Doctoral Dissertation

Enhancing Road Asset Management in Lao PDR Through Stochastic Deterioration Forecasting and Resource Optimization

(確率的劣化予測と資源最適化によるラオス人民民主共和国における道路資産管理の高度化)

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Table of Contents

Key Abbreviations

AADT	Average Annual Daily Traffic
AASHTO	American Association of State Highway and Transportation Officials
AC	Asphalt Concrete
DOR	Department of Roads
FHWA	Federal Highway Administration
GIS	Geographic Information System
HDM-4	Highway Development and Management Model – Version 4
IRI	International Roughness Index (m/km)
IRF	International Road Federation
ISO	International Organization for Standard
LCC	Life-Cycle Cost
LCCA	Life Cycle Cost Analysis
MCMC	Markov Chain Monte Carlo
MDP	Markov Decision Process
MTP	Markov Transition Probability
MPWT	Ministry of Public Works and Transport (Lao PDR)
MUSTEM	Multi-Stage Exponential Markov Hazard Model
NPV	Net Present Value
PDR	People's Democratic Republic
PMS	Pavement Management System
PPP	Public-Private Partnership
RF	Road Fund
RMS	Road Management System
SNP	Average annual adjusted structural number of pavements
ST	Surface Treatment
VOC	Vehicle Operating Cost
WB	The World Bank

Key Notations

i, j	Pavement condition states
J	Absorbing (terminal) condition state
t	Discrete time (year)
T	finite planning horizon
Z	Inspection interval
π_{ij}	Markov transition probability from state i to j
θ_i	Hazard rate in condition state i
β_i	Parameter for hazard rate estimation
$\boldsymbol{m_p}$	Maintenance strategy
$\boldsymbol{Pr}$	Proactive strategy
$\boldsymbol{Rt}$	Reactive strategy
CS_t	A $1 \times J$ road condition state vector at time t
$p(Z)$	The $J \times J$ MTP matrix
V_i^{t,s^k}	Total agency costs at time t for section s^k
$C_{R\leftrightarrow i}^{t,s^k}$	Intervention cost at time t for section s^k
ρ^r	Discount rate
$IRIAV_y$	The average roughness index in the year for the total network
IRI_k	The average roughness for each road section
Len_k	The length of each road section
dACA	Incremental change in area of all cracking during year, in percent of total carriageway area
CRP	Retardation of cracking progression due to preventative treatment, given by [CRP= $1 - 0.12$CRT]
K_{gm}	Calibration factor for environmental component of roughness (default value=1.0)
K_{cia}, K_{cpa}, K_{vi}	Calibration factors for respective models

List of Tables

List of Figures

Abstract

Maintaining road infrastructure under financial and environmental constraints is a significant challenge in developing countries such as the Lao People's Democratic Republic (Lao PDR or Laos). This dissertation explores the application of the Multi-Stage Exponential Markov (MUSTEM) model, a stochastic model, as a predictive tool for road deterioration and resource allocation optimization, specifically in Lao PDR's road management system. The study aims to develop and provide a robust framework for forecasting road conditions under uncertainty and determining optimal maintenance strategies, particularly under various budget constraints. The research is composed of six chapters. **Chapter 1** outlines the background, objectives, and significance of research on enhancing road asset management in Lao PDR. It highlights the crucial role of road infrastructure in socio-economic development in Laos, where transportation networks influence connectivity, trade, and productivity. The chapter examines the Laos Road Management System (RMS), its reliance on deterministic models like the Highway Development and Management model version four (HDM-4), and challenges such as funding limitations, reactive maintenance, and the lack of predictive modeling. It defines key research problems, focusing on the limitations of current asset management in forecasting deterioration and planning maintenance. Research objectives include evaluating the current Laos RMS, developing a stochastic deterioration model, optimizing resource allocation, and comparing HDM-4 with MUSTEM. The chapter concludes with anticipated contributions to academic research and practical road management, along with a brief dissertation overview. **Chapter 2** presents the theoretical foundations and reviews existing research on road asset management, deterioration models, maintenance strategies, and pavement optimization methods. The chapter discusses RMS and their role in national road maintenance planning, particularly in developing countries like Lao PDR. The chapter reviews and examines deterministic models, HDM-4, with stochastic approaches such as the MUSTEM, discussing their advantages, data requirements, applications, and limitations. Additionally, it highlights international practices and case studies in a global context. **Chapter 3** outlines the development and application of the Markov hazard model to Lao PDR's road networks. It details the modeling development process, factors influencing road deterioration, and the utilization of Laos's RMS data. Additionally, a detailed analysis of the Markov model is conducted using two core road networks, the ASIAN Highway and the National Road Network, to evaluate the differences between the two standards of roads. This comparative analysis aims to highlight how road deterioration varies between these networks and provides insights into optimizing maintenance strategies tailored to each road classification. **Chapter 4** develops and evaluates a stochastic Markov Decision Process (MDP) framework to optimize road network maintenance strategies, especially in Lao PDR. The existing road maintenance practices, limitations, and inefficiencies, particularly the significant use of reactive maintenance under various budget constraints, have been reviewed. Through a comprehensive empirical study utilizing historical inspection data, the study validates the effectiveness and practicality of the proposed optimization model. The results demonstrate how optimal road management requires simultaneous consideration of pavement condition deterioration, life-cycle costs (LCC), and financial limitations. Proposed maintenance strategies, including proactive and reactive approaches, are thoroughly analyzed across various budget scenarios. Furthermore, the study identifies a cost-effective target condition that balances acceptable road conditions and budget allocation ability. Finally, recommendations are provided for policymakers on effective budget allocation, emphasizing the significance of proactive maintenance to improve Lao PDR's road asset management system. **Chapter 5** compares the HDM-4 model, the Laos RMS, and the proposed MUSTEM model. The study examines each model's strengths and limitations. It presents a side-by-side comparison based on various criteria, such as data requirement, road performance estimation, LCC estimation, and ease of implementation, using empirical data from the Laos RMS. This research demonstrates how MUSTEM and HDM-4 effectively forecast road deterioration under varying conditions, such as traffic volumes, pavement types, and environmental factors. Particular emphasis is placed on the advantages of the MUSTEM model, which, through its stochastic structure, demonstrated superior performance in predicting pavement conditions and minimizing LCC, especially under unconstrained budget scenarios. The estimation provided by the MUSTEM model predicted a higher percentage of road conditions to be in fair to good condition throughout the analysis period in the context of a budget unconstraint scenario. In contrast, the HDM-4 excels in economic evaluation by incorporating road user and social benefits but demands extensive data inputs. Finally, the policy recommendations on integrating these models to support data-informed decision-making in road maintenance planning are provided for Laos and similar resource-constrained nations. Finally, **Chapter 6** synthesizes key findings from all previous chapters, emphasizing the research's contributions to road asset management, particularly in Lao PDR. It discusses research findings, policy and practical recommendations, knowledge contribution, limitations, and future research directions. This chapter evaluates the benefits of the integration of the MUSTEM model with HDM-4 in Laos's RMS to enhance predictive accuracy and cost-effectiveness in road maintenance. Key recommendations include adopting a hybrid RMS, improving data collection using Geographic Information Systems (GIS) and remote sensing, strengthening funding through Public-Private Partnerships (PPP), and incorporating AI and machine learning. Capacity building and climate change adaptation are also emphasized. The contributions to knowledge identified limitations and directions for future research, including model validation in other contexts and exploration of innovative maintenance strategies, are also discussed.

Chapter 1

Introduction

1. Introduction

1.1. Research Background

1.1.1. Road Asset Management

Road networks are not just part of a country's infrastructure; they are integral to its social and economic development and essential for societal advancement and generating income throughout the country. "The road network and sub-sector should substantially contribute to the Gross National Product (GDP)" [1]. The economic and social significance of road networks is pivotal to national progress. The economy of the Lao People's Democratic Republic (Lao PDR or Laos), encompassing agriculture, industry, service, and tax, is sustained by the transportation sector's direct and indirect revenues. Investing in transport infrastructure not only lowers the cost of production but also indirectly lowers the overall value of raw materials and labor by improving accessibility. Such investments also foster regional and international trade, promote economic diversification, and increase the economy's resilience to external shocks [2]. As a result, ensuring a well-managed road network is critical to sustaining these economic benefits and requires strategic planning, regular maintenance, and efficient resource allocation to optimize performance and longevity.

Road asset management is not merely a globalized systematic approach; it represents a strategic framework designed to ensure the efficient utilization and sustainability of road infrastructure. This system involves creating detailed road network inventories, monitoring their conditions over time, and developing cost-effective strategies to maintain desired service levels [3].

The primary objectives of road asset management are to ensure the defined level of service in the most cost-effective way while optimizing road user. The key objectives are [1, 4]:

- Delivering a defined level of service while monitoring network performance;
- Managing network growth through demand assessment and investment planning;
- Employing a life cycle approach to develop cost-effective management strategies for the medium and long term;

- Identifying, assessing, and effectively managing risks;
- Developing financial plans that align resource requirements with affordability and funding strategies.

1.1.2. Road Infrastructure in Lao PDR

In developing countries such as Lao PDR, road networks play a vital role in supporting socio-economic growth, ensuring connectivity, and enhancing transportation efficiency. Acknowledging this significance, the government of Lao PDR is committed to implementing comprehensive strategies in its 5-year National Socio-Economic Development Plan (NSEDP) [5] to enhance the effective management and sustainable development of national infrastructure and road networks. Through systematic asset management approaches, such as regular monitoring, prioritizing maintenance, and investing in infrastructure corresponding to developing and maintaining public infrastructure, the responsible authorities, particularly the Ministry of Public Works and Transport (MPWT), aim to optimize the condition, performance, and resilience of its road networks by adopting innovative technologies and best practices to improve road asset management, address infrastructure challenges, and meet evolving transportation needs across the country. Additionally, by fostering partnerships, promoting capacity-building initiatives, and leveraging international expertise, the government is committed to ensuring the long-term viability and sustainability of its road infrastructure. These efforts not only support socio-economic advancement but also contribute to enhancing the quality of life for its citizens.

In 1975, following its independence, Lao PDR had a road network spanning 11,462 kilometers. Of this total, 1,427 kilometers were paved roads, while the remaining roads were constructed with stone and soil (unpaved). The annual freight transport capacity on the road network was approximately 229.7 tons per year. Since 2003, the government of Lao PDR has established the Road Management System (RMS) as a tool for planning, operation, management, and monitoring under the Ministry of Public Works and Transport of Lao PDR (MPWT). The MPWT is represented as the chair of the Steering Committee, according to the Prime Minister Decree no.130/GoL, including the Ministry of Planning and Investment (MPI), the Ministry of Industry and Commerce (MOIC), the Ministry of Finance (MOF), the Ministry of Public Security (MOPS), the

Lao National Chamber of Commerce and Industry, the Lao Fuel and Gas Association, and various stakeholders. As of 2022, the Lao road network has experienced significant growth, reaching a total length of 59,646 km, according to the MPWT Statistic Year Book. This expansion includes 7,842 km of national roads, 45,737 km of provincial and local roads, and 6,066 km of special-purpose roads. Table 1.1 provides a detailed breakdown of road categories and surface types, highlighting the promising future of transportation in Lao PDR [6].

Table 1.1 Lao PDR Road Networks Length by Category in 2022 (km) [7]

Surface	National	Provincial	District	Urban	Rural	Special
Cement Concrete	165.53	133.15	87.83	304.86	106.18	58.40
Asphalt Concrete	1,092.56	63.60	-	151.03	4.00	11.53
Surface Treatment	4,975.72	2,466.84	1,009.87	1,514.73	1,019.55	357.39
Gravel	1,301.07	4,982.58	4,552.86	1,473.59	11,600.57	1,332.67
Earth	306.69	1,004.66	1,783.41	762.37	12,715.64	4,306.92

Figure 1.1 illustrates the distribution of the road network in Lao PDR in 2022 [7]. The rural road network accounts for approximately 43% of the total road network length, while the national road network occupies only about 13%, and the provincial road network constitutes only 15% of the total road network in Lao PDR. Although national roads cover a smaller proportion of the total network, they play a critical role in economic development and regional connectivity. Recent efforts to improve the national road network have focused on enhancing road quality, expanding paved road coverage, and upgrading key corridors that facilitate trade and mobility.

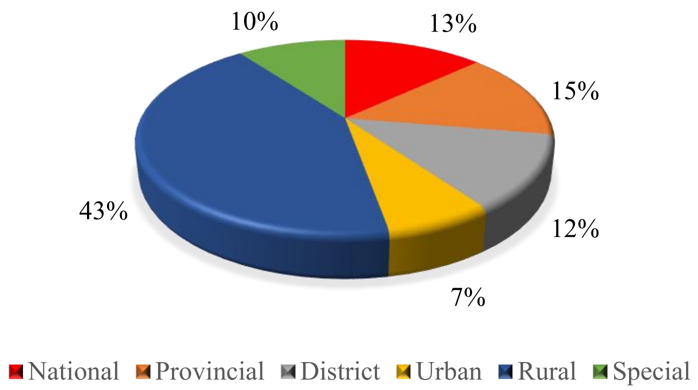


Figure 1.1 The Distribution of Lao PDR Road Network in 2022

In addition, the hierarchy of the Lao Road network is identified as the road classification and used as a key for the management committee to determine the inspection frequencies, maintenance regime, and standard of the maintenance methodology for each segment (road section) in the short-term and long-term plans. Within the National Road Network, the concept of "Core Network Level" is used to classify the road hierarchy, which consists of 3 levels of the core network [8]:

- Core-1, "Level 1", is the key national road section, including the ASIAN highway road (AH) and the national economic corridor road network;
- Core-2, "Level 2", is represents the national road connecting the capital with the provinces, provinces to provinces;
- Core-3, "Level 3", is the national road with low traffic volume that connects urban and district.

In addition, Core Network 1 connects Lao PDR with other ASEAN countries, this road network is commonly referred to as the ASIAN roads. Further, the ASIAN roads are designed with uniform standards to ensure traffic loads and interoperability, promoting smooth cross-border travel within the ASEAN region [9]. In contrast, Core Network 2 is built according to local standards that differ based on terrain and traffic needs. These roads connect provinces within the country, improving transportation for local communities, while Core Network 3 focuses on local communities and sub-communities.

Table 1.2 presents the number of national road core networks in Lao PDR, while Figure 1.2 illustrates the locations and differences of the Core Networks throughout the country.

Table 1.2 National Road Core Network in 2022

No.	Core Network	Road number	Length of Network (Km)
1	Core 1	NR13N, NR13S, NR2E, NR2W, NR03, NR08, NR09, NR12, NR18A, NR18B	2.421
2	Core 2	NR1A, NR1B, NR1C, NR1D, NR1E, NR1I, NR3A, NR3B, NR04, NR4A, NR4B, NR4C, NR5B, NR06, NR6A, NR6B, NR07, NR9B, NR10, NR11, NR15, NR16, NR16A, NR16B, NR3206, NR20, NR5101(21)	4.716
3	Core 3	NR1F, NR1H, NR1J, NR11A, NR11B, NR11SVK, NR14A	681
	Total		**7.818**

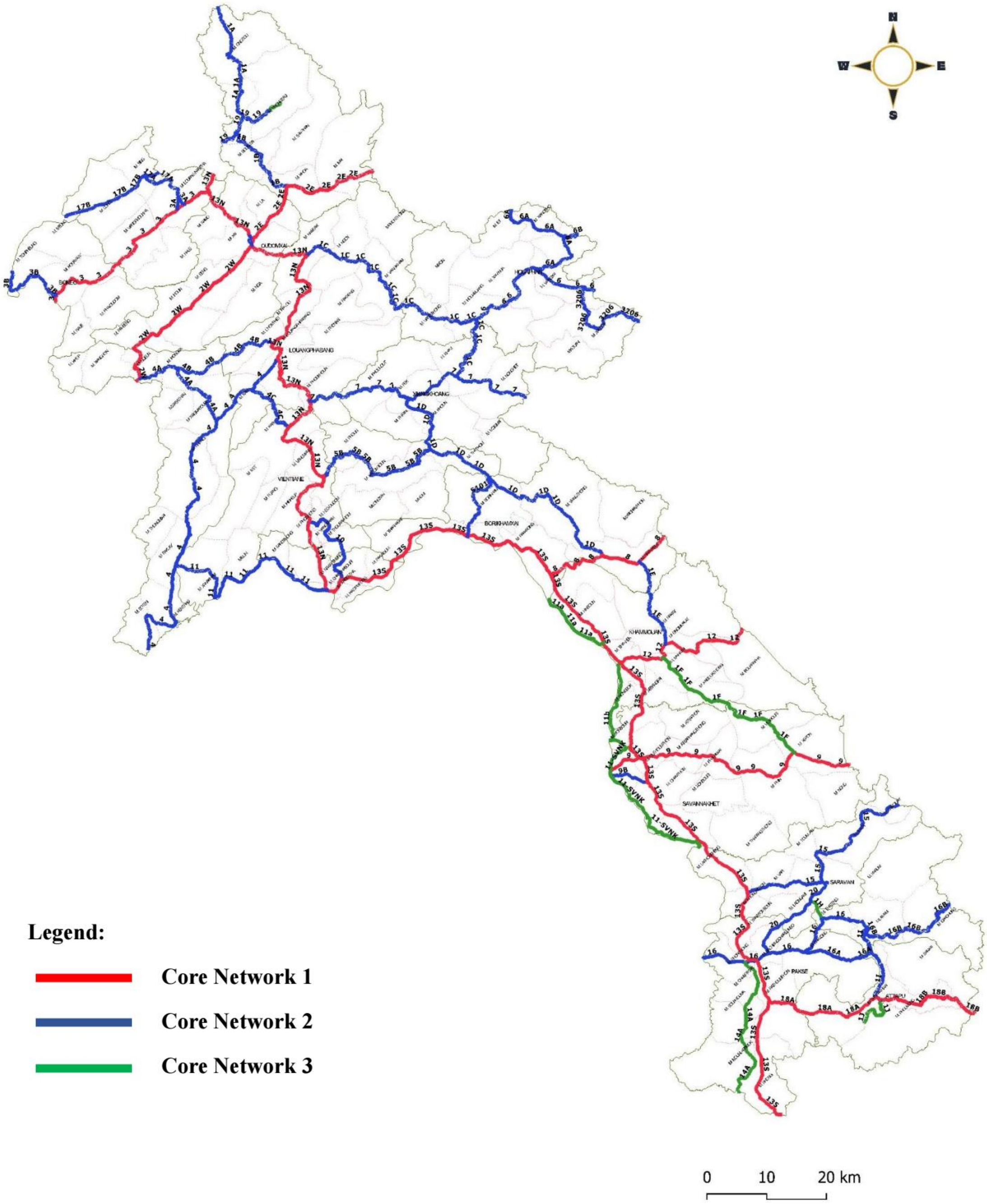


Figure 1.2 National Core Road Networks in Lao PDR

1.1.3. HDM-4 for Road Asset Management in Laos

Lao PDR has diverse environmental and landscape conditions, ranging from highlands to tropical plains. Similar to other developing countries in the region, Lao PDR faces the challenge of resource constraints, which necessitates a more efficient and cost-effective Road Management System (RMS).

Since 2003, the Government of Lao PDR has approved and implemented the RMS as a tool for management, planning, operating, and monitoring, which is the responsibility of the MPWT of Lao PDR. The Laos RMS utilizes the Highway Development and Management version 4 (HDM-4) software, a deterministic model, for long-term planning, maintenance funding allocation, and priority determination [10, 11]. The HDM-4 incorporates Lao road network characteristics to estimate surface deterioration by generating a matrix of work selection for all road sections with alternatives corresponding with the economic reward, including road user costs (RUC), net present value (NPV), and net present benefit (NPB) [12]. However, the system requires regular updates on lots of information, including conditions of the roads, traffic data, work unit costs, and social and environmental parameters, in order to generate a precise estimation.

1.1.4. Maintenance Strategy and Treatment Selection Practice in the Laos RMS

1.1.4.1. Maintenance Strategy

Road maintenance strategies in Lao PDR can be categorized into the following [13]:

- **Routine Maintenance (RM)**: Performed continuous maintenance to preserve road and roadside conditions and other road facilities as close to their original state as possible. The routine maintenance activities include surface patching, roadside drainage repair and cleaning, road shoulder and edge repair (reshaping), and repair of culverts.

- **Periodic Maintenance (PM)**: Conducted at regular intervals over several years to restore roads to their original conditions and prevent further deterioration. The activities include reshaping the carriageway and ditching by machine, re-graveling, and resealing.

- **Rehabilitation and improvement (RI)**: Applied to roads near the point of failure and almost unable to be used. The activities include the restoration of the road pavement, installing new culverts, and constructing a new roadside drain.
- **Emergency maintenance (EM)**: Addresses urgent situations such as landslides, flooding, or fallen debris. EM includes temporary road repair to restore road structure and accessibility by clearing blockages.

1.1.4.2. Treatment Selection Criteria

The treatment selection criteria allow for an efficient system for road treatment, providing an equilibrium between the needs for the treatment and the minimization of resources. Treatments are chosen according to the intensity of the defect, in the order of decreasing intensities, and triggered when the threshold intervention is reached. Inefficient selection may increase road deterioration, while unnecessary high-level treatment may waste resources [13].

The maintenance treatment selection criteria are intended to maximize resource use and maintain road infrastructure's long-term viability. The process consists of evaluating road conditions, applying the appropriate intervention based on set thresholds, and using cost-effective, labor-saving methods for road network efficiency.

The Surface Integrity Index (SII) in Lao RMS is important in the treatment selection process. It is primarily responsible for the selection of treatment for addressing road condition deficiencies. Although several parameters are also considered for treatment selection, SII is the most important, in combination with the availability of labor, accessibility of equipment, and cost.

The key factors influencing treatment selection in Lao RMS are as follows [13]:

1) **Traffic Volume:** The number of heavy vehicles using the road significantly impacts the need for maintenance and the selection of appropriate treatments. Higher traffic volumes typically lead to increased wear and tear, necessitating more robust maintenance solutions.

2) **Road Condition**: The features and existing road surface condition determine the type of treatment. Major defects need to be assessed in order to determine whether there should be a higher or lower level of treatment.

3) **Combination of Defects**: Multiple defects on the road surface may complicate the selection process. The interrelation among the defects must be analyzed in order for the selected treatment to be able to solve all the problems.

4) **Resources Availability**: Labor and equipment availability are practical initial considerations that may impact the types of treatment. Available resources may limit the kind of treatment that can be carried out.

5) **Economic Factors**: The cost-effectiveness of different treatment modalities should be weighed in the decision-making process. Cost-effectiveness should be evaluated for optimal utilization of resources.

6) **Engineering Judgment**: Engineering expertise plays an important role in intervention level setting and in making the decision about when maintenance should be performed. However, the decision-making depends on functional, serviceability, and whole-life cost principles.

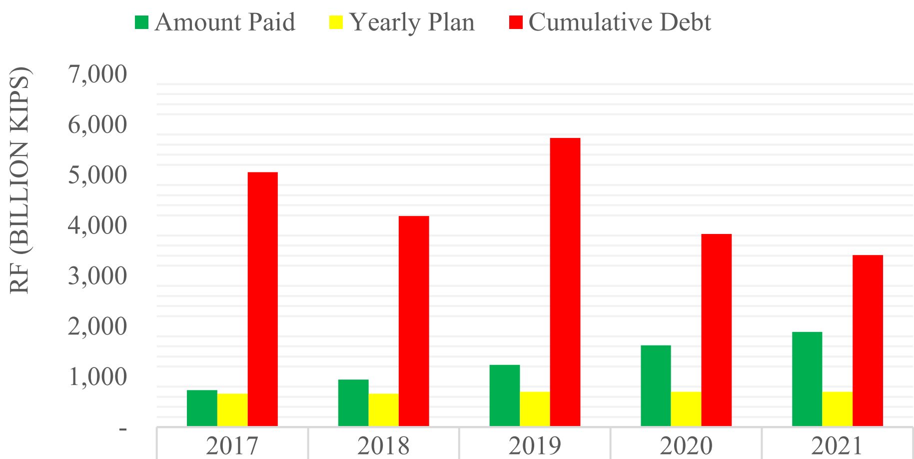
7) **Maintenance Standards:** In order to ensure the proper treatment for varying road conditions. Following the Standards can specify when and how treatment interventions must be applied, ensuring roadways remain safe, operational, and affordable throughout their lifespan.

1.1.5. Road Maintenance Funding and Challenges in Lao PDR

The Road Maintenance Fund or Road Fund (RF) in Lao PDR, established in 2001, was designed to secure financing for road maintenance. However, as of 2021, the fund faces a debt burden of approximately 2,433 billion Kips (USD 200 million) [8]. This growing debt raises concerns about the RF's ability to finance road maintenance effectively, leading to worsening road conditions, rising repair costs, and compromised road safety. The RF's growing debt also limits its capacity to invest in necessary infrastructure improvements and road network expansions, hindering the country's economic growth.

