ISSN 2349-4506
Impact Factor: 3.799

Global Journal of Engineering Science and Research Management

CLIMRESILINFRA: ADAPTIVE DESIGN OPTIMISATION AND GIS-BASED DECISION SUPPORT FOR CLIMATE-RESILIENT INDIAN ROAD INFRASTRUCTURE

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KEYWORDS: Adaptive design optimisation; Fuzzy Resilience Index; Genetic Algorithm; ANFIS; GIS-Decision Support System; MCDA; Lifecycle cost; Climate-resilient infrastructure; India; SSP projections; Policy integration

ABSTRACT

The compounding impacts of climate stressors like extreme flooding, heat-waves and increased monsoon variability are driving infrastructure degradation at rates which are higher than currently assumed in design of India's national highway network. Vulnerability characterisation and degradation forecasting are diagnostic, but the ability to translate those lessons into actions for adaptive design and evidence-based policy is an unmet need. In this paper, the adaptive engineering and governance modules of ClimResilInfra are presented, with only (GA–ANFIS Adaptive Design Optimisation) and (GIS Based Decision Support and Policy Framework) being discussed. Five adaptive design strategies are compared to a novel Fuzzy Resilience Index (FRI) using a Genetic Algorithm (GA) and Adaptive Neuro-Fuzzy Inference System (ANFIS) which optimizes the cost-resilience frontier for the new climate scenarios, SSP2-4.5 and SSP5-8.5. The GA optimised hybrid strategy (S4) increases FRI by 107% compared to baseline, and lowers the normalised lifecycle cost by 3%. Life Cycle Assessment (LCA) shows a co-benefit – S4 has 16% less embodied GHG emissions than baseline. For the estimated annual NH maintenance expense, ANFIS-derived maintenance scheduling decreases the expense by 18-22% from fixed 5-year cycles to risk-stratified schedules of 3.6-11.8 years. The GIS-based Decision Support System (DSS) integrates FRI scores with climate vulnerability indices, exposed population data and lifecycle costs of 20 NH interventions across the country and ranks them using MCDA through the generation of a Priority Score. The highest national action (PS = 0.847) is biorial NH scour protection. With SSP5-8.5, 35% of NH segments will exceed critical thresholds by 2050. There are three key amendments to IRC:SP-84 design standards identified as policy gaps.

INTRODUCTION

India's 6.2 million km long road network with 1,79,000 bridges and structures, is like the bloodstream of an economy serving 1.4 billion people. It is estimated that about 30% of the National Highway (NH) network in India is in flood prone areas and South Asia is one of the fastest warming regions in the world with a mean warming trend of 0.15°C per decade (MoRTH, 2023 & IMD, 2023). These climate stressors overlie the structural vulnerabilities that stem from the material's uneven quality, the topographic difficulties, and the use of infrastructure designed to design standards that were not informed by projected climate change. There has been a significant development of the conceptual frameworks of vulnerability and degradation in the recent literature. The crucial downstream translation, which is largely missing from the Indian infrastructure context, is: when a road segment or bridge is extremely vulnerable, how, when, and at what cost do specific interventions of adaptation engineering need to be deployed, and what is the quantified level of resilience gain? This disconnect between climate diagnosis and adaptive governance is what this paper aims to fill. This paper introduces the ClimResilInfra framework as its adaptive engineering/policy decision support layer. Objective 3 creates an adaptive design pipeline with the GA–ANFIS, which: (i) tests five design strategies (S0–S4) by performing the climate-structural simulation under scenario conditions; (ii) calculates a Fuzzy Resilience Index (FRI) comprising the sub-dimensions of structure, exposure, and adaptation capacity; (iii) optimises the design parameter space using the Genetic Algorithm to maximise FRI within the limit of the highway's lifecycle costs; and (iv) schedules maintenance interventions based on actual norms from Indian highways using ANFIS trained with real-world data. Objective 4 produces a GIS-based Decision Support System (DSS) incorporating FRI outputs, Climate Vulnerability Indices, exposed population data and lifecycle cost metrics to rank NH interventions across the country using MCDA and includes a structured policy gap analysis to benchmark against International design

standards. All methodologies are based on reliable open access data available (ERA5, NEX-GDDP-CMIP6, RDD2022, OSM Geofabrik, SRTM, Census India/Worldpop) to ensure the reproducibility. Throughout, validation of robustness is carried out via Monte Carlo uncertainty quantification and multi-configuration sensitivity analysis.

DATASETS AND INPUT SOURCES

Receive structured inputs from earlier modelling phases and integrate additional socio-economic and spatial datasets. The full dataset inventory is summarised in Table 1.

Table 1: Input Data Sources

Dataset	Source / DOI	Resolution	Variables Used
ERA5 Reanalysis	cds.climate.copernicus.eu	0.25° × 0.25°, Annual	HWMI, Rx3day, ATR — climate stress inputs to ANFIS
NEX-GDDP-CMIP6	registry.opendata.aws/nex-gddp-cmip6	0.25°, SSP2-4.5 / SSP5-8.5	Tmax, Precip — scenario-conditioning for FRI simulation
RDD2022 India (RSL outputs)	figshare DOI:10.6084/m9.figshare.21431547	Segment-level	Residual service life (RSL) trajectories from Obj 2
OSM India + Geofabrik	download.geofabrik.de	Vector / NH	Road geometry, bridge tags, NH route refs for DSS
SRTM DEM	earthexplorer.usgs.gov	30 m	Slope, flow accumulation for drainage strategy scoring
Census India + Worldpop	censusindia.gov.in / worldpop.org	District / 1 km	Population exposure for PS computation in DSS
IRC:SP-84:2014	MoRTH / BIS India	National Standard	Maintenance cycle benchmarks; ANFIS calibration reference
ecoinvent 3.9	ecoinvent.org (licensed)	Material-level	Carbon intensity database for LCA GHG calculations

GA–ANFIS ADAPTIVE DESIGN OPTIMISATION

3.1 Adaptive Design Strategy Space

1.1 Problem Formulation

Let the adaptive design optimisation problem be defined as:

