Use of Expert Opinion in Two Pavement Management Systems

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The application of a pavement management system (PMS) to optimize the allocation of scarce budgeting resources for a network of highways is becoming more common both in developed and in developing countries. The use of expert opinion and expert systems may help to improve a PMS as well as to ease the computational burden in some cases. In such systems, degradation models are necessary to predict the impact of scheduled maintenance so that both the long- and short-term results are optimized. Expert opinion is also often used to determine the feasible maintenance and rehabilitation actions for pavement in different condition states. From the set of feasible actions, the network level optimizer will select a multiyear optimal strategy. Two different approaches are illustrated: one for the Ohio Department of Transportation, and the second for Saudi Arabia. An algorithm is presented for updating expert opinion–based degradation models for pavements. Bayesian updating procedures are given that automatically update the degradation models with new network survey data. These procedures continually self-adjust the PMS to fit the specific conditions found in the network. This process results in improved prediction models and a better use of resources.

A pavement management system (PMS) should be able to predict the future degradation of the pavement as well as the improvement that results from a particular maintenance action. This ability to predict may depend on many parameters and may be the result of empirical, mechanistic, or empirical-mechanistic models. In order to provide a network-level solution, the condition prediction models must depend on readily available information on every segment in the network. Test results that will be available for only a small portion of the network may be used in a project-level analysis, but such information often cannot be incorporated into a network optimization model.

Condition prediction models usually are based on actual field data relevant to the network being modeled. A PMS requires a well-planned data base. Even with such a data base, degradation models are not always readily available for a given network even in well-developed countries.

Selected aspects of two different PMSs are briefly covered. One developed for the Ohio Department of Transportation (ODOT) has deterministic degradation models that are based on detailed statistical analysis of historical data. The ODOT PMS (*1*) predicts pavement condition rating (PCR) deduct values for a given pavement segment strategy considered in its network optimization. The second PMS discussed is part of a highway maintenance management system (*2*) developed for the Kingdom of Saudi Arabia that integrates a PMS, a bridges and structures management system, and a nonpavement management system. It is a stochastic optimization system based on minimal historical data. It predicts the probability of a pavement segment transitioning from Condition State i to Condition State j for the feasible maintenance and rehabilitation (M&R) actions.

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ODOT PMS

The ODOT network level optimization model is an integer 0–1 linear program that is approximated by a standard linear programming (LP) solution using generalized upper bounding (GUB) techniques. The use of the GUB in the standard LP allows large 0–1 problems to be solved quickly. For the few noninteger solutions [theoretically there will be only a small number (*3*)], these require a project-level choice by the decision maker.

The pavement condition rating (PCR) is one of the key ODOT factors in determining both the condition of given segment as well as the condition of the entire network. The PCR is a weighted average of many distresses, e.g., raveling, bleeding, patching, rutting, and cracking. Expert opinion from both ODOT and other pavement engineers was used to develop lumped distress groups. On the basis of the severity and extent of these lumped distress categories, feasible M&R actions were selected for the different pavement types (rigid, composite, flexible, and continuous reinforced concrete) using a panel of experts.

The ODOT PMS develops 6-year plans for each segment within the state-wide network. The plan is an ordered set of six M&R actions. Only a limited number of applicable plans can be associated with each segment while maintaining the entire highway system in satisfactory condition. Expert opinion was used to construct an expert system that develops the potential 6-year plans on a segment-by-segment basis. These feasible plans are then input to the optimization. On the basis of the available budget and desired performance goals specified, the optimization selects one of the individual segment feasible plans for each segment. The optimization will either maximize performance (in terms of PCR) subject to budgetary limitations or it will minimize cost subject to performance constraints.

The feasible 6-year plans are developed independently for each highway segment and thus represent the possible plans from a project-level point of view for a given segment. The optimization then selects one plan for each segment that is optimal from a network perspective. Thus the plan chosen for a given segment is determined considering all segments in the network simultaneously. This process could not be done without the use of sophisticated optimization packages. An engineer can consider the possible 6-year plans in isolation for a segment, but it would not be possible for that individual to perform the trade-offs necessary to arrive at a network-optimal solution. This expert system also reduces the solution space considerably and has resulted in lessening the computational burden.