To address these challenges, prudent financial management and strategic maintenance planning are essential.

Figure. 1.3 shows the Road Fund's requirements and capabilities from 2017 to 2021. This situation highlights the urgent need for innovative and cost-effective maintenance strategies to maximize the utility of limited resources. To ensure financial ability, it is essential to explore alternative funding sources, such as public-private partnerships, and implementing improved revenue collection mechanisms, including efficient toll systems or fuel taxes. Addressing these challenges is critical for ensuring the long-term sustainability of road maintenance, enhancing transportation efficiency, and supporting Lao PDR's broader socio-economic development goals.



	2017	2018	2019	2020	2021
Amount Paid	731.40	942.25	1,237.25	1,624.34	1,888.42
Yearly Plan	660.00	660.00	700.00	700.00	700.00
Cumulative Debt	5,054.65	4,183.01	5,735.81	3,831.66	3,410.21

Figure 1.3 Lao PDR Road Maintenance Fund from 2017-2021

1.2. Problem Statement

The road network in Lao PDR is essential to the country's socio-economic development by facilitating the movement of people and goods while supporting key industries such as agriculture and tourism. It also enhances regional connectivity, and integrates Lao PDR into global markets. However, the road infrastructure faces significant challenges that impact its performance and long-term sustainability.

1) Reactive Maintenance System

   The existing Laos RMS mostly relies on reactive interventions. This strategy often results to higher long-term costs and frequent road failures, because small defects become major issues before being addressed. Research by Obunguta, F. and K. Matsushima (2020) [14] revealed that proactive maintenance strategies could significantly increase road network condition in good condition and reduce LCC at the end of analysis period.

2) Financial Constraints

   The Lao PDR's road maintenance fund has inadequate funding, which results in high debt levels of approximately 200 million US dollars in 2021 [8] and restricts its capacity to organize and carry out efficient maintenance programs. Road deterioration is accelerated, and these budgetary limitations raise future maintenance costs. Furthermore, the government's debt load limits funding for necessary infrastructure maintenance and upgrades.

3) Inadequate Predictive Models

   The existing Laos RMS needs more sophisticated predictive models to accurately forecast road deterioration and maintenance needs. This limitation lowers effective planning and resource allocation. While tools like HDM-4 are applicable, they find it challenging to adapt to the specific conditions of Lao PDR, which include varying traffic volumes, diverse pavement types, and uncertainties caused by environmental factors.

4) Data Limitations

Incomplete and inconsistent data on road conditions, traffic volumes, and maintenance history, primarily due to budget constraints and limited inspection resources, pose a challenge to effective road asset management, as outlined in the Road Asset Management Plan report [4]. Consequently, robust data collection and integration with advanced analytical tools are crucial for developing accurate deterioration models and maintenance schedules.

5) Inefficiencies in Maintenance Practices

Current RMS maintenance practices are not cost-effective due to reactive maintenance, which leads to increasing RF debt and challenging contractor payment conditions [4]. A systematic approach is needed to prioritize maintenance activities based on road conditions, traffic levels, and budget constraints. Adopting modern practices and leveraging technology-driven solutions can significantly enhance efficiency and optimize resource allocation.

6) Research Gaps

- Proactive Maintenance Models

There is a critical need for developing proactive maintenance models that can predict road deterioration and optimize maintenance planning to prevent road failures while minimizing costs. Stochastic models, such as Markov models, offer a structured approach to model uncertainties and assess long-term outcomes. However, despite their potential, these models remain underexplored in Lao PDR, presenting an opportunity to develop tailored solutions that address the country's unique environmental and operational challenges. Incorporating these models could enhance decision-making, improve resource allocation, and extend the lifespan of critical infrastructure.

- Comparative Analysis

  A comprehensive comparison between existing models, such as HDM-4, and proposed stochastic models is essential to determine which approach best fits Lao PDR's specific needs. By evaluating their strengths and limitations, decision-makers can assess how each model addresses challenges like traffic variability, diverse environmental conditions, and budget constraints. This analysis will provide practical recommendations for selecting the most effective strategy to optimize maintenance planning and improve road network performance in Lao PDR.

- Resource Allocation Optimization

  Developing efficient maintenance resource allocation models is essential to ensure maximum maintenance impact, particularly under budget constraints. These models should incorporate life-cycle cost analysis to help planners evaluate the long-term economic benefits of maintenance decisions. By aligning maintenance planning with resource availability, these models can ensure sustainable road improvements, minimize resource wastage, prolong road network functionality, and enhance overall infrastructure reliability. Additionally, implementing tailored optimization strategies will enable Lao PDR to manage its road networks despite financial and operational resource limitations.

1.3. Research Objectives

The primary objectives of this research are as follows:

- **Evaluate the suitability of the current Laos RMS**: Evaluate the effectiveness of Laos Road Management System and long-term maintenance planning, with focus on identifying its strengths, limitations, and areas for enhancing in relation to data availability, model capacities, and decision-making support functions.
- **Develop a stochastic road surface prediction model**: Address data availability and variability limitations to improve forecasting accuracy for road deterioration and maintenance needs. This model is particularly relevant for resource-constrained regions like Lao PDR and other developing countries.

- **Optimize Resource Allocation Strategies**: Develop efficient maintenance plans that maximize sustainability and road network performance using a stochastic model framework.

- **Conduct a Comparative Analysis**: Evaluate the effectiveness of HDM-4, the current RMS, and the proposed stochastic model (MUSTEM) in road asset management. This analysis will highlight strengths, limitations, and provide practical recommendations, particularly for Laos RMS.
- **Provide Strategic Recommendations**: Offer guidance for project managers, road agencies, and policymakers on efficient road maintenance practices. These recommendations will enhance decision-making, encourage innovative methodologies, and support sustainable road infrastructure development in Lao PDR and similar developing countries.

1.4. Research Contributions

This research aims to make significant contributions to the field of road asset management, specifically tailored to the context of Lao PDR. The expected contributions are as follows:

1. Develop and provide a robust framework for predicting road deterioration, particularly beneficial for data-limited and constraint-prone countries like Lao PDR. This model and framework support proactive maintenance planning and efficient infrastructure management.

2. Enhanced Decision-Making for Resource Allocation: This research will propose optimized strategies for allocating maintenance resources, integrating life-cycle cost analysis to ensure budget optimization. These strategies will empower policymakers and road agencies to make data-driven decisions that balance economic and road network performance priorities.

3. A comprehensive comparative analysis of the Laos RMS model and proposed framework, highlighting the strengths and limitations of each model. This analysis

will guide policymakers in selecting the most effective maintenance strategies. This study will also offer application guidelines, particularly for Laos RMS.

4. This research will provide practical guidelines for policymakers, infrastructure planners, and project managers to implement more effective road maintenance practices by adopting innovative and sustainable road maintenance practices.

5. Supporting the development of sustainable road infrastructure in Lao PDR. Enhance the efficiency and sustainability of Lao PDR's Road network, supporting economic growth, reducing transportation costs, and improving regional connectivity. These outcomes align with national and international development goals.

- The findings in this research will serve as a knowledge base for training programs, fostering local expertise in road asset management and maintenance planning. This effort will provide long-term benefits for Lao PDR's infrastructure sector, particularly the Ministry of Public Works and Transport.

1.5. Structure of the Dissertation

The dissertation comprises six chapters dedicated to enhancing road asset management in Lao PDR through stochastic predictive modeling and optimal resource allocation. Figure 1.4 presents the dissertation diagram showing the consistency of each chapter. **Chapter 1** offers background information on the significance of road infrastructure in socio-economic development, research problems, objectives, and contributions. **Chapter 2** presents existing methods for road asset management, including stochastic Markov models and deterministic methods such as HDM-4, in order to identify gaps in the literature. **Chapter 3** develops and applies the MUSTEM model, including uncertainty, for the national road in Lao PDR. **Chapter 4** develops an optimization framework for resources in different budget conditions for the ASIAN and the National road network. **Chapter 5** compares the MUSTEM and HDM-4 performance utilizing empirical Laos RMS data, assessing results in terms of cost-effectiveness, as well as prediction in the shortest route condition. **Chapter 6** presents the findings, provides policy implications, and recommends future research and implementation in the road management system.

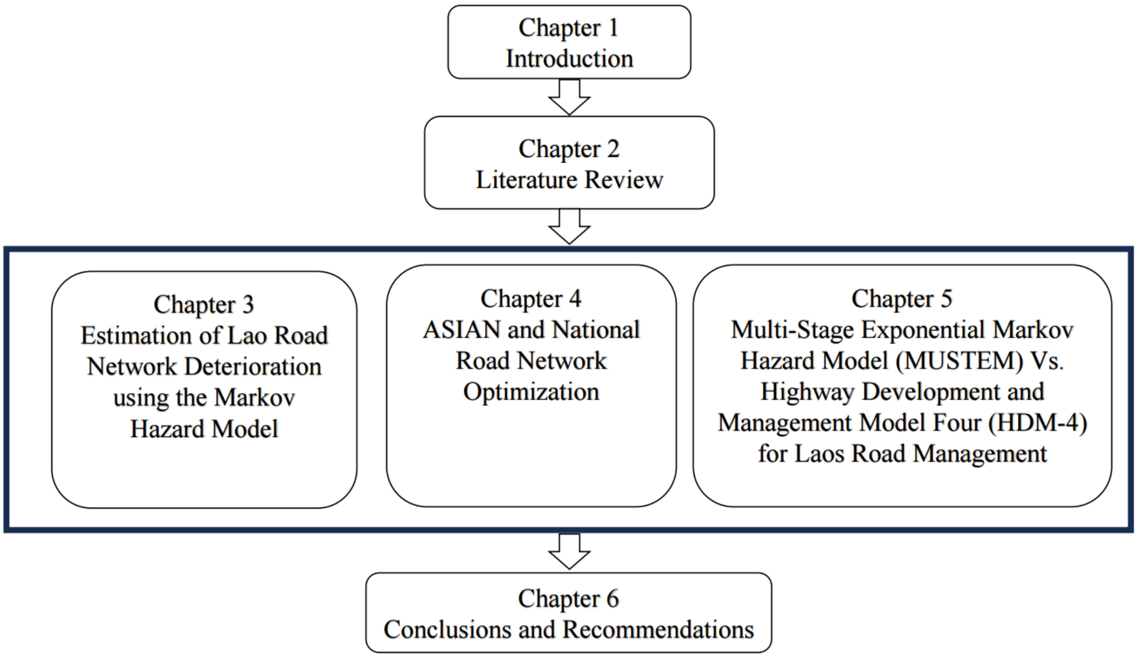


Figure 1.4 Dissertation's Structure

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Chapter 2

Literature Review

2. Literature Review

2.1. Road Management Systems

2.1.1. **Definition**

A road management system (RMS) involves the planning, development, maintenance, and optimization of road networks to ensure safe, efficient, and cost-effective transportation. The asset management system for roads is "a systematic process of maintaining, upgrading, and operating assets, combining engineering principles with sound business practice and economic rationale, and providing tools to facilitate a more organized and flexible approach to making the decisions necessary to achieve the public's expectations" [1]. This process encompasses a broader range of activities, including assessing road conditions, prioritizing maintenance works and rehabilitation projects or activities, allocating resources, and implementing technologies to monitor and improve the network's performance [2, 3].

The primary objectives of an RMS are to manage road infrastructure assets efficiently and effectively by ensuring safe, reliable, and sustainable transportation. These objectives aim to achieve a service level or performance of the roads at the lowest cost, deploying long-term maintenance planning that considers the future impact of current budget allocations [4].

Key processes of an RMS include [5, 6]:

1. Asset Inventory: Establishing a comprehensive inventory of the entire road network and its elements (road facilities).
2. Condition Assessment: Providing a clear picture of the current condition and performance of the road network.
3. Asset Valuation: Estimating the value of the assets to understand their economic significance.
4. Demand Forecasting: Predicting future traffic demands and service needs to plan accordingly.
5. Maintenance Planning: Estimating maintenance needs and costs to develop effective maintenance strategies.

6. Prioritization: Setting priorities related to the desired quality and performance of the road network.
7. Funding Scenarios: Developing funding scenarios for regular and timely maintenance and upgrades.
8. Strategy Development: Defining appropriate strategy to tackle different scenario.
9. Implement the RAM plan**:** implementing a Road Asset Management Plan (RAM Plan).

This process is continuous and demand regular updates to monitoring and reporting of changing and demands of road maintenance. As illustrated in Figure 2.1, the RMS structure in Lao PDR includes processes for data collection, planning, and implementation [7].

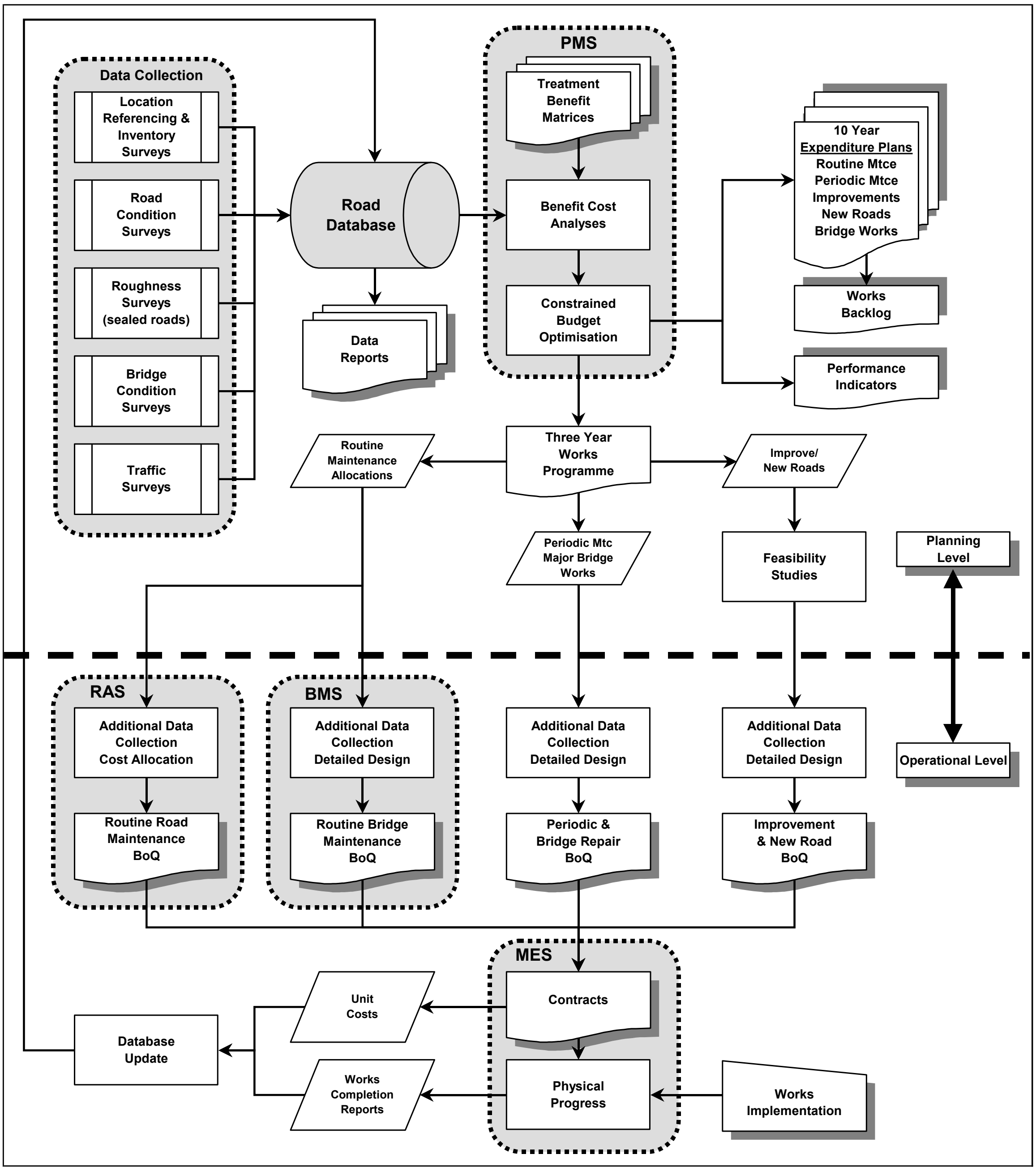

Figure 2.1 Structure of the Road Management System in Lao PDR [7]

A well-organized and implemented RMS plays a vital role in various aspects of national development; the key advantages of RMS and infrastructure contribution, including [8]:

1. Economic Growth: The development of efficient road networks plays a crucial role in driving economic progress by facilitating the smooth movement of goods and people. These functions can reduce transportation expenses and travel time, promote trade, expand market access, and stimulate economic activities across various sectors.
2. Safety Measures: Ensuring the safety of road users involves effective management practices that identify and address potential risks of accidents, such as potholes, structural weaknesses, and inadequate signage. Implementing proper maintenance procedures can minimize the occurrence of accidents and enhance overall road safety.
3. Cost Optimization: Proactive maintenance strategies implemented in road network management optimize resource utilization, leading to extended road asset lifespans and reduced long-term expenses. Preventive maintenance is generally more financially efficient compared to reactive maintenance.
4. Environmental Responsibility: Sustainable road management practices aim to minimize environmental impact by using eco-friendly materials, improving road conditions, reducing vehicle emissions, and preserving surrounding ecosystems. Effective road design and maintenance also mitigate issues like erosion and water runoff.
5. Inclusive Accessibility: Well-managed road networks improve accessibility for all members of society, including those residing in rural and remote areas. This enhanced accessibility contributes to social equity and inclusion by providing better access to essential services such as education, healthcare, and employment opportunities.
6. Infrastructure Durability: Regular maintenance and timely upgrades ensure the longevity and resilience of the road network against natural wear and tear and extreme weather conditions. This approach reduces the need for frequent, large-scale rehabilitations, resulting in cost savings and minimized disruptions to traffic flow.

7. Technological Advancements: Modern RMS incorporates advanced technologies such as Geographic Information Systems (GIS), remote sensing, and data analytics to improve decision-making. These tools enable real-time monitoring, predictive maintenance, and optimized resource allocation.

An RMS is not merely a tool for maintaining road infrastructure but a crucial driver of socio-economic progress. By embracing robust management practices and modern technologies, Lao PDR can build a road network that meets today's needs and builds a solid foundation for future growth and connectivity.

2.1.2. **Previous studies on road maintenance strategies**

Extensive research on road maintenance strategies has been conducted globally, focusing on enhancing road infrastructure's resilience, efficiency, and cost-effectiveness. These studies have delved into various maintenance approaches, including preventive inspection and maintenance, routine maintenance, and repair actions, all strategies aimed to extend road lifespan and minimize the costs of maintenance as well as traffic disruptions.

A key theme in prior studies is the comparison between preventive (proactive) and reactive maintenance strategies. Preventive maintenance involves regular inspection and scheduled intervention to address potential defects before they worsen, whereas reactive maintenance addresses damages after they arise. Eventually, most research consistently highlights that preventive strategies are more cost-effective in the long run, as they reduce the frequency and severity of significant repairs.

Furthermore, several innovative approaches, particularly in developed countries, have emerged, leveraging advanced predictive models and data analytics, like the stochastic method. Data analytics and predictive models have been employed to optimize maintenance decision-making and resource allocation. For instance, Obunguta, F., and Matsushima [9] developed an optimal pavement management strategy using a stochastic model. This study focused on creating a pavement management system (PMS) for countries such as Uganda. The PMS had limited data requirements and enhanced road maintenance planning. The maintenance strategies were developed based on time-dependent and condition-dependent policies related to pavement deterioration rates. The findings indicated that implementing preventive maintenance policies increased the percentage of roads in good condition and reduced the percentage of roads in poor condition, substantially reducing life cycle costs.

Another study by Van Hiep, D., and Tsunokawa, K. [10] created and investigated maintenance strategies for roads in sub-humid tropical environments in Vietnam, considering factors like IRI, aging, and cracking progression. This study employed the HDM-4 model to determine optimal maintenance options based on pavement conditions and traffic levels. Subsequently, different strategies were recommended based on those factors. The results of this study highlighted the effectiveness of maintenance actions like thick overlay, routine maintenance, and reconstruction based on pavement conditions and traffic volumes to improve road longevity and performance.

Further study by Kobayashi et al. [11] proposed a methodology to determine the optimal inspection policy for road pavement, considering the uncertain deterioration process using a stochastic approach. The Markov deterioration prediction model has been used to express the pavement deterioration process and then formulate an optimal inspection-repair model to minimize life-cycle costs at the specified risk control level. This study also compared the economic benefits of regular road condition inspections and proposed methods to gauge the benefits of two methods with empirical analysis of actual expressways in Japan. The finding highlighted the shift from a time-dependent to a condition-dependent repair policy and the importance of inspection for road asset management.

Recent studies offer valuable lessons for the road maintenance strategy in Lao PDR. The key takeaways include:

1. **Adopting Preventive Maintenance**: Prioritizing preventive over reactive maintenance can help reduce long-term costs and extend the lifespan of road assets.
2. **Utilizing Predictive Models**: Implementing predictive models, such as the Markov or HDM-4 models, can enhance decision-making by providing data-driven insights into maintenance needs.

3. **Applying Strategies to Local Conditions**: Maintenance strategies should be adapted to the specific environmental and traffic conditions in Lao PDR to ensure effectiveness.
4. **Leveraging International Best Practices**: By learning from successful case studies in similar developing countries, Lao PDR can adopt proven strategies and avoid common pitfalls in road management.

2.2. Markov Models

2.2.1. Fundamentals and Application of Markov Models

While RMS focuses on structured maintenance planning, predictive modeling techniques such as Markov models provide a probabilistic approach to forecasting road deterioration and optimizing maintenance strategies. The Markov model has emerged as a prominent tool in road asset management due to its ability to capture dynamic transitions between different states of infrastructure conditions. Over the past few decades, various statistical methods based on Markov models have been developed to model road pavement deterioration using inspection data.

Markov models operate under the assumption that the probability of transitioning from one condition state to another depends solely on the current state, not on the sequence of previous states. This memoryless property makes Markov models particularly suited for predicting the future condition of road assets based on present data [12]. Markov models are used to estimate the likelihood of pavement transitioning between different condition states over time. Transition probabilities are determined based on historical data and inspection records, enabling planners to predict future deterioration and schedule maintenance activities accordingly. Numerous studies have shown how Markov models can improve road asset management:

1. **Multi-Stage Exponential Markov (MUSTEM) Model**: This advanced model was developed to address common issues such as incomplete inspection data and varying deterioration rates. The studyies from Kobayashi et al. [13] and Tsuda et al. [12] have demonstrated its effectiveness in providing accurate predictions of road conditions, highlight the model's capacity to enhance road maintenance decision-making, leading to better maintenance planning and resource allocation.

Another study from Han et al. [14] investigated the behavior of advanced pavement materials using a Mixed Markov Hazard model based on Bayesian updating. The study concluded that the use of probabilistic methods significantly enhanced the precision of pavement condition predictions, which in turn facilitated more effective maintenance strategies and optimized resource allocation. While Angelo et al. [15] developed a safety-integrated pavement maintenance decision support framework for road networks in developing countries, using Addis Ababa, Ethiopia, as a case study. By incorporating safety considerations into Markov models, the researchers demonstrated that prioritizing road sections with high traffic volumes and poor safety conditions could improve both safety outcomes and pavement performance, highlighted the importance of combining safety and condition data for more effective maintenance planning.

The model has been modified and extended to account for specific challenges prevalent with inspection data, such as a small sample size, measurement errors, different deterioration modes, and composite deterioration structures such as Kobayashi et al. [13, 16]; Kaito et al. [17]; Han et al. [18].

2. **Markov Decision Processes (MDPs)**: Building on Markov models, MDPs incorporate decision-making into the prediction framework. A study from Gao and Zhang [19] proposed a Markov-based Road maintenance optimization model considering user costs. The key outcome was that incorporating user costs in the decision-making process leads to more user-friendly maintenance schedules. Another study by Obunguta and Matsushima [9] in Uganda highlighted how MDPs can help balance preventive maintenance with long-term benefits, ensuring optimal use of limited resources.

Markov models have been widely used to predict infrastructure deterioration. In order to generate highly accurate deterioration forecasts, the key challenges in developing the deterioration model were related to uncertainty, particularly traffic volume, road structures, environmental, and pavement thickness [20]. Powerful stochastic techniques of Markov models are used to predict degradation in numerous infrastructures. Particularly, consider the following: road surface pavement [14, 21, 22], bridges [12, 23], pipe networks [24, 25], and airports [26, 27].

