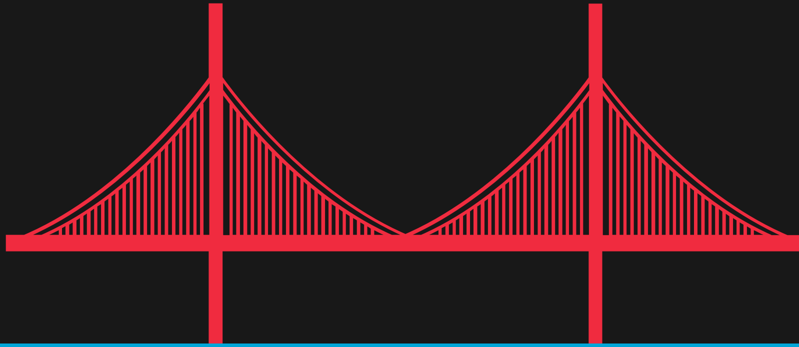
Bridge Maintenance
RL Project Idea



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01

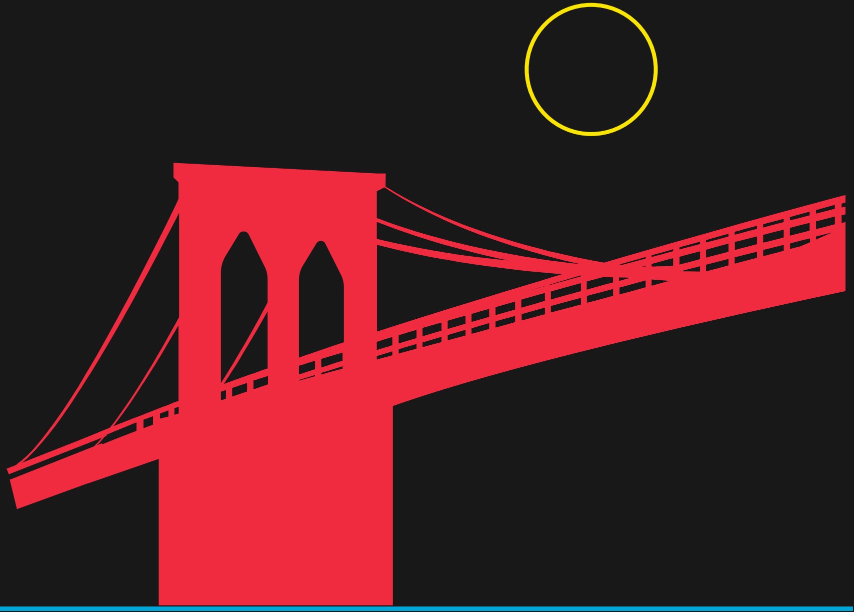
Problem

Challenges facing bridge infrastructure

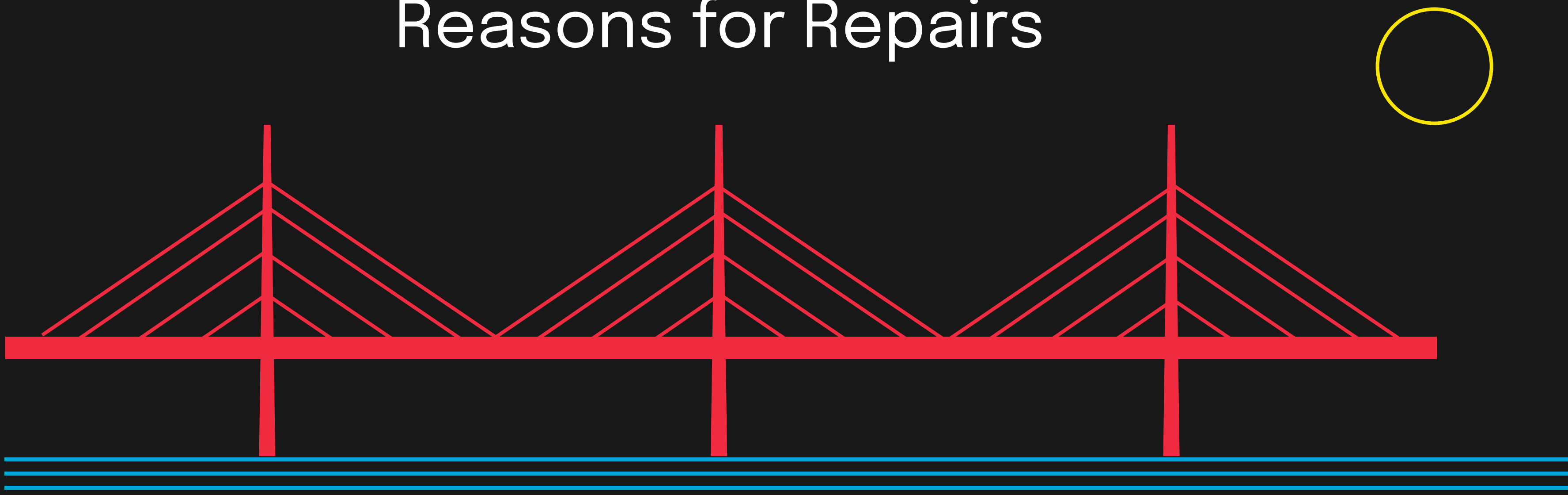
American Road & Transportation Builders Association

