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Multi-Objective Optimization of Maintenance, Rehabilitation, and Reconstruction Decision Making Considering Safety

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Abstract

Traditional pavement maintenance, rehabilitation, and reconstruction (MRR) planning accounts for user cost by maximizing drivers' comfort, reducing users' travel delay, and minimizing fuel consumption, while controlling the agency's costs of undertaking the necessary preservation activities. Safety performance is seldom considered in the MRR planning of pavements. However, the pavement condition has a large impact on the crash frequency and needs to be addressed in the process of pavement MRR planning. Therefore, this study first incorporates safety costs into the MRR planning process as a separate objective. To do so, the MRR planning process seeks to find an optimal maintenance strategy with the lowest agency cost while minimizing crash frequency and user cost based on the resulting pavement condition. A multi-objective optimization approach is proposed to identify the optimal MRR plans that utilize a semi-Markov international roughness index deterioration model developed based on real pavement condition inspection data from Pennsylvania between 2006 and 2018. The results suggest that the agency costs will increase by $9,716 (5.3%) per mile per lane during a 50-year analysis window for pavement starting in good condition when the crash frequency is considered in the MRR planning. This increased agency cost contributes to a reduction in predicted crash frequency by 0.27%. The results can be used to determine the amount agencies need to spend on MRR activities to reduce accidents under different traffic flow and vehicle fleet combinations. The conclusion of this study provided evidence that lower crash frequency can be achieved by developing better MRR planning from the roadway operation perspective.

Keywords

infrastructure management and system preservation, pavement management systems, life cycle cost analysis (LCCA), safety, crash frequency

Pavement maintenance, rehabilitation, and reconstruction (MRR) planning aim to allocate a limited budget to maintain a road network within a given service period to achieve maximum performance. Successful MRR planning considers multiple goals. A simple method to address multiple goals is to select a principal goal that is used as an objective function to optimize and incorporate secondary goals as constraints. Examples of constraints in MRR planning include minimum pavement condition level or budget limitations (*1*). Another way to incorporate multiple goals is to use a weighted sum of them in a single function; for example, converting all goals into an economic cost using a unit cost associated with each (*2*). However, the reliability of the weighted function is highly dependent on the selection of the weight coefficients. Some objectives are difficult to convert into specific costs, such as driver riding comfort, driver distraction, or vehicle wear-and-tear. Even if the weight coefficients can be determined well, studies show that optimal solutions based on the weighted function may be suboptimal under certain circumstances (*3*). Therefore, multi-objective optimization (MOO) has become popular over the past decades. MOO

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considers multiple goals at the same time to retrieve Pareto optimal solutions (i.e., those for which one objective cannot be improved without sacrificing another), and its solution typically is expressed via a Pareto frontier that provides a set of Pareto optimal solutions. Operators may then use the Pareto frontier to quantify trade-offs between the different objectives to select the final solution.

Two common approaches to MOO are the classic MOO and the preference-based MOO (*4*). The classic MOO procedure aims to cover the widest range of the solution space as possible to determine multiple trade-off optimal solutions. After retrieving the multiple trade-off optimal solutions (Pareto optimal), the final solution can be selected from the Pareto frontier by utilizing specific information related to the purpose of the optimization. A method commonly used to solve the classic MOO is to use a genetic algorithm, for example, NSGA-II (*5*). On the other hand, preference-based MOO utilizes specific information related to the purpose of the optimization to reduce the solution space *a priori* and improve the algorithm efficiency. In the preference-based MOO, an estimated relative importance vector, for example, that represent weights for different objectives or the approximate monetary cost of different objectives, is first used to reduce the MOO to a single-objective optimization. Considering different values of the importance vector, many of these single-objective optimizations are solved to derive a Pareto frontier. Many methods have been proposed to select the final solution from the Pareto frontier, including the absolute optimal solution method, weight method, deviation function, and knee point method (*3*, *6*). Because of the complexity of the MRR planning, heuristic methods—such as genetic algorithms and particle swarm algorithms—are usually adopted to solve the MOO model (*3*, *7*).

Objectives commonly included in MOO MRR planning consist of agency cost, user cost, performance level, and environmental impact. Agency cost is typically constrained by budget limitations and often needs to be minimized (*8*). This cost is determined by the number of activities required in the analysis window and the expected unit cost of each activity. Studies show that user cost is the dominant factor in MRR planning (*9*). One way to measure user cost is to measure the additional fuel consumption resulting from the deterioration of the pavement condition (*10*). Researchers have also considered the environmental impacts of the MRR planning process to achieve sustainable development, since road construction and maintenance lead to high carbon dioxide emissions. Environmental impacts are mainly addressed in the construction and usage phase of a segment (*11*). Other objectives that have been considered in the literature include social equity, maintenance mileage, and work production (*12*, *13*).

The objectives are integrated into the MRR planning using a pavement deterioration model, where the costs of each objective are estimated based on a predicted condition. Transportation asset deterioration modeling can be categorized into four types: (i) deterministic models such as linear regression (*14*) or polynomial regression (*15*), (ii) state-based stochastic models such as Markov models or semi-Markov models (*16*), (iii) time-based stochastic models such as the Cox model or the accelerated failure time (AFT)-Weibull model (*17*), and (iv) machine learning based survival models (*18*). Of the different models, the AFT-Weibull model has a flexible form that can take any bathtub shape distribution to fit the deterioration process with a simple formulation, and has been shown in the literature to achieve high accuracy (*16*, *19*).

Studies have also shown that the pavement condition can significantly influence the frequency of traffic crashes in a two-lane, two-way rural roadway (*20*). Chan et al. concluded that the international roughness index (IRI) or present serviceability index are significant predictor variables in various crash predictions models; for example, if IRI increases from 0–100 in./mile to 101–200 in./mile, the crash frequency would increase by 1.64 times (*21*). Elghriany et al. (*22*) suggested that pavements with IRI around 95 in./mile seem to suggest safer roadway conditions but pavements with IRI higher than 143 in./mile are susceptible to high crash frequencies. Chen and Zheng suggested that not including safety performance measures in pavement MRR planning activities will result in underestimating costs and incorrect decisions (*3*). Only one study considered the safety cost in the life cycle assessment of MRR planning; however, that work assumed pre-determined criteria for triggering MRR activities and did not consider the optimization of the MRR activities (*23*).

In light of the above, the goal of this paper is to evaluate the impact of safety costs on traditional MRR planning at the project level on a two-lane two-way rural roadway. Three main objectives will be fulfilled in this study to achieve this goal. First, a deterioration model and safety performance function are estimated based on the historical inspection data and traffic crash records. Then, the agency cost, user cost, and safety costs of the MRR plan are modeled. Finally, a MOO framework is proposed to identify the optimal MRR strategies considering these different costs and the various trade-offs between them.

The remainder of the paper is organized as follows. The methodology is presented in the next section, followed by the calculation of the model inputs. Next, the model results are presented, and sensitivity analyses are conducted. Finally, some concluding remarks are made.

