RISK-BASED MULTI-THREAT DECISION-SUPPORT METHODOLOGY FOR LONG-TERM BRIDGE ASSET MANAGEMENT

VOLUME 2: NETWORK-LEVEL DECISION SUPPORT

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16. Abstract

In the Volume 2 report, the bridge-level AI-based maintenance decision policy previously developed in the Volume 1 report is further integrated into a network-level decision support framework, by considering network-level budget and resource constraints. A Pareto Frontier based ranking approach is proposed to rank the maintenance projects suggested by the bridge-level maintenance policies by holistically considering multiple decision factors. The top ranked projects are then allocated with the funding and resources for actual implementation. A thorough comparative study is carried out by comparing the efficacy of the AI or other condition-based policies at the bridge level, under the proposed network-level decision framework. First, a sensitivity study is performed to investigate the influence of bridge related attributes in the Pareto Frontier ranking scheme. Next, 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, bridge conditions, and travel time, under different funding scenarios. It is observed that the AI-based policy outperforms other traditional condition-based policies in almost all considered cases. Also from some exemplary annual network-level decision illustration, it is found that the AI-based bridge-level decision policy when deployed into the network-level decision framework can offer reasonable budget and resource allocation. Finally, the open-sourced computer codes are shared and related hands-on tutorials are provided for better result dissemination. In conclusion, the research tools developed from this entire research project can not only offer proactive and adaptive bridge maintenance decisions at the individual bridge level, but can also optimize 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.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

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LIST OF ABBREVIATIONS AND SYMBOLS

Abbreviations

ADT	Average daily traffic
CB	Condition based
CR	Condition Rating
NBI	National Bridge Inventory
SPEA	Strength Pareto Evolutionary Algorithm
TAZ	Transportation analysis zones

Symbols

A	Adjacency matrix
a	Action
A_T	Total deck area for network
B_j	j^{th} bridge
BC	Betweenness centrality
CC	Closeness centrality
C_d	bridge construction cost per 1 ft^2 of deck area
D_{tot}	Total distance traveled in the network
d	Distance
L	Length of the link
N	Number of bridges in the network
n	Number of attributes/nodes
r_b	Budget ratio
$r_{p,q}$	number of paths connecting nodes p and q
s	State
T	Planning horizon
T_{tot}	Total travel time in the network
T_{cij}	Total travel time on each link
V	Traffic volumes
x	Ranking attributes
π	Policy

CHAPTER 1. INTRODUCTION

In the Volume 1 report [1] of this project, a bridge-level AI decision-support tool is developed to offer adaptive and proactive life-cycle sequential maintenance decisions aiming at reducing the expected cumulative direct and indirect costs. Despite their decision-support performance compared to other conventional condition-based maintenance policies; it is yet to be studied how to further implement the bridge-level AI policies into asset management for a network of bridges. With the rising costs of repairs and the growing demands of aging bridge networks, it is important to design maintenance, rehabilitation, and reconstruction programs that make the most out of the limited resources over the long term [2–4]. 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 [5–7].

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 [8–11]. 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 [12,13] 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 task will further couple the AI-based bridge-level maintenance policies developed in Volume 1 of this project with a Pareto Frontier ranking approach for network-level bridge asset management under budget and resource constraints.

CHAPTER 2. NETWORK-LEVEL BRIDGE ASSET MANAGEMENT METHODOLOGY

The bridge-level AI policy developed in Volume 1 was trained based on a virtual simulation environment consisting of an integrated aging deterioration module, life-cycle cost analysis module, and practical action constraints. In each year, the bridge-level AI policy takes inputs including current bridge component-level conditions along with other bridge-specific parameters such as deck area and ADT and outputs the suggested component-level maintenance actions. Although the bridge-level AI agent aims to minimize the weighted summation of direct costs (including maintenance and seismic retrofitting) and indirect costs (encompassing factors such as vehicle operation costs, time loss costs, and safety costs), it did not explicitly account for the actual budget and resource constraints over the network level. When it comes to network-level decision making, the actual budget and resource constraints should be explicitly considered, and hence the suggested maintenance actions from the bridge-level AI policy may not always be fulfilled for all the individual bridges.

To further integrate the bridge-level decision policy into network-level bridge asset management, 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 (i.e., the AI or condition-based policies) in Volume 1, 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.

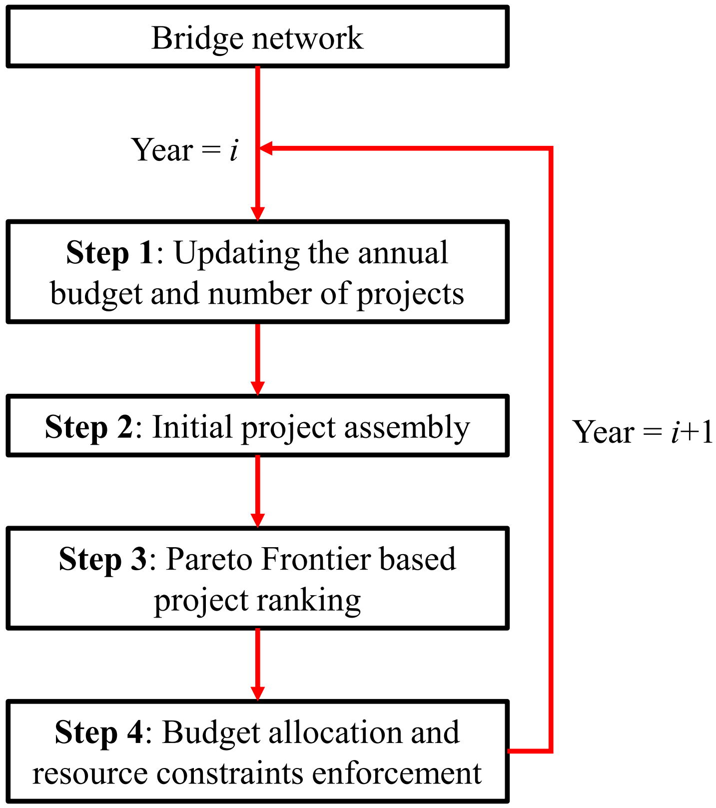


Figure 1. Overview of the proposed network-level bridge maintenance management framework

2.1. Step 1: Updating the annual budget and number of projects

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 (expressed as a constant user-specified percentage of the total bridge network reconstruction value) will be allocated annually. Moreover, depending on whether a cumulative budget is considered, 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 each year, the implemented bridge maintenance projects should not exceed the available budget of that year.

In addition to the budget constraints, real-world maintenance planning is also constrained by the availability of construction crews, specialized labor, and necessary equipment. To reflect these practical resource constraints, an upper limit on the number of maintenance projects that can be executed within a given year is enforced. This constraint prevents excessive projects implemented in a short time period to ensure that the selected projects can be realistically executed within operational limits.

In Step 1, the available annual budget will be updated, and the number of ongoing projects will be reset to zero (as it is assumed that all the maintenance projects can be completed within each decision step) at the beginning of each year.

2.2. Step 2: Initial projects assembly

At each decision timestep (i.e., year), the maintenance decision-making process begins with collecting the proposed maintenance actions for each of the bridges within the network. These actions are suggested 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. Note that if an AI-based policy is considered, the Q values corresponding to the optimal actions for each bridge will also be gathered. This process results in an initial set of maintenance projects, which will undergo further ranking and prioritization process in the subsequent steps.

2.3. Step 3: Pareto Frontier based project ranking

In this study, the Pareto Frontier method is implemented for project ranking. The Pareto Frontier method for multi-attribute bridge project ranking incorporates multiple distinct decision variables into a single ranking metric. To effectively combine different attributes without introducing bias through subjectively assigned weights, non-dominated sorting is introduced. Non-dominated sorting [14], is a technique that organizes sets of attributes into various tiers of non-domination according to their Pareto optimality. This approach avoids biases introduced by subjectively chosen weights. The algorithm works by comparing each set of attributes with every other set and assigning it a level of non-domination based on its 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. Alternatives to this method include best order sort (which improves computational efficiency), rank-based non-dominated Sorting (which eliminates costly dominance comparisons), crowding distance (which fosters diversity), hypervolume indicator (which assesses convergence and diversity), and strength Pareto evolutionary algorithm (SPEA) (which ranks solutions based on dominance strength) [15–19]. Non-dominated sorting was selected over these alternatives in this study due to its ability to maintain a diverse set of high-quality solutions. This technique excels in problems with multiple conflicting objectives by ranking solutions based on Pareto dominance, ensuring no solution in a given rank is dominated by any other in the same rank.

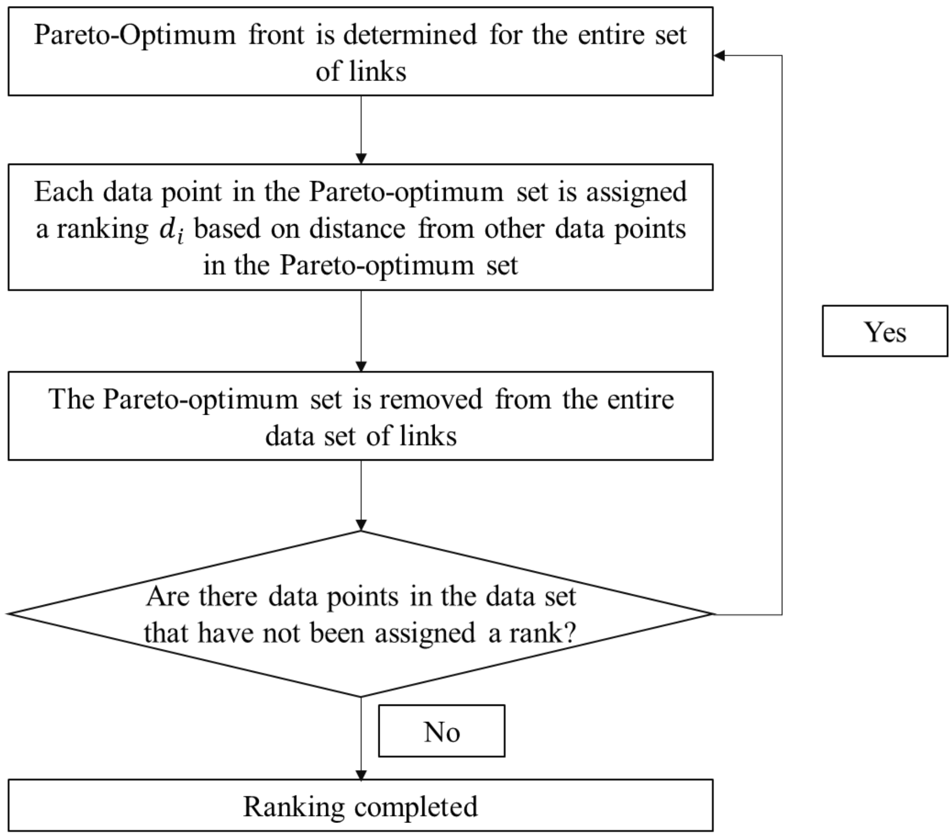


Figure 2. Overview of the Pareto Frontier ranking methodology

In the context of ranking of multiple bridges where each bridge has a set of n attributes, for each individual bridge B_i, its corresponding attributes are represented as $x_{1_i}, x_{2_i}, \ldots, x_{n_i}$. Here the attribute value maximization scenarios are considered (i.e., bridges with higher overall attribute values are ranked higher). A Pareto-optimum front is determined by identifying the set of non-dominated bridges, using the attributes for each bridge. In this process, first, an empty set is created for these non-dominated bridges. Then the attributes for each bridge are compared against the attributes of all the other bridges. A bridge B_i is considered to dominate another bridge B_k, if each attribute x_{r_i} is no worse than x_{r_k} and is strictly better in at least one of the attributes. If a bridge is not dominated by any other, it is added to the non-dominated set. Otherwise, any bridge that is dominated by another is not included in the non-dominated set. This process continues until all bridges have been examined, ensuring that no bridge in the non-dominated set is dominated by any other. The final set of non-dominated bridges represents the Pareto-optimal front. This is schematically illustrated in Figure 3, where a Pareto-optimal front for bridges with two attributes is shown on the red dashed line.

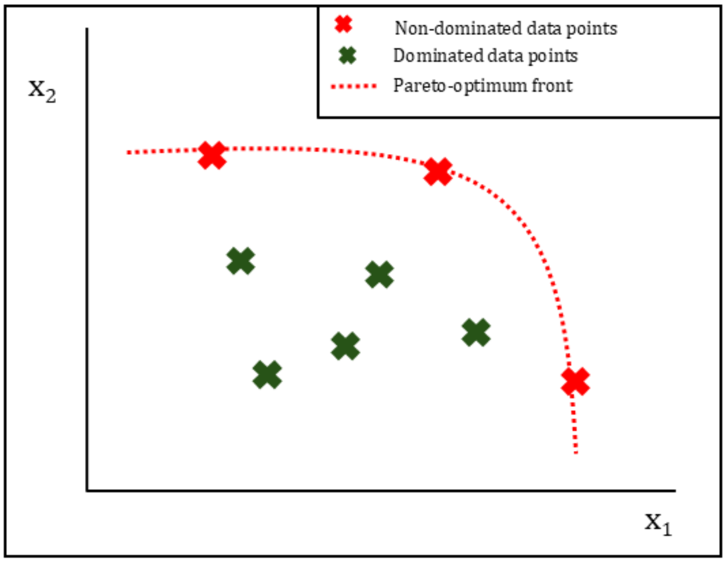


Figure 3. Pareto-optimal front for a two-dimensional set of attributes

Once the Pareto-optimum front is determined, the bridges in the front are given individual ranks based on their proximity to other bridges in the same front. For this purpose, the Euclidean distance is calculated based on each data point's attributes from each data point to every other data point. The sum of all such distances is calculated for each data point. Equation (1) shows the calculation of the summation of distances for bridge B_i.

$$d_i = \sqrt{\sum_{m=1}^{M}\left(\mathrm{x}_{mi} - \mathrm{x}_{mj}\right)^2} \qquad (1)$$

The bridges with the lowest distance sum are assigned the highest rank. This is because those data points will be closer to the middle of the Pareto-optimum front and will offer a good balance among all the attributes. Meanwhile, data points with a higher distance sum will be further away from the middle and may have extreme values for some of the attributes while having relatively low values for others. The most important data point in the network will have a rank value starting with 1, the next one will be 2, and so on.

Once all bridges in the current Pareto-optimum set have been assigned a rank, the data points of the Pareto-optimum front are removed from the overall bridge set. Then, the procedure is repeated on the remaining bridges to identify the next Pareto-optimum set and assign rank values to them. These rank values begin from where the rank values end in the previous set. For example, if the previous set of values ended with a rank value k, The current set would begin with rank $k + 1$.

In this study, the Pareto Frontier based ranking approach is introduced to systematically rank the initial set of bridge maintenance projects (from Step 2) based on multiple bridge- and project-specific attributes such as Q values, bridge system-level condition ratings, centrality measures, among others. This ranking approach is computationally efficient and can incorporate any number of parameters for ranking. It is important to note that bridges where the "do-nothing" actions are initially suggested for all three bridge components (i.e., deck, superstructure, and substructure) are excluded from the ranking process, as these bridges are considered to be in a satisfactory condition without the need for immediate interventions within the current decision step. Below is a brief introduction of the different bridge and project-specific attributes considered in the Pareto Frontier ranking approach. Note that all the considered ranking attributes are normalized between 0 to 1 prior to the Pareto-Frontier ranking to make sure no significant discrepancy exists in the attribute values.

1. Q values: Q values are the learned action-value function in the bridge-level AI policy, representing the long-term expected cumulative reward for taking a specific action combination under the current bridge conditions. Since the reward function was designed to be negative costs, the Q values are typically negative. At the bridge level, the action combination that leads to the lowest absolute expected life-cycle cumulative cost (i.e., the lowest -Q value) is selected among all the possible actions, as the bridge-level AI agent aims to minimize the long-term cumulative costs. When it comes to ranking multiple bridge projects at the network level, where each bridge already has their own optimal action and the associated Q value from the bridge-level AI agent, the projects with a higher -Q value, which reflects higher absolute life-cycle cumulative cost among all the bridge projects, are selected to be prioritized. Intuitively speaking, bridges with a higher -Q value likely have a larger deck area, higher ADT or truck traffic ratio, longer detour length, or inferior existing conditions, or any combination of these factors, and thus their

maintenance is chosen to be prioritized. As such, in the Pareto Frontier ranking, the negative Q values of each bridge are considered, and a higher -Q value is deemed more important as it reflects higher life-cycle costs. Note that the Q values are only exclusive to the AI policy, and are not available in other condition-based policies.

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.

4. Centrality measures: Centrality measures evaluate the importance of a bridge within the transportation network. Common metrics include betweenness centrality (quantifies how often a node appears on the shortest paths between other pairs of nodes), and closeness centrality (quantifies the importance of a node based on its average shortest distance to all other nodes), which can be commonly derived from graph theory and network connectivity information (for more details please see Appendix A). In the Pareto Frontier ranking, bridges with higher centrality measure values are deemed more important.

5. Travel time importance factor: This factor reflects the impact of closing a bridge on the overall road network travel time. Note that this factor will require detailed network-level traffic flow analyses (for more details please see Appendix A). In the Pareto Frontier ranking, bridges with higher travel time importance factors are deemed more important.

It is important to note that the centrality measures are relatively easy to compute. Whereas for the travel time importance factor will need network-level traffic flow analysis, hence more complex to calculate. Sensitivity analyses will be carried out in Section 4.1 and 4.2 to investigate the efficacy of involving different combinations of attributes in Pareto Frontier ranking.

2.4. Step 4: Budget allocation and resource constraints enforcement

Following the Pareto Frontier ranking process, the limited annual budget and resource are then allocated to the top ranked projects, so that those projects can be implemented as soon as possible. Specifically, the annual budget and resource allocation process proceeds as follows:

1. *Sequential Budget Allocation*: The annual maintenance budget is distributed progressively, starting from the highest-ranking bridge maintenance project and gradually moving down the ranking list. Each project's direct cost is deducted sequentially until the available annual budget is exhausted or insufficient to fully cover the next project.
2. *Selection of Top-Ranked Projects*: Following the sequential budget allocation, only the highest-ranked projects that are within the annual maximum number of allowable project limit will be approved for execution. These selected projects are then scheduled for implementation in the current decision cycle.
3. *Revised Actions for Unfunded Projects*: Any remaining projects that did not receive funding will have their maintenance actions revised to "do-nothing" for all three bridge components. This means that no intervention will be performed on these bridges for the current year, and their conditions will continue to evolve based on natural deterioration processes.

Once the final set of bridge maintenance projects has been determined based on the budget and maximum allowable projects, the corresponding maintenance actions are executed within the simulation environment. This step reflects the actual implementation of the selected interventions, updating the condition of each bridge based on the performed maintenance actions. The entire decision-making process is repeated annually throughout the planning time horizon (*T* years).

The proposed methodology introduces a robust and scalable network-level decision framework for bridge asset management, enabling efficient prioritization of interventions and optimized resource allocation. By systematically considering multiple bridge- and project-related attributes, the approach ensures that infrastructure investments yield the highest long-term benefits.

Table 1 presents a pseudo-code representation of the process for a structured overview of the proposed network-level decision framework. The pseudo-code outlines the key steps involved in prioritizing and selecting maintenance actions for a network of *N* bridges over a planning horizon of *T* years, demonstrating how the budget and resources are systematically allocated.

Table 1. Pseudo code of the proposed network-level budget and resource allocation

```
For a network of N Bridges and a planning horizon of T years
For i = 1: T (Loop over each year of the planning horizon)
    Reset annual available budget and number of allowable projects
    For j = 1: N (Loop over each bridge)
        Obtain the actions suggested by the considered bridge-level policy for bridge j
        Store the Q value, action, and direct cost for this bridge
    End
    Pareto Frontier ranking of the initial set of bridge projects
    Allocate the annual budget based on the bridge ranking and maximum allowable number
    of projects
    Change the actions to "do-nothing" for the rest of the bridges
    Execute the suggested actions on all the bridges and update their conditions accordingly
End
```

CHAPTER 3. 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 4. It is 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.

Based on the available NBI data for this bridge network, 4.8% (4 out of 83) bridges are in "Good" condition, 91.6% bridges (76 out of 83) are in "Fair" condition, and 3.6% (3 out of 83) bridges are in "Poor" condition as shown in Figure 5. The combined deck area of all bridges in the network (A_T) is 242,144 ft^2, serving as the basis for calculating maintenance costs and budget resource allocation as follows:

$$Annual\ budget = r_b \times C_d \times A_T \tag{2}$$

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, where any unused funds from the previous year are not carried forward to the following year, and (2) cumulative budget, where unused funds from the previous year are added to the next year's budget. A 30-year planning horizon is considered with a discount factor of 0.96 as outlined in Volume 1 for the life-cycle cost aggregation.

