

Application of Markov Process to Pavement Management Systems at Network Level

Abbas A. Butt, *Engineering & Research International*

M. Y. Shahin, *U.S. Army Construction Engineering Research Laboratory*

Samuel H. Carpenter, *University of Illinois*

James V. Carnahan, *University of Illinois*

The rate of pavement deterioration is uncertain, and a pavement management system (PMS) should portray this rate of deterioration as uncertain. A wide variety of PMSs are used, but unfortunately either these systems do not use a formalized procedure to determine the pavement condition rating, or they use deterministic pavement performance prediction models, or they assign the pavement state transition probabilities on the basis of experience. The objective of the research was to develop a probabilistic network-level PMS on the basis of pavement performance prediction with use of the Markov process. Pavements with similar characteristics are grouped together to define the pavement families, and the prediction models are developed at a family level. The pavement condition index (PCI), ranging from 0 to 100, is divided into 10 equal states. The results from the Markov model are fed into the dynamic programming model and the output from the dynamic programming is a list of optimal maintenance and repair (M&R) recommendations for each pavement family-state combination. If there are no constraints on the available budget, the M&R recommendations from the dynamic programming will give a true, optimal budget. However, because the budgets available are usually less than the needs, two prioritization programs have been developed to allocate the constrained budgets in an optimal way. The first prioritization program is based on simple ranking of the weighted optimal benefit/cost ratios, and the second is based on the incremental benefit/cost ratio. The output from the two programs is a list of sections to be repaired, type of M&R alternatives selected, cost of M&R al-

ternatives, and section and network benefits. The results from the two prioritization methodologies are compared through an actual implementation on an existing airfield pavement network. The prioritization using the incremental benefit/cost ratio program uses the available constrained budget to the best of the full limit. To maintain a specified network PCI, the optimal benefit/cost ratio program will spend less money than the incremental benefit/cost ratio program. The developed optimization programs are very dynamic and robust for network-level PMSs.

The major objectives of a network-level pavement management system (PMS) are to develop short- and long-term budget requirements and to produce a list of potential projects based on a limited budget. The optimum approach to achieve these objectives relies heavily on the prediction of pavement performance and life-cycle cost analysis of all feasible maintenance and rehabilitation (M&R) strategies. To find the optimal solution for the allocation of available funds, operations research techniques are used that may be either deterministic or probabilistic.

Because the rate of pavement deterioration is uncertain, the budget requirement developed at the network level should treat this rate of deterioration as uncertain. Modeling uncertainty requires the use of probabilistic operation research techniques. Most of existing PMSs use neither a formalized procedure to determine the pavement

condition rating nor a deterministic approach to model the pavement rate of deterioration. PMSs that use probabilistic prediction models such as Markov models mostly assign the state transition probabilities on the basis of the field staff's experience, which can affect the accuracy of pavement performance prediction. An approach based on the Markov process has been developed for network-level optimization. Homogeneous and nonhomogeneous Markov chains have been used in the development of pavement performance prediction models. The use of Markov chains in prediction models captures the uncertain behavior of pavement deterioration. Integration of the Markov chains-based prediction models with the dynamic programming and the prioritization programs produces a list of optimal M&R treatments and a budget that satisfies the given performance standards. Conversely, a list of potential projects can be generated so that a limited available budget is spent in an optimal way.

RESEARCH APPROACH

The overall flow chart for the research study is shown in Figure 1. The major portion of research was a part of an ongoing effort to improve the MicroPAVER system developed at U.S. Army Corps of Engineers Research Laboratory in Champaign, Illinois. The development of the Markov prediction model (1), the dynamic programming (2), and the prioritization based on optimal benefit/cost ratio (3) of the overall flow chart have been published earlier. This paper describes in detail the following research elements:

- Development of a prioritization program based on the incremental benefit/cost ratio technique,
- Integration of the Markov prediction process with the dynamic programming and the prioritization programs, and
- Example application of the network optimization system to an existing airport pavement network.

DEVELOPMENT OF MARKOV PREDICTION MODEL

A pavement begins its life in a near-perfect condition and is then subjected to a sequence of duty cycles that cause the pavement condition to deteriorate. In this study the state of a pavement is defined in terms of a pavement condition index (PCI) rating. The PCI, which ranges from 0 to 100, has been divided into 10 equal states, each of which is a PCI interval of 10 points. A duty cycle for a pavement is defined as 1 year's duration of weather and traffic. A state vector indicates the probability of a pavement section being in each of the 10 states in any given year. Figure 2 is the schematic representation of state, state vector, and duty cycle.