2.2.2. Markov Model Application Challenges

While Markov models offer significant benefits, they require reliable and comprehensive historical data to generate accurate predictions. The absence of such data can limit their effectiveness, especially in developing countries like Lao PDR, where data collection may be sporadic or incomplete. Previous studies by Han et al. [14]; Obunguta and Matsushima [9] have emphasized the importance of sufficient and high-quality data for improving the precision of model predictions. Calibration of these models using locally available data is critical to enhancing their accuracy and applicability, as demonstrated in research by Gao and Zhang [19]. Additionally, integrating external factors such as climate variability, traffic, and construction quality can further refine the predictions, as highlighted by Angelo et al. [15]. Despite these challenges, with proper adjustments and consistent monitoring, Markov models can serve as powerful tools for long-term infrastructure planning and maintenance, as shown in multiple case studies such as Tran et al. [24]; Sempewo and Kyokaali [25].

Given the challenges in data collection and the variability of road conditions in Lao PDR, a hybrid approach that combines the probabilistic strength of MUSTEM with the detailed analytical capabilities of HDM-4 (current RMS analysis tool) may offer the best results. Such a hybrid model would enable more flexible decision-making under uncertainty while taking advantage of localized data where available. This integrated approach could significantly improve the planning, budgeting, and execution of road maintenance strategies in Lao PDR, ultimately ensuring more efficient use of resources and better infrastructure outcomes. This research aims to bridge the gap by comparing these models in the context of Lao PDR, providing actionable recommendations for policymakers and road authorities.

Meanwhile, Markov models present a robust framework for proactive road asset management. By adopting these models, Lao PDR can enhance its ability to maintain a reliable and sustainable road network, ultimately supporting economic growth and social development.

2.3. Overview of Markov decision processes

Markov Decision Processes (MDPs) are an extension of Markov models that incorporate decision-making elements, making them particularly useful in the field of road asset management. Introduced by Bellman in 1957 [28], MDPs provide a structured framework for modeling decision-making in situations where outcomes are partly random and partly under the control of a decision-maker. An MDP framework consists of several key components [29]:

1. **Decision Epochs**: These are discrete points in time at which decisions are made.
2. **States**: Each state represents a specific condition of the road network at a given time.
3. **Actions**: Actions refer to maintenance strategies or interventions available to the decision-maker.
4. **Transition Probabilities**: These probabilities define the likelihood of moving from one state to another, given a specific action.
5. **Rewards**: A reward function quantifies the immediate benefit or cost associated with a particular action in a given state.

The objective of an MDP is to determine an optimal policy. In Road asset management, the objective is to optimize the decision-making process concerning the maintenance and improvement of road infrastructure by maximizing the benefits to road agencies and users. The system aids in making informed decisions regarding repairs, upgrades, and maintenance to achieve the maximum overall outcomes for the road network [30].

2.3.1. Application of MDPs in Road Asset Management

MDPs have been used to develop dynamic pavement management system (PMS) for road networks and enable decision-makers to balance competing objectives (Safety, social impact, economic costs) by offering options for maintenance, rehabilitation, or reconstruction based on long-term benefits and costs. For instance, Obunguta and Matsushima [9] demonstrated that using MDPs for Ugandan national roads led to more cost-effective maintenance schedules by balancing short-term expenses with long-term benefits; Angelo et al. [15] highlighted the integration of safety considerations in MDP-based models, showing that combining safety and pavement condition data can improve both safety outcomes and pavement performance.

Finding an optimal policy is significant for solving the MDP, which can be achieved using various algorithms [29, 31], including:

1. **Dynamic Programming**: Methods such as value iteration and policy iteration are commonly used to solve MDPs.
2. **Monte Carlo Methods**: These methods use random sampling to estimate the expected rewards and transition probabilities.
3. **Reinforcement Learning**: Techniques such as Q-learning and deep reinforcement learning have gained popularity for solving complex MDPs in environments with large state and action spaces.

Markov 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. This property allows for the creation of Markov models using states, actions, transition probabilities, and rewards. In this research, the MDP incorporates multiple condition states with a designated terminal state, discrete time periods, defined maintenance strategies, periodic inspection intervals, and corresponding maintenance actions. The analysis is conducted over a finite planning horizon from the initial to the designate year.

2.3.2. Challenges in Implementing MDPs

Despite their advantages, implementing MDPs in real-world road asset management faces several challenges:

- Data Requirements: MDPs require detailed and accurate data on road conditions, transition probabilities, and maintenance costs.
- Computational Complexity: Solving MDPs for large-scale road networks can be computationally intensive, especially when the state and action spaces are large.

- Transition Probabilities Estimation: Estimating transition probabilities accurately can be difficult due to variability in traffic loads, weather conditions, and other external factors.

2.3.3. Adaptation of MDP

Given the unique challenges faced by Lao PDR, including limited data availability and diverse environmental conditions, adopting an MDP-based approach could enhance the country's road asset management system. By incorporating economic and safety considerations regarding road conditions, MDPs can help decision-makers prioritize maintenance actions that offer the highest long-term value. Therefore, MDPs provide a robust framework for optimizing road maintenance strategies under uncertainty. Proper calibration and data integration can support more informed decision-making, ultimately leading to a more sustainable and cost-effective road network in Lao PDR.

2.4. Highway Development and Management Model

Highway Development and Management version 4 (HDM-4) is a well-established tool for infrastructure asset management, widely used for analyzing the life-cycle performance of road networks [32]. Unlike Markov models, which employ probabilistic decision-making, HDM-4 employs a deterministic approach, relying on known relationships and data-driven equations to predict road deterioration and guide maintenance planning. However, for better analysis and prediction, these models require an extensive database with various factors [33]. The standard PMS tools, such as Highway Development and Management and the Australian Road Research Board (ARRB) model, are categorized into mechanistic-empirical models [21, 34].

HDM-4 is acknowledged for its deterministic nature, which allows it to provide precise values of pavement performance metrics based on given input data. The model assesses road deterioration based on five key distress modes, including cracking, raveling, potholing, rutting, and roughness [35, 36]:

The general computational logic for estimating the deterioration of the HDM-4 is summarized as follows [36-39]:

- Initialize input data at the start point of the analysis year. This input data can be the first year of analysis or the previous year's condition after maintenance.

- Calculate the amount of change in each distress mode (majority 5): cracking, raveling, potholing, rutting, and roughness.
- The pavement strength, condition, and age of the infrastructure are considered, and the traffic volume per lane is computed.
- Estimate the distress of cracking, raveling, and pothole using progression criteria (regressive function) specific to each distress mode, and then adapt (calibrate) the estimation using the deterioration factor of the local condition.
- Lastly, the roughness increment based on traffic, surface distress, age, and environmental factors has been computed.

Notable, each distress mode is evaluated using calibrated progression criteria (calibration factor) specific to the local environment, including traffic loads and climate conditions [37, 38], which are tailored to the unique characteristics of the region where it is applied.

2.4.1. Application of HDM-4 in Road Asset Management

The HDM-4 model has been applied in practical asset management across various countries, particularly developing regions. The HDM-4 supports three main levels of analysis [40]:

1. **Project-Level Analysis**: Detailed evaluation of individual road projects, including cost-benefit analysis and selection of optimal maintenance strategies.
2. **Program-Level Analysis**: Medium-term planning that prioritizes maintenance and rehabilitation activities across a network under budget constraints.
3. **Strategic-Level Analysis**: Long-term policy development and resource allocation for sustaining the entire road network.

In Lao PDR, the Ministry of Public Works and Transport (MPWT) has adopted HDM-4 for pavement condition assessment and maintenance planning. This adoption has enabled more systematic and data-driven decision-making, resulting in better allocation of limited resources [41, 42]. Therefore, this software allows the MPWT decision-makers to accurately analyze road infrastructure performance and develop effective maintenance and investment strategies.

2.4.2. Calibration and Data Requirements

The HDM-4 depends on field data and independent variables, including road conditions, traffic, vehicle characteristics, and maintenance costs, in order to provide detailed insights into asset management [21]. The accuracy of HDM-4 predictions depends heavily on proper calibration. Calibration involves adjusting the model parameters to reflect local conditions, such as traffic composition, climate, and construction quality. Key data inputs required for HDM-4 include:

1. **Road Inventory**: Information on pavement type, age, and construction history.
2. **Traffic Data**: Vehicle counts, classification, and axle load distributions.
3. **Pavement Condition**: Periodic surveys measuring distress levels, roughness, and rutting.
4. **Economic Data**: Costs of maintenance activities, vehicle operating costs, and discount rates.

However, the HDM-4 calibration is necessary before utilizing the software to ensure accurate pavement performance prediction by reflecting observed deterioration rates through desk studies, verification with measured data, and long-term monitoring [37, 38, 42].

Advantages of Using HDM-4: HDM-4 provides performance metrics based on input data, making them particularly valuable for road asset management [32, 40]:

- **Detailed Cost-Benefit Analysis**: By evaluating multiple scenarios, HDM-4 helps decision-makers choose the most cost-effective maintenance strategies.
- **Long-Term Planning**: The model supports strategic planning by simulating future road network conditions and funding needs.
- **User-Friendly Interface**: HDM-4 comes with a well-documented interface that facilitates its use by practitioners and researchers alike.

- **Customizable Framework**: The ability to calibrate HDM-4 for local conditions makes it adaptable to diverse environments.

2.4.3. **Challenges and Limitations**

Despite its benefits and widespread used, in order to use HDM-4, some challenges need to be considered such as [37, 38, 40, 42] :

- **Intensive Data Requirement:** HDM-4 requires various types of data, such as road network information (including pavement inventory, condition, and type), vehicle fleet details (including classification), traffic patterns, environmental factors, and cost data (comprising operating costs and maintenance history), which can be difficult to obtain in developing countries.
- **Calibration complexity:** Proper calibration requires technical expertise and significant time investment.
- **Budget Constraints:** Implementing HDM-4 often requires substantial financial budget, which is challenging in low-income or developing countries.

2.4.4. **HDM-4 Application in Lao PDR**

In the context of Lao PDR, where budget constraints and data limitations are a challenge, HDM-4 offers significant advantages. Its ability to provide detailed cost-benefit analyses and supporting long-term planning enables decision-makers to prioritize interventions with the highest impact. HDM-4's framework also facilitates systematic data collection and management, which are crucial for improving infrastructure resilience. However, its application in Laos is not without limitations. The high data requirements and complexity of calibration processes pose challenges, particularly in regions with limited technical expertise and financial resources. Additionally, while HDM-4 provides deterministic outputs, it may not fully capture the uncertainty inherent in road deterioration, making it less adaptable to rapidly changing conditions. Integrating HDM-4 with stochastic models like MUSTEM could address these gaps by introducing probabilistic elements that enhance decision-making, particularly under uncertain and resource-constrained scenarios.

2.5. 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. [43] examined optimal repair policies using Monte Carlo simulations to minimize LCCs while improving infrastructure reliability. These authors showed the improvement in optimal intervention solution using Monte Carlo methods compared to the greedy algorithm. Similarly, Nakazato et al. [44] 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 and Mizutani. [45], 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. [46] 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. [47] and Harvey et al. [48] 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. [49] refined these approaches by enhancing a two-stage optimization framework, first at pavement segment level and secondly at 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 and Matsushima [9] 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.

2.6. International Practices and Case Studies

2.6.1. International Standards and Guidelines

International practices in road asset management provide valuable insights into how various countries have successfully developed and implemented efficient road network systems. These practices highlight the importance of adopting standardized frameworks, innovative strategies, and advanced technologies to enhance road networks' overall efficiency and sustainability.

There are many international standards and guidelines set by leading organizations, which form the backbone of modern road management systems, such as the International Road Federation (IRF), the World Bank, the Federal Highway Administration (FWHA), The American Association of State Highway and Transportation Officials (AASHTO), and the International Organization for Standard (ISO). These standards emphasize best practices for road design, construction, maintenance, and sustainability.

Key international standards in practice include:

- **International Road Federation (IRF):** The IRF provides guidelines and best practices for road asset management, emphasizing the importance of maintaining road infrastructure to ensure safety, efficiency, and sustainability. The IRF promotes the use of advanced technologies and innovative practices to enhance road maintenance and management [50].
- **The World Bank:** The World Bank has developed several frameworks and tools, such as the Highway Development and Management Model (HDM-4), which is a globally applicable model that assists countries in planning and managing their road networks. Nonetheless, HDM-4 is widely used for evaluating road investment projects, assessing maintenance strategies, and predicting road performance under different budget scenarios [51].
- **ISO Standards**: The ISO 55000 series for asset management are designed to be practical and comprehensive guidelines for managing physical assets, including road networks. These standards focus on optimizing asset performance, reducing costs, and ensuring sustainability through effective management practices. They

offer specific requirements for organizing and implementing an effective asset management system and guidance on implementing the requirements outlined in ISO 55001 [52].

- **American Association of State Highway and Transportation Officials (AASHTO)**: AASHTO offers technical standards for highway design, construction, and maintenance, ensuring consistency and safety across road projects [53].
- **Federal Highway Administration (FHWA)**: The FHWA emphasizes integrating advanced tools, such as Geographic Information Systems (GIS) and pavement management systems, to improve decision-making and enhance the efficiency of maintenance strategies [54].

2.6.2. Review of Global Practices and Case Studies

Adopting successful strategies from developed countries has significantly improved road management systems in various regions. Key lessons from these practices include:

- **Proactive Maintenance Strategies:** Developed countries such as the United States of America (USA) and the United Kingdom (UK) prioritize early intervention through routine inspections and preventive maintenance. This proactive approach reduces long-term costs, minimizes disruptions, and extends the lifespan of road assets, leading to optimal road quality and safety [55].
- **Data-Driven Decision Making**: In the Australian expressway, GIS is used to enhance data management, planning, resource allocation, and long-term maintenance activities in decision-making. This practical suggests that applying advanced tools like Geographic Information Systems (GIS) and automated road condition assessment systems has led to measurable improvements in resource allocation and cost efficiency [56].

▪ **Integration of Advanced Technologies**: Developed countries like Japan and Germany employ technologies such as remote sensing and intelligent transportation systems (ITS) to enhance road monitoring, improving traffic efficiency and maintenance panning. These technologies improve the accuracy and efficiency of road condition assessments [57, 58].

2.6.3. Conclusions

The global practices and case studies have shown several lessons for improving road network management. By embracing advanced technologies, proactive strategies, and sustainability-focused approaches, the country, particularly developing countries, can significantly improve road asset management, contributing to national development and connectivity.

The key takeaway lessons included, but were not limited to:

1. **Early intervention and proactive strategy**: Regular monitoring involves early intervention with a proactive strategy that can prevent road deterioration and extend the longevity of the road and transportation infrastructure.
2. **Technologies Integration**: Advanced technology such as GIS, online data inspection, remote sensing, and ITS can enhance the efficiency and accuracy of data analytics and predictions, enabling real-time monitoring and data-driven decision-making.
3. **Sustainable Development**: Incorporating sustainability into road management to ensure the road network is climate change resilient and environmentally friendly.
4. **Adaptability and Innovation**: Adapting other countries' best practices and innovation solutions into existing road management systems.
5. **Stakeholder Engagement**: In addition, collaboration and engagement with various stakeholders, including the public sector, private sector, education sector, and relevant stakeholders, to improve the existing road management system.

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Chapter 3

Estimation of Lao Road Network Deterioration Using the Markov Hazard Model

3. Estimation of Lao Road Network Deterioration Using the Markov Hazard Model

3.1. Introduction

The Highway Development Management Application (HDM-4) [1] is used by the Lao PDR's road maintenance management system to set priorities and allocate maintenance funds. The Laos national road network used the concept of core network level to classify the road hierarchy by different pavement structures, traffic, and environmental conditions. Three levels of the core network were introduced in order to classify the hierarchy of the national roads. The level of the core network is the key to determining inspection and maintenance frequencies. The total length of the road network in 2021 is 58,875 km and was categorized into six types: 1) National Roads, 2) Provincial Roads, 3) District Roads, 4) Urban Roads, 5) Rural Roads, and 6) Special Roads [2]. The lengths of the road network by category are shown in **Figure 3.1**.

HDM-4, which is a mechanistic model, is a tool to predict road network maintenance needs [3] . Besides, the Pavement Management System (PMS) is the Road Management System's module for optimal road maintenance in Lao PDR. However, the main objections to implementing road management system are budget constraints and limited technical resources. Furthermore, PMS is used to calculate road network deterioration and estimate maintenance needs by relating roughness to many explanatory variables such as pavement aging, surface distress, and the environment where the road is located for precise estimation, evaluate road damages based on current condition inspection data, and then allocate funding [4]. However, the number of data records is small and inspection intervals are uneven because data collection is time-consuming,

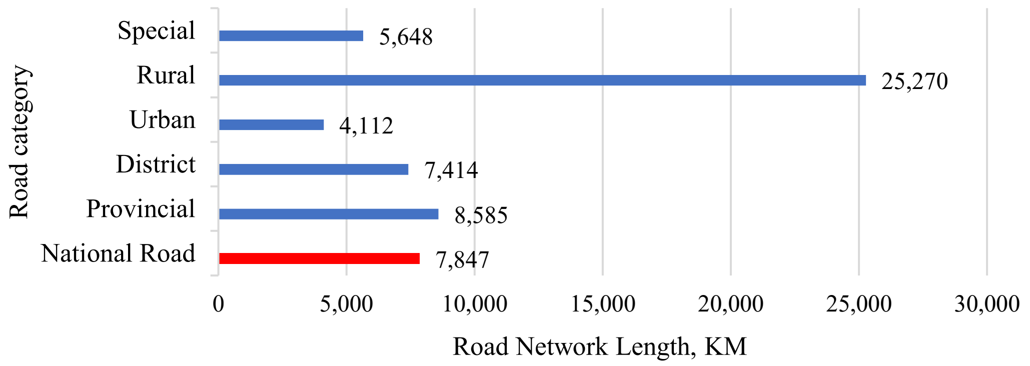

Figure 3.1 Lao PDR road network length by category in year 2021

resource-intensive, and costly, which are the major challenges for the Department of Roads (DoR) and the Ministry of Public Works and Transport (MPWT) in implementing the PMS.

The international roughness index (IRI) was introduced by researchers from the United States, Brazil, Belgium, France, and England [5]. IRI has been used globally as an indicator for evaluating the pavement quality of the road network. This research intends to construct a road deterioration forecasting model to estimate the life expectancy based on the IRI by using Markov transition probability [6]. The empirical analysis was conducted using historical inspection data from the Lao road database and covered two core networks (core networks 1, which are the ASIAN Highway network, and core network 2, which represents the National Road network) composed of 22 road sections totaling 2,769 km in length. The findings of this study will enable the road authorities (DoR, MPWT) to understand the service life expectancy of each different level of the core network and determine the best maintenance management plan, particularly for the approval of performance-based contracts for road maintenance projects.

3.2. Model Development

The Markov models have been adapted to meet the needs of various study fields and are now extensively used as a probabilistic estimation model for infrastructure performance. To estimate the Markov deterioration hazard model [7, 8] , the explanatory variables that are anticipated to be related to the rate of deterioration together with the pair of two conditions from a single point and their interval time of inspection have been acquired and collected. Therefore, past inspection data of the road network have been gathered and analyzed, and the road database has been acquired from the DoR and MPWT of Lao PDR in order to develop a road deterioration prediction model utilizing the Markov deterioration hazard model. According to a time series, the condition state of each road section is designated in a rank order. In order to compare the lifespan of each type of pavement, the 2,769 km road section condition data has been collected and categorized.

3.2.1. Markov Deterioration Hazard Model Estimation

The following presumptions are required in order to satisfy the Markov deterioration hazard model [9]:

1. No maintenance or restoration projects were required throughout the inspection period.
2. The deterioration of the road surface begins as soon as it is made available to the public at time τ_0.

The deterioration of road sections is accumulated in time series. It is expressed in terms of calendar time by $\tau_1, \tau_2, \tau_3, \ldots . \tau_i$ and the condition state is increased in unitary unit, the condition state at each point in the time axis is restricted by the time the inspection was carried out as shown in Figure 2, τ represent a calendar time and condition state expressed by a rank represents a state variable $i(i = 1, 2, \ldots., j)$ where $i = 1$ represents a section that has not deteriorated at all (in good condition), and the state variable value j is assumed to increase as deterioration progresses. Where $i = j$ indicates that a section has reached its service life (absorbing state of the Markov chain which requires maintenance activities)

The information on the periodic deterioration process of the road section is derived at the time of inspections. However, data on condition state based on continuous inspection is difficult to obtain due to the high cost, time, and resources required. Therefore, the Markov chain concept, it is assumed that the pavement conditions are discrete condition states. This model considers two periodical inspections at time $\tau_A\ and\ \tau_B$ on the time axis which its interval is denoted by $Z(Z = \tau_B - \tau_A)$ and the duration from $i = 1\ to\ i = j$ is called the life expectancy of the road sections. Based on these definitions, we can determine the Markov transition probability matrix (MTP) [10] or $\prod$ which composed of probability π_{ij} with the preconditions that $\pi_{ij} \geq 0$ and $\sum_{j=1}^{J} \pi_{ij} = 1$ are required to satisfy the axioms of probability, since the model does not consider repairs, $\pi_{ij} = 0(i > j)$ and $\pi_{ij} = 1$ become additional preconditions.

$$\text{Prob}[h(\tau_B) = j | h(\tau_A) = i] = \pi_{ij} \tag{3.1}$$

$$\prod = \begin{bmatrix} \pi_{11} & \cdots & \pi_{12} \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \pi_{jj} \end{bmatrix} \tag{3.2}$$

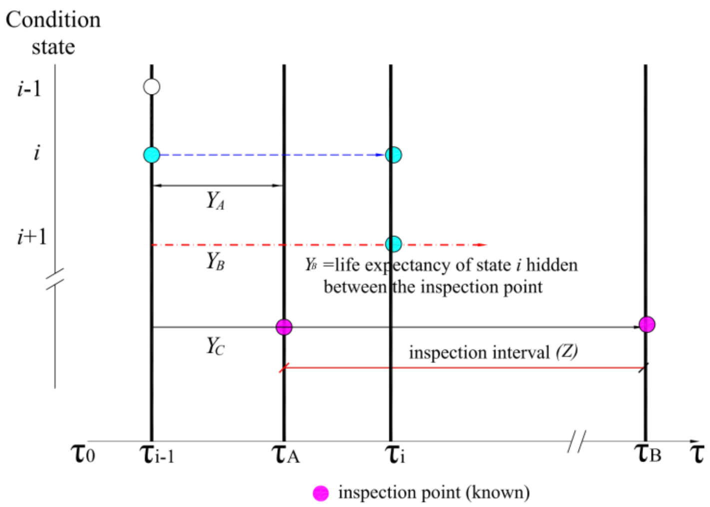

Figure 3.2 Deterioration process and inspection times [7, 8].

In **Figure 3.2**, it is supposed that at time τ_A, the condition state observed by inspection is i (i=1, 2, ..J-1). The deterioration process in future times is uncertain. Among the infinite set of possible scenarios describing the deterioration path, only one path is finally realized.

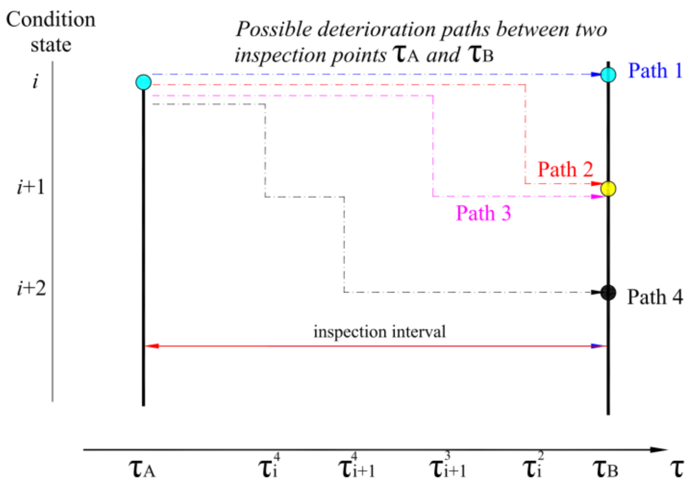

Figure 3.3 Condition states and possible paths [7, 8].

