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Research Article

A Two-Stage Stochastic Model for Maintenance and Rehabilitation Planning of Pavements

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Pavement maintenance and rehabilitation (M&R) plan for maintaining the pavement quality in an acceptable level has direct influence on the required budget. Deterministic budgeting is an unrealistic assumption, so, in this study, a two-stage stochastic model using integer programming is developed to address uncertainty in budgeting. Another aim of this study is to develop an executive model that considers a broad range of parameters at network level maintenance and rehabilitation planning. While having too many details in planning problems makes them more complicated, some restrictions called "technical constraints" were considered to reduce solution time of solving procedure as well as improve M&R activities assignment efficiency. Comparing results of the stochastic model with a deterministic model for a case study revealed that the two-stage stochastic model led to increased total cost compared to the deterministic one due to considering probability in budgeting. However, the developed model provides several M&R plans that are compatible with budget variation.

1. Introduction

Network level pavement management is complex due to the influential factors such as network size, available budget, pavement performance, distress and maintenance and rehabilitation (M&R) history, traffic and climatic conditions, nonuniform structural properties of pavement and construction operation [1–3]. Each of the aforementioned factors changes during the years, so it is crucial to estimate them within the life-span of pavement. On the other hand, the deviations between the predicted and actual values are inevitable. Thus, uncertainty in the predictions of the influential factors, in addition to their values change with elapse of time, makes the pavement management problems further complex.

Among the influential factors in Pavement Management System (PMS), the one dealing with the limited budget is of great importance. Taking limited budget into account, Wang, Zhang, and Machemehl proposed an optimization process based on the linear integer programming to select the best M&R strategies at the network level for a 5-year period of planning [4]. Wu, Flintsch, and Chowdhury focused on development of a decision-making model to optimize budgeting of the short-term preventive M&R actions [5]. They utilized goal planning methods for multiobjective problems and Analytic Hierarchy Process (AHP) for prioritization under multicriteria. The model was to achieve two objectives: minimizing the M&R costs and maximizing the pavement quality during its service life. Priya, Srinivasan, and Veeraragavan formulated the problems regarding determination of the appropriate types of M&R actions and the time for implementation of them using an effective optimization method [6]. Jesus et al. used a simple but practical model to optimize M&R management with limited budget using linear integer programing [7]. The model determined the budget assignments required to achieve the predetermined goals. Chai et al. established a correlation between the budget assignments and pavement quality indices for a road network in Queensland and, based on the correlation, a model developed [8]. In their study, an index, namely, pavement sustainability index, indicating budget deficit was introduced.

Single-objective optimization for M&R work planning deals with a function in which one independent variable is optimized. However, its main drawback is its suboptimal response compared to that obtained from multiobjective planning [9]. Nevertheless, various pavement management studies have developed and utilized multiobjective optimization models. A research developed a biobjective deterministic optimization model which simultaneously satisfied the objectives of both minimization of total maintenance costs and maximization of performance of the road network [10]. Also, an optimization methodology for county paved roads has been devised that identifies the best mix of preservation projects within budget, maximizing traffic (passengers and trucks traffic) on treated roads, maximizing the weighted average PSI, and minimizing risk [11].

There are also various optimization approaches for developing decision-making models in PMS. The Analytic Hierarchy Process (AHP) is the simplest and most popular method for multiobjective M&R action prioritization [12, 13]. Others are the life-cycle cost analysis for probabilistic model using fuzzy logic [14] and the application of Artificial Neural Network (ANN) for solving multiobjective optimization problems in PMS [15–20]. Moreover, an optimization tool based on a hybrid Greedy Randomized Adaptive Search Procedure (GRASP) has been developed. This tool facilitates the design of optimal maintenance programs subject to budgetary and technical restrictions and explores the effects of different budgetary scenarios on overall network conditions [21].

Budget restrictions have always been the main challenge of PMS to deal with. The PMS models can be developed based on available budget, with the assumption that the available budget is equal to the predicted budget. However, due to the political and economic risks involved in any financial system, there is uncertainty in budget allocations to organizations. Lack of budget can lead to postponing M&R actions implementation in some years during the planning period, which negatively affects the whole predictions. Therefore, deterministic budget cannot be a realistic assumption for planning purposes.

Most studies on PMS have considered pavement deterioration as nondeterministic variable [23–26]. Durango-Cohen took pavement deterioration models as nondeterministic models and evaluated the M&R policies efficiently when imprecise pavement deterioration models are available [27]. Some researchers found the uncertainty in pavement deterioration models as function of uncertainty in pavement structural design, traffic and climatic conditions, and pavement age [28–32]. However, it is important not to restrict the uncertainty to the pavement deterioration [23]. Kuhn [33] considered the uncertainty in the return of investment and Chootinan et al. [34] took the predicted traffic volumes as nondeterministic variable. Yet, there are few studies that considered future budget as uncertain [22, 35].

Gao and Zhang used robust optimization for budgeting M&R at project level considering uncertainty in the annual budget [36]. The approach efficiency was examined using a 20-year pavement performance data and it was found reasonable. Li developed a probabilistic model to allocate nondeterministic budget to the highway network [37]. The model was formulated as probabilistic multiobjective and multidimensional knapsack problem and the results indicated that the uncertainty has significant positive effect on the efficiency of investment.

It seems that the application of uncertainty in development of M&R planning is still immature [38]. Two-stage stochastic programming is useful tool to develop planning models [39–44]. Uncertainty in budgeting justifies application of two-stage stochastic planning in PMS. In the present study, a model for M&R work planning is developed using two-stage stochastic approach with nondeterministic budget. It renders a multi-optional M&R solution under the nondeterministic budget circumstance. Moreover, at network level PMS, consideration of more decomposed condition indicators and consequently extension of details are important study areas that need further investigation in models development. In previous studies, due to the complexity of the problem, especially in large-scale issues or long-term planning periods, less attention has been paid to increasing the number of details. Although the dimensions of the networks expanded as the studies developed, the number of M&R treatments used is still constant and limited [23]. Unlike most models that use four M&R strategies at the most, in this research, eight M&R categories were defined using four pavement quality indicators reflecting thermal distress, structural, skid, and roughness conditions and another that reflects a specific combination of them. Clearly, this level of detail and its application in pavement M&R planning have led to increased model accuracy as well as a higher degree of problem difficulty and complexity. As such, some restrictions called “technical constraints” were defined to reduce solution time of solving procedure. This advantage is applicable for huge networks or long-term planning durations and helps avoid expending too much time in solving M&R planning issues. Therefore, the development of a linear integer two-stage stochastic programming model, which can be used for large-scale networks or for long-term planning periods while also addressing the issue of a greater number of details and considering nondeterministic budget parameter, is one of the innovations of this study.

2. Literature

In this section, a comparison of the applied methodologies mentioned above is summarized in Table 1. As can be seen, there are few studies that utilize more than one condition indicator and at the same time consider uncertainty of budgeting in pavement M&R planning. Accordingly, this study attempts to develop a two-stage stochastic model involving a larger number of condition indicators which allow the network level M&R work planning to become closer to project-level one.

3. Research Approach

In this research, formulation of integer programing at the network level is developed based on a two-stage stochastic

Table 1: Comparison of applied methodologies in investigated studies.

