JOURNAL OF TRANSPORTATION
SYSTEMS ENGINEERING AND INFORMATION TECHNOLOGY
Volume 14, Issue 6, December 2014
Online English edition of the Chinese language journal

Cite this article as: J Transpn Sys Eng & IT, 2014, 14(6), 92−100.

RESEARCH PAPER

Managing Pavement Maintenance and Rehabilitation Projects under Budget Uncertainties

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Abstract: A well-developed and maintained pavement management system (PMS) empowers a decision maker to select the best maintenance program, i.e., which maintenance treatment to use and where and when to apply it, so that a maximum utilization of available resources can be achieved. This paper addresses a decision making problem for managing pavement maintenance and rehabilitation projects under budget uncertainty (MPMRPBU). A stochastic linear programming model is formulated and solved for the MPMRPBU so that a set of candidate projects can be optimally selected from the highway network over a planning horizon. Numerical results are discussed based upon a pilot case study. Different optimization solutions based on deterministic optimization and stochastic programming approaches are discussed and compared. The effect of the budget constraint on the optimized solutions is investigated. The computational result indicates a high quality MPMRPBU solution using stochastic programming approach, suggesting that there is a potential that the algorithm can be used for real world applications.

Key words: traffic engineering; pavement management systems; decision making; pavement maintenance and rehabilitation; optimization; stochastic programming

1 Introduction

Pavement management systems (PMS) have long been used as the primary tool to support pavement maintenance and rehabilitation (M&R) activities. Deciding which road pavement sections should be included in the yearly M&R project list for a planning horizon of several years is one of the major functions of a PMS system. Pavement maintenance is defined as routine, preventive, or reactive maintenance activities which often include but are not limited to filling cracks, patching potholes, and other applicable treatments such as chip seal coat or slurry seal. Pavement rehabilitation generally refers to major maintenance actions that are intended to enhance the structural capacity of pavements, such as resurfacing (overlay), resurfacing with partial reconstruction (localized reconstruction), and complete reconstruction. Both pavement maintenance and rehabilitation are costly with pavement rehabilitation being more expensive. The stringent yearly M&R budgets available to the state Departments of Transportation (DOT's) usually cannot support every M&R need. A practical procedure that can optimally manage and improve DOT's pavement maintenance and rehabilitation project selection process can potentially save M&R cost and improve pavement condition for the agency [1].

The pavement management information system (PMIS) is the automated portion of the PMS used by the Texas Department of Transportation (TxDOT). The PMIS is a set of computer programs for storing, retrieving, analyzing, and reporting information to assist decision makers (i.e., state/district pavement maintenance engineers/managers in TxDOT) to make cost-effective decisions regarding the maintenance and rehabilitation of pavements[2,3]. The PMIS consists of two major components: (1) pavement data and information management; and (2) decision support provision. PMIS databases are populated with various kinds of pavement-related data, one of the most important of which is the pavement condition data that have been collected annually or biannually since 1985. The decision support component provides essential functions that assist decision makers to manage pavement M&R activities in a cost-effective manner. Generally the decision support system in a typical PMS assists decision-makers at two levels of pavement management that

Received date: Nov 12, 2012; Revised date: Oct 24, 2013; Accepted date: Apr 11, 2014
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DOI: 10.1016/S1570-6672(13)60145-2

are referred to as the network level and the project level [4,5]. Pavement management at the network level considers for the whole pavement network the development of an M&R budget plan, prioritization program and schedule of work over the analysis period while pavement management at the project level deals with engineering concerns for the actual implementation for an individual project. The network-level decision support can be further divided into programming level and project selection level [4]. At the programming level, budgets are established and general resource allocations are made over the entire network. The project selection level involves prioritization to identify which projects should be carried out in each year of the programming horizon. In recent years, considerable research efforts were made to tackle the PMS network level decision-making problem, both in the programming topic[6-10] and in the project selection topic[11,12].

