

Article

Integrating Probabilistic Pavement Repair Effects for Network-Level Repair Optimization

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Abstract

Effective pavement repair planning is vital for sustaining performance and minimizing lifecycle costs. At the network level, most agencies still rely on deterministic repair-effect assumptions, where repair outcomes are defined by fixed restoration values derived from experience or experimental averages. However, such assumptions often deviate from actual field performance, leading to overestimated repair efficiency and suboptimal investment decisions. This study develops a framework that integrates stochastic repair effects estimated from historical repair data using a probabilistic model for estimating repair effects. The effects of different repairs are represented as probability distributions derived from the latent-variable projection of stochastic deterioration hazard functions, which define the repair transition probabilities. These stochastic transitions are embedded within a Markov Decision Process to optimize the selection of repair types according to condition state, repair effect, cost, and serviceability thresholds, all within a constrained budget. The framework's application to Addis Ababa's 150 km urban road network resulted in a five-year optimal strategy that prioritized cost-effective treatments, such as patching, leading to an improvement in network serviceability from 65.7% to 81.2% at a total cost of USD 11.12 million. A comparative analysis of the deterministic restoration approach, commonly used by the agency, overestimated network-level performance by approximately 19%, as it ignored the variability of recovery captured by the stochastic model. Hence, the proposed stochastic framework enables agencies to achieve realistic, data-driven, and sustainable repair optimization, avoiding overestimation of repair benefits while maintaining serviceability within budget constraints.

Keywords: pavement; stochastic repair optimization; Markov decision process; maintenance sustainability



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1. Introduction

Pavement Management Systems (PMSs) provide highway agencies with a structured framework for optimizing maintenance and rehabilitation decisions at both the network and project levels. A PMS is a comprehensive decision-support tool that coordinates and prioritizes pavement-related activities by integrating data management, performance analysis, and implementation subsystems, as described by Padigo et al. [1] and Li et al. [2]. Within this framework, deterioration models quantify the progressive decline in pavement conditions resulting from traffic loading and environmental effects. In contrast, repair-effect

models assess the degree of improvement achieved through maintenance or rehabilitation interventions. However, traditional repair-effect models are typically deterministic; i.e., they assume that each maintenance action results in a fixed level of restoration [3–5]. Such assumptions overlook the inherent variability in repair outcomes observed in real-world pavement performance. For instance, the Addis Ababa City Road Authority (AACRA) employs a deterministic assumption in its Road Maintenance for Management System (RMMS), where pavements are presumed to be fully restored to a Very Good condition after any corrective repair. This simplification disregards the influence of environmental variability, material quality, and execution factors on repair performance. Similar limitations were identified by Durango and Madanat [6], who emphasized that deterministic assumptions in maintenance modeling can lead to biased estimates of service life and sub-optimal investment policies. Consequently, there is a growing need for stochastic modeling approaches that can effectively represent the probabilistic nature of both the deterioration and repair processes, thereby enhancing decision accuracy and long-term reliability.

At the project level, structural repairs are intended to restore or increase load-bearing capacity. They are typically less suitable for network-level optimization, where the objective is to sustain serviceability through surface-level, non-structural repairs [7]. These surface treatments correct surface distress and improve ride quality without substantially enhancing structural strength [8]. Examples include patching, partial or full overlays, and light rehabilitation—collectively defined as corrective maintenance. As discussed by Durango and Madanat [6], the effectiveness of such treatments depends on pre-repair conditions, treatment quality, and environmental factors, resulting in varying post-repair performance outcomes. This variability highlights the importance of modeling repair effectiveness as a state-dependent probabilistic process rather than assuming a fixed improvement for each repair type.

Several studies have examined the influence of maintenance strategies and treatment effectiveness on pavement performance and life-cycle optimization. Ahmed S. Mohamed et al. [8] investigated the effect of corrective maintenance on pavement life-cycle performance using a genetic algorithm (GA) optimization framework. Their study compared maintenance policies that either included or excluded corrective treatments—such as shallow and deep patching, rut filling, and milling and patching—and found that including corrective maintenance significantly improved network performance and reduced total life-cycle costs. This finding confirmed the practical importance of reactive surface repairs in achieving sustainable pavement management. However, their model defines repair effectiveness deterministically, assigning fixed improvements to each treatment type.

A subsequent study by Mohamed et al. [9], intensively reviewed project-level pavement management systems for the construction and rehabilitation of flexible pavements. They observed that most decision-making frameworks still rely on deterministic representations of repair outcomes, with limited attempts to incorporate uncertainty into performance prediction. Few studies have modeled the performance jump probabilistically, and many continue to depend on field averages or engineering judgment to estimate post-repair improvements. This persistent assumption of constant or fully restorative repair effects highlights the lack of stochastic repair-effect formulations in the literature.

