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Optimization Framework for ASIAN and National Road Networks in Lao PDR Using the Stochastic Markov Model

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Abstract

Developing effective road network management is crucial for the socioeconomic development of developing countries, particularly the Lao People's Democratic Republic (Lao PDR or Laos). The current road maintenance system in Lao PDR uses a traditional reactive maintenance approach, addressing road deterioration only after the condition reaches a critical state. This study proposes a stochastic Markov Decision Process (MDP) framework to enhance traditional road management practices. The proposed MDP framework shifts from a conventional reactive to a proactive strategy by considering probabilistic pavement performance and optimally allocating funding to rapidly deteriorating sections. This study enables decision-makers to determine the optimal intervention strategies based on different scenarios. The comparison of the ASIAN Road network, high technical design and construction, and the National Road network, standard technical design and construction, in different scenarios provides a workable framework for maintaining Laos, and other developing countries, road condition despite limited resources and sustainable development concerns. This comprehensive framework includes estimating deterioration rates, defining policies, conducting life-cycle cost (LCC) analysis, and determining optimal strategies that minimize LCC subject to financial and performance constraints. This study highlights significant improvements in decision-making, particularly in resource allocation, by creating innovative and preventive approaches that enhance the efficiency of road management systems and ensure sustainable maintenance practices in Lao PDR.

Keywords: Optimum Road Intervention Strategy; Markov Decision Process; Laos Road Management Systems; Life-Cycle Cost Analysis.

1. Introduction

According to the Ministry of Public Works and Transport's (MPWT) statistics in 2021 [1], the road network in the Lao People's Democratic Republic (hereinafter referred to as Lao PDR or Laos) consists of six main categories: national, provincial, district, urban, rural, and special roads, with a total length of 59,645 km. National roads are classified into three core network levels. Core Network 1, which includes high-priority roads linking Laos to other ASEAN (Association of Southeast Asia Nations) road networks, Core Network 2 connecting major intranational towns, and Core Network 3 linking provincial to secondary municipalities with low traffic volume. Core Network 1 is referred to as the ASIAN network since it connects Laos with other ASEAN nations. ASIAN roads are constructed following uniform and high technical standards to ensure interoperability and facilitate smooth cross-border travel within the ASEAN region [2]. In contrast, Core Network 2, referred to as National roads, connects provinces within Laos, designed based on localized standards that vary according to geographic and traffic conditions. Figure 1 shows the location of the target study roads, including ASIAN highways and National roads. The classifications provide essential context for assessing road infrastructure needs, highlighting the importance of management strategies, and resource allocation challenges specific to Lao PDR.

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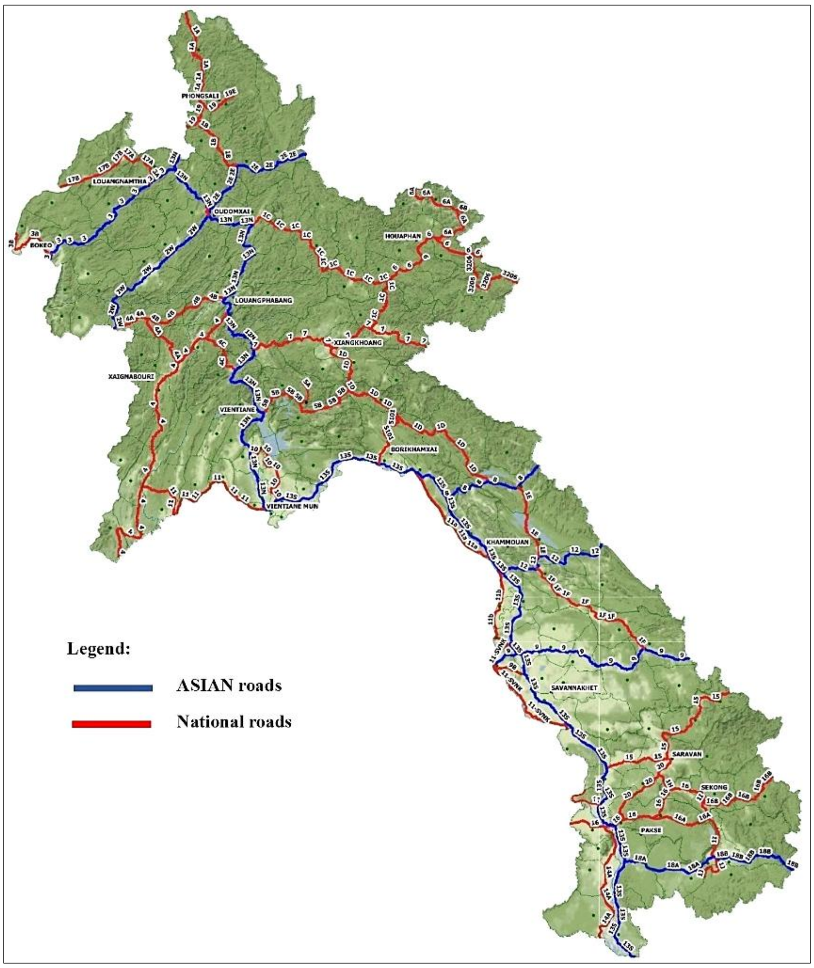

Figure 1. ASIAN highways and National roads in Lao PDR

1.1. Road Asset Management Challenges in Lao PDR

The socioeconomic development of developing countries often depends on efficient road network management. The Highway Development and Management Four (HDM-4) model, currently used by the road maintenance system (RMS) in Lao PDR, enables long-term planning to set priorities and allocate maintenance funds [3, 4]. However, HDM-4 needs extensive inputs, including pavement type, conditions, traffic patterns, environmental factors, and maintenance history. These data are challenging to collect and often used for specific projects. Additionally, provincial administrations independently develop road intervention strategies as they carry out inspections and submit reports to the MPWT for maintenance budget decisions. These reports, based on condition surveys, use one-time data for reactive planning. Given that decisions only depend on route importance, maintenance work and corresponding budget allocations are suboptimal [1, 5].

Traditional systems such as the Laos RMS base on route importance and professional engineering knowledge to determine decisions without capitalizing on their rich databases more objectively [6, 7]. This knowledge should be integrated with other information to support more efficient decision-making processes related to road network maintenance management and investment planning [8]. The Road Fund (RF) in Lao PDR, established in 2001, faces significant challenges due to escalating debt, approximately 2,433 billion Kips (USD 200 million) as of 2021 [5]. This situation highlights concerns about the fund's ability to sustain road maintenance, which may worsen road conditions. Subsequently, to addresses these issues, the government, particularly the MPWT, has to consider measures such as adopting cost-effective intervention strategies, finding alternative funding sources, improving revenue collection from road users, and optimizing resource allocation.

1.2. Study Objectives

The main objective of this research is to customize the stochastic Markov decision process (MDP) framework to improve road management in developing countries such as Laos. The specific objectives are:

- Develop a stochastic MDP framework for Laos RMS, particularly ASIAN highways and national roads.
- Prioritize road intervention by evaluating long-term impact on road network performance within budget constraints.

- Enhance the decision-making process; explore effective strategies to address the practical challenges in road network management in developing countries, particularly in Lao PDR.

