AI-DRIVEN DECISION SUPPORT FRAMEWORK FOR BRIDGE ASSET MANAGEMENT AT THE NETWORK LEVEL

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Abstract:

Bridge asset management is a complicated task considering bridge structures are facing various external threats (e.g., chronic deterioration and seismic hazards) over their lifecycle. Artificial Intelligence (AI) techniques have received emerging research attention in proactive and long-term oriented bridge asset management (BAM). However, the state-of-the-research in AI-based BAM mainly focused on decision support at the individual bridge level, whereas the applicability of such techniques in network-level BAM is yet to be explored. This study presents a network-level AI-based decision support framework for managing a portfolio of bridges under budget and resource constraints. To achieve this, bridge deterioration conditions are modeled using component-level Markovian transition matrices, a system-level seismic fragility is modeled, and mapping system-level seismic damage states to component condition ratings is considered. Based on the integrated and stochastic modeling of bridge condition ratings and seismic damage, both direct and indirect costs are considered. These costs account for multiple factors, including condition deterioration, maintenance, and seismic damage, within a life-cycle context. In order to prioritize the various maintenance projects within a bridge network, the proposed framework synergistically integrates bridge-level AI decision making with a Pareto-optimal front-ranking scheme. We leverage deep reinforcement learning based AI models, to dynamically offer bridge-level maintenance suggestions, and then optimize budget allocation over the entire bridge network. Comparative studies show that the AI-based strategy outperforms other conventional condition-based policies, providing a more proactive and effective bridge network management solution. This study provides a pioneering advancement in risk-informed, AI-driven decision-making for regional structural and infrastructure systems.

1. Introduction

With the rising costs of maintenance and rehabilitation for aging bridge networks, it has become more important than ever to design maintenance, rehabilitation, and reconstruction programs that make the most out of the limited resources over the long term [1–3]. In this regard, asset managers face significant challenges in considering and quantifying cost-effectiveness when prioritizing maintenance projects and evaluating strategies for fund allocation on a large and aging bridge inventory. This task is made even more complex by the limited budget and resources available for network-level infrastructure maintenance, along with the uncertainties in asset performance over a prolonged planning horizon [4–6].

A significant amount of research has been dedicated to network-level bridge maintenance decision making under multiple and often competing performance goals and constraints. The majority of the research has framed the network-level decision-making problem as a multi-criteria prioritization/ranking problem [7–10]. Among these studies, utility scores and weights for each individual performance measure are assigned, and a final aggregated utility score is obtained by weighted summation. Individual bridge maintenance projects are then ranked or prioritized based on their respective utility scores. This approach has been widely adopted due to its ease of implementation. However, the way the utility scores and weighting factors are designed is usually subjective, and it is difficult to estimate the associated long-term asset management performance.

Several other studies [11,12] framed the decision-making problem as a multi-objective optimization problem (e.g., using Mixed-Integer Programming methods or other meta-heuristic optimization techniques). Compared with the previous multi-criteria ranking based solutions, the optimization-based approaches can better incorporate the physics (e.g., deterioration, effects of maintenance actions) of bridge assets, and capture the long-term cumulative effects. Nevertheless, the computational expenses tend to increase dramatically as the size of the bridge network increases, hindering their scalability and applicability to large-scale bridge networks.

In order to develop a bridge network-level asset management approach that can offer bridge-level proactive maintenance decisions while maximizing the network-level long-term asset performance, this study will further couple an AI-based bridge-level maintenance policy previously developed by the authors with a Pareto Frontier based ranking approach for network-level bridge asset management under budget and resource constraints.

2. Bridge-level maintenance policies

In this study, the bridge-level maintenance policies considered include the AI-based policy, called parametrized DQN with prioritized experience replay (P-PERDQN) developed by the authors [13,14] and three condition-based policies (i.e., CB-1, CB-2, and CB-3), as follows:

AI-based bridge-level maintenance policy (P-PERDQN): This policy is trained using Deep Reinforcement Learning (DRL) technique under an integrated virtual simulation environment capturing bridge aging deterioration, life-cycle cost analysis, and practical action constraints. DRL uses a Q table to store Q values for each state-action pair, which are iteratively updated using Eq. 1, with "η" as the learning rate. The action-value function, $Q(\cdot)$, is updated from Q_{old} to Q_{new}.

$$Q_{new}(s_t, a_t) \leftarrow Q_{old}(s_t, a_t) + \eta[r(s_t, a_t) + \gamma_{a \in A} max Q_{old}(s_{t+1}, a\quad) - Q_{old}(s_t, a_t)] \tag{1}$$

where "*s*" denotes the state (condition rating), "*a*" shows the action, "*r*" represents the reward, and γ indicats the discount factor. Enabled by the recent advancements in deep neural networks with prioritized experience replay, DRL effectively combines the principles of RL with deep learning tools, where function approximators such as neural networks can be employed to estimate action values for any given state and is more capable of dealing with high-dimension problems.

