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Forecasting Pavement Deterioration and Optimizing Maintenance Strategies under Budget Constraints: A Markov Chain and Economic Evaluation of Caraga's Road Network

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Abstract: *This study applied a Markov chain model to assess the long-term pavement condition of Caraga's provincial road network under varying budget allocations. Using 2018–2023 road data from the DPWH's RBIA platform, transition probability matrices (TPMs) were computed and used to forecast 20-year deterioration trends. Maintenance and rehabilitation scenarios were tested under ₱200M, ₱300M, ₱400M, and actual average provincial budgets. Results showed Agusan del Norte deteriorates fastest (22%) but remains below serviceable thresholds even with cost-effective spending (BCR = 1.22). In contrast, Surigao del Norte achieved the highest BCR (1.42) by maintaining preventive maintenance. Forecasted state scores (FS₂₀) revealed critical intervention periods vary by province. The integration of TPMs with economic indicators (NPV, BCR) offers a practical framework for optimizing road investments. This approach supports data-driven, province-specific maintenance strategies essential for sustaining road quality in growing regions like Caraga.*

Keywords: Markov chain; Predictive Analytics; Provincial roads; Pavement deterioration; Economic evaluation.

1. INTRODUCTION

The condition of a nation's transportation system is closely linked to its overall development [1,2]. Well-maintained pavements contribute to economic efficiency, road safety, and reduced environmental impacts [3,4]. To maintain pavements in a serviceable state over time, decision-makers rely on a pavement management system (PMS) as a structured framework in identifying efficient and cost-effective maintenance and repair (M&R) strategies [5]. Monitoring pavement condition is a primary step in ensuring the effectiveness of a PMS [6]. For example, the Department of Public Works and Highways (DPWH) conducts the Road Condition (RoCond) monitoring to assess pavement condition annually [7]. Each section is rated (Good, Fair, Poor, or Bad) and uploaded to the Road and Bridge Information Application (RBIA). The RBIA serves as the DPWH centralized database system for managing road and bridge data across the Philippines [8].

Road pavements naturally undergo progressive deterioration due to continuous traffic loading, environmental exposure, and material aging [9]. As a result, maintaining and rehabilitating the global road network requires billions of dollars each year. However, limited budgets often delay maintenance and rehabilitation which leads to poor pavement performance [10]. Poor road surfaces have been linked to a higher risk and severity of accidents, especially across different speed zones [4]. Chun and Lin [11] emphasized that effective road management should include risk assessments related to pavement conditions to reduce accidents and enhance safety. Additionally, poor pavement contributes to traffic congestion, which not only slows mobility but also harms the environment [12]. High traffic congestion caused by poor pavement conditions leads to increased vehicle emissions. A local study found that this relationship contributed to 90.86% of the Caraga region's pollution [13]. These challenges underscore the urgent need for effective pavement

management strategies to ensure safe, efficient, and sustainable road networks.

Predictive analytics offers a practical and cost-effective method for forecasting pavement conditions based on historical data, thereby supporting long-term maintenance planning. Predictive models are generally classified into two categories: deterministic and probabilistic approaches [14,15]. Deterministic models, such as linear and multivariate regression, rely on detailed datasets and predefined equations to produce accurate forecasts. In contrast, probabilistic models are designed to account for the inherent uncertainties in pavement deterioration and are particularly useful when data is limited or incomplete [16]. Among these, the Markov chain model is one of the most widely applied techniques, utilizing transition probabilities derived from historical condition data to estimate future pavement performance [2,5,15]. It is relatively straightforward to implement and is especially well-suited for network-level pavement management applications [17,18]. Beyond forecasting, the Markov model also can optimize budget planning and maintenance and rehabilitation (M&R) strategies, making it a valuable tool for managing constrained resources within the PMS [5,24]

Given the practical advantages of the Markov chain model for forecasting and planning, this study applies it to the context of Caraga's provincial road network. By applying this method, the study seeks to provide practical insights into how different budget allocation affect long-term road conditions and resource allocation. The results are intended to support more data-driven and cost-effective pavement management strategies for regions facing budget and resource constraints.