If untreated, surface distress progressively worsens over time. Deterioration models, therefore, predict the evolution of pavement conditions under a scenario with no repairs. Common indicators, such as the International Roughness Index (IRI) or the Pavement Condition Index (PCI), are used to classify pavement conditions into discrete states, including Good, Fair, and Poor, which can be represented numerically as States 1, 2, and 3. Because condition transitions occur probabilistically even under similar exposure conditions, Markov models provide a practical framework for describing these stochastic transitions.

Each transition probability represents the likelihood that a pavement moves from one state to another within a given inspection period.

The Markov Transition Probability (MTP) model developed by Tsuda et al. [10] was initially formulated for bridge deterioration and has since been widely adopted for pavement performance modeling. Subsequent studies extended this approach through hierarchical and Bayesian formulations to capture heterogeneity and deterioration prediction accuracy [11–13]. These advancements laid the foundation for decision-based optimization frameworks, where deterioration, repair, and cost components are jointly modeled to support long-term planning and decision-making.

The Markov Decision Process (MDP) framework integrates deterioration models, repair-effect models, and cost structures to identify optimal maintenance strategies under budgetary and serviceability constraints. Numerous studies have demonstrated the capability of MDP-based models to support network-level optimization [14–17]. For example, Mandiarta et al. [14] applied dual linear programming to incorporate agency constraints, while Guignier et al. [15] developed probabilistic MDP formulations for maintenance policy optimization. However, these studies generally relied on predetermined repair effects derived from experience or assumed improvement ratios, which limit their ability to reflect the stochastic variability of repair outcomes. More recently, Yao et al. [17] introduced a deep reinforcement learning (DRL) framework for long-term pavement planning; yet, their model remained deterministic, representing both deterioration and repair processes as fixed transitions predicted by neural networks.

The present study addresses this research gap by conceptualizing repair effects as probabilistic performance jumps within a Markov-based optimization framework. The model quantifies the distributional variability of repair outcomes using historical data, enabling the stochastic estimation of post-repair transitions and the uncertainty-aware optimization of maintenance strategies. This work addresses the conceptual gap identified by Mohamed et al. [9] by developing a rigorous, data-driven probabilistic foundation for evaluating long-term pavement performance and cost-effectiveness under uncertain repair efficacy.

The stochastic recovery estimation framework was initially introduced by Kaito et al. [13] to evaluate deflection recovery through layer-based repairs. Their latent-variable approach captured unobserved heterogeneity in repair effectiveness across pavement layers. The current study extends this concept to the pavement surface level, modeling surface repair effects as stochastic transitions reflecting observed variability in field performance. By integrating stochastic deterioration and repair processes into a unified MDP optimization framework, this study derives optimal network-level repair policies that balance cost, effectiveness, and uncertainty for sustainable surface-level pavement management.

The following section presents the proposed methodology, detailing the stochastic deterioration and repair-effect models, network representation, cost structures, and policy constraints that define the optimal repair policy for flexible pavement networks.

2. Methods

The Markov Decision Process (MDP) has been widely adopted in pavement management research as a dynamic optimization framework for determining cost-effective maintenance and rehabilitation (M&R) policies. For instance, Wang et al. [18] developed a network-level pavement optimization system that combined a Markov process to model pavement condition transitions with a linear programming framework to minimize total agency costs over a multiyear planning horizon. In the MDP-based studies [14–17], the pavement condition state represents a node in the Markov chain, and each maintenance action, such as do-nothing, patching, overlay, or rehabilitation, has its own determined

transition matrix that reflects how the selected action influences future condition transitions. Durango and Madanat et al. [6] model stochastic deterioration, action-dependent transitions, and network-level constraints, demonstrating the flexibility of the MDP framework in addressing real-world uncertainties. Their model analyzes repair as a deterministic mean effect, while representing uncertainty through the deterioration rate, which is updated adaptively over time.

As discussed earlier, the proposed framework integrates probabilistic deterioration and repair-effect models to capture the stochastic nature of pavement performance over time. The deterioration process is modeled using the Markov Transition Probability (MTP) model developed by Tsuda et al. [10], which expresses the probabilistic evolution of pavement conditions under a no-repair scenario. Kaito et al. [13] apply the stochastic repair-effect model to the MTP concept, representing post-repair transitions for layer-based repairs. This formulation describes repair outcomes as probabilistic transitions rather than fixed improvements, thereby incorporating the variability observed in actual maintenance performance.

These probabilistic formulations establish the analytical foundation for the repair selection framework. The MDP framework for identifying the optimal repair actions across the network is outlined in Figure 1.