For simplicity, there are four possible sample paths described in **Figure 3.3**, as follows [8] :

- Path 1 indicates no transition in the condition state i during the periodic inspection interval.
- Path 2 indicates the transition of the pavement from condition state i to $i+1$ at time τ_i^2.
- Path 3 indicates the transition of the pavement from condition state i to $i+1$ at time τ_i^3.
- Path 4 indicates the transition of the pavement from condition state i to $i+1$ and $i+2$ at time τ_i^4 and τ_{i+1}^4 respectively. The condition state observed at τ_B is $i+2$

Referring to Tsuda et al (2006) [8] in **Figure 3.2**, the deterioration paths of the road pavement condition by the Markov chain concept are expressed, when deterioration status changes from i to $i+1$ at τ_i, the duration remains at status i can be expressed by $\zeta_i(\zeta_i = \tau_i - \tau_{i-1})$. The life expectancy of a condition state i is assumed to be a stochastic variable with a probability density function $f_i(\zeta_i)$ and distribution function $F_i(\zeta_i)$. The distribution function $F_i(\zeta_i)$ represents the cumulative probability of the transition in the condition state for i to $i+1$ when i is set at the initial point $y_i = 0$ (time τ_{i-1}). The cumulative probability $F_i(y_i)$ of a transition in the condition state i during the time points interval $y_i = 0$ to $y_i \in [0, \infty]$ is defined as:

$$F_i(y_i) = \int_0^{y_i} f_i\ (\zeta_i) d\zeta_i \tag{3.3}$$

Accordingly, the survival function $R_i(y_i)$ becomes $R_i(y_i) = prob\{(\zeta_i \geq y_i\} = 1 - F_i(y_i)$. The deteriorating process that satisfies the Markov property can be represented by the exponential hazard function. The probability density $\lambda_i(y_i)$, which is referred to as the hazard function, is defined in the domain [0, ∞] as:

$$\lambda_i(y_i) = \frac{f_i(y_i)}{R_i(y_i)} = \frac{\frac{dR_i(y_i)}{dy_i}}{R_i(y_i)} = \frac{e}{dy_i}(-logR_i(y_i)) \tag{3.4}$$

By hazard function $\lambda_i(y_i) = \theta_i$, the probability $R_i(y_i)$ that the life expectancy of the condition state i remains longer than y_i and its probability density function $f_i(\zeta_i)$ are expressed by the following:

$$R_i(y_i) = exp\left[-\int_0^{y_i} \lambda_i(u)du\right] = exp\,(-\theta_i y_i) \tag{3.5}$$

$$f_i(\zeta_i) = \theta_i exp\,(-\theta_i \zeta_i) \tag{3.6}$$

3.2.2. Determination of Markov Transition Probability

Again, in **Figure 3** the various deterioration paths are classified into $\pi_{ii}, \pi_{i,i+1}, \pi_{i,i+2}, and\ \pi_{ij}$. The Markov transition probabilities for these possible paths are based on the exponential hazard model can be explained for the three cases considering the condition state observed at periodic inspection time point as shown in **Figure 3.4**.

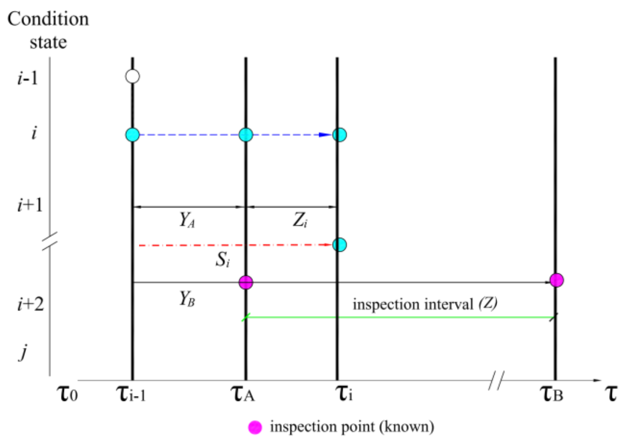

Figure 3.4 Periodic inspection practice of the condition state.

- **Case 1:** The condition state i keeping the current condition until the next inspection time

The condition state i obtain by inspection at time point y_A, the probability that the same state condition will be observe at the time point $y_B = (y_A + Z)$ is expressed by the following:

$$\pi_{ii} = Prob[h(\mathrm{y_B} = i|h(\mathrm{y_A}) = 1] = \exp(-\theta_i Z) \tag{3.7a}$$

Eq (7a), π_{ii} is dependent only on the hazard rate (θ_i) and inspection interval (Z).

Moreover, without using deterministic information at the time point $\mathrm{y_A}$ *and* $\mathrm{y_B}$, it is still possible to estimate the transition probabilities.

- **Case 2:** The condition state changes from i *to* $i+1$ during the inspection interval Z.

For the condition state i observed at inspection time point $\mathrm{y_A}$ changes to condition state $i+1$ at time point $\mathrm{y_B}$, the transition is assumed by exponential hazard function as: 1) the condition state i remain constant between a time point $\mathrm{y_A}$ to a time point s_i=$\mathrm{y_A}$+z_i, ($z_i \in [0, Z]$), 2) the condition state changes to $i+1$ at time point $\mathrm{y_A} + z_i$, and 3) the condition remain constant from $\mathrm{y_A} + z_i$ *and* $\mathrm{y_B}$. However, the exact time in which transition from i *to* $i+1$ cannot be trace by periodical inspection, and it can be temporally assumed that the transition occurs at the time point $(\mathrm{y_A} + \bar{z}_i) \in [\mathrm{y_A}, \mathrm{y_B})$. The Markovian transition probability that the condition state change from i to $i+1$ during the time points $\mathrm{y_A}$ and $\mathrm{y_B}$ is expressed by:

$$\pi_{i\,i+1} = Prob[h(y_B) = i+1 \mid h(y_A) = i]$$

$$\pi_{i\,i+1} = \frac{\theta_i}{\theta_i - \theta_{i+1}}\{-\exp(-\theta_i Z) + \exp(-\theta_{i+1} Z)\} \tag{3.7b}$$

Where, $\pi_{i,i+1} < 1$.

- **Case 3:** The condition state changes from i *to* $j (j \geq i+2)$ during the inspection interval time Z.

The transition from the condition state from i *to* j during the inspection time interval Z, the transition is assumed to occur as 1) the condition state i remains constant between a time point $\mathrm{y_A}$, $\bar{s}_i$= $\mathrm{y_A}$+$\bar{z}_i \in [\mathrm{y_A}, \mathrm{y_B}]$, 2) the condition state changes to $i+1$ at the time point $\bar{s}_1$= $\mathrm{y_A}$+$\bar{z}_1$, 3) the condition state $i+1$ remains constant during the time interval $\bar{s}_i = y_A + \bar{z}_i$, $\bar{s}_{i+1} = \bar{s}_i + \bar{z}_{i+1}$ ($\leq y_B$), and at this time point changes to $i + 2$. After repeating the same process 4) the condition state changes to j at some time point $\bar{s}_{j-1}$($\leq y_B$) remains constant until the time point y_B.

Therefore, the Markov transition probability changes from i to $j (j \geq i + 2)$ during the inspection time y_A and y_B is expressed by:

$$\pi_{ii} = Prob[h(y_B = j | h(y_A) = i]$$

$$\pi_{ij} = \sum_{k=i}^{j} \prod_{m=i}^{k-1} \frac{\theta_m}{\theta_m - \theta_k} \prod_{m=k}^{j-1} \frac{\theta_m}{\theta_{m+1} - \theta_k} exp(-\theta_k Z) \quad (3.7c)$$

where:

$$\prod_{m=i}^{k-1} \frac{\theta_m}{\theta_m - \theta_k} = 1, \text{at } (k \leq i + 1) \; and \; \prod_{m=k}^{j-1} \frac{\theta_m}{\theta_{m+1} - \theta_k} = 1 \text{ at } (k \geq j)$$

In equation (7c), π_{ij} $[0 < \pi_{ij} < 1]$, and π_{iJ} is arranged using the Markov transition probabilities conditions as follows:

$$\pi_{iJ} = 1 - \sum_{j=1}^{j-1} \pi_{ij} \quad (3.7d)$$

From equation (7a) - (7d), the Markov transition probability depend on the inspection interval Z. The Markov transition probability is expressed as $\pi_{iJ}(Z)$, Therefore, the transition probability matrix related to the inspection interval Z is expressed as follows

$$\prod(Z) = \begin{bmatrix} \pi_{11}(Z) & \cdots & \pi_{12}(Z) \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \pi_{jj}(Z) \end{bmatrix} \quad (3.8)$$

The MTP matrices $\prod(Z)$ and $\prod(nZ)$ describe the same deterioration process for two different intervals for an integer value n two inspection intervals (Z) and (nZ). Therefore, the MPT $\prod(nZ)$ is expressed as $\{\prod(Z)\}^n$ as the time adjustment condition of the MTP.

In equation (7), the multistage exponential hazard model has been defined. However, considering the explanatory variable to estimate hazard rate θ_i which is defined as the function of explanatory variables x^k and unknown parameters β_i. where $\beta_i = (\beta_{i,1},\ldots, \beta_{i,M})$, M (m=1,…..,M) is the number of explanatory variable and k(k=1,….K) is an individual sample of inspection data.

$$\theta_i^k = f(x^k : \beta_i) \tag{3.9}$$

In summary, the elements of the MTP matrix π_{iJ} are estimated using $\pi_{iJ}(Z^k, x^k : \beta_i)$. The unknown parameter $\beta_i (i=1,\ldots,J-1)$ is determined with Bayesian estimation method to obtain the hazard function θ_i^k (i =1,…..,J-1), the life expectancy of each condition state i can be defined by means of the survival function $R_i(y_i^k)$ [11].

$$LE_i^k \int_0^\infty \exp(-\theta_i^k y_i^k) dy_i^k = \frac{1}{\theta_i^k} \tag{3.10}$$

Life expectancy from i to J can be estimated using

$$\sum_{i=1}^{J-1} LE_i^k \tag{3.11}$$

For detailed description, it is recommended to refer to Tsuda et al (2016) [8].

3.2.3. Application of Bayesian Estimation for the Markov Hazard Model.

Because the classic Markov chain using the maximum likelihood estimation frequently fails to converge for a variety of reasons [7], the initial values of the parameters are frequently crucial [12]. Therefore, the Bayesian estimator is used to get around those issues, the Bayesian estimation is an iterative approach to statistical inference that uses data and prior knowledge to estimate the model's parameters. Bayesian estimation can be very helpful in the setting of a Markov deterioration hazard model to estimate the unknown parameter β_i(i=1, .., J-1). Bayesian estimation can be defined by 3 processes:

1. define the prior probability distribution $\pi(\beta)$,
2. define the likelihood function $L(\beta|\xi)$ by applying newly obtained data $\bar{\xi}$, and
3. modify the prior distribution $\pi(\beta)$ using Bayes' theorem and then update the posterior distribution $\pi(\beta|\xi)$ for parameter (β).

However, the normalizing constant $L(\bar{\xi})=\int L(\beta|\bar{\xi}) \prod_{i=1}^{j-1} g(\beta_i|\mu_i, \Sigma_i)d\beta$ is difficult to calculate. Therefore, we directly extract the statistical value for the posterior distribution of parameters using the Metropolis-Hastings algorithm, also known as the M-H algorithm [13, 14], in the Markov chain Monte Carlo (MCMC) simulation. The M-H algorithm procedure is explained below:

1. Define initial value of parameter vector $\beta(0)$.
2. Calculate current probability density $\pi(\beta(n))$ by using current $\beta(n)$.
3. Find a candidate value as $\tilde{\beta}(n) = \beta(n) + \varepsilon(n) \sim N(0,\sigma^2)$ where ε is the step width of the random walks.
4. Calculate the proposal density by using $\tilde{\beta}(n)$ as a candidate parameter $\pi\left(\tilde{\beta}(n)\right)$.
5. Apply the updating rule by comparing $\pi(\tilde{\beta}(n))$ and $\pi(\beta(n))$ with the following conditions

$$\beta(n+1) = \begin{cases} \pi\left(\tilde{\beta}(n)\right) > \pi(\beta(n)), & \beta(n+1) = \tilde{\beta}(n) \\ \pi\left(\tilde{\beta}(n)\right) \le \pi(\beta(n)), \begin{cases} R \le r, \\ \text{Otherwise}, \end{cases} & \begin{array}{l} \beta(n+1) = \tilde{\beta}(n) \\ \beta(n+1) = \beta(n) \end{array} \end{cases} \tag{3.12}$$

Where, $r = \pi\left(\tilde{\beta}(n)\right)/\pi(\beta(n))$, and R is a standard uniform for $R \sim U(0,1)$

6. Do sufficiently large numbers of iterations from step 2 to step 5, until sequence β^{n} becomes a stationary condition (that is close to convergence).
7. Cut burn-in samples and take the average of sample parameters.

The MCMC does not include any method to confirms that the initial value $\beta(0)$ reaches stationary distribution. Therefore, the Geweke's test is utilized to determine whether the Markov chain reaches convergence [15]. Refer to the following reference for a full explanation of the M-H method and the Geweke's test to verify the Markov chain's convergence [7].

3.3. Data Processing

The historical inspection data from the Lao RMS was inquired and examined following the model's estimation. Data inspection from the Lao RMS database for the years 2014–2016 and 2020 was obtained. However, it was difficult to attain the maintenance history from 2016–2020 and the conditions in 2020 being almost as good as those in 2016. Therefore, only the dataset from 2014–2016 has been used. Pavement materials, the IRI, and average annual daily traffic (AADT) are the only available data that have been gathered and analyzed because environmental uncertainty parameters like weather, rainfall, etc. have not been sufficiently covered by data collection. Without taking any maintenance action, the aberrant condition examined under improved conditions has been evaluated and checked [6]. According to the DoR, MPWT Lao PDR classification, two core road networks (core networks 1 and 2) are evaluated. The model's basic tenet is to anticipate the target core networks' life expectancy, IRI degradation process, and hazard rate in relation to the Lao road network's deterioration process.

The collected IRI data was used to calibrate the Markov model. The IRI data has been derived from periodic inspections since 2014–2016. In order to measure the IRI, the Dynamic Response Vehicle Intelligent Monitoring System equipment, which was supported by the Japan International Cooperation Agency (JICA) in 2012, has been used. The IRI was measured at a speed of around 80 km/h for each segment of 100 meters [16, 17]. The IRI circumstances are then classified into five groups based on preset criteria for roughness sufficiency [18] in order to estimate the Markov transition probability based on the exponential hazard model, according to **Table 3.1**. The IRI roughness scale, which ranks the conditions from excellent to failed (absorption state), indicates the need for maintenance or rehabilitation activities.

Table 3.1 The IRI Roughness Scale (condition state)

Pavement condition (State)	Excel/Good (1)	Fair (2)	Poor (3)	Bad (4)	Failed (5)
IRI (m/km)	IRI ≤ 3	3<IRI≤5	5<IRI≤7	7<IRI≤9	9 < IRI

After rejecting the incorrect information, the atypical condition, the data of road sections was divided into two core networks based on the definition and classification from DoR and MPWT. The total length was 2,769 km, or 35.29% of the total 7,847 km (national road network length), as presented in **Table 3.2**.

Table 3.2 Summary of data observation and variables

Core network	No. of routes	Total length of observations (km)	Number of sample (pairs)	Explanatory Variables	Length of AC/ST (km)
Core 1	8	1,900	18998	AADT, Road surface (AC/ST) *	778/1,122
Core 2	14	869	8690	AADT, Road surface (AC/ST)	50/819

*AC=Asphalt concrete; ST=Surface treatment

Asphalt concrete pavement and surface treatment (single and double bituminous) are the two main types of pavements. The traffic volume is gathered from the number of vehicles passing the counting location in each road section. The methodology for counting is either automatic or manual (by the traffic count form), and the vehicles are classified into 14 classes in order to apply the adjustment factors [19]. A number of adjustment factors are related to classified traffic counts to derive the average annual daily traffic. To normalize the traffic volume, the AADT has been classified into 3 bands: low, medium (mean), and high, as shown in **Table 3.3**.

Table 3.3 Traffic band classification

Band	From (AADT)	To (AADT)
Low	0	500
Mean	501	2000
High	2001	99999

3.4. Model Application and Results

The transition probability matrix of Core Networks 1, 2 were determined using the Markov Deterioration Hazard Model. The MTP for Core Networks 1 and 2 are shown in **Tables 3.4**, and **Table 3.5** respectively.

Table 3.4 MTP of the Core Network 1

State	1	2	3	4	5
1	0.487	0.442	0.063	0.006	0.002
2	0	0.761	0.203	0.026	0.010
3	0	0	0.732	0.167	0.101
4	0	0	0	0.378	0.622
5	0	0	0	0	1.000

Table 3.5 MTP of the Core Network 2

State	1	2	3	4	5
1	0.342	0.529	0.110	0.016	0.003
2	0	0.683	0.254	0.051	0.012
3	0	0	0.652	0.254	0.094
4	0	0	0	0.539	0.461
5	0	0	0	0	1.000

As a result of Tables 3.4 and Table 3.5, the transition probability in states 1-1, 2-2, and 3-3 shows that the core network 1 has a higher transition probability compared to the core network 2, meaning that the core network 1 will deteriorate more slowly than the core network 2, which in turn leads to a longer life expectancy.

The road network's hazard rate (deterioration rate) and interval life expectancy of each condition state of core networks 1 and 2 are computed using equations (10) and (11), the results are shown in **Tables 3.6** and **Table 3.7**:

Table 3.6 IRI mean hazard rate (θ_i) and life expectancy (LE_i) of Core Network 1

State	Mean hazard rate (θ_i)	Hazard rate (θ_i) (ST)	Hazard rate (θ_i) (AC)	LE_i (Year) (AV)	LE_i (Year) (ST)	LE_i (Year) (AC)
1-2	0.758	0.994	0.513	1.32	1.01	1.95
2-3	0.273	0.303	0.234	4.99	4.31	6.21
3-4	0.422	0.422	0.422	7.36	6.68	8.58
4-5	1.525	1.525	1.525	8.01	7.34	9.24

Table 3.7 IRI mean hazard rate (θ_i) and life expectancy (LE_i) of Core Network 2

State	Mean hazard rate (θ_i)	Hazard rate (θ_i) (ST)	Hazard rate (θ_i) (AC)	LE_i (Year) (AV)	LE_i (Year) (ST)	LE_i (Year) (AC)
1-2	1.682	1.774	0.700	0.59	0.56	1.43
2-3	0.909	0.912	0.870	1.69	1.66	2.58
3-4	0.465	0.465	0.465	3.85	3.81	4.73
4-5	0.584	0.584	0.584	5.56	5.52	6.44

The estimation results for the unknown parameters, which indicates the statistic properties (coefficient) of the explanatory variables of each parameters (traffic and surface pavement), and Geweke's z score, which verifies the convergence (stationary distribution) of the parameter [15], are shown in **Tables 3.8** and **Table 3.9** as follows:

Table 3.8 Unknown parameter and Geweke's test of Core Network 1

State	(β_{i0}) Absolute	(β_{i1}) Traffic	(β_{i2}) Pavement
1-2	-0.006 (-0.706)	-	-0.660 (0.918)
2-3	-1.251 (-0.699)	0.278 (0.864)	-0.255 (-0.585)
3-4	-0.863 (0.900)	-	-
4-5	0.422 (1.760)	-	-

The Geweke diagnostic values are stated in the parentheses

Table 3.9 Unknown parameter and Geweke's test of Core Network 2

State	(β_{i0}) Absolute	(β_{i1}) Traffic	(β_{i2}) Pavement
1-2	0.573 (0.863)	-	-0.930 (-1.527)
2-3	-0.092 (0.723)	-	-0.047 (0.507)
3-4	-0.766 (1.390)	-	-
4-5	-0.620 (-0.047)	0.241 (0.147)	-

The Geweke diagnostic values are stated in the parentheses

In **Table 3.8**, the β_{i1} indicate that the traffic volume had a significant impact on deterioration rate in condition 2-3. Higher traffic leads to faster deterioration rate. In order to verify the chain convergence, Geweke's test value for all β values should fall between the range [-1.96,1.96], where a value of 0 denotes perfect convergence. Additionally, the positive β values mean traffic strongly impacts the deterioration rate in Condition State 2 for ASIAN network and Condition State 4 for National network (**Table 3.9**). Consequently, higher traffic on ASIAN network significantly contributes to faster deterioration. However, thicker and stronger AC road sections exhibit a longer lifespan, hence the negative β values. Other β values were excluded due to sign restrictions.

The expected degradation path (deterioration processes) for 2 core networks is illustrated in **Figures 3.5 (a, b)** and **Figure 3.6 (a, b)** as a graph, describing the typical deterioration process over the duration of the core networks' life expectancy condition states from the starting state (excellent condition) to the absorption stage by time order in years.

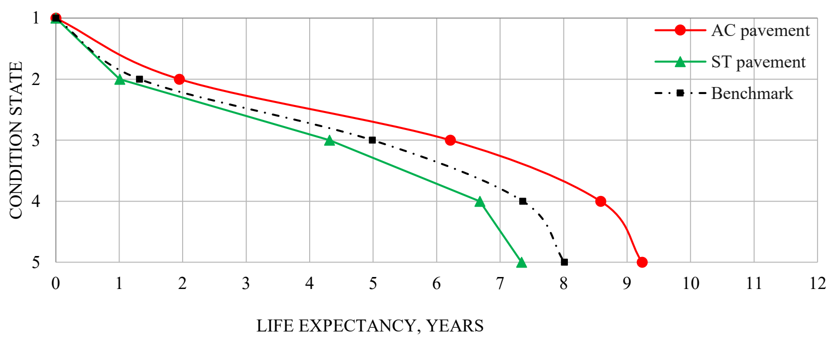

Figure 3.5a Life expectancy of pavement types (AC, ST) for Core Network 1

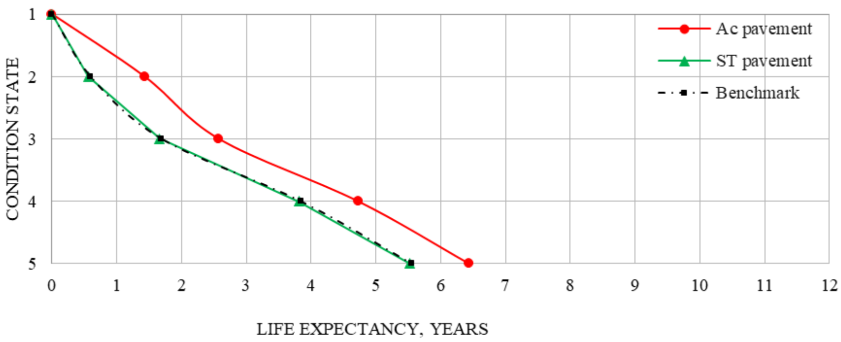

Figure 3.5b Life expectancy of pavement types (AC, ST) for Core Network 2

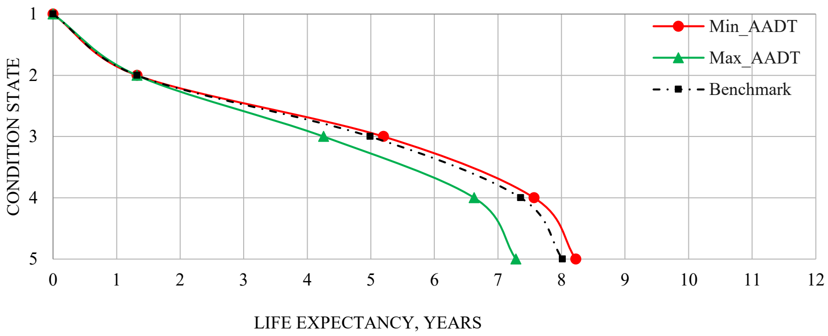

Figure 3.6a Life expectancy considering traffic volume (Min AADT, Max AADT) for Core Network 1

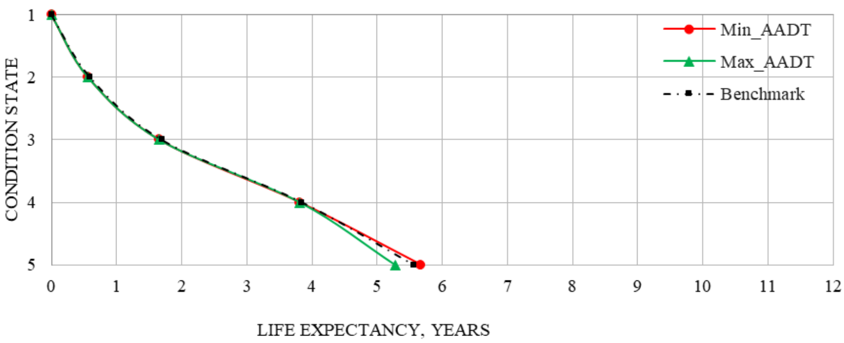

Figure 3.6b Life expectancy considering traffic volume (Min AADT, Max AADT) for Core Network 2

3.5. Discussion

While an extensive and high-quality Lao RMS database is necessary for validating the results, the life expectancies of the two networks were shorter than the expected design life, which is about 10-20 years from the design life manual [20]. This implication was probably due to the explanatory variables or the quality of the dataset. However, other researchers performed validation of the model [7-9, 21], which may point to the model being robust enough to generate acceptable estimates, Han et al., (2014) [7] validated the model by comparing its predictions with an accumulated dataset spanning eight years and confirmed its reliability. The results of the empirical study were based on historical inspection data gathered by the Lao RMS from 2014 to 2016. In other words, this study examined only three years deterioration trend of the Lao road network by using IRI data from Lao RMS. Due to financial and technical limitations of the Department of Road, MPWT, part of the Lao Road Authority aims to collect data on the condition state of the road network in 2024, the final year of the current long-term maintenance financial plan 2016–2025. They were unable to conduct the inspection every year; hence, some years' data were omitted. Due to incomplete data, the traffic volume sample data led to a convergence issue due to the number of observations and the difficulty in identifying the precise location of the traffic on specific road sections. However, the outcomes indicated that the two significant core road networks had different life expectancies considering traffic volume and pavement parameters; the deterioration process of network 1 was estimated to take 8.01 years on average, whereas network 2 was estimated to last for only 5.56 years.

