

OPTIMIZING BUDGET ALLOCATION FOR LOW-VOLUME ROADS THROUGH THE AHP-TOPSIS APPROACH

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Abstract

Rural road maintenance prioritization under constrained public budgets requires balancing engineering condition, economic efficiency, and strategic policy objectives. Conventional benefit-cost (B/C) analysis provides an economically grounded framework but may emphasize high-traffic corridors while considering accessibility and regional distribution. This study developed and empirically evaluated an integrated Analytic Hierarchy Process-Technique for Order Preference by Similarity to Ideal Solution (AHP-TOPSIS) framework to support multi-criteria prioritization of rural road maintenance. Using 724 one-kilometer road sections across eight regional bureaus of Thailand's Department of Rural Roads, expert-derived criteria weights were obtained through AHP with verified consistency ($CR < 0.10$) and incorporated into a TOPSIS-based ranking procedure. Comparative validation was conducted against historical allocation practices and conventional B/C prioritization under identical budget constraints. Our results indicate that the AHP-TOPSIS framework achieves comparable aggregate pavement performance, reduces inter-regional variability in post-maintenance International Roughness Index (IRI), and expands total maintenance coverage by 7.4% within the same fiscal envelope. Investment distribution across national strategic categories is more balanced under the multi-criteria framework, reflecting closer alignment with policy goals. These findings demonstrate that structured multi-criteria decision synthesis can provide a transparent and policy-explicit complement to traditional economic evaluation in large-scale rural road maintenance planning.

Keywords: Multi - Criteria Decision Making; Budget allocation; Rural Road Network; Strategic Policy; IRI

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Introduction

Sustaining an efficient rural road network poses a persistent challenge, where maintenance needs expand while budgets remain constrained. Thailand illustrates this condition clearly: the Department of Rural Roads (DRR) manages a network of 48,974 km, yet annual maintenance allocations consistently meet only 60-65% of estimated requirements (Figure 1). This structural funding gap necessitates selective intervention, often leading to deferred maintenance and accelerated deterioration. Evidence indicates that delayed treatment on low-volume roads (LVRs) can increase long-term costs by up to 300%, underscoring the importance of systematic prioritization under fiscal constraints (Fwa *et al.*, 2018).

Conventional benefit-cost (B/C) analysis has long provided the primary framework for infrastructure investment decisions (Boardman *et al.*, 2018). However, when applied to low-volume rural networks, structural limitations become evident. Monetized benefits are strongly influenced by traffic volume, favoring high-traffic corridors with substantial travel-time savings, while strategically relevant but low-traffic links may receive lower prioritization despite their roles in agricultural logistics and regional connectivity (Labi & Sinha, 2003; Santos *et al.*, 2019). Non-monetary dimensions - such as access to healthcare, education, and economic participation - remain difficult to internalize within standard economic evaluation frameworks (OECD/ITF, 2021). These characteristics suggest that B/C analysis, while an effective efficiency metric, does not fully represent the strategic, social, and spatial considerations embedded in rural road governance.

In response, multi-criteria decision-making (MCDM) frameworks have gained increasing attention. Methods such as AHP (Saaty, 1980) and TOPSIS (Hwang & Yoon, 1981) enable structured integration of heterogeneous criteria - including engineering condition, traffic demand, safety, accessibility, and policy relevance - within a unified prioritization model. In transportation contexts, hybrid AHP-TOPSIS models have incorporated condition indices, traffic measures, and stakeholder preferences within formal ranking procedures (Ishizaka & Labib, 2011; Tzeng & Huang, 2011). However, the explicit operationalization of nationally defined strategic policy frameworks within hierarchical weighting structures remains limited, and empirical comparisons between MCDM-derived rankings and historically implemented allocations under real fiscal constraints are still scarce in rural road contexts.

The DRR's four strategic pillars: logistic and integrated transport systems (LIS), urban traffic congestion reduction (TCA), tourism mobility (TSM), and transportation development for rural economic competitiveness (CED) provide a structured national policy framework for infrastructure investment that prior MCDM studies have not systematically incorporated within weighting hierarchies. This study developed and empirically evaluated an integrated AHP-TOPSIS prioritization framework aligned with this strategic structure. This was applied to 724 one-kilometer rural road sections under actual fiscal constraints using pavement condition data, traffic indicators, safety records, and socio-economic attributes.

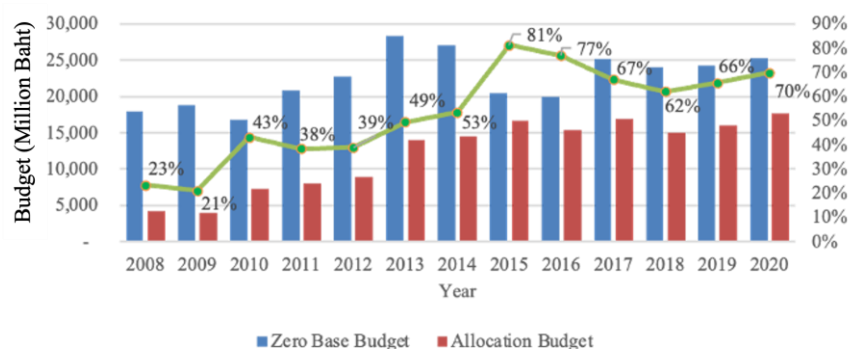


Figure 1. Shows The Annual Budget Report for Maintenance of Department of Rural Roads. (Department of Rural Roads, 2020)

The contribution of this research is threefold: it operationalizes nationally defined strategic pillars within a hierarchical multi-criteria structure, it provides an empirical comparison between MCDM-derived rankings and historically implemented allocations under real fiscal conditions, and it evaluates cost-performance dynamics by analyzing the relationship between roughness improvement and maintenance expenditure. Collectively, these contributions clarify whether multi-criteria decision synthesis provides measurable added value in rural road asset management beyond traditional economic evaluation.

Literature Review

In rural and low-volume road (LVR) networks, where budget constraints and regional equity concerns intersect, the choice of prioritization methodology critically shapes long-term development outcomes.

