DEVELOPMENT OF A PROBABILISTIC BASED, INTEGRATED PAVEMENT MANAGEMENT SYSTEM

by

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ABSTRACT

Accurate prediction of pavement structural and functional deterioration plays an essential role in the pavement management process and investment planning at both project and network levels. The investigation described in this study was primarily concerned with development of systematic concepts of pavement management and other type of infrastructure network management, such as highway bridges, airfield pavements and oil or gas pipelines. At present, there are still research needs for improving on the existing models and developing new methodologies of pavement preformance prediction.

This thesis describes the development of a probabilistic based, integrated pavement management system (PMS), which can assist pavement engineers or highway agencies to make strategic investment decisions in programming pavement maintenance and rehabilitation (M&R) projects for the preservation of a road network. The system developed has three major components: 1) using non-homogeneous (i.e., time-related) Markovian prediction models to forecast pavement deterioration, 2) employing stochastic theory and Monte Carlo simulation technique to establish the Markovian transition probability matrices (TPMs) for individual pavements, and 3) utilizing cost-effectiveness based prioritization program to select the optimal multi-year pavement M&R projects and action years.

The non-homogeneous Markov prediction models were established through a process of system conversion from deterministic to probabilistic model. The basic process of performing the prediction model system conversion is described. Each element of the time-related Markovian TPMs is calculated using Monte Carlo simulation. The validation and efficiency of the time-related Markov prediction models are demonstrated by a number of example applications.

A Bayesian technique is employed to update the predicted TPMs for accurate prediction of pavement deterioration carried out on a yearly basis through observed pavement performance data.

The determination of a set of standardized M&R treatment strategies for the preservation of a road network is based on the time-related Markov prediction models. Each of the

standardized M&R strategies is defined in terms of work content, treatment effect, cost and structural improvement on the existing pavement. The main purposes of standardizing M&R treatments are to: a) provide the highway agency with a list of cost-effective alternatives, b) modify efficiently the established TPMs after each M&R treatment is applied, and c) facilitate the cost-effectiveness based system optimization analysis.

Outputs of the non-homogeneous Markov prediction model include a series of time related TPMs, probability distribution vectors of the predicted pavement condition state in each year and pavement dynamic performance graphs for individual pavements. The year-by-year based integer programming is used to determine the optimal M&R projects and investments for the road network preservation. The optimality criterion is to maximize the effectiveness/cost ratio of total selected M&R treatment projects in each programming year. The key feature of the developed optimization model is the ability to integrate a set of standardized M&R treatment strategies with the predicted multi-year pavement performance into the network optimization analysis.

Both the proposed non-homogeneous Markovian prediction model and the integrated performance-treatment optimization model were tested using examples from Ontario pavement network. Reasonable results were produced in comparison with other existing methods.

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Dedicated to my mother— Liang Yingdi

献给我的母亲 一 梁英弟

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CHAPTER 1

INTRODUCTION

1.1 OVERVIEW OF EXISTING PAVEMENT MANAGEMENT

Looking at the history of this century, one of the most remarkable achievements in human civilization is the well constructed road networks for public transportation around the world. These road networks represent a very large amount of investment. Moreover, preservation of the paved roads implies continuous investments of a substantial amount for maintenance in order to have adequate serviceability required by the ever-increasing traffic and economic development.

Pavements are one of the most critical components of a road network in terms of asset value and transportation system in a regional or national economic development. Since pavements take a large part of expenditures during the initial construction and future maintenance or rehabilitation improvements, pavement management plays a very important role in managing efficiently the entire road network in terms of overall serviceability preservation.

Consequently, pavement maintenance and rehabilitation (M&R) have become the major concerns of many highway agencies, particularly in the developed countries where a large number of paved road networks have been established with a huge amount of previous investments. As a result, the development of pavement network optimization techniques is required for managing efficiently the existing road networks.

Pavement management systems (PMS) provide the tools that assist pavement engineers to forecast future pavement conditions and determine the optimal timing for maintenance and rehabilitation (M&R) treatment strategies that will address the requirements identified in the road network. The ability to program the optimal pavement maintenance and rehabilitation strategies is perhaps one of the most useful functions provided by a PMS.

The definition of "pavement management" and its functional relation with a national economic development used throughout this thesis is given in a recent invited distinguished lecture at IRF (International Road Federation) Asia-Pacific Regional Conference (1), which is quoted as follows:

> *" Paved roads represent a very large, in-place transport asset in most countries. The extent or value of this asset can be shown to be directly related to a nation or region's economic development. A major challenge to road engineers and administrators is preservation of the asset through good management and timely investments in maintenance and rehabilitation. The process used is termed pavement management."*

There are, basically, five major processes and mutually coordinated activities in a PMS. These are: 1) road network database acquisition and information access programming, 2) evaluation and identification of current and future serviceability and needs of pavements in the road network, 3) pavement performance based structural design and material selection, 4) implementation of selected M&R treatment strategies with detailed design and construction criteria and, 5) optimization of pavement M&R priority programming integrated with pavement life-cycle economic analysis.

A relationship between national economic development and paved road infrastructure, using per capita Gross National Product (GNP) as the dependent variable and magnitude of paved road and service condition of road networks as independent variables, was reported by Queiroz et al (2). A significant positive correlation between per capita GNP, paved road density and applied preservation investment strategies, has been observed. This positive correlation indicated that countries or regions with strong economies almost invariably have extensive and efficient highway transport networks. A comparison between road supply and road condition in 98 countries is shown in Figure 1.1, where three different levels of economic development are studied. The 98 countries in Figure 1.1 comprised: (i) 42 low-economies (average per capita GNP is \$320); (ii) 43 middle-income economies (average per capita GNP of \$1720; (iii) 13 high-income economies (average per capita GNP is \$17,420). Many developing countries, such as China, Malaysia, and many other countries, that represent the majority part of the world have realized this critical relationship and have started to accelerate their road infrastructure development in an unprecedentedly fast speed.

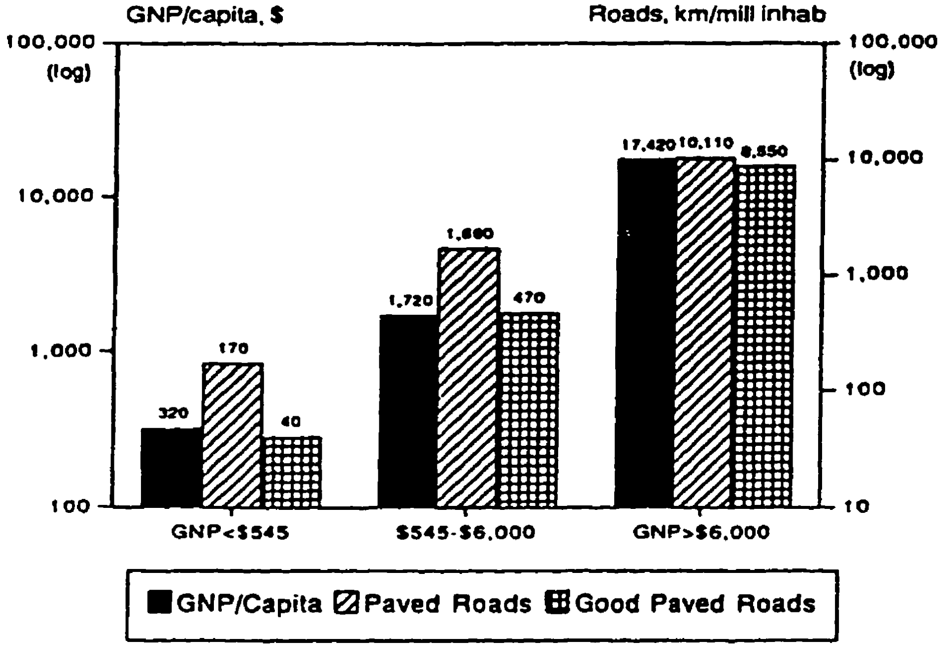

Figure 1.1 Relationships Between Road Supply and National Economies (After Ref. 2)

During the initial stage of the development of pavement management technology, a number of system approaches to pavement management and its guiding principles were discussed in the late 1960's in references (3 to 5). During that time period, a considerable effort had been made to develop the underlying theories and to apply them in North America's road network management systems. By the late 1970's the first two books on pavement management were published (6, 7). These two books have systematically expounded the philosophy of pavement management and have provided guidance for future research and technology development. By the mid 1980's significant progress had made, on a global scale, to the point where considerable amount of experience in practice had been gained and reported in various references, such as (8 to 10). Many of the existing pavement management systems are established individually in terms of agency-specific performance models and computer-aided decision priority programming of pavement network preservation and economic analysis methodologies (11, 12).

Turning to the 1990's, a world-wide recognition of pavement management technology and its impact on a national economic prosperity has been truly achieved. This globalization is symbolized by the third and the coming fourth international conferences on managing pavements (13). Furthermore, two new books on pavement management (14, 15) have been published to meet the potential demands by many highway agencies and pavement researchers around the world.

1.2 STATEMENT OF THE PROBLEM AND ITS SIGNIFICANCE

This section reviews the main components needed for an integrated pavement management system upon which this research focuses, including performance prediction modeling, selection of optimal pavement treatment alternative strategies and priority programming of multi-year maintenance and rehabilitation activities. The general context of the problem of interest in this work can be illustrated in Figure 1.2, where four major interactive activities are emphasized.

Whether a pavement management system can be effectively implemented by a highway agency will rely, among other factors, on the techniques employed in the operation processes, including pavement network database and information management, measurement and evaluation of pavement condition, modeling of pavement deterioration, determination of treatment strategies for a pavement network preservation, and the network M&R priority programming. In other words, effective application of a pavement management system in real situations can be assessed on the basis of the quality of the techniques used in these functional components. The problems dealt with in this study are described in the following subsections.

1.2.1 Performance Prediction Models

A good pavement management system should have the capacity of predicting pavement structural and functional deterioration versus pavement age. There are basically two types of performance prediction models (16, 17, 18) in pavement management: deterministic and probabilistic models. Although both deterministic and probabilistic models can be applied to predict pavement deterioration, the inherent relationship between these two types of models has not been explored yet. The investigation described in this thesis is directed, in part, to examine the system relationship between the two types of prediction models.

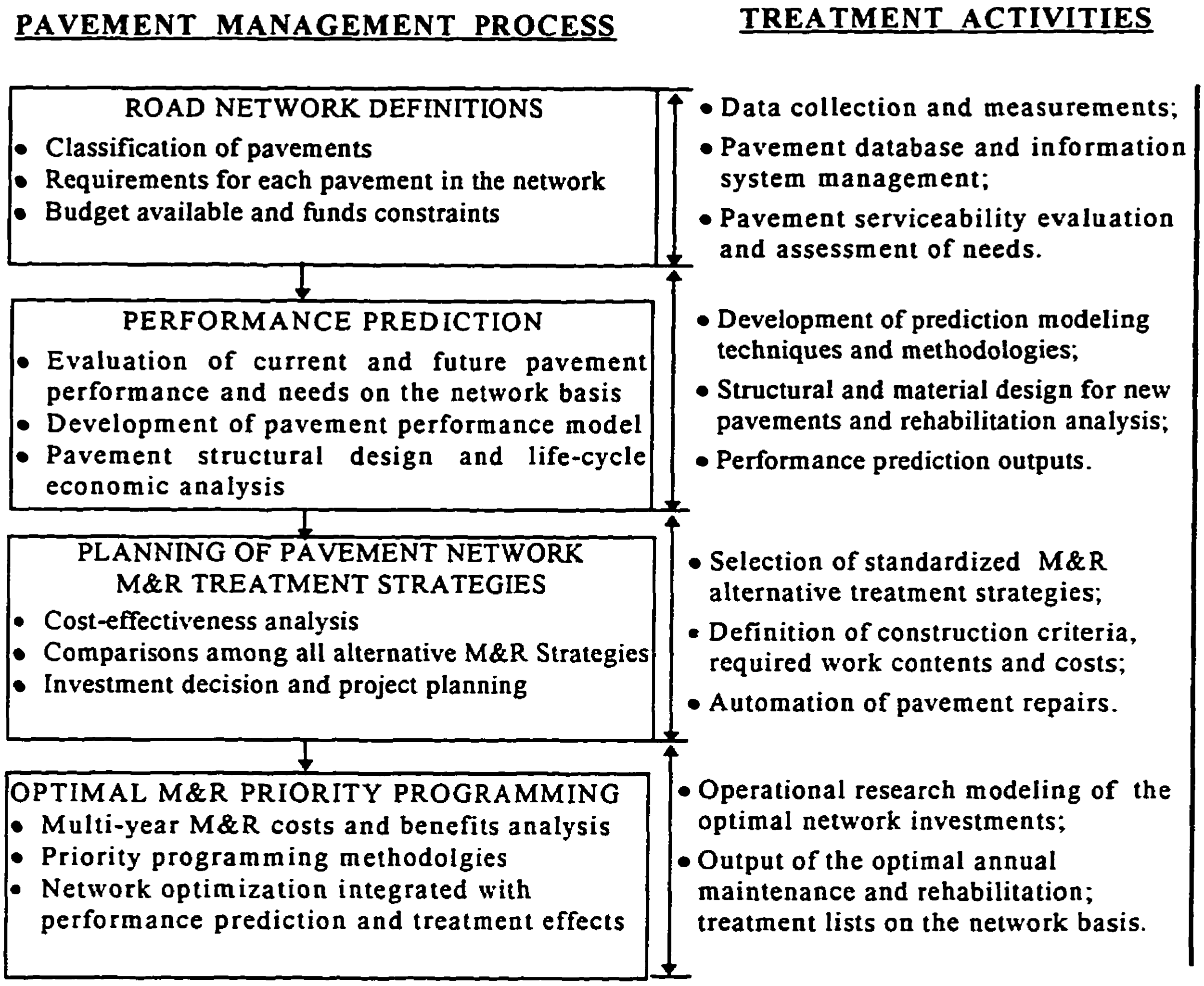

Figure 1.2 General Pavement Management Process and Context of the Problem

Since the 1970's, probabilistic models have been researched for their use in predicting pavement deterioration and dynamic programming of pavement maintenance and rehabilitation treatment strategies at the network level (19, 20, 21). One of the probabilistic prediction methods frequently used in the current pavement management systems is the time-independent (or homogeneous) Markov process. It is employed to model the overall performance of pavements with similar types of weather or/and traffic conditions. This approach is suitable particularly to the situations where traffic and environmental variables associated with a pavement deterioration rate are constant over the analysis period. The advantage of Markov-based models is that they accommodate uncertainties and variations of the variables used in the model development. In addition, they can incorporate the experience of an agency or pavement engineers into the models where there is no historical data available.

Traditionally, two common methods are used to establish a Markov transition probability matrix (TPM) for the prediction of pavement deterioration: a) by taking the average opinions of experienced pavement experts and field engineers through individual interviews or the use of questionnaires (22, 23), and b) by calculating the transition probabilities on the basis of a large number of observed long term pavement performance data (24). In the first approach, it normally takes a significant period of time to collect and process subjective information; plus there is the inavoidable bias of each individaul opinion. It is very difficult or impossible to use this approach to construct a set of consecutive (time-related) transition probability matrices, each of which represents pavement deterioration at different time period. The second approach needs a large number of measured or observed structural and performance history data for the pavements in the same classified category, which is very costly and time consuming. Although both methods can overcome the difficulty of inadequate data, their applications to real situations have been constrained because of the difficulties in establishing the transition probability matrices required for the prediction of pavement performance, which has been discussed by Li et al (25).

In essence, many of the Markov process modeling in pavement deterioration to date assumes time independence, i.e., the Markov transition probability matrix is considered to be constant throughout the period of pavement life-cycle analysis. This type of Markov process is classified as a homogeneous condition transition process (26, 27).

In recent years, non-homogeneous Markov process oriented prediction models have been developed to provide forecasts of infrastructure deterioration process, including highway bridge and pavement management (28 to 30). For example, Madanat et al. (31) developed incremental models that predict changes in pavement or bridge deck condition based on ordered probit techniques. The incremental models are more closer to the real deterioration process of infrastructures than models which predict condition directly because they take the form of difference equations where condition at a point in time is a function of both condition at a previous point in time and other explanatory variables such as age, traffic, weather and maintenance.

Consequently, there are many real situations where the use of homogeneous Markov process modeling is not appropriate. Compared to the existing Markov-based probabilistic modeling of pavement deterioration, the prediction methodology presented in this research has the following two significant features: a) pavement deterioration is modeled as a non-homogeneous (or time-related) Markov process with several different stages, where each stage has its unique transition probability matrix, and b) each element of the Markov transition probability matrix is, instead of taking average subjective opinion from many individuals or a large number of observed long-term pavement performance history data through regression analysis, calculated on the basis of reliability-performance concepts applied in the pavement management through prediction model system conversion approach developed by this research.

1.2.2 Selection of Pavement M&R Treatment Strategies

The selection of the most appropriate pavement maintenance and rehabilitation treatment strategies for a particular pavement section at scheduled timing requires consideration of a number of factors that can significantly influence the performance of the existing pavement and the overall long term costs. In order to rehabilitate the deteriorated pavements identified in a road network, it is desirable that all feasible treatments be considered to apply for each road section in the network be considered. The road sections may be individual pieces of road or representative sections for the network. The generation of proper M&R treatment alternatives lends itself to the application of knowledge based decision making techniques. The knowledge by which treatments are generated is represented by heuristic methods, which consider all alternative treatments strategies in order to meet the requirements for remedying the deteriorated pavements in a network. These treatments should also be standardized in structural design, construction quality, technical improvement and economic effects.

1.2.3 Pavement Maintenance and Rehabilitation Priority Programming

Pavement priority programming aims to select treatments that achieve a real or near optimization of a pavement network maintenance and rehabilitation needs. A variety of methods may be used for one-year or multi-year priority programming, as described in number of references (32 to 35). In many cases, highway agencies use cost-effectiveness or cost-benefit ratio to evaluate one treatment over another. This method requires the use of performance prediction model to analyze the life-cycle effectiveness of individual projects and to assess the trade-off between the alternative treatment strategies considered in the programming. It also requires the definition of trigger levels to identify future needs sections or projects during the analysis period.

With priority programming, the project selection process is carried out based on the pavement needs and some other technical or/and economic criteria. The process considers the application of the preferred treatment from a number of options for each year in the analysis period. For each treatment option there is a cost of undertaking the work and the associated benefit. The decisions on which treatment should be selected from the several treatments can be very complex, and a number of factors have to be considered, such as type, severity and density of pavement distress, material resources, cost and expected service life.

1.2.4 Reliability Concepts Applied to Pavement Structural Design

Since probabilistic-based performance models have been extensively used in this study for pavement performance prediction and maintenance priority programming, reliability-related pavement structural design and functional deterioration process should be firstly discussed. The concept of applying reliability in pavement structural design was initiated in the early 1970's. A major need for emphasizing reliability and its significance in pavement management systems has been discussed by Lemer, Darter, and Hudson during the 1970's (36, 37, 38).

Reliability of pavements is a measure of the probability that a pavement will provide satisfactory service to the user throughout its design service life. The prediction of pavement structural reliability and its use in providing economically efficient pavements requires consideration of all aspects of service life.

Reliability theory takes into account the random nature of many variables such as material properties, layer thickness, strength, variability between assumed design values and those actually constructed, and variability due to lack of fit of the empirical equations used in the structural system. Therefore, reliability could be calculated to quantify the uncertainty associated with design and performance predictions. Some basic methods of calculating pavement reliability are described in the 1986 AASHTO Pavement Design Guide (39) and its newer version (40) published in 1993, in which the distribution of pavement design variables are assumed and are generally represented by a mean value and overall variance. In reality, the mean value and variance of each variable are difficult to obtain if data is not available. As a result, a simulation model is developed to calculate the reliability and performance of pavement structural design (41, 42).

1.3 SUMMARY OF THE RESEARCH NEEDS

An accurate prediction of pavement deterioration over the period of pavement life-cycle analysis is absolutely important in pavement management because all other decisions, such as pavement rehabilitation design, selection of paving materials, determination of construction criteria or quality, economic analysis of pavement life cycle design and pavement priority programming, are carried out on the basis of the prediction. Consequently, prediction of pavement deterioration is the key part of a pavement management system.

The existing methods utilized for probabilistic prediction of pavement deterioration and priority programming need to be improved in certain aspects, which include: a) a more systematic approach to establishing efficiently the transition probability matrices (TPMs) for the prediction of pavement deterioration, b) consideration of all feasible treatments and their effects on the existing pavements within the analysis period, and c) integration of multi-year prioritization of pavement network maintenance and rehabilitation with comprehensive performance prediction.

1.3.1 General Goal and Conceptual Development

The general goal of this thesis is to develop an integrated pavement management system for optimizing multi-year pavement maintenance and rehabilitation program, which incorporates a probabilistic based, non-homogeneous Markov process modeling into the prediction of pavement deterioration and M&R treatment programming. The integrated system is intended to be applied at the network level of pavement management.

The overall approach to the system development is illustrated in Figure 1.3. There are five main functional components and processes in the proposed integrated pavement management system: 1) pavement network database information management, where all of the data is sorted and categorized based on the needs of the system, 2) classification of all the pavements in the network, 3) comprehensive prediction modeling of pavement functional and structural deterioration using Markov process, 4) generation of standardized regional pavement treatment strategies and, 5) integration of pavement maintenance and rehabilitation priority programming with the pavement performance prediction and treatment strategies on a network level.

In the first component, pavement network data is sorted and input in three different formats: 1)data needed for the network condition evaluation and assessment of needs, such as roughness, pavement condition index (PCI); 2) data used for modeling pavement performance, including traffic characteristics on each pavement in the network, pavement material moduli and environmental factors, where these variables are input in terms of probabilistic distributions; and 3) data required for the pavement network priority programming, such as system criteria, minimum acceptable serviceability of each pavement section, design and construction specifications, and budget constraints.

The function of second component develops a classification of the pavements in the network based on pavement structural design, traffic characteristics and environmental conditions. It should be noted that such a classification is different from the existing method of grouping the pavements with roughly categorized pavement thickness, traffic and subgrade strength.

In the third component, probabilistic-based Markovian prediction model is developed to forecast the deterioration process of individual pavement sections in a network. The method of establishing the Markov transition probability matrices (TPMs) through system conversion from a deterministic model to a probabilistic model is presented. This provides the performance characteristics required for the selection of future pavement preservation treatments.

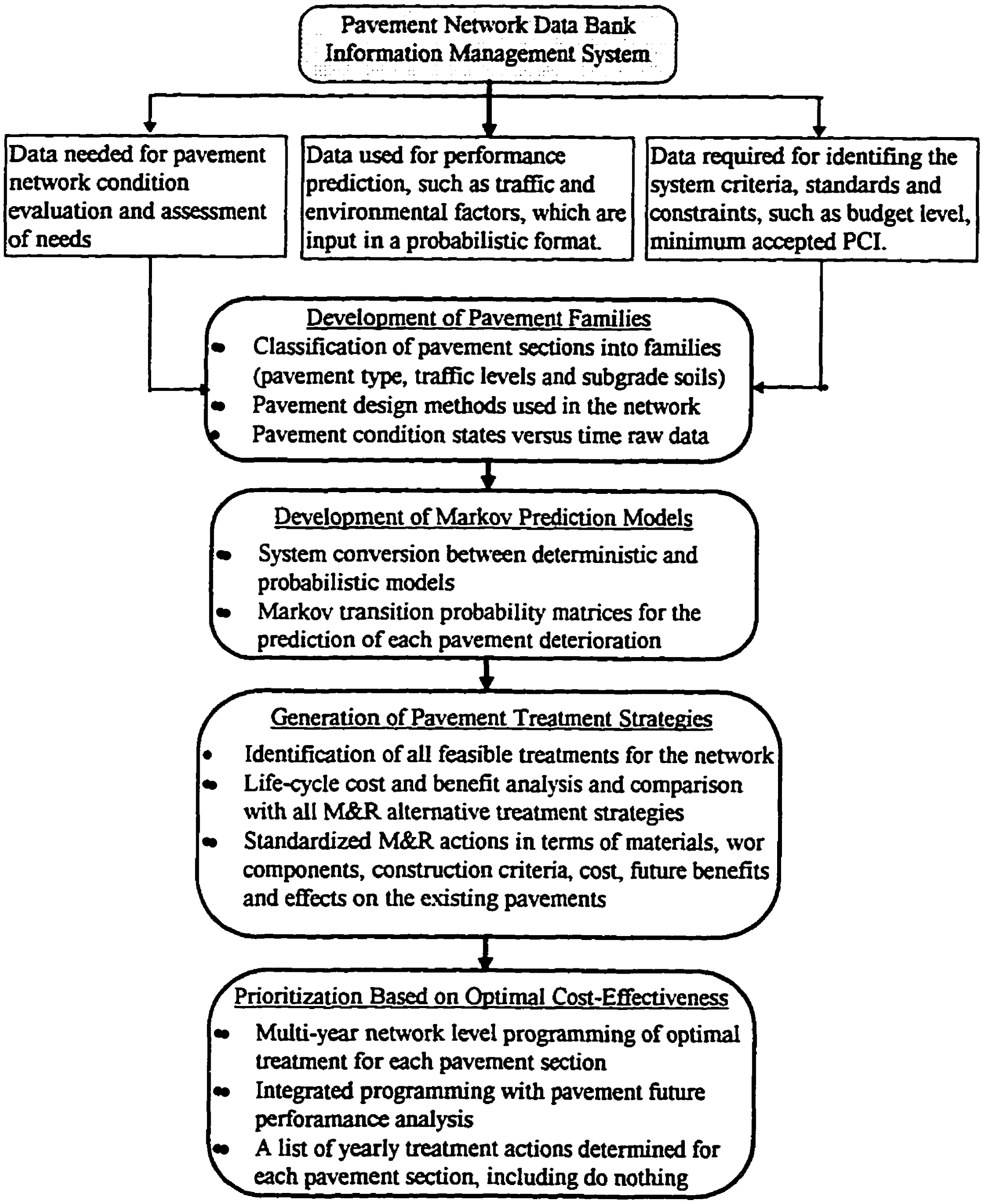

Figure 1.3 Overall Research Approach Flow Chart For the Proposed PMS

In the fourth component, a set of standardized alternative M&R treatment strategies is determined. Performance is predicted for each alternative, and the structural improvements on the existing pavement are calculated.

The last component produces a list of projects over the programming period through a mathematical optimization model. The projects are identified in the M&R alternative treatment decision process of the existing pavements within the previously selected programming period. The optimal M&R treatments for each project are selected on the basis of the maximum cost-effectiveness.

1.3.2 Specific Objectives and Scope of the Research

The main purposes of the research are: a) to develop an integrated system which is able to establish efficiently a probabilistic-based performance model for the prediction of pavement deterioration, b) to develop a new methodology of building time-related (or non-homogeneous) Markov transition probability matrices (TPMs) for each individual pavement section in the network, c) to incorporate the predicted pavement performance results with a set of standardized pavement network M&R treatment strategies, and d) to establish investment priority programming for the selected projects and optimization of the M&R treatment strategies for preservation of the pavement network. More specifically, the objectives are:

1. To define an integrated framework required for predicting pavement network performance in future years and modeling pavement life-cycle behavior.

2. To introduce the concepts of a non-homogeneous Markov process developed by this study and other previous researchers for the use in infrastructure management; also discussions on their applications in pavement management is exposed in terms of prediction of pavement structural and functional deterioration.

3. To present a new technique developed for establishing Markovian TPMs. For this purpose a detailed procedure of system conversion between deterministic and probabilistic prediction models is introduced. Example applications of the OPAC

(Ontario Pavement Analysis of Costs) system and AASHTO design method to the Ontario situations are demonstrated.

4. To define a set of standardized alternative maintenance and rehabilitation strategies, which is defined by detailed M&R treatment procedure, structural design criteria, materials, construction quality, costs and effects or functional improvement on the existing pavement.

5. To develop an efficient approach for carrying out sensitivity analysis of pavement performance prediction to the input variables, such as traffic volume, traffic growth rate, pavement thickness and subgrade soil strength.

6. To develop a practical process for optimizing pavement maintenance and rehabilitation priority programming at the network level in combination with the comprehensive performance prediction of each pavement section.

7. To demonstrate the application of the integrated pavement management system with a selected Ontario asphalt pavement network. Sensitivity of the system performance to some major input variables or parameters is examined in the case studies.

8. To propose an objective-oriented computer interface design of the integrated system for easy application in municipal and provincial pavement networks in the preservation and improvement.

1.4 ORGANIZATION OF THE THESIS

This thesis is organized in an order that starts with reviews of issues and demands of the current pavement management technologies. New concepts and methods that deal with structural design and maintenance models involved in the new PMS are introduced. It then describes the system applications, result verifications, and problems for future improvements. More specifically, the thesis is composed of the following chapters:

Chapter 1 states the general nature of pavement management and its significance to national economic development in terms of transport asset preservation. Some major concerns and issues are defined, including performance models, maintenance treatment strategies and optimization of pavement improvement priorities. The overall concept of the probabilistic-based performance models for the prediction of pavement deterioration versus time is described. In addition, an integrated system that incorporates pavement deterioration prediction, standardized alternative preservation strategies and priority programming of road network is presented.

In Chapter 2, the existing classification of pavement performance prediction models are reviewed for their applicability and their limitations to the real situations of road networks. It also describes the existing methods of optimizing pavement M&R programming. Evaluation and limitations of the existing methods are discussed at the end of this chapter.

Chapter 3 provides a conceptual framework of the proposed integrated system for predicting pavement deterioration and multi-year priority programming of road network maintenance. The objective-oriented process of pavement priority programming is developed to insure optimality in the selection of the pavement overall treatment actions. Three major components underlying the integrated system are described, including model development for predicting pavement deterioration, standardized alternative pavement maintenance and rehabilitation treatment strategies, and pavement M&R treatment priority programming on the basis of cost-effectiveness. The major components in the integrated PMS are illustrated. The basic structure of the proposed system is formulated in the light of these components.

Chapter 4 presents, in detail, the method of constructing the time-related (non-homogeneous) Markovian TPMs for the prediction of pavement deterioration versus time, expressed in a series of consecutive transition probability matrices. It emphases the techniques used to generate the yearly TPMs and the probability distributions of input variables. This allows the random nature of pavement behavior under changeable traffic loads and environmental conditions to be considered in the modeling of pavement deterioration. The idea of applying the time-related Markov chain to pavements is illustrated with reliability analysis. The process of system conversion from a deterministic to probabilistic models is introduced for the first time in this research. Sensitivities of pavement deterioration rate to the major factors, such as traffic, pavement structural thickness and subgrade soil strength, are investigated with some example illustrations. In addition, a Bayesian posterior probability technique is applied to modify the predicted pavement performance through observed pavement performance data.

Chapter 5 deals with standardization of pavement M&R treatment strategies for pavement network preservation. In particular, it provides an example application of this technology to the pavement maintenance programming with five specific treatments. The components of each standard treatment strategy are described in terms of economic benefits and structural improvements on the existing pavements. Each of the treatments represents a different work content, improvement effect on the existing pavement condition state (PCS) and influence on future performance of the pavement and total cost.

Chapter 6 describes the integrated priority programming combined with the time-related performance prediction model and standardized pavement preservation treatment strategies. A formulation of the optimization model is presented in this Chapter, together with the model input requirements and output format. The economic analysis is conducted in terms of cost-effectiveness, which is used in M&R treatment priority programming. The programming emphasizes pavement M&R treatment planning on a network basis. Advantages and limitations of the model are summarized at the end of this chapter.

Chapter 7 gives a comprehensive example application of the proposed integrated approach to the optimal pavement network maintenance and rehabilitation. The example used is taken from the Ontario road system. The sensitivity of the system performance to several input factors is illustrated with various examples.

The final chapter summarizes principal findings of the thesis and provides some recommendations for future work and improvement.

CHAPTER 2

REVIEW OF EXISTING PERFORMANCE MODELS AND OPTIMIZATION METHODS IN PAVEMENT MANAGEMENT

2.1 INTRODUCTION

The application of modeling the relationship between pavement functional deterioration and overall cost (including M&R costs and user costs) has become more significant with the fast development of pavement management techniques. The modeling of pavement deterioration and its relation to pavement maintenance and rehabilitation (M&R) treatment strategies have been investigated by many previous researchers (43, 44, 45). Determination of the optimal investments in operating pavement network preservation programs is concerned with pavement M&R priority programming prioritization, which may be carried out through pavement life-cycle analysis. There are many priority programming methods available in pavement management, ranging from simple subjective ranking to true optimization.

In reality, it is difficult to obtain a true optimization as many uncertain factors are involved in the mathematical programming model. Moreover, the optimization formula developed from one specific region is not likely to be fitted into another region. Consequently, a number of near optimization approaches, which are close to the true optimal and relatively easy to develop, have been widely utilized in pavement management.

Having a reliable pavement performance model in a PMS is essential for a highway agency to secure pavement life-cycle structural design, and to estimate the costs and benefits of the projects associated with M&R treatments. Pavement treatment actions should be planned on the basis of current needs and projected future needs with considerations of budget constraints. As mentioned in the previous chapter, pavement performance model is a critical component of the entire pavement management process and it is, therefore, the foundation of pavement network management.

In general, a pavement management system aims to provide the tools necessary to predict pavement future conditions so that the optimal pavement repair strategies and actions can be determined. Over the last 30 years, a considerable amount of effort has been made to the prediction of pavement deterioration in order to meet the requirements of each specific pavement management system. A number of different types of performance prediction models are available currently for highway agencies to use in their pavement management systems (46 to 48). The performance models used in these systems are presented in a variety of mathematical formulae. Each one is applicable but limited to a specifically defined pavement network with certain traffic magnitude, regional allocation and environmental conditions.

In this chapter the existing models for predicting pavement deterioration and optimization methods used in many North American highway agencies are briefly reviewed. Several generic algorithms that are frequently used for modeling pavement deterioration are first presented. A new concept applied in the modeling of pavement deterioration is then outlined. Following the discussion on performance, economic analysis in pavement priority programming is briefly described; in particular, multi-year linear programming approaches are emphasized for use in the road network preservation. The characteristics of each model and its potential applications in pavement management are addressed. In addition, some recent developments and future research directions in ranking and optimization methodologies are highlighted in this chapter.

2.2 EXISTING METHODS OF PAVEMENT DETERIORATION PREDICTION

The concept of pavement serviceability-performance developed at the AASHO Road Test (49) has become more significant in the overall context of pavement management. One of the most significant contributions of the AASTO Road Test is perhaps the quantification of serviceability and performance. It provided a means of directly measuring and evaluating the intended function of the pavement in relation to the road user. In other words, evaluation of pavement serviceability and performance can be measured in terms of pavement condition index (PCI), present serviceability index (PSI), and many other parameters used in current pavement management systems.

The methods of probabilistic-based Markov process modeling of pavement deterioration have been introduced in pavement network management since the 1970's. In such cases, knowledge based expert systems and the considerations of other factors, such as pavement materials, construction quality, local policy, etc., may be useful in helping a highway agency to carry out an appropriate priority programming of pavement network preservation. Without a reliable pavement performance model, it is not possible to execute a reasonable pavement treatment priority programming. This is because the process involved in the priority programming, such as decisions in selecting pavement projects, long term cost and effectiveness, pavement life-cycle structural design, etc., is developed mainly on the basis of pavement performance prediction.

Before discussing in detail the pavement performance models, it is necessary to state the definitions of some key terminology used in this research, including pavement performance, deterioration, reliability, serviceability and pavement condition state.

1. Performance is a general term for how pavements change their condition or serve their intended functions with time. Pavement performance was originally defined at the AASTO Road Test as the serviceability-age profile, where serviceability is a user-related measure of ride quality. Performance can be simply and more broadly defined as the history of a pavement with regard to general serviceability, roughness or riding comfort index, surface distress and safety in terms of skid resistance.

2. Pavement deterioration is defined as a decrease in pavement serviceability levels and/or an increase in pavement surface distresses with time. While the former is a functional deterioration, the latter represents structural deterioration*. Deterioration may also involve a loss of structural adequacy (in terms of deflection) over time.

3. Serviceability is a measure of the degree to which the pavement provides satisfactory service to the user at a given time. It should be noted that pavement roughness is one of the major indicators contributed to pavement serviceability.

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* It may be noted that pavement performance and pavement deterioration are often used synonymously. In a rigorous sense, performance should only be used according to the AASHO definition. By comparison, deterioration can have a broader definition.

4. Pavement condition state is a general definition of pavement current or predicted future serviceability, such as Riding Comfort Index, RCI, International Roughness Index, IRI, pavement condition index, PCI, pavement quality index, PQI, present serviceability index, PSI, pavement distress index, PDI, Structural Adequacy Index, SAI, etc.

5. Reliability is the probability that serviceability will be maintained at adequate levels or the pavement will perform its intended function over its design life and under the environment encountered during operation.

It should be noted that the accuracy of a pavement performance model is directly related to the quality of the database used for the model development. It is extremely important, therefore, to have a reliable database for the performance modeling process. The database should contain the variables and factors that influence previous performance, such as traffic levels, environment factors, pavement initial design, structural design and observed pavement condition. In pavement management, performance models use pavement conditions as one of the most important variables. Pavement condition, such as RCI, SDI, etc., is influenced by traffic levels, paving materials, construction quality and many other factors.

The following sub-sections describe the existing performance and/or deterioration prediction models that are most frequently used in North America and other pavement management systems (PMSs). A classification of the performance models is described in terms of model structure, and model development, and model characteristics. Limitations of the models are discussed in terms of applicability, economy, and effectiveness.

2.2.1 Classification of Prediction Models for Pavement Deterioration

It is very difficult and perhaps impossible to establish an universal, reliable performance prediction model for use in all regions. Instead, various prediction models are developed on the basis of pavement type, structural design, paving materials, traffic levels and other factors.

More specifically, a classification of pavement performance models and their relation to the levels of pavement management is summarized in Table 2.1. These performance models have been categorized into four levels according to their functions in pavement management systems, i.e., project level and three levels at local, provincial and national network, respectively. As described in Table 2.1, there are basically two types of prediction models used in current pavement management: deterministic and probabilistic.

The deterministic models predict an average single value of a dependent variable (such as PCI, PSI, etc.). Deterministic models can be further broken into three categories: mechanistic, empirical and regression models, depending on which dependent and independent variables are included in the models and how their relationship is established.

Most of the existing prediction models have been developed through regression analysis, combined mechanistic-empirical analysis, and subjective opinions from experienced pavement engineers and experts. These models are established on the basis of extensive data collection and tests along experimental or naturally exposed pavements under different traffic and environmental situations.

The probabilistic models predict a distribution and range of values for a dependent variables, such as pavement condition state vectors. Probabilistic models are more utilized in pavement and other infrastructure network management with concerning M&R priority programming.

Performance often has meanings ranging from specific to general when used at different levels of pavement management. For instance, at the project level, performance may be defined by distress and loss of serviceability. However, at say the provincial network level, performance may also be defined as the change with time of overall condition and the needs for current and future funding for the pavement network.

The principles underlying the two basic types of performance models (including model structure, mathematical form and application) are discussed in the following sections, with emphasizing on probabilistic models.

Table 2.1 Classification of Prediction Models and Levels of Pavement Management

Pavement Management	Types of Pavement Deterioration Prediction Models				
	Deterministic Models			Probabilistic Models	
	Mechanistic	Empirical / Mechanistic	Regression	Markov Transition Process	
	Primary Response • Deflection • Stress • Strain	Structural or Functional • Distress(cracks,etc) • PCI, PSI, RCI, etc. • Safety Index	Composite • Roughness • Skid Resist. • PCI, RCI, etc.	Time-Independent (Homogeneous) General Pavement Condition State Prediction	Time-Related (Non-homogeneous) General Pavement Condition State Prediction
Project Level	•	•			
Local Network		*	•	*	•
Provincial Network		*	*	*	*
National Network			*	*	*

2.2.2 Deterministic-Based Performance Prediction Models

The majority of the existing deterministic-based models may be classified as structural or functional performance models and primary response models. These models are developed using regression, empirical and combined mechanistic-empirical methods. The selection of a mathematical form to use for pavement performance models must fit the observed data and the regression-statistical analysis. Rating data are discrete ordinal measurement, which means that the numbers assigned do not indicate distances between ratings, but only a relative ordering. Linear regression is not appropriate as the assumptions of zero error mean and constant variance. While primary response based performance models relate pavement service life with measured pavement responses (such as deflection, stress and strain), structural or functional associated performance models are directed to establish the relationship between the dependent variable of measured functional deterioration and the selected independent variables (such as traffic loading, pavement layer thickness and subgrade soil modulus), based on a large number of observed long-term pavement performance history database.

The basic mathematical form for pavement structural or functional performance models can be generally expressed as follows:

$$PCS_t = f\left(P_0, ESALs_t,\ He \text{ or } SN,\ M_S,\ C,\ W,\ I\right) \qquad [2.1]$$

Definition and description of each of the elements in the above equation may be referred as follows:

PCS_t = generalised Pavement Condition State (such as Riding Comfort Index, RCI, Present Serviceability Index, PSI, Pavement Quality Index, PQI, etc.) at year t, where $t = 0,1,2,\cdots,T$

P_0 = initial pavement condition state

$ESALs_t$ = accumulated Equivalent Single Axle Load applications (ESALs) at age t

He = total equivalent thickness of pavement layers (usually in terms of granular base)

SN = structural number index of total pavement thickness

M_S = subgrade soil strength or resilient modulus

W = a set of climatic or environmental effects

I = interactions of the preceding effects

C = a set of construction effects

The independent variables in equation [2.1] are the main design variables and parameters that affect pavement functional deterioration rate. Each of the factors could be further subdivided into a set of individual factors. For example, the total equivalent pavement thickness, He, is a function of the structural or functional properties of each pavement layer, the equivalent layer factors defined for the pavement materials, and construction quality effects. Therefore, the difficulties of establishing reliable and practical performance prediction models have been overcome, to some degree, by developing simpler, regional based models. The argument here is that all the design variables and parameters may not be input as exactly the same values that actually appear in real situations. The reason is that uncertainties and variations are heavily involved in the process of estimating these variables. For example, the accumulated number of ESAL applications within t years predicted by a traffic input model may be quite different from what actually occurs because traffic growth rate, truck percent, traffic distribution on the pavement and truck factors can not be estimated precisely. Similarly, the input of subgrade soil strength or modulus, Ms, and equivalent pavement thickness, He, may not represent their real values in the field because of variations in determining these factors from testing samples, measuring the subgrade soil and construction quality. Therefore, it is both necessary and practical to use a reliability based probabilistic model for the prediction of pavement deterioration.

Primary response prediction models may be purely mechanistic or empirical-based for the prediction of pavement response, such as deflection, stress, strain, etc., to imposed loads and environmental conditions. Mechanistic models are based on the fundamental principles of pavement behavior under traffic loading and environmental conditions. Empirical models are established in accordance with results of experiment and experience.

Structural and functional performance prediction models are either mechanistic or mechanistic-empirical models, depending on the formulation and variables used in the model. These types of models predict either pavement surface distress, such as cracking and deformation, or a composite measurement of pavement serviceability, such as pavement condition index. The model can be developed by relating the structural or functional deterioration to observed data, such as cracking and roughness, through regression analysis.

In regression models, the dependent variable of pavement serviceability or some other indicators are related to one or more independent variables such as subgrade soil strength, total pavement layer thickness, material properties, traffic and environmental variables. The predicted relationship between independent variable(s) used in the model and general pavement condition state, such as Pavement Condition Index, PCI, Pavement Quality Index, PQI, or Pavement Distress Index, PDI, etc., can be expressed as a straight line if only one single powered independent variable is used in the model development, or a curved line where more than two independent variables (multiple regression) are employed to develop the performance model, as shown in Figure 2.1.

It is relatively easy to develop a straight regression line for a performance model where pavement deterioration is attributed to only one independent variable, such as pavement age or accumulated traffic volume. However, a single independent variable based linear regression model can not be expected to have higher accuracy simply because it does not account for other influential variables or factors. On the other hand, it could be a complicated mathematical process to develop a multi-variable and high power regression model. For example, the performance models developed for the Alberta Pavement Management System utilized up to 25 years of data on pavement deflection, traffic, roughness and distress and involved a recursive or multi-year regression analysis (50).

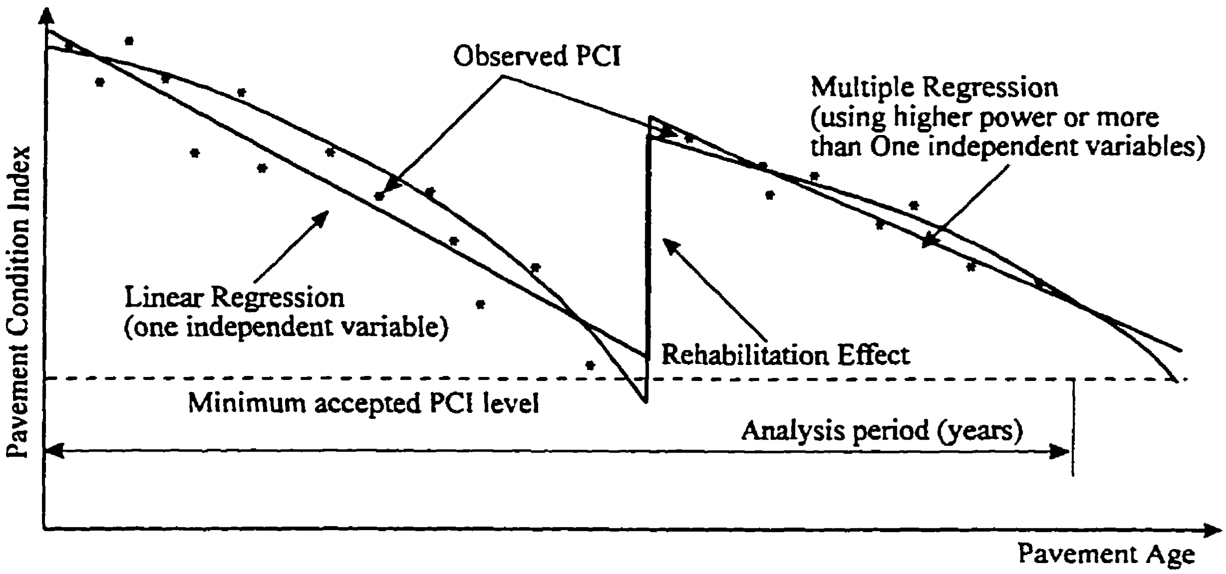


Figure 2.1 Illustration of Performance Model through Regression Analysis

Listed in Table 2.2 are several examples of deterministic performance prediction models developed for use in highway agencies around the world. For each of the models, both dependent variable and independent variables are explained.

The problem of deterministic-oriented prediction models is that the applicability of each individual model is restricted to a certain specific region where the model has been developed. It is inadequate to apply deterministic models to all situations of pavement management because of : 1) the uncertainties in pavement behavior under traffic load and environmental conditions, 2) the difficulties in quantifying the factors or parameters that affect the rate of pavement deterioration, and 3) the errors associated with acturally measured data and bias from subjective pavement condition evaluation.

