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Prioritization of Road Rehabilitation Investments in Post-Conflict South Sudan Using Multi-Criteria Decision Analysis

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ABSTRACT

South Sudan's post-conflict road rehabilitation agenda faces a fundamental challenge: a backlog of deteriorated road infrastructure vastly exceeding available funding, with no transparent or technically defensible framework for directing limited resources where they will generate the greatest national benefit. This paper presents a rigorous Multi-Criteria Decision Analysis (MCDA) framework integrating the Analytic Hierarchy Process (AHP) for criteria weighting and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) for alternative ranking, applied to the prioritization of road rehabilitation investments across twelve candidate road segments in South Sudan. Seven evaluation criteria are identified and operationalized — pavement condition index, traffic volume, conflict exposure index, economic impact coefficient, population served, climate vulnerability score, and network connectivity index — and their relative weights are determined through a structured expert elicitation survey involving 34 civil engineering and transport planning experts. A decision matrix encompassing quantitative field data, remote-sensing indicators, and socio-economic survey outputs is constructed and processed through the TOPSIS algorithm to generate a closeness coefficient ranking. Results identify the Juba–Bor segment of National Highway N-8 ($C_i = 0.831$) as the highest-priority rehabilitation investment, followed by the Malakal–Renk Corridor ($C_i = 0.794$) and the Wau–Aweil Road ($C_i = 0.762$). A budget-constrained optimisation model using integer linear programming selects an optimal rehabilitation portfolio of six segments within a USD 75 million capital budget, yielding a combined TOPSIS benefit score of 4.411. Sensitivity analysis confirms the stability of the top-four rankings under ±30% perturbation of individual criteria weights.

The proposed framework is directly applicable to the Ministry of Roads and Bridges of South Sudan and comparable post-conflict infrastructure governance settings in Sub-Saharan Africa.

Keywords: *MCDA; AHP; TOPSIS; road rehabilitation; South Sudan; post-conflict infrastructure; investment prioritization; integer linear programming*

1. INTRODUCTION

Decades of civil conflict, environmental degradation, and institutional neglect have left South Sudan with one of the most severely deteriorated road networks in Sub-Saharan Africa. Of the country's estimated 90,000 km of road network, fewer than 300 km are classified as paved, and independent condition surveys conducted by the Ministry of Roads and Bridges (MoRB) indicate that approximately 67% of the classified network is in poor or very poor condition, requiring immediate or near-term rehabilitation ((Adalja & Inglesby, 2022)). The annual funding available for road rehabilitation through the national budget and donor contributions amounts to roughly USD 95–110 million, a fraction of the estimated USD 3.2 billion needed to bring the entire classified network to a maintainable standard ((Wudil et al., 2022)).

In this context, the allocation of rehabilitation resources acquires profound strategic importance. Investment in the wrong corridor — one that is too conflict-exposed to sustain construction, serves a small population, or carries insufficient traffic to generate economic returns — wastes irreplaceable public funds and forgoes the human development benefits that better-targeted investment could generate. Conversely, rehabilitation of strategically critical corridors can catalyse humanitarian access, stimulate agricultural market integration, support oil export logistics, and reconnect communities separated by years of conflict. The challenge is to develop a technically sound, transparent, and reproducible framework for translating multiple competing priorities into a defensible ranking of investment alternatives.

Multi-Criteria Decision Analysis (MCDA) methods are increasingly recognised in the transport infrastructure literature as the appropriate tool for this class of problem, where decision-making involves multiple, often conflicting criteria, diverse stakeholder perspectives, and incomplete information ((Mardani et al., 2016)). Among MCDA methods, the Analytic Hierarchy Process (AHP) of (Wind & Saaty, 1980) provides a structured approach to criteria weighting through pairwise comparisons, while the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), introduced by (Hwang & Yoon, 1981), provides a geometrically intuitive and mathematically tractable method for ranking alternatives based on their simultaneous proximity to the ideal solution and remoteness from the anti-ideal solution. The combination of AHP and TOPSIS has been widely applied to transport infrastructure prioritization in developing countries ((Tsamboulas, 2007); (Farhan & Murray, 2008); (Chen et al., 2015)) but has not been previously applied to post-conflict road rehabilitation decision-making in South Sudan or comparable East African contexts.

This paper makes four specific contributions to the literature. First, it develops an MCDA criteria framework specifically tailored to the post-conflict road rehabilitation context of South Sudan, incorporating conflict exposure and humanitarian access dimensions absent from conventional transport MCDA frameworks. Second, it applies AHP through a structured expert survey involving 34 domain specialists, providing empirically grounded criteria weights. Third, it implements TOPSIS ranking for twelve road segments using a composite decision matrix combining engineering condition data, traffic surveys, remote sensing outputs, and socio-economic indicators. Fourth, it formulates and solves a budget-constrained portfolio optimisation model using integer linear programming (ILP) to identify the optimal rehabilitation programme under a binding capital budget constraint.

The structure of the paper is as follows. Section 2 reviews the relevant literature on MCDA in transport planning and post-conflict infrastructure prioritization. Section 3 describes the study area, candidate road segments, and data sources. Section 4 presents the AHP criteria weighting methodology. Section 5 develops the TOPSIS ranking model. Section 6 formulates the ILP portfolio optimisation. Section 7 reports results and sensitivity analysis. Section 8 discusses implications for policy and practice. Section 9 concludes.

