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16. Abstract

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CONCEPTUAL PLAN FOR CLOSER INTEGRATION OF NETWORK- AND PROJECT-LEVEL PAVEMENT MANAGEMENT

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This report presents an evaluation of current performance modeling concepts and a feasibility study of the possibility of integrating network- and project-level performance prediction. The widely differing modeling methods in use today are reviewed and the design and management systems in use in Texas are briefly discussed. Performance prediction is shown to be needed in at least four stages of planning and management, including the planning (or before-design) stage, the design stage, the construction stage, and then for the existing pavement after a number of years in service. A proposed method for the incorporation of project-level performance models into the PMIS and the possible use of PMIS condition data to improve performance models through regression are outlined based on the conclusion that project-level design and network-level planning should be two different pathways within the same system. It is proposed that all performance curves, from whatever source, be converted to sigmoidal coefficients, and that these be stored separately for each individual PMIS pavement section. It is then proposed that the mechanistic rigid pavement analysis system CRCP8 be incorporated as a test case for the prediction of rigid pavement distresses. It is proposed that one or more flexible pavement models be sought along similar lines. While the ideas presented in this interim report are necessarily conceptual and are presented for the purpose of generating discussion, the plan presented is a coherent whole and represents a general vision for the future of pavement management and design in Texas.

DISCLAIMERS

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IMPLEMENTATION RECOMMENDATIONS

The report outlines a conceptual plan for better integrating network- and project-level pavement management in Texas. The recommendations made in the report concern the whole spectrum of project-level design and data collection to network-level planning and condition surveys. Thus the proposals presented are far reaching and represent a framework within which a great deal of current and future research may be conducted. In spite of this wide applicability, the specific recommendations made in the report are concerned mainly with changes to the Texas Pavement Management Information System (PMIS). Because this is an interim report, the recommendations are largely conceptual at this stage, with the primary purpose of the report being to generate discussion on the subject. The finalization of these conceptual recommendations will require considerable attention from both TxDOT and the research community but, when finalized toward the end of the project, and including the input resulting from publication of this report, implementation of these proposals may be able to greatly influence the course of pavement management and design in Texas for many years to come.

Prepared in cooperation with the Texas Department of Transportation and the U.S. Department of Transportation, Federal Highway Administration.

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EXECUTIVE SUMMARY

The primary objective of this project is to evaluate and recommend improvements to pavement performance prediction models for the Texas Pavement Management Information System (PMIS). The secondary objective is to work toward better integration of network and project management levels, such that the models used at each level do not contradict each other and result in user loss of confidence. This first report details some of the early investigations in this regard and ultimately concludes that a considerable level of integration is possible. The report also outlines the proposed method for accomplishing this integration.

Chapter 1 introduces the problem by showing that the ideal would be to create a single seamless system. This system would incorporate both the project and the network levels, since these are, in concept, very similar; that is, both involve the collection of condition data, the prediction of future condition, and the development of cost-effective designs and rehabilitation strategies. A major barrier to this integration is that it is impossible to collect the kind of detailed data necessary for detailed design and analysis for *all* sections in the network. Furthermore, even preliminary design data are unlikely to ever be fully available on a network-wide basis because, among other reasons, the data collected for this level often depend on the particular section's pavement type, location, and condition. Such dependence precludes the use of the same performance models in design and planning, since adequate data will never be available for all sections and different models may be relevant in each case. As a result, with the network and project levels remaining separate (with necessarily separate data and models), the prediction curves and recommendations at each level will very often differ. In these instances, it is not that one prediction curve is wrong per se. The difference occurs primarily because of the different data (both quantity and quality) involved at each level; moreover, the network-level recommendation might have been obtained from some very general model that takes into account only pavement type, traffic, and possibly some basic environmental factors. In this case, while the prediction curve might be inaccurate for any specific section, it would provide a good average for planning purposes over the network. The project-level recommendation, on the other hand, might have been obtained from a highly detailed analysis using comprehensive mechanistic empirical models. It was thus apparent at an early stage that the answer was *to be able to upgrade any previous prediction curve coefficients on a particular section with the latest available* so that the general network prediction curve could be *replaced* with the project prediction curve if and when this became available.

Chapter 1, therefore, concludes with the recommendation that models be separated from their outcome (i.e., prediction curves) and that instead of storing models (from which prediction curves would be generated "at run time"), *the prediction curves themselves should be stored separately for each individual section as a set of curve coefficients.* While this recommendation represents a fundamental change in approach, it should not require major changes to the existing PMIS. In this way, we allow customization of individual curves based on whatever constitutes the best available prediction at the time. These predictions could be based on very general network-level models that are used when no other data are available, but could also be customized to reflect the output from a design program.

In order to support and to build on this proposed fundamental change, Chapter 2 provides some background on the general problem by discussing (1) the purposes of network- and project-level pavement management, (2) the different TxDOT decision makers involved at each level, (3) the fact that "networks" often consist of different subsets of segments based on district boundaries, and (4) different highway and activity types. The detail of data relevant to the different levels is also discussed. Finally, it is shown that one of the main objectives of the network system is to aid in *strategic* planning, where funding needs are identified and where the impacts of different funding policies are assessed. This strategic planning results in funds being allocated to certain funding categories and distinct district budgets before they are allocated to individual pavement segments. On the other hand, a *tactical* planning phase occurs at the district or area office level when the specific work on particular segments is programmed. In order to accommodate this type of management process, it is proposed that a third, intermediate, project selection level be identified in the process. The final design, plans, and specifications would then be completed based on the selected projects. By allowing customization of individual predictions for each section in the PMIS database, the resulting design prediction curve could then be used not only in updating the prediction curves stored in the PMIS, but also in future planning.

Having provided the background for the project in Chapter 2, this report next reviews the literature on models. The findings are documented in Chapter 3, where the pros and cons of a wide variety of models and general model forms are discussed. This literature review was undertaken to explore the possibility of proposing a change away from the basic sigmoidal models currently used in the PMIS.

In Chapter 4 the proposed integration concept is introduced. At this early stage the details of the concept are still unclear, though the requirements for the final product can be discussed. The objective of the early part of the chapter is to show that the system needs to be constantly evolving, with models and proposed strategies being continually updated as more data become available and new maintenance and rehabilitation projects are completed. Individual roads evolve through a number of stages that can include (1) being unimportant when still in good condition, (2) being selected for further investigation, (3) having maintenance or rehabilitation actually programmed and possibly designed, (4) implementing the rehabilitation and maintenance, and (5) returning to a relatively unimportant state where maintenance/rehabilitation intervention is again no longer imminent. We show that the selection of a particular maintenance strategy is theoretically extremely complex and requires general modeling that enables prediction for a number of possible actions at any point in time.

In the second part of Chapter 4, we discuss the problem of whether to continue to predict performance for individual data collection sections or predict performance for larger homogeneous sections that would constitute realistic projects. This problem is indirectly comparable to the problem of identifying the best way to create realistic actual projects by amalgamating individual PMIS data collection sections into realistic projects (called "management sections" in PMIS), which is required for any realistic integration of the current PMIS with the project level. Historically, the problem has been that, when distresses for individual data collection sections have been aggregated so as to report a single figure for a management section, particularly bad individual sections might go unnoticed because the aggregate value does not trigger a maintenance or rehabilitation "need." This problem is discussed and a conceptual solution using the concept of economies of scale is proposed. Under this proposal, the costs for specific actions would be broken down into a fixed portion, applicable only once to the management section, and a variable portion, based on the length or number of data collection sections actually worked on. Thereafter, calculation of effectiveness would be carried out in the standard way for individual data collection sections; but because the cost per unit area would decrease, this would tend to result in individual sections making the cut only if they were in very poor condition and, in general, would promote aggregation of data collection sections for a single action within a management section.

The two parts are then tied together at the end of Chapter 4, where the general integration concept is outlined. *It is concluded that distresses, etc., should be continued to be predicted for individual data collection sections using deterministic, absolute (as opposed to Markovian) models.* These prediction curves (not necessarily the models themselves) will then be stored individually using a set of sigmoidal coefficients for each data collection section and will become the mainstay of the PMIS. Finally, the prediction curves can be kept up to date by using the best data and performance models currently available for both levels. In order to accommodate the effects of maintenance actions, we propose that modifying coefficients be used to modify these initial curves. This proposal will be dealt with in a subsequent report.

Through prediction curve customization, it will be possible to change the prediction curves for individual or groups of data collection sections where this is deemed desirable. Specifically, if an actual design has been carried out for a new overlay on a CRCP section, the resulting prediction curve for failures could be used to replace the existing prediction curve. Conversely, if it were determined that the roughness progression was very much underpredicted for pavements on swelling clays in high rainfall areas, and if a new general empirical model had just been developed, the database could be filtered for these criteria, with the model used to replace the default PMIS model for this particular group.

The ultimate goal would be to store new network data — data that possibly differ from those currently being stored in the PMIS — so that an improved base level of data could be available to use with more project-level-oriented models. These models would then generate the "default" curves to be used when no other data were available and when the curves had not been customized in any way. Since it is impractical to attempt to incorporate new project-level models for *every* pavement and distress type currently covered by the PMIS, we propose that the general PMIS models remain for the present. However, in order to better integrate predictions with project-level design, we propose that this process be started with one or two example design/analysis type models, such as CRCP8 for CRC-type pavements. This issue is covered in more detail in Chapter 6.

It is generally envisaged that the conversion of external prediction models to sigmoidal parameters for storage for each individual section would be accomplished in a new, separate module. If the concept of using economies of scale to solve the management section problem is adopted, these relatively minor changes would have to be made to the PMIS program itself.

Using the integration concept proposed in Chapter 4, Chapter 5 then describes a staged method of actually integrating the changes necessary to the PMIS. The implementation plan is considered under three categories: decision integration, model integration, and data integration. The implementation plan is as follows:

Phase A: The original PMIS is altered such that the prediction curves are specific to each individual data collection section and are simply stored as a set of sigmoidal-shape coefficients. A new module is created to take over the function of calculating (or simply looking up) these shape coefficients based on the existing models.

Phase B(i): The new module is upgraded to include regression. The sigmoidal-shape coefficients are then calculated using weighted regression on a progressively expanding pool of data points. "Design" data points (initially the only ones in the regression pool) are generated using the original models or are input separately.

Phase B(ii): The economies-of-scale method of handling management sections is implemented in the PMIS.

Phase B(iii): The inventory data, now managed by the new module, are expanded to include fields for a standardized set of data. The new module is also expanded to calculate the "design" data points based on current project-level models when these are available and on the new standardized data set. Various changes to existing design programs, such as CRCP8 and FPS-19, will be made.

Phase C: This is not intended for immediate implementation but will mainly be concerned with decision integration and with the improvement of the optimization through operations research techniques.

The decision integration method is not yet fully developed; however, in order to achieve full network/project integration, the method of "designing" long-term maintenance and rehabilitation strategies at the project level will necessarily be similar to the method used in the PMIS. If strategies are to be developed using decision trees (and a number of distresses) and cost-effectiveness calculations in the PMIS, similar methods will have to be employed in project-level design systems (e.g., FPS).

Chapters 6 through 9 address the specific problem of upgrading the "default" models in the PMIS to more closely reflect project-level design models. Although this was initially considered an important goal, the greatly increased flexibility afforded by adoption of the "individual prediction model" concept described earlier would allow this phase to be an ongoing upgrade that would affect only the newly proposed external module. In fact, the project director instructed later on that the investigators were to concentrate their efforts on the steps necessary for integration at the network level, and were not to concentrate on specific project-level design models. In this way a structure was to be proposed — one that might accommodate whatever models were developed for the new AASHTO 2002 Design Guide. Nonetheless, considerable work was undertaken prior to this to investigate the additional data that might be required for more project-oriented "default" models for rigid and flexible pavements.

Chapter 6 begins by showing that the current PMIS uses a total of 370 potentially different models (although many are actually the same) that result from all the combinations of different pavement types, distresses, and maintenance actions. We conclude that the current distresses already monitored in the PMIS will suffice with one or two small exceptions. Thus, no changes to the current PMIS data collection program are proposed initially. We also propose that the current pavement type and maintenance type categories be retained. In theory, therefore, all 370 "default" models could eventually be upgraded. Since this is obviously impractical at this stage and will, in reality, be an ongoing requirement, we propose that CRCP8 and FPS-19 be investigated initially to determine whether PMIS default network models for punchouts and patches on CRCP and roughness on flexible pavements can be developed using current project-level models. To this end, the idea of creating a "tree" of required data items is discussed and the concept of using a single model (while continually upgrading the data in the tree) is introduced. In this concept, various submodels are used to predict items higher up in the tree hierarchy initially. An example of this would be the prediction of initial crack spacing distribution on CRCP from data on concrete properties, steel properties, thickness, and strength variability. When these "higher order" items actually become measurable, however, they can be replaced with actual measured values. In the example, after the CRCP is constructed, the *actual* initial crack spacing can be measured in the field and can therefore replace the value predicted during design.

In order to thoroughly investigate what additional data items might be needed if project-level models were introduced for punchouts and patching on CRCP and roughness on flexible pavements, we conducted sensitivity analyses for rigid and flexible pavements. These are reported on in Chapters 7 and 8. It is concluded from the rigid analysis that age, traffic, thermal coefficient, subbase friction, swelling potential, construction temperature, and coefficient of variation of early-age crack spacing are the most important parameters. We point out that while thickness is important on an *individual* basis, it is less important than other, more variable factors, given that the majority of CRCP in Texas is 8-inch pavement. For flexible pavements, it was concluded that the following independent variables were important (ranging from highest to lowest rank): design reliability, surface curvature index (SCI), initial serviceability, temperature, terminal serviceability, and traffic.

The identification of possible new inventory and condition variables that might be used in future default models is discussed in Chapter 9. From an analysis of average utility values in each county, it can be seen that failures per mile represent the most important CRCP distress, that failed joints and cracks are the most important for JCP, and that rutting and cracking are the most important distresses to monitor on flexible pavements. Such factors as applicability, statistical significance, and the attainability of variables are discussed in turn for rigid and flexible pavements. Although it is emphasized that it is too early to make a definite recommendation as to which specific additional variables should be included in the PMIS database, a number of conclusions and recommendations are made in sections 9.2.5 and 9.3.5 for rigid and flexible pavements, respectively.

Chapter 10 presents the recommendations and conclusions drawn from this first phase of the project. The major conclusion is that integration between the project and network levels of pavement management in Texas will depend on using the same or similar prediction models for planning (network level) and design (project level) activities. This is seen as unattainable for all models for all distresses and pavement types in the short term, though it is a worthy goal to work towards in the long term. It is further concluded that in order to begin this process, the single major change to the PMIS that is needed is that prediction curves need to be stored *specifically for each data-collection section* using a modified version of the sigmoidal curve currently used. At present a total of 370 sigmoidal coefficient sets are stored to serve as models. Under the new proposal, the prediction curves themselves (which could result from any desired external or internal model) would be stored for each section. It is therefore recommended that this change be implemented as a first stage.

The concept of specific prediction curves, assuming that it is feasible, will allow specific customization for individual or small subsets of sections. It will also allow for a wide range of possible future prediction models to be incorporated into the PMIS as "default" models that would operate on a core PMIS inventory database of data to be upgraded when new or more accurate data became available. Finally, it will also allow regression to be used on the valuable PMIS condition data to modify default prediction curves if a trend other than the default emerges.

Rather than move toward aggregate prediction curves for larger management sections, we recommend that prediction curves continue to be deterministic prediction curves for current PMIS distresses (with others added if necessary) involving individual data collection sections. A possible solution to the problem of recommending strategies for management sections is to use the concept of economies of scale. The final recommendation is that the concepts put forward in this report be condensed into a detailed implementation plan along the lines proposed.

CHAPTER 1. INTRODUCTION

1.1 PROBLEM

The planning, design, and implementation of roadway maintenance, rehabilitation, and reconstruction (MR&R) activities represent a continuous cycle. With the recent proposed shift toward more performance-oriented specifications and construction control, performance equations may be increasingly used to calculate contract pay factors. Performance equations are a vital link design with construction in project-level pavement management. The link to the planning and scheduling of MR&R actions should be made using these performance equations. This will help integrate the project and network levels of pavement management in Texas. (This is described later in the report.)

In his closing address, "Key Challenges for the Future of Pavement Management," at the Third International Conference on Asphalt Pavements in San Antonio in 1994 [Haas 95], Ralph Haas noted that one of the top seven key challenges was "integrating pavement management at the network and project levels." It is thus a universal problem and is vital for a number of reasons.

As the project director for this project has noted, one of the primary reasons is simply that, if network and project levels are separate, then they are likely to give different answers. This obviously greatly detracts from the confidence users have in either system. Which is right? Is either system right?

Another reason is that if the levels can be integrated, at least as far as data collection is concerned, these data theoretically need only be supplemented from the network level for use at the project level.

If, in addition to data collection and representation, the performance models themselves can be integrated, a third major benefit would be that only one set of performance models would need to be researched and periodically updated.

The aim of this research was, therefore, to investigate the problem in detail and to attempt to formulate a conceptual solution. If this conceptual solution is deemed feasible, the objective is then to develop a detailed plan for its implementation.

1.2 IDEAL SYSTEM

The ideal pavement management system would be a seamlessly integrated, single system, one that would perform both network analysis and project level design. The major reason why we are currently getting different answers to the same question is that two analyses are currently performed on different data — one at the network level and one at the project level. Both are aimed at recommending a "strategy" of maintenance options over a particular analysis period. This is illustrated in Figure 1.1. Although the figure is simplistic, it is nonetheless obvious that the basic steps are similar, if not identical. Both systems operate by progressive data flow around a loop: First, field data are collected and stored; then performance is predicted and a treatment or strategy is recommended. The two systems differ in the sequence of events as a section passes from the network level to project level and back again. The flow of information about specific sections can be described as:

1. Sections not selected for immediate treatment at the network level continue in the cycle until a treatment is recommended.
2. Sections selected at the network level for attention in the immediate future are passed to the project level.
3. When sections arrive at the project level, they are processed in isolation from other projects.
4. After the project has been designed and built, the changes are passed back to the network level and the cycle continues.

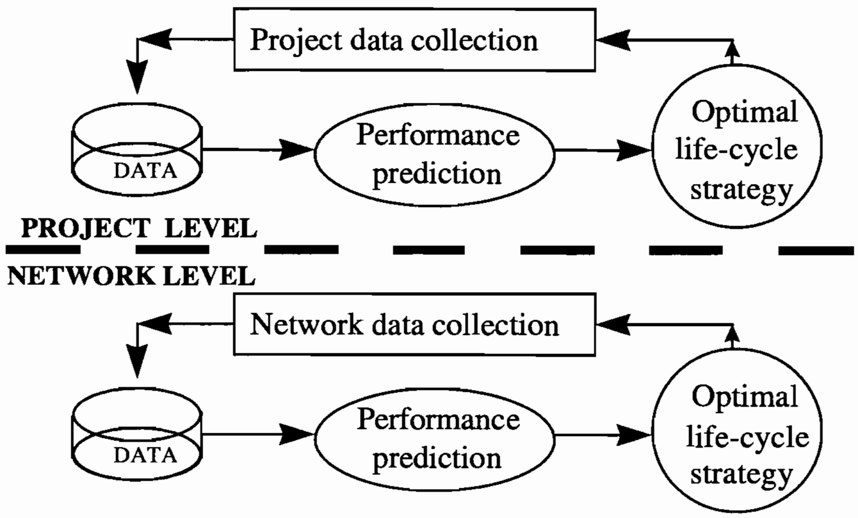


Figure 1.1 Existing network-level and project-level pavement management

Given that the same sections are being analyzed in much the same way, in an ideal system the performance models would be the same and the project-level life-cycle strategy optimization would no longer be carried out in isolation but, rather, performed within the overall network so that all possible trade-offs could be considered. The ideal system would therefore simply consider project-level management and design as nothing more than a detailed cycle (or even a number of cycles) for a particular project within the general system. This concept is illustrated in Figure 1.2.

Full integration requires that all three major subsystems be integrated. This is not a small undertaking and, in fact, is unlikely to be accomplished fully, even over the next several years. Nonetheless, if the concept can be accepted as worthwhile, this will give direction to a considerable amount of future research.

Even if only a limited degree of integration is possible at this stage, it is important that the steps should be conceptualized in reverse order. This implies that decision integration to produce optimal life-cycle strategies should be conceptualized first. This should dictate how performance prediction model integration should take place. Finally, the conceptual plan for model integration should define what sort of data integration needs to take place.

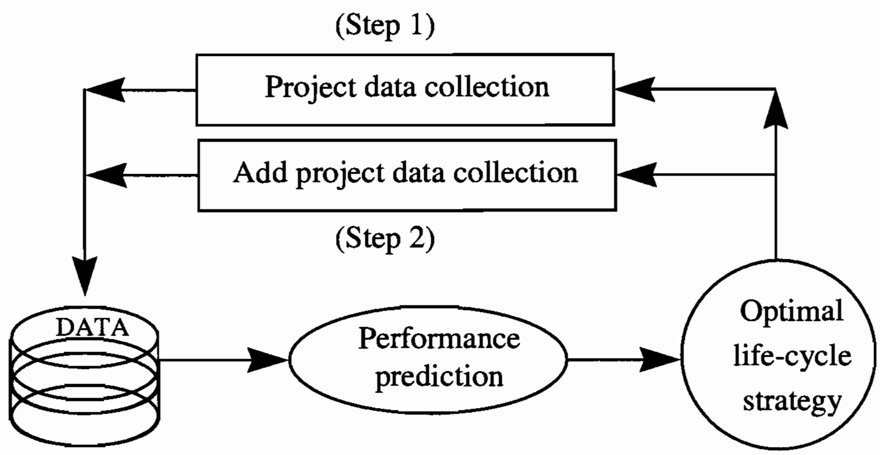


Figure 1.2 In the ideal system, network and project management would simply be different cycles around a single system

Aiming at an ideal system from the beginning will hopefully make future changes in that direction less difficult; additionally, the interim benefits will be considerable and will build in a great deal of flexibility at the same time.

1.3 EXISTING SYSTEM

The Pavement Management Information System (PMIS) is a sound system and was rightly aimed initially toward consolidating and reporting on the *current* condition of the road network in Texas. By now, a considerable amount of good quality, standardized condition data on a variety of distresses have been collected. These data have been used in some cases to develop empirical performance equations for predicting *future* condition. This empirical information could be combined with more mechanistic models to assist in recommending optimal maintenance strategies at the network level and in project design.

Project-level design in Texas is the responsibility of area engineers in most districts. Most maintenance and rehabilitation work is scheduled, designed, and carried out by experienced individuals who know their roads intimately and are continually called upon to use their experience in making decisions.

However, district engineers must decide where to use limited budgets. This is a network-level problem. Much has been said in recent years about the fact that a "worst first" strategy is seldom the best policy. So what is? By integrating the network and project levels, and by making the system more accessible to field personnel, we hope to provide a tool that can be used to recommend answers to some of these types of scheduling decisions.

1.4 INTEGRATION APPROACH

To integrate these two systems, and to span the entire spectrum of pavement management, we begin by recommending one fundamental change in approach that, in spite of the great many doors it opens for future opportunities, should not require major change to the existing PMIS. To implement many of the integration concepts we propose, we recommend that the first step be to *begin storing performance curves for each individual section separately*. In this way, with one act, we allow for the customization of individual curves, based on how much data are available. We allow (1) storage of original design curves, (2) the use of previously collected condition data to aid in prediction for individual curves, and (3) the continued use of the original models; moreover, we are not forced to do any of it.

Curves stored separately for each individual section can be changed as new data or even new project level design methods become available. In this way the best curve available (based on the current data and the best model that this data will support) can be stored for use at both the network and project level at any one time. Where no extra data or models are available, however, no harm will be done, since we may simply fall back on our original PMIS curves.

In the long term, design systems will have to be developed such that they use the same distresses that the PMIS uses; additionally, the decision trigger levels used by both the PMIS and the design systems will have to be integrated. Finally, it will also be possible to remove and add distresses to the PMIS so as to fall more in line with future project design methods.

CHAPTER 2. BACKGROUND

2.1 PAVEMENT MANAGEMENT LEVELS

In the broadest sense, pavement management covers all phases of planning, programming, budgeting, analysis, design, construction, and research. However, as currently practiced by the Texas Department of Transportation (TxDOT), the pavement management process includes only planning, programming, budgeting, analysis, and design. It is generally described in terms of two levels: network and project level. These two levels differ in both management application and data collected.

There are several differences between the network- and project-level pavement management processes. Although the differences vary among agencies, some or all of the following differences are generally found:

1. Goals or purposes of the decisions
2. Groups or levels within the organization making and reviewing the decisions
3. Number of management sections considered in the analysis
4. Detail of the data and information needed to support the decisions

The first three items define the decision support needed at each level, while the fourth item pertains to the data needed to support those decisions.

Purposes

The purposes of the network-level management process are normally related to the budget process and include:

1. Identifying pavement maintenance, reconstruction, and rehabilitation needs
2. Determining funds needed to address these needs
3. Selecting feasible funding options and strategies to be tested
4. Determining the impact of these funding options on the health of the pavement network as well as the overall welfare of the using public
5. Developing a recommended funding option and funding strategy
6. Selecting options to be recommended for funding within the selected funding option or strategy

The portion that deals with selecting sections to be funded may also be described as project selection and programming. The primary results of network level analysis include maintenance and rehabilitation needs, funding needs, forecasted future impacts for various funding options considered, recommendations for funding levels, allocation of funds and prioritized listings of candidate projects needing repair for the selected option.

At the project level, the purpose is to provide the most cost-effective, feasible original design, maintenance, rehabilitation, or reconstruction strategy possible for a selected section of pavement for the available funds. This generally includes:

1. An assessment of the need for construction or cause of deterioration leading to the need for maintenance, rehabilitation or reconstruction

2. Identification of design, maintenance, rehabilitation or reconstruction strategies
3. Analysis of the cost effectiveness of the feasible alternatives or treatments
4. Definition of imposed constraints
5. Selection of the most cost-effective strategy within imposed constraints

Many agencies call this stage "design." Depending on the detail of the analysis, it can include the complete alternative selection and preparation of plans and specifications. Although some authors include construction and quality control/quality assurance under project-level management, TxDOT places those activities under different management systems.

Decision Makers

Those who make the final network-level decisions are generally relatively high up in the organization, and they generally have some type of funding authority for the specific funds being managed. In Texas, the state legislature makes the ultimate decisions regarding the level of funding for transportation; however, the Transportation Commission is involved in making strategic-level decisions about how the funding is distributed among various activities, usually based on the recommendations of TxDOT staff. This includes allocation of funds for MR&R and other activities that affect pavements. Although the Executive Director and staff are involved in making many of the decisions about which individual segments will be selected for new construction, they are primarily involved in allocating MR&R funds to the districts. The decisions about which segments to fund for MR&R are generally made at the district level. Maintenance funds are generally allocated by the districts to area or section levels.

In most TxDOT districts, decisions regarding which segments of pavement to fund for MR&R are made through a process involving a series of steps. Although these steps will vary among districts, they generally include most of the following: At the appropriate time, the district puts out a program call for the work to the area engineers. Those districts using the TxDOT PMIS generally send a list of pavement segments that should be considered based on the PMIS when they contact the area engineers. Many of the area engineers solicit input from the section supervisors. A list of segments, generally with an initial recommendation on the treatment, will be submitted to the district office. From all of those segments submitted by the area engineers, a final list is selected by the district, often by a committee, with the list then approved by the district engineer. This list generally has an initial recommendation for treatment, a preliminary estimate of cost, and the program (or programs) from which the project will be funded.

At the project level, the decisions about which segments will receive work have been finalized; however, some adjustments are generally still made. The final plans, specifications, and contract documents must then be prepared. Although the work may have originally been selected based on pavement concerns, the project often expands to include additional work, such as culvert replacement, drainage repair, sign replacement, signal installation, safety devices, etc. This additional work can sometimes cost more than the pavement work. In addition, the actual treatment applied to the pavement may change based on laboratory tests, especially in the districts where the district laboratory completes a series of tests and develops a final recommended treatment.

Number of Segments

In network-level management activities, agencies generally include all the pavements under their jurisdiction. However, TxDOT, like most state transportation agencies, must actually manage subsets because of funding requirements. Although such funding has more flexibility than was available previously, specific funds are still generally defined at district level. Hence funds can be spent only on selected types of highways, or for selected types of activities. After funds have been allocated to specific funding categories, management is completed according to those categories. This probably means a less-than-optimum allocation of funds. For instance, only the farm-to-market (FM) system can be funded with FM funds, and only selected treatments can be funded with preventive maintenance funds.

The quantity of pavement considered in project-level management is normally a single management section, which also often corresponds to an original construction section, or to a part of an original construction section. However, during the analysis, some management sections may be combined into a single project for contracting purposes. Other sections may be subdivided into more than one segment so that different treatments can be applied to individual portions of the original management section.

Detail of Data and Information

Each purpose, decision level, and review level needs different amounts of information and detail. In general, as the purpose becomes broader, less detail is needed and more summarized information is used. Those making decisions at lower organizational levels make more detailed decisions requiring more complete data. Each level of review will vary with respect to type and amount of data needed.

Data collection is expensive, and funds spent on collecting data are then not available to be spent on applying treatments to pavements. While many agencies talk about cost trade-offs for data collection, no definitive analysis is available at this time to guide decisions on how much data should be collected. However, we have learned of some of the problems from agencies that have used pavement management systems to this point.

We know that we must have the necessary data to support the decisions being made at any given time at the appropriate level. In general we know that we will need relatively detailed data to make cost effective project-level design decisions. If we had those data for every section of pavement in the network we manage, we should certainly be able to also support network-level decisions. However, excessive data collection has created problems in the implementation and continued use of the PMS in the past [Anderson 74]. In general, it is not the initial data collection that has created the problems; rather, several agencies have simply not been able to keep the data current. This has led to a loss of confidence in the decision support of the PMS, and the decision support system was discontinued or used at a minimum level. To avoid this problem, it is recommended that only the needed data be collected at the time it is needed. However, as those data are collected, appropriate data should be retained for future use. Note, however, that this does not totally preclude the network- and project-level management being combined into a single management system based on the same data set. In this case, however, some of the data will be as accurate as required for the project level where it has been necessary to collect this; other data will be only as accurate as required for network management. Problems might nonetheless occur if different types of data — rather than simply different accuracies of data — are required at the two levels.

Interfacing Network and Project

Ideally, the network-level pavement management elements should identify funding needs and prioritize sections needing work. It should show the impact of different funding strategies to justify fund requests. However, in an agency such as TxDOT, the funds are allocated among a series of different funding categories before they are allocated to pavement segments. We can think of this as a strategic level, which is normally completed at the departmental level. This is followed by an intermediate, or tactical, level at the district level where segments are selected. The actual design of treatments normally is completed at district or area office level. To accommodate this type of management process, it is suggested that a third, intermediate level needs to be identified in the process.

2.2 PROJECT-SELECTION LEVEL

This intermediate level would operate between the network- and project-level analyses to assist with project selection and to develop more accurate funding estimates. One problem encountered is the short turn-around time imposed for developing reasonable cost estimates of the segments recommended for funding. Also, as the pavement segment recommended for repair is converted into a project that often includes various other work, the funds are often inadequate if they were based only on pavement repair. In addition, in some cases treatments are recommended without sufficient investigation; when the treatments are applied, change orders have to be made to prevent application of a structurally inadequate treatment that otherwise would allow the project to stay within funding limits.

The purpose of this intermediate level is to provide support at this level. This was identified as a project-selection level by Haas and Hudson [Haas 94], and would require more data than normally collected at network level but less data than needed for full project-level analysis and design. The number of segments that should be included should be much fewer than those in the network, but could include more than what will finally be funded.

After completing the normal network level analysis, those segments that are obviously not candidates for MR&R in the analysis period could be removed from further analysis. Those segments for which the appropriate levels of treatment and funding needed are accurate enough can be set for the analysis period, but additional funding for other activities could be added to the estimate. The remainder of the segments can then be identified for additional data collection and analysis; this could include coring and deflection testing for those asphalt pavement sections to determine if they can be repaired by patching and a seal coat or whether structural maintenance is required. Others might need additional soil tests or field visits to determine if some unique problem, such as swelling soils, is causing the problem that could lead to special repairs. It might include surveys of the drainage facilities or other cost items to determine if major corrections are needed that will lead to additional costs being added to the project.

Once the segments are selected, the final design, plans, and specifications can be completed. However, in trials of the operating systems with both network- and project-level elements, the agencies ran their network-level analysis and then put the resulting information into the project-level analysis [Butler 86]. If they did not get similar results they felt there was something wrong with the project-level system. Once the user becomes familiar with the network-level system, the project-level system (to have any credibility) needs to give similar results when the same data are used for the project-level system. The same general analysis concepts used in the network-level decision support software need to be employed in the project-level elements whenever appropriate. However, it should make full use of more complete data, cost information, and better life estimates.

CHAPTER 3. LITERATURE REVIEW

3.1 MODEL FORMS

3.1.1 Absolute vs. Memoryless Models

The majority of performance models in use in older network-level systems today are actually a mixture of these two types of model. Unfortunately, the mixture is not entirely rational.

If we consider that we have two different types of data available — inventory and condition — we can consider the use of only the former as giving rise to what we term "absolute" models, which give the condition of the pavement as a function of only the inventory variables and the age or accumulated traffic on a road section. These models generally take the form of a set curve originating at the origin of zero distress at zero age.

The general function is of the form:

$$D = f(I, age)$$

where

D = level of deterioration,

I = inventory data vector, and

age = age of the pavement (or accumulated load).

On the other hand, if we can include the current condition of the pavement as a primary input for the prediction of the deterioration in the future, the model becomes a derivative of the absolute model, such that the deterioration in the next time period (or incremental deterioration) is predicted as a function of the inventory data and condition (often called "state") at the beginning of that time period. The general form is thus:

$$dD/dt = f(I, C)$$

where

dD/dt = incremental deterioration in time dt,

C = condition vector at time t, and

I = as before.

The reason that the latter models are termed *memoryless* is that the deterioration in the future is assumed to depend *only* on the current condition or state. The classic implementation of this form in current pavement management practice is the use of Markov transition matrices.

The irrational mixture of these two model types occurs when an absolute model is used in a Markovian (memoryless) way. This occurs when a normally absolute curve is shifted along the age or load axis such that it goes through a surveyed condition point and its "theoretical age" is "looked up." Although not entirely meaningful, the method nonetheless gives a good approximation much of the time and is used effectively in many situations (e.g., in the Texas PMIS).

A more rational method of mixing the two would be to allow a model form that included both the current condition and age (or load) as inputs. The form is actually still fundamentally Markovian but the age and/or load are included as surrogate condition variables for factors that are unmeasurable directly (fatigue is the primary example of this). This model would be of the form:

$$dD/dt = f(I, C, age)$$

where

dD/dt = incremental deterioration in time dt,

C = condition vector at time t, and

I, age = as before.

3.1.2 Existing vs. Future Models

No matter what the exact values of the variables in any highly detailed mechanistic model, a pavement is only going to perform in a single unique way without any intervention. There can be only one curve, as it were. As we have already seen, however, in order to make maintenance strategy decisions, we need to predict performance for a number of possible future maintenance strategy options for a pavement in the future. We might need to evaluate, for instance, what the best strategy would be for a pavement over the next 10 years based on three possible levels of maintenance actions. That would require an upper bound of 3^{10}, or 59,049 performance curves for each distress. This necessarily requires a model utilizing general inputs, possibly taking the form of the model proposed in the previous section. Any one curve shape can be represented by relatively few parameters — a fact used to support the idea of using sigmoidal curves for existing pavements later in this report.

There is no real distinction therefore between models for the existing pavement and models for future options, except that there is only one curve for the existing pavement before intervention and there can be literally thousands of possible curves involved in evaluating different possible maintenance strategies. While it is not certain which of the options will be followed in the future, the one curve that *will definitely* be vital in evaluating any future maintenance strategies is the performance curve for the existing pavement. Therefore, as will be seen later, we propose to treat the performance curve for the existing pavement differently from the performance curves for the numerous different possible intervention options.

3.1.3 Specific vs. General Models

The ultimate general model would be some performance model that could be applied to any type of pavement, after any number of overlays, in any condition. "Models" such as linear elastic layer theory and finite element methods approach this ideal, but more often than not these models are combined with some fatigue model and then empirically calibrated for a particular country, state, or set of conditions. These models are necessarily characterized by the need for a large amount of input data — the more general the model, the more input data required. At the other end of the scale, if condition data are being collected every year on a 50-year-old CRC pavement with two asphalt overlays and a seal coat on it, and these data are showing a strong trend, the specific performance of this particular pavement can often be predicted with great accuracy with little or no additional input data.

As alluded to above, we intend to treat the existing pavement performance model differently from the performance models for different future maintenance strategy options. Based on what stage the planning is at (stages were discussed in a previous section), the performance model for a future option will begin as a general, but probably fairly inaccurate, model. As the option gets progressively closer to becoming reality as a result of its being selected in some short-list of preliminary designs, then chosen as the final design and finally built and operated, (note that those pavements that do not make the cut will obviously fall away as options and therefore no longer require performance models), the model will in turn become progressively more specific until finally it might well become purely empirical and based only on the specific performance of that particular section. This progression is described later in this report.

3.1.4 Empirical vs. Mechanistic Models

This is a commonly made distinction but, once again, in many cases it is not clear cut. It is often possible to generate purely empirical models using regression founded on statistically based sensitivity analyses and a chosen model form but with no knowledge whatsoever about the underlying mechanisms behind the phenomena. More often than not, however, variables and model forms are chosen from experience and hunches regarding the underlying mechanisms. Similarly, the vast majority of mechanistic models are developed from varying degrees of theory and then calibrated using empirical data. These are termed *mechanistic empirical models.*

The overwhelming advantage of mechanistically based models is that they are developed to be general models in the sense of the previous section. Because they are based on theory, they are supposedly much more robust than purely empirical models and therefore handle situations outside the range of the empirical data much better. As we have seen in our discussions of previous model types, an absolutely vast solution space exists where performance of pavements is concerned because there are so many levels of so many different factors involved.

Robustness is only a desirable quality, however, where the model is expected to operate outside its tested range where no empirical data exist. Where empirical data *do* exist, as in the case of a particular distress on a specific pavement section in the PMIS, it is likely that a relatively empirical model based on that specific data will be both much simpler and more accurate than a general mechanistic empirical model.

Once again, therefore, we propose a dynamic progression of the model type depending on the planning stages mentioned earlier: a general, robust mechanistic-based model using assumed and default data when the option in question is on the horizon; the same general, robust mechanistic-based model using more accurate data when the option is approaching actual design; the slow dropping off of parts of the mechanistic prediction as actual measurements become available after construction; and, finally, an almost totally empirical model after enough data have been collected on that particular section to justify this.

3.2 REVIEW OF GENERAL LITERATURE

Pavement performance prediction models are some of the most important components of a PMIS. Capabilities of a PMIS are largely dependent on these models. Prediction models are used in the following activities [Smith 96]:

- To estimate future pavement conditions
- To assess the type and timing of maintenance and rehabilitation actions
- To optimize or prioritize maintenance and rehabilitation actions for single and multiple years
- To analyze the impact of maintenance and rehabilitation on the future condition
- To determine the life-cycle cost
- To provide "feedback" to the pavement design process

Prediction models can predict a single pavement condition indicator, such as alligator cracking, roughness, etc., in terms of extent/severity or condition index (PCI) or an overall pavement condition index (combination of all distresses and ride quality), such as pavement serviceability index (PSI). "Some authors differentiate between performance and prediction models based on specific definitions developed for selected measures of condition; others discuss *prediction models* and *performance curves* as synonymous and do not differentiate between performance models and prediction models" [Smith 96].

Models are generally used for predicting [Smith 96]:

- Primary response
- Structural performance
- Functional performance
- Damage

Primary response models predict fundamental mechanical reactions, such as deflection, strain, stress, etc., which characterize the mechanical behavior of a system subject to an imposed load (structural or environmental). These models are generally used at the project or research level.

Structural performance models deal with the development of different types of pavement distresses, such as spalling in rigid pavement, rutting in flexible pavement, etc. Generally, these models relate one or more pavement distresses (as measured or converted to an index) to the repetition of traffic load (cumulative number of standard axles), structural properties, and environmental condition.

Functional performance models are used to predict functional condition, such as riding quality. Many of these models use a serviceability index (generally with a scale from 0 to 5) to express the functional condition of a pavement and consider it as a function of traffic load repetition. "This type of model can be derived from experience or experiment, primarily empirical in nature, but may also use material properties as model parameters" [Smith 96].

Damage models are developed from structural and/or functional models. Damage is commonly expressed as a normalized (dimensionless) measure of various types of pavement distresses, riding quality (roughness), skid resistance, and other conditions. The essence of this type of model is that it allows integration of different pavement condition measures with different limits to a single damage function [Smith 96].

A prediction model can be developed by one of the following methods [FHWA]:

- Empirical method
- Mechanistic method

- Mechanistic-empirical method
- Bayesian method

3.2.1 Empirical Models

Empirical models are constructed on the basis of the following statistical models using observed data and subjective data:

1. Stochastic models, such as:
    - Linear regression analysis on single or multiple independent variable
    - Nonlinear regression analysis on single or multiple independent variable

2. Probabilistic models, such as:
    - Survivor curve
    - Markov model
    - Semi-Markov model

In an empirical method, the data analysis procedure is generally completed using the following steps:

- Data familiarization
- Data censorship
- Model building
- Statistical analysis

A good explanation for the above steps in the development of a performance model is given by Kerali, Lawrance, and Awad [Kerali 96]. The California Bearing Ratio (CBR) method of flexible pavement design developed by the U.S. Corps of Engineers is a good example of the empirical model. In this model, thickness of pavement is correlated with the cumulative equivalent standard axle and the subgrade CBR.

One of the most important steps in constructing an empirical model is the selection of an appropriate form (though selection of relevant variables is also very important). There are various forms of regression models, such as linear, power, sigmoidal (S-shaped), log values, etc., which are shown in Figure 3.1.

Routine maintenance schedules, unrecorded corrective maintenance, and preventive maintenance can alter the condition of pavement vis-à-vis rate of deterioration; therefore, these aspects must be considered in developing a deterioration model [Smith 96]. A few of the empirical models that are currently being used by different state agencies are given below.

1. Used in the network-level PMS by the Washington Department of Transportation (WSDOT) [FHWA]:

$$PCR = 100 - 0.76(AGE)^{1.75}$$

where

PCR = Pavement condition rating, and

AGE = Pavement age (years) determined from the time of construction of the overlay to the time of the last condition survey.

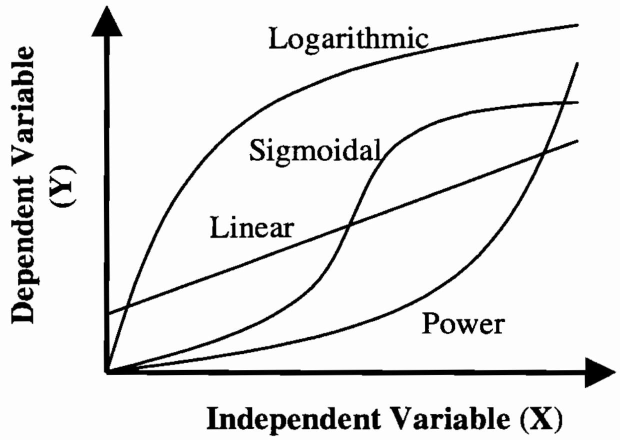


Figure 3.1 Typical regression curves

2. Used in the network-level PMS by the Nevada Department of Transportation (NDOT) [Sebaaly 96]:

$$\text{PSI} = -0.83 + 0.23\,\text{DTP} + 0.19\,\text{PMF} + 0.27\,\text{SN} + 0.078\,\text{TMIN} + 0.0037\,\text{FT}\,7.1\,e^{-7\text{ESAL}} - 0.14\,\text{YEAR}$$

where

DTP = Depth of overlay

SN = Structural Number of existing pavement

PMF = Percent mineral filler

TMIN = Average minimum annual air temperature (F)

ESAL = Equivalent single axle loads

YEAR = Year of performance (year of construction is zero)

FT = Number of freeze-thaw cycle per year

PSI = Present serviceability index defined as:

$$\text{PSI} = 5\,e^{-0.0041\,\text{IRI}} - 1.38\text{RD}^2 - 0.03(\text{C+P})^{0.5}$$

where

PSI = Present serviceability Index (in 0-5 scale),

IRI = International Roughness Index (mm/km),

RD = Rut depth (mm),

C = Cracking (sqm per 93 sqm), and

P = Patching (sqm per 93 sqm).

This is one of the sixteen performance models used in NDOT districts.

3. Used in the network-level PMS by the Texas Department of Transportation (TxDOT) [Stampley 96]:

$$L = \alpha e^{-\left[\frac{\chi \varepsilon \sigma \rho}{AGE}\right]^{\beta}}$$

where

L = Level of any distress type (such as alligator crack) or loss of ride quality,

AGE = Age of the pavement section (years after construction or rehabilitation),

α = Horizontal asymptote factor that controls the maximum range of percentage distress growth,

β = Slope factor that controls how rapidly condition changes in the middle of the curve,

ρ = Prolongation factor that controls "how long" the pavement will last,

χ = Traffic weighting factor that reflects the passes of standard axle loads,

ε = Climate weighting factor that controls the effect of rainfall and freeze-thaw cycles, and

σ = Subgrade support factor that controls effect of subgrade strength on pavement.

Most regression models are deterministic in that they yield a single value of dependent variable.

3.2.2 Mechanistic Models

Mechanistic models are developed on the basis of the theory of mechanics. Mechanistic models are often developed using:

- Elastic layer theory
- Visco-elastic theory
- Fracture mechanics
- Finite element analysis

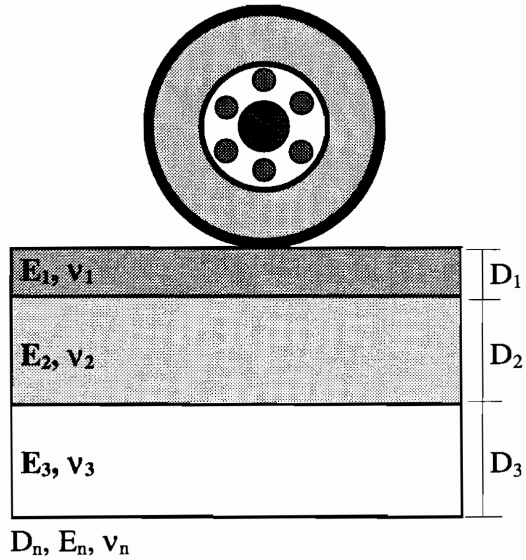


Figure 3.2 Typical three-layer elastic mode

Mechanistic models are used to obtain primary responses, such as stress, strain, deflection, etc., at critical points in a pavement structure under static or moving load conditions on the basis of some theory of mechanics of material mentioned above. In elastic layer theory, a pavement is considered a layered structure, each layer having different elastic property (modulus), Poisson's ratio, and thickness. Linear analysis assumes a linear relationship between stress and strain. Since granular materials and asphalt concrete exhibit nonlinear behavior, linear elastic models may not give realistic predictions for some situations. Displacements and stresses are obtained by solving the governing fourth-order differential equation under the given set of boundary conditions. A typical elastic layer model is shown in Figure 3.2, where, *En* and *Yn* are respectively the elastic modulus and Poisson's ratio of the nth layer from top.

