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A Genetic Algorithm-based Decision Framework to Incorporate Climate Impact on Pavement Maintenance Planning

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Abstract

A recent trend of increase in the vulnerable behavior of roads to potential climate events is observed worldwide. However, a few studies conducted incorporate climate impact into road maintenance and rehabilitation. To address this, a genetic algorithm (GA) based optimization approach is proposed in this study with a climate risk index (CRI) in terms of criticality of roads, probability of occurrence of a climate event, and existing severity level of pavement. Criticality is defined by road functional class, availability of alternative routes and land use. Probability is determined by historical events and topography, while severity is defined by existing pavement condition. The CRI is incorporated as a generic constraint to the GA-based optimization model to maximize the average network condition under a given budget. To demonstrate this, a case study is conducted using twenty roads in different climatic conditions in Sri Lanka. The results show that in 25% and 50% of required total budget conditions there is a clear separation between priority roads IRI and non-priority roads IRI due to the generic constraint. This is an indication that the optimization model effectively prioritizes roads when there is a budget constraint. This concludes that the proposed approach can be utilized to make the most of the available budget for road maintenance by prioritizing roads that are highly vulnerable to climate events without compromising the overall network condition. Further, the proposed maintenance optimization approach can be extended to long term maintenance planning economically for developing countries.

Keywords

genetic algorithm, climate impact, optimization, pavement management

1 Introduction

Recent studies provide evidence of rapid climate change, with the increasing global surface temperature (global surface temperature in 2022 being 0.86 °C higher than the 20th century average), and the rising sea level (Gu and Adler, 2023). Extreme weather events such as floods, hurricanes and heat waves have become more frequent in many regions, and this trend is expected to continue in future.

Road pavements have been designed and maintained based on assumptions of local climatic conditions, but the increasing frequency of extreme weather events like surface flooding and landslides means that road authorities may face additional costs to address these issues. If these issues are not addressed, users may experience losses in terms of fuel consumption, safety, and time. On the national level, the costs of climate change may become significant, requiring additional budgets for climate adaptation and mitigation in the future. Due to the increasing vulnerability of road infrastructures due to climate hazards, there is an urgent need to incorporate climate resilience into pavement design and management (Head et al., 2019). A Pavement Management System (PMS) is typically used to evaluate pavement performance, but most existing maintenance decision-making schemes do not take the impact of climate change into account (Al-Saadi et al., 2021; Huang et al., 2021; Pasindu et al., 2020). To address this problem, there is a need to develop a decision-making scheme that incorporates climate factors.

This paper proposes a Climate Risk Index (CRI) to incorporate climate impact on roads, which is derived as a function of severity, probability of a climate event, and

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criticality of the road. The proposed PMS framework can be used to identify the optimal maintenance work program to implement in a single financial year, addressing both pavement condition and climate effects. This paper serves as a guide for agencies, road users, researchers, and practitioners to understand climate change adaptation from a systematic perspective and synthesizes existing knowledge regarding climate risk and sustainable pavements.

2 Literature review

Pavement management involves a systematic and strategic approach to manage physical assets throughout the lifespan, including operation, maintenance, upgrading, and expansion. This approach combines business and engineering practices to ensure optimal allocation and utilization of resources (Ebinger et al., 2015). However, the stability of the asset management process is threatened by climate change, which is evidenced by changing average temperatures, rainfall, and other climate-related indicators, as well as by the increment in extreme weather events (Johnsson and Balstrøm, 2021). The World Bank has reported that the impacts of climate change will not be evenly distributed among countries, higher level of vulnerability can be seen in less developed countries (Ebinger et al., 2015). The rise in floods and storms, especially in the Southeast Asia region, is the most significant impact of climate change (The World Bank, 2023). However, climate change will affect everyone regardless of their location.

