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Enhancement of Pavement Maintenance Decision Making by Evaluating the Effectiveness of Pavement Maintenance Treatments

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To the Graduate Council:

I am submitting herewith a dissertation written by Qiao Dong entitled "Enhancement of Pavement Maintenance Decision Making by Evaluating the Effectiveness of Pavement Maintenance Treatments." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Civil Engineering.

Baoshan Huang, Major Professor

We have read this dissertation and recommend its acceptance:

Edwin G. Burdette, Stephen Richards, Alberto Garcia

Accepted for the Council:
Dixie L. Thompson

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

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Accepted for the Council:

Carolyn R. Hodges
Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

Enhancement of Pavement Maintenance Decision Making by Evaluating the Effectiveness of Pavement Maintenance Treatments

A Thesis Presented for the
Doctor of Philosophy
Degree
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Qiao Dong
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ABSTRACT

The performance of different pavement maintenance treatments were evaluated by investigating practical projects collected from Tennessee Pavement Management System (PMS) and Long Term Pavement Performance (LTPP) database. The influence of factors on the effectiveness, cost-effectiveness and cracking initiation of different treatment were evaluated by “Optime”, multiple linear regression and parametric survival analysis. Pavement roughness, pavement serviceability index (PSI) and the initiation time of cracking were used as pavement performance indicators.

Investigation on the pavement maintenance projects in Tennessee by Optime and multiple linear regression analysis indicated that HMA overlay had the highest effectiveness, followed by mill & fill and micro surfacing. Due to the relatively low cost, micro surfacing was the most cost-effective treatment, followed by HMA overlay and mill & fill. The effectiveness and cost-effectiveness decreased with the increase of traffic level and pre-treatment pavement condition.

Investigation on the LTPP resurfacing treatments indicated that thick overlay and milling reduced the roughness after rehabilitation. Thin overlay, high traffic level and poor pre-rehabilitation pavement condition increased the deterioration rate of new overlay. Using reclaimed asphalt material did not influence the treatment performance but was cost-effective in reducing the roughness of new overlay. For a certain deterioration rate, there was an optimized pre-rehabilitation roughness value or time for applying maintenance treatment.

Survival analysis on the crack initiation of asphalt overlay indicated that high traffic level accelerated the initiation of cracking. Thick overlay delayed the initiation of cracking except for the non-wheel path longitudinal crack. Mill retarded the occurrence of the non-fatigue cracks, whereas severe freeze thaw condition accelerated the occurrence of the two types of cracking. Using 30% RAP accelerated the initiation of longitudinal fatigue crack on wheel path but did not cause serious fatigue problem.

The performance curves of HMA resurfacing treatments used in Tennessee were calibrated by investigating the influence of different factors on the slopes and intercepts of post-treatment performance curves. The analysis indicated that pavement with high pre-treatment PSI, thick overlay and deep milling had low deterioration rate, whereas pavement with higher traffic level deteriorated faster.

Keywords: Pavement maintenance, Performance model, Cost-effectiveness, Multiple linear regression, Survival analysis

LIST OF ACRONYMS

AADT: Annual Average Daily Traffic

FHWA: Federal Highway Administration

IRI: International Roughness Index

HMA: Hot Mixed Asphalt

KESAL: Kilo Equivalent Single Axle Load

LTPP: Long Term Pavement Program

NCHRP: National Cooperative Highway Research Program

PDI: Pavement Distress Index

PMS: Pavement Management System

HPMA: Highway Pavement Management Application

Post_IRI: The International Roughness Index value right after the treatment

Post_PSI: The Present Serviceability Index value right after the treatment

PQI ; Pavement Quality Index

Pre_IRI: The International Roughness Index value right before the treatment

Pre_PSI: The Present Serviceability Index value right before the treatment

PSI: Present Serviceability Index

RAP: Reclaimed Asphalt Pavement

SPS: Specific Pavement Studies

TDOT: Tennessee Department of Transportation

Truck_AADT: Annual Average Daily Traffic of Trucks

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PART 1 RESEARCH BACKGROUND AND OBJECTIVES

1.1 Research Background

With most highway systems in place, an increasing emphasis has been placed on pavement maintenance and preservation. Pavement maintenance can enhance pavement performance and retard future deterioration by addressing minor distress and improving functional conditions (O'Brien 1989). Figure 1.1 shows the percent of funding for pavement new construction and preservation in USA at 2009. It can be seen that pavement maintenance and rehabilitation consume the majority of the pavement funds. Selecting the right pavement maintenance strategy considering the pavement condition, traffic level and desired performance period is an important issue for highway agencies.

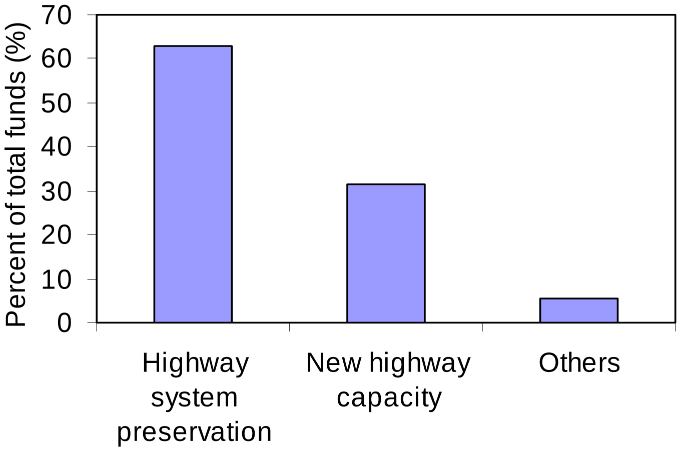

Figure 1.1 Funding for highway construction and preservation (Newton, 2009)

Pavement Management System (PMS) is a set of tools that assists decision-makers in finding optimum strategies for providing, evaluating, and maintaining pavement in a serviceable condition over a period of time. It generally includes two parts: the data base part which monitors and collects the pavement related data and the decision making part which aims to help highway agencies develop optimum maintenance strategies. Successful application of PMS plays an important role for the enhancement of pavement maintenance decision making. PMS and integrated pavement maintenance decision making function can use the expected impact of maintenance treatments on the future pavement performance to identify pavement segments that need treatment and select the appropriate treatment.

One critical factor in pavement maintenance decision making is to determine the effectiveness of various maintenance treatments from the perspectives of both cost and benefits (Labi et al. 2006). Thorough investigation into practical projects is necessary to evaluate treatment effectiveness which is improved pavement performance due to maintenance treatments.

1.2 Research Objectives and Significance

This research aims to enhance the pavement decision making by evaluating the performance of different pavement maintenance treatments. The objectives of this proposed research are as follows:

1. To evaluate effectiveness and cost-effectiveness of typical pavement maintenance treatments currently used in Tennessee and the Unite State;
2. To evaluate the influence of different factors on the effectiveness and cost-effectiveness of maintenance treatments. Those factors include pre-treatment

pavement condition, traffic level, overlay thickness, climatic condition, material and other related factors.

Due to limited data and analysis methods, limited conclusions were attained in previous studies. Currently, various pavement maintenance activities have been serving for sufficient years. The long term effect of those treatments in reducing the pavement roughness, improving the pavement riding quality, repairing pavement distress and retarding the pavement deterioration can be observed. It is timely and of great importance to take a deep investigation into the performance of the maintenance treatments. Comparing with previous studies, more pavement performance indicators, new measures of effectiveness and more influencing factors are included to evaluate the performance of different treatments. In view of the large number of factors included in the analysis and existence of uncensored data, two statistical methods (multiple regression and survival analysis) are employed to build the multiple variable models.

1.3 Research Plan and Methodology

Figure 1.3 shows the research plan. The main task of this research is to analyze the influence of different factors including different treatment methods on treatment performance. The following is a detailed discussion of each part, including data sources, pavement indicators, influencing factors and analysis method.

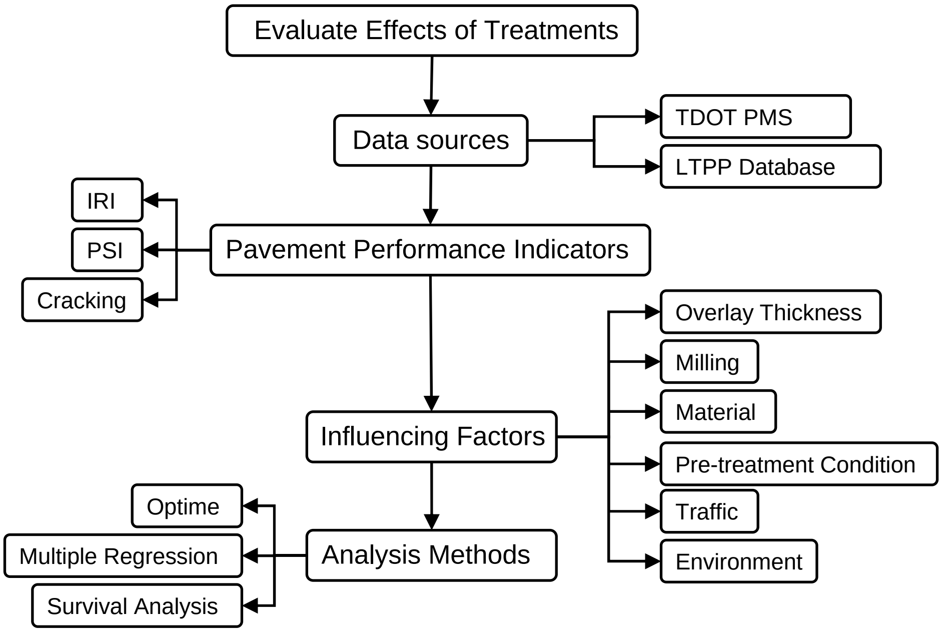

Figure 1.2 Main tasks of the research

1.3.1 Data Source

Two databases are investigated in this study: the Pavement Management System (PMS) used by Tennessee Department of Transportation (TDOT) and the Long Term Pavement Performance (LTPP). TDOT's current PMS is Highway Pavement Management Application (HPMA) developed by Stantec Inc.. TDOT has been systematically collecting the pavement condition data sine the 1990s. The pavement condition data are collected every two years on state routes and every year on interstates. LTPP program was established as part of the Strategic Highway Research Program (SHRP) in 1987 and managed by the Federal Highway Administration (FHWA). (Hanna, 1994) It has monitored more than 2,400 pavement test sections across North America and includes several specific experiment sections (GPS-6B, SPS-3, and SPS-5) specifically designed to evaluate the effects of pavement maintenance treatment.

To prepare the data for analysis, historical pavement maintenance projects are collected. The project related information, including treatment method, overlay thickness, application time, project locations are identified. Then, pavement related information including performance indicators, climatic condition, traffic level and material properties are collected from the two databases to build the effectiveness models.

1.3.2 Pavement Performance Indicators and Measures of Effectiveness

Selecting appropriate pavement performance indicators and measures of treatment effectiveness are two important prerequisites to evaluate the performance of maintenance treatments. Two types of pavement performance indicators are investigated in this study: roughness and cracking.

Roughness type performance indicators include International Roughness Index (IRI) and Present Serviceability Index (PSI). Roughness is the accumulated longitudinal irregularities in the pavement surface. High roughness values indicate lower level smoothness of the pavement surface. PSI is a 5-point ride quality rating of the pavement and is usually calculated from IRI. High PSI value means better riding quality. LTPP database uses roughness data as a main pavement performance indicator. HPMA use (PSI) as an important pavement performance indicator. The effectiveness in terms of roughness includes initial effects and long-term effects. The initial effects are the post-treatment IRI/PSI value and the IRI/PSI change after overlay. The long-term effects include the rate of IRI/PSI change after overlay and the benefit which is the area bounded by the pre-treatment and post-treatment performance curves, the higher threshold and the treatment service lives.

The initiation time of cracking on the pavement surface is used as another treatment performance indicator to evaluate the effect of different treatment on retarding the occurrence of pavement distress. The cracking data are collected from the LTPP database. After identifying specific pavement maintenance experiment road sections, historical pavement distress data are collected. The initiation time of different cracking then can be determined and used as responses to build parametric survival models.

1.3.3 Influencing Factors

Pavement deterioration is caused by the combined effects of traffic loading and environmental factors on the structure and materials (Hong, 2007). Construction, design, structure, material, environment and traffic, which play pivotal roles in the pavement deterioration process, also influence the effects of different treatments. Besides the traffic level and environmental condition analyzed by previous researchers, specific treatment method and pre-treatment pavement condition are also two important factors for the performance of maintenance treatments.

Specific treatment method is the primary factor determining the treatment performance. Even for one type of treatment with different designs including different overlay thickness, milling depth and material properties, the effect will be different. Pre-treatment pavement condition is another potential significant factor for the treatment performance.

The pre-treatment condition includes not the only the performance level but also the deterioration of old pavement. Since the new overlay will experience the same traffic and environmental conditions as the old pavement did, the deterioration of old pavement, which reflects the influence of the same traffic and environmental condition on the same structure, is believe to have significant influence on the deterioration of new overlay. Thus, it is necessary to include those pre-treatment pavement condition factors in the regression analysis.

1.3.4 Analysis Methodology

Firstly, a VBA (Visual Basic Application) based software "Optime", developed in the NCHRP Report 523 "Optimal Timing of Pavement Preventive Maintenance Treatment Applications" is utilized to evaluate the effectiveness of different treatment used in Tennessee. The Optime software is a tool used to determine the optimal application time of preventive maintenance by comparing the cost-effectiveness of different maintenance scenarios. The cost-effectiveness of collected maintenance projects are evaluated by using "Optime".

Two statistical regression methods are employed to establish the regression models for the effects of maintenance treatments. For the effectiveness in terms of IRI and PSI, a multiple linear regression method is employed to build the effectiveness model. Appropriate model format is determined by investigating the relationship between the responses and each of the factors. Survival analysis is employed to investigate the initiation time of cracking. Survival analysis can incorporate censored data in the statistical estimation of the model parameters and thus is capable of capturing the stochastic nature of crack initiation.

1.3.5 Calibration of Treatment Performance Curves for HPMA

In the last part, the performance curves of typical Hot Mix Asphalt (HMA) resurfacing treatments used in Tennessee are calibrated for the HPMA by investigating the historical maintenance projects in Tennessee. Those established curves are input into HPMA so that more realistic maintenance strategy analysis can be conducted.

First, the performance models of HMA resurfacing treatments are investigated by using multiple regression analysis. Significant factors influencing treatment performance were identified. Specific designs of HMA treatments and performance classes are determined based on the regression results. Then, the performance curves for the identified treatment methods at different performance classes are established and the parameters of the performance models in HPMA are calibrated. A example of maintenance strategy analysis using the calibrated models is presented.

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PART 2 COST-EFFECTIVENESS EVALUATION OF PAVEMENT MAINTENANCE TREATMENTS BY OPTIME

2.1 Abstract

The cost-effectiveness of different maintenance treatments including micro surfacing, HMA overlay and mill & fill were evaluated by using Optime. The treatment effectiveness was calculated as the difference in computed areas associated with the post-treatment performance indicator curve and the do-nothing curve. It was found that mill & fill had the highest unit costs, followed by HMA overlay and micro surfacing. HMA overlay had the highest effectiveness, followed by mill & fill and micro surfacing. Micro surfacing was found to be the most cost-effective treatment due to its low cost.

2.2 Introduction

With more and more pavement maintenance projects applied, there is a need to evaluate the cost and effectiveness of various maintenance treatments from the perspectives of both cost and effectiveness (O'Brien 1989). Investigation indicates that more than 3000 pavement resurfacing maintenance projects were applied in Tennessee State from 1987 to 2008. With so many maintenance projects applied, evaluating the cost-effectiveness of different treatments is of great importance.

In order to evaluate the effectiveness of different treatment, appropriate measures of effectiveness need to be defined first. Several existing measures of effectiveness include the performance jump, the improved pavement performance, the expected treatment life, the expected extended treatment life, the area between the performance curve and the threshold (Labi 2006, 2003, Rajagopal 1990). NCHRP report 523 presented a cost-effectiveness analysis method for determining the optimal timing for the application of preventive maintenance treatments (Peshkin and Hoerner 2004). An Excel VBA designated Optime software was presented in this report. As shown in Figure 2.1, the effectiveness (benefit) is defined as the difference in computed areas associated with the post-treatment performance curve and the do-nothing curve in the report. This method best reflects the effect of treatment since it not only involves both treatment service life and overall pavement condition, but also directly indicates how much the pavement performance is improved.

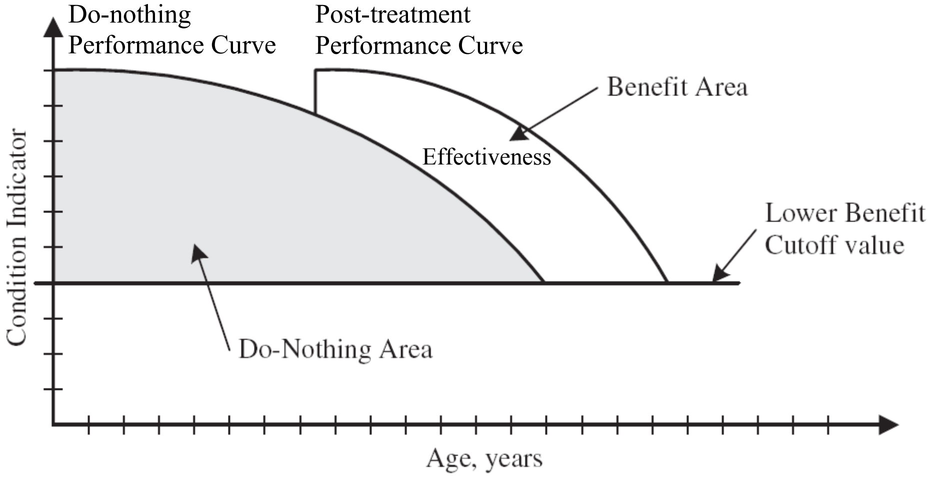


Figure 2.1 Conceptual illustration of effectiveness (Peshkin, 2004)

In this study, the methodology used in NCHRP 523 was investigated and a project case study was first conducted by using Optime. Then, the cost-effectiveness of three pavement maintenance treatments were evaluated and compared by using Optime.

2.3 Algorithm of Optime

The Optime software is a tool to determine the optimal application time of preventive maintenance based on the cost-effectiveness analysis of different maintenance scenarios. In Optime, ***Benefit*** is defined as the quantitative influence on pavement performance as measured by one or more condition indicators. The optimal application of a preventive maintenance treatment occurs at the point at which the benefit per unit cost is greatest. The following are three important conceptions for the optimal timing analysis.

2.3.1 Define Performance Indicators and Benefit Cutoff Values

The effect of a treatment on performance is determined by the changes in pavement performance indicators, such as International Roughness Index (IRI), present serviceability index (PSI), or other measure of performance. As shown in Figure 2.1, benefit cutoff values are defined as the y-axis boundary conditions for the performance curves that define the upper and lower limits for the benefit area calculations. Pavement failure trigger values are usually used as the benefit cutoff values.

2.3.2 Determine Do-nothing and Post-treatment Performance Relationships

The benefit associated with the application of a maintenance treatment is based on the improvement in performance compared with that for the “do-nothing” alternative. The do-nothing relationship defines the pavement performance over time that would be expected if only no or minor routine maintenance was conducted. The post-treatment relationship defines the pavement performance over time that would be expected if a treatment is applied. The two relationships can be determined by investigating the historical pavement performance data from Pavement Management System (PMS).

2.3.3 Identify Benefit of Treatments

As shown in Figure 2.1 and Equation 2.1~2.2, for a specific condition indicator, the benefit is determined by the difference in computed areas associated with the post-treatment performance indicator curve and the do-nothing curve. When there are more than one performance indicator included in the analysis, benefit weighting factors are used to combine the individual benefit values associated with the different condition indicators together as shown in Equation 2.3.

$$Area_{Benefit(i)} = Area_{Post-treatment(i)} - Area_{Do-nothing(i)} \tag{2.1}$$

$$\%Benefit_{(i)} = \frac{Area_{Benefit(i)}}{Area_{Do-nothing(i)}} \tag{2.2}$$

$$Overall\ Benefit = \sum \%Benefit_{(i)} \times Benefit\ Weighting\ Factor \tag{2.3}$$

2.4 Project Case Study

2.4.1 Project Summary

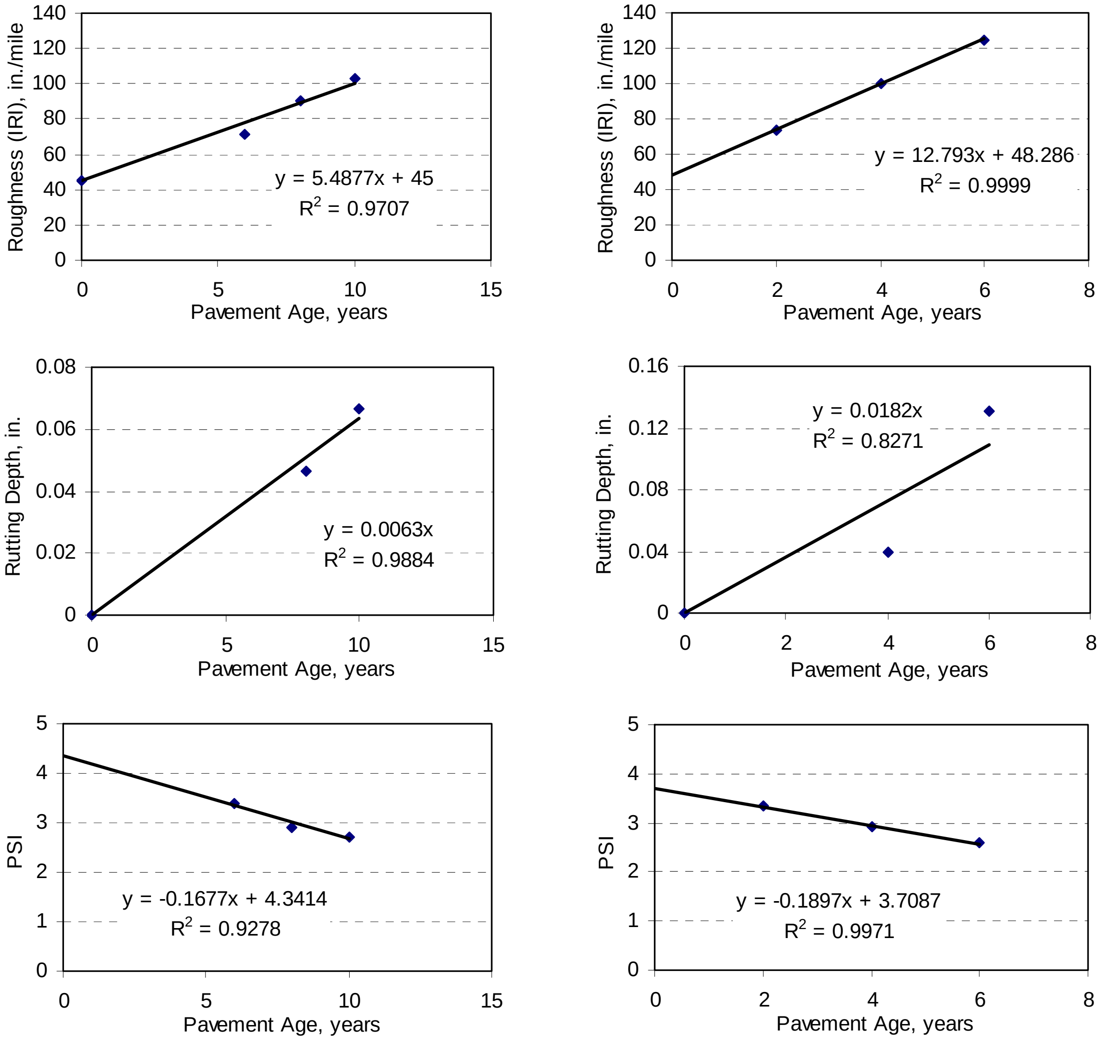
One micro surfacing treatment project applied at SR341 in Tennessee was investigated by using Optime. Micro surfacing is spreading a mixture of polymer modified asphalt emulsion, fine aggregate, mineral filler and water on an original pavement surface. The surface age, which is the time when the maintenance was applied, was 11 years. Three condition indicators: Roughness, rutting depth and PSI were selected. Benefit weighting factors for the three condition indicators were chosen as 20, 30 and 50, respectively. The average cost per mile was $42,173.

2.4.2 Pavement Performance Indicators

Three pavement performance indicators were selected to build the performance curves: International roughness index (IRI), rutting depth and Present Serviceability Index (PSI). IRI is the accumulated longitudinal irregularities in the pavement surface. High IRI values indicate lower level smoothness of the pavement surface. PSI is a 5-point ride quality rating of the pavement. High PSI value means better riding quality. PDI is also a 5-point pavement distress index measured in terms of extent of various pavement distress including cracking, patching, bleeding and etc. Lower PDI value indicates severe distress condition.

2.4.3 Do-nothing and Post-treatment Performance Curves

As shown in Figure 2.2, linear model was used to build the do-nothing and post-treatment performance curves. The pavement performance data of the adjacent road section, which had the same pavement structure, traffic and environmental condition, were used to build the do-nothing performance curves. The intercepts of the rutting depth linear model were set to be 0 while the intercepts of the IRI linear model were forced to be between 45in./mile to 60in./mile, since the IRI of newly constructed pavement are between 45~60 in./mile (Shafizadeh, 2003).



(a) Do-nothing performance curves (b) Post-treatment performance curves

Figure 2.2 Pavement performance relationships for micro surface project SR 341

It is noted that the post-treatment performance relationship in Figure 2.2 only represented the pavement performance when the treatment was applied at the pavement age of 11 years. The post-treatment performance relationship would be different when the treatment was applied at different pavement service age. Thus, it is necessary to estimate the post-treatment performance relationships for different application time. As shown in Equation 2.3 and Figure 2.3, interpolation is utilized to estimate the slopes for the post-treatment performance model at different application time. Table 2.1 presents the slopes for post-treatment performance curves at different application time. The intercepts of post-treatment performance curves were assumed to be the same at different application time.

$$Slope_i = Slope_0 + \frac{(Slope_N - Slope_0)}{N} i \tag{2.4}$$

Where, $Slope_i$: slope of the performance model at pavement age of i years.

$Slope_0$: slope of the do-nothing performance model.

$Slope_N$: slope of the post-treatment performance model at age of N years.

i: Assumed treatment application time, year.

N: Actual treatment application time, year.

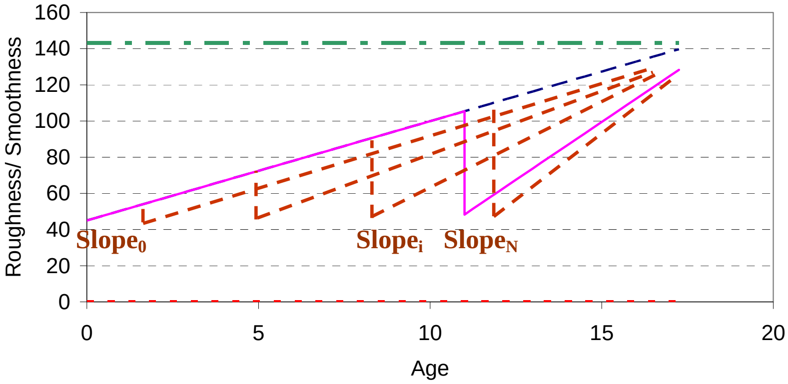


Figure 2.3 Slopes of post-treatment performance curves at different application times

Table 2.1 Slopes of post-treatment performance curves at different application time

Application time, year	Rutting	IRI	PSI
0	**0.0063**	**5.487**	**-0.1677**
3	0.0095	7.4795	-0.1737
5	0.0116	8.8079	-0.1777
7	0.0137	10.1363	-0.1817
9	0.0159	11.4646	-0.1857
11	**0.018**	**12.793**	**-0.1897**

2.4.4 Benefit Cutoff Values

Benefit cutoff values are determined by analyzing the do-nothing performance relationships over the condition indicator ranges. Details of this analysis are presented as follows:

1. Roughness: Because IRI increases with time, an upper IRI benefit cutoff value is required. A value of 143 in./mile was chosen because it indicated the transition from tolerable roughness level to a higher roughness level. According to the roughness regression Equation, this value is predicted at an age of 17 years. The lower benefit cutoff value was set to a value of 0 m/km (0 in./mi).
2. Rutting: Rutting depth value also increases with time, and an upper rutting benefit cutoff value is required. Although 0.5 in. rutting depth indicated the transition from tolerable rutting level to an unacceptable rutting level, this value was predicted at an age of 79 years which was obviously unpractical. Thus, 0.15 in. was chosen as the upper benefit cutoff value and it was predicted at an age of 15.8 years. The lower benefit cutoff value was set to a value of 0 in.
3. PSI: Because PSI decreases with time, a lower benefit cutoff value is required. For primary road with a flexible pavement, the PSI value are 2.5 ~ 4.2. Thus, 2.5

was chosen as the lower benefit cutoff value. According to the PSI regression Equation, 2.5 was predicted at an age of 11 years. The upper benefit cutoff value was set to 4.2.

2.4.5 Analysis Results Discussion

Since the PSI value reached its lower cutoff value at 11 years, a maintenance scenario of applying micro surfacing at 3, 5, 7, 9 and 11 years was investigated. Table 2.2 presents the analysis result. It indicated that of the 5 investigated application years; the optimal applicant year was 11 as indicated by the largest total benefit value (0.15) and the longest extension of life of 6.4 years. It can also be seen that the negative benefit values occurred at early application age and the optimal application time is the year when PSI reached its lower thread. This is mainly caused by the increased pavement deterioration rate after treatment. As shown in Figure 2.2, the absolute values of the slopes of the post-treatment pavement performance curves are higher than those of the do-nothing pavement performance curves.

Table 2.2 Benefit analysis results by using “Optime”

Application Time (years)	Benefit	Expected Life (years)	Life Extension (years)
3	-0.16	10.0	-1.0
5	0.01	11.8	0.8
7	0.14	13.7	2.7
9	0.23	15.5	4.5
11	**0.27**	**17.4**	**6.4**

2.5 Comparison of Different Treatments

The cost-effectiveness (benefit/cost) of three maintenance treatment methods: micro surfacing, HMA overlay and mill & fill were investigated by using Optime. HMA overlay is applying a dense or fine-graded hot-mixed asphalt mixture on an existing pavement surface Mill & fill is removing deteriorated existing asphalt pavement surface and replacing it with a new HMA mixture. The benefits and benefit/cost ratios were calculated as an indicator of cost-effectiveness. The treatment application ages were the real application time of the maintenance treatment. Three typical projects with similar traffic level (<5000 AADT) were investigated for each maintenance treatment. Related project information and pavement performance data were collected and analyzed.

Table 2.3 Comparison of the cost-effectiveness of different treatments

Treatment	Cost ($/mile)	Benefit	Expected Life (years)	Life Extension (years)	Benefit/Cost ($\times 10^{-5}$)
Micro Surfacing	32723	0.36	15	4.2	1.1
HMA Overlay	72719	0.57	20	10.6	0.8
Mill & Fill	175016	0.46	18	7.8	0.3

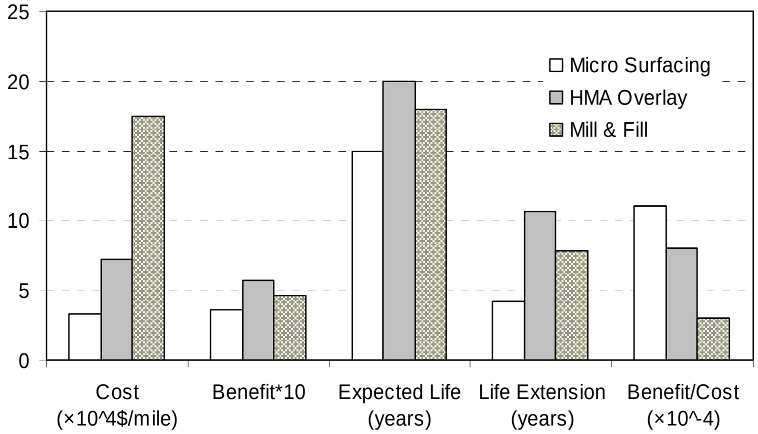


Figure 2.4 Comparison of the cost-effectiveness of different treatments

Table 2.3 and Figure 2.4 summarize the analysis results. It can be seen that among the three investigated maintenance treatments, mill & fill has the highest cost, followed by HMA overlay and micro surfacing. As indicated by the benefit, expected life and expected life extension, HMA overlay treatment has the highest benefit value, followed by mill & fill and micro surfacing. Similar conclusion could also be attained when life extension was used to evaluate the effectiveness. There are several potential reasons why HMA overlay has higher effectiveness than mill & fill. First, HMA overlay increases the pavement thickness and improves the pavement structure whereas mill & fill is usually applied on a relatively weak pavement structure and does not contribute to the pavement structure capacity. Second, milling is usually applied on the road sections where severe pavement distress occurred. The higher milling depth, the more severe the distress is. Thus, the overall pavement condition of the deep milling area is usually poor, resulting in bad pavement performance.

Micro surfacing had the highest cost-effectiveness (benefit/cost), followed by HMA overlay and mill & dill. Due to the low cost, micro surfacing was more cost-effective than other two treatments. However, mill & fill and HMA overlay have the ability to overcome pavement distress and increase the pavement structure capacity. The two surface treatments cannot simply replace the two new pavement layers when the pavement is in poor condition.

2.6 Conclusions

Optime from NCHRP Report 523 was utilized to evaluate the cost-effectiveness of three widely applied maintenance treatments: micro surfacing, HMA overlay and mill & fill. Based on the analysis, several conclusions can be summarized as follows:

1. Practical optimal time can be calculated by using Optime software and investigating the condition indicator performance relationships and is mainly determined by the do-nothing performance relationships.
2. Investigation on the practical projects indicated that mill & fill had the highest unit costs, followed by HMA overlay and micro surfacing and slurry seal.
3. As indicated by the benefit value, expected life and expected life extension, HMA overlay had the highest effectiveness, followed by mill & fill and micro surfacing.

Due to the relatively low cost, micro surfacing was the most cost-effective treatment, followed by HMA overlay and mill & fill. However, mill & fill has the ability to overcome severe pavement distress and HMA overlay can increase the pavement structure capacity. Thus, micro surfacing may be inapplicable in some situations.

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PART 3 EVALUATION OF EFFECTIVENESS AND COST-EFFECTIVENESS OF DIFFERENT PAVEMENT MAINTENANCE TREATMENTS IN TENNESSEE

3.1 Abstract

The effectiveness and cost-effectiveness of resurfacing maintenance treatments applied to low and moderate traffic roads in Tennessee was evaluated based on the pavement condition data and costs of identified maintenance projects by multiple variable models. The investigated treatments include HMA overlay, mill & fill and micro surfacing. Survey results indicated that treatment service life slightly decreased as the traffic volume increased and the service life of HMA overlay, mill & fill and micro surfacing are 11 years, 10 years and 8.5 years, respectively. Linear models were established for both pre-treatment and post-treatment pavement performance models. The treatment effectiveness was calculated as the area bounded by the pre-treatment and post-treatment performance curves, the lower threshold and the treatment service life. The costs of each treatment were analyzed using the costs of typical maintenance projects and the asphalt price index was incorporated to adjust the cost of asphalt materials. It was found that traffic level and pre-treatment pavement condition including the pre-treatment model slope and the pre-treatment PSI are all significant factors for the effectiveness and cost-effectiveness of treatments. The effectiveness and cost-effectiveness decreased with the increase of traffic level and pre-treatment pavement condition. HMA overlay had the highest effectiveness, followed by mill & fill and micro surfacing. Micro surfacing was the most cost-effective treatment due to its low cost.

3.2 Introduction

With most of the highway systems in place, an increasing emphasis has been placed on pavement maintenance and preservation. Various pavement maintenance activities have been applied to preserve the pavement and retard the future deterioration by addressing minor distress and improving functional conditions (O'Brien 1989). One important consideration in pavement maintenance is to optimize the application of different maintenance treatments. Thus, there is a need to evaluate the effectiveness of various maintenance treatments from the perspectives of both cost and benefits (Labi et al. 2006). A cost-effectiveness analysis (rather than cost or effectiveness information only) will help agencies develop or update decision matrices for pavement preventive maintenance.

Some research has been carried out to evaluate the cost-effectiveness of different maintenance treatments. Darter et al. (1985) found that micro surfacing can lead to a reduction in subsequent maintenance costs and is a viable constituent treatment for cost-effective preservation strategies. Hanna et al. (1994) evaluated various treatments including thin HMA (hot mixed asphalt) overlays in SHRP's Special Pavement Studies (SPS) No. 3 and found that thin HMA overlay can be cost-effective in the long term. Labi and Sinha (2003) found that micro surfacing improved pavement performance in the long term and extended pavement life by at least 3 years.