One of the common features among different types of deterministic models is that they are all based on a large number of long term observed field data and processed through regression analysis. In many cases, the regression based approach is not suitable for modeling actual deterioration process of pavements because the sampling data used in the regression analysis suffers from various limitations, such as pavement structure, traffic characteristics and many other environmental variables. On the other hand, deterioration is not an observable quantity but is evaluated by measuring surface distress such as roughness, cracking, and so on.

Table 2.2 A List of Example Deterministic-Based Pavement Performance Models

PREDICTION EQUATION	TYPE/CLASS	USER / DEVELOPER
$Log(QI) = 1.297 + 9.22 \cdot 10^{-3} Age + 5.57 \cdot 10^{-4} STEN1 \, Log \, N$ where QI = roughness (quarter-car index, in counts/km); $SEN1$ = strain energy at bottom of asphalt layer (10^{-4}kgfm); N = cumulated ESALs.	Empirical / Regression	Brazil by Queiroz et al (51)
$PCR = 100 - m(Age)^p$ where PCR = pavement condition rating, scale of 0 to 100; m = slope coefficient; p = parameter controlling the shape of curve.	Regression/ Empirical	the State of Washington, US, by Jackson et al (52)
$P = P_0 - \left[2.4455 \times 10^3 w_s^6 N + 8.805 \times 10^9 \left(w_s^6 N\right)^3\right] - \left(P_0 - \frac{P}{1 + B\, w_s}\right)\left(1 - e^{-\alpha Y}\right)$ where P = predicted PCI when the number of accumulated ESALs, is N, P_0 = initial pavement condition index, PCI_0 when the pavement is new or reconstructed, w_s = the calculated subgrade deflection, N= the total accumulated ESALs in Y years, starting from the year when $P = P_0$, Y = age of pavement in years, α, B = constants related with environment and subgrade soil.	Mechanistic/ primary response	OPAC model, by Ministry of Ontario Transportation (53)
$P = P_0 - c_1 A^{C_2} \cdot M^{C_3} \cdot T^{C_4}$ where P, P_0 = Pavement Condition Index (PCI) and Initial PCI, A = age in years since last pavement overlay, M = asphalt concrete overlay thickness, T = Annual Average Daily Traffic volume, C_1 to C_4 = regression coefficients which change by region.	Regression/ Empirical	PARS model, Ontario, Canada by MTO (54)
$PCI = PCI_0 - \alpha A^{\beta}$ $(PCI \geq 40)$ where A = age in years since last pavement overlay, α, β = section-specific regression coefficients or constants.	Regression	Single Power Curve model, Texas, US, by Texas Transportation Institute (55)
$P = \alpha \cdot \exp^{-(\rho/A)^{\beta}}$ where P = a pavement performance measure, A = the quantity of traffic loads or elapsed time required to reach P α, ρ, β = calibration constants obtained by a least-squares technique using non-linear regression analysis.	Regression/ Empirical	Sigmoidal Curve model, Texas, US, by the Texas Transportation Institute (56)

For example, Hajek (56) investigated several different types of deterministic models and compared the results predicted by each of these models for the same pavement. These models were the mechanistic-derived OPAC model (53) and empirical-based PARS model (54) developed by the Ontario Ministry of Transportation, and regression analysis-derived power curve and Sigmoidal curve developed by the Texas Transportation Institute, respectively. The model evaluation was based on a sample of 25 asphalt concrete pavement sections for which detailed structural data and pavement performance histories (including PCI) were assembled. The performance predicted by the models were compared to observed ones, as shown in the example of Figure 2.2. Prediction accuracy of the models was examined by comparing the observed terminal pavement age with the predict terminal pavement ages. Table 2.3 shows average terminal age of the pavement, in terms of mean value and standard deviation, predicted by each of the models. In addition, at a specific pavement age the pavement condition state predicted by each prediction model is given in Table 2.4. From the results shown in the these two tables, it is apparent that the Sigmoidal curve is the most suitable to the observed data in this case.

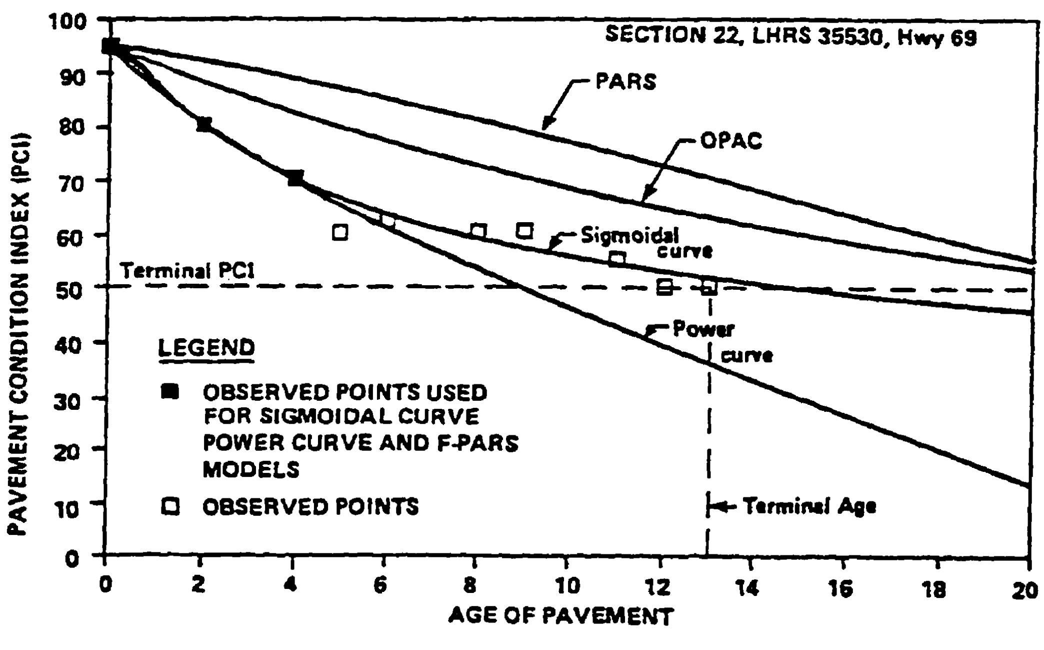


Figure 2.2 Example of Model Comparisons, Initial Planning Stage (After Ref. 56)

Table 2.3a Comparisons of the Observed Pavement Terminal Ages with the Predicted Ones

	INITIAL PLANNING STAGE				ADVANCED PLANNING STAGE			
METHOD OF ESTIMATION	Mean	Standard Deviation σ	Difference Between Observed - Predicted		Mean	Standard Deviation	Difference Between Observed - Predicted	
			Mean	σ		σ	Mean	σ
Observed	13	3	0	0	13	3	0	0
OPAC	18	3	-5	4	18	3	-5	4
PARS	17	3	-4	4	17	3	-4	4
Power	13	6	0	6	13	5	0	4
Sigmoidal	15	6	-2	6	16	5	-3	5

Table 2.3b Comparisons of the Observed PCI with the Predicted One in the 13th Year

	INITIAL PLANNING STAGE				ADVANCED PLANNING STAGE			
METHOD OF ESTIMATION	Mean	Standard Deviation σ	Difference Between Observed - Predicted		Mean	Standard Deviation	Difference Between Observed - Predicted	
			Mean	σ		σ	Mean	σ
Observed	54	5	0	0	54	5	0	0
OPAC	65	7	-11	10	65	7	10	4
PARS	63	9	-9	12	63	9	12	4
Power	54	13	0	15	53	9	11	4
Sigmoidal	58	10	-4	11	58	7	9	5

2.2.3 Probabilistic-Based Performance Prediction Models

Probabilistic models can be generally represented by the Markov processes for the prediction of pavement deterioration versus time, although some documents also include survivor curves in the category of probabilistic performance models. Basically, the Markov process is composed of system states, stages or successive time periods, and transition probability matrices.

In the application of a PMS, states are defined by levels of Pavement Condition States, PCS, and successive steps are the stages or the time periods for which the pavement condition states and time relationship is predicted, and each element of the transition probability matrices represents the probability that the pavement will change from one state level to another in a specified time period. Karan (57) in Ontario and Wang et al. (58) in the state of Arizona have successfully applied Markov models in regional pavement management systems.

Most of the Markov process incorporates both subjective and objective data in the development of a pavement performance model. For modeling purpose, the pavement state is defined with respect to a rank of condition measures, such as pavement condition index, riding comfort index, percent surface cracking, roughness and serviceability. Markov process modeling can be applied in the prediction of pavement future condition states for both existing pavements and new pavements.

Table 2.4 gives an example showing Markovian transition probability matrix (TPM) that represents the transition pattern of pavement deterioration from year N to year N+1.

Table 2.4 Example of Markov Transition Probability Matrix Structure

	Pavement Condition State (using Pavement Condition Indices, PCI)									
	10 100-90	9 89-80	8 79-70	7 69-60	6 59-50	5 49-40	4 39-30	3 29-20	2 19-10	1 9-0
10 (100-90)	$p_{10,10}$	$p_{10,9}$	$p_{10,8}$	$p_{10,7}$	$p_{10,6}$	$p_{10,5}$	$p_{10,4}$	$p_{10,3}$	$p_{10,2}$	$p_{10,1}$
9 (89-80)	0	$p_{9,9}$	$p_{9,8}$	$p_{9,7}$	$p_{9,6}$	$p_{9,5}$	$p_{9,4}$	$p_{9,3}$	$p_{9,2}$	$p_{9,1}$
8 (79-70)	0	0	$p_{8,8}$	$p_{8,7}$	$p_{8,6}$	$p_{8,5}$	$p_{8,4}$	$p_{8,3}$	$p_{8,2}$	$p_{8,1}$
7 (69-60)	0	0	0	$p_{7,7}$	$p_{7,6}$	$p_{7,5}$	$p_{7,4}$	$p_{7,3}$	$p_{7,2}$	$p_{7,1}$
6 (59-50)	0	0	0	0	$p_{6,6}$	$p_{6,5}$	$p_{6,4}$	$p_{6,3}$	$p_{6,2}$	$p_{6,1}$
5 (49-40)	0	0	0	0	0	$p_{5,5}$	$p_{5,4}$	$p_{5,3}$	$p_{5,2}$	$p_{5,1}$
4 (39-30)	0	0	0	0	0	0	$p_{4,4}$	$p_{4,3}$	$p_{4,2}$	$p_{4,1}$
3 (29-20)	0	0	0	0	0	0	0	$p_{3,3}$	$p_{3,2}$	$p_{3,1}$
2 (19-10)	0	0	0	0	0	0	0	0	$p_{2,2}$	$p_{2,1}$
1 (9-0)	0	0	0	0	0	0	0	0	0	1.000

In this transition probability matrix example, pavement condition state levels are defined by 10 ranges of Pavement Condition Index (PCI) values. Each state corresponds to a range of PCI values in order. For instance, state 10 corresponds to the range of PCI values from 100 to 90, state 9 represents the range of PCI values from 89-80, and so on. It should be noted that a large dimension of the matrices, or a large number of states is essential not only to the prediction accuracy but also to the feasibility of the matrix construction. However, by using the existing two approaches it would be very difficult or impossible to build a Markov transition probability matrix, especially when the dimension of the matrix is large and more sub-divisions of the PCI measures are needed.

2.2.3.1 Main Considerations in the Markov Process Modeling of Pavement Deterioration

To establish a Markovian transition probability matrix, the following major factors that affect a transition during a specified period of time are considered:

1) Pavement type and structural design,
2) Pavement materials and thickness,
3) Traffic volumes or number of equivalent standard axle load applications (ESALs),
4) Subgrade soil modulus and strength, and
5) Environmental and regional effects.

One example is the pavement performance models used in the pavement Network Optimization System (NOS) at Arizona Department of Transportation (59). In this system, Markov process-based probability matrices were established for each class of pavements. The highway system in Arizona is classified into 15 road categories based on traffic, region and functional class (interstate or non-interstate highways). Forty five pavement condition states are defined for the assessments of pavement overall quality or serviceability. The factors defining each of the condition states are roughness, crack and index to the first crack. All pavement sections within a road category are placed in one of the 45 condition states in accordance with the pavement assessment, as shown in Table 2.5.

Another application of the Markov process uses three levels for pavement thickness, three levels of traffic, and two levels of subgrade strength for a total of 3×3×2 or 18 combinations (57, 60). Thus, 18 transition probability matrices are constructed for this application. Table 2.6 shows how each of the transition probability matrices is combined with the classified pavement thickness, traffic levels and subgrade strength. Construction of each transition probability matrix is conducted through processing a large quantity of subjective judgment and opinions from many individual pavement engineers and experts.

Table 2.5 Arizona Pavement Condition State Numbering System (After Ref. 58)

Levels of Classification		45 pavement Condition States, Index to First Crack, I_c				
Roughness	Crack	Index (1)	Index (2)	Index (3)	Index (4)	Index (5)
1	1	1	10	19	28	37
1	2	2	11	20	29	38
1	3	3	12	21	30	39
2	1	4	13	22	31	40
2	2	5	14	23	32	41
2	3	6	15	24	33	42
3	1	7	16	25	34	43
3	2	8	17	26	35	44
3	3	9	18	27	36	45

Table 2.6 Classification of Transition Probability Matrix for Pavements (After Ref 57)

Class No.	Thickness* (mm)	Traffic (AADT)**	Subgrade Soil Strength***
1	375 - 500	<5,000	Strong (CBR>5)
2	375 - 500	<5,000	Weak (CBR<5)
3	375 - 500	5,000 - 10,000	Strong (CBR>5)
4	375 - 500	5,000 - 10,000	Weak (CBR<5)
5	375 - 500	>10,000	Strong (CBR>5)
6	375 - 500	>10,000	Weak (CBR<5)
7	500 - 625	<5,000	Strong (CBR>5)
8	500 - 625	<5,000	Weak (CBR<5)
9	500 - 625	5,000 - 10,000	Strong (CBR>5)
10	500 - 625	5,000 - 10,000	Weak (CBR<5)
11	500 - 625	>10,000	Strong (CBR>5)
12	500 - 625	>10,000	Weak (CBR<5)
13	>625	<5,000	Strong (CBR>5)
14	>625	<5,000	Weak (CBR<5)
15	>625	5,000 - 10,000	Strong (CBR>5)
16	>625	5,000 - 10,000	Weak (CBR<5)
17	>625	>10,000	Strong (CBR>5)
18	>625	>10,000	Weak (CBR<5)

* Total Equivalent Granular Thickness

** 90 % Passenger Cars, 6% Medium Trucks, 4% heavy Trucks

*** The terms " Strong " and " Weak " are subjective; an approximate division is based on a CBR value of about 5.

2.2.3.2 Existing Methods of Constructing Transition Probability Matrices

According to the characteristics of pavement functional deterioration, the applications of Markov process in modeling pavement deterioration can be mainly divided into two types: homogeneous and non-homogeneous. When a homogeneous Markov process is applied in modeling pavement deterioration, it has been assumed that the variables such as traffic (including volume or ESALs, truck percentage, etc.) and environmental conditions (including strength of subgrade soil, annual average temperature and precipitation, etc.) are constants throughout the analysis period, which is not correct in many real situations. On the other hand, non-homogeneous Markov process considers the rate of pavement deterioration incurred at each different stage. The methodology of establishing non-homogeneous Markovian TPMs, which has been developed in this study, is presented in detail in Chapter 4.

Figure 2.4 shows the classification of Markov process applied in pavements and the methodologies utilized to establish the relevant transition probability matrices. If a homogeneous Markov process is applied to model pavement deterioration, the establishment of a Markovian transition probability matrix can be traditionally done in two different ways: subjective opinion from individual engineers and statistical analysis from a large number of observed data. A summary of the two methods and their applications in pavement management systems can be stated as follows:

Statistical Method Each element of a TPM is calculated on the basis of a large number of performance observations of the pavements in the same category under different initial pavement conditions over a long period of time. Therefore, a large amount of measured performance data for all pavement categories in a road network is required, which is time consuming and costly.

A typical example is the Markov performance model used in the Arizona DOT Pavement Management System (58). In this system, the generation of the transition probability matrices was based on more than 10 years observed performance data of a large number of the pavements that are classified in the same group or type of pavements. The following equation is then applied to calculate each element of the transition probability matrix:

$$p_{ij}(a_k) = \frac{m_{ij}(a_k)}{m_i}; \quad for\ i,j = 1,\ 2,\ldots,45;\ \ k = 1,2,\ldots,6 \qquad [2.1]$$

where k represents the kth rehabilitation action, a total of 6 alternative rehabilitation strategies are defined; $p_{ij}(a_k)$= transition probability from state i to j after action k is taken; $m_{ij}(a_k)$= total number of kilometers of pavement the condition states of which before and after the action k are i and j, respectively; and m_i is total number of kilometers pavement the condition states of which before the action k is applied is i. The discussion on the state of the art on developing transition probability matrices is as follows:

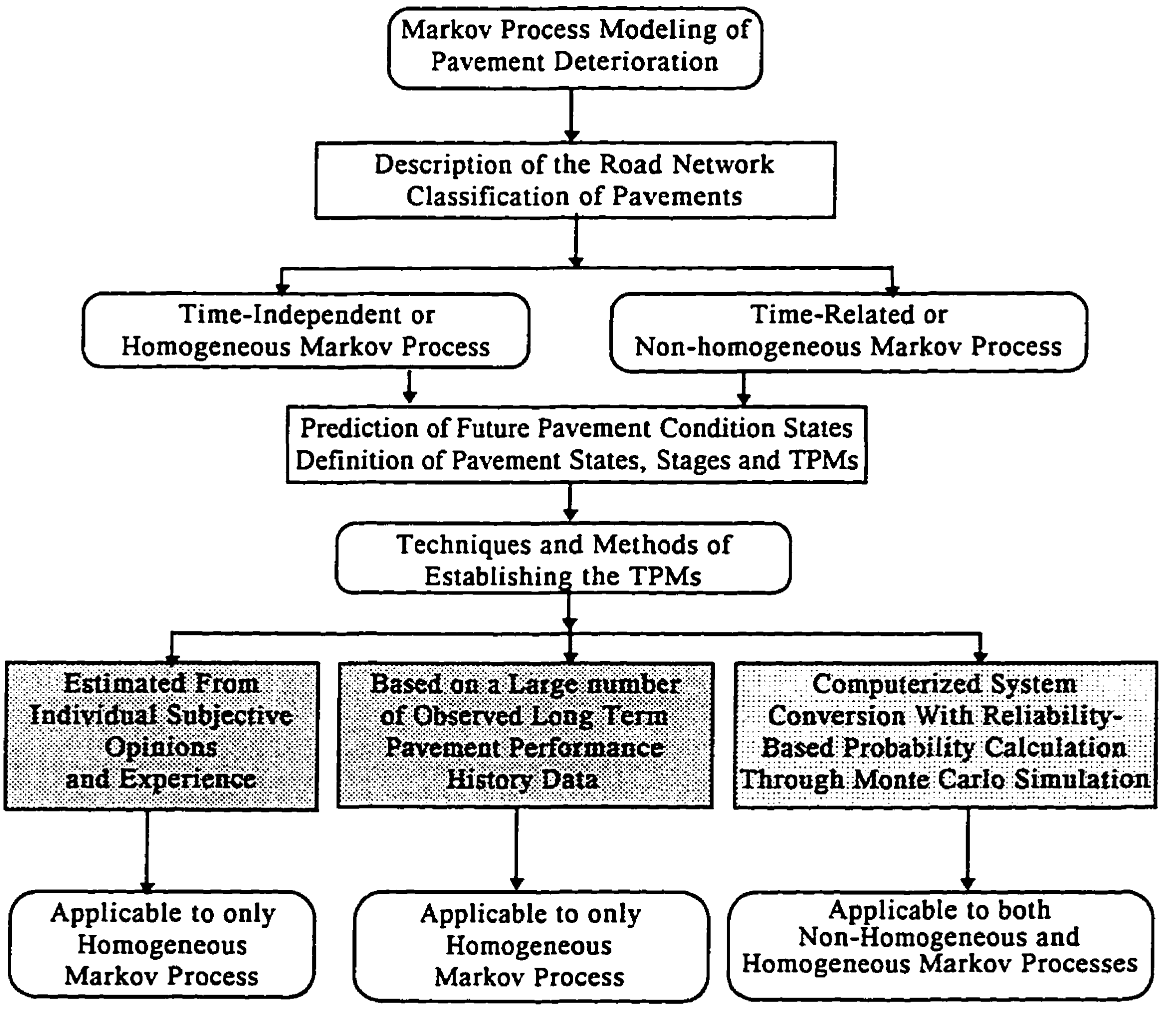


Figure 2.4 Classification of Markov Processes Applied in Pavement Performance Modeling

Transition matrices are estimated by minimizing a measure of distance between the expected value of the condition rating as predicted by a regression model and the expected value derived from the structure of the Markov chain. The theoretical expected value is a function of the transition probabilities to be estimated. The objective function is the sum of the squared difference between two expected values. The expected value method suffers from several limitations, including: 1) needs for segmentation for various pavement structure and age groups; 2) latent nature of deterioration. It should be emphasized that pavement deterioration is not directly measured but is ranked by observable distress ratings. The condition ratings are simply based on some indicators but not actual deterioration measurements. This limitation comprises an unrealistic representation of pavement condition and its deterioration.

Subjective Method Each element of the transition probability matrix is quantified by using the average of subjective opinions of experienced engineers through individual interviews and questionnaires. Table 2.7 is an example questionnaire table, which was designed by Karan (57) for establishing Markovian transition probability matrices for 18 classified asphalt pavements from the Ontario road system. The classification of the 18 pavement types is mainly based on 3 factors: 1) pavement thickness (total equivalent granular base thickness roughly classified into 3 types, i.e., thin (381-508 mm), medium (508-635 mm) and thick (>635 mm); 2) traffic magnitude (average annual daily traffic roughly divided into 3 levels, i.e., low (3000<AADT<5000), medium (5000<AADT<10,000) and high (AADT>10,000); and 3) subgrade condition (subgrade soil strength and stability only divided into 2 types for all of the roads in Ontario, i.e., strong (with CBR value larger than 5) and weak (with CBR value less than 5).

For each of the 18 classified pavements, a questionnaire table with 10 columns and 10 rows is given to individual pavement engineers or experts for filling the entries in the table, i.e., every transition probability of the pavement condition state $P_{i,j}$. The states on the left-hand side of the table (rows) represent the present state of the pavement and the states along the top of the table (columns) represent possible states after a one year period. $P_{i,j}$ represents the number of pavement sections out of one hundred of the same class with initial state i that would be expected to be in state j at the end of one year, assuming no major maintenance is performed during the year. For example, if it is felt that 15 out of one hundred pavement sections in this pavement class whose initial state is 5 (i = 5) would deteriorate to state 3 (j = 3) at the end of one year, then $P_{5,3} = 15$.

It is known that each individual has his or her own bias and different response or assessment on the same question; therefore, it is difficult for a pavement manager to deal with the variety of data and to transform the information into a transition probability matrix of pavement deterioration. Besides, it normally takes considerable time and expense to go through subjective information collection and processing.

Table 2.7 Example Transition Probability Questionnaire Table for a Pavement Class (Ref. 57)

Class 1
- Thin Pavement : 380-508 mm
- Low Traffic : 3000 < AADT < 5000
- Strong Subgrade : Strong (Granular)

	To State *j*											Description of State	
From State i	9	8	7	6	5	4	3	2	1	0	State No.	Roughness (in/mile)	Damaged Area (%)
9	$P_{9,9}$	$P_{9,8}$	$P_{9,7}$	$P_{9,6}$	$P_{9,5}$	$P_{9,4}$	$P_{9,3}$	$P_{9,2}$	$P_{9,1}$	$P_{9,0}$	9	0	0
8		$P_{8,8}$	$P_{8,7}$	$P_{8,6}$	$P_{8,5}$	$P_{8,4}$	$P_{8,3}$	$P_{8,2}$	$P_{8,1}$	$P_{8,0}$	8	20	0.4
7			$P_{7,7}$	$P_{7,6}$	$P_{7,5}$	$P_{7,4}$	$P_{7,3}$	$P_{7,2}$	$P_{7,1}$	$P_{7,0}$	7	65	1.5
6				$P_{6,6}$	$P_{6,5}$	$P_{6,4}$	$P_{6,3}$	$P_{6,2}$	$P_{6,1}$	$P_{6,0}$	6	110	4.0
5					$P_{5,5}$	$P_{5,4}$	$P_{5,3}$	$P_{5,2}$	$P_{5,1}$	$P_{5,0}$	5	160	12.0
4						$P_{4,4}$	$P_{4,3}$	$P_{4,2}$	$P_{4,1}$	$P_{4,0}$	4	210	25.0
3							$P_{3,3}$	$P_{3,2}$	$P_{3,1}$	$P_{3,0}$	3	260	43.0
2								$P_{2,2}$	$P_{2,1}$	$P_{2,0}$	2	310	63.0
1									$P_{1,1}$	$P_{1,0}$	1	370	80.0
0										$P_{0,0}$	0	>400	>90.0

In summary, the existing Markov prediction models are all developed or calibrated on a regional basis, it provides a partial means of incorporating probabilities into the management system if it is applied to a different environment. These drawbacks will, in turn, influence the correctness of many other decisions, such as needs years, selection of project programming and determination of the optimal pavement M&R treatment strategies.

There are many improvements needed for the existing methods of modeling pavement deterioration in a probabilistic approach. The applications are all subject to certain regional limitations even if the pavement type, traffic characteristics and other conditions are similar to each other. For a multi-step transition, the existing method employs the Chapman-Kolmogorov equation to calculate the future condition states.

2.3 LIMITATIONS OF THE EXISTING PERFORMANCE MODELS

In essence, the existing Markov prediction models have two major technical problems that make it difficult to predict pavement deterioration accurately. One is the actual assumptions made for pavement deterioration. All the variables that affect the rate of pavement functional deterioration are assumed to be constant throughout the analysis period, which can result in fundamental statistical problems and errors in the prediction of pavement deterioration. This problem can be reduced by segmenting pavement ages and other influential factors. Another problem is that the methodologies used for generating a TPM are biased, costly and time-consuming; plus there is the need for a large amount of observed performance data if the TPMs are depended on this basis.

By using the existing methods for establishing TPMs, it is impossible to establish multi-stage (or time related) TPMs for each individual pavement section in a network. Instead, the existing TPM building methods can only be used to construct a few of TPMs for a number of roughly classified (or functional and regional grouped) pavements, as previously described. The impacts on pavement deterioration by the design factors, such as pavement thickness, construction methods, traffic volume and growth rate, can not be specifically estimated by the existing methods. Each pavement section is placed into one of the classified categories so that the established TPMs can be applied. Moreover, for a defined pavement section, the existing methods are not able to establish a set of time related TPMs for the users in different stages. Obviously, this approach ignores the fact that the rate of pavement deterioration changes and therefore transition probability matrices should be adjusted from time to time. Consequently, it will cause certain errors and variations in the prediction process when applied to a different environment.

2.4 PRIORITY PROGRAMMING AND OPTIMIZATION METHODOLOGIES

Priority programming is a systematic process through which maintenance and rehabilitation actions needed by each pavement in a road network are ranked in a certain order. It is based on certain criteria and priority judgments, such as available funds, degree of needs and urgency, costs and benefits. Therefore, a comprehensive analysis has to be conducted by considering all of the criteria and factors in the selection of the best alternative from a number of possible treatment strategies.

Markov process-based probabilistic models has been applied in making decisions on selection of projects over the network. With program planning, the decision involves which projects are to be selected, when and what treatments should be used. These techniques are particularly useful for solving, technically and financially, the problems of pavement network maintenance and rehabilitation planning.

In recent years, probabilistic modeling has been applied in many other processes or subsystems of pavement management, such as dynamic programming of pavement maintenance incorporated with pavement deterioration modeling (61), pavement network budget planning (62), and cost-effectiveness analysis in financial planning of pavement network management (63, 64). Furthermore, probabilistic models have been used to minimize the total expected cost and to keep all pavement sections in the network above a required service level (65).

In some cases, issues such as political influence and other outside pressure can affect the decisions on project selection. For this reason, multi-year programming is a tool for providing information to assist the decision maker in selecting the most appropriate projects for the programming. In the following sub-sections, several methods of priority programming for pavement multi-year project improvements are briefly reviewed, including simple ranking, prioritization and optimization.

2.4.1 Subjective and Parameters Based Ranking Methods

Among many prioritization methods, the ranking method is the simplest way of establishing priorities for pavement improvement needs. In this method projects are ranked on the basis of subjective judgment or criteria which are determined by the highway agency's policy. The programming is based on either engineering judgment or on measured parameters, such as pavement riding condition, life-cycle cost, and benefit/cost ratio. The pavements are repaired or treated in rank order until the amount of money available for maintenance and rehabilitation is used up.

One example of applying the ranking method in the priority programming for a district level of pavement management is illustrated in Tables 2.8 and 2.9, which were explained in detail in reference (66). This method has been promoted by the China Highway Research Institute and was recommended for use at the provincial level of pavement management. In the condition survey a 0-100 point rating system is used to determine the needs of the existing network. The rating system consists of three sub-rating systems: pavement serviceability measurement, with maximum 40 points; surface distress or structural conditions, 35 points; and safety assessment, 25 points.

These individual ratings are then summed to yield one final rating for the pavement structural and functional condition. Each highway section is rated separately with the rating system and a total score is then calculated to describe the pavement condition level. This method is, in essence, similar to the methods applied in Arizona and Washington highway or airport pavement management systems (67 to 70).

After the process of ranking pavement treatments, the costs for each project can be calculated for the preferred treatment strategy. Projects to be scheduled are then selected from the ranked list until the available funding is depleted. By simply comparing the general pavement condition levels of pavements, the ranked listing of projects is determined in the order of the worst pavement first, as shown on the last column in Table 2.8.

If additional weighting factors are considered, such as traffic levels and road classes, the ranking process could be somewhat more sophisticated. In this example, three different traffic levels and four road class weighting factors are assigned to the pavement sections in the network. The revised ranked list of projects is determined by multiplying the previous pavement condition index by the factors concerned, as shown in Table 2.9.

Table 2.8 Example of Subjective Ranking Pavement Priorities for a Provincial Road Network in China

Pavement Section ID Hwy.No.	From --To	Serviceability (40 points)	Distress Index (35 points)	Safety Index (25 points)	General Condition Level	A List of Ranked Project Priority
109	Xiaoxia- Ledu	29	26	15	70	4
109	Ledu Minghe	30	11	21	62	3
Local	Wuhe-Tongren	25	12	17	54	1
Local	Zeku-Linchang	36	15	18	71	5
Urban	Pinan- Xining	35	15	22	73	6
Special	Wuhe-Li-Chun	27	13	19	59	2
56	Gebi- Zhongsan	35	20	21	76	7
37	Yili-Pingliang	38	25	23	86	8

Table 2.9 List of the Revised Project Ranking of the Pavement Priorities for the Road Network

Pavement Section ID Hwy.No.	From --To	Previous Condition Level (100 points)	Traffic Factor (0.1-3.0)	Road Class Factor (0.5-2.0)	Adjusted Condition Measurement	Revised List of Ranked Project Priority
109	Xiaoxia- Ledu	70	1.0	1.2	84	5
109	Ledu Minghe	62	1.5	1.0	93	6
Local	Wuhe-Tongren	54	1.5	1.2	97	7
Local	Zeku-Linchang	71	1.0	0.8	56	2
Urban	Pinan- Xining	73	0.5	0.8	29	1
Special	Wuhe-Li-Chun	59	1.0	1.0	59	3
56	Gebi- Zhongsan	76	1.5	1.2	136	8
37	Yili-Pingliang	86	1.0	0.8	69	6

2.4.2 Priority Programming with Maximum Benefits or Minimum Costs

Costs and benefits are two major economic evaluation factors in network priority programming and project level design. There are generally three forms in priority programming: benefit maximization, cost minimization, and benefits over costs ratio maximization. Benefit maximization or cost minimization with linear programming seem to have been the most popular approaches. The cost for improving general pavement serviceability, benefits accruing from the improvement and budgets are all considered in the analysis. The costs and benefits vary depending on the year of executing the improvements. In addition, the minimum acceptable serviceability level of each pavement is defined for identifying needs. Maintenance strategies that may defer or advance treatment actions from the needs year can also be considered in the priority programming.

With multi-year programming of projects, the effects of a large number of strategic treatment options to be applied in each year under the constraints of budgets and required performance standards are considered. For a large network this will definitely require the assistance of computers.

It is obvious that the projects with the greatest benefit should be highly ranked. Lytton (71) has investigated the multi-year prioritization analysis and mathematical optimization analyses such as dynamic programming. He concluded that the two approaches can achieve similar solutions. This is because the algorithms go through a similar sequence of operations to determine the projects that provide the greatest benefit for the same amount of money spent.

Prioritization techniques requires a comprehensive performance model for the prediction of pavement deterioration and for the measurement of the benefit or effectiveness of alternative projects or treatments. Figure 2.3 shows the relative benefit for two alternative treatments as the areas under the performance curves.

The prioritization methodology is based on maximizing cost-effectiveness ratio from the selected M&R projects for a road network within a limited budget. The higher the weighted optimal benefit/cost ratio of the section is, the higher the priority of that section will be for repair. A detailed description of this methodology is given by Feighan et al. (72).

The incremental benefit/cost ratio based prioritization method uses heuristic techniques for budget optimization. It can be used to maximize benefits from available project funds for a group of pavement sections to maximize the overall benefit. Butt et al (73) developed such a type of prioritization algorithm with the use of the incremental benefit/cost ratio technique.

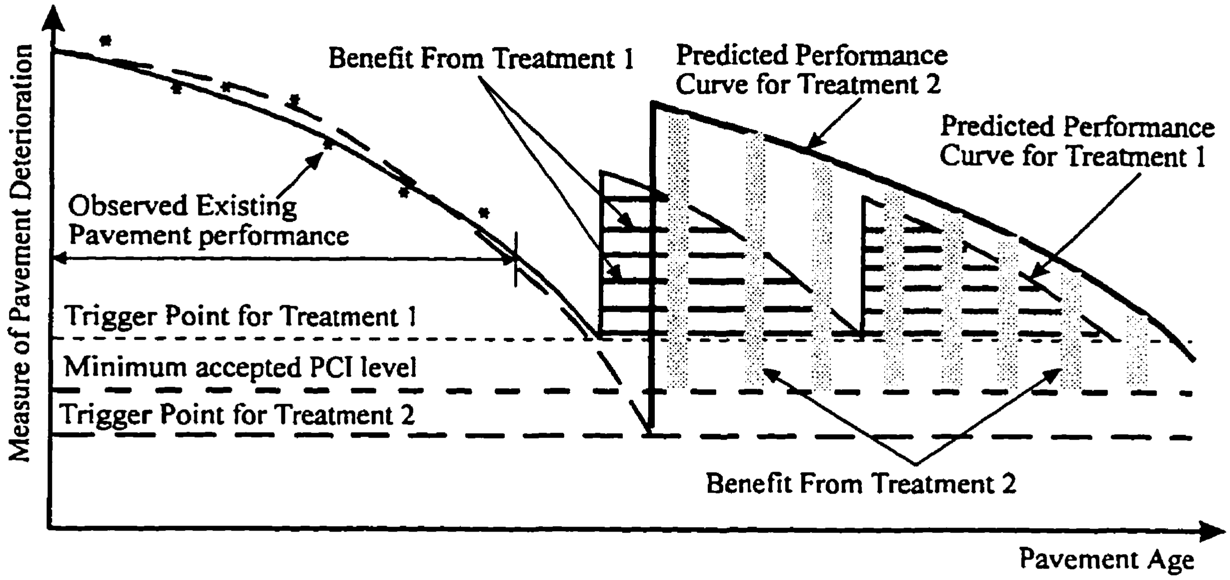


Figure 2.3 Illustration of Alternative M&R Treatment Effects and Benefits

2.4.3 Optimization Methods

Optimization is a branch of mathematics concerned with finding the most effective (optimum) solutions to complex problems in accordance with established objectives and constraints. The difference between optimization and the prioritization or ranking techniques described in the previous sections is that, in an optimization analysis, the functions of priority programming, program formulation and project scheduling are integrated into one operation which gives the optimum schedule of projects (74, 75).

Two important considerations that are not included in a prioritization analysis are: a) the evaluation of inter-project trade-off in selecting strategies, and b) the selection of treatment strategies which strictly adheres to budget constraints. These considerations are identified in the *Advanced Course in Pavement Management* (76). Consequently, mathematical optimization techniques have been recently employed by a number of highway agencies for programming investment priorities for pavement improvements. The use of mathematical optimization models is perhaps the most sophisticated for multi-year prioritization analysis, which include linear, non-linear, integer and dynamic programming methods (77, 78, 79).

It should be pointed that a reliable prioritization programming method is dependent, to a large degree, on the accuracy of the predicted pavement performance. The reason is that in the process of prioritization economic analysis of each treatment strategy is conducted on the basis of the predicted future pavement deterioration versus time. The following is a brief description of the basic components and functions of the mathematical programming models.

2.4.3.1 Basic Considerations

Generally speaking, a multi-year priority programming process is comprised of four major components: pavement performance analysis, identification of feasible alternative treatment strategies, costs and benefits based economic analysis, and final selection of projects.

The predicted pavement performance results can be used to determine the following:

- The appropriate maintenance or rehabilitation treatment(s).
- The best appropriate timing for the selected treatment project(s).
- The overall long-term impacts of the programming decisions on the road network performance.

As described in the previous sections of this chapter, there are many different ways of developing pavement performance models. Deterministic performance models most commonly used by many highway agencies in current practice; however, probabilistic models have desirable and potential applications in the future.

The identification of feasible treatment strategies may be one carried out by three approaches: a) decision trees through which each feasible treatment must meet a set of defined conditions; b) a treatment matrix that gives preferred treatments for various pavement distress conditions and; c) other decisions based on engineering judgment, political considerations, environmental or social factors, etc.

There are a number of factors that should be considered in the project selection process, which includes project limits, cost of each treatment, geographical boundaries and locally available resources, geometric constraints, safety related traffic operations, agencies and practices.

2.4.3.2 Linear and Integer Programming

The linear and integer programming approach can be applied for searching the optimal treatment strategies under maximization of benefits or minimization of costs. More commonly, the optimal allocation of investment to a particular treatment of a pavement section in a particular year is solved in an integer programming context. In an integer programming context, applying or not applying a treatment strategy is represented by a 0-1 integer dual variables. A decision variable assigned the value 1 means that a treatment strategy is applied; 0 means that no treatment is assigned.

The application of integer programming in the Texas Department of Transportation for strategic planning of pavement rehabilitation and maintenance provided a valuable tool for the highway agencies to manage the network properly (80). In this application, the overall effectiveness of all selected maintenance and rehabilitation projects is maximized in the 0-1 integer linear programming, which is subjected to the constraints of minimum pavement serviceability, available budget, and resource suppliers. However, an integer programming becomes computationally intensive and unreasonably long if it is applied to a large scale road network, in particular if multi-year decisions of pavement preservation strategies are considered.

Briefly, linear and integer programming can give the optimal schedule of projects. These methodologies can be applied to either single year or multiyear prioritization. Multi-year programming is a natural extension of the single year prioritizing of projects, where evaluation of inter-project tradeoffs in selecting strategies and their adherence to annual budget limitations are mainly considered.

2.4.3.3 Heuristic-Based Near Optimization Methods

There are several heuristic methods that can be used to determine a "near optimal" solution to priority programming. A heuristic method calculates the cost effectiveness of each strategy relative to the best existing strategy for the pavement. The method then proceeds to a sub-optimal solution through a form of replacement procedure. Applications of this technique to several regional highway or urban road networks have provided satisfactory results for all practical purposes (81, 82). This technique uses dynamic programming to select the best treatment actions on each pavement section, and then uses integer programming and an effective gradient technique to select the best set of projects.

Mahoney et al. (83) described a heuristic based method the priority programming of a large number of pavement rehabilitation projects under budget constraints. The heuristic method is a two-step procedure: 1) initial allocation of every project to its optimal period of realization and, 2) if the budget is not met, a reallocation of pavement treatments is assigned until the selection comes within "reasonable budget limits".

Some of the methodologies are a hybrid of integer and dynamic programming techniques, such as the method proposed by Chua et al. (84). The technique uses dynamic programming to select an optimal sequence of actions of each pavement, and then uses integer programming and an effective gradient technique to select the best set of projects.

Various other approximation procedures have been reported in the literature, which will not be reviewed in details here. They all subscribe to the concept that the straight forward integer programming approach is unmanageable , and therefore attempt to circumvent that process while trying to obtain a "good" but perhaps non-optimal solution. It must be emphasized that some of these good solutions provide an excellent selection of rehabilitation strategies and have been implemented on a micro computer.

Near optimization techniques, based on a heuristic, marginal cost-effectiveness method, provide simpler and more efficient mathematical programming methods. This type of priority programming method has been adopted for example by Idaho, Minnesota, and South Carolina in the United States, and by Alberta, Prince Edward Island, and Newfoundland in Canada. The near optimization method used by these agencies proceeds as follows:

- Consider each combination of section, treatment alternative, and year in the program period.
- Calculate the effectiveness of each combination, which is the area under the performance curve multiplied by AADT and section length.
- Calculate the cost in net present value of each treatment alternative in each combination.
- Calculate the cost-effectiveness of each pavement section and then sum up the ratios of effectiveness over cost of each pavement section in the network.
- Select the combination of treatment alternative and year for each section which has the best cost-effectiveness, until the budget is exhausted.
- The process is repeated until no further selections can be made in any year of the program period when the budget is exhausted.

2.4.3.4 Markov Dynamic Programming Approach to Optimization

Dynamic programming takes a complicated problem and breaks it down into a number of easily solved problems to obtain the final solution. The objective is to determine both short and long run network strategies for maintaining the system serviceability at some desired level. Theoretically, dynamic programming is a member of the family of mathematical programming. It provides a systematic procedure for the decision that increases the overall effectiveness considered in the system (85). The application of cost-effectiveness based optimization approach to transportation investments was demonstrated by Smeaton (86). He used this approach to solve for several case studies in transportation, including combination of routine maintenance with rehabilitation actions. Then Balta et al. (87) extended Smeaton's approach to solve the optimal rehabilitation structure, and quantified the parameters needed for solving realistic problems.

Many of the recent developments in pavement management, both in the areas of optimization and in performance prediction, have centered around the concept that pavement behavior changes with time. Therefore, planning for rehabilitation and maintenance is a dynamic rather than static process. This dynamic approach has spawned a great deal of interest in recent years, as evidenced by the amount of work relating to Markov prediction models (88). This type of prediction model can be extended into a non-homogeneous Markov probabilistic direction to account for the fact that the state-to-state transition may in fact be heavily dependent upon the history of the activities of a pavement. This work will involve large, more complex problems since the state space will be expanded.

The recent work by Cook (89, 90) may assist in this area, since it has provided a means of reducing the scale of the Markovian structure. Thompson et al. (91) described a micro-computer pavement management system which combines a Markovian economic optimization model to address network questions of optimal pavement rehabilitation policy and funding allocation, with a database-oriented project system which analyzes the priority and scheduling of individual projects.

2.4.4 Assessments and Limitations of Existing Methods

The most common problem with the rating methods of priority programming is that they depend primarily on subjective judgment and opinions. The weighting factors used in these methods are mostly based on personal judgments of engineers and may vary from one person to another. Therefore, it is very important to consider the economic consequences of project timing and the trade-off between costs and benefits. For example, a project might be needed in a particular year, but when its priority is examined at the network level, it might be more economical to delay the project for one year or more.

A priority program should deal with a programming period of at least 5 and up to 10 or more years, and should be able to produce a priority list for each year in the analysis period. This does not mean that these lists are final and will be implemented without any changes. In fact, the program should be rerun every year to update the previous runs. The idea of having a programming period gives a chance for each project to be examined in the process. The effect of timing is also taken into account when dealing with a period rather than just one year.

The mathematical optimization method overcomes the deficiency of not including economic analysis. Texas' linear programming model, for example, analyzes each project over a year analysis period and generates an optimum priority list for the next years. It is in effect a year by year programming approach. This may be a serious limitation because of the fact that the trade-off between costs and benefits in time may have a significant effect on the outcome of the process. It is therefore necessary to consider a programming period in order to take into consideration the effects of project timing.

2.5 CONCLUSIONS

Development of pavement performance prediction models, in terms of pavement condition state (PCS) versus pavement age or accumulated load applications, has been a major challenge to pavement engineers since pavement management was initiated in the late 1960's. The existing Markovian modeling applications in pavements have stayed in the homogeneous category. This is partly because there was no an adequate way to establish non-homogeneous Markovian transition probability matrices (TPMs) by using the existing approach.

Most of the existing pavement performance models suffer the major limitations that they can not be transferred directly to other environments. If a non-homogeneous Markov prediction model is considered for use in different environments, it does not require any significant change in the basic structure of the model. The only requirement is the development of a new set of transition matrices which are applicable to the environment under consideration.

Several optimization methods and the basic components required for single or multi-year pavement maintenance and rehabilitation priority programming have been discussed, which include heuristic near optimization, dynamic programming, linear and integer programming, pavement performance analysis with the incorporation of pavement preservation treatments, and economic analysis. A proper application of these methods should produce a consistent and effective priority programming by considering the pavement life-cycle condition, needs and recommended preservation strategies for all the pavements in a road network.

In summary, the existing methods of priority programming suffer from various limitations. Some of them are too subjective, and others are unnecessarily complex with respect to the mathematics involved.

CHAPTER 3

STRUCTURE OF THE INTEGRATED SYSTEM FOR OPTIMIZING MAINTENANCE AND REHABILITATION (M&R) PROGRAM

3.1 INTRODUCTION

In the previous chapter, the basic processes and major components required for pavement management were reviewed, and the classifications of pavement performance models and maintenance optimization methods were presented. In particular, the probabilistic-based pavement performance prediction models and optimization methodologies that are frequently used in the existing pavement management systems were examined.

A major challenge to the application of Markov process in modeling pavement deterioration is to find a better approach to establish Transition Probability Matrices (TPMs). The limitations of the two existing methods for building the Markovian TPMs were discussed in the previous chapter. By employing the existing methods, it is very difficult to establish a set of TPMs for each individual pavement section in a network. In fact, the existing TPM building methods can only construct a few TPMs for several roughly classified pavement categories, as previously described. The effects on pavement deterioration of many important factors, such as pavement thickness, construction methods, traffic volume and growth rate, are neglected. Each pavement is assigned to one of the categories so that the established TPMs can be applied. This approach can cause large variations in the prediction of pavement network deterioration. In addition, for a pavement section, the existing methods are not able to establish a set of time-related TPMs for use in different stages.