Study	Optimization Method			Level of Study		Formulation	Model Type	Condition Indicator
	MuOb	SiOb	Others	Net	Pro			
Fwa et al. [15]	√			√		GA	Det	PSI
Fwa et al. [16]	√			√		GA	Robust	PCI
Fwa et al. [17]	√			√		GA	Robust	PCI
Chen and Flintsch. [14]			√		√	LCCA	Fuzzy	PSI, PCI
Wu et al. [5]	√			√		GP & AHP	Det	Condition State
Wu and Flintsch. [22]	√			√		MDP	Prob	Condition State
Moazami et al. [13]			√	√		AHP	Fuzzy	PCI
Mathew and Isaac. [10]	√			√		GA	Det	PCI
Meneses and Ferreira. [9]	√			√		GA	Det	PSI
Saha, and Ksaibati. [11]		√		√		LCCA	Det	PSI
Yepes et al. [21]		√		√		GRASP	Det	PCI
Swei et al. [23]		√		√		MINLP	Det & Prob	PCR
Current study	√			√		MILP	Det & Prob	$q\dot{x}$ (qf, qt, qs, qr), qo

MuOb: multiobjective; SiOb: single objective; Net: network; Pro: project; Det: deterministic; Prob: probabilistic; PCI: Pavement Condition Index; PSI: present serviceability index; PCR: pavement condition rate; GA: Genetic Algorithm; LCCA: life cycle cost analysis; AHP: analytic hierarchy process; MDP: multidimensional problem; GRASP: greedy randomized adaptive search procedure; MINLP: Mix integer nonlinear programming; MILP: mix integer linear programming.

Table 2: Indices.

Index	Description
$t, (t \in \{1, 2, \ldots, T\})$	Period (year)
$n, (n \in \{1, 2, \ldots, N\})$	No. of section
$m, (m \in \{1, 2, \ldots, M\})$	M&R actions category
$s, (s \in \{1, 2, \ldots, S\})$	Budget scenarios
$b, (b \in \{1, 2, \ldots, B\})$	Auxiliary index corresponding to condition

model on the condition of nondeterministic budget. GAMS software was employed to solve the developed model using the CPLEX solver. A small network with 10 sections and a planning period of 3 years is considered as a case study. The results of deterministic and probabilistic models were compared for the case study to assess how budget uncertainty affects the results of M&R planning.

3.1. Model Development. Indices, parameters, and variables of the developed method were described in Tables 2, 3, and 4, respectively. t, n, m, and s are the main indices of the model corresponding to the year, section ID, M&R action ID, and budgeting scenario. Index b is an auxiliary index that was used to round the pavement quality indicator values with precision of 0.1. Notably, t addresses the end of a year in the planning period.

In accordance with Table 4, the goal of the model is to find the binary variables of x and y when, with application of the restrictions of the problem, the objective function is minimum. 1 represents implementation of an M&R action and 0 means no M&R application. Moreover, it can be found in Table 4 that there are four normalized indicators of $q\dot{x}$ (qf, qt, qs, and qr) as well as a compound index of qo to quantify pavement condition with respect to structural condition, thermal distresses, skid resistance, roughness, and a linear combination of them, respectively. Notably, the values of these indicators were normalized to be between 0 and 1.

As given in Table 5, there are 8 categories of M&R actions with an ID number attributed to them.

Generally, there is administration cost (AC) and user cost (UC) included in the work planning optimization models. The AC is M&R actions expenses that the administration pays while UC is the sum of vehicle operation cost (VOC), delay cost (DC), and crash cost (CC) that users of the road pay indirectly [45]. In this research, VOC, which depends on the pavement quality, and DC, which is due to treatment type and the time duration it blocks the road, were used in the developed model. It should be noted that a few efforts have been made in literature to determine how pavement condition affects accidents rate and crash costs and what these effects are. Therefore, in this study, due to absence of required data and models related to accidents rate and crash costs affected by pavement condition, the crash cost effects are not considered in the modeling.

Since the deviation in conditions in each scenario leads to the decision change, in the two-stage stochastic model of this article, a cost-based parameter (Ca) was defined to take the cost due to the difference between the first and second stage decision variables into account. Table 6 lists all types of the influential costs on objective functions that were utilized for cost analysis.

Equation (1) expresses the objective function (ob) where, in addition to minimization of all costs, maximization of pavement network condition at the end of analysis period is going to be achieved. Since the objective function is to be minimized, consumed pavement financial value was defined and considered in it, which should be minimized in order to have maximized pavement condition at the end of the analysis period. Simply, by multiplying a transformer term

Table 3: Parameters.

Parameter	Description	Domain
μ	Large value (a value close to infinity)	$(\mu \longrightarrow \infty)$
ε	Small value (a value close to zero)	$(\varepsilon \longrightarrow 0)$
$va_{n,t}$	Pavement financial value of section n at the year t while being in the best condition	$va_{n,t} \in [0,\infty)$
$drop\dot{x}_{n,t}$	Condition drop from t=1 to the target year of t if no M&R action is performed	$drop\dot{x}_{n,t} \in [0,1]$
$dropv\dot{x}_{n,m,t,b}$	Condition drop from the year of performing M&R action (m) on a pavement section (n) with condition index b to the target year of t	$dropv\dot{x}_{n,m,t,b} \in [0,1]$
$inq\dot{x}_n$	Initial condition	$inq\dot{x}_n \in [0,1]$
$im\dot{x}_m$	Condition improvement	$im\dot{x}_m \in [0,1]$
$crl\dot{x}_n$	Lower threshold of condition	$crl\dot{x}_n \in [0,1]$
$crlo_{n,s}$	Lower threshold of overall condition	$crlo_{n,s} \in [0,1]$
$crh\dot{x}_n$	Upper threshold of condition	$crh\dot{x}_n \in [0,1]$
$crho_n$	Upper threshold of overall condition	$crho_n \in [0,1]$
$bu_{t,s}$	Allocated budget	$bu_{t,s} \in [0,\infty)$
$co_{n,m,t}$	M&R action cost (Operating cost)	$co_{n,m,t} \in [0,\infty)$
prs_s	Probability of scenario	$prs_s \in [0,1]$
crq_n	Critical condition in the vehicle operation cost (VOC) vs overall condition curve	$crq_n \in [0,1]$
$cuc_{n,t}$	VOC at the critical condition	$cuc_{n,t} \in [0,\infty)$
$cub_{n,t}$	VOC at the worst condition (0)	$cub_{n,t} \in [0,\infty)$
$cug_{n,t}$	VOC at the best condition (1)	$cug_{n,t} \in [0,\infty)$
$ce_{n,m,t}$	Delay cost due to performing M&R actions	$ce_{n,m,t} \in [0,\infty)$
ca	Cost constant to address deference between first and second stage decisions	$ca \in [0,\infty)$
$k\dot{x}$	Coefficient of $\dot{x}$ condition in overall condition equation	$k\dot{x} \in [0,1]$
c	Deterioration constant in overall condition equation	$c \in [0,1]$

$\dot{x}$ can be replaced by f, t, s, or r which are, respectively, related to fatigue, thermal distress, skid, or roughness.