221,800

of America's **623,147 bridges** need repair, which span over **6,100 miles**



Reasons for Repairs



Aging, Usage & Deterioration

Maintenance & Intervention

Inspection and Monitoring Accuracy

02

Proposal

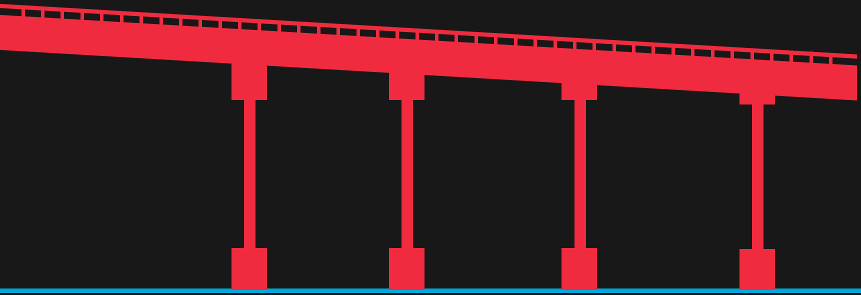
Explain the concept of the project and proposal

Research Paper on Bridge Maintenance

Hierarchical reinforcement learning for transportation infrastructure maintenance planning by Zachary Hamida and James-A. Goulet

Background of the paper

- Adaptive decision-making
- Resource optimization
- Policy for long-term planning and cost savings



Project proposal

Hierarchical Decision-Making

Using RL methods to breakdown bridge maintenance planning into different levels such as focusing various aspects to the bridge, with each level of hierarchy

Reward for Prioritization

Assign rewards based on the urgency and condition of bridge components to prioritize critical tasks, such as cracks or deteriorated beams

Cost-Efficiency Simulation

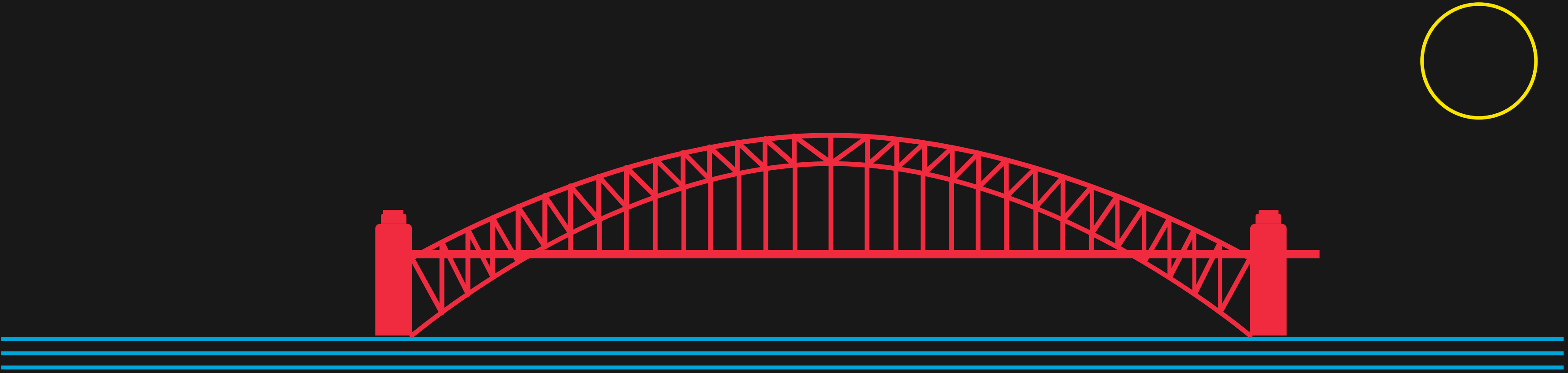
Apply multiple maintenance scenarios to help the model learn to optimize resources over time. Through situations, the agent will select maintenance actions that minimizes costs