International Roughness Index (IRI)

The International Roughness Index (IRI) is a globally standardized indicator of pavement surface condition derived from simulated vehicle suspension response (Sayers *et al.*, 1986). Since its adoption by the World Bank and the National Cooperative Highway Research Program (NCHRP), empirical studies associate higher IRI levels with increased vehicle operating costs and safety risks, particularly beyond moderate roughness thresholds (Zaabar & Chatti, 2010; Wang *et al.*, 2022).

However, the applicability of IRI as a standalone prioritization metric in low-volume rural roads (LVRs) requires caution. Deterioration mechanisms in LVR networks are often influenced by drainage deficiencies, environmental exposure, and intermittent heavy-vehicle loading, resulting in non-uniform roughness progression (Gedafa *et al.*, 2014; Torres-Machi *et al.*, 2017). Recent research highlights that deterioration rates in lightly trafficked rural corridors may deviate from conventional mechanistic-empirical models developed for higher-volume roads. These findings suggest that while IRI remains a necessary engineering indicator, comprehensive prioritization requires integrating it with traffic, safety, and socio-economic dimensions.

Limitations of Economic-Based Prioritization Approaches

Benefit-cost (B/C) analysis has long been recognized as a foundational framework for public

infrastructure decision-making because it quantifies economic efficiency under constrained budgets (Boardman *et al.*, 2018). In transportation planning, B/C analysis provides a structured method for comparing alternatives based on monetized user benefits, including travel time savings, reductions in vehicle operating costs, and safety improvements (Small & Verhoef, 2007). Its strengths lie in transparency, comparability, and alignment with principles of welfare economics.

However, several structural limitations have been documented when applying B/C analysis to rural and low-volume road contexts. First, monetized benefits are strongly influenced by traffic volume. Since vehicle operating cost savings and time savings increase with traffic demand, corridors with higher average daily traffic naturally generate larger quantified benefits, potentially leading to systematic prioritization of high-traffic routes (Labi & Sinha, 2003). In low-volume networks, where social accessibility and regional connectivity might be strategically important despite modest traffic flows, purely traffic-driven economic metrics may undervalue broader development impacts.

Second, conventional B/C frameworks depend on monetizing impacts, which can be challenging for social accessibility, spatial equity, and community development objectives (Boardman *et al.*, 2018). While shadow pricing and distributional weighting have been proposed in welfare economics, such adjustments are rarely operationalized in everyday maintenance prioritization practices. Consequently, infrastructure decisions may focus on overall economic efficiency over distributive or strategic considerations.

Third, pavement performance improvements do not always yield linear marginal benefits at all roughness levels. Experiential pavement management research indicates that the relationship between roughness reduction and user cost savings is nonlinear, particularly when initial IRI levels are already moderate (Chatti & Zaabar, 2012). Under such conditions, incremental smoothing may yield lower economic returns than maintenance expenditure. Standard B/C models may not fully capture these nonlinear cost-performance dynamics when applied uniformly across heterogeneous rural networks.

These limitations do not diminish the value of B/C analysis as an economic evaluation tool; rather, they highlight the need for complementary decision frameworks that incorporate technical condition indicators, policy priorities, and socio-economic considerations within a unified prioritization structure.

Emergence of Multi-Criteria Decision-Making (MCDM) Frameworks.

Multi-criteria decision-making (MCDM) methods have been widely used in infrastructure asset management as alternatives to single-objective economic optimization. Unlike cost-benefit analysis, which combines impacts into a monetary value, MCDM methods explicitly keep different evaluation factors within a structured decision-making process (Saaty, 1980; Hwang & Yoon, 1981). This feature is particularly relevant in public-sector road management, where engineering condition, traffic demand, safety, accessibility, and policy alignment must be considered concurrently.

Among the most established MCDM techniques, the Analytic Hierarchy Process (AHP) derives relative weights through pairwise comparisons and incorporates a formal consistency verification mechanism (Saaty, 1980). The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) ranks alternatives based on their geometric proximity to an ideal and anti-ideal solution (Hwang & Yoon, 1981). Outranking methods such as PROMETHEE (Brans & Vincke, 1985) and ELECTRE (Roy, 1991) determine preference relations based on dominance thresholds and are often characterized as non-compensatory decision models (Behzadian *et al.*, 2012). VIKOR introduces compromise solutions by balancing group utility and individual regret measures (Opricovic & Tzeng, 2004).

Recent review studies in transportation and infrastructure systems journals indicate growing application of hybrid MCDM models for road asset prioritization, particularly in contexts where social equity and policy alignment must complement technical condition indices (Ishizaka & Labib,

2011; Tzeng & Huang, 2011; Herabat *et al.*, 2019; Mishra & Sinha, 2020). Comparative assessments suggest that compensatory models such as AHP-TOPSIS provide transparent weighting structures and are easier to communicate to decision-makers, whereas outranking approaches may better handle strict threshold conditions but require more complex parameter calibration (Behzadian *et al.*, 2012).

Machine learning (ML) techniques have demonstrated strong predictive capability in modeling pavement deterioration (Li & Chen, 2023). However, predictive accuracy does not inherently translate into policy-explicit prioritization logic, particularly in public-sector contexts requiring transparency and accountability. Accordingly, predictive models and multi-criteria frameworks serve complementary roles: ML enhances forecasting accuracy, while MCDM structures normative allocation decisions.

Theoretical Positioning of AHP-TOPSIS Integration.

Prioritization of road maintenance projects constitutes a normative decision problem rather than a purely predictive task. While data-driven models enhance the accuracy of deterioration forecasting, investment allocation in public infrastructure requires explicit representation of trade-offs among economic efficiency, engineering condition, safety performance, and social accessibility. As discussed in multi-criteria decision literature (Saaty, 1980; Hwang & Yoon, 1981; Ishizaka & Labib, 2011), structured weighting and ranking mechanisms are necessary when heterogeneous objectives must be reconciled within budget constraints.

