Sensitivity of Pavement Network Optimization System to Its Prediction Models

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The prediction models in the network optimization system (NOS) are exhibited in the form of transition probability matrices (TPMs) in the newly implemented NOS (AZNOS) in the Arizona Department of Transportation. Due to variability in pavement performance parameters over time, it is necessary to study the effect of the influencing factors causing this variability. One such factor is annual expenditure on pavement rehabilitation, which is determined with the help of AZNOS results. In addition, rehabilitation budgets recommended by AZNOS are determined by the existing pavement network conditions, performance standards, and, more importantly, the prediction models through the use of the linear optimization routine. Even though it is evident that variations of transition probabilities from and to particular condition states will affect the recommended rehabilitation budgets from AZNOS, there is a lack of quantitative analysis in this relationship. AZNOS performance models' sensitivity to variations in transition probabilities and current pavement conditions is analyzed. This sensitivity study demonstrates the inherent relationship among prediction models (TPMs), rehabilitation needs, and current pavement conditions. This analysis also reveals an important property of AZNOS that large future savings in the pavement rehabilitation program may be obtained through the applications of effective preventive maintenance actions to existing pavements.

The major update of the Arizona Department of Transportation (ADOT) network optimization system (AZNOS) resulted in improved model structure and performance prediction (*1–4*). In addition, a model of pavement probabilistic behavior was developed in the process of implementing the new system (*2*). The pavement prediction models in AZNOS are exhibited in the form of transition probability matrices (TPMs), which determine the probabilities of pavements to progress from any condition state to all condition states in 1 year. Two major parameters—ride quality (*roughness*) and surface distress (*cracking*)—coupled with the third parameter *index to first crack*, determine the structure of the pavement condition states. The roughness and cracking parameters are also the barometers for pavement performance in NOS. Figure 1 illustrates in (a) and (b) the history of roughness levels and cracking levels for high-traffic interstate highways in the Arizona desert. The variations of the network's performance depicted in the figure in relation to roughness and cracking are due to a number of factors, one of which could be the actual budget allocated for the yearly rehabilitation. The transition probabilities used in the model are estimates based on past pavement performances (*2*). The transition probabilities directly affect the behavior of the prediction models in the optimization process and ultimately influence the results of the financial recommendations of AZNOS. As ADOT has more than 10-years' experience in using NOS in its pavement rehabilitation program, and rehabilitation expenditure is determined with the help of NOS results, it is reasonable to believe that the transition probabilities in the prediction models need further analysis. This paper presents the analysis of sensitivities of AZNOS to the variations in the transition probabilities, or TPMs, and actual pavement conditions.

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THEORETICAL BACKGROUND

The Markov process is a time-independent stochastic description of event development. Pavement behavior is modeled with the Markov process in 1980 in ADOT's pavement management system (*5*). The Markov property is equivalent to stating that the conditional probability of any future event, given any past event and the present state, is independent of the past event and depends only on the present state of the process. The conditional probability for the process to transition from one state to another is called transition probability. The transitions are also called steps. Therefore, the n-step transition probability $p_{ij}^{(n)}$ is defined as the conditional probability that the random variable X, starting in state i, will be in state j after exactly n steps, or time units.

A convenient notation for representing the transition probabilities is the matrix form

$$P^{(n)} = \begin{bmatrix} P_{00}^{(n)} & \cdots & P_{0M}^{(n)} \\ \vdots & & \vdots \\ P_{M0}^{(n)} & \cdots & P_{MM}^{(n)} \end{bmatrix} \tag{1}$$

$P^{(n)}$ is the n-step TPM. As applied in ADOT's NOS, the transition process of the pavement condition states conforms to the finite-state Markov chain process. Future pavement condition is dependent only on the current pavement condition. The performance model used in the NOS is based on transition probability matrices. A transition probability, $p_{ij}(a_k)$, is assumed to be equivalent to the proportion of roads in state i that move to state j in 1 year if the kth rehabilitation action is applied. It defines the probability of transition from one condition state to another in 1 year under one of the rehabilitation actions, including routine maintenance.

Chapman-Kolmogorov equations provide a method for computing the n-step transition probability matrix from a single-step transition probability matrix as used in NOS:

