engineering*, 132(2), pp. 141-161.

Papagiannakis, A., Gharaibeh, N., Weissmann, J. and Wimsatt, A. (2009). *Pavement Scores Synthesis*, Project 0-6386, Texas Department of Transportation, Austin, TX.

Park, E., Smith,R., Freeman, T., and Spiegelman, C. (2008). "A Bayesian approach for improved pavement performance prediction.", *Journal of Applied Statistics*, 35(11), pp. 1219-1238.

Rauhut, J., Lytton, R.L., Jordhal, P.R., and Kenis, W.J. (1983). "Damage Functions for Rutting, Fatigue Cracking, and Loss of Serviceability in Flexible Pavements.", *Transportation Research Record: Journal of the Transportation Research Board,* 943, pp. 1-9.

Rauhut, J. B., Lytton, R.L. and Darter, M.I. (1984). *Pavement Damage Functions for Cost Allocation: Damage functions and load equivalence factors*, Federal Highway Administration.

Sayers, M. W., Gillespie, T. and Queiroz, C.A.V (1986a). *The International Roughness Experiment: Establishing Correlation and a Calibration Standard for Measurements,* World Bank Technical Paper Number 45, World Bank, Washington, D.C.

Sayers, M., Gillespie,T. and Paterson, W. (1986b). *Guidelines for Conducting and Calibrating Road Roughness Measurements,* World Bank Technical Paper Number 46, World Bank, Washington, D.C.

Shahin, M., Nunez, M., Broten, M., Carpenter,S., and Sameh, A (1987). "New Techniques for Modeling Pavement Deterioration.", *Transportation Research Record: Journal of the Transportation Research Board*, 1123, pp. 40-46.

Tabatabaee, N. and Ziyadi, M. (2013). “Bayesian Approach to Updating Markov-Based Models for Predicting Pavement Performance.”, *Transportation Research Record: Journal of the Transportation Research Board*, 366, pp. 34-42.

UGA (2015). *Major Soil Provinces: College of Agricultural & Environmental Sciences*, University of Georgia.

Wang, K., Zaniewski, J. and Way,G. (1994). “Probabilistic Behaviors of Pavements.”, *Journal of Transportation Engineering*, 120(3), pp. 358-375.

Weingroff, R. (2017). *Origins of the Interstate Maintenance Program. Interstate System*. Available online: https://www.fhwa.dot.gov/infrastructure/intmaint.cfm/.

Wiegand, K. and Susten, S. (2016). “Prioritization of the Georgia State Highway System.”, *Transportation Research Board*.

Yang, J., Lu, J.J., Gunaratne, M., and Dietrich, B. (2006). “Modeling Crack Deterioration of Flexible Pavements: Comparison of Recurrent Markov Chains and Artificial Neural Networks.”, *Transportation Research Record: Journal of the Transportation Research Board*, pp. 18-25.

APPENDIX I: USER'S GUIDE FOR GDOT LP&S

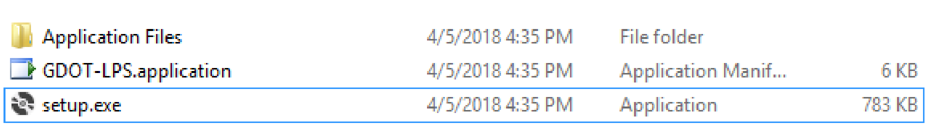
1. GDOT-LP&S Installation

GDOT Asphalt Pavement Network-Level Long-term Performance Forecasting and Simulation (in brief, GDOT-LP&S thereafter) program is to conduct long-term performance forecasting, what-if analysis, and need analysis for GDOT asphalt pavements. The following procedures guide you through the whole process to install this program.

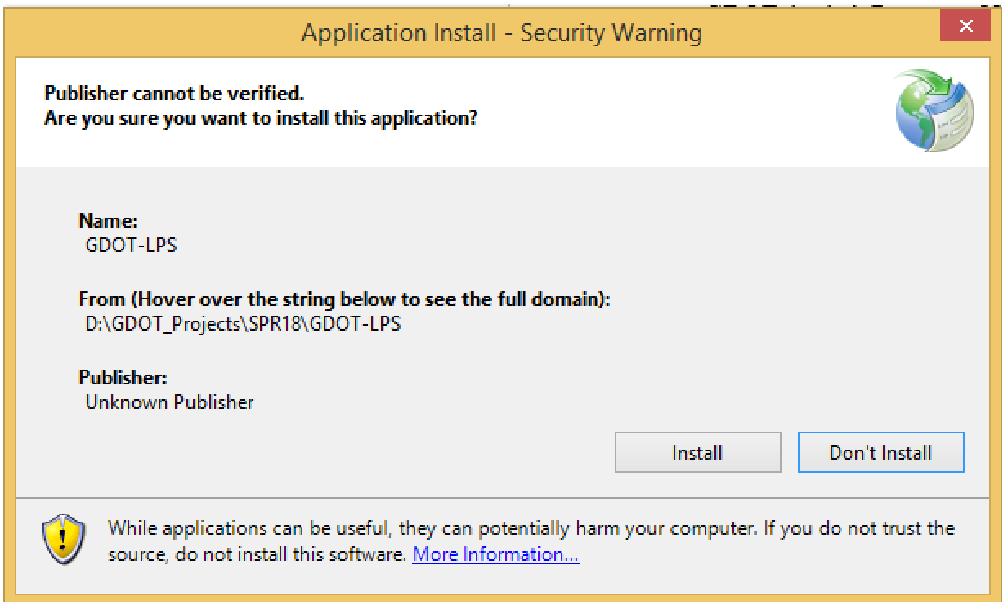
1.1 System Requirements

- Pentium IV 1.0G or above
- 1GB or above free hard drive space
- 1GB or above RAM
- Windows 8/8.1/10
- Office 2010 or above

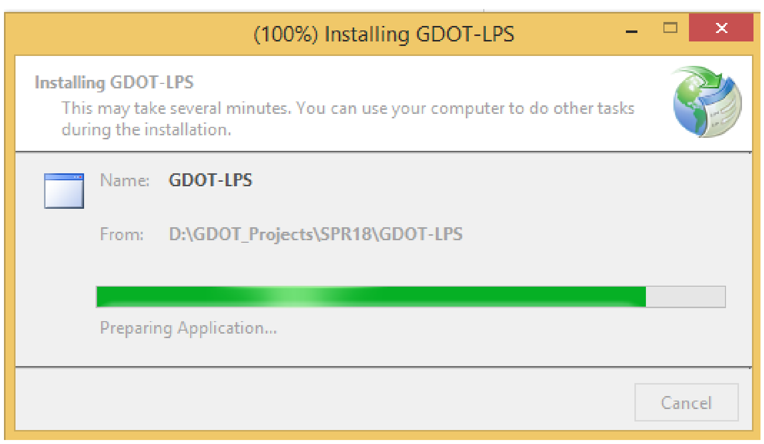
1.2 Installation Procedures

- Extract GDOT-LPS.zip to a local hard disk.
- Double-click setup.exe to launch the installation program.
- 

- Click "Install" to proceed the installation process.



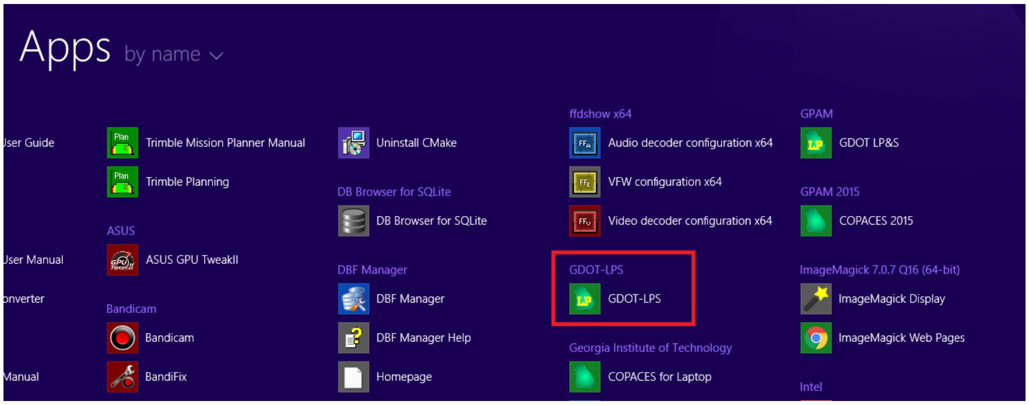
- The installation process takes several seconds but may take several minutes.



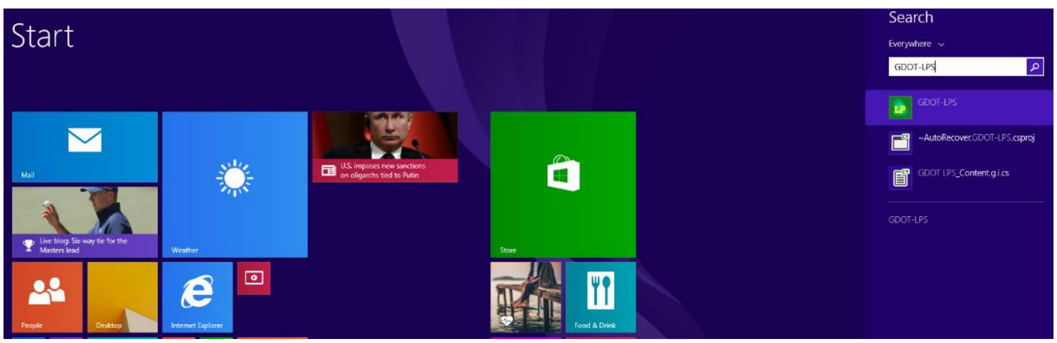
1.3 Launch Program

The GDOT-LPS program will be launched automatically after installation. In other cases, you can launch the program in the following way:

- Click Start Menu → Apps (or Programs) → GDOT-LPS



- You may also type the name of the App while you are at the Start menu. The app will show up in the right column.



2. GDOT-LPS Tutorial

This tutorial guides you through the whole process of using the GDOT LP&S.

The tutorial is divided into 8 steps.

