

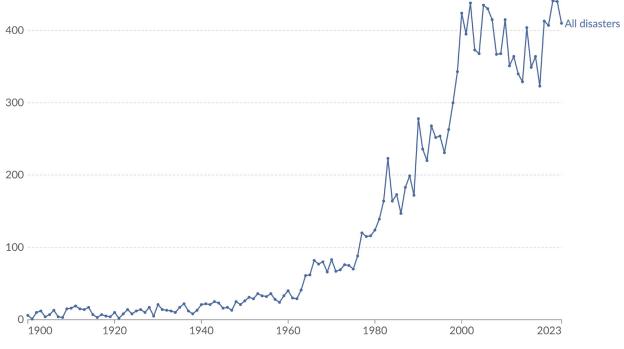
Q-RES MARL

A Resilience-Based MARL Framework for the Post-Earthquake Recovery of Interdependent Infrastructures

Antonios Mavrotas - AR3B05 - P5 Presentation - 23/06/2025

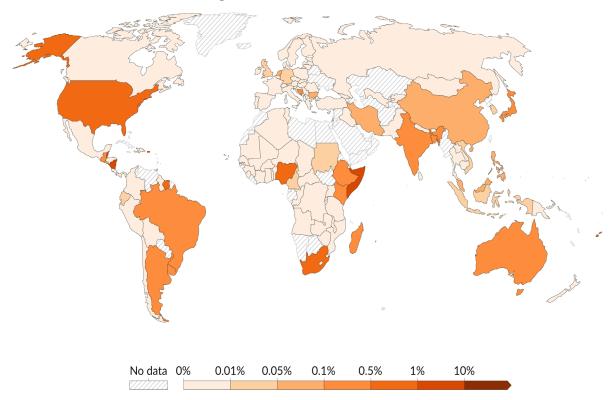
Mentors: Charalampos Andriotis and Simona Bianchi Invaluable assistance was also provided by Prateek Bhustali Natural Disasters: Wider Urban Impacts on Built Environment

