

# MDOT PAVEMENT MANAGEMENT SYSTEM

## PREDICTION MODELS AND FEEDBACK SYSTEM

### FINAL REPORT

by

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<p>16. Abstract</p> <p>As a primary component of a Pavement Management System (PMS), prediction models are crucial for one or more of the following analyses: maintenance planning, budgeting, life-cycle analysis, multi-year optimization of maintenance works program, and authentication of design alternatives. The main focus of the study is to develop pavement deterioration models. Four cycles of pavement condition data and the required inventory data are compiled from the Mississippi Department of Transportation (MDOT) PMS database. Though regression is the primary tool for developing models, Bayesian regression is also employed whenever feasible. Expert opinion regarding the major distresses in pavements are compiled, augmenting the field data. The study begins with a review of relevant literature with the aim of identifying the commonly employed explanatory variables and various model forms.</p> <p>Five pavement families are identified for the model development: original flexible, overlaid flexible, composite, jointed concrete, and continuously reinforced concrete pavements. Models for each family are developed for predicting distresses, roughness, and a composite condition index (Pavement Condition Rating). The database employed is divided into 'in-sample' data constituting a major portion (70 percent) with 'out-of-sample' data comprising the remaining. Totally 26 models are developed, with the in-sample data: six each for original flexible, overlaid flexible, and composite, and four each for jointed concrete and continuously reinforced concrete pavements. The models are subsequently verified with the 'out-of-sample' data.</p> <p>Among the scores of model forms attempted, power form or some variation of it fits all of the models while satisfying crucial boundary conditions. The out-of-sample data provides an independent database to verify the validity of the models. A sensitivity analysis of the model equation is presented in each case, substantiating the predictive capability of the model. In seven cases, incorporating expert opinion in the field data, employing Bayesian regression, resulted in better prediction models. While these equations form a nucleus for condition prediction of MDOT pavement network, for project level analyses, a shift adjustment of the prediction should be made to match the current observation.</p> <p>The feedback program developed in this study computes load index of original pavements of all types and overlaid flexible pavements. Load index is the ratio of the actual ESAL sustained by the pavement and the design ESAL. Also included is a routine to verify/substantiate the prediction models by comparing the actual to the predicted distresses.</p>					
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## DISCLAIMER

The opinions, findings and conclusions expressed in this report are those of the author and not necessarily those of the Mississippi Department of Transportation or the Federal Highway Administration. This does not constitute a standard, specification or regulation.

## ABSTRACT

As a primary component of a Pavement Management System (PMS), prediction models are crucial for one or more of the following analyses: maintenance planning, budgeting, life-cycle analysis, multi-year optimization of maintenance works program, and authentication of design alternatives. The main focus of the study is to develop pavement deterioration models. Four cycles of pavement condition data and the required inventory data are compiled from the Mississippi Department of Transportation (MDOT) PMS database. Though regression is the primary tool for developing models, Bayesian regression is also employed whenever feasible. Expert opinions regarding the major distresses in pavements were compiled, augmenting the field data. The study begins with a review of relevant literature with the aim of identifying the commonly employed explanatory variables and various model forms.

Five pavement families are identified for the model development: original flexible, overlaid flexible, composite, jointed concrete, and continuously reinforced concrete pavements. Models for each family are developed for predicting distresses, roughness, and a composite condition index (Pavement Condition Rating). The database employed is divided into 'in-sample' data constituting a major portion (70 percent) with 'out-of-sample' data comprising the remaining. Totally 26 models are developed, with the in-sample data: six for original flexible, six for overlaid flexible, six for composite, and four each for jointed concrete and continuously reinforced concrete pavements. The models are subsequently verified with the 'out-of-sample' data.

Among the scores of model forms attempted, power form or some variation of it fits all of the models while satisfying crucial boundary conditions. The out-of-sample data

provides an independent database to verify the validity of the models. A sensitivity analysis of the model equation is presented in each case, substantiating the predictive capability of the model. In seven cases, incorporating expert opinion in the field data, employing Bayesian regression resulted in better prediction models. While these equations form a nucleus for condition prediction of MDOT pavement network, for project level analyses, a shift adjustment of the prediction should be made to match the current observation.

The feedback program developed in this study computes load index of original pavements of all types and overlaid flexible pavements. Load index is the ratio of the actual ESAL sustained by the pavement and the design ESAL. Also included is a routine to verify/substantiate the prediction models by comparing the actual to the predicted distresses.

## METRIC CONVERSION CHART

To convert U.S. units to metric units, the following conversion factors should be used:

<u>Multiply U.S. Units</u>	<u>By</u>	<u>To Obtain Metric Units</u>
mils	0.0254	millimeters (mm)
inches (in)	2.5400	centimeters (cm)
feet (ft)	0.3048	meters
yards (yd)	0.9144	meters (m)
square inches (in <sup>2</sup> )	6.4516	square centimeters (cm <sup>2</sup> )
square feet (ft <sup>2</sup> )	0.0929	square meters (m <sup>2</sup> )
square yards (yd <sup>2</sup> )	0.8361	square meters (m <sup>2</sup> )
cubic inches (in <sup>3</sup> )	16.3872	cubic centimeters (cm <sup>3</sup> )
cubic feet (ft <sup>3</sup> )	0.0283	cubic meters (m <sup>3</sup> )
cubic feet (ft <sup>3</sup> )	28.3162	liters (l)
cubic yards (yd <sup>3</sup> )	0.7646	cubic meters (m <sup>3</sup> )
gallons (gal)	3.7854	liters (l)
pounds (lbs)	0.4536	kilograms (kgs)
pounds (lbs)	453.592	grams (g)
ounces (oz)	28.3495	grams (g)
pounds per square inch (psi)	0.0703	kilograms per cubic meter (kgs/cm <sup>2</sup> )
pounds per cubic foot (lbs/ft <sup>3</sup> )	16.091	kilograms per cubic meter (kgs/m <sup>3</sup> )
miles per hour (mph)	1.609	kilometers per hour (km/hr)
degrees Fahrenheit (°F) minus 32°	5/9	degrees Celsius (°C) °C = 5/9 (°F-32°)
British thermal units (BTU)	252.0	calories (cal)

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# **CHAPTER 1**

## **INTRODUCTION**

### **1.1 GENERAL**

With a large network of highways in place, the need for preservation and efficient maintenance of existing highways is growing. To find cost-effective strategies for providing, evaluating, and maintaining pavements in a serviceable condition, highway agencies are resorting to Pavement Management Systems (PMSs). However, with pavements deteriorating continually, preserving and managing pavements has become a complex task. The problem is further compounded by the fact that the funds available for maintenance and rehabilitation are dwindling. Maintenance at a given time necessitates the evaluation of pavement condition. The present condition of a network can be evaluated by condition surveys. For efficient and economical maintenance of pavements, not only the present condition but also the future condition of pavements should be considered. Prediction of future pavement condition, therefore, is a key component of a Pavement Management System.

### **1.2 PAVEMENT MANAGEMENT SYSTEM**

A Pavement Management System helps in making informed decisions enabling the maintenance of the network in a serviceable and safe condition at a minimum cost to both the agency and the road users. To adequately meet this requirement, well-documented information is essential to make defensible decisions on the basis of sound principles of engineering and management. The objective of establishing a PMS is to improve the efficiency of this decision making, expand its scope, provide feedback about the consequences of decisions, and ensure consistency of decisions made at different levels

within an organization. The elements and products of a Pavement Management System include:

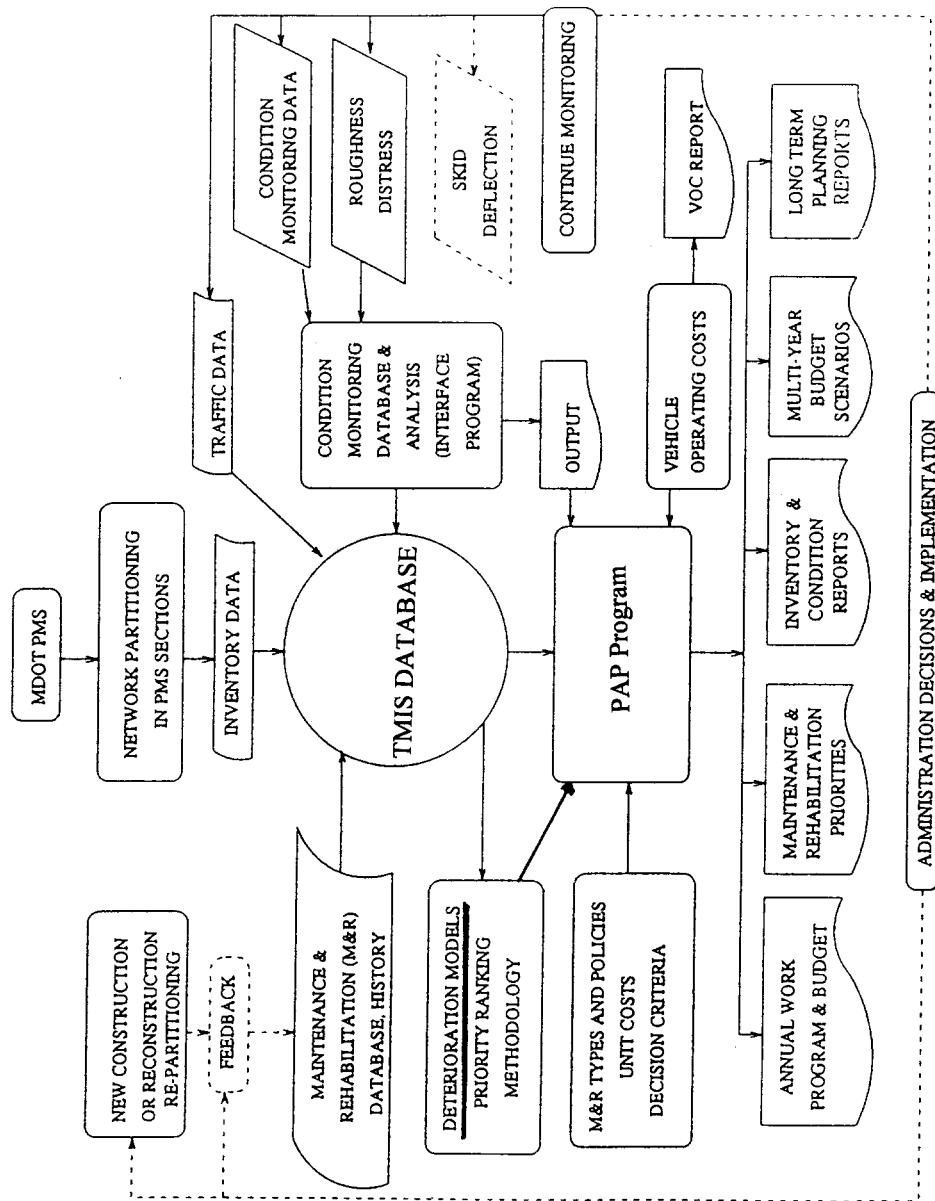
- an inventory of pavements in the network,
- a database of information pertinent to past and current pavement condition,
- an analysis program which, among other things, makes use of prediction models for forecasting pavement condition in the future or in the design horizon
- long range budgeting provisions
- prioritizing the annual work program,
- a basis for communication of the agency's plans,
- a feedback system.

The modules of the PMS (2) adopted by the Mississippi Department of Transportation (MDOT), with the logical structure, are shown in Figure 1. The basic modules include:

- A database that contains inventory, condition, traffic, and historical data
- A Pavement Analysis Program (PAP), which determines the condition of a pavement and selects a maintenance action based on its condition and other criteria. Also, it establishes an annual work program and estimates the budget required. A number of reports are generated from the analysis.

Many other modules are established which supply the necessary inputs for the PMS analysis. Deterioration models, maintenance and rehabilitation policies, their unit costs, and vehicle operating costs are such inputs. Deterioration models, which form an important element of PMS analysis, comprise this study.

Thus, a Pavement Management System can be applied in the areas of planning,



**FIGURE 1.1 Illustration of MDOT-PMS development and implementation program.**

budgeting, scheduling, performance evaluation, and research. It can be used for prioritization, funding, setting strategies, selecting alternatives, identifying problem areas, simplifying communications with the legislature, and providing general and specific information which is useful to decision makers and management. All these activities of a PMS use deterioration models.

### **1.3 PREDICTION MODELS**

A pavement deterioration model or prediction model is a “mathematical description of the expected values that a pavement attribute will take during a specified analysis period” (3). An attribute is a property of a pavement section or class of pavements that provides a significant measure of the behavior, performance, adequacy, cost, or value of the pavement (3). In other words, it is a mathematical description that can be used to predict future pavement deterioration based on the present pavement condition, deterioration factors, and the effect of maintenance (4).

The importance of accurate prediction of future pavement condition cannot be over-emphasized as it affects many other components of a Pavement Management System. Prediction models are indispensable for many processes of decision-making as they are useful in establishing answers to the questions of what, where, and when, with respect to maintenance actions. Simply put, the prediction models enable us to determine the type of maintenance treatment to be adopted, the portions of the network requiring treatment, and the timing of the maintenance actions. Life-cycle analysis and evaluation of rehabilitation alternatives can be performed using the prediction models. Used at network level, pavement deterioration models are helpful in planning, programming, and budgeting. Budget analyses include the following:

- Estimating the funds required to bring the total network from its current condition level to a desired condition level
- Estimating the budget required to maintain the network at specific levels of performance over multiple years
- Prioritizing projects when the available funding is less than that required to meet specific performance objectives.

Also, the ability to predict future pavement conditions can lead to the development of multi-year, network-level optimal maintenance actions. Prediction models permit increased understanding of pavement behavior so that steps can be taken to reduce the development of distress or to extend the service life of pavements. This includes an evaluation of cost-effectiveness of pavement maintenance treatments. Evaluation and refinement of design procedures are possible utilizing prediction models.

Other uses of prediction models at the network level include studies on pavement costs for different legal vehicle weights, sizes, tire pressures, and suspension systems, determination of equitable permit fees for overweight vehicles, etc. Since these network level usage predictions affect the level of taxation and fees, they form a rational basis for all public investments in highway transportation.

At the project level, prediction models are used to design pavements, to perform life-cycle cost analyses, to select optimal designs with least total costs, and in trade-off analyses in which the annualized costs of new construction, maintenance, rehabilitation, and user costs are considered for a specific pavement design. Simply put, prediction models affect a wide spectrum of services within a Pavement Management System. Better

prediction models make a better Pavement Management System, which leads to considerable cost savings (5-9).

#### **1.4 MANIFESTATION OF PAVEMENT DISTRESSES**

Typically, the deterioration of a pavement is represented by the development of distresses leading to a reduction in serviceability and/or structural breakdown of the pavement. Distress itself is a physical manifestation of damage caused to a pavement by loadings, environmental factors, etc. There are different kinds of distresses identified for various types of pavements. The Strategic Highway Research Program (SHRP)(10) lists 15 distress types for asphalt concrete surfaced pavements, sixteen for jointed concrete surfaced pavements, and fifteen for continuously reinforced concrete surfaced pavements. Relying on this, MDOT has adopted a short list of distresses, which are tabulated in reference (11). Besides being useful for condition evaluation, they play a vital role in rehabilitation selection. The decision trees for maintenance selection, developed for the MDOT, can be seen in the Appendix. Selected distresses/distress groups for each pavement type are entered in the decision tree to arrive at the appropriate rehabilitation action.

The listed distresses in the decision tree for each pavement type are briefly described:

##### **1.4.1 Asphalt Concrete Surfaced Pavement Distresses**

The asphalt concrete (ASP) surfaced pavement types include:

- original flexible pavements; i.e., asphalt pavements in their first performance period
- overlaid flexible pavements

- composite pavements; i.e., asphalt concrete overlays over Portland cement concrete pavements

For ASP pavements, cracking and rutting are the primary distresses that detract from serviceability.

Alligator Cracking. Alligator, fatigue, or map cracking is a series of interconnecting cracks caused by fatigue of asphalt concrete surface under repeated traffic loadings. Cracking begins at the bottom of the asphaltic layer where tensile stress/strain is highest under a wheel load. The cracks propagate to the surface initially as a series of parallel longitudinal cracks. Under repeated traffic they develop into many-sided, sharp-angled pieces into a pattern resembling chicken wire or the skin of an alligator. It is measured in square feet of surface area.

Other Cracks: These cracks include low severity alligator cracking, block cracking, edge cracking, longitudinal cracking, and transverse cracking (10), measured in square feet of surface area.

Rutting: A rut is a longitudinal surface depression in the wheel paths. Rutting arises from permanent deformation in any of the pavement layers or subgrade, usually caused by consolidation or lateral movement of the materials due to traffic load. Thus, densification (decrease in volume and, hence, increase in density), and shear deformation lead to rutting. It is usually measured by average depth in inches or millimeters.

#### **1.4.2 Jointed Concrete Pavement Distresses**

The distresses considered in jointed concrete pavements (JCP) are cracking and spalling.

Cracking: Cracks in jointed concrete pavements include durability or “D” cracking, longitudinal cracking, and transverse cracking. These cracks are caused by many factors,

such as loading, temperature, other environmental actions, and poor workmanship/quality of materials. The length of the cracks on a pavement are measured and recorded. The cracks are assumed to have influence on a pavement width of one foot. Accordingly, the area of pavement affected by cracks is obtained by multiplying length of cracks by one.

Spalling: Spalling is cracking, breaking, chipping, or fraying of slab edges or cracked edges. A spall usually angles downward to intersect a joint or a crack, and is caused by excessive loading caused by traffic or by infiltration of incompressible materials. It is usually measured in length and converted into the area affected.

### **1.4.3 Continuously Reinforced Concrete Pavement Distresses**

Punchouts and cracks are the major distresses considered in the decision trees for Continuously Reinforced Concrete (CRC) pavements.

Punchout: A punchout is an area enclosed by two closely spaced transverse cracks, a short longitudinal crack, and the edge of the pavement or a longitudinal joint. It also includes “Y” cracks that exhibit spalling, breaking, and faulting. This distress is caused by heavy repeated loads, inadequate slab thickness, loss of foundation support, and/or a localized concrete construction deficiency. It is recorded as number of punchouts per kilometer.

Cracks: The cracks in CRC pavements include durability, longitudinal, and transverse cracks. These are caused by loading, shrinkage, temperature effects, and other environmental factors. These cracks are measured as the area of the pavement affected.

In addition to the above-mentioned distresses, two other attributes of pavement deterioration requiring prediction models for all the three types of pavements include roughness, expressed in International Roughness Index (IRI), and a condition index, expressed in terms of Pavement Condition Rating (PCR).



Roughness: Roughness is deviations of the pavement surface from a true planar surface with characteristic dimensions that affect vehicle dynamics, ride quality, dynamic loads, and drainage. The roughness is measured in terms of IRI, which is a mathematically defined summary statistic of the longitudinal profile in the wheel path of a traveled road surface. It is defined by a mathematical simulation of a quarter car; i.e., one wheel with the associated dynamic characteristics of the suspension and sprung mass of a typical passenger car. IRI is a scale of roughness, which is zero for a true planar surface, increasing to about 6 for a moderately rough paved roads, and up to 12 for extremely rough paved roads with potholing and patching. The unit of measurement is m/km.

PCR: Pavement Condition Rating is a composite condition index developed by MDOT (12) as a function of distresses and roughness. Condition of a pavement is represented by PCR on a scale of 0 to 100, 100 representing pavement in excellent condition and 0 representing an impassable pavement.

With various distresses affecting the present and future pavement conditions, it is incumbent upon the pavement engineer to be able to forecast the magnitude/severity of those distresses, which is the driving force behind this research.

## **1.5 FEEDBACK SYSTEM**

Feedback refers to the transfer of part of the output to the input, as shown in the flow chart of Figure 1. A feedback system ensures continual feedback of information for assessing pavement system conditions, and verification/substantiation of the design standards and/or specifications. System conditions can be predicted using prediction models, and comparison with the feedback condition data provides a measure of predictive capabilities. It also provides procedures for evaluating other aspects of the highway

network, including observed life cycle costs and performance of rehabilitation treatments and of different pavement types. Identification of deleterious aggregates/materials is another area where feedback analysis can be extremely useful. In summary, a feedback system provides for measurement and evaluation of performance of the system in service.

In the context of a PMS, the on-going monitoring information is brought to bear on the initial input, making such comparisons as follows (11).

- Comparisons of actual costs of maintenance, rehabilitation, and reconstruction (available through contract bids and agency records) with those used in the PMS analysis.
- Evaluations of field observations of pavement conditions with those predicted by PMS models.
- Contrasts between actual performance standards achieved and those specified in the PMS analysis.

This report covers the development of prediction models and compilation of a feedback system. Heavy reliance is placed on historical data for developing both of these modules. That is, the main input for both subsystems is the historical database, such as condition history, pavement structure history, and deflection history, if available.

## **1.6 OBJECTIVES OF THE STUDY**

The primary objective of this study is to develop models that predict pavement performance. Two categories of models will be developed. The first category includes distress prediction models for five families of pavement: original flexible, flexible with

overlay, composite, jointed concrete, and continuously reinforced concrete. Performance such as PCR prediction models for both asphalt surfaced and concrete pavements comprise the second category. Whenever feasible, regression models are augmented with expert opinion employing Bayesian regression. A second objective is to design/develop a stand-alone feedback module to be used in the MDOT pavement management system. Three sub-modules comprising the main module, are the following:

- Load index ratio of flexible, jointed concrete and CRC pavements
- Load index ratio of overlaid flexible pavements
- Verification of distresses by comparing the actual to the predicted

## **1.7 SCOPE OF THE STUDY**

The MDOT-PMS has adopted a decision tree approach, based on distresses/distress groups, for the selection of maintenance actions. Models are sought for these distresses/distress groups and for MDOT's performance index (PCR) for both asphalt surfaced and concrete pavements. Three categories of asphalt-surfaced pavements are recognized for this purpose:

- original flexible pavements, i.e., pavements in their initial performance cycle,
- overlaid flexible pavements
- composite pavements.

Concrete pavements are classified into two groups:

- jointed concrete
- continuously reinforced concrete pavements.

As dictated by the rehabilitation selection decision trees, for each category of asphalt-surfaced pavement, six models are sought:

1. Area of alligator cracks of medium and high severity, percent
2. Area of 'other cracks' (combination of low severity alligator, block, edge, longitudinal, transverse, and reflection cracks), percent
3. Percent of medium and high severity 'other cracks' expressed as a percentage of total (low, medium, and high severity)
4. Eighty-fifth percentile rutting, mm
5. Roughness, IRI, m/km.
6. Pavement condition rating, on a scale of 0 to 100

For jointed concrete pavements, four distress models are to be developed:

1. Area of cracks (corner, D, longitudinal, and transverse cracks), percent
2. Area of spalling (longitudinal and transverse), percent
3. Roughness, IRI, m/km.
4. Pavement condition rating, on a scale of 0 to 100

The models required for continuously reinforced concrete pavements include:

1. Area of cracks (longitudinal and transverse), percent
2. Punchouts, #/km
3. Roughness, IRI, m/km.
4. Pavement condition rating, on a scale of 0 to 100

These models would become an integral part of the pavement management systems.

Current as well as future rehabilitation selection would be facilitated by the judicious use of the models discussed here. Model development entails the following specific tasks:

1. Extraction of the required data of different types in a suitable format
2. Selection of variables that affect the deterioration of pavements

3. Establishment of suitable regression models for prediction of performance as well as distresses.
4. Checking the predictive capability of the model.
5. Combining expert experience (for a few of the condition attributes) with data- models to improve the prediction capability.

The special features of the study include:

1. Data from in-service pavements (as opposed to accelerated test data) are used in model formulation.
2. SPSS software with stepwise regression capability is made use of in developing models.
3. Prediction capability of six models is enhanced by combining expert experience with condition data collected in the field.

## CHAPTER 2

### REVIEW OF LITERATURE

#### 2.1 INTRODUCTION

A regression technique is employed for modeling pavement deterioration. Relevant literature on this technique is included in Article 2.2. The following two topics are discussed with regard to regression models: requirements of regression models, and models developed in a few studies for various distresses.

#### 2.2 REGRESSION MODELS

Pavement deterioration models or prediction models express the future state of a pavement as a function of explanatory variables or causal factors. A partial list of causal factors includes: pavement structure, age, traffic loads, and environmental variables. Numerous models with those variables can be seen elsewhere (13,14,15,16).

Prediction models are classified into various categories depending on the predicted variable, method of development, and whether individual or composite attributes are predicted. A commonly used classification recognizes two types: deterministic and probabilistic. A deterministic model predicts a single value (16) of the dependent variable; e.g., level of distress, condition of pavement, life of pavement, etc. The probabilistic models on the other hand predict a distribution of the attribute; for example, mean and standard deviation.

Another classification groups the models into four categories: (1) mechanistic models, (2) empirical models, (3) mechanistic-empirical models, and (4) subjective models. Each of these models is briefly described below:

Mechanistic Models: These are derived based on purely mechanistic considerations. Purely mechanistic models exist only for such primary responses as stress,

strain, and deflection (17). Attributes such as fatigue cracking, rutting, joint faulting, etc., are so complex that mechanistic models have rarely been attempted.

Empirical Models: These models do not necessarily portray the theoretical mechanisms of the pavement response and are developed from measured/observed data. Empirical models are useful in situations where the theoretical mechanisms are not well understood.

Mechanistic-Empirical Models: These models are developed based on mechanistic responses complemented by empirical distress relations. The form of the model and the variables included are generally based on theoretical knowledge, but the coefficients are determined from regression analysis for which measured data is employed (16).

Subjective models: Here the experience is captured in a formalized or structured way; e.g., Bayesian methodology, allows utilization of both the judgments of experienced individuals and measured data to quantify mathematical models (18).

Depending on whether a single measure or a compound measure is predicted, other classifications in use are the disaggregate and aggregate models. Disaggregate models predict the evolution of an individual measure of distress. Aggregate models predict composite measures; for example, damage index, condition rating, or serviceability.

Regression analysis is a statistical methodology concerned with relating a response variable of interest, which is called the dependent or response variable, to a set of independent or explanatory variables (19). The objective is to build a regression model that will enable us to adequately *describe*, *predict*, and *control* the dependent variable on the basis of the independent variables.

Use of regression methods for model development requires that certain conditions be satisfied. Some of the common conditions are described next.

### **2.2.1 Requirements for a Reliable Regression Model**

The development of a reliable prediction model needs certain requirements to be satisfied. The requirements and general development of reliable pavement performance models are described in detail by Darter (20). The factors that must be considered include:

- *Adequate Database:* The database must be adequate and representative of the overall pavement network that the model is being developed to represent. The data collected must be measured accurately and without bias.
- *Reliable Data:* Care must be taken to assure the accuracy of the data obtained from historical records.
- *Sufficient Amount of Data:* The development of a reliable model requires the collection of a sufficient amount of data.
- *Inclusion of Variables:* Every possible variable that may affect the performance of pavement should be considered initially. This list will typically be large. However, development of best possible regression model involves extensive knowledge about the problem at hand, and of the regression analysis program.
- *Functional Form of the Model:* The functional form of the model or the way in which the variables are arranged has a great effect on the regression model's reliability.
- *Statistical Criteria:* The final model should explain a high percentage of total variation about regression (or  $R^2$ ). The standard error of the estimate should be



less than a practical value of usefulness. All estimated coefficients of the predictor variables should be statistically significant, and there should be no discernable patterns in the residuals.

- *Boundary Conditions:* The boundary conditions that the physical real-world situation dictates shall be represented as closely as possible. This necessitates a model that considers the appropriate shape, non-linearity, and interactions of variables (20). Some of the boundary conditions (16) which should be satisfied include:
  - *Initial Value:* The initial value of all damage is zero. Similarly the condition of a pavement at the beginning of its service life is excellent.
  - *Initial Slope:* Most damages have a slope that is initially zero. However, some damage types such as roughness or rutting have an initial upsurge.
  - *Overall Trend:* Most damage is irreversible and is non-decreasing, and the serviceability index is non-increasing.
  - *Variations in Slope:* Damages can be affected by variables such as changes in climatic conditions, which can lead to variations in slope.
  - *Final Slope:* Damage functions such as cracks, area of distress, and serviceability have an upper limit. In all these damage functions, the final slope must be zero, and this type of equation approaches a horizontal asymptote. By contrast, other types of damages such as roughness or rutting do not have such constraints.
  - *Final Value:* The maximum value of damage has an upper limit only for those types of distresses for which the final slope is zero.

To the extent practical, the aforementioned conditions would be adhered to in the model development, guaranteeing predictions that are rational, physically realistic, and accurate. For some models, those conditions have not been fully satisfied (21), due primarily to data limitations.

### **2.2.2 Review of Prediction Models**

Aggregate models predicting some form of condition index for pavements are widely used. Such models help in determining the overall health of the network. However, models for individual distresses such as cracks, rutting, and roughness are vital in a PMS. Models developed for important distresses similar to the ones used for maintenance strategy selection by MDOT (see Appendix), are briefly reviewed here. The review will focus on the explanatory variables used, the form of the model, and the attainable prediction capabilities. These three tasks comprise the primary model building effort.

In this article prediction models for asphalt surfaced pavements and rigid pavements are reviewed under different headings, as are the composite condition index models for all types of pavements. First, the prediction models for asphalt-surfaced pavements are considered.

#### ***2.2.2.1 Asphalt Surfaced Pavement Deterioration Models***

The distresses considered in this study for asphalt-surfaced pavements are cracks, rutting, and roughness. A few selected models for the prediction of these attributes are reviewed here.

##### ***2.2.2.1.1. Models for Prediction of Cracks.***

The prediction models for cracks in flexible pavements, in general, predict initiation of cracking, progression of cracking, or score for percent area of cracking.

Brazil UNDP Model(22): A model developed from this study predicts the number of equivalent single axles of 80 kN (18-kip) for the initiation of 1-mm-wide cracks. Initiation of cracking:

$$\text{Log}_{10}N_c = 1.205 + 5.96 \log_{10}\text{MSN} \quad (2.1)$$

$$R^2 = 0.52$$

where,  $N_c$  = the number of ESALs to first crack; and

MSN = modified structural number.

The calculation of the modified structural number (MSN) requires explanation. Structural number is defined (23) as an index number derived from an analysis of traffic, roadbed soil conditions, and a regional factor that may be converted to thickness of various flexible pavement layers through the use of suitable layer coefficients related to the type of material being used in each layer of the pavement structure. It is expressed as:

$$\text{SN} = a_1D_1 + a_2D_2m_2 + a_3D_3m_3 \quad (2.2)$$

where,  $a_i$  =  $i^{\text{th}}$  layer coefficient;

$m_i$  =  $i^{\text{th}}$  drainage coefficient; and

$D_i$  = depth of the  $i^{\text{th}}$  layer.

The contribution of subgrade to pavement load carrying capacity is considered (6) by defining a pseudo structural number for the subgrade.

$$\text{SN}_{\text{sg}} = 3.51 * \log_{10}\text{CBR} - 0.85(\log_{10}\text{CBR})^2 - 1.43 \quad (2.3)$$

where, CBR = California Bearing Ratio, %.

Now, modified structural number is determined by:

$$MSN = SN + Sn_{sg}$$

The progression of cracking is expressed in percentage area:

$$CR = -18.53 + 0.0458*B*LN + 0.000501*B*AGE*LN \quad (2.4)$$

$$R^2 = 0.64$$

where, CR = amount of cracking, in percentage area;

AGE = age of the pavement, years;

B = mean surface deflection by Benkelman beam, mm; and

LN = logarithm to base 10 of the number of cumulative equivalent axles.

The Brazil study was extended and data from other studies were combined to develop the World Bank Model described below.

HDM III Model (World Bank): Developed from a comprehensive, factorially designed database of in-service pavements, the HDM III (6) includes models for cracking, rutting, roughness, etc. The cracking models are developed for various types of surfaces of flexible pavements. Models are described here for original asphalt concrete and asphalt overlays for estimating the expected time or traffic for initiation of cracking:

Asphalt concrete original pavements:

$$Ty_{CR2} = 4.21 \exp(0.139 MSN - 17.1 YE_4/MSN^2) \quad (2.5)$$

$$TE_{CR2} = 0.0342 EHM^{-2.86} e^{-0.198 EY} \quad (2.6)$$

where,  $Ty_{CR2}$  = expected (mean) age of surfacing at initiation of narrow cracking, years;

$TE_{CR2}$  = expected (mean) cumulative traffic at initiation of narrow cracking, million ESALs;

MSN = modified structural number;

YE<sub>4</sub> = annual traffic loading, million ESALs/lane/year;

EHM = maximum tensile strain in surfacing, 10<sup>-3</sup>; and

EY = 1/(EHM<sup>4</sup> 1000 YE<sub>4</sub>), provided that EY ≤ 6.

RTIM2 MODEL (6): The model developed from the Transportation and Road Research Laboratory (TRRL) road costs study in Kenya combines cracking initiation and progression in one relationship expressed in terms of cracking plus patching, as follows:

For MSN < 4.0, C+P >= 0:

$$(C+P) = 21600 NE_s MSN^{-MSN} \quad (2.7)$$

where, (C+P) = sum of areas of cracking and patching (m<sup>2</sup>/km/lane);

MSN = modified structural number; and

NE<sub>s</sub> = cumulative traffic loadings since latest resurfacing (million ESALs);

This model in the incremental form is expressed for cracking progression as

$$\Delta(C+P) = 21600 MSN^{-MSN} \Delta NE_s \quad (2.8)$$

The occurrence of crack initiation is expressed as:

$$NCA = \max\{[4/MSN - 1][MSN^{(1+MSN)}]/72; 0\} \quad (2.9)$$

where NCA = cumulative ESALs applied during the period before crack initiation (million ESALs)

Texas Flexible Pavement Design System Model: The basic model utilized, a sigmoid curve, is a modification of the AASHO (American Association of State Highway Officials) Road Test damage function. The sigmoid, or S-shaped, curve is expected to capture the

long-term behavior of pavements (24). The assumed form of the model for alligator cracking is:

$$a = \exp (-\gamma/N)^{\beta} \quad (2.10)$$

where, a = decimal score for percent area of alligator cracking;

$$\gamma = [-0.97 + 0.039(T) + 0.0034(TI) + 0.018(d) - 0.0046(LL) + 0.0056(PI) + 0.0066(FTC)] * 10^6;$$

$$\beta = 0.14 (LL)^{1.29} (PI)^{-1.01} (FTC)^{0.21} (DMD)^{-0.39};$$

T = mean average monthly temperature - 50°F;

TI = Thornthwaite index + 50;

d = thickness of base course layer;

LL = subgrade liquid limit in percent;

PI = plasticity index of the subgrade soil, in percent;

FTC = number of annual freeze-thaw cycles;

DMD = maximum dynaflect deflection; and

N = the number of 18-kip equivalent single axle loads.