In this tutorial, you'll see how to handle each of the tasks in GDOT-LPS, including:

Step 1: Operations on Simulation

Step 2: Operations on Scenario

Step 3: Inputs for a Scenario (1): Initial States

Step 4: Inputs for a Scenario (2): Markov Chains

Step 5: Inputs for a Scenario (3): Budget Allocations

Step 6: Inputs for a Scenario (4): Treatments

Step 7: Inputs for a Scenario (5): Simulation Strategies

Step 8: Running Simulation and Reporting

3. Step 1 Operations on Simulation

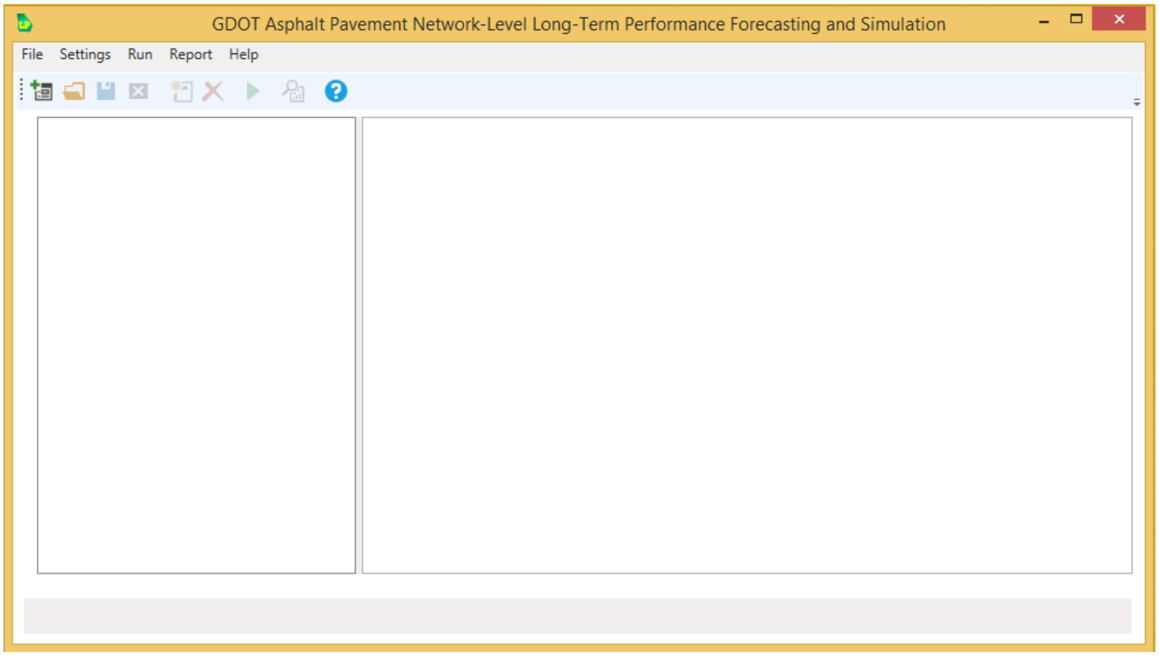
GDOT-LPS stores settings (inputs), scenario information and results in an MS Access database. Each simulation has a corresponding database, in which several scenarios can be constructed and analyzed.

The following steps walk you through the process to create a new simulation or open an existing simulation.

- Launch GDOT-LPS program
- Create a new simulation
- Rename a simulation
- Save a simulation
- Open an existing simulation
- Close the current simulation

3.1 Launch GDOT-LPS program

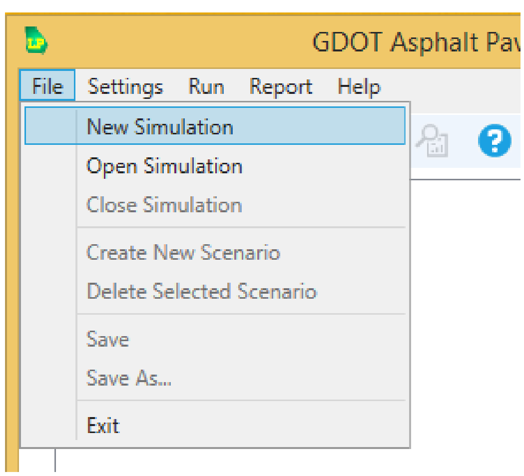
Refer to Installation to see how to launch GDOT-LPS program.



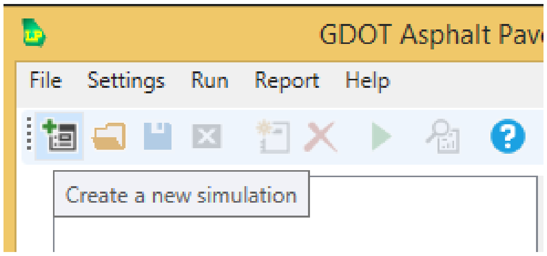
3.2 Create a new simulation

To start using GDOT-LPS, creating a new simulation is the first step. Within this simulation, you can customize all inputs and construct virtually unlimited scenarios to conduct what-if analyses. You can choose either of the following ways by selecting a menu item or clicking a toolbar button to create a new simulation.

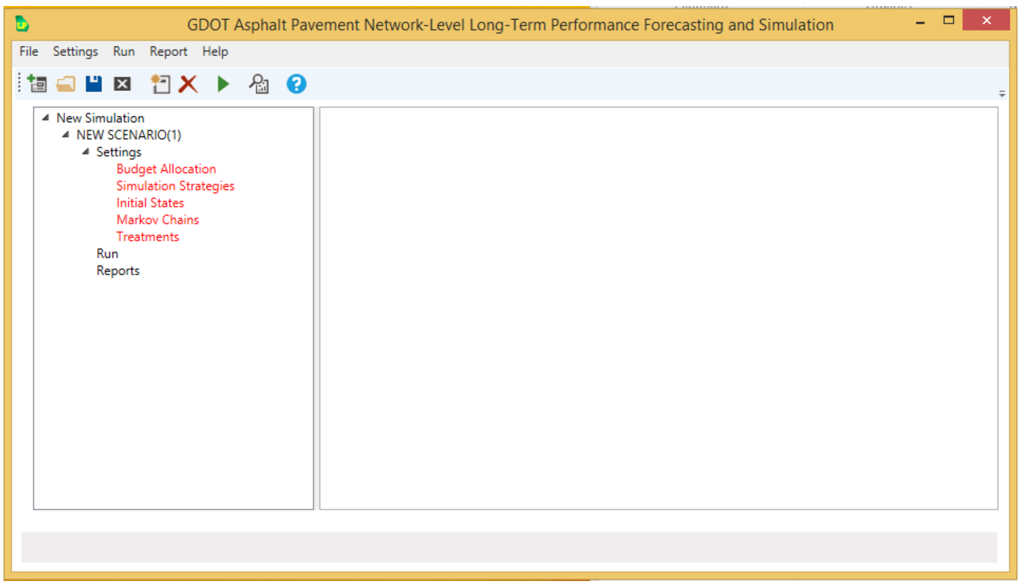
- Select menu item **File** → **New Simulation**



- Click the following button in the tool bar.



After the new simulation is created, the form changes its appearance as follows.



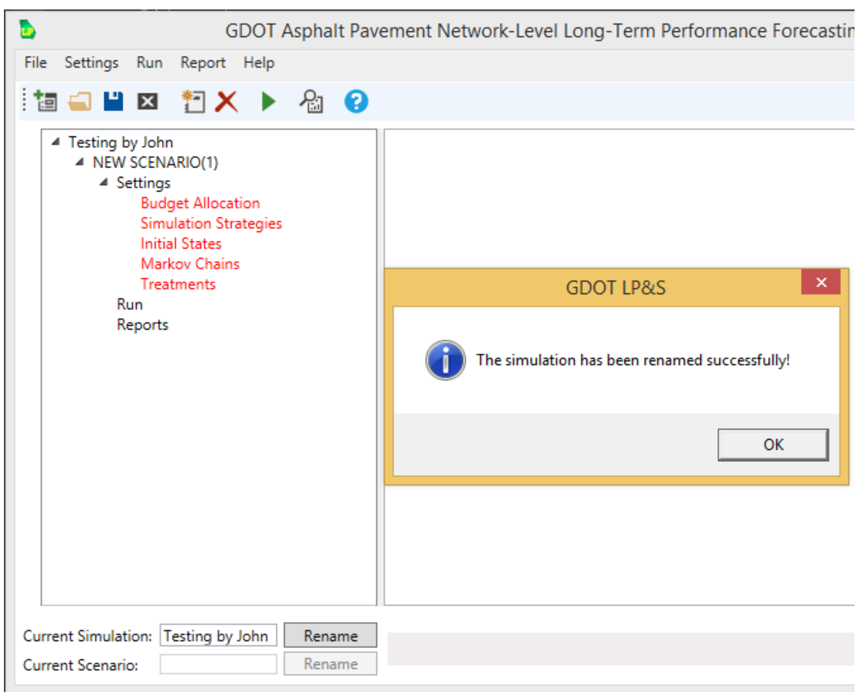
The remainder of the tutorial will introduce the use of all functions. A brief introduction is as follows.

In the left panel, the hierarchical structure illustrates the organization of the simulation. The **New Simulation** is the only root node (you can change its name to whatever you like). The **NEW SCENARIO** is the second-level node (again, you can change its name). In a simulation, several scenarios can be created. Under each scenario node, there are three third-level nodes: **Settings**, **Run** and **Reports**, which represents the main operation flow in using GDOT-LPS. Under **Settings** node, there are 5 items, which are inputs for a scenario. You may want to review or modify each input item before you run the scenario. After you successfully run a scenario, you can obtain the reports by clicking the **Reports** node.

3.3 Rename a simulation

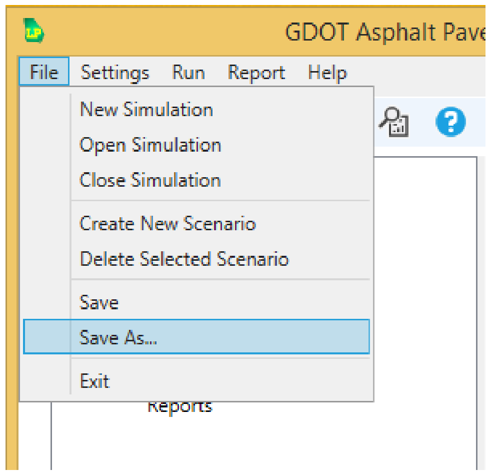
The term **New Simulation(1)** is given by the program as default, which means nothing other than a new simulation. You can change it by editing on the first textbox at the bottom-left corner or saving the simulation as a new name.