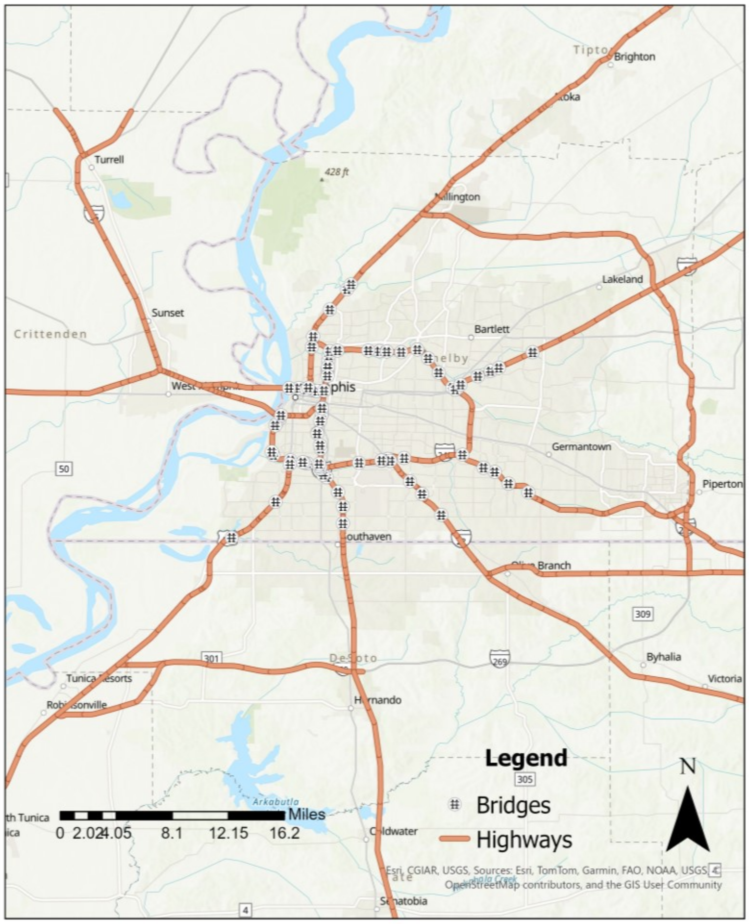


Figure 4. Case study bridge network located in Memphis, Tennessee

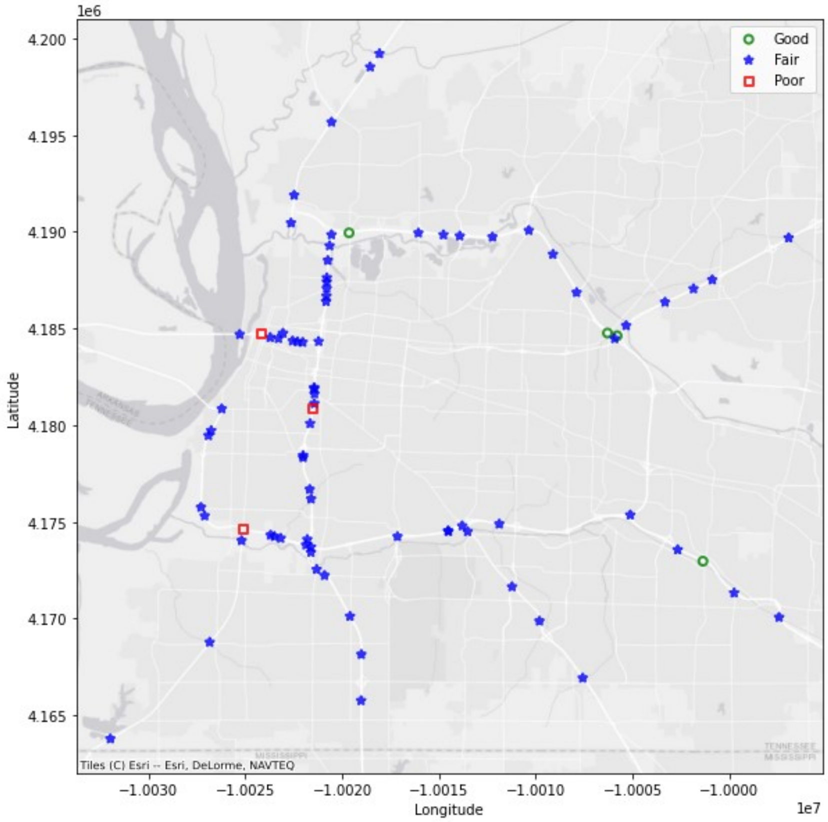


Figure 5. Bridge-level condition categories (i.e., “Good”, “Fair”, and “Poor”) of bridges in the case study network

To quantitatively evaluate the network-level asset management performance of various maintenance policies, several network-level performance measures are considered herein:

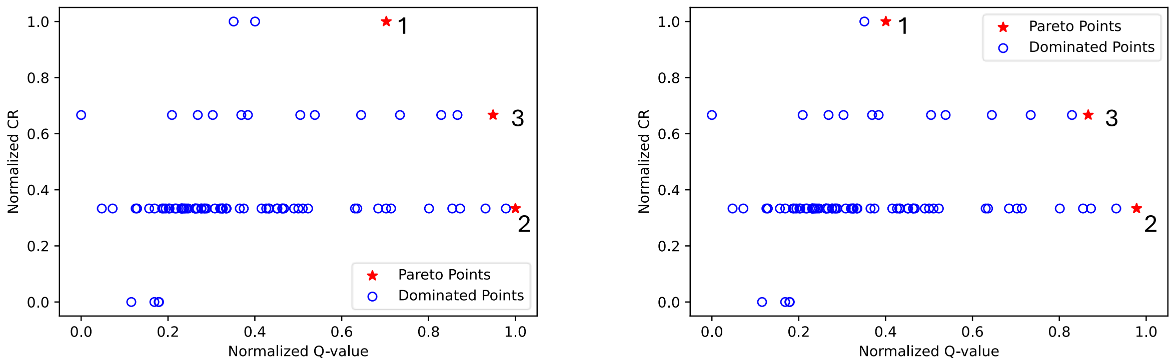
1. Aggregated direct cost: the aggregated direct costs from all individual bridges within the bridge network each year.
2. Aggregated indirect cost: the aggregated indirect costs from all individual bridges within the bridge network each year.
3. Average condition rating (by count) of bridge components (deck, superstructure, and substructure) across the entire network.
4. Distribution of bridges within different condition categories (“Good,” “Fair,” and “Poor”).
5. Network-level traffic flow performance measured by the network-level travel time, normalized against the first year’s travel time.

CHAPTER 4. RESULTS

In this section, a sensitivity analysis on the optimal Pareto Frontier ranking attributes is first conducted for the bridge-level maintenance policies (i.e., the condition-based policies and the AI-based policy) in the context of network-level decision making. This is needed because the selection of different ranking attributes may lead to different project ranking and prioritization results. Next, 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. Finally, an exemplary annual decision procedure is illustrated to help better understand how the bridge-level AI policy in conjunction with the network-level decision making can be utilized in practice. 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. All the subsequent results in Section 4.1 to 4.4 are based on statistics from 4,000 random episodes. Note that at the deployment phase, since the AI policy has already been trained, a lower number of episodes (compared to training) are needed to obtain the result statistics.

4.1. Pareto Frontier based project ranking demonstration

To demonstrate project ranking using the Pareto Frontier methodology, a case study network is examined to assess how this approach iteratively ranks bridges. In this analysis, two attributes, the Q-value and system-level CR, serve as inputs for the Pareto Frontier methodology to rank the selected bridges. **Figure 6**(a) illustrates the first iteration, where three Pareto-optimal points (bridges) are identified and ranked, while the remaining bridges are classified as dominated. In the second iteration, shown in **Figure 6**(b), the previously identified Pareto-optimal points are removed, and three new Pareto-optimal bridges are ranked. Pareto points represent solutions where no other solution improves one objective without worsening at least one other objective (i.e., they are not dominated by any other solution). Dominated points, on the other hand, are solutions that are inferior to at least one Pareto-optimal point across all objectives. Any point below the Pareto front is considered a dominated point, indicating that better solutions exist. The results of the first two iterations are summarized in **Table 2**. This iterative process continues until all bridges are assigned a rank.



(a) (b)

Figure 6. Pareto Frontier optimization process demonstration for the case study bridges network: (a) iteration 1, (b) iteration 2

Table 2. Pareto Frontier project-based ranking demonstration

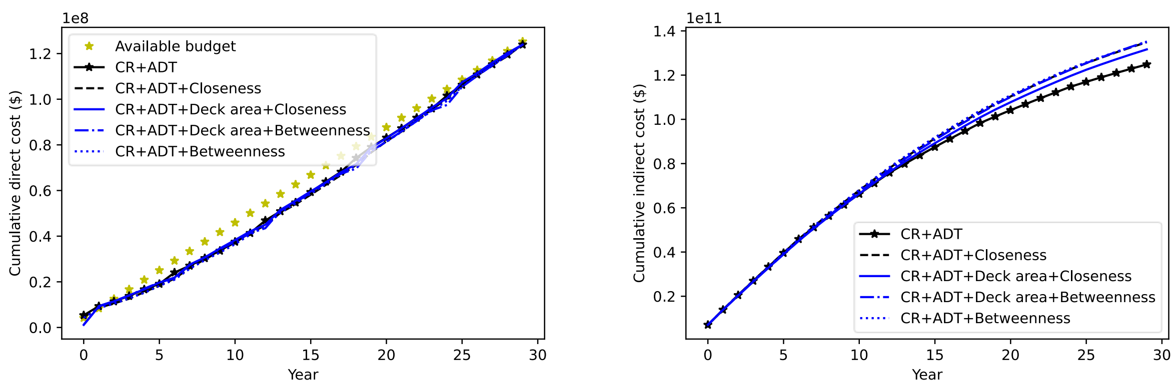
Iteration number	Bridge ID	Within-iteration ranking	Final ranking
1	14	1	1
	61	2	2
	52	3	3
2	51	1	4
	72	2	5
	1	3	6

4.2. Sensitivity analysis of Pareto Frontier attributes selection for the condition-based policies

In this section, a sensitivity analysis is conducted to evaluate different combinations of Pareto Frontier ranking attributes when the condition-based bridge-level maintenance policies are considered for network-level decision making. Without loss of generality, $r_b = 0.01$ (1% annual budget ratio) with cumulative budget for the CB-3 policy (as outlined in Volume 1, Chapter 4) is considered. To assess the impact of various ranking attribute combinations, five different combinations of independent bridge-level attributes are considered:

1. Bridge-level condition rating (CR), average daily traffic (ADT)
2. Bridge-level condition rating CR, ADT, and closeness centrality
3. Bridge-level CR, ADT, and betweenness centrality
4. Bridge-level CR, ADT, deck area, and closeness centrality
5. Bridge-level CR, ADT, deck area, and betweenness centrality

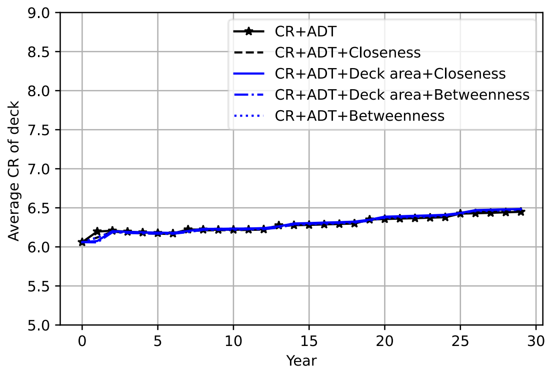
Figure 7 illustrates the impact of ranking attribute selection on the average network-level direct and indirect costs. It should be noted that the network-level direct and indirect costs are simply based on aggregating the costs from each individual bridge without considering the networked effects (e.g., traffic flow). From Figure 7(a), it is observed that the combination of "bridge-level CR, ADT, deck area, and closeness centrality" can better consume the available budget, with the smallest gap with respect to the available budget envelop. From Figure 7(b), the selection of ranking attributes has a negligible effect on the overall indirect costs, although the combination of bridge-level CR and ADT results in slightly lower indirect costs.

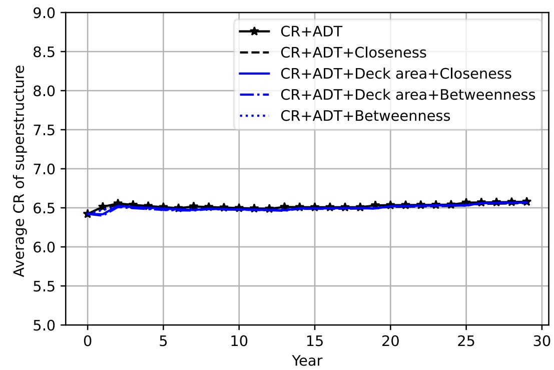


(a) (b)

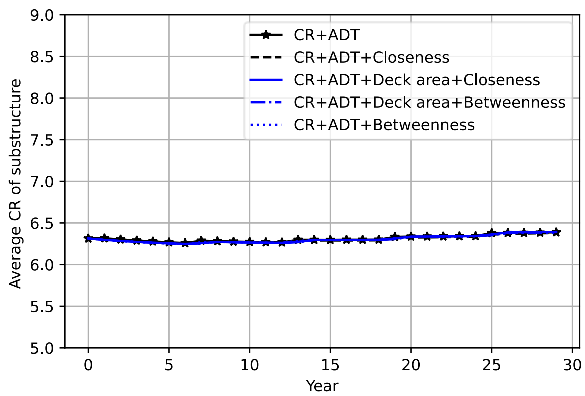
Figure 7. Average aggregated costs across the network under the CB-3 policy: (a) direct cost, (b) indirect cost

The average component CR across the network under the CB-3 policy is compared in **Figure 8**. It can be observed that all attribute combinations prevent the deterioration of CR for all three bridge components, following a similar trend.





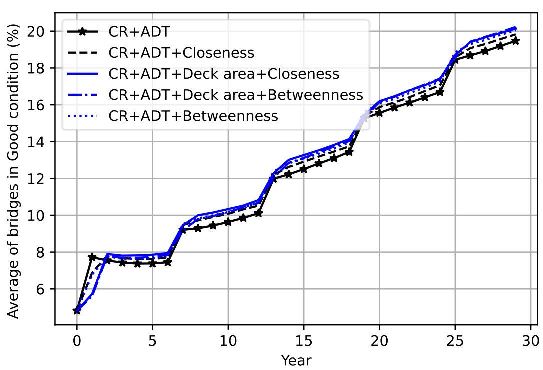
(a) (b)

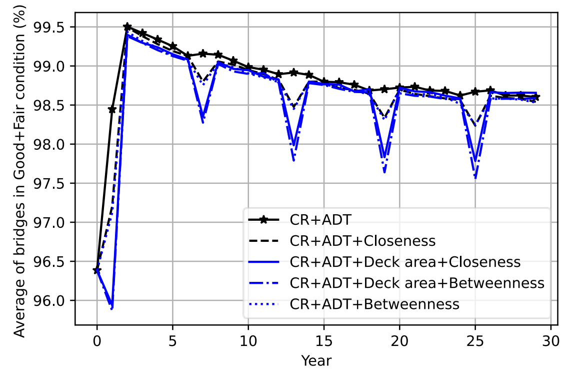


(c)

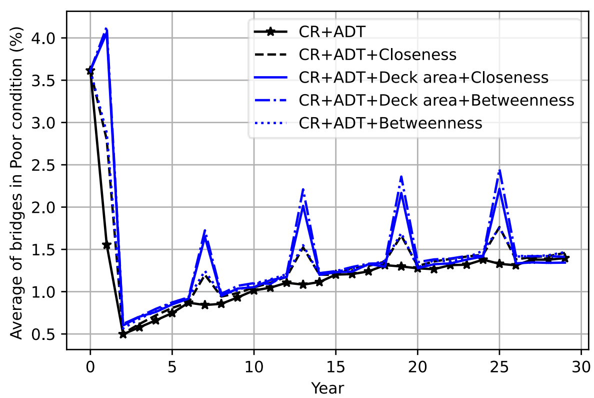
Figure 8. Average component condition rating across the network over the planning horizon under CB-3 policy: (a) deck, (b) superstructure, (c) substructure

In addition, Figure 9 illustrates the percentage of bridges under different bridge-level conditions. Overall, the attribute combination of "bridge-level CR, and ADT" gives the best overall asset condition, with higher percentage of bridges in "Good" or "Fair" conditions, and the least amount of bridge in "Poor" conditions. A sharp decline in the number of bridges in poor condition is noticed as shown in Figure 9(c). This is because initially there are three poor-condition bridges in the network, requiring the condition-based policy to immediately take replacement maintenance actions to improve their condition ratings.





(a) (b)



(c)

Figure 9. Average percentage of bridges across different condition categories under the CB-3 policy: (a) Good, (b) Good+Fair, and (c) Poor

Figure 10 presents the average network-level travel time (relative to the first year) when CB-3 is employed. Again, the attribute combination of "bridge-level CR, and ADT" gives the overall lowest network-level travel time among the different attribute combinations.

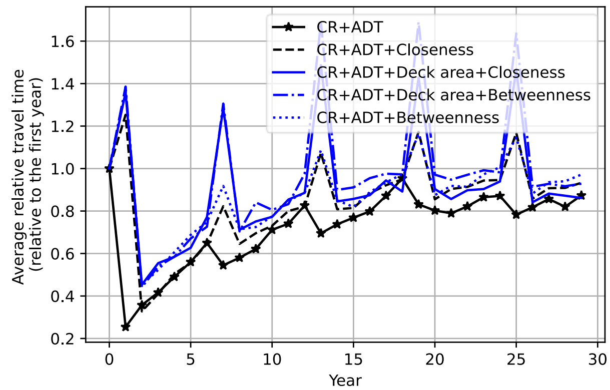


Figure 10. Average network-level travel time under the CB-3 policy

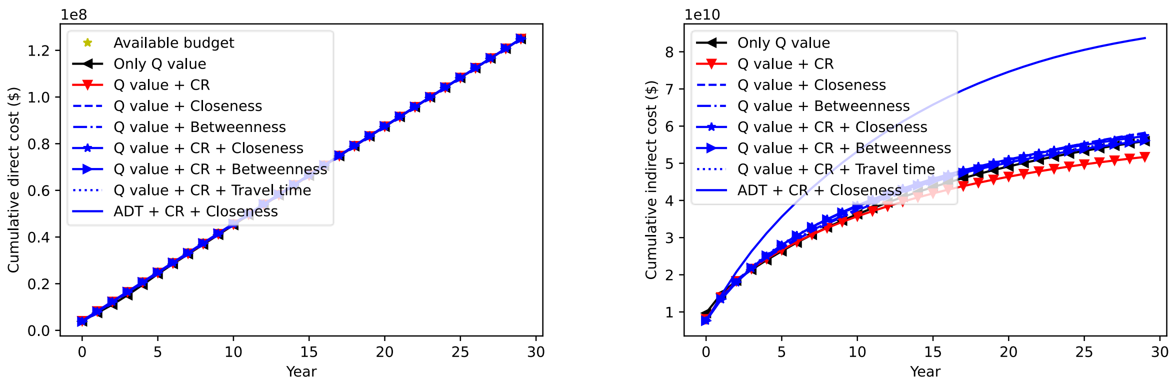
Based on the above results, the attribute combination of "bridge-level CR, and ADT" is selected for the condition-based policies in the subsequent sections, as the centrality measure did not provide significant benefits despite requiring additional computational effort.

4.3. Sensitivity analysis of Pareto Frontier attributes selection for the AI-based policy

This section presents the Pareto Frontier ranking attribute sensitivity analysis when the AI-based policy is considered in network-level decision making. To this aim, the P-PERDQN AI policy developed in Volume 1, Chapter 4 is employed. Again, a 1% annual budget ratio with the cumulative budget scenario is considered. The following attribute combinations are considered:

1. *Q* value only
2. *Q* value, bridge-level CR
3. *Q* value, closeness centrality
4. *Q* value, betweenness centrality
5. *Q* value, bridge-level CR, closeness centrality
6. *Q* value, bridge-level CR, betweenness centrality
7. *Q* value, bridge-level CR, travel time importance factor
8. Bridge-level CR, ADT, deck area, and closeness centrality

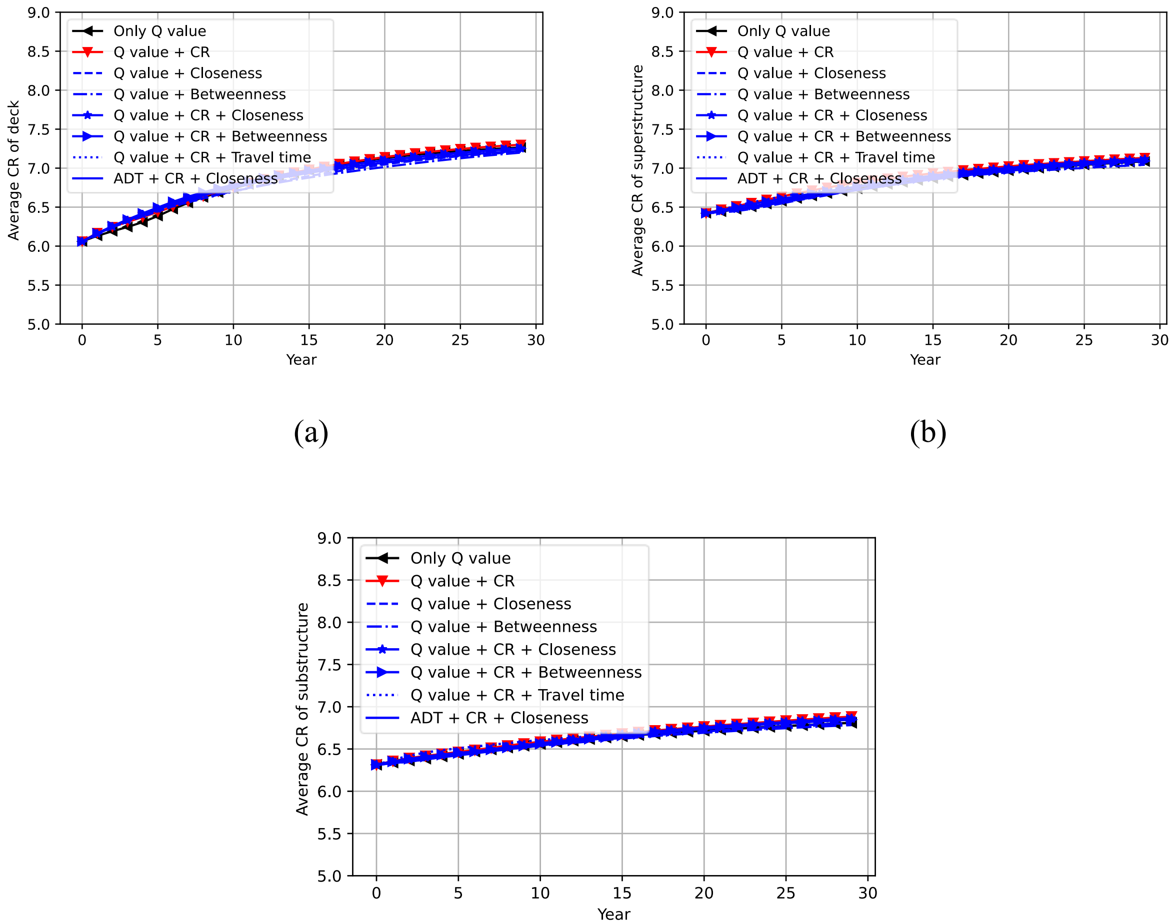
Figure 11 illustrates the associated network-level aggregated direct and indirect costs for each attribute combination. Figure 11(a) shows that the AI-based policy can effectively utilize the available budget, regardless of the ranking attributes selection. As shown in Figure 11(b), when *Q* value is included in the ranking attributes, lower network-level indirect costs can be expected.



(a) (b)

Figure 11. Average aggregated costs across the network under the AI-based policy: (a) direct cost, (b) indirect cost

The average component CR across the network under the AI-based policy is compared in **Figure 12**. It can be observed that all attribute combinations effectively improve the CR for all three bridge components, following a similar trend.