CB-1: Do nothing for bridge components in "*Good"* condition, do nothing for bridge components in "*Fair"* condition, replacement for components in "*Poor"* condition.

CB-2: Do nothing for bridge components in "*Good"* condition, Minor Maintenance for components in "*Fair"* condition, Replacement for components in "*Poor"* condition.

CB-3, Do nothing for bridge components in "*Good"* condition, Minor Maintenance for components in "*Fair"* condition with an NBI rating of 6, Major Maintenance for components in "*Fair"* condition with an NBI rating of 5, Replacement for components in "*Poor"* condition.

3. NETWORK-LEVEL BRIDGE ASSET MANAGEMENT METHODOLOGY

When it comes to network-level bridge asset management, the actual budget and resource constraints should be explicitly considered, and hence the suggested maintenance actions from the bridge-level maintenance policies may not always be fulfilled for all the individual bridges. To further extend the applicability of the bridge-level AI policy over to the network level, a hierarchical framework is proposed herein for optimal budget allocation at the network-level as shown in Figure 1, where the bridge-level maintenance decisions are largely delegated to the bridge-level policies, followed by a network-level project prioritization and budget/resource allocation module. Within this hierarchical framework, maintenance decisions are still made on a yearly basis with the following steps.

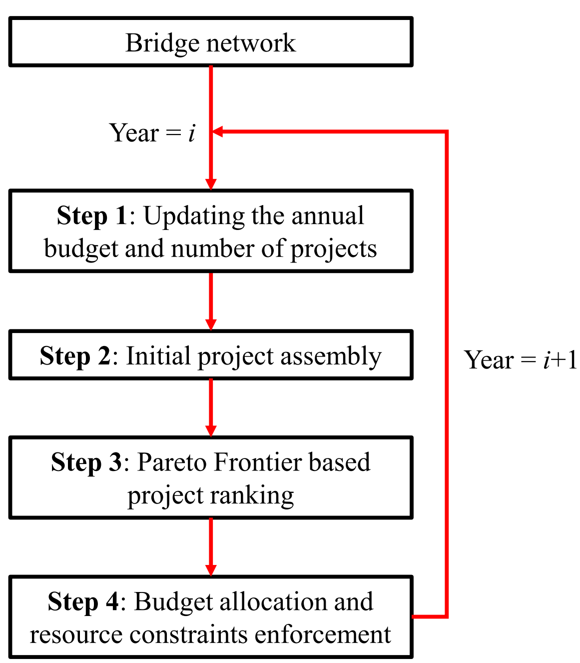


Figure 1. Overview of the proposed network-level bridge maintenance management framework

In the proposed framework, two types of constraints are considered. The first constraint is related to the annual available budget. It is assumed that a constant budget will be allocated annually as a ratio of the construction cost of the network. Moreover, two budget accumulation scenarios are further considered, including (1) non-cumulative budget: any unspent annual budget cannot be rolled over to the following years; (2) cumulative budget: the unspent annual budget will be rolled over to the following years. In addition to the budget constraints, real-world maintenance planning is also constrained by the availability of construction crews, specialized labor, and necessary equipment as percentage of the number of maintenance projects that can be executed within a given year.

In the second step, at each decision timestep (i.e., year), the maintenance decision-making process begins with collecting the proposed maintenance actions (i.e., do nothing, minor, major, replacement) for each of the bridges' components (i.e., deck, superstructure, substructure) within the network. These actions are recommended from a given bridge-level maintenance policy (e.g., AI-based or condition-based policies). For each bridge in the network, the suggested maintenance actions from a given policy, along with the associated direct costs, are systematically compiled to represent a candidate bridge project.

