Dynamic Decision Model for Pavement Management Using Mechanistic Pavement Performance Submodel

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A dynamic decision model for pavement management has been developed on the basis of a dynamic programming formulation. The transition probabilities are determined by a mechanistic pavement performance model formulated within a stochastic framework. In this way, the individual distress modes may be modeled in the pavement condition states, which can be helpful in identifying the proper rehabilitation treatment. Furthermore, the Markovian assumption that the transition probabilities are time-invariant is no longer necessary with the proposed methodology. A numerical illustration demonstrates that the impact of variations in excess user and highway agency costs and other management decisions on the optimal rehabilitation policy can be evaluated explicitly.

To meet the challenges posed by an aging pavement network and the problem of funding, a pavement management system (PMS) is necessary to determine the most cost-effective strategy for rehabilitating the network while sustaining a level of pavement performance for the users. A rehabilitation alternative may be more costly in the initial capital outlay, but it may perform better in terms of its life, needing fewer remedial actions and lower associated costs to the user and agency. The PMS should be able to provide the economic trade-offs between alternatives in terms of life-cycle costs.

In recent years, highway agencies have developed and implemented several PMSs, including the PAVER, PARS, WSPMS, RAMS, OPAC, CALTRANS PMS, and HDM III (*1–7*). Some use the present condition approach, wherein the structural and serviceability condition of the network are first evaluated by means of a condition survey of various distress indicators. The rehabilitation that best restores the deficiency in each pavement segment is identified. No life-cycle cost comparisons of the alternatives, however, are considered, with the result that the selected strategy may not be the most cost-effective. In this case, funds are usually allocated using a priority list based on highway use and condition of pavement. Those projects outside the available budget will be deferred to the next period for consideration.

Where life-cycle cost comparisons are available, the predictive models for pavement performance either are deterministic or consider only the mean value performance. Such systems use a static or open-loop decision process, since the analysis is based on projected performance derived from the current situation. The analysis yields a sequence of rehabilitation activities that minimizes an objective function without considering that the pavement may perform better or worse than predicted. The best strategy derived in this way is not the optimal.

Instead, a dynamic programming approach for PMS is presented herein. It takes into account the actual pavement performance at each stage and yields a rehabilitation policy that is most cost-effective for each pavement segment for the period of the planning horizon subjected to management policies and operation constraints. Other dynamic decision models have been formulated on the basis of the Markovian process, in which the transition probabilities are dependent only on the state of the pavement and independent of the history, thus time-invariant (*8,9*). However, in the present approach, such an assumption has not been made. Furthermore, a stochastic mechanistic pavement performance model provides the framework for determining the transition probabilities, unlike the time-variant transition probabilities based on the pavement condition index (PCI) that are employed in PAVER (*10,11*). A numerical illustration is also included to demonstrate its potential and implementation.

DYNAMIC PROGRAMMING OPTIMIZATION

At the beginning of a discrete time period, formally called a stage, a pavement section is said to be in one of a set of possible pavement conditions Z, also called states. These states are determined from condition surveys conducted at the beginning of each stage. At each stage, after observing the state, a rehabilitative activity λ from a set Λ of all possible actions is chosen and implemented. From the state at that time and the action chosen, an expected cost is incurred. Because of the stochastic nature of the problem, the state of this pavement at the next stage is not known deterministically; instead, there is a probability distribution for the transition. The objective for the dynamic program model is to determine a rehabilitation policy that minimizes the expected value of the sum of the costs incurred over the planning horizon. This is achieved through recursive relations based on the principle of optimality (*12*).

Consider a planning horizon of n stages and an objective value function

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$V_k(i_1)$ = minimum expected value of sum of costs incurred for remaining planning process given that at beginning of stage k, pavement is at state i_1 (1)

Suppose at stage k, the pavement is in state i_1 and the optimal policy is desired. If an action $\lambda' \in \Lambda$ is chosen at stage k, then cost $C(i_1,\lambda')$ is incurred and the next state will be i_2 with transition probability $P(i_1,i_2,\lambda')$. If the next state is i_2, then the problem becomes equivalent to one that starts in state i_2 at stage $k + 1$. Hence, with λ' chosen, the least expected cost at stage k is

$$C(i,\lambda') + \sum_{i_2} P(i_1,i_2,\lambda') \cdot V_{k+1}(i_2)$$

Thus, the least cost at stage k obtained without restricting the decision to λ' is given by

$$V_k(i_1) = \min_{\lambda \in \Lambda} \left[C(i_1,\lambda) + \sum_{i_2} P(i_1,i_2,\lambda) \cdot V_{k+1}(i_2) \right] \quad (2)$$

and the optimal decision is the action λ that yields the minimum in Equation 2, also known as the optimality equation.