Increasing Disaster Frequency



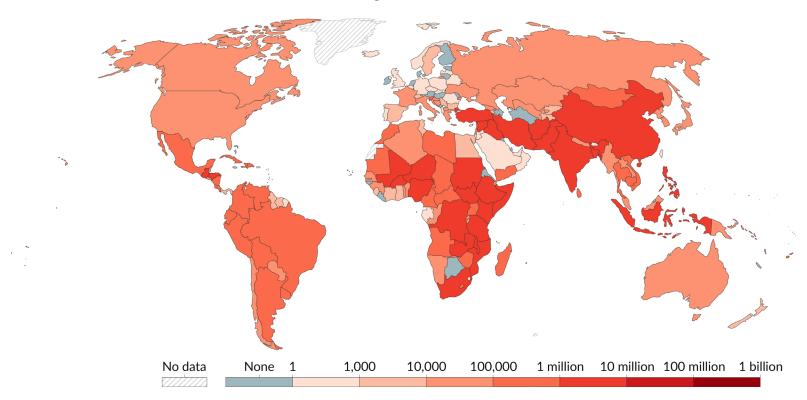
Disaster Frequency / #

Significant Economic Shocks

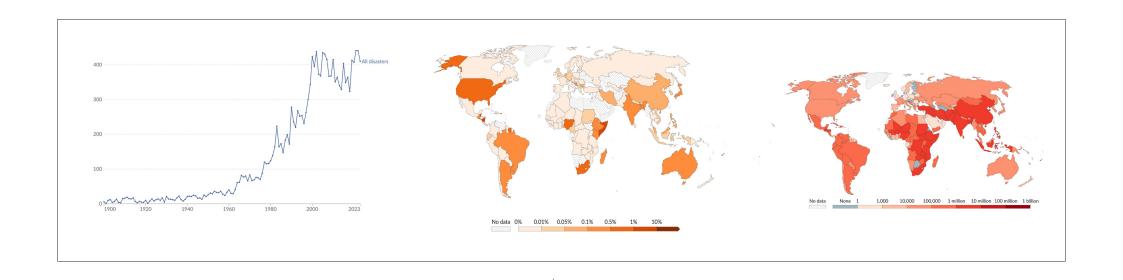


Economic Losses / % GDP / yr

Exceeding Human Losses

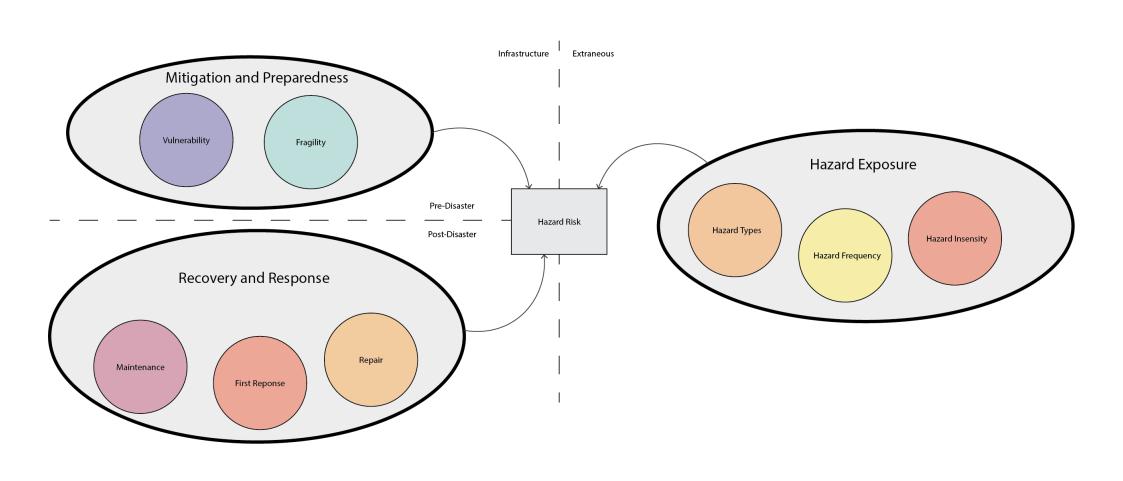


people req. assistance (2019)



Increased Global Hazard Risk

Hazard Risk Contributors



Traffic

Resilience

Reinforcement Learning

Reward

Experiment

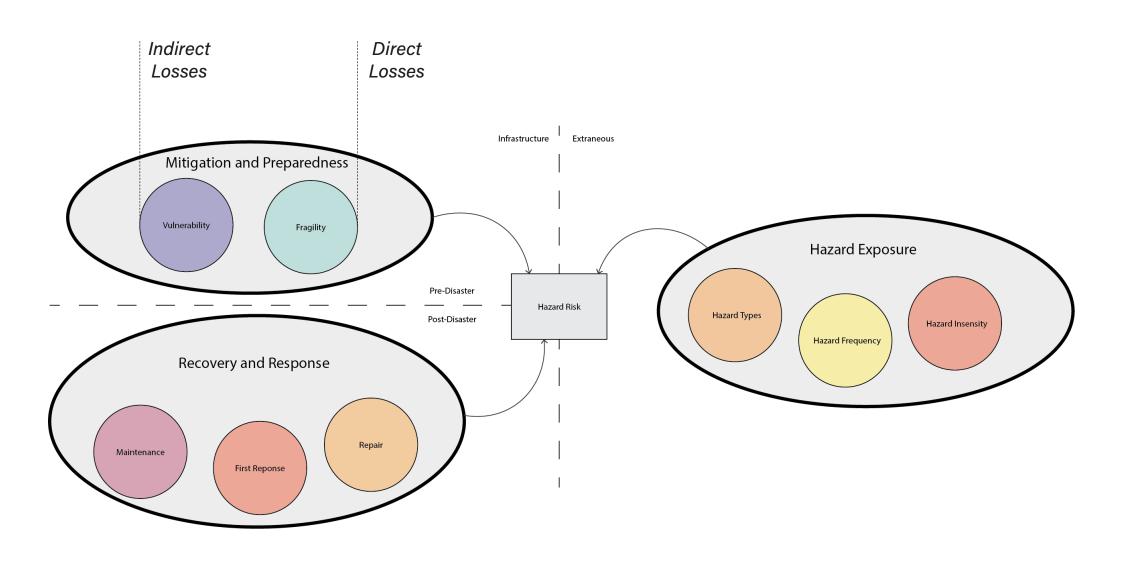
Conclusion

Fragility

Recovery

Context

Hazard Risk Contributors



Examples of Damage



Landslide in Switzerland Buildings are dependent on the damage from debris of neighbouring buildings.



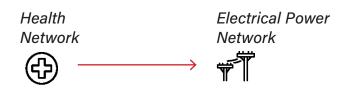
Flash floods in Spain Cascading effects of vehicle debris on traffic.



Earthquake in Morocco Lack of centralised planning in rural areas makes government financing challenging.

What are Interdependencies?

Interdependencies



Visibility and Rescue Operations affected by Smoke by Electrical Substation

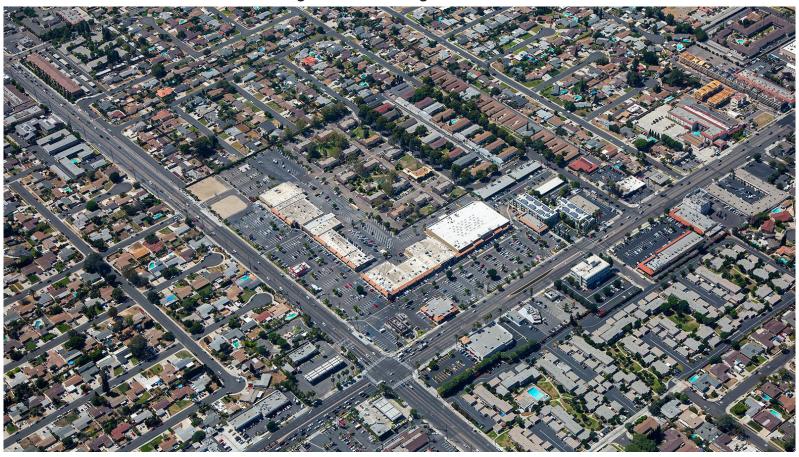
Road Capacity is Dependent on Building Debris