In this chapter three new concepts for developing an integrated pavement management system are first established, including: a) reliability design concepts applied to pavement structural design and performance prediction, b) application of non-homogeneous (or time-related) Markov process concepts to modeling pavement deterioration and, c) a standardized network treatment program in combination with multi-year pavement performance prediction. Then the basic structure of the proposed integrated system for optimizing multi-year pavement network maintenance and rehabilitation (M&R) program is presented. The optimization process considers the M&R treatment effects on pavement condition state (PCS); it also incorporates the M&R treatment effects into the prediction of pavement future deterioration.

It is the purpose of this chapter to outline the concepts and the basic structure of the integrated system. In the following chapters, the development of major components and their functions required for the integrated system will be discussed in details.

3.2 RELIABILITY CONCEPTS APPLIED TO PAVEMENT DESIGN

A major problem in pavement design has been the inherent uncertainty and variation of design variables and parameters involved in the pavement performance prediction, such as the predicted traffic loads, equivalent pavement thickness and subgrade soil strength. Since the probabilistic analysis of pavement behavior is related to design reliability, it is necessary to examine their relationship in the application of performance prediction.

The principle of applying reliability to flexible pavement design has been examined by previous researchers (92, 93, 94) during the 1970's. They stated that the determination of pavement performance over the analysis period should be in a probabilistic form because many uncertain factors are involved in the process of pavement design and construction. In their studies reliability is a measure of the degree of uncertainty. Such an approximation allows the pavement managers to predict serviceability with a particular degree of reliability throughout the design life. It was pointed out that an optimal pavement system design with a certain confidence level is associated with three major probabilistic variables: flexural strength or modulus of pavement materials, estimated actual traffic to be applied on the pavement in terms of accumulated ESALs, and subgrade soil strength.

3.2.1 Variability of Pavement Design Variables and Parameters

Variability of the pavement parameters, such as strength or modulus of each layer of pavement materials, equivalent total design thickness and bearing strength of the subgrade, may be assessed with laboratory and field testing. This variability is then used to assess the reliability of a pavement system. Reliability in pavements is defined as the probability that the pavement will not reach the failure condition after all of the design traffic, in combination with certain environmental conditions, has been applied to the pavement.

In the analysis of variability of pavement design parameters, probabilistic techniques can be used to characterize system reliability of a pavement structural design. Figure 3.1 illustrates a relationship between the probability distribution of predicted pavement condition state in each year and the probability distribution of estimated service years of the pavement before it reaches to the terminal serviceability level.

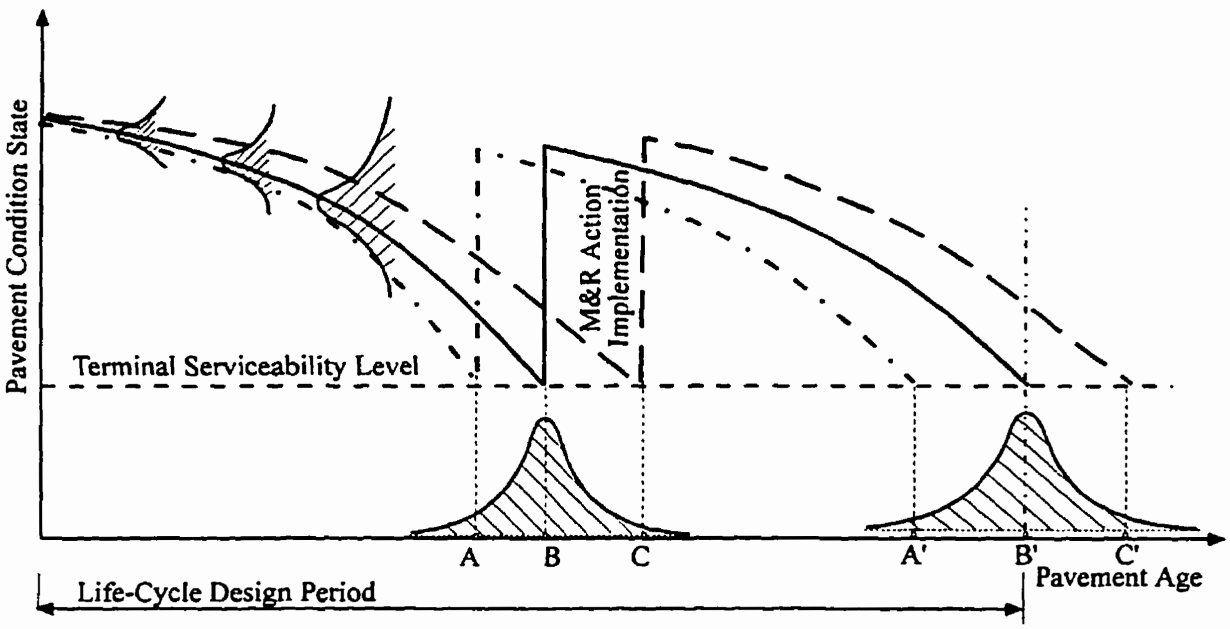


Figure 3.1 Probability Characteristics of Pavement Design and Performance Prediction

The solid line in the figure represents predicted pavement performance with a 50% reliability level. The two dotted lines imply that two different reliability levels have been considered for pavement life-cycle design with one higher than 50% and the other lower than 50% reliability level, respectively. In comparison with the 50% reliability level, the distance between A and B indicates the time period (years) that an M&R treatment has to be advanced if a higher reliability level (>50%) is chosen for the pavement design. On the other hand, the time distance between B and C indicates that a M&R treatment may be delayed for this time interval if a lower reliability level (<50%) is selected for the pavement design.

According to the reliability definition stated in the 1986 and 1993 AASHTO Guides, the number of Equivalent Single Axle Load applications (ESALs) that the pavement can withstand before the pavement serviceability level (or pavement condition state, PCS) drops from its current state to a lower state i defined in the system, $N_{pcs(i)}$, can be predicted. On the other hand, the actual number of ESALs that will be applied to the pavement at year t, N_t, can be estimated from a traffic prediction equation.

Based on the results of a statistical analysis conducted for the 1986 AASHTO Guide, and also incorporated in the 1993 AASHTO Guide, both the predicted pavement traffic (in ESALs) capacity $N_{pcs(i)}$ and actually accumulated traffic N_t at year t can be expressed by log-normal distributions. The safety margin (SM) or the difference between the logarithmic values of $N_{pcs(i)}$ and N_t is normally distributed, and

$$E[\log SM_{(i)}] = E\left[\log N_{pcs(i)}\right] - E\left[\log N_t\right] \qquad [3.1]$$

$$S_{SM}^2 = Var[\log N_{pcs(i)}] + Var[\log N_t] \qquad [3.2]$$

The reliability factor, log F_R, is defined as follows:

$$\log F_R = P\left\{[\log N_{pcs(i)} - \log N_t] = \log SM_{(i)} \geq 0\right\} \qquad [3.3]$$

The probability distribution for SM, shown in Figure 3.2, represents the set of all possible overall deviations that arise from the errors of predicted traffic and actual performance. The overall deviation, SM_i,, will be positive wherever the actual performance N_t of a pavement section exceeds the traffic capacity of the pavement possessed for the level of $N_{pcs(i)}$. The reliability design factor is used to provide probabilistic assurance that N_t will exceed $N_{pcs(i)}$, i.e., that the overall deviation will be positive.

Illustrated in Figure 3.2 is the relationships among overall deviation of pavement performance from the predicted annual traffic (ESALs), reliability design factor (log F_R) and the standard normal deviate.

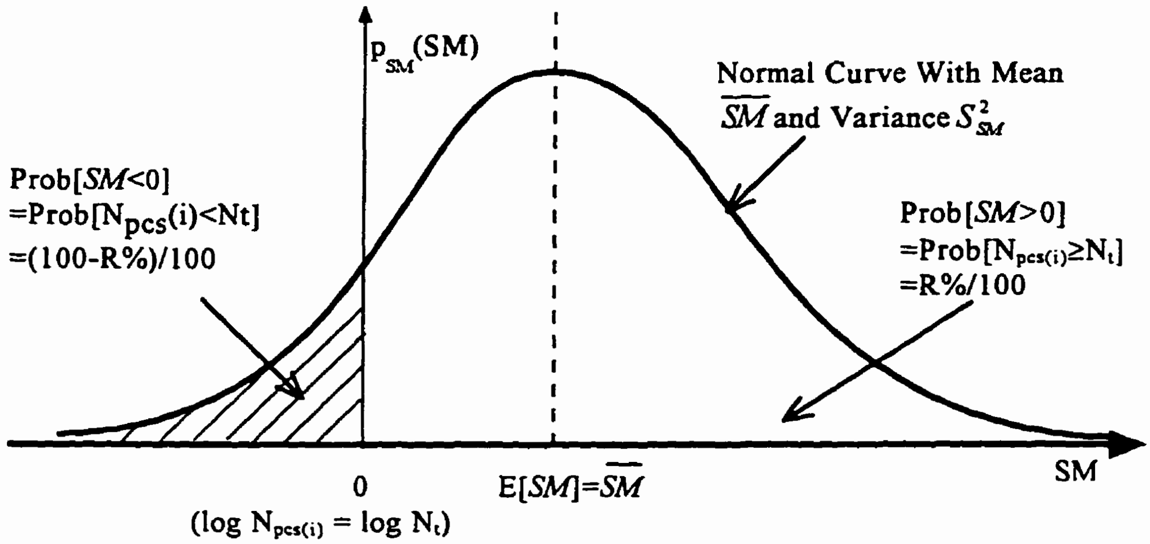


Figure 3.2 Basic Relationship between Pavement Reliability Design and Performance

3.2.2 Calculating Probability Vectors of Pavement Condition States

In reality, many uncertain factors are involved in all the aspects of pavement management systems. According to the results of statistical analysis of a large amount of observed pavement performance data collected on Brampton Road Test (95) in Ontario, the actual number of ESALs that cause a pavement to deteriorate from condition state i to state j cannot be calculated without error. Similarly, the actual predicted traffic in terms of ESALs in future years cannot be determined precisely.

The probability vector may be interpreted as the probabilities that the pavement will be in each of the possible condition states or the percentages of the pavement that is classified in each of the defined condition states, as shown in Figure 3.3. In the figure, a scale of only 10 units of pavement condition states is defined and only traffic variable is considered in the prediction of pavement deterioration; $p_{N_t}(N)$ is the probability density function of the predicted actual traffic (ESALs) accumulated in t years; $p_{N_{pcs(i)}}$ is the probability density function of $N_{pcs(i)}$, which is the traffic (ESALs) that forces the pavement to deteriorate from the initial condition state to condition state i; $\overline{N}_{pcs(i)}$ is the mean value of $N_{pcs(i)}$. This allows the random nature of pavement behavior prediction and reliability analysis to be included in the process of pavement deterioration modeling. In other words, the use of Markov transition process for modeling pavement deterioration has taken the random nature of both actual traffic variables and design parameters into consideration.

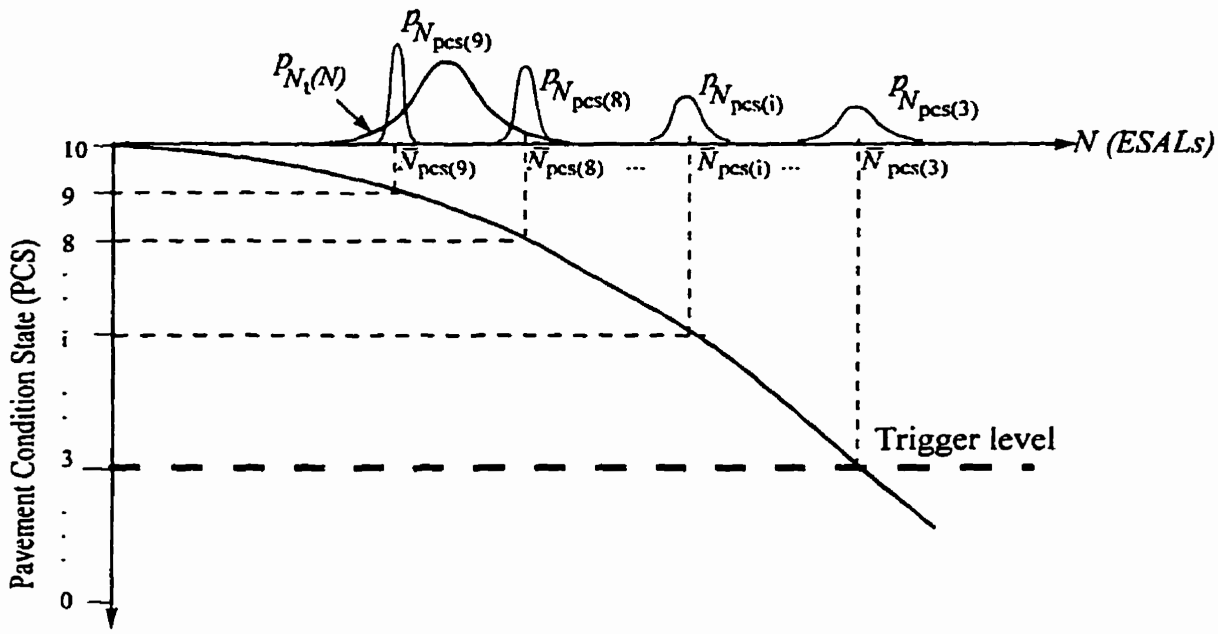


Figure 3.3 Probability Distribution of Predicted Performance and Traffic

3.3 PROBABILITY CONCEPTS APPLIED TO NON-HOMOGENEOUS MARKOV PROCESS MODELING OF PAVEMENT DETERIORATION

Since the technique of Markov process-based forecasting was developed, it has found application in a number of areas of infrastructure management, such as bridges, highways, and gas or oil pipeline networks. The main purpose of applying the Markovian theory in pavement management systems is to predict the changing pattern of pavement condition state-age relationship of each pavement section in the network. In other words, for a given current year pavement condition state, the probability (or percentage) that the pavement will be in each of the defined states including the current state in any specified future year can be predicted through Markov process modeling. The advantage of Markov-based models is that they accommodate uncertainty and capture the probabilistic nature in the pavement deterioration process. In addition, they can incorporate the experience of pavement engineers and experts, and can be used in situations where there is no historical database available.

Depending on the rate of pavement functional deterioration versus age or stage, application of Markov process in pavement performance modeling may be classified into two categories: homogeneous (or time-independent) and non-homogeneous (or time-related).

In the past, pavement engineers used frequently the homogeneous Markov process to predict pavement deterioration in many cases. This is partly because the difference between the two types of Markov processes has not been fully recognized; and partly, perhaps because it would be very difficult to build non-homogeneous Markovian TPMs if this approach had been considered. Pavement engineers may not be generally aware of the fact that in some situations the performance of a pavement predicted through the two different approaches may show a significant difference.

The investigation upon which this study is based uses a non-homogeneous Markov transition process in modeling pavement deterioration, as described in the following discussion.

3.3.1 Basic Characteristics of A Non-Homogeneous Markov Process

Because the rates of pavement deterioration from the current condition state to the lower states vary with traffic volume and environmental conditions it encounters within the stage, it is appropriate to apply non-homogeneous Markov process in the probabilistic modeling. Figure 3.4 shows schematically several possible patterns of pavement deterioration in non-homogeneous Markov process. Illustrated in Figure 3.4-A is the deterioration of condition state (PCS) of pavement for three different magnitudes of annual traffic volumes. For the same pavement structure, deterioration to the minimum acceptable PCS level can occur for quite different time periods if the annual traffic volume and growth rate change considerably. Illustrated in the Figure 3.4-B is deterioration of the pavement serviceability under three different environmental conditions, involving annual precipitation, temperature and maintenance actions.

To specify some of the significant features involved in a non-homogeneous process, a discussion of the following factors and elements is needed:

- factors considered in a non-homogeneous Markov process;
- definition of stages and states in a non-homogeneous Markov process modeling;
- major difference between a non-homogeneous and a homogeneous Markov process in the context of their applications in pavements;
- relationship between the two types of Markov process modeling.

3.3.2 Factors Considered in Non-Homogeneous Markov Process

The major factors that affect the rate of pavement deterioration include: 1) traffic related factors, 2) pavement material and structural design associated parameters, 3) environmental factors, and 4) the interactive effects of these factors and parameters. Traffic volume, truck factor and traffic growth rate play an important role in determining the process of pavement deterioration or the structure of Markov prediction modeling, i.e., homogeneous or non-homogeneous Markov process. Stability of pavement strength also has a significant impact on the rate of pavement structural and functional deterioration. However, all of these factors and parameters are usually determined on the basis of statistical analysis or field tests. For example, the prediction of future traffic characteristics on a pavement section is based on the statistical analysis of previous history data associated with traffic growth in a region; the resilient modulus or strength of pavement materials and subgrade soils tested from a laboratory may change with pavement age. If these design factors are different in quantity form their actual values, errors and variates may be expected in terms of a difference between the predicted value and the observed performance. Therefore, in pavement design each of these factors should not be decided by a single value but should be represented by a probability distribution with mean value and variance. Similarly, the predicted input traffic variables (including volume, truck percentage, growth rate and loading effect) on a pavement in a future year could be much different from the data actually observed from the field. Hence, applied probability concept for pavement structural design, reliability analysis and performance evaluation are needed in pavement management.

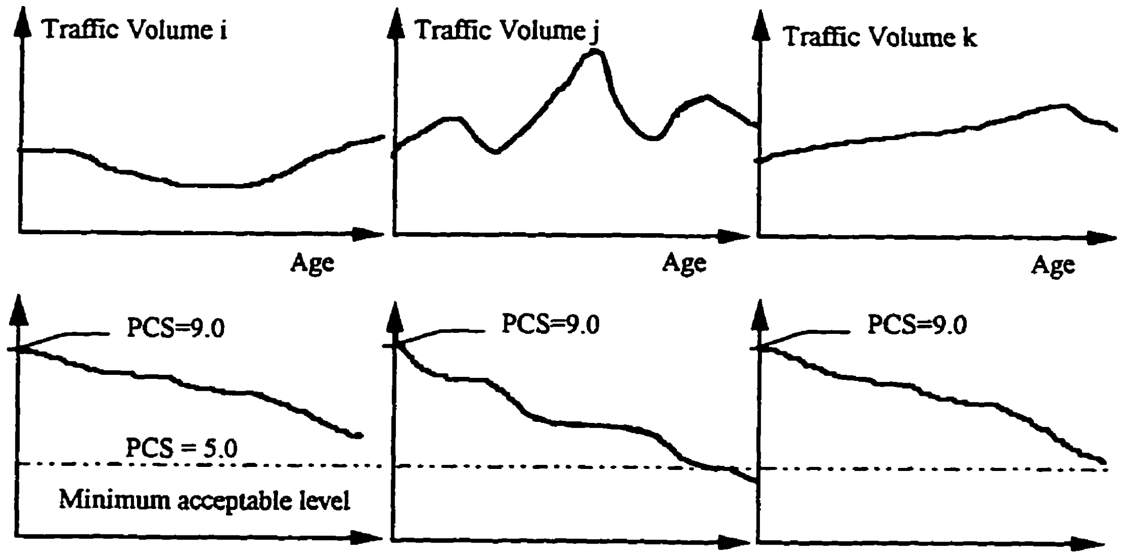


Figure 3. 4-A Pavement Deterioration for Three Different Annual Traffic Volumes

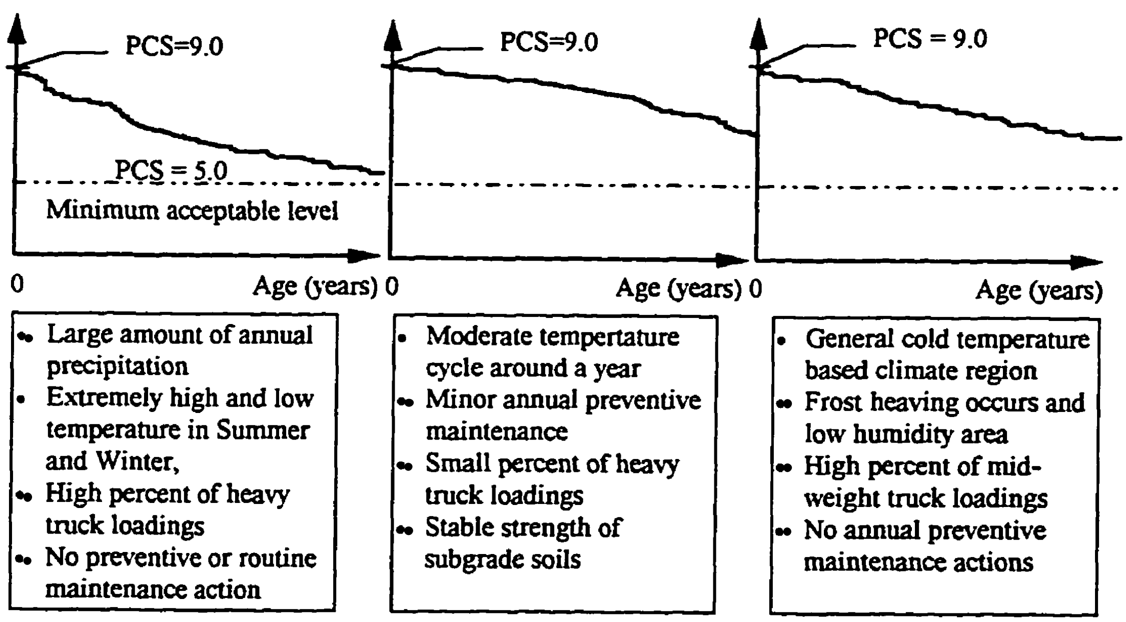


Figure 3. 4-B Pavement Deterioration for Three Different Environmental Conditions

Figure 3.4 Illustration of Non-Homogeneous Markov Process in Pavement Deterioration

3.3.3 Stages, States and Transition Probabilities Defined in Non-homogeneous Markov Process

In this study, stages are considered as a series of consecutive equal periods of time. The time interval between any two stages is determined on the basis of pavement deterioration rate of individual pavement sections. In pavement management, the length of each stage is one year as traffic is usually estimated on an annual basis and seasonal climate change (temperature and freeze-thaw) is cycled in one year. However, the duration of each stage may be individually defined for a pavement if the traffic and environmental variables change significantly at different stages and time intervals. For instance, if the length of a stage is defined as 5 years, the deterioration of the pavement condition state can be considered as within a homogeneous Markov process during the 5 years; therefore the same TPM may be used for the prediction. For the prediction beyond the five years, a different TPM has to be developed for the prediction.

The state of a pavement is defined in terms of the generalized Pavement Condition State (PCS) rating. The PCS may refer to any one of measurements commonly used by highway agencies, such as Riding Comfort Index (RCI), Present Serviceability Index (PSI), Pavement Condition Index (PCI), or single pavement distress index such as International Roughness Index (IRI), Surface Distress Index (SDI), and so on. Each of the measures is specifically ranked to a certain level according to the corresponding Pavement Condition States. Table 3.1 gives several PCS measurements that are frequently used by highway agencies in North America. The actual measurement for each parameter are different. However, they can be converted to the generalized 0-10 or 0-5 scale of a PCS system.

Table 3.1 Description of the Generalized Pavement Condition State

State	Pavement Condition State PCS	Present Serviceability Index PSI	Pavement Condition Index PCI	Surface Distress Index SDI
9	9.0 - 10	4.5 - 5.0	90 - 100	0.90 - 1.0
8	8.0 - 8.9	4.0 - 4.45	80 - 89	0.80- 0.89
7	7.0 - 7.9	3.5 - 3.95	70 - 79	0.70-.079
6	6.0 - 6.9	3.5 - 3.45	60 - 69	0.60-0.69
5	5.0 - 5.9	2.5 - 2.95	50 - 59	0.50-0.59
4	4.0 - 4.9	2.0 - 2.45	40 - 49	0.40-0.49
3	3.0 - 3.9	1.5 -1.95	30 - 39	0.30-0.39
2	2.0 - 2.9	1.0 - 1.45	20 - 29	0.20-0.29
1	1.0 - 1.9	0.5 -0.95	10 - 19	0.1-0.19
0	0.0 - 0.9	0.0 - 0.45	0 - 9	0.0-0.09

It should be noted that a higher PCS value represents a better pavement condition, i.e., 10 means perfect and 1 means extremely poor. If a different type and scale of pavement serviceability measurement is used, it should be convertible to the 0-10 scale of PCS system. For instance, if a pavement is ranked at 3.5 in the Present Serviceability Index (PSI) system, it can be converted to 7.0 in the 10-point PCS system by multiplying it by 2. As another example, if the pavement is valued at 75 in the Pavement Condition Index (PCI) system which ranges from 0 to 100, it may be converted to 7.5 in the 10-point PCS system by dividing it by 10. For this purpose, conversion between the generalized PCS and any one of the commonly used pavement serviceability measurements in the world can be conducted. Illustrated in Figure 3.5 are some examples of the system conversion, each of which emphasize a different functional measurement of the pavement.

Within the 0-10 scale, the number of points (or states) can be defined as are required for reasonable levels. In other words, the size of a TPM can be defined large enough so that a small amount of deterioration can be detected. The construction technique of such a large TPM has become available through this study, which will be discussed later in the Chapter.

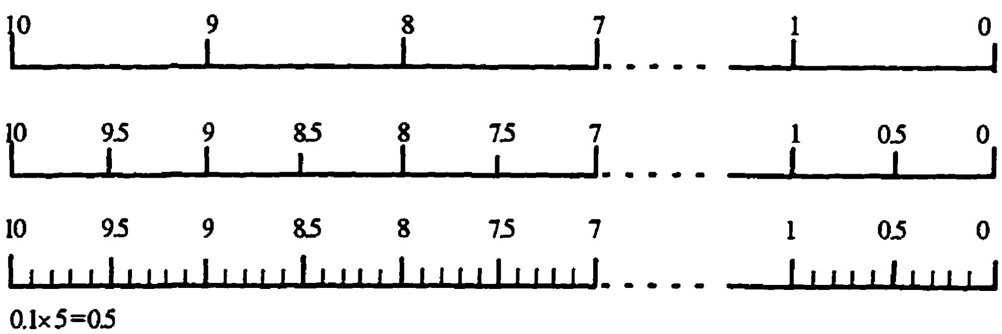


Figure 3.5 Levels and Divisions of Pavement Condition States

3.3.4 Contrast between Non-Homogeneous and Homogeneous Markov Processes

To differentiate the two types of Markov processes, Figure 3.6 illustrates the concept of homogeneous and non-homogeneous Markov processes and possible results of pavement deterioration predicted from the two difference models. In this figure the solid line, predicted by a non-homogeneous Markov Process, represents the pavement deterioration in five different stages. The three dotted lines represent the pavement deterioration rates based on the experience and performance data collected at different stages. The solid curve (non-homogeneous Markov) provides the following information:

- The pavement has experienced five stages with five different deterioration rates within the analysis period of 15 years. The interval of each of the five stages is different from each other.

- The highest deterioration rate of the pavement occurs at stage 2, between years 3 and 5. This may be due be, for example, to the fact that the pavement carries the highest volume of traffic or heavy trucks within that stage and/or encounters severe climate conditions (such as a large amount of precipitation, major frost heaving. etc.).

- The lowest deterioration rate of the pavement takes place in stage 3, between years 5 and 9. This may be due to traffic volume and truck percentage being reduced by a substantial amount, or the pavement is well maintained plus no severe climate conditions prevail during that stage.

The three dotted lines in the figure show the consequences of predicted pavement deterioration by means of a homogeneous Markov process. Each of the three dotted lines represents a rate of the pavement deterioration at a different stage, which can be considered as three individual partial experience or measured performance data obtained in a different period of time.

It may conclude that the homogeneous Markov process has, in essence, assumed that the pavement deteriorates at a constant rate and has taken the partial experience to project the future function of the pavement deterioration. This constant rate may be based on the measured data and information from one of the five stages, depending at which stage the experience is obtained or the measured pavement performance data are available. For example, the doted line 2 is only based on the experience of stage 2; hence, it can result in larger errors if the prediction line is used to forecast the pavement performance in all the stages except stage 2.

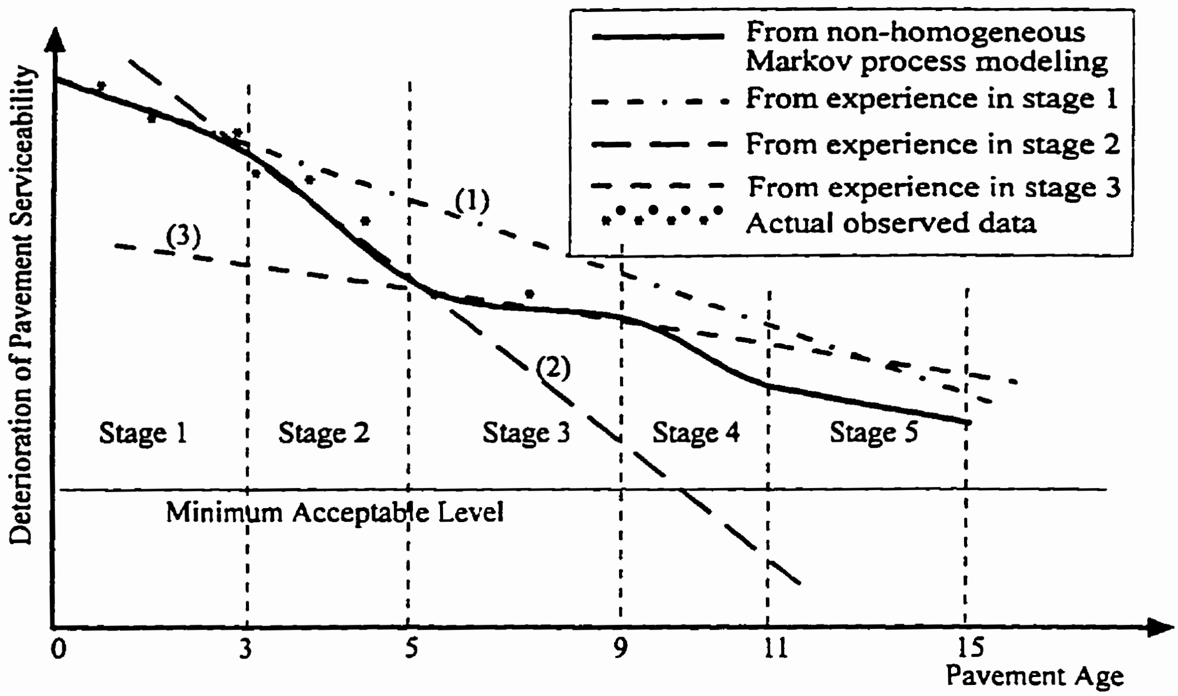


Figure 3.6 Illustration of Homogeneous and Non-Homogeneous Markov Processes

3.3.5 Time-Related Markov Transition Probability Matrices

In the application of a non-homogeneous Markov process, pavement deterioration is modeled as a time-dependent process and is governed by three components: states, stages, and transition probabilities. Stages are considered as a series of consecutive equal periods of time, usually one year. Deterioration is measured in terms of the Pavement Condition States (PCS). For practical purposes, it is convenient to divide PCS into ten states, each of which can be further divided if necessary. Finally, a set of transition probability matrices corresponding to each stage (one year period) is generated using a Monte Carlo simulation. Thus, the predicted PCS at the end of year t is expressed as follows:

$$\mathbf{p}(t) = \mathbf{P}(0)\,\mathbf{P}(1)\,\mathbf{P}(2)\cdots\,\mathbf{P}(t) \qquad [3.9]$$

where $\mathbf{p}(0) = \{PCS_{10}(0),\ldots,PCS_i(0),\ldots,PCS_0(0)\}$ is the initial PCS vector at the beginning of the analysis period, $\mathbf{p}(t) = \{PCS_{10}(t),\ldots,PCS_i(t),\ldots,PCS_0(t)\}$ is the predicted PCS vector at the end of year t, and

$$\mathbf{P}(t)=\begin{bmatrix} p_{10,10}(t) & \cdots & p_{10,j}(t) & \cdots & p_{10,0}(t) \\ \vdots & & \vdots & & \vdots \\ p_{i,10}(t) & \cdots & p_{i,j}(t) & \cdots & p_{i,0}(t) \\ \vdots & & \vdots & & \vdots \\ p_{0,10}(t) & \cdots & p_{0,j}(t) & \cdots & p_{0,0}(t) \end{bmatrix} \tag{3.10}$$

is the transition probability matrix at stage or year t. It is obvious that a homogeneous Markov chain is a special case of the non-homogeneous Markov chain when $\mathbf{P}(1)=\mathbf{P}(2)=\cdots=\mathbf{P}(t)$.

Because there is only one transition probability matrix involved in a homogeneous Markov process, prediction of future pavement condition state can be calculated by means of the Chapman-Kolmogorov equation. The matrix of n-step transition probabilities, $\mathbf{P}^{(n)}$, can be obtained by multiplying the one-step transition probability matrix n times. For example, if a pavement is assumed to deteriorate at a constant rate throughout all the stages, the pavement condition state after n steps will be:

$$\begin{aligned} \mathbf{P}^{(n)} &= \mathbf{P}\,\mathbf{P}\,\mathbf{P}\cdots\mathbf{P} \\ &= \begin{bmatrix} p_{10,10}^{(n)} & \cdots & p_{10,j}^{(n)} & \cdots & p_{10,0}^{(n)} \\ \vdots & & \vdots & & \vdots \\ p_{i,10}^{(n)} & \cdots & p_{i,j}^{(n)} & \cdots & p_{i,0}^{(n)} \\ \vdots & & \vdots & & \vdots \\ p_{0,10}^{(n)} & \cdots & p_{0,j}^{(n)} & \cdots & p_{0,0}^{(n)} \end{bmatrix}, \end{aligned} \qquad [3.11]$$

where $p_{i,j}^{(n)}$ is the probability that the pavement condition state will change from the current state i to state j after n steps (stages) of the transition process.

On the other hand, when a pavement deterioration is modeled as a non-homogeneous Markov process, the structure or each element of of TPM at one stage is different from that at another stage. In other words, the pavement condition state at any prediction year t is the product of the pavement initial condition state vector multiplied by a sequence of t different Markov transition probability matrices (each one represents a rate of pavement deterioration during the same amount of time but in different year), as shown in the following.

$$\mathbf{p}(t) = \mathbf{P}(0)\,\mathbf{P}(1)\mathbf{P}(2)\cdots\,\mathbf{P}(t-1)\mathbf{P}(t)$$

$$= \begin{bmatrix} p_{10,10}^{(1)} & \cdots & p_{10,j}^{(1)} & \cdots & p_{10,0}^{(1)} \\ \vdots & & \vdots & & \vdots \\ p_{i,10}^{(1)} & \cdots & p_{i,j}^{(1)} & \cdots & p_{i,0}^{(1)} \\ \vdots & & \vdots & & \vdots \\ p_{0,10}^{(1)} & \cdots & p_{0,j}^{(1)} & \cdots & p_{0,0}^{(1)} \end{bmatrix} \cdot \begin{bmatrix} p_{10,10}^{(2)} & \cdots & p_{10,j}^{(2)} & \cdots & p_{10,0}^{(2)} \\ \vdots & & \vdots & & \vdots \\ p_{i,10}^{(2)} & \cdots & p_{i,j}^{(2)} & \cdots & p_{i,0}^{(2)} \\ \vdots & & \vdots & & \vdots \\ p_{0,10}^{(2)} & \cdots & p_{0,j}^{(2)} & \cdots & p_{0,0}^{(2)} \end{bmatrix} \cdots \begin{bmatrix} p_{10,10}^{(t)} & \cdots & p_{10,j}^{(t)} & \cdots & p_{10,0}^{(t)} \\ \vdots & & \vdots & & \vdots \\ p_{i,10}^{(t)} & \cdots & p_{i,j}^{(t)} & \cdots & p_{i,0}^{(t)} \\ \vdots & & \vdots & & \vdots \\ p_{0,10}^{(t)} & \cdots & p_{0,j}^{(t)} & \cdots & p_{0,0}^{(t)} \end{bmatrix} \quad [3.12]$$

It is obvious that a homogeneous Markov process is the special case when $\mathbf{P}(1)$, $\mathbf{P}(2)$, ..., $\mathbf{P}(t-1)$ and $\mathbf{P}(t)$ are equal to each other for the analysis period.

As a part of this research, a non-homogeneous Markov chain modeling of pavement deterioration and the technique used to establish the time-related transition probability matrices have been documented in Ref. (96). This reference includes details for the generation of a set of time-related transition probability matrices by Monte Carlo simulation, model application to a case study, and a sensitivity analysis of pavement deterioration to traffic growth rate, pavement thickness, and subgrade soil strength.

3.3.6 General Discussion on the Relationship between the Two Types of Markov Process

If a sequence of transition probability matrices for a pavement section is provided, the future condition state vector, PCS(t), of the pavement at any stage (or pavement age) can be calculated by the following procedure:

$$\mathrm{PCS}\,(1) = \mathrm{PCS}(0)\,\mathbf{P}(1),$$
$$\mathrm{PCS}\,(2) = \mathrm{PCS}(1)\,\mathbf{P}(2) = \mathrm{PCS}(0)\,\mathbf{P}(1)\mathbf{P}(2),$$
$$\ldots$$
$$\mathrm{PCS}\,(t) = \mathrm{PCS}\,(t\text{-}1)\,\mathbf{P}(t) = \mathrm{PCS}\,(0)\,\mathbf{P}(1)\,\mathbf{P}(2)\cdots\mathbf{P}(t) \quad [3.13]$$

where $\mathbf{P}(t)$ is the transition probability matrix at stage t. Consequently, a multi-stage transition of pavement condition state is determined by a sequence of transition matrices $\mathbf{P}(1), \mathbf{P}(2), \mathbf{P}(3), \cdots$. Each of these transition probability matrices $\mathbf{P}(t)$ contains the conditional transition probabilities that hold at time t, given the status at time $t-1$.

In order to explore the concept of a pavement condition transition from one stage to the next in a non-homogeneous Markov chain, an accompanying sequence of matrices C(1), C(2), C(3), ···, which are called causative matrices (97), is introduced:

$$\mathbf{P}(1)\mathbf{C}(2) = \mathbf{P}(1),\ \ \mathbf{P}(2)\mathbf{C}(2) = \mathbf{P}(3),\ \ \cdots,\ \ \mathbf{P}(t)\,\mathbf{C}(t) = \mathbf{P}(t+1), \cdots. \qquad [3.14]$$

Each causative matrix can therefore be obtained from the following equations:

$$\mathbf{C}(t) = \mathbf{P}^{-1}(t)\mathbf{P}(t+1), \qquad t = 1,\ 2,\ \cdots. \qquad [3.15]$$

Thus, the causative matrices are analogous to derivatives in calculus as an indication of the rate of change. From these causative matrices, the change between the transition matrix at one stage and the transition matrix at the next stage can be determined. A homogeneous Markov process is the special case with C(t) = I, the identity matrix of dimension $n \times n$, where n is the number of states. If the transition matrices are different from each other, then none of the causative matrices will be equal to the identity matrix.

Illustrated in Figure 3.7 are several scenarios of transition probability matrices with different causative matrices versus pavement age. A homogeneous Markov process is the case when the causative matrix C = I. If all the causative matrices are equal or a constant, i.e., C(1) = C(2) = ··· = C(t), the non-homogeneous Markov chain is called constant causative. Using a causative matrix C(t), the relationship and change involved between two consecutive transition matrices P(t) and P(t+1) can be described. It then can be verified that

$$\mathbf{P}(t+s) = \mathbf{P}(t)\,\mathbf{C}(s), \qquad s = 0,\ 1,\ \cdots\ . \qquad [3.16]$$

Since $\mathbf{C} = \mathbf{P}^{-1}(1)\mathbf{P}(2) = \mathbf{P}^{-1}(2)\mathbf{P}(3)$, P(s) can be expressed in terms of P(1) and P(2) by the equation $\mathbf{P}(3) = \mathbf{P}_2(2)\mathbf{P}^{-1}(1)\mathbf{P}(2)$, and, in general,

$$\mathbf{P}(t+1) = \mathbf{P}(t)\mathbf{P}^{-1}(t-1)\mathbf{P}(t)\ . \qquad [3.17]$$

Therefore, every transition matrix P(t) of a constant causative chain may be expressed in terms of P(1) and P(2) by the following equation:

$$\mathbf{P}(t) = (\mathbf{P}(2)\mathbf{P}(1))^{t-2}\mathbf{P}(2) = \mathbf{P}(2)(\mathbf{P}^{-1}(1)\mathbf{P}(2))^{t-2}, \qquad t = 2,\ 3,\ \cdots. \qquad [3.18]$$

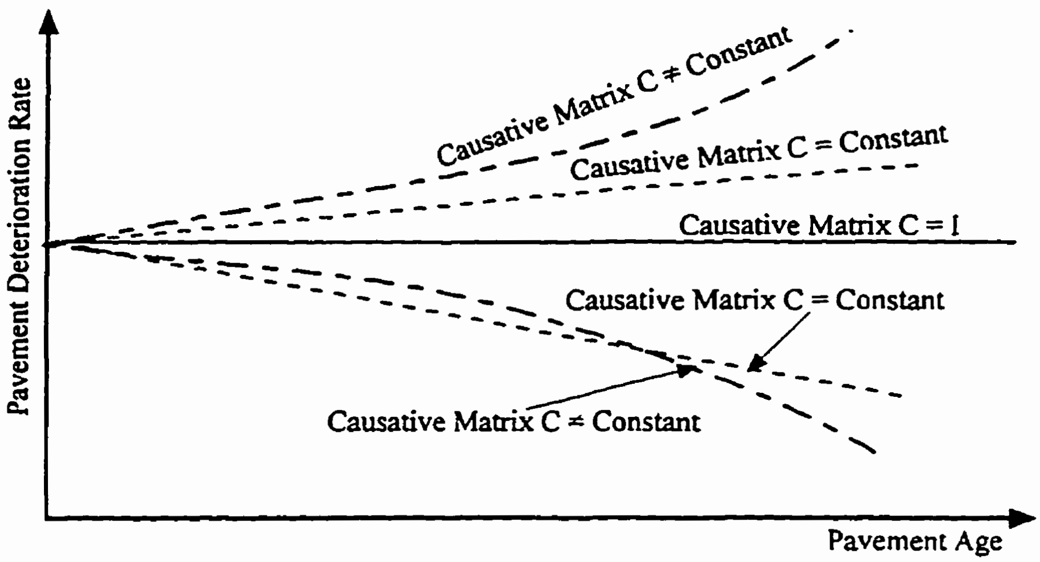


Figure 3.7 Scenarios of TPMs Calculation With Different Causative Matrices

3.4 DEVELOPMENT OF AN INTEGRATED SYSTEM FOR OPTIMIZING PAVEMENT NETWORK M&R TREATMENT PROGRAM

To achieve the most cost effective M&R treatment program for a pavement network, an integrated system has been developed. The basic structure and major components of the integrated system are shown in Figure 3.8. The major objectives of the integrated pavement management system are to develop multi-year budget planning and to produce a list of project priorities, which are based on the predicted pavement performance and certain constraints.

The prediction models are non-homogeneous Markov processes and are established by system conversion from the corresponding deterministic prediction models. The results from the Markov models are fitted into the multi-year dynamic priority programming model and the output from the priority programming is a list of optimal maintenance and rehabilitation recommendations during the analysis period for each pavement section in the network. The prioritization uses cost-effectiveness based economic analysis to utilize the limited budget with a set of standardized network maintenance and rehabilitation alternative strategies.

The functional structure of the integrated system is basically composed of the following five major interactive components and processes:

- Pavement network inventory data and information management subsystem,
- Evaluation and identification of the network current needs,
- Planning of standardized network maintenance and rehabilitation strategies,
- Comprehensive prediction of pavement deterioration on the basis of non-homogeneous Markov process, and
- Integration of the Markov prediction process with the standardized treatment effects and the priority programming.

Discussions on the development of major components and their functions in the structure are described in the subsequent chapters. The following sections present the general characteristics and functions that the integrated system should perform in terms of its objectives, technical applicability, data input and output products.

3.4.1.1 Pavement Network Database Management and Information Process

The pavement database and information system is used to define the physical characteristics of the pavement network. The contents of the database would include the network inventory data, major construction and rehabilitation records, traffic data, geometric data, performance and distress data, and environmental information. The quality of the database and information is assessed on the criteria of integrity, accuracy, validity, format stored in computers, database management process and access.

The network database and information system aims to provide information as needed by any specific pavement projects or the entire pavement network. Applications of the database system at the project level of a PMS include pavement condition evaluations within specified project limits and treatment identification methodologies.

On the other hand, applications of the database system at network level decisions deal with a wide range of pavement network condition reports and pavement deterioration models used in M&R projects prioritization.