$$P^{(n)} = P \cdot P \ldots P = P^n \tag{2}$$

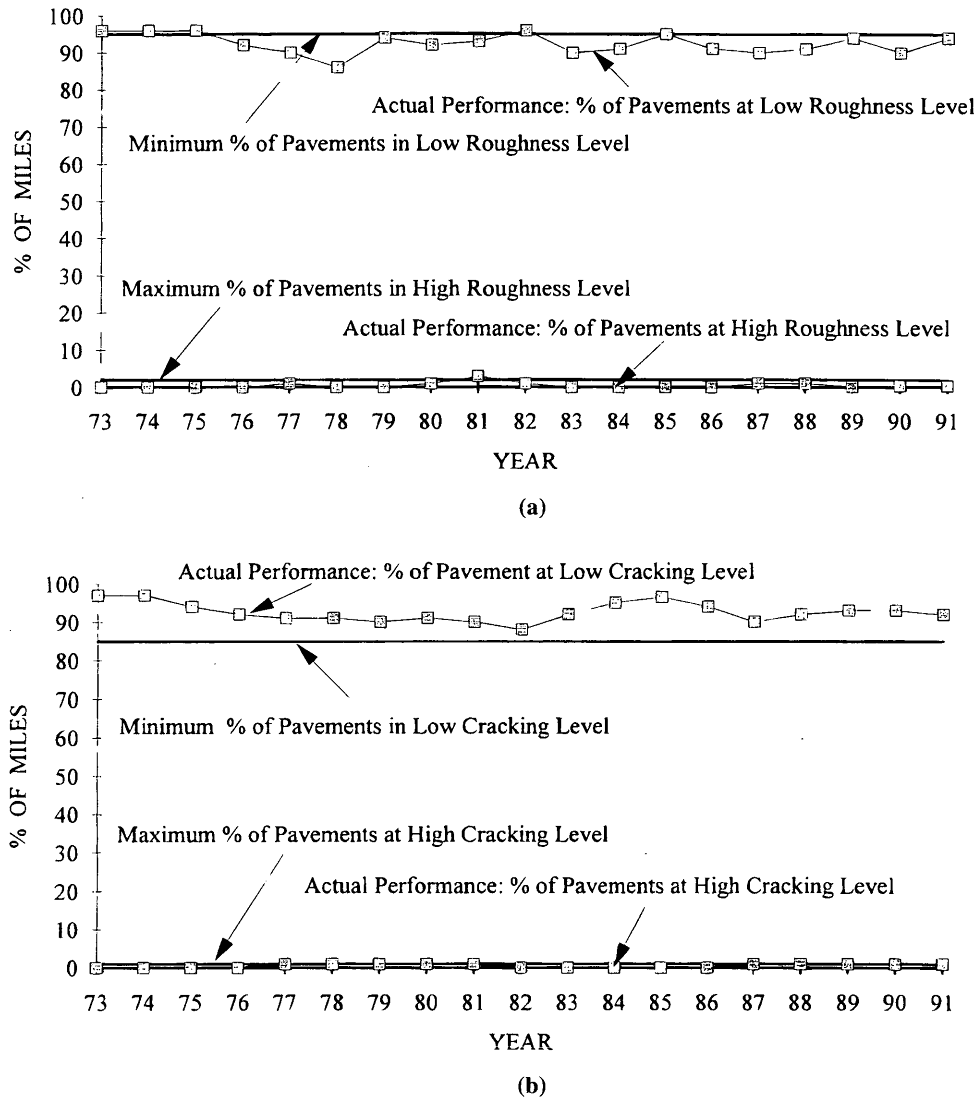


FIGURE 1 Pavement history of roughness (a) and cracking (b), high-traffic road category of Arizona Interstate network, AC pavement (2663 km) with ADT >10,000.

Therefore, the transition probabilities of pavement condition for a period of n years can be obtained based on the existing one-step transition probabilities of pavement condition. This allows a probabilistic prediction of pavement behavior over the life of the pavement structure. As shown in Equation 2, the transition probabilities for n number of periods or years can be calculated by multiplying the one-step or the original TPM n times. The following pavement probabilistic behavior equation for one rehabilitation action in vector form is established based on Equation 2 (*2*):

$$P^{(n)} = \begin{cases} P^{(n)}_{\text{routine}} & n \le v \\ P^{(v)}_{\text{routine}} \cdot P^{(1)}_{\text{rehab}} \cdot P^{(n-v-1)}_{\text{after rehab}} & n > v \end{cases} \quad (3)$$

where

$P^{(n)}$ = n-step TPM;
$P^{(n)}_{\text{routine}}$ = n-step TPM before the rehabilitation when $n \le v$;
$P^{(v)}_{\text{routine}}$ = v-step TPM when the rehabilitation is applied;
$P^{(1)}_{\text{rehab}}$ = the one-step TPM based on the effectiveness of the rehabilitation at the period of v immediately after the application; and
$P^{(n\text{-}v\text{-}1)}_{\text{after rehab}}$ = (n-v-1)-step TPM after the rehabilitation.

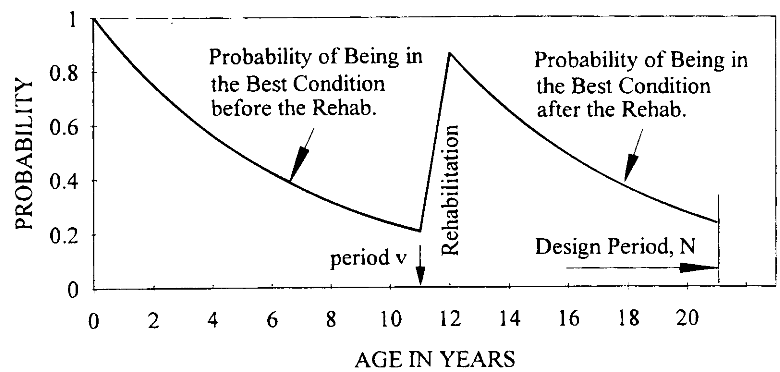
As indicated in the Equation 3, three TPMs are needed to conduct the analysis of long-term probabilistic behavior for the entire design period during which one rehabilitation is applied. The data generated based on Equation 3 can be used to plot pavement probabilistic behavior curves (PBCs). Pavement PBC is defined as the probability of being in a given condition state over time. Therefore, each condition state can have its own set of PBCs. An important performance standard set by ADOT is the minimum percentages of roads in the best condition state with the lowest roughness and cracking levels. Figure 2 in (a) illustrates typical long-term PBCs for the best condition state of design period N for interstate pavement for this condition state. The vertical axis represents the probability of pavements remaining in the best condition state. Figure 2 in (b) presents a traditional pavement performance curve. Note the sag shape of the probabilistic behavior curve in (a) versus the crest shape of the performance curve in (b).