The optimality equation provides the mechanism for recursively determining the value of the objective function at the start of the planning horizon beginning with the values at the boundary. Starting with boundary conditions $V_n(i_2)$, the objective value at stage $k = n - 1$, $V_{n-1}(i_1)$, is found according to Equation 2. Then with $k + 1 = n - 1$ in the equation, the objective value at stage $k = n - 2$, $V_{n-2}(i_1)$, is derived from $V_{n-1}(i_2)$ determined from the previous step. In this recursive fashion, the objective value at the start of the planning horizon $V_0(i_2)$ is eventually determined with $k = 0$. The set of optimal decisions for each state at each stage form the optimal rehabilitation policy for the problem.

States Classification

The pavement states are characterized by pavement features that will affect the rehabilitation costs and transition probabilities from stage to stage. Features that are also determinants of the costs or transition probabilities but invariant with respect to the rehabilitation decisions and stages (such as pavement width) are not included in the states classification. Accordingly, two pavement features—namely, pavement distress condition and pavement structure—are identified for the classification of pavement states.

Pavement Distress Condition

The proposed methodology measures pavement performance in terms of individual modes of distress, in contrast with systems that use a composite index that combines the individual distresses, such as the PCI in PAVER and PCR in WSPMS. In this way, the individual defects are not masked so that the rehabilitation alternative that can best correct the deficiency can be prescribed.

The level of distress for each distress mode in the pavement is discretized into a set of collectively exhaustive, mutually exclusive bounds corresponding to varying degrees of damage. Accordingly, the pavement distress condition for m distress modes can be described by a vector $(d_1, d_2, \ldots, d_m)$, where d_1 is the distress level for the first distress mode and d_m is the distress level for the mth distress mode. The greater the number of levels, the finer will be the discretization and the more accurate (but computationally more difficult) will be the optimization model. For demonstration purposes, a three-level discretization of the fatigue distress mode is shown in Table 1, characterized by a damage index according to some pavement performance model that is described later.

Pavement Structure

The pavement structure is adequately characterized when all relevant changes to the structure are known. These changes are recorded by a vector $(n_0, n_1, \ldots, n_q)$ corresponding to a sequence of q modifications to the structure. Considering only routine maintenance and overlay alternatives for the present illustration, one definition for the components $n_1, n_2, \ldots, n_q$ of the pavement structure vector is given in Table 2. In this case only the overlay alternatives will modify the pavement structurally, and only these decisions are recorded in the vector. A number of routine maintenance type activities may be performed on the pavement between these overlays. These do not modify the pavement structurally and hence are not recorded in the vector.

The first element in the pavement structure vector, n_0, denotes the number of underlying cracked asphalt layers. Thus, for a structure with q overlays, n_0 can take values from 0, 1, $\ldots$, q. For example, a pavement structure described by $(1,\lambda_{V1},\lambda_{V3},\lambda_{V2})$ will comprise three overlays—namely, thin

TABLE 1 Damage-Level Discretization for Fatigue Distress Mode

Damage Level	Description	Damage Index
D1	> 45% cracking (severe)	> 1.0
D2	10% - 45% cracking (intermediate)	0.72 - 1.0
D3	< 10% cracking (minimal)	0.0 - 0.72

TABLE 2 Rehabilitation Alternatives

Rehabilitation Type	Activity	Designation
Routine Maintenance	Do Nothing Patching	λ_{O1} λ_{O2}
Overlay	Thin Medium Thick	λ_{V1} λ_{V2} λ_{V3}

Examples:
Pavement structure after sequence of rehabilitation activities
λ_{O1} λ_{V1} λ_{O2} λ_{V2} -- (V1,V2)
λ_{V1} λ_{O1} λ_{O2} λ_{V2} λ_{O1} -- (V1,V2)
λ_{V1} λ_{V2} λ_{O2} λ_{V3} -- (V1,V2,V3)

followed by thick and medium overlays—with one cracked layer, that is, the original asphalt layer.

Objective Function and Optimality Equation

It is usual and appropriate to consider the rehabilitation policy with the lowest expected net present cost for the planning horizon to be the most efficient allocation of scarce rehabilitation funds while satisfying management constraints. Accordingly, the objective function can be defined as

$V_k(\mathbf{i},\mathbf{j})$ = minimum expected net present cost from start of year k to end of planning horizon given that distress condition vector is $\mathbf{i}$ and pavement structure vector is $\mathbf{j}$; $\mathbf{i} = (d_f)$ and $\mathbf{j} = (n_0, n_1, n_2, \ldots, n_q)$, $n_0 \leq q$ modifications to pavement structure (3)

where d_f is the distress level for fatigue mode.