ODOT'S DETERMINATION OF FEASIBLE M&R ACTION PLANS

Conceptually, the PMS network optimization models could allow the possibility of assignment of any M&R action to a pavement segment. Although this assignment would not theoretically cause any difficulties, it may create problems in practice. It is often mandatory to follow agency policies that may not permit certain M&R actions for pavement segments in given conditions. Thus it is reasonable to develop an expert system for the network-level selection procedures that determine the feasible M&R alternatives available to the optimizer.

The PCR for a given segment is the sum of weighted deduct values representing the severity and extent of many pavement distresses. Table 1 indicates how these individual distresses are lumped into categories for the four ODOT multilane pavement types. Jointed concrete, for example, has three lumped distress categories: surface, Joint 1, and Joint 2. Table 2 presents the possible M&R actions that may be applied to a segment in a given year. Table 3 presents the feasible M&R actions for Interstate jointed concrete pavements as a function of the severity and extent of these lumped distress categories. Majidzadeh et al. (*1*) give similar information for both Interstate and other multilane pavements for the four pavement types seen in Table 1.

Table 3 is used to select the maintenance actions that would be appropriate for each of the different distress groups. The

TABLE 2 DEFINITION OF ODOT M&R ACTIONS

Description	Action Code
Do nothing	000
Routine maintenance	010
Seal coat	020
Joint crack underseal repair	030
CPR	040
Non-structural overlay with minimum repairs	050
Non-structural overlay with repairs	060
Structural overlay with minimum repairs	070
Structural overlay with repairs	080
Crack and seat	090
PCC structural overlay	100
Reconstruction with flexible	110
Reconstruction with rigid	120
Reconstruction with composite	130

individual distresses are combined, and on the basis of expert opinion–established limits (*1*) the lumped distress categories are characterized by severity and extent.

As an example, let a given segment of jointed concrete Interstate have medium severity and extensive extent for both Joint 1 and Joint 2. This segment also has low severity and occasional extent for surface. These values result in Actions 010, 040, and 080 for Joint 1 and Joint 2, and Action 000 for surface. Thus, the possible actions for this pavement are 000, 010, 040, and 080. (The possible actions from each distress

TABLE 1 COMPOSITION OF ODOT PCR GROUPS FOR DIFFERENT PAVEMENT TYPES

Flexible	Composite[a]	Jointed Concrete	CRC
Structural 1: • potholes • bleeding • settlement	Surface 1: • raveling • popouts • longitudinal cracking • crack sealing	Surface: • surface deterioration • pumping • settlement • longitudinal cracking	Pavement: • patching • settlement • transverse cracking • longitudinal cracking • punchout
Structural 2: • rutting • wheel track cracking • block and transverse cracking • corrugation	Surface 2: • rutting • debonding • settlement	Joint 1: • pumping • faulting • transverse cracking • corner break	Surface: • spalling • pressure damage
Surface: • ravelling • bleeding • random cracking • crack sealing deficiency • longitudinal cracking • edge cracking	Joint 1: • pressure damage • patching • pumping • shattered slab	Joint 2: • pressure damage • patching • joint spalling • seal damage	
	Joint 2: • transverse cracking • joint reflection cracking • other reflection cracking		

[a]Either jointed concrete or CRC covered with an asphalt overlay.

TABLE 3 ODOT M&R SELECTION CHART FOR INTERSTATE JOINTED CONCRETE PAVEMENTS

Distress Group	Severity	Extent: Occasional	Frequent	Extensive
Joint 1 & 2	Low	000	000	010
	Medium	010/070	010/070	010/040/080
	High	030/080	040/090/100	040/090/120
Surface	Low	000	000	000/010
	Medium	000/010	000/010	060
	High	050	060	060

group are rank-ordered and duplicates eliminated.) Of course, only Action 080 (structural overlay with repairs) would repair all problems, but the other actions cannot be ruled out as being cost-effective when considering a multiyear planning period and a finite money supply.

The above scheme has resulted in reducing the possible number of actions from 14 to 4 in the example given, although some combinations of pavement distresses may result in more actions. Only the highest four actions are chosen if this list also contains Actions 000 or 010 (do nothing or routine maintenance); if one of these actions is not part of the list, Action 010 is inserted as a fifth action. This is necessary in order to deal with budget constraints.

The same procedure is used in other years of the planning horizon. First, the condition of the pavement 1 year after applying a particular action is predicted using PCR performance prediction models; then the appropriate tables are used to determine the proper actions for these (new) conditions. This procedure is carried out for each year in the planning period, except that the number of actions is restricted to three (or four if Action 010 has to be added) for the second year and two (or three if Action 010 has to be added) for the third through the sixth years.

