PROBABILISTIC MODELING OF FLEXIBLE PAVEMENT OVERLAY PERFORMANCE AND PERFORMANCE-RELATED PAY ADJUSTMENT

by

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ABSTRACT OF THE DISSERTATION

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The performance of pavement plays a critical role in maintenance, rehabilitation and reconstruction (MR&R) for highway agencies. Reliable and accurate estimation of pavement performance can be instrumental in prioritization of the limited resources and funding in highway agencies.

This dissertation presented a rational development of performance-related pay adjustments framework with deterministic and probabilistic models of pavement performance, with application to in-place air void contents and international roughness index (IRI) of asphalt pavements.

The analyses were performed based on the quality assurance data collected from construction database and pavement performance data extracted from pavement management system. Performance-related pay adjustments were formulated using

life-cycle cost analysis (LCCA) considering two different scenarios of maintenance strategy and the variations of pavement overlay life. Comparison was made between the calculated performance-related pay adjustments and the pay adjustments currently used by highway agency. The similarity and dissimilarity were discussed and recommendations were provided based on the analysis results.

The results indicate that there are unneglectable variations in the model parameters for estimating the expected pavement life due to deviations in acceptance quality characteristics. This implies that addressing the variations in pavement performance modeling is a critical issue in deriving performance-related pay adjustments. Probabilistic results show that the Bayesian approach with Markov chain Monte Carlo (MCMC) methods can capture unobserved variations in pavement condition data and relate the quality measure to the expected pavement life with satisfactory goodness of fit. The probabilistic modeling results reflect the need to consider the level of reliability in decision making of pay adjustments.

The pavement overlay performance after minor and major rehabilitation was evaluated considering the effect of pre-overlay condition. Through deterministic LCCA, optimal rehabilitation strategy can be recommended based on pre-overlay condition. Probability index, a risk related factor was proposed based on probabilistic LCCA and demonstrated its merit compared to the result from deterministic analysis. It can quantitatively show the risk of choosing inappropriate rehabilitation treatment under different scenarios for decision maker. The methodology can be implemented into PMS and reduce the failure risk of roadway network.

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Chapter 1: Introduction

1.1 Background

Highway stakeholders are interested in constructing highway pavements with high quality and maintain satisfactory pavement performance as the use of highway pavement is closely related to economy, environment, and public health. Accurate and reliable prediction of pavement performance is critical for economic investments during pavement construction, maintenance and rehabilitation processes.

The deterioration process of pavement performance is dynamic, sophisticated, and stochastic. It can be largely affected by a variety of inter-related factors such as traffic, climate, pavement structure, as well as some unobserved factors. Due to the complex problem, numerous studies have been conducted to analyze pavement performance using different types of statistical models.

One of the important applications of performance model is to develop performance-related specification (PRS) for pavement construction. Currently, the majority of pay adjustment procedures for pavement construction used by state agencies are based on engineering judgement and experience, which is based on the measurements of quality characteristics after the construction. The need to establish quality acceptance specifications that are related to pavement performance has motivated the development of performance-related specifications. PRS focuses more on long-term product performance instead of end results after construction. It heavily relies on performance models for determining the effects of material and construction variability on pavement performance. These effects should be translated into future pavement cost caused by rehabilitation and maintenance. Therefore, one key feature of PRS is using life-cycle cost analysis (LCCA) to relate quality characteristics, pavement performance, and pay adjustment. It requires reliable performance prediction models and maintenance cost models to calculate the difference between the life-cycle-cost value of the as-constructed pavement and that of the as-designed pavement.

1.2 Problem Statement

Deterministic pavement performance models have been extensively used in predicting pavement performance and aiding highway construction and rehabilitation strategy for state DOTs. When dealing with the aggregated impacts of various factors, they tend to rely on a single mean value to interpret the performance in certain period. A lot of modeling techniques have been used to improve the accuracy of deterministic model such as cluster-wise regression (Zhang and Durango-Cohen, 2014), artificial neural network (Attoh-Okine, 1999), finite element structural analysis (Saleh et al., 2000). Although the results are satisfactory for most of time, the inherent uncertainty and variability in the pavement deterioration process cannot be captured in the deterministic models. For instance, it is common to find out that the pavement segments with the similar structure, truck traffic, and environmental condition show large variations of pavement performance.

The variation may exist because of the effects of unobserved factors on pavement performance. In this case, the analysis result from the deterministic model becomes less convincing and reliable. The information regarding the uncertainty of pavement performance is vital to the decision-makers, especially when they need to identify the risks before making a decision. Thus, a probabilistic model is necessary in revealing the variation embedded in the performance development trend.

Likewise, in PRS, the difference between the life-cycle-cost value of the as-constructed pavement and that of the as-designed pavement can become complex due to the uncertain characteristics of maintenance and rehabilitation schedules used by highway agencies, and also due to possible correlation and interaction among the various quality characteristics. As the deterministic performance model may not fully account for the complexity, the introduction of probabilistic performance model into LCCA can help interpret the inherent complexity in performance modeling and establish more reliable PRS.

1.3 Objective and Methodology

The main goal of the dissertation is to analyze pavement overlay performance and develop performance-related pay adjustment for flexible pavements using deterministic and probabilistic modeling approaches. The objectives can be categorized into three parts with different focuses:

1. To evaluate the effect of pre-overlay condition on flexible pavement performance after minor rehabilitation and major rehabilitation for selection of

rehabilitation strategy.

2. To develop statistical models that can relate flexible pavement performance to the in-place air void after construction and develop performance-related pay adjustment.

3. To quantify the effect of initial IRI on flexible pavement performance deterioration and develop performance-related pay adjustment.

In order to achieve the goals, different datasets pertaining to pavement performance, traffic, construction quality information that covers a number of overlay sections in NJ were collected from the New Jersey Department of Transportation (NJDOT). Regression analyses were conducted to establish the correlation between different quality characteristics and pavement performance. The effectiveness of minor rehabilitation and major rehabilitation on pavement performance was analyzed considering the effect of pre-overlay condition. Life-cycle cost analysis was subsequently conducted to derive the performance-related pay adjustment. Various statistical tests, such as Mann–Whitney U test, Anderson-Darling test, were implemented to validate the significance of results. In an effort to conduct probabilistic analysis in modeling pavement performance deterioration, Monte Carlo simulation and Bayesian approach with Markov Chain Monte Carlo (MCMC) methods were used to quantify the uncertainty impact of various factors on pavement performance.

1.3 Organization of Dissertation

The dissertation is organized as follows. The background and objectives of the study are introduced in Chapter 1. The literature review regarding probabilistic models for pavement performance, pavement overlay performance analysis, and performance-related specifications are included in Chapter 2. Chapter 3 describes the analysis of pavement performance after minor and major rehabilitation. Chapter 4 contains the development of performance-related pay adjustment for in-place air voids. A new approach to determine the performance-related pay adjustment of IRI is proposed in Chapter 5. General conclusions and recommendations are presented in Chapter 6.

Chapter 2: Literature Review

2.1 Review of Probabilistic Models for Pavement Performance

A variety of probabilistic models have been developed and implemented in pavement related fields in trying to capture the uncertainty occurred in the dataset. These probabilistic models include Monte Carlo simulation, survival analysis, logistic regression, Markov Chain, and Bayesian analysis. The chapter is aiming to introduce the basic methodology and applications of the methods mentioned above, and compare the similarity and dissimilarity among the methods in order to select a suitable method to for pavement performance modeling.

2.1.1 Monte Carlo simulation

Monte Carlo (MC) simulation is one of the most popular sampling techniques used in engineering field. Generally, this approach first uses probability distribution functions (PDFs) to describe the observed variations of explanatory variables. Then, it randomly selects one value from the distribution and uses it for further deterministic computation to calculate the target response variable. The procedure iterates thousands of time depending on the desired reliability. Ultimately, the distribution of response variable can be generated. In principle, they are very helpful to solve problems that have probabilistic interpretations, especially the one that is difficult or impossible to use other mathematical methods to solve.

The popularity of Monte Carlo simulation comes from its simplicity and reliability. As a result, it has been extensively used in pavement related field. The method has been used in the determination of reliability of pavement structure since 1980s. A computer program, Reliability Analysis and Performance of Pavements I (RAPP - I) was developed which implemented Monte Carlo simulation techniques into different pavement design equations in which all of the design variables were assumed to be probabilistic and normally distributed. The expected life was calculated based on present serviceability index (PSI) and found to be a convenient measure for comparing the performance of various pavement design features (Alsherri and George, 1988; George et al., 1988).

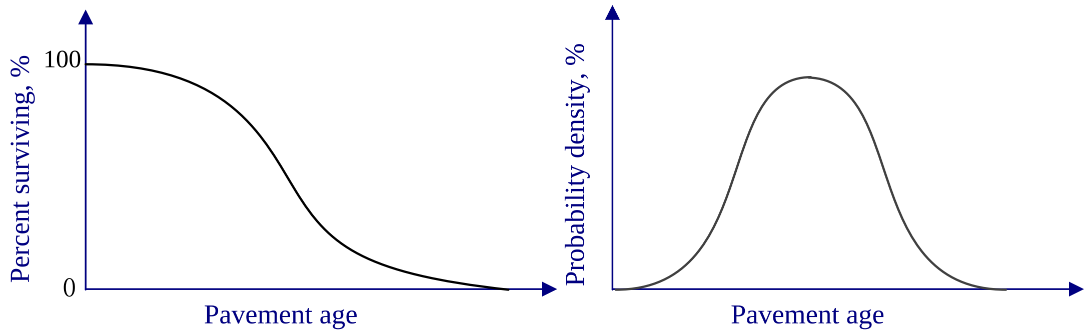
Prozzi et al. (2005) used mechanistic-empirical models and Monte Carlo simulation to evaluate the effects of environment, structural strength, and traffic volume on pavement reliability and performance. Yang and Wu (2013) conducted a regional sensitivity analysis (RSA) on the new mechanistic-empirical pavement design and analysis (MEPDG) design software (AASHTOWare Pavement ME Design) using the Monte Carlo filtering (MCF) method. The method is proved to be advantageous in identifying input parameters that are most influential to the designed pavement thickness using MEPDG.

Coleri and Harvey (2011) used Monte Carlo simulation to consider the variability in laboratory test results such as layer thickness, stiffness, and measured *in -situ* performance. The simulation makes it possible to predict rut depths for different reliability levels without performing computationally intensive calculations by the design software.

2.1.2 Survival analysis

Survival curves are efficient in presenting data regarding pavement life expectancy. In general, it can be regarded as a graph of probability versus time. For instance, as shown in Figure 1(b), when the probability density function (PDF) of pavement life is available, it can be transformed into the curve shown in Figure 1(a). The curve in Figure 1(a) can be quantified by Equation 1.

In practice, the PDF in Figure 1(b) is not assumed to be normally distributed. Many studies considered a more general distribution type to increase the accuracy of model, such as Weibull distribution (Li et al. 2002).



(a) (b)

Figure 1. (a) Pavement survival curve (b) Probability density function for pavement survival

$$S(t) = \Pr\{T \geq t\} = 1 - F(t) = \int_t^{\infty} f(x)dx \qquad (1)$$

Where,

S(t) = probability that the pavement age is larger than duration t;

T = pavement age;

F(t) = cumulative distribution of T;

f(x) = Probability density function for pavement age.

In survival analysis, Kaplan-Meier estimate is the basic way of computing the survival over time and dealing with censored data. It involves computing of probabilities of occurrence of event at a certain point of time and multiplying these successive probabilities by any earlier computed probabilities to get the final estimate (Madanat et al., 2005).

In practice, survival analysis can provide models for predicting the probability of failure for various designs of new pavements and asphalt concrete overlay. Gharaibeh and Darter (2003) conducted survival analysis for asphalt and concrete pavements in Illinois. The result shows that the pavements and overlays having approximately the same design and built under the same specifications, but located throughout the state of Illinois, show large variations.

Survival analysis can also evaluate the influence of certain factors on the probability of structure failure. Chen et al. (2014) employed parametric survival models to analyze the influence factors on the reflective cracking for different composite pavement rehabilitation methods. They found that traffic level was not a significant factor for reflective cracking development, while overlay and removal thickness could significantly delay the propagation of reflective cracking.

As a reliable survival analysis demands large amount of dataset, The Long-Term Pavement Performance (LTPP) database becomes one major data source for survival analysis. The LTPP program was established in order to collect pavement performance data as one of the major research areas of the Strategic Highway Research Program (SHRP). Over 2500 test sections located on in-service highways throughout North America are monitored. The collected data cover traffic, climate, distresses, and pavement structures.

As it was found that a large number of LTPP test sections exhibited a sudden burst of fatigue cracking after a few years of service, Wang et al. (2005) conducted survival analysis to investigate the relationship between fatigue failure time and various influencing factors. They used accelerated failure time models to show the quantitative relationship between fatigue failure time and asphalt concrete layer thickness, Portland cement concrete (PCC) base layer thickness, average traffic level, intensity of precipitation, and freeze-thaw cycles. The error distribution of the accelerated failure time model was found to be best represented by the generalized gamma distribution.

Gao et al. (2011) applied the frailty model in survival model to analyze the fatigue cracking data from LTPP database by adding a random term to the hazard function. The model is capable of addressing the effect of unobserved heterogeneity among different pavement sections.

Dong and Huang (2012a) used survival model with Weibull hazard function to evaluate the influence of different factors on the crack initiation of resurfaced asphalt pavement. Four types of cracks were included: fatigue crack, longitudinal crack in the wheel path, non–wheel path longitudinal crack, and transverse crack. Analyzed factors include overlay thickness, total pavement thickness, pretreatment pavement serviceability, traffic volume, freeze index, reclaimed asphalt pavement (RAP) content, and milling thickness. Conclusions from survival analyses showed that traffic level was a significant factor for all four types of cracks. High traffic level accelerated the initiation of cracking. Total pavement thickness only retarded the initiation of wheel path longitudinal cracking.

2.1.3 Logistic regression

Logistic model is widely used when the dependent variable is categorical. For instance, it can estimate the probability of an occurrence will happen or not happen. As a variant of multiple regressions, the influential factors that affect the probability can also be quantified in the logistic regression model.

The major characteristic of logistical regression function is that it has an S-shape curve. For instance, the function used by Henning et al. (2009) to estimate the probability of predicting defect (crack) initiation is illustrated in Equation 2.

$$P = \frac{1}{1+e^{a_1x_1+a_2x_2+x_1+a_3x_3+a_4x_4+b}} \qquad (2)$$

Where,

P= probability of a pavement section being crack;

a_1,a_2,a_3,a_4=model parameters;

x_1,x_2,x_3,x_4= pavement related factors such as traffic;

b= occurrence of initial crack (b=1), no occurrence of initial crack (b=0).

The major application of logistic regression in pavement performance is to predict the possibility of the initiation of cracking or whether the distress will progress to unacceptable level. Wang (2013) developed an ordinal logistic regression models based on 328 asphalt concrete (AC) overlay sections from the LTPP program to predict the probability of severity levels for alligator cracking. It was found that the alligator cracking is significantly affected by alligator cracking of the existing pavement, thickness of overlay, thickness of the existing AC, age of pavements after resurfacing, truck volume, freeze-thaw cycles, and the amount of precipitation per wet day. In addition, it was found that the use of recycled asphalt pavement in the amount specified in the SPS 3 experiment and pre-overlay treatment significantly affected overlay cracking.

Logistic model can be applicable in data mining process. Kaur and Pulugurta (2008) compared logistic regression methods and fuzzy decision tree for pavement treatment prediction. Yoo and Kim (2015) developed a crack recognition algorithm from non-routed pavement images using artificial neural network and binary logistic regression. The intelligent algorithm can distinguish crack and noise by eliminating the noise, to enable the ACSTM (Automated Crack Sealer with Telescopic Manipulator) equipment in easy detection of the non-routed cracks.

2.1.4 Markov Chain

As a popular stochastic model, Markov Chain has been used in pavement performance evaluation since 1980 (Golabi et al., 1982). The approach is built based on the premise that the future state of pavement is only dependent on current state and it is irrelevant to the past condition states. In other words, in Markov Chain, the probability of changing from one condition state to another condition state is independent of time.

The probability of changing from one state to another state is called Probability Transition Matrix (PTM). In pavement engineering, Markov Chain can categorize the pavement performance indicator into different states and determine the PTM by defining the probability of pavement condition falling into each condition state, as define in Equation 3 (Wang et al., 1994)

$$p_{ij} = \frac{N_{ij}}{N_i} \qquad (3)$$

Where,

p_{ij} is the transition probability from state i to state j;

N_{ij} is the total number of pavement sections whose condition states change from state i to state j;

N_i is the total number of pavement sections whose initial condition state.

PTM can be determined based on the expert's experience and the results from survival curves, which suggests that it requires less data than other statistical methods. The methods are suitable for pavement prediction at both network and project levels (Anderson, 1989; Tam and Bushby, 1995).

In 1987, Butt et al. established pavement performance prediction model based on the Pavement Condition Index (PCI) in order to predict pavement age. In the study, PCI ranging from 0 to 100 has been divided into ten equal condition states. A combination of homogeneous and nonhomogeneous Markov chains has been used in the development of the model. The life span of the pavement is divided into zones, with each zone representing a period of 6 years. The transition matrix of each zone is determined using nonlinear programming. If the state of any given pavement section is known, its future condition can be predicted efficiently from the corresponding transition. The model is useful in the decision-making procedure for determining optimal maintenance and repair strategies.

Camahan et al. (1987) developed a cumulative damage model based upon a Markov process to model pavement deterioration. Their objective was to ensure that pavements met certain performance criteria while minimizing the expected maintenance cost. Sensitivity studies were also performed to understand the variation in the expected cost in the study.

Wang et al. (1994) used Chapman−Kolmogorov method and pavement performance data from Arizona Department of Transportation (ADOT) to modify the generated TPMs to improve prediction of pavement performance. The newly generated TPMs used in Markovian prediction satisfactorily modeled actual pavement behavior.

Yang et al. (2006) compared the ability of recurrent Markov chains to model multiple-year prediction of crack performance using the Florida Department of Transportation’s pavement condition data. They found that the recurrent Markov chain tended to produce more consistent forecasts as compared to the neural network, which exhibited a tendency toward over predicting crack deterioration.

Kobayashi et al. (2010) estimated the Markov transition probability to forecast the deterioration process of road sections by using the empirical surface data set of the national highway in Korea. The deterioration states of the road sections were categorized into several ranks and the deterioration processes were characterized by hazard models. The Markov transition probabilities between the deterioration states, which were defined by the non-uniform or irregular intervals between the inspection points in time, were described by the exponential hazard models.

Lethanh and Adey (2012) used an exponential hidden Markov model to simulate a hidden pavement deterioration process when incomplete inspection data were available. It was assumed that the evolution of the physical condition, which was the hidden process, and the evolution of pavement distress indicators, could be adequately described using discrete condition states and modeled as a Markov processes.

There is a variation of Markov Chain called Semi-Markov Chain. It modifies the original Markov approach to make it more applicable to the practical problem. Basically, the PTM in the Semi-Markov approach is no longer a stationary matrix. It can be adjusted over time based on the data from the observation. Thomas and Sobanjo (2013) compared Markov Chain and Semi-Markov Chain models of crack deterioration in pavements. The result showed that in some cases the semi-Markov model appeared to be superior to the Markov chain model in modeling the actual deterioration patterns of flexible pavements.

2.1.5 Bayesian analysis

Bayesian inference is an important technique in mathematical statistics to capture uncertainty in performance modeling. The major difference between Bayesian inference and the classical approaches such as regression analyses lies in the model parameter. In the classical approaches, the model parameters determined based on the data are deterministic values, while Bayesian inference considers the model parameters as random variables with certain distributions.

The probabilistic expression of Bayesian approach can be illustrated through

Equation 4. It is capable of combining prior knowledge with observed data to produce a new adjusted distribution.

$$P(\theta/data) = \frac{P(data/\theta)*P(\theta)}{\int P(data/\theta)*P(\theta)*d\theta} \qquad (4)$$

Where,

P(θ) is prior knowledge of the model parameters (θ);

P(data/θ) is distribution of the observed data given the model parameters;

P(θ/ data) is posterior probability of model parameters based on data.

Bayesian theorem is a good candidate to interpret observed data with poor quality and it has been applied for development of pavement deterioration models. It initially uses prior models based on the observed data and then posterior models based on the prior model, the observed data, and expert experience (Winkler 2003).

Bayesian statistical framework is fundamental and has numerous applications in infrastructure evaluation (Box and Tiao, 1992; Katafygiotis et al., 1998; Vanik et al., 2000). Many powerful statistical tools and methodologies were built based on the Bayesian framework.

Golroo and Tighe (2012) used Bayesian statistical technique to develop performance model for pervious concrete pavement. The service life of pavement was estimated to be approximately nine years using the developed performance model. They concluded that, in general, the expert knowledge used in Bayesian approach led to more conservative results rather than experimental data.

Tabatabaee and Ziyadi (2013) proposed using Bayesian approach for periodically updating Markovian transition probabilities as new inspection data became available based on the dataset of asphalt concrete pavement observations from the Minnesota

Department of Transportation test facility.

Luo et al. (2016) implemented mechanistic–empirical models and the Bayesian framework to update design parameters (layer modulus and thickness) of flexible pavement based on different fatigue and rutting failure conditions. The developed spreadsheet-based approach for Bayesian updating is easy to use and can be adopted in the decision-making process of pavement maintenance and rehabilitation.

2.1.6 Markov Chain Monte Carlo

Another important application of Bayesian theorem is Markov Chain Monte Carlo (MCMC). The MCMC method combines Markov Chains, Monte Carlo simulation, and Bayesian analysis, which has been used in deterioration modelling of infrastructure (Hong and Prozzi, 2006; Onar et al., 2007; Kobayashi et al., 2012; Mills et al., 2012; Mills and Attoh-Okine, 2014; Dilip and Sivakumar, 2012; Karunarathna, 2013; Han et al., 2014; Kobayashi et al., 2014). In general, the method provides an effective and flexible alternative for model estimation and updating.

Basically, MCMC method can generate the probabilistic distribution of the parameters to reflect performance heterogeneity and provide comprehensive statistics of the individual parameters (Liu and Gharaibeh, 2014; Liu and Gharaibeh, 2015*)*. The basis of MCMC method usually comprises of two components: initial values of predicted parameters p_0 and transition kernel K. The prior distribution of predicted parameters is defined as $\pi(x)$ and determined by users based on their engineering knowledge for the parameters. The transition kernel is a transition probability matrix generated based on the principle of Markov chains and MHA (Metropolis-Hasting Algorithm). The MHA generates Markov chains and entails simulating $x^{(1)},\ldots, x^{(n)}$ after n iterations from the candidate proposal distribution. Each new point $x^{(j)}$, is essentially determined by the point generated one iteration earlier through transition matrix. The major functions used in the MHA during MCMC process are shown in Equation 5 and Equation 6. After n iterative processes that are based on the construction of a Markov chain, the ultimate model with stationary and posterior distribution p_0K^n for the model parameters can be generated.

$$\mathrm{K}(\mathrm{i},\mathrm{j}) = \mathrm{q}\left(x^{(i)}, x^{(j)}\right) * \alpha(x^{(i)}, x^{(j)}) \tag{5}$$

$$\alpha\left(x^{(i)}, x^{(j)}\right) = \min(1, \frac{q(x^{(i)},x^{(j)})\pi(x^{(j)})}{q(x^{(j)},x^{(i)})\pi(x^{(i)})}) \tag{6}$$

Where,

$\alpha\left(\mathrm{x}^{(\mathrm{i})}, \mathrm{x}^{(\mathrm{j})}\right)$ is defined as acceptance ratio to adjust the new model;

$\mathrm{q}\left(\mathrm{x}^{(\mathrm{i})}, \mathrm{x}^{(\mathrm{j})}\right)$ represents the proposal function, which is calculated based upon the difference between predicted data and measured data.

2.1.7 Comparison among different probabilistic models

In general, every probabilistic model has its advantage and limitation. The effective way to utilize the models depends on the available dataset and research objective. The above mentioned models were compared in terms of complexity of algorithm, data requirement, and application flexibility, as summarized in Table 1.

The complexity of algorithm represents the background knowledge needed to understand and use the model. Typically, the method that has relatively simple algorithm will be easier to implement into engineering fields. Data requirement suggests the amount of data and information needed to carry out the analysis. Application flexibility is used to indicate whether the method can be applied to analyze various types of data.

Monte Carlo simulation is extensively used in sampling process. Compared to other sampling techniques such as Latin Hypercube method or Rosenblueth point estimate method, Monte Carlo simulation outperforms them and gains major popularity in most of fields because of its high reliability. The reliability is achieved through large amount of data and more computational time. It can be easily executed in spreadsheets or other statistical tools. However, its main application focuses on the prediction of the distribution of response variable, which means that it is not capable of analyzing the characteristic pertaining to stochastic process.

Survival analysis is essentially a cumulative distribution curve. Its major application is to deal with time related data and can achieve very effective results.

Logistic regression undoubtedly dominates analysis related to binary data. However, when dealing with continuous response variables, it is not a good candidate.

Markov Chain is a power tool in the interpretation of stochastic process. The method can achieve satisfactory outcome without requiring large amount of data. Similar to logistic regression, it is specialized in handling discrete variables instead of continuous variables.

MCMC algorithm involves the principle from Monte Carlo method, Markov Chain, Bayesian theorem, which makes it more complex compared to other models. The implementation of MCMC algorithm heavily relies on professional software.

However, it has a wide range of applications. For example, it can be used to develop regression models and interpret the models from a probabilistic point of view.

Table 1. Comparison among different probabilistic models

Method	Complexity of algorithm	Data requirement	Application flexibility
Monte Carlo simulation	Low	High	High
Survival analysis	Medium	High	Low
Logistic regression	Medium	Medium	Low
Markov Chain	Medium	Low	Low
MCMC	High	Medium	High

The five methods all have their strong points in dealing with specific dataset at different areas. For instance, both survival analysis and logistic regression have irreplaceable usage in pharmaceutical research, as large amount of data generated in pharmaceutical area can be converted to binary variable and life.

The methods mentioned above can also be incorporated together to interpret more complex phenomenon. Yang et al. (2005) used a recurrent or dynamic Markov chain for modeling pavement cracking performance with time in which the transition probabilities were determined based on a logistic model in order to account for nonlinear surface layer properties and randomness in the cracking mechanism. The result shows that it outperforms the static Markov chain in terms of the forecasting accuracy and is a computationally efficient methodology.

Based on the objective of the study, which is analyzing the deterioration trend of pavement performance indicators and developing a performance-related specification, MCMC becomes a preferable candidate.

2.2 Review of Studies on Pavement Overlay Performance

The understanding of overlay performance is critical for highway agencies as timely rehabilitation of pavement systems and overlays built with longer service lives can minimize the limited agency's budget and maximize overall benefits. Pavement sections after overlay applications usually have different structure capacity compared to new pavement sections. Depending on existing pavement conditions and various overlay treatments, the performance of pavement overlay can vary significantly. It is important to evaluate pavement overlay performance models and understand the factors affecting the long-term performance of overlays.

A number of previous studies have investigated pavement overlay performance after different rehabilitation alternatives. Past efforts can be broadly divided into four areas as summarize below.

2.2.1 Studies on overlay performance using mechanistic-empirical approach

Abaza (2005) developed a mechanistic overlay design method that related pavement surface condition to in-service time or the accumulated 80-kN equivalent single axle load (ESAL) applications with a distinct performance curve constructed for each pavement structure. The model attempts to compensate an existing pavement structure for the loss in performance that it has endured over a specified time and determine equivalent overlay thicknesses.

Zhou et al. (2009) developed a comprehensive overlay thickness design and analysis software package for TxDOT. It incorporated the Paris law-based reflection cracking model to predict crack propagation caused by both traffic loading and thermal effects. A total of 34 regression equations for stress intensity factors (SIF) were developed based on more than 1.6 million finite element computations during analysis. The proposed reflective cracking model was preliminarily calibrated using three HMA overlay field case studies, and the calibrated model was verified using the reflective cracking data of six asphalt overlay sections collected from California's heavy vehicle simulator (HVS) test sites. A sensitivity analysis was conducted on the asphalt overlay thickness design using the software and the results indicated that not all of the input parameters had significant influence on the asphalt overlay performance in terms of reflective cracking and rutting. The nine most important input parameters identified for asphalt overlay design were found to be: traffic loading level, climate, asphalt overlay thickness, overlay mix type, asphalt binder type, load transfer efficiency (for existing JPCP pavements), crack severity level (for existing AC pavements), existing base layer modulus, and existing AC layer thickness (for existing AC pavements). It was found that asphalt overlay life in terms of reflective cracking was not linearly proportional to overlay thickness. A 4-inch asphalt overlay can have more than twice the life of a 3-inch overlay. The results suggested that it was beneficial to repair the joints/cracks before placing an asphalt overlay. It was also suggested that the bad joints/cracks where the load transfer efficiency was below 70 percent must be treated in order to have a longer overlay life.

Jannat (2012) developed a pavement database for local calibration using the newest AASHTO design software (Pavement ME Design). Clustering analysis and calibration-validation analysis were carried out for the IRI and total rutting depth. The result suggests that the IRI model can be best clustered based on the geographical zone.

Wang and Nie (2014) evaluated the effects of existing pavement condition and overlay material property on AC overlay design and performance using Pavement ME Design. The factors considered in the analysis include the modulus of exiting layers, the rut depth of existing layer, the interface condition between AC overlay and existing pavement, and the properties of AC overlay (performance grade of asphalt binder and Poisson's ratio of asphalt mixture). In addition to overlay thickness design, pavement performance analysis was used to evaluate the influence of existing pavement condition and overlay material properties on individual distresses. Several findings were concluded from this study. First, the sensitivity of overlay design thickness to the condition of the existing AC layer was proved to be dependent on the existing AC layer thickness and design traffic. Second, the existing condition of base layer and subgrade showed no significant influence regarding the overlay performance and thickness design. Third, the performance analysis results showed that the modulus of existing AC layer and interface bonding condition have more significant effects on fatigue cracking than on rutting of pavement overlay.

2.2.2 Studies on factors affecting overlay performance

A number of pavement related variables were intentionally recorded for the overlay sections in LTPP database. General results from the studies show that important factors such as traffic, temperature, thickness, pre-overlay condition, and overlay thickness have unneglectable influence in overlay performance (Perera and Kohn, 2001; Hall et al., 2003; Von Quintus et al., 2006; Kargah-Ostadi et al., 2010; Dong and Huang, 2012b).