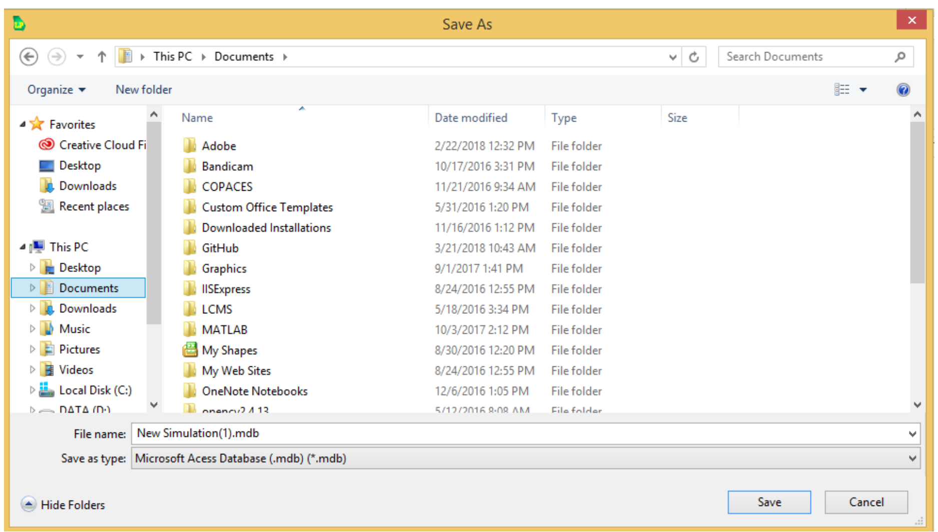
- Specify the name of the simulation in the first textbox at the bottom-left corner. Then click the “Rename” button on the right. Type in a meaningful name for it, for example, "Testing by John".



or

- Select menu item **File→Save As**. Then, an open file form pops up. Type in the name in the **File name** box and click **Open**.



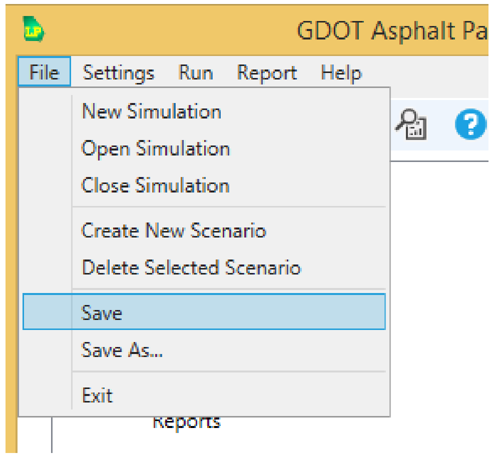


Note: The difference between the above two options is that the first operation doesn't save the simulation until you do it as described in Section 3.4.

3.4 Save a simulation

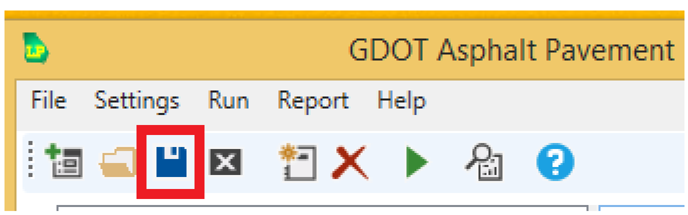
From the Section 3.3, you already know how to save the simulation by assigning a name to it. Another method to save a simulation is to do it without explicitly assigning a name. You also have two ways to do it.

- Select menu item **File→Save**



or

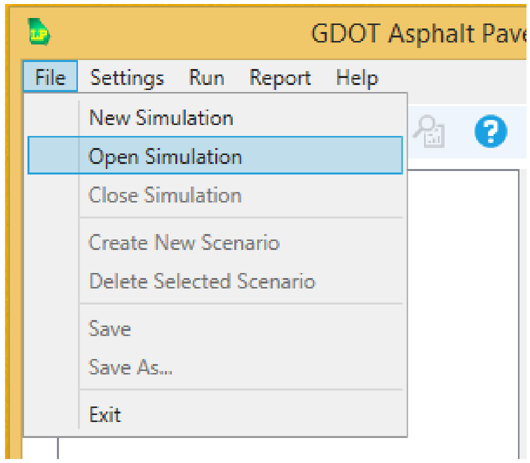
- Click the toolbar button (the red rectangle marker just indicates the location of the button on the form)



3.5 Open an existing simulation

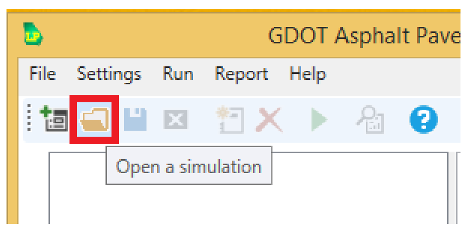
To open a simulation, you created previously, choose either of the following two methods:

- Select menu item **File→Open Simulation**

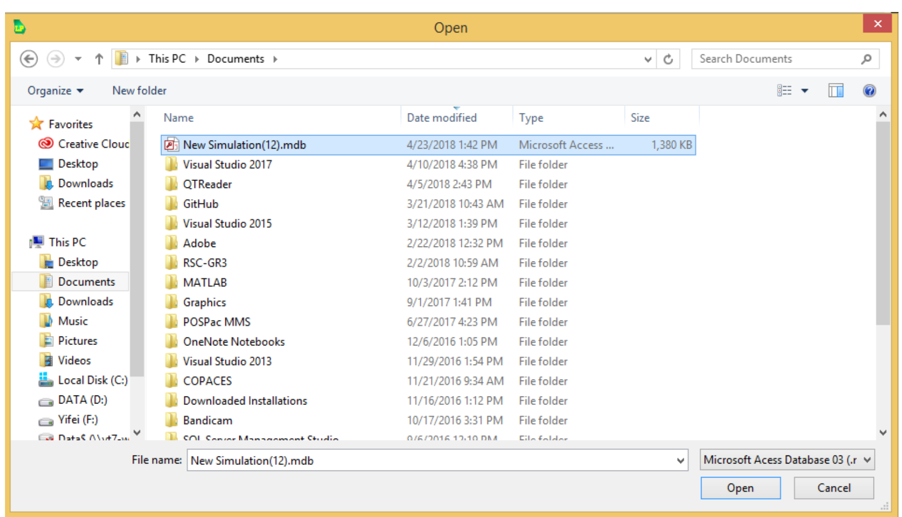


or

- Click the toolbar button



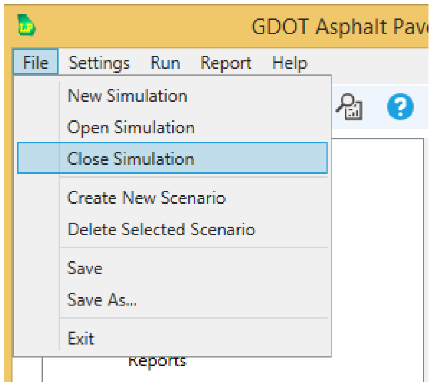
Then the Open file form pops up. Select the simulation database you are going to open and click **Open**.



3.6 Close the current simulation

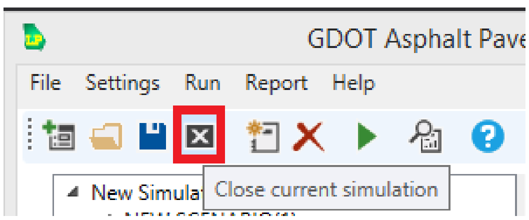
To close the current simulation, you can

- Select menu item **File→Close Simulation**



or

- Click the toolbar button



4. Step 2 Operations on Scenario

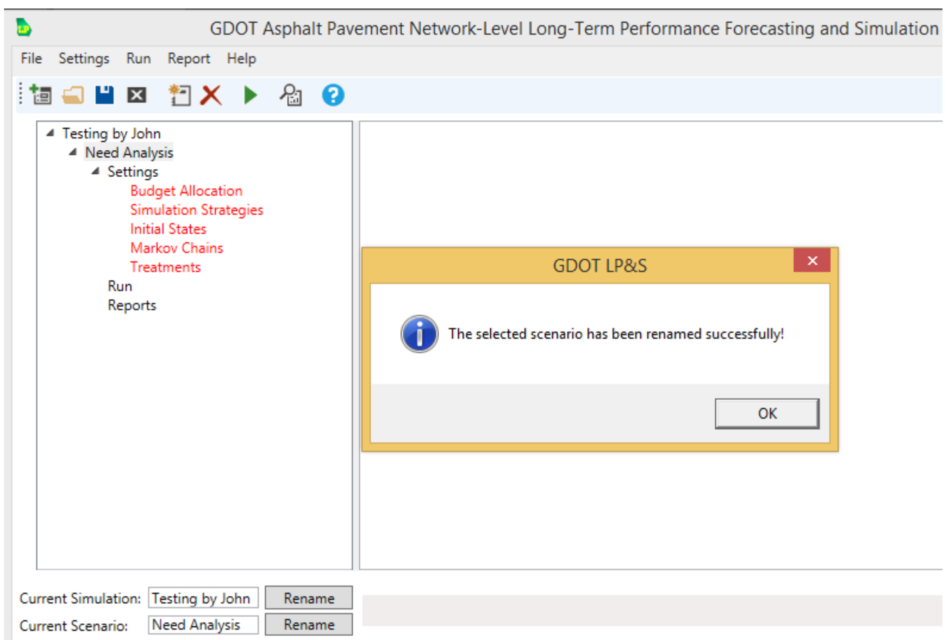
A scenario is one of the combinations of pavement initial conditions, pavement condition transition probabilities, funding allocations, treatment methods, and simulation strategy. By running different scenarios, you can forecast pavements performance, conduct some what-if analyses, and do need analyses under different constraints.

Sections 4.1, 4.2, and 4.3 walk you through the process to rename, create, or delete a scenario.

4.1 Rename a scenario

You may notice that a default scenario named as **New Scenario** is always there when a new simulation is created. You can change the meaningless name to a meaningful one, for example, "Need Analysis" by editing on it.