Table 1. Comparative evaluation of principal prioritization approaches in rural road management

Method	Decision Logic	Strengths	Limitations
Benefit–Cost (B/C)	Economic efficiency maximization	Intuitive; comparable across projects; budget-efficient	Traffic-volume bias; weak equity integration; may not fully capture nonlinear cost–performance dynamics.
AHP	Hierarchical pairwise weighting	Transparent weight derivation; expert-driven; aligns with strategic planning	Subjective bias risk; Allows trade-offs among criteria (fully compensatory).
TOPSIS	Distance to ideal solution	Handles benefit & cost criteria; computationally scalable; intuitive ranking	Fully compensatory; sensitive to normalization
AHP-TOPSIS (hybrid)	Policy-weighted + distance-based ranking	Balances strategic priorities & quantitative performance; scalable; transparent	Requires careful consistency validation
Machine Learning	Predictive modeling of deterioration	Captures nonlinear relationships; strong forecasting capability	Limited transparency in ranking logic; does not inherently embed policy trade-offs; high data demand

The integration of AHP and TOPSIS provides a theoretically coherent decision architecture for such contexts. AHP enables systematic elicitation of expert preferences through pairwise comparisons and incorporates a formal consistency verification procedure, ensuring logical coherence in derived weights (Saaty, 1980). TOPSIS subsequently operationalizes these weights by ranking alternatives according to their geometric proximity to an ideal and anti-ideal solution (Hwang & Yoon, 1981). This two-stage structure separates preference derivation from alternative evaluation, enhancing transparency and reproducibility.

Compared with single-objective economic rankings or purely predictive machine-learning systems, the AHP-TOPSIS framework embeds policy priorities directly within the decision structure. It enables precise adjustment of weighting schemes to reflect strategic goals across regions, thereby supporting accountability in governance and aligning regional policies. Importantly, the framework does not replace predictive deterioration models but complements them by translating multi-dimensional performance indicators into structured prioritization logic. The comparative characteristics of alternative prioritization approaches for low-volume roads are summarized in Table 1.

As summarized in Table 1, alternative prioritization methodologies exhibit different trade-offs among economic efficiency, interpretability, computational scalability, and policy integration. Conventional benefit-cost approaches emphasize economic return maximization but may place greater weight on higher-traffic corridors.

Within this methodological framework, the AHP-TOPSIS integration used in this study offers a clear division between preference elicitation and alternative evaluation. AHP enables explicit calibration of strategic weights, while TOPSIS offers computationally efficient ranking for large datasets. This combination aligns with the objective of embedding policy priorities into maintenance allocation decisions under budget constraints. Accordingly, the hybrid framework is selected not as a universal solution, but as a contextually appropriate decision architecture for large-scale rural road prioritization.

Methodology

This study used an integrated multi-criteria prioritization framework that combines expert judgment and empirical pavement data. The analysis focused on asphalt concrete pavements within the Department of Rural Roads (DRR) network. Although the total rural network exceeds

45,000 km, the analytical sample consisted of 724 one-kilometer road sections distributed across eight regional bureaus. The sections were selected based on data completeness, including pavement condition surveys, traffic statistics, accident records, and maintenance history. Sections with incomplete records were excluded to ensure analytical reproducibility.

The primary engineering indicator was the International Roughness Index (IRI), measured using automated survey technologies, including the Transverse Profile Logger (TPL) and the Laser Crack Measurement System (LCMS), in accordance with ASTM E950. Traffic variables included Average Annual Daily Traffic (AADT) and heavy truck volume. Safety data were derived from official accident records aligned with fiscal year 2019 condition data to ensure temporal consistency.

Socio-economic variables included population density (from the World Pop 2020 dataset), proximity to tourism centers, and business hubs. All datasets were harmonized to a standardized one-kilometer segmentation framework to ensure spatial consistency across criteria.

AHP-Based Weight Derivation

Criteria weights were derived using the Analytic Hierarchy Process (AHP). A structured questionnaire was administered to 20 purposively selected experts directly involved in rural road budgeting and strategic planning within DRR. The panel comprised senior administrators, bureau directors, division directors, and professional engineers with decision-making responsibility in annual maintenance allocation. Expert inclusion was based on two criteria: (i) a minimum of five years of direct involvement in DRR annual maintenance budget allocation, and (ii) active decision-making authority at the bureau or division level. Experts without budget-allocation responsibility or those serving in purely technical advisory roles were excluded to ensure that elicited preferences reflected operational institutional priorities. A panel size of 15-25 experts is commonly considered adequate for AHP group aggregation in infrastructure and management decision contexts, balancing judgment diversity and aggregation stability (Forman & Gass, 2001). The selected panel size ($n = 20$), therefore, aligns with established methodological guidance for structured multi-expert AHP applications.

The hierarchical structure consisted of three levels:

Level 1: Overall goal - prioritization of rural road maintenance sections.

Level 2: Primary criteria groups - Engineering Condition, Economic Efficiency, and Socio-Economic/Strategic Alignment.

Level 3: Sub-criteria - measurable indicators, such as IRI, traffic volume, heavy truck volume, accident frequency, population density, accessibility indicators, and alignment with DRR's four strategic pillars (LIS, TCA, TSM, CED).

Experts conducted pairwise comparisons using Saaty's 1-9 fundamental scale. For each expert k , a reciprocal comparison matrix $A^{(k)}$ was constructed such that:

$$a_{ij}^{(k)} = \frac{1}{a_{ji}^{(k)}}, a_{ii}^{(k)} = 1$$

Priority weights were derived using the principal eigenvector method:

$$A^{(k)} w^{(k)} = \lambda_{\max}^{(k)} w^{(k)}$$

where the normalized eigenvector satisfies:

$$\sum_{j=1}^n w_j^{(k)} = 1$$

To obtain group-level weights, individual comparison matrices were aggregated using the geometric mean method prior to eigenvector computation, consistent with AHP group decision theory (Saaty, 1980). This approach preserves reciprocal properties and is recommended for combining independent expert judgments.

The consistency of expert judgments was assessed using the Consistency Index (CI) and Consistency Ratio (CR) for each individual comparison matrix:

$$CI = \frac{\lambda_{\max} - 1}{n - 1}$$

$$CR = \frac{CI}{RI}$$

where RI denotes the Random Index (Saaty, 1980).

Aggregated CR at the strategic level was 0.023. Primary and sub-criteria matrices ranged between 0.002–0.032 and 0.006–0.031, respectively. All values were below the accepted threshold ($CR < 0.10$), indicating acceptable internal consistency and supporting integration of derived weights into the TOPSIS procedure. These weights serve as the input for the TOPSIS model (Chaipetch *et al.*, 2022) and are shown in Table 2.