At third step, the Pareto Frontier method is implemented for project ranking. The Parato Frontier method for multi-attribute bridge project ranking incorporates multiple distinct decision variables into a single ranking metric. In this study, Non-dominated sorting [15] is employed that is a technique organizes sets of attributes into various tiers of non-domination according to their Pareto optimality. This approach has found extensive application in fields like engineering, finance, and computer science. It is effective in addressing complex optimization problems with multiple objectives. Non-dominated sorting was selected over available alternatives [16–20] in this study due to its ability to maintain a diverse set of high-quality solutions.

In this study, the aforementioned Pareto Frontier based ranking approach is introduced to systematically rank the initial set of bridge maintenance projects (from Step2) based on multiple bridge- and project-specific attributes such as Q values, bridge system-level condition ratings (CR), and ADT. Below is a brief introduction of the different bridge and project-specific attributes considered in the Pareto Frontier ranking approach.

1. Q values: Q values represent the expected long-term reward for each action in the bridge-level AI policy, based on current bridge conditions. These values are unique to the AI-based approach and not used in traditional condition-based policies. Since the reward function is cost-related, Q values are typically negative, and their negatives ($-Q$) are used in Pareto frontier ranking. A higher $-Q$ value indicates greater life-cycle costs and thus a higher priority for maintenance. Conversely, higher Q values reflect better performance and lower long-term risk. Therefore, bridges with lower Q values (i.e., higher $-Q$) are prioritized to prevent further deterioration.

2. Bridge-level condition ratings: This metric quantifies the overall condition of a bridge on a standardized scale (i.e., 0–9 in the National Bridge Inventory). For any given bridge, the bridge-level condition rating is taken as the minimum condition rating among the three generic bridge components (i.e., deck, superstructure, and substructure). In the Pareto

Frontier ranking, bridges with lower system-level condition ratings are deemed more important.

3. ADT: Average daily traffic represents the average number of vehicles passing over a bridge per day. In the Pareto Frontier ranking, bridges with higher ADT values are deemed more important.

At the last step, the Pareto Frontier ranking process is followed to allocate the limited annual budget and resources to the top ranked projects, so that those projects can be implemented as soon as possible. The annual maintenance budget is sequentially allocated to top-ranked bridge projects until exhausted, with only the highest-ranked projects within the allowable limit approved for execution, while unfunded projects have their actions revised to "do-nothing" for all components. The entire decision-making process is repeated annually throughout the defined planning time horizon (T years).

4. NETWORK-LEVEL CASE STUDY

For demonstration purposes, a case study of 83 multi-span simply supported concrete bridges along with the backbone highway network located in Memphis, Tennessee, is considered as shown in Figure 2. It must be noted that the proposed network-level decision methodology can be readily scaled to a larger number of bridges and a larger network and can benefit from parallel computing. The combined deck area of all bridges in the network (A_T) is 242,144 ft², serving as the basis for calculating maintenance costs and budget resource allocation as follows:

$$Annual\ budget = r_b \times C_d \times A_T \quad (2)$$

where: r_b indicates the constant annual budget ratio, C_d is the bridge construction replacement cost per 1 ft^2 of deck area. As mentioned before, in this study, the available budget is considered under two scenarios: (1) non-cumulative budget, and (2) cumulative budget, by considering a 30-year planning horizon with a discount factor of 0.96 [21] for the life-cycle cost aggregation.

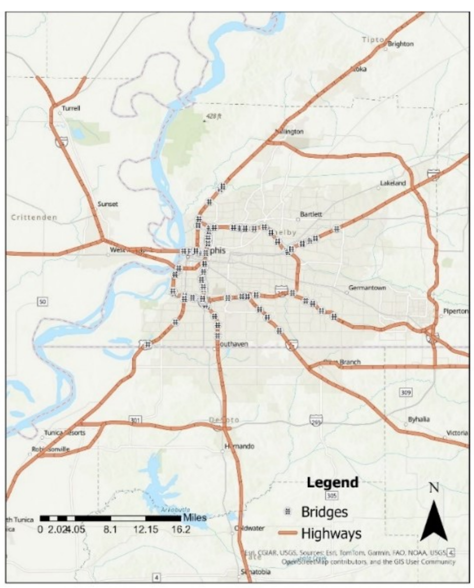


Figure 2. Case study bridge network located in Memphis, Tennessee

5. RESULTS

In this section, a comparative study is performed to examine the influence of different bridge-level maintenance policies on the network-level asset management performance under various budgetary constraints and scenarios. For the maximum allowable projects constraint, for demonstration purposes, it is enforced that no more than 10% of the bridges in the network can undergo maintenance actions each year throughout the subsequent analyses.