The optimization methods developed for network programming of finding optimal M&R actions generally fall into one of the following two categories: (1) maximization of pavement conditions subject to M&R budget constraints; or (2) minimization of M&R cost subject to minimum requirements on road conditions. Since the network programming is normally conducted on a planning horizon of several years, the modeling of the transition of pavement conditions is needed. For the prediction of network pavement conditions over multiple time periods, the transitions of network pavement conditions are frequently modeled as Markovian chain processes, and accordingly the decision variables of the optimization models are just the Markovian transition probabilities which are associated with the designated M&R actions. In previous studies, the Markovian transition probabilities were applied in the current time period to either proportions[7,8,10] or aggregate lane miles[6] of pavements in different condition states in order to predict the pavement condition proportions or the lane miles in each of the condition states in the next time period.

The above studies in network programming can help a pavement engineer/manager know the proportion or aggregate lane miles out of the whole pavement network that are in need of a designated M&R treatment in each year of the planning horizon. Therefore with the help of network programming, pavement engineers can understand the pavement needs in the future years and can proactively conduct need analysis and budget planning for the pavement network. However, the information about the M&R needs for proportions and lane miles of the pavement network is far from detail enough to know whether or not a specific pavement section should receive an M&R treatment within the year's M&R project program. A PMS should also have the function of assisting the decision maker in selecting the best maintenance program, i.e., what maintenance treatment to be applied for which pavement section at what time, so that a maximum utilization of available resources can be achieved for the pavement network. This is what the network level project selection programming is all about.

A PMS should have a function routine to establish maintenance and rehabilitation priorities to support project-selection decision making. Clearly the quality of the prioritization directly influences the effectiveness of the available M&R budget, which in most cases, is deemed a prime goal of a decision maker. Currently the project selection process in the TxDOT PMIS is first to prescreen the "in need" pavement sections from the pavement network using an experience based decision tree, then calculate the cost and benefit associated with the pre-selected M&R treatment for each of the "in need" pavement sections, and then rank all the sections in descending order of cost-effectiveness ratios[2,3]. Finally the top sections with a total cumulative cost equal to the current year's allowable budget are selected for the year's M&R program. However, there are two flaws in using this project selection method: (1) the prescreening approach favors the most severely damaged pavement sections which accordingly have the highest priorities, and only the top sections on the list consume the budget of the whole pavement network while ignoring the needs of the other sections; and (2) it does not handle maintenance timing wisely because a less severely damaged section may have a low rank and is not taken care of in the current year, but the pavement section may deteriorate so badly in only a few years that a much more costly treatment would be needed. Just like in network programming, an optimization method could also be applied to the prioritization of M&R projects for the whole highway network over a planning horizon of multiple years. Decision variables could be dummy variables with values of either 1 or 0 indicating whether or not a pavement section would be selected and treated with a specific M&R action for a specific year in the planning horizon. Each decision variable is associated with a gain or improvement in pavement condition and a cost induced in the M&R treatment. The summation of the gains obtained from the decision variables for all pavement sections in the network comprises the total M&R effectiveness over the analysis years, and the summation of the treatment costs due to the decision variables for all pavement sections in the network constitutes the total M&R cost over the analysis years. To extend the experience gained in the studies in network-level programming, an optimal solution to a set of integer decision variables for the pavement sections in the network could be developed to meet annual M&R budget constraints and minimum requirements on pavement conditions, and to pursue to the highest degree maximization of the total network M&R effectiveness. Therefore, an integer linear programming (ILP) model could be constructed for the network-level project selection problem.

The aforementioned two flaws in TxDOT's PMIS project ranking process could be eliminated by applying the optimization method to the project selection in which pavement sections are competing equally for M&R budget and project timing is considered fairly. In the optimization model the most severely damaged sections are no longer the most favored, rather projects with the highest effectiveness and best timing effect for the entire network and over the planning horizon would be selected for every individual year's M&R program. Several research efforts have been made in such areas. For examples, Sharaf [11]compared two ranking models with the ILP optimization model using data obtained from a comprehensive survey of Egyptian road network and concluded the superiority of the optimization model in terms of improved budget deficit and network condition over the analysis period. Zambrano et al. [12]compared two optimization models, multi-year optimization with multi-treatments (MYO-MT) and multi-year optimization, with single treatment (MYO-ST) with the current TxDOT PMIS ranking method and claimed the victory for the MYO-MT model in terms of accumulated cost-effectiveness ratio and backlogged mileage requiring medium and heavy rehabilitation treatments.