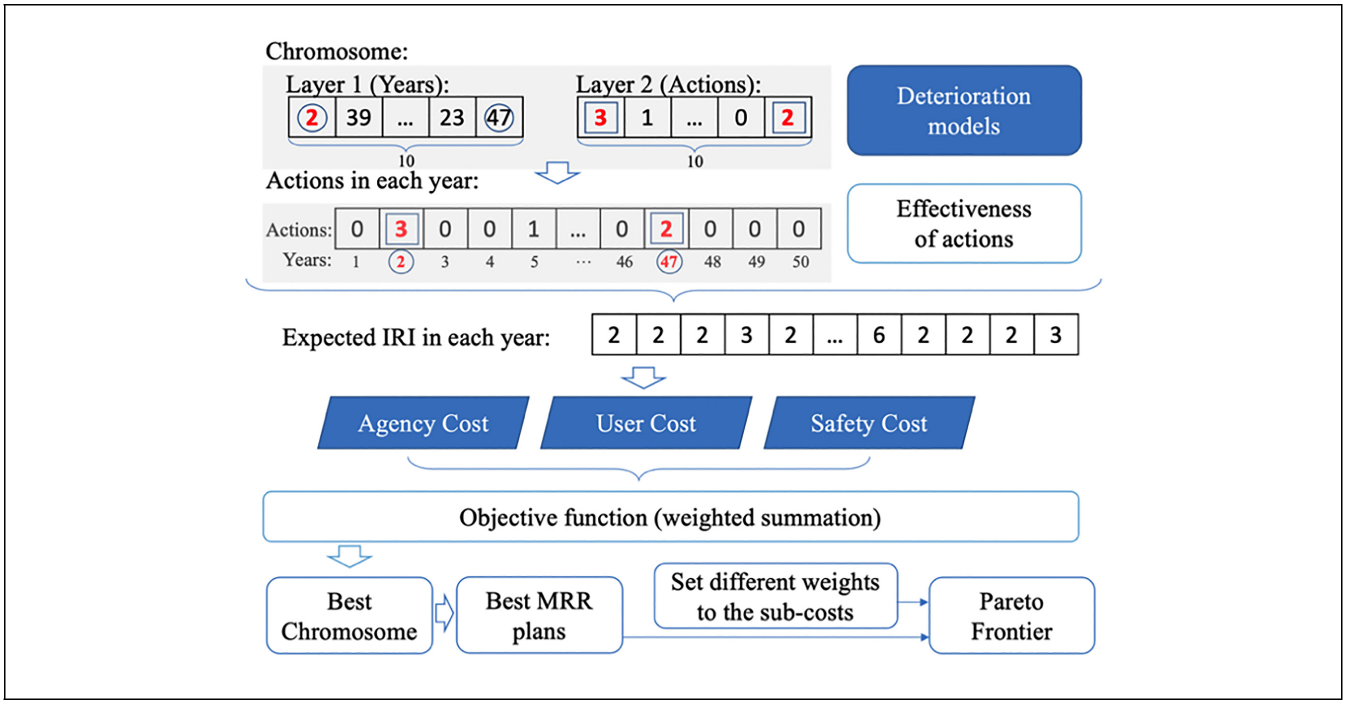

Figure 1. Flow chart of multi-objective optimization (MOO) framework.

Methodology

In this section, the basic framework of MOO is first described. The two critical inputs to the MOO framework—the deterioration model and the calculation of individual costs—are then presented in the following subsections.

MOO Framework

The goal of this study is to include the impacts of safety under different pavement conditions in MRR planning, while simultaneously considering agency and user costs. IRI is the default pavement condition indicator in Pennsylvania Department of Transportation (PennDOT)'s Roadway Management System database. It is used in this paper to assess pavement condition to develop the crash prediction model and pavement deterioration model and estimate the energy consumption under different pavement conditions. IRI is an index measured from the longitudinal profile of the roadway and often is thought to have less stochasticity and subjectivity compared with other indicators (*24*). Here, it is assumed that routine maintenance is performed at regular intervals; these activities are included in the "do-nothing" option in the MRR planning. The MRR plan also includes decisions on when to perform minor rehabilitation, major rehabilitation, or reconstruction. Agency costs are measured as a function of the required pavement maintenance activities and salvage value in the end of life cycle. User costs are calculated considering the fuel consumption in different pavement conditions. The safety performance is considered as a function of the pavement condition. The overall framework of the methodology is provided in Figure 1.

Calculation of Objective Function. The goal of MOO is to determine the series of actions and their timing that can minimize the sub-costs. The objective functions are defined as:

$$f_1 = min \sum_{i=1}^{N} C_A(IRI_i) \tag{1}$$

$$f_2 = min \sum_{i=1}^{N} C_U(IRI_i) \tag{2}$$

$$f_3 = min \sum_{i=1}^{N} cf(IRI_i) \tag{3}$$

Where f_1, f_2, and f_3 are the subobjective functions, N is the length of the planning horizon, IRI_i is the pavement condition in year i, $C_A(IRI_i)$ is the agency cost as a function of pavement condition IRI_i, $C_U(IRI_i)$ is the user cost of IRI_i, and $cf(IRI_i)$ is the predicted crash frequency of IRI_i.

In this study, the sub-objectives of the problem, for example, agency cost, user cost, and safety cost, are not directly comparable with each other. The agency cost is assumed to be the expected costs of the necessary MRR activities, and the user cost is assumed to be the expected cost of fuel consumption. Both of those sub-costs are

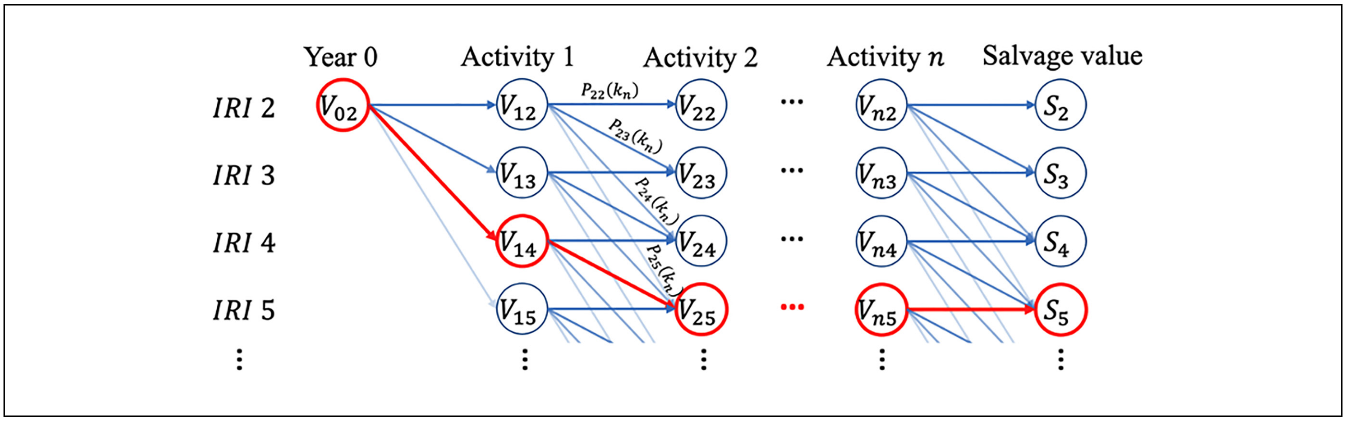

Figure 2. Illustration of backward dynamic programming approach.

measured in monetary units. However, the safety cost is measured in number of crashes. Here, to reduce the solution space, we apply a preference-based MOO procedure that assigns a vector of weights to incomparable subobjectives—in this case agency and user cost versus safety cost—since an approximate cost for crashes can be found from the literature. This improves the computational efficiency of the algorithm. The monetary estimation of safety cost is used as a baseline, and a wide range of weights, w, for the safety cost is tested to obtain the Pareto frontier. The final Pareto frontier of the MOO problem consists of a series of optimal solutions considering all weights, w, considered. In other words, the objective function of a single optimization instance is a weighted sum of the agency cost, user cost, and safety cost shown in Equation 4.

$$f = \sum_{i=1}^{N} C_A(IRI_i) + \sum_{i=1}^{N} C_U(IRI_i) + w * \sum_{i=1}^{N} cf(IRI_i) \tag{4}$$

where w is a weight assigned to crash frequency from the MOO framework.