DESIGN OF SENSITIVITY STUDY

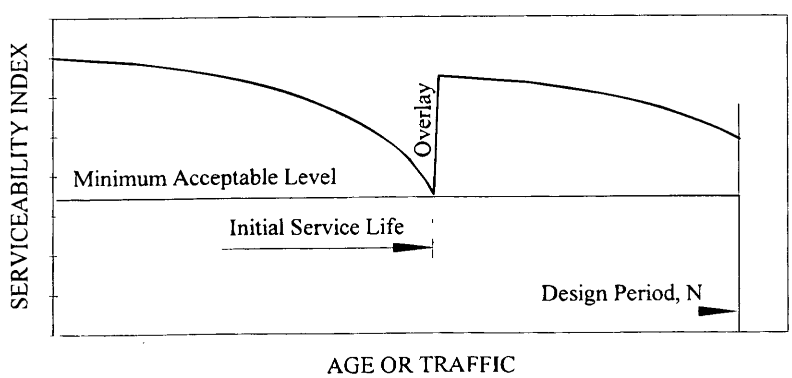
It is important to perform sensitivity analysis to investigate the effect on the optimal solution provided by the simplex method if the parameters take on other possible values. Usually, there will be some parameters that can be assigned any reasonable values without affecting the optimality of the solution. However, there may also be parameters with likely alternative values that would yield a new optimal solution. In the case of AZNOS, the optimal solution is expressed in the form of budget needs of pavement rehabilitation for each year in the planning horizon. It is certain that variations in the independent variables, such as transition probabilities, will affect the optimal solutions. The transition probabilities used in the AZNOS models are *estimates* used to predict future conditions. The approach used to develop these estimates are based on past pavement performances (2). Therefore, the basic objective of this analysis is to quantitatively identify the sensitivities of budget needs from AZNOS to variations in the independent variables, such as the transition probabilities, so that care can then be taken in the estimation of the parameters. In addition, this analysis may also provide quantitative data on the effective implementation of rehabilitation actions to existing pavement networks to improve future rehabilitation programs and reduce costs.

Transition Probabilities in NOS

Two submodels are used in the original NOS: steady state and multiperiod. It has been demonstrated that the multiperiod model is more practical for the management of statewide pavement networks (*3*). The following formulations indicate the main mathematical structure of the multistage AZNOS relating to the interested parameters.



(a) Typical pavement probabilistic behavior curves for the design period.



(b) Illustration of pavement performance and prediction.

FIGURE 2 Pavement probabilistic behavior curve and pavement performance curve.

The objective is to minimize

$$\sum_{l=1}^{T-1}\sum_{i,k} w_{i,k}^{l} \cdot d_l \cdot c(i,k) \tag{4}$$

subject to

$$\sum_{k} w_{j,k}^{l} = \sum_{i,k} w_{i,k}^{l-1} \cdot Pij(a_k), \text{ for } 1 < l \le T \tag{5}$$

$$\sum_{k} w_{j,k}^{l} = q_i \tag{6}$$

$$\sum_{j,k} w_{j,k}^{l} \le P_1(l) \cdot \gamma_i, \text{ for } i \in I, j \in j_1(i), 2 \le l \le T \tag{7}$$

$$\sum_{j,k} w_{j,k}^{l} \ge P_2(l) \cdot \varepsilon_i, \text{ for } i \in J, j \in j_2(i), 2 \le l \le T \tag{8}$$

where

$w_{j,k}^{l}$ = the proportion of roads of a given road category that are in condition state j at the beginning of the lth time period of horizon T, and to which the k preservation action is applied;
$p_{ij}(a_k)$ = pavement transition probability from condition state i to j due to the rehabilitation action k;
$c(i,k)$ = cost matrix for pavements in condition i receiving action k;
d = present worth of one dollar spent during lth time period;
q_i = current proportion of roads in ith condition state;
$p_1(l)$ = a multiplier ≥ 1 to permit a higher than γ_i proportion of roads in undesirable states at the lth time period;
$p_2(l)$ = a multiplier ≤ 1 to permit a higher than ϵ_i proportion of roads in undesirable states at the lth time period; and
γ_i and ϵ_i = performance standards set by ADOT management.

Equation 5 forms the core of pavement performance prediction in NOS. It presents the very basic relationship between transition probabilities and condition prediction in the classical formulation of linear programming in a Markov chain. This equation has also been proved to be compatible with Equation 3 used to define pavement probabilistic behavior curves (*2*).

It is clear that when current conditions of the pavement network q_i and performance standards γ_i and ϵ_i are known, transition probabilities $p_{ij}(a_k)$ determine the condition transitions of the network shown in Equation 5. Ultimately, rehabilitation needs ($w_{j,k}^{l}$) are resolved through the use of linear programming based on values of given parameters, including $p_{ij}(a_k)$.