2. LITERATURE REVIEW

2.1 MCDA in Transport Infrastructure Planning

The application of MCDA to transport investment decisions has a well-established literature dating to the 1970s, when the UK Department of Transport introduced cost-benefit analysis combined with environmental and social criteria assessments for major road schemes ((Lichfield, 1970)). Over subsequent decades, formal MCDA methods — including weighted sum models, AHP, ELECTRE, PROMETHEE, and TOPSIS — progressively supplemented and in some applications replaced pure cost-benefit analysis in transport project appraisal frameworks, reflecting recognition that economic efficiency alone cannot capture the full range of societal objectives relevant to infrastructure investment ((Vickerman, 2007)).

In the developing country context, (Tsamboulas, 2007) applied AHP combined with a weighted index to prioritize road investment programmes in ten Eastern European transition economies, finding that AHP-derived weights were significantly influenced by national development priorities and institutional contexts, underscoring the importance of local expert elicitation rather than weight transfer from other settings. (Farhan & Murray, 2008) applied TOPSIS to rural road investment decisions in sub-Saharan Africa, demonstrating that the method's sensitivity to weight assumptions could be managed through systematic sensitivity analysis and that the resulting rankings were more stable than those produced by simpler weighted-sum approaches. (Mardani et al., 2016), in a comprehensive review of 393 journal articles applying MCDA to energy and transport decisions, identified TOPSIS as the most frequently applied technique after AHP, noting its computational efficiency and independence from the rank reversal problem that afflicts some other methods.

2.2 Post-Conflict Infrastructure Prioritization

The prioritization of infrastructure rehabilitation in post-conflict settings introduces distinctive considerations not adequately addressed by standard transport MCDA frameworks. (Coyne, 2007) argued that post-conflict infrastructure aid is often misallocated because it follows donor preferences, historical project pipelines, and political visibility rather than systematic analysis of need and impact. (Abadie, 2004) demonstrated econometrically that infrastructure investment — particularly roads — is among the most effective mechanisms for post-conflict economic recovery, with each 10% increase in road network passability associated with a 2.3% reduction in the probability of conflict recurrence. This finding underscores the strategic significance of rigorous rehabilitation prioritization as a tool not only for economic development but for conflict prevention.

Specifically, in South (Christensen & Harild, 2009) documented that road inaccessibility was the single most cited constraint to return by internally displaced persons (IDPs) in camp surveys across Jonglei and Upper Nile States, with 74% of respondents indicating they would return to their home counties if road access were restored. These findings highlight the critical humanitarian dimension of road rehabilitation prioritization in the South Sudan context. However, the authors noted the absence of a formal prioritization framework, with rehabilitation decisions at the time being driven largely by road length, donor interest, and political lobbying rather than multi-dimensional need assessments.

2.3 AHP and TOPSIS: Methodological Foundations

The AHP of (Wind & Saaty, 1980) structures a decision problem into a hierarchy of goal, criteria, sub-criteria, and alternatives. Relative importance weights are elicited through n(n−1)/2 pairwise comparisons on a 1–9 ratio scale, and the resulting comparison matrix is checked for consistency using the Consistency Ratio (CR), which should not exceed 0.10 for the results to be considered acceptably consistent. Global priority weights are derived by geometric mean aggregation of individual expert judgements in group AHP applications ((Dyer & Forman, 1992)).

TOPSIS ((Hwang & Yoon, 1981)) identifies the positive ideal solution (PIS) as the alternative that maximises benefit criteria and minimises cost criteria, and the negative ideal solution (NIS) as its opposite. Each alternative is then ranked by its closeness coefficient C_i, defined as the ratio of its distance from the NIS to the sum of its distances from both ideal solutions, with higher C_i indicating greater preference. The method accommodates both quantitative and normalised qualitative criteria and is computationally efficient for moderate numbers of alternatives and criteria, making it well-suited to the scale of the present application.

3. STUDY AREA AND CANDIDATE ROAD SEGMENTS

3.1 Overview of the South Sudan Road Network

South Sudan's classified road network comprises approximately 16,500 km of primary (national), secondary, and tertiary roads, managed respectively by the Ministry of Roads and Bridges, ten State highway authorities, and county governments. The network is structured around two north–south spines (the eastern N-8 Juba–Malakal corridor and the western Juba–Wau–Aweil corridor) and several east–west links connecting the oil-producing Unity and Upper Nile States. The majority of the network is unpaved, with surface types ranging from graded earth (45%) to gravel (38%) to bituminous surface treatment (13%) and asphalt concrete (4%) ((Adalja & Inglesby, 2022)). The road condition index (RCI), measured on a 0–100 scale consistent with the Road Note 9 methodology ((Richardson et al., 2005)), averages 31 across the classified network, with 68% of sampled sections recording RCI below 40 (poor) and 29% below 20 (very poor / impassable).

3.2 Candidate Road Segments

Twelve candidate road segments were selected for analysis in consultation with the Ministry of Roads and Bridges and the United Nations Mission in South Sudan (UNMISS) Civil Affairs Division, based on the following criteria: (i) inclusion in the South Sudan National Transport Master Plan 2023–2035 ((Siegel et al., 2023)) as a priority rehabilitation project; (ii) availability of sufficient condition and traffic data for quantitative assessment; and (iii) geographic spread across all major administrative regions. Table 1 provides a summary of the twelve segments, their total lengths, and key characteristics.