To calculate the objective function value from Equation 4, a backward dynamic programming approach is adopted, as shown in Figure 2. Figure 2 shows the space of possible IRIs that a road segment could be in each year considering a series of actions taken over the planning horizon. Notice that in ear 0 the road segment is assumed to start at the best IRI (for illustrative purposes), however, in subsequent years when activities happen the possible IRI conditions are varied because of stochastic deterioration. For a given series of actions over the planning horizon, the probabilities of deteriorating from $IRI\ n$ to $IRI\ m$ in k_n years, $p_{nm}(k_n)$, are calculated based on a deterioration model (discussed in detail in the next subsection). These probabilities determine the potential future IRI states.

To determine the expected cost, a backward recursion is used. A salvage value for a given IRI value at the end of the asset's lifetime is assumed, and using the probabilities of deterioration the expected value of each state is determined in a backward fashion. This expected value is calculated as the summation of all the possible consequences weighted by the transition probability. The calculation of the expected cost after preservation activity n when the pavement condition is in IRI category i, V_{ni}, is shown in Equation 5.

$$V_{ni} = \sum_{m=i}^{9} p_{nm}(k_n) * \left(V_{(n+1)m} + k_n * (C_A(n,m) + C_U(n,m) + w * cf(n,m))\right) \tag{5}$$

where k_n is the number of years between preservation activity n and activity $n+1$, $C_A(n,m)$, $C_U(n,m)$, and $cf(n,m)$ are the average agency cost, average user cost, and average crash frequency when a pavement deteriorates from $IRI\ n$ to $IRI\ m$ over k_n years. For simplicity, they are calculated assuming the deterioration happens halfway through, for example, at $k_n/2$ years. The calculation of V_{ni} follows a backward manner starting from the salvage values, S_{IRI}.

Genetic Algorithm for the MOO Solution. The decision variable in the optimization is the MRR activity to be conducted (including do-nothing) every year over a planning horizon (i.e., $1 \times N$ vector where each element represents the MRR action for that year). For long-term planning, the solution space becomes too large to enumerate all possible combinations to obtain the global optimum solution. Instead, a heuristic genetic algorithm is adopted in this study. This approach is chosen over a traditional Markov decision process to incorporate dynamic transition probabilities of the pavement condition that are history-dependent. Each potential solution in the genetic algorithm is coded into a chromosome.

To improve the computational efficiency of the algorithm, it is assumed that at most 10 maintenance actions can be taken (excluding routine maintenance activities) over the lifetime of an infrastructure (assumed to be 50 years). A series of testing experiments suggest that the optimum solution never requires more than 10 actions in the 50-year planning horizon. Once this constraint is added, the structure of the chromosome is designed to have two layers: the first layer consists of 10 numbers denoting the year each of the 10 actions is taken while the second layer consists of another 10 numbers representing the specific action type in the corresponding year (0 for do-nothing, 1 for minor rehabilitation, 2 for major rehabilitation, and 3 for complete reconstruction). Note that, since one or more of the 10 actions that are assumed to be conducted within the 50-year analysis window can be "do-nothing," the actual number of maintenance activities, for example, minor and major rehabilitation or reconstruction, can be 10 or less than 10. For example, in Figure 1, the first genes in Layer 1 and Layer 2 in this chromosome are 2 and 3, respectively, which represent reconstruction (action 3) in the second year. However, the second to last gene in Layers 1 and 2 are 23 and 0, respectively. This implies that in year 23 do-nothing will be applied. Therefore, the total number of actual maintenance activities represented by this gene is less than 10. By doing so, the length of the chromosomes is reduced to 20 from 50. While large, this is still a much smaller solution space and thus improves the computational efficiency significantly when searching for the optimum solution.

A genetic algorithm is run for each weight, w, considered for the safety cost. The best MRR plan for each value placed on the safety impact is thus determined and the minimum value of each objective is calculated based on this MRR plan. A Pareto frontier is thereby created, which represents the best solutions for which none of the objectives can be improved and represents the trade-off among the different objectives.

Deterioration Model

The pavement deterioration is modeled using an AFT-Weibull model. The AFT-Weibull model assumes that the deterioration time follows a Weibull distribution and incorporates covariates into the model through the AFT approach. This AFT-Weibull model has been proven to provide a better model fit for pavement deterioration data than other statistical models (*18*). Therefore, a semi-Markov chain process with the transition matrix calculated based on the AFT-Weibull model is developed, which helps overcome the memoryless property of the exponential distribution-based Markov chain process.

Since the semi-Markov chain process considers the duration that a given discrete IRI category will last as the dependent variable, the original continuous IRI in the unit of inches per mile first needs to be discretized. The detailed categorization of original continuous IRI to discrete IRI categories is described in the "Model Inputs" section. The output of the AFT-Weibull model is the probability that a pavement section deteriorates from one IRI category to the next category (e.g., from IRI i to IRI $i+1$) within a fixed time increment , Δt. Using the AFT-Weibull model, a semi-Markov chain model is then used to determine the probability of a pavement segment deteriorating to any lower IRI category in any given year. The semi-Markov chain model first calculates the probability of a pavement remaining in its original IRI category i at time t, as $P_{ii}(t)$:

$$P_{ii}(t) = S_i(t) = 1 - F_i(t) = 1 - \int_0^t f_i(t')\, dt' \tag{6}$$

where $S_i(t)$ is the survival function of IRI i, which represents the probability of pavement not failing by time t; $F_i(t)$ is the cumulative density function of the AFT-Weibull model of IRI i; and, $f_i(t)$ is the probability distribution function (PDF) of the AFT-Weibull model of *IRI i*. Next, the PDF of a pavement segment deteriorating from IRI i to j, $f_{ij}(t)$, is calculated as in Equation 7. Note that it is assumed that a pavement segment deteriorates from a small i to a large j incrementally, that is, all intermediate IRI levels are visited.

$$f_{ij}(t) = \begin{cases} f_i(t) & \text{if } j = i+1 \\ \int_0^t f_{i(j-1)}(t') f_{j-1}(t-t')\, dt' & \text{if } j > i+1 \end{cases} \tag{7}$$

Calculating the value of $f_{ij}(t)$ requires considering all possible transition combinations, which results in a complicated multi-layer integral. A numerical approximation is therefore recommended to obtain those values. Finally, the probability of a pavement segment deteriorating from IRI i to j or higher, $P_{ij\ldots}(t)$, is calculated as in Equation 8. This is used to determine the probability of a pavement deteriorating from IRI i to j, $P_{ij}(t)$ as in Equation 9.

$$P_{ij\ldots}(t) = \int_0^t f_{i(j-1)}(t') F_{j-1}(t-t')\, dt' \tag{8}$$

$$P_{ij}(t) = P_{ij\ldots}(t) - P_{i(j+1)\ldots}(t) \tag{9}$$

Sub-Cost Determination

Three costs are considered to design an MRR schedule that improves the general performance of a pavement: (i) agency cost, (ii) user cost, and (iii) safety cost. The estimations of those sub-costs are described below.