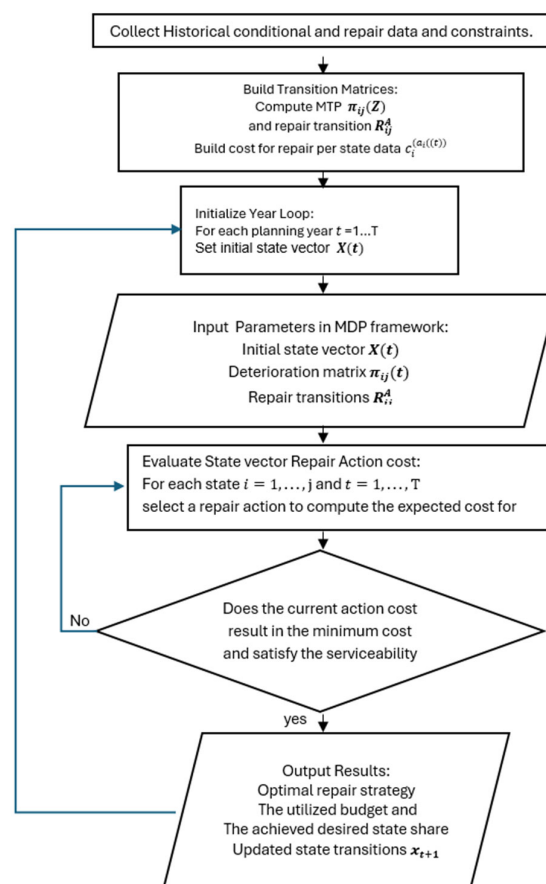


Figure 1. Proposed MDP optimization diagram.

The subsequent subsection presents the mathematical formulation of the MDP, defining the state transitions, cost structure, and Bellman recursion used to derive the optimal repair policy.

2.1. Transition Model (MTP) for Deterioration Estimation

The MTP model is a Markov-based model developed by Tsuda et al. [10], which estimates the trend of infrastructure deterioration using two-time inspection information. It defines the deterioration of infrastructure as the transition from its current condition to a state $h(\tau_0)$ obtained at inspection time τ_0 to the state $h(\tau_2)$ at τ_2 where there is no repair action in between the inspection time Z as presented in Equation (1).

$$\pi_{ij}(Z) = \text{Prob}[h(\tau_2) = j | h(\tau_0) = i] \quad (1)$$

Deterioration transition for every state condition of the infrastructure from i to J , where J is the absorbing state, represented by the matrix:

$$\pi_{ij} = \begin{pmatrix} \pi_{i1} & \dots & \pi_{iJ} \\ \vdots & \ddots & \vdots \\ 0 & \dots & \pi_{JJ} \end{pmatrix} \quad (2)$$

The deterioration state transitions are estimated based on the formulations presented in Equations (3) and (4).

$$\pi_{ij}(z) = \sum_{m=i}^j \prod_{m=i}^{k-1} \frac{\theta_m}{\theta_m - \theta_k} \prod_{m=k}^{j-1} \frac{\theta_m}{\theta_{m+1} - \theta_k} \exp(-\theta_m z) \quad (3)$$

where:

$$\begin{aligned} \prod_{m=i}^{k-1} \frac{\theta_m}{\theta_m - \theta_k} &= 1 \text{ when } k \leq i + 1 \\ \prod_{m=i}^{k-1} \frac{\theta_m}{\theta_{m+1} - \theta_k} &= 1 \text{ when } k \geq j \\ \pi_{ij}(z) &= 1 - \sum_{s=i}^{j-1} \pi_{is}(z) \end{aligned} \quad (4)$$

where, θ_i is the deterioration hazard function formulated as a function of the explanatory variables x and the associated parameters β , as in Equation (5).

$$\theta_i = f(x : \beta') \text{ \& } \beta' \text{ is the transpose of explanatory variables } \beta \quad (5)$$

This hazard function is later used to estimate the repair effects as latent variables just before and after repair, as presented in Section 2.2.

The deterioration hazard parameter (β) must be estimated to estimate the deterioration transition probability. One approach to (β) is using the Maximum Likelihood method. Another approach used by Kaito et al. [12] is through the Markov Chain Monte Carlo (MCMC) technique [19,20]. The parameter (β) is sampled by setting a prior distribution for β through the Bayesian framework, as shown in Equation (6). The prior assumption must be based on experience and knowledge. This research assumes that the parameter (β) is a multivariate normally distributed parameter sampled until the Geweke test [21].

$$\pi(\beta|\xi) = \frac{L(\xi|\beta) \cdot \pi(\beta)}{\int (L(\xi|\beta) \cdot \pi(\beta) d\beta)} \quad (6)$$

where:

- $\pi(\beta|\xi)$ is the posterior distribution of the parameter β given the data (ξ),
- $L(\xi|\beta)$ is the likelihood of the parameter β given the data,
- $\pi(\beta)$ is the prior distribution of the parameter β ,
- $\int (L(\xi|\beta) \cdot \pi(\beta) d\beta)$ is the marginal likelihood.

More detailed derivations of the deterioration model and parameter estimation methodology can be found in the work of Tsuda et al. [10].

