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Optimal Planning of Pavement Maintenance and Rehabilitation Considering Pavement Deterioration Uncertainty

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ABSTRACT: Optimization of pavement maintenance and rehabilitation (M&R) is one of the most substantial parts of the pavement management system (PMS). Highway agencies should plan M&R treatments efficiently. An accurate pavement performance model is required to predict pavements' future conditions. Thus, an accurate international roughness index (IRI) model was developed to predict IRI. Moreover, M&R was scheduled deterministically in many past studies, but this issue does not match the uncertain essence of deterioration and future M&R expenditures. Hence, the uncertainty associated with pavement deterioration and budget calculation should be considered in scheduling M&R activities. This study scheduled M&R activities deterministically and probabilistically to compare the solutions obtained from both approaches. The uncertainty of several features in the IRI model and budget calculation was not considered in the deterministic approach. Furthermore, in the probabilistic approach, historical data were employed to fit the distribution function for uncertain features in the model. Then, Monte Carlo simulation and optimizer were run to generate probability distributions for sections' IRI and required budget and optimize M&R scheduling. The IRI model was developed using 288 data. The testing data R-square of the model was 0.917. As a case study, the research results were applied to a network, including five sections during a 5-year-planning. Additionally, the costs of M&R scheduling in the deterministic and probabilistic approaches were $52,149 and $40,195. Hence, the cost of the deterministic approach was 29.7% higher than the probabilistic approach. Besides, the probabilistic method applied more preventive maintenance, desirable for users, than the deterministic one.

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1- Introduction

Infrastructures are vital in every country due to using valuable resources, including time, budget, and labor forces. Transportation infrastructures, as the main part of infrastructures, have a significant impact on transporting people and goods [1]. If transportation infrastructures are managed correctly to maintain their high quality of service, they will be one of the most significant factors for economic growth [2, 3]. Pavements are the most visible component of transportation infrastructure that highway agencies spend many resources to preserve pavements from failure. For instance, the United States spends more than $100 billion annually to maintain road networks at the desired condition [4, 5]. Nevertheless, 20% of highway pavements in the United States are in poor condition [5]. The highway agency and user costs will increase due to the deterioration of road conditions remarkably. If pavement maintenance and rehabilitation (M&R) treatments are performed on time, over half of the repair costs can be avoided [6]. Hence, highway agencies should optimize M&R scheduling. To this end, highway agencies should evaluate the pavement conditions to schedule M&R activities optimally.

Pavement condition analysis is essential for achieving optimum M&R actions. The pavement condition can be assessed by observing the type, severity, and density of present distresses, while the future condition of the pavement is essential for M&R scheduling. Therefore, pavement deterioration models are used to predict the future condition of the pavement. If the performance model predicts the future condition of pavement accurately, highway agencies can assign the required budget to M&R activities correctly. Performance models represent the condition of the pavement using either single or combined indexes. The indexes are selected based on data availability and the highway agencies' need.

Road roughness is one of the most important indicators in determining the pavements' performance [7]. Road roughness can be represented by the International Roughness Index (IRI) [6, 8]. The IRI, as one of the most common condition indexes, can present the ride quality and the comfort of users. Moreover, Odoki and Kerali (2000) indicated that IRI growth causes an increase in vehicle operating costs and the number of accidents [9]. Besides, it was indicated that there is a strong relationship between IRI and pavement distresses [8]. The pavements' IRI increases over time, leading to pavement

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deterioration [10]. Hence, IRI prediction models represent the IRI increment rate due to the passage of time. Furthermore, IRI is an appropriate index for M&R scheduling optimization [11]. An accurate IRI deterioration model is required to plan M&R treatments optimally.

The accuracy of the pavement performance model has a significant effect on scheduling M&R correctly. If trustworthy data and important parameters are used in a model generation, the desired accuracy can be fulfilled [12]. Some researchers have generated IRI performance models based on the Long-Term Pavement Performance (LTPP) database due to its reliability, accuracy, variety, and versatility [10, 13-17].

Two approaches can be employed to plan M&R treatments, including deterministic and probabilistic. The uncertainty associated with the pavement deterioration model and budget calculation is not considered in the deterministic method. The deterministic strategy is not appropriate for scheduling M&R treatments since the pavement deterioration and budget calculation are uncertain. Several variables are commonly employed in IRI performance models, such as climatic and traffic loading features, which are uncertain, and specific values cannot be assigned for them. Hence, it is not appropriate to use the deterministic approach to plan M&R treatments. On the other hand, using the deterministic method is simpler than the probabilistic one. Therefore, highway agencies commonly apply deterministic methods to optimize M&R scheduling. Nonetheless, ignoring the uncertainty associated with the mentioned variables leads to sub-optimal solutions [18, 19]. The probabilistic strategy calculates possible solutions by representing the probability distributions, while the deterministic strategy represents only one value [20]. Moreover, highway agencies and decision-makers can make decisions more efficiently in the probabilistic strategy. Nevertheless, the probabilistic approach considers the randomness of the uncertain variables resulting in representing probability distributions for pavement performance. Consequently, the probabilistic approach should be used to schedule M&R activities [21].

2- Background

Previous studies generated IRI prediction models using the data from the LTPP database, local agencies database, and direct measurements [13]. The data of initial IRI, climatic features, traffic characteristics, and/or structural parameters were employed to develop IRI performance models. Furthermore, some studies used pavement distresses data to generate the IRI model [13, 16, 22]. The data collection of pavement distresses is time-consuming and labor-intensive [23]. Hence, it is more appropriate to utilize initial IRI, climatic features, traffic characteristics, and/or structural parameters rather than pavement distresses to develop the IRI deterioration model. To this end, several researchers used these features to generate IRI performance models.