Agency Cost. Typically, three categories of pavement improvement activities are used: routine maintenance, rehabilitation, and reconstruction. Routine maintenance is a reactive, timed activity employed to ensure the basic function of pavement, such as cleaning roadside ditches and structures, or maintenance of pavement markings and crack filling. These activities usually do not disturb traffic and their costs are negligible compared with rehabilitation and reconstruction. Therefore, routine maintenance is treated as "do-nothing" in this study, and the associated agency cost is assumed to be zero. Rehabilitation is a series of activities that need to be employed when the pavement condition deteriorates to an unacceptable level. Based on the severity, it includes minor rehabilitation and major rehabilitation. The minor rehabilitation activity considered in this study is a 2 in. mill-and-fill for the asphalt top layer, and the major rehabilitation activity considered is a 4 in. asphalt overlay. Reconstruction is needed when the pavement becomes functionally useless. A typical reconstruction activity would be an 8 or 12 in. new asphalt pavement. Reconstruction is usually significantly more expensive than rehabilitation and is typically performed after two or three rehabilitation cycles. The expected costs of different activities are referred from the literature that estimated these based on publicly available bid data for highway projects (*2*).

At the end of its lifetime, an asset is assumed to still hold value, that is, salvage value. The salvage value of the top layers and base layers can be determined independently. For the top layers, the remaining lifetime is estimated using the deterioration models and the salvage value is assigned proportionally to the remaining lifespan since the last reconstruction. The salvage value of the base layers is assumed to be a constant value and is determined as the difference between major rehabilitation cost and reconstruction cost. These are included in the agency cost as negative numbers since they represent a benefit to the agency.

User Cost. The fuel consumption per unit distance is assumed to be the main component of user cost. An energy consumption regression model from the literature is adopted and formulated as Equation 10 (*10*):

$$E(v, IRI) = \frac{p}{v} + (k_a * IRI + d_a) + b * v + (k_c * IRI + d_c) * v^2 \tag{10}$$

where $E(v, IRI)$ is the expected energy consumption in units of kilojoules per mile when driving at average speed of v mph on a pavement condition of IRI in./mile. Since this mode was estimated based on experiments with relatively low average speed, for example, 6 mph to 70 mph, and the dataset used to develop the crash frequency prediction model and pavement condition deterioration model is collected from a two-lane, two-way rural roadway, the average speed is assumed to be 40 mph. Further, the impacts of IRI on travel speed are assumed to be negligible (*25*). The other variables are the model coefficients, which are provided in the literature (*10*). For a passenger car, $k_a = 0.67$, $d_a = 2175.7$, $k_c = 0.000281$, $d_c = 0.2186$, $p = 33753$, and $b = -16.931$; for a medium truck, $k_a = 0.918$, $d_a = 9299.3$, $k_c = 0.000133$, $d_c = 0.9742$, $p = 109380$, and $b = -264.32$.

The expected energy consumption at year i is calculated by multiplying the expected energy consumption per vehicle with the average annual daily traffic (AADT) in a year. The calculated total energy consumption is then converted to an economic cost, C_{Ui}, by converting kilojoules to gallons, and using the national average gasoline price, p_{gas}, as Equation 11.

$$C_{Ui}(IRI) = \frac{E(v, IRI) * AADT * 365}{c_{gj}} * p_{gas} \tag{11}$$

where $AADT$ is the average AADT of all pavements in the dataset, which is 3,196 vehicles/day; $c_{gj} = 121.300$ kJ/gallon, according to the U.S. Environmental Protection Agency (*26*); and $p_{gas} = 3.853$ %/gallon as of March 2022 (*27*).

Safety Performance. The safety cost of a segment can be represented by the expected fatal and injury crash frequency. A negative binormal (NB) model developed from a previous study is used here to estimate fatal and injury crash frequency as a function of IRI for a given segment over a year. The NB model is selected here for its ability to estimate positive counting data with overdispersion. Other than IRI, attributes including the presence of passing zone, shoulder rumble strips, AADT, roadside hazard rating, horizontal curve density, degree of curvature per mile, access density, and district indicators are also considered in the model as covariates (*20*). The NB model specification used in this study is shown as Equation 12 (*20*).

$$\begin{aligned} ln\lambda_i = {} & \beta_0 + \beta_1 lnL_i + \beta_2 AADT_i + \beta_3 (IRI_i * AADT_i) \\ & + \beta_4 X_{4,i} + \ldots + \varepsilon_i, \end{aligned} \tag{12}$$

where λ_i is the expected crash number of segment i over a year; L_i is the length of segment i; $AADT_i$ is the AADT of segment i; X_4, $X_5 \ldots$ are the covariates listed above such as the presence of passing zone, shoulder rumble strips, district, and so forth; $\beta_1, \beta_2 \ldots$ are the coefficients of corresponding variables and β_0 is the constant term

Table 1. Correspondence Between Actual International Roughness Index (IRI) and Categorized IRI in this Study

Actual IRI (in./mile)	Categorized IRI	Sojourn count	Average sojourn (years)	Sojourn standard deviation (years)
25–75	IRI 2	2,819	3.82	2.25
75–100	IRI 3	5,204	3.70	2.14
100–125	IRI 4	5,126	3.29	1.89
125–150	IRI 5	3,831	2.85	1.65
150–175	IRI 6	2,376	2.47	1.38
175–200	IRI 7	1,448	2.27	1.27
200–225	IRI 8	807	2.25	1.26
225–300	IRI 9	694	3.14	1.96

or intercept; ε_i is a random error term assumed to follow a gamma distribution.

The NB model is estimated with a maximum likelihood method based on datasets collected on two-lane two-way rural roadways across Pennsylvania (*28*, *29*). Most of the coefficients are estimated with a p-value less than 0.001, and the model achieved an acceptable accuracy measured by Root Mean Square Error (RMSE) and mean absolute error (MAE). The complete model estimations can be found in the literature (*20*). The result of this model provides an estimated number fatal and injury crashes on different road segments.

Model Inputs

The inputs to the model consist of the deterioration model and the calculated agency and user costs along with the safety performance, which is introduced in the next two subsections.

Estimated Deterioration Model

Pavement condition inspection data were obtained from PennDOT's Roadway Management System (RMS) database. The RMS database includes information for every roadway segment within Pennsylvania and records the annual traffic volume (i.e., AADT) and composition (i.e., truck percentage), cross-sectional information, number of access points, presence of a horizontal curve, and IRI value. Each segment has up to four IRI values recorded per year, and 99.5% of the IRI records are within the range of 25 to 300 in./mile. Therefore, IRI values within the range of 25 to 300 in./mile from the period 2006–2018 are used in this study and are cleaned and processed according to the literature (*20*).

A state-based deterioration model, such as the semi-Markov process, requires a discrete categorization of the IRI. To do so, the IRI is divided into eight categories, as shown in Table 1. This categorization is chosen to aid in the development of the semi-Markov chain process model to provide enough differentiation between each category while not leading to computational inefficiency. The National Performance Management Measure divides IRI into three categories: 1. good condition = IRI less than 95.04 in./mile, 2. fair condition = IRI between 95.04 and 169.80 in./mile, and 3. bad condition = IRI greater than 169.80 in./mile (*30*). First, a discretization at every 25 in./mile is adopted to remain relatively consistent with these criteria while obtaining categories with a relatively equal number of observations. To achieve enough data in each group, IRIs from 25 to 75 and from 225 to 300 are then combined as one group, respectively. Finally, the time each pavement spends in these IRI categories is extracted as the sojourn time. If the beginning or end time of a pavement being in a certain category is unknown, this is marked as censored data. A brief statistical summary of the extracted sojourn times is shown in Table 1.