Kandil (2001) investigated the effect of AC overlay thickness and mix type (virgin vs. recycled) on long-term performance by using the data available in C-LTPP, and evaluated the results using statistical models for Ontario test sections available in C-LTPP. The results suggested that overlay thickness and mix type might have limited effects on the expected service life under specific conditions. Therefore, pavement engineers must exercise a high degree of caution to select the most cost-effective overlay rehabilitation technique.

Gharaibeh and Darter (2003) conducted survival analysis to analyze the performance of various designs of AC overlays and original pavements in Illinois for use in pavement management. The results based on probabilistic analysis illustrated a wide variation in pavement life and traffic carried. Key findings showed the impact of pavement type (HMAC, JRCP, or CRCP), slab thickness, geographic location (north or south), durability cracking (D-cracking), and AC overlay thickness (coupled with pre-overlay condition) on pavement longevity and load-carrying capacity.

Fini and Mellat-Parast (2012) investigated the impact of overlay type (asphalt and concrete) on the progression of IRI. The data were collected from GPS6 and GPS7 sections in nine states in the LTPP database. Multivariate regression analysis was used to compare the effect of critical variables (age, temperature, freezing index, and surface thickness) on IRI. The results showed that there is a significant difference between the two overlay types in terms of the effect of key variables on IRI. Concrete overlay sections demonstrated a significantly better IRI performance than asphalt overlay sections in terms of age, temperature, and surface thickness. Asphalt overlay sections had a significantly better performance in terms of freezing index. The results suggested that if age, temperature, and surface thickness were considered as primary factors, concrete overlay provided a better IRI; but if freezing index was considered as a primary factor, asphalt overlay was a better candidate..

Madanat et al. (2005) used survival curves to develop an Empirical-Mechanistic performance models using data from the Washington State Department of Transportation Pavement Management System (PMS) databases. The study aimed at predicting the initiation of overlay cracking and progression of roughness on AC overlays, AC pavements, and PCC pavements. Through the study, several explanatory variables were found to be the most relevant predictors for the number of ESALs-to-cracking initiation of overlays on AC pavements. For instance, overlay thickness, type of AC mix used for the overlay, the thickness of the underlying AC layers prior to application of the overlay, the existing longitudinal and alligator cracking prior to application of the overlay, the base layer thickness and type (untreated, granular material, PC-treated, or AC-treated), the possible maximum temperature during the hottest month and the minimum temperature during the coldest month, the number of freeze-thaw cycles, and the precipitation.

Khattak et al. (2014) developed an IRI models for overlay treatment of composite and flexible pavements based on Louisiana pavement condition. Various factors affecting the IRI of overlay treatment were identified. Climatic indices pertaining to Louisiana were developed which exhibited strong statistical significance along with the other variables as used in the IRI models. The developed IRI models provided good agreement between the measured and predicted IRI values with the majority of data within 5% of prediction error.

Anastasopoulos and Mannering (2015) developed random parameters hazard-based duration models to analyze the performance of pavement overlay and replacement by using data from Indiana. The service life of the pavement was determined and random parameter duration models were estimated to identify influential factors affecting pavement service life. The model-estimation results provided some new insights into the interrelationships among pavement rehabilitation, pavement condition, pavement service life, road functional class, traffic loads and trucks, weather, and soil condition.

2.2.3 Studies on different overlay treatments regarding performance

Anastasopoulos et al. (2009) considered the performance of various combinations of pavement rehabilitation treatments (two-course HMA overlay with or without surface milling, concrete pavement restoration, three-course HMA overlay with or without surface milling, three-course HMA overlay with crack and seat of PCC pavement and 3-R and 4-R overlay or replacement treatments) in six road functional classes. The study estimated the performance and service life of the pavement, corresponding to each treatment and road functional class mainly through survival curves. The results concluded that three-course HMA overlays with or without surface milling treatments have a forecasted annual average deterioration in IRI of around 5 inch/mile. Three-course HMA overlays with crack and seat of PCC pavement treatments were found to have a predicted average annual deterioration in IRI of approximately 4 inch/mile. Pavement projects involved 3-R and 4-R overlay or replacement treatments were found to have a predicted average deterioration in IRI in the range of 4 to 5 inch/mile. Concrete pavement restoration treatments were found to have a predicted average annual deterioration in IRI of 7 inch/mile.

Li and Wen (2014) evaluated the effects of pre-overlay repair methods and pre-overlay pavement conditions on the performance of AC overlays. The data were collected from 449 AC overlays on existing pavements. The statistical analysis results indicated that for asphalt concrete pavements, milling is more effective in reducing fatigue cracking, longitudinal cracking, and raveling in AC overlay; for composite pavements, AC base patching is more effective in reducing longitudinal cracking, and doweled concrete base patching is more effective in reducing surface raveling in AC overlay; for joint plain concrete pavements, un-doweled concrete base patching is more effective in reducing transverse and longitudinal cracking; and for continuously reinforced concrete pavements, AC base patching is more effective in alleviating transverse and longitudinal cracking.

2.2.4 Studies on using LCCA for pavement maintenance analysis

The previous efforts on using LCCA for pavement maintenance analysis can be further subdivided into three categories. The first category focuses on the use of deterministic LCCA, as the dominant portion of highway agencies prefer its simplicity and convenience.

Chan et al. (2008) evaluated the LCCA procedure used by MDOT and identified the maintenance schedules with lower initial construction cost. Lee et al. (2011a) demonstrated a new value analysis (VA) procedure used in Caltrans for rehabilitation projects. The software Construction Analysis for Pavement Rehabilitation Strategies (CA4PRS) and performance attributes matrix (PAM) approach was used to determine the construction schedule and estimate agency costs and user costs during various construction activities. Lee et al. (2011b) conducted LCCA approach for a real rehabilitation project following the Caltrans procedure. Software CA4PRS and Real-Cost were used to quantitatively estimate construction schedule, work zone user cost, and agency cost for initial and future maintenance and rehabilitation activities.

Choi et al. (2015) created a future maintenance costs (FMC) predictive model for low-volume highway rehabilitation projects based on large quantity of real-world data. A series of sensitivity analyses were carried out to evaluate the impact of critical performance-driven factors on FMC.

Probabilistic LCCA falls into the second category and it is used to better incorporate the variability occurred during the whole pavement life cycle. Tighe (2001) used probabilistic LCCA to examine the data from Canadian long term pavement performance (LTPP) program and validated the distribution type of various input variables. Salem et al. (2003) used software “@RISK” along with field data to predict the probability distributions of the associated life-cycle costs of rehabilitation alternatives.

Whiteley et al. (2006) examined the effect of variability associated with overlay thickness, prior surface cracking, discount rate, and ESALs on life cycle cost distribution. In-service performance LCC and pay factors were correlated based on the analysis. Swei et al. (2013) quantified the uncertainty of unit price of bid items, maintenance timing, and material prices in LCCA based on empirical data.

Park et al. (2015) presents a decision framework to investigate the significant impact of flexural strength, air content, thickness, and smoothness on Portland cement concrete pavement (PCCP). Probability and user confidence were incorporated to address the risk of accepting failed materials because of inferior pavement performance. Swei et al. (2015) implemented a probabilistic LCCA model that consider the variability of maintenance schedules, initial and future material and construction costs maintenance schedules, and material quantity.

The third category focuses on optimization of rehabilitation strategy based on LCCA. Optimal application of pavement maintenance program is critical for every state agency to allocate the limited budget. A variety of studies have conducted to evaluate the effectiveness of pavement rehabilitation. However, due to the data availability and variability of the attributes, the optimal timing for different type of maintenance treatments remains ambiguous.

Abaza (2002) developed an optimal life-cycle cost analysis model for flexible pavements by introducing the ratio of life-cycle cost to life-cycle performance. Peshkin et al. (2004) considered weighting factors combining treatments, pavement conditions, costs, and expected benefits and developed an analysis tool called OPTime to calculate optimal timing of maintenance treatments based on the benefit-cost ratio of agency cost, work zone-related user delay costs, and etc.

Wei and Tighe (2004) computed the optimal timing of application for each treatment based on cost-effectiveness analysis and applied it for a decision tree. Li and Madanu (2009) established a stochastic optimization model to assess impacts of risk and uncertainty on estimated project benefits and network-level project selection. Significant differences were revealed with and without uncertainty considerations through the study.

Haider and Dwaikat (2010) developed mathematical models to estimate the optimum timing on the basis of different treatment effectiveness evaluation criteria and the area-based effectiveness was used in the exemplary analysis.

Zhang et al. (2010) proposed a life-cycle optimization (LCO) model to determine an optimal preservation strategy for a pavement overlay system and to minimize the total life-cycle energy consumption, greenhouse gas (GHG) emissions, and costs within an analysis period. They used dynamic programming optimization techniques to integrate dynamic life-cycle assessment and life-cycle cost analysis models with an autoregressive pavement overlay deterioration model.

Mandapaka et al. (2012) evaluated the optimal Maintenance and Rehabilitation

(M&R) strategy for flexible pavement by combining LCCA and California Mechanistic-Empirical design procedures (CalME). Wang et al. (2013) analyzed the optimum timing of treatment application using benefit-cost analysis and found that the relationship between pavement life extension and the overall performance index at the time of treatment could be modeled using second-order polynomial functions. Zhang et al. (2013) developed a new network-level pavement asset management system (PAMS) that integrates life-cycle analysis, optimization, and geographic information system (GIS). The proposed system can minimize life-cycle energy consumption, greenhouse gas (GHG) emissions under budget constraints.

2.3 Performance-Related Specifications

2.3.1 Quality Assurance Specifications

In order to provide the drivers with smooth and long lasting pavement, the state highway agency uses specifications as a way to motivate pavement contractors to resolve the technical problems associated with the construction and construct the pavement with high quality.

Currently, the majority of state agencies adopt Quality Assurance Specifications and in the meanwhile aiming to develop their own Performance-Related Specification. Quality Assurance Specifications began in 1960's and it is a popular specification nowadays. It was derived from U.S. Department of Defense specifications. As statistically-based specifications, it includes quality control by contractor and acceptance activities by agency in the production process. The Quality Assurance

Specification is also called QA/QC specification (quality assurance/quality control specification). It combines end-result specifications and methods specifications. In order to produce a pavement product which can pass the specifications stipulated by the highway agency, the contractor keeps implementing the quality control to adjust the production. The highway agency identifies the specific quality characteristics to be evaluated for quality acceptance (sampling, testing, and inspection). Through the result from acceptance by agency, the price adjustments related to quality level of the final product is decided.

Generally, final acceptance uses multiple measurements within an entire lot (random sampling and lot-by-lot testing) rather than individual measurements. Final acceptance of the product is usually based on a statistical sampling of the measured quality level for key quality characteristics. The quality level is typically presented in statistical terms such as the mean and standard deviation, percent within limits, average absolute, etc. The mathematical probability approach increases the precision of the test and reduces both buyer’s risk and seller’s risk.

In the current Quality Assurance Specifications used by most states, for superior quality product, the contractor may receive bonus payment typically 1% to 5% of the bid price; contractor with low quality work will receive 0% to 99% reduced payment or the product may even be rejected by the agency.

2.3.2 Quality characteristic

Quality characteristics are those material characteristics or properties that are measured in the acceptance plan to determine quality. Agencies usually want to relate quality characteristics to long-term pavement performance. These quality characteristics typically include mix properties (such as aggregate gradation, asphalt content, and mix volumetrics), in-place density, thickness, and pavement smoothness (Schmitt, et al., 1998). Table 2 list the most commonly used quality characteristics for quality control and acceptance test (NCHRP synthesis 346). It shows that the quality characteristic most often used for QA is compaction (in-place air void or density) by 44 agencies, followed by the asphalt content by 40 agencies. Thickness, used in pay adjustment in NJ QA specification, is relatively less used by 22 agencies.

Table 2. Most commonly used quality characteristics for QC and QA
(After NCHRP Synthesis 346)

Quality Characteristic	Number of Agencies	
	QC	QA
Asphalt content	40	40
Gradation	43	33
Compaction	28	44
Ride quality	16	39
Voids in total mix	20	26
Voids in mineral aggregate	26	23
Aggregate fractured faces	25	23
Thickness	13	22
Voids filled with asphalt	19	13

A survey conducted by Butts and Ksaibati (2002) also indicates that mat density, asphalt content, air voids, aggregate gradation, and smoothness are commonly used asphalt pavement attributes used in the adjustment of contractor pay. Voids in mineral aggregate (VMA), thickness, theoretical maximum density (TMD), cross-slope, and lab densities are some of the others that are considered by a few of the SHAs.

In recent years, there has been movement in the HMA industry toward defining HMA quality on the basis of the performance of in-place pavement. The outcome of NCHRP Project 9-15 (2001) recommended five in-place quality characteristics to be considered in the performance-related specification: segregation, ride quality, in-place density, longitudinal construction joint density, and in-place permeability. These quality characteristics were selected because of their importance in determining the overall performance of HMA pavements.

There are two principles in choosing quality characteristic: (1) The quality should represent the overall pavement quality; (2) The selected qualities should be independent of each other. Though most of the chosen quality characteristics are believed to be related to performance, the exact relationships are not firmly established. Therefore, the pay adjustments currently used by most states are based on the values of the quality themselves and not on expected performance of the constructed pavement.

In addition, the measurement of the quality characteristics needs to be considered when choosing quality characteristics is. The test methods employed in measuring quality characteristics should be rapid, reliable and relatively inexpensive.

2.3.3 Previous studies on Performance-Related Specifications

After the 1980's, some transportation agencies started to investigate a specification that can correlate construction quality to long-term performance. In fact, Performance-Related Specifications are improved Quality Assurance Specifications that use Life Cycle Cost (LCC) to relate the quality characteristics and pay adjustment. Compared to Quality Assurance Specifications which only measure the instantaneous quality characteristics after the construction, Performance-Related Specifications focus more on long-term product performance. The pay adjustment in Quality Assurance Specifications is usually empirical and relatively simple while it is complicated in Performance-Related Specifications. Performance-Related Specifications may build a model that considers multiple material and construction quality characteristics (such as air void, density), design variables (such as traffic, climate, structural conditions), and pavement performance indicators (such as roughness, distresses) to calculate the LCC and adjust the payment.

Monte Carlo simulation was widely used in life cycle cost analysis. The method enables the researchers to consider the variability of materials and construction (M&C) characteristics to develop rational pay-adjustment procedures (Walls and Smith, 1998; Epps et al., 2002; Choi and Bahia, 2004; Whiteley et al., 2005; Graveen et al., 2009; Keith, 2009; Apuzzo and Nicolosi, 2010; Arizona State University, and Furgo Consultants Inc., 2011; Gedafa et al., 2012; Mensching et al., 2013; Wang et al., 2015).

Anderson et al. (1990) proposed a preliminary framework for PRSs for asphalt concrete pavements. Target material and construction-related variables include thickness, compaction, roughness, asphalt content, gradation and others. The design algorithms are used to determine the predicted life cycle cost (LCC) for the target and as-built pavement. Acceptance plan and payment schedule are then adjusted according to the result. The pay adjustment considers the maintenance, rehabilitation, and user costs. The pay factor (PF) is calculated in Equation 7.

$$PF=100(LBP-C)/LBP \quad (7)$$

Where,

LBP =lot bid price;

$C = (A_c-A_t)\{[(1+i)^{Lc}-1]/[i(1+i)^{Lt}\}$;

A_c = annualized total cost at economic life of as-constructed pavement;

A_t = annualized total cost at economic life of target pavement;

L_c = economic life of as-constructed pavement;

L_t = economic life of target pavement.

Shook et al. (1992) used the AASHTO Guide equations which estimate pavement service life as the number of equivalent single axle loads (ESALs) to failure. Material- and construction-related variables include asphalt content, percent passing the #30 sieve and the #200 sieve, VMA, and air voids. The pay factor methods related to LCC is shown in Equation 8.

$$PF=100[1+C_0 (R^{Ld}-R^{Le})/C_p (1-R^{Lo})] \quad (8)$$

Where,

Cp = percent unit cost of pavement;

Co = percent unit cost of overlay;

Ld = design life of pavement;

Le = expected life of pavement;

Lo = expected life of overlay;

$R = (1 + R_{inf} / 100) / (1 + R_{int} / 100)$;

R_{inf} = annual inflation rate;

R_{int}= annual interest rate.

Solaimanian et al. (1998) developed a prototype PRS based on VESYS. VESYS was the first model developing the prediction algorithms for various types of distress such as fatigue cracking, rutting, roughness and present serviceability index (PSI) (Kenis et al. 1977). Real data from Interstate highways and urban highways were used to predict the rut depth. A variability analysis procedure was implemented and determined the critical limit on rut depths to guarantee 95 percent reliability that the predicted rut depths will be smaller than the critical value. Then, the pay factor can be determined according to the means and standard deviations of the rutting within the as-designed and as-built pavement lots, as shown in Equation 9 and Figure 3. In this case, the pay factor is related to pavement performance but not the life cycle cost of pavement.

$$\text{Payment Adjustment Factor (PAF)} = \min\left(1.05, \frac{B}{A}\right) \tag{9}$$

Where,

A = the reliability that the predicted rut depth of the standard design will be less than the critical limit;

B = the reliability that predicted rut depth of a contractor's construction will be less than the critical limit.

Caltrans have conducted several studies to develop performance-related pay factors mainly considering fatigue cracking and rutting. The performance model used for predicting fatigue cracking is based on the mix analysis and design system developed as a part of SHRP study (Deacon et al., 1994) and calibrated to the Caltrans flexible-pavement design system. Original model used for rutting is based on mix performance data developed at WesTrack (Monismith et al., 2000). In the developed models, the pavement is simplified as a multilayer elastic system to estimate the damage under traffic loading. Monte Carlo simulations (MCS) are used to predict the probabilistic distributions of pavement lives due to material and construction variability, which was represented by the means and variances of asphalt content, air-void content, asphalt-concrete thickness, and aggregate gradation. The performance model used to predict the allowable ESALs with respect to fatigue cracking in the study is shown in Equations 10 and 11.

$$N_f=\exp(1-22S_{mix}-0.17V_{AV}+0.58V_{AC}-3.72\ln\varepsilon_t) \quad (10)$$

$$\text{ESALs} = \frac{N_f \times SF}{TCF} \quad (11)$$

Where,

S_{mix} =mixtures stiffness;

V_{AV} =air void content;

V_{AC} =asphalt content;

N_f =fatigue life to cause 10% cracking;

TCF =temperature conversion factor;

SF =shift factor to consider the differences between laboratory and t in-situ pavement.

The performance model used to predict the allowable ESALs with respect to rutting is shown in Equation 12. Compared to the model for fatigue cracking, the effect of aggregate gradation on rutting was considered.

$$\begin{aligned} ln(ESALs) &= a_0 + a_1V_{AC} + a_2V_{AV} + a_3 fa + a_4V_{AC}^2 + a_5V_{AV}^2 + a_6 fa^2 \\ &+ a_7V_{AC}V_{AV} + a_8V_{AC} fa + a_9P_{200} fa \end{aligned} \quad (12)$$

Where,

ln (*ESALs)* = natural logarithm of *ESALs* to specific rut depth (mm), e.g. 15mm;

fa = Fine aggregate content (passing the No. 8 sieve and retained on No. 200 sieve);

V_{AV} =air void content;

V_{AC} =asphalt content;

P_{200} = mineral filler content;

a_0……. a_9 = regression coefficients.

The cost model to be discussed subsequently is based on a comparison between the as-constructed pavement performance and the expected performance. In the cost model, the relative performance (RP) can be calculated as the ratio of off-target traffic (ESALs) to target (design) traffic (ESALs) using Equation 13. Then the off-target pavement life is obtained using Equation 14 after assuming the traffic growth rate. Finally, the pay factor for each specific distress mode was calculated using the cost model shown in Equation 15. The cost model considers only agency cost consequences of delaying or accelerating the time to next rehabilitation.

$$RP = \frac{off-target\_ESALs}{on-target\_ESALs} \tag{13}$$

$$OTY = \frac{\ln(1+RP\left|(1+g)^{TY}-1\right|}{\ln(1+g)} \tag{14}$$

$$\Delta PW = C\left(\frac{(1+r)^{OTY}}{(1+d)^{OTY}-1}-\frac{(1+r)^{20}}{(1+d)^{20}-1}\right)\left(\frac{(1+r)^{OTY}-1}{(1+d)^{OTY}}\right) \tag{15}$$

Where,

OTY = off-target pavement life in years due to material and construction variability;

TY = target pavement life (design life) in years, usually 20 years;

g = the annual rate of traffic growth expressed as a decimal;

ΔPW = rehabilitation cost difference in net present worth caused by OTY and TY;

C = the resurfacing /rehabilitation cost in current-year dollars;

d = the annual discount rate;

r = the annual rate of growth in rehabilitation cost.

In 2010, the NCHRP 9-22 project developed a HMA performance-related specification (PRS) that used the link between HMA volumetric properties, engineering properties (dynamic modulus and creep compliance), and pavement performance to develop pay adjustment. The Mechanistic-Empirical Pavement Design Guide software produced in NCHRP Project 1-37A is used as the “engine” for performance prediction models in the HMA PRS. The MEPDG contains models for predicting HMA permanent deformation, fatigue cracking, and thermal cracking. Smoothness is then calculated based on the other distresses predicted as well as the original, initial as-built smoothness level of the project. One of the major benefits of this approach is that it tied together the structural distress (performance) prediction of a pavement system to the real properties of the mixtures.

In order to provide instantaneous estimates of the AC distresses in flexible pavements, a solution methodology was derived from predictive (closed form) models developed from a comprehensive set of factorial runs of the MEPDG software. As a result, a stand-alone program - Quality-Related Specification Software (QRSS) is developed. The QRSS calculates the predicted performance of an HMA pavement from the volumetric and materials properties of the as-designed HMA and compares it with that of the as-built pavement. The calculated differences for the permanent deformation, fatigue cracking, low-temperature cracking, and IRI determine pay factors for each lot or sub-lot. The predictions are probabilistic; they are calculated through a Monte Carlo procedure that uses historical standard deviations of the input properties in order to account for construction and testing variability.

In the QRSS, pay factors (PF) are developed from predicted life difference (PLD) that is defined as the difference in predicted service life between the as-designed mix and the as-built mix, as shown in Figure 5. The Pay Factor Penalty/Bonus is estimated from the PLD for each lot. The criterion relating the PLD and PF for each distress is solely defined by the user agency. The summation of the pay factors for the lots provides the total project pay factor. No life cycle cost is considered in the development of pay factor. Based on the brief review of several studies related to PRS, it can be seen that tin order to develop the PRS, reasonable performance-prediction models and maintenance-cost models are needed. Although several research studies have been conducted by the FHWA and NCHRP, only few agencies implement it into the real construction specification due to lack of agency specific data.

2.3.4 Pay adjustment for in-place air voids

Pay factor is a multiplication factor (often expressed as a percentage) used to adjust the contractor's bid price based on the estimated quality of work. If the percent-within-limit (PWL) or percent defective (PD) is used as quality measure, pay factor is a function relate to the PD or PWL of a certain quality characteristic. Theoretically, material produced at AQL should receive a pay factor of 1.00, material produced reached RQL should be rejected, material quality between AQL and RQL receives a pay factor smaller than 1.00. A recent survey conducted as part of NCHRP 10-79 project (2011) showed that of 31 SHAs (out of 37 responding) use incentives (bonus) which range from one percent to 15 percent; 18 of which use a 5 percent maximum. Typically, the 15 percent incentives are restricted only to ride quality.

In current practice for air voids pay adjustment, many SHAs use the AASHTO pay equation (Equation 16) that results in a straight-line relationship with 105% pay at PWL=100 and 100% pay at PWL=90 (AQL). However, other SHAs have developed their individual equations that follow the AASHTO form, but establish different incentive values. For example, Equation 17 is used by Vermont DOT for the pay adjustment based on air void, which has a maximum pay at 103%.

$$PF = 55 + 0.5\ PWL \tag{16}$$

$$PF = 83 + 0.2\ PWL \tag{17}$$

In order to develop performance-related specifications that concern air voids, the effect of air voids on pavement performance needs to be investigated. Reliable performance-prediction models and maintenance-cost models are also needed.

In-pace air void content (or density) is an important quality characteristic for asphalt pavements, which is dependent on the asphalt content, aggregate gradation, and nominal maximum aggregate size (NMAS). Overall, air void has a direct impact on density, rutting, fatigue life, permeability, oxidation, bleeding, and so on. The in-place air void content has been found as the most influential property affecting the performance and durability of asphalt pavements (Linden et al., 1989). The relatively smaller air voids can contribute to longer fatigue life due to the increased homogeneity of asphalt mixture and reduced stress concentration.

A study conducted in California evaluated the effects of asphalt content and air void content on the fatigue response of a typical California asphalt concrete mix. Lab result demonstrated that accurate construction control of air void content is more important than accurate control of asphalt content relative to the design target values in pavement fatigue life (Harvey et al., 1995). Previous studies also concluded that mixtures must have air voids contents lower than 8 percent to avoid rapid oxidation and subsequent cracking or raveling. These studies indicate that 8 percent air voids content appears to be a critical value dividing permeable and impermeable HMA mixtures (Brown et al., 2004; Vivar and Haddock, 2005).

A recent survey showed that the quality characteristic most often used for QA is compaction (in-place air void or density) by 44 agencies (Hughes 2005). In most construction specifications, in-place air void (or density) is measured as a percent of maximum theoretical density in statistical terms. However, the current pay adjustment procedures for air voids are mainly based on empirical field data and engineering experience. They are practical and easy to follow. However, they may not fairly award contractors for providing work that equals or exceeds the acceptable quality level, and recoup expected future expenses resulting from substandard work.

A number of research studies have been conducted (Anderson et al., 1990; Shook et al., 1992; Solaimanian et al., 1998; Epps et al., 2002; Popescu and Monismith, 2006) and proposed the framework for PRS based on LCCA to relate the quality characteristics, pavement performance, and pay adjustment have been proposed as improved quality assurance (QA) specifications. However, due to lack of data, few studies have developed performance-related pay adjustment based on air voids.

Therefore, pay factors due to variability of in-place air voids in the as-constructed pavements should be developed to reflect expenses or savings expected to occur in the future as the result of a departure from the specified level of pavement quality. It is strongly desired by agencies to develop a simple but scientifically based performance-related pay adjustment methodology that is practical and effective, fair to both the highway agency and the construction industry, and legally defensible.

2.3.5 Pay adjustment for IRI

The roughness of a road can be regarded as an indicator of how soon a road needs maintenance or reconstruction. The pavement roughness is usually expressed as International Roughness Index (IRI), which is defined as a mathematical property of a longitudinal road profile. It can be interpreted as accumulated displacement of the simulated suspension from quarter-car model in meters per kilometer.

As a widely-adopted standard scale, IRI was initially proposed by the World Bank to globally define the roughness of roadway (Sayers et al. 1986). “IRI summarizes the roughness qualities that impact vehicle response and relates most to overall vehicle operating cost, overall ride quality, dynamic wheel loads (that is damage to the road from heavy trucks and braking and cornering safety limits available to passenger cars), and overall surface condition” (Sayers and Karami, 1998).

One of the major impacts from rougher pavement surface is that it significantly increases the vehicle operating cost (VOC). As a total cost of road transport, VOC includes fuel consumption, tire consumption, oil and lubricant consumption, parts consumption, labor hours, depreciation, interest, and overheads (Bennett and Greenwoord, 2001). Many studies have shown the impact of IRI on VOC (Wang et al., 2014; Louhghalam et al., 2015).

Dynamic loads imposed by moving vehicles have variations in load magnitude due to the surface roughness of the pavement system. Many studies has investigated and demonstrated the correlation among IRI and moving dynamic loads (Liu and Gazis, 1999; Guo et al., 2012). Generally, rough surface will induce larger dynamic loads which are greater than the design loads and thus has adverse impact on the pavement performance and life.

Smith et al. (1997) evaluated the effect of initial pavement smoothness on the future smoothness and life of AC, PCC and AC overlays of existing AC and PCC pavements. The result demonstrates that initial pavement smoothness has a significant effect in 80 percent of new construction (both AC and PCC pavements) and in 70 percent of AC-overlay construction. Combined results of roughness-model and pavement-failure analyses indicate at least a 9 percent increase in life corresponding to a 25 percent increase in smoothness from target profile index (PI) values of 7 and 5 inch/mile for concrete and asphalt pavements, respectively.

Ksaibati and Mahmood (2002) analyzed a large number of test sections from the LTPP database. The statistical tests performed in the study indicate that asphalt and concrete pavements with low initial smoothness stay smooth over time.

The current pay adjustment for IRI usually is not based on percent-defective (PD) for most state agencies, but based on the exact magnitude of IRI. Some states have different IRI pay factors for different classifications of routes or routes with different posted speed limits (Wilde, 2007). Typically, the pay adjustment of IRI for rigid pavement and flexible pavement are different. For instance, the pay adjustment for PCC pavement in New Mexico DOT is based on percentage of bid price, as shown in Table 3. Two types of pay adjustments are used for national highway (NH) routes and other routes. The maximum bonus and penalty are all 10% of bid price. If the IRI values is greater than 72.8 inch/mile in national highway or 76 inch/mile in non-NH routes, the corrective work are required instead of penalty.

Table 3. Pay adjustment for PCC pavement in New Mexico DOT

IRI at NH Routes, inch/mile		IRI at Non-NH Routes, inch/mile		Pay Factor,%
<52.2		<49.5		110
52.2	53.2	49.6	50.9	109
53.3	54.2	51	52.1	108
54.3	55.2	52.2	53.4	107
55.3	56.2	53.5	54.7	106
56.3	57.2	54.8	55.9	105
57.3	58.2	56	57.2	104
58.3	59.2	57.3	58.5	103
59.3	60.2	58.6	59.8	102
60.3	61.3	59.9	61.1	101
61.4	62.3	61.2	61.4	100
62.4	63.3	62.5	63.8	99
63.4	64.4	63.9	65.1	98
64.5	65.4	65.2	66.4	97
65.5	66.4	66.5	67.8	96
66.5	67.5	67.9	69.1	95
67.6	68.5	69.2	70.5	94
68.6	69.6	70.6	71.8	93
69.7	70.7	71.9	73.2	92
70.8	71.7	73.3	74.6	91
71.8	72.8	74.7	76	90
>72.8		>76		Corrective work

For flexible pavement, most states assign a specific dollar amount as a bonus or penalty in dollars per square yard or per segment based on the measured initial IRI value after construction. The pay equation for ride quality in New Jersey DOT is shown in Table 4. It can be seen that for freeway there is no bonus or penalty when the initial IRI ranges from 55 inch/mile to 65 inch/mile. When IRI is within 35 inch/mile to 55 inch/mile or 65 inch/mile to 135 inch/mile, the correlation between initial IRI and payment is linear. When IRI is beyond 135 inch/mile, the contractor has to remove and replace the corresponding segment. Comparably, the pay adjustment for Non-freeway road is more generous.