TOPSIS for Segment - Level Prioritization.

Segment ranking was conducted using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). A decision matrix $D = [x_{ij}]$ was constructed, where m denotes the number of road sections, and n denotes the evaluation criteria.

Table 2. Shows the Summary of the analysis of Priority Factor

Factor/Strategic	LIS		TCA		TSM		CED	
	Priority Value	CR	Priority Value	CR	Priority Value	CR	Priority Value	CR
	27	0.023	27	0.023	22	0.023	24	0.023
Economic	46	0.002	40	0.030	43	0.027	45	0.032
Engineering	29	0.002	28	0.030	23	0.027	20	0.032
IRI	3	0.014	3	0.014	2	0.006	2	0.006
V/C Ratio	4	0.014	5	0.014	4	0.006	3	0.006
Traffic Volume	4	0.014	4	0.014	3	0.006	2	0.006
The volume of Heavy Truck	5	0.014	3	0.014	3	0.006	2	0.006
Lifeline	3	0.014	2	0.014	2	0.006	2	0.006
Connectivity to the road network	5	0.014	5	0.014	4	0.006	4	0.006
Accident data	5	0.014	6	0.014	5	0.006	4	0.006
Social	25	0.002	32	0.030	33	0.027	35	0.032
Population density	4	0.031	6	0.007	4	0.015	7	0.016
Tourist spots.	4	0.031	5	0.007	10	0.015	7	0.016
Business Center	5	0.031	6	0.007	6	0.015	7	0.016
Government office.	3	0.031	4	0.007	3	0.015	4	0.016
Hospital	3	0.031	4	0.007	5	0.015	5	0.016
Industrial Area	8	0.031	6	0.007	4	0.015	6	0.016

^a Strategic for logistic and integrated transport systems (LIS). Strategic for reducing traffic congestion in urban areas. (TCA) Strategic for tourism. (TSM) Strategic for developing transportation to strengthen competitiveness and rural economic development. (CED).

1. Construction and Normalization of Decision Matrix: Let $D = [X_{ij}]$ denote the decision matrix of dimension $m \times n$, where m represents the number of road sections (alternatives), and n denotes the number of evaluation criteria.

$$D = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

To eliminate scale differences across criteria, vector normalization was applied:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (2)$$

2. The normalized matrix was weighted using AHP-derived weights (w_j):

$$v_{ij} = w_j r_{ij} \quad (3)$$

The resulting matrix $V = [V_{ij}]$ embeds policy-calibrated importance weights into the segment-level evaluation.

3. Determination of Ideal and Negative-Ideal Solutions. For each criterion (j), the positive ideal solution (V_j^+) and negative ideal solution (V_j^-) were defined as:

For benefit-type criteria

$$v_j^+ = \max_i (V_{ij})$$

$$v_j^- = \min_i (V_{ij})$$

For cost-type criteria

$$v_j^+ = \min_i (V_{ij})$$

$$v_j^- = \max_i (V_{ij})$$

$$A^+ = \{V_1^+, V_1^+, \dots, V_n^+\} \quad (4)$$

$$A^- = \{V_1^-, V_1^-, \dots, V_n^-\} \quad (5)$$

4. The Euclidean distances from the positive and negative ideal solutions were calculated as:

$$S_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2} \quad (6)$$

$$S_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2} \quad (7)$$

5. Closeness coefficient and ranking. The relative closeness to the ideal solution was computed as:

$$C_i = \frac{S_i^-}{(S_i^+ + S_i^-)} \quad (8)$$

Sections were ranked in descending order of C_i . Higher values indicate closer proximity to the ideal multi-criteria performance profile under the AHP-weighted structure. and the final rank of maintenance priorities in the first iteration is shown in Table 3.

Table 3. Example of S^+ , S^- and C_i of each road maintenance section

Section	S^-	S^+	C_i	Rank
S1	0.0202	0.0022	0.902	3 rd
S2	0.0659	0.0689	0.489	5 th
S3	0.0222	0.0003	0.987	1 st
S4	0.0219	0.0006	0.973	2 nd
S5	0.0236	0.0255	0.480	6 th
S6	0.0175	0.0061	0.741	4 th

Comparative Evaluation Framework.

To assess the robustness and practical applicability of the proposed AHP-TOPSIS prioritization model, a structured comparative validation framework was designed. The validation utilized maintenance implementation records from fiscal year 2020 obtained from the Bureau of Maintenance, Department of Rural Roads (DRR).

The validation dataset comprised 724 one-kilometer road sections distributed across 24 districts within eight regional bureaus, with a total implemented budget of 3,716.25 million THB. All comparative simulations were conducted under identical total budget constraints to ensure methodological fairness across prioritization approaches.

The validation framework consists of two benchmark comparisons: (i) historical allocation practice, (ii) conventional benefit-cost (B/C) analysis, and (iii) Cost-Performance Analysis.

1. Historical Allocation Validation. Route-level and section-level alignment were assessed by comparing selected corridors and one-kilometer sections with historically implemented maintenance decisions. Implementation consistency was quantified using proportional spatial overlap:

$$\text{Route Consistent} = \frac{\text{Route Allocate by AHP} - \text{TOPSIS}}{\text{Route Historical Allocation}}$$

$$\text{Section Consistent} = \frac{\text{Section Allocate by AHP} - \text{TOPSIS}}{\text{Section Historical Allocation}}$$

Paired statistical tests were conducted to assess differences between route-level and section-level consistency.

2. Conventional Benefit–Cost Validation. Maintenance priorities were recalculated using conventional B/C procedures incorporating vehicle operating cost savings, travel-time reductions, and accident cost benefits. Comparative performance indicators included:

- Total maintained length (km).
- Average pre-treatment IRI.
- Average IRI improvement.
- Spatial Variability (standard deviation)
- Strategic allocation distribution

Paired t-tests and effect size (Cohen's d) were applied to examine differences in performance outcomes between AHP-TOPSIS and B/C selections.