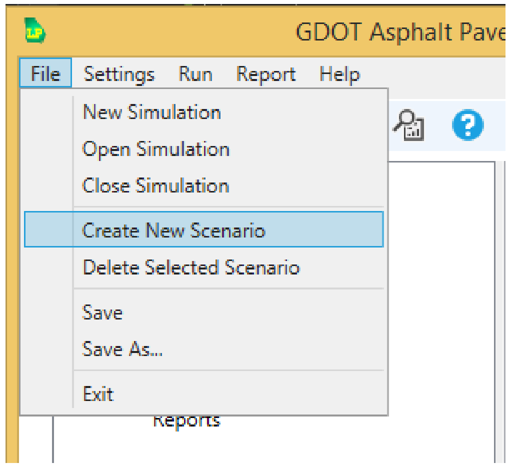
- Highlight the **New Scenario** node first. Then specify the name in the bottom textbox at the bottom-left corner. Type in a meaningful name for it, for example, "Need Analysis". Finally, click the “Rename” button next to the textbox.



4.2 Create a new scenario

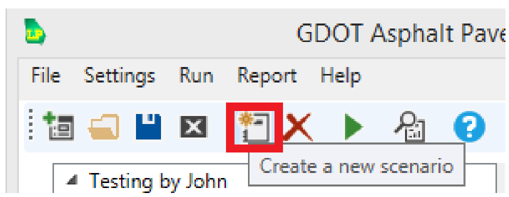
To construct another scenario with different combination of inputs, you may want to create a new scenario instead of overwriting the existing one. Either of the following ways can be used to create a new scenario:

- Select menu item File→Create New Scenario



or

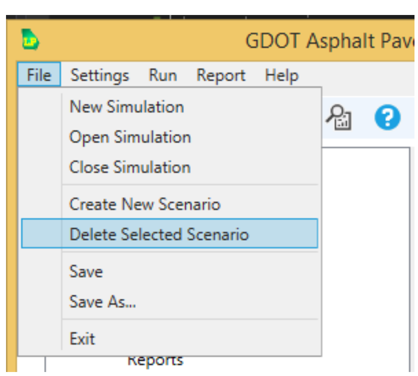
- Click the toolbar button



4.3 Delete a scenario

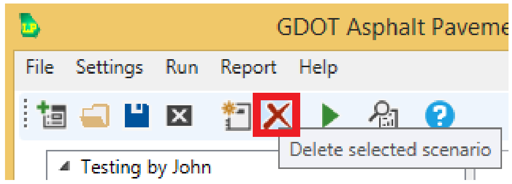
To delete a scenario from the current simulation database, you need to first highlight the scenario. Then you can do one of the following:

- Select menu item File→Delete Selected Scenario



or

- Click the toolbar button



NOTE: If only one scenario exists in the current simulation database, you cannot delete it.

5. Step 3 Inputs for a Scenario (1): Initial States

Before you can run a simulation, you need to review or modify 5 settings (inputs).

Each time when you create a new scenario, the program will assign each input with some default values, which don't necessarily fit your needs. So, review each setting to make sure everything is okay before you run the simulation. The red right-direction arrow icon means the corresponding setting is not reviewed or modified (or simply not touched by the user). Otherwise, it is changed to a green OK marker.

The **Initial States** represents the condition distribution of the pavement network at the starting point of an analysis period. In GDOT-LPS, the whole Georgia pavements are divided into 35 families (categories) as follows:

No.	Family
1	District 1, Critical Interstate Route
2	District 1, Critical Non-Interstate Route
3	District 1, High-Priority Non-Interstate Route

4	District 1, Medium-Priority Non-Interstate Route
5	District 1, Low-Priority Non-Interstate Route
6	District 2, Critical Interstate Route
7	District 2, Critical Non-Interstate Route
8	District 2, High-Priority Non-Interstate Route
9	District 2, Medium-Priority Non-Interstate Route
10	District 2, Low-Priority Non-Interstate Route
…	…
31	District 7, Critical Interstate Route
32	District 7, Critical Non-Interstate Route
33	District 7, High-Priority Non-Interstate Route
34	District 7, Medium-Priority Non-Interstate Route
35	District 7, Low-Priority Non-Interstate Route

For each family, the following attributes should be provided as the initial states.

1	Condition distributions (mileage percentages of Excellent, Good, Fair, Poor and Bad)
2	Total mileage (in mile)
3	Composite rating for each state (Excellent, Good, Fair, Poor or Bad)

The definition of a State is as follows.

State	Rating Range
Excellent	91~100
Good	81~90
Fair	71~80
Poor	55~70
Bad	<55

Sections 5.1, 5.2, and 5.3 walk you through the process of inputting initial states for a scenario:

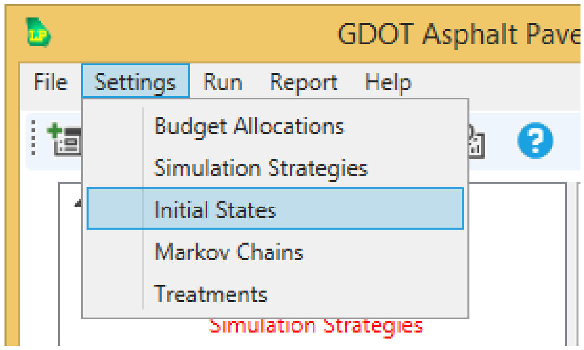
5.1 Open the input form

To open the form, you may

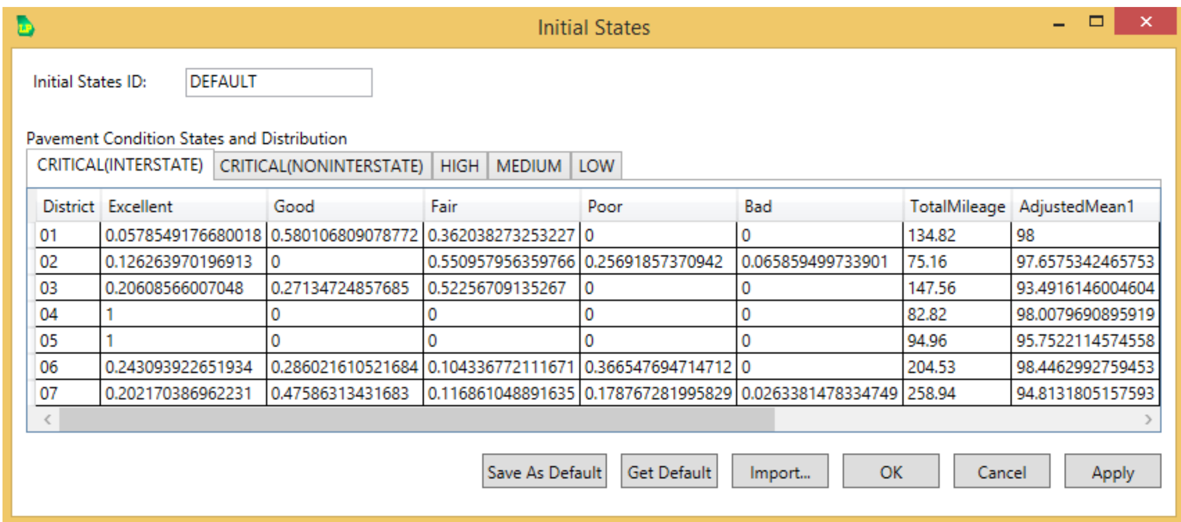
- Click the **Initial States** node under the scenario you are working on.

or

- Select menu item Settings→Initial States



NOTE: You need to make sure the proper scenario is selected when you open the form by selecting menu item.



District	Excellent	Good	Fair	Poor	Bad	TotalMileage	AdjustedMean1
01	0.0578549176680018	0.580106809078772	0.362038273253227	0	0	134.82	98
02	0.126263970196913	0	0.550957956359766	0.25691857370942	0.065859499733901	75.16	97.6575342465753
03	0.20608566007048	0.27134724857685	0.52256709135267	0	0	147.56	93.4916146004604
04	1	0	0	0	0	82.82	98.0079690895919
05	1	0	0	0	0	94.96	95.7522114574558
06	0.243093922651934	0.286021610521684	0.104336772111671	0.366547694714712	0	204.53	98.4462992759453
07	0.202170386962231	0.47586313431683	0.116861048891635	0.178767281995829	0.0263381478334749	258.94	94.8131805157593

The program has already assigned this input as a default ID, **DEFAULT**. You can change it or just leave it as default. The 14 families are arranged on two tab grids. To input data for Interstate or Non-interstate, you need to click the corresponding tab button to make it visible. The meanings of the 5 buttons are as follows:

- **Set as Default**: Set as default the set of initial conditions shown on the form. Next time, the program will use the current setting as the default value assigned to a new scenario.
- **Get Default**: Load the default initial conditions, and set them set as current

- **Import**: Load a saved set of initial conditions, and set it as current.
- **Save**: Save the set of initial conditions on the form, and set it as current.
- **Cancel**: Close form without saving.

5.2 Edit on the form

To modify a value, just simply click on it and change it. Some rules for the data are described as follows.

	Rule
1	Each value for Excellent, Good, Fair, Poor or Bad should be less than or equal to 1.0
2	Each value for Excellent, Good, Fair, Poor or Bad should be greater than or equal to 0.0
3	In each family, the sum of Excellent, Good, Fair, Poor and Bad should be equal to 1.0
4	Total mileage for each family should be greater than 0
5	The values for Ave_Rating1, Ave_Rating2, Ave_Rating3, Ave_Rating4 and Ave_Rating5 should fall into the same range with the definition of Excellent, Good, Fair and Poor respectively.

If any of the above rules is violated, an error message will pop up when you try to save the current modifications.

5.3 Save the inputs

After you finish inputting initial states, click **Save** to save the setting and exit the form. If you don't want to make any change, just click **Cancel** to exit the form. If a set of inputs is saved, the program will automatically assign a ID to it according to current date and time (for example, 20180101100523 represents 10:05:23 at January 1st, 2018).

When you quit the form, you can find the red right-direction arrow is changed to a green OK marker.

6. Step 4 Inputs for a Scenario (2): Markov Chains

A Markov chain is an important attribute of a pavement network. It represents the deterioration of a pavement network. In GDOT-LPS, 1 year is the basic time unit, which means the Markov chain represents the deterioration probabilities in a one-year period. Generally, a Markov chain has the following items.

