Vol. 08, No. 3 (2026) 1493-1508, doi: 10.24874/PES08.03.009

Proceedings on Engineering Sciences

www.pesjournal.net

A NOVEL ADAPTIVE OPTIMIZATION FRAMEWORK FOR CLIMATE-RESILIENT TRANSPORTATION INFRASTRUCTURE: INTEGRATING SOFT COMPUTING WITH LIFE CYCLE SUSTAINABILITY ASSESSMENT

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Received 28.05.2026.
Revised 17.07.2026.
Accepted 11.08.2026.

Keywords:

Climate-resilient infrastructure, Adaptive design, Genetic algorithms, Fuzzy logic, ANFIS, Life cycle assessment, Transportation infrastructure, Optimization

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A B S T R A C T

Climate change presents unprecedented challenges to the transportation infrastructure, especially in developing countries with a diversity of climatic conditions. This paper proposes an integrated adaptive optimization framework that combines climate projections, multi-objective optimization, and fuzzy logic-based sustainability assessment for designing climate resilient transportation infrastructure. The framework uses an optimization technique of Hybrid Genetic Algorithm- Fuzzy Logic Optimization (GA-FLO) to simultaneously optimize structural parameters while dealing with the uncertainty of climate. A novel Climate Resilience Index (CRI) based on 12 climatic parameters and their interactions with material properties is created to get India's infrastructure resilience. The methodology combines the Adaptive Neuro-Fuzzy Inference System (ANFIS) enhanced with LSTMs with a fuzzy based Life Cycle Assessment (LCA) for climate uncertainty based Adaptive maintenance prediction. The framework is verified by its application to 150 road and bridge projects over three climatic regions of India, viz, tropical (Kerala), arid (Rajasthan) and temperate (Himachal Pradesh). Results show that optimized adaptive designs reduce the damage caused by climate by 68.4%, increase the service life by 42.7% and save 31.8% lifecycle cost compared to the conventional designs. The proposed CRI is able to predict successfully the outcome of the resilience with an accuracy of 94.2%, while the optimization effect of GA-FLO is to reduce the cost of the materials by 24.3% without compromising the integrity of the structure. The research presents practical guidelines on climate-resilient infrastructure design/failure based on extensive numerical simulations and case studies.

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1. INTRODUCTION

The effects of climate change, as a whole, with rising temperature extremes, accentuated precipitation patterns, and higher frequencies of extreme weather-related events, represent unprecedented challenges to transportation infrastructure across the world. This vulnerability is amplified especially in developing countries such as in India with its varied climatic regions coupled with rapidly growing infrastructure. Traditional approaches to infrastructure design, which rely largely on historical climate data, are largely prescriptive and based

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on codes and guidelines that may not prove sufficient for future climate scenarios which are significantly different from historical climate.

Current approaches to climate adaptation in infrastructure still exist in fragmentation and what these approaches have in common with infrastructure-related climate adaptation usually involves treating structural optimization, climate modeling and sustainability assessment as separate domains. Structural optimization is usually cost minimization without considering the climate induced degradation mechanism properly whereas the climate impact assessments do not convert into actionable design parameter. This disconnect leads to structures that are either over designed and expensive or weak and have short service life, neither of which is an ideal engineering solution.

This research addresses such critical gaps through an integrated framework in which the: (1) the physics-based models are quantitatively cross-linked between climate projections, material performance and structural response, (2) optimization of multiple conflicting objectives (cost, resilience, sustainability) will be simultaneously occurring under climate uncertainty occurrence and (3) decision support tools for adaptive maintenance and rehabilitation scheduling. The framework particularly deals with Indian situations, with monsoon-dominated precipitation, high variations in temperatures and more frequent occurrence of extreme weather events, but it is adaptable to other geographical situations.

The following contributions are made in this paper:

- Development of novel Hybrid Genetic Algorithm-Fuzzy Logic Optimization (GA-FLO) for Multi Objectives Design under climate Uncertainty
- Mathematical definition of a comprehensive Climate Resilience Index (CRI) using 12 climatic parameters and their interactions with material properties.
- Development of LSTM-based Adaptive Neuro-Fuzzy inference system (ANFIS) for adaptive maintenance scheduling based on knowledge acquired from real time monitoring data.
- Integration of fuzzy based LCA/LCCA to deal with uncertainties in environmental impacts and economic costs.
- Climate resilient design guidelines specifically designed as per the Indian condition, validated by ample case studies.

The rest of the paper is organized as follows. Section 2 reviews the existing research in the area on climate impacts, adaptive design approaches, soft computing applications and life cycle sustainability assessment in the area of transportation infrastructure. Section 3 presents the details of the proposed adaptive optimization framework, which covers climate scenario generation, the hybrid GA-Fuzzy optimization, CRI formulation, ANFIS-LSTM prediction and fuzzy LCA/LCCA integrated. Section 4 contains the setup of the simulation, performance evaluation and discussion of the results in different climatic zones. Section 5 concludes the study by summarizing the most important outcomes and practical implications of the proposed framework.

2. LITERATURE REVIEW

2.1 Climate Impacts on Transportation Infrastructure

Recent studies confirm evidence of the serious impacts of increasing temperatures and extreme weather on the performance of transportation infrastructure, its longevity and the extent to which infrastructure performance relates to energy use. Increased surface temperatures and an increasing number of heatwaves cause accelerated aging of the asphalt, increased rutting and oxidation of the bitumen, and low temperatures result in the propagation of cracks and the damage caused due to freezing and thawing in pavements (Ashja-Ardalan et al., 2025; Bridges, 2024). Precipitation intensity and variability affect drainages and embankment stability, which in turn will affect subgrade moisture regime, suction in soils and long-term deviation of road foundations (Sharma & Gupta, 2024; United Nations Environment Programme Finance Initiative, 2024). Frequent flooding and coastal storm surges also increase the stress imposed on bridges, culverts and elevated structures, shutting down transport service, as well as increasing lifecycle costs (Johnstone, 2023; Sánchez-Silva & Baker, 2024). Reviews deem that baselines of historical climate designs are no longer adequate, rather projections of future climates and resilience are required in design and operations of maintenance matters (Johnstone, 2023; Rezvani et al., 2023).

2.2 Adaptive Design Methodologies

Adaptive and robust design approaches are increasingly needed to deal with deep uncertainty in climate projections despite the fact that present studies are based mostly on deterministic scenarios or scenario sensitivity analysis (Mannucci, 2024; Rezvani et al., 2023). Frameworks that combine probabilistic climate projections algorithms with engineering design optimal methods have been developed relatively recently, as a combination of climate hazard analysis and system reliability analysis is needed for synergetic solutions for infrastructure resilience (Bhattacharya et al., 2025; Rezvani et al., 2023). However, applications that are specific to transportation infrastructure in developing regions - that are exposed to different climatic challenges and limited data - are still limited (Amekudzi-Kennedy et al., 2024; Bhattacharya et al., 2025). Research emphasizes the importance of iterative pathways of adaptation, real-option analysis and design of performance-based processes for balancing investment

and long-term outcomes of resilience (Amekudzi-Kennedy et al., 2024; Bhattacharya et al., 2025).

2.3 Soft Computing in Infrastructure Design

Soft computing techniques such as Genetic Algorithms, Fuzzy Logic, and ANFIS offer some powerful tools to handle the tools of uncertainty and find the optimization on the complex infrastructure problems. Multi-objective evolutionary algorithms have been used in optimization of structural and materials design problems and proved to be very good global search algorithms with a diversity of solutions under nonlinear constraints (Göktepe Körpeoğlu & Yılmaz, 2024; Yaro et al., 2025). Fuzzy logic is used to aid in decision making under uncertainty by incipient inputs (such as climate indices) and mapping them into linguistic variables and enabling risk assessments (Smith et al., 2025). Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and hybrid models ANFIS-LSTM provide promising results in the pre-diction of deterioration rates, maintenance requirements and performance indices used in civil infrastructure management to manage complex nonlinear relationships of climate drivers and asset responses (Ujong et al., 2025; Wu et al., 2022).