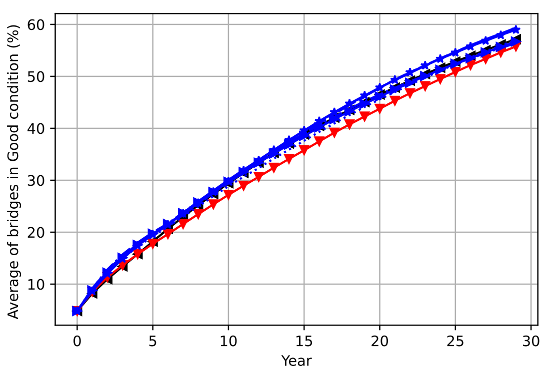


(a) (b)

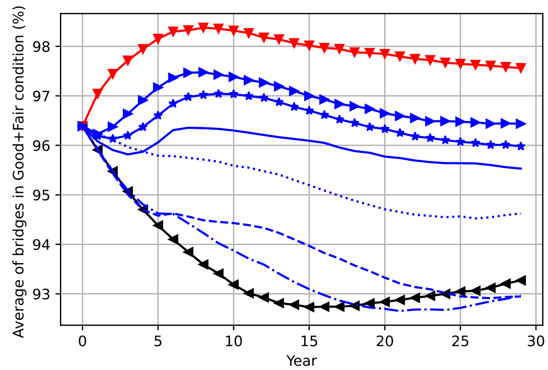
(c)

Figure 12. Average component condition rating across the network over the planning horizon under AI-based policy: (a) deck, (b) superstructure, (c) substructure

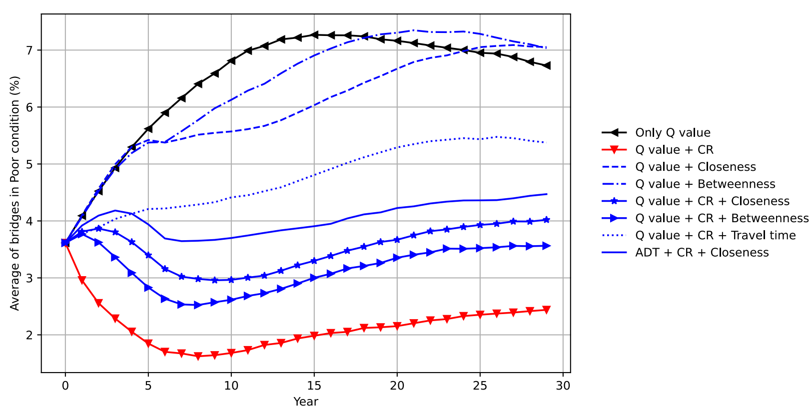
In addition, Figure 13 illustrates the average percentage of bridges under different condition categories. It is observed that for the attribute combinations which include the *Q* value but without bridge-level CR, there are relatively lower percentages of bridges in the "Good" or "Fair" conditions, and a higher percentage of bridge in the "Poor" conditions. When both *Q* values and bridge-level CR are considered, a noticeable improvement in bridge conditions can be obtained. This is because the bridge-level condition ratings focus on the near-term asset performance, whereas the *Q* values represent the long-term cumulative effects. As such, by including both the *Q* values and bridge-level CR in the ranking attributes, better bridge asset conditions can be expected. Overall, the attribute combination of "*Q* value and CR" gives the best network-level bridge conditions, with the highest percentage of bridges in “Good” or “Fair” conditions, and the lowest percentage of bridges in the “Poor” condition among all combinations involving Q-values.



(a)



(b)



(c)

Figure 13. Average percentage of bridges across different condition categories under AI-based policy: (a) Good, (b) Good+Fair, and (c) Poor

Figure 14 presents the average network-level travel time under different ranking attribute combinations. It is observed that the attribute combination of “*Q* value and CR” performs the best among all the compared attribute combinations.

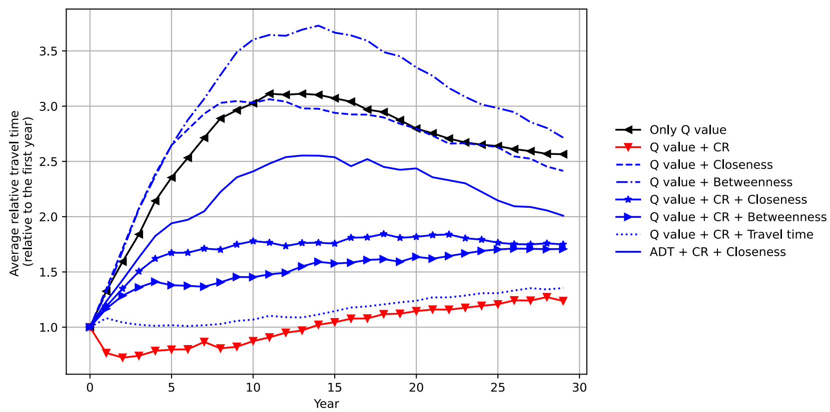


Figure 14. Average network-level travel time under the AI-based policy

Based on all the previous results in this subsection and also by considering the ease of ranking attribute calculation, the attribute combination of "*Q* value and bridge-level CR" gives the best overall performance. Therefore, the attribute combination of "*Q* value, and bridge-level CR" is considered thereafter. This attribute combination holistically incorporates and balances the long-term cumulative reward (*Q* value), and the short-term target (bridge conditions).

4.4. Network-level asset management comparison

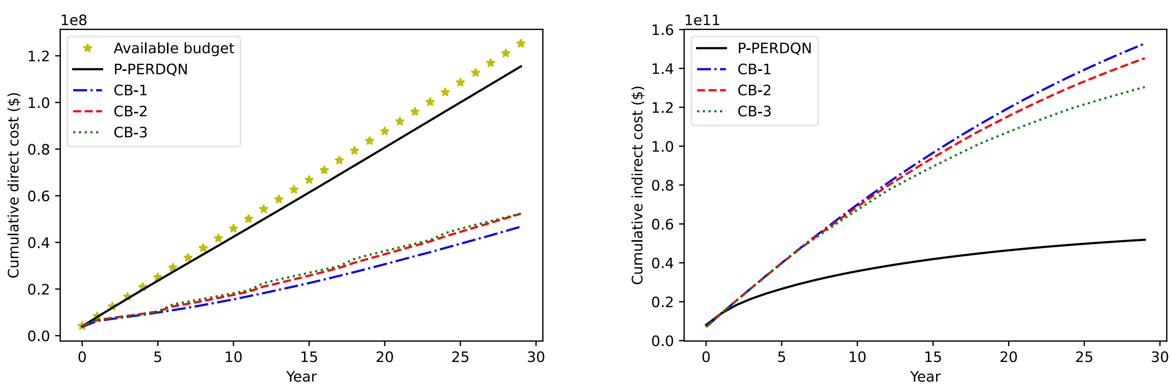
In this section, the influence of bridge-level maintenance policies on network-level asset management performance is evaluated. The bridge-level maintenance policies considered include the AI-based policy (i.e., P-PERDQN) and the condition-based policies (i.e., CB-1, CB-2, and CB-3), as mentioned in Volume 1, Chapter 4. According to Section 4.3, the Pareto Frontier ranking attributes of "*Q* value and bridge-level CR" are considered for the AI-based policy; and the ranking attributes of "bridge-level CR and ADT" are considered for the condition-based policies as discussed in Section 4.2.

In this comparative study, different annual maintenance budget availability, expressed as the ratio of the total replacement value of the bridge assets, is considered. Three levels of annual budget ratio (i.e., 0.5%, 1%, and 2%) [20] 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 and network performance, under budgetary and resource constraints.

4.4.1. 1% annual budget ratio with non-cumulative budget

4.4.1.1. Network-level asset management performance comparison

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 15(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 15(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.

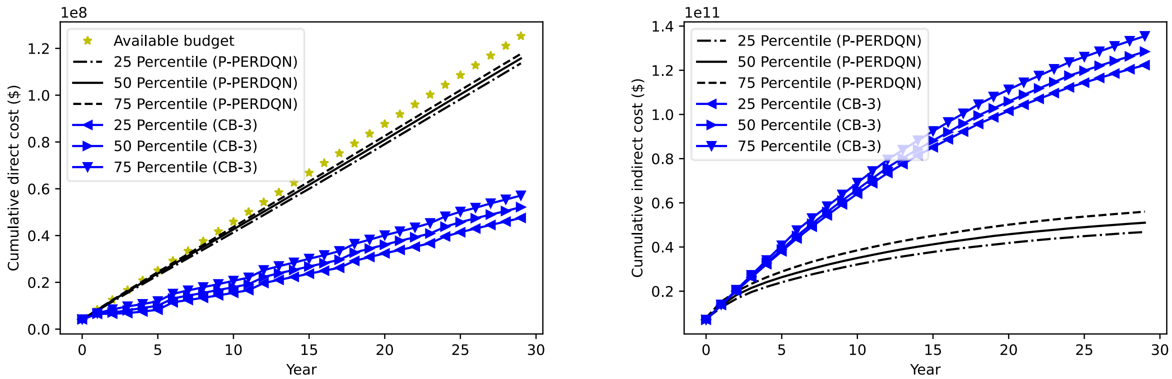


(a) (b)

Figure 15. Average aggregated costs across the network under various maintenance policies (1% non-cumulative budget): (a) direct cost, (b) indirect cost

Figure 16 compares the 25th, 50th, and 75th percentiles of aggregated direct and indirect costs for the AI-based and CB-3 policies, highlighting the superior performance of the AI-based policy compared to the condition-based policy in terms of cost dispersion across various time points. The

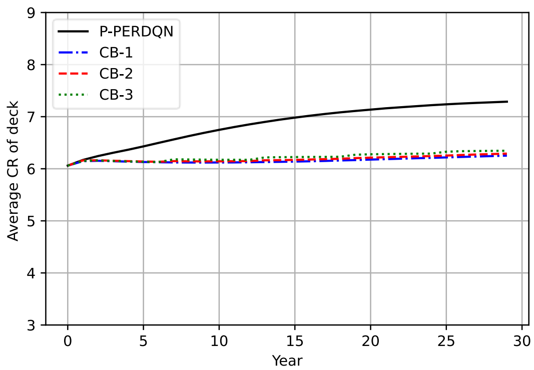
AI-based policy demonstrates greater consistency and reduced variability in both direct and indirect costs, underscoring its effectiveness in maintaining cost efficiency over time.

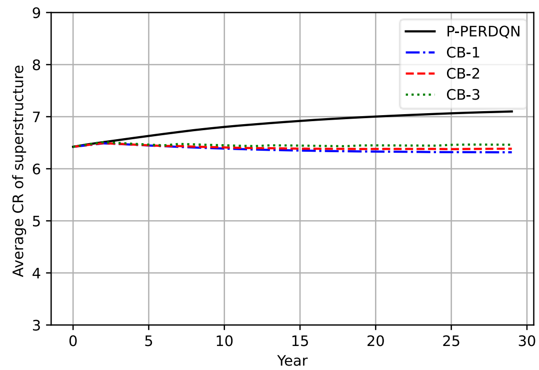


(a) (b)

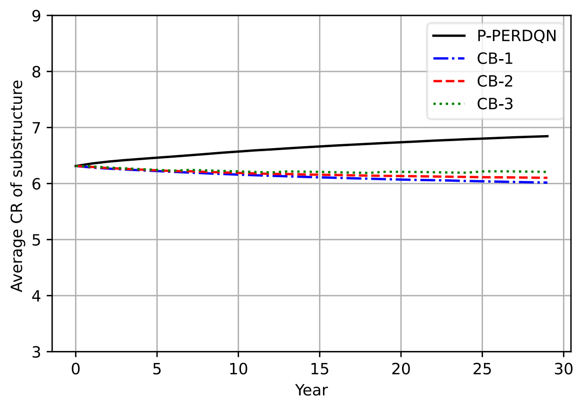
Figure 16. Percentiles of aggregated costs across the network under various maintenance policies (1% non-cumulative budget): (a) direct cost, (b) indirect cost

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 17. 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.





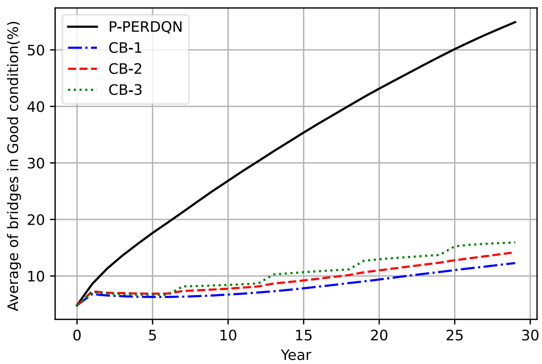
(a) (b)



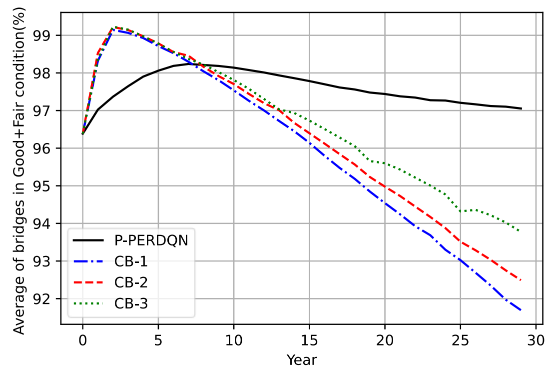
(c)

Figure 17. Average component condition rating across the network (1% non-cumulative budget): (a) deck, (b) superstructure, (c) substructure

Figure 18 provides further insights into the average proportion of bridges in "Good," "Fair," or "Poor" conditions. These results clearly show that the AI policy has a much better performance compared to the condition-based policies, with the highest percentage of bridges in "Good" or " Fair" conditions, and the lowest percentage of bridges in "Poor" condition. This suggests that the AI-based policy is more effective in maintaining bridge conditions across the network.



(a)



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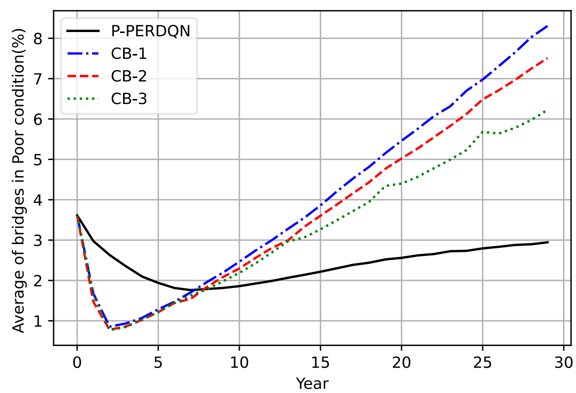


(c)

Figure 18. Average percentage of bridges across different condition categories (1% non-cumulative budget): (a) Good, (b) Good+Fair, and (c) Poor

The above results only focus on the aggregated or average asset management performance across all the individual bridges in the network, whereas the bridge network functionality in the context of network topology and traffic impact is yet to be examined. Here, the influence of bridge-level maintenance policy on the network travel time is further studied as shown in Figure 19. Again, the AI-based policy exhibits the best overall performance in terms of reducing the network travel time compared with other condition-based policies.

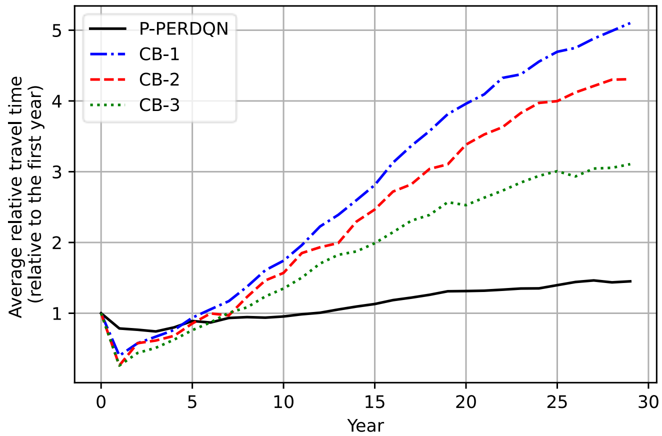
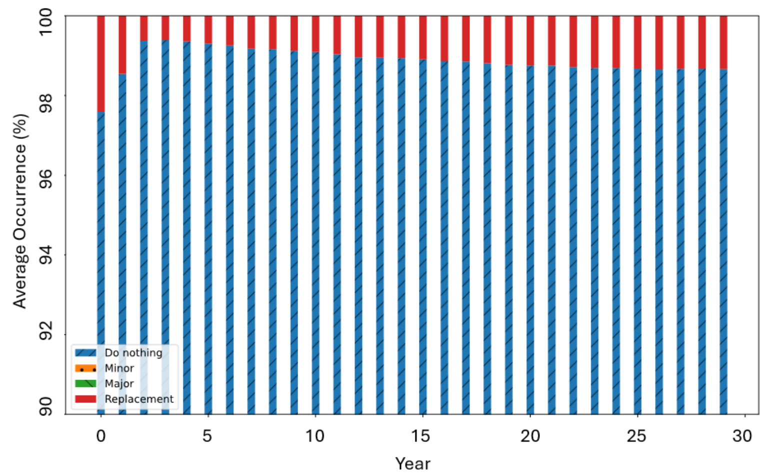


Figure 19. Average network-level travel time under various maintenance policies (1% non-cumulative budget)

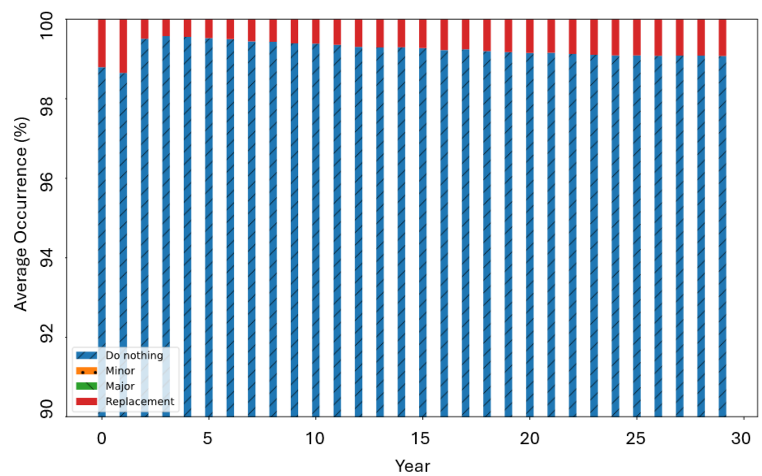
4.4.1.2. Work type distribution comparison

Addtional analysis is conducted to examine the annual distribution of work types (i.e., do-nothing, minor maintenance, major maintenance, and replacement) across the bridge network under different bridge-level maintenance policies. By evaluating the work type distributions, the efficiency and effectiveness of each policy in addressing the maintenance needs of the bridge network throughout the planning horizon is investigated.

Figure 20 presents the annual work type distribution for the three bridge components with 1% non-cumulative budget scenario under the CB-1 policy. As observed, replacement (which is the only available maintenance action under the CB-1) occurs for a small portion of the bridges in the network each year, due to the high direct cost of replacement actions.



(a)



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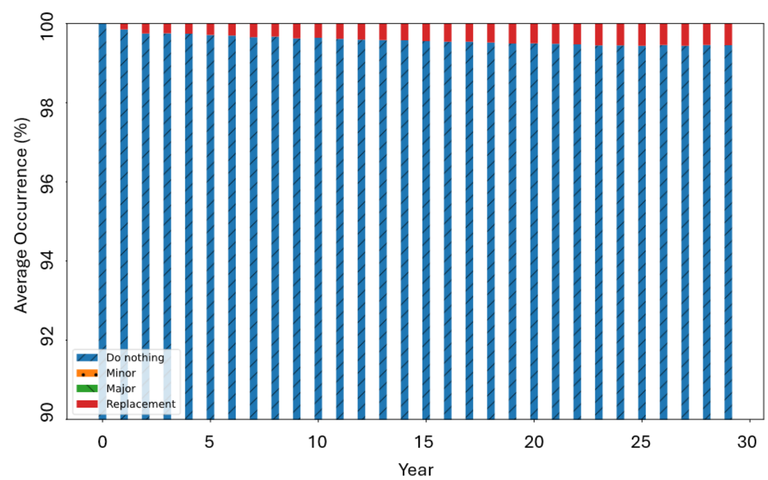
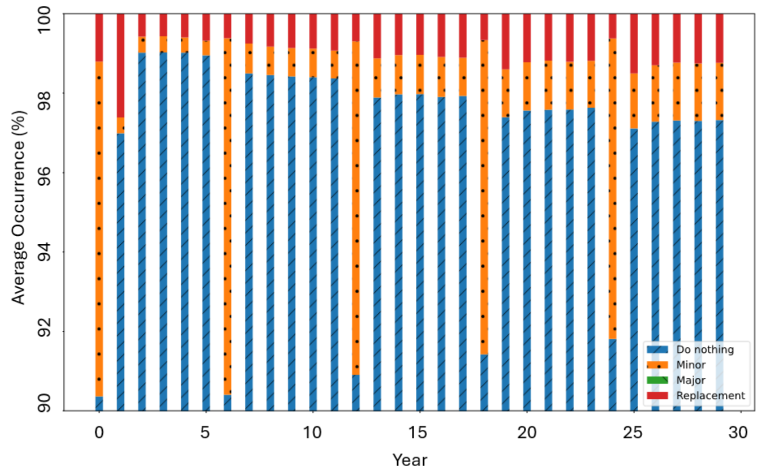


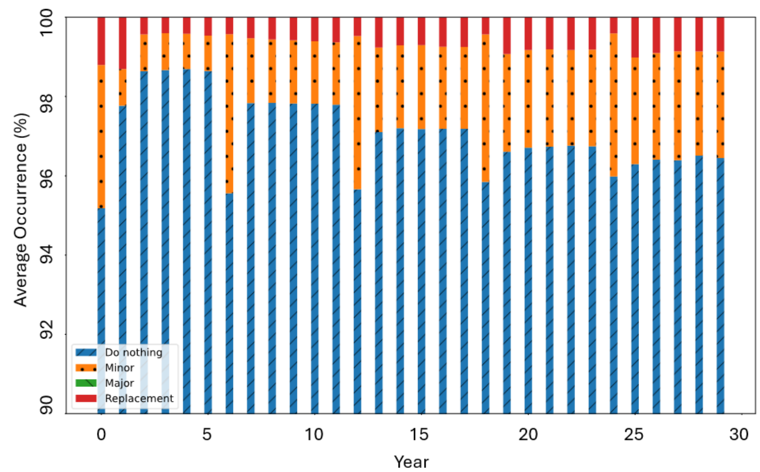
(c)

Figure 20. Annual work type distribution for bridge components under the CB-1 policy (1% non-cumulative budget): (a) deck, (b) superstructure, and (c) substructure

Figure 21 presents the work type distribution for the CB-2 policy, where only the minor maintenance and replacement are the possible actions. As observed, minor maintenance is predominantly suggested to preserve the condition of bridge components. Additionally, a noticeable increase in the number of bridges maintained occurs every five years due to the action constraints (i.e., for a given bridge, no consecutive actions on the same bridge component within 5 years) provided in Volume 1, Chapter 4. Such a clustering of maintenance projects in a single year will likely lead to shortages of maintenance crews and increased traffic congestion.



