Dynamic Decision Model for a Pavement Management System

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ABSTRACT

Pavements represent gradually deteriorating structures for which observations of advance signs of impending failure are possible. Most agencies collect pavement condition data on a regular basis to identify such signs. However, neither the timing of occurrences of these signs nor the timing of actual failure following the signs can be predicted with certainty. Given this probabilistic behavior of pavements and the availability of periodic pavement condition data, a dynamic decision model is much more appropriate for such pavement management decisions as the selection of cost-effective pavement preservation actions and forecasting of future performance of a highway network. In this paper the basic structures of static and dynamic decision models, and a special class of dynamic decision models called a Markovian decision process, are described. Among the significant advantages of this model are reliable predictions of the future performance of a highway network and the identification of preservation actions that are generally less conservative (and less costly) than traditional choices of actions and yet maintain the network performance at prescribed standards. A successful application of the Markovian decision process to the pavement management system in Arizona is described.

A major objective of a pavement management system (PMS) is to assist highway managers in making consistent and cost-effective decisions related to maintenance and rehabilitation of pavements. An integral part of a PMS is a decision model that can be used to determine the optimum type and timing of preservation actions for different pavement segments. A dynamic decision model is described in this paper that permits the selection of a preservation action for a given pavement based on the most recent information on pavement condition.

Two factors have a major influence on the choice of a decision model to be used in a PMS. First, the future performance of a pavement cannot be predicted with certainty. Thus the behavior of pavements with time is probabilistic in nature. Because the future pavement condition is uncertain, the selection of a rehabilitation action appropriate for a given pavement at some future time is also uncertain. The second factor influencing the choice of a decision model is the periodic collection of pavement condition data. Most highway agencies conduct pavement condition surveys at some selected frequency (e.g., annually or biennially). Therefore the actual choice of a rehabilitation action at some future time can be made based on the most recent condition survey. Because the planning period for any rehabilitation action is relatively short (generally less than 2 years), it is unnecessary and inefficient to choose a rehabilitation action for a given pavement several years in advance.

These two factors strongly suggest that the decision model for a PMS should be dynamic; that is, one in which the choice of a future action depends on the new information that would be available before making the choice. This is in contrast to a static decision model in which future actions are fixed at the present time based on present information.

The following sections of this paper cover the important aspects of a dynamic decision model:

1. An evaluation of dynamic and static decision models (discussion on the shortcomings of a static model and the advantages of a dynamic model),
2. Description of a Markovian decision model (this dynamic model is particularly suitable for a PMS), and
3. A successful application of the Markovian decision process (the development of a PMS for the Arizona Department of Transportation by using a Markovian decision process).

EVALUATION OF STATIC AND DYNAMIC MODELS

The major differences between the two types of models can be best illustrated by means of a simple example. Assume that the decisions of a rehabilitation action for a given pavement will be based on a single criterion, namely, the present serviceability index (PSI). The minimum acceptable PSI level is considered to be 2 for this example. Assume that the current PSI of the pavement is 3. Only three alternative actions will be considered: routine maintenance only, a 1-in. overlay, and a 3-in. overlay.

Static Decision Model

In a static decision model, future pavement performance following any of the rehabilitation actions is assumed to be known with certainty. Alternatively, only the expected performance is considered, thereby ignoring the possibilities of better- or worse-than-expected performance. Hypothetical performance curves for the three rehabilitation actions are shown in Figure 1. A major rehabilitation action will be selected for the pavement when it reaches

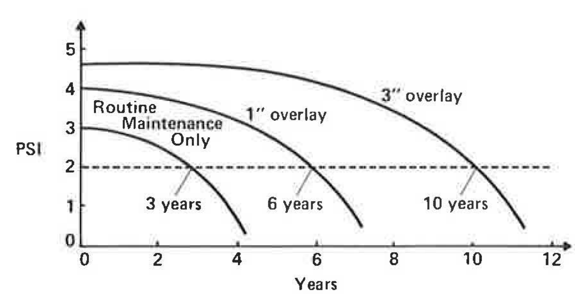

FIGURE 1 Performance curves for the illustrative example.

the threshold PSI of 2.0. Thus one rehabilitation strategy might be to apply a 1-in. overlay at year 3, a 3-in. overlay at year 9, and a 1-in. overlay at year 19 (see Figure 2). This strategy will maintain the pavement condition at or above the PSI of 2.0 during a selected analysis period of 20 years. Several alternative rehabilitation strategies can be defined. The total present worth cost of each strategy during the analysis period can be calculated, including construction cost, maintenance cost, user cost, and salvage value. All alternative strategies are then ranked based on the total present worth cost, and the one with the minimum cost is selected for implementation.