An AFT-Weibull deterioration model is estimated for each category of IRI, considering the dependent variable as the time spent in each IRI category. The covariates considered in this model include PennDOT engineering district, average annual daily truck traffic, access point density, and degree of curvature per mile. These deterioration models are estimated using a maximum likelihood approach. The accuracy of the models is measured using the concordance index (C-index), which reflects the ability of the model to predict the ranking of which infrastructure elements will survive the longest. The models for IRI 3 and IRI 4 had the highest accuracy measured by the C-index, at 0.74 and 0.64, respectively since these two categories had the most available data. The results suggest that the district plays an important role in the deterioration model because of differences in the natural and human environment, as well as the available budget. The average daily truck traffic is negatively correlated to most of the IRI groups, which indicates that higher truck traffic leads to lower expected lifespan, which is consistent with expectation. Based on the deterioration models for each IRI category which provide the probabilities of each IRI category to deteriorate to a lower condition in the future, the one-year transition matrix to different conditions is calculated assuming a semi-Markov chain model, see Equations 6 through 9. Using these equations for all combinations of starting and ending IRI values,

Table 2. Transition Matrix from AFT-Weibull of Do-Nothing in One Year

	IRI 2	IRI 3	IRI 4	IRI 5	IRI 6	IRI 7	IRI 8	IRI 9
IRI 2	0.9104	0.0895	0.0001	0	0	0	0	0
IRI 3	0	0.9955	0.0045	0	0	0	0	0
IRI 4	0	0	0.9854	0.0146	0.0001	0	0	0
IRI 5	0	0	0	0.975	0.0249	0.0001	0	0
IRI 6	0	0	0	0	0.9655	0.0343	0.0002	0
IRI 7	0	0	0	0	0	0.9577	0.042	0.0003
IRI 8	0	0	0	0	0	0	0.9487	0.0513
IRI 9	0	0	0	0	0	0	0	1

the one-year transition probability matrix is as shown in Table 2. From Table 2, it can be seen that more than 90% of pavement will stay in the same condition level in the next year and have a very small chance of deteriorating by one or two IRI categories.

Further, one-year transition matrices for the three maintenance activities considered—minor rehabilitation, major rehabilitation, and reconstruction—are also developed based on the one-year do-nothing transition matrix. It is assumed that minor rehabilitation will improve the condition by one IRI category based on a study which found that minor rehabilitation such as crack maintenance, sealing, patching, or spalling is likely to improve the condition rating by 0.48, 0.41, and 0.79, respectively (*31*). It is also assumed that major rehabilitation will improve the condition by three IRI categories based on a study which found that IRI could be improved by 80.47 to 88.80 in./mile after maintenance (*32*). The transition matrix after applying preservation action is thus determined by "shifting" the probabilities shown in Table 2 by one or three IRI levels to the left for the minor and major rehabilitations. Reconstruction will reset the pavement to the best condition, for example, IRI 2, no matter what the current condition is.

Cost Calculations

To demonstrate the methodology at the project level, a specific two-way two-lane pavement segment within the PennDOT RMS database is chosen. This segment is one mile long with an AADT of 3,196.11 vehicles/day of which 8.96% is truck traffic. There are no passing zones or shoulder rumble strips within this segment, and the access point density is 16.33 points/mile. This segment is located in district 2 with a roadside hazard rating of 4 or 5, the horizontal curve density is 2.24 degrees/mile, and the degree of curvature per mile is 17.25 degrees/mile. Note that the methods presented here are generalizable to any segment.

For this case study, the sub-cost in different pavement conditions is estimated based on the methodology presented in the "Methodology" section. A 50-year planning horizon is considered, and the agency cost, user cost, and crash frequency are estimated per mile per lane over the 50 years. The results are presented in Table 3. In this table, all costs are calculated per lane per mile, and an average gas price of $3.853 per gallon in 2022 is used.

MOO Model Results and Discussion

The MOO takes as inputs the deterioration model and costs calculated above. The *geneticalgorithm* library in Python (*33*) is used here to implement the genetic algorithm to find the optimal solution. The population size is set at 50, the iteration is set at 500, the crossover type among different chromosomes is set as one point mutation, and the mutation probability is set as 0.2, the other hyperparameter settings follow the default values in the *geneticalgorithm* library.

Experiments are performed to explore the impact of safety costs on MRR planning. Safety cost is incorporated into the model in units of the number of fatal or injury crashes. To analyze the impact of safety costs on MRR planning, different weights of crash frequency are considered and the optimal solutions for different weights are obtained. A basic reference of the economic cost associated with a fatal or injury crash is adopted according to *Pennsylvania Crash Facts & Statistics*, which states that the average economic losses of fatal and injury crashes are about $13,383,153 and $759,652, respectively (*34*). Those numbers are weighted by the number of actual fatal and injury crashes that occurred on Pennsylvania roads during 2020, which was 1,129 and 61,248, respectively, to derive the average economic cost of a fatal and injury crash as $988,133. However, this single cost associated with a traffic crash is somewhat subjective. Therefore, denoting this value as E_S, a range of weights, w, from 0 to $10 \times E_S$ to the predicted crash frequency are considered in this study.

The results are presented to examine the sensitivities to three variables: (i) starting conditions, (ii) the transition probability, and (iii) traffic volume level.

Table 3. Cost Calculations for Different Pavement Conditions

Costs calculation	IRI 2	IRI 3	IRI 4	IRI 5	IRI 6	IRI 7	IRI 8	IRI 9
Agency cost								
Do-nothing ($)	0	0	0	0	0	0	0	0
Minor rehabilitation ($)	48,365	48,365	48,365	48,365	48,365	48,365	48,365	48,365
Major rehabilitation ($)	87,014	87,014	87,014	87,014	87,014	87,014	87,014	87,014
Reconstruction ($)	261,501	261,501	261,501	261,501	261,501	261,501	261,501	261,501
Salvage value								
Remaining lifespan (year)	44.1	39.1	24.7	16.5	10.3	5.6	0	0
Remaining lifespan value ($)	261,501	231,852	146,464	97,840	61,076	33,206	0	0
Base value ($)	174,486	174,486	174,486	174,486	174,486	174,486	174,486	174,486
Total salvage value ($)	435,987	406,339	320,951	272,327	235,563	207,693	174,486	174,486
User cost								
Car energy consumption (MJ)	7,996	8,118	8,199	8,281	8,362	8,444	8,525	8,688
Truck energy consumption (MJ)	2,311	2,323	2,331	2,339	2,347	2,355	2,363	2,379
Total energy consumption (MJ)	10,306	10,441	10,530	10,620	10,709	10,799	10,888	11,067
Gas consumption (gallon)	85	86	87	88	88	89	90	91
User cost ($)	119,490	121,048	122,086	123,124	124,162	125,200	126,238	128,314
Safety cost								
Number of predicted crashes	0.0626	0.0637	0.0645	0.0653	0.0661	0.0669	0.0677	0.0694