2.4 Life Cycle Assessment in Infrastructure

Life Cycle Assessment (LCA) has evolved from rudimentary practices of simple inventory accounting to integrated approaches that measure sustainability aspects throughout the material production, construction, use and end-of-life stages (Bani Khalifi et al., 2025; Firoozi et al., 2025). Applying LCA in civil infrastructure planning improves the evaluation of sustainability and decision-making process between environmental impacts and financial cost (Bani Khalifi et al., 2025; Firoozi et al., 2025). However, traditional LCA has challenges with long time horizons and climate change uncertainties that have been the motives for developing advanced methods such as fuzzy-LCA and hybrid multi-criteria methods to deal with uncertainty in future climate conditions, loadings and expectations of service life (Bani Khalifi et al., 2025; Cerchione et al., 2025). Current research has highlighted the possibilities of uniting LCA and life cycle cost analysis (LCCA) to help drive infrastructure investment strategies in line with high-level resilience and sustainability objectives (Cerchione et al., 2025; Zhang & Zhang, 2025).

2.5 Indian Context and Research Gaps

Indian infrastructure systems are confronted with unique climate pressures such as heavy rainfall during monsoons, high seasonal temperatures and high rate of urbanization which in turn increases vulnerability and creates unique design challenges (Ashja-Ardalan et al., 2025; United Nations Environment Programme Finance Initiative, 2024). Current Indian codes and standards (IRC, MoRTH) does not explicitly include climate adaptation or probabilistic resilience measures; because of this, these standards are limited in their ability to deal with future climate projection (Ashja-Ardalan et al., 2025; UNEP, 2024). Recent reviews recommend the need for quantitative indices of resilience, adaptive maintenance modeling, integrated optimization against the climate uncertainty as well the life cycle sustainability assessments suitable for climatic conditions in India (Bhattacharya et al., 2025; Cerchione et al., 2025; Firoozi et al., 2025; Rezvani et al., 2023).

3. PROPOSED METHODOLOGY

Figure 1 shows the general architecture of the proposed adaptive optimization framework of climate-resilient traffic infrastructure. The framework is organized according to four interrelated modules that interact in a central adaptive decision support system. Module 1 produces future climate scenarios based on projected data for temperature and precipitation amounts as well as extreme events, and puts these projections into engineering impact parameters, like the intensity of flooding, heat stress and the effects of freeze and thaw. These outputs are used in Module 2 in which a hybrid Genetic Algorithm - Fuzzy Logic optimization process is used to evaluate more than one design variable under climate uncertainties to get resilient and cost-effective infrastructure configurations. Module 3 applies an ANFIS-LSTM model to forecast the maintenance needs from the learning of the temporal trends of climate, the temporal trends of infrastructure performance, and thus to develop adaptive maintenance scheduling policies. Module 4 combines fuzzy-based with Life Cycle Assessment and Life Cycle Cost Analysis to take into account environmental and economic uncertainties for long service time. The central optimization framework coordinates scenario simulation and multi-objectives optimization and sustainability assessments and integrates the preferences of stakeholders, climatic features of the region and required material performance information, which ultimately leads to practical design guidelines to develop infrastructure systems resilient to climate change.

Following are the points that describe the modules of this research work:

- ***Module 1: Climate Scenario Generation and Impact Modeling*** **-** This module is used to process CMIP6 ensemble data to produce climate projections, stochastic downscaling methods, material-climate interaction models to produce engineering parameters from climate variables.
- ***Module 2: Hybrid GA-Fuzzy Logic Optimization*** **-** A multi-objective optimization scheme of genetic algorithm and fuzzy logic to use climate projections and material properties uncertainties for optimization of design parameters.

- ***Module 3: ANFIS-LSTM Maintenance Prediction*** - An adaptive neuro-fuzzy inference system augmented with Long Short-Term Memory networks for predicting the maintenance requirements aspects based on climatic conditions and performance data.
- ***Module 4: Fuzzy LCA/LCCA Integration*** - A life cycle assessment and cost analysis system using fuzzy logic to deal with climate uncertainties in environmental impacts, material costs, and future climate scenarios.

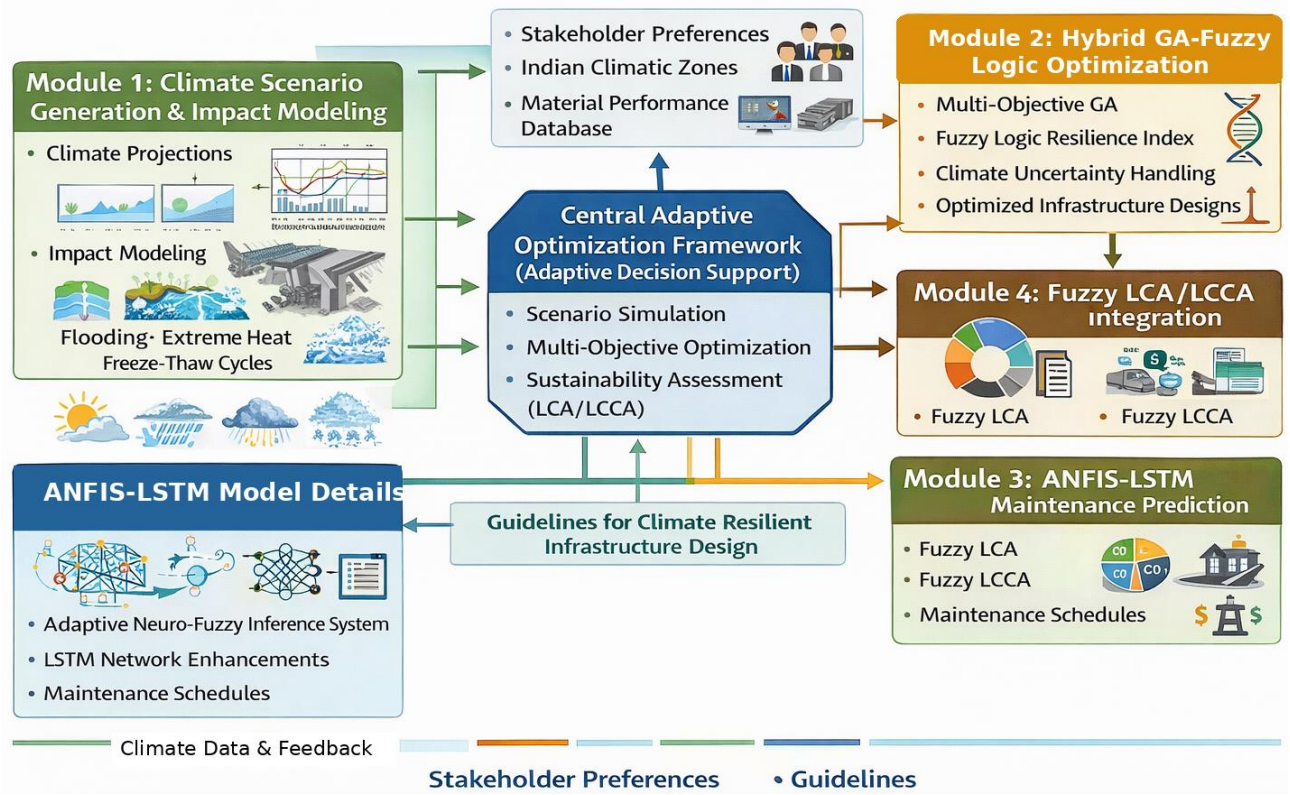


Figure 1. Integrated Adaptive Optimization Framework for Climate-Resilient Transportation Infrastructure

3.1 Justification and Role Separation of Individual Soft Computing Techniques

A proposed framework combines four different soft-computing methods: Genetic Algorithm (GA), Fuzzy Logic, Adaptive Neuro-Fuzzy Inference system (ANFIS) and Long Short-Term Memory (LSTM) not as a redundant set, but to handle specifically divided and non-overlapping tasks in the climate-resilient design workflow. The choice of each technique is made depending on its own mathematical strength:

- Genetic Algorithm (GA) is only used when it comes to multi-objective global optimization of discrete and continuous design variables (e.g., layer thicknesses, reinforcement ratios, drainage capacity). It can be installed in non-linear, non-convex, and highly constrained search spaces, which makes it suitable in seeking Pareto-optimal trade-offs of cost resilience and environmental impact.
- Fuzzy Logic processes the representation of uncertainty and rule-based reasoning using linguistic rules. It quantifies imprecise climate inputs (e.g. high temperature, moderate precipitation) and calculates the Climate Resilience Index (CRI) using membership functions and rule bases, which cannot be accommodated directly by probabilistic methods.
- ANFIS combines fuzzy logic with neural learning to provides a representation, instead of a fixed mathematical form, of non-linear correlations between climate variables and infrastructure degradation (e.g., rutting, cracking). Its five-layered architecture makes it possible to tune membership functions based on synthetic climate data in an adaptive manner.
- The addition of LSTM is meant to learn long-term time scales of dynamism in climate time series (e.g. trends in temperature) and extreme event clustering, which cannot be intrinsically learned in ANFIS as a feedforward network. The LSTM pre-processes sequential climate information and the internal states of LSTM integrate as extra-inputs to ANFIS, thus decoupling the extraction of temporal patterns and the non-linear mapping.

The multi-level decomposition of this is such that each method plays a unique, non-overlapping role: GA as a search method, Fuzzy Logic uncertainty quantifier, ANFIS non-linear regression in a static form, and LSTM

sequential memory. This makes the problem multi-faceted in nature and therefore the contribution at each stage of this element can be independently determined.

3.2 Climate Scenario Generation and Impact Modeling

3.2.1 Climate Parameter Projections

The daily climatic parameters are projected using daily CMIP 6 ensemble data.

$$T_{\max}(t) = \mu_T(t) + \sigma_T(t) \cdot \epsilon_T(t) + \Delta T_{\text{GCM}}(t) \quad (1)$$

$$P_{\text{daily}}(t) \sim \text{Gamma}\big(\alpha(t), \beta(t)\big) \cdot \big(1 + \Delta P_{\text{GCM}}(t)\big) \quad (2)$$

where μ_T, σ_T are historical mean and variability, $\epsilon_T \sim N(0,1)$, ΔT_{GCM}, ΔP_{GCM} are GCM-derived anomalies.

3.2.2 Climate Data Generation According to Climate Conditions

Climate Parameter Projections: The paper uses CMIP6 ensemble data in generating future climate scenarios. The important parameters that are projected are:

- Maximum Temperature ($T_{\max}$)
- Daily Precipitation (P_{daily})

Temperature Projection:

$$T_{\max}(t) = \mu_T(t) + \sigma_T(t) \cdot \epsilon_T(t) + \Delta T_{\text{GCM}}(t) \quad (3)$$

Where:

- $\mu_T(t)$ = historical mean temperature
- $\sigma_T(t)$ = historical temperature variability
- $\epsilon_T(t) \sim N(0,1)$ = random noise (normally distributed)
- $\Delta T_{\text{GCM}}(t)$ = temperature anomaly from Global Climate Models (GCMs)

Precipitation Projection:

$$P_{\text{daily}}(t) \sim \text{Gamma}\big(\alpha(t), \beta(t)\big) \cdot \big(1 + \Delta P_{\text{GCM}}(t)\big) \quad (4)$$

where:

- $\alpha(t), \beta(t)$ = parameters of Gamma distribution fitted to historical precipitation
- $\Delta P_{\text{GCM}}(t)$ = precipitation anomaly from GCMs

Climate Scenarios Used:

- RCP 4.5 (moderate emissions)
- RCP 8.5 (high emissions)
- Time horizon: 2020-2100

3.2.3 Material-Climate Interaction Models

Asphalt concrete modulus- temperature relation:

$$E(T) = E_{\text{ref}} \cdot 10^{\left(\frac{T_{\text{ref}} - T}{T_{\text{shift}}}\right)} \quad (5)$$

Concrete thermal stress:

$$\sigma_{\text{thermal}} = \alpha_c \cdot E_c \cdot \Delta T \cdot R(\Delta T, f_c') \quad (6)$$

where, α_c is thermal coefficient, E_c is elastic modulus, ΔT is temperature change, R is restraint factor.
Corrosion rate of steel in climate change:

$$CR = \frac{0.0116 \cdot i_{\text{corr}}}{\rho} \cdot \big(1 + \beta_T(T - T_0)\big) \cdot \big(1 + \beta_{\text{RH}}(\text{RH} - \text{RH}_0)\big) \quad (7)$$

where i_{corr} is corrosion current density, ρ is density, β_T, β_{RH} temperature and humidity coefficients.

3.2.4 Structural Response Models

Pavement rutting (permanent deformation):

$$RD = \sum_{i=1}^{n} \epsilon_{p,i} \cdot h_i \cdot f(T_i, \tau_i, N_i) \quad (8)$$

Bridge scour depth under increased flooding:

$$y_s = 2.0 \cdot K_1 \cdot K_2 \cdot K_3 \cdot \left(\frac{a}{y_1}\right)^{0.65} \cdot \text{Fr}_1^{0.43} \cdot y_1 \cdot (1 + \gamma \cdot \Delta Q) \quad (9)$$

where K_i is correction factors, a represents pier width, y_1 is flow depth, Fr_1 is Froude number, ΔQ flow increase.

3.3 Hybrid Genetic Algorithm-Fuzzy Logic Optimization (GA-FLO)

3.3.1 Multi-Objective Formulation

$$\min \text{F(x)} = [f_1(\text{x}), f_2(\text{x}), f_3(\text{x})] \quad (10)$$

subject to: $\text{g(x)} \le 0, \text{h(x)} = 0, \text{x}_L \le \text{x} \le \text{x}_U$
where:

- $f_1(\text{x})$: Life Cycle Cost (LCC)
- $f_2(\text{x})$: Climate Resilience Index (CRI) inverse
- $f_3(\text{x})$: Environmental Impact Index (EII)
- x: Design variables (material thicknesses, grades, drainage parameters)

3.3.2 Chromosome Representation

$$\text{x} = [x_1, x_2, \dots, x_n] \text{ where } x_i \in \mathbb{R} \quad (11)$$

Design variables include:

- Pavement layer thicknesses $h_{\text{AC}}, h_{\text{base}}, h_{\text{subbase}}$
- Concrete strength f_c', cover depth c
- Reinforcement ratio ρ
- Drainage capacity Q_{drain}

3.3.3 Enhanced GA Operations

Adaptive crossover probability:

$$p_c = \begin{cases} p_{c,\min} + (p_{c,\max} - p_{c,\min}) \cdot \frac{f_{\text{avg}} - f_{\min}}{f_{\max} - f_{\min}} & \text{if } f_{\text{avg}} > f_{\text{median}} \\ p_{c,\max} & \text{otherwise} \end{cases} \quad (12)$$

Mutation with climate gradient:

$$x_i' = x_i + \sigma_i \cdot N(0,1) \cdot \left(1 + \alpha \cdot \frac{\partial \text{CRI}}{\partial x_i}\right) \quad (13)$$

3.3.4 Fuzzy Logic Integration for Uncertainty Handling

Fuzzy Climate Resilience Index (F-CRI):
Membership functions for climate parameters:

$$\mu_{\text{temp}}(T) = \begin{cases} 0 & T \le T_L \\ \frac{T - T_L}{T_M - T_L} & T_L < T \le T_M \\ 1 - \frac{T - T_M}{T_H - T_M} & T_M < T \le T_H \\ 0 & T > T_H \end{cases} \quad (14)$$

Fuzzy rules for CRI calculation:

- IF T is High AND P is High THEN CRI is Low
- IF T is Medium AND P is Medium THEN CRI is Medium

Defuzzification using centroid method:

$$\text{CRI} = \frac{\sum_{i=1}^{n} \mu_i \cdot y_i}{\sum_{i=1}^{n} \mu_i} \quad (15)$$