$(1 - qo_{n,T,s})$, the utility related parameter (va: pavement financial value) was converted to the cost related variable (Va: consumed pavement financial value) which caused the objective function to be formulated as (1) in the form of a single minimizing function. Actually, in this way, a multiobjective function has been changed to a single-objective function.

$$\begin{aligned} ob = \min \Bigg[& \sum_{n=1}^{N}\sum_{m=1}^{M}\sum_{t=1}^{T}\left(co_{n,m,t} \times Z_{n,m,t,1} + ce_{n,m,t} \times y_{n,m,t,1}\right) \\ & + \sum_{n=1}^{N}\sum_{t=1}^{T}\left(\left(cub_{n,t} \times cuqb_{n,t,1} - cb_{n,t,1} \times \left(\frac{cub_{n,t} - cuc_{n,t}}{crq_n}\right)\right) + \left(cuc_{n,t} \times cuqg_{n,t,1} - \left(cg_{n,t,1} - crq_n \times cuqg_{n,t,1}\right) \times \left(\frac{cuc_{n,t} - cug_{n,t}}{1 - crq_n}\right)\right) - cug_{n,t}\right) \\ & + \sum_{n=1}^{N} va_{n,T} \times \left(1 - qo_{n,T,1}\right) + \sum_{n=1}^{N}\sum_{m=1}^{M}\sum_{t=1}^{T}\sum_{s=1}^{S} prs_s \times \left(ca \times \left|x_{n,m,t} - y_{n,m,t,s}\right| + co_{n,m,t} \times Z_{n,m,t,s} + ce_{n,m,t} \times y_{n,m,t,s}\right) \\ & + \sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{s=1}^{S} prs_s \times \left(\left(cub_{n,t} \times cuqb_{n,t,s} - cb_{n,t,s} \times \left(\frac{cub_{n,t} - cuc_{n,t}}{crq_n}\right)\right) + \left(cuc_{n,t} \times cuqg_{n,t,s} - \left(cg_{n,t,s} - crq_n \times cuqg_{n,t,s}\right) \times \left(\frac{cuc_{n,t} - cug_{n,t}}{1 - crq_n}\right)\right) - cug_{n,t}\right) \\ & + \sum_{n=1}^{N}\sum_{s=1}^{S} prs_s \times \left(va_{n,T} \times \left(1 - qo_{n,T,s}\right)\right) \Bigg] \end{aligned} \tag{1}$$

Table 4: Variables.

Variable	Description	Domain
$x_{n,m,t}$	First stage decision variable for M&R action m, section n and year t in the M&R work planning	$x_{n,m,t} \in \{0,1\}$
$y_{n,m,t,s}$	Second stage decision variable for M&R action m, section n, year t and scenario s in the M&R work planning	$y_{n,m,t,s} \in \{0,1\}$
$q\dot{x}_{n,t,s}$	Condition index	$q\dot{x}_{n,t,s} \in [0,1]$
$w\dot{x}_{n,t,s,b}$	Auxiliary variable of condition	$w\dot{x}_{n,t,s,b} \in [0.5-10\varepsilon,1]$
$kw\dot{x}_{n,t,s,b}$	Binary variable determining whether (1) or not (0) auxiliary variable of condition is in index b	$kw\dot{x}_{n,t,s,b} \in \{0,1\}$
$cuqb_{n,t,s}$	Binary variable determining whether (1) or not (0) the condition is in the poor zone in the VOC vs overall condition curve	$cuqb_{n,t,s} \in \{0,1\}$
$cuqg_{n,t,s}$	Binary variable determining whether (1) or not (0) the condition is in the good zone in the VOC vs overall condition curve	$cuqg_{n,t,s} \in \{0,1\}$
$cb_{n,t,s}$	Auxiliary variable for the effect of poor condition on the VOC	$cb_{n,t,s} \in [0,1]$
$cg_{n,t,s}$	Auxiliary variable for the effect of good condition on the VOC	$cg_{n,t,s} \in [0,1]$
$qo_{n,t,s}$	Overall condition index	$qo_{n,t,s} \in [0,1]$
$k_{n,m,t,s}$	Intensity of distress variable	$k_{n,m,t,s} \in [0,1]$
$z_{n,m,t,s}$	Auxiliary variable for intensity of distress	$z_{n,m,t,s} \in [0,1]$
$da\dot{x}_{n,t,s}$	Condition drop	$da\dot{x}_{n,t,s} \in [0,1]$
$dd\dot{x}_{n,t,s}$	Auxiliary variable for condition drop	$dd\dot{x}_{n,t,s} \in [0,1]$
$d\dot{x}_{n,m,t,t',s}$	Condition drop at t' once M&R action was performed at t	$d\dot{x}_{n,m,t,t',s} \in [0,1]$

$\dot{x}$ can be replaced by f, t, s, or r which are, respectively, related to fatigue, thermal distress, skid, or roughness.

Table 5: List of M&R action categories.

ID No.	Action category	Policy
1	Localized safety maintenance	Temporary
2	Localized preventive maintenance	Preventive
3	Level 1: Global preventive maintenance with the objective of improving thermal distresses	
4	Level 2: Global preventive maintenance with the objective of improving skid resistance in addition to level 1 objective	
5	Level 3: Global preventive maintenance with the objective of surface irregularity correction in addition to improving level 2 objective	
6	Surface rehabilitation	Corrective (rehabilitation and reconstruction)
7	Deep rehabilitation	
8	Reconstruction	

Equations (2) to (45) present all of the constraints of the model. Equations (2) to (7) indicate the constraints of auxiliary variables of pavement condition. These equations convert the continuous values of the input parameters corresponding to condition indicators (between 0 and 1) into discretized values with increment of 0.1.

$$w\dot{x}_{n,t,s,b} = \left(\frac{\max\left\{\min\left\{\max\left\{0,\left(inq\dot{x}_{n}-drop\dot{x}_{n,t}\right)\right\}-\varepsilon-0.1\times b+0.1,0.1\right\},\min\left\{\left(0.1\times b-\max\left\{0,\left(inq\dot{x}_{n}-drop\dot{x}_{n,t}\right)\right\}\right),0.1\right\}\right\}}{0.1}\right) \quad \forall n,s,b,\ t=1,\ b\neq 1 \tag{2}$$

$$w\dot{x}_{n,t,s,b} = \left(\frac{\max\left\{\min\left\{\max\left\{0,\left(q\dot{x}_{n,t-1,s}-da\dot{x}_{n,t,s}\right)\right\}-\varepsilon-0.1\times b+0.1,0.1\right\},\min\left\{\left(0.1\times b-\max\left\{0,\left(q\dot{x}_{n,t-1,s}-da\dot{x}_{n,t,s}\right)\right\}\right),0.1\right\}\right\}}{0.1}\right) \quad \forall n,t,s,b,\ t\neq 1,\ b\neq 1 \tag{3}$$

Table 6: Different cost-based functions used in this study.