3. Cost-Performance Analysis. To examine whether observed differences arise from intrinsic cost behavior or allocation logic, quadratic regression models were estimated separately for B/C- and AHP-TOPSIS-selected sections. Maintenance cost per kilometer was modeled as a nonlinear function of initial IRI (IRI_{BF}) and roughness improvement (ΔIRI), including squared terms to capture marginal effects. The functional specification is:

$$Cost_i = \beta_0 + \beta_1 IRI_{initial,i} + \beta_2 \Delta IRI_i + \beta_3 \Delta IRI_i^2 + \varepsilon_i$$

Table 4. Shows the result evaluation data between AHP – TOPSIS and historical maintenance data

Bureau	District	Maintenance History Data		Maintenance Route ^a		Maintenance Section Consistency ^b	
		Distance (Km.)	Budget (Baht ×10 ⁶)	Traditional	AHP – TOPSIS	Route Consistency (%)	Consistency (%)
Rural Road 3 (Chonburi)	Chonburi	59.600	403.271	19	18	94.74%	68.29%
	Chanthaburi	25.890	110.190	10	6	60.00%	48.07%
	Trat	39.484	203.619	15	10	66.67%	79.42%
	Bo Thong	44.560	288.347	8	7	87.50%	66.18%
	Rayong	17.164	118.005	8	4	50.00%	69.64%
	Bang Lamung	36.236	185.287	8	8	100.00%	98.48%
	Klang	13.750	89.525	7	5	71.43%	77.65%
Rural 6 (Khon Kaen)	Khon Kaen	32.723	192.008	8	8	100.00%	65.88%
	Maya Sarakham	36.534	162.977	12	10	83.33%	63.32%
	Roi Et	24.628	108.733	8	6	75.00%	86.41%
	Loei	30.725	101.498	11	10	90.91%	64.83%
Rural Road 7 (Ubon Ratchathani)	Yasothon	56.664	240.558	12	10	83.33%	72.40%
	Amnat Charoen	70.378	355.590	11	11	100.00%	67.35%
Rural Road 8 (Nakhon Sawan)	Kamphaeng Phet	13.749	240.558	12	10	83.33%	72.40%
	Uthai Thani	21.668	84.818	3	3	100.00%	60.30%
Rural Road 10 (Chiang Mai)	Mae Hong Son	15.088	57.474	5	4	80.00%	44.23%
	Lampang	8.882	43.649	6	5	83.33%	22.86%
	Lamphun	38.77	128.375	7	5	71.43%	77.29%
Rural Road 11 (Surat Thani)	Surat Thani	25.504	135.090	12	6	50.00%	78.84%
Rural Road 13 (Chachoengsao)	Nakhon Nayok	17.914	238.728	7	4	57.14%	100.00%
	Prachinburi	11.566	75.975	6	3	50.00%	89.73%
	Sa Kaeo	14.750	75.029	4	2	50.00%	100.00%
Rural Road 18 (Suphan Buri)	Kanchanaburi	42.68	262.907	6	4	66.67%	76.57%
	Nakhon Pathom	11.422	95.056	9	7	77.78%	35.89%
	Supan Buri	13.795	81.456	6	6	100.00%	35.81%
Average		28.965	163.149	8.80	6.88	77%	69%
Standard Deviation		16.637	95.362	3.59	3.49	17%	20%

Statistical comparison between route-level and section-level consistency (n = 24 districts):

Mean difference = 8.43 percentage points.

paired t-test $t(23) = 1.36$, $p = 0.186$,

Cohen's d = 0.27; 95% CI = [−4.36%, 21.22%].

^a Maintenance Route Consistent refers to the alignment between methods in selecting the same road corridors for maintenance budgeting, indicating whether both approaches prioritize the same routes at the network level

^b Maintenance Section Consistent refers to the alignment in identifying the same specific road sections or kilometer-based sections within a route. It reflects micro-level agreement and functions as a subset of route consistency.

Both models exhibited moderate raw R^2 values, negative adjusted R^2 , and insignificant F-tests, reflecting the limited sample size. The models were therefore interpreted as exploratory structural diagnostics rather than predictive estimators.

Results

Implementation Precision Compared with Historical Budget allocations

To evaluate practical coherence, implementation precision was assessed by comparing AHP-TOPSIS-selected sections with historically implemented maintenance decisions across 24 districts within eight regional bureaus (Table 4). Two levels of spatial consistency were examined: (i) route-level corridor alignment and (ii) section-level (1-km section) targeting precision.

Across the 724 km analyzed sections, average route-level consistency reached 77% (SD = 0.17), indicating substantial convergence in corridor identification. Several districts, including Bang Lamung, Khon Kaen, Amnat Charoen, and Suphan Buri, exhibited 100% route-level agreement, suggesting strong alignment in areas characterized by clear deterioration patterns or strategic importance.

At the section level, mean agreement was 69% (SD = 0.20), reflecting greater dispersion in sub-kilometer targeting. While districts such as Sa Kaeo and Nakhon Nayok achieved complete segment-level overlap, others, including Nakhon Pathom (35.89%) and Suphan Buri (35.81%), showed lower agreement. These differences indicate that corridor-level identification tends to be more stable than micro-level segment selection.

A paired-sample t-test was conducted to assess statistical differences between route- and section-level consistency. The mean difference was 8.43 percentage points, with route-level agreement higher on average; however, the difference was not statistically significant ($t = 1.36$, $p = 0.186$). The effect size was small (Cohen's $d = 0.27$), and the 95% confidence interval (-4.36% to 21.22%) included zero.

Overall, the findings indicate that the AHP-TOPSIS framework maintains alignment with historical allocation practices at the corridor level while exhibiting moderate divergence in sub-segment targeting. This pattern suggests refinement of spatial precision rather than structural deviation from established administrative priorities.

Pavement Performance: International Roughness Index (IRI)

Table 5 summarizes post-maintenance pavement performance across eight DRR regional bureaus under both prioritization approaches. Under identical budget constraints, the B/C method reduced the average IRI from 2.97 to 2.67 m/km, corresponding to a mean improvement of 0.30 m/km (10.30%). The AHP-TOPSIS approach reduced the average IRI from 2.97 to 2.71 m/km, yielding a mean improvement of 0.26 m/km (8.80%).

A paired t-test indicated that post-maintenance IRI values were lower under B/C than under AHP-TOPSIS (mean difference = -0.044 m/km; $t(7) = -3.46$, $p < 0.010$). The effect size was large (Cohen's $d = 1.23$), and the 95% confidence interval for the mean difference was [-0.074, -0.014].