George (2000) developed two IRI performance models based on the Mississippi Department of Transportation Database [24]. The author employed equivalent single axle load (ESAL), structural number (SN), and pavement age to develop the first model. Besides, in addition to the parameters used in the first model development, the pavement's thickness was used to generate the second model. The coefficient of determination (R^2) of the first model was 0.35. Moreover, the second model could predict IRI with an R^2 of 0.48. Choi et al. (2004) developed an IRI model [14]. They applied cumulative ESAL, SN, and the thickness of the top layer to develop the model. The model achieved an R^2 of 0.71 based on 117 observations from LTPP. Albuquerque and Núñez (٢٠١١) established two IRI performance models for low-volume roads using the regression analysis technique [25]. They employed precipitation, ESAL, and SN to form IRI models with coefficients of determination of 0.94 and 0.87 based on 18 and 27 observations, respectively. Mazari and Rodriguez (2016) used 98 observations from the LTPP to develop an IRI prediction model [10]. The IRI performance model was generated as a function of initial IRI, ESAL, and pavement age. Jaafar and Fahmi (2016) utilized 34 observations from the LTPP database to develop two IRI prediction models [26]. The researchers used initial IRI, ESAL, SN, pavement age, and construction number to establish the models. Dallarosa et al. (2017) proposed two IRI performance functions for low-volume and medium-volume roads [27]. The data of the texas department of transportation was employed to generate the models using initial IRI and pavement age. The root-mean-square error (RMSE) of the developed models was presented, which was equal to 0.21 for both models. Besides, Pérez-Acebo et al. (2020) generated an IRI performance model for flexible pavements whose coefficient of determination was equal to 0.44 [28].

Many studies developed IRI performance models utilizing the Markov chain process to consider the uncertainty [29, 30]. For instance, Alimoradi et al. (2020) used the Markov chain to predict pavement roughness considering its initial value. This method applies the probability of transferring from a current state of pavement to another state (or staying in the same state) in a one-time interval, which is called stage, to predict the future condition of the pavement. Markovian models change the format of the M&R scheduling problem from integer programming to linear one. Additionally, Markovian models have two major deficiencies. Markovian models categorize pavements' IRI into various levels. Several pavement performance indicators are continuous, such as the IRI, but the Markov chain process makes pavement condition indicators discrete, reducing IRI prediction accuracy. Besides, these models classify pavement sections into identical categories based on their features and schedule M&R activities for groups of segments [4]. Hence, Markovian models are not able to plan M&R treatments for each section separately. Therefore, Markovian models are not qualified enough to schedule M&R treatments probabilistically.

One appropriate method to take into account the uncertainty is to use Monte Carlo simulation (MCS), which has received inadequate attention in the field of M&R scheduling. MCS is a type of simulation that computes the results based on iterative random sampling and statistical assessment. This simulation is a useful probabilistic tool for evaluating and modeling real-world problems to consider uncertainty and analyze risks quantitatively. For instance, Rose et al. (2018) employed the MCS to transform deterministic models into probabilistic ones [20]. The authors at first selected reliable deterministic prediction models for pothole progression, edge failure, and raveling progression. Then, appropriate Probability Distribution Functions (PDFs) and Probability Mass Functions (PMFs) were fitted to the data collected for independent variables. Afterward, the probabilistic prediction models were developed using MCS.

Typically, there are two main strategies to form an M&R scheduling optimization model. In the first strategy, the highway agencies minimize the required budget, which is subject to acceptable pavement performance. In the second strategy, the pavement performance is maximized considering the available budget. Time in optimization models can be considered as a discrete or continuous variable. Discrete-time intervals have been preferred by highway agencies since they practically perform M&R actions annually. After the determination of the highway agency's desired strategy, the M&R optimization problem can be modeled.

The Integer Programming (IP) or Mixed-Integer Programming (MIP) models have been utilized for M&R scheduling in some studies. Wang et al. (2003) represented a multi-objective MIP model for scheduling M&R activities [31]. Available annual budget and minimum acceptable condition of pavements were considered as constraints. The results were applied to a pavement network consisting of ten sections. A binary linear IP was proposed to determine optimal M&R treatments by Chakroborty et al. (2012) [32]. Fani et al. (2020) proposed a multistage stochastic MIP model to identify an optimal possible plan from all possible scenarios under uncertainty [18]. The minimization of deviations of each section's IRI from desired highway agency's IRI in the last year of the analysis period was the objective function of their model constrained to the available budget. The authors investigated two pavement networks as case studies, which included 4 and 21 sections.

While the mentioned studies used exact algorithms to find optimum solutions for M&R scheduling, some studies employed evolutionary and metaheuristic algorithms to solve the problem [4, 7, 33-37]. For instance, Naseri et al. (2021) employed five metaheuristic algorithms to solve the M&R scheduling problem [37]. Nevertheless, the evolutionary and metaheuristic algorithms may not find the global optimum solution. Due to the mentioned problem, the results of M&R treatments of different metaheuristic algorithms of Naseri et al. (2021) differed significantly since these algorithms reached various results and could not reach global solutions[37]. In other words, using these algorithms may result in sub-optimal solutions [4]. Therefore, it is more appropriate to employ exact algorithms to solve the M&R scheduling optimization problem, which leads to optimum solutions.

To sum up, although several IRI prediction models were developed, these models have not achieved a high quality of fit, which significantly affects the efficiency of M&R scheduling optimization. On the other hand, several IRI prediction models employed pavement distress, whose data collection is time-consuming and labor-intensive, to generate the model. Besides, pavement deterioration and budget calculation are uncertain, which have not received enough attention in previous studies. This study aimed to fill such gaps.