ID	Cost
Ca	Cost due to deference between the variables of first and second stage decisions
Ce	Delay cost due to performing M&R actions
Co	Operating cost
Cu	Vehicle operation cost
Va	Consumed pavement financial value compared to the highest pavement value

$$w\dot{x}_{n,t,s,1} = \left(\frac{\max\left\{\min\left\{\max\left\{0,\left(inq\dot{x}_{n} - drop\dot{x}_{n,t}\right)\right\} - \varepsilon, 0.1\right\}, \min\left\{\left(0.1 - \varepsilon - \max\left\{0,\left(inq\dot{x}_{n} - drop\dot{x}_{n,t}\right)\right\}\right), 0.1\right\}\right\}}{0.1}\right) \quad \forall n, s,\ t = 1 \tag{4}$$

$$w\dot{x}_{n,t,s,1} = \left(\frac{\max\left\{\min\left\{\max\left\{0,\left(q\dot{x}_{n,t-1,s} - da\dot{x}_{n,t,s}\right)\right\} - \varepsilon, 0.1\right\}, \min\left\{\left(0.1 - \varepsilon - \max\left\{0,\left(q\dot{x}_{n,t-1,s} - da\dot{x}_{n,t,s}\right)\right\}\right), 0.1\right\}\right\}}{0.1}\right) \quad \forall n, t, s,\ t \neq 1 \tag{5}$$

$$kw\dot{x}_{n,t,s,b} \geq \left(1 - w\dot{x}_{n,t,s,b}\right) \quad \forall n, t, s, b \tag{6}$$

$$kw\dot{x}_{n,t,s,b} \leq \left(1 - w\dot{x}_{n,t,s,b}\right) \times \mu \quad \forall n, t, s, b \tag{7}$$

Equations (8) to (11) define the constraints of pavement deterioration rate and yield the condition deterioration rate for each condition indictor.

$$dd\dot{x}_{n,t',s} = \left(drop\dot{x}_{n,t'} - drop\dot{x}_{n,t'-1}\right) + \mu \times \left[\sum_{t<t'}\sum_{m=1}^{M} y_{n,m,t,s}\right] \quad \forall n, t'\left(t' > 1\right), s \tag{8}$$

$$d\dot{x}_{n,m,t,t',s} = \left[\sum_{b}\left(kw\dot{x}_{n,t,s,b} \times dropv\dot{x}_{n,m,t'-t,b}\right)\right] + \mu \times \left(1 - y_{n,m,t,s}\right) \quad \forall n, m, t, t', s,\ \left(t' = t + 1\right) \tag{9}$$

$$d\dot{x}_{n,m,t,t',s} = \left[\sum_{b}\left(kw\dot{x}_{n,t,s,b} \times dropv\dot{x}_{n,m,t'-t,b}\right) - \sum_{b}\left(kw\dot{x}_{n,t,s,b} \times dropv\dot{x}_{n,m,(t'-t)-1,b}\right)\right] + \mu \times \left(1 - y_{n,m,t,s}\right) \quad \forall n, m, t, t', s,\ \left(t' > t + 1\right) \tag{10}$$

$$da\dot{x}_{n,t',s} = \min_{\forall m, t (t<t')}\left\{d\dot{x}_{n,m,t,t',s}, dd\dot{x}_{n,t',s}\right\} \quad \forall n, t'\left(t' > 1\right), s \tag{11}$$

Subsequently, (12) shows the constraints of pavement condition at each year and was defined to compute the values of pavement condition indictors at the end of each year.

$$q\dot{x}_{n,t,s} = \begin{cases} \min\left\{1, \left(\max\left\{0, \left(inq\dot{x}_{n} - drop\dot{x}_{n,t}\right)\right\} + \sum_{m=1}^{M}\left(im\dot{x}_{m} \times y_{n,m,t,s}\right)\right)\right\}, & \forall n, s, t \in \{1\} \\ \min\left\{1, \left(\max\left\{0, \left(q\dot{x}_{n,t-1,s} - da\dot{x}_{n,t,s}\right)\right\} + \sum_{m=1}^{M}\left(im\dot{x}_{m} \times y_{n,m,t,s}\right)\right)\right\}, & \forall n,, s, t \in \{2, \ldots, T\} \end{cases} \tag{12}$$

Equation (13) is the constraint of the overall condition computation and gives the linear relation between the overall condition (qo) and condition indicators ($q\dot{x}$: qf, qt, qs and qr).

$$qo_{n,t,s} = kf \times qf_{n,t,s} + kt \times qt_{n,t,s} + ks \times qs_{n,t,s} + kr \times qr_{n,t,s} + c \quad \forall n, t, s \tag{13}$$

With the aid of (14) to (16), the calculation of M&R costs based on distress intensity level is possible. As such, these equations define the constraints related to the intensity of distress for localized maintenance application.

$$k_{n,m,t,s} = \begin{cases} 1 - (kf \times inqf_n + kt \times inqt_n + ks \times inqs_n + kr \times inqr_n + c); & m \in \{1, 2\} \\ 1; & m \in \{3, \dots, 8\} \end{cases} \quad \forall n, s, t = 1 \tag{14}$$

$$k_{n,m,t,s} = \begin{cases} 1 - qo_{n,t-1,s}; & m \in \{1, 2\} \\ 1; & m \in \{3, \dots, 8\} \end{cases} \quad \forall n, s, t \neq 1 \tag{15}$$

$$\begin{aligned} Z_{n,m,t,s} &\leq y_{n,m,t,s} \\ Z_{n,m,t,s} &\leq k_{m,n,t,s} \\ Z_{n,m,t,s} &\geq k_{m,n,t,s} - (1 - y_{n,m,t,s}) \end{aligned} \quad \forall n, m, t, s \tag{16}$$

The constraint for budget allocation (17) relates to the restriction on the annual budget.

$$\sum_m \sum_n (co_{n,m,t} \times Z_{n,m,t,s}) \leq bu_{t,s} \quad \forall t, s \tag{17}$$

Equation (18) is the constraint that determines the applications of localized maintenance or corrective rehabilitation which is done based on cost comparison. The equation imposes a restriction that recommend a corrective M&R action instead of several localized preventive M&R actions if the costs of the former is less than the latter.

$$co_{n,1,t} \times Z_{n,1,t,s} \leq co_{n,m,t} \quad \forall n, t, s, \; m \in \{6, 7, 8\} \tag{18}$$

Equations (19) to (27) are used for user cost computations. The constraints of auxiliary variables for vehicle operation cost are defined by (19) to (23), and the constraints of vehicle operation cost calculation are defined by (24) to (27).