2. STUDY AREA

This study focuses on Region XIII (Caraga), Philippines, which occupies the northeastern section of Mindanao (see Fig. 1). It consists of five provinces, namely: Agusan del Norte, Agusan del Sur, Surigao del Norte, Surigao del Sur, and the Dinagat Islands. Six cities are also located

within the region: Bayugan, Bislig, Cabadbaran, Surigao, Tandag, and Butuan, which is classified as a highly urbanized city [20]. The Dinagat Islands an island province was excluded from this study due to the low Annual Average Daily Traffic (AADT) recorded in the province.

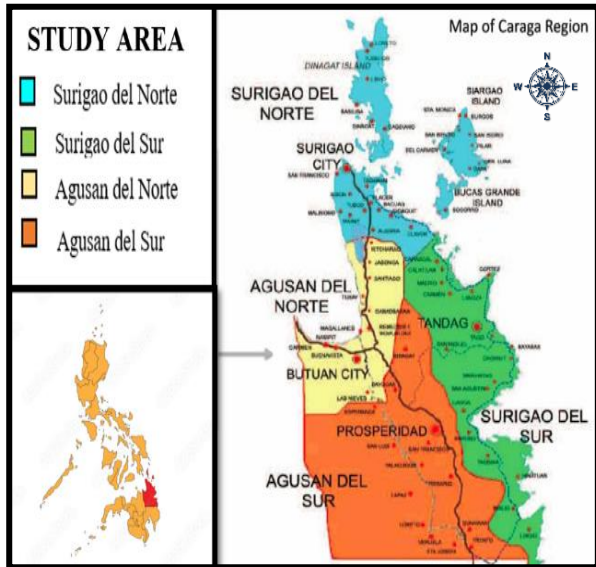


Fig. 1. Map of Caraga Region.

This study contributes to the economic development of the Caraga Region by supporting more efficient and data-driven management of its road network. With Caraga ranking as the second fastest-growing regional economy in 2024, at a 6.9% growth rate, maintaining reliable and well-performing roads becomes increasingly important [21]. Since transportation infrastructure directly supports trade, mobility, and employment [22]. Markov chain presents a simplified tool for pavement management that support local decision makers to improve maintenance strategies and budget allocation. This ensures that limited resources are directed toward timely repairs, reducing road deterioration and minimizing disruptions to economic activities. By enhancing road serviceability, the study ultimately supports sustained economic growth and regional competitiveness.

3. METHODOLOGY

3.1 Overview

Figure 2 shows the research flow used for this analysis. The process begins with the collection and preparation of road condition data. Transition Probability Matrices (TPMs) are then calculated to represent the likelihood of pavement condition transitioning from one state to another. Utilizing these TPMs, a Markov chain model is applied to forecast pavement conditions over a 20-year period, with each cycle representing one year. To simulate the M&R strategies, Equation 6 was used to adjust the predicted proportion distribution of pavement segments that could undergo maintenance or rehabilitation based on the available budget allocation scenarios (PHP 200M, PHP 300M, PHP 400M, and the actual budget) and the unit cost per kilometer (see Table 3). The results of the M&R simulation are then evaluated for cost-effectiveness, focusing on two key economic indicators: Net Present Value (NPV) and Benefit-Cost Ratio (BCR). Both metrics help determine which budget

scenario provides the most efficient use of resources for long-term pavement management.