2023 Inskenderun Earthquake, Turkey

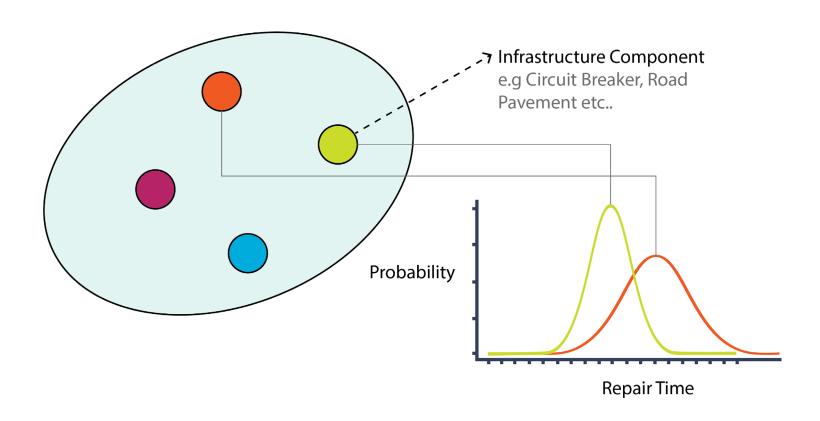
How Can We Predict Damage To Infrastructure?