Although this procedure has drastically limited the number of possible action plans for a particular pavement segment, the resulting number of plans (a maximum of 1,620 plans are possible) is still too large to be practical either in real life or as far as the optimizer is concerned. Therefore, a set of heuristic rules has been developed to further reduce the number of possible plans to be considered by the optimizer. These rules have been developed in consultation with ODOT design and maintenance engineers.

By definition,

k_n = number of actions in Year n,
C_n = pavement condition at the beginning of Year n,
A_n = action taken in Year n, and
P_n = PCR at end of Year n (after Action A_n taken).

The rules used to reduce the number of action plans are presented in Table 4. The rules to reduce the possible number of actions for Year $n + 1$ are applied according to Table 5 for Year n. The following considerations apply:

1. Actions A_n are selected on the basis of pavement condition C_n. The maximum number of actions is five for the first year, four for the second year, and three for subsequent years (see Rule 3 of Table 4).
2. If Action $A_n \geq 050$, $P_n = 100$; otherwise only those distresses directly addressed by Action A_n are eliminated.
3. Using Action A_n, the amount of distress in each distress group expected in Year $n + 1$ is predicted from the PCR performance prediction equations. The condition C_{n+1} is obtained from the condition C_n and the predicted distresses developed during 1 year.
4. For mandatory projects $k_1 = 1$ and the action is that specified for the mandatory project for Year $n = 1$. Actions for years $n > 1$ can be selected in the normal fashion or the entire action plan over the planning period can be input as mandatory.

This expert system has been extensively tested and validated. It is an important part of an efficient multiyear PMS that also provides guidance to the project-level analyses that

TABLE 4 ODOT RULES FOR REDUCING THE POSSIBLE NUMBER OF ACTION PLANS

Rule No.	Rule
1.	If year n action $\geq$ 020, year n+i action $\leq$ 010, i = 1,3
2.	If year n action $\geq$ 040, year n+i action $\leq$ 010, i = 1,5
3.	The maximum number of actions considered each year are k_1=4, k_2=3, k_3 to k_6=2 if either action 000 or 010 are among the feasible actions; otherwise action 010 is added to the list and the maximum number of actions is increased by one.
4.	If year n action is m$\geq$ 020, year n+i action cannot equal m; i = 1,4.

TABLE 5 APPLICATION OF ODOT RULES FOR YEAR n TO DETERMINE FEASIBLE ACTIONS FOR YEAR $n + 1$

Year n action	Apply rule(s)
000/010	None
020	4,1
≥ 040	4,2,1

Note: If $k_{n+1} = 0$ as a result of applying the above rules, then $k_{n+1} = 2$ and actions are 000 and 010

follow the completion of the optimization runs. Complete documentation of the entire system was provided by Majidzadeh et al. (*1*).

SAUDI ARABIAN PMS

Saudi LP Formulation Illustrating Restriction to Feasible M&R Actions

The Saudi PMS uses a different approach that is more applicable to the situation with limited historical data. The Saudi PMS uses a stochastic network-level optimization that is based on a Markov process and automatically updates its condition prediction models using Bayesian procedures discussed later. In addition, it also uses expert opinion to determine the feasible actions for pavement in any condition state. It explicitly addresses the limited number of feasible M&R actions in its network optimization models. An example of this is given later, but it is worthwhile to briefly describe the three network-level LP models used in this PMS.

The first is a long-term (or steady state) goal-setting model. It determines the optimal condition states of the network so that cost is minimized subject to top management's performance objectives. In all three models (solved for each stratum), top management specifies lower and upper bound constraints for the minimum and maximum proportion of the stratum that should be in desirable and undesirable condition states, respectively.

The second network optimization model is the multiyear model that determines the optimal policy to move from the current network condition levels to the optimal steady state levels determined by the long-term model mentioned in the previous paragraph. This model is also solved separately for each stratum. If the sum of the desired budget from all strata is within the amount that can be obtained, then this is the last model run in the sequence of the three optimization models. These first two models closely parallel the Arizona models (*4*) that have become well known.

The third network model is a financial exigency model that ties together all the strata with a global first-year budget constraint. This budget constraint links together the individual multiyear optimization models described briefly in the previous paragraph by the use of a Lagrange multiplier and parametric programming techniques.

Obviously, the computational burden of solving these three LP models can be considerable. This is especially true of the latter two models that are large linear programs.