Table 4. Pay adjustment for IRI in NJDOT

Freeway		Other than freeway	
Initial IRI, inch/mile	PA on lots of 0.01mile length,$	Initial IRI, inch/mile	PA on lots of 0.01mile length,$
IRI<35	50	IRI<45	50
35≤IRI<55	137.5-2.5IRI	45≤IRI<65	162.5-2.5IRI
55≤IRI≤65	0	65≤IRI≤75	0
65<IRI≤135	-7.14(IRI-65)	75<IRI≤145	-7.14(IRI-75)
IRI>135	Remove and replace	IRI>145	Remove and replace

In order to compare the practice of pay adjustment in different states, the study plots typical pay adjustments currently used in three states, as shown in Figure 2. It can be seen that the ranges of pay adjustments are in the same magnitude. The major differences can be found in maximum bonus, range of IRI under 0% pay adjustment, and IRI threshold for the requirement of corrective work. The pay adjustment in Kentucky has highest bonus with widest range of IRI under 0% pay adjustment (40 inch/mile to 70 inch/mile), and lowest IRI threshold for the requirement of corrective work (85 inch/mile); The pay adjustment in Texas has narrow range of IRI under 0% pay adjustment (60 inch/mile to 65 inch/mile). The IRI threshold for the requirement of corrective work is 95 inch/mile; Comparably, NJDOT gives significant higher penalty but allows 135 inch/mile of IRI threshold for the requirement of corrective work.

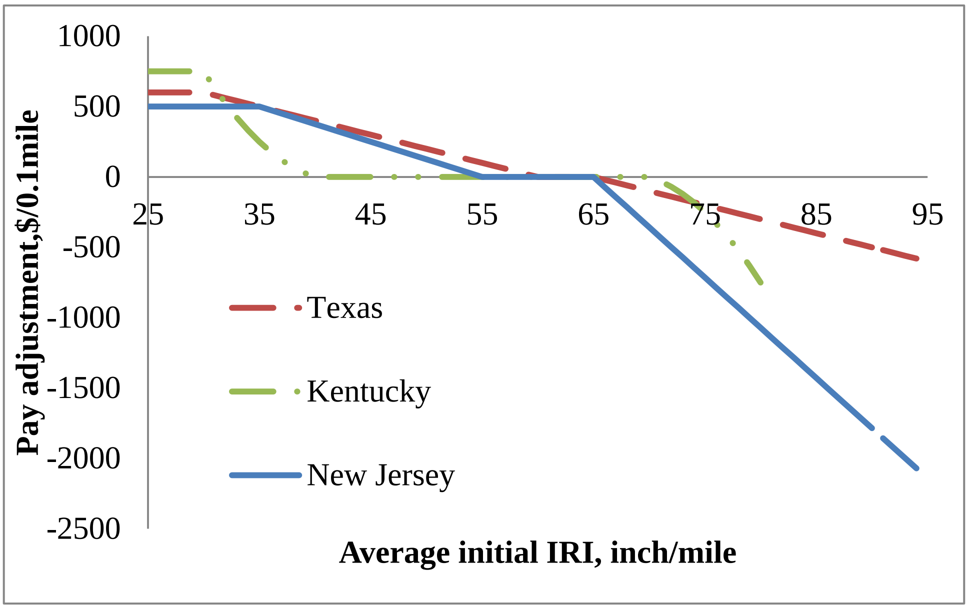


Figure 2. IRI Pay adjustment for flexible pavement in NJ, TX, and KY

Currently, NJDOT also develops a new specification that implements nonlinear curve into IRI payment. However, the current pay adjustment for IRI is mainly based on empirical experience, the correlation between IRI, pavement life, and pay adjustment based on performance related specification is more convincing and reliable. Various studies have considered the issue and developed new pay adjustment for initial pavement roughness. Weed (2002) presented various mathematical models to link IRI and pavement life based on the data published by previous studies. A practical and effective performance-related specification for IRI was then developed based on the models. Chou and Pellinen (2005) used the artificial neural network methodology to develop roughness prediction models based on the profile index of the California Profilograph measurements for three types of pavements: Portland cement concrete pavement, asphalt overlay over concrete pavement, and asphalt pavement. Rational pay factor limits were proposed based on the established relationship between pay factors and the pavement life determined by roughness progression.

Chapter 3: Overlay Performance Model and Probabilistic Analysis

Currently in practice, the selection of rehabilitation treatment is based on engineering judgement. While many studies analyzed the effects of various factors on pavement overlay performance, few studies focused evaluating the effect of pre-rehabilitation condition on post-rehabilitation pavement performance. Moreover, the selection between major rehabilitation and minor rehabilitation are rarely addressed from the perspective of life-cycle cost.

As pre-rehabilitation condition is an important factor to select the cost-effective rehabilitation alternatives, there is a need to fill the gap in this research area and provide an easy-to-use approach and practical recommendation to highway agencies. To that end, LCCA that incorporates the effect of pre-rehabilitation condition is critical for the optimal treatment selection. The probabilistic LCCA that considers uncertainty and variability of important inputs can further capture the general trend at network level.

This chapter aims at using deterministic and probabilistic approaches to model performance deterioration trends of asphalt concrete overlay. The focus is to investigate the effect of pre-overlay condition on the performance of various rehabilitation treatments. A probabilistic LCCA model is developed to further identify the optimal rehabilitation treatment under different pre-overlay conditions and assess the factors that have significant influences on pavement overlay performance.

3.1 Analysis of Overlay Performance

3.1.1 Data summary

In order to collect sufficient overlay information, data pertaining 195 pavement sections that were rehabilitated with asphalt concrete overlays were gathered from NJDOT PMS. The overlay sections spread within NJ and cover Interstate highway, state highway, and NJ highway. The extracted performance data span from 2000 to 2015 and include IRI, SDI, and rutting for every 0.1 mile. The typical types of rehabilitation activities in New Jersey include milling 2'' and overlay 2'', milling 3'' and overlay 3'', milling 4'' and overlay 4'', milling 2'' and overlay 4'', milling 2'' and overlay 6'', and milling 3'' and overlay 6''. In practice, the overlay that adds the overall pavement thickness is treated as major rehabilitation, while overlay that does not increase the overall pavement thickness is treated as minor rehabilitation.

The SDI indicates pavement surface condition with a scale of 0-5 and incorporates both the non-load-related distress index (NDI) outside the wheel paths and the load-related distress index (LDI). The LDI considers load-related cracking in the wheel path and the rutting depth; while the NDI considers the non-load-related cracking outside the wheel path. An average SDI was obtained for each pavement section from the original SDI measurement taken at every 0.1 mile to eliminate the variations in the SDI within one pavement section.

3.1.2 Determination of overlay Life

The NJDOT defines the pavement condition as poor when SDI is smaller than 2.4 or IRI is greater than 170 inch/mile and as good when SDI is greater 3.5 and IRI is smaller than 95. It was found that the IRI usually does not reach the failure criteria after 10 years. Therefore, overlay life in the study is determined as the time period before the SDI drops to 2.4.

It is expected that when rehabilitation is conducted, the SDI usually increases to close to 5. An example of the development trends of average SDI for NJ 173 (minor rehabilitation section with low traffic volumes) and I-295 (major rehabilitation section with high traffic volumes) is shown in Figure 3.

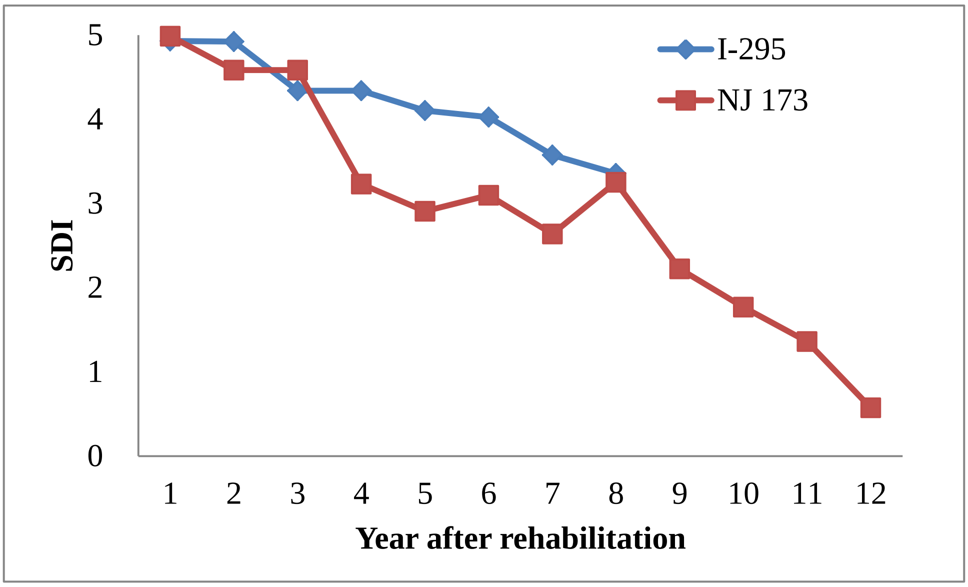


Figure 3. Illustration of Development Trend of Surface Distress Index

Various model forms (such as linear, exponential, logarithmic, power, and polynomial models) can be used to estimate the best fit to pavement condition data, A majority of them do not constrain the curve to fit within the boundaries and may not simulate the development trend for SDI accurately. For instance, it can be observed from Figure 3 that during the first couple of years, the SDI declines slowly. Afterward, it may start to drop rapidly and finally decrease gradually as a step function. Under this scenario, the linear model and exponential model can hardly predict the trend. Sigmoidal (S-shape) model has been shown to provide high accuracy as well as constraining the curve to fit within pavement condition boundaries (Jackson et al., 1996; Wang et al., 2015).

The development trend of SDI was simulated as Sigmoidal (S-shape) model, as shown in Equation 18. The function is developed by Stantec (2007) and it is currently implemented by VDOT to predict pavement deterioration for various pavement performance indicators. Both coefficients b_1 and c_1 can depict the deterioration process. Coefficient b_1 focuses more on the rate of deterioration of different pavement section, which is sensitive to structural capacity, while coefficient c_1 explains the change in the deterioration rate over time.

$$SDI = SDI_0 - \exp(a_1 - b_1 * c_1^{(\ln(\frac{1}{Age}))}) \quad (18)$$

Where,

SDI = Surface distress index;

SDI_0 = Surface distress index at year zero (usually 5);

Age = the year since the initial construction of the last rehabilitation treatment;

a_1,b_1,c_1 = model coefficients with a = ln(SDI_0) and $SDI_{terminal}$=0.

In the study, nonlinear regression analysis using least squares method was conducted to obtain three model parameters for each pavement section. Overlay life was calculated from the regression equation when SDI reaches 2.4. In order to construct a robust and reliable model, the outliers are identified and excluded in the regression model. The outliers are usually the data points that are significantly larger or smaller than the adjacent data points. For example, if the change of SDI is greater than 3 within one year, the data are considered invalid and excluded from the analysis. The sections with missing SDI data were also excluded from the regression analysis. Ultimately, there are 145 sections remained. Regression analysis was conducted for each individual section to calculate pavement life. The average R-square value for the 145 sections is 72%, which suggests that generally the model fit well the data. The frequency distribution of R-square values can be found in Figure 4.

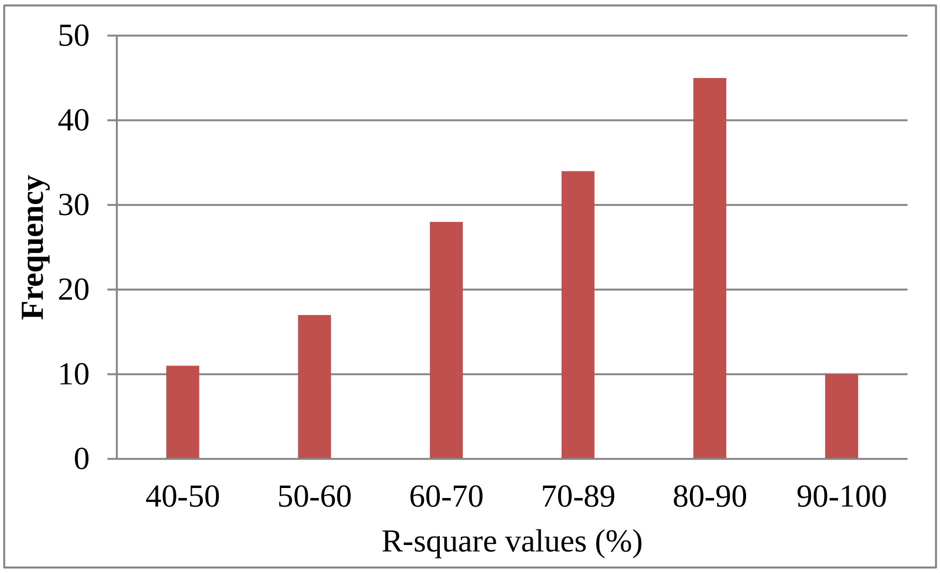


Figure 4. Frequency Distribution of R-square values

Figure 5 demonstrates the distribution of calculated overlay service life for all the sections. The study used the Anderson–Darling test to assess whether a sample comes from a specified distribution and check the type of distribution. According to the Anderson-Darling test, the distribution of overlay life was found being lognormal distributed with p-value equal to 0.14, which is significantly higher than the threshold value of 0.05.

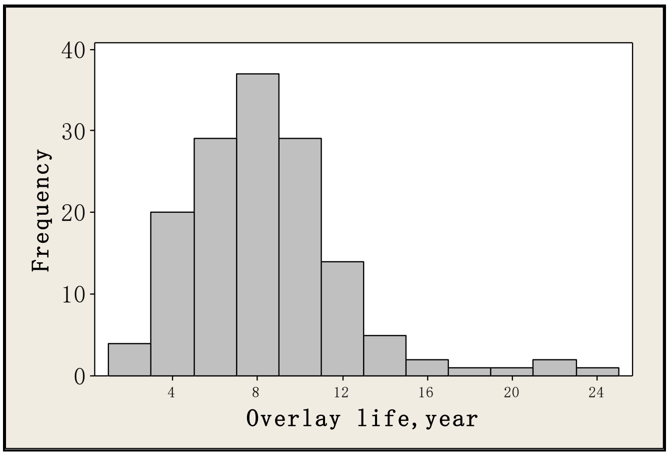


Figure 5. Frequency distribution of calculated overlay life for all 145 sections

Among all the sections with different overlay treatments, 38 pavement sections with milling 2” and overlay 2” demonstrate the lowest average life. The average life of these sections is 5.9 years and the coefficient of variation (CV) is 53%; On the other hand, 13 pavement sections with milling 3” and overlay 6” have the highest average life of 11.7 years with 24% CV.

In order to make the result more succinct and refined, the study divided the available sections into two parts: the sections with minor rehabilitation treatment and the ones with major rehabilitation treatment. In this case, there are 112 sections with minor rehabilitation and 33 sections with major rehabilitation. The average overlay life after minor rehabilitation was found being 8 years with 50% CV, while the average overlay life after major rehabilitation was found being 10 years with 27% CV. The boxplot of frequency distribution of pavement life after two rehabilitation treatments is shown in Figure 6. Boxplot is a convenient way of graphically describing groups of numerical data through five statistical indexes: the minimum sample value, the lower quartile (Q1), the median(Q2), the upper quartile (Q3), and the maximum sample value. From the boxplot results, the majority of sections with major rehabilitation clearly demonstrate longer life than the sections with minor rehabilitation. In addition, the results show that the pavement life in minor rehabilitation sections shows relatively higher variations with a few outliers.

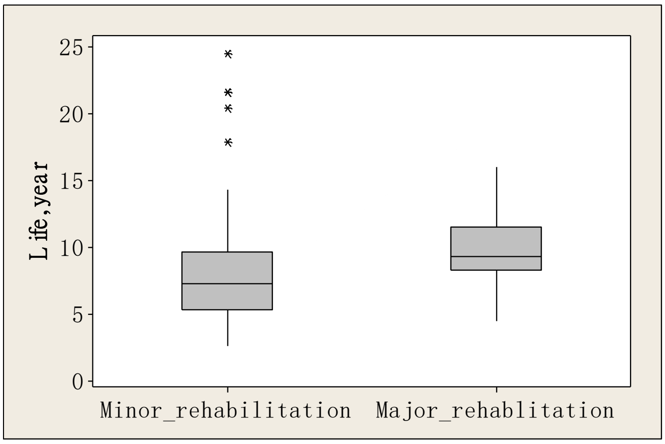


Figure 6. Boxplot of overlay life

In order to identify whether the overlay lives with different rehabilitation treatments are statistically significant, non-parametric statistic test was conducted. Since some of the data sets are skew distributed, the Mann–Whitney U test is preferred because it can be used for multiple comparisons without making assumptions on the distribution of the data (e.g. normality). It was found that the overlay life after minor rehabilitation is significantly lower than the overlay life after major rehabilitation (one sided p-value equal to 0.0001). The result indicates that the performance of minor rehabilitation section and major rehabilitation section is distinctive and the difference is worth to be further investigated.

3.1.3 Evaluation of pre-overlay and post-overlay condition

After the rehabilitation treatment, the pavement condition is expected to be highly improved. The extent of improvement can be dependent on the type of treatment, existing pavement condition, pavement structure, and environment.

The study further divide the sections based on the highway system they belong to, as overlay should also performs differently in Interstate highway and non-Interstate highway. The pavement sections in Interstate highway usually carry heavy truck traffic and have thicker pavement structure, while non-Interstate highway such as state highway and local highway are designed with relatively thinner layer thickness to carry light or moderate truck traffic.

As initial overlay performance right after the application of overlay may not be recorded promptly at some pavement sections, regression analysis was used to estimate the initial overlay performance measures for each section. The SDI model, IRI model, and rutting model are shown in Equation 18, Equation 19 and Equation 20, respectively. The parameters a_1, a_2, a_3 in the equations essentially represent the initial pavement condition and can be calculated by fitting the available pavement condition data at different years after the rehabilitation treatment.

$$IRI = a_2 e^{b_2 Age} \tag{19}$$

Where,

a_2 = Initial IRI;

b_2= IRI deterioration rate;

Age= the year since the initial construction of the last rehabilitation treatment.

$$Rutting = a_3 e^{b_3 Age} \tag{20}$$

Where,

a_3 = Initial rut depth;

b_3= rutting deterioration rate;

Age= the year since the initial construction of the last rehabilitation treatment.

Table 5 shows the summary of pre-overlay condition and post-overlay performance measures including SDI, IRI and rutting depth. Overall, there is disparity among different performance indicators. For SDI, it can be seen that there is no obvious difference observed among four groups for either pre-overlay condition or post-overlay performance. After the application of overlay, SDI values usually recover to the maximum value of 5.

Table 5. Pre-overlay performance vs Post-overlay performance

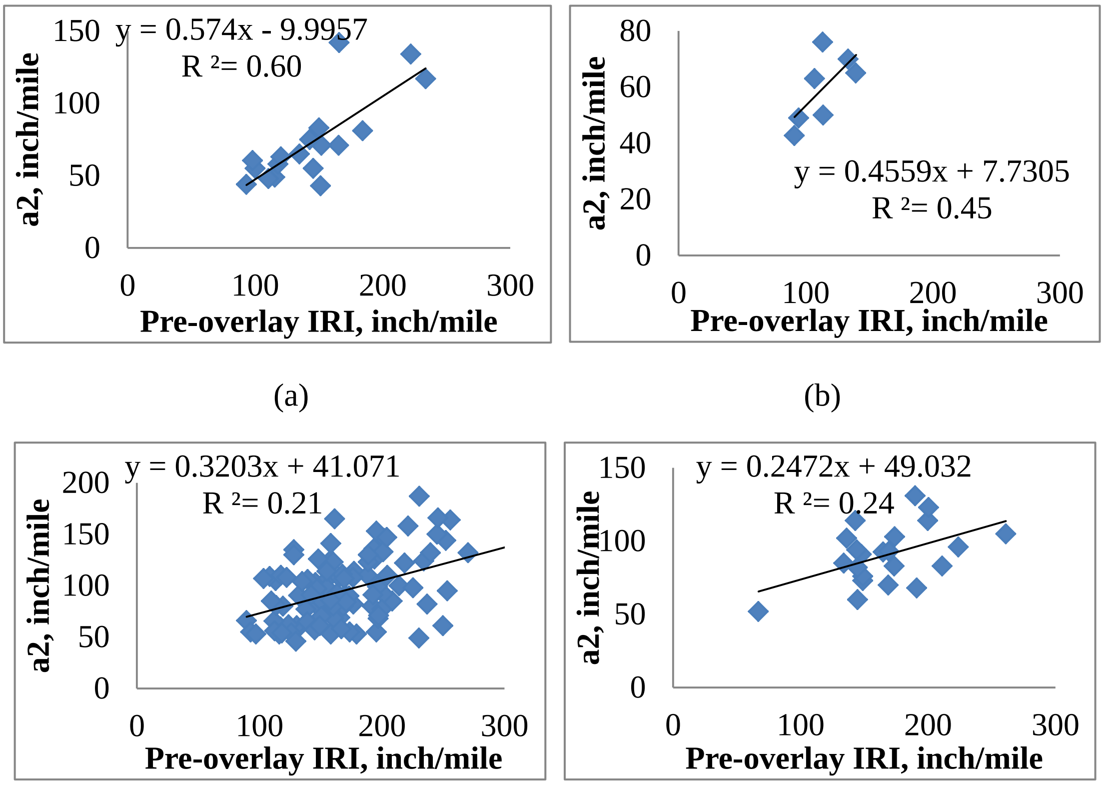
Measure	Highway system	Rehabilitation type	Pre-overlay value	CV, %	Post-overlay value	CV, %
SDI (scale 1-5)	Interstate	Minor	1.8	48	5.0	1
		Major	2.0	39	4.9	2
	Non-Interstate	Minor	2.1	47	4.9	6
		Major	2.2	39	4.9	3
IRI, inch/mile	Interstate	Minor	145	27	73	41
		Major	121	16	60	22
	Non-Interstate	Minor	177	31	96	34
		Major	169	23	90	25
Rutting, inch	Interstate	Minor	0.25	29	0.10	11
		Major	0.23	30	0.11	11
	Non-Interstate	Minor	0.27	28	0.11	10
		Major	0.30	24	0.11	10

Compared to SDI, IRI seems varying depending on the type of rehabilitation treatment and highway system. The study conducted the Mann–Whitney U test and found that the pre-overlay IRI values in Interstate highway sections is significantly lower than the pre-overlay IRI values in non-Interstate highway sections (p-value<0.001). The Mann–Whitney U test also proved that the pre-overlay IRI values in minor rehabilitation sections are significantly greater than the pre-overlay IRI values in major rehabilitation sections (p-value=0.049). The result suggests that, in practice, major rehabilitation is not necessarily applied to those pavement sections with worse pre-overlay condition due to other considerations.

As for rutting, it was found that the pre-overlay condition was better in Interstate highway sections. However, after the rehabilitation, it seems that the initial rut depths, regardless of existing pavement condition, highway system, and rehabilitation treatment, are rather similar. The Mann-Whitney U test results show that pre-overlay rutting depths in Interstate highway sections are significantly lower than the pre-overlay rutting depths in non-Interstate highway sections.

It is meaningful to know if the post-overlay performance highly depends on pre-overlay condition. Figure 7 shows the relationship between pre-overlay IRI and post-overlay IRI for different rehabilitation treatments and highway systems. It can be observed that there is a proportional linear correlation between the two variables. The slope of the linear curve reflects the extent of sensitivity. For instance, the slope in Figure 7(a) is significantly higher than the slope in Figure 7(b). It implies that for Interstate highway sections, the post-overlay IRI after minor rehabilitation is more sensitive to the pre-overlay IRI, as compared to major rehabilitation. One of the underlying reasons is that after the major rehabilitation, the existing pavement roughness can be significantly corrected due to the thicker overlay. The similar trend was observed for non-Interstate highway sections although the R-square values are relatively low for linear correlation between the pre-overlay and post-overlay IRI values. Similarly, the distinction can be found in Interstate highway and non-Interstate highway sections. The result shows that generally the post-overlay IRI is more affected by pre-overlay condition in Interstate highway sections.

The analysis result can be applicable to the IRI specification of highway agencies, as it is capable of estimating the post-overlay condition considering the effects of pre-overlay condition, rehabilitation activities, and highway system. For instance, current specifications in Montana stipulate that when pre-paving IRI values are greater than or equal to 110 inch/mile and less than 190 inch/mile, the target post-paving IRI values should be 55 to 60 inch/mile. The results from the study can help derive the requirement of post-overlay IRI based on different pre-overlay conditions.



(a) (b)

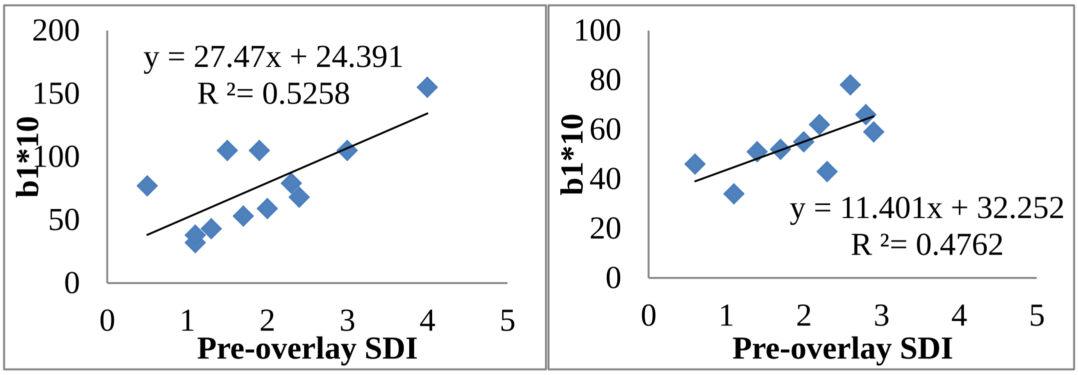
(c) (d)

Figure 7. Correlation between pre-overlay IRI and initial IRI values: a_2 for (a) minor rehabilitation in Interstate highway; (b) major rehabilitation in Interstate highway; (c) minor rehabilitation in non-Interstate highway; (d) major rehabilitation in non-Interstate highway

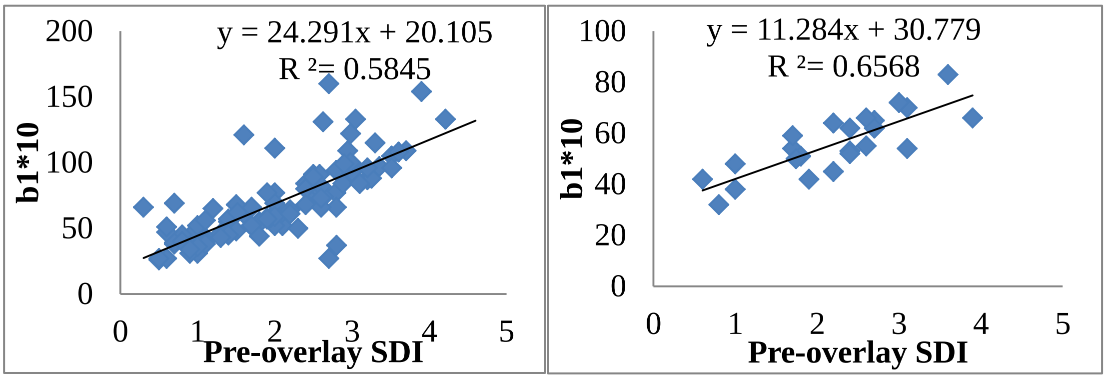
3.1.4 Evaluation of overlay performance progression

Other than post-overlay condition right after rehabilitation, pre-overlay condition also affects performance deterioration of overlays. It is necessary to evaluate the effect of pre-overlay condition on the overlay deterioration rate after the overlay application.

For SDI, it was found that pre-overlay SDI mainly influences model parameter b_1 in Equation 18. The relationships between pre-overlay SDI and the deterioration rate (b_1 in Equation 18) of SDI after overlay are shown in Figure 8. It was found that the performance deterioration after minor rehabilitation is considerably more affected by pre-overlay SDI compared to the case of major rehabilitation. This is reasonable since the minor rehabilitation does not increase the asphalt layer thickness after milling and overlay. With the established quantitative relationship, the effect of pre-overlay SDI on overlay performance can be quantified for different rehabilitation treatments, which can provide information for further life-cycle cost study.