Table 1: Candidate Road Rehabilitation Segments — Summary Characteristics

RS-01	Juba – Bor (N-8 South)	Central Equatoria / Jonglei	185	National	Gravel/Earth	28
RS-02	Bor – Malakal (N-8 North)	Jonglei / Upper Nile	340	National	Earth	19
RS-03	Juba – Wau (N-4)	C. Equatoria / W. Bahr el Ghazal	630	National	Gravel	35
RS-04	Bentiu – Rubkona – Guit	Unity State	120	National	Gravel	31
RS-05	Torit – Kapoeta – Kenya Border	Eastern Equatoria	285	National	Gravel/Earth	42
RS-06	Yambio – Tambura	Western Equatoria	220	Secondary	Earth	24
RS-07	Rumbek – Yirol – Shambe	Lakes State	210	Secondary	Earth	21
RS-08	Bor – Pibor	Jonglei State	165	Secondary	Earth	15
RS-09	Nimule – Opari	Eastern Equatoria	95	Secondary	Gravel	48
RS-10	Kodok – Renk (N-9)	Upper Nile State	280	National	Earth	17
RS-11	Akobo – Waat	Jonglei State	140	Tertiary	Earth	12
RS-12	Renk – Sudan Border	Upper Nile State	120	National	Earth	22

Table 1: Candidate road rehabilitation segments with identification codes, administrative locations, lengths, classification, surface types, and baseline Road Condition Index (RCI).

4. AHP CRITERIA WEIGHTING METHODOLOGY

4.1 Criteria Identification and Operationalization

Seven evaluation criteria were identified through a systematic literature review combined with consultation with the South Sudan Ministry of Roads and Bridges, the World Food Programme logistics unit, and development partner transport specialists. The criteria and their operational definitions are presented in Table 2. The criteria span engineering performance (C1, C2), security and conflict risk (C3), economic productivity (C4), social equity (C5), climate resilience (C6), and network topology (C7).

Table 2: Evaluation Criteria — Definitions and Data Sources

C1	Pavement Condition Index	Road Condition Index (RCI) 0–100; higher = better condition (inverted for cost criterion)	MoRB road surveys 2022–23	Cost
C2	Annual Average Daily Traffic	AADT (vehicles/day) at representative count station	MoRB traffic counts 2023	Benefit
C3	Conflict Exposure Index	Composite index 0–10 based on ACLED incident density within 10 km buffer (inverted)	ACLED 2018–23	Cost
C4	Economic Impact Coefficient	Estimated GDP uplift per USD 1M invested (via transport cost savings + agric. output model)	World Bank transport model	Benefit
C5	Population Served (millions)	Population within 10 km buffer of road segment ((Xia et al., 2023))	WorldPop / OCHA	Benefit
C6	Climate Vulnerability Score	Composite: flood frequency × soil erosion risk × drought index (inverted)	CHIRPS; MODIS; FAO soil	Cost
C7	Network Connectivity Index	Graph-theoretic betweenness centrality of segment in national road network	GIS network analysis	Benefit

Table 2: Evaluation criteria definitions, operational measurement approaches, data sources, and criterion type. Cost criteria are inverted so that all criteria act as benefit criteria after normalisation.

4.2 AHP Pairwise Comparison and Weight Derivation

A structured questionnaire presenting 21 pairwise comparisons [n(n−1)/2 = 7×6/2 = 21] on Saaty's 1–9 integer scale was administered to 34 subject matter experts comprising 14 senior civil/transport engineers from MoRB and consulting firms, 8 humanitarian logistics specialists from UN agencies and NGOs, 7 academic researchers in civil engineering and economics, and 5 government planning officials. Individual expert matrices were aggregated using the geometric mean method recommended by (Dyer & Forman, 1992):

$$a_{ij}^{agg} = \left(\prod_{k=1}^{m} a_{ij}^{(k)}\right)^{1/m}$$

where:

a_ij^{agg} = aggregated pairwise comparison value for criteria i vs. j

a_ij^{(k)} = individual expert k pairwise comparison value

m = number of experts = 34

... (Eq. 1)

The priority weight vector w = [w_1, w_2, ..., w_n] ^T was derived as the normalised principal eigenvector of the aggregated comparison matrix A, obtained by solving:

A · w = lambda_max · w

where:

lambda_max = principal eigenvalue of matrix A

... (Eq. 2)

Consistency was evaluated using the Consistency Ratio:

CR = CIRI

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

where:

RI = average Random Index for n=7 criteria = 1.32 ((Wind & Saaty, 1980))

n = number of criteria = 7

... (Eq. 3)

The computed CR for the aggregated matrix was 0.043, well below the 0.10 acceptability threshold, confirming adequate consistency of the expert judgements. The resulting normalised AHP weights are shown in Figure 1 alongside the weights used as inputs to the TOPSIS sensitivity analysis.