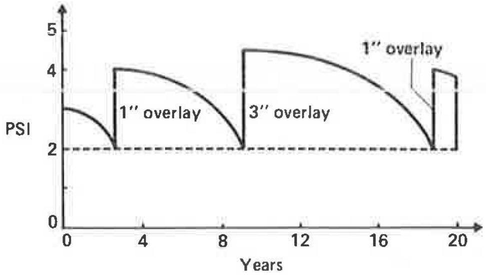

FIGURE 2 Example of a static rehabilitation strategy.

Some implications of this approach are worth noting. The choice of the action at the present time is strongly dependent on the actions selected for future time periods. Yet future actions may not be taken at the designated time periods because the pavement may perform better or worse than expected. This implies that not only the future choices of rehabilitation actions might be inappropriate, but also that the choice of an action at the present time could be ineffective.

For decisions under uncertainties, the expected cost is considered to be a rational criterion for ranking alternative courses of action (1). However, a static model generally would not result in the least expected cost strategy because of the nonlinear relationships between user cost and maintenance cost, and PSI. Thus the cost calculated on the assumption of expected PSI behavior with time would not be equal to the expected cost of that strategy. In fact, it is likely that a strategy with significantly higher expected cost than some other strategy would be selected as being the best (the most cost effective).

Dynamic Decision Model

Consider how a dynamic model would analyze this problem. In this model it is recognized that the future PSI following any of the actions is not known with certainty. However, probabilities of reaching different PSI levels as a function of time can be estimated.

Furthermore, only the decision of what needs to be done right now is to be made at the present time. Decisions of future actions will be dependent (conditional) on the future performance of the pavement. The dynamic model can be illustrated in the form of a decision tree, as shown in Figure 3.

A decision tree consists of two types of nodes--a decision node and a chance node--and several alternatives shown as branches at each of these nodes. At

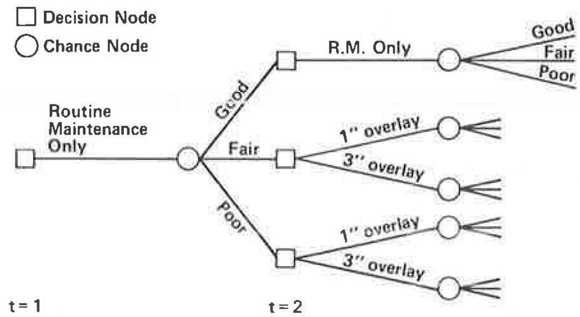

FIGURE 3 Example of a decision tree.

a decision node the branches represent feasible alternative actions. The branches at a chance node represent the possible outcomes of the action taken at the previous decision node. The probabilities of these possible outcomes are estimated.

Now follow this structure for the illustrative example. Because the present PSI of the pavement is 3, the only feasible action is routine maintenance only. This is shown as the only branch at the decision node at present time (t=1).

The PSI of the pavement at the end of one time period cannot be determined with certainty. However, knowing pavement characteristics, traffic, and environmental conditions, probabilities that the pavement will be at different PSI levels can be estimated. For simplicity, consider three discrete levels of PSI: good (greater than 3), fair (2 to 3), and poor (less than 2). These three outcomes are shown as alternative branches at the first chance node in Figure 3. Conditional on each outcome, appropriate alternative actions are selected at the beginning of the second year (t=2). For example, if the outcome is poor PSI, the two alternative actions are a 1-in. overlay and a 3-in. overlay. Following each alternative action, the probabilities of three PSI levels are again estimated at the end of the second time period. This process is continued until the end of the analysis period is reached.

The analysis of a decision tree requires the estimation of probabilities and costs of different outcomes at each chance node. The costs would include construction cost, maintenance cost, and user cost associated with a given PSI level. The analysis is conducted by "folding" the tree backwards. Assuming n to be the analysis period, expected costs are calculated at each chance node at the end of the nth time period. At the decision nodes at the beginning of the nth period, the alternative actions with the minimum expected costs are selected. Then the chance nodes at the end of the (n-1)th time period are considered. Expected costs are again calculated, assuming that the minimum expected cost actions would be selected at the following decision node. The actions with minimum expected costs are again selected at the decision node at the beginning of the (n-1)th time period. This process is continued until the first decision node is analyzed to select the action that has the minimum total expected cost.

Note that the optimum strategy determined from a decision tree fixes the action only at the first time period. At each of the following time periods, the optimal actions are conditional on the possible outcomes at the preceding chance node. Thus the optimum strategy might be identified as follows: Do only routine maintenance at t=1. If the pavement is found to be at a good PSI level at t=2, continue with routine maintenance only; if found at a fair PSI level, select a 1-in. overlay; and if found at a poor PSI level, select a 3-in. overlay.

