DEVELOPMENT OF ALTERNATIVE PAVEMENT DISTRESS INDEX MODELS

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Executive Summary

Alternative models to predict pavement distress index (DI) for different pavement/fix types were developed. The models were developed at the pavement/fix level (for freeway and non-freeway routes). Future DI values were predicted incrementally in two-year steps. The models are auto-regression type. The models predict a future DI value based on its first lag (i.e., immediate past value) and the corresponding chronological age. The models were developed for DI values of up to 50, and as such may not be used for ranges beyond a DI of 50. The models were validated by testing their ability to predict past observed DI's. The models were able to predict "observed" DI values reasonably well although the accuracy differed among pavement types. In general, the models were more successful for non-freeway routes.

The data analysis showed clearly that significant variability exists among similar pavement sections of similar age, pavement type and DI values. This suggests that other factors that impact Distress progression are missing. Data on those factors should be assembled and used in future models and/or to refine current models. Improvements or advantages offered by any modeling approach should not be a substitute for identifying and using missing relevant causal factors.

Chapter 1

INTRODUCTION

1.1 Background

The Michigan Department of Transportation (MDOT) uses the Distress Index (DI) as one measure of pavement performance within its pavement management system. DI measures the extent of surface distress and is currently used to determine the remaining service life (RSL) of a pavement. Currently, MDOT uses a threshold of DI of 50 to indicate the need for pavement rehabilitation or reconstruction. The number of years remaining to reach a DI of 50 is defined as the remaining service life (RSL). Accordingly, the DI and RSL values have significant implication in pavement management resource allocation and budgeting. MDOT currently uses a logistic function with chronological age (time) as its independent variable to predict DI and RSL. The logistic regression model is a "logical" choice since its s-shaped function mimics the path of DI over time.

As part of its effort to always seek more efficient alternatives and possible improvements to its adopted models and analysis protocols, MDOT sough to evaluate the potential of other approaches to modeling DI. Exploring alternative models, though, should not be construed to mean that current models are defective.

1.2 Hypothesis and Objectives

The main hypothesis of this research study is as follows: as time progresses the pavement distress index (DI) follows a non-decreasing path which can be modeled by an s-shaped curve that can be modeled using logistic regression. The objectives of this study are to: 1) test the above hypothesis using data that MDOT currently has in its database; and 2) explore other modeling approaches to improve the ability to predict the DI. The outcome of this research is to be used to help MDOT in its allocation of pavement management resources.

These objectives will be achieved by using statistical, probabilistic, and other suitable modeling approaches. These approaches will make it possible to confirm, modify or propose an alternate model to the models currently used for different pavement types and rehabilitation treatments.

Chapter 2

LITERATURE REVIEW

Pavement Management System (PMS) is defined as a system that consists of set of engineering tools for performing pavement condition surveys and condition prediction, and developing work plans with the objective of optimizing spending. According to AASHTO " A pavement management system is designed to provide objective information and useful data for analysis so that highway managers can make more consistent, cost-effective and defensible decisions related to the preservation of a pavement network"(1).

The Federal Highway Administration (FHWA) developed a clear definition of PMS (2):" A set of tools or methods that can assist decision makers in finding cost-effective strategies for providing, evaluating and maintaining pavements in serviceable conditions". In general, PMS is used for three W's

- 1. What: Rehabilitation needs in terms of the amount of equivalent asphalt concrete overlay
- 2. Where: The selection of pavement segments for rehabilitation is based on pavement structural conditions
- 3. When: The determination of when to rehabilitate a specific pavement segments, based on Age performance curves or equations.

This research project is limited to the last "W": "When". The main objective of this research is to develop prediction models for the distress index from which the remaining life of the pavement and the time at which the rehabilitation is needed can be determined.

Many techniques are available for developing pavement distress index (DI) prediction models. These include straight-line extrapolation, regression (empirical), polynomial constrained least square, S- shaped curve, probability distribution and Markovian chain models (3). The selection of particular technique depends upon local conditions and deterioration rate of pavement. In the USA, departments of transportations use their own prediction models.

Colorado department of transportation currently used remaining service life in pavement management program, whereas previously they used the number of years of remaining design life as the basis for pavement life (4). According to Colorado DOT methodology, first the distress index (DI) is calculated for any pavement section. The DI value ranges from 1 to 100. A rating 100 indicates a perfect pavement and a rating of 50 or less indicates pavement failure. A performance curve is developed for each distress type. There are three levels of performance curves, site-specific (base upon previous data), pavement family (based on pavement type, traffic volume, climate and pavement thickness) and default curves. The most desirable is site-specific. If site-specific curve is not available because of lack of data, family curves are used, and in a worst case, if both are not available then default curves are used.

Significant work was done by the Texas Department of Transportation to from and analyse prediction models for pavement distress. In their latest research, Artificial Neural Network-based models were used for rational assessment of remaining life of existing pavements (5). The main objective of their research is to develop Artificial Neural Network (ANN) models to compute the remaining lives of flexible pavements associated with rutting and fatigue cracking failure modes. 360,000 examples (observations) were used from the database. Each example consists of an input vector with nine elements that represent the thickness of the asphalt concrete (AC) and base layers and seven falling weight deflectometer (FWD) readings and an output vector. The out put vector is the remaining life of the pavement when it experiences either fatigue cracking or rutting. This remaining life was calculated by using the Asphalt Institute equations. Four ANN models were developed for a three layer flexible pavement. Two of the models predict rutting and fatigue cracking remaining lives according to the Asphalt Institute equations. The other two models predict the maximum tensile and compressive strains at the layer interfaces. The fatigue cracking ANN model predicts 86% of the desired values within a \pm 20% error. The ANN model for rutting cracking predicts 95% of the desired values within a \pm 20% margin of error. The ANN model for the tensile, compressive str4ains predicts 96% of the desired values with \pm 10% error.

Washington State Department of Transportation (WSDOT) used performance equations to predict the pavement condition (6). The generalized equation used by WSDOT is

$$psc = c - m \times A^p$$

Where:

psc = pavement structure condition A = age which represent time since construction or last resurfacing C = model constant for maximum ration (100) m = slope co-efficient p = selected constant which controls the degree of curvature of the performance curve

To calculate the best fitted parameters (m, p) for the above equation, the State is divided into two zones, western Washington and eastern Washington. Each zone is further divided into district like Seattle, Wenatchee, Tumwater etc. Within a district, projects are divided into type of construction and pavement resurfacing. By dividing the pavement data into several groups parameters like climate, traffic volume, etc are accommodated (i.e., in a statistical sense these factors are controlled for). Arizona department of transportation used Markov chain to predict pavement network performance. There are also many other studies done by agencies other than DOT's to predict the distress index and remaining life of pavement. Fernando et al (7) analysed the proposed pavement performance models for Michigan. They compared Logistic Growth Model (deterministic) and Markov Model (Probabilistic) with the actual data taken from two Michigan counties. (The formulas used in Logistic growth model is similar to the one currently used by MDOT). The potential initial distress index used for each model was 10. Both models show little difference from the actual data. Due to its current usein Michigan, the Logistic model was recommended.

Amado (8) predicted the Pavement Serviceability Rating (PSR) value on the basis of historical data. The analysis was for pavement condition data from 1995 to 1999 provided by the Missouri Department of Transportation. The PSR value was predicted by dividing the data in different homogenous groups with respect to pavement type.

Lukanen et al (9) investigated the performance history and prediction modeling for Minnesota pavements. The prediction models purposed by him were based on about 13,000 surface condition data records collected on the entire pavement system between 1983 and 1991. Two major variables included were distress density and age. They grouped the pavements based on different attributes to accommodate additional variables such as traffic, surface type and structure.

Mansour (10) developed a pavement performance models for Riyadh street network in Saudi Arabia. He divided the pavement section into different groups based on drainage, traffic and maintenance type. The generalized equation used to predict the distress index is

Urban Distress Index = $a + b \times AGE^{n} + c \times ADT + d \times DR$

Where ADT = Annual daily traffic (0 for low traffic and 1 for high traffic) DR = Drainage (0 for without drainage and 1 for with drainage)

Part of the data was used to find the regression equation parameters and the other part was use to valid the regression equations.

Dossey (11) studied the distress as a function of age in continuously reinforced concrete pavement models developed for Texas Pavement Management Information System. The distress models consider age, temperature, rainfall, pavement thickness and traffic for predicting Distress Index. The equation used is:

$$D = \alpha \times e^{-(\frac{\chi \varepsilon \delta \rho}{N})^{\beta}}$$

Where:

 $\begin{array}{l} D = \mbox{Predicted Level of Distress} \\ N = \mbox{Age of Pavement} \\ \alpha, \beta, \rho = \mbox{Shape parameters estimated by regression} \\ \varepsilon, \chi, \delta = \mbox{Adjustment for Environment, Traffic, Pavement structure, respectively.} \end{array}$

Chan (11) analyzed pavements in North Carolina to develop a pavement performance prediction model. He used Power curve to estimate pavement condition rating (PCR)

$$PCR = C_0 + C_1 \times Age^{C_2}$$

Pavement sections were divided into Normal and Abnormal sections. Abnormal sections have the following properties:

a) small variation in PCR for few years

b) no valid performance period

c) unreasonably rapid decline of PCR between 70 to 40

Normal sections were divided into five groups:

- a) all sections
- b) plant mix

c) plant mix with ADT ≥ 1000

d) plant mix with ADT ≤ 1000

e) Bituminous surface treatment

't' test was applied to check the significance of the difference between the groups on the basis of pavement life. Only differences between groups with ADT \geq 1000 and ADT \leq 1000 were statistically significant. Models were validated by using 1982, 1984, 1986, 1988, 1990 data to predict 1992 and 1994 data. Comparisons show that predications were very close to the actual data for those years.

Hence a lot of research was done to analysis the prediction models for distress index. It is difficult to set a universal model for distress index as it depends upon many factors like temperature, traffic volumes and load, types of pavements, rehabilitation methodology and age of pavements.

It is apparent from the above summary that a variety of approaches were used to model DI and other pavement distress-related indices. The success in many cases may have been the result of the aggregation/disaggregating of the data and/or the specific factors that were included. It is true that specific modeling approaches have strengths and attributes that may make them more suitable than others. However, the inclusion of some of the causal factors, and controlling for other unimportant ones has significant impact on the quality of the final outcome.

Chapter 3

DATA CHARACTERISTICS

The source of data for analysis and model development for this project is the extensive database on pavement distress that MDOT maintains. This chapter presents a brief description of the data used in this project along with an account of how it was used in the model development and validation. The database has significantly more detailed information than was necessary in this project.

3.1 Pavement Distress Data Composition:

As used in this research, the pavement distress index (DI) data for the State of Michigan is divided into two large groups: Freeway and Non-freeway. Within each of the two groups, distress data is further divided into categories according to pavement fix or rehabilitation type, which includes all types of pavement (i.e. Rigid, Flexible, and Composite). In all, there are 10 and 9 pavement/fix types for freeways and non-freeways, respectively. DI data is organized as shown in Figure 3.1

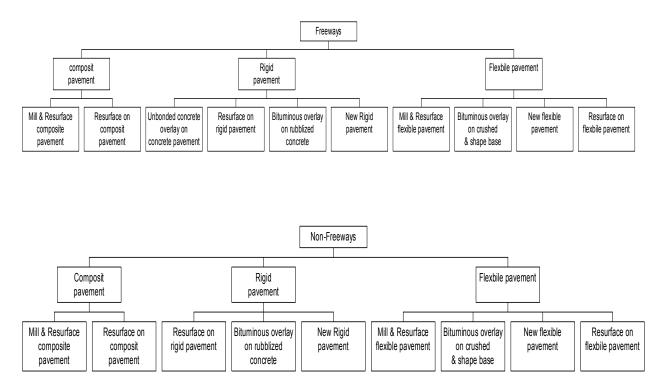


Figure 3.1: DI data organization for freeways and non-freeways

3.2 Pavement Distress at the Project Level

Distress data used in this research are at the project level. Although MDOT maintains data on distress at one-tenth of a mile frequency, the data used in this work was for individual projects. A project may vary in length but will have the same pavement and fix (rehabilitation) type. Cross-section design and timing of construction and/or rehabilitation, and roadway characteristics are uniform for the section. Traffic data including average daily traffic volume and the percentage of trucks are reasonably uniform. Other factors like the environment and jurisdiction may or may not be the same over the entire section. All projects for the State of Michigan were candidates for inclusion in the analysis.

For the purpose of this research project, projects were classified according to the type of roadway (freeway, non-freeway) and pavement/fix type. The *noun* "fix" here refers to the type of treatment or rehabilitation that was applied to the existing or reconstructed pavement.

Not all projects for which distress data is available were used in the analysis and model development. Projects with one or no data points were not used in the model development. Also, projects with unexpected and/or unexplained decline in the DI value were eliminated from the model development. It is understood that there are cases where pavement may have actually shown a decline in DI over time even without rehabilitation--this would be the case if the first DI reading was taken during time of cold temperatures and later reading during relatively higher temperature time. However, since no data is available to discern this type of information, projects with a decline in DI but no rehabilitation was not used in the model development. A summary of the number of projects available, projects that were eliminated and projects that were used in the modeling are summarized in tables 3.1 and 3.2 for non-freeways and freeways, respectively.

Pavement Fix	Total number of projects	Number of projects with one or no DI data	Number of project segments with decreasing DI without rehabilitation	Number of projects used for Auto regression
Mill & Resurface Composite Pavement	131	78	0	44
Mill & Resurface Flexible Pavement	27	6	4	17
Resurface on Composite Pavement	145	51	7	87
Bituminous Overlay on Rubblized Concrete	9	4	0	5
Resurface on Rigid Pavement	14	4	3	7
New/ Reconstructed Flexible Pavement	30	8	5	20
Bituminous Overlay on Crush & Shape Base	59	38	0	21
Resurface on Flexible Pavement	114	36	5	73

Table 3.1: Summary of non-freeways projects within each pavement/fix class

Pavement Fix	Total number of projects	Number of Project with one or no DI data	Number of Projects segments with decreasing DI without rehabilitation	Number of Projects Used for Auto regression
Mill & Resurface Composite Pavement	31	14	1	16
Mill & Resurface Flexible Pavement	35	18	2	17
Resurface on Composite Pavement	26	4	5	21
New/ Reconstructed Rigid Pavement	162	24	13	103
Unbounded Concrete Overlay on Concrete Pavement	27	19	0	8
Bituminous Overlay on Rubblized Concrete	67	37	4	28
Resurface on Rigid Pavement	94	24	13	67
New/ Reconstructed Flexible Pavement	61	26	6	29

Table 3.2: Summary of Freeway projects within each pavement/fix class

3.3. Observation and Discussion of Data

Initial screening and diagnostics of the DI data revealed some trends and characteristics that are significant for the modeling process. The following sections present a brief account of those trends and characteristics.

3.3.1. Variability of Distress Index Values within Pavement/Fix Type

Initial examination of the DI for individual projects within a pavement/fix class revealed significant variation in the DI among different projects for the same age. This variability is demonstrated clearly in Figure 3.2 for one of the pavement/fix classes. Similar variations/trends were observed among other pavement/fix types. The graphs in the Figure show clearly that for the same pavement/fix type and similar age, there are projects with distinctly different DI values. And there is no obvious "concentration" of projects around a DI value for a given pavement age. This suggests, among other things, that pavement chronological age is unable to determine the DI value even after controlling for pavement and fix types.

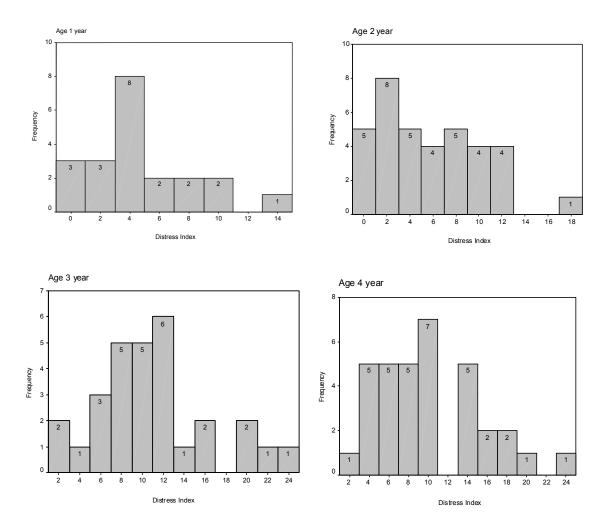


Figure 3.2: Frequency of projects with specific DI values within specific age groups (Mill & Resurface Composite Pavement Freeway, Family 1).

As a way to possibly see things beyond the wide variation of DI values within the same pavement/fix type and age, projects were grouped based on ranges of age instead of a single age (e.g., projects 0 to 3 years old as one group, or 4 to 7 years old as a group, etc.). The hope here was to determine if this aggregation will help flush out any trends that may have been obscured by the fine one-year age grouping. Several of those age combinations were tried (one of which is shown in Figure 3.3). Although with this aggregation some "concentrations" are somewhat apparent, these concentrations are not consistent in that they all show that for a given age range higher number of projects exhibit lower DI values. Had age been a sufficient predictor, as one would suspect, the concentration of projects will shift to higher DI's as age increases. This is yet another indication that age is not a sufficient predictor of DI.

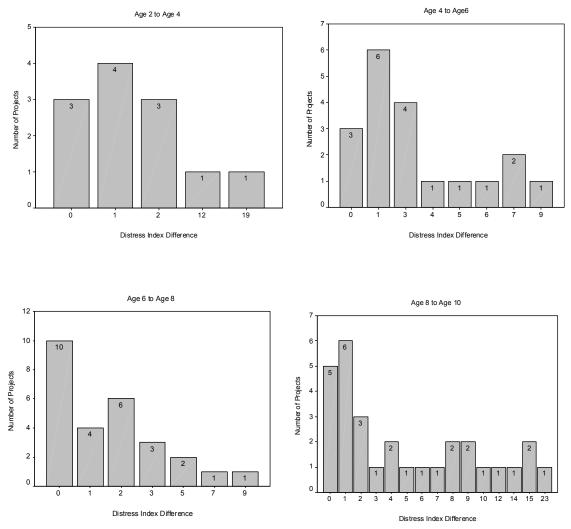


Figure 3.3: Change in DI within two years at different time steps for New/Reconstructed Rigid Pavement Freeway

Figures 3.2 and 3.3 clearly demonstrate two interrelated points: 1) pavement age by itself is not enough to explain the change in DI values even after accounting for such factors as pavement/fix type, and 2) the incremental change in DI is quite different for the same pavement/fix type. These trends and observations point strongly to the fact that other factors beside chronological age need to be considered in predicting and projecting DI values.

3.3.2. Trend of DI within Families

A "Family" is a group of projects that exhibit similar DI trend. The idea behind grouping of projects into families is to isolate projects with similar DI behavior thus reducing unexplained variability. In some respects this is an indirect way to account/control for variables that impact the DI but for which no specific information is available.

A closer look at DI trends within individual families shows that the deterioration rate of projects within the same family is still significantly different (see Figure 3.4, each line is a different project). The graphs in Figure 3.4 are only a sample; other families (within other pavement/fix types) exhibit similar degree of variation.

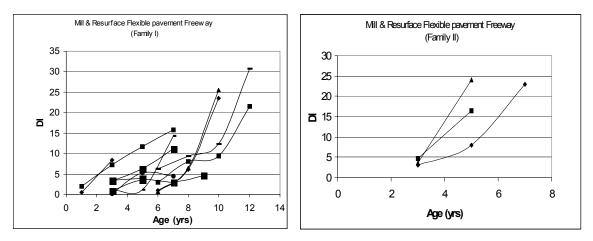


Figure 3.4: Trend of DI for Different Projects (each line is a different project)

Once again, the plots in Figure 3.4 point to the fact that other important factors are missing. Even when considering separate families within the same pavement/fix type. Those "other" factors should be considered in projecting DI values for future years. There are two possible ways to account for the other factors that influence the DI; one direct, and the other is indirect.

The direct way is to simply determine which factors are important, inventory information on those factors and then explicitly use the information in developing appropriate DI models. Once data on "other" factors is available many modeling techniques can be used. The indirect way involves the use of appropriate "surrogate" measures (provided those surrogate measures can be identified). The surrogate measures should capture the *after effects* of the "other" factors without having to deal with those factors explicitly. This will become clearer in the following chapter when the indirect way is used along with Autoregression modeling to develop DI new models.

3.3.3 DI Data for Rehabilitated Sections

There is a number of pavement sections that were subject to some rehabilitation actions since 1991 (i.e., the time when the current system of DI data inventory started). As a result of the rehabilitation action, the DI value for these sections drops down to a new, very low DI value. Per current MDOT procedures, these sections get "reassigned" to an age group with a similar DI value but a completely different (younger) chronological age. As a result there are sections with different chronological age but similar DI values grouped together. For example, a section that is chronologically 12-years old may get reassigned to the group of 5-years old sections after rehabilitation simply because the section's DI value is similar to those

sections in the 5-years old group. It is obvious that these sections present a special case, for although their DI values are similar, the sections are "structurally" different.

The rehabilitated sections do not, in the long run, behave like the other sections. The rehabilitated sections actually have higher distress value before the rehabilitation; the rehabilitation action only causes a temporary let-up in the progression of the distress. With time, the effect of the rehabilitation action diminishes down and the section is back to its natural behavior. The assumption that these sections can be treated like the other sections that have the same DI value may not be an entirely flawless assumption. For this research, the rehabilitated (reassigned) sections were treated as the rest of the sections that are in the same age group (i.e., those that were not subject to any rehabilitation action).

Chapter 4

AUTO-REGRESSION MODELS

4.1 Regression-Based Modeling

Different forms of regression models were initially evaluated (summarized in the Quarterly Report; also shown in Appendix I). Auto-regression models produced the best results. The following sections describe, for each pavement and fix type, the best autoregression models. First, a brief description of the autoregression modeling process is presented.

4.2 Autoregression

Auto-regression analysis is the estimation of the value of a random variable given that the value of an associated variable is known. In this study, the *random variable* is the DI for a given project and the *associated variable* is the previous DI value (the *previous* DI is the DI value 2 years earlier—called the "first lag"). In other words, the DI would be regressed on its "first lag". For this study, the DI was regressed against its first lag and the age that corresponds to the first lag as follows:

$$DI(t+1) = f[DI(t), Age(t)]$$
 (4.1)

DI(i) is the DI value at age i.

Various models with one or more lags were developed initially. However, models with the first lag only were sufficient; inclusion of other lags did not improve the models' ability to predict.

4.3 Auto-regression Models

The general model shown in Equation 4.1 was used for each pavement/fix type for freeway and non-freeway routes. That is, the models were developed at the pavement/fix type level both for freeway and non-freeway routes. The resulting models are presented in the following sections. Although for several pavement/fix types there were statistical outliers, those outliers were NOT removed from the database (they were included in the model development.)

4.3.1 Models for Non-freeway Pavements

Table 4.1 presents the Non-freeway pavement DI models. The table also shows the R^2 value along with the standard error for each model. The R^2 values ranged from 0.67 to 0.99. A sample of the regression plots is shown in Figures 4.1 and 4.2; the rest of the plots are in Appendix II.

	Regression Model Equation		
Pavement Fix	(Auto regression)	R ²	*SE
Mill &			
Resurface			
Composite	Predicted DI =1.107*DI (2 year before)+1.114* Age (2 year before) + 1.714	0.95	5.65
Mill &			
Resurface			
Flexible	Predicted DI (Present) = $1.27*DI$ (2yr before)+ $0.5*Age$ (2yr before)+ 2.96	0.99	4.08
Resurface on			
Composite			
Pavement	Predicted DI (Present) =1.34* DI (2yr before)+0.012*Age (2yr before) + 2.96	0.71	11.97
Bituminous			
Overlay on		0.6	
Rubblized	Predicted DI (Present) = $1.02*$ DI (2yr before)+ $0.11*$ Age (2yr before) + 2.57	0.67	2.46
Resurface on			
Rigid			
Pavement	Predicted DI (Present) = 0.77*DI (2 yr before)+1.48*Age (2 yr before)+1.09	0.98	1.89
New/			
Reconstructed			
Flexible	Predicted DI (Present) =1.407*DI (2 yr before) +0.25*Age (2 yr before)+0.63	0.85	5.80
Bituminous			
Overlay on			
Crush & Shape	Predicted DI (present) = 1.351*DI (2 yr before) +0.121age (2 yr before)+2.60	0.91	5.90
Resurface on			
Flexible			
Pavement	Predicted D I (Present) = $1.49*$ DI (2yr before)+ $0.05*$ Age (2yr before) + 3.806	0.85	12.51

Table 4.1: Auto-regression Models for Non-freeways

*SE: standard error

Note that no models were developed for New/Reconstructed rigid pavement because not enough number of data points was available to generate meaningful models (limited number of projects and/or limited number of observations for the given projects were available).