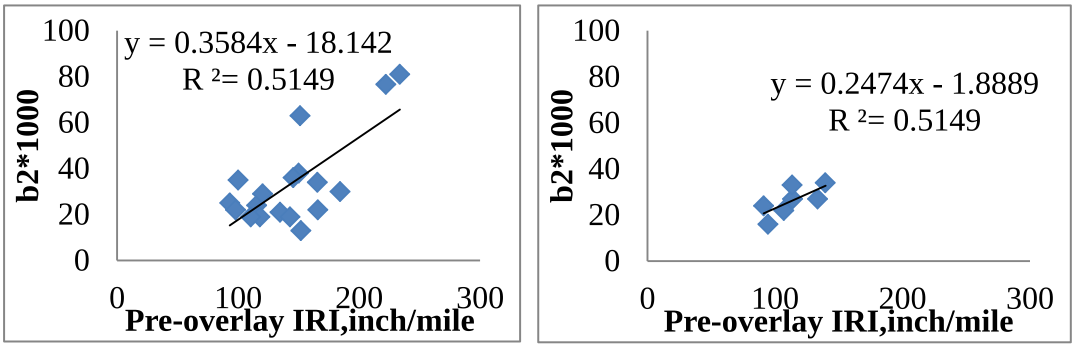
(a) (b)



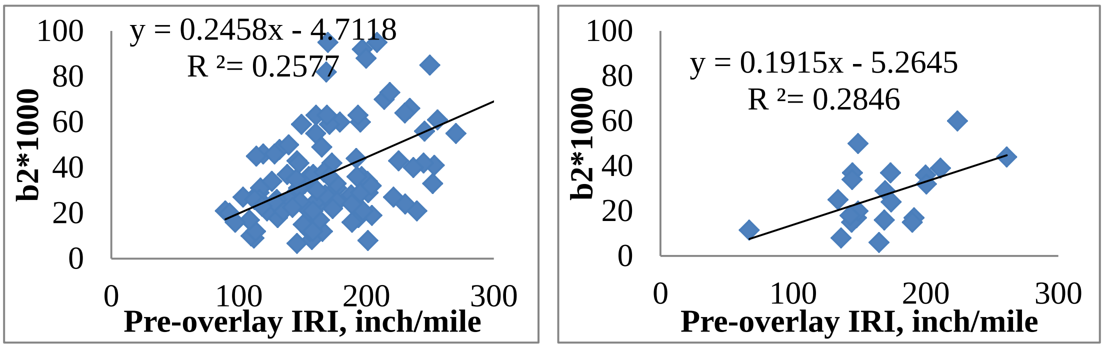
(c) (d)

Figure 8. Correlation between pre-overlay SDI and deterioration rates of SDI (b1 in Equation 18) for (a) minor rehabilitation in Interstate highway; (b) major rehabilitation in Interstate highway; (c) minor rehabilitation in non-Interstate highway; (d) major rehabilitation in non-Interstate highway

Similar plots were derived for pre-overlay IRI and rutting and their deterioration rates (b_2 in Equation 19 and b_3 in Equation 20) after overlay, as shown in Figure 9 and Figure 10, respectively. It was observed that the post-overlay deterioration rate of IRI was more sensitive to pre-overlay condition in Interstate highway sections compared to non-Interstate highway sections. However, this trend was not observed for the rutting depth. In general, the effects of pre-overlay condition on the deterioration rate of overlay performance are more significant for SDI, as compared to IRI and rutting depth.

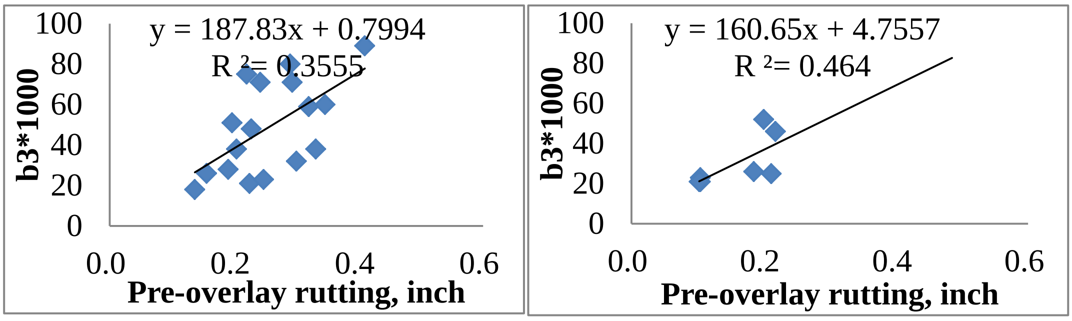


(a) (b)

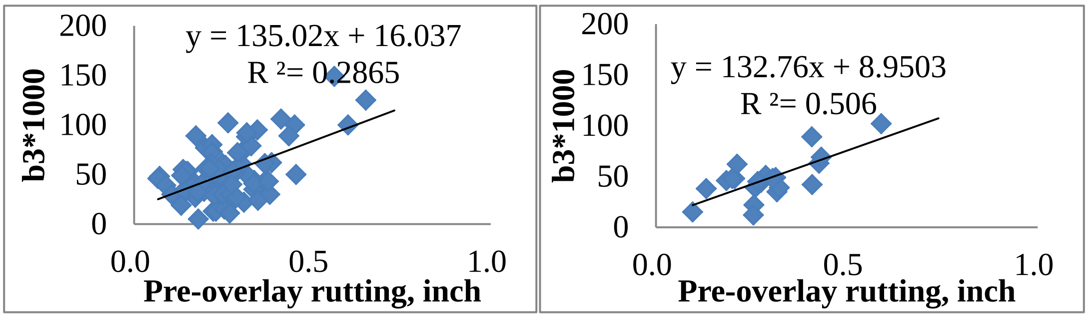


(c) (d)

Figure 9. Correlation between pre-overlay IRI and IRI deterioration rate (b_2 in Equatin 19) for (a) minor rehabilitation in Interstate highway; (b) major rehabilitation in Interstate highway; (c) minor rehabilitation in non-Interstate highway; (d) major rehabilitation in non-Interstate highway



(a) (b)



(c) (d)

Figure 10. Correlation between pre-overlay rutting and rutting deterioration rate (b_3 in Equation 20) for (a) minor rehabilitation in Interstate highway; (b) major rehabilitation in Interstate highway; (c) minor rehabilitation in non-Interstate highway; (d) major rehabilitation in non-Interstate highway

3.2 Deterministic LCCA

3.2.1 LCCA model

Previous analysis demonstrates the substantive influence of pre-overlay condition on pavement performance after rehabilitation. In this part, all data were clustered together to analyze the effect of pre-overlay condition on pavement performance after minor and major rehabilitation treatments. After that, LCCA is used to select the most appropriate rehabilitation type.

In an effort to make the model more applicable for field practice, SDI is used to indicate pavement performance and predicted treatment life. Due to the lack of data, the model doesn't consider the effect of traffic on rehabilitation performance. The consideration of rehabilitation in LCCA is illustrated in Figure 11. The LCCA model considers two rehabilitation options: a costly way is to apply major rehabilitation such as milling 2'' and overlay 3'' or milling 2'' and overlay 4'', which may demonstrate slower deterioration trend. The other option is minor rehabilitation such as milling 2'' and overlay 2'', which is more vulnerable to pre-overlay condition compared to major rehabilitation according to previous analysis results. The relationship between the pre-overlay SDI and the deterioration rate of SDI after rehabilitation was shown in Equation 21 and Equation 22. The treatment life is then determined based on the SDI threshold of 2.4.

Minor rehabilitation: b_1= 2.4*pre-overlay SDI + 2.1 R^2=56% (21)

Major rehabilitation: b_1= 1.2*pre-overlay SDI + 3.1 R^2=61% (22)

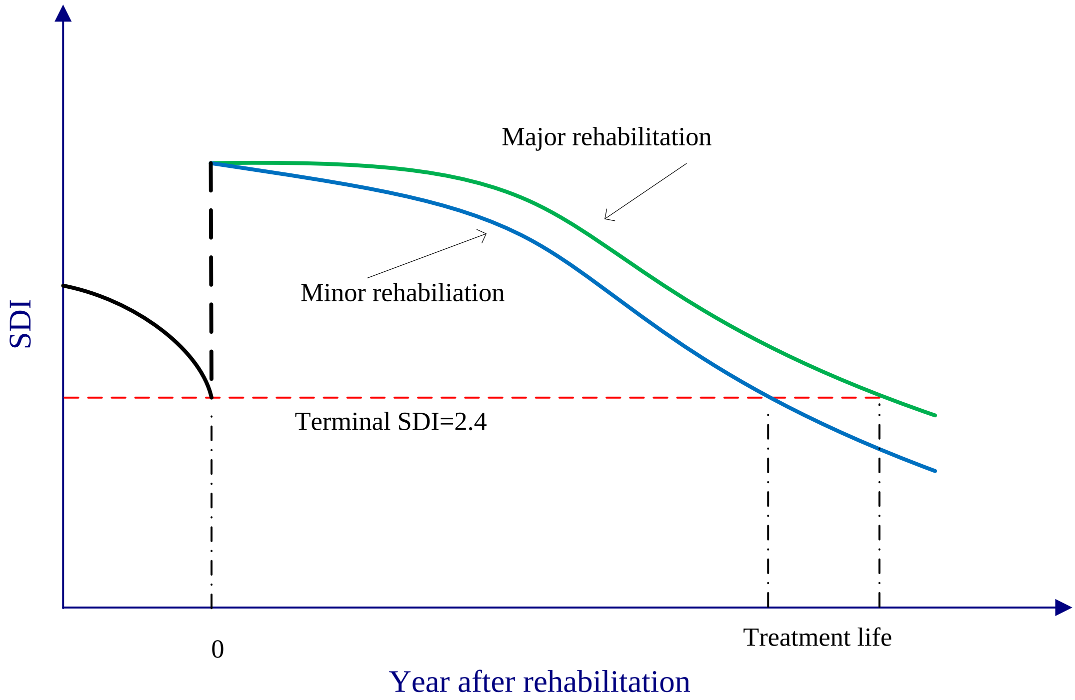


Figure 11. Illustration of rehabilitation consideration in LCCA model

Served as an analytical technique for assessing potential economic impacts, LCCA provides an effective methodology to compare the difference among the competing alternatives considering different costs. Two economic indicators are usually used in the LCCA: net present value (NPV) and equivalent uniform annual costs (EUAC) (Jones and Smith, 1982). NPV converts all costs occurred at different years to one single base year in order to conduct the comparison, while EUAC distributes NPV to a yearly cost within the whole life cycle, as shown in Equation 23 and Equation 24. The study selected EUAC as a major indicator since it is applicable to compare different rehabilitation strategies when the budgets for pavement maintenance are usually established annually. Additionally, it is capable of comparing the LCCA results with different analysis periods.

$$\text{NPV}=\sum_{0}^{t}\frac{C}{(1+i)^t} \tag{23}$$

$$\text{EUAC} = NPV \frac{i(1+i)^t}{(1+i)^t - 1} \tag{24}$$

Where, C is the agency cost of treatment or the VOC induced by the IRI; i is discount rate (assumed to be 4% in the study); t is the year when the treatment is applied

Based on field data collected from New Jersey DOT, the typical treatment cost per square yard in New Jersey for mill 2" and overlay 2", mill 3" and overlay 3", mill 2" and overlay 4", mill 2" and overlay 6" are \$25, \$32, \$43, \$58, respectively. As mill 3" and overlay 3" and mill 2" and overlay 4" are frequently applied in New Jersey, their costs (\$25 and \$43) were treated as the initial default values for minor rehabilitation and major rehabilitation. The treatment life of major and minor rehabilitation was calculated based on Equation 18 and the terminal SDI value of 2.4. Previous analysis results indicate that the parameter b_1 in Equation 18 shows linear relationship with pre overlay SDI, while the other two parameters a_1 and c_1 has no obvious correlation to the pre-overlay SDI value. Thus, the study used the average value of two model parameters a_1 and c_1 based on the data of all pavement sections. The average values of parameter a_1 are 1.58 and 1.6, respectively, for minor and major rehabilitation; while the average values of parameter c_1 are 3.4 and 2.6, respectively, for minor and major rehabilitation.

Figure 12 demonstrates the calculated EUAC for minor and major rehabilitation with different pre-overlay conditions. The results clearly show the cost difference between the two treatments varies with the pre-overlay condition in terms of EUAC. The general trend shows that when pre-overlay SDI is low, the EUAC of minor rehabilitation is higher than the EUAC of major rehabilitation; when pre-overlay SDI reach around 2.5, the EUACs of two rehabilitations become equivalent; Afterward, the EUAC of major rehabilitation is slightly greater than the EUAC of minor rehabilitation. The trend suggests that the more cost-effective treatment can be minor or major rehabilitation that depends on pre-overlay condition. The SDI value in which the EUAC of minor and major rehabilitation is equal is defined as the SDI threshold of determining the cost-effective rehabilitation treatment. In other words, the minor rehabilitation is more cost-effective when the pre-overlay SDI is greater than the SDI threshold, and vice versa.

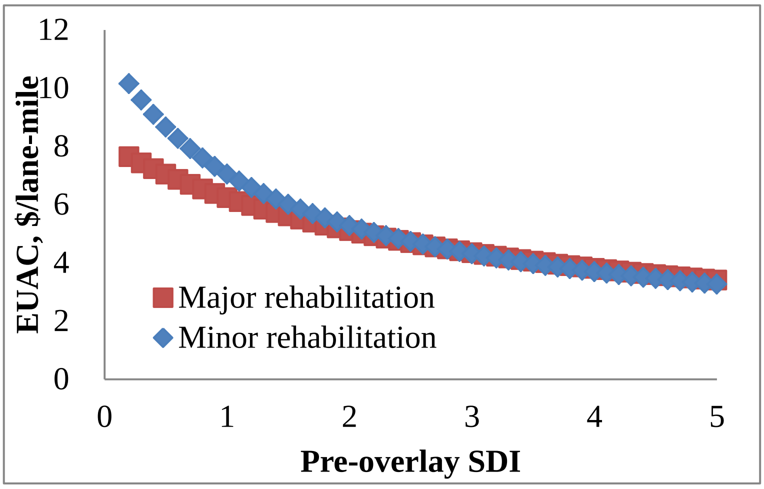


Figure 12. LCC of rehabilitation under different pre-overlay SDI

3.2.2 Sensitivity analysis of treatment cost and discount rate

As it is well known that the treatment cost and discount rate may exert certain influences on LCCA, sensitivity analysis was conducted for these two factors. Sensitivity analysis results for the effect of treatment cost on the SDI threshold were shown in Figure 13. It shows that the cost ratio between major rehabilitation and minor rehabilitation significantly affects the SDI threshold. The introduction of cost ratio instead of real costs can easily indicate the cost difference among various treatments. For the current treatment costs experienced by the New Jersey DOT, as compared to milling 2” and overlay 2”, the cost ratio of milling 2” and overlay 3” is 1.4 and the cost ratio of milling 2” and overlay 4” is 1.7. On the other hand, the cost ratio between milling 3” and overlay 5” and milling 4” and overlay 4” is 1.2.

Figure 13 indicates that as the cost ratio increases, the SDI threshold dramatically decreases. The relationship can be fitting with a power function with a very high R-square value. This finding provides practical guidance for highway agencies to select the optimal treatment based on treatment cost.

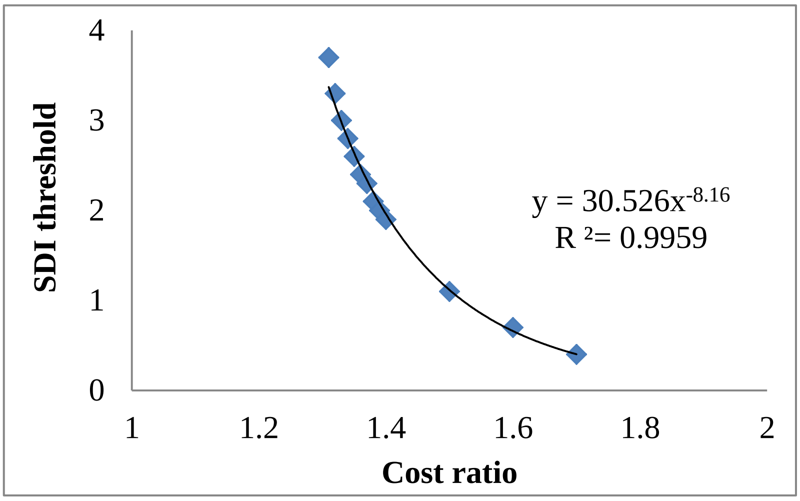


Figure 13. Effect of cost ratio on SDI threshold (Discount rate=0.03)

In a similar manner, Figure 14 shows the effect of discount rate on SDI threshold for two different cost ratios of major and minor rehabilitation. It can be seen that the effect of discount rate is not as influential as the effect of treatment cost considering the practical range of discount rate. The effect of discount rate on the SDI threshold is more prominent when cost ratio decreases. It also can be seen that the SDI threshold is more sensitive to the discount rate when the discount rate falls into the range of 1% to 4%.

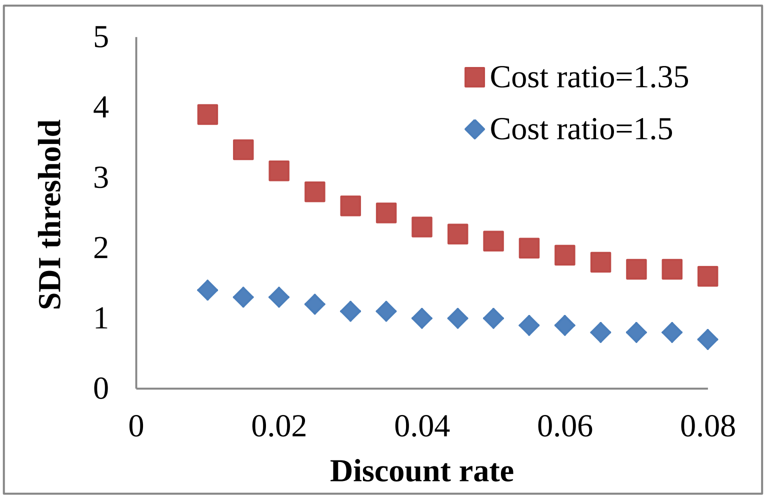


Figure 14. Effect of discount rate on SDI threshold

3.3 Probabilistic LCCA

3.3.1 Variations considered in LCCA model

Although the deterministic LCCA model is straightforward, it is not capable of incorporating the variability and uncertainty of input variables and showing their influences on economical consideration. The analysis results regarding SDI deterioration trends based on 112 minor rehabilitation sections and 33 major rehabilitation sections show noticeable variations in the deterioration model of SDI (parameters a_1, b_1, and c_1 in Equation 18), as shown in Table 6. The variations can affect the accuracy of LCCA results. Thus, the incorporation of variations of the input parameters in LCCA can yield a more general range of life cycle cost instead of single cost values.

In the probabilistic LCCA, the variations of SDI model parameters (a_1, b_1, c_1), discount rate, and treatment cost are considered. The SDI model parameters a_1, and c_1 for minor and major rehabilitation are assumed to be normally distributed, and the means and standard deviations were obtained as shown in Table 6. The variation of model parameters a_1 and c_1 were considered through random sampling. However, for the SDI model parameter b_1, the relatively large variation among different sections is mainly contributed by the variation of pre-overlay SDI, as shown in Figure 8. Therefore, it is unreasonable to use Monte Carlo simulation for random sampling of the model parameter b_1. In this case, Bayesian analysis with MCMC method is used to interpret the variability of the parameter due to the affecting factor (pre-overlay SDI).

Table 6. Summary of variation in regression coefficients

	a_1		b_1		c_1	
	Mean	CV,%	Mean	CV,%	Mean	CV,%
Minor	1.58	4	3	42	3.4	26
Major	1.60	2	1.2	22	2.6	11

3.3.2 Estimated distributions of model parameters by MCMC

The MCMC methods were used to account for variations of the SDI model parameter b_1 with respect to pre-overlay SDI, as shown in Equation 25. The statistical software, WinBUGS, was used to estimate model parameters for expected overlay life (Ntzoufras 2009).

The likelihood function in Equation 25 can be defined as Equation 26. An error term is added to incorporate the majority of the model's uncertainty. It is assumed that the error term is independently and normally distributed.

$$b_1 = d*\text{pre-overlay SDI} + e \qquad (25)$$

$$P(\text{data}/\theta) = \prod_i p_N[b_{1i}|G_i(\text{pre}-\text{overlay SDI}_i, d_i, e_i), \sigma] \qquad (26)$$

Where,

b_{1i} = deterioration rate of SDI for pavement section i;

$G_i(\text{pre}-\text{overlay SDI}_i, d_i, e_i) = b_1 = d * \text{pre} - \text{overlay SDI} + e$;

σ = standard deviation of error term $\varepsilon_i \sim N(0, \sigma)$;

$p_N()$ = normal density function.

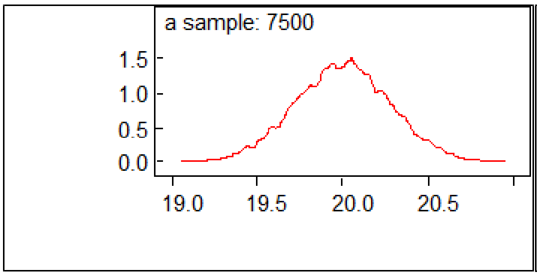
In the MCMC analysis, the prior information regarding the model parameters in Equation 25 were initially assumed to be independent and normally distributed based on the statistics in Table 6. The variance in the parameters may result from the combined effects of construction quality, traffic level, and environment condition.

After the data from all the pavement sections were loaded, a total of 7500 iterations were run during the burn-in stage in the software until the convergence of model was reached. This step could make the draws closer to the stationary distribution and less dependent on the initial values. Subsequently, another set of 7500 iterations were executed so that the model was able to learn from observations in the dataset and correct any bias contained in the priors and thus produce posterior distributions for the model parameters.

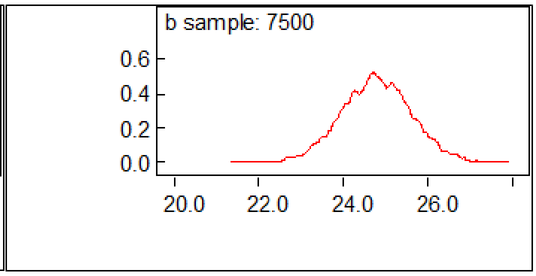
The distributions of model parameters in Equation 25 calculated from the MCMC methods are shown in Figure 15. It can be observed that with the probabilistic approach, the estimated parameters demonstrate certain variations. The statistical summary of model parameters is shown in Table 7. These variations can be incorporated into probabilistic LCCA through Monte Carlo simulation to interpret the effect of pre-overlay condition.

Table 7. Summary of MCMC results for SDI model parameters

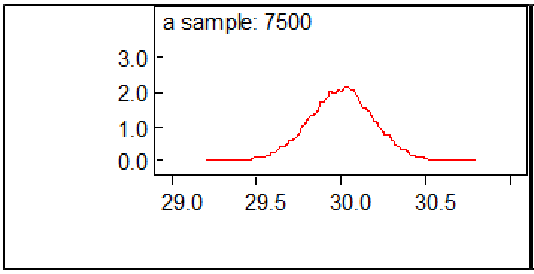
Model Parameters (Equation 25)	Minor Rehabilitation		Major Rehabilitation	
	Mean	Standard Deviation	Mean	Standard Deviation
d	2	0.03	3	0.02
e	2.5	0.08	1.2	0.06



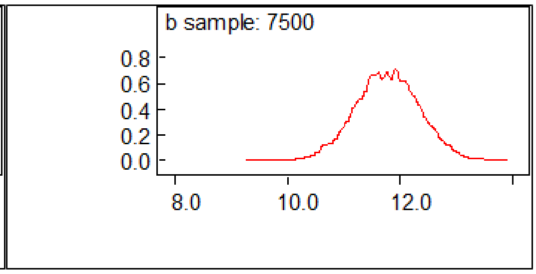
(a)



(b)



(c)



(d)

Figure 15. Distribution of (a) d*10 for minor rehabilitation; (b) e*10 for minor rehabilitation; (c) d*10 for major rehabilitation; (d) e*10 for major rehabilitation

3.3.3 Probabilistic LCCA

After the Bayesian analysis of the critical model parameter b_1 is known, the probability distribution of overlay life for different pre-overlay SDI can be calculated using the terminal SDI value of 2.4. Figure 16 shows the distribution of predicted overlay life after minor rehabilitation when pre-overlay SDI value is equal to 1. It can be seen that the distribution of overlay life is skewed.

The relationship between the pre-overlay SDI value and overlay life considering different percentiles is shown in Figure 17. It was found that as the pre-overlay SDI value increased, overlay life increased. Due to the skewed distribution of overlay life, the mean value of overlay life and the life at 75th percentile is considerably close. It can be seen that as the pre-overlay SDI value increases, the variation of predicted overlay life increases accordingly. On the other hand, statistics-based median values show that the overlay life difference between major rehabilitation and minor rehabilitation ranges from 2 to 4 years.

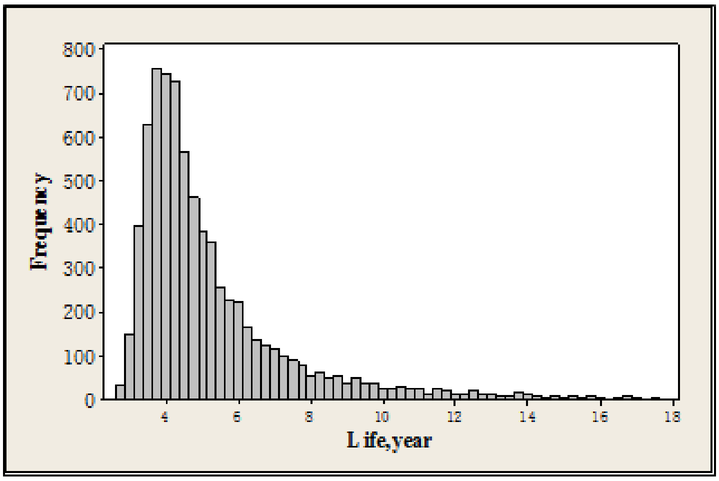
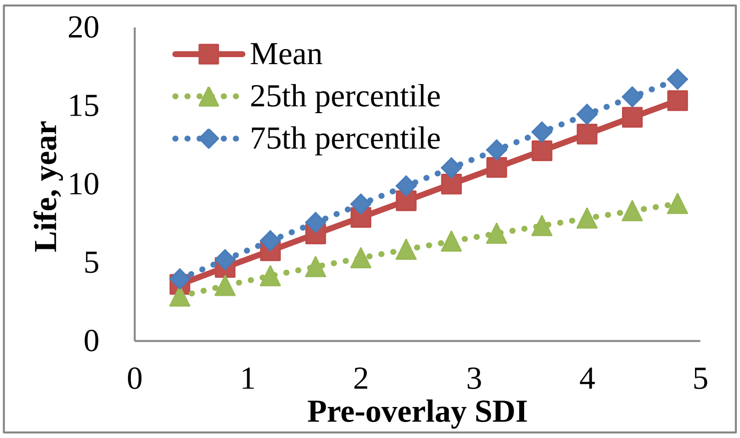
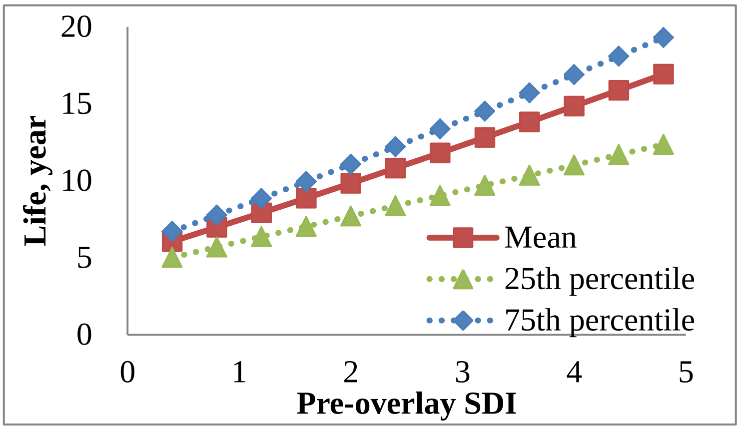


Figure 16. Distribution of overlay life after minor rehabilitation (pre-overlay SDI=1)



(a)



(b)

Figure 17. Relation between pre-overlay SDI and pavement life after (a) minor; and (b) major rehabilitation

After the distribution of overlay life is determined, LCCA considering the variation in discount rate and treatment cost can be executed. The discount rate is assumed to be uniformly distributed from 1% to 7% to cover the majority of the possible fluctuation due to economic markets. The treatment cost is assumed normally distributed with 10% CV to account for a medium degree of variation. The mean cost of minor rehabilitation is assumed to be $25 per square yard. In order to cover the scenarios with different treatment costs, major rehabilitations with two different mean cost ratios of 1.3 ($33 per square yard) and 1.5 ($38 per square yard) were considered in the analysis. The variations of the aforementioned inputs were simulated by Monte Carlo simulation.

Figure 18 shows the EUAC for minor rehabilitation when pre-overlay SDI value is equal to one. It can be obtained that compared to the frequency distribution of pavement overlay life, the distribution of EUAC is more symmetric.