After filtering and outlier analysis, all the surveyed pavement sections of a family are categorized into 1 of the 10 states at a particular age. A pavement section is defined as a part of the pavement network that has same type, structure, construction history, condition, use, and rank. A pavement family is defined as a group of pavement sections of similar characteristics. It is assumed that all the pavement sections are in State 1 (PCI of 90 to 100) at an age of 0 years. Thus, the state vector in Duty Cycle 0 (age = 0) is given by (1, 0, 0, 0, 0, 0, 0, 0, 0, 0), because it is known (with probability of 1.0) that all the pavement sections must lie in State 1 at an age of 0 years.

To model the way in which the pavement deteriorates with time, it is necessary to establish a Markov probability transition matrix. In this research, the assumption is made that the pavement condition will not drop by more than one state (10 PCI points) in a single year. Thus, the pavement will either stay in its current state or transit to the next lower state in 1 year. Consequently, the probability transition matrix has the form

$$P = \begin{matrix} p(1) & q(1) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & p(2) & q(2) & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & p(3) & q(3) & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & p(4) & q(4) & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & p(5) & q(5) & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & p(6) & q(6) & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & p(7) & q(7) & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & p(8) & q(8) & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & p(9) & q(9) \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{matrix}$$

where $p(j)$ is the probability of a pavement staying in State j during one duty cycle, and $q(j) = 1 - p(j)$ is the probability of a pavement's transiting down to next state ($j + 1$) during one duty cycle. The entry of 1 in the last row of the transition matrix corresponding to State 10 (PCI of 0 to 10) indicates an "absorbing" state. The pavement condition cannot transit from this state unless repair action is performed.

The state vector for any duty cycle t is obtained by multiplying the initial state vector $\tilde{p}(0)$ by the transition matrix P raised to the power of t . Thus,

$$\tilde{p}(1) = \tilde{p}(0) * P$$

$$\tilde{p}(2) = \tilde{p}(1) * P = \tilde{p}(0) * P^2$$

...

$$\tilde{p}(t) = \tilde{p}(t - 1) * P = \tilde{p}(0) * P^t$$

With this procedure, if the transition matrix probabilities can be estimated, the future state of the pavement at any duty cycle, t , can be predicted.