Table 5. Shows the result evaluation data of International Roughness Index (IRI) between AHP – TOPSIS and B/C methodology

Bureau of Rural Road	International Roughness Index (IRI): m/km				
	Before Maintenance	After Maintenance		% difference (After Maintenance)	
		B/C	AHP-TOPSIS	B/C	AHP-TOPSIS
3 (Chonburi)	2.97	2.64	2.67	11.11%	10.10%
6 (Khon Kaen)	2.93	2.56	2.58	12.63%	11.95%
7 (Ubon Ratchathani)	2.79	2.42	2.54	13.26%	8.96%
8 (Nakhon Sawan)	2.91	2.69	2.71	7.56%	6.87%
10 (Chiang Mai)	3.30	2.97	3.01	10.00%	8.79%
11 (Surat Thani)	2.98	2.76	2.77	7.38%	7.05%
13 (Chachoengsao)	2.77	2.47	2.54	10.83%	8.30%
18 (Suphan Buri)	3.11	2.81	2.85	9.65%	8.36%
Average	2.97	2.67	2.71	10.3%	8.8%
Standard Deviation	-	0.183	0.165	-	-
Statistical comparison IRI After Maintenance:					
Mean difference (B/C – AHP) = -0.044 m/km					
paired t-test $t(7) = -3.46$, $p = 0.010$,					
Cohen's $d = 1.23$ (large) ; 95% CI = [-0.074, -0.014].					

Table 6. Shows the result evaluation data of length of road maintenance between AHP – TOPSIS and B/C methodology

Bureau of Rural Road	Length of Road Maintenance (km)			
	B/C	AHP-TOPSIS	Difference	% of Difference
3 (Chon Buri)	425.189	454.52	29.331	6.90%
6 (Khon Kaen)	219.919	233.46	13.541	6.16%
7 (Ubon Ratchathani)	316.241	314.193	-2.048	-0.65%
8 (Nakhon Sawan)	67.457	66.457	-1.000	-1.48%
10 (Chiang Mai)	80.171	86.780	6.609	8.24%
11 (Surat Thani)	51.789	56.089	4.300	8.30%
13 (Chachoengsao)	187.134	198.030	10.896	5.82%
18 (Suphan Buri)	171.858	223.260	51.402	29.91%
Sum	1,519.758	1,632.789	113.031	7.4%

Statistical comparison Length of road maintenance:
Mean difference (B/C – AHP) = 14.13 km, paired t-test $t(7) = 2.17$, $p = 0.067$,
Cohen's $d = 0.77$ (large); 95% CI = $[-1.26, 29.52]$.

Despite statistical significance, the absolute difference of 0.044 m/km is small in practical engineering terms. Both methods reduced IRI values to approximately 3.0 m/km or below across most bureaus, maintaining acceptable serviceability levels.

Post-maintenance variability across bureaus was slightly lower under AHP-TOPSIS ($SD = 0.165$) than under B/C ($SD = 0.183$), indicating marginally more uniform regional performance under the multi-criteria approach.

Overall, the findings indicate that B/C achieves slightly greater mean roughness reduction, whereas AHP-TOPSIS delivers comparable engineering performance with reduced inter-regional variability.

Cost Efficiency and Maintenance Coverage

Under identical budget limits, AHP-TOPSIS selected a larger total maintenance length than B/C. As shown in Table 6, total maintained length reached 1,632.789 km under AHP-TOPSIS, compared with 1,519.758 km under B/C—an increase of 113.031 km (7.44%).

At the bureau level, the mean increase in maintenance length was 14.13 km. A paired t-test indicated that the difference was not statistically significant at the 5% level ($t(7) = 2.17$, $p = 0.067$). The effect size was moderate-to-large (Cohen's $d = 0.77$), and the 95% confidence interval for the mean difference ranged from -1.26 km to 29.52 km.

The difference reflects contrasting prioritization structures. B/C tends to concentrate investment in sections with higher monetizable returns, frequently associated with more intensive rehabilitation. In contrast, AHP-TOPSIS distributes resources across a broader set of moderately deteriorated sections by incorporating engineering, accessibility, and strategic criteria.

Bureau 18 (Suphan Buri) exhibited the largest increase in coverage (29.91%). Overall, the findings indicate that AHP-TOPSIS expands spatial coverage without increasing total expenditure while maintaining comparable engineering outcomes.

Strategic Alignment with DRR's National Pillars

A clear structural distinction between the two prioritization approaches emerges in their alignment with DRR's four national strategic pillars: LIS, TCA, TSM, and CED as summarized in Table 7.

Under B/C, maintenance allocation is heavily concentrated in LIS corridors. Across eight regional bureaus, the mean LIS share reached 80.6% of total maintained length, with several bureaus exceeding 90%. In contrast, AHP-TOPSIS distributed allocations more evenly, with an average LIS share of 29.9%, alongside substantial representation of TCA (24.5%), TSM (23.0%), and CED (23.6%).

A paired t-test confirmed that LIS concentration under B/C was significantly greater than under AHP-TOPSIS (mean difference = 50.7 percentage points; $t(7) = -16.4$, $p < 0.001$). The associated effect size was extremely large (Cohen's $d = 5.8$), indicating a pronounced structural redistribution of maintenance coverage.

These results show that B/C concentrates investment primarily in economically dominant corridors, whereas AHP-TOPSIS reallocates maintenance length across multiple strategic categories. Importantly, this redistribution occurs under identical fiscal constraints and reflects differences in prioritization structure rather than budget expansion.

Overall, AHP-TOPSIS yields a substantially more diversified strategic portfolio compared to conventional economic prioritization.