On the basis of this objective function, the optimality equations for "not failed" conditions are defined as follows:

$$V_k(\mathbf{i}, \mathbf{j}) = \min \begin{cases} \lambda_{V1}: & r_1 \cdot C_a(\mathbf{i},\lambda_{V1}) + r_2 \cdot C_u(\mathbf{i},\lambda_{V1}) \\ & + \sum_{\mathbf{i}_2} \left\{ P(\mathbf{ij},\mathbf{i}_2\mathbf{j}_2,\lambda_{V1},k,y) \cdot \left[\frac{r_3 \cdot y \cdot U(\mathbf{i},\mathbf{i}_2)}{(1+r)^{y/2}} + \frac{V_{k+y}(\mathbf{i}_2,\mathbf{j}_2)}{(1+r)^y} \right] \right\} \\ \vdots & \\ \lambda_{Vp}: & r_1 \cdot C_a(\mathbf{i},\lambda_{Vp}) + r_2 \cdot C_u(\mathbf{i},\lambda_{Vp}) \\ & + \sum_{\mathbf{i}_2} \left\{ P(\mathbf{ij},\mathbf{i}_2\mathbf{j}_2,\lambda_{Vp},k,y) \cdot \left[\frac{r_3 \cdot y \cdot U(\mathbf{i},\mathbf{i}_2)}{(1+r)^{y/2}} + \frac{V_{k+y}(\mathbf{i}_2,\mathbf{j}_2)}{(1+r)^y} \right] \right\} \\ \lambda_{O1}: & r_1 \cdot C_a(\mathbf{i},\lambda_{O1}) + r_2 \cdot C_u(\mathbf{i},\lambda_{O1}) \\ & + \sum_{\mathbf{i}_2} \left\{ P(\mathbf{ij},\mathbf{i}_2\mathbf{j}_2,\lambda_{O1},k,y) \cdot \left[\frac{r_3 \cdot y \cdot U(\mathbf{i},\mathbf{i}_2)}{(1+r)^{y/2}} + \frac{V_{k+y}(\mathbf{i}_2,\mathbf{j}_2)}{(1+r)^y} \right] \right\} \\ \vdots & \\ \lambda_{Oq}: & r_1 \cdot C_a(\mathbf{i},\lambda_{Oq}) + r_2 \cdot C_u(\mathbf{i},\lambda_{Oq}) \\ & + \sum_{\mathbf{i}_2} \left\{ P(\mathbf{ij},\mathbf{i}_2\mathbf{j}_2,\lambda_{Oq},k,y) \cdot \left[\frac{r_3 \cdot y \cdot U(\mathbf{i},\mathbf{j}_2)}{(1+r)^{y/2}} + \frac{V_{k+y}(\mathbf{i}_2,\mathbf{j}_2)}{(1+r)^y} \right] \right\} \end{cases}$$

$$\text{for } k = 0, 1, \ldots, H - 1 \qquad (4)$$

where

y = number of stages for transition, defined by
$$y = \begin{cases} y_\lambda & \text{if } k + y_\lambda \leq H \\ H - k & \text{if } k + y_\lambda > H \end{cases}$$
H = number of stages in planning horizon (years);
y_λ = minimum life of rehabilitation activity λ, during which nothing should be done to pavement section;
$\lambda_{V1},\lambda_{V2}, \ldots, \lambda_{Vp}$ = elements of Λ_V, set of overlay alternatives considered;
$\lambda_{O1},\lambda_{O2}, \ldots, \lambda_{Oq}$ = elements of Λ_O, set of routine maintenance alternatives considered;
$C_a(\mathbf{i},\lambda)$ = agency cost for implementing alternative λ at distress condition $\mathbf{i}$;
$C_u(\mathbf{i},\lambda)$ = cost to users as a result of ongoing rehabilitation activity at distress condition $\mathbf{i}$;
$U(\mathbf{i},\mathbf{i}_2)$ = average annual excess cost to users as a result of pavement condition going from $\mathbf{i}$ to $\mathbf{i}_2$;
r = discount rate;
r_1, r_2, r_3 = parametric weightings of costs to agency and users;
$P(\mathbf{ij},\mathbf{i}_2\mathbf{j}_2,\lambda,k,y)$ = transition probability for rehabilitation activity λ, from pavement state $\mathbf{ij}$ at stage k to pavement state $\mathbf{i}_2\mathbf{j}_2$ at y stages ahead; and
$\mathbf{i}_2,\mathbf{j}_2$ = new condition and pavement structure states as a result of rehabilitation.

Accordingly, with λ_V, $\mathbf{j}_2$ is defined as $\mathbf{j}_2 = (n_0, n_1, \ldots, n_m, \lambda_V)$; with λ_O, $\mathbf{j}_2$ remains unchanged.

In the case of "failed" pavement sections, only overlay alternatives are considered in Equation 4. In most situations it is reasonable to assume that the maximum tensile strain occurs at the bottom of the uncracked asphalt-bound layer. The fatigue cracks generated then propagate to the surface. Thus, when the pavement becomes severely cracked, $\mathbf{j}_2$ is defined by $\mathbf{j}_2 = (m + 1, n_1, \ldots, n_m)$.

The optimal objective function is computed as a parametric sum of both agency and excess user costs so that the respective cost components can be weighted differently as judged by the management using cost parameters r_1, r_2, and r_3. In Equation 4, $C_a(\mathbf{i},\lambda)$ and $C_u(\mathbf{i},\lambda)$ are assumed to be incurred at the beginning of the stage, which can be easily modified to account for any time delay. In the case of excess user costs $U(\mathbf{i},\mathbf{i}_2)$ associated with pavement condition, the average of the excess user costs associated with the pavement conditions at the beginning of stage k and those at the beginning of stage $(k + y)$ is taken to be representative. Thus, these costs have been factored by the discount factor for $y/2$ years.