(a)



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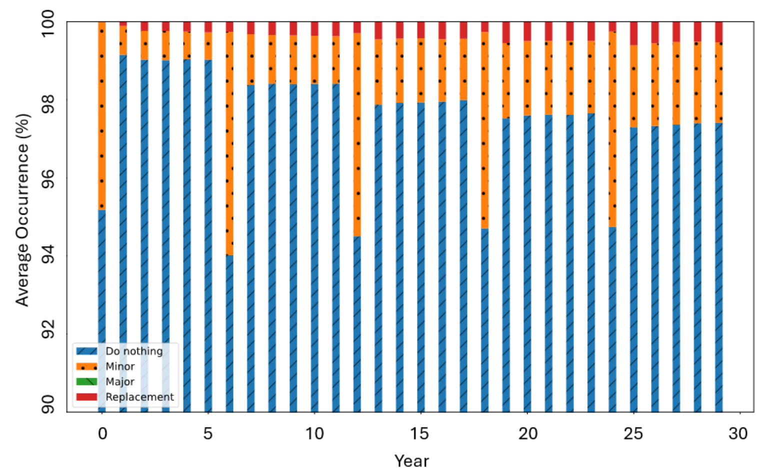
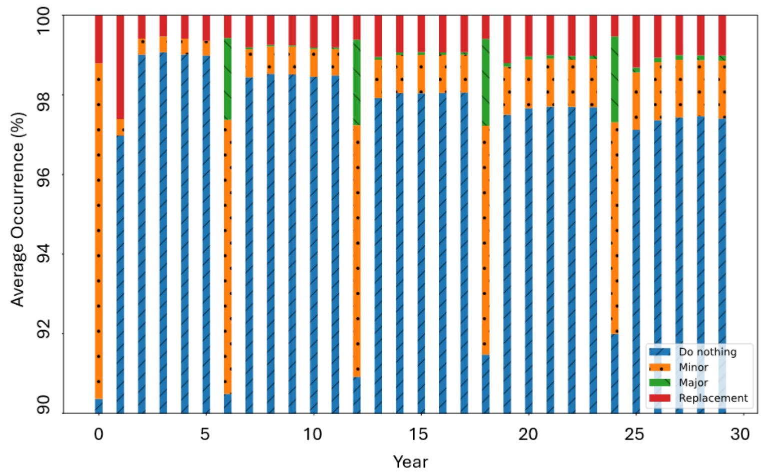


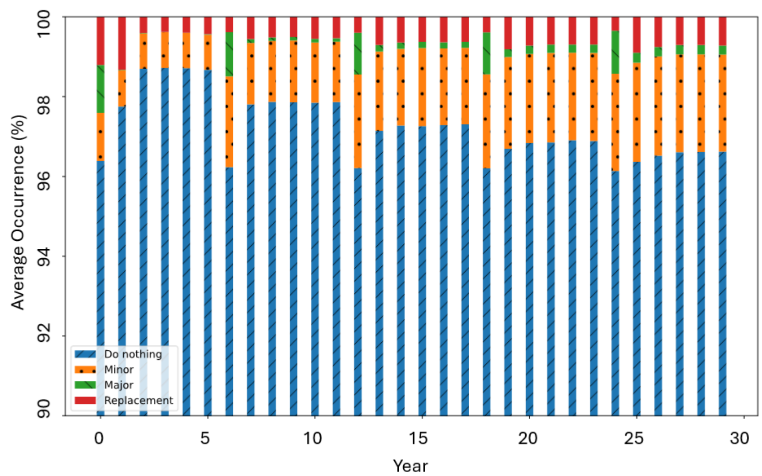
(c)

Figure 21. Annual work type distribution for bridge components under the CB-2 policy (1% non-cumulative budget): (a) deck, (b) superstructure, and (c) substructure

Figure 22 illustrates the work type distribution for CB-3 with 1% non-cumulative budget scenario. As observed, the distribution is not uniform, with a noticeable increase in the number of maintained bridges every five years. Among the three possible maintenance actions, minor maintenance is the most frequently performed, especially on the deck component.



(a)



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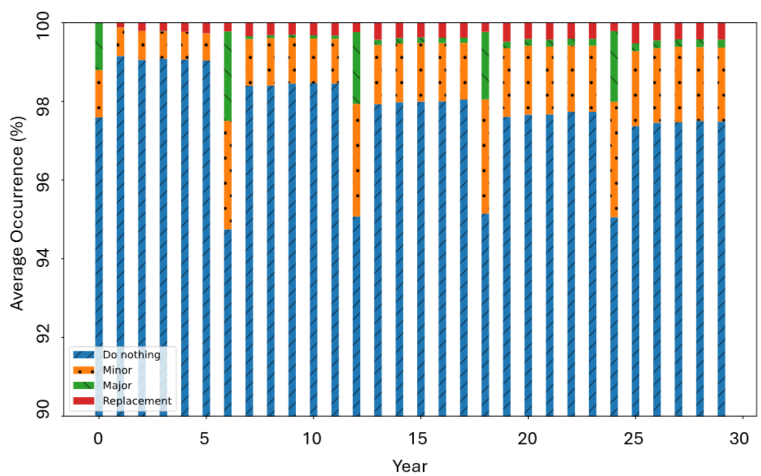
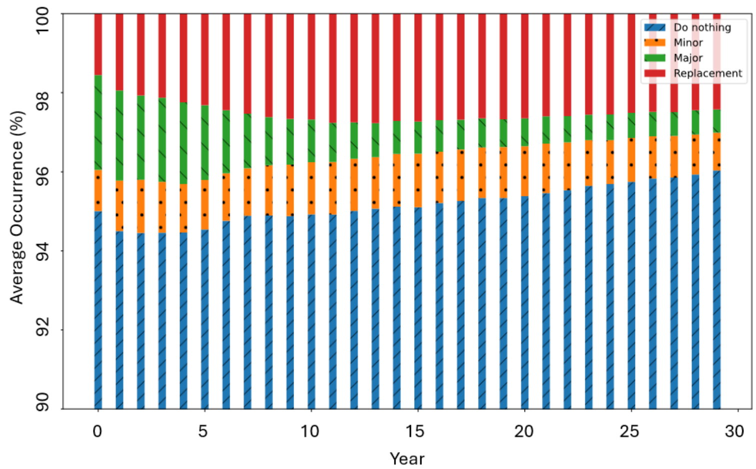


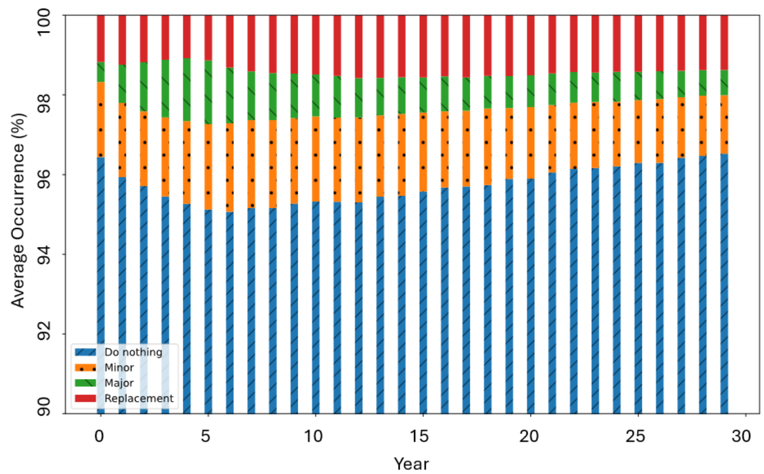
(c)

Figure 22. Annual work type distribution for bridge components under the CB-3 policy (1% non-cumulative budget): (a) deck, (b) superstructure, and (c) substructure

Finally, Figure 23 presents the average work type distribution under the AI-based policy. Compared with the above condition-based policies, the AI-based policy achieves a well-balanced work type distribution, and the annual number of maintenance actions are more evenly spread across the whole planning horizon for all bridge components. It is also noticed that the AI policy tends to suggest more major maintenance and replacement actions, which are more effective in preserving or improving the asset conditions over time. This approach effectively leverages the various types of maintenance actions (minor, major, and replacement), ensuring a more consistent and proactive management strategy for bridge networks.



(a)



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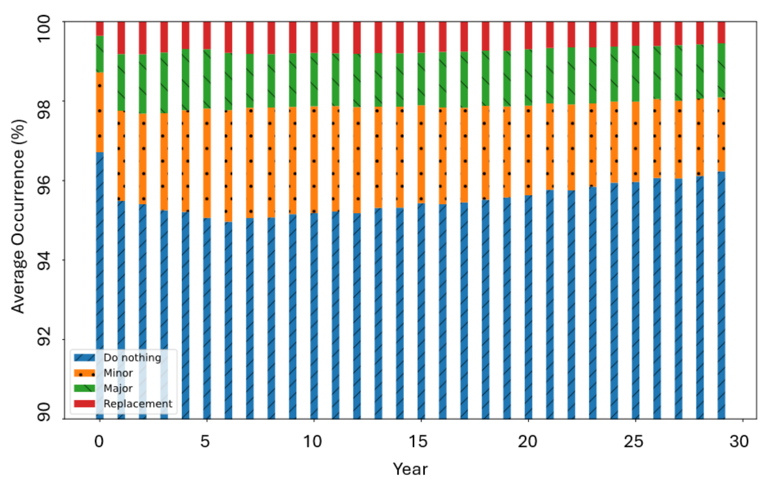


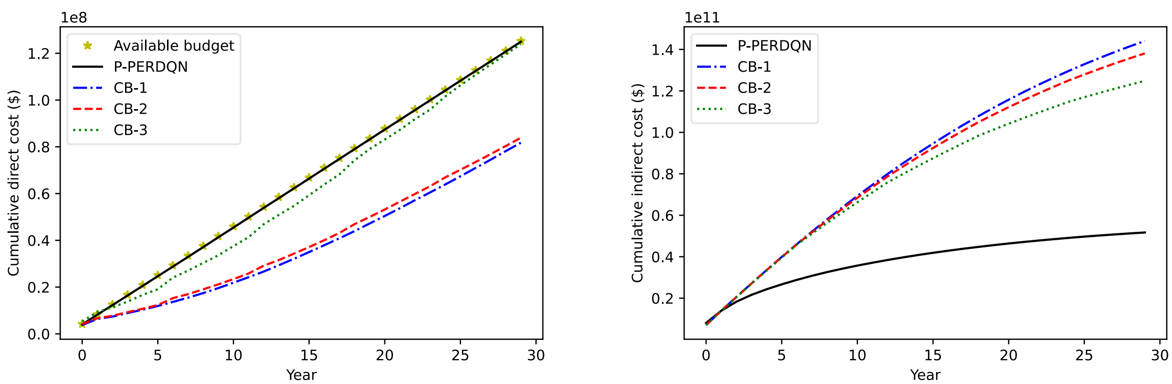
(c)

Figure 23. Annual work type distribution for bridge components under the AI-based policy (1% non-cumulative budget): (a) deck, (b) superstructure, and (c) substructure

4.4.2. 1% annual budget ratio with cumulative budget

4.4.2.1. Network-level asset management performance comparison

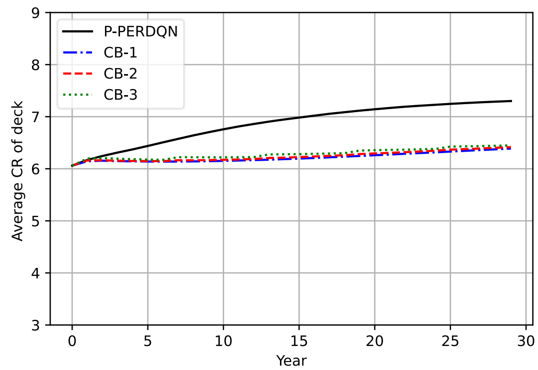
In this subsection, the network-level bridge asset management performance is investigated considering an annual budget ratio of 1% with the cumulative budget assumption. The aggregated direct and indirect costs are first examined in Figure 24. Figure 24(a) indicates that the AI-based policy effectively utilizes the entire available budget, while the CB-3 policy uses slightly less than the AI-based policy but more than the other condition-based policies, which show noticeable budget underutilization. Figure 24(b) shows that the AI-based policy leads to significantly lower aggregated indirect costs compared to the condition-based policies.



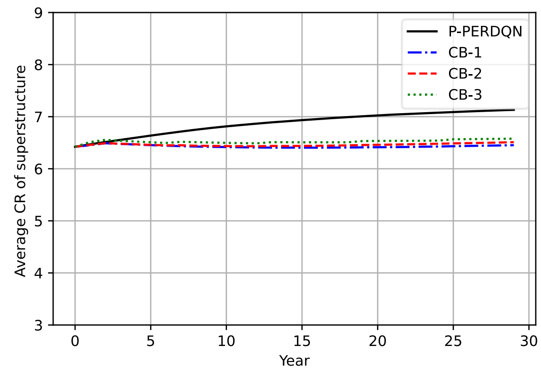
(a) (b)

Figure 24. Average aggregated costs across the network under various maintenance policies (1% cumulative budget): (a) direct cost, (b) indirect cost

The average component CR over the bridge network is examined in Figure 25. It is observed that the AI-based policy leads to a continuous improvement in CR, constantly ensuring a higher bridge condition over time. In contrast, the condition-based policies lead to relatively stagnant and lower CR values, indicating their limited effectiveness in preserving or improving asset conditions.



(a)



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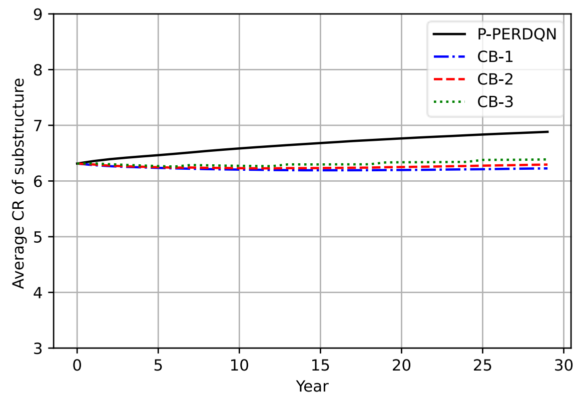
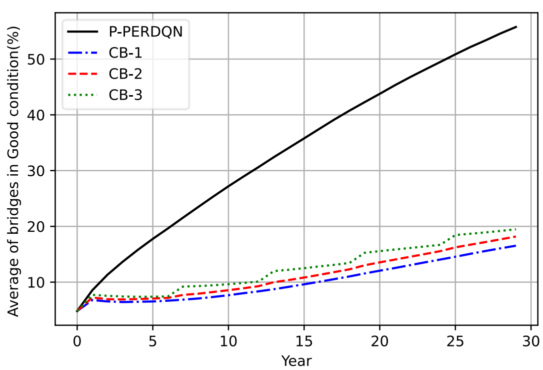


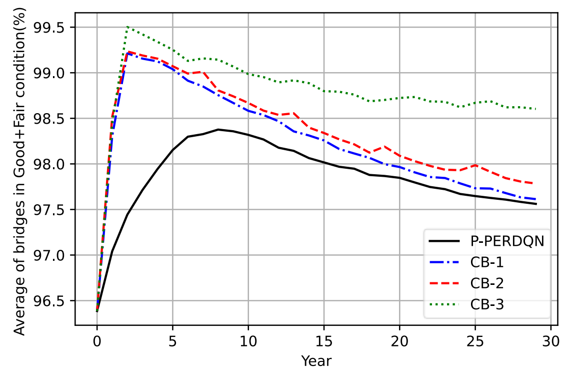
(c)

Figure 25. Average component condition rating across the network over the planning horizon (1% cumulative budget): (a) deck, (b) superstructure, (c) substructure

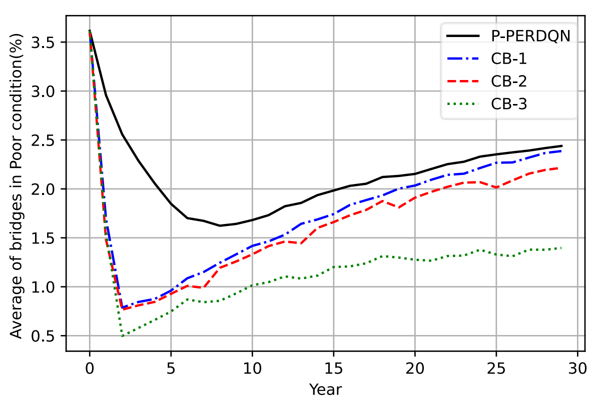
The bridge condition category distribution across the network is further presented in Figure 26. Figure 26(a) shows the AI-based policy demonstrates a noticeable improvement in "Good" condition, with approximately 60% of bridges reaching the "Good" condition by the end of the planning horizon. In contrast, the condition-based policies result in a much slower increase, maintaining a lower percentage of bridges in "Good" condition throughout the planning horizon. Figure 26(b) illustrates that the AI-based policy and the condition-based policies show the same performance for percentage of "Good" or "Fair" condition. Figure 26(c) demonstrates that, the condition-based policies are more effective in reducing the "Poor" condition bridges in this case. This is because a very limited annual budget (1% annual budget ratio) is considered along with the cumulative budget assumption in this subsection. When the AI-based bridge-level policy is considered, due to its higher action variability and granularity, smaller projects will more likely to be prioritized when those higher-cost and higher-ranked projects cannot be implemented due to the insufficient budget. Therefore, it takes a longer time for the AI-based policy to save up enough budget for those larger projects. Whereas for the condition-based policies, since the ranking attributes (i.e., bridge-level CR, and ADT) used in the Pareto Frontier ranking did not include any measure related to long-term benefits, the condition-based policies will prioritize more on those "Poor" condition bridges. Moreover, since there is less action variability or granularity in the initial set of suggested projects when condition-based policies are considered, those larger projects (e.g., replacement) will have a higher chance to be implemented since the budget can be accumulated more quickly.



(a)



(b)



(c)

Figure 26. Average percentage of bridges across different condition categories (1% cumulative budget): (a) Good, (b) Good+Fair, and (c) Poor

Moreover, Figure 27 compares the network-level travel time under different maintenance policies. CB-3 is found to lead to the lowest travel time among all the policies compared. This can be attributed to the fact that under this budget scenario, CB-3 is more effective in addressing the "Poor" condition bridges, which tend to have the most impact on the network-level travel time for the skeleton highway network considered in this case study. Nevertheless, the AI policy performs also reasonably well.

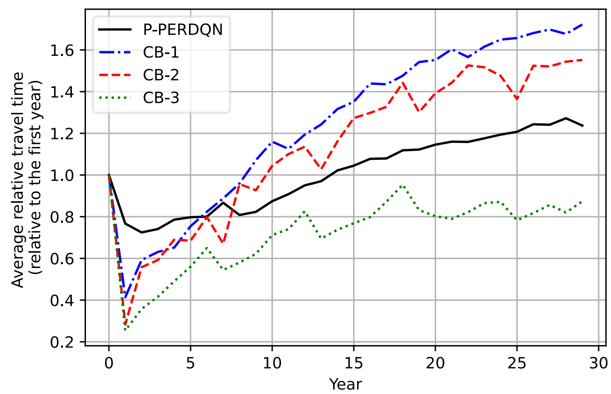
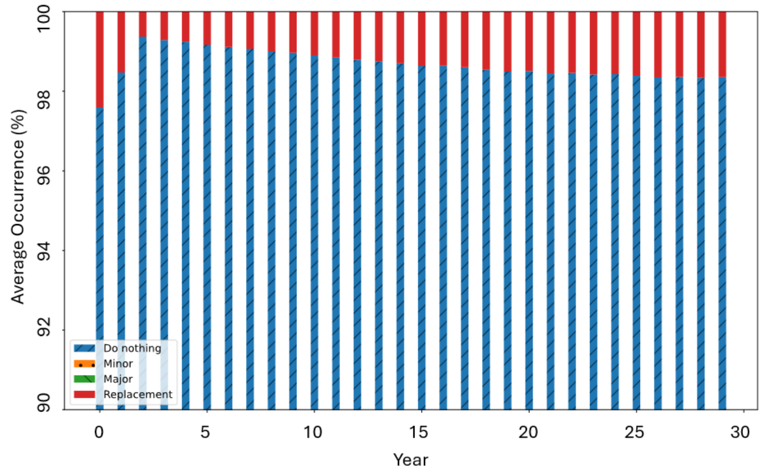


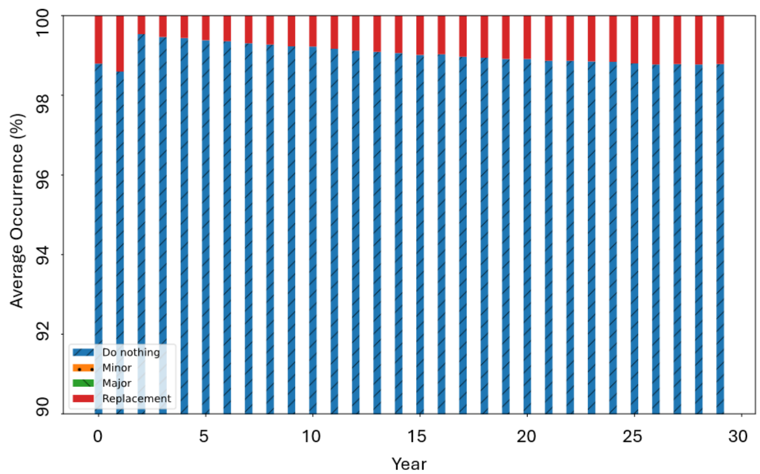
Figure 27. Average network-level travel time under various maintenance policies (1% cumulative budget)

4.4.2.2. Work type distribution comparison

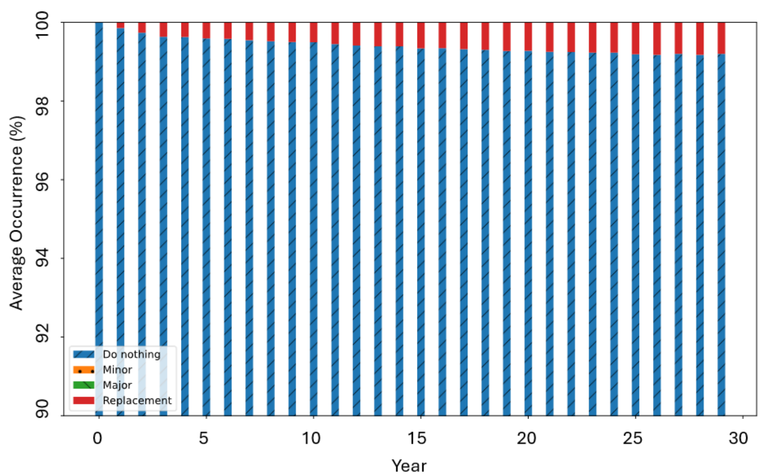
Figure 28 presents the work-type distribution for the three bridge components under the CB-1 policy. Again, a very small portion of bridges are considered for replacement due to the high cost of replacement and constraints on budget and resources.