In the visco-elastic method, materials are considered as visco-elastic, having both the viscous (time-dependent stress-strain) and elastic (steady-state) properties. Different combinations of viscous and elastic properties modeled by Maxwell, Kelvin, Burgers, etc., may be used to simulate actual behavior of pavement and its foundation. Elastic-visco-elastic principles of correspondence may be applied to obtain a visco-elastic solution from an elastic solution using inverse Laplace transform [Huang 93]. In this method, the time variable is removed. Figure 3.3 shows a typical form of Maxwell, Kelvin, and Burgers, as well as generalized models.

Fracture mechanics deals with the cracking phenomenon of materials. Several types of pavement distress mechanisms, such as cracking, spalling, corner breaks, blowups, etc., can be explained using fracture mechanics. The magnitude of stress (imposed by traffic and/or environment) responsible for the growth of a microcrack in the pavement structure can be determined by this method. Generally such findings are subsequently analyzed using damage analysis techniques to frame a prediction model for pavement distress.

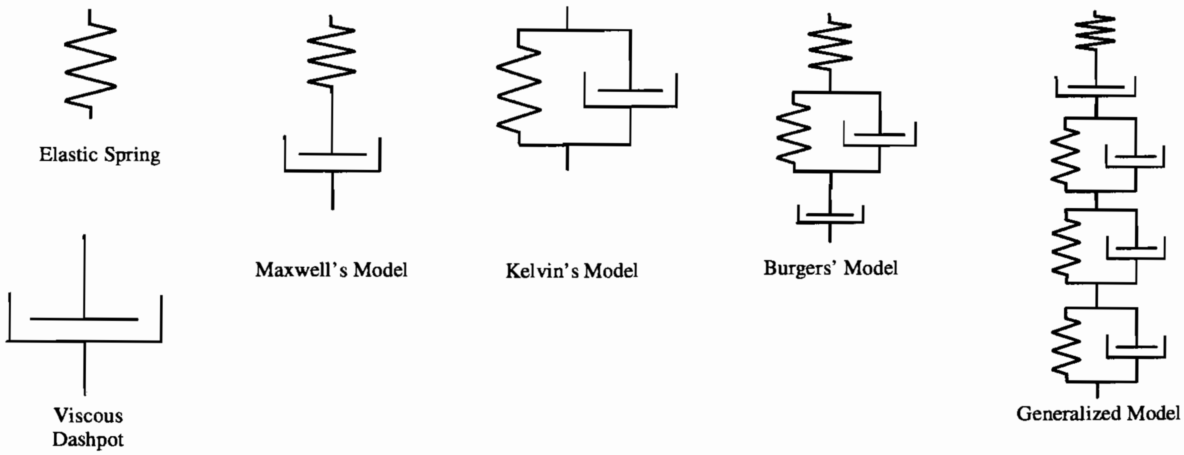


Figure 3.3 Typical visco-elastic models

Besides several mathematical methods, finite and discrete element methods are often used to predict stress and other responses by solving differential equations with appropriate numerical approximation methods [Smith 96].

Several computer programs have been developed for mechanistic analysis and design. The *DAMA* program developed by the Asphalt Institute in 1979 considers the pavement as nonlinear elastic layers. *BISAR,* developed by Shell in 1973, considers both vertical and horizontal loads. *ELSYM5,* developed at the University of California at Berkeley in 1986, considers the pavement as an elastic layered system and can analyze up to five layers under multiple wheel loads. *VESYS IVB,* developed by Jordahl and Rauhut in 1983, is based on visco-elastic theory. *ILLI-PAVE,* developed by Raad and Figueroa in 1980, was based on finite element method. The nonlinear finite element method was used in the *MICH-PAVE* computer program developed at Michigan State University in 1989. The *KENLAYER* and *KENSLAB* computer programs developed by Huang for flexible and rigid pavements, respectively, can be applied to layered systems, such as linear elastic, nonlinear elastic, or visco-elastic, under single, dual, dual-tandem, and dual-tridem wheels [Huang 93]. However, because of their requirements for large amounts of computer time, storage, and input, these programs are not used in PMIS. Moreover, the type of input data, such as pavement material characteristics, environmental data, loading pattern, etc., required for mechanistic analysis is generally not available in PMIS.

Note that these models do not predict performance: They predict only primary responses in terms of strain, stress, deflection, etc.

3.2.3 Mechanistic-Empirical Models

Mechanistic-empirical models are developed by correlating a primary response predicted by a mechanistic model with a usage or environmental cumulative variable at a particular level of distress. Pavement condition data obtained from a mechanistic model are subsequently adjusted to fit observed performance using a suitable statistical method. These models are generally not used in the network-level PMIS because of the large data requirements. An example of a mechanistic-empirical model is the AASHTO (1986) rigid pavement design equation, which was developed from the road test data. In the AASHTO method, pavement condition can be predicted from pavement material properties, thickness, traffic, and climate parameters. At present, most of the state agencies in the U.S. use the AASHTO model (1986), as do performance models in the project-level PMIS. The AASHTO rigid pavement design equation is given below [AASHTO 86]:

$$\log_{10}(W_{18}) = Z_R \, x \, S_o + 7.35 x \log_{10}(D+1) - 0.06 + \frac{\log_{10}\left[\frac{\Delta PSI}{4.5-1.5}\right]}{1+\frac{1.624 x 10^7}{(D+1)^{8.46}}} + (4.22 - 0.32 x P_t) x \log_{10}\left[\frac{S'_c \, x \, C_d \, x \left(D^{0.75} - 1.132\right)}{215.63 x J\left[D^{0.75} - \frac{18.42}{(Ec/k)^{0.25}}\right]}\right]$$

where

W_{t18} = predicted number of 18 kip equivalent single axle load applications,
Z_R = standard normal deviate,
S_o = combined standard error of the traffic and performance prediction,
D = thickness (inches) of pavement slab,
P_o = initial serviceability index,
P_t = terminal serviceability index,
ΔPSI = difference between the initial and terminal serviceability index (P_o - P_t),
S'_c = modulus of rupture (psi) for portland cement concrete used,
J = load transfer coefficient used to adjust for load transfer characteristics of a specific design,
C_d = drainage coefficient,
E_c = modulus of elasticity (psi) for portland cement concrete used, and
k = modulus of subgrade reaction (psi).

The mechanistic-empirical model for flexible pavement used by the Maryland Department of Transportation (MDOT) in the project-level PMIS is given below [AASHTO 86].

$$\log_{10}(W_{t18}) = Z_R \, x \, S_o + 9.36 x \log_{10}(SN+1) - 0.20 + \frac{\log_{10}\left[\frac{P_o - P_t}{4.2-1.5}\right]}{0.40 + \frac{1094}{(SN+1)^{5.19}}} + 2.32 x \log_{10}(M_R) - 8.07$$

where

W_{t18} = cumulative 18 KSAL repetition,
Z_R = standard normal deviate,
S_o = combined standard error of traffic and performance prediction,
P_o = initial serviceability level,

P_t = terminal serviceability level,

SN = structural number = sum of the products of layer coefficient, thickness, and drainage coefficient, and

M_R = resilient modulus of subgrade.

3.2.4 Bayesian Models

Bayesian models are generally developed by combining observed data and expert experience using Bayesian regression techniques that are primarily based on a paper published by the Rev. Thomas Bayes (1702-1761). In Bayesian regression analysis, the regression parameters are considered random variables with associated probability distribution. Bayes' theorem can be expressed mathematically as [Calvin]:

$$P(p|:x) = \frac{P(x|p) \times P(p)}{\Sigma[P(x|p) \times P(p)]}$$

where

P(x) = distribution of variants over all possible fraction variants,

P(p) = prior distribution,

P(x|p) = sampling distribution, and

P(p|x) = posterior distribution.

The main advantage of the Bayesian model is that these models do not require large amounts of data. Prediction equations can also be formulated exclusively from past experience. An application of the Canadian Strategic Highway Research Program (C-SHRP) Bayesian statistical analysis methodology for pavement deterioration modeling by the Ministry of Transportation, Ontario, Canada, is described by Hajeck and Bradbury [Hajeck 96]. In this application, several distress prediction models were constructed initially based on the data alone using linear regression technique as required for the C-SHRP Bayesian analysis. After evaluation, the best one was selected for further analysis. Subsequently, five experts with 10 to 30 years of relevant experience and knowledge of past failures of pavement surface containing steel slag aggregate were requested to rate the level of distress at different ages with different traffic levels and asphalt binder contents using a scale from 0 (no distress) to 10 (sufficient distress that unmistakably requires a rehabilitation treatment). Separate matrices for cracking and raveling were used, since the distress index was considered a linear function of cracking (C) and raveling (R). The distress index (DI) matrices were then obtained by adding two matrices (each having 18 cells) coded by each expert, using the equation DI = 6R+12C. Five different prior (experience-based) models were developed using the C-SHRP Bayesian statistical analysis software, XLBays, keeping the same format as that used for the data-based model. Finally, posterior models were developed from the prior models and field data using "N-prior" analysis option available in the software. After carrying out a sensitivity analysis of these models, the final distress prediction model was selected. As indicated in the paper, "the C-SHRP Bayesian statistical analysis software provides a unique feature that enables the user to obtain a probability density function for regression coefficients (for the data-based, expert-based, and combined models) and plot them in one composite figure for easy comparison." The data-based model, prior models, posterior models, and recommended model are given in the tables below (also shown in Figure 3.4) [Hajeck 96] :

Data based Model : DI = 127 + 5.64AGE - 18.6AC - 5.88logTRAFFIC

where

DI = distress index,

AGE = age of the pavement surface course,

AC = percentage by mass of asphalt cement in the surface course, and

TRAFFIC = AADT volume per lane.

Table 3.1 Prior models (based on experience)

Expert	Constant B_0		Regression Coefficients						Standard Error of Estimate, DI units
			AGE, B_1		AC, B_2		logTraffic, B_3		
	Mean	P	Mean	P	Mean	P	Mean	P	
1	176	0.05	10.6	0.001	-20.0	0.001	-17.7	0.300	11.4
2	14.1	0.80	12.8	0.001	-25.0	0.001	28.8	0.200	10.0
3	-64.0	0.10	8.8	0.001	-24.0	0.001	53.2	0.001	7.5
4	-25.1	y0.50	11.1	0.001	-6.0	0.020	11.1	0.500	5.3
5	-420	0.01	9.8	0.001	-13.5	0.001	123	0.001	15.4

Table 3.2 Posterior models (based on expert judgment and field data)

Expert	Constant B_0	Regression Coefficients						Standard Error of Estimate, DI units
		AGE, B_1		AC, B_2		logTraffic, B_3		
	Mean	Mean	P	Mean	P	Mean	P	
1	141	6.15	0.001	-23.0	0.001	-2.93	0.7	11.4
2	142	6..39	0.001	-27.4	0.001	3.21	0.8	10.0
3	137	5.71	0.001	-26.5	0.001	4.29	0.7	7.47
4	94.8	6.29	0.001	-15.4	0.001	-2.57	0.8	5.26
5	80.7	6.08	0.001	-19.6	0.001	7.30	0.5	20.0

The form of the model is $DI = B_o + B_1AGE + B_2AC + B_3logTRAFFIC$
P = probability that the mean of the regression coefficients or constants is equal to zero.

Recommended Model : $DI = 94.8 + 6.29AGE - 15.4AC - 2.57logTRAFFIC$

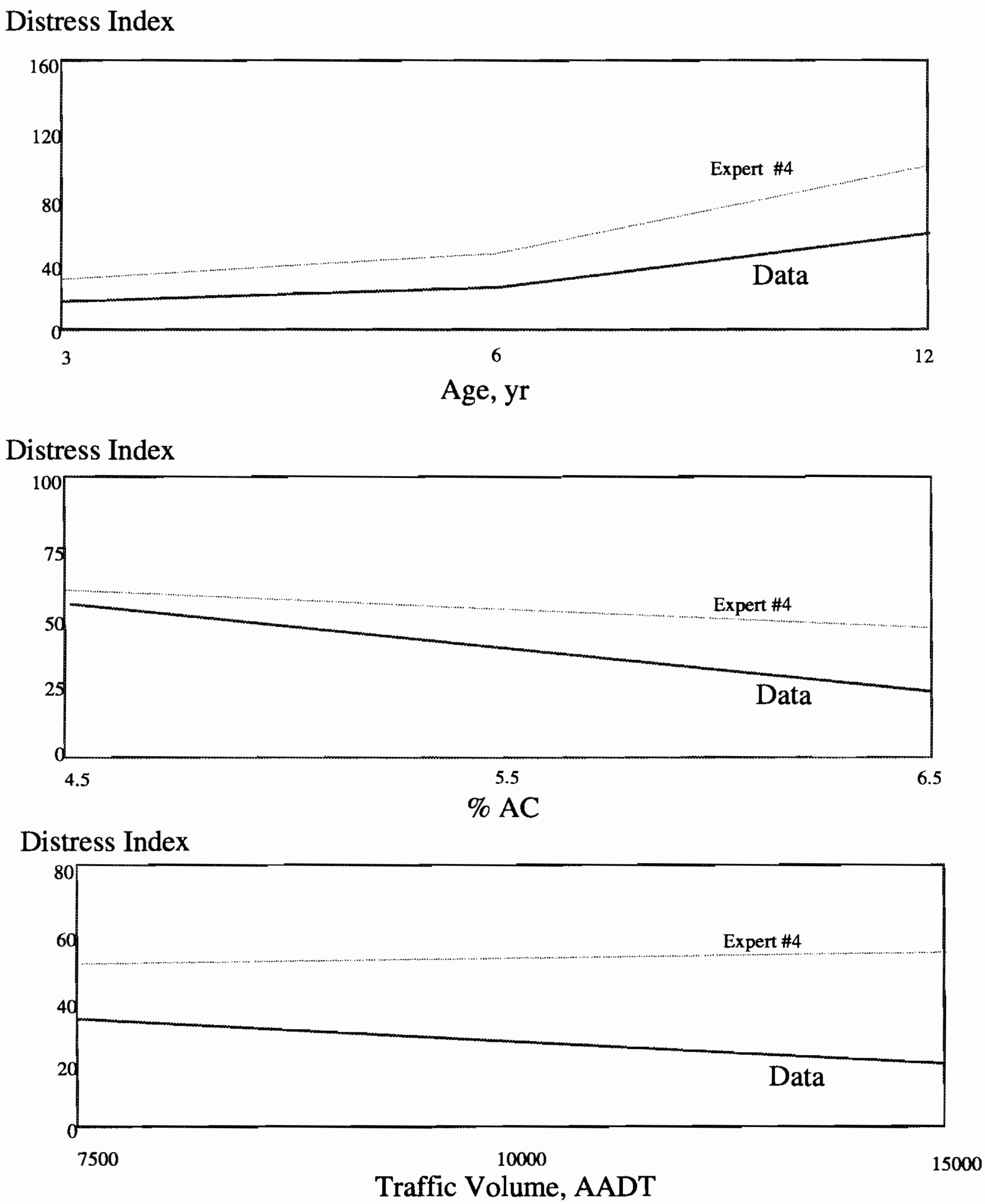


Figure 3.4 Data-based and experienced-based models

3.2.5 Survivor Curves

Survivor curves (also known as mortality curves) were developed in the actuarial process and have been used extensively in the utility industry. Insurance companies, for example, use these curves to determine insurance premium values. The use of survivor curves in assessing pavement service life started in 1934. A survivor curve is defined by Winfrey [Winfrey 67] as

> ...the curve that shows the number of units of a given group which are surviving in service at given ages. The ordinates to the curve give at any particular age the percentage (or the actual number) of the original number which are yet surviving in service. The abscissa is measured in years or other suitable service unit.

The number of units surviving is generally expressed as percentages. The area under the curve divided by 100 (if units are expressed in percentage) gives the average service life of the units. The survivor curve gives the probable life of units at any particular age. The area under the curve to the right of the vertical line drawn at any age gives the service remaining at that age. The expectancy of remaining life at any age can be computed by dividing the service remaining by the number of units surviving at that age. The probable average life at any age can be obtained by adding the expectancy to the age for which the expectancy is computed. Considerable error may be found in the estimate of life expectancy if retirement data of a small group of units are used. However, the probability of error can be reduced if adequate representative data are used and if service conditions are evaluated by the experts. A typical survivor curve is shown in Figure 3.5.

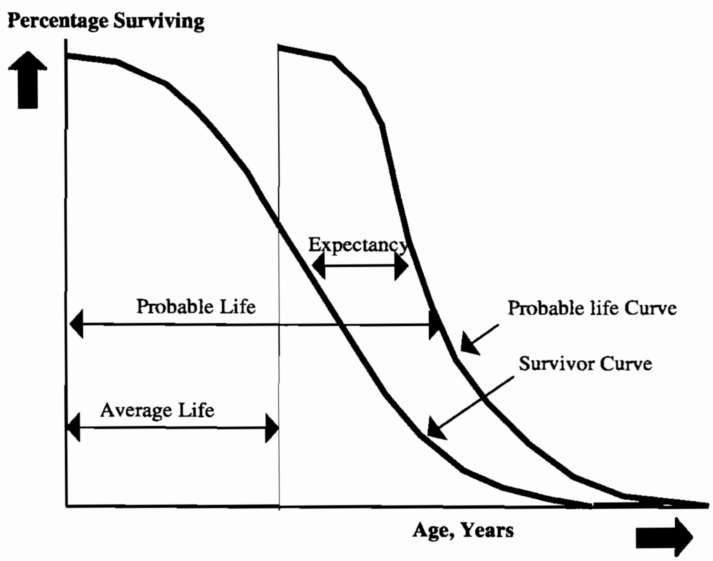


Figure 3.5 Typical survivor curve

Six different methods for developing survivor curves using retirement data have been described elsewhere [Winfrey 67]. Retirement in case of pavement survivor curves is defined by Winfrey as "the removal from service of a significant portion of a highway facility through abandonment or reconstruction to a different type." Pavement resurfacing, reconstruction, abandonment, and transfer can be considered as retirement [Winfrey 68]. Therefore, the retirement is a function of the policy used for a pavement rehabilitation measure. An application of survivor curves for the determination of pavement service life is explained by R. Winfrey and P. D. Howell [Winfrey 68].

A survivor curve can be modeled using the following mathematical form [Smith 96]:

$$PS = 1 - e^{\left[\frac{\rho}{AGE}\right]^{\beta}}$$

where

PS = probability of surviving,

e = base of natural logarithm,

ρ = a coefficient to control life of the curve,

AGE = age of pavement, and

β = a coefficient to control the shape of the curve.

3.2.6 Markov Models

Markov models use transition probability matrices. A transition probability matrix is a collection of probabilities of pavement condition transitions from one level to another. In this method it is assumed that the future condition is a function of the present condition only and is not dependent on the past performance. Transition probabilities can be obtained by observing the performance of a large number of pavements under different rehabilitation actions over a long period of time. Following the Markovian chain method, the future condition state vector, *PCS(t),* of the pavement at any stage, *t,* can be calculated from the initial condition state vector *PCS(0)* as:

$$PCS(1) = P_1 PCS(0)$$
$$PCS(2) = P_2 PCS(1) = P_2 P_1 PCS(0)$$
$$PCS(t) = P_t PCS(t-1) = P_t P_{t-1} \ldots P_1 PCS(0)$$

where P_t is the transition probability matrix at stage *t* and *PCS(t)* is the condition vector at stage *t.* PCS refers to the pavement condition states, such as serviceability index, pavement condition index, etc., suitably scaled for quantitative analysis. If a scale of 1-5 is used, where 5 and 1 represent the best and the worst condition, respectively, *PCS(2),* which is the condition vector at stage 2, can be typically expressed as {0.4, 0.3, 0.2, 0.1, 0.0}, where the elements of the vector represent the percentage of pavement section in five condition states (1 to 5) for PCS level from 1 to 5. Generally stages are considered as a series of consecutive periods of one year. A Markov transition process can be either homogeneous or nonhomogeneous. In a homogeneous transition, variables such as traffic load, environmental conditions, subgrade strength, etc., are considered constant over the entire analysis period; for this reason the probability matrix *(P)* remains unchanged at all stages. For all practical applications in pavement management, nonhomogeneous models are commonly used. The development of a nonhomogeneous Markov model with determination of transition probability matrix using

Monte Carlo simulation technique is described by Li, Xie, and Haas [Li 96].

3.2.7 Semi-Markov Models

Semi-Markov models are developed using available data and the judgment/experience of the pavement experts. The main advantage of this type of model is the use of subjective inputs that reduce large requirements of field data. However, unlike Markov models, these models may predict future conditions from past conditions through transition probability matrices. "It is unique in seeking no cause-and-effect relationship but in simply estimating the rate of deterioration of the pavement" [Smith 96]. These models may be used at the project level.

Types of performance models that may be used at different levels of pavement management are given by the FHWA [FHWA]. A comparison of the models described is given in Table 3.3.

3.2.8 Summary

Several fundamentally different approaches to performance modeling are used in pavement management today. These vary from relatively simplistic models that require little data (since they are primarily for network-level purposes but which are likely to be relatively inaccurate and are therefore often stochastic), to highly mechanistic models that require both considerable input data and computational effort.

In selecting approaches for this study it is necessary to emphasize that relatively high quality condition data are already being collected by TxDOT over 100 percent of the network at least every two years for the Texas PMIS. The organization and technical support for this data collection effort is strong and of a relatively very high resolution (for a network-level system) of 0.85-km (half-mile) segments. An approach that takes full advantage of this should be pursued if possible.

One factor that is inherent in network-level pavement management data is variability. With fewer data and at a lower quality it is vital that this variability be taken into account by generating general performance models that are stochastic in nature. Most of the uses of Markov transition matrices mentioned above fall into this category, and certainly the use of survivor curves incorporates general variability in the pavement network. Bayesian models are a further example. All these modeling approaches explicitly include randomness or variability as a direct requirement to be assessed from the network at large. In our case, where the discretization is currently 0.85 km (half a mile) and may even be reduced further by the implementation of dynamic segmentation, this variability can now be *implicitly* included in the modeling approach by returning to mechanistic, deterministic models that can be applied to smaller portions of pavement. The variability is then modeled implicitly through the variability of the input parameters. It is this approach, the adoption of more mechanistically oriented models for both network and project level, that will therefore be recommended in this report for modeling pavements after future rehabilitation.

For prediction on existing pavements before rehabilitation, the observation that the Texas PMIS currently works with 0.85-km (half-mile) sections is equally important. Because the discretization is relatively fine it is possible to employ the regression techniques mentioned for individual pavement segments when data of sufficient quality and quantity have accumulated and begin forming a trend. This represents almost the best possible approach to prediction models, since no matter what the myriad input parameters, if a particular section of pavement begins showing a trend, this is likely to be the best prediction for that pavement and the regression models can take over from the mechanistic models.

Table 3.3 Comparison of models

Models	Advantages	Disadvantages
Regression	• Microcomputer software packages are now widely available for analysis, which makes modeling easy and less time consuming. • Models can be easily installed in a PMS. • Models take less time and storage to run.	• Needs large database for a better model. • Works only within the range of input data. • Faulty data sometimes get mixed up and induce poor prediction. Needs data censorship. • Selection of proper form is difficult and time consuming.
Survivor Curve	• Comparatively easy to develop. • It is simpler as it gives only the probability of failure corresponding to pavement age.	• Considerable error may be expected if small group of units is used.
Markov	• Provides a convenient way to incorporate data feedback. • Reflects performance trends regardless of nonlinear trends.	• No ready made software is available. • Past performance has no influence. • Does not provide guidance on physical factors that contribute to change. • Needs large computer storage and time.
Semi-Markov	• Can be developed solely on subjective inputs. • Needs much less field data. • Provides a convenient way to incorporate data feedback. • Past performance can be used.	• No ready-made software is available. • Needs large computer storage and time.
Mechanistic	• Prediction is based on cause-and-effect relationship, hence gives the best result.	• Needs maximum computer power, storage and time. • Uses large number of variables (e.g., material properties, environment conditions, geometric elements, loading characteristics, etc.). • Predicts only basic material responses.
Mechanistic-empirical	• Primarily based on cause-and-effect relationship; hence, its prediction is better. • Easy to work with the final empirical model. • Needs less computer power and time.	• Depends on field data for the development of empirical model. • Does not lend itself to subjective inputs. • Works within a fixed domain of independent variable. • Generally works with large number of input variables (material properties, environment conditions, geometric elements, etc.) that are often not available in a PMS.
Bayesian	• Can be developed from past experience and limited field data. • Simpler than Markov and Semi-Markov models. • Can be suitably enhanced using feedback data.	• May not consider mechanistic behavior. • Improper judgment can lead to erroneous model.

CHAPTER 4. INTEGRATION CONCEPT

4.1 DATA AND PERFORMANCE MODELING REQUIREMENTS FOR MANAGEMENT AND DESIGN

4.1.1 Different Requirements at Different Stages

Managing a network of pavements implies planning cost-effective maintenance, rehabilitation, and reconstruction (simply "maintenance" under our definition) strategies for each pavement for some time into the future. At the project level, this planning horizon might include only projects that need to be started in the current year. For analyzing funding scenarios, the planning horizon might be 10 to 20 years. Planning, in turn, implies that certain vital information about the pavements and maintenance actions on them is known or can be predicted. The following are some fundamental classes of such information:

1) The cost of treatments
2) The initial improvement in condition resulting from applying these treatments
3) The deterioration over time of that condition

While the first two data categories are by no means easily obtainable, it is the third that is probably the least easily obtained and yet the most important of the three. In order to use pavement management to assist in planning, it is vital to be able to predict performance.

Predicting performance in a network environment should entail a number of progressive stages. The stages may be roughly broken down into the following:

1) Before design
2) At design
3) After construction
4) After a number of years in service

The data available for use in prediction vary according to which of these progressive stages is of interest. In almost any model the expected error in the prediction increases with the length of the projection into the future. Predicted pavement performance for 1 or 2 years will generally be more accurate than predictions about its condition in 10 or 15 years.

Before Design

In a long-term planning environment it is necessary to know what the performance of a pavement *would* be if a certain maintenance action (including the "do nothing" option) were carried out on a particular pavement when it is in a particular condition. In most cases no detailed design yet exists and only a very general prediction can be made based on engineering experience or possibly based on previous empirical data. Such curves already exist in the PMIS for the broad levels of maintenance actions. These predictions are mainly used in a very general network environment where the emphasis is understandably on obtaining approximate networkwide needs levels and showing the effects of different budget levels, etc. Because of their extremely general nature, these predictions tend to be relatively inaccurate for any one specific case, but on average are still able to provide good networkwide information.

These predictions cover, however roughly, the performance of all levels of possible maintenance actions on all the relevant distresses on all types of pavement. This implies that we know the following:

(1) The relevant different types of pavement
(2) The different distresses (failure modes) relevant to each type of pavement
(3) The relevant levels of maintenance actions
(4) A standardized measure, including method and units, of each distress
(5) A model to predict the change in these standardized measures of distress on each pavement after each identified maintenance action
(6) Relevant inventory input data to make this prediction such as pavement type, traffic loading, etc.

The accuracy of the predictions in *(5)* will obviously depend to some extent on the data available in *(6).*

At Design

A higher level of performance prediction accuracy is attainable after some preliminary designs have been carried out for a particular pavement at the project level. If a number of preliminary designs have been carried out for different alternative maintenance actions (maybe even at different timings), the earlier performance curves for these specific actions on this particular pavement may be updated to reflect this more accurate prediction.

These predictions now cover only a selection of maintenance actions on a single pavement in a certain condition at a certain time.

Once a particular maintenance action has been chosen (probably based on some sort of prioritization involving the preliminary alternatives) a detailed design is carried out. This detailed design should use performance prediction methods in order to identify the "best" design. That performance prediction method will likely use more detailed inventory data from the specific pavement than was available at the previous stage. It should also use additional information collected about material properties, causes of deterioration, and additional work needed for the specific section of pavement. In addition, the design method should take into account the different distresses identified to determine the mode of failure in this particular case. For instance, will the design be governed by cracking concerns or rutting concerns? The models used will probably be the same as those used in the previous phase, except that more accurate data are used.

After Construction

Even during design, a number of assumptions must be made regarding the average strength, thickness, and variability of pavement layers to be constructed. Once the pavement has been constructed, however, the actual means and variability of the layer strength, etc., can replace the original assumptions. The design equations can then be rerun using the measured values to further improve the performance prediction for that pavement. This is especially true of CRC pavements, where actual initial crack distributions can be measured soon after construction.

In this case, the whole mechanistic prediction model for initial crack distribution used in the design may be replaced by the measured crack distribution.

The performance models at this stage are thus still identical to the design and predesign phases, though the input data are now different since certain assumptions made prior to construction can now be replaced with actual measurements.

After a Number of Years in Service

Before the pavement is constructed and trafficked, the performance prediction will be based on empirical comparison with previous similar projects, or theoretical, mechanistically based design models calibrated using previous similar projects. After a number of years in service, however, the observed performance generally differs from that predicted at the design stage or even at the "after construction" stage. Although it may be years before any distress is shown at all, once distress *does* begin to appear, a trend in its increase may well become apparent. It is generally desirable to utilize this information and to incrementally keep improving the performance prediction curve for the section as more condition data become available. This is true for pavements that exhibit distress earlier than expected and also for those that continue to exhibit no distress even after it has been predicted. As with all the previous stages, however, the fundamental performance models remain the same but predicted condition is adjusted based on the latest measured condition

Return to the First Phase

In fact, even before the design phase, the cycle is already starting again, since future options of when next to perform maintenance need to be investigated with regard to how they affect life-cycle costs. Once again, these are often nothing more than very general assumptions about the performance of different maintenance actions. What becomes obvious is that it is desirable to store more than just the prediction curve for the current structure. This may not be possible, however, for implementation in the short term.

In order to summarize in more theoretical terms, Figure 4.1 shows how pavement management might be viewed given even a simple set of two alternatives: "rehabilitate" or "do nothing," in each year of a five-year planning horizon. This is a simple combinatorial optimization problem that might be solved by integer programming, and it can be seen that even with only two alternatives in each year, the total number of possible maintenance strategies is already 2^5 (or 32).

To find the optimal maintenance strategy by exhaustive enumeration (as opposed to some more sophisticated technique), all 32 options need to be evaluated. This would require 32 performance curves assuming the maintenance was carried out instantaneously. If maintenance actions actually took an average of one year to complete as implied by the sloping "maintenance" lines in the diagram, this number would simply be half of 32, or 16, because half of the options would be under construction during the last year and, by strict application of the five-year horizon, would not require prediction. This assumes that even if the "rehabilitation" is the same maintenance action in all cases, the subsequent performance will depend on the condition of the pavement at the time of the maintenance action. This condition is assumed to be different in different years.

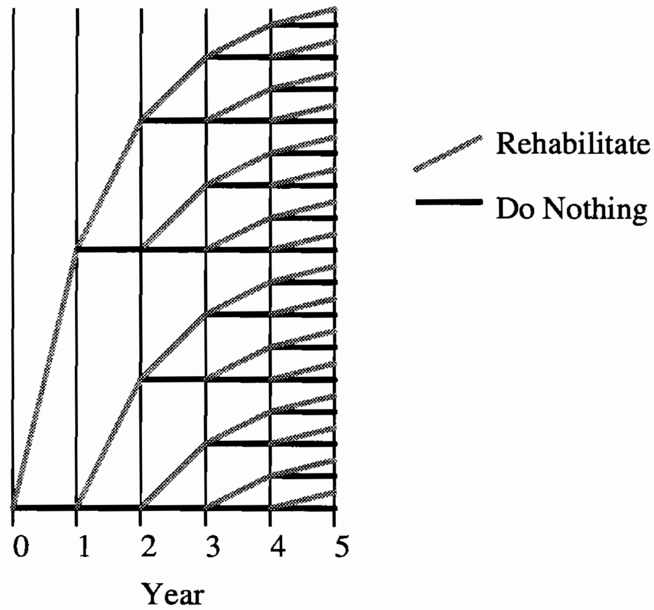


Figure 4.1 Maintenance strategies that would have to be analyzed to optimize maintenance over a five-year horizon in a simplified scenario of two maintenance actions per year

Figure 4.2 shows that at the "Before Design" stage any one particular maintenance action in a certain sequence will require some prediction of deterioration. As mentioned, this prediction need not be highly accurate, but it is one of a great many that would theoretically have to be made. Assuming that the path containing this particular action was indeed followed, this same prediction is still needed but now at a much higher level of accuracy at the "At Design" stage. Immediately after construction the prediction can again be improved and, finally, at the "After Some Years in Service" stage, the prediction might be able to be made based on collected survey data.

At the "Before Design" stage, although Figure 4.2 showed only 32 different options, the need to evaluate all possible strategies on a single pavement section using five possible maintenance actions (four plus a "Do Nothing" option) over the next ten years would require an upper bound of 5^{10}, or almost 10 million performance curves for each section! Even assuming that nothing like this number would actually be evaluated in practice owing to the use of much more efficient algorithms than simple exhaustive enumeration, there is no way of telling *a priori* which of these will be needed; thus we still need to provide the *means* to evaluate all of them. Nonetheless, as long as we had this means, given a highly efficient search algorithm to find near optimal solutions which requires only a very few of these to actually be evaluated, the search for this evaluation model is definitely a worthy one. What we need ideally is a general model to predict initial serviceability gain and then subsequent performance after any maintenance action is performed when the pavement is in any future condition. This general model should apply to all types of rehabilitation on all types of pavement but, in practice, would probably be restricted to the standardized individual distresses on certain pavement types.

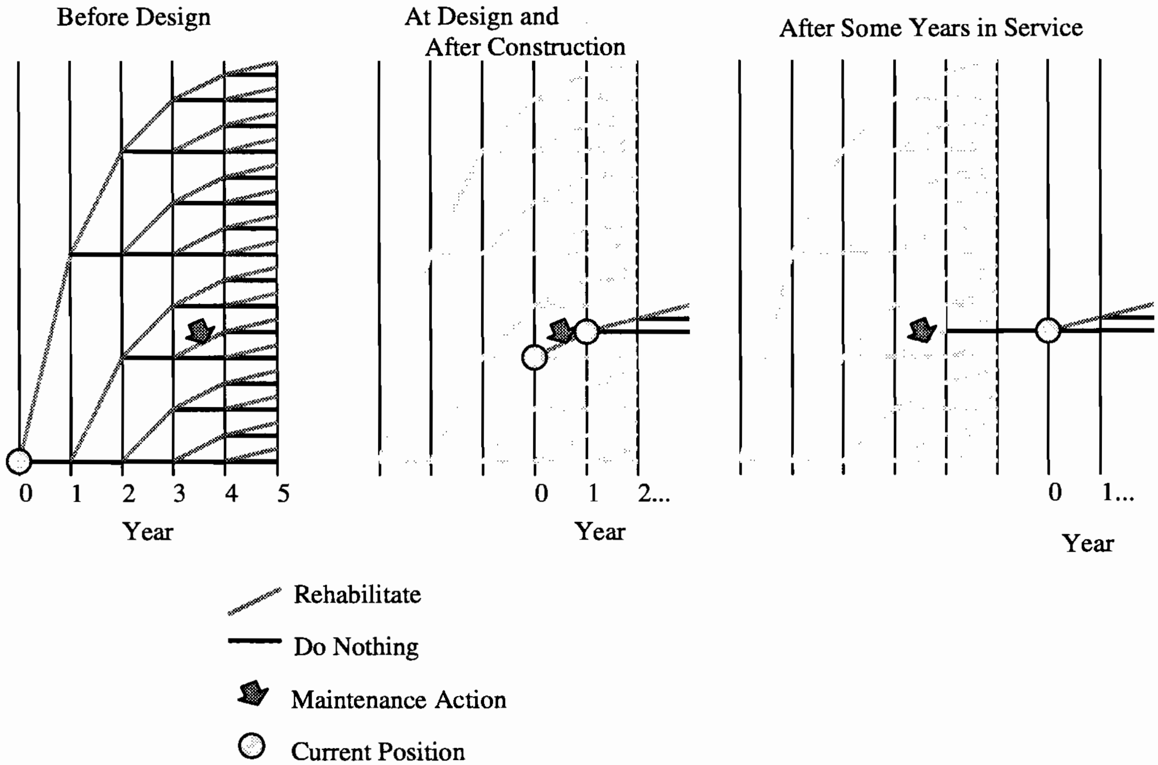


Figure 4.2 Summary of different stages in pavement management

In fact, this is the nature of most design models. The whole purpose of project-level design is to assess the improvement and subsequent performance of various maintenance options given the current condition of the pavement. So why do we not just substitute these into the network models? We are, of course, faced with a trade-off: complexity for dubious gains in accuracy. With simple but readily available and relatively accurate data, we might as well adopt very simple models, since we cannot obtain high accuracy anyway. The accuracy problem, however, is more often than not a data problem and need not be a model problem. Another benefit of more complex models, therefore, is that as data accuracy increases, so does the accuracy of the prediction. To achieve as high an accuracy as possible at the "At Design" stage, why not use these project-level models at the "Before Design" stage with whatever data are available at the time and make assumptions regarding the rest? As more data become available during the different phases described above, these data can replace the original assumptions.

Ideally, the performance model form to be used should predict the incremental deterioration of the different types of distress possible in a pavement based on the current level of distress of all the components. Such a model, called the *interactivity model,* is described in a paper recently submitted for publication at the Fourth International Conference on Managing Pavements in South Africa [Pilson 97]. At least a simplified version of this model, which could predict incremental roughness deterioration as a function of the current state of all the relevant failure modes (thus completing the connection between the failure modes which we wish to track and the actual serviceability on which we wish to base our final decisions), would be desirable. While this might be implementable some time in the future, this study will not attempt to develop completely new models but rather utilize existing ones and concentrate on their integration. We do nonetheless describe various categories of models later in the report.

Whether the prediction models for the innumerable maintenance options are original design models, some generalized regression equations or ANNs, the input data should be the same and depend on the variables to which the prediction is most sensitive. In the case of very general network level prediction we have seen that less accuracy and therefore less input data is both expected and necessary. However, we have seen that it would be desirable to employ design-like prediction models that would allow use of average or assumed values for the slightly less important data items initially, and then to supplement or replace these if more data became available.

4.1.2 Project Requirements

Project-level pavement management basically requires enough information to reliably design a new pavement or rehabilitation such that it performs in a desired way in the future. This design is preferably the design that will result in the lowest life-cycle cost while maintaining a certain minimum serviceability level. In order to choose this "optimum" design, it is necessary to predict the performance of a number of different options. It is necessary initially to perform preliminary designs for a selected list of maintenance options and to choose the best of these for immediate implementation. This requires prediction of their future performance. When designing for an analysis period longer than the initial design period, it is necessary to be able to predict performance for different maintenance actions over the analysis period.

Unfortunately the prediction of performance is not as simple as it sounds. The reason for this is that "performance," as we have defined it previously, is a measure of serviceability over time. This serviceability in turn is normally a measure of roughness or ride quality (and, to a lesser extent, safety). For project-level design especially, we therefore need to know and predict individually the different modes of serviceability failure. These modes are the distresses we continuously refer to. Therefore, in spite of the fact that FPS-19 still bases the design of a direct prediction on ride quality, the more specific requirements of a general project-level design system would be to predict the different distresses individually by different models (say, a rutting model and a cracking model) and then employ a further model to predict ride quality as a function of these distresses. This would effectively identify the major distress and main *mode* of failure. In practice this last model is often absent, and the critical distress (i.e., mode of failure) is identified by predicting the distresses individually and then comparing them to certain minimum acceptable levels. The first distress to fall below its minimum level is deemed the critical one.

Having discussed the various stages of pavement distress prediction in the context of general network level management above, we see that the "At Design" level is really the project level stage. As such it is merely a stage in the overall evolution of the planning and management process and there is no reason to separate it out from the other stages.

In conclusion, the basic requirements for both network- and project-level pavement management are twofold:

1) Some means of predicting future performance on a section of pavement. This can be further categorized into:
   a) A performance curve/model for the existing pavement
   b) A performance model(s) to predict performance after any maintenance action, *a*, given any pavement condition, *c*.

2) The necessary inventory and condition data to obtain this performance prediction to the desired accuracy.

The exact data items themselves, and those measured at each different stage, would necessitate a study of the sensitivity of the prediction to numerous trial variables. As we have said, the detail of the models must be dictated by project-level requirements. At the network level, the less sensitive variables may be assumed or given average default values until better information is available.

4.2 USE OF MANAGEMENT SECTIONS AND ECONOMIES OF SCALE

4.2.1 The Problem

Having discussed the general requirements of pavement management above and concluding that we need certain data items to be able to predict performance on a particular section of pavement, another fundamental question is necessarily "how long should that section be?" We cannot practically predict performance for every square meter of pavement individually, yet predicting an average performance for a large section of 10 km or more is not sufficient for predicting future "needs" on the section at either the network- or project-level.

The Texas PMIS currently uses half-mile sections and offers a structure called a *Management Section* that is optionally definable by the districts and can be of any length (generally to the nearest half mile). The reason for the introduction of Management Sections is that it is impractical to perform moderate to major rehabilitation on single half-mile sections individually. Without Management Sections, this is basically the output of the PMIS. Management Sections are therefore, in essence, user-defined, real project sections. In order to simplify the terminology we will refer in this report to Management Sections as *Projects* and half-mile sections as *sections.* It would seem that if these Projects are to be the physical units that will actually be worked on as projects, should we not be simply predicting the performance of the entire Project?

4.2.2 Weighting Methods for Individual Sections

An underlying problem is in the triggering of maintenance by the use of decision criteria from the PMIS decision trees. At present very few Projects would be listed for rehabilitation because the condition of the Project is calculated as an average of the component individual half-mile sections. As a result of this, individual sections that would normally trigger some maintenance action "get lost" in the averaging. The first approach taken in the study was therefore to search for a weighting method for the sections other than pure averaging to try to alleviate this problem.

The first improvement suggested was that the utilities of the different distresses should be used rather than the distresses themselves. This makes sense because the PMIS uses utilities to compare different sections in the first place, and therefore if utility drops off drastically after a certain level of distress is reached, this should certainly be accounted for in any Project "average." After assuming that utility should be used, the question of weighting still needed to be addressed. Some of the weighting methods considered are listed below:

1) Use a multiplication of the section utilities. In this way, if even one section within the Project had a very low utility, this would bring down the overall value.
2) Use utility of average distress of the component sections.
3) Use average utility of the component sections.
4) Use a higher order (e.g., squared) weighting of disutility. (the first order would be equivalent to the mean.)
5) Use the utility of the worst section.
6) Use the mean utility of the worst 20-40% of the sections.
7) Employ a dual factor utility surface for "extent" and "severity" separately.
8) Use the utility of the worst section to trigger maintenance but calculate the benefits and costs individually.

While options 1-6 all have their advantages and disadvantages, they were discarded mainly because the fundamental problems always remained unanswered: When is it most cost effective to ignore the few bad sections until the majority of the Project has reached that state? When is it most cost effective to step in and do some low-level maintenance on those few while the rest catch up? And when is it cost effective to simply overlay the entire Project even though certain sections did not originally trigger this treatment?

Options 7 and 8 were more promising. It was slowly accepted that some idea of the actual distribution of distress levels in the Project rather than just a single number was vital if the fundamental management questions alluded to above were to be answered. Option 7, that of representing the Project distresses in terms of both their extent (how many sections) and severity (at what level of distress), retains the idea that the Project's ultimate utility can be represented as a single figure. Both this and any performance predictions would, however, take account of this by keeping track of both the mean and variance of the distribution of each level of distress rather than just the mean of a number of discrete sections. In other words, the Project is no longer discretized into discrete sections but is represented as a continuous distribution. Nonetheless, the major benefit of only having to have a single performance model (even though this now models the distribution) is still attainable. The major drawback of the concept is that while possibly excellent for the network level, it is unfortunately not suitable for the project level, where it is vital that the exact location of various distresses be known.

Option 8 is not entirely separate from 7 but better addresses how the actual management decisions might be made. The main idea behind option 8 is the way in which the original management decisions are handled: When is it most cost effective to ignore the few bad sections until the majority of the Project has reached that state? When is it most cost effective to step in and do some low-level maintenance on those few while the rest catch up? And when is it cost effective to simply overlay the entire Project even though certain sections did not originally trigger this treatment? Note, however, that the concept makes no prescription about the individual lengths of these internal sections.

4.2.3 Economies of Scale

In the original plan, Projects are the "project units" defined as such by the districts themselves. As such, the basic premise is that either the whole Project is worked on or none of it is. The question therefore is: Should the whole Project be listed for an overlay when actually only a single half-mile section actually needs one, and, if not, should the single bad individual section go completely unnoticed? Some would contend that if such a situation occurs, the problem is in the definition of the Project: Obviously the section is not uniform and therefore should be split into two or more Projects. Unfortunately, the fact that a set of sections is defined as a Project or Management Section does not necessarily mean that the sections will be homogeneous in practice. In fact, in spite of the wealth of methods developed to identify just such regions for just such a purpose, there are many cases where working on only a single homogeneous section is actually not desirable. The reason is that the overlaying or reconstructing of small sections is fundamentally bad economic practice: It simply is not worth setting up a whole construction project around a single very short section (even if it is homogeneous) and this is actually the reason for specifying Projects in the first place.

The above phenomenon is the result of economies of scale. In general, major rehabilitation or reconstruction projects tend to be longer (and often involve various slightly *different* homogeneous sections) than small seal coat projects and the like. This is because the set-up costs for the bigger projects are fairly large so that "once we're here we might as well do the whole 10 miles!" Actually, the basis of economies of scale can be elegantly simple. At the simplest level the costs involved in a process may be divided into two parts:

1) Fixed costs (those involved in setting up the process)
2) Variable costs (the cost per unit manufactured)

Economies of scale result because once a process has been set up, the cost per unit manufactured drops as the total number of units is increased. The same is true of pavement maintenance: Once the project has been set up and all the fixed costs already sunk, the average cost per unit length will decrease the more sections are worked on. It is for this reason that major rehabilitation and reconstruction projects tend to be longer; the set-up costs are high, the average cost per mile is reduced, and good economies of scale are realized. On the other hand, when set-up costs are low or nonexistent, no economies of scale are available. The concept of stipulating fixed costs for a whole Project is shown in Figure 4.3.

