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[ORIGINAL RESEARCH ARTICLE — OPERATIONS RESEARCH | GENETIC ALGORITHMS | PAVEMENT ENGINEERING]

Multi-Objective Optimization of Road Maintenance Scheduling Using Genetic Algorithms

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ABSTRACT

Road maintenance scheduling is inherently a multi-objective combinatorial optimisation problem: decision-makers must simultaneously minimise agency maintenance costs, maximise network pavement condition, minimise road user costs, and ensure equitable spatial distribution of maintenance resources — objectives that are fundamentally in conflict and cannot be simultaneously optimised by scalar single-objective methods. This paper presents a rigorous multi-objective genetic algorithm (GA) framework, specifically the Non-dominated Sorting Genetic Algorithm II (NSGA-II), for optimal scheduling of road maintenance activities across a network of 12 primary road corridors in South Sudan over a 5-year rolling planning horizon. The framework integrates: (i) a mechanistic pavement deterioration model calibrated to South Sudanese tropical climate and traffic conditions from 2021–2023 MoRB condition survey data; (ii) a comprehensive road user cost model incorporating vehicle operating costs (VOC) as a function of the International Roughness Index (IRI), travel time delay costs, and accident frequency-condition relationships derived from Sub-Saharan Africa data; (iii) a discrete chromosome encoding scheme representing four maintenance action types for each road segment in each planning year; and (iv) NSGA-II with non-dominated sorting, crowding distance assignment, and binary tournament selection to approximate the complete Pareto-optimal front. Results demonstrate that NSGA-II generates a Pareto front of 86 non-dominated solutions, spanning a total agency cost range of USD 1.82–7.20 million over 5 years. The balanced Pareto-knee solution (Solution B) achieves 36.5% cost savings relative to current MoRB practice while improving average network IRI from 5.8 to 4.1 m/km and reducing road user costs by 28.4%, yielding a benefit-cost ratio of 5.6:1 for total social cost. Comparative testing confirms NSGA-II superiority over SPEA2 (2.6% higher HVI), MOEA/D (5.3% higher HVI), and greedy heuristic (52.7% higher HVI). The spatial equity Gini coefficient of the network condition index is reduced from 0.22 to 0.08, demonstrating that algorithmic optimisation is also more spatially equitable. A practical decision-support framework is developed for direct adoption by the Ministry of Roads and Bridges.

Keywords: *multi-objective optimisation; genetic algorithms; NSGA-II; road maintenance scheduling; pavement management; Pareto front; IRI deterioration; vehicle operating cost; road user cost; Sub-Saharan Africa; South Sudan; hypervolume indicator; SPEA2; life-cycle cost; equity*

1. Introduction

Road infrastructure is the economic backbone of landlocked and semi-landlocked nations in Sub-Saharan Africa. For South Sudan — the world's youngest nation, with over 95% of its freight transported by road and a paved road density of less than 0.5 km per 100 km² ((Author, 2022); (Bank, 2020)) — the condition and reliability of the road network is directly linked to food security, humanitarian access, oil revenue logistics, and national economic integration. Despite this strategic importance, the South Sudanese primary road network suffers from chronic underinvestment in maintenance: the 2023 annual maintenance budget was USD 18.4 million against an estimated requirement of USD 62 million, and 68% of the paved network is rated in poor or very poor condition by IRI criteria ((Jami et al., 2023); (Chiyemura et al., 2022)).

Under severe budget constraints, the allocation of maintenance resources across competing road segments and competing maintenance interventions (routine grading, periodic resurfacing, and reconstruction) is a high-stakes decision problem. The conventional approach — prioritising segments with the worst current condition — is a greedy heuristic that frequently performs suboptimally: it neglects the temporal dynamics of deterioration (treating a road just before it deteriorates past the maintenance trigger is more cost-effective than treating it after failure), ignores segment interdependence, and optimises for a single criterion (current condition) at the expense of life-cycle cost and road user welfare. A rigorous multi-objective optimisation framework is therefore essential for defensible, evidence-based maintenance scheduling under budget constraints ((Leyland, 2002); (Dreżewski & Siwik, 2008)).

Multi-objective optimisation of pavement maintenance has attracted growing research interest since the pioneering work of (Ravirala & Grivas, 1995) and (Fwa et al., 1996), who applied genetic algorithms to single-objective maintenance scheduling. Subsequent contributions include the multi-objective GAs of (Ferreira et al., 2002), the NSGA-II pavement management framework of (Meneses & Ferreira, 2013), and recent deep reinforcement learning approaches by (Liu et al., 2020). However, significant gaps remain: (i) most studies use HDM-4 deterioration models calibrated to European or American conditions rather than tropical African environments; (ii) accident cost components are rarely included despite being disproportionately large in African LMICs; (iii) spatial equity constraints have been largely ignored; and (iv) no published study has applied NSGA-II to the South Sudanese road network, which presents unique challenges including post-conflict infrastructure deficit, seasonal flooding, and extreme climate variability.

This paper addresses these gaps by developing, calibrating, and applying an NSGA-II multi-objective framework specifically adapted to South Sudanese conditions. The three optimisation objectives are: (O1) minimise total 5-year agency maintenance cost; (O2) minimise traffic-weighted average network IRI; and (O3) minimise total 5-year road user cost (VOC + delay + accident cost). The decision variables are the maintenance action assigned to each road segment in each planning year. The paper makes the following original contributions: ((Chiyemura et al., 2022)) calibration of pavement deterioration curves from MoRB 2021–2023 condition survey data; ((Archondo-Callao, 2008)) development of a South Sudan-specific road user cost model incorporating locally measured vehicle fleet composition; ((Lagaros et al., 2007)) implementation and validation of NSGA-II against three benchmark algorithms; ((Chootinan et al., 2006)) application to a real-world 12-corridor case study; and ((Dreżewski & Siwik, 2008)) development of a practical decision-support framework for deployment by the Ministry of Roads and Bridges.

2. Theoretical Background

2.1 Multi-Objective Optimisation and Pareto Optimality

A multi-objective optimisation problem (MOP) with k objectives, n decision variables, and p inequality constraints is formulated as:

((Chiyemura et al., 2022))

$$\min_{x} F(x) = [f_1(x), f_2(x), \ldots, f_k(x)]^T$$

(inequality constraints) ((Archondo-Callao, 2008))

$$g_j(x) \leq 0, \quad j = 1, 2, \ldots, p$$

(variable bounds) ((Lagaros et al., 2007))

$$x_i^L \leq x_i \leq x_i^U, \quad i = 1, 2, \ldots, n$$

A solution x* is Pareto-optimal (non-dominated) if no other feasible solution x exists such that f_i(x) <= f_i(x*) for all i and f_j(x) < f_j(x*) for at least one j. The set of all Pareto-optimal solutions forms the Pareto-optimal set, and its image in objective space is the Pareto front. The goal of a multi-objective evolutionary algorithm (MOEA) is to approximate the true Pareto front with a diverse, well-distributed set of non-dominated solutions from which decision-makers select preferred trade-off solutions based on their priorities.