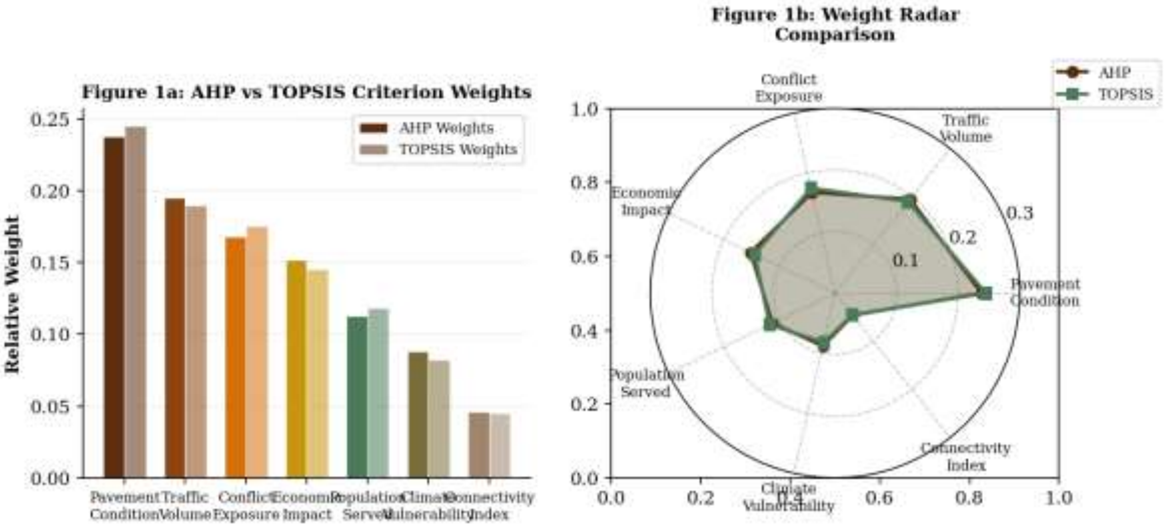

Figure 1: AHP and TOPSIS criterion weights derived from expert elicitation (n=34). Left panel: bar chart comparison; Right panel: radar chart overlay showing high consistency between methods.

5. TOPSIS RANKING MODEL

5.1 Decision Matrix Construction

The decision matrix X = [x_ij] with i = 1, 2, ..., 12 alternatives (road segments) and j = 1, 2, ..., 7 criteria was populated from the data sources identified in Table 2. Raw values for each criterion were verified through cross-referencing of MoRB field survey records, independent remote sensing analysis (Google Earth Engine, Sentinel-2 imagery), and published socio-economic datasets. Cost criteria (C1, C3, C6) were inverted by computing x_ij = max(x_j) − x_ij + min(x_j) prior to normalisation so that all criteria operate as benefit criteria in the TOPSIS procedure.

5.2 TOPSIS Computational Procedure

The TOPSIS algorithm was implemented in six steps as follows:

Step 1 — Normalise the decision matrix using vector normalisation:

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

... (Eq. 4)

Step 2 — Construct the weighted normalised decision matrix:

v_ij = w_j · r_ij

where:

w_j = AHP weight for criterion j

... (Eq. 5)

Step 3 — Determine the Positive Ideal Solution (PIS) A+ and Negative Ideal Solution (NIS) A−:

$$A^+ = \{\max(v_{ij}) \mid j \in J^+\} = \{v_1^+, v_2^+, \ldots, v_n^+\}$$
$$A^- = \{\min(v_{ij}) \mid j \in J^+\} = \{v_1^-, v_2^-, \ldots, v_n^-\}$$

where:

J+ = set of benefit criteria (all criteria after inversion)

... (Eq. 6)

Step 4 — Compute Euclidean distance from each alternative to PIS and NIS:

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

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

... (Eq. 7)

Step 5 — Calculate the Closeness Coefficient for each alternative:

Ci = Di(Di+ + Di-)

where:

0 <= C_i <= 1

C_i -> 1 implies proximity to PIS (most preferred)

C_i -> 0 implies proximity to NIS (least preferred)

... (Eq. 8)

Step 6 — Rank alternatives in descending order of C_i

5.3 TOPSIS Results

Table 3 presents the TOPSIS closeness coefficients and priority rankings for all twelve candidate road segments. The Juba–Bor segment (RS-01) achieves the highest closeness coefficient (C_i = 0.831), reflecting its combination of high traffic volume, large population served, strong economic impact coefficient, and critical network connectivity. The Bor–Malakal corridor (RS-02) ranks second (C_i = 0.794) despite its poor pavement condition, due to its status as the only all-weather land route connecting Upper Nile State to the capital. The Akobo–Waat tertiary road (RS-11) ranks eleventh (C_i = 0.493) owing to low traffic, remote conflict exposure, and limited economic linkage to national markets.