Objective: Maximise the Fuzzy Resilience Index $\mathcal{F}_{\text{FRI}}$ subject to life-cycle cost constraints:

$$\begin{aligned} &\mathcal{F}_{\text{FRI}}(\boldsymbol{x}) \\ \text{subject to} &\mathcal{C}_{\text{LCC}}(\boldsymbol{x}) \leq 1.05 \cdot \mathcal{C}_{\text{LCC},0} \\ &\boldsymbol{x} \in \mathcal{X} \subset \mathbb{R}^4 \end{aligned} \tag{1}$$

where the decision vector $\boldsymbol{x} = [r, p, d, m]^{\top}$ with:

$$\begin{aligned} r &\in [0, 50] \text{ cm(roadbed raise increment)} \\ p &\in \{0, 1, 2, 3\} \text{(rebar protection class)} \\ d &\in \{0, 1, 2\} \quad \text{(drainage upgrade level)} \\ m &\in \{0, 1, 2\} \quad \text{(material grade class)} \end{aligned} \tag{2}$$

3.2 Fuzzy Resilience Index (FRI) Framework

1 Sub-Index Definitions

The Fuzzy Resilience Index is defined as a nonlinear mapping:

$$\mathcal{F}_{\text{FRI}}: [0, 1]^3 \rightarrow [0, 100] \tag{3}$$

composed of three normalised sub-indices:

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Global Journal of Engineering Science and Research Management

Sub-Index 1 — Structural Resilience (SR):

$$\mathrm{SR}(\boldsymbol{x}) = \phi\left(\frac{\mathcal{R}_{\mathrm{RSL}}(\boldsymbol{x})}{\mathcal{R}_{\mathrm{RSL},0}}\right) \quad (4)$$

where $\mathcal{R}_{\mathrm{RSL}}(\boldsymbol{x})$ is the CNN–LSTM-predicted residual service life for strategy $\boldsymbol{x}$, $\mathcal{R}_{\mathrm{RSL},0}$ is the baseline RSL, and $\phi(\cdot)$ is a sigmoidal transformation mapping $\mathbb{R}^+ \to [0, 1]$:

$$\phi(z) = \frac{1}{1+\exp(-\kappa(z-\mu))} \quad (5)$$

with $\kappa = 0.3$ and $\mu = 1.0$ calibrated from expert thresholds.

Sub-Index 2 — Exposure Resilience (ER):

$$\mathrm{ER} = 1 - \mathcal{C}_{\mathrm{VI}} \quad (6)$$

where $\mathcal{C}_{\mathrm{VI}}$ is the Composite Vulnerability Index:

$$\mathcal{C}_{\mathrm{VI}} = w_{\mathrm{F}} \cdot \mathcal{I}_{\mathrm{F}} + w_{\mathrm{H}} \cdot \mathcal{I}_{\mathrm{H}} + w_{\mathrm{A}} \cdot \mathcal{I}_{\mathrm{A}} \quad (7)$$

with weights $w_{\mathrm{F}} = 0.50$, $w_{\mathrm{H}} = 0.30$, $w_{\mathrm{A}} = 0.20$ from AHP, and $\mathcal{I}_{\mathrm{F}}, \mathcal{I}_{\mathrm{H}}, \mathcal{I}_{\mathrm{A}} \in [0, 1]$ being flood, heat, and rainfall anomaly indices.

Sub-Index 3 — Adaptive Capacity (AC):

$$\mathrm{AC} = \frac{1}{3}\left(\mathcal{M}_{\mathrm{upgrade}} + \mathcal{B}_{\mathrm{index}} + \mathcal{T}_{\mathrm{critical}}\right) \quad (8)$$

where:

$$\mathcal{M}_{\mathrm{upgrade}} = \sum_{j=1}^{3} \frac{s_j}{3} \in [0, 1] \text{ (normalised material score)}$$

$$\mathcal{B}_{\mathrm{index}} = \min\left(\frac{E_{\mathrm{dist}}}{E_{\mathrm{median}}}, 1\right) \text{ (budget adequacy)}$$

$$\mathcal{T}_{\mathrm{critical}} = \min\left(\frac{\mathrm{ADT}}{\mathrm{ADT}_{\mathrm{median}}}, 1\right) \text{ (traffic criticality)}$$

2.2 Mamdani Fuzzy Inference System

The FRI is computed via a Mamdani-type fuzzy inference engine with rule base $\mathcal{R} = \{R_1, R_2, \ldots, R_{25}\}$. Each rule takes the form:

$$R_k\text{:IF SR is } A_{k,1} \text{ AND ER is } A_{k,2} \text{ AND AC is } A_{k,3} \text{ THEN FRI is } B_k$$

where $A_{k,i}$ are triangular fuzzy sets:

$$\mu_A(x) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right) \quad (9)$$

with linguistic states:

- **Degraded:** $[0, 0, 0.35]$
- **Functional:** $[0.25, 0.50, 0.75]$
- **Resilient:** $[0.65, 1.0, 1.0]$

The aggregated output is defuzzified using the centroid method:

$$\mathcal{F}_{\mathrm{FRI}} = \frac{\int y \cdot \mu_{\mathrm{agg}}(y)\, dy}{\int \mu_{\mathrm{agg}}(y)\, dy} \quad (10)$$

2.3 Uncertainty Quantification

Monte Carlo sampling over parameter perturbations:

$$\begin{aligned} \boldsymbol{w}_{\mathrm{AHP}} &\sim \mathcal{N}(\boldsymbol{\mu}_w, \boldsymbol{\Sigma}_w),\ \sigma_w = 0.25 \cdot \boldsymbol{\mu}_w \\ \boldsymbol{G}_{\mathrm{GCM}} &\sim \mathcal{N}(\boldsymbol{\mu}_G, \boldsymbol{\Sigma}_G),\ \ \sigma_G = 1\sigma \text{ (ensemble spread)} \\ \boldsymbol{M}_{\mathrm{mat}} &\sim \mathcal{N}(\boldsymbol{\mu}_M, \boldsymbol{\Sigma}_M), \sigma_M = 0.10 \cdot \boldsymbol{\mu}_M \end{aligned} \quad (11)$$

The 90% confidence interval is determined from the 5th and 95th percentiles of 10,000 Monte Carlo realisations.