$$cuqb_{n,t,s} \leq 1 - (kf \times inqf_n + kt \times inqt_n + ks \times inqs_n + kr \times inqr_n + c - crq_n) \quad \forall n, t \, (t = 1), s \tag{19}$$

$$cuqb_{n,t,s} \leq 1 - \left(qo_{n,t-1,s} - crq_n\right) \quad \forall n, t \, (t > 1), s \tag{20}$$

$$cuqg_{n,t,s} < 1 - (crq_n - (kf \times inqf_n + kt \times inqt_n + ks \times inqs_n + kr \times inqr_n + c)) \quad \forall n, t \, (t = 1), s \tag{21}$$

$$cuqg_{n,t,s} < 1 - \left(crq_n - qo_{n,t-1,s}\right) \quad \forall n, t \, (t > 1), s \tag{22}$$

$$cuqb_{n,t,s} + cuqg_{n,t,s} = 1 \quad \forall n, t, s \tag{23}$$

$$cb_{n,t,s} = (kf \times inqf_n + kt \times inqt_n + ks \times inqs_n + kr \times inqr_n + c) \times cuqb_{n,t,s} \quad \forall n, t \, (t = 1), s \tag{24}$$

$$\begin{aligned} cb_{n,t,s} &\leq cuqb_{n,t,s} \\ cb_{n,t,s} &\leq qo_{n,t-1,s} \\ cb_{n,t,s} &\geq qo_{n,t-1,s} - \left(1 - cuqb_{n,t,s}\right) \end{aligned} \quad \forall n, t \, (t > 1), s \tag{25}$$

$$cg_{n,t,s} = (kf \times inqf_n + kt \times inqt_n + ks \times inqs_n + kr \times inqr_n + c) \times cuqg_{n,t,s} \quad \forall n, t \, (t = 1), s \tag{26}$$

$$\begin{aligned} cg_{n,t,s} &\leq cuqg_{n,t,s} \\ cg_{n,t,s} &\leq qo_{n,t-1,s} \\ cg_{n,t,s} &\geq qo_{n,t-1,s} - \left(1 - cuqg_{n,t,s}\right) \end{aligned} \quad \forall n, t \, (t > 1), s \tag{27}$$

Equations (28) and (29) are the constraints to avoid the application of more than one M&R action from a M&R policy

Table 7: Limits of condition indicators for ignoring M&R action.

m	1	2	3	4	5	6	7	8
qo	$crl <$	$< crl*$	$< crl$	$< crl$	$< crl$	-	-	$** crh <$
qf	-	$< crl$	$< crl$	$< crl$	$< crl$	-	-	-
qt	-	-	$crh <$	-	-	-	-	-
qs	-	-	-	$crh <$	-	-	-	-
qr	-	-	-	-	$crh <$	-	-	-

∗ < crl indicates the lower threshold value for a condition index that performing M&R action over section with value less than it is not justified.
∗∗ crh < indicates the upper threshold value for a condition index that performing M&R action over section with value greater than it is not justified.
- There is not any limitation for performing M&R action.

during each year. These restrictions do not allow applying more than one strategy from Table 5 within a year.

$$y_{n,1,t,s} + y_{n,2,t,s} + y_{n,6,t,s} + y_{n,7,t,s} + y_{n,8,t,s} \le 1 \quad \forall n,t,s \tag{28}$$

$$\left(\sum_{m} y_{n,m,t,s}\right) \le 1 \quad \forall n,t,s,\ m \ne 2 \tag{29}$$

Equation (30) is the constraint to correlate between first and second stage decision variables.

$$x_{n,m,t} = y_{n,m,t,1} \quad \forall n,m,t \tag{30}$$

As well, extra constraints are defined according to the existence criteria in Table 7 which are named technical constraints ((31) to (44)). These constraints determine the appropriate limits with using some threshold values which create the zone for ignoring M&R action.

$$crho_n + 1 - qo_{n,t-1,s} \ge y_{n,8,t,s} \quad \forall n,t\ (t>1),s \tag{31}$$

$$crho_n + 1 - (kf \times inqf_n + kt \times inqt_n + ks \times inqs_n + kr \times inqr_n + c) \ge y_{n,8,t,s} \quad \forall n,t\ (t=1),s \tag{32}$$

$$crlo_n + 1 - qo_{n,t-1,s} \ge y_{n,1,t,s} \quad \forall n,t\ (t>1),s \tag{33}$$

$$crlo_n + 1 - (kf \times inqf_n + kt \times inqt_n + ks \times inqs_n + kr \times inqr_n + c) \ge y_{n,1,t,s} \quad \forall n,t\ (t=1),s \tag{34}$$

$$qo_{n,t-1,s} \ge crlo_n \times y_{n,m,t,s} \quad \forall n,t\ (t>1),s,\ m \in \{2,3,4,5\} \tag{35}$$

$$(kf \times inqf_n + kt \times inqt_n + ks \times inqs_n + kr \times inqr_n + c) \ge crlo_n \times y_{n,m,t,s} \quad \forall n,t\ (t=1),s,\ m \in \{2,3,4,5\} \tag{36}$$

$$qf_{n,t-1,s} \ge crlf_n \times y_{n,m,t,s} \quad \forall n,t\ (t>1),s,\ m \in \{3,4,5\} \tag{37}$$

$$inqf_n \ge crlf_n \times y_{n,m,t,s} \quad \forall n,t\ (t=1),s,\ m \in \{3,4,5\} \tag{38}$$

$$crht_n + 1 - qt_{n,t-1,s} \ge y_{n,3,t,s} \quad \forall n,t\ (t>1),s \tag{39}$$

$$crht_n + 1 - inqt_n \ge y_{n,3,t,s} \quad \forall n,t\ (t=1),s \tag{40}$$

$$crhs_n + 1 - qs_{n,t-1,s} \ge y_{n,4,t,s} \quad \forall n,t\ (t>1),s \tag{41}$$

$$crhs_n + 1 - inqs_n \ge y_{n,4,t,s} \quad \forall n,t\ (t=1),s \tag{42}$$

$$crhr_n + 1 - qr_{n,t-1,s} \ge y_{n,5,t,s} \quad \forall n,t\ (t>1),s \tag{43}$$

$$crhr_n + 1 - inqr_n \ge y_{n,5,t,s} \quad \forall n,t\ (t=1),s \tag{44}$$

In order to have realistic M&R planning, since each scenario is based on the variation in annual budget, it is crucial to have the same M&R actions for those scenarios with similar budgets in past years. In other words, budget of each year is effective in the M&R assignment of the same and coming years and has no influence on the past years' M&R assignment. Accordingly, (45) presents the restriction titled "nonanticipative constraint in scenarios" (this formulation is developed based on sequence in budgeting order given in Table 9).

$$y_{n,m,t,s} = y_{n,m,t,s+1} \quad \forall n,m,t,s,b,\ s < 2^{T-t} \times b,\ s > 2^{T-t} \times (b-1),\ t < T,\ b \le \frac{S}{2^{T-t}} \tag{45}$$

3.2. Problem Solving Procedure. This study develops an integer programming-based model involving a multiobjective function. The multiobjective function was changed to a single-objective function by consideration of the transformer term which converts the utility related parameter to the cost related variable. The General Algebraic Modeling System (GAMS) software was used to solve the linear integer programming problem. GAMS is a high-level modeling system for mathematical programming and optimization. GAMS is specifically designed for modeling linear, nonlinear, and mixed integer optimization problems. The settings of the software were modified to meet the specifications of the

Table 8: Budgets ($1000) and their probabilities for each year of planning period.

t	Budget		Probability	
	Predicted	30% reduction	Predicted	30% reduction
1	2518	1763	0.9	0.1
2	2946	2062	0.8	0.2
3	3450	2415	0.7	0.3

Table 9: Budgets ($1000) and the probability of each scenario.