Data Selection

Sensitivity analysis is a statistical study to determine the sensitivity of dependent variables, such as $w_{j,k}^{l}$ and $\sum_{l=1}^{T-1}\sum_{i,k} w_{i,k}^{l} \cdot d_l \cdot c(i,k)$, to variations in independent variables, such as the transition probabilities $p_{ij}(a_k)$, q_i, *and* γ_i and ε_i over reasonable ranges. This analysis involves investigating the effect on the optimal solution by making changes in the values of these model parameters.

The prediction models' sensitivities to performance standards γ_i and ϵ_i were carefully analyzed by Wang et al. (*4*). In this analysis, performance standards were increased incrementally in the form of maximum percentages of roads at high roughness and cracking levels and minimum percentages of roads at low roughness and cracking levels. The corresponding rehabilitation needs in the form of an AZNOS budget recommendation were also increased along the higher standards. Based on the data presented to ADOT management on the analysis of statewide pavement rehabilitation needs (*4*), ADOT set the performance standards for Arizona pavement networks. Therefore, it has been determined that pavement performance standards are used as given data. Since the focus of the study is on the prediction models or the transition probabilities, cost matrix $c(i,k)$ is also used as given data in this analysis.

As a result, current pavement conditions q_i and transition probabilities $p_{ij}(a_k)$ are the only independent sets of parameters in the AZNOS model that need further analysis in this paper. As shown in Equation 5, variations in the transition probabilities play the determining role in the transition of pavement condition states. Therefore, the sensitivity analysis will concentrate on the roles of prediction models or TPMs in determining AZNOS budget recommendations. As performance predictions are made from existing pavements, the current pavement conditions directly affect the result of optimization. As such, current pavement conditions q_i are also used as independent parameters for this analysis.

There are 15 road categories in Arizona. Each road category was determined based on its traffic level, geographical region, and rainfall. Each road category can be perceived as a highway subnetwork. There are performance prediction models for each subnetwork. The road category (subnetwork) of high traffic, desert interstate highways is chosen for this sensitivity analysis since it has the largest pavement area among the 15 road categories and carries the traffic load for the Phoenix metropolitan area and adjacent regions. Therefore, the rehabilitation needs for this network are very large compared with other networks. Six rehabilitation actions are shown below with corresponding costs for this interstate subnetwork:

Rehabilitation Action	*Cost($)*
ROUTINE	0.12
SEAL COAT	1.38
ACFC;ACSC	2.30
ACFC + AR;ARAC;2″AC + FC	6.90
2″AC + FC + AR;3″AC + FC(W/O AR)	10.35
4″AC + FC;4″/5″AC + FC	13.80

ACFC and ACSC stand for asphalt concrete friction course and asphalt concrete surface course, respectively. AR is asphalt rubber. ARAC is asphalt rubber plus asphalt concrete. The preset pavement performance standards for this interstate network are 95 percent for minimum percentage of roads in the low roughness level, 2 percent for maximum percentage of roads in high roughness level, 85 percent for minimum percentage of roads in the low cracking level, and 1 percent for maximum percentage of roads in high cracking level.

Data Requirements and Analysis

The independent variables in the prediction equations must be statistically linear and contain a minimum collinearity between independent variables, for the following reasons (*6*):

- The magnitudes of the effects from varying the individual nonlinear independent variables would not be directly comparable.
- As collinearity must be minimized for any meaningful analysis, and nonlinear regression techniques are deficient to identify

collinearity, the use of nonlinear analysis could seriously limit confidence in the results.

- There are no existing procedures for conducting sensitivity analyses on nonlinear models.

It is clear that the relationships among parameters in AZNOS are all linear. In addition, current conditions q_i and transition probabilities $p_{ij}(a_k)$ are independent of each other. However, there exist properties for both q_i and $p_{ij}(a_k)$ that may pose difficulties in meeting the minimum collinearity requirement:

$$\sum_i q_i = 1 \tag{9}$$

$$\sum_j P_{ij}(a_k) = 1 \tag{10}$$

Apparently, parameters q_i in $\sum_i q_i$ or $p_{ij}(a_k)$ in $\sum_j p_{ij}(a_k)$ are not completely independent of each other. Instead, as a result of the requirements in Equations 9 and 10, the degrees of freedom for both sets of parameters are reduced by one. This property should be taken into consideration in the analysis design.