Similar models are developed for longitudinal and transverse cracking.

Rauhut, et al.(25,26) previously described the sigmoid form and proposed a relation to transform damage index (DI, a damage function) to percentage of area cracking (AC) as follows:

$$AC = 0.19 \gamma^{3.96 DI} \quad (2.11)$$

In summary, the important explanatory variables for cracking employed in these studies are cumulative ESAL, age, and structural number. Other variables used for

prediction of cracking include surface deflection, subgrade characteristics, and environmental characteristics.

2.2.2.1.2 Models for Prediction of Rutting: Rutting, caused by repeated application of traffic loading, may result from the permanent deformation of all the pavement layers. Traffic loading causes deformation when the stresses induced in the pavement materials are sufficient to cause shear displacements within the materials. Thus single loads or a few excessive loads or tire pressures, causing stresses that exceed the shear strengths of the materials, can cause plastic flow, resulting in depressions under the load. Repeated loadings at lesser load and tire pressure levels cause smaller deformations which accumulate over time and manifest as a rut if the loadings are channelized into wheel-paths. In modern pavement construction, rutting due to densification and deformation in the lower layers under traffic loading is usually minor because it is taken into account in the structural design methods, but can become significant when the pavement is weakened by water ingress (6). Indeed, rutting develops by plastic flow in bituminous surface layers if the bituminous materials are soft under high temperatures. Various models for prediction of rutting are developed based on mechanistic responses, strength of pavement, age, cumulative traffic, etc. A model based (27) on permanent strain is:

$$\log \epsilon_p = a + b \log N \text{ or } \epsilon_p = AN^b \quad (2.12)$$

where,  $\epsilon_p$  = permanent strain;

$N$  = number of load repetitions;

$a$  &  $b$  = experimentally determined factors; and

$A$  = antilog of “ $a$ ”.

HDM Model(6): Mean rut depth:

$$RDM = t^{0.166} MSN^{-0.502} COMP^{-2.30} NE_4^{ERM} \quad (2.13)$$

$$R^2 = 0.42, SEE = 1.71 \text{ mm}, N = 2546$$

$$\text{where, } ERM = 0.0902 + 0.0384 DEF - 0.009 RH + 0.00158 MMP A_{crx} \quad (2.14)$$

RDM = mean rut depth in both wheel paths, mm;

t = age of pavement since rehabilitation or construction, year;

MSN = modified structural number;

COMP = compaction index of flexible pavements, fraction;

$NE_4(t)$  = cumulative traffic loading at time t, million ESAL;

DEF = mean peak Benkelman beam deflection under 80 kN standard axle load of both wheel paths, mm;

RH = rehabilitation state (=1 if pavement overlay, =0 otherwise);

MMP = mean monthly precipitation, mm per month; and

$A_{crx}$  = area of indexed cracking, percent of total surfacing area.

Texas Transportation Model(24): The model form is identical to that for alligator cracking (see Equation 2.10)

$$s = \exp(-\beta/N)^\beta \quad (2.15)$$

where, s = decimal severity score for rutting;

$$\beta = [3.24 - 4.89(DMD) + 0.083(T) - 0.030(TI)] * 10^6;$$

$$\beta = 0.39 (PI)^{-0.63} (DMD)^{0.54} (T)^{1.02}; \text{ and}$$

N = the number of 18-kip (80 KN) ESALs.



Rutting, as can be seen from the above models, is predominantly affected by traffic, structural number, deflection, and subgrade characteristics.

2.2.2.1.3 Models for Prediction of Roughness: Roughness has an important bearing on the performance of a pavement. Most of the roughness prediction models developed are for flexible pavements, with some of them for unpaved roads. The models for paved roads are briefly reviewed.

The AASHO Road Test (28) quantified the effects of pavement strength and traffic loading on road roughness. Roughness models from the Transportation and Road Research Laboratory (TRRL) study also show strong effects of pavement strength and traffic loading (29).

TRRL Model:

$$R_t = R_0 + s(S) N_t \quad (2.16)$$

where,  $s(S)$  = function of modified structural number;

$R_0, R_t$  = roughness at time  $t=0$ , and at  $t$ , respectively; and

$N_t$  = cumulative number of equivalent 80 kN standard axle loads to time  $t$ .

Arizona Model(30):

$$R_i = C_0 + C_1 + C_2 T^2 \quad (2.17)$$

where,  $R_i$  = roughness for homogeneous section (in/mile)

$T$  = years since the treatment, and

$C_0, C_1$  and  $C_2$  = regression coefficients.

The study indicated that  $C_2$  coefficient was not significant, and hence roughness showed a linear relationship with time.

Brazil-Study Model: Empirical relationships were developed from an extensive database from the Brazil-UNDP (22) study for predicting roughness in terms of Quarter Car Index (QI):

$$\begin{aligned} \text{QI} = & 12.63 - 5.16\text{RH} + 3.31\text{ST} + 0.393\text{AGE} + 8.66(\text{LN}/\text{MSN}) + \\ & 7.17 \times 10^{-5}(\text{B} \times \text{LN})^2 \end{aligned} \quad (2.18)$$

$R^2 = 0.52$ ,  $\text{SEE} = 10.22$  counts/km.

where, RH = state of rehabilitation, dummy variable:

=0 as constructed,

=1 overlaid;

ST = surface type dummy variable:

=0 asphaltic concrete

=1 surface treatment;

AGE = number of years since construction or overlay;

LN =  $\log_{10}$  of cumulative equivalent axles;

MSN = modified structural number; and

B = Benkelman beam deflection, (0.01 mm).

Alberta Riding Comfort Index: A recursive model was developed (31) to predict riding comfort index, a roughness measure determined by the Portland Cement Association roadmeter. Among the many variables considered, such as traffic, climatic zone, subgrade soil type, and others, only pavement age, AGE, and  $\text{RCI}_B$  (previous riding comfort index) were found to be statistically significant. The equation is:

$$\begin{aligned}
RCI = & -5.998 + 6.870 \cdot \text{LOG}_7(RCI_B) - 0.162 \cdot \text{LOG}_7(AGE^2 + 1) \\
& + 0.185 \cdot AGE - 0.084 \cdot AGE \cdot \text{LOG}_7(RCI_B) \\
& - 0.093 \cdot ? AGE
\end{aligned} \tag{2.19}$$

$$R_2 = 0.84, \text{SEE} = 0.38$$

where, RCI = Riding Comfort Index (state of 0 to 10) at any AGE;

$RCI_B$  = previous RCI;

AGE = age in years; and

? AGE = 4 years.

Summarizing, the literature indicates that the most important variables employed in estimating roughness are age, and traffic (cumulative ESALs).

#### 2.2.2.2 Rigid Pavement Deterioration Models

The literature reveals that studies to develop rigid pavement deterioration models are not as extensive as for flexible pavements. The COPES (14) study was the first comprehensive study in this area. Separate models were developed for jointed plain concrete and jointed reinforced concrete pavements. The distresses predicted include: pumping, joint faulting, joint deterioration, slab cracking, and Present Serviceability Rating (PSR). ‘National’ models (14) were developed using COPES database, compiled from six states and other studies. The model to predict the slab cracking of jointed plain concrete pavements follows:

$$\begin{aligned}
\text{CRACKS} = & \text{ESAL}^{2.755} [3092.4(1-\text{SOILCRS})\text{RATIO}^{10}] \\
& + \text{ESAL}^{0.5} (1.233 \text{ TRANGE}^{2.0} \text{RATIO}^{2.868}) \\
& + \text{ESAL}^{2.416} (0.2296\text{FI}^{1.53} \text{RATIO}^{7.31})
\end{aligned} \tag{2.20}$$

$$R_2 = 0.69, \text{ SEE} = 176 \text{ ft/mile}, \text{ N} = 303$$

where, CRACKS = total length of cracking of all severities, ft/lane mile;

ESAL = accumulated 18-kip equivalent single-axle loads, millions;

SOILCRS = 0, if subgrade is fine-grained; 1, if subgrade is coarse grained;

RATIO = Westergaard's edge stress/modulus of rupture (stress computed under a 9- kip wheel load);

FI = freezing index; and

TRANGE = difference between average maximum temperature in July and average minimum temperature in January.

A different model for jointed reinforced concrete was developed:

$$\begin{aligned} \text{CRACKS} = & \text{ESAL}^{0.897} [7130.0 \text{ JTSPACE} / (\text{ASTEEL} * \text{THICK}^{5.0})] \\ & + \text{ESAL}^{0.10} (2.281 \text{ PUMP}^{5.0}) + \text{ESAL}^{2.16} [1.81 / (\text{BASETYP} + 1)] \\ & + \text{AGE}^{1.3} [0.0036(\text{FI} + 1)^{0.36}] \end{aligned} \quad (2.21)$$

$$R^2 = 0.41, \text{ SEE} = 280 \text{ ft/mile}, \text{ n} = 314$$

where CRACKS = total length of medium- and high-severity deteriorated

temperature and shrinkage cracks, ft/mile;

ESAL = accumulated 18-kip equivalent single-axle loads, millions;

JTSPACE = transverse joint spacing, ft;

ASTEEL = area of reinforcing steel, in<sup>2</sup>/ft width;

THICK = slab thickness, in;

PUMP = 0, if no pumping exists; 1, low severity; 2, medium severity; 3 high severity;

BASETYP = 0, if granular base; 1, if stabilized base (cement,

asphalt, etc.);

AGE = time since construction, years (indicator of cycles of cold and warm

temperatures stressing reinforcing steel); and

FI = freezing index.

Texas Models for Distresses in CRCP: The Texas models (32) make use of age as the only explanatory variable to predict distresses in continuously reinforced concrete pavements. Developed using a database containing 20 years of historical condition survey data, the models predict punchouts (minor and severe), patches (asphalt and Portland cement concrete), crack spacing, loss of ride quality, and spalling. A generalized sigmoidal function, specified by Texas Department of Transportation, is adopted for predicting the distresses:

$$D = a \exp(-(\beta/N)^s) \quad (2.22)$$

where, D = predicted level of distress;

N = age of the pavement;

a,  $\beta$  and  $\beta$  = shape parameters estimated by regression;

$\beta$  = a factor to adjust for traffic;

e = a factor to adjust for environment; and

s = a factor to adjust for pavement structure.

For the purpose of analysis  $\beta$ , e, and s were fixed at 1.0, due to a lack of required data.

The resulting model form is the same as Equation 2.10.

Different models are used to predict minor punchouts and severe punchouts. a,  $\beta$  and  $\beta$  for prediction of minor punchouts are 82.9, 1.33, and 18.6, respectively. For

prediction of severe punchouts the corresponding values are 35, 0.57, and 144, respectively.

Crack spacing is the dependent variable in the crack prediction model. Separate equations are developed for CRC pavements with siliceous river gravel aggregate, and limestone aggregate. The values of parameters  $a$ ,  $\beta$  and  $\gamma$  for CRCP with siliceous gravel are, respectively 34.9, 1.00, and 0.06; while those for CRCP with limestone are 19.79, 1.06, and 0.05.

The loss of smoothness is molded in this study as Normalized Serviceability Loss (NSL):

$$NSL = (4.5 - PSI) / 4.5 \quad (2.23)$$

Where PSI is the Present Serviceability Index. NSL ranges from 0 ( $PSI \geq 4.5$ ) to 1 ( $PSI = 0$ ). For example, if the PSI of a section is 3.5, then the section is assumed to have lost 1 Serviceability Index (SI) unit of ride quality, giving an NSL of 0.22. This means that the section has lost 22 percent of its initial smoothness.

### **2.2.2.3 Models for prediction of Composite Condition Index**

A composite condition index indicates the overall condition of a pavement. In general, it is a function of surface distress or roughness or both, and measures indices of damage, condition or serviceability. Different indices are used by various agencies to indicate the condition of pavement. Starting from the AASHO Road Test (28) when the concept of serviceability was proposed, many models have been developed to predict the condition index of a pavement. The Present Serviceability Index (PSI) developed from the AASHO Road test is a function of slope variance (a measure of roughness), average rut depth, and area of cracking and patching.

AASHO PSI Model: In conjunction with the AASHO Road Test, a road user definition of pavement failure was introduced. For flexible pavements, the model for serviceability in terms of PSI follows:

$$PSI = 5.03 - 1.91 \log(1+SV) - 1.38 (RD)^2 - 0.01 (C+P)^{0.5} \quad (2.24)$$

where,  $SV$  = slope variance;

$RD$  = average rut depth; and

$C+P$  = area of cracking plus patching per 1000 ft<sup>2</sup>.

PENNDOT Performance Prediction Model: PENNDOT model (29) is developed to estimate PSI of reinforced concrete pavements, solely as a function of pavement age. The equation presented in a linear form is,

$$PSI = 4.24 - 0.0420(AGE) \quad (2.25)$$

where,  $PSI$  = the mean PSI predicted for concrete pavements with joint spacing of 61.5 ft; and

$AGE$  = the age of the pavements in years.

State of Washington Model: The Pavement Condition Rating (PCR), a measure of pavement surface distress (ranges from 100-no distress, to 0-extensive distress), is predicted (29) as a function of two variables—age, and ESAL or thickness of overlay (THICK). The equations for asphalt concrete (new or reconstruction) and asphalt concrete overlay are, respectively:

$$PCR = 100 - 3.08 (AGE) - 1.4 \times 10^{-6} (ESAL) \quad (2.26)$$

$$PCR = 95.1 - 4.51 (AGE) + 2.69(THICK) \quad (2.27)$$

Mississippi PCR Models: Pavement Condition Rating (PCR), a performance indicator developed for MDOT (33) is a function of distresses and roughness. PCR, on a scale of 0-

100, is a function of age, traffic, and structural number or thickness of overlay. The equations for flexible pavements with no overlay, those with overlay, and composite pavements are, respectively:

$$PCR = 90 - a[\exp(AGE^b)-1] \log[ESAL/MSN^c] \quad (2.28)$$

$$PCR = 90 - a[\exp(AGE^b)-1] \log[ESAL/MSN^c] \quad (2.29)$$

$$PCR = 90 - a[\exp(AGE/T)^b-1] \log(ESAL) \quad (2.30)$$

where, AGE = time in years since last construction;

ESAL = yearly 18-kip single axle load;

T = thickness of asphalt concrete surface for composite pavements;

MSN = modified structural number; and

a,b,c = regression constants.

Uzan and Lytton Model: A model for PSI (34), similar to the one developed from the AASHO Road test follows:

$$\begin{aligned} PSI = & 4.436 - 1.686 \log_{10}(1+350 \text{ Var}(\text{RD})) - 0.881 \text{ RD}^{2.5} \\ & - 0.031(\text{C}+\text{P})^{0.5} \end{aligned} \quad (2.31)$$

$$R^2 = 0.80$$

where, RD = average rut depth; and

C+P = area of cracking plus patching per 1000 ft<sup>2</sup>.

Here the intercept coefficient (4.436) is very close to the average value of the pavement serviceability after construction (34).



HPMS Models: Models to predict Present Serviceability Rating (PSR) are developed using data from HPMS (Highway Performance Monitoring System) databases and other databases. The model (35) has existing pavement structure (e.g. SN), age, and cumulative ESAL, as predictor variables. Five types of pavements are recognized:

Flexible Pavement Models:

$$\begin{aligned}\log_{10}(4.5\text{-PSR}) = & 1.1550 - 1.8720*\log_{10}\text{SN} + 0.3499*\log_{10}\text{AGE} \\ & + 0.3385*\log_{10}\text{CESAL}\end{aligned}\quad (2.32)$$

$$R^2 = 0.52, \text{SEE} = 0.45, N = 522$$

Composite Pavement Model:

$$\begin{aligned}\log_{10}(4.5\text{-PSR}) = & -0.4185 - 0.1458*\log_{10}\text{OLTHK} + 0.5732*\log_{10}\text{AGE} \\ & + 0.1431*\log_{10}\text{CESAL}\end{aligned}\quad (2.33)$$

$$R^2 = 0.58, \text{SEE} = 0.38, N = 509$$

Jointed Plain Concrete Pavement Model:

$$\begin{aligned}\text{Log}_{10}(4.5\text{-PSR}) = & 0.5104 - 1.770*\log_{10}\text{THICK} + 1.0713*\log_{10}\text{AGE} \\ & + 0.2493*\log_{10}\text{CESAL}\end{aligned}\quad (2.34)$$

$$R^2 = 0.79, \text{SEE} = 0.26, N = 117$$

Jointed Reinforced Concrete Pavement Model:

$$\begin{aligned}\text{Log}_{10}(4.5\text{-PSR}) = & 1.7241 - 2.7359*\log_{10}\text{THICK} + 0.3800*\log_{10}\text{AGE} \\ & + 0.6212*\log_{10}\text{CESAL}\end{aligned}\quad (2.35)$$

$$R^2 = 0.57, \text{SEE} = 0.40, N = 254$$

Continuously Reinforced Concrete Pavement Model:

$$\begin{aligned}\text{Log}_{10}(4.5\text{-PSR}) = & 0.7900 - 1.312*\log_{10}\text{THICK} + 0.1849*\log_{10}\text{AGE} \\ & + 0.2634*\log_{10}\text{CESAL}\end{aligned}\quad (2.36)$$

$$R^2 = 0.37, SEE = 0.31, N = 1204$$

where,  $PSR_i$  = initial value of PSR at construction (4.5 used in the analysis);

STR = existing pavement structure as follows:

1. THICK, slab thickness for concrete pavements, inches
2. SN, structural number for flexible pavements,
3. OLTHK, total asphalt concrete overlay thickness for composite pavements, inches.

AGE = age of pavement since construction or since major rehabilitation (overlay), years; and

CESAL = cumulative 18-kip ESAL applied to the pavement (in the heavily trafficked lane), millions.

Damage Index Model: The Texas Transportation Department employs a sigmoidal (S-shaped) curve, a shape that appears to reproduce long term pavement performance data (24), in modeling. Note this equation form is analogous to Equation 10.

$$g = \exp(-(\lambda/N)^\beta) \quad (2.37)$$

where,  $g$  = damage =  $(P_i - P)/(P_i - P_f)$ ;

$\lambda$  = a constant which equals the number of 18-kip equivalent single axle loads when  $g=1$ ;

$\beta$  = a power which dictates the curvature of the damage function;

$P_i$  = initial serviceability index;

$P$  = present serviceability index; and

$P_f$  = asymptote serviceability index.

South Carolina and Tennessee Models: Both agencies use identical form, with different model coefficients (36):

$$PSI = PSI_0 - \exp(a-b*c^t) \quad (2.38)$$

where, PSI = predicted PSI;

$PSI_0$  = PSI at age = 0 (t=0);

t =  $\log_e(1/AGE)$ ; and

a,b,c = model coefficients.

COPES Model: COPES (14) model makes use of age, traffic, distress, and environmental factors to predict the Present Serviceability Rating (PSR). The models for jointed concrete pavements follows:

Jointed Plain Concrete Pavement:

$$\begin{aligned} PSR = 4.5 - 1.486*ESAL^{0.1467} + 0.4963*ESAL^{0.265}*RATIO^{-0.5} \\ - 0.01082*ESAL^{0.644}*(SUMPREC^{0.91}/AVGMT^{1.07}) \\ *AGE^{0.525} \end{aligned} \quad (2.39)$$

$$R^2 = 0.69, SEE = 0.25, N = 316$$

Jointed Reinforced Concrete Pavement:

$$\begin{aligned} PSR = 4.5 - ESAL^{0.424} - (1.88*10^{-3} + 14.417 RATIO^{3.58} + 0.0399 PUMP \\ + 0.0021528 JTSPACE + 0.1146 DCRACK \\ + 0.05903 REACTAG + 4.156E-5 FI + 0.00163 SUMPREC \\ - 0.070535 BASETYP) \end{aligned} \quad (2.40)$$

where, PSR = present serviceability rating;

ESAL = accumulated 18-kip equivalent single-axle loads, millions;

RATIO = Westergaard's edge stress/modulus of rupture;

SUMPREC = average annual precipitation, cm;

AVGMT = average monthly temperature, degrees C;

AGE = time since construction, years;

PUMP = 0, is none or low pumping; 1, if medium or high pumping;

JTSPACE = transverse joint spacing, ft;

DCRACK = 0, if no “D” cracking exists, 1, if “D” cracking exists;

REACTAG = 0, if no reactive aggregate exists; 1, if reactive aggregate exists;

FI = freezing index; and

BASETYP = 0, if granular base; 1, if stabilized base (asphalt, cement, etc.).

CRS Models for Illinois Interstate Highway System: The pavement condition indicator used for the Illinois Interstate Highway system (37) is designated as Condition Survey Rating System (CRS). Pavements are rated on a 1 to 9 scale on the basis of distresses observed. The best rating of 9 is assigned to a newly constructed or resurfaced pavement. Prediction models are developed for JRCP, CRCP, and asphalt concrete overlay of JRCP (JROL) and CRCP (CROL). The following functional form of the model is assumed:

$$CRS = 9 - 2*a*THICK^b.AGE^c.CESAL^d \quad (2.41)$$

The equation is expressed in the linear form by logarithmic translation and solved. The variables are:

CRS = panel condition survey rating (1 to 9);

THICK = slab thickness for JRCP or CRCP and overlay thickness for AC overlay;

AGE = years since construction or overlay;

CESAL = accumulated million ESALs in outer lane since construction or overlay;

a,b,c,d = constants for each pavement type.

The review indicates that composite condition index models assume varying complexity: a simple model involving only age to that involving many such factors as roughness, traffic, structure of pavement, to name the important ones. Age is a common explanatory variable in most of the models. The other important variables include structural number/thickness of overlay or slab and traffic. A few models make use of distresses for prediction of composite index.

#### **2.2.2.4 Other Model Types**

Recursive Model: Another type of model to predict distress or condition index is the incremental, or in its purest sense, derivative model(6). It not only permits the prediction of future deterioration as a function of time, imposed traffic, structural, and environmental conditions, but also employs the current condition of pavement. This property is advantageous, since the distress/condition of the pavement can be utilized as data become available from condition surveys. The form of the model can be expressed as:

? (future deterioration over incremental time) = f (current condition, traffic, strength, environment, maintenance) (2.42)

The generally slow rate of deterioration of pavements, however, means that the changes of condition observed in empirical deterioration studies are usually small, and

very sensitive to measurement error. Such models also require extensive time-series data. Therefore, incremental models are not attempted here.

All the models described above are deterministic models. However, probabilistic models are also attempted in a few studies. Markov models and survivor curves are examples of probabilistic models. The principles involved in the development of these models are briefly discussed.

Markov Model: A Markov model employs a transition matrix that expresses the probability that a group of pavements of similar age or level of traffic will move from one state of distress or serviceability to another within a specified time period. The Markov process describes a probable “before” and “after” condition of the pavement. The before condition is described by probabilities that the pavement will be found in each of the assumed finite number of states. The after condition is described in a similar manner. With appropriate data, Markov transition matrices can be constructed for any mode of pavement deterioration, for example, cracks, punchouts, and serviceability.

Survivor Curves: A survivor curve is a function indicating the probability of survival of pavements with time or traffic. The probability drops off from a value of 1.0 down to zero, and expresses the percentage of pavements that remain in service after a number of years or passes of traffic load without requiring major maintenance or rehabilitation. The slope of the survivor curve is the probability density of survival. Survivor curves are developed from historical data of pavements and are useful in planning maintenance and rehabilitation alternatives on pavement networks.

Probabilistic models are not attempted in this study and, therefore, will not be discussed further. Another relatively novel approach for formulating prediction

algorithms, namely Bayesian regression modeling, is briefly discussed in the ensuing section.

### **2.2.3 Bayesian Regression**

An emerging technique for performance modeling is to incorporate expert opinion in the observed data. Use of expert opinion falls generally into two categories: First, when performance data is lacking expert opinion is sought and used as a surrogate for observations. Second, expert opinion is employed in Bayesian regression, which explicitly allows expert judgment collected from in-house or external experts to complement the “poor quality” data for model building. Bayesian statistics were developed specifically to cope with small and noisy sample data by providing a structured way to introduce prior information into the regression analysis. Given certain constrained assumptions, Bayesian regression develops a statistically optimal posterior multivariate regression model based on a defined prior and field models (38).

In summary, the survey of literature indicates that many different types of regression models are developed for the prediction of pavement distresses. They include disaggregate models for prediction of cracks, rutting, punchouts, etc. Aggregate models, encompassing pavement condition index/rating, are reviewed as well. Finally, Bayesian regression analysis, which includes a detailed analysis of the prior, a classical regression of the data, is included in this chapter. Prior to attempting the models, a brief discussion of the database employed is presented.

## **CHAPTER 3**

### **PMS DATABASE AND DATA FOR MODELING**

#### **3.1 INTRODUCTION**

A comprehensive database is a major component/module of a pavement management system, which serves as the basis of analyses for maintenance work programs including prediction models. The MDOT PMS database comprises the information on the network, with data on more than 12,000 two-lane miles.

For the purpose of collecting data, the road network is partitioned into 'homogeneous sections'. A homogeneous section can be defined (14) as a section of pavement that has along its length uniform characteristics, for example, structural design, joint and reinforcement design, number of lanes, subgrade condition, construction (by the same contract), age since opening for service, pavement materials, proportion of truck traffic, and maintenance applied. An identification code (SECIDNUM-section identification number) is adopted to describe each homogeneous section. It is a unique combination of the following attributes: route number, county number, direction of survey (N, S, E, or W), and beginning accumulated log mile. For each homogeneous section the following classes of data are available in MDOT-PMS:

- inventory
- geometry
- construction
- history including maintenance
- traffic
- condition



The database is the central feature of a pavement management system as seen in Figure 1.1, and forms a foundation for a successful PMS.

These diverse items of information are needed for fully describing a pavement section, conducting various analyses related to PMS, and establishing links between different modules of the PMS. Easy accessibility is also paramount, for which it is necessary to utilize a versatile database. FOXPRO software is adopted by MDOT-PMS.

### **3.2 DESCRIPTION OF DATABASE**

For ease of access, handling, and storage, the basic pavement data is stored in five main databases. The database names and brief descriptions follow:

TESTDATA.DBF: Describing the inventory data, which are the physical features of the pavement sections, this database includes the route number, name of the county in which it is located, direction of travel, beginning accumulated log mile, ending accumulated log mile, length of the section, type of pavement surface, classification of road according to HPMS functional class, number of lanes, and width of lanes.

TESTORGM.DBF: The details of pavement construction are stored in this database. Included in the database are depth of each layer, type of material used in each layer, subgrade type, and year of construction, among others.

OVERLAY.DBF: Historic data of maintenance data is stored here, which includes the year of maintenance, various details of type of maintenance, and overlay, if any. This chronological data is necessary to take into account the effect of maintenance actions, improvement in conditions due to overlay, etc.

TRAFFIC.DBF: Traffic database contains the details of traffic for each section, such as average daily traffic (ADT), percentage of trucks in the traffic mix, and traffic

growth rate.

RATING.DBF: Included in this database are electronic data such as rutting, IRI and faulting, and the PCR values calculated from the condition data. Also included are the percentage lengths of each section with low, medium, and high severity levels of rutting as well as 85<sup>th</sup> percentile rutting.

Environmental conditions are considered to be uniform throughout Mississippi. Consequently, environmental data is not collected.

Apart from the data stored in the above-mentioned basic databases, condition data which is voluminous in nature is stored in many other database files. Storing them in different database files yields many advantages such as ease of identification, management, analysis, and storage. Physical distresses form the main condition data. The other condition data collected are roughness and rutting (in the case of asphalt surfaced pavements). A brief description of physical distresses, roughness, and rutting are included.

Physical Distresses: Physical distresses, collected as a part of condition data, appear in pavements over a period of time, due to different mechanisms. The SHRP-LTPP Distress Identification Manual (10) describes the distresses which occur in each pavement type. It recognizes 15 distress types for asphalt surfaced pavements, 16 for jointed concrete pavements, and 15 for continuously reinforced concrete pavements. These distresses are listed in Table 3.1.

For the purpose of data collection, each highway is partitioned into homogeneous sections. A 'video inspection vehicle' is used in collecting distress data. Instruments for measuring roughness and rutting are mounted on the same vehicle along with five high resolution electronic color cameras for the distress survey. Video-photographs of the

pavement surface are taken with the vehicle moving at normal highway speeds. These video-photographs are projected onto a computer-screen in the office and distress type, severity, and extent are manually recorded using SHRP-LTPP distress identification manual (10). To suit the conditions of Mississippi, MDOT has made minor changes in describing the severity levels of some distresses as documented in reference (11).

Though the distress survey covers 100% of the homogeneous section, only two samples of 500 feet per mile are examined in detail for distresses. In the case of sections that are less than ½ a mile in length, the entire section is evaluated.

Roughness: The roughness data is collected using South Dakota type profilometer (11). It consists of a linear accelerometer and a non-contact laser device mounted on a standard van and controlled by an on-board microcomputer measuring roughness at normal highway speeds. Profilometer measurements taken every 10 inches are compiled, and the IRI in m/km for the entire length of each homogeneous section is provided as output.

Rutting: Rutting, collected as a part of the condition data, is the longitudinal depression in the wheel paths. It is measured by a rut bar with three laser sensors. The software records the following severity levels as proposed for rutting by MDOT:

Low severity      > 6.4mm (1/4 inch) <= 12.8mm (1/2 inch)

Moderate severity > 12.8 (1/2 inch) <= 25.4mm (1 inch)

High severity      > 25.4mm (1 inch)

Employing the above-mentioned severity levels, the percentage of length of the section in each category is recorded.

**Table 3.1. Distresses in Different Types of Pavements (Adapted from SHRP LTPP(10))**

<b>Asphalt Concrete Surfaced Pavement distress types</b>	<b>Jointed Concrete Pavement distress types</b>	<b>Continuously Reinforced Concrete Pavement distress types</b>
Alligator Cracking	Corner Breaks	Durability Cracking
Block Cracking	Durability Cracking	Longitudinal Cracking
Edge Cracking	Longitudinal Cracking	Transverse Cracking
Longitudinal Cracking	Transverse Cracking	Map Cracking and Scaling
Reflection Cracking	Joint Seal Damage	Polished Aggregate
Transverse Cracking	Spalling of Longitudinal Joints	Popouts
Patch/Patch Deterioration	Spalling of Transverse Joints	Blowups
Potholes	Map Cracking and Scaling	Water Bleeding and Pumping
Rutting	Polished Aggregate	Lane-to-Shoulder Dropoff
Shoving	Popouts	Lane-to-Shoulder Separation
Bleeding	Blowups	Patch/Patch Deterioration
Polished Aggregate	Faulting	Punchouts
Raveling	Lane-to-Shoulder Dropoff	
Lane-to-Shoulder Dropoff	Lane-to-Shoulder Separation	
Water Bleeding and Pumping	Patch/Patch Deterioration	
	Water Bleeding and Pumping	

Composite Condition Index: Based on the physical distresses, rutting, faulting, and roughness data, a composite condition index called Pavement Condition Rating is calculated and stored in the database. Pavement Condition Rating (PCR) (11) is a rater's assessment on a scale of 0 to 100, of the serviceability of a pavement with respect to quality of ride, surface defects, pavement deformation, cracking distress and maintenance patches. PCR, as used by MDOT, is an objective statistic determined by combining ride

quality and distress manifestations. The ride quality or roughness rating is obtained from road roughness measurements, while the distress rating employs severity, extent, and type of distress. Deduct values, much like weighting factors, are introduced to signify the magnitude of the effect that each particular distress type, severity, and extent combination has on pavement condition. Continuous deduct point curves/equations are developed (12) for each distress type. Finally, the roughness rating and distress rating are combined to yield PCR using the formula:

$$PCR = 100((12-IRI)/12))^a ((DP_{max} - DP)/DP_{max}))^b \quad (3.1)$$

where, IRI = road roughness, m/km;

$DP_{max}$  = probable maximum deduct points with 205, 230, 185, and 145,

respectively for flexible, composite, jointed, and continuously reinforced concrete pavements;

DP = total deduct points for a pavement section;

a = 0.9567 for flexible, jointed concrete, and continuously reinforced concrete pavements; and 1.11 for composite pavements; and

b = 1.4857 for flexible, jointed concrete, and continuously reinforced concrete pavements; and 1.5429 for composite pavements.

The distress attributes from a maintenance point of view, and the factors affecting those attributes are identified from among the various available details of a pavement in the database. Selected from this voluminous database are the required dependent (response) and independent (explanatory) variables required for performance modeling. For performance modeling, a pavement family approach is employed in this study.

### **3.3 PAVEMENT FAMILY APPROACH**

The behavior of different types of pavements or even individual pavements within a given type is different. This would entail developing a model for each pavement unit, otherwise known as site-specific models. Time series data over a long period would be needed for site-specific models. By necessity, therefore, a ‘pavement family’ approach is adopted in this study, wherein pavements with similar surface characteristics and/or deterioration are grouped together into ‘families’ or groups (13,39,41). Grouping pavements into families differs from agency to agency. In consultation with the MDOT personnel, the pavement sections in the statewide network are grouped into the following families or groups:

- original flexible pavements
- overlaid flexible pavements
- composite pavements
- jointed concrete pavements
- continuously reinforced concrete pavements.

A brief description of each of these groups with special reference to the predominant distresses is presented.

Original Flexible Pavements: These are the flexible pavements that are in their first performance period. The development of distresses in these pavements, therefore, is not influenced by the pre-existing cracks.

Overlaid Flexible Pavements: Rehabilitated flexible pavements are those that are overlaid at least once. They form a different group owing to factors which affect the development of distresses. With one or more layers having undergone deterioration/cracking, they become active in reflecting these distresses in the overlaid

layer unless special provisions are made to arrest the development. Also, if the overlay is not adequately bonded to the original surface, the tendency to develop low temperature cracks would be greater. Another difference lies in the fact that the original pavement structure may have undergone substantial rutting during its “lifetime,” therefore, the overlay would be susceptible to further rutting.

Composite Pavements: These pavements possess characteristics derived from both flexible and rigid pavements, because they are rigid pavements with asphalt overlay. The structural capacity realized is due to load dispersion in the asphaltic overlay and slab action of the concrete slab. Some of the distresses are unique to this kind of pavement, for example, joint reflection cracking.

Jointed Concrete Pavements: These consist of concrete slabs typically 15 to 60 feet long. Because of the joints, shrinkage related cracks are minimal. But joint-related distresses are to be reckoned with in these pavements.

Continuously Reinforced Concrete Pavements: Continuously reinforced concrete pavements consist of slabs typically hundreds of feet long. They are provided with reinforcement to hold tight the cracks that develop. Thus, cracks are allowed to develop, but are kept intact. Punchout is a distress in this type of pavement. Because of fewer joints per unit length, the rate of increase in roughness is generally lower than that of jointed concrete pavements.