Boundary Conditions

The boundary conditions at the end of the planning horizon should reflect the long-term expected costs obtained by following an optimal rehabilitation policy from that time on. These costs are not easily established, requiring extensive analyses for a wide range of initial pavement conditions and structures. Instead, it is usual to characterize the value of the pavement section at the end of the cycle by a salvage value (*13*). These are assessed as negative costs according to

$$V_H(\mathbf{i},\mathbf{j}) = -S(\mathbf{i},\mathbf{j}) = -\left(\frac{L_R}{L_O}\right)E_k \qquad (5)$$

where $S(\mathbf{i},\mathbf{j})$ is the salvage value at the end of the planning horizon, determined as a simple proportion of the cost of the last overlay, E_k, according to the ratio of the remaining life, L_R, to the expected life of the overlay, L_O.

With this model, a pavement section with a lower amount of distress and longer mean life to failure at the end of the planning horizon will have a higher salvage value and may have a lower long-term expected cost.

TRANSITION PROBABILITIES

Mechanistic Pavement Performance Model

The transition probabilities are determined within a framework of a mechanistic pavement performance model of Chua et al. (*14*). The pavement section is first analyzed to determine the controlling structural response that governs the extent of damage for each distress mode. For the present purpose, a multilayered elastic analysis is adequate. The remaining life of the pavement before the distress exceeds prescribed levels can then be determined from the distress submodels.

For fatigue cracking, the maximum tensile strain in the asphalt bound layer is the controlling structural response, and the criteria adopted for fatigue cracking in the distress submodel are similar to those obtained from the AASHO Road Test (*15*). Accordingly, the allowable number of load repetitions at maximum tensile strain ε_t can be expressed as

$$N_{f45} = 18.4C\left[4.325 \times 10^{-3}\varepsilon_t^{-3.291}\left|\frac{E^*}{6.89}\right|^{-0.854}\right] \quad (6)$$

$$N_{f10} = 13.3C\left[4.325 \times 10^{-3}\varepsilon_t^{-3.291}\left|\frac{E^*}{6.89}\right|^{-0.854}\right] \quad (7)$$

where

N_{45}, N_{10} = allowable number of repetitions for 45 and 10 percent cracking, respectively;
$|E^*|$ = dynamic asphalt mixture modulus (kPa); and
C = factor accounting for asphalt content and degree of compaction suggested by Pell and Cooper (*16*).

The accumulated damage caused by a range of strain levels due to varying applied load and temperature changes (which affect the stiffness of the asphalt bound layer) is determined by the linear summation of cycle ratios (*17*) as

$$\sum_i \left(\frac{n_i}{N_{wi}}\right) \leq 1 \quad (8)$$

where n_i is the number of load applications at tensile strain ε_t and N_{wi}, the corresponding allowable number of load applications for w percent cracking. When the sum reaches unity, w percent cracking in the pavement—in particular, 45 or 10 percent cracking corresponding to Equations 6 and 7, respectively—is deemed to have taken place.

Stochastic Framework

Generally, a distress state such as depicted in Table 1 is characterized by two damage indexes: L_{w_j} and L_{w_k}, representing the lower and upper bounds, respectively. For a failed section (severely cracked), only a lower bound applies. The damage index is defined so that a value of unity denotes 45 percent fatigue cracking, whereas a value of 0.72 denotes 10 percent cracking derived from the ratio of N_{10}/N_{45}. For w percent cracking, the damage index L_w is determined by the ratio N_w/N_{45}.

Consider a limit-state function $g_{wT}(\mathbf{x})$ such that

$$g_{wT}(\mathbf{x}) = L_w - \sum_{t=1}^{T}\sum_i \left(\frac{n_{it}}{N_{45i}}\right) \quad (9)$$

where

$\mathbf{x}$ = vector of input variables in mechanistic model;
n_{it} = actual number of load applications at tensile strain ε_i in tth year;
N_{45i} = allowable number of load applications at tensile strain ε_i, corresponding to 45 percent cracking; and
L_w = damage index corresponding to w percent extent of fatigue cracking.