In this sensitivity analysis, the dependable variables include the proportion of roads in condition state j at the beginning of lth time period, and to which the k preservation action is applied ($w_{j,k}^l$), and total agency cost $\left[\sum_{l=1}^{T-1}\sum_{i,k} w_{i,k}^l \cdot d_l \cdot c(i,k)\right]$, which is the objective function. The independent variables include transition probabilities $p_{ij}(a_k)$ and current conditions q_i. Table 1 shows the current pavement conditions for the road category of desert interstate highways. There are 45 condition states, determined by three factors: ride level (roughness), distress level (cracking), and index to first crack. The index to first crack was conceptually an estimate of the time between the construction or rehabilitation of the pavement to occurrence of the first crack. However, this index is used in both the original NOS and AZNOS to select a TPM based on the most recent rehabilitation. There are five levels of the index to first crack based on the type of rehabilitation treatment as shown in Table 1, corresponding to five levels of rehabilitation actions. For example, 18.25 percent of the pavement area was in Condition State 1 (low roughness and cracking levels, and never rehabilitated except for routine maintenance). There were 20.44 percent of the pavements in Condition State 19 (low roughness and cracking levels, and the last rehabilitation is Action Number 4). It should be noted that pavements with the most recent treatment of Action 2 or 3 converge to Conditions 10 to 18 after the action is applied. Condition States 10 to 18 fall within Index to First Crack 2. However, these two treatments of seal coat and ACFC are different in their effectiveness, resulting in the two different transition probabilities for Actions 2 and 3 for the year that the actions are applied. With the exception of seal coat and ACFC, a probability of 1 is assumed for the transition from any condition state to the condition state with low roughness and cracking levels during the year the rehabilitation action is applied. Table 2 presents the complete sets of transition probabilities, or transition probability matrices under routine maintenance, for the subnetwork under study.

The majority of pavement (65.81 percent) is at the levels of low cracking and low roughness, or the best condition state (see Table 1). In addition, the majority of pavements receive only routine maintenance. Because 20.44 percent of pavements are in Condition 19, it is determined to start the analysis by varying the transition probabilities from Condition State 19 to States 19, 20, 22, and 23. The second analysis includes simultaneously varying the transition probabilities from States 1, 10, 19, and 28. Data relating to State 37

TABLE 1 Current Pavement Conditions in Percentage of Area for the 45 Condition States, Road Category of High-Traffic and Desert Interstate Highways in Arizona (1992)

Ride Level	Distress Level	Index[a] 1		Index 2		Index 3		Index 4		Index 5		Total
		CS[b]	% of Area	CS	% of Area	CS	% of Area	CS	% of Area	CS	% of Area	
Low	Low	1	18.25	10	10.54	19	20.44	28	15.17	37	1.41	65.81
Low	Medium	2	5.27	11	1.93	20	3.60	29	2.31	38	0.26	13.37
Low	High	3	1.67	12	0.64	21	0.77	30	0.90	39	0.00	3.98
Medium	Low	4	3.08	13	0.90	22	2.06	31	2.44	40	0.77	9.25
Medium	Medium	5	1.67	14	0.39	23	0.39	32	0.26	41	0.00	2.71
Medium	High	6	1.29	15	0.26	24	0.64	33	0.13	42	0.00	2.32
High	Low	7	0.13	16	0.00	25	0.13	34	0.13	43	0.13	0.52
High	Medium	8	0.51	17	0.13	26	0.00	35	0.00	44	0.00	0.64
High	High	9	1.40	18	0.00	27	0.00	36	0.00	45	0.00	1.40
Total			33.28		14.79		28.03		21.34		2.57	100.00

[a] Index stands for index to first crack.
[b] CS stands for condition states.

TABLE 2 Transition Probabilities Under Routine Maintenance for High-Traffic and Desert Interstate Highways in Arizona (Truncated from 6 Decimals to 4)

From[a]	To[b]	Tran Prob[c]	From	To	Tran Prob	From	To	Tran Prob	From	To	Tran Prob	From	To	Tran Prob
1	1	0.8540	10	10	0.8372	19	19	0.8477	28	28	0.8577	37	37	0.8547
1	2	0.0545	10	11	0.0465	19	20	0.0700	28	29	0.0300	37	38	0.0800
1	4	0.0836	10	13	0.1093	19	22	0.0786	28	31	0.1086	37	40	0.0572
1	5	0.0078	10	14	0.0070	19	23	0.0037	28	32	0.0037	37	41	0.0080
2	2	0.7237	11	11	0.6452	20	20	0.8137	29	29	0.8237	38	38	0.8512
2	3	0.1447	11	12	0.0645	20	21	0.1091	29	30	0.0991	38	39	0.0855
2	5	0.0833	11	14	0.2258	20	23	0.0748	29	32	0.0748	38	41	0.0619
2	6	0.0482	11	15	0.0645	20	24	0.0025	29	33	0.0025	38	42	0.0013
3	3	0.7391	12	12	0.9211	21	21	0.8209	30	30	0.8209	39	39	0.8709
3	6	0.2609	12	15	0.0789	21	24	0.1791	30	33	0.1791	39	42	0.1291
4	4	0.8707	13	13	0.8835	22	22	0.8276	31	31	0.8676	40	40	0.8513
4	5	0.0532	13	16	0.1068	22	23	0.1010	31	32	0.0610	40	41	0.0929
4	7	0.0722	13	17	0.0097	22	25	0.0659	31	34	0.0659	40	43	0.0515
4	8	0.0038			N/A	22	26	0.0055	31	35	0.0055	40	44	0.0043
5	5	0.6429	14	14	0.7868	23	23	0.7970	32	32	0.7970	41	41	0.7992
5	6	0.1607	14	15	0.0336	23	24	0.0273	32	33	0.0273	41	42	0.0237
5	8	0.0357	14	17	0.1724	23	26	0.1699	32	35	0.1699	41	44	0.1720
5	9	0.1607	14	18	0.0072	23	27	0.0059	32	36	0.0059	41	45	0.0051
6	6	0.8732	15	15	0.8230	24	24	0.8229	33	33	0.8229	42	42	0.8229
6	9	0.1268	15	18	0.1770	24	27	0.1771	33	36	0.1771	42	45	0.1771
7	7	0.9400	16	16	0.8681	25	25	0.8590	34	34	0.8590	43	43	0.8935
7	8	0.0600	16	17	0.1319	25	26	0.1410	34	35	0.1410	43	44	0.1065
8	8	0.9456	17	17	0.9577	26	26	0.9607	35	35	0.8662	44	44	0.9711
8	9	0.0544	17	18	0.0423	26	27	0.0393	35	36	0.1338	44	45	0.0289
9	9	1.0000	18	18	1.0000	27	27	1.0000	36	36	1.0000	45	45	1.0000