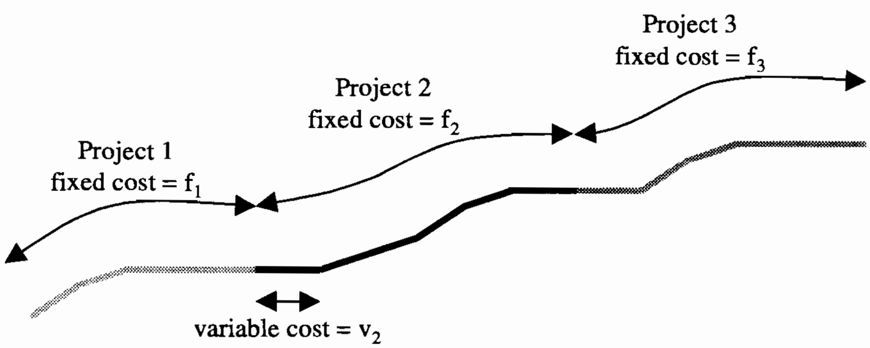


Figure 4.3 Fixed costs for a project are incurred only once, whether the whole project or a single half-mile section is worked on

In option 8 above, the idea of including economies of scale was not explicitly mentioned. However, if we consider the benefits *and* costs of the sections separately while still identifying them as part of the Project, we then admit the possibility of utilizing economies of scale because we may now split the individual cost for the section into fixed costs associated with the Project and variable costs associated with the section. In this way, if more than one section is worked on within a management section, the fixed costs are applied only once and the more sections worked on within the management section, the cheaper the average cost per section.

4.2.4 Recommended Incorporation into PMIS

Discretization

The original problem was one of discretization in the PMIS: What is the smallest section that should be represented by a performance curve? By increasing that minimum size to a Project we would limit the potential to integrate project-level considerations where exact location of distresses is important. By trying to work with continuous (discretizations of the order of 150mm as is currently the case for roughness measurement) data we would be required to dynamically partition the data into homogenous sections. These homogenous sections would still not be operated on as Projects, however, because of the economic reasons cited earlier.

One of the most powerful aspects regarding the economies of scale method of handling weighting of individual sections within a Project is that it is not prescriptive about the length of these sections. The method will work equally well whether the sections are of equal or variable length; it is simply that the performance on each is assumed to be uniform. We must make only the assumption that there are fixed costs associated with larger Projects and that performance should be tracked for individual homogeneous subsections within these Projects.

In the future, therefore, where homogeneous subsections are dynamically defined (dynamic segmentation in GIS terms), the exact location of distresses would be known (these levels of distress for this homogeneous section) and both levels of management decisions could be made. This dynamic segmentation issue is already a much-discussed topic that needs to be addressed for any future implementation of GIS in the pavement management arena. However, while this will probably be implemented eventually, it is not actually necessary to dynamically define homogeneous sections if a reasonably small discretization is used with the assumption that the performance can be considered the same for each discrete section. (Note that the economies of scale decisions would not be affected by having a homogeneous section discretized into smaller sections.)

The final question is then: What is the largest discretization we can reasonably use, such that the assumption of homogeneous performance is acceptable at the project level? Because the implementation of the economies of scale approach should not be affected by future changes made to this discretization, we propose that the currently used half-mile sections be retained as a perfectly adequate discretization. If in the future, through further study and possible GIS implementation, dynamic partitioning into variable length homogeneous subsections is deemed highly desirable, this may be implemented with little change to the economies of scale concept.

Differing Cost Prediction

One difference in the output of the PMIS resulting from implementation of economies of scale weighting is that costs of recommended future strategies and projected needs would be less in cases where more than one section was selected from a Project. This would be a result of savings realized from having the fixed cost now distributed across more sections. The amount of this saving would depend on the number of sections in the Project selected and on the proportion of the fixed cost. If the fixed cost proportion was high, the savings would be considerable. The problem would be not so much that the costs would now be inaccurate (in fact they would likely be more accurate), but that the costs of projected needs would no longer be directly comparable with postimplementation costs. In order to alleviate this temporary problem, it may be possible to assume an average number of sections likely to be selected from each Project and to calculate the fixed cost such that the average total cost per section equals the original cost. If the method is taken beyond being only a method of "weighting individual sections within Projects" and it is desired to improve the accuracy of the cost prediction, the best method for determining the actual fixed and variable portions of the treatments would be to gather data on the total costs of numerous projects of varying lengths and to perform a linear regression. This has not been investigated in detail under this project.

The idea of using economies of scale and making the simple distinction between fixed and variable costs is a paradigm shift from the original mindset of adjusting the weights of the individual distresses in the Project to get a single "weighted average." Nonetheless, the idea not only solves the problem but also could greatly increase the potential for solving the management problems associated with individual sections within a Project. A proposed method for its actual integration into a PMIS is detailed below.

4.2.5 Implementation Method

Implementing this concept into the PMIS should be relatively simple. The proposed method incorporates the following:

1) For each level of rehabilitation, the currently used associated cost should be split into a fixed fraction (percent) and a variable fraction. These would remain costs per unit length, so that the fixed costs would be directly proportional to the length of the management section. This assumption is debatable but is proposed for the present.
2) The triggering of maintenance actions by individual sections remains unchanged. When any one level of maintenance is triggered within a Project, however, all sections are forwarded for effectiveness calculation for this triggered level of maintenance.
3) Once the effectiveness of the maintenance action on each of the sections has been calculated, the costs and, thus, the cost effectiveness (CE) ratios for doing only the worst, only the worst two, worst three, etc., up to the entire management section are calculated.
4) The best option (lowest CE ratio) combining level of maintenance action and the number of sections to perform this action on is chosen to go forward to the list of projects ranked in CE ratio order in the normal way.

An example of this method is illustrated in Table 4.1, which shows four hypothetical Projects broken up into varying numbers of individual half-mile sections. It is assumed that the benefit is calculated by the normal means for every section in the management section for a particular maintenance action even if only a single section triggered this action. The cost is split into variable and fixed costs. To calculate the total cost, it is then assumed that the section in question is worked on as well as any sections for which the benefit is equal or higher (sections in a similar or worse condition). In this way the total cost is calculated as the fixed cost for the Project plus the total variable costs for the individual sections. The total effectiveness is also calculated by adding the benefits of the individual section and all sections in a similar or worse condition. The cost effectiveness (CE) ratio is then calculated as the total cost divided by the effectiveness. The cost effectiveness of working on the whole management section and the cost effectiveness for the best option (a single section, part of the Project, or the whole Project) is then given.

Table 4.1 Hypothetical example application of economies of scale concept

M-SECTION	1/2 MILE SECTION		BENEFIT		FIXED COST	VAR. COST	TOT. COST	EFFECTIVENESS	C-E RATIO	C-E RATIO M-SECT	BEST C-E RATIO	NO. OF SECTIONS	OUT OF TOTAL		
1	1		10		115	5	130	120	1.1			3	4		partial
1	2		90		115	5	120	90	1.3			1	4		single
1	3		20		115	5	125	110	1.1			2	4		partial
1	4		5		115	5	135	125	1.1	1.1	**1.08**	4	4		whole M-section
2	1		20		60	60	240	130	1.8	1.8		3	3		whole M-section
2	2		30		60	60	180	110	1.6			2	3		partial
2	3		80		60	60	120	80	1.5		**1.5**	1	3		single
3	1		20		100	20	180	190	0.9			4	5		partial
3	2		80		100	20	120	80	1.5			1	5		single
3	3		60		100	20	140	140	1			2	5		partial
3	4		10		100	20	200	200	1	1		5	5		whole M-section
3	5		30		100	20	160	170	0.9		**0.94**	3	5		partial
4	1		80		100	20	140	170	0.8	0.8	**0.82**	2	2		whole M-section
4	2		90		100	20	120	90	1.3			1	2		single

It is quite clear from the table that the simple act of splitting the cost into fixed and variable costs is the key to finding the optimum number of sections within the Project to work on; that is, whether it is more cost effective to work on a single section, only part of the Project, or the whole thing. Where the fixed cost is high, as in the case of Project 1 where perhaps a major rehabilitation is being considered, it can be seen that it is often more cost effective to work on the entire Project even though perhaps this action was triggered only by half-mile section 2. On the other hand, in the case of Project 2 where the variable cost proportion is much higher as might be the case for a light rehabilitation, it can be seen that working on only the worst section would be the most cost effective option.

Therefore, rather than resort to assumptions regarding the basically irrational notion of weighting factors, we need now only assume proportions of the original total costs for the now separate fixed and variable costs. These can be rationally estimated by practitioners with the requisite experience or calculated averages from previous cost data.

It can be seen that the method is still simplistic but powerful nonetheless. Individual sections are no longer treated separately, but an optimum solution is generated for each Project. While we still have to track performance for each half-mile section, the projects going through to the final list are always for whole or partial Projects and therefore realistic projects. The reason for the original inclusion of Projects as a user definable structure can thus be vindicated in a fundamentally rational manner without having to resort to highly irrational weighting functions and the like. Rather than pursue the previously mentioned weighting function type options, we propose that this method be incorporated into the PMIS.

4.2.6 Evidence for Economies of Scale in Practice

Up until this point the discussion has been totally theoretical with no tangible proof that economies of scale do indeed exist in practice. While more analysis has yet to be performed, considerable evidence for economies of scale can be found by looking at historical data.

In a brief review of seven large construction projects, Jones [Jones 93] found evidence for the existence of economies of scale by regressing the total costs against the lengths and areas. In the case of lengths, the regression equation was: Total Cost = 7.39 + 2.96(Length), where the total cost is given in millions of dollars and the lengths are in miles. The correlation coefficient (R^2) value was 0.49. The implications of the equation are that the fixed cost is \$7.39 million and thereafter the variable cost is \$2.96 million per mile. For the regression against the area, the equation was: Total Cost = 4.36 + 0.00005(Area), where the total cost is again given in millions of dollars and the area is in square yards. The R^2 for this regression was 0.73. This indicates a fixed cost of \$4.36 million and a variable cost of \$50 per square yard. The total costs for the seven projects ranged from \$8 to \$13 million.

Another source of evidence was found using information obtained from Dr. Khali Persad of TxDOT's Design Division. Using bid data from the DCIS (TxDOT's Design and Construction Information System), Dr. Persad compiled estimates of unit prices for bidding in a number of ways. Where bid items are not used often, only average values are available. For common bid items, however, estimates for different quantities are available and for very common items, a regression equation relating the unit price to the quantity is available. In preliminary studies it appears that in general about 70% of the total cost of typical overlay-type projects is attributable to hot mix. At the time of this writing, for instance, Dr. Persad's regression equation for Hot Mix Type D (item 3022 5008), was ln(Price) = 4.9752 – 0.1717ln(Quant), where *Price* is the unit price in dollars and *Quant* is the quantity in metric tons. While this equation is not of the same form as the simple fixed/variable form proposed, it too shows a clear reduction in the estimated unit price depending on the quantity. Converted to the simpler form by a further regression for the typical quantity range, the equation is Total Cost = 61753 + 23.207(Quant).

While not yet pursued in detail, it appears that it may be possible to characterize each permissible maintenance action by a number of standard specification items and obtain cost data (including regression formulae where available) for these items from the Web site currently being set up by Dr. Persad for use by consultants and district estimators. By updating the PMIS cost data from the Web site once or twice a year, a typical equation, either of the simple fixed/variable form or of the ln/ln form, could be compiled for individual sections and used in the concept set out above. In this way the economies of scale will be able to be incorporated, and the costs can be based on actual and current data obtained from a continuously used and maintained TxDOT database.

4.3 GENERAL INTEGRATION CONCEPT

We have previously defined the object of network-level pavement management as being an effort to develop an "optimum construction, maintenance and rehabilitation strategy" for a road network giving locations, actions, and times; we also defined the object of project-level design as being an effort to develop an "optimum construction, maintenance and rehabilitation strategy" for a road section giving actions and times.

Because these are so similar and because both require distresses to be predicted for certain sections of pavement, the integration concept we have adopted is to try to use the best data and performance models currently available for both levels in order to obtain the same answers from each if we have the same data. Conceptually, we envisage a large proportion of pavement management and design being carried out under a single seamless system. While this will not be possible in the immediate future, it should remain a goal towards which we should direct future efforts. Specifically, we believe that the individual performance models used for the PMIS should be, wherever possible, those that are used at the design stage. As can be seen by the previous section, it is not practical at this stage to try to adopt a mechanistic-empirical design level model for every one of the 370 models required by the PMIS. It is certainly not worth trying to adopt models that are not currently used for design; moreover, only a very small proportion of the total 370 will be able to be covered in the near future. This entails looking in detail at such systems as the rigid pavement CRCP8 system and the currently used FPS-19 to investigate whether they can be incorporated into the PMIS. This will necessitate the inclusion of more input data than is currently stored for the PMIS. It is envisaged that the current inventory data will be expanded to allow for the additional data items, although the exact variables to be added have yet to be decided. It is likely that much of the data will not be available for many sections in many cases, but it is envisaged that the best available data (even if this is based simply on location averages) be stored; if the section is identified as needing further work and project-level studies are undertaken, this new data will also be able to be stored — thus replacing the original default data. This will obviously require that the expanded data set be stored for each section.

In order to broaden the flexibility of the PMIS distress models, we also envisage that the actual prediction curves themselves will be stored specific to each section. In this way, not only the data but also the models themselves will be relatively easily updatable and can be based on the best available data.

The integration concept involves continuing to use PMIS-type sigmoidal curves as sets of specific shape coefficients for each section along with an expanded data set for each section.

We envisage that the means of obtaining the shape coefficients from the original project models will be by weighted least squares regression. In this way a project curve of any form can be converted to a best fit sigmoid and the resulting shape coefficients passed to the PMIS. In cases where no project-level models are available, these coefficients may simply be the original coefficients. The use of regression also allows advantage to be taken of the measured field data to greatly improve prediction when trends in these data begin to become apparent.

Another method of updating the shape parameters may be to use adjustment factors as in the current method. Whichever method is finally chosen, the concept would still be to change the parameters by whatever means in an outside module and keep just the current set of five (and possibly one or two previous sets) in the main PMIS inventory database.

CHAPTER 5. PROPOSED INTEGRATION METHOD

5.1 OVERVIEW

The proposed integration method is divided into three general categories termed "Data Integration," "Performance Model Integration," and "Decision Integration." It is important to note that the method is intended to be *directed* at both the long term and relatively long term in itself. Implementation steps in the Data and Model Integration categories retain almost all the existing PMIS structure and certainly retain both the 0.85-km (half-mile) section discretization and the Cost Effectiveness ranking decision concept. As such there need be little, if any, change in the data collection procedures and the storing of these data in the PMIS (although the collection of additional data such as that proposed in the Road Life system is strongly supported, since these data will be needed to improve the models). The actual implementation is subdivided into three integration phases termed Phases A, B, and C. All initial implementation is contained in Phases A and B, which involve mainly Data and Model Integration. Phase C is more concerned with the longer-term implementation of Decision Integration; while it is not intended that this phase will be fully detailed and implemented in this project, it is laid out conceptually in order to provide a definite direction for the Data and Model Integration to follow.

In this interim report the intention is to lay out the phases conceptually but in enough detail to show that the proposed changes are both significant improvements and are practically attainable. It is *not* the intention to provide a fully detailed implementation plan. The development of a detailed practical implementation plan will be carried out in the next phase of the project.

The categories are discussed separately below but in reverse order, since the Model Integration must be directed by the Decision Integration and, similarly, Data Integration phase must be driven by Model Integration.

5.2 DECISION INTEGRATION

While this will not be fully developed in this report, outlines for the integration of network- and project-level decision criteria are discussed.

As introduced previously, the primary aim of pavement management is to optimally plan future maintenance, rehabilitation, and reconstruction such that the best average level of service is maintained for the money spent. In a theoretical sense, we see pavement management as maximizing some objective function (such as performance or serviceability) over time, subject to various constraints such as budgets, by choice of optimum maintenance strategies. This, we said, applies to both the network and project levels of pavement management, except that network-level pavement management involves decisions regarding (1) what to do, (2) when to do it, and (3) where to do it, while project-level pavement management involves only (1) what to do and (2) when to do it.

Ideally, we envisage both levels eventually being accomplished in a single seamless system, in which case project-level management becomes part of overall pavement management. This is not likely to happen quickly, and the first phases of implementation would retain much of the existing system.

Phase A

In the first stage of implementation, there will be no implementation of Decision Integration. This phase is more fully explained under Model Integration and Data Integration.

Phase B. i

In phase B the objective function would remain the same as that of the existing Cost Effectiveness (CE) ratio. The current method of generating alternatives based on decision trees and ranking these based on the CE ratio in each year and then selecting the best that fall within the budget each year would therefore also remain. The integration of some project-level management (as well as network-level management) into the PMIS would result in not only independent network-level options triggered by the existing decision trees, but also in mutually exclusive project-level options.

The major Decision Integration change in phase B to the current PMIS structure would be the implementation of the "economies of scale" method described earlier. This would require the inclusion of an extra submodule within PMIS to filter out the best of various mutually exclusive options that might now arise for a single PMIS Management Section or "Project."

Mutually exclusive options would then occur at two stages. First, in the "before design" stage a section might trigger some level of maintenance and all sections in the Project would go through for CE ratio calculation (see the section on economies of scale for details of the method). The new submodule would then identify, for each Project in which one or more sections triggered one or more maintenance levels, a single best option (a certain level of maintenance on a whole or partial Project) that would go forward to the prioritized list in the normal way. There is also the possibility that different sections within the Project would trigger different treatments. In this case, the extra mutually exclusive options generated would all still be ranked by CE ratio and the best would again be forwarded to the prioritized list in the normal way.

The second way in which mutually exclusive options would be generated would be when a whole or partial Project had been selected for treatment in the near future such that project level design was necessary. In this case a number of alternatives which had been designed using normal project level methods would be put forward for CE ratio calculation. Once the CE ratios for all the options were calculated, the option with the best CE ratio would be selected and fine tuned, again using the relevant project level design methods. When the final design had been selected, this would once again go forward to the prioritized list in the normal way.

Phase B. ii

In this subphase it will be necessary to change some of the ways in which decisions are made in those project-level models that are currently used. Referring to the detailed review of FPS-19 in the beginning of the report, for instance, it can be seen that all optimization is based on roughness (actually a serviceability loss function). PMIS decisions are based on decision trees and are made with regard to traffic and ride score in most cases, taking account of alligator cracking, rutting, etc., as well. The obvious question that needs to be asked is: Which is right? If we are to retain the decision tree method of decision making for PMIS in the short to medium term, it would appear that FPS-19 should be modified such that decisions regarding when to overlay and whether to make a thin or thick overlay are made on a similar basis. On the other hand, if we retain the current basis of FPS methodology, major changes to the PMIS decision-making concept will have to be made. We propose that the FPS performance models be incorporated into the PMIS (as is more fully discussed in the next section) and that the initial strategy be generated from the PMIS. Note that this incorporates all network as well as project trade-offs and should thus be a globally better decision. The strategy from the PMIS, including maintenance levels and timing, should then be fine tuned using a modified version of FPS in which the basic PMIS strategy can be input as a constraint. (Note that this is only an option and not a necessity at this stage.)

Phase C

The next phase of implementation would probably be accomplished only in the longer term. TTI has looked into the use of operations research techniques, such as linear and integer programming, at various stages. In 1978 TTI report 207-3, Ahmed et al. consider eleven different maintenance levels and nine different distresses for asphalt pavements [Scullion 84]. Many of the original ideas for PMIS have their roots in this system. More recently, TTI research report 1989-2F [Zambrano 95] investigates the possibility of using operations research methods of optimization in the PMIS. This study showed convincingly that true operations research techniques are becoming viable options for the solution of pavement management problems; the report authors gave four options that were directly implementable into the PMIS in its current form. All the methods, however, retained the PMIS measure of effectiveness as the measure of the "goodness" of the option to be balanced against the cost (maximize effectiveness subject to cost or minimize cost subject to effectiveness). While it will be relatively easy to implement any one of these options directly, we now believe that the basic concept of using operations research techniques should be considerably extended in order to implement directly an even more rational optimization system less bounded by the current limitations of the PMIS. The first change from these methods proposed by Zambrano should be the simple use of a single roughness-based index (see previous discussions in the background, etc.) rather than the currently used CE ratio. As discussed, an index based on present roughness is, in our opinion, the best method of representing serviceability and, hence, performance. Currently the CE ratio is calculated as a ratio of the average effectiveness per year (the benefit [B] per mile multiplied by the length divided by the effective life) to the average cost per year multiplied by the traffic [Stampley 95]. When we measure the performance (as the average area under the "ride quality" curve per year, for instance, also multiplied by the lane miles and traffic as is currently done) and simply use the cost in the budget constraint, not only is the problem simpler and more elegant but it is also more general and a fuller solution space will be considered. In the case where a budget is already defined there appears to be no reason why it should be included in the objective function. The tracking of both the performance and cost in a genetic algorithm search is, however, a possibility, as discussed later. In addition, the "benefit" (the benefit [B] is basically defined as the average area between the "before" and "after" distress and ride score performance curves [Stampley 95]) of performing the maintenance over not performing it is automatically taken into account in the optimization method, so it is also undesirable to use it in the objective function. (The actual practicality of this and the extent to which it might improve the decision making should, however, be the subject of a future study.)

In addition to the above, any of the basic Zambrano methods would also have to be changed to accommodate the mutually exclusive options generated at project level and as a result of consideration of economies of scale. This will be necessary, because, as we have already mentioned, it is not good enough to choose the best mutually exclusive options in each case and then send these forward to some further independent level optimizer. This should be able to be accommodated by use of a simple constraint; further study is required to confirm this.

Third, we believe that the current method of using decision trees should eventually be omitted completely so that all options are considered in the optimization and not just those forwarded by the decision trees (again resulting in a larger solution space).

Finally, it is our contention that rather than pursue the more classic operations research techniques such as those pursued by Zambrano, this would be an excellent area for the application of genetic algorithms. Because pavement management is far from an exact science, obtaining the absolute best solution is not necessary. In fact, a single solution, even if it is supposedly the best, is not even desirable. What is really needed are a number of good solutions, and this is exactly what genetic algorithms give. In addition to this, as mentioned earlier, it is also possible to set up a multiobjective GA, such that an efficient frontier is generated giving the best performance attainable for a range of budgets.

In general, the interesting questions posed by Decision Integration concerns represent a complex problem that easily warrants an entire study on its own.

5.3 MODEL INTEGRATION

By reference to our previous discussion on network-level and project-level requirements, we note that if we are to make our decisions in the ideal case based on roughness (serviceability level), this roughness needs to be predicted at a number of different stages. It is also apparent that the roughness can be caused by a number of different mechanisms and these correspond to different distresses. The conclusion is that all the roughness deterioration mechanisms need to be predicted at all these different stages, from the network level before design through to project level at design and back to network level after construction, until the pavement is again identified for maintenance. In our discussion of different model forms we also proposed the need for a general model initially for the prediction of distresses in order to cover the wide range of possible permutations and combinations, such as different levels of maintenance (including "do nothing" and "reconstruct") on the pavement at different conditions.

We propose that the general models adopted be the best design level models available where these exist. The reason for this is that for full integration with project-level management we need the most accurate prediction tools available that are still usable on a wide scale and these are embodied by current design models. As a result, it is proposed that currently used (and future) design models be modified to always give prediction curves for whatever distress (or roughness index) the method is using as an output.

In order to define the concept more realistically, it is now necessary to introduce an example. While dealing with this example, however, references will continually be made to how the concept can be applied to the data integration problem at large.

We begin by considering the first stage — "Before Design" — and we take the specific option of a CRCP reconstruction on a badly deteriorated, heavily trafficked section of interstate highway. Note that this is just one of a great many options that need to be considered at network level and the specific option could just as well have been a medium rehabilitation to a thin, lightly trafficked asphalt pavement. What we really need to know in order to evaluate this option is a prediction of the progression of the roughness or serviceability of the pavement if it were constructed. In our example we define two modes of deterioration: spalling and punchouts. In practice the step of using these "modes" in a final model to predict roughness has not yet been made (but note that it theoretically should be and it is in places like this where the need for future research becomes apparent). At present, spalling and punchouts are still predicted separately and "failure" is deemed to have occurred when the number of punchouts reaches, say, ten punchouts per mile, or when spalled cracks attain to greater than 20 percent of the surface. In order to predict these at the "Before Design" stage we need general models; as we have said, even at this stage we should be using models based on design-level models.

Let us now look only at the CRCP8 analysis method [Won 91] as an example of a suitably general and fairly sophisticated design tool. In the case of CRCP8, the analysis is based on the prediction of punchouts per mile on continuously reinforced concrete pavement (CRCP). Note that in the case of FPM19, the design method is based on roughness. While FPM19 will have to be modified slightly in order to be able to physically produce a roughness prediction curve, in the case of CRCP8, the major output is exactly this, a prediction curve for punchouts per mile. The obvious question is: What are we going to do for input data for the CRCP8 model? Bearing in mind that a major reconstruction is already a simplified case because the condition of the existing pavement is no longer a factor, there is still a wealth of other data that would normally be needed. This is discussed in more detail under the Data Integration Phase but we could assume that not just some but all of the necessary input data could be assumed. If only statewide averages for all these data were used, we would effectively have a single curve giving us the predicted number of punchouts at any age of the pavement for all options. (This is no different from the current situation.) If we took district or county averages we would have different curves depending on location. In this particular case we would need to convert accumulated ESALs to age but still, in general, we would have what we set out to obtain. Problem solved!

The major problem with this is that we still need to have similar models for every type of maintenance on every type of pavement. We also need one model for each relevant type of distress. For instance, in our new CRCP example we need one for spalling. We also need one for punchouts and one for spalling for bonded concrete *overlays*. In the case of asphalt pavements, although FPM19 is capable of producing a model for roughness, we would also need one for cracking and one for rutting.

Although some of these models are available immediately, a great many do not exist at all for all the modes of failure (distresses) identified in the current PMIS. This is the major reason why the current empirically derived sigmoidal curves are used in the PMIS, and similar empirical models with varying degrees of simplicity are used for network pavement management all over the world. If we are considering using statewide averages, then is it really necessary to use project-level models at network level?

In the current PMIS, the sigmoidal equations are essentially supposed to be general models that can account for different traffic, climate, and subgrade. This is acceptable at the network level (remember we were even considering using statewide averages in CRCP8). It is at the next stage — the Design Stage — where the problems now become apparent because the models are no longer sufficiently detailed. For any sort of project-level integration, we need first to be able to use information from the previous network-level stage. Again, if the models are basically the same, then all that is necessary is that the data be updated from some average value to a more accurate value. Where previously a general thermal coefficient for limestone was used, this can now be changed to an actual measured value. Even if we do not have all the models, however, why is it not possible to use the models when we have them and fall back on our simple original empirical curves when they are not available?

This is in fact what we propose. However, in order even to utilize the project-level design models where we have them we have to consider that the data items required will be, first, very numerous and, second, very varied (depending on what design model is required). On top of this, if we are storing the data as an integral part of the PMIS system, as soon as a different design model is introduced, or even a slight modification is made to an existing one, the data items will change.

We thus propose to remove the use of general models from the PMIS system completely. In order to free the system from the limitations of having to predict performance in the general sense, we propose that an externally produced specific prediction curve is stored for each section.

This would in fact require a specific curve for each distress on the existing structure, as well as specific curves for each distress after Preventative Maintenance, Light Rehabilitation, Medium Rehabilitation, and Heavy Rehabilitation (the currently used maintenance levels in PMIS). This is almost exactly the same as in the current system, but instead of the curves being general, they need now to be specific. This requires that for each section, curves for the following are needed for each distress:

1) No maintenance
2) Preventative Maintenance
3) Light Rehabilitation
4) Medium Rehabilitation
5) Heavy Rehabilitation/Reconstruction

Note that we would assume for simplicity in the meantime that only one alternative for each of the maintenance levels was possible for each pavement type. This is of course a major simplification but is in keeping with the current PMIS where each maintenance level on each pavement type is designated one treatment and one cost [Stampley 96]. Should a rigid pavement receive an AC overlay, however, it would be a relatively simple matter to automatically change the database fields to allow for the extra distresses.

One limitation of this approach, however, is that it will still be difficult to incorporate the condition at the time of the maintenance action, since the curve stored will be an absolute one. This of course is no different from the current scenario, but it might be possible to have the curve coefficients calculated only when a particular maintenance action is triggered by the decision trees. The newly calculated curve could then include the predicted current condition if this was available as an input to the calculation. In the CRCP example we might consider a bonded concrete overlay (BCO). In this case, given a certain thickness (i.e., a fixed cost), the future performance will be determined by the so-called "effective thickness" of the existing concrete. This effective thickness could be assessed from the distresses predicted in the PMIS. Accounting for condition at the time of the maintenance action is therefore difficult but not insurmountable as long as the calculation of the curve coefficients is done for a certain time such that the predicted levels of the relevant distresses on the existing pavement are known. This amounts to updating the curves when needed — a process suspiciously similar to using general models back in the main PMIS again. This apparent contradiction is addressed in phase C below.

Whenever the curves are calculated and whether or not the existing condition is taken into account, in order to accommodate the storing of specific prediction curves, it is proposed that the sigmoidal curve continue to be used at least until phase C and, therefore, probably for the foreseeable future. However, with the burden of any general model responsibilities now removed, the curves may be just that: sigmoidal curves, defined by certain shape coefficients, predicting level of distress with age (the continued use of sigmoidal curves is discussed in a later section). The shape of these curves can now be derived in any way from any source. In cases where no more detailed data or models exist, the current models can be used to obtain curves. Where some interest is being taken in the section, for whatever reason, the curves can be modified to reflect the users increased knowledge. At the pre- or detailed-design stage the curve can now be made to reflect the actual design curve (in the case of CRCP8 the coefficients can be adjusted to represent the CRCP8 "punchouts per mile" curve). Finally, when actual data begin to accumulate, the curves can be adjusted to reflect the actual trend for that particular section. These examples are covered in more detail elsewhere in this report.

Although the main PMIS is now completely dissociated from general prediction, in order to obtain the sigmoidal shape coefficients for each section, a separate module will be needed.

It is thus proposed that a new module be developed to generate the shape coefficients by use of least squares regression. This module will have a large database component and will store all basic inventory data required for prediction. The module will then generate the curve coefficients, either in the original way (in which case the regression may be omitted) or by some new general method, where only the original PMIS data are available and no trend is yet apparent in the actual field survey data for the section. Where basic data regarding the shape of the curve are available from other sources, such as project-level analyses (two points on the curve will be sufficient as is shown later), simple least squares regression will be used to fit the sigmoid through these points using certain assumptions regarding the maximum distress, etc. When survey data are also available, the module will use these data and the design points in a weighted least squares regression, which will result in a rational estimation of the curve coefficients as described later in this report.

Phase A

The major initial change to the PMIS will be that five sets (one for each level of maintenance, including the "do-nothing" option) of five coefficients will now need to be stored for each distress in each 0.85-km (half-mile) section record (a maximum of 200 fields). This will have to be accompanied by changes to all modules that currently require calculation of future performance such that the calculations are now done based on the section specific curves rather than on the currently used general curves. If this is handled currently in a single module, the changes should be easily implemented.

In addition to the changes in the handling of performance curves, it is envisaged at this stage that the current PMIS database be split into inventory and survey data. Since the reason for inventory data (e.g., traffic, climate, structure) was previously stored for use in performance prediction, the inventory data (except for basic inventory such as location and highway type data which will remain) will be removed from the current PMIS and placed under the new module mentioned above to handle coefficient calculations.

Where the survey data are stored will not be as important, as the data will be used extensively in both the original PMIS module (for reporting purposes) and in the new module. It can therefore either remain under the PMIS module or be transferred along with the inventory data to the new module. In the former case this will allow the more reporting-oriented procedures within PMIS that interact with the data presently to remain unchanged and intact. Because the new module will need to access the data in phase B, however, methods for accomplishing this will have to be built in to the new module. If the entire database is moved, it will be easier for the new module to link to the survey data in phase B, but new linkage procedures will have to be programmed for the original PMIS. We are more in favor of the neater second option, although the first may require less work.

In the first implementation phase A, we envisage the new module calculating coefficients identically to the original system, such that the new system will operate identically to the original. In this way the new structure can be thoroughly tested and validated by comparison with the old system.

Phase B. i

In phase B, the additional module will be expanded to incorporate regression modeling using original PMIS curve data, external "design" data, and collected survey data. This is described later in the report. It is after implementation of this phase that curves specific to each section will begin to be calculated and the output from the PMIS will begin to change.

Phase B. ii

As noted under Decision Integration, it is also envisaged that in this phase the economies of scale method of handling Projects will be implemented. This will require Decision Integration changes to the PMIS but no additional changes to the new module.

It will probably be desirable to implement and test phase B.i on the new module before implementing phase B.ii. In this way, the implementation of the regression can be thoroughly tested and validated by comparison with the original PMIS output before the Decision Integration changes are made to the PMIS.

Phase B. iii

In order to realize many of the benefits of Data Integration, we believe it is necessary to have implemented all the previous phases so that the final subphase that we envisage is Phase B. The first part of this subphase involves the adoption of an extended standardized set of data that would be stored as the inventory data in the new module. This is discussed under "Data Integration."

The Model Integration part of phase B. iii is the possible inclusion in the new module of a submodule to calculate the "design data" points mentioned in phase B. i. This will be used to generate "design" points that are included in the initial regression pool of B. i. where it is considered desirable to use models other than the existing PMIS sigmoidal models.

Although these "design points" could be input manually such that it is left up to the user to generate them in any way he/she likes, the submodule should include certain (possibly simplified) common project-level models that operate on a standardized data set defined below to calculate the relevant prediction curves. This will also require changes to current project-level models both in order to make them "PMIS friendly," so that they can be incorporated into PMIS, and also to ensure that the recommended maintenance strategies output by the PMIS can be used as a guideline in the project-level models. These models could include CRCP8 and FPS-19 as well as possibly rigid and flexible overlay design procedures.

For instance, CRCP8 will need to be slightly modified to predict punchouts per mile with age and not ESALs (though this has in fact already been accomplished as part of the PAVLIF program).

In the case of FPS-19, the current program will probably first need to be modified to give roughness against time for the first performance period as an output. This is easily attainable and the existing FPS-19 "serviceability loss" prediction equations can be easily used in the new module for the generation of "ride score design points" if a reasonable correlation between these is assumed. In addition to this, however, the fact that FPS-19 is a more comprehensive design program, one that not only gives optimum designs for the first performance period but also defines overlay times, etc., means that considerably more will need to be changed before FPS-19 and PMIS strategies will ever be similar. Attaining some measure of Decision Integration was mentioned briefly in the previous section, and in this regard it will also be necessary to use the overlay performance predictions from FPS in the PMIS. Since FPS-19 does not currently predict cracking and rutting, either all decisions will have to be made with regard to ride score (at least when an FPS design is run) or the PMIS cracking and rutting predictions will have to be incorporated into FPS-19. Ideally, the initial FPS "design" should be able to be run on the PMIS with the FPS serviceability loss function simply replacing the ride score prediction. Once a good cost-effective basic strategy is output from the PMIS (note that this will now have automatically taken into the account the "network" or "independent level tradeoffs"), this could then be fine tuned using the FPS optimization procedures (possibly with the inclusion of user costs, etc.). In fact, these changes should not be as difficult to implement as may be thought initially, but the details will require attention in the second half of the project.

So, while the points could be generated on an *ad hoc* basis if and when desired using external data and external models, this submodule developed in phase B. iii. would provide a more standardized and automated means of using the standard data set discussed below to produce this so-called "design" data.

Phase C

Although certain commonly used prediction models will be incorporated into the new module in phase B. iii, this incorporation of project-level models should be an ongoing process, and future research work on this level should be aimed at producing "PMIS friendly" models so that these can be added to the new module as they are implemented in the field.

Eventually it will be proposed that interactivity models of the type discussed previously be developed for the predictions of the distresses, and that these "distresses" include the condition of underlying layers (perhaps by using their moduli). In this way distresses will be predicted based not only on inventory data in absolute models, but also on the latest survey information of both the other distresses and the condition of other layers in semi-Markovian models. In this way, too, the condition of the pavement at the time of the maintenance action will be more easily taken into account.

In order to implement the above, it should only be necessary to eventually replace the sigmoidal equation (which currently would not consider other distresses) with an interactive equation (which would). This equation would be very similar in that the model would be represented by a small number of "shape" coefficients. These would basically be the interactivity matrix. One fundamental change, however, would be that the models would no longer be "absolute" but would predict only the deterioration in the next time step (in other words, the new model would now be a model giving the first derivative of the distress or the *rate* of deterioration, rather than the *level*). In order to generate a curve over time, the models would have to be used iteratively. This Markovian-type approach, however, is the key to Decision Integration and the use of operations research methods. This also removes the problem referred to earlier of having to perform the major recalculation (and subsequent regression) of curves when these need to be updated (since the curves are effectively continuously recalculated with each iteration within the PMIS). All this, however, requires considerable further study.

5.4 DATA INTEGRATION

The aim of this phase is threefold:

1) Provide a system where data collected at network level can be used at the project level.
2) Provide for data collected in more detailed project level studies to be used in future network-level decisions.
3) Retain a reasonable balance between network-level and project-level data collection.

The realization of these objectives can only lie in some degree of standardization such that where any commonality exists between the two levels, the variables are measured in the same units and apply to the same sections of pavement. It is also vital, however, to ensure the highest degree of commonality possible.

This vital requirement for standardization and commonality is a major driving force behind our push for adopting currently used project-level models for calculating sigmoidal shape coefficients in the above section.

Forgetting for the moment the physical time involved in calculating thousands of curves using a sophisticated analysis program like CRCP8, no matter how automated, let us examine the concept a little more closely. Reverting to our CRCP8 example, let us look in more detail at the input data that would be required for each section. A list of some of the data is given below:

- Steel Properties
  - Percent reinforcement
  - Bar diameter
  - Yield stress
  - Elastic modulus
  - Thermal coefficient
- Concrete Properties
  - Pavement thickness
  - Thermal coefficient
  - Strength, modulus and drying shrinkage during curing
  - Minimum air temperatures during curing
  - Tensile strength coefficient of variance
- Loads
  - Days before concrete sets before wheel load applied
  - Wheel load
  - Wheel base radius
  - Modulus of subgrade

Subbase Friction Relationship
- Maximum force
- Movement at maximum force

Punchout Prediction Parameters
- Swelling condition
- Reliability
- Concrete flexural strength
- Fatigue Coefficient A
- Fatigue Coefficient B
- Coefficient of variance for fatigue failure

At first glance it would seem impossible to provide all these data for a 0.85-km (half-mile) section whose detailed data had not been collected for fifteen years and for which there is no scheduled data collection over the next fifteen years! Actually, however, a great deal of these data could be assumed without major loss of accuracy. In some cases statewide averages could be used; in others, district or even county norms could be used. Still more could be assumed (such as the thickness, course aggregate type and percent steel), which would then become attached to the option.

Still, in order to utilize any data later at the project level, they have to be stored at the network level; in theory this entails storing all the project-level data for all different maintenance options. This amounts to an enormous number of extra data fields; and given that all these data would have to be provided for every single section, it is quite easy to see why the current simpler network models took the form they did. Once again we are stuck with the perennial problem of data storage. Two important things mitigate this problem however. The first is that obtaining this data is not the problem (since simple default values are used where no other information is available); only storing it is. The second is that modern relational databases as well as the storage hardware to support them have seen huge improvements over the last few years and, as a result, we are capable of storing, accessing, and handling data quantities orders of magnitude greater than those planned for in the original PMIS.

As a result we propose that the currently stored data should be expanded to include more of the data items considered important at project-level design. These will contain only the best and most current data available at the time and as such the values will change progressively depending on whether the option is considered in more detail. We propose that the data items be chosen based on two criteria. First, the data item should be statistically significant in the prediction of the distress, and, second, the data item should be applicable to as many different distresses and maintenance options as possible. These data items should also be chosen such that in the event of modifications to design models or introduction of new ones, the model modifications will be unlikely to affect the way (units and to a lesser extent applicable section length) in which these standardized data items are measured and stored.

In order to accomplish the proposal above it is necessary to perform the following steps:

1) Identify the distresses to be predicted on all types of pavement.
2) Identify the project-level design models most likely to be used on all types of pavement and for common rehabilitation actions.

3) Perform sensitivity analyses, using either empirical data on the distresses themselves where data are available or using the project-level models to identify a number of statistically significant variables and rank these in order of importance. (Note that the significance must be based on network-level criteria, as is more fully explained later.)
4) Look at the data items identified and their assumed importance and pick a certain standard set of these for each pavement type also considering whether the item is able to be used for more than one distress prediction.

Phase B. iii

Once the standardized data items are identified, the database containing the inventory data (which now reside in the new module) will be modified to include fields for these items. The physical fields provided will be dependent on the basic pavement type.

5.5 IMPLEMENTATION PLAN SUMMARY

Although the implementation plan is discussed by the Integration category above, the physical implementation steps are summarized below:

Phase A: The original PMIS is altered such that the prediction curves are specific to each individual and simply stored as a set of sigmoidal shape coefficients. A new module is created to take over the function of calculating (or simply looking up) these shape coefficients based on the existing models.

Phase B. i: The new module is improved to include regression. The sigmoidal shape coefficients are then calculated using weighted regression on a progressively expanding pool of data points. "Design" data points (initially the only ones in the regression pool) are generated using the original models or are allowed to be input separately.

Phase B. ii: The economies of scale method of handling management sections is implemented in the PMIS.

Phase B. iii: The inventory data, now managed by the new module, are expanded to include fields for a standardized set of data. The new module is also expanded to calculate the "design" data points based on current project-level models, when these are available, and the new standardized data set. Various changes to existing design programs such as CRCP8 and FPS-19 will be made.

Phase C: This is not intended for immediate implementation but will mainly be concerned with Decision Integration and the improvement of the optimization through operations research techniques.

The proposed changes to the PMIS are summarized in Figure 5.1. It should be noted that the changes are mainly confined to a new proposed module except those proposed for changing the output to management section strategies (as opposed to the previous data collection strategies) using the economies of scale concept which are optional.

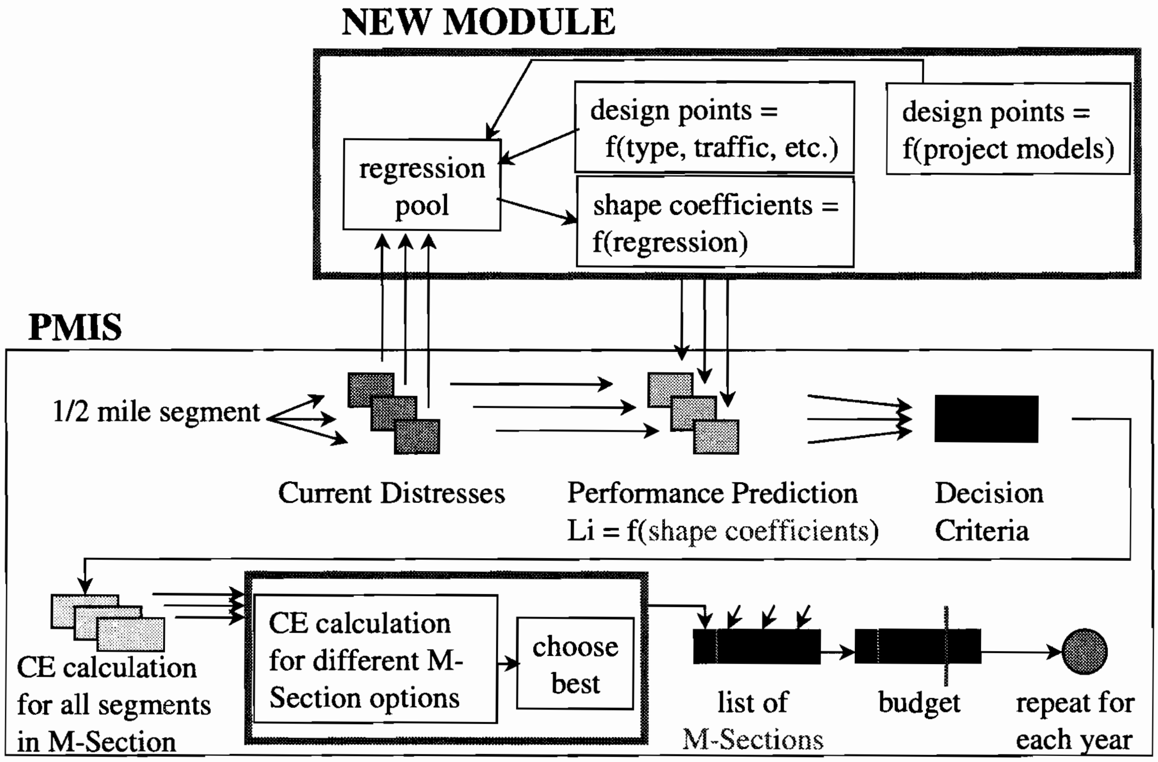


Figure 5.1 Proposed changes to PMIS

CHAPTER 6. PROJECT MODEL INTEGRATION

6.1 SCOPE OF THE PROBLEM

In order to put the problem of project-level model integration into context, let us look at the different models contained in the PMIS. Currently the PMIS provides for performance prediction curves for a number of different maintenance actions on the various pavement types. In fact, there are four levels on six distresses for the three rigid pavement types, and four levels on eight distresses for the seven flexible pavement types, or 296 prediction curves. These are all fixed curves that apply to a whole pavement type regardless of subgrade, climate, traffic, or, for that matter, current condition. Because of this, the predictions are of very limited accuracy, with the result that they cannot possibly be used at the "At Design" stage. Not included in these 296, however, is the "Do Nothing" option (prediction for the existing pavement). These also predict the six different distresses for the three rigid pavement types and the eight distresses for the seven types of rigid pavement types. These other seventy-four curves (making a total of 370) are similar but do provide for slightly improved accuracy by use of traffic, climate, and subgrade factors. This accuracy is still not sufficient, however, at the "At Design" stage. We thus need to provide a mechanism for increasing the accuracy of the models as the data become available. The 370 models whose accuracy we must eventually increase are shown in Figure 6.1.

Obviously, it will not be possible to provide project-level models for all of these. Nonetheless, where project-level models are currently used for design it will be necessary to incorporate these models into PMIS in order to move toward our goal of obtaining the same answers from different systems. At present we intend to test feasibility by using the CRCP8 and FPS-19 systems as examples in order to test what changes will be necessary for certain levels of integration.

6.2 DIFFERENT STAGES AT WHICH PROJECT LEVEL PREDICTION MODELS ARE REQUIRED

In the ideal case, based on the previous discussion on the different stages a particular performance model will go through, it can be seen that prediction models will be needed from the time when the actual maintenance option is only one of many possible future options, through design, to some time after the option has already been constructed. Only when a discernible trend in the actual field data begins to become apparent will the initial prediction models begin to lose importance.