03

Environment

Existing working environment

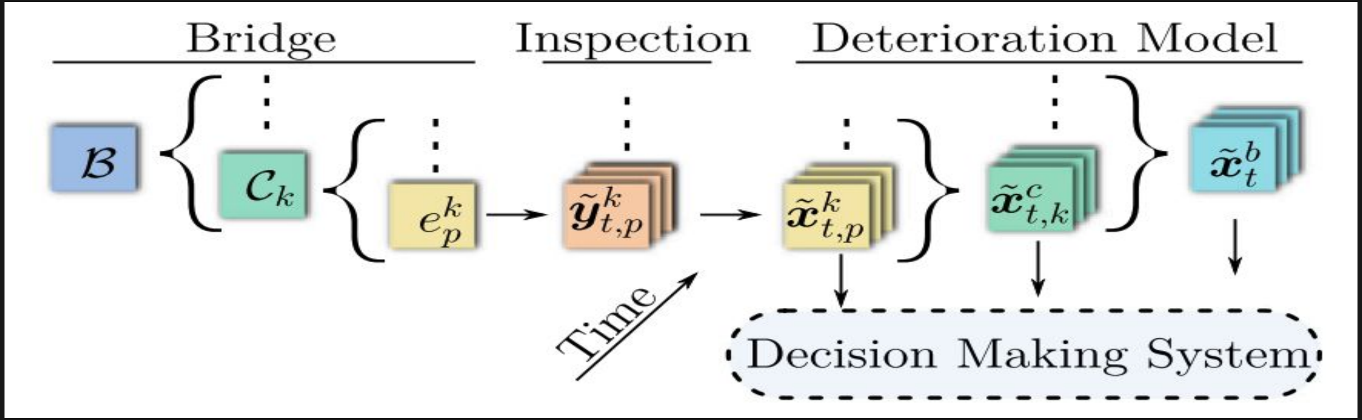
Environment Provided on Github



https://github.com/CivML-PolyMtl/InfrastructuresPlanner/blob
/main/infra_planner.py

Structure of the Environment:

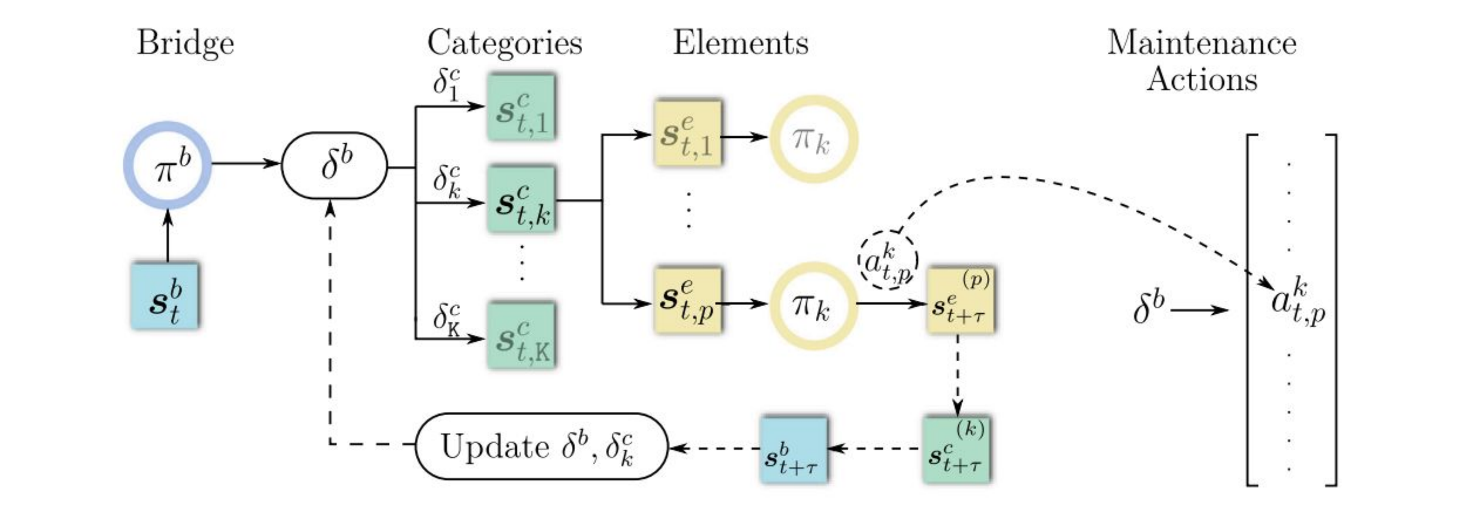
Bridge Inspection and Deterioration Model