The Pareto Frontier ranking attributes of "Q value, bridge-level CR" are considered for the AI-based policy; and the ranking attributes of "bridge-level CR, ADT" are considered for the condition-based policies.

In this comparative study, different annual maintenance budget availability, expressed as the ratio of the total replacement value of the bridge assets, is considered. Two levels of annual budget ratio (i.e., 1%, and 2%) [22] are investigated, under the cumulative or non-cumulative budget assumptions. This analysis assesses the effectiveness of each policy in resource allocation for maintaining bridge conditions, under budgetary and resource constraints.

5.1. 1% annual budget ratio with non-cumulative budget

This subsection investigates the influence of different bridge-level maintenance policies on the network-level asset management performance, considering an annual budget ratio of 1% with the non-cumulative budget assumption. Figure 3(a) illustrates the aggregated direct cost comparison, demonstrating the AI-based policy can more effectively utilize the available budget with a much narrower gap to the available budget envelope, whereas the condition-based policies tend to leave a significant portion of budget unused. Note that even under this non-cumulative budget scenario, the AI policy is still able to effectively utilize most of the available budget. The difference in budget utilization can be attributed to the fact that the AI-based policy is more versatile in providing adaptive maintenance actions tailored to different bridges with varying conditions, whereas the condition-based policies only follow a prescribed decision tree with much less action variability and granularity. Figure 3(b) presents the aggregated indirect cost comparison. The AI-based policy is found to lead to much less indirect costs owing to the more effective maintenance actions and hence improved overall bridge conditions, compared to the condition-based policies.

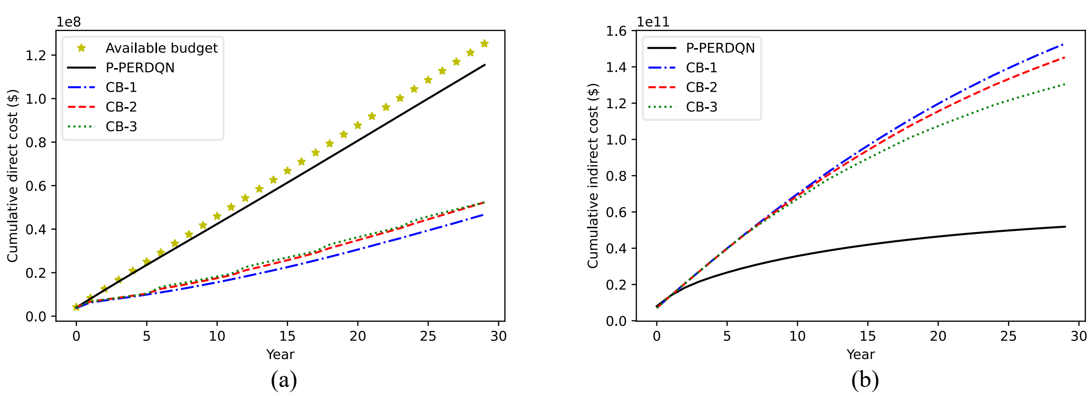
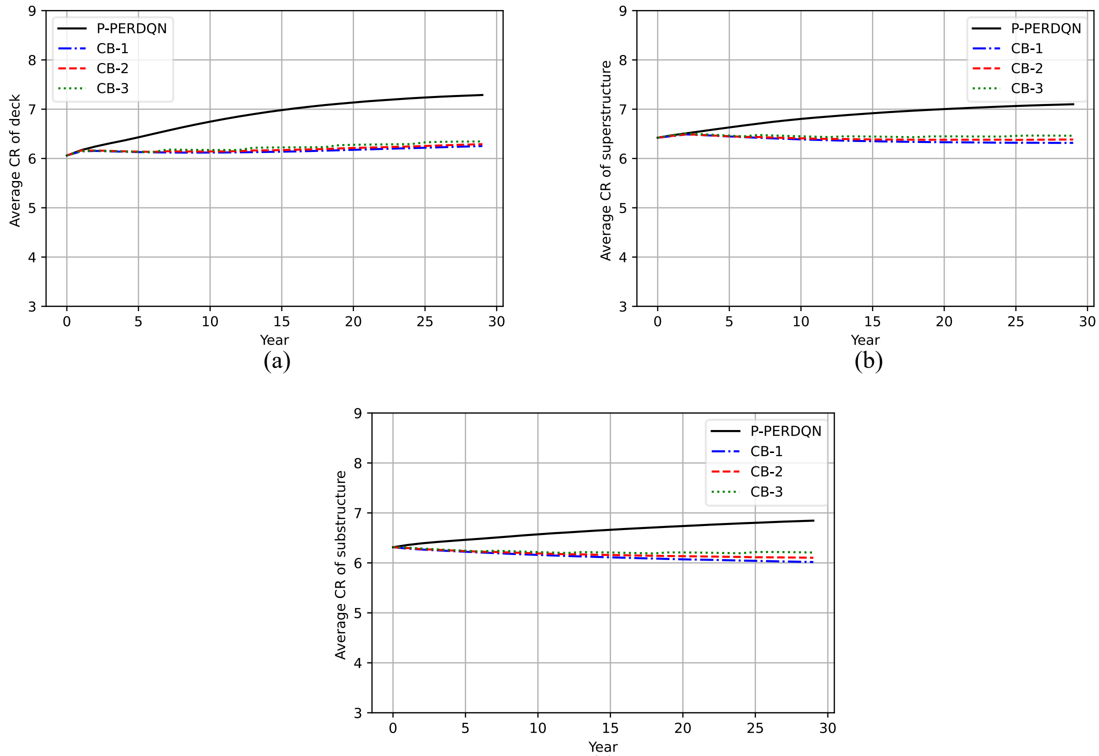