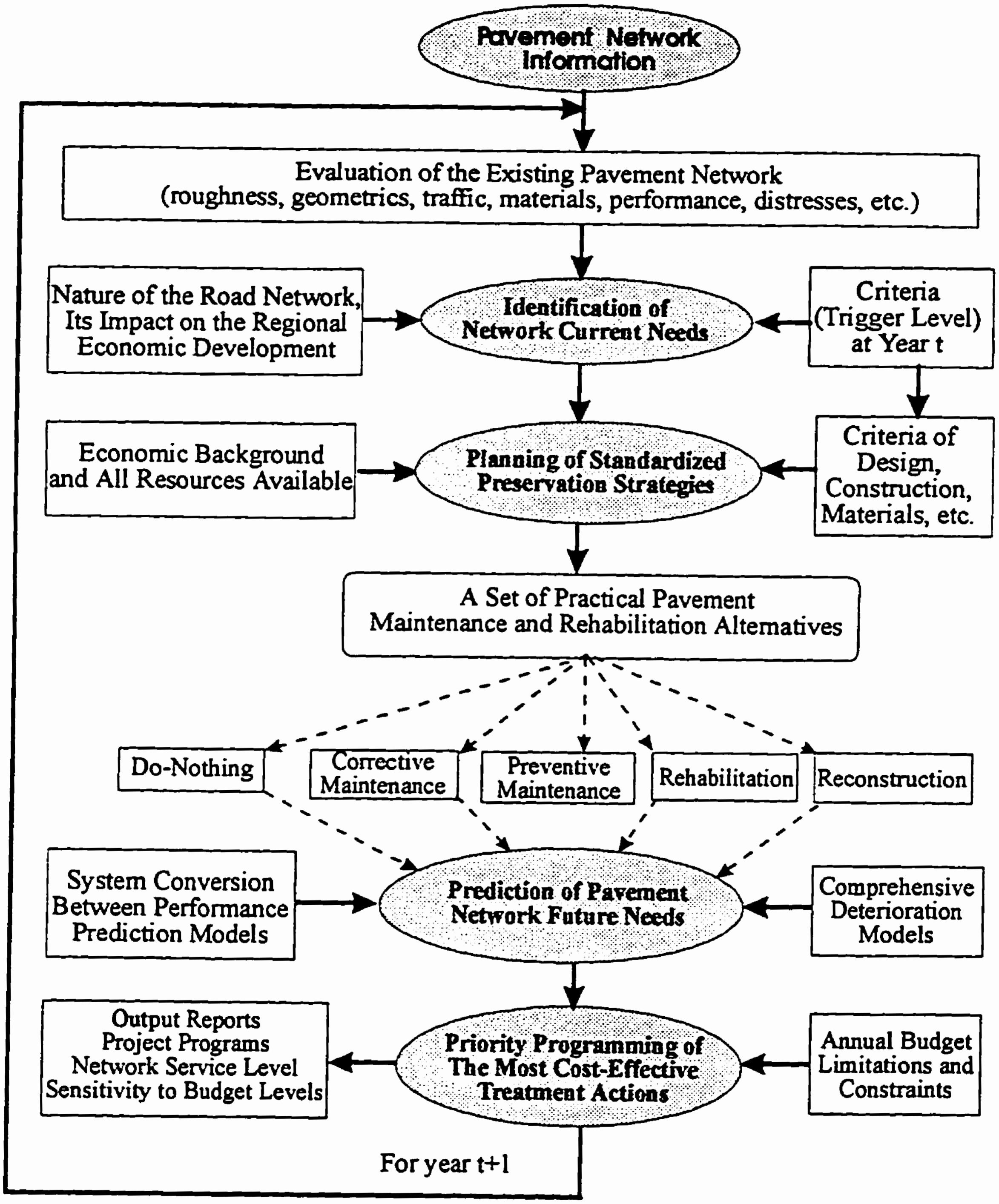


Figure 3.8 Framework of the Integrated Pavement Management System

Access to the database and specific information in developing prediction models, for example, is achieved through a hierarchical menu scheme as illustrated in Figure 3.9. This process can be used to model the multiyear non-homogeneous Markov pavement deterioration for each pavement section in the road network. The data and information requested and reported from the database system include the following:

- Pavement design methods and performance models, including expected pavement structural and functional performance, design variables, and design parameters, such as the design models used in Ontario Pavement Analysis of Costs (OPAC), AASHTO Guide for Pavement Design, etc.
- Traffic characteristic reports, which include traffic volume in terms of Average Annual Daily Traffic (AADT), traffic growth rate, truck percent, average weight truck factor (ESALs per truck), etc.
- Initial construction and subsequent major maintenance history reports, which are used to analyze pavement life-cycle costs and selection of appropriate M&R treatment strategies.
- Pavement performance and distress history reports, which are applied to assess the level of pavement network serviceability and to modify the predicted TPMs by means of a Bayesian approach.

3.4.1.2 Evaluation and Identification of the Network Current and Future Needs

In the process of the network database and observed performance history information, the current condition state of the existing road network can be evaluated so that current needs can be identified. To do this requires information on one or more of the following:

a) roughness profile for arriving at a riding comfort measurement,
b) surface distress survey for selecting feasible maintenance treatment strategies,
c) pavement materials and structural strength tests, such as dynamic deflection tested by Falling Weight Deflectometer (FWD), for rehabilitation design purposes, and
d) skid resistance testing for safety assessment.

The general considerations in generating a hierarchical data menu for developing pavement performance prediction models have been described in references (98). Those sections in the network which are at or below the minimum acceptable levels (or "trigger levels") on these items would constitute current needs.

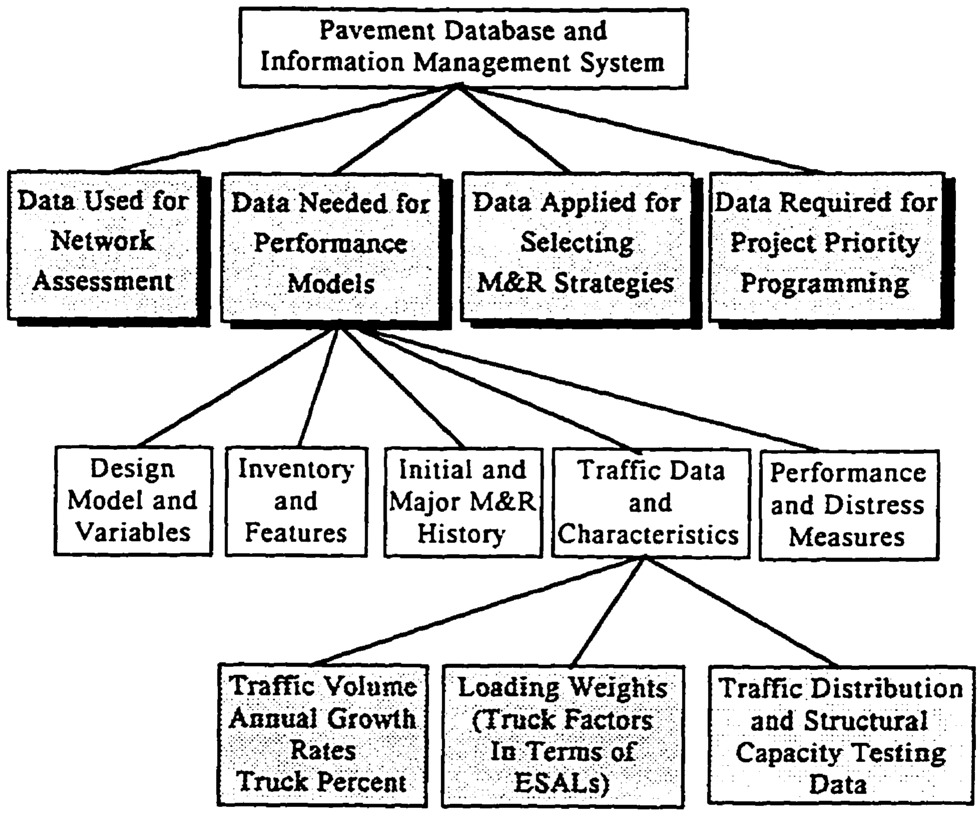


Figure 3.9 A Hierarchical Data Menu for Developing Performance Prediction Models

3.4.1.3 Planning of Standardized Pavement Network M&R Treatment Strategies

In order to establish a set of standardized maintenance and rehabilitation (M&R) treatments for the multi-year program, it is imperative to: a) establish a list of feasible treatments that are rational and practical for the region of the road network and, b) set up constraints and rules (policies) by which a set of standardized treatments should be established.

In an integrated PMS, each of the M&R treatment options has associated with cost, benefit and performance impacts on the pavement. The main objective is to produce the most cost-effective pavement network preservation program.

The concept of introducing standardized network M&R treatment strategies in pavement management has been reported earlier in reference (99, 100). For each individual treatment in the standardized M&R alternative treatment strategies, whether it is minor maintenance or a major treatment such as a structural overlay, should be well defined in terms of structural design, construction procedure and quality control, required materials, improvement effect on the existing pavement, and costs.

The effectiveness of each standardized treatment option requires to prediction or estimation of its expected service life and performance. All feasible combinations of treatments over the analysis period for each pavement section need to considered in the analysis in order to maximize the total program benefits or cost-effectiveness.

After each treatment, the prediction model has new design input parameters for the following period of performance until the next M&R action is applied. For example, if an overlay of 50 mm is applied to a section, the design thickness in the prediction model should be adjusted, and the new "current" pavement condition state in year t should also be adjusted.

3.4.1.4 Computer Program for Establishing Non-homogeneous Markovian TPMs

A diagram of the computer program for establishing the time-related Markov TPMs for an individual pavement section is described in Figure 3.9. There are six functional processes: 1) data input of pavement design variables and parameters, 2) design criteria and resource constraints, 3) reliability-based performance analysis model and system conversion, 4) generation of Markovian TPMs and predicted condition state vectors, 5) Bayesian update of the TPMs and, 6) output of the predicted TPMs and vectors for pavement performance prediction.

The pavement design subsystem first selects the corresponding deterministic model for each pavement among the design input models in the system. The data input model generates design variables and parameters in log-normal (or other type) distribution required by the prediction model. Then a Monte Carlo simulation method is employed to generate a set of random numbers corresponding to the variables and their probability distributions. It calculates probability vectors that the pavement condition state will deteriorate from a current state to the states which are equal or lower than the current state in one single transition period. The generation of the TPMs and modifications of the matrices with observed data are specifically described in a subsequent part of the thesis. The program output give a series of yearly-based transition probability matrices for each pavement section in the network.

A probability vector indicates the proportions of the pavement section in each of the possible condition states. For example, at a given stage, say stage 5, the probability vector p(5) or PCS(5) = (0, 0, 0, 0.4, 0.4, 0.2, 0, 0, 0, 0) means that there are 10 defined pavement condition states and, at five years age, 40% of the pavement section will be in state 7, 40% in state 6, and 20% in state 5.

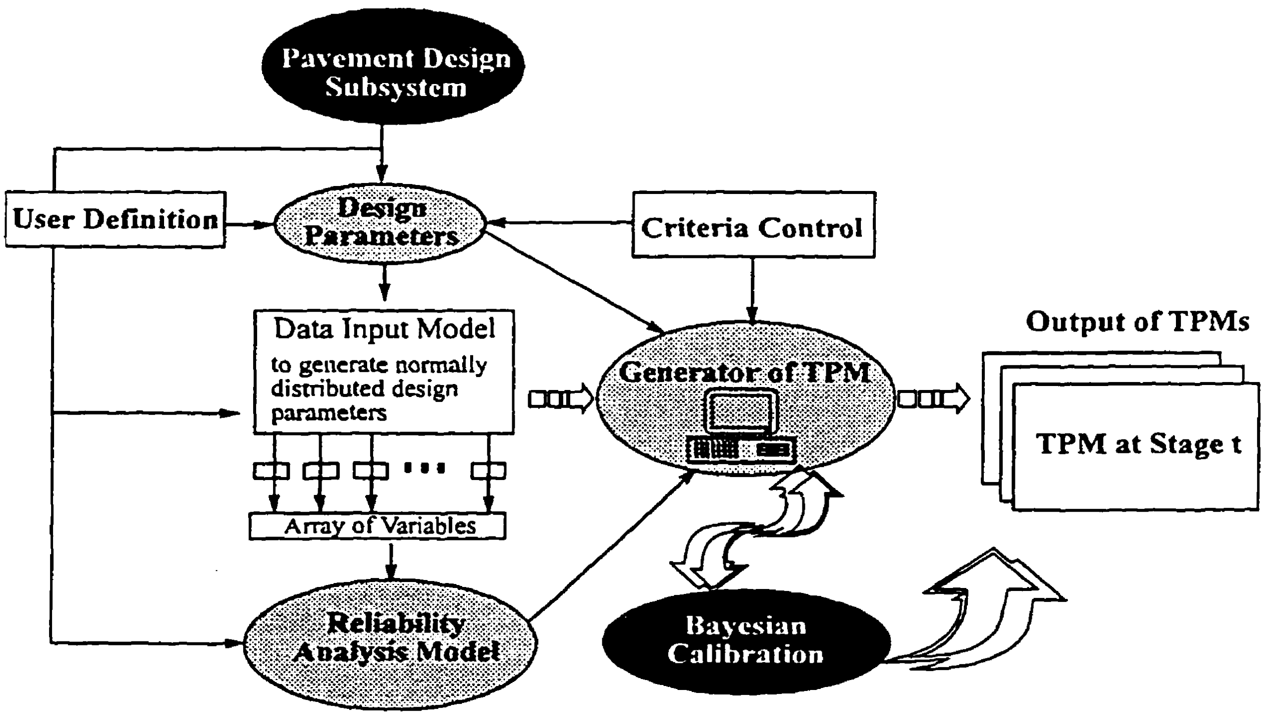


Figure 3.10 Establishing Non-Homogeneous TPMs for Individual Pavements

3.4.1.5 Cost-Effective Analysis and Priority Programming of Pavement M&R Treatments

Economic implications and overall improvement of the road network are calculated for each combination of treatment and year for each section in the network. The optimization then finds the most cost-effective M&R treatment combination for each pavement section in the analysis period, subject to annual budget limitations.

This process uses the output of the Markov predicted performance of each pavement section as input in a mathematical priority programming model. All feasible combinations of alternative treatments for each section for each year are analyzed in the model. Outputs of this process are a list of pavement sections with selected maintenance and rehabilitation strategies, and costs, and the associated performance improvements on the overall network.

The methodology developed for optimizing the pavement network multi-year M&R program is subsequently presented in Chapter 6, and a comprehensive example application of the method to a network from Ontario is demonstrated in Chapter 7. In addition, sensitivity analysis of the optimization model is presented in Chapter 7.

3.5 BAYESIAN UPDATE OF THE TRANSITION PROBABILITY MATRICES

In the situation of pavements, if observed pavement performance data is available and properly processed, then a Bayesian posterior probability calibration model can be used to update the TPMs of the non-homogeneous Markov process. Many highway agencies collect such data on an ongoing basis. The largest ongoing co-operative program is the Strategic Highway Research Program (SHRP, and C-SHRP in Canada). SHRP products should eventually be capable of being used towards the development of more cost-effective pavement maintenance and rehabilitation treatments and programs.

From a statistical analysis point of view, the uncertainty about random variables is described by probability distributions which can be updated on the basis of observed data. The basic theoretical foundation that connects a Markov process and the Bayesian posterior probability approach has been summarized in references (101, 102). It is based on the assumption that the prior distribution function of the matrix of the transition probabilities belongs to a family of distributions which is closed under consecutive sampling. Concisely, by means of the Bayes' approach, the predicted pavement condition states in terms of probability distribution and the associated Markov transition probability matrices can be updated through actually observed or measured pavement performance data.

By applying Bayes' theorem, the posterior probabilities for the updated transition probability vectors can be determined if additional data become available. With this approach, individual bias of subjective judgment of the pavement functional performance and variation or errors of the performance measurement (such as cracking, surface deformation or deflection and surface defects) can be considered in the prediction model.

3.6 SUMMARY

The concepts and basic structure of the integrated system for optimizing pavement network maintenance and rehabilitation programming have been presented in this Chapter. The unique features and major functions of the integrated system include:

a) Time-related Markov process of modeling pavement deterioration.
b) Technological development for establishing the time-related TPMs.
c) A set of standardized pavement network maintenance and rehabilitation treatment strategies,
d) Update or modification of the predicted TPMs by Bayesian approach through observed data.
e) Multi-year optimization of the pavement network M&R alternative treatments.

Integration of the non-homogeneous Markov process with the standardized pavement strategies and the multi-year priority programming makes it possible to produce an optimal set of M&R treatments for a given analysis period. Since modeling pavement deterioration or performance is subject to error due to variations in the materials, thickness, construction quality, traffic loads, environment, etc., it is desirable to deal with the problem in a stochastic way. The methodology developed in this study is able to explain systematically the uncertainties and probabilistic behavior of pavement deterioration.

CHAPTER 4

DEVELOPMENT OF A NON-HOMOGENEOUS MARKOV PROCESS FOR MODELING PAVEMENT DETERIORATION

4.1 INTRODUCTION

An accurate prediction of pavement future condition states or a relationship between pavement age and serviceability is very important in the whole process of pavement management. Many decisions, such as identification of pavement needs, determination of timing and type of M&R treatments, selection of projects and priority programming of a road network preservation, are all based on performance prediction.

Some problems and limitations of the existing transition probability matrix (TPM) building techniques have been discussed in the previous two chapters. The objective of this chapter is to describe the technical development of a non-homogeneous Markov process for modeling pavement deterioration. In particular, a new approach to establishing Markov TPMs is introduced. This newly developed approach deals with a system conversion from an existing deterministic model to its corresponding probabilistic model for the prediction of pavement deterioration. The principles underlying the system conversion and the TPM building methods are discussed in great detail. As well, a Bayesian technique is employed to modify the predicted TPMs by taking into account of the measured pavement performance data or information, through which the probability vectors of the Pavement Condition States (PCS) in different years are determined from the established Markov TPMs.

The uncertainties and the variations of pavement design parameters involved in performance prediction, such as the forecast Equivalent Single Axle Load applications (ESALs), pavement thickness in terms of equivalent granular base thickness, and subgrade soil modulus, are also discussed in this chapter.

In addition, sample applications of the system conversion applied to the OPAC model and the AASHTO model for the prediction of pavement deterioration are demonstrated with case studies. In the example studies, pavement performance predicted by both the existing deterministic models and the converted probabilistic models is compared with the actually observed pavement performance history data.

4.2 DEVELOPMENT OF THE NON-HOMOGENEOUS MARKOVIAN TPMS FOR THE PREDICTION OF PAVEMENT DETERIORATION

As described previously, there are basically two types of pavement performance prediction models: deterministic and probabilistic. While deterministic models predict a single value for distress, serviceability, etc., for each year in the life of a pavement, probabilistic models predict a distribution of such values.

The development of non-homogeneous (time-related) Markov transition probability matrices consists of three major components: 1) formulating the concepts of non-homogeneous Markov process modeling and system conversion between deterministic and probabilistic models, 2) development of new methodologies for establishing the time-related Markov TPMs, and 3) Bayesian update of the predicted non-homogeneous Markovian TPMs through observed data. Each of the three components is described in the following sections.

4.2.1 Concept of Non-Homogeneous Markov Process Modeling and System Conversion between Deterministic and Probabilistic Models

In a deterministic model, prediction of the future pavement condition state (PCS) in terms of serviceability, distress, etc., may be directly obtained from the pavement design equation. Variables such as traffic loads in terms of equivalent single axle load applications (ESALs), pavement thickness and subgrade soil strength are generally the major factors associated with the pavement deterioration.

In a probabilistic model, at each stage (year) the number of ESALs that the pavement structure can withstand before its condition state drops to a certain level can be compared with the actual predicted number of ESALs. On the basis of such a comparison, whether the pavement is in failure relative to a defined condition state level can be determined. When a large number of such comparisons are generated randomly through Monte Carlo simulation process, probabilities that the pavement will be in each of the defined condition states can be calculated as a PCS vector.

The concept of system conversion from a deterministic model to a probabilistic model has recently been explored (103) and is shown in Figure 4.1. In a deterministic model, pavement condition state (PCS) is represented by a single value, which is a function of pavement age, traffic loading and other independent variables through regression analysis. On the other hand, in a probabilistic model, pavement condition state (PCS) is predicted as a probability distribution vector, which is a function of the pavement original condition state, multiplied by a series of time-related TPMs. Each of the TPMs is calculated on the basis of the pavement condition state in the previous year and influential variables in the current year, such as traffic volume, subgrade soil strength, maintenance actions, so on. The result of a converted probabilistic model is a series of time-related TPMs.

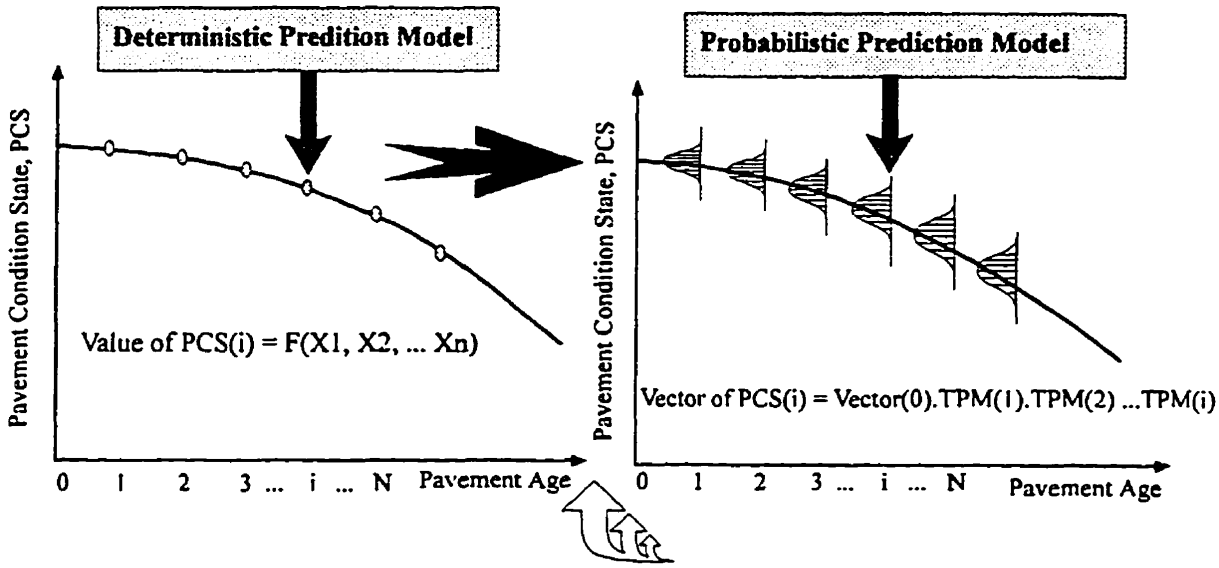


Figure 4.1 Concept of System Conversion between Deterministic and Probabilistic Models

The probabilistic model can then be used to perform the following functions: 1) simulate the probabilistic behavior of pavement deterioration in each prediction year, 2) determine pavement needs, and 3) provide information and data required for dynamic priority programming of pavement rehabilitation and maintenance at the network level.

The basic procedure of performing the system conversion from a deterministic model to its corresponding probabilistic model is described as follows:

1. Select the deterministic model to be used;

2. Understand the relationship between the predicted value (dependent variable) and all the independent variables considered in the deterministic model or equation;
3. Analyze the characteristics and probability distributions of all the variables;
4. Generate a set of random variables according to their probability distributions through simulation techniques;
5. Calculate each element of the non-homogenous Markovian transition probability matrices and/or predicted pavement condition state vectors.

In this research two different methodologies of establishing Markovian TPMs for the prediction of pavement functional or structural deterioration have been developed: 1) reliability-based calculation of the Markov transition probability matrices (TPMs), and 2) Monte Carlo simulation approach based calculation of the Markov TPMs. These two methods are fundamentally different from the existing TPM building methods. As a result, a set of time-related Markovian TPMs can be established for each section numerically. Each element of the TPMs is calculated for a corresponding set of input variables (such as traffic loading, pavement structural strength or thickness and subgrade soil strength).

The existing deterministic-based performance prediction models such as in Ontario's OPAC 2000 system, may be classified as mechanistic-empirical, in which a response parameter is related to measured structural or functional deterioration. Regression models, using long-term pavement performance data, establish the relationship between the structural or functional variable and the independent variables, such as traffic loads, pavement thickness, subgrade soil strength, etc. Generally, the relationship may be expressed as given previously in Chapter 2 (Equation 2.1). Each factor included in the equation could be further divided into sub-factors or variables so that a suitable performance prediction model for a specific region can be obtained. However, it would be extremely difficult and not appropriate to apply a particular agency's model to another region. In fact, difficulties have often been encountered even in developing regional-based models. Table 4.1 lists some deterministic-based models that can be converted to Markovian probabilistic prediction models. In each of the equations, there is a relationship between a pavement condition state (such as pavement condition index, PCI, present serviceability index, PSI, etc.) and independent variables including traffic loads, pavement thickness and subgrade soil strength.

Table 4.1 A List of Some Deterministic-Based Pavement Design and Performance Models

Name of Model and Reference	Design Equation or Prediction Model	
AASHTO (40)	$\log_{10}(W_{i-j}) = Z_R \times S_0 + 9.36 \times \log_{10}(SN+1) + \dfrac{\log_{10}\left(\dfrac{\Delta PSI}{4.2-1.5}\right)}{0.40 + \dfrac{1094}{(SN+1)^{5.19}}} + 2.32 \times \log_{10}(M_R) - 8.27$	[4.1]
OPAC 2000 (104)	$PCI = PCI_0 - \left[2.4455 \times 10^3 w_s^6 N + 8.805 \times 10^9 \left(w_s^6 N\right)^3\right] - \left(PCI_0 - \dfrac{PCI}{1+B\,w_s}\right)\left(1-e^{-\alpha T}\right)$	[4.2]
SAMP6 (105)	$P = P_1 - (P_1 - 1.5)\left\{R\left(N-N_k\right)\left[\dfrac{1.051}{(\mathrm{SN}+1)X_j}\right]^{9.3633}\right\}^{\beta} + 0.335\, C_1 C_2 \left(e^{-\theta t} - e^{-\theta t_k}\right)$	[4.3]
HDM III (106)	$R_t(\text{Roughness}) = 1.04\, e^{mt}\left[\mathrm{RI}_0 + 263\ (1+\mathrm{SNC})^{-5}\,\mathrm{NE}_t\right]$	[4.4]
C-SHRP (107)	$Y(\text{rutting}) = \mathrm{B}_0 + \mathrm{B}_1(\text{Voids}) + \mathrm{B}_2(\text{Traffic}) + \mathrm{B}_3(\text{Thickness}) + \mathrm{B}_4(\text{Age}) + \mathrm{B}_5(\%\ \text{Retained on \#4 sieve})$	[4.5]

Taking the AASHTO flexible pavement design equation for example, the basic procedure of establishing the non-homogeneous Markovian TPMs is described as follows:

1. Definitions of all variables in Equation [4.1] and their functional relationship are:

$W_{i\text{-}j}$ = the number of accumulated 18-kip equivalent single axle load applications that make the pavement deteriorate from a level of serviceability i to a specified terminal level of serviceability j.

Z_R = standard deviate corresponding to reliability level R,

S_0 = overall standard deviate,

ΔPSI = difference between the pavement initial design serviceability index, PSI_0, and the design terminal serviceability index, PSI_t, and

M_R = resilient modulus of subgrade material.

$SN = a_1H_1 + a_2H_2 + a_3H_3$ is the structural number which is indicative of the total pavement thickness required, where a_i = i^{th} layer coefficient, H_i = i^{th} layer thickness, and m_i = i^{th} layer drainage coefficient.

2. Analysis of probability distribution of each design variable included in the equation, such as pavement thickness or structural number, *SN*, subgrade soil strength, M_R.

3. Generating of random variables of *SN* and M_R by computer simulation, then a value of W_{i-j} is determined by means of Equation [4.1]. Illustrated in Figure 4.2 is a scheme showing that each W_{i-j} is defined by an interval of PSI.

4. Predicting the number of ESALs that will be applied on the pavement in each prediction year, N_Y, as calculated by a traffic prediction model. For example, the traffic prediction model used in the Ontario Pavement Analysis of Costs (OPAC) is:

$$N_Y = \frac{N_f}{A_p}\left[\frac{2 \times \mathrm{AADT}_i}{(\mathrm{AADT}_i + \mathrm{AADT}_f)}Y + \frac{\mathrm{AADT}_f - \mathrm{AADT}_i}{A_p(\mathrm{AADT}_i + \mathrm{AADT}_f)}Y^2\right] \qquad [4.6]$$

where

$$N_f = \frac{A_p}{2}\left(\frac{\mathrm{AADT}_i}{2} \times \mathrm{DAYS} \times T_i \times \mathrm{LDF}_i \times \mathrm{TF}_i + \frac{\mathrm{AADT}_f}{2} \times \mathrm{DAYS} \times T_f \times \mathrm{LDF}_f \times \mathrm{TF}_f\right) \qquad [4.7]$$

where N_Y is total number of Equivalent Single Axle Load applications (ESALs) of 80 kN applied on the pavement in *Y* years; *T* is the percentage of trucks; AADT is the two-directional Average Annual Daily Traffic; LDF is the Lane Distribution Factor (0.8 for 4-lane highways); TF is the truck factor; DAYS is the number of days per year for truck traffic (generally 300); *i* and *f* denote "initial" and "final", respectively.

5. Comparison of the value of N_Y with each W_{i-j} and repetition of steps 3 and 4 for a large number of iterations by computer to develop a set of yearly based transition probability matrices (TPMs) for the prediction of pavement deterioration.

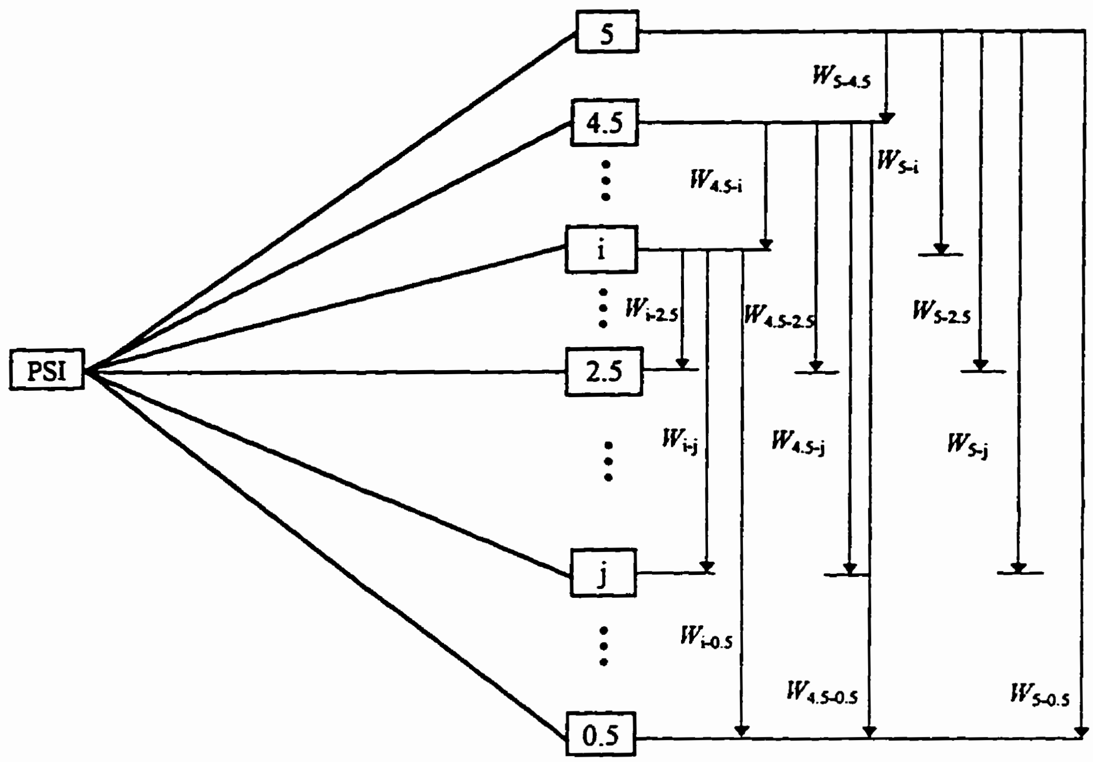


Figure 4.2 A Scheme of the ESALs That Cause Pavement to Deteriorate From PSI Level i to j

4.2.2 New Methodologies for Establishing Time-Related Markovian TPMs

4.2.2.1 Reliability-Based Method of Calculating the Markovian TPMS

In the reliability-based calculation of the probability of pavement condition state transition, traffic is generally considered as a major factor associated with pavement deterioration. Probability analysis of pavement condition states at each stage (year) can be performed by comparing the potential traffic loading in ESALs that the pavement structure can withstand before its condition state drops to a defined level.

According to the reliability definitions in Chapter 3, the number of ESALs ($N_{\mathrm{pcs}(i)}$) that the pavement can withstand before its PCS drops from its initial state to the state i can be calculated. As illustrated in Figure 3.3 of the previous chapter, $p_{N_t}(N)$ is the probability density function of the predicted actual traffic (ESALs) accumulated in t years; $\overline{N}_{\mathrm{pcs}(i)}$ is the mean value of the traffic (ESALs) that drives the pavement condition state to deteriorate from the initial state to state i; $p_{N_{pcs(i)}}$ is the probability density function of $N_{pcs(i)}$, which is the traffic (ESALs) that causes the pavement to deteriorate from the initial condition state to condition state i.

According to previous studies, the predicted values of both N_t and $N_{pcs(i)}$ are log-normally distributed variables (108). By comparing $\log N_t$ with $\log N_{pcs(i)}$, the reliability R_i at stage t (or year t) can be calculated by the following equations:

$$R_i = P\left[(\log N_{pcs(i)} - \log N_t) > 0\right]$$
$$= \Phi\left[\frac{\overline{\log N_{pcs(i)}} - \overline{\log N_t}}{\sqrt{S^2_{\log N_{pcs(i)}} + S^2_{\log N_t}}}\right] = \Phi(z), \qquad [4.8]$$

where $\Phi(z)$ is the probability distribution function for the standard normal random variable, $\overline{\log N_{pcs(i)}}$ is the mean value of $\log N_{pcs(i)}$, $\overline{\log N_t}$ is the mean value of $\log N_t$, $S_{\log N_{pcs(i)}}$ and $S_{\log N_t}$ are the standard deviations of $\log N_{pcs(i)}$ and $\log N_t$, respectively. These variance are combined into an overall variance term, S_0^2, that represents the total variance. Probability defined in Equation [4.8] can be generally calculated by means of the following formulation:

$$R = \frac{1}{\sqrt{2\sigma}} \int_{-\infty}^{z_0} \exp\left(\frac{-z^2}{2}\right) dz \qquad [4.8a]$$

Furthermore, by applying these formulas to calculate the probability, Pavement condition state or serviceability level in each year can be expressed in a probability vector. Each element of the probability vector at year t can be calculated by $P\left[(\overline{logN_{pcs(i)}} - \overline{logN_{pcs(j)}}) - (\overline{logN_{t+1}} - \overline{logN_t})\right]$, where i and j vary from the maximum level to the minimum level of a scale defining PCS with an interval of any defined value, such as PCI ranging from 100 to 0, PSI ranging from 5 to 0. Thus, Markov transition probability matrix corresponding to each year and the pavement condition state vector PCS(t) at stage t can be determined.

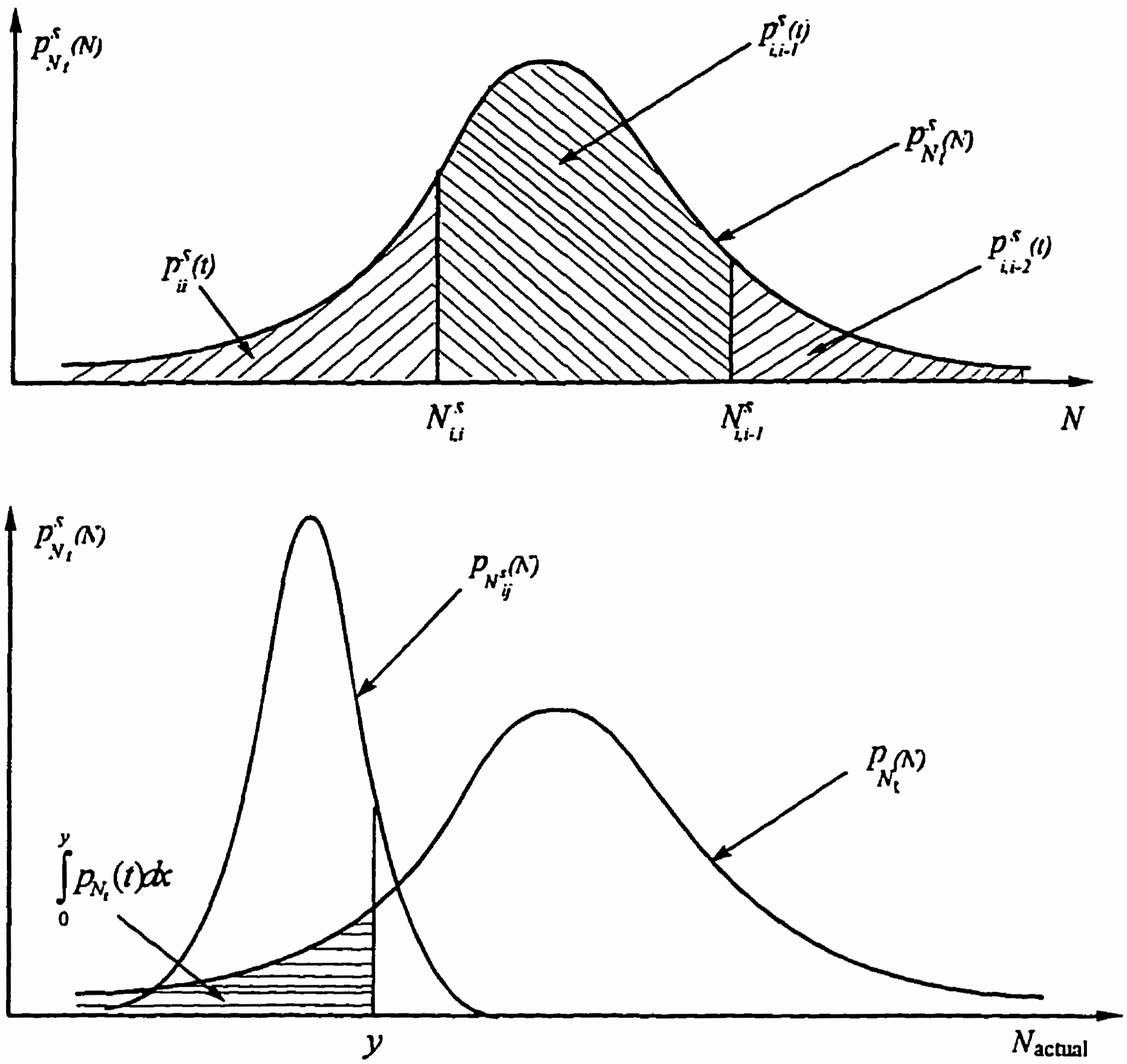


Figure 4.3 Probability Calculation of A PCS Transition From State i to State j at Year t

Making use of one set of selected input design factors (a single value randomly selected for each factor) a pair of $N_{pcs(i)}$ and N_t values are computed using the design model. The calculations are repeated a large number of times before one element of the TPMs is determined. If a pavement section serves a higher traffic volume with a certain growth rate and the traffic is the major factor affecting pavement deterioration, then the non-homogeneous Markov TPMs of pavement deterioration may be determined as follows.

1. Let N_{ij}^s be the maximum number of ESALs that a pavement section s can carry before it drops from condition state i to state j, and let $p_{N_t}^s$ be the probability density function of

the predicted number of ESALs, N_t, accumulated in stage t. If N_{ij}^s are deterministic numbers or constants, then the transition probabilities of pavement sections from state i to state j ($p_{ij}^s(t)$) during the year t, as shown in the upper part of Figure 4.3, are calculated as follows:

$$\begin{aligned} p_{ij}^s(t) &= P(N_{i,j+1}^s < N_t < N_{ij}^s) \\ &= P(N_t < N_{ij}^s) - P(N_t < N_{i,j+1}^s) \\ &= \int_0^{N_{ij}^s} p_{N_t}^s(N)dN - \sum_{k=i}^{j+1} p_{ik}^s(t), \qquad j < i. \end{aligned} \qquad [4.9]$$

2. However, N_{ij}^s are in general random variables with a probability density function $p_{N_{ij}^s}(N)$ as shown in the lower part of Figure 4.3. Thus, the following equations can be established:

$$p_{ij}^s(t) = 0, \;\; j > i, \qquad [4.10]$$

$$\begin{aligned} p_{ii}^s(t) = P(N_t < N_{ii}^s) &= \int_0^{\infty}\left[\int_0^{y} p_{N_t,N_{ii}^s}^s(x,y)dx\right]dy \\ &= \int_0^{\infty}\left[\int_0^{y} p_{N_t}^s(x)dx\right]p_{N_{ii}^s}(y)dy, \end{aligned} \qquad [4.11]$$

$$\begin{aligned} p_{ij}^s(t) = P(N_{i,j+1}^s < N_t < N_{ij}^s) &= P(N_t < N_{ij}^s) - P(N_t < N_{i,j+1}^s) \\ &= \int_0^{\infty}\left[\int_0^{y} p_{N_t}^s(x)dx\right]p_{N_{ij}^s}(y)dy - \sum_{k=i}^{j+1} p_{ik}^s(t), \quad j < i. \end{aligned} \qquad [4.12]$$

By applying these equations to each specific section of pavement in a road network, the final format of a non-homogeneous Markov transition probability matrix for the pavement section s at stage t is given as follows:

$$P^s(t) = \begin{bmatrix} p_{10,10}^s(t) & p_{10,9}^s(t) & \cdots & p_{10,0}^s(t) \\ p_{9,10}^s(t) & p_{9,9}^s(t) & \cdots & p_{9,0}^s(t) \\ \vdots & \vdots & \cdots & \vdots \\ p_{0,10}^s(t) & p_{0,9}^s(t) & \cdots & p_{0,0}^s(t) \end{bmatrix}. \qquad [4.13]$$

4.2.2.2 Monte Carlo Simulation Approach to Establishing the TPMs

The alternative approach to calculating each element of the transition probability matrices is to utilize a Monte Carlo simulation. The first step is to identify the deterministic model indicating the relationship between pavement condition state and the independent variables, as well the probability distribution and limits of each of the variables. Then a computer program can be developed to generate a set of random variables for the calculation of transition probability of a pavement condition state. A flow chart of the computer program to carry out the system conversion from a deterministic model to a corresponding probabilistic model is shown in Figure 4.4. Finally, a transition probability that the pavement deteriorates from the initial state to each of the lower state levels is determined by summarizing the statistics conducted in the previous steps.

It is a convenient method to use Monte Carlo simulation for generating normal or other types of random variates by computer. This technique has provided the basis for establishing a set of time-related TPMs efficiently for the prediction of individual pavement deterioration in the road network. The framework described in Figure 4.4 presents the main components of the system conversion and the procedures of obtaining a probabilistic model in terms of time-related transition probability matrices. Starting from the inputs of the deterministic model to final outputs of the converted probabilistic model, the whole process has been programmed and can be performed on DOS-based IBM personal computers. There are two key elements of the prediction model system conversion that should be explained as follows:

a) Data Input Format of Pavement Design Parameters in the Simulation

In the process of system conversion, each of the design variables is considered as a normally distributed (or other appropriate distributions) random variable with a mean value and deviation. Typical input data for a flexible pavement design equation include an initial pavement condition state (PCS) immediately after construction or rehabilitation, initial annual traffic characteristics (including traffic volume and growth rate, truck percent and truck factor), number of traffic lanes in each direction, subgrade deflection or resilient modulus (M_r), and equivalent granular thickness or structural number.

The most commonly used non-uniform distributions are those of the normal family with mean μ and variance σ^2, which are denoted as $N(\mu, \sigma^2)$. Since a random variate from the standard normal distribution $N(0, 1)$ can be easily transformed into the $N(0, 1)$, it may only consider generation of variates from the standard normal distribution of the pavement design variables. Very good descriptions of some general techniques for generation of non-uniform random deviates and the basics of the Monte Carlo method are given in the books by Kennedy (109) and Lewis (110), in which Marsaglia's technique for generating multivariate normal distributions is discussed. The main steps of the random number generating subroutine can be summarized as follows:

1. Generate U_1 and U_2 as two independent, standard uniformly distributed random numbers. Let $V_i = 2U_i - 1$ for $i = 1, 2$, and $W = V_1^2 + V_2^2$.
2. Convert the generated, uniformly distributed numbers into standard normal random numbers. If $W > 1$, go back to step 1. Otherwise, let $Y = \sqrt{(-2\ln W)/W}$, $Z_1 = V_1Y$, and $Z_2 = V_2Y$. Then Z_1 and Z_2 are independent standard normal random numbers.
3. A normally distributed design parameter $X \sim N(\mu, \sigma)$ may be generated as $X = \mu + \sigma Z$, where Z is a standard normal random number generated in step 2.

b) Output Format of the Prediction of Pavement Deterioration

For the purpose of a wide application and information output, the predicted pavement performance can be expressed in three different formats: a set of time-related transition probability matrices (TPMs), predicted pavement condition state vectors, and expected mean value of the pavement condition state vectors. Furthermore, the probability distribution of the predicted pavement condition states may be modified by using a Bayesian method through observed pavement performance data or field tests.

Suppose that pavement condition state (PCS) is rated on the scale of 0-10 with the highest representing perfect and the lowest representing the poorest in order. The unit interval of the scale defining pavement condition state should be small enough so that even a slight deterioration in the condition state can be predicted. For example, if only 10 pavement condition states are defined for a road network, a possible minimum drop within one stage of, say 0.2 unit, will not be detected. In such a case, the number of condition states should be divided into 50 states or more so that a slight deterioration can be detected.

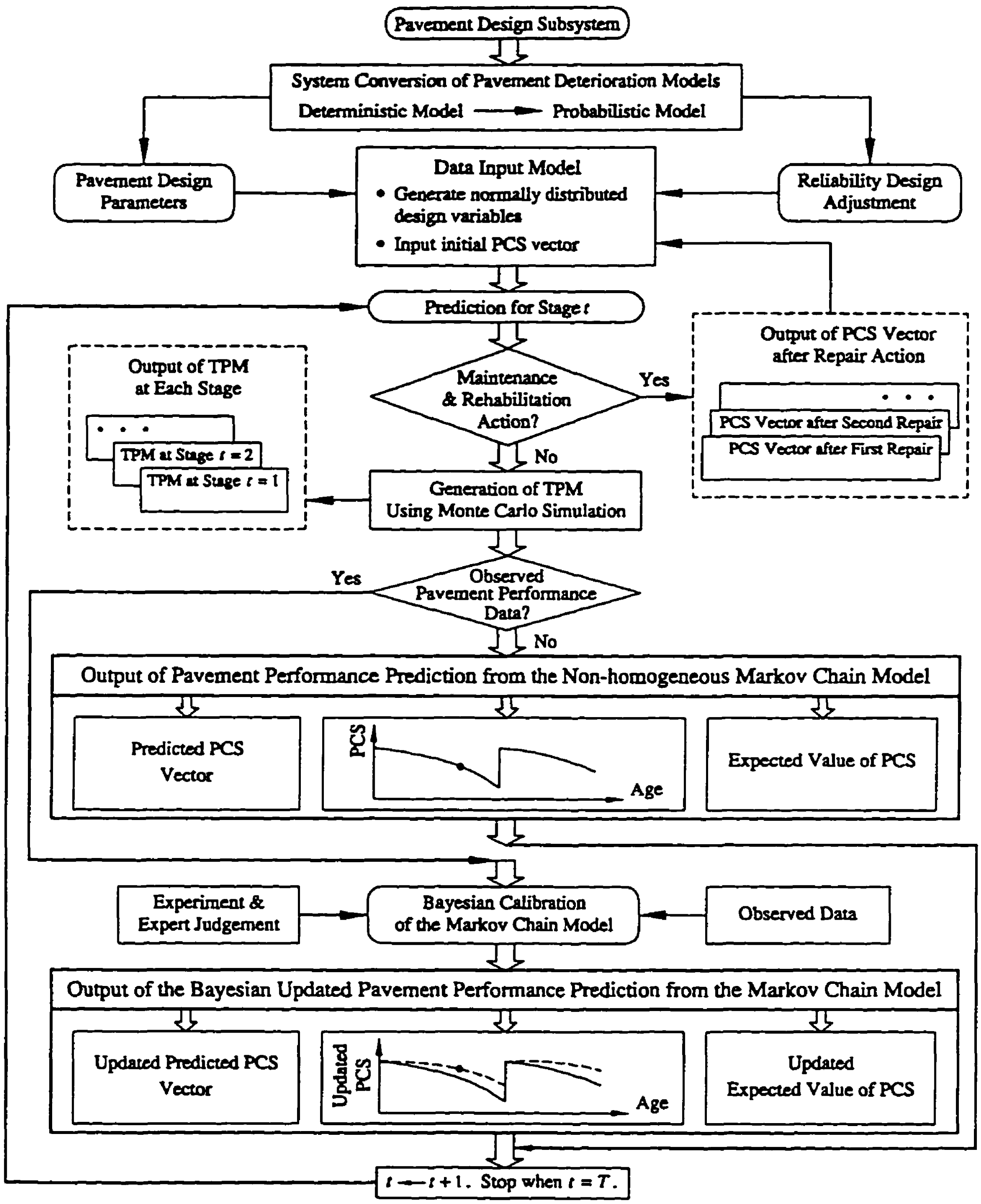


Figure 4.4 Flow Chart for Calculating Each Element of the Markov TPMs

In summary, the prediction of pavement deterioration versus pavement age through the newly developed method uses and transforms the existing deterministic models into the probabilistic models. Then the prediction of pavement deterioration can be carried out individually in terms of constructing a set of time-related transition probability matrices for each pavement section in a road network. Each element of the TPMs is calculated using Monte Carlo simulation. The results of predicted pavement performance are comparable to that predicted from its corresponding deterministic prediction model. The TPMs for the prediction of pavement deterioration predicted by the non-homogeneous Markov process can be updated by means of Bayesian techniques on a yearly basis through observed data.