It should be noted that the using of pavement management system (PMS) has been a common practice for every state DOT. Pavement sections are regularly (annually or biannually) assessed for performing conditions, and the pavement assessment data are readily stored in the state DOT's PMS databases. Therefore, it would be reasonable to employ a performance transition function for each of the pavement sections to predict the pavement conditions in multiple years of the planning horizon for the project-selection optimization model. In particular, it should be noted that the yearly budgets available for a transportation agency to use in pavement preservation are always changing over time due to unpredictable circumstances. The instable federal funding due to the overdue enacting of the new surface transportation bill, the dynamics of federal, state, and local highway laws, and the reduced State and Federal Excise Gas Tax Funds due to the ever increasing gas prices are a few contributors to the uncertainty in the yearly pavement M&R budget [13].Though the previous research was helpful, few involved the possibility of Managing Pavement Maintenance and Rehabilitation Projects under Budget Uncertainty (MPMRPBU). Economic recession has produced tight budget, even triggered additional budget cuts, and imposed many economic and human resources constraints on many government and state agencies such as TxDOT. A natural question is raised: As future funding levels become more uncertain, what is the best strategy out there for the pavement engineer/maintenance managers to make informed decision and make the best out of limited financial resources. This paper will formulate and solve the MPMRPBU under a finite rolling planning horizon. Particular attention is given to MPMRPBU model formulation and the stochastic programming approach to solving this multistage stochastic model.

Stochastic programming has many applications in the transportation research areas and examples can be found in freight fleet management [14] and car sharing systems [15]. Solid theoretical foundation regarding large scale linear programming and multistage stochastic programming were built in Dantzig[16], Dantzig and Wolfe[17], Ziemba[18], Wollmer[19], Wets[20], Birge[21], Birge and Louveaux[22], Morton[23], Wallace[24], and Beale et al.[25] Some good applications and techniques used for generating scenario trees for multistage stochastic programming decision problems can be found in Zenios[26], Kouwenberg[27], Hoyland and Wallace[28], and Fleten et al.[29]

Based on all previous discussions, the purpose of this paper is to address a decision making problem for the MPMRPBU. A stochastic linear programming model is constructed in this paper to solve the project-selection problem at the network level in a PMS, which seeks to select a set of candidate projects from the highway network over a planning horizon of five years, which meet the annual M&R budget and pavement condition constraints, and at the same time maximize the total M&R treatment effectiveness. Numerical results will be discussed based upon a pilot case study.

The subsequent sections of this paper are organized as follows: Section 2 discusses the problem statement and assumptions. Section 3 presents the stochastic programming model formulation for the MPMRPBU. Section 4 illustrates the scenario tree generation for the stochastic programing (SP) approach. Section 5 presents the comprehensive computational results of the experimental network as a pilot study. Finally, a summary and discussion of future research directions concludes this paper in section 6.

2 Problem statement

As known, M&R treatments could be at any level, from the simplest and cheapest in preventive maintenance to the most complicated and expensive in rehabilitation. However, it is generally not necessary (and sometime also impossible) for programming at the network level to be as detailed as it is at the project level. In this regard, five simplified M&R treatment levels are assumed and listed as follows:

(1) Needs nothing (NN);
(2) Preventive maintenance (PM);
(3) Light rehabilitation (LRhb);
(4) Medium rehabilitation (MRhb);
(5) Heavy rehabilitation (HRhb).

Each road section in the optimization method is actually a so-called management section and should receive only one of the above five treatments. A management section is a section of pavement, of similar structure, that could be treated in a uniform manner. By grouping together similar pavement sections, the idea of a management section could reduce the number of sections in the highway network and therefore reduce the total number of decision variables in the optimization model, making the problem simpler and easier to handle[2,12].

The M&R benefit (or effectiveness) and cost for each of the five M&R treatments are closely related to the length and traffic volume of the road section. Generally, road sections with longer section length and/or higher traffic volume tend to have bigger M&R benefits and M&R costs. Similarly, the improvement in pavement condition and extended effective life with each of the five candidate M&R treatments could be determined individually for every road section. Normally, a more expensive rehabilitation treatment should yield bigger and longer condition improvement to the road section than a preventive maintenance treatment. The before- and after-treatment effects on road condition are depicted over time in Fig. 1, where e_{ij} represents the improvement in condition score.