[a] Condition states to be transitioned from.
[b] Condition states to be transitioned to.
[c] Transition probabilities.
Note: refer to Table 1 for the corresponding roughness level, cracking level, and index number for each condition state.

were not used because a relatively small number of pavements (1.41 percent) were in this particular state. The third analysis includes varying the transition probabilities and current condition states in relation to data for the transitions from State 19 to States 19, 20, 22, and 23.

RESULTS OF SENSITIVITY ANALYSES

Varying Transition Probabilities from State 19

In Table 2 the transition probabilities from states at low roughness and cracking levels to states at the same levels fall within the range of 0.8372 to 0.8577. These probabilities play a critical role in keeping the pavements in the best condition states. Probabilities related to Index to First Crack 3 were selected in this analysis by varying the probabilities in the order shown in Table 3. Six runs were conducted. It should be noted that the transition probabilities for pavements in State 19 to stay in State 19 were varied from 0.6 to 0.7, 0.8, and 0.9 with the increment of 0.1, and from 0.9 to 0.95 and 0.99 with the increments of 0.05 and 0.04. Different increments were used to vary the probabilities because in initial AZNOS runs when transition probabilities were lower than 0.8, there were only small variations among the different AZNOS budget recommendations. That is to say, the AZNOS-based budget recommendations stay relatively stable when the probability to stay in the best state is smaller than 0.8. Figure 3 is a three-dimensional chart for these six runs. The following data show the budget recommendations of the six AZNOS runs based on the transition probabilities in Table 3 (in millions of dollars):

TABLE 3 Variations of Transition Probabilities from State 19 to States 19, 20, 22, and 23

Run Number	$p_{19,19}(1)$	$p_{19,20}(1)$	$p_{19,22}(1)$	$p_{19,23}(1)$
1, (TPM 1)	0.600	0.175	0.175	0.050
2, (TPM 2)	0.700	0.135	0.135	0.030
3, (TPM 3)	0.800	0.095	0.085	0.001
4, (TPM 4)	0.900	0.050	0.050	0.000
5, (TPM 5)	0.950	0.025	0.025	0.000
6, (TPM 6)	0.990	0.005	0.005	0.000

Run 1	Run 2	Run 3	Run 4	Run 5	Run 6
(TPM 1)	(TPM 2)	(TPM 3)	(TPM 4)	(TPM 5)	(TPM 6)
\$99.949	\$98.673	\$97.051	\$86.525	\$78.783	\$67.545

Based on the data above and the data in Table 3 and Figure 3, it is evident that a small increase for the transition probabilities to stay in the best state from 0.8 may introduce sizable savings in pavement rehabilitation costs.

Simultaneously Varying Transition Probabilities from Multiple States

The second analysis was conducted through the simultaneous varying of the transition probabilities from States 1, 10, 19, 28, and 37 to all the possible states as indicated in Table 4. Six runs were conducted on the six sets of transition probabilities. The following data show the AZNOS budget recommendations from the six runs (in millions of dollars):

Run 1	Run 2	Run 3	Run 4	Run 5	Run 6
(TPM 1)	(TPM 2)	(TPM 3)	(TPM 4)	(TPM 5)	(TPM 6)
\$124.076	\$116.951	\$106.951	\$68.713	\$33.216	\$23.209

This analysis reveals that a compounding effect occurred as a result of the simultaneous change of the transition probabilities. When the probabilities changed from 0.8 to 0.99, the budget recommendations from AZNOS were reduced drastically from \$106.51 million to \$23.209 million. Figure 4 illustrates the recommended rehabilitation costs for each action and each set of transition probability matrices.

Varying Transition Probabilities and Current Conditions

The third analysis focused on actual pavement Conditions 19 to 25 and their related transition probabilities. For each set of transition probabilities in Table 3, six runs of AZNOS were conducted based on six sets of pavement condition data. Six proportions of roads in State 19 with low roughness and cracking levels were used as follows: 0.04, 0.07, 0.1, 0.13, 0.16, and 0.204. The last proportion (0.204) represents the actual pavement condition in 1991. The other proportions of pavement condition data were adjusted proportionally to their actual pavement conditions in Table 1. Figure 5 shows