The effects of climate change affect the long-term performance of pavements. Climate stressors such as temperature, precipitation, groundwater conditions, wind speed, and others have been identified as influential factors on pavement performance (Dawson, 2014; Martínez Díaz and Pérez, 2015). While engineers design pavements to withstand local climatic conditions, the impact of extreme weather events and long-term changes in climatic conditions can affect pavement performance significantly. Therefore, it is essential to evaluate how climate change impacts on key indicators of pavement performance and identify trends over extended periods throughout the pavement's design life to understand gradual changes in these factors. Despite these impacts, only a limited number of studies have integrated pavement performance with climate change impacts as presented in Table 1.

Climate importance can be integrated into the prioritization and optimization process as an objective function or priority index. The Research for Community Access Partnership-UK (Head et al., 2019) proposed a systematic approach to evaluate the impact of climate change on roads,

Table 1 Pavement performance evaluation Studies conducted by considering climate stressors

Reference	Climate factors		
	Temperature	Precipitation	Humidity
Head et al. (2019)	√	√	
Swarna and Hossain (2022)	√	√	
Enríquez-de-Salamanca (2019)	√	√	
Swarna et al. (2023)	√	√	
Underwood et al. (2017)	√		
Stoner et al. (2019)	√	√	
Shao et al. (2017)	√	√	
Qiao et al. (2022)	√	√	√
Dawson (2014)	√	√	

based on road functional level. The evaluation involved two types of approach: project-level and local-level. For project-level evaluation, a road vulnerability index was used, which considered three climate events: surface flooding, extreme rainfall, and hot days as illustrated in Eq. (1).

$$\mathrm{RVI} = D_i^{0.7} \times Mn^{0.15} \times Cr^{0.15} \tag{1}$$

Where, RVI is the road vulnerability index, Di is the deficiency score, Mn is the maintenance score, Cr is the road criticality score. Moreover, Eq. (2) has been employed to integrate the pavement climate Resilient Modulus into maintenance decision-making processes (Mohammed et al., 2021).

$$\mathrm{RM} = 625.33 + 151.92 \times e^{-0.21x} \tag{2}$$

Where RM is the pavement resilience modulus, x is the number of freeze-thaw cycles per year.

Further, an index to assess vulnerability has been developed for GIS-based road screening to identify roads that may face potential climate-related threats (Johnsson and Balstrøm, 2021). This index is based on flooding and landslides, and attributes are assigned to evaluate the vulnerability of the road. Additional factors such as AADT and the surrounding environment are also considered, as presented in Eq. (3).

$$\text{Vulnerability Index} = X_1 + X_2 + X_3 + 0.5X_4 + 0.5X_5 \tag{3}$$

Where, X_1 is the vulnerability to pluvial flood event based on 100-year rain event (0 or 1), X_2 is the vulnerable to fluvial flood event based on 100-year flow event (0 or 1), X_3 is the vulnerable to coastal flood event (0 or 1),

X_4 is the vulnerable to landslides, X_5 is the vulnerable to major traffic disruption. Maintenance planning nowadays has become more complex, and to achieve objectives, it is necessary to optimize them through various objective functions. These functions may include minimizing total cost, maximizing overall condition, maximizing reliability, maximizing performance (Yu et al., 2015). Moreover, the mathematical illustration of the optimization problem is shown in Eq. (4) (Santos et al., 2017).

$$\text{Minimize/maximize } F(\bar{\boldsymbol{X}}) = \left[f_1(\bar{X}), f_2(\bar{X}), I, f_n(\bar{X})\right]^T$$
$$\text{subject to } \bar{X} \in \Omega \tag{4}$$

Where, $F(\bar{\boldsymbol{X}})$ is the vector of objective functions, n is the number of objective function, $\bar{\boldsymbol{X}} = [x_1, x_2, ..., x_n]^T$ is the vector of decision variables, Ω is the set of the solutions, and $Z = f(\Omega)$ is the feasible solution set in the domain (Santos et al., 2017).

Most of the existing PMSs mainly focus on optimizing either pavement condition or maintenance cost. Nevertheless, some PMSs also prioritize other objectives such as minimizing user cost, maximizing pavement residual value, reducing system-level travel time, and minimizing accident cost. Table 2 summarizes recent studies that have addressed the optimization problem by incorporating the effects of climate stressors.