Scenario	Probability			Total probability (PRS)	Budget			Total budget
	t=1	t=2	t=3		t=1	t=2	t=3	
1	0.9	0.8	0.7	0.504	2518	2946	3450	8914
2	0.9	0.8	0.3	0.216	2518	2946	2415	7879
3	0.9	0.2	0.7	0.126	2518	2062	3450	8030
4	0.9	0.2	0.3	0.054	2518	2062	2415	6995
5	0.1	0.8	0.7	0.056	1763	2946	3450	8159
6	0.1	0.8	0.3	0.024	1763	2946	2415	7124
7	0.1	0.2	0.7	0.014	1763	2062	3450	7275
8	0.1	0.2	0.3	0.006	1763	2062	2415	6240

solving algorithm of the work planning problem. The CPLEX solver and the MIP (Mix Integer Programming) option were set to solve the model since this study dealt with a linear integer programming problem. CPLEX is a GAMS solver that allows users to combine the high-level modeling capabilities of GAMS with the power of CPLEX optimizers. Notably, this software was used because it is widely used for accurate problem solving of linear models; however, any software with the ability to solve mathematical models can be employed for the purpose of this research.

3.3. Case Study. Since the runtime for problem solving is directly related to the length of the analysis period and the size of the pavement network, a small pavement network and short analysis period have been selected for evaluating the model and comparing the approaches. A 3-year data collection on pavement conditions and M&R implementation was carried out covering 10 pavement network sections in Mashhad, Iran. In order to be concise and since the aim of this article is to compare results of probabilistic model in condition of budget uncertainty with those of deterministic model, the budget specifications were brought here and values for the other parameters of the models were not described (S1).

In this case study, two budget modes were considered for each year. Table 8 gives the predicted budget for each year as well as the probability of it. If the predicted budget is not provided, 30% of relative deficit was estimated for each year's budget. The budget values were predicted by inquiry from undertaken administration, but the related probabilities were estimated based on an obvious assumption; if the forecast is longer, the probability of occurrence of the event will be relatively reduced. As there are two budget allocations for each year of the planning period, subsequently, 8 scenarios exist for the planning period of 3 years ($2^3 = 8$). The scenarios are defined according to the whole situations can be possible for budgeting at each year. Accordingly, the budgets and their probabilities for each scenario could be determined as given in Table 9. Notably, the sum of probabilities is equal to 1.

4. Results Analysis

In the developed two-stage stochastic model, parameter '*Ca*' is defined as the cost of inequality of the first stage variable and the second stage variable. Due to the decision change, the value of *Ca* is added to the costs. *Ca* is the cost that is paid by decision maker to mitigate the effect of budget variation on planning and total cost due to the scenario change. Thus, by minimizing the total cost, the decision made in the second stage has less variation compared to the first stage. On the other hand, the greater the value of *Ca*, the less the variation at the second stage in comparison with first stage and vice versa. Even so, if the value of *Ca* is greater than a boundary threshold, the increase in *Ca* has no influence on the decision and, subsequently, on the costs. The boundary threshold is the point where the decisions of the first and second stages are the same and that is why (based on the line plotted in Figure 1) the result of the model shows no sensitivity to the budget variation after that point (for the case study, $Ca = 60000$).

The value of *Ca* is dependent on the conditions of each project. *Ca* values of the case study are presented in Table 10 as a percentage of the total budget and the developed model was solved for each *Ca* value. Also, the total cost for each *Ca* was computed by finding the response value of the objective function (*ob* according to (1)) using the developed model.

Based on the results of Table 10, the total cost versus *Ca* is plotted in Figure 1. It can be observed that, with *Ca* increase, the total cost increases up until a point that the increase in *Ca* has no impact on total cost. As mentioned earlier, the reason of it is the same values for the first and second stage

Table 10: The default values of Ca and their corresponding total costs.

Percent of Total budget (%)	Ca ($1000)	ob (total cost) ($1000)
0	0	38173.463
0.001	0.08914	38293.675
0.01	0.8914	38495.21
0.1	8.914	38877.417
1	89.14	38732.591
10	891.4	39579.052
100	8914	40482.297
432	38500	43184.203
673	60000	43813.052
774	69000	43813.052

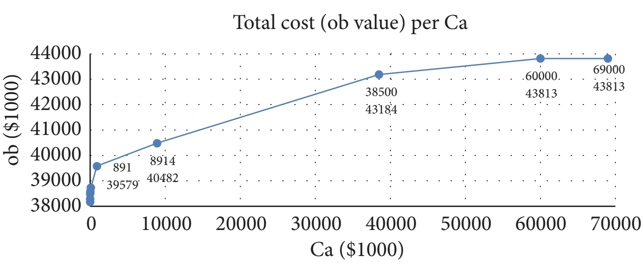

Figure 1: Total cost versus Ca.

decision variables ($x = y$) from that point on. As shown in Figure 1, Ca of 60000 is approximately corresponding to the boundary threshold for the case study of this research. For the Ca less than the boundary threshold, first, there is smooth total cost decrease with the Ca reduction. Then, there is turning or break-even point on the line where the slope of the line increases dramatically with Ca decrease. This point is considered the best value for Ca because the values less than it lead to the high sensitivity of the results of the model to the variation of Ca. Also, as the Ca approaches zero, it can be inferred that the decision and plan alteration do not impose any additional cost which is contrary to the reality. Therefore, in the case study, 891 is the appropriate value for the Ca based on Figure 1.

Once Ca is determined, the effects of budget uncertainty on the results of M&R planning can be assessed with comparing the results obtained from the two-stage stochastic and the deterministic models. Notably, the deterministic model was developed similar to the probabilistic model except that the "s" index was eliminated from formulations. Consequently, some terms in the objective function and some restrictions were omitted or changed in the deterministic model. More precisely, in addition to using "x" as the decision variable instead of "y" in all of the equations, (30) and (45) were eliminated and objective function was changed as (46) in the deterministic model.

$$ob = \min \Bigg[\sum_{n=1}^{N} \sum_{m=1}^{M} \sum_{t=1}^{T} \left(co_{n,m,t} \times Z_{n,m,t} + ce_{n,m,t} \times x_{n,m,t} \right) + \sum_{n=1}^{N} \sum_{t=1}^{T} \left(\left(cub_{n,t} \times cuqb_{n,t} - cb_{n,t} \times \left(\frac{cub_{n,t} - cuc_{n,t}}{crq_n} \right) \right) + \left(cuc_{n,t} \times cuqg_{n,t} - \left(cg_{n,t} - crq_n \times cuqg_{n,t} \right) \times \left(\frac{cuc_{n,t} - cug_{n,t}}{1 - crq_n} \right) \right) - cug_{n,t} \right) + \sum_{n=1}^{N} va_{n,T} \times \left(1 - qo_{n,T} \right) \Bigg] \quad (46)$$

Finally, parameter values corresponding to the first scenario were used to solve the deterministic model. According to (30), since the first stage decision variable is equal to the second stage decision variable in the first scenario ($x_{n,m,t} = y_{n,m,t,1}$), the values obtained for first scenario could correspond to the first stage decision variable. Therefore, in order to make the comparison between the deterministic and stochastic models possible, the results of the first stage decision variable of the two-stage stochastic model were compared to the decision variable of deterministic model.