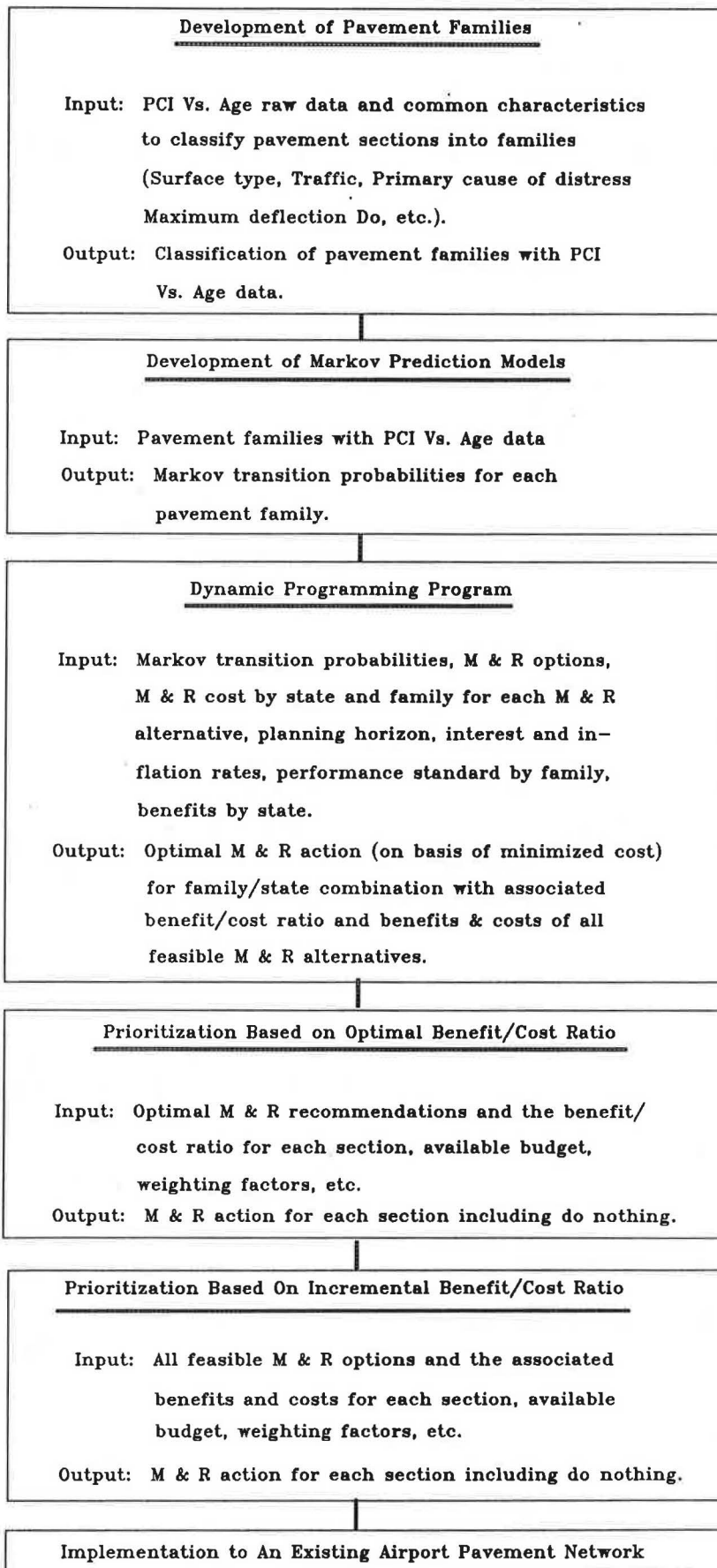


FIGURE 1 Research approach flow chart.

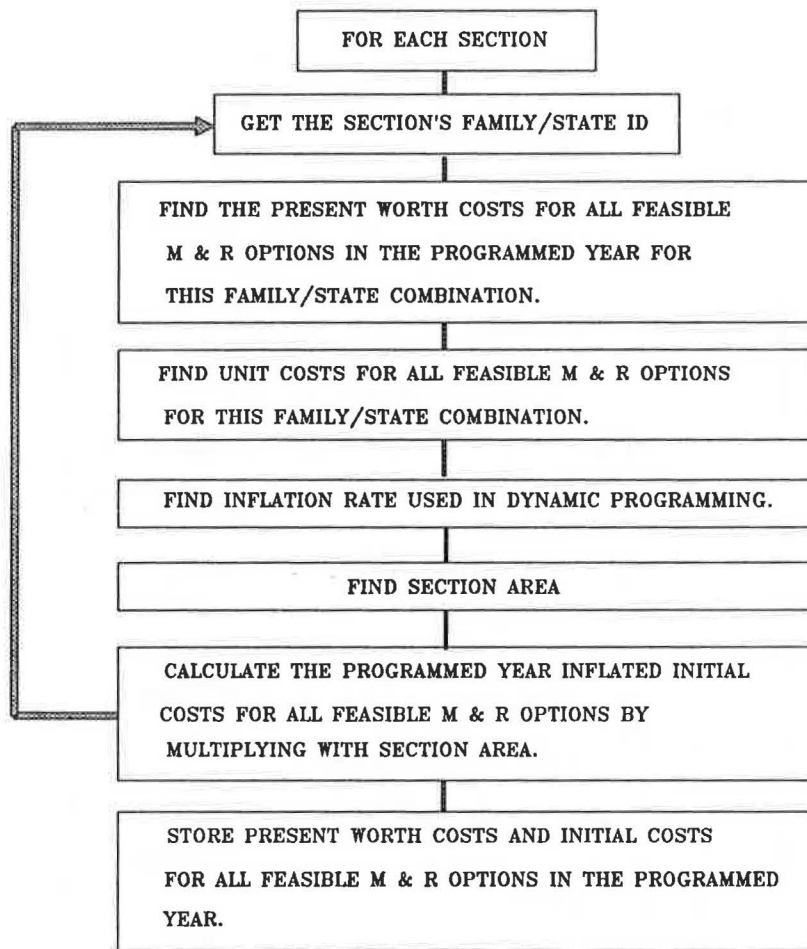


FIGURE 6 Cost computation module.

ues, because the comparison of the Markov prediction model results with constrained least-squares model showed similar trends.

IMPLEMENTATION

The purpose of this section is to demonstrate the applicability of the developed pavement management tools through implementation on an actual pavement network. The pavement performance prediction models that use the Markov process have been developed from data collected from 22 airports. Dynamic programming and prioritization schemes were applied at one airport to develop an optimal M&R plan. The following sections describe in detail the various steps of implementation.