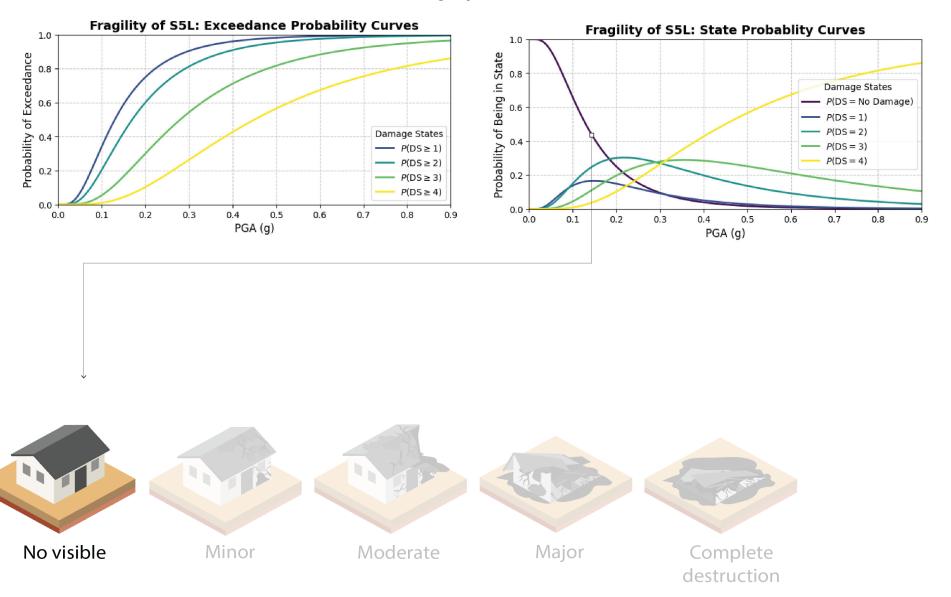
Large Scale Damage Prediction

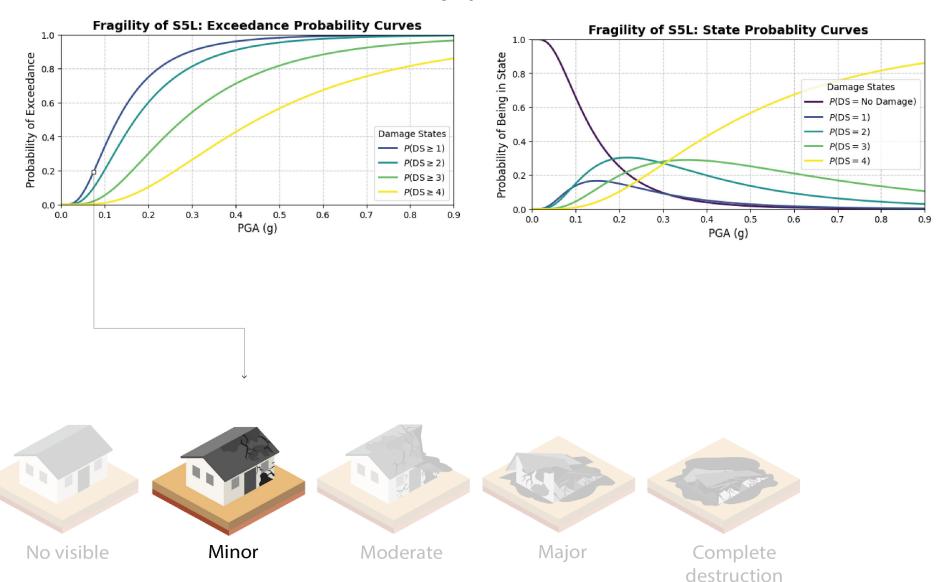


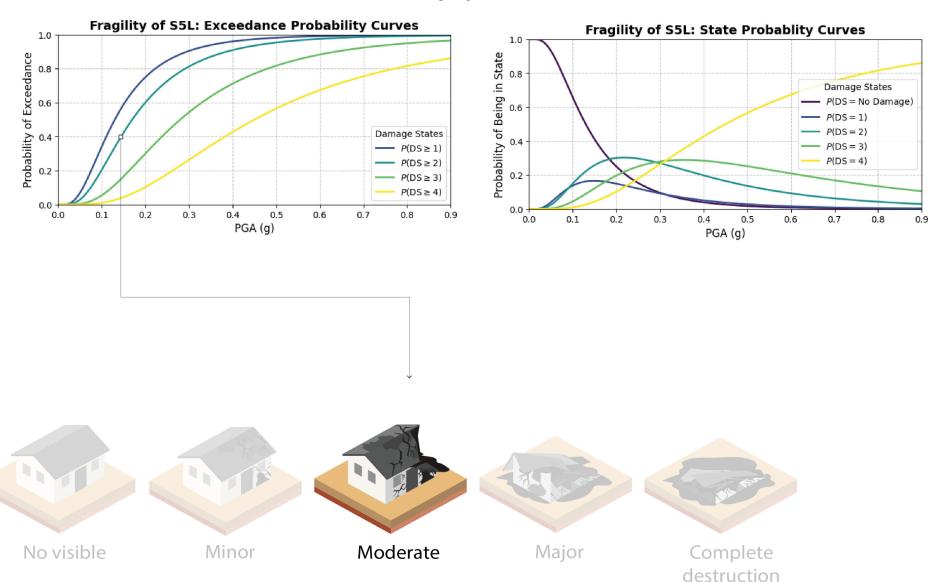
Infrastructure in Anaheim, US.