The size of a decision tree can become extremely large for a real-life problem. This is because several distress types (instead of just PSI) may have to be considered separately in defining pavement condition, and a large number of alternative actions may have to be evaluated at each time period. The problem is further complicated when a network of pavements needs to be analyzed to determine the minimum cost actions subject to the constraints of prescribed performance standards. In these situations it would be impractical to analyze a decision tree by complete enumeration (i.e., by drawing all possible branches of the tree and evaluating each branch to determine the minimum cost actions). Fortunately, a special class of dynamic decision models, called the Markovian decision process, can incorporate several pavement condition variables and alternative actions, and also can analyze a large number of pavement segments. Details of this model are given in the next section.

MARKOVIAN DECISION PROCESS

The problem of determining the optimum pavement preservation policies for a network of pavements can be formulated as a Markovian decision process that captures the dynamic and probabilistic aspects of pavement management. The main components of a Markovian decision process are condition states, alternative pavement preservation actions, and cost and performance of these actions. A condition state is defined as a combination of the specific levels of the variables relevant to evaluating pavement performance. For example, if pavement roughness and cracking were the only relevant variables, one condition state might be defined as the combination of roughness = 50 in./mile and cracking = 5 percent. Note that the definition of a condition state retains the descriptions of individual pavement distresses; consequently, better matching of preservation actions to pavement condition is possible. This is in contrast with an alternative approach in which a combined score is calculated from the levels of individual pavement distresses. In the latter approach the specific causes of deteriorated pavement condition cannot be identified if only the combined scores are predicted for future time periods.

Alternative pavement preservation actions could vary from do-nothing to routine maintenance only to minor and major rehabilitation. The performance of these actions is specified through transition probabilities. A transition probability [$p_{ij}(a_k)$] specifies the likelihood that a road segment will move from state i to state j in unit time (e.g., 1 year) if action a_k is applied to the pavement at the present time. A Markovian process is assumed to have only a one-step memory. Thus the transition probability is assumed to depend only on the present condition state i and not on how the pavement reached that condition state. Note, however, that by including factors such as age and design life of the last rehabilitation action in the definition of a condition state, the one-step memory can be made to consider the effect of type and time of the last action. A preservation policy for the entire network is the assignment of an action to each state at each time period.

Under the assumptions of a Markovian process, the specification of condition states and transition probabilities for alternative actions permits the calculation of the probabilities that a road segment would be in different condition states at any future time period for an assumed preservation policy (2). The probability that a road segment is in a given condition state can also be interpreted as the expected proportion of all segments in that condition state. This allows the calculation of the expected proportion (q_i) of the network of road segments in the ith condition state at the nth time period for a given preservation policy. Figure 4 shows the behavior of a network under the assumption of a Markovian process. The performance of the network can be evaluated in terms of these proportions. For example, desirable and undesirable condition states can