Once the pavement families are identified and the sections grouped accordingly, the data for homogeneous PMS sections are compiled. A distinction was made between response and explanatory variables when compiling the data.

### **3.4 RESPONSE VARIABLES**

The response variables identified in Chapter 1 are extracted from the PMS database. For this purpose and other PMS analyses requirements, the data from the condition survey is summarized to yield distress type, severity, and extent. The condition data analysis yields two reports, The Sample Summary Report, and The Section Summary Report. The sample summary report summarizes the distress type, severity, and extent found in each sample, generally 500 feet in length. The data of several samples is extrapolated to the whole section to produce the section summary report. Mandated by the MDOT PMS, models are required for individual distresses and distress groups as well. Referred to as response variables, they are briefly described in the following section.

#### **3.4.1 Response Variables in Asphalt Surfaced Pavements**

Original flexible pavements, rehabilitated flexible pavements, and composite pavements make up the asphalt-surfaced pavement group. For asphalt-surfaced pavements, alligator cracking of medium and high severity is combined to form a single attribute. The second distress group comprises alligator cracking of low severity and all other cracks of all severities; i.e., block, edge, longitudinal, transverse, and reflection cracks, and is referred to as ‘other cracks.’ Medium and high severity other cracks expressed as a percentage of ‘other cracks’ of all severities constitute the third group. The other three attributes, i.e., roughness, PCR, and rutting complete the list of response variables. The calculation of the 85<sup>th</sup> percentile rutting needs some explanation. Eighty-fifth percentile rutting is a required input in the strategy selection tree, sketched in Appendix A. Available from the PMS database are the percent lengths of the section exhibiting low severity 6.4 to 12.8mm (0.25 to 0.5 inch), medium severity 12.8 to 25.4mm (0.5 to 1.0 inch), and high severity >25.4mm (>1.0 inch) rutting. The 85<sup>th</sup> percentile rutting is now obtained by



interpolation. To illustrate, consider a section exhibiting rut depths of low, medium, and high severity over 30% and 10% of the length. This is indicated schematically in Figure 3.1. From the diagram it is seen that 85<sup>th</sup> percentile rutting is between 12.8 and 25.4mm (0.5 and 1 inch). By linear interpolation between 12.8 and 25.4mm (0.5 and 1.0 inch), 85<sup>th</sup> percentile rutting is calculated to be 22.9mm (0.9 inch). Since the field data does not include the maximum rut depth in a section, for calculation purposes, a probable maximum rut depth of 31.8mm (1.25) inch is used in the routine used to calculate 85<sup>th</sup> percentile rutting.

### **3.4.2 Response Variables in Jointed Concrete Pavements**

The distresses considered in maintenance strategy selection for jointed concrete pavements are cracks and spalling. The cracks (corner, durability, longitudinal, and transverse) include all three severities with the extent expressed as the percentage affected area of section (length of cracks multiplied by 1 foot). The other distress of importance, spalling of longitudinal and transverse joints, is also expressed as percentage area affected. Roughness, directly available in the database, is the third variable that enters the maintenance decision tree.

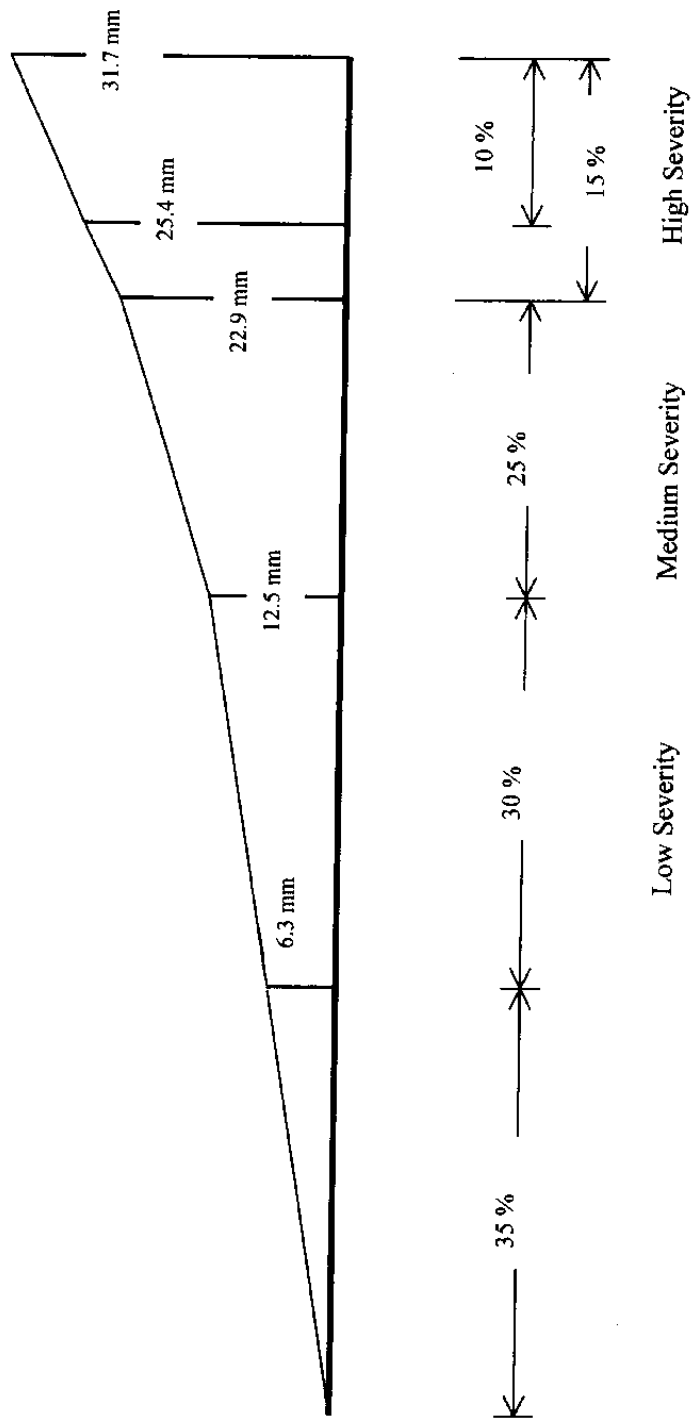


FIGURE 3.1 Determination of 85<sup>th</sup> percentile rutting.

### **3.4.3 Response Variables in Continuously Reinforced Concrete Pavements**

Punchout is considered the most severe form of all the distresses in continuously reinforced concrete pavements, expressed as the number of punchouts per km for a given section. Longitudinal and transverse cracks constitute the other major distress class used in the decision tree. The roughness statistic is directly available in the database.

## **3.5 IDENTIFICATION OF EXPLANATORY VARIABLES**

Every likely variable that may affect pavement performance should be considered initially (20). This list will typically be large. For their implementation within a PMS, however, predictive models must utilize only those variables that can be directly measured within acceptable cost and time constraints (6), retrieved from historical records, or computed or estimated. A study (42) funded by SHRP-LTPP prepared a summary of significant data elements in the SHRP National Information Management System. The lists for asphalt surfaced and Portland cement concrete surfaced pavements are presented in Tables 3.2 and 3.3, respectively.

For identifying variables, one suggested method (20), is to categorize the variables under major topics that are known to affect performance, such as layer material properties, subgrade characterization, layer geometry, climate, traffic, maintenance, and drainage. If each of these general topics is adequately represented by one or more variables, then the model should contain most of the important variables known to affect performance (20).

A preliminary list of important explanatory variables is prepared under four major categories which affect long-term pavement behavior. Those categories include loading, material properties, environment, and maintenance as listed in Table 3.4. This list will be the primary source for explanatory variables.

**TABLE 3.2 - Significant Data Elements in the SHRP National Information Management System for Pavements with Asphalt Concrete Surfaces (42)**

Significant Data Elements			
1	Surface Thickness	16	Subsurface Drainage
2	Base/Subbase Thickness	17	Geological Classification of Coarse Aggregate in HMA
3	Surface Stiffness	18	% of Subgrade Soil Passing #200 Sieve
4	Unbound Base/Subbase Stiffness	19	Plasticity Index of Subgrade Soil
5	Bound Base/Subbase Stiffness	20	Liquid Limit of Subgrade Soil
6	Subgrade Stiffness	21	% of Subgrade Soil Finer than 0.075 mm
7	Age of Pavement	22	Type of Environment
8	Cumulative ESALs	23	Average Max. Daily Temp. By Month
9	Asphalt Viscosity	24	Average Min. Daily Temp. By Month
10	Asphalt Content	25	Thornthwaite Index
11	Percent Air Voids	26	Freeze Index
12	HMA Aggregate Gradation	27	No. of Days Min. Temp. < 32°F
13	Percent Compaction of Base/Subbase	28	No. of Days Max. Temp. > 90°F
14	Subgrade Soil Classification	29	Number of Air Freeze Thaw Cycles
15	In-situ Moisture Content of Subgrade	30	Annual Precipitation

**TABLE 3.3 - Significant Data Elements in the SHRP National Information Management System for Pavements with Portland Cement Concrete Surfaces (42)**

Significant Data Elements			
1	PCC Surface Thickness	15	AASHTO Soil Classification of Subgrade
2	Base Thickness	16	Subgrade % Passing #200 Sieve
3	PCC Surface Thickness	17	Moisture Content of Subgrade
4	Base Stiffness	18	Joint Efficiency
5	Subgrade Stiffness	19	Thornthwaite Index
6	Age of Pavement	20	Annual Precipitation
7	Cumulative ESALs	21	Precipitation Days by Year
8	Type of Coarse Aggregate for PCC	22	Shoulder Type
9	Gradation of Coarse Aggregate for PCC	23	Subsurface Drainage Type
10	PCC Compressive Strength	24	Average Max. Daily Temp. By Month
11	AASHTO Soil Class Base/Subbase	25	Average Min. Daily Temp. By Month
12	% Compaction of Base/Subbase	26	No. of Days Min. Temp. <32F
13	Coarse Aggregate Gradation of Base/Subbase	27	No. of Days Max. Temp. >90F
14	Fine Aggregate Gradation of Base/Subbase	28	Air Freeze-Thaw Cycles

**TABLE 3.4 - Factors Affecting Pavement Condition**

Load	Geometry /Material Properties	Environment	Maintenance
Average daily traffic	Type of material in each layer	Rainfall	Type of overlay
Percentage of trucks in traffic mix	Thickness of each layer	Temperature	Thickness of overlay
Axle load	Type of subgrade soil	Freezing Index	
Tire pressure	Thickness of slab (layer)		

Loading is the primary factor for which the pavements are designed. Loads applied on pavements vary in nature depending on the wheel configuration, gross vehicle weight, tire pressure, volume of traffic, number of lanes in the direction of travel, and others. The effect of mixed traffic loads is converted to a standard axle (18 kips) referred to as equivalent single axle load--ESAL. ESALs for any section per day can be calculated using the following formula:

$$ESAL = ADT * DF * LF * TP * ESALF \quad (3.2)$$

where, ADT = average daily traffic;

DF = a directional factor expressed as a ratio that accounts for the distribution of ESAL units by direction, e.g., east, west, north, south, etc. It is 0.5 if there is traffic in both directions, and 1 if there is traffic in one direction only.

LF = a lane distribution factor, expressed as a ratio, that accounts for the distribution of traffic when two or more lanes are available in one direction.

As suggested in AASHTO Guide (23), the following values are used: for the number of lanes in each direction = 1, 2, 3, and 4, LF = 1, 0.9, 0.7, and 0.625, respectively;

TP = number of trucks in total traffic expressed as a ratio; and

ESALF = Truck factor to convert axle loads to ESAL, 0.55-1.2.

To estimate the cumulative traffic, the initial traffic on a section is to be calculated. From the known daily ESAL on a section in the  $n^{\text{th}}$  year, initial yearly ESAL is calculated as:

$$ESAL_o = (ESAL_n / (1+i)^n) \cdot 365 \quad (3.3)$$

where,  $ESAL_n$  = ESAL in any year  $n$ ;

$ESAL_o$  = initial daily ESAL on the day traffic is opened on the road; and

$i$  = rate of traffic increase expressed as a percent per year, found in the PMS database.

Thus, ESAL is determined for use in calculating cumulative ESAL (CESAL) (43) in any year as:

$$CESAL = \sum_{n=0}^n ESAL = \frac{ESAL_o 365}{\log_e(1+i)} [(1+i)^n - 1] \quad (3.4)$$

Material characteristics are the next important group of factors affecting the behavior of pavements. The structural capacity of the pavement determines largely how safely a load can be carried by a pavement, and how long it can last in a serviceable condition. The structural properties of different types of pavements are taken into account by the following variables:

Flexible – modified structural number, MSN

Composite – thickness of last overlay in inches, TOPTHK

Concrete (both jointed and CRC) – slab thickness in inches, SLABTHK

In addition to the above variables, other structural attributes are considered. These include:

SURTK - thickness of surface course, mm;

BASTK - thickness of base course, mm;

SUBTK - thickness of subbase course, mm;

STABBAS - A categorical variable for the type of base/subbase course underneath the PCC slab. The values of variable assigned are as follows:

10 - if the base course is stabilized; and

1 - if the base course is not stabilized.

CEM - A categorical variable to represent whether the base course or subbase course underneath the AC surface is cement stabilized. This distinction is necessary because cement stabilized layers develop shrinkage cracks which eventually reflect to the surface layer. The categorical variable takes on a value of 10 if there is a cement stabilized layer, and 1 otherwise.

For the purpose of analysis, the environmental conditions are considered to be uniform throughout Mississippi, and therefore, the variables listed under environmental factors in Table 3.4 do not warrant further discussion. However, coastal regions are expected to have unique conditions, for example, type of subgrade (mostly sandy) soil, shallow water table, and relatively large precipitation, which are different from those prevalent in non-coastal areas. A pavement in a coastal region is represented by a categorical variable (COAST) of 10. For the purpose of this study the following counties belong to the coastal region: Hancock, Harrison, Jackson, Stone, Pearl River, and George. Another variable which takes into account the amount of exposure of a pavement to environmental effects (e.g., number of cyclic hot and cold temperatures) is the AGE of the pavement, represented by number of years since construction or last overlay.

The last group of variables considered in Table 3.4 is maintenance. Major maintenance actions such as overlay are taken into account either by the modified structural number or by thickness of overlay. But, if resurfacing is applied, the type of resurfacing plays an important role in the future distress manifestations. Therefore, asphalt concrete resurfacing is represented by a categorical variable (RES) of value 10, with Single



Bituminous Surface Treatment (SBST) and Double Bituminous Surface Treatment (DBST) being represented by 1.

Another categorical variable which does not fall under any of the major groups in Table 3.4 is the HPMS functional classification for highways. A categorical variable value of 10 indicates Rural Principal Arterial, Rural Other Principal Arterial, Rural Minor Arterial, Urban Principal Arterial–Interstate, Urban Freeway/Expressway, Urban Other Principal Arterial and Urban Minor Arterial. For brevity this group is referred to as HPMS, Class I. A value of 1 is used for Rural Major Collector, Rural Minor Collector and Rural Local and referred to as HPMS, Class II. Classification of routes into these groups is expected to reflect the differences in the strength of sections, quality of construction, volume of traffic, and type of maintenance applied, among others.

In order to take into account the effect of interaction between the explanatory variables, the product of the variables is considered. As an example, age alone causes certain deterioration, and traffic alone causes certain deterioration; however, the synergism resulting from the combined effect of age and traffic is expected to be more than the sum of individual effects on pavement deterioration. Interaction terms account for this synergetic effect.

Mechanistic parameters such as those indicating strength; e.g., modulus values of materials in different layers of the pavement, are expected to be factors having significant influence on the long-term behavior of pavements. The limitations of the database precluded the use of these variables. Other desirable explanatory variables, particularly for the prediction of rutting, are type of coarse aggregate used, aggregate gradation, voids

in mineral aggregates, properties of bitumen, etc., cannot be included in the analysis owing to lack of data.

Summarizing, the MDOT PMS database includes a series of databases that cover many aspects of the road network. The six modules of inventory, geometry, construction, maintenance, traffic, and condition data make up the database. PCR calculated from the condition data is also stored in the database. Pavements are classified into families and distress attributes required for their maintenance evaluation are listed. Many explanatory variables that are expected to influence the performance are elucidated. They include age, cumulative ESAL, slab thickness, thickness of overlay, modified structural number, etc. By necessity, categorical variables are also employed to augment the pavement attributes. Making use of these data elements from the database, deterioration/performance models will be developed. The details of the developmental effort comprise the next chapter.

## CHAPTER 4

### MODELING METHODOLOGY

#### 4.1 INTRODUCTION

As the performance and distress history of a pavement depends on many variables in extremely complex ways, pavement deterioration models are, in general, empirical or semi-empirical. Also, purely mechanistic models predicting primary responses such as stress, strain, or deflection are not commonly adopted (44) since these responses are not used as ends in themselves for design, maintenance, or rehabilitation of pavements. The prevalent method, however, is to employ time series data and develop regression models. This study attempts regression models, and in a few cases they are augmented by Bayesian models as well.

A database of response variables along with all the potential explanatory variables is compiled from the PMS database. Usually a PMS database is arranged in some order. The MDOT-PMS is arranged according to district, route number, county number, direction of travel, and beginning accumulated log mile. To eliminate any possible bias, the database is randomly sorted and divided into two parts, referred to as ‘in-sample’ and ‘out-of-sample’ data. The in-sample part forms the bulk of the data, about 70 percent, which will be used in developing the regression equations.

The remaining 30 percent of the data, referred as the “out-of-sample” or “testing data,” is used for assessing the prediction accuracy of the regression equation. The out-of-sample data constitutes approximately 30 percent of the total to ensure that it is statistically “large.” Random sorting is important to retain prominent features of data in the “in-sample” as well as the “out-of-sample” data.

## 4.2 REGRESSION MODELING TECHNIQUES

The models for prediction of response variables are developed using the regression technique. Initially, scatter plots of response variables against each of the potential explanatory variables are obtained, determining the likely relationships between response and explanatory variables. Also, the plots help in locating obvious errors in the data, if any. Various model forms are attempted in an effort to develop the best possible model. This includes trials with various techniques, such as multiple linear, model with interacting terms, stepwise, and non-linear regression. SPSS (45) package is utilized for regression analysis.

### 4.2.1 Multiple Linear Forms

Multiple linear regression is one of the most time-honored and widely used regression techniques for the study of linear relationships among a group of measurable variables (47). The basic assumptions are that the random errors are independent, and normally distributed with zero mean and constant variance. Based on these assumptions, multiple regression tries to find a set of parameters  $a_i$  such that the sum of squared residuals is minimized, also known as the least squares method. A linear model uses the following general form of the equation:

$$y = a_0 + a_1x_1 + a_2x_2 + \dots + a_nx_n \quad (4.1)$$

where,  $y$  = the response variable to be predicted, such as pavement condition, distresses, etc.

Multiple linear models are simple and yield solutions easily, as described in the literature (47-53). It is imperative that these models be so formatted that they satisfy physically meaningful boundary conditions.

HPMS Type Model: The Highway Performance Monitoring System (HPMS) predictive models (35) for all major pavement types use an implicit linear equation. The nonlinear form is converted to linear form by logarithmic transformation as seen in Equations 2.32 – 2.36. Such models are used to predict a composite condition index (namely Present Serviceability Rating, PSR) in HPMS studies.

#### **4.2.2 Nonlinear Regression**

Nonlinear regression models are those in which the parameters of the model are nonlinearly related. In many cases nonlinear models are sought instead of linear models because of certain advantages:

- To retain a clear interpretation of parameters (54)
- Uncertainty of linear approximation used for inference can be avoided
- Parameter estimates of linear models may have undesirable properties
- Practical, real-world problems are often nonlinear in nature

The linear models, on the other hand, are mathematically easier, with the estimators of the parameters being obtained from an explicit mathematical expression (55). For nonlinear regression models, one must use either an iterative procedure employing a mathematical algorithm or an exhaustive search procedure. Also, nonlinear regression models with more than one explanatory variable, with few exceptions, tend to be algebraically very complicated.

Different forms of nonlinear models are considered for modeling. Though two forms are employed in this study, only power form turned out to be relevant in this study.

##### **4.2.2.1 Power Form**

A typical power form model employs the product of explanatory variables raised to

some power. This type of model is adopted in HPMS (35), Illinois (37), and Virginia (21) studies. The general form of the equation is as follows:

$$y = A_0 + A_1 X_1^{A_2} X_2^{A_3} X_3^{A_4} \quad (4.2)$$

where y the response variable,  $X_i$  are the explanatory variables, and

$A_0, A_1, A_2, A_3$ , and  $A_4$  the parameters of the equation.

The desirable properties of the power form of the equation, shown in Figure 4.1, are listed below:

- (a) The response variable increases or decreases monotonically which represents the real-world physical condition. The distresses increase monotonically as represented by curves A, B, C, and PCR decreases monotonically as represented by the curve D.
- (b) The initial condition is satisfied; i.e., the curve starts with an initial value, which can be employed to represent the zero initial distress (curve B), a fixed value of initial roughness (curve A), or a starting value of PCR (curve D).
- (c) The delay in the development of distress can be represented, e.g., alligator cracks, or punchouts might appear after a few years as represented by the curve C.
- (d) Random distresses appear initially, increase slowly and, thereafter, increase rapidly due to wear-out, and can be represented by this form of the equation.

### 4.3 MODELING BY BAYESIAN REGRESSION

In some models a Bayesian regression approach was adopted augmenting the classical regression approach for a number of reasons. Generally, the Bayesian approach allowed the development of better models than could be possible with data alone. This

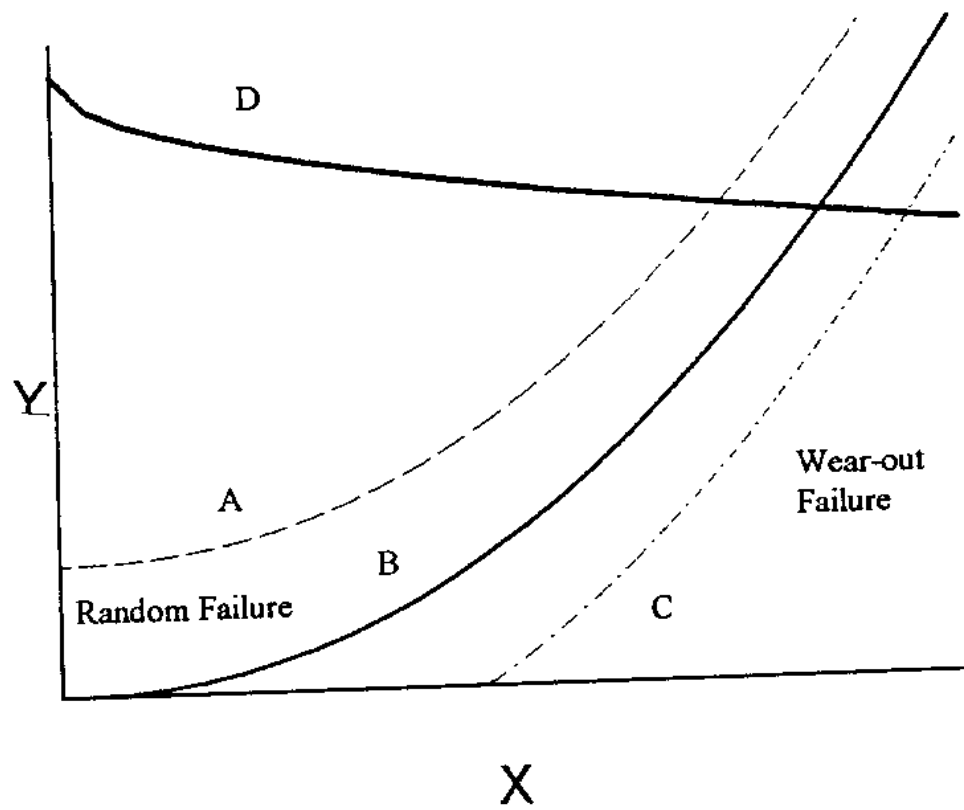


FIGURE 4.1 Typical power form curves.

was achieved by combining, using Bayesian regression, the performance data with prior experience and knowledge (expert opinion) that was available through the engineering staff of MDOT.

Predictive models require a large number of observations in order to provide a good coverage of all factors included over a reasonable reference space. Since the performance models are fundamentally a function of time, data needs to be available over a reasonable time span (10-20 years) for pavement being observed. One solution lies in the use of Bayesian regression in which the data collected in the traditional manner is supplemented with “prior” knowledge. The so-called prior knowledge may be drawn from expert judgment, “old” data sets, or knowledge that is generally accepted in the field. Expert judgment can also be encoded by polling experts and asking them to estimate the value of the dependent variable for a combination of contributory/explanatory variables. Once compiled, this information would supplement the primary database at hand. The prior experience ensures that the resulting performance models spanned the service life of the pavements.

Bayesian regression relies on two models, the prior model developed from expert judgment, and the data-model from field data. The data employed was the same as that used in classical regression. Ten experts, each with 10 to 35 years of experience, participated in developing the prior data. Experts were briefed on the purpose of the data explaining the causal variables chosen for predicting a response variable, say, PCR. Their judgments (expressed in terms of numerical scores) were encoded using a full-orthogonal matrix elicitation technique. Experts were briefed with respect to the problem and variables in the specified model. Subsequently they were requested to complete one



encoding matrix for each pavement similar to the one in Figure 4.2. Each cell in the matrix defines a pavement with a specific combination of the four explanatory variables. Illustrated in Figure 4.2, is a matrix for the PCR of original flexible pavements, duly filled in by one expert. Each entry reflects his experience in working with original flexible pavements in Mississippi. Since only one equation was desired for each pavement family, the responses of the 10 experts were pooled to give a single collective prior.

The analysis was performed using XL-BAYS Bayesian regression software, which runs as an add-in to Microsoft Excel (38). The program sequentially analyses the prior and the field data thereby generating the “posterior” model. For comparison purposes, it provides a complete statistical summary for the prior model, the data model (identical to classical regression), and the posterior model. As the Bayesian regression software is constrained to use only linear models, Bayesian could not improve all of the prediction models. Linear and power equations could be handled, the latter using a linearization procedure by taking the logarithm of the variables.

In summary, chapter 4 describes modeling methodologies employed in developing prediction equations. In essence, regression techniques form the basis of all models, with some models augmented by expert opinion, for which Bayesian regression methodology is employed. Chapter 5 presents the models, explaining in some detail how they were developed. The reasonableness of these models is verified by sketching the variation of the response variable with age and traffic volume (CESAL).

Expert # 6

Date: 12-11-98

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FIGURE 4.2 Encoding matrix for Pavement Condition Rating (PCR), original flexible pavement.

## **CHAPTER 5**

### **MODELS, RESULTS, AND DISCUSSIONS**

#### **5.1 GENERAL**

This chapter documents the models developed for the prediction of distress (distress groups)/performance of each family of pavements. Specifically, the explanatory variables for the models, the forms of the models used and their statistics are explained. Also documented are Bayesian models for prediction as well as improvement accomplished using the latter approach. The last section of this chapter briefly describes a feedback analysis program.

The sequential steps involved in modeling by regression and by Bayesian are outlined briefly:

##### Classical Regression:

1. A database is created which contains the response variables and all the potential explanatory variables.
2. The database is split into “in-sample” data comprising 70 percent of the data, with the remaining designated “out-of-sample” for model verification.
3. A form of the model is chosen, and analyzed by stepwise regression. The procedure aids in the identification of significant explanatory variables.
4. Regression models are developed with the in-sample data.
5. The predictive capability of the models is evaluated by comparing the predictions with the out-of-sample data.

### Bayesian Regression:

1. Select independent variables for inclusion in the prediction model. They need to be the same as these used in regression modeling.
2. Either by interview or by group discussion, encode the expert's knowledge in the form of a matrix (see Figure 4.2).
3. Using the encoding matrix, histograms are prepared to ensure that the expert opinions are consistent and reasonable.
4. The results provided by the expert-based models (prior data) are combined with field data using the Bayesian regression software, XL-BAYES (38).
5. The goodness-of-fit of the posterior model is judged by testing for the significance of the regression parameters.

For each pavement family, the models developed with the in-sample data are described for each distress/distress group with the corresponding coefficient of determination ( $R^2$ ), and root mean square error (RMSE). Following this a few of the regression models are augmented by expert opinion increasing the inference space of the data-based model.

## **5.2 ORIGINAL FLEXIBLE PAVEMENT MODELS**

The original flexible pavements are those that are not overlaid, and are in their first performance period. The explanatory variables considered are age, CESAL, MSN, classification of road according to the HPMS system, thickness of surface, and base and subbase courses. Note that age enters in the calculation of CESAL. To evaluate whether multicollinearity exists between the independent variables, a correlation matrix involving the dependent variable and the independent variables was computed. A high  $R^2$  value between any pair of independent variables was construed as an indication of

multicollinearity . Another method of checking multicollinearity entails conducting a residual analysis, the details of which can be seen in references [47](#) and [48](#). The range of response variables employed in model development is given in Table 5.1, while that for explanatory variables is given in Table 5.2. Models developed for each distress/distress group or performance are described.

**Table 5.1 Range of Response Variables Employed in the Development of Models, Original Flexible Pavements**

Response Variable	Description	Range
<b>WCAMH</b>	Weighted alligator cracking of medium and high severity, percent	0 - 28.61
<b>OC</b>	Other cracks, percent	0 - 99.98
<b>OCMH</b>	Other cracks of medium and high severity, percent	0 - 86.11
<b>RT85</b>	85 <sup>th</sup> percentile rutting, mm	0 - 23.9
<b>IRI</b>	Roughness, m/km	0.62 - 3.21
<b>PCR</b>	Pavement condition rating	32 - 94

**Table 5.2 Range of Explanatory Variables Used in the Development of Models, Original Flexible Pavements**

Explanatory Variable	Range of Explanatory Variables of Models					
	<b>WCAMH</b>	<b>OC</b>	<b>OCMH</b>	<b>RT85</b>	<b>IRI</b>	<b>PCR</b>
<b>Age, years</b>	0 - 49	0 - 47	0 - 57	1 - 41	0 - 46	0 - 57
<b>18-kips CESAL, millions</b>	0 - 5.66	0 - 5.17	0 - 13.24	0.01-7.08	0 - 9.29	0 - 13.24
<b>MSN</b>	1.71 - 8.14	1.21 - 9.67	1.21 - 9.67		1.77 - 7.93	1.21 - 9.67

### 5.2.1 Medium and High Severity Alligator Cracking Model

Here the percentage area of medium and high severity alligator cracking is the response variable. Efforts to predict medium and high severity alligator cracking areas (percentage), failed to yield satisfactory prediction models. This may be due to the fact that some of the medium severity alligator cracking is transformed into high severity

alligator cracking in subsequent years. In such cases, though the percentage area of these cracks remains the same, there is an increase in severity. To take into account the severity effect, weights are introduced for each of these severities: 0.7 for medium severity alligator cracking, and 1.0 for high severity alligator cracking. Assigning weights equal to or less than one ensures that the area of cracking does not exceed the actual pavement area (100 percent). The weighted percentage alligator cracking of medium and high severity (WCAMH) is the response variable to be predicted.

The percentages of alligator cracking for the original flexible pavements are observed to be low. Alligator cracking, especially high severity levels, being a serious distress is probably not allowed to spread over a large area. Another observation is that pavements with a modified structural number greater than 5.0 exhibit zero or very low alligator cracking.

Alligator cracks develop due to fatigue from repeated loading cycles, and are generally confined to wheelpaths. Cumulative 18-kip ESAL is, therefore, an important explanatory variable for the model to predict alligator cracking. Another explanatory variable considered is the modified structural number (MSN), an indicator of overall strength of a pavement. To account for differences in the design standards, volume of traffic, and quality of construction, a categorical variable—classification according to HPMS system—is considered as well.

With little success using the above explanatory variables, age of pavement is introduced as the fourth explanatory variable. Age is expected to account for the hardening of asphalt resulting from loss of volatiles. Aging of bituminous binder, due primarily to oxidation, increases the stiffness of both the binder and the surfacing material over time.

Consequently aging strongly reduces the fatigue life of thin to medium thick surfacing, but probably has little effect on thick bituminous layers (6).

Using thickness of various layers instead of MSN did not result in a good model. The best possible model obtained for weighted alligator cracking of medium and high severity is:

$$\text{WCAMH} = 0.6956 \text{ AGE}^{1.3686} \text{CESAL}^{0.8050} \text{MSN}^{-1.961} \quad (5.1)$$

$$R^2 = 0.43, \text{RMSE} = 0.22, N = 241$$

(Note: CESAL is expressed in millions in Equations 5.1 – 5.35)

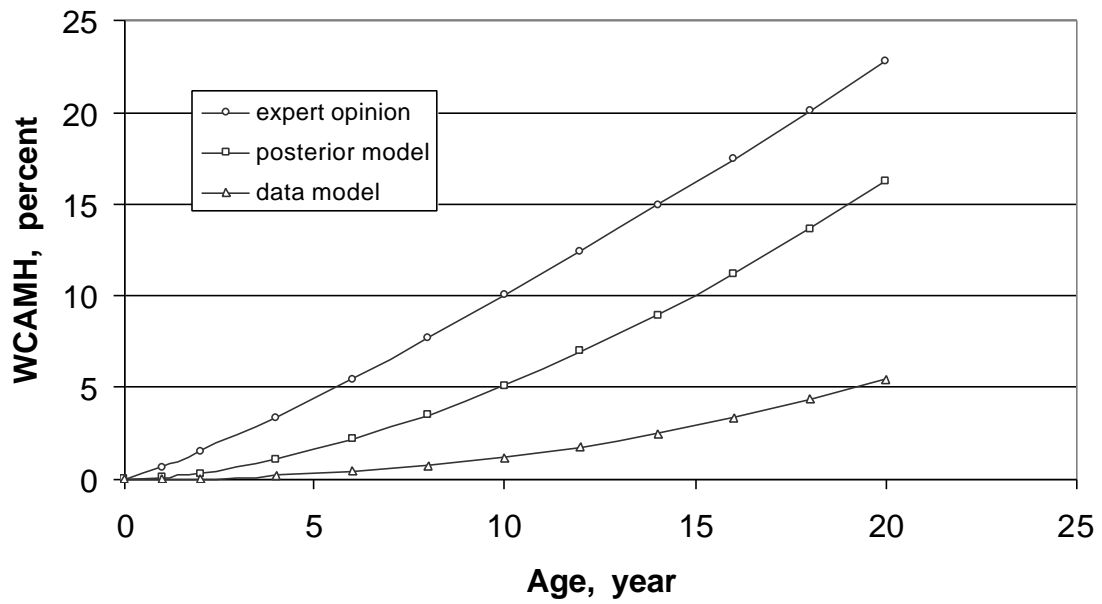
The above regression model shows that WCAMH increases with age and cumulative traffic. The higher the MSN or the strength of pavement, the lesser the alligator cracks.