Moreover, in order to assess the impact of technical constraints on the results, the deterministic model was also solved without any technical constraints addressed by (31) to (44). As such, adding technical constraints to the deterministic model resulted in a 91% decrease in runtime for solving the problem. Therefore, considering the technical constraints in the model reduces the solution time of solving procedure. This advantage is applicable for huge networks or long-term planning durations and helps avoid expending too much time in solving M&R planning issues.

Table 11 presents the results of M&R actions assignment for the deterministic and stochastic models. Each number in Table 11 refers to M&R action category ID presented in Table 5. "Noting" shows that any M&R action was not assigned to the related section at the investigated year. It can be seen that 23 percent of the assignments in the stochastic model, i.e., 7 out of 30, are different from deterministic ones.

Based on the definitions given in Table 2, Figure 2 compares the component costs of the deterministic and stochastic models, while Figure 3 makes the comparison between the total costs of them. The total cost of the stochastic model is higher than the deterministic one due to the uncertainty. It can be inferred that considering the probability in budgeting variation within the modeling process and, subsequently, alteration in M&R plan, results in an increase in the costs at the network level during the planning period. Instead of

Table 11: Comparison between the deterministic and stochastic assignment results.

n	Deterministic			Stochastic		
	t=1	t=2	t=3	t=1	t=2	t=3
1	noting	6	2	noting	5	2
2	noting	6	2	noting	6	noting
3	6	4	noting	6	2, 4	noting
4	6	2	noting	6	2	noting
5	6	noting	noting	6	noting	noting
6	5	2	2	5	2	2
7	6	2	noting	6	2	2
8	6	2	noting	6	2	noting
9	2, 4	2	noting	4	2	noting
10	noting	noting	2	2	noting	noting

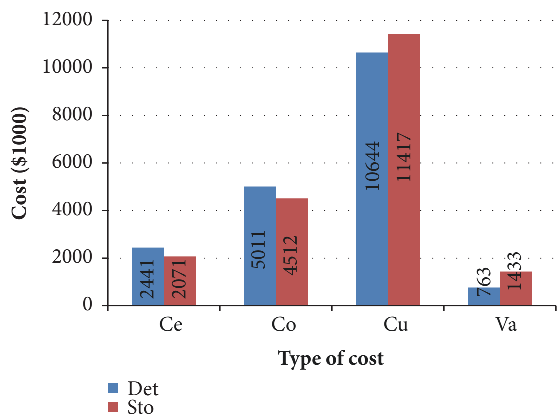

Figure 2: Comparison between the costs of the deterministic and stochastic models.

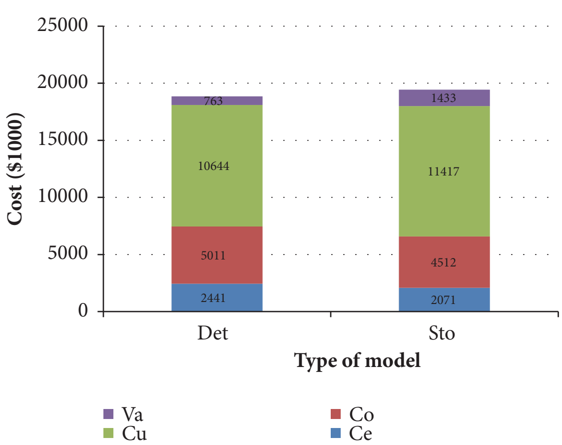

Figure 3: Comparison between the total costs of the deterministic and stochastic models.

this, the stochastic model provides several M&R plans that are compatible with budget variation.

Figure 4 illustrates the ratios of the effective costs to the total cost for both models. It can be seen that a significant portion of the total cost is due to the vehicle operation cost

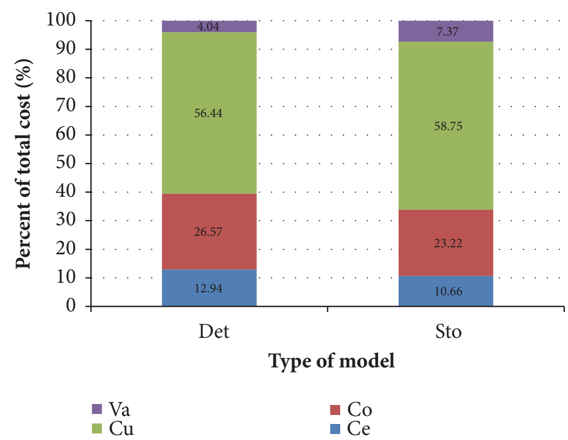

Figure 4: Comparison between portions of costs for deterministic and stochastic models.

(*Cu*) indicating the higher sensitivity of it in both models. Thus, minimizing *Cu* has more impact on minimization of the total cost. As shown in Figures 2 and 3, although the M&R operation cost (*Co*) of deterministic model is higher than those of stochastic model, the lower cost of *Cu* of deterministic model leads to lessened total cost compared to the stochastic model.

Figure 5 shows each year's consumed budget as well as the average consumed budget within the planning period for deterministic and stochastic models. In order to better distinguish the cost values in each year, Figure 6 gives each year's effective costs separately for deterministic and stochastic models. It can be observed that each model consumed the most out of the available budget for first year. In other words, more budgets are used in the initial years of the planning period. This proves that the objective functions of the models have more sensitivity to the initial years of the planning period. The reason of it is the high influence of the vehicle operation cost (*Cu*) and, subsequently, the pavement condition on the total cost. Therefore, the model suggests that the maximum M&R operation costs (*Co*) in the initials years reach the desired pavement condition in order to reduce the *Cu* costs substantially. In the last year of the planning period,

Table 12: Comparison between the total costs ($1000) of deterministic model and each scenario of the stochastic model.

s	Total cost in stochastic model	PRS	Cost ∗ PRS	Total cost in deterministic model	Percent of cost increased	Percent ∗ PRS
1	19433.54	0.504	9794.503	18858.65	3.048389	1.536388
2	19433.54	0.216	4197.644	18858.65	3.048389	0.658452
3	19433.04	0.126	2448.563	18858.65	3.045753	0.383765
4	19433.04	0.054	1049.384	18858.65	3.045753	0.164471
5	26490.95	0.056	1483.493	18858.65	40.47109	2.266381
6	26490.95	0.024	635.7829	18858.65	40.47109	0.971306
7	26807.14	0.014	375.3	18858.65	42.1477	0.590068
8	26807.14	0.006	160.8428	18858.65	42.1477	0.252886
Average	23041.17		20145.51		22.17823	6.823717

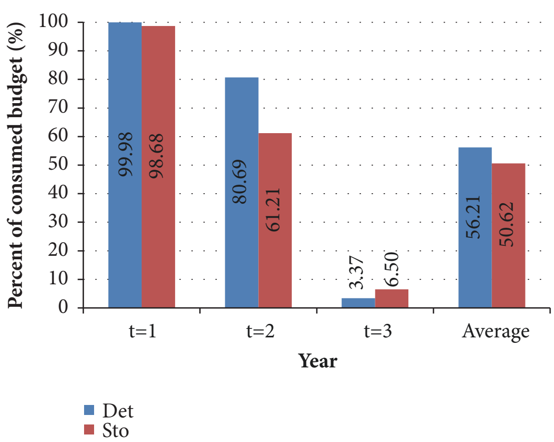

Figure 5: Comparison between the percent of consumed budget to available budget for deterministic and stochastic models.