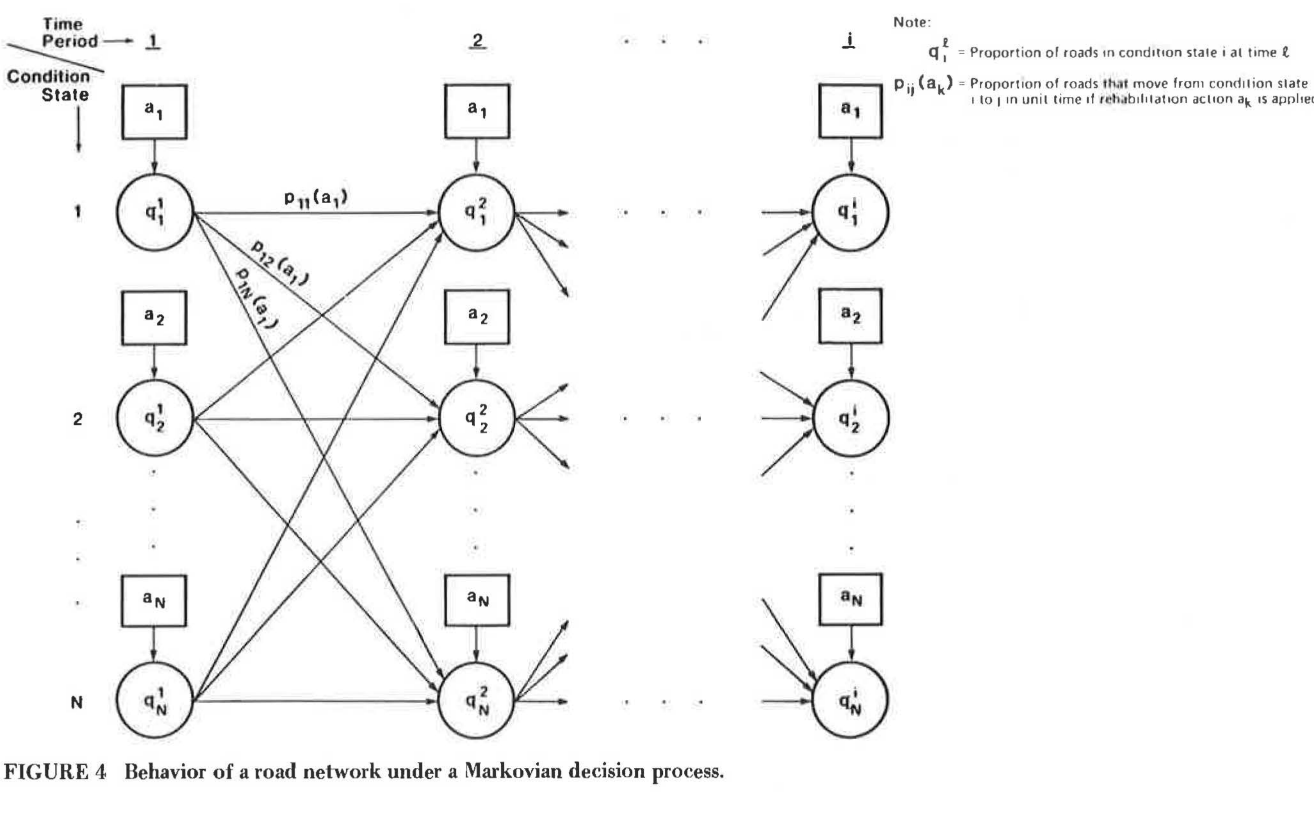

FIGURE 4 Behavior of a road network under a Markovian decision process.

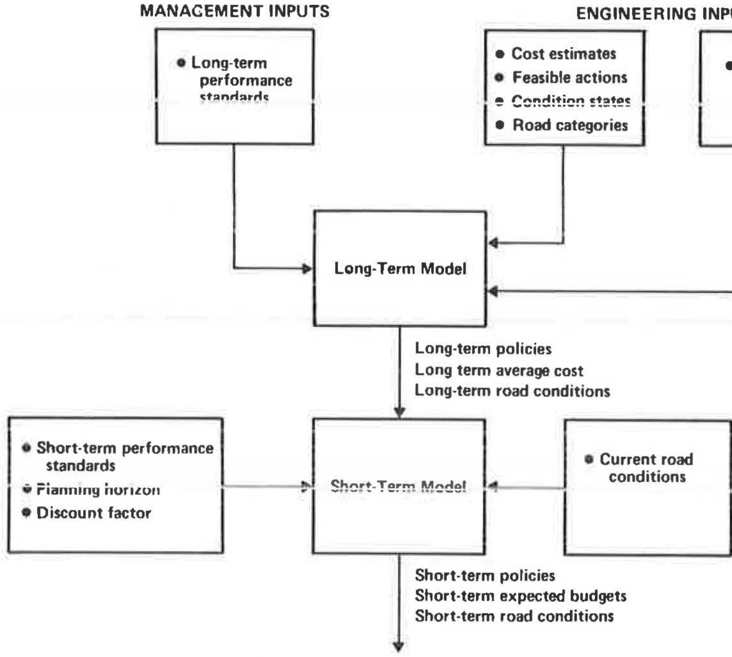

FIGURE 5 Determination of short- and long-term rehabilitation policies.

be defined, and the proportions of the network in these two categories can be plotted as a function of time. Also, whether the "health" of the network is improving or deteriorating can be assessed. A major objective of pavement management would be to find the preservation policy that would maintain desired performance standards over a long period of time at the lowest possible cost.

From a planning point of view, it is desirable that after some initial transition period (T) the network achieves a steady-state condition. A steady-state condition means that the proportion of road segments in each condition state remains constant over time. Mathematically, this implies that

$$q_i^T = q_i^{T+1} = q_i^{T+2} = \ldots, \text{ for all i.}$$

The advantages of reaching a steady-state condition is that the preservation policy will be stationary after time T (i.e., the selection of the preservation actions will be a function of condition state only and will not be affected by time). The expected budgetary requirements will also remain constant once a steady-state condition is obtained.

The user agency may desire to have control over the time (T) it would take for the network to reach the steady state. Depending on the initial conditions and the available budgets during the T time periods, short-term standards that are somewhat lower than the long-term standards may be acceptable. Optimal short-term policies (which may be different from the optimal long-term policy) can be determined to upgrade the network from its present condition to the long-term standards in time period T with minimum total expected cost while maintaining short-term standards during the first T time periods. Figure 5 shows the overall approach to determining the optimal long- and short-term preservation policies. Mathematical formulations are presented in Kulkarni et al. (3).