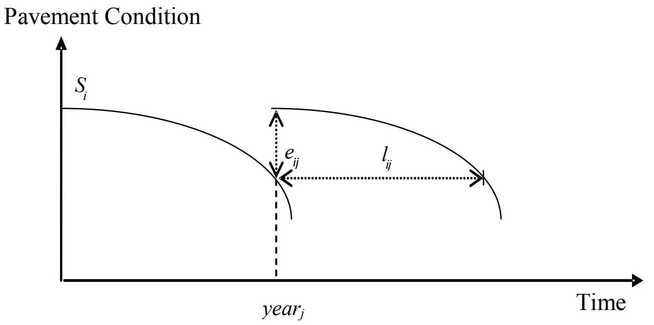

Fig. 1 Pavement condition score and M&R effectiveness

The improvement in road condition could be measured in two parameters: M&R treatment effectiveness and increased condition score. M&R treatment effectiveness is defined as the area between the two curves in Fig. 1 over the effective life of the treatment. The road condition score (0-100) that combines distress and ride quality is regarded as a stable index for road condition and used by TxDOT. The treatment effectiveness over the effective life of the M&R treatment could be estimated by multiplying the initial increased condition score by the treatment's effective life. Normally a condition score below 50 indicates that the pavement section requires some type of remedial attention [1]. Although it is known that network level pavement condition scores of many road sections among many states have a skewed (sometime even heavily skewed) distribution, more towards the excellent or good category where they are bounded by 100, for modeling simplicity, road sections in the highway network are still assumed to have condition scores that are normally distributed, i.e., $S \sim N(\mu, \sigma^2)$, where S is the condition score of a section in the highway network; μ and σ^2 are mean value and variance of the normal distribution N respectively. It is generally believed that statistics observed from sampling can be described with the t distribution, which closely approximates the normal distribution, when degrees of freedom exceed 30. Therefore the normal distribution assumption for condition scores could be assumed to be satisfied with the large number of pavement sections in the network although in reality the condition scores may actually follow a skewed distribution.

To estimate a road condition in a future time and formulate a road state transition process, an additive condition transition model with constant deterioration rates is assumed. As shown in Fig. 1, road section i is given an M&R treatment at year j and improved by e_{ij} in condition score. A constant deterioration rate π_i that is specific to section i could be determined using historical data. If the initial condition score is measured at S_{i0}, and road condition score is increased by e_{ij} at year j for j = 1, 2, ⋯, then in a future time t ($t > j$) road score S_{it} can be calculated in the following formula:

$$S_{it} = S_{i0}\left(1-\pi_i\right)^t + \sum_{j=1}^{t} e_{ij}\left(1-\pi_i\right)^{t-j} \tag{1}$$

Clearly, pavement sections may behave very differently and a constant deterioration rate model is far from precise enough to describe the complex transition process of road conditions. Furthermore, pavement may behave differently after a major maintenance and rehabilitation treatment and therefore substitution of a different deterioration rate may be appropriate after each M&R treatment. However, the more accurate performance curves and deterioration characteristics of every pavement could be obtained from history or other relevant data [2]. In other words, a road condition prediction model similar to the one shown in Eq. (1) could be established and calibrated for each road section and employed in this optimization model.

The TxDOT PMIS databases hold various pavement-related history data that can be used to determine the parameters discussed earlier. It is assumed in this paper that the data for initial road condition score, condition deterioration rate, M&R unit cost, and M&R effectiveness and effective life associated with each of the five M&R treatments can be retrieved or calculated from the PMIS databases for every road management section in the network. To make the model simpler, discount rate for cash flows is not considered in this study and all costs are assessed and represented in present dollar values. Each road management section is assumed to receive at most one M&R treatment in one year and a limited total number of treatments during the planning horizon of five years. Finally, a planning horizon of five years is assumed since during this short period of time only a few M&R treatments are applied to a pavement section. Five to ten years are a popular analysis period for pavement maintenance and rehabilitation planning at the network level [10,12].

3 Model formulation

Based on the previous discussions, an ILP optimization model is formulated as follows.

Indices/Sets:

i——pavement section;

j——year;

k——treatment.