Development of Pavement Performance Prediction Models

The Markov model defined earlier was used to develop the probabilistic pavement performance prediction models. The program was run on each of the pavement fami-

lies from 22 airports. Table 1 presents the Markov transition probabilities for each pavement family.

Application of Dynamic Programming

One of the outputs from the dynamic programming is the optimal M&R recommendation for every family/state combination in every year of the analysis period. Dynamic programming does not produce the M&R recommendation directly at the section level. The following paragraphs describe the input data used in the dynamic programming and the output from dynamic programming.

Input Data for Dynamic Programming

1. Number of families: 13.
2. Interest rate: 9 percent.
3. Inflation rate: 6 percent.
4. Life-cycle cost analysis period: 20 years.
5. Number of maintenance options: three, which are (a) routine maintenance, (b) surface treatment, and (c) structural overlay.

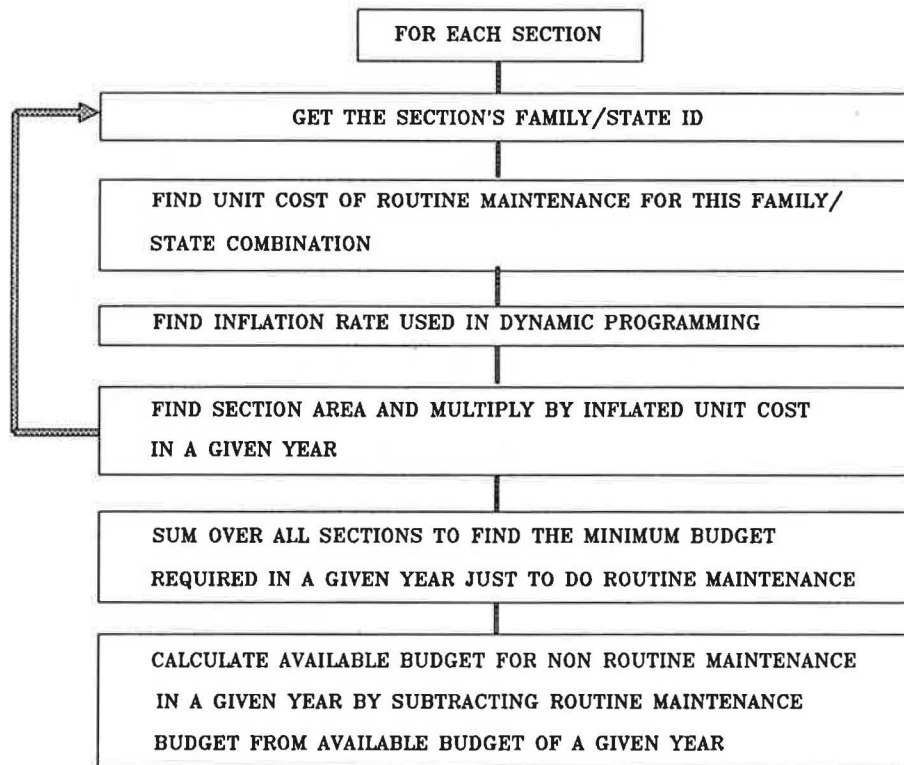


FIGURE 7 Routine maintenance module.