To evaluate the cost-effectiveness of different treatments, correctly identifying the effectiveness is a key initial requirement. Treatment performance models established at different traffic or environmental conditions needed for evaluating treatment effectiveness (Labi et al. 2003 and 2006). Many models have been employed to predict treatment performance including regression (George 1987, Madanant 1995, Prozzi 2004 and Yu 2007), Markovian (Butt 1987 and Yang 2005), neural network (Fwa 1993 and Terzi 2007) and fuzzy set models (Elton 1988 and Pan 2007). Regression models and neural network are deterministic while Markovian models are probabilistic. Fuzzy set could be combined with both of them to incorporate uncertainties. Deterministic methods use models from which performance is predicted as a precise value by mathematical deterioration functions, whereas probabilistic models utilize a transition probability matrix to predict future performance (Jose et al. 2006). Although probabilistic models incorporate uncertainties more effectively, regression models are the most practical methods and have been widely used in existing PMS systems.

Based on the established treatment performance model, measures of effectiveness can be accomplished by comparing the treatment performance. Several existing measures of effectiveness include the PSI jump, the improved average pavement condition, the treatment service life, the extended surface layer life, the area between the performance curve and lower threshold (such as the condition before the treatment or a pre-specified condition trigger) and the area between the pre-treatment performance curve and post-treatment performance curve in the treatment service life (Rajagopal 1990 and Labi 2006). Among them, the area bounded by the pre-treatment and post-treatment performance curves, the lower threshold and the treatment service life (Figure 3.1) best reflects the effect of treatment since it involves both treatment service life and overall pavement condition.

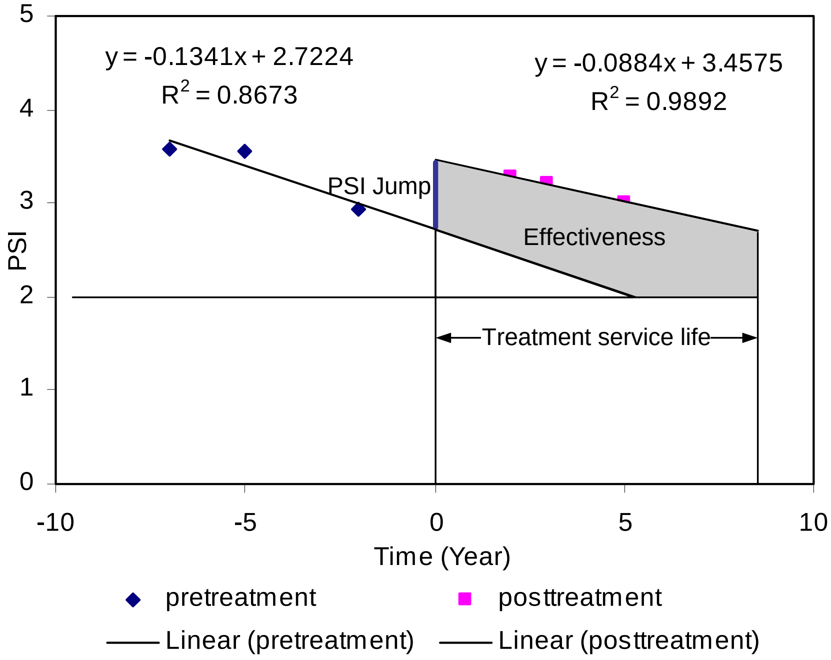
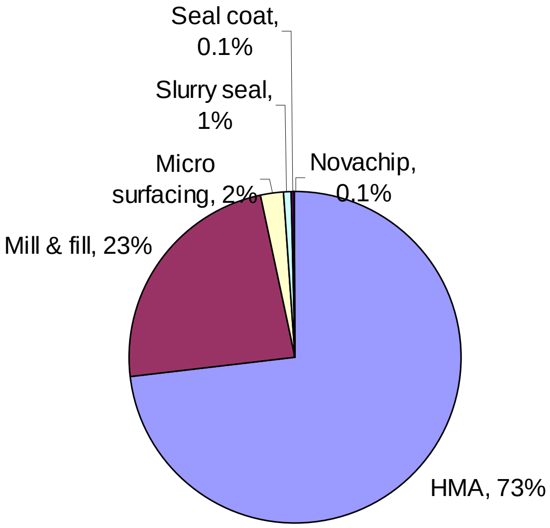


Figure 3.1 Illustration of treatment effectiveness

Since 1980s, Tennessee has been applying various pavement maintenance treatments on state routes and interstates. The most frequently used pavement resurfacing treatments include HMA overlay, mill & fill and micro surfacing. HMA is a dense-graded HMA mixture applied over an existing bituminous surface with the thickness between about 2cm and 4cm. Mill & fill includes removing approximately 2cm of existing asphalt pavement first and replacing it with a suitable thickness of new hot mix asphalt. Micro surfacing consists of a mixture of polymer-modified emulsified asphalt, mineral aggregate, mineral filler, water, and additives applied in a process similar to slurry seals (Peshkin 2004). Generally, HMA overlay and mill & fill are new pavement layers;

whereas, micro surfacing is a simple surface treatment. From 1987 to 2008, around 4000 pavement resurfacing maintenance projects were finished in Tennessee. Figure 3.2 presents the percentage of different treatments. It can be seen that HMA overlay accounted for 73% of the total, followed by mill & fill (23%), micro surfacing (2%) and other surface treatments (1%). With so many pavement maintenance projects applied, investigating the effectiveness and cost-effectiveness of different treatments is of great importance.



Number of identified projects and representative samples:

	HMA	Mill & fill	Micro surfacing
Project no.	147	47	90
Representative sample no.	79	39	50

Figure 3.2 Pavement treatments applied in Tennessee and number of identified projects

The effectiveness and cost-effectiveness of the three resurfacing treatments frequently used in Tennessee were evaluated in this study. The pre-treatment and post-treatment performance models of were first established for identified resurfacing maintenance projects. The effectiveness, costs and the cost-effectiveness of the treatments were investigated and compared by using multiple variable models.

3.3 Pre-treatment and Post-treatment Performance Models

3.3.1 Data Preparation

In order to develop realistic treatment performance models, it is necessary to collect information from sufficient numbers of maintenance projects that can reflect various traffic levels. Figure 3.2 summarizes the number identified resurfacing maintenance projects and road sections. Each road section has a unique traffic volume and is one sample dataset. Traffic volume and the pavement condition data of each road section were exported from the pavement management system (PMS).

3.3.2 Selection of Performance indicators

Three pavement condition indicators including PSI (Present Serviceability Index), rutting depth and PDI (Pavement Distress Index) were investigated. PSI is a 5-point ride quality rating of the pavement. Low PSI value means poor riding quality. Rutting depth is the depth of the surface depression in the wheel path, which is mainly caused by the consolidation or lateral movement of the asphalt mixture due to traffic or insufficient compaction of asphalt mixture during construction. PDI is also a 5-point pavement distress index measured in terms of extent of various pavement distresses. Low PDI value indicates severe distress condition.

Investigation results indicated that PSI values were proved to provided smooth decreasing performance curves; whereas, only a few curves were attained using rutting depth and PDI. Besides, PSI reflects the overall riding condition of pavement. Thus, PSI was selected as the pavement performance indicator.

3.3.3 Selection of Model Function

Regression models are usually established by using pavement age as a predictor. Among various regression models, the simplest and most widely used ones are linear or exponential functions. Equations 3.1 and 3.2 present the linear and exponential treatment performance function respectively.

$$PSI = k \cdot Age + b \tag{3.1}$$

$$PSI = a \cdot e^{b \cdot Age} \tag{3.2}$$

Where, PSI = Present Serviceability Index (from 0 to 5);

Age = Pavement surface layer age, year;

k, a, b = Model coefficients.

Investigation on the raw data indicated that no obvious exponential form or curvature was observed in the pavement performance data. A regression goodness-of-fit analysis also indicated that R^2 values were not improved by using exponential function comparing with linear function, indicating a fairly strong linear relationship existing between PSI and treatment age. Thus, linear function was selected to establish the performance models in this study. Table 3.1 presents examples of the established pre-treatment and post-treatment performance models. Since PSI is supposed to decrease as the surface layer age increase, the k values (slope) were all negative. The R^2 values of both pre-treatment and post-treatment performance models are higher than 0.5.

Table 3.1 Data prepared for the effectiveness analysis

Sample	AADT	Truck_AADT	Pre-treatment model		Post-treatment model		Effectiveness
			k_1	b_1	k_2	b_2	
1	3787	271	-0.1878	2.3194	-0.0332	2.9839	11.2
2	757	65	-0.3385	1.5736	-0.0291	2.8237	21.8
3	560	43	-0.2116	2.2574	-0.0998	3.3686	13.5
4	507	37	-0.1817	2.4069	-0.0426	3.1871	11.7
5	1420	111	-0.1561	2.5848	-0.0537	3.3742	10.4
6	803	57	-0.1507	2.7268	-0.0306	3.311	9.3
…							

Note: k_1, b_1 = the slope and intercept of pre-treatment linear performance curve, b_1 is also the pre-treatment PSI; k_2, b_2 = the slope and intercept of post-treatment linear performance curve.

3.4 Effectiveness of Treatments

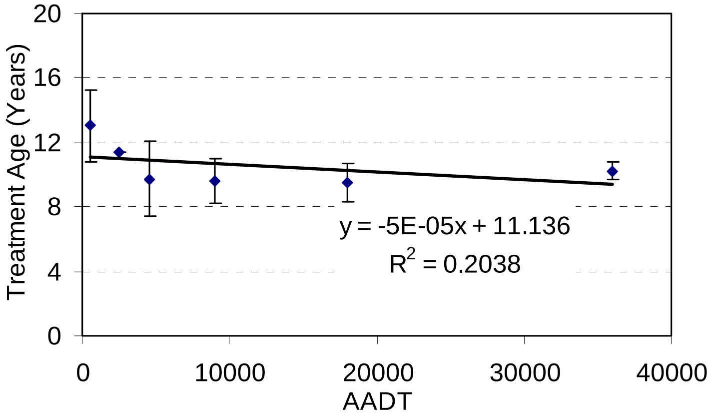
3.4.1 Investigation on Treatment Service Life

Peshkin et al. (2004) suggested the maintenance treatment service life was the time when the performance curve reached the lower threshold value. However, treatment service lives calculated by using this method are usually much higher than 15 years, which is unrealistic. Normally, maintenance treatment can serve 10~15 years. At around 10~15 years, although the overall PSI value may not be low enough to trigger a lower threshold value, a severe distress might occur and a new maintenance treatment is required. In this study, the treatment service lives for different treatments were investigated and used for calculating effectiveness.

The average treatment service lives for different treatments are summarized in Table 3.2 and Figure 3.3. It can be seen that the treatment service life decreases slightly as the traffic volume increases. The average maximum treatment service life for HMA overlay, mill & fill and micro surfacing are 11 years, 10 years and 8.5 years respectively, which is also an indication of treatment effectiveness.

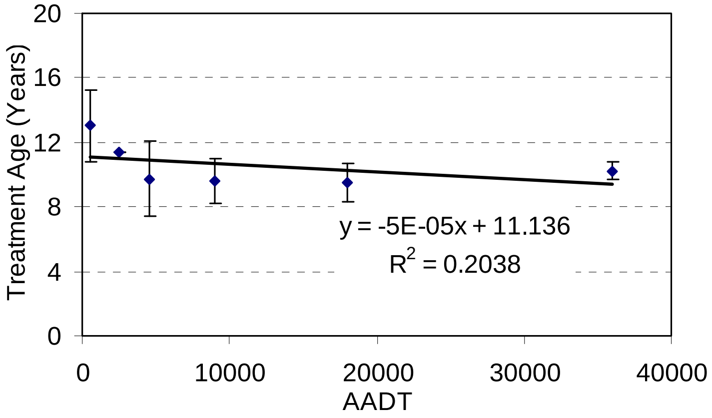
Table 3.2 Treatment service life (Average ± SD (sample no.))

AADT	HMA Overlay	Mill & fill	Micro surfacing
0-1000	12 ± 2 (7)	13 ± 2 (2)	9 ± 1 (4)
1000-2000	12 ± 1 (3)	9 ± 1 (2)	9 ± 2 (6)
2000-3000	11 ± 1 (2)	11 ± 0 (1)	9 ± 1 (3)
3000-6000	10 ± 1 (9)	10 ± 2 (4)	9 ± 2 (6)
6000-12000	11 ± 1 (4)	10 ± 1 (5)	8 ± 2 (6)
12000-24000	10 ± 3 (7)	10 ± 1 (6)	7 ± 2 (6)
24000-48000	9 ± 2 (2)	10 ± 1 (5)	7 ± 0 (1)
Total	11 ± 1.7 (32)	10 ± 1.6 (20)	8.5 ± 1.7 (31)

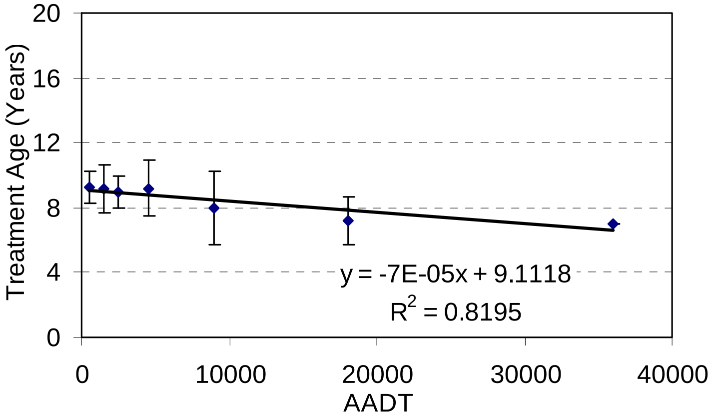


(a) HMA Overlay

(Figure 3.3 continued)



(b) Mill & fill



(c) Micro surfacing

Figure 3.3 Treatment service lives at different traffic levels

3.4.2 Calculation of Effectiveness

In this study, treatment effectiveness was calculated as the area bounded by the pre-treatment and post-treatment performance curves, the lower threshold and the treatment service life as shown in Figure 1. AASHTO recommends 2.0 as the terminal PSI value triggering resurfacing for highways with lower traffic (Huang 2003). Equation 3 was used to calculate the effectiveness for each model.

$$Benefit=\begin{cases}\dfrac{(p-b_2)^2}{2k_2}, & \text{if } b_1<p\ \&\ k_2t+b_2<p\\ \dfrac{t}{2}(k_2t+2b_2-2p), & \text{if } b_1<p\ \&\ k_2t+b_2\ge p\\ \dfrac{t}{2}(k_2t+2b_2-k_1t-2b_1), & \text{if } b_1\ge p\ \&\ k_2t+b_2\ge p\ \&\ k_1t+b_1\ge p\\ \dfrac{t}{2}(k_2t+2b_2-2p)+\dfrac{(b_1-p)^2}{2k_1}, & \text{if } b_1\ge p\ \&\ k_2t+b_2\ge p\ \&\ k_1t+b_1<p\\ -\dfrac{(b_2-p)^2}{2k_2}-\dfrac{t}{2}(k_1t+2b_1-2p), & \text{if } b_1\ge p\ \&\ k_2t+b_2<p\ \&\ k_1t+b_1\ge p\\ -\dfrac{(b_2-p)^2}{2k_2}+\dfrac{(b_1-p)^2}{2k_1}, & \text{if } b_1\ge p\ \&\ k_2t+b_2<p\ \&\ k_1t+b_1<p\end{cases} \tag{3.3}$$

Where, Effectiveness = treatment effectiveness, calculated as the area between the post-treatment performance curve and pre-treatment performance curve in the treatment service life (as shown in Figure 3.1);

t = treatment service life, year;

p = PSI low trigger value;

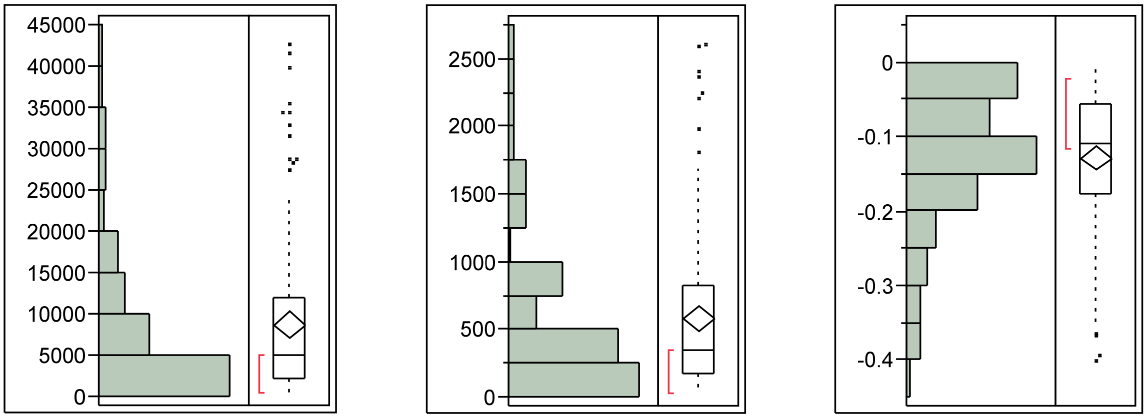
k_1, b_1 = the slope and intercept of pre-treatment linear PSI curve;

k_2, b_2 = the slope and intercept of post-treatment linear PSI curve.

3.4.3 Distribution of Data

Figure 3.4 presents the distribution of collected sample data. The two response variables, effectiveness and cost-effectiveness are generally normal distribution with a little skewness. A total of 133 samples were collected. It can be seen that all traffic volumes are lower than 45,000 AADT and 75% of them are lower than 12,000 AADT. The average pre-treatment model slope is higher than that of the post-treatment model slope, indicating the old pavement generally deteriorated faster than the new pavement surface.

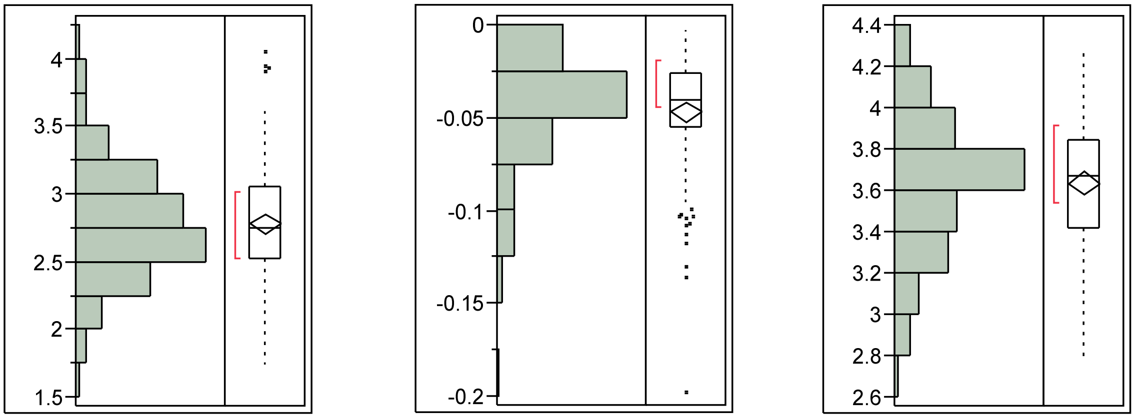
The average pre-treatment PSI is lower than the average post-treatment PSI, indicating an improvement brought by the applied surface treatment.



(a) AADT

(b) Truck_AADT

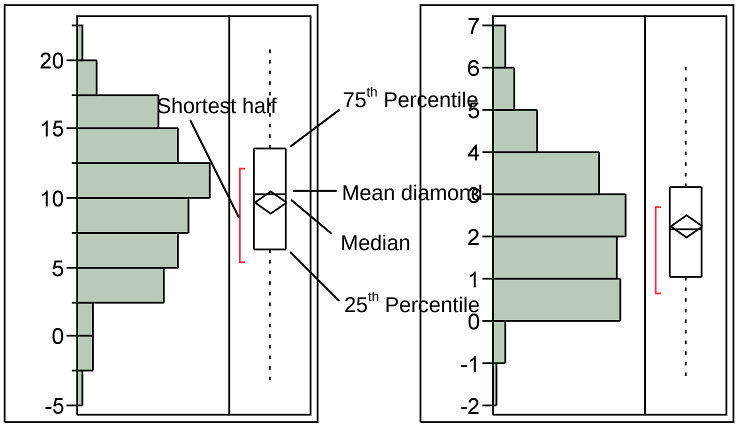
(c) Pre-treatment model slope (k_1)



(d) Pre-treatment PSI (b_1)

(e) Post-treatment model slope (k_2)

(f) Post-treatment PSI (b_2)



(g) Effectiveness

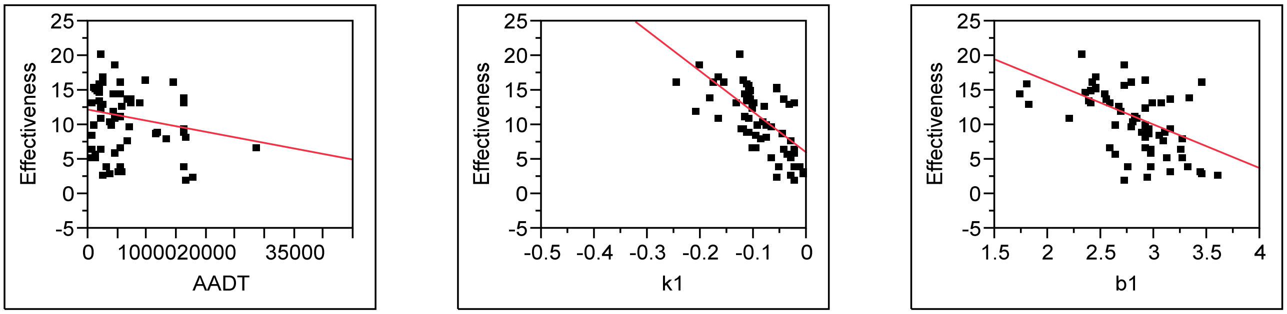
(h) Cost-effectiveness

Figure 3.4 Distribution of data prepared for effectiveness analysis

3.4.4 Influence of Different Factors on Effectiveness

Investigation the traffic volume of collected maintenance projects indicated that no more than 5% of the resurfacing projects were applied on interstates where the traffic levels are higher than 100,000 AADT. The traffic levels for all the samples were lower than 50,000 AADT. The presented analyses focused on state routes with low/moderate traffic volume. Truck traffic was thought to be a more significant factor affecting pavement performance than the overall AADT since heavy truck load tended to accelerate pavement deterioration. However, the analysis results indicated that the R^2 were not improved by using Truck_AADT instead of AADT in the treatment effectiveness model. Thus, AADT was used as the indicator of traffic level in this study.

The influence of pre-treatment pavement condition and traffic level on the treatment effectiveness was investigated through single variable model analysis first. Figure 3.5 summarize the results of linear fit for the effectiveness of the three treatments. Goodness of fit (indicated by R^2 value) and significance test (indicated by p-value) are presented. High R^2 value indicates high correlation between the factors and the target. Small p-value (usually lower than 0.05) indicates that the factor is significant for the target. It can be seen that AADT, k_1 and b_1 are all significant for the effectiveness of treatments. Although AADT is not significant for the effectiveness of HMA overlay, it still can be seen that the effectiveness of HMA overlay decrease as the AADT increase which is consistent that of mill & fill and micro surfacing. Higher R^2 values were attained by for k_1 and b_1, indicating the pre-treatment pavement condition is more significant than AADT. It can also be seen from Figure 3.5 that the slopes of those linear models were negative, indicating the effectiveness decrease as the traffic level or the pre-treatment pavement condition (k_1 and b_1) increase.

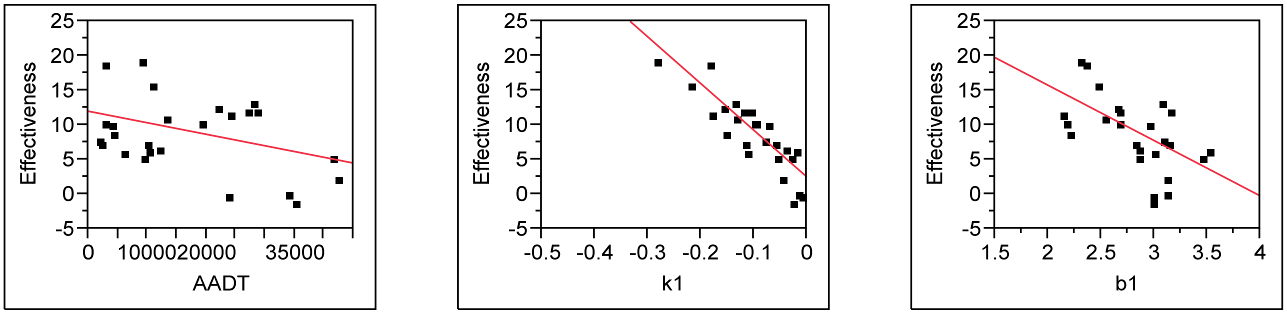


Effectiveness = 12.31 - 0.00016*AADT
$R^2 = 0.04$
P-value = 0.1042

Effectiveness = 5.95 - 59.12*k1
$R^2 = 0.47$
P-value <.0001*

Effectiveness = 29.09 - 6.36*b1
$R^2 = 0.29$
P-value <.0001*

HMA overlay

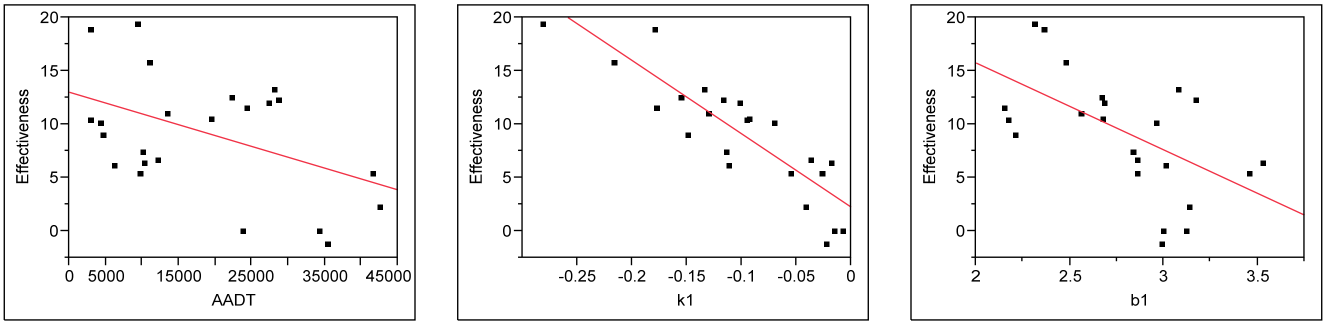


Effectiveness = 12.11 - 0.00017*AADT
$R^2 = 0.17$
P-value = 0.0424*

Effectiveness = 2.49 - 67.51*k1
$R^2 = 0.76$
P-value <.0001*

Effectiveness = 31.51 - 7.91*b1
$R^2 = 0.32$
P-value = 0.0029*

Mill & fill



Effectiveness = 13.06063 - 0.0002048*AADT
$R^2 = 0.21$
P-value = 0.0268*

Effectiveness = 2.3025209 - 68.333581*k1
$R^2 = 0.76$
P-value <.0001*

Effectiveness = 20.79 - 4.52*b1
$R^2 = 0.33$
P-value = 0.0043*

Micro surfacing

Figure 3.5 The influence of different factors on treatment effectiveness

3.5 Treatment Cost Analysis

3.5.1 Adjustment of Asphalt Material Cost

Asphalt cost usually accounts for the majority of the material cost and changes along time since the asphalt price is time-varying. An Asphalt Price Index, which is the historical asphalt price, should be utilized to calculate the adjusted cost of asphalt materials. Figure 3.6 presents the Asphalt Price Index of last 20 years. The adjusted cost of asphalt was calculated by using Equation 3.4:

$$C_{Adjust} = \frac{C_{Original}}{A_{Original}} A_{Current} \tag{3.4}$$

Where, C_{Adjust} = Adjusted asphalt cost, \$;

$C_{Original}$ = Original asphalt cost in the project, \$;

$A_{Orignal}$ = Original asphalt price of the maintenance project, \$/ton;

$A_{Current}$ = Current asphalt price Index, 600\$/ton (at the time of this study).

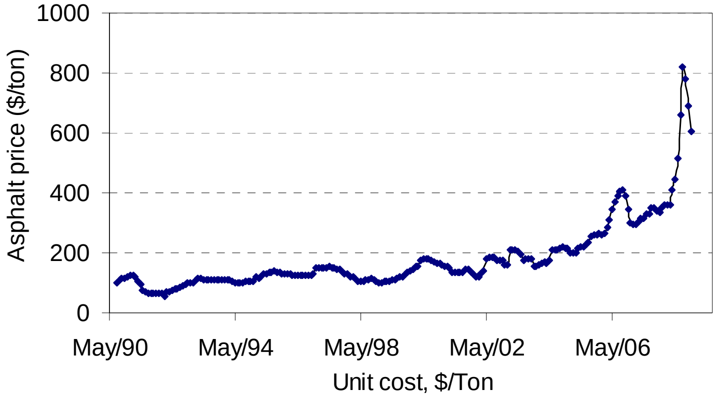


Figure 3.6 Asphalt Price Index of recent 20 years (NJ DOT, 2010)

Equation 3.5 was used to calculate the adjusted cost of hot mixed asphalt mixture:

$$M_{Adjust} = Q_m(U_m - P_b A_{Original} + P_b A_{Current}) \tag{3.5}$$

Where, M_{Adjust} = Adjusted asphalt mixture cost, \$;

Q_m = Asphalt mixture quantity, ton;

U_m = Original unit cost of asphalt mixture, \$/ton;

P_b = Asphalt content;

$A_{Orignal}$ = Original asphalt price of the maintenance project, \$/ton;

$A_{Current}$ = Current asphalt price Index, 600\$/ton.

Equation 3.6 was used to calculate adjusted cost of emulsified asphalt or tack coat bituminous materials:

$$E_{Adjust} = Q_a(U_a - A_{Original} + A_{Current}) \tag{3.6}$$

Where, E_{Adjust} = Adjusted emulsified asphalt or other bituminous material cost, \$;

Q_a = Emulsified asphalt or other bituminous material quantity, ton;

U_a = Original unit cost of emulsified asphalt or other bituminous material, \$/ton;

$A_{Orignal}$ = Original asphalt price of the maintenance project, \$/ton;

$A_{Current}$ = Current asphalt price Index, 600\$/ton.

3.5.2 Current Value of Costs

Resurfacing maintenance projects at different road sections were usually applied in different years. In order to compare their costs, the current value (Equation 3.7) of the costs needs to be calculated to account for inflationary effects.

$$FV = PV(1+i)^n \tag{3.7}$$

Where, FV = Future value or current value, \$;

PV = Present value, original costs, \$

i = Discount rate, 4% is used;

n = Age of the maintenance project, year.

3.5.3 Classification of Treatment Costs

The treatment costs were analyzed by investigating five typical maintenance projects for each treatment. Investigation results indicated that the total costs mainly included five parts:

1. Material: aggregate, asphalt, tack coat bituminous and etc;
2. Preparation: seal joints, remove original pavement, clear and etc;
3. Management: traffic control, traffic sign, flexible drums to channelize traffic, construction signs, arrow board and mobilization;
4. Pavement mark: plastic pavement mark, painted pavement marker and spray thermo pavement marking;
5. Other facilities: pipe culvert, lateral under drain, loop wire, saw slot and etc.

Among the five parts, the material cost is mainly determined by the treatment type and area. The preparation cost is not only related to the treatment type but also depends on the original pavement condition. The pavement marking, management and other facilities cost depend on the pavement geometric characteristics.

Unit cost ($\$/m^2$) of each treatment was calculated and illustrated in Figure 3.7. It can be seen from Figure 3.7 that the material cost accounts for 75% ~ 88% of the total cost. In this study, the total cost was used as the treatment cost in this study. Among the three treatments, mill & fill had the highest cost, followed by HMA overlay and micro surfacing.

Table 3.3 Unit costs of different treatments (Average ± SD)

Unit costs ($\$/m^2$)	Total	Material	Preparation	Management	Mark	Facilities
HMA overlay	2.2 ± 1.5	2 ± 1.4	0.001 ± 0.001	0.11 ± 0.05	0.2 ± 0.1	0.001 ± 0.002
Mill & fill	5.9 ± 2.2	5.2 ± 1.9	0.1 ± 0.1	0.19 ± 0.14	0.4 ± 0.2	0.107 ± 0.158
Micro surface	1.1 ± 0.5	0.8 ± 0.4	0 ± 0	0.07 ± 0.04	0.2 ± 0.1	0.002 ± 0.006

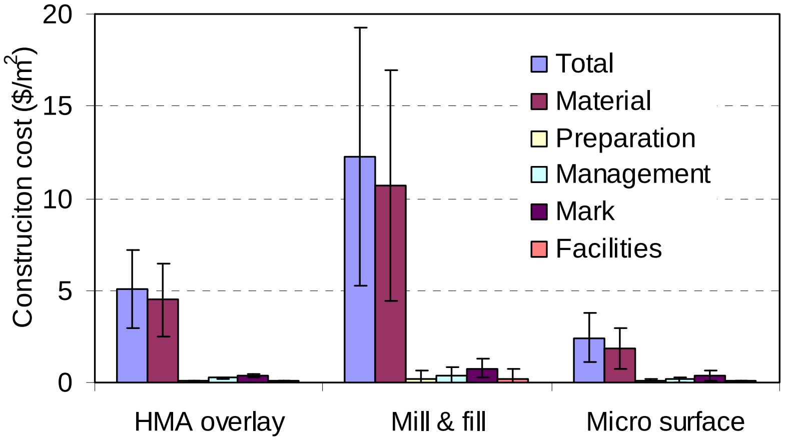


Figure 3.7 Unit costs of different treatments

3.6 Evaluation of Effectiveness and Cost-effectiveness

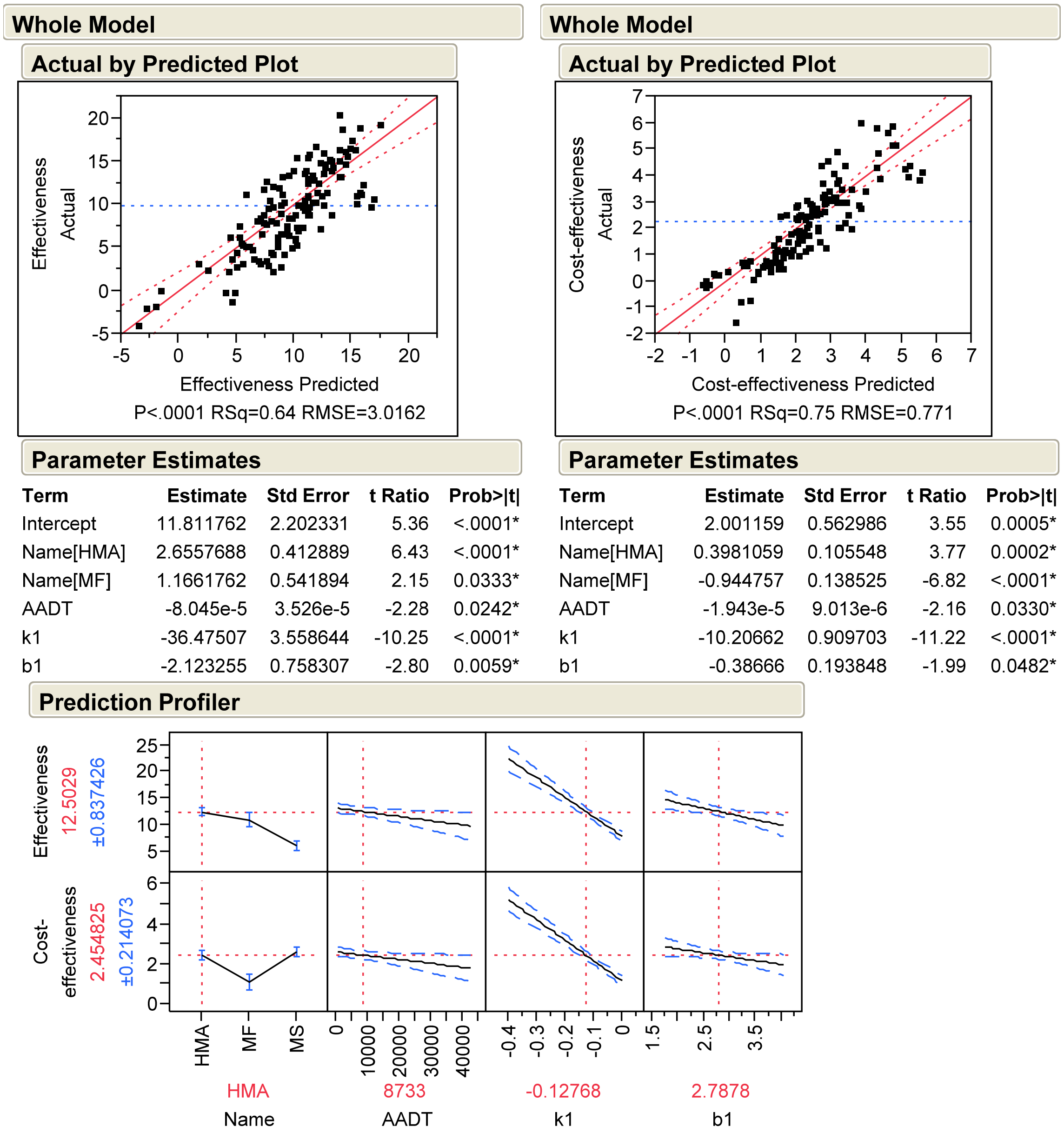
Since AADT, k_1 and b_2 were significant factors for the effectiveness of treatment, Multiple variable models were built for both the effectiveness and cost-effectiveness (effectiveness/cost). The treatment type was also incorporated in the model as a nominal variable. The function of multiple regression model is shown as Equation 3.8.