(a)



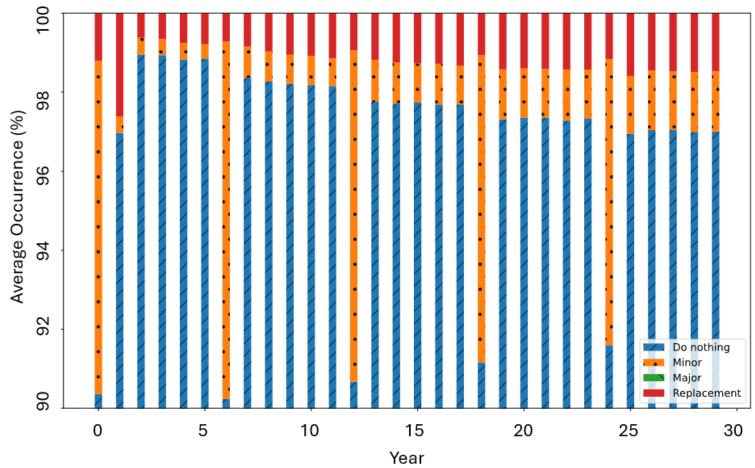
(b)



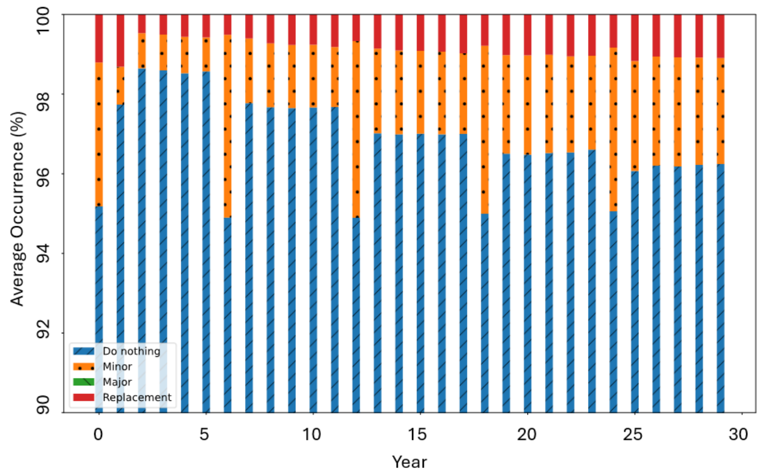
(c)

Figure 28. Annual work-type distribution for bridge components under the CB-1 policy (1% cumulative budget): (a) deck, (b) superstructure, and (c) substructure

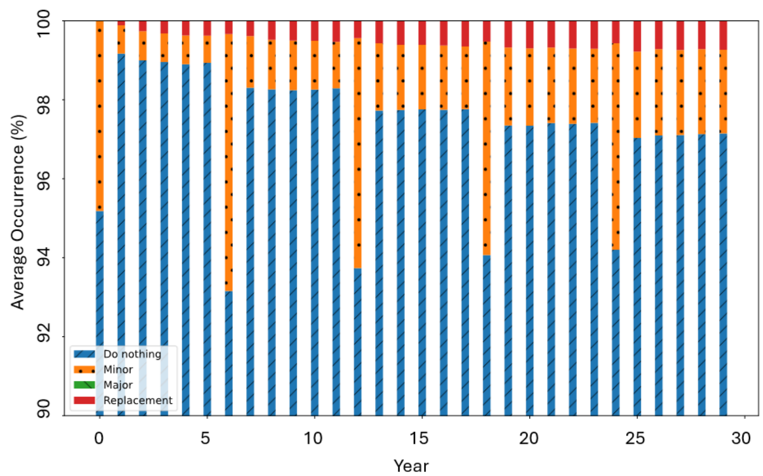
Figure 29 illustrates the average occurrence of maintenance actions under the CB-2 policy. The results indicate a higher frequency of “Minor” maintenance particularly every five years due to the action constraints provided in Volume 1, Chapter 4.



(a)



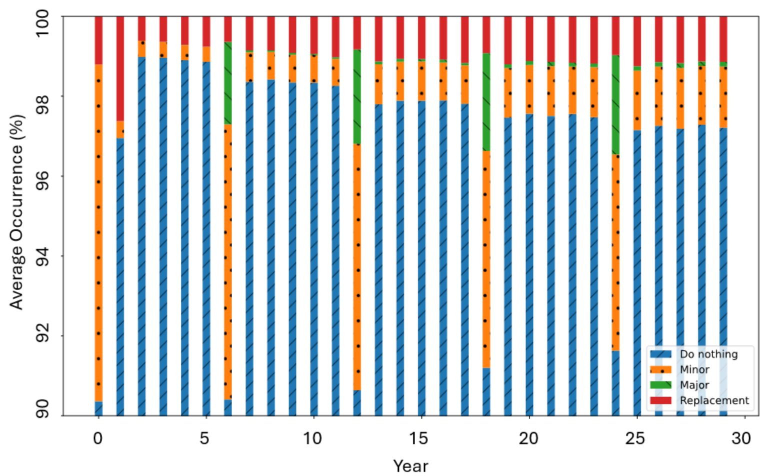
(b)



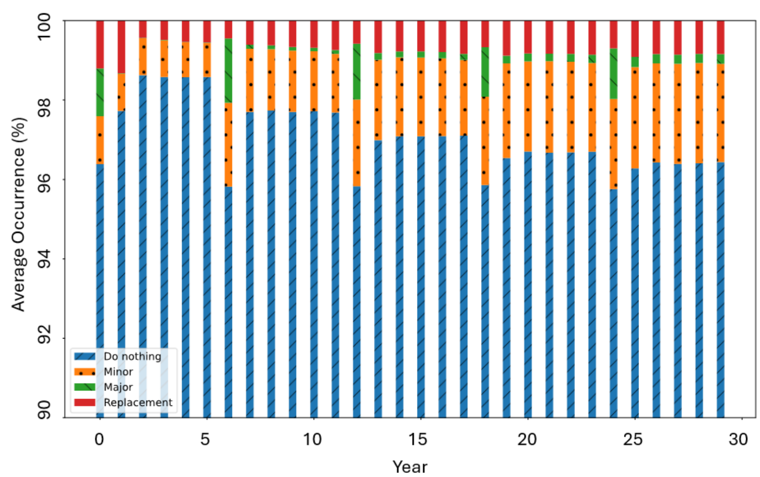
(c)

Figure 29. Annual work-type distribution for bridge components under the CB-2 policy (1% cumulative budget): (a) deck, (b) superstructure, and (c) substructure

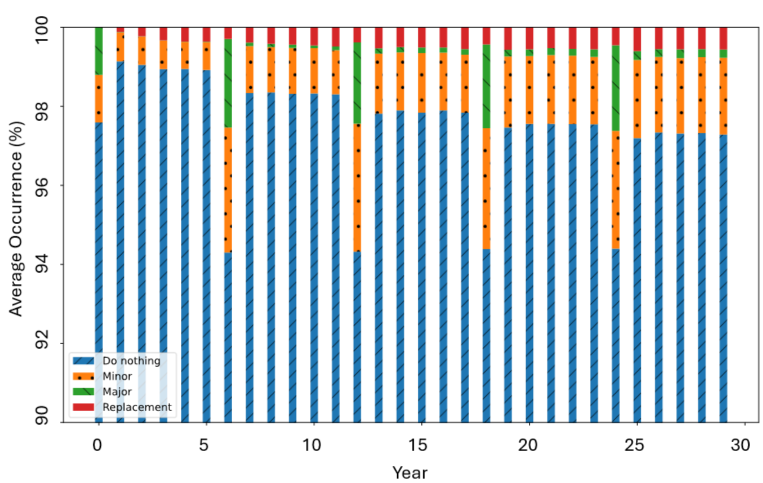
In addition, Figure 30 illustrates the average occurrence of maintenance actions under the CB-3 policy. Again, due to action constraints, a spike in the number of maintenance actions is observed every five years.



(a)



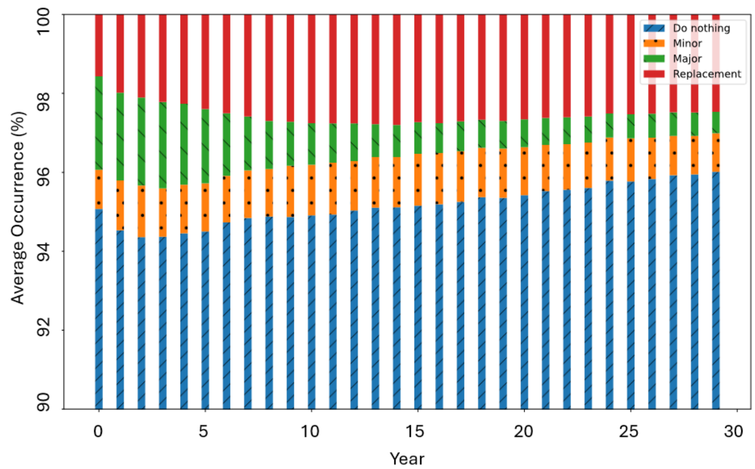
(b)



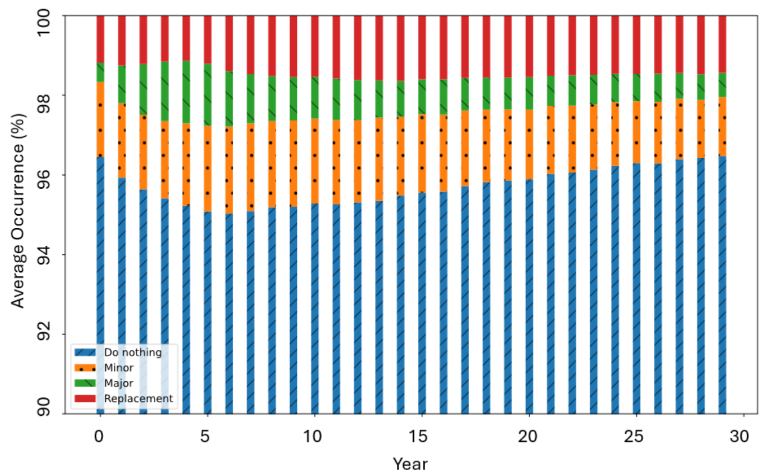
(c)

Figure 30. Annual work-type distribution for bridge components under the CB-3 policy (1% cumulative budget): (a) deck, (b) superstructure, and (c) substructure

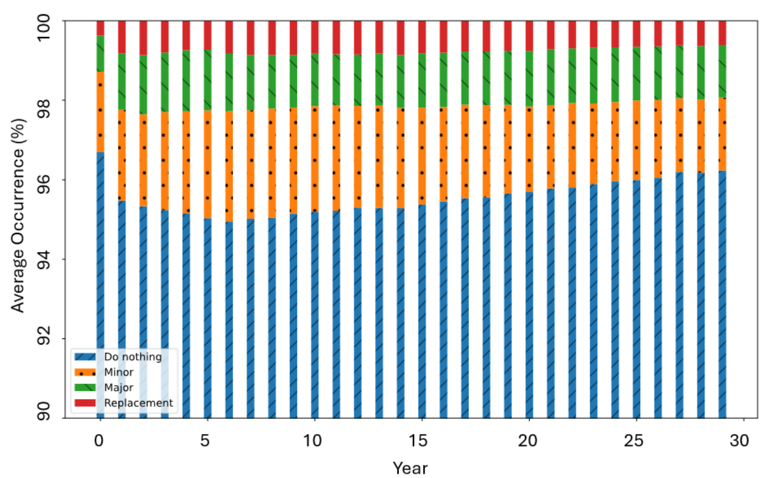
Finally, Figure 31 presents the average occurrence of maintenance actions under the AI-based maintenance policy. Compared with the above condition-based policies, the AI-based policy achieves a well-balanced work type distribution, and the annual number of maintenance actions are more evenly spread across the whole planning horizon for all bridge components. It is also noticed that the AI policy tends to suggest more major maintenance and replacement actions, which are more effective in preserving or improving the asset conditions over time.



(a)



(b)



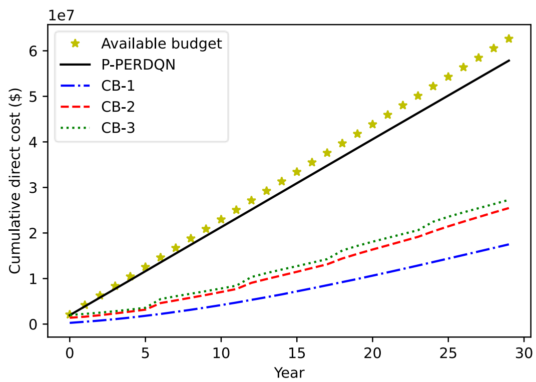
(c)

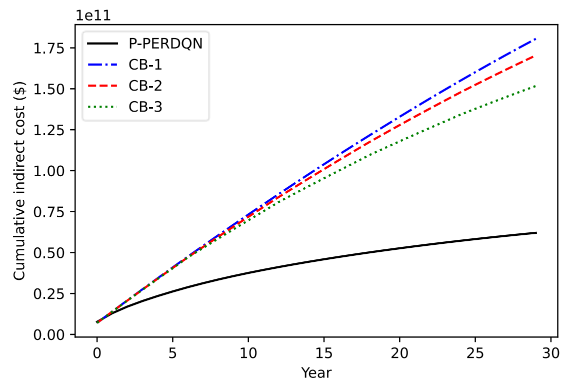
Figure 31. Annual work-type distribution for bridge components under the AI-based policy (1% cumulative budget): (a) deck, (b) superstructure, and (c) substructure

4.4.3. 0.5% annual budget ratio with non-cumulative budget

In this subsection, network-level bridge asset management performance is examined by considering an annual budget ratio of 0.5% with the non-cumulative budget assumption.

Figure 32 compares the aggregated direct and indirect costs under various maintenance policies. The AI-based policy effectively utilizes most of the available budget, whereas the condition-based policies lead to budget underutilization, even when operating with a very limited annual budget ratio. Figure 32(b) further indicates that the aggregated indirect cost under the AI-based policy is significantly lower compared to the condition-based policies.

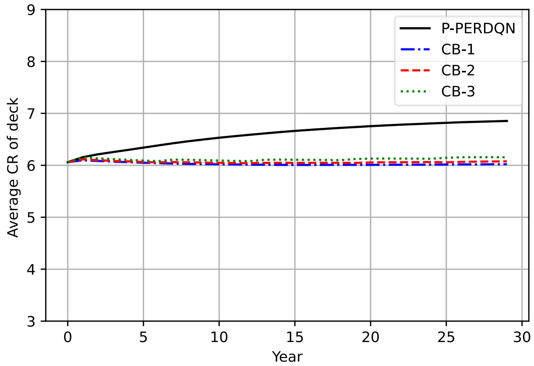




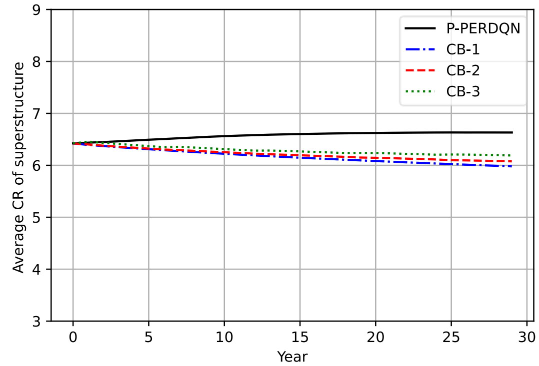
(a) (b)

Figure 32. Average aggregated costs across the network under various maintenance policies (0.5% non-cumulative budget): (a) direct cost, (b) indirect cost

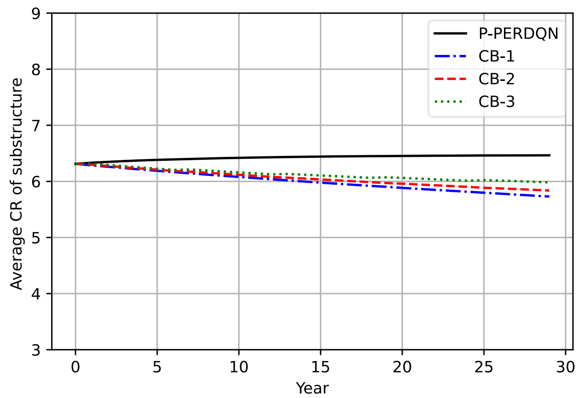
The average component CR across the network is compared in Figure 33. Compared to the condition-based policies, it can be seen that the AI-based policy can more effectively enhance the CR of all three bridge components despite the limited budget.



(a)



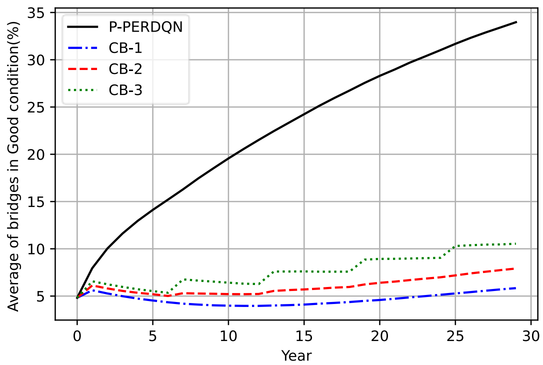
(b)



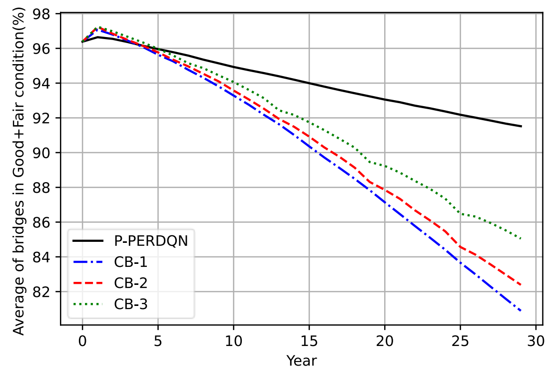
(c)

Figure 33. Average component condition rating across the network (0.5% non-cumulative budget): (a) deck, (b) superstructure, (c) substructure

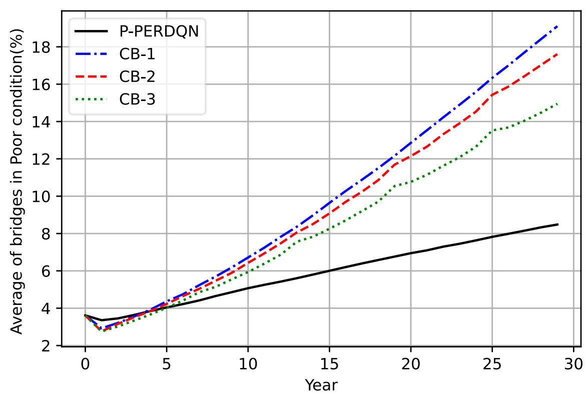
Figure 34 presents the percentage of bridges in different condition categories, highlighting the superior performance of the AI-based policy in improving network-level asset conditions within the “Good” or “Fair” levels. In terms of the percentage of “Poor” condition bridges, the AI-based policy is found to be more effective under the tight budget.



(a)



(b)



(c)

Figure 34. Average percentage of bridges across different condition categories (0.5% non-cumulative budget): (a) Good, (b) Good+Fair, and (c) Poor

Figure 35 shows the network-level travel time comparison. Overall, the AI-based policy significantly outperforms the condition-based policies in reducing the network travel time.

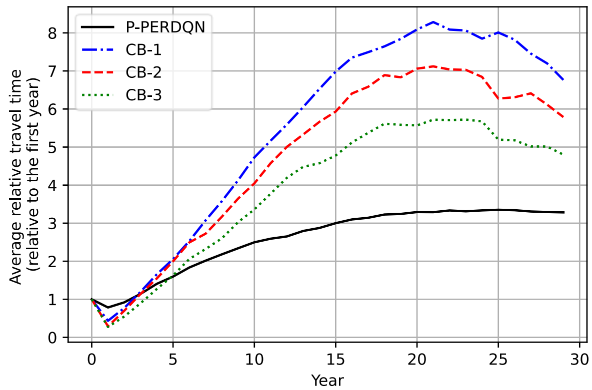
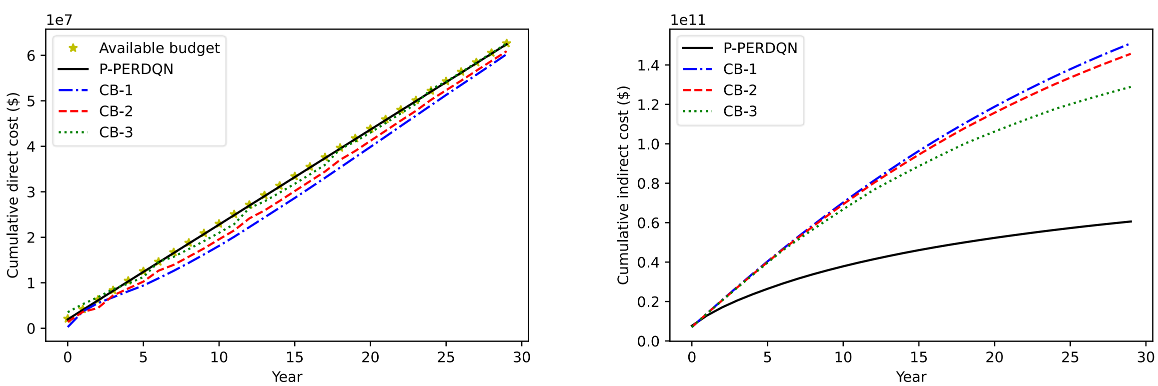


Figure 35. Average network-level travel time under various maintenance policies (0.5% non-cumulative budget)

4.4.4. 0.5% 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 0.5% with the cumulative budget assumption.

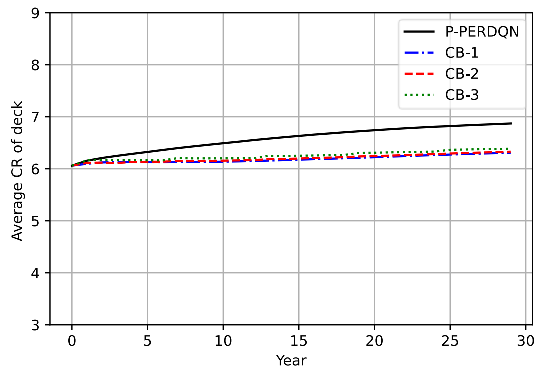
Figure 36 illustrates that AI-based policy and condition-based policies effectively allocate almost the entire available budget, with only a small amount remaining unutilized, while the AI-based policy leads to the lowest aggregated indirect costs.