3- Objectives and Scope

The objective of this study was to provide an optimum M&R plan through the application of the developed IRI prediction model. The IRI performance model was generated by using regression analysis based on the LTPP database. The aim of this study was to consider the pavement deterioration and budget calculation uncertainties by employing historical data and MCS. The best cost and improvement models were applied based on the related literature to the best of the authors' knowledge. The results obtained from deterministic and probabilistic approaches were compared to determine the optimal solution. The applied data corresponded to flexible asphalt pavement under urban and rural areas with various climate and traffic conditions.

4- Methodology

As previously mentioned, IRI is a representative performance indicator, which was selected in this study. Afterward, the required data for IRI performance model generation was collected from the LTPP database. After the IRI prediction model was developed, types of M&R activities, their IRI drop, and their unit cost were gathered from the literature. Then, M&R treatments were optimally planned by using two approaches, including deterministic and probabilistic. Finally, the solutions obtained from both approaches were compared. The flowchart of the methodology is indicated in Fig. 1. In the following sections, a comprehensive explanation of the steps adopted in this research is presented.

4- 1- IRI prediction model development

As mentioned, IRI, as one of the most common and widely-used pavement condition indexes, was selected in this study. Since the developed IRI prediction models were neither accurate nor considered enough relevant variables, a prediction model was developed to predict the IRI annually. According to previous studies, initial IRI, climatic, traffic, and structural parameters can be used to develop the IRI prediction model [13]. To this end, from all four mentioned categories, appropriate features were chosen to generate the IRI performance function. Five variables were selected, including initial IRI, the number of annual freeze-thaw cycles, annual precipitation, ESAL, its growth rate, and SN. In addition, several studies represented that employing only one climatic parameter was not adequate, and other features should have been used to increase the precision of their IRI prediction models [16, 38]. On the other hand, Gong et al. [16] represented that there was an insignificant relationship between IRI and freeze index. Thus, the authors decided to consider the number of annual freeze-thaw cycles as a novelty to increase the accuracy of the IRI model. In this regard, by employing this feature, the precision of the IRI model was raised noticeably. The number

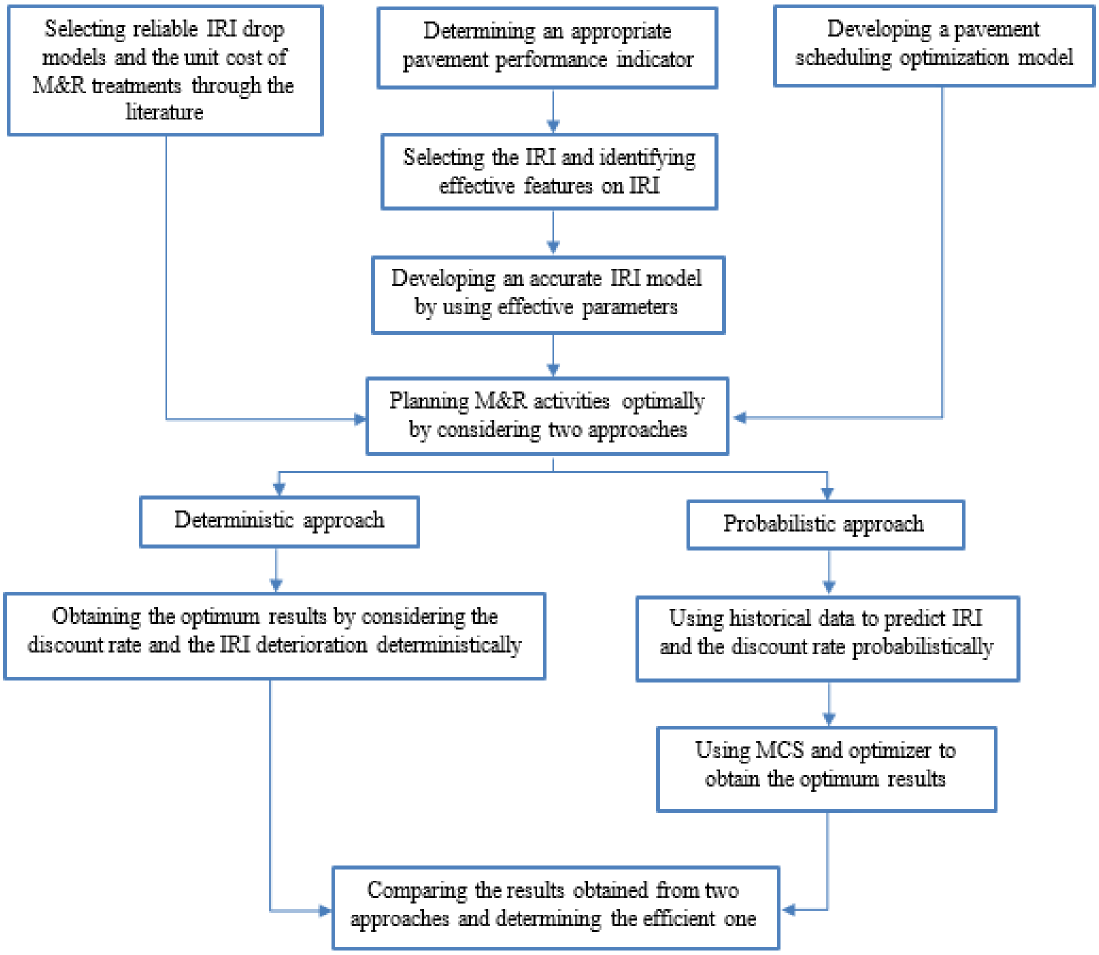

Fig. 1. The flowchart of the methodology.

of annual freeze-thaw cycles applied herein has not received close attention in the IRI prediction model developed in previous studies.