To improve the data-model, expert opinion was compiled for WCAMH in the three families of pavements: original flexible, overlaid flexible and composite. How does expert opinion compare with the field data? With 86.3 percent of observations reporting zero WCAMH (see Table 5.3), the data-model predictions are well below those of the experts (see Figure 5.1). Nevertheless, combining the expert opinion (prior model) with data-model is considered important.

The coding results provided by the ten raters were aggregated to form one prior model which was then combined with the data model. The analysis was performed using Bayesian regression software, XL-BAYS. Since XL-BAYS can handle only linear models, the model form needs to be restricted to the power form, noting that power

Table 5.3 and Table 5.4 appear in the original document, but are missing in the files.





**Figure 5.1** Comparison of medium and high severity alligator cracks (WCAMH) predicted by data-model, expert model, and posterior model in flexible original pavement.

models could be linearized by logarithmic transformation. With this transformation the program sequentially analyses the prior and the field data, thereby generating the posterior model. For comparison purposes, it provides a complete statistical summary of the prior model, the data model, and the posterior model. XL-BAYS provides a unique feature which enables the user to obtain probability density functions for the regression coefficients (for the data-based, expert-based and the combined models) and plot them in one composite figure for easy comparison. Comparison of the probability density functions of a parameter, for example, that of CESAL, is presented in Figure 5.2. The shape of the probability density functions (pdf) indicates uncertainty associated with the model estimates. Clear from the pdf plots in Figure 5.2 is that the data-model is influenced by the expert opinion, resulting in a larger exponent for CESAL swinging the trend in favor of the prior model (expert judgment). This is an intuitively expected result indicating that the posterior (combined) model is influenced by both field data and expert judgment.

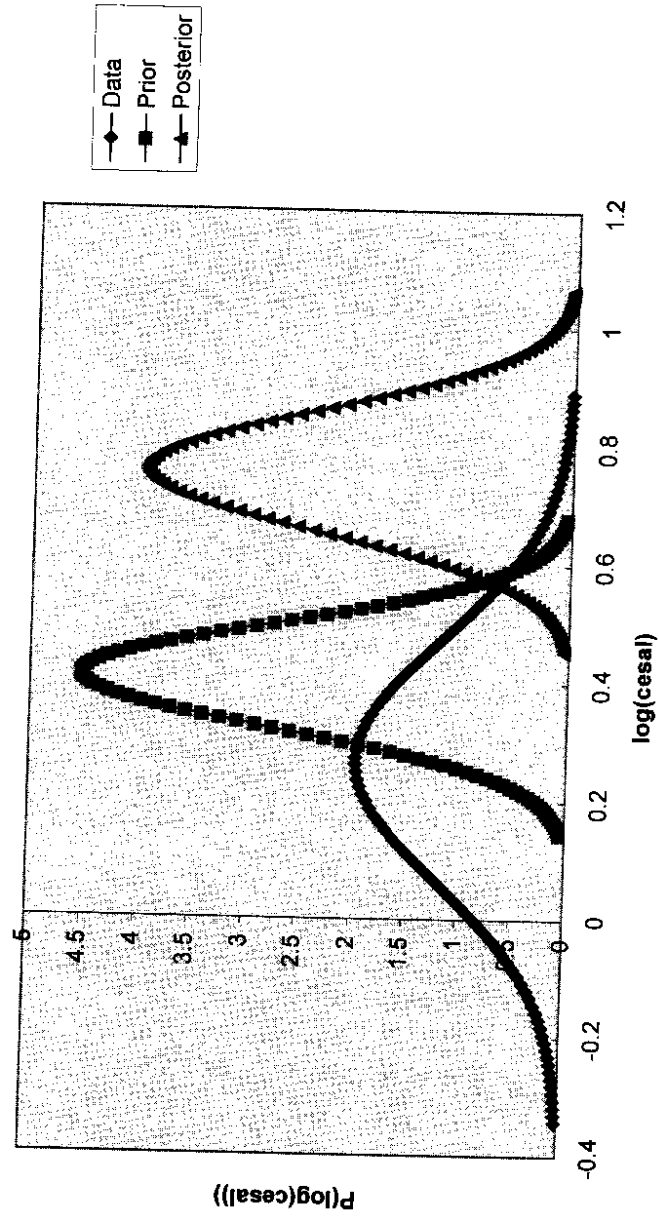
The posterior model is defined in the following equation:

$$\text{WCAMH} = \text{Age}^{0.9329} \text{CESAL}^{0.7331} \text{MSN}^{-0.6348} \quad (5.2)$$

$$R^2 = 0.29, \text{RMSE} = 2.03$$

As indicated by t-statistics, the significance of the explanatory variables in descending order is Age, CESAL and MSN.

Comparing the data-model, Equation 5.1, and posterior model, Equation 5.2, it is noted that predictability of the latter is diminished, as indicated by low  $R^2$  and high RMSE. This anomalous result could be attributed to exceedingly large expert WCAMH values as compared to MDOT data (see Figure 5.1). As will be seen again in later



**FIGURE 5.2 Comparison of the Normal Probability Plots for:  $\log(\text{CESAL})$**

sections, whenever the two sets of data are exceedingly disparate, the prediction accuracy of posterior model would invariably suffer.

Comparison predictions graphed in Figure 5.1 clearly show that the posterior model predicts intermediate values as it is shaped by both data-model and expert opinion. Nonetheless, posterior model is dominated by expert opinion resulting in relatively high WCAMH predictions, a valid argument for not recommending this model.

Sensitivity analysis of the influence of age on WCAMH for different traffic levels- in terms of yearly ESAL (YESAL)-plotted in Figure 5.3, indicates reasonable predictions throughout a typical life span of 20 years. Convinced that the predicted values are in the expected range, this data model (Equation 5.1) is recommended for MDOT PMS.

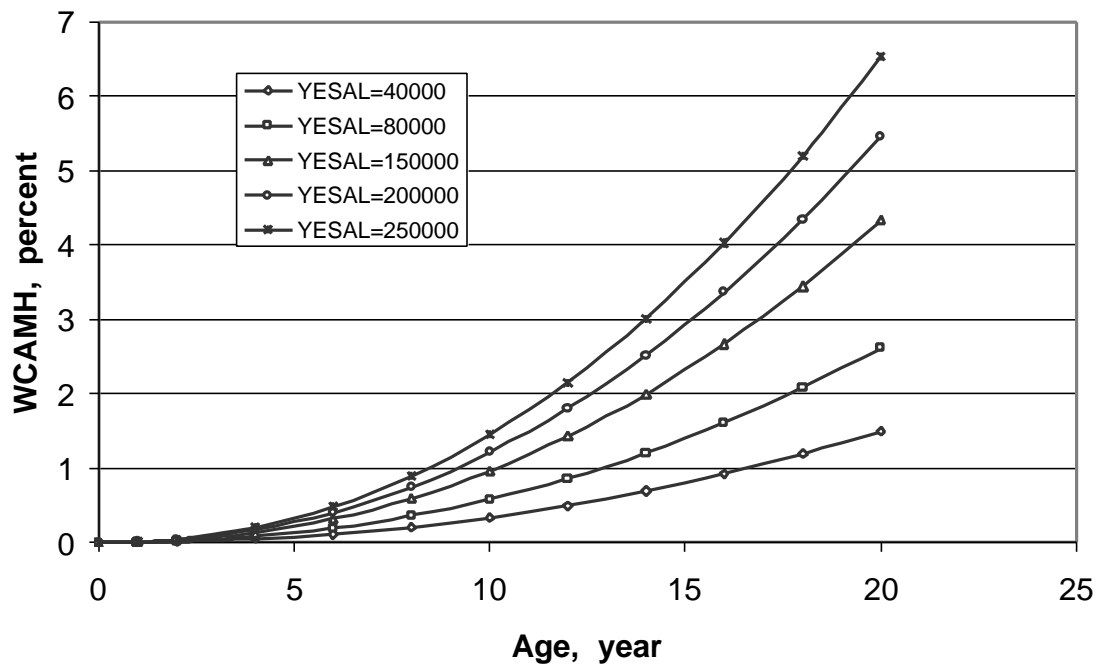
### 5.2.2 Model for “Other Cracks” (OC)

The other cracks include low severity alligator, block, edge, longitudinal, and transverse cracking. An overall summary of OC cracks and other cracks of medium and high severity (OCMH) is presented in Table 5.4. Though only 2.7% of the data registers zero, numerous sections show extremely small OC crack density, presenting some problems in developing a satisfactory model. As in WCAMH cracks, the explanatory variables identified to have significant influence on other cracks percentage are: AGE, CESAL and MSN. Derived from the in-sample data is the following model:

$$OC = 0.8892 AGE^{1.2128} CESAL^{0.6612} MSN^{-0.4606} \quad (5.3)$$

$$R^2 = 0.44, RMSE = 6.0, N = 718$$

It is noteworthy that the modified structural number, a measure of load capacity of flexible pavements, appears in the equation with a negative coefficient. The negative sign



**Figure 5.3** Variation of medium and high severity alligator cracks (WCAMH ) with age for a range of traffic levels. Flexible original pavement, (MSN=5). YESAL =yearly equivalent single axle loads.

indicates that the stronger the pavement, the lesser the potential for cracking.

A sensitivity analysis is performed where the evolution of cracks is depicted for various yearly ESAL levels (see Figure 5.4). The exponential increase of cracks with age seems to be in agreement with the field observations in original flexible pavements. As no expert opinion was available for OC cracks, Bayesian regression could not be attempted.

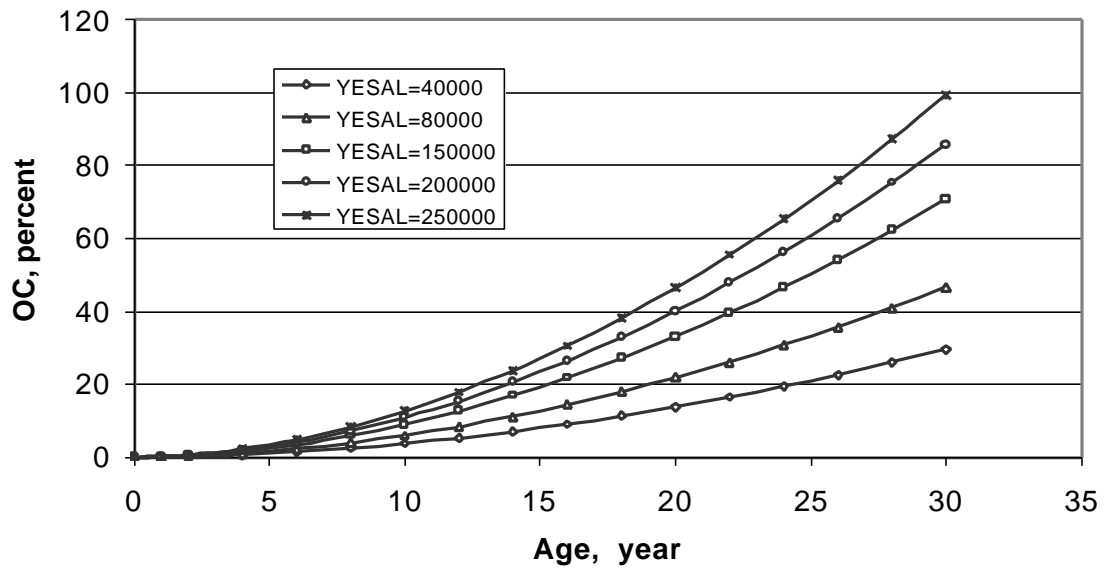
### 5.2.3 Model for “Other Cracks” of Medium and High Severity (OCMH)

This distress group is recognized by MDOT-PMS as a factor in the maintenance strategy selection. As encountered with other models of cracking, numerous OCMH values (79 percent) are zero (see Table 5.4). Power and exponential models are attempted among the nonlinear forms. Though exponential models could yield predictions with medium and high severity cracks attaining maximum (100 percent) asymptotically, the data structure was not amenable to this form of equation. A power model with age and CESAL, therefore, is adopted here.

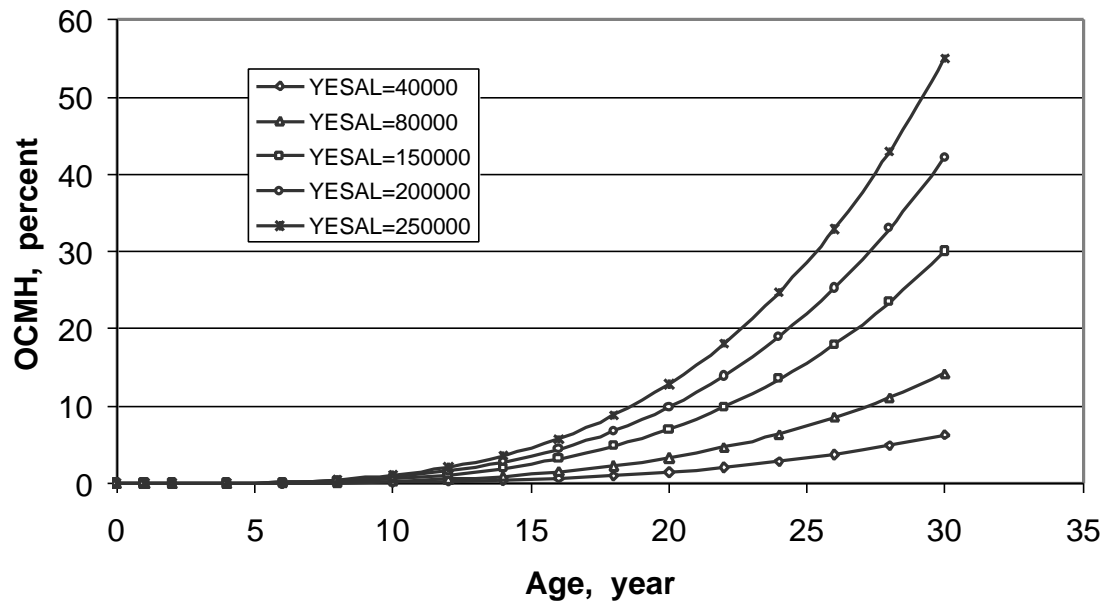
$$\text{OCMH} = 1.4378\text{E-}3 \text{ AGE}^{2.3998} \text{CESAL}^{1.1863} \quad (5.4)$$

$$R^2 = 0.86, \text{RMSE} = 1.62, N = 790$$

The predicted OCMH for the out-of-sample data looked skewed owing to extreme data spread and numerous zero values. The trend lines in Figure 5.5 depict the evaluation of cracks for various traffic levels. As expected, the OCMH cracks develop at a rapid rate beyond 10 years, with traffic level playing a major role in crack widening process. The Bayesian regression model is not attempted for want of expert opinion data.



**Figure 5.4** Variation of other cracks (OC) with age for a range of traffic levels. Flexible original pavement, (MSN=5)



**Figure 5.5** Variation of medium and high severity other cracks (OCMH) with age for a range of traffic levels. Flexible original pavement.

#### 5.2.4 Rutting Model

Rutting is primarily caused by the loading of channelized traffic in a lane. Therefore, traffic is bound to be an explanatory variable for predicting rutting. Whether stronger pavements should show lesser rutting has been debated. However, the ten experts seem to be divided on this issue. Mechanistic parameters such as strength or modulus values of the various materials could not be included as they are not available in the database. A model developed with traffic and MSN did not provide good prediction. Another model with thickness of surface, base and subbase courses instead of MSN did not yield good predictions either.

The database compiled from these consecutive surveys (1991, 1993 and 1995) resulted in the following power model, expressing RT85 in millimeters.

$$RT85 = 0.4917 AGE^{0.2852} CESAL^{0.1441} \quad (5.5)$$

$$R^2 = 0.59, RMSE = 0.15, N = 145$$

This model, rightly so, shows increased rutting with age and traffic.

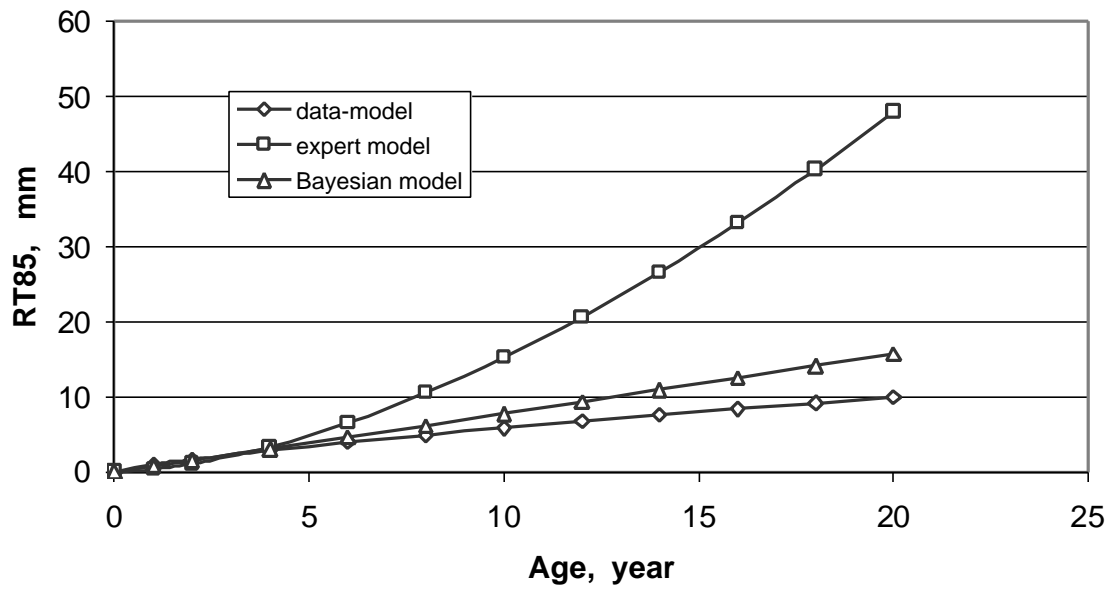
In order to augment the model, the data-model and the expert model are combined employing XL-BAYS. The resulting two-term model is,

$$RT85 = AGE^{0.8307} CESAL^{0.1929} \quad (5.6)$$

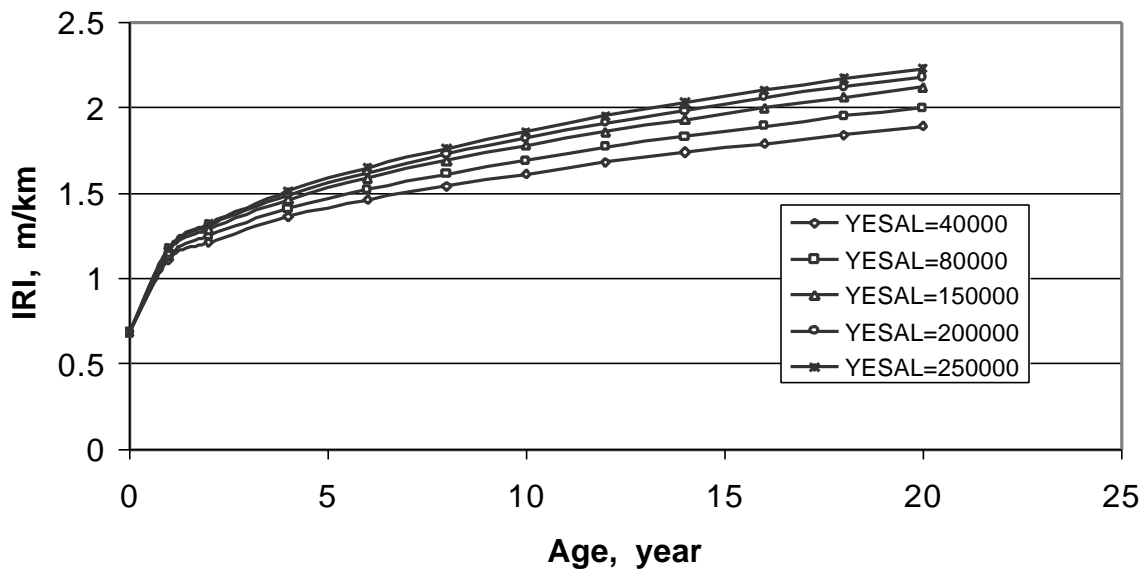
$$R^2 = 0.68, RMSE=4.4$$

Since the posterior model captures both field data characteristics and expert opinion, it is not expected to give good predictions with the out-of-sample data. The data-model, Equation 5.5, provides good predictions using the 30 percent out-of-sample data.





**Figure 5.6** Comparison of rutting prediction using data-, expert and Bayesian models.  
Flexible original pavement with yearly ESAL=200,000



• **Figure 5.7** Variation of International Roughness Index (IRI) with age for a range of traffic levels. Flexible original pavement, (MSN=5).

The comparison of RT85 prediction employing the three models resulted in Figure 5.6, where rut increase is graphed against age for yearly traffic of 200,000 ESAL. Primarily, owing to larger data population the posterior model is closer to the data-model than to the expert model. That none of the structural variables appears in the model should not be construed to mean that rutting is not influenced by pavement thickness. It simply means that both databases do not suggest such a causal factor. Having established that the Bayesian model predicts realistic rutting, we recommend Equation 5.6 for use in the PMS.

### **5.2.5 Roughness Model**

The task here is twofold: first, to determine the initial value of roughness of newly constructed roads, and second, to determine the trend of roughness progression. A study (50) of roughness values of newly constructed asphalt surfaced pavements in various states (Kentucky, Georgia, Iowa, and Wisconsin) indicates that an initial IRI of 0.5 m/km is common for the pavements constructed over the last two decades. A study of the MDOT-PMS database shows slightly different numbers, thicker pavement showing smoother surface initially.

Another special feature of the IRI data, and, for that matter, PCR data as well, is for the IRI to increase abruptly with low CESAL, say in the zero to  $1 \times 10^6$  CESAL interval. Another trend appears where the IRI increased slowly in the zero to  $3 \times 10^6$  CESAL range. The pavements in the first group belong to low volume traffic roads where the pavement roughness increases due primarily to environmental effects. It is the age that matters in this group of pavements since traffic causes minimal roughness. In the second group; however, traffic volume seems to be the key factor that contributes to pavement roughness. To take

into account these two groups of pavements, a nonlinear form is selected and fitted to the data to result in the following equation:

$$\text{IRI} = (2.4169 + \text{Age}^{0.2533} (1 + \text{CESAL}^{0.2572})) \text{MSN}^{-0.7753} \quad (5.7)$$

$$R^2 = 0.35, \text{RMSE} = 0.34, N=690$$

The predictability of the model is substantiated by plotting the calculated IRI against the measured IRI for the out-of-sample data (see Figure 5.7). Upon plotting the IRI with age for typical traffic volumes (MSN constant at 5.0), it is noted that IRI increases swiftly during the first five years followed by a slow change in the latter years.

### 5.2.6 PCR Model

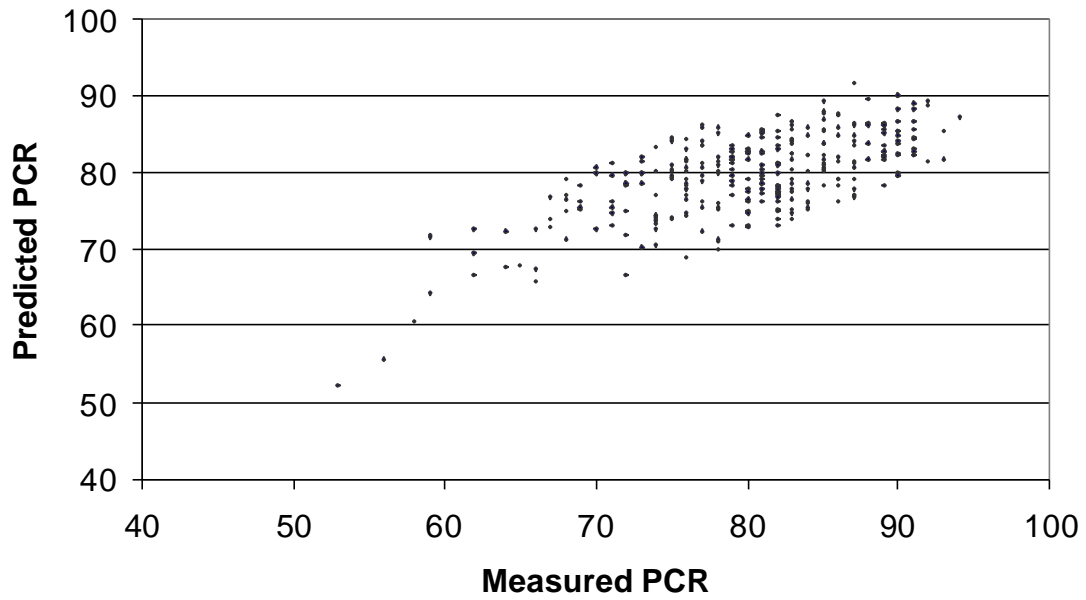
Here again, the question of factors affecting the PCR of a newly constructed pavement arose. It can be argued that initial PCR may be a function of MSN. Accordingly, a model of the type in Equation 5.7 is suggested with Age, CESAL, MSN, and other explanatory variables such as HPMS classification, with the best model emerging incorporating three variables: Age, CESAL and MSN.

$$\text{PCR} = (76.10 - \text{Age}^{0.6696} (1 + \text{CESAL}^{0.7100})) \text{MSN}^{0.0979} \quad (5.8)$$

$$R^2 = 0.53, \text{RSME} = 5.0, N = 720$$

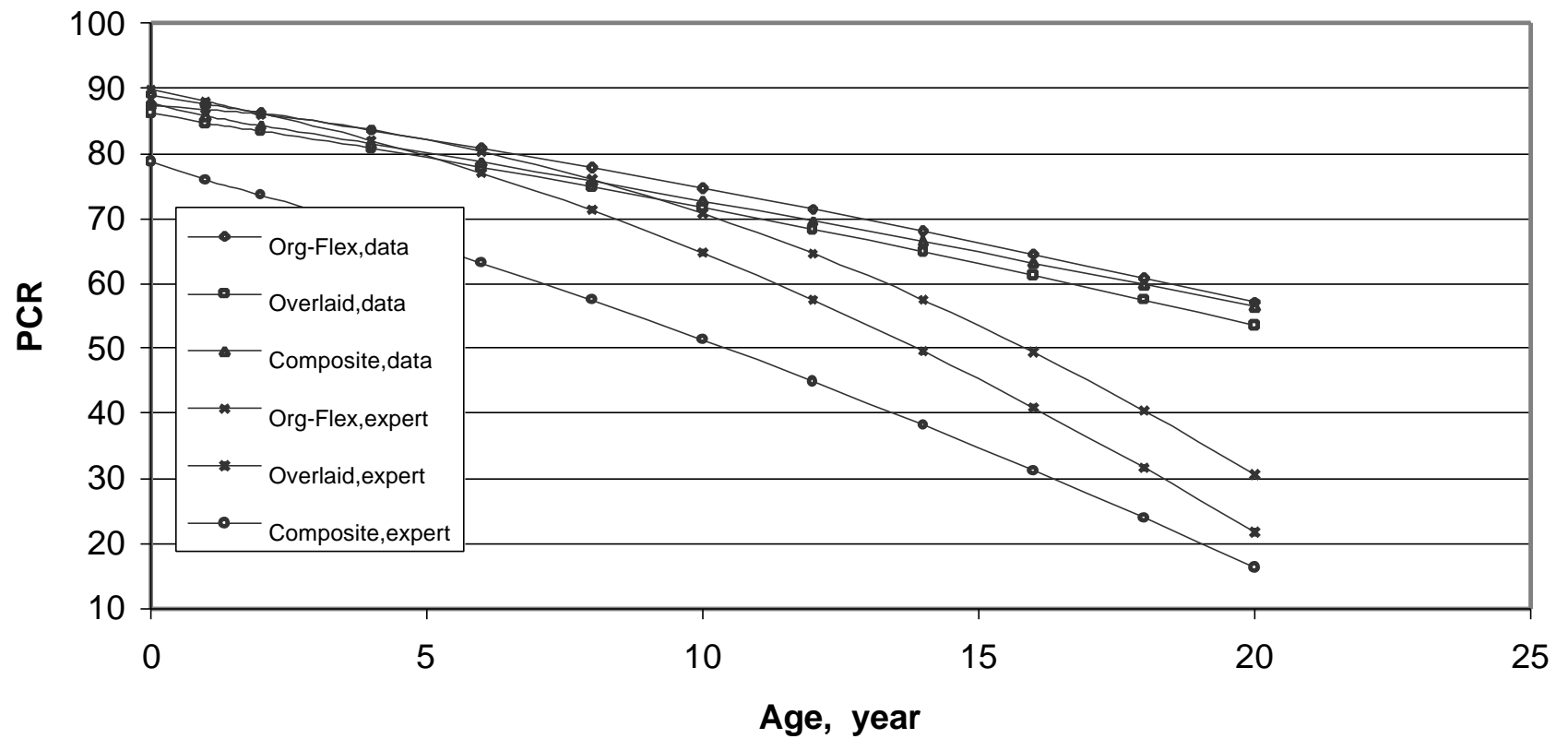
In order to establish the robustness of the model, measured versus actual PCRs of the out-of-sample data are plotted in Figure 5.8 showing satisfactory prediction capability.

With the expert opinions available, an attempt is made to augment the data-model using the expert opinion. Since the field data is not amenable to modeling using the linear/power forms, the XL-BAYS program could not be used.



0

**Figure 5.8** Comparison of measured and predicted Pavement Condition Rating using original flexible pavement out-of-sample data.



**Figure 5.9** Comparison of Pavement Condition Rating (PCR) estimated by experts and predicted by data-models. Yearly ESAL 200,000

A comparison of the data-model and the expert opinion model, however, is taken up for which expert opinion model similar to Equation 5.8 is derived. The expert model matches the data model for the first eight years, beyond which, however, the experts believe the PCR drops at a faster pace (see Figure 5.9). Recognizing that steep PCR drop is inconsistent with the field observations, the data-model in Equation 5.8, is recommended for PMS use.

### 5.3 OVERLAID FLEXIBLE PAVEMENT MODELS

Overlaid flexible pavements are flexible pavements that are overlaid at least once and form a different pavement family requiring separate models. The response variables used and their ranges are shown in Table 5.5, while those of explanatory variables are in Table 5.6.

#### 5.3.1 Medium and High Severity Alligator Cracking Model

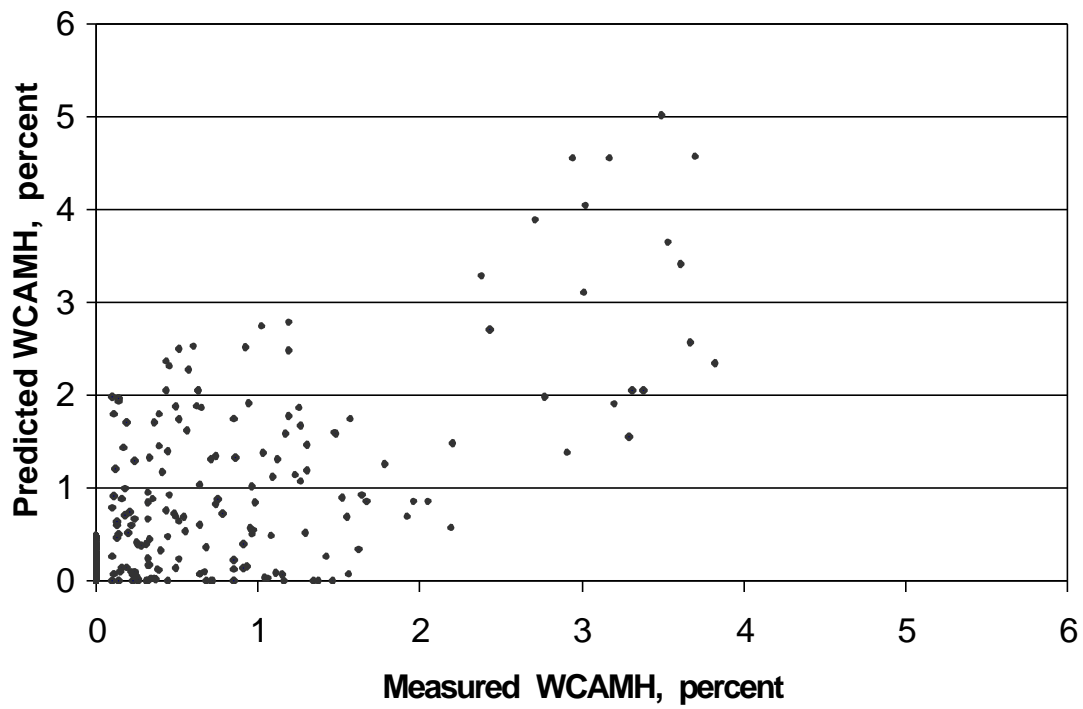
In addition to the three response variables declared in the alligator crack model for original asphalt pavements, one additional variable, surface type, was found significant. The model equation is:

$$\text{WCAMH} = 0.977\text{E-}1 \text{ AGE}^{1.8548} (1 + \text{CESAL}^{0.5336}) \text{MSN}^{-1.9370} \text{RES}^{0.1618} \quad (5.9)$$

$$R^2 = 0.48, \text{RMSE} = 0.32, N = 4353$$

**Table 5.5 Range of Response Variables Employed in the Development of Models, Overlaid Flexible Pavements**

Response Variable	Description	Range
WCAMH	Weighted alligator cracking of medium and high severity, percent	0 – 13.10
OC	Other cracks, percent	0 – 89.6
OCMH	Other cracks of medium and high severity, percent	0 – 68.80
RT85	85 <sup>th</sup> percentile rutting, mm	0 – 30.2
IRI	Roughness, m/km	0.45 – 9.25
PCR	Pavement condition rating	57 – 95



**Figure 5.10** Comparison of measured and predicted medium and high severity alligator cracks(WCAMH) using out-of-sample data. Overlaid flexible pavement.

The out-of-sample data is predicted with the model equation plotting the results in Figure 5.10. That the agreement is fair attests to the viability of the model. Yet another plot, relating the variations of alligator cracks with age for typical traffic levels is shown in Figure 5.11. It is noted that very little alligator cracking develops during the early life, say, up to 6 years.