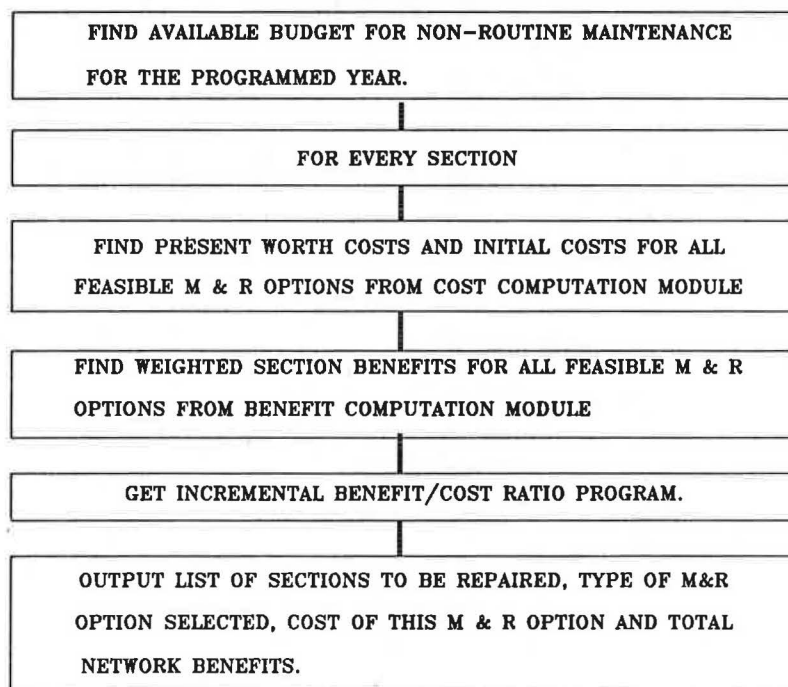


FIGURE 8 Budget optimization module.

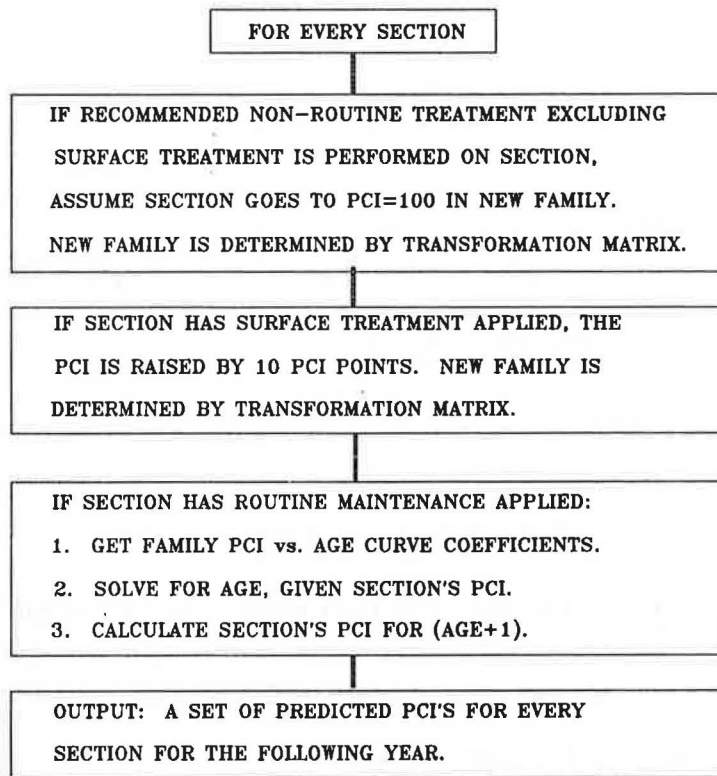


FIGURE 9 PCI adjustment module.

TABLE 1 Markov Transition Probabilities

Family Name	Zone	Age (Years)	State 1	State 2	State 3	State 4	State 5	State 6	State 7	State 8	State 9	State 10
RUNA	1	5	0.7000	0.9891	0.7661	0.7606	0.8750	0.4931	0.5006	0.3002	0.6454	1.0000
	2	18	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	1.0000
RUNB1	1	14	0.2111	0.5998	0.5839	0.6184	0.6344	0.2071	0.2639	0.3123	0.3534	1.0000
RUNB2	1	8	0.3184	0.1203	0.9485	0.7875	0.9898	0.3939	0.0950	0.9637	0.9046	1.0000
RUNB3	1	18	0.9900	0.6222	0.6205	0.6238	0.0012	0.5760	0.4346	0.2838	0.2147	1.0000
RUNB4	1	9	0.6000	0.6000	0.9900	0.9900	0.5059	0.5003	0.6896	0.2866	0.1905	1.0000
	2	14	0.9900	0.9900	0.9900	0.9900	0.0944	0.9681	0.9669	0.9669	0.9669	1.0000
RUNC	1	5	0.7000	0.7000	0.9900	0.9424	0.7441	0.6255	0.5620	0.5376	0.5322	1.0000
	2	18	0.0010	0.6999	0.4620	0.9900	0.8547	0.8351	0.7478	0.6269	0.8862	1.0000
RUNEND	1	11	0.8647	0.8992	0.8975	0.8964	0.4898	0.4857	0.5577	0.4752	0.2344	1.0000
	2	18	0.6000	0.6000	0.8742	0.7390	0.6395	0.5977	0.5809	0.5739	0.5709	1.0000
PTW1	1	9	0.3000	0.3568	0.8544	0.4733	0.0010	0.0325	0.0489	0.2845	0.3251	1.0000
PTW2	1	14	0.6993	0.8201	0.7765	0.7531	0.0016	0.0005	0.0010	0.0102	0.0447	1.0000
PTW3	1	18	0.9209	0.9349	0.9780	0.9821	0.9820	0.8822	0.8795	0.8794	0.8794	1.0000
CTW	1	4	0.4995	0.8005	0.0489	0.0013	0.4772	0.5003	0.5003	0.4607	0.9471	1.0000
	2	12	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	1.0000
	3	18	0.9000	0.9000	0.9900	0.9900	0.9900	0.9127	0.8966	0.8931	0.8925	1.0000
APRAC	1	6	0.6000	0.6000	0.7739	0.4853	0.5343	0.5498	0.5025	0.5002	0.9620	1.0000
	2	16	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9900	0.9613	0.7733	1.0000
APRPC	1	14	0.6635	0.9628	0.9013	0.9011	0.2129	0.6280	0.6435	0.6502	0.6527	1.0000
	2	25	0.5000	0.5000	0.8270	0.7102	0.6418	0.6154	0.5837	0.5452	0.5160	1.0000