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_i X_i + \cdots + \beta_k X_k + \varepsilon \tag{3.8}$$

Where, β_0, β_1, …, β_i, ..., β_k = Partial regression coefficients or estimates of the regression parameters, β_i is the magnitude and direction change in response with each one-unit increase in predictor_i, provided other predictors are held constant.

ε = random error term.

Linear least squares approach was used to fit the multiple model. Figure 3.8 presents the multiple regression results. The goodness of fit (R^2), partial t-test of each predictor, parameter estimates and predictor profiler were summarized for each model. The R^2 measures the proportion of variation in response explained by the model. The partial t-test tests the significance of each predictor by testing the significant increase in explained variation by adding that predictor to the reduced model. The null hypothesis of the partial t-test tests is H_0: $\beta_i = 0 \mid \beta_0, \beta_1, \ldots, \beta_{i-1}, \beta_{i+1}, \ldots, \beta_k$. The significance level was 0.05, meaning that the probability of getting this result by chance is less than 5%. The parameter estimates and the predictor profiler show the predicted response as one predictor is changed while the others are held constant at the current values and thus the influence of each predictor on the response can be clearly illustrated.



Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	11.811762	2.202331	5.36	<.0001*
Name[HMA]	2.6557688	0.412889	6.43	<.0001*
Name[MF]	1.1661762	0.541894	2.15	0.0333*
AADT	-8.045e-5	3.526e-5	-2.28	0.0242*
k1	-36.47507	3.558644	-10.25	<.0001*
b1	-2.123255	0.758307	-2.80	0.0059*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	2.001159	0.562986	3.55	0.0005*
Name[HMA]	0.3981059	0.105548	3.77	0.0002*
Name[MF]	-0.944757	0.138525	-6.82	<.0001*
AADT	-1.943e-5	9.013e-6	-2.16	0.0330*
k1	-10.20662	0.909703	-11.22	<.0001*
b1	-0.38666	0.193848	-1.99	0.0482*

Figure 3.8 Multiple variable models for effectiveness and cost-effectiveness

It can be seen from Figure 3.8 that the R^2 values are 64% for effectiveness and 76% for cost-effectiveness, indicating the fitting are fairly good. The results of partial t-tests indicate all the factors are significant. In the presented prediction profiler, the black lines within the plots show how the predicted value changes when changing the current value of an individual X variable. The 95% confidence interval for the predicted values is shown by a dotted blue curve surrounding the prediction trace (for continuous variables) or the context of an error bar (for categorical variables). It can be seen that the effectiveness and cost-effectiveness decrease with the increase of traffic level and pre-treatment pavement condition.

For the effectiveness, it can be seen from the profiler that HMA overlay had the highest effectiveness, followed by mill & fill and micro surfacing. Although mill & fill includes removing old deteriorated surface layer and placing new surface, it was usually applied at the roads where severe pavement deterioration and distress had occurred. Thus, it was actually applied on a relatively weak pavement structure and tended to deteriorate faster. This might be the reason why mill & fill was a new pavement but did not provide best effectiveness.

For the cost-effectiveness, it can be seen from the profiler that micro surfacing has the highest cost-effectiveness, followed by HMA overlay and mill & fill. The relatively low costs of micro surfacing made it more cost-effective than other two treatments. It seems the surface treatment is even more cost-effective than the two new pavement layers. However, whether a maintenance treatment is optimized or not also depends on the original pavement conditions. Micro surfacing can only be applied on pavement with relatively good condition. The two new pavement layers have the ability to overcome and repair severe pavement distress. The surface treatment cannot simply replace the two new pavement layers when the pavement is in poor condition.

3.7 Conclusions

The cost-effectiveness of resurfacing maintenance treatments applied in the low/moderate traffic volume roads in Tennessee was evaluated through investigating the pavement conditions and costs of maintenance projects. Multiple variable treatment effectiveness models were established to evaluate the effectiveness and cost-effectiveness of different treatments. The influence of different factors on the effectiveness was evaluated. Based on the analysis, several conclusions can be summarized as follows:

1. Survey results indicated that treatment service life slightly decreased as the traffic volume increased. The service life of HMA overlay, mill & fill and micro surfacing are 11 years, 10 years and 8.5 years, respectively.
2. Mill & fill had the highest unit costs, followed by HMA overlay, micro surfacing.
3. Traffic level and pre-treatment pavement condition including the pre-treatment model slope and the pre-treatment PSI were significant factors for the effectiveness and cost-effectiveness of treatments. The effectiveness and cost-effectiveness decreased with the increase of traffic level and pre-treatment pavement condition.

4. HMA overlay had the highest effectiveness, followed by mill & fill and micro surfacing. Micro surfacing was the most cost-effective treatment due to its low cost. However, the two new pavement layers (HMA Overlay and mill & fill) can overcome severe pavement distress and can be applied on pavement with poor condition. Micro surfacing may be inapplicable in some situations.

3.8 Acknowledgement

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PART 4 EVALUATION OF EFFECTIVENESS AND COST-EFFECTIVENESS OF HMA RESURFACING PAVEMENT MAINTENANCE TREATMENT UTILIZING LTPP DATA

4.1 Abstract

This paper analyzed the effectiveness and cost-effectiveness of several asphalt pavement rehabilitation procedures through investigating the LTPP database. The multiple regression method was employed to build the effectiveness models and evaluate the influencing factors such as overlay thickness, pavement thickness, traffic volume and pre-overlay pavement conditions on the effectiveness and cost-effectiveness. International Roughness Index (IRI) was selected as an indicator of the pavement performance. The post-rehabilitation IRI, IRI-drop, roughness increase after rehabilitation and the “benefits” were employed as the measures of effectiveness.

The results of the present analyses indicated that traffic level, pre-rehabilitation roughness and rate of roughness increase before rehabilitation have the same effect on both the effectiveness and cost-effectiveness, whereas overlay thickness, milling and material have different effect on the effectiveness and cost-effectiveness due to the increased costs. Pavement with thick overlay, milling before rehabilitation and low pre-rehabilitation roughness has low roughness after rehabilitation. Pavement with thick overlay, milling before rehabilitation and high pre-rehabilitation roughness has high roughness drop due to the rehabilitation. Thick overlay, using RAP, high traffic level and poor pre-rehabilitation condition increase the rate of deterioration of new overlay. Pavement with thick overlay and high rate of deterioration before rehabilitation has high benefit. For a certain rate of roughness increase before rehabilitation, there is an optimized pre-rehabilitation roughness or treatment application time.

4.2 Introduction

4.2.1 Research Background

With most of the highway systems in place in the United States, emphasis has shifted from design and construction to maintenance. Pavement maintenance and rehabilitation in most states consume the majority of highway funds. Selecting the right pavement maintenance strategy considering the pavement condition, traffic, and desired performance is an important issue for all highway agencies. One critical factor in selecting the right maintenance strategy is to determine the effectiveness of different treatments. Thorough investigation into practical projects will be necessary to evaluate the effectiveness which is the improved pavement performance due to maintenance treatments and to develop the effectiveness model

A good source for selecting practical projects is the Long Term Pavement Performance (LTPP) database, which has monitored more than 2,400 pavement test sections across North America. LTPP program was established as part of the Strategic Highway Research Program (SHRP) in 1987 and managed by the Federal Highway Administration (FHWA). One of LTPP's objectives is to develop improved design methodologies and strategies for the maintenance and rehabilitation of existing pavements. LTPP includes several experiment sections (GPS-6B, SPS-3, and SPS-5) designed for this purpose (Hanna 1994). Some pavement network data including traffic loads, weather condition, pavement structure, in-place material properties, and detailed treatment information are also collected systemically.

The SPS-3 experiment was designed to evaluate the effectiveness of different preventive maintenance treatments on asphalt pavement. The treatments evaluated in this experiment included thin asphalt overlays (approximately 3.2 cm or 1.25 in. in thickness), slurry seals, crack seals, and chip seals. The SPS-5 experiment was designed to assess the effects of overlay thickness, overlay type, and pavement surface preparation on the performance of asphalt concrete pavements after rehabilitation. The GPS-6B experiment was designed to monitor the performance of conventional asphalt concrete overlays of at least 1 in. thick that were applied on asphalt concrete pavements.

4.2.2 Previous Studies on LTPP Maintenance Experiment

Daleiden et al. (1998) reported a study conducted in 1995 to identify initial findings in the early performance data from the SPS-5 experiment. No significant distinctions were found between the performances of different treatments. The limited amounts of data were considered as the main limitations to the analysis.

Rohan et al. (1999) evaluated the roughness reduction of asphalt pavement after rehabilitation by using the data from SPS-5 experiment. The IRI values before and after the rehabilitation were compared by using the two-factor analysis of variance (ANOVA), t-test and simple linear regression method. They found that the IRI values before rehabilitation, surface preparation before overlay (milling versus no milling), type of asphalt concrete used for the overlay (virgin versus recycled), and overlay thickness (50 mm versus 125 mm) are all not significant for the IRI values after rehabilitation. They pointed out that the overlay thickness and milling before overlay would influence the overlay performance and they recommended others perform such an analysis when sufficient data are available.

Eltahan et al. (1999) investigated the SPS-3 experiment and compared the survival times and life expectancy of different treatments by using the Kaplan-Meier survival analysis method. The results showed the probability of failure is 2 to 4 times higher for the sections that are in poor condition before treatment than those sections in better conditions. Chip seals outperform thin overlays, slurry seals, and crack seals in controlling the reappearance of distress. They also pointed out that parametric methods could be employed to develop distribution functions for the failure curves that can help in the prediction of survival times at any given failure probability.

Rauhut et al. (2000) investigated the performance trends and initial observations of SPS-5 and GPS-6 experiments by developing graphs of performance indicators (or distress types) versus time. These performance indicators included fatigue cracking, longitudinal cracking within the wheel path and outside the wheel path, transverse cracking, rutting, and roughness. They found that thicker overlays generally exhibit less cracking distress than the thinner ones, but have little effects on the occurrence of rutting and no apparent effect on roughness. The test sections that had been milled prior to overlay generally performed better than those without milled. The different type of mixtures (virgin or reclaimed asphalt mixtures) appeared to have the least effect on performance. However, for those sites where there was a difference, the virgin mixtures generally performed slightly better than the recycled concrete mixtures.

Hall et al. (2003) evaluated the performance of different asphalt pavement rehabilitation treatments including the influence of pre-overlay condition and other factors by using the data from the SPS-5 and GPS-6B experiments. The author used paired-difference tests to determine if there was significant difference between specific groups of test sections. They discovered that overlay thickness and pre-overlay roughness levels are the two factors that significantly influence the performance of asphalt overlays with respect to roughness, rutting, and fatigue cracking. Over the long term, the 5-in. overlays outperformed the 2-in. overlays. Overlay mixture type (virgin versus recycled) and pre-overlay preparation (with or without milling) had slight and inconsistent effects. The data show a slight but statistically significant tendency for asphalt pavements overlaid when they were rougher to have more initial roughness after overlay than asphalt pavements overlaid when they were smoother.

Due to limited time durations reported in previous research, the long-term effectiveness and especially the cost-effectiveness of different asphalt pavement rehabilitation procedures have not been investigated in a comprehensive scale. Currently, since the LTPP program has been in existence for more than twenty years and the pavement session monitored by the LTPP program have received multiple resurfacing treatments. It would be expedient to conduct comprehensive analyses on the accumulated rehabilitation data and compare the effectiveness and the cost effectiveness of different procedures.

4.2.3 Research Objectives and Scope

The objective of this study is to utilize LTPP database for evaluating the effectiveness and the cost-effectiveness of different asphalt pavement rehabilitation methods and to identify the major influencing factors through multiple regression analyses. Factors to be considered included the pre-overlay pavement condition, traffic volume and overlay thickness. International Roughness Index (IRI) was elected as an indicator for pavement performance.

4.3 Multiple Regression Analysis

Firstly, the data of the rehabilitation method, pavement structure, annual pavement performance and traffic volume were collected from the SPS-3, SPS-5 and GPS-6B experiments of LTPP database. The effectiveness of rehabilitation was calculated for each test section by investigating the service lives of the rehabilitation treatments and establishing the pavement performance models before and after the rehabilitation. The cost-effectiveness was calculated by considering the nominal cost of each rehabilitation treatment. Then, the multiple regression method was employed to analyze the influence of different factors on the effectiveness and cost-effectiveness of asphalt pavement rehabilitations.

4.3.1 Types of Rehabilitations

Table 4.1 presents the 6 types of asphalt pavement rehabilitation monitored by LTPP. The column “Count” shows the number of collected test sections. Since there are only 2 cold-mix recycled asphalt overlay test sections, the present study focused on the 4 types of hot-mix asphalt rehabilitations. The milling depth is 1.5~2 in. The recycled asphalt overlay mixtures contains 30% reclaimed asphalt pavement material (Daleiden, 1998).

Table 4.1 Asphalt pavement rehabilitation methods in LTPP

Code	Description	Mixture	Rap	Mill	Count
19	Asphalt Concrete (AC) Overlay	Hot-mix	No	No	**318**
43	Hot-Mix Recycled AC	Hot-mix	Yes	No	**43**
44	Cold-Mix Recycled AC	Cold-mix	Yes	No	0
51	Mill Off AC and Overlay With AC	Hot-mix	No	Yes	**100**
55	Mill Off AC and Overlay With Hot-Mix Recycled AC	Hot-mix	Yes	Yes	**58**
56	Mill Off AC and Overlay With Cold-Mix Recycled AC	Cold-mix	Yes	Yes	2

4.3.2 Overlay Service Life

Peshkin et al. (2004) suggested the maintenance overlay service life is the time when the performance curve reaches the lower/upper threshold value. However, treatment service lives calculated through this method are usually very high. The actual service life of asphalt overlays are 10~15 years. At around 10~15 years, although the roughness may not be low enough to trigger a lower threshold value, a severe distress condition might occur and a pavement maintenance or rehabilitation is required.

In this study, the treatment service lives for different rehabilitations were investigated and used to calculate the effectiveness. The time between one rehabilitation activity and the next one was used as the service life of that rehabilitation. As shown in Table 4.2, it can be seen that, except for type 43 (HMA with 30%RAP), the other three rehabilitations have similar average service lives. The overall average service life for asphalt pavement rehabilitation is 9.6 years.

Table 4.2 Service lives of different rehabilitations

Code	Rehabilitation type	Average service life (year)	Sample no.
19	HMA	9.7 ± 1.6	18
43	HMA (30%RAP)	n/a	n/a
51	HMA + Mill	9.3 ± 1.1	8
55	HMA (30%RAP) + Mill	9.7 ± 0.002	2
All		9.6 ± 1.4	27

4.3.3 Establishment of Pavement Roughness Model

The time series pavement performance data are usually collected to evaluate the effect of pavement treatment (Rajagopal 1990). Roughness was selected as the indicator of the pavement serviceability since it affects not only ride quality but also vehicle delay costs, fuel consumption and maintenance costs. Pavement roughness models were established by using pavement age as a predictor. Since no obvious curvature was observed for the relationship between roughness and pavement age, linear function was selected to establish the performance models in this study as shown in Equation 4.1.

$$IRI = k \cdot Age + b \tag{4.1}$$

Where, IRI = International roughness index, m/km;

Age = Age of overlay, year;

k, b = The slope (the rate of pavement deterioration) and the intercept.

Table 4.3 Data prepared for effectiveness analysis using LTPP data

No.	Type	KESAL per Year	Overlay Thick. (in.)	Total Pav. Thick. (in.)	Pre-model		Post- model		Pre IRI	Post IRI	IRI Drop	Benefit
					k1	b1	k2	b2				
1	51	53	13.5	84.1			0.01	0.52	1.25	0.55	0.69	
2	19	395	11.4	73.4	0.16	2.25	0.02	0.50	2.22	0.52	1.70	16
3	19	339	6.6	86.9	0.33	1.99	0.01	0.38	1.75	0.45	1.30	17
4	51	64	14.0	92.2			0.05	0.43	1.02	0.65	0.37	
5	19	77	3.8	36.3	0.22	1.88	0.02	0.77	1.78	0.77	1.01	13
…												
Counts	**519**		**515**	**519**	**192**	**192**	**511**	**511**	**429**	**516**	**429**	**154**

Note: k_1, b_1 = the slope and intercept of pre-rehabilitation linear performance curve, b_1 is also the pre-rehabilitation PSI; k_2, b_2 = the slope and intercept of post-rehabilitation linear performance curve.

Both the pre and post rehabilitation pavement performance models were established and the responses for the multiple regression analyses were calculated based on the established roughness model for each road test section. Table 4.3 presents examples of the established pre-rehabilitation and post-rehabilitation performance models as well as other related information of each test section.

4.3.4 Calculation of Benefit Value

The measures of effectiveness used by previous researchers include the pavement performance jump, the improved average pavement condition, the treatment service life, the extended surface layer life, deterioration rate of pavement, the area between the performance curve and lower threshold (such as a pre-specified condition trigger) and the area between the pre-treatment performance curve and post-rehabilitation performance curve in the overlay service life (Rajagopal, 1990; Peshkin, 2004 and Labi, 2005). Among them, the area bounded by the pre-treatment and post-treatment performance curves, the lower threshold and the overlay service life (Figure 4.1) best reflects the effect of treatment since it considers both overlay service life and overall pavement condition.

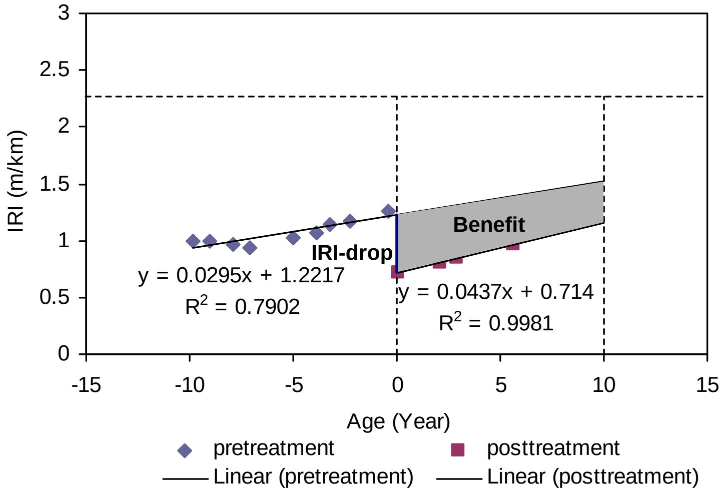


Figure 4.1 Illustration of IRI drop and benefit (SHRP-ID: 30-7076)

The measures of effectiveness used in this study can be divided into 2 types: the initial effects, including the post-rehabilitation IRI value and the IRI-drop due to the rehabilitation; and the long-term effects, including the IRI trend after the rehabilitation and the "benefit" which is the area bounded by the pre and post rehabilitation performance curves, the higher threshold and the overlay service life. Equation 4.2 is used to calculate the benefit value.

$$Benefit=\begin{cases}\dfrac{(p-b_2)^2}{2k_2}, & \text{if } b_1 \geq p \;\&\; k_2t+b_2 \geq p \\ \dfrac{t}{2}(2p-2b_2-k_2t), & \text{if } b_1 \geq p \;\&\; k_2t+b_2 < p \\ \dfrac{(p-b_2)^2}{2k_2}-\dfrac{(p-b_1)^2}{2k_1}, & \text{if } b_1 < p \;\&\; k_2t+b_2 \geq p \;\&\; k_1t+b_1 \geq p \\ \dfrac{(p-b_2)^2}{2k_2}-\dfrac{t}{2}(2p-2b_1-k_1t), & \text{if } b_1 < p \;\&\; k_2t+b_2 \geq p \;\&\; k_1t+b_1 < p \\ \dfrac{t}{2}(2p-2b_2-k_2t)-\dfrac{(p-b_1)^2}{2k_1}, & \text{if } b_1 < p \;\&\; k_2t+b_2 < p \;\&\; k_1t+b_1 \geq p \\ \dfrac{t}{2}(2p-2b_2-k_2t)-\dfrac{t}{2}(2p-2b_1-k_1t), & \text{if } b_1 < p \;\&\; k_2t+b_2 < p \;\&\; k_1t+b_1 < p \end{cases} \quad (4.2)$$

Where, Benefit = the area bounded by the pre and post rehabilitation performance curves, the higher threshold and the overlay service life (Figure 4.1);

t = Overlay service life, year;

p = Pavement performance high trigger value;

k_1, b_1 = the slope and intercept of pre-rehabilitation linear performance curve;

k_2, b_2 = the slope and intercept of post-rehabilitation linear performance curve.

4.3.5 Estimation of Nominal Costs of rehabilitations

For the 519 investigated test sections, LTPP only have the cost information for 129 test sections, which is not sufficient for conducting the cost-effectiveness analysis. Nominal costs of different rehabilitations were estimated by investigating the unit cost of HMA overlay, RAP and asphalt pavement surface milling.

The average unit cost of HMA overlay for the LTPP test roads is 1.06 \$/m^2 per 1cm depth (Jackson 2006). Brown (1999) and Kandhal (1997) investigated the economic characteristics of using RAP materials, and found that using 30% RAP materials could save 20%. Thus, the unit cost of HMA overlay containing 30% RAP is 0.85\$/m^2 per 1cm depth. The unit cost of pavement surface milling is around 6\$/m^2. The nominal unit costs (\$/m^2) for the 4 rehabilitations can be estimated by Equation 4.4. It can be estimated from Equation 4 that the costs of 51 and 55 are relatively higher than those of 19 and 43 because the cost of milling is much higher than the material cost.

$$\text{Unit cost} = \begin{cases} \textit{Overlay thickness} \times 1.06 & \text{if type} = 19 \\ \textit{Overlay thickness} \times 0.85 & \text{if type} = 43 \\ \textit{Overlay thickness} \times 1.06 + 6 & \text{if type} = 51 \\ \textit{Overlay thickness} \times 0.85 + 6 & \text{if type} = 55 \end{cases} \qquad (4.3)$$

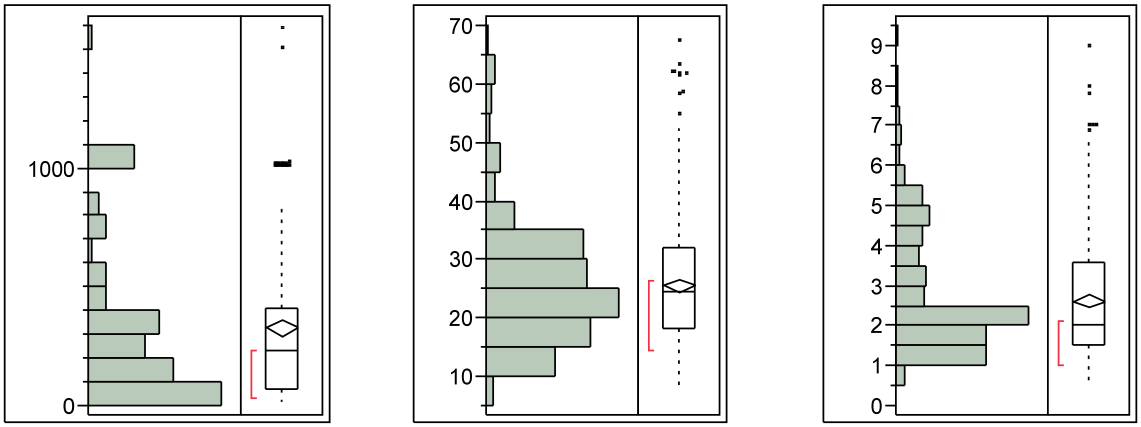
4.3.6 Predictors and Responses

Table 4.4 presents the responses and predictors for the multiple regression analyses. The overlay thicknesses and the total thickness of the pavement structure were extracted from the TST-L05B table in the LTPP database. The annual 18-kip equivalent single-axle loads (ESALs) were collected as the traffic volume factor since it converts wheel loads of various magnitudes and repetitions ("mixed traffic") to an equivalent number of "standard" or "equivalent" loads. ESAL Calculator was used to compute annual ESALs for identified rehabilitation projects.

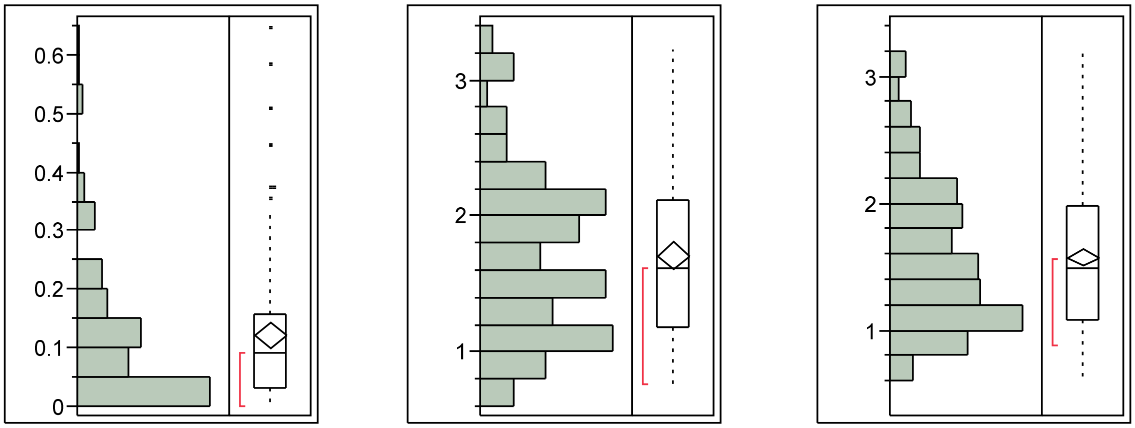
Totally, 526 road sections were collected from LTPP database. Among those identified road sections, 71 of them showed that IRI decreased as the increase of treatment age. Those sections were regarded as outliers and dropped from the analysis. 72 outliers were deleted by investigating the histogram plots of the responses. 383 road sections were used for the regression analysis. Figure 4.2 and 4.3 show the distribution of the data prepared for the multiple regression analysis. All the predictors are not correlated with each other with the exclusion of b1 and pre-IRI. Thus, b1 and pre-IRI can not be both predictors in the same model.

Table 4.4 Summary of the responses and predictors for effectiveness analysis

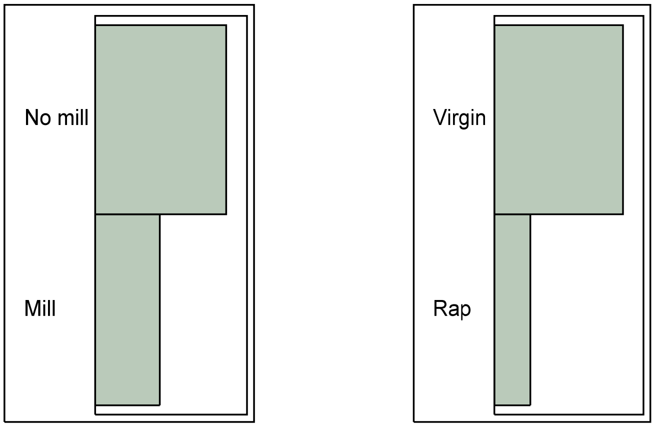
Variables		Descriptions
Predictors	Mill	Include milling or not.
	Material	Use RAP or not
	Total thickness	Total thickness of pavement
	Overlay thickness	Thickness of overlay
	Pre-IRI	IRI value before rehabilitation
	k1	Roughness increase before rehabilitation
	b1	IRI value before rehabilitation
	Annual KESALs	Annual kilo-ESALs
Response	Post-IRI	IRI value after rehabilitation
	IRI-drop	IRI reduction due to the rehabilitaion
	k2	Roughness increase after rehabilitation
	Benefit	Improved area as shown in Figure 4.1
	Post-IRI*cost	Cost-effectiveness
	IRI-drop/cost	
	k2*cost	
	Benefit/cost	



(a) Annual KESALs (b) Total thickness (in.) (c) Overlay thickness (in.)

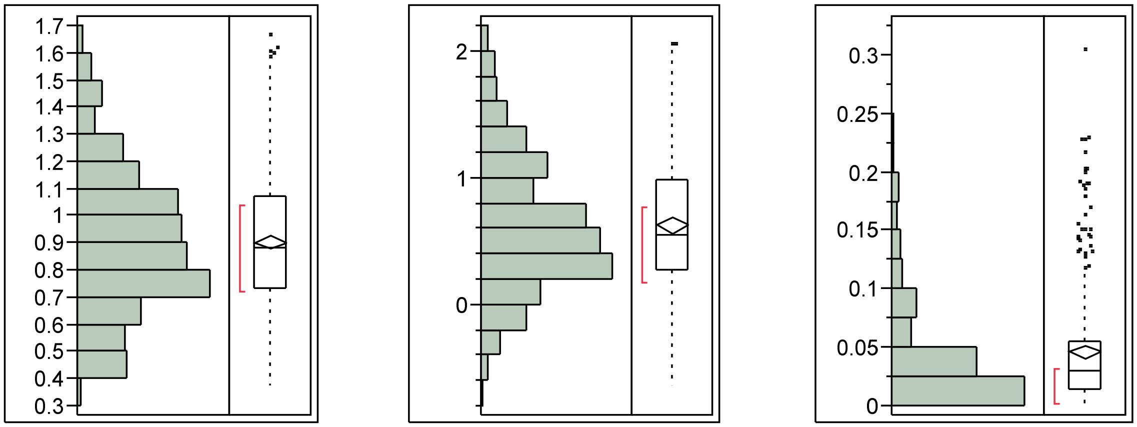


(d) k1 (e) b1 (f) Pre_IRI

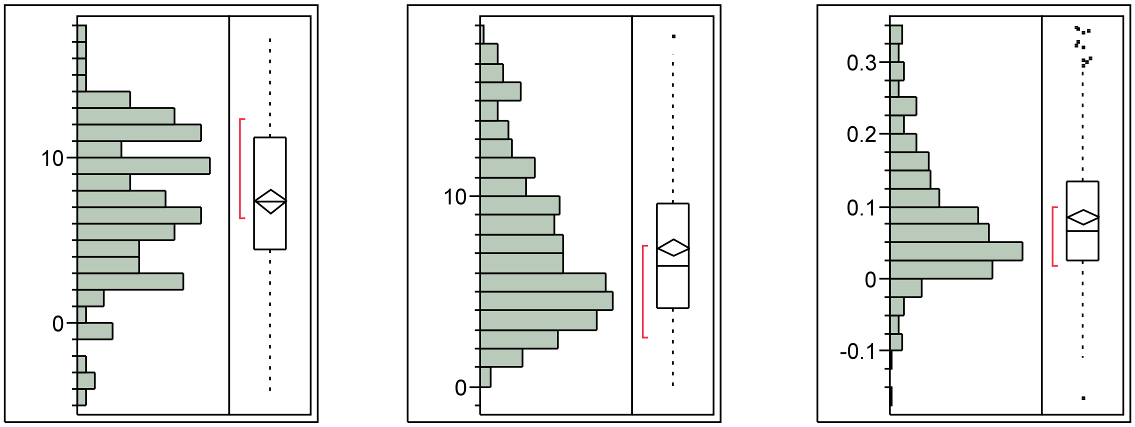


(g) Mill (h) Material

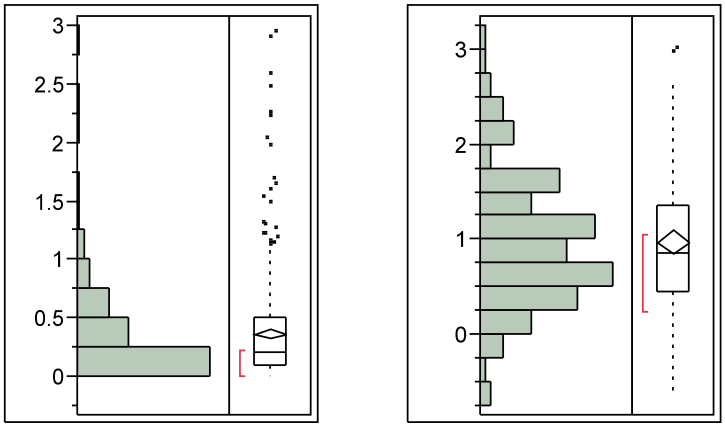
Figure 4.2 Distribution of the data for effectiveness analysis (predictors)



(a) Post_IRI (b) IRI_Drop (d) k2



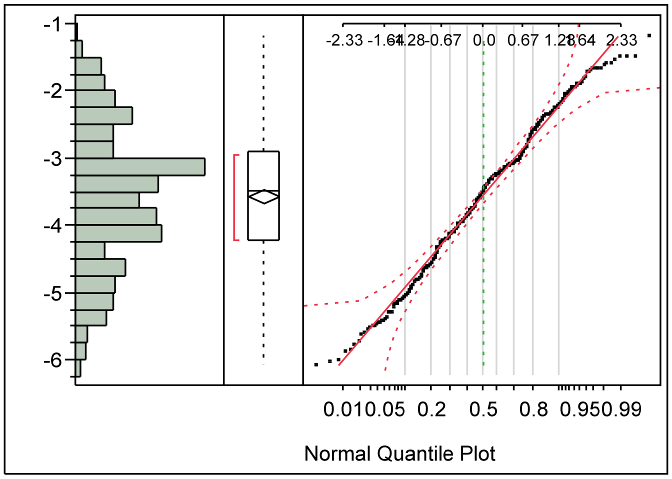
(d) Benefit (e) Post_IRI*cost (f) IRI_Drop/cost



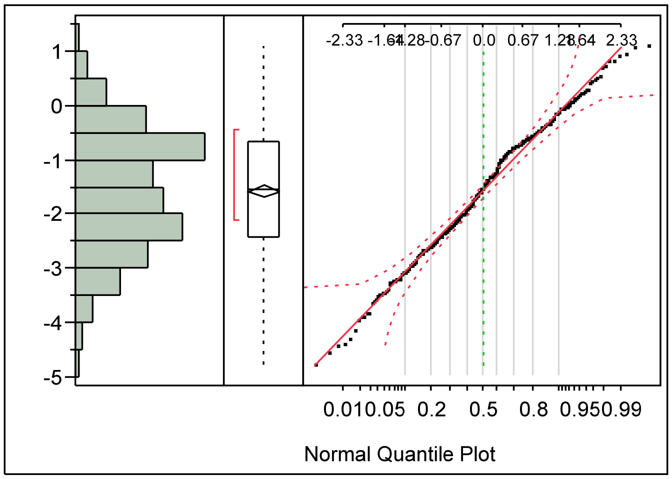
(g) k2*cost (h) Benefit/cost

Figure 4.3 Distribution of the data for effectiveness analysis (responses)

It can be seen from Figure 4.3 that, responses k2 and k2*cost have severe skewness; responses Post_IRI, Post_IRI*cost, IRI_dump and IRI_jump/cost have slightly skewness. Logarithmic transformation and square root transformation were utilized to normalize those variables as shown in Figure 4.4. Comparing with the original histogram plot, the transformed variables show fairly good normal distribution. Those transformed variables would be used instead as responses in the multiple linear regression models and ordinary least square method would be utilized to estimate the model parameters.