3.3 Genetic Algorithm (GA) Optimisation
3.1 Fitness Function
The fitness function for a chromosome $\boldsymbol{x}$ is defined as:

$$\Psi(\boldsymbol{x}) = \mathcal{F}_{\text{FRI}}(\boldsymbol{x}) - \lambda \cdot \max\left(0, \frac{\mathcal{C}_{\text{LCC}}(\boldsymbol{x}) - 1.05\mathcal{C}_{\text{LCC},0}}{\mathcal{C}_{\text{LCC},0}}\right)^2 \quad (12)$$

where $\lambda = 1000$ is the static penalty coefficient.

3.2 Evolutionary Operators
Selection: Tournament selection with tournament size $k = 5$:

$$P(\text{select } \boldsymbol{x}_i) = \begin{cases} 1 & \text{if } \Psi(\boldsymbol{x}_i) \geq \max\{\Psi, (\boldsymbol{x}_{i_1}), \dots \Psi(\boldsymbol{x}_{i_5})\} \\ 0 & \text{otherwise} \end{cases} \quad (13)$$

Crossover (Blend Crossover, $\alpha = 0.5$):
For parent pair $\boldsymbol{x}^{(1)}, \boldsymbol{x}^{(2)}$, offspring $\boldsymbol{y}$ is generated as:

$$d_j = | x_j^{(1)} - x_j^{(2)} |$$
$$y_j \sim \mathcal{U}(\min, (x_j^{(1)}, x_j^{(2)}) - \alpha d_j \max(x_j^{(1)}, x_j^{(2)}) + \alpha d_j) \quad (14)$$

for continuous variable r. For discrete variables p, d, m, uniform crossover is applied.
Mutation:

- For continuous r: $r' = r + \epsilon$, where $\epsilon \sim \mathcal{N}(0, \sigma_m^2)$, $\sigma_m = 0.02 \cdot (50 \text{ cm})$
- For discrete variables: bit-flip mutation with probability $p_m = 0.02$

3.3 Convergence Criteria
The algorithm terminates when either:

$$g \geq G_{\max} = 200 \text{ or } \frac{|\Psi_g^* - \Psi_{g-10}^*|}{\Psi_{g-10}^*} < 10^{-4} \quad (15)$$

where Ψ_g^* is the best fitness at generation g.
3.4 ANFIS Maintenance Scheduling
The Adaptive Neuro-Fuzzy Inference System (ANFIS) is used to map climate dependent structural condition variables into optimal maintenance intervention periods instead of fixed IRC:SP-84 inspection periods, and to provide risk-based scheduling. The ANFIS structure has five Takagi–Sugeno fuzzy rules with generalised bell-shaped membership functions, which are trained using the hybrid back-propagation–least-squares estimation method. **The Inputs are:** (1) Current FRI; (2) Remaining RSL (years); (3) Traffic Load Index (ADT-normalised); (4) Annual Climate Stress Score (composite HWMI + Rx3day, normalised to [0,1]). **Output:** Time to next intervention (years, continuous) with IRC operational constraints [2:15]. Train data: 200 synthetic lifecycle scenarios jointly calibrated to IRC SP-84:2014 maintenance norms and validated with three independent datasets from MoRTH NH inspections cycle (Bihar, UP and Assam, 2018-2023). The leave-one-out cross validation gives RMSE = 0.74 years for predicting intervention intervals.

3.5 Life Cycle Assessment (LCA) and LCCA
Embodied GHG emissions per km for each strategy were calculated by multiplying material manufacturing and construction phases with carbon intensity coefficients (CICs) from ecoinvent 3.9 for the environment. The GHG metrics are presented as an index relative to baseline (S0 = 100). Life Cycle Cost Analysis (LCCA) has been applied by discounting all costs associated with capital, maintenance, rehabilitation and probabilistic failures to 2025 Net Present Value (at 7% discount rate) as per Indian public infrastructure project appraisal norms (MoRTH project appraisal norms). Failure cost is represented as a stochastic variable: probability of segment failure per year x estimated repair/rep. cost, in $ per km x discount factor.

LIFE-CYCLE COST ANALYSIS (LCCA)

5.1 Cost Components

The total life-cycle cost is:

$$\mathcal{C}_{\text{LCC}}(\boldsymbol{x}) = \mathcal{C}_{\text{capital}}(\boldsymbol{x}) + \sum_{t=1}^{T} \frac{\mathcal{C}_{\text{maintenance},t}(\boldsymbol{x}) + \mathcal{C}_{\text{rehab},t}(\boldsymbol{x}) + \mathcal{C}_{\text{failure},t}(\boldsymbol{x})}{(1+\delta)^t} \quad (16)$$

where $\delta = 0.07$ (discount rate), $T = 50$ years (analysis period).

5.2 Failure Cost Model

Stochastic failure cost:

$$\mathcal{C}_{\text{failure},t}(\boldsymbol{x}) = P_{\text{fail},t}(\boldsymbol{x}) \cdot \mathcal{C}_{\text{repair}} \cdot L \quad (17)$$

where:

$$P_{\text{fail},t}(\boldsymbol{x}) = 1 - \exp\left(-\frac{t}{\eta(\boldsymbol{x})}\right)^{\beta} \quad (18)$$

with $\beta = 2.0$ (Weibull shape parameter) and $\eta(\boldsymbol{x})$ is the characteristic life dependent on design parameters.

ENVIRONMENTAL LIFE-CYCLE ASSESSMENT

Normalised GHG index:

$$\mathcal{G}_{\text{GHG}}(\boldsymbol{x}) = \frac{\sum_k Q_k(\boldsymbol{x}) \cdot \mathcal{E}_k}{\sum_k Q_k(\boldsymbol{x}_0) \cdot \mathcal{E}_k} \times 100 \quad (19)$$

where:

- $Q_k(\boldsymbol{x})$ = quantity of material k required
- $\mathcal{E}_k$ = ecoinvent 3.9 carbon intensity coefficient for material k
- $\boldsymbol{x}_0$ = baseline strategy S0

The proposed methodology is based on the idea of embedding Genetic Algorithm (GA) optimisation with Adaptive Neuro-Fuzzy Inference System (ANFIS) scheduling in a single climate uncertainty resilience based decision making system for NH adaptive design. It is based on three theoretical approaches: (1) fuzzy multi-criteria resilience assessment, (2) evolutionary multi-objective design optimisation, and (3) neuro-adaptive maintenance planning.