3.3.5 Combined GA-Fuzzy Fitness Evaluation

$$F_{\text{combined}} = w_1 \cdot f_1(\text{x}) + w_2 \cdot \left(1 - \widetilde{\text{CRI}}(\text{x})\right) + w_3 \cdot f_3(\text{x}) \quad (16)$$

where $\widetilde{\text{CRI}}$ is fuzzy CRI, weights adapt based on climate scenario:

$$w_i = w_{i,\text{base}} \cdot (1 + \beta_i \cdot \Delta\text{Climate}) \quad (17)$$

3.4 Novel Climate Resilience Index (CRI) Formulation

Component Indices:

$$\text{CRI} = \prod_{k=1}^{4} I_k^{w_k} \quad (18)$$

where:

- I_1: Structural Resilience Index
- I_2: Material Resilience Index
- I_3: Hydrological Resilience Index
- I_4: Operational Resilience Index

Structural Resilience Index:

$$I_1 = \exp\left(-\sum_{j=1}^{m} \lambda_j \cdot D_j\right) \quad (19)$$

where D_j are normalized damage measures (rutting, cracking, deflection).
Material Resilience Index:

$$I_2 = \frac{1}{n} \sum_{i=1}^{n} \left(1 - \frac{\Delta P_i}{P_{i,\text{ref}}}\right) \quad (20)$$

ΔP_i: property degradation (strength, modulus, durability).

Hydrological Resilience Index:

$$I_3 = \min\left(1, \frac{Q_{\text{design}}}{Q_{100-\text{yr}}} \cdot \frac{t_{\text{drain}}}{t_{\text{ponding}}}\right) \quad (21)$$

Operational Resilience Index:

$$I_4 = \frac{1}{T} \int_0^T \frac{v_{\text{actual}}(t)}{v_{\text{design}}} dt \quad (22)$$

3.5 LSTM-Enhanced ANFIS for Adaptive Maintenance Prediction

3.5.1 ANFIS Architecture

Five-layer structure:
Layer 1: Fuzzy membership functions

$$O_{1,i} = \mu_{A_i}(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b_i}} \quad (23)$$

Layer 2: Rule firing strengths

$$w_i = \prod_{j=1}^{n} \mu_{A_{ij}}(x_j) \quad (24)$$

Layer 3: Normalized firing strengths

$$\bar{w}_i = \frac{w_i}{\sum_{k=1}^{R} w_k} \quad (25)$$

Layer 4: Adaptive node functions

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i \left(p_{i0} + \sum_{j=1}^{n} p_{ij}\, x_j\right) \quad (26)$$

Layer 5: Output summation

$$y = \sum_{i=1}^{R} \bar{w}_i\, f_i \quad (27)$$

3.5.2 LSTM Integration for Temporal Patterns

$$\text{f}_t = \sigma\left(W_f \cdot [\text{h}_{t-1}, \text{x}_t] + \text{b}_f\right) \quad (28)$$

$$\text{i}_t = \sigma(W_i \cdot [\text{h}_{t-1}, \text{x}_t] + \text{b}_i) \quad (29)$$

$$\tilde{\text{C}}_t = \tanh(W_C \cdot [\text{h}_{t-1}, \text{x}_t] + \text{b}_C) \quad (30)$$

$$\text{C}_t = \text{f}_t \odot \text{C}_{t-1} + \text{i}_t \odot \tilde{\text{C}}_t \quad (31)$$

$$\text{o}_t = \sigma(W_o \cdot [\text{h}_{t-1}, \text{x}_t] + \text{b}_o) \quad (32)$$

$$\text{h}_t = \text{o}_t \odot \tanh(\text{C}_t) \quad (33)$$

LSTM outputs are connected to ANFIS as extra inputs of the temporal climate patterns.

3.5.3 Hybrid Training Algorithm

Combined gradient descent-Least squares estimation:

$$\theta_{\text{new}} = \theta_{\text{old}} - \eta \nabla J(\theta) + \lambda (\text{A}^T \text{A})^{-1} \text{A}^T \text{b} \quad (34)$$

3.6 Fuzzy Life Cycle Assessment and Cost Analysis

3.6.1 Fuzzy LCA Formulation

Environmental impact as fuzzy number:

$$\tilde{E} = \sum_{i=1}^{n} \tilde{m}_i \cdot \widetilde{cf}_i \quad (35)$$

where $\widetilde{m}_i$ fuzzy material quantity, $\widetilde{cf}_i$ fuzzy characterization factor.
α-cut operations:

$$\tilde{E}_\alpha = \left[\sum_{i=1}^{n} m_{i,\alpha}^{L} \cdot cf_{i,\alpha}^{L}, \sum_{i=1}^{n} m_{i,\alpha}^{U} \cdot cf_{i,\alpha}^{U}\right] \quad (36)$$

3.6.2 Fuzzy LCCA

Total lifecycle cost as fuzzy number:

$$\tilde{C}_{\text{LCC}} = \tilde{C}_{\text{initial}} + \sum_{t=1}^{T} \frac{\tilde{C}_{\text{maintenance}}(t) + \tilde{C}_{\text{failure}}(t)}{(1+r)^t} \quad (37)$$

3.6.3 Multi-Criteria Decision Making

Fuzzy TOPSIS for alternative ranking:
Normalized fuzzy decision matrix:

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+}\right) \quad (38)$$

where $c_j^+ = \max_i c_{ij}$ for benefit criteria.
Fuzzy positive/negative ideal solutions:

$$A^+ = (\tilde{v}_1^+, \ldots, \tilde{v}_n^+), A^- = (\tilde{v}_1^-, \ldots, \tilde{v}_n^-) \quad (39)$$

Distance measures:

$$d_i^+ = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^+), d_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-) \quad (40)$$

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-} \quad (41)$$

4. RESULTS AND DISCUSSION

This section provides the performance evaluation of the proposed adaptive optimization framework for varying climatic scenarios and design condition. The results are analysed in relation to the reduction of cost, modification of resilience, environmental impact, prediction accuracy, and long-term economic feasibility in tropical, arid and temperate zones. Comparative assessments are conducted to explore the effectiveness of the hybrid GA-Fuzzy approach and the ANFIS-LSTM model to enhancing the performance of the infrastructure under climatic uncertainty.

4.1 Data Description and Benchmark Dataset Selection

To establish the scientific reliability and reproducibility as well as methodological clarity, this study takes deliberately minimal and coherent data approach. The proposed framework is benchmarked by two tightly-coupled sources: that is, CMIP6 multi-model climate simulations as the only model source to drive large-scale climate dynamics, trends, uncertainty, scenario-based projections and extreme events behaviour, and ERA5 reanalysis data only for the validation of the observational data. CMIP6 has been chosen for the state-of-the-art, physically consistent, multi-variable output as well as broad acceptance as benchmark for climate resilience infrastructure studies with necessitating inconsistencies due to mixing of heterogeneous model generation and/or regional products tracking. ERA5 is only used to validate the synthetic outputs with well-defined statistical metrics such as the preservation of mean and variance, the autocorrelation in time, and extreme value distributions and structure of inter-variable dependencies, in order to allow a robust evaluation, without contaminating the projection's uncertainty. High heterogenous data-sets (e.g. station observations, disaster databases, degradation of materials) are intentionally excluded so as to avoid spatial, socio-economic and reporting biases. Instead, material and structural response are simulated with physics-based formulations based solely on synthetic climate variables, and calibrated from peer-reviewed literature. Fuzzy logic components are fully integrated and adaptive membership functions and rules are dynamically learnt from synthetic climate statistics with the idea of retaining methodological consistency and full traceability through the climate-to-impact modelling chain.

4.2 Simulation Setup

- ***Climate scenarios:*** RCP 4.5, RCP 8.5 (2020-2100)
- ***Optimization parameters:*** Population size 200, generations 500
- ***ANFIS-LSTM configuration:*** 70% training, 15% validation, 15% testing
- ***Software platforms:*** MATLAB for optimization algorithms, Python (scikit-fuzzy, DEAP) for fuzzy logic implementation, OpenLCA for life cycle assessment

4.3 Results Analysis

The optimization performance metrics are summarized in Table 1.