For some of the models in Table 4.1, the age coefficients (see Equation 4.1) were constrained to be positive. This was necessary to ensure intuitive relationships between age and the predicted DI value. The impact of this constraint was that the constant in the regression equation changed value—in most cases became larger—and the R² decreased slightly. More discussion on this point is provided in Section 4.8.

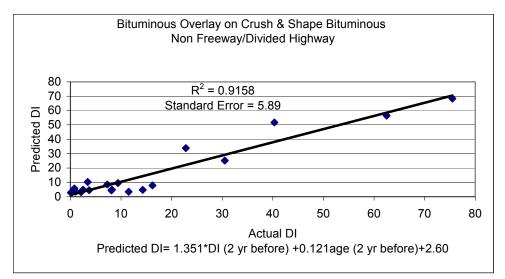


Figure 4.1: Auto-regression model for Bituminous overlay on crush & shape bituminous non freeway

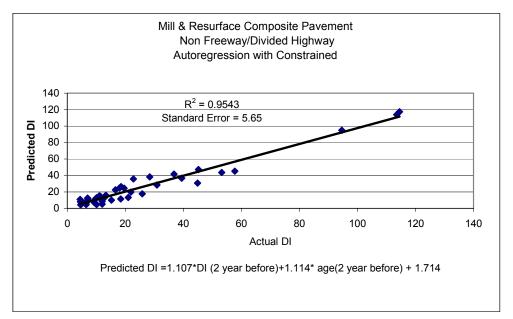


Figure 4.2: Auto-regression model for Mill & resurface composite pavements—non freeway

4.3.2 Models for Freeway Pavements

Table 4.2 presents Freeway pavement DI prediction models. The table also shows the R^2 value along with the standard error for each model. The R^2 values ranged from 0.5 to 0.85. A sample of the regression plots is shown in Figures 4.3 and 4.4. The remaining plots are in Appendix III.

Pavement	Regression Model Equation		
Fix		\mathbf{R}^2	*SE
Mill &			
Resurface			
Composite	Predicted DI (Present) = 1.007*DI (2 yr before) +0.5*Age (2 yr before)+3.86	0.58	7.68
Mill &			
Resurface			
Flexible	Predicted DI (Present) = 0.92*DI (2 yr before) +1.49*Age (2 yr before)+2.99	0.63	5.25
Resurface on			
Composite			
Pavement	Predicted DI (Present) = $0.95*DI$ (2 yr before) + $0.8*Age$ (2 yr before)+ 4.2	0.77	16.94
New/			
Reconstructed			
Rigid	Predicted DI (Present) = 1.02*DI (2 yr before) +0.4 age (2 yr before)+0.194	0.85	4.78
Unbounded			
Concrete			
Overlay on		0.50	5.02
Concrete	Predicted DI (Present) = 1.22*DI (2 yr before) +0.6*Age (2 yr before)+1.2	0.50	5.02
Bituminous			
Overlay on Rubblized	$D_{12} = \frac{1}{2} 1$	0.02	4 70
	Predicted DI (Present) =0.794*DI (2 yr before) +0.934*Age (2 yr before)+3.413	0.62	4.70
Resurface on			
Rigid	$D_{rodiated} DI (D_{rodaut}) = 1.4(*DI (2 - m hofers) + 0.47* A as (2 - m hofers) + 0.05$	0.70	10.04
Pavement	Predicted DI (Present) = $1.46*DI (2 \text{ yr before}) + 0.47*Age (2 \text{ yr before}) + 0.05$	0.70	10.04
New/			
Reconstructed Flexible	$D_{rodicted} DI (D_{rocont}) = 1.50 \times DI (2 - m hofers) + 0.8 \times A = (2 - m hofers) + 1.2$	0.70	42.0
*SE: Stone	Predicted DI (Present) = 1.59*DI (2 yr before) +0.8*Age (2 yr before)+1.2	0.70	42.0

Table 4.2: Auto-regression Models, Freeways

*SE: Standard error

Note that no models were developed for the following freeway pavements:1) Bituminous Overlay on Crush & Shape base, 2) Resurface on Flexible pavement. This was because not enough number of data points was available to generate meaningful models (e.g., limited number of projects and/or limited number of observations for the given projects). Similar to non-freeway pavements, for some of the models the age coefficients (see Equation 4.1) were constrained to be positive. This was necessary to maintain meaningful relationships between age and the predicted DI value. The impact of this constraint was that the constant in the equation changed value—in most cases became larger—see related discussion in Section 4.8.

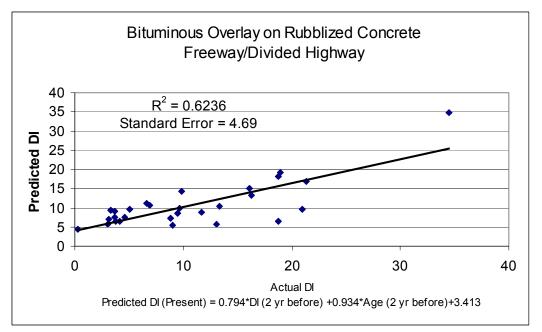


Figure 4.3: Auto-regression model for Bituminous overlay/on rubblized concreted--freeway

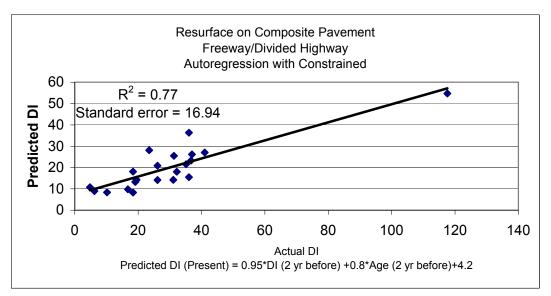


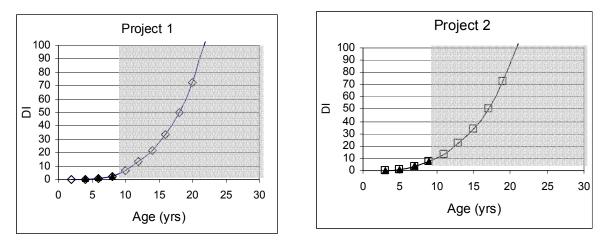
Figure 4.4: Auto-regression model for Resurface on composite pavement—freeway. For this pavement/fix type the constraint to ensure positive

4.4. Validation of Autoregression Models

The various autoregression models were validated by comparing *observed* to *modeled* DI values using "backcasting". Backcasting, simply, is to use current *observed* DI values to predict previous *observed* DI values. The objective of backcasting is to validate

autoregression modeling by testing its ability to replicate actual DI values that were observed during previous years. The assumption is that if autoregression models are able to predict observed data reasonably well then the same modeling approach would work equally well for predicting future DI values. Although this is a reasonable assumption, there is nothing inherent in autoregression to ensure that it does hold. For purposes of this work, the *observed* DI values are those from the MDOT database, and the *modeled* ones are those that were generated by the respective models. For each project, this was done for each of the data points that are available for the years 1991 through 2000. In some cases, projects did not have actual field observation for each of the scheduled years (typically, a project is surveyed once every two years).

Model validation was done in two steps. First, the best regression model is developed for each pavement/fix type. That is, the model is developed at the *pavement/fix level*. Second, the best model is used to predict the *observed* DI values (i.e., DI's of previous years). This prediction was done at the *project level*. The closeness of the observed and predicted values indicates the goodness of the model. Closeness of the predicted to the observed DI values was judged visually. The results shown below are for selected projects with different pavement/fix types. The project number noted on each graph corresponds to the listing in MDOT's database for the shown pavement/fix type. More of these validation predictions are given in Appendix IV.



4.4.1 Non-Freeway Pavements

Figure 4.5: Sample of validation results for Bituminous Overlay on Crush & Shape Bituminous (see Key below for meaning of symbols– DI values in the shaded areas are future projections)

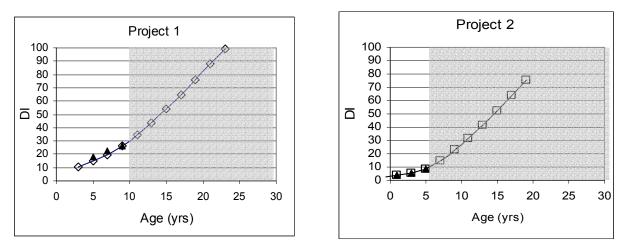


Figure 4.6: Sample of validation results for Resurface on Rigid Pavement, non- freeways (see Key below for meaning of symbols– DI values in the shaded areas are future projections)

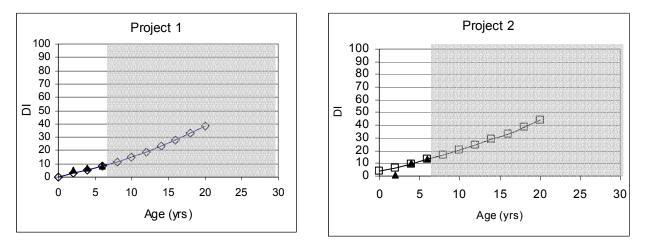


Figure 4.7: Sample of validation results for Bituminous Overlay on Rubblized Concrete, nonfreeways (see Key below for meaning of symbols– DI values in the shaded areas are future projections)



4.4.2 Freeway Pavements

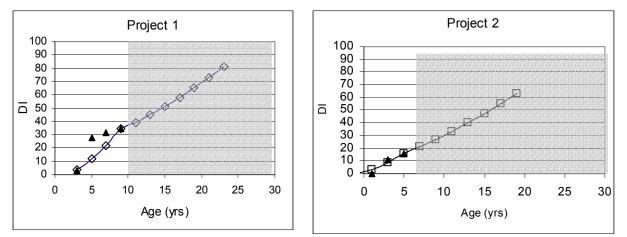


Figure 4.8: Sample of validation results for Bituminous Overlay on Rubblized Concrete Concrete, freeways (see Key below for meaning of symbols– DI values in the shaded areas are future projections)

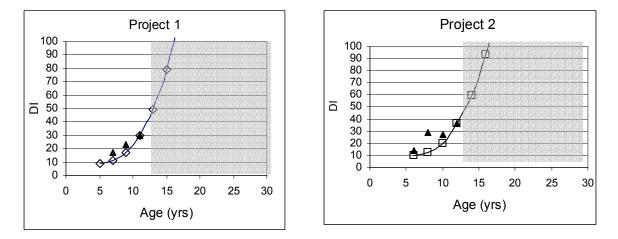


Figure 4.9: Sample of validation results for Resurface on Rigid Pavement, freeways (see Key below for meaning of symbols– DI values in the shaded areas are future projections)

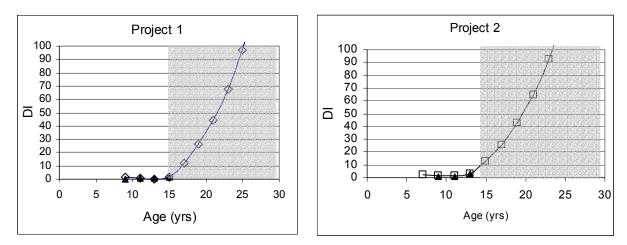


Figure 4.10: Sample of validation results for Unbounded Concrete Overlay on Concrete Pavement, freeways (see Key below for meaning of symbols– DI values in the shaded areas are future projections)

Key:

Fut

Future Prediction 🚫 Predicted DI values by Models 🛛 Actual DI values 🔺

It is noted from Figures 4.5 through 4.10 that the models are able to predict the existing (observed) non-freeway DI values more closely than freeway DI values. This is consistent with the results presented in Tables 4.1 and 4.2.

4.5 Future Projections of DI Values

The autoregression models were used to project DI values for future points that are 2, 4, 6, etc., years ahead (i.e., ahead of the latest age for which an observed DI value is available), or until the DI value reaches 50 (per MDOT's current practice, a DI of 50 is the threshold value that triggers pavement rehabilitation/maintenance action). Although projections beyond DI value of 50 are shown in the previous figures, those projections should not be used because they are beyond the intended range of the models. No attempt was tried to put a ceiling on DI projections even though it is known that the DI rate of increase starts to decline past a certain age. However, until actual (observed) DI values become available for the later stages of the DI, that range of the DI can not be accurately modeled; only its general behavior may be described.

Future projections were done sequentially as follow: A DI is projected for time t first, then DI for time t+1 is projected. DI for t+2 is projected only after DI for t+1 is at hand, and so on. This sequence is repeated until the projected DI value is 50, or until certain age is

reached. This process can be easily programmed into a spreadsheet or a simple computer code to make long-term projections more convenient to make.

4.6 Discussion of the Projections

The models developed in this project should NOT be to be used beyond the age where DI is 50. It is known that DI will not continue to increase indefinitely, as currently implied by the models (see Figures 4.5-4.10). Once observed data becomes available on how DI actually changes with time at later stages of the pavement life, that data should be used to refine or adjust the models presented in this report.

4.7 Why Auto-Regression Seems to Generate Better Results

The main reason why auto-regression models were more successful than other modeling approaches is the fact that they implicitly account for the many factors that impact pavement distress. Referring to Equation 4.1 above, the influence of the many other factors is included in the term DI(t). When DI at time t+1 is projected, the influence of the various factors is already captured in the term DI(t). While this feature is convenient in capturing the influence of different factors, it limits the ability to conveniently project DI values for long term; the projections will have to be developed in steps. As noted in Section 4.5, this little inconvenience can be easily overcome through some automation of the projection process. This can be done easily with a computerized spreadsheet.

4.8 Discussion on Autoregression Models

Given the above results, the following two points are relevant

1. Obtaining a counterintuitive coefficient in regression models is not unusual. In such cases this could be an indication of some issues or problems with the data and/or the characteristics of the data vis-à-vis the modeling approach that is being used. For example co-linearity between independent variables can lead to counterintuitive results.

With respect to the results of this research project, for the cases where the constraint on the Age coefficient was necessary (i.e., when the coefficient obtained was negative), that result might be yet another indication that age is not a sufficient predictor of DI. This highlights the need to account for the other factors that impact DI.

2. An implicit and important assumption was used in preparing the DI projections for this study. The assumption is that a regression model is valid for subsequent age and DI points as it is for the age and DI values used to develop it in the first place. This is a reasonable but a significant assumption. It should be verified as more *observed* future DI reading become available.

Chapter 5

RESULTS AND APPLICATION OF MODELS

This chapter reports on the practical usage of the models that were described in Chapter 4. The goal for developing the models is to establish a procedure whereby future pavement rehabilitation needs can be predicted with reasonable accuracy. Such projections are necessary for budgetary and resource allocation purposes; it is necessary to know which projects will need rehabilitation and when (what year). The models that were developed in this research can be used to answer these questions. There are several ways to present the results of the models.

The results are presented in tabular format, two examples of which are shown in Tables 5.1 and 5.2. The tables are arranged to be used as follows: For the given pavement/fix type, the present age and present DI value, the cells show the age at which the DI will reach 50 (DI of 50 is the threshold when rehabilitation becomes necessary). For example, in Table 5.1 if the present age of the pavement is 10 years and the present DI value is 15 then that pavement will reach a DI of 52.5 at age 16 years. In other words, that particular pavement has about 6 more years of useful life.

The fact the DI values in Tables 5.1 and 5.2 are not exactly 50 is easily explainable. This is because the age is projected in whole-year increments. If necessary, an exact time (fraction of a year) can be determined when the DI value will be exactly 50.

The information in tables 5.1 and 5.2 can also be presented in a 3-diminsional graph. For practical applications, however, the graph will not be as useful as the tabular format. Tables for the remaining types of pavements/fix are presented in Appendix V.

Table 5.1: Projected pavement age when rehabilitation is needed-Resurface on Rigid Pavement, Non-Freeways

Pred	Predicted Pavement Age when DI = 50, Given Present age and Present DI value																				
Resu	Resurface on Rigid Pavement - Non Freeway/Divided Highway DSL = 16 yesrs																				
	P-A	GE 1	P-A	GE 2	P-A	GE 3	P-A	GE 4	P-A0	GE 5	P-AGE 6 P-AGE 7				P-AGE 8 P-AGE			GE 9	E 9 P-AGE 10		
P-DI	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	
5	53.2	15.0	47.8	14.0	52.9	15.0	47.0	14.0	51.7	15.0	45.0	14.0	49.2	15.0	53.3	16.0	50.0	15.8	48.0	16.0	
10	54.0	15.0	48.8	14.0	53.9	15.0	48.4	14.0	53.1	15.0	46.7	14.0	50.9	15.0	50.0	15.1	46.8	15.0	50.3	16.0	
15	54.8	15.0	49.9	14.0	54.9	15.0	49.7	14.0	54.4	15.0	48.5	14.0	52.6	15.0	45.5	14.0	49.0	15.0	52.5	16.0	
20	45.8	13.0	50.9	14.0	56.0	15.0	51.0	14.0	46.0	13.0	50.2	14.0	54.4	15.0	47.8	14.0	51.3	15.0	54.8	16.0	
25	46.8	13.0	51.9	14.0	47.7	13.0	52.4	14.0	47.8	13.0	52.0	14.0	56.1	15.0	50.1	14.0	53.6	15.0	45.8	14.0	
30	47.9	13.0	52.9	14.0	49.0	13.0	53.7	14.0	49.5	13.0	53.7	14.0	48.8	13.0	52.3	14.0	46.2	13.0	48.8	14.0	
35	48.9	13.0	54.0	14.0	50.4	13.0	47.1	12.0	51.3	13.0	47.6	12.0	51.1	13.0	54.6	14.0	49.1	13.0	51.7	14.0	
40	49.9	13.0	47.0	12.0	51.7	13.0	48.8	12.0	46.4	11.0	49.9	12.0	53.4	13.0	49.4	12.0	52.1	13.0	54.7	14.0	

Predicted Pavement Age when DI = 50, Given Present age and Present DI value

	P-AG	E 11	P-AG	GE 12	P-AGE 13 P-AGE 14				P-AG	E 15	P-AG	GE 16	P-AG	GE 17	P-AG	SE 18	P-AG	SE 19	P-AG	GE 20
P-DI	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age
5	51.5	17.0	55.0	18.0	50.0	18.0	50.0	18.6	47.1	19.0	49.8	20.0	52.4	21.0	55.0	22.0	50.0	22.4	50.0	23.2
10	53.7	17.0	50.0	17.0	45.0	17.0	47.5	18.0	50.1	19.0	52.7	20.0	50.0	20.5	50.0	21.3	50.0	22.1	50.0	22.9
15	50.0	16.1	50.0	16.7	47.8	17.0	50.4	18.0	53.0	19.0	50.0	19.4	50.0	20.2	50.0	21.0	50.0	21.8	50.0	22.6
20	45.5	15.0	48.1	16.0	50.8	17.0	53.4	18.0	50.0	18.3	50.0	19.1	50.0	19.9	50.0	20.7	50.0	21.5	46.1	22.0
25	48.5	15.0	51.1	16.0	53.7	17.0	50.0	17.1	50.0	17.9	61.6	18.7	45.5	19.0	47.0	20.0	48.5	21.0	49.9	22.0
			-							-		-								
30	514	15 0	54 0	16 0	50.0	16 0	50.0	16 7	46 4	17 0	47 8	18 0	49 3	19 0	50.8	20.0	52 3	21.0	53 8	22.0
35	54 4	15.0	45 8	14 0	47 2	15.0	48 7	16.0	50.2	17 0	517	18.0	53.2	19.0	54 6	20.0	50.0	20.4	50.0	21.3
	57.7	10.0	10.0	14.0	TT . Z	10.0	10.7	10.0	50.2	11.0	51.7	10.0	50.2	10.0	54.0	20.0	50.0	20.4	50.0	21.0
40	48 1	13.0	49.6	14 0	51 1	15.0	52.6	16.0	54 0	17 0	50.0	17.3	50.0	18.2	50.0	19 1	50.0	20.0	50.0	20.9
-10	40.1	10.0	40.0	14.0	01.1	10.0	02.0	10.0	04.0	17.0	00.0	17.0	00.0	10.2			resen			

P-Age = Present Age in Year

Table 5.2: Projected pavement age when rehabilitation is needed— Mill & Resurface Flexible Pavement, Freeways

	lill & Resurface Flexible Pavement Freeway/Divided Highway DSL = 11.3 years																			
	P-A	GE 1	P-A	GE 2	P-A	GE 3	P-A	GE 4	P-A	GE 5	P-AGE 6		P-AGE 7		P-AGE 8		P-AGE 9		P-AG	GE 10
P-DI	DI	Aqe	DI	Aqe	DI	Age	וח	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Aqe	DI	Age
		Aye		Aye		Aye		Aye		Aye		Aye		Аус		Aye		Aye		Aye
5	50.2	11.0	50.0	11.1	47.2	11.0	52.6	12.0	50.0	12.0	45.8	12.0	50.0	13.0	54.1	14.0	50.0	14.5	50.0	14.8
10	53.6	11.0	45.5	10.0	50.9	11.0	50.0	11.2	45.6	11.0	49.8	12.0	53.9	13.0	50.0	13.4	50.0	13.8	46.0	14.0
15	50.0	9.9	49.2	10.0	54.5	11.0	45.4	10.0	49.5	11.0	53.7	12.0	50.0	12.3	50.0	12.6	47.4	13.0	50.2	14.0
20	47.5	9.0	52.8	10.0	45.2	9.0	49.3	10.0	53.5	11.0	50.0	11.1	45.9	11.0	48.7	12.0	51.6	13.0	54.5	14.0
25	51.1	9.0	45.0	8.0	49.1	9.0	53.2	10.0	50.0	9.9	47.3	10.0	50.1	11.0	53.0	12.0	55.0	13.0	50.0	13.5
30	54.7	9.0	48.9	8.0	53.0	9.0	45.8	8.0	48.6	9.0	51.5	10.0	54.4	11.0	50.0	11.3	50.0	11.7	45.6	12.0
35	48.7	7.0	52.8	8.0	47.1	7.0	50.0	8.0	52.9	9.0	55.0	10.0	45.7	9.0	47.2	10.0	48.7	11.0	50.2	12.0
40	52.6	7.0	48.5	6.0	51.4	7.0	54.3	8.0	47.4	7.0	48.9	8.0	50.4	9.0	51.8	10.0	53.3	11.0	54.8	12.0

Predicted Pavement Age when DI = 50, Given Present age and Present DI value	
Mill & Resurface Flexible Pavement Freeway/Divided Highway	

	P-AG	GE 11	P-AGE 12		P-AGE 13		P-AGE 14		P-AGE 15		P-AGE 16		P-AGE 17		P-AGE 18		P-AGE 19		P-AGE 20	
P-DI	DI	Age	DI	Ane	DI	Ane	וח	Ane	DI	Ane	וח	Age	וח	Age	וח	Age	וח	Age	וח	Age
		Age		Age		Age		Age		Age		Age		Age		Age		Age		Age
5	45.0	15.0	47.5	16.0	50.3	17.0	53.2	18.0	50.0	18.5	50.0	19.3	50.0	20.2	50.0	21.0	50.0	21.9	50.0	22.8
10	10.0	45.0	54 7	40.0	54.0	47.0	50.0	47.4	50.0	40.0	50.0	40.0	50.0	40.0	50.0	00.7	50.0		50.0	00 F
10	48.9	15.0	51.7	16.0	54.6	17.0	50.0	17.4	50.0	18.2	50.0	19.0	50.0	19.9	50.0	20.7	50.0	21.6	50.0	22.5
15	53.1	15.0	50.0	15.4	50.0	16.2	50.0	17.0	50.0	17.8	50.0	18.7	50.0	19.6	50.0	20.4	45.2	21.0	46.7	22.0
20	50.0	14.2	50.0	15.0	50.0	15.8	50.0	16.6	50.0	17.5	45.4	18.0	46.8	19.0	48.3	20.0	49.8	21.0	51.3	22.0
25	50.0	12.0	50.0	14.6	4E E	15.0	47.0	16.0	10 E	17.0	50.0	19.0	51 5	10.0	52.0	20.0	5 A A	21.0	55.0	22.0
25	50.0	13.0	50.0	14.0	45.5	15.0	47.0	16.0	46.5	17.0	50.0	16.0	51.5	19.0	53.0	20.0	54.4	21.0	55.0	22.0
30	47.1	13.0	48.6	14.0	50.1	15.0	51.6	16.0	53.1	17.0	54.6	18.0	50.0	18.5	50.0	19.5	50.0	20.4	50.0	21.3
35	51.7	13.0	53.2	14.0	54.7	15.0	50.0	15.4	50.0	16.3	50.0	17.2	50.0	18.2	50.0	19.1	50.0	20.0	50.0	21.0
40	50.0	12.2	50.0	13.1	50.0	14.0	50.0	15.0	50.0	15.9	50.0	16.8	50.0	17.8	50.0	18.7	50.0	19.7	50.0	20.9
	25													P-DI = Present Distress Index						

Chapter 6

CONCLUSIONS AND RECOMMENDATIONS

Based on the analysis and results presented in the previous chapters, the following conclusions may be drawn. Several recommendations are also presented:

1. Pavement chronological age by it self does not seem sufficient to predict change in DI values. This is evidenced by the wide variation in the DI values that correspond to the same age when we control for pavement and rehabilitation type. This strongly suggests that the other causal factors should be identified and then included in appropriate models.