Table 2 Road maintenance optimization models developed incorporating climate stressors

Reference	Analysis method	Climate related objective functions
Al-Saadi et al. (2021)	Simulated Constraint Boundary Model (SCBM) method	Minimize environmental impact (in terms of CO_2 emission)
Santos et al. (2017)	GA	Minimize GHG emissions
Zhang et al. (2023)	Non-dominated Sorting Genetic Algorithm II (NSGA-II)	Performance level under climate impact
Gosse et al. (2013)	GA	Minimize GHG emissions
Huang et al. (2021)	LCA-based programming optimization	Minimize environmental damage cost
Yu et al. (2015)	GA	Minimize environmental impacts
Torres-Machi et al. (2017)	Hybrid GRASP model	Maximize Long-term effectiveness of the maintenance program Minimize GHG emissions
Kothari et al. (2022)	GA	Minimize GHG emission

3 Materials and methods

This methodology integrates development of climate risk index concerning climate events happened. Moreover, this study further focused on developing a framework for network level optimization incorporating climate risk.

3.1 Development of climate risk index

A climate risk index (CRI) is developed to assess the vulnerability of a specific road against identified climate hazards. There are several climate hazards observed in Sri Lankan context, among them surface flooding, roadside landslide was selected to be included in the CRI. Those climate events are found to be more critical in the perspective of road users due to the immediate and long-term effect and the fatality. CRI is a function of probability, severity, and criticality as defined in Eq. (5). Moreover, CRI is defined as a multiplication of three indices such as probability index (P_i), severity index (S_i) and criticality index (C_i) which range from 1 to 5.

$$\text{CRI}_s = P_s \times S_s \times C_s \tag{5}$$

Where, CRI is the climate risk index of road section S, P_S is the probability index of road section S, S_S is the severity index of road section S, C_S is the criticality index of road section S.

3.1.1 Probability index

The probability index is defined using two climate disasters: roadside landslides and surface flooding. These disasters are mutually exclusive, so their probabilities are analyzed separately. According to statistics from the Disaster Mitigation in Asia and the Pacific, the Asia-Pacific region is known for its high frequency of disasters (Asian Development Bank, 2013). Landslides are a major issue in Sri Lanka, affecting around 30% of the land area and several districts. Until 2002, landslides were considered as minor disasters and were not common in Sri Lanka, with an annual average of less than 50 recorded occurrences.

However, from 2003 to 2008, there was a sudden increase in recorded landslides. This increment may be shown due to better record-keeping rather than an actual increase in the number of occurrences since it is possible that more landslides occurred before this period but were not recorded due to undeveloped communication methods and poor record-keeping. Roadside landslides are identified as a critical hazard and the probability index for this type of disaster is defined in Eq. (6). Table 3 and Table 4 define P_1 and P_2, respectively, considering the spatial distribution and topography of the road link.

$$P_{s,\text{landslide}} = \sqrt{\prod_{i=1}^{2} P_i} \tag{6}$$

Where, $P_{S,\text{landslide}}$ is the probability index of road segment S for a landslide event, P_i is the probability rating score of parameters i (i = 1 for spatial distribution and i = 2 for topography). When considering the spatial distribution of floods in Sri Lanka, the criterion used for surface floods shows that Kalutara, Rathnapura, Gampaha, Ampara, and Jaffna are the districts where floods tend to occur most frequently. Meanwhile, when looking at the incidence of flooding in different divisional secretariats divisions, it appears that the Western parts of the island experience the highest frequency of floods, while most other divisions have a relatively low incidence. Moreover, Table 5 and Table 6 define P_3 and P_4 respectively considering spatial distribution and topography while probability index for surface flooding is defined by Eq. (7).

$$P_{s,\text{flooding}} = \sqrt{\prod_{i=3}^{4} P_i} \tag{7}$$

Table 3 Probability rating based on spatial distribution of landslides events for last 20 years in Sri Lanka