This study integrated a proactive maintenance strategy with stochastic deterioration forecasting and life cycle costs (LCC) analysis, creating a framework for optimizing road network asset management under different financial constraints and minimum road performance targets in Laos that faces data and resource constraints. The remainder of this paper is organized as follows: Section 2 reviews relevant literature. Section 3 describes the methodology used, detailing the stochastic MDP model development and the LCC estimation. Section 4 presents the empirical study, describing data collection, processing, and analysis methods applied to the ASIAN and national roads. Section 5 discusses the results obtained from different maintenance policy scenarios and budget constraints. Finally, Section 6 concludes the study, summarizing key findings and providing recommendations for future research and policy implications. A list of notations is given at the end of this paper.

2. Review of Pavement Optimization Methods

Many recent studies have shown the advantages and importance of integrating stochastic deterioration modeling and proactive maintenance strategies to optimize road network management, particularly under budget constraints. Obunguta et al. (2024) [9] examined optimal repair policies using Monte Carlo simulations to minimize LCCs while improving infrastructure reliability. These authors showed the improvement in optimal intervention solutions using Monte Carlo methods compared to the greedy algorithm. Similarly, Nakazato et al. (2023) [10] proposed repair policies focusing on LCC minimization and cost-leveling strategies across infrastructure systems, highlighting significant advancements in proactive infrastructure maintenance approaches. Another study, Nakazato & Mizutani (2024) [11], developed an optimization approach for sectional work zone scheduling considering economies of scale and user cost. These authors particularly addressed user disruption over extended planning horizons by prioritizing user cost reduction through optimized scheduling over a 365-day cycle. Additionally, Zhang et al. (2023) [12] discussed the uncertainties and heterogeneities in pavement management systems and suggested a “belief update” process to improve maintenance decisions under uncertainty. Other studies, such as Obunguta et al. (2022) [13] and Harvey (2024) [14], also underscored the importance of optimizing pavement maintenance decisions by minimizing social costs using a greedy algorithm and employing bottom-up approaches to address rehabilitation planning under constrained budgets, respectively. Zeng et al. (2024) [15] refined these approaches by enhancing a two-stage optimization framework, first at the pavement segment level and secondly at the network level, for pavement rehabilitation planning decisions.

Despite advancements in optimizing road network management systems using stochastic modeling, a significant gap remains in applying such integrated frameworks, specifically in developing countries, where resource constraints and limited data availability pose challenges. Building on work including Obunguta & Matsushima (2020) in Uganda, this study aims to further bridge this gap by developing a stochastic MDP framework tailored explicitly for Lao PDR, integrating probabilistic pavement deterioration forecasting, proactive maintenance strategies, and LCC analysis under realistic budget constraints by using historical data from the 2014–2015 Lao RMS database.

3. MDP Framework Development

3.1. Markov Decision Process

The MDP model is used to represent decision-making in environments where outcomes are influenced by both probabilistic events and the choices of a decision-maker. It consists of states, actions, transitions, rewards, and policies. The goal of the MDP in road maintenance decisions is to choose actions that minimize long-term costs while considering the tradeoff between budget constraints and road performance [16, 17]. In this process, a road agency makes decisions based on road conditions at each time step and selects an action to implement. Road condition then transitions to a new state, and the agency or road user receives a reward for improved road performance. From the perspective of rewards, the objective is to maximize the cumulative benefits over time.

The stochastic Markov model processes assume that the probability of transitioning to a new state depends only on the current state and action, not on any previous states or actions [16]. This property allows for creating Markov models using states, actions, transition probabilities, and rewards. MDP can be solved using algorithms such as dynamic programming, Monte Carlo methods, and reinforcement learning. These algorithms find optimal policies by mapping states to actions to maximize the expected cumulative reward [16, 18].

The developed model incorporates condition states $i(i = 1, 2, 3, \dots, J)$ with J as the absorbing state, discrete time periods $t(t = 0, 1, 2, \dots)$, intervention strategies (m_p), inspection intervals Z ($Z = 1, 2, 3, \dots$), and repair actions (R). The analysis considers a finite period from $t = 0$ to $t = T$.

Figure 2 illustrates the general model framework, which includes defining the network, estimating Markov Transition Probabilities (MTPs), proposing policies and strategies, estimating LCCs, and determining the optimal strategy that minimizes LCCs. This framework guides the development of the stochastic MDP model for road asset management in Lao PDR.

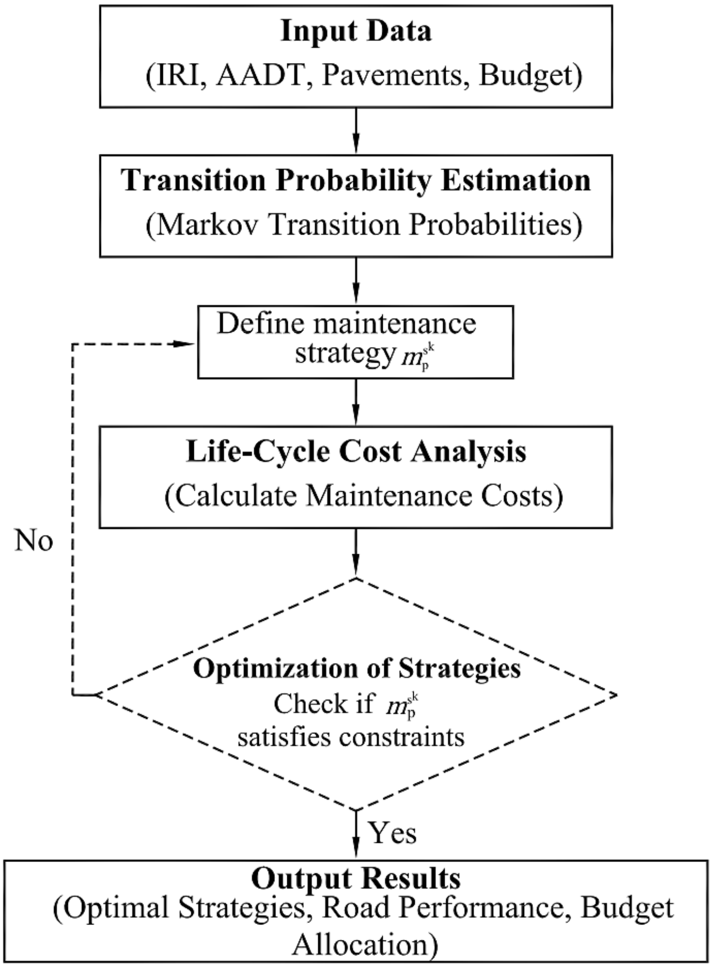

Figure 2. Stochastic optimizing framework for Laos RMS

3.2. MTP and Performance Estimation

The MTP models the transition of road conditions from $h(t) = i$ to $h(t + Z) = j$ after an interval Z, with periodic inspections at time t and $t + Z$ [19, 20]. The probability of this transition is:

$$\text{Prob}\ [h(t) = j | h(t + Z) = i] = \pi_{ij} \tag{1}$$

As a function of hazard rates, the MTP is estimated by:

$$\pi_{ij} = \sum_{\tilde{k}=i}^{j} \prod_{\tilde{m}=i}^{\tilde{k}-1} \frac{\theta_{\tilde{m}}}{\theta_{\tilde{m}} - \theta_{\tilde{k}}} \prod_{\tilde{m}=\tilde{k}}^{j-1} \frac{\theta_{\tilde{m}}}{\theta_{\tilde{m}+1} - \theta_{\tilde{k}}} \exp(-\theta_{\tilde{k}} Z) \tag{2}$$

where θ_i is the hazard rate and, $\tilde{k}$ and $\tilde{m}$ are indices. The MTP matrix ($\prod$) can be defined using transition probabilities between each pair of condition states (i, j)

$$\Pi = \begin{bmatrix} \pi_{11} & \pi_{12} & \cdots & \pi_{1J} \\ 0 & \pi_{22} & \cdots & \pi_{2J} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \pi_{JJ} \end{bmatrix} \tag{4}$$

Here, π_{ij} is the transition probability from condition state *i* to *j* within one inspection interval.