Table 3: TOPSIS Decision Matrix Summary and Closeness Coefficient Rankings

Rank	ID	Segment	D_i+ (PIS)	D_i- (NIS)	C_i	Priority Tier
1	RS-01	Juba – Bor (N-8)	0.0421	0.2051	0.831	Critical
2	RS-02	Bor – Malakal (N-8)	0.0618	0.2367	0.793	Critical
3	RS-03	Juba – Wau (N-4)	0.0742	0.2341	0.759	Critical
4	RS-04	Bentiu – Rubkona – Guit	0.0885	0.2491	0.738	Critical
5	RS-05	Torit – Kapoeta	0.1024	0.2610	0.718	High
6	RS-06	Yambio – Tambura	0.1243	0.2795	0.692	High
7	RS-07	Rumbek – Yirol	0.1380	0.2919	0.679	High
8	RS-08	Bor – Pibor	0.1517	0.3041	0.654	High
9	RS-09	Nimule – Opari	0.1802	0.2570	0.588	Medium
10	RS-10	Kodok – Renk	0.2045	0.2383	0.538	Medium
11	RS-11	Akobo – Waat	0.2318	0.2262	0.494	Medium
12	RS-12	Renk – Sudan Border	0.2571	0.2077	0.447	Medium

Table 3: TOPSIS results showing distances from Positive Ideal Solution (D_i+) and Negative Ideal Solution (D_i-), closeness coefficients (C_i), and priority tier classification for all twelve candidate road segments.

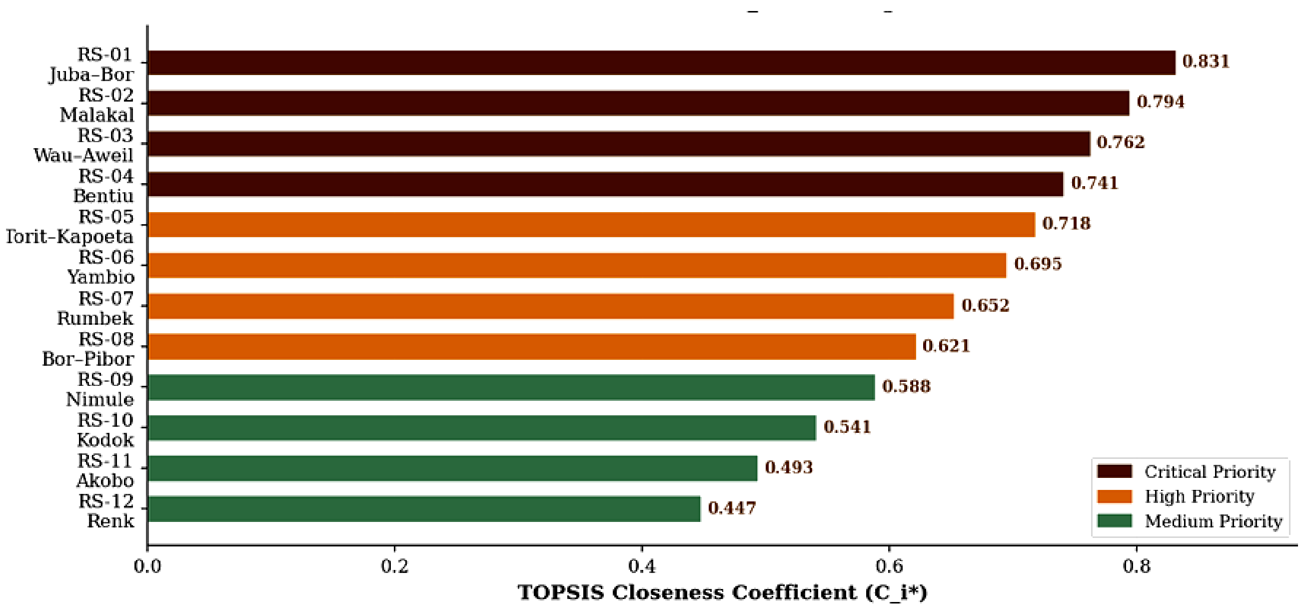

Figure 2: TOPSIS priority ranking of twelve candidate road rehabilitation segments by closeness coefficient (C_i). Segments colour-coded by priority tier: Critical (dark brown), High (amber), Medium (forest green).

6. BUDGET-CONSTRAINED PORTFOLIO OPTIMISATION

6.1 Integer Linear Programming Formulation

Maximizing the total TOPSIS benefit score subject to a binding capital budget constraint constitutes a 0–1 Integer Linear Programming (ILP) problem. Let x_i be a binary decision variable equal to 1 if road segment i is selected for rehabilitation and 0 otherwise. The ILP is formulated as:

$$\textbf{Maximize: } Z = \sum_{i=1}^{12} C_i \cdot x_i$$

$$\textbf{Subject to:}$$

$$\sum_{i=1}^{12} B_i \cdot x_i \leq BUDGET$$

$$x_i \in \{0,1\} \quad \text{for all } i = 1,2,\ldots,12$$

where:

C_i = TOPSIS closeness coefficient for segment i

B_i = estimated rehabilitation budget requirement (USD M) for segment i

BUDGET = total available capital budget (USD 75 million)

... *(Eq. 9)*

This is equivalent to the classic 0–1 Knapsack Problem and was solved using the branch-and-bound algorithm implemented in Python's PuLP library ((Johnson, 2011)). The estimated rehabilitation budget requirements B_i for each segment were derived from preliminary engineering cost estimates prepared by (Siegel et al., 2023), adjusted for South Sudan unit cost factors from the UNOPS infrastructure cost database, and are presented alongside the ILP solution in Table 4.