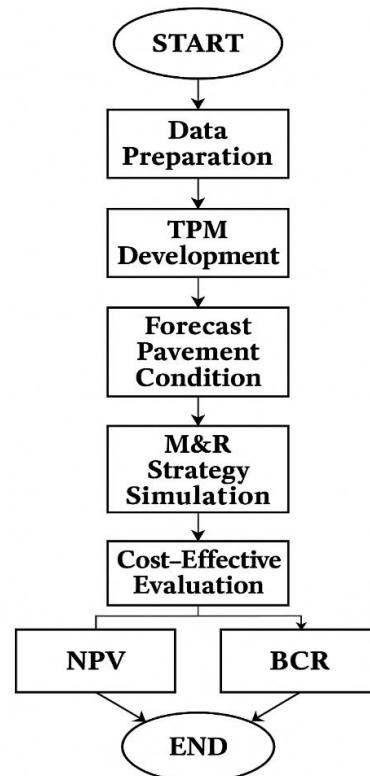


Fig. 2 Overview of the Methodology

3.2 Data Extraction and Preparation

The data used in this study were collected from the RBIA, a GIS-based platform developed by the Department of Public Works and Highways (DPWH) to support infrastructure planning and monitoring. RBIA is an accessible online database that includes road classification, surface type, pavement geometry (such as carriageway width, shoulder type, and number of lanes), road condition, and the year of last resurfacing. These road condition ratings are based on the RoCond survey, which is conducted annually to assess the state of road pavements [8]. This study will focus on concrete pavements since it is the dominating surface type that covers 77% of the total length of the Caraga region road network (see Fig 3). Furthermore, the calculation of Visual Condition Index (VCI) depends on the surface type being assessed [7].

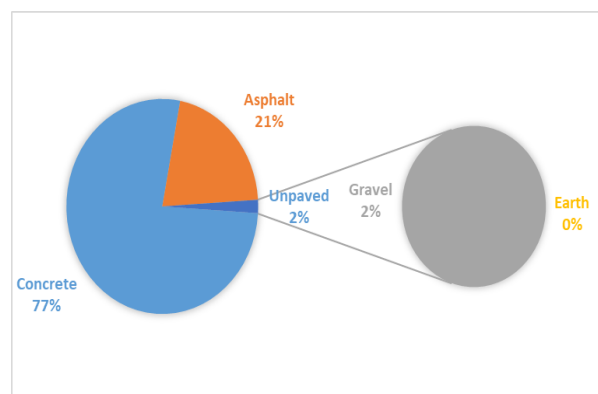


Fig. 3. Percentage of Road by Surface Type.

Visual condition index (VCI) is a key performance indicator (KPI) to measure the pavement performance of

a road network. The VCI assigns a numerical value based on observed surface distresses and classifies pavement sections into four categories: Bad, Poor, Fair, and Good, as detailed in Table 1. It is also used to evaluate the effectiveness of asset preservation strategies. These classifications allow for a uniform interpretation of pavement condition across the network [6]. The dataset used in this study covers the period from 2018 to 2023 obtained from DPWH database, providing a multi-year basis for analyzing deterioration trends.

Table 1. Condition Rating and Maintenance Actions

| VCI Range | Pavement Condition Rating | Recommended Rectification Measures |
|------------|---------------------------|---|
| 1 – 20 | Bad | Total reconstruction (need to rebuild the pavement) |
| 20.1 -40 | Poor | Need for extensive and full-depth repairs, and some full slab replacement or rehabilitation |
| 40.1 – 70 | Fair | Preventive Maintenance |
| 70.1 - 100 | Good | Routine Maintenance |

3.3 Markov Chain Process

Since pavement deterioration follows a stochastic process [16], the Markov chain model is one of the most widely used, especially for network-level analysis [18]. It applies transition probabilities to estimate the likelihood of condition changes over time, allowing for realistic performance predictions under uncertainty [5]. Magdy et al. [5], Sati et al. [15] and Tran et al. [23] demonstrated that the stochastic Markov chain model is well-suited for modeling pavement deterioration, where randomness stems from environmental variability and uncertainties in construction practices.