4.2.3 Bayesian Update of the Markov Chain With Observed Data

4.2.3.1 Basic Concept of the Bayesian Approach in the Updating Process

Many highway agencies have collected data through observation or field experiments in order to manage the road network efficiently. The observed data can be utilised to update the predicted pavement condition transition probabilities using a Bayesian approach. According to Bayes' theorem, the posterior probabilities of a updated pavement condition states estimated by Markovian TPMs can be determined if additional actual pavement performance data become available.

Let m denote the measured value of the PCS in terms of say the Pavement Condition Index (PCI) or the Riding Comfort Index (RCI). The value of PCI in Ontario is determined by incorporating a measurement of the pavement Distress Manifestation Index (DMI) with the Ride Comfort Rating (RCR), as described in (111). Then, from Bayes' theorem, the posterior probabilities are calculated as follows:

$$P''\{\mathrm{PCS}_i\} = P\{\mathrm{PCS}_i \mid m\} = \frac{P\{m \mid \mathrm{PCS}_i\}\, P'\{\mathrm{PCS}_i\}}{\sum_j P\{m \mid \mathrm{PCS}_j\}\, P'\{\mathrm{PCS}_j\}} \qquad [4.14]$$

where $P'\{\mathrm{PCS}_i\}$ is the prior probability that the predicted PCS is at level i, which is determined from the non-homogeneous Markov chain modeling of pavement deterioration; $P\{m \mid \mathrm{PCS}_i\}$ is the likelihood of observing a value m of the pavement performance, given that the PCS is at level i; $P''\{\mathrm{PCS}_i\}$ is the posterior probability that the PCS is at level i, which is the updated probability given that a value m of the pavement performance has been measured; the summation is over all defined pavement condition states. Hence, the posterior probabilities are determined by combining the prior probabilities obtained from the structure of non-homogeneous Markov chain modeling with the observed pavement performance data.

Due to the uncertainties and errors in the measurement, the measured value m of the PCS may not be the actual value of the PCS. The likelihood function $P\{m \mid \mathrm{PCS}_i\}$ is then given by

$$P\{m \mid \mathrm{PCS}_i\} = \frac{1}{\sqrt{2\pi}\,\sigma} \exp\left\{-\frac{(m - \mathrm{PCS}_i)^2}{2\sigma^2}\right\} \qquad [4.15]$$

which amounts to the probability of drawing a normal random number m from a random variable with the mean value PCS_i and the standard deviation σ. The value of the standard deviation σ is a measure of the accuracy of the method of measurement and the equipment of measurement. The higher the accuracy of the measuring method and equipment, the smaller is the value of σ. The value of the standard deviation σ is determined based on: a) an investigation of individual bias in rating pavement serviceability, and b) a statistical analysis of the variation of a given parameter measured by different people and equipment.

Equation [4.16] below gives the posterior probability mass functions of the PCS. The updated expected value of the PCS at the end of each year is the commonly used Bayesian estimator

$$\mathrm{PCS}'' = \mathrm{E}[\mathrm{PCS} \mid m] = \sum_i \mathrm{PCS}_i \, P''\{\mathrm{PCS}_i\} \qquad [4.16]$$

where E is Bayesian estimator. In equation [4.16], the predicted pavement performance from the non-homogeneous Markov chain modeling of pavement deterioration and the measured data or observed information is combined in a systematic way to estimate the pavement condition state at the end of each year within the life-cycle analysis period.

4.2.3.2 Calculation of Bayesian Posterior Probabilities of the Markovian TPMs

When actually measured pavement performance data is available, the Bayesian approach can be applied to calibrate pavement deterioration prediction from the non-homogeneous Markov chain modeling of pavement deterioration in terms of the PCS vectors.

Suppose the possible values of the PCS are a set of discrete values PCS_i, which are determined from the non-homogeneous Markov chain modeling of pavement deterioration. The probability that the pavement condition state takes the value PCS_i is $P\{PCS_i\}$. If additional measured data becomes available, the prior probabilities of the PCS at the end of each year may be modified using Bayes' theorem. The basic procedure of Bayesian update of the pavement condition states is as follows:

- For the first year, the predicted pavement condition state vector at the end of the year is determined as $\mathbf{p}'(1) = \mathbf{p}(0)\ \mathbf{P}_1$. Using Equation [4.16], the posterior pavement condition state vector $\mathbf{p}''(1)$ may be determined by incorporating the observed pavement condition state m_1 measured at the end of the first year.
- For the kth year, $k > 1$, in the analysis period, the predicted pavement condition state vector at the end of the kth year is given by $\mathbf{p}'(k) = \mathbf{p}''(k-1)\ \mathbf{P}_k$. Using equation [4.16], the posterior pavement condition state vector $\mathbf{p}''(k)$ is then determined by incorporating the measured pavement condition state m_k..

4.2.3.3 Demonstration of Updating the Predicted TPMs by the Bayesian Technique

To demonstrate application of the Bayesian update procedure, suppose that the possible values of the *PCS* are assumed to be a set of discrete values *PCS*(i), i=1,2...,10, with relative likelihood *P*(*PCS*(i)). Then, if additional observed data becomes available, the prior probability vector of *PCS* at each year may be modified formally through Bayes' theorem. The basic procedure of updating the transition probability is: (a) to calculate the PCS vector of each year from the established Markov TPMs, (b) to treat the PCS vector of each year as prior information of the probability distribution within the scale of PCS range, and (c) to combine the probability distribution of the observed *PCS* for the pavement at each corresponding year t with the prior probability.

As illustrated in Figure 4.5, for example, the prior probability distribution of the pavement condition state at a given year ranges from *PCS*(4) to *PCS*(8) with *PCS*(6) as the most likely value. The observed probabilities of the pavement condition states are distributed between 4 and 7 of PCS values with PCS(5) as the largest probability. Thus, the expected value E'(PCS) of the pavement condition state at year *t* is:

$$E'(PCS) = (4.0)(0.05) + (5.0)(0.2) + (6.0)(0.6) + (7.0)(0.1) + (8.0)(0.05) = 5.9$$

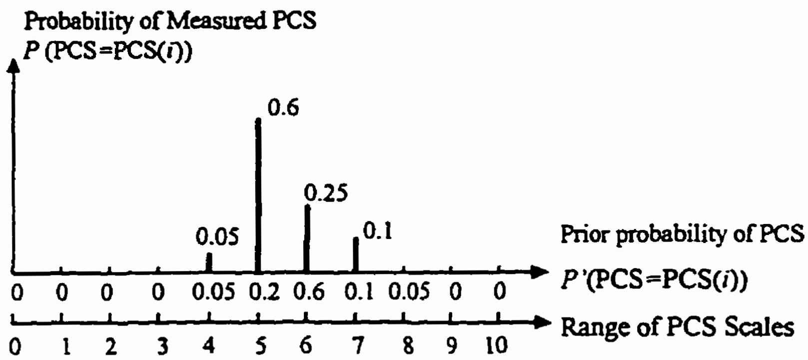


Figure 4.5 Prior Probability and Measured Probability of PCS

In order to supplement the transition probabilities, which may be treated as prior probabilities, calculated by the converted TPMs, Bayesian posterior probabilities can be obtained by combining the probability distribution of the measured or observed PCS with the estimated prior probabilities, as shown in the following:

$$\begin{aligned} m &= \text{observation} \\ P''(PCS = PCS(i)) &= P(PCS = PCS(i) \mid m) \\ &= \frac{P(m \mid PCS = PCS(i))P(PCS = PCS(i))}{P(m)} \\ &= \frac{P(m \mid PCS = PCS(i))P(PCS = PCS(i))}{\sum_{j=1}^{N} P(m \mid PCS = PCS(j))P(PCS = PCS(j))} \end{aligned}$$

$$P''(PCS{=}PCS(5)) = \frac{(0.6)(0.2)}{(0.05)(0.05)+(0.6)(0.2)+(.25)(0.6)+(0.1)(0.1)} = 0.391$$

and, similarly, $P''(PCS{=}PCS(6)) = 0.531$, $P''(PCS{=}PCS(7)) = 0.041$, the probabilities of other pavement condition states PCS(i) are zero, which are shown graphically in Figure 4.6. The Bayesian updated estimate for PCS is:

$$E''(PCS) = (4.0)(0.01) + (5.0)(0.42) + (6.0)(0.531) + (7.0)(0.041) = 5.39$$

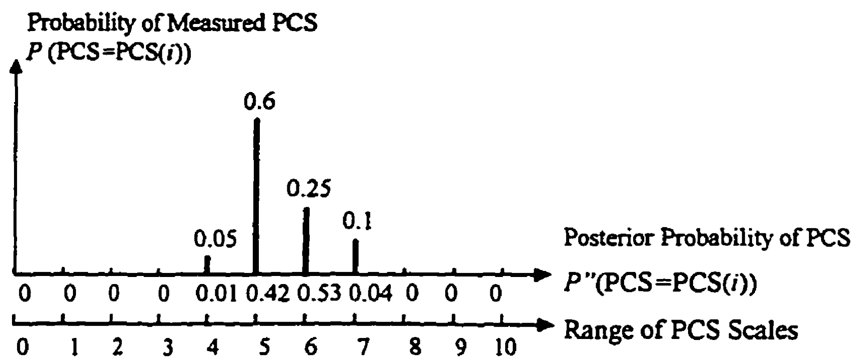


Figure 4.6 Bayesian Posterior Probability of PCS

4.3 APPLICATIONS OF THE SYSTEM CONVERSION TO EXISTING DETERMINISTIC MODELS

To illustrate the system conversion, two major deterministic models which are commonly used for project level pavement management systems in North America, are used for the application demonstration. The deterministic models that are to be converted to probabilistic models are the flexible pavement deterioration model used in Ontario Pavement Analysis of Costs (OPAC) system and the flexible pavement design model recommended in the 1986 and 1993 AASHTO Design Guide.

4.3.1 Example Application of the System Conversion Method to OPAC Model

The OPAC performance model is selected for demonstrating system conversion from a deterministic model into a probabilistic model without loss of generality. This model uses a deflection-based deterministic model for selecting the best pavement structural design alternative in terms of pavement functional and structural performance and the total life-cycle costs. The performance equation of the OPAC deterioration model in Table 4.1 is expanded as follows:

$$\Delta PCI^{*} = PCI_0 - (P_T + P_E)$$
$$= PCI_0 - \left[(2.4455\Psi + 8.805\Psi^3) + (PCI_0 - \frac{PCI_0}{1+Bw})(1 - e^{-\alpha Y})\right] \qquad [4.17]$$

where $\Psi = 3.7238\times10^{-6}w^6N$; w is the subgrade deflection (in mm) and is determined by the following equation:

$$w = \frac{9000\times25.4}{2M_s\left(0.9He\sqrt[3]{\frac{M_2}{M_s}}\right)\sqrt{1+\frac{6.4}{0.9He\sqrt[3]{\frac{M_2}{M_s}}}}} \quad ; \qquad [4.18]$$

ΔPCI = the total pavement condition index (PCI) loss at age or year Y after the accumulated number of ESALs, N, is applied on the pavement

PCI_0 = as-built initial pavement condition state, usually taken as 9.5 for newly constructed or overlaid asphalt pavement;

P_T = traffic-induced deterioration of PCI;

P_E = environment-induced deterioration of PCI;

H_e = total pavement equivalent granular base thickness;

N = the number of ESALs that changes the pavement by an amount P_T;

M_2 = modulus of granular base layer;

M_s = modulus of subgrade soil;

B = regional factor 1, B = 60 in southern Ontario;

α = regional factor 2, α = 0.006 in southern Ontario;

Y = number of years.

It is obvious that the amount of PCI loss in Y years predicted by Equation [4.17] is a function of three independent variables, i.e., N (ESALs), M_s (subgrade soil modulus), and H_e (total equivalent thickness of the pavement). In other words, if the value of each of the three variables is known, the PCS in year Y can be determined simply by the equation. However, it is impossible to know the exact values of these three variables in any future year. As a result, the value of N cannot be calculated without error or variation. Similarly, neither the modulus of subgrade soil M_s or the equivalent pavement thickness H_e can be determined correctly. However, the pavement deterioration rate is very sensitive to each of these three factors, which has been evidenced by many previous researches. Therefore, it is appropriate to employ a probabilistic approach to model the pavement deterioration.

4.3.1.1 Ontario Highway 402 Case Study

Highway 402 is a 4-lane, 102 km long rural freeway located in southern Ontario from London to Sarnia. This highway was built in the early 1970's on a subgrade of clay or sandy loam using three different pavement types: (a) asphalt concrete pavement with a granular base, (b) composite pavement, involving a Portland Cement Concrete (PCC) slab with a thin asphalt concrete surface, and (c) full depth Asphalt Concrete (AC) pavement. A detailed descriptions of pavement design variables, such as traffic loading, property of paving materials in each layer, subgrade soil modulus, etc., for one of the asphalt concrete pavement sections is given in Table 4.2.

Table 4.2 Pavement Structural and Traffic Design Variables for Highway 402

Design Parameters	Descriptions of the Variables
Structure	h_1 = 90 mm asphalt surface, layer coefficient M_1 = 400,000 h_2 = 150 mm granular base, layer coefficient M_2 = 50,000 h_3 = 300 mm granular subbase, layer coefficient M_3 = 15,000 Subgrade soil modulus or layer coefficient M_s = 5,000 Total equivalent granular base thickness: $H_e = 2h_1 + h_2 + \frac{2}{3}h_3 = 2 \times 90 + 150 + \frac{2}{3} \times 300 = 530$ mm Coefficient of variation of the total equivalent thickness = 0.1
AADT (two directions)	$AADT_1$ = 6500, $AADT_{20}$ = 9012, traffic growth rate is 2.5% per year Analysis Period A_p = 20 years Lane Distribution Factor $LDF_i = LDF_f$ = 0.8 Coefficient of variation of the AADT = 0.05
Truck factor	Truck fraction T_i = 25% at the initial year and T_f = 35% at the end of analysis period Truck factor TF_i = 0.91 at the initial year and TF_f = 1.14 at the end of analysis period

The subgrade strength in OPAC is represented by a subgrade layer coefficient M_s, which is actually approximately equal to the resilient modulus in psi. An M_s value of 5,000 would be indicative of a weak subgrade and would correspond to a California Bearing Ratio, CBR, value of about 3.3.

4.3.1.2 Calculation of the Markovian TPMs

Based on the design inputs of Table 4.2, the TPMs of the pavement condition state transition or the rate of deterioration in year 1, 5, 7 and 10, are calculated respectively and shown in Table 4.3. It should be indicated that, in addition to the four TPMs, all of the other TPMs corresponding to different time (or year) of the pavement deterioration, can also be generated at the time by the simulation program. Generally speaking, if there is no M&R action to be applied to the pavement, the rate of pavement deterioration in each year tends to become higher with pavement age given that this section is subject to a high traffic volume and growth rate. In other words, the proportion remaining in the same level of PCS in the following year will gradually decrease as compared with the previous year. For example, if the current pavement condition state is 9.2 in PCI, then the transition probabilities of transferring to the next two lower levels of PCI is 0.985 and 0.013 in year 1, 0.808 and 0.176 in year 5, 0.330 and 0.600 in year 7, 0.446 and 0.394 in year 10, as shown in Table 4.3 (A) through (D). Thus, this pavement deterioration has been proved to be a non-homogeneous Markov process based on the pavement design variables and environmental conditions given in Table 4.2.

Figure 4.7 presents the pavement condition index (PCI) versus age or accumulated ESALs relationship predicted by the OPAC method and its converted probabilistic model. The diagram illustrates that the deterioration estimated by the probabilistic model is close to that predicted by the deterministic model in the early years, but then starts to deviate somewhat after about 7 years of the OPAC system. Comparisons with the actually observed performance history are also show indicated in the figure. It appears that the probabilistic model "tracks" this actual history more closely than the deterministic model after the 7 years. To estimate the deviates of the converted probabilistic model it should be to observe many differences between observed and predicted outputs. The observed values can be compared with model predicted values to yield data from which estimates of appropriate type of probability distributions for each of the input variables can be modified. For the case of normal distribution, the error of the prediction associated with a standard deviation as well as the error due to uncertainty in the input factors may be adjusted by modifying the standard deviation.

Table 4.3 TPMs Established for the Prediction of Pavement Deterioration of Highway 402

(A) TPM of the Pavement Deterioration of Highway 402 in the First Year

	10	9.6	9.2	8.8	8.4	8.0	7.6	7.2	6.8	6.4	6.0	5.6	5.2	4.8	4.4	4.0	3.6
10	0.000	0.981	0.019														
9.6		0.002	0.985	0.013													
9.2			0.006	0.982	0.012												
8.8				0.024	0.966	0.010											
8.4					0.043	0.949	0.008										
8.0						0.070	0.926	0.004									
7.6							0.109	0.888	0.003								
7.2								0.164	0.833	0.003							
6.8									0.235	0.763	0.002						
6.4										0.320	0.679	0.001					
6.0											0.403	0.594	0.003				
5.6												0.473	0.525	0.002			
5.2													0.543	0.456	0.001		
4.8														0.503	0.489	0.007	

(B) TPM of the Pavement Deterioration of Highway 402 in the 5th Year

	10	9.6	9.2	8.8	8.4	8.0	7.6	7.2	6.8	6.4	6.0	5.6	5.2	4.8	4.4	4.0	3.6
10	0.001	0.794	0.190	0.016													
9.6		0.002	0.808	0.176	0.015												
9.2			0.004	0.818	0.167	0.012											
8.8				0.009	0.825	0.155	0.012										
8.4					0.016	0.832	0.141	0.012									
8.0						0.028	0.828	0.133	0.012								
7.6							0.036	0.831	0.124	0.010							
7.2								0.043	0.836	0.112	0.010						
6.8									0.062	0.828	0.101	0.010					
6.4										0.073	0.826	0.093	0.009				
6.0											0.090	0.818	0.084	0.009			
5.6												0.109	0.801	0.083	0.008		
5.2													0.132	0.786	0.075	0.008	
4.8														0.121	0.797	0.074	0.009

Table 4.3 (Cont.) TPMs Established for the Prediction of Pavement Deterioration of Highway 402

(C) TPM of the Pavement Deterioration on Highway 402 in the 7th Year

	10	9.6	9.2	8.8	8.4	8.0	7.6	7.2	6.8	6.4	6.0	5.6	5.2	4.8	4.4	4.0	3.6
10	0.000	0.456	0.400	0.130	0.016												
9.6		0.002	0.330	0.600	0.050	0.020											
9.2			0.002	0.3800	0.5300	0.060	0.0100	0.020									
8.8				0.002	0.4100	0.450	0.1000	0.0300	0.0100								
8.4					0.001	0.4900	0.4400	0.0500	0.0200								
8.0						0.001	0.5200	0.4400	0.040								
7.6							0.003	0.5500	0.4200	0.0300							
7.2								0.002	0.5600	0.4000	0.0200						
6.8									0.001	0.0480	0.4900	0.0300					
6.4										0.001	0.5600	0.3700	0.0600	0.010			
6.0											0.003	0.5200	0.4300	0.0400	0.0100		
5.6												0.002	0.6300	0.3000	0.0600	0.0100	
5.2													0.001	0.6200	0.3000	0.0700	0.010
4.8														0.002	0.6100	0.3400	0.0400

(D) TPM of the Pavement Deterioration of Highway 402 in the 10th Year

	10	9.6	9.2	8.8	8.4	8.0	7.6	7.2	6.8	6.4	6.0	5.6	5.2	4.8	4.4	4.0	3.6
10	0.000	0.436	0.400	0.120	0.029	0.017											
9.6		0.000	0.446	0.394	0.115	0.029	0.017										
9.2			0.002	0.456	0.385	0.112	0.029	0.017									
8.8				0.002	0.470	0.377	0.107	0.028	0.017								
8.4					0.002	0.477	0.376	0.102	0.027	0.017							
8.0						0.002	0.492	0.362	0.101	0.028	0.016						
7.6							0.005	0.499	0.355	0.099	0.027	0.016					
7.2								0.007	0.508	0.349	0.096	0.025	0.016				
6.8									0.010	0.513	0.343	0.095	0.024	0.016			
6.4										0.013	0.519	0.336	0.093	0.026	0.014		
6.0											0.017	0.528	0.327	0.090	0.026	0.013	
5.6												0.024	0.533	0.319	0.089	0.023	0.013
5.2													0.028	0.535	0.318	0.085	
4.8														0.031	0.522	0.359	0.034

One of the features in the probabilistic prediction model is that not only the rate of pavement deterioration in each year can be predicted in terms of expected means but also the predicted pavement condition state vectors for all the analysis years (or stages) are provided. Entries in Table 4.4 are the predicted pavement condition state vectors versus prediction years, which is obtained from the pavement initial condition state by multiplying the multi-step transition probability matrices corresponding to year 1 to year t. Each of the vectors indicates a probability distribution of the pavement condition state in a specific year. The results of the prediction vectors can be used in dynamic programming of pavement maintenance and rehabilitation at the network level. For example, the pavement condition state vector of Highway 402 (section LHRS = 48228) in 1986 is (0.01, 0.22, 0.59, 0.17, 0.01, 0, 0, 0, 0, 0), which means the percentage of the pavement condition being in state 10, 9, 8, 7, and 6 is 1%, 22%, 59%, 17% and 1%, respectively, and 0 for the rest of the 5 states.

It should be noted that the predicted pavement deterioration curves and the condition vectors presented in Figure 4.7 and Table 4.3 are produced by assuming that no major rehabilitation or maintenance is implemented throughout the analysis period.

Table 4.4 Predicted Pavement Condition State Vectors for Highway 402

Prediction Year	Predicted Probability of Pavement Condition in Each of the Defined PCI									
	10-9	9-8	8-7	7-6	6-5	5-4	4-3	3-2	2-1	1-0
1981(initial)	0.96	0.04	0	0	0	0	0	0	0	0
1982	0.38	0.61	0.01	0	0	0	0	0	0	0
1983	0.40	0.77	0.09	0	0	0	0	0	0	0
1984	0.05	0.61	0.33	0.01	0	0	0	0	0	0
1985	0.02	0.39	0.53	0.06	0	0	0	0	0	0
1986	0.01	0.22	0.59	0.17	0.01	0	0	0	0	0
1987	0	0.11	0.53	0.31	0.04	0	0	0	0	0
1988	0	0.05	0.41	0.41	0.11	0.02	0	0	0	0
1989	0	0.02	0.28	0.45	0.19	0.06	0.01	0	0	0
1990	0	0.01	0.17	0.40	0.28	0.12	0.02	0	0	0
1991	0	0	0.10	0.32	0.32	0.18	0.06	0.02	0	0
1992	0	0	0.05	0.23	0.32	0.23	0.11	0.04	0.01	0

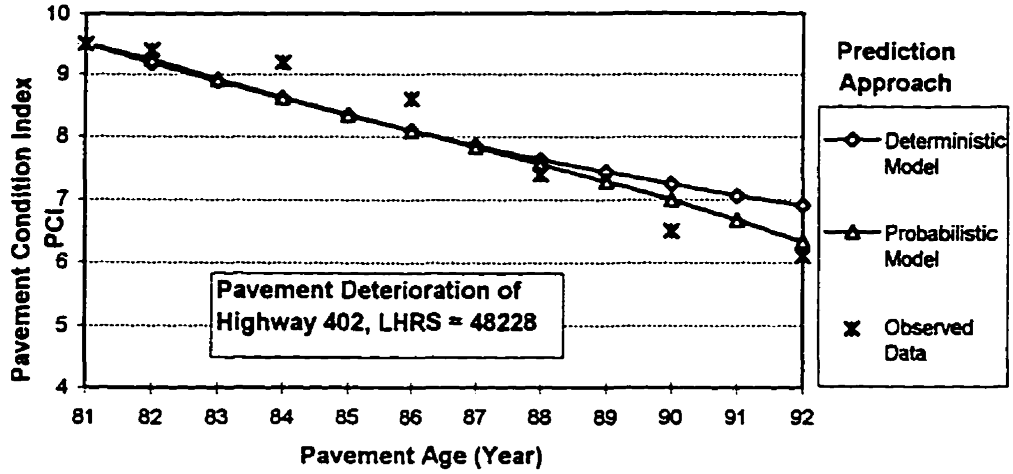


Figure 4.7 Comparison of the Pavement Performance Predicted by the OPAC Model

4.3.1.3 Bayesian Update of the Predicted TPMs Through Observed Data

Employing the Bayesian approach for calculating posterior probabilities presented in Section 4.2 of this chapter, the predicted pavement condition state vectors at the end of each year can be updated if additional measured pavement performance data is available. In this case, the measured pavement performance data from 1982 to 1993, as listed in the last column of Table 4.5, is available for the Highway 402 section from the Ministry of Transportation of Ontario. The values in Table 4.5 do not include the effects of major maintenance or rehabilitation actions. In other words, only routine maintenance has been considered.

As a parametric study, three values of the standard deviation $\sigma = 1.0$, 0.5, and 0.1 are used to obtain the updated predicted PCS using the Bayesian approach presented in the previous section. The numerical results are listed in Table 4.5. If the measured values of the PCS are considered as correct, the updated predicted values of the PCS using the Bayesian approach give a better prediction of pavement deterioration than the expected values. It is seen that the smaller the value of the standard deviation, σ, the closer the updated predicted values of the PCS to the measured values. Hence, the standard deviation, σ, may be used as a control parameter of the confidence of the pavement managers on the measured or predicted values of PCS. If the pavement managers have high confidence in the pavement deterioration model, a larger value of σ may be taken so that a smaller weight is placed on the measured values. On the other hand, if there exists a database of measured values of the PCS of good accuracy, then a smaller value of σ should be used to take the advantage of this database.

The numerical results listed in Table 4.5 are plotted in Figure 4.8. It is seen that the non-homogeneous Markov chain modeling of pavement deterioration provides a very good prediction of pavement performance. If additional measured information on pavement performance exists, a better updated prediction may be obtained using the Bayesian approach.

Table 4.5 The Measured and Predicted Mean Values of PCS

	Expected	Bayesian Updated Expected PCS			Measured
Year	PCS	$\sigma = 1.0$	$\sigma = 0.5$	$\sigma = 0.1$	PCS
1982	9.5000	9.5000	9.5000	9.5000	9.5
1983	9.1126	9.1126	9.1126	9.1126	9.0
1984	8.7318	8.7314	8.7301	8.6895	8.5
1985	8.3559	8.3525	8.3420	8.1986	8.2
1986	7.9814	7.9755	7.9586	7.8342	8.4
1987	7.6083	7.6272	7.6617	7.8026	7.2
1988	7.2360	7.2359	7.2231	6.9071	6.9
1989	6.8631	6.8454	6.7956	6.5396	6.5
1990	6.4882	6.4481	6.3639	6.1510	6.2
1991	6.1102	6.0487	5.9450	5.7868	5.8
1992	5.7284	5.6484	5.5390	5.4301	5.5

In Figure 4.8, it is seen that an exception exists in 1987 in which the Bayesian update technique did not give a better prediction than that obtained without Bayesian update. The reason is that the measured value of PCS in 1986 is peculiar; when this measured value is used to modify the predicted value for year 1986, the updated value of PCS will affect the prediction for 1987. The peculiarity in the measured value of PCS may be from an unrecorded routine maintenance performed in 1986 or due to error in carrying out the measurement of PCI. In other words, "you can't win them all"!

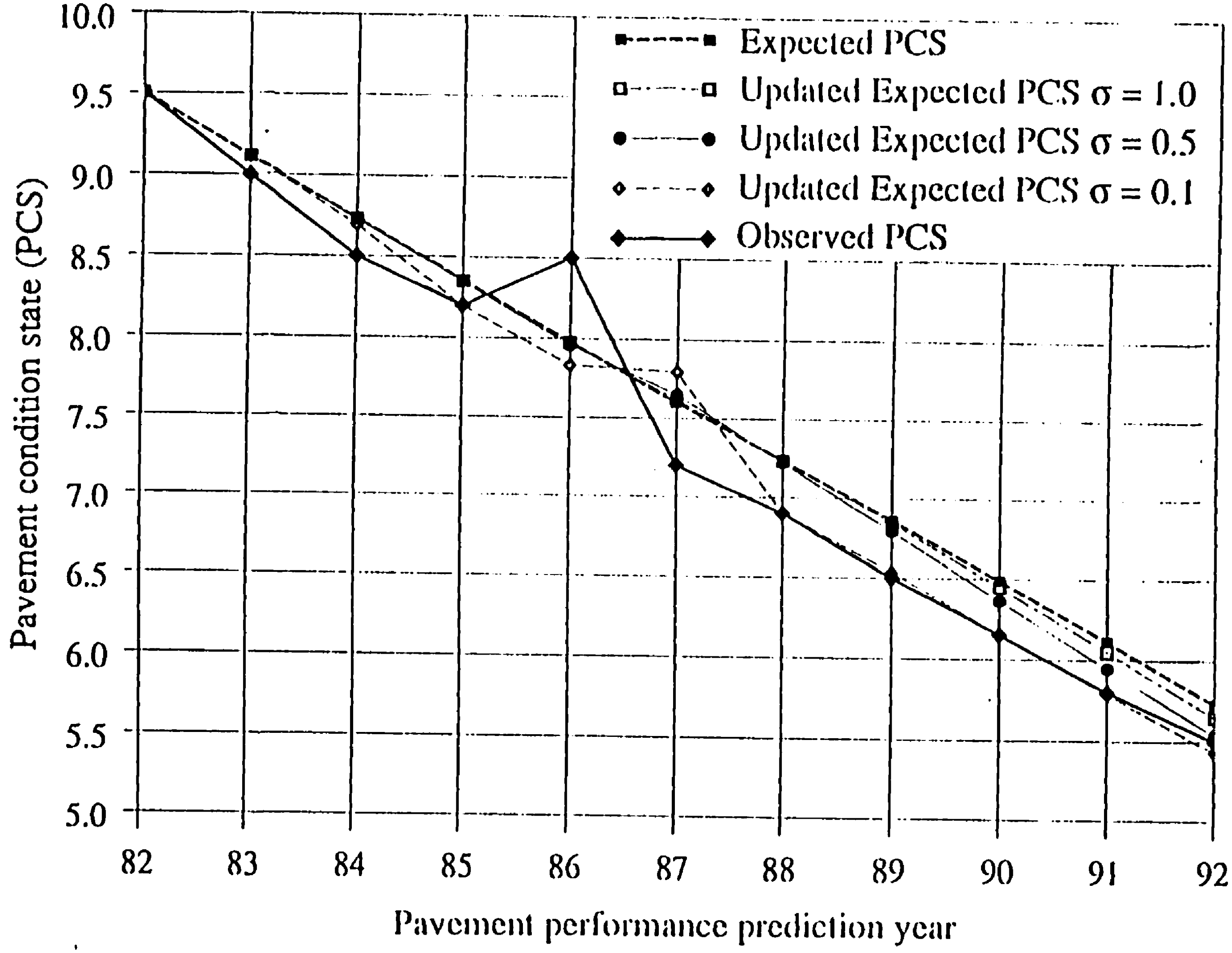


Figure 4.8 Observed and Predicted Pavement Condition States Versus Age

4.3.2 Example Application of the System Conversion Method to AASHTO Model

The second example application is to convert the flexible pavement design model used in the AASHTO system to its corresponding probabilistic model. In comparison with the OPAC-based performance prediction model, this AASHTO guide model, Equation [4.1], can be reorganized in the following form:

$$\log_{10}(\Delta PSI) = 0.5682 + \left[0.4 + \frac{1094}{(SN+1)^{5.19}}\right]\Big[\log_{10} N_t - Z_R S_0 \\ -9.36 \times \log_{10}(SN+1) - 2.32 \times \log_{10} + 8.27\Big] \qquad [4.19]$$

where

$\Delta PSI = PSI_0 - PSI_t$, i.e., difference between the initial design serviceability index, PSI_0, and the serviceability index at year t, PSI_t.

Z_R and S_0 = standard normal deviate and combined standard error of the traffic prediction and performance prediction, respectively,

M_R = subgrade soil resilient modulus,

N_t = predicted total number of 80 kN (18-kip) equivalent single axle load (ESAL) applications in t years that deteriorate a pavement by an amount of ΔPSI,

SN = the structural number indicative of the total pavement thickness required; it is a function of layer thickness, Layer coefficient and drainage coefficient.

It is apparent from Equation [4.19] that the amount of decrease in the level of pavement condition state (i.e., ΔPSI) is a function of predicted number of ESALs, N_t,, structural number, SN, and subgrade soil resilient modulus, M_R. As previously discussed, the input variables in Equations [4.19] could not easily be estimated for a real situation like Highway 402, but the sensitivity of pavement deterioration to changes of these variables could be significant (112, 113).

In order to compare the pavement performance-age (or traffic loading) relationship predicted by the model in the 1993 AASHTO Guide with that predicted by the converted probabilistic model, Ontario Highway 6 was taken. The design variables and traffic inputs for the pavement are described below in Table 4.6.

Table 4.6 Design Variable Inputs of Asphalt Pavements of Ontario Highway 6

Initial Present Serviceability Index, PSI_0	4.4	
Effective subgrade soil modulus, M_R	5,000 psi	
Layer thickness, H_i, and coefficient, a_i	H_i	a_i
Asphalt concrete surface	27 mm (5 in)	0.44
Granular Base	152 mm (6 in)	0.14
Sandy gravel subbase	305 mm (12 in)	0.11
Pavement Structural Number, SN	5×0.44+6×0.14+12×0.11 = 4.36	
Traffic Data	AADT of two directions in 1981= 11000	
	Traffic growth rate = 6.4%	
	Truck percent = 6% in 1981, and 8.5% in 1991	
	Truck factor = 1.2 in 1981, and 1.35 in 1991	
	Traffic lane distribution factor, LDF = 1.0	

If the structural number, *SN*, accumulated number of ESALs in year t, N_t , and subgrade soil modulus, M_s, are entered as independent normal variates with means 4.36, $1.65\times10^5(1+0.025)^t$, and 5000, respectively, and coefficients of variation are 0.05, 0.1 and 0.05, respectively, then the non-homogeneous Markovian TPMs for prediction of the pavement condition state transition versus age can be established, as shown in Table 4.7. In this table only four TPMs corresponding to the first, third, sixth and tenth years are provided.

Figure 4.9 shows the comparison between the observed pavement performance data, the predictions by the AASHTO model and the converted probabilistic model. The diagram, again shows fairly close agreement between the two models in the early years but some divergence occurs in late years.

In addition, pavement condition state vectors of the pavement condition state for all the prediction years can be estimated in the same form as shown in Table 4.8. With the PCS vectors, a general distribution of the pavement condition in terms of PSI in each year can be determined.

Table 4.7 A Set of Time-Related Markovian TPMs Established for the Prediction of Highway 6

(A) TPM of the Pavement Deterioration of Highway 6 in the First Year

	5	4.75	4.5	4.25	4.0	3.75	3.50	3.25	3.00	2.75	2.50	2.25	2.00	1.75	1.50	1.25	1.00
5	0.9000	0.0800	0.000														
4.75		0.9300	0.0500	0.0200													
4.5			0.9000	0.0800	0.0200												
4.25				0.940	0.0600	0.000											
4.0					0.9500	0.050	0.000										
3.75						0.960	0.040	0.0000									
3.50							0.950	0.0400	0.010								
3.25								0.9400	0.050	0.010							
3.00									0.940	0.040	0.020						
2.75										0.940	0.040	0.0200					
2.50											0.930	0.0700	0.000				
2.25												0.9500	0.040	0.0100			
2.00													0.960	0.0400	0.000		
1.75														0.9700	0.300	0.000	

(B) TPM of the Pavement Deterioration of Highway 6 in the 3rd Year

	5	4.75	4.5	4.25	4.0	3.75	3.50	3.25	3.00	2.75	2.50	2.25	2.00	1.75	1.50	1.25	1.00
5	0.8100	0.1900	0.000														
4.75		0.8900	0.1100	0.000													
4.5			0.7500	0.2500	0.000												
4.25				0.870	0.1300	0.000											
4.0					0.8200	0.180	0.000										
3.75						0.850	0.150	0.000									
3.50							0.810	0.1800	0.010								
3.25								0.8400	0.160	0.000							
3.00									0.840	0.160	0.000						
2.75										0.840	0.150	0.0100					
2.50											0.770	0.2300	0.000				
2.25												0.8300	0.170	0.000			
2.00													0.800	0.2000	0.000		
1.75														0.8200	0.160	0.020	

Table 4.6 (Cont.) A Set of Time-Related Markov TPMs Established for the Prediciton of Highway 6

(C) TPM of the Pavement Deterioration of Highway 6 in the 6th Year

	5	4.75	4.5	4.25	4.0	3.75	3.50	3.25	3.00	2.75	2.50	2.25	2.00	1.75	1.50	1.25	1.00
5	0.6500	0.3300	0.0200														
4.75		0.7100	0.2600	0.0300													
4.5			0.5100	0.4800	0.0100												
4.25				0.620	0.3600	0.020											
4.0					0.6600	0.330	0.010										
3.75						0.660	0.340	0.0000									
3.50							0.620	0.3500	0.030								
3.25								0.6800	0.310	0.010							
3.00									0.580	0.042	0.000						
2.75										0.600	0.390	0.0100					
2.50											0.640	0.3500	0.010				
2.25												0.6400	0.340	0.0200			
2.00													0.660	0.3200	0.020		
1.75														0.5800	0.400	0.020	

(D) TPM of the Pavement Deterioration of Highway 6 in the 10th Year

	5	4.75	4.5	4.25	4.0	3.75	3.50	3.25	3.00	2.75	2.50	2.25	2.00	1.75	1.50	1.25	1.00
5	0.0400	0.9400	0.0200														
4.75		0.0700	0.9000	0.0300													
4.5			0.0800	0.9200	0.000												
4.25				0.080	0.9000	0.020											
4.0					0.0200	0.970	0.010										
3.75						0.050	0.950	0.000									
3.50							0.030	0.9400	0.030								
3.25								0.0600	0.930	0.010							
3.00									0.070	0.930	0.000						
2.75										0.040	0.950	0.0100					
2.50											0.020	0.9700	0.010				
2.25												0.0400	0.940	0.0200			
2.00													0.070	0.9100	0.020		
1.75														0.020	0.980	0.000	

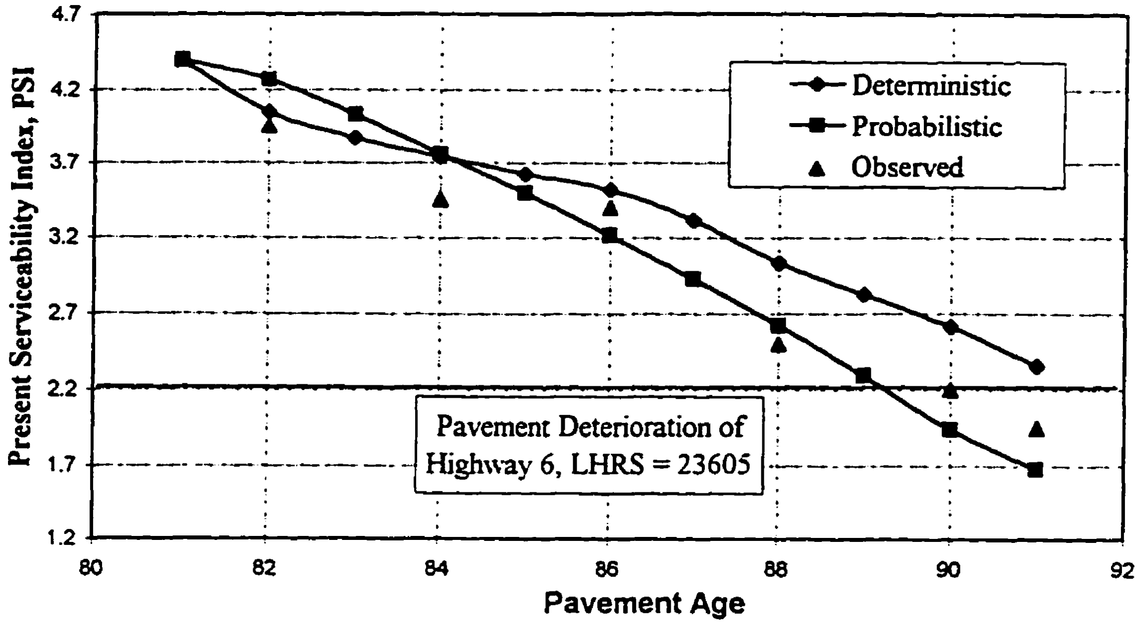


Figure 4.9 Comparison of Pavement Performance Predicted from the AASHTO Model

Table 4.8 Predicted Pavement Condition State Vectors for Ontario Highway 6

Prediction Year	Predicted Probability of Pavement Condition in Each of the Defined PSI									
	5.0-4.5	4.5-4.0	4.0-3.5	3.5-3.0	3.0-2.5	2.5-2.0	2.0-1.5	1.5-1.0	1.0-0.5	0.5-0
1981	0	1	0	0	0	0	0	0	0	0
1982	0	0.1244	0.8756	0	0	0	0	0	0	0
1983	0	0.0030	0.9358	0.0612	0	0	0	0	0	0
1984	0	0	0.1091	0.8859	0.0050	0	0	0	0	0
1985	0	0	0.0023	0.7999	0.1966	0.0012	0	0	0	0
1986	0	0	0	0.0811	0.8674	0.0509	0	0	0	0
1987	0	0	0	0.0016	0.5536	0.4239	0.0206	0	0	0
1988	0	0	0	0	0.0459	0.7244	0.2211	0.0086	0	0
1989	0	0	0	0	0.0007	0.2675	0.6140	0.1140	0.0037	0
1990	0	0	0	0	0	0.0180	0.4629	0.4525	0.0664	0
1991	0	0	0	0	0	0	0.0151	0.4668	0.4545	0.046

4.4 SUMMARY

In this chapter the principles involved in the system conversion between two different types of prediction models have been described. Also described were the differences between deterministic and probabilistic performance prediction models in terms of prediction outputs format, model development and input data process.

While deterministic models are essentially developed on the basis of a relationship between observed structural or functional deterioration (such as Riding Comfort Index, RCI, Present Serviceability Index, PSI, cracking, roughness, etc.,) and several independent pavement structural and environmental variables through regression analysis, probabilistic prediction models are built by applying a Markov transition process to model pavement deterioration. In previous Markov process modeling efforts, each element of the TPMs is obtained either by taking the average subjective opinions of experts, or by observing the performance of a large number of pavements under different initial pavement condition states over a long period of time, both of which are costly and time-consuming.

Through this research, a new methodology of predicting pavement deterioration by using non-homogeneous Markov process modeling and system conversion between a deterministic model and a probabilistic model has been described. The transformed probabilistic model is constructed by generating a set of time-related non-homogeneous Markovian Transition Probability Matrices (TPMs), using Monte Carlo simulation. In addition, a Bayesian technique is employed to update the expected PCS values by integrating additional information such as actually measured pavement performance data.

The probabilistic model gives not only an expected value, which may be comparable with the predicted value calculated by a deterministic model, but also provides a predicted pavement condition state vector in each year. The predicted pavement condition state vectors indicate the probabilities (or percentage of a pavement in terms of length or area) that a pavement will be in each of the defined pavement conditions states after one or more years of deterioration.

A summary of the non-homogeneous Markovian process of modeling pavement performance conducted by this research includes:

1. Compared with the traditional Markovian TPMs building approaches, this new methodology avoids the problems of either processing a large amount of individual, possibly biased, subjective opinions or the requirement of observing long term performance data.

2. The system conversion process from a deterministic-based deterioration model into a probabilistic-base model provides a workable, reliable and step-by-step approach for developing Markov prediction models.

3. Pavement condition state in terms of Pavement Condition Index (PCI), etc., at each year (stage) can be expressed in the form of a probability vector in the probabilistic model.

4. The use of a Bayesian approach to update the predicted pavement condition state vector at the end of each year is a very effective way to fit the prediction results to the actually measured pavement condition states.

5. The combined Markov-Bayesian analysis approach provides pavement managers with a practical and efficient technique for the prediction of asphalt pavement performance. It is can be particularly useful in calibration of the OPAC and AASHTO pavement design models.

CHAPTER 5

STANDARDIZATION OF PAVEMENT M&R TREATMENT STRATEGIES

5.1 INTRODUCTION

Usually, in a road network pavement structures can be classified into several different types based on their surface properties and materials, such as asphalt concrete (or flexible) pavements, Portland cement concrete (or rigid) pavements, composite pavements, granular base with asphalt surface treatment, etc. Each type can be further classified into several different categories on the basis of the pavement thickness, paving materials, properties of structural design and construction quality. Consequently, it is necessary to have available a number of different maintenance and rehabilitation (M&R) treatment strategies for the preservation of each type of pavement. In other words, each pavement should be treated individually regarding M&R treatments. At present, there are a number of different methodologies that can be used to select appropriate M&R treatments for pavements. Some of these methodologies are sophisticated and computerized, while others are subjective decisions made by experienced pavement engineers and managers. The methods most frequently used by Canadian provincial highway agencies and US state highway departments include pavement condition analysis, priority assessment models and network optimization models, which have recently been summarized by Carnahan (114) and Zimmerman (115).

The choice of M&R selection methods is related to the technical level of a highway agency, available resources and environmental concerns. This chapter emphasizes the concept of standardizing pavement maintenance and rehabilitation treatments for a regional or local network level of pavement management. By standardization, several preferred pavement maintenance and rehabilitation treatment strategies are selected for all projects considered within a specified programming period.