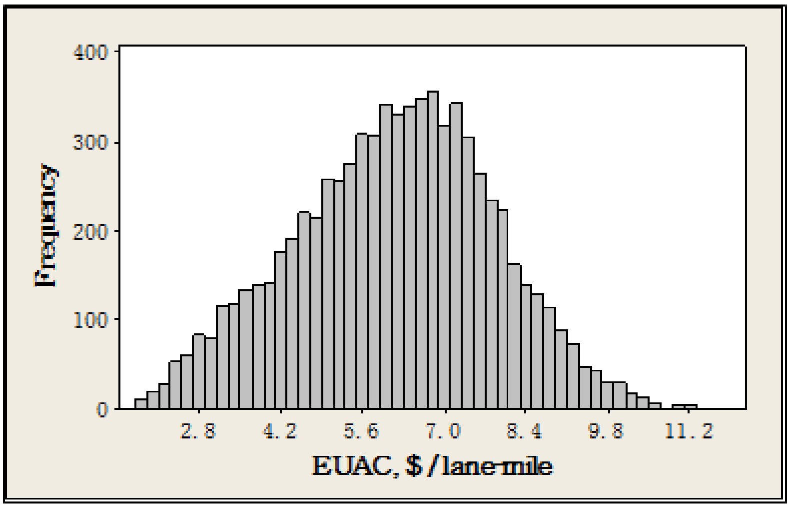
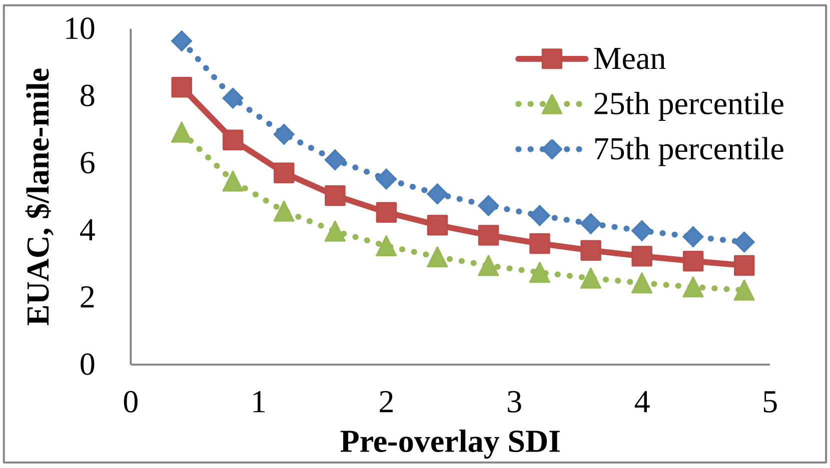
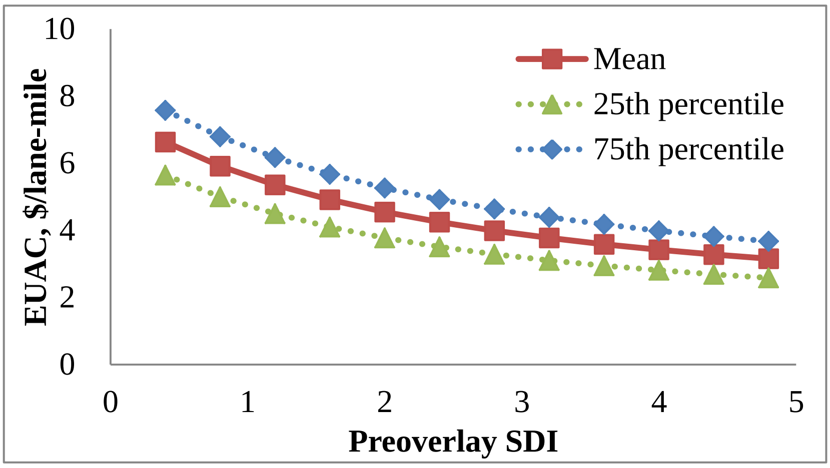


Figure 18. Distribution of EUAC after minor rehabilitation (pre-overlay SDI=1)

Figure 19 demonstrates the relationship between pre-overlay SDI and EUAC for minor rehabilitation considering different percentiles. It can be seen that the overall trend is similar to the trend shown in the deterministic analysis. However, after the consideration of uncertainty in LCCA, there is in general 25% to 35% of CV associated with the calculated EUAC. In addition, it was found that the CV of EUAC increased as the pre-overlay SDI value increased. This is because the variation range of EUAC kept relatively constant as the EUAC value decreased.



(a)



(b)

Figure 19. Relation between pre-overlay SDI and EUAC after (a) minor; and (b) major rehabilitation (Cost ratio=1.3)

Table 8 summarizes the mean, 25rh percentile, and 75th percentile values of EUAC of minor and major rehabilitation with different pre-overlay conditions. As shown in Table 8, the mean value of EUAC is similar to the result from deterministic analysis. The EUAC at different percentiles demonstrates the possible variation ranges with different pre-overlay SDI conditions. For instance, when the pre-overlay SDI value is 2, it can be seen that in terms of mean values, the EUAC of minor rehabilitation and major rehabilitation with cost ratio of 1.3 is close to each other. However, for the EUAC at 25th percentile, the EUAC of major rehabilitation surpasses the EUAC of minor rehabilitation; while for the EUAC at 75th percentile, the EUAC of major rehabilitation become smaller than the EUAC of minor rehabilitation. In this case, the EUAC of minor rehabilitation is not necessarily greater than the EUAC of major rehabilitation, and there is unneglectable possibility that the EUAC of major rehabilitation can be greater than the EUAC of minor rehabilitation.

Table 8. EUAC for minor and major rehabilitation sections with different pre-overlay conditions

Pre-overlay SDI	25th percentile			Mean			75th percentile		
	Minor rehab	Major rehab, cost ratio=1.3	Major rehab, cost ratio=1.5	Minor rehab	Major rehab, cost ratio=1.3	Major rehab, cost ratio=1.5	Minor rehab	Major rehab, cost ratio=1.3	Major rehab, cost ratio=1.5
0.4	6.9	5.6	6.5	8.3	6.6	7.7	9.6	7.6	8.7
0.8	5.5	5.0	5.8	6.7	5.9	6.8	7.9	6.8	7.8
1.2	4.6	4.5	5.2	5.7	5.4	6.2	6.9	6.2	7.1
1.6	4.0	4.1	4.7	5.0	4.9	5.7	6.1	5.7	6.5
2	3.5	3.8	4.4	4.5	4.5	5.2	5.5	5.3	6.1
2.4	3.2	3.5	4.0	4.2	4.2	4.9	5.1	4.9	5.7
2.8	2.9	3.3	3.8	3.9	4.0	4.6	4.7	4.6	5.3
3.2	2.7	3.1	3.6	3.6	3.8	4.4	4.4	4.4	5.1
3.6	2.6	2.9	3.4	3.4	3.6	4.1	4.2	4.2	4.8
4	2.4	2.8	3.2	3.2	3.4	3.9	4.0	4.0	4.6
4.4	2.3	2.7	3.1	3.1	3.3	3.8	3.8	3.8	4.4
4.8	2.2	2.6	3.0	3.0	3.2	3.6	3.6	3.7	4.2

3.3.4 Probability index for comparison of EUAC

From deterministic analysis results, the threshold of selecting different rehabilitation treatments is usually straightforward. The deterministic analysis result is derived based on the specific performance model and it may become biased if pavement conditions vary from the major trend. Probabilistic analysis, on the other hand, can provide more informative outputs regarding the selection of cost-effective treatment type.

Based on the probabilistic result, a probability index is proposed to compare the EUAC between major and minor rehabilitation that considers the uncertainties involved in the LCCA. The index is defined as the probability that the EUAC of minor rehabilitation sections is greater than the EUAC of major rehabilitation sections.

In other words, if the probability index is more than 50%, it indicates that minor rehabilitation is less cost-effective than major rehabilitation in terms of LCC. If the probability index is smaller than 50%, it indicates that the minor rehabilitation is more cost-effective.

In the analysis, for each pre-overlay SDI value, simulations were run for calculating the distributions of EUACs of minor and major rehabilitation sections, respectively. The study used simple random sampling (Yates et al, 2008) to randomly select one EUAC from minor rehabilitation sections and one EUAC from major rehabilitation sections. Then the comparison was made between the two EUACs to determine the one with greater value. Finally, after the process is iterated 30000 times, the probability index can be determined as the proportion that the EUAC of minor rehabilitation sections is greater than the EUAC of major rehabilitation sections. As a large number of samples were drawn from the distribution of EUAC, the use of simple random sampling can guarantee that the average sample would accurately represent the population. As a result, the calculated probability index is reliable. As for the parametric method that can also compare the difference between two groups, such as Z-test, it usually assumes that the test statistics follow normal distribution. Since the distribution of the calculated EUAC does not resemble normal distribution, the probability index calculated by Z-test is not as accurate as the one calculated by simple random sampling.

The probability index that compares EUACs of major and minor rehabilitation treatments at different pre-overlay SDI values is shown in Figure 20. It can be seen that generally probability index decreases as pre-overlay SDI increases. This is reasonable because the minor rehabilitation becomes more cost-effective as the pre-overlay SDI value increases. When the pre-overlay SDI value is within the range of 0-3, the probability index is considerably sensitive to the change of pre-overlay SDI. This indicates that pre-overlay SDI significantly affects selection of treatment type in terms of life-cycle cost when the pre-overlay condition is poor or fair. However, when pre-overlay SDI value is greater than 3, the probability index tends to stabilize. This indicates that the cost-effectiveness of treatment is not dependent on pre-overlay SDI when pre-overlay pavement condition is good.

The results shown in Figure 20 provide an effective way to select the cost-effective rehabilitation type when the rehabilitation cost is known. For example, when the cost ratio of major and minor rehabilitation is 1.3, the major rehabilitation is more cost-effective when pre-overlay SDI value is smaller than 2. However, when the cost ratio is 1.5, the major rehabilitation becomes more cost-effective when the pre-overlay SDI value is lower than 0.8. In this case, the minor rehabilitation would be always cost-effective since the pavement is usually rehabilitated before the SDI reaches a very small value. In general, the probability index between major and minor rehabilitation treatments becomes lower as the cost ratio of major rehabilitation with respect to minor rehabilitation increases.

Compared to the deterministic result, the proposed probability index based on probabilistic analysis provides more reliable and comprehensive information. Acting as a risk factor, it can quantitatively show the risk of choosing inappropriate treatment under different scenarios for decision makers. It can be implemented into PMS and reduce failure risk of pavement overlays in the roadway network.

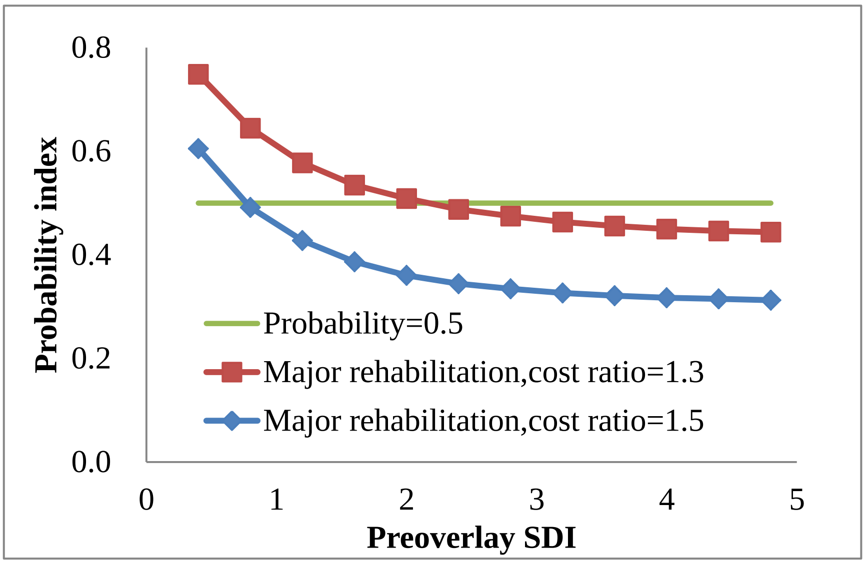


Figure 20. Probability index for major rehabilitation with different pre-overlay SDI

3.4 Chapter Summary

The understanding of overlay performance is vital for highway agencies as timely rehabilitation can minimize agency's costs and maximize overall benefits. This chapter analyzed the effect of pre-overly condition on pavement overlay performance. The following findings were concluded from analysis:

Overlay life was found to be log-normal distributed rather than normal distributed. Statistical test proves that the estimated overlay life for major rehabilitation is significantly higher than the overlay life for minor rehabilitation. The post-overlay SDI and rut depth is not sensitive to pre-overlay condition. On the contrast, post-overlay IRI is highly dependent on pre-overlay condition, treatment type, and highway system.

The study quantified the effect of pre-overlay condition on deterioration rates of

SDI, IRI, and rutting. It was found that SDI deterioration rate after minor rehabilitation is considerably sensitive to pre-overlay condition compared to the case of major rehabilitation. The result also shows that the IRI deterioration rate is more sensitive to pre-overlay condition in Interstate highway section compared to non-Interstate highway section.

Deterministic LCCA results show that there exists the SDI threshold where the EUCA is equal between major and minor rehabilitation. When the pre-overlay SDI value is smaller than the threshold, the EUAC of minor rehabilitation is higher than the EUAC of major rehabilitation; and vice versa. Sensitivity analyses show that the cost ratio between major and minor rehabilitation has significant influence on the SDI threshold.

Probabilistic LCCA results demonstrate the possible variations of LCC for different rehabilitation treatments. A probability index is proposed to quantify the probability that the EUAC of minor rehabilitation sections is greater than the EUAC of major rehabilitation sections. The analysis results show that generally probability index decreases as the pre-overlay SDI value increases or the cost ratio increases. The cost-effectiveness of rehabilitation treatments can be interpreted from probability point of view with the proposed probability index. It can quantitatively predict the risk of choosing inappropriate rehabilitation treatment under different scenarios.

Chapter 4: Performance-Related Pay Adjustment for In-Place Air Voids

4.1 Deterministic Analysis of Performance Based Pay Adjustment

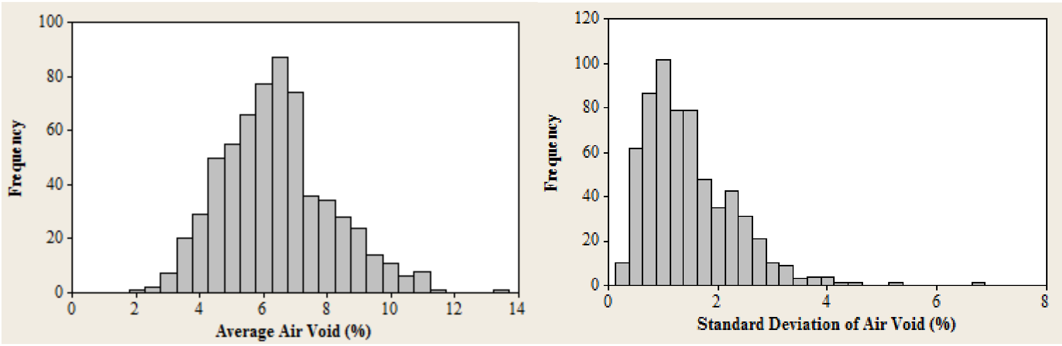
4.1.1 Analysis of in-place air void data

In an effort to empirically quantify the effect of air void variation on pavement performance, a large data set was initially collected from NJDOT for the pavement projects constructed within 1995 to 2007. The construction information usually comprise of route number, direction, section ID, milepost, station number, construction year, and application activity. The quality assurance data were obtained from construction records. Detailed quality assurance data were available at each lot including station number, lane, offset, air voids, and thickness of surface layer and intermediate/base layer. The number of lots at each project varies primarily depends on construction length.

The traffic data were collected through the NJDOT website, either from weigh-in motion (WIM) reports or the automatic vehicle classification (AVC) data. The traffic data show that the pavement sections have a wide range of traffic volumes. After that, quality assurance data were matched with the corresponding pavement performance data for each pavement segment. The construction projects without sufficient performance data or quality assurance data were excluded from the analysis. Finally, 55 sites were selected for further analysis, including 18 composite pavement sections and 37 flexible pavement sections.

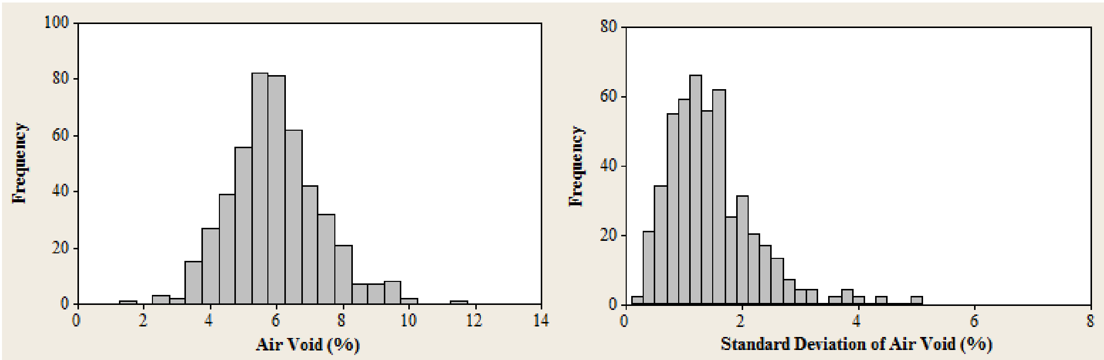
Totally there are 731 lots for the surface layer and 539 lots for the intermediate/base layer in the selected 55 construction projects. Figures 21 and 22 show the frequency distributions of averages and standard deviations of the air voids, respectively, for the surface layer and the intermediate/base layer. The results show that the average surface air voids are around 6% for both the surface and intermediate/base layers; while the standard deviations of air voids are around 1.5% for both layers. Statistical tests show that there is no significant difference in the air voids between the surface and intermediate/base layer. The NJDOT specification regulates that the constructed air voids for surface and base layer should be greater than 2% and smaller than 8%, the frequency distributions demonstrate that most of pavement sections have satisfied the construction quality requirement. Very few sections have air voids smaller to 3%.

To better understand the distribution characteristic, the Anderson-Darling test was used in the study. It is a statistical test to check whether a given sample of data is drawn from a given probability distribution (Anderson and Darling, 1952). The Anderson-Darling test results show that the normal distribution of air voids is only valid when the air void data greater than 8% are excluded from the data set. The data presented here also provides the variation range of in-place air voids that can be used in probabilistic analysis of the relationship between construction quality and pavement performance using the appropriate sampling technique.



(a) (b)

Figure 21. Frequency distributions of (a) averages and (b) standard deviations of air voids for surface layer



(a) (b)

Figure 22. Frequency distributions of (a) averages and (b) standard deviations of air voids for intermediate/base layer

4.1.2 Analysis of pavement performance data

Figure 23 illustrates the SDI development trends for all the 55 pavement sections considered in the analysis. The data shows a general pattern with sparse distribution. A linear regression model was used to capture the general development trend with the R-square value of 0.667. The linear regression equation shows that the SDI drops approximately 0.22 per year in the network level.

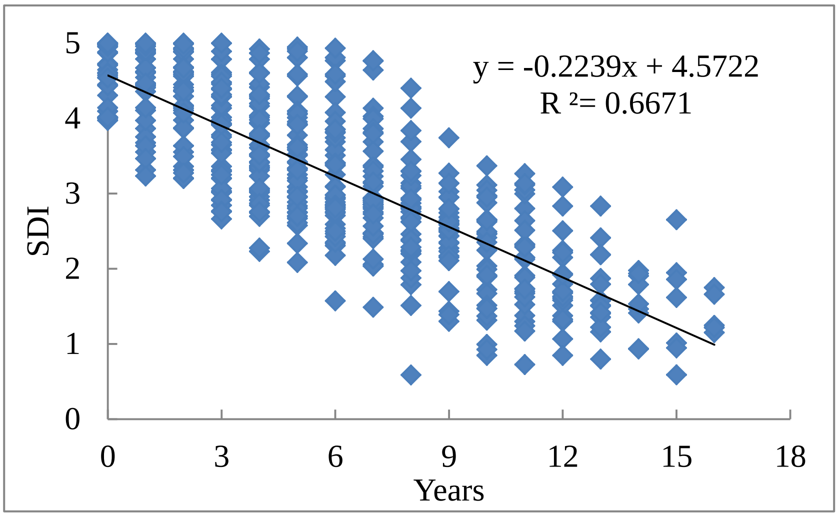


Figure 23. SDI developments for all the selected pavement sections

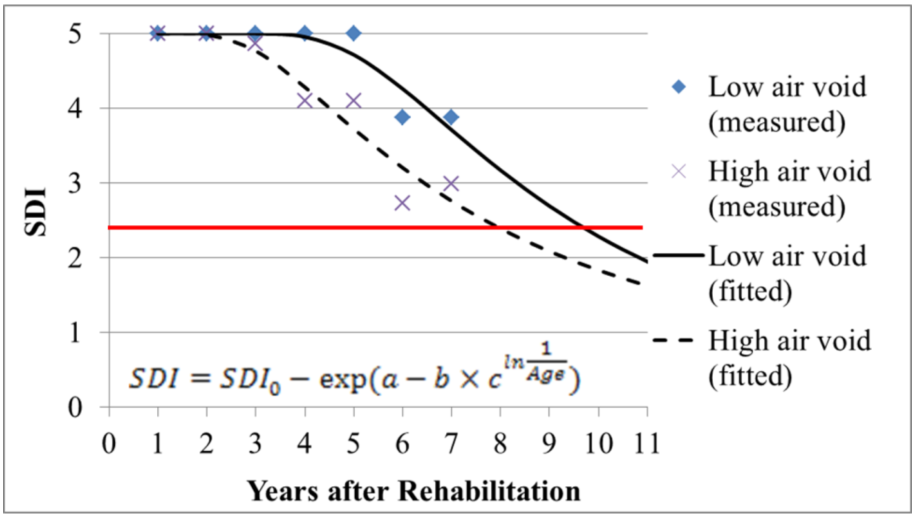


Figure 24. Examples of pavement performance deterioration at construction lots with different air voids

During the nonlinear regression, due to the variation of data, some regression parameters may become extremely large in order to achieve a good fitting. However, it is not reasonable as most of sites should have similar development trends. Therefore, certain boundary values were used to constrain the parameter to avoid the over fitting issue. For instance, the initial SDI should be greater than 4 and less than 5. It is noted that the development trends of SDI in several sections cannot be fitted with the sigmoidal function well, the service life were directly obtained from the observed SDI values. In addition, a comprehensive sigmoidal mode based on 55 sites can be established, as shown in Equation 27. The parameters are taken as the median values of parameters in all sections.

$$\mathrm{SDI} = 4.7 - \exp(1.54 - 11.4 \times 3.5^{ln\frac{1}{Age}}) \tag{27}$$

The goodness of fit was evaluated based on the coefficient of determination (R-square value). Figure 25 shows the histogram distribution of R-square values for all the regression models, The average R-square value for all the regression models is 0.66, which suggests that generally the model fit well the data. Since the goal of the regression is to predict the pavement life which is defined as the time when SDI drops to 2.4, the accuracy of the predicted pavement life will affect the further probabilistic analyses. Among all the analyzed sections, 35 sections (66%) contain the SDI data that is smaller than 2.4, which suggests that the real pavement life can be roughly estimated. For instance, in one section, the SDI after 7 years and 8 years are 2.9 and 2.1, respectively. It is safe to deduce that the real pavement life should be between 7 and 8 years. As the predicted life calculated based on regression analysis for the section is 7.4 years, the bias in the section is less than 1 year. In fact, it is found that the biases in the 35 sections are all smaller than 1 year, which suggests that the regression models are acceptable. Although the dynamic heteroscedasticity in variance is inevitable in the regression analysis regarding deterioration process, it doesn't result in fatal estimation biases in the study. The regression results for the rest 34% sections cannot be verified, however, the biases of the sections should not be significant different to the verified sections.

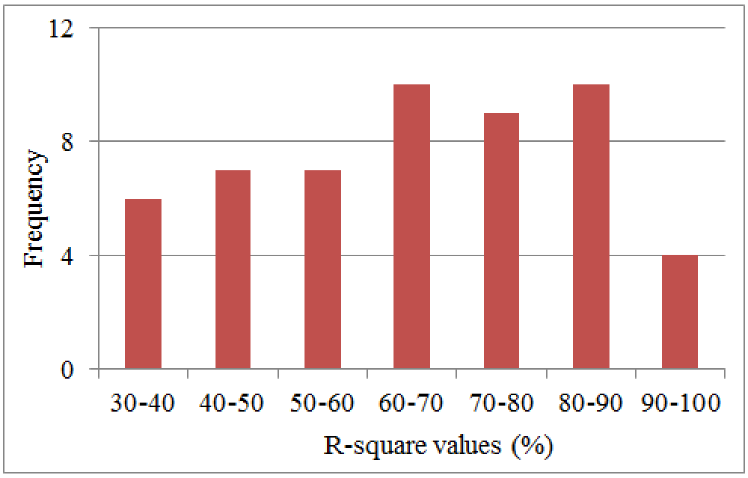


Figure 25. Frequency Distribution of R-square values

Figure 26 demonstrates the frequency distribution of pavement service life for all the pavement sections. The pavement life ranges from 5 to 15 years with the mean value and standard deviation of 9.8 years and 2.3 years, respectively. According to the Anderson-Darling test, the distribution of service life was found normally distributed.

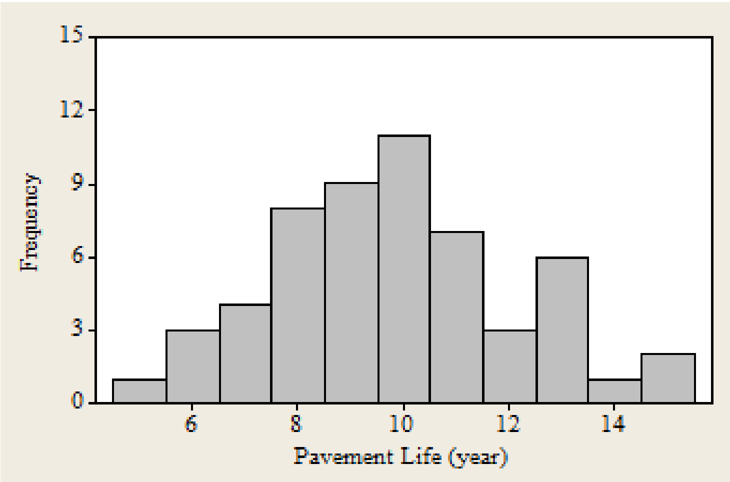
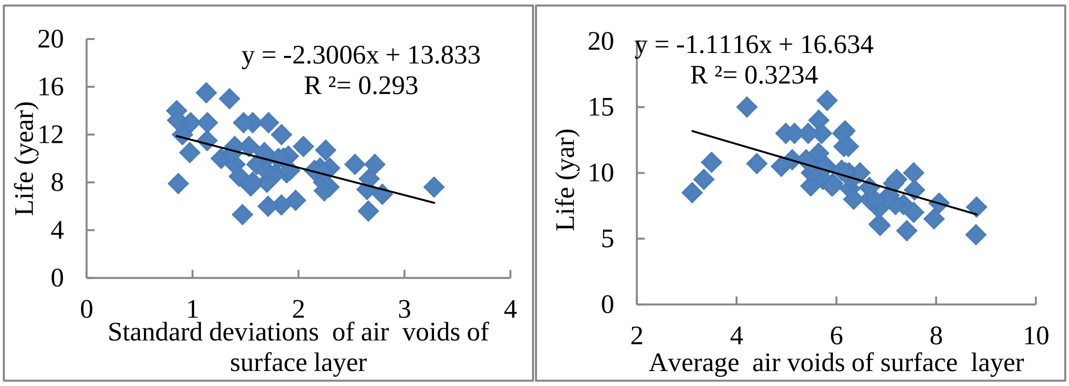


Figure 26. Frequency distribution of pavement life for all the sections

Although the pavement performance model used in this study only considers the age variable, non-parametric statistical tests were conducted to identify whether pavement structure or traffic level has statistically significant effects on pavement life in general. Since some of the data sets are skew distributed, the Mann–Whitney U test is preferred because it can be used for multiple comparisons without making assumptions on the distribution of the data (e.g. normality). It was found that there was no significant difference between the service life of composite pavement and flexible pavement (the two sided p-value is equal to 0.47 that is greater than 0.05) or between the pavement sections with different traffic volumes (the two sided p-value is equal to 0.66 that is greater than 0.05). This suggests that these pavement sections were well designed based on the expected traffic loading.

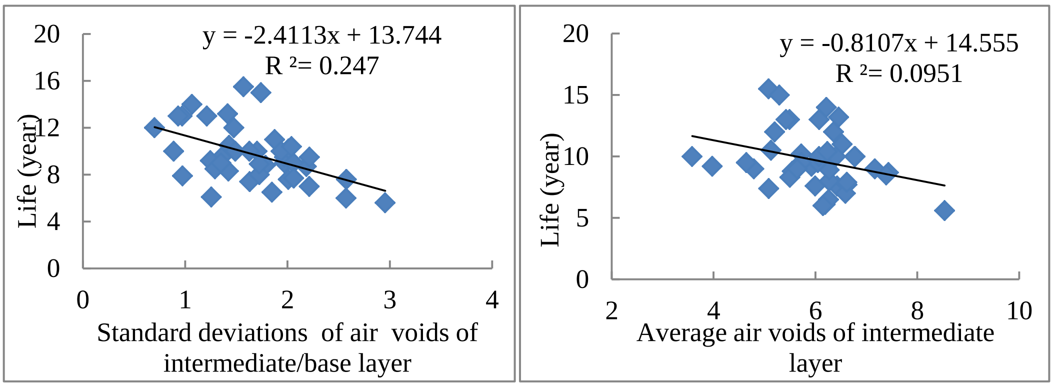
4.1.3 PD-based exponential performance model

The relationship between air voids and pavement life was investigated. Figure 27(a) and Figure 28(a) plot the variation of pavement life with the average air voids of surface layer and intermediate layer, respectively. Similarly, Figure 27(b) and Figure 28(b) plot the variation of pavement life with the standard deviations of air voids of the surface layer and intermediate layer, respectively. Regardless of other factors such as traffic and structure, the data indicate that the pavement life decreases as the air void increases or the standard deviation of air void increases. The results show that the air void of surface layer shows the relatively more significant effect on pavement life than the air void of intermediate layer. Approximately one percent increase in air voids of surface layer results in one year reduction of pavement life.



(a) (b)

Figure 27. Corrleations between (a) averages and (b) standard deviations of air voids of surface layer and pavement life



(a) (b)

Figure 28. Corrleations between (a) averages and (b) standard deviations of air voids of intermediate/base layer and pavement life

However, either average air voids or standard deviations of air voids cannot sufficiently explain the variation of pavement service life at a significant level. This indicates that both the magnitude and distribution of air voids may affect the real pavement life. A quality measure that combines both the sample mean and standard deviation into a single measure of quality, such as percent defective (PD) serves better for quality assurance. The PD can be regarded as the percentage of the sample which is not qualified (outside specification limits) and is related to PWL by the simple relationship: PD = 100 – PWL. Recent studies have recommended using PWL (or PD) in the QA over other quality measures (such as average absolute deviation (AAD), average and range) because it combines both the sample mean and standard deviation into a single measure of quality.

The study aims to develop a performance relationship to estimate expected pavement service life from as-constructed quality levels measured in the field. The exponential performance model that relates the expected life of as-constructed pavement to the quality characteristics is used (Weed, 2006). The performance model was developed including two quality characteristics (air voids of surface layer and intermediate layer). The thickness factor is not considered since it is not used as a quality measure for pay adjustment of pavement overlay projects in the current NJDOT specification. On the other hand, the pay adjustment for ride quality is based on the average smoothness value instead of PDs (NJDOT, 2007).

The final fitting equation is shown in Equation 28. It can be obtained that the R-square value is relatively high even though the model is developed at a network level. Originally, the data were separated into several categories based on the traffic level and structure types of pavement sections. However, it turned out that there is no significant difference among regression equations between different categories. For instance, the R-square value for composite pavements is 81% while the R-square value for flexible pavements is 71% when the data were separated for fitting.

$$\mathrm{EI} = e^{(2.47 - 0.003145\mathrm{PD}_1^{1.35} - 0.000023\mathrm{PD}_2^{2.36})} \qquad R^2=79\% \qquad (28)$$

Where,

PD_1 is percent defective of air void of the surface layer;

PD_2 is percent defective of air void of the intermediate layer.