Markov chain uses transition probability matrix (TPM) which is an $n \times n$ matrix used to define the likelihood of moving from one condition state to another. Eq. (1), for example, shows a 4×4 TPM that captures transitions between four pavement condition states. Element P_{11} is the probability that the pavement remains in State 1, and P_{12} is the probability of moving from State 1 to State 2. The other entries represent similar interpretations for States 3 and 4, where State 4 represents 'Bad' condition.

$$TPM = \begin{pmatrix} P_{11} & P_{12} & 0 & 0 \\ 0 & P_{22} & P_{23} & 0 \\ 0 & 0 & P_{33} & P_{34} \\ 0 & 0 & 0 & P_{44} \end{pmatrix}^t \quad (1)$$

Faris and Mahir [24] describe a road network as a collection of roads, each consisting of multiple sections. The initial state vector (IP_o) represents the current condition distribution of the network. It is derived from inspection data by calculating the proportion of road sections in each condition state at the starting year, as shown in Eq. (2) and (3).

$$IP_o = [V_1, V_2, V_3, V_4] \quad (2)$$

$$V_i = \sum \frac{v_i}{n}; \quad i = 1, 2, 3 \dots \quad (3)$$

Where $V_1, V_2, V_3,$ and V_4 represent the proportions of road sections in Good, Fair, Poor, and Bad condition states, respectively. Eq. (3) calculates the proportion of road sections V_i in condition state i by dividing the number of sections in that state by the total number of sections (n). In Markov models, it is assumed that pavement deteriorates progressively, the time interval that state condition changes from state t to $t+1$ is usually one year. This assumption has been used in many studies [see, e.g., 5,9,14,19,25]. Given the initial condition vector (IP_o), the future condition (FPt), after (t) periods, can be determined using Eq. (4) [25]:

$$FPt = IP_o \times TPM^t \quad (4)$$

Then the future state (FS_t) of the pavement can be calculated as presented in Eq. (5) [16].

$$FS_t = IP_o \times TPM^t \times PS \quad (5)$$

where PS denotes the possible states which uses weight factors based on Table 1: $PS = [100, 70, 40, 20]$. The analysis produces a score from 0 to 100, where 100 is the best condition and 0 is the worst.

3.4 Budget Allocation Scenarios

The 2023 proportion distribution of pavement conditions for each province (see Table. 2) was used as the initial state vector to model the progression of the pavement condition across a 20-year cycle. Markov chain model was used to forecast pavement deterioration under a do-nothing (DN) scenario for each province. Then the future state FS_t which is the result of the simulation will serve as a baseline to understand how pavements deteriorate over time without any maintenance or rehabilitation interventions. The expected result for FS_t is the percentage of the total road network in each condition state. For example, [0.44, 0.52, 0.04, 0.01] means 44% are in Good, 52% in Fair, 4% in Poor, and 1% in Bad condition.

$$Kt = \frac{\text{Budget allocation}(Ct)}{\text{Unit Cost}(Uc)} \quad (6)$$

For realistic maintenance and rehabilitation (M&R) simulations, the pavement condition forecasts were adjusted based on specific budget scenarios. These scenarios included ₱200M, ₱300M, ₱400M, and the average provincial budget calculated from 2018 to 2023 (Table 4). The length of road segments that could undergo M&R for each budget was determined by dividing the allocated funds by DPWH's unit costs per kilometer (Table 3), as defined in Eq. (6). It was assumed that all segments receiving M&R would revert to a 'Good' condition, consistent with common assumptions in pavement lifecycle modeling. Budget data were sourced from the Department of Public Works and Highways (DPWH) [26].

Table 2. Proportion Distribution per Province

| | Good | Fair | Poor | Bad |
|-------------------|------|------|------|------|
| Surigao del Norte | 0.44 | 0.52 | 0.04 | 0.01 |
| Surigao del Sur | 0.24 | 0.48 | 0.17 | 0.11 |
| Agusan de l Norte | 0.25 | 0.54 | 0.13 | 0.09 |
| Agusan Del Sur | 0.19 | 0.49 | 0.17 | 0.15 |

Table 3. Unit Cost/Km of M&R treatments

| Surface Type | Scope of Work | Php/Km |
|--------------|----------------------------------|-----------------|
| Concrete | Reconstruction | ₱ 23,455,395.96 |
| | (Assumption with base Failure) | |
| | Rehabilitation | ₱ 11,033,629.28 |
| | (Assumption with 50% reblocking) | |
| | Preventive Maintenance | ₱ 16,329,754.82 |
| | (Assumption with 30% reblocking) | |