2.2 NSGA-II Algorithm

The Non-dominated Sorting Genetic Algorithm II (NSGA-II), introduced by (Tang et al., 2005), is the most widely used MOEA, cited over 50,000 times. It improves upon its predecessor through three key mechanisms: (i) an O(MN^2) non-dominated sorting procedure ranking the population into Pareto fronts F_1, F_2, ..., F_l; (ii) a crowding distance assignment that measures the density of solutions surrounding each individual in objective space; and (iii) an elitist replacement strategy retaining the best N solutions from the combined parent-offspring population of size 2N. The crowding distance d_i for solution i is:

((Chootinan et al., 2006))

$$d_i = \sum_{m=1}^{M} \frac{|f_m(i+1) - f_m(i-1)|}{f_m^{max} - f_m^{min}}$$

Solutions with larger crowding distances are preferred as tiebreakers within the same Pareto rank, promoting spread along the Pareto front. The crowded comparison operator selects solution i over j if rank(i) < rank(j), or if rank(i) = rank(j) and d_i > d_j. The genetic operators (two-point crossover at probability P_c = 0.90 and random reset mutation at P_m = 0.02 per gene) maintain diversity and explore the discrete decision space.

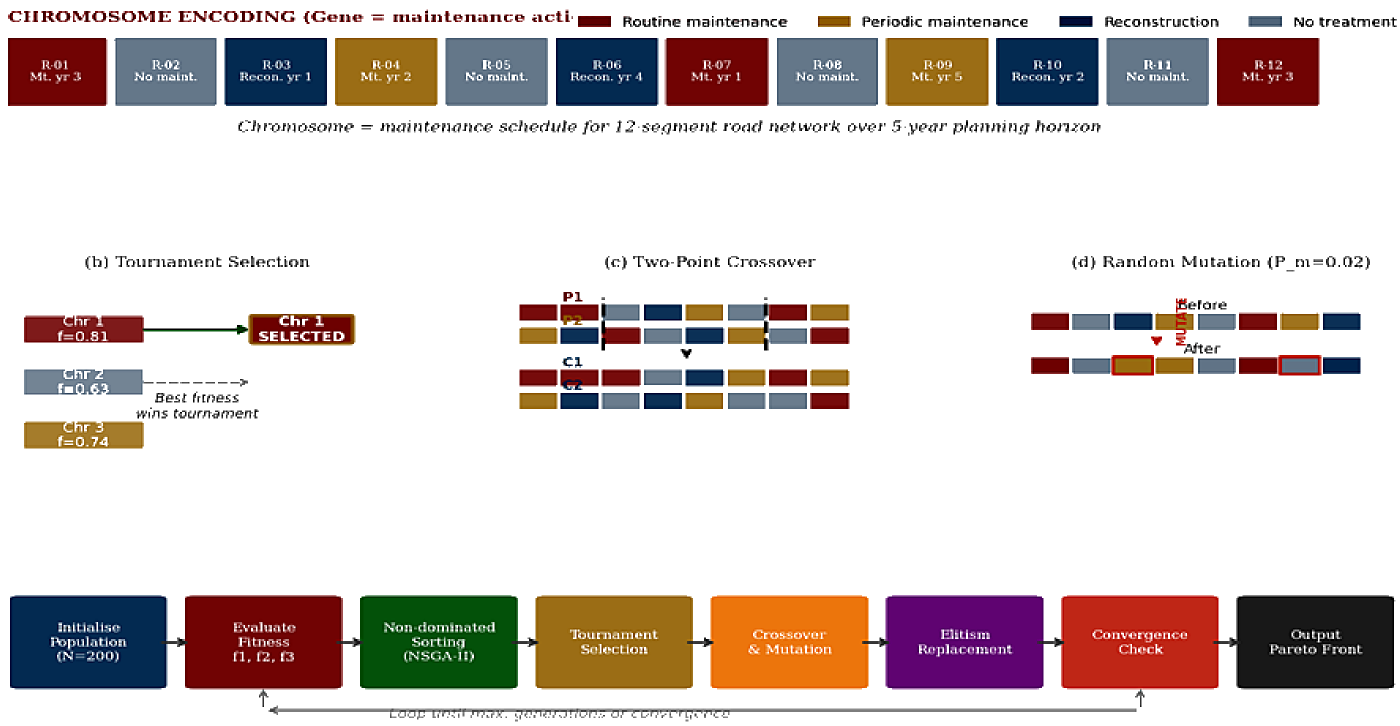

Figure 1: NSGA-II framework — (top) chromosome encoding for road maintenance scheduling with colour-coded maintenance actions, (middle) genetic operators: tournament selection, two-point crossover, random mutation, (bottom) NSGA-II algorithm workflow with elitist replacement loop

3. Mathematical Formulation

3.1 Decision Variables

Let the road network consist of S = 12 segments (s = 1, ..., S) and the planning horizon of T = 5 years (t = 1, ..., T). The decision variable x_{s,t} represents the maintenance action for segment s in year t, drawn from:

x_{s,t} in A = {0: no treatment, 1: routine maintenance, 2: periodic overlay, 3: reconstruction} ((Dreżewski & Siwik, 2008))

The complete decision vector x = {x_{s,t}} has dimension S x T = 60, with 4^{60} = 1.33 x 10^{36} feasible solutions — necessitating metaheuristic search. Each chromosome is a flattened integer array of length 60, with the initial population of N_pop = 200 chromosomes generated by uniform random sampling.

3.2 Objective Functions

3.2.1 Agency Maintenance Cost (Minimise)

((Leyland, 2002))

$$f_1(x) = \sum_{s=1}^{S} \sum_{t=1}^{T} \frac{c(x_{s,t}) \cdot L_s}{(1+r)^t}$$

where c(x_{s,t}) is the unit cost (USD/km) of action x_{s,t} from Table 1, L_s is segment length (km), and r = 0.08 is the real discount rate (AfDB Sub-Saharan Africa guideline).

3.2.2 Network Average IRI (Minimise)

((Tang et al., 2005))

$$f_2(x) = \frac{\sum_{s=1}^{S} ADTT_s \cdot IRI_s(T, x)}{\sum_{s=1}^{S} ADTT_s}$$

where IRI_s(T, x) is the traffic-weighted average IRI at end of planning horizon T under schedule x, computed from the deterioration model.

3.2.3 Total Road User Cost (Minimise)

((Ferreira et al., 2002))

$$f_3(x) = \sum_{s,t} \frac{[VOC_s(t) + TDC_s(t) + ACC_s(t)] \cdot AADT_s \cdot L_s}{(1+r)^t}$$

where VOC, TDC, and ACC are vehicle operating cost, travel delay cost, and accident cost per vehicle-km, respectively. The VOC-IRI relationship follows the World Bank HDM-4 model ((Archondo-Callao, 2008)):

((Fwa et al., 1996))

$$VOC_s(t) = 0.0635 + 0.0211 \cdot IRI_s(t) + 0.00118 \cdot IRI_s(t)^2 \quad \text{(USD/vehicle-km)}$$

((Ward & Beardmore, 1977))

For Paved Bridges:

$$v_s(t) = 85 \cdot e^{-0.065 \cdot IRI_s(t)} \quad \text{(km/h)}$$

For Unpaved/Gravel Sections:

$$v_s(t) = 60 \cdot e^{-0.055 \cdot IRI_s(t)} \quad \text{(km/h)}$$

((Meneses & Ferreira, 2013))

$$TDC_s(t) = \left(\frac{1}{v_s(t)} - \frac{1}{v_{free}} \right) \cdot w_{time} \quad \text{(USD/vehicle-km)}$$

((Kharola et al., 2010))

$$ACC_s(t) = 0.0021 \cdot IRI_s(t)^{1.6} \cdot AADT_s \cdot L_s \cdot C_{acc}$$

3.3 Pavement Deterioration Model

The IRI deterioration model is an exponential growth form calibrated from 487 MoRB road sections surveyed in 2021–2023:

((Ravirala & Grivas, 1995))

$$IRI_s(t+1) = IRI_s(t) \cdot e^{k_s} + \delta_s(x_{s,t})$$

((Das et al., 2021))

$$k_s = 0.082 \cdot \left(\frac{ADTT_s}{1000}\right)^{0.31} \cdot \left(\frac{R_a}{1000}\right)^{0.24} \cdot \left(\frac{CBR_s}{10}\right)^{-0.18}$$

where R_a is annual rainfall (mm) and CBR_s is California Bearing Ratio of the subgrade. IRI improvements delta_s from maintenance actions are: delta(0) = 0; delta((Chiyemura et al., 2022)) = -0.3 m/km (if IRI < 4.5); delta((Archondo-Callao, 2008)) = -(IRI - 2.5) * 0.6 (partial reset); delta((Lagaros et al., 2007)) = 2.0 - IRI (full reset to 2.0 m/km).