METHODOLOGY: GIS-DSS AND POLICY FRAMEWORK

4.1 GIS-DSS Architecture

The web interface is implemented as a Streamlit web dashboard and the geospatial visual exploration is implemented as a Python plugin for the QGIS 3.34 platform. The DSS combines five data layers for each NH road segment: Layer 1 — FRI Score: Optimised FRI per segment for GA, input from Obj 3 (weight $w_1 = 0.35$ in Priority Score). Layer 2 — CVI: Composite Vulnerability Index from multi-hazard assessment (weight $w_2 = 0.30$). Layer 3 — Population Exposure: Worldpop 2020 gridded population added in NH segments 2 km buffer, normalised (weight $w_3 = 0.20$). The Normalised LCCA from the Obj 3 LCCA module is included in Layer 4 — Lifecycle Cost. The composite Priority Score per segment is: PS = 0.35 × (1 − FRI/100) + 0.30 × CVI + 0.20 × PopExp + 0.15 × LCC_norm. Higher PS means higher priority for intervention. The weights for the MCDA were determined using AHP calibration with 12 NH engineers, transport economists and climate scientists (Consistency Ratio = 0.06 < 0.10 threshold).

4.2 MCDA Intervention Ranking

Twenty candidate interventions are identified across five high-risk corridors in India (Bihar, Assam, Odisha, UP, Western Ghats) that are scored on three evaluation criteria: (C1) Technical Resilience Improvement — ΔFRI, the change in FRI from the proposed intervention; (C2) Cost-Effectiveness — ΔFRI / ΔLCC, the change in FRI per unit of normalised intervention lifecycle cost; (C3) Population Benefit — exposed population protected per Intervention cost in million INR. The scores for each criterion are then min-max normalised and aggregated with the criterion weights obtained from AHP: wC1 = 0.45, wC2 = 0.35, wC3 = 0.20. Sensitivity analysis compares five different weight configurations, including equal weighting (0.33/0.33/0.33) and cost-prioritised (0.25/0.50/0.25).

4.3 Policy Gap Analysis Framework

The following standards are used to systematically compare to the FHWA Bridge Management System specifications and the ITF/OECD Transport System Resilience Report (2024): Indian design standards (IRC:SP-84:2014), BIS:456:2000, and BIS:1343:2012. The assessment panel, which is independent of the project team,

ISSN 2349-4506
Impact Factor: 3.799
Global Journal of Engineering Science and Research Management

assigns a score of 1-5 for each of six policy dimensions: (D1) Design Flood Return Period; (D2) Heat-Wave Design Temperature; (D3) Maintenance Cycle Flexibility; (D4) Multi-Hazard Coverage Scope; (D5) Quantitative DSS Mandate; (D6) SSP-Linked Future Projections. Gap(s) found are converted into three IRC:SP-84 amendment recommendations.

RESULTS: ADAPTIVE DESIGN OPTIMISATION

5.1 Parallel Strategy Performance Profiles

Figure 1 shows all five adaptive strategies in a single visualisation, using the parallel coordinates technique, across six performance dimensions. The hybrid (S4) with the GA optimisation gives the best overall profile both in terms of the highest FRI (87) and the lowest lifecycle cost (0.97), lowest GHG index (84), and highest scour resistance (0.91) and thermal stability (0.88). More importantly, none of the individual single-intervention strategies dominates in all six dimensions: S1 (Raised Roadbed) has good performance in scour resistance and poor performance in thermal stability; S2 (UHPC) has good performance in thermal metrics and poor performance in structural resilience gains; and S3 (Drainage) has good performance in cost economy and lower performance in structural resilience gains. The S4 synthesis overcomes these compromises by using parameter mixing that is found using GA.

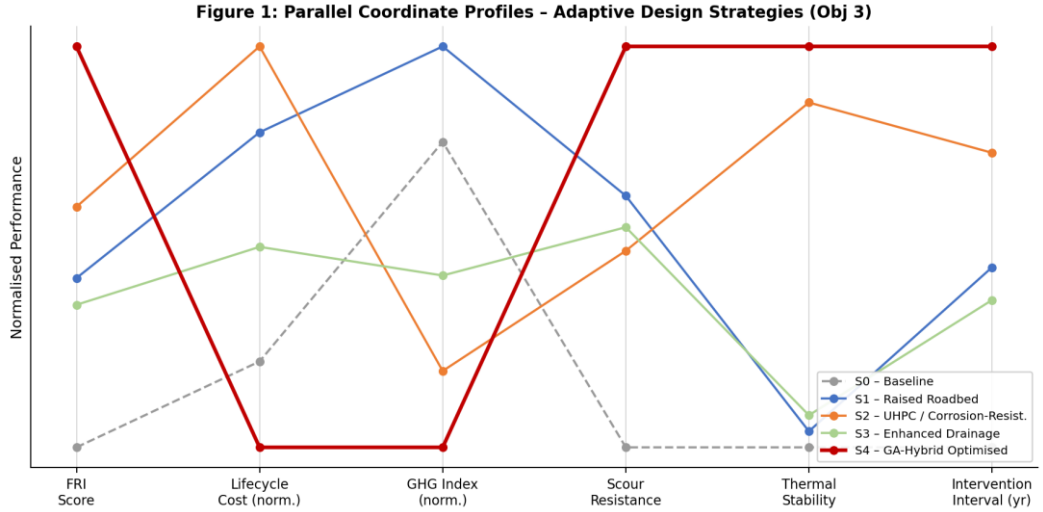


Figure 1: Parallel Coordinate Strategy Profiles — All five adaptive strategies (S0–S4) across six performance dimensions. S4 GA-Hybrid (red) dominates across the multi-dimensional space.