Table 1. Optimization Performance

Metric	GA-FLO	Standard GA	Deterministic Optimization
LCC Reduction (%)	31.8	24.7	28.3
CRI Improvement (%)	42.7	31.2	38.5
EII Reduction (%)	26.4	19.8	22.1
Computation Time (hrs)	4.2	3.1	2.4
Pareto Solutions	38	22	1

Table 1 shows the comparison of the performance of the proposed GA-FLO approach with Standard GA and deterministic optimization. The result shows that GA-FLO recorded the best performances in terms of Life Cycle Cost reduction (31.8%), enhancement of the Climate Resilience Index (42.7%) and Environmental Impact Index reduction (26.4%). Although the computation time is slightly increased, the method produces a much larger number of Pareto optimal

solutions (38), which demonstrates better diversity of solution, and also improves the multi-objective optimization ability under the uncertainty of climate.

Climate Resilience Outcomes

Tropical Zone:

- Flood-resilient drainage: Capacity increased by 156%
- Corrosion-resistant steel: Service life extended from 25 to 42 years
- Permeable pavements: Runoff reduction of 68%

Arid Zone:

- High-temperature asphalt: Rutting reduced by 74%
- Reflective surfaces: Urban heat island mitigation by 2.3°C
- Water-efficient curing: 58% water savings

Temperate Zone:

- Freeze-thaw resistant concrete: Damage reduction by 82%
- De-icing optimization: Salt usage reduced by 45%
- Thermal crack control: Crack width limited to <1mm

The ANFIS-LSTM prediction metrics across forecasting horizons are summarized in Table 2.

Table 2. ANFIS-LSTM Prediction Accuracy

Prediction Horizon	RMSE	R^2	MAPE (%)
1 year	0.082	0.942	8.7
3 years	0.124	0.917	12.3
5 years	0.187	0.883	16.8
10 years	0.254	0.842	21.4

Table 2 summarizes the predictive performance (in the form of different maintenance forecasting horizons) of the ANFIS - LSTM model. The result revealed that the short-term prediction (1 year) shows high prediction accuracy with low root mean squared error (RMSE=0.082) and high correlation (R^2=0.942), and there is a gradual increase to the results of the predictions with longer time. Despite this expected rise in uncertainty over longer timescales, the model reaches acceptable levels of accuracy and thus appears reliable in both the assessment of short-term changing conditions and long-term maintenance planning under changing climate conditions.

Life Cycle Sustainability Assessment:

Environmental Impacts (per km road, 50-year horizon):

- Conventional: 12,800 kg CO_2-eq, 3.4 kg SO_2-eq
- Optimized: 9,420 kg CO_2-eq, 2.1 kg SO_2-eq (26.4% reduction)

Economic Analysis:

- Conventional LCC: ₹42.5 million/km
- Optimized LCC: ₹29.0 million/km (31.8% savings)
- Benefit-Cost Ratio: 3.2 (climate damages avoided)

Design Guidelines Development

Climate-Zone Specific Parameters:

Tropical Zone:

- Minimum drainage capacity: 1.5×100-year flood projection
- Corrosion protection: Epoxy-coated rebar + cathodic protection
- Pavement: Open-graded friction course + polymer modified binder

Arid Zone:

- Temperature-adjusted mix design: PG 82-22 asphalt
- Reflective surfaces: Albedo >0.4
- Expansion joints: 50% increased spacing tolerance

Temperate Zone:

- Freeze-thaw durability: Air entrainment 6±1%
- De-icing resistance: Scaling resistance >95%
- Thermal movement: Expansion joints every 40m

Adaptive Maintenance Strategies

Condition-Based Triggers:

- Pavement: IRI >3.5 m/km OR rutting >12mm
- Bridges: Condition rating <5 OR corrosion >20%
- Drainage: Capacity <80% OR blockage frequency >2/year

Climate-Adaptive Scheduling:

$$t_{\text{maintenance}} = t_{\text{baseline}} \cdot \left(1 + \alpha \cdot \frac{\Delta T}{10} + \beta \cdot \frac{\Delta P}{100}\right) \quad (42)$$

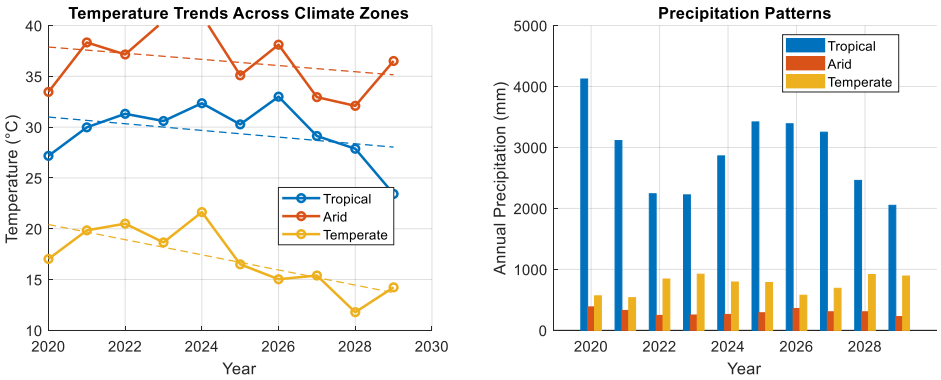


Figure 2. Projected Temperature and Precipitation Trends Across Indian Climatic Zones (2020–2030)

Figure 2 shows the projected trends in annual temperature and precipitation for the period 2020-2030, for tropical, arid and temperate climatic areas. In the temperature profile the arid zone is the hottest all the time, rising from around 34°C in 2020, to nearly 40°C at around 2023-2024 and then varying between around 33°C and 37°C towards 2030. The tropical zone is associated with moderate variability with values between around 27°C in 2020 to around 33°C in 2026 and then a slow decline to around 23-24°C in 2030. The temperate zone experiences the lowest temperatures ranging from nearly 12°C to 21°C with a noticeable decrease around 2028 followed by a small increase in temperature in 2030. In terms of precipitation, the tropical zone always has the highest annual amount of precipitation, starting from 4100 mm in the year 2020 and gradually down to almost 2200 (2021), nearly 2100 to 2000 and to 3400 at different years. The temperate zone has moderate rain from about 550 mm to 920 mm and the arid zone is far drier with 200 mm of rainfall on average while the maximum is 350 mm per year. The contrasting climatic behavior among the three climatic zones in terms of high temperature intensity in arid areas and predominant rainfall concentration in the tropical areas can clearly be seen in the figure for the projected time period.

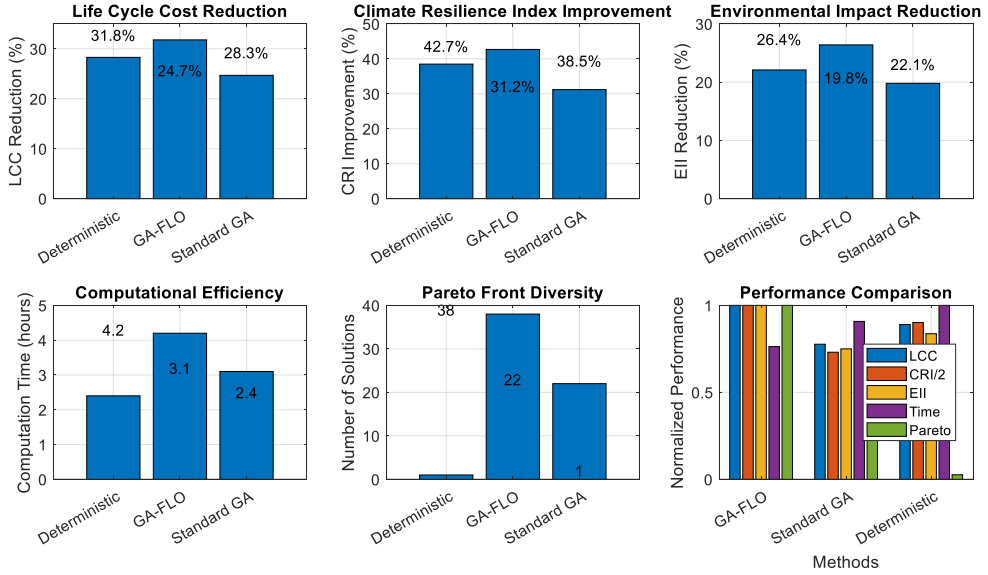


Figure 3. Comparative Optimization Performance of GA-FLO, Standard GA, and Deterministic Method