If $g_{wT}(\mathbf{x}) < 0$, the linear sum of cycle ratios after T years of load applications would have exceeded the damage index, and fatigue cracking would have exceeded w percent extent of pavement surface. Thus, the probability of transition into a distress state bounded by L_{w_j} and L_{w_k} would be given by

$$P_F = P[g_{w_jT}(\mathbf{x}) < 0] - P[g_{w_kT}(\mathbf{x}) < 0] \quad (10)$$

For a pavement with initial condition L_{w_i}, the limit-state function should be modified to

$$g_{wT}(\mathbf{x}) = L_w - \sum_{t=1}^{T}\sum_i \left(\frac{n_{it}}{N_{45i}}\right) - L_{w_i} \quad (11)$$

Each term in the right-hand side of Equation 10 is evaluated as

$$P[g_{wT}(\mathbf{x}) \leq 0] = \int_{g_{wT}(\mathbf{x}) \leq 0} f_{\mathbf{x}}(\mathbf{x})d\mathbf{x} \quad (12)$$

where $f_{\mathbf{x}}(\mathbf{x})$ is the joint probability density of variables $\mathbf{x}_1$, $\mathbf{x}_2$, . . . , $\mathbf{x}_n$. The exact solution to Equation 12 involves an n-fold integration of the joint probability density of the n basic variables. In general, numerical integration is necessary since an analytical evaluation is possible only in a few special cases. However, it becomes computationally difficult when the number of variables is more than just a few. Instead, the solution is determined by full-distribution reliability methods (*14,18*).

MANAGEMENT DECISION PROCESS

The decision process for pavement management is shown schematically in Figure 1. The inputs to the optimization model include the transition probabilities derived from the mechanistic distress submodels, a matrix of agency and user excess costs, and salvage values derived via a cost submodel in StoMe, a stochastic mechanistic PMS (*19*), and a set of management policies. The management policies comprise a set of rehabilitation alternatives and their minimum lives, y_λ of Equation 4; a rehabilitation-condition policy that determines the range of alternatives feasible for each pavement condition (e.g., overlay when failed and routine maintenance/overlay otherwise); a performance criterion that defines the minimum reliability of the rehabilitation activity or, conversely, the maximum probability of transition to failure; the cost weightings of Equation 4; and the discount rate.

The result from the optimization is the optimal strategy for each pavement section along with the associated expected annual performance and capital outlay. The expected performance gives the probability that the pavement section can be found in the various states at the beginning of each year in the planning horizon, and the expected capital outlay gives the expected cost of rehabilitation to be expended by the agency at the start of each year, expressed in present money value. Depending on the actual performance of the pavement section, the true capital expenditure can be higher or lower than the expected. Since all costs are expressed in dollars per lane mile, the sum of the expected annual capital outlay weighted by the lane miles of the section will yield the expected yearly budget requirements to implement the optimal policy for the network. The policy is optimal in the sense of least total expected cost discounted to present value terms.

The sum of the expected performance of each pavement section weighted by the lane miles will yield the expected fraction of the network that will be found in the various pavement condition states at the beginning of each year through the planning horizon. In this way, management can predict the expected fraction of the network that will manifest a specified physical distress indicative of poor ride quality to the users.

NUMERICAL EXAMPLE

Data

The pavement section used in the present illustration is a three-layered system comprising a 7-in. asphalt concrete layer over a 12-in. granular base layer underlain by subgrade. The properties of the pavement layers, environment, and traffic variables are given in Table 3. The table also shows the distribution type and variation in the variables. Most of the distributions are similar to those obtained from available data (*20,21*).

For simplicity, a single category of truck traffic and a single seasonal variation in air temperature, base, and subgrade stiffnesses have been assumed, although the stochastic model is capable of handling multiple categories of truck traffic and seasonal variations. The effect of increasing the number of random variables in the data set to account for more general applications will only mean more computer processing time for each analysis.

Management Inputs

The rehabilitation alternatives considered in the present study include routine maintenance, 2-in. asphalt concrete overlay (thin, λ_{V1}), and 4-in. asphalt concrete overlay (medium, λ_{V2}). The rehabilitation-condition policy adopted will require an overlay when the pavement is failed (i.e., $D1$), and either an overlay or routine maintenance otherwise. Furthermore, a minimum life of 7 years is imposed on overlays so that no further overlay is permitted within this time after an overlay