The notation for the multiyear model objective function is defined as follows:

Parameter notation:

I = index set of condition states (= 1, 2, . . . , n);
M_i = index set of feasible Maintenance Actions a for pavement segments in Condition State i (a_1, a_2, . . . , a_{mi});
$C_{ia}(s)$ = average cost of applying Maintenance Action a to one pavement segment in Stratum s and Condition State i; and
r = discount rate for computing net present value.

Decision variable notation:

$w^t_{ia}(s)$ = proportion of the segments in Stratum s that is in Condition State i and should receive Maintenance Action a in Year t.

Dependent variable notation:

$\hat{C}(s)$ = expected net present value of cost per segment in Stratum s of a maintenance policy.

The multiyear optimization model objective function for Stratum s follows:

$$\text{Minimize } \hat{C}(s) = \sum_{t=1}^{T} \sum_{i \in I} \sum_{a \in M_i} (1 + r)^{1-t} w^t_{ia}(s) C_{ia}(s) \qquad (1)$$

As seen in Equation 1, the summation of the objective function is over Time t, Condition States i, and Actions a. However, instead of all possible Actions a, only those that are determined to be feasible (based on expert opinion) for Condition State i are allowed as choices in the LP (as indicated by the summation over $a \in M_i$ instead of over all possible actions). This procedure results in savings of computational resources because only a subset of the possible M&R actions is considered for each condition state.

Saudi Prediction Models

Expert opinion has played a major role in the development of the initial condition prediction equations for the Saudi PMS. An extensive search of the literature as well as use of mechanistic models was used to develop initial empirical regression equations. Because of the lack of historical field data, the initial regression equations could not be directly developed for actual Saudi conditions. Expert opinion from pavement engineers was used to modify published prediction models, where available, for the variables used to determine the condition state of each pavement segment in the Markovian-based network optimization models used in this PMS.

The Saudi PMS classifies a pavement segment into one of 324 possible condition states on the basis of rutting, cracking, delta-cracking (1-year change in cracking), index to first crack, and roughness. Three condition prediction equations are required for each M&R action within each stratum. Within the PMS, there are 20 possible M&R actions (Table 6) and various strata (based on functional class, climate, etc.). Condition prediction equations for the change in rutting, change in roughness, and change in cracking were developed. These equations predict the 1-year change in the corresponding distress for a given M&R action. The change in cracking prediction model is used to produce joint probabilities for cracking and delta-cracking. No prediction equation is required for index to first crack because it is a table look-up based on the chosen M&R action.

Past published work for a similar climate in the state of Arizona (*5*) in the United States resulted in empirical linear regression models for cracking and roughness; however, the literature review could not find any similar empirical prediction equations for rutting. Stepwise regression analysis of available data combined with expert opinion was used to develop an empirical regression for rutting. A team of pavement engineers worked to modify these equations to adjust them as much as possible to conditions in Saudi Arabia.

Automated annual surveys will be performed for the entire pavement network in the Kingdom. This procedure provides the field values for the variables defined earlier as well as others, e.g., raveling and skid resistance. These annual network surveys will provide the field data necessary to improve all the prediction equations. The initial regression equations will be automatically adjusted using Bayesian statistical updating techniques.

TABLE 6 LIST OF POSSIBLE M&R ACTIONS FOR SAUDI HIGHWAY NETWORK

Action No.	M&R Action
1	Do Nothing
2	Minor Maintenance (Crack Sealing, Pothole, Patching)
3	Seal Coat (Sand, Slurry, or Fog Sealing)
4	Surface Treatment (Aggregate Chip Seal)
5	Overlay with Repair - 30 mm
6	Overlay with Repair - 50 mm
7	30 mm mill + 30 mm replace
8	30 mm mill + 60 mm replace
9	50 mm mill + 50 mm replace
10	50 mm mill + 80 mm replace
11	80 mm mill + 80 mm replace
12	80 mm mill + 110 mm replace
13	110 mm mill + 110 mm replace
14	>110 mm mill + >110 mm replace
15	50 mm Recycling
16	80 mm Recycling
17	110 mm Recycling
18	> 110 mm Recycling
19	Reconstruction on Aggregate Base
20	Reconstruction on Asphalt Concrete Base

Bayesian Updating of Condition Prediction Parameters

The condition prediction models mentioned earlier generate the transition probabilities that drive the Markov-based linear programs. They also provide the prior distributions required for the Bayesian updating (*6*). The regression parameters of the prediction models are self-adjusted using new annual survey data and result in improved transition probabilities. This automatic adaptation of the condition prediction models results in more accurate degradation estimates over time.