**Table 5.6 Range of Explanatory Variables Used in the Development of Models, Overlaid Flexible Pavements**

Explanatory Variable	Range of Explanatory Variables of Models					
	WCAMH	OC	OCMH	RT85	IRI	PCR
Age, years	0 - 49	0 - 37	0 - 26	1.00-9.00	0 - 41	0 - 32
18-kip CESAL, million	0 - 2.30	0 - 6.76	0 - 4.03	0.30-1.81	0 - 6.76	0 - 6.76
MSN	1.77-9.67	0.61 - 9.52	0.61 - 9.52		0.61-9.52	0.61-9.52
TOPTHK (mm)		3.1-304.8	3.1-254.0		3.1-304.8	3.1-254
RES (categorical)	AC Surface DBST or SBST					10 1

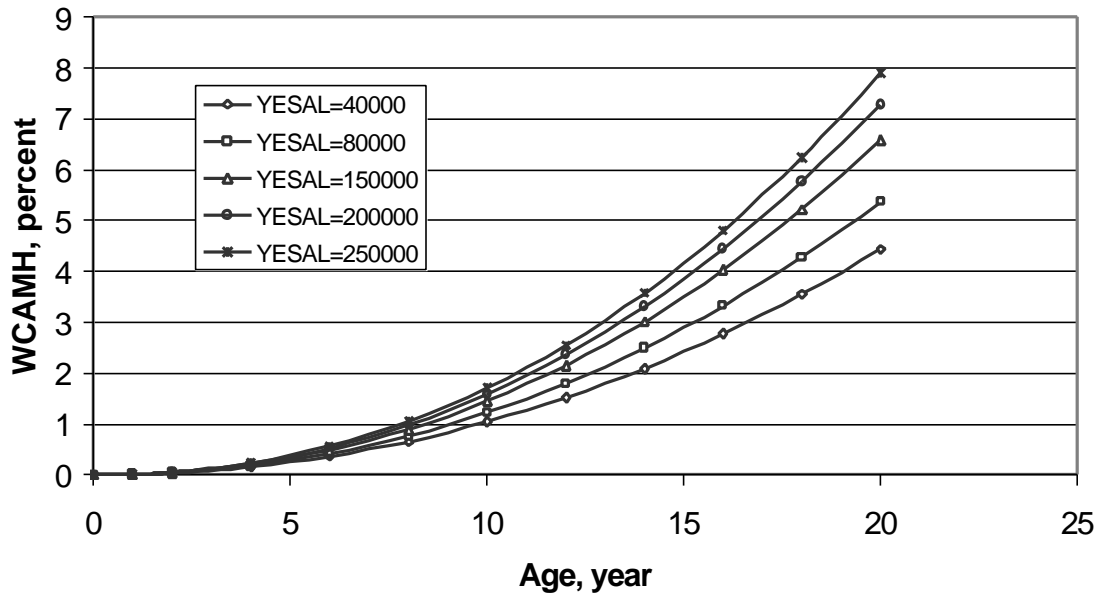
In order to improve the validity of the model, the expert model (prior model) is now augmented by the data-model employing XL-BAYS. The experts predicted a different trend in that the WCAMH increase was slower in the latter years. The resulting posterior model, as in the original flexible family, includes only three explanatory variables, AGE, CESAL, and MSN. These were the three variables employed in compiling expert opinion. The posterior model is,

$$\text{WCAMH} = \text{AGE}^{0.5621} \text{CESAL}^{0.1214} \text{MSN}^{-0.4962} \quad (5.10)$$

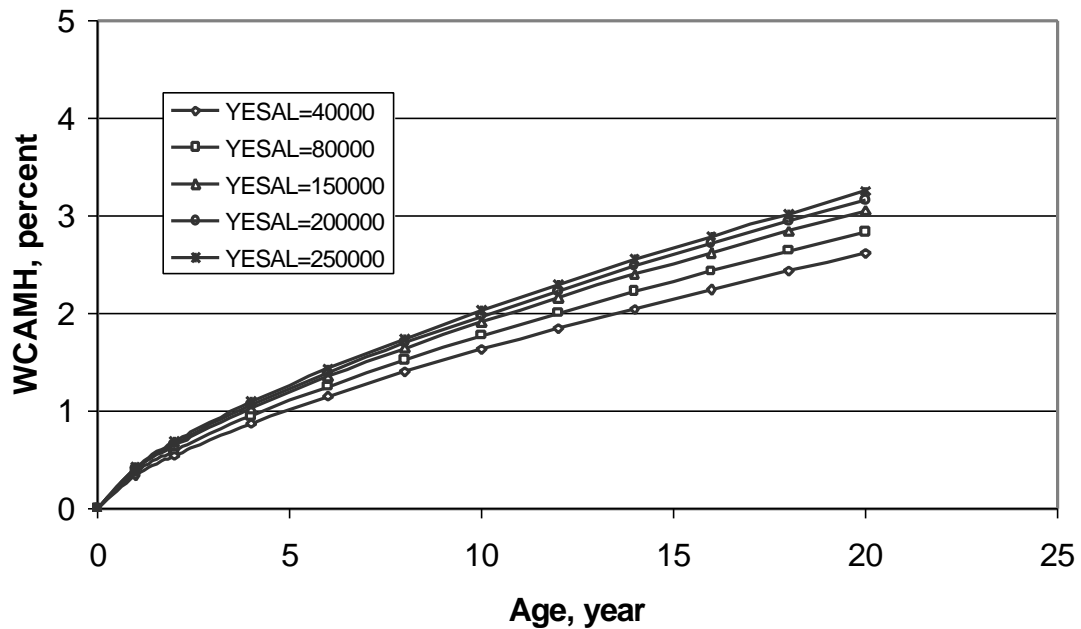
$$R^2 = 0.31, \text{RMSE} = 2.54$$

The sensitivity of WCAMH to load levels is graphed in Figure 5.12, with MSN kept constant (4.0). Showing little sensitivity to traffic level, alligator cracks begin to appear at a





**Figure 5.11** Variation of medium and high severity alligator cracks (WCAMH) with age for a range of traffic levels using data-model. Overlaid flexible pavement, (MSN=4, RES=10)



**Figure 5.12** Variation of medium and high severity alligator cracks (WCAMH) with age for a range of traffic levels using Bayesian model. Overlaid flexible pavement, (MSN=4).

very early age, though, the maximum value reaching only 3 percent level after 20 years. For the reason that the posterior model underpredicts WCAMH the writer recommends the data model found in Equation 5.9.

### 5.3.2 Model for Other Cracks

Besides Age and CESAL, the model warranted two more explanatory variables, namely, top thickness of the top-most overlay (TOPTHK) and the resurfacing type (RES). As dictated by the data, the best-fit model turned out to be of the following form:

$$OC = 19.1244 AGE^{0.6167} (1 + CESAL^{0.500}) TOPTHK^{-0.6752} RES^{0.2713} \quad (5.11)$$

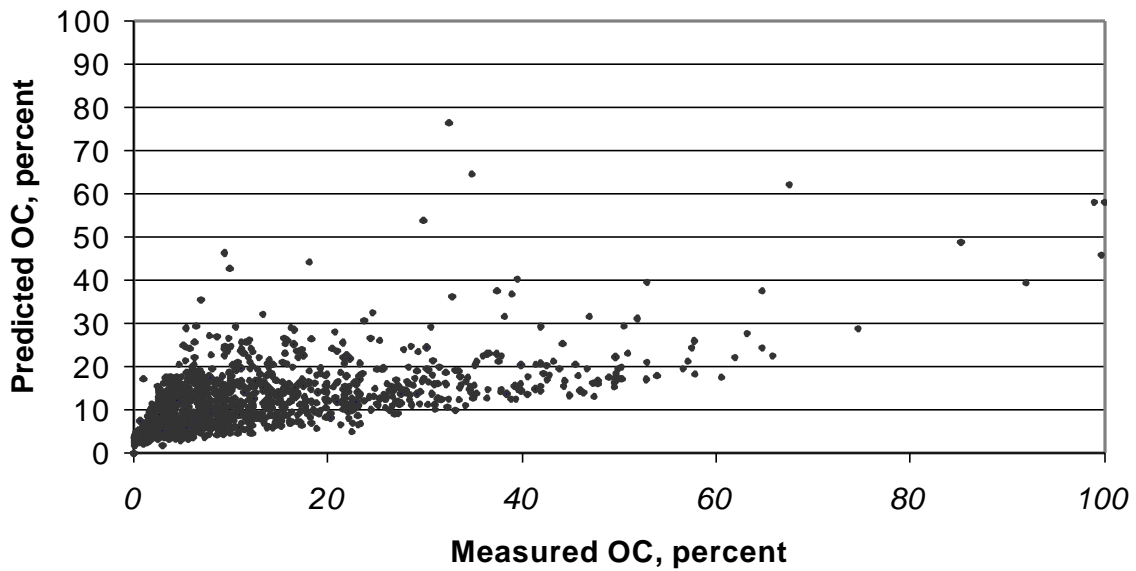
$$R^2 = 0.32, \text{ RMSE} = 10, \text{ N} = 3036$$

Among the significant explanatory variables included in the model age, traffic as well as RES (HMA surface) tend to increase this mode of cracking. Because of the surface texture and flexibility perhaps, surface treatment (for example, single or double bituminous surface treatment) inhibits cracking.

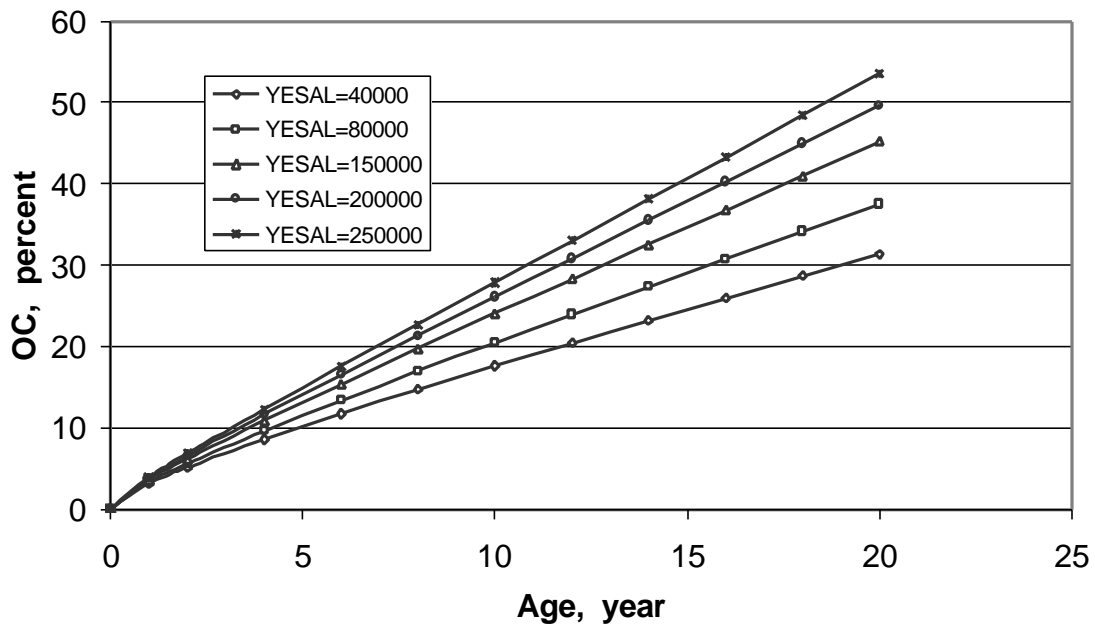
The predictability of the model is investigated employing the out-of-sample data, as shown in Figure 5.13. Evident from the data is that the model somewhat under-predicts the crack density, especially at crack levels above 30%. The progression of cracks with age for various traffic volumes (TOPTHK = 50.8 mm (2 inch) and RES = 10) is graphed in Figure 5.14. It is noteworthy that the cracks begin to develop at very early ages, unlike that in the original flexible pavements where they are delayed for a few years before they begin spreading the pavement surface.

### 5.3.3 Models for Other Cracks of Medium and High Severity

An equation similar in form to that for OC cracks with the same set of five variables is found to predict medium and high severity other cracks.



**Figure 5.13** Comparison of measured and predicted other cracks (OC) using out-of-sample data. Overlaid flexible pavement.



**Figure 5.14** Variation of other cracks (OC) with age for a range of traffic levels using data model. Overlaid flexible pavement, (TOPTHK=50.8mm, RES=10).

$$\text{OCMH} = 61.367 \text{ AGE}^{1.4025} (1 + \text{CESAL}^{1.6154}) \quad (5.12)$$

$$\text{TOPTHK}^{-2.6379} \text{ RES}^{1.3710}$$

$$R^2 = 0.51, \text{ RMSE} = 3.6, N = 4286$$

The cause-and-effect relationship of this model is identical to that for other cracks, with a better  $R^2$ , however. Note that the large exponent of RES and large negative exponent of TOPTHK play opposite roles in Equation 5.12, indicating that cracks on HMA surface generally overtakes those on surface treatment.

The predicted values for the out-of-sample data appear in a horizontal band (see Figure 5.15), an indication that the model is likely to underpredict. That numerous sections are reported to have zero cracks regardless of age and CESAL could be a reason for this anomalous result. Figure 5.16 plots the evolution of crack with age for various traffic volumes (TOPTHK = 50.8 mm (2 inch), HMA resurfacing). Note that beyond 10 years the crack density increases at an exponential rate.

#### 5.3.4 Rutting Model

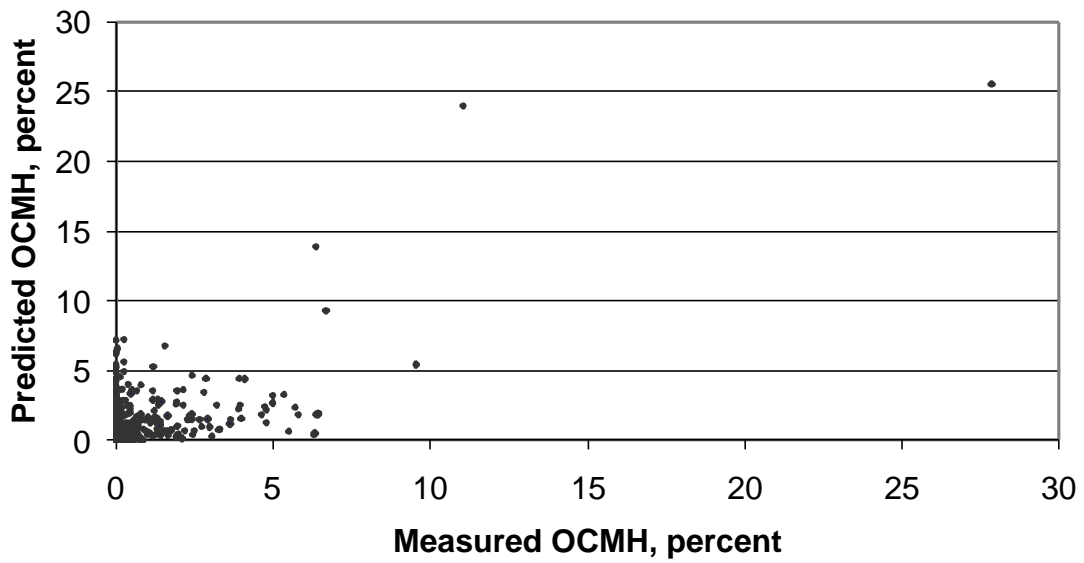
Cumulative traffic and age are identified to be the significant variables for predicting rutting. The model for 85<sup>th</sup> percentile rutting in millimeter units is:

$$\text{RT85} = 5.22 \text{ AGE}^{0.27} \text{ CESAL}^{0.0600} \quad (5.13)$$

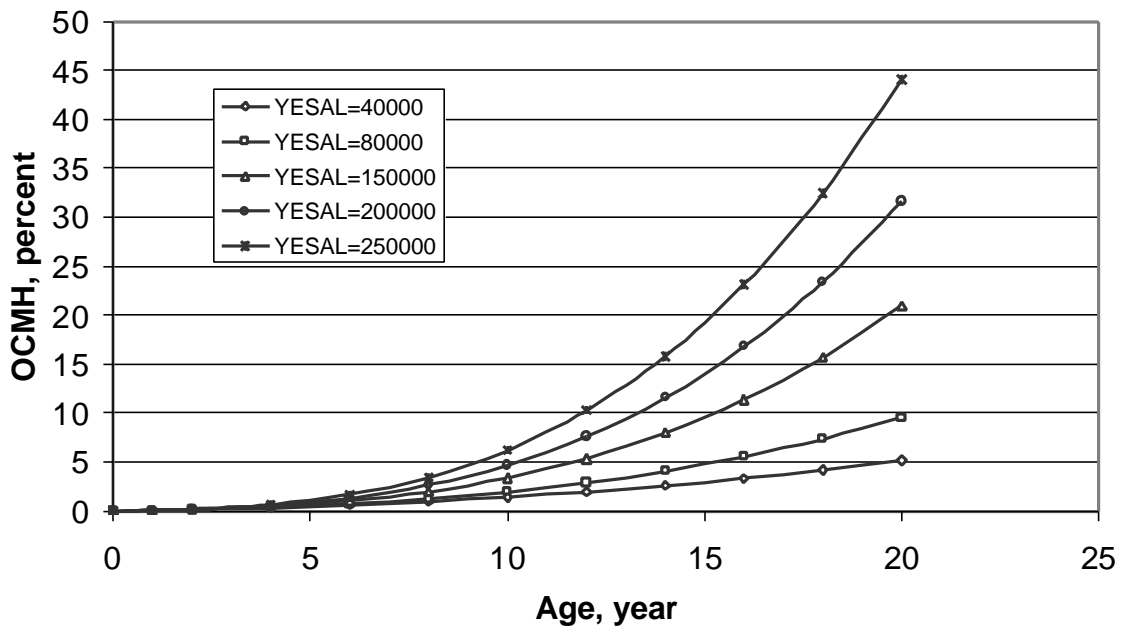
$$R^2 = 0.47, \text{ RMSE} = 4.3$$

Rutting is shown to increase with traffic and age, traffic playing a minor role according to the data-model (Equation 5.13).

The expert opinion is brought to bear on the data-model employing XL-BAYS. A power model with experts' data is now developed and compared with the data-model noting that the former predicts much higher rutting distress than that obtained from the data-model.



**Figure 5.15** Comparison of measured and predicted medium and high other cracks (OCMH) using out-of -sample data. Overlaid flexible pavement.



**Figure 5.16** Variation of medium and high other cracks(OCMH) with age for a range of traffic levels using data-model. Overlaid flexible pavement, (TOPTHK=50.8mm, RES=10)

This finding is not unexpected because of numerous sections (nearly 60 percent) showing rutting less than 6.4mm (1/4 inch). With such large disparity between the prior model and the data-model, a compromise model is sought with Bayesian regression. The model with the same two variables is:

$$RT85 = 5.2498 \text{ AGE}^{0.3583} \text{ CESAL}^{0.2524} \quad (5.14)$$

$$R^2=0.47, \text{RMSE}=4.3, N=252$$

The sensitivity of the posterior model is investigated by plotting the rutting progression with age at various traffic volumes as shown in Figure 5.17. Unlike the data-model, rutting is strongly influenced by traffic in the posterior model. With a traffic volume of 150,000 ESALs annually, a rutting of 17 mm in 15 years is judged to be reasonable; accordingly, Equation 5.14 is recommended for MDOT's pavement management.

### 5.3.5 Roughness Model

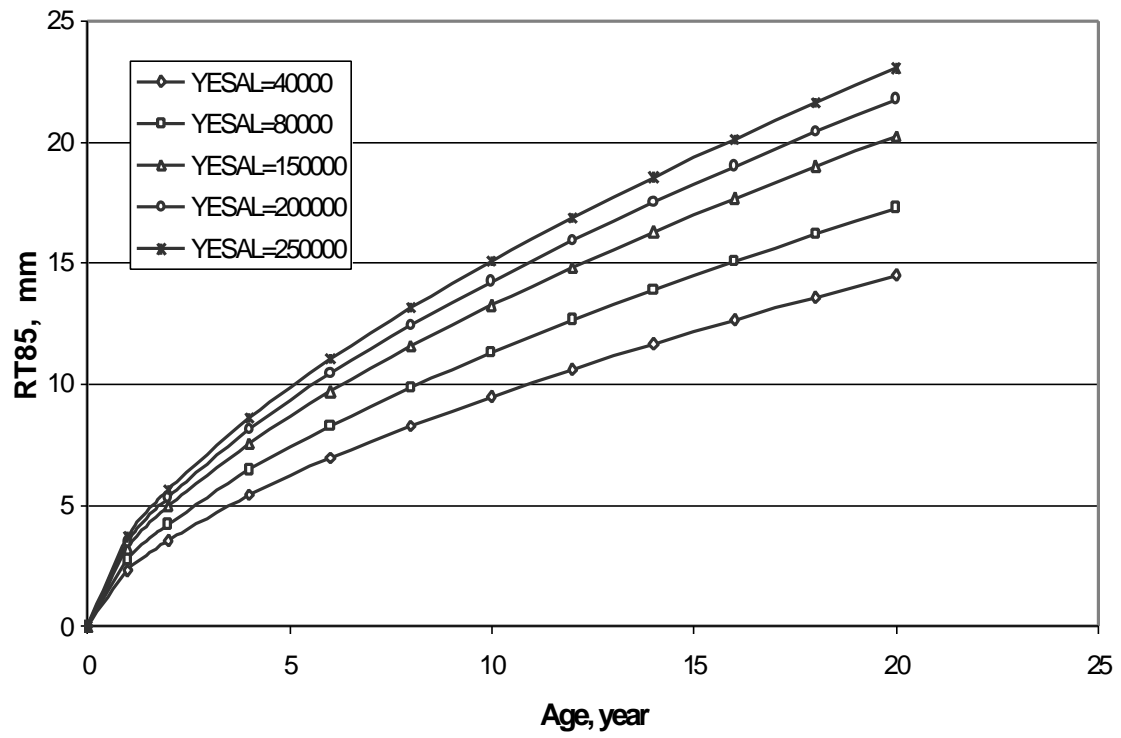
The roughness model has to satisfy the initial condition in that the initial IRI soon after overlay should be a function of structural number, the most recent overlay thickness and a secondary variable, the resurfacing type. The model form with five variables satisfies those criteria.

$$IRI = (3.5746 + \text{Age}^{0.1701} (1 + \text{CESAL}^{0.6972})) \quad (5.15)$$

$$\text{MSN}^{-0.3438} \text{ TOPTHK}^{-0.1313} \text{ RES}^{-0.1056}$$

$$R^2 = 0.48, \text{RMSE} = 0.38, N = 4109$$

Note that the initial value of IRI is not only a function of MSN, as in the original flexible pavement model, but also influenced by overlay thickness and surface type. As expected, a HMA surface results in lower initial roughness than surface treatment. The thicker the



**Figure 5.17** Variation of 85<sup>th</sup> percentile rutting (RT85) with age for a range of traffic levels using Bayesian model. Overlaid flexible pavement.

overlay the smoother the road initially, continuing to be smooth throughout its life span. As in the original flexible pavement model, thicker pavements inhibit road roughness.

The predictability of the model is substantiated by comparing the measured and predicted IRI values of the out-of-sample data (see Figure 5.18). That the plotted points align along the line of equality indicates the robustness of the model. How the model predicts road roughness with age for various traffic levels (keeping MSN=4.0, TOPTHK=50.8mm (2 inch) and RES=10) is graphed in Figure 5.19. The predictions are judged to be reasonable, attesting the viability of the model.

### 5.3.6 PCR Model

Not only does the model need to describe the trend in PCR, it also has to predict the initial PCR. As in the IRI model, five variables are included in the analysis to result in the following equation:

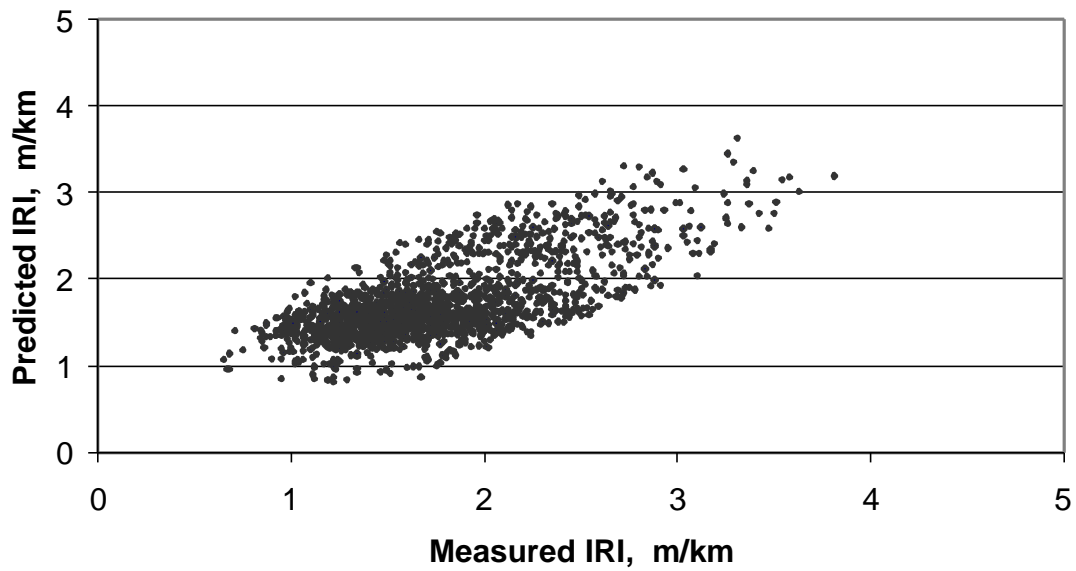
$$\text{PCR} = (70.69 - \text{Age}^{0.6471} (1 + \text{CESAL}^{0.7564})) \text{MSN}^{0.0291} \text{TOPTHK}^{0.0272} \text{RES}^{0.0198} \quad (5.16)$$

$$R^2 = 0.43, \text{RMSE} = 4.7, N = 4062$$

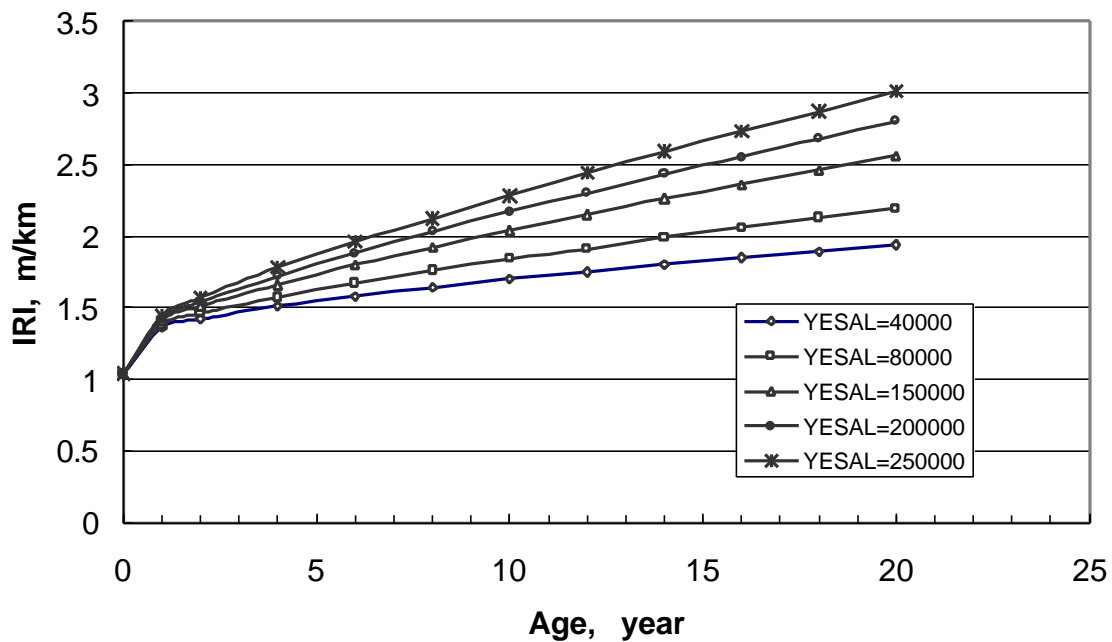
As expected, the model predicts slightly higher PCR for HMA surface. Increased MSN, TOPTHK or HMA surface, in contrast to surface treatment, results in higher PCR in this family of pavements.

The adequacy of the model is investigated by comparing the predicted and measured PCR values of the out-of-sample data (see Figure 5.20). That the plotted points align along the line of equality attests to the validity of the model. Figure 5.21 depicts how PCR

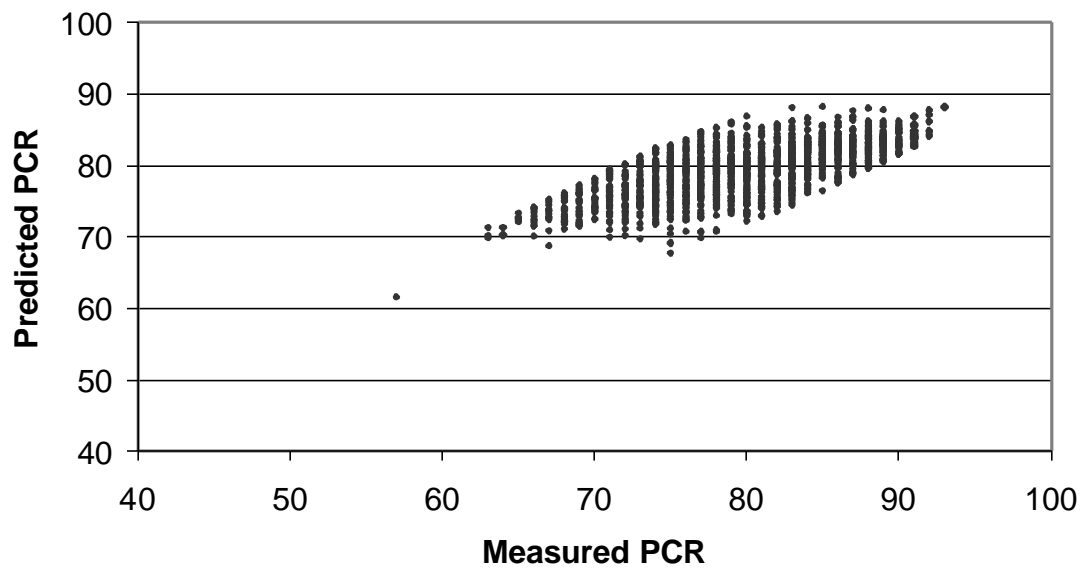




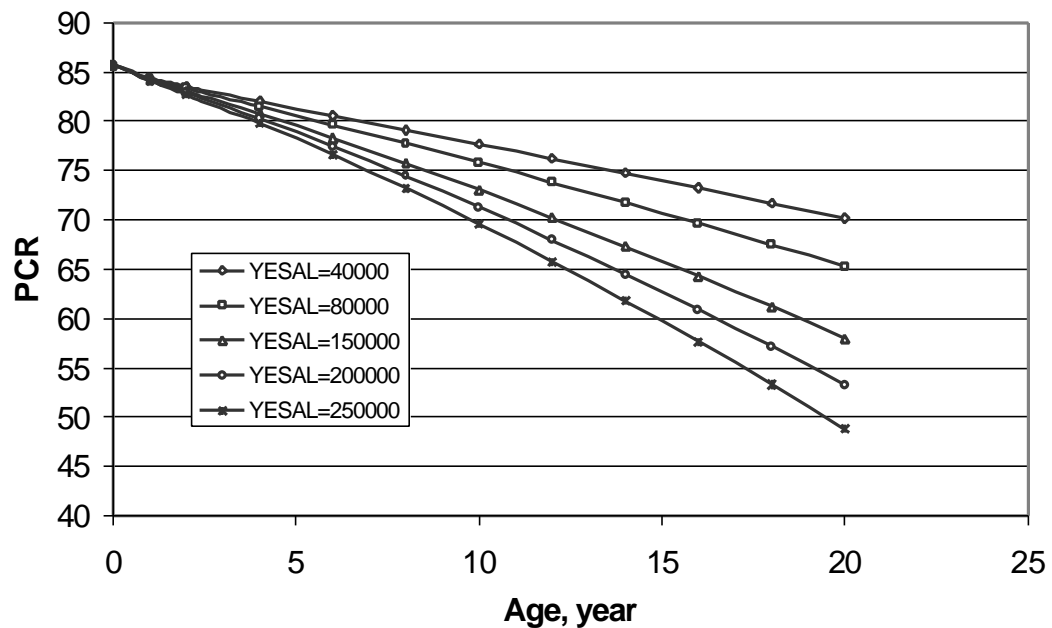
**Figure 5.18** Comparison of measured and predicted International Roughness Index (IRI) using out-of-sample data. Overlaid flexible pavement.



**Figure 5.19** Variation of International Roughness Index (IRI) with age for a range of traffic levels using data-model. Overlaid flexible pavement, (MSN=4, TOPTHK=50.8mm, RES=10).



**Figure 5.20** Comparison of measured and predicted Pavement Condition Rating (PCR) using out-of -sample data. Overlaid flexible pavement.



**Figure 5.21** Variation of Pavement Condition Rating (PCR) with age for a range of traffic levels using data-model. Overlaid flexible pavement, (MSN=4, TOPTHK=50.8mm, RES=10)

decreases with age for various traffic levels, with MSN = 4.0, TOPTHK = 50.8mm (2 inch) and HMA surface. The predicted PCRs at different ages seem to be reasonable.

With the expert opinion available, an attempt is made to augment the data-model with the expert opinion model. For not being able to develop a linear or power model with the field data, a necessary requirement to use XL-BAYS program, the Bayesian model could not be pursued.

Nonetheless, it is interesting to investigate how the data model compares with the expert opinion model. With a power model fitted for the expert opinion, the PCR trend of the two models with age is plotted in Figure 5.9. As in the original flexible models, the trend lines nearly coincide for the first seven-year life span, beyond which the expert predictions substantially deviate from the data model, with the expert opinion model under-predicting PCR, and in turn, the road's condition. Accordingly, the data-model, Equation 5.16, is recommended in lieu of the expert opinion model.

## 5.4 COMPOSITE PAVEMENT MODELS

As in overlaid flexible pavements, the primary explanatory variables considered include age and traffic. As a measure of structural capacity, thickness of the last overlay is considered as an explanatory variable as well. Tables 5.7 and 5.8 present the range of response and explanatory variables, respectively.