To satisfy the Markov chain property, the following conditions should be met.

1) No maintenance or reconstruction projects were undertaken during the inspection period.

2) The road surface starts deteriorating as soon as it becomes accessible to the public.

Therefore, the preconditions $\pi_{ij} \geq 0$ and $\sum_{j=1}^{J} \pi_{ij} = 1$ are defined to satisfy the axioms of probability. Since the model does not consider repairs, $\pi_{ij} = 0$ for $(i > j)$ and $\pi_{JJ} = 1$.

The hazard rate θ_i^k , representing the rate at which pavement deteriorates from condition state i to i+1, is expressed as a function of explanatory variables x^k and unknown parameters $\boldsymbol{\beta}_i$ where $\boldsymbol{\beta}_i = (\boldsymbol{\beta}_{i,1}, \dots, \boldsymbol{\beta}_{i,M})$, $m\ (m = 1, \dots, M)$ is the number of explanatory variables and $k(k = 1, \dots . K)$ is the number of inspected element groups.

$$\theta_i^k = f(x^k : \beta_i) = \exp(x^k \beta_i') \ (i = 1, \dots, J - 1) \tag{4}$$

The unknown parameters $\boldsymbol{\beta}_i (i = 1, \dots, J - 1)$ can be determined using an iterative method such as Newton’s method or through Bayesian estimation [21, 22].

The life expectancy LE_i^k in each condition state i can be defined by means of a survival function [23].

$$LE_i^k = \frac{1}{\theta_i^k} \tag{5}$$

The total life expectancy from i to J can be estimated as $\sum_{i=1}^{J-1} LE_i^k$, and the deterioration curve can be plotted. For a detailed description of MTP derivation, it is recommended to refer to Tsuda et.al [19].

3.3. Pavement Maintenance Model

Road agencies need to implement optimal maintenance plans that provide the highest value. The optimal policy is the policy that keeps more roads in good condition while minimizing the overall LCCs. This study focuses on road agency costs, excluding user and social costs. The term "intervention strategy" can be used to refer to a combination of road repair activities, including pothole patching, resurfacing, reconstruction, and inspection.

Pavement repair activities denoted by $R(R_0, R_1, R_2, R_{3,} \dots, R_{J-1})$ are carried out in correspondence with the condition after inspection (time-dependent rule) or deterioration rate (condition-dependent rule) following Kobayashi et al. and Obunguta and Matsushima [24, 25]. At the end of the planning period, time T, reconstruction R_{J-1} is considered for all sections. Figure 3 illustrates the correspondence between intervention and uncertain pavement deterioration. Once action is taken, pavement condition state i is assumed to improve to $\hat{\imath}$. This improvement is denoted by i_{rep}

$$i_{rep} = \begin{cases} i & \text{if } R_0 \text{ (no action)} \\ \hat{\imath} & \text{otherwise } (R_1, R_2, R_3, \dots, R_{J-1}) \end{cases} \ (i = 1, \dots, J) \tag{6}$$

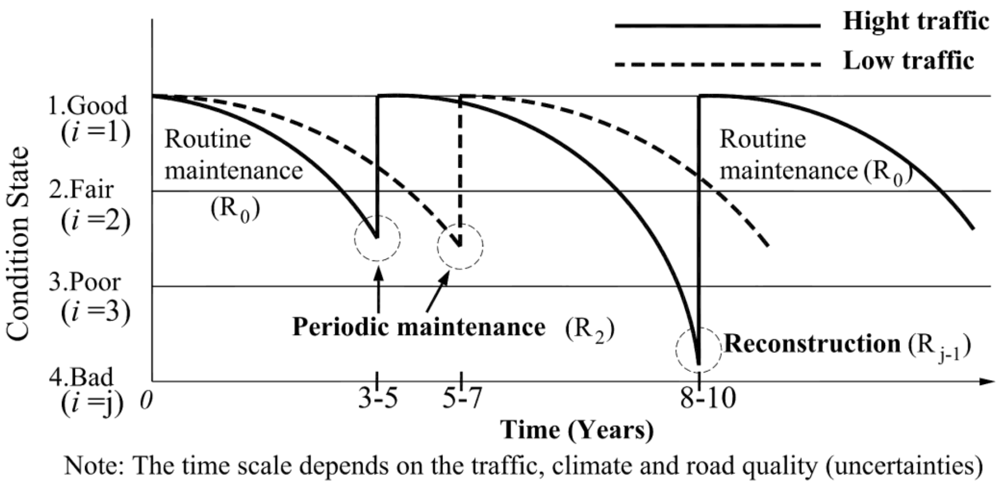

Figure 3. Correspondence between interventions and uncertainty

Preventive repair actions can be performed on pavements before they reach the terminal state. The expected expenditure necessary for planning purposes is estimated from the maintenance plans. Inspected roads are grouped based on administration, i.e., ASIAN and National, into groups $k(k = 1, \dots \dots K)$ each with pavement sections $s^k(s^k = 1, \dots S^k)$. The intervention strategy $\boldsymbol{m}_{\boldsymbol{p}}^{s^k}(\boldsymbol{m}_{\boldsymbol{R}\leftrightarrow\boldsymbol{i}}^{s^k}, Z^{s^k})$ is a set of repair actions done in correspondence to condition $\boldsymbol{m}_{\boldsymbol{R}\leftrightarrow\boldsymbol{i}}^{s^k} = (R_0^{s^k} \leftrightarrow 1, \dots . . R_{i-1}^{s^k} \leftrightarrow i)$ and inspection intervals $Z^{s^k} = (Z_1^{s^k}, \dots . . Z_T^{s^k})$ [25].