2.2. Repair Transition (Repair Effect Model)

There must be no repair action on the MTP deterioration model between the first inspection and the second inspection time. However, when a repair occurs between these inspection time points, the complete process follows a deterioration path until the repair is made, and the repaired pavement then deteriorates again until the next inspection. This approach to model repair effect is developed by Kaito et al. [13]. In their research study model, the state variables before and after repairs are the projected MTP hazard function projections. The matrix representation for the transition due to the repair effect is as presented in Equation (7):

$$R_{ij}^A = \begin{pmatrix} r_{11}^a & \dots & 0 \\ \vdots & \ddots & \vdots \\ r_{1I}^a & \dots & r_{II}^a \end{pmatrix} \quad (7)$$

The time for repair is designated as τ_r with repair action a , where different repair actions, i.e., $\{a = 1 \dots A\}$, are grouped to form a probability distribution from repair historical data. In the case of repair transition, the repairs will transition the condition state from the pre-repair current state i to a better state j . The time intervals before and after the repair action are z_1 and z_1 respectively. At time τ_r , the condition projected states are modeled as the latent trajectory variables of the deterioration hazard function. These latent variables are designated as d and u respectively. These variables represent the repair process due to repair action a , r_{du}^a .

Since the complete process, which occurs between inspections, includes both deterioration and repair transitions, the joint probability of these two processes is formulated in Equation (8).

$$\pi_{i_0 i_2} = \pi_{i_0 d}(z_1) \cdot \pi_{ui_2}((z)_2) \cdot R_{ij}^A \quad (8)$$

The repair transition probability has the probability form as Equation (10) where, for different repair types $\{a = 1 \dots A\}$,

$$\begin{aligned} r_{du}^a &\geq 0 & (d \geq u) \\ r_{du}^a &= 0 & (d < u) \\ \sum_{u=1}^d r_{du}^a &= 1 \end{aligned} \quad (9)$$

The joint process of deterioration and repair transition probability of a pavement segment transitioning from the observed state i_0 to i_2 is the product of the deterioration transition probability and the repair effect, as shown in Equation (10).

$$Prob[\beta, \omega, h \mid a, z_2, z_1] = \sum_{\omega=i_0}^I \pi_{i_0 \omega} \omega(z_1) \cdot \sum_{h=1}^{i_2} r_{du}^a \pi_{hi_2}(z_2) \quad (10)$$

where:

- $\pi_{i_0 \omega}$ is the deterioration transition probability from i_0 to the latent state ω over z_1 to be a state d
- $r_{\omega h}^a$ is the repair transition probability from the latent deterioration state ω to the post-repair latent state h under action a .
- $\pi_{(hi)_2}$ is the deterioration the transition probability from the latent state h to i_2 over z_1 to be a state u .
- J is the worst possible state before repair & I = best achievable state.

The latent state variables d and u are sampled via MCMC ($i_0 \leq \omega \leq I$), and ($d \leq h \leq J$), capturing deterioration d during z_1 and repair effect u before the next inspection state i_2 . The repair transition due to each repair action a , r_{ij}^a , is the converged repair effect representing the probability of transitioning from the rank d (before repair) to

rank u (after repair). For each repair type, the probability is estimated using the Dirichlet distribution (α), which serves as a flexible prior for the probabilities of repair effects, as presented in Equation (11).

$$r_{ij}^a = \begin{cases} \alpha_{ij}^a & (i \geq j) = 0 \\ 0 & (i < j) = 0 \end{cases} \quad \sum_{j=1}^i \alpha_{ij}^a = 1 \quad (11)$$

Gibbs sampling is used to assign latent variables randomly d and u , as formulated in Equations (12) and (13), and iteratively update parameters conditioned on β as outlined in Kaito et al. [13].

$$\text{Prob}[u = i | \alpha, \beta, u, d, b, z_2] = \frac{\tilde{L}(\alpha, \beta, u^i, d, b, z_2)}{\sum_{j=1}^I \tilde{L}(\alpha, \beta, u^j, d, b, z_2)} \quad (12)$$

$$\text{Prob}[d = i | \alpha, \beta, u, d, b, z_2] = \frac{\tilde{L}(\alpha, \beta, d^i, u, b, z_2)}{\sum_{j=1}^I \tilde{L}(\alpha, \beta, d^j, u, b, z_2)} \quad (13)$$

Initially, the parameters α are assigned prior values and updates from historical data through conditional distributions of joint probability through the Gibbs sampling procedure. This approach is adapted from the study by Kaito et al. [13] to estimate the effects of pavement surface repair in this study. This provides the foundational input for the subsequent optimization process using a Markov Decision Process (MDP) framework. Further details on the formulation and sampling of latent variables can be found in their work.