When the life expectancy was analyzed based on traffic volume (AADT), differences in life expectancies in AADT were revealed (Figure 3.6a and Figure 3.6b). The sections with low AADT showed a much higher life expectancy of 8.23 and 5.67 years for Core Network 1 and 2, respectively. On the other hand, the maximum AADT sections deteriorated faster and brought down the life expectancy to around 7.28 and 5.27 years, respectively. Furthermore, the life expectancy of the AC pavement road section in network 1 was 9.24 years, while that in network 2 was 6.44 years (Figure 3.5a and Figure 3.5b). Due to the ST pavement road section being the majority portion of the road network, both networks 1 and 2. Therefore, the predicted life expectancy of the ST pavement road section was nearly the same as the life expectancy of the whole networks 1 and 2 (average), which were 7.34 and 5.52 years, respectively. However, the life expectancies of two core road networks in this research were evaluated using only the traffic and pavement type parameters, which may not be the only factors that affect the deterioration process of the two road networks in Lao PDR. The results, which indicate the transition year, can be used to evaluate the maintenance plans of each network in order to restore their condition. Moreover, it gives the road decision-maker time for intervention in terms of the maintenance plan.

3.6. Conclusions

Understanding the lifespan of infrastructure is essential for asset management planning and prioritizing maintenance activities. The Markov deterioration hazard model was used to forecast the deterioration of the road network in Lao PDR because this is an essential step before carrying out infrastructure planning. The estimated life expectancy of the core network 1 and core network 2 in the Lao road network shown in Tables 3.6 and Table 3.7, respectively, using the IRI data in the historical inspection dataset from RMS, is an essential prerequisite to maintenance planning for the two road groups. The decision maker could use this information to determine the maintenance frequency and prioritization at the network level. However, this study has only taken into account the traffic volume AADT and pavement type variables to predict the deterioration process because of the incomplete Lao RMS data sets. Nonetheless, some critical parameters, such as the commercial vehicle weight, the Pavement Structure Number (pavement strength), and other uncertain environmental variables, such as rainfall, temperature, and terrain, should be taken into account for better prediction. Therefore, in future studies, these significant parameters should be collected and included in the model in order to generate more precise information that can be used for prioritization and allocation of the maintenance fund.

Furthermore, in the interest of developing the unpaved road network, other key performance measures, such as the Surface Integrity Index (SII), which is used to evaluate the condition of unpaved roads, should be considered in the future. However, the results from this study will assist in improving the PMS, which will be utilized to determine the performance-based contract for upcoming road maintenance projects in Lao PDR.

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Chapter 4
Asian and National Road Network Optimization

4. Asian and National Road Network Optimization

4.1. 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 4.1 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.

4.2. 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].

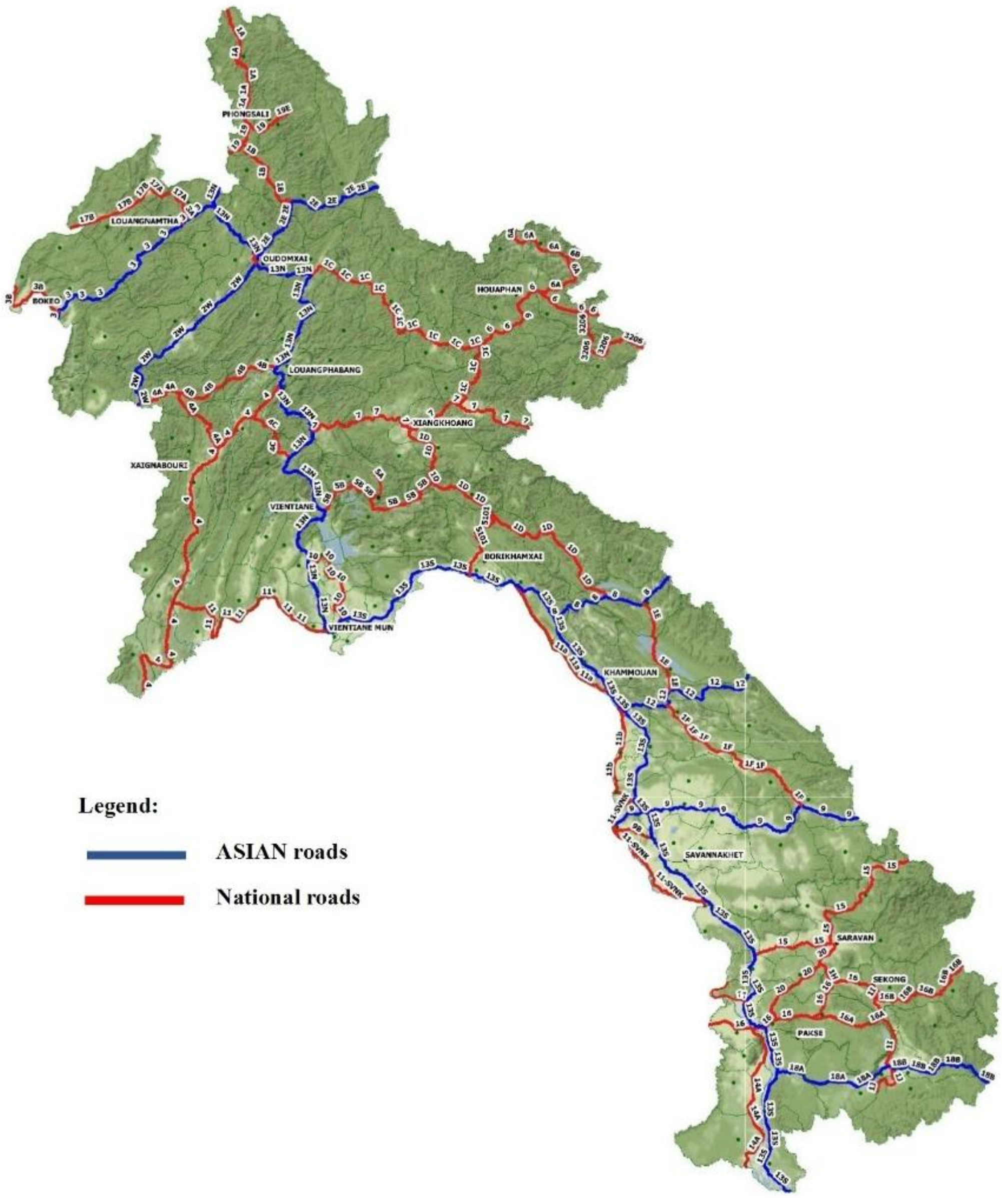


Figure 4.1 ASIAN highways and National roads in Lao PDR

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

4.3. 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.

4.4. Model Framework Development

4.4.1. Markov Decision Process

MDP is a model 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 [9, 10]. In this process, a road agency makes decisions based on the condition of a road at each time step and selects an action to implement. The road's 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 [9]. 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 [9, 11].

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

Figure 2 illustrates the general diagram of the model framework, which includes defining the network, estimating Markov Transition Probability (MTP), 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

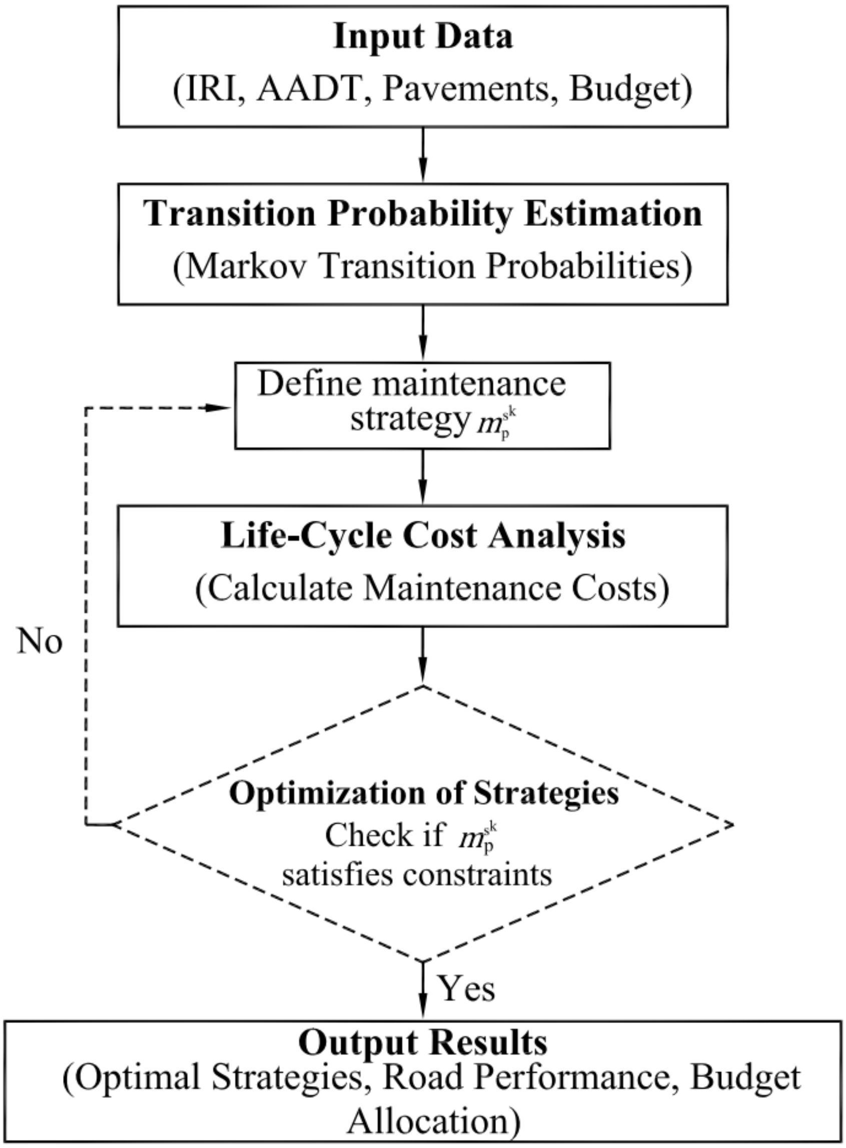


Figure 4.2 Stochastic optimizing framework for Laos RMS

4.4.2. 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 $t + Z$ [12, 13]. The probability of this transition is:

$$\text{Prob}\ [h(t) = j | h(t+Z) = i] = \pi_{ij} \tag{4.1}$$

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

$$\pi_{ij} = \sum_{\tilde{k}=i}^{j} \prod_{\tilde{m}=i}^{\tilde{k}-1} \frac{\theta_{\tilde{m}}}{\theta_{\tilde{m}} - \theta_{\tilde{k}}} \prod_{\tilde{m}=\tilde{k}}^{j-1} \frac{\theta_{\tilde{m}}}{\theta_{\tilde{m}+1} - \theta_{\tilde{k}}} \exp(-\theta_{\tilde{k}} Z) \tag{4.2}$$

where θ 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)

$$\prod = \begin{bmatrix} \pi_{11} & \cdots & \pi_{12} \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \pi_{JJ} \end{bmatrix} \tag{4.3}$$

To satisfy the Markov chain property, the following assumptions are required:

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

$$\theta_i^k = f(x^k : \beta_i) = \exp(x^k \beta_i') \qquad (i = 1, \dots, J-1) \tag{4.4}$$

The unknown parameters $\beta_i (i = 1, \dots, J-1)$ can be determined using an iterative method like Newton's method or through Bayesian estimation [14, 15].

The life expectancy LE_i^k in each condition state i can be defined by means of a survival function [16].

$$LE_i^k = \frac{1}{\theta_i^k} \tag{4.5}$$

The life expectancy from i to J can be estimated as $\sum_{i=1}^{J-1} LE_i^k$, and the deterioration curve is attained by the relation of life expectancies. For a detailed description of MTP derivation, it is recommended to refer to Tsuda et.al [12].

4.4.3. 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 [17, 18]. At the end of the planning period, time T, reconstruction R_{J-1} is considered for all sections. **Figure. 4.3** illustrates the correspondence between intervention and uncertainty. Once action is taken, pavement condition state i is assumed to improve to $\hat{\imath}$. This improvement is denoted by i_{rep}.

$$i_{rep} = \begin{cases} i & \text{if } R_0 \text{ (no action)} \\ \hat{\imath} & \text{otherwise } (R_1, R_2, R_3, \dots, R_{J-1}) \end{cases} \quad (i = 1, \dots, J) \tag{4.6}$$

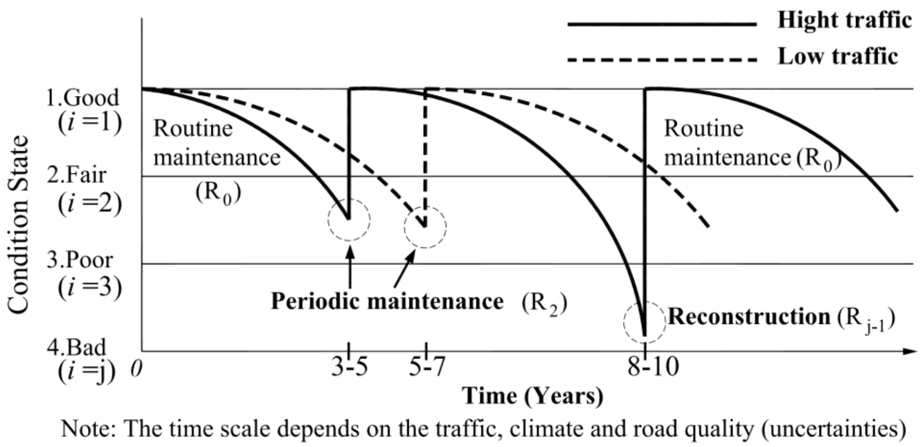


Figure 4.3 Correspondence between interventions and uncertainty

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 condition state into groups $k(k = 1, \ldots \ldots K)$ with pavement sections $s^k(s^k = 1, \ldots S^k)$. The intervention strategy $\boldsymbol{m}_{\boldsymbol{p}}^{\boldsymbol{s^k}}(\boldsymbol{m}_{\boldsymbol{R\leftrightarrow i}}^{\boldsymbol{s^k}}, Z^{s^k})$ is a set of repair actions done in correspondence to condition $\boldsymbol{m}_{\boldsymbol{R\leftrightarrow i}}^{\boldsymbol{s^k}} = (R_0^{s^k} \leftrightarrow 1, \ldots\ldots R_{i-1}^{s^k} \leftrightarrow i)$ and inspection intervals $Z^{s^k} = (Z_1^{s^k}, \ldots\ldots Z_T^{s^k})$ [18].

Table 4.1 Repair actions, correspondence costs, and condition after intervention.

Condition state, $\boldsymbol{i}$	Repair actions consideration	Correspondence Costs	Condition state after repair, $\hat{\boldsymbol{\imath}}$
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
…	…	…	…
$\boldsymbol{J}$	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

Table 4.1 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.

$$C_{R_0} \leq C_{R_1} \leq C_{R_2} \leq \cdots \leq C_{R_{J-1}} \tag{4.7}$$

4.4.4. Repair Transition Probability

The transition probability will be modified when a road section is maintained because the pavement system has become newer. The MTP matrix will be multiplied with an intervention matrix P_{rep}. The elements of the J x J matrix is denoted as $\pi_{ij}^{rep} = (i = 1, \ldots J), (j = 1, \ldots J)$. In case of no repair or intervention, the matrix will be 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.

$$P_{rep} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{4.8}$$

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

$$\pi_{ij}^{rep} = \begin{cases} 1 & if\ i_{rep} = \hat{\imath} \\ 0 & otherwise \end{cases} \quad (i = 1, \ldots J) \tag{4.9}$$

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

$$P_{trans} = \prod(Z) * P_{rep} \tag{4.10}$$

4.4.5. 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 [19]. MDPs can be solved with a diversity of algorithms such as value iteration, policy iteration, and Monte Carlo methods [20]. This study optimizes the agency costs estimated from exogenously set strategies. The intervention costs referred to Obunguta, F. and K. Matsushima [18], for each pavement section can be expressed as

$$V_i^{t,s^k} = (1+\rho^r)^{-t} * \pi_{ij}^{trans} * C_{R\leftrightarrow i}^{t,s^k} \tag{4.11}$$

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

4.4.6. Optimization Process

The LCCs of each intervention strategy are the summation of all agency costs for all sections $s^k(s^k = 1, \dots, S^k)$ assuming the salvage value at T, $C_v^{s^k} = 0$ [17, 18].

$$LCC = \sum_{t=0}^{T} \sum_{s^k=1}^{s^k} \sum_{i=1}^{J} V_i^{t,s^k} \tag{4.12}$$

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

$$\min_{\boldsymbol{m_{p\leftrightarrow i}^{t,s^k}},\, \boldsymbol{Z}^{s^k}} LCC \quad (i = 1, \dots, J) \tag{4.13}$$

subject to

$$\sum_{k=1}^{K} \sum_{s^k=1}^{s^k} C_{R\leftrightarrow i}^{t,s^k} \in \Omega_t \qquad \forall t \tag{4.14}$$

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

The optimization problem was solved using the greedy algorithm [21, 22]. The priority was given to the sections in worse condition.

4.4.7. Road Network Condition Estimation

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

$$CS_{t+Z} = p(Z) * CS_t \tag{4.15}$$

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 will inform the decision-making process for selecting the most appropriate intervention strategy, especially when faced with budget constraints.

$$V_i^{*t,s^k} = CS_{t+Z}^{*} * C_{R\leftrightarrow i}^{t,s^k} \tag{4.16}$$

subject to

$$CS_{t+Z}^{*} = p(Z)^{-1} * CS_t \tag{4.17}$$

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.

4.5. Empirical Study

4.5.1. 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 4.2**.

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 to generate adjustment factors for deriving AADT [23].

Table 4.2 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

4.5.2. Classification of Condition States

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 [24, 25].

To estimate MTP, the IRI was classified into five condition states [26]. This thorough classification process ensures the accuracy of the results. **Table 3** shows the number of sections per condition state for each network in the datasets.

Table 4.3 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

4.5.3. 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 were carried out with the Markov Chain Monte Caro (MCMC) method using the Metropolis-Hastings (MH) algorithm [27, 28]. The unknown β parameters converged and life expectancy of two networks are shown in Table 4. To satisfy the convergence, the Geweke diagnostic value should fall within [-1.96, 1.96] limits with 0 denoting perfect convergence.

Table 4.4 Markov Estimated β parameters and life expectancy in year.

State	Core Network 1 (ASIAN)				Core Network 2 (National)			
	$\boldsymbol{\beta_{0i}}$ ***Absolute***	$\boldsymbol{\beta_{1i}}$ ***Traffic***	$\boldsymbol{\beta_{2i}}$ ***Pavement***	$\boldsymbol{LE_i^k}$ ***Life***	$\boldsymbol{\beta_{0i}}$ ***Absolute***	$\boldsymbol{\beta_{1i}}$ ***Traffic***	$\boldsymbol{\beta_{2i}}$ ***Pavement***	$\boldsymbol{LE_i^k}$ ***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 $\boldsymbol{\theta_i^k}$ can be estimated as the inverse of $\boldsymbol{LE_i^k}$ according to Equation (4.5).

The positive β values mean traffic strongly impacts the deterioration rate in Condition State 2 for ASIAN network and Condition State 4 for National network. Consequently, higher traffic on ASIAN network significantly contributes to faster deterioration. However, thicker and stronger AC road sections exhibit a longer lifespan, hence the negative β values. Other β values were excluded due to sign restrictions. The estimated condition performance curves show a higher life expectancy of 8.01 years for Core Network 1 (ASIAN roads) compared to 5.56 years for National network (Figure 4.4). This better life performance for ASIAN network is due to their stronger pavement materials, about 40.9% is constructed using AC. In contrast, only 5.8% of the National network is constructed with AC (**Table 4.2**)

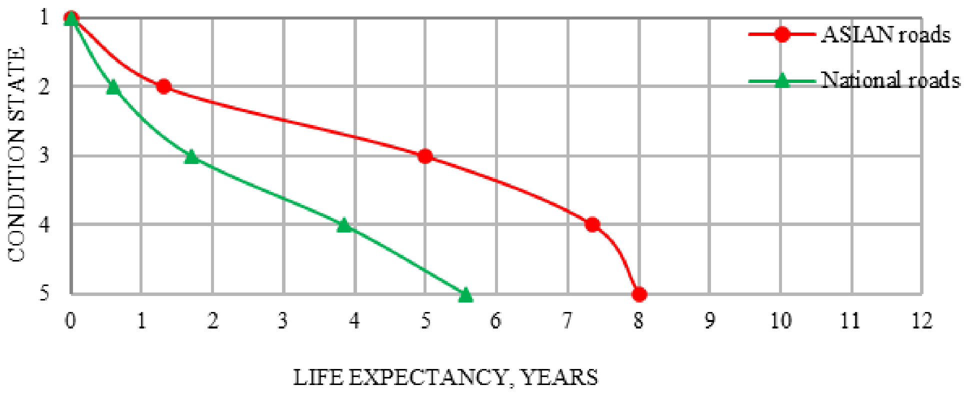


Figure 4.4. Performance curves for ASIAN and National Road network

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.

$$\mathrm{MTP}_{C1} = \begin{bmatrix} 0.487 & 0.442 & 0.063 & 0.006 & 0.002 \\ 0 & 0.761 & 0.203 & 0.026 & 0.010 \\ 0 & 0 & 0.732 & 0.167 & 0.101 \\ 0 & 0 & 0 & 0.378 & 0.622 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{4.18}$$

$$\mathrm{MTP}_{C2} = \begin{bmatrix} 0.342 & 0.529 & 0.110 & 0.016 & 0.003 \\ 0 & 0.683 & 0.254 & 0.051 & 0.012 \\ 0 & 0 & 0.652 & 0.254 & 0.094 \\ 0 & 0 & 0 & 0.539 & 0.461 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{4.19}$$

4.5.4. Policy and Strategy Setting for Laos RMS.

The study examined different intervention strategies ($\boldsymbol{m_p^{s^k}}$) for the two core networks, considering budget and road network performance targets. The aim was to regulate 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 involves road intervention when a road network reaches 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 allows road conditions to deteriorate naturally over time based on the transition probabilities of the road network. These probabilities are influenced by explanatory variables such as traffic volume, pavement type, and environmental factors.

A greedy algorithm was used to solve intervention actions, focusing on sections in the worst condition. According to Laos RMS practice [29], various intervention actions were applied, each associated with a specific cost, as shown in **Table 4.5**.

Table 4.5 Laos RMS maintenance, costs, and conditions after repair.

Condition state i	**Repair actions**	**Costs (Mil. Kips/m2)**	**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 in an intervention matrix were defined (Equations 20 to 23), with two strategies for each policy (preventive or reactive). An optimal intervention strategy was selected initially in 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 budget limit scenario was introduced, with priority given to ASIAN roads that connect nations.

$$\boldsymbol{Pr_1} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{4.20}$$

$$\boldsymbol{Pr_2} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{4.21}$$

$$\boldsymbol{Rt_1} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{4.22}$$

$$\boldsymbol{Rt_2} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{4.23}$$

4.6. Results

4.6.1. 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 4.5**). 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 4.6), 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.