However, including other causal factors in the models requires collection and maintenance of extensive amounts of data. In many cases data on these factors may not be conveniently available. However, it might be a worthwhile effort to start assembling such information. Studies suggest that the list of "other" causal factors may include: environment (e.g., temperature, precipitation), traffic volumes, truck volumes and pavement cross-section design.

3. The models that MDOT currently uses to project DI values are not too unreasonable given that no information is available on the many other factors that are believed to influence pavement distress. It is possible that the lack of information on the "other" causal factors is a major determinant of the quality of the DI predictions. (current MDOT models use only pavement *age* as an independent variable)

The logistic regression-based models that MDOT uses follow an S-shaped curve. However, for just about all pavement/fix types, the DI observations that are currently in the MDOT database cover only the early to mid stages of the "S-shaped" deterioration process. Even for the early and mid stages of the deterioration process, there is a wide variation in the DI values that the S-shaped logistic regression predicts. This wide variation suggests that other independent variables (causal factors) are at play and therefore should be included in the models.

4. The use of Logistic Regression is one among many analytical techniques that other state departments of transportation are using to predict DI values. In many cases, a clearly advantageous modeling approach is not available. In part this due to the fact that all these models are missing other important variables (beside age). In addition to Logistic Regression, Linear Regression, Marcovian chains, and Neural Networks have been used.

The limited success of the above modeling techniques—for the case of Michigan and other states—is not necessarily due to shortcomings in the techniques themselves. Rather it is due to the lack of sufficient information on the factors that are believed to impact pavement distress. It is important, therefore, that more effort be directed at identifying those causal factors and then including them in the models. Effort to

identify the best modeling technique(s) should continue. However, it is unrealistic to expect any model to work with sufficient reliability when many of the causal factors are missing.

6. As an intermediate measure to account for the effects of the missing causal factors, indirect or surrogate measures need to be found. Those surrogate measures should have the capability of capturing the after-effects of the *real* causal factors.

This research adopted this approach by using the first lag of the DI (i.e., the immediate past DI value) as a surrogate measure of the missing causal factors. The DI was regressed on its *first lag* and the corresponding *age*. The results were very encouraging. Obtaining long-term projections of DI values using this approach can't be done directly; they have to be done in a step-wise process that is easily programmable in a spreadsheet.

7. The projections of DI values obtained by the new (autoregression) models will have to be compared to actual future DI values when those future values become available. Only then the accuracy of the predictions of the new models may be determined. This, however, is true for any modeling technique.

The above implies that the models developed in this project should be viewed as dynamic ones in that they should be refined as more observed DI values become available.

8. It is recommended that data on other causal factors be assembled for future modeling efforts. Part of this data may currently be available, although it may not be in ready-to-use format.

For example, data on the design of pavement cross-section is available for most projects. However, the format may not be convenient for immediate use in DI models. Such data should be prepared for future inclusion in new or modified DI prediction models.

- 10. The models developed in this project should NOT be used beyond the age where DI is 50. It is known that DI will not continue to increase indefinitely as currently implied by the models. Once observed data becomes available on how DI actually changes with time at the later stages of the aging process, this data should be used to refine or adjust the models presented in this report.
- 11. It is recommended that DI progression for rehabilitated sections be evaluated separately to determine if significant difference exist between sections that were rehabilitated and those that were not.

The models developed in this project did not differentiate, for a given pavement/fix type, between sections with the same DI values based on rehabilitation history. In other words, an implicit assumption was made that, for a given pavement/fix type,

sections with similar DI values will behave similarly regardless of whether or not the sections were rehabilitated). If a significant difference exists, the DI prediction models need to be modified to account for this. One possible modification is to include categorical variables (with values like Yes or No, or 1 and 0) in the regression models.

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12. Paulk Chan. "North Carolina's Experience in Development of Pavement Performance Prediction and Modeling." Transportation Research Board No 1592, TRB, National Research Council, Washington, D.C., 1997, pp 80-88.

APPENDICES

Appendix I: Quarterly Report

Appendix II: Non-freeway Regression Graphs and Models

Appendix III: Freeway Regression Graphs and Models

Appendix IV: Graphs of Validation of Autoregression Models

Appendix V: Results of Autoregression Models: Age at which DI becomes 50

Appendix I Quarterly Report

DEVELOPMENT OF AN IMPROVED PAVEMENT DISTRESS INDEX MODELS

Quarterly Report No.1

August - October 2002

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November 2002

1.0 GENERAL

This quarterly report presents the accomplishments of the research team during the first quarters of the project. The work planned for the second (and last) quarter is also included.

2.0 HYPOTHESIS AND OBJECTIVES

The main hypothesis of this research study is as follows: as time progresses the pavement distress index (DI) follows a non-decreasing path which can be modeled by an s-shaped curve can be modeled using logistic regression. The objectives of this study are to: 1) test the above hypothesis using data that MDOT currently has in its database; and 2) explore other modeling approaches to improve the ability to predict the DI. The outcome of this research is to be used to plan (timing and location) preventive maintenance activities.

These objectives will be achieved by using statistical, probabilistic, and other suitable approaches modeling approaches. These approaches will make it possible to confirm, modify or propose an alternate model to the models currently used for different pavement types and rehabilitation treatments.

3.0 DELIVERABLES

The deliverables of this study include:

One quarterly reports

Final report

A recommendation on a methodology for modeling DI; either current Logistic Regression or a possible new approach

4.0 ACCOMPLISHMENTS

The accomplishments of the research team during this quarter are as follows:

4.1 Regression-Based Modeling

4.1.1 Replication of Current MDOT Logistic Regression

In this task, the current approach MDOT uses to model DI over time was replicated using the statistical analysis package SPSS. SPSS' logistic regression module was used in the same form and with the same parameter values as MDOT's current models. All "combined projects" and "families" models were replicated for all pavement and

rehabilitation/fix types for both freeway and non-freeway routes. The objective of this task was to ensure that current models are easily reproduced and then used as a benchmark to assess all subsequent models. SPSS can model different types of logistic regression, and various restrictions on the parameter can be easily specified. Further, SPSS can automatically search for the best combination of parameters so that the best fit between observed and modeled values is obtained. This feature offers wide flexibility and ease to customize logistic regression. Results of this analysis are shown in the tables of Appendix A.

4.1.2 Logistic Regression Improvements over Current MDOT's Models

SPSS can be used to "optimize" the choice of parameters of the model so that the resulting model is the best fit for the data at hand. The results of this effort are included in tables A.1 and A.2 of Appendix A. The tables show the standard error for all types of pavements/fixes. A graphical presentation of these results is shown in the figures of Appendix B. The results demonstrate that while some improvements were achieved, they are somewhat minor.

Other variations of the Logistic Regression approach were tried. These included models that are different in structure and use of parameters but are functionally similar to the models currently used by MDOT. These alternate models were of the following form:

$$DI(t) = 1/[(1/u)+b_o(b_1)^t]$$

In this form, \mathbf{u} is the upper boundary of the dependent variable, and \mathbf{b}_0 and \mathbf{b}_1 are constants, and \mathbf{t} is time.

The improvements from these alternate models were also marginal as noted in the tables of Appendix A and graphs of Appendix B. The combined results of the three models (current MDOT, MDOT with improvements, and alternative logistic) are summarized in Appendices A and B. It is clear from the tables and figures that all improvements over current models are only marginal; in some cases (particularly for high DI values), the alternative models are somewhat inferior.

4.1.3 Linear Regression Models

Some literature on pavement management suggests that linear regression models can be used for individual pavement sections. It is less obvious, however, if such models can be generalized and applied to other pavement sections¹. This type of modeling assumes that similar traffic loading and previous maintenance levels were consistent over the past. The linear regression modeling was used to model progression of DI over time for the different types of pavements/fixes of freeway roads. The results are shown in Appendix C

¹ M.Y. Shahin: Pavement Management for Airports, Roads and Parking Lots. Chapman Hall, NY, 1994.

along with results of other regression models. The results show that there are some improvements for some pavement/fix type combination; in other cases the improvements were only marginal. A summary table of the result is shown in Tables C.1 and C.2. Comparable models for non-freeway roads were not developed since it is not clear at this point if linear models are a viable alternative.

4.2 Probabilistic Models

Two types of probability-based modeling approaches were evaluated: Markov Chains and Frequency based analysis. In both cases, the current information in the DI database was used to determine the likelihood of change in DI values based on the current conditions and the future point (time) for which the DI is to be projected.

4.2.1 Markov Chains

A Markov chain is a discrete time stochastic process in which each random variable depends only on the previous one and affects only the subsequent one. Markov chains have been used before to model different time-dependent processes including pavement condition deterioration. The random variable in our case would be the state (as expressed by the DI) of the pavement section under consideration. A Markov chain for the pavement DI gives the probability that a pavement section would *transition* to a future specific state given its current state. For the purpose of this study, the pavement DI was divided into different categories. Each category represents a specified range of DI values, or a *state*. The probabilities of transitioning from one category to another were developed based on the information in the MDOT database (i.e., number of projects, their specific DI values and corresponding ages). Results from Markov chains are typically used to determine the likelihood (probability) of a section or group of sections being in a specific category at some future point given their current category. In practice, this type of information can then be used to decide on location and timing of maintenance activities. A sample of the transition probabilities for rigid new/reconstructed freeway pavement is shown in Tables D.5 and D.6. Table D.5 is for a section that is currently in Category 1. In this case, we can see, for example, that the probability of the subject section staying in Category 1 after years 2 is 0.859, and the probability of the same section staying in Category 1 after 14 years is 0.342. The table shows a 0.3015 probability of transitioning to Category 3 in 16 years. No probability is shown for transitioning to Category 2. This "gap" indicates a problem since it is normally expected that the pavement section would transition to Category 2 at some point before it gets to Category 3. This gap may have resulted because of lack of sufficient data points, or the specific type of grouping adopted in the analysis. Table D.6 shows the probabilities for a section that is in Category 2. The interpretation of the probabilities shown in bold is similar to the case of the Category 1 section.

4.2.2 Frequency based Analysis

This analysis focused on the DI change-Age combinations (that is, the change in DI

values that occurred during different time frames-e.g., 2, 4, 6, and 8 years--for known initial pavement ages) The outcome of this type of analysis is the number of projects in each DI change-Age combination. For example, Figure E.1 shows that 4 projects (age 2-4) had a change of only 1 DI point in 2-years time; one project had a 19 DI point change in 2-years.

In theory, with these numbers and frequencies we can determine the probabilities for the occurrence of each of the DI Change-Age combinations. The probabilities would then be used to determine the likelihood of a given section being in a different DI "state" after a known number of years given its current age. This was done for only new/reconstruction freeway rigid pavements. In principle, the Frequency analysis approach leads to similar results as Markov Chains. The difference is only in how the project information is utilized.

The results of this modeling approach were of limited use because in many cases only limited number of "points", or observations, were available in several of the DI change-Age combinations (see Appendix E). This approach will not be pursued unless we are to use the 0.1-mile DI data. If this to be done, then it is likely--though not guaranteed--that enough observations will be found for each DI change-Age combination to make the frequency analysis practically useful.

4.3 Autoregression

Autoregression analysis is the estimation of the value of a random variable given that the value of an associated variable is known. In this study, the *random variable* is the DI for a given project and the *associated variable* is the previous DI value (the *previous* DI is the DI value 2 years earlier—called the "first lag"). In other words, the DI was regressed on its "first lag". For the propose of this study, the DI was regressed against its first lag and the age that correspond to the first lag:

DI(t+1) = f[DI(t), Age(t)]

DI(i) is the DI value at age i. Sample results from this analysis are shown in Figures F.1 and F.2 for non-freeway mill and resurface and freeway rigid new pavements, respectively. The R² value for both pavements show excellent correspondence between actual and modeled DI values.

The auto-regression models were then used to forecast DI values for future points 2, 4, 6 years ahead (i.e., ahead of the latest age for which a DI value is available), or until the DI value reaches 50. Per MDOT's current practice, a DI of 50 is the threshold that triggers pavement rehabilitation/maintenance action. Similarly, the Autoregression approach was used to produce models to "backcast" DI values. That is, to use current known DI value to predict previous DI values. The objective of the backcasting is to validate this type of modeling by testing its ability to replicate actual DI values that were collected in the field during previous years. The results of the backcasting are not complete as of this writing.

4.4 Neural Network-based Models

Neural Networks (NNets) is an information-processing paradigm inspired by the way the densely interconnected, parallel structure of the mammalian brain processes information. Unlike traditional approaches, NNets are "trained" to learn relationships in the data they have been given. Just like a child learns the difference between a chair and a table by being shown examples, a neural net learns by being given a training set. Due to it's complex, non-linear structure, the neural net can find relationships in data that humans are unable to do. Learning in NNets occurs by example through training, or exposure to a representative set of input/output data where the training algorithm iteratively adjusts the connection "weights". These connection weights store the knowledge necessary to solve specific problems. Figure 1 shows a general structure of the NNet used to model DI over time.

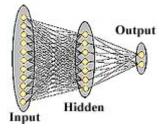


Figure 1: General structure of the NNet

For the DI models, an NNet was built of the following general form:

Current DI = *NNet (DI value 2 years ago, Age 2 years ago).*

The variables between parenthesis are *input variables*, and the current DI is the *output variable*. This form of the network makes it easy to compare its performance to Autoregression. Two NNets were initially developed and their performance evaluated: one for rigid new/reconstruction (freeways routes) pavement and one for mill and resurface (non-freeways routes). Results of the NNet-based modeling are shown in Appendix G. Similar NNets are being developed and tested for all pavement/fix type combinations.

The NNet models were developed as follows: For *training* the network, 85% of the data points were used. A data point here refers to a project with all its chronological DI readings. The remaining 15% of the data points were used to *test* the network. The results of the developed network are shown in Figures G.1 and G.2 for Mill and Resurface (non-freeways) and G.3 and G.4 for Rigid/ new-reconstruct (freeways), respectively.

For the case of Mill and Resurface, the training results show that the network is fairly successful ($R^2=0.95$). The limited success of the testing results is due in part to the limited number of points used. This outcome means that the NNet has "learned" the

knowledge that is present in the DI observations but its ability to accurately predict DI for cases that it has not seen is still limited. The results for the Rigid-new/reconstruct indicate that the NNet was successfully trained and was able to generalize the knowledge as demonstrated by the high R^2 for the testing results.

The NNets thus far are very encouraging but that does not mean the NNets will work for all pavement/fix type combinations--that outcome will be determined once NNets are actually developed for the subject pavement/fix type combinations.

For practical applications, NNet can be used to predict future DI conditions as follow: 1) train the NNet based on available DI data, 2) use the trained NNet to predict the DI value for two year from now (2YAhead) (i.e., two years form the last date for which an actual DI is available). Once the 2YAhead value is predicted, use it as input and now predict the following DI values (4 years from now, or 4YAhead). Similarly one can predict the DI for 6, 8, 10 years a head using this repeated process. Using this process, one can determine the point in time (age of section) when the DI value is 50, since this is the value that triggers maintenance action--in practical terms, we would not be interested in DI values higher than 50 or the time (age) when such values are reached.

5. Selection of a Modeling Technique and Developing models for all Pavement and Fix Types

The first round of analyses was directed primarily at identifying a promising modeling technique in some cases using a sample of the different pavement/fix type combinations. A Complete set of models for all pavement/fix type combinations is being developed in the second quarter of this research using only the most promising modeling techniques discussed above.

At this point, the Autoregression and NNet approach seem to outperform other modeling approaches. However, a complete assessment—with MDOT's input--will have to be made once models have been developed for all combinations of pavements/fixes types (for both freeways and non-freeway roads). It is conceivable that different modeling approaches will have to be used for different types of pavements and/or fixes.

5.0 WORK PLANNED FOR NEXT QUARTER

The following activities are scheduled for next quarter:

- 1) Complete development of models to all types of pavements and fixes
- 2) Determine the best models for each pavement type and fix
- 3) Prepare future forecast of DI values based on the recommended models
- 4) Prepare a final Report

APPENDICES TO THE QUARTERLY REPORT

Appendix A

Table A.1. Standard Error Comparison for Models of Freeway Pavements

			Standard Error of Models			
Pavement	Family	MDOT MODEL	MDOT MODEL (MODIFIED BY SPSS)	SPSS LOGISTIC MODEL		
	Composite	2.73	0.60	6.79		
Mill & Resurface Composite	Family I	4.57	4.21	9.45		
Pavement	Family II	8.674	7.11	6.95		
	Composite	1.80	1.38	2.93		
	Family I	4.0073	3.97	4.17		
Mill & Resurface Flexible	Family II	5.388	5.35	5.51		
Pavement	Family III	1.964	0.987	9.21		
	Composite	2.41	2.176	5.409		
Resurface on Composite	Family I	6.470	6.24	8.18		
Pavement	Family II	14.385	13.72	15		
	Composite	3.53	3.28	9.89		
Resurface on Flexible	Family I	26.407	26.27	26.36		
Pavement	Family II	1.7939	1.75	2.39		
	Composite	1.734	1.73	7.11		
	Family I	4.799	4.54	7.56		
New/ Reconstructed Rigid	Family II	8.167	7.20	9.00		
Pavement	Family III	3.978	3.91	4.24		
Bituminous Overlay on Crush & Shape Base	All points	2.7514	2.718	2.49		

	Composite	0.8846	0.633	0.90
	Family I	2.11	1.82	2.46
	Family II	1.842	1.51	1.68
	Family III	1.221	0.82	1.13
Unbounded Concrete Overlay	Family IV	0.0805	0.022	0.039
on Concrete Pavement	Family V	0.151	0.057	0.13
	Composite	0.688	0.596	4.35
	Family I	3.33	3.29	3.40
Bituminous Overlay on	Family II	4.618	4.33	7.46
Rubblized Concrete	Family III	14.918	13.76	18.501
	Composite	0.643	0.626	5.57
	Family I	5.465	5.35	6.61
	Family II	12.99	12.98	13.09
Resurface on Rigid Pavement	Family III	2.153	2.13	2.34
New/Reconstructed Flexible pavement	All points	38.99	38.64	41.75

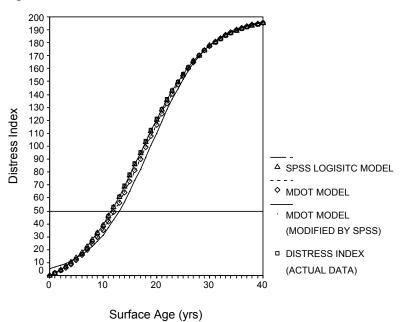
Table A.2. Standard Error Comparison for Models of Non-Freeway Pavements

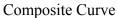
			Standard Error of Models	
Pavement	Family	MDOT MODEL	MDOT MODEL (MODIFIED BY SPSS)	SPSS LOGISTIC MODEL
	Composite	2.682	2.51	8.8
New/Reconstructed Asphalt	Family I	26.53	20.27	27.55
Pavements	Family II	3.68	3.53	4.85
	Composite	1.40	1.21	6.41
	Family I	2.4992	2.41	2.67
Bituminous Overlay on Crush &	Family II	8.72	8.58	9.41
Shape Bituminous	Family III	1.644	1.641	1.75
	Composite	0.328	0.18	4.87
Resurface on Composite	Family I	8.143	8.05	8.14
Pavement	Family II	19.85	19.71	19.61
	Composite	1.264	1.147	5.43
	Family I	5.704	5.227	8.00
Mill & Resurface Flexible	Family II	2.40	2.38	2.66
Pavement	Family III	6.946	6.90	7.25
	Composite	0.3022	0.2835	4.92
	Family I	5.33	5.27	5.46
-	Family II	24.28	24.07	25.59
Resurface on Flexible Pavement	Family III	1.84	1.81	1.98

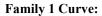
Resurface on Rigid Pavement	All Points	7.95	7.23	6.18
New concrete pavement	All Points	1.15	1.14	1.44
Mill and Resurface composite pavement	All Points	12.69	12.63	10.23
Bituminous Overlay on Rubblized Concrete	All Points	3.251	3.25	3.644

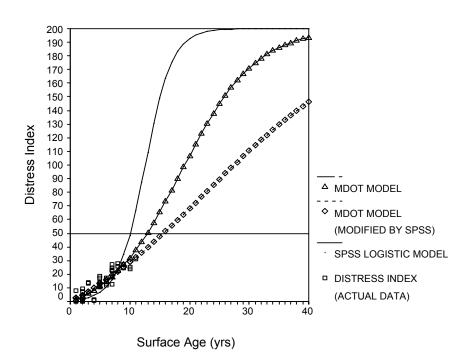
Appendix B

Mill & Resurface Composite Pavement - Freeway

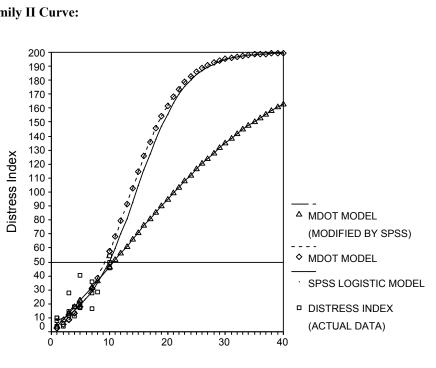








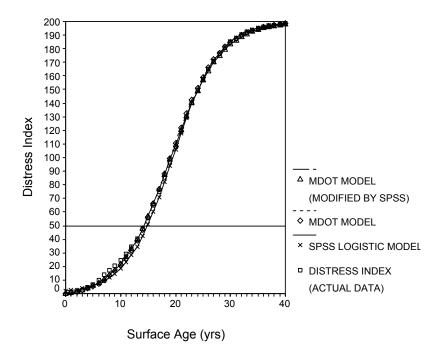
Family II Curve:



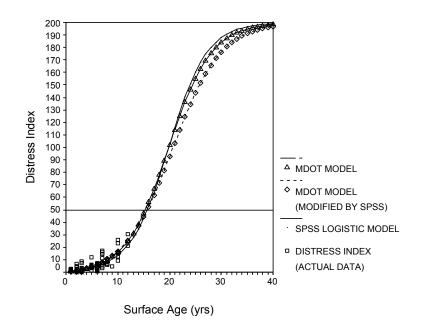
Surface Age (yrs)

Mill & Resurface Flexible Pavement - Freeway

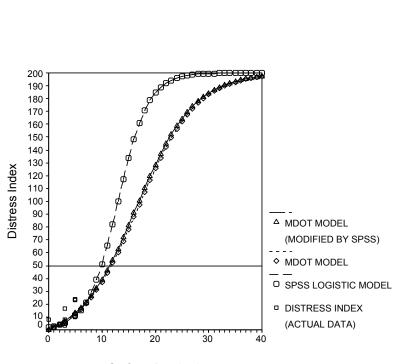




Family 1

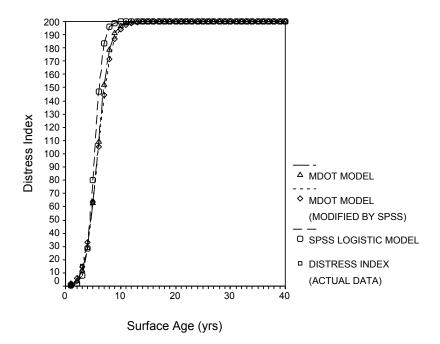


Family 2

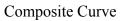


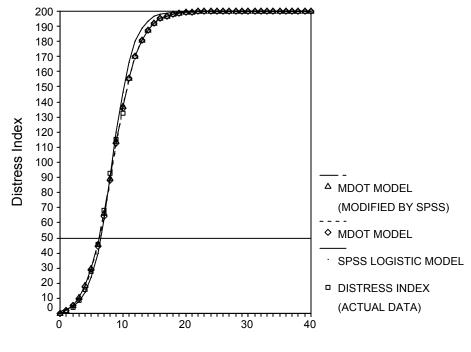
Surface Age (yrs)