6. Minimum allowable state for each family: five for Families 1 through 13.

7. State benefits: the benefit is defined as the area under the PCI-versus-age curve over 1 year. The midpoint of each state was used to represent the benefit over 1 year. State benefits used in this analysis are given in Table 2.

8. Markov transition probabilities for each family: Markov transition probabilities given in Table 1 were used in the analysis.

9. Transformation matrix: transformation matrix defines the new pavement family to move to if a certain M&R action is taken.

10. M&R Cost: PCI-versus-M&R cost relationships were used to calculate M&R cost of application of each of three maintenance options to each pavement family-state combination.

Dynamic Programming Output

The output from dynamic programming for every family-state combination consists of

1. Optimal M&R recommendations in every year,
2. Present-worth cost of optimal M&R recommendations,
3. Benefit/cost ratio of optimal M&R recommendations,

4. Benefits and costs of all feasible M&R alternatives, and

5. Optimal M&R recommendations and the corresponding present-worth costs, benefits, and benefit/cost ratio in Years 1, 2, 3, 4, 5, 10, 15, and 20 for pavement states equal to or less than 5.

The data in Elements 1 through 4 listed previously are directly used in the prioritization programs.

Prioritization

Two computer programs have been written for prioritization;

1. Prioritization using optimal benefit/cost ratio, and
2. Prioritization using incremental benefit/cost ratio.

Both programs were used to develop a 5-year M&R plan for the airport.

Prioritization Using Optimal Benefit/Cost Ratio

Five budget scenarios were considered for the 5-year analysis period; the scenarios are given in Table 3. Budget Scenario 1 had available budgets of \$5 million, \$4 million, \$3 million, \$2 million, and \$1 million, respectively for the programmed Years 1 through 5. The reason that a very high budget was selected for the first year of the analysis period was that most of the sections at the airport require major rehabilitation during the first year of the analysis period. Another reason that higher available budgets were selected for the remaining years of the analysis period was to determine the budget required if no budgetary constraints are applied. Budget Scenarios 2, 3, and 4 had uniform available budgets of \$1.5 million, \$1.0 million, and \$500,000, respectively, for every year of the analysis period. Budget Scenario 5 had \$4.5 million available for the first year so that all major M&R requirements are satisfied and then a uniform budget of \$100,000 for the remaining years of the analysis period. The effect of different budget scenarios on network PCI is shown graphically in Figure 10.

The curves of Budget Scenarios 1 and 5 are almost identical because both scenarios have enough money allocated during the first year that all optimal M&R requirements identified by the dynamic programming are satisfied. Budget Scenarios 2, 3, and 4 have uniform budgets allocated over the 5 years of the analysis period. Budget Scenario 4 shows a decrease in network PCI with time.