Advantages of Markovian Decision Process for Pavement Management

A Markovian decision process provides the capability to address two key questions of pavement management:

1. What are the minimum budget requirements to maintain desired performance standards for a network of pavements?
2. What maximum performance standards can be maintained for a fixed budget?

The first question is answered directly because for fixed performance standards, optimal policies and the corresponding minimum budget requirements are identified (see Figure 6). Note that both short- and long-term budget requirements are shown in Figure 6. The second question can be answered by varying performance standards until the minimum budget of the optimal policies matches the available budget.

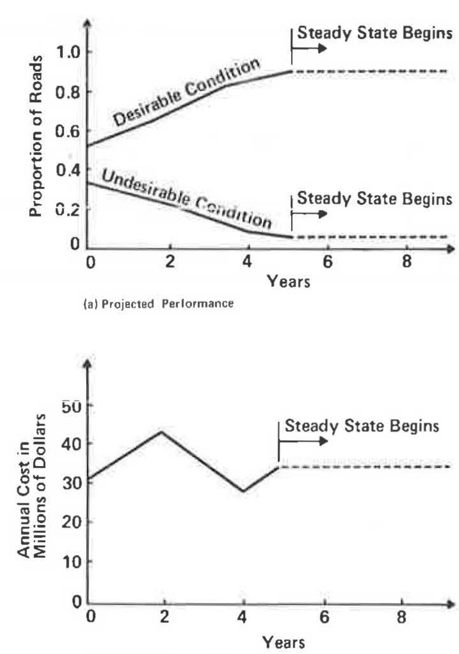

FIGURE 6 Projected performance and budgets under optimum policies.

The formulation of a PMS as a Markovian decision process offers certain distinct advantages.

1. Possibilities of pavement performance better or worse than expected are recognized and properly accounted for in the selection of preservation policies.
2. Future decisions of preservation actions for different roads are not fixed. They depend on how the pavements actually perform, and hence would be more realistic and cost effective.
3. The actions to be taken at the present time for different roads are uniquely identified. This is essential for planning purposes. In addition, the most likely actions to be taken during the next 2 to 3 years are also identified with a high degree of reliability.
4. Performance of a pavement following any given preservation action needs to be predicted only for one time period into the future. The prediction of pavement performance at succeeding time periods is conditional on how the pavement behaves and what action is taken. In contrast, a static decision model requires long-term predictions that are unconditional (i.e., independent of how the pavement may behave in the future). Such predictions are known to have poor reliability.
5. The success or failure of pavement management decisions can be evaluated by comparing the expected proportions of roads in desirable and undesirable condition states with the observed proportions of roads in those condition states. If the observed performance is significantly worse than expected, causes for this situation can be searched, identified, and corrected. Examples of such causes are poor quality control during construction, different materials, extreme environmental conditions, higher-than-expected traffic, and so forth.
6. A dynamic decision model has the potential for significant cost savings through the selection of less conservative preservation actions that still maintain the desired performance standards. Because a small proportion of a highway network can be accepted to be in poor condition at any given time, the model can consider actions for which there is some probability of pavement failure before reaching a prescribed design life. The probability of pavement failure along with the cost of repairing the deteriorated pavement are properly weighted to evaluate the options of substantial corrective actions when a pavement is in poor condition versus some moderate preventive actions before reaching poor condition.

ARIZONA'S PMS: A SUCCESSFUL APPLICATION OF THE MARKOVIAN DECISION PROCESS

The heart of the PMS in Arizona is an optimization model termed the network optimization system (NOS). It recommends pavement preservation policies that achieve long- and short-term standards for road conditions at the lowest possible cost. The NOS is based on formulating the problem as a constrained Markovian decision process that captures the dynamic and probabilistic aspects of the pavement management problem. Linear programming is used to find the optimal solution. The details of this system are provided in Kulkarni et al. (3) and Golabi et al. (4). The main steps involved in the development of the NOS were

1. Definition of condition states,
2. Selection of maintenance actions,
3. Development of transition probabilities,
4. Specification of performance standards, and
5. Development of computer software.

A brief description of each step is given in the following sections. The implementation of the system and its benefits are also summarized.

Condition States

The variables used to define the condition states were present roughness (three levels), present amount of cracking (three levels), change in amount of cracking during previous year (three levels), and index to the first crack (five levels). A total of 135 combinations of these variables are possible. However, 15 of these combinations are considered highly unlikely, which left 120 condition states.