States	Excellent	Good	Fair	Poor	Bad
Excellent	p_{11}	p_{12}	0	0	0
Good	0	p_{22}	p_{23}	0	0
Fair	0	0	p_{33}	p_{34}	0
Poor	0	0	0	p_{44}	p_{45}
Bad	0	0	0	0	1.0

According to the above table, we can say in a pavement network, p_{11} (percentage) of pavements in Excellent this year will stay in the same condition next year if no treatment is applied, but p_{12} of pavements will deteriorate to the second state (Good). Similarly, p_{22} of pavements in Good will stay in the same condition next year if no treatment is applied, but p_{23} of pavements will deteriorate to the third state (Fair). And so on and so forth. For simplicity, we assume that in a one-year period, pavement can only deteriorate to the next state. So, only 8 numbers need to be identified for the Markov matrix of a family. Based on the nature of Markov chain, the following 3 rules will be applied on the matrix items.

	Rule
1	p_{11}, p_{12}, p_{22}, p_{23}, p_{33}, p_{34}, p_{44}, p_{45}, p_{55} should be a number between 0 and 1

2	All other items should be equal to 0
3	$p_{11} + p_{12} = 1$; $p_{22} + p_{23} = 1$; $p_{33} + p_{34} = 1$; $p_{44} + p_{45} = 1$; $p_{55} = 1$;

Section 6.1, 6.2, and 6.3 walk you through the process of inputting Markov chains for a scenario.

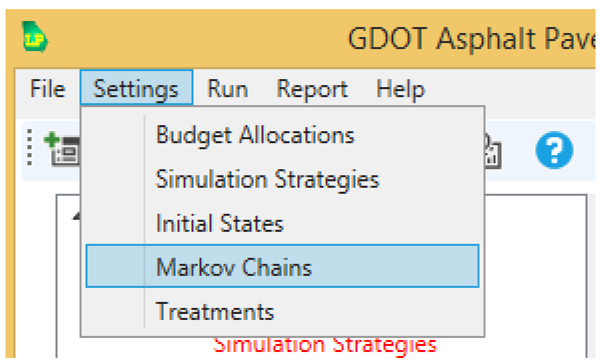
6.1 Open the Markov chain input form

To open the form, you may

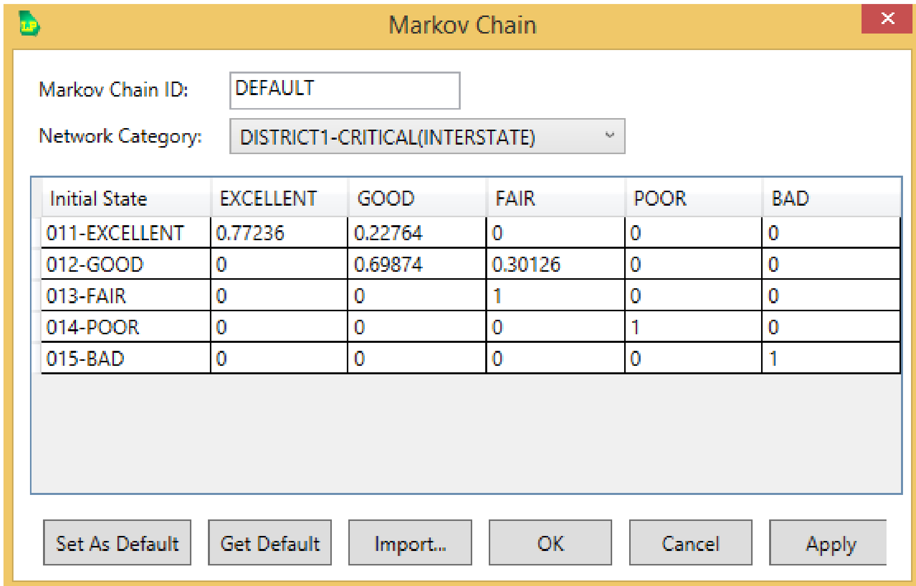
- Click the **Markov Chains** node under the scenario you are working on.

or

- Select menu item Settings→Initial States



Please note that you need to make sure the proper scenario is selected when you open the form by selecting menu item.



Initial State	EXCELLENT	GOOD	FAIR	POOR	BAD
011-EXCELLENT	0.77236	0.22764	0	0	0
012-GOOD	0	0.69874	0.30126	0	0
013-FAIR	0	0	1	0	0
014-POOR	0	0	0	1	0
015-BAD	0	0	0	0	1

The program has already assigned a default ID, **DEFAULT**. You can change it or just leave it as default. The 35 families can be selected by clicking **Network Category** dropdown list. To review or modify a Markov matrix for a family, you need to click the **Network Category** dropdown list and select the corresponding family. The meanings of the 5 buttons are as follows:

- **Set as Default**: Set as default the set of Markov chains shown on the form. Next time, the program will use the current setting as the default value assigned to a new scenario.
- **Get Default**: Load the default Markov chains, and set them set as the current
- **Import**: Load a saved set of Markov chains, and set it as current.
- **Save**: Save the set of Markov chains on the form, and set it as current.
- **Cancel**: Close form without saving.

6.2 Edit on the form

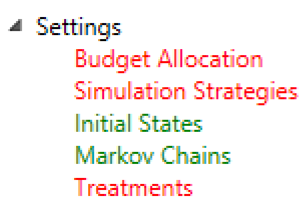
To modify a value, just simply click on it and change it. The above 3 rules for the data are required to be followed.

If any of the above rules is violated, an error message will pop up when you try to save the current modification.

6.3 Save the inputs

After you finish inputting Markov chains, click **Save** to save the setting and exit the form. If you don't want to make any change, just click **Cancel** to exit the form. If an input is saved, the program will automatically assign an id to it according to current date and time (for example, 20180101100523 represents 10:05:23 at January 1st, 2018).

When you quit the form, you can find the red right-direction arrow is changed to a green OK marker.



7. Step 5 Inputs for a Scenario (3): Budget Allocations

Budget is the main issue of a pavement management system. With the given total annual budgets, the program can work out a set of optimal budget allocations to achieve the maximum composite rating. Users can also manually allocate budget to each family to conduct performance forecasting and simulation. In these two cases, budgets are inputs. The output is its allocations (e.g., how to spend the money). Another case is given the annual pavement conditions requirements, the program will find the minimum cost to meet these requirements in which budgets will be the outputs.

Section 7.1, Section 7.2, and Section 7.3 walk you through the process to input Budgets for a scenario.

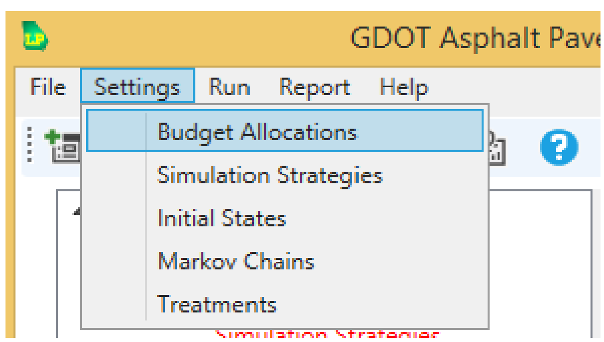
7.1 Open the Budget Allocations form

To open the form, you may

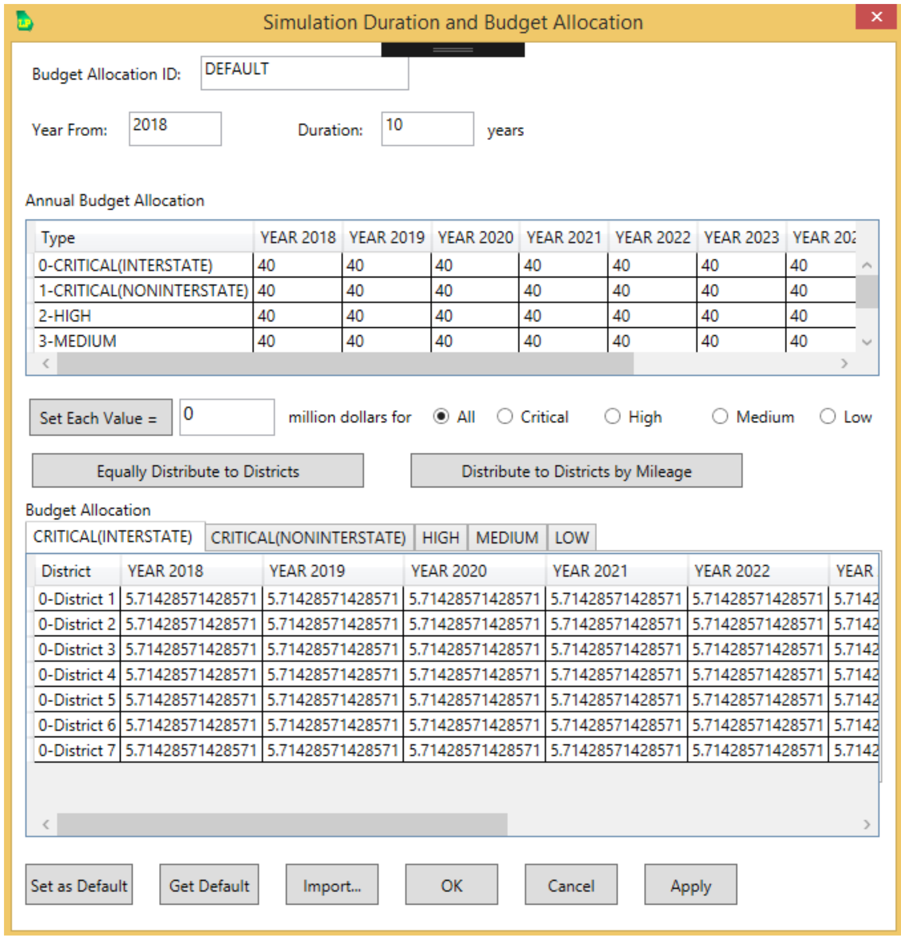
- Click the **Budget Allocations** node under the scenario you are working on.

or

- Select menu item **Settings→Budget Allocations**



NOTE: You need to make sure the proper scenario is selected when you open the form by selecting menu item.



The program has already assigned a default ID, **DEFAULT**. You can change it or just leave it as default.

On this form, you will input simulation starting year and duration. Also, you need to give a budget allocation for each family each year.

The meanings of the 5 buttons are as follows.

- **Set as Default**: Set as default the set of budget allocations shown on the form. Next time, the program will use the current setting as the default value assigned to a new scenario.
- **Get Default**: Load the default budget allocations, and set them set as the current

- **Import**: Load a saved set of budget allocations, and set it as current.
- **Save**: Save the set of budget allocations on the form, and set it as current.
- **Cancel**: Close form without saving.