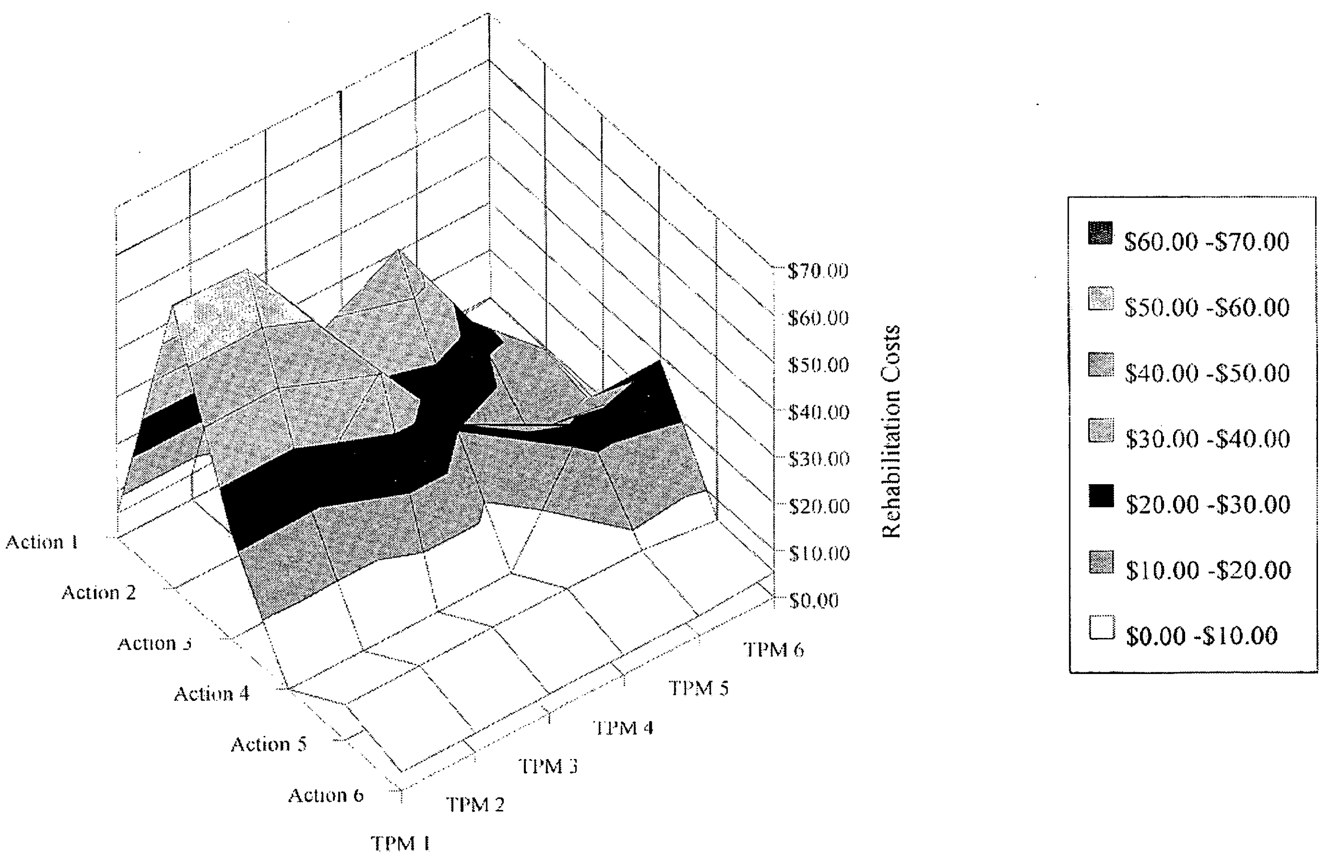


FIGURE 3 Sensitivity of AZNOS to six sets of transition probabilities from State 19 to all other states ($million).

TABLE 4 Variations of Transition Probabilities from States 1, 10, 19, 28, and 37 to All Possible States

Run Number	Probabilities to stay in the best state	Probabilities to state 2/ 11/20/29/37	Probabilities to state 4/ 13/22/31/40	Probabilities to state 5/ 14/23/32/41
1, (TPM 1)	0.600	0.130	0.240	0.030
2, (TPM 2)	0.700	0.100	0.180	0.020
3, (TPM 3)	0.800	0.070	0.120	0.010
4, (TPM 4)	0.900	0.030	0.060	0.010
5, (TPM 5)	0.950	0.015	0.035	0.000
6, (TPM 6)	0.990	0.003	0.007	0.000

the results of this analysis through the use of a three-dimensional surface. CC1 to CC6 represent the six sets of pavement condition data. Figure 5 indicates that the changing proportions of pavement conditions have limited effects on recommended budget needs when the transition probabilities to stay in Condition 19 were smaller than 0.8. However, when the transition probabilities to stay in the best state changed from 0.8 to 0.99, for each set of pavement condition data, a large decline in recommended budget needs was exhibited. The sharp declining slope toward the right-front corner of the three-dimensional surface in Figure 5 demonstrates the compounding effect of improved pavement condition and higher transition probabilities for pavements to stay in the best condition with low roughness and cracking levels.