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 4.6, Figure 4.6a and 4.6b**). This scenario emphasizes the importance of considering network conditions and cost-effectiveness in the decision-making process

Table 4.6 LCCs for Laos roads considering a limitless budget scenario (Mkips)

Strategy $\boldsymbol{m_p^{s^k}}$	**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

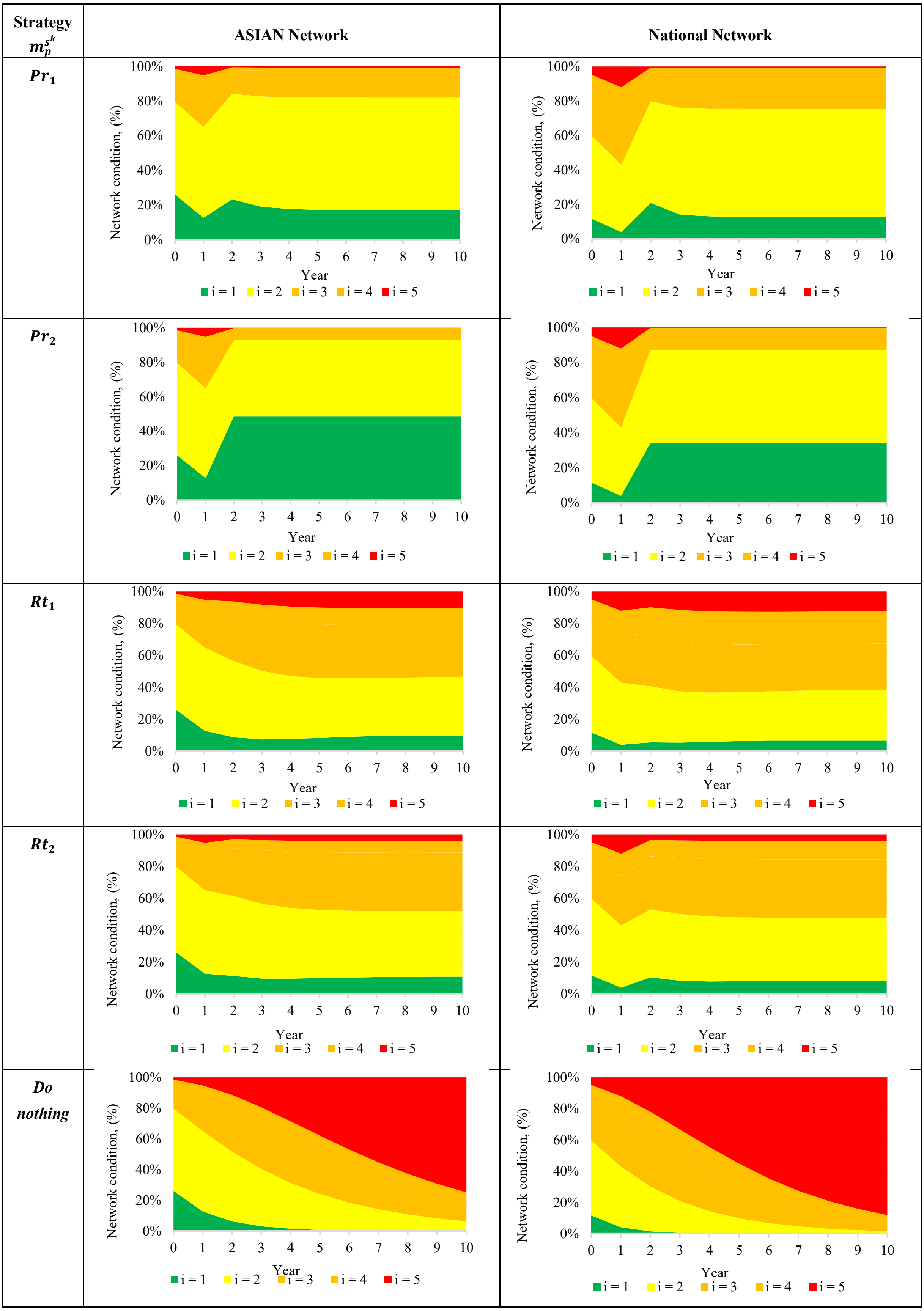


Figure 4.5. Comparison of road condition for different maintenance policies considering a limitless budget

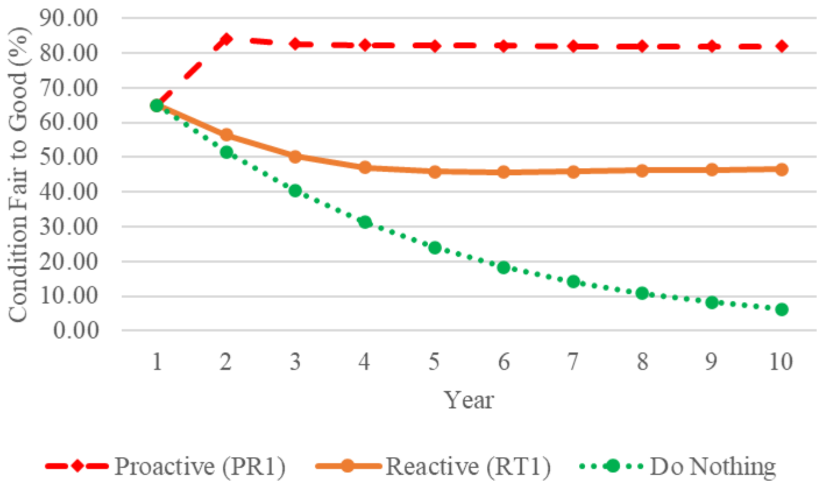


Figure 4.6a Comparison of three Maintenance Policies in ASIAN network

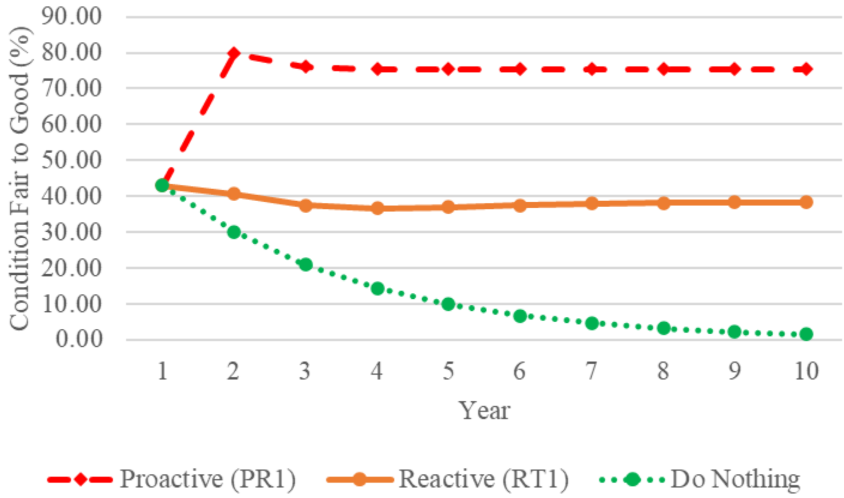


Figure 4.6b Comparison of three Maintenance Policies in National network

4.6.2. 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 4.7**). 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.

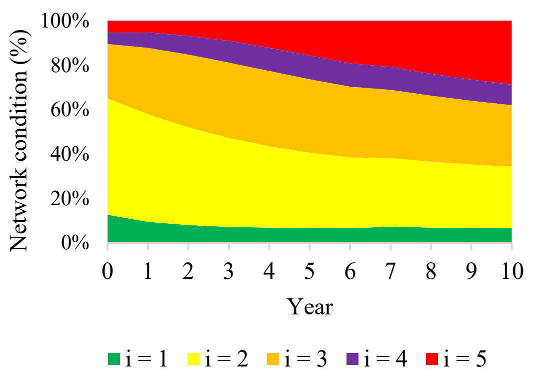
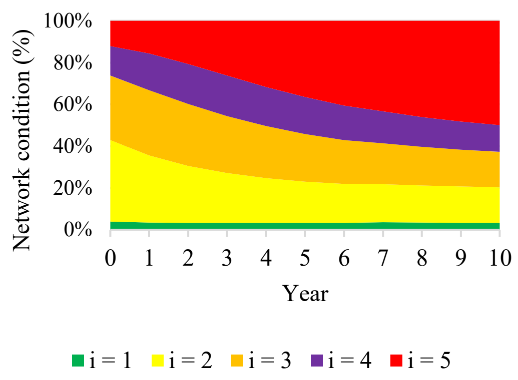
Strategy	ASIAN Network	National Network
$\boldsymbol{Pr_1}$		

Figure 4.7 Condition of network considering 50% budget constraint

4.6.3. 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 4.8 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

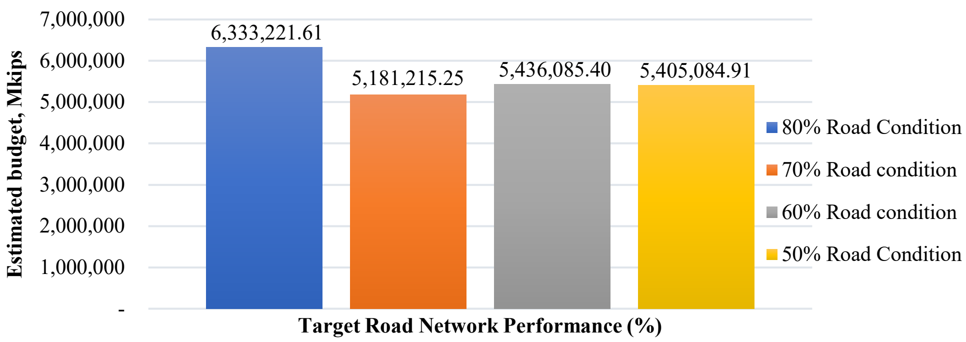


Figure 4.8 The cumulative 10-year budget for different road performance targets

4.7. 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.

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Chapter 5

Multi-Stage Exponential Markov (MUSTEM) Model Vs. Highway Development and Management Model Four (HDM-4) for Laos Road Management

5. Multi-Stage Exponential Markov (MUSTEM) Model Vs. Highway Development and Management Model Four (HDM-4) for Laos Road Management.

5.1. Introduction

5.1.1. Road Pavement Performance Models

Infrastructure assets, such as roads and bridges, have many impacts on countries in terms of social and economic development. However, maintaining and managing these assets, especially in developing countries facing capacity and funding constraints, presents significant challenges. Proper infrastructure management has a huge impact, particularly on safety, connectivity, and the overall well-being nationwide. There are two notable methodologies, i.e., stochastic and deterministic methods for infrastructure management [1]. Stochastic models, such as the MUSTEM model, offer a probabilistic approach to predicting asset condition evolution over time. These models provide a comprehensive framework, simpler implementation, and an advantage with limited data or resources. Stochastic models incorporate uncertainty which is typical of pavement degradation. These merits aid infrastructure preservation in good condition. However, they may require expertise for accurate estimation [2]. On the other hand, deterministic models like the HDM-4 despite providing precise performance metrics and cost-effectiveness do not incorporate uncertainty. These deterministic models require a lot of data to obtain detailed insights into asset condition and maintenance requirements. Moreover they also demand expertise in calibration for effective utilization [3].

5.1.2. Road Management System in Lao PDR

Lao PDR is a country with diverse environmental conditions and terrain ranging from highlands to tropical plains. Similar to other developing countries in the region, Laos faces with the challenge of limited resources, which necessitates a more efficient and cost-effective Road Management System (RMS).

Since 2003, the Government of Lao PDR has approved and established the RMS as a tool for management, planning, operating, and monitoring, which is the responsibility of the Ministry of Public Works and Transport of Lao PDR (MPWT).

The Laos RMS utilizes the Highway Development and Management (HDM-4) software, a deterministic model, as a tool for long-term planning to allocate maintenance funding and determine priorities [4, 5]. On the other hand, the Road Maintenance Fund (RF), which is used to maintain the road network in Laos, is challenged due to its mounting debt of approximately 2,433 billion Kips (USD 200 million) as of 2021, this is because of the gap of annual budget plan and the capacity of reimbursement as well as the emergency maintenance from uneven disaster [6].

5.1.3. Study Objectives

The objective of this study is to carry out a comparative analysis of popular Markov models such as MUSTEM and well-known deterministic models, particularly HDM-4. Laos road network datasets will be utilized to compare the comprehensiveness of both models. The primary objectives of this research are to:

1) Conduct a comparative analysis of the probabilistic MUSTEM model and the deterministic HDM-4 model for infrastructure asset management in Laos.
2) Assess the performance and reliability of Markov models in predicting pavement deterioration, optimizing maintenance strategies, and minimizing life-cycle costs (LCCs) compared to the HDM-4 prediction in the Laos RMS.
3) Evaluate how each modeling approach influences resource allocation decisions, considering factors such as data availability, environmental conditions, level of serviceability, and budget constraints.
4) Provide practical guidance and recommendations to asset managers, government agencies, and policymakers particularly in Laos and similar nations for improved infrastructure management.

The comparison of MUSTEM and HDM-4 in terms of road deterioration estimation and LCC analysis for different budget scenarios addresses an academic study gap in the field of road asset management systems, particularly on road performance prediction in developing countries. Understanding the application of these models in various management scenarios is limited due to lack of explicit comparative studies. This study aims to enhance the understanding of applications and key considerations in order to utilize each model and guide decision-making for better Pavement Management Systems

(PMSs) in developing countries, specifically Lao PDR. Additionally, the comparison between the proposed stochastic model, MUSTEM, with the current RMS will provide insights into the potential benefits and advantages of adopting the new approach. This comparison will ultimately improve road asset management sustainability in Lao PDR.

5.2. Literature Review

5.2.1. Introduction

One of the main goals of road authorities is to slow down pavement deterioration rate, lower the cost of vehicle operation by enhancing driving conditions, and maintain a continuous flow of traffic [7]. The RMS, used by many road agencies, includes data collection, planning, and programming, comprises a model of road network deterioration, a maintenance strategy, optimization (prioritization), implementation, and assessment. [8]. Therefore, in order to preserve the quality and efficiency of highway and road networks, it is important to establish a comprehensive road management system [9].

The use of road deterioration modeling to forecast and enhance the performance of road pavements has been extensive in the field of infrastructure asset management. This literature review examines the existing work that has been done on deterministic pavement performance modeling (HDM-4) and stochastic Markov models, as well as how each is applied in asset management.

5.2.2. HDM-4 in Asset Management

Deterministic methods model pavement performance through known relationships between state and event. They provide exact values without consideration of uncertainties. Furthermore, deterministic methods apply mechanical, mechanistic-empirical, and regression models. However, for better analysis and prediction, these models require a large database with a variety of factors [10]. The common PMS tools, such as HDM-4 and the Australian Road Research Board (ARRB), are examples of mechanistic-empirical models popularly applied in practice [7, 11].

The deterministic pavement performance model, the HDM-4 software, is a well-known tool that has made a substantial impact on infrastructure asset management [4].

HDM-4 is acknowledged for its deterministic nature, allowing it to provide precise values of pavement performance metrics based on given input data.

The HDM-4 road deterioration is predicted through five separate distress modes, including cracking, raveling, potholing, rut depth, and roughness, with surface distress characterized by initiation and progression phases. Deformation distress, such as rut depth and roughness, is computed after the change in surfacing distress has been calculated [12, 13].

The general computational logic for estimating the deterioration is summarized as follows [13-16]:

- Initialize input data at the start point of the analysis year. This input data can be the data of the first year of analysis or the previous year's condition after maintenance.
- Calculate the amount of change in each distress mode (majority 5): cracking, raveling, pothole, roughness, and rutting.
- The pavement strength, condition, and age of the infrastructure are considered, and the traffic volume per lane is computed.
- Estimate the distress of cracking, raveling, and pothole using progression criteria (regressive function), which are specific to each distress mode, and then adapt (calibrate) the estimation using the deterioration factor of the local condition.
- Lastly, the roughness increment based on traffic, surface distress, age and environment factors are computed.

The HDM-4 model has been applied in practical asset management across various nations, particularly in developing countries[17]. For example, in Lao PDR, the Lao RMS utilizes the HDM-4 tool for pavement condition assessment and deterioration prediction [18, 19]. This software allows decision-makers, MPWT, to perform accurate analysis of road infrastructure performance and develop effective maintenance and investment strategies. HDM-4 comes with three specialized application tools. One is for analyzing projects at a detailed level; another helps plan road work within tight budgets; and the third supports strategic planning for the long-term performance and expenditure needs of a road network. It's meant to be a decision-support tool within a road management system [17].

HDM-4 requires field data and independent variables, including road conditions, traffic, vehicle characteristics, and maintenance costs, in order to provide detailed insights into asset management [11]. However, the HDM-4 calibration is necessary before utilizing the software to ensure accurate prediction of pavement performance by reflecting observed rates of deterioration through desk studies, verification with measured data, and long-term monitoring [15].

HDM-4 provides performance metrics based on input data, making them particularly valuable for detailed cost-benefit analysis. The strong framework of HDM-4, which takes into account a wide range of economic factors, makes it stand out. This robust approach leads to a detailed examination of different project scenarios and pavement types. The users can thoroughly examine the complicated processes involved in planning construction projects and maintaining roads. Additionally, HDM-4 offers a user-friendly interface and extensive documentation, providing valuable assistance to practitioners and researchers as they navigate its features. This combination of accessibility and detail improves its usability and ensures that users can effectively utilize its capabilities to address a wide range of transportation challenges and optimize decision-making processes [4, 17].

HDM-4 requires numerous types of data, including road network data (pavement inventory, condition, type), vehicle fleet (classification), traffic patterns, environmental factors, cost data (operating cost, maintenance history) and etc., that is difficult to collect at once and is often utilized for specific projects [20]. In the short term, the local department of public works and transport provinces in Laos carries out condition inspections and present reports to the MPWT for decisions on maintenance financing annually. The provincial reports are made based on condition surveys and provide one-time data used for planning which is reactive. Maintenance is also based on road importance/hierarchy level [19].

In recent years, The Laos RMS utilizes various inputs, including road characteristics, traffic data, and pavement conditions, to assess overall road performance based on roughness, ride quality, and skid resistance. These indicators provide insights into the current road condition and facilitate the identification of areas requiring maintenance or improvements as well as rehabilitation. However, the RMS requires a large dataset and calibration of parameters to align with each country [8] [14]. It should be used in conjunction with other information to support decision-making processes related to road network management and investment planning. Nevertheless, budgetary restrictions and a lack of technical resources hinder its efficiency.

5.2.3. Markov Models in Asset Management

Road pavement deterioration has been modeled to follow Markov theory. In the last few decades, there has been a rise in the number of statistical methods for modeling deterioration using inspection data. Among these methods, the MUSTEM, proposed by [21, 22], enables the estimation of transition probabilities using inspection records at two-time points and overcomes many challenges associated with incomplete inspection data. The model has been modified and augmented to account for specific challenges prevalent with inspection data, such as a small sample size, measurement errors, uncertain deterioration modes, composite deterioration structures, etc. [21, 23-25].

Markov models, a class of probabilistic models, have become prominent in asset management due to their capacity to capture dynamic transitions between asset condition states. These models have been widely used for the prediction of infrastructure deterioration. In order to generate highly accurate deterioration forecasts, the key challenges in developing the deterioration model were related to uncertainty, particularly, traffic volume, road structures, and pavement thickness [5]. A study by [26] employed a Markov chain model to estimate the transition probabilities of road pavement condition moving between various condition states. Their research found that Markov models provide a robust framework for assessing critical road sections considering uncertainties in pavement deterioration. Additionally, Markov models have been used in determining the optimal timing for maintenance interventions. In a comprehensive study, [27] demonstrated how Markov Decision Processes (MDPs), an extension of Markov models, can be used to find the most cost-effective maintenance strategies for Uganda national roads. The study highlighted the capability of Markov models to address both short-term and long-term decision-making in asset management.

The powerful statistical techniques employed by Markov models are used to predict infrastructure degradation , particularly, road surface pavement [11, 28, 29], bridges [22, 30] , pipe networks [31, 32], and airports [33, 34].

MUSTEM, with the probabilistic structure, depicts stochastic processes and transitions between asset states over time, providing a holistic view of asset condition evolution [35]. This allows for a probabilistic prediction of how the road condition will evolve based on the historical data. However, probabilistic predictions of distress, based on the variability observed in the data, are currently being developed to provide a more accurate assessment of the risks associated with managing pavement infrastructure [36]. Optimized maintenance strategies, adaptability to limited data, efficient LCC estimates, and transparent decision support, its flexibility and simplicity make MUSTEM a valuable tool for decision-makers in infrastructure management [27, 35, 37-39].

While both models, MUSTEM and HDM-4, provide valuable insights into asset management and decision-making, their differences lie in their basic principles, both in road performance and maintenance estimation, and their range of applicability. In the context of developing countries, e.g. Lao PDR, which may face unique infrastructure challenges, the choice between these modeling approaches becomes pivotal. This research seeks to address this gap by conducting a comparative analysis of MUSTEM and HDM-4, especially in the practical context of the Lao RMS, to provide insights relevant to similar regions facing resource constraints, and diverse environmental conditions.

5.3. Methodology

5.3.1. Model Comparison

The MUSTEM model was extensively utilized for comparative purposes with the current Laos RMS system that uses HDM-4 for a comprehensive analysis of road network performance and maintenance costs within the context of the Road Asset Management Plan from 2016 to 2025. The MUSTEM model was used to evaluate road network conditions and total maintenance LCCs, utilizing the same survey data set recorded in Laos RMS database. The estimates generated by MUSTEM were compared to those of the existing RMS, which relies on the HDM-4 software [18].

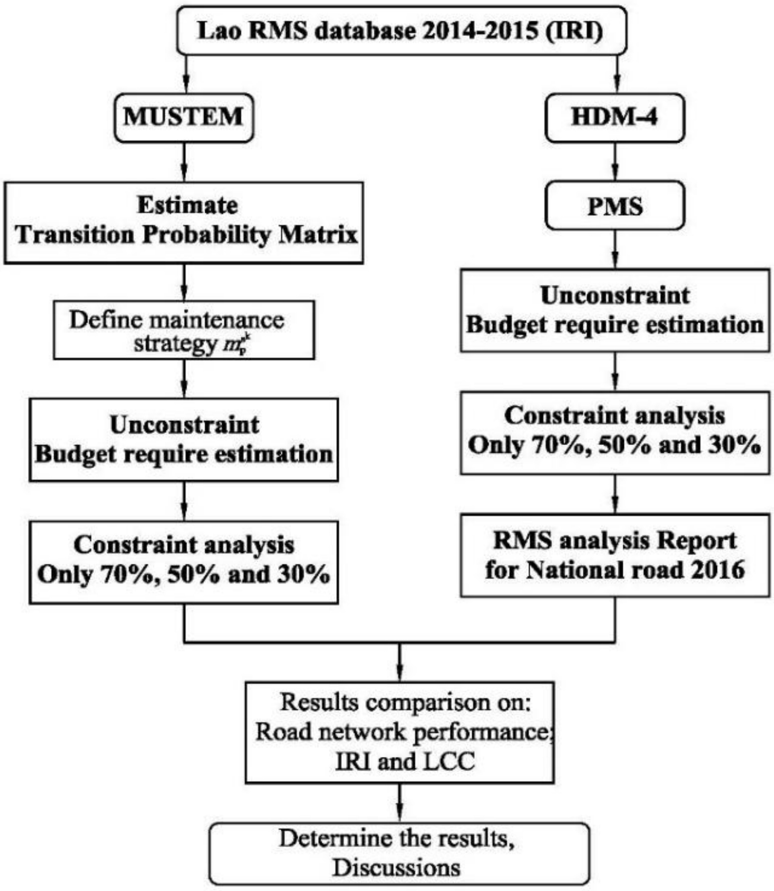

Figure. 5.1 Comparison flow diagram.

The PMS is the RMS's module for optimal road maintenance in Laos [40]. Two budget scenarios were evaluated: unconstraint and constraint maintenance budget considering an intervention strategy in which road condition always improves to the best. The aim was to determine which model is more effective and suitable for managing Laos roads. **Figure. 5.1** provides a detailed illustration of the comparison flow diagram used in this comparative analysis, giving a clearer understanding of the entire process.

5.3.2. MUSTEM model Description

The road condition at each time step has been utilized to make decision and determine an action to execute. The primary objective of road agency decision maker is to optimize the total benefits obtained for agency and road user.

The MUSTEM is a mathematical framework used for estimating the transitioning between multiple states over time. Presumptions are necessary before utilization the MUSTEM [41]

1. No maintenance or restoration projects were implemented throughout the inspection period.
2. The deterioration of the road surface begins as soon as it is made available to the public at time τ_0.

The stochastic Markov model assumes that the probability of transitioning to a new state depends only on the current state and action, not on any previous states or actions. This property allows for the construction of Markov models using states, actions, transition probabilities, and rewards. Multiple algorithms can be used to solve MDP problems. These algorithms include dynamic programming, Monte Carlo methods, and reinforcement learning [42]. In this study, the MUSTEM incorporates condition states $i(i = 1, 2, 3, \dots, J)$ with J as the absorbing state, discrete time periods $t(t = 0, 1, 2, \dots)$, maintenance strategies (m_p), inspection intervals Z $(Z = 1, 2, 3, \dots)$, and maintenance actions (A). The analysis considers a finite period from $t = 0$ to $t = T$.

The deterioration, intervention, and recovery process of the road network have been simply presented in **Figure. 5.2**.