Probability rating 1 (P_1)	Description	Spatial distribution (Total events per 20 years)
1	Slight	≤7
2	Slight to warning	7–22
3	Warning	22–44
4	Warning to severe	44–88
5	Severe risk	>88

Table 4 Probability rating based on topography for landslides

Probability rating 2 (P_2)	Topography	Criteria
1	Flat	No landslide risk
2–4	Rolling	Slight slope failure
5	Mountainous	Severe slope failure

Table 5 Probability rating based on spatial distribution of flooding events for last 20 years in Sri Lanka

Probability rating 3 (P_3)	Description	Spatial distribution (Total events per 20 years)
1	Slight	≤14
2	Slight to warning	14–61
3	Warning	61–71
4	Warning to severe	71–90
5	Severe risk	>90

Table 6 Probability rating based on topography for flooding

Probability rating 4 (P_4)	Topography	Criteria
5	Flat	Severe flooding risk
2–4	Rolling	Slight flood inundation
1	Mountainous	No flooding risk

Where, $P_{S,\text{flooding}}$ is the probability index of road segment S for a flooding event, P_i is the probability rating score of parameters i (i = 1 for spatial distribution and i = 2 for topography).

Moreover, probability index of road section $S(P_S)$ is defined as Eq. (8).

$$P_s = \sqrt{P_{s,\text{landslide}} \times P_{s,\text{flooding}}} \tag{8}$$

Where, P_S is the probability score of road segment S.

3.1.2 Severity index

The severity level reflects the existing road condition, means a road with good structural condition would have better climate resilience compared with poor conditioned road. In the study, road condition is measured in terms of existing international roughness index (IRI) and distress condition. The severity index (S_s) is defined in scale of 1 to 5 as same as the probability index as given in Eq. (9).

$$S_s = \text{Max}\{S_1, S_2\} \tag{9}$$

Where, S_S is the severity index of road segment S, S_1 is the severity rating based on IRI, S_2 is the severity rating based on distress level.

Moreover, Tables 7 and 8 illustrate S_1 and S_2 respectively.

3.1.3 Criticality index

The Criticality Index (C_S) is defined in terms of road functional level, availability of alternative routes and predominant land use pattern. The evaluation of transport routes' criticality is extremely significant for infrastructure providers, emergency management officials, and city planners because it facilitates the conduction of proper

Table 7 Severity rating based on distress condition

Severity rating 1 (S_1)	Description	General condition
1	None	New construction or recent overlaid section
2	Slight	First signs of pavement deterioration with slight cracks with significant structural capacity
3	Slight to warning	Significant number of distresses including slight potholes can be visible; Need for a structural overlay
4	Warning	Severely deteriorated road with moderate extend of potholes, ravelling, rutting; Need localized patching prior to structural overlay
5	Severe	Failed road; Need for a reconstruction

Table 8 Severity rating based on existing IRI

Severity rating 2 (S_2)	Existing IRI (m/km)
1	<4
2	4–6
3	6–8
4	8–10
5	>10

resilience assessments and allows them to implement targeted improvement, intervention, and investment strategies. The formulation of C_S is defined as in Eq. (10).

$$C_s = \sqrt[3]{\Pi_{i=1}^{3} C_i} \tag{10}$$

Where, C_S is the criticality index of road segment S, C_i is the severity scores of each attribute defined as in Tables 9–11.

Table 9 Criticality rating based on road functional level

Criticality rating 1 (C_1)	Road functional level
5	Major arterial
4	Minor arterial
2–3	Collector
1	Local

Table 10 Criticality rating based on availability of alternative routes

Criticality rating 2 (C_2)	Number of alternative routes
5	0
4	1
2–3	2
1	3 or more

Table 11 Criticality rating based on land use pattern

Criticality rating 3 (C_3)	Predominant land use pattern
5–4	Mixed developed area
3	Residential with civic centres
2	Residential without civic centres
1	Agricultural area

3.2 Development network level optimization model

An optimization model that utilizes genetic algorithm (GA) was developed to improve the condition of roads. This model prioritizes roads that are more susceptible to the impact of climate. The objective function, constraints, and decision variables are clearly defined in Eq. (11)–(14):

- Objective function: minimize average network IRI

$$\text{Minimize } Q = \frac{\sum_{S=1}^{n} \text{IRI}_S(r) \times L_S}{\sum_{S=1}^{n} L_S} \tag{11}$$

Where, Q is the average network IRI in m/km, $\text{IRI}_S(r)$ is the IRI after applying strategy r for road S in m/km, L_S is the length of the road link S in km, n is the total number of roads in the network, r is the selected maintenance strategies for road links S from the optimization model.