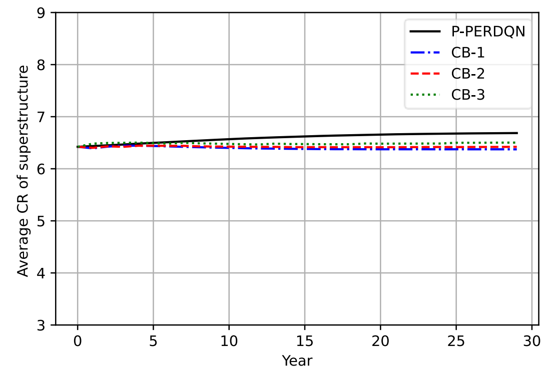
(a) (b)

Figure 36. Average aggregated costs across the network under various maintenance policies (0.5% cumulative budget): (a) direct cost, (b) indirect cost

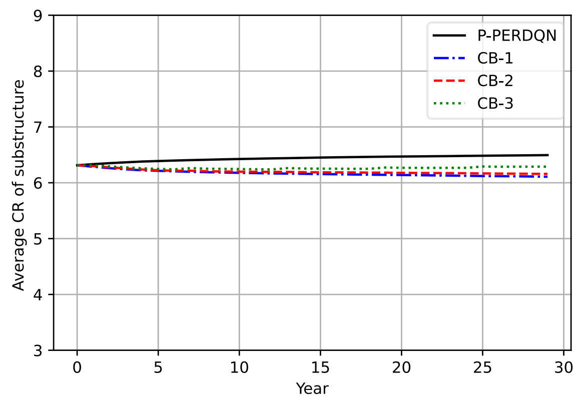
Figure 37 compares the average component CR across the network, again highlighting the superior performance of the AI-based policy in improving component conditions compared to the condition-based policies across all components.



(a)



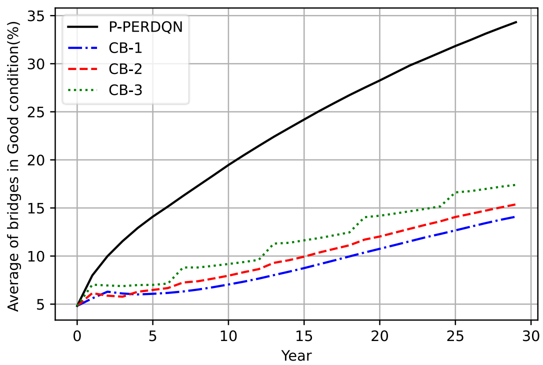
(b)



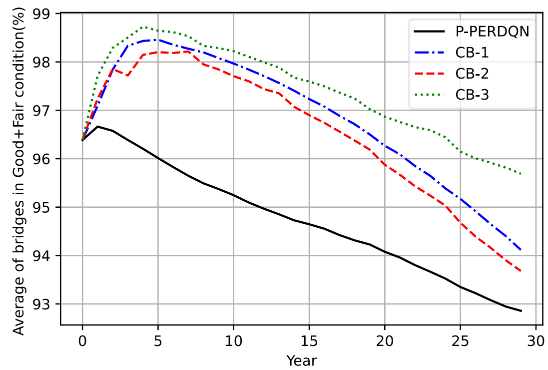
(c)

Figure 37. Average component condition rating across the network over the planning horizon (0.5% cumulative budget): (a) deck, (b) superstructure, (c) substructure

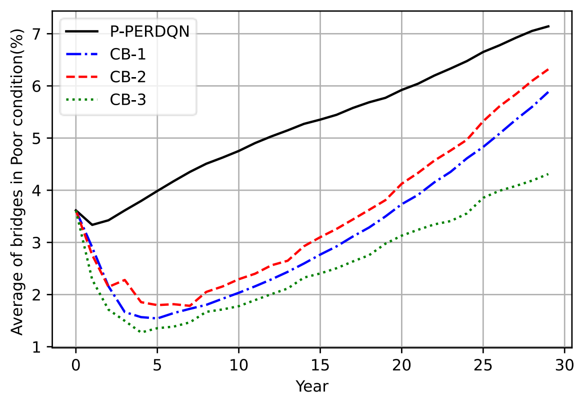
In terms of the proportion of bridge under different condition categories. Figure 38(a) shows that the AI-based policy is more effective in improving bridge conditions to the "Good" level. Figure 38(b) illustrates that the number of bridges in "Good" or "Fair" condition is lower for the AI-based policy compared to the condition-based policies. In addition, Figure 38(c) demonstrates that, the condition-based policies are more effective in reducing the "Poor" condition bridges in this case due to a very limited annual budget (0.5% annual budget ratio) is considered along with the cumulative budget assumption.



(a)



(b)



(c)

Figure 38. Average percentage of bridges across different condition categories (0.5% cumulative budget): (a) Good, (b) Good+Fair, and (c) Poor

Figure 39 compares the average network-level travel time under different policies. Among all the policies evaluated, CB-3 results in the lowest travel time. This outcome can be attributed to CB-3's effectiveness in addressing bridges classified as "Poor," which have the greatest impact on network-level travel time within the skeleton highway network considered in this case study. While the AI-based policy shows similar performance to CB-3 in terms of relative travel time by the end of the planning horizon, CB-3 performs better throughout the earlier stages of the planning period.

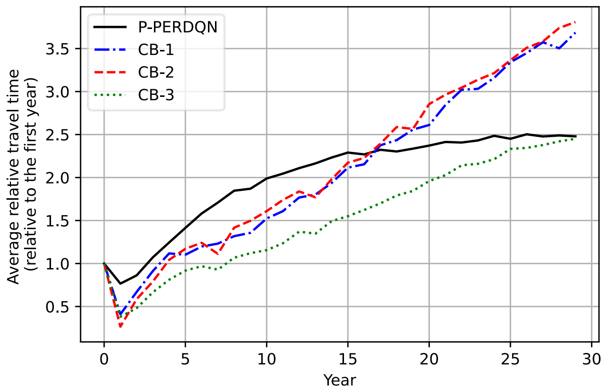
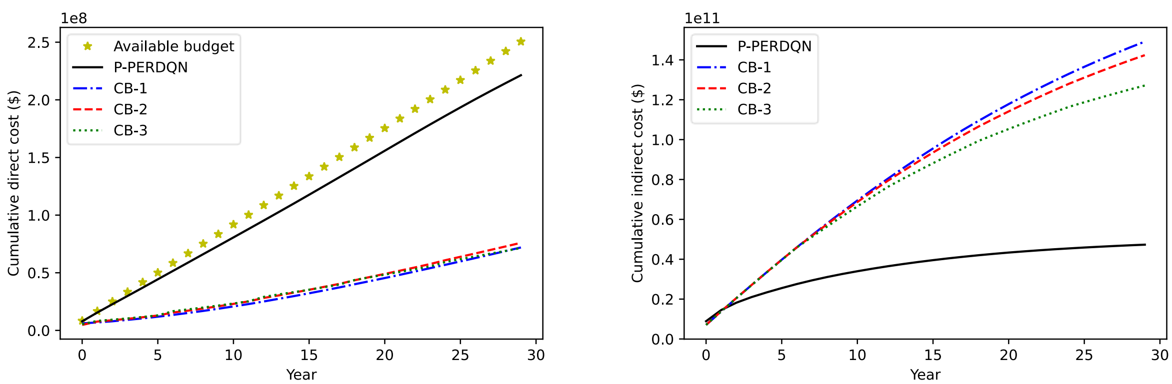


Figure 39. Average network-level travel time under various maintenance policies (0.5% cumulative budget)

4.4.5. 2% annual budget ratio with non-cumulative budget

In this subsection, the network-level bridge asset management performance is investigated by considering an annual budget ratio of 2% with the non-cumulative budget assumption.

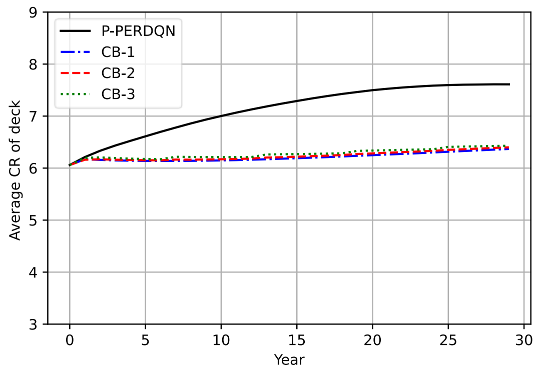
Figure 40 demonstrates the superiority of the AI-based policy in utilizing the budget while minimizing the network's indirect costs. The result also suggests that the available budget is more than sufficient, as the AI-based policy did not utilize all the available budget particularly toward the latter half of the planning horizon.



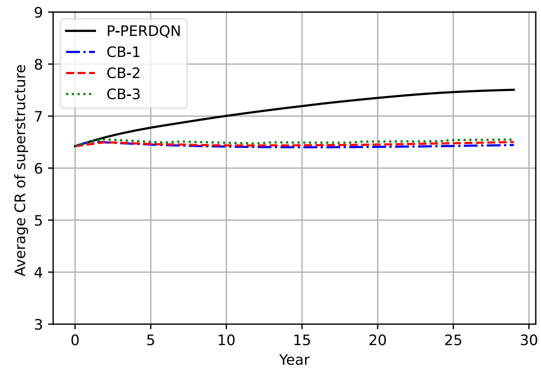
(a) (b)

Figure 40. Average aggregated costs across the network under various maintenance policies (2% non-cumulative budget): (a) direct cost, (b) indirect cost

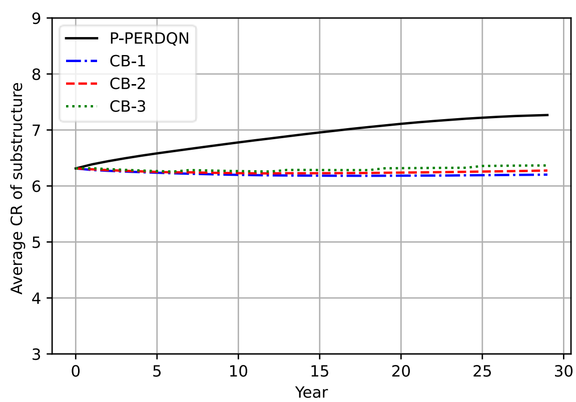
Figure 41 further illustrates that condition-based policies maintain the component CR at a stagnant level, whereas the AI-based policy significantly enhances the CR of all components, achieving higher component CR for all three bridge components. This improvement underscores the AI-based approach's effectiveness in optimizing maintenance strategies to ensure better long-term infrastructure performance.



(a)



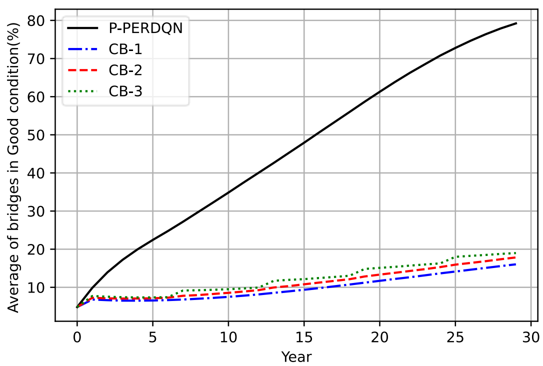
(b)



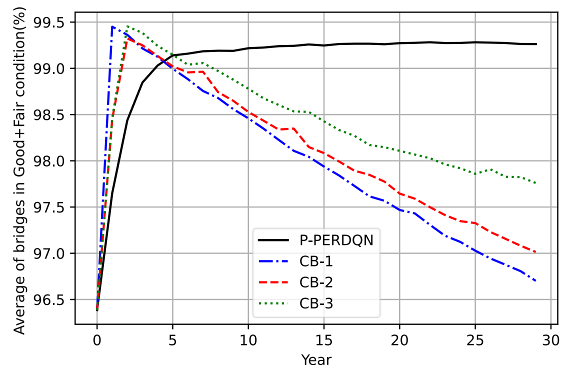
(c)

Figure 41. Average component condition rating across the network (2% non-cumulative budget): (a) deck, (b) superstructure, (c) substructure

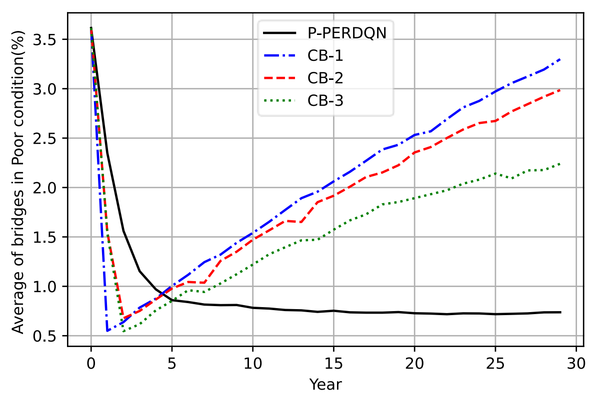
The proportion of bridges under different condition categories is further compared in Figure 42. Figure 42(a) illustrates that the AI-based policy significantly increases the number of bridges in "Good" condition, reaching nearly 80% of the bridges in the network by the end of the planning horizon, while this value is around only 20% for the condition-based policies. Compared to the condition-based policies, the AI-based policy also leads to a higher percentage of bridges in the "Good" or "Fair" conditions according to Figure 42(b), and a lower percentage of "Poor" condition bridges as per Figure 42(c).



(a)



(b)



(c)

Figure 42. Average percentage of bridges across different condition categories (2% non-cumulative budget): (a) Good, (b) Good+Fair, and (c) Poor

Figure 43 indicates that the AI-based policy contributes to a steady reduction in network-level travel time, suggesting improved network functionality. In contrast, the condition-based policies result in an increase in travel time.

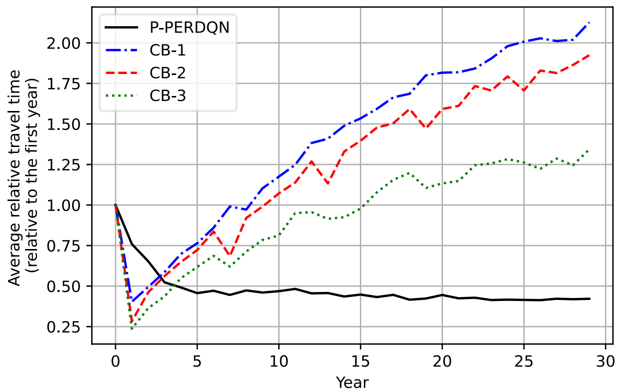
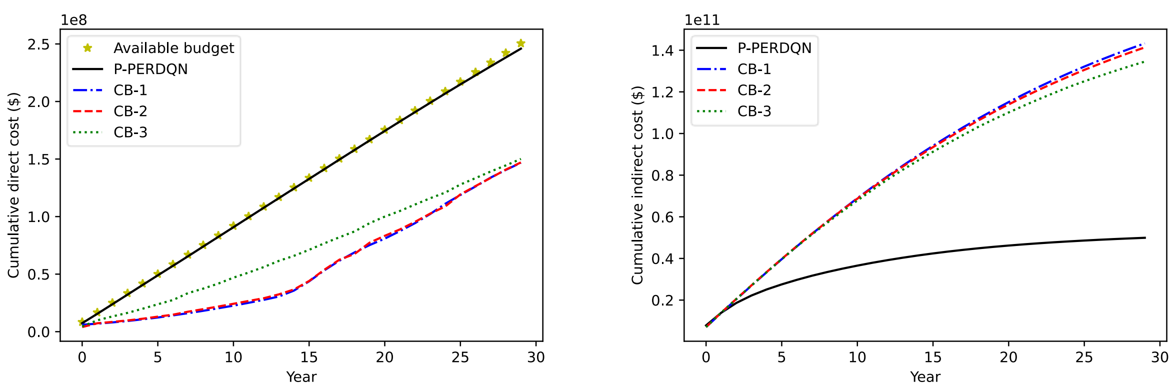


Figure 43. Average network-level travel time under various maintenance policies (2% non-cumulative budget)

4.4.6. 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 44(a) indicates the AI-based policy can more effectively utilize the available budget compared to the condition-based policies. Figure 44(b) illustrates the AI-based policy also leads to the lowest level of aggregated indirect costs.



(a) (b)

Figure 44. Average aggregated costs across the network under various maintenance policies (2% cumulative budget): (a) direct cost, (b) indirect cost

Figure 45 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.

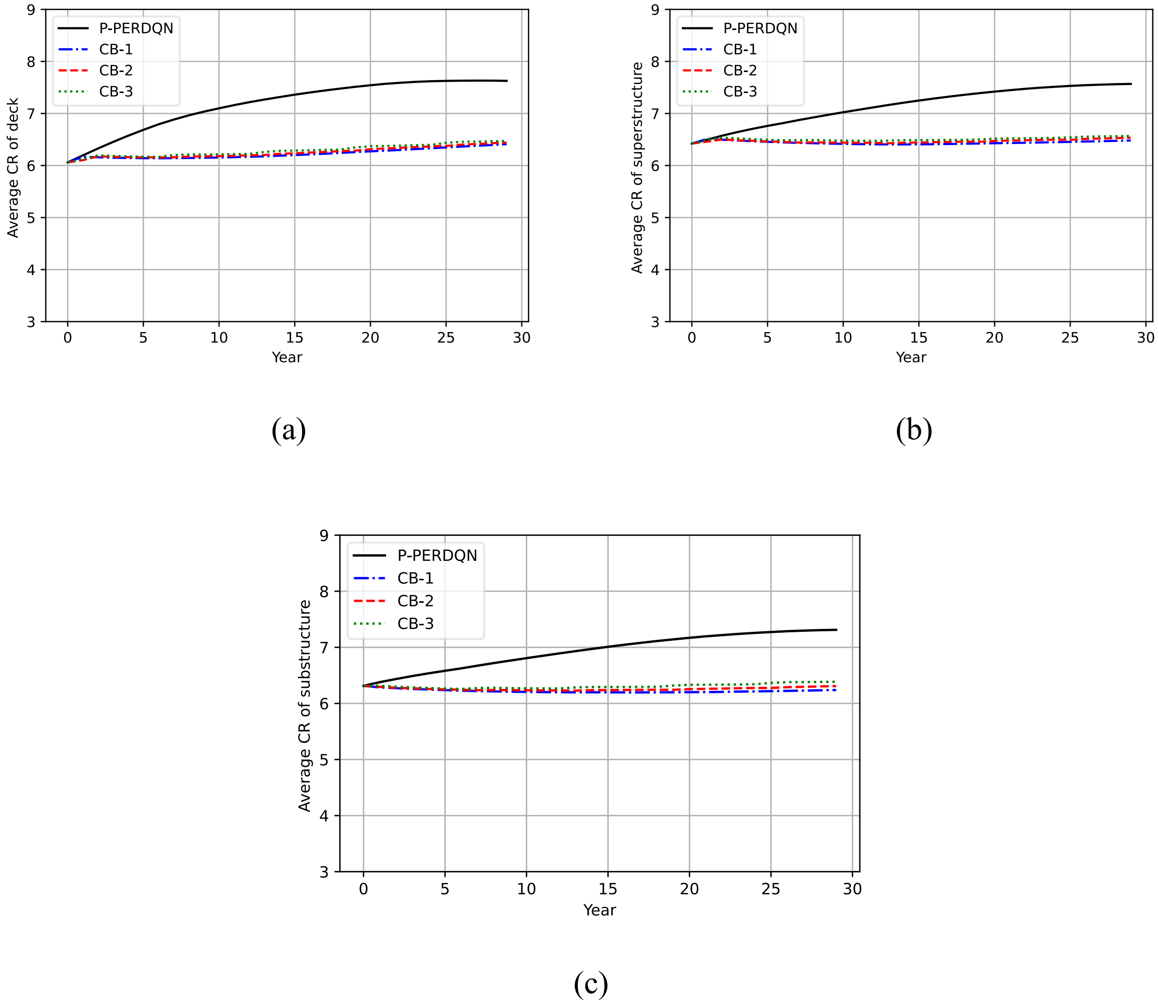
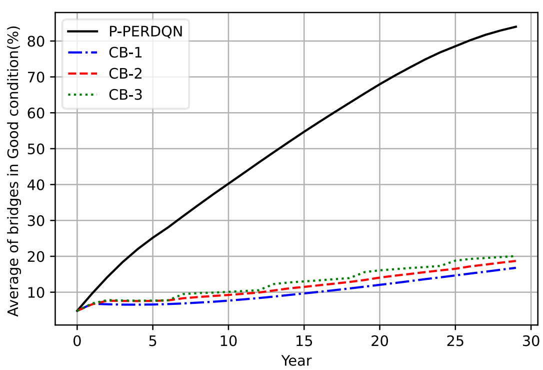
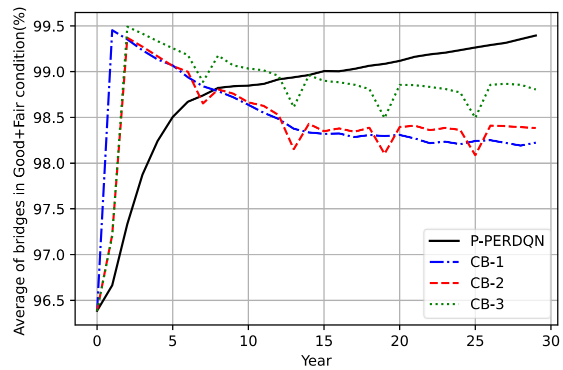


Figure 45. Average component condition rating across the network (2% cumulative budget): (a) deck, (b) superstructure, (c) substructure

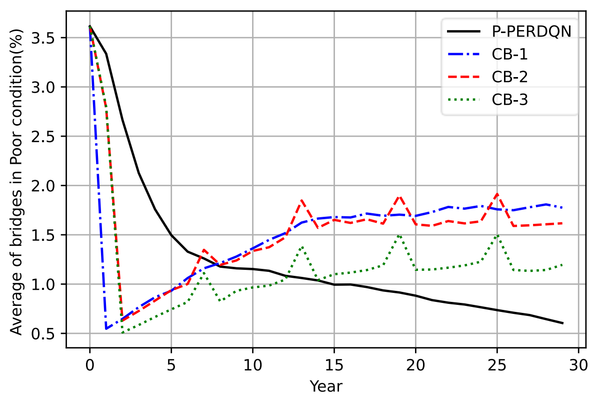
Figure 46 shows the AI-based maintenance policy leads to a higher percentage of bridges in "Good" and "Fair" conditions compared to the condition-based policies. Moreover, the AI-based policy significantly reduces the number of bridges in "Poor" condition compared to the condition-based policies, further emphasizing its advantage in asset condition preservation and improvement.



(a)



(b)



(c)

Figure 46. Average percentage of bridges across different condition categories (2% cumulative budget): (a) Good, (b) Good+Fair, and (c) Poor

Figure 47 presents the average network-level travel time over the planning horizon. The AI-based maintenance policy consistently demonstrates superior performance by maintaining a lower travel time with a decreasing trend over time. In contrast, the condition-based policies exhibit much higher network-level relative travel time.