- **Bridge (B) -** entire bridge system being monitored
- **Categories (C*k*) -** The bridge is divided into different categories (e.g., structural components, sections, or materials). The bridge is divided into different categories (e.g., structural components, sections, or materials)
- **Inspection (ykt,p) -** inspection process generates observations or measurements that will observe wear, detect defects, or measurements of structural integrity
- **Deterioration Model -** Uses inspection data to update the predicted condition for each element

Structure of the Environment, Cont'd:

Decision-Making Flow for Maintenance Actions



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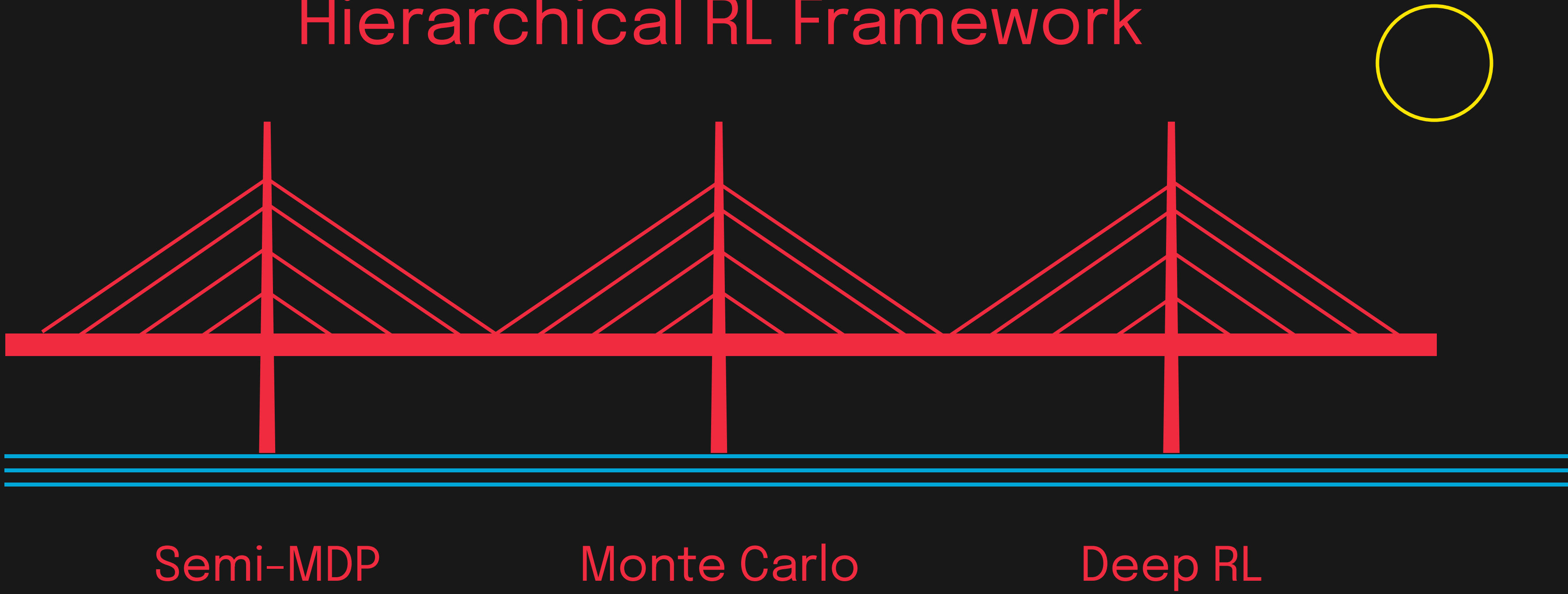
Methodologies