In theory, then, the early stages will require almost completely hypothetical prediction based on little real data and many assumptions, and this must be borne in mind when candidate project-level systems for integration are chosen. In practice, however, the existing PMIS at present only evaluates a single path (and possibly a few extra branches) by using the relatively shortsighted method of choosing the branches at each decision point for a single section by using decision trees (answering the "what" and "when" questions) and then choosing from among the different section options by adopting those having the best CE ratio (answering the "where" question). The implication of this is that, at least for the mean time, we need not concern ourselves with cutting down computation time for each prediction. This would be desirable only if more general optimization techniques were introduced, techniques that required all (in the case of exhaustive enumeration) or at least many more (in the case of more efficient algorithms) prediction calculations to be performed. Although it may become necessary later to investigate reducing some of the more complicated project-level systems such as CRCP8 to simple Artificial Neural Networks (ANNs) or using some similar computation time saving method, for the initial model and data integration it will be necessary only to transport the existing equations and provide the necessary data.

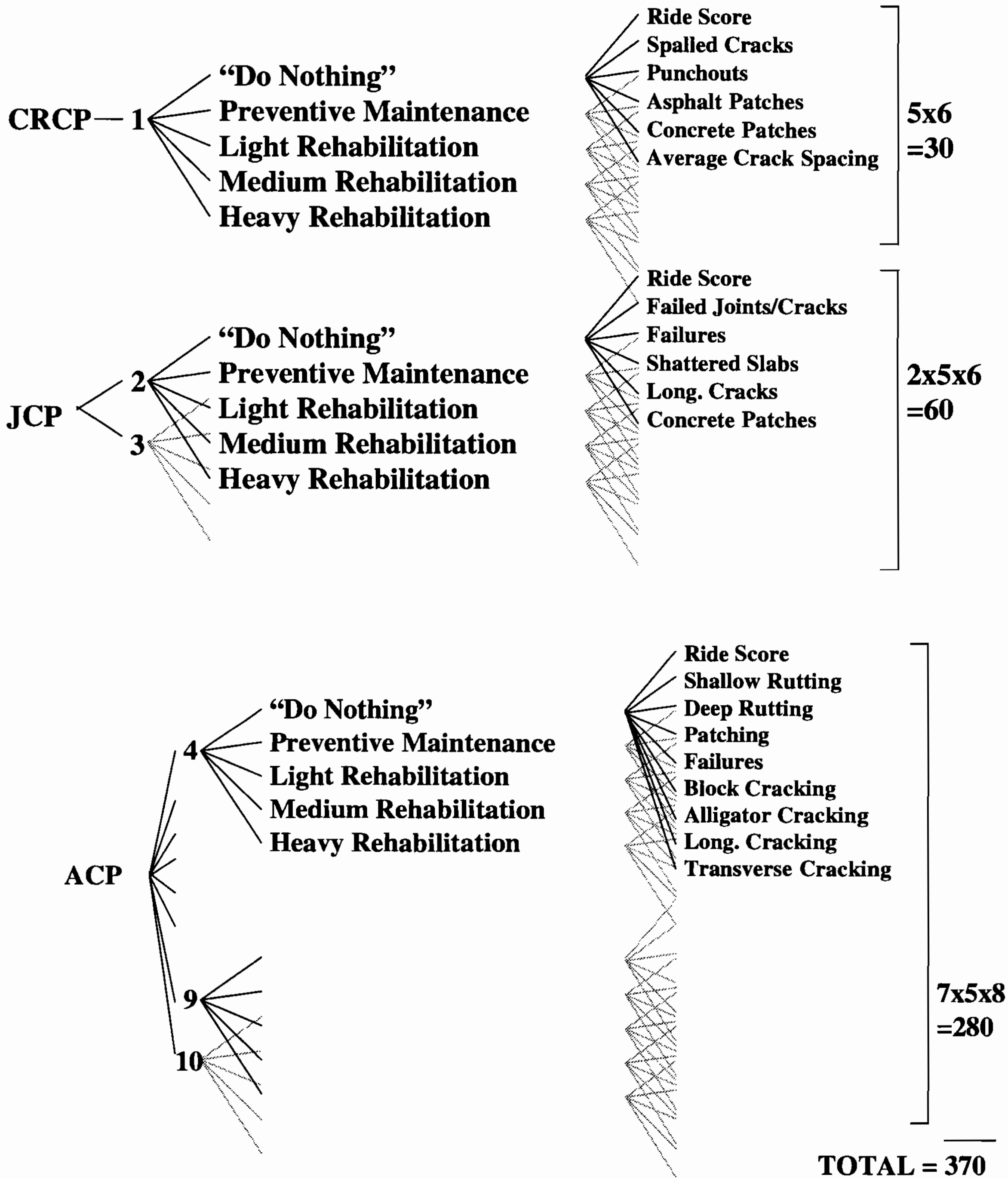


Figure 6.1 The PMIS currently uses 370 discrete models for distress prediction

In the case of the CRCP8 system, punchouts and cracking can be predicted in a general model; and although the physical coding of the method into the new model might be somewhat complex, the concept of integrating it into the new module is relatively simple. For FPS-19, which not only predicts roughness but also includes a certain amount of optimization, the prediction models will be able to be integrated much like the CRCP8 models (although certain data concerns arise, as will be seen later). At some time in the future, the optimization portion, along with the decision criteria, will have to be integrated as well in order to obtain similar answers from the PMIS and FPS-19. In the initial stages of integration, however, the models for roughness prediction alone will be inserted into the new module. This will suffice for long-term general planning and prediction.

Similar improvements can be expected in prediction for both the CRCP8 method and FPS if previous assumptions regarding as-constructed variables (such as crack distribution in CRCP or final moduli and thicknesses in FPS) are replaced by actual measurements after construction.

6.3 DISTRESSES AND MAINTENANCE OPTIONS

As we have already seen, the PMIS requires 370 different prediction models at present. A large contributor to this diversity is the fact that models are required not only for different distresses but also for the "Do Nothing" periods after different maintenance options.

The PMIS currently provides prediction models for the distresses given below in Table 6.1. (Note that certain other distresses are also collected for information only and are not predicted or used in the decision trees.)

The first question that must be resolved, therefore, is whether these distresses will suffice for the initial phases of integration implementation. It appears from the expert panel discussions and through practical considerations that these will almost certainly suffice for the present, with one possible major exception. While rigid pavements are not as affected by moduli changes in the different layers making up the system, it would appear that reductions in moduli in asphalt pavement layers may be a very useful "distress" to monitor, since so much of the "cracking type" distresses are highly dependent on the horizontal strain at the bottom of the surface layer. To a certain extent this information is already being collected in the form of FWD deflection data. However, while it may be desirable to predict this in the future for use in more mechanistic approaches, monitoring as opposed to prediction may suffice for the present.

Table 6.1 PMIS distress and ride score prediction models [Stampley 95]

CRCP Distress Types	JCP Distress Types	ACP Distress Types
Spalled Cracks	Failed Joints and Trans. Cracks	Shallow Rutting
Punchouts	Failures	Deep Rutting
Asphalt Patches	Shattered (Failed) Slabs	Failures
Concrete Patches	Slabs with Long. Cracks	Block Cracking
Average Crack Spacing	Concrete Patches	Alligator
Ride Score	Ride Score	Longitudinal Cracking
		Transverse Cracking
		Ride Score

As far as modeling for CRCP is concerned, it is recommended that the interactivity between the different distresses be taken full advantage of, such that the crack spacing is initially predicted, and from this the accumulating punchouts (or failures per mile) are predicted. The prediction of patching should then be reduced to a simple location-dependent model based on the failures per mile, since almost all punchouts are relatively quickly patched in most cases.

The same is true for flexible pavements where it should be possible to predict all relevant distresses from four equations: one for shallow and deep rutting, one for block and transverse cracking, one for alligator and longitudinal cracking, and one for ride score. Failures would be obtained from other distresses.

At present the PMIS utilizes four different levels of maintenance in addition to the "Do Nothing" option implied in the normal prediction models. Since we propose at present to retain at least this many options, it will be vital to account for as many of these different levels and options as possible when we choose the project-level models we wish to attempt to integrate. In the case of CRCP8, we believe that with a little modification, assuming the right data are available, the models can be used to predict cracking and punchouts after a number of different maintenance options. The present PMIS maintenance options for the two examples of CRCP and Thick ACP are given in Table 6.2.

As for the distresses, it must be decided initially whether these will suffice for the immediate future. We propose that they be retained for the present but would like to allow for the future possibility of a user-customizable system in which treatments and their associated prediction models can be inserted with relative ease.

Table 6.2 PMIS maintenance options for pavement types 1 and 4

Treatment Type	**Pavement Type**	
	1 (CRCP)	***4 (Thick Hot Mix)***
Preventive Maintenance (PM)	Crack (or Joint) Seal	Crack Seal or Surface Seal
Light Rehabilitation (LRhb)	CPR (Concrete Pavement Restoration)	Thin Asphalt Overlay
Medium Rehabilitation (LRhb)	Patch and Asphalt Overlay	Thick Asphalt Overlay
Heavy Rehabilitation (LRhb)	Concrete Overlay	Remove Asphalt Surface, Replace and Rework Base

This means that eventually we need to aim at predicting each of the current distresses for each type of pavement after the various maintenance options. For our initial implementation, however, we will be required to choose a few particular currently used design methods and plan to integrate these into the PMIS in order to accomplish our original objective of obtaining the same or similar answers from both the PMIS and the design system in question. If, as we propose, we investigate the incorporation of CRCP8 as a good, mechanistically based project-level prediction system for CRCP, and FPS-19 as a widely used flexible pavement design system, we will only be filling in a small proportion of the total prediction equations required by the PMIS; nonetheless, this will give us insight into the concepts and mechanism of integration and also give direction to future research efforts by way of highlighting and prioritizing the next gaps to be filled.

Once the initial models to be integrated have been chosen it is necessary to consider the data necessary to support them. A generalized conceptual way of doing this is discussed in the next section.

6.4 HIERARCHICAL TREE CONCEPT

In order to accomplish the Data and Model Integration in a more structured manner, it is proposed that hierarchical data trees be set up for all relevant distresses on each pavement type. This is an excellent way of visualizing both what data are considered relevant and what exactly the data are needed for.

The idea of representing the data in a tree stems from the fact that "performance models" often consist of a series of submodels. These submodels require certain inputs and result in certain outputs. These outputs in turn often become inputs to another model, and so on. The main objective for the data structure is to accommodate the goal of using the best available prediction curves for each project.

In order to make decisions on a networkwide basis, the hypothetical root of the tree should in theory be some combination index so that the seriousness of different problems on different pavement types can be compared. This final combination of models into a single root is currently accomplished in the PMIS by use of utility curves, such that the utility of, for instance, a certain extent of cracking on a flexible section can be directly compared with a certain number of punchouts on a CRCP section.

It is important to note that the proposed data structure need not necessarily be a physical database but more of a virtual structure primarily for use as a visualization tool in the standardization of data items and the hierarchy among these. As such, it is a data structure (where nodes represent data items) that also implies models wherever the combination of a number of input data items are combined for output. Whether physically implemented or not, the documentation of the existing systems in this form within Texas provides a very valuable means of assessing current practice and identifying locations where improvements might be made.

Returning to our example of a new CRC pavement, the distresses predicted currently in the PMIS for the CRCP type are the following [Stampley 96]:

Severe Punchouts per Mile
Portland Cement Patches
Asphalt Patches per Mile
Loss of Ride Score
Cracks per 100 feet
Percent Severely Spalled Cracks

For the present, therefore, it is these distresses that need to be linked to the currently used project models where these exist. Since the vast majority of decision tree statements in PMIS use Average Crack Spacing and the sum of (Punchouts + Asphalt Patches + Concrete Patches) [Stampley 96], what we really need to predict is crack distribution and total accumulated punchouts per mile, or as we have chosen to call it, Failures per Mile (FPM). This is in fact exactly what the CRCP8 model mentioned earlier accomplishes, and so we will continue with the example developed earlier. In fact, what now transpires is that the prediction of crack distribution (from which Average Crack Spacing can be obtained) is a step in the process of predicting punchouts per mile, since various data are used to predict the initial crack spacing distribution, with fatigue equations then used to predict the progression of this to the formation of punchouts. An example of part of such a tree structure is shown in Figure 6.2.

It can thus be seen that with relatively minor modifications, the current CRCP8 analysis model could be used to predict both the Average Crack Spacing and the accumulating Failures per Mile.

The concept of using the best available data in the data structure at any one time means that even if the same structure is being used (and remember that this implies the same models in most cases but not always), the actual shape of the prediction curves can change continuously as the data become more accurate. Let us assume, for instance, that the thermal coefficient of the coarse aggregate has been selected as statistically significant. Initially it might be assumed that the aggregate was most likely to be limestone (based on the aggregate mainly used in that area recently) and a relatively accurate assumption about the thermal coefficient made. If the option of a new CRCP for the section really did come up, the aggregate type might actually be confirmed or the coefficient actually measured. If necessary, a new value could then replace the original assumption in the data tree. Another example is initial crack spacing distribution. Before the project is built this would be predicted using assumed concrete properties (including the thermal coefficient mentioned above), curing temperatures, etc. Once the pavement had actually been constructed, however, the distribution could then actually be measured and the subtree below this item would then fall away and would no longer be needed.

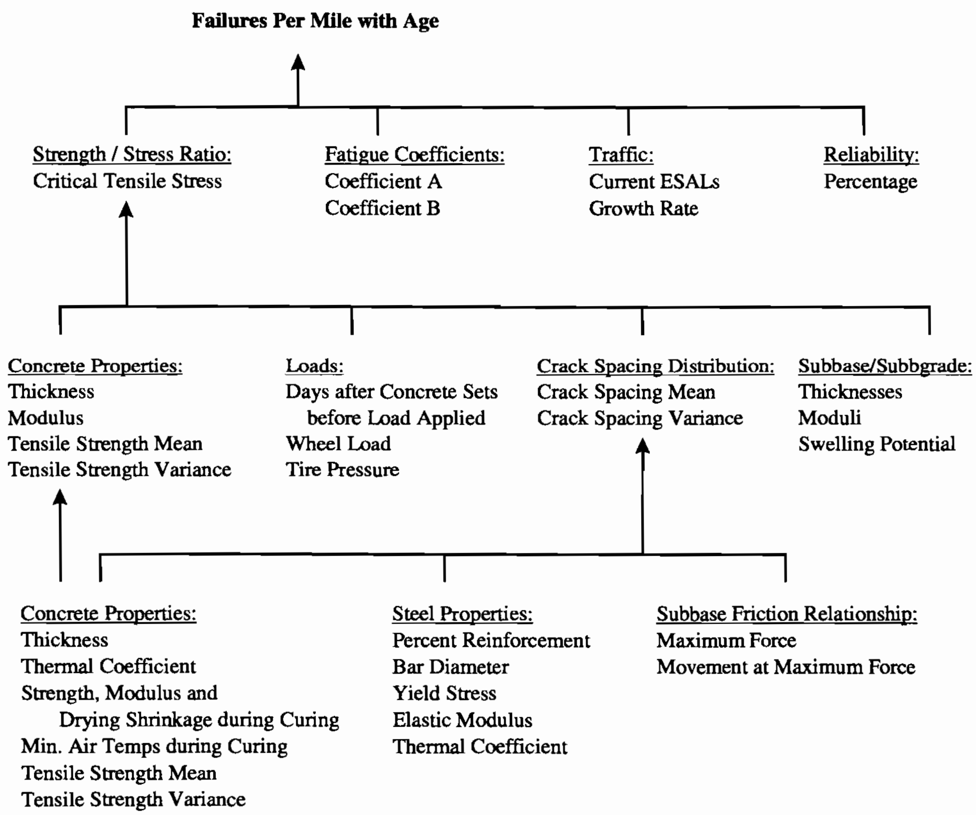


Figure 6.2 Example portion of a hierarchical data structure for the CRCP8 analysis system

Note on Performance-Oriented Specifications

An interesting side benefit of being able to store specific prediction curves is that the prediction curve used to calculate pay factors in any future implementation of performance-oriented specifications could be stored for comparison with actual subsequent performance. This would provide a very good way to test and validate these pay factor calculations in the future.

6.5 CHOICE OF INITIAL PROJECT-LEVEL MODELS

6.5.1 CRCP8

The first project-level model system chosen for possible integration is the CRCP8 analysis method. The reasons that this was chosen are that this represents a state of the art, mechanistic analysis model that has been calibrated empirically and it is also a comprehensive system in that it could be used to predict all the PMIS CRCP distresses except spalling.

CRCP8 currently predicts total accumulated punchouts per mile (called failures per mile, or FPM) on CRCP as a function of total accumulated equivalent single axle loads (ESALs). As already described in the example of the hierarchical tree concept above, FPM is predicted by first stochastically predicting the initial crack distribution using Monte Carlo simulation, and then using this crack distribution coupled with fatigue equations to predict FPM. If it is also accepted that patching may be modeled relatively simply by adopting a simple model (such as after each year x percent of the new punchouts are patched using asphalt, y percent are patched using concrete, and z remain unpatched) relating the patching to the punchouts by location, it can be seen that all except spalling distress can be predicted using the same system. The relationships between the distresses are shown in Figure 6.3.

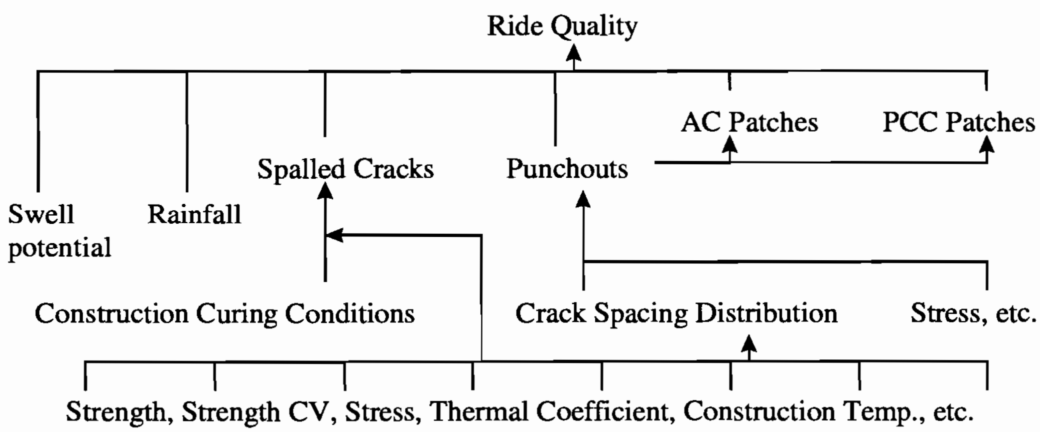


Figure 6.3 Interactions between different condition variables for CRCP

Assuming that we can predict punchouts and cracking using the CRCP8 system (with a conversion of ESALs to age), we then need to consider the input variables for this prediction. In order to identify a standardized set as proposed in the integration method, it is necessary to first consider a wide set and perform an analysis of the sensitivity of the failures per mile prediction to the various inputs. The variables currently considered in CRCP8 are summarized in Figure 6.4. The sensitivity analysis is discussed in the next section.

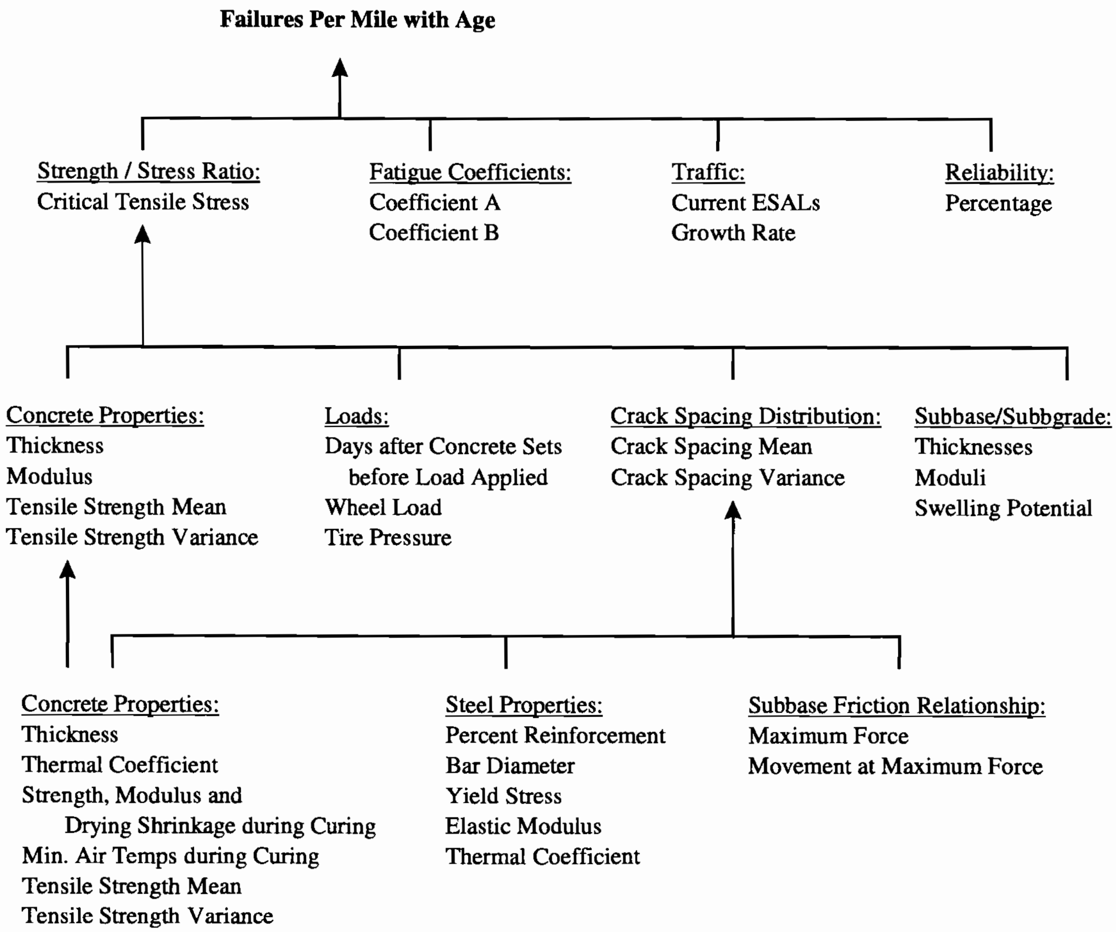


Figure 6.4 Summary of parameters currently considered in the CRCP8 analysis system

6.5.2 FPS-19

Because FPS-19 is so widely used in designing flexible pavements in Texas, it is desirable to choose this as the flexible pavement project-level design system for further study regarding integration into the PMIS. FPS-19 is very different from the CRCP8 system discussed above in two main ways. First, it is more empirical than CRCP8 (although not totally so since it is based very solidly on the surface curvature index [SCI]). Nonetheless, as a result of this it makes no attempt to calculate cracking, rutting, or any other distresses individually but provides an equation for the calculation of serviceability loss directly. Second, the system is not merely an analysis system in the way that CRCP8 is because FPS-19 actually optimizes the thickness design of both the initial structure and any necessary overlays based on life-cycle cost criteria. While the first difference does not pose an immediate problem for integration (other than data concerns), the second difference results in considerable decision integration concerns if the objective of obtaining similar answers from the PMIS and FPS is to be realized.

In FPS, the total serviceability loss is assumed to be proportional to the square of the accumulated number of load cycles given a constant SCI. However, the incremental serviceability loss for a changing SCI is assumed proportional to the fourth power of the SCI for each increment in which the SCI stays constant. In addition to this the serviceability loss is also assumed to be roughly inversely proportional to the mean air temperature squared during this increment. As mentioned previously, the fact that only the serviceability loss is predicted does not result in a problem in itself and is more of a simple limitation in the distresses predicted. Given that SCI and temperature appear important, however, this means that these may need to be collected as data items in the standardized data set we propose. (Note, however, that temperature and SCI will have to be given values such that the total deterioration calculated per year is the integral of the incremental deteriorations due to changing temperatures and SCI during a whole yearly cycle.) The actual importance of SCI and temperature will depend on the sensitivity analysis discussed next.

Assuming it is possible to integrate the serviceability loss equations as ride quality prediction curves as well as provide the relevant data, we are still left with the decision integration problem. At present, FPS uses a minimum serviceability level, such that when the serviceability drops below this level, an overlay is triggered. This in fact is not dissimilar to the way in which PMIS operates. The only difference is that PMIS utilizes many more decision criteria, and these are based on many more distresses and factors other than serviceability (or ride quality) alone. In order to resolve this difference, either FPS (as the design system used in the field) needs to include and use the missing PMIS distress predictions and corresponding decision criteria, or the decision criteria in PMIS need to be changed such that they operate on ride quality alone.

CHAPTER 7. SENSITIVITY ANALYSES FOR RIGID PAVEMENTS

7.1 STATISTICAL ANALYSIS TECHNIQUES

Analysis of Variance (ANOVA)

Analysis of variance can generally be viewed as an analysis of the amount of variation in a dataset that can be explained by a proposed model containing a number of main effects and their interactions. The analysis admittedly gives a good indication of whether a factor is significant in explaining variation in the data, though this variation is almost always confined to that between means and thus does not give any indication of whether the model is reasonable from an intuitive standpoint. No information is given, for instance, on whether there are any sorts of trends in the data; and even if the dependent variable jumps around apparently randomly as the level of some factor is increased, if the majority of data points are associated with different levels of the factor, the factor will be returned as highly significant. Furthermore, the analysis is much more suited to properly designed, balanced factorial experiments where the effects of various factors are being investigated with a view to some future design. As mentioned earlier, this is emphatically *not* the case here, as we wish to predict serviceability on *existing* pavements using a representative sample dataset. As a result, analysis of variance is not really appropriate in this case.

Linear Regression

As opposed to the analysis of variance discussed above, regression is geared toward both curve fitting and the investigation of trends. In addition to this, regression is also much better suited to the analysis of the type of "unplanned data" that we have. Although we list this as a benefit, Draper provides a few compelling caveats [Draper 80]. He first notes that the error may not be random but may result from variables and effects not included in the regression model; he further notes that "provided the system continues to run in the same way as when the data was recorded this will not mislead." This should certainly be the case here.

He also points out that often the most effective predictor variables are kept within a small range to keep the output within the specified limits of the system. This is exactly our problem and the resulting effect — that the corresponding regression coefficients are found to be insignificant (even though we knew they would be significant in a design environment) — is not only acceptable but also desirable. A classic example of this in our case is pavement thickness. Although we know that thickness has a considerable effect on the performance of the pavement, the fact is that in Texas the overwhelming majority of pavements are 20.3 cm (8 in.) thick; thus if we assumed this thickness, we would be right more than 90 percent of the time! In the prediction of serviceability on a network scale, therefore, the thickness is indeed insignificant and we wish the analysis to show this. Draper comments that this "nonsignificance" is "a conclusion which practical workers will interpret as ridiculous because they 'know' the variable is effective. Both viewpoints are, of course, compatible; if an effective predictor variable is not much varied, it will show little effect.

Draper finally notes that the operating policy (if $X1$ is high, reduce $X2$ to compensate) often causes large correlations between variables. This makes it impossible to see if changes in Y are due to $X1$, $X2$, or both. In fact, in our network-level prediction scenario, it is once again more desirable to incorporate both of these variables than neither, since our primary objective is prediction; being able to separate them and track their contribution is only secondary.

While Draper has no problem concluding that "happenstance" data may still be analyzed, he does emphasize that the additional risk of jumping to erroneous conclusions must be kept in mind.

Therefore, because of the nature of our objectives in this case, it is desirable that we use representative sample data and, as shown by the discussion of Draper's cautions above, the normal pitfalls are not only understood but seen as benefits. As a result, it appears that the method of choice in this case should be regression analysis.

Least Squares Quadratic Surface Modeling

This regression, really a special case of general linear regression, is more desirable than inclusion of only the main factors in the regression model, which is the simplest case. The reason for this is twofold: First, the inclusion of quadratic terms enables the modeling of nonlinear data and, second, at least all two-factor interactions are included. The model for two factors appears below, though this can obviously be generalized to any number of variables (the case for twelve variables, for instance, would contain twelve main factor terms, twelve quadratic terms, and sixty-six interaction terms, for a total of ninety without the mean and error terms).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1^2 + \beta_4 X_2^2 + \beta_5 X_1 X_2 + e$$

The model, while not ideal, does at least allow limited curved surface modeling with interactions and will certainly suffice for our sensitivity analysis purposes. An example of a two-factor quadratic surface model is shown in Figure 7.1. The figure was produced from the output of the SAS procedure RSREG and uses the "coded data" parameters. This is very useful check data because all factors are normalized to a range between -1 and +1. The implication of this is that single factors or individual interactions can be isolated and investigated while all other factors are assumed to be set at their mean levels (zero in the coded data). This is not always desirable but suffices much of the time. As a result, the effects of increasing or decreasing the factor over its range in the data can be analyzed relatively easily without having to include all parameters for all other factors and their interactions.

Stepwise Regression

In a sensitivity analysis of this kind, the objective is to find the model with the least number of variables that will still provide good prediction accuracy. Accomplishing this when numerous variables are involved would normally require testing all possible combinations of these variables: all single variables, all combinations of two variables, all combinations of three variables, and so on (a total of 4,095 combinations for 12 variables). This is impractical, and various methods exist to systematically search the solution space in order to find at least a good model (the best is not guaranteed) for any specific number of variables. The Statistical Analysis System (SAS) computer program has a set of such procedures that allows the use of various methods for accomplishing this. Unfortunately, the procedures do not allow automatic inclusion of quadratic and cross product terms that have to be added to the dataset manually.

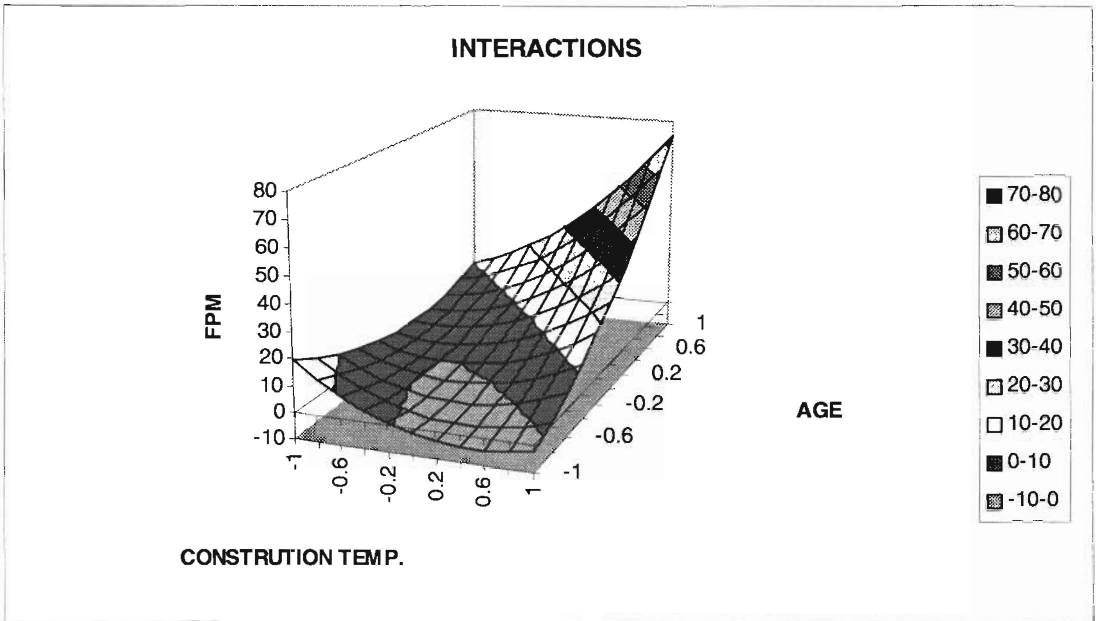


Figure 7.1 Example of quadratic surface model using "Coded Data"

7.2 QUADRATIC SURFACE MODELING FOR RIGID PAVEMENTS USING ABSOLUTE MODELS

7.2.1 Introduction

The following study concerns the performance prediction for continuously reinforced concrete pavements in Texas, with a view to eventually developing performance equations that may be used for both network and project pavement management. The main objective of the project is to develop plausible regression models using regression and, in the process, to perform a sensitivity analysis for a number of possible independent variables. In this way, it should be possible to obtain both quantitative measures of how good the models are for different variables (as measured by the correlation coefficients) as well as some idea of which factors are important. The latter information is vital in order to make recommendations on which variables should be collected and stored in performance databases in the future. Clearly the R-squared values are important to ensure that the model is worth using in the first place, and that they give an idea of its accuracy.

The major observation in the following analyses is that the models required are *not* for the purpose of future design (which would require a properly designed factorial experiment) but rather for the purpose of predicting performance for the *existing* population of in-service Texas rigid pavements. The implication of this is that it is not only acceptable but *desirable* to use a dataset consisting of a *representative sample of the existing pavements in Texas* rather than a designed factorial for the regression analyses. For this reason, the database compiled by CTR described below is used as the dataset for regression.

Data Description: The Center for Transportation Research (CTR) Rigid Pavement Database consists of two parts [Dossey 94a]: (1) the Continuously Reinforced Concrete

Pavement (CRCP) database, which contains condition survey data collected from 1974 to the present on CRC pavements across the state, and (2) the Jointed Concrete Pavement (JCP) database, which includes condition data from 1982, 1984, and 1993/4. Both databases contain a number of subsidiary files arranged in a hierarchical structure and contain both inventory data and condition survey data. The condition surveys were initially conducted on every CRCP section in the state, though this was later reduced to a representative sample of the total CRCP inventory. The JCP sections were also chosen to adequately represent the state inventory [Dossey 94a].

The major distresses collected for all surveys on the CRCP sections and those used in this analysis are the following:

Minor Punchouts
Major Punchouts
AC Patches
PCC Patches

In addition to these distresses that have been measured at various times, a number of inventory data items describe "fixed" aspects of the pavement sections. These include such items as the highway name, the county, etc., but also include possible independent predictor variables, such as the annual average rainfall and the type of aggregate. Based on a search of the literature and on a consideration of mechanistic aspects, a number of variables were calculated from the inventory data for use in the regression modeling. These are discussed in more detail below. (Distributions of all variables are given in the appendices.)

7.2.2 Dependent and Independent Variables for CRCP Serviceability Prediction

Dependent Variables: It was decided that the best dependent variable to use for regression models was a composite measure of the distresses mentioned above termed "total failures per mile." The reason for this is that the majority of the decisions for CRCP maintenance and rehabilitation in the PMIS decision trees [Stampley 96] use the sum of punchouts and patches. This is also a good measure to use intuitively, since we really need to be predicting what would happen to the pavement if no maintenance or rehabilitation was carried out. Finally, the project-level analysis method, CRCP8 [Won 91] predicts punchouts per mile. Results from the regression models developed here will thus be totally comparable with this system. As a result, an additional variable, FPM, was calculated from the original database for the purposes of this analysis using the following equation:

$$FPM = (ACP+PCCP+MPO+SPO)*5282/LEN;$$

where

FPM = failures per mile,

ACP = no. of asphalt concrete patches in section,

PCCP = no. of portland cement patches in section,

MPO = no. of minor punchouts in section,

SPO = number of severe punchouts in section, and

LEN = length of section in feet.

While no attempt was made to incorporate the size of the patches at this stage, this should possibly be considered in the future.

Independent Variables: As a result of the previous discussion regarding possible independent variables (and within the limitations of the database information), the dependent variables discussed in more detail below were chosen.

AGE

The age of the pavement is certainly suspected to be a major factor in the prediction of failures per mile: indeed the current PMIS model for CRCP uses age as the sole predictor variable. We shall see how little of the total variance is explained by this single factor in the analyses that follow.

Age is not actually given directly in the database but is calculated and rounded to the nearest year using the following equation:

AGE = INT(YR+1900-CDATE+0.5);

where

AGE = the age of the pavement to the nearest year,

INT = an operator that returns the integer value,

YR = the two-digit year value after 1900 that indicates when the survey was conducted, and

CDATE = the construction date given as a decimal to include the month.

ADT85

This represents the annual daily traffic on the section in 1985. Note that the total accumulated number of ESALs is never calculated directly, and that no information about the percentage trucks, the number of lanes, or the growth rate is included. The quantity is nonetheless a good indicator of how much traffic the section generally carries.

TCOEFF

The thermal coefficient of the concrete is estimated from the coarse aggregate type used:

IF CAT = 1 THEN TCOEFF = 8.18;
IF CAT = 2 THEN TCOEFF = 6.29;

where

CAT = course aggregate type (1=SRG, 2=LS).

SBF / SBMV

Maximum subbase friction and the total movement at which it occurs are estimated from the subbase type, SBT, using the figures determined in a study by Wimsatt et al. [Wimsatt 87] and used in the CRCP8 computer program [Suh 92]

```
IF SBT = 1 THEN SBF =1.9; SBMV =-0.034;
IF SBT = 2 THEN SBF =15.4; SBMV =-0.001;
IF SBT = 3 THEN SBF =1.7; SBMV =-0.011;
IF SBT = 4 THEN SBF =13.0; SBMV =-0.020;
```

where

SBT = subbase type (1=asphalt treated, 2=cement treated, 3=lime treated, 4=crushed stone).

RAIN

The average annual rainfall is given in the database but is rounded to the nearest 12.7 cm (5 in.) for the purposes of the regression analysis.

RAIN = INT((RAIN+2.5)/5)*5

TEMP

The yearly temperature range is also rounded to the nearest 10 degrees F.

TEMP = INT((TEMP+5)/10)*10

CTEMP / CEVAP

In order to estimate the temperature and evaporation potential at construction, the average during each month for each county was roughly stored using the weather data CD-ROM for a number of larger cities in Texas. Based on the construction date, the construction month, and on the construction temperature, the construction evaporation can then be roughly estimated for each section as follows:

```
IF INT((CDATE-INT(CDATE))*12+0.5)+1 = 3 THEN DO
        CMONTH='MAR'
        CTEMP=TMAR
        CEVAP=EMAR
```

where

CDATE = construction date from database,

CMONTH = construction month,

CTEMP = construction temperature, and

CEVAP = construction evaporation potential.

TDIFF

The difference between the construction temperature and the likely coldest temperature during the year is then calculated as follows:

TDIFF = CTEMP-TJAN

SWELL

The swell potential is converted to numerical form from the SOIL variable stored in the database.

IF SOIL = 'L' THEN SWELL = 1;
IF SOIL = 'H' THEN SWELL = 2;

MCRK78 / CVCRK78

From mechanistic considerations, it appears important that the initial mean crack spacing and the variability in this be included as factors for the prediction of failures per mile over time. For smaller crack spacings it is intuitively obvious that the stresses and thus the fatigue in the transverse direction will be higher, resulting in earlier punchouts. In addition, if this crack spacing is uniform, the punchouts might be expected to remain low for a considerable length of time prior to the whole pavement failing at roughly the same time. Conversely, if the variability is high, the punchouts may be expected to increase steadily over time.

The mean and variance of the crack spacing for the 1978 survey are thus included as possible factors. (Note that the earlier the survey, the better, and the use of only one survey is appropriate in our non-Markovian approach to the serviceability prediction.)

Correlation Analysis

A ranked correlation matrix of Pearson Correlation coefficients is included in the appendix for the independent variables. This shows fairly high correlations of around 0.9 between the construction temperature, CTEMP, the temperature difference, TDIFF, and the construction evaporation, CEVAP. There is also some negative correlation (0.8) between mean crack spacing, MCRK78, and thermal coefficient, TCOEFF, as expected. Correlations of around 0.4 also exist between traffic, ADT85, and crack spacing variability, CVCRK78, and between average rainfall, RAIN, and mean crack spacing, MCRK78.

7.2.3 Quadratic Regression Analysis of Data To Develop Simple "Absolute" Models

Model and Objectives

In the example quoted here, the emphasis is on a simple "absolute" model that does not make use of "current state" data, as is the case with Markovian models. In other words, only a single prediction curve is developed based on all the historic data; but once this is set, the only way that future prediction is affected by the current state is in the way the curve is used in practice. In many pavement management systems (including PMIS), this involves "looking up" the "theoretical age" on the curve based on the current distress and using this as a starting point for the prediction into the future. A dataset was created in order to make use of this data, which is explained in a later section. This section, however, discusses the typical "absolute" models developed in previous studies.

Various previous analyses carried out on these data have focused on setting up and maintaining the database itself [Dossey 89], as well as on calibrating the mechanistic models [Won 91, Suh 92] and developing initial models for the PMIS [Singh 93, Robinson 95]. The current analysis differs in that it is an attempt to quantify the importance of the individual factors and also to make use of the findings of many of these individual studies to develop a set of broadly applicable models that incorporate in some way or another all the factors that have been found to be significant in the past. The models are therefore based on the unaggregated data and not on the means for each year. Finally, and perhaps most importantly, the analysis is also an attempt to show the improvements in prediction accuracy gained by utilizing factors beyond simply age, as is currently the case for the rigid pavement PMIS models. The objectives for the analyses below can therefore be summarized as follows:

1. Utilize a large number of independent variables chosen by reference to previous studies and mechanistic understanding to develop a "best case" regression model with a relatively high correlation coefficient.
2. Quantify the expected prediction accuracy for various models involving different numbers of variables.
3. Use the above results to recommend a set of independent factors that should form the backbone set of data items stored in a pavement management database for each project and that should be used for CRCP performance prediction in a possible future integrated pavement management system.

As discussed above, the models for these analyses will, as far as possible, be of a quadratic surface model form similar to that described previously. The maximum number of independent variables will be the following twelve variables detailed above and listed below:

AGE
ADT85
TCOEFF
SBF
SBMV
RAIN
CTEMP
CEVAP
TDIFF
SWELL
MCRK78
CVCRK78

Quadratic Model Using All Variables

The quadratic regression model using all twelve of the predictor variables listed above yields the statistics shown in Table 7.1 for the dataset containing 298 points. The SAS procedure RSREG was used to obtain the statistics.

Table 7.1 Regression statistics for full twelve-variable model

Regression	Degrees of Freedom	Type 1 Sum of Squares	R-Square	F-Ratio	Prob > F
Linear	12	99176	0.2752	22.490	0.0000
Quadratic	9	65667	0.1822	19.855	0.0000
Cross Product	16	100037	0.2776	17.014	0.0000
Total Regress	**37**	**264880**	**0.7349**	**19.481**	**0.0000**

It can be seen from these statistics that the multiple correlation coefficient given by the R-square value is, relatively speaking, very good at 0.73, meaning that 0.73 of the total variation in the data is explained by the model and the remainder results in an error distribution associated with each predicted point. It is also noteworthy that more than half of the total R-square is contributed by the cross-product and quadratic terms. With a purely linear model, the R-square would be an uninspiring 0.28. This emphasizes the importance of utilizing a quadratic model instead of a simplified simple linear model.

The next exercise should be to analyze the data for outliers. This was done by plotting the residuals and using the Cook's D influence statistic [Draper 80], which gives an idea of how much influence each data point has on the regression model. A plot of the residuals and influence statistic is shown in Figure 7.2.

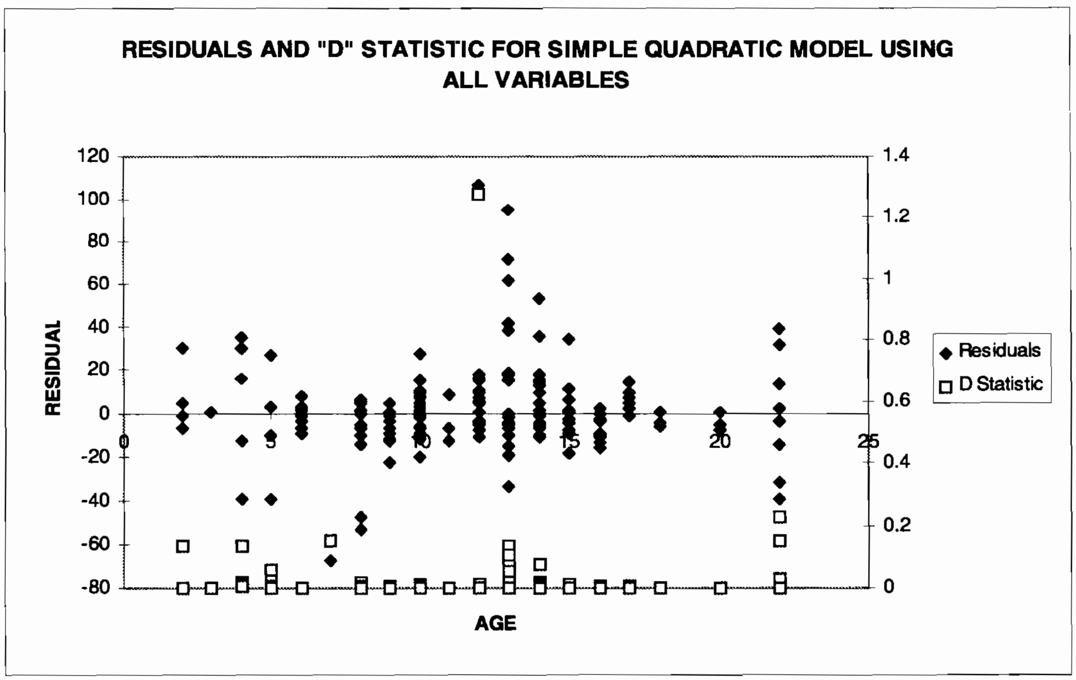


Figure 7.2 Plot of residuals and Cook's D statistic for full dataset

It can clearly be seen that, while the vast majority of the D values are close to zero, a single outlier has a much greater value of over 1.0. This finding is somewhat suspect, and a look at the data reveals that it supposedly has 275 failures per mile. While this is not in itself impossible (other sections have comparably high figures), the fact that it is extremely out of character with the remaining points prompts us to assume that some other very unusual (compared with the remaining data) factor is responsible. This can either be a factor that has not been included in the model at all or an included factor that has not been measured accurately. Whatever the reason, it seems reasonable to disregard at least this single point. The model was therefore rerun for the modified dataset. The new residual and D statistic are plotted in Figure 7.3 and the new statistics shown in Table 7.2.