Family 3



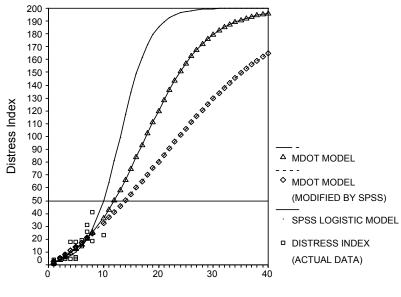






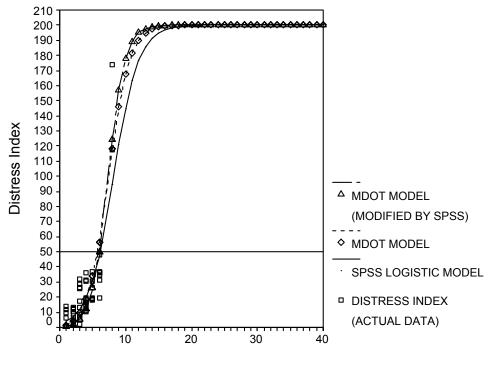
Surface Age (yrs)

Family I



Surface Age (yrs)

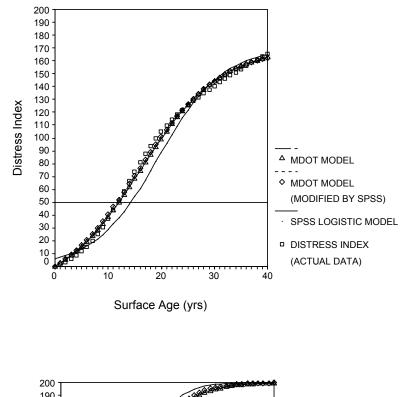
Family II



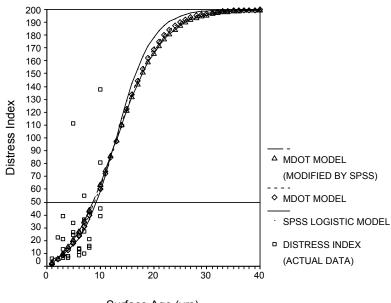
Surface Age (yrs)

Resurface on Flexible Pavement - Freeway/Divided Highway

Composite Curve

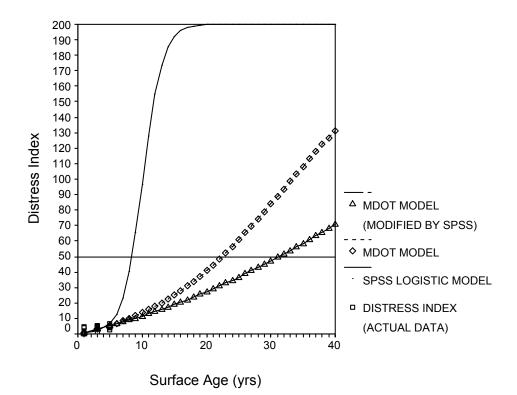






Surface Age (yrs)

Family II



Appendix C

Table C.1. Linear Model Standard Error Comparison with other Models for Freeway Pavements

			Standard Error of M	odels	
Pavement	Family	MDOT MODEL	MDOT MODEL (MODIFIED BY SPSS)	SPSS LOGISTIC MODEL	Linear Model
	Composite	2.73	0.60	6.79	
Mill & Resurface Composite	Family I	4.57	4.21	9.45	3.87
Pavement	Family II	8.674	7.11	6.95	7.07
	Composite	1.80	1.38	2.93	
	Family I	4.0073	3.97	4.17	4.48
Mill & Resurface Flexible	Family II	5.388	5.35	5.51	5.39
Pavement	Family III	1.964	0.987	9.21	6.08
	Composite	2.41	2.176	5.409	
Resurface on Composite	Family I	6.470	6.24	8.18	6.18
Pavement	Family II	14.385	13.72	15	15.17
	Composite	3.53	3.28	9.89	
Resurface on Flexible	Family I	26.407	26.27	26.36	26.65
Pavement	Family II	1.7939	1.75	2.39	1.70
	Composite	1.734	1.73	7.11	
	Family I	4.799	4.54	7.56	4.67
New/ Reconstructed Rigid	Family II	8.167	7.20	9.00	8.28
Pavement	Family III	3.978	3.91	4.24	4.21
Unbounded Concrete Overlay	Composite	0.8846	0.633	0.90	

	Family I	2.11	1.82	2.46	3.16
	Family II	1.842	1.51	1.68	1.80
	Family III	1.221	0.82	1.13	0.63
	Family IV	0.0805	0.022	0.039	0.05
	Family V	0.151	0.057	0.13	0.12
	Composite	0.688	0.596	4.35	
	Family I	3.33	3.29	3.40	3.56
Bituminous Overlay on	Family II	4.618	4.33	7.46	4.58
Rubblized Concrete	Family III	14.918	13.76	18.501	13.7
	Composite	0.643	0.626	5.57	
	Family I	5.465	5.35	6.61	4.23
	Family II	12.99	12.98	13.09	14.14
Resurface on Rigid Pavement	Family III	2.153	2.13	2.34	1.84

Appendix D Markov Chain Analysis

New/ Reconstructed Rigid Pavement Freeway:

	DI Range					
Categories	Lower value	Higher value				
1	0	10				
2	10	20				
3	20	30				
4	30	40				
5	40	50				
6	50	60				
7	60	70				
8	70	80				
9	80	90				
10	90	100				

Table D.1 Ranges of Pavement Distress Index for Different Categories

Table D.2. Frequencies of Segments Changing From one Category to other

Categories change	
(Within two years)	No of segments
1 to 1	189
1 to 2	31
2 to 2	21
2 to 3	11
3 to 3	8
3 to 4	4
4 to 4	
4 to 5	1
5 to 5	
5 to 6	1
6 to 6	
6 to 7	1
7 to 7	1
7 to 8	
8 to 8	
9 to 9	
9 to 10	
10 to 10	
Total number of segments	268

Table D.3. Markovian Transition Matrix

	Transition Matrix										
Category	1	2	3	4	5	6	7	8	9	10	Total
1	189	31									220
2		21	11								32
3			8	4							12
4					1						1
5						1					1
6							1				1
7							1				1
8											0
9											0
10											0

Table D.4. Markovian transitional Probability Matrix

	Transitional Probability Matrix										
Category	1	2	3	4	5	6	7	8	9	10	
1	0.859	0.141									
2		0.656	0.344								
3			0.667	0.333							
4					1						
5						1					
6							1				
7							1				
8											
9											
10											

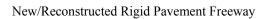
	Probability Distribution values from Markov Model										
Category	Year 2	Year 4	Year 6	Year 8	Year 10	Year 12	Year 14	Year 16			
1	0.859	0.74	0.642	0.55	0.464	0.398	0.342	0.294			
2	0.141	0.212	0.242	0.247	0.238	0.221	0.2013	0.18			
3		0.0485	0.104	0.1529	0.1858	0.2047	0.2123	0.3015			
4			0.016	0.0347	0.051	0.062	0.068	0.0709			
5				0.016	0.0347	0.051	0.063	0.068			
6					0.016	0.0347	0.051	0.063			
7						0.0507	0.51	0.063			
8											
9											
10											

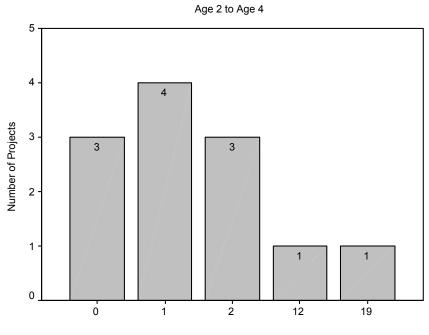
Table D.5. Probability Distribution for the Segment at Category 1

Table D.6. Probability Distribution for the Segment at Category 2

	Probability Distribution values from Markov Model										
Category	Year 2	Year 4	Year 6	Year 8	Year 10	Year 12	Year 14				
2	0.656	0.43	0.282	0.1851	0.1214	0.0796	0.0522				
3	0.344	0.4547	0.4507	0.3971	0.328	0.2602	0.125				
4		0.144	0.1518	0.1505	0.1326	0.109	0.0869				
5			0.114	0.1518	0.1505	0.1326	0.109				
6				0.114	0.1518	0.1505	0.1326				
7											
8											
9											
10											

Appendix E Frequency-based Models Change in Distress Index within two years at different time steps





Distress Index Difference



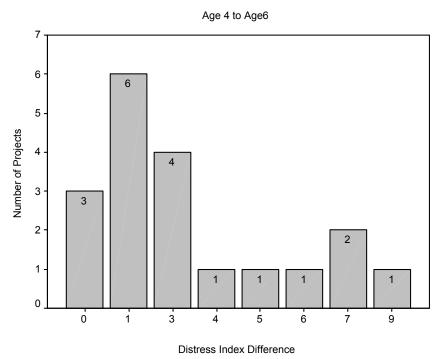
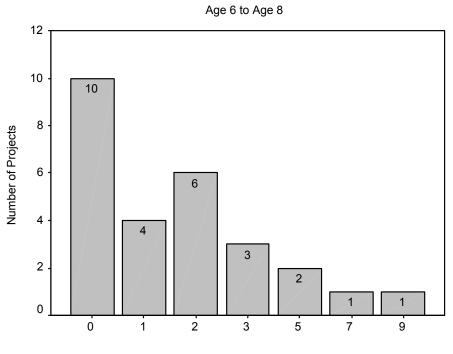


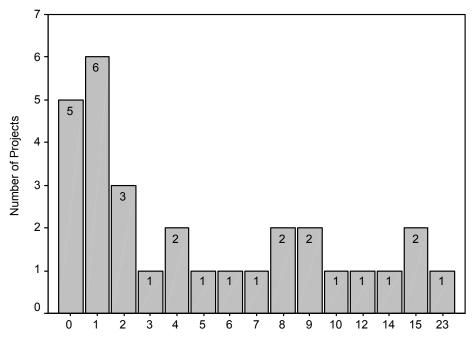
Figure: E.2.



Distress Index Difference

Figure: E.3.

Age 8 to Age 10



Distress Index Difference

Figure E.4

Appendix F Autoregression

Auto regression

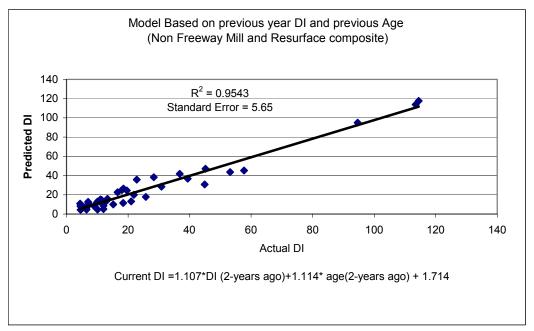


Figure F.1

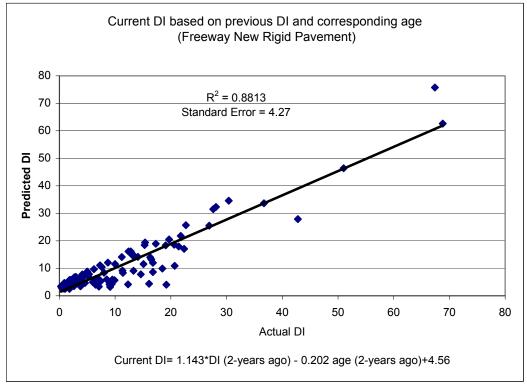


Figure F.2

Appendix G Neural Network Models

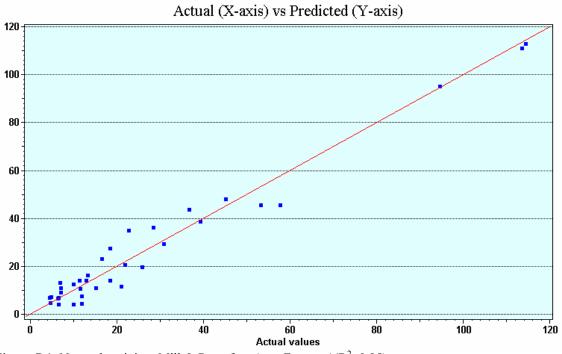


Figure G.1: Network training, Mill & Resurface (non-Freeway)(R²=0.95)

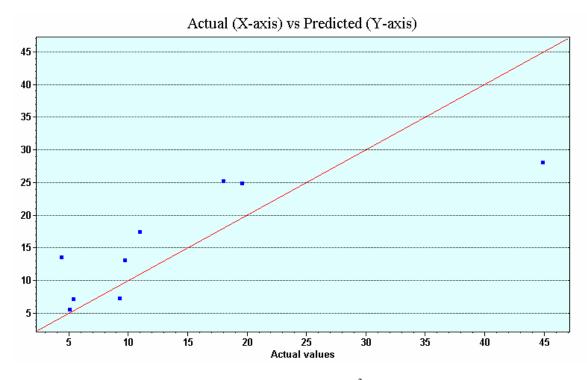


Figure G.2: Network testing, Mill & Resurface (non-Freeway)(R²=0.6)

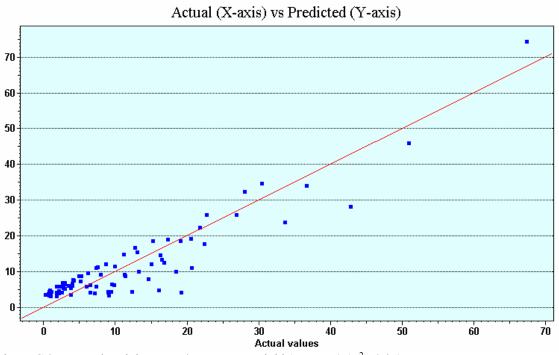


Figure G.3: Network training, New/Reconstruct Rigid (Freeway) ($R^2 = 0.85$)

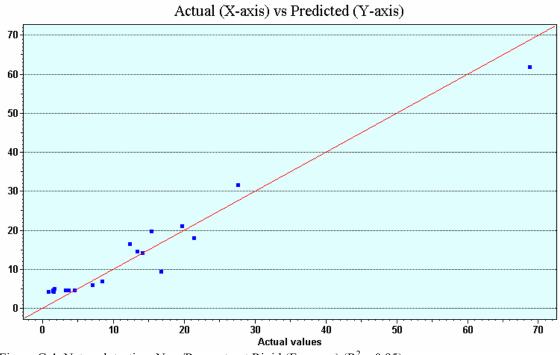
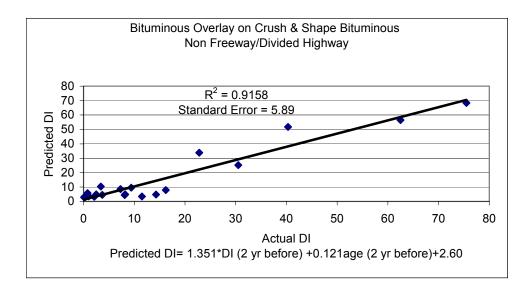
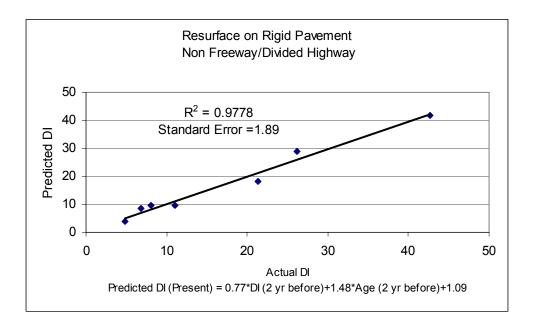
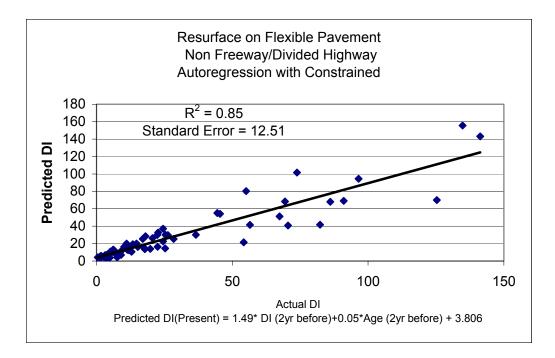


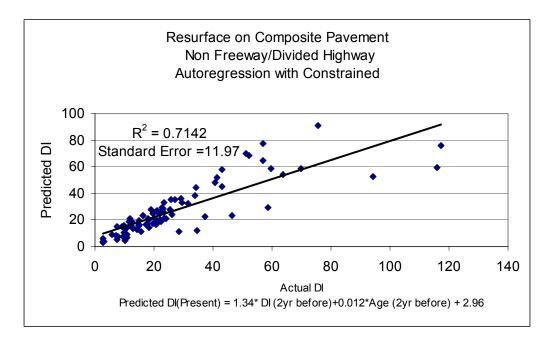
Figure G.4: Network testing, New/Reconstruct Rigid (Freeway) ($R^2 = 0.95$)

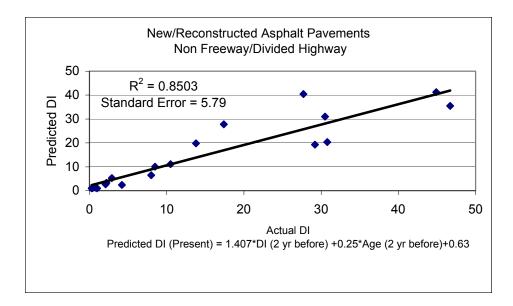
Appendix II Non-Freeway Regression Graphs and Models

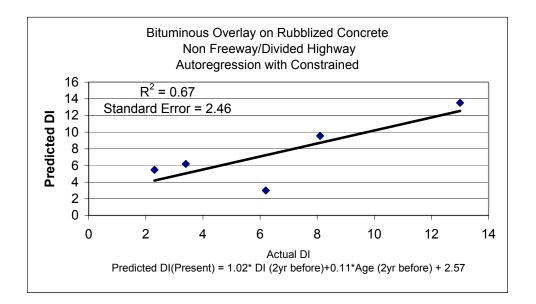


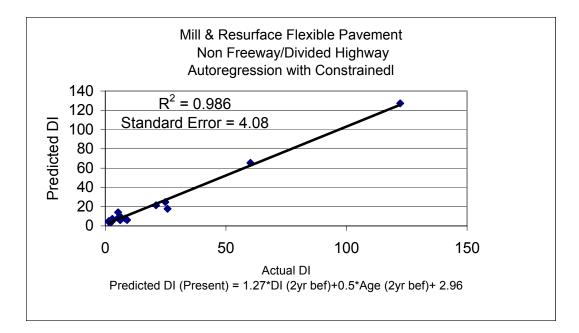


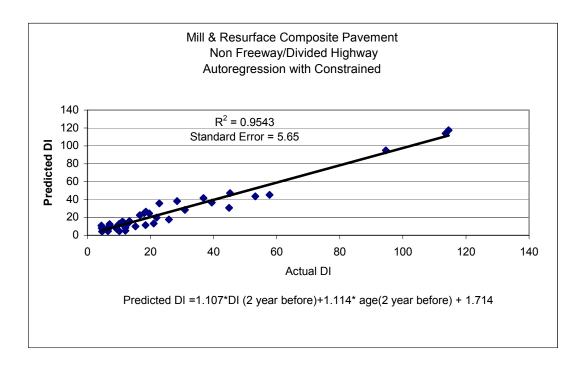




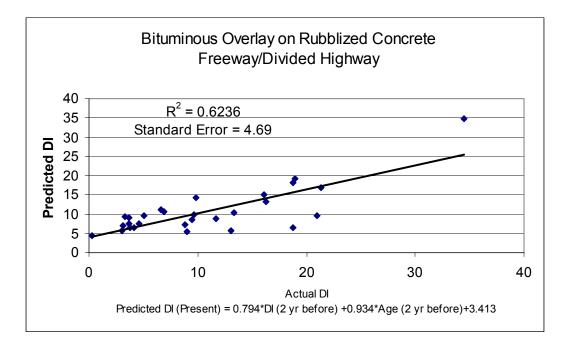


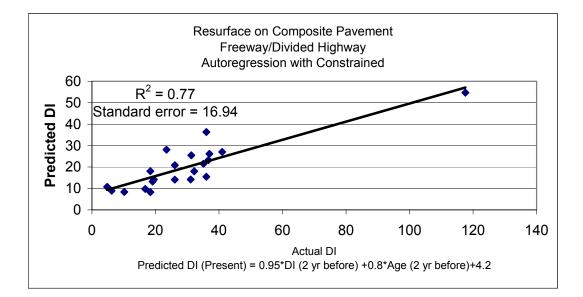


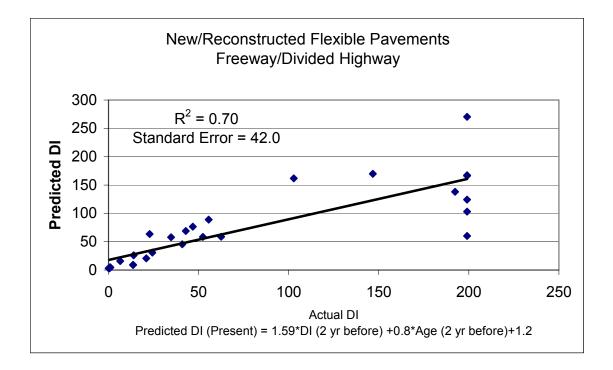


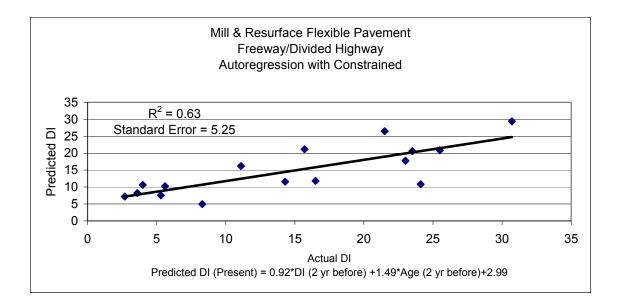


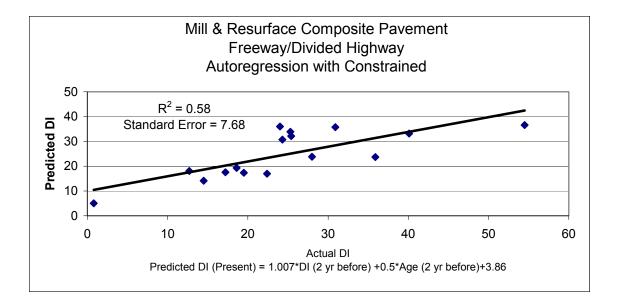
Appendix III Freeways Regression Graphs and Models