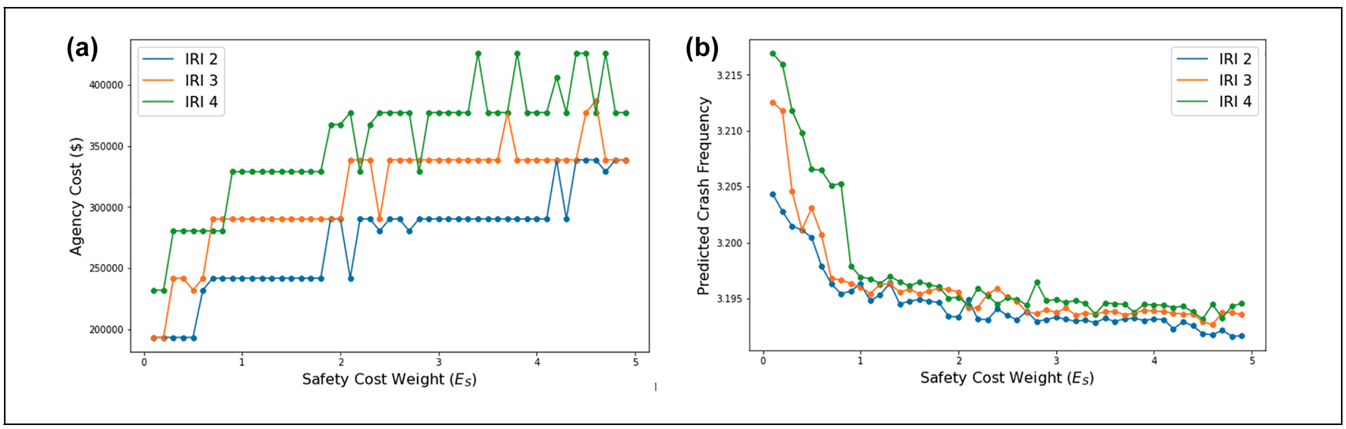

Figure 3. Impact of safety cost weight on agency cost as safety cost: (*a*) agency cost and (*b*) predicted crash frequency.

Sensitivity to the Starting Condition

When the pavement starts from different conditions, the optimal MRR plan varies as different weights of the safety cost are considered. Here, three possible initial IRI conditions are assumed: IRI 2, 3, and 4. Figure 3 provides the change in agency cost and predicted crash frequency for different weights of the safety costs. As shown, the necessary agency cost increases as the safety cost weight increases to maintain the pavement in a higher condition and reduce the predicted crash frequency. A pavement that starts from a worse condition requires not only higher agency costs but also a larger crash frequency, as expected. Note that crash frequency cannot be reduced much after a safety cost weight of $2E_S$, even with more MRR activities.

Pareto frontiers to show the trade-off between agency cost and safety cost are shown in Figure 4 as dashed lines. The corresponding safety weights for points on the Pareto frontier are also marked for a pavement starting from IRI 2 as an example. As the predicted crash frequencies reduce, the agency costs increase as expected. Further, if safety is not considered in the MRR planning ($w = 0$), the predicted crash frequency is the highest, as expected. As the weight of safety cost increases, the benefits of a pavement in good condition become more significant. Therefore, the optimal MRR plan chooses to adopt more maintenance activities to keep the pavement in a higher condition. In this scenario, the increased agency cost is offset by a lower safety cost. As the safety cost is valued more, initially crash frequency can be decreased without much increase in agency cost.

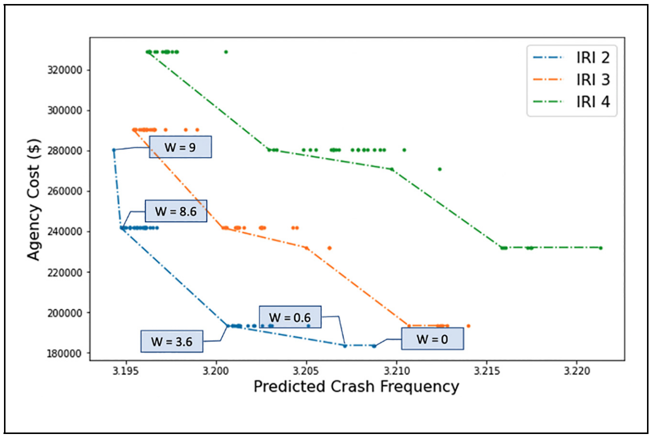

Figure 4. Pareto frontiers for pavements starting from different conditions (Pareto optimal solutions of pavement starting from IRI 2 are marked in this plot).

However, as the safety cost is weighed more, the agency cost needs to increase significantly more to reduce the crash frequency further. Note that after a weight of 3.6 it appears that the agency cost needs to increase significantly to reduce the predicted crash frequency, that is, there are diminishing returns on safety.

The change in the agency, user, and safety costs as a function of the weight of safety cost is shown in Table 4 for pavement starting from IRI 2. Notice that agency cost is the smallest component, always accounting for less than 3% of the total cost. When only the agency cost is considered in the objective function, the resulting user cost and expected crash frequency are the highest since the optimal MRR plan only adopts MRR activities at the end of the lifespan to achieve a higher salvage value. When user cost and agency cost are considered without safety cost, the user cost and expected crash frequency decrease considerably, leading to a significant decrease in total cost. When the safety cost is also included in the objective function with a weight of E_S, the predicted crash frequency decreases by 0.27%, which leads to the agency cost increasing by 5.3%. Further, this leads to a slight decrease in user costs since the overall pavement condition improves. As the safety cost is weighted more, the trade-off between agency cost and crash frequency becomes more obvious. When the safety cost weight increases to $10E_S$, the reduction of predicted crash frequency is minor but leads to a significant increase in agency cost. Further, when the safety weights increase from E_S to $4E_S$ or from $5E_S$ to $8E_S$, the agency costs do not change, which indicates that the same number of activities are being performed, however, the user cost and crash frequency are different, indicating that the activities are scheduled at different times, likely as a result of the algorithm terminating in a suboptimal solution.

To further explore the change in MRR plans as the safety cost and starting condition vary, Figure 5 visualizes the best MRR plans with different safety cost weights for pavements starting from IRI 2 and IRI 4. For comparison, the case where user cost is excluded is also shown. To achieve the minimum cost in this scenario, the agency will leave the pavement to deteriorate to the lowest condition in the analysis window but only adopt two consecutive major rehabilitation actions at the end of the life cycle to achieve a higher salvage value. Two consecutive major rehabilitations is the most cost-efficient way to restore the pavement to high condition for higher salvage value at the end of the analysis window. Compared with the other scenarios in Figure 5, it can be seen that the user cost and safety cost shift the MRR plan from only pursuing the salvage value at the end to achieving an overall good pavement condition during the whole life cycle. Further, as the safety weight increases, the maintenance schedule becomes more

Table 4. Subobjective Costs of Pavement Start from IRI 2

Objective function	Agency cost ($) (% change*)	User cost ($) (% change)	Safety cost ($) (% change)	Total cost (% change)
Only A	174,028 (−5.3%)	6,138,800 (2.1%)	3,265,876 (2.9%)	9,578,704 (2.24%)
A + U	183,744 (0)	6,011,814 (0)	3,173,585 (0)	9,369,143 (0%)
A + U + S (w = 1 E_S)	193,460 (5.3%)	6,000,411 (−0.19%)	3,164,974 (−0.27%)	9,358,845 (−0.11%)
A + U + S (w = 2 E_S)	193,460 (5.3%)	5,998,737 (−0.22%)	3,163,771 (−0.31%)	9,355,968 (−0.14%)
A + U + S (w = 3 E_S)	193,460 (5.3%)	5,998,090 (−0.23%)	3,163,302 (−0.32%)	9,354,852 (−0.15%)
A + U + S (w = 4 E_S)	193,460 (5.3%)	5,997,591 (−0.24%)	3,162,952 (−0.34%)	9,354,003 (0.16%)
A + U + S (w = 5 E_S)	241,825 (31.6%)	5,990,776 (−0.35%)	3,158,082 (−0.49%)	9,390,683 (0.23%)
A + U + S (w = 6 E_S)	241,825 (31.6%)	5,990,191 (−0.36%)	3,157,665 (−0.50%)	9,389,681 (0.22%)
A + U + S (w = 7 E_S)	241,825 (31.6%)	5,990,841 (−0.35%)	3,158,136 (−0.49%)	9,390,802 (0.23%)
A + U + S (w = 8 E_S)	241,825 (31.6%)	5,989,226 (−0.38%)	3,156,980 (−0.52%)	9,388,031 (0.20%)
A + U + S (w = 9 E_S)	280,474 (52.6%)	5,988,469 (−0.39%)	3,156,442 (−0.54%)	9,425,385 (0.60%)
A + U + S (w = 10 E_S)	241,825 (31.6%)	5,989,247 (−0.38%)	3,156,994 (−0.52%)	9,388,066 (0.20%)