7.2 Edit on the form

To modify a value, just simply click on it and change it. In the **Year From** box, you need to type in the year the simulation starts with. In the **Simulation Duration** box, you need to decide how many years the simulation will cover. The default is 10 years.

The upper grid lists the annual budgets for interstate and non-interstate of the whole state. You can manually click each number to edit it. The program also provides some convenient functions to quickly assign budgets. For example, if you want to assign 30 million dollars to interstate and non-interstate for each year, just type in 30 in the box to the right of **Set Each Value =** button and make sure the **All** option button is selected, then click **Set Each Value =**. If you just want to assign the number to interstate or non-interstate, type in the number and select the corresponding option button and click **Set Each Value =** to assign the number.

The lower two grids (click the tab button to read different grid for interstate and non-interstate) list the detail budget allocations for each family each year. Because you have already input the total budget for interstate and non-interstate, you can just simply distribute the budgets to each family equally or proportional to the mileage of each family. To do it, click **Equally Distribute to Districts** or **Distribute to Districts by Mileage**. Of course, you can manually modify the budget for each family, the total budget will be automatically adjusted.

Please note that for some simulation strategies (i.e. cases, will be introduced in Step 7), only part of the information on this form is useful. The following table lists the required information on this form for each simulation strategy.

Simulation Strategy	Starting Year	Duration	Budget for each type	Budget for each family
Optimization on each family	Y	Y	Y	Y
Optimization on all families	Y	Y	Y	N
Need analysis	Y	Y	N	N
Need analysis on each type	Y	Y	N	N

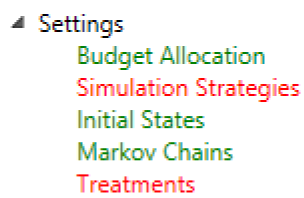
* You can specify the scope for each simulation strategy by setting the budget to 0 for types that are out of the scope.

** Y means the attribute is needed for the strategy. N means it is not required. You can input the non-required information, but it won't affect simulation results.

7.3 Save the inputs

After you finish inputting budget allocations, click **Save** to save the setting and exit the form. If you don't want to make any change, just click **Cancel** to exit the form. If a input is saved, the program will automatically assign an id to it according to current date and time (for example, 20180101100523 represents 10:05:23 at January 1st, 2018).

When you quit the form, you can find the red right-direction arrow is changed to a green OK marker.



8. Step 6 Inputs for a Scenario (4): Treatments

Treatment strategies are directly associated with cost. In essence, each simulation strategy is to find optimal treatment strategies to maintain the pavement systems to a serviceable condition.

Sections 8.1, Section 8.2, and Section 8.3 walk you through the process to input treatments for a scenario.

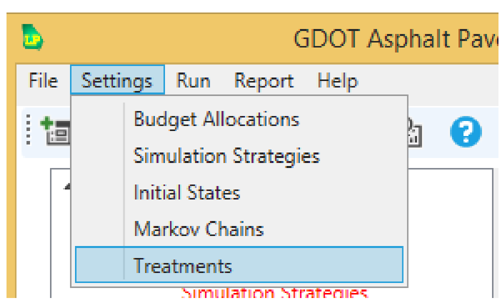
8.1 Open the Treatments form

To open the form, you may

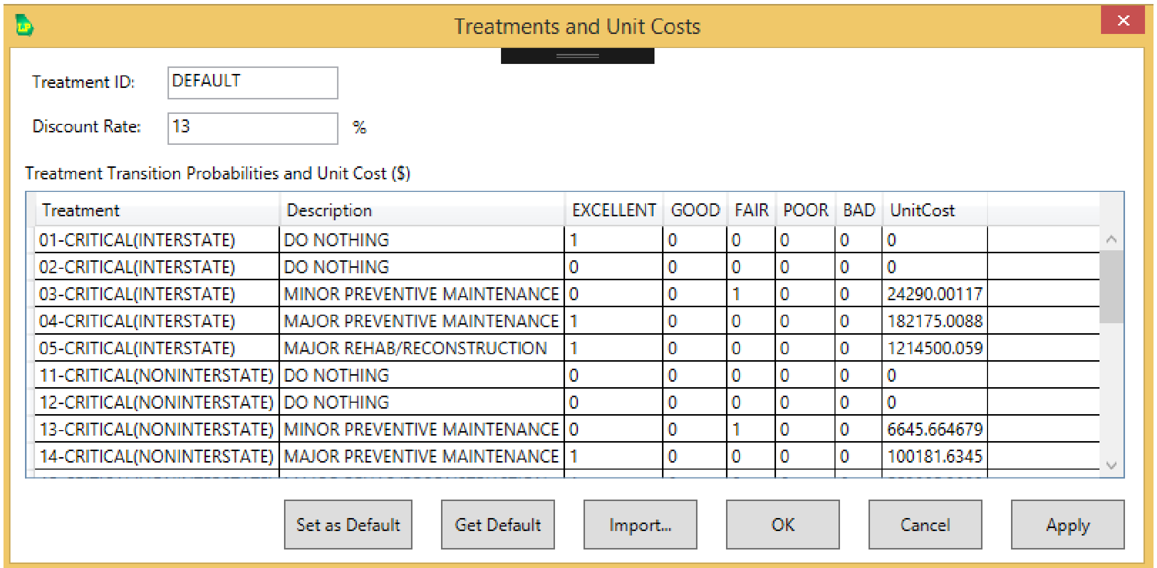
- Click the **Treatments** node under the scenario you are working on.

or

- Select menu item **Settings→Treatments**



NOTE: you need to make sure the proper scenario is selected when you open the form by selecting menu item.



The program has already assigned a default ID, **DEFAULT**. You can change it or just leave it aside.

On this form, you will input inflation rate. Also, you need to give the transition probabilities and unit costs for all possible treatments for interstate and non-interstate respectively.

- **Set as Default**: Set as default the set of treatments shown on the form. Next time, the program will use the current setting as the default value assigned to a new scenario.
- **Get Default**: Load the default Markov chains, and set them set as the current
- **Import**: Load a saved set of Markov chains, and set it as current.
- **Save**: Save the set of budget allocations on the form, and set it as current.
- **Cancel**: Close form without saving.

8.2 Edit on the form

To modify a value, just simply click on it and change it.

In the **Discount Rate** box, you need to type in percentage of discount rate.

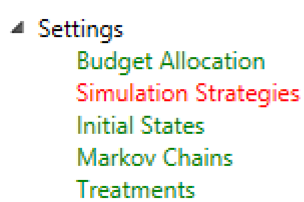
In the grid, there are total 10 treatments associated with 5 states for interstate and non-interstate. For Excellent and Good, no treatment is needed (i.e. do nothing). Minor preventive maintenance, major preventive maintenance, and major rehab/reconstruction are associate with Fair, Poor and Bad respectively. In each row, the values for Excellent, Good, Fair, Poor, and Bad represent the transition probabilities when the treatment is applied.

The unit for unit cost is a million dollars.

8.3 Save the inputs

After you finish inputting treatments, click **Save** to save the setting and exit the form. If you don't want to make any change, just click **Cancel** to exit the form. If an input is saved, the program will automatically assign an id to it according to current date and time (for example, 20180101100523 represents 10:05:23 at January 1st, 2018).

When you quit the form, you can find the red right-direction arrow is changed to a green OK marker.



9. Step 7 Inputs for a Scenario (5): Simulation Strategies

GDOT-LPS provides 4 simulation strategies: worst first, user specified, optimization on each family, optimization on all families and need analyses. The following describes each strategy.

- **Optimization on each family**

In this strategy, the program will automatically decide the treatments for each family with the budget you manually assigned in each year. The objective is to achieve maximum composite rating for each family.

- **Optimization on all families**

In this strategy, the program will automatically decide the treatments for all families with the total budget you assign in each year. The objective is to achieve maximum composite rating for all family.

- **Need analyses**

In this strategy, the program will decide the optimal treatments for all families with the minimum total cost needed in each year. You can specify the requirements that should be satisfied. In GDOT-LPS, the need analyses can have two requirements: (1) composite rating should be greater than a value, say 85; (2) the total percentage of pavements in Bad and Poor should not exceed a percentage, say 10%.

- **Need analyses for each type**

In this strategy, the program will decide the optimal treatments for all families with the minimum total cost needed in each year. You can specify the requirements that should be satisfied. In GDOT-LPS, the need analyses for each type can have five requirements (that is, the minimum composite rating for each type). For example, the minimum composite ratings are 85 for critical interstate, 85 for critical non-interstate, 82 for high-priority non-interstate, 72 for medium-priority non-interstate, and 68 for low-priority non-interstate.

Section 9.1, Section 9.2, and Section 9.3 walk you through the process to input simulation strategy for a scenario.

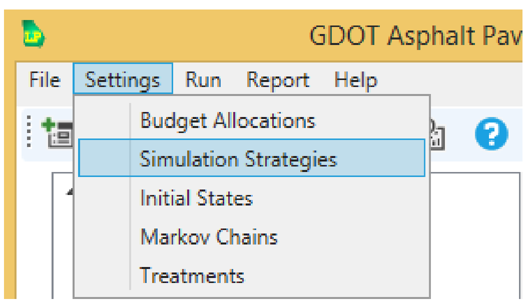
9.1 Open the Simulation Strategies form

To open the form, you may

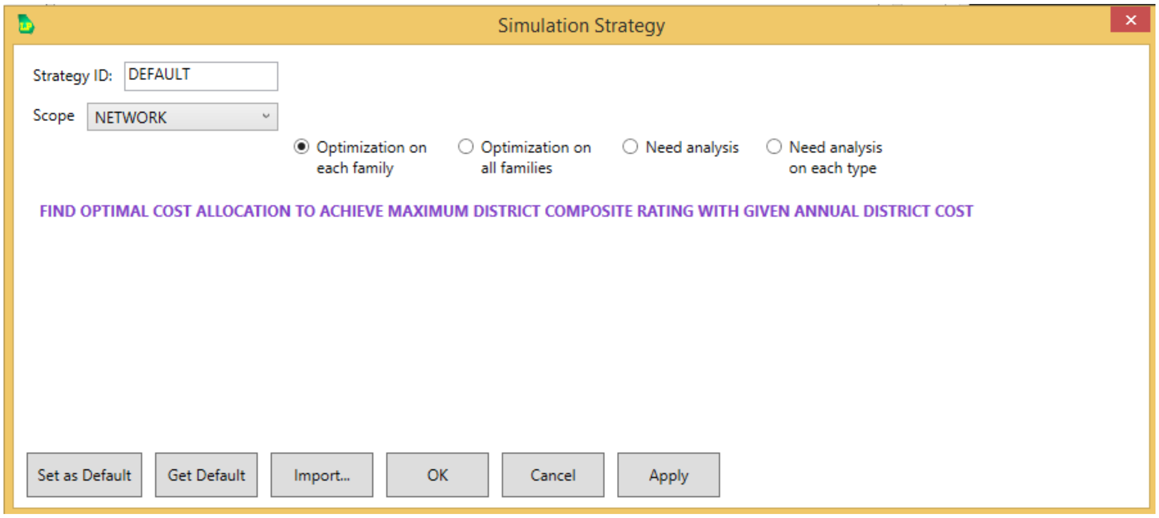
- Click the **Simulation Strategies** node under the scenario you are working on.

or

- Select menu item **Settings→Simulation Strategies**



Please note that you need to make sure the proper scenario is selected when you open the form by selecting menu item.