Table 4 Average Budget Allocation per Province

| Province | Avg. Budget Allocation | Length (km) |
|-------------------|------------------------|-------------|
| Agusan del Sur | ₱ 82,010,714.29 | 395.751 |
| Agusan del Norte | ₱ 67,532,961.54 | 120.398 |
| Surigao del Sur | ₱ 89,639,125.00 | 333.283 |
| Surigao del Norte | ₱ 71,515,769.23 | 283.237 |

3.5 Economic Analysis

Economic analysis was also conducted to examine the extent to which each maintenance and rehabilitation (M&R) financial allocations is economically sustainable. The evaluation focused on two indicators, Net Present Value (NPV) and Benefit–Cost Ratio (BCR), which measured the scale of condition improvement alongside the efficiency of resource use across different budget scenarios. These economic indicators provide quantitative insights into the long-term return on investment for maintenance and rehabilitation (M&R) expenditures at the network level [12].

The NPV was computed by discounting the annual gain in Visual Condition Index (VCI) between each treatment scenario and the baseline (do-nothing). This reflects the accumulated performance improvement attributable to M&R strategies, expressed in VCI points over 20 years. The official social discount rate (SDR) prescribed by the Philippine National Economic Development Authority is 10%. However, this study applied a more conservative 7% rate based on the Ramsey formula and international recommendations for low- to middle-income countries [27].

$$NPV = \sum_{t=1}^j \frac{VCI(Mi) - VCI(DN)}{(1-r)^t} \quad (7)$$

Where $VCI(Mi)$ scenario is the forecasted VCI under a given treatment budget, $VCI(DN)$ is the baseline scenario without intervention, r is the Social Discount Rate and j is the service life.

The Benefit–Cost Ratio (BCR) was calculated by dividing the NPV of condition improvement by the total cumulative cost of implementation:

$$BCR = NPV / TC \quad (8)$$

A BCR score greater than 1 indicates that the discounted performance gain outweighs the total expenditure, implying cost-effective investment [12]. Benefit-Cost Ratio (BCR) enabled a comparative assessment across

scenarios and supports rational budget allocation by quantifying the value of pavement condition improvement per peso spent.

4. RESULTS AND DISCUSSION

4.1 TPM Development

Transition Probability Matrices (TPMs) were calculated for each province using the road condition data from 2018 to 2023. The transition counts are summarized in

Table 5. Transition count matrix– Based on RBIA data

| | Good | Fair | Poor | Bad | Total |
|------------|------|------|------|-----|------------|
| ADS | | | | | |
| Good | 563 | 181 | - | - | 744 |
| Fair | - | 955 | 121 | - | 1076 |
| Poor | - | - | 224 | 42 | 266 |
| Bad | - | - | - | 292 | <u>292</u> |
| | | | | | 2378 |
| ADN | | | | | |
| Good | 254 | 92 | - | - | 346 |
| Fair | - | 356 | 48 | - | 404 |
| Poor | - | - | 50 | 19 | 69 |
| Bad | - | - | - | 37 | <u>37</u> |
| | | | | | 856 |
| SDS | | | | | |
| Good | 637 | 182 | - | - | 819 |
| Fair | - | 870 | 94 | - | 964 |
| Poor | - | - | 131 | 26 | 157 |
| Bad | - | - | - | 52 | <u>52</u> |
| | | | | | 1992 |
| SDN | | | | | |
| Good | 466 | 112 | - | - | 578 |
| Fair | - | 384 | 20 | - | 404 |
| Poor | - | - | 24 | 5 | 29 |
| Bad | - | - | - | 8 | <u>8</u> |
| | | | | | 1019 |

Table 5 shows the number of road segments that transitioned between condition states during each inspection cycle. This matrix serves as the basis for computing the Transition Probability Matrix (TPM) by dividing each count by the total number of segments in the same row, as indicated in Eq. (3). For instance, in Agusan del Sur (ADS), 181 segments transitioned from Good to Fair out of a total of 744 segments initially in Good condition. This results in a 24% probability of transitioning from Good to Fair. Meanwhile, 563 segments remained in Good condition. The sum of each row must equal 1, as the model assumes that all segments will transition to some state in the following period [5,9].