Note: A = agency cost; U = user cost; S = safety cost; w = weight; E_s = average economic cost of a fatal and injury crash
*Changes are calculated compared with the case when only agency cost and user cost are in the objective function.

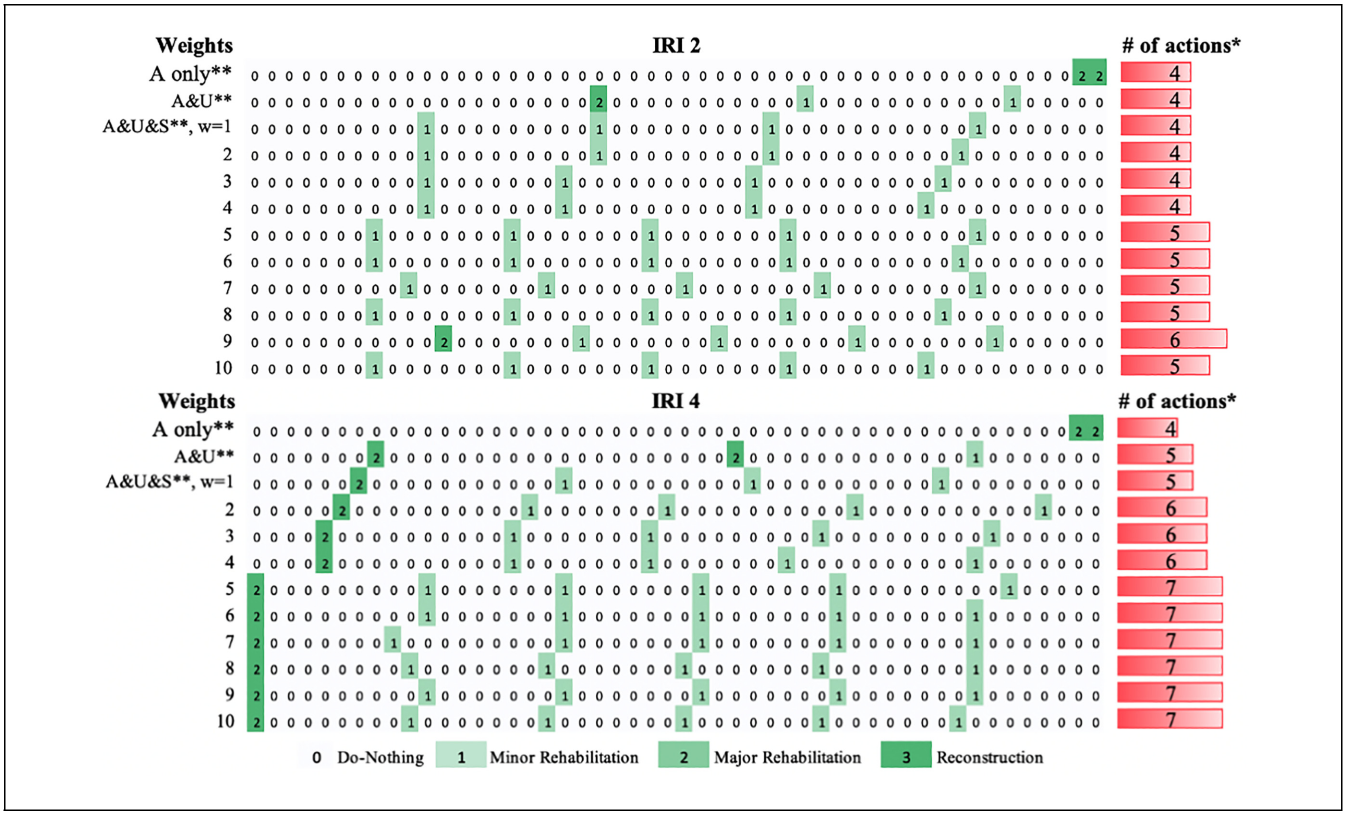

Figure 5. Maintenance, rehabilitation, and reconstruction (MRR) plans for different safety weights when starting at IRI 2 and IRI 4.
Note:
*For visualization, minor rehabilitation, major rehabilitation, and reconstruction are counted as 1, 2, and 3 of unit actions, respectively.
**"*A only*" denotes the best MRR plan when only considering the agency cost and salvage value; "*A&U*" denotes considering the agency cost, user cost; "*A&U&S*" denotes considering the agency cost, user cost, and safety cost in the objective function but safety costs are considered in the weight of wE_S.

frequent, and tends to use a series of minor rehabilitations regularly to maintain the pavement in a better condition. For a pavement starting from a worse condition (i.e., IRI 4), a major rehabilitation is employed in the beginning to reset the condition to the best level. The number of actions for each scenario is also domesticated on the right side of Figure 5. This is only used for visualization to estimate the required MRR workload for different scenarios. To compute this value, each minor rehabilitation is treated as one-unit action, each major rehabilitation is treated as two-unit action, and each reconstruction is treated as three-unit action. From the results, as the weight of safety costs increase in the objective function, about one and three extra unit actions are required to achieve the lowest total cost for pavement starting from IRI 2 and IRI 4, respectively.

Sensitivity to the Transition Probability Matrix

To explore the transition probability's impact on MRR planning, the transition probability matrix is altered to an assumed matrix. The goal is to understand how incorrect estimations of the transition matrix would affect the resulting MRR planning. The average deterioration rates are kept the same as the AFT-Weibull model-based transition matrix, but the variation is eliminated by setting constant probabilities of remaining at the same IRI level, deteriorating to one lower level, and deteriorating to two lower levels as 0.9, 0.07, and 0.03, respectively. For example, assuming the current condition as IRI i, the probability of remaining in IRI i in one year is 0.9, the probability of deteriorating to IRI $i+1$ is 0.07, and the probability of deteriorating to IRI $i+2$ is 0.03 for all $i = 2 \dots 7$. For IRI 8, the probability of remaining in IRI 8 is 0.9 and the probability of deteriorating to IRI 9 is 0.1. The corresponding transition matrix for minor, major rehabilitation, and reconstruction is derived in the same way as previously. The best MRR plan for pavement starting from IRI 2 for this new set of transition matrices is shown in Figure 6.

From Figure 6, it can be observed that with the new transition matrix the most frequent activity becomes major rehabilitation instead of minor rehabilitation. The main reason for this is that the new transition matrix lowered the probability that a minor rehabilitation can improve the IRI category, and so the major rehabilitation is chosen more often.