**Table 5.7 Range of Response Variables Employed in the Development of Models, Composite Pavements**

ResponseVariable	Description	Range
<b>WCAMH</b>	Weighted alligator cracking of medium and high severity, percent	0 – 3.0
<b>OC</b>	Other cracks, percent	0 – 51.6
<b>OCMH</b>	Other cracks of medium and high severity, percent	0 – 14.0
<b>RT85</b>	85 <sup>th</sup> percentile rutting, mm	0 – 30.2
<b>IRI</b>	Roughness, m/km	0.66 – 3.25
<b>PCR</b>	Pavement condition rating	56 – 94

**Table 5.8 Range of Explanatory Variables Used in the Development of Models for Composite Pavements**

Explanatory Variable	Range of Explanatory Variables of Models					
	WCAMH	OC	OCMH	RT85	IRI	PCR
Age, years	0 – 22	0 - 30	0 - 28	1.00-11.00	0 - 30	0 - 29
18-kip CESAL, million	0 - 6.40	0 - 8.94	0 - 8.64	0.08-2.15	0 - 8.94	0 - 8.94
TOPTHK , mm	6.4 - 457.2	6.4 - 457.2	6.4 - 457.2	2.65-11.56	6.4 - 356.0	6.4 - 356.0

#### 5.4.1 Medium and High Severity Alligator Cracking Model

Besides age and traffic, the data dictated one more explanatory variable for Predicting WCAMH in composite pavements. The thickness of the most recent overlay (TOPTHK) emerged as that variable. As can be seen in Table 5.3, numerous sections were devoid of alligator cracking. A three-variable equation is derived as follows:

$$\text{WCAMH} = 0.7213\text{E-}4 \text{ Age}^{4.0617} (1 + \text{CESAL}^{0.5940}) \text{ TOPTHK}^{-0.5690} \quad (5.17)$$

$$R^2 = 0.53, \text{ RMSE} = 0.10, N = 1143$$

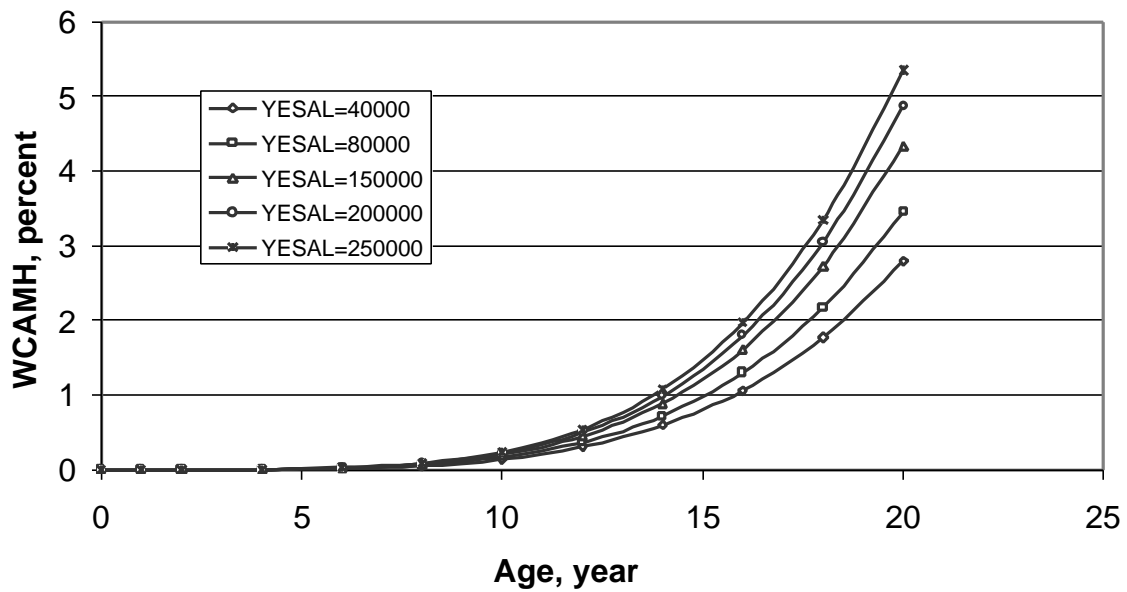
Evaluations of WCAMH with age for various traffic volumes are graphed in Figure 5.22. The alligator cracks increase exponentially beyond 15 years.

With expert opinion tabulated and available, it is incorporated in the data-model employing XL-BAYS. The resulting posterior equation again includes the same three variables as in Equation 5.17.

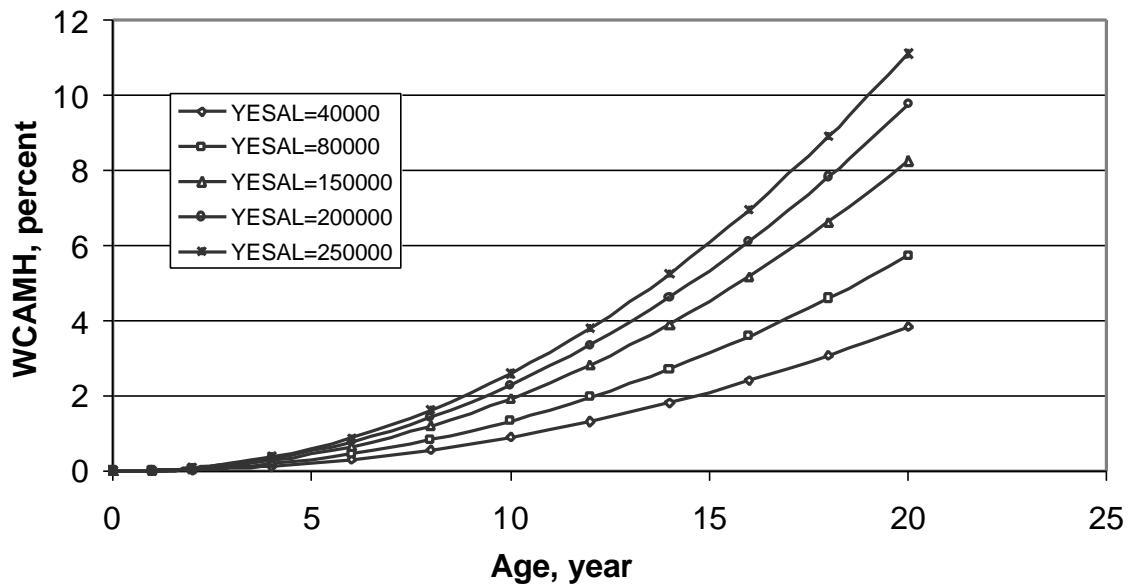
$$\text{WCAMH} = \text{Age}^{1.5150} \text{ CESAL}^{0.5800} \text{ TOPTHK}^{-0.7800} \quad (5.18)$$

$$R^2 = 0.34, \text{ RMSE} = 0.98$$

Evolution of alligator cracking when subjected to various levels of traffic loading TPTHK = 50.8mm (2 inch), is shown in Figure 5.23. Comparing Figures 5.22 and 5.23, it is noted that the posterior model predictions are high compared to the other two families of flexible pavements, intuitively an unacceptable result. With reasonable WCAMH predictions as



**Figure 5.22** Variation of Medium and high severity alligator cracks (WCAMH) with age for a range of traffic levels using data model. Composite pavement, (TOPTHK=50.8mm).



**Figure 5.23** Variation of Medium and high severity alligator cracks (WCAMH) with age for a range of traffic levels using Bayesian model. Composite pavement, (TOPTHK=50.8mm).

shown in Figure 5.22, the data-model, Equation 5.17 is recommended in lieu of Equation 5.18.

#### 5.4.2 Other Cracks Model

The same three variables as for WCAMH evolved as the prominent explanatory variables. The equation is:

$$OC = 15.50 \text{ Age}^{0.5786} (1 + \text{CESAL}^{0.5345}) \text{ TOPTHK}^{-0.4298} \quad (5.19)$$

$$R^2 = 0.43, \text{ RMSE} = 5.53, \text{ N} = 1292$$

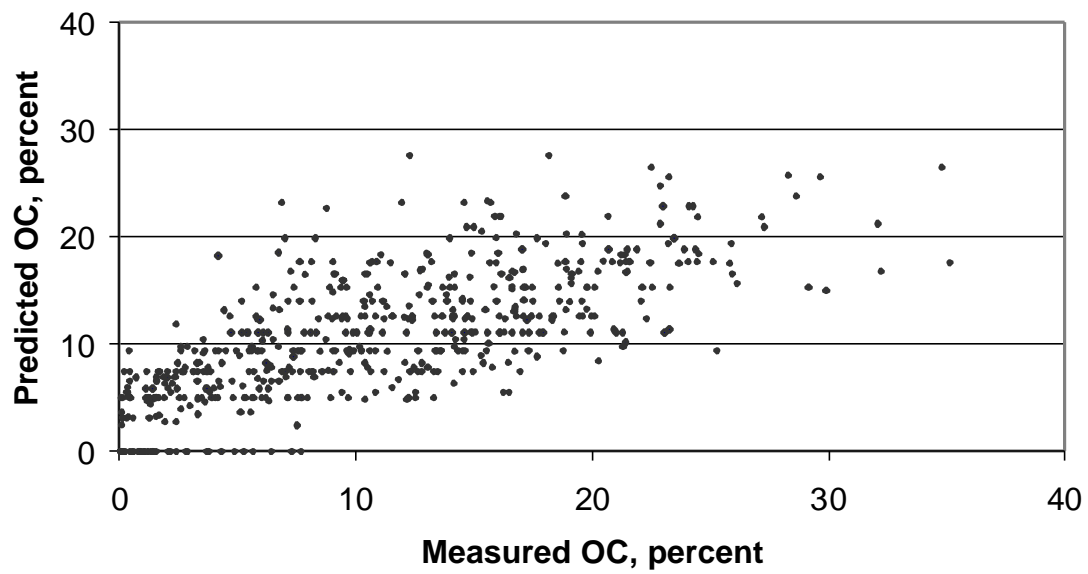
The model predictability is illustrated by plotting the actual OC against predicted OC of the out-of-sample data (see Figure 5.24). Note that the plotted points are aligned close to the line of equality. Further investigation of the effect of age and traffic level on OC cracks is undertaken, keeping TOPTHK constant at 50.8mm (2 inches), with the results graphed in Figure 5.25. The cracks begin to appear at early age and continue to accumulate until the pavement is totally cracked. The early distresses could be attributed to block cracking and reflection cracking, which are caused by thermal shrinking, an age-dependent phenomenon. This is especially true for thin overlays, typically 76.2mm (3 inches) or less. In general, reflection cracks develop fairly early in composite pavements due to differential movement of underlying slab. On the other hand, block cracking progresses at a steady rate in the early period, attaining a maximum value of 100 percent in due course.

#### 5.4.3 Models for Other Cracks of Medium and High Severity

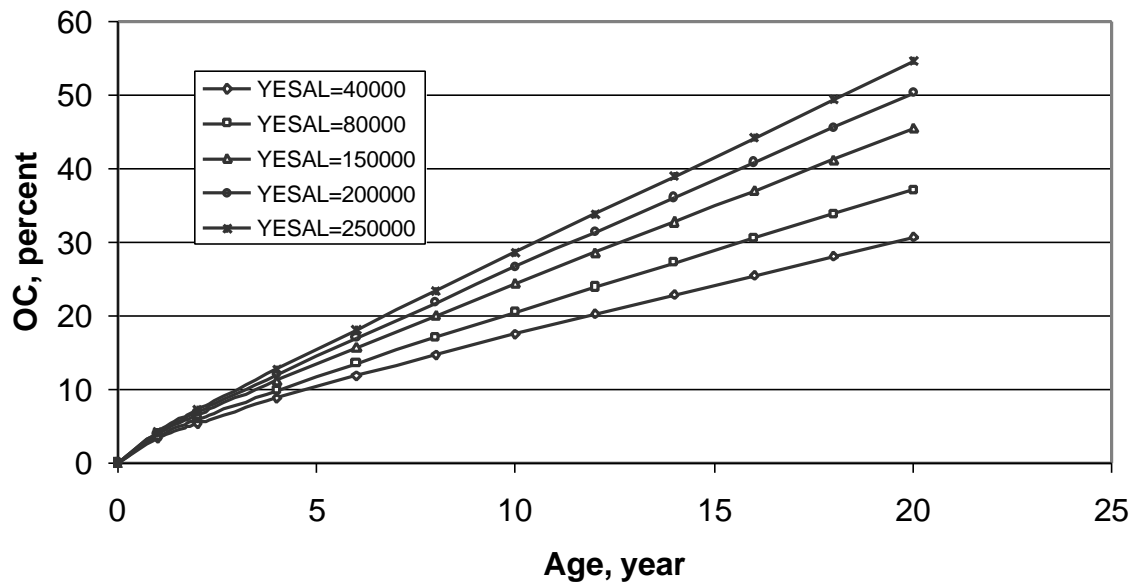
The model for predicting other cracks of medium and high severity (OCMH percentage) is:

$$\text{OCMH} = 0.8267\text{E-}2 \text{ Age}^{2.309} (1 + \text{CESAL}^{1.4460}) \text{ TOPTHK}^{-0.2338} \quad (5.20)$$

$$R^2 = 0.68, \text{ RMSE} = 0.56, \text{ N} = 1148$$



**Figure 5.24** Comparison of measured and predicted other cracks (OC) using out-of-sample data. Composite pavement.



**Figure 5.25** Variation of other cracks (OC) with age for a range of traffic Levels using data model. Composite pavement, (TOPTHK=50.8mm).

OCMH tends to increase with age and traffic volume. Thicker overlays inhibit this class of cracks. First, the OCMH of the out-of-sample data is predicted with the equation and plotted against the measured values, (see Figure 5.26). While the agreement is good, it is noted that the crack density is relatively small, for instance, less than 4 percent. Second, the evolution of OCMH at different traffic levels (at constant TOPTHK of 50.8mm) is graphed in Figure 5.27. As these cracks form through an evolutionary process, it may be several years before they would become noticeable. The delay period appears to be approximately 6 years, as per the model equation.

#### 5.4.4 Rutting Model

In addition to age and traffic volume, thickness of the most recent overlay is significant in the prediction of pavement rutting (85<sup>th</sup> percentile):

$$RT85 = Age^{0.3690} CESAL^{0.1300} TOPTHK^{0.4200} \quad (5.21)$$

Unlike that in the overlaid pavement the thickness of the most recent overlay appears to be a significant variable, where rutting increases with overlay thickness.

With realistic expert opinion on pavement rutting, the data-model is incorporated in the expert model employing XL-BAYS. The resulting posterior model has the same variables but with somewhat different exponents:

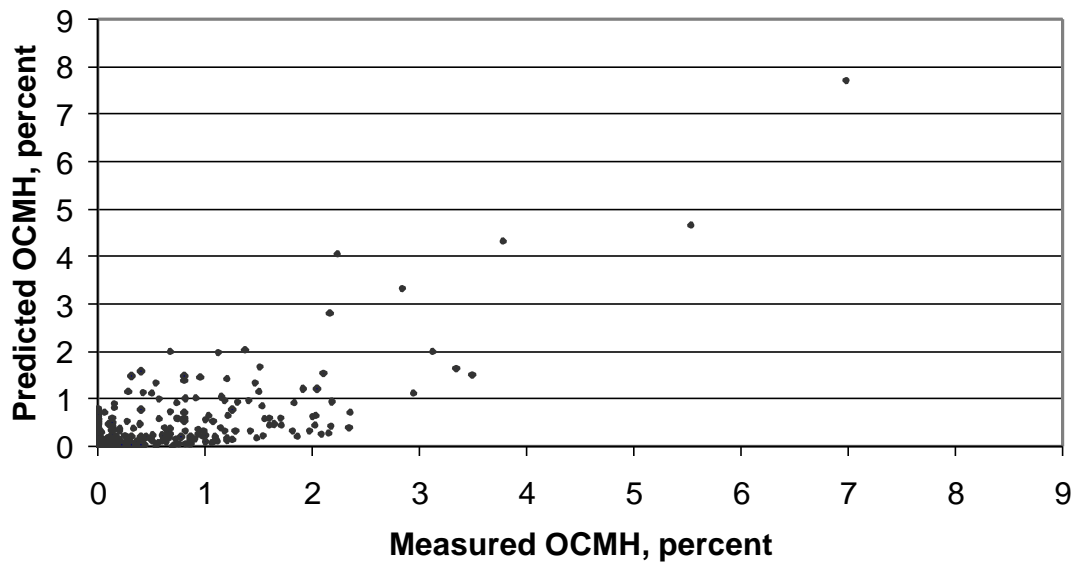
$$RT85 = Age^{0.1217} CESAL^{0.4973} TOPTHK^{0.4506} \quad (5.22)$$

$$R^2 = 0.78, RMSE = 3.4$$

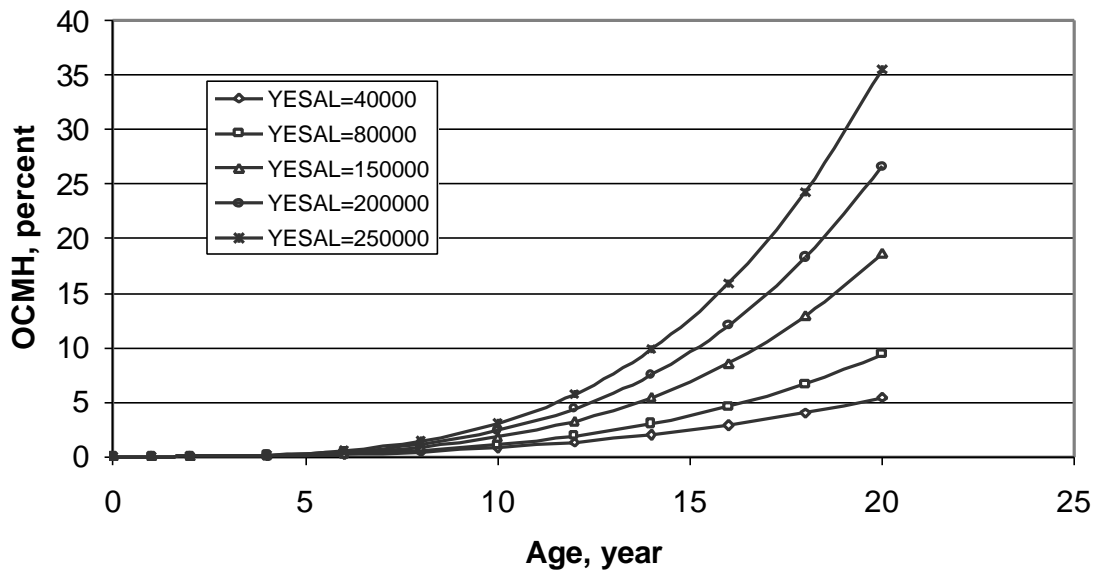
Note that the exponent of traffic is increased from 0.13 to 0.50 signifying that the posterior model relies heavily on traffic volume to predict rutting. Importance of age is overshadowed by CESAL in this model.

The sensitivity of the model is explored by predicting rutting with age in roads





**Figure 5.26** Comparison of measured and predicted medium and high other cracks (OCMH) using out-of-sample data. Composite pavement.



**Figure 5.27** Variation of medium and high other cracks (OCMH) with age for a range of traffic levels using data-model. Composite pavement, (TOPTHK=50.8mm).

with various traffic volumes, keeping the TOPTHK constant at 50.8mm (2 inch). It is encouraging to note that the rate of rutting declines with age. Eighty-fifth percentile rutting of the order of 15mm in 15 years and  $2.25 \times 10^6$  CESAL seems reasonable (see Figure 5.28). Accordingly, the Bayesian Model (Equation 5.22) is recommended for MDOTs' PAP.

#### 5.4.5 Roughness Model

The roughness model needs to satisfy an initial condition which in all likelihood would be dependent on the overlay thickness. Only three explanatory variables appear significant in the following model for IRI:

$$IRI = (3.095 + Age^{0.3571} (1 + CESAL^{0.3054})) TOPTHK^{-0.3235} \quad (5.23)$$

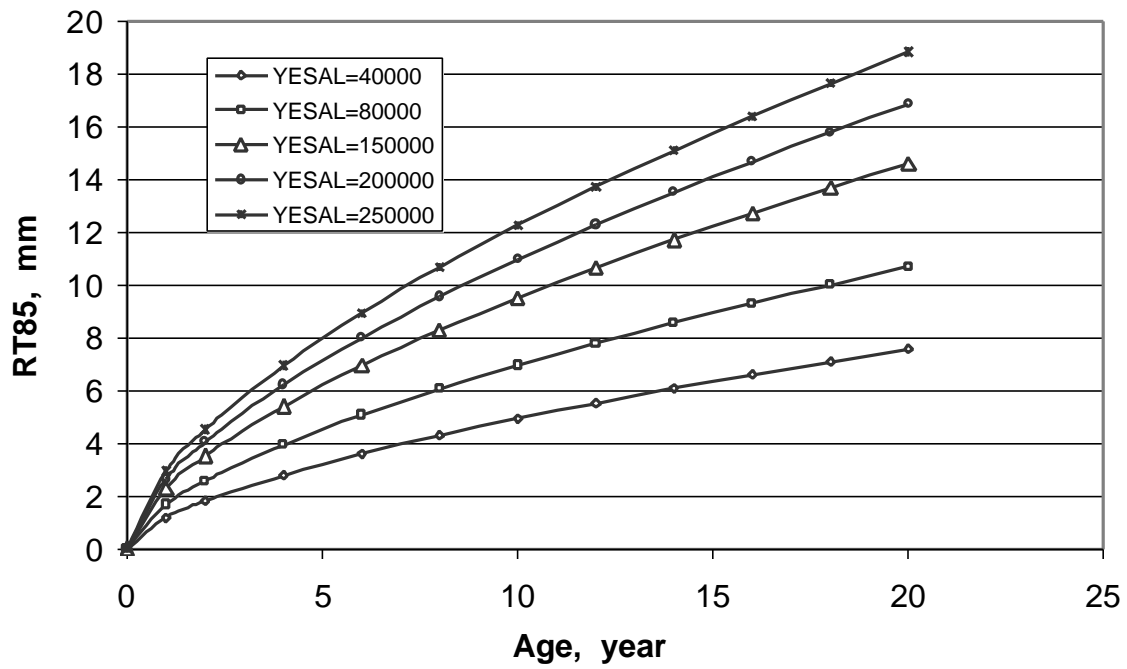
$$R^2 = 0.53, RMSE = 0.10, N = 1143$$

Note the initial roughness decreases with increase in overlay thickness. While IRI increases with age and CESAL, TOPTHK promotes smoother road surface.

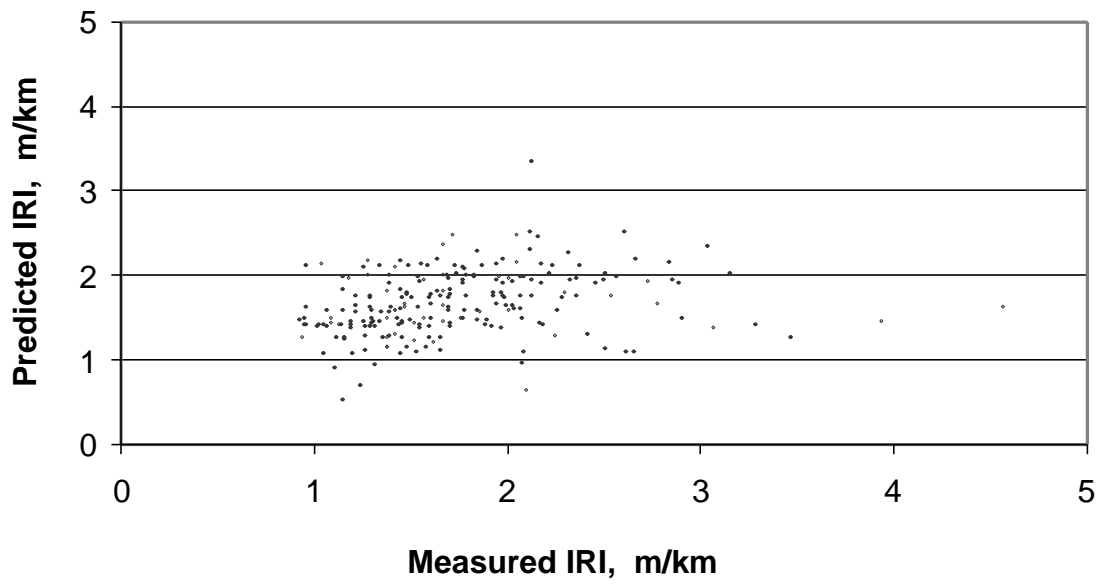
The predictability of the model is substantiated by comparing measured and predicted IRI values of the out-of-sample data. The scatter of plotted points in Figure 5.29 indicates that the model could under-predict the IRI of very rough roads. How roughness evolves with age at various traffic levels, for a typical overlay thickness of 50.8mm (2 inches), can be seen in Figure 5.30. With reasonable predictions recorded, the model is recommended for MDOT pavement management system.

#### 5.4.6 PCR Model

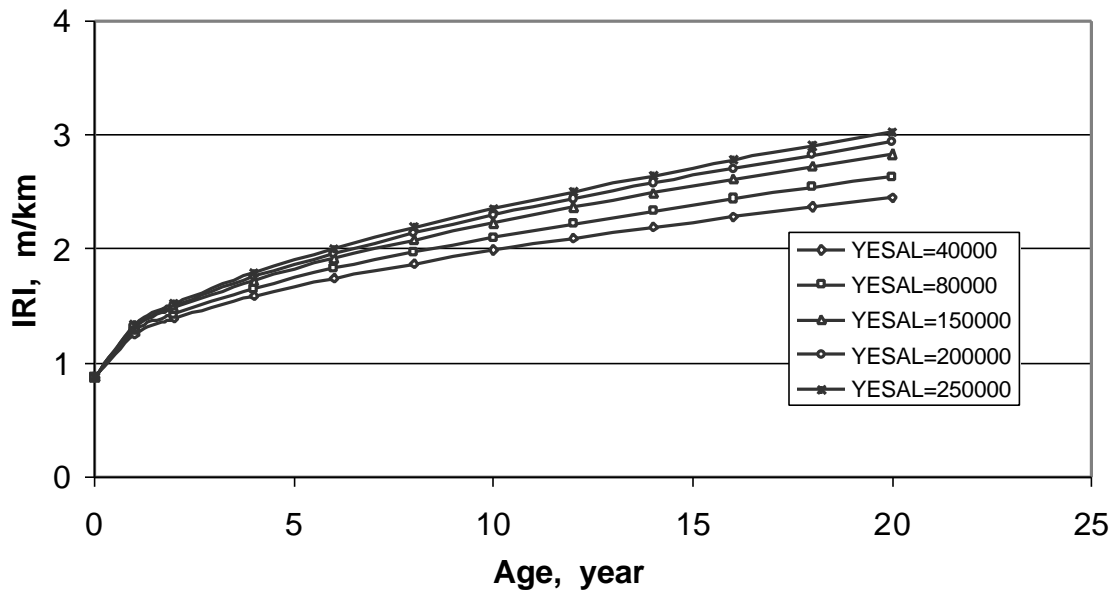
Again, the model has to describe the trend in PCR with time and traffic as well as predict an initial value. A three-variable equation is found to fit these requirements:



**Figure 5.28** Variation of 85<sup>th</sup> percentile rutting (RT85) with age for a range of traffic levels using Bayesian model. Composite pavement, (TOPTHK=50.8mm).



**Figure 5.29** Comparison of measured and predicted roughness, IRI, using out-of-sample data. Composite pavement.



**Figure 5.30** Variation of roughness, IRI, with age for a range of traffic levels using data-model. Composite pavement, (TOPTHK=50.8mm).

$$PCR = (56.87 - \text{Age}^{0.5681} (1 + \text{CESAL}^{0.7154})) \text{TOPTHK}^{0.1045} \quad (5.24)$$

$$R^2 = 0.53, \text{RMSE} = 4.00, N = 1060$$

The thicker overlay not only results in higher initial PCR but also maintains a superior pavement surface with time/traffic. The predictability of the model is investigated by computing the PCR of the out-of-sample data and comparing them with the measured values (see Figure 5.31). The agreement is satisfactory. Graphed in Figure 5.32 are trend lines depicting PCR decrease with age at various traffic levels, holding the overlay thickness constant at 50.8mm. Note that realistic PCRs are predicted by the model.

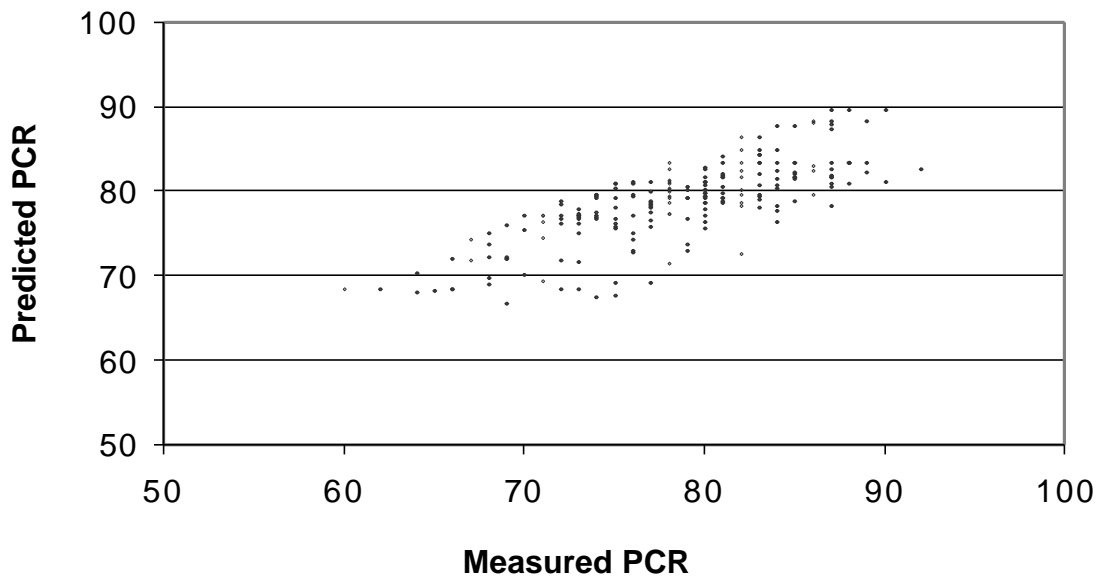
The quest for a Bayesian regression model is dropped as the expert opinion model projects very low PCR values all throughout the life of the pavement (see Figure 5.9). Neither the initial PCR of 76 nor the 15-year projected PCR of 43 for a 76mm overlay seems reasonable. Accordingly, the data-model, Equation 5.24, is recommended for PCR prediction.

## 5.5 MODELS FOR JOINTED CONCRETE PAVEMENTS

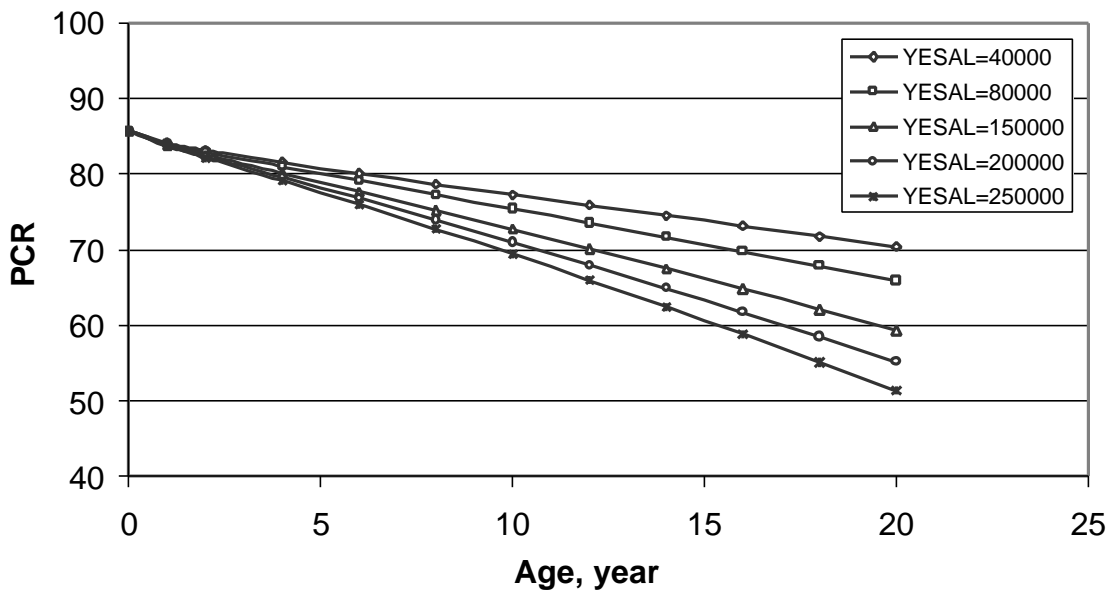
For jointed concrete pavements the following explanatory variables are considered: age, CESAL, thickness of slab, type of base course, and classification of road according to the HPMS system. The range of the response variables are listed in Table 5.9 and the explanatory variables in Table 5.10.

**Table 5.9 Range of Response Variables Used in the Development of Models for Jointed Concrete Pavements**

Response Variable	Description	Range
AC	Cracks, percent	0 – 4.63
SP	Spalling, percent	0 – 1.4
IRI	Roughness, m/km	0.70 – 5.77
PCR	Pavement Condition Rating	42 – 94



**Figure 5.31** Comparison of measured and predicted Pavement Condition Rating (PCR) using out-of-sample data. Composite pavement.



**Figure 5.32** Variation of Pavement Condition Rating (PCR) with age for a range of traffic levels using data-model. Composite pavement, (TOPTHK=50.8mm).

**Table 5.10 Range of Explanatory Variables Used in the Development of Models, Jointed Concrete Pavements**

Explanatory Variable	Range of Explanatory Variables of Models			
	AC	SP	IRI	PCR
Age, years	0 - 60	0 - 65	0 - 65	0 - 65
18-kip CESAL, million	0 - 26.83	0 - 13.5	0 - 34.3	0 - 34.3
Slab thickness, mm	127 - 330		127 - 330	127 - 330

### 5.5.1 Model for Cracking

Amongst the many explanatory variables considered, only three appear significant: age, traffic, and slab thickness. The model is:

$$AC = 2.4118 (\text{Age} - 3)^{0.2465} \text{CESAL}^{0.5473} \text{SLABTHK}^{-0.3735} \quad (5.25)$$

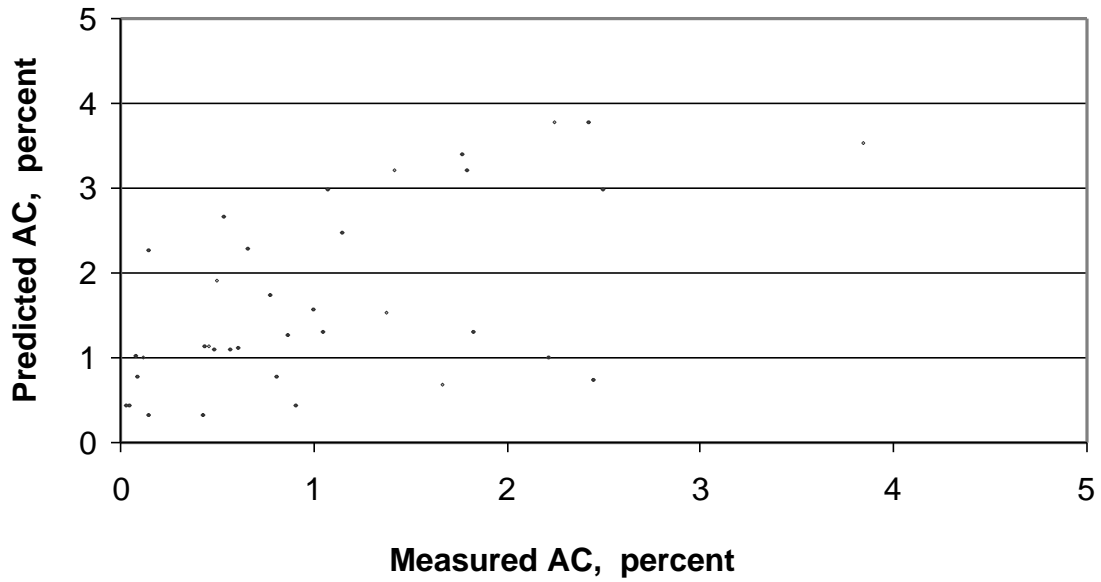
$$R^2 = 0.28, \text{RMSE} = 0.88, N = 213$$

The age-shift of three years simply means that the pavement could be practically crack-free during this period. As per the model, thicker slab, rightly so, inhibits crack density. Understandably, cracks increase with age and traffic.

