RL-Empowered Optimizer for Bridge Fortification: A Novel Decision-Making Mechanism to Optimize Bridge Fortification in Disaster-Prone Communities

Quarterly Progress Report
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1. Problem Description and Background

Effective operation of any society is heavily dependent on its critical infrastructures. Road infrastructure is an essential component of societies, facilitating access to different areas [1]. This infrastructure is an integration of several modalities such as roads, highways, bridges, rails, and public transit. Among these modalities, bridges are the most vulnerable ones against disasters such as earthquakes, floods, hurricanes, and fires. This poses significant risks to the integrity and functionality of road infrastructure. Bridges have experienced the highest rates of damage during past disasters [17]. For instance, the collapse of the I-95 bridge in Philadelphia, Pennsylvania, in June 2023, due to a tanker truck fire, disrupted transportation across a significant portion of the Eastern Seaboard, illustrating how critical this structure was in connecting the surrounding road network.

Given the increasing frequency and severity of natural disasters, the fortification of bridges (through using flexible bearings, elevating the structure, creating wind-resistant foundations, installing protective barriers, and using high-impact material) has become essential to ensure their resilience. This fortification not only enhances the resilience of this modality but also improves the post-disaster recovery process for the entire road infrastructure. Due to the high number of bridges and resource-consuming (time, budget, workforce, etc.) nature of fortification projects, having a decision-support mechanism to optimize this process for road infrastructure is vital.

This **proposal aims** to develop a novel decision-making framework that combines and leverages optimization, Markov Decision Processes (MDP), and Reinforcement Learning (RL) to optimize bridge fortification process in road infrastructure of disaster-prone communities. Referred to as "RL-empowered Optimizer for Bridge Fortification," the proposed framework determines the optimal level, technology, and sequence or concurrency for fortifying bridges in a community over a planning period to maximize the post-disaster resilience of road infrastructure. The expected outcomes are (1) mathematical framework and software codes, (2) a computational platform for practitioners and researchers, and (3) journal publications and conference presentations.

While some recent studies have analyzed interdependencies within and between infrastructures [1-6] and developed integrated policies for their concurrent restoration [7-11], they do not specifically address the effects of pre-disaster fortification - particularly bridge fortification - on post-disaster traffic movement efficiency [12-14]. Furthermore, prior works mainly rely solely on optimization techniques [10, 11], limiting their capacity to handle uncertainties that arise during fortification and processes [6, 14-16], nonlinear relationships in fortification operations, as well as their ability to manage large-scale, real-world infrastructure. The proposed "RL-empowered Optimizer for Bridge Fortification" fills these gaps and contributes to the resilient infrastructure literature as follows:

1. This framework will be the first systematic decision-making approach developing coordinated bridge fortification policies for multi-modal road infrastructure.
2. The proposed decision-making framework leverages AI techniques, such as RL, to enhance its scalability and capacity to manage the complexities (e.g., nonlinear relationships and computational complexities) of concurrently modeling pre-disaster bridge fortification and post-disaster restoration of road infrastructure.

3. Integrating MDP and AI within the decision-making framework significantly improves its ability to address a broad spectrum of uncertainties associated with bridge fortification, such as varying fortification durations and strengths.
4. This approach can adapt to changes occurring within road infrastructure of communities over the planning horizon, allowing it to generate flexible and responsive bridge fortification policies that can inform local, state, and federal policymakers and disaster management agencies such as FEMA or Miami-Dade County Office of Resilience.

2. Objectives and Research Approach

The **research objective** is to develop a novel decision-making framework, called RL-empowered Optimizer for Bridge Fortification, that combines and leverages optimization, Markov Decision Processes (MDP), and Reinforcement Learning (RL) to optimize bridge fortification process in road infrastructure of disaster-prone communities. This framework determines the optimal level, technology, and sequence or concurrency for fortifying bridges in a community over a planning period to maximize the post-disaster resilience of road infrastructure.

Figure 1 illustrates the structure of the proposed framework, which is an RL-based mechanism with an iterative optimization-based algorithm to simulate day-to-day traffic evolution in a road infrastructure. In RL, an agent learns by interacting with a learning environment, adjusting its decisions based on feedback to maximize long-term cumulative reward through a trial-and-error process [18, 19]. The iterative feedback received from the environment will train the agent to revise its decisions in a way to optimize an objective function. In other words, the agent tries to optimize its decisions through learning from the experiences it gains while interacting with the environment [20].