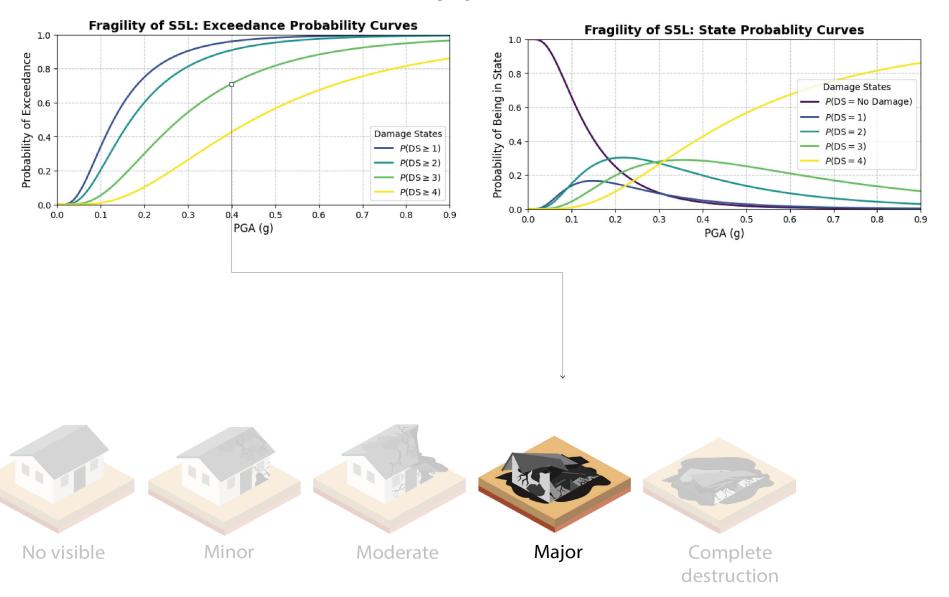
Stochastic Damage Prediction

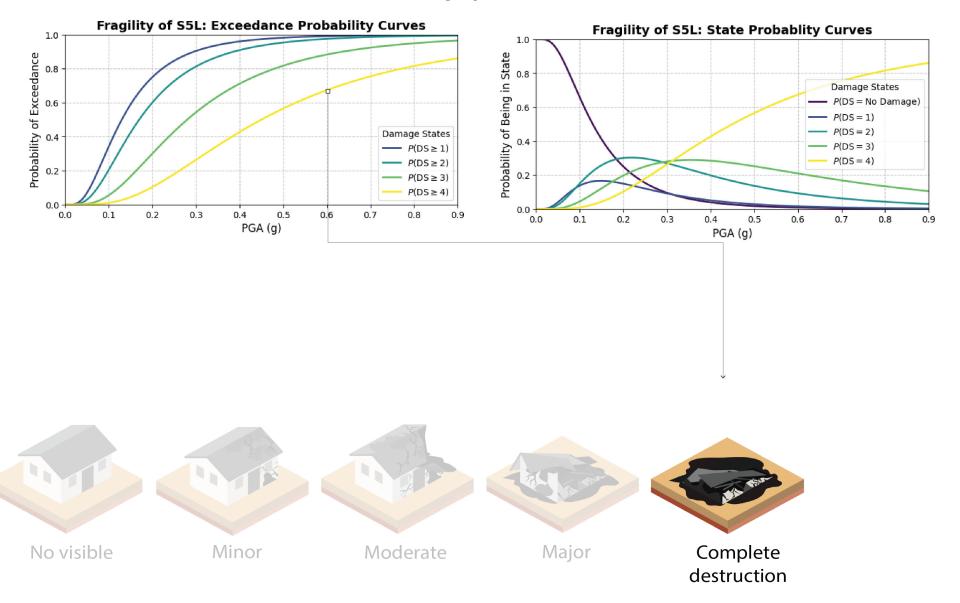








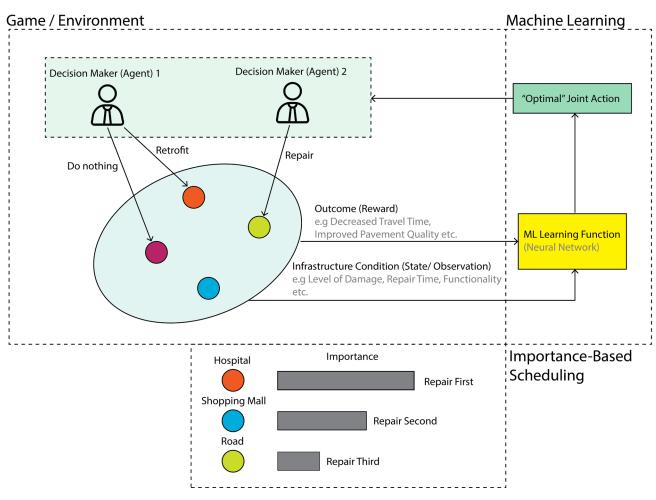




Devising Optimal Repair Strategies

Hypothesis

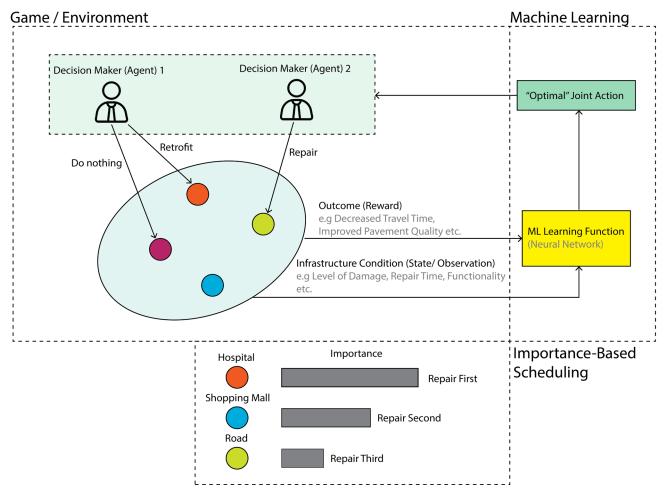
MARL can perform better than Importance-based repair scheduling of interdependent infrastructure networks.

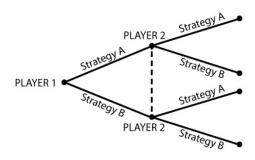


MARL vs Importance-Based decision making

Hypothesis

MARL can perform better than Importance-based repair scheduling of interdependent infrastructure networks.





Players, Decision Makers = Agents

Importance Index =
$$\frac{dem(t)}{cap(t)}$$

Performance Index =
$$\frac{q(t)}{q^*(t)}$$

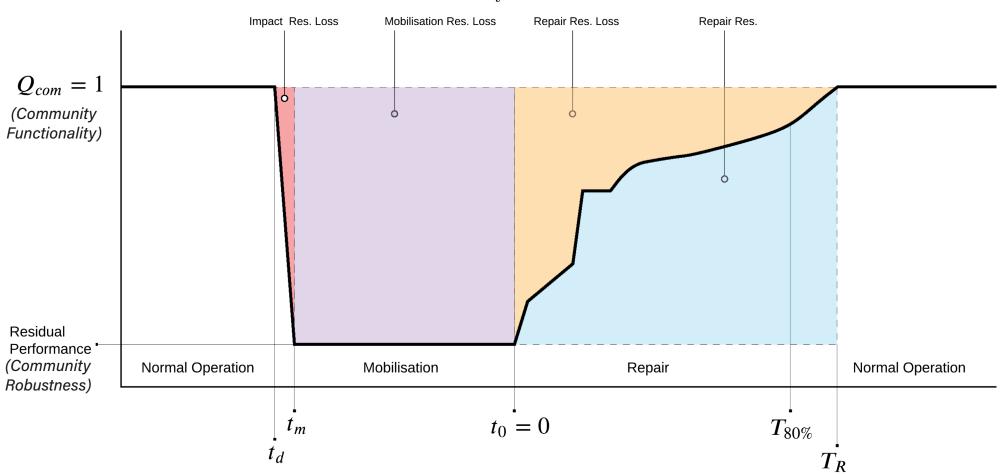
Examples Of General Importance-Based Ranking

MARL vs Importance-Based decision making

How Do We Measure The Success Of A Repair Policy?

Measuring Success With Resilience

$$Q_{com} = \sum_{i}^{i=N_{sub}} w_i \cdot q_i(t)$$



Community Functionality / Time

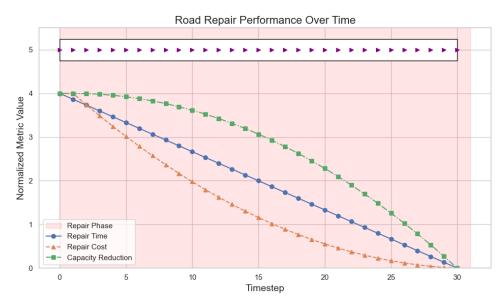


Measuring Functionality

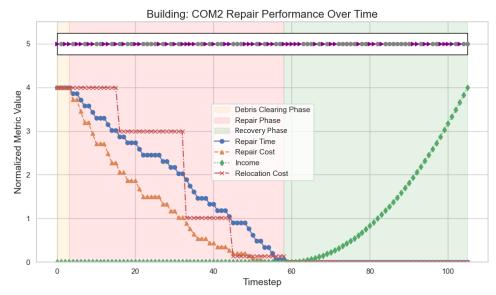
Community Functionality
$$Q_{com} = \sum_{i}^{i=N_{sub}} w_i \cdot q_i(t)$$