The purposes of standardizing pavement maintenance and rehabilitation activities are to: a) provide the highway agency with a list of recommended treatments available to the priority programming, b) establish effectively time-related TPMs of pavement deterioration models after each M&R treatment is applied, c) conduct cost-effectiveness analysis and evaluation over the life-cycle, and d) promote the automation of M&R treatment activities on a network level. The recommended M&R treatments for all the pavements in a regional road network should meet the basic design and construction criteria as well as the factors that may limit the applicability of some treatment strategies.

5.2 MAJOR CONSIDERATIONS IN THE STANDARDIZATION OF PAVEMENT M&R TREATMENTS

As discussed in Chapter 4, one of the major functions in an integrated PMS is to select the most cost-effective M&R treatments for each pavement in the network over the analysis period. It should be noted that each standardized treatment action is defined by its work content, treatment effect, treatment costs and influence on the future pavement deterioration. Pavement life cycle analysis involves initial structural design and construction followed by a series of periodic Maintenance and Rehabilitation treatments to cost effectively extend the service life of the pavement. The selection of feasible M&R treatments is usually based on a pavement surface condition evaluation, pavement performance experience and safety concerns.

Pavement maintenance may consist of relatively inexpensive, corrective types of treatments to address specific problems such as localized potholes, or it may take the form of preventive action, such as crack sealing to slow down further deterioration. Pavement rehabilitation usually involves a larger amount of investment for extending the pavement life when it has reached some limit of acceptability.

In order to select appropriate treatments for pavement long term preservation, it is necessary to evaluate each treatment effect in terms of functional and structural improvement over the existing pavement. It should be noted that in this study a pavement performance prediction model is modified after each maintenance or rehabilitation treatment is applied to the pavements except for the do-nothing treatment. Each standardized M&R treatment is designed by considering the pavement deterioration characteristics, treatment effects and the impacts of the treatments on the future deterioration or M&R needs. Therefore, it is imperative to prepare a set of standardized M&R treatment alternatives for the optimization model.

5.2.1 Factors Affecting Pavement M&R Treatment Strategies

For a given road network, the treatment strategies should cover all kinds of pavement surface distresses and structural inadequacy. Each standardized treatment action needs to consider the following factors:

- Type of existing pavement structure,
- Effect of the treatment in terms of increasing the level of pavement condition state (PCS), and influence on the rate of future deterioration,
- Automation in the process of all maintenance and rehabilitation treatment construction,
- Pavement material resources, available budget and environmental concerns.

5.2.2 Process of Standardizing Pavement M&R Treatment Strategies

The basic process of developing a set of standardized pavement M&R treatment strategies is illustrated in Figure 5.1. It starts with a classification of all pavement sections by type, the reason being that each type may require different treatment strategies. For each type of the classified pavements, a set of standardized M&R treatments is selected from all feasible M&R, considering such factors as materials, costs, construction, etc. The treatments range from do-nothing to major rehabilitation or reconstruction. Finally, a list of standardized M&R treatment strategies is recommended for implementation.

In brief, the integrated PMS developed in this research can provide the highway agency with a project treatment selection method. The number of treatments for each type of pavement in the road network is limited to several standardized M&R treatments. The performance model itself needs to be periodically adjusted, as do the costs of the various alternative treatments. The integrated PMS also provides the information necessary to evaluate the long-term impacts of various M&R strategies.

It is appropriate that a pavement management system should be developed to have its generality and particularity. While the generality ensures that the system possesses a similar structure and functions to widely accepted pavement management systems, the particularity means that a treatment should be designed to meet the specific requirements of local situations. Table 5.1, which is taken from the Pavement Design and Rehabilitation Manual of the Ontario Ministry of Transportation (116), is an example scheme of all feasible pavement M&R treatment alternatives for preservation of Ontario's highway system.

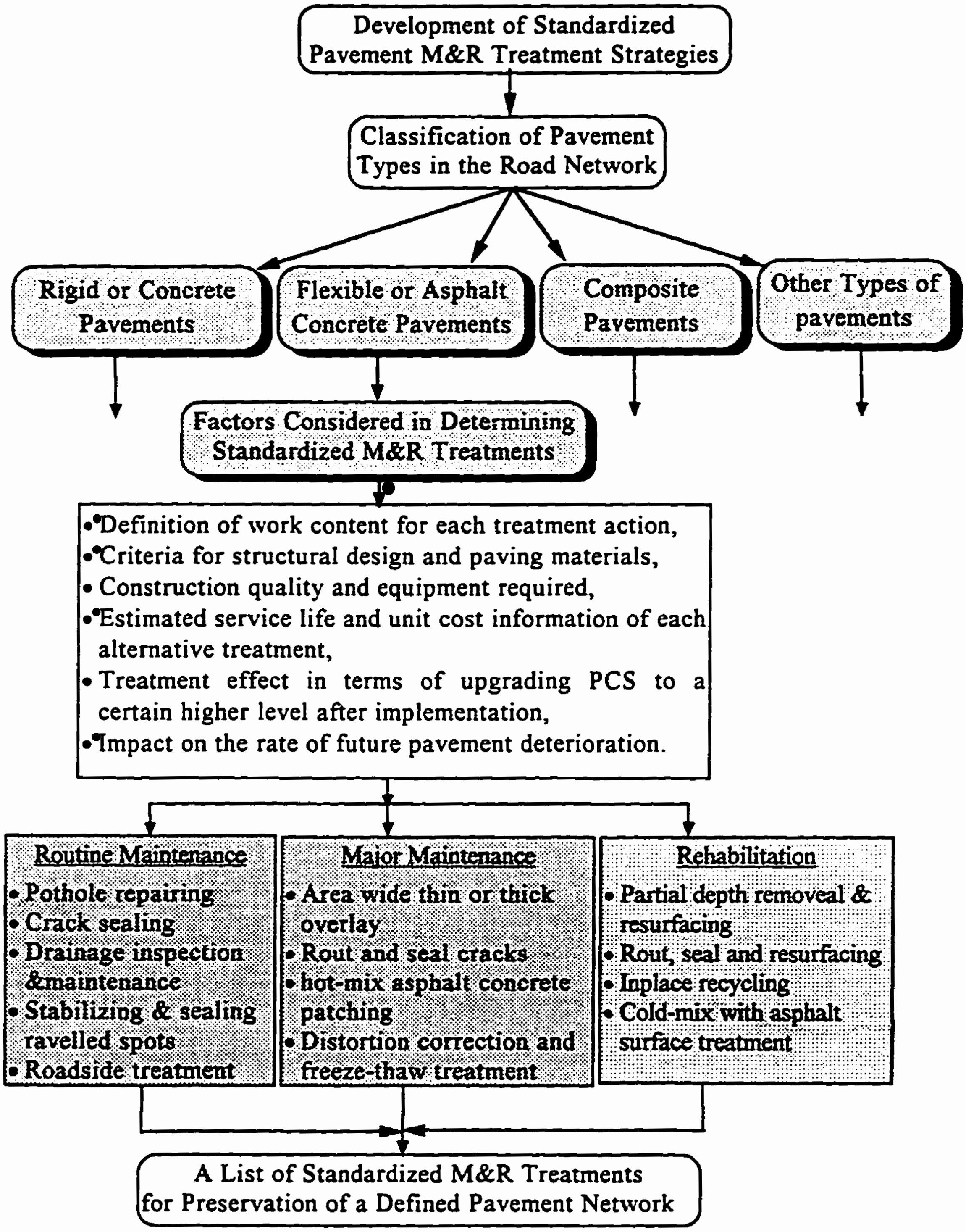


Figure 5.1 Process of Standardizing Pavement M&R Treatment Strategies

Table 5.1 Pavement Maintenance and Rehabilitation Actions in Ontario

	Flexible	Rigid
Routine Maintenance	Potholes Roadside Maintenance Drainage Maintenance Localized Spray Patching Localized Distortion Repair Minor Crack Sealing	Potholes Spall Repairs Blow Ups Localized Distortion Repair Minor Crack and Joint Sealing
Minor & Major Maintenance	Rout and Seal Cracks Hot-Mix Patching Surface Sealing Asphalt Strip Repairs Distortion Corrections Drainage Improvements Frost Treatments Roadside Slopes and Erosion Control	Full Depth Joint Repairs Full Depth Stress Relief Joints Resealing Joints and Sealing Cracks Full Depth Slab Repair Milling of Stepped Joints and Distortion
Rehabilitation or Re-Construction	Hot-Mix Resurfacing Partial Depth Removal & Resurfacing In-place Recycling Full Depth Removal and Resurfacing Cold-Mix with Sealing Course Surface Treatments Pulverization, Re-mix & Resurfacing	Unbounded Concrete Overlays Bonded Concrete Overlays Subsealing Slab Jacking Surface Texturization Cracking and Seating (with Resurfacing)

5.3 PREDICTION OF PAVEMENT DETERIORATION IN COMBINATION WITH M&R TREATMENT EFFECTS

As discussed earlier, prediction of pavement performance versus age plays a very important role in the decisions of multi-year priority programming of pavement network M&R activities. It is critical that the integrity of the performance curves be maintained and updated over time if life cycle analysis and economic evaluation of various alternative designs are considered. When a pavement performance analysis period goes beyond the initial service life of the pavement, the performance prediction model should take into account the effects of each maintenance or rehabilitation applied to the pavement during the analysis period.

5.3.1 Concept of Elastic Pavement Deterioration Models

When a pavement section reaches the minimum acceptable service level specified, it becomes a need. In identifying deficient pavements and estimating future needs, the integrated PMS provides a comprehensive (or elastic) prediction model for evaluating all feasible treatment effects and influence on the rate of pavement future deterioration or future maintenance needs.

The terminology "elastic pavement deterioration models" used in this study means that pavement serviceability is recoverable if a major maintenance or rehabilitation treatment is applied to the pavement. Thus, the elastic performance prediction model must be able to determine the expected serviceability-age relationship over the entire analysis period, including the prediction model for the initial pavement structure and the new prediction models for the pavement structure after each preservation action. After a preservation action, pavement serviceability level is improved or recovered to a certain higher level, depending on which maintenance or rehabilitation alternative is selected.

Illustrated in Figure 5.2 is an example showing the treatment effects of two alternative M&R action streams on the existing pavement and their influence on the pavement future deterioration in terms of separate performance prediction models.

In the alternative M&R action stream 1, for instance, two individual performance prediction models have to be applied for the prediction of pavement deterioration during the entire analysis period: one covers phase I starting from the initial year Y_0 to year Y_k, another covers phase II from Y_k to Y_n. Between phase I and phase II, a major M&R treatment action is applied in year k, and the pavement condition state is recovered in amount of PCS_k. The treatment effect and the change of the pavement structure after the M&R implementation in year k are all considered in the prediction model of phase II. Similarly, if the alternative M&R action stream 2 is recommended, then three separate prediction models are needed as indicated by the dashed line in the figure.

While this discussion indicates separate prediction models, in reality one model form can be used if the input variables, such as pavement thickness, traffic loading and subgrade soil strength, are changed to reflect the M&R treatments.

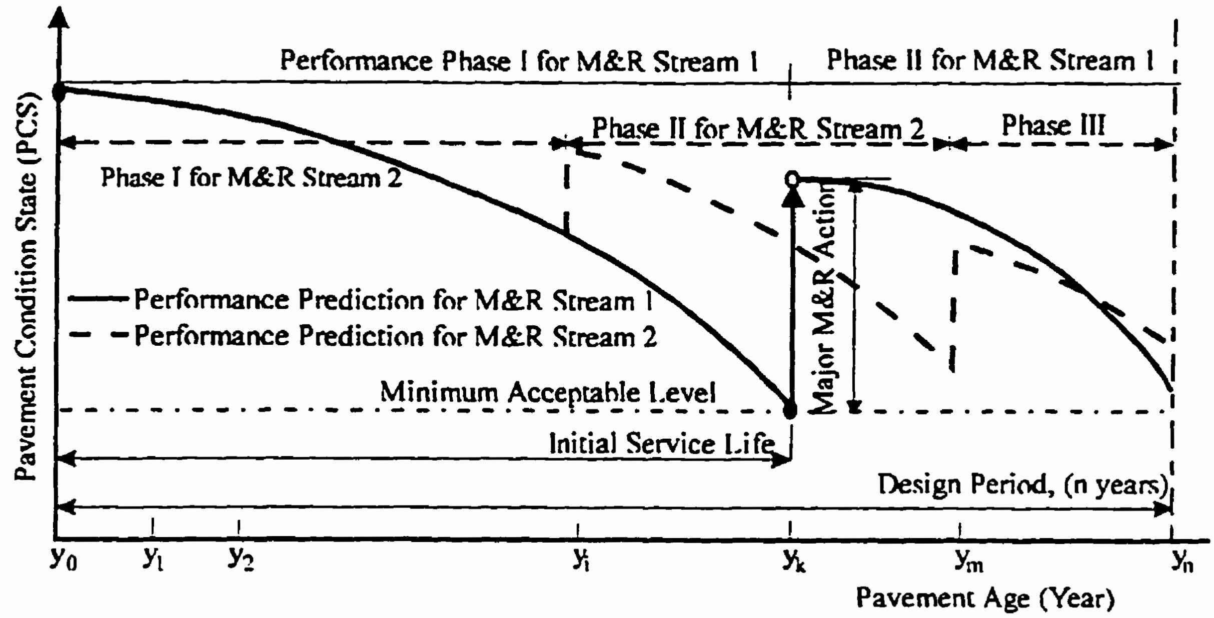


Figure 5.2 Illustration of Integrated Pavement Performance Prediction Models

5.3.2 Modification of the Time-Related TPMs for Pavement Deterioration Modeling

The reasons for taking pavement deterioration as an elastic process and the underlying principles are described as follows:

1. Suppose an asphalt overlay is applied to the existing pavement, then the pavement total thickness (or equivalent granular base layer thickness) and structural strength will be increased. Consequently, the parameter(s) used in the pavement deterioration model, which is modeled as Markov process described in this study, should be changed because the model was developed on the basis of the original pavement structure.

2. The rates of the pavement functional deterioration at different stages are not constant in most cases. The use of non-homogeneous Markov chains in prediction models captures the transition probabilities of the pavement deterioration. The relationship between an overall pavement condition state and time (age) is usually a non-linear curve with some "jump" points (as M&R treatment applications), as illustrated in Figure 5.2.

3. Integration of the time-related Markov process with standardized M&R treatments produces a list of optimal M&R strategies that can maximize the cost-effectiveness of the investments in the road network preservation program.

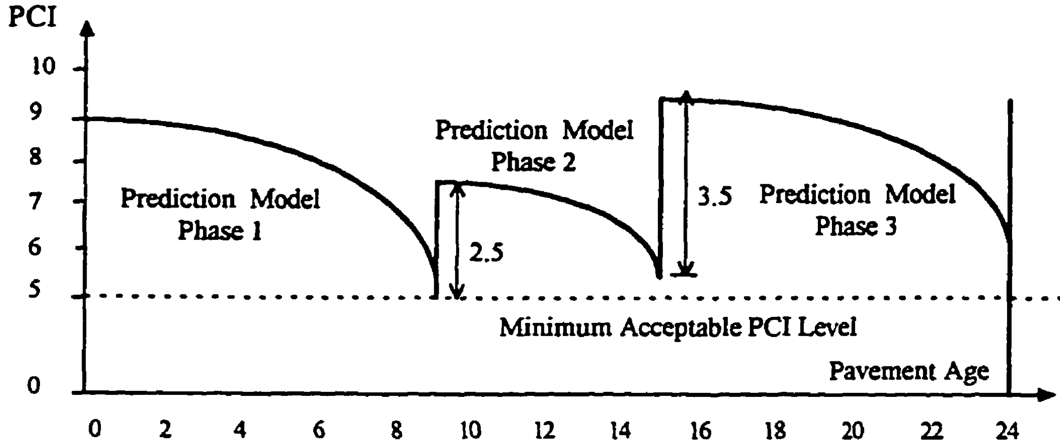
Additionally, the standardized M&R program also provides the highway agency with the ability to evaluate benefits and the budget requirements for various overall treatment alternatives. These benefits include the following:

- The ability to forecast future pavement conditions in the form of pavement condition state vectors.
- The ability to evaluate the effectiveness of various M&R treatment strategies for each pavement section quickly and efficiently.
- The ability to perform economic analysis of various maintenance and rehabilitation strategies.
- The ability to analyze options for timing the application of M&R treatments.
- The use of an objective process for considering projects for funding in a multi-year program.
- The provision of information needed by decision makers to effectively prioritize rehabilitation projects within the available funding constraints
- The ability to project funding needs to achieve overall agency goals, such as maintaining a particular condition level over time.

5.4 ILLUSTRATIVE EXAMPLE

The purpose of this section is to illustrate the integrated prediction of pavement performance with standardized M&R treatments and their impacts on the rate of pavement future deterioration. Figure 5.3 provides an example.

Within the analysis period of 24 years, two standardized pavement M&R treatments are applied. The first recovers the pavement PCI by 2.5 in the 9th year, while the second recovers PCI by 3.5 in the 15th year. After implementation of the two M&R treatments, the pavement structural thickness is increased to 808 mm after the 9th year and 868 m after the 15th year, respectively.



M&R Action Time		Year 9	Year 15
Type of M&R Treatment		Thin overlay (30 mm)	Milling, 50% Recycling, and resurfacing (30 mm increase in thickness)
M&R Treatment Effect		PCI is raised by 2.5 (or ΔPCI=2.5)	PCI is raised by 3.5 (or ΔPCI = 3.5)
Structural Changes	Initial Structure $H_e = 748$ mm	After treatment 1 $H'_e = 748+30\times2$ $= 808$ (mm)	After treatment 2 $H''_e = 828+30\times2$ $= 868$ (mm)
Prediction Model	Phase 1 ($PCI_0 = 9.0$)	Phase 2 ($PCI_0 = 7.5$)	Phase 3 ($PCI_0 = 9.5$)
Traffic	AADT in year 1 = 6500	AADT in Year 9 = 9200	AADT in Year 15 =12,000

* Equivalent granular base layer thickness

Figure 5.3 Integrated Multi-Year Prediction of Pavement Performance

Consequently, three separate pavement performance prediction models have to be developed by using the time-related Markov transition process modeling. Each one corresponds to one of three different pavement structures, initial pavement condition states and traffic volumes, as shown in the upper part of the figure. In this way, both the pavement treatment effects and their impacts on the rate of pavement future deterioration can be considered in the time-related performance prediction models. The input data for the pavement structure described in this example is taken from Highway 25 which is located in southern Ontario. The initial pavement thickness above the subgrade, H_e, is 748 mm in terms of equivalent granular base layer thickness, and its initial pavement condition index (PCI) is 9.0. The non-homogeneous Markov model defined in Chapter 4 was used to develop the performance predictions.

5.5 SUMMARY

In this chapter the concept of standardizing pavement maintenance and rehabilitation (M&R) for preservation of a road network has been discussed. The integrated performance prediction model with standardised M&R treatments provides a rational and dynamic pavement serviceability-age relationship over the entire analysis period, including the prediction model for the initial pavement structure and modified prediction models for the pavement structure after implementing each of the preservation actions. The objective of the integrated pavement management system is to provide decision makers with processed quantitative data for examining the impact of various alternative scenarios and probability analysis results to assist them in managing the pavement network more effectively and efficiently. Whether a pavement section should be selected or not for repair is directly influenced by performance models used in the PMS.

The process of determining a set of appropriate standardized M&R treatments for a regional road network has also been described in this chapter. It is required that each standardized treatment action include specific work content, structural design and construction criteria, treatment effect in terms of raising the PCS to a certain higher level, and treatment cost.

In conclusion, if the pavement performance analysis period goes beyond the initial service life, then separate or modified deterioration models should be developed to consider the effects of the selected preservation actions applied to the pavement within the design period. Thus, a comprehensive performance prediction model must be able to calculate the expected serviceability-age relationship over the entire analysis period, including the prediction model for the initial pavement structure and new or modified prediction models for the pavement structure after each preservation action.

CHAPTER 6

DEVELOPMENT OF MULTI-YEAR PRIORITIZATION PROGRAMS

6.1 INTRODUCTION

In the previous two chapters a non-homogeneous Markov model for predicting pavement deterioration and a set of M&R treatment strategies for pavement network preservation have been described. The next step in the integrated PMS is the multi-year priority programming which determines the optimal M&R projects or program for the network. Integer programming is a convenient tool for this purpose but it must be recognised that there can be different investment objectives for each of many individual pavement sections in the network and that considerable uncertainty may exist for future funding availability and prediction of individual pavement deterioration.

The basic components and requirements for the integrated PMS have been discussed in Chapter 3, together with the general structure of the network optimization model used to select projects and M&R treatments for pavement network preservation. The optimization is formulated on the concept of maximizing cost-effectiveness of the selected M&R projects through the time-related Markov prediction model combined with standardized M&R treatment strategies. Constraints include budget limitation, maximum improvement effect of a M&R treatment and the required minimum pavement serviceability levels.

Effectiveness is calculated as the product of the area under the performance curve and minimum acceptable PCS level, multiplied by section length and traffic volume. The life-cycle costs are expressed on a present worth basis.

The input requirements for the integer programming include the pavement network inventory data, available M&R treatment alternatives and their associated costs, the budget for each year in the programming period and the predicted performance for each pavement section. The outputs of the program include details of the recommended M&R projects for each pavement section in the program years, including their expected performance. Sensitivity to different budget levels, and summaries of the recommended M&R actions for each year in the analysis period are provided.

6.2 DEVELOPMENT OF THE NETWORK OPTIMIZATION SYSTEM

The objectives of the network optimization system are to determine the investments needed for the pavement network preservation and to produce the most cost-effective program of projects for each year. The optimization system can also be used to calculate the minimum budget requirements for maintaining a prescribed level of the pavement network performance or serviceability. In such a case, sensitivity analysis can be performed to test or evaluate annual budget effects.

As shown in Figure 6.1, the entire framework for carrying out the priority programming consists of five main components or subsystems: 1) classification of all pavements in the network and network information subsystem, 2) establishment of time-related Markov transition probability matrices for prediction of individual pavement condition deterioration and identification of current and future needs, which can be modified by means of Bayesian techniques through the observed pavement performance data, 3) development of a set of standardized M&R treatment strategies for each type of pavement in the network, 4) integer programming with a set of standardized M&R alternative actions and, 5) prioritization based on cost-effectiveness maximization.

The principles and methodology of establishing the non-homogeneous Markov prediction models have been discussed in Chapter 4. The identification of future needs employs the Markov model for the prediction of pavement deterioration section by section, where pavement network functional criteria or serviceability is defined.

Generation of a set of standardized and practical M&R treatment alternatives for the network preservation was discussed in Chapter 5. The purposes of using standardized M&R treatment strategies for the network are: a) to define the improvement effect of the treatment in terms of Pavement Condition State, PCS, which could be Pavement Condition Index (PCI), Pavement Serviceability Index (PSI), etc., b) to capture the impact or change on the existing pavement deterioration rate after applying any one of the standardized treatments.

Classification of Pavements in a Regional Highway Network

Input: Data of pavement inventory, design, materials and construction, Pavement types by structure and paving materials,

Output: Lists of classified pavements in the highway network

↓

Development of Non-Homogeneous Markov Prediction Models

Input: Traffic prediction model and environmental information, Computer programming of system conversion for establishing the non-homogeneous Markovian probabilistic prediction models,

Output: Time-related Markov transition probability matrices (TPMs), Bayesian update of the predicted PCS through observed data.

↓

Selection of A Set of Standardized M&R Strategies

Input: All feasible M&R treatments for the region where the pavement network is considered, local construction techniques & equipment, the existing pavement conditions and the minimum acceptable serviceability levels required for the pavements.

Output: A set of standardized M&R treatment strategies, defined by detailed work contents, treatment effects and costs.

↓

Cost-Effectiveness Based Integer Programming of M&R Treatments

Input: Time-related Markov transition probability matrices, all of the M&R strategy alternatives and corresponding treatment effects, costs and benefits,

Output: Optimal M&R treatment stream actions for each pavement, associated with treatment effects, benefits and costs.

↓

Prioritization of the Optimal Cost-Effectiveness

Input: All feasible M&R treatment alternatives and the associated benefits and costs for each section, performance prediction model for each pavement, available budget, weighting factors, etc.

Output: M&R actions during the programming years for each pavement section including do-nothing.

↓

A List of Optimal M&R Actions and Timing for All Pavement Sections

Figure 6.1 Overall Flow Chart of the Network Optimization Process

6.2.1 Cost-Effectiveness Based Pavement Network Optimization Model

In this study, probabilistic based integer programming is used to develop the multi-year M&R program of pavement network preservation. The probabilistic approach means that the state (pavement condition) at the next stage (year) is determined in the form of a probabilistic distribution or a mean value by the state and M&R strategy decision at the current stage. The time-related Markov transition probabilities generated from the non-homogeneous Markov prediction model are entered into the integer programming model and the output from the integer programming is a list of optimal M&R recommendations for the network.

The main variables used in the integer programming include pavement age, a number of defined pavement condition states, decision variables or M&R action alternatives, and treatment effects in terms of cost-effectiveness.

The optimal allocation of resources to a particular year and to the application of a particular treatment to a particular section can be determined by the integer programming. In this program, applying or not applying a M&R treatment action is represented by a 0-1 integer switch variable. A decision variable assigned the value 1 means that a treatment is applied; 0 means no treatment is assigned. The basic steps of carrying out this developed integer programming are summarized as follows:

1. Definitions of the pavement network to be considered for Multi-year M&R program, including pavement inventory data input, traffic prediction model, stages, programming period, condition states, terminal serviceability levels for all the pavements, cost, effectiveness, objective function and constraints, etc. In this study, the effectiveness is the areas between the pavement deterioration curve and the minimum acceptable level multiplied by the traffic volume and section length.
2. Select all feasible M&R treatments and then determine a set of standardized M&R strategies for the pavement network. Each standardized M&R action is defined by design, construction, cost and treatment effect.
3. Assign all possible M&R treatment strategies for the network in the first programming year, then find the most cost-effectiveness M&R treatment strategy. The cost for all of the selected M&R treatments in the first year should be less than the budget.

4. Determine pavement condition states in the second year. If a treatment was applied in the first year, the treatment effect in terms of rise in PCI of the pavement and adjustment of the pavement performance prediction model should be considered. If no treatment was assigned to a pavement, then the pavement condition state is determined by the original prediction model.

5. After completion of the second step described above, the condition state of each pavement section is known, than select the most cost-effectiveness M&R treatment strategies for the second programming year, under all the constraints and conditions in the second year.

6. Repeat steps 2 and 3 until all the programming years are considered with the optimal M&R treatment strategies assigned to each pavement.

7. Determine the cost and effectiveness for each pavement section and find the ratio of the total cost-effectiveness for each programming year.

The results from the integer programming produce the optimal M&R treatment strategies for each section on a year-by-year basis for a given budget and other constraints. The following is a list of definitions used in the integer programming:

- Each stage represents 1 year in the planning horizon. Because the cycle of seasonal climate occurs over one year, the stages are each individual year during the life-cycle or analysis period.

- The objective function is subject to three constraints: 1) the programming must choose but only one of the standardized M&R treatment strategies for each pavement section in each program year, 2) total cost for all the M&R strategies determined for the network in each programming year must be equal to or less than the budget of the year, and 3) the treatment effect of any M&R strategy including re-construction can not raise the pavement serviceability level higher than the highest serviceability level defined for the pavement.

- States are 10, 20, or 50 points of the general PCS value, which may be between 0 and 5 (Present Serviceability Index, PSI), 0 and 10 (Riding Comfort Index, RCI), or 0 and

100 (Pavement Condition Index, PCI). For example, the measure of PCI and 20 points of states can be defined as follows:

State	PCI value
20	100 - 95
19	94 - 90
18	89 - 85
17	84 - 80
16	79 - 75
15	74 - 70
14	69 - 65
13	64 - 60
12	59 - 55
11	54 - 50
9	49 - 45
8	44 - 40
7	39 - 35
6	34 - 30
5	29 - 25
4	24 - 20
3	19 - 15
2	14 - 10
1	9 - 5
0	4 - 0

- Decision variables represent a number of different maintenance and rehabilitation treatment strategies which can be applied to each pavement section.
- The objective function maximizes the total cost-effectiveness of all the M&R treatments applied to the network over the programming period.

6.2.2 General Formulation of the Optimization Model

The general formulation developed for the network optimisation, as shown in Equations [6.1] to [6.5], is multi-year integer programming of the optimal M&R actions for a given road network on a year-by-year basis. In the process of programming both M&R the treatment effects and their potential impacts on the rate of pavement future deterioration (or future M&R needs) are considered in the prediction model. This optimisation model is designed to maximise the total value of effectiveness/cost ratio for a pavement network with total S sections, M standardised M&R alternative treatment strategy options, and T programming years of analysis period. The objective function of the optimisation models, given budget limitations and other constraints, is to maximise the total value of cost-effectiveness, i.e., the total effectiveness/cost ratio of the network. The M&R treatment strategies (or projects) that produce the greatest cost-effectiveness of the network in each programming year are considered as the optimal M&R treatment actions, and therefore are given to the first priority as compared to all other alternative M&R programs. The total cost of implementing all the optimal M&R treatment actions assigned to the network in each programming year is calculated as the present worth. The effectiveness credited (or debited) to each pavement section is considered as the area between the predicted pavement performance curve and the minimum acceptable level multiplied by length and traffic volume of the pavement, and the sum of the effectiveness for all of the pavements in the network is the total effectiveness gained in that programming year. It should be noted that effectiveness calculated by using this method can be a positive value or a negative value, depending on whether the predicted pavement performance curve (i.e., the predicted pavement condition state) is above or below the minimum acceptable serviceability level of the pavement. For example, if the average PCI on a 10-km long highway section is now 43, the minimum acceptable PCI level required for the highway pavement is 45, assuming that this highway services traffic in amount of 50,000 ESALs during the programming year, then the calculated effectiveness will be $(43-45)\times 10\times 50000 = -100000$ (PCI-Length-Traffic).

As concerning negative effectiveness, it means that travel condition is below an economic evaluation based standard level or minimum acceptable serviceability level, which is related to speed, roughness and safety, etc. In other words, if pavement condition state is below the minimum acceptable level, it means extra user costs, including travel delay, extra gas consuming, fast vehicle depreciation, uncomfortable or unsafe driving environment, etc.

Generally, the objective function of the network optimisation model is:

$$\text{Maximise:} \quad \sum_{s=1}^{N}\left\{\sum_{m=1}^{M} X_{stm}\times\left[\frac{(PCS_{stm}-A_{st})\times L_{st}\times AADT_{st}\times D_{st}}{L_{st}\times W_{st}\times C_{stm}\times(1+R)^{-t}}\right]\right\}, \qquad \forall\, t \qquad [6.1]$$

and the objective function is subject to the following conditions or constraints:

$$\sum_{m=1}^{M} X_{stm} = 1, \qquad \forall\ s,\ t \tag{6.2}$$

$$X_{stm} = \begin{cases} 1 & \text{if maintenance alternative } m \text{ is selected for section } s \text{ in year } t \\ 0 & \text{otherwise} \end{cases} \tag{6.3}$$

$$\sum_{s=1}^{S}\sum_{m=1}^{M} X_{stm} \times \left(L_{st} \times W_{st} \times C_{stm}\right) \le B_t,\ for\ t = 1,\ 2,\ 3,\ \ldots, T \tag{6.4}$$

$$PCS_{s(t+1)} = PCS_{st} + (X_{stm}\Delta PCS_m) \le PCS_{\max}. \qquad \forall\ s,\ t, m \tag{6.5}$$

where

PCS_{st} = generalised Pavement Condition State (such as Pavement Condition Index, PCI, Present Serviceability Index, PSI, etc.) for section s (of S total sections in a road network) at year t (of T years of analysis period)

A_{st} = the minimum acceptable level of PCS required for pavement section s at year t, and (PCS_{st} - A_{st}) can be either positive or negative value,

L_{st} = length (km) of pavement section s in year t,

$AADT_{st}$ = Annual Average Daily Traffic carried on pavement section s in year t

D_{st} = number of service days for traffic flows by pavement section s in year t if treatment alternative strategy m is selected,

W_{st} = width (m) of pavement section s in year t,

C_{stm} = unit cost ($ / per square meter) of a standardised M&R treatment alternative strategy m is applied to pavement section s in year t,

R = discount rate for calculating present value of future cost,

B_t = budget limit for all the M&R actions in the network in programming year t

ΔPCS_m = treatment effect of a standardised M&R action, which is defined as an amount of PCS that can be recovered, from the existing Pavement Condition State, by the M&R action alternative m,

PCS_{max} = A maximum value of pavement condition state defined for a pavement. For examples: if PCS is defined by PSI in one case, which is measured on a scale of 0 to 10, with 10 being perfect, then the highest level of the PCS is 10, i.e., PSI_{max} is 10; if PCS is defined by PCI in another case, which is measured on a scale of 0 to 100, with 100 being perfect, then the highest level of the PCS is 100, i.e., PCI_{max} is 100. Considering the construction quality, reliability and many other factors, the maximum PCI of a pavement is usually defined as 95 in stead of 100 in real situations.

Detailed description of each above equation is stated as follows:

Equation [6.1] is the objective function of the optimisation model, which maximises the value of the total cost-effectiveness over the entire programming period. It is used to find the optimal M&R action program for the network in each programming year, as compared to all other alternative M&R action programs.

Equations [6.2] and [6.3] state that the total number of available standardised M&R treatment strategy options designed for the network is M. In each programming year one and only one of these M&R options for pavement section s must be chosen, which produces the highest cost-effectiveness from the network system point of review.

Equation [6.4] controls the maximum investments or annual budget available for the network maintenance and rehabilitation projects of each year. Within the period of multi-year M&R program, available budget of each programming year can be different from each other.

Equation [6.5] indicates that a pavement serviceability level (or pavement condition state, PCS) can not be higher than its the maximum level at any time. Actually, this constraint plays a role of "penalty function", which avoids the optimisation model from selecting projects for those pavements that have a high PCI but generate low economic benefit or effectiveness. For example, if a standardised M&R treatment strategy (such as rehabilitation action with 40 mm Hot-Mix asphalt overlay) that has the treatment effect of 40 points increase in PCI, i.e., $\Delta PCI = 40$, is applied to an existing pavement, it should raise PCI of the existing pavement by 40 after implementation of the action. However, if PCI of the existing pavement is currently 85, this M&R action can only raise the PCI of this pavement from 85 to the maximum level at 100 under the constraint by the penalty function, i.e., the actual treatment effect is 15 points of increase in PCI. As a result, effectiveness gained from this action will not be as much as expected. On the other hand, the cost for this action remains the same as it is applied to any other exiting pavements whose current PCI is 70 or even 50. Consequently, the cost-effectiveness is not significant in such a case, and the optimisation function will give up this M&R strategy option automatically and try other less costly but more effective M&R strategy.

6.2.3 Output Format of the Optimization model

The final products from the yearly based multi-year M&R integer programming for a pavement network includes costs for the selected M&R projects, treatment effects and total effectiveness/cost ratio. The output format is shown in Table 6.1, in which all pavement sections of the road network considered in the programming are listed in the first column, the remaining columns are the programming years in sequence.

Table 6.1 Output Format of M&R Network Program with Five Standardized Treatments

Pavement Section or LHRS Number	Programming Year of Pavement Network M&R Action															
	Year 1 (1993) M&R Alternative					Year 2 (1994) M&R Alternative					...	Year T (2003) M&R Alternative				
	1	2	3	4	5	1	2	3	4	5		1	2	3	4	5
1	X_{111}	X_{112}	X_{113}	X_{114}	X_{115}	X_{121}	X_{122}	X_{123}	X_{124}	X_{125}		X_{1T1}	X_{1T2}	X_{1T3}	X_{1T4}	X_{1T5}
2	X_{211}	X_{212}	X_{213}	X_{214}	X_{215}	X_{221}	X_{222}	X_{223}	X_{224}	X_{225}		X_{2T1}	X_{2T2}	X_{2T3}	X_{2T4}	X_{2T5}
⋮											⋮					
s	X_{s11}	X_{s12}	X_{s13}	X_{s14}	X_{s15}	X_{s21}	X_{s22}	X_{s23}	X_{s24}	X_{s25}		X_{sT1}	X_{sT2}	X_{sT3}	X_{sT4}	X_{sT5}
⋮											⋮					
N	X_{N11}	X_{N12}	X_{N13}	X_{N14}	X_{N15}	X_{N21}	X_{N22}	X_{N23}	X_{N24}	X_{N25}	...	X_{NT1}	X_{NT2}	X_{NT3}	X_{NT4}	X_{NT5}

Entries in the table are the most effective M&R treatments determined through the multi-year optimisation analysis for all of pavement sections in the network, with five standardised M&R treatment alternatives for *T* years of programming period. In each programming year, one of the five standardised M&R treatment alternatives, including do-nothing, has to be selected by the optimisation model for implementation. Taking highway section number 2 and s for example, in 1993 (year 1 of the program) treatment strategy 4 (i.e., Minor Rehabilitation) should be applied to the pavement 2, X_{224}, and strategy 1 (Do-Nothing) should be applied to Section s, X_{S11}; in 1994 (year 2 of the program) treatment strategy 1 (Do-Nothing) should be *applied* to the pavement 2, X_{221}, and strategy 3 (Major Maintenance) should be applied to Section s, X_{S23}; and so on. It should be noted that only one of the five alternative decision strategies can be selected for each pavement section at each year on the basis of the optimisation formulation and the annual budget constraints.

6.2.4 Example Application of the Optimization Model

To describe explicitly how the optimization model works, consider the following example, which involves five asphalt pavement sections and three standardized M&R strategies. The pavement condition state is determined by the time-related Markov probabilistic prediction model. Entries in Table 6.2 are section number, length and width, the number of 80 kN equivalent single axle loads (ESALs), condition state of the current year and predicted pavement condition states in the next 5 years. The prediction of future pavement condition state is based on the total number of 80 kN equivalent single axle loads (ESALs), pavement structural thickness, subgrade soil strength and no treatment action is applied in each year if the Ontario Pavement Analysis of Costs (OPAC) is employed.

Table 6.2 Predicted PCI Values of Pavement Sections in the Next Five Years

Section Number	Length/Width of Section (m)		Traffic Volume Annual 80 kN ESALs*	PCI**					
				Current Year	Programming Year 1	2	3	4	5
1	1500	15	2.9×10^5	79	74	68	63	55	50
2	1200	7.5	2.1×10^5	61	57	54	50	46	42
3	900	7.5	0.8×10^5	49	44	40	36	32	29
4	1400	12	1.4×10^5	89	84	79	74	70	64
5	1100	7.5	2.2×10^5	83	79	74	69	63	57

* 80 kN Equivalent Single Axle loads (ESALs)

** PCI values are calculated by Markov process-based prediction model.

The additional information needed includes the available treatment strategies, treatment effect and the cost of applying each alternative. Table 6.3 lists three standardized M&R treatment strategies for the small pavement network. Each of the strategies includes: 1) treatment effect in terms of raising the existing pavement condition state by a certain amount of PCI points, 2) treatment impact on the existing pavement in terms of structural change or increase on the pavement thickness as compared with the existing pavement and, 3) unit cost for implementing the M&R action.

Table 6.3 An Example Showing Feasible M&R Treatment Strategies

No. of Treatment Strategy	Treatment Effect and Impact	Cost ($/M^2)
No.1 Routine Maintenance	• Raise PCI by 0 • No structural change to pavement	0.3
No.2 Major Maintenance	• Raise PCI by 15 • Correct all pavement surface distresses (crack sealing, distortions and pothole patching, etc.) • Thin coat, or spraying • No structural change to pavement	9
No.3 Minor Rehabilitation	• Raise PCI by 30 • Milling old surface and resurfacing • 40 mm asphalt overlay resurfacing • Increase structural thickness by 40 mm of asphalt concrete surface layer	15

The objective to be achieved in this example is to maximize the total cost-effectiveness ratio of all M&R treatments over a 5-year programming period. To make the example as simple as possible, assume that the minimum acceptable PCI level is 45 for all of the pavement sections and the annual budgets are is $200,000, $150,000, $350,000, $150,000 and 100,000 for the programming years 1 through 5. In addition, annual traffic growth rate for all pavement sections is 4 % and discount rate is 5%. The solution obtained using the cost-effectiveness based optimization model is summarized as follows:

1. Optimal Multi-Year M&R Program for the Network

Table 6.4 gives a five-year M&R program developed for the small pavement network, together with the predicted PCI and the treatment effect for each pavement section in each programming year. The PCI at the first column in each programming year is predicted by the time-related Markov prediction model described in Chapter 4. The second column is outputs of the optimal M&R treatment strategies, which is based on the greatest yearly total effectiveness/ratio. The ΔPCI at the third column is the treatment effect corresponding to the selected M&R action in the programming year.

If action 1 (Routine Maintenance) is selected for a section in a programming year, there will be no rise in PCI of the pavement, and the PCI in the following year is input from the previously predicted PCI as shown in Table 6.2. However, if action 2 (Major Maintenance) or action 3 (Minor Rehabilitation) is selected, the treatment effect of the selected M&R action will be shown as a ΔPCI value at the end of this year. Then the PCI in the following year is the sum of PCI predicted by the previous time-related Markov model and the ΔPCI. The value of the modified PCI is marked by a bar at the bottom of it, i.e., <u>PCI</u> as shown in the table. Furthermore, after a PCI is assigned, the PCI in the following years are predicted by a new set of time-related Markov Tams, which are developed in considering the change in pavement structure or thickness. In other words, the impacts of the selected M&R action on the pavement future deterioration is considered.

For example, if we track down the optimal M&R program for pavement section 2 in the table, the PCI in the current year is 61, then M&R action 2, which raises the PCI of the pavement by 15, is selected as the optimal M&R strategy for this section in the first programming year. The 15 points of ΔPCI is added to the predicted PCI in the following programming year, i.e., PCI = 57, as shown in Table 6.1.

As a result, the total PCI in the beginning of the second year is 57+15 = 72. During year 2 and year 3, no major M&R action is needed, so there is no rise in PCI of the pavement, and the deterioration of the PCI in these two years is predicted by a adjusted Markov TPMs, which turns the PCI into 67 in year 2 and 62 in year 3, respectively. At the end of year 3, 30 points of PCI is added to the pavement at the beginning of year 4 as action 3 is selected as the optimal M&R treatment for this section. Finally, at the end of year 4, 15 points of PCI is added to this pavement section because alternative M&R action 2 has been chosen for the programming year 5.

Table 6.4 Program of Multi-Year M&R Treatment Strategies in the Next Five Years

Section Number	Predicted PCI, Selected Optimal M&R Actions for Programming Years 1 through 5														
	Current year	Year 1			Year 2			Year 3			Year 4			Year 5	
	PCI	PCI *	M&R **	ΔPCI ***	PCI	M&R	ΔPCI	PCI	M&R	ΔPCI	PCI	M&R	ΔPCI	PCI	M&R	ΔPCI
1	79	79	1	0	74	1	0	68	3	30	93	1	0	89	1	0
2	61	61	2	15	72	1	0	67	1	0	62	3	30	87	2	15
3	49	49	3	30	74	1	0	70	1	0	66	1	0	61	1	0
4	89	89	1	0	84	1	0	79	1	0	74	1	0	70	1	0
5	83	83	1	0	79	3	30	95	1	0	92	1	0	89	1	0

* Pavement Condition Index (PCI) predicted in each year.

** Maintenance or Rehabilitation (M&R)action selected for implementation.

*** Rise in Pavement Condition Index (ΔPCI) after implementing a R&M action.

2. Cost-Effectiveness Analysis of the M&R Program of the Network

Information about costs and benefits in terms of effectiveness is summarized in Table 6.5 and Table 6.6, respectively. Entries in Table 5 include pavement section number, area of pavement surface of each section and allocation of the annual budget to the network. In the column of each programming year are the selected optimal M&R actions and the corresponding costs for all the pavement sections. In addition, the annual budget limitation and actual spending in each programming year are listed in the last two rows of the table. The total cost of M&R program for each pavement section during the five years analysis period is provided in the last column of the table.

Table 6.6 demonstrates the calculated effectiveness that can be produced by the network under the condition of the recommended M&R program. It should be indicated that traffic growth is not considered in the calculations of effectiveness of each programming year. The very important information included in the table is the calculated total effectiveness of each pavement shown in the last column. The order of the most effectiveness produced by each pavement during the analysis period is the section No. 1, 2, 5, 4 and 3. The section 1 services the highest traffic volume and it takes about one quarter of the total length of the network. Logically, this pavement section should have a high priority for its preservation program on the basis of cost-effectiveness evaluation. As a matter of fact, this pavement has received a good M&R treatment program developed by the optimization model since its PCI is maintained at a high level, as shown in Table 6.4. The same conclusions can be applied to section 2 and 5.

As pavement section 3 is concerned, there is no significant effectiveness that can be generated because this pavement services low traffic and it is relatively short in length. Therefore, the section should have the lowest priority in M&R programming. As a matter of fact, the optimization programming did not assign any major M&R treatment action to it in the programming period except in the current year.

The reason for receiving the major M&R action in the current is due to the minimum acceptable requirement and the penalty function (may appear negative effective if no major M&R action is applied on it) in the optimization model. Much more information and optimization analysis can be drawn from these table on the basis of economic evaluation, but it is not necessary to list all of them in this study.

Table 6.5 M&R Treatment Actions and Costs for Each Section in Each Programming Years

Section Number	Section Area	Allocation of the Annual Investment to the M&R Program										
		Year 1		Year 2		Year 3		Year 4		Year 5		Total Cost
	L×W(m^2)	M&R	$ $\times 10^3$	M&R	$ $\times 10^3$	M&R	$ $\times 10^3$	M&R	$ $\times 10^3$	M&R	$ $\times 10^3$	$ ($\times 10^3$)
1	22500	1	6.7	1	6.7	3	338	1	6.7	1	6.7	364.8
2	9000	2	81	1	2.7	1	2.7	3	135	2	81	302.4
3	6750	2	101	1	2	1	2	1	2	1	2	109.0
4	16800	1	5	1	5	1	5	1	5	1	5	25.0
5	8252	1	2.5	3	124	1	2.5	1	2.5	1	2.5	134.0
Budget ($\times 10^3$)		200		150		350		150		100		950
Spending ($\times 10^3$)		196.2		140.4		350.2		151.2		97.2		935.2

This example has illustrated the M&R program for the five pavement sections in the period of five analysis years with 3 alternative M&R strategy options. The cost of M&R treatments assigned to each pavement section listed in Table 6.4 can be calculated for the programming years 1 through 5, as shown in Table 6.5. Similarly, effectiveness provided by the selected optimal M&R projects for each pavement can also be calculated on the basis of predicted PCI, served traffic volume and the minimum acceptable PCI level, as shown in Table 6.6.