As seen in the figure, the proposed framework includes two RLs, one nested within the other:

- **The outer RL**: The agent of the outer RL represents the Department of Transportation as the bridge fortifier. Due to the sequential nature of the fortification process, it uses a Markov Decision Process (MDP) as its decision-making procedure. Considering resource limitations, at each stage of the MDP, a subset of bridges in the road infrastructure is selected by the agent for fortification. The consequence of this decision on improving the post-disaster restoration resilience of the road infrastructure is measured in the RL's learning environment. This learning environment is the inner RL (will be explained in the next bullet). It measures how much the restoration process of the road infrastructure will be accelerated after fortifying the bridges selected in that stage. This value will be considered as the reward for selecting this decision and sent back to the agent as feedback. This feedback helps the agent improve its selection in the next learning iteration. After a large number of iterations, the agent is trained to select the best fortification decision at each stage of the MDP.
- **The inner RL**: The agent of the inner RL represents the Federal Highway Administration (FHWA) that plans road restoration activities after disasters. For each fortification decision made by the agent of the outer RL, this agent optimizes the restoration operation for the road infrastructure for a bunch of most likely disaster scenarios that may happen for the community and make disruption in its road infrastructure. This agent employs a different MDP to identify the best sequence/concurrency for recovering damaged components (e.g., roads or bridges) in the road infrastructure. The agent prioritizes the

components according to the traffic improvement that can be achieved by their restoration in the road infrastructure. The impacts of restoration decisions on traffic improvement are evaluated in the learning environment of the inner RL that will be explained in the next bullet.

- **Day-to-day traffic simulator**: The learning environment of the inner RL evaluates the agent's decisions via simulating the traffic movements in the road infrastructure. It includes an iterative optimization-based algorithm that employs the behavior of travelers to predict traffic evolution in the links of the road network after terminating each restoration decision toward reaching the final equilibrium situation. This evolution deviates toward a new equilibrium condition when a new set of disrupted roads is restored and readded to the structure of the road network. To simulate traffic evolutions over the restoration horizon, we apply a day-to-day traffic assignment algorithm [49]. The day-to-day traffic models include the fact that the route choice decisions of travelers are made daily and may change day-to-day according to traffic variations in the road infrastructure. This algorithm captures both the time-minimization behavior of travelers and their inertia to shift to new and uncustomary routes. This makes the proposed mechanism applicable to a wide range of communities with different traveler behaviors.