Sub-system Functionality
$$\,q_i(t)=1-L_i(t)\,$$

Sub-system Loss
$$L_{\mathrm{i}}(t)=\frac{C_{\mathrm{i}}(t)}{C_{\mathrm{i}}^{+}(t)}, \quad 0 \leq L_{\mathrm{i}}(t) \leq 1$$



Optimal Repair (Repair at Every Timestep) of a Highway Road Segment



Sub-optimal Repair (Random Intervention at Every Timestep) of a large shopping mall

Methodology

Testbed Production Data INCORE API COM8_11 COM6_10 Ground Motion COM8_12 HRD1_2 HRD1_1 RES5_6 Residential GOV2_8 Essential Commercial Other Roads Traffic Routes Toy City 30 Commercial Residential Essential Other Roads Traffic Routes Toy City 4 Traffic Context Fragility Recovery Resilience Reinforcement Learning Reward Experiment Conclusion

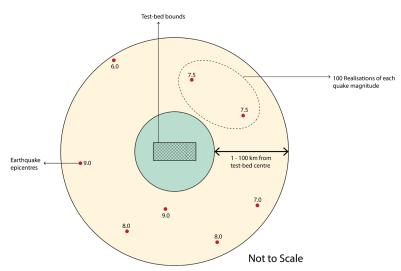
Data INCORE API Ground Motion

Fragility

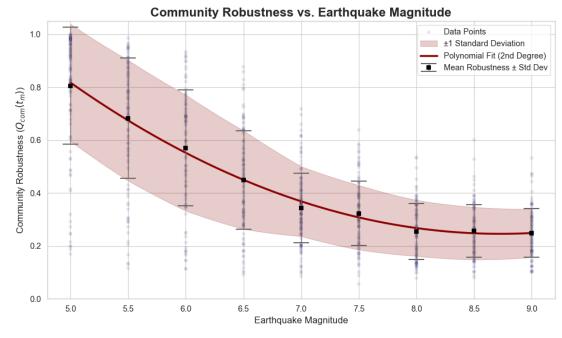
Context

Recovery

Seismic Hazard Assessment



Dataset of Earthquakes from 5.0 - 9.0 M with 0.5 increments for 100 realisations per magnitude



Reward

Conclusion

Experiment

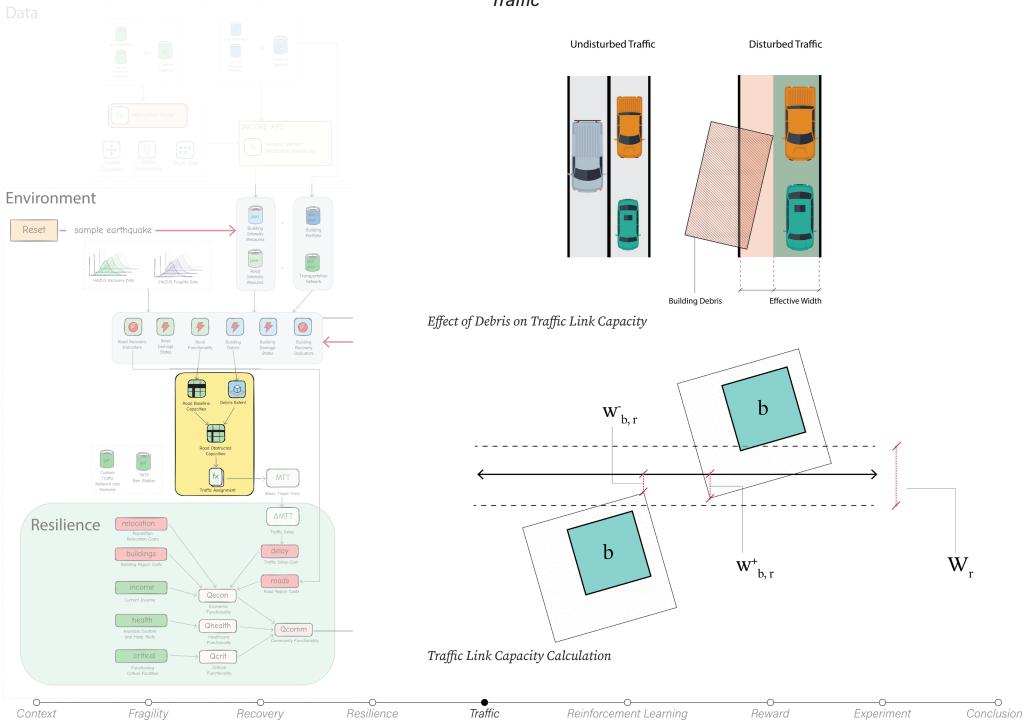
Results of Earthquake Impact to Community Functionality