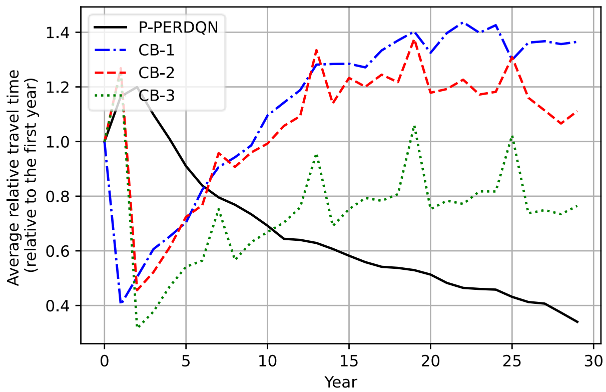


Figure 47. Average network-level travel time under various maintenance policies (2% cumulative budget)

All the above results in Section 4.4 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) preserve or improve CR of bridge components, (4) increase the proportion of bridges in “Good” or “Fair” conditions while decreasing the number of bridges in “Poor” condition, and (5) deliver overall reduced network-level travel time.

4.5. Illustration of annual decision process via the AI-based network-level decision framework

In this section, a demonstration on a small-scale bridge portfolio is performed to showcase how the network-level project prioritization and decisions are made in a given year. For this purpose, ten bridges from the original case study network outlined in Section 3 are selected for analysis as shown in Table 3. In this table, bridge parameters including: deck area, detour length, ADT, truck ratio, closeness centrality, and current initial condition ratings, are provided for each bridge.

Table 3. Selected Bridges from the Case Study Network

Bridge #	Deck area (m^2)	Detour length (km)	ADT	Truck ratio	Initial CR [deck, super, sub]
B1	1082	64	12139	0.09	[6,5,6]
B2	425	1	42038	0.09	[7,6,6]
B3	2046	1	118031	0.08	[6,6,6]
B4	4377	1	118031	0.08	[6,6,6]
B5	582	26	18011	0.09	[6,6,6]
B6	1166	1	37267	0.09	[6,7,6]
B7	1949	1	70582	0.08	[6,7,6]
B8	2566	1	90458	0.08	[6,8,7]
B9	2546	1	112715	0.08	[6,8,6]
B10	1039	8	23253	0.09	[5,6,6]

4.5.1. Step 1: Updating the annual budget and number of projects

In this step, the annual budget is set at 1% of the total construction cost, amounting to \$306,544. Since 10 bridges are selected, up to 20% of the bridges are eligible for maintenance each year, indicating that most two projects can be implemented annually. Note that the maximum allowable number of projects can be determined by the users.

4.5.2. Step 2: Initial project assembly

In this step, the AI-based and CB-3 policies suggest maintenance actions for each bridge in the network at the bridge level for this current decision step, as detailed in Table 4. The table presents the following information for each bridge: the initial annual budget calculated in Step 1, the initial condition ratings for the three bridge components (deck, superstructure, and substructure), and the suggested maintenance actions for each component from the AI-based bridge-level and CB-3 policies. The maintenance actions are annotated as follows: 0 – “Do Nothing,” 1 – “Minor,” 2 – “Major,” and 3 – “Replacement.” Additionally, the table includes the direct costs associated with these maintenance actions. It can be seen that the AI-based and CB-3 policies initially offered maintenance suggestions for all bridges.

Table 4. Initial project assembly results

Year	Budget ($)	Bridge #	Initial CR	Actions		Direct cost ($)	
				AI	CB-3	AI	CB-3
1	306,544	B1	[6,5,6]	[2,2,2]	[1,2,1]	419,901	182,143
		B2	[7,6,6]	[3,3,2]	[0,1,1]	650,568	24,745
		B3	[6,6,6]	[3,3,2]	[1,1,1]	3,129,896	158,734
		B4	[6,6,6]	[3,3,2]	[1,1,1]	6,696,367	339,610
		B5	[6,6,6]	[2,2,2]	[1,1,1]	225,628	45,125
		B6	[6,7,6]	[1,0,2]	[1,0,1]	229,662	64,023
		B7	[6,7,6]	[1,0,2]	[1,0,1]	384,030	107,058
		B8	[6,8,7]	[1,0,0]	[1,0,0]	49,769	49,769
		B9	[6,8,6]	[1,0,2]	[1,0,1]	501,580	139,827
		B10	[5,6,6]	[3,3,2]	[2,1,1]	1,590,299	161,306

4.5.3. Step 3: Pareto Frontier based project ranking

In this step, bridges undergo the Pareto Frontier ranking according to their Q value, and bridge-level CR for AI-based policy, and bridge-level CR, and ADT for CB-3 policy, as illustrated in Table 5. This ranking method allows for systematic prioritization of bridges by considering multiple criteria simultaneously.

Table 5. Pareto Frontier based project ranking results

Year	Bridge #	Ranking	
		AI	CB-3
1	B1	1	4
	B2	5	8
	B3	8	2
	B4	7	3
	B5	3	10
	B6	4	9
	B7	6	7
	B8	9	6
	B9	10	5
	B10	2	1

4.5.4. Step 4: Budget allocation and resource constraints enforcement

In this step, the budget is allocated to the bridges based on their ranking, budget availability and the maximum allowable number of projects. Note that up to 2 bridges can be selected for maintenance annually due to the maximum number of allowable projects. The budget allocation for the bridges in the case study is shown in **Table 6**, illustrating how the funds are utilized. The AI-based policy allocated budget to the second-ranked bridge, B5, then AI-based policy allocated the remaining budget to B8 as the third-ranked. While, the CB-3 policy allocates the budget to

B10, and then to B9. As only two bridges can be selected for maintenance within the given budget, no additional bridges are funded, and the budget allocation process is terminated for the year.

Table 6. Budget allocation

Year	Budget ($)	Bridge #	Ranking		Applied actions		Applied cost		Remained budget ($)	
			AI	CB-3	AI	CB-3	AI	CB-3	AI	CB-3
		B1	1	4	[0,0,0]	[0,0,0]	0	0		
		B2	5	8	[0,0,0]	[0,0,0]	0	0		
		B3	8	2	[0,0,0]	[0,0,0]	0	0		
		B4	7	3	[0,0,0]	[0,0,0]	0	0		
1		B5	3	10	[2,2,2]	[0,0,0]	225,628	0		
	306,544	B6	4	9	[0,0,0]	[0,0,0]	0	0	31,147	5,411
		B7	6	7	[0,0,0]	[0,0,0]	0	0		
		B8	9	6	[1,0,0]	[0,0,0]	49,769	0		
		B9	10	5	[0,0,0]	[1,0,1]	0	139,827		
		B10	2	1	[0,0,0]	[2,1,1]	0	161,306		

CHAPTER 5. CONCLUSION

In Volume 2 of this project, a network-level bridge maintenance decision-making and planning framework is developed by coupling the bridge-level AI decision policy (developed in Volume 1 of this project) 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, among others). 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. First, a sensitivity study is performed to investigate the influence of bridge- and project-related attributes selection in the Pareto Frontier ranking scheme. Results suggest that the optimal attribute selection should include "bridge-level CR, ADT" for the condition-based policies, and the optimal attributes are "Q value, bridge-level CR" for the AI-based policy. Next, 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, bridge conditions, and travel time, 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 the 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, increasing the number of bridges classified as "Good" or "Fair" while reducing those in the "Poor" category. Conversely, the condition-based policies primarily focus on preserving bridge components with minimal condition improvement. Furthermore, the AI-based policy demonstrates superior overall performance in reducing network travel time compared to the condition-based policies. Also, from an exemplary annual network-level decision illustration, it is highlighted that the AI-based bridge-level decision policy when deployed into the network-level decision framework can offer reasonable budget and resource allocation.

In conclusion, the research tools developed from this entire research project can not only offer proactive and adaptive bridge maintenance decisions under both deterioration and seismic hazard threats at the individual bridge level but can also optimize 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. Finally, the open-sourced computer codes are shared and related hands-on tutorials are provided for better result dissemination.

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APPENDIX A. NETWORK CENTRALITY MEASURES

In this study, the road network was modeled using a graph-based approach. The intersections were the nodes in the graph, and the roadway segments between the intersections were considered as links. Each node was numbered to provide a unique identification. Similarly, each link was numbered and the nodes at its beginning and end were recorded. This process resulted in the creation of an edge list, i.e., a list of edges along with the node numbers corresponding to the link's starting and ending points. This edge list was used to create an adjacency matrix to represent the road network. An adjacency matrix (A) is a square matrix with its dimension corresponding to the number of the nodes in the network. Element A_{ij} was assigned a value of one if there exists a link connecting nodes i and j, else it was assigned a value of zero. Herein, all links were assumed as two way links, i.e., all roadway segments carry two-way traffic. So, if $A_{ij} = 1$, then $A_{ji} = 1$.

Using this mathematical representation of the road network, detailed modeling such as bridge centrality measure calculation, and traffic flow analysis can be performed. Network centrality metrics are often used to understand the importance of nodes (e.g., intersections) based on network topology information, without detailed traffic flow analysis. Many centrality measures have been proposed in the literature for nodes and links prioritization in a road network [21,22]. Herein, the following commonly used centrality metrics were used to determine the nodal importance of bridges in the road network.

(1) Closeness centrality: it quantifies the importance of a node based on its average shortest distance to all other nodes. It shows how quickly all nodes in the network can be reached from a given node. A low closeness centrality would indicate that a node is near the periphery of the network and is away from most of the other nodes. A high closeness centrality value would indicate a well-connected node located in the center of the network with closer distances to all other nodes. The following equation demonstrates how to calculate closeness centrality:

$$CC_i = \frac{n-1}{\sum_{j=1}^{n} d(i,j)} \tag{A-1}$$

where: CC_i is the closeness centrality of node i, n is the number of nodes in the network, $d(i,j)$ is the distance between nodes i and j.

(2) Betweenness centrality: it quantifies how often a node appears on the shortest paths between other pairs of nodes. To calculate this centrality measure mathematically, for each node pair, the number of shortest paths that connect the two nodes and pass through the node of interest are determined and divided by the total number of shortest paths between the two nodes. This ratio is summed for all node pairs. A high value of betweenness centrality will indicate that the node is crucial for maintaining connectivity in the network. Conversely, a low betweenness centrality value would indicate that the node is not important for maintaining connectivity in the network. The following equation shows how to calculate betweenness centrality:

$$BC_i = \sum_{i \neq p \neq q} \frac{r_{p,q}(i)}{r_{p,q}} \tag{A-2}$$

where BC_i is the betweenness centrality of node i, $r_{p,q}$ is the number of all paths connecting nodes p and q, and $r_{p,q}(i)$ are the number of paths connecting nodes p and q that pass through the node i.

Herein, bridges were assigned to links (i.e., roadway segments) that they are a part of. So, to determine the centrality value for each bridge, the average of the centrality value corresponding to the start and end nodes of the bridge's link was used.

APPENDIX B. TRAFFIC FLOW ANALYSIS

In addition, traffic flow analysis was conducted to evaluate the performance of the road network in the Memphis region under different maintenance policies. For this purpose, Memphis MPO's travel demand model was used, which covered eight counties in Tennessee, Arkansas, and Mississippi. Detailed discussion on the implementation of the Travel Demand Model is provided in Vishnu et al. [23]. The 8 county MMA region was divided into 798 transportation analysis zones (TAZ). Using the travel demand model, the number of passenger car trips from each to all other TAZs (O-D matrix) was obtained for various times of the day.

For the development of the O-D matrix, a high resolutions road network, which consisted of primary, secondary, and tertiary roads were considered. However, the road network used in this study only consisted of the primary roads (i.e., the highways). Therefore, the O-D matrix was condensed to match the resolution of the road network used in this analysis following the procedure outlined by Zhou et al. [24]. The first step in the O-D matrix condensation process involves generating Thiessen polygons around each node of the road network used in this study. Since Thiessen polygons ensure that any point within a given polygon is closest to its corresponding node, trips originating from or ending at TAZs were assigned to the road network node associated with the Thiessen polygon containing the TAZ's centroid. This resulted in the O-D matrix which was used for traffic flow analysis.

In this study, an iterative user equilibrium solution was used for traffic flow analysis. According to the user equilibrium principle, the network reaches a state where no traveler can reduce their travel time between a given origin-destination (O-D) pair by choosing a different route. This approach as implemented following the steps outlined in Vishnu et al [23]. This traffic flow analysis provided the traffic volume on each link. Using the traffic volume, the total distance traveled in the network (D_{tot}) was calculated as:

$$D_{tot} = \sum_{\forall i,j\ pairs} L_{ij} V_{ij} \tag{B-1}$$

where, V_{ij} are the final traffic volumes on each link and L_{ij} is the length of the link between nodes i and j. The total travel time in the network was determined by summing the total travel time on each link ($T_{c_{ij}}$), which was calculated as:

$$T_{tot} = \sum_{\forall i,j\ pairs} T_{c_{ij}} \tag{B-2}$$

The above process was used for the network shown in Chapter 3. In this process, to model the effects of deterioration in the bridges' condition, the traffic flow capacity of bridges was reduced based on their conditions, as mentioned in Volume 1, Chapter 3. Correspondingly, using the bottleneck assumption, the traffic flow capacity of the link containing the deteriorated bridge was reduced to the capacity of the bridge. The reduced capacities of links were used in the above-mentioned traffic flow analysis to determine the effects of bridge deterioration on travel time and distance in the road network.

The above-mentioned process is computationally intensive and integrating it directly into the framework presented in section 2 would be prohibitively expensive. Therefore, a surrogate model was developed to determine the travel time using the level of functionality of each of the bridges in the network. To train the surrogate model, a training data set was created where it was assumed that approximately 1-12% of bridges will be closed, 30-50% of the bridges would have reduced capacity due to deterioration. For bridges with reduced capacity, the remaining capacity was varied between 75 to 100% of the original capacity. With these assumptions, for each of the 83 bridges in the road network, a traffic flow capacity was assigned. Using this process, a set of 10,000 different random realizations of network-level bridge capacities was generated. For each of these bridge capacity combinations, the traffic flow analysis was conducted, and total network-level travel time was determined. 90% of the data was used to train a machine learning model that can predict the total travel time for given bridge capacity values. For this purpose, several machine learning models were considered, such as random forests and neural networks. Based on preliminary analysis, neural networks were observed to perform the best. Herein, based on trial and error, a neural network with 3 hidden layers (each with 240, 160, 80 neurons) and CeLU activation function, was determined to provide maximum accuracy in predicting the total travel time. The performance of this model was tested on the remaining 10% of the data and was found to have a median error of 5%.

APPENDIX C. COMPUTER CODES INSTRUCTIONS

Tutorials and instructions on how to access and use the open-source computer codes for deploying the proposed network-level asset management framework are provided herein. GitHub, a free web-based platform, is used for web-based code storage and sharing. Below is the GitHub repository link: https://github.com/AlirezaGhavidel70/AI-based-bridge-network-analysis/

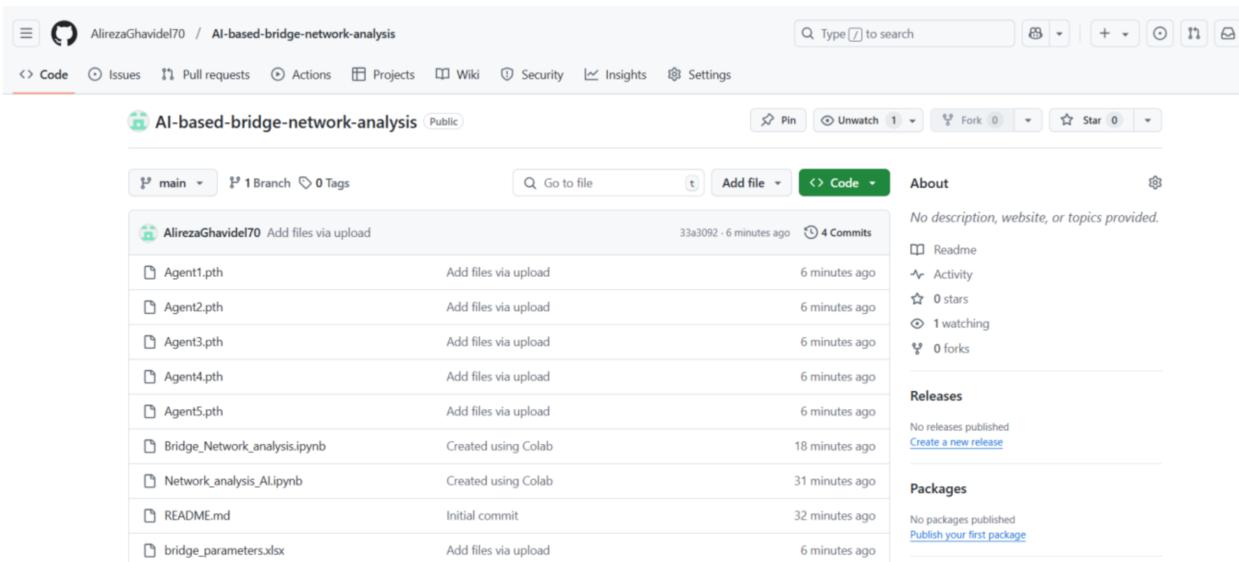
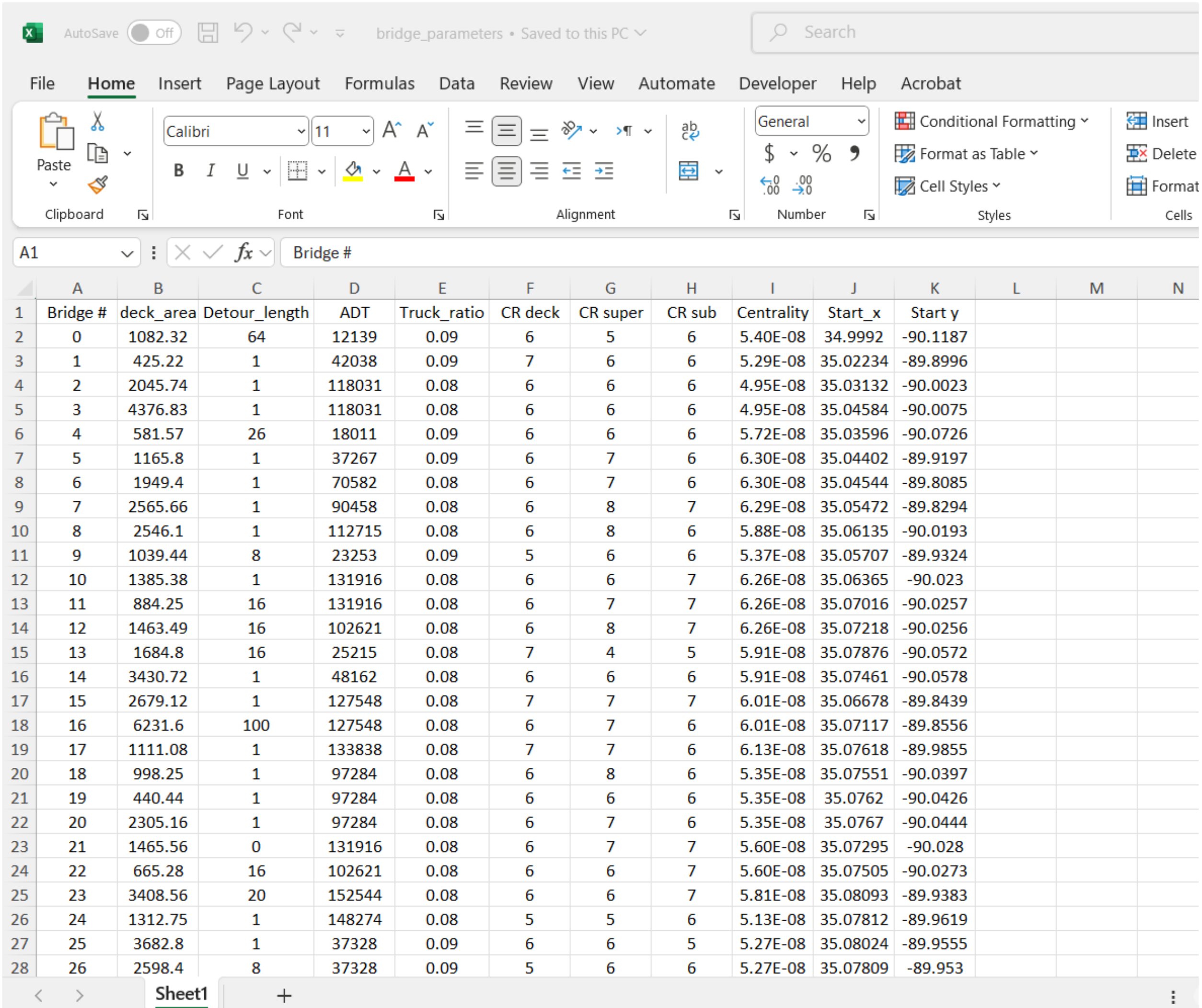


Figure C- 1. GitHub repository page

In the above link, you will find all the necessary codes and files required to execute the program. You can download five pre-trained bridge-level AI policies named "Agent1, Agent2, Agent3, Agent4, and Agent5" from the provided link for testing or deployment purposes. Here multiple AI policies trained under the same settings were considered (instead of relying on a specific policy) to offer more stable and robust results, due to the stochastic nature of AI model training. These AI policies were trained using the AI algorithm presented in Volume 1 and are dedicated for the multi-span simply-supported concrete girder bridge class for the case-study region in Memphis. For other use cases, the users will need to train dedicated AI models using region- and asset-specific data.

Additionally, an Excel file named "bridge_parameters" contains the necessary user inputs on the detailed bridge-specific data for each of the bridges involved in the network-level analysis, as shown in Figure C- 2. This file includes various bridge parameters such as deck area, detour length, average daily traffic (ADT), truck ratio, initial condition ratings for bridge components, centrality measures, and the coordinates of bridges within the network (see Table C-1).