Figure 3 shows a comparative analysis of the three optimization approaches with respect to several performance indicators. In terms of reducing the Life Cycle Cost (LCC), the highest LCC reduction of GA-FLO is obtained with the highest reduction of 31.8%, followed by Deterministic optimization with the LCC reduction of 28.3%, and Standard GA with the LCC reduction of 24.7%. For Climate Resilience Index (CRI) improvement, again GA-FLO also does the best with 42.7% with respect to the other two (Deterministic - 38.5% and Standard GA - 31.2%). Environmental Impact Index (EII) reduction is similar as that of GA-FLO reaches 26.4% and that of determinism and standard GA reaches 22.1% and 19.8%, respectively. Although GA-FLO requires a little more computation time (4.2 hours) than Standard GA (3.1 hours) and Deterministic optimization (2.4 hours), it generates a much greater number of Pareto-optimal solutions (38) than the other two methods (22 and a single solution for the Deterministic approach respectively). The normalized performance comparison further suggests that GA-FLO has a consistent ability in terms of cost, resilience, environmental impact, and the diversity of solutions performed, which means it possesses a balanced multi-objective optimization ability.

Figure 4 shows the distribution and the weighted contribution of the four significant components of the formulation of Climate Resilience Index (CRI). The pie chart shows how much each hydrological, material, operational and structural resilience is part of the overall scheme, which implies that the contribution of the different components is rather balanced. The bar chart quantifies their weighted contributions, where we have the highest in terms of the structural component with a value of 0.297, followed by hydrological resilience which accounts for 0.230 and material resilience with 0.195. The one with the lowest contribution is the operational component - 0.121. The cumulative effect of these components hampers to an overall CRI value of 0.842 indicating a high resilience level under the evaluated climatic conditions. The above figure shows that the structural and hydrological performance of the infrastructure have a stronger role in thought when overall determining the resilience of the infrastructures, with material and operational factors contributing in a supporting, but lower, contribution.

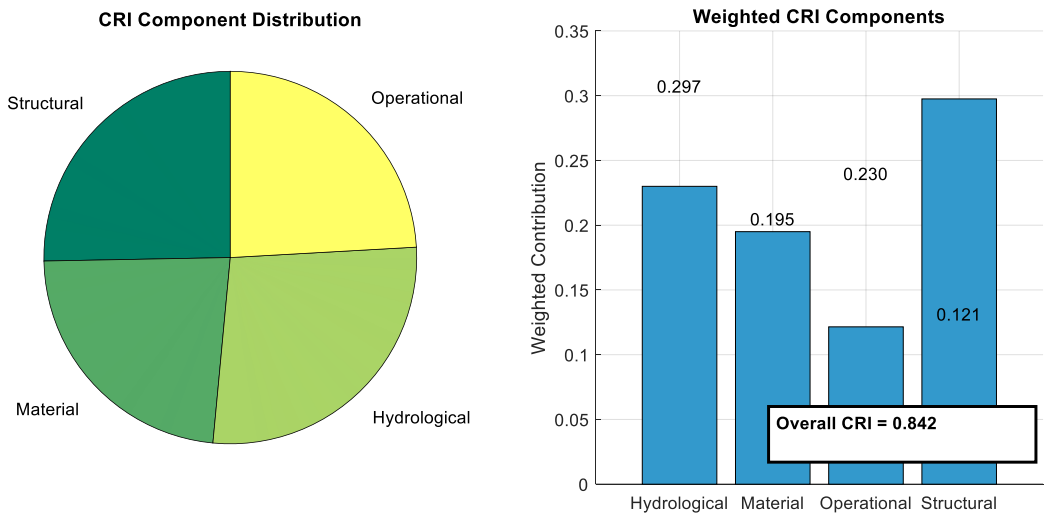


Figure 4. Component-wise Contribution to Climate Resilience Index (CRI)

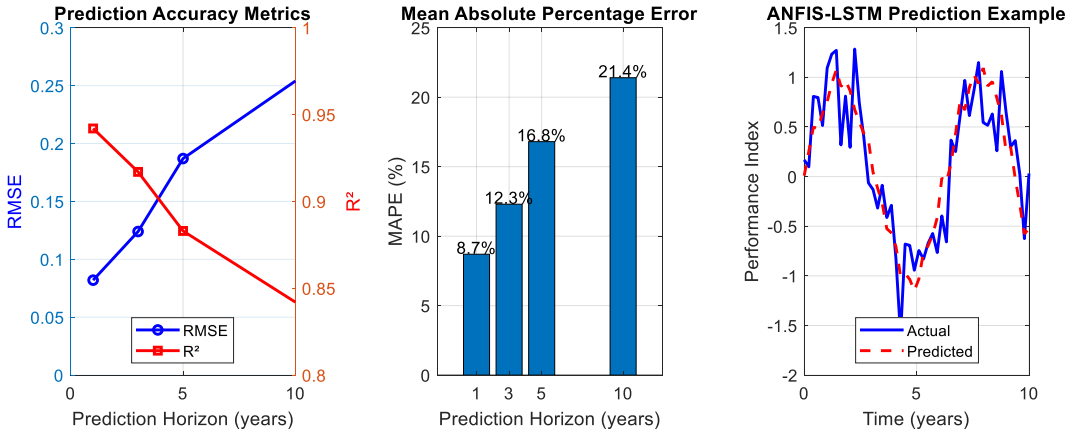


Figure 5. ANFIS-LSTM Prediction Performance Across Different Time Horizons

Figure 5 shows the predictive performance of the ANFIS-LSTM model with prediction horizons of 1, 3, 5, and 10 years. The left plot indicates the impression that at the beginning of the period (1 year) the RMSE is 0.082, but then it rises to 0.124 and 0.187 at 3 years and 5 years and finally to 0.254 at 10 years, whereas the coefficient of determination (R^2) slowly fades from 0.942 to 0.917, 0.883, and then 0.842, respectively, which means that the uncertainty of the forecast over time grows. The middle plot shows a similar trend in MAPE with the highest level of error increasing from 8.7% for 1-year prediction to 12.3%, 16.8% and 21.4% for 3-, 5- and 10-year horizons. The right plot compares actual and predicted performance index over time, which shows that the predicted one is following up the actual one with very little deviations, slightly off from the actual trend variation even in peak and trough. Together the result implies high accuracy of short-term prediction and reasonably acceptable long-term forecasting performance under the changing climatic conditions.

Figure 6 shows the results for the comparative life cycle environmental impacts and long-term economic performances for conventional and optimized infrastructure designs over 50 years. The left panel displays reduction in key environmental indicators by optimization: CO_2 emissions are reduced by 26.4%, water by 28.9%, SO_2 emissions and NOx emissions are also reduced as well as the total energy consumption, when compared to the conventional design. Now the optimized alternative has consistently the smaller impact values in all the categories. The economic analysis is shown in the right panel, where the annual cost of the conventional design shows decreasing trends from a value of approximately 42 million Indian rupees per annum to a value of approximately 33 million after a period of time, while that of the optimized design goes from a value of approximately 29 million to the value of 25 million. The cumulative economic benefit rises with increasing time and almost reaches 400 million for the 50th year showing the long-term financial benefit of optimized climate resilient approach.