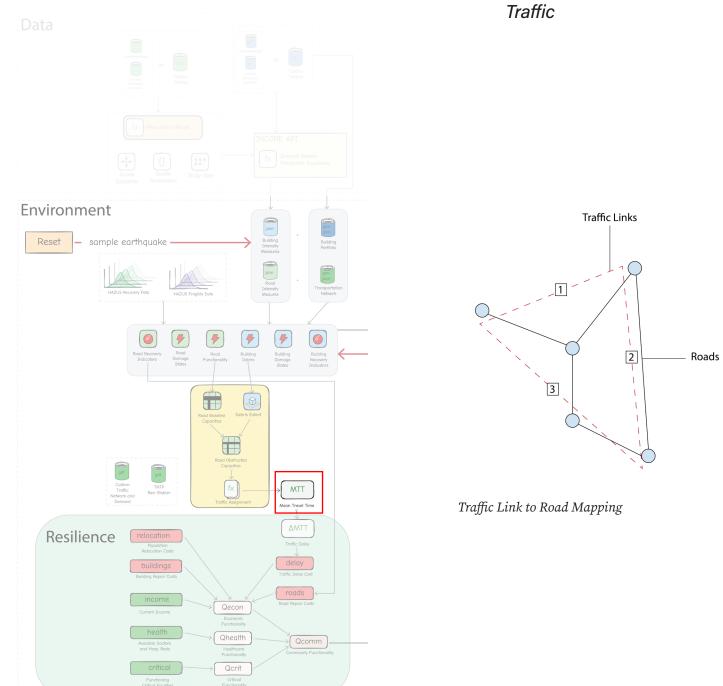
Reinforcement Learning

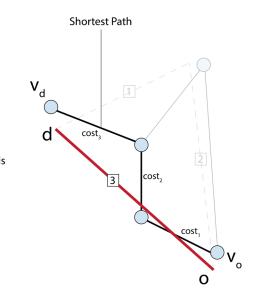
Traffic

Resilience