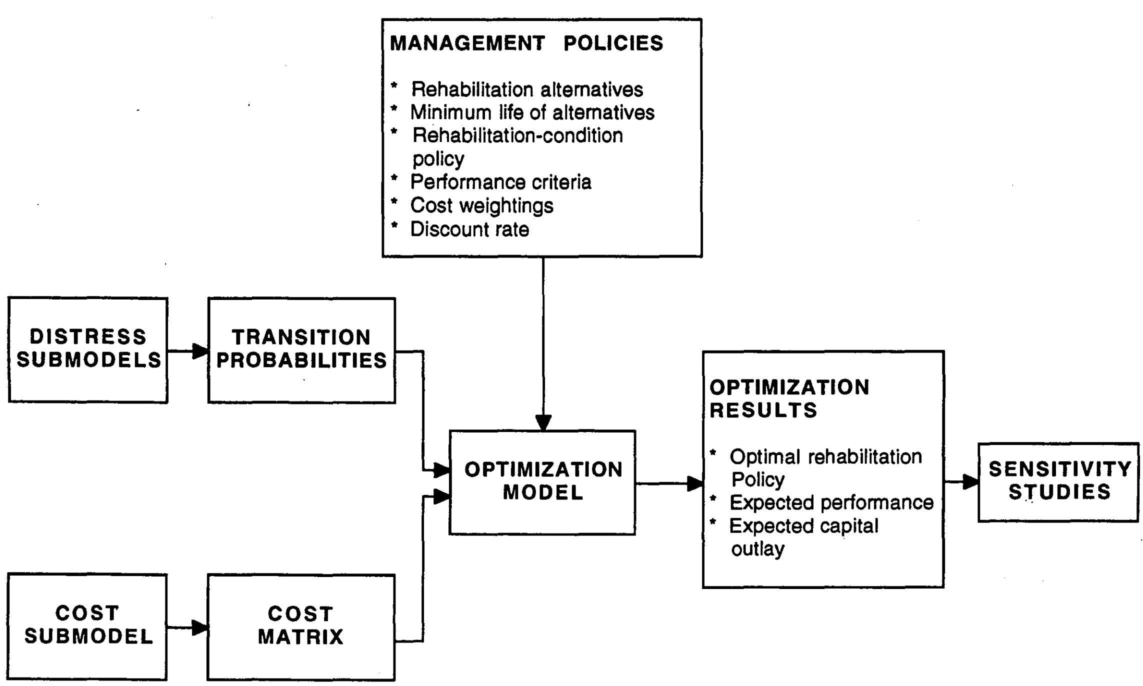

FIGURE 1 Management decision process.

TABLE 3 Distribution of Variables

Variable Description	Distribution Type	Mean	Standard Deviation
Mean monthly temperature	Weibull	14.56°C	4.21°C
Annual traffic volume	Lognormal	12,000,000	504,000
Annual growth rate	Lognormal	4.5%	1.0%
Axle load[c]	Shifted Exponential	75.65 kN	13.35 kN[a]
Tire pressure[c]	Normal	620 kPa	103.4 kPa
Truck percentage	Lognormal	10.0%	0.1%
Axle factor	Normal	3.5	0.175
Wheel distance	Deterministic	450 mm	-
Lane factor	Deterministic	1.0	-
Loading time	Deterministic	0.02 sec	-
Asphalt content	Uniform[b]	10.0%	11.0%
Volume of air voids	Uniform[b]	4.0%	5.0%
Penetration index	Deterministic	0.0	-
Ring & Ball Softening Point	Deterministic	59°F	-
Poisson's ratio (asphalt)	Deterministic	0.3	-
Base stiffness	Lognormal	206.7 MPa	30.94 MPa
Subgrade stiffness	Lognormal	68.9 MPa	10.27 MPa
Poisson's ratio (base)	Deterministic	0.35	-
Poisson's ratio (subgrade)	Deterministic	0.40	-
Base thickness[d]	Lognormal	300 mm	20 mm
Asphalt concrete thickness[d]	Lognormal	175 mm	10 mm
Overlay thickness	Lognormal	as specified	10 mm

Notes:
a) Shift in Exponential distribution
b) Lower and upper limits for uniform distribution indicated in the mean and standard deviation columns, respectively
c) Axle load and tire pressure are positively correlated with coefficient 0.85
d) Base and asphalt concrete thicknesses are negatively correlated with coefficient -0.85

is laid. The analysis is performed over a planning horizon of 14 years at a 4 percent discount rate.

The costs to the agency for the various alternatives are presented in Table 4. It is expected that preparation costs will increase with deteriorating condition of the pavement. Furthermore, with a thicker overlay less preparation will be necessary since the minor defects can be ignored. The placement costs are a function of the volume of asphalt needed for the overlay. The corresponding excess user costs associated with the rehabilitation works are also included in the table for day- and night-time lane closures. In essence, these costs are contributed by the increased time and fuel expended in the queue at the lane closure (*19*). For the present study, r_1 and r_2 are unity in value. The excess user cost due to deteriorating pavement condition has not been included in the study for lack of quantification.

Analysis

Transition Probabilities

The 1-year transition probabilities to failed states for routine maintenance from not-failed states are shown in Figure 2 for Years 0 to 13. It can be seen that the transition probabilities increase by up to 34 percent in that period. An increase by up to 46 percent is evident in the case of 8-year transition probabilities for thin overlays also shown in the figure. The increases can be attributed to the annual growth in the traffic volume. Thus, the assumption of a constant transition matrix in the Markov decision process is invalid when traffic growth is considered.

Optimal Rehabilitation Policy

Without any rehabilitation treatment, it is expected that the condition of the pavement section will deteriorate with time as demonstrated in Figure 3, which depicts the probability that the pavement is in the not-failed state. By the end of the planning period, the probability of not-failed has fallen below 50 percent. With a rehabilitation strategy, the rapid deterioration of the pavement section is impeded when the pavement structure is restored and strengthened by the asphalt concrete overlays. The probability of the not-failed condition is maintained above 78 percent throughout the planning period, averaging about 81 percent.