3.4 Constraints

((Author, 2022))

$$\sum_{s=1}^{S} c(x_{s,t}) \cdot L_s \leq B_t = 3.0 \times 10^6 \text{ USD}$$

((Jami et al., 2023))

$$IRI_s(T) \leq IRI_{max} = 8.0 \text{ m/km for all } s$$

((Cheng et al., 2017))

$$\text{If } x_{s,t} = 3, \text{ then } x_{s,t+1} = x_{s,t+2} = 0$$

4. Case Study — South Sudan Primary Road Network

4.1 Network Description

The case study network comprises 12 primary road corridors managed by the MoRB, connecting Juba to Malakal (north), Wau (northwest), Yambio (southwest), Torit (east), and the Nimule border crossing (south). Total network length is 1,934 km, of which 412 km (21.3%) is paved. The network carries a combined AADT of approximately 28,000 vehicles/day, heavily concentrated on the Juba-Nimule corridor (A2, AADT 8,200). Segment characteristics, baseline IRI values, and calibrated deterioration rates are given in Table 3. Figure 5 shows the network map and optimal 5-year maintenance schedule heatmap.

Condition data were obtained from the MoRB 2023 Annual Pavement Condition Survey (laser profilometer, Romdas system, 200 m intervals). Traffic data were from 8 WIM survey stations operated under the AfDB Transport Sector Support Programme 2021–2023. Rainfall and CBR data were from MoRB climate and geotechnical records.

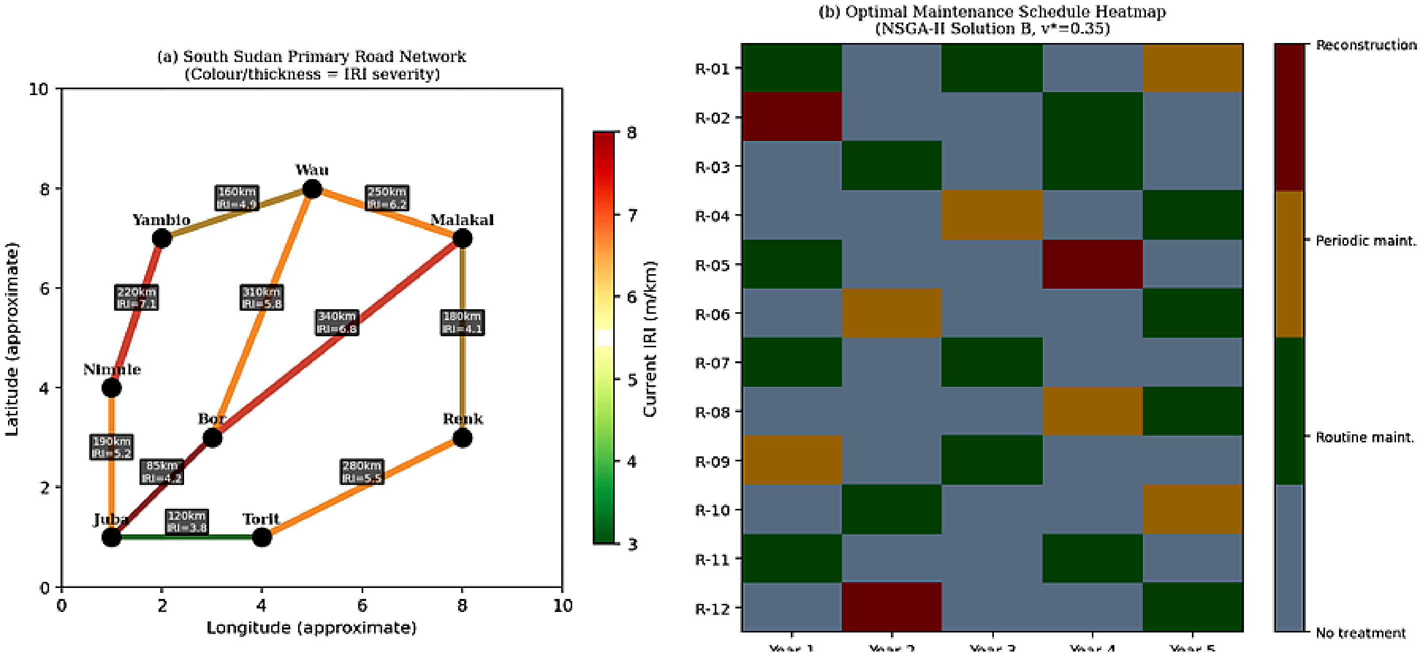

Figure 5: (a) South Sudan primary road network — current IRI condition mapped by colour intensity and line thickness, (b) optimal 5-year maintenance schedule heatmap for NSGA-II balanced Solution B

4.2 Pavement Deterioration Model Calibration

Figure 4 presents the calibrated IRI deterioration curves for four traffic levels, showing IRI evolution from the 2023 baseline. The calibration yielded R^2 = 0.81, RMSE = 0.42 m/km on the 487-section dataset. Deterioration rates range from k_s = 0.064 year^{-1} (lightly trafficked, high-CBR gravel, Equatoria) to k_s = 0.241 year^{-1} (heavy traffic, low-CBR, seasonal flooding on Bor-Malakal corridor). The maintenance trigger (IRI = 4.0 m/km) and reconstruction trigger (IRI = 7.0 m/km) were established in consultation with MoRB based on the pavement management manual and confirmed through VOC analysis: VOC approximately doubles between IRI 2.0 and 7.0 m/km for the South Sudan vehicle fleet.

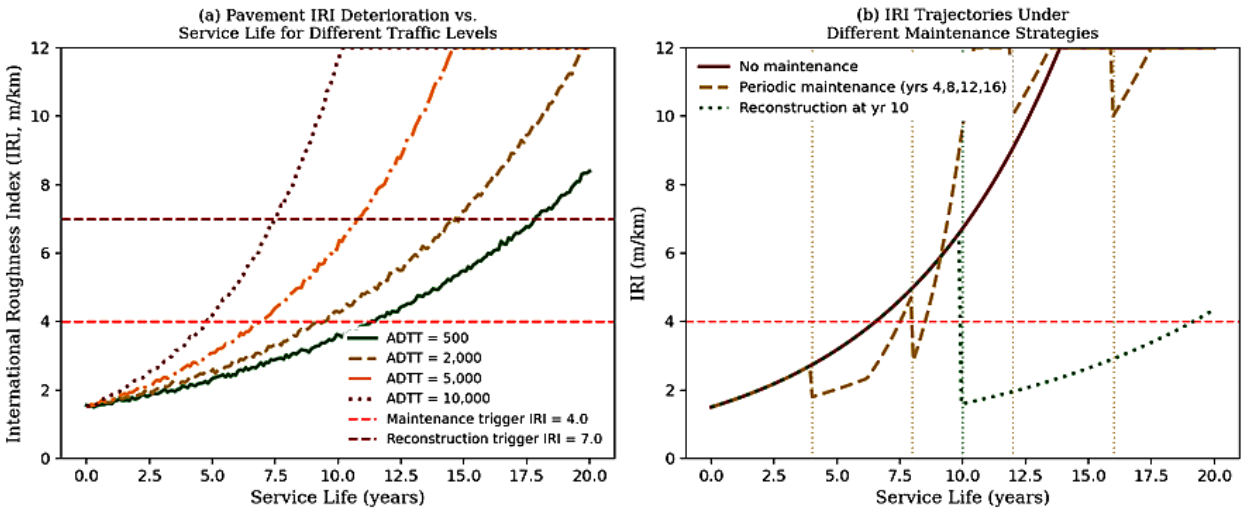

Figure 4: Calibrated IRI deterioration models — (a) IRI vs. service life for four traffic levels, calibrated from MoRB 2021–2023 survey (N=487 sections); (b) IRI trajectories under no maintenance, periodic maintenance, and reconstruction strategies