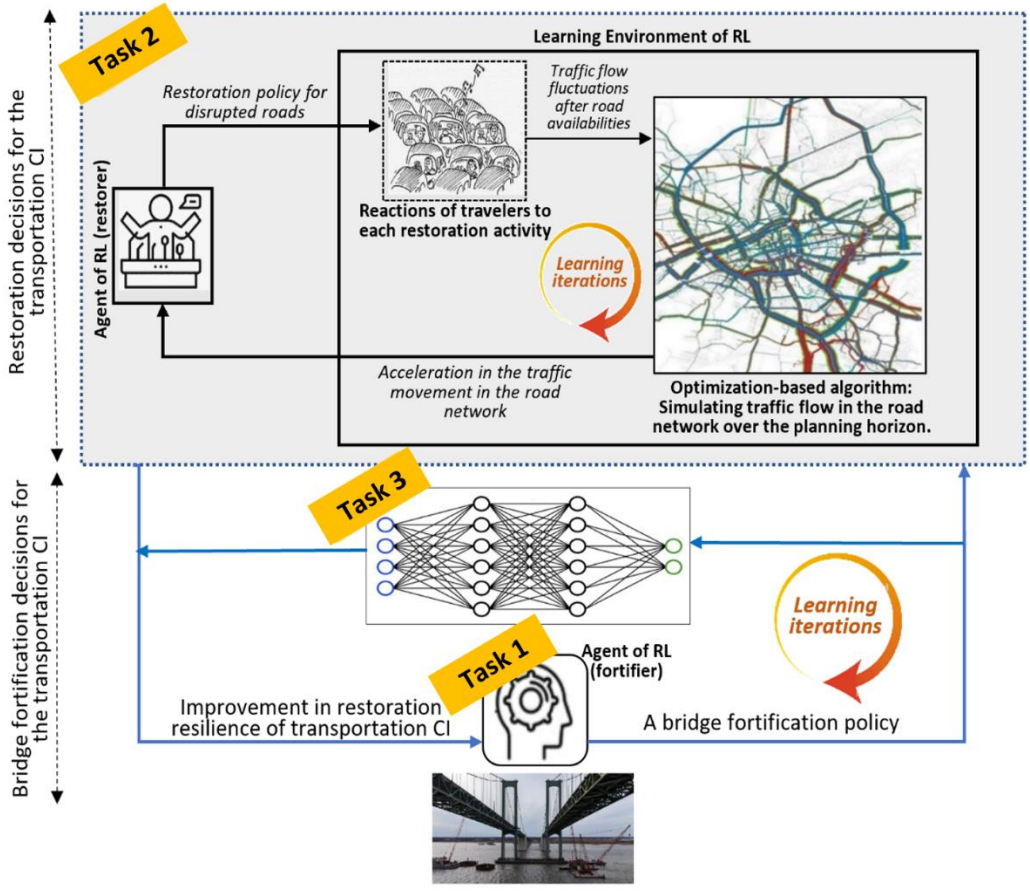


Figure 1. The structure of RL-Empowered Optimizer for Bridge Fortification.

3. Description of Research Project Tasks

To design the proposed framework, the following tasks will be accomplished:

- **Task 1: Day-to-day traffic simulator.** An iterative optimization-based algorithm will be developed to predict the behavior of travelers and model traffic evolution in the links of the road network after terminating each restoration decision toward reaching the final equilibrium situation.

  Progress level of Task 1: 100%

- **Task 2: The inner RL development.** An RL-based framework will be developed to optimize the restoration process for damaged roads and bridges in the road infrastructure and estimate post-disaster traffic acceleration that can be caused by pre-disaster bridge fortification decisions.

  Progress level of Task 2: 100%

- **Task 3: The outer RL development.** To design optimal bridge fortification policies for road infrastructures in disaster-prone communities, an RL-based framework will be developed. Considering the resource constraints that necessitate sequential decision-making and the stochastic nature of bridge fortification (e.g., uncertain fortification duration and effectiveness), the agent's decision-making process will be formulated as an MDP. The inner RL developed in Task 2 will constitute the learning environment of this framework.

  Progress level of Task 3: 50%

- **Task 4: Computational platform development.** In addition to mathematical foundation, a computational platform (including software code and documentations of the developed computing models) will be developed for the framework, making it accessible to researchers and practitioners with limited optimization and AI expertise.

  Progress level of Task 4: Has not started yet.

4. Results So Far

One journal article:

- Babaee M, Saha N, Ponce FM, Rezapour S, Amini MH (2026). Robust supply chain network design with service level against disruptions and demand uncertainties: A real-life case. Reliability Engineering & System Safety 273, 112371.

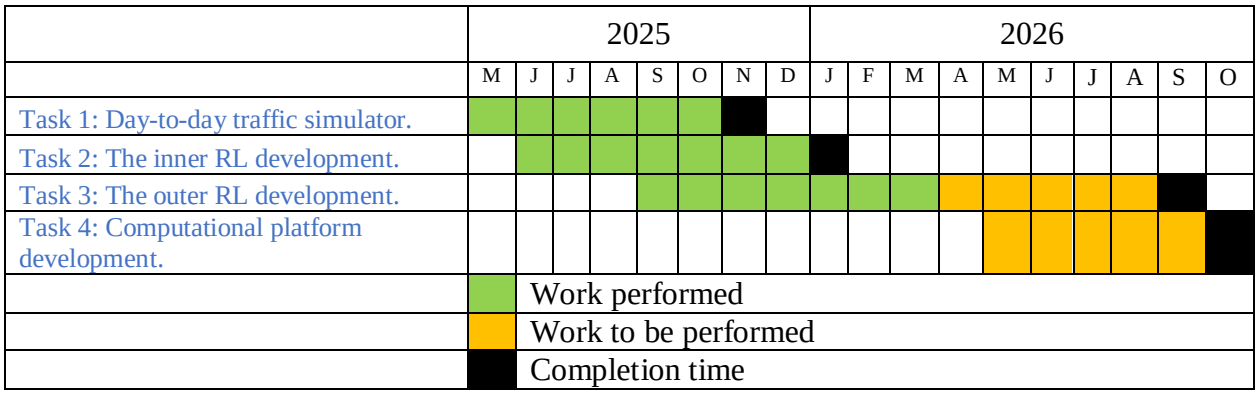
One conference presentation:

- Ahmed SW, Rezapour S, Amini MH (2026). AI-Driven Optimization for Prioritizing Bridge Fortification in Hazard-Prone Transportation Networks. Submitted to 2026 World Bridge Engineering Conference, December 1-2, 2026, Miami FL.

5. Schedule

Progress of tasks in this project is shown in the table below.

Item	% Completed
Task 1: Day-to-day traffic simulator.	100%
Task 2: The inner RL development.	100%
Task 3: The outer RL development.	50.0%
Task 4: Computational platform development.	0.00%



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