The optimal policy is to provide a thin overlay whenever the pavement fails and routine maintenance otherwise. The expected capital outlays required at the end of each year to implement the optimal policy are shown in Figure 4. At the end of Year 0, the capital outlay is only $95/lane-mi for routine maintenance. Subsequently, the actual expenditure will depend on the actual condition of the pavement at the end of that year.

Effect of Time of Lane Closures

The excess user costs are higher during daytime lane closures because of increased delays and more fuel consumed as a

TABLE 4 Agency and User Excess Costs

		Condition States		
		D1	D2	D3
Agency Costs				
Preparation	Routine Maintenance	$0	$1240	$95
	Thin Overlay	$3280	$1540	$955
	Medium Overlay	$1910	$1195	$955
Placement	Routine Maintenance	$0	$0	$0
	Thin Overlay	$29850	$29850	$29850
	Medium Overlay	$59700	$59700	$59700
Excess User Costs				
0% Day-time Closure	Routine Maintenance	$0	$72	$48
	Thin Overlay	$95	$95	$95
	Medium Overlay	$190	$190	$190
100% Day-time Closure	Routine Maintenance	$0	$15990	$10660
	Thin Overlay	$21320	$21320	$21320
	Medium Overlay	$42640	$42640	$42640

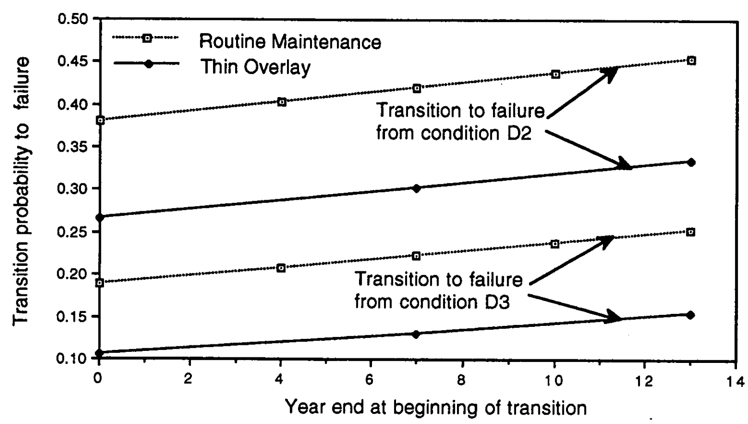

FIGURE 2 Variation of transition probabilities with time.

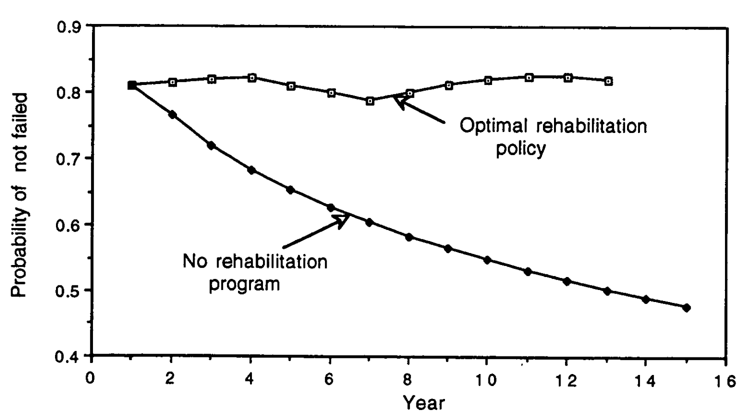

FIGURE 3 Effect of rehabilitation policy on pavement condition.

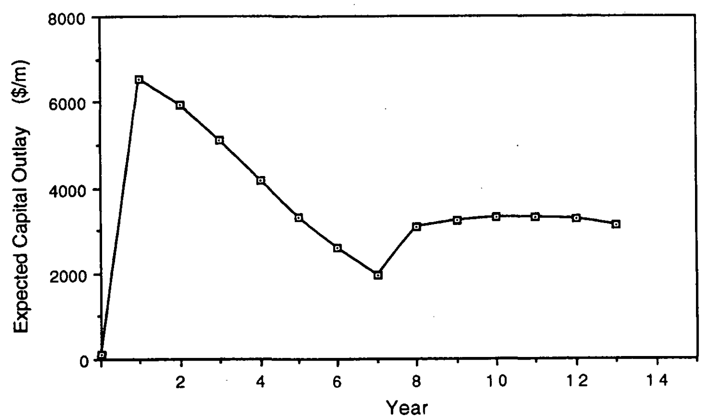

FIGURE 4 Expected capital outlay for optimal rehabilitation policy.

result of longer queues due to heavier daytime traffic. For demonstration purposes, the excess user costs for various proportions of day- and nighttime construction are obtained simply by direct proportioning from the values indicated in Table 4.

The optimal policy with the increasing proportion of daytime closures is no longer overlay only when failed. For example, the optimal policy for 40 percent daytime closure is shown in Table 5 as a function of pavement condition and structure. The effect of increasing user costs is summarized in Table 6, which gives the number of not-failed condition states that require thin overlays. Essentially, overlays are preferable to reduce the number of rehabilitation activities to keep down excess user costs as they become more and more substantial compared with total rehabilitation costs, especially with routine maintenance.