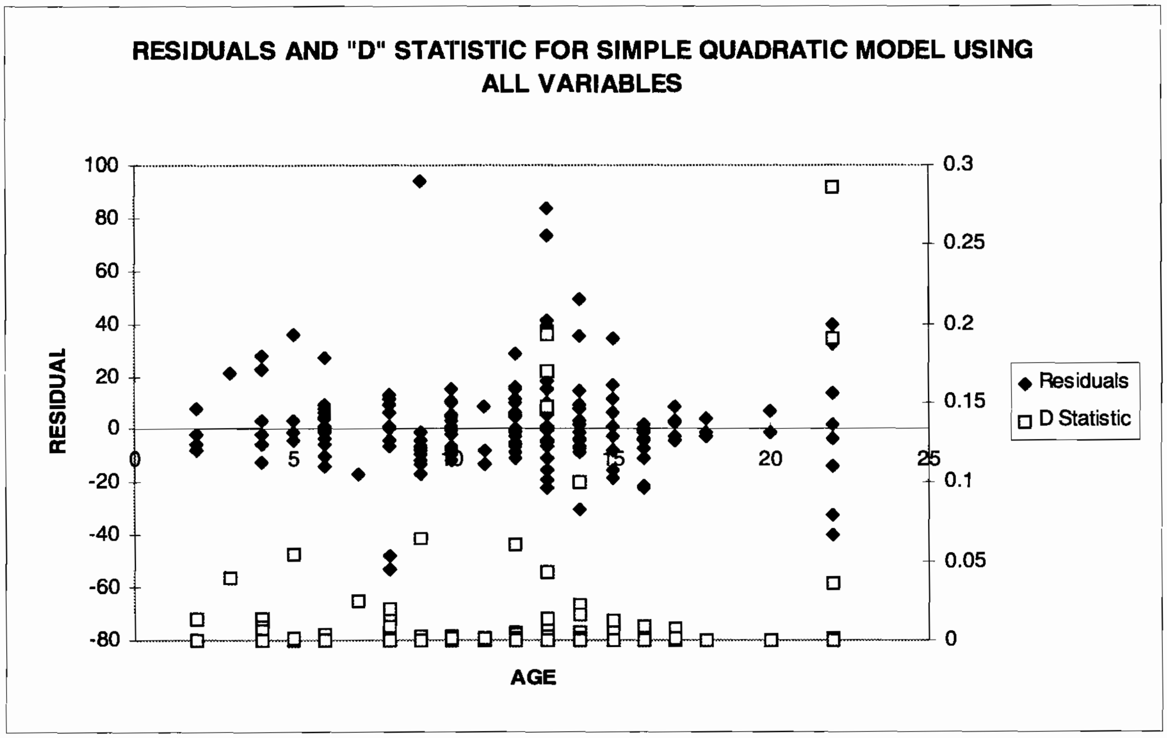


Figure 7.3 Plot of residuals and Cook's D statistic for dataset excluding outlier

Table 7.2 Regression statistics for full twelve-variable model on modified dataset

Regression	Degrees of Freedom	Type 1 Sum of Squares	R-Square	F-Ratio	Prob > F
Linear	12	97559	0.3343	28.240	0.0000
Quadratic	9	50720	0.1738	19.576	0.0000
Cross Product	16	68996	0.2364	14.979	0.0000
Total Regress	**37**	**217275**	**0.7445**	**20.398**	**0.0000**

It can be seen that there is an expected small increase in the R-square value. The relatively high contributions to the total R-square of the quadratic and cross-product terms also remains true. All further analysis is therefore carried out using this modified dataset.

In spite of the high R-square value, it should be noted that there is still a fairly wide margin of error associated with any one particular prediction. This is shown in an example in Figure 7.4, where different points from three sections on US 75 in Grayson County with the same predictor variable values are plotted along with the values predicted by the model and the upper and lower 95% confidence limits.

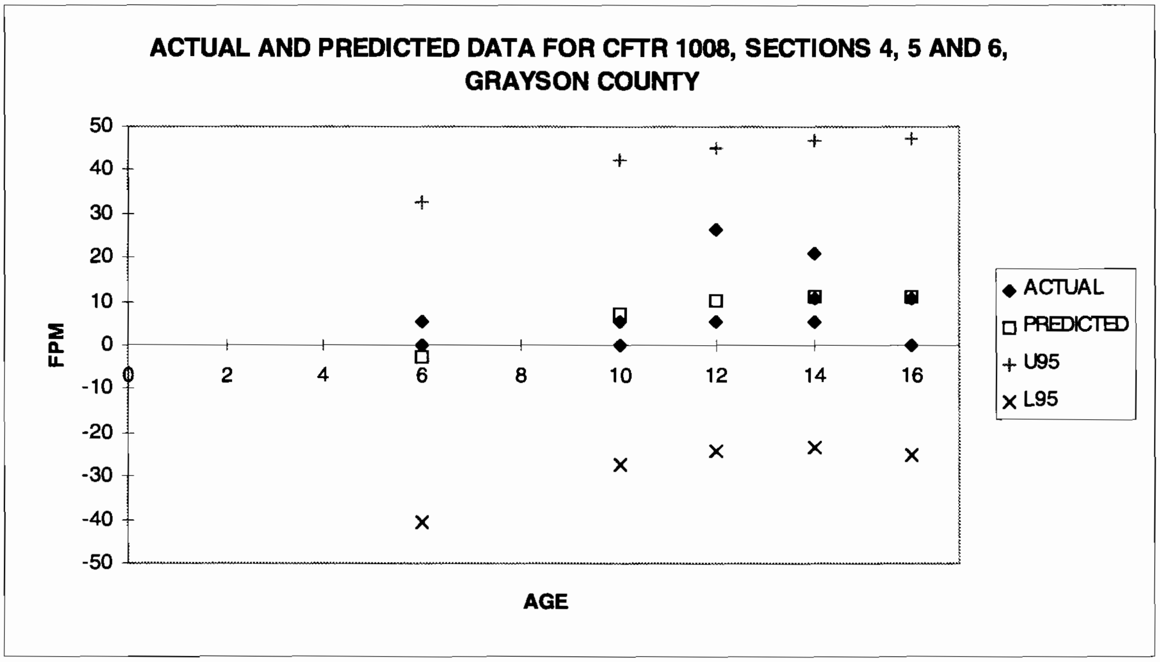


Figure 7.4 Plot of actual failures per mile, predicted failures per mile, and upper and lower 95% confidence limits for three sections on US 75 in Grayson County

The fact that the lower confidence limits are negative shows that the original data are not normally distributed but are skewed toward zero. Although this could be addressed by transforming the data, it is felt that the error introduced into the predicted values is not appreciable and represents an over-prediction of failures per mile in most cases (which is conservative).

Quadratic Model Using AGE Only

Having attained a 0.74 R-square value for the full model (in which case the model is certainly worth using), we should now check the other end of the scale and obtain the R-square value for a model that utilizes AGE as the only independent variable, as is currently the case for the CRCP models in PMIS. The same quadratic modeling method (the SAS procedure RSREG) using only AGE in the model was thus used to obtain the statistics shown in Table 7.3. It is obvious from the extremely low value of 0.03 for the R-square that the model is all but useless in predicting failures per mile based on the CTR Rigid Pavement Database data.

Note, too, however, that the models are actually *not* used as purely "absolute" models where the age is known and the distress is predicted directly from this, but rather the age is "looked up" by using the current, measured distress. The inaccuracy is therefore not as pronounced as implied by the very low R-square value. Nonetheless, it is equally obvious that a large variability in the curve gradients must exist, and that therefore the distress progression is extremely variable even after fixing one point on the curve by "looking up" the "theoretical age." Therefore, while distress prediction for the immediate future after the previous condition survey is relatively accurate, the accuracy quickly degrades with time if only age is used in the model, as is currently the case.

Table 7.3 Regression statistics for "age only" model similar to current PMIS

Regression	Degrees of Freedom	Type 1 Sum of Squares	R-Square	F-Ratio	Prob > F
Linear	1	11131	0.0301	11.324	0.0008
Quadratic	1	0.964	0.0000	0.0010	0.9750
Cross Product	0	0	0.0000	-	-
Total Regress	**2**	**11132**	**0.0301**	**5.662**	**0.0038**

The R-square values for the two cases are plotted for comparison in Figure 7.5.

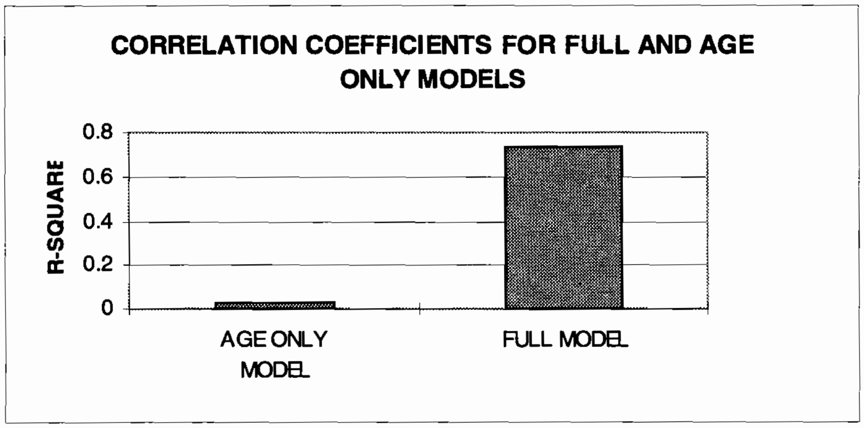


Figure 7.5 Comparison of correlation coefficients for the full and age-only models

STEPWISE Regression To Find Best n-Variable Model

We have found that a model utilizing AGE as the sole predictor variable is really unacceptable; but because we may not need to use all of the twelve variables initially tested to obtain a reasonable prediction model, it is necessary to investigate other models in between these two extremes that require fewer variables but retain an acceptable level of predictive accuracy. As mentioned previously, to find the optimum models for one, two, or three variable models (and so on) by exhaustive enumeration techniques would require 4,095 runs. However, various methods exist that are capable of finding good models through mechanisms that do not require having to analyze every combination separately; the STEPWISE procedure in SAS [SAS 85] provides five of these methods, of which the maximum R-square improvement method (MAXR) [Draper 80] was used in the analysis that follows.

Unfortunately, this and other similar procedures do not cater to the more specialized quadratic surface modeling that we have already proved is important owing to the high contributions of the quadratic and cross-product terms. As a result, it was necessary to individually calculate all the seventy-eight cross-product and quadratic terms and add these to the database. The procedure could then be run using all the extra terms as independent variables. The problem remains, however, that although the STEPWISE procedure returns the best (or near best) models for different numbers of variables from a single variable upwards, no *direct* information is given regarding which of the original twelve factors may be omitted from the analysis and still result in an acceptable model, since the procedure cannot distinguish between the original variables and the calculated quadratic and cross-product terms. The analysis is nonetheless instructive, since models *may* result that omit an original variable; and even if none do, models with only one instance of an original variable may result that can provide starting points for an investigation into closely related models from which the variable is omitted.

Mallows' Cp Statistic

One method of selecting a good model from the "best" models resulting from the procedure was proposed by Mallows [Draper 1980]. For a selection of models with *p* variables plus the intercept, Mallows recommends the model where *Cp* first approaches *p*. The R-square values, the *Cp* statistic, and the *Cp* = *p* line are therefore shown in Figure 7.6 for the modified dataset.

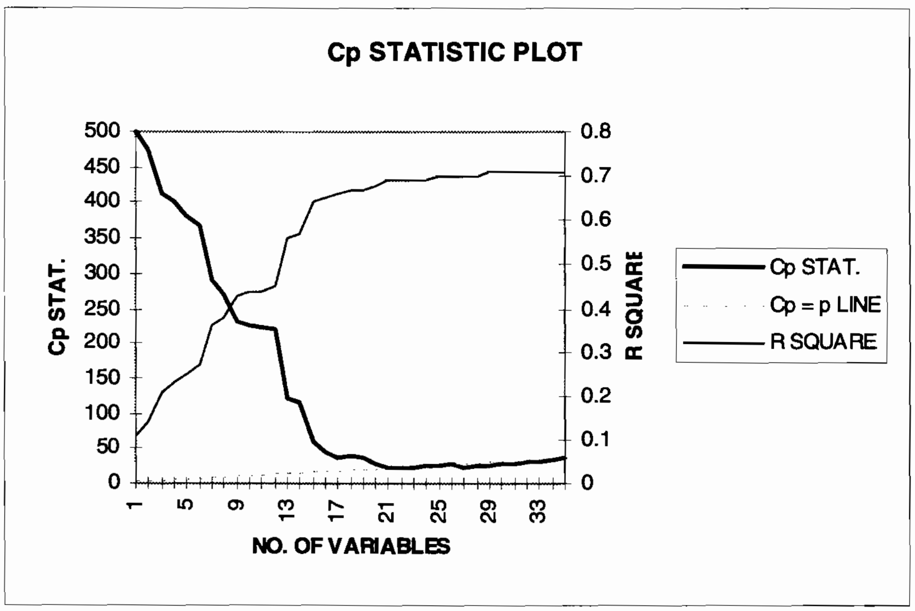


Figure 7.6 Plot of Cp *statistic and R-square value for the "Best" models for 1, 2, 3, etc., variables from the SAS procedure STEPWISE*

It can be seen from the plot that the *Cp* value approaches *p* for about twenty-one variables. These variables and the associated statistics are given in Table 7.4. Note that interactions and quadratic terms appear simply as other variables in this analysis.

Table 7.4 Statistics for best twenty-one variable model returned by the SAS procedure "STEPWISE"

R-square = 0.69	C(p) = 22.6

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	21	248849.7	11849.98	29.31	0.0001
Error	276	111575.8	404.2601		
Total	297	360425.4			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	288.0046	32.55789	31633.5	78.25	0.0001
AGE	-60.2776	4.824838	63096.88	156.08	0.0001
SWELL	105.9153	25.08456	7207.173	17.83	0.0001
AGESQ	-0.37525	0.063329	14193.68	35.11	0.0001
TCOAGE	3.800797	0.367142	43325.28	107.17	0.0001
SBFAGE	-0.76119	0.065541	54528.16	134.88	0.0001
SBFADT	0.001121	8.61E-05	68532.59	169.53	0.0001
SBFTCO	-4.23217	0.442261	37019.47	91.57	0.0001
SBFSQ	2.429467	0.364209	17987.93	44.5	0.0001
CVCAGE	41.62418	3.550363	55565.67	137.45	0.0001
CVCSBF	-56.845	5.451068	43962.51	108.75	0.0001
MCAGE	0.660805	0.169504	6143.966	15.2	0.0001
MCADT	-0.00356	0.000277	66942.53	165.59	0.0001
MCSBF	2.447548	0.309775	25236.66	62.43	0.0001
CTEMAGE	0.643188	0.05929	47574.17	117.68	0.0001
CTEMTCO	-0.59281	0.084663	19820.35	49.03	0.0001
TDIFAGE	-0.64762	0.065418	39619.25	98	0.0001
TDIFADT	0.000231	6.17E-05	5646.214	13.97	0.0002
TDIFRAIN	0.15505	0.025569	14865.96	36.77	0.0001
SWELAGE	-3.78706	0.812824	8775.511	21.71	0.0001
SWELADT	-0.00201	0.000937	1863.466	4.61	0.0327
SWELTDIF	-3.16564	0.591117	11594.08	28.68	0.0001

where

AGE = age of section in years,

ADT85 = average daily traffic in 1985,

SWEL = swell potential (1=low, 2=high),

TCO = thermal coefficient,

SBF = subbase friction,

CVC = coefficient of variation of crack spacing in 1978,

MC = mean crack spacing in 1978,

CTEM = construction temperature,

TDIF = temperature difference between CTEM and the average coldest annual temperature, and

RAIN = annual rainfall.

Combinations represent cross-products and SQ denotes "squared."

It can be seen that the model involves only the ten variables above. Interestingly, all but two of these are in the form of a cross-product. In order to consider the further omission of any of these variables, it should be possible to identify a variable that appears infrequently and has a low significance, as given by a low F value. Although RAIN appears only once as a cross-product with TDIF, the F value is relatively high at 36. Nonetheless, for the sake of example, the full quadratic model statistics are given in Tables 7.5 and 7.6 for the ten-variable model and for the model with RAIN omitted.

Table 7.5 Regression statistics for ten-variable model

Regression	Degrees of Freedom	Type 1 Sum of Squares	R-Square	F-Ratio	Prob > F
Linear	10	79952	0.2740	27.728	0.0000
Quadratic	8	66558	0.2281	28.864	0.0000
Cross Product	17	70097	0.2402	14.305	0.0000
Total Regress	**35**	**216606**	**0.7422**	**21.471**	**0.0000**

Table 7.6 Regression statistics for nine-variable model

Regression	Degrees of Freedom	Type 1 Sum of Squares	R-Square	F-Ratio	Prob > F
Linear	9	62806	0.2152	24.152	0.0000
Quadratic	7	56558	0.1938	27.964	0.0000
Cross Product	18	96772	0.3316	18.607	0.0000
Total Regress	**34**	**216137**	**0.7406**	**22.001**	**0.0000**

By juggling the variables, it was seen that further dropping of MC and either TDIF or CTEM reduced the R-square to only 0.69. However, dropping any of the remaining factors results in large drops in the R-square to 0.64 or below. The R-square values for the successive inclusion of variables are shown in Figure 7.7.

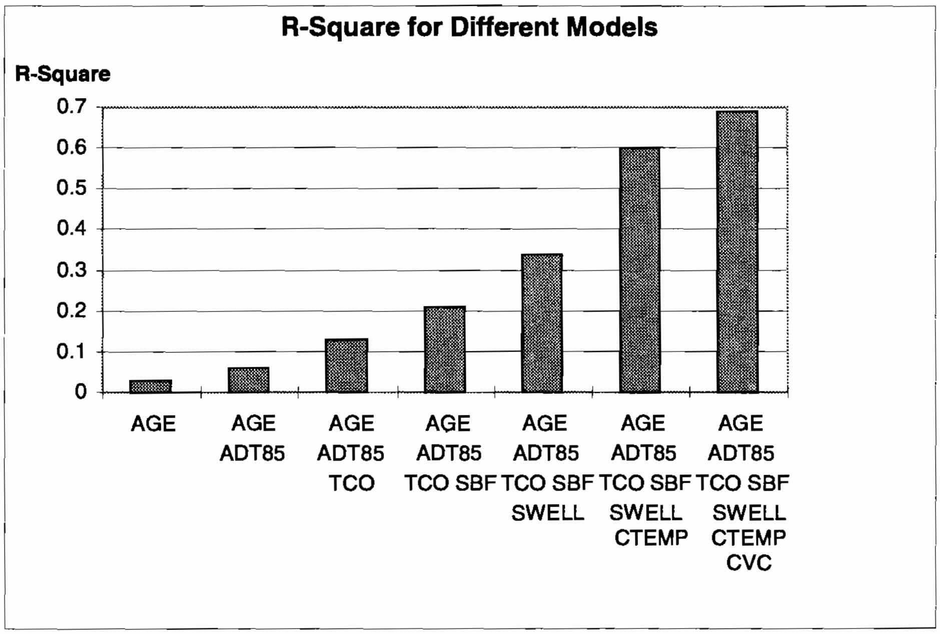


Figure 7.7 Increase in R-square for successive inclusion of variables

Note that these are not necessarily the best combinations but merely serve to illustrate the lower-bound R-square values possible.

Modification of Data To Rectify Apparent Reductions in Distress

One of the common problems with condition survey data is that distress levels often appear to decrease rather than increase as expected in certain cases. There are various reasons for this and the first of these is simple human error (when visual distress surveys are used) or random error (when distress surveys are automated). Another reason — in the case of failures per mile on CRCP — is that multiple patches tend to coalesce into fewer but larger patches. The same may be true for unpatched punchouts.

If data collection is relatively well controlled and survey personnel are trained and experienced, the problem of decreasing distress may not affect regression models a great deal and therefore may not need to be rectified. In the case of the CTR database, a small study was conducted to determine how much of a problem this was: It was found that as much as 20% of the incremental observations showed reduced rather than stationary or increased failures per mile (52 observations out of 257). We therefore decided to modify the data and rerun the regression in order to determine if the effect on the regression models was significant.

If it is desired to modify the data to try to alleviate this problem, the modification method should obviously reflect the suspected underlying cause. Where it is suspected that the cause is purely random, then one would expect that half of the decreases are due to single observations that are too high (causing a subsequent decrease the next time the pavement is surveyed) and half are due to single observations that are too low (in which case the decrease would show up immediately). In this case, the method of modification should be to look at the overall trend and detect whether the decrease was the reversion to the trend after a peak caused by a random high observation, or the result of a downward peak caused by too low an observation. Depending on whether there was an upward or downward peak away from the trend, the offending observation could then be modified to be back on the trend. Theoretically, however, there should be as many erroneous decreases as increases.

On the other hand, if the cause was suspected to be a result of multiple patches coalescing into single ones, then in some cases where a decrease, no change, or a small increase was recorded, there should have been increases in all cases in the overall distress level. In this case the modification method might be to assume that decreases were due only to aggregation of distresses (in which case the level would be retained at the prereduction level) and any subsequent increases (from the lower level) were due to genuine new distress, in which case they would be added to the old retained, higher level.

Since it is fairly difficult to distinguish between the various causes of decreasing distress observations, we decided to modify the data such that if an apparent decrease was recorded, the new level was simply modified to the previous level. This is a simplification and not true of either of the cases above. However, assuming that the decreasing distress cases are a mixture of the two, this method results in increases in recorded distress levels for some cases, but not as many as would be the case if aggregation was being assumed, and no decreases as should be the case for random fluctuations. As a result, it should be fairly representative of what is actually occurring in the field.

The SAS data steps that accomplish this are shown below:

```
RETAIN OFPM;
IF CFTR=LAG(CFTR) AND SECT=LAG(SECT) THEN IFPM=FPM-OFPM;
IF IFPM < 0 AND IFPM NE. THEN FPM=OFPM;
OFPM=FPM.
```

where

FPM = currently recorded failures per mile,

OFPM = failures per mile from previous survey, and

IFPM = increase in failures per mile.

The quadratic regression, which was then rerun as before, yielded a correlation coefficient (R-squared value) of 0.74, with a slight increase in the root mean square error from 17.0 to 17.6. Because this is basically the same as for the previously run case, we can conclude that the slight reductions in the recorded level of distress that occur in the data are insignificant.

7.2.4 Conclusions

The primary conclusion that can be drawn from the above analyses is that it is extremely important to include other factors besides merely age in any models for the prediction of failures per mile in CRCP. It was seen that the R-square value could be improved from 0.03 for an AGE-only model to 0.74 for a full quadratic model including all of the twelve variables considered in this analysis.

It was also seen that a model including the seven variables below still resulted in an R-square of 0.69:

AGE
ADT85
TCO
SBF
SWELL
CTEMP
CVCRK78

This R-square is still reasonable if it is considered necessary to restrict the number of factors to a minimum.

Finally, it should be remembered that models considered in this analysis are "absolute" models and thus require only "inventory" variables. These theoretically need only be collected once for each project section, which has important implications for data collection since they do not need to form any part of the typical PMIS annual data collection effort but should be available from such databases as the ROADLIFE or the proposed forensic database. This of course does not mean that the annual collection efforts serve no purpose, because these are used in the looking up of "theoretical age" as discussed earlier.

7.3 VALIDATION OF RIGID MODELS AND VARIABLES BY USE OF HOLDOUT DATA

7.3.1 Introduction

As discussed in Technical Memorandum 1727-1, there are at least four basic phases in building regression models. These are [Neter 96]:

1. Data collection and preparation
2. Reduction of explanatory or predictor variables
3. Model refinement and selection
4. Model validation

Having discussed the data, the sensitivity of various variables, and the different model forms culminating in the "absolute," "Markovian," and "mixed" model forms developed in the previous study, it is necessary to validate the models to show that they would be useful for prediction using data other than those used in actually developing the models.

While there are a number of ways of validating models, the best known and most widely used is the method of data splitting. This involves holding back a certain amount of the available data in order to use this later to test the developed model. It is, of course, important to leave sufficient data in the model building set to allow development of a reasonable model. This method of data splitting is also common in the training of artificial neural networks (ANNs). If the test proves successful, the usual practice is to then go back and redevelop the model using all of the data. Splitting the available data into a model-building set and a so-called holdout set is relevant in this context.

There are also a number of ways in which a holdout data set can be obtained. In some cases a new set of data is measured and used to test the original model. More often, however, a portion of the existing data is held back. In many cases the model is being developed in order to predict the level of some dependent factor in the future. In this case the data are usually collected at particular times and the model predicts future outcomes based on trends in the historic record so far. In these cases the obvious method of obtaining a holdout data set is to use the latest data. The model is thus developed using all previous data and used for prediction of the latest data. A comparison of the predicted data and the actual holdout data then provides a good idea of how effective the model is.

In the case of the mixed model in the previous study, it would seem that the obvious method of showing whether or not the model is valid would be to use all condition surveys done so far and subtract the latest survey (1994) to use as validation or holdout data. This is discussed in the next section.

Other ways of choosing holdout data are to take out random samples, "every fifth data point," for instance. Another method is to remove some or all the repetitions or replicates, thus restraining the holdout data to the "neighborhood" of the original model building data.

Finally, there are various ways of measuring exactly how "valid" a particular model is. For instance, if the holdout data points fall within the confidence intervals for the model, the model might be deemed acceptable. More understandable, perhaps, is to measure how well a certain model fits the data by using the R^2 value, or correlation coefficient. This is basically a measure of the fraction of the total sum of squares explained by the model as shown below.

$$R^2 = 1 - \frac{\text{SSmodel}}{\text{SStotal}}$$

where

SSmodel = sum of squares of the residuals, and

SStotal = sum of squares of the variations about the mean.

Thus, the model's validity may be gauged by the amount the R^2 for the holdout data, calculated using the differences between the predicted and actual holdout values, drops below the R^2 for the original model development.

7.3.2 Model To Be Validated

Our objectives in this particular model building process are not necessarily to develop exact models to be used for prediction at this stage, but rather to identify a model form and certain input variables as being relevant. We concluded, first, that it is absolutely vital to include more than simply AGE as an input factor in our models. We then showed that models that include the latest, previously surveyed data result in a considerable improvement over models that utilize only basic initial inventory data.

The next stage, therefore, is to show that this form of model is valid, at least within the bounds of the original input data. The model used in this particular exercise is the "mixed" model from the previous study. The data have been expanded slightly to include more survey data from nonoverlaid pavements (previously only the preoverlay data from overlaid pavements were used). This and the removal of the holdout set resulted in a slightly lower initial R^2 value of 0.7. It should be remembered, however, that we are attempting to validate a whole class of models and not necessarily any individual model. The model validation given here is therefore mainly for the purpose of showing that both the model form (utilization of both initial inventory data and continuous actual distress data) and the additional input factors (thermal coefficient, rainfall, coefficient of variation in crack spacing) are both reasonable and usable.

7.3.3 Choice of Holdout Data

In our particular case the different survey year data were often found to have very different means owing to changing survey objectives pursued over various years. Another result of the differing objectives was that different combinations of input variables were tested during the different years. In regression terms this is akin to filling different parts of the multidimensional regression surface in different years. In this case, if the model is developed from certain parts of the total surface (thus generating certain curvatures in these areas to best fit those data) and is then tested using data from different parts of the surface, the curvatures set up for the previous data may result in ridiculous predictions, where the model is expected to extrapolate into areas not previously used to develop the original model. While good holdout R^2 values *may* be obtained, therefore, it was also found that *negative* R^2 values resulted in some cases! This indicates that the quadratic models, limited as they are to a constant rate of curvature (second derivative) and developed from our rather sparse data in this case, are *not* valid for extrapolated prediction outside of the original input data combinations used.

Although the *aggregate* of the data is therefore still completely valid as a model building data set, where new portions of the regression surface are being filled with each survey it is not acceptable to use any one particular year as the holdout data. In summary, the holdout data need to include only input data combinations in the vicinity of those used to develop the model; the model is then verified only for prediction using these similar input data.

The choice of holdout data in this case, therefore, needed to be limited to the regions of the regression surface covered by the original model building data set. Since the data in the CTR Rigid Pavement Database are subdivided into projects (or CFTR), sections, and then into up to six or seven individual 3,300-m (1000-ft) sections within those projects, an ideal way of choosing a holdout data set for our purposes was to choose a subset of the individual sections — at most one from each CFTR section. In this way it would be possible to restrict the holdout data roughly to similar input variable combinations, since these are generally similar for each CFTR section.

In validating the model previously developed, therefore, all sections numbered "3" were assigned to the holdout group designated GROUP 2, and all other sections were assigned to the model building set, GROUP 1.

7.3.4 Validation

As discussed above, the model validation given is merely a typical example. In this case the "mixed" quadratic surface model (obtained using the SAS procedure RSREG) used in the previous study was used on an expanded data set to accommodate additional nonoverlaid pavements. As with the previous models, remedial measures were taken to ensure the model did not contain too many outliers by calculating Cook's D influence statistic and removing data points with abnormally high D values. Printouts verified that the R^2 for the model building set was 0.70. When the R^2 was calculated for this model on the holdout data set the R^2 dropped to 0.47.

7.3.5 Conclusions

The main conclusion to be drawn from this brief validation study is that even when the models are developed for a particular set of CFTR projects, prediction for individual sections within those projects is still far from exact and further input variables (such as possibly cut and fill position) and/or better accuracy on already included variables (traffic) are still needed to attain high accuracy models. Nonetheless, even a 0.47 R^2 value is not unacceptable and is still a vast improvement over the extremely low R^2 values obtained from general models that utilize only AGE as an input factor.

The secondary conclusion is that any basic quadratic surface type performance prediction models that are developed for multiple input factors must include all combinations of those input factors for which the model is to be used for prediction. In the case of the CTR Rigid Pavement Database this means that a model developed using data from a certain set of CFTR project sections should not be used for prediction on any sections not within that original CFTR set. (Although good prediction might be obtained in some cases, in general the model would not be reliable for these extrapolated cases.) This, however, should not be a problem for PMIS data since *all* pavements are rated every two years. As a result, if a model is constructed using even only the previous two years, most of the regression surface will be covered. (Of course the PMIS database does not necessarily include some of the more important input data items at this stage and the models will suffer from this problem instead.)

The final conclusion to be drawn from this exercise is that even though quadratic surface multiple regression is an excellent exploratory model for assessing input variables and model forms, it is not very useful as a prediction tool because of its limited curvature capabilities. This indicates that it is a useful tool for the identification of grouping variables, but that the final models generated from these groups should be of a more flexible form.

CHAPTER 8. SENSITIVITY ANALYSIS FOR FLEXIBLE PAVEMENTS

8.1 GENERAL

We analyzed the sensitivity of variables relevant to the first performance for different pavement systems to determine the impact of various independent variables and to better understand the performance of FPS-19. FPS-19 is necessarily meant for the project-level design of pavements in TxDOT. Although 70 percent of the roads in TxDOT are thin-surfaced, two-layer systems (AC on granular base) constructed over natural subgrade, we also considered in the analysis two-layer-thick surfaced systems, three-layer systems, and four-layer systems. In general, the following pavement systems were analyzed:

- Two layers (AC [thin] + granular base) over subgrade
- Two layers (AC [thick] + granular base) over subgrade
- Three layers (AC + asphalt base + granular base) over subgrade
- Four layers (AC [overlay] + AC + granular base + subbase) over subgrade

8.2 SENSITIVITY ANALYSIS

All sensitivity analyses were performed considering the subgrade soil to be nonswelling. This was considered to eliminate cases with the loss of serviceability owing to swelling soil and reduction in performance period thereof. Since FPS-19 uses only one performance measure, serviceability index (SI), for pavement design, the first performance period was selected as the dependent variable.

FPS-19 uses the following independent variables for prediction of performance period employing the serviceability model:

- Initial Serviceability Index
- Terminal Serviceability Index
- Reliability
- Initial ADT / Final ADT
- Design traffic load (cumulative number of 18-kip axles over design period)
- District Temperature Constant
- Elastic Modulus of all layers including subgrade
- Poisson's ratio of all layers including subgrade
- Thickness of all layers

$\left.\begin{array}{l}\text{Elastic Modulus of all layers including subgrade}\\ \text{Poisson's ratio of all layers including subgrade}\\ \text{Thickness of all layers}\end{array}\right\}$ affect surface curvature index

Some values were considered for the other input parameters (program constraints and cost data) and were kept unchanged throughout the analysis. A design period of 20 years was used in all analyses. To avoid the case of "no feasible solution," all program constraints were removed.

Since several variables influence performance period, a factorial experiment would need too many runs of the program to evaluate the variables. A sensitivity analysis was performed using a "one factor at a time" method. This is a well-recognized method of sensitivity analysis. In this method the variables are varied one at a time, with the remaining factors held constant. This method provides an estimate of the effect of a single variable at fixed conditions of the other variables. The disadvantage of this method is that it does not consider interaction between variables. However, this disadvantage has the least effect on the set of variables considered in the analysis, especially in the context of FPS-19.

The analysis for a particular pavement system was completed by first running FPS-19 with normal average values for all relevant independent variables. Subsequently, FPS-19 was run by changing only one parameter at a time, keeping other variables at their average value. The highest and the lowest values of each variable were assigned from a practical range corresponding to the type of pavement. The first performance periods along with relevant independent variables were then analyzed using the "General Linear Model" of ANOVA (analysis of variance) module of the SAS software. The F-values obtained from the analysis of variance were then sorted to determine the rank of each variable. A variable with rank 1 is the most sensitive variable. Ranks of the first ten relevant variables obtained from the sensitivity analyses are given in Table 8.1.

Table 8.1 Ranks of the first ten variables

Two Layers (Thin surface)		Two Layers (Thick surface)		Three Layers over Subgrade		Four Layers over Subgrade	
Variable	Rank	Variable	Rank	Variable	Rank	Variable	Rank
Traffic-ESAL	1	Traffic- ESAL	1	Traffic-ESAL	1	Traffic- ESAL	1
Reliability	2	Reliability	2	Reliability	2	Reliability	2
Modulus-2	3	Thickness-1	3	Thickness-2	3	Thickness-2	3
Thickness-2	4	Temperature	4	Temperature	4	Temperature	4
Temperature	5	Terminal SI	5	Terminal SI	5	Terminal SI	5
Terminal SI	6	Modulus-2	6	Thickness-1	6	Thickness-1	6
Modulus-Sg	7	Modulus-1	7	Modulus-2	7	Modulus-2	7
Initial SI	8	Initial SI	8	Initial SI	8	Initial SI	8
Thickness-1	9	Thickness-2	9	Modulus-3	9	Modulus-3	9
Modulus-1	10	Modulus-Sg	10	Modulus-Sg	10	Modulus-Sg	10

In Table 8.1, layer characteristics (modulus, thickness, etc.) are represented by the name of the variable with a layer number (e.g., "Thickness-1"). Layers are numbered successively from 1 (top). Subgrade is abbreviated as "Sg." It may be seen from the analyses that *design traffic* (ESAL) is the most sensitive variable (Rank 1) followed by *reliability* (Rank 2) for all types of pavements. Rank 3 is occupied by the thickness of the second layer (one below the surface) for three- and four-layer pavement systems. The thickness of the surface is the third most sensitive variable for two-layer-thick surfaced pavements, and the elastic modulus of the second layer is the third most sensitive parameter for two-layer, thin-surfaced pavements. District *temperature* constant has Rank 4 in all types except thin-surfaced pavements, where the thickness of the second layer has Rank 4. It may further be seen that the pavement systems listed above more or less respond alike except thin-surfaced, two layer systems, in which case the dissimilarity may be because thin surfacing does not provide significant structural strength. The most interesting result of the analysis is that the *modulus of subgrade* does not have much influence on performance period. However, in the case of two-layer, thin-surfaced pavements the rank of subgrade modulus is more important (7 instead of 10). The importance of pavement structural parameters such as modulus (E), thickness (T) and Poisson's ratio (P) are given below (suffix indicates layer number with surface as 1, underline indicates the same importance) starting from most important on the left:

- Two layer thin: $E_2, T_2, E_s, T_1, E_1, \underline{P_1, P_2, P_s}$
- Two layer thick: $T_1, E_2, E_1, T_2, E_s, P_1, \underline{P_2, P_s}$
- Three layer: $T_2, T_1, E_2, E_3, E_s, \underline{E_1, T_3}, P_1, \underline{P_2, P_3, P_s}$
- Four layer: $T_2, T_1, E_2, E_3, E_s, \underline{E_1, T_3}, P_1, \underline{E_4, T_4, P_2, P_3, P_4, P_s}$

Sensitivity analysis details, along with the input data, are given in Tables 8.2 through 8.5.

8.2.1 Inference of Analysis

FPS-19 computes the performance period *(t)* using the following equations:

$$N = \frac{N_c}{C(r_o + r_C)}\left(2r_o t + \frac{(r_C - r_o)t^2}{C}\right) \qquad \text{(Eq 8.1)}$$

where

C = design period in years (input),

r_o = initial ADT in vehicles per day (input),

r_c = ADT at the end of design period in vehicles per day (input),

t = performance period in years,

N_c = one direction cumulative number of ESAL over the design period (input), and

N = one direction cumulative number of ESAL at the end of performance period computed using the following equation for different levels of reliability:

$$\log N = \log N_k - Z\sigma \qquad \text{(Eq 8.2)}$$

where

Z = normal deviate which depends on level of reliability (input),

σ = standard deviation (computed using Equation 8.4), and

N_k = one direction cumulative number of traffic loads computed from given loss of SI (Q), temperature (T), and surface curvature index (SCI) using the following equation (see page 94):

Table 8.2 Sensitivity analysis of two-layered (thin) system

Run	Problem No.	Terminal Serviceability	Reliability	Initial ADT	Terminal ADT	Traffic (ESAL)	Temperature	Initial Serviceability	First Layer Elastic Modulus	First Layer Poisson's Ratio	First Layer Layer Thickness	Second Layer Elastic Modulus	Second Layer Poisson's Ratio	Second Layer Layer Thickness	Subgrade Elastic Modulus	Subgrade Poisson's Ratio	First Performance Period	Life-Cycle Cost
		A	B	C		D	E	F	G	H	I	J	K	L	M	N		
		PSI	-	'000 vpd		Mill	°C	PSI	ksi	-	in	ksi	-	in	ksi	-	years	$/sqyd
1	MED	2.5	C	5	10	1	24	4.2	500	0.35	1.5	50	0.33	10	14	0.28	10	8.00
2	AH	3.5															4	11.28
3	AL	1.5															13	7.23
4	BH		E														2	12.39
5	BL		A														20	6.48
6	CH			9.00	19.80												10	8.02
7	CL			1.10	1.92												9	8.04
8	DH					0.1											40	6.48
9	DL					2											5	9.43
10	EH						38										14	7.19
11	EL						9										4	10.30
12	FH							4.6									12	7.57
13	FL							3.8									7	8.29
14	GH								750								10	8.00
15	GL								250								10	8.00
16	HH									0.40							10	8.00
17	HL									0.20							10	8.03
18	IH										2.5						11	8.90
19	IL										0.5						10	6.74
20	JH											80					17	7.08
21	JL											20					3	11.12
22	KH												0.40				10	8.00
23	KL												0.20				10	7.73
24	LH													16			16	9.67
25	LL													6			5	7.73
26	MH														24		12	7.28
27	ML														4		6	9.01
28	NH															0.45	9	8.10
29	NL															0.20	10	8.00
F-values		111.01	422.86			2256.05	131.12	32.47	0.21		3.48	252.21		157.77	48.83			
RANK		6	2	x	x	1	5	8	10	x	9	3	x	4	7	x		

Note : x means insignificant

Table 8.3 Sensitivity analysis of two-layered (thick) system

Run	Problem No.	Terminal Serviceability	Reliability	Initial ADT	Terminal ADT	Traffic (ESAL)	Temperature	Initial Serviceability	First Layer: Elastic Modulus	First Layer: Poisson's Ratio	First Layer: Layer Thickness	Second Layer: Elastic Modulus	Second Layer: Poisson's Ratio	Second Layer: Layer Thickness	Subgrade: Elastic Modulus	Subgrade: Poisson's Ratio	First Performance Period	Life-Cycle Cost
		A	B	C		D	E	F	G	H	I	J	K	L	M	N		
		PSI	-	'000 vpd		Mill	°C	PSI	ksi	-	in	ksi	-	in	ksi	-	years	$/sqyd
1	MED	2.5	C	5	10	4	24	4.2	500	0.35	6	50	0.35	15	14	0.40	12	15.88
2	AH	3.5															5	19.14
3	AL	1.5															17	15.68
4	BH		E														3	20.43
5	BL		A														25	15.05
6	CH			9.00	19.80												12	15.89
7	CL			1.10	1.92												12	15.87
8	DH					10											6	17.91
9	DL					1											34	15.05
10	EH						38										18	15.65
11	EL						9										5	18.23
12	FH							4.6									16	15.71
13	FL							3.8									9	16.42
14	GH								750								16	15.71
15	GL								250								8	16.87
16	HH									0.40							13	15.83
17	HL									0.20							11	15.93
18	IH										8						19	18.18
19	IL										3						5	14.23
20	JH											80					16	15.71
21	JL											20					7	17.00
22	KH												0.40				12	15.88
23	KL												0.30				13	15.83
24	LH													20			15	18.09
25	LL													10			10	14.31
26	MH														24		14	15.78
27	ML														4		10	16.61
28	NH															0.45	12	15.88
29	NL															0.20	13	15.83
F-values		0.96	3.59			10.47	1.09	0.29	0.39	0.03	1.24	0.52		0.15	0.10			
RANK		5	2	x	x	1	4	8	7	11	3	6	x	9	10	x		

Note : x means insignificant

Table 8.4 Sensitivity analysis of three-layered system

									First Layer			Second Layer			Third Layer			Subgrade			
Run	Problem No.	Terminal Serviceability	Reliability	Initial ADT	Terminal ADT	Traffic (ESAL)	Temperature	Initial Serviceability	Elastic Modulus	Poisson's Ratio	Layer Thickness	Elastic Modulus	Poisson's Ratio	Layer Thickness	Elastic Modulus	Poisson's Ratio	Layer Thickness	Elastic Modulus	Poisson's Ratio	First Performance period	Life-Cycle Cost
		A	B	C		D	E	F	G	H	I	J	K	L	M	N	O	P	Q		
		PSI	-	'000 vpd		Mill	°C	PSI	Ksi	-	In.	Ksi	-	In.	Ksi	-	In.	Ksi	-	Years	$/sqyd
1	MED	2.5	C	5	10	8	24	4.2	500	0.35	4	400	0.35	6	50	0.35	10	14	0.40	12	16.35
2	AH	3.5																		5	19.80
3	AL	1.5																		16	16.18
4	BH		E																	3	21.08
5	BL		A																	24	15.52
6	CH			9.00	19.80															12	16.36
7	CL			1.10	1.92															12	16.34
8	DH					20														5	18.54
9	DL					2														34	15.52
10	EH						38													17	16.15
11	EL						9													5	18.75
12	FH							4.6												15	16.22
13	FL							3.8												9	16.90
14	GH								750											13	16.30
15	GL								250											10	17.08
16	HH									0.40										13	16.30
17	HL									0.20										11	16.72
18	IH										6									18	18.68
19	IL										2									8	14.78
20	JH											600								16	16.18
21	JL											200								7	17.52
22	KH												0.40							12	16.35
23	KL												0.20							12	16.35
24	LH													10						22	19.11
25	LL													3						6	15.27
26	MH														75					14	16.26
27	ML														25					9	17.19
28	NH															0.40				12	16.35
29	NL															0.20				12	16.35
30	OH																16			13	19.12
31	OL																5			10	14.74
32	PH																	24		13	16.30
33	PL																	4		9	17.19
34	QH																		0.45	12	16.35
35	QL																		0.20	12	16.35
F-values		0.98	3.76			13.09	1.11	0.25	0.08	0.03	0.72	0.60		2.05	0.19		0.08	0.17			
Rank		5	2	X	X	1	4	8	12	13	6	7	X	3	9	X	11	10	X		

Note: x means insignificant

Table 8.5 Sensitivity analysis of four-layered system

Run	Problem No.	Terminal Serviceability	Reliability	Initial ADT	Terminal ADT	Traffic (ESAL)	Temperature	Initial Serviceability	First Layer Elastic Modulus	First Layer Poisson's Ratio	First Layer Layer Thickness	Second Layer Elastic Modulus	Second Layer Poisson's Ratio	Second Layer Layer Thickness	Third Layer Elastic Modulus	Third Layer Poisson's Ratio	Third Layer Layer Thickness	Fourth Layer Elastic Modulus	Fourth Layer Poisson's Ratio	Fourth Layer Layer Thickness	Subgrade Elastic Modulus	Subgrade Poisson's Ratio	First Performance Period	Life-Cycle Cost
		A	B	C		D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T		
		PSI	-	'000 vpd		Mill	°C	PSI	ksi	-	in	ksi	-	in	ksi	-	in	ksi	-	in	ksi	-	years	$/sqyd
1	MED	2.5	C	5	10	8	24	4.2	500	0.35	3	450	0.35	5	50	0.35	10	25	0.35	10	14	0.40	9	19.06
2	AH	3.5																					4	22.51
3	AL	1.5																					13	18.17
4	BH		E																				2	23.71
5	BL		A																				20	17.95
6	CH			9.00	19.8																		10	19.02
7	CL			1.10	1.92																		9	19.04
8	DH					20																	4	21.12
9	DL					2																	27	17.39
10	EH						38																14	18.13
11	EL						9																3	21.81
12	FH							4.6															12	18.52
13	FL							3.8															7	19.29
14	GH								750														10	18.68
15	GL								250														8	19.22
16	HH									0.40													10	18.96
17	HL									0.20													8	19.17
18	IH										5												14	20.69
19	IL										1												6	17.67
20	JH											700											12	18.22
21	JL											200											5	20.41
22	KH												0.40										9	19.06
23	KL												0.20										10	18.96
24	LH													8									17	21.86
25	LL													3									6	17.67
26	MH														75								12	18.22
27	ML														25								7	19.40
28	NH															0.40							9	19.06
29	NL															0.20							10	18.96
30	OH																16						10	21.74
31	OL																6						8	17.30
32	PH																	50					10	18.92
33	PL																	15					9	19.10
34	QH																		0.45				9	19.06
35	QL																		0.20				10	19.00
36	RH																			16			10	20.27
37	RL																			6			9	18.21
38	SH																				24		10	18.96
39	SL																				4		8	19.22
40	TH																					0.45	9	19.06
41	TL																					0.20	10	19.00
F-values		1.14	5.18			14.52	1.71	0.32	0.08	0.08	0.83	0.71		1.81	0.32		0.08				0.08			
RANK		5	2	x	x	1	4	8	9	9.00	6	7	x	3	8	x	9	x	x	x	9	x		

Note : x means insignificant

$$Q = \frac{53.6SCI^2 N_k}{T} \quad \text{(Eq 8.3)}$$

and

$$\sigma^2 = \frac{0.0471}{\left(\sqrt{5-P_2}-\sqrt{5-P_1}\right)^2} x \left(\frac{0.01P_2^2}{5-P_2}+\frac{0.01P_1^2}{5-P_1}\right)+\frac{3.3894}{T^2}+\frac{0.755}{SCI^2}\left((\alpha SCI)^2+(\beta SCI)^2\right)+0.0631$$

(Eq 8.4)

where

- P_1 = initial serviceability index (input),
- P_2 = terminal serviceability index (input),
- Q = serviceability loss function (computed) as $\sqrt{5-P_2}-\sqrt{5-P_1}$,
- T = district temperature constant (input) in °F. This is a harmonic mean of average daily temperature minus 32 °F,
- SCI = surface curvature index computed from layer properties (in inches), and
- •&• = variances as fraction (0.3 & 0.34 for new construction) of SCI. FPS-19 considers the variation of surface curvature index along a pavement the same for every pavement structure by using an average coefficient of variation of 34 percent. This value was an average obtained from many in-service pavements. It also considers a regression error (in predicting surface curvature) coefficient of variation of 30 percent for new construction and 38 percent for overlays.