The dataset used in this study consists of 288 pavement sections taken from the LTPP database covering different climatic areas and various traffic conditions. No M&R treatments have been performed on the sections used to develop the model. Hence, the segments' IRI has not been reduced, and annual IRI increment can be calculated by the features employed to generate the model. Moreover, 70% of the data was used to train the model, and 30% was utilized to test the developed model [39]. Besides, the linear regression technique was employed to generate the model. Although several researchers used various machine learning methods such as artificial neural networks to develop the IRI performance functions [13], these algorithms are categorized as black-box tools [40]. Hence, these algorithms cannot present practical prediction models. In other words, the mentioned algorithms can only be employed to predict the pavement's future condition, and these methods cannot be used to schedule M&R activities. The IRI performance model generated in this study can predict the next year's IRI, which is required for scheduling M&R activities. Since the IRI model predicts IRI annually to plan M&R treatments yearly, the developed model can achieve higher accuracy compared to previous studies.

4- 2- Optimization model formulation

There are two main approaches to schedule M&R activities, including deterministic and probabilistic. Both of these approaches were investigated in this research to address which one is more appropriate to be used by highway agencies for M&R scheduling. The main difference between these two approaches is to consider the variables uncertain or constant which is explained in the following. The optimization model was developed based on a single objective function of minimizing the discounted M&R treatment costs subject to maintaining pavements' IRI at a minimum acceptable level in the planning horizon. The optimization model's objective function is presented as follows:

$$\text{Minimize } f = \frac{\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T} A_i \, c_{ijt} \, x_{ijt}}{(1+i_{dis})^t} \quad (1)$$

where I, J, and T signify the number of pavement sections in the investigated network, the number of M&R treatments, and the number of years the pavement network is analyzed, respectively. A_i and c_{ijt} imply the area of section i and the cost of treatment j applied to a section i at the time of t. i_{dis} is the annual discount rate employed to make the M&R scheduling costs discounted. x_{ijt} is a binary decision variable of the model which represents whether the activity j is performed on the section i at the time of t.

Eq. (1) minimizes the discounted cost of M&R treatments in the planning horizon. Hence, highway agencies can be informed of the minimum required budget to preserve sections at an acceptable level.

As mentioned previously, the model maintains pavement sections at allowable limits in the analyzing period. To this end, Eq. (2) states that the sections' IRI in the planning period must be lower than the maximum allowable IRI, which is determined by the highway agency. The network's IRI at each period has to be lower than highway agencies' determined value. Hence, Eq. (3) ensures that the networks' IRI is lower than a predetermined level. On the other hand, the value of sections' IRI has to be rational. Hence, by using Eq. (4), the sections' IRI must be more than minimum logical IRI.

$$IRI_{i,t} \le IRI_{\max} \tag{2}$$

$$\frac{\sum_{i=1}^{I} IRI_{i,t} \times A_i}{\sum_{i=1}^{I} A_i} \le U \tag{3}$$

$$IRI_{i,t} \ge IRI_{\min} \tag{4}$$

where $IRI_{i,t}$ is the IRI of section i at the time of t. Besides, $IRI_{\max}$ and $IRI_{\min}$ signify the maximum allowable IRI and minimum value of IRI. The maximum acceptable IRI is specified by the highway agency. U denotes the maximum acceptable value of IRI for a pavement network. In addition, the minimum value of IRI must be more than 0.

Due to the practical limitations, highway agencies prefer to perform the uttermost M&R treatment on each pavement section at each time point. To this intent, Eq. (5) states that uttermost one M&R activity can be scheduled for each segment at each time point. Hence, by employing this constraint, the applicability of the proposed model increases notably. As mentioned, the decision variable of the model is binary. As indicated in Eq. (6), the decision variable can be equal to 1 or 0.

$$\sum_{j=1}^{J} x_{i,j,t} = 1 \qquad \forall i \in \{1,2,...,I\},\ \ \forall t \in \{1,2,...,T\} \tag{5}$$

$$x_{i,j,t} \in \{0,1\} \tag{6}$$

4- 3- Deterministic and probabilistic approaches

The mentioned optimization model was used in both deterministic and probabilistic approaches. The differences between the two approaches in M&R scheduling were in the uncertain features employed in the objective function and the IRI prediction model. In the deterministic approach, the discount rate was considered constant and equal to its initial value, but in the other approach, a probability function was fitted to the discount rate. In reality, the discount rate is not constant, therefore, the deterministic approach cannot solve the problem accurately. Furthermore, Wu et al. (2017) compared constant and probabilistic discount rates and concluded that using probabilistic discount rates results in more precise solutions [41].

In the deterministic approach, the independent variables utilized in the IRI prediction model were assumed to be constant while the essence of some parameters, such as climatic features, is uncertain. The values of variables employed in the IRI performance function and objective function were presumed equal to the first year of the analysis. The optimization problem type is MIP, and General Algebraic Modeling System (GAMS) can solve the deterministic optimization problem [42]. This software solves such a problem using the branch-and-bound algorithm, and the outcomes are treatment schedules on the sample network. Therefore, this software was used to solve the problem deterministically.

In the probabilistic approach, historical data of uncertain features of the developed model and the objective function were collected. Afterward, @risk™ software was used to fit appropriate PMFs and PDFs to the collected data [43]. Then, MCS as an appropriate risk analysis tool was employed to generate probability distributions of each section's annual IRI and total required budget in the analysis period. As the number of MCS iterations increases, the accuracy of the results increases. Moreover, by using @risk™ software, optimization and simulation were carried out simultaneously to obtain the best solutions. The outcomes of the probabilistic approach were histograms whose maximum, mean, and the minimum was presented.