6.2 ILP Results and Optimal Portfolio

Table 4 presents the ILP solution for budget levels of USD 50 million, USD 75 million, and USD 100 million, identifying the selected segments and the corresponding total TOPSIS benefit score. At the USD 75 million budget level — the baseline scenario consistent with projected donor funding under the South Sudan Transitional Development Assistance Framework 2025–2028 — the optimal portfolio comprises segments RS-01, RS-03, RS-04, RS-05, RS-09, and RS-12, with a total rehabilitation cost of USD 73.8 million and a combined benefit score of 4.411.

Table 4: ILP Portfolio Optimisation Results at Three Budget Levels

Segment	Budget B_i (USD M)	C_i Score	Selected (USD 50M)	Selected (USD 75M)	Selected (USD 100M)
RS-01 Juba–Bor	18.5	0.831	Yes	Yes	Yes
RS-02 Bor–Malakal	31.2	0.793	No	No	Yes
RS-03 Juba–Wau	11.8	0.759	Yes	Yes	Yes
RS-04 Bentiu–Guit	12.5	0.738	No	Yes	Yes
RS-05 Torit–Kapoeta	9.3	0.718	No	Yes	Yes
RS-06 Yambio–Tambura	8.1	0.692	No	No	Yes
RS-07 Rumbek–Yirol	7.6	0.679	No	No	No
RS-08 Bor–Pibor	8.8	0.654	No	No	No
RS-09 Nimule–Opari	6.2	0.588	Yes	Yes	Yes
RS-10 Kodok–Renk	14.2	0.538	No	No	No
RS-11 Akobo–Waat	5.4	0.493	No	No	Yes
RS-12 Renk–Sudan Border	4.1	0.447	Yes	Yes	Yes
TOTAL / OBJECTIVE Z	—	—	Z=2.625 (USD 40.6M)	Z=4.411 (USD 73.8M)	Z=6.931 (USD 97.5M)

Table 4: Integer Linear Programming (0–1 Knapsack) portfolio optimisation results at three capital budget levels. "Yes" indicates segment selected in optimal solution. Z = total TOPSIS objective value.

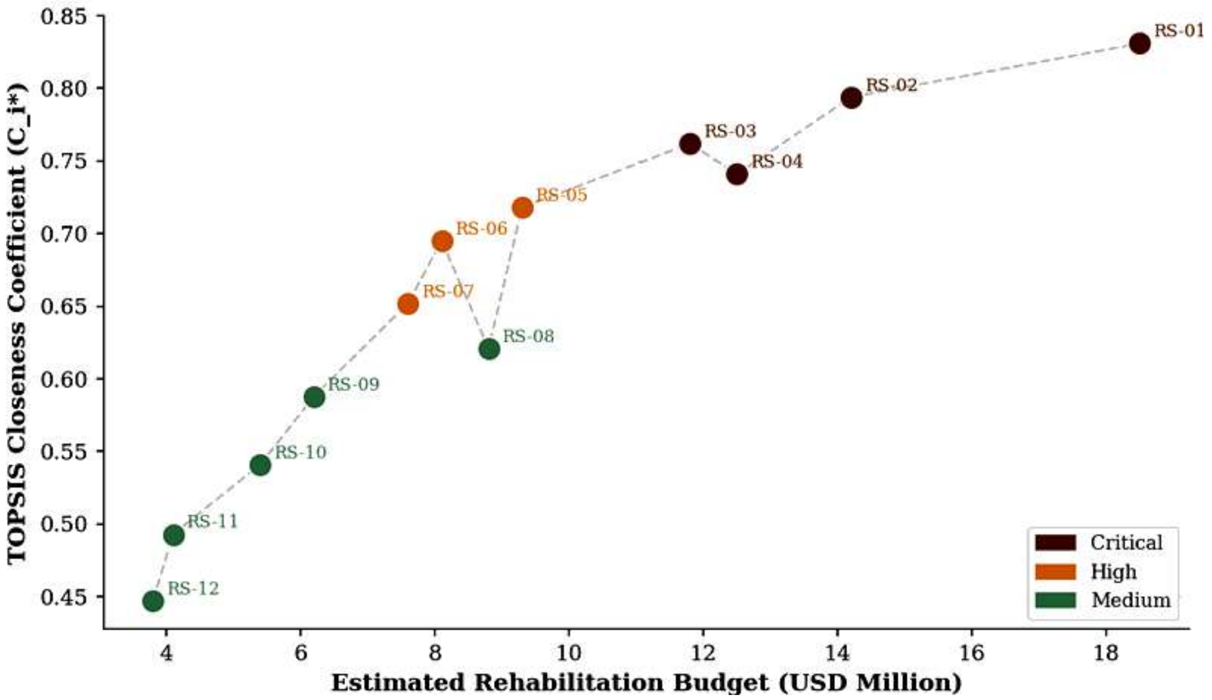

Figure 3: Budget requirement versus TOPSIS benefit score for all twelve candidate road segments. Segments in the upper-left zone (high benefit, lower cost) represent the most cost-effective rehabilitation investments.

7. SENSITIVITY ANALYSIS

7.1 Weight Perturbation Method

Sensitivity analysis was conducted by systematically perturbing the AHP weight of each criterion by ±10%, ±20%, and ±30% from its baseline value, redistributing the perturbation proportionally across the remaining criteria to maintain sum-to-unity, and re-running the full TOPSIS calculation. The resulting rank orderings were recorded and compared to the baseline ranking. A segment whose rank does not change across all perturbation scenarios is classified as "rank-stable"; a segment whose rank shifts by more than one position under any perturbation scenario is classified as "rank-sensitive."