CONCLUSION

The higher the transition probabilities for pavements to stay in the best condition state, the less proportions of pavements will transition to worse states. As a result, a smaller budget will be needed. It is also evident that the better the pavement conditions, the smaller the needed budget will be for future pavement rehabilitation. These two properties were quantitatively analyzed in this paper by using AZNOS. An interesting property was also revealed in the analysis: when transition probabilities were increased from 0.8, budget needs for pavement rehabilitation based on AZNOS were drastically decreased, disproportionally against the increasing rate of the probabilities. As transition probabilities were determined based on past pavement performance in Arizona, this newly revealed property encourages preventive pavement improvements to reduce future rehabilitation needs. This property also illustrates that a modest increase in costs for preventive maintenance may well generate large future savings. Therefore, efforts to improve current pavement roughness and cracking levels, which will be used to update future TPMs as past pavement performance data, will ultimately improve the lifelong cost-effectiveness of rehabilitation programs for pavement networks. It should be pointed out that this paper does not discuss the sensitivities to cost matrices and discount rates. These two factors also play important roles in determining long-term pavement rehabilitation costs.

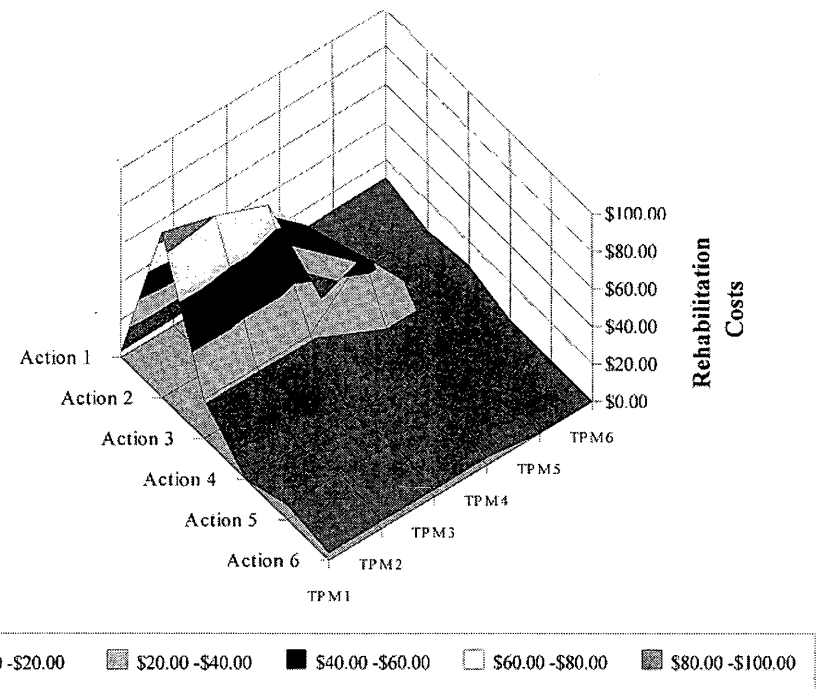


FIGURE 4 Sensitivity of AZNOS to simultaneous variations of transition probabilities from States 1, 10, 19, and 28 to all other states ($million).

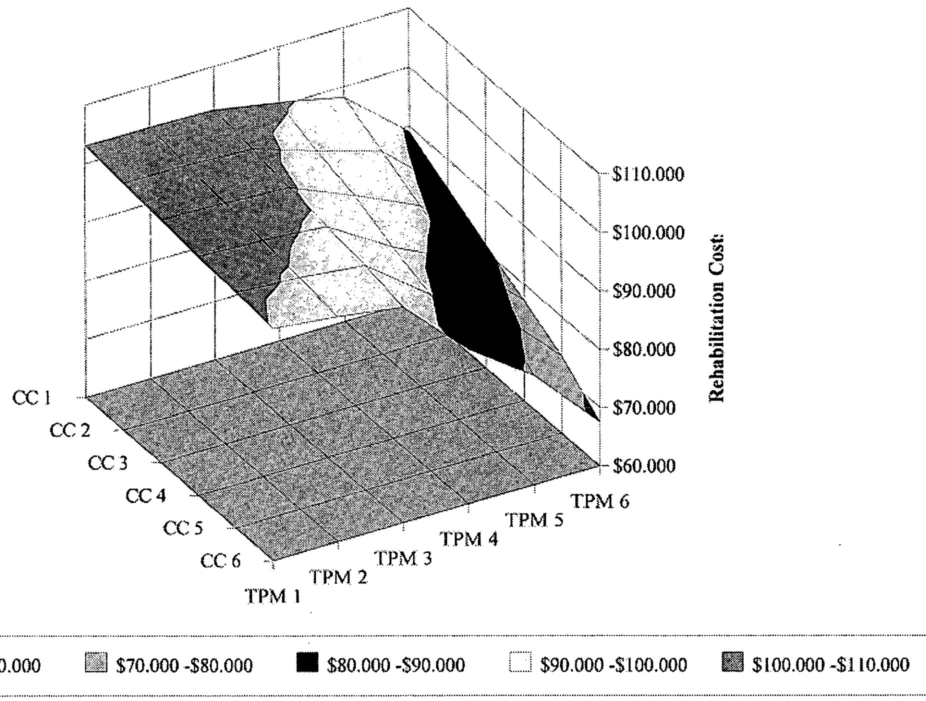


FIGURE 5 Sensitivity of AZNOS to simultaneous variations in transition probabilities from State 19 and current-condition States of 19 to 24 ($million).

ACKNOWLEDGMENTS

We thank George Way and James Delton for their contributions to the development of the new AZNOS in the 32-bit microcomputer environment. We also thank Fengxian Liu for conducting a portion of the computer runs for this analysis.

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