Roughness represents the traveling public's perception of pavements in terms of comfort and the wear and tear on the vehicle caused by rough roads. It is measured by a Mays meter, which records deviations between the axle and the body of the car and adds up the number of inches of bumps per mile. Cracking is the highway engineers' rating of the structural adequacy of the pavement and its need for corrective maintenance. The road surface is compared with pictures showing different percentages of cracking.

Index to the first crack is a number that is linked to the last nonroutine maintenance action taken on the road. It is used to account for differences between the probabilities of deterioration of roads with no visible cracks, but with different last nonroutine actions. To understand the significance of the index, consider two road segments: A and B. The last nonroutine action on A has been resurfacing with 1 in. of asphalt and the last action on B has been resurfacing with 3 in. of asphalt. No cracks are visible on either road, and routine maintenance is planned for the current year. The two roads will have significantly different probabilities of developing cracks during the next year. Because the indices are different, the model assigns these roads to two different states with different probabilities of deterioration. However, once a road shows some cracks, the amount of future cracking depends only on the current cracking and on the rate of change in cracking; it is not important anymore to know the last nonroutine action taken or the time the action was taken. It is worthwhile to note that roads with the same age may behave differently because of other factors (for instance, subsurface moisture and deflection). The net effect of all these factors, including aging, is captured by the two condition variables: cracking and the rate of change in cracking.

To summarize, a state is defined by a vector $(u, \Delta u, r, z)$, where u denotes the present amount of cracking, Δu the change in cracking during the previous year, r the roughness, and z the index to the first crack. The index z changes only if a nonroutine maintenance action is taken.

The statewide network was divided into nine road categories that were defined as combinations of average daily traffic and a regional environmental factor that depends on several climatic conditions; elevation and rainfall were the primary variables used to define the regional factor on a scale of 0 to 5. Because traffic density and the regional factor are independent of the preservation action, each pavement remains in one road category. This in effect made nine networks, each of which was characterized by a set of 120 condition states.

Maintenance Actions

A total of 17 alternate maintenance actions, ranging from routine maintenance to substantial corrective measures, were selected for asphalt concrete pavements. From this master list, a set of feasible actions was specified in the model for each state. The average number of feasible actions for each state was about six.

Transition Probabilities

The existing models for predicting road deterioration depend, for the most part, on empirical equations relating long-term deterioration to the structural properties of the pavement. Although these models are suitable for cases where adequate data do not exist, they were not appropriate for Arizona. Over the years Arizona had accumulated extensive data on its road conditions and the corrective actions taken on those roads. To obtain better predictions, regression equations were developed that concentrated on short-term deterioration, and Arizona's data base was used.

First a set of independent variables that are traditionally used for predicting deterioration were considered: deflection, spreadability, subgrade support, and so forth. However, the correlations obtained with these variables were rather poor. Second, it was argued that the influence of the engineering and environmental factors was captured by the observed pavement conditions. Hence the present values of the condition variables and the rate of change in these variables should reveal a strong correlation with future pavement condition, an assumption that was confirmed by the analysis of data (correlation coefficients for regression equations ranged from 0.81 to 0.95). This approach was consistent with the requirements of the optimization model, because it requires only what (condition) state the pavement would be in, and not why it would deteriorate to that state.

With this approach, the independent variables considered were present pavement condition (roughness or cracking), change in pavement condition during the previous year, maintenance actions, traffic densities, and the regional environmental factor. The dependent variables were changes in roughness and cracking in 1 year.

The (normal) continuous probability distributions of the dependent variables were discretized to give the probability of going from one level of roughness and cracking to another level in 1 year. It is reasonable to assume that roughness and cracking are probabilistically independent. Thus if the roughness associated with state i is denoted by r_i, the cracking by u_i, and the change in cracking in the previous year by Δu_i, then

$$p_{ij}(a) = P \text{ (moving from } r_i \text{ to } r_j \text{ in 1 year under action a) or}$$
$$= P \text{ (moving from } u_i \text{ and } \Delta u_i \text{ to } u_j \text{ and } \Delta u_j \text{ in 1 year under action a).}$$

As mentioned earlier, the index to the first crack for state j is the same as that of state i if a is routine maintenance, and is the index associated with a if a is nonroutine maintenance.

The data for the regression equations were derived from a randomly selected group of 270 road segments within the Arizona network. For each road segment, 2 or 3 years of data were available, leading to about 700 data points for each regression equation. To verify the accuracy of the predictions, an independent data set of 53 road segments not included in the initial development was selected at random from the Arizona Department of Transportation (ADOT) files. Verification was obtained by comparing predictions of roughness and cracking with actual measurements and observations for 5 years. The correlation coefficient between observed and predicted values was greater than 0.9 for the first year, and between 0.7 and 0.8 for the fifth year (the model needs only predictions from 1 year).