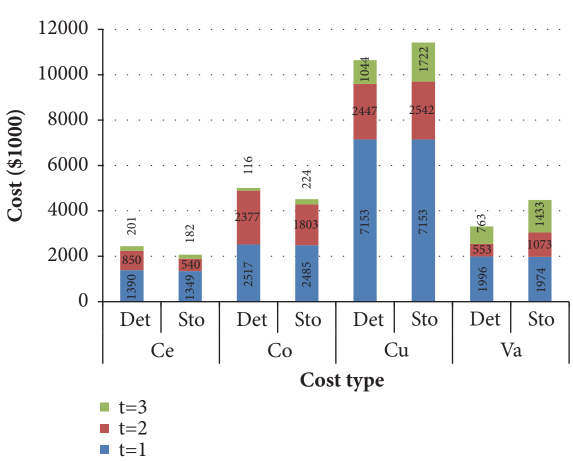

Figure 6: Comparison between each year's effective costs of the deterministic and stochastic models.

the pavement condition is approximately in a desired level and, consequently, the *Cu* does not increase rapidly as any dramatic deterioration exists. Therefore, in the last year of the planning period, M&R operation cost has greater effect on the results of the model compared to the *Cu* and the model intends to reduce M&R operation cost (*Co*). Subsequently, the total cost reduces gradually in the last year of the planning period.

Table 12 yields the total costs of each scenario for deterministic and stochastic model. Also, the percentage increases in the total costs in accordance with the deterministic model are given. It can be observed that the total costs of the stochastic model are higher than those of the deterministic one. For scenario 1, it is 3%, and in the worst scenario that there is deficit in all of years of the planning period, it is obtained as 42%. According to Table 9, the maximum budget deficit in the stochastic model can be 2674 (difference between 8914 and 6240) thousand USD by comparing the best and worst case scenarios (the 1st and 8th scenarios). In accordance with Table 12, this amount resulted in an increase of 7374 (difference between 26807 and 19433) thousand USD in the total cost which is approximately three times greater than the maximum budget deficit. This indicates the importance of funding in pavement management.

Although using the two-stage stochastic model increases the total cost, it has some advantages. Table 13 presents the results of M&R assignments in each planning year for each scenario. Since the different conditions of budgeting are considered in the planning process, a flexible M&R planning is resulted for the budget variations.

Due to the Nonanticipative constraint considered in scenarios, it can be seen that in all scenarios with equal budgets at prior years, similar M&R actions were assigned. Such M&R assignment gives a plan that can be pursued at any year of the planning period according to budgets which had been implemented in prior years.

5. Summary and Conclusion

An M&R planning model which considers nondeterministic budget was developed in this study based on a linear integer two-stage stochastic programming approach. The model can be used for large-scale networks or for long-term planning periods, although it addresses a great number of details. As such, the effects of budget uncertainty on results of M&R planning were assessed by comparing the results obtained from the two-stage stochastic and the deterministic models. From the comparison of the results of the deterministic and stochastic models, following conclusions can be drawn:

Table 13: Results of two-stage model M&R assignments.

n	s=1			s=2			s=3			s=4		
	t=1	t=2	t=3	t=1	t=2	t=3	t=1	t=2	t=3	t=1	t=2	t=3
1	noting	5	2	noting	5	2	noting	5	2	noting	5	2
2	noting	6	noting	noting	6	noting	noting	6	noting	noting	6	noting
3	6	2, 4	noting	6	2, 4	noting	6	2, 4	noting	6	2, 4	noting
4	6	2	noting	6	2	noting	6	2	noting	6	2	noting
5	6	noting	noting	6	noting	noting	6	noting	noting	6	noting	noting
6	5	2	2	5	2	2	5	2	2	5	2	2
7	6	2	2	6	2	2	6	2	2	6	2	2
8	6	2	noting	6	2	noting	6	2	noting	6	2	noting
9	4	2	noting	4	2	noting	4	2	noting	4	2	noting
10	2	noting	noting	2	noting	noting	2	noting	noting	2	noting	noting
n	**s=5**			**s=6**			**s=7**			**s=8**		
	t=1	**t=2**	**t=3**	**t=1**	**t=2**	**t=3**	**t=1**	**t=2**	**t=3**	**t=1**	**t=2**	**t=3**
1	noting	5	2	noting	5	2	noting	5	2	noting	5	2
2	noting	6	noting	noting	6	noting	noting	6	noting	noting	6	noting
3	6	2, 4	noting	6	2, 4	noting	6	2	noting	6	2	noting
4	noting	2	noting	noting	2	noting	noting	2	noting	noting	2	noting
5	noting	6	noting	noting	6	noting	noting	noting	noting	noting	noting	noting
6	5	2	2	5	2	2	5	2	2	5	2	2
7	6	2	2	6	2	2	6	2	2	6	2	2
8	6	2	noting	6	2	noting	6	2	noting	6	2	noting
9	4	2	noting	4	2	noting	4	2	noting	4	2	noting
10	2	noting	noting	2	noting	noting	2	noting	noting	2	noting	noting

(i) Taking the probabilistic effect of the budgeting within modeling process and, subsequently, alteration in M&R planning into account results in an increase in the costs of the planning period. It was computed as 3% for the case study. However, considering the various conditions for budgeting in the two-stage stochastic model leads to flexible M&R actions planning for budget variation so that it can be followed at any year of the planning period regardless of having the exact expected budget in that year.

(ii) The annual budget deficit leads to the increased costs during the planning period. The total financial loss could reach 3 times as much as the total deficit for the case study.

(iii) Both deterministic and stochastic models have the most sensitivity to the vehicle operation cost (Cu). Thus, minimization of the Cu has the greatest impact on the minimization of the total cost.

(iv) Both deterministic and stochastic models used the most of the available budget in the first year of the planning period. In other words, the total cost has greater sensitivity to the initial years of the planning period, so providing sufficient budget for the initial years is of much importance.

This study can be helpful to other researchers in area relevant to pavement M&R planning since it employs a linear integer programming model. There is not any limitation for application of the model if the parameters values are fully available. However, completely gathering data for a huge network or for a long time planning period could impose considerable costs to undertaking administrations. It would be worthwhile for other researchers and scholars to develop this model by using heuristic and metaheuristic methods like genetic algorithm (GA) and others which also reduce runtime in solving the problem. In addition to budgeting, this study can be considered by other researchers as it takes into account uncertainty in some other parameters such as pavement performance deterioration, traffic estimations, and other similar items. Moreover, determining pavement condition effects on accidents rate and related crash costs and, consequently, considering the crash cost effects in the modeling can be taken into account by other researches. Also, a comparison of the model, not only with the deterministic approach but also with other approaches such as robust optimization or fuzzy mathematical programming that allow for inclusion of the uncertainty of budgeting, could be greatly noteworthy for researchers.

Data Availability

The GAMS software input data used in this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Supplementary Materials

An example of coding in the GAMS software that contains all the input data about the model parameters. *(Supplementary Materials)*

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