Figure 3. Average aggregated costs across the network under various maintenance policies (1% non-cumulative budget): (a) direct cost, (b) indirect cost

The better budget utilization along with the more effective and optimized maintenance actions by the AI policy also contributes to better average component CR across the bridge network, as illustrated in Figure 4. A gradually increasing trend in the average component CR is observed for the AI-based policy, with average CRs above 7 toward the end of the planning horizon. In contrast, the average component CRs from the condition-based policies remain pretty much stagnant, with very limited improvement over time.

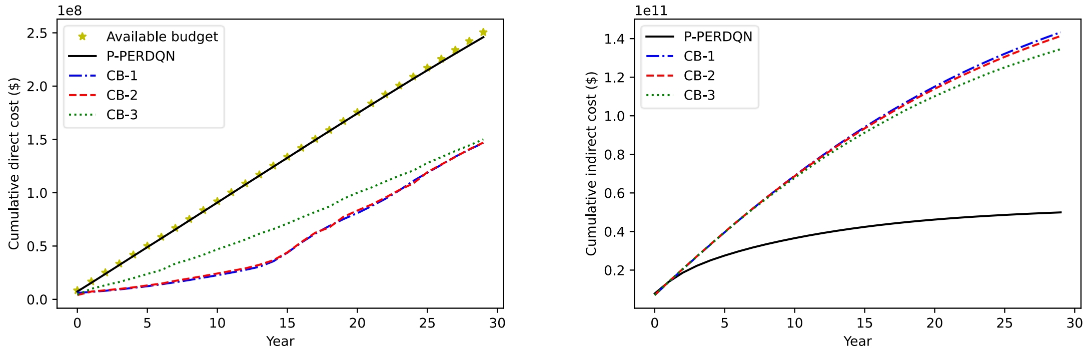


(a) (b) (c)

Figure 4. Average component condition rating across the network (1% non-cumulative budget): (a) deck, (b) superstructure, (c) substructure