Table 1 displays the attained conditions after actions. The interventions are set by balancing the cost and frequency of repairs. It was assumed that patching and crack sealing improved condition by one step while overlay improved condition by two steps. Routine maintenance maintains the road in its current condition. Reconstruction (R_{J-1}) is done at the end of pavement service life (terminal state). The intervention cost $C_{R_{i-1}}$ is an increasing monotone function with action.

$$C_{R_0} \leq C_{R_1} \leq C_{R_2} \leq \cdots \leq C_{R_{J-1}} \tag{7}$$

Table 1. Repair actions, correspondence costs, and condition after intervention

Condition state, i	Repair actions consideration	Correspondence Costs	Condition state after repair, $\hat{\imath}$
1	R_1 (routine)	C_{R1}	1
2	R_1 (routine)	C_{R1}	2
	R_2 (patching + sealing)	C_{R2}	1
	R_3 (overlay)	C_{R3}	1
3	R_1 (routine)	C_{R1}	3
	R_2 (patching + sealing)	C_{R2}	2
	R_3 (overlay)	C_{R3}	1
…	…	…	…
J	R_0	C_{R1}	J
	R_2 (patching + sealing)	C_{R2}	$J-1$
	R (overlay)	C_{R3}	$J-2$
	…	…	…
	R_{J-1}	$C_{R_{J-1}}$	1

3.4. Repair Transition Probability

The transition probability is modified when a road section is maintained because the pavement system has become newer. The MTP matrix is multiplied with an intervention matrix P_{rep}. The elements of the J x J matrix are denoted as $\pi_{ij}^{rep} = (i = 1, \ldots J), (j = 1, \ldots J)$. In case of no repair or intervention, the matrix is an identity matrix $P_{rep} = I$. This is the default state of the repair matrix with all values in the major diagonal being 1 and all other matrix elements being 0.

$$P_{rep} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{8}$$

For all repair matrices, the values of π_{ij}^{rep} above the major diagonal must be 0 because it is not expected that any repair action will worsen pavement condition. The values on the major diagonal or below it can take the value of either 1 or 0. The condition $\sum_{j=1}^{j} \pi_{ij}^{rep} = 1$ must be met within P_{rep}. The repair probability

$$\pi_{ij}^{rep} = \begin{cases} 1 & if\ i_{rep} = \hat{\imath} \\ 0 & otherwise \end{cases} \quad (i = 1, \ldots J) \tag{9}$$

The transition probability matrix P_{trans} is the transition probability after maintenance, with elements $\pi_{ij}^{trans} (i = 1, \ldots, J), (j = 1, \ldots, J)$

$$P_{trans} = \prod(Z) * P_{rep} \tag{10}$$

3.5. Intervention Strategy

The intervention strategy $\boldsymbol{m_p^{s^k}}$ is proposed by road managers within a finite planning horizon ($t = T$). It is assumed that there is no salvage value at the end of T [26]. MDPs can be solved with a diversity of algorithms such as value iteration, policy iteration, and Monte Carlo methods [27]. This study optimizes the agency costs estimated from exogenously set strategies. The intervention costs for each pavement section can be expressed as [25]

$$V_i^{t,s^k} = (1 + \rho^r)^{-t} * \pi_{ij}^{trans} * C_{R\leftrightarrow i}^{t,s^k} \tag{11}$$

where V_i^{t,s^k} is total agency costs at time t for section s^k, $C_{R\leftrightarrow i}^{t,s^k}$ is intervention cost at time t and condition i for section s^k, ρ^r is the discount rate and π_{ij}^{trans} is the transition probability

3.6. Optimization Process

The LCCs of each intervention strategy are the summation of all agency costs for all sections $s^k (s^k = 1, \ldots., S^k)$ assuming the salvage value at T, $C_v^{s^k} = 0$ [24, 25].

$$LCC = \sum_{t=0}^{T} \sum_{s^k=1}^{s^k} \sum_{i=1}^{J} V_i^{t,s^k} \tag{12}$$

The optimization problem to find the optimum strategy $\boldsymbol{m_p^{s^k *}}$ is expressed as

$$\min_{\boldsymbol{m_{p\leftrightarrow i}^{t,s^k}}, \boldsymbol{Z^{s^k}}} LCC \quad (i = 1, \dots, J) \tag{13}$$

subject to

$$\sum_{k=1}^{K} \sum_{s^k=1}^{S^k} C_{R\leftrightarrow i}^{t,s^k} \in \Omega_t \qquad \forall t \tag{14}$$

where $\boldsymbol{m_p^{t,s^k}}$ is the intervention strategy and Ω_t is the budget limit at t.

The optimization problem is solved using the greedy algorithm [28, 29]. Priority is given to the sections in worse condition.

3.7. Road Network Condition Estimation

The condition of the network in each state is estimated following:

$$CS_{t+Z} = p(Z) * CS_t \tag{15}$$

where CS_t is a $1 \times J$ vector of the number of road sections per condition state at time t, and $p(Z)$ is the $J \times J$ MTP matrix. Understanding the condition distribution of road networks informs the decision-making process for selecting the most appropriate intervention strategy when faced with budget constraints.

$$V_i^{*t,s^k} = CS_{t+Z}^{*} * C_{R\leftrightarrow i}^{t,s^k} \tag{16}$$

subject to;

$$CS_{t+Z}^{*} = p(Z)^{-1} * CS_t \tag{17}$$

where V_i^{*t,s^k} is total agency costs at time t for the desired condition for section s^k, CS_{t+Z}^{*} is a vector $1 \times J$ of the desired condition, $C_{R\leftrightarrow i}^{t,s^k}$ is intervention cost. and $(p(Z))^{-1}$ is the inverse $J \times J$ MTP matrix transition probability. The demanded budgets can be derived from the estimated undiscounted agency costs, which were assumed to be only intervention costs.

4. Empirical Study

4.1. Data Processing

The empirical model application used Laos RMS historical inspection data and intervention works unit costs for deterioration and LCC estimation. The 2014–2015 and 2020 inspection data were obtained from the Lao RMS database. It was challenging to determine maintenance history for 2015–2020, and pavement condition in 2020 was almost as good as in 2015. Thus, only datasets from 2014–2015 were used excluding data records between 2015-2020 due to possible repair following the Markov property that does not consider repair between inspection intervals. The 2014-2015 dataset with about 30,000 data records was robust enough to capture the deterioration trends of Laos road infrastructure. The dataset contained pavement materials, the International Roughness Index (IRI), and average annual daily traffic (AADT) for 22 paved national roads.

The road routes were grouped based on the Laos road classification into Core Network 1 and Core Network 2 with lengths of 1,900 km and 869 km, respectively. This road information, approximately 47.26% of the total national road network, is presented in Table 2.

Table 2. Dataset and explanations

Description	Core Network 1 (ASIAN)	Core Network 2 (National)
No. of routes	8	14
Total length (km)	1,900	869
Number of datasets	18998	8690
Explanatory Variables	AADT, Road surface (AC/ST) *	
Length of AC/ST (km)	778/1,122	50/819

* AC=Asphalt concrete; ST=Surface treatment

The two primary types of pavements constructed in Laos are asphalt concrete pavement and surface treatment (single and double bituminous). The traffic volume was obtained by counting the vehicles passing at a specific location on each road section. This count was done either automatically or manually using a traffic count form. The vehicles were classified into 14 classes and class specific adjustment factors used to estimate AADT [30].

4.2. Condition States Classification

The road conditions were quantified using IRI data. The dynamic response Vehicle Intelligent Monitoring System (VIMS) equipment, supported by the Japan International Cooperation Agency (JICA) in 2012, was used to measure IRI. The IRI was measured at around 80 km/h for each 100-meter segment [31, 32].

To estimate MTP, the IRI was classified into five condition states [33]. Table 3 shows the number of sections per condition state for each network in the datasets.