Table 6.6 Pavement PCI and Effectiveness of Each Section in Each Programming Year

Section Number	Section Length (M)	ESALs ($\times 10^5$)	PCI and Effectiveness Based on the M&R Program										
			Year 1		Year 2		Year 3		Year 4		Year 5		Total
			M&R No.	Effec. ($\times 10^8$)	M&R No.	Effec. ($\times 10^8$)	M&R No.	Effec. ($\times 10^8$)	M&R No.	Effec. ($\times 10^8$)	M&R No.	Effec. ($\times 10^8$)	Effectiveness ($\times 10^8$)
1	1500	2.9	1	126.15	1	100.05	3	208.80	1	191.40	1	169.65	796.05
2	1200	2.1	2	68.04	1	55.44	1	42.84	3	105.84	2	126.00	398.16
3	900	0.8	3	20.88	1	18.00	1	15.12	1	11.55	1	8.64	74.19
4	11400	1.4	1	76.44	1	66.64	1	56.84	1	49.00	1	37.24	286.16
5	1100	2.2	1	82.28	3	121.00	1	113.74	1	106.48	1	96.80	520.30
Total Effectiveness ($\times 10^8$)			373.79		361.13		437.37		464.24		438.33		2074.86

6.3 SUMMARY AND DISCUSSIONS

This Chapter discussed the integrated multi-year M&R optimization model developed for pavement network preservation through cost-effectiveness analysis. The optimization model can be used in the integrated PMS to produce the optimal multi-year M&R program for the network preservation under the constraints of annual budget limitation and requirements of pavement serviceability. The decisions made on the M&R treatment strategies for each pavement section are based on the integration of the optimization system with the following three sub-systems:

1. The time-related Markov probabilistic prediction model
2. A set of standardized M&R treatment strategies to be used in the network preservation, which consider treatment effects of the M&R actions and their impacts on future deterioration or pavement future M&R needs.
3. Cost-effectiveness based yearly integer programming of multi-year M&R actions for the pavement network under the constraints of available funds.

The output from this program are a list of M&R treatment strategies for the network in each programming year and a list of M&R program for individual pavement improvements within the programming analysis period. All feasible combinations of M&R treatment strategies for each pavement section along the programming years are compared in the process of year-by-year integer programming, and the best one is selected for implementation on the basis of their economic consequences.

The developed multi-year integer programming uses the concept of maximizing the total effectiveness/cost ratio of the network as a objective function. Although a minimum acceptable serviceability level is defined for each pavement, a M&R project may be assigned to the pavement that has not reached, or even fairly higher than, its minimum acceptable serviceability level. This is different from many existing priority programs which will not consider a major M&R action for the pavement until it reaches the minimum acceptable serviceability level. In other words, many of the existing priority programs may be suffered a serious limitations because, under certain circumstance, the rehabilitation of a pavement before its terminal serviceability level is reached may be more economical.

In conclusion, the time-related Markov process based multi-year integer programming developed in this study provides a very powerful tool for selecting the optimal M&R treatment strategies and programming pavement network improvements. It has been shown to be an efficient means of solving the pavement management optimization problems. The results from the model are promising, but more work should be conducted to make the procedure directly implemented by provincial departments of transportation for their PMSs.

CHAPTER 7

APPLICATION OF THE INTEGRATED PMS TO AN ONTARIO HIGHWAY NETWORK

A comprehensive application of the pavement network multi-year project selection and M&R treatment strategy priority programming to an Ontario highway network is described in this Chapter. Through this study, the potential applications of the computerized integration of pavement performance prediction model with network M&R optimization system are demonstrated. Some issues on data sets with standard format input, features of the outputs, sensitivity of the network optimization model to some of the input factors, and summary of findings are briefly discussed.

7.1 BACKGROUND AND STATEMENT OF THE APPLICATION

To demonstrate the potential applications of the multi-year pavement network M&R optimization model, a total of 670 lane-kilometers of different class of highways is taken from the Ontario highway system as an example application. The network is composed of 18 asphalt pavement sections with different lengths (ranging from 1.5 to 15.2 kilometers) and widths (ranging from 6.5 to 17 meters). Table 7.1 shows the pavement network information data, including pavement section code, section length and width, daily traffic volume including truck percent, pavement thickness, subgrade soil modulus and PCI in 1993.

The deterministic-based prediction model which was converted into a Markov probabilistic prediction model is the existing Ontario Pavement Analysis of Costs (OPAC) model. It is a deflection-based model for the prediction of flexible pavement deterioration and life-cycle cost analysis. The model was originally developed in the early 1970's through a combination of the outcomes of three fundamental research: 1) the performance of pavements measured at the AASHO Road Test; 2) the principles of applied mechanics in multi-layered asphalt elastic pavement systems, and 3) the long-term environment-oriented Brampton Road Test in Ontario. The OPAC performance model is one of the few models that separate traffic-induced deterioration from environment-induced deterioration. The Model is based on the assumption

Table 7.1 Sectional Data for A Sample Ontario Asphalt Pavement Network

Ontario Highway Number	Pavement Code (LHRS[1])	Section Length/Width (m)	Traffic Volume AADT/Truck% (in Year 1993)	Thickness[2] (mm)	Subgrade Layer Coeff.[3] /Code	Observed PCI[4] in 1993
79	37320	15200 / 6.7	2150 / 13.0	871	4500 / 3	63
25	25480	9000 / 6.8	5700 / 11.7	1110	4500 / 3	74
28	26420	9300 /6.5	500 / 11.0	531	5000 / 2	67
11-A	17000	2900 /14.6	21250 / 10.0	690	6000 / 1	60
132	44720	2500 / 6.5	1000 / 38.0	531	5000 / 2	69
1	10014	7500 / 7.1	28000 / 21.0	1193	4500 / 3	62
7-A	14421	4900 /17.0	57300 / 6.4	1107	4500 / 3	64
2-A	10850	4700 / 15.8	28000 / 3.1	681	6000 / 2	68
2-B	10840	6700 / 14.6	28100 / 3.6	844	5000 / 2	70
11-B	16970	8200 / 14.6	18200 / 14.0	779	5000 / 2	47
402	48225	7200 / 14.6	14500 / 35.0	738	6000 / 1	66
60	33250	1600 / 6.7	1850 / 11.0	550	5000 / 2	83
31	27060	8800 / 7.3	6000 / 11.5	831	5000 / 2	85
7-B	14530	1700 / 7.3	6200 / 10.9	891	4500 / 3	66
138	45420	1290 / 7.3	6000 / 13.4	951	4500 / 3	63
36	28245	4000 / 6.7	1350 / 5.7	671	4500 / 3	71
148	46280	5300 / 6.7	3150 / 7.0	688	4500 / 3	75
16	20200	1500 / 14.6	3000 / 12.1	810	5000 / 2	52

Notes:

1) Linear Highway Reference System (LHRS), coded in the Highway Inventory Management System (HIMS), Ministry of Transportation of Ontario, Canada.
2) Total equivalent granular thickness of pavement calculated by OPAC Model.
3) Resilient modulus of subgrade soil.
4) PCI is a function of measured riding comfort rating (RCR) and distress manifestation index (DMI) and it is on a scale of 0-100.

that repeated subgrade deflections will eventually lead to a decrease in riding quality. The subgrade deflection is calculated using the Odemark procedure in which the pavement structure is assumed to be a multi-layered system and is then transformed into an equivalent granular system by means of equivalency factors. A detailed description of the performance prediction model, including variables input, calculation of traffic and environment related deterioration, and some constraints of using this system, is documented in OPAC (117).

In the OPAC deterioration model, the amount of decrease in pavement condition state in terms of PCI is a function of the following input variables:

1) number of 80 kN Equivalent Single Axle Load (ESAL) applications to be applied on the pavement,
2) subgrade modulus coefficient or soil strength,
3) total equivalent pavement granular base layer thickness, and
4) environment related factors.

In real situations, it is difficult to determine the values of these variables because of uncertainties and variations involved. For example, the number of annual ESAL applications forecast by the OPAC traffic model is not likely to be the same number of 80 kN ESALs that are actually applied on the pavement. This is because such factors as traffic volume, growth rate, truck percent, traffic distribution factor, and truck factors can not be predicted with a great degree of certainty. Similarly, the input values of subgrade soil strength or modulus coefficient and equivalent pavement thickness may not represent their actual values in the field because of the variations in determining these factors by testing samples.

However, each of these factors or variables, such as traffic loads in terms of ESALs, traffic growth rate, pavement thickness, subgrade soil strength, etc., has a significant influence on the rate of pavement deterioration in the OPAC system. Therefore, it is essential to use a probabilistic-based prediction model for the performance-age relationship and analysis of the pavement network M&R optimization.

Based on the investigations conducted by many previous pavement researches and engineers, the input pavement design variables such as number of ESALs applied on a pavement in each year, subgrade soil strength and pavement thickness in terms of equivalent granular base layer, will not be the same values as they actually appear in the real situations. As a result, it was concluded that each of these design variables should be considered as normally distributed random variables (118, 119).

In Ontario, pavement condition index (PCI) is a function of two measured pavement parameters: the ride comfort rating (RCR) and the distress manifestation index (DMI). The RCR is directly related pavement roughness and DMI stands for a composite, subjective measure, multi-attribute measure of extent and severity of 15 pavement distress manifestations:

$$\mathrm{DMI} = \sum_{i=1}^{15} w_i (s_i + d_i) \qquad [7.1]$$

where w_i is a weighting value representing the relative weight of the distress manifestation i, d_i and s_i are a measured density (or extent) and severity for the distress type i, respectively.

7.2 APPLICATION AND OUTPUTS OF THE INTEGRATED PMS

All of the pavements in this highway network are flexible or asphalt pavements. The OPAC flexible pavement design model considers both the traffic effects (P_T) and the environmental effects (P_E) on pavement deterioration. Formulations for the traffic and environment related deterioration, P_T and P_E, are expressed in the following equations:

$$P_T = 2.4455\Psi + 8.805\Psi^3, \qquad [7.2]$$

$$P_E = (PCI_0 - \frac{PCI_0}{1+Bw})(1-e^{-\alpha Y}), \qquad [7.3]$$

where $\Psi = 3.7238\times 10^{-6} w^6 N$, w is the subgrade deflection (mm) and is determined by equation:

$$w = \frac{9000\times 25.4}{2M_s\left(0.9H_e\sqrt[3]{\frac{M_2}{M_s}}\right)\sqrt{1+\frac{6.4}{0.9H_e\sqrt[3]{\frac{M_2}{M_s}}}}} \; ; \qquad [7.4]$$

PCI_0 = as-built Pavement Condition Index, PCI (scale of 0 to 100);
H_e = total pavement equivalent granular base thickness;
N = the number of ESALs that changes the pavement by an amount P_T;
M_2 = modulus of granular base layer;

M_s = modulus of subgrade soil;
B = regional factor 1, B = 60 in southern Ontario;
α = regional factor 2, α = 0.006 in southern Ontario;
Y = number of years.

The typical steps for performing the pavement network multi-year project selection M&R treatment strategies priority programming include the following:

1. Computer programming of the system conversion process from the OPAC-based deterministic model to a multi-year Markov probabilistic prediction model.
2. Prediction of the pavement deterioration-age relationship for each individual pavement section in the network by using the time-related Markov prediction model.
3. Development of feasible pavement repair alternatives and determination of a set of standardized M&R treatment strategies for the pavement network preservation purposes.
4. Selection of appropriate projects for each programming year, determination of multi-year M&R treatment strategies for the network optimization through integer programming, and integration of pavement performance prediction with M&R treatment effects.

7.2.1 Computer Program of the System Conversion Between Prediction Models

The concepts and principles underlying the system conversion between deterministic and probabilistic prediction models have been described in Chapter 4. The output from the process is a sequence of time-related transition probability matrices (TPMs).

A FORTRAN program was written to increase the computation efficiency of the prediction model conversion and calculation of the time-related TPMs for all pavement sections in the network. The priority programming is performed by means of an optimization package called GAMS, which performs a life-cycle economic analysis to identify the optimal cost-effective M&R treatment strategies for the pavement network.

The program works in two main phases. In the first phase the prediction of pavement condition states is performed for each individual pavement section in the network, based on the existing pavement network database and information input. The prediction of future pavement condition states is obtained from the Markov process without considering major

M&R project actions. In the second phase, the GAMS optimization programming uses the information supplied by the first phase and produces a multi-year M&R treatment priority list for the network on a year-by-year basis. The data input for the second phase includes the M&R treatment effect in terms of rise in PCI and new pavement thickness in addition to the previous database and information input. The programming period and budget for each programming year are also required for the program. Some numerical methods and computations involved in this subroutine include the following:

1. Definition of a set of appropriate independent variables (or variable string) that are included in the OPAC performance model for the prediction of pavement deterioration versus age.
2. Generation of independent random variables of the normal distribution (or other types of probability distribution) through Monte Carlo simulation techniques.
3. Calculation of each element of the probability transition matrix to be used in the time-related Markov chain modeling of pavement deterioration on the basis of applied reliability concept in pavement design analysis.
4. Establishment of the time-related Markov TPMs and pavement condition state vectors for all the pavement sections in the network. Outputs of the TPMs and vectors in each year for each pavement section are saved as database for pavement needs identification and multi-year M&R treatment programming.
5. Bayesian update of the predicted TPMs and pavement condition state vectors through observed pavement performance data.

The FORTRAN program subroutine for converting the deterministic-based OPAC prediction model to its corresponding time-related Markov probabilistic prediction model is presented in Appendix.

7.2.2 Prediction of Pavement Deterioration Using the Markov Probabilistic Model

Through the process of prediction model system conversion described in the previous section, the OPAC prediction model can be transformed into a sequence of time-related Markov transition probability matrices (TPMs), which can be used to predict future pavement condition states with the following unique features:

1. Given the input data and information required for the OPAC prediction model, the computerized computation of a corresponding probabilistic Markov prediction model in terms of TPMs can be established. The model and technique developed for the prediction model system conversion provides a special tool to build the Markov TPMs effectively and efficiently.

2. The TPMs are developed for each individual pavement section. In this application, each of the 18 pavement sections is modeled individually on the basis of pavement prediction input variables, such as annual traffic volume and growth rate, pavement structural thickness and subgrade soil conditions.

3. The deterioration of each pavement is modeled as a non-homogeneous (or time-related) Markov transition process. In other words, if the analysis period for a pavement performance is 10 years, and every single year is considered as a stage, then a sequence of 10 TPMs will be established for the prediction of the pavement deterioration in each of the 10 years.

4. Prediction accuracy is achieved by dividing the Pavement Condition Index (PCI) into more detailed grades, so that a small amount of pavement functional deterioration in terms of losing PCI points can be measured or captured by using the Monte Carlo simulation techniques.

5. Determination of optimal maintenance or rehabilitation projects in terms of cost-effective benefits for each section in the network and action years, which is based on the current and future needs analysis associated with the comprehensive pavement performance prediction.

Entries in Table 7.2 (A) through (C) are the outputs of three TPMs established for prediction of pavement deterioration in year 2, year 4 and year 7, respectively. The pavement is taken from Highway 31, which is listed in Table 7.1. The PCI is classified by 25 grades, with the interval being 4 units of PCI. It may be seen that the TPMs are different from each other, implying that the rate of the pavement deterioration changes from year to year.

Table 7.2 A Set of Time-Related TPMs for Predicting Pavement Deterioration

(A) TPM of the Pavement Deterioration in Year 2

	96	92	88	84	80	76	72	68	64	60	56	52	48	44	40
96	0.156	0.785	0.052	0	0	0	0	0	0	0	0	0	0	0	0
92		0.190	0.757	0.049	0	0	0	0	0	0	0	0	0	0	0
88			0.224	0.732	0.039	0	0	0	0	0	0	0	0	0	0
84				0.274	0.686	0.037	0	0	0	0	0	0	0	0	0
80					0.313	0.663	0.020	0	0	0	0	0	0	0	0
76						0.378	0.595	0.023	0	0	0	0	0	0	0
72							0.445	0.530	0.023	0	0	0	0	0	0
68								0.493	0.486	0.020	0	0	0	0	0
64									0.529	0.450	0.021	0	0	0	0
60										0.563	0.413	0.022	0	0	0
56											0.582	0.393	0.022	0	0
52												0.624	0.359	0.016	0
48													0.674	0.316	0.010

(B) TPM of the Pavement Deterioration in Year 4

	96	92	88	84	80	76	72	68	64	60	56	52	48	44	40
96	0.220	0.703	0.060												
92		0.234	0.700	0.056											
88			0.273	0.661	0.060										
84				0.311	0.638	0.045									
80					0.330	0.629	0.033								
76						0.391	0.563	0.035							
72							0.446	0.510	0.040						
68								0.485	0.477	0.034					
64									0.505	0.456	0.031				
60										0.537	0.423	0.035			
56											0.555	0.405	0.032		
52												0.587	0.380	0.027	
48													0.628	0.344	0.026

(C) TPM of the Pavement Deterioration in Year 7

	96	92	88	84	80	76	72	68	64	60	56	52	48	44	40
96	0.274	0.602	0.095												
92		0.281	0.618	0.071											
88			0.302	0.602	0.076										
84				0.328	0.573	0.077									
80					0.339	0.578	0.065								
76						0.384	0.541	0.054							
72							0.425	0.498	0.060						
68								0.459	0.463	0.062					
64									0.476	0.447	0.062				
60										0.490	0.422	0.067			
56											0.497	0.433	0.047		
52												0.529	0.395	0.060	
48													0.548	0.396	0.046

7.2.3 Generation of a Set of Standardized M&R Treatment Alternatives

For the example application, a set of five standardized asphalt pavement M&R treatment strategies has been developed for use in the network optimization system. As shown in Figure 7.1, these five M&R treatment strategies are: 1) Do-Nothing, 2) Routine Maintenance, 3) Major Maintenance, 4) Minor Rehabilitation, and 5) Major Rehabilitation. Each of the five treatment strategies is defined by pavement repair action, work content, construction quality, unit cost and treatment effect on the existing pavement.

It should be noted that these pavement M&R treatment strategies were designed in accordance with the *Pavement Design and Rehabilitation Manual* (116), which was developed by the Ontario Ministry of Transportation in 1990 and was directed to guiding asphalt M&R treatment strategies for Ontario situations.

The minimum level of PCI for all the pavements in the network was chosen to be 45. The unit cost for each of the five treatments is based on the information of average pavement construction and maintenance costs in Ontario. In this example, the cost for each treatment activity is 0, 5, 7, 14, and 20 dollars per square meter.

In addition, the treatment effect of a M&R action on improvement of the existing pavement serviceability is defined in terms of rising the existing pavement PCI up to a certain amount. In other words, after implementation of a preservation action, the pavement surface quality in terms of Pavement Condition Index, PCI, will rise to a higher level, depending on which treatment strategy is selected. For instance, if a Routine Maintenance is selected for year t, then a rise of 0-5 units of PCI can be obtained in that year, and there should be a small jump in that year on the performance prediction curves. Alternatively, if a minor rehabilitation treatment, i.e., strategy 4 is selected in year t, then the PCI of the pavement will be increased by 25-35 units in that year. Following the PCI jump point, where a treatment action is applied, a new deterioration model, which reflects the improved pavement structure by the treatment, should be established to predict the pavement deterioration in year $t+1$. The procedure is repeated in each consecutive year until the entire analysis period is completed for the integrated performance prediction.

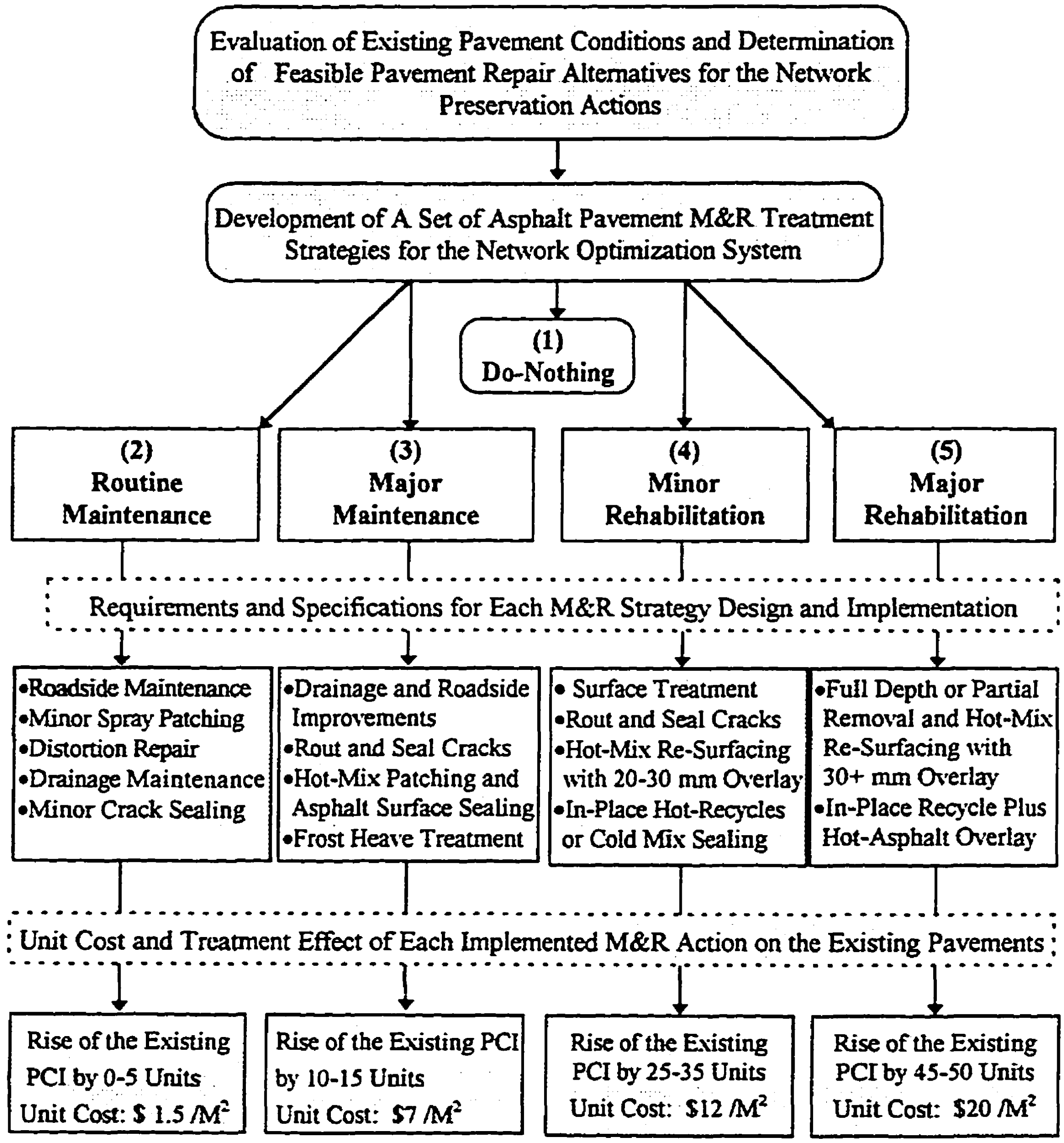


Figure 7.1 Generation of Five Standardized Asphalt M&R Treatment Strategies

7.2.4 Selection of Optimal M&R Strategies for The Network Preservation

After completion of the steps shown in Figure 7.2, a foundation on which a multi-year project selection and M&R treatment strategy for the pavement network optimization can be established. Outputs from the previous steps provide the following information and database:

- A framework and computer program for establishing a time-related Markov probabilistic prediction model, which is achieved by step 1 through the process of OPAC prediction model system conversion.
- A sequence of TPMs and pavement condition state vectors predicted for each of the 18 pavement sections in the network. It should be noted that outputs from step 2 are the predicted pavement condition states (or PCI) without considering M&R treatment actions except for Do-Nothing strategy. In addition, Bayesian update of the predicted pavement condition states in each programming year can be performed in this step if observed pavement performance database becomes available in the future. These predicted PCI's for each pavement are then saved as a database that will be used for project identification and M&R priority programming in step 4.
- Step 3 exports a set of standardized M&R treatment strategies for appropriate applications in the network optimization programming.

The next step is to select appropriate projects and determine multi-year M&R treatment strategies for the pavement network through the computerized optimization programming. In this case study, the optimization model presented in Chapter 6 has been used to perform project selection and M&R treatment strategy assignments to the pavement network. The objective function of the optimization model is to maximize total cost-effectiveness calculated from the network performance and M&R costs on a year-by-year basis.

Formulation of the pavement network optimization model and some conditions subjected to the optimization are described by Equations [6.1] to [6.4]. In addition, a penalty function, as described by Equation [6.5] in the model, is used to identify the optimal cost-effective M&R treatment strategies for the pavement network preservation.

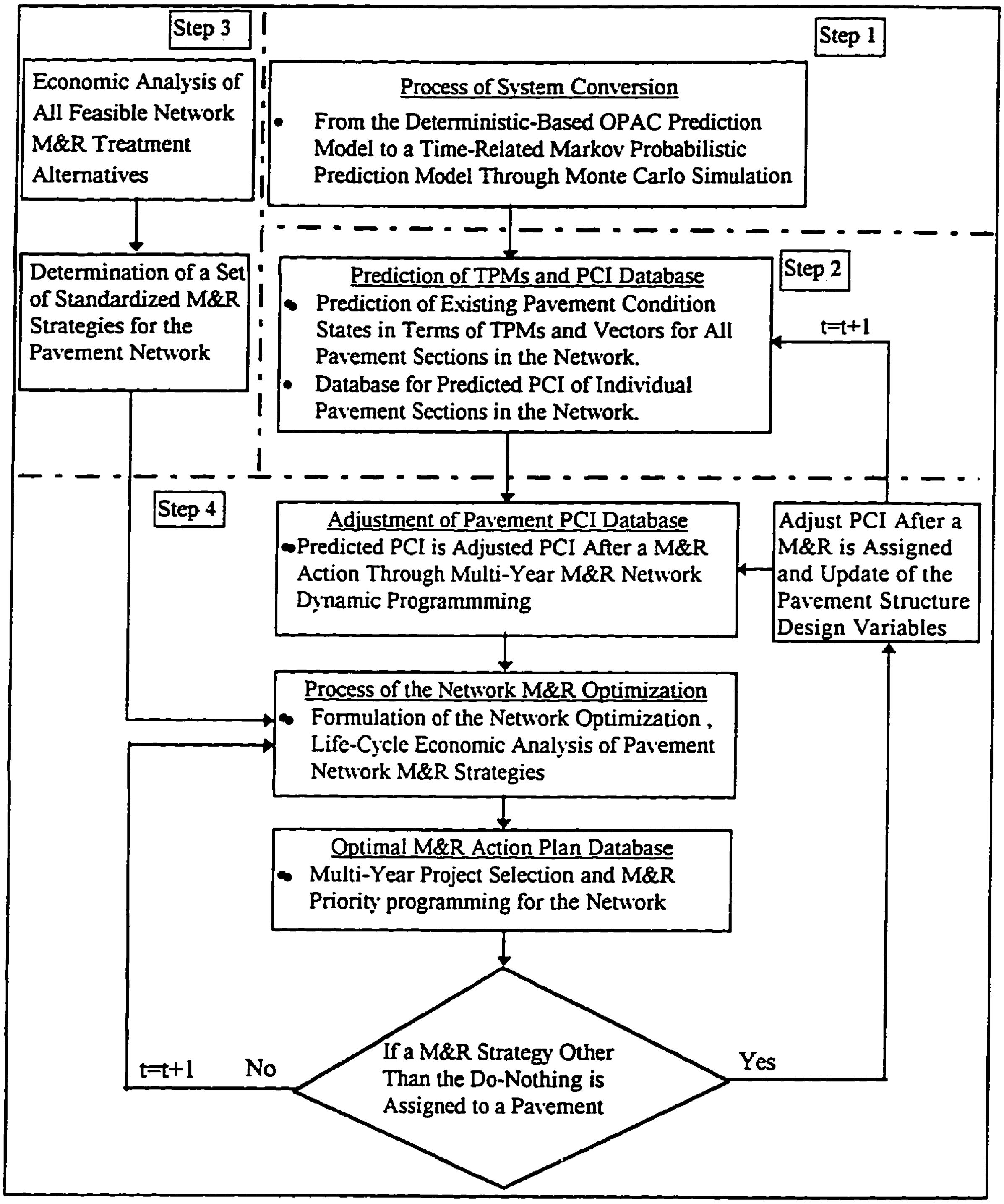


Figure 7.2 Flow Chart of the Integrated Pavement Network Optimization System

One of the main features designed for the network optimization system is that, after the selection of the appropriate projects and the assignment M&R treatment actions to the network in each year, the predicted PCI for each pavement is updated if other than Do-Nothing strategy option is assigned for the pavement in year t. The updated PCI is recorded as the pavement condition state in year t. Then the time-related Markov model is modified by using new data of the input variables, such as initial PCI_0 (PCI_t is now considered as PCI_0) and total pavement thickness after the M&R treatment. In other words, the treatment effect and its impact on the rate of future pavement deterioration (after year t) are considered for the prediction of pavement deterioration after the M&R treatment is applied in year t. The process is repeated until completion of the M&R action assignments for the all the programming years.

Tables 7.3A and 7.3B are the outputs showing the recommended pavement network multi-year projects and M&R treatment strategies for the pavement network optimization, integrated with time-related Markov prediction of pavement deterioration. Table 7.3A shows the priority programming of the pavement network preservation action plans for the first five years (from 1993 to 1997), and Table 7.3B presents the second five years (from 1998 to 2003) of priority programming. The predicted pavement condition state in terms of PCI of all the pavement sections in each year is also shown in the tables. It should be indicated that an annual budget of $3 million dollars is used to perform the network multi-year maintenance and rehabilitation programming. It is obvious that, from these two tables of the programming outputs, priorities for pavement treatments are given to those sections which have lower PCI, but higher traffic volume. In other words, if two pavement section have the same PCI but different traffic volume in a programming year, then a treatment priority will be given to the one with higher traffic volume if the budget is available in that year. It should be noted that the mean value of the network PCI will be increased to 7.88 in 2003 from 6.70 in 1993 if the annual budget of $3 million can be provided for 10 years period.

Illustrated in Figure 7.3A and Figure 7.3B are an alternative way to present the predicted pavement performance integrated with M&R strategy priority programming. Each of the figures gives the integrated pavement performance, M&R action and age relationship for four different highways. The programming results for other pavement sections in the network can also be displayed in the same way.

Table 7.3A Multi-Year Pavement Network M&R Treatment Action Plans (1992-1997)

Ontario Highway No. /LHRS No.	Multi-Year Pavement Condition States and M&R Treatment Strategies											
	1992		1993		1994		1995		1996		1997	
	PCI	M&R No.	PCI	M&R No.	PCI	M&R No.	PCI	M&R No.	PCI	M&R No.	PCI	M&R No.
79 / 37320	63	4	92	1	87	1	79	1	70	1	59	3
25 / 25480	74	1	70	1	66	1	59	1	50	4	80	1
28 / 26420	67	3	79	1	75	2	72	1	67	1	59	1
11-A / 17000	60	1	55	1	47	1	38	5	95	1	87	1
132 / 44720	69	1	66	3	71	1	65	1	55	1	50	4
1 / 10014	62	1	59	1	57	1	53	1	48	4	78	1
7-A / 14421	64	1	63	1	56	1	47	4	77	1	75	1
2-A / 10850	68	1	65	1	59	1	50	1	46	2	55	4
2-B / 10840	70	1	68	1	64	1	59	1	59	1	47	4
11-B / 16970	47	3	56	4	79	1	70	1	57	1	87	1
402 / 48225	66	1	58	3	62	4	84	1	75	1	66	1
60 / 33250	83	1	78	1	69	1	56	1	52	1	82	1
31 / 27060	85	1	83	1	75	1	64	4	90	1	86	1
7-B / 14530	66	1	64	1	57	1	48	2	51	1	48	1
138 / 45420	63	1	60	1	55	3	77	1	71	1	65	1
36 / 28245	71	1	69	2	68	1	65	3	80	1	76	1
148 / 46280	75	1	74	1	68	1	60	1	55	3	70	1
16 / 20200	52	4	81	1	80	1	73	1	64	1	58	4

Table 7.3B Multi-Year Pavement Network M&R Treatment Action Plans (1998-2003)

Ontario Highway No. /LHRS No.	Multi-Year Pavement Condition States and M&R Treatment Strategies										
	1998		1999		2000		2001		2002		2003
	PCI	M&R No.	PCI	M&R No.	PCI	M&R No.	PCI	M&R No.	PCI	M&R No.	PCI
79 / 37320	74	1	74	2	72	2	72	3	83	2	83
25 / 25480	78	1	73	3	88	1	83	2	84	1	80
28 / 26420	53	4	83	1	79	2	77	3	89	2	90
11-A / 17000	76	3	89	1	80	1	77	1	72	3	82
132 / 44720	76	1	73	1	63	4	88	1	83	1	79
1 / 10014	76	1	72	1	65	1	61	1	56	1	52
7-A / 14421	70	1	65	1	61	4	87	1	83	1	79
2-A / 10850	85	1	80	1	76	1	72	1	68	1	60
2-B / 10840	85	1	83	1	79	1	76	1	70	3	80
11-B / 16970	78	4	69	3	81	1	78	3	88	1	82
402 / 48225	61	1	96	1	82	1	78	3	89	2	89
60 / 33250	79	3	91	1	77	2	77	1	71	3	82
31 / 27060	77	1	71	3	83	1	77	1	72	3	81
7-B / 14530	43	4	72	1	67	1	63	1	56	1	51
138 / 45420	60	4	83	1	79	2	79	1	76	1	70
36 / 28245	69	3	80	2	78	3	79	2	79	3	88
148 / 46280	70	1	65	4	91	1	870	1	82	1	79
16 / 20200	83	1	79	1	76	3	77	3	72	3	81

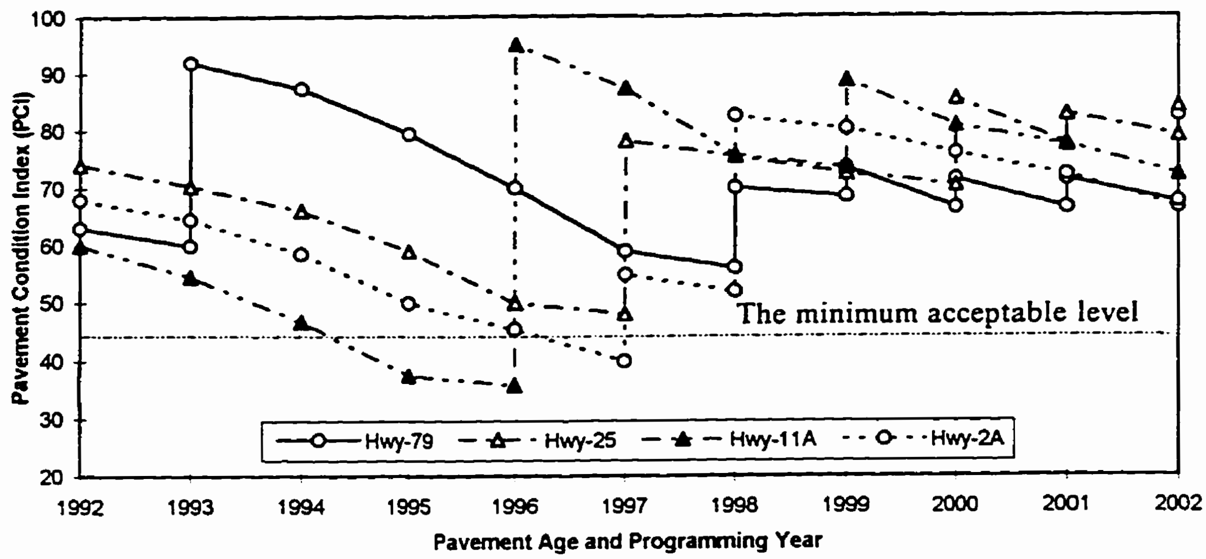


Figure 7.3A Integrated Performance Prediction with M&R Treatment Programming

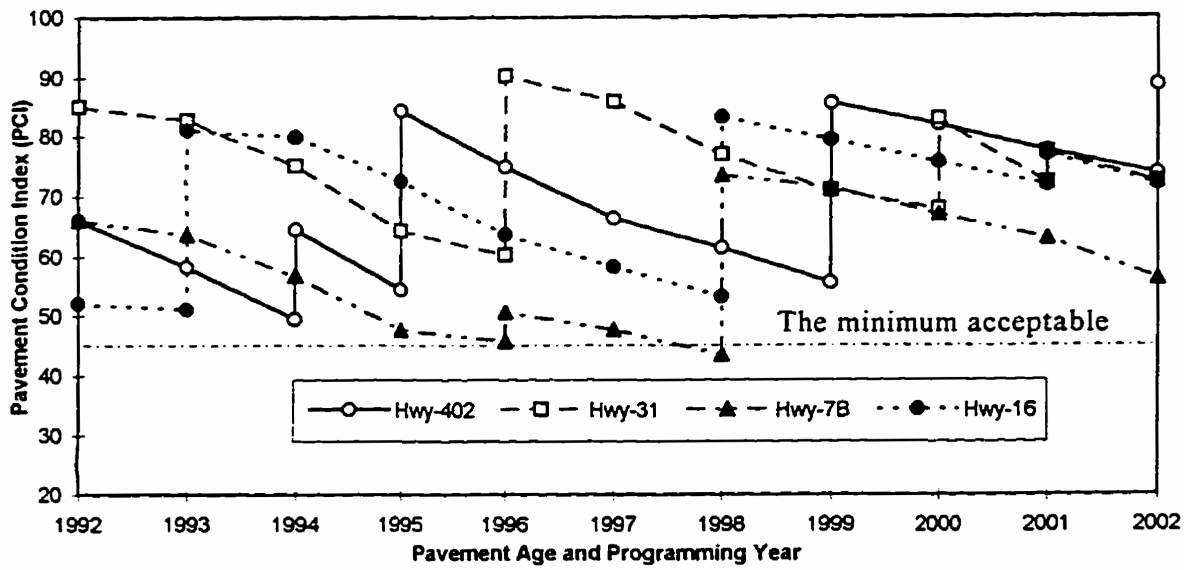


Figure 7.3B Integrated Performance Prediction with M&R Treatment Programming

7.3 SENSITIVITY ANALYSIS

Sensitivity of pavement performance, predicted by the time-related Markov probabilistic model, to some design variables included in the OPAC prediction model is investigated in this study. When each of the variables, such as traffic loads in terms of ESALs, pavement thickness, subgrade soil resilient modulus, etc., is used as an input in the OPAC prediction model, sensitivity of pavement deterioration rate to these variables can be conducted for the following two reasons:

1. It is a function of many other variables that have to deal with uncertainties and variations. For example, the number of traffic loads (or ESALs) applied on a pavement in t years is estimated by a traffic prediction model. In the model it is a function of numerous independent variables, such as average annual daily traffic (AADT) volume, truck percentage and its growth rate, lane distribution factor, etc. Each of these individual independent variables is determined with a certain probability distribution. In other words, the traffic data is predicted with a certain error; it may not be equal to the actually observed traffic data in t years.
2. It is a result from statistical analysis of many experiments or samples conducted in different areas, such as resilient modulus of subgrade soil strength, equivalent granular base thickness of pavement structure, etc.

The input values for these variables in the OPAC prediction model will most likely not be the same values as they will actually appear in the field since errors and variations are unavoidable in the determination of these variables. For example, the number of traffic counted or observed on a highway in 5 years is different from the one that is predicted from a traffic prediction model. However, the amount of pavement deterioration in PCI is affected to a certain degree by the these variables. This is one of the major reasons that a predicted pavement condition state will be different from the actually observed one.

It is important to know the variations in each element of the transition probability matrices as prediction of future pavement condition states is mainly based on these elements. Therefore, it is necessary to conduct a sensitivity analysis in order to know the variations in the TPMs developed for the prediction of pavement deterioration versus age.

For the purpose of illustration, a quantitative analysis on the sensitivity of pavement performance to traffic variables, pavement thickness and subgrade soil strength is performed. Besides, sensitivity of pavement performance to different budget levels for the pavement network preservation is also examined in the application study. Some outputs from the sensitivity analyses are described in the following sections.

7.3.1 Sensitivity of Pavement Deterioration to Traffic Loads

The sensitivity of pavement deterioration to annual traffic volume (or level of ESALs) is shown in Figure 7.4. In this case total equivalent granular base layer thickness of the pavement structure *He*, is 550 mm, strength coefficient of the subgrade soil (or resilient modulus), M_s , is 5000. The values of these two variables are fixed throughout the analysis period. Then five different levels of annual ESALs ranging from 10,000 per year to 400,000 per year are used to test the rate of pavement deterioration. The graphs in the figure give the following information:

- If the annual ESALs is 10,000, the initial service life of the pavement will 24.
- If the annual ESALs is increased to 50,000 and further to 100,000, the pavement service life will be reduced to 14 years and 9 years, respectively.
- When the annual ESALs are up to the level of 400,000 ESALs, the expected service life of the pavement will not be more than 3 years.

It should be mentioned that Hutchinson et al. (120) conducted a similar analysis on the sensitivity of pavement deterioration to different annual ESALs. In his study, sensitivity of pavement deterioration to different annual ESAL magnitudes from OPAC model in terms of Riding Comfort Index (RCI) versus age profiles was analyzed. The several other flexible pavement performance prediction models were compared with those estimated form a deterioration mode developed for Ontario condition.

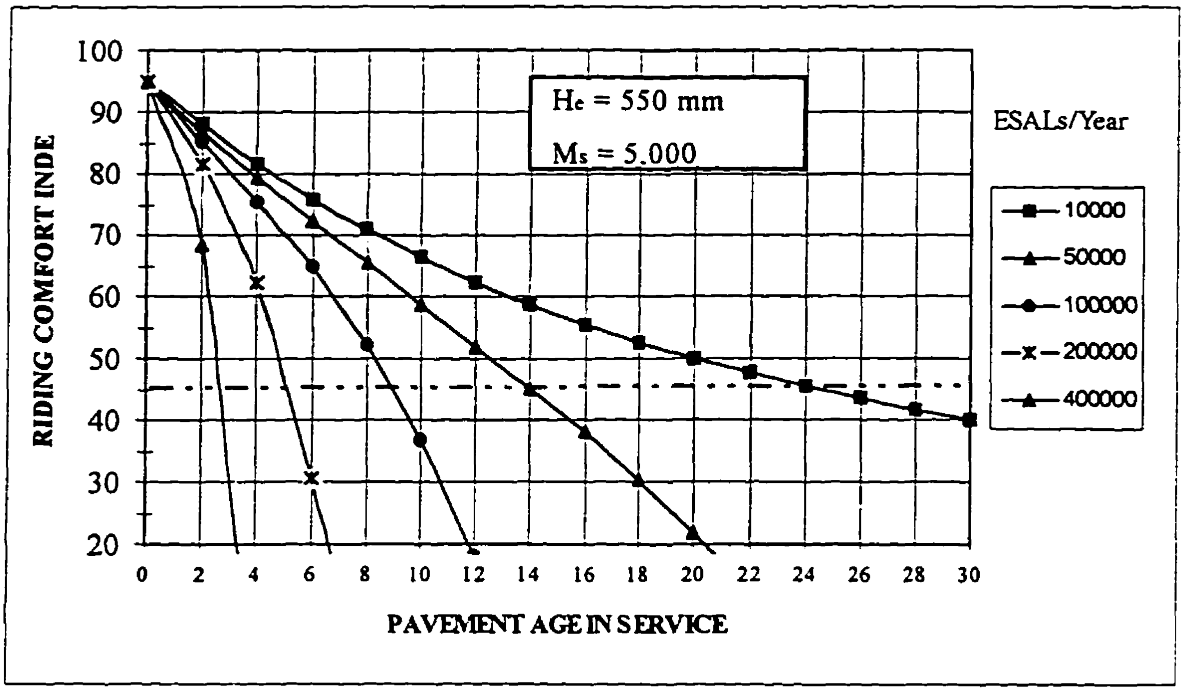


Figure 7.4 Sensitivity of PCI Deterioration to Annual Traffic Volume

7.3.2 Sensitivity of Pavement Deterioration to Pavement Thickness

Illustrated in Figure 7.5 are the sensitivities of pavement deterioration to different pavement thickness, H_e,, under the conditions of: 1) annual ESALs is 100,000 and is constant throughout the analysis period, and 2) subgrade layer coefficient is 5,000. As a result, the diagram displays that the pavement deteriorates to an unacceptable condition in quite different years if the pavement equivalent thickness varies from 300 mm to 700 mm. The following conclusions can be drawn from the figure:

- The pavement thickness should be at least 500 mm in order to expect that the pavement can last 14 years in service before its PCI drops to the minimum acceptable level. If the pavement thickness is less than 400 mm, then the highway can only maintain above its required serviceability level for maximum 6 years.
- If the pavement thickness can be increased to 600 mm, the pavement service life can be extended to 20 years under the same conditions of traffic loads and subgrade soil strength as defined above.
- The pavement will last for more than 30 years if its thickness is larger than 700 mm.

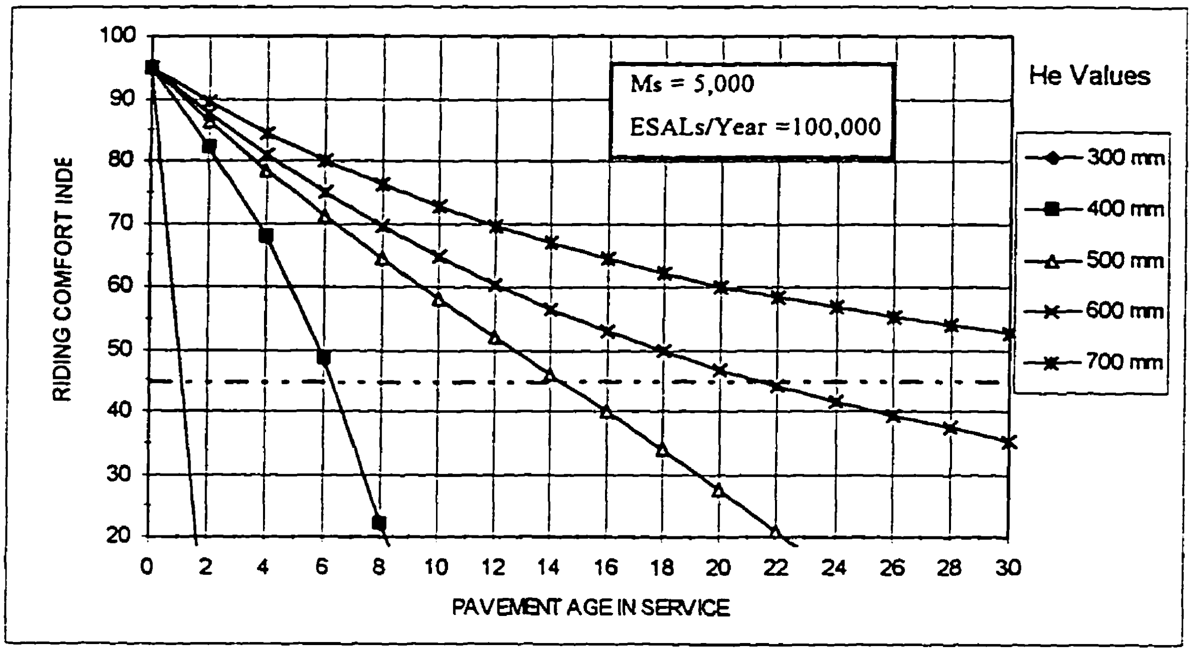


Figure 7.5 Sensitivity of PCI Deterioration to Total Pavement Thickness

7.3.3 Sensitivity of Pavement Deterioration to Subgrade Soil Strength

Sensitivity of pavement deterioration to subgrade soil strength was conducted by changing the subgrade modulus coefficient from M_s = 4,000 to M_s = 10,000, with the pavement thickness and annual ESALs being fixed at 550 mm and 100,000, respectively. In this case, given the minimum acceptable PCI level being 45, the pavement service life would be 13 years if the subgrade modulus coefficient is 6000; a more interesting fact is that if the subgrade modulus coefficient is increased to 8000, then the pavement service life would be 24 years, as shown in Figure 7.6.