Table 7. Shows the ratio of budget allocation in each strategy compares between B/C analysis and AHP-TOPSIS

Bureau of Rural Road	Ratio of length of maintenance in each strategy (%)							
	B/C Ratio				AHP-TOPSIS			
	LIS	TCA	TSM	CED	LIS	TCA	TSM	CED
3 (Chonburi)	67	29	1	2	29	26	21	24
6 (Khon Kaen)	75	25	-	-	26	18	31	24
7 (Ubon Ratchathani)	74	22	-	4	23	24	19	34
8 (Nakhon Sawan)	97	3	-	-	41	26	22	18
10 (Chaing Mai)	81	18	1	1	27	24	21	28
11 (Surat Thani)	86	14	-	-	37	23	24	17
13 (Chachoengsao)	73	23	1	3	29	26	21	24
18 (Suphan Buri)	92	3	-	5	27	29	25	20
Average	80.6	17.1	0.4	1.9	29.9	24.5	23.0	23.6

Statistical comparison Maintenance Length Across DRR Strategic Pillars:
Mean difference = 50.7 percentage points paired t-test $t(7) = -16.4$, $p = 0.001$,
Cohen's $d = 5.8$ (extremely large).

^a Strategic for logistic and integrated transport systems (LIS). Strategic for reducing traffic congestion in urban areas. (TCA) Strategic for tourism. (TSM) Strategic for developing transportation to strengthen competitiveness and rural economic development. (CED).

Table 8. Shows the result of Quadratic Cost-Performance Regression Results

Variable	B/C		AHP-TOPSIS	
	Coefficient	p-value	Coefficient	p-value
Constant	-43.5235	0.773	-7.4579	0.965
ΔIRI	-39.3958	0.716	-66.9437	0.588
IRI _{BF}	34.1165	0.724	13.1640	0.903
ΔIRI^2	54.4208	0.766	100.1506	0.631
IRI _{BF} ²	-5.4460	0.733	-2.0551	0.908
R ²	0.406	-	0.361	-
F-statistic (p-value)	0.736	-	0.787	-

Note: Dependent variable: maintenance cost per kilometer (million baht/km)

$\Delta IRI = IRI \text{ Before Maintenance} - IRI \text{ After Maintenance}$

IRI_{BF} = Initial Roughness Before Maintenance.

Models estimated using Ordinary Least Squares (OLS).

Small sample size ($n=8$) limits statistical power, results are interpreted as exploratory structural diagnostics rather than predictive estimator.

Budget Prediction Models and Cost-Performance Dynamics

To examine whether differences between B/C and AHP-TOPSIS arise from intrinsic cost behavior or allocation structure, quadratic regression models were estimated separately for each method. Maintenance costs per kilometer (million baht/km) were specified as a nonlinear function of initial pavement condition (IRI_{BF}) and roughness improvement (ΔIRI), including squared terms to capture marginal effects. The results are summarized in Table 8 and illustrated in Figure 2.

Although raw R^2 values appear moderate (0.406 and 0.361), the statistically insignificant F-tests ($p = 0.736$ and 0.787) indicate limited explanatory power given the small sample size, reflecting the limited sample size ($n = 8$; $df = 3$). The models are therefore interpreted as exploratory

structural diagnostics rather than predictive estimators.

In both specifications, positive coefficients on the squared ΔIRI terms indicate increasing marginal costs as reductions in roughness become greater, consistent with pavement engineering principles that require more intensive interventions to achieve substantial IRI improvement. The comparable R^2 magnitudes suggest broadly similar nonlinear cost behavior under both prioritization approaches.

Taken together with earlier findings-broader maintenance coverage under AHP-TOPSIS, reduced post-maintenance variability, and more balanced strategic distribution. The regression results indicate that observed differences primarily arise from allocation structure rather than intrinsic treatment cost regimes.

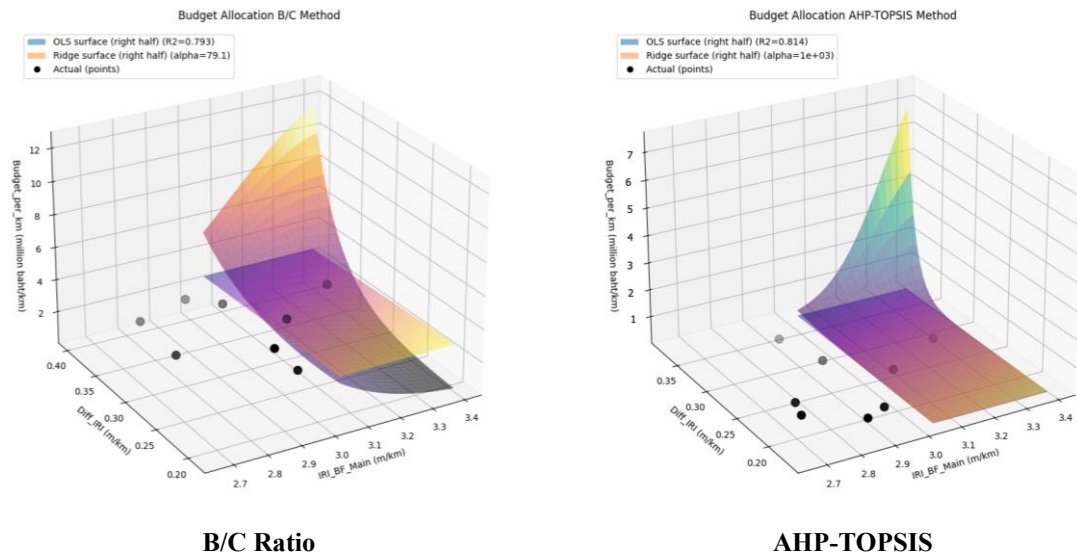


Figure 2. Exploratory cost-performance regression surfaces under B/C and AHP-TOPSIS prioritization frameworks

Discussion

Interpretation of Structural Differences Between Prioritization Frameworks

The comparative validation shows that the difference between the B/C and AHP-TOPSIS frameworks is structural rather than just numerical. Although both methods operate within similar nonlinear engineering cost systems and achieve similar total roughness improvements, they vary considerably in allocation logic and portfolio composition.

The B/C framework focuses resources on corridors with high monetizable returns, resulting in dominant allocation toward LIS corridors and increased treatment intensity per selected segment. In contrast, the AHP-TOPSIS framework allocates investments wider across strategic categories and geographic regions. This redistribution does not fundamentally alter engineering cost behavior, as suggested by the exploratory regression diagnostics, but it modifies the spatial and strategic configuration of maintenance delivery.

The observed reduction in post-maintenance IRI variability under AHP-TOPSIS further suggests that multi-criteria synthesis promotes network-level service stability rather than localized performance maximization. Accordingly, the empirical differences between frameworks appear to arise from decision architecture and prioritization structure rather than from intrinsic differences in treatment efficiency.