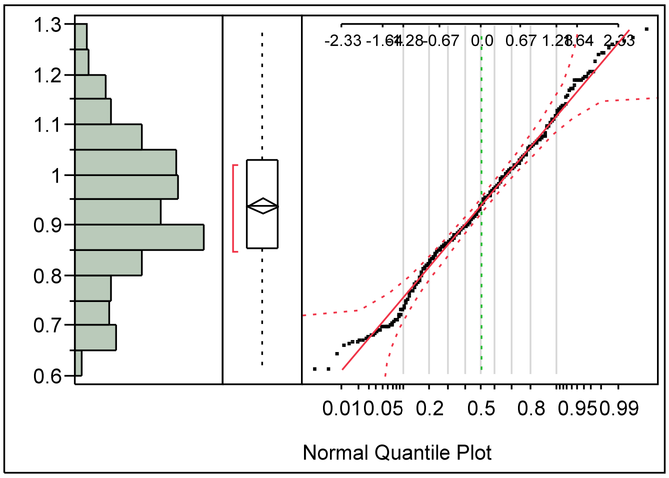


(a) Ln(k2)

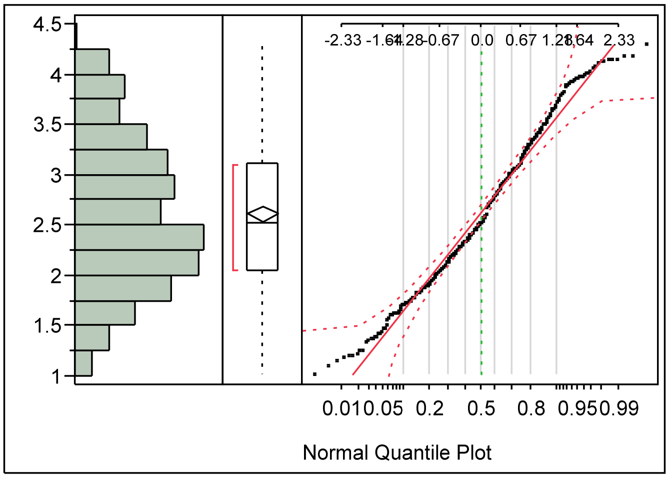


(b) Ln(k2*cost)

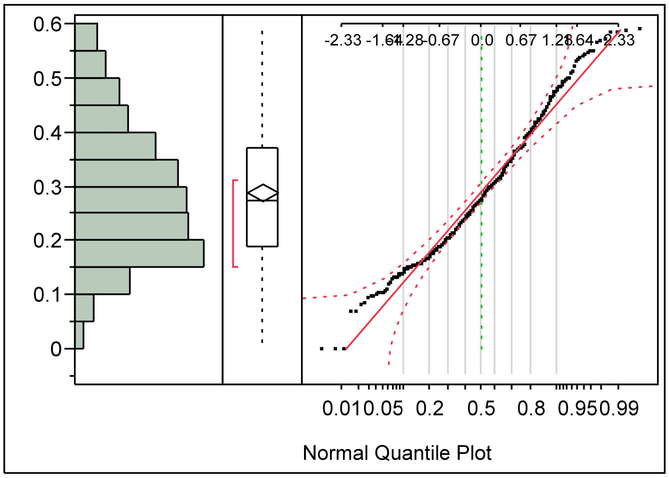
(Figure 4.4 continued)



(c) Sqrt(Post_IRI)

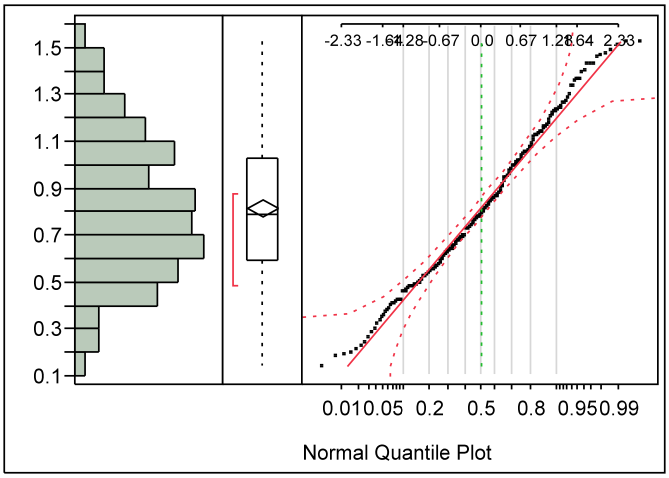


(d) Sqrt(Post_IRI*cost)



(e) Sqrt(IRI_Drop)

(Figure 4.4 continued)



(f) Sqrt(IRI_Drop/cost)

Figure 4.4 Distribution of the transformed variables

4.3.7 Multiple Regression Method

Instead of using directed paired comparison or simple linear regression as what previous researchers did, multiple regression method was utilized to analyze the influence of different factors (X_i) on the effectiveness (Y) of different rehabilitations. The function of multiple regression model is shown as Equation 4.4.

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_i X_i + \cdots + \beta_k X_k + \varepsilon \tag{4.4}$$

Where, β_0, β_1, …, β_i, ..., β_k = Partial regression coefficients or estimates of the regression parameters, β_i is the magnitude and direction change in response with each one-unit increase in predictor$_i$, provided other predictors are held constant.

ε = random error term.

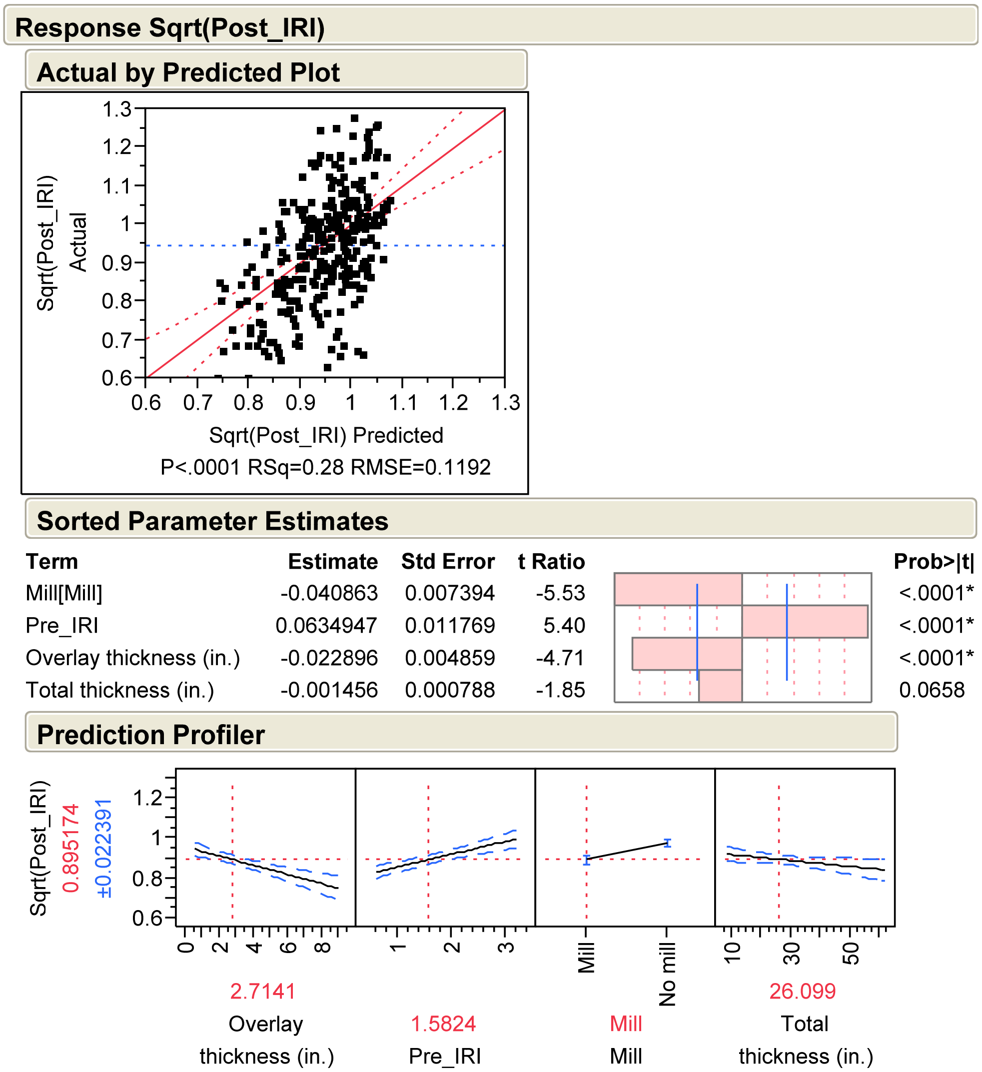
Least squares approach was used to fit the multiple model. Stepwise regression method, an iterative variable-selection procedure, was firstly used to select the significant predictors. After determining the significant factors, the ordinal least square method was used to build the multiple model. The outliers are checked based on the criterion that the standardized residual is greater than two and then dropped from the model (Paul 1991). The goodness of fit (R^2), partial t-test of each predictor, parameter estimates and predictor profiler were summarized for each model.

4.4 Discussion of Results

4.4.1 Roughness after Rehabilitation

Figure 4.5 shows the multiple regression results of the effectiveness and cost-effectiveness for the roughness after rehabilitation (Post-IRI). According to the significance test, the most significant factor for post-IRI is mill, followed by pre-IRI, overlay thickness. Total pavement thickness is a marginal significant factor. Material and annual KESALs are not significant. It can be seen from the sorted parameter estimates and the prediction profiler that thick overlay, thick original pavement and milling significantly reduced the roughness of new overlay. Pavement with higher pre-IRI has higher post-IRI.

The product of post-IRI and cost is used as a cost-effectiveness indicator for post-IRI since low post-IRI and cost were expected. It can be seen that besides overlay thickness, mill, and pre-IRI, material is also a significant predictor. Higher overlay thickness, milling and using virgin material reduced the cost-effectiveness indicated as post-treatment roughness due to the increased costs.



Response Sqrt(Post_IRI)

Actual by Predicted Plot

P<.0001 RSq=0.28 RMSE=0.1192

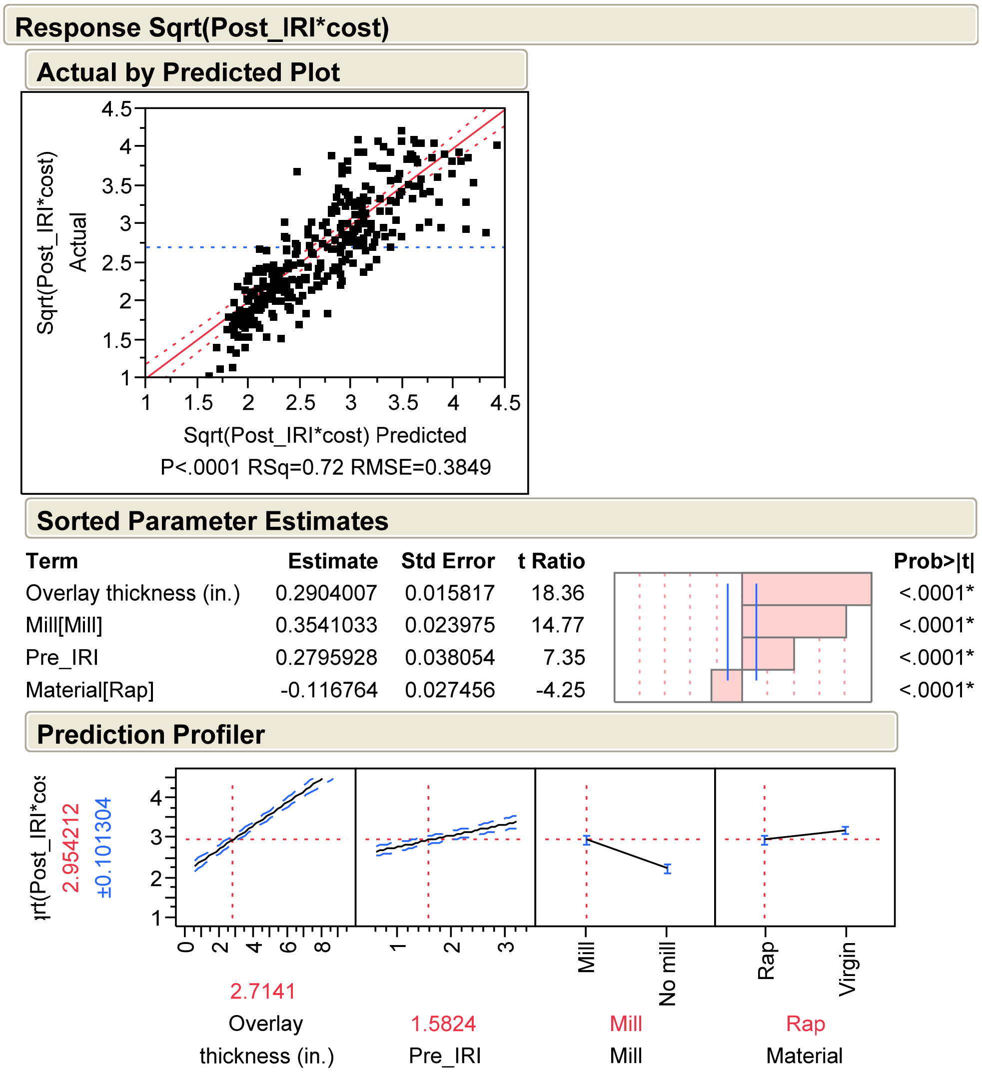
Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Mill[Mill]	-0.040863	0.007394	-5.53	<.0001*
Pre_IRI	0.0634947	0.011769	5.40	<.0001*
Overlay thickness (in.)	-0.022896	0.004859	-4.71	<.0001*
Total thickness (in.)	-0.001456	0.000788	-1.85	0.0658

Prediction Profiler

(a) Sqrt(Post-IRI)

(Figure 4.5 continued)



Response Sqrt(Post_IRI*cost)

Actual by Predicted Plot

P<.0001 RSq=0.72 RMSE=0.3849

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Overlay thickness (in.)	0.2904007	0.015817	18.36	<.0001*
Mill[Mill]	0.3541033	0.023975	14.77	<.0001*
Pre_IRI	0.2795928	0.038054	7.35	<.0001*
Material[Rap]	-0.116764	0.027456	-4.25	<.0001*

Prediction Profiler

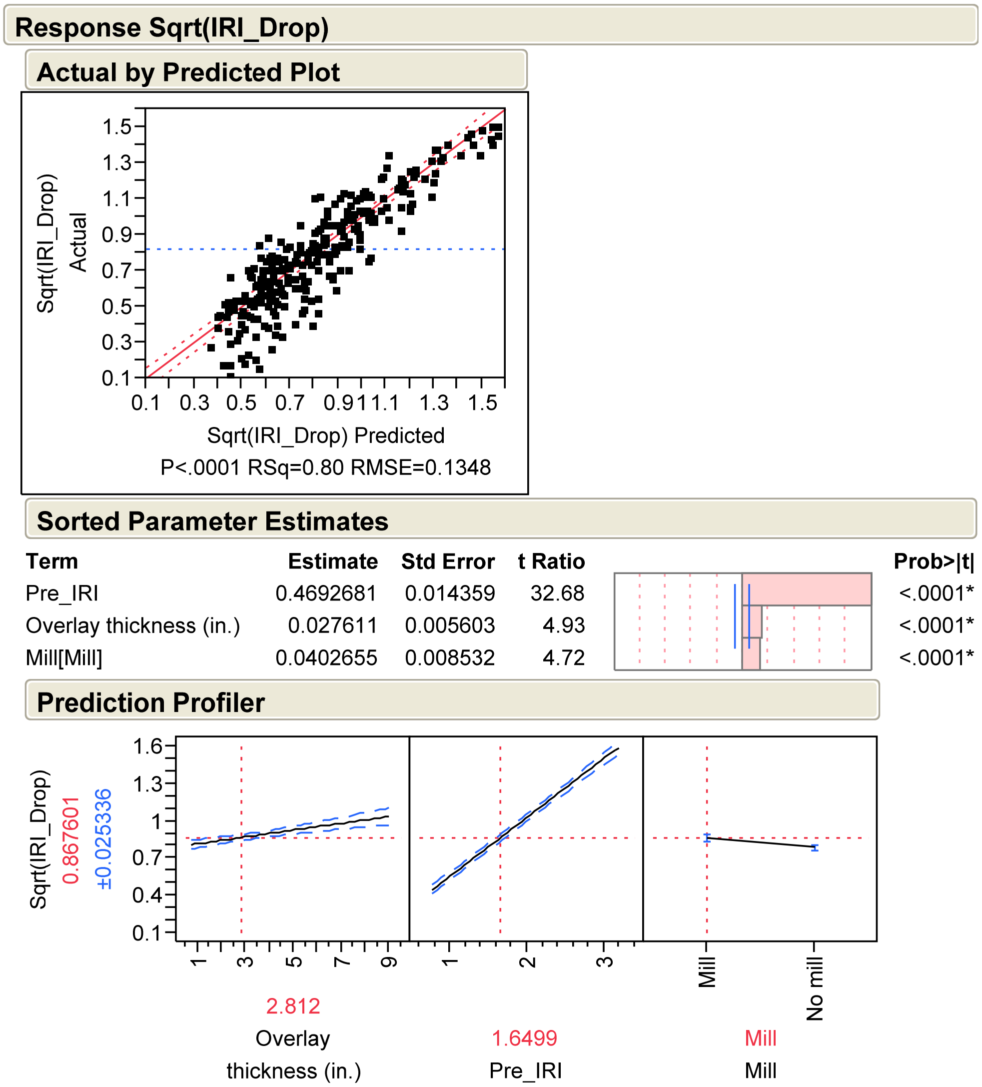
(b) Sqrt(Post-IRI*cost)

Figure 4.5 Multiple regression results for the roughness after rehabilitation

4.4.2 Roughness Drop

Figure 4.6 shows the multiple regression results for the roughness drop (IRI-drop). The three significant predictors for IRI-drop and IRI-drop/cost are generally the same with those for post-IRI and post-IRI*cost. The R^2 for IRI-drop and IRI-drop/cost are 0.86 and

0.63 respectively, indicating fairly good fit. It can be seen that thicker overlay and milling increase the roughness drop. Pavement with higher pre-IRI also has higher roughness drop. Pavement with higher overlay thickness, including milling before rehabilitation or using virgin material has lower IRI-drop per unit cost, which is also because higher overlay thickness and milling increase the costs.

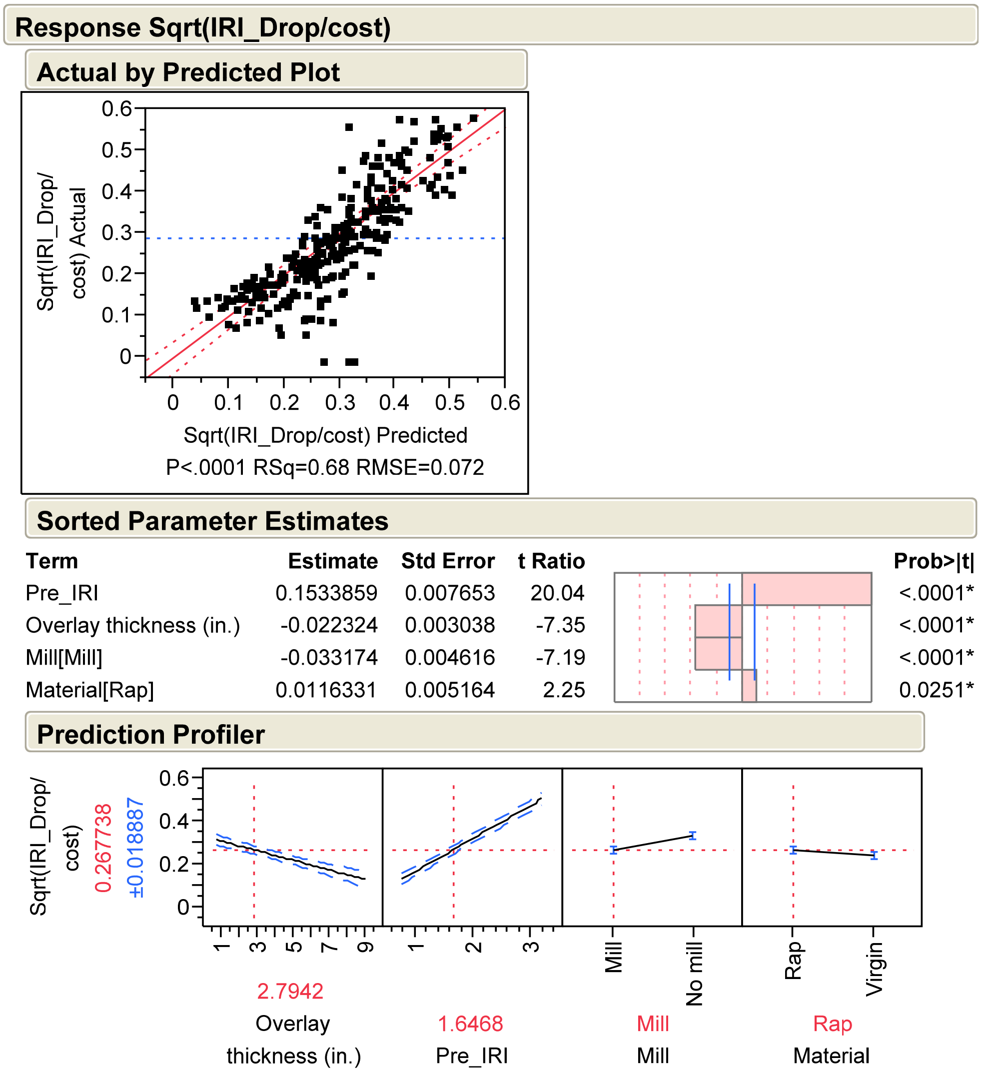


P<.0001 RSq=0.80 RMSE=0.1348

Term	Estimate	Std Error	t Ratio	Prob>|t|
Pre_IRI	0.4692681	0.014359	32.68	<.0001*
Overlay thickness (in.)	0.027611	0.005603	4.93	<.0001*
Mill[Mill]	0.0402655	0.008532	4.72	<.0001*

(a) Sqrt(IRI-drop)

(Figure 4.6 continued)



Response Sqrt(IRI_Drop/cost)

Actual by Predicted Plot

P<.0001 RSq=0.68 RMSE=0.072

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Pre_IRI	0.1533859	0.007653	20.04	<.0001*
Overlay thickness (in.)	-0.022324	0.003038	-7.35	<.0001*
Mill[Mill]	-0.033174	0.004616	-7.19	<.0001*
Material[Rap]	0.0116331	0.005164	2.25	0.0251*

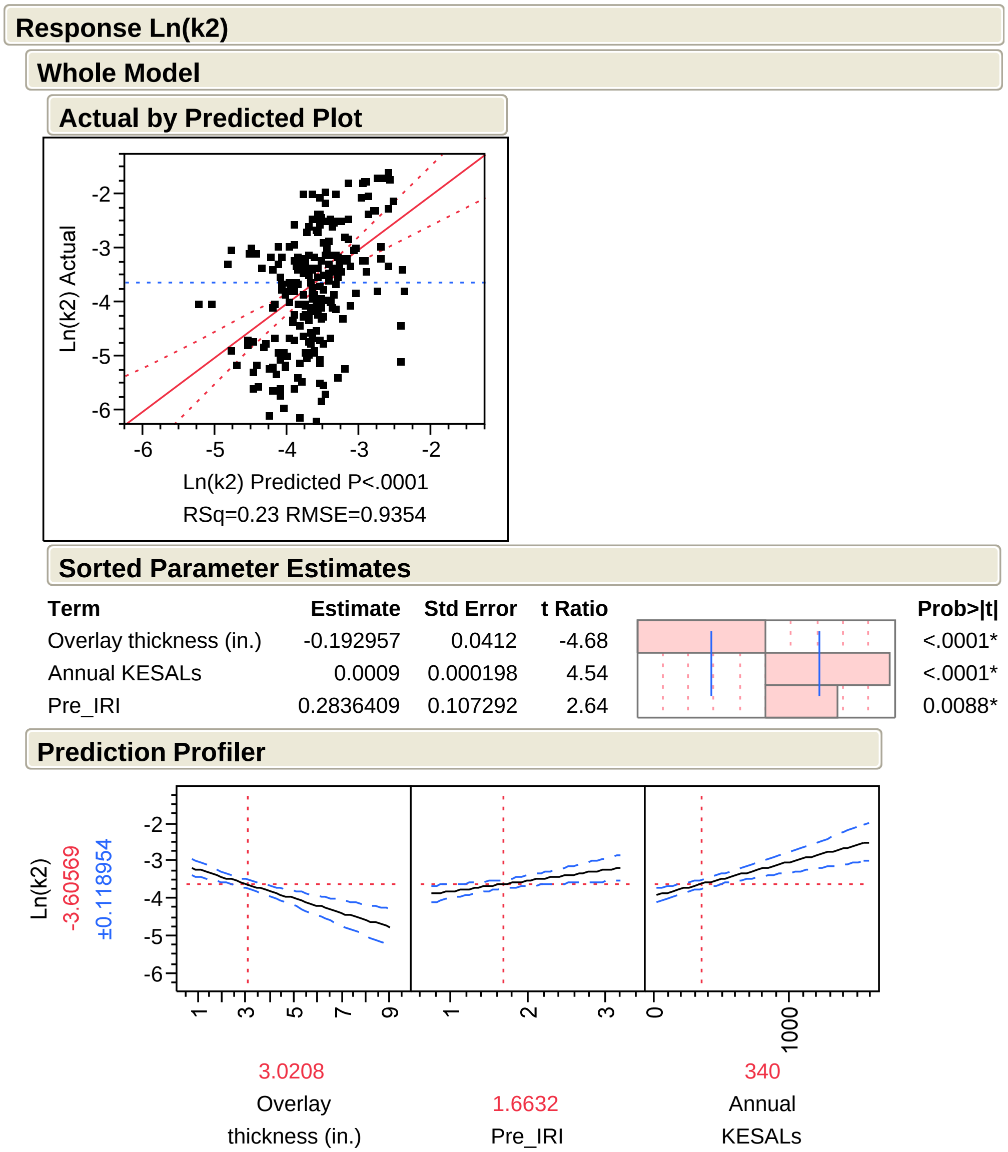
Prediction Profiler

(b) Sqrt(IRI-drop/cost)

Figure 4.6 Multiple regression results for the roughness drop

4.4.3 Roughness Increase after Rehabilitation

Figure 4.7 shows the multiple regression results for the rate of roughness increase after rehabilitation Ln(k2). The most significant factor for Ln(k2) is overlay thickness, followed by annual KESALs and pre-IRI. It can also be seen that high overlay thickness reduced the roughness increase after rehabilitation. Pavement with high annual traffic or poor pre-rehabilitation condition had high roughness increase after rehabilitation. Ln(k2*cost) is used as an cost-effectiveness indicator for the roughness increase after rehabilitation. Annual KESALs, mill and pre-IRI are significant predictors for Ln(k2*cost). Pavement with high annual traffic or poor pre-rehabilitation condition had high Ln(k2*cost). Again, milling reduced k2*cost since it largely increased the costs.



Response Ln(k2)

Whole Model

Actual by Predicted Plot

Ln(k2) Predicted P<.0001

RSq=0.23 RMSE=0.9354

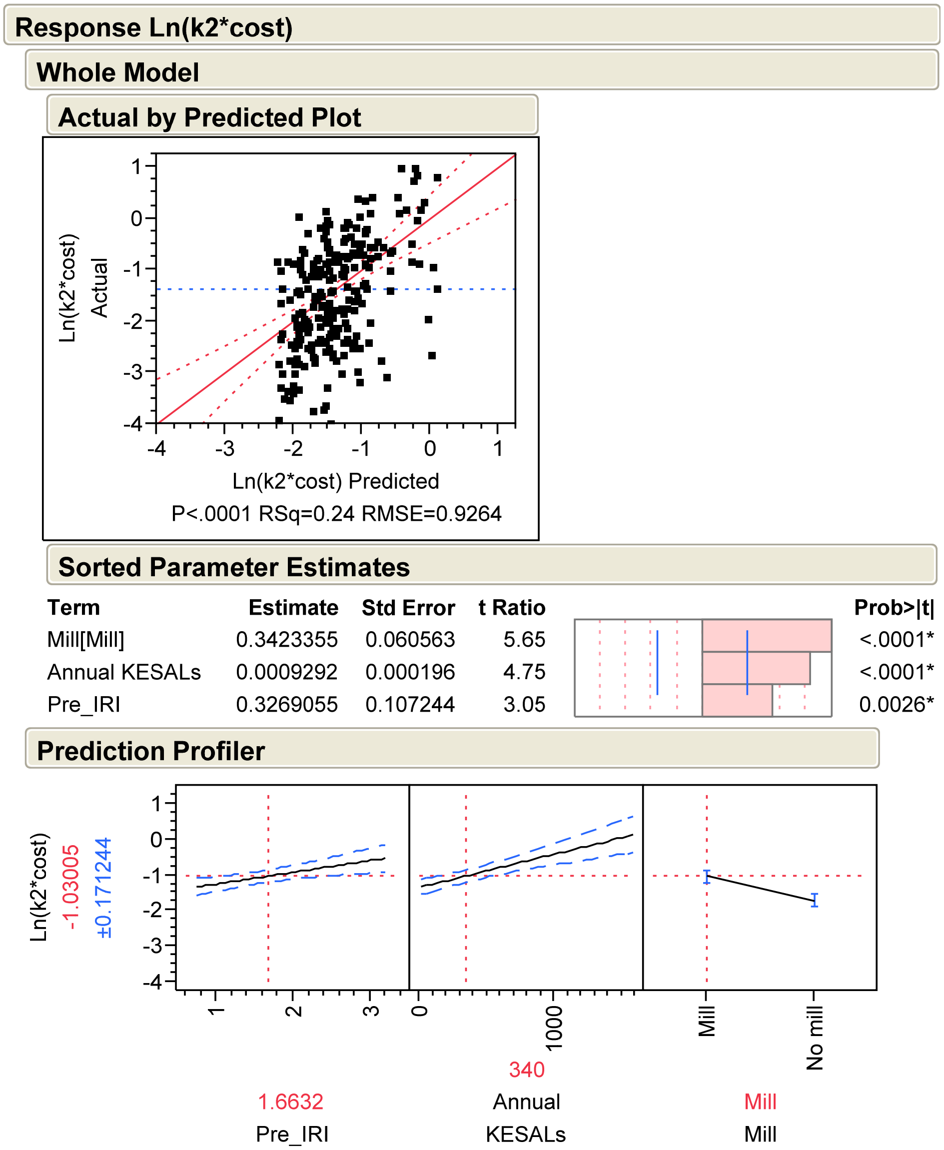
Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio		Prob>|t|
Overlay thickness (in.)	-0.192957	0.0412	-4.68		<.0001*
Annual KESALs	0.0009	0.000198	4.54		<.0001*
Pre_IRI	0.2836409	0.107292	2.64		0.0088*

Prediction Profiler

(a) Ln(k2)

(Figure 4.7 continued)



Response Ln(k2*cost)

Whole Model

Actual by Predicted Plot

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Mill[Mill]	0.3423355	0.060563	5.65	<.0001*
Annual KESALs	0.0009292	0.000196	4.75	<.0001*
Pre_IRI	0.3269055	0.107244	3.05	0.0026*

Prediction Profiler

(b) Ln(k2*cost)

Figure 4.7 Multiple regression results for rate of roughness increase after rehabilitation

4.4.4 Benefit

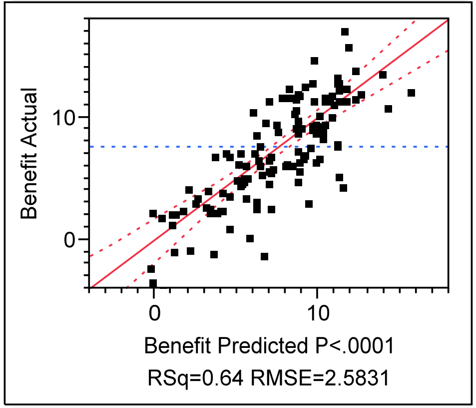
The matrix plot of predictors and responses indicated that a curvature existed between k1/b1 and benefit. Thus, three more items including k1*k1, k1*b1 and b1*b1 were added to build the new multiple regression model. Figure 4.8 shows the multiple regression results for the benefit.

Test results indicate that the most significant factor for the benefit is b1, followed by k1 and overlay thickness. The R^2 is as high as 60%. It can be seen that pavement with higher overlay thickness and the roughness increase before rehabilitation had higher benefit. Clear quadratic relationship is observed for the relationship between b1 and a maximum benefit value can be attained for certain b1 and k1. For a fixed k1, b1 is an indicator of pavement age. The result indicates that there is an optimal timing for pavement rehabilitation which agrees with the views of Peshkin (2004). Besides b1, k1 and overlay thickness, mill is a significant predictor for benefit/cost. The influence of k1 and b1 on Benefit/cost is similar with that on benefit. However, thicker overlay and milling reduced the benefit/cost due to the increased costs.

Response Benefit

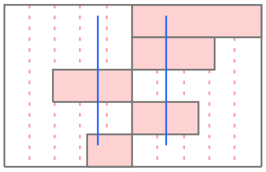
Whole Model

Actual by Predicted Plot

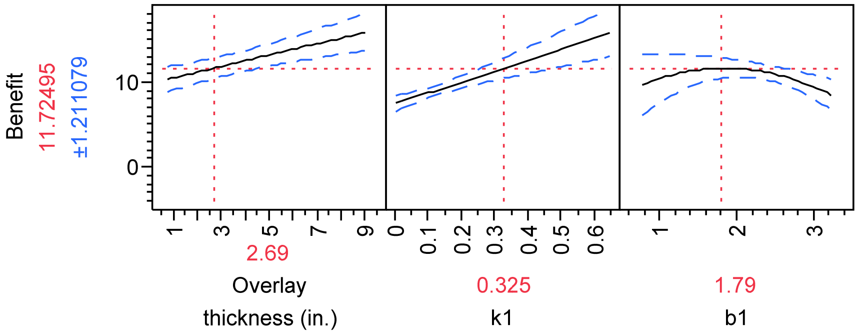


Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
b1	3.8328561	0.502051	7.63	<.0001*
k1	14.050867	2.849634	4.93	<.0001*
(k1-0.12545)*(b1-1.72331)	-17.2755	3.679246	-4.70	<.0001*
Overlay thickness (in.)	0.6742127	0.169216	3.98	0.0001*
(b1-1.72331)*(b1-1.72331)	-1.659128	0.6159	-2.69	0.0080*

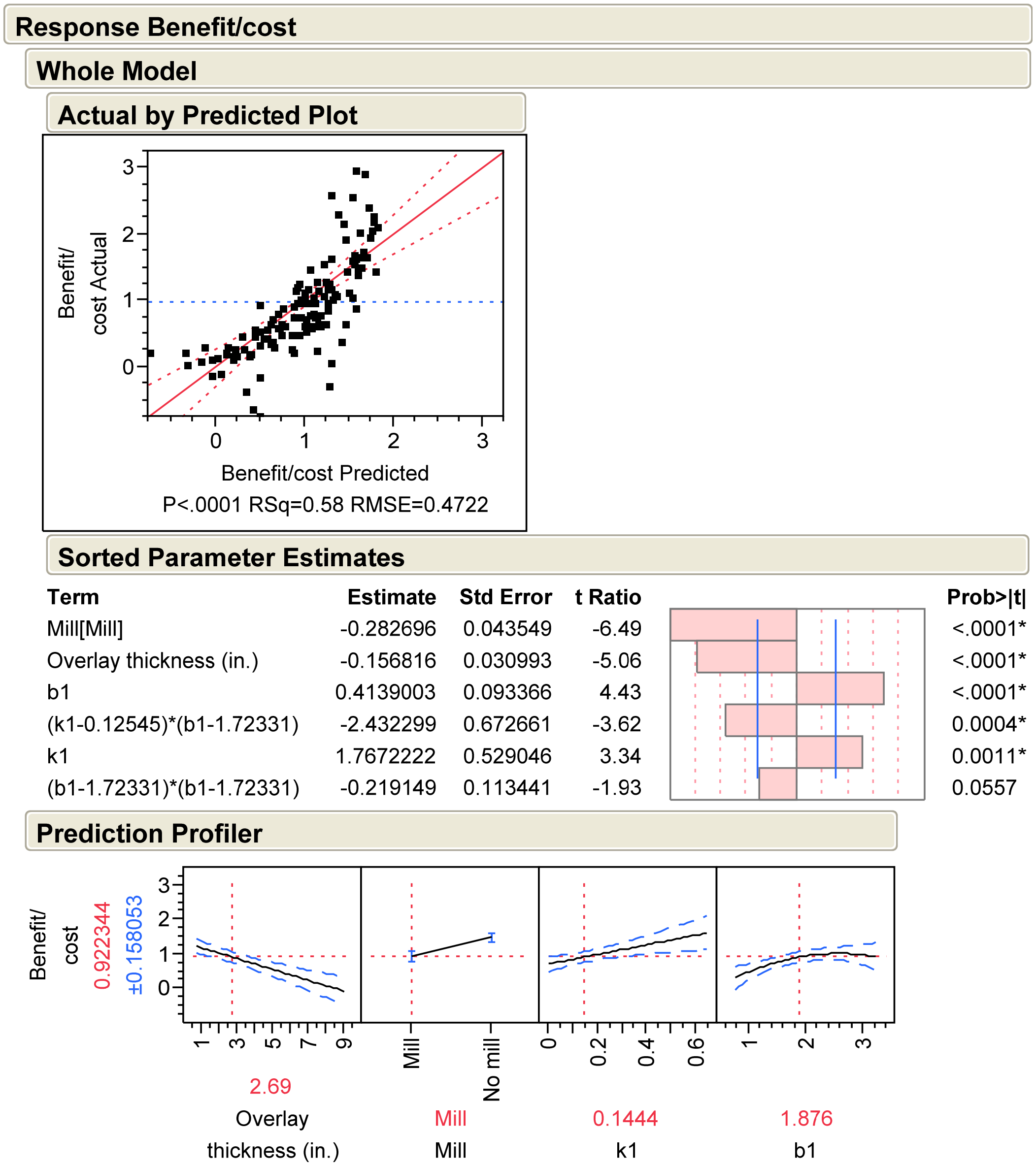


Prediction Profiler



(a) Benefit

(Figure 4.8 continued)



Response Benefit/cost

Whole Model

Actual by Predicted Plot

P<.0001 RSq=0.58 RMSE=0.4722

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Mill[Mill]	-0.282696	0.043549	-6.49	<.0001*
Overlay thickness (in.)	-0.156816	0.030993	-5.06	<.0001*
b1	0.4139003	0.093366	4.43	<.0001*
(k1-0.12545)*(b1-1.72331)	-2.432299	0.672661	-3.62	0.0004*
k1	1.7672222	0.529046	3.34	0.0011*
(b1-1.72331)*(b1-1.72331)	-0.219149	0.113441	-1.93	0.0557

Prediction Profiler

(b) Benefit/cost

Figure 4.8 Multiple regression results for the benefit

4.5 Summary and Conclusions

The effectiveness and cost-effectiveness of different asphalt pavement rehabilitations including the influence of different factors was analyzed by investigating the LTPP database. Pavement performance models before and after rehabilitation were established to calculate the effectiveness for each test section. Multiple regression method was used to develop the effectiveness models for different rehabilitations. Table 4.5 shows the results of the multiple regression analyses. The conclusions are summarized as follows:

1. Traffic level, pre-rehabilitation roughness and rate of roughness increase before rehabilitation have the same effect on both the effectiveness and cost-effectiveness, whereas overlay thickness and milling have different effect on the effectiveness and cost-effectiveness due to the increased costs. Incorporating 30% reclaimed material does not influence the performance of rehabilitation but will improve the cost-effectiveness in terms of roughness after rehabilitation and roughness drop.
2. Pavement with thick overlay, milling before rehabilitation and low pre-rehabilitation roughness has low roughness after rehabilitation.
3. Pavement with thick overlay, milling before rehabilitation and high pre-rehabilitation roughness has high roughness drop due to the rehabilitation.
4. Thick overlay, and high traffic level and poor pre-rehabilitation condition increase the rate of deterioration of new overlay.
5. Pavement with thick overlay and high rate of deterioration before rehabilitation has high benefit. For a certain rate of roughness increase before rehabilitation, there is an optimized pre-rehabilitation roughness or treatment application time.