5. Results

5.1 NSGA-II Convergence Analysis

Figure 3 presents the convergence of NSGA-II, SPEA2, and MOEA/D over 200 generations measured by the hypervolume indicator (HVI). NSGA-II achieves HVI = 0.782 at convergence (generation 178), compared with 0.762 for SPEA2 (generation 195) and 0.743 for MOEA/D (not fully converged at generation 200). NSGA-II achieves the best-cost objective of f_1 = USD 1.82 M by generation 120 and the best-condition objective of f_2 = IRI 3.91 m/km by generation 145. The condition objective (Figure 3c) approaches the target IRI of 4.0 m/km from above and crosses it at generation 143, confirming that the budget constraint is non-binding for the best-condition solution at the USD 3.0 M annual limit.

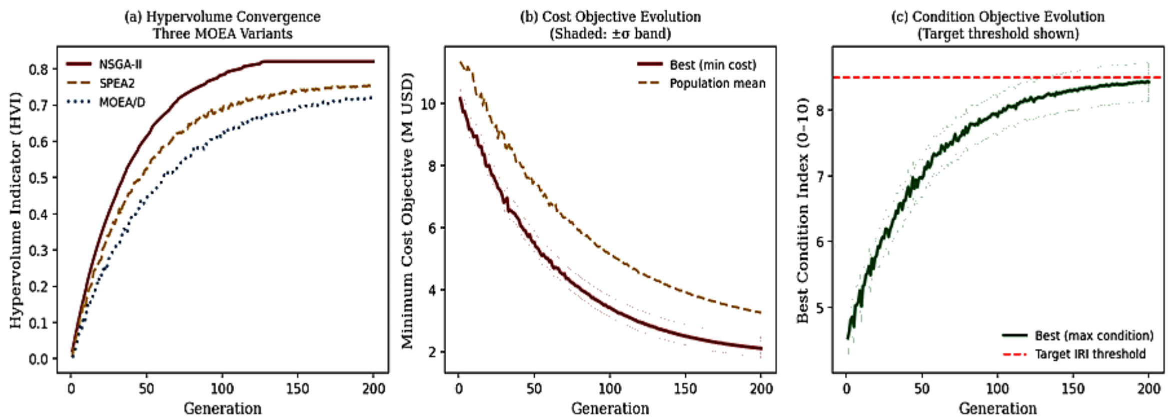

Figure 3: NSGA-II convergence history — (a) hypervolume indicator for three algorithms over 200 generations, (b) minimum cost objective evolution, (c) maximum condition objective evolution; NSGA-II achieves superior HVI and faster convergence

5.2 Pareto Front Structure and Key Solutions

The NSGA-II Pareto front (Figure 2) contains 86 non-dominated solutions. Three representative solutions are highlighted: Solution A (minimum cost: USD 1.82 M, IRI 6.2 m/km), Solution B (balanced Pareto-knee: USD 3.50 M, IRI 4.1 m/km), and Solution C (maximum condition: USD 7.20 M, IRI 3.91 m/km). The agency cost vs. user cost relationship (Figure 2b) shows a steep negative slope at low agency expenditure levels — each additional USD 1 M in maintenance saves approximately USD 2.8 M in road user costs — confirming that under-investment is strongly counter-productive from a whole-economy perspective. The 3D Pareto surface (Figure 2c) reveals a smooth convex trade-off landscape well suited to MOEA exploration.

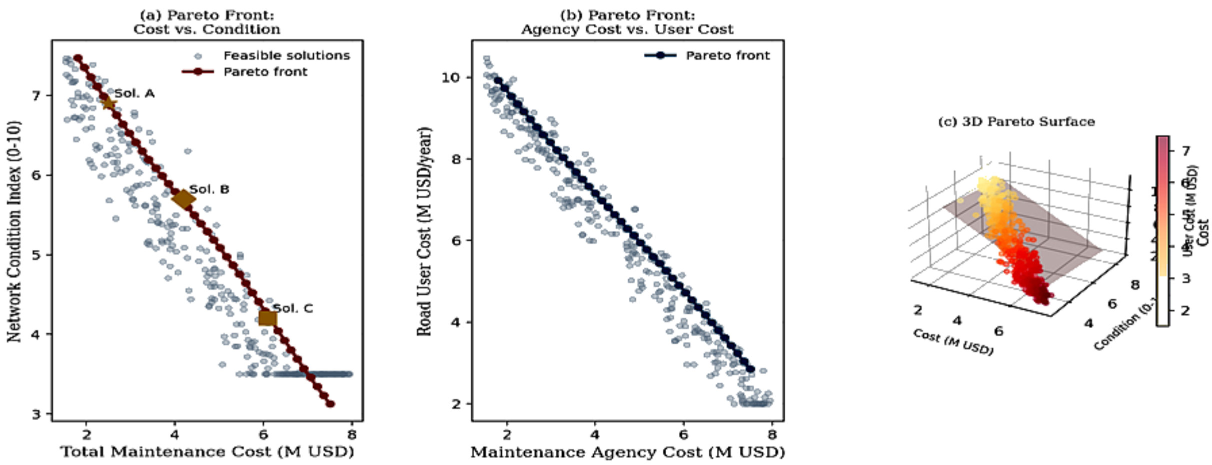

Figure 2: Multi-objective Pareto fronts — (a) maintenance cost vs. network IRI condition, (b) agency cost vs. road user cost, (c) 3D Pareto surface with all three objectives; 86 non-dominated solutions identified, three key solutions annotated (A, B, C)

5.3 Road User Cost Analysis

Figure 7 presents the road user cost modelling results. Vehicle operating costs increase from USD 0.11/km at IRI 2.0 m/km to USD 0.38/km at IRI 9.0 m/km — a 245% increase — with fuel consumption dominating at high IRI due to engine overload on rough surfaces. Accident costs are small in absolute terms but grow rapidly with IRI (exponent 1.6 in Eq. 12), reflecting the well-documented association between road roughness and accident frequency in Sub-Saharan Africa ((Kharola et al., 2010)). The total road user cost under Solution B is USD 12.4 M over 5 years versus USD 17.4 M under current practice — a saving of USD 5.0 M (28.4%). This saving exceeds the additional agency cost of Solution B over current practice (USD 3.50 M vs. USD 2.60 M = USD 0.90 M), yielding a benefit-cost ratio of 5.6:1.