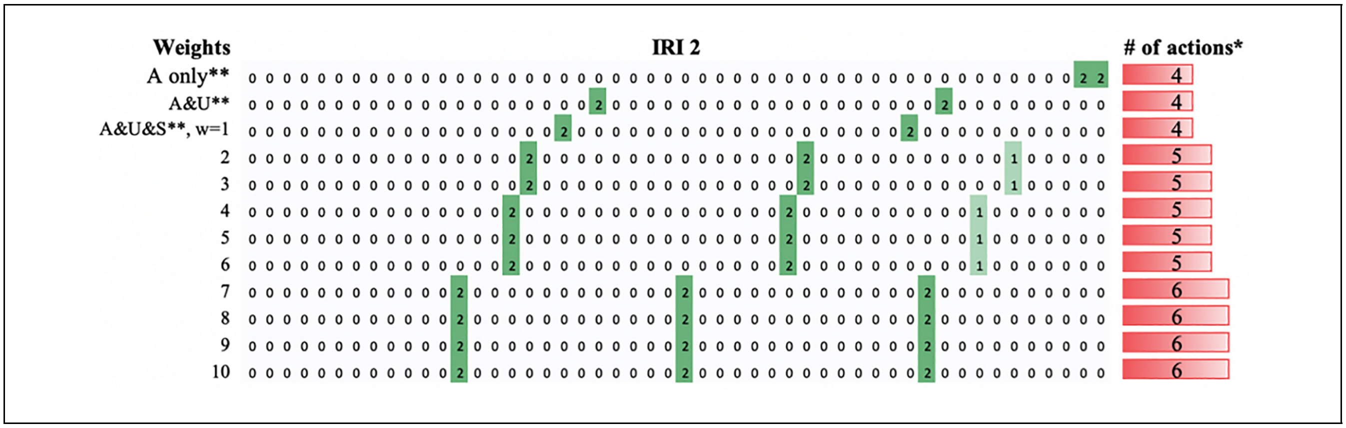

Figure 6. Best maintenance, rehabilitation, and reconstruction (MRR) plans using assumed transition probability matrix.
*For visualization, minor rehabilitation, major rehabilitation, and reconstruction are counted as 1, 2, and 3 of unit actions, respectively.
***"A only"* denotes the best MRR plan when only considering the agency cost and salvage value; *"A&U"* denotes considering the agency cost, user cost; *"A&U&S"* denotes considering the agency cost, user cost, and safety cost in the objective function but safety costs are considered in the weight of wE_s."

The slight variation of the transition matrix leads to completely different MRR planning, and the safety impact on the best MRR plan changes as well. These results therefore highlight the importance of using an accurate deterioration matrix when optimizing MRR plans.

Sensitivity to AADT

Crash frequency is closely correlated to traffic volume. Therefore, the impact of safety cost on MRR planning varies under different traffic loads. The AADT used for the experiment in the "Estimated Deterioration Model" section was the average AADT of all pavements in the dataset, which is 3,196 vehicles/day. In this section, two comparative case studies with low AADT levels (set at 1,100 vehicles/day) and high AADT levels (set at 11,000 vehicles/day) are analyzed to explore the impact of traffic load.

For different AADT levels, the associated user cost (fuel consumption in this study) and safety cost (predicted crash frequency for each unit length of a segment), are different. Further, since the AADT is an input to the deterioration model, the transition matrix also varies. The calculation of user cost and predicted crash frequency under different AADT levels suggests that the user costs and predicted crash frequencies increase as AADT increases. A pavement starting from IRI 2 is selected to test the influence of traffic load. The two comparison cases have the same parameters except for the AADT level. Figure 7 shows the change in agency cost as the safety cost weight increases.

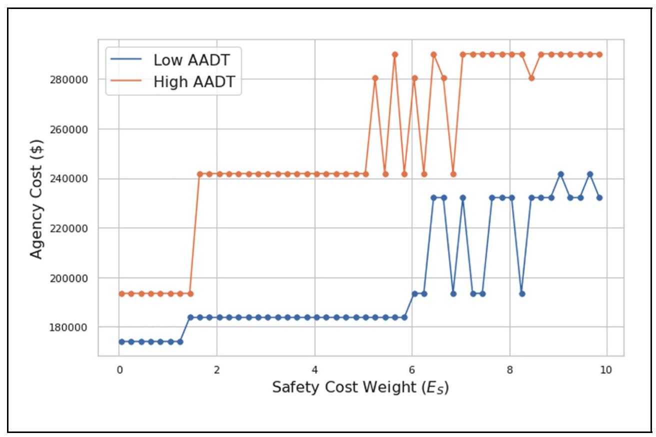

Figure 7. Agency costs change as safety cost weight varies for different average annual daily traffic (AADT) levels.

From Figure 7, it can be found that the safety cost has a greater impact on MRR planning when the AADT is high. The agency cost increases more in the high AADT situation when considering safety costs. When the safety cost weight increased to 10 E_S, the necessary number of actions increased from four to nine in the high AADT situation, but only increased to six in the low AADT condition. This is expected since, as the traffic load increases, the predicted crash frequency increases as well. This will lead the agency to conduct more maintenance activities to improve the pavement condition, thereby reducing the safety cost.

Conclusion

This study is the first to consider the cost of safety in the pavement management process and provide evidence that lower crash frequency can be achieved by developing better MRR plans. This was achieved through a MOO approach that considered the user cost, agency cost, and safety cost. The MOO approach utilizes a genetic algorithm, and also utilizes a deterioration model to understand the impact of different MRR plans on the objective function. By conducting a series of experiments, this study first examined the impact of safety costs on MRR plans for pavements starting from different conditions. The results show that as a larger weight is put on the safety cost, the required maintenance activities increase so that the pavement can be kept in good condition. Specifically, when adding the safety cost into the objective function with a weight of E_S, the predicted crash frequency decreased by 0.0087 fatal or injury crashes, which led to the agency cost increasing from $183,744 to $193,460 for pavement deteriorated from IRI 2. In other words, when the safety cost is considered in the MRR planning with an economic cost suggested by *Pennsylvania Crash Facts & Statistics*, the agency cost increased by 5.29% for good pavement condition. The optimal MRR plans suggested that one extra maintenance activity is needed in 50 years of MRR planning when considering the cost of crashes economically with a weight of $10E_S$ for pavements starting from IRI 2. Compared with this, a pavement starting from a worse condition, that is, IRI 4, three more activities are needed for the same safety weight. This indicates that traffic safety has a greater impact on pavements in worse condition in the MRR planning process compared with that of pavements in better condition. Finally, this study examined the impact of safety costs on MRR planning for segments with different traffic loads. Additional maintenance activities are needed for segments with higher traffic loads compared with segments with low AADT.

This study used simplified user cost calculations and assumptions about the deterioration of the pavement to demonstrate the methodology of how to incorporate safety on MRR planning and its impacts. When available, agencies should utilize location-specific data to transfer the models to the specific location of interest. In this study, IRI is adopted as the pavement condition indicator, but different indicators that are more relevant to the crash frequency, such as pavement frictional characteristics, could be explored based on the proposed methodology framework for other case studies given available datasets.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: M. Lu, S. Ilgin Guler, V. V. Gayah; data collection: M. Lu, S. Ilgin Guler; analysis and interpretation of results: M. Lu, S. Ilgin Guler, V. V. Gayah; draft manuscript preparation: M. Lu, S. Ilgin Guler. All authors reviewed the results and approved the final version of the manuscript.

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