Parameters/Data:

n——total number of road sections in network;

m —— total number of years in planning horizon;

r —— total number of candidate M&R treatments;

a_i—— average daily traffic per lane for section i;

d_i —— section length in kilometers for section i;

e_{ik}—— improvement in condition score for road section i due to treatment k;

l_{ik} —— treatment effective life in years for treatment k applied to section i;

c_{ik}—— M&R unit cost for treatment k applied to section i in thousands of dollars per lane km;

b_j —— available budget in thousands of dollars for year j ;

π_i—— deterioration rate for section i;

g_1 —— minimum requirement on road condition score for each of all road sections;

g_2 —— maximum possible road condition score for each of all road sections;

g_3 —— maximum number of treatments allowed for each road section over the design period; and

g_4 —— statistically minimum requirement on mean value of network road condition scores.

Random variables:

$\tilde{b}_j$ —— available budget in thousands of dollars for year j, $j = 2, \cdots, m$.

Decision variables:

x_{ijk}—— decision variable for section i at year j with treatment k, valued at 1 if selected, 0 otherwise;

S_{ij} —— derivative decision variable of road condition score for section i at year j with initial condition score S_{i0};

Objective function:

$$\text{Max} \quad Z = \sum_{i=1}^{n} \sum_{j=1}^{m} \sum_{k=1}^{r} a_i d_i e_{ik} l_{ik} x_{ijk} \tag{2}$$

$$\text{s.t.} \quad \sum_{i=1}^{n} \sum_{k=1}^{r} d_i c_{ik} x_{i1k} \le b_1 \tag{3}$$

$$\sum_{i=1}^{n} \sum_{k=1}^{r} d_i c_{ik} x_{ijk} \le \tilde{b}_j, \quad j = 2,3, \cdots \tag{4}$$

$$S_{ij} = S_{i0} \left(1 - \pi_i\right)^j + \sum_{t=1}^{j} \sum_{k=1}^{r} x_{itk} e_{ik} \left(1 - \pi_i\right)^{j-t} \quad i = 1,2, \cdots \quad \cdots \tag{5}$$

$$S_{ij} \ge g_1 \ , \quad i = 1,2, \cdots \quad \cdots \tag{6}$$

$$S_{ij} \le g_2 \ , \quad i = 1,2, \cdots \quad \cdots \tag{7}$$

$$\sum_{j=1}^{m} \sum_{k=1}^{r} x_{ijk} \le g_3 \ , \quad i = 1,2, \cdots \tag{8}$$

$$\sum_{i=1}^{n} S_{ij} d_i \ge g_4 \sum_{i=1}^{n} d_i \ , \quad j = 1,2, \cdots \tag{9}$$

$$\sum_{k=1}^{r} x_{ijk} \le 1 \ , \quad i = 1,2, \cdots \quad \cdots \tag{10}$$

$$x_{ijk} = \{0,1\} \ , \ i = 1,2, \cdots \quad \cdots \quad \cdots \tag{11}$$

As can be seen in Eq.(2), the objective is to maximize the total network M&R effectiveness in planning horizon in weighted condition score points. Eq.(3) and Eq.(4) refer to the budget constraints at the first year and all future years, respectively. Other equations are self-explained in most senses.

4 Scenario tree generation

Fig. 2 illustrates a complete scenario tree for multi-stage stochastic programming models. In this figure, the nodes in the tree represent states at a particular period, t. Decisions are made at the nodes and the arcs represent realizations of the uncertain variables. Decisions to be made further down the scenario tree depend on the decisions already made through parent nodes and the uncertain properties of children nodes - such as the three L(ow), M(edium) and H(igh) annual budget scenarios in this Fig. 2. Note that the generation of scenarios is based on the assumed discrete distribution and the decision makers can specify the probability distribution function so that the statistical properties of the problem are preserved. A complete scenario tree consists of realizations of the uncertain variables in each time period (or each stage). In practice, only the first-stage solution at the top node will be used for decision making. The decisions made at stage two or after that are only made in order to find the right incentives for the first-stage decisions [29].

At the beginning of the first period, decisions are made based on current information (and realizations of the stochastic future) at the end of the first period consequences of this decision are seen. Given this consequence and new information for the next period, a new decision is made at the beginning of the second period. Based on the outcomes from the second period and given new information for the third period, the decision is made again. The whole process continues indefinitely in principle. Note that for each scenario tree with generated random variable, one can use exact optimization methods (e.g. L-shaped Method [22]) to solve it. In fact, the first-stage decision is obtained this way.