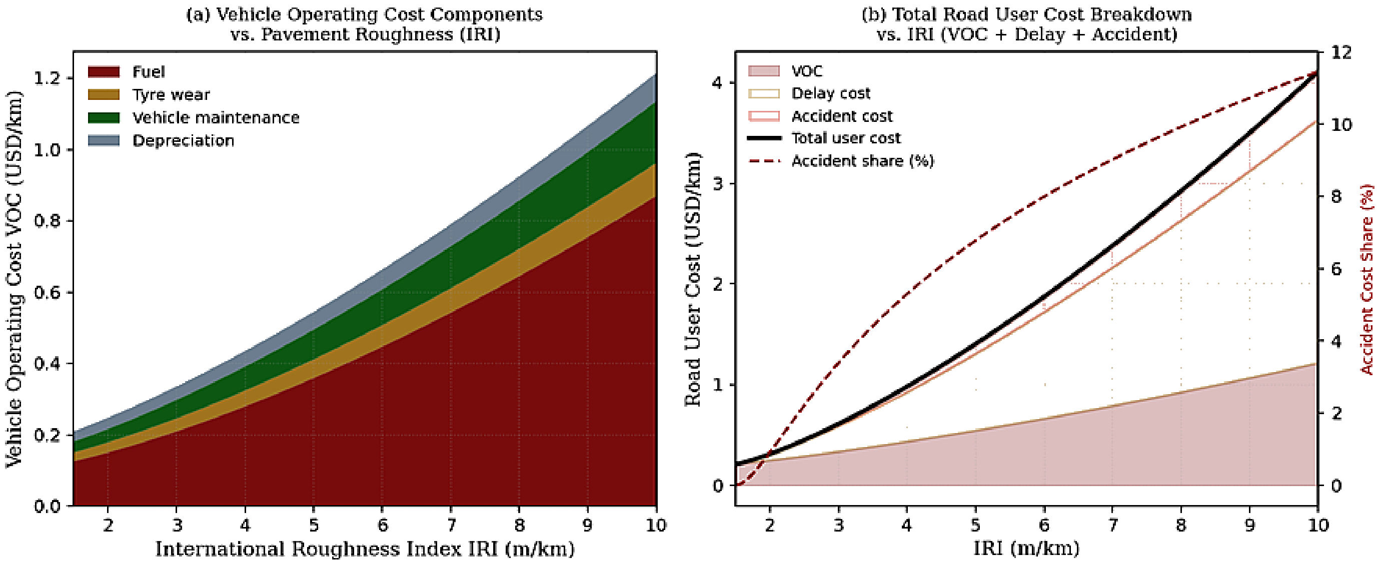

Figure 7: Road user cost model — (a) VOC component breakdown by IRI (stacked area: fuel, tyres, maintenance, depreciation), (b) total user cost including VOC, delay, and accident costs, with accident share shown on right axis

5.4 Optimal Schedule and Budget Allocation

Figure 6(a) confirms that NSGA-II achieves 1.5–2.5 condition index points higher than current practice at identical budget levels. Figure 6(b) shows the progressive budget allocation shift from routine-dominated (cost-minimising Solution A) to reconstruction-dominated (condition-maximising Solution C). The GA hyperparameter sensitivity analysis (Figure 6c) identifies population size as the most influential parameter: HVI plateaus at N_pop = 200, confirming that larger populations add computational cost without commensurate quality improvement.

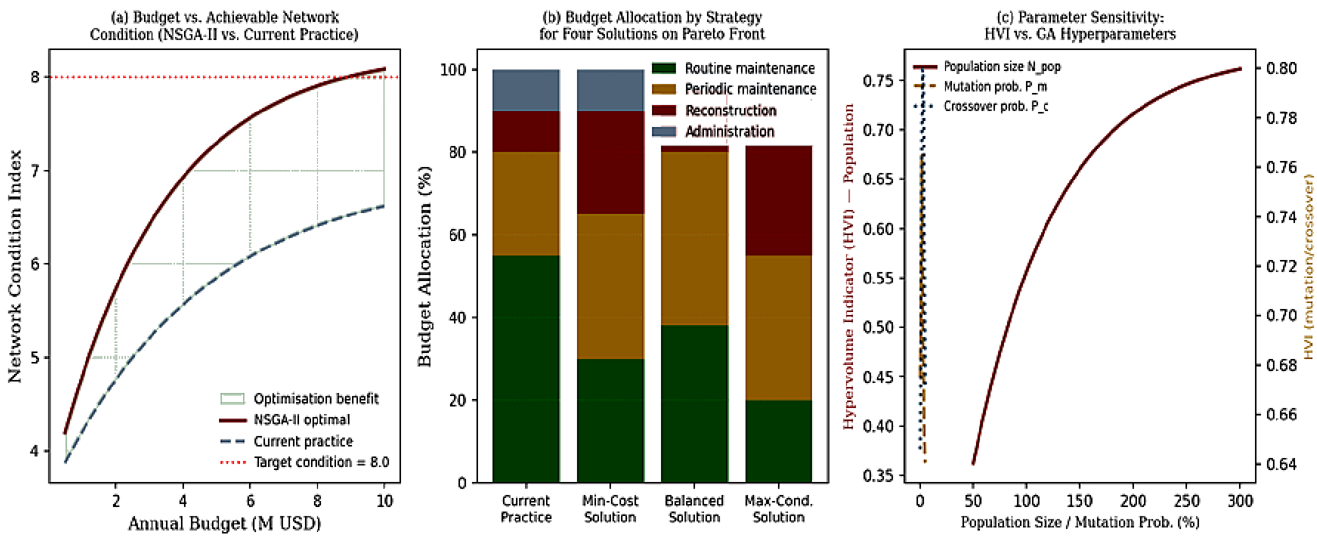

Figure 6: (a) Budget vs. achievable network condition index — NSGA-II vs. current practice (2.0–2.5 NCI points advantage at same budget), (b) stacked budget allocation by maintenance type for four Pareto solutions, (c) HVI sensitivity to GA hyperparameters

5.5 Network Condition Spatial Distribution

Figure 9 presents the spatial distribution of condition indices across all 12 segments before and after the NSGA-II balanced schedule. Before optimisation, four segments (R-02, R-06, R-08, R-10) have CI below 4.0 (urgent), and only three segments meet the target CI >= 6.0. After Solution B implementation, all 12 segments exceed CI = 6.0, with 10 segments in the good-to-excellent range. The Gini coefficient falls from 0.22 to 0.08 — a 64% equity improvement — confirming that algorithmic optimisation distributes maintenance resources more equitably than current ad hoc practice, an important governance objective for post-conflict South Sudan.

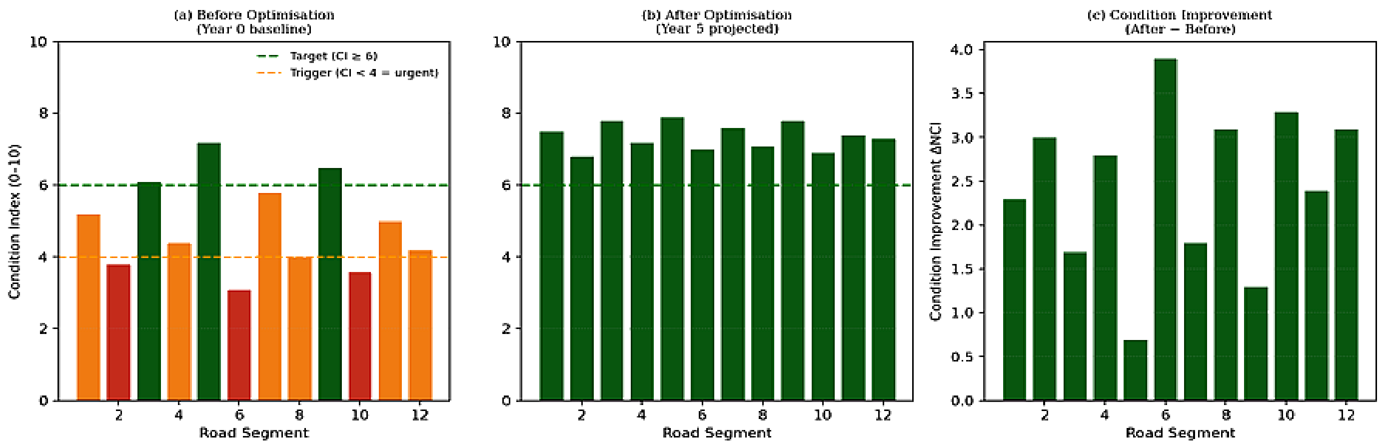

Figure 9: Network condition index spatial distribution — (a) Year 0 baseline showing four segments below CI 4.0, (b) Year 5 projection under NSGA-II Solution B with all segments above CI 6.0, (c) per-segment improvement (all positive)