Effect of Discount Rates

There have been controversies over the rate of discounting that should be applied for the economic evaluation of public projects. A real rate of 4 percent, reflecting the yield for long-term government bonds, has been used in this study (*22*). As the discount rate is increased, the more-expensive rehabilitation alternative is deferred in favor of cheaper alternatives. Thus, routine maintenance tends to be favored to postpone the cost of overlays, as demonstrated in Table 7, which shows the number of not-failed condition states requiring overlays decreasing with increasing discount rate for the case of 40 percent daytime lane closure.

At a 0 percent discount rate, thin overlays are optimal for some not-failed condition states at the early years, even in Year 1. At 6 percent upwards, thin overlays for not-failed condition states are deferred until after Year 7. Eventually, at 15 percent and up, thin overlays are restricted to the failed states.

Modified Rehabilitation Policies

As seen in the preceding sections, a rehabilitation-condition policy that stipulates overlays only when failed can be simplistic and may not be the optimal in many situations. The result is increased costs, as shown in Figure 5, when compared

TABLE 5 Optimal Policy for 40 percent Daytime Lane Closures

Year End	Pavement Structure	Alternative at Condition State D1	D2	D3	Year End	Pavement Structure	Alternative at Condition State D1	D2	D3
0	(0)	2	2	1	1-6	(0)	2	1	1
7	(0)	2	2	2	8	(0)	2	2	2
	(0,V1)	2	2	2		(0,V1)	2	2	1
	(0,V2)	2	2	1		(0,V2)	2	2	1
	(1,V1)	2	2	1		(1,V1)	2	2	1
	(1,V2)	2	2	2		(1,V2)	2	1	1
9	(0)	2	1	2	10-13	(0)	2	1	1
	(0,V1)	2	1	1		(0,V1)	2	1	1
	(0,V2)	2	1	1		(0,V2)	2	1	1
	(1,V1)	2	1	1		(1,V1)	2	1	1
	(1,V2)	2	1	1		(1,V2)	2	1	1

Notes: 1 denotes routine maintenance
2 denotes thin overlay

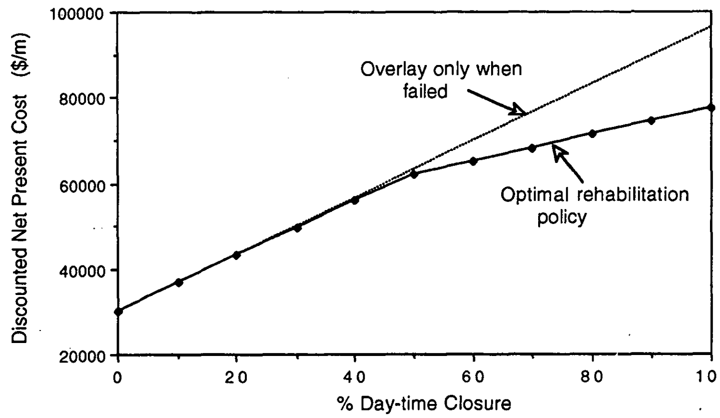

FIGURE 5 Effect of nonoptimal policy.

TABLE 6 Effect of Time of Lane Closures

Proportion of Day-time closures (%)	Discounted net present cost ($/lane-mile)	Number of not-failed states requiring overlay
0	30,130	0
10	36,750	0
20	43,370	0
30	49,830	4
40	56,170	15
50	62,100	22
100	77,380	44

TABLE 7 Effect of Discount Rates

Discount rate (%)	Discounted net present cost ($/lane-mile)	Number of not-failed states requiring overlay
0	62,330	19
4	56,170	15
6	52,450	11
10	46,060	4
15	39,650	0
20	34,740	0

with the optimal. Discounted net present cost departures from the optimal are more when excess user costs become more substantial, up to 25 percent higher than the optimal for the 100 percent daytime lane closure. The optimal strategy derived from the dynamic programming decision process can be very different from any heuristic-type rehabilitation-condition policy. In fact, a more restrictive rehabilitation-condition policy always incurs a discounted net present cost that is never less than the optimal unrestricted case.

CONCLUSIONS

The optimization is formulated in a dynamic programming model that incorporates a closed-loop decision process. The optimal policy obtained from the model always yields a discounted net present cost that is lower than any heuristic type rehabilitation-condition policy. The optimal policy will also be more cost-effective than one with imposed overlays regardless of pavement condition, which is characteristic of the open-loop decision process that most PMSs use.

The formulation of the states classification in the optimization model permits the individual modes of distress to be modeled without masking the individual defects by a composite index of pavement performance. It also provides the framework for using stochastic mechanistic distress submodels to derive the transition probabilities. In this way, the Markovian time-invariant assumption used in some PMSs is no longer necessary. In fact, for a mean of 3 percent annual growth in traffic, the results in the present study have shown that the transition probabilities do change, and by as much as 46 percent over the planning period.

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