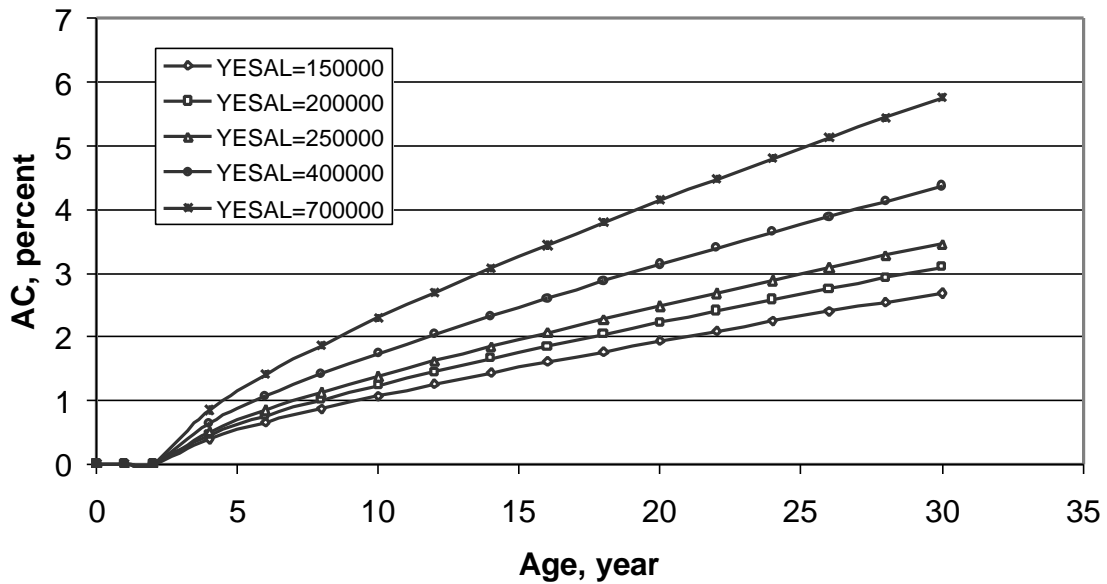
Illustrated in Figure 5.33 is a comparison of measured versus predicted cracks employing the out-of-sample data. The plotted points are distributed over a wide band with respect to the line of equality, a marginally acceptable result. The sensitivity of the model is investigated in Figure 5.34, where crack density is plotted against age at various traffic volumes, keeping the slab thickness constant at 254mm (10 inch). Two and one-half percent cracks in 20 years for a yearly traffic volume of 250,000 ESALs appears reasonable.

### 5.5.2 Spalling Model

Initiated by ambient environment, joints begin to spall rapidly with traffic volume aided by extreme temperature variations (51). With only two variables significant in



**Figure 5.33** Comparison of measured and predicted all cracks (AC) using out-of-sample data. Jointed concrete pavement.



**Figure 5.34** Variation of all cracks (AC) with age for a range of traffic levels using data-model. Jointed concrete pavement, (SLABTHK=254mm).



predicting spall, the model becomes:

$$SP = 0.4647 * E^{-2} Age^{0.7885} CESAL^{0.8506} \quad (5.26)$$

$$R^2 = 0.59, RMSE = 0.13, N = 117$$

Judging from the nearly equal exponents for age and traffic, it may be in order to presume their influence on spall to be nearly identical. Despite expectations that HPMS Class I pavements might show fewer spalled joints, the data fails to reflect such a trend. Thickness of slab is not found to be significant either.

The model predictability is evaluated by comparing the predicted spalling with the measured, for the out-of-sample data (see Figure 5.35). In pavements with minor spalling, the agreement is marginal, to say the least. The question whether the model can predict realistic spalling density can be seen in Figure 5.36, where spalling with age is plotted for a range of traffic levels. Spalling of the order of 0.5% in 30 years is considered realistic, a testament to the validity of the model.

### 5.5.3 Roughness Model

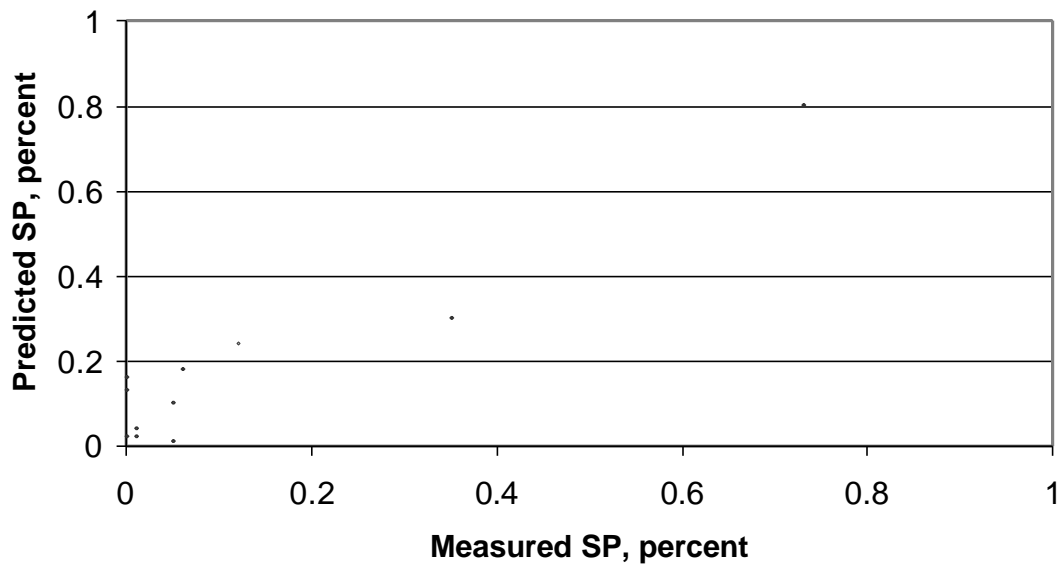
A survey (50) of initial roughness of jointed concrete pavements constructed in various states indicates that many newly constructed jointed concrete pavements exhibit an initial roughness of 0.7m/km. A slightly higher value is indicated by MDOT data, however.

The best-fit model for IRI is:

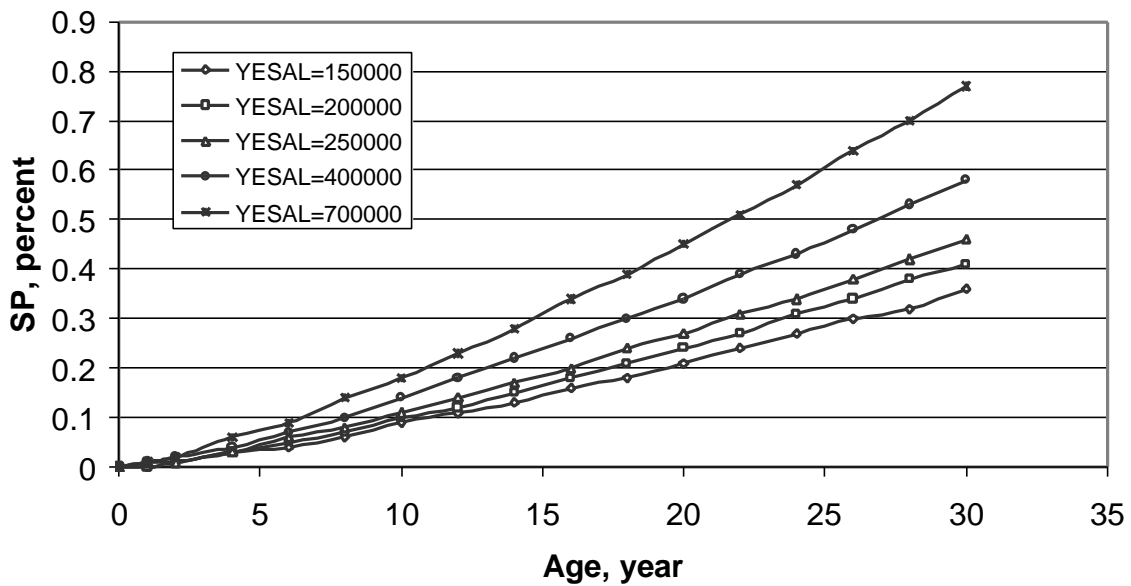
$$IRI = 1.1 + 23.3647 Age^{0.2952} CESAL^{0.3152} SLABTHK^{-0.8071} \quad (5.27)$$

$$R^2 = 0.30, RMSE = 0.54, N = 205$$

The model indicates that roughness increases with age and traffic, but decreases with slab thickness. Because of higher load carrying capacity thicker slabs deflect less at joints, reducing the potential for loss of support, and in turn, reduced faulting. Pumping



**Figure 5.35** Comparison of measured and predicted spalling (SP) using out-of-sample data. Jointed concrete pavement.



**Figure 5.36** Variation of spalling (SP) with age for a range of traffic levels using data-model. Jointed concrete pavement.

tendency is also reduced with thicker slab, leading to a smoother pavement.

The out-of-sample data is employed to plot predicted versus actual IRI, resulting in Figure 5.37. That the data points cluster along the line of equality is an indication of acceptable predictability of the model. Another plot depicting IRI increase with age for various traffic levels for SLABTHK = 254mm (10 inch) is presented in Figure 5.38. That the pavement roughness increases to 2.5 m/km in 30 years at 250,000 yearly ESAL is judged to be reasonable, providing the necessary credence to the model.

#### 5.5.4 PCR Model

With the basic premise that the model has to satisfy both initial pavement condition and change in PCR with time/traffic, a three-variable model is derived employing the database:

$$\text{PCR} = (51.1 - 0.1603 \text{ E-3 Age}^{1.9270} (27 + \text{CESAL}^{1.9000})) \text{SLABTHK}^{0.1000} \quad (5.28)$$

$$R^2 = 0.48, \text{RMSE} = 5.82, N = 154$$

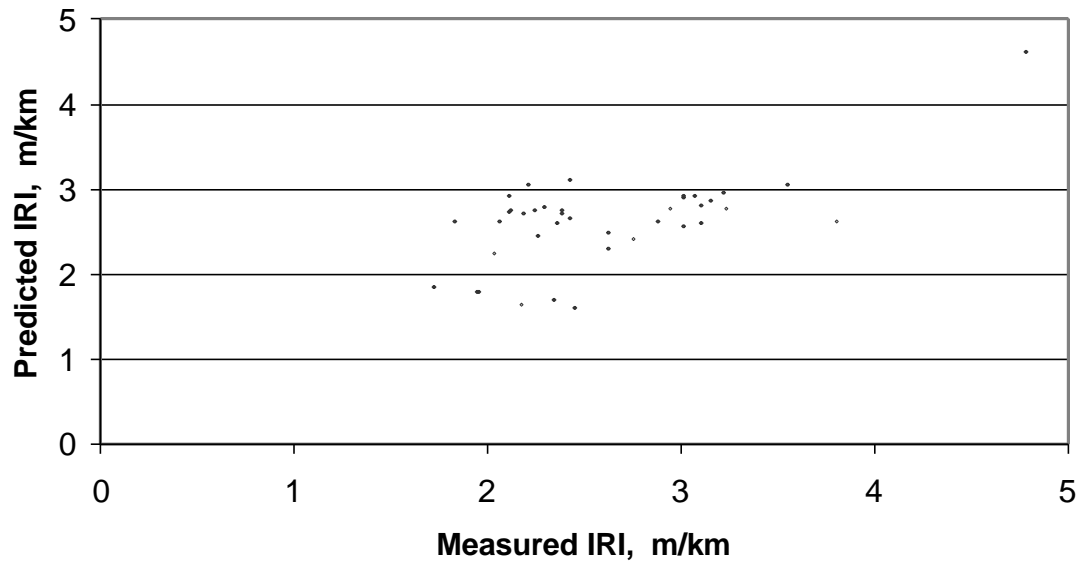
The model, rightly so, predicts better pavement condition with thicker slabs.

Comparing the expert model with the data model, it becomes clear that the experts believe that the pavement condition deteriorates faster than that predicted by the data-model. Therefore, a compromise model is sought employing Bayesian regression. By necessity the data-model, the expert model, and the posterior model should be in power form. In the Bayesian formulation slab thickness is not significant:

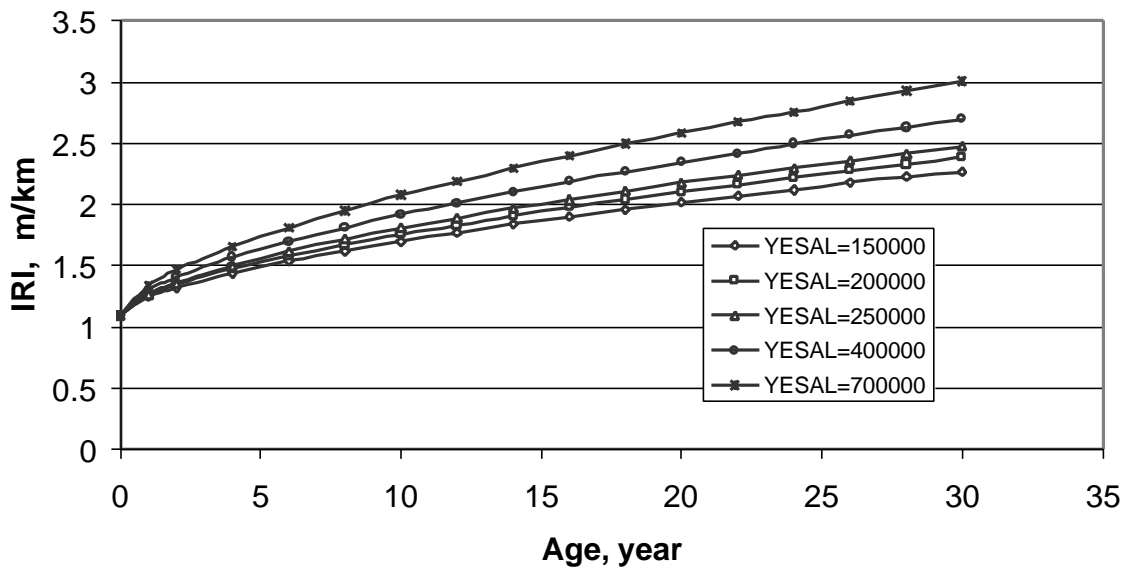
$$\text{PCR} = 90 - \text{Age}^{0.6741} \text{CESAL}^{0.4924} \quad (5.29)$$

$$R^2 = 0.59, \text{RMSE} = 7.25, N = 398$$

The sensitivity of the model is investigated by plotting PCR with age at various traffic



**Figure 5.37** Comparison of measured and predicted International Roughness Index (IRI) using out-of-sample data. Jointed concrete pavement.



**Figure 5.38** Variation of International Roughness Index (IRI) with age for a range of traffic levels using data-model. Jointed concrete pavement, (SLABTHK=254mm).

levels. It is noteworthy that both time as well as traffic affect the pavement condition with nearly equal weight, signifying the importance of both environmental and load factors (see Figure 5.39). Being able to predict realistic PCR values, the Bayesian model, Equation 5.29, is recommended for MDOT PMS.

## 5.6 CONTINUOUSLY REINFORCED CONCRETE PAVEMENT MODELS

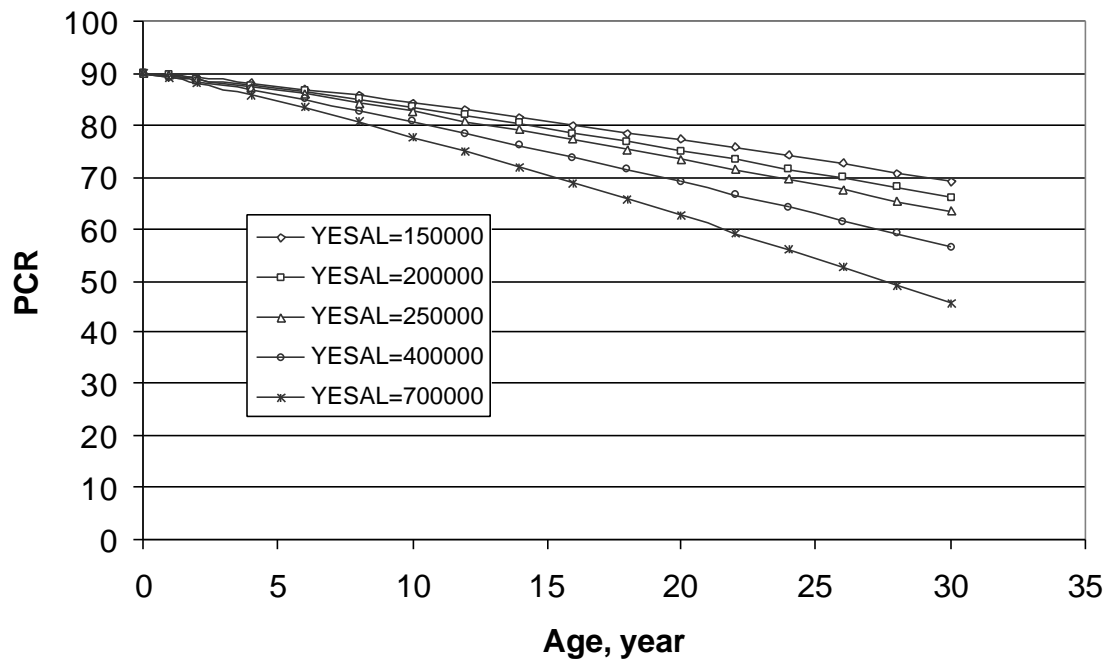
The explanatory variables considered for this pavement type are age, CESAL, and slab thickness. A cursory study of the data revealed that almost all of the CRC pavement sections (approximately 98 percent) in Mississippi have one thickness, namely 202mm (8 inches). Without data from a range of slab thickness, it could not be included as an explanatory variable. The range of response variables is listed in Table 5.11 and the explanatory variables in Table 5.12.

**Table 5.11 Range of Response Variables Used in the Development of Models, Continuously Reinforced Concrete Pavements**

Response Variable	Description	Range
AC	Cracks, percent	0 – 7.2
PO	Punchouts, number/km	0 – 26.2
IRI	Roughness, m/km	1.4 – 4.1
PCR	Pavement Condition Rating	60 – 90

**Table 5.12 Range of Explanatory Variables Used in the Development of Models for Continuously Reinforced Concrete Pavements**

Explanatory Variable	Range of Explanatory Variables of Models			
	AC	PO #	IRI	PCR
Age, years	0 - 36	0 - 35	0 – 33	0 - 36
18-kip CESAL, million	0 - 32.9	0 - 18.3	0 - 20.8	0 - 41.8



**Figure 5.39** Variation of Pavement Condition Rating (PCR) with age for a range of traffic levels, using Bayesian model. Jointed concrete pavement.

### 5.6.1 Model for Cracks

At the outset it should be remarked that low severity transverse cracks caused by shrinkage (inherent in CRC pavements) are not counted while quantifying this distress category. The model for medium and high severity transverse cracks (including other modes of cracks) is:

$$AC = 0.1013 (\text{Age}-10)^{0.5837} \text{CESAL}^{0.6095} \quad (5.30)$$

$$R^2 = 0.44, \text{RMSE} = 0.87, N = 91$$

The age-shift indicates that those medium/high severity cracks would be delayed for about 10 years. Even with substantial exponents for age and traffic, the model under-predicts in comparison to experts' opinion. In order to strengthen the model, therefore, expert opinion is incorporated employing Bayesian regression. The posterior model again with the two variables is:

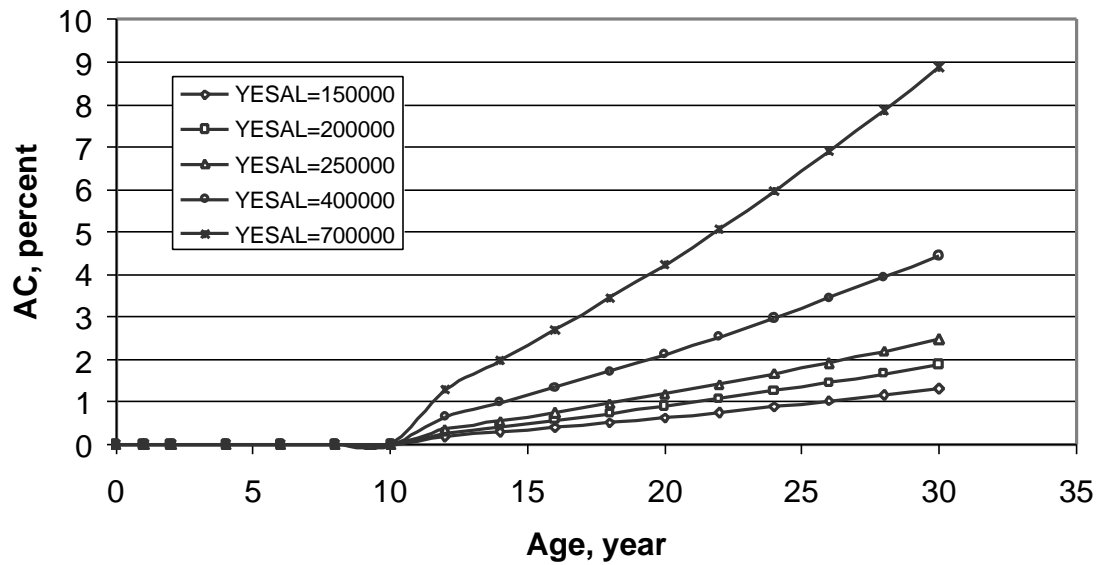
$$AC = 0.731\text{E-}1 (\text{Age}-10)^{0.3448} \text{CESAL}^{1.2377} \quad (5.31)$$

$$R^2 = 0.63, \text{RMSE} = 1.34, N = 179$$

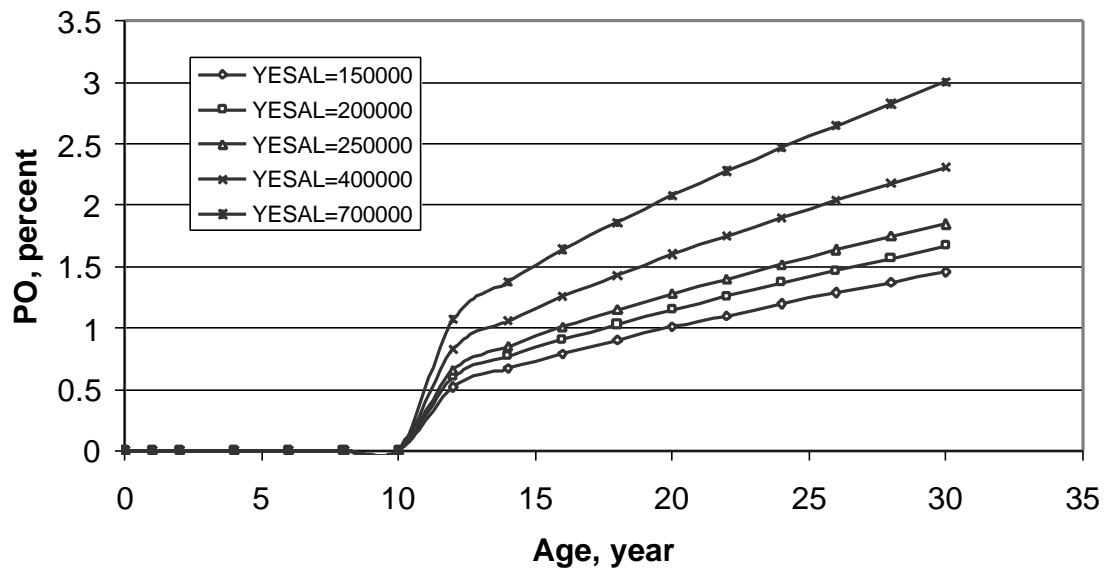
The age-shift of 10 years is again retained in the model. Note the posterior model predictions fall between the expert opinion and the data-model predictions. That is, the posterior model reconciles the expert opinion and the data. Presented in Figure 5.40 is a graphical representation of increase in cracks with age for a range of traffic volumes. Typically, a prediction of 4.5 percent cracks in 30 years when sustaining an annual traffic of 400,000 is reasonable. The Bayesian model, Equation 5.31 is the writer's recommendation.

### 5.6.2 Punchout Model

A cursory examination of the data reveals that out of the sections for which



**Figure 5.40** Variation of all cracks (AC) with age for a range of traffic levels using Bayesian model. Continuously reinforced concrete pavement.



**Figure 5.41** Variation of punchouts (PO) with age for a range of traffic levels using Bayesian model. Continuously reinforced concrete pavement.



punchout information is available, only 24 percent of the data had more than one punchout/km. This low punchout count could perhaps be attributed to MDOT practice of rehabilitating them promptly and, therefore, not interpretable in the video survey. A two-variable model is derived for punchouts in CRC:

$$PO = 0.4454 * E-3 (Age - 10)^{1.4095} CESAL^{1.3575} \quad (5.32)$$

$$R^2 = 0.75, RMSE = 0.13, N = 151$$

That punchouts begin to appear only after 10 years in service is noted from the equation. Even with sufficiently large exponents for age and CESALs, the model under-predicts punchout, for example 0.9 punchouts/km with 30 years of 400,000 ESALs annually.

The experts predict much higher punchout counts, as verified in the expert opinion matrix. Encouraged by this data, Bayesian regression is employed to incorporate data-model in the expert model. The posterior equation is:

$$PO = 0.33 (Age - 10)^{0.2571} CESAL^{0.4163} \quad (5.33)$$

$$R^2 = 0.48, RMSE = 0.57, N = 110$$

Why  $R^2$  decreased from 0.75 for the data-model to 0.48 for the posterior model warrants explanation. That the expert opinion differed significantly from the field data could be the major reason for this anomaly. Combining two disparate databases to develop a single model would likely bring down the coefficient of determination from their individual coefficients.

A sensitivity study, where punchout count is plotted against age for various traffic levels, can be seen in Figure 5.41. The resulting model is improved, in that it predicts 2.2 punchouts/km after 30 years of traffic at 400,000 ESAL yearly. The posterior model is the choice of the writer for MDOT PMS.

### 5.6.3 Roughness Model

Newly constructed CRC pavements show initial roughness somewhat comparable to that in jointed concrete pavements. CRC pavements in Illinois showed an average roughness value of 1.18m/km, while those in Kansas showed 0.94m/km (50). These high values are expected because of longer slabs which undergo warping. An IRI of 1.0m/km, therefore, is chosen as the initial condition. The roughness model developed is:

$$IRI = 1 + 0.4218 \text{ Age}^{0.1008} \text{ CESAL}^{0.4186} \quad (5.34)$$

$$R^2 = 0.48, \text{ RMSE} = 0.32, N = 146$$

Employing the out-of-sample data, the predictability of the model is checked plotting actual versus predicted IRI values. The large scatter in Figure 5.42, perhaps, is an indication of the influence of other variables, such as construction quality, that are not quantifiable at this time. Graphs in Figure 5.43 support the view that IRI is sensitive to both age and traffic volume, though the predominance of the latter factor cannot be overlooked. With reasonable predictions, Equation 5.34 is recommended to MDOT.

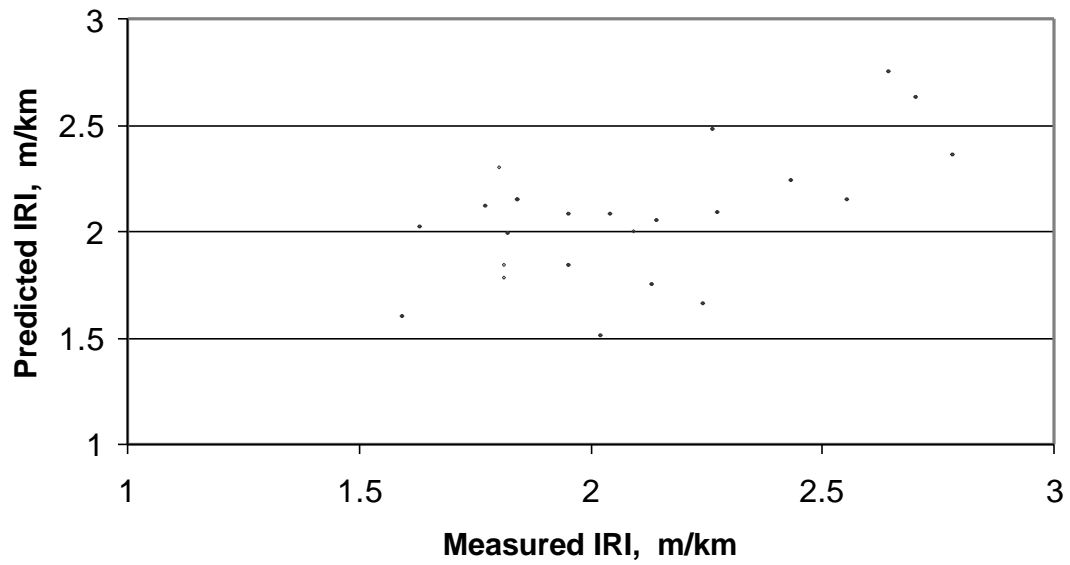
#### 5.6.4 PCR Model

As in all other four PCR models, the model should accommodate an initial value, consistent with the roughness of new construction. A two-variable model is shown to forecast pavement condition, as per the MDOT pavement data:

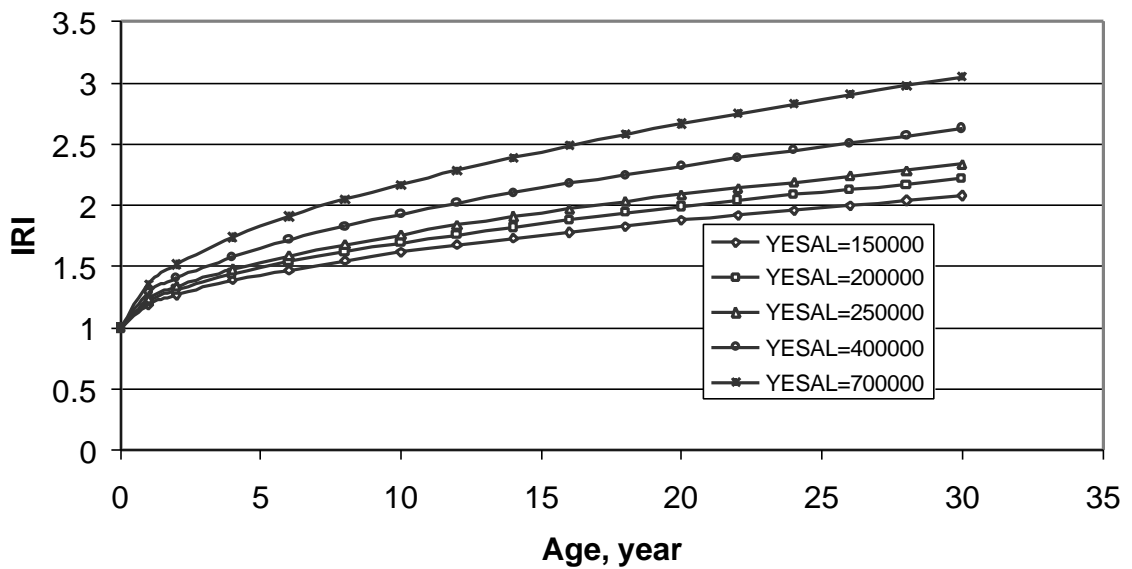
$$PCR = 91 - \text{Age}^{0.4085} \text{ CESAL}^{0.5299} \quad (5.35)$$

$$R^2 = 0.65, \text{ RMSE} = 2.72, N = 119$$

With the model generally over-predicting the pavement condition in relation to what the experts believe, Bayesian regression is employed to combine the two. A power model resulted from this analysis with nearly same coefficient of correlation:



**Figure 5.42** Comparison of measured and predicted International Roughness Index (IRI) using out-of-sample data. Continuously reinforced concrete pavement.



**Figure 5.43** Variation of International Roughness Index (IRI) with age for a range of traffic levels using data-model. Continuously reinforced concrete pavement.

$$\text{PCR} = 92 - \text{Age}^{0.6463} \text{CESAL}^{0.2731} \quad (5.36)$$

$$R^2 = 0.61, \text{RMSE} = 2.75, N = 181$$

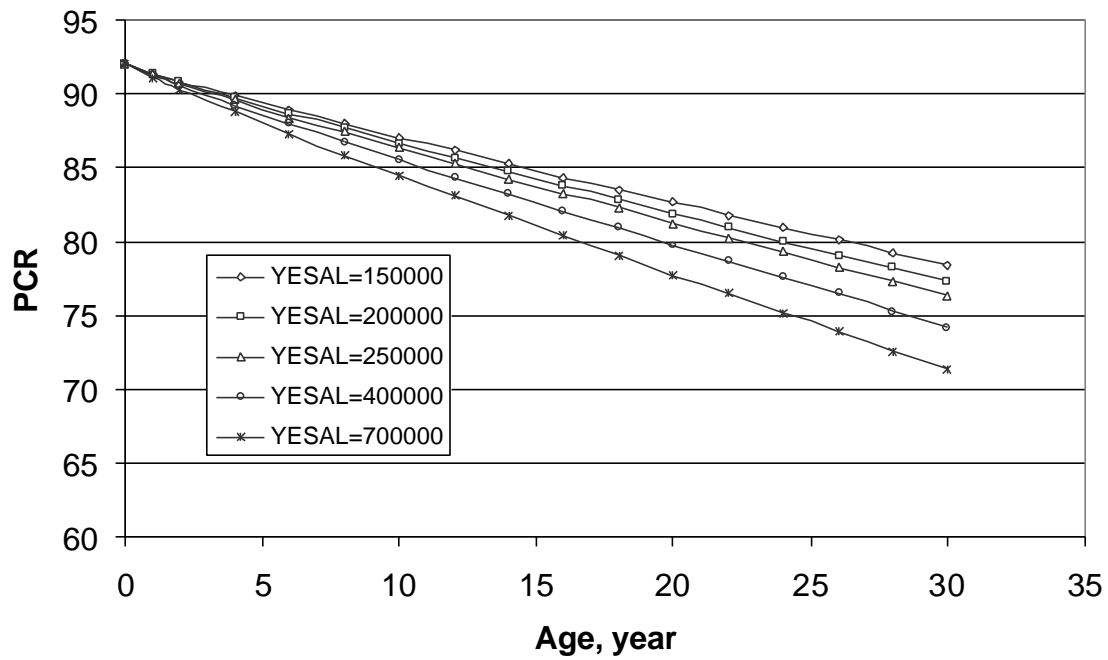
Judged by the t-statistic, the age variable is highly significant. It is noteworthy that the initial PCR value of 92 corresponds to an IRI of 1m/km, exactly matching the initial value of IRI model for CRC pavement. Graphing the Bayesian model (see Figure 5.44), we note that pavement condition is influenced by both time and traffic. The traffic seems to have less effect in comparison to age, for the reason CRC is structurally sound to resist traffic loads. Judging the model to be providing reasonable predictions, the Bayesian model, Equation 5.36, is recommended to MDOT.