Table 4.5 The influence of different factors on the effectiveness of rehabilitations

Variables	Total thickness	Overlay Thickness	Milling	RAP	Annual KESALs	k1	Pre-IRI (b1)
Post-IRI	↓	↓[1]	↓				↑
Post-IRI*cost		↑	↑	↓			↑
IRI-drop		↑[2]	↑				↑
IRI-drop/cost		↓	↓	↑			↑
k2		↓			↑		↑
k2*cost			↑		↑		↑
Beneft		↑				↑	downward quadratic
Beneft/cost		↓	↓			↑	downward quadratic

Note: 1. "↑" means the Post-IRI decreases with the increase of overlay thickness
2. "↓" means the Post-IRI decreases with the increase of overlay thickness.

4.6 References

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PART 5 EVALUATION OF INFLUENCE FACTORS TO THE CRACK INITIATION OF LTPP RESURFACED ASPHALT PAVEMENTS BY USING PARAMETRIC SURVIVAL ANALYSIS

5.1 Abstract

Survival model with Weibull hazard function was employed to evaluate the influence of different factors on the crack initiation of resurfaced asphalt pavement. Data from SPS-5 experiments of LTPP program were utilized to conduct the analysis. The initiation time of four types of cracks including alligator (fatigue) crack, longitudinal crack on wheel path, non-wheel path longitudinal crack and transverse crack was evaluated. Analyzed factors include overlay thickness, traffic volume, freeze index, mixture (whether or not including reclaimed asphalt pavement) and mill (or no mill) before overlay. It was found that traffic level was a significant factor for all the four types of cracks. High traffic level accelerated the initiation of cracking. Thick overlay delayed the initiation of cracking except for the non-wheel path longitudinal crack, which is mainly caused by poor construction. Total pavement thickness only retarded the initiation of wheel path longitudinal cracking. Incorporating 30% reclaimed asphalt pavement in the overlay accelerated the initiation of early age fatigue cracking; however, it was not a significant cause for severe fatigue cracking. Severe freeze thaw condition accelerated the occurrence of the non-wheel path longitudinal and transverse cracks; whereas, mill before overlay significantly retarded the occurrence of the two types of cracks.

5.2 Introduction

5.2.1 Research Background

One important purpose of pavement maintenance and rehabilitation is to extend the pavement life through repairing pavement distress and hence retard future deterioration. Extensive research has been conducted to evaluate the effect of different pavement treatments on the deterioration of pavement. Among various pavement distress types, cracking has been a critical distress in asphalt surface layer. Cracking allows moisture infiltration, increases the roughness, and may further deteriorate to potholes or other more severe distress. It usually indicates the aging the asphalt binder or even a structural failure. Investigating the initiation time of various cracks on well observed in service pavement is of great importance.

5.2.2 LTPP Program

A good source for selecting well observed pavement projects is the Long Term Pavement Performance (LTPP) database, which has monitored more than 2,400 pavement test sections in North America since 1987. Two of LTPP's main objectives are to develop improved design methodologies and strategies for the maintenance and rehabilitation and to determine the effect of loading, environment and material properties on pavement performance. LTPP includes several experiment sections (GPS-6B, SPS-3, and SPS-5) designed to address those two purposes (Hanna, 1994). Comparing to other test roads, the LTPP program contains several experimentally designed test sections over the States and systematically collects pavement data including traffic loads, climatic, pavement structure and in-place materials. This study utilized the data from the SPS-5 experiment of the LTPP program.

Since 1995, several specific FHWA studies have been conducted to evaluate the effect of different pavement maintenance or rehabilitations using the LTPP database. The studies used paired-difference tests (t/F-test), simple linear regression analysis and survival analysis to identify the improvement of the pavement performance brought by the pavement treatments and to investigate whether there are significant difference between different treatment methods (Daleiden, 1998; Rohan, 1999; Eltahan, 1999; Rauhut, 2000; Hall, 2003). Two of the studies addressed the issues of the effect of different treatments on the deterioration of asphalt pavement (Eltahan, 1999; Rauhut, 2000).

Eltahan et al. (1999) investigated the SPS-3 experiment and compared the survival time of different treatments using survival analysis. The results showed that the failure probability of sections that are in poor condition before treatment is two to four times higher than those of the sections in better conditions. Chip seals outperform thin overlays, slurry seals and crack seals in controlling the reoccurrence of distress. They pointed out that parametric methods could be employed to develop distribution functions for the failure curves that can help predict survival time at any given failure probability.

Rauhut et al. (2000) investigated the performance trends of the test sections in SPS-5 and GPS-6 experiments by developing graphs of distress indicators versus time. They found that the test sections that had been milled prior to overlay generally performed better than those without milling. Different types of mixtures (virgin or with reclaimed asphalt pavement) appeared to have the least effect on performance. However, for those sites where there was a difference, the virgin mixtures generally performed slightly better than the reclaimed concrete mixtures.

5.2.3 Survival Analysis

Data censoring is a common problem for determine the initiation time of cracks. Some cracks will appear during the survey period, while others will not appear after the survey is concluded. Traditional deterministic modeling method can only consider the events observed during the survey, which may suffer from statistical biases. Survival analysis, which is the modeling of time to event, incorporates censored data in the statistical estimation of the model parameters and thus is capable of capture the stochastic nature of crack initiation. It has been extensively employed to deal with the death in biological organisms and failure in mechanical systems. In this study, survival analysis method was employed to analyze the crack initiation time.

Survival analysis was first used in pavement performance modeling in 1930s (Winfrey 1969) based on empirical methods. The Highway Design and Maintenance Standards Study (HDM), initiated by the World Bank, employed survival analysis to predict the initiation of fatigue cracking in the HDM-III model (Paterson, 1986). Prozzi et al. (2000) re-analyzed the AASHO road test data by using survival analysis and found that the survival model is more appealing than the original AASHO formulations. Shin et al. (2003) used the duration model to predict the pavement distress initiation. He found that the duration model is more accurate than the original AASHO model. Loizos et al. (2005) developed the surface distress prediction models for pavement failure time (the initiation of cracking). The results indicate that the most significant factors explaining the initiation of cracking are traffic and climatic factors. Hong et al. (2008) used survival analysis to model the initiation of transverse cracks using in-service data for LTPP test roads. The surface layer thickness and freeze index are found to be significant factors influencing the initiation of transverse cracking. Most of the previous researches focused on the initiation of distress, while Wang et al. (2005) employed the survival analysis to model the pavement failure time which is indicated as the rapid increase of fatigue cracking. In the same study, accelerated failure time models were developed to predict the fatigue failure time based on asphalt concrete layer thickness, Portland cement concrete base layer thickness, average traffic level, intensity of precipitation, and freeze-thaw cycles.

5.2.4 Research Objective and Scope

The objectives of the present study are to compare the initiation time of different cracks and to evaluate the influence of different factors on the crack initiation of different asphalt overlays using parametric survival analysis method. The SPS-5 experiment of LTPP program, which focuses on the asphalt pavement resurfacing treatments, was used to establish the survival model. Comparing to previous studies, more types of cracking were investigated in this study. Besides, instead of selecting one or several typical projects, all the 18 projects in SPS-5 experiment were investigated in this study.

5.3 Parametric Survival Analysis Method

5.3.1 Survival Function

The survival time, T, is defined as the time elapsed until the initiation of cracks. For a given density function, f(t), of the initiation of cracks, the duration function (the cumulative distribution function) is shown as Equation 5.1.

$$F(t) = P(T \leq t) = \int_0^t f(u)du \qquad (5.1)$$

The duration function, F(t), gives the probability that the pavement will not survive before time t. Equation 5.2 shows the survival function, S(t), which is the probability that the pavement will survive at least time t.

$$S(t) = P(T \geq t) = 1 - F(t) \qquad (5.2)$$

5.3.2 Hazard (rate) Function

Equation 5.3 presents the hazard (rate) function, h(t), which is the conditional probability that the pavement will not survive between time t and t+dt, given that the pavement has survived up to time t. The hazard function is also the ratio of the probability density function f(t) to the survival function S(t).

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T \leq t + \Delta t)}{\Delta t} = \frac{f(t)}{S(t)} \qquad (5.3)$$

Three widely used hazard function for survival model include: exponential, Weibull and lognormal (Hong, 2008). An exponential function suggests that the hazard rate is a constant along time. A Weibull function indicates that the hazard rate can monotonically increase or decrease. A lognormal function indicates that the hazard rate increase first to a certain point and then decreases. Previous studies suggest that Weibull function can capture the pavement failure since the probability of distress initiation increases with the increase of time (Hong, 2008). For example, aged asphalt is more prone to crack and strip. In this paper, Weibull hazard function (Equation 5.4) was used to describe the crack initiation.

$$h(t) = \lambda p(\lambda t)^{p-1} \tag{5.4}$$

Where, λ is a scale parameter and p is a shape parameter. If p > 1, the hazard rate increase with time; while p<1, the hazard rate decrease with time.

With parameters λ > 0 and p > 0, the Weibull distribution has the density function:

$$f(t) = \lambda p(\lambda t)^{p-1} EXP(-(\lambda t)^{p}) \tag{5.5}$$

5.3.3 Censored Data

For the observation of pavement distress, two typical sceneries can occur as shown in Figure 5.1. The first one is the full observation, in which the survival time of the pavement is observed. The second one is called the right censored, in which we only know the survival time of the pavement is longer than a certain time t. For example, when no cracking was observed during the entire observation period, the survival time is equal to the longest observation time and it is right censored. Survival model is capable of incorporating those right censored data in analyzing the pavement survival probability.

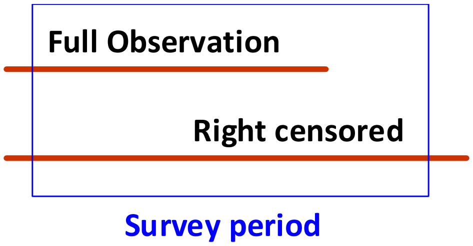


Figure 5.1 Full observation and right censored survey

5.3.4 Estimation of Parameters

In order to investigate the influence of one or more variables on the survival time or hazard rate, as shown in Equation 5.6, the parameter λ is usually expressed as the functions of those factors. An exponential form is adopted to ensure that is a positive value (Hong, 2008).

$$\lambda = EXP(\beta_0 + \beta_1 X_1 + \cdots + \beta_i X_i + \cdots + \beta_k X_k + \varepsilon) \tag{5.6}$$

Where, X_1, …, X_i, ..., X_k = factors or independent variables;

β_0, β_1, …, β_i, ..., β_k = Estimates of the regression parameters;

ε = random error term.

Since the response variables (initiation times of cracking) are not normally distributed, the ordinary least squares method does not apply. The survival model is usually estimated by taking a log transformation and using the Maximum Likelihood Estimation (MLE) method. For the full observation, its likelihood function is the probability density function, f(t). If an observation is right censored, the survival function, S(t), can be used as its likelihood function (Wang, 2008). Equation 5.7 is the log-likelihood function for the survival model (Hong, 2008). The maximum likelihood estimation procedure is to find the parameter θ that maximize the log-likelihood function.

$$\ln L(\theta) = \sum_{D_i=1} \ln f(t_i|\theta) + \sum_{D_i=0} \ln S(t_i|\theta) \tag{5.7}$$

Where, D_i is dummy variable, $D_i = 1$ means censored, $D_i = 0$ means right censored;

θ are the parameters (λ and p) to be estimated.

5.4 Preparation of Data

5.4.1 LTPP SPS-5 Experiments

The SPS-5 experiment, “Study of Rehabilitation of Asphalt Concrete Pavements”, is designed to evaluate the effect of overlay thickness, overlay type and pavement surface preparation on the performance of asphalt concrete pavements after rehabilitation (Elkins, 2008). The SPS-5 experiment has 18 projects located in different states. Each SPS-5 project consists of 9 test sections. The length of each test section is 152 m. Details of the experimental design for each project are shown in Table 5.1. The 9 test sections consist of one control section (no rehabilitation applied to the surface) and 8 test sections with different combinations of the following strategies:

- Thin and thick overlays. It is noted that although the actual thickness might not be exactly 2 or 5 in., the overlay thickness is not designed based on traffic levels.
- Virgin and reclaimed asphalt pavement (RAP) mixtures used for the overlay. The content of RAP is 30%.
- Milled and non-milled surfaces prior to overlay placement.

Table 5.1 Experimental design for each SPS-5 project

Section	Surface preparation	Mill	Designed thickness, in.	Mixture
1 (Control)				
2	Minimum	No	2	Rap
3	Minimum	No	5	Rap
4	Minimum	No	5	Virgin
5	Minimum	No	2	Virgin
6	Intensive	Yes	2	Virgin
7	Intensive	Yes	5	Virgin
8	Intensive	Yes	5	Rap

Although several SPS-5 test roads have received multiple resurfacing treatments, most of the pavement distress data were monitored and collected between the first and the second resurfacing treatments. Thus, only the rehabilitation projects with the construction no. of 2 (indicating the first resurfacing treatment) were collected from the RHB_IMP table in LTPP database (LTPP, 2010). There are totally 162 test sections in 18 states. However, eight states did not provide the distress data of the control section and one state did not have the distress data of section 2. Thus, 153 sections were collected for the analysis. The thickness of pavement structure including all types of asphalt concrete layers and base layers were calculated for each test road and used as an indicator of pavement structural capacity. The preparation (mill or no mill before overlay) and the material (using RAP or virgin material) were identified and collected. The corresponding pavement distress data were collected from the MON_DIS_AC_REV table (LTPP, 2010). Then, the initiation times and censoring status for the four types of cracking were determined.

5.4.2 Cracking Types

LTPP hired national distress data collection contractor to collect pavement condition data. The visual interpretation of high-resolution photographic images of the pavement surface was the primary means used to obtain the surface distress data for LTPP test roads. The cracking classifications were distinguished by following the "Distress Identification Manual for the LTPP Project" (Miller, 2003). The crack data recorded by LTPP include alligator (fatigue) crack, block crack, edge crack, longitudinal crack (wheel path and non-wheel path) and transverse crack. The block crack and edge crack are rarely observed while most of the test roads experienced the occurrence of the others. This study focused on the initiation time of the four types of cracking. Figure 1 shows the typical pattern of the four cracking (Muench, 1998; Asphalt Institute Inc, 2009). The definitions and the main causes are summarized as follows (Muench, 1998; Huang, 1993; Miller, 2003):

1. Alligator cracking is a series of interconnected cracks in early stages of development and can develop into many-sided, sharp-angled pieces, usually less than 0.3 meters on the longest side. It is mainly caused by the fatigue failure of

the asphalt pavement surface under repeated traffic loading and usually indicates severe fatigue failure.

2. Longitudinal cracking is the type of cracks parallel to pavement centerline either on or not on the wheel path. Non-wheel path longitudinal cracking is mainly caused by poor joint construction while wheel path longitudinal cracking is caused by the fatigue failure of the asphalt surface under repeated traffic loading or frost heaves of the base layer or subgrade. The longitudinal fatigue cracking usually indicates a low level fatigue failure at early age and may develop into alligator cracking as the fatigue failure increases.
3. Transverse cracking is the type of cracks perpendicular to the pavements centerline and is a type of thermal cracking or reflective cracking. Thermal cracking is mainly caused by the shrinkage of the asphalt surface due to low temperatures or asphalt binder hardening. Reflective cracking is mainly due to the upward progress of the cracks on base layer.

(a) Alligator cracking

(b) Longitudinal cracking (wheel path)

(Figure 5.2 continued)


(c) Longitudinal cracking (non-wheel path)

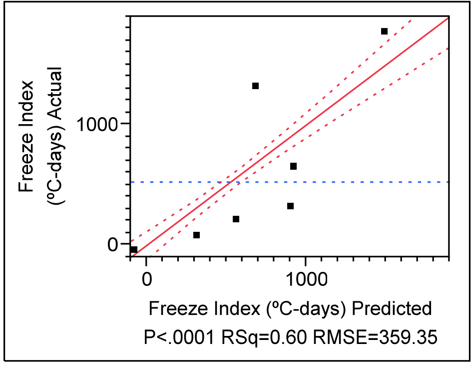
(d) Transverse cracking

Figure 5.2 Typical pattern of the four investigated cracking

5.4.3 Data Collection

In addition to the crack data and the resurfacing treatment data, other potential factors were collected from specific LTPP tables. The overlay thicknesses of different pavement overlays were extracted from the TST-L05B table. The annual 18-kip equivalent single-axle loads (ESALs) were collected as the traffic volume factor. ESAL Calculator on the datapave websites was used to calculate the annual ESALs for identified rehabilitation projects. Freeze indexes were collected from the CLM_VWS_TEMP_ANNUAL table as the climatic indicator. Generally, the predictors include two nominal variables: Mill (Yes/no) and Mixture (RAP/Virgin) and three continuous numerical variables: Annual KESALs, overlay thickness and freeze index.

Actual by Predicted Plot

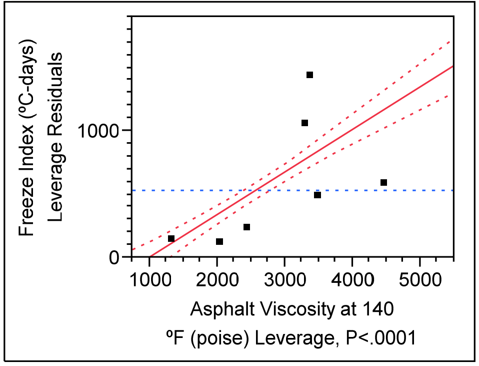


Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-1654.873	174.5161	-9.48	<.0001*
Asphalt Viscosity at 140 ºF (poise)	0.3366364	0.034031	9.89	<.0001*
Penetration at 77 ºF (.1mm)	17.839489	1.311964	13.60	<.0001*

Asphalt Viscosity at 140 ºF (poise)

Leverage Plot



Penetration at 77 ºF (.1mm)

Leverage Plot

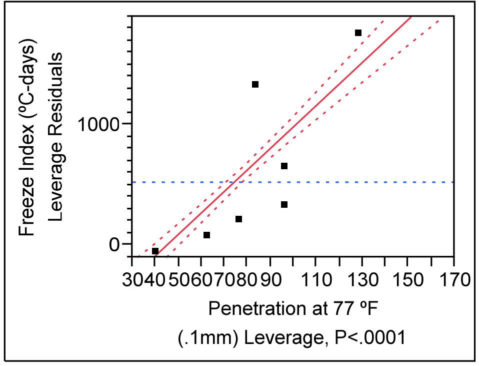
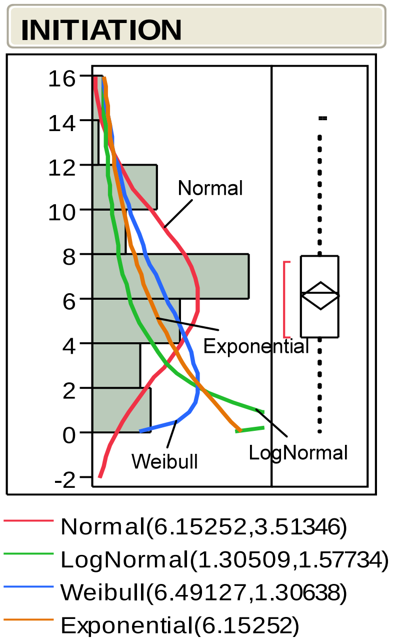


Figure 5.3 The relationship between asphalt grades and freeze index

Hong et al. (2008) suggested that asphalt grade correlates with freeze index since the asphalt grade is usually determined based on the weather condition. Figure 5.3 shows the relationship between freeze index and the viscosity and penetration of asphalt. It can be seen that freeze index is highly correlated with the viscosity and penetration of asphalt. Thus, the asphalt grade was not included in the analysis. Besides, the authors also investigated the influence of pre-treatment pavement roughness on cracking initiation.

The analysis results indicated the pre-treatment pavement roughness is not a significant factor and thus it is not included in the analysis.



```
Fitted Normal
  Goodness-of-Fit Test
  Shapiro-Wilk W Test
            W          Prob<W
       0.966386        0.0019*

Fitted LogNormal
  Goodness-of-Fit Test
  Kolmogorov's D
            D              Prob>D
       0.307056     <    0.0100*

Fitted 2 parameter Weibull
  Goodness-of-Fit Test
  Cramer-von Mises W Test
     W-Square             Prob>W^2
       1.328793     >        0.2500

Fitted Exponential
  Goodness-of-Fit Test
  Kolmogorov's D
            D              Prob>D
       0.269119     <    0.0100*
```

Note: H_0 = the data is from the tested distribution. Small p-values reject H_0.

Figure 5.4 The distribution test results for the initiation time of alligator cracking

Figure 5.4 shows the distribution test results for the initiation time of alligator cracks. The initiation time is the time when the first crack is recorded. The tested four distributions include normal, lognormal, Weibull and exponential. Shapiro-wilk W test was used to test whether the sample is a normally distributed population. Cramer-von Mises w test was employed to test whether the sample is a Weibull distribution. The Kolmogorov-Smirnov test was employed to test whether the sample is lognormal or exponential distributed. All of the three goodness-of-fit test methods are empirical distribution function tests used to decide if a sample comes from a population with a specific distribution (SAS Institute Inc., 2008). It can be seen from Figure 5.2 that only the p-values of the Weibull distribution test are higher than 0.05, indicating the initiation time of alligator cracking is Weibull distributed. The parameter p = 1.3 > 1, indicating the failure rate increases with time. Table 5.2 presents the distribution test results for all four cracks. It can be seen that all the initiation times are Weibull distributed. The values of parameters p are all larger than 1, indicating the probability of cracking increases with the increase of pavement age.

Table 5.2 P-values of the distribution tests for the four types of cracking

Cracking types	Normal	Lognormal	Exponential	Weibull	Weibull parameters	
					λ	p
Alligator crack	0.0019*	<0.0100*	<0.0100*	>0.25	6.50	1.30
Longitudinal crack (Non wheel path)	0.0015*	<0.0100*	<0.0100*	>0.25	6.60	1.16
Longitudinal crack (Wheel path)	<.0001*	<0.0100*	<0.0100*	>0.25	5.49	1.25
Transverse crack	0.0003*	<0.0100*	<0.0100*	>0.25	5.94	1.27

Note: 1. H_0 = the data is from the tested distribution. Small p-values reject H_0.
2. * indicates the p-value is less than 0.05 and the factor is significant.

5.5 Discussion of Results

5.5.1 Survival Probability of Different cracks

A commercial statistic software JMP 8.0 was employed to conduct the survival analysis. Figure 5.5 presents the survival curves of the four cracks, which shows the survival probabilities at different treatment age. It can be seen that the survival probability decreased as the pavement age increased. Generally, alligator crack has the highest survival probability, followed by longitudinal crack on wheel path, transverse crack and non-wheel path longitudinal crack.

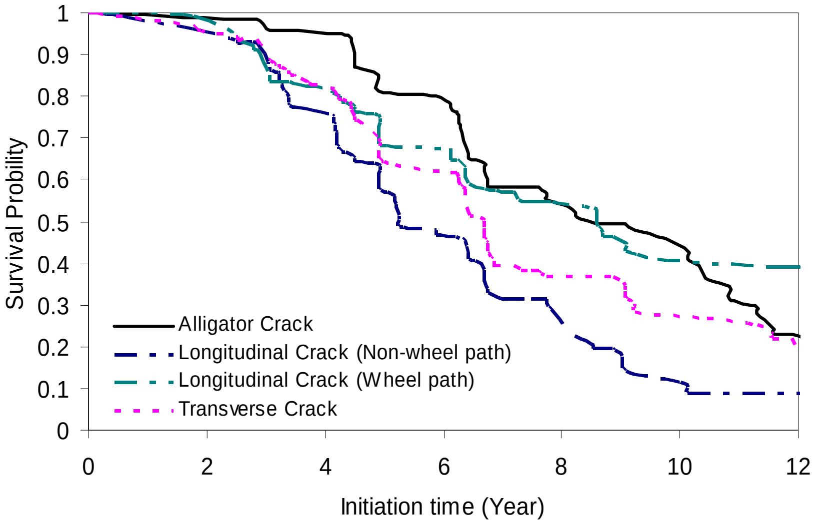


Figure 5.5 Survival probabilities of the four cracks

5.5.2 Parametric Survival Analysis

Survival models using Weibull hazard function were established for all the four cracks to conduct the parametric survival analysis. Table 5.3 presents the results of likelihood ratio tests of all the predictors for the four cracks. The likelihood ratio test tests the significance of each predictor by comparing the log-likelihood from the fitted model to the one that removes each term from the model individually. The null hypothesis of the likelihood ratio test is H_0: $\beta_i = 0 \mid \beta_0, \ldots, \beta_{i-1}, \beta_{i+1}, \ldots, \beta_k$. Small p-value rejects the null hypothesis, which means the factor is significant. The significance level was 0.05, meaning that the probability of getting this result by chance is less than 5%. Figure 5.6 presents the failure probability profiler for the four cracks. The failure probability profiler shows the predicted probability of crack initiation as one predictor is changed while the others are held constant at the current values and thus the influence of each predictor on the probability of crack initiation can be clearly illustrated.

Table 5.3 Likelihood ratio test results for each predictor

Crack types	Predictors	DF	L-R ChiSquare	Prob>ChiSq
Alligator crack	Annual KESAL	1	42.01	<.0001*
	Overlay Thickness (cm)	1	6.57	<.0103*
Longitudinal crack (Non wheel path)	Annual KESAL	1	28.55	<.0001*
	Freeze Index (°C-days)	1	22.70	<.0001*
	Mill	1	6.33	0.0119*
Longitudinal crack (Wheel path)	Annual KESAL	1	19.16	<.0001*
	Total Thickness (cm)	1	5.45	0.0239*
	Mixture	1	5.10	0.0350*
	Overlay Thickness (cm)	1	4.45	0.0195*
Transverse crack	Annual KESAL	1	33.19	<.0001*
	Freeze Index (°C-days)	1	14.84	0.0005*
	Overlay Thickness (cm)	1	4.70	0.0301*
	Mill	1	4.70	0.0302*

Alligator Crack

According to the likelihood ratio tests, the most significant factor for the initiation of alligator (fatigue) cracking was annual KESAL, followed by overlay thickness. Mill, mixture, freeze index and total pavement thickness were not significant. It can be seen from the failure probability profiler that pavement with high traffic level and thin overlay had high probability to experience alligator cracking. The failure probability increased from 0.1 to 0.5 as the annual kilo-ESAL increased from 300 to 900. Milling before overlay did not retard the initiation of alligator cracking. Using RAP or severe freeze thaw condition did not accelerate the occurrence of alligator cracking.

Non-wheel Path Longitudinal Crack

The most significant factor for the initiation of non-wheel path longitudinal cracking was annual KESAL, followed by freeze index and Mill. Mixture, total thickness and overlay thickness were not significant. Severe freeze thaw environment and high traffic level accelerated the occurrence of this type of longitudinal cracking. Milling before overlay significantly retarded the initiation of non-wheel path longitudinal cracking. It can be seen from Figure 5.6 that, the failure probability was reduced from 0.6 to 0.3 by milling. The reason is that milling eliminated the pavement distress on the old pavement and improved the bond between overlay and the old pavement structure. Using RAP and thin overlay did not influence the initiation of non-wheel path longitudinal cracking.

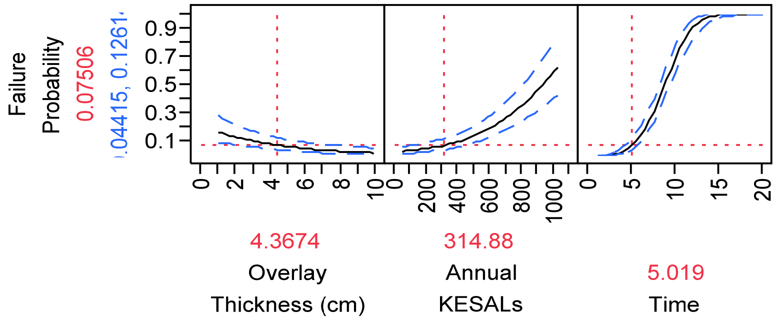
Longitudinal Crack on Wheel Path

Annual KESAL is the most significant factor for the initiation of longitudinal cracking on wheel path, followed by total thickness, mixture and overlay thickness. Freeze index and mill were not significant. High traffic level, using RAP, thin overlay or thin pavement structure accelerated the initiation of the longitudinal cracking on wheel path. It can be seen from Figure 5.6 that using RAP increased the failure probability from 0.15 to 0.25. Comparing with the 2 in. thick overlay, the 5 in. thick overlay reduced the failure probability from 0.4 to 0.2. Environmental condition and mill seems insignificant to the initiation of the longitudinal cracking on wheel path.

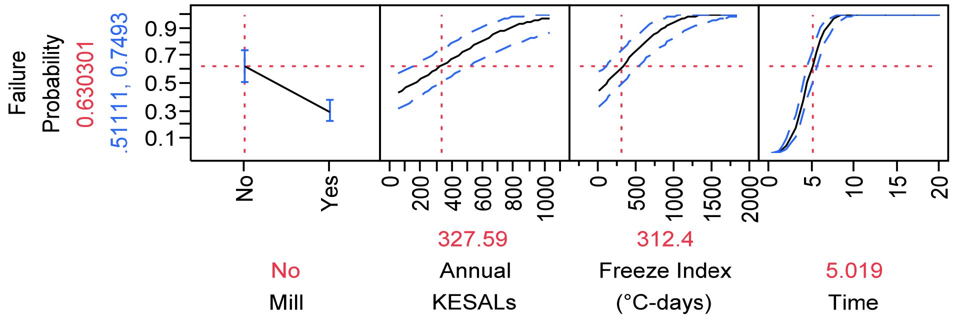
By incorporating more factors, this study found that using RAP caused some early age fatigue failure problem, but was not a significant factor contributing to severe fatigue cracking. Due to lower effective binder content and brittle binder, RAP may cause early age fatigue cracking in the form of wheel-path longitudinal cracking. However, alligator cracking is a more severe fatigue cracking and is caused by multiple reasons including decrease in pavement load supporting, heavier loads than anticipated in design, aging of both virgin and recycled binder and inadequate compaction during the construction (Muench, 1998). RAP was not a significant factor causing severe fatigue failure. Thus, incorporating 30% RAP is acceptable. Several reported studies on in situ performance of RAP mixtures found that asphalt mixture with low or moderate RAP content (<25%) performed as well as or even better than mixtures made of new materials (Newcomb, 2007 and McDaniel 2009). Hong et. al (2010) utilized sigmoid model to simulate the development of rutting, roughness and transverse cracking based on 16 years data of SPS5 experiment in Texas. He also found that mixtures with RAP content as high as 35% could perform as well as that with virgin materials.

Transverse Crack

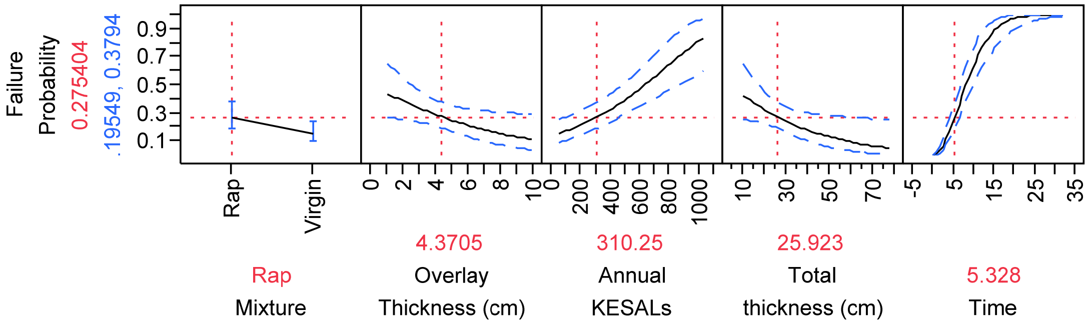
The most significant factor for the initiation of transverse cracking is annual KESAL, followed by freeze index, mill and overlay thickness. Transverse cracking is mainly caused by the shrinkage of the asphalt surface due to low temperatures or the upward progress of the cracks on base layer. Mixture and total thickness are not significant factors. High traffic level and severe freeze thaw environment accelerated the initiation of transverse cracking while milling before overlay and thick overlay retarded the occurrence of transverse cracking. Using RAP did not influence the occurrence of transverse crack.



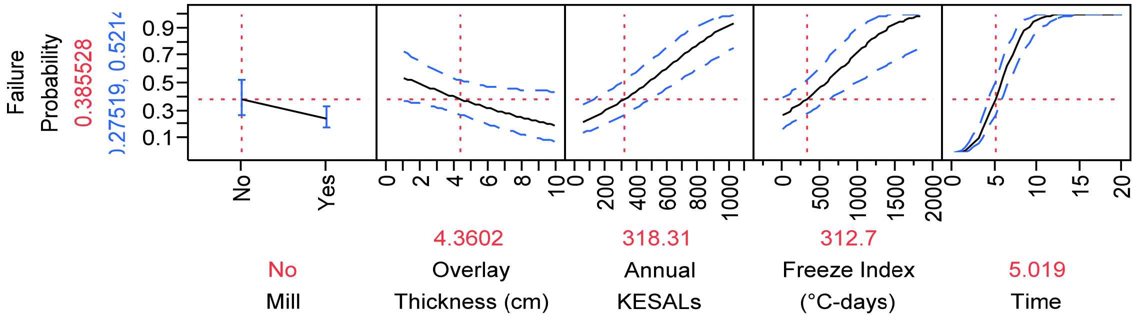
(a) Alligator crack



(b) Longitudinal crack (Non wheel path)



(c) Longitudinal crack (Wheel path)



(d) Transverse crack

Figure 5.6 The influence of factors on the probability of crack initiation (failure)

5.6 Conclusions and Future Research

Parametric survival analysis with Weibull hazard function was employed to evaluate the influence of different factors on the crack initiation of asphalt pavement overlays. By incorporating more factors and all the 18 SPS-5 test sites, broader conclusions can be attained. Table 5.4 presents the analysis results. Several conclusions can be summarized as follows:

1. Traffic level was a significant factor for all four types of cracks. A higher traffic level would accelerate the initiation of cracking.
2. Thick overlay effectively retarded the initiation of cracking except the non-wheel path longitudinal cracking, which is mainly caused by poor joint construction.
3. Thick pavement structure retarded the initiation of wheel-path longitudinal cracking which is an early age fatigue cracking or caused by the frost heaves of base layer or subgrade while had no significant influence on non wheel-path longitudinal cracking, thermal cracking and alligator cracking.
4. Incorporating 30% reclaimed asphalt pavement in the overlay accelerated the initiation of longitudinal cracking on wheel path which is a type of early age fatigue cracking, while it did not cause serious fatigue problem.
5. Severe freeze thaw environment accelerated the occurrence of non-wheel path longitudinal cracking and transverse cracking, while milling retarded the occurrence of the two non-fatigue cracking. This is because mill is capable of eliminating the pavement distress on the old pavement and improving the bond

between overlay and the old pavement structure. Severe freeze thaw environment and mill have no significant influence on the initiation of the two fatigue cracking.