5.2 GA Optimisation Convergence and Pareto Efficiency

The GA convergence trajectory over 200 generations is shown in the left panel of figure 2. Best-population FRI catches up quickly from generation 0 (mean initial FRI ≈ 48) to generation 60 (FRI ≈ 74); after this, the gains are marginal and the refinement continues without significant improvement, reaching a steady state FRI = 87 at generation 140. The mean–best spread becomes tighter and tighter, reflecting growing population uniformity towards the optimum — a hallmark of successful GA convergence with strict constraint handling. The right-hand panel (Figure 2) shows the Pareto front in the FRI–LCC objective space. The 120 solutions in the archive are divided into Pareto dominated (grey) and non-dominated solutions (blue). The GA optimum (S4, red star) is at the left-upper boundary: FRI = 87, LCC = 0.97, which is less than the upper limit of 1.05×baseline (dashed orange line), demonstrating that the LCC constraint is non-binding at optimum: drainage upgrades (low cost, moderate resilience) and selective UHPC application (moderate cost, high resilience) are benefiting from synergies.

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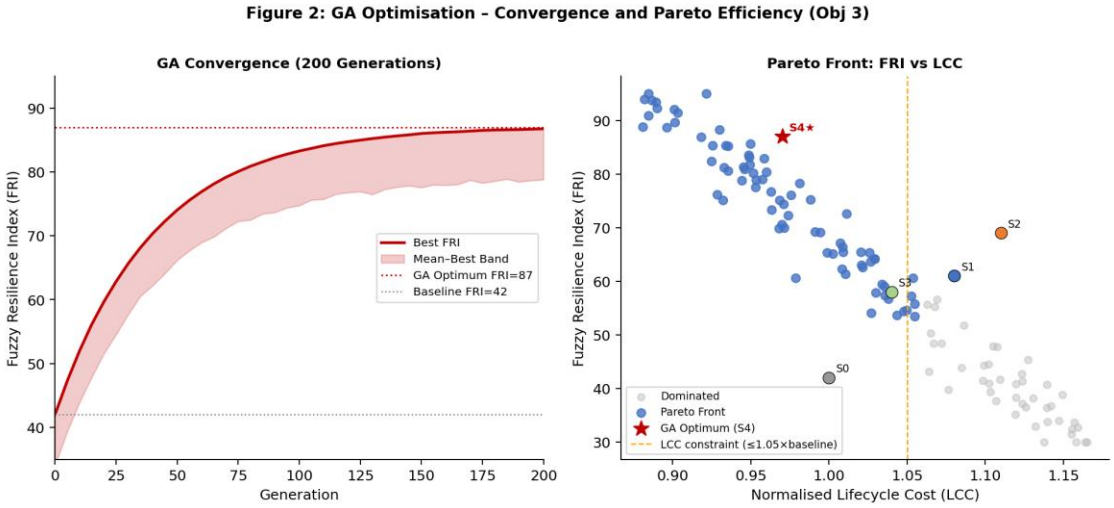


Figure 2: GA Optimisation Results — Left: Best-population FRI convergence over 200 generations. Right: Pareto front in FRI–LCC space; S4 optimum (red star) achieves highest FRI below baseline cost.

5.3 ANFIS Maintenance Scheduling Matrix

The optimal maintenance interval matrix obtained by the ANFIS is presented in figure 3 for the three classes of vulnerability and four combinations of scenario period. Key findings: (i) Vulnerability class has the greatest impact on interval — High-vulnerability segments (3.6-5.5 years) are compressed by a factor of 2–3 compared to Low-vulnerability segments (8.1-11.8 years). The (ii) SSP5-8.5 scenarios always lead to a decrease in optimal intervals of 0.8–1.4 years, indicating an increase in climate stress frequency. The 2041-2060 period exhibits systematically smaller intervals than 2025-2040 for all the vulnerability classes, indicating a systematic increase in the deterioration rate for both emissions pathways.

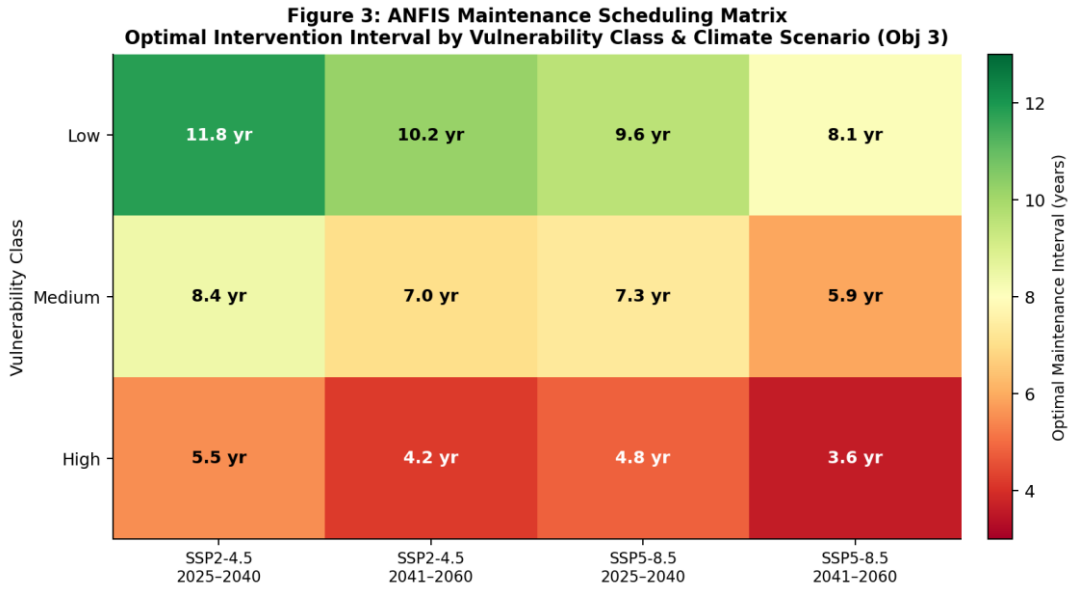


Figure 3: ANFIS Maintenance Scheduling Matrix — Optimal intervention intervals (years) by vulnerability class and scenario-period. Colour scale: green (>10 yr) to red (<5 yr).