Application of reinforcement learning methods

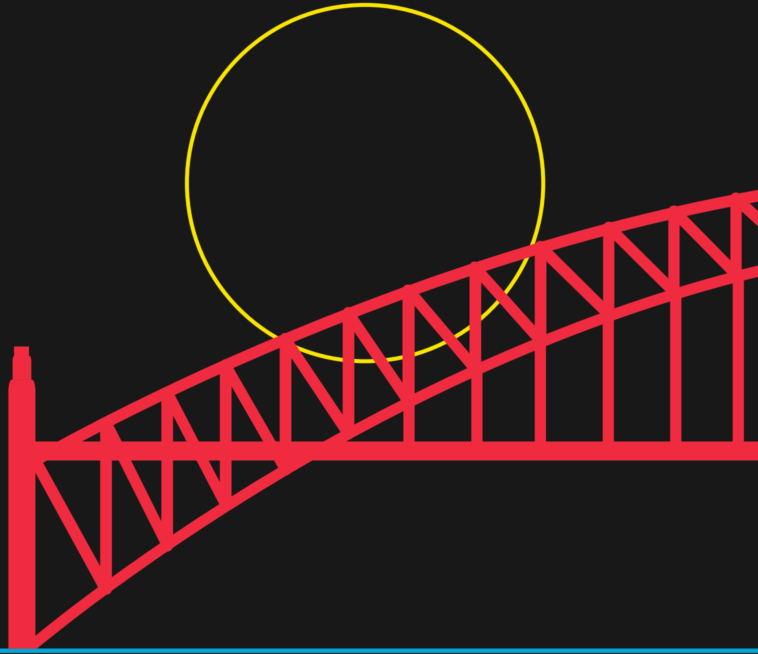
Hierarchical RL Framework



Semi-Markov decision processes (SMDP)

- Model sequential decision making
- Handle actions over time intervals with varying duration
- Accommodate temporal flexibility

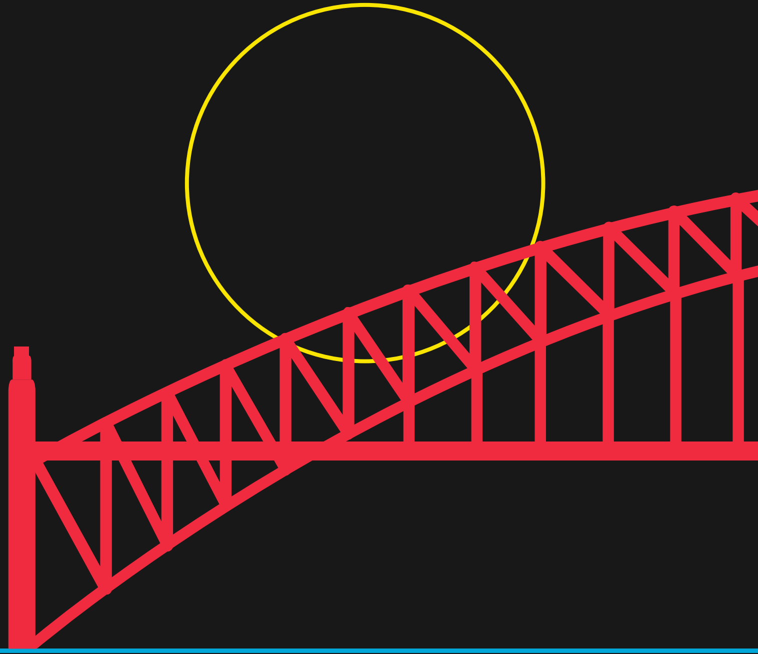
All leads to more realistic representation