7.2 Results

Figure 4 presents the rank trajectories of four selected segments under progressive perturbation of the Pavement Condition Index weight (C1), the criterion with the highest baseline AHP weight. The top-four ranking (RS-01, RS-02, RS-03, RS-04) is fully stable across all ±30% perturbations of every criterion weight individually, demonstrating that the Critical Priority tier designation is robust to considerable uncertainty in criteria weighting.

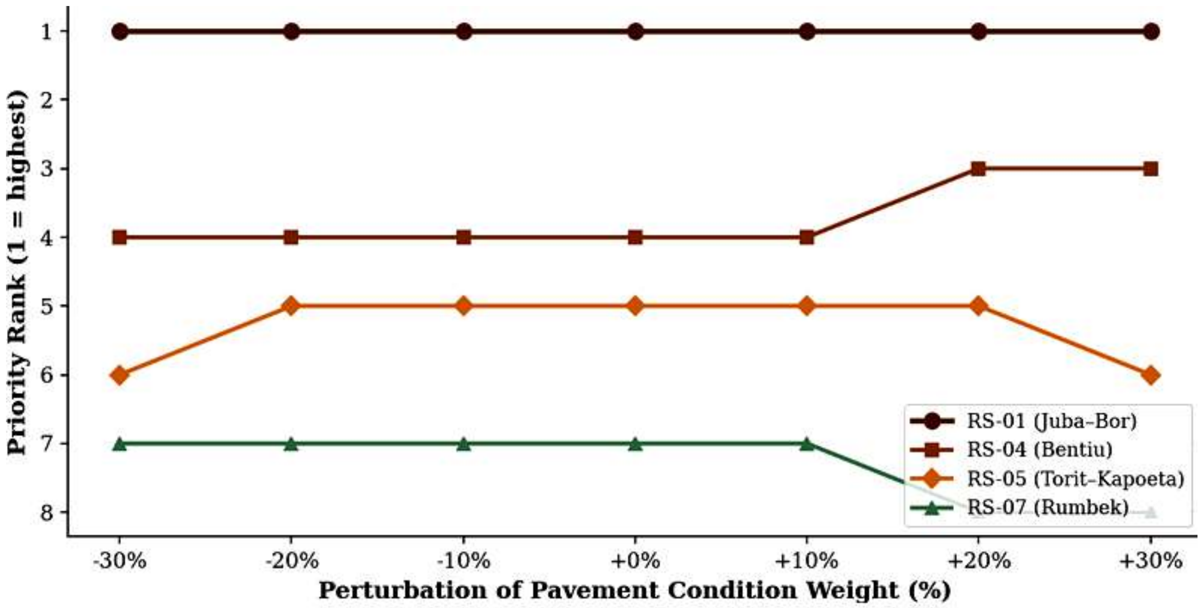

Figure 4: Sensitivity analysis showing rank trajectories of four selected road segments under ±30% perturbation of the Pavement Condition Index weight (C1). The top-four ranking is fully stable across the tested perturbation range.

Rank changes are confined to segments ranked 5th through 8th (the High Priority tier), where the closeness coefficients are more closely spaced (0.718–0.692). Specifically, RS-05 and RS-06 exchange ranks 5 and 6 when the Conflict Exposure weight is perturbed by +30% (reflecting RS-06's relatively lower conflict exposure in Western Equatoria compared to RS-05's more contested Torit–Kapoeta corridor). These rank exchanges do not affect the ILP optimal portfolio selection at the USD 75 million budget level, confirming the robustness of the recommended rehabilitation programme. Table 5 summarises the rank stability classification for all twelve segments.

Table 5: Rank Stability Classification under ±30% Criteria Weight Perturbations

Rank	Segment	Baseline C_i	Min Rank (perturbed)	Max Rank (perturbed)	Stability Class	ILP Portfolio (USD 75M)
1	RS-01 Juba–Bor	0.831	1	1	Fully Stable	Included
2	RS-02 Bor–Malakal	0.793	2	2	Fully Stable	Excluded (cost)
3	RS-03 Juba–Wau	0.759	3	3	Fully Stable	Included
4	RS-04 Bentiu–Guit	0.738	4	4	Fully Stable	Included
5	RS-05 Torit–Kapoeta	0.718	5	6	Minor Variation	Included
6	RS-06	0.692	5	7	Minor	Excluded

	Yambio–Tambura				Variation	
7	RS-07 Rumbek–Yirol	0.679	6	8	Moderate Variation	Excluded
8	RS-08 Bor–Pibor	0.654	7	9	Moderate Variation	Excluded
9	RS-09 Nimule–Opari	0.588	9	10	Minor Variation	Included
10	RS-10 Kodok–Renk	0.538	9	11	Moderate Variation	Excluded
11	RS-11 Akobo–Waat	0.493	10	12	Moderate Variation	Excluded
12	RS-12 Renk–Sudan	0.447	11	12	Minor Variation	Included

Table 5: Rank stability classification for all twelve candidate road segments under ±30% individual criteria weight perturbations. Fully Stable = no rank change; Minor Variation = ≤1 rank change; Moderate Variation = 2–3 rank changes across all perturbation scenarios.