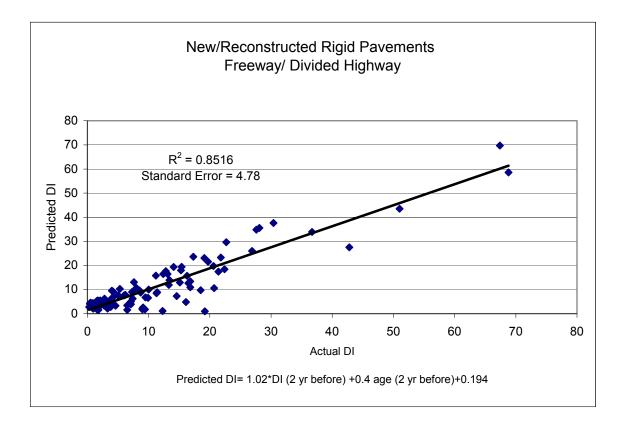


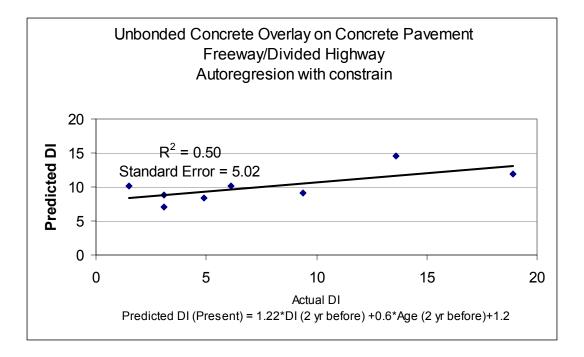


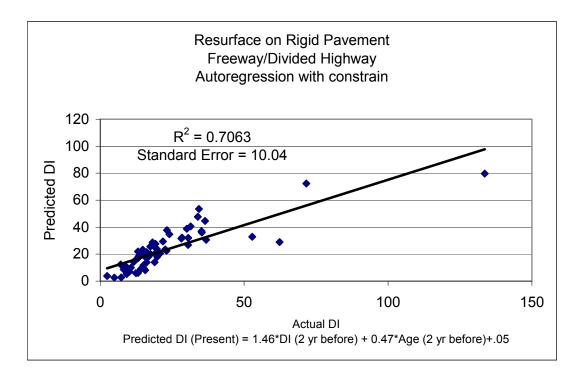






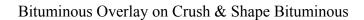


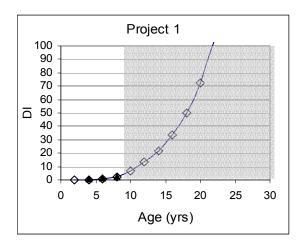


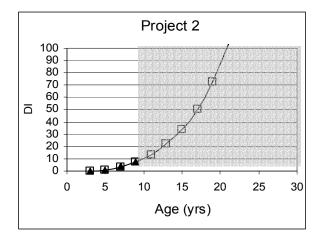


Appendix IV Graphs for Validation of Autoregression Models

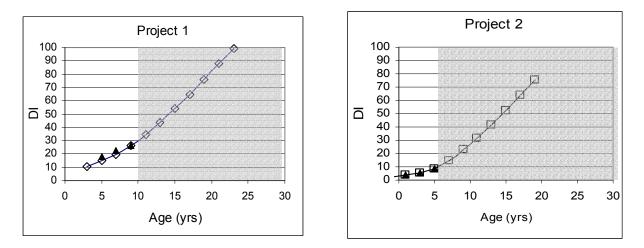
Non-Freeways





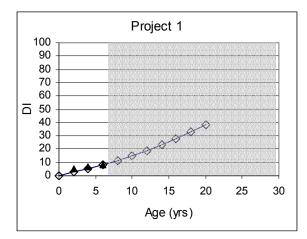


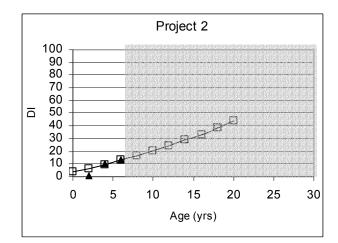
Resurface on Rigid Pavement



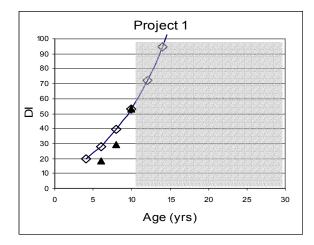
80

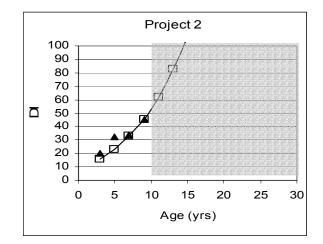
Bituminous Overlay on Rubblized Concrete

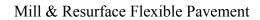


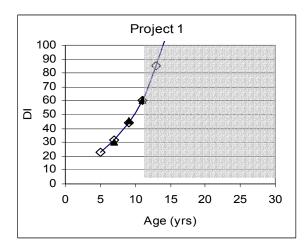


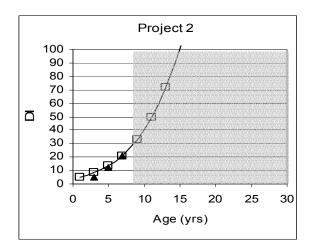
Mill & Resurface Composite Pavement



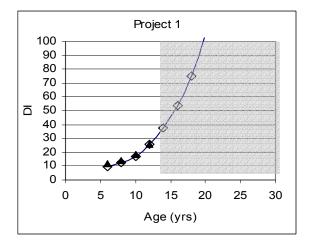


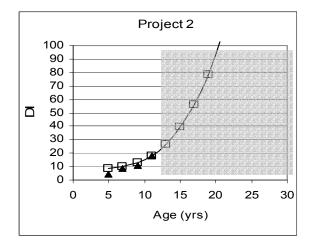




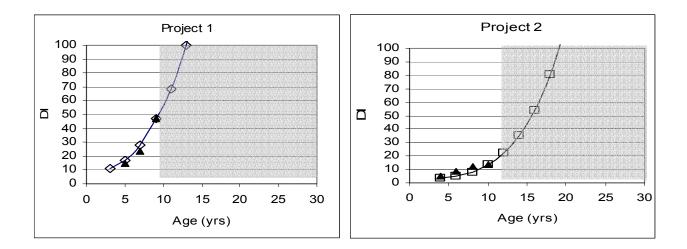


Resurface on Composite Pavement

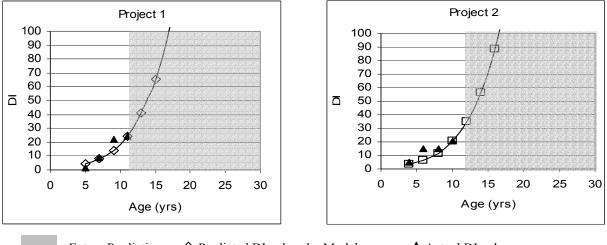




New/Reconstructed Flexible Pavement



Resurface on Flexible Pavement

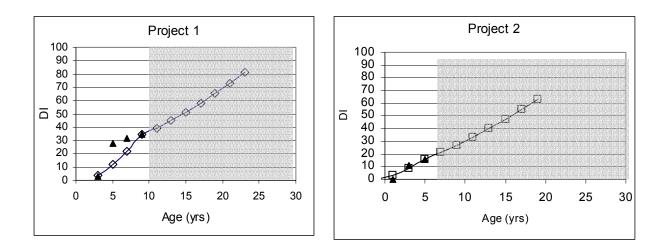


Future Prediction \diamond Predicted DI values by Models

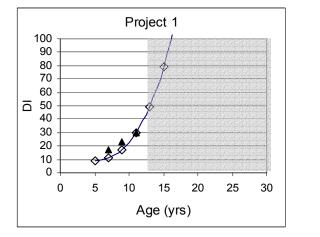
▲ Actual DI values

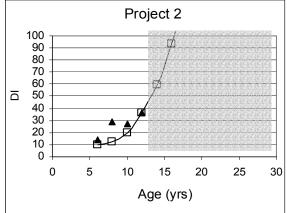
Freeways

Bituminous Overlay on Rubblized Concrete

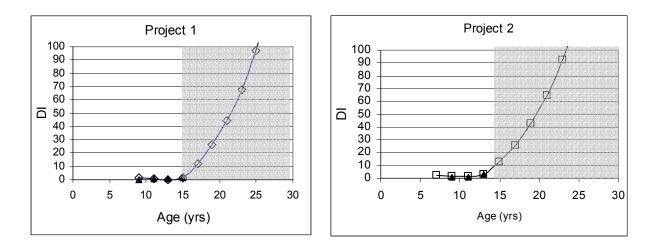


Resurface on Rigid Pavement:

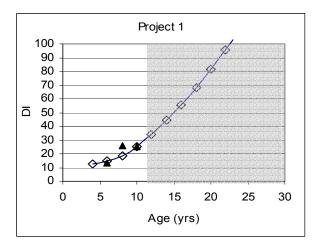


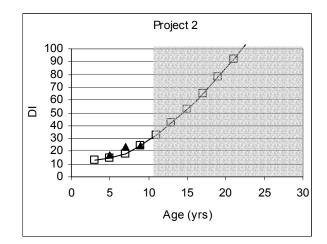


Unbounded Concrete Overlay on Concrete Pavement:

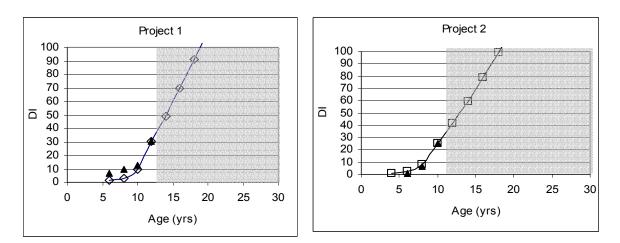


Mill & Resurface Composite Pavement

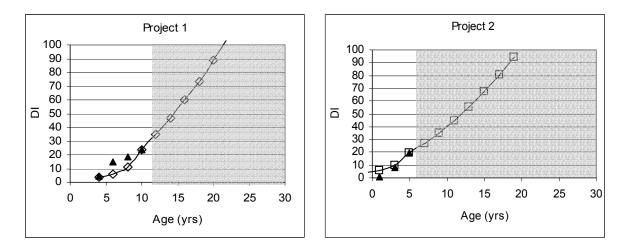




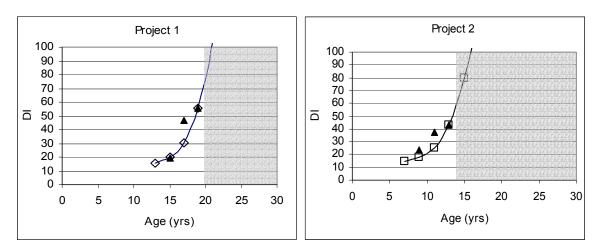
Mill & Resurface Flexible Pavement



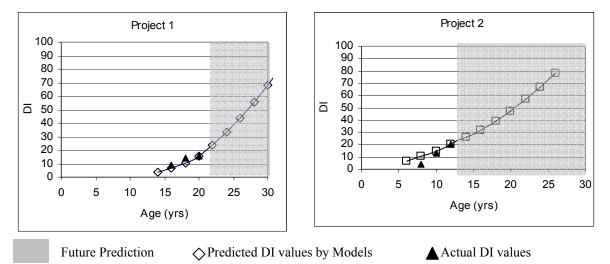
Resurface on Composite Pavement



New/Reconstructed Flexible Pavement



New/Reconstructed Rigid Pavement



Appendix V Result of Autoregression Models: Pavement Age at which DI becomes 50

Non-Freeways

Res	urfac	e on	Rigid	l Pav	emer	nt - N	on Fi	reewa	ay/Div	video	l Higl	hway				D	SL =	16 y	esrs	
	P-A	GE 1	P-A	GE 2	P-A	GE 3	P-A	GE 4	P-A0	GE 5	P-A	GE 6	P-A	GE 7	P-A	GE 8	P-A	GE 9	P-AG	GE 10
P-DI	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age
5	53.2	15.0	47.8	14.0	52.9	15.0	47.0	14.0	51.7	15.0	45.0	14.0	49.2	15.0	53.3	16.0	50.0	15.8	48.0	16.0
10														15.0						
															45.5					
														15.0						
														15.0						
30														13.0						
														13.0						
40														13.0						
40	49.9	13.0	47.0	12.0	51.7	13.0	40.8	12.0	40.4	11.0	49.9	12.0	55.4	13.0	49.4	12.0	JZ.1	13.0	54.7	14.0

Pred	licted Pav	ement Ag	e when Dl	= 50, Giv	en Presen	t age and	Present DI	value		
Resi	urface on	Rigid Pav	ement - N	on Freewa	ay/Divided	l Highway		0	OSL = 16 y	vesrs
		D 10 E 0	D 10 E 0		D 10 F F	D 1050	D 105 -		D 1050	

	P-AG	E 11	P-AG	6E 12	P-AG	GE 13	P-AG	E 14	P-AG	GE 15	P-AG	GE 16	P-AG	GE 17	P-AG	SE 18	P-AG	SE 19	P-AG	6E 20
	-				E E				6											
P-DI	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age
5	51.5	17.0	55.0	18.0	50.0	18.0	50.0	18.6	47.1	19.0	49.8	20.0	52.4	21.0	55.0	22.0	50.0	22.4	50.0	23.2
10	53.7	17.0	50.0	17.0	45.0	17.0	47.5	18.0	50.1	19.0	52.7	20.0	50.0	20.5	50.0	21.3	50.0	22.1	50.0	22.9
15	50.0	16.1	50.0	16.7	47.0	17.0	50.4	10.0	52.0	10.0	50.0	10.4	50.0	20.2	50.0	21.0	50.0	01.0	50.0	22.6
15	50.0	16.1	50.0	16.7	47.8	17.0	50.4	18.0	53.0	19.0	50.0	19.4	50.0	20.2	50.0	21.0	50.0	21.8	50.0	22.6
20	45.5	15.0	48.1	16.0	50.8	17.0	53.4	18.0	50.0	18.3	50.0	19.1	50.0	19.9	50.0	20.7	50.0	21.5	46.1	22.0
25	48.5	15.0	51.1	16.0	53.7	17.0	50.0	17.1	50.0	17.9	61.6	18.7	45.5	19.0	47.0	20.0	48.5	21.0	49.9	22.0
30	51 4	15.0	54 0	16.0	50.0	16.0	50.0	16 7	46.4	17 0	47.8	18.0	49.3	10.0	50.8	20.0	523	21.0	53.8	22.0
- 50	51.4	10.0	54.0	10.0	50.0	10.0	50.0	10.7	40.4	17.0	-11.0	10.0	-+3.5	13.0	50.0	20.0	52.5	21.0	55.0	22.0
35	54.4	15.0	45.8	14.0	47.2	15.0	48.7	16.0	50.2	17.0	51.7	18.0	53.2	19.0	54.6	20.0	50.0	20.4	50.0	21.3
40	48.1	13.0	49.6	14.0	51.1	15.0	52.6	16.0	54.0	17.0	50.0	17.3	50.0	18.2					50.0 ress I	20.9

				-							-		Prese Highv	ent DI vav	valu		L = 1	1.7 v	ears	
		GE 1		GE 2		GE 3		GE 4			P-A			GE 7	P-A				P-AC	SE 10
P-DI	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age
5	50.7	11 0	50.0	11 1	45.6	11 0	50.8	12.0	50.0	12 3	50.0	12.8	45.4	13.0	49.1	14 0	52.9	15.0	50.0	15 A
5	50.7	11.0	50.0		40.0	11.0	50.0	12.0	50.0	12.0	50.0	12.0	40.4	10.0	45.1	14.0	52.5	10.0	50.0	10.4
10	50 O	0.0	47.0	10.0	50 A	11.0		11.0	50.0	11.0	40 F	10.0	50.0	12.0	50.0	40 5	50.0	44.4	50.0	11.0
10	50.0	9.9	47.9	10.0	53.1	11.0	50.0	11.0	50.0	11.6	48.5	12.0	52.2	13.0	50.0	13.5	50.0	14.1	50.0	14.8
15	50.2	9.0	50.0	9.3	50.0	9.7	47.9	10.0	51.6	11.0	50.0	11.4	50.0	12.0	50.0	12.7	45.4	13.0	47.7	14.0
20	50.0	7.9	47.2	8.0	51.0	9.0	54.7	10.0	50.0	10.0	50.0	10.6	46.8	11.0	49.2	12.0	51.5	13.0	53.9	14.0
25	50.3	7.0	54.0	8.0	50.0	7.9	45.9	8.0	48.2	9.0	50.6	10.0	52.9	11.0	50.0	11.4	50.0	12.2	50.0	13.0
30	45.0	5.0	47.3	6.0	49.7	7.0	52.0	8.0	54.4	9.0	50.0	9.1	50.0	9.9	50.0	10.7	45.0	11.0	46.1	12.0
35	51.1	5.0	53.5	6.0	50.0	6.0	50.0	6.8	46.1	7.0	47.2	8.0	48.3	9.0	49.4	10.0	50.5	11.0	51.6	12.0
40	47 1	3.0	48.2	40	49 A	50	50 5	6.0	51.6	70	527	8.0	53.8	90	54 9	10.0	50.0	10.2	50.0	11.5
40	-11.1	0.0	-0.2	7.0		0.0	00.0	0.0	01.0	1.0	02.1	0.0	00.0	0.0	04.0	10.0	00.0	10.2	00.0	11.0
		7.1 3.0 48.2 4.0 49.4 5.0 50.5																		
	P-AG	GE 11	P-AG					GE 14	P-A		P-A	GE 16	P-AC	GE 17	P-AG	E 18	P-AG	E 19	P-AG	SE 20
	P-AG	GE 11	P-AC					GE 14	P-A0		P-A	GE 16	P-AC	GE 17	P-AG	E 18	P-AG	E 19	P-AC	GE 20
P-DI		GE 11 Age			P-AC		P-AC			GE 15		GE 16 Age		GE 17 Age					P-AG	
P-DI				GE 12	P-AC	GE 13	P-AC			GE 15										
P-DI 5	DI	Age	DI	GE 12 Age	P-AC	GE 13	P-AC	Age	DI	GE 15	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age
	DI	Age	DI	GE 12 Age	P-AC	GE 13	P-AC	Age	DI	GE 15	DI	Age	DI		DI	Age	DI	Age	DI	Age
5	DI 50.0	Age 16.1	DI 50.0	Age 16.8	P-A(Age	P-A0	Age 18.6	DI 47.2	GE 15	DI 0 49.5	Age 5 20.0	DI 51.9	Age 21.0	DI 54.2	Age 22.0	DI 50.0	Age 22.5	DI 50.0	Age 23.4
5	DI 50.0	Age 16.1	DI 50.0	Age 16.8	P-A(Age	P-A0	Age 18.6	DI 47.2	GE 15	DI 0 49.5	Age 5 20.0	DI 51.9	Age	DI 54.2	Age 22.0	DI 50.0	Age 22.5	DI 50.0	Age 23.4
5	DI 50.0 50.0	Age 16.1 15.5	DI 50.0 46.3	GE 12 Age 16.8 16.0	P-AC DI 50.0	Age 17.6	P-AC DI 50.0	Age 18.6 18.0	DI 47.2 53.3	GE 15	DI 49.5	Age 5 20.0 0 19.5	DI 51.9	Age 21.0 20.4	DI 54.2 50.0	Age 22.0 21.2	DI 50.0 50.0	Age 22.5 22.1	DI 50.0 50.0	Age 23.4 23.0
5	DI 50.0 50.0	Age 16.1 15.5	DI 50.0 46.3	GE 12 Age 16.8 16.0	P-AC DI 50.0	Age 17.6	P-AC DI 50.0	Age 18.6 18.0	DI 47.2 53.3	GE 15	DI 49.5	Age 5 20.0 0 19.5	DI 51.9	Age 21.0	DI 54.2 50.0	Age 22.0 21.2	DI 50.0 50.0	Age 22.5 22.1	DI 50.0 50.0	Age 23.4 23.0
5 10 15	DI 50.0 50.0	Age 16.1 15.5 15.0	DI 50.0 46.3 52.4	Age 16.8 16.0	P-A(DI 50.0 48.6 54.8	Age 17.6 17.0	P-A(DI 50.0 51.0	Age 18.6 18.0 17.4	DI 47.2 53.3 50.0	Age 19.0	DI 49.5 50.0 50.0	Age 5 20.0 19.5 19.1	DI 51.9 50.0	Age 21.0 20.4 19.9	DI 54.2 50.0 50.0	Age 22.0 21.2 20.8	DI 50.0 50.0 50.0	Age 22.5 22.1 21.7	DI 50.0 50.0 50.0	Age 23.4 23.0 22.6
5	DI 50.0 50.0	Age 16.1 15.5 15.0	DI 50.0 46.3 52.4	Age 16.8 16.0	P-A(DI 50.0 48.6 54.8	Age 17.6 17.0	P-A(DI 50.0 51.0	Age 18.6 18.0 17.4	DI 47.2 53.3 50.0	Age 19.0	DI 49.5 50.0 50.0	Age 5 20.0 19.5 19.1	DI 51.9 50.0	Age 21.0 20.4	DI 54.2 50.0 50.0	Age 22.0 21.2 20.8	DI 50.0 50.0 50.0	Age 22.5 22.1 21.7	DI 50.0 50.0 50.0	Age 23.4 23.0 22.6
5 10 15	DI 50.0 50.1 50.0	Age 16.1 15.5 15.0 14.4	DI 50.0 46.3 52.4 50.0	Age 16.8 16.0 15.2	P-A0	Age 17.6 17.0 17.0	P-A0	Age 18.6 18.0 17.4 16.9	DI 47.2 53.3 50.0 50.0	Age 19.0 19.0 18.2	DI 49.5 50.0 50.0	Age 5 20.0 19.5 19.1 18.6	DI 51.9 50.0 50.0	Age 21.0 20.4 19.9 19.5	DI 54.2 50.0 50.0	Age 22.0 21.2 20.8 20.4	DI 50.0 50.0 45.0	Age 22.5 22.1 21.7 21.0	DI 50.0 50.0 46.1	Age 23.4 23.0 22.6 22.0
5 10 15	DI 50.0 50.1 50.0	Age 16.1 15.5 15.0 14.4	DI 50.0 46.3 52.4 50.0	Age 16.8 16.0 15.2	P-A0	Age 17.6 17.0 17.0	P-A0	Age 18.6 18.0 17.4 16.9	DI 47.2 53.3 50.0 50.0	Age 19.0 19.0 18.2	DI 49.5 50.0 50.0	Age 5 20.0 19.5 19.1 18.6	DI 51.9 50.0 50.0	Age 21.0 20.4 19.9	DI 54.2 50.0 50.0	Age 22.0 21.2 20.8 20.4	DI 50.0 50.0 45.0	Age 22.5 22.1 21.7 21.0	DI 50.0 50.0 46.1	Age 23.4 23.0 22.6 22.0
5 10 15 20	DI 50.0 50.1 50.0	Age 16.1 15.5 15.0 14.4	DI 50.0 46.3 52.4 50.0	Age 16.8 16.0 15.2	P-A0	Age 17.6 17.0 17.0	P-A0	Age 18.6 18.0 17.4 16.9	DI 47.2 53.3 50.0 50.0	Age 19.0 19.0 18.2	DI 49.5 50.0 50.0	Age 5 20.0 19.5 19.1 18.6	DI 51.9 50.0 50.0	Age 21.0 20.4 19.9 19.5	DI 54.2 50.0 50.0	Age 22.0 21.2 20.8 20.4	DI 50.0 50.0 45.0	Age 22.5 22.1 21.7 21.0	DI 50.0 50.0 46.1	Age 23.4 23.0 22.6 22.0
5 10 15 20	DI 50.0 50.1 50.0	Age 16.1 15.5 15.0 14.4 13.8	DI 50.0 46.3 52.4 50.0	Age 16.8 16.0 15.2 14.7	P-A0	Age 17.6 17.0 16.0 15.5	P-A0 DI 50.0 50.0 50.0 45.0	Age 18.6 18.0 17.4 16.9	DI 47.2 53.3 50.0 50.0 46.1	Age 19.0 19.0 18.2	DI 49.5 50.0 50.0 50.0	Age 5 20.0 19.5 19.1 18.6 2 18.0	DI 51.9 50.0 50.0 48.3	Age 21.0 20.4 19.9 19.5	DI 54.2 50.0 50.0 49.5	Age 22.0 21.2 20.8 20.4 20.0	DI 50.0 50.0 45.0 50.6	Age 22.5 22.1 21.7 21.0 21.0	DI 50.0 50.0 46.1 51.7	Age 23.4 23.0 22.6 22.0
5 10 15 20 25	DI 50.0 50.1 50.0	Age 16.1 15.5 15.0 14.4 13.8	DI 50.0 46.3 52.4 50.0	Age 16.8 16.0 15.2 14.7	P-A0	Age 17.6 17.0 16.0 15.5	P-A0 DI 50.0 50.0 50.0 45.0	Age 18.6 18.0 17.4 16.9	DI 47.2 53.3 50.0 50.0 46.1	Age 19.0 19.0 18.2	DI 49.5 50.0 50.0 50.0	Age 5 20.0 19.5 19.1 18.6 2 18.0	DI 51.9 50.0 50.0 48.3	Age 21.0 20.4 19.9 19.5 19.0	DI 54.2 50.0 50.0 49.5	Age 22.0 21.2 20.8 20.4 20.0	DI 50.0 50.0 45.0 50.6	Age 22.5 22.1 21.7 21.0 21.0	DI 50.0 50.0 46.1 51.7	Age 23.4 23.0 22.6 22.0
5 10 15 20 25	DI 50.0 50.1 50.0 50.0 47.2	Age 16.1 15.5 15.0 14.4 13.8 13.0	DI 50.0 46.3 52.4 50.0 48.3	Age 16.8 16.0 15.2 14.7 14.0	P-A0 DI 50.0 48.6 54.8 50.0 50.0 49.4	Age 17.6 17.0 15.5 15.0	P-A0 DI 50.0 50.0 50.0 45.0 50.5	Age 18.6 18.0 17.4 16.9 16.0	DI 47.2 53.3 50.0 50.0 46.1 51.7	Age 19.0 19.0 18.2 17.0	DI 49.5 50.0 50.0 50.0 50.0 50.0 50.0	Age 5 20.0 19.5 19.1 18.6 2 18.0 3 18.0	DI 51.9 50.0 50.0 48.3 53.9	Age 21.0 20.4 19.9 19.5 19.0	DI 54.2 50.0 50.0 49.5 55.0	Age 22.0 21.2 20.8 20.4 20.0 20.0	DI 50.0 50.0 50.6 50.6 50.0	Age 22.5 22.1 21.7 21.0 21.0 20.5	DI 50.0 50.0 46.1 51.7 50.0	Age 23.4 23.0 22.6 22.0 22.0 21.5
5 10 15 20 25 30	DI 50.0 50.1 50.0 50.0 47.2	Age 16.1 15.5 15.0 14.4 13.8 13.0	DI 50.0 46.3 52.4 50.0 48.3	Age 16.8 16.0 15.2 14.7 14.0	P-A0 DI 50.0 48.6 54.8 50.0 50.0 49.4	Age 17.6 17.0 15.5 15.0	P-A0 DI 50.0 50.0 50.0 45.0 50.5	Age 18.6 18.0 17.4 16.9 16.0	DI 47.2 53.3 50.0 50.0 46.1 51.7	Age 19.0 19.0 18.2 17.0	DI 49.5 50.0 50.0 50.0 50.0 50.0 50.0	Age 5 20.0 19.5 19.1 18.6 2 18.0 3 18.0	DI 51.9 50.0 50.0 48.3 53.9	Age 21.0 20.4 19.9 19.5 19.0 19.0	DI 54.2 50.0 50.0 49.5 55.0	Age 22.0 21.2 20.8 20.4 20.0 20.0	DI 50.0 50.0 50.6 50.6 50.0	Age 22.5 22.1 21.7 21.0 21.0 20.5	DI 50.0 50.0 46.1 51.7 50.0	Age 23.4 23.0 22.6 22.0 22.0 21.5
5 10 15 20 25 30	DI 50.0 50.1 50.0 50.0 47.2 52.7	Age 16.1 15.5 15.0 14.4 13.8 13.0	DI 50.0 46.3 52.4 50.0 50.0 48.3 53.8	Age 16.8 16.0 15.2 14.7 14.0	P-A0 DI 50.0 48.6 54.8 50.0 50.0 49.4 55.0	Age 17.6 17.0 15.5 15.0	P-A0 50.0 51.0 50.0 50.0 50.5 50.5	Age 18.6 18.0 17.4 16.9 16.0 16.0 15.4	DI 47.2 53.3 50.0 50.0 46.1 51.7 50.0	→E 15 Age 19.0 19.0 18.2 17.0 17.0	DI 49.5 50.0 50.0 50.0 50.0 50.0 50.0	Age 5 20.0 19.5 19.1 18.6 2 18.0 3 18.0 17.3	DI 51.9 50.0 50.0 48.3 53.9 50.0	Age 21.0 20.4 19.9 19.5 19.0 19.0	DI 54.2 50.0 50.0 49.5 55.0 50.0	Age 22.0 21.2 20.8 20.4 20.0 20.0 19.6	DI 50.0 50.0 50.0 50.6 50.0 50.0	Age 22.5 22.1 21.7 21.0 21.0 20.5 20.1	DI 50.0 50.0 46.1 51.7 50.0 50.0	Age 23.4 23.0 22.6 22.0 22.0 21.5 21.1