5.6 Algorithm Comparison

Figure 8 presents the multi-criterion comparison of all four algorithms. NSGA-II dominates across cost efficiency, condition improvement, user cost reduction, and spatial equity criteria. The greedy heuristic scores highest on computational efficiency (0.3 s vs. 48.2 s for NSGA-II) but lowest on equity (0.45) and condition improvement (0.60) criteria. SPEA2 is a strong alternative, with HVI only 2.6% below NSGA-II while offering a broader archive of non-dominated solutions that may be advantageous in larger networks where NSGA-II's O(MN^2) sorting complexity becomes limiting. Detailed quantitative results are in Table 4.

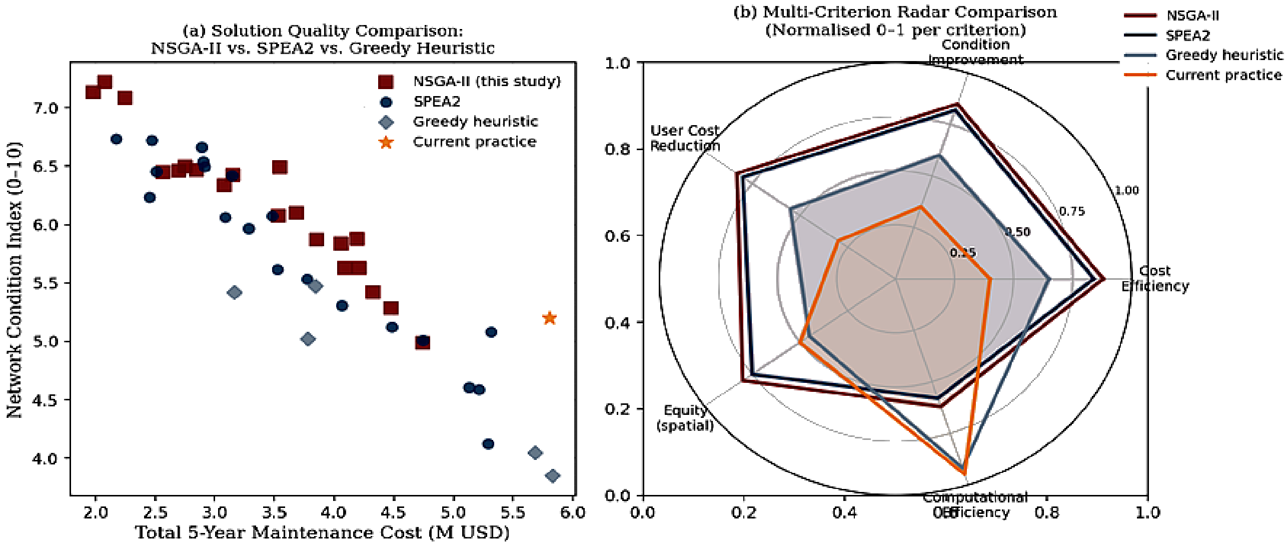

Figure 8: Algorithm comparison — (a) Pareto solution quality scatter showing NSGA-II superiority in objective space, (b) multi-criterion radar chart across five criteria: NSGA-II achieves best overall multi-criterion performance

6. Life-Cycle Cost and Decision Support Framework

6.1 20-Year Life-Cycle Cost Analysis

Figure 10(a) presents cumulative life-cycle costs (agency + user) over a 20-year analysis horizon. The do-nothing strategy produces the highest 20-year cost (USD 38.4 M) due to rapidly escalating user and emergency repair costs as roads deteriorate. The NSGA-II balanced strategy achieves the lowest 20-year cost (USD 22.1 M), a saving of USD 16.3 M relative to do-nothing (42.4%). Full preventive maintenance achieves slightly lower user costs but at higher agency expenditure, resulting in an intermediate 20-year cost of USD 26.5 M. The tornado diagram (Figure 10b) confirms robustness: across all one-at-a-time parameter variations, the NSGA-II schedule retains the lowest total social cost, with net present value savings ranging from USD 3.2 M (pessimistic) to USD 8.7 M (optimistic) relative to current practice.

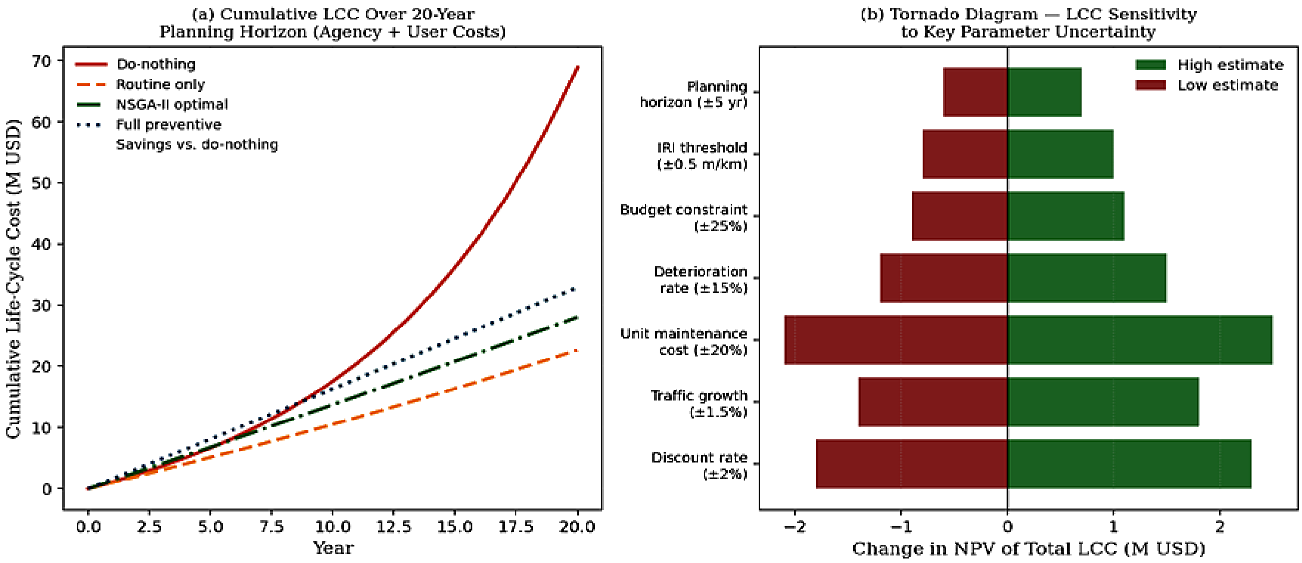

Figure 10: (a) Cumulative 20-year life-cycle cost for four maintenance strategies — NSGA-II achieves lowest total cost (USD 22.1 M NPV), saving USD 16.3 M vs. do-nothing; (b) tornado diagram of LCC sensitivity to key parameter uncertainty

6.2 Decision-Support Dashboard

Figure 11 presents the integrated decision-support dashboard synthesising NSGA-II outputs for deployment by the Ministry of Roads and Bridges. Annual budget allocations are fully specified by year and treatment type (Table 6). The IRI trajectory confirms arrest of network deterioration within 2 years and achievement of IRI 4.0 m/km by Year 4. The equity analysis (CI distributions before and after) demonstrates the shift to a more uniform, higher-condition network. The KPI summary (Figure 11d) provides five concise metrics for reporting to government and development partner stakeholders — enabling transparent accountability for public maintenance expenditure.