It also shows that if the subgrade modulus coefficient, M_s , is doubled from 4,000 to 8,000, the expected service life will be increased by about five times for the same pavement structure and traffic loading.

For Southern Ontario situations, typical subgrade layer coefficients range from 3500 to 6000 in natural conditions or after construction in most cases. However, it would be very costly or difficult to treat and reinforce the soil strength up to a level of higher than 8000 in terms of its subgrade layer coefficient.

Sensitivity of the developed TPMs to subgrade soil modulus or deflection (w) was also studied. In the study, w was varied from 0.6604 mm (0.026 in) to 0.7336 mm (0.029 in) with an increment of 0.0254 mm, while all other design parameters remain the same as in Table 7.1. It is found that the strength of subgrade soil is most critical to pavement deterioration, as might be expected.

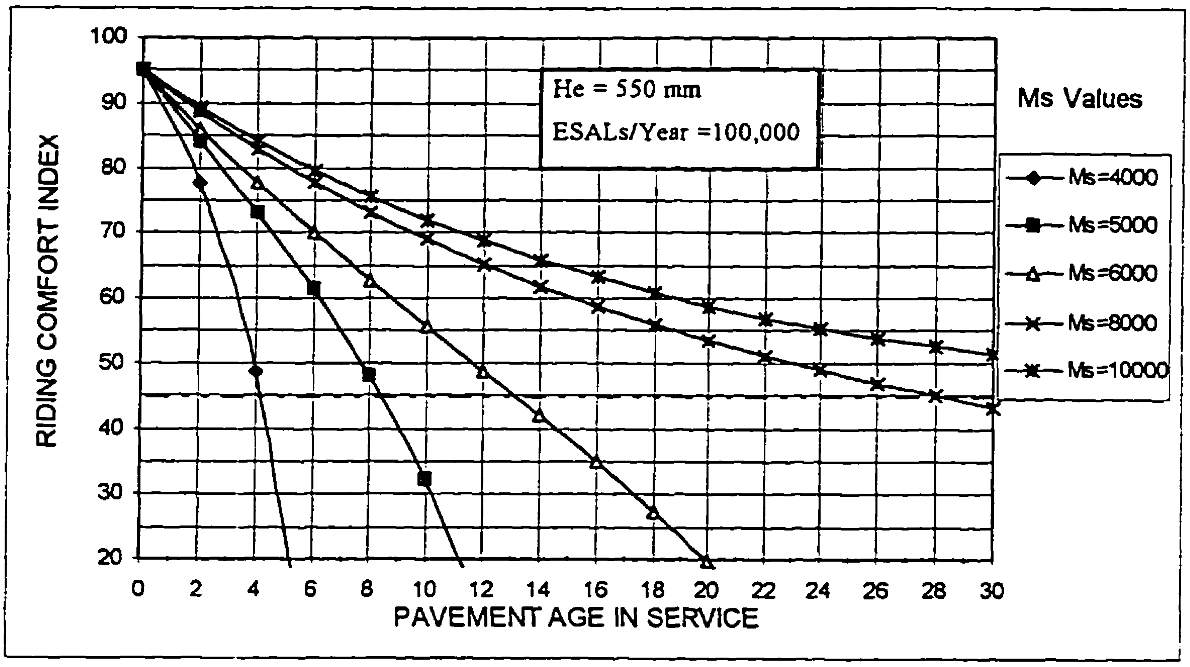


Figure 7.6 Sensitivity of PCI Deterioration to Subgrade Strength

7.3.4 Sensitivity of the Pavement Network Performance to Budget Levels

From the network Highway 402 is taken to illustrate the relationship between pavement performance and annual budget level for the network preservation. This highway is a 102 kilometers long, 4-lane rural expressway built in southern Ontario during the early 1980's. The main characteristics of the pavement on Highway 402 include strong subgrade soil (M_s = 6000), relatively high traffic volume (AADT = 14500 in 1993) and high truck percent which means high ESALs, and relatively low pavement thickness. A detailed description of this highway is shown in Table 7.1.

Sensitivity of the pavement performance of Highway 402 and M&R treatment action plans to three different annual budget levels (i.e., 1, 2 and 3 million dollars for the network preservation, respectively) has been conducted and the result is shown in Figure 7.7. Sensitivity analysis of pavement performance to annual budget level for other pavements in the network can also be conducted in the same way.

It should be noted that in Figure 7.7, all the PCI points corresponding to the level of 3 million dollars annual budget are taken from Table 7.3A and Table 7.3B. The rest of the points that correspond to the budget level of 1 million per year or 5 million dollars per year can be obtained by conducting the multi-year pavement network M&R dynamic programming.

Generally speaking, the pavement of Highway 402 will be well maintained and its PCI will be upgraded to the average of 82 during the second five years form the average of 69 PCI during the first five years if the annual budget of $ 3 million is provided. In addition, sensitivities of the TPMs to traffic growth rates (2%, 5% and 8%) were studied. It is concluded that the higher the traffic growth rate, the larger the difference between any two consecutive TPMs.

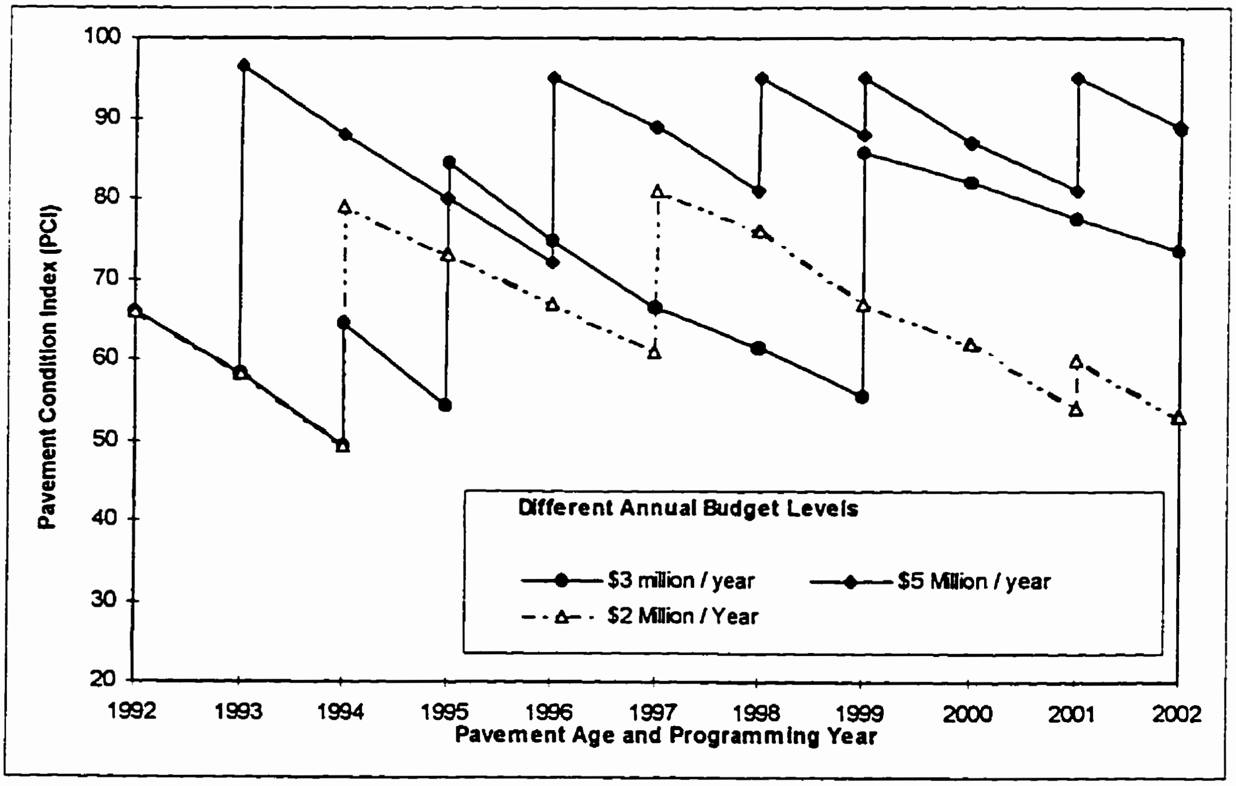


Figure 7.7 Sensitivities of Pavement Performance (Hwy. 402) to Different Budget Levels

7.4 SUMMARY

This chapter presented a comprehensive and practical example application of the integrated pavement management system to the real situation of an Ontario highway network. The application of the time-related Markov transition process in pavement management has provided an effective approach to the prediction of the pavement performance-age relationship, as well as the construction of transition probability matrices (TPMs) for each individual pavement section in the network. The probabilistic based, integrated pavement network optimization model has been shown to be quite efficient for multi-year pavement network M&R project selection and priority management. It has also been shown that the integrated optimization model can be used for financial planning purposes to test the effects of different budget levels on the mean serviceability level of the pavement network. Based on the analysis results from the example highway network application discussed in this chapter, some major conclusions can be summarized as follows:

1. As compared to the existing TPM-building methods and many TPMs that have been used in PMSs, this system conversion-based probabilistic prediction model has the following features:

- Substantial time-saving in building the Markov TPMs for pavement performance prediction. While a questionnaire-based subjective method may need a few weeks to develop a TPM, and the data analysis-based statistical method requires over 10 years long term observed pavement performance data in order to build a TPM, the newly developed system conversion-based method takes only a few minutes to build a series of TPMs by means of Monte Carlo simulation.
- This system conversion-based TPM building method takes advantage of existing deterministic prediction models, carries on the experience and achievements possessed in the deterministic models, and improves the prediction accuracy by using Bayesian approach through observed data on a year-by-year basis.

2. The system transformation process from deterministic into probabilistic-based model provides a workable, reliable and step-by-step approach to the prediction of pavement deterioration. Outputs of the predicted pavement deterioration versus age can be

expressed in three different forms: Pavement Condition State (PCS) vectors at each year, expected mean values of the PCS vectors, and a sequence of time-related Markov TPMs.

3. The combined Markov-Bayesian analysis methodology of modeling pavement deterioration provides pavement mangers with a practical and efficient approach to pavement performance prediction, and is therefore recommended to use particularly for calibration and verification of the performance prediction from the OPAC system.

4. From the sensitivity analysis, it may be concluded that a certain amount of change in annual ESALs, subgrade modulus coefficient or soil strength, and pavement thickness for a pavement input will result in different forecast of the expected pavement service years. Consequently, the budget planning and M&R treatment strategy programming for a pavement network preservation are mainly influenced by the predicted pavement performance. This means that uncertainties in estimating these factors or parameters as input design variables introduce a dilemma for pavement managers to decide which prediction is accurate and which preservation action should be taken in a given year. Therefore, accurate prediction of pavement performance is one of the most important tasks in having a reasonable road network optimization program for pavement maintenance/rehabilitation alternative strategies. In other words, the efficiency of the budget plan and the expected pavement serviceability level depend mainly on the accuracy of the pavement performance prediction.

5. The pavement network M&R treatment strategies recommended by the optimization model have been found quite sensitive to the terminal serviceability level. Therefore, it is necessary to run the network optimization model several times with different terminal serviceability levels to determine the level that produces the greatest benefit/cost ratio. In such a way, a reasonable range of terminal serviceability level can be determined for the pavement network. It should be noted that in this example application, the minimum acceptable serviceability level (i.e., PCI) is 45 for all the pavements in the network. However, the minimum pavement serviceability level should be defined individually based on certain criteria, such as class of highway, traffic volume, political influence factors, etc., so that the greatest benefits with overall serviceability requirements and economic considerations can be obtained for real situations.

6. The level of annual budget has a significant effect on the outcome of the network optimization model. The number of pavement sections that can receive M&R strategy 4 or 5 (rehabilitation or reconstruction) within the programming period increases as the budget increases. In order to avoid spending funds in an inefficient way, the network optimization model uses the penalty function, i.e., Equation [6.5] of the network optimization model, to make sure that only the optimal cost-effective M&R treatment strategies can be chosen for implementation. The computerized pavement network optimization model can provide enough information for determining this situation, as well as determining the minimum budget level needed to maintain or improve the serviceability of the pavement network at a certain level.

CHAPTER 8

SUMMARY OF PRINCIPAL FINDINGS AND UNSOLVED PROBLEMS

8.1 MAJOR ACHIEVEMENTS

Accurate prediction of pavement functional and structural deterioration versus age plays a very important role in a pavement management system (PMS). This is simply because many other decisions made in a pavement management, such as identification of pavement current and future needs, selection of pavement projects, and determination of the optimal M&R treatment strategies for the network improvements, etc., are all dependent on the output of the pavement performance prediction.

Because uncertainties and variations are always involved in the process of pavement design and materials, such as traffic loads, strength of pavement materials, and stability of subgrade soils, the rate of pavement deterioration is uncertain, or it is not appropriate to use deterministic-based models for the prediction of pavement deterioration. Consequently, a probabilistic-based prediction model should be used to model pavement deterioration, but unfortunately the existing probabilistic-based prediction models either have some technical problems in building the pavement condition transition probabilities effectively and efficiently, or subject to some major limitations and conditions in their applications. This research had the basic premise that a new, more efficient, probabilistic-based pavement management system should be developed for highway agencies to use in their PMSs.

This research was directed towards developing this probabilistic-based, integrated pavement management system for regional or provincial pavements. The use of non-homogeneous Markov chain in prediction models captures the probabilistic nature of pavement deterioration process. The Markov process integrated with multi-year prioritization using total effectiveness/cost ratio produces the optimal investments and M&R treatment strategies under certain budget limitations. The optimization model can also be used to produce the budget requirements for the given programming analysis period by releasing the constraint of budget limitation in the model.

The major achievement of the study, in a broad sense, is the development of a probabilistic-based, integrated pavement management system for solving the problems in modeling pavement network optimization and programming the optimal M&R program for the network preservation, which can be applied to different levels of pavement networks, including local, regional, municipal and provincial pavements. More specifically the major achievements and findings can be listed as follows:

1. A non-homogeneous (or time-related) Markov chain concept for modeling pavement structural and functional deterioration has been developed and verified by case studies on a variety of highway pavements in Ontario.

2. The proposed concept of a system conversion from a deterministic-based prediction model to its corresponding time-related Markov probabilistic prediction model has been successfully applied and shown to be reasonable and applicable to the performance-oriented pavement design models, such as OPAC model and AASHTO pavement design methods.

3. The methods and techniques used to perform the prediction model system conversion and to eventually establish a set of time-related transition probability matrices (TPMs) for the prediction of a pavement deterioration-age relationship have been developed through this research, which are based on the reliability concepts applied in pavements, probability nature of the pavement design variables, and Monte Carlo simulation.

4. The approach to improve the prediction accuracy of a converted non-homogeneous Markov probabilistic prediction model has been investigated, and Bayesian posterior probability method has found its very useful application in this aspect in terms of modifying the prediction through observed pavement performance data.

5. The concepts of standardizing pavement maintenance and rehabilitation (M&R) treatment strategies for use in the pavement management have been described, including the concepts of M&R treatment effect and its impact on the pavement future deterioration or future needs.

6. The developed network optimization system for the probabilistic-based, integrated PMS is a year-by-year integer programming based on optimal effectiveness/cost ration to select the network M&R projects.

7. The integration of pavement performance prediction with a set of standardized M&R treatment strategies has been formulated to provide practical and useful outputs or information for a highway agency to use in its PMS. This method can also be applied to studies on many other infrastructure management, such as airport pavements, bridges, gas and oil pipelines, etc.

8. The sensitivity of the system to several input factors and different budget levels has been tested. The system has been computerized for easy application and its use has been demonstrated by an example application to a selected Ontario highway network.

In conclusion, this study has shown that better management of highway pavements at network levels can be achieved by the use of a comprehensive, multi-purposes, and efficient system as developed in this research. The objective of the research was to develop a probabilistic-based pavement network optimization system on the basis of pavement performance prediction with use of the time-related Markov process. The results from the Markov model are fit into the multi-year optimization model in which a set of standardized M&R treatment strategies are provided for the use in selecting pavement projects, and the output from the prioritization is a list of optimal maintenance and rehabilitation recommendations for the pavement network. The results from the developed system are promising, but it does have certain limitations, and more work should be conducted to make the system directly implemented by a provincial or municipal department of highway transportation. The following sections contain a brief summary of the entire research work.

8.2 SUMMARY OF THE RESEARCH WORK

This thesis has discussed three major issues related to the probabilistic-based, integrated PMS at the network level: non-homogeneous Markov process-based probabilistic modeling of pavement deterioration, determination of standardized pavement maintenance and rehabilitation treatment strategies for a network preservation, and multi-year M&R optimization by the integer programming,

First of all, results and information from pavement performance prediction may influence, on a large degree, many other decisions and related activities of pavement management, such as determination of needs years, selection of maintenance time and proper treatments, optimization of pavement network rehabilitation and maintenance priority programming. Over the last 30 years, although considerable progress has been made towards the achievement of effective pavement performance prediction models, there is still a need for probabilistic-based prediction models for use in PMS.

8.2.1 Review of Existing Technology

An overall review of the existing technology has shown the lack of a comprehensive model which can establish pavement repair priorities on the basis of integrating pavement prediction model with treatment strategies.

In most of the existing pavement management systems, both the deterministic and probabilistic based prediction models have commonly been used for determining future pavement condition state or future needs analysis. The deterministic-based prediction models can be established by using mechanistic, empirical, or regression method and techniques. The main problem with deterministic-based prediction models is that they ignore the uncertainties and variations involved in the pavement performance. The probabilistic-based models have the advantages of being able to capture the uncertainties and variations through probability analysis of the prediction model. However, the existing methods for developing the probabilistic prediction models seem to have some difficulties in building the transition probability matrices.

In addition to simple ranking methods and the ranking methods based on parameters, such as deflection, serviceability, etc., mathematical optimization techniques such as linear programming and dynamic programming have recently been used in pavement management for determining investment priorities for highway improvements. However, all of these methods of priority programming have certain limitation. The most common problem with the ranking methods is that they depend primarily on subjective judgments or on one of a few parameters.

The existing mathematical optimization methods have the advantage of being able to deal with programming period based on objective methods. However, they do not consider the treatment effects and their impacts on future pavement deterioration in the multi-year programming, which should be included in the pavement performance prediction model.

8.2.2 General Structure of the Proposed Probabilistic-Based, Integrated PMS

The proposed probabilistic-based, integrated pavement management system contains three sub-systems: 1) time-related Markov modeling system for predicting pavement deterioration and identifying future pavement needs, 2) maintenance and rehabilitation (M&R) treatment strategy generating system for standardizing pavement network preservation activities, 3) cost-effectiveness based integer programming system for selecting optimal multi-year M&R treatment projects for the network.

The major features in this newly developed Markov prediction models include: a) non-homogeneity (or time-related Markov process), b) approach to building the transition probability matrices, and c) modification of the predicted pavement condition states by Bayesian method through observed performance data.

The Markov prediction model is established by using the prediction model system conversion concepts developed in this study, which can be achieved through three basic steps: a) selection of a deterministic-based pavement design model, b) data input of pavement design parameters as random variables, and c) construction of a set of time-related transition probability matrices.

It should be noted that, in constructing the transition probability matrices, this newly developed methodology avoids processing a large amount of individual, possibly biased, subjective opinions or observing a large number of pavement long term performance data. The application of the time-related Markov transition process in pavement management has provided an efficient approach to the prediction of pavement performance-age relationship, as well the construction of transition probability matrices for each individual pavement section in the network.

The purpose of standardizing maintenance and rehabilitation (M&R) treatment strategies is to provide intermediary data and information for the network optimization system, which include treatment effects and impacts of the M&R strategies on future pavement deterioration or future M&R needs.

In this study, the selection of all feasible M&R treatments and timing intervals for each type of pavement is based on performance evaluation and life-cycle cost analysis. Perhaps the most concerned economic element in pavement management is the costs spent, after the initial construction, on maintaining pavements above certain serviceability levels throughout the analysis period. These costs are mainly related to the pavement life-cycle economic analysis and cost effective evaluation of the planned M&R treatment projects.

The multi-year integer programming uses time-related Markov prediction model and takes treatment effects into the prediction model to produce a list of optimal M&R recommendations for every pavement in the network. The objective of the optimization is to determine the most cost-effective treatment strategies that will maximize the pavement network above a specified serviceability level. Each of the selective pavement treatment, including minor and major maintenance, and rehabilitation, is defined by its treatment effect and influence on the pavement future deterioration rate.

A general framework for the integrated system and the key components in each of the sub-systems have been discussed in the thesis. The objectives, inputs, outputs and constraint factors of the system are presented.

8.2.3 Investment Planning for Network Optimization

Network level planning is a problem of "many projects", and the decisions that accompany them. While at the project level inter project trade-off and budget limitations were not at issue, these two factors take on paramount importance in the analysis of the network. It is in fact these two features which create the greater complexity inherent in the network modeling problem. Since network models may address either M&R program planning or financial planning, the components of the newly developed network optimization system involves some combination of :

- project and treatment strategy selection,

- project scheduling in the presence of budget constraints,
- budget selection in the presence of performance targets.

Prioritization of M&R projects is one of the end central tasks of a pavement management system. It involves the use of economic analysis and investment-related policy decisions to determine the priority programs for pavement treatment projects, i.e., what, when and where the projects should be. The priority analysis was conducted through an integer programming which produces the most cost-effective section-specific treatment strategies for pavement network management.

It should be noted that, by developing a set of standardized M&R treatments, the integrated pavement management system has the following three major functions:

- to analyze quantitatively the improvement of a standardized treatment to the existing pavement and its influence on the future performance in the time-related performance prediction model.
- to forward specification and automation of pavement maintenance and rehabilitation treatment strategies. The application of automation technologies in pavement maintenance is a rapid growing area, and potential opportunities exist for rehabilitation automation as well in the future.
- To provide highway agencies with advanced information and data that are used in the optimization of the pavement M&R priority programming.

8.2.4 Application of the Integrated PMS and Sensitivity Analysis

The proposed model has been computerized for easy application. The program was tested for various conditions. A small pavement network from the Ontario highway system was selected for this trial application. The methodology developed in this thesis for determining the optimal pavement network maintenance and rehabilitation projects for pavement improvements appeared to be satisfactory.

The sensitivity of M&R program of a pavement network to various input factors such as traffic, pavement structure, subgrade soil conditions, budget and terminal serviceability levels was then analyzed. All these factors were found to have certain significant effect on the outcome of the network optimization.

For example, it was suggested that different terminal serviceability levels for individual pavements be applied on the basis of traffic volume, class of highway and other factors. A rural road with low volume traffic should have a lower terminal serviceability level as compared to an arterial highway or freeway carrying on high volume traffic. Field investigations and socio-economic analysis are needed to establish these terminal serviceability levels. This may lead to a rationale in the determination of the current and future pavement maintenance or rehabilitation needs.

The prioritization technique used in the network level of pavement management was to find the optimal maintenance and rehabilitation treatment strategies for the selected projects over a analysis period.

In conclusion, this probabilistic-based, integrated pavement management system has the following several functions: a) simulate the probabilistic behavior of pavement deterioration by means of time-related Markov process, b) establish the non-homogeneous Markov transition probability matrices through Monte Carlo simulation, c) determine the needs year(s) and M&R projects for each pavement section for each year in the network, d) consider a set of standardized network M&R treatment strategies and, e) provide a foundation for optimizing pavement rehabilitation and maintenance. While the formulations using Markov-Bayesian probabilistic concepts applied in this study seem somewhat imposing, the effort has been to emphasize practical applicability of the resulting models for pavement performance prediction and network M&R program optimization.

8.3 RECOMMENDATIONS FOR FUTURE WORK

The methodology developed in this these for determining the optimal M&R program for pavement network preservation appears to be satisfactory in its approach. However, these are still some problems to be solved for future improvements and actual applications as described in the following:

1. Although the system conversion-based probabilistic prediction model has conceptually been formulated for all types of pavements, only the type of flexible pavements has directly been considered in the study. Rigid pavements and other type of pavements have not been taken into account in the research, due to time and resource limitations.

   The concept of the prediction model system conversion has been applied to the OPAC for Ontario conditions. It may be applied to many other existing deterministic-based prediction models used in pavement management. Thus, applications of the model can be expanded to other types of infrastructure (121) and their deterioration prediction models.

   Modifications of the prediction model system conversion for applications to other types of pavements should be individually straightforward. The relationship between observed pavement performance data and that predicted by the converted probabilistic prediction model should be examined for verification of the prediction accuracy, and Bayesian technique is recommended for this purpose.

2. The optimization model used in the system is a year-by-year based zero-one integer programming for optimizing the pavement network project decisions and investments, and prioritization uses optimal benefit/cost ratio for the selection of the network M&R projects. The optimal solutions to the pavement network multi-year maintenance and rehabilitation program are determined on a year-by-year basis. As a result, some of the optimal network M&R treatment projects selected for a specific year may not be the optimal solutions from the long term point of view. Although there are some alternative optimization methods available for solving this problem, it is recommended that dynamic programming be used to improve the optimization model.

   Similarly, the prioritization of pavement network M&R treatment projects uses effectiveness/cost ratio method, and some other economic evaluation based approaches can be applied, such as present worth method and rate of return method. Consequently, the optimization formulation and prioritization method used in this integrated PMS can be replaced by any one of these alternative approaches if necessary, depending on what objective and economic evaluation factor are used.

3. The process of system conversion model requires that design variables, such as traffic volume, pavement thickness and subgrade modulus coefficient, be input in a probabilistic format in Monte Carlo simulation and transition probability calculations. Although normal distribution has been considered for each of the variables in the example application of OPAC model, some other type of probability distributions, such as lognormal distributions may be the best one to fit the individual situations.

   Determination of a type of probability distribution and parameters for each of these variables should be based on field data collections and statistical analysis. All the observed data and related information should be stored in a pavement data bank. The periodically collected data stored in the bank can be used for updating the transition probability matrices.

4. The terminal or minimum acceptable serviceability level has a significant effect on the outcome of the network optimization model. The terminal serviceability level has been considered to be the same level for all the pavements in the network. However, it is suggested that different terminal serviceability levels for individual pavements be applied on the basis of traffic volume, class of highway and other factors. For example, a rural road with low volume traffic should have a lower terminal serviceability level as compared to a highway carrying on high volume traffic. Field investigations and socio-economic analysis are needed to establish these terminal serviceability levels. This may lead to a rationale in the determination of the current and future pavement maintenance or rehabilitation needs.

5. Development of a computer application software for this probabilistic based, integrated pavement management system is the final goal of this study. The engineering and model development for the software and its application has been considered at present. A Windows operating system based computer interface design for the application should be developed for the use in regional or provincial departments of highway transportation.

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APPENDIX

FORTRAN Program Subroutine for Converting OPAC Performance Model to a Time-Related Markov Probabilistic Prediction Model

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WATFOR-77 V3.1 Copyright WATCOM Systems Inc. 1984,1989 97/07/16 01:54:12

Options: list, disk, warnings, edit, xtype, terminal, logio, check, arraycheck

```
C       ACESAL (IYEAR) Accumulated number of ESAL's up to year IYEAR
     C  ESAL (IYEAR) Number of ESAL's in year IYEAR
     C  ECOV      Coefficient of variation for number of ESAL's in any year
     C  PROB      Probability transition matrix
     C  DPE       Environment related decrease in PCI
     C  DPT       Traffic related decrease in PCI
     C  DP=DPE+DPT   Total decrease in PCI
     C  W0        Mean value of subgrade deflection
     C  WCOV      Coefficient of variation for subgrade deflection
     C
     1     IMPLICIT DOUBLE PRECISION (A-H,O-Z)
     2     PARAMETER (NITER=1000, NYEAR=11, NSTATE=25, NMAT=NSTATE)
     3     PARAMETER (ALPHA=0.06D0, B=60.D0)
     4     PARAMETER (W0=0.022D0, WCOV=0.10D0)
     C     where h1=140mm, h2=152, h3=457mm, Ms=4,000, coeff.of W =0.1
     5     PARAMETER (AP=20.D0, IAP=20, DAYS=365.D0, DTRAF=0.06D0)
     6     PARAMETER (AADTI=7500.D0, ECOV=0.05D0)
     7     PARAMETER (TI=0.25D0, TLDFI=1.00D0, TFI=0.95D0)
     8     PARAMETER (TF=0.35D0, TLDFF=1.00D0, TFF=1.14D0)
     9     DIMENSION ACESAL(0:IAP), ESAL(IAP)
     10    DIMENSION PROB(NMAT,NMAT), PCST(NMAT), C(NMAT)
     11    DIMENSION WBAYES(NMAT),POSTV(NMAT),BAYESV(NMAT),
         * OBSERV(NYEAR),SIGMA(NYEAR)
     12    OPEN (1,FILE='LIMAT.DAT')
     13    OPEN (2,FILE='LIPCS.DAT')
     14    OPEN (3,FILE='LIBAY.DAT')
     15    ACOE=DEXP(ALPHA)-1.D0
     C
     CCC Input observed pavement condition state in each year observed year
     C
     16    DATA OBSERV/9.5, 9.3, 9.0, 8.7, 8.4, 7.9, 7.4, 6.9, 6.4, 6.1, 5.6/
     17    DO 20 IYEAR = 1,NYEAR
     18    SIGMA(IYEAR)=0.25D0
     C     SIGMA(IMAT)=0.4D0
```

```
20    CONTINUE
C
C Input for initial condition state
C
      STATE=9.5D0
      IMAT=INT((10.D0-STATE)*DBLE(NSTATE)/10.D0)+1
      CALL ZERO(PCST,NMAT,1)
      PCST(IMAT)=1.D0
      IYEAR=0
      WRITE (*,*) 'Initial Condition State Vector'
      WRITE (*,109) (PCST(IMAT),IMAT=1,NMAT)
      WRITE (*,509) IYEAR,STATE
      WRITE (*,*)
      WRITE (1,*) 'Initial Condition State Vector'
      WRITE (1,109) (PCST(IMAT),IMAT=1,NMAT)
      WRITE (1,509) IYEAR,STATE
      WRITE (1,*)
      WRITE (2,509) IYEAR,STATE
C
C Traffic input model
C
      ACESAL(0)=0.D0
      AADTF=AADTI*(1.D0+DTRAF)**IAP
      ESALF=AP/2.D0*DAYS*(AADTI/2.D0*TI*TLDFI*TFI
     *           +AADTF/2.D0*TF*TLDFF*TFF)
      C1=2.D0*AADTI/(AADTI+AADTF)
      C2=(AADTF-AADTI)/(AP*(AADTI+AADTF))
      DO 1 I=1,IAP
      Y=DBLE(I)
      ACESAL(I)=ESALF/AP*(C1*Y+C2*Y**2)
      ESAL(I)=ACESAL(I)-ACESAL(I-1)
 1    CONTINUE
      DO 1000 IYEAR=1,NYEAR
      IDUM=-1
      WRITE (1,1009) IYEAR
      WRITE (*,1009) IYEAR
1009    FORMAT ('YEAR:',2X,I3)
      CALL ZERO(PROB,NMAT,NMAT)
      DO 2000 IMAT=1,NMAT
      P0=DBLE(NMAT-IMAT)*10.D0/DBLE(NSTATE)+1
      DO 3000 ITER=1,NITER
```

```
      CALL NORMAL(IDUM,RN1,RN2)
C
C Determine environment related decrease in PSI
C
      W=DEFW(RN1,W0,WCOV)
      PINF=P0/(1.D0+B*W)
      DPE=(P0-PINF)*ACOE*DEXP(-ALPHA*IYEAR)
C
C Determine traffic related decrease in PSI
C
         ESALN=TRAFF(RN2,ESAL(IYEAR),ECOV)
         PSI=1000.D0*W**6*ESALN
         DPT=2.4455D0*PSI+8.805D0*PSI**3
C
C Determine the total decrease in PCI
C
         DP=(DPE+DPT)*DBLE(NSTATE)/10.D0
         JMAT=IMAT+INT(DP)
         IF (JMAT.GT.NMAT) JMAT=NMAT
         PROB(IMAT,JMAT)=PROB(IMAT,JMAT)+1.D0
 3000    CONTINUE
 2000  CONTINUE
C
C Normalize the probability transition matrix
C
      DO 100 JMAT=1,NMAT
       DO 100 IMAT=1,NMAT
        PROB(IMAT,JMAT)=PROB(IMAT,JMAT)/DBLE(NITER)
 100    CONTINUE
C
C Print the probability transition matrix
C
      DO 200 IMAT=1,NMAT
        P0=DBLE(NMAT-IMAT)*10.D0/DBLE(NSTATE)
        WRITE (1,108) IMAT,P0
        WRITE (1,109) (PROB(IMAT,JMAT),JMAT=1,NMAT)
 200    CONTINUE
 108    FORMAT ('ROW',I4,10X,'PCS =',F5.1)
 109    FORMAT (10(1X,F6.4))
C
C Determine the pavement condition state vector at year t
C
```

```
      DO 300 IMAT=1,NMAT
      C(IMAT)=0.D0
      DO 310 JMAT=1,NMAT
         C(IMAT)=C(IMAT)+PCST(JMAT)*PROB(JMAT,IMAT)
310      CONTINUE
300    CONTINUE
      DO 400 IMAT=1,NMAT
        PCST(IMAT)=C(IMAT)
400    CONTINUE
      WRITE (1,*) 'Condition State Vector'
      WRITE (1,109) (PCST(IMAT),IMAT=1,NMAT)
      WRITE (*,*) 'Condition State Vector'
      WRITE (*,109) (PCST(IMAT),IMAT=1,NMAT)
C
C Expected Pavement Condition states
C
      EXPST=0.D0
      DO 500 IMAT=1,NMAT
        P=DBLE(NMAT-IMAT)*10.D0/DBLE(NSTATE)+10.D0/DBLE(NSTATE)
        EXPST=EXPST+P*PCST(IMAT)
500    CONTINUE
      WRITE (1,509) IYEAR,EXPST
      WRITE (2,509) IYEAR,EXPST
      WRITE (*,509) IYEAR,EXPST
509    FORMAT ('Expected state',' after ',I2,' years: ',F5.2)
      WRITE (1,*)
      WRITE (*,*)
C
CCC  Calculate probability vector of pavement condition state through observed data
C    OBSERV(IYEAR)=DBLE(1-MAT)/10.D0*OBSERV(IYEAR)+DBLE(NMAT)
      DO 600 IMAT =1, NMAT
         Z1=(DBLE(IMAT*(10.0D0/NMAT))-BSERV(IYEAR))/SIGMA(IYEAR)
     PHIZ1=PHI(Z1)
         Z2=(DBLE(IMAT*(10.D0/NMAT)+10.D0/NMAT)-OBSERV(IYEAR))
    * /SIGMA(IYEAR)
              PHIZ2=PHI(Z2)
      WBAYES(IMAT)=PHIZ2-PHIZ1
600    CONTINUE
      TOTAL=0
      DO 700 IMAT=1,NMAT
         POSTV(IMAT)=WBAYES(NMAT+1-IMAT)*PCST(IMAT)
      TOTAL=TOTAL+POSTV(IMAT)
```

```
700   CONTINUE
      DO 800 IMAT=1,NMAT
      BAYESV(IMAT)=POSTV(IMAT)/TOTAL
800   CONTINUE
      WRITE (3,*) 'BAYES-Condition State Vector'
      WRITE (3,109) (BAYESV(IMAT),IMAT=1,NMAT)
      WRITE (*,*) 'BAYES-Condition State Vector'
      WRITE(*,*) OBSERV(IYEAR)
      WRITE (*,109)(BAYESV(IMAT),IMAT=1,NMAT)
C
CCC  Determine the post-expected condition state after each year
C
      POSEXP=0.0
      DO 900 IMAT=1,NMAT
        P=DBLE(NMAT-IMAT)*10.D0/DBLE(NSTATE)
        POSEXP=POSEXP+P*BAYESV(IMAT)
900   CONTINUE
      WRITE(3,510) IYEAR,POSEXP
      WRITE(*,510) IYEAR,POSEXP
510   FORMAT ('POST-EXPECTED STATE AFTER ',I2,' YEARS: ',F5.2)
1000  CONTINUE
      STOP
      END
C=============================================================C
C Evaluate a random value for the subgrade deflection
      DOUBLE PRECISION FUNCTION DEFW(RAN,W0,WCOV)
      IMPLICIT DOUBLE PRECISION (A-H,O-Z)
      DEFW=W0*(1.D0+WCOV*RAN)
      RETURN
      END
C=============================================================C
C Evaluate a random value for the number of ESAL's in the given year
      DOUBLE PRECISION FUNCTION TRAFF(RAN,E0,ECOV)
      IMPLICIT DOUBLE PRECISION (A-H,O-Z)
      TRAFF=E0*(1.D0+ECOV*RAN)
      RETURN
      END
C=============================================================C
C  Generating 2 independent N(0,1) normal random numbers.
C  Call with IDUM a negative integer to initialize; thereafter.
C  Do not alter IDUM between successive random numbers in a sequence.
      SUBROUTINE NORMAL(IDUM,RN1,RN2)
```

```
      IMPLICIT DOUBLE PRECISION (A-H,O-Z)
 1    RN1=RAN1(IDUM)
      RN2=RAN1(IDUM)
      W1=2.D0*RN1-1.D0
      W2=2.D0*RN2-1.D0
      W=W1**2+W2**2
      IF (W.GT.1.) GOTO 1
      VAL=DSQRT(-2.D0*DLOG(W)/W)
      RN1=W1*VAL
      RN2=W2*VAL
      RETURN
      END
      DOUBLE PRECISION FUNCTION RAN1(IDUM)
      IMPLICIT DOUBLE PRECISION (A-H,O-Z)
      PARAMETER (IA=16807,IM=2147483647,AM=1.D0/IM,IQ=127773,IR=2836)
      PARAMETER (NTAB=32,NDIV=1+(IM-1)/NTAB,EPS=1.2D-7,RNMX=1.D0-
     EPS)
      DIMENSION IV(NTAB)
      SAVE IV,IY
      DATA IV/NTAB*0/,IY/0/
      IF (IDUM.LE.0 .OR. IY.EQ.0) THEN
        IDUM=MAX(-IDUM,1)
        DO 11 J=NTAB+8,1,-1
          K=IDUM/IQ
          IDUM=IA*(IDUM-K*IQ)-IR*K
          IF (IDUM.LT.0) IDUM=IDUM+IM
          IF (J.LE.NTAB) IV(J)=IDUM
 11     CONTINUE
        IY=IV(1)
      ENDIF
      K=IDUM/IQ
      IDUM=IA*(IDUM-K*IQ)-IR*K
      IF (IDUM.LT.0) IDUM=IDUM+IM
      J=1+IY/NDIV
      IY=IV(J)
      IV(J)=IDUM
      RAN1=MIN(AM*IY,RNMX)
      RETURN
      END
C==========================================================C
      SUBROUTINE ZERO(A,NROW,NCOL)
      IMPLICIT DOUBLE PRECISION (A-H,O-Z)
      DIMENSION A(NROW,NCOL)
```

```
      DO 1 J=1,NCOL
      DO 1 I=1,NROW
        A(I,J)=0.D0
 1    CONTINUE
      RETURN
      END
C=====================================================================C
C Probability distribution function PHI(Z) of an N(0,1) random variable
      DOUBLE PRECISION FUNCTION PHI(Z)
      IMPLICIT DOUBLE PRECISION (A-H,O-Z)
      IF (Z.LT.-40.D0) THEN
        PHI=0.D0
      ELSE
        X=Z/1.414213562D0
        PHI=0.5D0*(1.D0+ERF(X))
      ENDIF
      RETURN
      END
      DOUBLE PRECISION FUNCTION ERF(X)
      IMPLICIT DOUBLE PRECISION (A-H,O-Z)
      IF (X.LT.0.D0) THEN
        ERF=-GAMMP(.5D0,X**2)
      ELSE
        ERF=GAMMP(.5D0,X**2)
      ENDIF
      RETURN
      END
      DOUBLE PRECISION FUNCTION GAMMP(A,X)
      IMPLICIT DOUBLE PRECISION (A-H,O-Z)
      IF (X.LT.0.D0 .OR. A.LE.0.D0) PAUSE
      IF (X.LT.A+1.D0) THEN
        CALL GSER(GAMSER,A,X,GLN)
        GAMMP=GAMSER
      ELSE
        CALL GCF(GAMMCF,A,X,GLN)
        GAMMP=1.-GAMMCF
      ENDIF
      RETURN
      END
      SUBROUTINE GSER(GAMSER,A,X,GLN)
      IMPLICIT DOUBLE PRECISION (A-H,O-Z)
      PARAMETER (ITMAX=100,EPS=3.D-7)
      GLN=GAMMLN(A)
```

```
      IF (X.LE.0.D0) THEN
        IF (X.LT.0.D0) PAUSE
        GAMSER=0.D0
        RETURN
      ENDIF
      AP=A
      SUM=1.D0/A
      DEL=SUM
      DO 11 N=1,ITMAX
        AP=AP+1.D0
        DEL=DEL*X/AP
        SUM=SUM+DEL
        IF( DABS(DEL).LT.DABS(SUM)*EPS) GO TO 1
11    CONTINUE
      PAUSE 'A too large, ITMAX too small'
1     GAMSER=SUM*DEXP(-X+A*DLOG(X)-GLN)
      RETURN
      END
      SUBROUTINE GCF(GAMMCF,A,X,GLN)
      IMPLICIT DOUBLE PRECISION (A-H,O-Z)
      PARAMETER (ITMAX=100,EPS=3.D-7)
      GLN=GAMMLN(A)
      GOLD=0.D0
      A0=1.D0
      A1=X
      B0=0.D0
      B1=1.D0
      FAC=1.D0
      DO 11 N=1,ITMAX
        AN=DBLE(N)
        ANA=AN-A
        A0=(A1+A0*ANA)*FAC
        B0=(B1+B0*ANA)*FAC
        ANF=AN*FAC
        A1=X*A0+ANF*A1
        B1=X*B0+ANF*B1
        IF (A1.NE.0.D0) THEN
          FAC=1.D0/A1
          G=B1*FAC
          IF (DABS((G-GOLD)/G).LT.EPS) GO TO 1
          GOLD=G
        ENDIF
```

```
11    CONTINUE
      PAUSE 'A too large, ITMAX too small'
1     GAMMCF=DEXP(-X+A*DLOG(X)-GLN)*G
      RETURN
      END
      DOUBLE PRECISION FUNCTION GAMMLN(XX)
      IMPLICIT DOUBLE PRECISION (A-H,O-Z)
      DIMENSION COF(6)
      DATA COF,STP/76.18009173D0,-86.50532033D0,24.01409822D0,
     *  -1.231739516D0,.120858003D-2,-.536382D-5,2.50662827465D0/
      DATA HALF,ONE,FPF/0.5D0,1.0D0,5.5D0/
      X=XX-ONE
      TMP=X+FPF
      TMP=(X+HALF)*DLOG(TMP)-TMP
      SER=ONE
      DO 11 J=1,6
        X=X+ONE
        SER=SER+COF(J)/X
11    CONTINUE
      GAMMLN=TMP+DLOG(STP*SER)
      RETURN
      END
```

```
Compile time:                 00.71  Execution time:        02:15.23
Size of object code:           6518  Number of extensions:         0
Size of local data area(s):    3141  Number of warnings:           0
Size of global data area:      6680  Number of errors:             0
Object/Dynamic bytes free: 311496/45648  Statements Executed:   15946798
```

```
C==================================================================C

BAYES-Condition State Vector
 0.0000 0.1048 0.8862 0.0090 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
 0.0000 0.0000 0.0000 0.0000 0.0000
POST-EXPECTED STATE AFTER  1 YEARS:  8.84

BAYES-Condition State Vector
 0.0000 0.0094 0.4483 0.5387 0.0037 0.0000 0.0000 0.0000 0.0000 0.0000
 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
 0.0000 0.0000 0.0000 0.0000 0.0000
POST-EXPECTED STATE AFTER  2 YEARS:  8.59

BAYES-Condition State Vector
 0.0000 0.0002 0.0595 0.6761 0.2627 0.0016 0.0000 0.0000 0.0000 0.0000
 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
 0.0000 0.0000 0.0000 0.0000 0.0000
POST-EXPECTED STATE AFTER  3 YEARS:  8.32
```

BAYES-Condition State Vector
0.0000 0.0000 0.0023 0.1929 0.6907 0.1136 0.0005 0.0000 0.0000 0.0000
0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
0.0000 0.0000 0.0000 0.0000 0.0000
POST-EXPECTED STATE AFTER 4 YEARS: 8.03

BAYES-Condition State Vector
0.0000 0.0000 0.0000 0.0146 0.3813 0.5638 0.0402 0.0001 0.0000 0.0000
0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
0.0000 0.0000 0.0000 0.0000 0.0000
POST-EXPECTED STATE AFTER 5 YEARS: 7.75

BAYES-Condition State Vector
0.0000 0.0000 0.0000 0.0000 0.0106 0.3354 0.5936 0.0600 0.0004 0.0000
0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
0.0000 0.0000 0.0000 0.0000 0.0000
POST-EXPECTED STATE AFTER 6 YEARS: 7.32

BAYES-Condition State Vector
0.0000 0.0000 0.0000 0.0000 0.0000 0.0070 0.2718 0.6178 0.1019 0.0015
0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
0.0000 0.0000 0.0000 0.0000 0.0000
POST-EXPECTED STATE AFTER 7 YEARS: 6.87

BAYES-Condition State Vector
0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0036 0.1874 0.6214 0.1824
0.0052 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
0.0000 0.0000 0.0000 0.0000 0.0000
POST-EXPECTED STATE AFTER 8 YEARS: 6.40

BAYES-Condition State Vector
0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0014 0.1053 0.5818
0.2942 0.0171 0.0001 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
0.0000 0.0000 0.0000 0.0000 0.0000
POST-EXPECTED STATE AFTER 9 YEARS: 5.91

BAYES-Condition State Vector
0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0050 0.1922
0.5846 0.2114 0.0068 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
0.0000 0.0000 0.0000 0.0000 0.0000
POST-EXPECTED STATE AFTER 10 YEARS: 5.59