5 Numerical results

5.1 Example network and data preparation

To run the established model, an instance of the MPMRPBU problem represented by a 5-stage (i.e., year) experimental network with 10 road sections is chosen and included in this pilot study to test the solution quality and efficiency using the developed stochastic programming method to solve the MPMRPBU. The input data for π_i, S_{i0}, a_i, and d_i for each of the ten road sections and c_{ik}, e_{ik}, and l_{ik} for the ten road sections and the five candidate M&R treatments are prepared based on information from TxDOT reports. The first year M&R budget b_1 is known at the time of running this optimization model and assumed to be \$364,000/year. However, for all future four years, budget data b_j's (j = 2, 3, 4, 5) are all stochastic and also assumed to follow a discrete distribution with three scenarios (with expected budget being \$364,000/year) for the model. In other words, they are LOW budget scenario b_j = \$300,000/year (j = 2, 3, 4, 5) with probability being 0.4, MED(ium) budget scenario b_j = \$360,000/year (j = 2, 3, 4, 5) with probability being 0.4, and HIGH budget scenario b_j = \$500,000/year (j = 2, 3, 4, 5) with probability being 0.2. The input data set for a typical pavement management section is illustrated in following Table1.

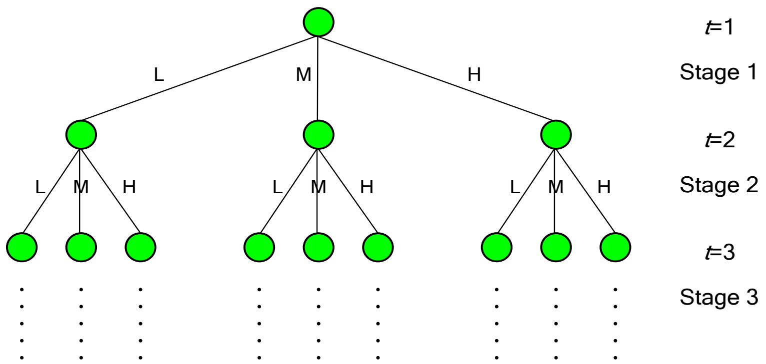

Fig. 2 Scenario tree for multi-stage stochastic programming models

Table 1 Data input for road section i

k	c_{ik} (\$k/lane km)	e_{ik}	l_{ik}(year)
NN	0	0	0
PM	6.1	3	3
LRhb	21	15	5
MRhb	46	25	7
HRhb	110	40	9
p_i = 0.05, S_{i0} = 95, a_i = 20,000 vehicles per lane, d_i = 2.4 km			

Note that the M&R treatment unit cost is measured in thousand US dollars per lane kilometer. The values for g_1 through g_4 are also determined. According to the practice at TxDOT, g_1 = 50, and g_2 = 100. The g_3 value limits the total number of treatments allowed for each road section during the design period of 5 years and should not be larger than 5 (In the worst case a road section is given a treatment for every year in the design period). The g_4 value is determined from the assumed normal distribution of condition scores in the network, i.e., $S \sim N(\mu, \sigma^2)$. From the parameters μ and σ, one can say statistically for a probability of α that road sections in the whole network are better than a condition score of S_α. The g_4 value can be computed from the formula: $\mu = g_4 = S_\alpha + (Z_\alpha)(\sigma)$. For example, the Texas Transportation Commissioner Johnson's statement of minimum required network pavement condition "90% of the road sections in the network should have 70 or higher condition scores" could be interpreted as g_4 = 70+(1.29)(10) = 83 (if σ is assumed to be 10). The σ value or standard deviation in pavement condition scores could be obtained using historical data. The α and S_α values should be input as user requirements and used to calculate the minimum requirement on the mean value of future condition scores in the network [1]. Also the optimization model is solved using OPTMODEL [30] based on SAS macro.