Table 6 TPM per Province

| | Good | Fair | Poor | Bad |
|------------|------|------|------|------|
| ADS | | | | |
| Good | 0.76 | 0.24 | - | - |
| Fair | - | 0.89 | 0.11 | - |
| Poor | - | - | 0.84 | 0.16 |
| Bad | - | - | - | 1 |
| ADN | | | | |
| Good | 0.73 | 0.27 | - | - |

| | | | | |
|------|---|------|------|------|
| Fair | - | 0.88 | 0.12 | - |
| Poor | - | - | 0.72 | 0.28 |
| Bad | - | - | - | 1 |

| | | | | |
|------------|------|------|------|------|
| SDS | | | | |
| Good | 0.78 | 0.22 | - | - |
| Fair | - | 0.90 | 0.10 | - |
| Poor | - | - | 0.83 | 0.17 |
| Bad | - | - | - | 1 |

| | | | | |
|------------|------|------|------|------|
| SDN | | | | |
| Good | 0.81 | 0.19 | - | - |
| Fair | - | 0.95 | 0.05 | - |
| Poor | - | - | 0.83 | 0.17 |
| Bad | - | - | - | 1 |

Following the transition count matrix in Table 5, Table 6 presents the calculated transition probabilities for each province. Agusan del Norte (ADN) has the highest average probability of deterioration at 22%, indicating a faster decline in road condition compared to the others. Surigao del Norte (SDN) shows the lowest average at 14%, suggesting slower deterioration. Agusan del Sur (ADS) and Surigao del Sur (SDS) fall in between, showing moderate deterioration patterns. These results indicate that deterioration rates vary across provinces, likely due to differences in traffic, climate, and maintenance practices. This supports the use of localized models when predicting pavement performance. The TPMs presented form the foundation for the Markov simulation, which forecasts long-term pavement conditions and evaluates maintenance strategies under varying budget constraints.

4.2 Degradation Forecast

Figures 4 to 7 show the observed (2018–2023) and predicted (2024–2043) distribution of pavement conditions in ADS, ADN, SDS, and SDN. The data reflect the percentage distribution of roads in Good, Fair, Poor, and Bad states based on VCI classification. These figures provide the basis for identifying optimal schedule for maintenance and rehabilitation (M&R) interventions. In ADS (see Fig. 4), the proportion of Good roads drops sharply after 2025, with a rapid increase in Poor condition by 2027. Preventive maintenance should be applied between 2024 and 2026 to reduce future rehabilitation costs. In ADN (see Fig.5), deterioration is advanced by 2024, with Poor and Bad roads already dominating. Immediate rehabilitation or reconstruction is required starting 2024. SDS (see Fig. 6) maintains a stable condition profile until 2029. Preventive maintenance between 2026 and 2029 is recommended to maintain network performance. In SDN (see Fig. 7), deterioration is minimal. The network remains mostly in Good and Fair condition through 2032, allowing preventive actions to be scheduled between 2029 and 2032.

Each province follows a distinct deterioration pattern. M&R timing should be based on condition trends rather than reactive maintenance schedules. ADN requires urgent corrective action. ADS should apply preventive maintenance before significant deterioration. SDS can extend pavement life through timely preventive works, and SDN can defer intervention without compromising

condition. Aligning interventions with these deterioration points minimizes total cost and supports long-term network performance.