Table 5.4 The influence of different factors on the initiation of cracking

Factors	Alligator crack	Longitudinal crack (Non-wheel path)	Longitudinal crack (Wheel path)	Transverse crack
High Annual KESAL	↑*	↑	↑	↑
High Overlay Thickness	↓*		↓	↓
High Freeze Index		↑		↑
Mill (Yes)		↓		↓
Mixture (RAP)			↑	
High Pavement Thickness			↓	

Note: 1. "↑" means the failure probability increases with the increase of annual KESALs,
2. "↓" means the failure probability decreases with the increase of overlay thickness.

This study focused on the initiation of cracks but did not incorporate the propagation of the cracks. A potential future research area is to determine an appropriate pavement crack failure threshold so that a survival model can be developed to analyze the crack propagation. Because of the high variance of construction quality, pavement structure and overlay material, the survival model developed in this study was mainly used to analyze the influence of different factors but was not sufficient to predict the survival time nationwide. It is suggested that survival models at different traffic, environmental, and highway classifications can be developed to predict the failure times.

5.7 Acknowledgement

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assistance on the data inquiry. The contents of this paper reflect the views of the authors, who are responsible for the facts and the accuracy of the data presented herein, and do not necessarily reflect the official views or policies of the FHWA, nor do the contents constitute a standard, specification, or regulation.

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PART 6 CALIBRATION OF THE HMA TREATMENT PERFORMANCE MODELS FOR HPMA

6.1 Abstract

The performance curves of typical Hot Mix Asphalt (HMA) resurfacing treatments used in Tennessee were calibrated for the PMS system of TDOT. The linear treatment performance curves over time were established first by investigating the collected historical maintenance projects. Multiple regression methods were employed to analyze the influence of pre-treatment PSI, traffic level, overlay thickness and milling depth on the slopes and intercepts of post-treatment linear performance curves. The specific designs of HMA treatments and performance classes were determined based on the regression results. Then, the performance curves for each identified treatment methods at different performance classes were established and the parameters of the corresponding performance models in the PMS system are calibrated.

The multiple regression analysis results indicated that pavement with high pre-treatment PSI, thick overlay and deep milling had low deterioration rate, whereas pavement with higher traffic level deteriorated faster. Pavement with high pre-treatment PSI, thick overlay and high traffic level tended to have high post-treatment PSI. Investigation on the PDI curves indicates that PDI decreased much faster than PSI and accounts larger proportion of PQI which is an overall pavement condition indicator.

6.2 Introduction of HPMA

TDOT currently uses Highway Pavement Management Application (HPMA) as its PMS system. HPMA can be divided into two functional parts: the information system and the management system. The information system part provides a straight forward access for users to retrieve, edit and report the pavement and road related data. The management system part allow the user to objectively assess the current pavement status and estimate the maintenance or rehabilitation needs at both project and network level.

The impact of different pavement maintenance treatments on the pavement performance can be evaluated by the performance prediction curves. HPMA has a specific curve format as shown in Equation 6.1. Users can define the parameters for pavement condition prediction models for various maintenance treatments.

$$\text{Index} = o - e\,\hat{}\,(\,a - b * c\,\hat{}\,t\,) \qquad (6.1)$$

Where: Index = pavement performance index including PSI and PDI;

o = starting value at age zero;

e = Euler's number;

^ = indicates exponent;

a,b,c = model coefficients;

t = Ln(1/Age).

Table 6.1 and Figure 6.1 present the default 12 HMA treatment methods and the PSI prediction models defined in HPMA. It can be seen that, although the model format is complicated, the models are generally linear with a little curvature. If 2 is set as the PSI trigger value, most treatment will last for 10~20 years, which agrees with practical experience. By calibrating the model parameters using the data of practical maintenance projects, more realistic treatments and the corresponding prediction models can be applied in HPMA and the accuracy of the maintenance strategy analysis will be greatly improved.

Table 6.1 Treatment activities defined in HPMA

Code	**ID**	**Activity**	**Type**
1	M1_2	Mill & Replace 1"-2"	Rehabilitation
2	M2_4	Mill & Replace 2"-4"	Rehabilitation
3	MO2200	MR 1-2" + OL 200 PSY	Rehabilitation
4	MO4200	MR 2-4" + OL 200 PSY	Rehabilitation
5	MO2400	MR 1-2" + OL 400 PSY	Rehabilitation
6	MO4400	MR 2-4" + OL 400 PSY	Rehabilitation
7	O200	Overlay < 200 PSY	Rehabilitation
8	O400	Overlay 200-400 PSY	Rehabilitation
9	O>400	Overlay > 400 PSY	Rehabilitation
10	RECON	Reconstruction	Construction
11	RO800	Rubblize OL 900 PSY	Rehabilitation
12	OC-BIT	Orig. BIT Constr	Construction

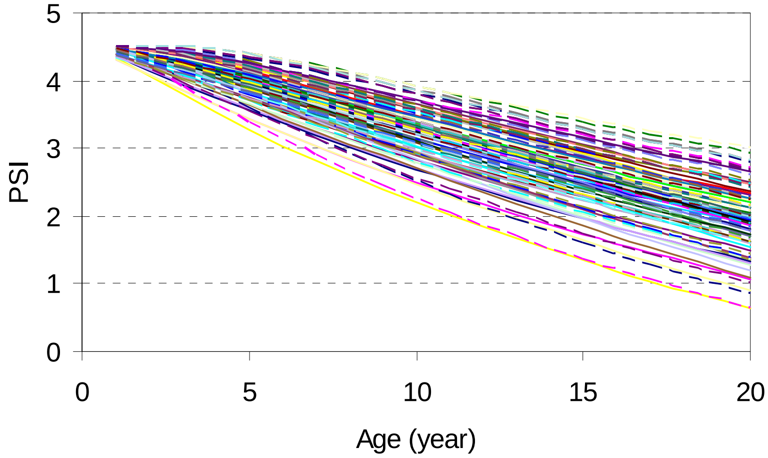


Figure 6.1 The default treatment performance PSI curves in HPMA

6.3 Calibration of PSI Performance Models

The calibration model will focus on HMA resurfacing treatments, which account for majority of all the pavement maintenance activities as shown in Figure 3.2. As shown in Figure 6.2, the procedures to develop and calibrate the HPMA performance models are summarized as follows:

1. Develop linear PSI curve for each road section.
2. Investigate the influence of different factors on the slopes and intercepts of the linear curves.
3. Identify typical treatment methods and significant performance classes.
4. Develop new linear performance models for different treatment methods at different performance classes.
5. Calibrate the HPMA models based on the developed new linear models.

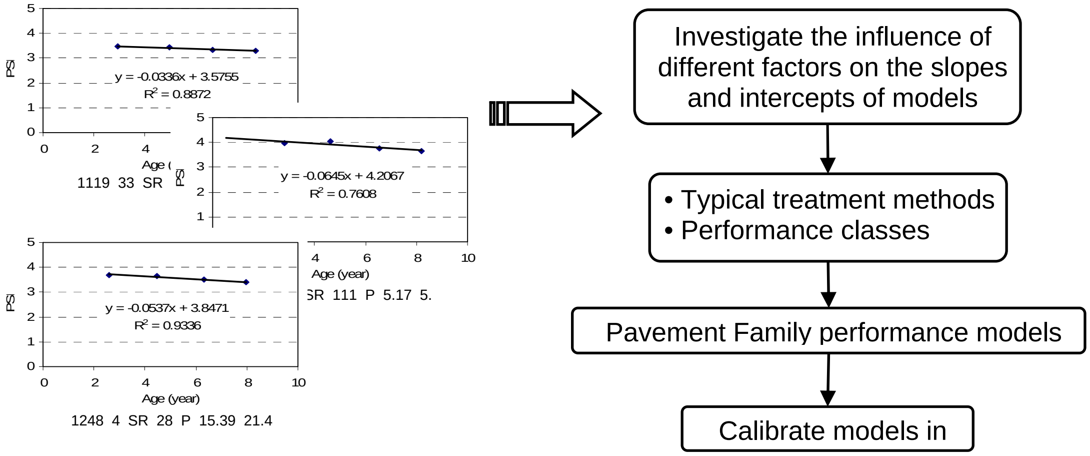


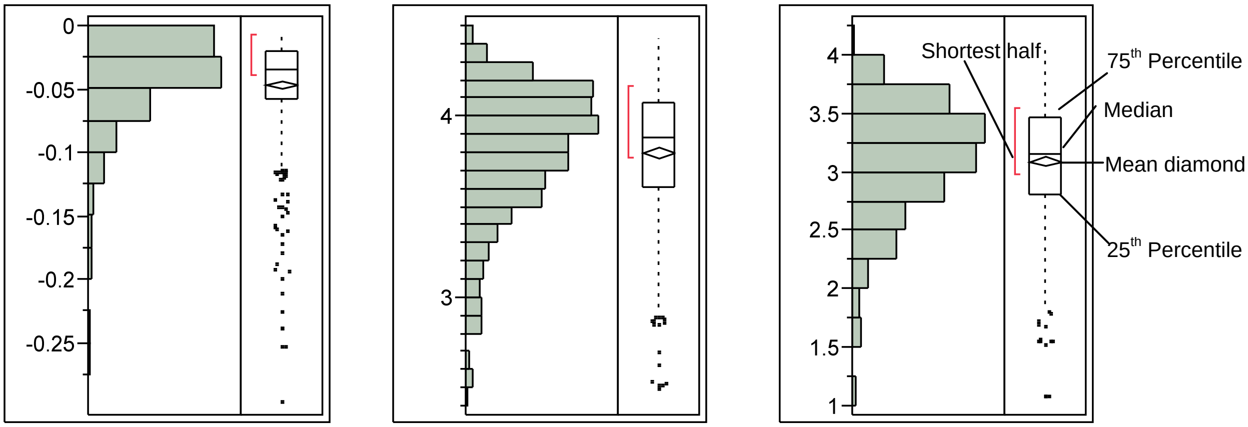
Figure 6.2 Procedures of calibrating HPMA models

6.3.1 Data Collection and Distribution

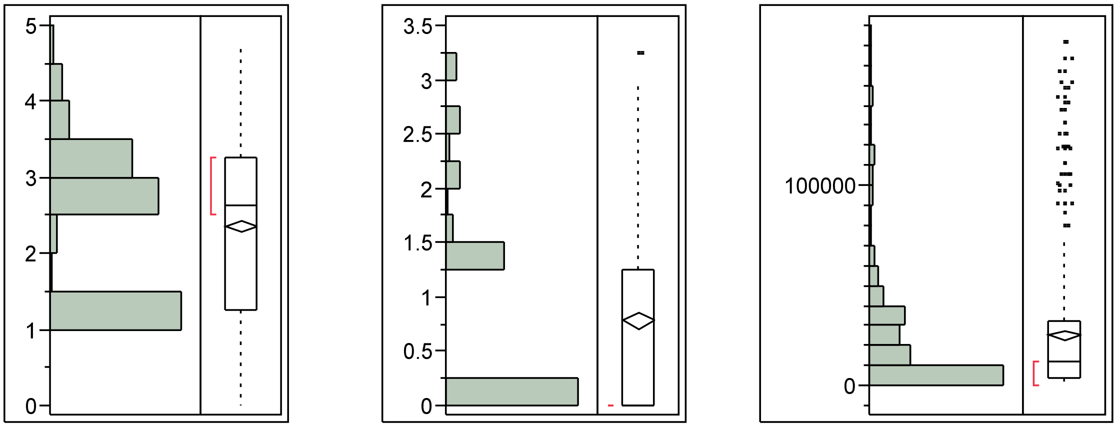
Region 2 office of TDOT keeps a detailed record of highway maintenance activities applied in that region. This record was investigated to identify sufficient HMA resurfacing treatment projects. With the collected the project location and application time, the pavement condition data, environmental, geometry and traffic volume data were exported from HPMA. Then, each project was subdivided into small road sections with unique traffic volume, geometry and environmental condition. The milling depth and overlay thickness were also calculated. Totally, 700 road sections were identified. Among those identified road sections, 48 of them show that PSI values increased as the increase of treatment age. Those road sections were regarded as outliers and dropped from the model analysis. Since no obvious curvature was observed for the post-treatment curves, linear performance curves were built for all of the road sections. The slopes (PSI_k) and intercepts (PSI_b) were determined for further analysis. Table 6.2 shows an example of the data prepared for the model analysis. Figure 6.2 shows the distributions of the collected data. Outliers were deleted by checking the histogram plots of the two responses. Totally, 625 samples were prepared for the model analysis.

Table 6.2 Data prepared for the regression analysis

Road Section	PSI_k	PSI_b	Pre_PSI	AADT	Milling depth (in.)	Overlay thickness (in.)
1	-0.058	4.24	3.15	10493	2.5	2.75
2	-0.063	4.09	2.97	10648	0	2.5
3	-0.083	4.16	2.96	10493	0	1.25
4	-0.063	3.42	2.35	11795	1.25	2.75
5	-0.043	2.97	2.28	11378	2.5	2.75



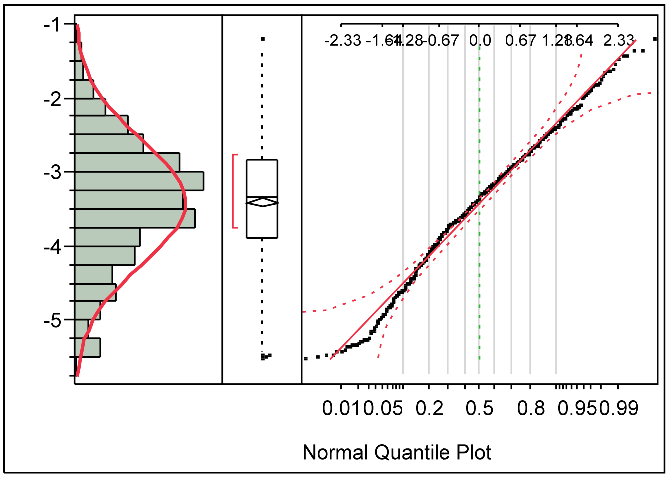
(a) PSI_k (b) PSI_b (c) Pre-PSI



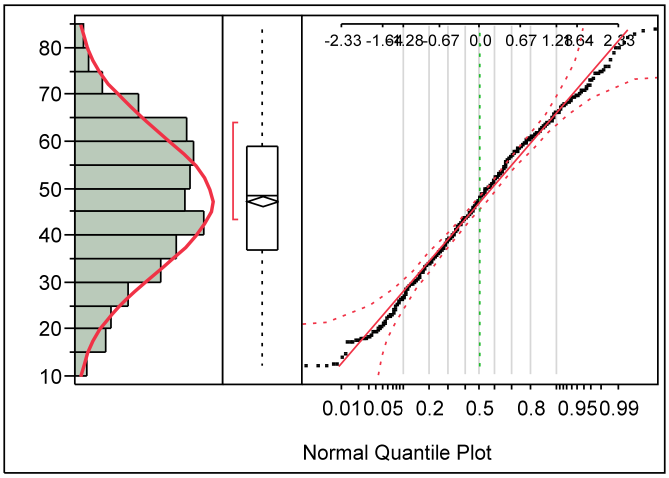
(d) Overlay thickness (in.) (e) Milling depth (in.) (f) AADT

Figure 6.3 Distribution of data for the regression analysis

It can be seen from Figure 6.3 that the two responses, PSI_k and PDI_b have severe skewness. Logarithmic and exponential transformations were utilized to normalize the two variables. Figure 6.4 presents the distribution and normal quintile plot of Ln(-PSI_k) and EXP(PSI_b). It can be seen that the data fall approximately along a straight line except a little tail on the left indicating a generally normal distribution. Ln(-PSI_k) and EXP(PSI_b) would be used as responses to build the multiple regression models. Ordinary linear square method can be used to estimate the model parameters.



(a) Normal quantile plot of Ln(-PSI_k)



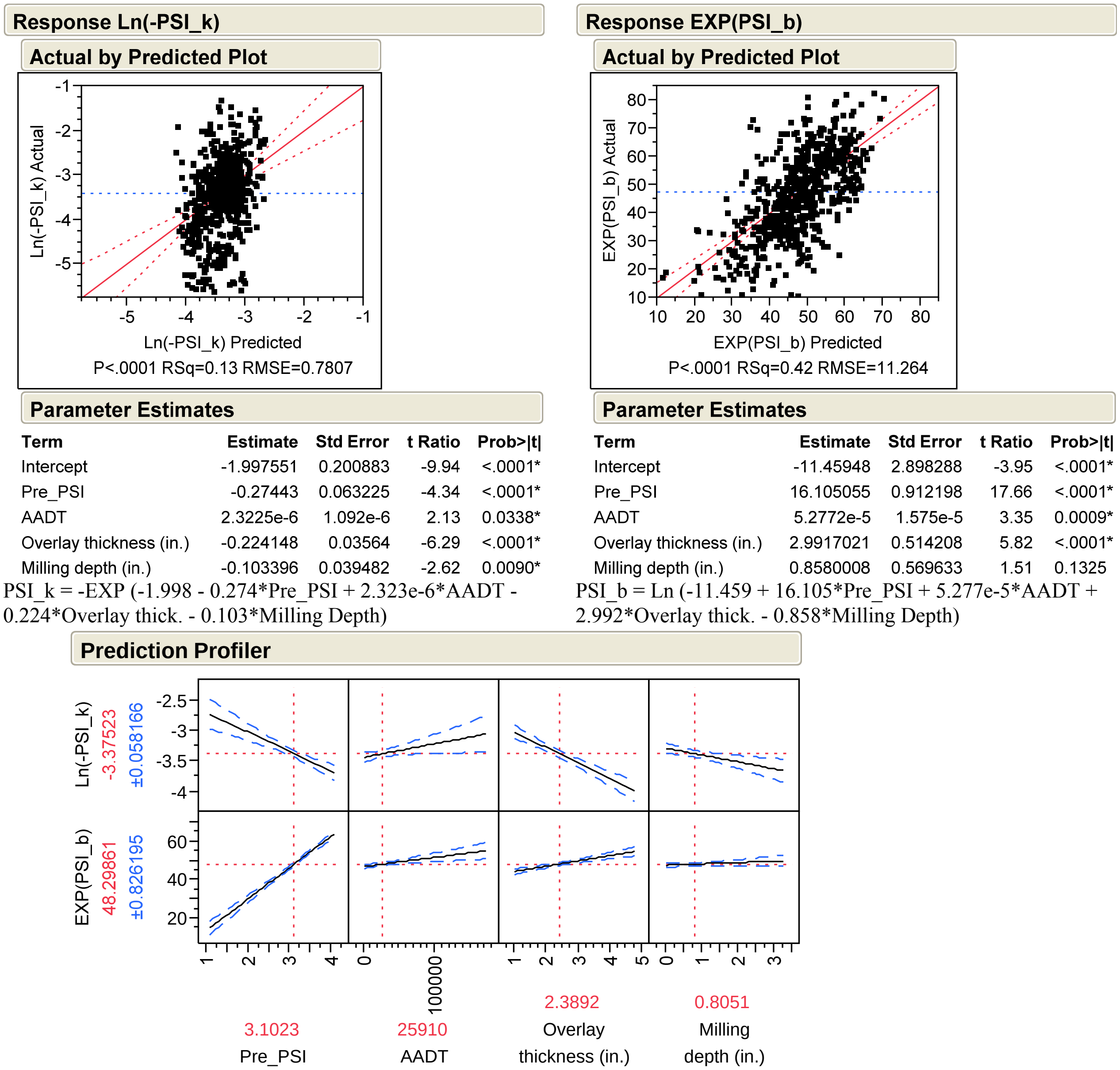
(b) Normal quantile plot of EXP(PSI_b)

Figure 6.4 Normal quintile plot of Ln(-PSI_k) and EXP(PSI_b)

6.3.2 Influence of Factors on Treatment Performance

Multiple linear regression method was employed to investigate the influence of different factors on the treatment performance models. Investigated predictors include pre-treatment PSI, traffic level indicated as AADT, overlay thickness and milling depth. The slopes (Ln(-PSI_k)) and intercepts (PSI_b) of the linear post-treatment performance curves were used as the dependent variables. Figure 6.5 shows the results of the two multiple regression models.

It can be seen from Figure 6.5 that the most significant factor for PSI_k is overlay thickness, followed by Pre_PSI, milling depth and AADT. Pavement with high pre-treatment PSI, thick overlay and deep milling had low deterioration rate, whereas pavement with high traffic level deteriorate faster. The most significant factor for PSI_b is Pre_PSI, followed by overlay thickness and AADT. Pavement with high pre-treatment PSI, thick overlay and high traffic level tended to have high post-treatment PSI. Milling depth is not a significant factor for post-treatment PSI.



Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-1.997551	0.200883	-9.94	<.0001*
Pre_PSI	-0.27443	0.063225	-4.34	<.0001*
AADT	2.3225e-6	1.092e-6	2.13	0.0338*
Overlay thickness (in.)	-0.224148	0.03564	-6.29	<.0001*
Milling depth (in.)	-0.103396	0.039482	-2.62	0.0090*

PSI_k = -EXP (-1.998 - 0.274*Pre_PSI + 2.323e-6*AADT - 0.224*Overlay thick. - 0.103*Milling Depth)

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-11.45948	2.898288	-3.95	<.0001*
Pre_PSI	16.105055	0.912198	17.66	<.0001*
AADT	5.2772e-5	1.575e-5	3.35	0.0009*
Overlay thickness (in.)	2.9917021	0.514208	5.82	<.0001*
Milling depth (in.)	0.8580008	0.569633	1.51	0.1325

PSI_b = Ln (-11.459 + 16.105*Pre_PSI + 5.277e-5*AADT + 2.992*Overlay thick. - 0.858*Milling Depth)

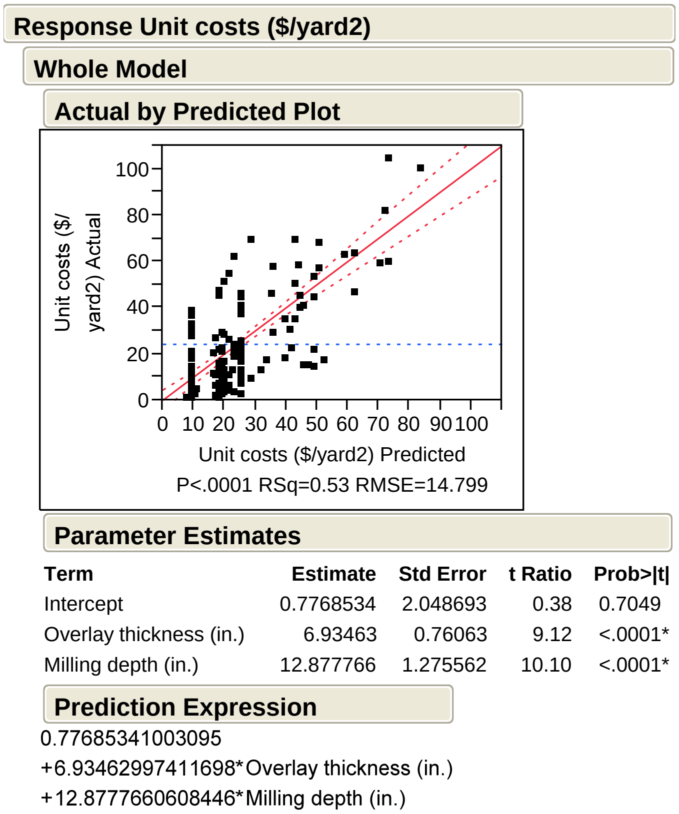
Figure 6.5 Multiple linear regression results for treatment performance

6.3.3 Identifying Typical Treatment Methods

The multiple regression analyses indicated that overlay thickness and milling depth were significant factors for treatment performance. By checking the commonly used overlay thickness and milling depth as shown in Figure 6.2, typical HMA resurfacing treatment methods were identified as shown in Table 6.3.

Table 6.3 Classified treatment methods in Region 2

Milling depth (in.)		Total overlay thickness (in.)		Treatment method	Unit Cost ($/yard^2)	Sample no.
Value	Level	Value	Level			
0	0	1.25	1~2	O1	$9.4	125
0	0	2.5	2~3	O2	$18.1	188
0	0	3.75	>3	O3	$26.8	29
1.25	1~2	1.25	1~2	M1O1	$25.5	88
1.25	1~2	2.5	2~3	M1O2	$34.2	15
1.25	1~2	3.75	>3	M1O3	$42.9	101
2.5	>2	1.25	1~2	M2O1	$41.6	10
2.5	>2	2.5	2~3	M2O2	$50.3	14
2.5	>2	3.75	>3	M2O3	$59.0	55



Response Unit costs ($/yard2)

Whole Model

Actual by Predicted Plot

P<.0001 RSq=0.53 RMSE=14.799

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.7768534	2.048693	0.38	0.7049
Overlay thickness (in.)	6.93463	0.76063	9.12	<.0001*
Milling depth (in.)	12.877766	1.275562	10.10	<.0001*

Prediction Expression

0.77685341003095
+6.93462997411698*Overlay thickness (in.)
+12.8777660608446*Milling depth (in.)

Figure 6.6 Multiple linear regression model for unit construction costs of treatments

Figure 6.6 shows multiple linear regression model for unit cost ($/yard^2) of HMA treatments. Overlay thickness and milling depth were used as predictors. The cost information of 225 projects applied in Tennessee from 1995 to 2005 was collected to build the cost models. Asphalt Index (Figure 3.6) and 5% inflation rate were considered to calculate the present value of the costs. It can be seen from Figure 6.5 that the unit costs increase as the overlay thickness or milling depth increase. With the established cost model for unit costs, the unit costs of the classified treatments were calculated as shown in Table 6.3 and would be input into HPMA for maintenance strategy analysis.

6.3.4 Determining Performance Classes

Different performance classes can be defined in HPMA for the treatment performance models. HPMA allow users define at most 4 types of performance classes. Table 6.4 lists the parameters that can be used to define performance class and the default performance classes in HPMA. It can be seen that only one class is defined for the environment type. Although equivalent thickness is used as a pavement structural capacity indicator, HPMA does not have the equivalent thickness information. The only useful performance class is traffic level (ESALs). The analyses above show that pre-treatment pavement condition was a significant factor for treatment performance. Thus, the most recent PSI, PDI and PQI values are suggested to be used as performance classes. Table 6.5 presents suggested performance classes as well as the sample numbers for each performance class.

Table 6.4 The configuration of performance classes in HPMA

Class Parameters	HPMA default	Potential significant parameters
Hwy ID: Route type		
Functional Class		
Environment Type	1: Tennessee	
Traffic level: AADT		1: < 10,000 2: 10,000 ~ 90,000 3: > 90,000
Traffic: ESAL Annual	1: < 300,000 2: 300,000 ~ 1,000,000 3: > 1,000,000	
Thickness (Equiv.)	1: < 3 2: 3 ~ 4 3: > 4	
PSI Most Recent		1: < 2 2: 2 ~ 3 3: > 3
PDI Most Recent		1: < 3 2: 3 ~ 4 3: > 4
SAI Most Recent		
PQI Most Recent		1: < 3 2: 3 ~ 4 3: > 4
Subgrade Modulus		
Act. Category Count 1		

Table 6.5 Recommended performance classes

Factors	Levels	Values	Sample no.
Pre-PSI	1: < 2 (1~2)	1.5	20
	2: 2 ~ 3	2.5	211
	3: > 3 (3~4)	3.5	394
AADT	1: 0-10,000	5,000	285
	2: 10,000-90,000	50,000	295
	3: >90,000	120,000	45

6.3.5 Calibrating Performance Models

Based on the established multiple regression models for post-treatment performance curves, the slopes and intercepts of the new linear performance curves for the typical treatments at suggested performance classes were estimated. Totally, 81 linear performance curves were developed. The estimated slopes and intercepts are shown in Appendix A. Figure 6.7 shows the clusters of estimated performance curves based on the multiple regression results for suggested treatments at different performance classes.

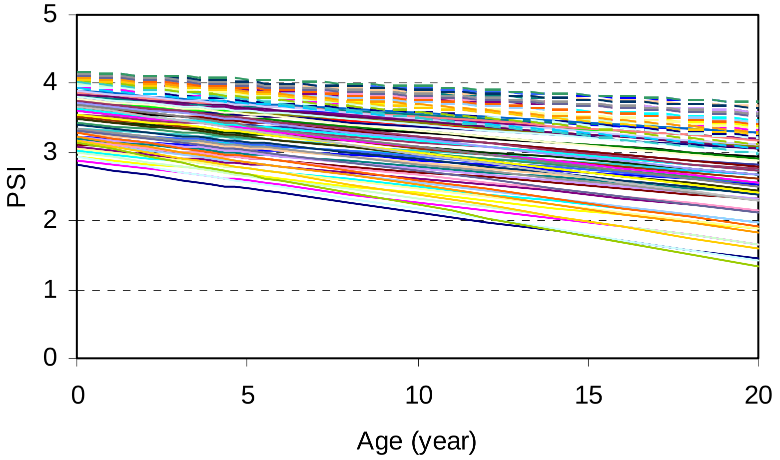
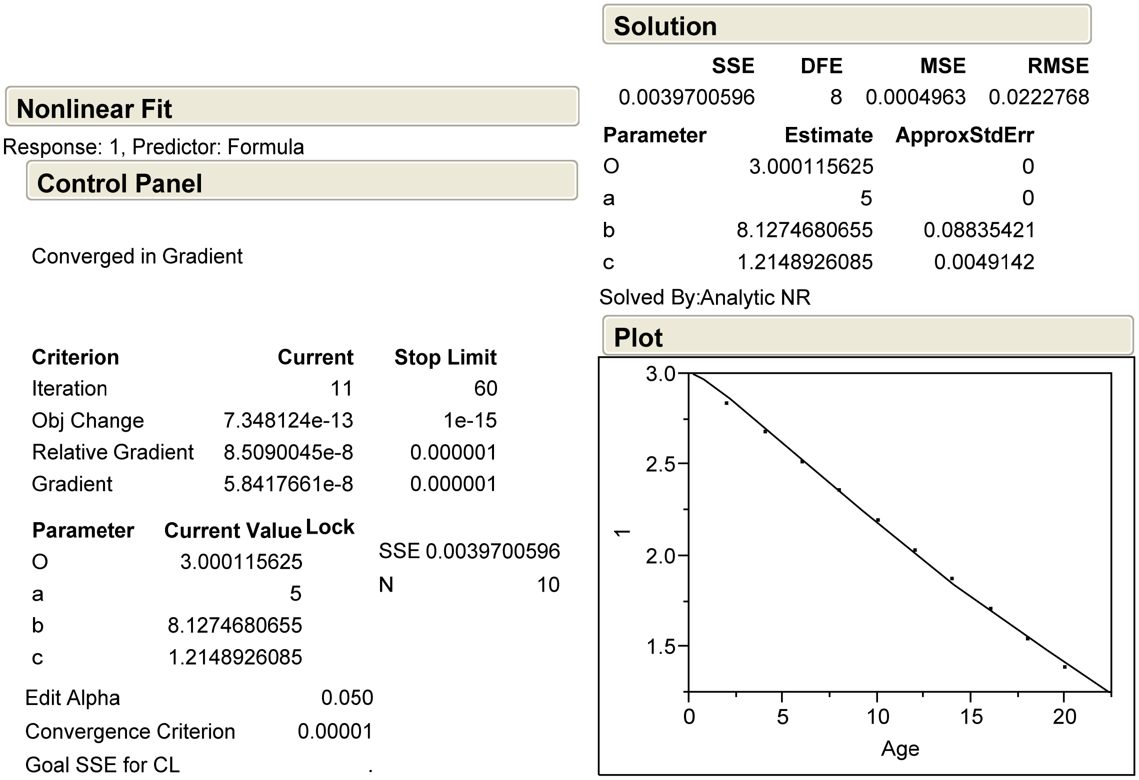


Figure 6.7 Established PSI performance curves

PSI values at every two years were first calculated by each of the 81 linear models, then commercial statistical software JMP was used to calibrate the HPMA model as shown in Figure 6.8. Iterative methods were used to search for the least-squares estimates. Comparing with linear models, nonlinear models require more preparation with the specification of the model and initial guesses for parameter values. Parameter O is the intercept of the curve, which was already estimated by Equation 6.2. Since there are 3 parameters, the nonlinear models were hard to converge. By locking parameter *a* at 5, the model converged in gradient much faster. The estimated HPMA model parameters are shown in Appendix A. Figure 6.9 shows the calibrated models. Comparing with Figure 6.1, it can be seen that HPMA default performance models are more conservative.



Nonlinear Fit

Response: 1, Predictor: Formula

Control Panel

Converged in Gradient

Criterion	Current	Stop Limit
Iteration	11	60
Obj Change	7.348124e-13	1e-15
Relative Gradient	8.5090045e-8	0.000001
Gradient	5.8417661e-8	0.000001

Parameter	Current Value	Lock
O	3.000115625	
a	5	
b	8.1274680655	
c	1.2148926085	

SSE 0.0039700596

N 10

Edit Alpha 0.050

Convergence Criterion 0.00001

Goal SSE for CL .

Solution

SSE	DFE	MSE	RMSE
0.0039700596	8	0.0004963	0.0222768

Parameter	Estimate	ApproxStdErr
O	3.000115625	0
a	5	0
b	8.1274680655	0.08835421
c	1.2148926085	0.0049142

Solved By:Analytic NR

Plot

Figure 6.8 Calibrating HPMA models using nonlinear fit function of JMP

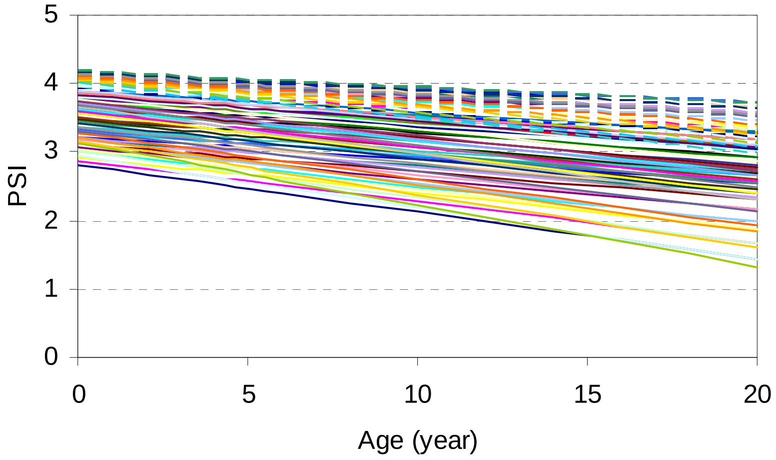
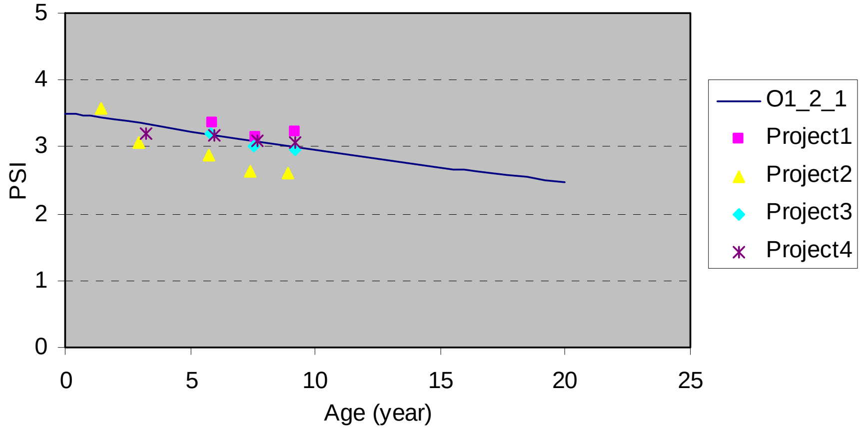


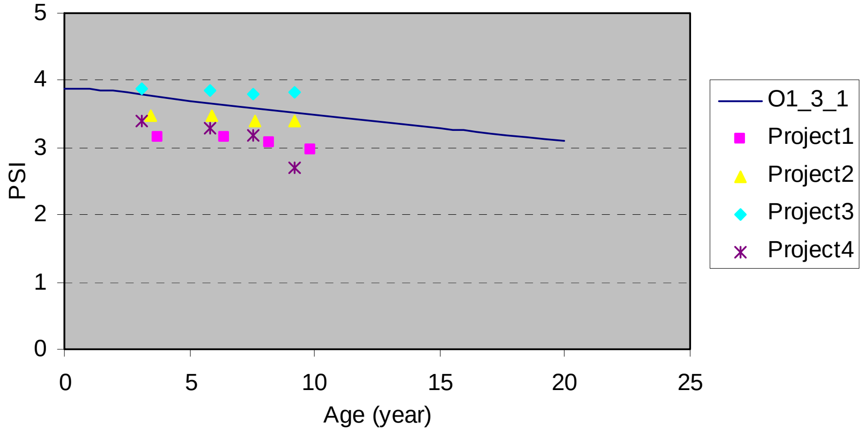
Figure 6.9 Summary of calibrated PSI performance curves

6.3.6 Validation of Models

The maintenance records of Region 1 office of TDOT include several projects with detailed treatment information. Those projects were collected to validate the calibrated models. Figure 6.10 shows the comparison of the calibrated performance curves and the actual performance data. It can be seen that for most of the classifications, the deviations of the curves and the actual data are not high.