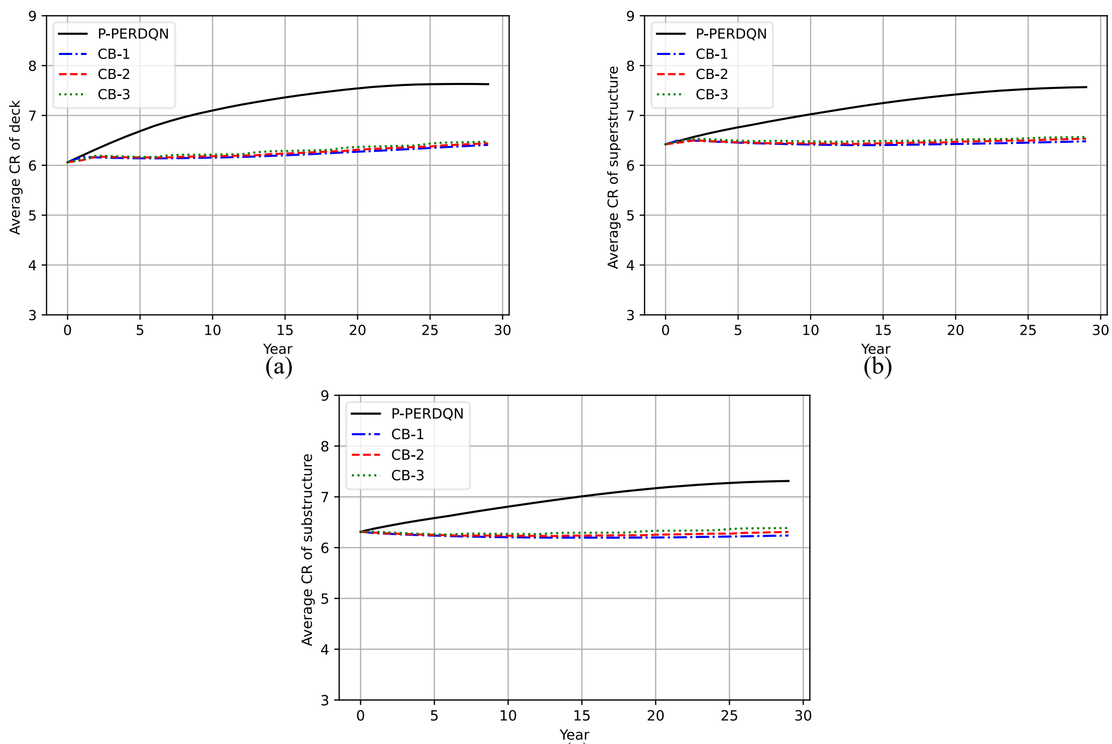
5.2. 2% annual budget ratio with cumulative budget

In this subsection, the network-level bridge asset management performance is investigated by considering an annual budget ratio of 2% with the cumulative budget assumption. Figure 5(a) indicates the AI-based policy can more effectively utilize the available budget compared to the condition-based policies. Figure 5(b) illustrates the AI-based policy also leads to the lowest level of aggregated indirect costs. Figure 6 shows that the AI-based policy demonstrates a significant improvement in all component conditions, increasing steadily and stabilizing at a higher level. In contrast, the condition-based policies maintain a relatively stagnant and lower CR, indicating limited condition improvements over time. All the above results highlight the benefits of integrating AI into network-level bridge asset management. The AI-based bridge-level maintenance policy in conjunction with the proposed network-level decision framework can effectively: (1) utilize the available budget, (2) reduce the aggregated indirect costs, (3) improve CR of bridge components.



(a) (b)

Figure 5. Average aggregated costs across the network under various maintenance policies (2% cumulative budget): (a) direct cost, (b) indirect cost



(a) (b) (c)

Figure 6. Average component condition rating across the network (2% cumulative budget): (a) deck, (b) superstructure, (c) substructure

6. CONCLUSION

In this study, a network-level bridge maintenance decision-making and planning framework is developed by coupling bridge-level AI decision policy with a multi-criteria project ranking and prioritization approach. The bridge-level AI policy provides an initial set of suggested maintenance actions for each individual bridge within the bridge network. Note that other conventional condition-based policies can also be considered at the bridge level. The initial set of projects are then further ranked and prioritized via a Pareto Frontier based approach by systematically balancing multiple and potentially conflicting bridge- and project-specific attributes (e.g., Q values, condition ratings, average daily traffic). Practical budget and resource constraints are then enforced according to the resulting project ranking.

A comparative study is carried out by comparing the efficacy of different bridge-level maintenance policies, under the proposed network-level decision framework. The influence of using different bridge-level policies within the proposed network-level decision framework is examined by considering multiple network-level asset management performance measures such as the overall funding usage, indirect costs, and bridge conditions, under different funding scenarios. It is observed that, under the same budgetary and resource constraints, the AI-based policy achieves superior outcomes by strategically distributing resources to maximize effectiveness. Specifically, the AI-based policy more effectively allocates the available budget, resulting in lower aggregated indirect costs. In contrast, the condition-based policies often leave a significant portion of the budget unused, leading to substantially higher indirect costs. Additionally, the AI-based policy efficiently enhances bridge asset conditions. Conversely, the condition-based policies primarily focus on preserving bridge components with minimal condition improvement. In conclusion, the proposed framework optimizes the budget and resource allocation at the network level by better utilizing the limited resources, preserving the overall asset conditions, and reducing the socioeconomic impact due to deteriorating bridge assets.

7. ACKNOWLEDGMENTS

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