2.3. Stochastic Deterioration and Repair Effect Integrated MDP Framework

The components of the MDP framework, illustrated in Figure 1, are grounded by the deterioration and repair transition models described above. These models are integrated within an MDP structure that operates at the network level to determine the optimal repair types and treatment proportions for each pavement condition state of the network. Thus, the subsequent sections present the formulations for network representation, state transition processes, budget and serviceability constraints, and the optimization objective function.

2.3.1. Network State Representation

This study conceptualizes pavement repair planning using a network-level, state-wise decision framework. An agency inspects all pavement segments in the network at predetermined intervals t . The segments' condition in the network is then aggregated to a pavement state vector $X(t)$. This vector represents the fraction of the network in each discrete condition state at a given time t , as formulated in Equation (14).

$$X(t) = [X_1(t), X_2(t), \dots, X_5(t)] \quad (14)$$

The proportion $X(t)$ is calculated using the number of segments in each state as

$$x_i(t) = \frac{N_i}{N}, i = 1, 2, \dots, J \quad (15)$$

where N_i is the number of pavement segments in the state i at time t , and N is the total number of segments in the network, and the vector satisfies:

$$\sum_{i=1}^J (x_i(t)) = 1 \text{ and } 0 \leq x_i(t) \leq 1 \quad (16)$$

This normalization ensures full network coverage at each time step in the planning horizon, where, based on the inspection results, the agency selects repair types for each state vector, aiming to optimize repair costs while improving surface riding quality.

For each state in the state vector, a repair action transforms the condition state according to the repair transition probabilities or the natural deterioration transitions at each time step $t \in \{1, 2, \dots, T\}$ within the planning horizon (T). Repair decisions are assumed to be applied immediately after inspection, instantly improving the condition state according to the selected repair type.

2.3.2. Partial-Treatment Variable

To represent the partial application of each repair action within available funds, a continuous decision variable $\rho_i(t) \in [0, 1]$ is defined as the fraction of the state treated by action during the year t . Thus, $\rho_i(t) = 1$ means all segments in the state i are treated, while $\rho_i(t) = 0$ indicates no treatment.

2.3.3. Network Transition Process

The network evolves according to a combined deterioration–repair mechanism.

The probability of deterioration (transition from one state to another in a defined period) is π_{ij} when no repair is applied, and when repaired $R_{ij}^{a_i(t)}$ denotes the repair transition probability under action a at time t . Then, the expected proportion of segments in the state at time $t + 1$ is given by:

$$X_j(t+1) = \sum_{i=1}^J X_i(t) [(1 - \rho_i(t)) \pi_{ij} + \rho_i(t) R_{ij}^{a_i(t)}] \quad (17)$$

where $\rho_i(t)$, is a portion of the network that allows each state to be partially treated. A fraction of the network $X_i(t)$ i.e., $\rho_i(t)$, follows the repair transition $R_{ij}^{a_i(t)}$, while the remaining portion deteriorates naturally according to π_{ij} .

2.3.4. Repair Cost and Budget Constraint

The expected annual repair cost C_t is computed as:

$$C_t = N \sum_{i=1}^J (X_i(t) \rho_i(t) C(i, a_i(t))) \quad (18)$$

where $C(i, a_i(t))$ is the unit repair cost for applying the action to state i , and is the total number of pavement segments.

A rigid budget constraint restricts total expenditure in each period:

$$(C_t \leq B_t, t = 1, 2, \dots, T) \quad (19)$$

where B_t denotes the available annual budget.

This ensures that the total allocated cost does not exceed the financial limit for the respective year.

2.3.5. Optimization Objective

The optimization problem aims to minimize total repair cost while maintaining the share of pavements in satisfactory condition above a predefined serviceability target, denoted as $\tau_{service}$.

$$\text{Such that, } S_{ser} \subseteq \{1, \dots, J\}, \tau_{service} = \sum_{(i \in S_{ser})} X_i(t) \quad (20)$$

and $w_{share} \cdot \min(0, \tau_{service} - \sum_{(i \in S_{ser})} X_i(t))$ is the penalty term in the objective function in Equation (21).

Objective function

$$\text{Min}_{\rho_{i(t)}, a_{i(t)}} \sum_{t=1}^T [N \sum_{i=1}^J X_i(t) \rho_{i(t)} (C(i, a)_{(t)}) + w_{share} \cdot \text{Max}(0, \tau_{service} - \sum_{i \in S_{ser}} X_i(t))] \quad (21)$$

Subject to the constraints:

$$\begin{aligned} X_{j(t+1)} &= [\sum_{i=1}^J X_i(t) (1 - \rho_{i(t)}) \pi_{ij} + \rho_{i(t)} R_{ij}^{a_i(t)}], \quad \forall i, t \\ C_t &= N \sum_{i=1}^{S_{ser}} (X_i(t) \rho_{i(t)} C(i, a_i(t))) \leq B_t, \quad \forall i, t \\ 0 &\leq \rho_i(t) \leq 1, a_i(t) \in \{1, \dots, A\}, \quad \forall i, t \\ \sum_{i=1}^J X_i(t) &= 1, S_i(t) \geq 0, \quad \forall i, t \end{aligned} \quad (22)$$

The optimization algorithm employs a one-step optimization per planning year, striking a balance between computational tractability and decision accuracy. It updates the network state vector at each time step using transition matrices derived from deterioration and repair models.