Predicted Pavement Age when DI = 50, Given Present age and Present DI value)
Mill & Resurface Composite Pavement - Non Freeway/Divided Highway	DSL = 11

	urfac										•				Turu)SL =	= 10 y	vears	
	P-A	GE 1	P-A	GE 2	P-A	GE 3	P-A	GE 4	P-A	GE 5	P-A	GE 6	P-A	GE 7	P-A	GE 8	P-A	GE 9	P-AC	SE 10
P-DI	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age
5	50.0	9.4	50.0	0.4	50.0	10.3	50.0	11 2	50.0	12.5	50.0	12.2	50.0	14.6	50.0	15.2	50.0	16.4	50.0	17.1
5	50.0	0 8.4 50.0 9.4 50.0 4 6 7.0 51.8 8.0 52.1					50.0	11.5	50.0	12.0	50.0	13.2	50.0	14.0	50.0	10.2	50.0	10.4	50.0	17.1
10	51.6	7.0	51.8	8.0	52.1	9.0	52.3	10.0	52.5	11.0	52.8	12.0	53.0	13.0	53.2	14.0	53.5	15.0	53.7	16.0
15	50.0	5.6	50.0	6 5	50.0	75	50.0	0 5	50.0	0.0	50.0	11.0	50.0	11.5	50.0	12.0	45.0	12.0	50.0	14.4
15	50.0	5.0	50.0	0.5	50.0	7.5	50.0	0.0	50.0	9.0	50.0	11.0	50.0	11.5	50.0	13.0	45.0	13.0	50.0	14.4
20	54.1	5.0	54.2	6.0	54.4	7.0	54.5	8.0	54.6	9.0	54.7	10.0	54.9	11.0	55.0	12.0	50.0	12.5	50.0	13.8
25	50.0	3.7	50.0	4.7	50.0	5.7	50.0	6.8	50.0	7.7	50.0	8.9	50.0	9.7	50.0	10.9	50.0	11.7	50.0	12.9
30	48.6		50.0					6.1					48.9							12.0
30	40.0	5.0	50.0	4.1	40.7	5.0	50.0	0.1	50.0	7.5	40.9	9.0	40.9	9.0	40.9	10.0	49.0	11.0	49.0	12.0
35	50.0	2.4	50.0	3.4	50.0	4.4	50.0	5.6	50.0	6.4	50.0	7.8	50.0	8.4	50.0	9.7	50.0	10.4	50.0	11.6
40	50.0	1.9	50.0	3.1	50.0	3.8	50.0	4.8	50.0	6.0	50.0	7.1	50.0	7.8	50.0	8.8	50.0	9.8	50.0	11.0

Predicted Pavement Age when DI = 50, Given Present age and Present DI value
Resurface on Flexible Pavement - Non Freeway/Divided Highway

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	P-AG	E 11	P-AG	E 12	P-AG	E 13	P-AG	E 14	P-AG	E 15	P-AG	6E 16	P-AG	E 17	P-AG	E 18	P-AG	E 19	P-AG	GE 20
P-DI	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age										
F	50.0	10.2	50.0	10.1	50.0	20.0	50.0	21.0	50.0	22.0	50.0	22.5	50.0	22.0	50.0	25.0	50.0	25.0	50.0	27.0
5																				27.0
10	53.9	17.0	54.2	18.0	54.4	19.0	54.7	20.0	54.9	21.0	50.0	21.5	50.0	22.8	50.0	23.5	50.0	24.9	50.0	25.4
15	50.0	15.4	50.0	16.4	50.0	17.7	50.0	18.4	50.0	19.5	50.0	20.4	45.0	21.0	50.0	22.4	45.2	23.0	50.0	24.3
20	50.0	14.5	50.0	15.8	50.0	16.5	50.0	17.6	50.0	18.8	50.0	19.4	50.0	20.7	50.0	21.4	50.0	22.4	50.0	23.4
25	50.0	13.7	50.0	14.7	50.0	15.9	50.0	16.7	50.0	17.9	50.0	18.6	50.0	19.6	50.0	20.9	50.0	21.6	50.0	22.8
30	49.1	13.0	49.1	14.0	50.0	15.1	49.2	16.0	50.0	17.1	49.3	18.0	50.0	19.0	49.4	20.0	50.0	21.0	50.0	22.0
35	50.0	12.4	50.0	13.4	50.0	14.6	50.0	15.4	50.0	16.8	50.0	17.4	50.0	18.8	50.0	19.4	50.0	20.7	50.0	21.4
40																				21.2
															_				ress I	

	urfac													ent Di V	valu)SL =	: 11 y	ears	
	P-A	GE 1	P-AC	GE 2	P-A	GE 3	P-A	GE 4	P-A	GE 5	P-A	GE 6	P-A	GE 7	P-A	GE 8	P-A	GE 9	P-AG	GE 10
P-DI	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age
5	48.7	9.0	18.8	10.0	18.0	11.0				13.0	50.0	14 1	10.3	15.0	50.0	16.0	10.5	17.0	50.0	18.0
	-																			
10	47.2	7.0	47.2	8.0	47.3	9.0	50.0	10.2	47.4	11.0	50.0	12.2	47.5	13.0	50.0	14.2	47.6	15.0	47.7	16.0
15	50.0	5.8	50.0	6.8	50.0	7.8	50.0	8.8	50.0	9.8	50.0	10.8	50.0	11.8	50.0	12.9	50.0	13.8	50.0	14.8
20	51.8	5.0	51.9	6.0	51.9	7.0	51.9	8.0	52.0	9.0	52.0	10.0	52.0	11.0	52.0	12.0	52.1	13.0	52.1	14.0
25	50.0	3.9	50.0	4.9	50.0	5.9	50.0	6.9	50.0	8.0	50.0	8.9	50.0	10.1	50.0	10.8	50.0	12.0	50.0	12.8
30	50.0	3.2	47.7	4.0	50.0	5.2	47.7	6.0	50.0	7.2	48.2	8.0	47.7	9.0	50.0	10.2	50.0	11.6	47.8	12.0
0.5	50.0	0.5	50.0	0.5	50.0	4 7	50.0			7.0	50.0	7 5			50.0	0.5	FF 0	11.0		40.0
35	50.0	2.5	50.0	3.5	50.0	4.7	50.0	5.5	55.0	7.0	50.0	7.5	50.0	8.5	50.0	9.5	55.0	11.0	55.0	12.0
40	50.0	1.9	50.0	2.9	50.0	4.0	50.0	4.9	50.0	5.7	50.0	6.9	50.0	8.1	50.0	8.9	50.0	9.7	50.0	11.0

Pred	licted Pav	ement Ag	e when Dl	= 50, Give	en Presen	t age and	Present DI	value					
Resu	urface on	Composit	e Paveme	nt - Non F	reeway/D	n Present age and Present DI value eeway/Divided Highway DSL =							
	P-AGE 1	P-AGE 2	P-AGE 3	P-AGE 4	P-AGE 5	P-AGE 6	P-AGE 7	P-AGE 8	P-AG				

	P-AG	E 11	P-AG	GE 12	P-AG	GE 13	P-AG	GE 14	P-AG	GE 15	P-AG	GE 16	P-AG	GE 17	P-AG	SE 18	P-AG	SE 19	P-AG	GE 20
P-DI	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	וח	Age	DI	Age	DI	Age	DI	Age	DI	Age
		rige		rige		rige		rige		rige		rige		rige		rige		rige		/ ige
5	49.7	19.0	50.0	20.0	50.0	21.2	49.9	22.0	50.0	23.0	50.1	24.0	50.2	25.0	50.3	26.0	50.4	27.0	50.5	28.0
10	50.0	17.2	47.0	19.0	50.0	10.2	50.0	20.2	48.0	21.0	50.0	22.1	19.1	23.0	19.1	24.0	19.2	25.0	19.2	26.0
10	50.0	17.2	47.9	10.0	50.0	19.2	50.0	20.2	40.0	21.0	50.0	22.1	40.1	23.0	40.1	24.0	40.2	25.0	40.2	20.0
15	50.0	15.9	50.0	16.8	50.0	17.5	50.0	18.8	50.0	19.8	50.0	20.8	50.0	21.8	50.0	22.7	50.0	23.7	50.0	24.8
20	52.1	15.0	52.2	16.0	52.2	17.0	52.2	18.0	52.3	19.0	52.3	20.0	52.3	21.0	52.3	22.0	52.4	23.0	52.4	24.0
25	50.0	14.1	50.0	14.8	50.0	15.8	50.0	16.7	50.0	17.8	50.0	18.8	50.0	19.8	50.0	20.8	50.0	21.8	50.0	22.9
								-												
30	50.0	13.2	47.9	14.0	50.0	15.2	50.0	16.2	48.0	17.0	50.0	18.2	48.0	19.0	48.0	20.0	47.9	21.0	50.0	22.2
35	50.0	12.5	50.0	13.6	50.0	14.5	50.0	15.5	50.0	16.5	50.0	17.5	50.0	18.5	50.0	19.5	50.0	20.7	50.0	21.5
40	50.0	11.9	50.0	12.9	50.0	13.9	50.0	15.1	50.0	15.9	50.0	16.9	50.0	18.1						20.9 ndex

P-DI = Present Distress Index

				-							-			ent DI hway	valu		L = 1	5.4 y	ears	
	P-A0	GE 1	P-A	GE 2	P-A	GE 3	P-A	GE 4	P-A	GE 5	P-A	GE 6	P-A	GE 7	P-A	GE 8	P-A	GE 9	P-AG	E 10
P-DI	DI	Age	DI	Age	DI	Age	DI	Age												
5	50.0	11.5	47.6	12.0	50.3	13.0	53.1	14.0	50.0	14.4	50.0	15.1	50.0	15.9	50.0	16.7	50.0	17.5	45.9	18.0
10	49.4	9.0	51.2	10.0	53.0	11.0	54.8	12.0	50.0	12.3	50.0	13.1	50.0	14.0	50.0	14.9	50.0	15.7	50.0	16.6
15	47.3	7.0	48.4	8.0	49.5	9.0	50.6	10.0	51.7	11.0	52.8	12.0	53.9	13.0	55.0	14.0	50.0	14.4	50.0	15.3
20	50.0	5.8	50.0	6.7	50.0	7.7	50.0	8.6	50.0	9.5	45.2	10.0	45.8	11.0	46.4	12.0	47.0	13.0	47.6	14.0
25	52.1	5.0	52.7	6.0	53.3	7.0	53.9	8.0	54.5	9.0	50.0	9.4	50.0	10.4	50.0	11.3	50.0	12.3	50.0	13.2
30	50.0	3.7	50.0	4.7	50.0	5.7	50.0	6.6	50.0	7.6	50.0	8.5	50.0	9.5	50.0	10.5	45.1	11.0	45.3	12.0
35	50.1	3.0	50.4	4.0	50.6	5.0	50.9	6.0	51.1	7.0	51.4	8.0	51.6	9.0	51.9	10.0	52.1	11.0	52.4	12.0
40	50.0		50.0		50.0			5.2				7.3				9.2			50.0	

	P-AG	E 11	P-AG	SE 12	P-AG	GE 13	P-AG	6E 14	P-AC	GE 15	P-AG	GE 16	P-AG	6E 17	P-AG	SE 18	P-AG	SE 19	P-AC	GE 20
P-DI	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age
5	47.7	19.0	49.5	20.0	51.3	21.0	53.1	22.0	54.9	23.0	50.0	23.5	50.0	24.2	50.0	25.1	50.0	25.9	50.0	26.8
10	50.0	17.1	45.5	18.0	46.6	19.0	47.7	20.0	48.8	21.0	49.9	22.0	51.0	23.0	52.1	24.0	53.1	25.0	54.2	26.0
15	50.0	16.2	50.0	17.1	50.0	18.0	50.0	18.9	50.0	19.8	50.0	20.8	50.0	21.7	50.0	22.6	50.0	23.6	50.0	24.5
20	48.2	15.0	48.8	16.0	49.4	17.0	50.0	18.0	50.6	19.0	51.2	20.0	51.8	21.0	52.4	22.0	53.0	23.0	53.6	24.0
25	50.0	14.2	50.0	15.1	50.0	16.1	50.0	17.0	50.0	18.0	50.0	19.0	50.0	19.9	50.0	20.9	50.0	21.8	50.0	22.8
30	45.6	13.0	45.8	14.0	46.1	15.0	46.3	16.0	46.6	17.0	46.8	18.0	47.1	19.0	47.3	20.0	47.6	21.0	47.8	22.0
35	52.6	13.0	52.9	14.0	53.1	15.0	53.4	16.0	53.6	17.0	53.9	18.0	54.1	19.0	54.4	20.0	54.6	21.0	54.9	22.0
40	50.0	12.1	50.0	13.0	50.0	14.1	50.0	15.0	50.0	16.0	50.0	17.0	50.0	17.9	50.0	18.9	50.0	20.0	50.0	20.8
																	resen = Pros			

Mill	& Re			exibl	e Pav	veme	nt No	on Fr	eewa	y/Div	•	High		int Di			L = 1	1.2 ye	ears	
	P-A	GE 1	P-AC	GE 2	P-AC	GE 3	P-AC	GE 4	P-AC	GE 5	P-A0	GE 6	P-A	GE 7	P-A	GE 8	P-A	GE 9	P-AG	GE 10
P-DI	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age
5	50.0	10.0	50.0	10.6	47.0	11.0	50.0	12.0	53.0	13.0	50.0	13.4	50.0	14.1	50.0	14.9	50.0	15.7	50.0	16.5
10	54.2	9.0	50.0	9.2	50.0	9.9	50.0	10.7	50.0	11.5	47.2	12.0	49.2	13.0	51.1	14.0	53.1	15.0	55.0	16.0
15	50.0	7.2	49.8	8.0	51.7	9.0	53.7	10.0	50.0	10.4	50.0	11.2	50.0	12.0	50.0	12.9	50.0	13.7	50.0	14.6
20	50.0	6.0	50.0	6.9	50.0	7.7	50.0	8.5	50.0	9.4	47.0	10.0	48.2	11.0	49.3	12.0	50.4	13.0	51.6	14.0
25	49.5	5.0	50.6	6.0	51.7	7.0	52.9	8.0	54.0	9.0	50.0	9.9	50.0	10.3	50.0	11.2	50.0	12.1	50.0	13.0
30	50.0	4.0	50.0	4.9	50.0	5.9	50.0	6.8	50.0	7.7	50.0	8.6	50.0	9.5	50.0	10.5	45.7	11.0	46.2	12.0
35	48.1	3.0	48.6	4.0	49.1	5.0	49.6	6.0	50.1	7.0	50.6	8.0	51.1	9.0	51.6	10.0	52.1	11.0	52.6	12.0
40	54.4	3.0	54.9	4.0	50.0	4.3	50.0	5.3	50.0	6.2	50.0	7.2	50.0	8.1	50.0	9.1	50.0	10.1	50.0	11.2
				-																
												GE 16	P-AC	SE 17	P-AG	F 18	P-AG	F 10	P-AG	E 20
												GE 16	P-AC	GE 17	P-AG	E 18	P-AG	E 19	P-AG	GE 20
P-DI	P-AG	GE 11	P-AC	GE 12	P-AC	GE 13	P-AC	GE 14	P-A	GE 15	P-A									
P-DI	P-AG		P-AC	GE 12	P-AC	GE 13	P-AC	GE 14	P-A	GE 15	P-A			GE 17 Age						
<u>P-DI</u> 5	P-AG DI	Age	P-AG	GE 12 Age	P-AC	GE 13 Age	P-AC	GE 14 Age	P-A	GE 15 Age	i P-A	Age	DI	Age	DI	Age	DI	Age	DI	Age
	P-AG DI	Age	P-AG	GE 12 Age	P-AC	GE 13 Age	P-AC	GE 14 Age	P-A	GE 15 Age	i P-A	Age	DI		DI	Age	DI	Age	DI	Age
	P-AG DI 46.6	GE 11 Age 17.0	P-AC DI 48.6	GE 12 Age 18.0	P-A0	GE 13 Age 19.0	P-A(GE 14 Age 20.0	P-A(DI 54.4	GE 15	DI 50.0	Age 21.4	DI 50.0	Age 22.3	DI 50.0	Age 23.1	DI 50.0	Age 24.0	DI 50.0	Age 24.9
5	P-AG DI 46.6	GE 11 Age 17.0	P-AC DI 48.6	GE 12 Age 18.0	P-A0	GE 13 Age 19.0	P-A(GE 14 Age 20.0	P-A(DI 54.4	GE 15	DI 50.0	Age 21.4	DI 50.0	Age	DI 50.0	Age 23.1	DI 50.0	Age 24.0	DI 50.0	Age 24.9
5	P-AG DI 46.6 50.0	Age 17.0	P-AC DI 48.6 50.0	Age 18.0	P-AC DI 50.5	Age	P-A(DI 52.5	Age 20.0	P-A(DI 54.4	GE 15 Age 21.0	 P-A DI 50.0 50.0 	Age 21.4 20.6	DI 50.0	Age 22.3	DI 50.0 50.0	Age 23.1 22.4	DI 50.0 45.6	Age 24.0 23.0	DI 50.0 46.7	Age 24.9 24.0
5	P-AG DI 46.6 50.0	Age 17.0	P-AC DI 48.6 50.0	Age 18.0	P-AC DI 50.5	Age	P-A(DI 52.5	Age 20.0	P-A(DI 54.4	GE 15 Age 21.0	 P-A DI 50.0 50.0 	Age 21.4 20.6	DI 50.0	Age 22.3 21.5	DI 50.0 50.0	Age 23.1 22.4	DI 50.0 45.6	Age 24.0 23.0	DI 50.0 46.7	Age 24.9 24.0
5	P-AC DI 46.6 50.0	Age 17.0 16.3	P-AC DI 48.6 50.0 45.7	Age 18.0 17.2 16.0	P-AC DI 50.5 50.0 46.9	GE 13 Age 19.0 18.0	P-A0 DI 52.5 50.0	GE 14 Age 20.0 18.9	P-A0 DI 54.4 50.0	GE 15 Age 21.0 19.8	DI 50.0 50.0 50.3	Age 21.4 20.6 20.0	DI 50.0 50.0 51.4	Age 22.3 21.5	DI 50.0 50.0 52.6	Age 23.1 22.4 22.0	DI 50.0 45.6 53.7	Age 24.0 23.0 23.0	DI 50.0 46.7 54.8	Age 24.9 24.0 24.0
5 10 15	P-AC DI 46.6 50.0	Age 17.0 16.3	P-AC DI 48.6 50.0 45.7	Age 18.0 17.2 16.0	P-AC DI 50.5 50.0 46.9	GE 13 Age 19.0 18.0	P-A0 DI 52.5 50.0 48.0	GE 14 Age 20.0 18.9	P-A0 DI 54.4 50.0	GE 15 Age 21.0 19.8	DI 50.0 50.0 50.3	Age 21.4 20.6 20.0	DI 50.0 50.0 51.4	Age 22.3 21.5 21.0	DI 50.0 50.0 52.6	Age 23.1 22.4 22.0	DI 50.0 45.6 53.7	Age 24.0 23.0 23.0	DI 50.0 46.7 54.8	Age 24.9 24.0 24.0
5 10 15	P-AG DI 46.6 50.0 50.0	GE 11 Age 17.0 16.3 15.5 15.0	P-AC DI 48.6 50.0 45.7 53.9	GE 12 Age 18.0 17.2 16.0	P-AQ DI 50.5 50.0 46.9 55.0	GE 13 Age 19.0 18.0 17.0	P-AC	GE 14 Age 20.0 18.9 18.0	P-A0	GE 15	DI 50.C	Age 21.4 20.6 20.0 19.2	DI 50.0 51.4 50.0	Age 22.3 21.5 21.0 20.2	DI 50.0 52.6 50.0	Age 23.1 22.4 22.0 21.1	DI 50.0 45.6 53.7 50.0	Age 24.0 23.0 23.0 22.0	DI 50.0 46.7 54.8 50.0	Age 24.9 24.0 24.0 22.9
5 10 15 20	P-AG DI 46.6 50.0 50.0	GE 11 Age 17.0 16.3 15.5 15.0	P-AC DI 48.6 50.0 45.7 53.9	GE 12 Age 18.0 17.2 16.0	P-AQ DI 50.5 50.0 46.9 55.0	GE 13 Age 19.0 18.0 17.0	P-AC	GE 14 Age 20.0 18.9 18.0	P-A0	GE 15	DI 50.C	Age 21.4 20.6 20.0 19.2	DI 50.0 51.4 50.0	Age 22.3 21.5 21.0	DI 50.0 52.6 50.0	Age 23.1 22.4 22.0 21.1	DI 50.0 45.6 53.7 50.0	Age 24.0 23.0 23.0 22.0	DI 50.0 46.7 54.8 50.0	Age 24.9 24.0 24.0 22.9
5 10 15 20 25	P-AG DI 46.6 50.0 50.0 52.7 50.0	E 11 Age 17.0 16.3 15.5 15.0 13.9	P-AC DI 48.6 50.0 45.7 53.9 50.0	E 12 Age 18.0 17.2 16.0 14.9	P-AC DI 50.5 50.0 46.9 55.0 50.0	GE 13 Age 19.0 18.0 17.0 17.0	P-A0 DI 52.5 50.0 48.0 50.0	GE 14 Age 20.0 18.9 18.0 17.4	P-A0	3E 15 Age 21.0 19.6 19.6 19.7	P-A DI 50.0 50.0 50.0 50.0 50.0 50.0 50.0	Age 21.4 20.6 20.0 19.2 18.6	DI 50.0 51.4 50.0 50.0	Age 22.3 21.5 21.0 20.2 19.5	DI 50.0 52.6 50.0 50.0	Age 23.1 22.4 22.0 21.1 20.5	DI 50.0 45.6 53.7 50.0 50.0	Age 24.0 23.0 23.0 22.0 21.4	DI 50.0 46.7 54.8 50.0 50.0	Age 24.9 24.0 24.0 22.9 22.4
5 10 15 20	P-AG DI 46.6 50.0 50.0 52.7 50.0	E 11 Age 17.0 16.3 15.5 15.0 13.9	P-AC DI 48.6 50.0 45.7 53.9 50.0	E 12 Age 18.0 17.2 16.0 14.9	P-AC DI 50.5 50.0 46.9 55.0 50.0	GE 13 Age 19.0 18.0 17.0 17.0	P-A0 DI 52.5 50.0 48.0 50.0	GE 14 Age 20.0 18.9 18.0 17.4	P-A0	3E 15 Age 21.0 19.6 19.6 19.7	P-A DI 50.0 50.0 50.0 50.0 50.0 50.0 50.0	Age 21.4 20.6 20.0 19.2 18.6	DI 50.0 51.4 50.0 50.0	Age 22.3 21.5 21.0 20.2	DI 50.0 52.6 50.0 50.0	Age 23.1 22.4 22.0 21.1 20.5	DI 50.0 45.6 53.7 50.0 50.0	Age 24.0 23.0 23.0 22.0 21.4	DI 50.0 46.7 54.8 50.0 50.0	Age 24.9 24.0 24.0 22.9 22.4
5 10 15 20 25 30	P-AC DI 46.6 50.0 50.0 52.7 50.0	E 11 Age 17.0 16.3 15.5 15.0 13.9 13.3	P-AC DI 48.6 50.0 45.7 53.9 50.0 47.2	E 12 Age 18.0 17.2 16.0 16.0 14.9	P-AC DI 50.5 50.0 46.9 55.0 50.0 47.7	F 13 Age 19.0 18.0 17.0 17.0 15.8 15.0	P-A0 DI 52.5 50.0 48.0 50.0 50.0 48.2	GE 14 Age 20.0 18.9 18.0 17.4 16.7 16.0	P-A0 DI 54.4 50.0 49.2 50.0 50.0 48.7	3E 15 Age 19.6 19.6 18.3 17.7	P-A DI 50.0 50.0 50.0 50.0 50.0 50.0 50.0 50.0 50.0 50.0 50.0 50.0 50.0 50.0 50.0 50.0 49.2	Age 21.4 20.6 20.0 19.2 18.6 18.0	DI 50.0 51.4 50.0 50.0 49.7	Age 22.3 21.5 21.0 20.2 19.5 19.0	DI 50.0 52.6 50.0 50.0 50.2	Age 23.1 22.4 22.0 21.1 20.5 20.0	DI 50.0 45.6 53.7 50.0 50.0	Age 24.0 23.0 23.0 22.0 21.4 21.0	DI 50.0 46.7 54.8 50.0 50.0 51.2	Age 24.9 24.0 24.0 22.9 22.4 22.0
5 10 15 20 25	P-AC DI 46.6 50.0 50.0 52.7 50.0	E 11 Age 17.0 16.3 15.5 15.0 13.9 13.3	P-AC DI 48.6 50.0 45.7 53.9 50.0 47.2	E 12 Age 18.0 17.2 16.0 16.0 14.9	P-AC DI 50.5 50.0 46.9 55.0 50.0 47.7	F 13 Age 19.0 18.0 17.0 17.0 15.8 15.0	P-A0 DI 52.5 50.0 48.0 50.0 50.0 48.2	GE 14 Age 20.0 18.9 18.0 17.4 16.7 16.0	P-A0 DI 54.4 50.0 49.2 50.0 50.0 48.7	3E 15 Age 19.6 19.6 18.3 17.7	P-A DI 50.0 <th>Age 21.4 20.6 20.0 19.2 18.6 18.0</th> <th>DI 50.0 51.4 50.0 50.0 49.7</th> <th>Age 22.3 21.5 21.0 20.2 19.5</th> <th>DI 50.0 52.6 50.0 50.0 50.2</th> <th>Age 23.1 22.4 22.0 21.1 20.5 20.0</th> <th>DI 50.0 45.6 53.7 50.0 50.0</th> <th>Age 24.0 23.0 23.0 22.0 21.4 21.0</th> <th>DI 50.0 46.7 54.8 50.0 50.0 51.2</th> <th>Age 24.9 24.0 24.0 22.9 22.4 22.0</th>	Age 21.4 20.6 20.0 19.2 18.6 18.0	DI 50.0 51.4 50.0 50.0 49.7	Age 22.3 21.5 21.0 20.2 19.5	DI 50.0 52.6 50.0 50.0 50.2	Age 23.1 22.4 22.0 21.1 20.5 20.0	DI 50.0 45.6 53.7 50.0 50.0	Age 24.0 23.0 23.0 22.0 21.4 21.0	DI 50.0 46.7 54.8 50.0 50.0 51.2	Age 24.9 24.0 24.0 22.9 22.4 22.0
5 10 15 20 25 30	P-AC DI 46.6 50.0 50.0 52.7 50.0 50.0 53.1	E 11 Age 17.0 16.3 15.5 15.0 13.9 13.3 13.0	P-AC DI 48.6 50.0 45.7 53.9 50.0 47.2 53.6	SE 12 Age 18.0 17.2 16.0 14.9 14.0 14.0	P-AC DI 50.5 50.0 46.9 55.0 50.0 47.7 54.1	E 13 Age 19.0 18.0 17.0 15.8 15.0	P-A0 DI 52.5 50.0 48.0 50.0 50.0 48.2 54.6	3E 14 Age 20.0 18.9 18.0 18.0 16.7 16.0	P-A0 DI 54.4 50.0 49.2 50.0 50.0 48.7 50.0	3E 15 Age 19.6 19.6 18.3 17.7 17.0	P-A DI 50.0	Age 21.4 20.6 20.0 19.2 18.6 18.0 17.5	DI 50.0 51.4 50.0 50.0 49.7 50.0	Age 22.3 21.5 21.0 20.2 19.5 19.0	DI 50.0 52.6 50.0 50.0 50.2 50.2	Age 23.1 22.4 22.0 21.1 20.5 20.0 19.4	DI 50.0 45.6 53.7 50.0 50.0 50.7 50.0	Age 24.0 23.0 23.0 22.0 21.4 21.0 20.5	DI 50.0 46.7 54.8 50.0 50.0 51.2 50.0	Age 24.9 24.0 24.0 22.9 22.4 22.0 21.3