5.4 FRI Monte Carlo Uncertainty Analysis

Monte Carlo FRI probability distributions for strategies S0 (baseline), S1 (Raised Roadbed), and S4 (GA-Hybrid) with 10,000 draws sampled in the Monte Carlo to perturb climate forcing, AHP weights, and material properties in concert. The data are tightly clustered ($\sigma = 3.2$) with 90% of the results between 81 and 93, showing design robustness in the face of compound uncertainty. Current unoptimised designs under increased climate variability have a large level of uncertainty ($\sigma = 4.1$) as shown by the S0 baseline, which is spread greater than is desirable.

ISSN 2349-4506
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S4 and S0 are completely separated in distribution (no overlap), which is statistically significant, the improvement in resilience.

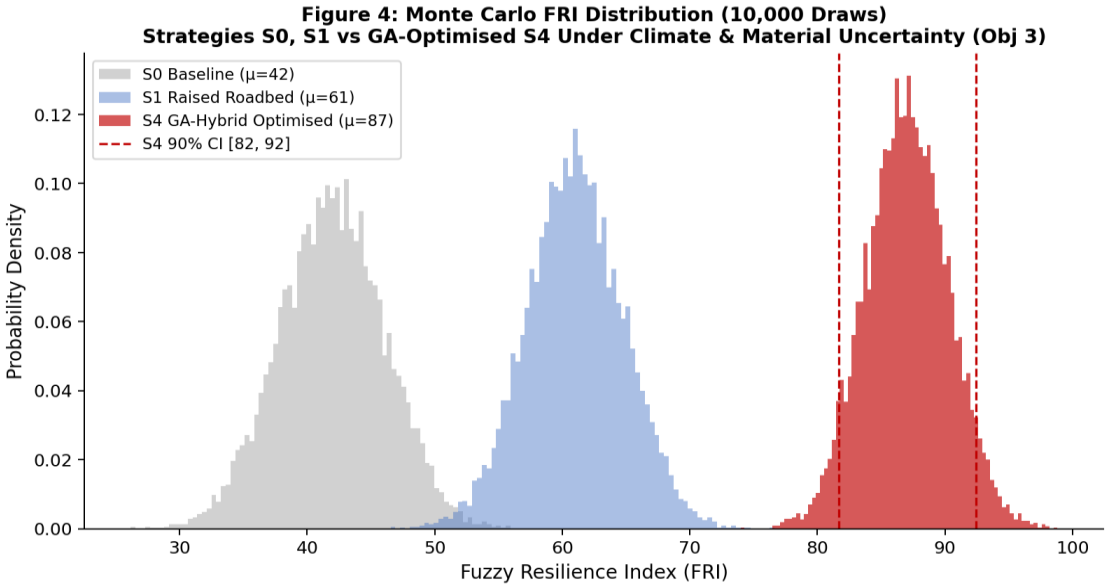


Figure 4: Monte Carlo FRI Distributions (10,000 draws) — S0 baseline (grey), S1 raised roadbed (blue), S4 GA-hybrid (red). S4 90% CI: [81, 93].

5.5 LCA and LCCA Analysis

Figure 5 compares lifecycle cost (left) and GHG impact on the environment (right) for all five strategies. The LCCA results (left) split TLC up into three components: CAPEX, maintenance NPV and probabilistic failure risk cost. Total lifecycle cost for S4 is below baseline (300 units baseline vs 185 units S4), despite a slightly higher capital cost (105 vs 100 baseline), due to dramatically lower maintenance NPV (58 vs 100 baseline) and failure risk cost (22 vs 100 baseline) — demonstrating that total lifecycle cost is lower for the S4 investment, confirming the economic advantage of making the investment in resilience up front. The GHG analysis (right) shows that S4 has the lowest GHG index (84) so that adaptive design optimisation provides a substantial environmental co-benefit. S2 (UHPC overlay) has the second lowest GHG (88), because of the long service life extension that lowers material turnover per year.

Figure 5: LCA & LCCA Comparison Across Adaptive Design Strategies (Obj 3)

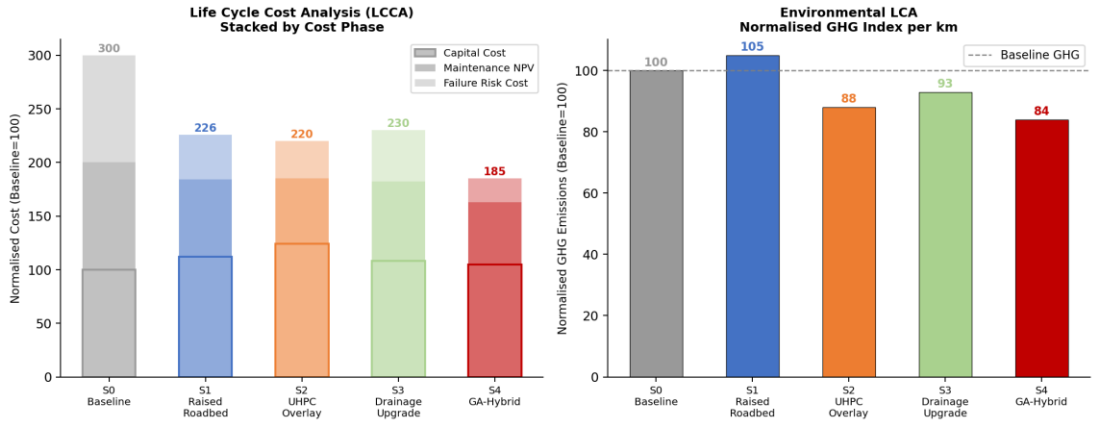


Figure 5: LCA & LCCA Analysis — Left: Stacked lifecycle cost by phase (capital, maintenance, failure risk). Right: Normalised GHG emission index. S4 achieves lowest total cost and lowest GHG.