The program has already assigned a default ID, **DEFAULT**. You can change it or just leave it as default.

On this form, you will input simulation scope. Also, you need to specify which strategy you are going to use and the type in the corresponding parameters for the selected strategy.

The meanings of the 5 buttons are as follows.

- **Set as Default**: Set as default the set of simulation strategy shown on the form. Next time, the program will use the current setting as the default value assigned to a new scenario.
- **Get Default**: Load the default simulation strategy, and set it set as the current
- **Import**: Load a saved simulation strategy, and set it as current.
- **Save**: Save the simulation strategy on the form, and set it as current.
- **Cancel**: Close form without saving.

9.2 Edit on the form

To modify a value, just simply click on it and change it.

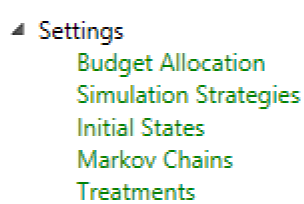
In the **Scope** dropdown list, you can choose **NETWORK**, **INTERSTATE** or **NON-INTERSTATE**. If an item other than **NETWORK** is selected, please note that only the corresponding results in the reports (see Step 8) are meaningful.

Only one of the 5 strategy option buttons can be selected at a time. If **User specified** or **Need analyses** is selected, you need to input some other information for it. For **User specified**, you need to input the budget distribution on treatments for Fair, Poor, and Bad conditions of interstate and non-interstate. For **Need analyses**, you need to input the values for composite rating and total percentage of pavements in Poor and Bad conditions, which are two requirements for need analyses.

9.3 Save the inputs

After you finish inputting initial states, click **Save** to save the setting and exit the form. If you don't want to make any change, just click **Cancel** to exit the form. If an input is saved, the program will automatically assign an id to it according to current date and time (for example, 20180101100523 represents 10:05:23 at January 1^{st}, 2018).

When you quit the form, you can find the red right-direction arrow is changed to a green OK marker.



10. Step 8 Running Simulation and Reporting

After you have input all required information, it is time to run the simulation and get results.

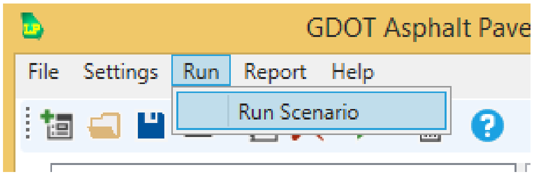
10.1 Running the simulation

To run the simulation, you can

- Click the **Run** node under the scenario you are working on.

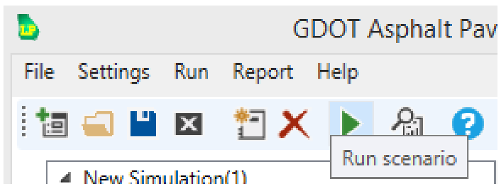
or

- Select menu item **Run→Run Scenario**



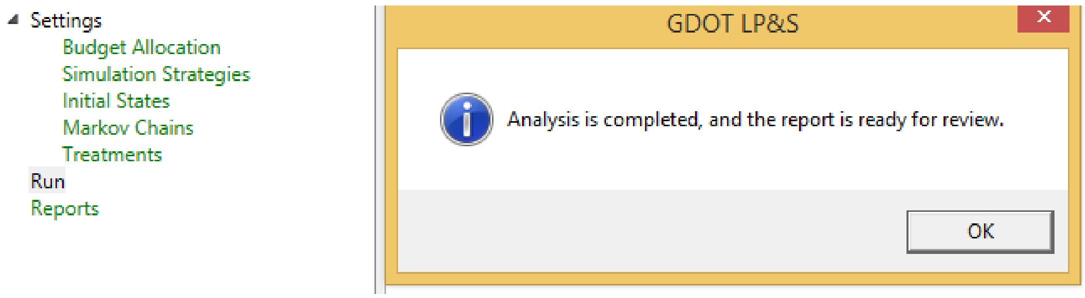
NOTE: You need to make sure the proper scenario is selected when you run the simulation by selecting menu item.

- Click the toolbar button



10.2 Reporting

If the simulation succeeds, you will get a popup information. Click **OK** to confirm it. You will find the red flag beside the **Reports** node is changed to green, which means the reports are ready for review.

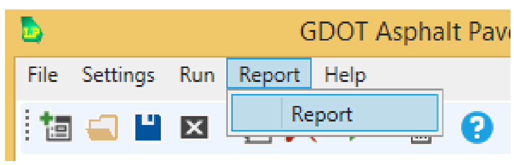


To open the reports, you can

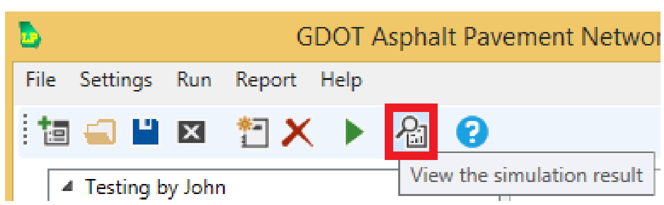
- Click the **Reports** node under the scenario you are working on.

or

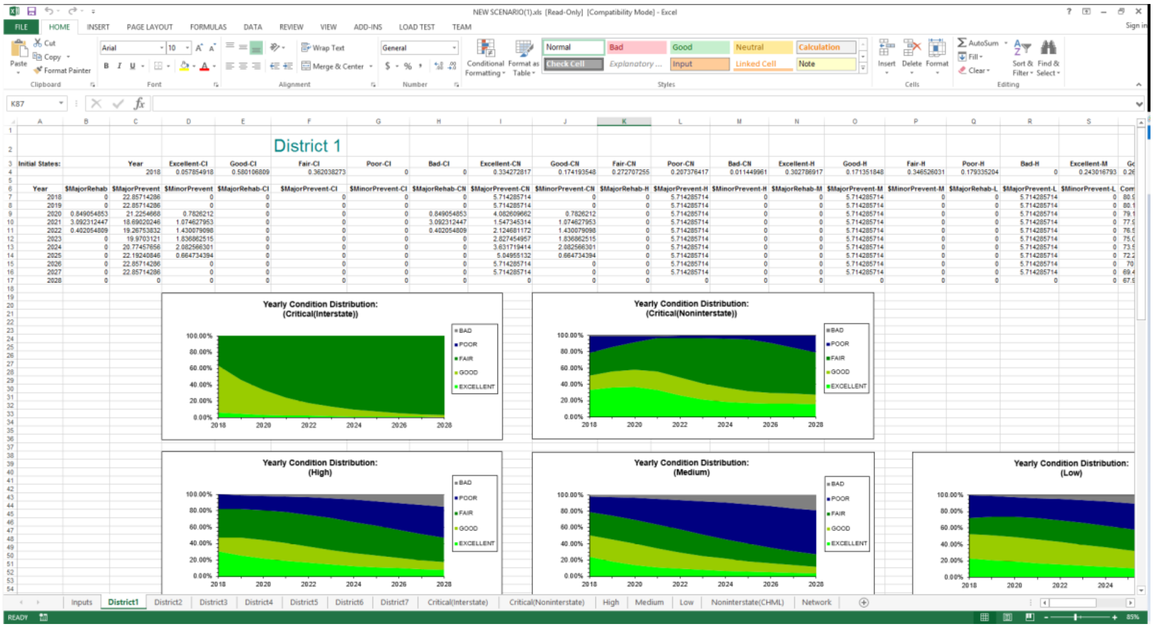
- Select menu item **Report** → **Report**



- Click the toolbar button



Please wait for a while, the report in a format of MS Excel will be generated as follows.



There are 15 worksheets in the report: Input, District 1 to 7, Critical (Interstate), Critical (Non-interstate), High, Medium, Low, Non-interstate (CHML), and the whole network. In the worksheet for each district, there are 12 graphs, (1) yearly condition distribution for critical interstate in this district; (2) yearly condition distribution for critical non-interstate in this district; (3) yearly condition distribution for high-priority non-interstate in this district; (4) yearly condition distribution for medium-priority non-interstate in this district; (5) yearly condition distribution for low-priority non-interstate in this district; (6) yearly condition distribution for the whole district; (7) composite ratings for critical interstate, critical non-interstate, high-priority non-interstate, medium-priority non-interstate, low-priority non-interstate, and the whole district; (8) yearly cost distributions for critical interstate in this district; (9) yearly cost distributions for critical non-interstate in this district; (10) yearly cost distributions for high-priority non-interstate in this district; (11) yearly cost distributions for medium-priority non-interstate in this district; and (12) yearly cost distributions for low-priority non-interstate in this district. You can find the corresponding tabular data in each worksheet. In the worksheet for critical (interstate), critical (non-interstate), high, medium, low, non-interstate (CHML) and the whole network, there are 3 graphs, (1) yearly condition distributions; (2) yearly composite rating; and (3) yearly cost distributions.