5- Results and Discussion

A pavement network containing five flexible pavement sections was evaluated. As mentioned, the model aimed to minimize the M&R scheduling required budget in the analysis period. Furthermore, the case study was evaluated for five years. The data of pavement sections were extracted from the LTPP database. The length and width of each section were 152.4 m and 11 m roughly. Therefore, the area of pavement sections was the same, and their area was equal to 1673 m^2. The required data for each section were gathered, including initial IRI, the number of annual freeze-thaw cycles, ESAL, annual precipitation, and SN. The required data for the last year of each section is presented in Table 1. As mentioned previously, the M&R treatments were planned over five years.

Table 1. The pavement sections' data of the initial year of analysis used in the deterministic approach.

Parameter Section	Initial IRI (m/km)	The number of freeze-thaw cycles	ESAL	Precipitation (mm)	SN
1	3.226	111	691000	718.4	4.4
2	3.739	111	868204	718.4	4
3	3.669	111	691000	718.4	4.6
4	3.253	111	691000	718.4	4.6
5	3.489	111	691000	718.4	6.8

Table 2. The IRI drop and the unit cost of each M&R activity.

M&R activity type	IRI drop (m/km)	Cost ($/m^2)
Do nothing	0	0
Preventive maintenance	0.3	2.0
Light rehabilitation	1.2	5.8
Medium Rehabilitation	2	11.9
Heavy rehabilitation (reconstruction)	Change IRI of the pavement to a newly constructed pavement section, ($IRI_{new} = 1.5$)	28.5

The minimum value of the IRI is equal to 0. Besides, according to the results obtained from Hu et al.'s (2017) research, if each section's IRI is less than 3.9 m/km, the pavement network will be at the safe level [44]. Therefore, the maximum acceptable IRI was presumed equal to 3.9 m/km. Moreover, since the areas of the investigated sections are equal, there is no need to employ Eq. (3). Five M&R treatments were taken into consideration to improve the sections' IRI. The treatments and their IRI drop were extracted from literature [4, 7, 18]. Additionally, the average unit costs of the indicated treatments were calculated based on the costs derived from the study of Kiihnl and Braham (2019) [45]. Applying each treatment leads to the IRI drop and is associated with a specific cost, which is indicated in Table 2. As can be perceived from Table 2, do nothing, preventive maintenance, light rehabilitation, medium rehabilitation, and heavy rehabilitation were considered as M&R treatments. The "do nothing" strategy signifies that no M&R treatment is scheduled to be performed on the pavement section. As the cost of treatments increases, the IRI drop increases too. If heavy reconstruction is selected by the model, the entire pavement's structure replaces with new pavement, and its IRI is equal to 1.5 m/km [18, 33]. Each treatment should improve the IRI of each section not to exceed the maximum acceptable IRI range defined by the highway agencies.

5- 1- IRI prediction model

One of the objectives of this study was to develop an accurate IRI performance model. As mentioned previously, the model was developed using the LTPP data of 288 pavement sections. Besides, 75% of the data (training set) was utilized to develop an IRI prediction model, and the rest (testing set) was applied for model validation [39]. The multiple linear regression techniques were employed to develop the model. Initial IRI, the number of annual freeze-thaw cycles, annual precipitation, ESAL, and SN were employed as features to form the IRI model. The most correlated independent variables with IRI were initial IRI, the number of annual freeze-thaw cycles, ESAL, annual precipitation, and SN, respectively. All variables have positive signs except the SN, which makes logical sense. Moreover, the SN coefficient was much less than the other, which has been proven in previous research [46]ote>. On the other hand, by increasing the annual precipitation, the IRI of the pavement section must be increased. To this intent, the power of the annual precipitation feature was increased to make the model logical. The formulation of the generated IRI model is presented in Eq. (7).

$$IRI = 0.9951(IRI_0) + 0.0272(FTCs) + 0.0221(ESAL)(\beta) + 0.0027(Precip)^{10} - 0.0003(SN) - 0.0027 \quad (7)$$

Table 3. Machine learning performance indicators used to measure the accuracy of the IRI model.

Performance indicators	Training data	Testing data
R	0.957	0.955
R^2	0.917	0.902
MAE (m/km)	0.079	0.119
RMSE (m/km)	0.121	0.198

where IRI and IRI_0 signify the predicted IRI and the initial IRI of a pavement section. $FTCs$ and $ESAL$ are the number of annual freeze-thaw cycles and equivalent single axle load. To consider the annual ESAL growth rate β was employed in the model, which denotes the annual ESAL growth rate. $Precip$ and SN signify the annual precipitation and the structural number of the pavement section, respectively.

Four machine learning performance indicators, including correlation coefficient (R), coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE), was employed to measure the accuracy of the developed model. The formulation of the mentioned performance indicators is presented in Eqs. (8) to (11). The value of the mentioned indicators is represented in Table 3. As can be perceived from Table 3, the model achieved high quality of fit. Testing data R of the model was equal to 0.955. Furthermore, the R^2 of the testing set of the developed model was 0.902. Besides, the developed model can predict the IRI of unseen data with an MAE of 0.119 m/km. Hence, because of the low value of MAE, the IRI model can predict the pavements' future IRI accurately. Moreover, the testing set RMSE of the model was equal to 0.198 m/km. According to the mentioned machine learning performance indicators, the developed IRI model can predict the IRI of unseen pavements' data accurately. Therefore, the generated IRI performance model can be used to plan M&R treatments precisely.

$$R = \frac{\sum_{i=1}^{n}(x_i - \overline{x_i}) \times (y_i - \overline{y_i})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x_i})^2 \times \sum_{i=1}^{n}(y_i - \overline{y_i})^2}} \tag{8}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}(x_i - \overline{x_i}) \times (y_i - \overline{y_i})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x_i})^2 \times \sum_{i=1}^{n}(y_i - \overline{y_i})^2}} \right)^2 \tag{9}$$

$$MAE = \frac{\sum_{i=1}^{n}|x_i - y_i|}{n} \tag{10}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}} \tag{11}$$

where x_i and y_i signify the measured IRI, predicted IRI, respectively. Moreover, n is the number of data. Besides, $\overline{x_i}$ and $\overline{y_i}$ denote the average of measured IRI and average of predicted IRI, in the order mentioned.