Combining Equations 8.1 to 8.4, the quadratic equation of *t* in the form $\underline{A\,t^2 + B\,t + G = 0}$ can be constructed such that it will give the solution of *t* as:

$$t = \frac{-B+\sqrt{B^2-4AG}}{2A}$$

(Eq 8.5)

where

$A = 2\,r_o$, $\quad B = (r_c - r_o)/C \quad$ and $\quad G = \dfrac{-\left(\sqrt{5-P_2}-\sqrt{5-P_1}\right)TC(r_C+r_o)10^{-Z\sigma}}{53.6SCI^2 N_C}$

(Eq 8.6)

From the above relations it appears that surface curvature index (SCI) is the most sensitive parameter among all performance related parameters P_1, P_2, T, N_c, Z, and SCI because of its exponent. But the analysis of sensitivity using ANOVA indicates that design traffic is the most sensitive, followed by reliability and, next, followed by pavement properties, which constitute the function of surface curvature index. A study of standard deviation was completed to determine if any parameter is losing or gaining its effect on performance period owing to a reliability factor.

It is apparent from Equation 8.4 that standard deviation *(σ)* is a function of temperature *(T)* and initial *(P_1)* and terminal serviceability *(P_2)* and is not dependent on surface curvature index (SCI cancels out). The study of standard deviation reveals that σ varies inversely with *T* and directly with P_1 and P_2. Variation (0.004524) of σ due to change of P_2 (1.5 to 2.0) is more than that (0.004077), owing to change of P_1 (4.0 to 4.5). Values of σ at temperature 10, 20, 30, and 40 (with P_1=4.5 and P_2=1.5) are 0.517, 0.492, 0.487, and 0.485, respectively, which indicate that the rate of change of σ decreases as temperature increases.

Figure 8.1, which presents the graphs of the above variations, shows that the standard deviation decreases with an increase in temperature, increases with an increase in terminal SI, and increases with an increase in initial SI (P_1>3.7). Equations 8.5 and 8.6 indicate that without considering reliability, performance period varies directly with *T* and P_1 and inversely with P_2. Therefore, reliability (in effect, standard deviation) enhances the sensitivity of *T* and P_2 and reduces the same of P_1 (when P_1>3.7).

In order to justify the analysis result, two important parameters, surface curvature index *(S)* and reliability *(Z),* are selected for further analysis using calculus. Partial derivatives of the performance period *(t)* with respect to *S* and *Z* were taken using Equations 8.5 and 8.6 and the ratio of these two are computed, as shown hereinafter.

$$\frac{\partial t}{\partial S}=\frac{2G}{S\sqrt{B^2-4AG}},\quad \frac{\partial t}{\partial Z}=\frac{\sigma C}{0.434\sqrt{B^2-4AG}},\Rightarrow \frac{\frac{\partial t}{\partial S}}{\frac{\partial t}{\partial Z}}=\frac{0.869}{S\sigma}=14476.48$$

For $\sigma = 0.6$ and *S*=0.0001 in.

From the above ratio it becomes evident that a change of *t* with respect to *S* is more prominent than that with respect to *Z*. The value of standard deviation *(σ)* is taken from Figure 8.1, which is a higher value than normal, whereas the value of surface curvature index is assumed to be normal (0.1 mil) for a new construction.

8.2.2 Verification Result

The verification of performance period obtained as output from FPS-19 was completed by computing the same *(t)* using an EXCEL spreadsheet format following the quadratic form given in Equation 8.5. FPS-19 calculates the SCI from layer properties (modulus, Poisson's ratio, and thickness) using elastic layer analysis. FPS-19 does not display the value of SCI computed in the program. Moreover, the performance period is also expressed as an integer (only in years) in FPS-19. Therefore, in the verification, a range of SCI values was backcalculated from one output (one run), which has been subsequently used in four runs. Performance periods obtained in the two methods show close agreement. The results of this analysis are presented in Table 8.6 and described in the following:

- Considering the input values of medium value run (Run-1) for two layer (thick surface as described in Table 8.3), SCI is backcalculated and found in the range of 0.0001462 to 0.0001538 in., corresponding to a performance period of 12.4 years to 11.5 years, respectively, which, when rounded, gives 12 years.

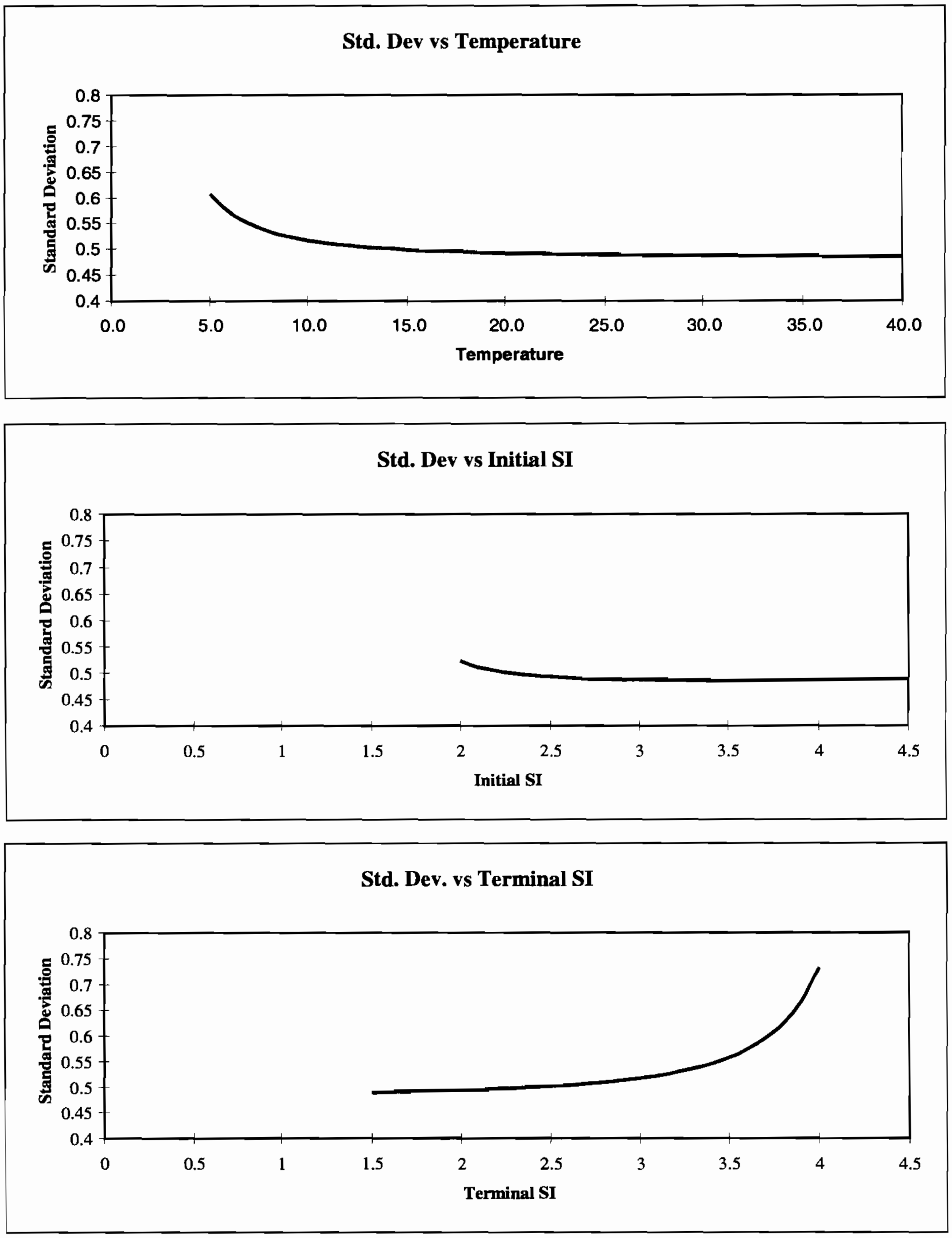


Figure 8.1 Variation of standard deviation of logN with temperature, initial SI, and terminal SI

Table 8.6 Verification of performance period obtained from FPS-19 by worksheet computation

RUN NO.	Initial Serviceability	Terminal Serviceability	Dist. Temperature Constant	Standard Deviation	Design Period (years)	Initial ADT (nos)	Final ADT (nos)	Design 18 kip ESAL (Million)	Surface Curv.Index (1/1000 in)	SI Loss Function	Mean 18 kip ESAL	Reliability (%)	Normal Deviate	**Reliable 18 kip ESAL**	Performance Period (yrs)	Performance Period from FPS
	P_1	P_2	T	SD	C	r_O	r_c	N_C	SCI	Q	N_K	R	Z	N	t	
	4.2	2.5	24	0.499	20	5000	10000	4.00	0.1461	0.687	14.405	95.0	1.6450	2.178	**12.5**	
	4.2	2.5	24	0.499	20	5000	10000	4.00	0.1462	0.687	14.386	95.0	1.6450	2.175	**12.4**	
1	4.2	2.5	24	0.499	20	5000	10000	4.00	0.1487	0.687	13.906	95.0	1.6450	2.103	**12.1**	12
	4.2	2.5	24	0.499	20	5000	10000	4.00	0.1512	0.687	13.450	95.0	1.6450	2.034	**11.8**	
	4.2	2.5	24	0.499	20	5000	10000	4.00	0.1538	0.687	12.999	95.0	1.6450	1.966	**11.5**	
	4.2	2.5	24	0.499	20	5000	10000	4.00	0.1539	0.687	12.982	95.0	1.6450	1.963	**11.4**	
	4.2	3.5	24	0.596	20	5000	10000	4.00	0.1461	0.330	6.929	95.0	1.6450	0.726	**4.9**	
	4.2	3.5	24	0.596	20	5000	10000	4.00	0.1462	0.330	6.920	95.0	1.6450	0.725	**4.9**	
2	4.2	3.5	24	0.596	20	5000	10000	4.00	0.1487	0.330	6.689	95.0	1.6450	0.701	**4.7**	5
	4.2	3.5	24	0.596	20	5000	10000	4.00	0.1512	0.330	6.470	95.0	1.6450	0.678	**4.6**	
	4.2	3.5	24	0.596	20	5000	10000	4.00	0.1538	0.330	6.253	95.0	1.6450	0.655	**4.4**	
	4.2	3.5	24	0.596	20	5000	10000	4.00	0.1539	0.330	6.245	95.0	1.6450	0.654	**4.4**	
	4.2	1.5	24	0.485	20	5000	10000	4.00	0.1461	0.976	20.482	95.0	1.6450	3.260	**17.1**	
	4.2	1.5	24	0.485	20	5000	10000	4.00	0.1462	0.976	20.454	95.0	1.6450	3.256	**17.1**	
3	4.2	1.5	24	0.485	20	5000	10000	4.00	0.1487	0.976	19.772	95.0	1.6450	3.147	**16.7**	17
	4.2	1.5	24	0.485	20	5000	10000	4.00	0.1512	0.976	19.124	95.0	1.6450	3.044	**16.2**	
	4.2	1.5	24	0.485	20	5000	10000	4.00	0.1538	0.976	18.483	95.0	1.6450	2.942	**15.8**	
	4.2	1.5	24	0.485	20	5000	10000	4.00	0.1539	0.976	18.459	95.0	1.6450	2.938	**15.8**	
	4.2	2.5	24	0.499	20	5000	10000	4.00	0.1461	0.687	14.405	99.9	3.0900	0.414	**2.9**	
	4.2	2.5	24	0.499	20	5000	10000	4.00	0.1462	0.687	14.386	99.9	3.0900	0.414	**2.9**	
4	4.2	2.5	24	0.499	20	5000	10000	4.00	0.1487	0.687	13.906	99.9	3.0900	0.400	**2.8**	3
	4.2	2.5	24	0.499	20	5000	10000	4.00	0.1512	0.687	13.450	99.9	3.0900	0.387	**2.7**	
	4.2	2.5	24	0.499	20	5000	10000	4.00	0.1538	0.687	12.999	99.9	3.0900	0.374	**2.6**	
	4.2	2.5	24	0.499	20	5000	10000	4.00	0.1539	0.687	12.982	99.9	3.0900	0.373	**2.6**	
	4.2	2.5	24	0.499	20	5000	10000	4.00	0.1461	0.687	14.405	80.0	0.8415	5.481	**25.2**	
	4.2	2.5	24	0.499	20	5000	10000	4.00	0.1462	0.687	14.386	80.0	0.8415	5.473	**25.2**	
	4.2	2.5	24	0.499	20	5000	10000	4.00	0.1487	0.687	13.906	80.0	0.8415	5.291	**24.6**	
5	4.2	2.5	24	0.499	20	5000	10000	4.00	0.1512	0.687	13.450	80.0	0.8415	5.117	**24.0**	25
	4.2	2.5	24	0.499	20	5000	10000	4.00	0.1538	0.687	12.999	80.0	0.8415	4.946	**23.4**	
	4.2	2.5	24	0.499	20	5000	10000	4.00	0.1539	0.687	12.982	80.0	0.8415	4.939	**23.4**	

Notes: Refer to Table 8.3 for output data obtained from FPS-19 corresponding to above run numbers. A range of SCI is backcalculated from a performance period of 12 years (as per FPS) in run no. 1. Output obtained from FPS-19 is satisfied in run nos. 2 to 5, hence output is OK (verified).

- Next, keeping all input the same as that of Run 2 (changing only terminal SI to 3.5) and the range of SCI as obtained (because SCI should remain the same), the range of performance period obtained was 4.9 to 4.4 years, whereas FPS-19 gives a value of 5 years with the same input. An SCI of 0.0001462 gives 4.9 years, which, when rounded, gives 5 years.
- Keeping input data the same as those for Runs 3, 4, and 5, and with the same range of backcalculated SCI, performance periods are computed as 17.1-15.8 years vs. 17 years as per FPS-19, 2.9-2.6 years vs. 3 years, and 25.2-23.4 years vs. 25 years, respectively.
- SCI of 0.0001462 inch satisfies all FPS-19 output.

Subsequently, the effects of each relevant parameter have been checked along with the computation of the approximate partial derivative *(D)* of performance period with respect to the selected parameter using the same spreadsheet format. The results obtained are summarized below.

Initial SI (P_1) — *D* decreases with a decrease in P_1 more or less uniformly up to P_1 of 3.0 and then increases with further decrement of P_1. The range of *D* is 7.673-6.222 for P_1 values of 4.4-3.0. Table 8.7 provides the values and a graph of the performance period versus P_1.

Terminal SI (P_2) — *D* increases with an increase in P_2 for the entire range of P_2. The range of *D* is 3.850-6.609 for P_2 values of 1.6-3.0. Table 8.8 provides the values and a graph of the performance period versus P_2.

Temperature (T) — *D* decreases with an increase in *T* for the entire range of *T*. The range of *D* is 0.935- 0.555 for *T* values of 10-33. Table 8.9 provides the values and a graph of the performance period versus *T*.

Initial ADT (r_o) — *D* remains more or less uniform with a value of 4E-05 for the entire range of r_o. Table 8.10 provides the values and a graph of the performance period versus r_o.

Design Traffic (N_C) — *D* decreases with an increase in N_C. The change of *D* is very sharp for low values of N_C. The range of *D* is 4E-05 to 5E-07 for N_C of 1.0 to 12.5 million. Table 8.11 provides the values and a graph of the performance period versus N_C.

Surface Curvature (SCI) — *D* decreases with an increase in SCI. *D* is very high at low values of SCI. The range of *D* is 4E+05 to 3E+04 for SCI of 0.11 to 0.34 mil (1/100 in.). Table 8.12 provides the values and a graph of the performance period versus SCI.

Reliability (R) — *D* increases with increase in *R*. The range of *D* is 1.217-4.177 for reliability levels of *B* to *D*. Table 8.13 provides the values and a graph of performance period versus *R*.

In Table 8.11 it is observed that the change of performance period (year) per unit change of ESAL is very small (smaller than that owing to temperature). This observation is true in reality, because one cannot expect any appreciable change in performance period owing to change of one standard axle. At this point, it is understood that the analyses done using the SAS program is correct provided the values entered are practical and the units used are normal. For

Table 8.7 Effect of initial SI on performance period

Initial Serviceability	Terminal Serviceability	Temperature	Standard Deviation	Design Period (years)	Initial ADT (nos)	Final ADT (nos)	Design 18 kip ESAL	Surface Curvature Index	SI Loss Function	Mean 18 kip ESAL	Reliability (%)	Normal Deviate	**Reliable 18 kip ESAL**	Performance Period	Partial Derivative wrt P_I
P_I	P_2	T	SD	C	r_O	r_c	N_C	SCI	Q	N_K	R	Z	N	t	dt/dP_I
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.37**	
4.4	1.5	24	0.487	20	5000	10000	4.00E+06	0.000146	1.096	2.30E+07	95	1.6450	3.6E+06	**18.59**	7.673
4.3	1.5	24	0.486	20	5000	10000	4.00E+06	0.000146	1.034	2.17E+07	95	1.6450	3.4E+06	**17.84**	7.443
4.2	1.5	24	0.485	20	5000	10000	4.00E+06	0.000146	0.976	2.05E+07	95	1.6450	3.3E+06	**17.10**	7.233
4.1	1.5	24	0.485	20	5000	10000	4.00E+06	0.000146	0.922	1.93E+07	95	1.6450	3.1E+06	**16.39**	7.048
4.0	1.5	24	0.484	20	5000	10000	4.00E+06	0.000146	0.871	1.82E+07	95	1.6450	2.9E+06	**15.69**	6.888
3.9	1.5	24	0.484	20	5000	10000	4.00E+06	0.000146	0.822	1.72E+07	95	1.6450	2.8E+06	**15.01**	6.751
3.8	1.5	24	0.484	20	5000	10000	4.00E+06	0.000146	0.775	1.62E+07	95	1.6450	2.6E+06	**14.34**	6.633
3.7	1.5	24	0.484	20	5000	10000	4.00E+06	0.000146	0.731	1.53E+07	95	1.6450	2.4E+06	**13.69**	6.534
3.6	1.5	24	0.484	20	5000	10000	4.00E+06	0.000146	0.688	1.44E+07	95	1.6450	2.3E+06	**13.04**	6.450
3.5	1.5	24	0.484	20	5000	10000	4.00E+06	0.000146	0.646	1.35E+07	95	1.6450	2.2E+06	**12.40**	6.381
3.4	1.5	24	0.484	20	5000	10000	4.00E+06	0.000146	0.606	1.27E+07	95	1.6450	2.0E+06	**11.76**	6.326
3.3	1.5	24	0.484	20	5000	10000	4.00E+06	0.000146	0.567	1.19E+07	95	1.6450	1.9E+06	**11.13**	6.283
3.2	1.5	24	0.485	20	5000	10000	4.00E+06	0.000146	0.529	1.11E+07	95	1.6450	1.8E+06	**10.50**	6.251
3.1	1.5	24	0.485	20	5000	10000	4.00E+06	0.000146	0.492	1.03E+07	95	1.6450	1.6E+06	**9.88**	6.231
3.0	1.5	24	0.486	20	5000	10000	4.00E+06	0.000146	0.457	9.57E+06	95	1.6450	1.5E+06	**9.26**	6.222
2.9	1.5	24	0.486	20	5000	10000	4.00E+06	0.000146	0.422	8.83E+06	95	1.6450	1.4E+06	**8.64**	6.224
2.8	1.5	24	0.487	20	5000	10000	4.00E+06	0.000146	0.388	8.12E+06	95	1.6450	1.3E+06	**8.01**	6.238
2.7	1.5	24	0.488	20	5000	10000	4.00E+06	0.000146	0.354	7.42E+06	95	1.6450	1.2E+06	**7.39**	6.264
2.6	1.5	24	0.490	20	5000	10000	4.00E+06	0.000146	0.322	6.74E+06	95	1.6450	1.1E+06	**6.76**	6.304
2.5	1.5	24	0.492	20	5000	10000	4.00E+06	0.000146	0.290	6.07E+06	95	1.6450	9.4E+05	**6.13**	6.359
2.4	1.5	24	0.494	20	5000	10000	4.00E+06	0.000146	0.258	5.41E+06	95	1.6450	8.3E+05	**5.49**	6.432
2.3	1.5	24	0.498	20	5000	10000	4.00E+06	0.000146	0.228	4.77E+06	95	1.6450	7.2E+05	**4.84**	6.528
2.2	1.5	24	0.503	20	5000	10000	4.00E+06	0.000146	0.198	4.14E+06	95	1.6450	6.2E+05	**4.18**	6.653
2.1	1.5	24	0.510	20	5000	10000	4.00E+06	0.000146	0.168	3.52E+06	95	1.6450	5.1E+05	**3.51**	6.815
2.0	1.5	24	0.522	20	5000	10000	4.00E+06	0.000146	0.139	2.91E+06	95	1.6450	4.0E+05	**2.82**	

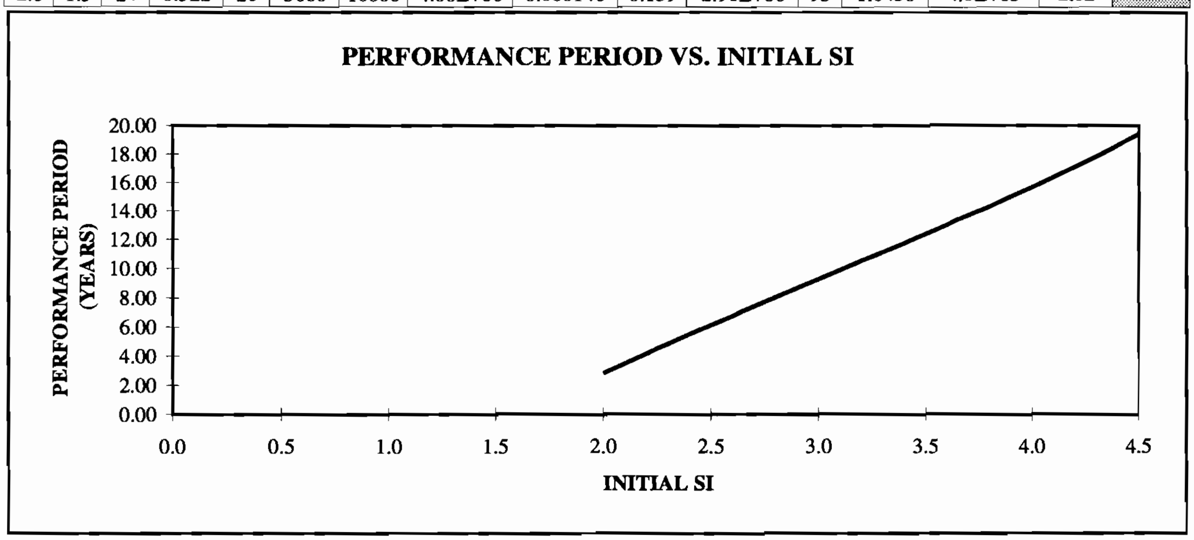


Table 8.8 Effect of terminal SI on performance period

Initial Serviceability	Terminal Serviceability	Temperature	Standard Deviation	Design Period (years)	Initial ADT (nos)	Final ADT (nos)	Design 18 kip ESAL	Surface Curvature Index	SI Loss Function	Mean 18 kip ESAL	Reliability (%)	Normal Deviate	**Reliable 18 kip ESAL**	Performance Period	Partial Derivative wrt P_2
P_1	P_2	T	SD	C	r_O	r_c	N_C	SCI	Q	N_K	R	Z	N	t	dt/dP_2
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.37**	
4.5	1.6	24	0.489	20	5000	10000	4.00E+06	0.000146	1.137	2.38E+07	95	1.6450	3.7E+06	**18.99**	3.850
4.5	1.7	24	0.490	20	5000	10000	4.00E+06	0.000146	1.109	2.32E+07	95	1.6450	3.6E+06	**18.60**	3.960
4.5	1.8	24	0.491	20	5000	10000	4.00E+06	0.000146	1.082	2.27E+07	95	1.6450	3.5E+06	**18.20**	4.077
4.5	1.9	24	0.492	20	5000	10000	4.00E+06	0.000146	1.054	2.21E+07	95	1.6450	3.4E+06	**17.79**	4.202
4.5	2	24	0.493	20	5000	10000	4.00E+06	0.000146	1.025	2.15E+07	95	1.6450	3.3E+06	**17.36**	4.337
4.5	2.1	24	0.494	20	5000	10000	4.00E+06	0.000146	0.996	2.09E+07	95	1.6450	3.2E+06	**16.92**	4.482
4.5	2.2	24	0.495	20	5000	10000	4.00E+06	0.000146	0.966	2.02E+07	95	1.6450	3.1E+06	**16.46**	4.640
4.5	2.3	24	0.497	20	5000	10000	4.00E+06	0.000146	0.936	1.96E+07	95	1.6450	3.0E+06	**15.99**	4.811
4.5	2.4	24	0.499	20	5000	10000	4.00E+06	0.000146	0.905	1.90E+07	95	1.6450	2.9E+06	**15.50**	4.998
4.5	2.5	24	0.501	20	5000	10000	4.00E+06	0.000146	0.874	1.83E+07	95	1.6450	2.7E+06	**14.99**	5.202
4.5	2.6	24	0.503	20	5000	10000	4.00E+06	0.000146	0.842	1.76E+07	95	1.6450	2.6E+06	**14.46**	5.428
4.5	2.7	24	0.506	20	5000	10000	4.00E+06	0.000146	0.809	1.70E+07	95	1.6450	2.5E+06	**13.91**	5.676
4.5	2.8	24	0.509	20	5000	10000	4.00E+06	0.000146	0.776	1.63E+07	95	1.6450	2.4E+06	**13.32**	5.953
4.5	2.9	24	0.512	20	5000	10000	4.00E+06	0.000146	0.742	1.55E+07	95	1.6450	2.2E+06	**12.71**	6.262
4.5	3	24	0.516	20	5000	10000	4.00E+06	0.000146	0.707	1.48E+07	95	1.6450	2.1E+06	**12.07**	6.609
4.5	3.1	24	0.521	20	5000	10000	4.00E+06	0.000146	0.671	1.41E+07	95	1.6450	2.0E+06	**11.39**	7.001
4.5	3.2	24	0.527	20	5000	10000	4.00E+06	0.000146	0.635	1.33E+07	95	1.6450	1.8E+06	**10.67**	7.445
4.5	3.3	24	0.535	20	5000	10000	4.00E+06	0.000146	0.597	1.25E+07	95	1.6450	1.6E+06	**9.90**	7.951
4.5	3.4	24	0.544	20	5000	10000	4.00E+06	0.000146	0.558	1.17E+07	95	1.6450	1.5E+06	**9.08**	8.527
4.5	3.5	24	0.557	20	5000	10000	4.00E+06	0.000146	0.518	1.08E+07	95	1.6450	1.3E+06	**8.20**	9.180
4.5	3.6	24	0.572	20	5000	10000	4.00E+06	0.000146	0.476	9.97E+06	95	1.6450	1.1E+06	**7.25**	9.909
4.5	3.7	24	0.594	20	5000	10000	4.00E+06	0.000146	0.433	9.07E+06	95	1.6450	9.6E+05	**6.22**	10.69
4.5	3.8	24	0.623	20	5000	10000	4.00E+06	0.000146	0.388	8.14E+06	95	1.6450	7.7E+05	**5.11**	11.46
4.5	3.9	24	0.666	20	5000	10000	4.00E+06	0.000146	0.342	7.16E+06	95	1.6450	5.7E+05	**3.93**	12.02
4.5	4	24	0.731	20	5000	10000	4.00E+06	0.000146	0.293	6.14E+06	95	1.6450	3.8E+05	**2.70**	

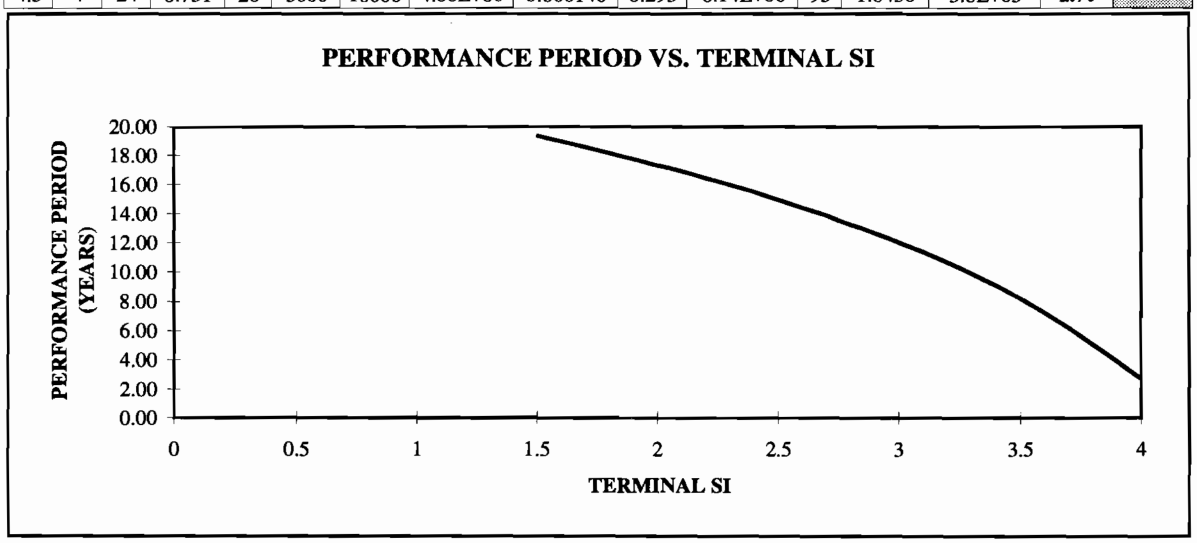


Table 8.9 Effect of temperature on performance period

Initial Serviceability	Terminal Serviceability	Temperature	Standard Deviation	Design Period (years)	Initial ADT (nos)	Final ADT (nos)	Design 18 kip ESAL	Surface Curvature Index	SI Loss Function	Mean 18 kip ESAL	Reliability (%)	Normal Deviate	**Reliable 18 kip ESAL**	Performance Period (yrs)	Partial Derivative wrt T
P_1	P_2	T	SD	C	r_O	r_c	N_C	SCI	Q	N_K	R	Z	N	t	dt/dT
4.5	1.5	9	0.524	20	5000	10000	4.00E+06	0.000146	1.164	9.14E+06	95	1.6450	1.3E+06	**7.87**	
4.5	1.5	10	0.516	20	5000	10000	4.00E+06	0.000146	1.164	1.02E+07	95	1.6450	1.4E+06	**8.83**	0.935
4.5	1.5	11	0.511	20	5000	10000	4.00E+06	0.000146	1.164	1.12E+07	95	1.6450	1.6E+06	**9.74**	0.895
4.5	1.5	12	0.506	20	5000	10000	4.00E+06	0.000146	1.164	1.22E+07	95	1.6450	1.8E+06	**10.62**	0.861
4.5	1.5	13	0.503	20	5000	10000	4.00E+06	0.000146	1.164	1.32E+07	95	1.6450	2.0E+06	**11.47**	0.831
4.5	1.5	14	0.500	20	5000	10000	4.00E+06	0.000146	1.164	1.42E+07	95	1.6450	2.1E+06	**12.28**	0.804
4.5	1.5	15	0.498	20	5000	10000	4.00E+06	0.000146	1.164	1.52E+07	95	1.6450	2.3E+06	**13.07**	0.780
4.5	1.5	16	0.496	20	5000	10000	4.00E+06	0.000146	1.164	1.63E+07	95	1.6450	2.5E+06	**13.84**	0.758
4.5	1.5	17	0.494	20	5000	10000	4.00E+06	0.000146	1.164	1.73E+07	95	1.6450	2.7E+06	**14.59**	0.738
4.5	1.5	18	0.493	20	5000	10000	4.00E+06	0.000146	1.164	1.83E+07	95	1.6450	2.8E+06	**15.32**	0.720
4.5	1.5	19	0.492	20	5000	10000	4.00E+06	0.000146	1.164	1.93E+07	95	1.6450	3.0E+06	**16.03**	0.704
4.5	1.5	20	0.491	20	5000	10000	4.00E+06	0.000146	1.164	2.03E+07	95	1.6450	3.2E+06	**16.73**	0.688
4.5	1.5	21	0.490	20	5000	10000	4.00E+06	0.000146	1.164	2.13E+07	95	1.6450	3.3E+06	**17.41**	0.674
4.5	1.5	22	0.490	20	5000	10000	4.00E+06	0.000146	1.164	2.23E+07	95	1.6450	3.5E+06	**18.07**	0.661
4.5	1.5	23	0.489	20	5000	10000	4.00E+06	0.000146	1.164	2.34E+07	95	1.6450	3.7E+06	**18.73**	0.648
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.37**	0.636
4.5	1.5	25	0.488	20	5000	10000	4.00E+06	0.000146	1.164	2.54E+07	95	1.6450	4.0E+06	**20.00**	0.625
4.5	1.5	26	0.487	20	5000	10000	4.00E+06	0.000146	1.164	2.64E+07	95	1.6450	4.2E+06	**20.62**	0.615
4.5	1.5	27	0.487	20	5000	10000	4.00E+06	0.000146	1.164	2.74E+07	95	1.6450	4.3E+06	**21.23**	0.605
4.5	1.5	28	0.487	20	5000	10000	4.00E+06	0.000146	1.164	2.84E+07	95	1.6450	4.5E+06	**21.83**	0.596
4.5	1.5	29	0.486	20	5000	10000	4.00E+06	0.000146	1.164	2.95E+07	95	1.6450	4.7E+06	**22.42**	0.587
4.5	1.5	30	0.486	20	5000	10000	4.00E+06	0.000146	1.164	3.05E+07	95	1.6450	4.8E+06	**23.01**	0.578
4.5	1.5	31	0.486	20	5000	10000	4.00E+06	0.000146	1.164	3.15E+07	95	1.6450	5.0E+06	**23.58**	0.570
4.5	1.5	32	0.486	20	5000	10000	4.00E+06	0.000146	1.164	3.25E+07	95	1.6450	5.2E+06	**24.15**	0.562
4.5	1.5	33	0.486	20	5000	10000	4.00E+06	0.000146	1.164	3.35E+07	95	1.6450	5.3E+06	**24.70**	0.555
4.5	1.5	34	0.485	20	5000	10000	4.00E+06	0.000146	1.164	3.45E+07	95	1.6450	5.5E+06	**25.26**	

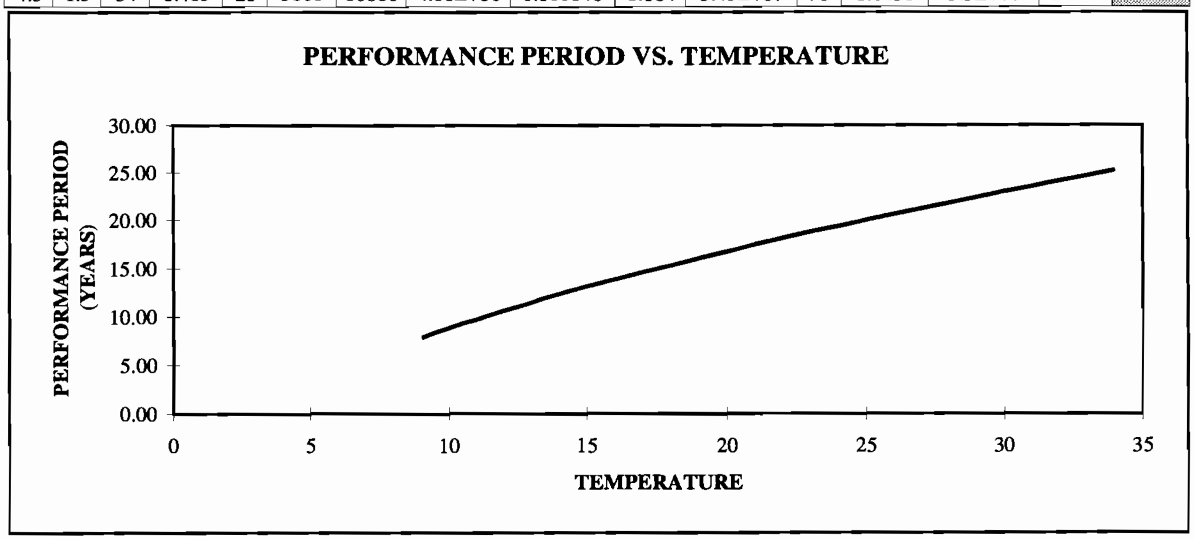


Table 8.10 Effect of initial ADT on performance period

Initial Serviceability	Terminal Serviceability	Temperature	Standard Deviation	Design Period (years)	Initial ADT (nos)	Final ADT (nos)	Design 18 kip ESAL	Surface Curvature Index	SI Loss Function	Mean 18 kip ESAL	Reliability (%)	Normal Deviate	**Reliable 18 kip ESAL**	Performance Period (yrs)	Partial Derivative wrt r_O
P_1	P_2	T	SD	C	r_O	r_c	N_C	SCI	Q	N_K	R	Z	N	t	dt/dr_O
4.5	1.5	24	0.488	20	3770	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.42**	
4.5	1.5	24	0.488	20	3863	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.42**	4E-05
4.5	1.5	24	0.488	20	3956	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.41**	4E-05
4.5	1.5	24	0.488	20	4050	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.41**	4E-05
4.5	1.5	24	0.488	20	4143	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.41**	4E-05
4.5	1.5	24	0.488	20	4236	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.40**	4E-05
4.5	1.5	24	0.488	20	4329	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.40**	4E-05
4.5	1.5	24	0.488	20	4422	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.39**	4E-05
4.5	1.5	24	0.488	20	4516	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.39**	4E-05
4.5	1.5	24	0.488	20	4609	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.39**	4E-05
4.5	1.5	24	0.488	20	4702	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.38**	4E-05
4.5	1.5	24	0.488	20	4795	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.38**	4E-05
4.5	1.5	24	0.488	20	4888	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.38**	4E-05
4.5	1.5	24	0.488	20	4982	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.37**	4E-05
4.5	1.5	24	0.488	20	5075	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.37**	4E-05
4.5	1.5	24	0.488	20	5168	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.36**	4E-05
4.5	1.5	24	0.488	20	5261	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.36**	4E-05
4.5	1.5	24	0.488	20	5354	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.36**	4E-05
4.5	1.5	24	0.488	20	5448	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.35**	4E-05
4.5	1.5	24	0.488	20	5541	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.35**	4E-05
4.5	1.5	24	0.488	20	5634	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.34**	4E-05
4.5	1.5	24	0.488	20	5727	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.34**	4E-05
4.5	1.5	24	0.488	20	5820	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.34**	4E-05
4.5	1.5	24	0.488	20	5914	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.33**	4E-05
4.5	1.5	24	0.488	20	6007	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.33**	4E-05
4.5	1.5	24	0.488	20	6100	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.33**	

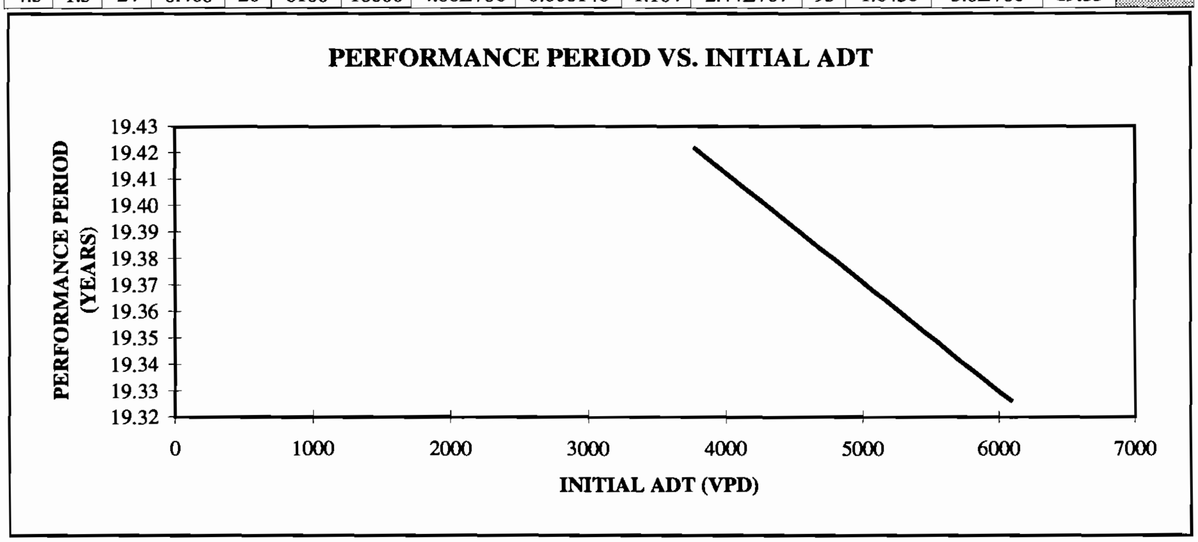


Table 8.11 Effect of design ESAL on performance period

Initial Serviceability	Terminal Serviceability	Temperature	Standard Deviation	Design Period (years)	Initial ADT (nos)	Final ADT (nos)	Design 18 kip ESAL	Surface Curvature Index	SI Loss Function	Mean 18 kip ESAL	Reliability (%)	Normal Deviate	**Reliable 18 kip ESAL**	Performance Period (yrs)	Partial Derivative wrt N_C
P_1	P_2	T	SD	C	r_O	r_c	N_C	SCI	Q	N_K	R	Z	N	t	dt/dN_C
4.5	1.5	24	0.488	20	5000	10000	5.00E+05	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**77.98**	
4.5	1.5	24	0.488	20	5000	10000	1.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**50.71**	4E-05
4.5	1.5	24	0.488	20	5000	10000	1.50E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**38.88**	2E-05
4.5	1.5	24	0.488	20	5000	10000	2.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**31.96**	1E-05
4.5	1.5	24	0.488	20	5000	10000	2.50E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**27.33**	8E-06
4.5	1.5	24	0.488	20	5000	10000	3.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**23.97**	6E-06
4.5	1.5	24	0.488	20	5000	10000	3.50E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**21.40**	5E-06
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.37**	4E-06
4.5	1.5	24	0.488	20	5000	10000	4.50E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**17.71**	3E-06
4.5	1.5	24	0.488	20	5000	10000	5.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**16.33**	3E-06
4.5	1.5	24	0.488	20	5000	10000	5.50E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**15.16**	2E-06
4.5	1.5	24	0.488	20	5000	10000	6.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**14.16**	2E-06
4.5	1.5	24	0.488	20	5000	10000	6.50E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**13.28**	2E-06
4.5	1.5	24	0.488	20	5000	10000	7.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**12.51**	1E-06
4.5	1.5	24	0.488	20	5000	10000	7.50E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**11.83**	1E-06
4.5	1.5	24	0.488	20	5000	10000	8.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**11.23**	1E-06
4.5	1.5	24	0.488	20	5000	10000	8.50E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**10.68**	1E-06
4.5	1.5	24	0.488	20	5000	10000	9.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**10.19**	9E-07
4.5	1.5	24	0.488	20	5000	10000	9.50E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**9.74**	9E-07
4.5	1.5	24	0.488	20	5000	10000	1.00E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**9.33**	8E-07
4.5	1.5	24	0.488	20	5000	10000	1.05E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**8.95**	7E-07
4.5	1.5	24	0.488	20	5000	10000	1.10E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**8.60**	7E-07
4.5	1.5	24	0.488	20	5000	10000	1.15E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**8.28**	6E-07
4.5	1.5	24	0.488	20	5000	10000	1.20E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**7.99**	6E-07
4.5	1.5	24	0.488	20	5000	10000	1.25E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**7.71**	5E-07
4.5	1.5	24	0.488	20	5000	10000	1.30E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**7.46**	

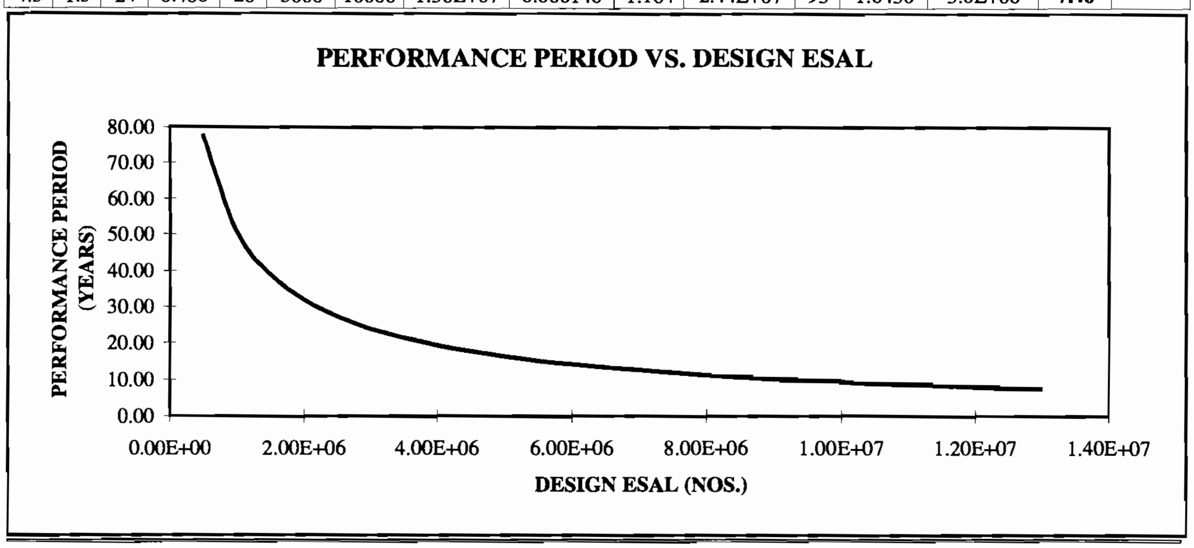


Table 8.12 Effect of surface curvature on performance period

Initial Serviceability	Terminal Serviceability	Temperature	Standard Deviation	Design Period (years)	Initial ADT (nos)	Final ADT (nos)	Design 18 kip ESAL	Surface Curvature Index	SI Loss Function	Mean 18 kip ESAL	Reliability (%)	Normal Deviate	**Reliable 18 kip ESAL**	Performance Period (yrs)	Partial Derivative wrt SCI
P_1	P_2	T	SD	C	r_O	r_c	N_C	SCI	Q	N_K	R	Z	N	t	dt/dSCI
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000100	1.164	5.21E+07	95	1.6450	8.2E+06	**33.46**	
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000110	1.164	4.31E+07	95	1.6450	6.8E+06	**29.31**	4E+05
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000120	1.164	3.62E+07	95	1.6450	5.7E+06	**25.90**	3E+05
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000130	1.164	3.08E+07	95	1.6450	4.8E+06	**23.06**	3E+05
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000140	1.164	2.66E+07	95	1.6450	4.2E+06	**20.67**	2E+05
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000150	1.164	2.32E+07	95	1.6450	3.6E+06	**18.63**	2E+05
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000160	1.164	2.04E+07	95	1.6450	3.2E+06	**16.88**	2E+05
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000170	1.164	1.80E+07	95	1.6450	2.8E+06	**15.36**	1E+05
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000180	1.164	1.61E+07	95	1.6450	2.5E+06	**14.04**	1E+05
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000190	1.164	1.44E+07	95	1.6450	2.3E+06	**12.88**	1E+05
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000200	1.164	1.30E+07	95	1.6450	2.0E+06	**11.85**	1E+05
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000210	1.164	1.18E+07	95	1.6450	1.9E+06	**10.94**	9E+04
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000220	1.164	1.08E+07	95	1.6450	1.7E+06	**10.13**	8E+04
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000230	1.164	9.85E+06	95	1.6450	1.5E+06	**9.41**	7E+04
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000240	1.164	9.05E+06	95	1.6450	1.4E+06	**8.75**	6E+04
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000250	1.164	8.34E+06	95	1.6450	1.3E+06	**8.17**	6E+04
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000260	1.164	7.71E+06	95	1.6450	1.2E+06	**7.63**	5E+04
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000270	1.164	7.15E+06	95	1.6450	1.1E+06	**7.15**	5E+04
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000280	1.164	6.65E+06	95	1.6450	1.0E+06	**6.71**	4E+04
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000290	1.164	6.20E+06	95	1.6450	9.7E+05	**6.31**	4E+04
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000300	1.164	5.79E+06	95	1.6450	9.1E+05	**5.94**	4E+04
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000310	1.164	5.42E+06	95	1.6450	8.5E+05	**5.61**	3E+04
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000320	1.164	5.09E+06	95	1.6450	8.0E+05	**5.30**	3E+04
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000330	1.164	4.78E+06	95	1.6450	7.5E+05	**5.01**	3E+04
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000340	1.164	4.51E+06	95	1.6450	7.1E+05	**4.75**	3E+04
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000350	1.164	4.25E+06	95	1.6450	6.7E+05	**4.51**	