2.4. Empirical Application Setup

The city of Addis Ababa has a road network of more than 4800 km. The city road authority, Addis Ababa City Road Authority (AACRA), uses a PMS, namely Road Maintenance Management System (RMMS), which was established in 2018 [22,23]. The road network is divided into unit segments that are lane-wide and 100 m in length. It assesses its road conditions segment-wise using a standardized roughness measure, the International Roughness Index (IRI). It conducts an annual assessment to evaluate its current road network conditions and plan repairs for the coming budget year, i.e., $Z = t = 1$ year to analyze the deterioration transition. The RMMS manual ranks the pavement conditions into five states, as shown in Table 1.

Table 1. Condition state rank.

Pavement Condition	IRI Measure		State Rank
Very Good	$0 \geq \text{IRI}$	<2	1
Good	$2 \geq \text{IRI}$	<4	2
Fair	$4 \geq \text{IRI}$	<6	3
Poor	$6 \geq \text{IRI}$	<8	4
Very Poor	$8 \geq \text{IRI}$	—	5

Even though the Authority uses the MTP to estimate its road deterioration prediction in RMMS, the system uses a deterministic repair effect to optimize the repair plan, assuming pavement conditions will be restored (return to the best condition) after the repair. The types of repairs for surface condition improvement are as follows.

1. Spot Repair (Patching): Patching asphalt for spot repair involves cutting and removing the damaged section, cleaning and preparing the base, and then applying a tack coat for bonding. Hot asphalt mix is placed, compacted in layers, and leveled to match the surrounding pavement.
2. Partial Overlay: The process involves preparing the surface layer by removing or scarifying the areas connecting multiple damage
3. d spots. After cleaning the surface, a tack coat is applied, and a new hot mix asphalt layer is placed and compacted over the prepared area to restore uniformity and riding quality. This method provides a smooth, sealed surface but remains a non-structural repair.

4. **Full Overlay:** This method involves scarifying or milling the entire surface layer across the full width of the road, cleaning it, and applying a tack coat before placing and compacting a new hot mix asphalt layer. The overlay is relatively thin and does not add structural thickness; its primary purpose is to restore riding quality, smoothness, and waterproofing rather than to strengthen the pavement.
5. **Light Rehabilitation:** In this method, localized failures extending into the base layer are first excavated and repaired to restore uniform support. After these base spots are corrected, the entire surface is cleaned, a tack coat is applied, and a thin hot mix asphalt overlay is placed over the area. The overlay enhances riding comfort and seals the surface, but remains non-structural, as its thickness is insufficient to significantly increase the pavement's overall load-bearing capacity.

Other maintenance activities, such as crack sealing and cold asphalt patching, are also practiced, addressing minor surface defects and preventing moisture intrusion. However, these treatments are not evaluated due to the limited inspection data.

The agency uses its road maintenance guidelines, which instruct on the type of repairs to use for each type of distress. The result of the repair (repair effectiveness) is taken to restore the pavement to its best state (state 1) after the repairs are carried out. The optimization framework is applied to 3014 inspected segments with repair history data from 2019 to 2022. The agency's desired serviceability, as outlined in the Authority RMMS manual [23,24], is to have 85% of its roads in good condition, i.e., in State 1 and 2.

The corresponding average cost of action on each state is presented in Table 2. Based on actual field practice and unit rates, the estimated average cost of applying that specific repair method is calculated. For example, if patching is used to address localized distress in State 2 pavement segments, the average repair volume is first estimated for pavements in that state. For a representative segment, the corresponding repair cost is calculated based on the expenses associated with patching activities, including materials, labor, and equipment. This unit cost is subsequently multiplied by the state vector proportion to obtain the total repair cost for all pavements in that state.

Table 2. Repair action cost per segment in US Dollars.

State	Cost for No Repair	Patching	Partial Overlay	Full Overlay	Light Rehabilitation
1	-	5.92	15.38	26.33	35.33
2	-	15.87	18.46	31.33	38.33
3	-	18.26	21.79	33.33	45.33
4	-	24.36	26.15	38.33	48.31
5	-	27.97	43.1	45.33	50.1

3. Results

The network condition state at the end of the 2022 fiscal year, as reported in the inspection, was used to optimize the best repair policy for a five-year planning horizon, i.e., $T = 5$ years. A five-year strategic planning horizon was chosen because the repair actions are primarily based on surface conditions inspection rating (IRI). Interventions targeting deeper structural health must be integrated after at least five years to incorporate more substantial measures that do not rely solely on surface-level repairs.