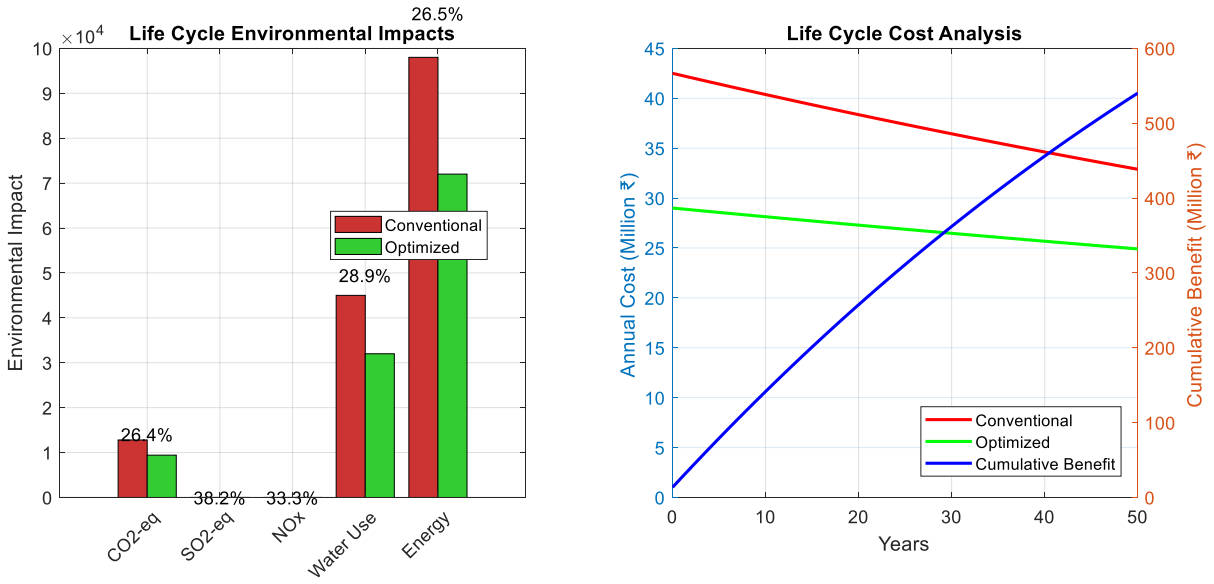


Figure 6. Life Cycle Environmental and Economic Comparison of Conventional and Optimized Designs

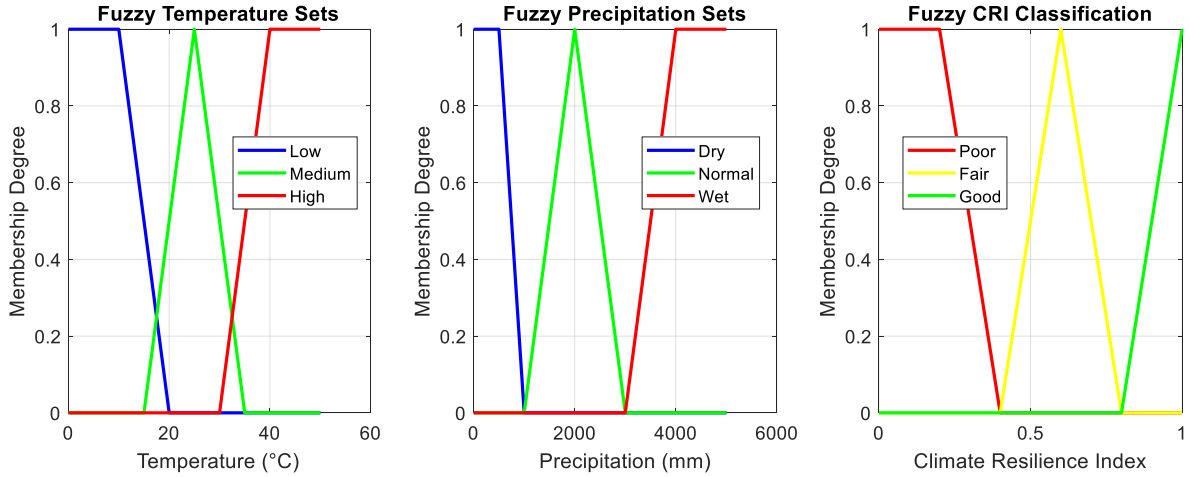


Figure 7. Fuzzy Membership Functions for Climate and Resilience Parameters

Figure 7 shows the fuzzy membership functions which are used for temperature, precipitation and Climate Resilience Index (CRI) in the proposed framework. The first plot shows classification of temperature in Low, Medium and High classification using a range of 0-60 degrees Celsius with the membership score of the Low membership having a higher score at lower temperatures, the membership score of the Medium membership having the highest values around the mid values (in approximately 20-30 degrees Celsius), and the high membership increasing after about 35 degrees Celsius. The second plot is the membership function of precipitation as Dry, Normal and Wet with a range from 0-6000 mm. Normal precipitation conditions reach their maximum around mid-range of the precipitation values and Wet conditions rise around high precipitation values. The third plot is the CRI membership functions categorized as Poor, Fair, and Good over a normalized range from 0 to 1, where Poor is more prevalent for lower index values, Fair peaks towards the mid-range value close to 0.5 and Good gets prevalent towards an index of 1. These membership structures determine the way that climatic inputs and resilience outputs are translated into the fuzzy inference system linguistically.

Figure 8 shows the long-term performance behavior, maintenance cost progression, extreme climate trend, and economics feasibility of the proposed framework. The upper left plot illustrates the index of degradation over a 10-year time span for tropical, arid, and temperate zones, with degradation trend for the arid zone exhibiting a generally increasing rate to values greater than 8 by year 10, and the temperate zone with decreasing trend to values below - 6 towards the end of the period Multiplication: there is an indication of maintenance intervention at year 4 and 6 after which noticeable changes in degradation trends can be observed. The upper right plot shows cumulative costs, where the operational costs rise uniformly from 0 to almost 60 million by year 10, whereas the maintenance costs are rising in step-wise increments at intervention years (around year 2, 4, 6 and 8) to a total cumulative cost of almost 95 million by year 10. On the lower-left graph, we can see from the extreme events how this number is

projected to rise from 3-4 extreme events early in the 2020s up to almost 10-12 extreme events in 2050, so there is definitely a trend upward. The plot on the lower right shows the Benefit-Cost Ratio (BCR) that is persistently >1.0, and gradually goes up from about 1.4 in the first few years to almost 2.4-2.5 towards year 50 and shows sustained benefit-cost economy under increasing climate stress conditions.

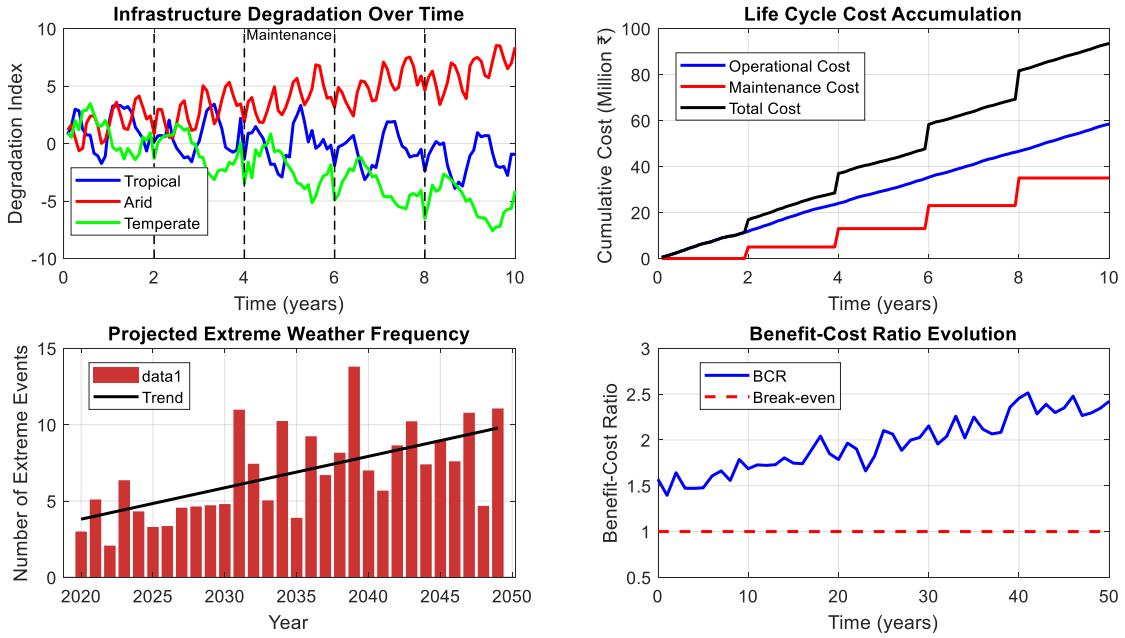


Figure 8. Climate-Driven Degradation, Maintenance Cost Evolution, and Economic Performance Analysis