5.2 Computational results

5.2.1 Deterministic optimization approach

In this section, the deterministic optimization approach (DOA) also refers to the expected budget solution. In other words, it is common practice to ignore the uncertainty associated with system parameters because of the computational inconveniences they may cause and to develop heuristic decisions by using the expected value of these random variables instead. In other words, the pavement district engineer/maintenance manager may make the decision using expected annual budgets and then execute the optimal solution by optimizing this "average" scenario only. Numerical results of such deterministic optimization are illustrated as follows.

(1) Effect of annual budgets.

Sensitivity analysis is conducted for the annual budget constraints. Fig. 3 shows the effect of changed budget constraints on objectives Z. As one can see in this figure, as the annual budget increases from \$200,000, the M&R effectiveness objective Z gains improvements for a very large budget range before it becomes insensitive to further budget increases. This result clearly shows that increase of annual budgets is one effective method to increase total M&R effectiveness.

(2) DOA solution results.

Table 2 lists the solutions for the decision variables in two budget conditions. The solutions to the dummy variables show the tendency of having less costly M&R treatments when budget becomes more stringent for pavement maintenance and rehabilitation. However in this case, to keep pavement sections in acceptable conditions, more frequent maintenance or rehabilitation may be required for pavement sections with high deterioration rates. This tendency actually reflects the difference in pavement maintenance and rehabilitation strategies. In the pavement arena there are two opposite strategies to a pavement problem, i.e., "to cover it up" or to "fix it for good". In reality, when only preventive maintenance or light rehabilitation are applied to roads with structural problems, then the structural problems are covered up for only short periods of time and the same problems come back quickly in the future. The optimization results in Table 2 show that for abundant M&R budgets, high cost treatments (normally combinations of preventive maintenances and rehabilitations) are more cost effective than low cost treatments and therefore included in the M&R projects list. And for stringent M&R budgets, only preventive maintenance or light rehabilitation make up the feasible solution. Although the feasible solution is still optimal for the network, these treatments may not necessarily be the most cost-effective for every individual pavement section.

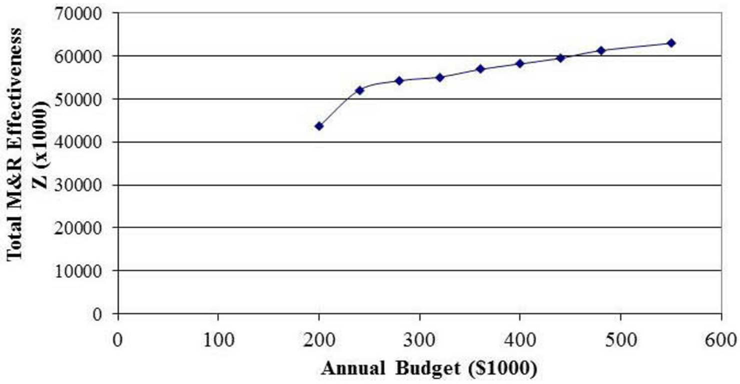

Fig. 3 Objective Z versus annual budget

5.2.2 Stochastic programing approach

As mentioned before, *Stochastic Programing* (SP) is a modeling framework for handling uncertainty in some of the problem data (e.g., the stochastic budget in this paper). The uncertainty is expressed as three budget scenarios (namely HIGH, MEDIUM and LOW budget) allowing the MPMRPBU problem to be solved taking the uncertainty into account rather than finding a way to deal with it afterwards. Since the future budget is unknown and a decision must be made in the current period (i.e., Stage 1), and the values of all first period variables must be the same for all scenarios. Using the developed SAS macro code, the SP solution is obtained for the three-level case and the result as shown in Table 3 is SP = 55,733,760 incorporating all possible scenarios. In other words, this value means that one can expect a sum of 55,733,760 in total M&R effectiveness if such SP solution decision is executed.

In other words, as presented above, the pavement district engineer/maintenance manager may make the decision to compute the average budget (i.e., $364,000/year) of the three scenarios as shown in section 5.2.1 and then execute the optimal solution by optimizing the "average" scenario only. By doing so in the pilot study problem, the problem is solved replacing random budgets by their expected values and the result as shown in Table 3 is: EB = 57,312,000, which means that the total M&R effectiveness will be 57,312,000.However, if the SP solution is executed, the SP solution is only 55,733,760. This is expected because the problem has changed from a stochastic programming problem to a deterministic optimization problem. When the budget is deterministic instead of random, one has perfect budget information and, as a result, one can get a better solution compared to the stochastic programming approach with an objective function value of SP = 55,733,760. Also the magnitude of the objective function for the expected value problem is more than that of the stochastic problem, which is in accord with the principle of Jensen's inequality [22,23].