Table 1. IRI condition classification and datasets

IRI (m/km)	Condition state	Core Network 1 (ASIAN)		Core Network 2 (National)	
		2014	2015	2014	2015
≤ 3	1.Good	9612	4950	2648	1007
3<IRI≤5	2.Fair	8182	10177	4323	4178
5<IRI≤7	3.Poor	1086	3119	1340	2309
7<IRI≤9	4.Bad	85	478	267	771
>9	5.Failed	33	274	112	425

4.3. Transition Probability and Deterioration Estimation

The estimation for deterioration rate was done for the two networks using traffic volume, and road surface type as explanatory variables (Equation 4). The estimation of the unknown parameters was carried out with the Markov Chain Monte Caro (MCMC) method using the Metropolis-Hastings (MH) algorithm [34, 35]. The unknown β parameters converged and life expectancy of two networks was obtained as shown in Table 4 and Figure 4. To satisfy convergence, the Geweke diagnostic value should fall within [-1.96, 1.96] limits with 0 denoting perfect convergence.

Table 2. Markov Estimated β parameters and life expectancy in year

	Core Network 1 (ASIAN)				Core Network 2 (National)			
State	β_{0i} *Absolute*	β_{1i} *Traffic*	β_{2i} *Pavement*	LE_i^k *Life*	β_{0i} *Absolute*	β_{1i} *Traffic*	β_{2i} *Pavement*	LE_i^k *Life*
1-2	-0.006 (-0.706) *	-	-0.660 (0.918)	1.319	0.573 (0.863) *	-	-0.930 (-1.527)	0.595
2-3	-1.251 (-0.699)	0.278 (0.864)	-0.255 (-0.585)	3.669	-0.092 (0.723)	-	-0.047 (0.507)	1.100
3-4	-0.863 (0.900)	-	-	2.370	-0.766 (1.390)	-	-	2.151
4-5	0.422 (1.760)	-	-	0.656	-0.620 (-0.047)	0.241 (0.147)	-	1.773

*The values in parentheses are the Geweke diagnostic for β.

The hazard rate θ_i^k can be estimated as the inverse of LE_i^k according to Equation 5.

The estimation for deterioration rate was done for the two networks using traffic volume, and road surface type as explanatory variables (Equation 4). The estimation of the unknown parameters was carried out with the Markov Chain Monte Caro (MCMC) method using the Metropolis-Hastings (MH) algorithm [34, 35]. The unknown β parameters converged and life expectancy of two networks was obtained as shown in Table 4. To satisfy convergence, the Geweke diagnostic value should fall within [-1.96, 1.96] limits with 0 denoting perfect convergence.

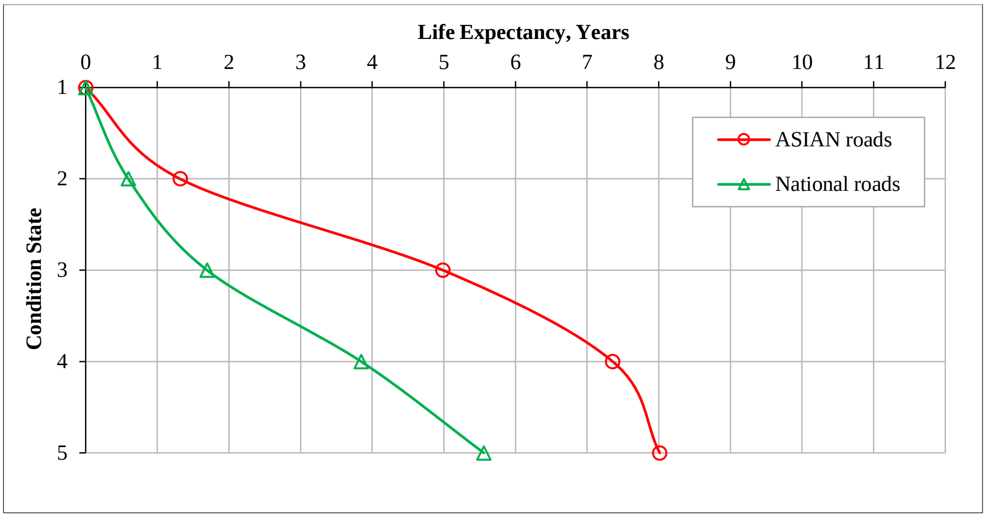

Figure 1. Performance curves of ASIAN and National Road network

The MTPs for Core Networks 1 and 2 are shown in Equations 18 and 19. The MTPs show that National network undergoes faster deterioration with a higher probability of transitioning to a worse state.

$$\mathbf{MTP}_{C1} = \begin{bmatrix} 0.487 & 0.442 & 0.063 & 0.006 & 0.002 \\ 0 & 0.761 & 0.203 & 0.026 & 0.010 \\ 0 & 0 & 0.732 & 0.167 & 0.101 \\ 0 & 0 & 0 & 0.378 & 0.622 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{18}$$

$$\mathbf{MTP}_{C2} = \begin{bmatrix} 0.342 & 0.529 & 0.110 & 0.016 & 0.003 \\ 0 & 0.683 & 0.254 & 0.051 & 0.012 \\ 0 & 0 & 0.652 & 0.254 & 0.094 \\ 0 & 0 & 0 & 0.539 & 0.461 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{19}$$

4.4. Policy and Strategy Setting for Laos RMS

The study examined different intervention strategies ($\boldsymbol{m}_p^{sk}$) for the two core networks, considering budget and road network performance targets. The aim was to obtain the optimal strategy by comparing each strategy's LCCs and condition performance. The inspection interval for all strategies was set at 1 year. Hence, three target policies were considered:

- Policy 1: Reactive Maintenance (Rt) - This approach involved road intervention when a road network reached condition 4 or 5. Reactive works were conducted in response to the deterioration of the roads to the worst states.
- Policy 2: Proactive Maintenance (Pr) - In addition to the works performed in Policy 1, this policy included preventive maintenance works from conditions 2 to 3. The goal was to prevent further deterioration and maintain the roads in better condition.
- Policy 3: Do Nothing - This policy let road conditions to deteriorate over time based on transition probabilities. These probabilities were influenced by explanatory variables such as traffic volume and pavement type.

A greedy algorithm was used to determine intervention actions, prioritizing sections in worse condition. According to Laos RMS practice [36], various intervention actions were applied, each associated with a specific cost, as shown in Table 5.

Table 5. Laos RMS maintenance, costs, and conditions after repair

Condition state i	Repair actions	Costs (Mil. Kips/m^2)	Condition state after action, $\hat{\imath}$
1	R1 RM	0.0008	1
2	R1 RM	0.0008	2
	(R2 patching+ crack sealing)	0.065	1
	(R3 overlay)	0.072	1
3	R1 RM		3
	(R2 patching+ crack sealing)	0.065	2
	(R3 overlay)	0.072	1

4	R1 RM	0.0008	4
	(R2 patching+ crack sealing)	0.065	3
	(R3 overlay)	0.072	2
	(R4 reconstruction)	0.221	1
5	(R4 reconstruction)	0.221	1

The study also investigated the effect of prioritizing one network over another. Four intervention strategies were defined using matrices in Equations 20 to 23, with two strategies for each policy (preventive or reactive). An optimal intervention strategy was selected initially considering a limitless budget scenario. The default strategy of "do nothing," where the repair matrix is an identity matrix, was also investigated. Following the selection of the optimal strategy in the context of a limitless budget scenario, a limited budget scenario was introduced, with priority given to ASIAN roads that connect nations.

$$\boldsymbol{Pr_1} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{20}$$

$$\boldsymbol{Pr_2} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{21}$$

$$\boldsymbol{Rt_1} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{22}$$

$$\boldsymbol{Rt_2} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{23}$$

5. Results

5.1. Limitless Budget Scenario

Both policies, i.e., preventive and reactive, were evaluated considering a limitless budget scenario for both core networks. The condition of the network at the end of the analysis period considering different intervention strategies was determined. The empirical dataset from the Laos road network (ASIAN and National network) was about 47.26% of the total national road network. The final condition and LCC estimates were converted to the total road network in order to compare with the current Laos RMS predictions.