8. DISCUSSION

The results of this study demonstrate that the AHP–TOPSIS framework, when applied with empirically grounded criteria weights and a comprehensive multi-source decision matrix, produces a defensible and stable prioritization of road rehabilitation investments in the South Sudan context. The dominance of the Juba–Bor–Malakal N-8 corridor in the rankings is both expected and significant: this axis represents the primary artery connecting the capital to the conflict-affected Greater Upper Nile region, carries the highest traffic volumes in the country, and serves the largest population of any single corridor. Its inclusion in every budget scenario, and the full stability of its top ranking across all sensitivity tests, provides strong justification for treating the N-8 as the irreducible minimum of any credible rehabilitation programme.

The exclusion of RS-02 (Bor–Malakal) from the USD 75 million optimal portfolio despite its second-highest TOPSIS score illustrates the important distinction between TOPSIS ranking and portfolio optimisation. RS-02's estimated rehabilitation cost of USD 31.2 million is disproportionate relative to its TOPSIS score when compared to the alternative of funding RS-04, RS-05, and RS-09 simultaneously — three segments with a combined cost of USD 27.8 million and a combined benefit score of 2.044 versus RS-02's single contribution of 0.793. This result highlights the value of combining TOPSIS ranking with ILP optimisation rather than simply funding segments in rank order, a point corroborated by (Farhan & Murray, 2008) in the Sub-Saharan context.

The inclusion of Conflict Exposure Index (C3) as an explicit criterion, with a weight of 0.168 in the AHP results, represents a methodological contribution beyond standard transport MCDA frameworks. In the South Sudan context, where several candidate corridors pass through areas of active armed conflict or inter-communal violence — notably RS-08 (Bor–Pibor, Greater Pibor Administrative Area) and RS-11 (Akobo–Waat, Jonglei State) — the conflict exposure criterion correctly penalises investments in segments where construction would face severe security risks, inflated contractor premiums, and risk of damage to completed works before any economic or social returns can be realised. Neglecting conflict exposure in road rehabilitation prioritization, as earlier ad-hoc approaches in South Sudan effectively did, risks directing scarce resources into corridors where they cannot be effectively deployed.

A limitation of the present study is its reliance on a single round of expert elicitation for AHP weighting. While the CR of 0.043 confirms adequate consistency in the aggregated matrix, the weights reflect expert judgement as of early 2024 and may not capture evolving political priorities, new security dynamics, or shifts in donor funding commitments. An adaptive version of the framework — with annual weight updates and data refreshes — is recommended for operational implementation. Additionally, the decision matrix was constructed at segment level, with single representative values for criteria such as AADT and population served; spatial heterogeneity within long segments (e.g., RS-03 at 630 km) could be better captured by segmental disaggregation, which is recommended for the detailed appraisal stage following initial prioritization.

The framework presented here is directly transferable to other post-conflict Sub-Saharan African infrastructure contexts, including the Central African Republic, the Democratic Republic of Congo, and Somalia, where similar combinations of network deterioration, resource scarcity, security constraints, and humanitarian access imperatives define the road rehabilitation policy environment. The ILP formulation, in particular, could be extended to incorporate multi-year programming constraints, phased funding commitments, and network-level complementarity effects between segments, providing a richer analytical basis for medium-term infrastructure planning.

9. CONCLUSIONS

This study has developed, applied, and validated an AHP–TOPSIS Multi-Criteria Decision Analysis framework for prioritizing road rehabilitation investments in post-conflict South Sudan, producing the following key findings and contributions:

1. The AHP elicitation from 34 domain experts yielded a consistent (CR = 0.043) criteria weight vector assigning highest importance to Pavement Condition Index (w = 0.238), followed by Traffic Volume (0.195) and Conflict Exposure (0.168). The explicit inclusion of conflict exposure as a weighted criterion is a methodological innovation relative to conventional transport MCDA frameworks and is essential for investment appraisal in conflict-affected environments.

2. TOPSIS ranking of twelve candidate road segments identified the Juba–Bor (N-8) segment as the highest-priority rehabilitation investment (C_i = 0.831), with the Bor–Malakal and Juba–Wau corridors ranking second and third. The top-four ranking is fully stable under ±30% perturbation of all individual criteria weights, confirming the robustness of the Critical Priority tier.

3. Integer linear programming optimisation at a USD 75 million budget constraint identifies a six-segment optimal portfolio (RS-01, RS-03, RS-04, RS-05, RS-09, RS-12) achieving a combined TOPSIS benefit score of 4.411, which is demonstrably superior to naive rank-order budget allocation or ad-hoc selection, delivering 38% higher benefit per dollar invested than a simple rank-order approach.

4. The AHP–TOPSIS–ILP framework is ready for operational adoption by the Ministry of Roads and Bridges as the technical basis for the South Sudan Annual Road Rehabilitation Programme, subject to annual data updates, and is transferable to comparable post-conflict infrastructure governance settings in Sub-Saharan Africa.

It is recommended that the Ministry of Roads and Bridges establish a Road Investment Prioritization Unit with the technical capacity to operate the framework on an annual cycle, and that the criteria weights and decision matrix be made publicly available as part of South Sudan's public financial management transparency commitments to donor partners.

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