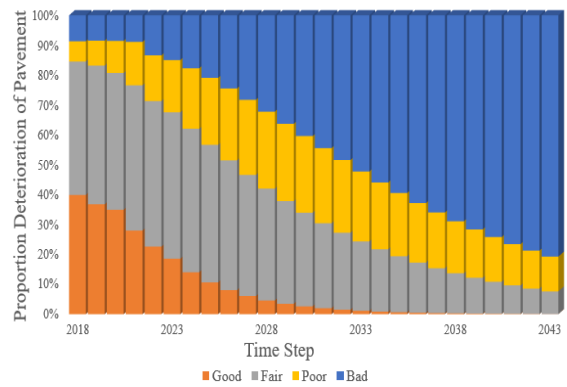


Fig. 4 Proportion Deterioration of ADS

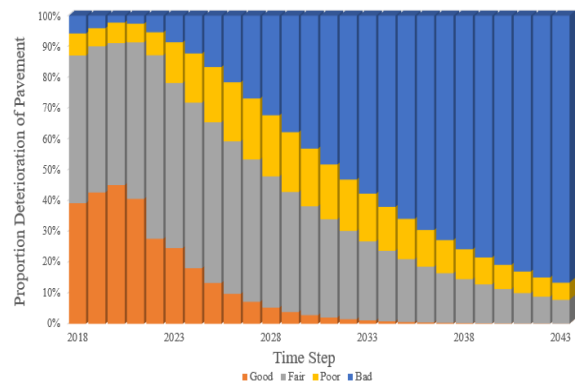


Fig. 5 Proportion Deterioration of ADN

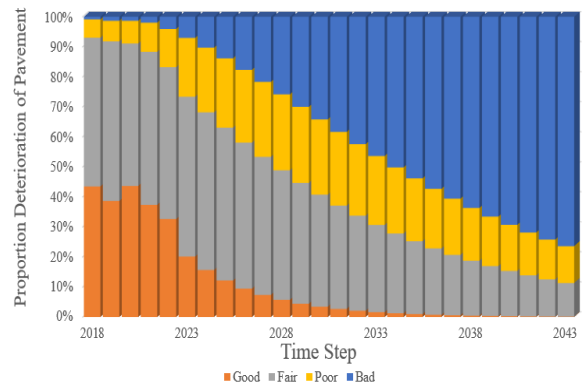


Fig. 6 Proportion Deterioration of SDS

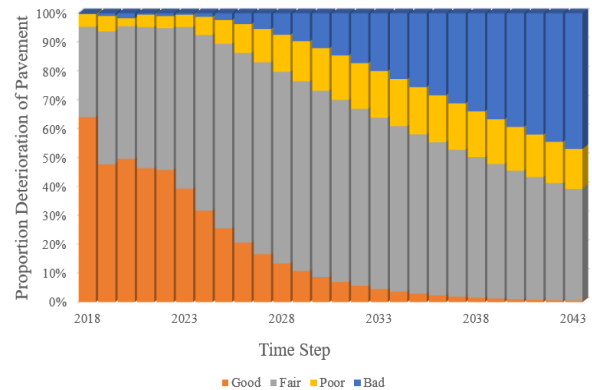


Fig. 7 Proportion Deterioration of SDN

4.3 NPV and BCR Results

Table 7 presents the economic analysis of various budget allocations for pavement maintenance across Caraga’s provinces, using three indicators: the forecasted condition score after 20 years (F_{s20}), Net Present Value (NPV), and Benefit-Cost Ratio (BCR). In Agusan del Sur (ADS), both the actual and 200M allocations were cost-effective, yielding BCRs above 1.0 and F_{s20} values exceeding 59. The actual budget produced the highest F_{s20} of 80.24, indicating that existing funding is sufficient to maintain acceptable pavement conditions without overinvestment. While increasing the budget to 400M raised the total benefits (NPV), the BCR declined to 1.03, reflecting reduced efficiency per peso spent. This suggests that the current allocation is optimal for sustaining network performance in ADS.