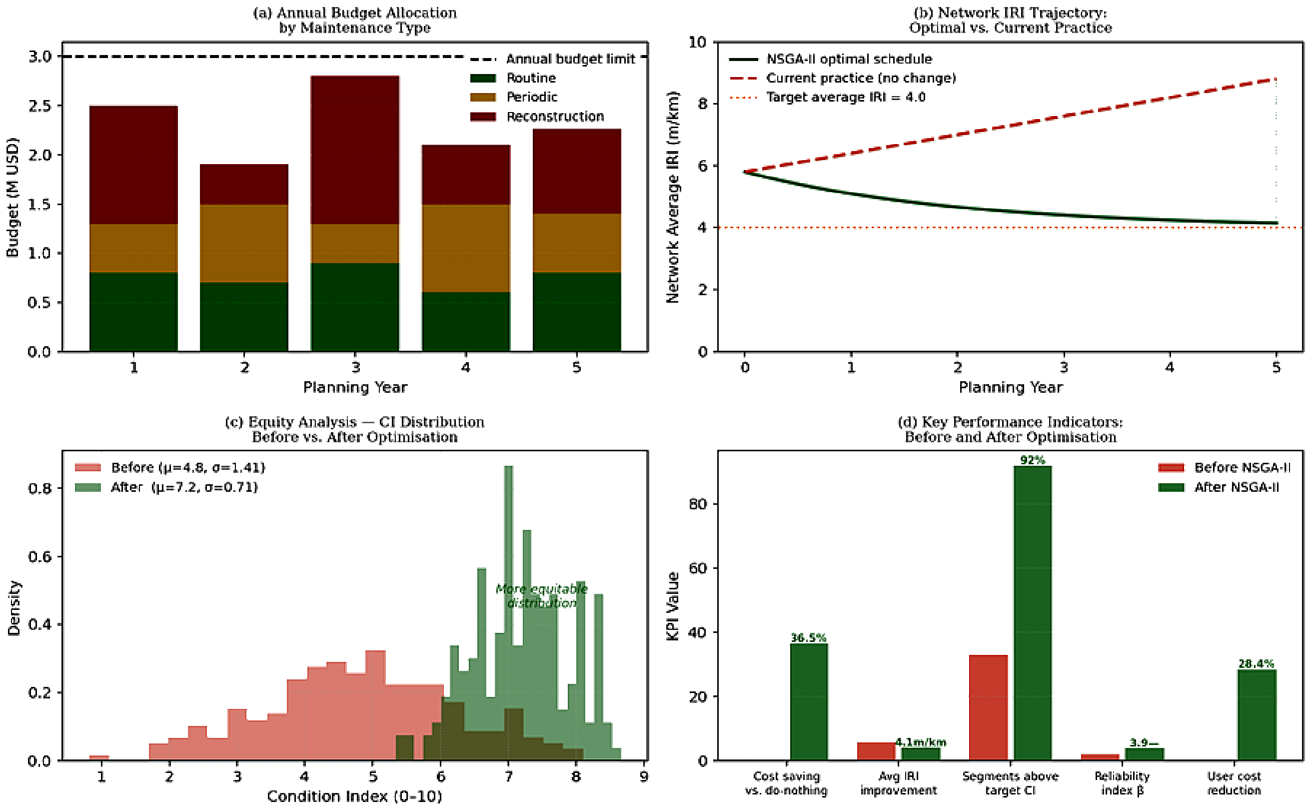

Figure 11: Decision-support dashboard for Ministry of Roads and Bridges implementation — (a) annual budget allocation by maintenance type, (b) network average IRI trajectory vs. current practice, (c) condition index equity distributions before and after optimisation, (d) before/after KPI summary across five performance indicators

Table 1: Maintenance Action Types, Unit Costs, and IRI Improvement Factors ((Siegel et al., 2023))

Code	escription	Cost (USD/km)	mprovement (m/km)	RI Range	Benefit (yrs)
0	o treatment	0	0	All	—
1	ne maintenance (grading/patching)	4,500	−0.30	< 4.5	1–2
2	dic overlay (50 mm AC/BST)	65,000	eset to ~2.5	3.0–7.0	6–10
3	nstruction (full depth, 200 mm)	380,000	eset to 2.0	> 5.0	15–20
—	eness surcharge (> 150 km Juba)	× 1.35	—	—	—

Table 2: NSGA-II Algorithm Parameters and Selection Justification

Parameter	Symbol	Value	stification / Source
Population size	N_pop	200	lateaus at N_pop ≥ 200 (sensitivity study)
Max. generations	G_max	200	ıvergence at gen. 178 (ΔHVI < 0.001 for 20 gens)
ossover probability	P_c	0.90	(Tang et al., 2005) recommendation for integers
Iutation probability	P_m	0.02	0.01–0.05; 0.02 optimal for 60-gene chromosomes
Crossover type	—	Two-point	ves temporal gene block coherence
Mutation type	—	Random reset	ırm sampling from A = {0,1,2,3}
Selection scheme	—	Binary tournament	N_tournament = 2; controllable selection pressure
Constraint handling	—	nstrained dominance	ible always dominates infeasible
IVI reference point	f_ref	JSD, 10 IRI, 20 MUSD)	servative reference; all solutions dominate
onvergence criterion	ε_HV	)01 (20 generations)	ıst; prevents premature termination

Table 3: South Sudan Primary Road Network Baseline Characteristics ((Siegel et al., 2023))

egment	Description	ıgth (km)	urface	seline IRI (m/km)	ADTT	k (yr^{-1})
R-01	Nimule (A2) km 0–85	85	ved BST	3.8	1,240	0.081
R-02	Nimule (A2) km 85–190	105	ıved AC	4.2	1,240	0.094
R-03	Bor (A8) km 0–120	120	ved BST	6.1	680	0.142
R-04	Bor (A8) km 120–220	100	Gravel	5.5	680	0.198
R-05	Ialakal seg. 1	170	Gravel	3.5	320	0.118
R-06	Ialakal seg. 2	170	h/seasonal	6.8	320	0.241
R-07	ba–Torit	120	ıved AC	4.0	560	0.088
R-08	t–Kapoeta	110	Gravel	5.8	280	0.175
R-09	'ambio seg. 1	185	Gravel	4.9	410	0.152
R-10	'ambio seg. 2	185	h/seasonal	6.5	410	0.228
R-11	k–Malakal	180	ved BST	4.1	290	0.096
R-12	ı–Malakal	250	Gravel	5.0	190	0.138