The resulting deterioration and repair transitions, as discussed in Sections 2.1 and 2.2, are presented in Sections 3.1 and 3.2, respectively. The repair selection optimization analysis result is discussed in Section 3.3.

3.1. Deterioration Transition Result and Discussion

Addis Ababa has approximately 4800 km of road network, of which 1090 km, i.e., 22% of the network, is flexible asphalt-paved roads. The dataset used for deterioration estimation comprises 3034 pavement segments, representing approximately 150 km of flexible asphalt roadway that were inspected in 2018 and 2019. The deterioration parameter β is obtained from 20,000 sample iterations of MCMC sampling. Subsequently, the deterioration transition is calculated using Equations (3)–(6) as presented in Table 3.

Table 3. Deterioration transition.

Rating	1	2	3	4	5
1	0.531	0.337	0.1	0.024	0.008
2		0.532	0.308	0.109	0.051
3			0.446	0.309	0.245
4				0.325	0.675
5					1

The transition results indicate that pavement segments in Good condition states exhibit higher resistance to deterioration, meaning they are more likely to remain in the same state over the observation period ($Z = 1$ year). In contrast, segments in Poor or Bad condition states show faster deterioration rates, reflecting their greater susceptibility to further decline in condition within the same analysis period.

3.2. Repair Transition Result and Discussion

For the repair estimation, pavement segments with recorded repair actions were analyzed using the repair timing (z_1) and inspection intervals (z_2) and as defined in Equations (8)–(13). From the total of 3014 segments, 1577 repaired segments were utilized, incorporating their respective repair types and timing information for this analysis. The resulting repair transition probabilities for each repair action are summarized in Tables 4–7.

Table 4. Repair transition for patching action.

State	1	2	3	4	5
1	1	-	-	-	-
2	0.98	0.02	-	-	-
3	-	-	1	-	-
4	-	-	-	1	-
5	-	-	-	-	1

Table 5. Repair transition for Partial Overlay action.

State	1	2	3	4	5
1	1	-	-	-	-
2	0.86	0.14	-	-	-
3	-	-	1	-	-
4	-	-	-	1	-
5	-	-	-	-	1

Table 6. Repair transition for Full Overlay action.

State	1	2	3	4	5
1	1	-	-	-	-
2	0.36	0.64	-	-	-
3	0.25	0.64	0.11	-	-
4	0.55	0.34	0.07	0.04	-
5	0.16	0.73	0.04	0.04	0.03

Table 7. Repair transition for Rehabilitation action.

State	1	2	3	4	5
1	1	-	-	-	-
2	0.5	0.5	-	-	-
3	0.33	0.33	0.33	-	-
4	0.58	0.16	0.13	0.13	-
5	0.66	0.1	0.08	0.08	0.08

For cases without data on Patching and Partial Overlay repairs corresponding to states 4 and 5, where no repair records were available, the non-parametric Dirichlet distributions representing the repair transitions produced equal transition probabilities across the possible improved states, as no updating could occur due to the absence of data. These distributions were then adjusted to a no-transition scenario by applying identity matrix elements, implying that the pavement state remained at least unchanged after repair.

Similarly, for states 2 and 3, where Light Rehabilitation repairs were not observed, the Dirichlet distributions yielded equal probabilities of transitioning to better states. However, using identity matrices for these cases was considered unrealistic, as light Rehabilitation repairs are expected to definitively improve pavement conditions, at least to the extent that the equal transition distribution generated by the Dirichlet process is consistent.

The repair transition analysis reveals counterintuitive findings regarding the effectiveness of different repair actions across pre-repair condition states. Interestingly, patching, typically considered a localized and minor treatment, exhibited the most potent recovery effect from all other repairs when the pre-repair condition was state 2, with 98% of the segments transitioning to State 1 and only 2% remaining in State 2.

Similarly, partial overlay demonstrated its highest improvement potential compared to Full overlay and Light rehabilitation for pavements in state 2, where 86% of the segments were re-covered to state 1, and 14% remained in state 2.

As anticipated, Light Rehabilitation produced the most comprehensive improvement compared to all repair types for severely deteriorated pavement states (State 3 and above). Segments initially in state 5 exhibited substantial recovery, with 66% improving to state 1. In comparison, state 4 improved predominantly to state 1 (58%) and state 2 (16%), confirming the high restorative capability of Light Rehabilitation treatments in restoring severely damaged pavements to near-optimal conditions.

3.3. Optimized Repair Policy

The optimization was performed for a network of 3014 segments from inspection in 2022. The inspection condition on the network is then aggregated to give the initial state network at time $t = 0$ in Table 8. The planning Horizon for optimization is taken to be 5 years.

Table 8. Initial condition state vector.