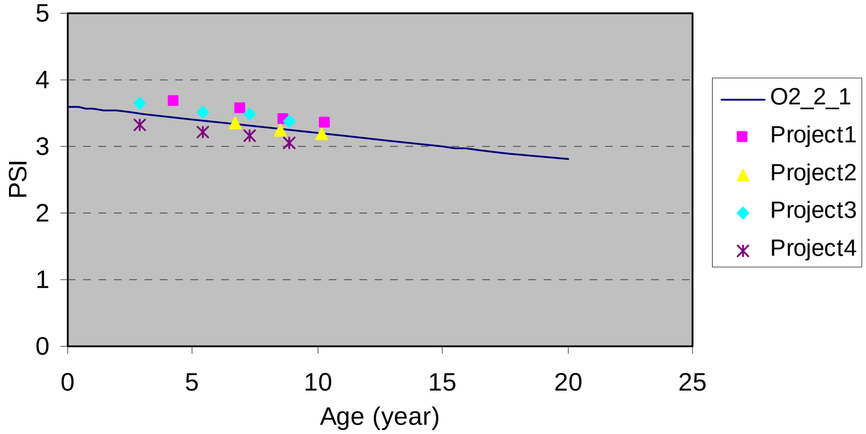


(a) Treatment: O1, pre-PSI level = 2, AADT level = 1

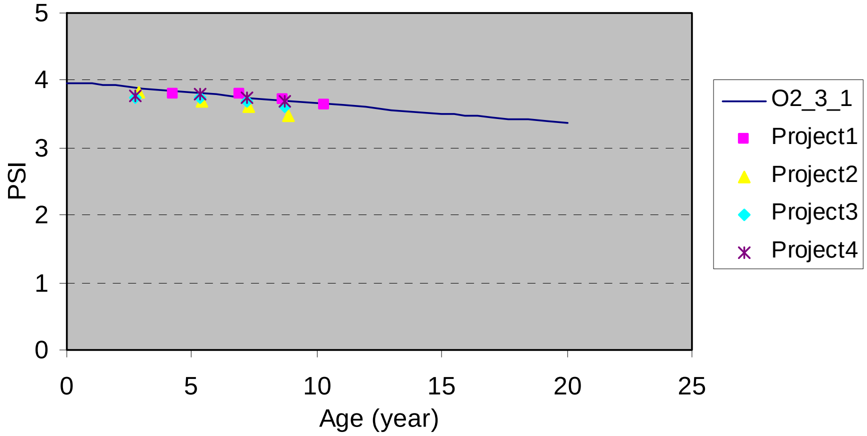


(b) Treatment: O1, pre-PSI level = 3, AADT level = 1

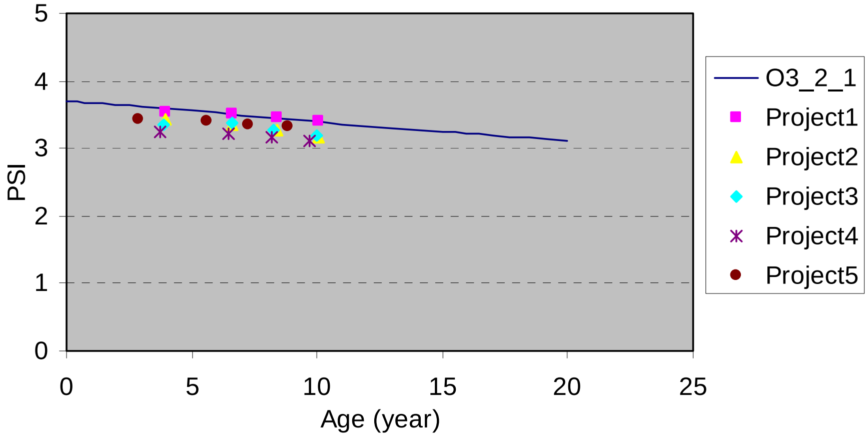
(Figure 6.10 continued)



(c) Treatment: O2, pre-PSI level = 2, AADT level = 1

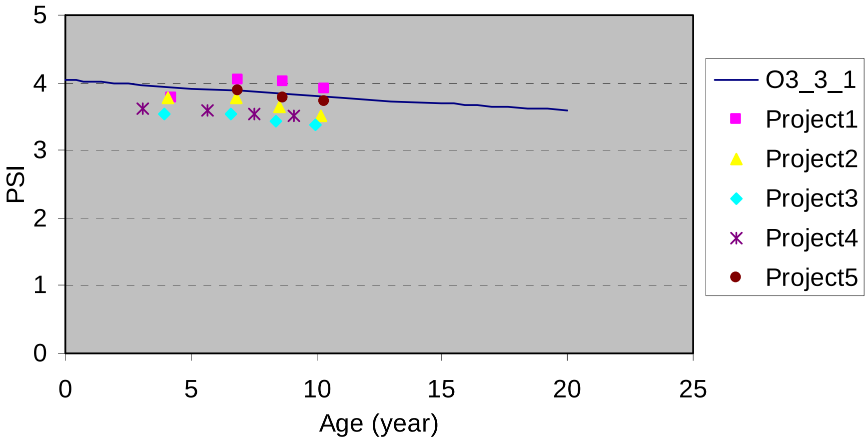


(d) Treatment: O2, pre-PSI level = 3, AADT level = 1



(e) Treatment: O3, pre-PSI level = 2, AADT level = 1

(Figure 6.10 continued)



(f) Treatment: O3, pre-PSI level = 3, AADT level = 1

Figure 6.10 Validation of the calibrated performance curves using actual data

6.4 Investigation on PDI and PQI Curves

There are several advantages of using PSI as a pavement performance indicator. PSI values are easy to measure and collect. Standard pavement profilers have been developed for routine measurement. The variance of the data is also small. However, PSI values only reflect the roughness of the pavement, which is only one aspect of pavement condition. Pavement distress directly influences the pavement riding quality and even the pavement structural condition, and is also an important indicator of pavement condition. In HPMA, PDI is calculated based on the extent and the severity levels of distress.

1. The DVs (Deduct Values) which provide the weighting for the relative importance of the distresses/severity levels in terms of the pavement performance.

$$DV = 10 \wedge (a + b * \log_{10}(PDA)) \tag{6.2}$$

Where, DV = calculated in the ADV_TDV model;

PDA = percent distressed area;

a , b = coefficients which define the shape of each distress at each severity level.

2. The Total Distress Value (TDV) is then calculated as the sum of the individual distress values:

$$TDV = \sum DV_i \tag{6.3}$$

3. The Number of Equivalent Distresses (NED) is calculated as the sum of the ratios of each distress value to the maximum distress value (DV_{max}). The DV_{max} is the largest DV observed for the data). This can be expressed as:

$$NED = \sum(DV_i / DV_{max}) \tag{6.4}$$

Where, DV_i = distress value for distress/severity level;

DV_{max} = highest distress value observed.

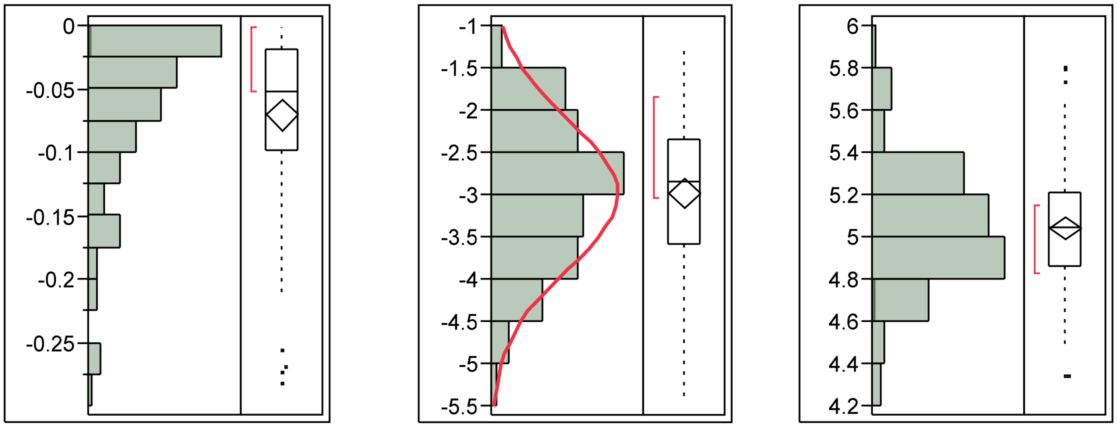
4. The Adjusted Distress Value (ADV) is then calculated from the TDV based on the NED present.

$$ADV = 10\wedge(0.0014 - 0.396*\log_{10}(NED) + 0.9565*\log_{10}(TDV)) \tag{6.5}$$

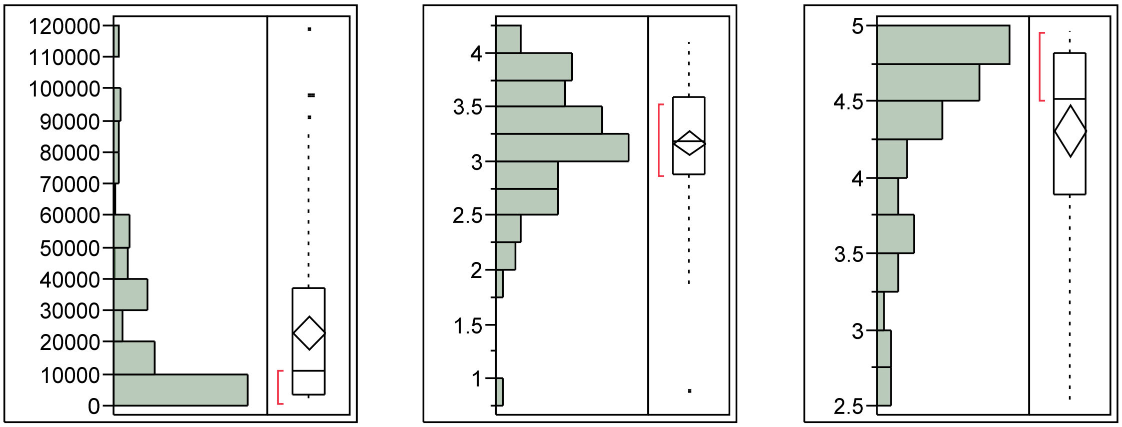
5. The PDI then can be calculated as the function of ADV.

$$PDI = 5 - ADV \tag{6.6}$$

Multiple linear regression method was employed again to investigate the influence of different factors on the slopes and intercepts of post-treatment PDI curves. Due to the technique difficulty to identify and evaluate the pavement distress, the amounts of collected PDI data are not as many as PSI data. The author investigated 2742 HMA maintenance road sections in the whole state. Only 215 of them have sufficient data to form PDI curves, 176 (82%) of the 215 road sections show that PDI decrease with the increase of age, and 60 of 176 road sections have pre-treatment PDI values. Only one of the 60 road sections has detailed treatment information. Thus, three variables, pre-treatment PSI, pre-treatment PDI and AADT, were included in the multiple regression analysis. Figure 6.11 shows the distribution of the data. Ln(-PDI_k) was used instead of PDI_k as response.



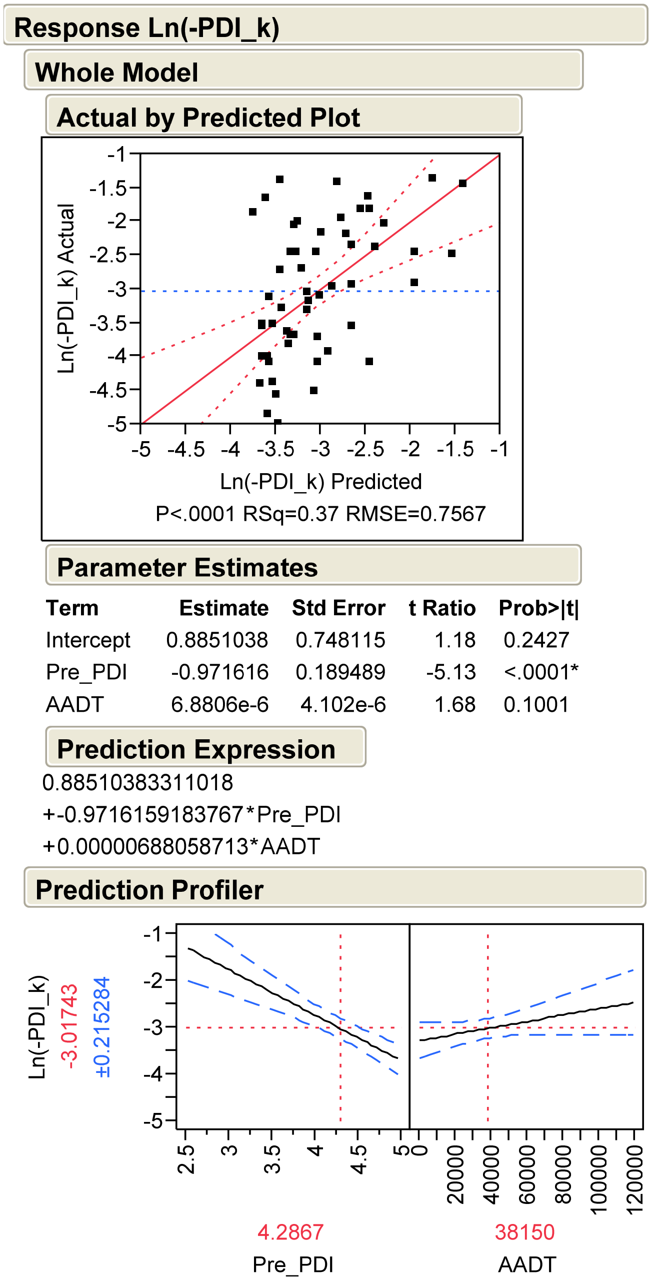
(a) PDI_k (b) Ln(-PDI_k) (c) PDI_b



(d) AADT (e) Pre-PSI (f) Pre-PDI

Figure 6.11 Distribution of data for PDI model analysis

The multiple regression results are shown in Figure 6.12. It can be seen that pavement with higher pre-PDI had lower post-PDI level and rate of deterioration. Pavement with higher pre-PSI had lower post-PDI level. Although traffic level is not significant factor for both post-PDI level and rate of deterioration, pavement with higher traffic level tended to have higher post-PDI and rate of PDI deterioration. All of the three factors were used as performance class parameters for PQI models. Figure 6.13 presents the linear PDI models at different performance classes. Figure 6.14 presents the calibrated PDI models for HPMA. The estimated HPMA model parameters are shown in Appendix B. Figure 6.15 shows the default PDI models in HPMA. It can be seen that the real PDI deterioration curves are similar with the default curves but less conservative.



Response Ln(-PDI_k)

Whole Model

Actual by Predicted Plot

P<.0001 RSq=0.37 RMSE=0.7567

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.8851038	0.748115	1.18	0.2427
Pre_PDI	-0.971616	0.189489	-5.13	<.0001*
AADT	6.8806e-6	4.102e-6	1.68	0.1001

Prediction Expression

0.88510383311018
+-0.9716159183767*Pre_PDI
+0.00000688058713*AADT

Prediction Profiler

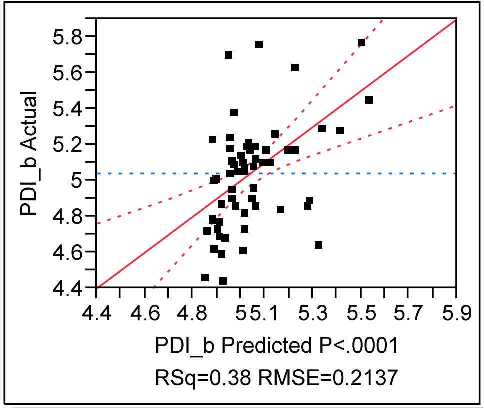
(a) Multiple linear model for slopes of post-treatment PDI curves

(Figure 6.12 continued)

Response PDI_b

Whole Model

Actual by Predicted Plot



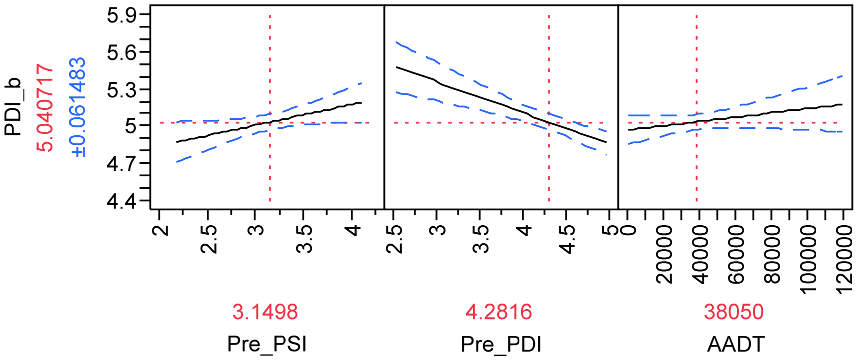
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	5.52425	0.303859	18.18	<.0001*
Pre_PSI	0.1656677	0.076378	2.17	0.0354*
Pre_PDI	-0.250269	0.054584	-4.59	<.0001*
AADT	1.7398e-6	1.301e-6	1.34	0.1878

Prediction Expression

5.52424998619199
+0.16566765638655*Pre_PSI
+-0.2502689575637*Pre_PDI
+0.00000173977999*AADT

Prediction Profiler



(b) Multiple linear model for intercepts of post-treatment PDI curves

Figure 6.12 Multiple regression results of PDI models

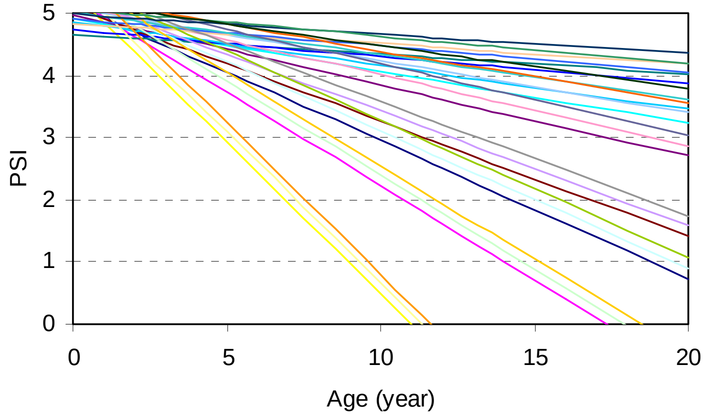


Figure 6.13 Established PDI performance curves

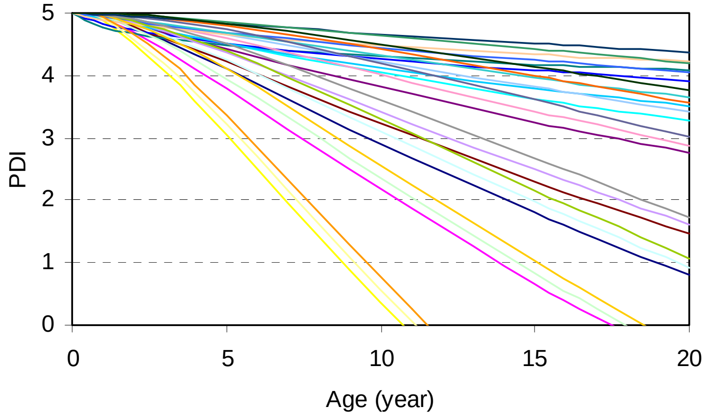


Figure 6.14 Summary of calibrated PDI performance curves

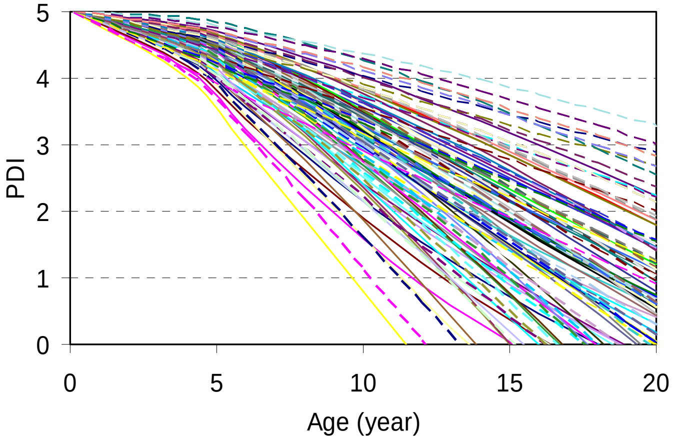


Figure 6.15 The default PDI performance curves in HPMA

To evaluate the pavement condition from different aspects, an overall pavement condition index combining PSI, PDI is usually developed. TDOT uses Pavement Quality Index (PQI) as an overall pavement condition index. PQI can be calculated by using the following Equation when both PDI and PSI are available. Equation 6.7 shows the formula TDOT used to calculate PQI. Figure 6.16 shows typical PSI, PDI and PQI curves for 1.25 in. thick overlay with pre-PSI of 1~2 and AADT of 0~10,000. It can be seen that PDI decrease much faster than PSI and accounts larger proportion of PQI. PQI is the combination of the PSI and PDI and is considered to be a better overall pavement performance indicator.

$$PQI = PDI^{0.7} * PSI^{0.3} \tag{6.7}$$

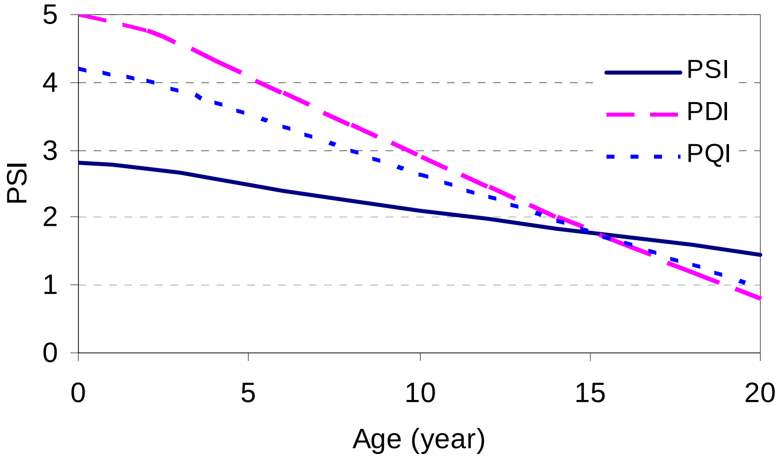


Figure 6.16 Comparison of PDI, PSI and PQI curves in HPMA

6.5 Test Run of the Strategy Analysis

The established pavement performance models of typical treatment methods at different performance classes provide a good basis for the maintenance strategy analysis. The strategy analysis function of HPMA was investigated and tested. The process of decision making at a project level in HPMA are shown in Figure 6.17. The optimal timing decision making for a specific road section can be divided into 2 steps:

1. The decision tree selects treatment candidates based on current pavement condition and the pre-defined rehabilitation trigger values.
2. The historical pavement performance data and defined treatment performance models will be used as do-nothing performance curve and post-treatment performance curve respectively to calculate the effectiveness and cost-effectiveness. The effectiveness is indicated as PQI areas. The cost-effectiveness of different treatment candidates applied at different years are different, the scenario that achieves the highest cost-effectiveness will be selected as the optimized treatment and application time.

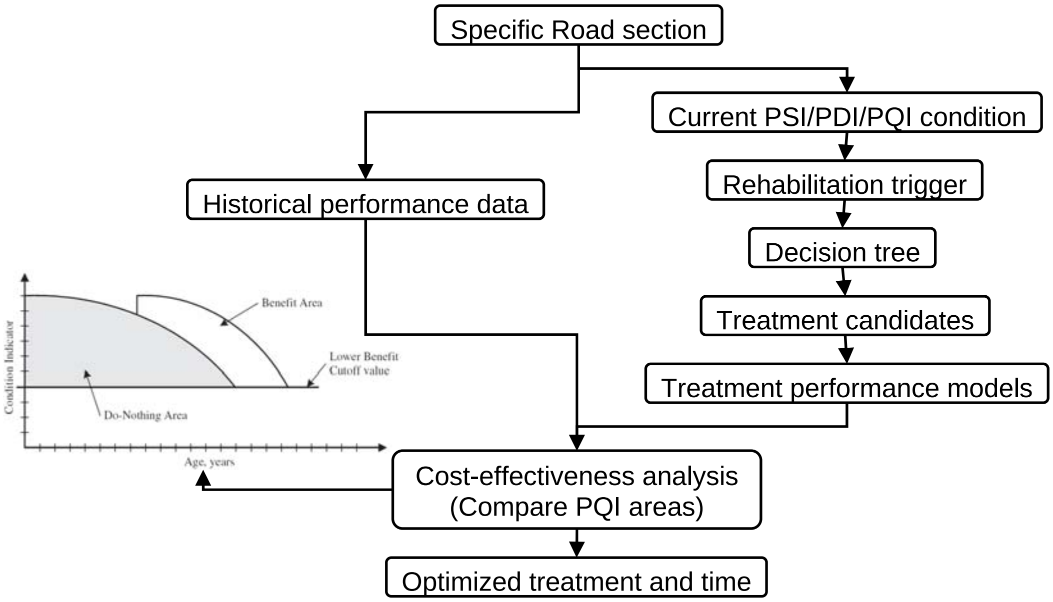
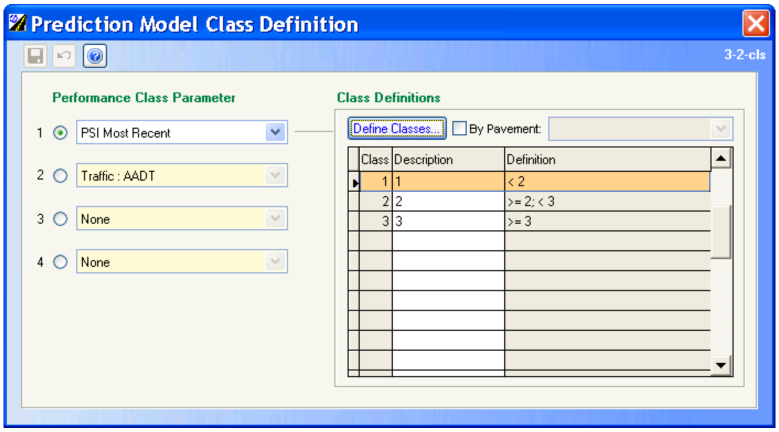


Figure 6.17 The methodology of decision making in HPMA (project level)

6.5.1 Application of Established HPMA Models

The following are the steps of defining calibrated pavement performance models in HPMA:

1. Define performance classes: most recent PSI and AADT.



Performance Class Parameter

1 ● PSI Most Recent
2 ○ Traffic : AADT
3 ○ None
4 ○ None

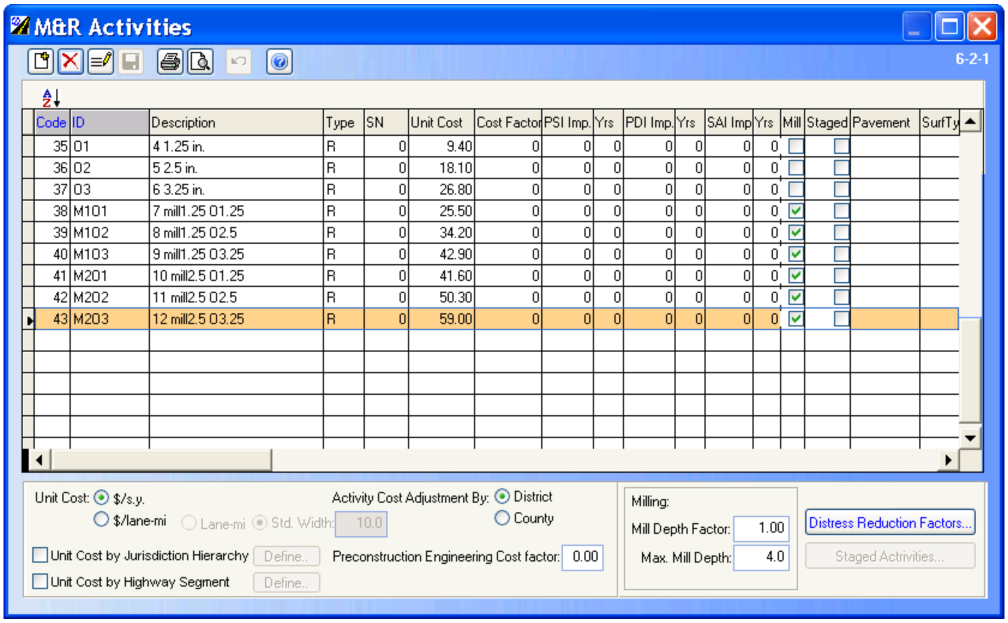
Class Definitions

☐ By Pavement:

Class	Description	Definition
1	1	< 2
2	2	>= 2; < 3
3	3	>= 3

Figure 6.18 Define Performance classes in HPMA

2. Define new treatment methods.



Code	ID	Description	Type	SN	Unit Cost	Cost Factor	PSI Imp.	Yrs	PDI Imp.	Yrs	SAI Imp	Yrs	Mill	Staged	Pavement	SurfTy
35	01	4 1.25 in.	R	0	9.40	0	0	0	0	0	0	0	☐	☐		
36	02	5 2.5 in.	R	0	18.10	0	0	0	0	0	0	0	☐	☐		
37	03	6 3.25 in.	R	0	26.80	0	0	0	0	0	0	0	☐	☐		
38	M101	7 mill1.25 01.25	R	0	25.50	0	0	0	0	0	0	0	☑	☐		
39	M102	8 mill1.25 02.5	R	0	34.20	0	0	0	0	0	0	0	☑	☐		
40	M103	9 mill1.25 03.25	R	0	42.90	0	0	0	0	0	0	0	☑	☐		
41	M201	10 mill2.5 01.25	R	0	41.60	0	0	0	0	0	0	0	☑	☐		
42	M202	11 mill2.5 02.5	R	0	50.30	0	0	0	0	0	0	0	☑	☐		
43	M203	12 mill2.5 03.25	R	0	59.00	0	0	0	0	0	0	0	☑	☐		

Unit Cost: ● $/s.y. ○ $/lane-mi ○ Lane-mi ● Std. Width: 10.0

Activity Cost Adjustment By: ● District ○ County

☐ Unit Cost by Jurisdiction Hierarchy

☐ Unit Cost by Highway Segment

Preconstruction Engineering Cost factor: 0.00

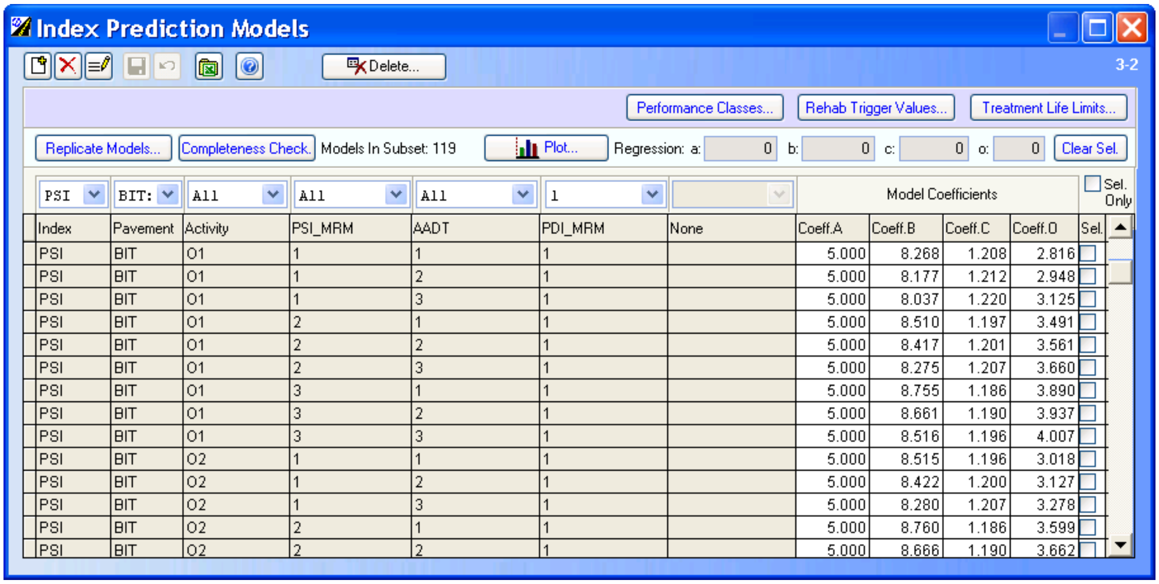
Milling:

Mill Depth Factor: 1.00

Max. Mill Depth: 4.0

Figure 6.19 Add treatment methods into HPMA

3. Input model parameters for all performance classes.



Models In Subset: 119

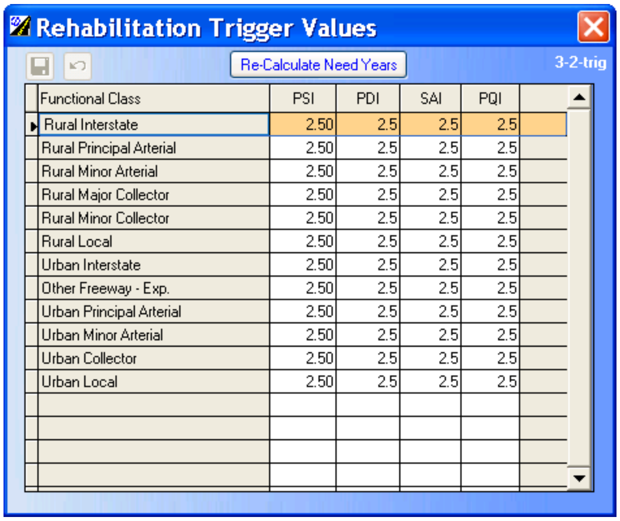
Regression: a: 0 b: 0 c: 0 o: 0

Filters: PSI | BIT: | All | All | All | 1 | ☐ Sel. Only

Index	Pavement	Activity	PSI_MRM	AADT	PDI_MRM	None	Coeff.A	Coeff.B	Coeff.C	Coeff.O	Sel.
PSI	BIT	01	1	1	1		5.000	8.268	1.208	2.816	☐
PSI	BIT	01	1	2	1		5.000	8.177	1.212	2.948	☐
PSI	BIT	01	1	3	1		5.000	8.037	1.220	3.125	☐
PSI	BIT	01	2	1	1		5.000	8.510	1.197	3.491	☐
PSI	BIT	01	2	2	1		5.000	8.417	1.201	3.561	☐
PSI	BIT	01	2	3	1		5.000	8.275	1.207	3.660	☐
PSI	BIT	01	3	1	1		5.000	8.755	1.186	3.890	☐
PSI	BIT	01	3	2	1		5.000	8.661	1.190	3.937	☐
PSI	BIT	01	3	3	1		5.000	8.516	1.196	4.007	☐
PSI	BIT	02	1	1	1		5.000	8.515	1.196	3.018	☐
PSI	BIT	02	1	2	1		5.000	8.422	1.200	3.127	☐
PSI	BIT	02	1	3	1		5.000	8.280	1.207	3.278	☐
PSI	BIT	02	2	1	1		5.000	8.760	1.186	3.599	☐
PSI	BIT	02	2	2	1		5.000	8.666	1.190	3.662	☐

Figure 6.20 Input model parameters in HPMA

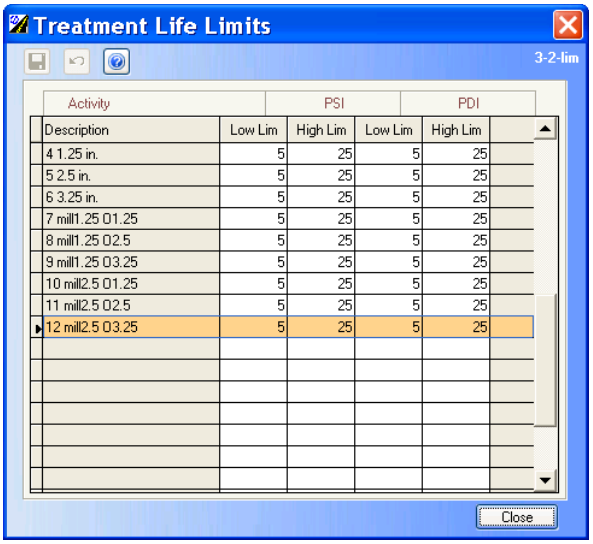
The rehabilitation trigger values at different Functional classes and treatment life limits also need to be defined. As shown in Figure 6.21, 2.5 was used as the rehabilitation trigger values at each functional class for this test run of maintenance strategy analysis. When a pavement reaches the trigger value, it becomes a rehabilitation need. The remaining service life (RSL) is calculated based on the rehabilitation trigger levels. If the trigger values are changed, the rehabilitation needs years and remaining life may be affected. Needs years are initially calculated when the section data view is built.