Predicted Pavement Age when DI = 50, Given Present age and Present DI value Mill & Resurface Flexible Pavement Non Freeway/Divided Highway DSL

								·						Highw			SL =	24 y	ears	
	P-A	GE 1	P-A	GE 2	P-A	GE 3	P-A	GE 4	P-A	GE 5	P-A	GE 6	P-A	GE 7	P-A	GE 8	P-A	GE 9	P-AG	GE 10
P-DI	DI	Aqe	וח	Age	וח	Aqe	וח	Age	וח	Age	וח	Age	DI	Aqe	DI	Aqe	DI	Age	DI	Aqe
		Age		Age		rige		Age												
5	51.7	23.0	53.0	24.0	48.3	23.0	49.5	24.0	50.7	25.0	51.9	26.0	53.1	27.0	54.3	28.0	49.0	27.0	50.1	28.0
10	52.0	21.0	53.2	22.0	48.5	21.0	49.6	22.0	50.7	23.0	51.8	24.0	52.8	25.0	53.9	26.0	55.0	27.0	49.6	26.0
15	52.4	19.0	53.4	20.0	48.9	19.0	49.8	20.0	50.8	21.0	51.7	22.0	52.7	23.0	53.6	24.0	54.5	25.0	49.3	24.0
20	52.8	17.0	48.5	16.0	49.3	17.0	50.1	18.0	50.9	19.0	51.8	20.0	52.6	21.0	53.4	22.0	54.2	23.0	55.0	24.0
25	48.4	13.0	49.1	14.0	49.8	15.0	50.5	16.0	51.2	17.0	51.9	18.0	52.6	19.0	53.3	20.0	54.0	21.0	54.7	22.0
30	49.3	11.0	49.9	12.0	50.5	13.0	51.0	14.0	51.6	15.0	52.2	16.0	52.7	17.0	53.3	18.0	53.9	19.0	54.5	20.0
35	50.3	9.0	50.7	10.0	51.2	11.0	51.6	12.0	52.1	13.0	52.5	14.0	53.0	15.0	53.4	16.0	53.9	17.0	49.0	16.0
40	51.3	7.0	51.7	8.0	52.0	9.0	52.3	10.0	52.7	11.0	53.0	12.0	53.3	13.0	48.8	12.0	49.0	13.0	54.3	16.0

Predicted Pavement Age when DI = 50, Given Present age and Present DI value	
Bituminous Overlay on Rubblized Concrete - Non Freeway/Divided Highway	DSL

	P-AG	6E 11	P-AG	GE 12	P-AG	SE 13	P-AG	6E 14	P-AG	GE 15	P-AG	GE 16	P-AG	GE 17	P-AG	GE 18	P-AG	SE 19	P-AG	GE 20
P-DI	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age
5	51.1	29.0	52.2	30.0	53.3	31.0	54.4	32.0	55.0	33.0	49.4	32.0	50.4	33.0	51.3	34.0	52.3	35.0	53.2	36.0
10	50.6	27.0	51.5	28.0	52.5	29.0	53.4	30.0	54.3	31.0	55.0	32.0	49.3	31.0	50.1	32.0	50.9	33.0	51.7	34.0
15	50 1	25.0	50.9	26.0	51 7	27 0	52.6	28.0	53 4	29.0	54 2	30.0	55.0	31.0	49 0	30.0	49 7	31.0	50.4	32.0
10	00.1	20.0	00.0	20.0	01.7	21.0	02.0	20.0	00.4	20.0	04.2	00.0	00.0	01.0	40.0	00.0	40.1	01.0	00.4	02.0
20	49.8	23.0	50.5	24.0	51.1	25.0	51.8	26.0	52.5	27.0	53.2	28.0	53.9	29.0	54.6	30.0	55.0	31.0	49.1	30.0
25	10.5	21.0	50 1	22.0	50.7	23.0	51 2	24.0	51.8	25.0	52 A	26.0	53.0	27.0	53 5	28.0	54 1	20.0	54 7	30.0
25	49.5	21.0	50.1	22.0	50.7	23.0	51.2	24.0	51.0	25.0	52.4	20.0	55.0	27.0	55.5	20.0	54.1	29.0	54.7	30.0
30	55.0	21.0	49.8	20.0	50.3	21.0	50.8	22.0	51.2	23.0	51.7	24.0	52.1	25.0	52.6	26.0	53.0	27.0	53.5	28.0
			10 -	10.0													50.4			
35	54.8	19.0	49.7	18.0	50.0	19.0	50.4	20.0	50.7	21.0	51.1	22.0	51.4	23.0	51.7	24.0	52.1	25.0	52.4	26.0
40	E 4 7	17.0	FF O	10.0	40.0	17.0	50.4	10.0	50.4	10.0	50.0	20.0	50.0	21.0	E1 0	22.0	E1 0	22.0	E1 F	24.0
40	54.7	17.0	55.0	18.0	49.9	17.0	50.1	18.0	50.4	19.0	50.6	20.0	50.8	21.0						24.0 ndex

	icted			•						•										
Bitui		_	<u> </u>									<i>.</i>		lighwa	·		SL = 1			
	P-A	GE 1	P-A	GE 2	P-A	GE 3	P-A	GE 4	P-A	GE 5	P-A	GE 6	P-A	GE 7	P-A	GE 8	P-A	GE 9	P-AG	5E 10
		A		A		A	DI	A	DI	A	DI	A		A = =		A		A		A
P-DI	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age
5	52.9	11.0	54.1	12.0	50.0	12.4	50.0	13.3	50.0	14.1	50.0	15.0	50.0	15.9	50.0	16.8	50.0	17.7	50.0	18.6
10	50.0	• •	50.0	10.0	54.0	11.0	50.0		50.0	40.0	50.0	40.0	50.0		50.0	45.4	50.0	10.0	50.0	10.0
10	53.0	9.0	53.8	10.0	54.0	11.0	50.0	11.4	50.0	12.3	50.0	13.2	50.0	14.1	50.0	15.1	50.0	16.0	50.0	16.9
15	49.0	7.0	50.0	8.0	50.1	9.0	50.0	10.0	F 1 1	11.0	E1 C	10.0	FO 1	13.0	50.0	11.0	EQ 4	15.0	F2 6	16.0
15	49.0	7.0	50.0	8.0	50.1	9.0	50.6	10.0	51.1	11.0	51.6	12.0	52.1	13.0	52.6	14.0	53.1	15.0	53.6	16.0
20	50.0	5.8	50.0	6.7	50.0	7.7	50.0	8.6	50.0	9.6	50.0	10.6	50.0	11.5	50.0	12 5	50.0	13.5	50.0	14 4
20	00.0	0.0	00.0	0.7	00.0		00.0	0.0	00.0	0.0	00.0	10.0	00.0	11.0	00.0	12.0	00.0	10.0	00.0	
25	52.2	5.0	52.5	6.0	52.8	7.0	53.0	8.0	53.3	9.0	53.6	10.0	53.9	11.0	54.2	12.0	54.5	13.0	54.7	14.0
30	50.0	3.8	50.0	4.7	50.0	5.6	50.0	6.7	50.0	7.7	50.0	8.7	50.0	9.6	50.0	10.6	50.0	11.6	50.0	12.6
								-				-								-
35	50.0	3.0	50.1	4.0	50.2	5.0	50.3	6.0	50.4	7.0	50.6	8.0	50.7	9.0	50.8	10.0	50.9	11.0	51.1	12.0
40	50.0	2.2	50.0	3.2	50.0	4.4	50.0	5.2	50.0	6.2	50.0	7.2	50.0	8.1	50.0	9.4	50.0	10.1	50.0	11.3

	P-AG	GE 11	P-AG	GE 12	P-AG	GE 13	P-AG	6E 14	P-AG	GE 15	P-AG	GE 16	P-AG	GE 17	P-AG	GE 18	P-AG	SE 19	P-AG	GE 20
P-DI	DI	Age	DI	Age	DI	Age														
5	50.0	19.5	50.0	20.5	50.0	21.4	50.0	22.3	47.6	23.0	48.4	24.0	49.2	25.0	50.0	26.0	50.8	27.0	51.6	28.0
10																			46.3	
15																			50.0	
20	50.0	15.4	50.0	16.4	50.0	17.3	50.0	18.3	47.0	19.0	47.3	20.0	47.6	21.0	47.9	22.0	48.2	23.0	48.5	24.0
25	55.0	15.0	50.0	15.4	55.6	16.4	50.0	17.3	50.0	18.3	50.0	19.3	50.0	20.3	50.0	21.2	50.0	22.2	50.0	23.2
30	50.0	13.6	50.0	14.5	64.7	15.5	50.0	16.5	45.0	17.0	45.0	18.0	45.1	19.0	45.3	20.0	45.4	21.0	45.5	22.0
35	51.2	13.0	51.3	14.0	51.4	15.0	51.5	16.0	51.7	17.0	51.8	18.0	51.9	19.0	52.0	20.0	52.1	21.0	52.3	22.0
40	50.0	12.1	50.0	13.1	50.0	14.1	50.0	15.1	50.0	16.1	50.0	17.1	50.0	18.1					50.0	
															P-D)I = P	resen	t Dist	ress l	ndex

Freeways

Predicted Pavement Age when DI = 50, Given Present age and Present DI value Mill & Resurface Flexible Pavement Freeway/Divided Highway DSL = 11.3 years P-AGE 1 P-AGE 2 P-AGE 3 P-AGE 4 P-AGE 5 P-AGE 6 P-AGE 7 P-AGE 8 P-AGE 9 P-AGE 10														alue						
Mill 8	& Res	surfa	_		_		_		<u> </u>							DS	5L = 1	1.3 y	ears	
	P-AC	GE 1	P-A0	GE 2	P-A	GE 3	P-A	GE 4	P-A	GE 5	P-A	GE 6	P-A	GE 7	P-A	GE 8	P-A	GE 9	P-AC	SE 10
P-DI	DI	Age	DI	Age	וח	Age	וח	Age	DI	Age	וח	Age	DI	Age	DI	Age	וח	Age	וח	Age
		Aye		Age		Age		Aye		Aye		Age		лус		Age		Age		Age
5	50.2	11.0	50.0	11.1	47.2	11.0	52.6	12.0	50.0	12.0	45.8	12.0	50.0	13.0	54.1	14.0	50.0	14.5	50.0	14.8
10	53.6	11.0	45.5	10.0	50.9	11.0	50.0	11.2	45.6	11.0	49.8	12.0	53.9	13.0	50.0	13.4	50.0	13.8	46.0	14.0
15	50.0	۹۹	49.2	10.0	54 5	11 0	454	10.0	49 5	11 0	53.7	12.0	50.0	12.3	50.0	12.6	47 4	13.0	50.2	14 0
15	50.0	0.0	40.Z	10.0	04.0	11.0		10.0	40.0	11.0	55.7	12.0	50.0	12.0	50.0	12.0	т, т	10.0	50.2	14.0
20	47.5	9.0	52.8	10.0	45.2	9.0	49.3	10.0	53.5	11.0	50.0	11.1	45.9	11.0	48.7	12.0	51.6	13.0	54.5	14.0
25	51.1	9.0	45.0	8.0	49.1	9.0	53.2	10.0	50.0	9.9	47.3	10.0	50.1	11.0	53.0	12.0	55.0	13.0	50.0	13.5
30	54.7	9.0	18.0	8.0	53.0	9.0	15.8	80	18.6	٥ ٥	51 5	10.0	5A A	11.0	50.0	11 3	50.0	11 7	45.6	12.0
50	54.7	3.0	40.3	0.0	55.0	3.0	40.0	0.0	40.0	3.0	51.5	10.0	54.4	11.0	50.0	11.5	50.0	11.7	45.0	12.0
35	48.7	7.0	52.8	8.0	47.1	7.0	50.0	8.0	52.9	9.0	55.0	10.0	45.7	9.0	47.2	10.0	48.7	11.0	50.2	12.0
40	52.6	7.0	48.5	6.0	51.4	7.0	54.3	8.0	47.4	7.0	48.9	8.0	50.4	9.0	51.8	10.0	53.3	11.0	54.8	12.0

Predicted Pavement Age when DI = 50, Given Present age and Present DI value

	_		_		_				-								-		-	
	P-AC	E 11	P-AC	E 12	P-AC	SE 13	P-AG	6E 14	P-AG	6E 15	P-AG	6E 16	P-AG	E 17	P-AG	SE 18	P-AG	SE 19	P-AG	E 20
P-DI	DI	Age	וח	Age	וח	Age	וח	Age	וח	Age	וח	Age	וח	Age	וח	Age	וח	Age	וח	Age
	01	7.90	01	7.90	01	, igo		Jigo	5.	Jigo		Jigo		7.90		7.90		7.90	D.	7.90
5	45.0	15.0	47.5	16.0	50.3	17.0	53.2	18.0	50.0	18.5	50.0	19.3	50.0	20.2	50.0	21.0	50.0	21.9	50.0	22.8
10	48.9	15.0	51.7	16.0	54.6	17.0	50.0	17.4	50.0	18.2	50.0	19.0	50.0	19.9	50.0	20.7	50.0	21.6	50.0	22.5
15	53.1	15.0	50.0	15.4	50.0	16.2	50.0	17.0	50.0	17.8	50.0	18.7	50.0	19.6	50.0	20.4	45.2	21.0	46.7	22.0
20	50.0	14.2	50.0	15.0	50.0	15.8	50.0	16.6	50.0	17.5	45.4	18.0	46.8	19.0	48.3	20.0	49.8	21.0	51.3	22.0
25	50.0	13.8	50.0	14.6	45.5	15.0	47.0	16.0	48.5	17.0	50.0	18.0	51.5	19.0	53.0	20.0	54.4	21.0	55.0	22.0
30	47.1	13.0	48.6	14.0	50.1	15.0	51.6	16.0	53.1	17.0	54.6	18.0	50.0	18.5	50.0	19.5	50.0	20.4	50.0	21.3
35	51.7	13.0	53.2	14.0	54.7	15.0	50.0	15.4	50.0	16.3	50.0	17.2	50.0	18.2	50.0	19.1	50.0	20.0	50.0	21.0
40	50.0	12.2	50.0	13.1	50.0	14.0	50.0	15.0	50.0	15.9	50.0	16.8	50.0	17.8	50.0	18.7	50.0	19.7	50.0	20.9
															P-D)l = P	resen	t Dist	ress l	ndex

													hway	/	ruiu		L = 10	0.2 ye	ears	
	P-A	GE 1	P-A	GE 2	P-A	GE 3	P-A	GE 4	P-A	GE 5	P-A	GE 6	P-A	GE 7	P-A	GE 8	P-A	GE 9	P-AG	E 10
P-DI	DI	Age	DI	Age	DI	Age														
5	50.0	8.0	50.0	8.6	50.0	9.3	48.4	10.0	52.5	11.0	50.0	11.5	50.0	12.6	50.0	13.0	50.0	13.9	50.0	14.7
10	50.0	6.5	50.0	7.2	50.0	8.0								11.0	46.6	12.0	48.6	13.0	50.7	14.0
15	50.0	5.3	46.8	6.0	48.8	7.0								10.5						
20	50.0	4.4	50.0	5.2	50.0	6.3	50.0	7.0	50.0	7.9	50.0	8.8	50.0	9.7	50.0	10.7	50.0	11.6	50.0	12.5
25	50.0	3.6	50.0	4.5	50.0	5.7	50.0	6.4	45.0	7.0	45.7	8.0	46.5	9.0	47.3	10.0	48.1	11.0	48.9	12.0
30	49.7	3.0	50.5	4.0	51.3	5.0	52.1	6.0	52.9	7.0	53.7	8.0	54.5	9.0	55.0	10.0	50.0	10.5	50.0	11.5
35	50.0	2.3	50.0	3.6	50.0	4.2	50.0	5.2	50.0	6.5	50.0	7.1	50.0	8.5	50.0	9.1	50.0	10.0	50.0	11.0
40	50.0	1.8	50.0	3.0	50.0	3.7	50.0	4.9	50.0	6.2	50.0	6.7	50.0	8.2	50.0	8.6	50.0	9.6	50.0	10.6

Predicted Pavement Age when DI = 50, Given Present age and Present DI value)
New/Reconstructed Flexible Pavements - Freeway/Divided Highway	DSL = 10.