The evaluation of various strategies showed notable differences in road condition performance at the end of the analysis period. Strategy $\boldsymbol{Pr_2}$ was found to maintain a larger proportion of the network in fair to good condition. Specifically, it resulted in 92.88% of ASIAN network and 87.10% of National network being in fair to good condition at the end of the analysis period (Figure 5). Strategy $\boldsymbol{Pr_1}$ was second best in maintaining a larger proportion of fair to good condition at the end of the analysis period, with 82.01% and 75.36% for ASIAN network and National network, respectively. Notably, the LCC associated with this strategy was relatively lower than the total budget needs of the Lao RMS estimation (see Table 6), demonstrating its cost-effectiveness. The results underscore the significance of preventive maintenance works that are generally low-cost. These activities include routine inspections, minor repairs, and timely maintenance that address minor defects before they escalate into significant damage, leading to fewer significant and intensive road interventions and lower long-term maintenance costs.

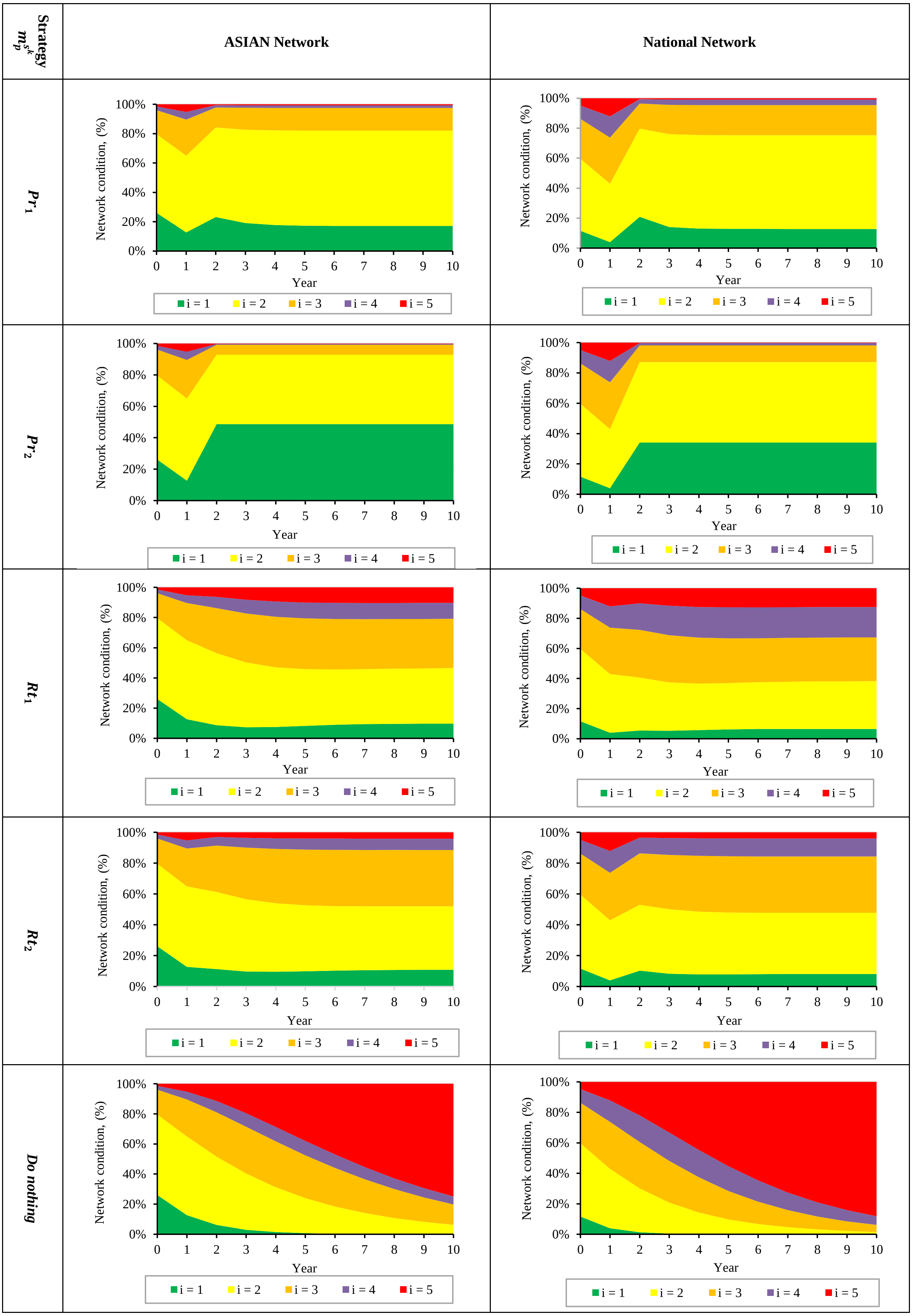

Figure 5. Comparison of road condition for different maintenance policies considering a limitless budget

Table 6. LCCs for Laos roads considering a limitless budget scenario (Mkips)

Strategy $m_p^{s^k}$	Surveyed network (47.26%)		Whole network (100%)
	ASIAN Network	National Network	Total
$\boldsymbol{Pr_1}$	1,341,903.17	978,759.38	4,909,934.60
$\boldsymbol{Pr_2}$	2,680,382.03	1,651,018.12	9,164,146.41
$\boldsymbol{Rt_1}$	1,264,847.74	802,409.57	4,373,793.24
$\boldsymbol{Rt_2}$	1,554,660.95	1,118,096.58	5,654,878.45
Laos RMS	-	-	6,426,029

On the other hand, the reactive strategies, particularly strategy $\boldsymbol{Rt_1}$, had the lowest LCC estimate compared to other strategies, with 46.50% of ASIAN network and 38.23% of National network deteriorating to poor, bad, and failed conditions. While strategy $\boldsymbol{Rt_2}$ retained 52.02% of ASIAN network and 47.82% of National network in fair to good condition. This comparison revealed that simply minimizing LCC may not lead to the optimal strategy choice. It is important to consider maintaining better network condition while keeping the LCC reasonably low through preventive rather than reactive policies.

In summary, strategy $\boldsymbol{Pr_1}$ was optimal, considering network conditions and cost-effectiveness. This strategy effectively slowed down the degradation of the network, resulting in a greater proportion of the network being in fair to good condition, 82.01% of the ASIAN network and 75.36% of the National network, at a reasonably low LCC at 4,909,934.60 Mkips. The LCCs for ASIAN and National networks under various intervention strategies highlight the cost-effectiveness of proactive policy $\boldsymbol{Pr_1}$ (see Table 6, Figures 6-a and 6-b). This scenario emphasizes the importance of considering network conditions and cost-effectiveness in the decision-making process.