Functional Class	PSI	PDI	SAI	PQI
Rural Interstate	2.50	2.5	2.5	2.5
Rural Principal Arterial	2.50	2.5	2.5	2.5
Rural Minor Arterial	2.50	2.5	2.5	2.5
Rural Major Collector	2.50	2.5	2.5	2.5
Rural Minor Collector	2.50	2.5	2.5	2.5
Rural Local	2.50	2.5	2.5	2.5
Urban Interstate	2.50	2.5	2.5	2.5
Other Freeway - Exp.	2.50	2.5	2.5	2.5
Urban Principal Arterial	2.50	2.5	2.5	2.5
Urban Minor Arterial	2.50	2.5	2.5	2.5
Urban Collector	2.50	2.5	2.5	2.5
Urban Local	2.50	2.5	2.5	2.5

Figure 6.21 Rehabilitation trigger values for different treatments

Figure 6.22 shows the treatment life limits which define the minimum and maximum number of years that a treatment will provide in terms of life from treatment until reaching the rehabilitation trigger value. The life limits are defined separately for PSI and PDI. The life limits are used to eliminate site-specific models that produce an expected life outside the defined bounds.

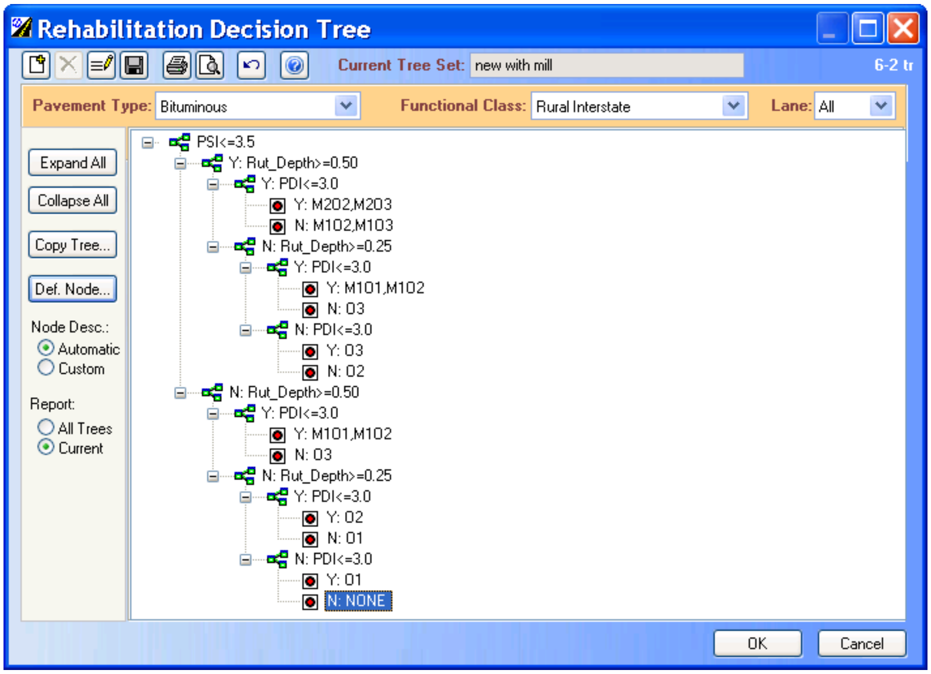


Activity	PSI		PDI	
Description	Low Lim	High Lim	Low Lim	High Lim
4 1.25 in.	5	25	5	25
5 2.5 in.	5	25	5	25
6 3.25 in.	5	25	5	25
7 mill1.25 01.25	5	25	5	25
8 mill1.25 02.5	5	25	5	25
9 mill1.25 03.25	5	25	5	25
10 mill2.5 01.25	5	25	5	25
11 mill2.5 02.5	5	25	5	25
12 mill2.5 03.25	5	25	5	25

Figure 6.22 Treatment service life limits

Figure 6.23 shows an example of designed decision tree using calibrated HPMA treatments. The purpose of setting a decision tree is to select appropriate treatment candidates based on the current pavement condition. The analyses above suggest that HMA treatments with milling might not be the most cost-effective. However, milling is critical to eliminate severe pavement distress. By defining a decision tree, the HMA treatments with milling can be selected as treatment candidates when the pavement condition is poor.

The decision tree is composed of two parts: Branches are represented by the green branch symbol and are used to define decision rules (logic expression); Nodes are represented by the red Y/N symbol and are used to define decision results (maintenance or rehabilitation alternatives). Three pavement condition indicators: PSI, PDI and rutting can be used as branches. The nodes are the typical maintenance treatments. For example, for a road section with PSI of 3.5, rutting depth of 0.55 in., and PDI of 2.3, the suggested pavement treatment candidates are M1O1, M1O2.



Current Tree Set: new with mill

Pavement Type: Bituminous

Functional Class: Rural Interstate

Lane: All

Node Desc.:
● Automatic
○ Custom

Report:
○ All Trees
● Current

```
PSI<=3.5
  Y: Rut_Depth>=0.50
    Y: PDI<=3.0
      Y: M2O2,M2O3
      N: M1O2,M1O3
    N: Rut_Depth>=0.25
      Y: PDI<=3.0
        Y: M1O1,M1O2
        N: O3
      N: PDI<=3.0
        Y: O3
        N: O2
  N: Rut_Depth>=0.50
    Y: PDI<=3.0
      Y: M1O1,M1O2
      N: O3
    N: Rut_Depth>=0.25
      Y: PDI<=3.0
        Y: O2
        N: O1
      N: PDI<=3.0
        Y: O1
        N: NONE
```

(a) HPMA decision tree function

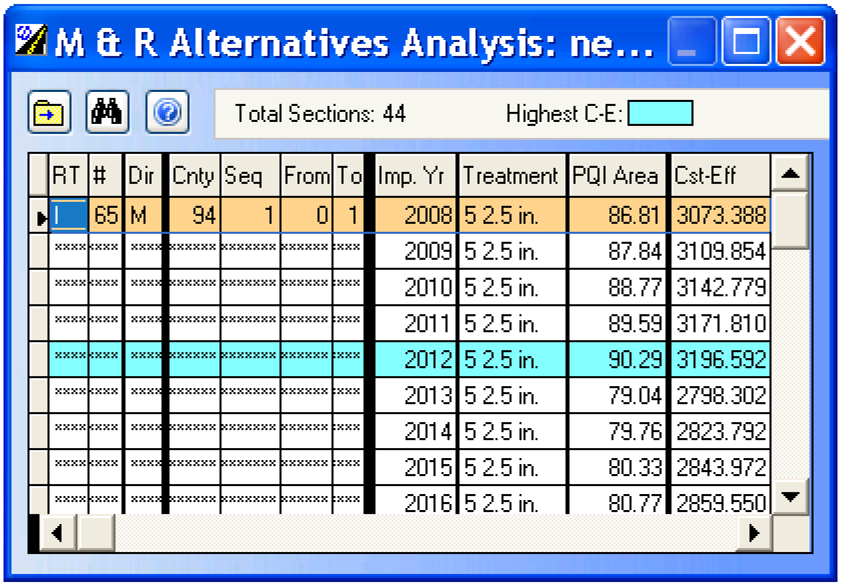
$$
PSI \le 2.5 \begin{cases}
Y: Rutting \ge 0.5 \begin{cases}
Y: PDI \le 3.0 \begin{cases} Y: M2O2, M2O3 \\ N: M1O2, M1O3 \end{cases} \\
N: Ruting \ge 0.25 \begin{cases}
Y: PDI \le 3.0 \begin{cases} Y: M1O1, M1O2 \\ N: O3 \end{cases} \\
N: PDI \le 3.0 \begin{cases} Y: O3 \\ N: O2 \end{cases}
\end{cases}
\end{cases} \\
N: Rutting \ge 0.5 \begin{cases}
Y: PDI \le 3.0 \begin{cases} Y: M1O1, M1O2 \\ N: O3 \end{cases} \\
N: Ruting \ge 0.25 \begin{cases}
Y: PDI \le 3.0 \begin{cases} Y: O2 \\ N: O1 \end{cases} \\
N: PDI \le 3.0 \begin{cases} Y: O1 \\ N: unnecessary \end{cases}
\end{cases}
\end{cases}
\end{cases}
$$

(b) Designed decision tree

Figure 6.23 Define decision trees in HPMA

6.5.2 An example of Strategy Analysis

Interstate I-65 in Anderson County was selected for the strategy analysis. The total length of I-65 in Williamson county is 21.38 miles. It is divided into 22 road sections at each direction. In HPMA, P (Plus) direction is from west to east or south to north, while M (Minus) direction is from east to west or north to south. Each road section is 1 mile long except the last one which is 0.38 mile long (20~21.38). The analysis base year is 2005 and the analysis period is 20 years. Figure 6.24 shows strategy analysis results and the most cost-effectiveness application time (optimal time) is highlighted. It can be seen that the most cost-effective strategy for road section M 0-1 mile is to apply 2.5 thick overlay at 2012. Figure 6.25 presents the do-nothing and post-treatment performance curves for road section M 0-1 mile.

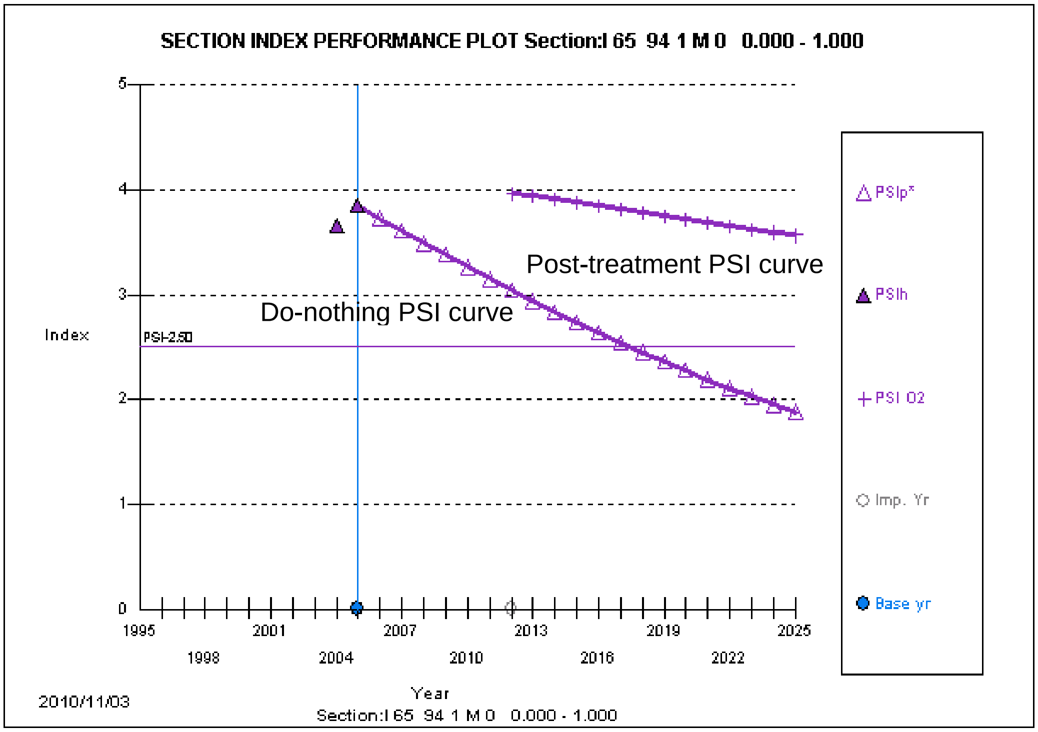


Total Sections: 44

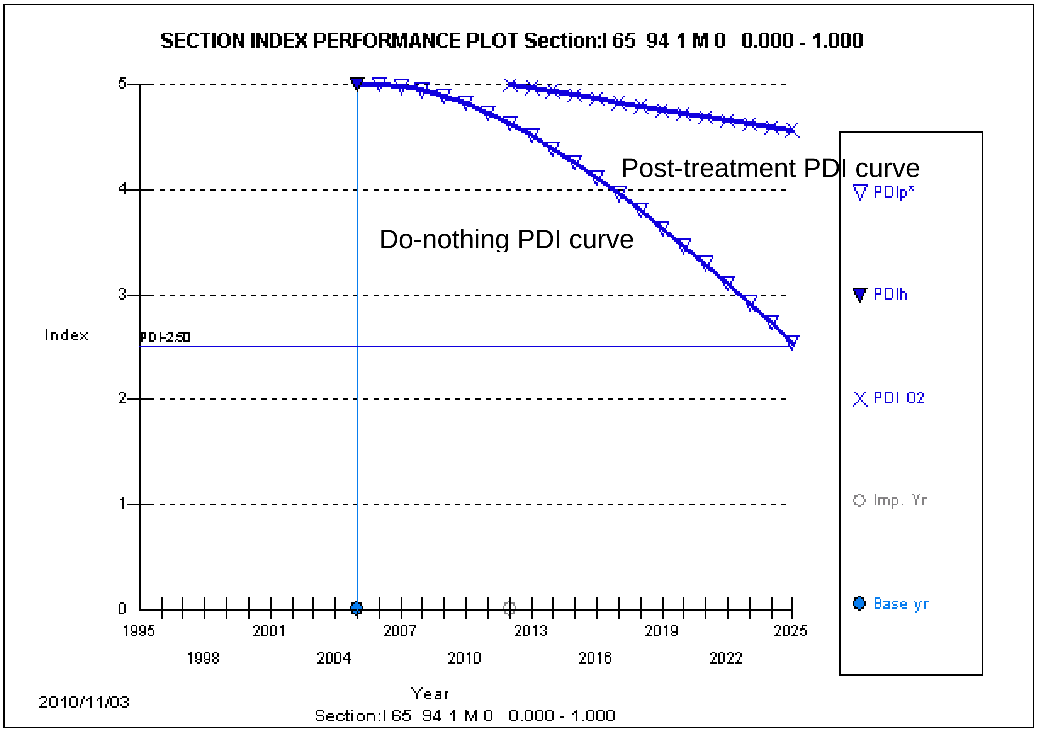
Highest C-E: 🟦

RT	#	Dir	Cnty	Seq	From	To	Imp. Yr	Treatment	PQI Area	Cst-Eff
I	65	M	94	1	0	1	2008	5 2.5 in.	86.81	3073.388
xxxx	xxxx	xxxx	xxxxxx	xxxxxxx	xxxxxx	xxxx	2009	5 2.5 in.	87.84	3109.854
xxxx	xxxx	xxxx	xxxxxx	xxxxxxx	xxxxxx	xxxx	2010	5 2.5 in.	88.77	3142.779
xxxx	xxxx	xxxx	xxxxxx	xxxxxxx	xxxxxx	xxxx	2011	5 2.5 in.	89.59	3171.810
xxxx	xxxx	xxxx	xxxxxx	xxxxxxx	xxxxxx	xxxx	2012	5 2.5 in.	90.29	3196.592
xxxx	xxxx	xxxx	xxxxxx	xxxxxxx	xxxxxx	xxxx	2013	5 2.5 in.	79.04	2798.302
xxxx	xxxx	xxxx	xxxxxx	xxxxxxx	xxxxxx	xxxx	2014	5 2.5 in.	79.76	2823.792
xxxx	xxxx	xxxx	xxxxxx	xxxxxxx	xxxxxx	xxxx	2015	5 2.5 in.	80.33	2843.972
xxxx	xxxx	xxxx	xxxxxx	xxxxxxx	xxxxxx	xxxx	2016	5 2.5 in.	80.77	2859.550

Figure 6.24 Results of maintenance strategy analysis

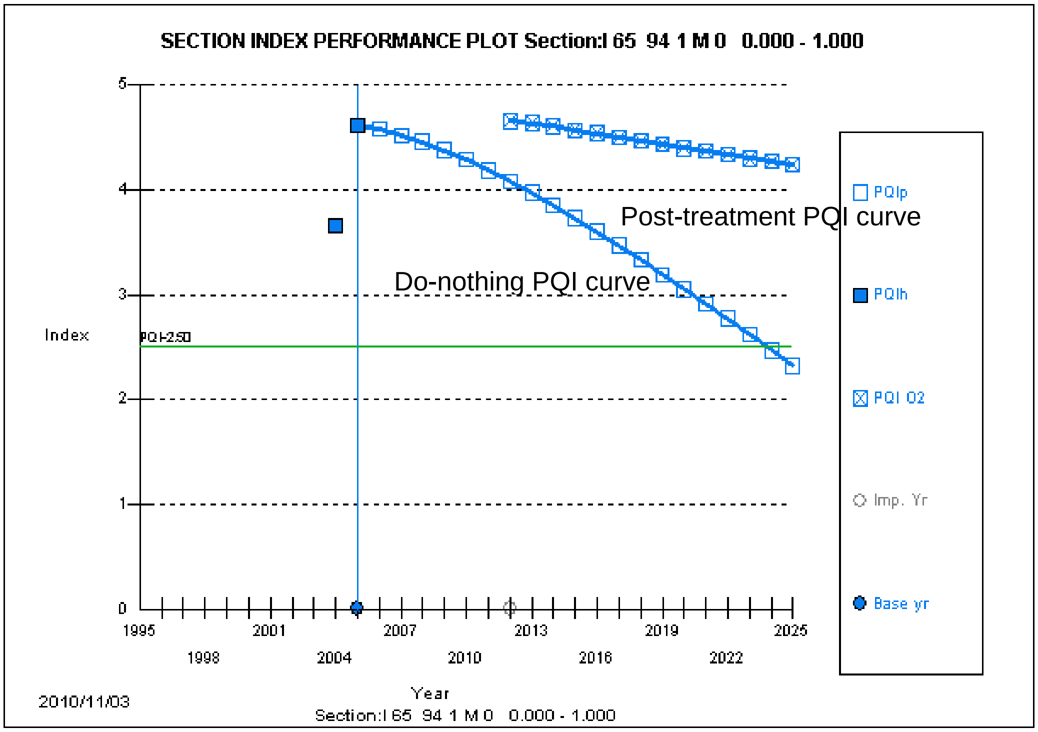


(a) PSI curves

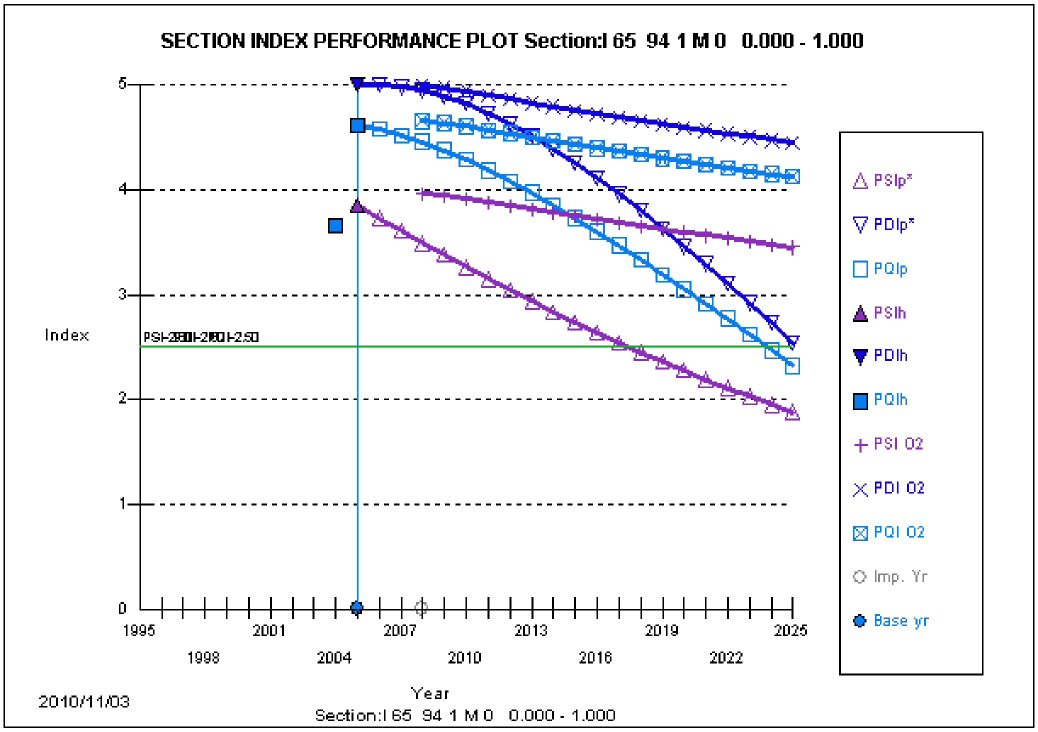


(b) PDI curves

(Figure 6.25 continued)



(c) PQI curves



(d) All curves

Figure 6.25 Performance curves of analyzed road section

6.6 Conclusions and Summary

The performance curves of typical HMA resurfacing treatments used in Tennessee were calibrated for the PMS system of TDOT. Multiple regression method was employed to analyze the influence of pre-treatment PSI, traffic level, overlay thickness and milling depth on the slopes and intercepts of post-treatment linear performance curves. The specific designs of HMA treatments and performance classes were determined based on the regression results. Then, the performance curves for each identified treatment methods at different performance classes were established and the parameters of the corresponding performance models in the PMS system are calibrated. A test run of maintenance strategy analysis using calibrated models was also presented. Several conclusions can be drawn as follows:

1. Pavements with high pre-treatment PSI, thick overlay and deep milling have low deterioration rate, whereas pavements with high traffic level deteriorate fast.
2. Pavements with high pre-treatment PSI, thick overlay and high traffic level tend to have high post-treatment PSI.
3. PDI decreases faster than PSI and accounts larger proportion of PQI. PQI is a better overall pavement condition indicator. Since the amount of PDI data in the current PMS are not as abundant as PSI, it is recommended to collect more PDI data for the highway systems in Tennessee.

PART 7 CONCLUSIONS AND RECOMMENDATIONS

7.1 Conclusions

The effectiveness of typical pavement maintenance treatments were evaluated by using the data collected from HPMA and LTPP database. The influence of different factors on the effectiveness and cost-effectiveness of treatments were evaluated by the Optime software and multiple linear regression method. The influence of different factors on the crack initiation of asphalt resurfacing treatments was analyzed by parametric survival analysis. The pavement roughness, pavement serviceability index and initiation time of cracking were used as the pavement performance indicators. The performance curves of HMA resurfacing treatments used in Tennessee were calibrated by investigating the influence of different factors on the post-treatment pavement performance curves. Based on the analysis above, several conclusions can be summarized as follows:

1. Optime analysis on the pavement maintenance projects in Tennessee indicated that HMA overlay had the highest effectiveness. Due to the relatively low cost, micro surfacing was the most cost-effective treatment, followed by HMA overlay and mill & fill. However, mill & fill has the ability to overcome severe pavement distress and HMA overlay can increase the pavement structure capacity. Micro surfacing may be inapplicable in some situations.

2. Multiple linear regression analysis on the performance of maintenance treatments used in Tennessee indicated that the effectiveness and cost-effectiveness decreased with the increase of traffic level and pre-treatment pavement condition. HMA overlay

had the highest effectiveness, followed by mill & fill and micro surfacing. Micro surfacing was the most cost-effective treatment due to its low cost, which agreed with the results of Optime analysis. The effectiveness and cost-effectiveness decreased with the increase of traffic level and pre-treatment pavement condition.

3. Analysis of the effectiveness of HMA resurfacing treatments by using LTPP database indicated that traffic level, pre-rehabilitation roughness, and rate of roughness increase before rehabilitation have the same effect on both the effectiveness and cost-effectiveness, whereas overlay thickness and milling have different effects on the effectiveness and cost-effectiveness due to the increased costs. Incorporating 30% reclaimed material does not influence the performance of rehabilitation but will improve the cost-effectiveness in terms of roughness after rehabilitation and roughness drop. Pavement with thick overlay, milling before rehabilitation and low pre-rehabilitation roughness has low roughness after rehabilitation. Pavement with thick overlay, milling before rehabilitation, and high pre-rehabilitation roughness has high roughness drop. Thin overlay, high traffic level, and poor pre-rehabilitation condition increase the rate of deterioration of new overlay. Pavements with thick overlay and high rate of deterioration before rehabilitation have high benefit. For a certain rate of roughness increase before rehabilitation, there is an optimized pre-rehabilitation roughness or treatment application time.

4. Investigation of the initiation time of different cracking of asphalt resurfacing treatment indicated that high traffic level accelerated the initiation of all the four

investigated cracks. Thick overlay delayed the initiation of cracking except for the non-wheel path longitudinal crack, which is mainly caused by poor construction. Total pavement thickness only retarded the initiation of wheel path longitudinal cracking. Incorporating 30% reclaimed asphalt pavement in the overlay accelerated the initiation of early age fatigue cracking; however, it was not a significant cause for severe fatigue cracking. Severe freeze thaw condition accelerated the occurrence of the non-wheel path longitudinal and transverse cracks; whereas, mill before overlay significantly retarded the occurrence of the two types of cracks.

5. Investigation of the treatment performance curves of typical HMA treatments used in Tennessee indicated that pavements with high pre-treatment PSI, thick overlay and deep milling have low deterioration rates, whereas pavements with higher traffic level deteriorate faster. Pavement with high pre-treatment PSI, thick overlay, and high traffic level tend to have high post-treatment PSI. Investigation on the PDI curves indicated that PDI decreases much faster than PSI and accounts larger proportion of PQI. PQI is a better overall pavement condition indicator.

7.2 Recommendations

This study focuses on evaluating the performance of different pavement resurfacing maintenance treatments and the influence of different factors by multiple regression methods and survival analysis. Pavement performance data of practical maintenance projects were collected to conduct the regression analysis. Future research work is recommended as follows:

1. Predictors of treatment performance used in the presented study include detailed treatment methods, pre-treatment pavement condition, traffic level and environmental condition. Other potential significant variables including pavement structural index and detailed material properties are recommended to be included in the effectiveness models.

2. For the survival analysis, this study focused on the initiation of cracks but did not incorporate the propagation of the cracks. A potential future research area is to determine an appropriate pavement crack failure threshold so that a survival model can be developed to analyze the crack propagation. Because of the high variance of construction quality, pavement structure, and overlay material, the survival model developed in this study was mainly used to analyze the influence of different factors but was not able to predict the survival time nationwide. It is suggested to build survival models at different traffic, environmental, and highway classifications so that more accurate models can be developed to predict the failure times.

3. Keeping a detailed record of maintenance history and collecting accurate pavement performance data are critical for the successful application of PMS for pavement maintenance decision making. Investigation of the PSI and PDI curves

of the HMA resurfacing treatments applied in Tennessee indicated that PDI and PQI are also important pavement condition indicators. In the case that the amount of PDI data in current HPMA are not as abundant as PSI, it is recommended to collect more PDI data for the highway systems in Tennessee so that more accurate PDI models of the treatments can be established and calibrated to support the maintenance strategy analysis.

APPENDICES

Appendix A: Calibrated Parameters for PSI Curves

k and b are the slopes and intercepts of the linear models for different treatments at different pre-treatment PSI and AADT levels. a, b, c and O are the four calibrated parameters for the performance models in HPMA.

Treatment	Pre-PSI level	AADT level	Linear models		HPMA models			
			k	b	a	b	c	O
O1	1	1	-0.069	2.816	5	8.268	1.208	2.816
O1	1	2	-0.076	2.948	5	8.177	1.212	2.948
O1	1	3	-0.090	3.125	5	8.037	1.220	3.125
O1	2	1	-0.052	3.491	5	8.510	1.197	3.491
O1	2	2	-0.058	3.561	5	8.417	1.201	3.561
O1	2	3	-0.068	3.660	5	8.275	1.207	3.660
O1	3	1	-0.040	3.890	5	8.755	1.186	3.890
O1	3	2	-0.044	3.937	5	8.661	1.190	3.937
O1	3	3	-0.052	4.007	5	8.516	1.196	4.007
O2	1	1	-0.052	3.018	5	8.515	1.196	3.018
O2	1	2	-0.058	3.127	5	8.422	1.200	3.127
O2	1	3	-0.068	3.278	5	8.280	1.207	3.278
O2	2	1	-0.039	3.599	5	8.760	1.186	3.599
O2	2	2	-0.044	3.662	5	8.666	1.190	3.662
O2	2	3	-0.052	3.752	5	8.521	1.196	3.752
O2	3	1	-0.030	3.964	5	9.008	1.177	3.964
O2	3	2	-0.033	4.008	5	8.913	1.181	4.008
O2	3	3	-0.039	4.073	5	8.766	1.186	4.073
O3	1	1	-0.039	3.186	5	8.765	1.186	3.186
O3	1	2	-0.044	3.279	5	8.671	1.190	3.279
O3	1	3	-0.051	3.409	5	8.527	1.196	3.409
O3	2	1	-0.030	3.696	5	9.013	1.177	3.696
O3	2	2	-0.033	3.753	5	8.918	1.180	3.753
O3	2	3	-0.039	3.836	5	8.772	1.186	3.836
O3	3	1	-0.023	4.032	5	9.263	1.169	4.032
O3	3	2	-0.025	4.074	5	9.168	1.172	4.074
O3	3	3	-0.030	4.135	5	9.020	1.177	4.135
M1O1	1	1	-0.060	2.878	5	8.382	1.202	2.878
M1O1	1	2	-0.067	3.003	5	8.290	1.207	3.003
M1O1	1	3	-0.079	3.171	5	8.149	1.214	3.171
M1O1	2	1	-0.046	3.523	5	8.625	1.192	3.523
M1O1	2	2	-0.051	3.591	5	8.532	1.196	3.591
M1O1	2	3	-0.060	3.688	5	8.388	1.202	3.688
M1O1	3	1	-0.035	3.912	5	8.871	1.182	3.912
M1O1	3	2	-0.039	3.958	5	8.777	1.186	3.958

M1O1	3	3	-0.046	4.026	5	8.631	1.191	4.026
M1O2	1	1	-0.046	3.069	5	8.630	1.191	3.069
M1O2	1	2	-0.051	3.173	5	8.537	1.195	3.173
M1O2	1	3	-0.060	3.317	5	8.393	1.202	3.317
M1O2	2	1	-0.035	3.628	5	8.876	1.182	3.628
M1O2	2	2	-0.038	3.689	5	8.782	1.185	3.689
M1O2	2	3	-0.045	3.777	5	8.636	1.191	3.777
M1O2	3	1	-0.026	3.984	5	9.125	1.173	3.984
M1O2	3	2	-0.029	4.027	5	9.030	1.176	4.027
M1O2	3	3	-0.034	4.091	5	8.883	1.182	4.091
M1O3	1	1	-0.034	3.229	5	8.882	1.182	3.229
M1O3	1	2	-0.038	3.319	5	8.787	1.185	3.319
M1O3	1	3	-0.045	3.444	5	8.642	1.191	3.444
M1O3	2	1	-0.026	3.722	5	9.131	1.173	3.722
M1O3	2	2	-0.029	3.778	5	9.036	1.176	3.778
M1O3	2	3	-0.034	3.859	5	8.888	1.181	3.859
M1O3	3	1	-0.020	4.051	5	9.382	1.165	4.051
M1O3	3	2	-0.022	4.092	5	9.286	1.168	4.092
M1O3	3	3	-0.026	4.152	5	9.137	1.173	4.152
M2O1	1	1	-0.053	2.936	5	8.496	1.197	2.936
M2O1	1	2	-0.059	3.055	5	8.403	1.201	3.055
M2O1	1	3	-0.069	3.215	5	8.261	1.208	3.215
M2O1	2	1	-0.040	3.554	5	8.740	1.187	3.554
M2O1	2	2	-0.045	3.620	5	8.647	1.191	3.620
M2O1	2	3	-0.053	3.714	5	8.502	1.197	3.714
M2O1	3	1	-0.031	3.933	5	8.988	1.178	3.933
M2O1	3	2	-0.034	3.978	5	8.893	1.181	3.978
M2O1	3	3	-0.040	4.045	5	8.747	1.187	4.045
M2O2	1	1	-0.040	3.117	5	8.746	1.187	3.117
M2O2	1	2	-0.045	3.217	5	8.652	1.191	3.217
M2O2	1	3	-0.052	3.355	5	8.507	1.197	3.355
M2O2	2	1	-0.030	3.656	5	8.993	1.178	3.656
M2O2	2	2	-0.034	3.715	5	8.899	1.181	3.715
M2O2	2	3	-0.040	3.801	5	8.752	1.187	3.801
M2O2	3	1	-0.023	4.004	5	9.243	1.169	4.004
M2O2	3	2	-0.026	4.046	5	9.148	1.173	4.046
M2O2	3	3	-0.030	4.109	5	9.000	1.178	4.109
M2O3	1	1	-0.030	3.271	5	8.999	1.178	3.271
M2O3	1	2	-0.034	3.357	5	8.904	1.181	3.357
M2O3	1	3	-0.040	3.478	5	8.757	1.186	3.478
M2O3	2	1	-0.023	3.748	5	9.249	1.169	3.748
M2O3	2	2	-0.026	3.802	5	9.153	1.172	3.802
M2O3	2	3	-0.030	3.882	5	9.005	1.177	3.882
M2O3	3	1	-0.018	4.070	5	9.502	1.162	4.070
M2O3	3	2	-0.019	4.109	5	9.405	1.165	4.109
M2O3	3	3	-0.023	4.168	5	9.255	1.169	4.168

Appendix B: Calibrated Parameters for PDI Curves

k and b are the slopes and intercepts of the linear models for different treatments at different pre-treatment PSI and AADT levels. a, b, c and O are the four calibrated parameters for the performance models in HPMA.

Pre-PSI level	Pre-PDI level	AADT level	Linear models		HPMA models			
			k	b	a	b	c	O
1	1	1	-0.221	5.156	5	7.731	1.295	5
1	1	2	-0.301	5.234	5	7.566	1.325	5
1	1	3	-0.488	5.356	5	7.244	1.377	5
1	2	1	-0.084	4.906	5	7.570	1.194	5
1	2	2	-0.114	4.984	5	7.760	1.229	5
1	2	3	-0.185	5.106	5	7.779	1.277	5
1	3	1	-0.032	4.655	5	6.435	1.083	5
1	3	2	-0.043	4.734	5	6.800	1.114	5
1	3	3	-0.070	4.855	5	7.376	1.171	5
2	1	1	-0.221	5.321	5	8.267	1.320	5
2	1	2	-0.301	5.400	5	7.974	1.345	5
2	1	3	-0.488	5.522	5	7.508	1.391	5
2	2	1	-0.084	5.071	5	8.580	1.237	5
2	2	2	-0.114	5.149	5	8.635	1.267	5
2	2	3	-0.185	5.271	5	8.400	1.306	5
2	3	1	-0.032	4.821	5	7.199	1.111	5
2	3	2	-0.043	4.899	5	7.737	1.152	5
2	3	3	-0.070	5.021	5	8.413	1.215	5
3	1	1	-0.221	5.487	5	8.896	1.349	5
3	1	2	-0.301	5.565	5	8.434	1.367	5
3	1	3	-0.488	5.687	5	7.793	1.406	5
3	2	1	-0.084	5.237	5	10.082	1.297	5
3	2	2	-0.114	5.315	5	9.814	1.315	5
3	2	3	-0.185	5.437	5	9.149	1.339	5
3	3	1	-0.032	4.987	5	8.759	1.171	5
3	3	2	-0.043	5.065	5	9.549	1.223	5
3	3	3	-0.070	5.187	5	10.066	1.280	5

VITA

Qiao Dong was born in China in 1982. He entered Southeast University, Nanjing, China in 1999 and received his Bachelor's Degree in Civil Engineering in 2003. He studied as a master student in the Department of Highway and Railway Engineering in Southeast University from 2003 to 2006, where his research interest concentrated on the pavement materials and finite element analysis. Mr. Dong entered the Department of Civil and Environmental Engineering in The University of Tennessee (UTK) at Knoxville to pursue the PH. D. degree in August 2006. During his stay in UTK, he extended his research area to pavement performance modeling and pavement management system application.