Figure 29 plots the variation of expected pavement life with the PDs of air voids. The different parameters in Equation 28 for PD_1 and PD_2 indicate different decaying trends of performance with the air voids of surface layer and intermediate/base layer. It shows that the expected pavement life decreases relatively quickly if the air voids of surface layer are deviated out of the required range (2 to 8 percent).

Acceptable quality limit (AQL) and rejectable quality limit (RQL) are two important components in the statistical acceptance plan. Theoretically, material produced at acceptance quality level (AQL) should receive a pay factor of 1.00, material produced reached rejectable quality level (RQL) should be rejected, and material quality between AQL and RQL receives a pay factor smaller than 1.00. The values of RQL and AQL are usually based on the state experience rather than scientific analysis. Most AQL and RQL values are set using a combination of historical data, experience, and statistical tradition. State-of-the-practice suggests that AQL value of PD equaling 10 is commonly specified by agencies. However, RQL value can vary from a high value of PD equaling 75 to a low value of PD equaling 40 (Burati et al., 2004, Hughes et al., 2011).

Table 9. Rational check of pavement performance model with PDs

Percent Defective (PD) of air void		Expected Life (EL) in year
surface layer	Intermediate layer	
0	0	11.8

0	10	11.7
10	0	11.0
10	10	10.9
10	75	5.9
75	10	4.1
75	75	2.2

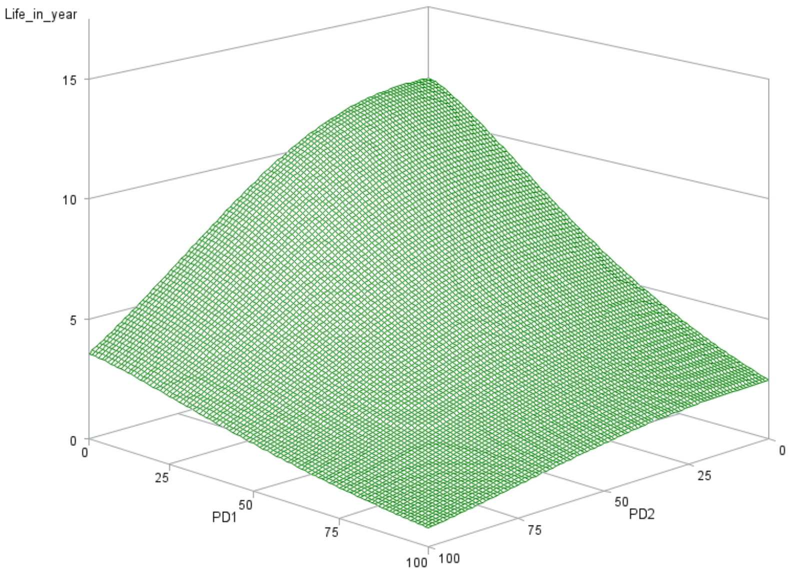


Figure 29. Illustration of exponential performance model with percent defectives

The exponential performance model was checked at AQL and RQL and extreme values to see if it is reasonable, Table 9. It can be seen that the when the air voids in pavement are in perfect condition (PD_1= PD_2=0), the life is 11.8 years. If both PDs are equal to 10 (AQL), the life is 10.9 years. This is reasonable because the reduction of PD to zero will not cause dramatic change of pavement life. If either of PDs reaches 75 (RQL), the pavement life will drop to 4 to 5 years. In the extremely worst case where both PDs are equal to 75, the life is reduced to 2.2 years. Although the zero defective or the large PD values may not be a frequent occurrence in practice, the range of predicted life is considered reasonably representative of field experience for typical overlay projects. Thus the model can rationally represent most of pavement conditions in New Jersey.

4.1.4 Pay adjustment derived from LCCA

After the relationship between quality measures and pavement life was established, pay factor can be determined using a life-cycle cost analysis approach. LCCA makes it possible to obtain a realistic and direct estimate of the cost of pavement premature failure resulting from deviations of construction and/or material quality. The development of pay factors based on LCCA can reflect the economic impacts to the highway agency brought by contractors. The underlying assumption is made that an appropriate disincentive (penalty) for inferior construction should be the added cost to the agency and that the incentive (bonus) for superior construction should be no greater than the added savings to the agency.

Realistic assumptions about analysis period and maintenance strategies are needed to derive simple equations that compute the net present values (NPVs) so that cost differences due to construction/material variations can be assessed for pay adjustment. Although the Federal Highway Administration (FHWA) suggests a standard analysis period chosen from the range of 35 to 40 years for pavement design decisions (Weed, 2001), there is no consensus on which method is the best for selecting an analysis period. A road segment is generally intended to remain in service indefinitely, and pavement overlays are expected to be applied continuously, although the service life of an overlay is finite. Therefore, there are two analysis period boundaries in the life-cycle cost analysis. The shortest analysis period is setting the analysis period equal to the shortest life before next resurfacing overlay; while the longest analysis period is setting the analysis period equal to the longest pavement life (infinity).

The model assumes that successive overlays are expected in an infinite horizon. Currently, most highway projects by NJDOT are resurfacing project on an existing pavement. In this case, if experience has shown that a typical resurfacing lasts 10 years, which is also proved in previous analysis of pavement performance data, then it is expected that additional overlays will continue to be required at approximate 10-year intervals after that. If the initial resurfacing were to fail one or two years prematurely, a practical decision would be to reschedule the overlay that was planned for the 10th year and do it one or two years sooner and then all future overlays would be moved earlier in time as well (Figure 30). It is noted that routine annual maintenance cost and user cost were not considered in the life cycle cost model.

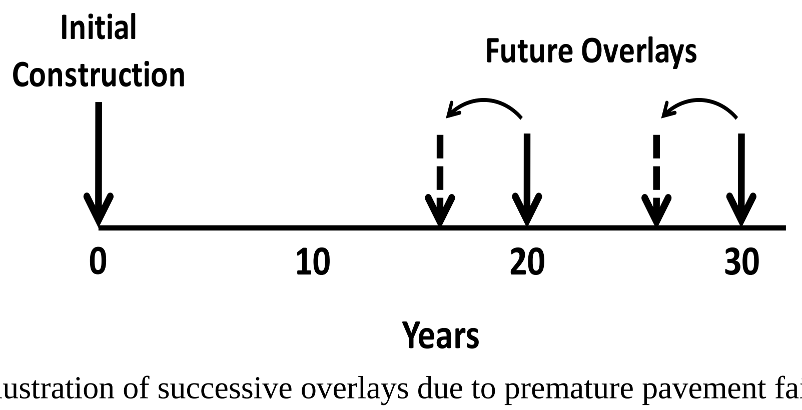


Figure 30. Illustration of successive overlays due to premature pavement failure (After Weed 2001)

The pay adjustment (PA) can be calculated as the difference of NPV from life-cycle cost models ($NPV_{as\text{-}constructed}$ - $NPV_{as\text{-}designed}$), Equations 29 and 30. In

Equation 29, the model assumes that future resurfacing overlays are expected in an infinite horizon (FHWA, 2004). In this case, if each resurfacing overlay lasts n years, additional overlays will continue to be required at approximate n-year intervals after that. If the pavement fails one or two years prematurely due to construction/material quality, all future overlays are moved earlier as well. On the other hand, in Equation 30, only the first resurfacing overlay occurred at the end of pavement life is considered. It is noted that routine annual maintenance cost and user cost were not considered in the life-cycle cost models.

$$PA = C\,(R^{DESLIF}-R^{EXPLIF}) / (1-R^{OVLIF}) \qquad (29)$$

$$PA = C/(1+DIS)^{DESLIF} - C/(1+DIS)^{EXPLIF} = C\,(R^{DESLIF}-R^{EXPLIF}) \qquad (30)$$

Where,

PA = pay adjustment for construction (same unit as C);

C = present total cost of future overlay;

DESLIF = design life of pavement (years) (pavement life at PD=AQL here);

EXPLIF = expected life of pavement that varies depending on construction/material quality;

OVLIF = expected life of successive overlays depending on overlay thickness;

R = (1 + INF) / (1 + INT) in which INF is the long-term annual inflation rate (4% here) and INT is the long-term annual interest rate (8% here);

DIS=discount rate which is calculated based on INF and INT.

Maintenance costs for rehabilitation treatments were estimated from a previous study conducted for the NJDOT (Zaghloul et al., 2006). The unit cost (per square yard) equations used for milling and overlay of asphalt layer are shown in Equation 31. These equations provide the flexibility to incorporate the actual design thickness and also eliminate the need for assumptions about the components of the treatments.

$$\text{Cost (\$)} = 3.98M + 7.0T_{ac} \qquad (31)$$

Where,

M = thickness of milling in inches;

T_{ac} = thickness of asphalt overlay in inches;

Table 10. Pay adjustment calculated from life-cycle cost analysis
(For one lane-mile pavement segment in $1000)

Percent Defective (PD) of air voids		Mill 2" + overlay 2" with 7.2-year overlay life	
Surface layer	Intermediate layer	Analysis period with successive overlays	Analysis period with one overlay
0	0	14	3
0	10	13	3
10	0	1	0
10	10	0	0
10	30	-11	-3
30	10	-39	-9
30	30	-49	-12
30	75	-114	-27
75	30	-132	-32

Table 10 shows the pay adjustment calculated from the life-cycle cost analysis for 2-inch milling and 2-inch overlay. The service life of 7.2 years is assumed for the 2-inch milling and 5-inch overly as it was calculated in Chapter 3 and represents the mean value of life for minor rehabilitation. Pay adjustments were calculated for the shortest and longest analysis periods. This determines the boundary values for determining the performance-related pay adjustment. In other words, the performance-related pay adjustment should fall in the two boundary values depending on the real practice of maintenance strategy in pavement management systems used by state agencies. The results show that the max bonus is around one tenth of max penalty, which is consistent with the rule of thumb currently used in quality assurance specifications. The pay adjustment could be significantly affected by the maintenance strategy if it is estimated using the short analysis period; while the pay adjustment calculated using the long (infinite) analysis period provides a conservative boundary that is not sensitive to the maintenance strategy. Therefore, the framework provides the flexibility of determining the pay adjustment based on the state agencies' maintenance practice.

4.2 Probabilistic Analysis of Performance-Related Pay Adjustment

4.2.1 Analysis framework using MCMC

The part of the dissertation aims at developing performance-related pay adjustments for in-place air void of asphalt pavements using a probabilistic modeling approach. In the current pavement performance models for PRS, pavement service life and pay adjustments are solely determined by the distribution of AQCs. However, a balance need to be considered between selecting many key AQCs affecting pavement quality and maintaining a simple and easily-understood model function for practical implementation. During pavement construction, aside from the AQCs considered in PRS, differences in contractors' procedures may exert certain influence in as-constructed pavement quality and thus produce unavoidable variability in pavement performance. Apart from that, the existing pavement conditions may have considerable impact on the variability in pavement performance. While the traffic, pavement structure, and other factors may result in additional variability, the effects of these variations on pay adjustments in PRS have not been modeled in common analysis for PRS. In order to capture the unobserved variability and establish a more robust pay adjustments for PRS, a probabilistic model using Bayesian approach with Markov chain Monte Carlo (MCMC) methods was proposed.

Figure 31 illustrates the development framework of the performance-related pay adjustments. Quality assurance data were collected from construction database and pavement performance data were extracted from pavement management system. The Bayesian approach with Markov chain Monte Carlo methods was used to develop the probabilistic model between expected pavement life and the level of deviation of in-place air voids. The significance, sensitivity, and consistency of the regression parameters involved in the model were investigated. Life-cycle cost analysis was performed to derive pay adjustments using different analysis periods and maintenance strategies. The probabilistic distribution of pay adjustments was presented after consideration of variations in design life, expected life and overlay life.

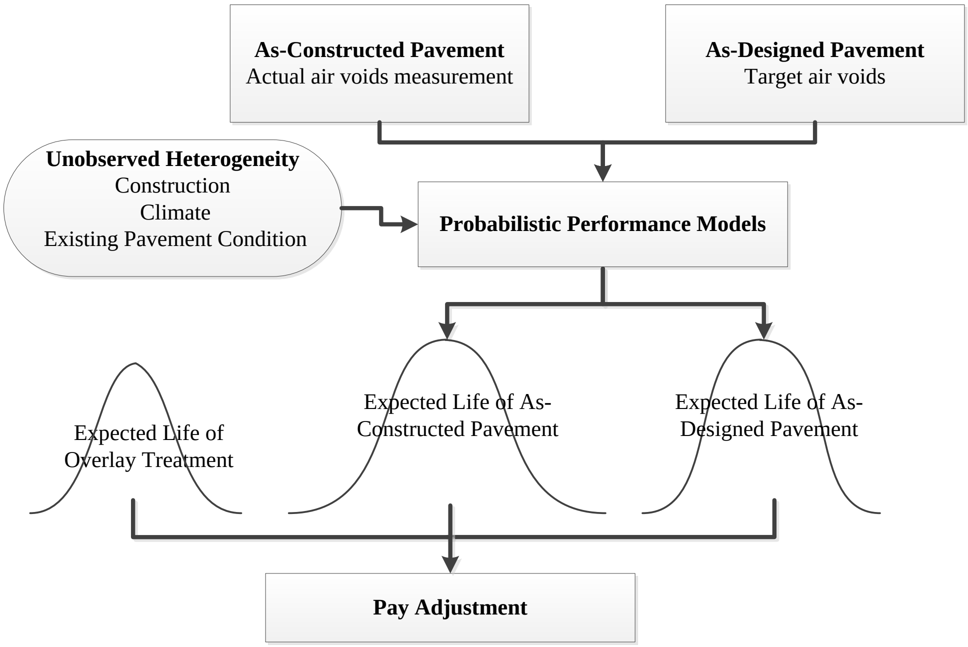


Figure 31. General diagram of developed PRS methodology

4.2.2 Estimated Distributions of Model Parameters

In Given the data consisting of calculated expected pavement life and PDs, the study aims at estimating the statistics of model parameters in Equation 32. The likelihood function in Equation 32 can be defined as Equation 33. An error term is added to incorporate the majority of the model's uncertainty. It is assumed that the error term is independently and normally distributed.

$$\mathrm{EL} = \mathrm{e}^{(\mathrm{a} - \mathrm{bPD}_1^{\mathrm{c}} - \mathrm{dPD}_2^{\mathrm{e}})} \tag{32}$$

$$\mathrm{P}(\mathrm{data}/\theta) = \prod_{\mathrm{i}} \mathrm{p_N}[\mathrm{EL_i} | \mathrm{G_i}(\mathrm{PD_{1i}}, \mathrm{PD_{2i}}, \mathrm{a_i}, \mathrm{b_i}, \mathrm{c_i}, \mathrm{d_i}, \mathrm{e_i}), \sigma] \tag{33}$$

Where,

$\mathrm{EL_i}$ = expected pavement life for pavement section i;

$\mathrm{G_i}(\mathrm{PD_{1i}}, \mathrm{PD_{2i}}, \mathrm{a_i}, \mathrm{b_i}, \mathrm{c_i}, \mathrm{d_i}, \mathrm{e_i}) = \mathrm{EL} = \mathrm{e}^{(\mathrm{a} - \mathrm{bPD}_1^{\mathrm{c}} - \mathrm{dPD}_2^{\mathrm{e}})}$;

σ = standard deviation of error term $\varepsilon_\mathrm{i} \sim \mathrm{N}(0, \sigma)$;

$\mathrm{p_N}()$ = normal density function.

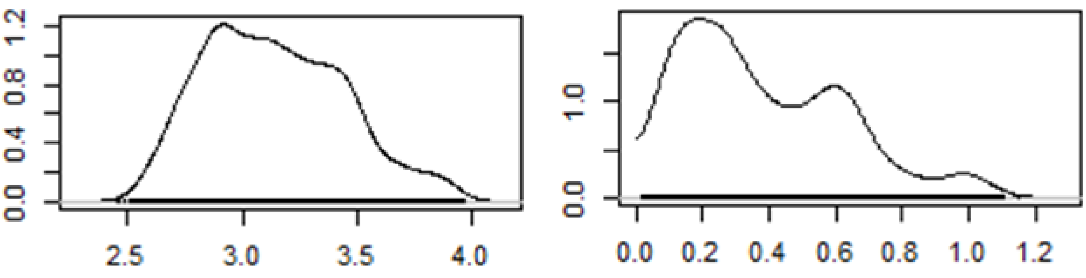
The model parameters in Equation 32 were initially assumed to be independent and normally distributed with mean values equal to a_1, b_1, c_1, d_1, e_1 and standard deviation values equal to $\sigma_a, \sigma_b, \sigma_c, \sigma_d, \sigma_e$, respectively. The variance may result from the combined effects of construction quality, traffic level, and environment condition.

Unlike the linear function or simple nonlinear function, the exponential function of expected pavement life (as shown in Equation 32) includes multiple exponents, which makes the execution of MCMC more challenging. Due to the complexity of the target function, the prior knowledge of model parameters becomes a major concern. Without proper setting, the Markov chains cannot be successfully generated for the proposed function.

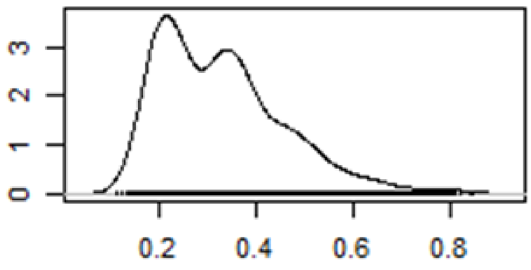
In this study, the five parameters calculated from the deterministic model served as initial values for the MCMC execution. Gamma distribution was assigned to be the distribution type for five parameters, as it can approximate many important types of distributions, such as exponential distribution and normal distribution. After the data from all the pavement sections were loaded, a total of 3000 iterations were run during the burn-in stage in the software until the convergence of model was reached. This step could make the draws closer to the stationary distribution and less dependent on the initial values. Subsequently, 5500 iterations were executed so that the model was able to learn from observations in the dataset and correct any bias contained in the priors and thus produce posterior distributions for the model parameters.

The Geweke statistical test was used to verify the convergence of simulated chains. The test can compares the means of two non-overlapping portions selected from the generated Markov chain, and test if the two portions of the chain are from the same distribution. If the values of the Geweke test are less than 1.96, the convergence is reached. The study compared the first 15% and last 50% proportions of 5500 sampling values, the values for a, b, c, d, e are 1.76, 1.26, -1.87, 0.07, -1.00, respectively, which suggests that the chain has converged.

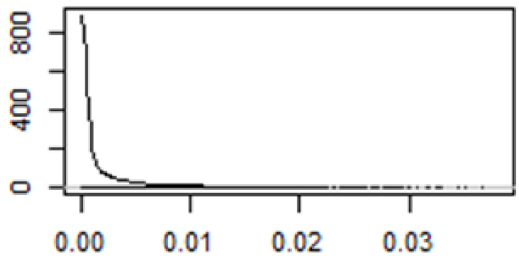
The distributions of five model parameters in Equation 32 calculated from the MCMC methods are shown in Figure 32. The types of distribution for five parameters seem complex and none of them has symmetric pattern. Table 11 summarizes the mean value, median value, and standard deviation of each model parameters. It can be observed that with the probabilistic approach the estimated parameters demonstrate unneglectable variations. The probabilistic model has a high level of goodness of fit for the dataset since after considering the variability of model parameters, all the data points fall within 95% confidence envelope of model predictions. In summary, the probabilistic distributions of model parameters in the expected pavement life model essentially reflect the impact from the variations in different pavement sections, which is influential in the prediction of pavement life.



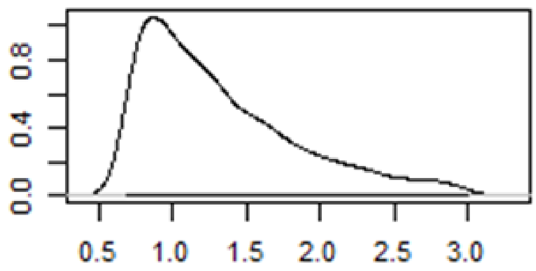
(a) (b)



(c)



(d)



(e)

Figure 32. Probabilistic distributions of model parameters of (a) a; (b) b; (c) c; (d) d; (e) e in the Expected Pavement Life Model

Table 11. Statistics of regression parameters calculated from MCMC methods

Parameter in expected pavement life model (Eq. 32)	Mean	Median	Standard deviation
a	3.14	3.11	0.3
b	0.39	0.33	0.24
c	0.33	0.31	0.13
d	0.0028	0.0005	0.005
e	1.33	1.19	0.53

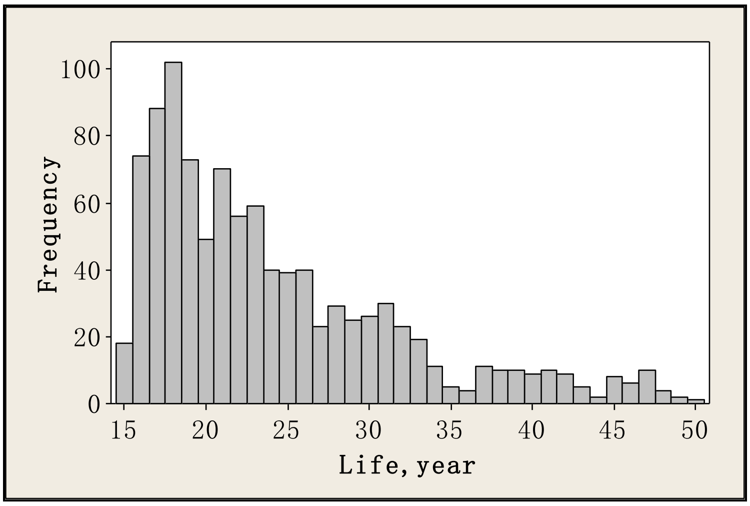
As the distributions of five parameters seem to be skewed and complex, it is difficult to use common types of distribution to describe the data. If they are assumed to be normal distributions, the further computation may yield great bias. Nevertheless, the complex distributions can be flawlessly recreated using sampling technique in the analysis. As each complicated distribution consists of 5500 values generated from the

MCMC process, a random selection of 1000 generated values from the samples is sufficient to represent the shape of distribution curve for each parameter.

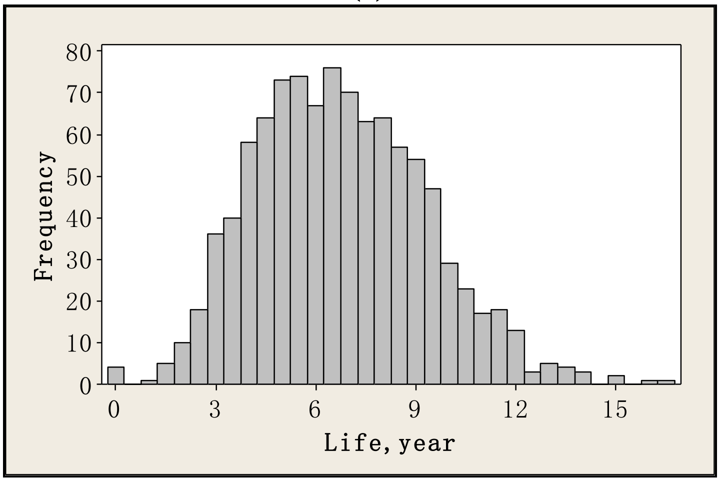
4.2.3 Estimated results of expected pavement life

After the distributions of model parameters were determined, the pavement life under different combinations of PDs of air void contents of the surface layer and the base layer can be computed using Monte Carlo simulation. During each simulation, five model parameters were randomly generated based on their distributions and the pavement life was calculated accordingly. After that, the distribution of predicted pavement life at the specific level of PDs can be computed.

Figure 33 demonstrates the distribution characteristics of the predicted pavement life at different combinations of PDs of air void contents (0 and 30) of the surface and base layers. These PDs were selected since they were critical control points in the pay equations used by many state agencies (Hughes 2005). It was found that the distribution patterns varied as the PDs of air void contents increased. The distribution of expected pavement life was found concentrated in a small range with a tail on the right side when the PDs were small. However, as the PDs increases, the distribution of expected life spreads in a wide range. This suggests that when the air void content is well controlled within the specification limits (such as PDs are small than 10), the pavement exhibits good performance with small variations. However, when the air void content is off specification limits (such as PDs are greater than 30), the pavement performance could exhibit large variations. Note that these observations are based on the current dataset and the model can be updated when more data are available.



(a)

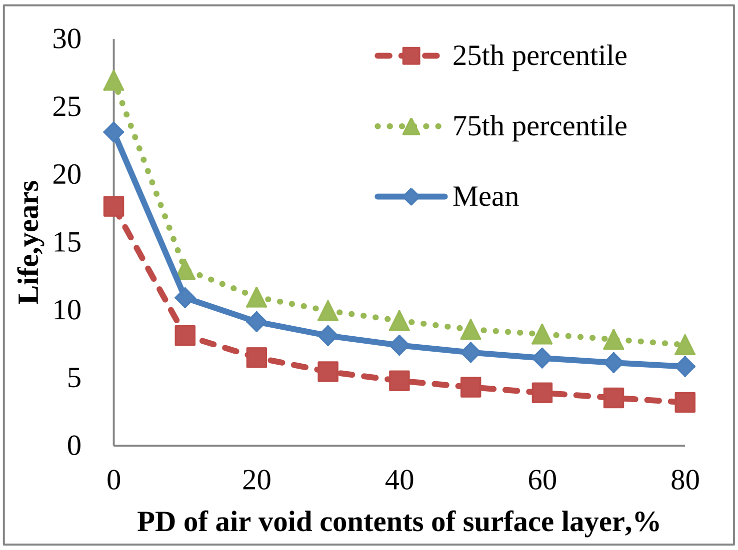


(b)

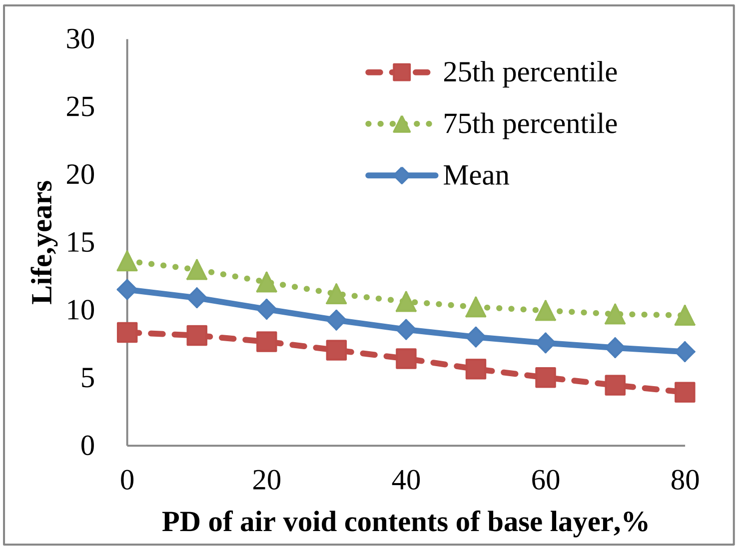
Figure 33. Distribution of expected pavement life when (a) PD_1=0 and PD_2=0 and (b) PD_1=30 and PD_2=30 (PD_1 is for air void of the surface layer; PD_2 is for air void of the intermediate/base layer)

In order to illustrate the variation of pavement life in pavement performance prediction, the 25th and 75th percentile of predicted pavement life were calculated to account for the range of variation, as shown in Figure 34. The results show that the standard deviation of expected pavement life ranges from 2.3 years to 5 years depending on different combinations of air void contents in the surface and base layer.

Similar with the observation from Figure 3, it was found that the variation of expected life increased when the air void content was off the specification limits at certain degrees, especially for air void contents of the surface layer. Therefore, more caution is needed to consider the variation of pavement life for the pavement sections having the relatively worse construction quality.



(a)



(b)

Figure 34. Expected pavement life with PD=10 for air void contents of (a) base and (b) surface layer

4.2.4 Analysis of pavement overlay life

In an effort to estimate pavement overlay life for different rehabilitation treatments, pavement performance data for 145 overlay sections were collected from the pavement management system of the NJDOT. These sections involved minor rehabilitation treatments such as 2-inch milling with 2-inch overlay without major structure restoration. The overlay life was calculated using the SDI data in a similar way as shown in Equation 18.

Figure 35(a) shows the distribution of calculated overlay life for minor rehabilitation treatments. The average life was found to be 7.5 years with the coefficient of variance (COV) of 43%. The data show that the life distribution is skewed and unsymmetrical. Figure 35(b) shows the Anderson–Darling test result. If the distribution is lognormal, the cumulative probability will follow approximately a straight line with p value greater than 0.05. Results show that the p value is 0.063 that suggests the lognormal distribution for overlay life.

The overlay life was then sampled from the lognormal distribution for further probabilistic analyses of pay adjustments. Given the means and standard deviation of a dataset X, the lognormal distribution can be generated using Equations 34 and 35 (Johnson et al. 1994).

$$\sigma_{lnX}^2 = \ln(CV_X^2 + 1) \tag{34}$$

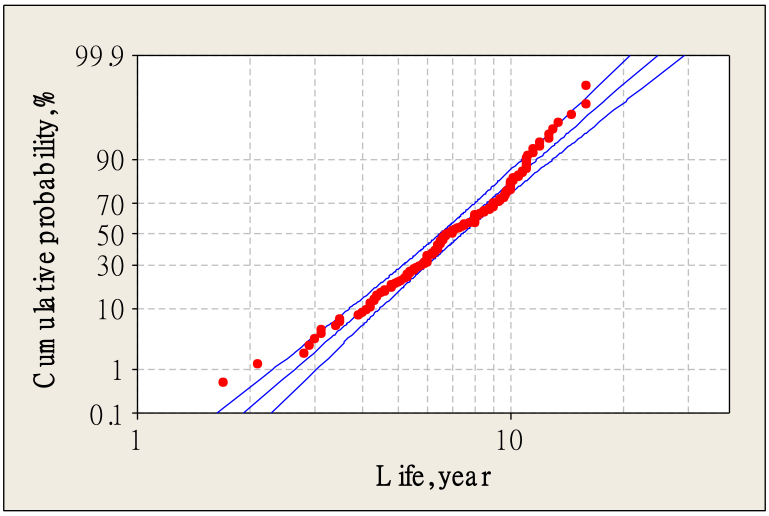
$$\mu_{\ln(X)} = \ln(\mu_X) - 0.5\sigma_{lnX}^2 \tag{35}$$

Where,

μ_X and CV_X are the means and coefficient of variation of original dataset;

$\mu_{\ln(X)}$ and $\sigma_{\ln X}^2$ are the means and variance of lognormal distribution.