Monte Carlo

- Simulate various maintenance policies over multiple scenarios to estimate long-term costs associated with different strategies

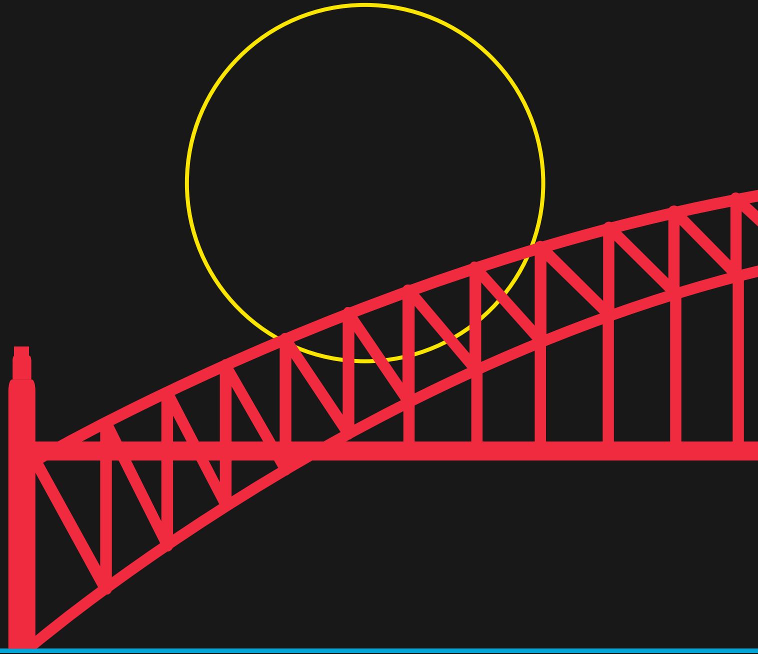
Helps evaluate effectiveness of maintenance plans without needing a complete model of the system



Deep RL

- Addresses complexity of large state-action spaces
- Provides scalable alternative to tabular Q-learning

Makes capable of generalizing from experiences, efficiently solving problems in complex environments → like bridge maintenance



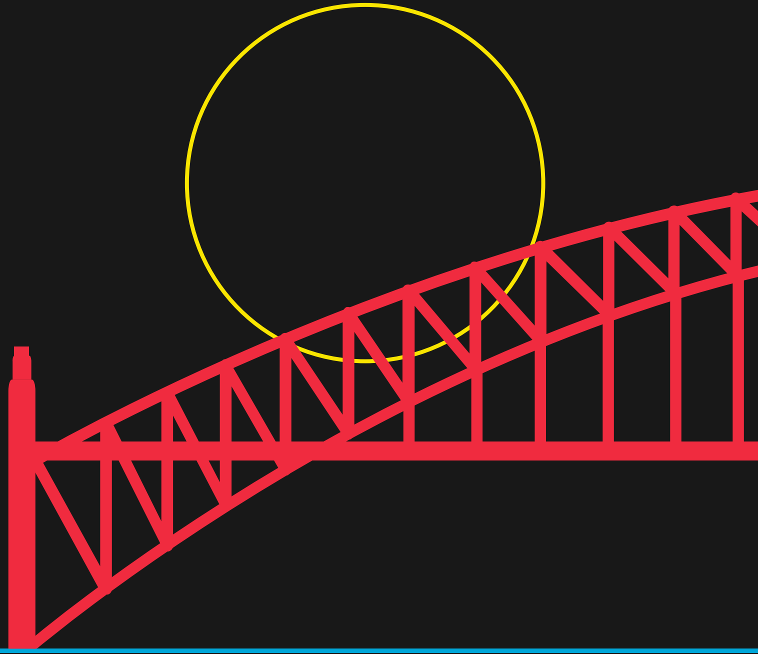
05

Benefits & Results

Our goal is to reduce costs, prioritize repairs, and allocate resources efficiently