Bridge #	deck_area	Detour_length	ADT	Truck_ratio	CR deck	CR super	CR sub	Centrality	Start_x	Start y
0	1082.32	64	12139	0.09	6	5	6	5.40E-08	34.9992	-90.1187
1	425.22	1	42038	0.09	7	6	6	5.29E-08	35.02234	-89.8996
2	2045.74	1	118031	0.08	6	6	6	4.95E-08	35.03132	-90.0023
3	4376.83	1	118031	0.08	6	6	6	4.95E-08	35.04584	-90.0075
4	581.57	26	18011	0.09	6	6	6	5.72E-08	35.03596	-90.0726
5	1165.8	1	37267	0.09	6	7	6	6.30E-08	35.04402	-89.9197
6	1949.4	1	70582	0.08	6	7	6	6.30E-08	35.04544	-89.8085
7	2565.66	1	90458	0.08	6	8	7	6.29E-08	35.05472	-89.8294
8	2546.1	1	112715	0.08	6	8	6	5.88E-08	35.06135	-90.0193
9	1039.44	8	23253	0.09	5	6	6	5.37E-08	35.05707	-89.9324
10	1385.38	1	131916	0.08	6	6	7	6.26E-08	35.06365	-90.023
11	884.25	16	131916	0.08	6	7	7	6.26E-08	35.07016	-90.0257
12	1463.49	16	102621	0.08	6	8	7	6.26E-08	35.07218	-90.0256
13	1684.8	16	25215	0.08	7	4	5	5.91E-08	35.07876	-90.0572
14	3430.72	1	48162	0.08	6	6	6	5.91E-08	35.07461	-90.0578
15	2679.12	1	127548	0.08	7	7	7	6.01E-08	35.06678	-89.8439
16	6231.6	100	127548	0.08	6	7	6	6.01E-08	35.07117	-89.8556
17	1111.08	1	133838	0.08	7	7	6	6.13E-08	35.07618	-89.9855
18	998.25	1	97284	0.08	6	8	6	5.35E-08	35.07551	-90.0397
19	440.44	1	97284	0.08	6	6	6	5.35E-08	35.0762	-90.0426
20	2305.16	1	97284	0.08	6	7	6	5.35E-08	35.0767	-90.0444
21	1465.56	0	131916	0.08	6	7	7	5.60E-08	35.07295	-90.028
22	665.28	16	102621	0.08	6	6	7	5.60E-08	35.07505	-90.0273
23	3408.56	20	152544	0.08	6	6	7	5.81E-08	35.08093	-89.9383
24	1312.75	1	148274	0.08	5	5	6	5.13E-08	35.07812	-89.9619
25	3682.8	1	37328	0.09	6	6	5	5.27E-08	35.08024	-89.9555
26	2598.4	8	37328	0.09	5	6	6	5.27E-08	35.07809	-89.953

Figure C- 2. Bridge parameters input file

Moreover, you will find two ".ipynb" files named "Bridge_Network_Analysis" and "Network_Analysis_AI", were developed based on the proposed framework in this study. These files incorporate aging deterioration modeling through Markov chains, seismic risk analysis, maintenance effects, and cost estimations, as outlined in Volume 1. Additionally, the trained bridge-level AI-based policy and condition-based policies are incorporated to suggest maintenance actions, as mentioned in Volume 1. Finally, the proposed framework for network-level decision making in Volume 2 is implemented.

The "Bridge_Network_Analysis" code as illustrates in Figure C- 3 conducts a comparative study, evaluating the AI-based policy against the condition-based policies on the overall network-level bridge asset management performance. It analyzes the aggregated direct and indirect costs, component conditions, and the distribution of bridges across different condition categories throughout the planning horizon, presenting the results in both graphical and tabular formats as shown in Section 4.3.

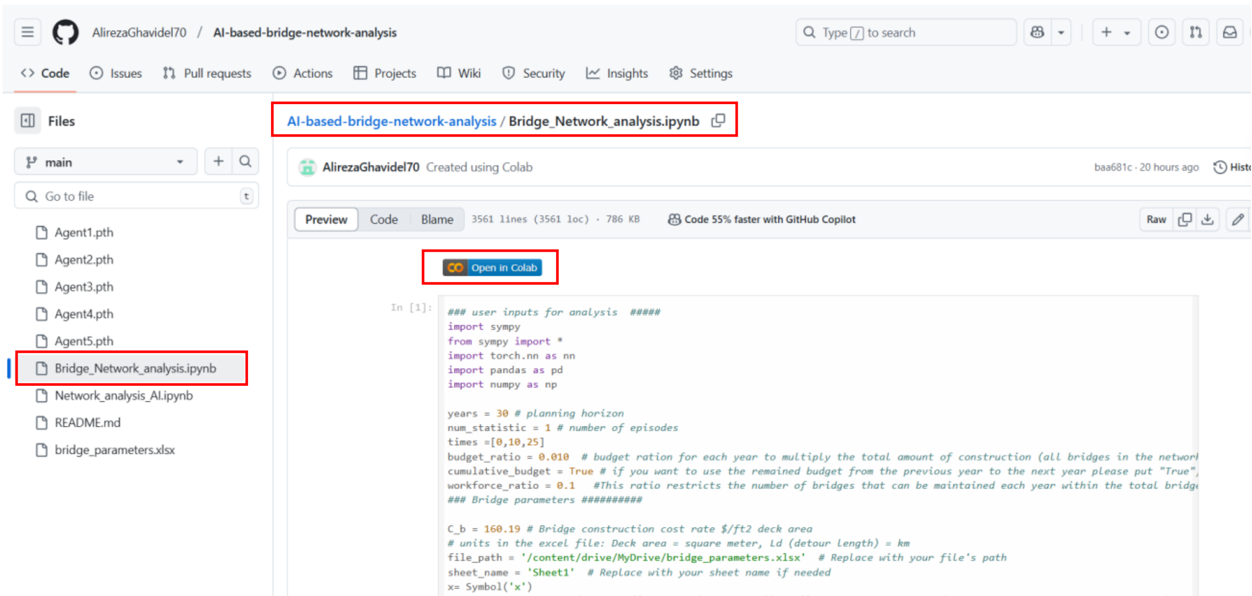


Figure C- 3. “Bridge_Network_Analysis” file in the GitHub repository

The "Network_Analysis_AI" code (see Figure C- 4) suggests optimal actions for a given year while considering the annual budget and resource constraints.

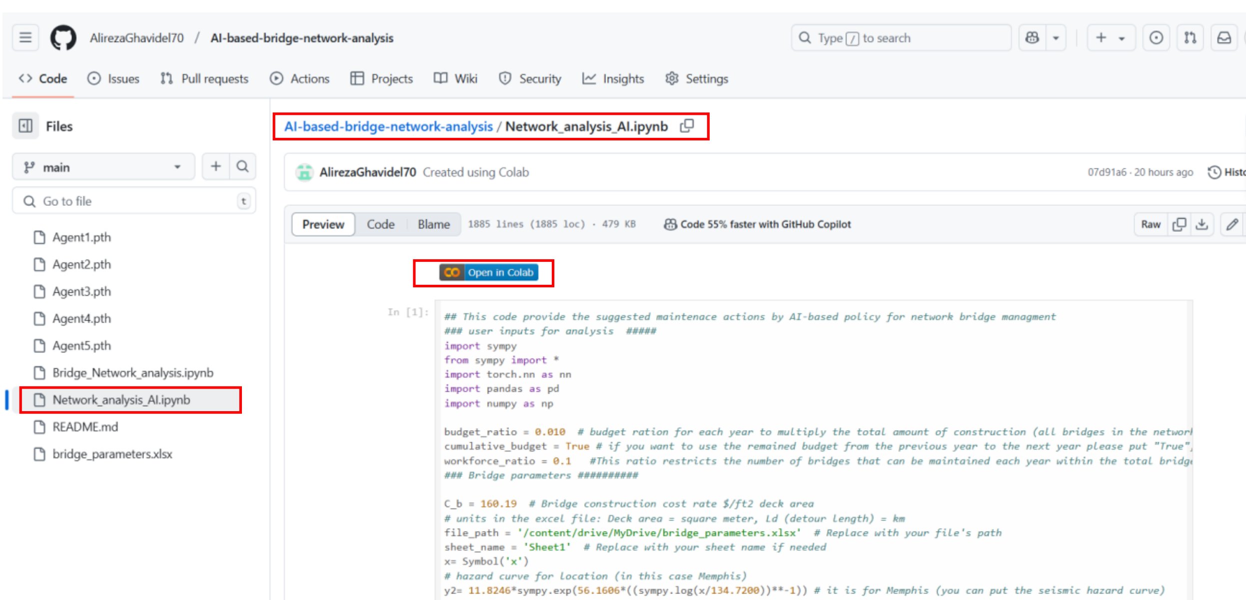


Figure C- 4. "Network_analysis_AI" file in the GitHub repository

The results include:

- A map visualizing the network and the condition of bridges after the suggested actions, such as Figure C- 5.

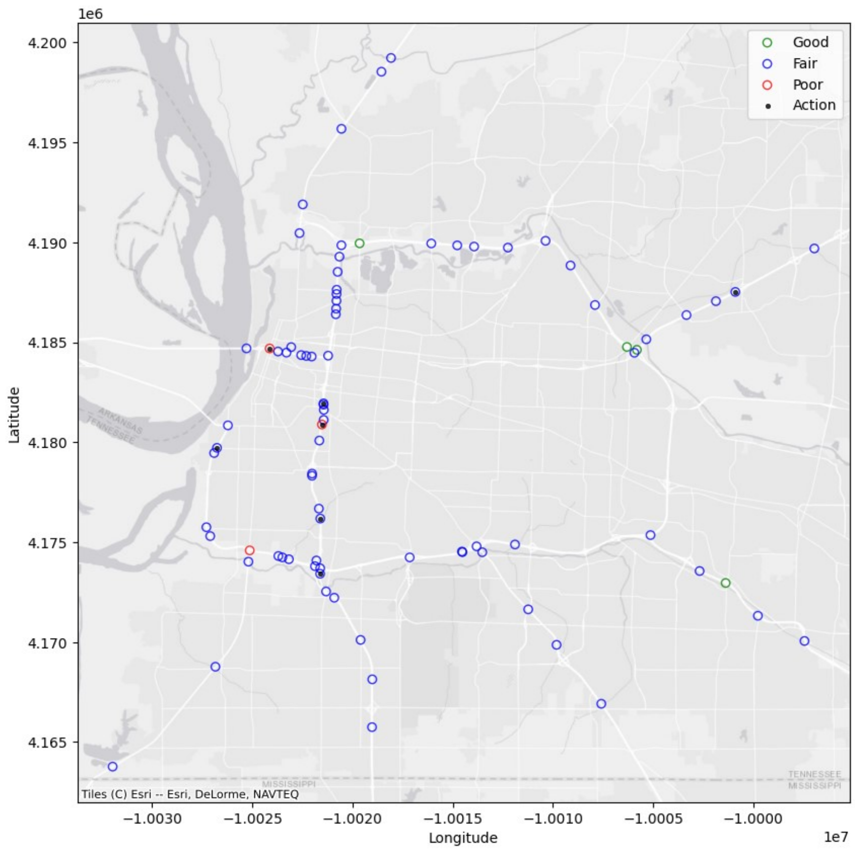
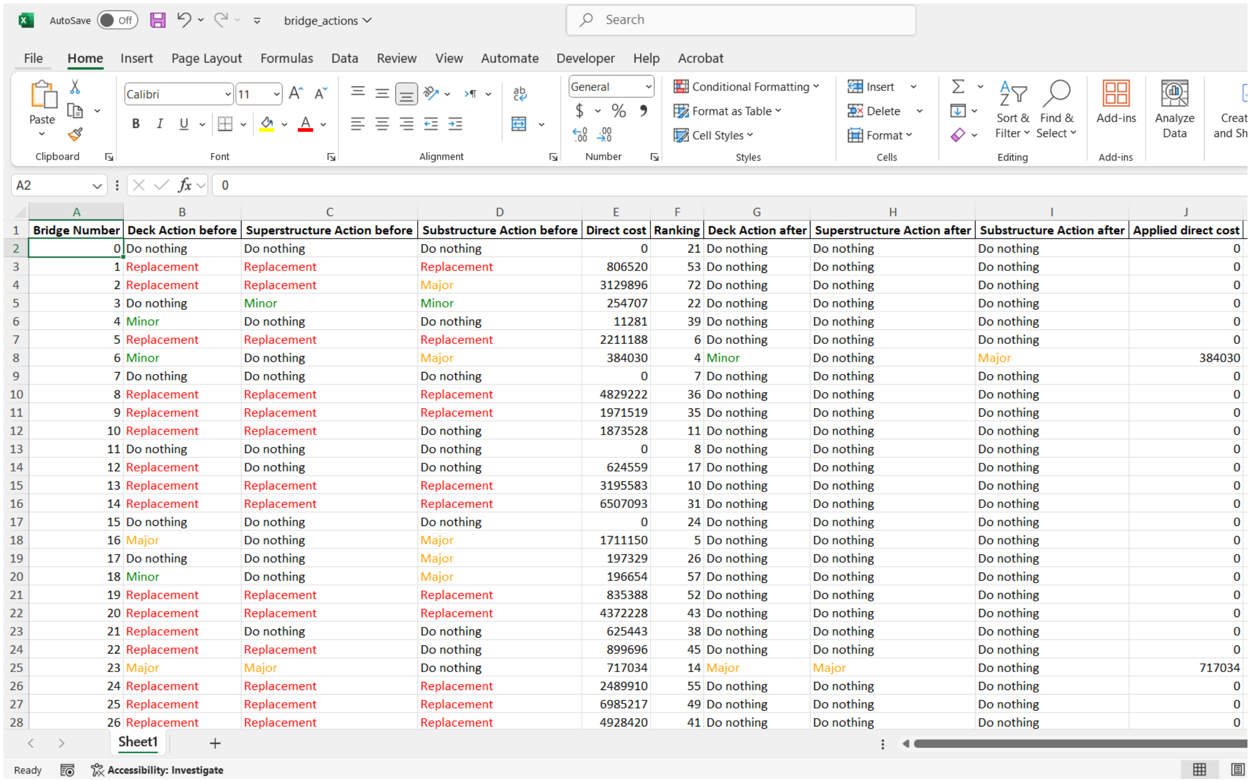


Figure C- 5. Map visualizing the network

- An Excel file as shown in Figure C- 6 containing:
  The suggested actions and associated costs before enforcing budget and resource constraints, and the suggested actions and associated costs after enforcing budget and resource constraints.



Bridge Number	Deck Action before	Superstructure Action before	Substructure Action before	Direct cost	Ranking	Deck Action after	Superstructure Action after	Substructure Action after	Applied direct cost
0	Do nothing	Do nothing	Do nothing	0	21	Do nothing	Do nothing	Do nothing	0
1	Replacement	Replacement	Replacement	806520	53	Do nothing	Do nothing	Do nothing	0
2	Replacement	Replacement	Major	3129896	72	Do nothing	Do nothing	Do nothing	0
3	Do nothing	Minor	Minor	254707	22	Do nothing	Do nothing	Do nothing	0
4	Minor	Do nothing	Do nothing	11281	39	Do nothing	Do nothing	Do nothing	0
5	Replacement	Replacement	Replacement	2211188	6	Do nothing	Do nothing	Do nothing	0
6	Minor	Do nothing	Major	384030	4	Minor	Do nothing	Major	384030
7	Do nothing	Do nothing	Do nothing	0	7	Do nothing	Do nothing	Do nothing	0
8	Replacement	Replacement	Replacement	4829222	36	Do nothing	Do nothing	Do nothing	0
9	Replacement	Replacement	Replacement	1971519	35	Do nothing	Do nothing	Do nothing	0
10	Replacement	Replacement	Do nothing	1873528	11	Do nothing	Do nothing	Do nothing	0
11	Do nothing	Do nothing	Do nothing	0	8	Do nothing	Do nothing	Do nothing	0
12	Replacement	Do nothing	Do nothing	624559	17	Do nothing	Do nothing	Do nothing	0
13	Replacement	Replacement	Replacement	3195583	10	Do nothing	Do nothing	Do nothing	0
14	Replacement	Replacement	Replacement	6507093	31	Do nothing	Do nothing	Do nothing	0
15	Do nothing	Do nothing	Do nothing	0	24	Do nothing	Do nothing	Do nothing	0
16	Major	Do nothing	Major	1711150	5	Do nothing	Do nothing	Do nothing	0
17	Do nothing	Do nothing	Major	197329	26	Do nothing	Do nothing	Do nothing	0
18	Minor	Do nothing	Major	196654	57	Do nothing	Do nothing	Do nothing	0
19	Replacement	Replacement	Replacement	835388	52	Do nothing	Do nothing	Do nothing	0
20	Replacement	Replacement	Replacement	4372228	43	Do nothing	Do nothing	Do nothing	0
21	Replacement	Do nothing	Do nothing	625443	38	Do nothing	Do nothing	Do nothing	0
22	Replacement	Replacement	Do nothing	899696	45	Do nothing	Do nothing	Do nothing	0
23	Major	Major	Do nothing	717034	14	Major	Major	Do nothing	717034
24	Replacement	Replacement	Replacement	2489910	55	Do nothing	Do nothing	Do nothing	0
25	Replacement	Replacement	Replacement	6985217	49	Do nothing	Do nothing	Do nothing	0
26	Replacement	Replacement	Replacement	4928420	41	Do nothing	Do nothing	Do nothing	0

Figure C- 6. Excell file for suggested actions by AI-based policy

To run the code, first, click on the desired notebook, either "Bridge_Network_Analysis" or "Network_Analysis_AI", from the provided GitHub link. In the newly opened window, select the "Open in Colab" button to be redirected to Google Colab, which is an online coding and computing platform for code running and execution. To run the codes, the users need to have access to use Google Colab, where a Gmail account is required. In Google Colab, it is possible to run the codes either on your local computer or using the free cloud computing resources (i.e., virtual machine) provided by Google.

To use a virtual machine, select the “Runtime > Change runtime type” option from the top menu bar in Colab as shown in Figure C- 7:

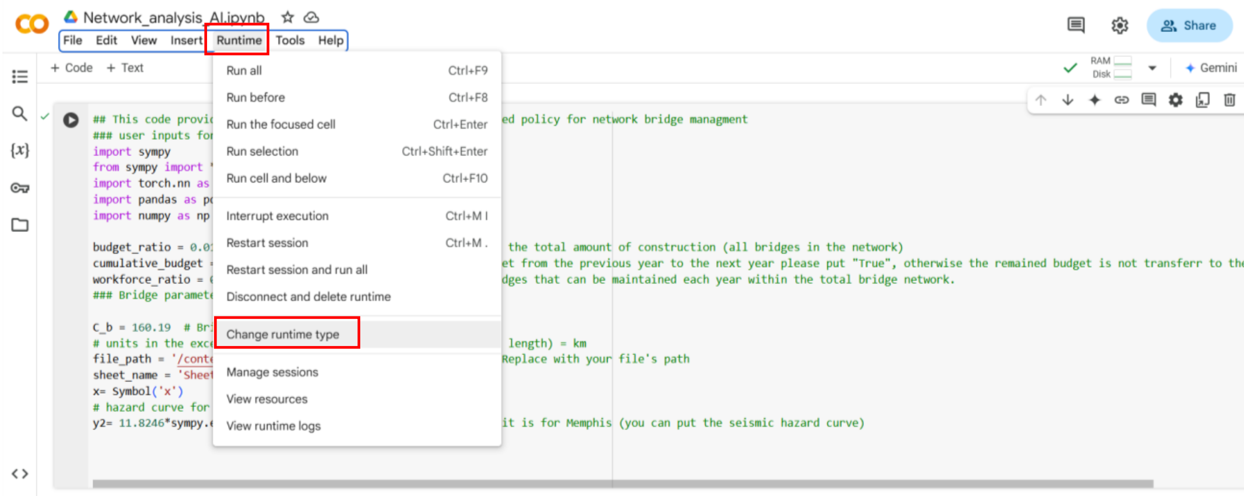


Figure C- 7. Change runtime type in Colab

In the pop-up window, you can choose either CPU or GPU from the hardware acceleration options based on your preference. If you want to run the codes on your local computer, select the drop-down menu in the top-right corner of the code script (next to the small RAM and Disk performance charts).

Additionally, the users will need to download the pre-trained AI agents and the Excel file, and upload them to their Google Drive as illustrates in Figure C- 8. To do this, follow these steps:

- Open your Google Colab account.
- Go to File > Drive > My Drive.
- Upload the pre-trained models and the Excel file to your Google Drive

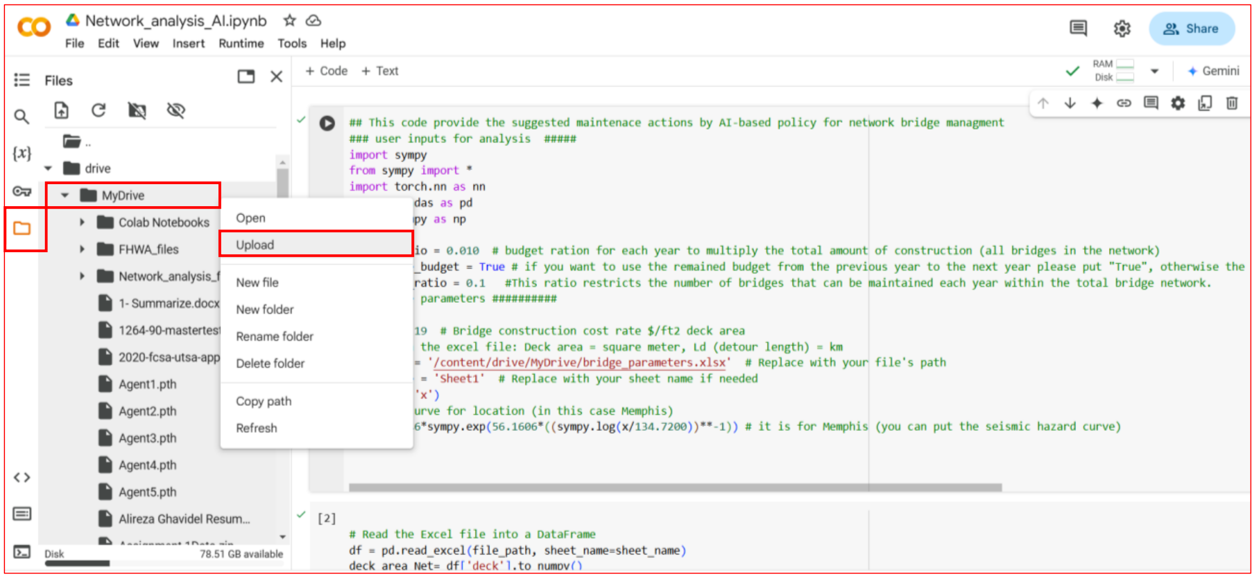


Figure C- 8. Upload files into Google Drive

Now you can easily run the codes. The codes are open-source so can be modified depending on the specific use cases. If the users wish to change any parameters, the parameters that can be modified, along with the default values used in this study, are provided for your reference below:

Table C- 1. User inputs for codes

ID	User inputs	Description	Default value(s)
1	num_statistic	Number of episodes	4,000
2	Years	Lifetime horizon	30
3	Times	Years to print tabular results	[0,5,15,25]
4	budget_ratio	Ratio respect to total construction cost of bridges	0.010
5	cumulative_budget	Rolling the remaining budget each year to the next year (True or False)	True
6	workforce_ratio	Man-power constraint that shows how many bridges can be maintained each year within the total bridge network	0.10
7	deck_area	Deck areas of bridges in the network (m^2)	Case study (83 bridges)
8	Detour_length	Detour length of bridges in the network (km)	Case study (83 bridges)
9	ADT	Average daily traffic of bridges in the network	Case study (83 bridges)
10	Truck_ratio	Truck ratio of bridges in the network	Case study (83 bridges)
11	initial_state (CRs)	Initial (current) condition rating of bridges in the network	Case study (83 bridges)
12	Start_x , Start_y	Bridge location coordinates	Case study (83 bridges)
13	centrality_parameter	Centrality measure parameter related to the network topology	Case study (closeness)
14	Hazard Curve	Hazard curve for city/location for risk analysis	Memphis

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