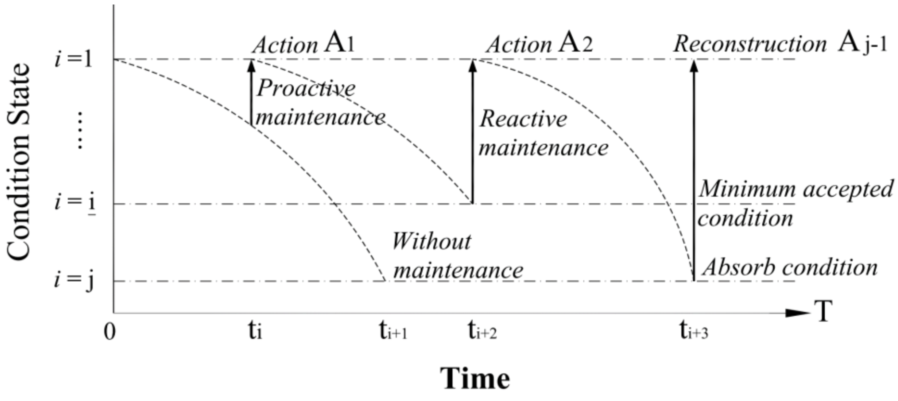

Figure. 5.2 Intervention responsiveness

a) Markov Transition Probability (MTP) and Deterioration Estimation

The pavement condition transition process is uncertain, and the future states' forecasting is difficult to accurately estimate. Because the Markov Transition Probability (MTP) incorporates uncertain, it is suitable to model pavement condition transition. MTP requires a minimum of two-time inspection data. Notation $h(\tau_A) = i$ is the observed condition the road condition at time τ_A. MTP defines the probability that the future condition state at time τ_B will change to $h(\tau_B) = j$ after an interval Z, with periodic inspections at time t and $t + Z$ [22, 28]. The probability of this transition is:

$$\text{Prob}\ [h(\tau_B) = j | h(\tau_A) = i] = \pi_{ij} \tag{5.1}$$

where, $\pi_{ij} \geq 0$

$\pi_{ij} = 0$ (when $i > j$)

$\sum_{j=1}^{J} \pi_{ij} = 1$

In **Figure. 5.3**, it is supposed that at time τ_A and τ_B are inspection time while τ_i is any arbitrary time between two inspections, the condition state observed by inspection is i (i=1, 2, ..J-1). The deterioration process in future times is uncertain. Among the infinite set of possible scenarios describing the deterioration path, only one path is finally realized [21].

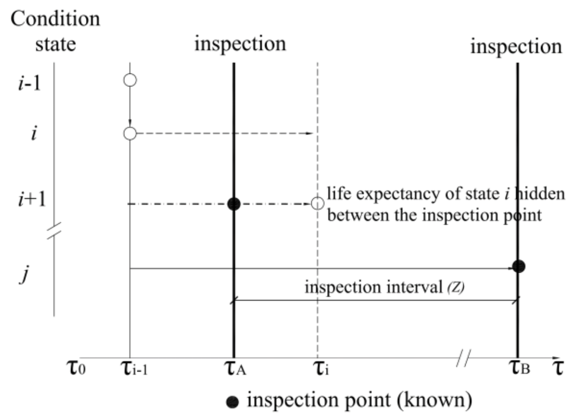

Figure. 5.3 Road deterioration process and inspection interval

The Markov transition probability matrix is defined by using transition probabilities between each pair of condition states (i, j)

$$\Pi = \begin{bmatrix} \pi_{11} & \cdots & \pi_{1j} \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \pi_{JJ} \end{bmatrix} \tag{5.2}$$

The deterioration process of a road section is estimated by utilizing inspection data. The information obtained from inspection, including visual inspection, structural characteristics, pavement condition and inspection intervals is used to estimate MTP.

The hazard model is introduced to clarify the basic concept of the deterioration. More detailed explanations on the Markov model estimation can be found in [21, 22, 41].

The hazard rate θ_i can be expressed as a function of explanatory variables x^k and unknown parameters β_i where $\beta_i = (\beta_{i,1}, \dots, \beta_{i,M})$, m $(m = 1, \dots, M)$ is the number of explanatory variables and $k(k = 1, \dots. K)$ is the number of inspected element groups.

$$\theta_i^k = f(x^k\colon \beta_i) = \exp(x^k \beta_i') \\ (i = 1, \dots, J-1) \tag{5.3}$$

The unknown parameters $\beta_i (i = 1, \dots, J-1)$can be determined using an iterative method like Newton's method or through Bayesian estimation [21].

As a function of hazard rates, the MTP can be estimated:

$$\pi_{ij} = \sum_{\tilde{k}=i}^{j} \prod_{\tilde{m}=i}^{\tilde{k}-1} \frac{\theta_{\tilde{m}}}{\theta_{\tilde{m}} - \theta_{\tilde{k}}} \prod_{\tilde{m}=\tilde{k}}^{j-1} \frac{\theta_{\tilde{m}}}{\theta_{\tilde{m}+1} - \theta_{\tilde{k}}} \exp(-\theta_{\tilde{k}} Z) \tag{5.4}$$

where θ_i is the hazard rate and, $\tilde{k}$ and $\tilde{m}$ are indices.

The life expectancy LE_i^k in each condition state i can be defined by means of a survival function [43].

$$LE_i^k = \frac{1}{\theta_i^k} \tag{5.5}$$

The average life expectancy from i to J can be estimated as:

$$\sum_{i=1}^{J-1} LE_i^k \tag{5.6}$$

b) Determination of maintenance strategy

The target of road agencies is to optimize the road condition while minimizing LCCs including maintenance and road user cost. The comparison in this study is focused on only road maintenance cost considering different budget scenario. Regarding the maintenance policy and strategies of Laos RMS, the general repair rule is based on level of defects or road condition. Intervention is set basing on minimum acceptable condition state being exceeded [44].

This study considered the same standard criteria as the Laos RMS strategy, which is that the estimated LCCs depends on intervention cost in correspondence to condition within financial constraints. The maintenance strategy is referred to a combination of maintenance actions, including pothole patching, crack resealing and overlay.

Pavement maintenance activities are denoted by $M(M_0, M_1, M_2, M_{3,} \dots, M_{J-1})$ and completed in accordance with the condition state after inspection (time-dependent rule) or deterioration rate (condition-dependent rule) [27, 45]. At the end of the planning period, time T, the reconstruction M_{J-1} is applied for all sections. Fig. 3 also indicates the correspondence between observed condition and maintenance action. Once action is taken, pavement condition state i is assumed to improve to $\hat{\imath}$. This improvement is denoted by i_{mp}

$$i_{mp} = \begin{cases} i & \text{if} \quad M_0 \text{ (no action)} \\ \hat{\imath} & \text{otherwise } (M_1, M_2, M_3, \dots, M_{J-1}) \end{cases} \qquad (5.7)$$
$$(i = 1, \dots, J)$$

Table 5.1 Repair identification and related intervention costs

Condition state, $\boldsymbol{i}$	Repair actions	Costs	Condition state after action, $\boldsymbol{\hat{\imath}}$
1	M_1 (routine)	C_{M1}	1
2	M_1 (routine)	C_{M1}	2
	M_2 (patching + sealing)	C_{M2}	1
	M_3 (overlay)	C_{M3}	1
3	M_1 (routine)	C_{M1}	3
	M_2 (patching + sealing)	C_{M_2}	2
	M_3 (overlay)	C_{M3}	1
…	…	…	…
$\boldsymbol{J}$	M_1	C_{M1}	J

M_2 (patching + sealing)	C_{M2}	$J-1$
M_3 (overlay)	C_{M3}	$J-2$
…	…	…
M_{J-1}	$C_{M_{J-1}}$	1

Table 5.1 displays the attained condition after maintenance. It was assumed that patching and crack sealing improved condition by one step while overlay improved condition by two steps. Routine maintenance maintains the condition in its current level. Reconstruction (M_{J-1}) is applied at the end of pavement service life (terminal state). The maintenance cost $C_{M_{-i-1}}$ is an increasing monotone function with action determined based on condition state.

$$C_{M_0} \leq C_{M_1} \leq C_{M_2} \leq \cdots \leq C_{M_{J-1}} \tag{5.8}$$

c) MUSTEM Life-cycle cost estimation

The transition probability will change when a road section is maintained due to pavement condition improvement. The MTP matrix is multiplied with a repair maintenance matrix P_{mp}. The elements of the J x J repair matrix is denoted as $\pi_{ij}^{mp} = (i = 1, \dots J)$, $(j = 1, \dots J)$. In case of do-nothing, the repair matrix will be an identify matrix when $P_{mp} = I$, with all values in the major diagonal being 1 and all other matrix members being 0.

$$P_{mp} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{5.9}$$

The condition $\sum_{j=1}^{j} \pi_{ij}^{mp} = 1$ must be met within P_{mp}. The repair probability.

$$\pi_{ij}^{mp} = \begin{cases} 1 & if\ i_{mp} = \hat{\imath} \\ 0 & otherwise \end{cases} \qquad (i = 1, \dots J) \tag{5.10}$$

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

$$P_{trans} = \prod(Z) * P_{mp} \tag{5.11}$$

This study focuses the maintenance costs which is estimated from exogenously set strategies. The maintenance costs for each pavement section can be expressed as [27]

$$V_i^{t,s^k} = (1 + \rho^r)^{-t} * \pi_{ij}^{trans} * C_{A\leftrightarrow i}^{t,s^k} \tag{5.12}$$

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

The LCCs of each strategy are the summation for all maintenance sections in road network sections $s^k(s^k = 1, \dots., S^k)$ assuming the salvage value at T [46], $C_v^{s^k} = 0$.

$$LCC = \sum_{t=0}^{T} \sum_{s^k=1}^{s^k} \sum_{i=1}^{J} V_i^{t,s^k} \tag{5.13}$$

A greedy algorithm has been utilized to solve the optimization problem [47, 48]. To find the optimum strategy $\boldsymbol{m}_{\boldsymbol{p}}^{\boldsymbol{s^k}*}$ is expressed as

$$\min_{\boldsymbol{m}_{\boldsymbol{A\leftrightarrow i}}^{\boldsymbol{t,s^k}}, Z^{s^k}} LCC \tag{5.14}$$

subject to

$$\sum_{k=1}^{K} \sum_{s^k=1}^{S^k} C_{A\leftrightarrow i}^{t,s^k} \in \Omega_t \qquad \forall t \tag{5.15}$$

Where $\boldsymbol{m}_{\boldsymbol{p}}^{\boldsymbol{s^k}*}$ is the maintenance strategy and Ω_t is the budget constraint at t.

d) Road network condition estimation

Estimating the condition of the road network in each state can support making decisions when selecting suitable maintenance activities, especially when faced with budget constraints.

The road network condition in each state can be estimate using:

$$RC_{t+Z} = p(Z) * RC_t \tag{5.16}$$

where RC_t is a $1 \times J$ road condition state vector at time t, and $p(Z)$ is the $J \times J$ MTP matrix.

e) Road network average IRI

The average road network roughness is estimated using:

$$IRIAV_y = \frac{\sum_{i=1}^{k} IRI_k * Len_k}{\sum_{i=1}^{k} Len_k} \tag{5.17}$$

Where $IRIAV_y$ is the average roughness index in the year for the total network, IRI_k is the average roughness for each road section, and Len_k is the length of each road section. **Table 5.2** indicates the average value of IRI determined in this study. MPWT, (2016) [18].

Table 5.2 Average Laos road roughness

Condition state	IRI (m/km)	IRI_k consideration
Good	≤ 4	2
Fair	4<IRI≤6	5
Poor	6<IRI≤8	7
Bad	8<IRI	9

5.3.3. HDM-4 Description

The main functions of the HDM-4, particularly in road maintenance, are: planning, programming, preparation, and operation. The analytical framework is based on the concept of pavement life-cycle analysis, which is normally between 15 and 40 years [4, 49]. Particularly, road deterioration prediction and maintenance sub-models are utilized to estimate the maintenance costs (agency costs) and road user costs [13].

a) Road deterioration computational

HDM-4 enable the computation of pavement deterioration considering different defects. The model employs factors like traffic load, environmental influences, and maintenance intervention to forecast pavement deterioration and estimate road user costs based on pavement condition [50]. HDM-4 road deterioration models are based on functions of distress progression [7, 12, 13, 15]. The pavement deterioration computation model is characterized by two phases using different functions i.e. linear and non-linear models. The deterioration modeling comprises of initiation (absolute) and progression (incremental) model.

Table 5.3 HDM-4 deterioration models for paved road

1. Cracking initiation

$$\mathbf{ICA} = \boldsymbol{K}_{\mathbf{cia}}\left[\mathbf{CDS^2} * \mathbf{4.21EXP}\{\mathbf{0.14SNP} - \mathbf{17.1}\left(\mathbf{YE4/SNP^2}\right)\} + \mathbf{CRT}\right]$$

2. Cracking progression

$$\mathbf{dACA} = \boldsymbol{K}_{\mathrm{cpa}}\,(\mathbf{CRP/CDS}) \times \left[\left(\mathbf{1.84} * \mathbf{0.45} * \boldsymbol{\delta}\mathbf{t_A} + \mathbf{SCA^{0.45}}\right)^{\mathbf{1/0.45}} - \mathbf{SCA}\right]$$

3. Raveling initiation

$$\mathbf{IRV} = \boldsymbol{K_{vi}}\mathbf{CDS^2} * \mathbf{10} * \mathbf{RRF} * \mathbf{EXP}[-\mathbf{0.156} * \mathbf{YAX}]$$

4. Raveling progression

$$\mathbf{dARV} = \boldsymbol{K_{vp}}(\mathbf{1/RRF})\left(\mathbf{1/CDS^2}\right)[(\mathbf{0.6} + \mathbf{3.0} * \mathbf{YAX}) * \mathbf{0.352} * \boldsymbol{\delta}\mathbf{t_v} + \mathbf{SRV^{0.35}})^{\mathbf{1/0.35}} - \mathbf{SRV}]$$

5. Pothole initiation

$$\mathbf{IPT} = \boldsymbol{K_{pi}}\mathbf{2.0} * \left[\frac{(\mathbf{1} + \mathbf{0.05} * \mathbf{HS})}{(\mathbf{1} + \mathbf{1} * \mathbf{CDB})(\mathbf{1} + \mathbf{0.5} * \mathbf{YAX})(\mathbf{1} + \mathbf{0.01} * \mathbf{MMP})}\right]$$

6. Pothole progression

$$\mathbf{dNPT}_i = \mathbf{K_{pp}} * \mathbf{ADIS_i}\left[\frac{(\mathbf{1}+\mathbf{1}*\mathbf{CDB})(\mathbf{1}+\mathbf{10}*\mathbf{YAX})(\mathbf{1}+\mathbf{0.005}*\mathbf{MMP})}{(\mathbf{1}+\mathbf{0.08}*\mathbf{HS})}\right]$$

7. Roughness progression

$$\begin{gathered}\mathbf{\Delta RI} = \boldsymbol{K_{gp}}\left[\mathbf{134} * \mathbf{EXP}\left(\mathbf{m}\boldsymbol{K_{gm}}\mathbf{AGE3}\right) * (\mathbf{1}+\mathbf{SNP}\boldsymbol{K_b})^{-\mathbf{5}}\mathbf{YE4}\right] \\ +[\mathbf{0.0066} * \mathbf{\Delta ACRA}] + [\mathbf{0.088} * \mathbf{\Delta RDS}] + [\mathbf{0.00019}(\mathbf{2}-\mathbf{FM}) \\ \times\left\{\left((\mathbf{NPT}_{\boldsymbol{a}} * \mathbf{TLF}) + (\mathbf{\Delta NPT} * \mathbf{TLF/2})\right)^{\mathbf{1.5}} - (\mathbf{NPT}_{\boldsymbol{a}})^{\mathbf{1.5}}\right\}\Big] \\ +\left[\mathbf{m}_{\boldsymbol{gm}}\mathbf{RI}_{\boldsymbol{a}}\right]\end{gathered}$$

Note: Jain et al., 2005 [15].

Table 5.3 contains the HDM-4 deterioration model formulae. In order to estimate roughness progression, it is required to calculate the incremental change in the area of cracking (dACRA), the incremental change of rut depth (dRDS), and the incremental change in the number of the pothole (dNPT) during the analysis year. To estimate pavement deterioration usingHDM-4 deterioration formula, it is important to consider and determine the calibration factor for the respective model ($K_{\text{cia}}, K_{\text{cpa}}, K_{\text{vi}}$) and related parameters, including time interval, traffic growth rate, modified structure number (SNP), etc., for more accurate estimations [15].

b) Life-cycle cost analysis in HDM-4

The rate of pavement deterioration and distress is directly affected by the maintenance applied to the defects. Maintenance works such as pothole patching, crack resealing, and surface overlay have been considered; thus, the long-term road pavement condition depends on the improvement applied [49]. The HDM-4 mainly focuses on maximizing the Net Present Value (NPV) of the investment in terms of road maintenance and user costs during the analysis period with less consideration for road condition[51].

The LCC analysis in HDM-4 is associated with road maintenance costs, road user costs, and other social and environmental costs. Road user costs comprise vehicle operating costs, travel time costs; and road accident costs. Social and environmental costs comprise emissions, energy consumption, traffic noise, and other welfare factors impacted by roads.

Since there are several processes and forms to compute the LCCs in the HDM-4, it is recommended to refer to the references [4, 12, 49] for a better understanding of the framework, data requirements, and LCC analysis capabilities of the HDM-4.

5.3.4. Empirical Data

The empirical study used input data from the Laos RMS database in 2014–2015. For comparison purposes, the maintenance unit costs applied for are same as the 2016 RMS unit costs in the RMS Analysis report [18] using HDM-4. The collected data contained pavement materials, the IRI, and the average annual daily traffic (AADT) for 19 paved national roads.

The Laos road network includes two categories, the ASEAN highway road and the National Road with a total length of 4,301.7 km, about 73.43% of the total national road network in 2016, as shown in **Table 5.4**.

Table 5.4 Input data

Description	(ASEAN road)	(National road)
No. of rout	9	10
(links)	(108)*	(71)
Length (km)	2,624.3	1,677.4
Number of pairs	26243	16774
Uncertainty Variables	AADT, Road surface (AC/ST)**	
Number of AC/ST	7882/35135	

*Number of links, **AC=Asphalt concrete; ST=Surface treatment (bituminous).

5.3.5. Road Condition States

The road conditions were categorized using IRI data surveyed in 2014–2015 from RMS database. The IRI was measured using the dynamic response Vehicle Intelligent Monitoring System (VIMS) equipment during the Japan International Cooperation Agency project (JICA) starting in 2012. The roughness values were collected for each 100-meter segment [52, 53].

The IRI was classified into four condition states based on the same criterion for roughness and recent RMS classification in the RMS report [18]. The number of sections per condition state in the survey year for each network is shown in **Table 5.5**.

Table 5.5 IRI classification and condition state in year 2014-2015.

Condition state	IRI (m/km)	IRI condition (2014)	(2015)
1 (Good)	≤ 4	24455	22034
2 (Fair)	4<IRI≤6	11392	12642
3 (Poor)	6<IRI≤8	4244	5234
4 (Bad)	8<IRI	2926	3107

5.3.6. Road Network Deterioration Rate and Transition Probability

The deterioration rate estimation for the entire Laos road network, including the ASEAN and National roads, was done using explanatory variables such as AADT and road surface type. As a function of unknown parameter and explanatory variables, the hazard rate in exponential form as:

$$\theta_i = \exp\left(\beta_{0,i} + \beta_{1,i}x_1 + \beta_{2,i}x_2\right) \tag{5.18}$$

$$x_2 = \begin{cases} 1 & \text{for } AC \\ 0 & \text{for } ST \end{cases} \tag{5.19}$$

surface type dummy variable; AC is Asphalt Concrete, and ST is surface treatment (bituminous).

The unknown parameters were estimated using the Markov Chain Monte Caro (MCMC) methodology using the Metropolis-Hastings (MH) algorithm [54, 55]. The MCMC was employed because the log-likelihood function was dependent on numerous unknown parameters. The unknown parameters (β) converged as shown in **Table 5.6**. To test convergence, the Geweke diagnostic should ideally fall within the limits of [-1.96, 1.96], with a value of 0 indicating perfect convergence. The traffic parameters in this study have an insignificant effect on the road deterioration process. The reason for insignificant traffic could be improper data collection and input. However, the pavement parameters significantly impact road deterioration, particularly when transitioning from condition 1 to 2.

Table 5.6 Estimated β parameters and life expectancy in years.

State	*Absolute* ($\boldsymbol{\beta_{i,0}}$)	*Traffic* ($\boldsymbol{\beta_{i,1}}$)	*Pavement* ($\boldsymbol{\beta_{i,2}}$)	*Life* ($\boldsymbol{LE_i^k}$)
1-2	-0.643	-	-0.629	2.13
	(0.491) *	-	(-0.822)	
2-3	-0.290	-	-	1.34
	(-1.102)	-	-	
3-4	0.081	-	-	0.92
	(1.247)	-	-	

** The values in bracket are the Geweke's diagnostic for β.*

The life expectancy LE_i^k are estimated as the inverse of hazard rate θ_i^k according to Equation (5.5).

As a result, the MTP for the national road network was estimated and shown in Equation (20). The MTPs indicate that the road network tends to remain in its current state, with the highest transition probability being for condition state 1 at the rate of 66.7%, while the probability of remaining in condition state 2 is 63.1% and condition state 3 is 55.8%, respectively.

$$\mathrm{MTP} = \begin{bmatrix} 0.667 & 0.262 & 0.057 & 0.012 \\ 0 & 0.631 & 0.273 & 0.095 \\ 0 & 0 & 0.558 & 0.441 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{5.20}$$

The life expectancy of the road network was estimated employing Equation (5). The **Figure. 5.4** shows the life expectancy for asphalt and surface treatment pavements, which were used as explanatory variables in this study. AC pavements had longer life expectancy of about 5.9 years compared to 4.1 years for ST because AC pavements were constructed with stronger materials.

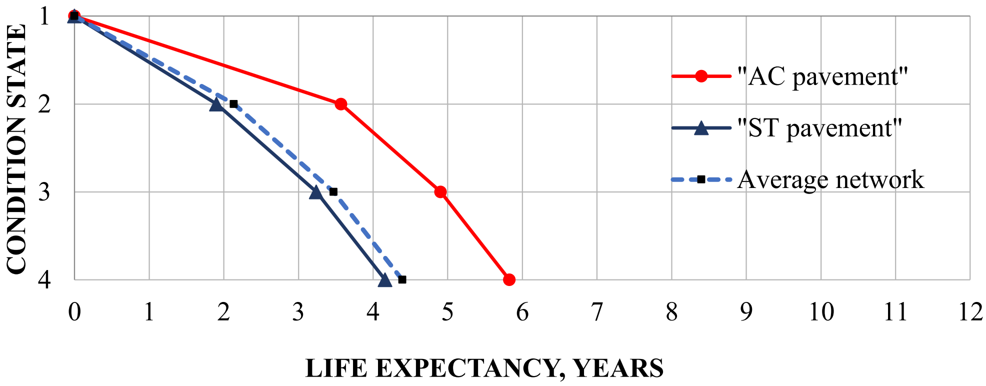

Figure. 5.4 Life expectancy for paved Laos roads using MUSTEM

5.3.7. Road Network Maintenance Strategy for Laos

In this subsection, the study aims to estimate the road condition performance and LCCs considering a basic intervention strategy ($\boldsymbol{m_{p1}}$) in which road sections are repaired to the best condition regardless of their observed condition (Equation 21). Different budget scenarios are considered, i.e., unconstrained, and constrained at 70%, 50%, and 30% of total intervention needs. These scenarios using MUSTEM's estimation aided comparison with the results derived from the HDM-4 estimation report for 2016-2025 in terms of network performance and LCCs estimation as shown in the Road Asset Management Plan 2016 report [18].

Regarding the specific maintenance policy, the maintenance matrix (strategy) was defined (Equation 2 1). We explored a limitless scenario assuming an unconstrained budget. However, we also investigated the practical strategy of the 'constraint scenario.' The criteria were set based on budget limits of 70%, 50%, and 30%. Finally, we compared the results of each strategy with the RMS practical approach outlined in the Road Asset Management Plan 2016 report [18]

$$\boldsymbol{m_{p1}} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix} \tag{5.21}$$

The intervention prioritization was determined using a greedy algorithm associated with specific costs. **Table 5.7** contains the interventions and their associated costs.

Table 5.7 Unit cost for maintenance works in RMS.

Maintenance works	Costs (Mkips/m^2)*
Routine maintenance	0.0008
Patching and sealing	0.065
Surface overlay	0.072
Rehabilitation/Reconstruction	0.221

Source: MPWT, Laos [18] , * Mkips = million Kips

5.4. MUSTEM Vs HDM-4 Considering Different Budget Scenarios

5.4.1. Limitless Budget Scenario Evaluation

The unconstrained budget scenario was implemented, considering maintaining condition state 1 and repairing road condition states 2–4 with corresponding actions (Table 1) to improve the conditions to the best condition state 1. Road network condition for a 10-year life-cycle was compared with the estimation results from the current Laos RMS.