For every feasible action, a pavement in a given condition state can only go to three or four states. Thus, for feasible actions, only 3 percent of the elements in the transition probability matrix were nonzero. Because for each state 6 of the 17 actions are feasible, the number of nonzero $p_{ij}(a)$'s is about 2,600 (for each road category), or slightly more than 1 percent.

Specifying Performance Standards

To set performance standards, acceptable and unacceptable states were defined and ADOT's management specified the minimum proportion of roads required to be in acceptable states and the maximum proportion of roads permitted to be in unacceptable states. The performance standards may vary as a function of average daily traffic (see Table 1).

TABLE 1 Performance Standards for the NOS

Average Daily Traffic	Minimum Proportion of Roads with Acceptable Roughness	Maximum Proportion of Roads with Unacceptable Roughness	Minimum Proportion of Roads with Acceptable Cracking	Maximum Proportion of Roads with Unacceptable Cracking
0-2,000	0.50	0.25	0.60	0.25
2,001-10,000	0.50	0.15	0.70	0.20
>10,000	0.80	0.05	0.80	0.10

Note: Acceptable pavement condition is defined as roughness of less than 165 in./mile and cracking less than 10 percent. Unacceptable pavement condition would mean roughness of more than 256 in./mile or cracking of more than 30 percent.

Development of Computer Software

A coordinated set of computer programs was developed to accept the engineering and management inputs shown in Figure 4 and to generate matrices suitable for a linear programming (LP) software package. The output report after obtaining the optimal solutions summarizes the NOS actions and costs year by year for each mile of highway in the statewide network. The present condition of each mile and the last nonroutine action are used to determine the condition state, which is then matched to the NOS output file to determine the appropriate action for the current year. For subsequent years, the NOS predicts the most likely condition state of each mile, the corresponding action, and the estimated expected cost.

Implementation and Benefits

After extensive testing with real and hypothetical data, the NOS was fully implemented in the summer of 1980. A pavement management group comprising 11 people was formed at ADOT. The group is responsible for collecting data on road conditions, providing engineering inputs, eliciting management inputs to the system, reviewing inputs with district engineers, running the NOS, and recommending pavement preservation policies to management. The NOS is now routinely being used to prepare pavement preservation budgets and policies.

The PMS has changed the pavement management decision process in Arizona from a subjective, nonquantitative method to a modern system that integrates managerial policy decisions and engineering inputs through an optimization system. The significant benefits of the system to ADOT are as follows.

Cost Reductions

During the first year of implementation (fiscal year 1980-1981), the PMS saved $14 million of preservation funds. Because pavement condition data were available since 1974, it was possible to calculate the proportions of roads in acceptable and unacceptable conditions for past years. Those proportions have remained fairly stable. The amount budgeted by ADOT for 1980-1981 to keep the network at the same standards was $46 million. Using the PMS and following its recommended policies, ADOT was able to achieve the same standards with $32 million. The long-range standards used in the model (Table 1) were also the historical standards. The $14 million were subsequently spent on other highway-related projects. Because the NOS ties present actions and conditions to long-range performance standards, and large fluctuations in total annual expected costs are not allowed, the cost reduction in 1980-1981 was not at the expense of either poor future road conditions or costly measures in subsequent years. This is confirmed by the 1981-1982 preservation budget, which was only $28 million to keep the roads above acceptable standards.

There were two reasons for the cost reduction. First, traditionally, the roads have been allowed to deteriorate to a rather poor condition before any preservation action was taken. The roads then required substantial and costly corrective measures. The actions recommended by the PMS are mostly preventive measures; that is, it recommends less substantial measures before the road deteriorates to an extremely poor condition. Analysis indicates that less substantial but slightly more frequent measures not only keep the roads in good condition most of the time, but the measures are overall less costly; they prevent the road from reaching poor conditions that require much costlier corrective measures.

Second, in the past corrective actions were too conservative; it was common to resurface a road with 5 in. of asphalt concrete. The assumption was that the thicker the asphalt layer, the longer it would take for the road to deteriorate below acceptable standards. Although this assumption is correct, the time it takes for a road to deteriorate is not proportional to the asphalt layer. For example, the prediction model indicates that there is no significant difference between the rate of deterioration of a road resurfaced with 3 in. of asphalt concrete and a road resurfaced with 5 in. Therefore the policies recommended by the PMS are less conservative; for example, a recommendation of 3 in. of overlay is rather rare and is reserved for the worst conditions. It is important to note that the results of the prediction model are not sufficient for determining the optimal maintenance policy. Although the prediction model enhances highway engineers' understanding of the general effectiveness of actions, the final recommendation depends on considering the costs versus benefits of all actions in the context of short- and long-term standards and current road conditions. Given the size of the problem, this would only be possible through the use of a formal optimization model.