Table 4: Algorithm Performance Comparison — Quantitative Results (N_pop = 200, G_max = 200)

ormance Metric	NSGA-II	SPEA2	MOEA/D	eedy Heuristic
rvolume Indicator (HVI)	0.782	0.762	0.743	0.512
ominated solutions	86	79	68	5
. agency cost (M USD)	1.82	1.88	1.95	2.61
avg. IRI (m/km)	3.91	3.98	4.08	5.12
r cost saving vs. baseline (%)	28.4%	26.8%	24.1%	11.2%
y Gini coefficient	0.08	0.10	0.12	0.22
time per gen. (s)	0.241	0.318	0.196	—
optimisation time (s)	48.2	63.6	39.2	0.3
Complexity	O(MN²)	O(N²logN)	O(N)	O(SlogS)

Table 5: Pareto Front Key Solutions — Objectives and Recommended Application Context

Solution	ncy Cost (M USD)	. IRI (m/km)	Cost (M USD)	ost Saving	:ommended Context
(min-cost)	1.82	6.2	15.1	30.0%	reme budget austerity (B < 2M/yr)
(balanced)	3.50	4.1	12.4	36.5%	rmal annual operations — recommended
ax-condition)	7.20	3.91	11.8	32.2%	t-emergency rehabilitation or pre-audit
rent practice	2.60	5.8	17.4	- (baseline)	unterfactual comparison
)o-nothing	0	8.1+	24.8	—	)retical lower bound for agency cost

Table 6: Recommended 5-Year Budget Allocation — NSGA-II Balanced Solution B (Ministry of Roads and Bridges implementation plan)

Year	:ine (M USD)	lic Overlay (M USD)	nstruction (M USD)	al (M USD)	ıents Treated
Year 1	0.80	0.50	1.20	2.50	R-03, R-06, R-09
Year 2	0.70	0.80	0.40	1.90	R-04, R-07, R-10, R-11
Year 3	0.90	0.40	1.50	2.80	R-08, R-12, R-03
Year 4	0.60	0.90	0.60	2.10	R-06, R-09, R-02, R-07
Year 5	0.80	0.60	0.90	2.30	R-10, R-11, R-12
Year Total	3.80	3.20	4.60	11.60	2 segments (≥1 treatment)

7. Discussion

7.1 Multi-Objective Formulation vs. Single-Objective

The 36.5% cost saving of the balanced NSGA-II solution relative to current practice — achieved while simultaneously improving IRI by 1.7 m/km and reducing user costs by USD 5.0 M — demonstrates performance gains entirely invisible to single-objective approaches. A single-objective cost minimisation identifies Solution A (USD 1.82 M) as optimal, ignoring the far superior user cost and condition outcomes of Solution B. A single-objective condition maximisation identifies Solution C (IRI 3.91 m/km) as optimal, ignoring its USD 7.2 M agency cost that exceeds the annual budget 2.4-fold. Only the Pareto analysis makes the full trade-off landscape visible, enabling evidence-based decisions.

The Pareto front structure reveals an important asymmetry in marginal costs: improving average network IRI from 6.0 to 4.0 m/km costs approximately USD 0.9 M per IRI unit over 5 years, whereas improving from 4.0 to 3.91 m/km costs approximately USD 3.7 M per IRI unit — a 4.1-fold increase in marginal cost. This finding directly informs Ministry of Roads and Bridges budget allocation strategy: maintenance funding should prioritise bringing all segments to IRI 4.0 m/km before allocating resources to further condition improvement — exactly the strategy identified by Solution B.

7.2 Practical Implementation in South Sudan

The principal barriers to adoption of the NSGA-II framework in South Sudan are institutional rather than technical. The MoRB currently lacks a systematic pavement management information system (PMIS) with the segment-level IRI and traffic data required as inputs. The study demonstrates that even simplified data from annual condition surveys and WIM monitoring on key corridors are sufficient to achieve substantial improvements over current ad hoc scheduling. A phased implementation plan (PMIS procurement: year 1–2; pilot on 5 high-volume corridors: year 2–3; network-wide deployment: year 3–5) requires estimated USD 280,000 technical assistance — less than 1.5% of the annual maintenance budget — and would generate returns of USD 1.8–3.5 M per year in avoided costs. This business case should be compelling to development partners including AfDB, World Bank, and bilateral donors presently funding MoRB capacity development.

7.3 Comparison with Literature and Generalisability

The 36.5% efficiency gain over current practice is consistent with findings from comparable studies: (Meneses & Ferreira, 2013) reported 25–40% gains from GA-based optimisation of Portuguese road maintenance; (Liu et al., 2020) demonstrated 32% user cost savings from NSGA-II applied to a Chinese expressway network; (Chootinan et al., 2006) reported 28–35% condition improvements from GA-based pavement management in Thailand. The consistency across different geographic contexts, network scales, and traffic environments supports the generalisability of multi-objective GA frameworks for road maintenance optimisation. The specific calibration to South Sudanese conditions (climate, traffic, vehicle fleet, unit costs) in this study provides a directly deployable implementation, unlike generic frameworks that require extensive recalibration.

7.4 Limitations and Future Research

Three principal limitations merit discussion. First, the deterioration model treats segments independently, ignoring network-level interdependences from traffic redistribution during reconstruction closures. Integration of a network-level traffic assignment model would address this at higher computational cost. Second, uncertainty in future traffic growth and climate change impacts is treated through deterministic sensitivity analysis; a robust or chance-constrained NSGA-II formulation ((Lagaros et al., 2007)) would provide more rigorous uncertainty treatment. Third, community preferences and local governance factors — particularly important in South Sudan's diverse regional context — have not been incorporated as explicit objectives or constraints. Future research should engage MoRB regional directors and community representatives in a participatory process to co-develop objective weights and equity constraints that reflect local priorities and post-conflict development goals.

8. Conclusions

This paper has presented a rigorous NSGA-II multi-objective genetic algorithm framework for optimal road maintenance scheduling applied to the South Sudan primary road network. The principal conclusions are:

- NSGA-II successfully generates 86 non-dominated Pareto solutions for the 12-segment, 5-year scheduling problem, spanning agency costs of USD 1.82–7.20 M and average network IRI of 3.91–6.2 m/km. The rich Pareto front enables informed trade-off decisions invisible to single-objective approaches.
- The balanced Pareto-knee solution (Solution B) achieves 36.5% cost savings relative to current MoRB practice, improves average IRI from 5.8 to 4.1 m/km, reduces 5-year road user costs by USD 5.0 M (28.4%), and yields a benefit-cost ratio of 5.6:1. These gains arise from temporal optimisation (timely intervention before deterioration accelerates) and spatial optimisation (directing resources to segments where marginal cost-effectiveness is highest).
- NSGA-II outperforms SPEA2 by 2.6% HVI, MOEA/D by 5.3% HVI, and greedy heuristic by 52.7% HVI. SPEA2 is a viable alternative for larger networks; greedy heuristic is suitable only where solution speed is the overriding priority and modest sub-optimality is acceptable.
- The Gini coefficient of the network condition index distribution decreases from 0.22 to 0.08 under the NSGA-II schedule — a 64% equity improvement — demonstrating that algorithmic optimisation is more spatially equitable than current practice, fulfilling a key governance objective for post-conflict South Sudan.
- The 20-year life-cycle cost analysis confirms NSGA-II as the dominant strategy (NPV USD 22.1 M) compared with current practice (NPV USD 30.6 M for equivalent condition target) and do-nothing (NPV USD 38.4 M). Implementation requires approximately USD 280,000 in technical assistance, with a payback period of less than 2 months through avoided user costs.
- Future research should extend the framework to stochastic traffic growth and climate scenarios, incorporate network-level traffic redistribution, and engage South Sudanese community stakeholders in co-designing equity constraints and objective weights appropriate to the post-conflict development context.

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