In Agusan del Norte (ADN), condition improvement was more responsive to budget increases. The F_{s20} peaked at 91.68 under the 400M scenario, but all allocations above the actual level yielded BCRs below 1.0. Only the actual budget achieved a cost-effective outcome (BCR = 1.22), though the resulting F_{s20} was only 50.57, barely within the fair condition range. This indicates a trade-off: while the actual budget is economically efficient, it may be insufficient to lift a poorly performing network to a fully serviceable level. In contrast, Surigao del Sur (SDS), which has the second-longest network (333.28 km), performed well under the 300M allocation, with a favorable balance of condition improvement (F_{s20} = 73.53) and cost-efficiency (BCR = 1.27), justifying increased investment for long-term network sustainability.

The role of network length, summarized in Table 4, adds further context to these results. ADS, with the longest road length (395.75 km), maintains high performance under its current budget, showing effective resource allocation. ADN, despite having the shortest network (120.40 km), struggles to achieve both serviceable conditions and cost-efficiency beyond its existing budget, suggesting allocation inefficiencies. Surigao del Norte (SDN), with a shorter network (238.24 km) and the lowest deterioration rate, achieved the highest BCR (1.42) under the actual allocation by maintaining quality through timely preventive maintenance. These findings emphasize that budget decisions must account for both the current state of the network and its deterioration behavior. While actual allocations may appear efficient, they must be assessed in the context of baseline conditions to ensure that all networks reach and sustain fair or better pavement performance, especially in a region like Caraga where reliable road infrastructure supports a growing PHP362.8 billion economy [25].

Table 7 Economic Evaluation Results

| | F_{s20} | NPV (in Billions) | BCR |
|------------|-----------|----------------------|------|
| ADS | | | |
| No_MR | 26.89 | - | - |
| 200M | 59.44 | ₱ 4.84 | 1.21 |
| 300M | 74.06 | ₱ 7.05 | 1.17 |
| 400M | 79.07 | ₱ 8.25 | 1.03 |
| Actual | 80.24 | ₱ 1.98 | 1.21 |
| ADN | | | |

| | | | |
|------------|-------|--------|------|
| No_MR | 25.66 | - | - |
| 200M | 79.63 | ₱ 3.86 | 0.96 |
| 300M | 85.97 | ₱ 4.52 | 0.75 |
| 400M | 91.68 | ₱ 5.09 | 0.64 |
| Actual | 50.57 | ₱ 1.65 | 1.22 |
| SDS | | | |
| No_MR | 28.92 | - | - |
| 200M | 58.66 | ₱ 5.10 | 1.27 |
| 300M | 73.53 | ₱ 7.64 | 1.27 |
| 400M | 78.59 | ₱ 9.23 | 1.15 |
| Actual | 42.24 | ₱ 2.30 | 1.27 |
| SDN | | | |
| No_MR | 43.50 | - | - |
| 200M | 77.60 | ₱ 3.95 | 0.99 |
| 300M | 82.04 | ₱ 4.69 | 0.78 |
| 400M | 86.27 | ₱ 5.40 | 0.67 |
| Actual | 61.62 | ₱ 2.03 | 1.42 |

5. CONCLUSION

This study employed the Markov chain model to forecast pavement deterioration across Caraga’s provincial road network, focusing on how different levels of budget allocation influence long-term network performance. Using condition data from 2018 to 2023, the model projected pavement state transitions over a 20-year horizon. Results revealed varying deterioration rates among provinces, demonstrating the model’s capability to capture realistic pavement behavior essential for scheduling maintenance and rehabilitation activities.

While the Markov chain model provided condition forecasts, economic indicators; Net Present Value (NPV) and Benefit-Cost Ratio (BCR) were used to evaluate the effectiveness of each investment scenario. These indicators measured the economic return of different funding levels relative to pavement needs. Provinces like SDS and SDN achieved high cost-efficiency by applying timely preventive maintenance, while ADN highlighted the challenge of maintaining network serviceability under constrained budgets and high deterioration risk.

Integrating pavement deterioration modeling with economic analysis offers a practical framework for transportation agencies and Local Government Units (LGU) to optimize road asset management. The Markov chain model supports long-term planning by identifying when and where interventions are most needed, while NPV and BCR help prioritize limited resources for best results. This approach is critical for regions like Caraga, where reliable road connectivity underpins economic activity and access to essential services.

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