Fig. 2 indicates the predicted IRI values versus the measured IRI for the training and testing data. As Fig. 2 presents, the data points are almost on the line of equality, which proves that the predicted and measured IRI are approximately in the line of equality. Moreover, it can be perceived from Fig. 2 that the model can predict the IRI of unseen data perfectly.

5- 2- Results of deterministic M&R scheduling

As mentioned previously, the historical data was not considered in the deterministic approach. Hence, the last year's value of each parameter, which exists in the IRI model and objective function were taken into consideration in this approach. On the other hand, in the probabilistic approach, historical data for uncertain parameters were extracted to make the model probabilistic. The amount of the discount rate, which was wielded in the objective function of the deterministic model in early 2021, was 0.25% in the United States. As mentioned, annual ESAL was multiplied by its annual growth rate. According to the extracted data, the initial year ESAL growth rate was equal to 6%. Hence, the ESAL annual growth rate was assumed to be equal to 6% in the planning horizon. The optimization problem type is MIP, and General Algebraic Modeling System (GAMS) is able to solve this type of optimization problem [42]. This software solves such a problem

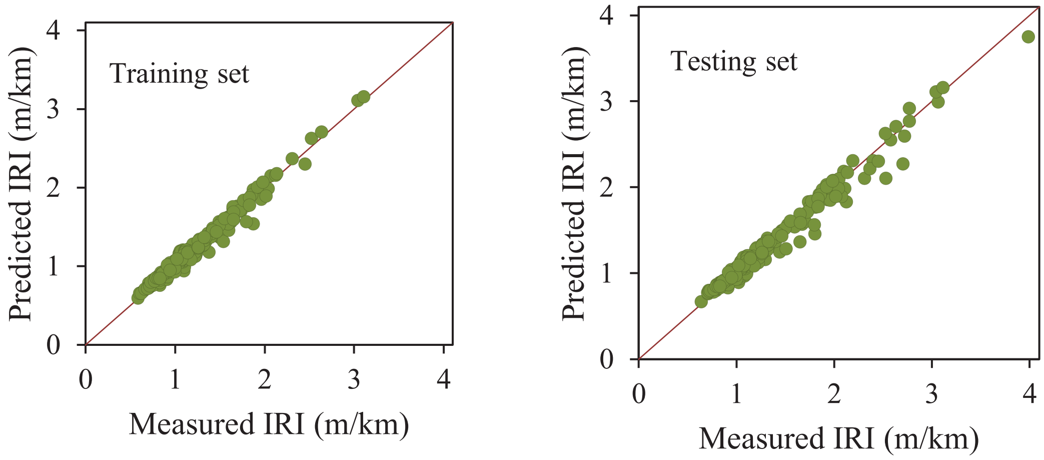

Fig. 2. Performance of the IRI model for both training and testing data.

Table 4. The IRI of each section for five years planning in the deterministic method.

Year / Section	The value of IRI of each section in each year, m/km				
	1	2	3	4	5
1	3.477	3.742	2.822	3.065	3.322
2	2.825	3.075	3.341	3.621	3.618
3	2.935	3.177	3.432	3.702	3.686
4	3.505	3.771	2.852	3.097	3.355
5	3.751	2.827	3.067	3.321	3.588

using the branch-and-bound algorithm, and the outcomes are M&R treatment scheduled on the sample network. The IRI of each section after applying treatments in each year is represented in Table 4. To this end, the optimization model assigned various M&R treatments to the pavement sections to reduce the IRI value. As can be seen, each section's IRI was lower than the acceptable IRI, which was equal to 3.9 m/km. The minimum required budget for M&R scheduling for five years in the deterministic approach was $52,149.

5- 3- Results of probabilistic M&R scheduling

In the probabilistic approach, the probabilistic IRI prediction model was used. In the probabilistic IRI performance model, appropriate PDFs and PMFs were fitted to uncertain features of the model, including the number of annual freeze-thaw cycles, annual precipitation, and ESAL growth rate. On the other hand, the discount rate employed in the objective function was an uncertain parameter. Hence, an appropriate PDF was fitted to the mentioned parameter. Therefore, the historical data employed from the LTPP database to fit PDFs and PMFs on them. The most appropriate PDFs and PMFs were fitted to the uncertain IRI prediction model parameters and the discount rate. Negative binomial, normal, Laplace, and triangle distributions were recognized as the best fit to the number of annual freeze-thaw cycles, annual precipitation, annual ESAL growth rate, and discount rate, respectively, by @risk™ [43]. The fitted PDFs were consistent with the results of previous studies [41, 47].

The above-mentioned PDFs and PMFs were applied in the objective function and the IRI performance model, which are indicated in Eqs. (1) and (7), respectively. Then, the IRI prediction model was utilized to predict the future pavement IRI probabilistically. To this intent, the MCS was employed to simulate the IRI prediction model and objective function. The number of MCS iterations plays a significant role in the accuracy of the results. The minimum required number of iterations of MCS was obtained by using Eq. (12).

$$n = \left(\frac{z_{\frac{\alpha}{2}} \times s}{E}\right)^2 \qquad (12)$$

Table 5. Calculating the least number of iterations needed for the IRI prediction and the M&R planning costs.

Parameters	$Z_{\frac{\alpha}{2}}$	E	S	The least number of iterations needed	The selected number of iterations
The IRI prediction	1.96	0.01	0.0001	38416	100000
The M&R planning costs	1.96	150	1	86436	100000

Table 6. The mean IRI of each section for five years planning in the probabilistic method.