TABLE 2 State Benefits Used in Dynamic Programming

State	PCI Range	Benefit
1	90-100	95
2	80-90	85
3	70-80	75
4	61-70	65
5	50-60	55
6	40-50	45
7	30-40	35
8	20-30	25
9	10-20	15
10	0-10	5

TABLE 3 Prioritization Using Optimal Benefit/Cost Ratio

Budget Scenario	Year	Budget Available	Budget Used	PCI Before	PCI After	Network Benefit
1	1	5,000,000	2,706,638	60	88	8,065
	2	4,000,000	60,823	88	86	5,393
	3	3,000,000	40,260	86	84	5,093
	4	2,000,000	108,502	84	83	4,869
	5	1,000,000	160,390	83	82	4,555
2	1	1,500,000	1,355,013	60	72	7,998
	2	1,500,000	1,207,587	72	82	5,759
	3	1,500,000	575,695	82	85	5,277
	4	1,500,000	108,502	85	84	4,869
	5	1,500,000	160,390	84	83	4,555
3	1	1,000,000	927,987	60	67	7,690
	2	1,000,000	904,262	67	73	5,931
	3	1,000,000	163,949	73	72	5,161
	4	1,000,000	233,174	72	70	4,971
	5	1,000,000	292,543	70	69	4,646
4	1	500,000	465,113	60	61	7,546
	2	500,000	412,670	61	60	6,357
	3	500,000	302,562	60	58	5,678
	4	500,000	380,103	58	56	5,437
	5	500,000	423,289	56	54	5,024
5	1	4,500,000	2,706,638	60	88	8,065
	2	100,000	60,823	88	86	5,393
	3	100,000	40,260	86	84	5,093
	4	100,000	45,510	84	82	4,865
	5	100,000	79,489	82	81	4,557

Prioritization Using Incremental Benefit/Cost Ratio

The same five budget scenarios were used in this program. A summary of the output results from this program is given in Table 4. Figure 11 represents the effect of different budget scenarios on network PCI. Budget Scenarios 1 and 5 show almost identical trends, and Budget Scenarios 2, 3, and 4 show that with the gradual increase in the available budget, the network PCI improves. This improvement in network PCI is more significant in the later years of the analysis period.

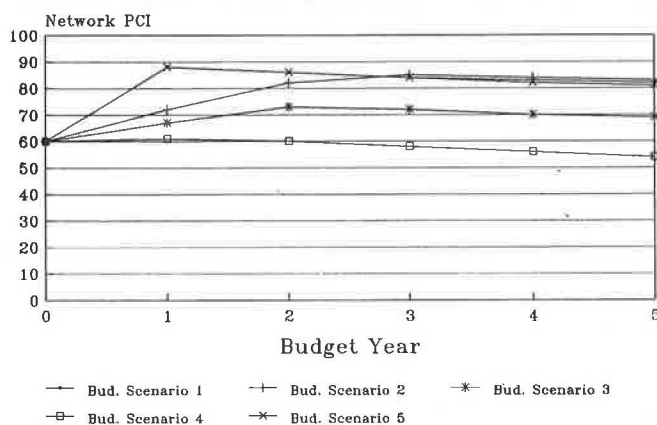


FIGURE 10 Effect of different budget scenarios on network PCI using optimal benefit/cost ratio.

Comparison of Two Prioritization Methodologies

The comparative network PCI-versus-budget profiles obtained from the two prioritization programs showed that prioritization using incremental benefit/cost ratio method results in higher network PCI values than prioritization using the optimal benefit/cost ratio. The other trend noticed from prioritization results indicated in Tables 3 and 4 is that the optimal benefit/cost ratio program consistently results in a lower amount of the budget being utilized compared with the incremental benefit/cost ratio program.

The yearly budget used from each budget scenario was converted into present-worth cost and then summed up as the total budget used over 5 years. The plot of total budget used from each budget scenario versus final-year network PCI is shown in Figure 12. It is observed in this figure that for a given network PCI, the incremental benefit/cost ratio program will require that more money be spent to maintain that level of PCI. The advantage of the incremental benefit/cost ratio program is that the available budgets are best used to their full limit.

CONCLUSIONS

The developed optimization scheme uses a formalized pavement condition survey procedure and is dynamic and robust for network-level PMS. The pavement performance prediction model based on nonhomogeneous