Theoretical Implications for Infrastructure Prioritization.

From a theoretical perspective, maintenance prioritization constitutes a normative decision-making problem rather than a purely predictive optimization task. Traditional economic evaluation operates under a single-objective paradigm, maximizing aggregate monetized benefit subject to budget constraints. However, public infrastructure systems function within multi-dimensional governance environments that incorporate equity, accessibility, regional balance, and long-term strategic alignment.

The findings of this study support the proposition that multi-criteria decision-making (MCDM) frameworks provide a more appropriate institutional architecture in pluralistic governance contexts. The use of AHP for structured preference elicitation and TOPSIS for geometric compromise ranking enables explicit representation of policy trade-offs while maintaining methodological transparency and reproducibility.

Importantly, the results indicate that adding more strategic and accessibility criteria does not necessarily diminish aggregate engineering performance. Instead, it redistributes performance outcomes across a broader strategic portfolio. This challenges the implicit assumption that economic efficiency and strategic alignment are inherently

conflicting objectives, suggesting that these factors can be reconciled through structured decision synthesis.

For national rural road agencies operating under fixed annual budgets, the central policy challenge extends beyond aggregate benefit maximization to the simultaneous balancing of performance, equity, and strategic mandates. The empirical evidence presented here suggests that a multi-criteria framework can operationalize such a balance within technical allocation processes without increasing total expenditure.

Methodological Considerations and Future Research.

Several limitations warrant acknowledgment. First, the regression-based cost-performance models were exploratory and did not yield statistically significant coefficients, reflecting both limited sample size ($n = 8$) and the influence of contextual variables not captured in the current specification. Maintenance cost behavior is likely affected by treatment type, procurement mechanisms, geographic factors, and material price variability. Future research utilizing larger segment-level datasets and treatment-disaggregated models may allow more precise estimation of cost elasticities and nonlinear response functions.

Second, although expert-derived AHP weights satisfied internal consistency criteria ($CR < 0.10$), they reflect institutional priorities during the study period. Sensitivity analysis across alternative weighting structures or stakeholder groups would further strengthen robustness evaluation.

Notwithstanding these limitations, the findings provide empirical support that multi-criteria decision synthesis can systematically reshape maintenance allocation patterns while preserving engineering effectiveness under constrained fiscal conditions.

Conclusions

This study developed and empirically validated an integrated AHP-TOPSIS framework for rural road maintenance prioritization under constrained budget conditions. By combining structured expert-based weight derivation with geometric compromise ranking, the framework operationalizes multi-dimensional decision criteria encompassing engineering condition, economic efficiency, accessibility, and strategic policy alignment within a transparent and reproducible architecture.

Comparative validation against historical allocation practices and conventional benefit-cost

(B/C) analysis demonstrates that the proposed framework systematically reshapes maintenance allocation patterns rather than merely altering ranking outputs. Under identical fiscal constraints, the AHP-TOPSIS approach:

1. Achieves aggregate pavement performance outcomes comparable to B/C-based prioritization,
2. Reduces post-maintenance IRI variability across regions, indicating improved network-level service homogeneity,
3. Expands total maintenance coverage without increasing total expenditure, and
4. Significantly redistributes investment across DRR's four national strategic pillars.

Statistical testing confirms that the observed redistribution effects reflect structural differences in allocation logic rather than random variation. While the conventional B/C approach focuses investment in economically dominant corridors, the multi-criteria framework yields a more diversified and policy-aligned portfolio without compromising engineering effectiveness.

Exploratory cost-performance modeling further indicates that both frameworks operate within similar nonlinear engineering cost regimes. The main difference, therefore, lies in the prioritization architecture rather than the intrinsic treatment cost structure.

These findings contribute to the infrastructure asset management literature by demonstrating that multi-criteria decision synthesis can reconcile economic efficiency with strategic equity objectives in large-scale rural road networks. Rather than replacing economic evaluation, the AHP-TOPSIS framework complements it by embedding policy-driven preferences into formal allocation processes.

For public agencies managing extensive low-volume road systems, the results suggest that structured multi-criteria prioritization can enhance spatial equity, strategic coherence, and governance transparency while maintaining fiscal discipline and engineering performance stability.

Future research may extend this framework by incorporating treatment-specific cost modeling, integrating with dynamic deterioration forecasting, and sensitivity analyses of alternative weighting scenarios under evolving policy contexts.

Nomenclature

AADT	– Average Annual Daily Traffic
AHP	– Analytic Hierarchy Process
B/C	– Benefit–Cost Ratio
CED	– Transportation Development for Rural Economic Competitiveness

IRI	– International Roughness Index
IRI_BF	– Initial Roughness Before Maintenance
LIS	– Logistic and Integrated Transport Systems
MCDM	– Multi-Criteria Decision Making
TCA	– Urban Traffic Congestion Reduction
TOPSIS	– Technique for Order Preference by Similarity to Ideal Solution
TSM	– Tourism Mobility
Δ IRI	– Change in International Roughness Index (IRI_Before – IRI_After)

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Author Contributions

Conceptualization: P.C., C.A.; Methodology: P.C.; Formal Analysis: P.C.; Data Curation: P.C.; Writing – Original Draft: P.C.; Writing – Review & Editing: P.C., C.A., W.L.; Supervision: P.C., C.A., W.L. All authors have read and agreed to the published version of the manuscript.

Ethics Statement

Ethical approval was not required for this study because it did not involve vulnerable human subjects, medical interventions, or identifiable personal data. The research solely engaged qualified domain experts in professional consultations regarding technical methodologies. Informed consent was explicitly obtained from all participating experts prior to their participation.

Declaration of Generative AI Use

During the preparation of this manuscript, the authors used Claude (Anthropic) for English language and grammar checking. The authors reviewed and edited the content as necessary and take full responsibility for the content of the published article.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability Statement

The budget allocation data used in this study were derived from the annual budget documents published by the Bureau of the Budget, Office of the Prime Minister of Thailand (<https://www.bb.go.th/topic3.php?gid=862&mid=545&page=1&catID=0&sort=1>).

Additional data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to access restrictions. The expert questionnaire responses cannot be shared publicly in order to protect respondent confidentiality.

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