Objectives

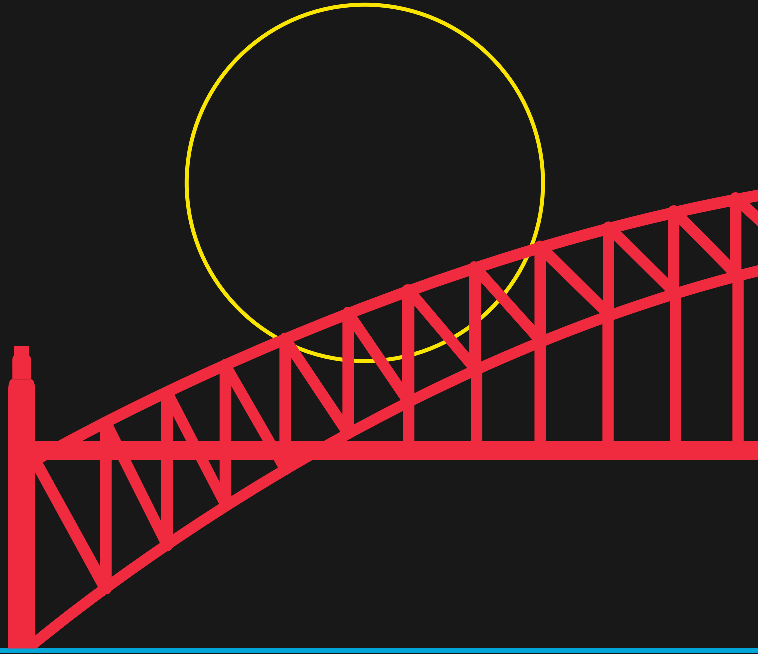
- Save money by planning our repairs better
- Fixing urgent issues when they need attention
- Manage large networks easily and efficiently



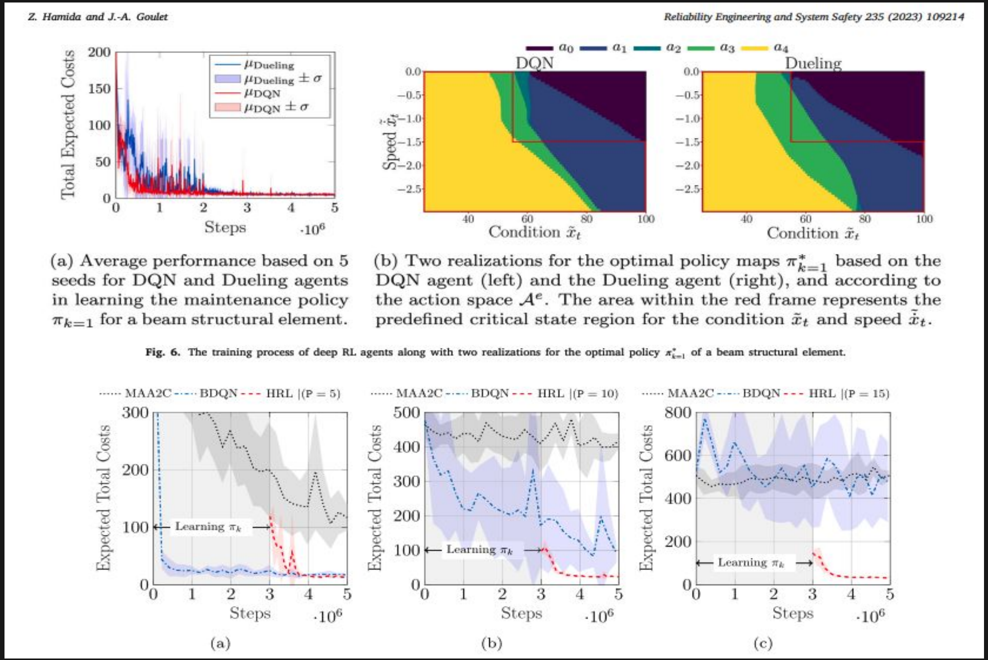
The Benefits

- Reduces disruptions by planning smarter repairs
- Provides clear, easy to understand policies
- Works well for large and complex systems
- Tracks damage to make fast decisions

HRL helps prevent costly breakdowns, improves safety and makes sure everything works well by fixing the most important things in a timely manner.