TABLE 4 Prioritization Using Incremental Benefit/Cost Ratio

Budget Scenario	Year	Budget Available	Budget Used	PCI Before	PCI After	Network Benefit
1	1	5,000,000	4,161,751	60	99	9,720
	2	4,000,000	91,820	99	96	6,021
	3	3,000,000	87,613	96	93	5,825
	4	2,000,000	286,295	93	93	5,721
	5	1,000,000	288,774	93	93	5,503
2	1	1,500,000	1,499,414	60	73	5,872
	2	1,500,000	1,498,240	73	85	6,538
	3	1,500,000	1,490,785	85	95	6,423
	4	1,500,000	250,591	95	94	5,688
	5	1,500,000	166,248	94	93	5,388
3	1	1,000,000	999,567	60	67	8,351
	2	1,000,000	997,522	67	73	6,882
	3	1,000,000	996,461	73	78	6,250
	4	1,000,000	970,779	78	82	6,068
	5	1,000,000	350,127	82	80	5,526
4	1	500,000	498,460	60	61	8,162
	2	500,000	499,637	61	62	6,991
	3	500,000	495,490	62	61	6,234
	4	500,000	478,642	61	60	5,980
	5	500,000	488,286	60	58	5,515
5	1	4,500,000	4,161,751	60	99	9,720
	2	100,000	91,821	99	96	6,021
	3	100,000	87,613	96	93	5,825
	4	100,000	99,086	93	92	5,624
	5	100,000	93,177	92	90	5,197

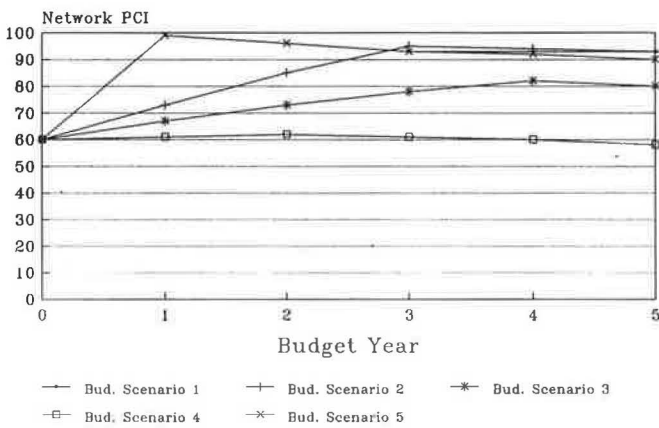


FIGURE 11 Effect of different budget scenarios on network PCI using incremental benefit/cost ratio.

Markov chains successfully captures the probabilistic pavement deterioration process. The Markov process in conjunction with the dynamic programming produces the optimal budget requirements for the given analysis period. The prioritization schemes have been developed to allocate the constrained budget. The prioritization method using incremental benefit/cost ratio provides the best use of available limited funds, when the funds must be completely exhausted during the assigned year. However, if the available funds can be carried over the next years, then the optimal benefit/cost ratio program provides the best use of available limited funds. The findings of this re-

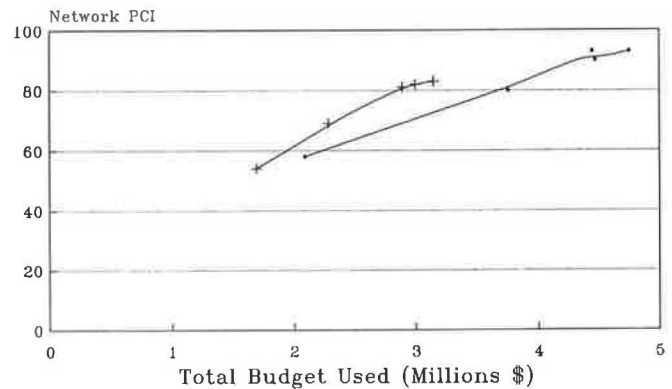


FIGURE 12 Network PCI versus total budget used.

search effort will be incorporated in the MicroPAVER Version 5.

REFERENCES

- Butt, A.A., K.J. Feighan, M.Y. Shahin, and S.H. Carpenter. Pavement Performance Prediction Process Using the Markov Process. In *Transportation Research Record 1123*, TRB, National Research Council, Washington, D.C., 1987.
- Feighan, K.J., M.Y. Shahin, and K.C. Sinha. A Dynamic Programming Approach to Optimization for Pavement Management Systems. *Proc. 2nd North American Confer-*

- ence On Managing Pavements*, Toronto, Ontario, Canada, Nov. 1987.
3. Feighan, K.J., M.Y. Shahin, K.C. Sinha, and T.D. White. A Prioritization Scheme for the Micro PAVER Pavement Management System. In *Transportation Research Record 1215*, TRB, National Research Council, Washington, D.C., 1989.
 4. Shahin, M.Y., S.D. Kohn, R.L. Lytton, and E. Japel. *Development of a Pavement Maintenance Management System, Volume VIII, Development of an Airfield Pavement Maintenance and Repair Consequence System*. Report ESL-TR-81-19. Engineering and Services Laboratory, Air Force Engineering and Services Center, April 1981.