5.2.3 Value of Stochastic Solution

The difference between the SP solution cost and the expected total cost of using the "expected budget" solution (where the solution for the expected budget case is used as the "average" scenario solution and evaluated under stochastic environment) corresponds to the Value of Stochastic Solution (VSS).

In other words, if the solution of the expected value problem is evaluated in the random budget environment, the objective function of the stochastic problem becomes: EEB = 54,769,926, which indicates that this is an actually worse solution than the SP solution (SP = 55,733,760). That is, the VSS can be calculated as VSS = SP - EEB = 963,834, which can be explained as the cost of executing optimal M&R decisions by ignoring budget uncertainties and always using their expected annual budget values instead. Although this amount might not seem that large in magnitude, the aggregate value for a large network under a long time horizon can be significant. Therefore, stochastic solutions are always preferable to expected value solutions.

Table 2 Optimal decision variables in different budget cases for doa

Section. Year	M&R Treatment (Budget=$200 000/yr)					M&R Treatment (Budget=$200 000/yr)				
	NN	PM	LRhb	MPhb	HRhb	NN	PM	LRhb	MPhb	HRhb
A.1		1					1			
A.2		1					1			
A.3										
A.4			1					1		
A.5										
B.1		1								
B.2										
B.3			1							
B.4		1								
B.5									1	
C.1		1					1			
C.2		1								
C.3							1			
C.4								1		
C.5			1							
D.1		1								
D.2		1								
D.3		1								
D.4		1								
D.5			1						1	
E.1		1								
E.2		1								
E.3		1								
E.4		1								
E.5									1	
F.1		1								
F.2		1					1			
F.3							1			
F.4			1					1		
F.5										
G.1							1			
G.2		1					1			
G.3			1							
G.4								1		
G.5		1					1			
H.1		1					1			
H.2							1			
H.3			1							
H.4								1		
H.5		1					1			
I.1		1								
I.2		1					1			
I.3							1			
I.4			1					1		
I.5		1								
J.1		1								
J.2		1					1			
J.3		1					1			
J.4								1		
J.5			1							
Sum	0	26	9	0	0	0	16	7	3	0
Obj. Value Z	43 632 033					57 312 000				

Table 3 Pilot study numerical results

Formulation Approach	Solution Scenarios	Objective Function Value
Deterministic Optimization	Expected Budget (EB)	57,312,000
Stochastic Programming with Recourse	Three-level Case (SP) HIGH, MEDIUM and LOW Budget	55,733,760
Evaluating Solutions under Stochastic Environment	Evaluating EB (EEB)	54,769,926
Value of Stochastic Solution	SP - EEB	963,834

6 Conclusions

This paper addresses a decision making problem for managing pavement maintenance and rehabilitation projects under budget uncertainty (MPMRPBU). A stochastic linear programming model is formulated and solved for the MPMRPBU. Numerical results are presented based upon a pilot case study. Different optimization solutions based on deterministic optimization and stochastic programming approaches are discussed and compared. The effect of the budget constraint on the optimized solutions is investigated, which shows that "the maximization of total M&R effectiveness" objective is positively related to budget increase. Analysis of the decision variables shows that increased budget may lead to the inclusions of more expensive rehabilitation treatments in the M&R projects list. The computational result indicates a high quality MPMRPBU solution using stochastic programming approach, suggesting that there is a potential that the algorithm can be used for real world applications.

However, it should be pointed out that due to limitations of computation time and SAS/OPTMODEL solver capability, the execution time for solving the MPMRPBU using stochastic programming approach could be unnecessarily long for a certain number of scenarios and the convergence could be a realistic issue for future more-realistic case studies. In such cases, accepting good-enough feasible solutions with tolerable convergence gap may have to be the way to go. As an important part of future research, CPLEX, which is commonly known for its superior speed and ability to deal with large scale optimization, may worth a serious try. Nonetheless, solving the MPMRPBU using stochastic programming approach does show a high potential and can be promising as this line of research matures.

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