(a)



(b)

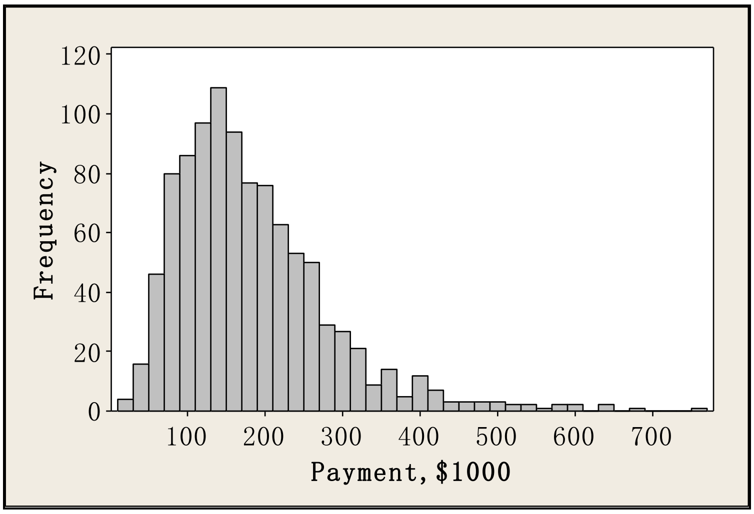
Figure 35. (a) Frequency distribution of overlay life and (b) Anderson–Darling test for lognormal distribution of overlay life

4.2.5 Probabilistic distribution of pay adjustments

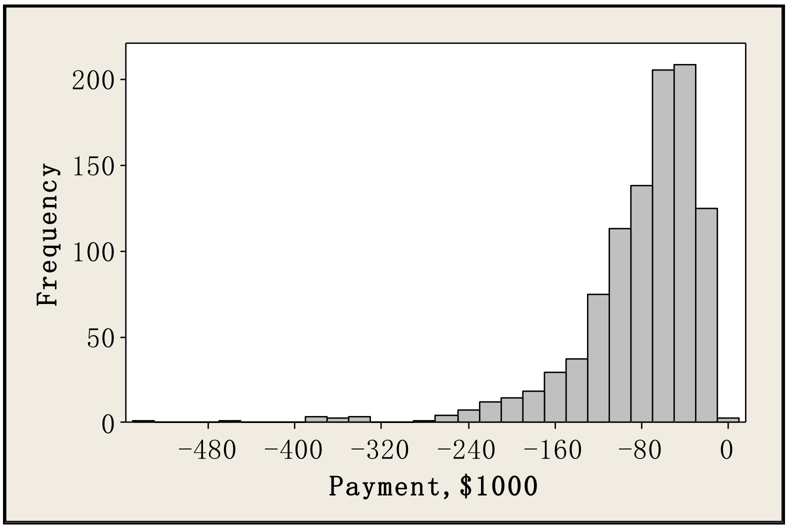
In the calculation of pay adjustment, the LCCA parameters in Equation 29 and Equation 30 were considered deterministic except for design life, overlay life, and expected life. The design life was calculated as the expected life when both PDs of air void contents of the surface layer and the base layer are equal to 10, which is the 100%

payment threshold in most pay equations used by state agencies (Hughes 2005).

The probabilistic distributions of pay adjustments at different combinations of PDs of air void contents of the surface and base layers are shown in Figure 36. The data demonstrate different patterns compared to the distributions of expected pavement life (Figure 33) because the model of pay adjustment considered variations of multiple life parameters (design life, expected life, and overlay life). The distribution of pay adjustment has a skew toward the more positive pay adjustment when PDs of air void contents are small, but a skew toward the more negative pay adjustments when PDs of air void contents are relatively large. This indicates that the possibility of having extremely high bonus or penalty is very small.



(a)



(b)

Figure 36. Distribution of pay adjustment when (a) PD_1=0 and PD_2=0 and (b) PD_1=30 and PD_2=30 (PD_1 is for air void content of the surface layer; PD_2 is for air void content of the base layer)

The pay adjustments derived from the probabilistic approaches were shown in Tables 12 and 13. The pay adjustments were calculated assuming the successive overlays in an infinite horizon and one single overlay, respectively. It is noted that the pay adjustments calculated with two maintenance scenarios determines the upper and lower boundary values of pay adjustments. In other words, the pay adjustment should fall in the two boundary values depending on the real practice of maintenance strategy in pavement management systems used by state agencies. It is noted that only the cost of pavement rehabilitation (milling and overlay) is considered in the current pay adjustment. However, the analysis approach can be extended to consider pavement preservation or routine pavement maintenance in the framework of LCCA.

Table 12. Comparison of pay adjustments using deterministic and probabilistic approaches assuming successive overlays

Percent Defective (PD) of air void content		Pay adjustment from probabilistic model ($1000)		
Surface layer	Base layer	25^{th} percentile	Mean	75^{th} percentile
0	0	114	167	235
0	10	104	151	219
10	0	0	2	10
10	10	0	0	0
30	30	-101	-65	-44
10	75	-113	-22	-2
75	10	-127	-85	-55
75	75	-192	-125	-84

Table 13. Comparison of pay adjustments using deterministic and probabilistic approaches assuming single overlay

Percent Defective (PD) of air void content		Pay adjustment from probabilistic model ($1000)		
Surface layer	Base layer	25^{th} percentile	Mean	75^{th} percentile
0	0	28	39	48
0	10	26	37	47
10	0	0	0	3
10	10	0	0	0
30	30	-21	-15	-11
10	75	-25	-5	0
75	10	-28	-20	-13
75	75	-41	-29	-21

The probabilistic results of pay adjustments literally provide the possible ranges of pay adjustments due to the variation in pavement performance modeling. It allows state agencies to have the flexibility of developing pay adjustments based on engineering judgement and the preferred level of reliability. It is important to build a level of confidence when determining economic gain or loss in agency cost for pay adjustment due to the variations in the material or construction related parameters.

4.3 Summary

This chapter presented the development of performance-related pay adjustments with deterministic and probabilistic modeling of pavement performance, with application to in-place air void contents of asphalt pavements. The following findings were concluded from analysis:

Analysis based on pavement management data from 55 projects shows that average surface air voids are around 6% and the standard deviations of air voids are around 1.5% for both layers. Statistical tests show that there is no significant difference in the air voids between the surface and intermediate/base layer. The mean value and standard deviation of pavement life is 9.8 years and 2.3 years, respectively. An exponential model was successfully developed to relate pavement service life to two quality characteristics (air voids of surface layer and intermediate layer). It shows that the expected pavement life decreases relatively quickly if the air voids of surface layer are deviated.

Deterministic LCCA results show that the pay adjustment could be significantly affected by the maintenance strategy if it is estimated using the short analysis period until the first overlay; while the pay adjustment calculated using the infinite analysis period provides a conservative boundary that is not sensitive to the maintenance strategy. It is expected that the successful implementation of performance-related pay adjustment greatly depends on the availability of pavement performance data, quality assurance data, and construction and maintenance costs.

Probabilistic LCCA results show that the Bayesian approach with Markov chain Monte Carlo methods can capture unobserved variations in the dataset and relate the quality measure of in-place air void contents to the expected pavement life with high goodness of fit. Compared to the deterministic approach, the probabilistic analysis could be more reliable in simulating the realistic pavement performance.

The analysis results indicate that there may be significant variations in the model parameters for estimating the expected pavement life due to deviations in acceptance quality characteristics. This implies that addressing considering variations in pavement performance modeling is a critical issue in deriving performance-related pay adjustments. The probabilistic modeling results facilitate considering the level of reliability in decision making of pay adjustments._

Chapter 5: Development of Performance-Related Pay Adjustment for IRI

5.1 Performance-Related Pay Adjustment of IRI

5.1.1 IRI deterioration model

Initial pavement smoothness after construction has significant impact on the long-term serviceability of pavements. A National Cooperative Highway Research Program (NCHRP) conducted by Smith et al. (1997) found that initially smooth pavements remain smoother over the life of the pavement. The study further showed that at least a 9 percent increase in pavement life could be resulted from a 25 percent increase in initial smoothness. This indicates that the initial IRI plays an important role in the deterioration process.

The dataset used by the study is collected from New Jersey DOT PMS. The pavement sections considered in the analysis are pavement projects constructed from 1999 to present that have the treatment of milling 2 inches and overlay 2 inches. Both the initial and annual IRI data for these sections were collected to determine the change in IRI over the years since the pavement was initially constructed. The dataset of 0.1 mile sections was subdivided into groups that have initial IRI ranging from 30 to 140 inch/mile in ten unit increments. The average IRI values at each year were calculated within each category for further analysis to reduce the measurement variation, as shown in Table 14.

Table 14. Summary of IRI dataset at each category

Year after application	IRI, inch/mile				
	30-40	40-50	50-60	60-70	70-80
2	37	45	54	65	74
3	38	48	59	71	78
4	40	49	58	75	81
5	52	59	62	77	87
6	49	58	65	81	87
7	59	64	69	76	88
8			71	91	100
9				70	95
10				78	95
11					97
12					102
IRI, inch/mile					
80-90	90-100	100-110	110-120	120-130	130-140
84	95	104	114	124	130
89	97	109	117	131	128
93	101	111	121	131	134
95	104	115	124	134	132
97	104	115	125	137	145
99	104	117	127	133	147
104	110	120	131	139	161
104	109	125	138	148	160
102	112	127	134	148	183
107	113	137	141	151	156
107	123	146	153	174	169

Regression analysis with exponential models was conducted to predict the IRI development with pavement age. If single-parameter regression analysis is applied to the whole dataset, the result turns out to be poor, as shown in Equation 36. However, after the initial IRI was considered as an explanatory variable in the model, the model function has much better accuracy, as shown in Equation 37. A response surface plot shown in Figure 37 illustrates the combined effect of initial IRI and age on IRI deterioration trend. It can be obtained that as the initial IRI increases, the deterioration rate increases significantly. The plot emphasizes the importance of the inclusion of initial IRI as an independent variable in the model.

Based on Equation 36 and Equation 37, there is a big discrepancy between the IRI deterioration rate in the single-parameter regression model and multiple-parameter regression models. The calculated deterioration rate in the multiple-parameter regression model is more realistic because it considered different initial IRI conditions.

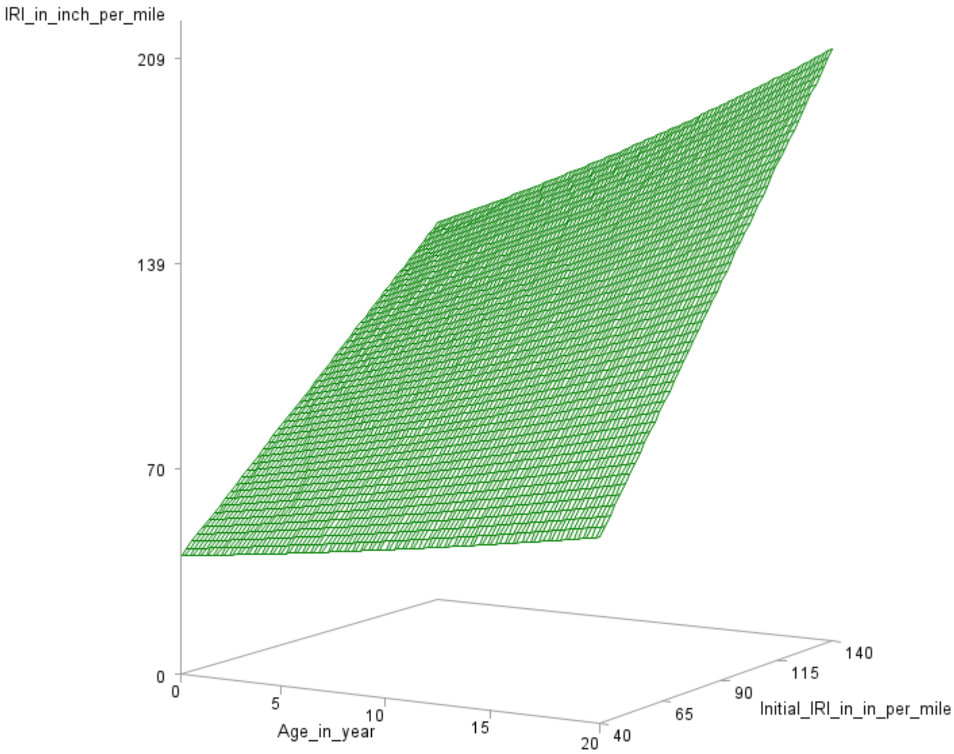


Figure 37. 3D plot of IRI development trend

$$IRI=88e^{0.029age} \qquad R^2=19\% \qquad (36)$$

$$IRI=IRI_0e^{0.02age} \qquad R^2=97\% \qquad (37)$$

5.1.2 Determination of pavement life and terminal IRI

After an accurate deterioration rate was determined, the IRI value at any given time for a pavement segment can be predicted. As for the determination of pavement life, a threshold of terminal IRI is needed. Table 15 demonstrates the typical threshold of IRI for different pavement condition recommended by FHWA. It can be seen that 170inch/mile has been regarded as terminal IRI value and widely adopted by previous researchers to determine pavement life. In reality, due to the fact that the IRI deterioration rate is usually small, when initial IRI is smaller than 60 inch/mile, the predicted pavement life predicted based on the criterion of 170 inch/mile will be beyond 40 years. This is considered as impractical as many overlay sections with the initial IRI value smaller than 60 inch/mile actually reach their life expectancy within 10 years. The phenomenon suggests that there is a need to adjust current terminal IRI threshold in order to meet the practical condition. It will be more accurate and meaningful to establish a pay adjustment for IRI that is based on real pavement life condition.

Table 15. Categories of pavement roughness thresholds (FHWA, 2001)

Condition Term	IRI, inch/mile
Very good	<60
Good	60-94
Fair	95-119
Mediocre	120-170
Poor	>170

Based on the previous analysis effort, the study found that, in practice, SDI is a good indicator to predict reasonable pavement life. It may become more accurate if the pay adjustment for IRI can incorporate the information regarding pavement life determined by SDI.

As the initial IRI after rehabilitation is widely used to determine pay adjustment for ride quality, it is critical to find the relationship between the initial IRI and pavement life determined based on SDI. With this thought in mind, the study collected another set of pavement performance data for the pavement sections that were treated with milling 2” and overlay 2”. Totally 43 sections were selected with initial IRI values smaller than 140 inch/mile.

The SDI and IRI measurement data at every 0.1mile were collected for each pavement section. The average values of SDI and IRI of each pavement section were calculated for each year. Figure 38 shows an example of SDI and IRI development trends for the pavement section in NJ 173.

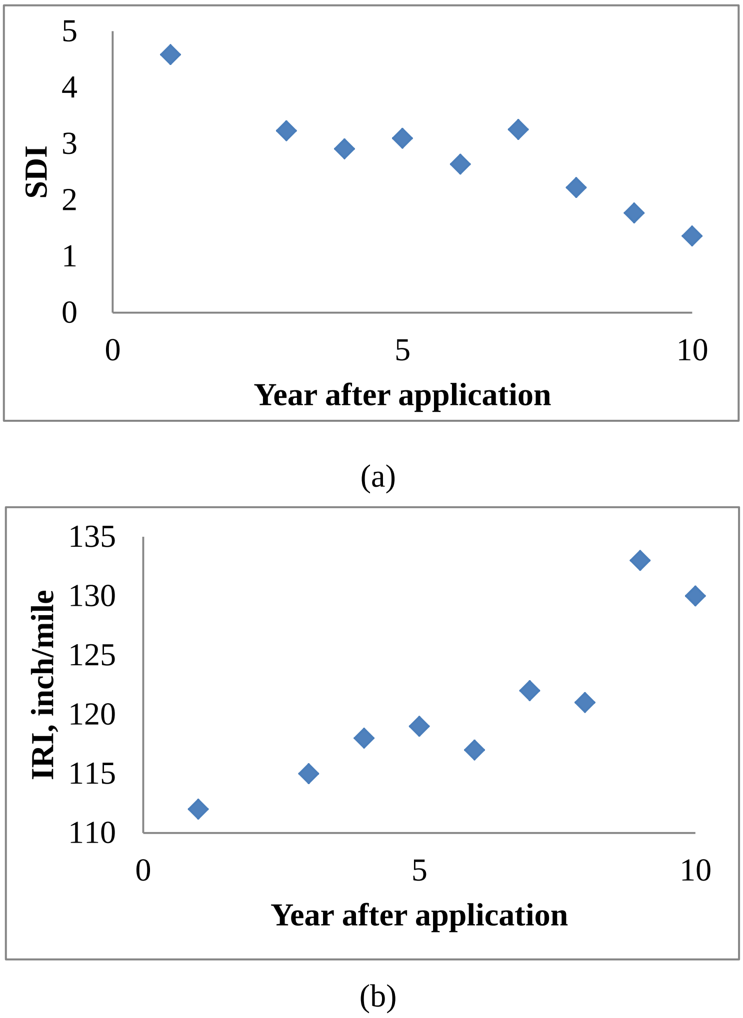
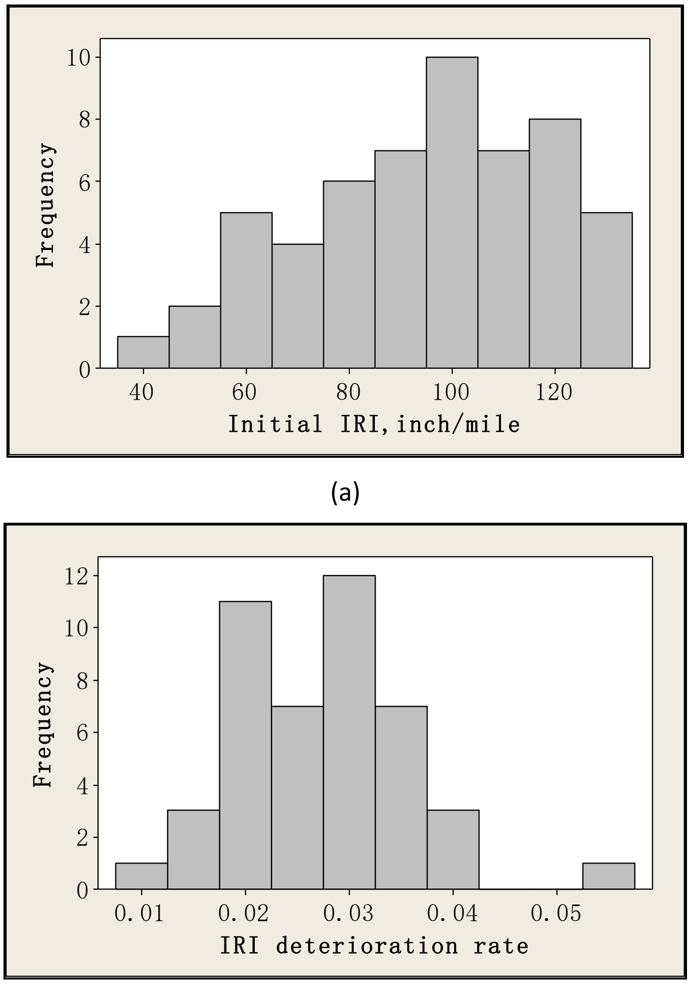


Figure 38. Pavement performance data in NJ 173 for (a) SDI; and (b) IRI

The study analyzed IRI data and SDI data for each section by using ordinary least square regression. The IRI development trend is simulated as an exponential function shown in Equation 19; while the SDI development trend is regressed based on sigmoidal function shown in Equation 18. After regression analysis, the average R-square value is 71% for SDI data and 62% for IRI data. Figure 39 shows the distribution of the calculated IRI deterioration rates and initial IRI values. It can be obtained that the initial IRI value after overlay application has relatively large variation. The majority of IRI deteriorate rates are within 0.02 to 0.04.



(b)

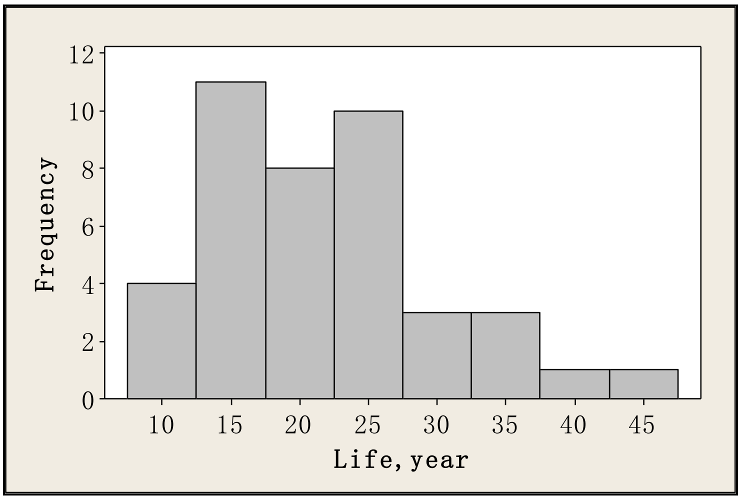
Figure 39. Distribution of (a) initial IRI value; and (b) IRI deterioration rate

In this study, two different performance indicators were used to determine pavement life. One is determined as the pavement age when IRI attains 170 inch/mile. The other pavement life is calculated when the SDI reaches the failure criteria

(SDI=2.4). The distributions of pavement life calculated by the two indicators are shown in Figure 40. It can be seen that for the SDI, the majority of life values are around 8 years. The pavement life at some pavement sections can reach up to 17 years, which is in accordance with common sense. As for IRI, the majority of life values are around 20 years if the terminal IRI is selected as 170 inch/mile. The pavement sections with good performance can have service life beyond 40 years, which is highly unconvincing. Thus, the result shows that the SDI is a better indicator in terms of pavement life.

The underlying reason for the high accuracy in the determination of pavement life by SDI is that SDI has small and standard scales (0 to 5), and its determination is comprehensive. On the contrary, IRI usually demonstrates large variation. Some pavement sections with poor condition may have an IRI value that is greater than 300 inch/mile. In this case, pavement life computed by IRI usually show significant large variation.

(a)



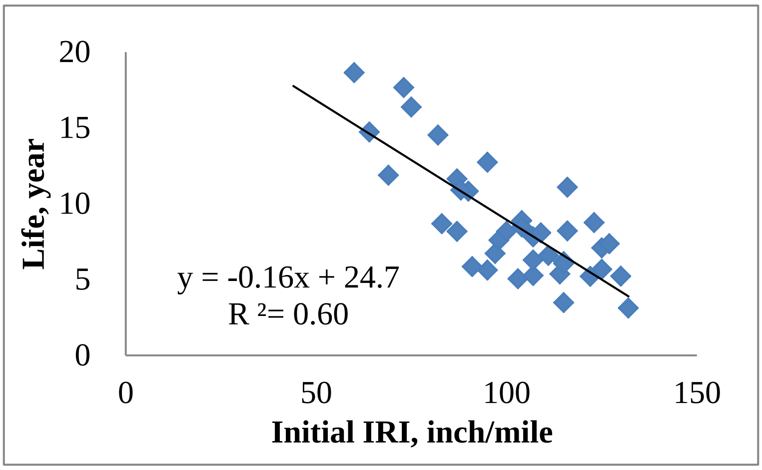
(b)

Figure 40. Pavement life distribution determined by (a) SDI; and (b) IRI

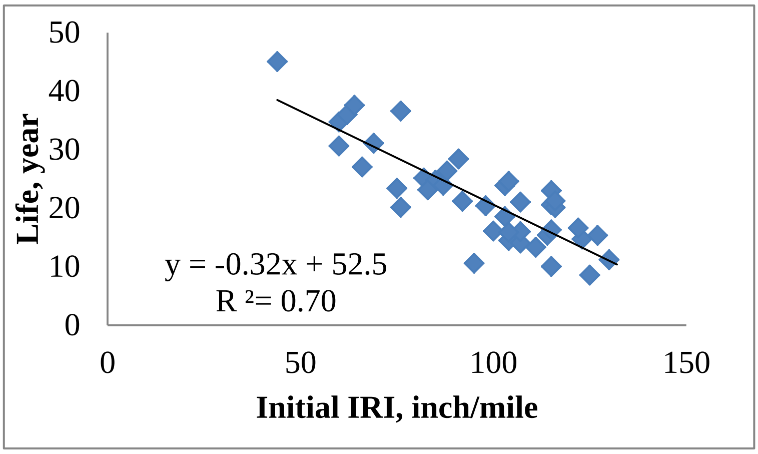
Based on the results from regression analysis, the correlation between the initial IRI value and pavement life can be established. Previous study usually considers the relationship between the initial IRI on pavement life determined by IRI, few studies considered the use of SDI to correlate initial IRI and pavement life. The key of the method proposed by the study is to link initial IRI and life determined by SDI. As shown in Figure 41, as initial IRI increases, predicted pavement life drops linearly.

Significant difference regarding the correlation for the two performance indicators can also been found. The study combines the predicted lives determined by SDI and IRI in one graph (Figure 42) based on the regression function shown in Figure 41. It can be clearly seen that when the initial IRI value is low, the predicted life based on IRI is significantly higher. As the initial IRI value increases, the gap between the two indicators decreases. The major reason for the difference is that when the initial IRI is low, the pavement service life determined by IRI is excessively large, while the service life determined by SDI is more realistic as compared to real condition.

Based on the figure, the study is able to predict pavement life for the pavement sections with different initial IRI values for the two indicators.



(a)



(b)

Figure 41. Correlation between initial IRI and pavement life calculated based on (a) SDI; and (b) IRI

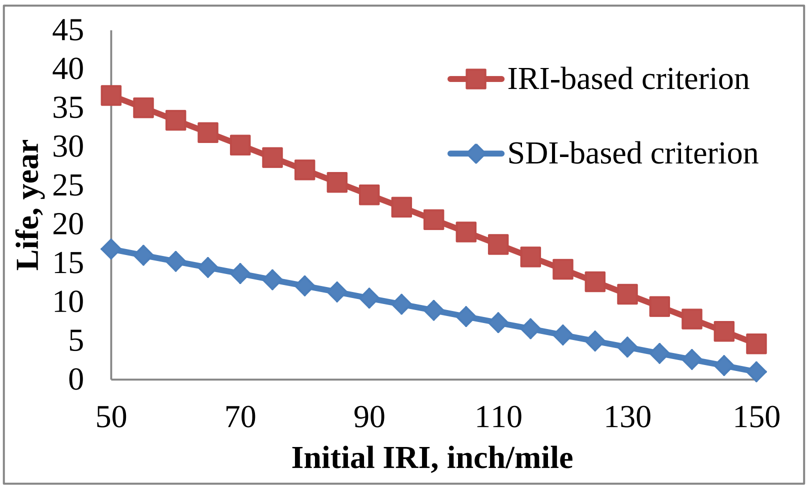


Figure 42. Comparison between pavement lives determined using different performance indicators

5.1.3 Determination of terminal IRI value

As pavement life determined by a terminal threshold of 170 inch/mile is not realistic, the prediction of possible IRI values when true pavement life is reached will be beneficial to provide practical recommendation for highway agencies.

For each section, initial IRI, IRI deterioration rate, as well as pavement life predicted based on SDI has already been determined. Based on Equation 19, the IRI values when pavement life is reached can be determined. After the process, the calculated IRI distribution can be plotted, as shown in Figure 43. It can be observed that the IRI values vary significantly from 90 inch/mile to 160 inch/mile. The mean of terminal IRI value is 128 inch/mile with a standard deviation of 15 inch/mile, which is much lower than 170 inch/mile. It may suggest that the majority of pavement sections need rehabilitation before IRI reaches 170 inch/mile.

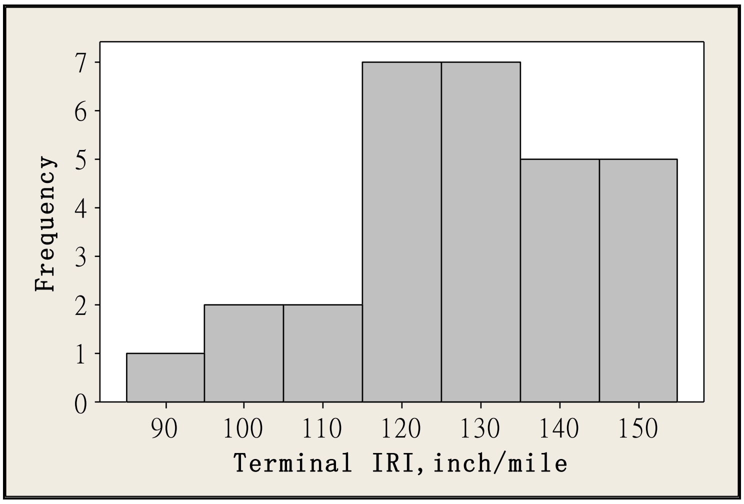


Figure 43. Distribution of terminal IRI when SDI reaches 2.4

Moreover, it is reasonable to believe that the initial IRI value may affect the terminal IRI value when pavement life is reached based on the criterion of SDI. The correlation between the initial and terminal IRI values for all sections were analyzed, as shown in Figure 44. It can be seen that there is a strong correlation regarding the initial IRI and the calculated terminal IRI. It is interesting to find out that the terminal IRI increases as initial IRI increases. The result implies that when consider IRI as an indicator for pavement serviceability, the terminal IRI should be adjustable instead of a constant value. In other words, the effect of initial IRI on the deterioration of pavement performance was considered because the terminal IRI is determined based on the realistic indicator of pavement failure (SDI in this study).