PERFORMANCE PERIOD VS. SURFACE CURVATURE INDEX

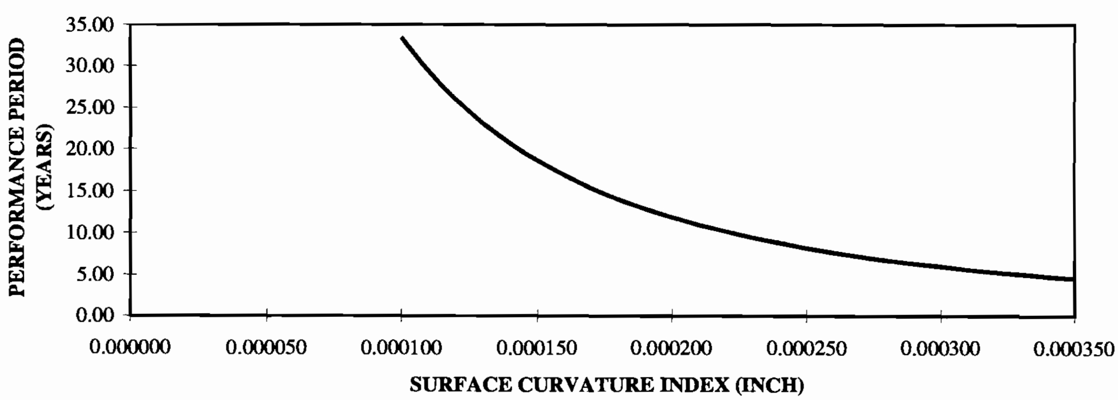


Table 8.13 Effect of reliability on performance period

Initial Serviceability	Terminal Serviceability	Temperature	Standard Deviation	Design Period (years)	Initial ADT (nos)	Final ADT (nos)	Design 18 kip ESAL	Surface Curvature Index	SI Loss Function	Mean 18 kip ESAL	Reliability (%)	Normal Deviate	**Reliable 18 kip ESAL**	Performance Period (yrs)	Partial Derivative wrt R
P_1	P_2	T	SD	C	r_O	r_c	N_C	SCI	Q	N_K	R	Z	**N**	**t**	dt/dR
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000146	1.164	2.44E+07	80	0.8415	9.5E+06	**36.91**	
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000146	1.164	2.44E+07	90	1.2810	5.8E+06	**26.17**	1.217
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**19.37**	1.781
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000146	1.164	2.44E+07	99	2.3267	1.8E+06	**10.57**	4.177
4.5	1.5	24	0.488	20	5000	10000	4.00E+06	0.000146	1.164	2.44E+07	###	3.0900	7.5E+05	**5.03**	

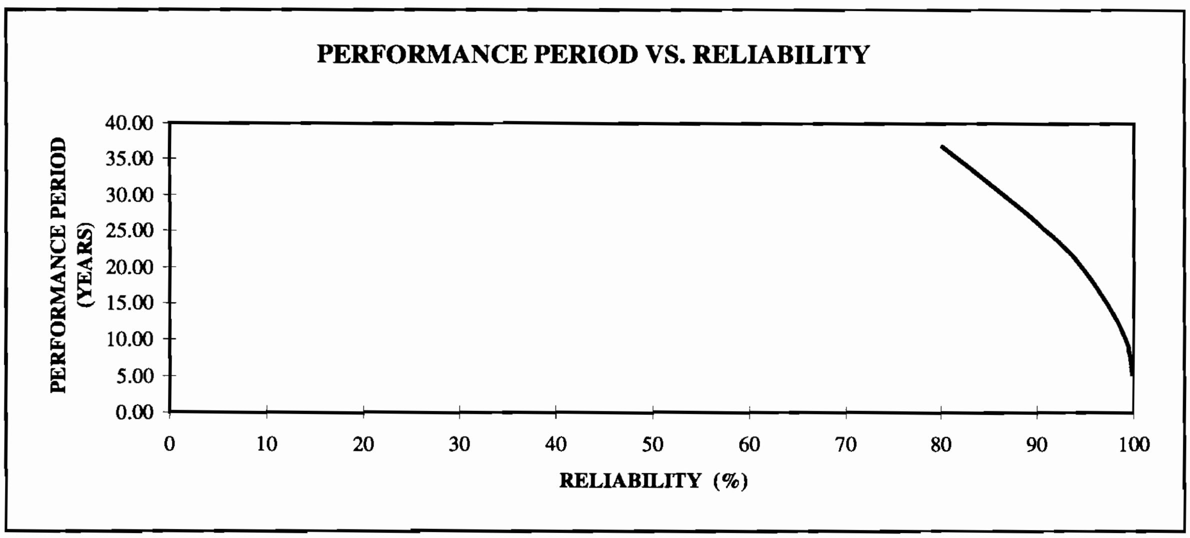


Table 8.14 Effect of design ESAL (per million) on performance period

Initial Serviceability	Terminal Serviceability	Temperature	Standard Deviation	Design Period (years)	Initial ADT (nos)	Final ADT (nos)	Design 18 kip ESAL	Surface Curvature Index	SI Loss Function	Mean 18 kip ESAL	Reliability (%)	Normal Deviate	**Reliable 18 kip ESAL**	Performance Period (yrs)	Partial Derivative wrt N_C
P_1	P_2	T	SD	C	r_O	r_c	N_C	SCI	Q	N_K	R	Z	N	t	dt/dN_C
4.5	1.5	24	0.488	20	5000	10000	5.00E+05	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**77.98**	
4.5	1.5	24	0.488	20	5000	10000	1.50E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**38.88**	25.33
4.5	1.5	24	0.488	20	5000	10000	2.50E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**27.33**	8.738
4.5	1.5	24	0.488	20	5000	10000	3.50E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**21.40**	4.808
4.5	1.5	24	0.488	20	5000	10000	4.50E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**17.71**	3.121
4.5	1.5	24	0.488	20	5000	10000	5.50E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**15.16**	2.215
4.5	1.5	24	0.488	20	5000	10000	6.50E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**13.28**	1.665
4.5	1.5	24	0.488	20	5000	10000	7.50E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**11.83**	1.302
4.5	1.5	24	0.488	20	5000	10000	8.50E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**10.68**	1.049
4.5	1.5	24	0.488	20	5000	10000	9.50E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**9.74**	0.864
4.5	1.5	24	0.488	20	5000	10000	1.05E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**8.95**	0.726
4.5	1.5	24	0.488	20	5000	10000	1.15E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**8.28**	0.619
4.5	1.5	24	0.488	20	5000	10000	1.25E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**7.71**	0.534
4.5	1.5	24	0.488	20	5000	10000	1.35E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**7.22**	0.466
4.5	1.5	24	0.488	20	5000	10000	1.45E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**6.78**	0.410
4.5	1.5	24	0.488	20	5000	10000	1.55E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**6.40**	0.364
4.5	1.5	24	0.488	20	5000	10000	1.65E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**6.05**	0.325
4.5	1.5	24	0.488	20	5000	10000	1.75E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**5.75**	0.293
4.5	1.5	24	0.488	20	5000	10000	1.85E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**5.47**	0.265
4.5	1.5	24	0.488	20	5000	10000	1.95E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**5.22**	0.240
4.5	1.5	24	0.488	20	5000	10000	2.05E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**4.99**	0.219
4.5	1.5	24	0.488	20	5000	10000	2.15E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**4.78**	0.201
4.5	1.5	24	0.488	20	5000	10000	2.25E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**4.59**	0.185
4.5	1.5	24	0.488	20	5000	10000	2.35E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**4.41**	0.171
4.5	1.5	24	0.488	20	5000	10000	2.45E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**4.24**	0.158
4.5	1.5	24	0.488	20	5000	10000	2.55E+07	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**4.09**	

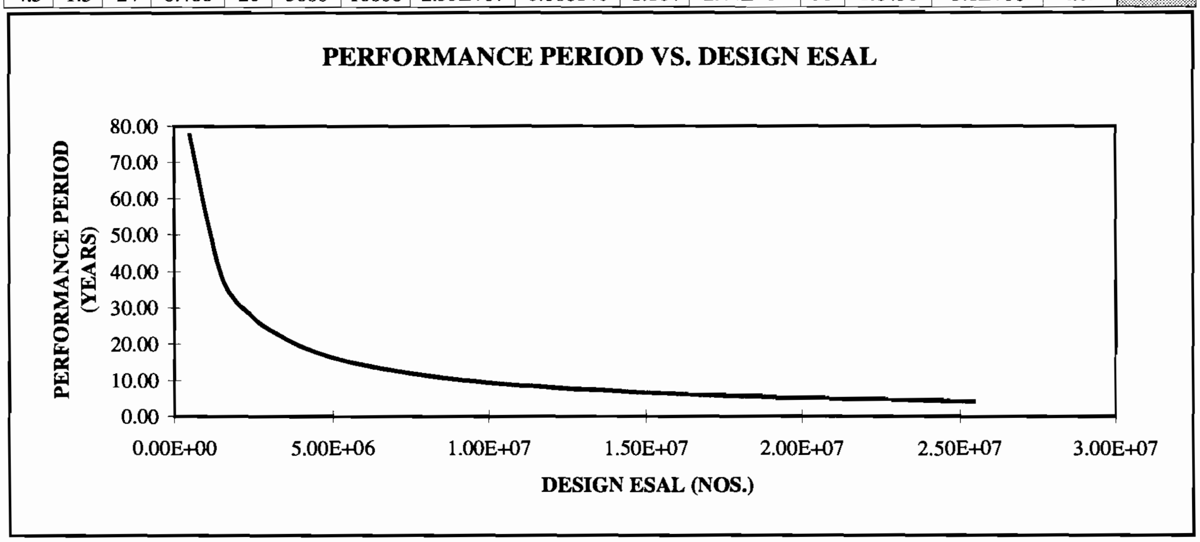
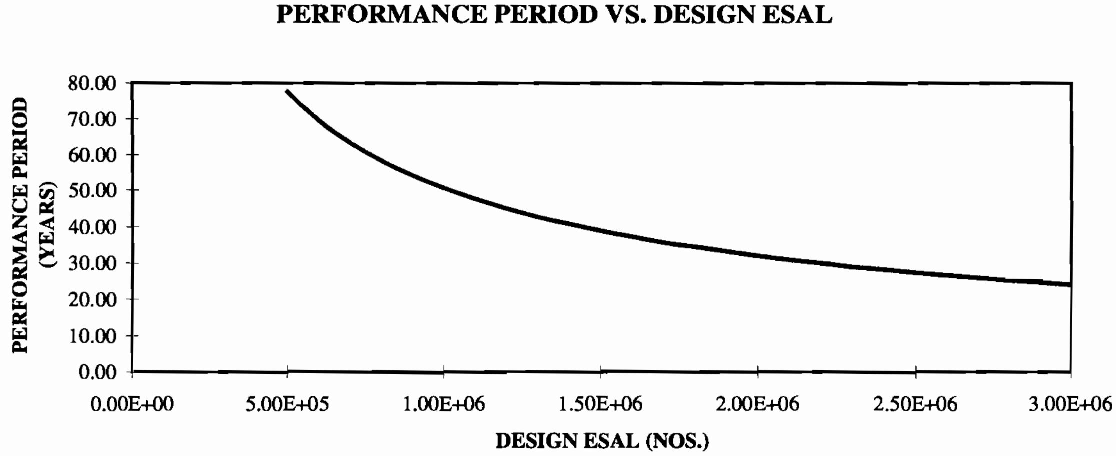


Table 8.15 Effect of design ESAL (per 0.1 million) on performance period

Initial Serviceability	Terminal Serviceability	Temperature	Standard Deviation	Design Period (years)	Initial ADT (nos)	Final ADT (nos)	Design 18 kip ESAL	Surface Curvature Index	SI Loss Function	Mean 18 kip ESAL	Reliability (%)	Normal Deviate	**Reliable 18 kip ESAL**	Performance Period (yrs)	Partial Derivative wrt N_C
P_1	P_2	T	SD	C	r_O	r_c	N_C	SCI	Q	N_K	R	Z	**N**	**t**	dt/dN_C
4.5	1.5	24	0.488	20	5000	10000	5.00E+05	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**77.98**	
4.5	1.5	24	0.488	20	5000	10000	6.00E+05	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**69.82**	7.243
4.5	1.5	24	0.488	20	5000	10000	7.00E+05	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**63.50**	5.697
4.5	1.5	24	0.488	20	5000	10000	8.00E+05	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**58.42**	4.629
4.5	1.5	24	0.488	20	5000	10000	9.00E+05	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**54.24**	3.856
4.5	1.5	24	0.488	20	5000	10000	1.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**50.71**	3.274
4.5	1.5	24	0.488	20	5000	10000	1.10E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**47.69**	2.823
4.5	1.5	24	0.488	20	5000	10000	1.20E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**45.07**	2.466
4.5	1.5	24	0.488	20	5000	10000	1.30E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**42.76**	2.177
4.5	1.5	24	0.488	20	5000	10000	1.40E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**40.71**	1.939
4.5	1.5	24	0.488	20	5000	10000	1.50E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**38.88**	1.741
4.5	1.5	24	0.488	20	5000	10000	1.60E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**37.23**	1.574
4.5	1.5	24	0.488	20	5000	10000	1.70E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**35.73**	1.431
4.5	1.5	24	0.488	20	5000	10000	1.80E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**34.37**	1.308
4.5	1.5	24	0.488	20	5000	10000	1.90E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**33.12**	1.202
4.5	1.5	24	0.488	20	5000	10000	2.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**31.96**	1.108
4.5	1.5	24	0.488	20	5000	10000	2.10E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**30.90**	1.026
4.5	1.5	24	0.488	20	5000	10000	2.20E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**29.91**	0.953
4.5	1.5	24	0.488	20	5000	10000	2.30E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**28.99**	0.889
4.5	1.5	24	0.488	20	5000	10000	2.40E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**28.13**	0.831
4.5	1.5	24	0.488	20	5000	10000	2.50E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**27.33**	0.778
4.5	1.5	24	0.488	20	5000	10000	2.60E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**26.58**	0.731
4.5	1.5	24	0.488	20	5000	10000	2.70E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**25.87**	0.689
4.5	1.5	24	0.488	20	5000	10000	2.80E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**25.20**	0.650
4.5	1.5	24	0.488	20	5000	10000	2.90E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**24.57**	0.614
4.5	1.5	24	0.488	20	5000	10000	3.00E+06	0.000146	1.164	2.44E+07	95	1.6450	3.8E+06	**23.97**	



example, in Tables 8.14 and 8.15, which give the effect of design traffic on performance period, respectively, with change of traffic as 1 million and 0.1 million, it may be seen that the partial derivatives differ by a factor of 10. This indicates that it is important to know which unit is to be used. Change of performance period (years) per standard axle load is negligible. For a change of one standard axle, the performance period may change by a few minutes. In the sensitivity analyses (using SAS), units of ESAL used were in million axles and, therefore, it showed the greatest effect. However, with the same unit if the values of ESAL were high (more than 10 million), the scenario would have been different because at higher ESAL values the rate of change in performance period is less. The concept of units that must be understood in the previous exercise is explained in the next paragraph.

Length can be expressed in Angstrom units as well as in light-years, but its use depends on the subject to be represented. For example, to express the diameter of an atom, the former unit is used, whereas, for the distance between two stellar objects the later unit is suitable. Therefore, if the effect of *length* of a road versus *speed* of a car on *time* required to travel is needed to be analyzed, then if units are not chosen properly the analysis may yield erroneous results. The proper unit depends on variation expected in the application. In case of the length of road, a *millimeter* does not matter, whereas a *meter* may matter. So, in such a sensitivity analysis the unit of length should be meter and not kilometer; otherwise there is a greater chance of getting length more sensitive than speed, as change of time per km will be 1,000 times change of time per meter. To be more precise, it is not only the unit but also the precision used to express the value. For example, if length is expressed as 12.525 km, then the precision is three places after the decimal, and for this case the rate of change should be expressed as change per 0.001km or change per m. It implies that the last digit really matters (so it is used), and for that matter the sensitivity should be checked per unit change of the last digit. Sensitivity will naturally increase in the previous example if change per km is used.

One more important aspect is the domain of the parameter used in the sensitivity analysis. This is because in general there is a possibility that the rate of change of the dependent variable is not constant with respect to that independent parameter. It may be high at low values of dependent parameters or vice-versa.

Therefore, in accordance with the above hypothesis, the magnitude of change of independent parameters has been chosen and rates of change of performance period have been computed for medium, high, and low values of independent parameters. Tables 8.16 through 8.18, respectively, show variations corresponding to medium, high, and low values of relevant parameters. These values are summarized in Table 8.19.

It is clear from Table 8.19 that reliability is the most sensitive factor, followed by surface curvature index. Now, the ratio of $\delta t/\delta S$: $\delta t/\delta Z$ becomes 0.14476 for the same data but with a change of SCI per 0.01 mil instead of per inch as considered earlier. This explains the recent findings. However, it may be seen that the ranges of rate of change of performance period with respect to several parameters are overlapping. Statistical methods have been used to solve the overlapping problem and to obtain the ranks. Table 8.20 presents the ranks of relevant parameters along with their probability of holding that rank.

8.2.3 Final Ranks

The final ranks of the relevant parameters studied are summarized in Table 8.21. Since surface curvature index has been considered as one parameter, this ranking system is independent of the pavement layer system. The relative importance of pavement characteristics (layer thicknesses, elastic moduli, and Poisson's ratios) as indicated earlier may still hold true. The most important pavement character has a 67% chance of holding the second rank.

Table 8.16 Effect of relevant parameters on performance period (medium range)

Initial Serviceability	Terminal Serviceability	Temperature	Standard Deviation	Design Period (years)	Initial ADT (nos)	Final ADT (nos)	Design 18 kip ESAL	Surface Curvature Index	SI Loss Function	Mean 18 kip ESAL	Reliability (%)	Normal Deviate	**Reliable 18 kip ESAL**	Performance Period (yrs)	Approx Partial Derivative
P_1	P_2	T	SD	C	r_O	r_c	N_C	SCI	Q	N_K	R	Z	N	t	
4.15	2.5	24	0.499	20	5000	10000	4.00E+06	0.000146	0.659	1.38E+07	95	1.6450	2.1E+06	**12.03**	
4.20	2.5	24	0.499	20	5000	10000	4.00E+06	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**12.44**	0.826
4.25	2.5	24	0.499	20	5000	10000	4.00E+06	0.000146	0.715	1.50E+07	95	1.6450	2.3E+06	**12.86**	
4.2	2.45	24	0.498	20	5000	10000	4.00E+06	0.000146	0.702	1.47E+07	95	1.6450	2.2E+06	**12.72**	
4.2	2.50	24	0.499	20	5000	10000	4.00E+06	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**12.44**	0.561
4.2	2.55	24	0.500	20	5000	10000	4.00E+06	0.000146	0.671	1.41E+07	95	1.6450	2.1E+06	**12.16**	
4.2	2.5	23.5	0.499	20	5000	10000	4.00E+06	0.000146	0.687	1.41E+07	95	1.6450	2.1E+06	**12.22**	
4.2	2.5	24.0	0.499	20	5000	10000	4.00E+06	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**12.44**	0.438
4.2	2.5	24.5	0.498	20	5000	10000	4.00E+06	0.000146	0.687	1.47E+07	95	1.6450	2.2E+06	**12.66**	
4.2	2.5	24	0.499	20	4995	9995	4.00E+06	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**12.44**	
4.2	2.5	24	0.499	20	5000	10000	4.00E+06	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**12.44**	0.002
4.2	2.5	24	0.499	20	5005	10005	4.00E+06	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**12.44**	
4.2	2.5	24	0.499	20	5000	10000	3995000	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**12.46**	
4.2	2.5	24	0.499	20	5000	10000	4000000	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**12.44**	0.025
4.2	2.5	24	0.499	20	5000	10000	4005000	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**12.43**	
4.2	2.5	24	0.499	20	5000	10000	4.00E+06	0.000141	0.687	1.54E+07	95	1.6450	2.3E+06	**13.16**	
4.2	2.5	24	0.499	20	5000	10000	4.00E+06	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**12.44**	1.378
4.2	2.5	24	0.499	20	5000	10000	4.00E+06	0.000151	0.687	1.34E+07	95	1.6450	2.0E+06	**11.78**	
4.2	2.5	24	0.499	20	5000	10000	4.00E+06	0.000146	0.687	1.44E+07	90	1.2812	3.3E+06	**17.30**	
4.2	2.5	24	0.499	20	5000	10000	4.00E+06	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**12.44**	5.435
4.2	2.5	24	0.499	20	5000	10000	4.00E+06	0.000146	0.687	1.44E+07	99	2.3267	9.9E+05	**6.43**	

Table 8.17 Effect of relevant parameters on performance period (high range)

Initial Serviceability	Terminal Serviceability	Temperature	Standard Deviation	Design Period (years)	Initial ADT (nos)	Final ADT (nos)	Design 18 kip ESAL	Surface Curvature Index	SI Loss Function	Mean 18 kip ESAL	Reliability (%)	Normal Deviate	**Reliable 18 kip ESAL**	Performance Period (yrs)	Approx Partial Derivative
P_1	P_2	T	SD	C	r_O	r_c	N_C	SCI	Q	N_K	R	Z	**N**	**t**	
4.55	2.5	24	0.502	20	5000	10000	4.00E+06	0.000146	0.910	1.91E+07	95	1.6450	2.9E+06	**15.43**	
4.60	2.5	24	0.503	20	5000	10000	4.00E+06	0.000146	0.949	1.99E+07	95	1.6450	3.0E+06	**15.87**	0.875
4.65	2.5	24	0.505	20	5000	10000	4.00E+06	0.000146	0.990	2.07E+07	95	1.6450	3.1E+06	**16.30**	
4.2	3.45	24	0.582	20	5000	10000	4.00E+06	0.000146	0.351	7.34E+06	95	1.6450	8.1E+05	**5.37**	
4.2	3.50	24	0.596	20	5000	10000	4.00E+06	0.000146	0.330	6.92E+06	95	1.6450	7.3E+05	**4.85**	1.050
4.2	3.55	24	0.612	20	5000	10000	4.00E+06	0.000146	0.310	6.49E+06	95	1.6450	6.4E+05	**4.32**	
4.2	2.5	37.5	0.495	20	5000	10000	4.00E+06	0.000146	0.687	2.25E+07	95	1.6450	3.4E+06	**17.86**	
4.2	2.5	38.0	0.495	20	5000	10000	4.00E+06	0.000146	0.687	2.28E+07	95	1.6450	3.5E+06	**18.04**	0.369
4.2	2.5	38.5	0.495	20	5000	10000	4.00E+06	0.000146	0.687	2.31E+07	95	1.6450	3.5E+06	**18.23**	
4.2	2.5	24	0.499	20	8995	19795	4.00E+06	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**12.62**	
4.2	2.5	24	0.499	20	9000	19800	4.00E+06	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**12.62**	0.007
4.2	2.5	24	0.499	20	9005	19895	4.00E+06	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**12.63**	
4.2	2.5	24	0.499	20	5000	10000	9995000	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**5.71**	
4.2	2.5	24	0.499	20	5000	10000	10000000	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**5.71**	0.005
4.2	2.5	24	0.499	20	5000	10000	10005000	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**5.71**	
4.2	2.5	24	0.499	20	5000	10000	4.00E+06	0.000244	0.687	5.16E+06	95	1.6450	7.8E+05	**5.19**	
4.2	2.5	24	0.499	20	5000	10000	4.00E+06	0.000249	0.687	4.96E+06	95	1.6450	7.5E+05	**5.00**	0.362
4.2	2.5	24	0.499	20	5000	10000	4.00E+06	0.000254	0.687	4.77E+06	95	1.6450	7.2E+05	**4.82**	
4.2	2.5	24	0.499	20	5000	10000	4.00E+06	0.000146	0.687	1.44E+07	95	1.2812	3.3E+06	**17.30**	
4.2	2.5	24	0.499	20	5000	10000	4.00E+06	0.000146	0.687	1.44E+07	99	2.3267	9.9E+05	**6.43**	7.201
4.2	2.5	24	0.499	20	5000	10000	4.00E+06	0.000146	0.687	1.44E+07	###	3.0900	4.1E+05	**2.89**	

Table 8.18 Effect of relevant parameters on performance period (low range)

Initial Serviceability	Terminal Serviceability	Temperature	Standard Deviation	Design Period (years)	Initial ADT (nos)	Final ADT (nos)	Design 18 kip ESAL	Surface Curvature Index	SI Loss Function	Mean 18 kip ESAL	Reliability (%)	Normal Deviate	**Reliable 18 kip ESAL**	Performance Period (yrs)	Approx Partial Derivative
P_1	P_2	T	SD	C	r_O	r_c	N_C	SCI	Q	N_K	R	Z	N	t	
3.75	2.5	24	0.504	20	5000	10000	4.00E+06	0.000146	0.463	9.70E+06	95	1.6450	1.4E+06	**8.82**	
3.80	2.5	24	0.503	20	5000	10000	4.00E+06	0.000146	0.486	1.02E+07	95	1.6450	1.5E+06	**9.22**	0.794
3.85	2.5	24	0.502	20	5000	10000	4.00E+06	0.000146	0.509	1.07E+07	95	1.6450	1.6E+06	**9.62**	
4.2	1.45	24	0.485	20	5000	10000	4.00E+06	0.000146	0.990	2.07E+07	95	1.6450	3.3E+06	**17.30**	
4.2	1.50	24	0.485	20	5000	10000	4.00E+06	0.000146	0.976	2.05E+07	95	1.6450	3.3E+06	**17.10**	0.394
4.2	1.55	24	0.486	20	5000	10000	4.00E+06	0.000146	0.963	2.02E+07	95	1.6450	3.2E+06	**16.90**	
4.2	2.5	8.5	0.538	20	5000	10000	4.00E+06	0.000146	0.687	5.09E+06	95	1.6450	6.6E+05	**4.47**	
4.2	2.5	9.0	0.534	20	5000	10000	4.00E+06	0.000146	0.687	5.39E+06	95	1.6450	7.1E+05	**4.79**	0.624
4.2	2.5	9.5	0.530	20	5000	10000	4.00E+06	0.000146	0.687	5.69E+06	95	1.6450	7.7E+05	**5.10**	
4.2	2.5	24	0.499	20	1095	1915	4.00E+06	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**12.17**	
4.2	2.5	24	0.499	20	1100	1920	4.00E+06	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**12.17**	0.008
4.2	2.5	24	0.499	20	1105	1925	4.00E+06	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**12.17**	
4.2	2.5	24	0.499	20	5000	10000	995000	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**34.99**	
4.2	2.5	24	0.499	20	5000	10000	1000000	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**34.87**	0.238
4.2	2.5	24	0.499	20	5000	10000	1005000	0.000146	0.687	1.44E+07	95	1.6450	2.2E+06	**34.75**	
4.2	2.5	24	0.499	20	5000	10000	4.00E+06	0.000107	0.687	2.71E+07	95	1.6450	4.1E+06	**20.36**	
4.2	2.5	24	0.499	20	5000	10000	4.00E+06	0.000112	0.687	2.47E+07	95	1.6450	3.7E+06	**19.00**	2.583
4.2	2.5	24	0.499	20	5000	10000	4.00E+06	0.000117	0.687	2.26E+07	95	1.6450	3.4E+06	**17.77**	
4.2	2.5	24	0.499	20	5000	10000	4.00E+06	0.000146	0.687	1.44E+07	80	0.8415	5.5E+06	**25.19**	
4.2	2.5	24	0.499	20	5000	10000	4.00E+06	0.000146	0.687	1.44E+07	90	1.2812	3.3E+06	**17.30**	6.372
4.2	2.5	24	0.499	20	5000	10000	4.00E+06	0.000146	0.687	1.44E+07	###	1.6450	2.2E+06	**12.44**	

Table 8.19 Summary of partial derivatives

Parameters	Unit	Change of Per.Period in years	Change per	At Value of independent parameter	Reason because the data is generally expressed as
Initial SI	SI	0.875 0.826 0.794	0.1 SI	4.6 4.2 3.8	4.2, 4.5 and not as 4.23 or only as 4
Parameters	Unit	Change of Per.Period in years	Change per	At Value of independent parameter	Reason because the data is generally expressed as
Terminal SI	SI	1.050 0.561 0.394	0.1 SI	3.5 2.5 1.5	1.5, 1.8 and not as 1.56 or only as 2
Temperature	Const.	0.369 0.438 0.624	unit	38 24 9	9, 24, 34 and not as 10.2 or as 10.22
ADT	Vpd	0.007 0.002 0.008	10 vpd	9.0/19.8 5.0/10.0 1.1/1.92	Rounding to nearest 10's and not as 1123
ESAL	Million Std. Axles	0.005 0.025 0.238	0.01 M standard axles	10.0 4.0 1.0	12.53 million and not as 12.528329 million or only as 12.5 or 13 million
SCI	mil	0.362 1.378 2.583	0.01 mil	0.2490 0.1462 0.1116	FWD can give a datum of 20.42 mil
Reliability	Level	7.201 5.435 6.372	Level	D C B	80%, 95% and not as 82%
Thickness	inch		0.5 inch 1.0 inch		For thin-surface thickness may be 1.5 inch, but for thick surface 0.1 inch doesn't matter
Modulus	Ksi		1 Ksi		50, 750, 14 and not as 14.234
Poisson's ratio			0.01		0.33, 0.28 and not only as 0.4

Table 8.20 Analysis of sensitivity

A. Summary of Data obtained from Tables 8.16 through 8.18

Parameter Names	Value of Parameter			Rate of change of Perf. Period at value		
	High	Medium	Low	High	Medium	Low
Initial SI	4.6	4.2	3.8	0.875	0.826	0.794
Terminal SI	3.5	2.5	1.5	1.050	0.561	0.394
Temperature	38	24	9	0.369	0.438	0.624
ADT	9000/19800	5000/10000	1190/1920	0.007	0.002	0.008
ESAL	10,000,000	4,000,000	1,000,000	0.005	0.025	0.238
SCI	0.000249	0.0001462	0.0001116	0.362	1.378	2.583
Reliability	D	C	B	7.201	5.435	6.372

B. Sensitivity of Parameters in Three Scenarios Separately

Rank	High Value		Medium Value		Low Value	
	Parameter	R.O.C	Parameter	R.O.C	Parameter	R.O.C
1	Reliability	7.201	Reliability	5.435	Reliability	6.372
2	Terminal SI	1.050	SCI	1.378	SCI	2.583
3	Initial SI	0.875	Initial SI	0.826	Initial SI	0.794
4	Temperature	0.369	Terminal SI	0.561	Temperature	0.624
5	SCI	0.362	Temperature	0.438	Terminal SI	0.394
6	ADT	0.007	ESAL	0.251	ESAL	0.238
7	ESAL	0.005	ADT	0.002	ADT	0.008

ROC means rate of change of performance period

C. Sensitivity Considering Parameters Can Assume Value of Any Level with Equal Chance

Rank	Parameter	ROC	Value	Parameter to hold rank with Probability		
				Highest	Medium	Low
1	Reliability	7.201	D	Reliability		
	Reliability	6.372	B	with prob	Nil	Nil
	Reliability	5.435	C	p=1.0		
2	SCI	2.583	0.0001116	SCI	Initial SI	Terminal SI
	SCI	1.378	0.0001462	with prob	with prob	with prob
	Terminal SI	1.050	3.5	p=0.67	p=0.22	p=0.11
3	Initial SI	0.875	4.6	Initial SI	Terminal SI	Temperature
	Initial SI	0.826	4.2	with prob	with prob	with prob
	Initial SI	0.794	3.8	p=0.56	p=0.33	p=0.11
4	Temperature	0.624	9	Temperature	Terminal SI	Initial SI
	Terminal SI	0.561	2.5	with prob	with prob	with prob
	Temperature	0.438	24	p=0.45	p=0.33	p=0.22
5	Terminal SI	0.394	1.5	Temperature	SCI	Terminal SI
	Temperature	0.369	38	with prob	with prob	with prob
	SCI	0.362	0.000249	p=0.45	p=0.33	p=0.22
6	ESAL	0.238	1,000,000	ESAL	ADT	
	ESAL	0.025	4,000,000	with prob	with prob	
	ADT	0.008	1190/1920	p=0.67	p=0.33	
7	ADT	0.007	9000/19800	ADT	ESAL	
	ESAL	0.005	10,000,000	with prob	with prob	Nil
	ADT	0.002	5000/10000	p=0.67	p=0.33	

Table 8.21 Final rank of the independent variables with associated probability

Parameter	Probability of holding the following ranks						
	1	2	3	4	5	6	7
Reliability	**1.0**						
Surface Curvature Index		**0.67**			0.33		
Initial Serviceability		0.22	**0.56**	0.22			
Temperature			0.11	0.45	**0.45**		
Terminal Serviceability		0.11	0.33	**0.33**	0.22		
Design Traffic (ESAL)						**0.67**	0.33
ADT (Initial/Final)						0.33	**0.67**

CHAPTER 9. IDENTIFICATION OF INVENTORY AND CONDITION VARIABLES

9.1 MOST IMPORTANT CONDITION VARIABLES IN TEXAS

One method of identifying important condition variables in Texas is to make use of the distress utilities assigned originally in the PMIS. Utilities were originally developed with the express purpose of being able to compare the seriousness of different distresses. Utilities therefore enable the comparison of, say, ten punchouts per mile with twenty spalled cracks per mile or even 15% deep rutting on an asphalt concrete pavement; they were developed using the combined experience of a number of people having intimate knowledge of Texas pavements. Utilities, therefore, are a good way of deciding which distresses engineers consider the most serious. The following figures show the percentage of the CRCP, JCP, and ACP road networks with excellent (utility between 1.0 and 0.99), fair (utility between 0.99 and 0.7), and poor (utility between 0 and 0.7) average utility. In order to give an idea of the spatial distribution at the same time, the figures actually portray the percentage of counties having certain utility levels. The averages are, however, still based on the number of lane miles. The graphs are plotted from 1997 PMIS data.

It can be seen from Figure 9.1 that the percentage of counties having average utilities for "punchouts" less than 0.99 is considerably higher than similar percentages for other CRCP distresses, with the exception of "PCC patches." Since "patches" are very often a consequence of previous punchouts, however, it can be concluded that total "failures per mile" is the most important CRCP distress and that prediction of this at project level and incorporation of the model or models into PMIS should be a priority of any integration effort.

From Figure 9.2 it appears that "failed joints and cracks" and "failures," together with the associated "PCC patches," are the most important condition variables which need to be collected and predicted for JCP.

Figure 9.3 shows that "shallow rutting" and "alligator cracking" should be the priorities, and, again, that "patching" and the presumably associated "failures" will also be important.

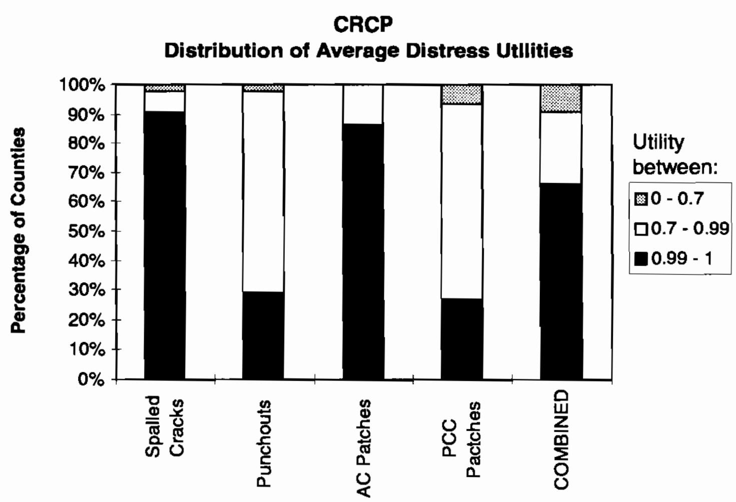


Figure 9.1 Percentage of counties in which CRCP distress utilities are between the given limits

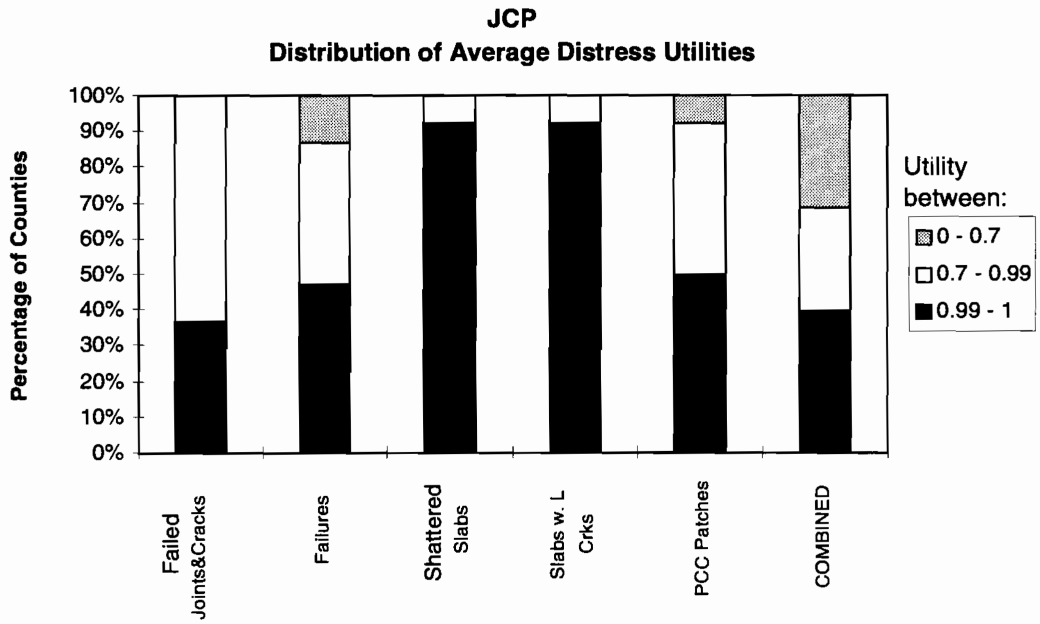


Figure 9.2 Percentage of counties in which JCP distress utilities are between the given limits

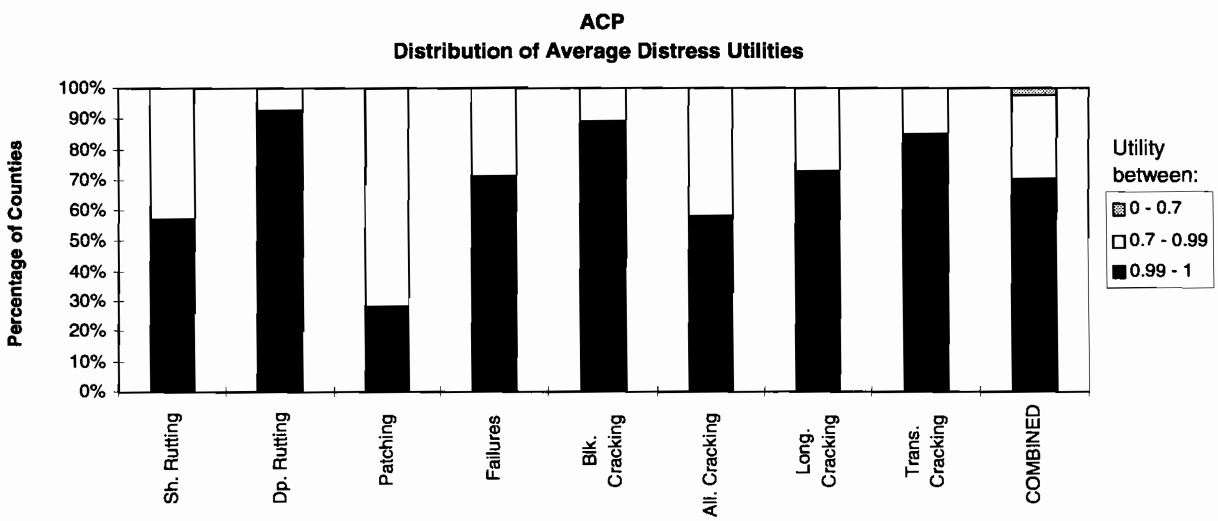


Figure 9.3 Percentage of counties in which ACP distress utilities are between the given limits

9.2 CRCP CONDITION AND INVENTORY VARIABLES

9.2.1 Most Common

The most common independent variables used in performance prediction that appear in the literature were identified using a 1996 study by Gräter for the purposes of identifying significant factors for use in calculation of pay factors for CRCP in Texas [Gräter 96]. A list of the factors considered by Gräter appears below:

- Strength
- Thickness
- Subgrade modulus
- Subbase type
- Concrete modulus
- Subgrade type
- Placement time
- Thermal coefficient
- Coarse aggregate type
- Load transfer
- Drainage
- Drying shrinkage
- Curing
- Strength variance
- Overall variance
- Seal type
- Pumping
- Initial serviceability
- Swelling
- Dowel support modulus
- D-cracking
- Percent steel
- Air content
- Crack width
- Fine aggregate durability
- Ion levels
- Macro texture
- Permeability
- W/C ratio

Because the original study was conducted in order to identify variables that were significant for calculation of pay factors, the variables considered were generally those considered to be under the control of the contractor. In addition to the above variables, therefore, the following design, load, and environmental variables were identified from the literature as possibly being significant in predicting performance.

- depth to steel reinforcement (cover)
- bar diameter
- percent steel
- steel coefficient of expansion
- steel elastic modulus
- steel yield stress
- temperature at construction
- average minimum annual temperature
- evaporation potential at construction
- time to opening to traffic
- average rainfall
- total accumulated ESALs
- age

In order to put the variables in the context of pavement management serviceability prediction, it is necessary to remember that we are concerned with predicting the serviceability of pavements *in Texas*. The implication of this is that if all of the CRCP in a particular district are 20.3 cm (8 in.) thick, then by assuming the thickness is 20.3 cm (8 in.) we will always be right except for the construction variance. In this case, therefore, it can be assumed that although future serviceability is very sensitive to thickness, thickness may not be a statistically significant factor in the prediction of serviceability in that district. The generalized conclusion is that we need to consider variables that, by nature of their variability within the population of pavements for which we are predicting serviceability, significantly affect that prediction.

To identify the variables most common in the literature, Gräter [Gräter 96] considered a number of different models from the literature and simply ranked the variables according to how many models the variables appeared in.

Among the variables mentioned above that may be expected to affect the prediction by nature of their variance within Texas, the variables shown in Table 9.1 were short listed and ranked simply according to the number of models they appear in.

Lastly, some of these variables can be expected to be measured only once (possibly at the time of construction) and are therefore termed "inventory" variables. Although in the strictest sense "condition" variables (which are assumed to change continuously) are also "inventory" variables, since they describe the inventory as it is *currently*, they are considered here as a separate class. As has been noted on various previous occasions, the prediction of many "condition" variables is a function of other condition variables, whereas inventory variables are considered constants. The list obtained from the literature is therefore finally split into inventory and condition variables.

Table 9.1 Most common variables from the literature

Variable	Number of models
Age	8
Total ESALs	8
Strength	6
Thickness	5
Subgrade modulus	5
Subbase type	4
Concrete modulus	4
Average minimum annual temperature	4
Subgrade type	3
Average Rainfall	3
Placement time	2
Thermal coefficient	2
Coarse aggregate type	2
Load transfer	2
Drainage	2
Drying shrinkage	2
Curing	2
Average temperature range	2
Strength variance	1
Overall variance	1
Seal type	1
Pumping	1
Initial serviceability	1
Swelling	1
Temperature at construction	1
Evaporation potential at construction	1

9.2.2 Most Widely Applicable

In fact, the most widely applicable variables, or those that are used in predicting the most condition or distress variables, are in effect the same as those identified as being the most common variables from the literature. The reason for this is that, in his analysis, Gräter [Gräter 96] considered a number of different models that were used to predict a wide range of distresses or conditions that influence serviceability. As a result, the number of models in which the variables are used gives a good idea of how many different distress prediction models may use the variables.

The different performance variables and the associated models considered by Gräter included the following:

- PSI (using the AASHTO method)
- Punchouts (using the CRCP8 method)
- Faulting (using a model developed by Darter et al.)
- Cracking (using the same set of models developed by Darter et al.)
- Pumping (using the same set of models developed by Darter et al. and a model developed by Bhatti et al. in 1996 at Purdue)
- Spalling (using the same set of models developed by Darter et al. and another developed by Senadheera and Zollinger in 1994)
- Skid Resistance (using work done by Ludema and Gujrati in 1973 and Croney and Croney in 1991)
- Concrete Durability (Neville 1975 and Mindess and Young 1981)

9.2.3 Statistically Significant

How statistically significant a variable is in the prediction of different distresses is probably the most important criterion in choosing variables that should be collected and included in the PMIS database. In order to assess how statistically significant different variables are it is necessary to perform sensitivity analyses. The sensitivity analyses performed by both Gräter and as part of this study are described in detail elsewhere. The findings are summarized here for the purpose of choosing a standardized set of variables.