Performance of Different RL Agents



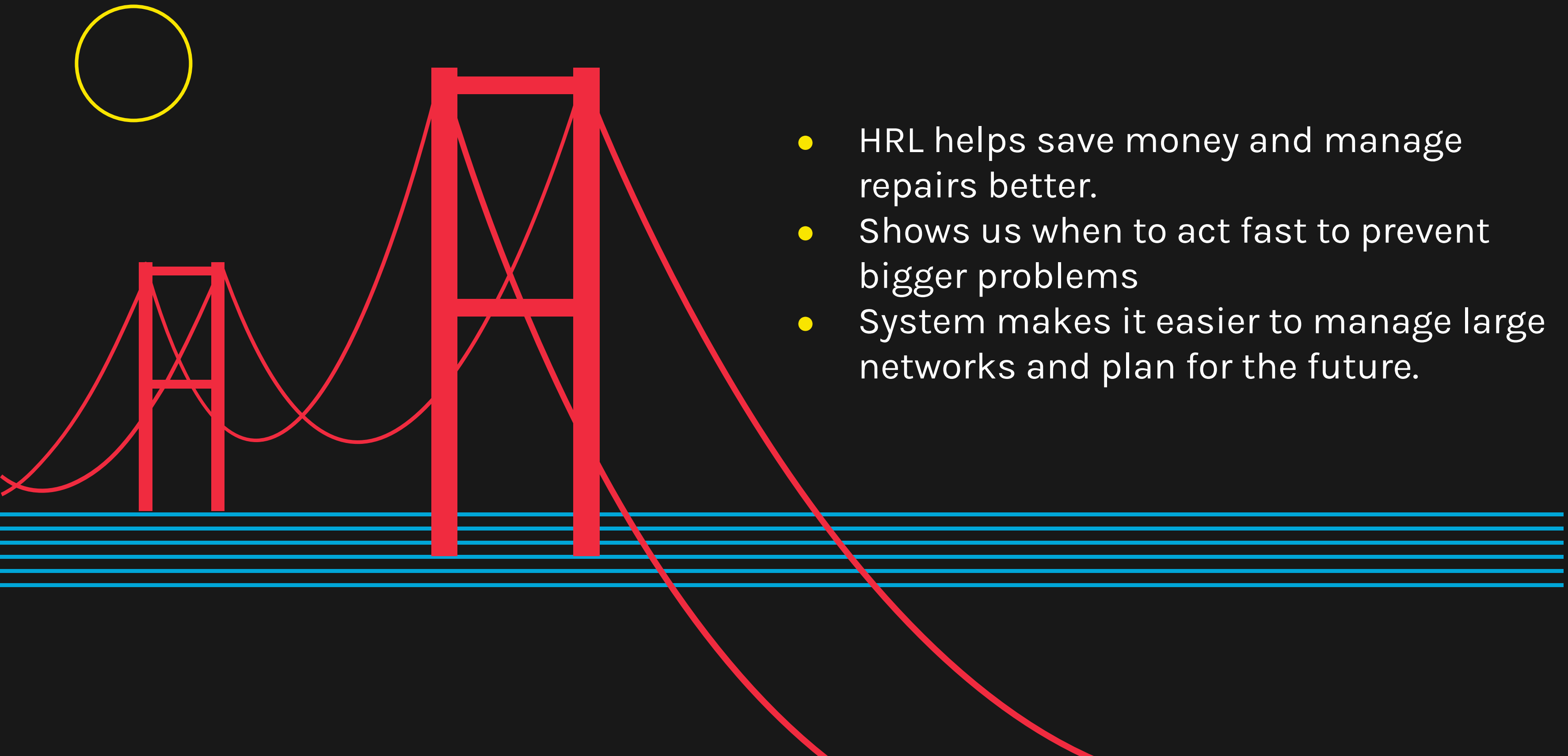
Performance Results

- We compared the average performance using different agents to learn the best maintenance policy
- HRP demonstrated better long-term cost savings across multiple tests

Optimal Policy Maps:

- Maps show how agents select actions based on infrastructure condition and deterioration speed.
- The red highlighted region marks critical areas that need to be quickly handled.

Conclusion and Future Potential



- HRL helps save money and manage repairs better.
- Shows us when to act fast to prevent bigger problems
- System makes it easier to manage large networks and plan for the future.

Thank you!

06

Q&A

Questions from the class