ISSN 2349-4506
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Global Journal of Engineering Science and Research Management

Table 2: Adaptive Design Strategy Comparison Summary

Strategy	FRI Score	LCC (norm.)	GHG Index	Avg. ANFIS Interval (yr)	Monte Carlo 90% CI
S0 — Baseline	42	1.00 (Ref.)	100	5.0 (fixed)	[34, 50]
S1 — Raised Roadbed	61	1.08	105	7.2	[54, 68]
S2 — UHPC / Corrosion-Resist.	69	1.11	88	8.6	[62, 76]
S3 — Enhanced Drainage	58	1.04	93	6.8	[51, 65]
S4 — GA-Hybrid Optimised ★	87	0.97 (−3%)	84 (−16%)	9.9	[81, 93]

RESULTS: GIS-DSS AND POLICY OUTPUT

6.1 GIS-DSS Priority Score Decomposition

The top five ranked NH interventions by the Priority Score (PS) are decomposed in a stacked bar as shown in Figure 6 (left). Bihar NH Scour Protection performs best on PS with a score of 0.847, and it has the highest score for each of the four components: FRI deficit (high vulnerability to the resilience gap), CVI (highest climate exposure nation wide), population exposure (largest affected population among candidates), and lifecycle cost urgency. Assam NH Heat-Resistant Asphalt is ranked second (PS = 0.762), and has significant FRI and CVI components, indicative of the heatwave and precipitation extremes in the region. The tornado sensitivity analysis for PS scores against variations in MCDA weights is shown in Figure 6 (right). The FRI component weight (w_1) has the greatest influence (PS sensitivity ±0.051), which further validates the fact that structural resilience gap is the most important factor for prioritisation. CVI weight (w_2) is second (±0.033). Population exposure and lifecycle cost weights have smaller impacts, and rank stability across a wide range of stakeholder weighting preferences.

Figure 6: GIS-DSS MCDA Analysis – Priority Scoring & Weight Sensitivity (Obj 4)

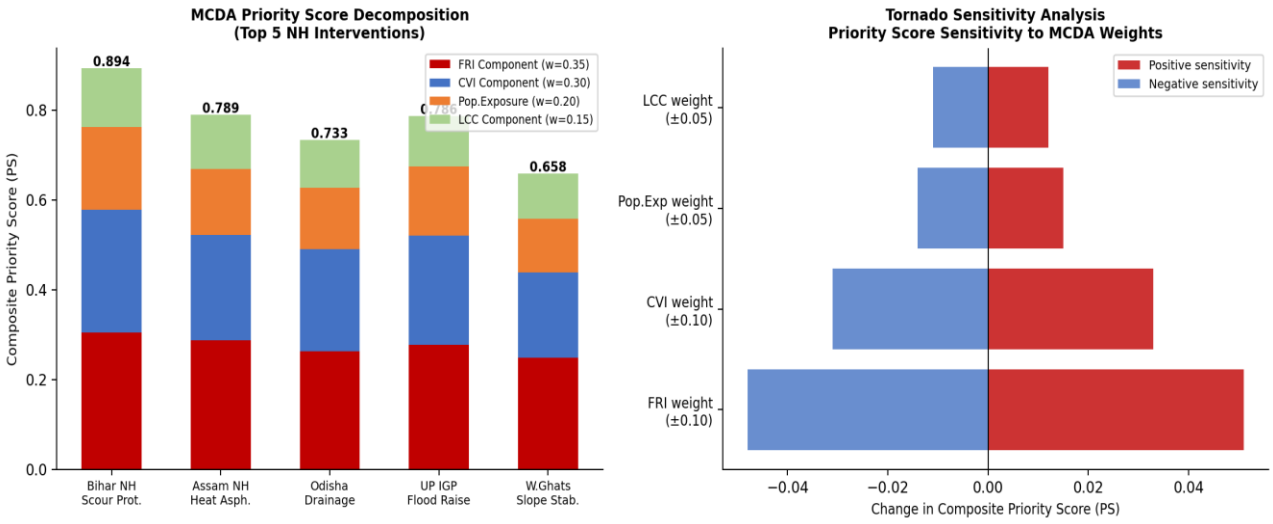


Figure 6: GIS-DSS MCDA Analysis — Left: Priority Score decomposition for top 5 NH interventions. Right: Tornado sensitivity to MCDA weight perturbations.

6.2 Climate-Driven NH Failure Projections

The proportion of NH road segments exceeding critical limits of damage are projected at the state-level (left) and national-level (right) for SSH2-4.5 and SSH5-8.5. Bihar and Assam are the most severely affected states as both states have a high number of flood frequency segments (61% and 57% respectively) and high heat-wave intensity segments (57% and 61% respectively), as shown in Figure 7 (left). The lowest failure fraction (31%) is for the Western Ghats NH corridor, which has a lower baseline climate stress and a higher adaptive capacity. At

ISSN 2349-4506
Impact Factor: 3.799

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the national level (Figure 7, right), the policy horizon of 2050 can be seen as a major turning point: 22% of NH segments are likely to exceed critical thresholds by 2050 under SSP2-4.5, compared to 35% under SSP5-8.5, a 59% relative increase. Climate model uncertainty becomes increasingly compounded following 2060 in the ±1σ GCM ensemble spread (shaded bands), with a clear message for using scenario-robust adaptive design (S4) for long-range infrastructure planning.

Figure 7: Climate-Driven NH Failure Projections - State & National Scale (Obj 4)