		P-AG	E 11	P-AG	SE 12	P-AG	SE 13	P-AG	6E 14	P-AG	GE 15	P-AG	GE 16	P-AG	SE 17	P-AG	GE 18	P-AG	SE 19	P-AG	GE 20
P-	DI	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age
Ę	5	50.0	15.5	50.0	16.4	45.0	17.0	46.4	18.0	48.4	19.0	50.5	20.0	52.6	21.0	54.6	22.0	50.0	22.6	50.0	23.5
1	0	50.0	15.0	54.0	16.0	50.0	16 5	50.0	17 4	50.0	10.2	50.0	10.2	50.0	20.1	50.0	21.0	50.0	22.0	50.0	22.9
	0	52.0	15.0	54.9	10.0	50.0	10.5	50.0	17.4	50.0	10.3	50.0	19.2	50.0	20.1	50.0	21.0	50.0	22.0	50.0	22.9
1	5	50.0	14.0	50.0	14.9	50.0	15.9	50.0	17.3	50.0	17.7	50.0	18.6	50.0	19.6	50.0	20.5	50.0	21.5	50.0	22.4
2	0	50.0	13.9	50.0	14.4	50.0	15.3	45.0	16.0	45.0	17.0	45.8	18.0	46.6	19.0	47.4	20.0	48.2	21.0	49.0	22.0
2	5	10.7	13.0	50 5	14.0	51 3	15.0	52 1	16.0	52 0	17.0	53 7	18.0	54 5	10.0	55.0	20.0	50.0	20.8	50.0	21.6
	5	43.7	13.0	50.5	14.0	51.5	15.0	JZ.1	10.0	52.5	17.0	55.7	10.0	54.5	19.0	55.0	20.0	50.0	20.0	50.0	21.0
3	0	50.0	12.4	50.0	13.9	50.0	14.6	50.0	15.3	50.0	16.6	50.0	17.8	50.0	18.2	50.0	19.8	50.0	20.2	50.0	21.1
3	5	50.0	12.3	50.0	13.0	50.0	13.9	50.0	15.0	50.0	15.9	50.0	17.1	50.0	17.8	50.0	18.9	50.0	19.8	50.0	20.8
4	0	50.0	11.8	50.0	12.9	50.0	13.6	50.0	14.6	50.0	15.5	50.0	16.8	50.0	17.9						20.6 ndex

New	/Reco	onstr	ucte	d Rig	id Pa	vem	ents	- Free	eway	/ Divi	ded I	High	way			DS	SL = 2	22.2 y	/ears	
	P-A0	GE 1	P-A	GE 2	P-A	GE 3	P-A	GE 4	P-A	GE 5	P-A	GE 6	P-A	GE 7	P-A	GE 8	P-A	GE 9	P-AC	E 1
P-DI	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Ag
5	50.7	21.0	55.0	22.0	49.9	21.0	53.8	22.0	48.1	21.0	51.6	22.0	55.0	23.0	48.5	22.0	51.4	23.0	54.4	24.
10														21.0						
-														19.0						
														19.0						
25														17.0					49.3	
-																				
30														15.0						
35	50.1	11.0	52.1	12.0	48.6	11.0	50.3	12.0	51.9	13.0	53.6	14.0	48.8	13.0	50.0	14.0	51.3	15.0	52.5	16.0
40	50.8	9.0	52.4	10.0	49.2	9.0	50.5	10.0	51.7	11.0	52.9	12.0	48.5	11.0	49.3	12.0	50.1	13.0	51.0	14.

Predicted Pavement Age when DI = 50, Given Present age and Present DI value	
New/Reconstructed Rigid Pavements - Freeway/ Divided Highway	I

	P-AG	E 11	P-AG	6E 12	P-AG	6E 13	P-AG	E 14	P-AG	GE 15	P-AC	GE 16	P-AC	GE 17	P-AC	SE 18	P-AC	SE 19	P-AC	GE 20
P-DI	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age
5	47.0	23.0	49.6	24.0	52.1	25.0	54.6	26.0	46.0	25.0	48.1	26.0	50.2	27.0	52.3	28.0	54.3	29.0	50.0	29.5
10	52.7	23.0	55.0	24.0	47.4	23.0	49.5	24.0	51.5	25.0	53.6	26.0	50.0	26.0	55.0	28.0	47.9	27.0	49.5	28.0
15	48.7	21.0	50.8	22.0	52.9	23.0	55.0	24.0	46.7	23.0	48.4	24.0	50.0	25.0	51.7	26.0	53.3	27.0	55.0	28.0
20	54.3	21.0	47.2	20.0	48.8	21.0	50.5	22.0	52.1	23.0	53.8	24.0	55.0	25.0	46.3	24.0	47.6	25.0	48.8	26.0
25	51.0	19.0	52.6	20.0	54.3	21.0	46.8	20.0	48.0	21.0	49.2	22.0	50.4	23.0	51.7	24.0	52.9	25.0	54.1	26.0
30	48.4	17.0	49.6	18.0	50.8	19.0	52.1	20.0	53.3	21.0	54.5	22.0	46.2	21.0	47.0	22.0	47.8	23.0	48.6	24.0
35	53.7	17.0	47.4	16.0	48.2	17.0	49.0	18.0	49.8	19.0	50.6	20.0	51.4	21.0	52.2	22.0	53.0	23.0	53.8	24.0
40	51.8	15.0	52.6	16.0	53.4	17.0	46.6	16.0	55.0	19.0	47.4	18.0	47.8	19.0	48.2	20.0	48.6	21.0	49.0	22.0

	& Re			•											ruiu		L = 1	4.2 y	ears	
	P-A	GE 1	P-A	GE 2	P-A	GE 3	P-A	GE 4	P-A	GE 5	P-A	GE 6	P-A	GE 7	P-A	GE 8	P-A	GE 9	P-AG	GE 10
P-DI	DI	Age	DI	Age	DI	Age														
5	47.1	13.0	50.1	14.0	53.2	15.0	45.0	14.0	47.6	15.0	50.1	16.0	52.6	17.0	55.0	18.0	45.0	17.0	47.0	18.0
10	52.3	13.0	55 0	14.0	47.7	13.0	50.2	14.0	52.8	15.0	55.0	16.0	16 1	15.0	18 1	16.0	50.2	17.0	52.2	18.0
10	52.5	13.0	55.0	14.0	47.7	13.0	50.2	14.0	52.0	15.0	55.0	10.0	40.1	15.0	40.1	10.0	50.Z	17.0	52.2	10.0
15	47.8	11.0	50.3	12.0	52.9	13.0	55.4	14.0	58.0	15.0	49.3	14.0	51.3	15.0	53.3	16.0	50.0	16.1	45.1	16.0
20	52 0	11.0	55 0	12.0	10.2	11 0	50.4	12.0	52 A	12.0	5A A	14.0	45.7	13.0	47.2	14.0	10 7	15.0	50.3	16.0
20	55.0	11.0	55.0	12.0	40.5	11.0	50.4	12.0	52.4	13.0	54.4	14.0	45.7	13.0	47.2	14.0	40.7	15.0	50.5	10.0
25	49.4	9.0	51.5	10.0	53.5	11.0	55.0	12.0	47.8	11.0	49.3	12.0	50.8	13.0	52.3	14.0	53.9	15.0	50.0	15.2
30	46.9	7.0	48.4	8.0	49.9	9.0	51.4	10.0	52.9	11.0	54.4	12.0	46.2	11.0	47.2	12.0	48.2	13.0	49.3	14.0
35	52.0	7.0	53.5	8.0	55.0	9.0	48.3	8.0	49.3	9.0	50.3	10.0	51.3	11.0	52.3	12.0	53.3	13.0	54.3	14.0
40	50.4	5.0	51.4	6.0	52.4	7.0	53.4	8.0	54.4				47.7							12.0

Predicted Pavement Age when DI = 50, Given Present age and Present DI value	
Mill & Resurface Composite Pavement - Freeway/Divided Highway	DSL = 14.2 year

	P-AG	6E 11	P-AG	6E 12	P-AG	SE 13	P-AG	6E 14	P-AG	GE 15	P-AC	GE 16	P-AG	6E 17	P-AG	SE 18	P-AG	SE 19	P-AG	GE 20
P-DI	DI	Age	DI	Age	DI	Age														
5	49.1	19.0	51.1	20.0	53.1	21.0	50.0	22.4	50.0	22.9	50.0	23.1	45.5	23.0	47.0	24.0	48.5	25.0	50.0	26.0
10	54.2	19.0	50.0	19.1	50.0	19.9	46.1	20.0	47.6	21.0	49.1	22.0	50.6	23.0	52.1	24.0	53.6	25.0	50.0	25.4
15	46.7	17.0	48.2	18.0	49.7	19.0	51.2	20.0	52.7	21.0	54.2	22.0	55.0	23.0	50.0	23.1	50.0	24.0	50.0	24.7
20	51.8	17.0	53.3	18.0	54.8	19.0	50.0	19.6	50.0	19.9	45.1	20.0	46.1	21.0	47.1	22.0	48.1	23.0	49.1	24.0
25	45.2	15.0	46.2	16.0	47.2	17.0	48.2	18.0	49.2	19.0	50.2	20.0	51.2	21.0	52.2	22.0	53.2	23.0	54.2	24.0
30	50.3	15.0	51.3	16.0	52.3	17.0	53.3	18.0	54.3	19.0	55.0	20.0	50.0	20.2	50.0	21.5	50.0	21.9	50.0	22.8
35	50.0	14.0	50.0	15.0	50.0	15.8	46.1	16.0	46.6	17.0	50.0	18.5	47.6	19.0	48.1	20.0	48.6	21.0	49.1	22.0
40	50.0	13.1	50.2	14.0	50.7	15.0	51.2	16.0	51.7	17.0	52.2	18.0	52.7	19.0	53.2	20.0	53.7	21.0	54.2	22.0
																	resen			

	urface			•							•			ent Di	valu		SL = 1	ر 2.9	/ears	
	P-AC	GE 1	P-AC	GE 2	P-AC	GE 3	P-AC	GE 4	P-A	GE 5	P-A	GE 6	P-A	GE 7	P-A	GE 8	P-A	GE 9	P-AG	GE 10
P-DI	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age
5	52.6	13.0	45.3	12.0	48.9	13.0	52.6	14.0	50.0	14.2	46.7	14.0	49.7	15.0	52.7	16.0	50.0	16.2	50.0	16.8
10	45.6	11.0	49.2	12.0	52.8	13.0	50.0	12.9	47.9	13.0	50.8	14.0	53.8	15.0	50.0	15.0	45.8	15.0	48.1	16.0
15	49 4	11 0	53 1	12 0	46 0	11 0	49 0	12 0	519	13 0	54 9	14 0	45 5	13.0	47 8	14 0	50 1	15.0	524	16.0
									0.10		0.110								0	
20	533	11 0	17 1	10.0	50 1	11 0	53.0	12.0	153	11 0	175	12.0	10.8	13.0	52.1	14.0	51 1	15.0	50.0	15.0
20	55.5	11.0	47.1	10.0	50.1	11.0	55.0	12.0	40.0	11.0	47.5	12.0	43.0	15.0	52.1	14.0	34.4	15.0	50.0	15.0
05	40.0	0.0	E1 0	10.0	E 4 4	11.0	47.0	10.0	40 F	11.0	E1 0	10.0	E 4 4	12.0	50.0	10.0	46.4	10.0	40.0	14.0
25	4ŏ.Z	9.0	51.Z	10.0	J4.1	11.0	41.3	10.0	49.5	11.0	01.0	12.0	34. 1	13.0	50.0	12.9	40.4	13.0	4ö.U	14.0
	FO O	0.0	47 0		40.0	<u> </u>	- 4 -	10.0	F0 0	14.0	40.0	10.0	47.0	44.0	10.0	10.0	F0 0	10.0	F0 -	44.0
30	52.3	9.0	47.0	8.0	49.3	9.0	51.5	10.0	53.8	11.0	46.2	10.0	47.8	11.0	49.3	12.0	50.9	13.0	52.5	14.0
35	49.0	7.0	51.3	8.0	53.6	9.0	47.6	8.0	49.2	9.0	50.7	10.0	52.3	11.0	53.9	12.0	50.0	12.1	45.5	12.0
40	53.3	7.0	49.0	6.0	50.6	7.0	52.1	8.0	53.7	9.0	47.0	8.0	47.8	9.0	48.6	10.0	49.4	11.0	50.2	12.0
	P-AG	SE 11	P-AC	GE 12	P-AC	GE 13	P-AC	GE 14	P-A	GE 15	P-A	GE 16	P-AC	GE 17	P-AG	E 18	P-AG	E 19	P-AG	E 20
										Ī		T								
P-DI	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age
5	46.1	17.0	48.4	18.0	50.7	19.0	52.9	20.0	50.0	20.4	50.0	21.2	50.0	22.8	50.0	23.0	50.0	23.6	45.5	24.0
10	50.4	17.0	52.7	18.0	54.9	19.0	50.0	19.1	50.0	19.9	50.0	20.7	45.3	21.0	46.9	22.0	48.5	23.0	50.0	24.0
15	54.7	17.0	50.0	17.1	50.0	17.8	45.2	18.0	46.7	19.0	48.3	20.0	49.8	21.0	51.4	22.0	53.0	23.0	54.5	24.0
											1									
20	45.0	15.0	46.6	16.0	48.1	17.0	49.7	18.0	51.2	19.0	52.8	20.0	54.4	21.0	50.0	21.4	50.0	22.2	50.0	23.1
											1	$\begin{bmatrix} 1 \end{bmatrix}$								
25	49.5	15.0	51.1	16.0	52.6	17.0	54.2	18.0	50.0	18.3	50.0	19.1	50.0	20.0	50.0	20.8	50.0	21.7	50.0	22.6
											1									
30	54.0	15.0	50.0	15.2	50.0	16.0	50.0	16.8	50.0	17.7	45.5	18.0	46.3	19.0	47.1	20.0	47.9	21.0	48.7	22.0
											1									
35	46.3	13.0	47.1	14.0	47.9	15.0	48.7	16.0	49.5	17.0	50.3	18.0	51.1	19.0	51.9	20.0	52.7	21.0	53.5	22.0
40	51.0	13.0	51.8	14.0	52.6	15.0	53.4	16.0	54.2	17.0	55.0	18.0	50.0	18.3	50.0	19.6	50.0	20.1	50.0	21.8
																l = Pr Ago =			ress I	ndex

Predicted Pavement Age when DI = 50, Given Present age and Present DI value

				Rigid										1100		Vulu		SL = '	14.3 <u>y</u>	years	;
I		P-A	GE 1	P-A	GE 2	P-A	GE 3	P-A	GE 4	P-A	GE 5	P-A	GE 6	P-A	GE 7	P-A	GE 8	P-A	GE 9	P-AG	SE 10
	P-DI	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age
Ī	5	FF 0	11.0	50.0	11.0										14.4	50.0			15.0	50.0	16.7
ł	5	55.0	11.0	50.0	11.3	50.0	11.8	46.0	12.0	49.6	13.0	53.3	14.0	50.0	14.4	50.0	15.1	50.0	15.9	50.0	16.7
	10	50.0	8.2	50.0	8.9	50.0	9.7	50.0	10.5	46.1	11.0	48.3	12.0	50.4	13.0	52.6	14.0	54.8	15.0	50.0	15.4
	15	53.2	7.0	50.0	74	50.0	0.2	50.0	0.1	50.0	0.0	50.0	10.8	50.0	11.7	50.0	12.6	50.0	13.5	45.0	14.0
ŀ	15	55.Z	7.0	50.0	7.4	50.0	0.5	50.0	9.1	50.0	9.9	50.0	10.0	50.0	11.7	50.0	12.0	50.0	15.5	45.0	14.0
	20	45.4	5.0	46.6	6.0	47.7	7.0	48.9	8.0	50.0	9.0	51.2	10.0	52.4	11.0	53.5	12.0	54.7	13.0	55.0	14.0
	25	50.0	4.3	50.0	56	50.0	62	50.0	77	50.0	8.0	50.0	8 9	50.0	9.3	50.0	10.8	50.0	11 7	50.0	12.7
Ì	-																				
ł	30	50.0	3.5	45.1	4.0	45.5	5.0	46.0	6.0	46.5	7.0	46.9	8.0	47.4	9.0	50.0	10.2	48.4	11.0	48.8	12.0
	35	51.9	3.0	52.4	4.0	50.0	4.7	50.0	5.6	53.8	7.0	54.3	8.0	54.8	9.0	55.0	10.0	55.0	11.0	50.0	11.4
	40	50.0	2.0	50.0	35	50.0	13	50.0	5.0	50.0	50	50.0	7.2	50.0	70	50.0	0.3	50.0	10.3	50.0	10.0
L	40	50.0	2.0	50.0	3.5	50.0	4.3	50.0	5.0	50.0	5.9	50.0	7.2	50.0	7.9	50.0	9.3	50.0	10.3	50.0	1

Predicted Pavement Age when DI = 50, Given Present age and Present DI value
Resurface on Rigid Pavement - Freeway/Divided Highway

	D 4 0					F 40	D 40			- 4-										
	P-AG	E 11	P-AG	6E 12	P-AG	iE 13	P-AG	6E 14	P-AG	iE 15	P-AG	6E 16	P-AG	6E 17	P-AG	6E 18	P-AG	6E 19	P-AG	5E 20
P-DI	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age
5	50.0	17.5	45.4	18.0	47.6	19.0	49.8	20.0	52.0	21.0	54.1	22	50.0	22.5	50.0	23.3	50.0	24.2	50.0	25.5
10	50.0	16.2	50.0	17.1	50.0	18.0	50.0	18.8	50.0	19.7	50.0	20.6	50.0	21.5	50.0	22.4	50.0	23.3	45.9	24
15	46.2	15.0	50.0	16.2	48.5	17.0	49.7	18.0	50.8	19.0	52.0	20	53.2	21	54.3	22	55.0	23	50.0	23.5
20	50.0	14.4	50.0	15.3	50.0	16.2	50.0	17.1	50.0	18.1	50.0	19	50.0	19.9	50.0	20.9	50.0	21.8	50.0	22.9
25	50.0	13.6	50.0	14.6	50.0	15.5	50.0	16.5	50.0	17.4	50.0	18.4	50.0	19.3	45.2	20	45.7	21	46.2	22
30	49.3	13.0	50.0	14.0	50.2	15.0	50.7	16.0	51.2	17.0	51.6	18	52.1	19	52.6	20	53.1	21	53.5	22
35	50.0	12.6	50.0	13.4	50.0	14.3	50.0	15.6	50.0	16.3	50.0	17.3	50.0	18.2	50.0	19.5	50.0	20.2	50.0	21.4
	-																			
40	50.0	11.8	50.0	13.2	50.0	13.8	50.0	14.9	50.0	15.8	50.0	16.8	50.0	17.7	50.0	19.2	50.0	19.7	50.0	21.1
	-			1										1			resen			

											•		High	way	varu		SL =	: 16 y	ears	
	P-A0	GE 1	P-A	GE 2	P-A	GE 3	P-A	GE 4	P-A	GE 5	P-A	GE 6	P-A	GE 7	P-A	GE 8	P-A	GE 9	P-AC	SE 10
P-DI	DI	Age	DI	Age																
5	54 1	17.0										16.0	49 Q	17.0	53.0	18.0	46.3	17.0	49.0	18.0
-														17.0						
														17.0						
														17.0						
														15.0						
30	51.1	15.0	48.2	14.0	51.6	15.0	48.5	14.0	51.6	15.0	48.1	14.0	50.8	15.0	53.5	16.0	48.9	15.0	51.2	16.0
35	46.0	13.0	49.4	14.0	52.8	15.0	50.0	14.0	53.1	15.0	50.1	14.0	52.8	15.0	49.1	14.0	51.4	15.0	53.7	16.0
40	47.3	13.0	50.7	14.0	48.5	13.0	51.6	14.0	49.3	13.0	47.1	12.0	49.4	13.0	51.6	14.0	48.3	13.0	50.0	14.0

	P-AG	E 11	P-AG	6E 12	P-AG	SE 13	P-AG	6E 14	P-AG	GE 15	P-AG	GE 16	P-AG	GE 17	P-AG	GE 18	P-AG	GE 19	P-AG	GE 20
	ī	• • •	L L		ī		Ē												D	• • •
P-DI	DI	Age																		
5	51 8	19.0	54 5	20.0	45.4	19.0	47 7	20.0	50.0	21.0	52.2	22.0	54 5	23.0	50.0	23.1	50.0	23.9	50.0	24 6
<u> </u>	01.0	10.0	01.0	20.0	10.1	10.0		20.0	00.0	21.0	02.2	22.0	01.0	20.0	00.0	20.1	00.0	20.0	00.0	21.0
10	53.8	19.0	45.7	18.0	47.9	19.0	50.2	20.0	52.5	21.0	54.7	22.0	50.0	22.0	50.0	22.7	46.1	23.0	47.8	24.0
15	55.0	19.0	48.2	18.0	50.4	19.0	52.7	20.0	55.0	21.0	50.0	20.9	45.9	21.0	47.6	22.0	49.3	23.0	51.0	24.0
20	48.4	17.0	50.7	18.0	52.9	19.0	50.0	19.1	45.7	19.0	47.4	20.0	49.1	21.0	50.8	22.0	52.4	23.0	54.1	24.0
25	50.9	17.0	53.2	18.0	45.5	17.0	47.2	18.0	48.9	19.0	50.6	20.0	52.2	21.0	53.9	22.0	50.0	22.2	50.0	23.1
30					48.7															
35					51.8															
- 55	40.0	13.0	50.Z	10.0	51.0	17.0	55.5	10.0	4J.Z	17.0	40.1	10.0	47.1	19.0	40.0	20.0	40.9	21.0	49.9	22.0
40	51.7	15.0	53.3	16.0	47.3	15.0	48.3	16.0	49.2	17.0	50.1	18.0	51.1	19.0						22.0 ndex

Predicted Pavement Age when DI = 50, Given Present age and Present DI value Bituminous Overlay on Rubblized Concrete - Freeway/Divided Highway

Unbonded Concrete Overlay on Concrete Pavement - Freeway/Divided Highw												hway	DSL = 13.6 years							
	P-AGE 1		1 P-AGE 2		P-AGE 3		P-AGE 4		P-AGE 5		P-AGE 6		P-AGE 7		P-AGE 8		P-AGE 9		P-AGE 10	
P-D	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age
5	50.0	11.9	46.7	12.0	51.3	13.0	50.0	13.3	50.0	13.8	45.6	14.0	48.9	15.0	52.2	16.0	50.0	16.4	50.0	17.1
10	55.0	11.0	50.0	11.1	46.7	11.0	50.0	12.0	53.3	13.0	50.0	13.2	50.0	13.9	50.0	14.6	46.3	15.0	48.5	16.0
15	51.0	9.0	54.3	10.0	50.0	10.0	50.0	10.7	46.4	11.0	48.6	12.0	50.8	13.0	53.0	14.0	50.0	14.4	50.0	15.2
20	46.5	7.0	48.7	8.0	50.9	9.0	53.2	10.0	50.0	10.5	50.0	11.1	50.0	11.8	50.0	12.7	45.4	13.0	46.8	14.0
25	55.0	7.0	50.0	7.2	50.0	7.7	46.2	8.0	47.5	9.0	48.8	10.0	50.2	11.0	51.5	12.0	52.8	13.0	54.2	14.0
30	49.6	5.0	50.9	6.0	52.2	7.0	53.6	8.0	54.9	9.0	50.0	9.2	50.0	10.0	50.0	10.9	50.0	11.8	50.0	12.7
35	50.0	3.9	45.0	4.0	45.6	5.0	46.2	6.0	46.8	7.0	47.4	8.0	48.0	9.0	48.6	10.0	49.2	11.0	49.8	12.0
40	50.5	3.0	51.1	4.0	51.7	5.0	52.3	6.0	52.9	7.0	53.5	8.0	54.1	9.0	54.7	10.0	50.0	10.3	50.0	11.5

Predicted Pavement Age when DI = 50, Given Present age and Present DI value	
Unbonded Concrete Overlay on Concrete Pavement - Freeway/Divided Highway	DSL = 13.6 y

	P-AGE 11		P-AGE 12		2 P-AGE 13		P-AGE 14		P-AGE 15		P-AGE 16		P-AGE 17		P-AGE 18		P-AGE 19		P-AGE 20	
	DI	A a a		A go		A 90		A 90		A go		A g g		A g g		A		A		A a a
P-DI	וט	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age	DI	Age
5	50.0	17.8	50.0	18.6	46.1	19.0	48.3	20.0	50.6	21.0	52.8	22.0	55.0	23.0	50.0	23.3	50.0	24.5	50.0	25.0
																		~ -		
10	50.7	17.0	52.9	18.0	50.0	18.6	50.0	19.3	50.0	20.1	50.0	20.9	50.0	21.8	50.0	22.6	50.0	23.5	45.3	24.0
15	50.0	16.0	50.0	16.8	50.0	17.6	50.0	18.5	46.0	19.0	47.3	20.0	48.7	21.0	50.0	22.0	51.3	23.0	52.7	24.0
20	48.1	15.0	49.4	16.0	50.7	17.0	52.1	18.0	53.4	19.0	54.7	20.0	50.0	20.4	50.0	21.3	50.0	22.2	50.0	23.5
25	50.0	14.4	50.0	15.2	50.0	16.1	50.0	17.0	50.0	17.9	50.0	18.8	50.0	19.8	50.0	20.7	50.0	21.6	50.0	22.5
30	50.0	13.6	50.0	14.5	45.5	15.0	46.1	16.0	46.7	17.0	47.3	18.0	47.9	19.0	48.5	20.0	49.1	21.0	49.7	22.0
35	50.4	13.0	51.0	14.0	51.6	15.0	52.2	16.0	52.8	17.0	53.4	18.0	54.0	19.0	54.6	20.0	50.0	20.5	50.0	21.4
10	50.0	10.0	50.0	10.4	50.0	14.1	50.0	15.0	50.0	16.1	50.0	17.0	50.0	10.0	50.0	10.0	50.0	10.0	50.0	21.2
40	50.0	12.2	50.0	13.4	50.0	14.1	50.0	15.3	50.0	10.1	50.0	17.0	50.0	10.2			resen			21.2