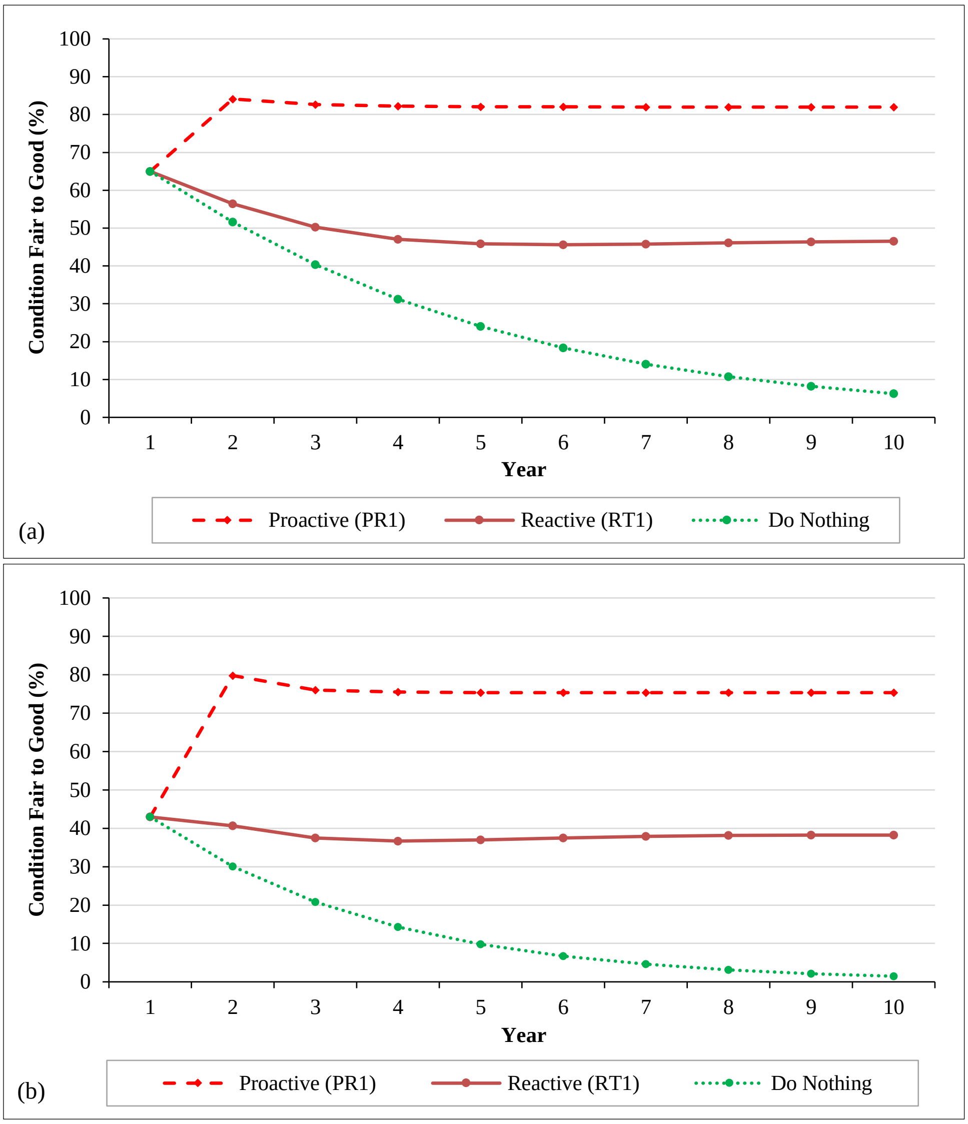

Figure 6. a) Comparison of three maintenance policies in ASIAN network, b) Comparison of three maintenance policies in National network

5.2. Limited Budget Scenario

In this scenario, we assumed that the limited budget could only cover 50% of the total budget needs for Laos' roads, so prioritization was necessary. Accordingly, 70% of the budget was spent on improving Core Network 1, consisting of international ASIAN roads, and the remaining 30% of the budget was allocated to the National roads network. This prioritization was based on the fact that many foreign loans are dedicated to improving international roads, ASIAN network. The optimal strategy $\boldsymbol{Pr_1}$, previously determined, was applied.

When selecting candidate sections for intervention, it was determined that all sections in the worst state would be repaired. Additionally, 1,718,477.11 Mkips were allocated to improve the ASIAN sections in other improvable states, while 736,490.19 Mkips were designated for improvements in the National network. The results showed that the proportion of sections in fair to good condition for both networks, were 47.63% for ASIAN network and 55.02% for National network (Figure 7). This scenario maintains about half of roads in higher functional state for either network, maintaining both inter and intra national travel. This result highlights the importance of budget allocation based on each network's priority level and minimum condition performance requirements.

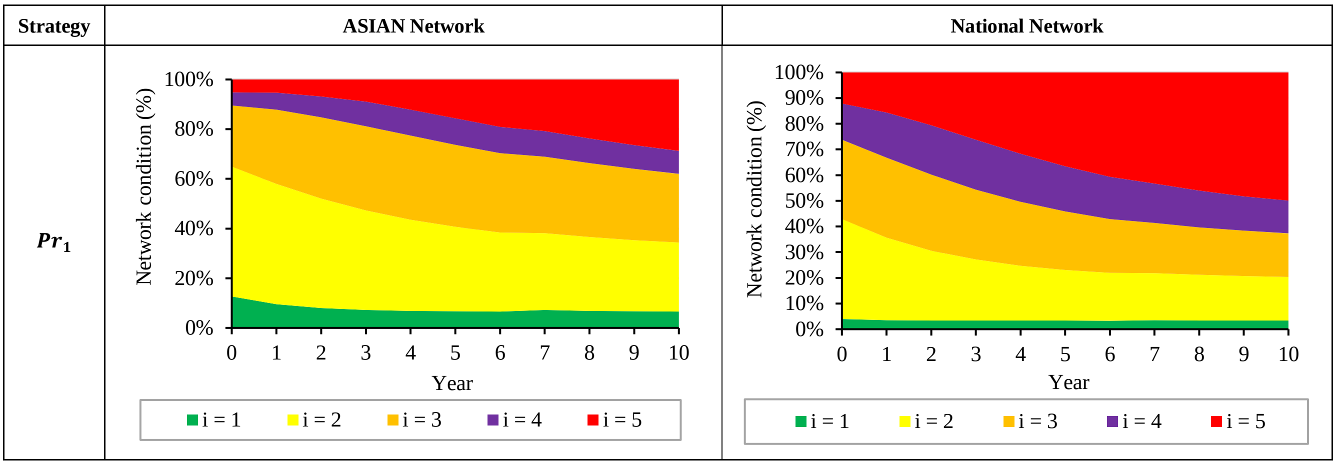

Figure 7. Condition of network considering 50% budget constraint

5.3. Target Road Performance

Road agencies are also faced with decisions on determining required budgets for target road performance thresholds, minimum acceptable road conditions. We set the target conditions in fair to good condition for both networks at 80%, 70%, 60%, and 50%. The optimal proactive strategy $\boldsymbol{Pr_1}$ from the limitless budget scenario was applied. Budget requirements for desired road network conditions were estimated using Equation 16.