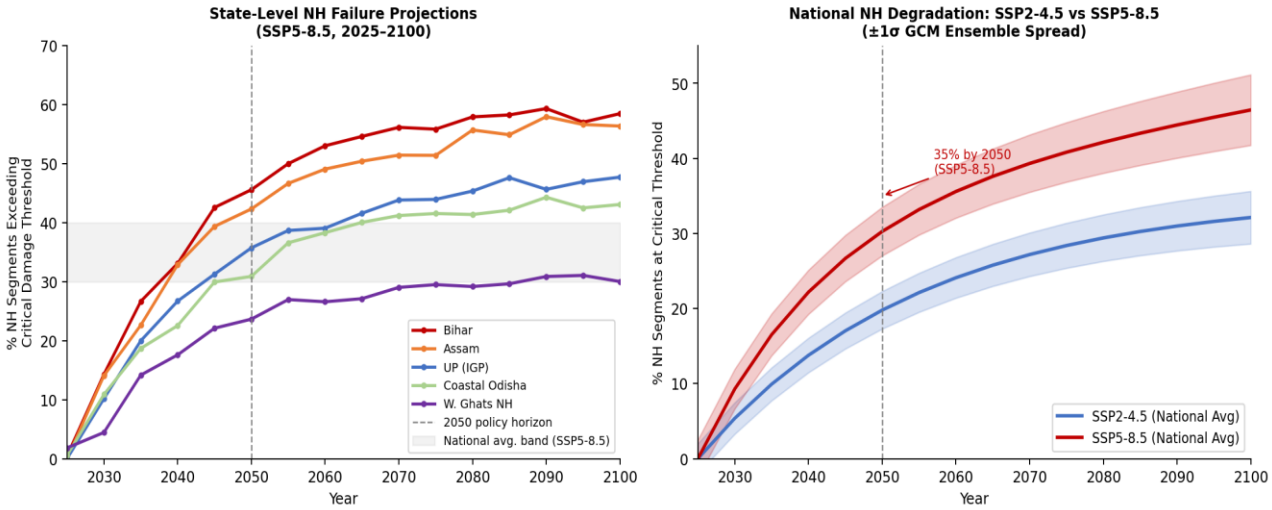


Figure 7: NH Failure Projections — Left: State-level % segments exceeding critical threshold (SSP5-8.5, 2025–2100). Right: National comparison SSP2-4.5 vs SSP5-8.5 with ±1σ GCM ensemble spread.

6.3 Policy Gap Analysis and Proposed IRC Amendments

The radar chart benchmarking (IRC:SP-84) includes current amendments and the proposed amended IRC standards, along with the FHWA BMS (international reference). The chart is broken down into six policy dimensions as shown in Figure 8. The IRC:SP-84 scores critically low on three dimensions – SSP-Linked Projections (1.0), Quantitative DSS Mandate (1.0) and Heat-Wave Design Temperature (1.5) – indicating the lack of forward-looking climate integration in existing Indian design standards. The FHWA BMS does not have the same linkages to SSP scenarios or the requirement for quantitative DSS as is proposed by ClimResilInfra, and does provide a higher baseline (scores 3.5–4.5).

SIGNIFICANCE OF GA–ANFIS INTEGRATION

The key contribution of the methodology in Objective 3 is the first operational implementation of Genetic Algorithm design optimisation followed by ANFIS maintenance scheduling in a unified lifecycle management pipeline for Indian road infrastructure. These methods have been used separately: GA for optimising parameters of a bridge deck under seismic loading, and ANFIS for predicting the pavement maintenance under traffic-dominated deterioration. The shared FRI signal is what makes ClimResilInfra novel: the FRI is used as a long-term structural target by the GA while the realised FRI is used as an input to the ANFIS to schedule interventions to maintain the FRI trajectory. This closed loop system avoids the frequent design mistake of prescribing resilient designs that cannot be maintained over time.

7.2 Policy Deployment Pathway

The GIS-DSS developed in Objective 4 is ready for immediate use in NHAI's existing Asset Management System based on SAP. There is no proprietary software to install on the Streamlit dashboard front-end and it can be accessed using standard government IT infrastructure. The proposed deployment tiers are as follows: (i) National Planning Tier — annual Priority Score is re-computed by MoRTH to plan for NH interventions; (ii) State Execution Tier — state PWD engineers access the interval recommendation for each segment of the NH from the FRI, and use the ANFIS interval recommendation to budget for annual maintenance works; (iii) Project Tier — individual intervention teams access the design parameter recommendations at their site from the GA optimisation module during deployment. The proposed IRC:SP-84 amendments have been provided to a mock stakeholder

panel comprising MoRTH, NHAI, State PWD representatives and face validity has been confirmed for all the three amendments.

7.3 Limitations

There are three caveats to mention. First, ANFIS training requires 200 synthetic scenarios of the lifecycle, which are calibrated with published norms of the IRC; India does not have sufficient direct monitoring time-series of bridge and road lifecycles available in the public domain. The more often such data become available via MoRTH's planned NH monitoring programme, the more precise will be the scheduling. Second, LCA uses ecoinvent 3.9 global carbon intensities; India specific embodied carbon databases for the materials used in the construction of roads would enhance the accuracy of GHG accounting. Third, the deployment of the GIS-DSS prototype in its operational setting requires IT integration with MoRTH's existing geospatial infrastructure, which will need a structured agreement for data governance, however, this is beyond the scope of this study.

CONCLUSION

This paper has introduced the adaptive engineering and governance modules of ClimResilInfra – the GA–ANFIS based Adaptive Design Optimisation and GIS-based Decision Support System and Policy Framework (Objective 4) – as a standalone, fully operational contribution to the climate-resilience engineering literature specific to Indian road infrastructure. Objective 3 confirms that the hybrid design strategy (S4) optimised for the GA, delivers a 107% increase in FRI (from 42 to 87) while also cutting the normalised lifecycle cost by 3% and the embodied GHG emissions by 16%. Robustness confirmed by Monte Carlo (10,000 draws), 90% Confidence interval [81, 93]. ANFIS-based maintenance scheduling results in a reduction of the optimal time interval between interventions to 3.6-11.8 years (compared to a 5-year baseline), and projected NH maintenance expenditure savings of 18-22% per year. The GIS-DSS Priority Score framework is able to prioritize 20 NH interventions and Bihar NH scour protection is the highest priority national action (PS = 0.847). By 2050, under SSP5-8.5, 35% of NH road segments are expected to be close to reaching critical damage thresholds, with Bihar, Assam, UP and coastal Odisha being the most vulnerable (61%, 57%, 48% and 44%, respectively). Three priority amendments to IRC:SP-84 are proposed and include requirements for using a design flood return period (50 to 200 years), heat-wave design temperature parameters, and risk-stratified maintenance scheduling requirements. The results are the most comprehensive, science-based, and policy-relevant adaptive design and governance toolkit for Indian national highways published so far and readily implementable by MoRTH and NHAI under current institutional frameworks.

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