Year / Section	The value of IRI of each section in each year, m/km				
	1	2	3	4	5
1	3.467	3.719	3.668	3.616	3.874
2	2.764	2.999	3.243	3.496	3.764
3	2.678	2.897	3.124	3.361	3.608
4	3.496	3.437	3.688	3.638	3.897
5	3.742	3.640	3.899	3.858	3.814

Where n signifies the least number of iterations needed. In addition, S and E denote the estimated standard deviation of the output and the desired margin of error, respectively. Besides, $Z_{\frac{\alpha}{2}}$ is the critical value of the normal distribution for $\frac{\alpha}{2}$. The number of MCS iterations was calculated using Eq.

(12). The minimum number of iterations required for the IRI prediction model and the M&R planning costs are presented in Table 5. For the sake of reducing the biased error, the iteration numbers were rounded up to 100,000. A large number of MCS iterations were considered to increase the accuracy of the solutions obtained from the probabilistic approach.

The model assigned optimal M&R treatments to each pavement section in each year to minimize M&R costs in the planning period considering the IRI probability distributions. Each section's mean IRI in each year after applying M&R treatments is represented in Table 6. As can be seen in Table 6, each section's mean IRI value is lower than the allowable limitations of the highway agency. Moreover, the probability distribution of the total M&R scheduling cost during the analysis period is indicated in Fig. 3. The mean required budget of M&R scheduling for five years in the probabilistic approach was $40,195, while the maximum and minimum of the M&R costs were $42,255 and $36,485, respectively.

5- 4- Comparison of the solutions obtained from two approaches

As mentioned, using only one value (i.e., the deterministic approach) for the random features led to unreliable M&R scheduling, which was not consistent with the uncertain essence of pavement deterioration and budget calculation. On the other hand, the outcomes of the probabilistic approach were PDFs that express various types of information, such as the maximum, minimum, mean, spread, and shape. The comparison between the calculated costs of M&R scheduling in the deterministic and probabilistic approaches in each year is represented in Table 7. The required budget of M&R scheduling in the deterministic approach was higher than the probabilistic one in the planning period. As can be perceived from Table 7, the mean costs of M&R scheduling in the deterministic approach were 29.7% higher than the probabilistic one. Hence, it is more cost-effective for highway agencies to plan M&R treatments probabilistically. Therefore, highway agencies will be able to maintain pavement sections t acceptable levels by spending less financial resources if they employ the probabilistic approach instead of the deterministic one. In both methods, sections 2 and 3 had a higher cost due to their poor initial IRI. Furthermore, the cost of M&R scheduling on both sections 2 and 3 in the deterministic strategy was 32% lower than the probabilistic strategy. On the other hand, sections 1 and 4 cost less than the other sections in both

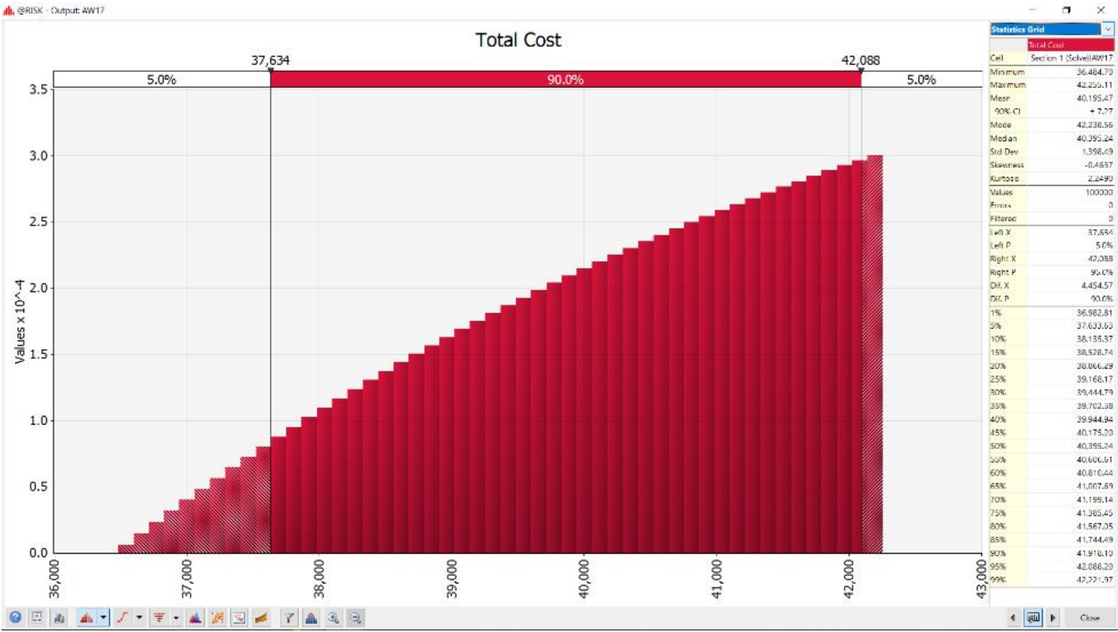

Fig. 3. Probability distribution of the total cost of M&R scheduling during the analysis period in the probabilistic approach.

Table 7. The comparison between the costs of the M&R planning in two approaches, $.

Year / Section	The value of IRI of each section in each year, m/km				
	1	**2**	**3**	**4**	**5**
1	3.467	3.719	3.668	3.616	3.874
2	2.764	2.999	3.243	3.496	3.764
3	2.678	2.897	3.124	3.361	3.608
4	3.496	3.437	3.688	3.638	3.897
5	3.742	3.640	3.899	3.858	3.814

approaches. Moreover, by applying a probabilistic strategy instead of a deterministic one in scheduling M&R treatments on sections 1 and 4, the M&R mean costs of the mentioned sections decreased by 48% and 46%, respectively. Hence, the deterministic approach not only costs more but also provides limited insight for decision-makers and policy-makers. Therefore, it is suggested that highway agencies manage pavement networks employing probabilistic methods, which makes more practical and engineering sense.