State	1	2	3	4	5
Proportion of the network	0.16	0.4	0.24	0.12	0.08

The RMMS manual recommends maintaining road serviceability at a roughness level below 3, thereby keeping 85% of the road network in good (state 2) or very good (state 1) condition. The proposed Markov Decision Process (MDP) for 3031 segments (1105 km road network) was executed under an annual budget constraint of \$2.5 million USD, applied through a fixed budget condition and a penalty for the shortfall in serviceability. For each condition state i , the repair decision R_{ij}^a and treatment proportion $\rho(X_i) \in [0, 1]$ were selected to maximize the expected network serviceability while satisfying the budget constraint

The solution employed a single-step lookahead optimization with a greedy continuous knapsack allocation that iteratively selected repair fractions based on the marginal improvement in serviceability per unit cost. This procedure allowed dynamic allocation of limited funds across condition states and repair types, generating realistic percentage-based treatment plans and cost expenditures presented in Tables 9 and 10, respectively

Table 9. Selected repair action for each year.

State	Year 1	Year 2	Year 3	Year 4	Year 5
	Action	Action	Action	Action	Action
1	Patching	Patching	Patching	Patching	Patching
2	Patching	Patching	Patching	Patching	Patching
3	Full	Full	Full	Full	Full
	Overlay	Overlay	Overlay	Overlay	Overlay
4	Full	Full	Full	Full	Full
	Overlay	Overlay	Overlay	Overlay	Overlay
5	Rehabilitation	Rehabilitation	Rehabilitation	Rehabilitation	Rehabilitation

Table 10. Budget Expenditure and improved Desired state share (state 1 and state 2).

State	Action	Year 1 Treated Network %	Year 1 Treated Network %	Year 1 Treated Network %	Year 1 Treated Network %	Year 1 Treated Network %
1	Patching	0	0	0	0	0
2	Patching	100	100	100	100	100
3	Full	70.5	100	100	100	100
	Overlay					
4	Full	100	100	100	100	100
	Overlay					
5	Light					
	Rehabilitation	0	65.9	100	100	100
Achieved State1_2 Share (%)		65.7	74.9	79.7	80.9	81.2
Expenditure (USD)		2,500,000	2,500,000	2,285,107	1,954,323	1,881,088
		Total 5 Years = 11,120,518 USD				

Over the five-year horizon, the optimized plan consistently prioritized patching for state 2, full overlay for states 3 and 4, and selective rehabilitation for state 5, reflecting both cost-effectiveness and practical implementation patterns. Network serviceability improved from 65.7% in Year 1 to 81.2% in Year 5, with a total expenditure of approximately USD 11.12 million. The MDP model excluded the Partial Overlay action across all states due to its low cost-efficiency, favoring treatments that delivered greater long-term benefits per unit cost.

Integrating stochastic repair-effect estimations derived from historical data enhanced the realism and sustainability of the optimization framework by capturing the variability of repair outcomes observed in practice. This probabilistic representation yielded more accurate estimates of treatment efficiency and mitigated the systematic bias inherent in deterministic assumptions. Despite all treatable states being repaired in later years, network serviceability stabilized at around 81%, indicating that surface-level treatments had reached their practical limit of improvement. This stabilization highlights the inherent variability in repair effectiveness and suggests that achieving the authority's 85% service-ability target would require deeper structural interventions beyond surface maintenance.

Even with full budget utilization, complete (100%) recovery remained unattainable. This highlights the uncertainty and overoptimism inherent in the deterministic restoration approach commonly employed by the agency, which assumes full recovery regardless of treatment type or pre-repair condition. Under this assumption, network performance is overestimated by approximately 19%, suggesting that the agency's reliance on fixed restoration effects may have resulted in inflated estimates of repair efficiency and network achievement.

4. Conclusions

We developed a pavement management framework that integrated stochastic repair-effect estimation within a Markov Decision Process (MDP) to optimize network-level sustainable repair planning. Unlike most PMS approaches that assume uniform repair outcomes, the proposed model captures the probabilistic variability of repair performance derived from historical inspection and repair data. This probabilistic formulation enables road agencies to assess repair outcomes more realistically, thereby improving the efficiency of maintenance investments and extending the service life of pavement networks.

Applying the framework to the Addis Ababa urban road network demonstrated that incorporating empirically estimated stochastic repair transitions leads to more cost-effective and performance-consistent repair strategies. The optimized five-year repair policy maintained up to 81% of the network in Good or Very Good condition within the available annual budget, indicating that surface-level treatments alone cannot achieve the full serviceability target without structural interventions. These results underscore the importance of data-driven and evidence-based decision-making in achieving sustainable infrastructure management through optimal resource allocation, minimizing maintenance waste, and prolonging pavement functionality.

Overall, the primary contribution of this research lies in integrating probabilistic repair effects and stochastic deterioration processes within an operational MDP framework, providing an adaptive planning tool for sustainable pavement networks under financial and performance constraints.

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