Two estimation dimensions were compared: estimation of road condition distribution from 2016–2025, and LCCs during the analysis period. **Table 5.8** presents the LCC estimation, considering both the limitless and constrained budget scenarios.

Table 5.8 LCC's Comparison between MUSTEM and Laos RMS

Strategy $\boldsymbol{m_p^{s^k}}$	Estimated LCC (Million kips)		
	Empirical network (73.43%)	Whole network (100%)	Lao RMS estimation
	MUSTEM		(HDM-4)
Limitless	4,017,171	5,470,608	6,426,029
70% budget constraint	2,812,020	3,829,425	4,473,864
50% budget constraint	2,010,671	2,738,143	3,209,855
30% Budget constraint	1,206,402	1,642,886	1,926,466

The estimated road conditions using the MUSTEM and HDM-4 at the end of the analysis period (2016-2025) were compared as shown below.

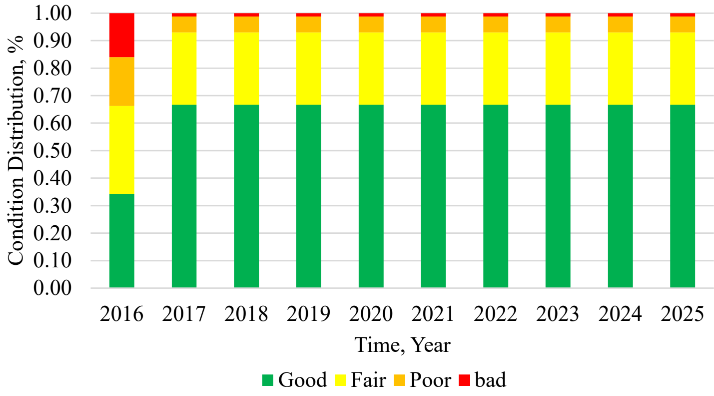

Figure. 5.5a MUSTEM road condition distribution estimation (limitless budget scenario).

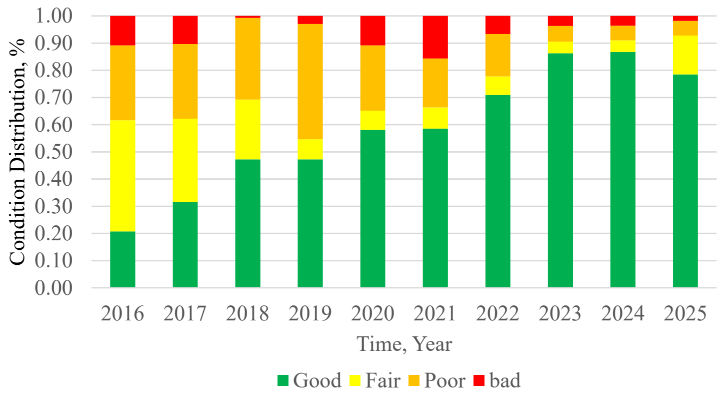

Figure. 5.5b HDM-4 road condition distribution estimation (limitless budget scenario).

Considering a limitless budget, the MUSTEM was found to maintain a larger percentage of the network in fair to good condition compared to HDM-4 considering the entire analysis period. This stark difference stems from the fact that the MUSTEM captures the deterioration uncertainty typical of pavements which enables better intervention prescription compared to HDM-4 that considers deterministic deterioration. At the end of the analysis period, MUSTEM and the Laos RMS based on HDM-4 estimated about 92.99% and 92.81% of the road network in fair to good condition, respectively (see **Figure. 5.5a** and **Figure. 5.5b**). Additionally, LCCs of 5,470,608 Mkips estimated with MUSTEM were relatively lower than Laos RMS estimate of 6,426,029 Mkips (85.13% of the Laos RMS estimate). **Figure. 5.6** illustrates the average roughness estimation during the analysis period (2016-2025).

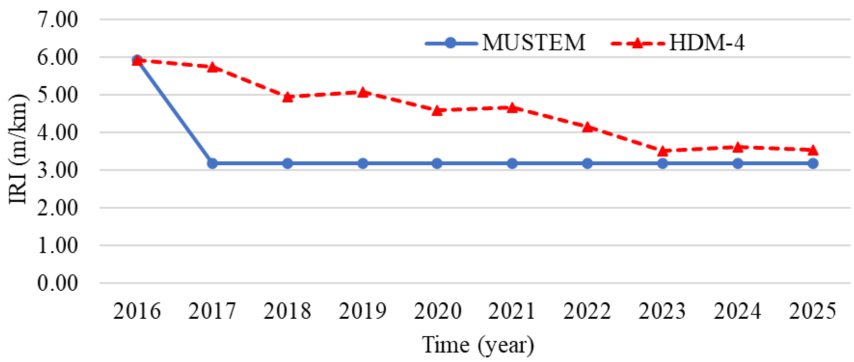

Figure. 5.6 Average IRI estimation comparison (limitless budget scenario).

The average IRI estimated by MUSTEM was significantly better than that estimated by the Laos RMS. The predicted average IRI at the end of the analysis year of the MUSTEM was approximately 3.18m/km, which is lower than the 3.53 m/km estimated by RMS in 2025. The reason behind this improvement is that the MUSTEM captures pavement deterioration uncertainty and specifies more optimal interventions. In contrast, based on HDM-4, the RMS estimation prioritizes benefits for road users and social advantages over road performance. Hence, the interventions applied may differ due to the distinct objectives of the two models in terms of road network performance and LCCs.

The LCC estimate by MUSTEM was better than the HDM-4 estimate. However, the MUSTEM framework of the limitless scenario proposed in this study demands a substantial maintenance budget from the start of the analysis year. **7** shows the cumulative maintenance cost under the limitless scenario, highlighting the total maintenance expenditure at the end of each year during the analysis period from 2016 to 2025.

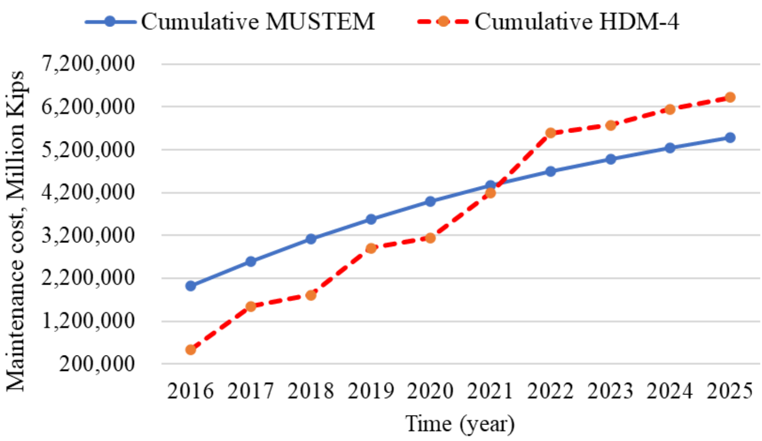

Figure. 5.7 Cumulative maintenance costs (million Kips).

5.4.2. Budget Constraint Scenario Evaluation

In the context of budget constraints, prioritization was employed to allocate limited resources for maintenance. Specifically, the available budget was considered to account for only 70%, 50%, and 30% of the total maintenance requirements. As a result, the top priority was to keep road sections that required minor maintenance in good condition. Consequently, any remaining maintenance tasks were deferred to next year. Consequently, more roads were expected to be in poor condition, necessitating significant maintenance efforts and/or new construction and rehabilitation projects.

Table 8 presents the MUSTEM estimation, with budget constraints of 70%, 50%, and 30% of the total demand. The predicted LCCs were 3,829,425 Mkips, 2,738,143 Mkips, and 1,642,886 Mkips, respectively. Notably, these results slightly differ from the RMS estimation.

However, when comparing the overall road condition and the average IRI of the road network at the end of the analysis year, there are noticeable differences. At a budget availability of 70%, the road condition estimation was 36.94% in fair to good condition by MUSTEM, while the RMS estimation was 72.57%. Furthermore, the average IRI estimation was 6.67 m/km by MUSTEM and 5.05 m/km by RMS.

At a 50% budget level, the road condition estimation was 27.17% by MUSTEM and 55.41% by RMS, and the average IRI was 7.28 m/km by MUSTEM and 6.30 m/km by RMS estimation. Lastly, at a 30% budget availability, the road condition estimation was 17.41% by MUSTEM and 41.76% by RMS, while the average IRI was 7.88 m/km by MUSTEM and 7.21 m/km by RMS estimation, respectively.

5.4.3. Do nothing scenario

The road condition deteriorates over time as the pavement experiences accelerated wear and tear due to traffic, weather, and other stressors. **Figure. 5.8** illustrates the comparison of the road condition performance predictions between MUSTEM and HDM-4.

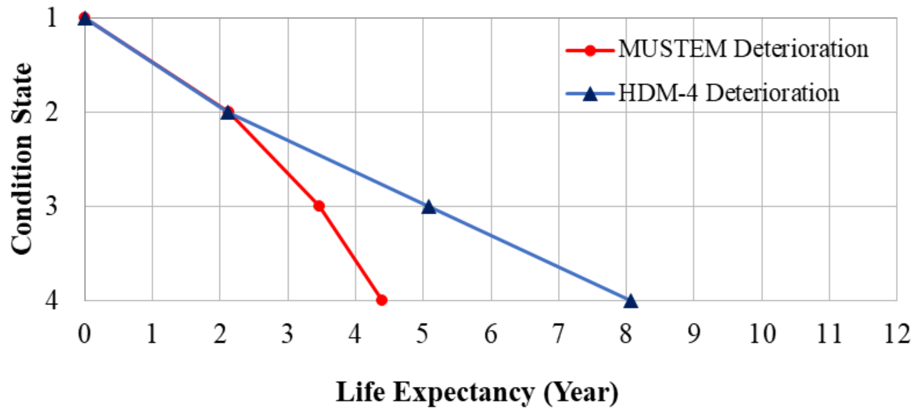

Figure. 5.8 Road network IRI deterioration estimation comparison.

The road condition (IRI) will reach the maximum worse condition (absorbing state) by 4.39 years from the MUSTEM estimation, while the predicted IRI from HDM-4 will reach the maximum condition state at around 8 years. The difference in the life expectancy can be attributed to the different modeling approaches for the MUSTEM and HDM-4. MUSTEM incorporates uncertainty in pavement deterioration, which is suitable for modeling pavement degradation, unlike the deterministic deterioration model in HDM-4, which considers linear/ non-linear deterioration without incorporating uncertainty (see in Table 3). Also, HDM-4 estimation is based on a set of parameters, including IRI, cracking, pothole, and raveling, as well as traffic data and environmental factors to estimate the total performance.

Figure. 5.9 shows the Laos road network condition distribution estimation using MUSTEM with no intervention (Do nothing). It shows a rapid degradation of the network with about 94% deteriorating to terminal state within 10 years if nothing is done. A similar degradation may be expected for the Laos RMS using HDM-4, but this is not shown here due to model inaccessibility

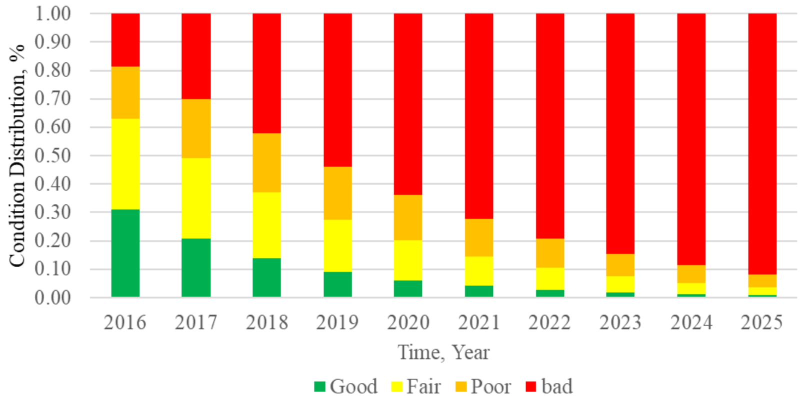

Figure. 5.9 Road conditions distribution with no intervention.

5.5. Conclusions

The results of the study provide valuable insights into the respective efficacy and limitations of MUSTEM and HDM-4, particularly in road network performance estimation, and optimal maintenance/ intervention strategies. These results provide details on the superiorities and limitations of each approach for decision-makers, i.e., road administrators and governments, in charge of road and infrastructure development and maintenance.

This research reveals that the MUSTEM model and the HDM-4 model are efficient in predicting road conditions in cooperation with parameters such as traffic loading, pavements, and environment. Specifically, this study highlights the merits of the MUSTEM model in empirically analyzing the road network in Laos. The estimation provided by the MUSTEM model predicted a higher percentage of road conditions to be in fair to good condition throughout the analysis period in the context of a budget unconstraint scenario.

A comparative analysis using data from Laos RMS highlights notable differences between both models. The study has implied the minimum data requirements and differences in model performance and LCC prediction at different budget levels. The MUSTEM model has been widely recommended for its effectiveness in predicting road deterioration, even when faced with uncertainties, aligning well with the actual road degradation characteristics observed in Laos. Additionally, in this study, the LCCs associated with the different scenarios identified by MUSTEM were relatively lower than the total budget needs estimated by HDM-4. However, the MUSTEM may not inherently include economic analysis and the impact of road condition on vehicle operating costs.

On the other hand, the HDM-4 offers precise performance metrics and cost-effectiveness that incorporate traffic benefits (user costs) and society. The HDM-4 model also considers various cost components in order to estimate the whole life-cycle cost, including construction costs, operation and maintenance costs, rehabilitation costs, road users' costs, and environmental costs. Therefore, they ask for a bunch of data to estimate precise values.

The comparison between the MUSTEM and HDM-4 in various aspects, for instance, data requirements, road performance estimation, and LCC analysis, underscores the importance of carefully considering multiple factors or limited data when employing each model in road management. Both models need capacity building to improve the proficiency of users, as well as balancing costs and performance when adopting advanced modeling in the road maintenance system, to support precise road intervention decisions.

In conclusion, comparing the stochastic model, MUSTEM, and the deterministic model, HDM-4, highlights their respective efficacy and limitations in estimating road network performance and optimizing maintenance strategies. MUSTEM uses a probabilistic approach to account for uncertainties, while HDM-4 uses a deterministic approach that simplifies calculations but demands extensive data to generate precise estimations. Balancing these trade-offs is crucial for effective road network management and maintenance planning.

Future research endeavors could focus on exploring novel maintenance strategies and further validating the accuracy and applicability of the MUSTEM model. Investigating alternative maintenance approaches, such as innovative materials or technology-driven solutions, could offer insights into optimizing road maintenance practices and enhancing infrastructure resilience. Furthermore, the expansion of the analysis to incorporate data from other developing countries would enable a comprehensive evaluation of the MUSTEM model's performance in diverse settings. These comparative studies could provide valuable insights into the generalizability and robustness of both models, facilitating informed decision-making in road maintenance management globally.

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Chapter 6

Conclusions and Recommendations

6. Conclusions and Recommendations

6.1. Summary of Findings

This research investigated the effectiveness of a proposed road management model incorporating stochastic pavement deterioration and life-cycle cost estimation using a Markov hazard model and a Markov decision process. By comparing the proposed models, MUSTEM, with the extensive employed HDM-4 system, the study identified critical strengths and limitations of both frameworks. While HDM-4 excels in economic evaluation and policy planning, it requires extensive datasets and calibration, making it challenging for resource-limited scenarios like Lao PDR. MUSTEM, on the other hand, enhances predictive accuracy through stochastic modeling, allowing for better planning under uncertainty but requiring careful balancing between condition-dependent and time-dependent strategies. As a result, the findings identified the critical strengths and limitations of both frameworks, ultimately enhancing the efficiency and cost-effectiveness of the road network management system, particularly in the context of the Lao PDR road management system.

The findings are summarized as follows:

1) Current RMS Evaluation

   The existing Road Management System (RMS) in Lao PDR is hindered by insufficient data collection, limited funding, and a lack of advanced analytical capabilities. For instance, inadequate traffic data often leads to poorly informed maintenance schedules, resulting in the rapid deterioration of key road sections. Limited funding restricts the ability to address critical repairs promptly, thereby escalating overall maintenance costs. Additionally, the lack of advanced analytical tools makes it challenging to prioritize interventions effectively, further compounding inefficiencies and contributing to mounting debt of approximately 2,433 billion Kips (USD 200 million) as of 2021. This debt is largely attributed to the gap between the annual budget plan and the reimbursement capacity, as well as emergency maintenance needs arising from unpredictable disasters.

2) The HDM-4 Application

The HDM-4 model is widely used in comprehensive road condition assessments and economic impact evaluations. However, its reliance on extensive datasets, such as traffic volume, pavement conditions, and vehicle operating costs, requires significant investment in data collection infrastructure. Furthermore, the calibration process involves complex adjustments to local conditions, including climate, terrain, and material specifications, making it challenging to implement in resource-constrained environments like developing countries, particularly in the Lao PDR.

3) MUSTEM Application

The MUSTEM model, based on stochastic methodologies, provides accurate predictions of road deterioration by accounting for uncertainties in pavement condition transitions. While the model does not prescribe specific maintenance intervention for decision-makers, its outputs can assist both condition and time-dependent intervention policies, enabling more effective prioritization of maintenance funding under budget constraints. MUSTEM provides a cost-effective forecasting framework but does not directly assess broader economic indicators such as Net Present Value (NPV), Vehicle Operating Costs (VOC), or user costs, which are typically addressed by models like HDM-4.

Developing the stochastic road condition prediction model in Chapter 3, optimizing maintenance strategy and budget allocation in Chapter 4, and the comparative analysis between the existing tool and framework with the proposed model framework in Chapter 5 underscore the value of integrating MUSTEM and MDP framework, the proposed model, into the existing RMS framework (Lao's RMS). Integrating both frameworks allows for a more practical road maintenance system by combining HDM-4's economic assessment capabilities with MUSTEM's predictive accuracy. This hybrid approach ensures data-driven decision-making that optimizes maintenance schedules while improving cost efficiency and resource allocation, which could significantly enhance condition prediction accuracy, account for uncertainties, and improve both short-term and long-term maintenance planning in Lao PDR.

6.2. Policy and Practical recommendations

Based on the findings and proposed model development, this research offers recommendations in order to enhance road network management, particular in Lao PDR, as follows:

1) Develop a hybrid road management system

   Developing an integrated framework that combines the predictive strength of the MUSTEM model with the economic evaluation capabilities of HDM-4 can significantly enhance the effectiveness of the Road Management System (RMS), particularly in Lao PDR. While HDM-4 is already used as a core tool for long-term maintenance planning and budget allocation, its integration with MUSTEM would provide a more robust decision-making process. Specifically, HDM-4 can continue to support high-level economic analyses such as evaluating Net Present Value, Vehicle Operating Costs, and user benefits. At the same time, MUSTEM strengthens condition-based forecasting by incorporating deterioration uncertainty. MUSTEM could identify critical road sections at risk of fast deterioration, informing prioritization decisions. HDM-4 would then be used to design targeted interventions and assess long-term economic plans. This integrated approach would enhance the precision of maintenance scheduling, optimize resource allocation, and enhance road network management.

2) Improving data collection methodologies

   Integrating advanced technologies such as GIS, remote sensing, and automated road condition survey equipment to support reliable data collection. Implement regular and systematic data collection to support accurate condition estimation and maintenance needs. For example, In Australian expressway, GIS has been employed to enhance data collection, management, planning, resource allocation, and long-term maintenance activities.

3) Capacity building and Research and Development

   Developing training programs, enhancing capacity and methodologies for central and local road authorities, and improving their skills in using advanced modeling techniques and data analytics. In addition, collaborate with international experts to build capacity and transfer knowledge.

4) Strengthening Funding Mechanisms

Reducing public funding by developing a Public-Private partnership (PPP) system to reduce dependence on public funding. Given the financial constraints of Lao PDR, Build-Operate-Transfer (BOT) and Performance-Based Contract (PBC) could be cost-effective options for the government and private sector. In the meantime, developing an allocation funds strategy to prioritize critical road sections, optimize maintenance interventions, and enhance financing management using innovative and transparent mechanisms.

5) Address climate change adaptation

Invest in road infrastructure resilient to climate change impact using climate-resistant materials and advanced construction techniques that can withstand extreme climate conditions. Integrate predictive climate models and environmental impact assessment into the road design process, considering uncertainties from climate changes to ensure the sustainability and reliability of road networks under changing climate conditions.

6) Incorporate Artificial Intelligence (AI) and Machine Learning

Utilize the robustness of AI and machine learning to enhance road condition predictions and maintenance planning. Nowadays, AI-driven systems have been successfully implemented in developed countries to forecast pavement deterioration using real-time sensor data, enabling proactive maintenance planning. Similarly, machine learning models can analyze historical data to predict optimal intervention timings. However, as Laos is a developing country, significant efforts are required to build AI and machine learning capacity. This includes investing in technical education, fostering collaborations with international technology experts, and developing infrastructure that supports data-driven innovations.

6.3. Contribution of Knowledge

This research aims to provide significantly to both the academic and practical domains of road network management by introducing the MUSTEM model as a novel application of stochastic methodologies for road maintenance planning. Unlike traditional deterministic models, MUSTEM incorporates the uncertainty of pavement deterioration and provides optimized life-cycle cost estimates. This research bridges the gap between theoretical and real-world applications, particularly in the context of developing countries like Lao PDR.

On the academic side, this study extends the boundaries of understanding stochastic models in road network management. It uniquely emphasizes the potential of the MUSTEM model, a stochastic approach that can significantly enhance traditional maintenance planning and cost-effectiveness. Demonstrating the effectiveness of this model also enriches the existing knowledge base in road network management. Moreover, introducing a comparative analysis framework as a new evaluation approach for different road management systems is a methodological innovation that advances research methods in the field and can be applied in other developing countries facing similar challenges.

From a practical perspective, this research's findings provide valuable workable insights for road management authorities, specifically for the Lao PDR and similar contexts. The findings and recommendations can guide these authorities in improving their road network management practices. Furthermore, integrating stochastic methodology into road network management underscores the practical implications of embracing advanced methodology in maintenance planning and decision-making processes. By showcasing the potential of these approaches, this research highlights their usefulness and opens up new opportunities for enhancing the efficiency and effectiveness of road management practices.

6.4. Limitations

This study provides valuable insights into optimizing road network asset management in Lao PDR. However, several limitations need to be acknowledged. First, the accuracy of the MUSTEM model depends on the quality and availability of input data, which remains a challenge in data-limited environments. Second, integrating MUSTEM with HDM-4 requires substantial capacity-building efforts among road authorities, which may delay implementation. Third, financial constraints may hinder the adoption of the proposed model, limiting the practical application of predictive maintenance strategies. Lastly, the study's findings are based on data from the Lao PDR. At the same time, other developing countries can adapt the proposed framework. However, additional validation is required to assess its effectiveness in diverse geographic and economic contexts.

6.5. Future Research

This study highlights the effectiveness of enhancing existing Lao's RMS by integrating road condition prediction and finding optimal maintenance strategy and allocation by stochastic deterioration and decision process. However, this study revealed the model application using Lao road network data, which may differ from other counties. Therefore, the following areas are the suggestions for future research:

1) **Extend case study**: Apply the conceptual model to other developing countries to validate its findings and assess its adaptability to different contexts and practices. For instance, countries like Cambodia, Myanmar, and Nepal, which share similar challenges in road network management due to limited resources and rugged topographies, could provide relevant contexts for testing the model.

2) **Investigate and explore the influences of innovative technology**: Employing AI and machine learning on road and infrastructure management to enhance prediction model accuracy and improve decision-making.

3) **Different Policy and strategy impact assessment**: Investigate the impact of various policy changes on road maintenance; this includes evaluating different types of maintenance interventions and budget allocations based on specific constraints in different regions to develop the most appropriate maintenance strategy.

4) **Research on Climate change adaptation**: Climate change poses challenges to road networks, and investigating its short-term and long-term impact helps us design resilient infrastructure. Evaluate the effectiveness of resilient infrastructure and sustainable infrastructure to ensure the road's service longevity.

5) **Pilot Project Implementation in Lao PDR**: Implement a pilot project to apply the proposed MUSTEM model in a real-world road maintenance project,

particularly in Lao PDR, as recommended by the authorities in charge in Laos's MPWT. This pilot project will test the model's predictive accuracy and operational efficiency using the dataset in real road maintenance projects. The implementation and results from the pilot project will serve as a practical validation of the model regarding prioritizing maintenance interventions, optimizing budget allocation, and estimating road conditions under limited budget scenario.