## 5.7 PROJECT LEVEL DISTRESS/PERFORMANCE PREDICTION

For applications at the project level, corrections are to be applied to the predictions based on the observed data. These corrections are necessary to account for the differences in the long-term behavior of individual pavements from the predictions that are mean deterioration trends of the pavement family.

Different procedures are suggested in the literature (52, 21) for adjustment of the pavement family model for individual projects. The prediction relation of a pavement family represents the average behavior of all the sections of that family. The prediction of each project/section is accomplished by shifting its position relative to the family prediction curve. It is assumed that the deterioration of all pavements in a family is similar. In practice, therefore, when the observed deterioration of pavement differs from that predicted by the model, the model should be adjusted to pass through the observed point. Predictions for future years are then made using this augmented curve.

One method (52) is to draw a curve through the observed point parallel to the



**Figure 5.44** Variation of Pavement Condition Rating (PCR) with age for a range of traffic levels using Bayesian model. Continuously reinforced concrete pavement.

developed model as shown in Figure 5.45. Since age is predominant explanatory variable, the horizontal shift is mathematically performed by solving the model equation for the AGE that corresponds to the observed pavement deterioration. Future predictions are made assuming that the calculated age is the current age for the section.

A second approach (53) is to shift the curve vertically instead of horizontally as in Figure 5.46, so that it passes through the observed point. This is done by using the actual deterioration (D1) of the pavement and the predicted deterioration (D2) for computing an adjustment factor defined by  $AF = D1/D2$ . Future predictions are made by multiplying the predicted deterioration by the adjustment factor (AF). This method seems to be more appropriate where all the involved explanatory variables are employed in prediction rather than adjusting for only the main explanatory variable.

## **5.8 ENGINEERING FEEDBACK SYSTEM**

The feedback module, as envisioned in the original proposal, was to ensure continual feedback of information assessing pavement system condition, and also for verification/substantiation of the design standards and/or specifications. Described briefly are three submodules of the feedback system that were completed and submitted to MDOT on 31 July 1998.

1. The module that calculates the load index for the three types of pavements (flexible, CRC and jointed concrete), as originally built. Load index is the ratio of the actual ESAL and the design ESAL. Design ESAL is calculated using the design equations proposed in the 1993 Revised AASHTO Guide.
2. The module that calculates the load index of overlaid flexible pavements, and

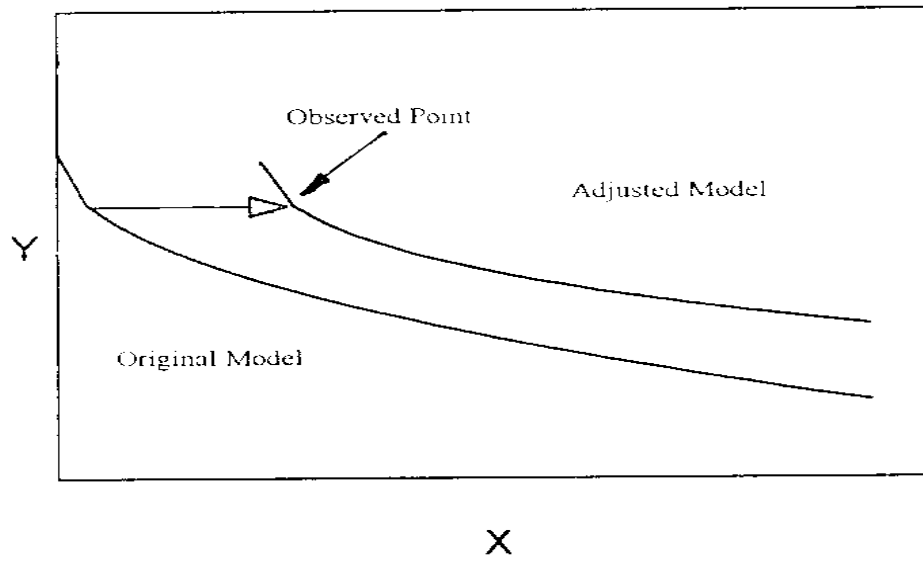


FIGURE 5.45 The horizontal-shift model adjustment.

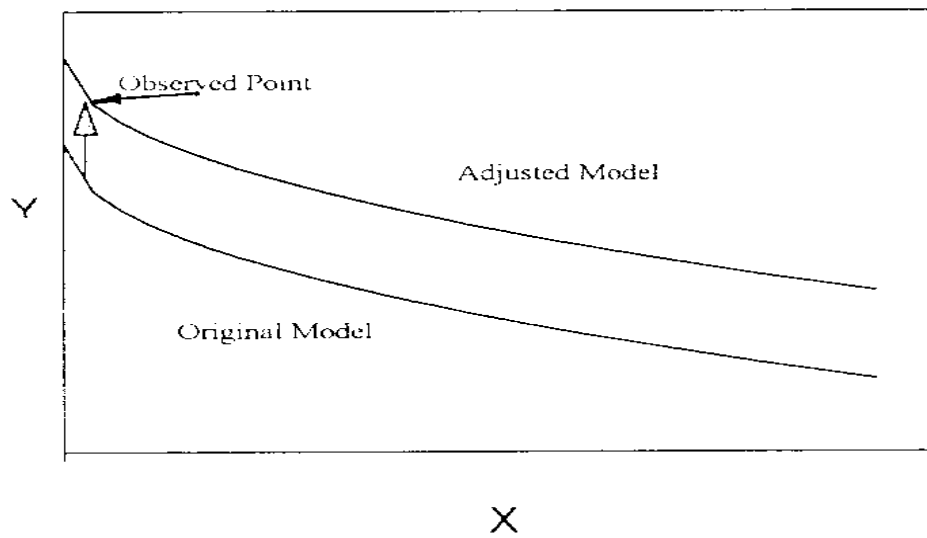


FIGURE 5.46 The vertical-shift model adjustment.

that too only for the first overlay. Again, AASHTO flexible pavement design equation is used for this purpose. For use in the equation, the structural number of an overlaid pavement is calculated with the revised layer coefficient of the asphalt concrete surface, according to Transportation Management Information System (TMIS). Design equations for other types of overlaid pavements are not readily available, therefore, those calculations are deferred in this version of the program.

3. The third module calculates the ratio of the actual and the predicted distress of each section of each pavement family; for example, five distresses and PCR for original flexible, overlaid flexible, and composite pavement types. For distress predictions, equations submitted to MDOT on 1 July 1997 were employed. Note the feedback program was submitted to MDOT on 31 July 1998. This comparison enables us to validate the prediction models.

The feedback module may be implemented in such a way that it can access present and past condition data and all other inventory databases. With this information assembled from the MDOT PMS databases, feedback analyses results can be output in the form of reports and tables.

## **5.9 Summary**

The models developed in the study indicate that the most important variables affecting deterioration of all pavement types are age, cumulative traffic, and modified structural number/slab thickness. Thickness of overlay is a significant explanatory variable in composite pavements. HPMS functional classification and resurfacing type are other variables in overlaid flexible pavement.



Age is a factor that appears in all of the models. It is a factor that represents deterioration of pavements due to environment and/or other damage that cannot be accounted for by traffic or other factors. A question arises as to why age plays such a dominant role in relation to the cumulative traffic. That age can be determined very precisely is the first and foremost reason for its significance in the model. Second, age enters into the estimation of cumulative traffic as well as the environmental loading cycles (33). Between age and ESAL, ESAL would be the weakest link in the cumulative traffic computation because of inclusion of several questionable input parameters for ESAL calculation (these include sample traffic count, growth factor, and truck factor). Between age and CESAL, the former satisfies the assumptions required for regression modeling, discussed herein. Age is nonstochastic, that is, its value is fixed and it is measured without error. By virtue of these facts, age would be a better explanatory variable than CESAL.

Modified structural number, as seen in models for flexible (both original and overlaid), does not seem to play a major part in the prediction. The first reason is that the pavements are designed for the expected level of traffic, with heavily trafficked roads being provided with thicker pavement sections compared to lightly trafficked ones. Therefore, the deterioration rates of thick and thin pavements are expected to be nearly identical. The second reason is that even nominally identical pavement sections show spatial variation in strength properties, local deficiencies in construction, change in conditions along stretches (for example, high water table), and other variations making the MSN data ‘noisy’. Noisy data simply suppresses the explanatory variables’ effect on the response variable.

Cumulative traffic, expected to be the main factor causing deterioration, is also a significant factor in all the models. Stronger pavements, in general, should undergo slower

deterioration, and the inclusion of a strength indicator (MSN, thickness of overlay, or thickness of slab) in most of the models is justified.

#### **5.9.1 Summary of Significant Variables for Each Pavement Family**

The results of the sensitivity-study suggest that age is the most significant factor affecting the deterioration of original flexible pavements. Cumulative traffic, rightly so, is the second most significant factor for the prediction of other cracks, roughness, and PCR. The modified structural number appears in four models except in those for medium and high severity other cracks, and rutting.

As in the case of original flexible pavements, age and traffic play the most significant role in distress prediction for overlaid flexible pavements. Modified structural number and/or TOPTHK and resurfacing type are other explanatory variables in all of the models except for WCAMH.

For composite pavements, besides age and traffic, thickness of overlay is the most important variable affecting deterioration. In the same vein, in the models for jointed concrete pavements, slab thickness appears in addition to age and traffic. In the case of continuously reinforced concrete pavements, age and traffic are the only two variables significant enough to appear in the models.

## **CHAPTER 6**

### **SUMMARY AND CONCLUSIONS**

#### **6.1 SUMMARY**

The focus of the study has been to develop deterioration/performance models for pavements for use in pavement management analysis algorithms. The models are derived such that they satisfy many physical and boundary conditions with known causal variables. In contrast to many other studies cited in the literature, actual data on pavements are employed rather than accelerated road test data. Another characteristic feature of the study is the application of Bayesian regression employing expert opinion to augment data-models.

Deterioration models are developed for distress/distress groups employed in the decision tree for maintenance strategy selection adopted by MDOT-PMS. The models are derived using the in-sample data and subsequently verified using the out-of-sample data. As deemed appropriate, Bayesian models are attempted in 14 different distresses. Only seven of them are found to generate models superior to the corresponding data models.

##### **6.1.1 Regression Models**

Various model forms were attempted in the study but only nonlinear ones are employed because of their prediction capability. Multiple linear models do not satisfy the required boundary conditions, including monotonic variation (increase or decrease) of the deterioration rates. The primary advantage of the general power form and exponential form of the nonlinear models is that they do not rely on fixed exponents, such as squares or cubic powers. This flexibility in the exponent immensely improves the modeling process. Lack of distress data in severely deteriorated pavements precluded the use of exponential forms in any of the models. Out of a total of 26 equations, 19 are regression models and the remaining 7

are Bayesian models. Because of the large disparity between the field data and the expert opinion, Bayesian regression for four distresses produced models whose predictions are suspect. In three cases - PCR models of three flexible families - the data models appeared satisfactory, accordingly, they are preferred over Bayesian models. The models are listed in Tables 6.1-6.5, one table for each family.

**Table 6.1 - Deterioration Models for Original Flexible Pavements**

<b>DISTRESS</b>	<b>MODEL</b>
Weighted Alligator Cracking of Medium and High Severity, percent	$WCAMH = 0.6956 \text{ AGE}^{1.3686} \text{ CESAL}^{0.8050} \text{ MSN}^{-1.961}$
Other Cracks, percent	$OC = 0.8892 \text{ AGE}^{1.2128} \text{ CESAL}^{0.6612} \text{ MSN}^{-0.4606}$
Other Cracks of Medium and High Severity, percent	$OCMH = 0.1438 \text{ E-2 AGE}^{2.3998} \text{ CESAL}^{1.1863}$
85 <sup>th</sup> Percentile Rutting, mm	$RT = \text{AGE}^{0.8307} \text{ CESAL}^{0.1929}$
Roughness, (IRI) m/km	$IRI = (2.4169 + \text{AGE}^{0.2533} (1 + \text{CESAL}^{0.2572})) \text{ MSN}^{-0.7753}$
PCR	$PCR = (76.10 - \text{AGE}^{0.6696} (1 + \text{CESAL}^{0.7100})) \text{ MSN}^{0.0979}$

**Table 6.2 – Deterioration Models for Overlaid Flexible Pavements**

<b>DISTRESS</b>	<b>MODEL</b>
Weighted Alligator Cracking of Medium and High Severity, percent	$WCAMH = 0.977\text{E-1 AGE}^{1.8548} (1 + \text{CESAL}^{0.5336}) \text{ MSN}^{-1.9370} \text{ RES}^{0.1618}$
Other Cracks, percent	$OC = 19.1244 \text{ AGE}^{0.6167} (1 + \text{CESAL}^{0.5000}) \text{ TOPTHK}^{-0.6752} \text{ RES}^{0.2713}$
Other Cracks of Medium and High Severity, percent	$OCMH = 61.367 \text{ AGE}^{1.4025} (1 + \text{CESAL}^{1.6154}) \text{ TOPTHK}^{-2.6379} \text{ RES}^{1.3710}$
85 <sup>th</sup> Percentile Rutting, mm	$RT85 = 5.2498 \text{ AGE}^{0.3583} \text{ CESAL}^{0.2524}$
Roughness, (IRI) m/km	$IRI = (3.5746 + \text{AGE}^{0.1701} (1 + \text{CESAL}^{0.6972})) \text{ MSN}^{-0.3438} \text{ TOPTHK}^{-0.1313} \text{ RES}^{-0.1056}$
PCR	$PCR = (70.69 - \text{AGE}^{0.6471} (1 + \text{CESAL}^{0.7564})) \text{ MSN}^{0.0291} \text{ TOPTHK}^{0.0272} \text{ RES}^{0.0198}$

**Table 6.3 – Deterioration Models for Composite Pavements**

<b>DISTRESS</b>	<b>MODEL</b>
<b>Weighted Alligator Cracking of Medium and High Severity, percent</b>	$WCAMH = 0.7213 \text{ E-4 AGE}^{4.0617} (1 + \text{CESAL}^{0.5940}) \text{TOPTHK}^{-0.5690}$
<b>Other Cracks, percent</b>	$OC = 15.50 \text{ AGE}^{0.5786} (1 + \text{CESAL}^{0.5345}) \text{TOPTHK}^{-0.4298}$
<b>Other Cracks of Medium and High Severity, percent</b>	$OCMH = 0.8267 \text{ E-2 AGE}^{2.3090} (1 + \text{CESAL}^{1.4460}) \text{TOPTHK}^{-0.2338}$
<b>85<sup>th</sup> Percentile Rutting, mm</b>	$RT85 = \text{AGE}^{0.1217} \text{CESAL}^{0.4973} \text{TOPTHK}^{0.4506}$
<b>Roughness, (IRI) m/km</b>	$IRI = (3.095 + \text{AGE}^{0.3571} (1 + \text{CESAL}^{0.3054})) \text{TOPTHK}^{-0.3235}$
<b>PCR</b>	$PCR = (56.87 - \text{AGE}^{0.5681} (1 + \text{CESAL}^{0.7154})) \text{TOPTHK}^{0.1045}$

**Table 6.4 – Deterioration Models for Jointed Concrete Pavements**

<b>DISTRESS</b>	<b>MODEL</b>
<b>Cracks, percent</b>	$AC = 2.4118(\text{AGE}-3)^{0.2465} \text{CESAL}^{0.5473} \text{SLABTHK}^{-0.3735}$
<b>Spalling, percent</b>	$SP = 0.4647\text{E-2 AGE}^{0.7885} \text{CESAL}^{0.8506}$
<b>Roughness, (IRI) m/km</b>	$IRI = 1.1 + 23.3647 \text{AGE}^{0.2952} \text{CESAL}^{0.3152} \text{SLABTHK}^{-0.8071}$
<b>PCR</b>	$PCR = 90.00 - \text{AGE}^{0.6741} \text{CESAL}^{0.4924}$

**Table 6.5 – Deterioration Models for Continuously Reinforced Concrete Pavements**

<b>DISTRESS</b>	<b>MODEL</b>
<b>Cracks, percent</b>	$AC = 0.731\text{E-1 (AGE-10)}^{0.3448} (\text{CESAL})^{1.2377}$
<b>Punchout, #/ km</b>	$PO = 0.33 (\text{AGE-10})^{0.2571} (\text{CESAL})^{0.4163}$
<b>Roughness, (IRI) m/km</b>	$IRI = 1 + 0.4218 \text{AGE}^{0.1008} \text{CESAL}^{0.4186}$
<b>PCR</b>	$PCR = 92.00 - \text{AGE}^{0.6463} \text{CESAL}^{0.2731}$

## 6.2 CONCLUSIONS

Making use of data collected in four cycles (1991, 1993, 1995 and 1997), 26 distress/performance models were developed. The models were evaluated and shown to provide adequate prediction capability. The explanatory variables strike physically meaningful relationships with the response variables, indicating that the equations more or less assume a cause-effect relationship. Comparing the models' prediction with observed

values from a sample data set not used in their development (out-of-sample) demonstrated their accuracy to be quite reasonable.

Although this study focused on MDOT's data, many of the following conclusions may be applicable to other pavement networks:

1. By adopting an appropriate classification scheme, pavement age can be the most significant predictor of deterioration.
2. Second only to age, traffic plays a role in pavement deterioration. One reason for this is the fact that age and cumulative traffic for each pavement section are correlated, though overall correlation between the two causal factors is very low. Moreover, age can be determined so precisely in comparison to the traffic that the former factor alone can explain a large portion of the variation (33).
3. The use of categorical variables to differentiate between different bases, surface types, etc., helps account for the discrete characteristics of materials.
4. For all pavement types, the power model form seems adequate.
5. For prediction models to be applicable in individual sections shift adjustment is necessary.

### **6.3 Implementation**

The models developed in the first phase of the study have already been incorporated in the Pavement Analysis Program (PAP) of MDOT. They serve a pivotal role in pavement analysis, namely, forecasting future distress levels of the network thereby enabling engineers and managers in estimating resources required to maintain the system at acceptable levels. Also, planning future maintenance will be immensely benefited from the models. Not only

future maintenance, but also future conditions could be estimated by making use of PCR models.

The feedback system also can be implemented in the MDOT PMS with ease. Menu driven and user friendly, the program interacts with the five PMS databases and can access summary distress data from the interface program. The feedback module works in conjunction with prediction models, verifying condition prediction and design assumptions.

#### **6.4 Benefits**

The principal benefit of pavement performance models stems from being able to assess the overall condition of the network in the future years. Distress prediction models forecast anticipated distress in the future, subscribing to cost-effective rehabilitation strategy selection. Performance models are extremely useful at the management/policy-making levels. At project level, the remaining life of the pavement sections can be objectively assessed employing distress prediction models. Information of this type provides for identifying unforeseen/premature failure of pavement sections. Prediction models in general are useful for evaluating new designs, and provide a tool which can be used readily to refine designs and evaluate the long-term effects of specific design assumptions.

The feedback module, utilizing the PMS database, makes calculations substantiating/reinforcing the existing design procedures. Specifically it can evaluate the effectiveness of design procedures, and importantly verify the accuracy of the prediction models.

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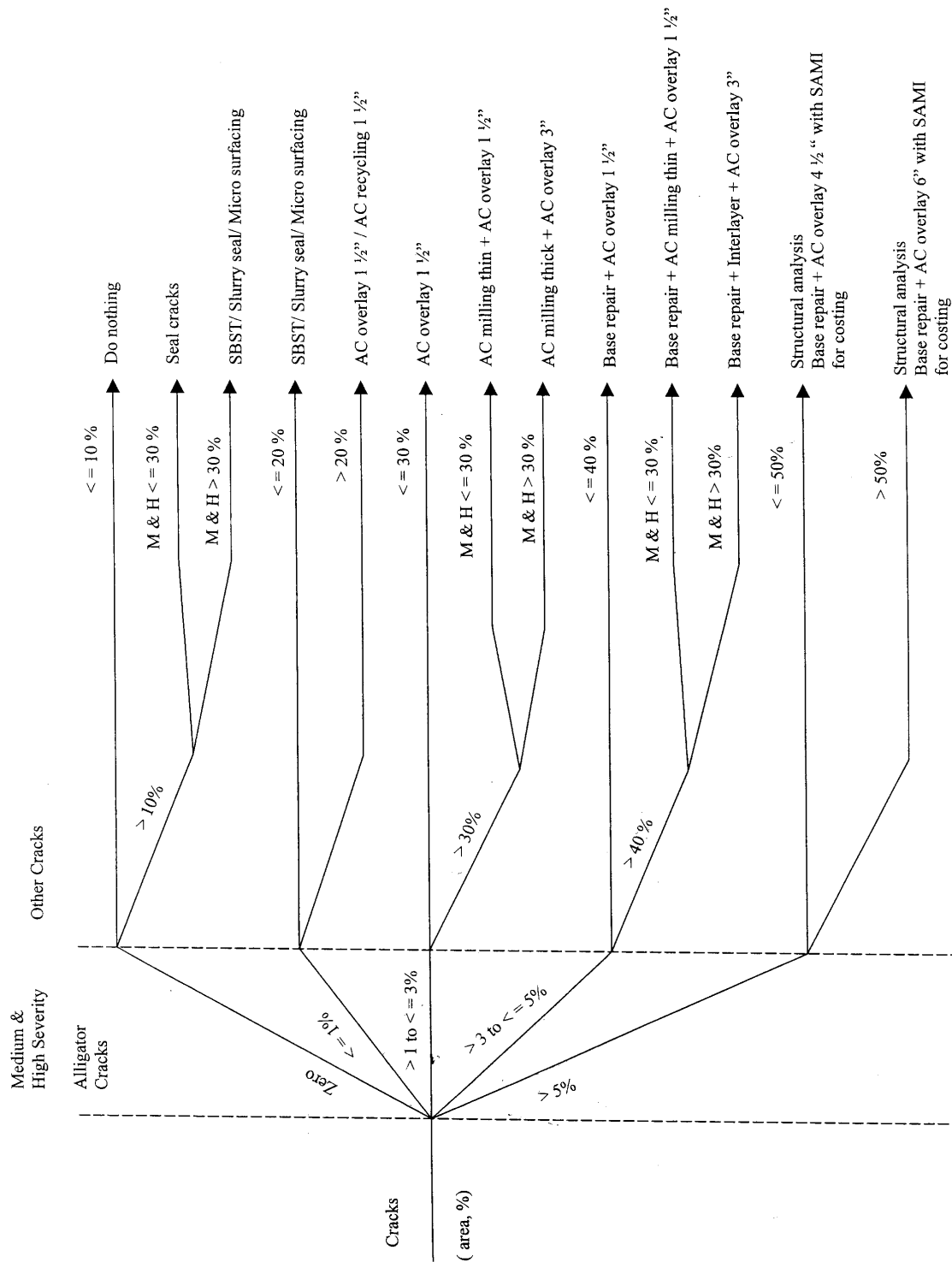
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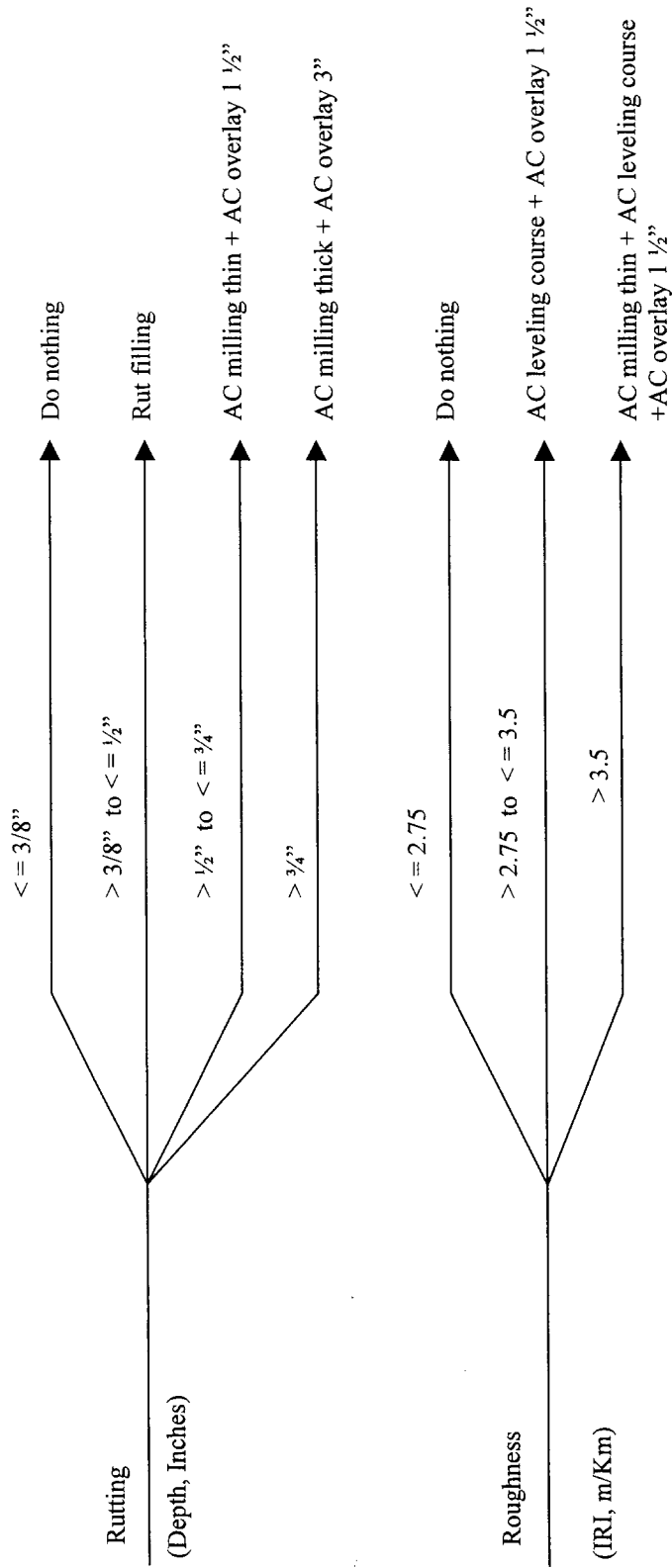
## **APPENDIX**

### **PAVEMENT REHABILITATION STRATEGY SELECTION DECISION TREES OF MISSISSIPPI DEPARTMENT OF TRANSPORTATION**



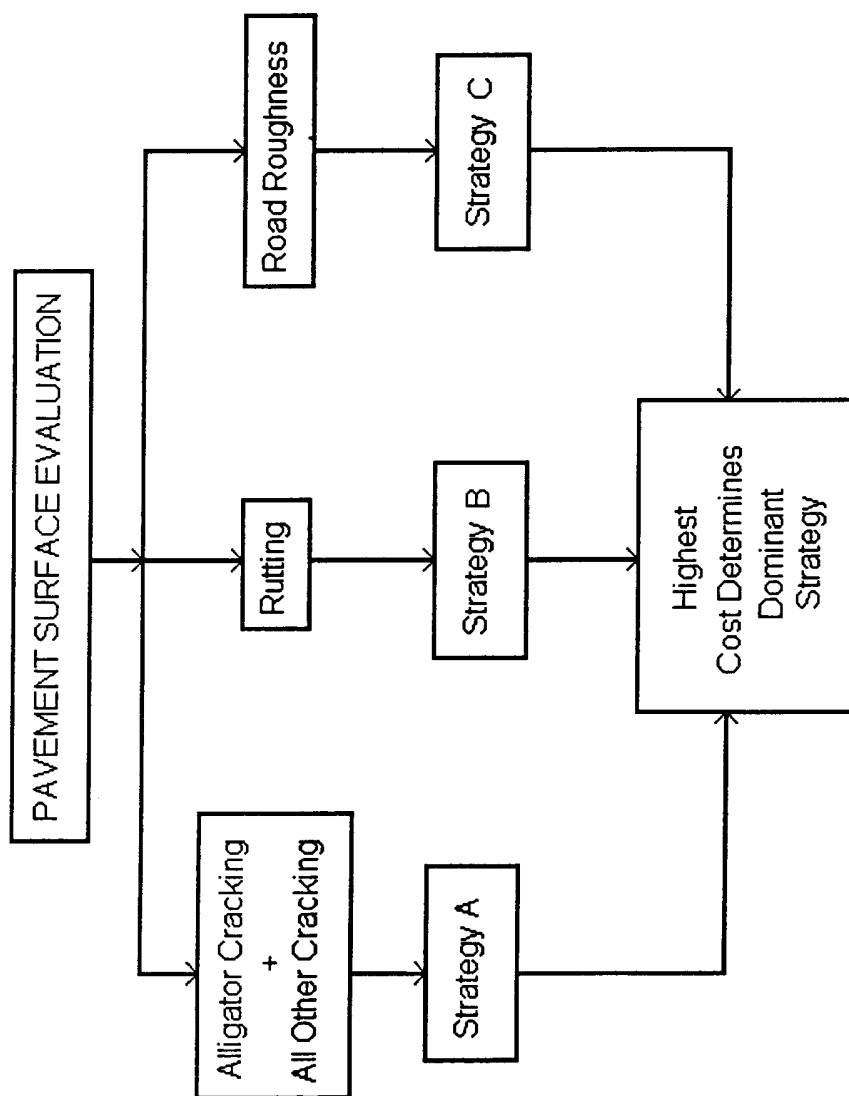


**Figure A1 Rehabilitation strategy selection decision tree for flexible and composite pavements.**



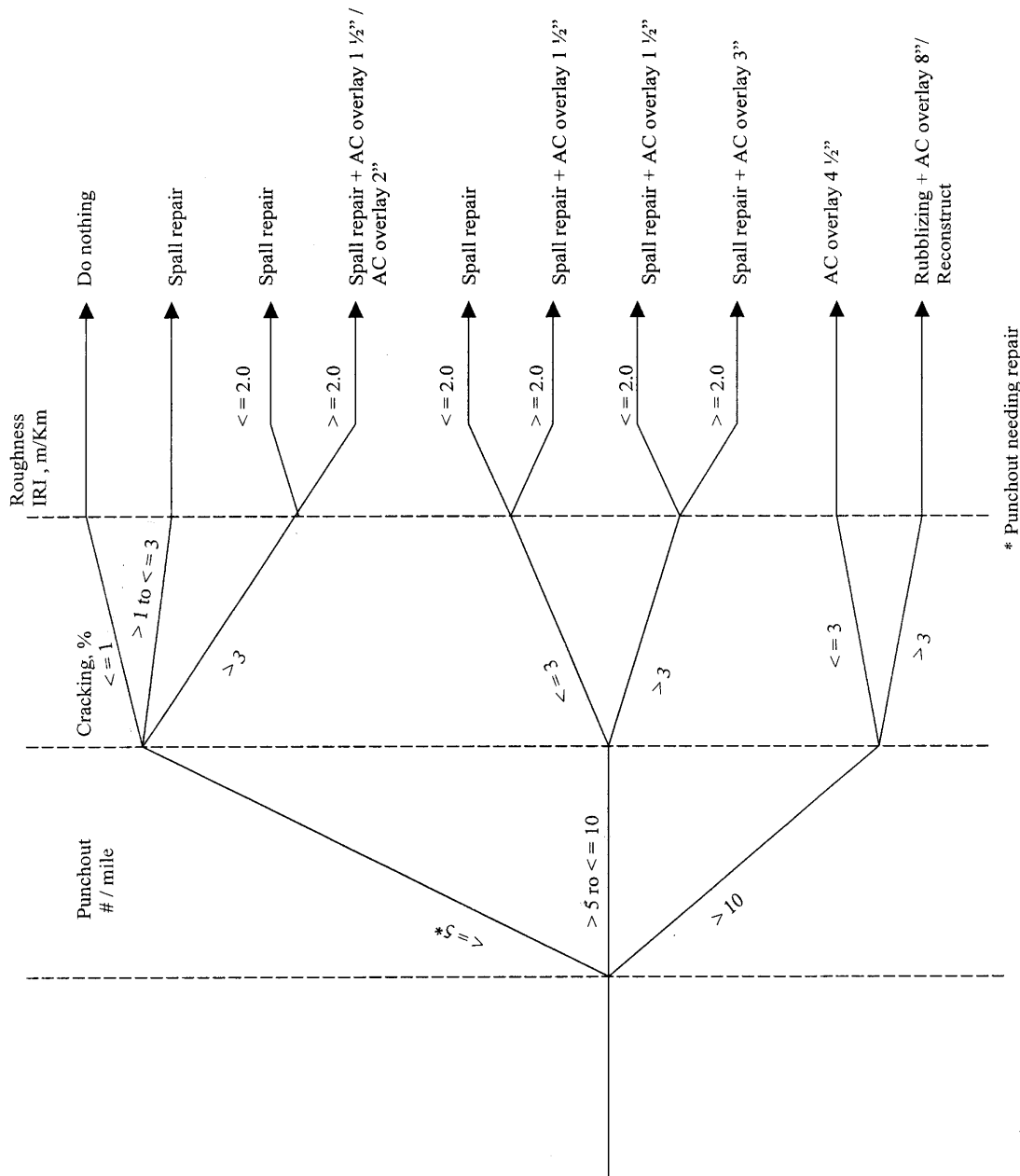
\* Limit values represent 85<sup>th</sup> percentile rut in a given section.

**Figure A1 (Continued).**



**FIGURE A2** Schematic diagram showing the dominant strategy selection.





\* Punchout needing repair

Figure A4 Rehabilitation strategy selection decision tree for continuously reinforced concrete pavements.