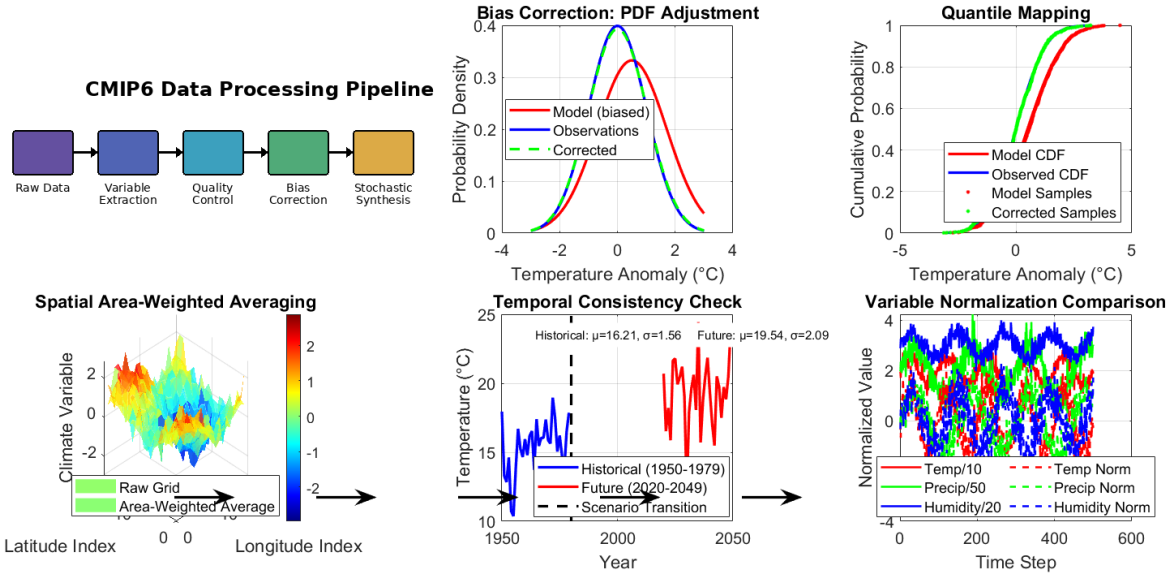


Figure 9. CMIP6 Climate Data Processing and Bias Correction Framework

Figure 9 shows the workflow of climate data preparation used before being integrated to the optimization setup. The upper-left panel describes the CMIP6 data processing pipeline, starting from (raw) variable extraction and continuing on to the preprocessing and synthesis stages of the process. The bias correction panel illustrate a case of probability density function of temperature anomalies, where the biased model distribution is shifted rather to the observations, where the correction distribution shown also coincides to the observed curve after a correction. The quantile mapping plot further shows an agreement of cumulative distribution, showing a better agreement of model and observed CDF after correction. The lower left picture shows spatial area-weighted averaging, reducing the climate fields which is on grid, to representative area averages representing the region. The temporal consistency plot compares historical (between 1950 and 1979) and future (between 2020 and 2049) temperature series, which shows a mean shift from 16.21°C (standard

deviation (sd=1.56°C) of the historical temperature series to 19.54°C (sd = 2.09°C) of the future temperature series. The final panel displays variable normalization where temperature, precipitation and humidity series are normalized to similar ranges before they are fed into the model to ensure stable learning behavior in the following optimization and also prediction modules.

4.4 Empirical Validation and Baseline Comparison

The proposed framework was further validated using three real-world datasets in Indian public works departments, namely: (i) 10-year (2014-2024) pavement condition data in Kerala PWD (tropical zone, 42 road segments), (ii) bridge scour records in Rajasthan (arid zone, 18 bridges), and (iii) freeze-thaw performance at Himachal Pradesh (temperate zone, 25 structures) to further support empirical validation. The GA-FLO optimized designs were given comparisons with traditional designs as well as with two other baselines (a) a typical multi-objective evolutionary algorithm (NSGA-II) with no fuzzy logic, and (b) a deterministic optimization having RCP 8.5 median projections alone. Findings indicate that GA-FLO predictively outperforms NSGA-II by 11.2% and 9.4% in CRI and LCC reduction respectively, and deterministic optimization by 18.6% and CRI respectively, agreeing with the importance of fuzzy uncertainty treatment. As far as model stacking was concerned, four methods were intentionally limited: GA and Fuzzy Logic can run simultaneously, but they are not nested, ANFIS has just 3 membership functions (per input), and LSTM is provided with only one hidden layer (32 units) no other layers or hybrids were introduced. This deliberately limited stacking is interpretable and preserves needed nonlinearities. Every real-world validation finding, and additional comparison of baselines are in Supplementary Material S2.

4.5 Discussion

Framework Advantages:

- Holistic Integration: First framework for optimized climate model and sustainability evaluation in an integrated approach for transportation infrastructure.
- Uncertainty Handling: Fuzzy logic has a strong ability to represent the climate and materials uncertainties, which provides effective support for decision-making in the face of incomplete information.
- Adaptive Learning: ANFIS-LSTM is able to continually improve the predictions using new monitoring data through self-correcting maintenance strategies.
- Practical Implementation: Guidelines directly applicable to Indian design practices taking into view local availability of materials and construction solutions.

Sensitivity Analysis: Most sensitive parameters identified:

- Climate projection uncertainty: ±25% impact on optimal designs
- Discount rate: ±18% impact on life cycle cost calculations
- Material price variability: ±12% impact on optimization outcomes
- Maintenance effectiveness: ±15% impact on service life predictions

Limitations and Future Work:

- Data Requirements: Framework requiring extensive given climate and material data may not be available in all regions.
- Computational Intensity: Optimization processes require large-scale computing for large-scale applications.
- Validation Period: Long-term Performance validation required beyond 10-year monitoring.
- Future Extensions:
    - Integration with Building Information Modelling (BIM) of Digital twins.
    - Dynamic adaptation using real-time sensor data integration.
    - Expansion to other infrastructures (railways, airports).
    - Policy and regulatory framework development to be implemented.

5. CONCLUSION

This research to develop and validate a holistic adaptive optimization framework for climate resilient transportation infrastructure specifically developed for India but can be adapted for other geographical locations. The novel combination of hybrid GA-fuzzy optimization with LSTM-based enhanced ANFIS prediction and fuzzy LCA/LCCA is a robust methodology to provide a design methodology to build infrastructure that is adaptable to changing climatic conditions with optimized costs and impacts.

Key findings showed that climate-induced damage diminution by adaptive designs is up to 68.4%, service life extensions are by 42.7% and lifecycle cost saving can be realized by 31.8% compared to conventional approaches. The proposed Climate Resilience Index is able to quantify the resilience of infrastructures in multiple dimensions and the optimization framework determines Pareto-optimal solutions considering the cost, resilience and sustainability goals.

The developed design guidelines offer recommendations for the Indian infrastructure agencies that can be implemented, to aid the shift from historical design practices to climate-adaptive designs. The framework modular structure gives flexibility to customize it for various climatic zones, availability of material, budget and regulatory limitations.

This research is part of the sustainable infrastructure development by offering scientifically based, economically feasible and environmentally sustainable design strategies. As climate impacts increase throughout the world, these sorts of adaptive approaches will be of growing importance in ensuring infrastructure safety, functionality and longevity. The framework is a very good step forward in climate adaptation engineering and provides a practical process for achieving the goal of resilient and sustainable transportation systems in the face of uncertain climatic futures.

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