Figure 8 shows the budget requirements to maintain road conditions above the specific performance targets. The lowest cumulative 10-year budget corresponded to the 70% performance target. The 70% performance target enabled more preventive maintenance while repairing worst condition sections, resulting in better network conditions at a lower cost compared to the 60% and 50% targets. The 60% and 50% targets left more pavements to deteriorate faster to worse state requiring more extensive and costly maintenance. However, achieving the 80% performance target incurred significantly higher costs, as this target requires more expensive works for the more roads in worse condition. Achieving high targets, such as 80%, results in diminishing returns from overly ambitious targets due to the increase in maintenance frequency and intensity.

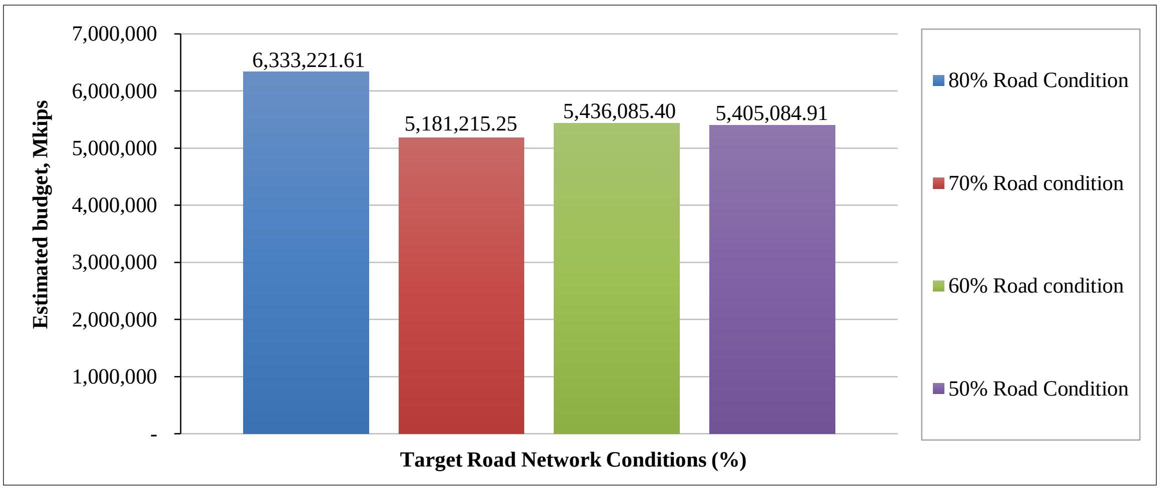

Figure 8. The cumulative 10-year budget for different road performance targets

6. Conclusions

The study provided valuable insights into the decision-making process regarding network maintenance and intervention strategies when considering different scenarios. In the first scenario, a limitless budget was assumed resulting in proactive strategy $\boldsymbol{Pr_1}$ emerging as the optimal choice. This strategy maintained a larger proportion of both networks in fair to good condition and incurred relatively lower LCCs. These findings show the superior performance of strategy $\boldsymbol{Pr_1}$ underscoring the critical role of preventive interventions. By performing preventive routine maintenance and minor repairs, road deterioration slows significantly, leading to fewer costly interventions in later stages. This result highlights how timely and preventive actions not only maintain higher road network quality but are also economically beneficial, particularly for developing countries, such as Laos, facing budget shortfalls

The study then looked at the scenario of limited budgets requiring a prioritization strategy. In this scenario, applying the optimal strategy, greedy algorithm and allocating a bigger proportion of the budget to the more important roads, ASIAN in this case, achieved at par performance ensuring continued higher functionality of networks for both inter and intra national travel.

After that, the research determined different budgets required to achieve target performance levels. The results showed that at a not so high/ low target, 70% in good to fair condition, lowest 10-year cumulative budget could be achieved at acceptable performance levels. This target enabled a good balance between extensive and preventive interventions compared to other targets, i.e., 50%, 60%, 80%. Fewer extensive works ensure lower costs and preventive maintenance reduced the speed of deterioration to worse state.

The developed stochastic MDP framework in this study, specifically demonstrated for Lao PDR, is inherently adaptable to other developing countries encountering similar financial constraints, limited data availability, and road maintenance management challenges. Due to its modular and probabilistic nature, the framework can accommodate varying road classifications, pavement types, traffic characteristics, and other deterioration patterns. However, applying the framework to other contexts would require modifications, particularly estimating the deterioration rates and transition probabilities, updating repair costs and intervention policies based on local conditions, adjusting inspection intervals based on local practices, and incorporating local environmental and climatic factors.

In conclusion, the findings explicitly suggest that policy makers and road agencies in Lao PDR and other developing countries should adopt a proactive approach integrated with stochastic deterioration forecasting. Implementing such strategic preventive maintenance will optimize resource allocation, extend pavement life, and sustainably manage road networks even under financial constraints to ensure the effective utilization of available resources and the provision of reliable and safe road infrastructure.

Future research in similar decision-making processes could explore more alternative strategies set endogenously and allocation models that specifically address other resource limitations such as technical labor in road network maintenance. The MDP model can be adapted for broader use in developing countries with similar constraints. Technologies like machine learning can be integrated to enhance the accuracy of prediction. Additionally, a comprehensive cost-benefit analysis could be conducted to evaluate the long-term effects of different budget scenarios and policies on overall network performance and user satisfaction.

7. List of Notations

$h(t)$	Pavement condition state at time (t)	i	Initial pavement condition state
j	Terminal pavement condition state (Absorbing state)	Z	Inspection interval
$\boldsymbol{\pi}_{ij}$ ($\prod$)	Markov transition probability (probability of transitioning from state i to state j)	θ_i	Hazard rate associated with condition state i
LE_i^k	Life expectancy associated with condition state i	x^k	Vector of explanatory variables
β_i	Vector of unknown parameters related to explanatory variables at condition state i	R_i	Repair intervention type i
$C_{R\leftrightarrow i}^{t,s^k}$	Intervention cost at time t and condition i for section s^k,	LCC	Life-Cycle Cost
$\boldsymbol{m_p^{s^k}}$	Intervention strategy	V_i^{t,s^k}	Agency costs at time t for section s^k
ρ^r	Discount rate	$\boldsymbol{CS}_{t+Z}$	A vector $1 \times J$ of the desired condition
$\boldsymbol{CS}_t$	Road condition state distribution vector at time t	$\boldsymbol{p}(Z)$	A $J \times J$ MTP matrix
$\boldsymbol{P}_{trans}$	The transition probability matrix after intervention	$\boldsymbol{P}_{rep}$	A repair matrix
$\mathbf{MTP}_{C1}$	Markov transition probability of ASIAN highways	$\mathbf{MTP}_{C2}$	Markov transition probability of National roads
$\boldsymbol{Pr}$	Proactive maintenance	$\boldsymbol{Rt}$	Reactive maintenance
AC	Asphalt Concrete	ST	Surface Treatment

8. Declarations

8.1. Author Contributions

Conceptualization, S.H. and F.O.; methodology, S.H. and F.O.; software, S.H.; validation, S.H., F.O., and K.S.; formal analysis, S.H.; investigation, S.H.; resources, S.H; data curation, S.H.; writing—original draft preparation, S.H. and F.O; writing—review and editing, S.H., F.O., and K.S.; visualization, S.H.; supervision, K.K.; project administration, S.H., F.O., and K.S. All authors have read and agreed to the published version of the manuscript.

8.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

8.3. Funding

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8.4. Acknowledgements

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8.5. Conflicts of Interest

The authors declare no conflict of interest.

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