The different types of planned M&R treatments in both deterministic and probabilistic approaches are presented in Table 8. To this end, different treatment IDs were assigned to various M&R activities. In this regard, treatment ID 1 signifies a do-nothing strategy. Moreover, treatment ID 2 denotes preventive maintenance. Besides, treatment IDs 3, 4, and 5 are light rehabilitation, medium rehabilitation, and heavy rehabilitation, respectively. As can be perceived from Table 8, the deterministic approach tended to employ more rehabilitation treatments than the probabilistic one.

The M&R treatments selected in the deterministic and probabilistic approaches are indicated in Table 9. As can be seen in Table 9, both methods selected the “do nothing” strategy more than the other activities. Moreover, the deterministic method allocated the “do nothing” strategy more than the probabilistic method. Besides, the deterministic approach selected rehabilitation treatment more than preventive maintenance. Hence, due to excessive selection of the “do nothing” strategy in the deterministic approach, the pavement IRI increased, and this approach chose rehabilitation treatment more than preventive maintenance to maintain the pavement IRI within the highway agency’s allowable limits. Since preventive maintenance prevents the pavement from being de-

Table 8. The optimum M&R activities for each section in both deterministic and probabilistic approaches in each year.

Section	Approach	Year				
		1	2	3	4	5
		Treatment ID				
1	Deterministic	1	1	3	1	1
	Probabilistic	1	1	2	2	1
2	Deterministic	3	1	1	1	2
	Probabilistic	3	1	1	1	1
3	Deterministic	3	1	1	1	2
	Probabilistic	3	1	1	1	1
4	Deterministic	1	1	3	1	1
	Probabilistic	1	2	1	2	1
5	Deterministic	1	3	1	1	1
	Probabilistic	1	2	1	2	2

Table 9. The comparison of the percentage of M&R treatments applied in the deterministic and probabilistic approaches.

Treatment Approach	Do nothing	Preventive maintenance	Light rehabilitation	Medium rehabilitation	Heavy rehabilitation
Deterministic	72	8	20	0	0
Probabilistic	64	28	8	0	0

teriorated until it needs rehabilitation, road users prefer this treatment to be implemented. Hence, it is more desirable to apply more preventive maintenance on the pavement sections. Besides, preventive maintenance costs are lower than the other activities. Therefore, the deterministic approach not only incurred more costs on highway agencies to implement heavier treatments but also increased the road user costs since it selected less preventive maintenance, which is desirable for users.

6- Conclusion

In modern PMS, generating an efficient M&R approach is critical. The pavement scheduling problem can be solved using a variety of mathematical models. Most of the M&R scheduling models plan treatments deterministically. Nonetheless, the model contains several uncertain features that have a significant effect on the optimum solution. This study presented a MIP pavement M&R planning model to find optimal solutions. To this intent, two approaches were employed to solve the problem, including deterministic and probabilistic. The objective function of the optimization model in both approaches aimed to minimize M&R costs in the planning horizon constrained to acceptable pavement conditions. One of the main requirements for M&R scheduling problem modeling is the pavement performance function. Hence, an accurate IRI performance model was developed to predict the future pavement's IRI. Some features employed in the IRI performance model and objective function were uncertain. Nevertheless, the uncertain variables were considered equal to their value of the initial year of analysis for the planning period in the deterministic approach. On the other hand, in the probabilistic strategy, appropriate PDFs and PMFs were fitted to the uncertain features. Then, MCS with a large number of iterations and optimizer was run to obtain the probability distributions for each section's IRI and the minimum required budget to maintain pavement sections at allowable limits. Ultimately, the solutions obtained from the deterministic and probabilistic strategies were compared. The following results could be drawn from this study:

- The initial IRI, the number of annual freeze-thaw cycles, annual precipitation, ESAL, and ESAL growth rate, and SN were employed to develop the IRI prediction model with a high model fitness. Moreover, 288 data were used to generate the model. Since the model is an annual IRI prediction model and significant features were employed in the model development, it reached a high accuracy with a testing R^2 of 0.958.

- Both probabilistic and deterministic maintenance scheduling optimization approaches were investigated on a pavement network as a case study. The results indicated that the cost of M&R scheduling treatments in the deterministic strategy is 29.7% higher than the probabilistic one in this study. Therefore, the probabilistic method is cost-effective based on the results of this article.
- It is more appropriate for users that highway agencies use preventive maintenance instead of rehabilitation. According to the results of the case study, 28% of the treatments selected by the probabilistic model were preventive maintenance, while only 8% of the activities selected by the deterministic model were preventive. On the other hand, the deterministic strategy employed rehabilitation treatments more than preventive maintenance in this study, which is not desirable for users.
- The deterministic approach provides limited insight for decision-makers and highway agencies since this method presents one value as a result. On the other hand, the probabilistic approach presents probabilistic distributions for IRI and the minimum required budget. Moreover, decision-makers can be informed about the minimum, mean, and maximum of IRI using the probabilistic method. Therefore, it is suggested that highway agencies manage pavement networks using the probabilistic method, which makes more practical and engineering sense.

7. Limitations and recommendations for future studies

The limitations and recommendations of the current study for consideration in future research are indicated in the following section:

- Utilizing only IRI as the pavement performance indicator is one of the limitations of this study. In this regard, it is suggested that various pavement performance indicators should be considered simultaneously in future research.
- Analyzing a pavement network consisting of 5 sections is one of the limitations of this study. It is recommended that larger pavement networks should be utilized in future studies.

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