Because failures per mile (FPM) were considered to be the dominant cause of reduced serviceability and are included in the majority of the decision criteria in the PMIS, a detailed sensitivity analysis was performed on FPM for a number of variables using the CTR Rigid Pavement Database. In the analysis, numerous basic model forms were considered and all two-way interactions as well as curvature were included by using a quadratic model for the underlying regression. A number of different variables were analyzed and a statistically significant group of these was chosen by use of Mallows' *Cp* Statistic. The statistically significant variables were found to be as follows:

AGE	age of the pavement
ADT85	total traffic carried in 1985
TCO	thermal coefficient of concrete (based on course aggregate type)
SBF	subbase friction (based on subbase type)
SWELL	swelling potential
CTEMP	construction temperature (based on month of construction and location)
CVC	coefficient of variation of the crack spacing (this is intended to give an idea of variability in the pavement)

The plot in Figure 9.4 shows the total R^2 values obtained for quadratic regressions on different combinations of variables.

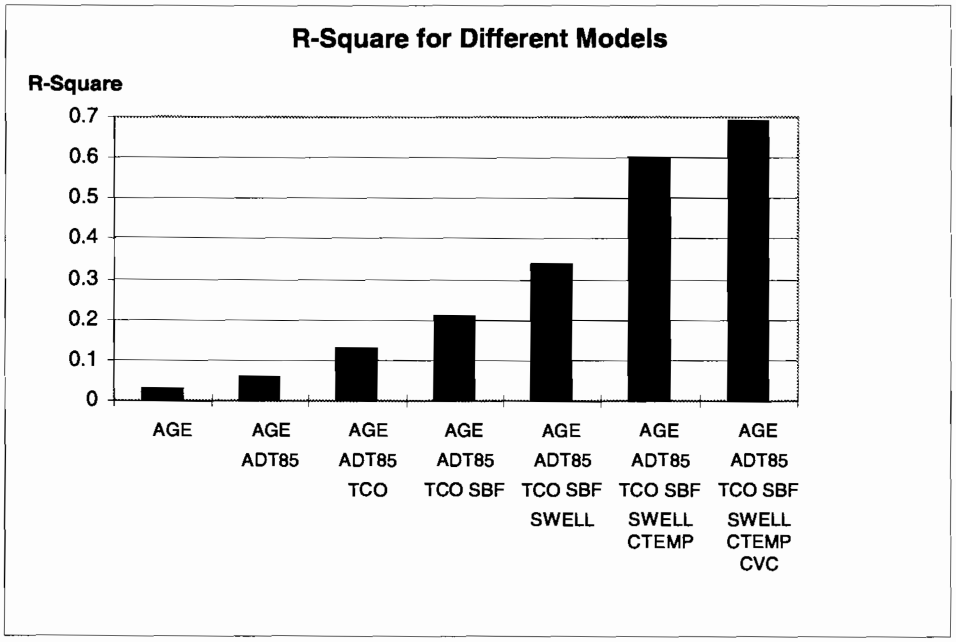


Figure 9.4 Increase in R^2 *for successive inclusion of variables*

It should be noted that no information about the relative importance of individual variables is given in this plot because of the interactions, but it can be seen that the more variables included, the better the prediction. For example, if traffic, thermal coefficient, subbase friction and swell potential were able to be included in addition to age, the prediction R^2 could be increased from below 0.1 to almost 0.6. Based on this analysis it can be concluded that a strong recommendation can be made for including at least some form of some of these variables in any standardized set.

Since the empirical analysis performed above could not adequately include some of the variables identified previously, such as strength and the variability of strength, owing to lack of data, we need to resort to mechanistic models such as CRCP8 to gain final insight into the probable statistical significance of some of the other variables. For those models considered by Gräter [Gräter 96], which were quantitative, he also performed a range sensitivity analysis. This was done by initially assuming an average value for all variables and calculating a corresponding value for the independent variable. He then varied each variable in turn by one standard deviation above and below the mean and calculated the range of the ratios of the upper and lower dependent variable values to the mean case. He then ranked the variables using this range in each of the models he considered. Finally, he calculated a "cumulative performance ranking" for each variable by adding the ranges for all the models. The variables shown in Table 9.2 below are ranked according to this "cumulative performance ranking," with the additional variables considered added to the end of the list. Where zeros appear for the variable ranking in each of the listed models, the variable was either included as a qualitative variable or no range analysis was performed.

The most interesting observation from the table is the huge range in the punchout prediction resulting from the assumed variation in strength variation. Although strength variation is only a factor in the CRCP8 model to predict punchouts, this large value is intuitively right, since in the case of punchouts we are concerned with only the worst couple of percent of the pavement area that is highly influenced by the variability. In the original analysis this results in a strong reason for the contractor to pay very close attention to the variability in strength. In our case it shows that the variability in strength should be highly recommended for inclusion in any standard data set to be used for punchout prediction. This is very much in line with reliability considerations, and it can also be seen that overall variance ranks relatively highly.

It is interesting that placement time ranks so highly, but in fact this is not unexpected if it is assumed that this is highly correlated with construction temperature, evaporation potential, and other conditions specific to the actual time of construction. In a list of desired variables, this might be sufficient but would require the additional storage of a record of the exact air temperatures and evaporation potential on an hourly basis during placement and curing. This, however, constitutes a considerable volume of data; and while this should possibly be stored in a forensic database, it is not recommended for storage for performance prediction in the PMIS. As discussed below, we therefore recommend that temperature and evaporation potential at placement be stored specifically.

Thickness does not appear to be highly significant from the empirical sensitivity analysis; this is expected since so many pavements in Texas are 20.3 cm (8 in.) thick. The construction variability is still important, however, as can be seen by the relatively high ranking of thickness in the range analysis table. This implies that it might still be worth measuring the exact as-built thickness and variability of this for prediction purposes. Subbase type and thermal coefficient are variables that were also identified as being significant in the empirical analysis. The thermal coefficient is highly correlated with coarse aggregate type.

The subgrade modulus and type both appear in the list and are both used in the faulting, cracking, and pumping models. It is possible that both modulus and some other parameter such as drainage coefficient might be stored in order to characterize subgrade. These could be filled with default values based on the type in most cases. Since this appears to be the primary variable in the prediction of pumping, it is recommended that this be recorded.

Because load transfer is important in the prediction of faulting, it is also recommended that this be considered, although faulting is not a widespread cause of serviceability loss.

Although swelling potential was included only in the punchouts model and ranked 6, it was also identified in the empirical analysis and therefore should be considered.

Although no range analysis was done for the various temperature statistics, it is apparent from a mechanistic point of view that the temperature at construction (or at least during curing) is significant in affecting the initial crack spacing. In addition to this, the general temperature cycles experienced in that location appear to be important, as shown by the two occurrences of yearly temperature range and four concerning the minimum temperatures. In fact, some of these actually use the mean freezing index: a simple minimum temperature value would not be sufficient.

Evaporation potential is another variable related to exact conditions at the time of construction that has recently been identified as important to the prediction of spalling. Although spalling is, again, not a major trigger of major rehabilitation, this may be considered if spalling prediction is considered necessary.

Average rainfall also appears to be relatively important, as shown by its occurrence in three models; interestingly, this was not identified as being significant in the empirical analysis.

Table 9.2 List of significant variables ranked by sensitivity [Gräter 96]

				Variable ranking in listed model							
Variable	**Number of models including**			**AASHTO**	**Punchouts**	**Faulting**	**Cracking**	**Pumping**	**Spalling**	**Durability**	**Skid resistance**
Strength variance	1	54.4	0		1						
Strength	6	12.5	3	2	2		1		0	0	0
Placement time	2	5.8	1		3				0		
Thickness	5	4.1	1	3	4	6	2	2			
Subbase type	4	2.9	1		11	7	3	0			
Thermal coefficient	2	2.1	0		5	8					
Overall variance	1	1.3	0	1							
Coarse aggregate type	2	1.0	2		7					0	
Subgrade modulus	5	0.9	1	7	12	4	5	0			
Seal type	1	0.8	0						2		
Load transfer	2	0.7	0	4		1					
Pumping	1	0.6	0				3				
Drainage	2	0.3	1	5				0			
Initial serviceability	1	0.3	0	6							
Concrete modulus	4	0.3	0	8	9	5	6				
Subgrade type	3	0.2	1			3	7	1			
Swelling	1	0.2	0		6						
Drying shrinkage	2	0.0	0		10	9					
Curing	2	0.0	2							0	
Age	8			0	0	0	0	0	0	0	0
Total ESALs	8			0	0	0	0	0	0	0	0
Average minimum annual temperature	4			0			0	0	0		
Average Rainfall	3			0				0	0		
Average temperature range	2					0	0				
Temperature at construction	1				0						
Evaporation potential at construction	1								0		

While age and traffic are not "controllable by the contractor" and therefore are not included in Gräter's analysis, it is obvious that these are implicitly or explicitly included in all models. Theoretically, load-related distresses should require only accumulated traffic, and purely environment-related distresses should require only age, but in practice both will be vital to most predictions. It should be noted that although we need eventually to predict everything with respect to age, it is not imperative that this be included for this reason alone. However, in a further empirical analysis performed as part of this project, it was shown that knowledge of the age of a pavement can still result in considerable increases in prediction accuracy. Traffic was also identified as being significant in the empirical analysis.

A final categorized list of desirable variables for our standardized data set is thus given below, with one or two items not yet considered quantitatively but intuitively important:

CONCRETE PROPERTIES (WHETHER ORIGINAL SURFACE OR OVERLAY):

- Strength
- Strength variance
- Constructed thickness
- Constructed thickness variance
- Concrete modulus
- Thermal coefficient
- Coarse aggregate type
- Drying shrinkage
- Underlying surface preparation (if overlay)

SUBBASE PROPERTIES:

- Subbase type
- Subbase modulus

SUBGRADE PROPERTIES:

- Subgrade type
- Subgrade modulus
- Swelling potential

ENVIRONMENTAL CONDITIONS AT CONSTRUCTION:

- Temperature at construction
- Evaporation potential at construction

GENERAL LOCATION DEPENDENT ENVIRONMENTAL CONDITIONS:

- Average minimum annual temperature
- Average rainfall
- Average temperature range

OTHER FIXED INVENTORY DATA:

- Drainage (cut, fill or transition)

CONDITION DATA (updated at condition surveys):

- Age
- Total ESALs

- Spalled cracks
- Punchouts
- AC patches
- PCC patches
- Crack spacing (or apparent crack spacing)
- Crack spacing variance
- Failed joints and cracks
- Failures
- Shattered slabs
- Slabs with longitudinal cracks
- Load transfer

Note that this list is merely an attempt to identify and categorize some general variable types; whether age is stored separately or construction date is stored and age calculated is immaterial at this stage. The same applies to accumulated ESALs. These need to be reduced further, with exact details and units to be worked out.

The final selection of proposed variables will obviously require considerable input from many parties if this involves changing the current PMIS variables and collection methods in any way. Nonetheless, one final consideration that may be mentioned here is the attainability of these different variables.

9.2.4 Most Attainable

In all such situations where an existing database and collection procedure already exist, very careful consideration needs to be given to whether the extra effort in collecting more data or collecting the same sort of data differently is worth it. The cost and effort involved in collecting different data are highly dependent on whether the data are already being collected elsewhere, already exist in some other database, or can at least be coordinated with some other planned data collection effort.

At present there are a number of other relevant databases either existing or in some state of planning. Some of these are listed below:

PMIS
TRM
MMIS
CMS
ROAD LIFE
Forensics Database

The ideal future system, in our view, would consist of a number of different databases containing data that are maintained by different individual sections. Instead of the considerable overlap that exists at present, however, numerous links between these databases would be maintained to vastly reduce the amount of superfluous data. Considerable progress has and is being made toward this ideal at the time of writing, but it is strongly recommended that close coordination be maintained between the various groups and research teams involved.

At present it is envisaged that the main database (whether it be the PMIS, ROAD LIFE, a combination of these, or the new Forensics Database) be structured such that almost all inventory and condition data are stored by "layers," as was the original concept for the ROAD LIFE database. These layers, however, will not always be able to be directly mapped to physical layers because a new "layer" will be recorded for each maintenance or rehabilitation action performed. Layer "descriptions," such as CRCP, BCO, patching, and even crack sealing, will therefore all be acceptable. As such each layer will have its own data regarding construction, accumulated traffic, etc. In this way, condition data such as cracking, punchouts, and patching will then also be stored for the current surface layer (although if subbase modulus was continually updated as a condition variable then the subbase modulus would be continuously updated); and if an overlay was placed, the previous condition data would still be accessible from the original surface layer data.

In order to implement the concept of continually revisable data, we propose that many data items include an attached "source" field in order to track whether the value is an original default, an assumed design value, or an actually measured value. It could also be used, for that matter, to record by what method the "strength" value was measured. If it is desired to store more than just the current value (perhaps in the case of forensic studies it might be valuable to record both the design and actually measured values for comparison purposes) then it would be necessary to store a number of value-source pairs depending on how many historical values needed to be retained. In our case, where we wish to set up a regression pool, it might be necessary to provide a larger number (say fifteen) for condition items such as punchouts. Because the distress would be stored by layer, however, this would provide an automatic "reset" of the regression pool if rehabilitation or maintenance was performed.

From the point of view of attainability, it is apparent that data items need to be standardized not just within the PMIS but in general. It is worth noting that many of the data recorded for QC/QA purposes, for forensic purposes, and for final design purposes are items that are collected ultimately to check, control, or predict the performance of the pavement in the future. For our specific purposes, the standardized set for PMIS performance prediction needs to be chosen in close collaboration with other databases and data collection efforts.

Inventory Data

It should be recognized that a great many data items need to be updated only once or possibly twice (if both design and as-constructed values are to be stored) from a basic default value. As such the collection effort is often a "once off" occurrence which might take place anyway as part of normal design procedures before construction or as part of QC/QA procedures during construction. Examples of these types of data items are thermal coefficient and subbase friction. In addition, some very useful data items are solely location dependent, such as swelling and average rainfall, and only have to be recorded once. These will simply remain as default, location-dependent items and, as such, will never have to be updated.

Condition Data

While inventory data items need only be updated from some default value once or twice as described above, data items assumed to be changing continuously need to be monitored as part of the annual or biennial condition survey. Classic examples of these include distresses and roughness. These are already being collected and are therefore certainly attainable. A further set of variables that could be classified as either inventory or condition are the moduli of layers. If a single inventory value for the modulus of a certain layer were stored as being representative of that type of material along with its thickness, this would obviously greatly contribute to mechanistic performance models and would still be relatively attainable, since it could be input once and left. If, on the other hand, it was decided that the moduli deteriorated over the life of the pavement and was a vital condition variable, the measuring of moduli (using whatever means) would have to be part of the condition survey. The measuring of modulus can be accomplished to a certain degree of accuracy using the current FWD back-calculation methods and various other methods using SASW, etc., which are becoming more and more available for network condition monitoring. Nonetheless, the effort of continuous collection must be balanced against its impact on the accuracy of prediction models.

9.2.5 Final Possible Proposed Selection

It is premature to make a final selection at this stage, but from a consideration of all the various criteria involved in choosing a standardized data set that will hopefully suffice for many years to come, it appears that the following conclusions and recommendations can be made with regard to rigid pavement data items.

1. Items should be chosen to a certain extent independent of specific models but should relate closely to the mechanisms involved in pavement distress. In this way new models can be developed as necessary based on the same pool of data.
2. Mechanistic properties should be stored (and models should be based on these) even if these are initially given default values depending on material type or location.
3. In order to more accurately predict punchouts (and cracking) on CRCP, it is vital that more variables be used.
4. From a mechanistic standpoint it appears that some measure of variability (of strength, thickness, stress/strength ratio, crack spacing, etc.) is highly desirable for more accurate prediction of distress; it is strongly recommended that constructed variability be measured and stored in some form.
5. It is known that conditions at the time of construction are also highly significant in the prediction of distress in rigid pavements. It is thus recommended that these be recorded (as is being proposed for QC/QA) and be made available for distress prediction.
6. It is recommended that construction dates (and possibly even times) and maintenance actions be recorded by layer in the future. This information, together with generally available climatic data or possibly even on-site weather stations, will allow some estimate of the conditions at construction to be made if necessary. It will also allow simple calculation of age. Finally it will provide the essential data regarding "what" was done and "when" it was done so that the regression pool data can be reset (removal of old field data points and calculation of new design points).
7. Although traffic data are currently being maintained, it is recommended that this be included in future prediction models.
8. Mechanistically, it has been seen that thermal coefficient, drying shrinkage, and subbase friction are important parameters in predicting crack distribution and ultimately punchouts. It is recommended that fields for these be included even if the values are initially estimated from coarse aggregate type and subbase type.

9.3 FLEXIBLE PAVEMENT CONDITION AND INVENTORY VARIABLES

9.3.1 Most Common

A large number of pavement performance models are reported in the literature. Different performance measures and the corresponding independent variables are described below.

Roughness

Roughness may be defined as an irregularity along the longitudinal profile of a pavement surface. Roughness is one of the most widely modeled performance measures. It is a functional measure and generally does not represent structural adequacy. A structurally strong pavement can show high roughness and vice-versa. Some roughness is created by the construction procedures and type of materials used. Development of additional roughness can be attributed to several factors, including spatial variation in permanent deformation (rutting) of pavement and subgrade, erosion of surface aggregate, swell and shrinkage of subgrade, pavement distress (e.g. potholing, raveling, cracking, patching, etc.), pavement structure, and type of surface layer.

There are various models of roughness reported in the literature, some based on structural effect, others based on time-related effects, and still others based on mechanistic parameters (like variance of rut depth). However, most of the models are empirical and deterministic. The following roughness models are commonly referred to in the literature:

1. AASHO [AASHO 62]
2. TRRL Study [Hodges 75]
3. Arizona Model [Way 88, Zaniewski 90]
4. Australian, 1972 [Potter 72]
5. Querioz [Quieroz 81]
6. Uzan and Lytton, 1982 [Uzan 82]
7. UNDP-Brazil [Paterson 87]
8. Alberta [Karan 88]
9. VESYS [Thompson 90]
10. ARE Study [Butler 86]
11. EAROMAR-2 System [Markow 81]
12. Highway Design and Maintenance Standard Model HDM3, World Bank [Watanatada 87]
13. Nationwide Pavement Cost Model (NAPCOM) [FHWA 90, Mohseni 90]

The following are the various independent variables found in the above models:

- Pavement Age
- Time
- Pavement Type
- Equivalent Single Axle Loads (ESALs)
- Structural Number (SN)
- Modified Structural Number
- Layer Thickness
- Soil Support

- Drainage Coefficient
- Initial Roughness
- Riding Comfort Index (RCI)
- Mean Rut Depth
- Variance of Rut Depth
- Cracking Area
- Patching Area
- Temperature
- Rainfall
- Freeze-Thaw Cycle

Fatigue Cracking

Fatigue cracking models are often developed based on concepts identified in the following:

1. A primary response model estimates the maximum tensile strain at the bottom of the asphalt layer. This is commonly done using a mechanistic model, like an elastic layer model or a finite element model. Some models/computer programs use regression equations, developed from numerous runs of the mechanistic model, to predict the maximum strain.
2. A transfer function relates this maximum strain to the number of loads to expected crack development (failure). There are several such empirical relations developed from laboratory tests. However, various researchers have found differences between laboratory test results and actual performance of pavement with a shift factor in the range of 2 to 700.
3. A damage model predicts the amount of cracked area from actual and allowable repetition of load; Miner's hypothesis is often used in this model. Some models use probability distribution of damage (considering log-normal, Weibull, or Gumbel type of distribution [Lytton 93]) in embedding reliability in the model.

The following fatigue models were identified from the literature. Some of these models (like Asphalt Institute) predict allowable load to fatigue failure with certain percent of fatigue cracking. However, all of these models use mechanistic-empirical approach.

1. HDM [Watanatada 87]
2. ARE Study [Butler 86]
3. Asphalt Institute [AI 81]
4. VESYS [Thompson 90]
5. Cost Allocation Study, FHWA [Villarreal 87]
6. EAROMER - 2 [Markow 81]
7. NCHRP Project 14-6 [Butler 86]
8. NAPCOM [FHWA 90, Mohseni 90]
9. MICH-PAVE [Harichandran 89]
10. Arizona Model [Way 88, Zaniewski 90]

Fatigue depends on the number of application of critical stress, magnitude of critical stress, and properties of material. Fatigue accumulates as a result of stress repetitions. Cracks appear when fatigue reaches a threshold value represented by a number of repetitions of stress. For this reason, pavement layer thickness, material properties (elastic moduli, Poisson's ratio), and traffic loads are the most important input variables in fatigue models. Since asphalt concrete is a very temperature-susceptible material, temperature is also an important variable. However, there are several simple empirical models for fatigue cracking used for network-level pavement management around the world. These empirical models may not provide satisfactory results if they are not developed for specific locations and materials. The following variables are commonly used for fatigue cracking prediction:

- Pavement Age
- ESAL
- Axle Load Distribution
- Duration of Load
- Stress/Strain in the Asphalt Layer
- Subgrade Soil Classification
- Permanent Deformation
- Surface Deflection
- Percent Asphalt Content
- Percent Air Void
- Layer Thickness
- Resilient Moduli
- Kinematic Viscosity
- Drainage Property
- AASHTO Regional Factor
- Current Condition
- Annual Air Temperature
- Mean Temperature of AC layer
- Rainfall
- Freezing Index

Rutting

Generally rutting models predict mean rut depth. Rutting develops as a result of permanent deformation in wheel paths. Permanent deformation can occur due to any one layer or all layers, including the subgrade. There are several rutting models found in the literature. Rutting models are often mechanistic-empirical and developed almost in the fashion a fatigue model is developed, except that:

1. Maximum compressive strain on the subgrade is used.
2. A different transfer function is used that relates maximum compressive strain to allowable number of repetitions to rut development.

Rutting may occur owing to plastic movement of asphalt mix in hot weather or inadequate compaction during construction. Rutting distress also accumulates with the number of repetitions of load, but in a way different than fatigue accumulates. Some models predict permanent deformation of the wheel paths as the primary response instead of maximum compressive strain on the top of subgrade. The following models were found in the literature:

1. HDM III [Watanatada 87]
2. ARE Study [Butler 86]
3. Asphalt Institute [AI 81]
4. Ohio State [Majidzadeh 81]
5. VESYS [Thompson 90]
6. Cost Allocation Study, FHWA [Villarreal 87]
7. EAROMER - 2 [Markow 81]
8. NAPCOM [FHWA 90], [Mohseni 90]
9. MICH-PAVE [Harichandran 89]
10. Arizona Model [Way 88, Zaniewski 90]

Input variables in the above models are the same as those used for predicting fatigue cracking.

Raveling, Potholing, and Skid Resistance

Raveling is a localized wearing away of pavement surface. Generally, it is caused by disintegration of the surface owing to striping and hardening of the asphalt layer. Therefore, raveling can be tackled by proper asphalt mix design (using a softer grade binder, anti-striping agent, etc.) and construction practice. Potholes are bowl-shaped holes of various sizes extending even below subgrade. These are developed from alligator cracking, raveling, and freeze-thaw cycles. Potholing can be reduced through proper maintenance of raveling and alligator cracking. Skid resistance deteriorates owing to polished aggregates. This occurs as a result of the use of nonangular aggregates, very small-sized aggregate, and the gradual wearing down of aggregates. The problem of skid resistance can be tackled by using proper aggregate size and type and by employing sound construction practice. Since these distresses can be tackled by proper engineering practices, there are very few models on these types of pavement distress. The following models are reported in the literature.

Potholing Models:

1. HDM III [Watanatada 87]
2. ARE Study [Butler 86]
3. EAROMER-2 System [Markow 81]

Ravelling Models:

1. ARE Study [Butler 86]
2. LCC Study [Markow 88]

Skid Resistance Models:

1. NAPCOM [FHWA 90, Mohseni 90]

The following independent variables are used in the above models:

- Pavement Age
- Pavement Type
- ESAL
- Layer Thickness
- Resilient Moduli
- Soil Support
- Strain
- Environmental Factors

Composite Indices

Composite indices are used to represent pavement condition in terms of more general measures, commonly indices of damage, condition, and serviceability. Present serviceability index (PSI), pavement condition index (PCI), and pavement condition rating (PCR) are the most widely used composite measures. Some indices, like PSI (developed from subjective ratings of pavement users), reflect more functional measures. Some indices, like PCI (developed from ratings of pavement experts), represent functional and structural measure. These indices are generally functions of roughness and pavement distress. Minnesota's pavement quality index (PQI) is a function of roughness, distress, and structural adequacy. Generally, composite index prediction models are empirical and deterministic.

The following are some of the several models for the prediction of composite indices reported in the literature:

PSI
1. AASHTO [AASHTO 93]
2. HPMS [FHWA 84]
3. Idaho State DOT
4. Minnesota State DOT
5. Pennsylvania State DOT [Grambling 87]

PCR
1. Washington State DOT [Mahoney 88]
2. Mississippi State DOT [George 89]

PCI
1. PAVER [Shahin 82]

DMR (Damage Maintenance Rating)
1. Virginia State DOT

The most common independent variables used for prediction of composite measures are given below:

- Pavement Age
- Pavement Type
- ESAL

- Traffic Volume
- Structural Number
- Layer Thickness
- Thickness of Overlay
- Soil Support
- Soil Type
- Mean Rut Depth
- Cracking Area
- Patching Area
- Slope Variance
- PSR (one year previous)

The names of the independent variables and number of models in which they are used out of 39 models, are given in Table 9.3.

Table 9.3 Most common variables from the literature

Independent Variable	Number of models in which used
Age	27
ESAL	29
Layer Thickness	33
Layer Stiffness	25
Asphalt Properties	20
Base Properties	24
Subgrade Properties	24
Subgrade Moisture	8
Subsurface Drainage	3
Type of Environment	29
Monthly Temperature	13
Freeze Index	11
Annual Rainfall	11
Thornthwaite Index	11
Distress	9

9.3.2 Most Widely Applicable

The most widely applicable variables are the same as the most commonly used variables described previously. However, the number of models in which each variable is applicable can vary significantly. In Table 9.3, it may seen that out of thirty-nine models, thirty-three models use layer thickness, whereas only three models use subsurface drainage. Therefore, to identify the most widely applicable variable, independent variables are ranked on the basis of their application and given in Table 9.4. Rank 1 presents the most widely applicable variable.

Table 9.4 Most widely applicable variables and their rank

Independent Variable	Rank
Layer Thickness	1 (greatest application)
ESAL	2
Type of Environment	2
Age	3
Layer Stiffness	4
Base Properties	5
Subgrade Properties	5
Asphalt Properties	6
Monthly Temperature	7
Freeze Index	8
Annual Rainfall	8
Thornthwaite Index	8
Distress	9
Subgrade Moisture	10
Subsurface Drainage	11 (least application)

9.3.3 Statistically Significant

There are hundreds of factors that can affect performance of a pavement. However, many of them may have very little effect compared with others. Since it is neither feasible nor viable to develop performance models for the pavement management with all relevant independent variables, identification of the significant variables is an important task towards development of performance models vis-à-vis a database.

Dr. Rauhut and several researchers analyzed the significance of 117 data elements of the National Information Management System (NIMS) for asphalt-surfaced pavements. This analysis is presented in "Early evaluation of the SHRP-LTPP data and planning for sensitivity analysis," Chapter 3 [Rauhut 91].

In this analysis, relative significance rankings from the experts in pavement performance modeling were used for preliminary elimination of less significant variables. In this preliminary round, three levels of significance were considered: level 1 for clear significance, level 2 for moderate significance, and level 3 for little or no significance. The experts filled out the significance rating forms entering one of the three level number for each of the 117 variables. The average rating was computed by taking the average of the ratings from all the experts. Variables having an average level of more than 2 were dropped from further analysis. Table 9.5 presents the significant independent variables for pavements having AC surfaces.

Table 9.5 Significant variables in the SHRP NIMS [Rauhut 91]

No.	Independent Variable	No.	Independent Variable
1	Surface Thickness	16	Surface Drainage
2	Base/Subbase Thickness	17	Geological Class of Coarse Aggregate
3	Surface Stiffness	18	Subgrade Soil Passing #200 Sieve
4	Unbound Base/Subbase Stiffness	19	Plasticity Index of Subgrade Soil
5	Bound Base/Subbase Stiffness	20	Liquid Limit of Subgrade Soil
6	Subgrade Stiffness	21	Subgrade Soil Finer than 2 micron
7	Age of Pavement	22	Type of Environment
8	Cumulative ESAL	23	Average Max Daily Temp by Month
9	Asphalt Viscosity	24	Average Min Daily Temp by Month
10	Asphalt Content	25	Thornthwaite Index
11	Percent Air Void	26	Freeze Index
12	HMAC Aggregate Gradation	27	No. of Days Min Temp >30F
13	Percent Compaction of Base/Subbase	28	No. of Days Max Temp >90F
14	Subgrade Soil Classification	29	No. of Air Freeze-Thaw Cycle
15	In-situ Moisture in Subgrade	30	Annual Rainfall

9.3.4 Most Attainable

A discussion on the most attainable variables is presented in paragraph 9.2.4.

9.3.5 Final Possible Proposed Selection

It is too early to decide on the final set of data items as previously mentioned in section 9.2.5. However, based on the future requirements, the following factors can be recommended:

1. A data continuum process is needed along with the parallel process of development and continuous modification of prediction models during the transition from the present state to the targeted future state. During this transition, material properties obtained in the construction will gradually replace typical values and back-calculated values. Data evolution must go together with model evolution.
2. More mechanistic-empirical models need to be developed. In the beginning, typical default values or back-calculated values can be used. FPS-19 uses only serviceability criterion. Fatigue cracking and rutting need to be considered initially and other measures of condition added over time.
3. PMIS uses general location data (district and county) to determine the type of subgrade from five types of subgrade (very good to poor). Models based on this type of subgrade data cannot provide the required accuracy because even within a single county there are

significant variations in subgrade strength. Subgrade strength needs to be considered in the models.

4. Traffic data along with axle load distribution are necessary for the computation of cumulative ESAL values. ESAL data are required in mechanistic-empirical models.
5. Pavement age data are important. However, instead of age data, date of construction/opening to traffic for each layer can be considered.
6. Similar to its application in rigid pavements, variability data are highly desirable, especially for embedding reliability in the models.

CHAPTER 10. CONCLUSIONS AND RECOMMENDATIONS

10.1 CONCLUSIONS

1. Our basic objective for this phase of the project was to investigate the feasibility of closing the gap between pavement management recommendations and predictions given by the network-level PMIS system and the often very different recommendations and predictions given by various project-level design systems. It can be concluded from the work described in this report that a considerable amount of integration will certainly be feasible by implementing the concept of always using the best information available at both levels.

2. It was concluded at an early stage after discussions with the project director and with an expert panel set up for this project that a considerable amount of integration could be achieved by ensuring that the prediction models and data used to support them should be the same at both the network and project levels. This is a long-term goal that will be accomplished in the interim by using the best data available, together with the best models that these data will support. It can be further concluded from subsequent work that the integration can be categorized into three phases — data, model, and decision integration — and that for the recommendations for both levels to be the same, integration of decision methodology, as well as data and model integration, needs to take place eventually.

3. By the development of a conceptual implementation plan for initial integration steps it can be seen that implementation of proposed changes could be staged such that individual changes would be tested and debugged before progressing to the next phase.

4. It can be concluded that by adopting the concept of storing prediction curves individually for each specific data collection section, it will be possible to create a very flexible skeleton structure which will be able to store customized prediction curves regardless of the source of this information. This ensures powerful flexibility and a robust foundation for long-term goals that should not require major changes in the foreseeable future.

5. Assuming that the concept of specific prediction curves is feasible we conclude that it will then be possible to generate considerably more accurate prediction curves than are used currently in the PMIS.

    - The first method of increasing accuracy is the adoption of relevant project-level models and the storage of a standardized data set for each data collection section.

    - The second method for considerably increasing accuracy that becomes possible after implementing specific prediction curves is the use of continuously updated regression to incorporate emerging trends in the actual field data.

6. By the development of a conceptual integration method that considers the current form of the PMIS and selected project-level models, it can be concluded that implementing the above methods should be feasible.

7. One of the current questions regarding the PMIS is exactly how to incorporate the practically necessary concept of management sections. The question specific to this project is: If prediction curves are now to be stored specific to small individual sections, to what length of section should these specific curves apply? From a study of the problem, it is concluded that the splitting of costs into "fixed" and "variable" portions so as to incorporate economies of scale is a powerful and flexible method of combining individual data collection sections and generating recommendations applicable to whole management sections.

8. From the perspective of discretization of prediction models it was therefore concluded that prediction should still be carried out using deterministic prediction models specific to small data collection sections, rather than models applicable to whole management sections. By the development in concept of an implementation plan, it is concluded that implementation of the method would be feasible.

10.2 RECOMMENDATIONS

1. It is recommended that the ability to model specific sections be incorporated into the PMIS by storing a set of sigmoidal shape coefficients for each data collection section.

2. For the initial implementation planned for in this project, it is recommended that the existing structure of the PMIS not be changed radically and that the distresses predicted and the maintenance options they are predicted for remain for the most part the same.

3. As a result, it is recommended that a set of shape coefficients be stored for each distress currently predicted.

4. It is recommended that these shape coefficients be produced externally, either by a new module developed for this purpose, or by modified versions of project level models, or both.

5. In order to increase the accuracy of these specific prediction curves, it is recommended that initially one rigid project-level model and one flexible project-level model be incorporated into the new module, as well as a standardized set of data, to generate as many prediction curves as possible for the PMIS.

6. It is recommended that the standardized data be chosen after consideration of which data are the most commonly quoted in the literature, which data are the most statistically significant, which can be used in the prediction of the most distresses, and, finally, which are the most attainable. It is strongly recommended that close coordination with other groups and research teams involved in setting up other databases be maintained at all times.

7. It is recommended that detailed tree structures be drawn up for all data and distress prediction in the manner proposed in the report. This will aid considerably in the visualization of the interaction between the data items and will provide an effective means of identifying the nature and type of future research work required for continuous progress towards ultimate full integration of network- and project-level pavement management.

8. To convert the prediction curves produced by the project-level models to sigmoidal shape coefficients, it is recommended that the new module include regression capabilities. It is also recommended that, where possible, project-level models should generate shape factors directly.

9. It is then a possibility that the regression capabilities needed to convert project-level model prediction curves to sigmoidal shaped coefficients could be expanded to make use of the condition data, such that if any significant trends begin to emerge from the data, these can also be converted to shape coefficients.

10. It is recommended that prediction curves remain standard deterministic models initially but that these specific models predict distresses on small enough sections of pavement that these sections can be assumed to be homogeneous.

11. In order to generate recommendations relevant to whole management (or "Project") sections, however, it is recommended that predictions remain specific to individual homogeneous sections but that costs be divided into "fixed" and "variable" portions and that cost effectiveness calculations be carried out for all homogeneous sections in the whole management system using this information. In this way the existing ranking system using cost effectiveness may be retained but extended to generate a ranked list of management section projects as opposed to a ranked list of individual sections as is generated currently.

Finally, it is recommended that a detailed implementation plan be drawn up along the lines proposed in the report that would include two initial phases, A and B. Phase A would alter only the structure of the PMIS initially (i.e., not the answers); Phase B would be divided into three subphases to develop and expand a new module to generate sigmoidal shape coefficients through regression from project-level models and incoming condition data; Phase B would also alter the PMIS to utilize the economies of scale concept described in this report, thereby producing management-section-oriented recommendations.

REFERENCES

[AASHO 62] AASHO Road Test, American Association of State Highway Officials, Report 61E, 1962.

[AASHTO 86] "Guide for Design of Pavement Structures," ASSHTO, Washington, D.C., 1986.

[AI 81] "Thickness Design — Asphalt Pavements for Highway and Streets, MS-1," The Asphalt Institute, 1981.

[Butler 86] Butler, B. C. , R. F. Carmichael, P. Flanagen, and F. N. Finn, "Evaluating Alternative Maintenance Strategies," NCHRP Report 285, Transportation Research Board, 1986.

[Calvin] Thomas, W. Calvin, "*Bayesian Analysis*" published in "Handbook of Statistical Methods for Engineers and Scientists," Chapter 10.

[Dossey 89] Dossey, T., Weissmann, A., "A Continuously Reinforced Concrete Pavement Database," Research Report 472-6, Center for Transportation Research, The University of Texas at Austin, November 1989.

[Dossey 94a] Dossey, T., McCullough, B. F., "Updating and Maintaining the Rigid Pavement Database," Research Report 1342-3F, Center for Transportation Research, The University of Texas at Austin, November 1994.

[Draper 80] Draper, N. R., Smith, H., *Applied Regression Analysis, Second Edition*, John Wiley & Sons, Inc., New York, 1980.

[FHWA] *"An Advance Course in Pavement Management Systems,"* U.S. Dept. of Transportation, FHWA. Section 1.0 - Introduction to Prediction Models and Performance Curves, Section 2.0 - Washington State Pavement Management System. Appendix to Chapter 6.0 Performance, pp. D-1 to D-75.

[FHWA 90] "Pavement Cost Model for Truck Policy Analysis," Draft Final Report, Volume 1, Technical Documentation, Contract No. DTFH61-88-C-00091, U.S. Department of Transportation, FHWA, 1990.

[Grater 96] Grater, S., *An Investigation Toward Performance-Oriented Specifications for Portland Cement Concrete Pavement*, doctoral dissertation, The University of Texas at Austin, December, 1996.

[Haas 94] Haas, R., Hudson, R., Zaniewski, J., *Modern Pavement Management,* Kriegler Publishing Company, Malabar, Florida, 1994.

[Haas 95] Haas, R., *Key Challenges for the Future of Pavement Management*, Volume 3, Proceedings of the Third International Conference on Asphalt Pavements, San Antonio, Texas, National Academy Press, Washington, D.C., 1995.

[Hajek 96] J. J. Hajek and A. Bradbury, *"Pavement Performance Modeling Using Canadian Strategic Highway Research Program Bayesian Statistical Methodology,"* pp.160, Transportation Research Record No. 1524, National Academy Press, Washington, D.C., 1996.

[Harichandran 89] Harichandran, R. S., G. Y. Baladi, M. S. Yhe, "Development of a Computer Program for Design of Pavement Systems Consisting of Bound and Unbound Materials," Final Report on a Highway Planning and Research Investigation conducted in cooperation with the U.S. Department of Transportation, FHWA, Michigan State University, 1989.

[Hodges 75] Hodges, J.W., J. Rolt, and T. E. Jones, "The Kenya Road Transport Cost Study: Research on Road Deterioration," Laboratory Report 673, TRRL, Crowthorne, England, 1975.

[Huang 93] Y. H. Huang, *Pavement Analysis and Design,* Prentice-Hall Inc., Englewood Cliffs, New Jersey, 1993.

[Jones 93] Jones, M. A., "Cost Differences between Expediting and Standard Urban Freeway Construction," Master's thesis, The University of Texas at Austin, December 1993.

[Karan 88] Karan, M. A., et al., "Development and Implementation of Alberta's Pavement Information and Needs System," Transportation Research Record 938, 1988.

[Kerali 96] H. R. Kerali, A. J. Lawrence, and K. R. Awad, *"Data Analysis Procedures for Long-Term Pavement Performance Prediction,"* pp.152, Transportation Research Record No. 1524, National Academy Press, Washington, D.C., 1996.

[Li 96] N. Li, W. Xie, and R. Haas, *"Reliability-Based Processing of Markov Chains for Modeling Pavement Network Deterioration,"* pp.203, Transportation Research Record No. 1524, National Academy Press, Washington, D.C., 1996.

[Lytton 93] Lytton, R. L., and D. Zollinger, "Modeling Reliability in Pavement," Paper No. 931133, Presented at the 72nd Annual Meeting, Transportation Research Board, Washington, D. C., 1993.

[Markow 81] Markow, M. J., and B. D. Brademeyer, "Modification of the System EAROMAR," Final Technical Report, Contract No. DTO-FH-11-9350 for FHWA, Washington, D. C., 1981.

[Markow 88] Markow, M. J., F. F. Humplick and B. D. Brademeyer, "Life Cycle Cost Evaluation of Pavement Construction, Maintenance and 4R Projects: Final

Report," Center for Transportation Studies, MIT, Cambridge, Massachusetts, 1988.

[Majidzadeh 81] Majidzadeh, K., et al., "Implementation of Pavement Design System," Volumes 1 & 2, Final Report, Research Project EES 579, Ohio State University, 1981.

[Mohseni 90] Mohseni, A., Y. H. Lee, and M. I. Darter, "Pavement Model Enhancement for the Highway Performance Monitoring System (HPMS)," Interim Report, Literature Review and Feasibility Study, University of Illinois, Department of Civil Engineering, Prepared for Illinois Department of Transportation and FHWA, 1990.

[Neter 96] Neter, J., Kutner, M., Nachtsheim C., Wasserman W., *Applied Linear Statistical Models, Fourth Edition*, Richard D. Irwin, Inc., 1996.

[Paterson 87] Paterson, W. D. O., *Road Deterioration and Maintenance Effects: Models for Planning and Management*, The Highway Design and Maintenance Standards Series, World Bank, The John Hopkins University Press, Baltimore and London, 1987.

[Pilson 97] Pilson, C., Hudson, R., "An Interactivity Model for Memoryless Performance Prediction," paper accepted for publication at Fourth International Conference on Asphalt Pavements, Durban, South Africa, 1998.

[Potter 72] Potter, D. W., "The Development of Road Roughness with Time- An Investigation," Internal Report AAIR 346-1, Australian Road Research Board, Melbourne, 1972.

[Queiroz 81] Queiroz, C. A. V., "Performance Prediction Models for Pavement in Brazil," doctoral dissertation, University of Texas, Austin, 1981.

[Robinson 95] Robinson, C. A., Anderson, V. A., Dossey, T., Hudson, W. R., "Improved Distress Prediction Models for Rigid Pavements in Texas," Research Report 1908-4, Center for Transportation Research, The University of Texas at Austin, August 1995.

[Rauhut 91] Rauhut, B., M. Darter, O. Pendleton, N. Hawks, P. Jordahl, and E. Owusu-Antwi, "Early evaluations of SHRP-LTPP data and planning for sensitivity analyses," Statens Vaeg-Och Transport forsknings institut, Linkoping, Sweden, 1991.

[SAS 85] SAS Institute, Inc., *SAS User Guide: Basics, Version 5 Edition*, Carey, NC: SAS Institute INC., 1985.

[Scullion 84] Scullion, T., Lytton, R., "The Development of the RAMS-State Cost Estimating Program," Report 239-6F, Texas Transportation Institute, College Station, 1984.

[Sebaaly 96] P. E. Sabaaly, A. Hand, J. Epps, and C. Bosch, *"Nevada's Approach to Pavement Management,"* pp.109, Transportation Research Record No. 1524, National Academy Press, Washington, D.C., 1996.

[Singh 93] Singh N., Dossey, T., Weissmann, J., Hudson, W. R., "Preliminary Distress and Performance Prediction Models for Concrete Pavements in Texas," Research Report 1908-1, Center for Transportation Research, The University of Texas at Austin, August 1993.

[Smith 96] R. E. Smith, *"Infrastructure Management System: Course Notes*," Texas A&M University, 1996.

[Stampley 95] Stampley, B. E., B. Miller, R. Smith, and T. Scullion, "Pavement Management Information System Concepts, Equations, and Analysis Models," Research Report 1989-1, Texas Transportation Institute, The Texas A&M University System, College Station, August 1995.

[Stampley 96] Stampley, B. E., Miller, B., Smith, R., Scullion, T., "Pavement Management Information System Concepts, Equations and Analysis Models," Research Report 1989-1, Texas Transportation Institute, The Texas A&M University System, College Station, November 1993.

[Suh 92] Suh, Y-C., Hankins, K., McCullough, B. F., "Early Age Behavior of Continuously Reinforced Concrete Pavement and Calibration of the Failure Prediction Model in the CRCP-7 Program," Research Report 1244-3, Center for Transportation Research, The University of Texas at Austin, March 1992.

[Thompson 90] Thompson, M. A., and E. J. Barenberg, NCHRP 1-26, "Calibrated Mechanistic Structural Analysis Procedures for Pavements," National Cooperative Highway Research Program, NCHRP 1-26, Transportation Research Board, 1990.

[Uzan 82] Uzan, J., and R. L. Lytton, "Structural Design of Flexible Pavements: A Simple Predictive System," Transportation Research Record 888, Washington, D. C., 1982.

[Villarreal 87] Villarreal, A., A. Garcia-Diaz, R. L. Lytton, "Pavement Cost Allocation Model Updates," Contract No. DTFH61-87-00021, FHWA, Washington, D.C., 1987.

[Watanatada 87] Watanatada, T., C. G. Harral, and W. D. O. Paterson, "Highway Design and Maintenance Standard Model -HDM3," World Bank, John Hopkins Press, Baltimore, MD, 1987.

[Way 88] Way, G. B., and J. Eisenberg, "Pavement Management System for Arizona Phase II: Verification of Performance Prediction Models and Development of Data Base," Arizona Department of Transportation, 1988.

[Wimsatt 87] Wimsatt, A. W., McCullough, B. F., Burns, N. H., "Methods of Analyzing and Factors Influencing Frictional Effects of Subbases," Research Report 459-2F, Center for Transportation Research, The University of Texas at Austin, November 1987.

[Winfrey 67] R. Winfrey, "Statistical Analysis of Industrial Property Retirements," Revised by H. A. Cowles, 1967.

[Winfrey 68] R. Winfrey, and P. D. Howell, "Highway Pavements — Their service Lives," Highway Research Record No. 252, Highway Research Board, 1968.

[Won 91] Won, M., Hankins, K., McCullough, B. F., "Mechanistic Analysis of Continuously Reinforced Concrete Pavements Considering Material Characteristics, Variability, and Fatigue," Research Report 1169-2, Center for Transportation Research, The University of Texas at Austin, March 1991.

[Zambrano 95] Zambrano, F., T. Scullion, and R. Smith, "Comparing, Ranking, and Optimization Procedures for the Texas Pavement Management Information System, Research Report 1989-2F, Texas Transportation Institute, The Texas A&M University System, College Station, TX, November 1995.

[Zaniewski 90] Zaniewski, J. P., R.W. Perera, and M. S. Mamlouk, "Feedback of Pavement Management Performance Data for Pavement Design," Transportation Research Record 1272, Washington, D.C., 1990.