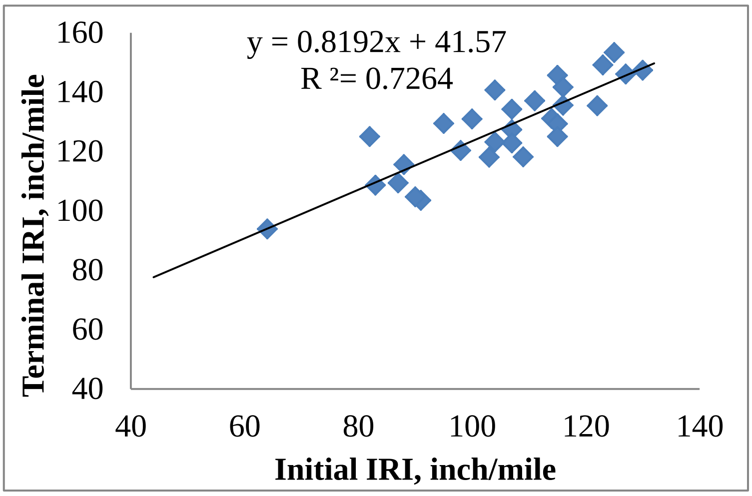


Figure 44. Correlation between initial IRI and calculated terminal IRI

5.1.4 Pay adjustment based on LCCA

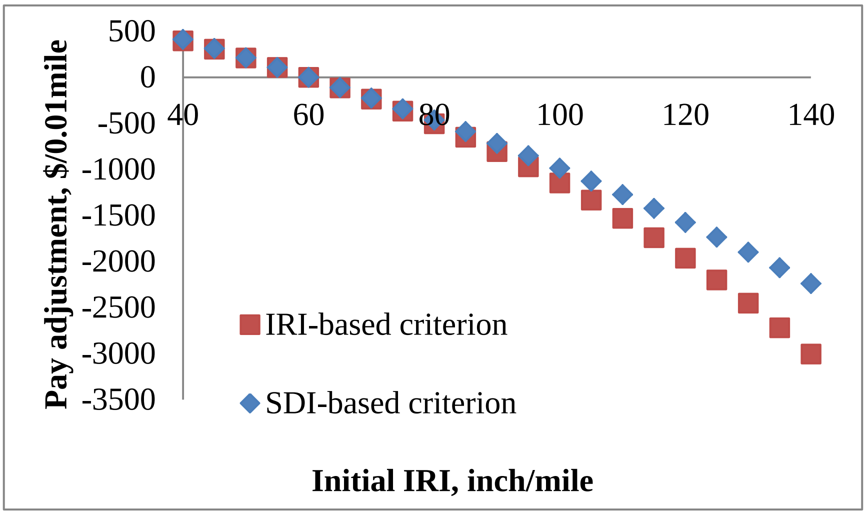
This study proposed to use pavement life computed by SDI to account for LCCA. The LCCA function is similar to the calculation of pay adjustment for air voids. The pay adjustments for IRI are determined by Equation 29 and Equation 30 to represent the scenarios of the application of one overlay and successive overlays, respectively. In this case, it is assumed that the pay adjustment for IRI is determined mainly based on the cost from application of treatment with milling 2-inch and overlay 2-inch asphalt surface. It is also assumed that the pavement sections have similar traffic condition, environmental condition, pavement structure, and material properties, thus the pay adjustment is only affected by initial IRI.

Figures 45(a) and (b) demonstrate the difference in the pay adjustments calculated based on the criteria of SDI and IRI, respectively, considering successive overlay application and single overlay application. The reference IRI value for zero pay adjustment is 60 inch/mile. The average of overlay life is assumed to be 7.5 years, which is based on the overlay analysis result in Chapter 3. Generally, the pay adjustment considering the application of one overlay suggests the lower bound of pay adjustment while the pay adjustment considering successive overlay applications represents the upper bound of pay adjustment.

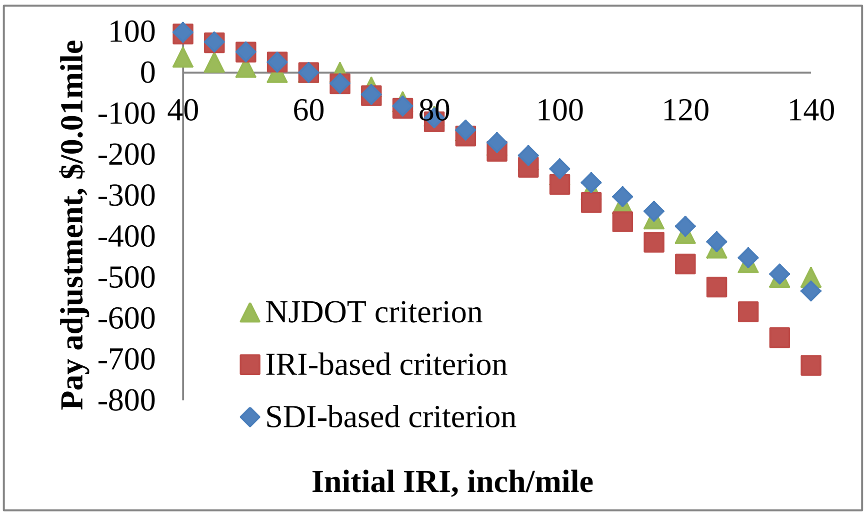
The results show that the difference between the two methods is not as significant as the difference in pavement life. It can be seen that compared to the pay adjustment calculated based on the criterion of SDI, the pay adjustment calculated based on the criterion of IRI has more penalties and slightly less bonus. It is noted that although the pavement lives calculated using two different criteria are much different, the difference of pay adjustment becomes significant only when the IRI value is greater than 100 inch/mile. This is because the pay adjustment is dependent on the relative life difference as compared to the pavement life with the reference IRI value, regardless of performance criteria.

The performance-related IRI pay adjustment was compared to the current pay factor used by the NJDOT, as shown in Figure 45(b). It can be found that the pay adjustment considering single overlay application is close to the pay adjustment currently used by the NJDOT when the IRI is greater than 70 inch/mile. On the other hand, the pay adjustment calculated based on SDI criterion tends to give more bonuses when the initial IRI value is low. It is noted that the current pay adjustment for IRI in NJDOT is a step function instead of a smooth curve.

The pay adjustment for the initial IRI was compared to the pay adjustment of in-place air void considering single overlay application. The maximum bonus of air voids when both PDs are zero values is $30/0.01mile; when initial IRI is as low as 45 inch/mile, the bonus can reach $75/0.01mile. On the other hand, when the air void content is high (PD_1=75, PD_2=30), the penalty can reach $320/0.01mile; and when the initial IRI value is as high as 140 inch/mile, the penalty is $533/0.01mile. It can be roughly deduced that the pay adjustment for IRI is twice as high as the pay adjustment for air voids. The result suggests that, in practices, initial IRI may play a more important role in pavement performance compared to in-place air voids content.



(a)



(b)

Figure 45. Comparison among different pay adjustments based on (a) application of

successive overlays; (b) application of single overlay

5.2. Probabilistic Pay Adjustment of IRI

5.2.1 Estimated distributions of model parameters through MCMC

As a major performance indicator, the initial IRI value can represent existing pavement condition and has strong effect on further performance deterioration rate. However, inevitable uncertainty exists among pavement sections due to various factors such as traffic level, climate, and subgrade. As a result, the deterministic pay adjustment for IRI is less convincing when dealing with pavement sections under different conditions. In this case, it is more beneficial to consider a probabilistic way to calculate the pay adjustment at different reliability levels. The probabilistic analysis can be used to develop more comprehensive performance-related specifications for IRI.

In order to achieve the goal, the MCMC methods were used to interpret the performance data and account for variations occurred in pavement performance modeling with respect to different initial IRI values.

Based upon the dataset containing initial IRI values and pavement life, the study targets at estimating the statistics distribution of model parameters (a and b) in Equation 38, respectively, considering the performance criteria of SDI and IRI. The likelihood function in Equation 38 can be defined as Equation 39. An error term with normal distribution is included to consider the uncertainty of model.

$$\text{Pavement life} = b * \text{Initial IRI} + a \tag{38}$$

$$\mathrm{P(data/\theta)} = \prod_{\mathrm{i}} \mathrm{p_N}[\text{Pavement life}_{\mathrm{i}} | \mathrm{G_i}(\text{Initial IRI}_{\mathrm{i}}, \mathrm{a_i}, \mathrm{b_i}), \sigma] \quad (39)$$

Where,

$\text{Terminal IRI}_{\mathrm{i}}$ = the calculated IRI value when pavement life is reached for pavement section i;

$\mathrm{G_i}(\text{Initial IRI}_{\mathrm{i}}, \mathrm{a_i}, \mathrm{b_i}) = \text{Pavement life} = \mathrm{b} * \text{Initial IRI} + \mathrm{a}$;

σ = standard deviation of error term $\varepsilon_{\mathrm{i}} \sim \mathrm{N}(0, \sigma)$;

$\mathrm{p_N}()$ = normal density function.

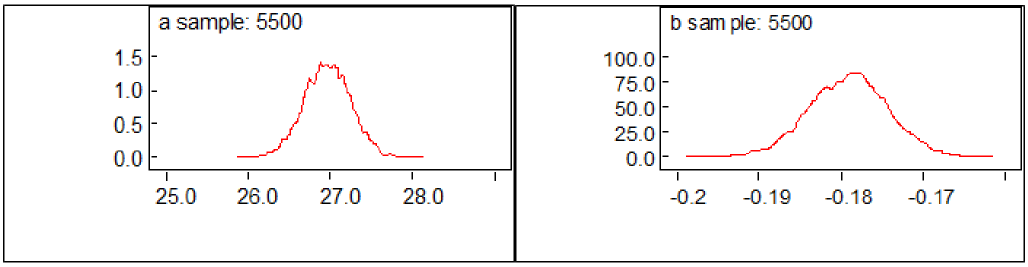
In the MCMC analysis, the prior information regarding the model parameters in Equation 38 were initially assumed to be independent and normal distributed based on the regression parameters determined in Figure 41.

After the data for all pavement sections were loaded into the WinBUGS software, a total of 5500 iterations were ran during the burn-in stage in the software until the convergence of model was reached. This step could make the draws closer to the stationary distribution and less dependent on the initial values, and additional 5500 iterations were executed so that the model was able to learn from observations in the dataset and correct any bias contained in the priors and thus produce posterior distributions for the model parameters.

The distributions of model parameters in Equation 38 calculated from the MCMC methods are shown in Figures 46 and 47. It can be observed that with the probabilistic approach the estimated parameters demonstrate unneglectable variations. The summary of model parameters is shown in Table 16. The types of distribution for the parameters seem close to be symmetric. The average value is similar to the parameters estimated by the deterministic approach. The probabilistic distributions of model parameters further reflect the impact from the variations in different pavement sections, which is influential in the prediction of pavement life. The variation can be incorporated into probabilistic LCCA through Monte Carlo simulation to show the effect of initial pavement smoothness on pay adjustment.

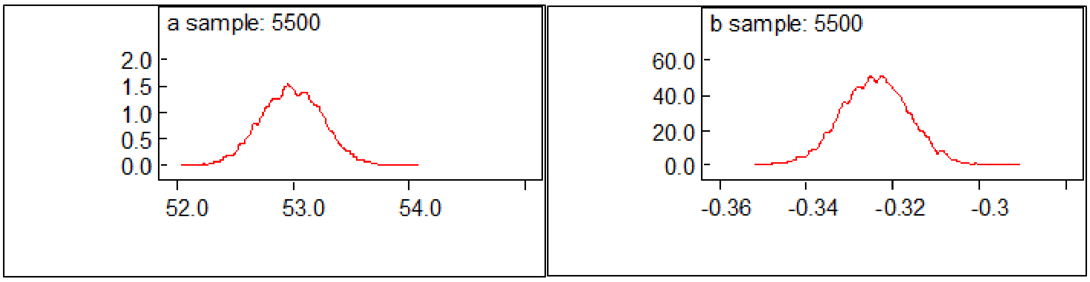
Table 16. Summary of MCMC results

Performance criteria	Parameter	Mean	SD	2.5th percentile	97.5th percentile
SDI	a	26.96	0.282	26.41	27.51
	b	-0.179	0.005	-0.189	-0.170
IRI	a	53	0.2674	0.00102	53
	b	-0.324	0.00794	2E-05	-0.324



(a) (b)

Figure 46. Distribution of parameter (a) a; and (b) b using SDI as performance criterion



(a) (b)

Figure 47. Distribution of parameter (a) a; and (b) b using IRI as performance criterion

5.2.2 Estimated distributions of pavement life

After the distribution of model parameters were determined by MCMC, the distribution of pavement life for a given initial IRI can be obtained subsequently. For every initial IRI value, 5500 Monte Carlo simulations were executed. During each run, the pavement life was determined based on the random sampling from the distribution of model parameters shown in Figures 46 and 47. Figure 48 shows the distribution of pavement life calculated based on SDI when the initial IRI value is 60 inch/mile. It can be seen that the distribution is close to symmetrical with the means value of 16.2 years.

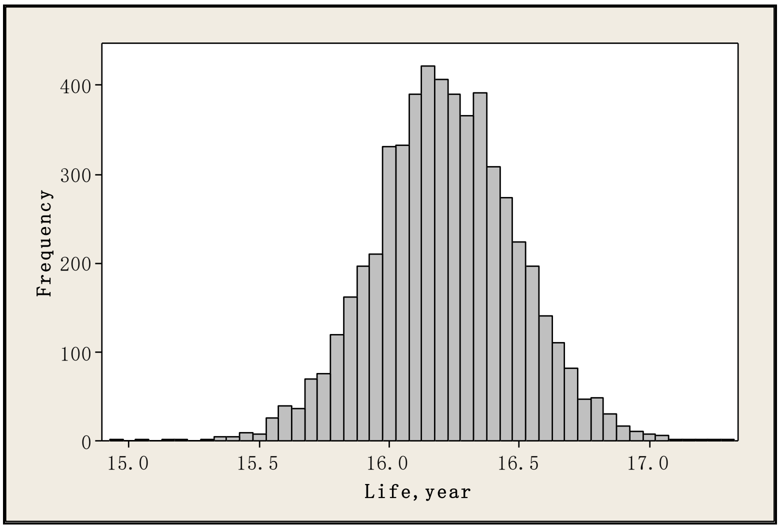


Figure 48. Distribution of pavement life when the initial IRI value is 60 inch/mile

The correlation between the initial IRI value and the mean value of pavement life is demonstrated in Figure 49. The pavement life was calculated using two different performance criteria. It can be seen that the trend is identical to the trend obtained using the deterministic approach with similar values (Figure 42).

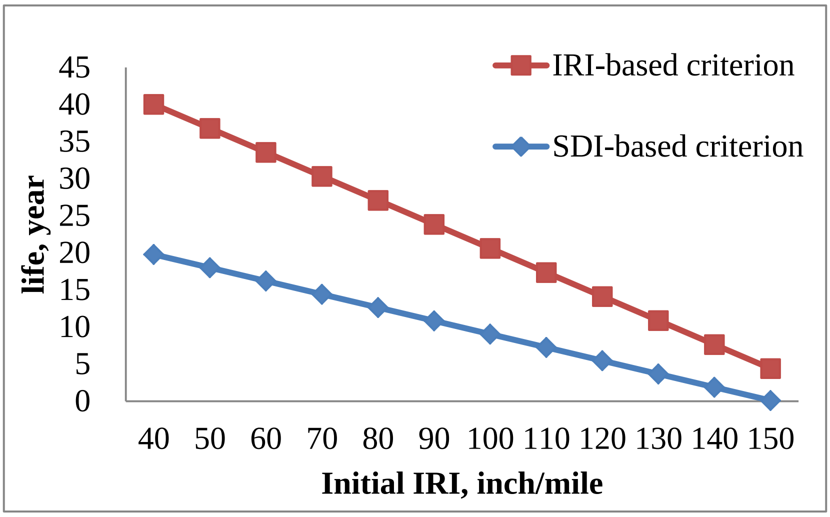


Figure 49. Correlation between initial IRI and mean pavement life

5.2.3 Estimated distributions of pay adjustment for IRI

After the distribution of pavement life is decided, pay adjustment for IRI can be finally determined by LCCA through Equation 29 and Equation 30. The variation of design life and expected life for different initial IRI values are considered in the analysis. Similar to the analysis of in-place air void in the previous chapter, the overlay life is assumed to be lognormal distributed with an average value of 7.5 years. Figure 50 demonstrates the estimated distribution of pay adjustment based on the performance criterion of SDI when the initial IRI value is 60 inch/mile considering the application of successive overlay. It can be seen that the distribution can be regarded as symmetrical with the mean value of zero pay adjustment.

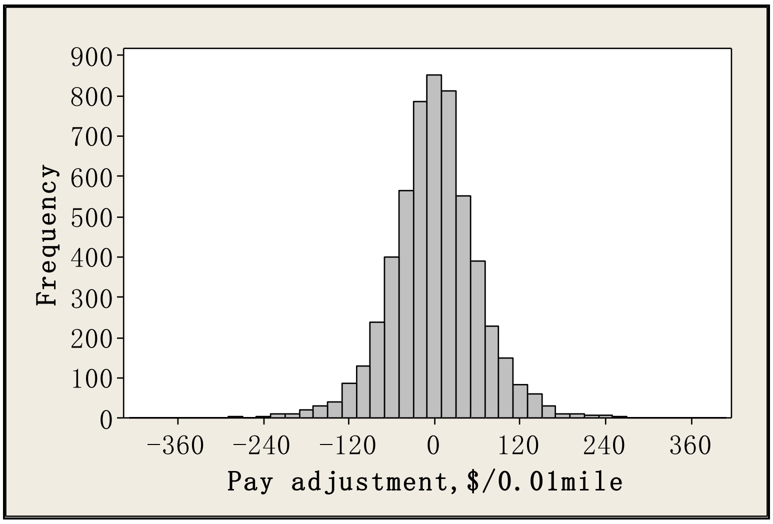
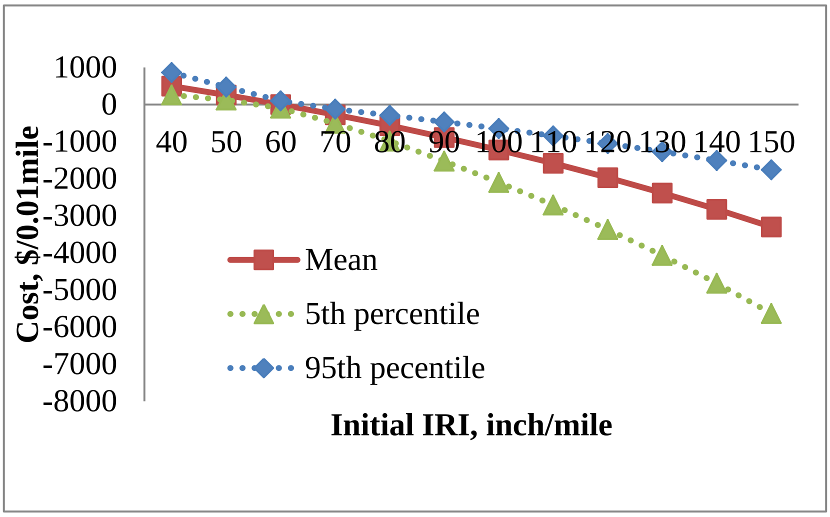


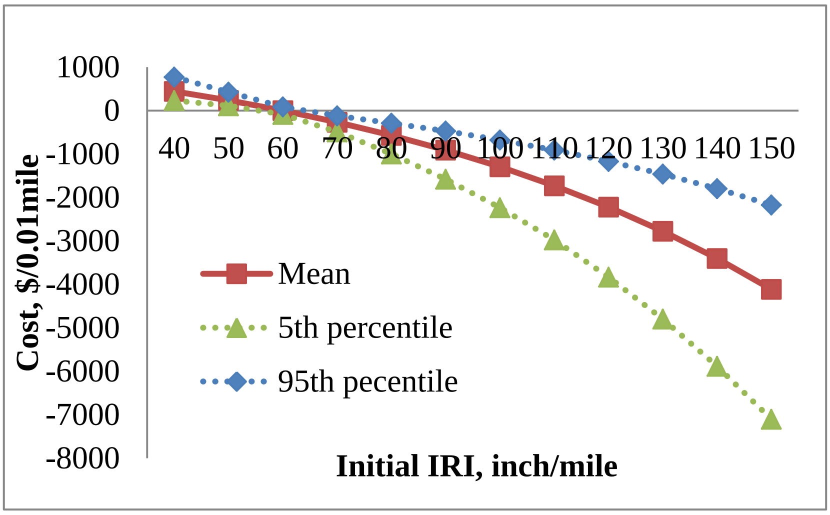
Figure 50. Distribution of pay adjustment when initial IRI=140inch/mile considering successive overlay application

Figure 51 shows the pay adjustment for IRI when successive overlay application is considered. In terms of mean values, the overall trend of pay adjustment based on probabilistic approach is similar to the trend determined based on the deterministic approach. Nevertheless, the probabilistic pay adjustment demonstrates the variation range of pay adjustment. The 5th percentile curve and 95th percentile curve were plotted to show the possible variation range of pay adjustment for different initial IRI values. It can be seen than the variation increases dramatically as the initial IRI value increases from 60inch/mile. The major difference between the pay adjustments using two different performance criteria can be found in the penalty region, which is similar to the case of deterministic analysis

Figure 52 shows the pay adjustment for IRI considering single overlay application. Compared to successive overlay scenario, the variation of pay adjustment for single overlay application shows much less variation. This is because the variation of overlay life was not considered.

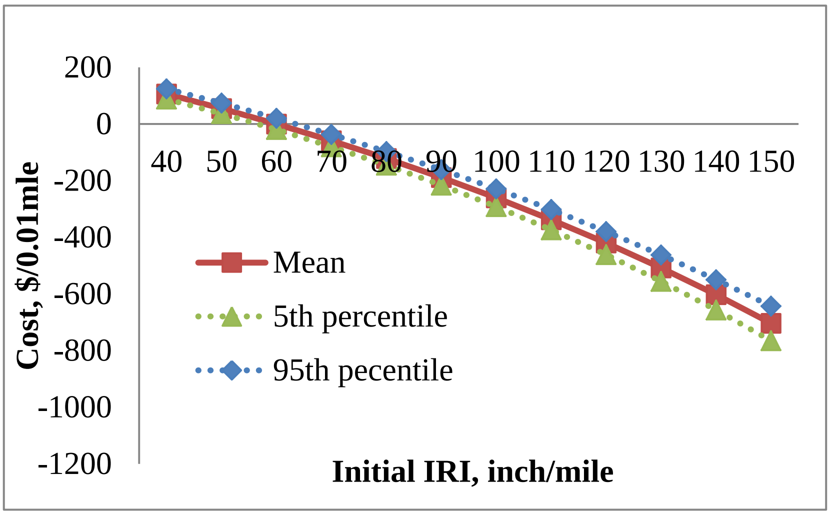


(a)

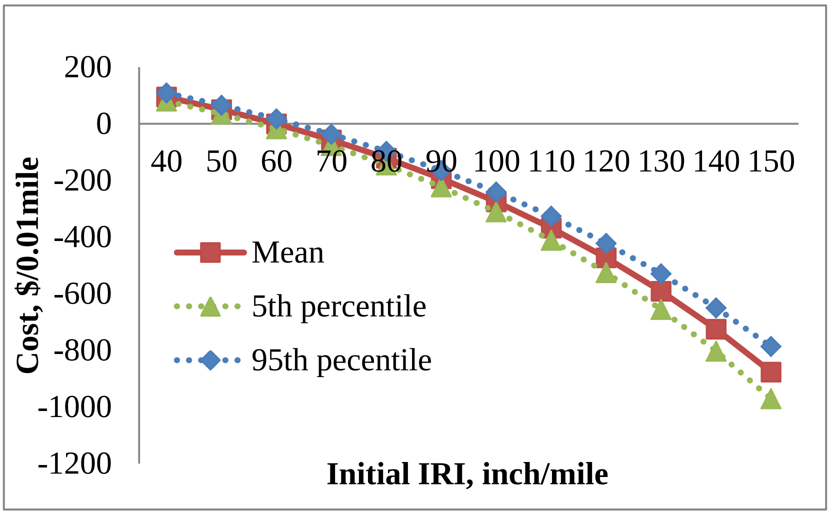


(b)

Figure 51. Pay adjustment for IRI considering successive overlay application using (a) SDI; and (b) IRI as performance criteria



(a)



(b)
Figure 50. Pay adjustment for IRI considering single overlay application using (a) SDI; and (b) IRI as performance criteria

5.3 Summary

The chapter discussed the processes of determining pay adjustment for IRI considering the effect of initial IRI values on pavement life. The following findings were concluded from analysis:

Based on the performance data from 43 pavement sections with the same minor rehabilitation treatment, it was found that pavement life determined by a terminal IRI value of 170 inch/mile is much greater than the pavement life determined by terminal SDI value of 2.4. The result suggests that it is more realistic to determine pavement life based on SDI instead of IRI.

The real IRI values when pavement life is reached based on the performance criterion of SDI. The results show that the average IRI value is 128 inch/mile with a standard deviation of 15 inch/mile, which is much lower than the traditional terminal threshold of 170 inch/mile. It suggests that the majority of pavement sections will have rehabilitation before IRI reaches 170 inch/mile. Moreover, the relationship between the initial IRI values and the real terminal IRI values was found. It was found that the pavement section with lower initial IRI values tend to have lower terminal IRI values.

The study established the relationship between the initial IRI value and pavement life determined by two different performance indicators based on regression analysis. This relationship was further incorporated into LCCA to determine pay adjustment of IRI for two different overlay application scenarios. Compared to the pay adjustment calculated using performance criterion of SDI, the pay adjustment calculated using the performance criterion of IRI shows greater penalties and slightly less bonus. It was found that the proposed pay adjustment based on single overlay application is close to than the current pay adjustment used by NJDOT.

Finally, MCMC method and Monte Carlo simulation were used to determine probabilistic range of pay adjustment. Compared to the deterministic approach, the probabilistic analysis results in slightly greater pavement life and pay adjustment in terms of mean values. Pay adjustment at different percentiles were plotted to show the possible variation range of pay adjustment. It shows that as the initial IRI value increases, the variation of penalty increases.

Chapter 6 Conclusions and Recommendations

6.1 Conclusions

The research focused on pavement performance modeling and its applications in PRS and LCCA using deterministic and probabilistic analysis. Compared to the deterministic approach, the probabilistic analysis could be more reliable in simulating the realistic pavement performance and considering variations caused by unobserved factors. The following conclusions were concluded from analysis:

The research started with the evaluation of the effect of pre-overlay condition on post-overlay performance under different rehabilitation treatments. Statistical analysis proved that the estimated overlay life for major rehabilitation is significantly higher than the overlay life for minor rehabilitation. It was found that performance deterioration rate of SDI after minor rehabilitation is considerably affected by pre-overlay condition as compared to major rehabilitation.

The deterministic and probabilistic LCCA were conducted to compare the cost-effectiveness of overlay treatment between minor and major rehabilitation in terms of EUAC. The general trend shows that when pre overlay condition is poor, the EUAC of minor rehabilitation section is higher than major rehabilitation section; when pre-overlay condition passes certain threshold, the EUAC of minor rehabilitation section becomes lower than major rehabilitation section. Based on the analyses, the optimization of treatment selection can be reached under different pre-overlay conditions. Based on the probabilistic result, a risk related factor, probability index, is proposed to quantify the probability that the EUAC of minor rehabilitation is greater than the EUAC of major rehabilitation. The analysis results show that generally probability index decreases as pre-overlay SDI increases or the cost ratio between minor and major rehabilitation increases.

The second objective of the research was the development of performance-related pay adjustment for air voids using pavement management data and quality assurance data. An exponential model was successfully developed to relate pavement service life to two quality characteristics (air voids of surface layer and intermediate layer). Deterministic LCCA results show that the pay adjustment could be significantly affected by the maintenance strategy if it is estimated using the short analysis period until the first overlay; while the pay adjustment calculated using the infinite analysis period provides a conservative boundary that is not sensitive to the maintenance strategy. Probabilistic analysis results show that Bayesian approach with MCMC methods can capture unobserved variations in the dataset and relate the quality measure of in-place air void contents to the expected pavement life with high goodness of fit. The probabilistic LCCA results facilitate considering the level of reliability in decision making of pay adjustments.

The third objective of the research was to develop performance-related pay adjustment of IRI. The analysis shows that the average IRI value is 128 inch/mile with a standard deviation of 15 inch/mile when the SDI reaches the terminal value of 2.4. It suggests that the majority of pavement sections receive rehabilitation before IRI reaches 170 inch/mile. It was found that the pavement section with lower initial

IRI resulted in the lower terminal IRI. The result suggests that it is more applicable to determine pavement life based on SDI instead of IRI in order to get more accurate performance prediction. The LCCA results show that compared to the pay adjustment calculated by SDI, the pay adjustment calculated based on IRI shows more penalties and slightly less bonus. It was found that the proposed new pay adjustment based on single overlay application shows less penalty than the current pay adjustment used by NJDOT.

6.2 Future Research Recommendations

The performance of overlay plays a critical role in the selection of rehabilitation treatments for highway agencies. It is vital to predict the performance of pavement after rehabilitation with better accuracy. There are a variety of factors that can affect the effectiveness of different rehabilitation activities. The research mainly investigated the effect of pre-overlay condition on performance of minor and major rehabilitation. Other important factors can also be included in the model and generate more reliable predictions. These include but are not limited to detailed traffic data, information regarding existing pavement structure, and environmental conditions.

The research developed PRS pay adjustment for in-pace air voids and IRI. The results shows that the proposed pay adjustments of air voids and IRI are comparable. The pay adjustment of IRI is approximately twice the pay adjustment of air voids. It will be meaningful to develop PRS pay adjustment for other important quality characteristics, such as asphalt content, gradation, bonding strength of layer interface. It will be highly beneficial if a comprehensive pay adjustment can be developed to account for all of the qualify characteristics.

In terms of the use of MCMC in pavement performance prediction, further research can be conducted to effectively account for both observed and unobserved heterogeneity in pavement performance data with a hierarchical parameter structure (Archilla 2006; Hong and Prozzi, 2006). Hierarchical models are inherently superior in population-based problem (Ntzoufras, 2009). The current model used by the study assumed that the distribution of model parameters is identical across different pavement sections. Comparably, a hierarchical parameter structure postulates that the distribution of model parameters is different (but related) across different pavement sections. The consideration of hierarchical models can further account for the unobserved heterogeneity among different pavement sections and thus result in a more accurate model.

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