- Constraint: total yearly maintenance budget

$$\text{Minimize } B \geq \frac{\sum_{i=1}^{n} \text{Cost}_S(r) \times L_S}{\sum_{i=1}^{n} L_S} \tag{12}$$

Where, B is the total budget available for the analysis year, $C_S(r)$ is the cost of operation r applied on road link S.

- Generic constraint: minimum functional level for priority roads

$$\forall i \in P\, Q_{\min} \geq \text{IRI}_S \tag{13}$$

Where, P is the set of priority roads selected based on the CRI value, $Q_{\min}$ is the minimum acceptable IRI value should be obtained after applying operation r for a priority road segment.

- Decision variable: annual maintenance operation

$$r \in \{1, 2, 3, ., R\} \;\; \forall S \; \exists r \text{ such that } n(r) = 1 \tag{14}$$

Where, R is the number of maintenance strategies considered in the optimization model.

4 Results

The proposed approach is demonstrated through a road network consisting of 20 road segments with a total length of 326.5 km. All the road segments in this network are paved with asphalt concrete and were selected from the Sri Lankan national road network. These roads represent all climate zones in Sri Lanka with varying topography.

IRI values of the selected roads were measured using the Roadroid mobile application (Sandamal and Pasindu, 2022), with an existing network IRI of 7.68 m/km. Based on the CRI threshold of 25, seven priority roads were identified. Initially, an analysis was conducted without considering budgetary constraints, and found that the network IRI could be improved to 2.79 m/km with a budget of USD $5.87 million. Secondly, an optimization model was utilized to identify the optimal work program by considering priority roads based on their CRI value.

Results showed that the condition of the priority roads had improved significantly compared to the overall network condition, as illustrated in Fig. 1. The network IRI and the priority roads' IRI under different budgetary levels are presented in Table 12.

Fig. 2 shows the improvement in pavement condition with CRI priority value at different budgetary

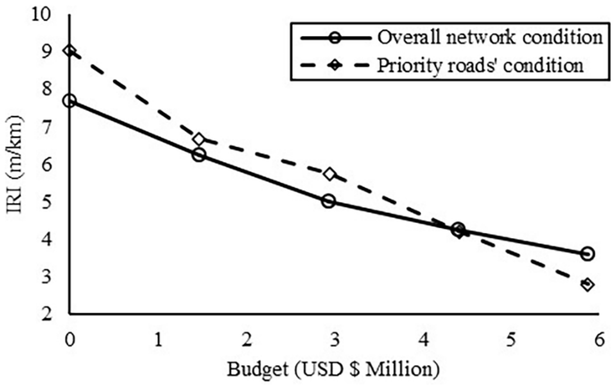

Fig. 1 IRI distribution of overall network and priority roads under different budgetary scenarios

Table 12 IRI distribution of overall network and priority roads under different budgetary scenarios

Budget scenario	Budget (B) (USD $ million)	Network IRI (Q) (m/km)	Priority roads' IRI (m/km)
Existing condition	-	7.68	9.02
25% of total budget	1.47	6.22	6.68
50% of total budget	2.94	4.98	5.75
75% of total budget	4.41	4.23	4.19
No budget constraints	5.87	3.60	2.79