APPENDIX II: MARKOV CHAIN TRANSITION PROBABILITY MATRICES (TPMS)

TPMs for Critical Interstate Families for 7 Working Districts

District 1					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.77236	0.22764	0	0	0
Good	0	0.69874	0.30126	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 2					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.9695	0.0305	0	0	0
Good	0	0.6667	0.3333	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 3					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.9695	0.0305	0	0	0
Good	0	0.53	0.4	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 4					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.861	0.139	0	0	0
Good	0	0.8986	0.1014	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 5					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.8928	0.1072	0	0	0
Good	0	.8986	0.1014	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 6					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.9396	0.0603	0	0	0
Good	0	0.5976	0.4024	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1

District 7					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.8234	0.1766	0	0	0
Good	0	0.6666	0.3334	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1

TPMs for Critical Non-Interstate Families for 7 Working Districts

District 1					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.7034	0.2966	0	0	0
Good	0	0.5501	0.4499	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 2					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.7867	0.2133	0	0	0
Good	0	0.8082	0.1918	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 3					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.6704	0.3296	0	0	0
Good	0	0.7318	0.2682	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 4					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.8225	0.1775	0	0	0
Good	0	0.7008	0.2992	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 5					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.7821	0.2179	0	0	0
Good	0	0.7046	0.2954	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1

District 6					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.5995	0.4005	0	0	0
Good	0	0.6834	0.3166	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 7					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.4161	0.5839	0	0	0
Good	0	0.6435	0.3565	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1

TPMs for High, Non-Interstate Families for 7 Working Districts

District 1					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.5947	0.4053	0	0	0
Good	0	0.5603	0.4397	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 2					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.8672	0.1327	0	0	0
Good	0	0.7219	0.2781	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 3					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.752	0.248	0	0	0
Good	0	0.6862	0.3138	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 4					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.75	0.25	0	0	0
Good	0	0.5828	0.4172	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1

District 5					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.7528	0.2472	0	0	0
Good	0	0.7268	0.2732	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 6					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.7629	0.2371	0	0	0
Good	0	0.6062	0.3938	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 7					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.6647	0.3353	0	0	0
Good	0	0.6435	0.3565	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1

TPMs for Medium, Non-Interstate Families for 7 Working Districts

District 1					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.5947	0.4053	0	0	0
Good	0	0.6732	0.3268	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 2					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.7835	0.2165	0	0	0
Good	0	0.7223	0.2777	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 3					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.752	0.248	0	0	0
Good	0	0.6862	0.3138	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1

District 4					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.7789	0.2211	0	0	0
Good	0	0.7091	0.2909	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 5					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.7873	0.2127	0	0	0
Good	0	0.7282	0.2718	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 6					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.6893	0.3107	0	0	0
Good	0	0.7866	0.2134	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 7					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.6082	0.3718	0	0	0
Good	0	0.6913	0.3087	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1

TPMs for Low, Non-Interstate Families for 7 Working Districts

District 1					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.6433	0.3567	0	0	0
Good	0	0.7358	0.2642	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 2					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.7967	0.2033	0	0	0
Good	0	0.7565	0.2435	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1

District 3					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.7557	0.2443	0	0	0
Good	0	0.8266	0.1734	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 4					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.7407	0.2593	0	0	0
Good	0	0.74	0.26	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 5					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.7421	0.2579	0	0	0
Good	0	0.7741	0.2259	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 6					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.8545	0.1455	0	0	0
Good	0	0.7065	0.2935	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1
District 7					
	Excellent	**Good**	**Fair**	**Poor**	**Bad**
Excellent	0.5	0.5	0	0	0
Good	0	0.5401	0.4599	0	0
Fair	0	0	0.4	0.6	0
Poor	0	0	0	0.95	0.05
Bad	0	0	0	0	1

APPENDIX III: LINEAR PROGRAMMING MODEL FORMULATIONS

1. Optimization on Each Family

$$\text{Max } R_{t+1}^{f^k}$$

$$\sum_{i=3}^{5} X_t^{f_i^k} \leq c_t^{f_k}$$

$$s_t^{f^k} - X_t^{f^k} \cdot U_t^{-1}/l^{f^k} \geq 0$$

$$X_t^{f^k} \geq 0$$

Where $c_t^{f_k}$=annual budget for category f^k

Scalar Form

Max

$$R_{t+1}^{f^k} = \sum_{i=3}^{5} a_t^{f_i^k} X_t^{f_i^k} + b_t^{f^k}$$

Subject to

$$\sum_{i=3}^{5} X_t^{f_i^k} \leq c_t^{f_k}$$

$$X_t^{f_i^k} T_t^{f_i^k} \leq s_t^{f_i^k}, i = 3,4,5$$

$$X_t^{f_i^k} \geq 0, i = 3,4,5$$

Where:

$$a_t^{f_i^k} = T_t^{f_i^k} \sum_{j=1}^{5} \left(p'_{ij} - p_{ij}^{f^k}\right) m_j^{f^k}, i = 3,4,5$$

$$b_t^{f^k} = \sum_{i=1}^{5} \sum_{j=1}^{5} s_t^{f_i^k} p_{ij}^{f^k} m_j^f$$

$$T_t^{f_i^k} = \frac{1}{u_i \cdot (1+r)^{t-1} \cdot l^{f^k}}, i = 3,4,5$$

2. Optimization on All Family

$$\text{Max } R_{t+1}$$

Subject to:

$$\sum_{f=1}^{7}\sum_{k=1}^{5}\sum_{i=1}^{5} X_t^{f_i^k} \le c_t$$

$$s_t^{f^k} - X_t^{f^k} \cdot \frac{U_t^{-1}}{l^{f^k}} \ge 0 , f = 1,2, \dots ,7, k = 1,2, \dots ,5$$

$$X_t^{f^k} \ge 0, f = 1,2, \dots 7, k = 1,2, \dots ,5$$

Where c_t=annual budget

Scalar Form

Max

$$R_{t+1} = \sum_{f=1}^{7}\sum_{k=1}^{5}\sum_{i=3}^{5} a_t^{f_i^k} X_t^{f_i^k} + b_t$$

Subject to

$$\sum_{f=1}^{7}\sum_{k=1}^{5}\sum_{i=3}^{5} X_t^{f_i^k} \le c_t$$

$$X_t^{f_i^k} T_t^{f_i^k} \le s_t^{f_i^k}, f = 1,2, \dots ,7, k = 1,2, \dots ,5, i = 3,4,5$$

$$X_t^{f^k} \ge 0, f = 1,2, \dots 7, k = 1,2, \dots ,5$$

Where:

$$a_i^{f_i^k} = \left\{ l^{f^k} T_t^{f_i^k} \sum_{j=1}^{5} \left(p'_{ij} - p_{ij}^{f^k} \right) m_j^{f^k} \right\} / (\sum_{f=1}^{7}\sum_{k=1}^{5} l^{f^k}), f = 1,2, \dots ,7, k = 1,2, \dots ,5, i = 3,4,5$$

$$b_t = \sum_{f=1}^{7}\sum_{k=1}^{5}\sum_{i=1}^{5}\sum_{j=1}^{5} s_t^{f_i^k} p_{ij}^{f^k} m_j^{f^k} \, l^{f^k} / (\sum_{f=1}^{7}\sum_{k=1}^{5} l^{f^k})$$

$$T_t^{f_i^k} = \frac{1}{u_i \cdot (1+r)^{t-1} \cdot l^{f^k}}, i = 3,4,5$$

3. Need Analysis

Min

$$c_t = \sum_{f=1}^{7} \sum_{k=1}^{5} \sum_{i=3}^{5} X_t^{f_i^k}$$

Subject to:

$$\sum_{f=1}^{7} R_{t+1}^{f^1} \geq 85$$

$$\sum_{f=1}^{7} R_{t+1}^{f^2} \geq 85$$

$$\sum_{f=1}^{7} R_{t+1}^{f^3} \geq 82$$

$$\sum_{f=1}^{7} R_{t+1}^{f^4} \geq 72$$

$$\sum_{f=1}^{7} R_{t+1}^{f^5} \geq 68$$

$$s_t^{f^k} - X_t^{f^k} \cdot \frac{U_t^{-1}}{l^{f^k}} \geq 0 , f = 1,2, \ldots ,7, k = 1,2, \ldots ,5$$

$$X_t^{f^k} \geq 0, f = 1,2, \ldots 7, k = 1,2, \ldots ,5$$

Scalar Form

Min

$$c_t = \sum_{f=1}^{7} \sum_{k=1}^{5} \sum_{i=3}^{5} X_t^{f_i^k}$$

Subject to:

$$\sum_{f=1}^{7} R_{t+1}^{f^1} = \sum_{f=1}^{7}\sum_{i=3}^{5} a_t^{f_i^1} X_t^{f_i^1} + b_t^1 \geq 85$$

$$\sum_{f=1}^{7} R_{t+1}^{f^2} = \sum_{f=1}^{7}\sum_{i=3}^{5} a_t^{f_i^2} X_t^{f_i^2} + b_t^2 \geq 85$$

$$\sum_{f=1}^{7} R_{t+1}^{f^3} = \sum_{f=1}^{7}\sum_{i=3}^{5} a_t^{f_i^3} X_t^{f_i^3} + b_t^3 \geq 82$$

$$\sum_{f=1}^{7} R_{t+1}^{f^4} = \sum_{f=1}^{7}\sum_{i=3}^{5} a_t^{f_i^4} X_t^{f_i^4} + b_t^4 \geq 72$$

$$\sum_{f=1}^{7} R_{t+1}^{f^5} = \sum_{f=1}^{7}\sum_{i=3}^{5} a_t^{f_i^5} X_t^{f_i^5} + b_t^5 \geq 68$$

$$X_t^{f^k} T_t^{f^k} \leq s_t^{f^k}, f = 1,2,\ldots,7, k = 1,2,\ldots,5$$

$$X_t^{f^k} \geq 0, f = 1,2,\ldots 7, k = 1,2,\ldots,5$$

Where:

$$a_i^{f_i^1} = \left\{ l^{f^1} T_t^{f_i^1} \sum_{j=1}^{5} \left(p'_{ij} - p_{ij}^{f^1}\right) m_j^{f^1} \right\} / \sum_{f=1}^{7} l^{f^1}, f = 1,2,\ldots,7, i = 3,4,5$$

$$b_t^1 = \sum_{f=1}^{7}\sum_{i=1}^{5}\sum_{j=1}^{5} s_t^{f_i^1} p_{ij}^{f^1} m_j^f\, l^{f^1} / (\sum_{f=1}^{7} l^{f^1})$$

$$T_t^{f_i^1} = \frac{1}{u_i \cdot (1+r)^{t-1} \cdot l^{f^1}}, i = 3,4,5$$

The rest can be deduced by analogy.

**k* denotes priority, 1 stands for interstate critical; 2 stands for non-interstate critical; 3 stands for non-interstate high; 4 stands for non-interstate medium; 5 stands for non-interstate low.