A general description of Bayesian updating of the regression parameters follows. The notation is generalized from the explicit equations used for the condition prediction of individual variables. The following notation is to be used:

$\mathbf{Y}$ = Vector of dependent values, e.g., the data for the actual change in cracking;
$\mathbf{X}$ = Design matrix created from the independent variables, e.g., from the variables in the right hand side of a condition prediction equation; and
$\mathbf{b}$ = Regression parameter vector to be estimated. These are the coefficients of the prediction models.

Then the least squares solution for the initial prediction equations is

$$\mathbf{b}_{\text{init}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y} \tag{2}$$

The prior distribution for the $\mathbf{b}$ is then a multivariate normal (MVN) as follows:

$$\text{Prior distribution of } \mathbf{b} = \text{MVN}(\mathbf{b}_{\text{init}}, \mathbf{V}_{\text{init}})$$

where $\mathbf{V}_{\text{init}}$ = covariance matrix of $\mathbf{b}_{\text{init}}$.

These equations address the development of the initial prior distribution, i.e., $\mathbf{V}_{\text{init}}$ becomes the first $\mathbf{V}_{\text{prior}}$ and $\mathbf{b}_{\text{init}}$ becomes the first $\mathbf{b}_{\text{prior}}$. After each Year t, the prior will be updated to develop a posterior distribution that will be used to calculate updated transition probabilities. Upon completion of that, the posterior distribution for Year t becomes the prior distribution for Year $t + 1$. In the development of the posterior distribution, it is assumed that Year t data have just been collected. From this, ordinary least squares parameter estimates for Year t data will be used to perform the Bayesian updating resulting in posterior parameter estimates.

For Year t,

$$\mathbf{b}_t = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}$$

$$\mathbf{V}_t = \text{Year } t \text{ covariance matrix for } \mathbf{b}_t \tag{3}$$

where $\mathbf{X}$ and $\mathbf{Y}$ now represent the current year's data.

Then the posterior distribution for the desired regression parameter vector $\mathbf{b}_{\text{post}}$ is calculated.

Posterior distribution of $\mathbf{b} = \text{MVN}(\mathbf{b}_{\text{post}}, \mathbf{V}_{\text{post}})$

where

$$\mathbf{V}_{\text{post}}^{-1} = \mathbf{V}_{\text{prior}}^{-1} + \mathbf{V}_t^{-1} \tag{4}$$

$$\mathbf{b}_{\text{post}} = \mathbf{V}_{\text{post}}(\mathbf{V}_{\text{prior}}^{-1}\mathbf{b}_{\text{prior}} + \mathbf{V}_t^{-1}\mathbf{b}_t). \tag{5}$$

This process will continue annually, and the posterior parameters will be used to develop the updated transition probabilities. In the following simple example, the regression is modeling only a simple straight-line relationship between the dependent variable y and a single independent variable x. The prior estimates were formed using ordinary least squares with the following results:

$$y = 11.33 + 4.38x$$

$$\mathbf{b}'_{\text{prior}} = (11.33, 4.38)$$

$$\mathbf{V}_{\text{prior}} = \begin{bmatrix} 69.80 & -4.56 \\ -4.56 & 0.32 \end{bmatrix}$$

The current survey data (time period t) results in the following (using ordinary least squares):

$$y = 17.43 + 3.92x$$

$$\mathbf{b}'_t = (17.43, 3.92)$$

$$\mathbf{V}_t = \begin{bmatrix} 31.40 & -2.16 \\ -2.16 & 0.16 \end{bmatrix}$$

Following these mathematical formulations results in the following posterior parameter estimates.

$$y = 15.56 + 4.04x$$

$$\mathbf{b}'_{\text{post}} = (15.56, 4.04)$$

$$\mathbf{V}_{\text{post}} = \begin{bmatrix} 21.49 & -1.45 \\ -1.45 & 0.11 \end{bmatrix}$$

From these updated parameter coefficients, the desired transition probabilities are generated.

CONCLUSION

Pavement management systems are becoming more sophisticated with the use of both expert opinion and expert systems. Two PMSs that make use of expert opinion in reducing computational burden by forcing the network optimization models to select from a subset of the possible M&R actions were described. Additionally, a Bayesian statistical procedure that provides automatic condition prediction model updating was given for a Markovian-based linear program.

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Publication of this paper sponsored by Committee on Pavement Management Systems.