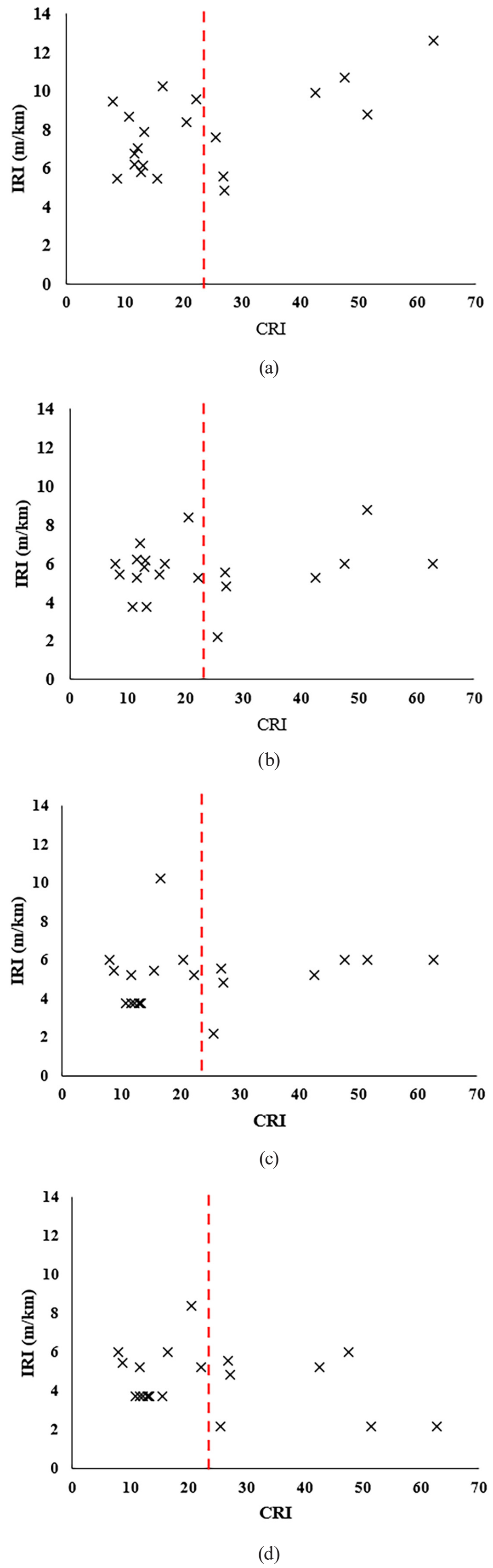

Fig. 2 IRI vs CRI variation under different budgetary levels (a) existing condition, (b) 25% of total budget, (c) 50% of total budget, (d) 75% of total budget

levels. The incorporation of CRI in the optimization model through a generic constraint has significantly increased the condition of priority roads under budget constraints. A comparison of Fig. 2 (a) and Fig. 2 (d) reveals a marked improvement in priority roads (i.e., those on the right side of the red color dashed line) due to the assignment of a minimum functional level of 6 m/km to priority roads in the optimization model.

In conclusion, roads that are susceptible to climate hazards can be prioritized in maintenance planning by adopting similar approaches proposed in this study. This approach can be further developed for long-term performance planning. In the first stage, priority road conditions can be improved by capping the non-priority road conditions, and in the second stage, based on the funding availability, the non-priority road conditions can be improved.

5 Conclusions

This paper introduces an optimization model that considers the impact of climate on maintenance and repair program budget allocation. Firstly, a climate risk index (CRI) is proposed, which takes the probability and severity of surface flooding and roadside landslide events, as well as the criticality of the road into account. The CRI can be used to rank roads and structures based on priority for maintenance or adaptation. Secondly, the CRI is included in the optimization model as a generic constraint to prioritize roads with higher climate risk. To mitigate this risk, the model assigns priority in the maintenance program by considering the condition of non-priority roads with minimal influence on the overall network condition.

The effectiveness of the proposed model was evaluated through a case study, where different budget allocation models were compared using a GA-based optimization algorithm. As expected, the optimization model prioritized roads in terms of their climate impact, particularly when there was a lack of budget. The results of the case study suggest that the proposed budget allocation model is effective in helping decision-makers to incorporate climate impact into their decision-making process without compromising the overall network condition.

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