Sources of Funds

A major source of funds for highway maintenance is FHWA. These funds, called restoration, rehabilitation, resurfacing, and reconstruction (4R) funds, are based on factors such as miles of Interstate, the amount of land owned by the federal government in the state, and population. The estimated amount of 4R funds available to Arizona for preservation of the Interstate highway during the next 5 years is $167.5 million. By using the PMS, ADOT estimates that only $91.7 million is needed to maintain Interstate roads in acceptable conditions during the next 5 years. The surplus of $75.8 million will be allocated to other construction projects over the next 5 years (Table 2).

In addition to the 4R funds, the federal government provides Arizona with funds for maintaining and constructing primary and secondary roads [called primary-secondary construction funds (PSCF)], of which a minimum of 20 percent has to be spent on preservation. Traditionally, ADOT has allocated 50 percent of these funds for this purpose. By using the PMS, ADOT finds that only 20 percent of the PSCF is needed for preservation during the next 5 years. The difference of $25.6 million that would have been spent on preservation of secondary and primary roads will now be allocated to construction projects (Table 2).

Budgets

The PMS has provided a defensible procedure for preparing 1- and 5-year budgets for preservation of pavements. This has helped ADOT's management to justify the revenue requests before oversight legislative committees.

SUMMARY AND CONCLUSIONS

Pavements represent gradually deteriorating structures for which advance signs of impending failure can be observed. Most agencies collect pavement

TABLE 2 PMS Plan for Preservation Funds

	Funds ($000,000)						
Fiscal Year	Interstate Preservation Funds Needed	4R Funds Available	Surplus 4R Funds	Non-Interstate Primary/ Secondary Funds Needed	PSCF Funds Available	Surplus PSCF	Total Surplus
1982-1983	13.2	17.0	3.8	23.1	23.1	0.0	3.8
1983-1984	18.5	28.3	9.8	30.3	36.7	6.4	16.2
1984-1985	19.0	37.1	18.1	36.6	43.0	6.4	24.5
1985-1986	20.0	37.1	17.1	38.3	44.7	6.4	23.5
1986-1987	21.0	48.0	27.0	40.9	47.3	6.4	33.4
Total	91.7	167.5	75.8	169.2	194.8	25.6	101.4

Note: The data in this table give the funds needed to preserve present road and cracking conditions for the next 5 years (1982-1983 to 1986-1987), the funds available, and the resulting surplus.

condition data on a regular basis to identify such signs. However, neither the timing of occurrences of these signs nor the timing of actual failure following the signs can be predicted with certainty. Thus pavements designed and built the same way under the same traffic and environmental conditions reveal signs of distress at different times. Given this probabilistic behavior of pavements and the availability of periodic pavement condition data, a dynamic decision model, rather than a static decision model, is much more appropriate for such pavement management decisions as the selection of cost-effective preservation actions for pavements in different conditions and forecasting the future performance of a highway network.

In a dynamic decision model the choice of a future action depends on the pavement condition that would be observed before making the choice. Although future pavement condition would not be known with certainty at the present time, probabilities of different pavement conditions can be estimated based on the past performance of the pavement and factors such as traffic and environment. In contrast, in a static decision model future actions are fixed at the present time based on present information.

A special class of dynamic decision models--called a Markovian decision process--is described in this paper. This model is particularly suitable for pavement management decisions because it can incorporate multiple pavement condition variables, a large number of alternative actions, and a large-sized highway network. The model provides the capability to determine the minimum budget requirements to maintain desired performance standards for the highway network or, alternatively, to determine the maximum performance standards that can be maintained for a fixed budget. Among the significant advantages of a PMS using a Markovian decision process are reliable prediction of future performance of the network and identification of preservation actions that are generally less conservative (and less costly) than the traditional choices of actions and yet maintain the network performance at prescribed performance standards.

The development of a PMS for Arizona represents a successful application of the Markovian decision process to pavement management. Significant cost savings have resulted from the use of this system.

REFERENCES

1. H. Raiffa. Decision Analysis: Introductory Lectures on Choices Under Uncertainty. Addison-Wesley Publishing Company, Reading, Mass., 1968.
2. R.A. Howard. Dynamic Probabilistic Systems, Volume 1. Wiley, New York, 1971.
3. R.B. Kulkarni et al. Development of a Pavement Management System for the Arizona Department of Transportation. Proc., 5th International Conference on the Structural Design of Asphalt Pavements, 1982, Volume 1, pp. 575-585.
4. K. Golabi, R. Kulkarni, and G. Way. A Statewide Pavement Management System. Interfaces, Vol. 12, 1982, pp. 5-21.

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