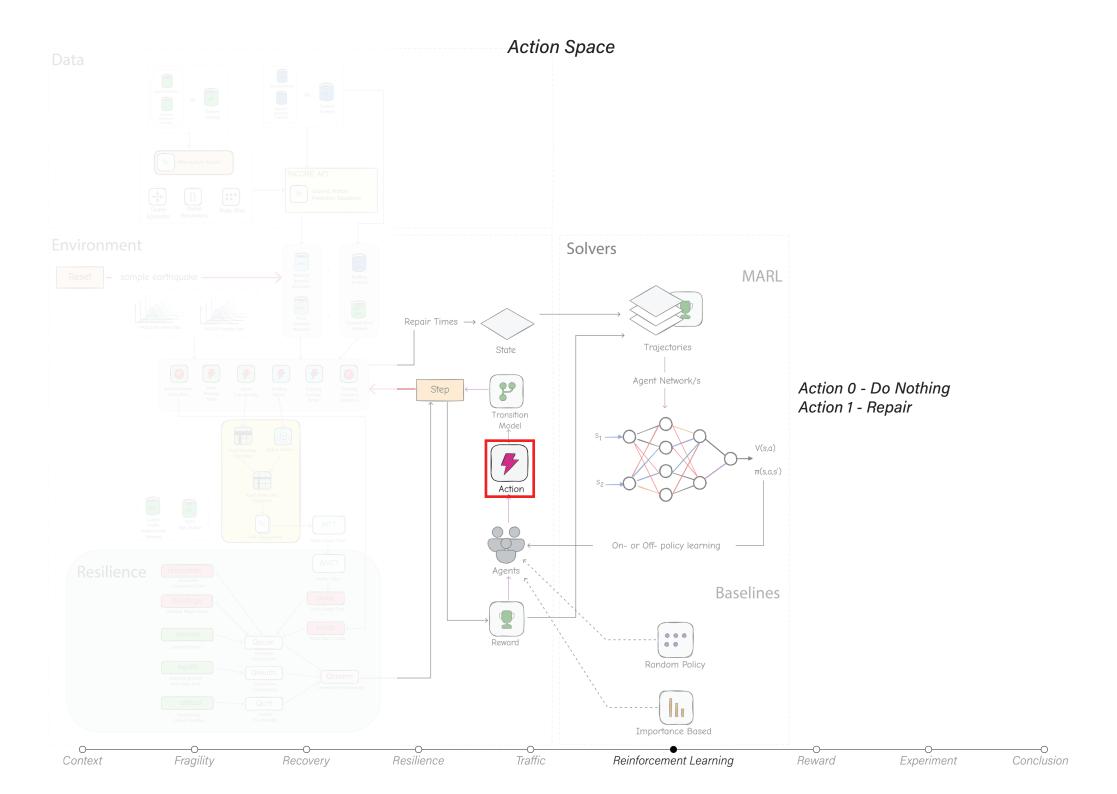
Traffic

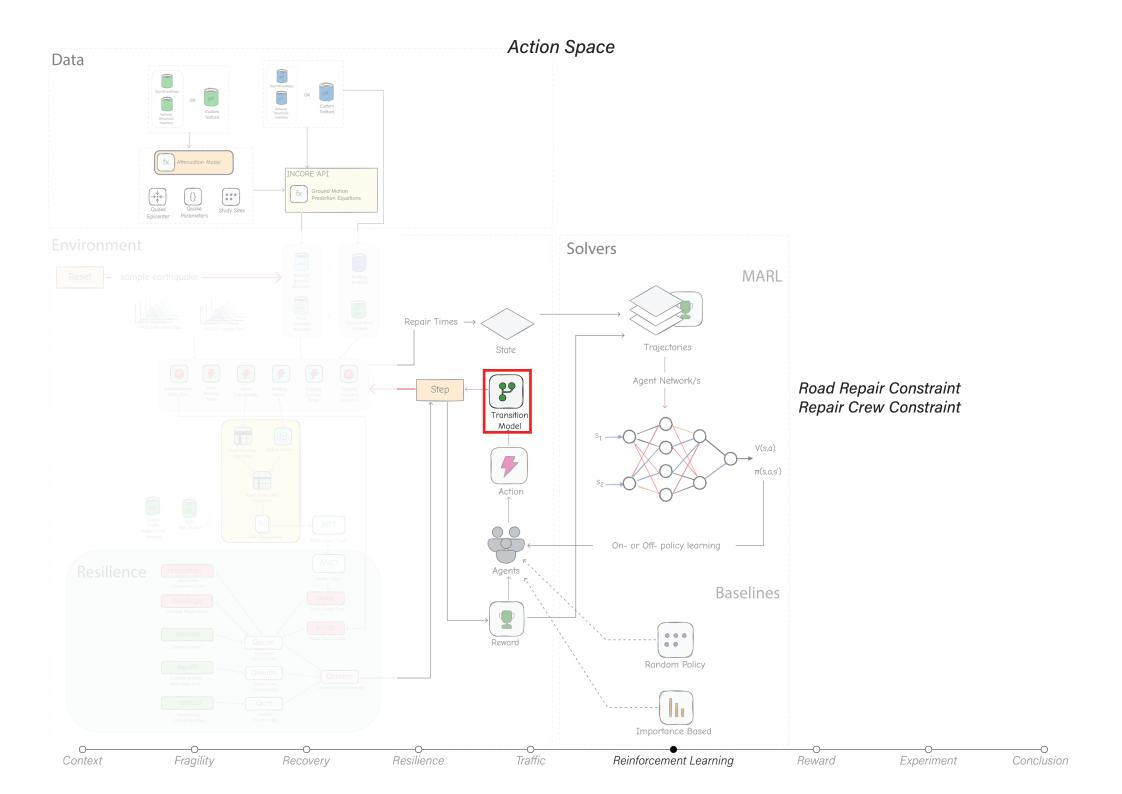


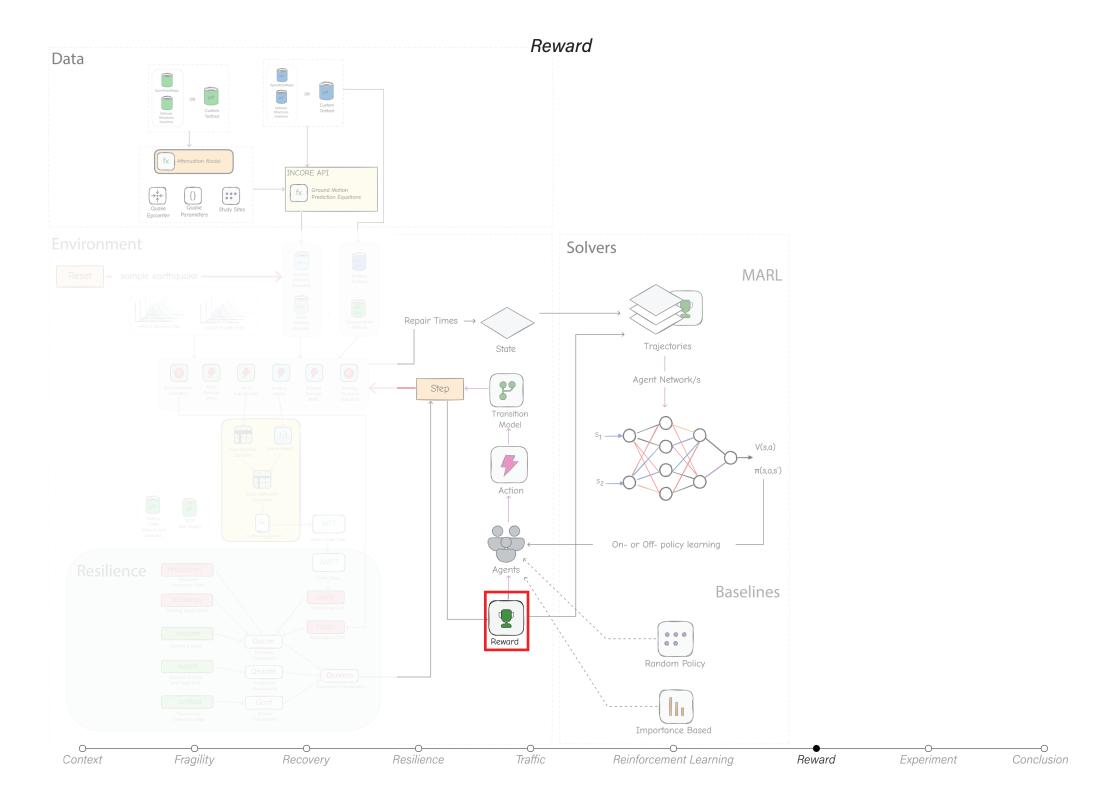


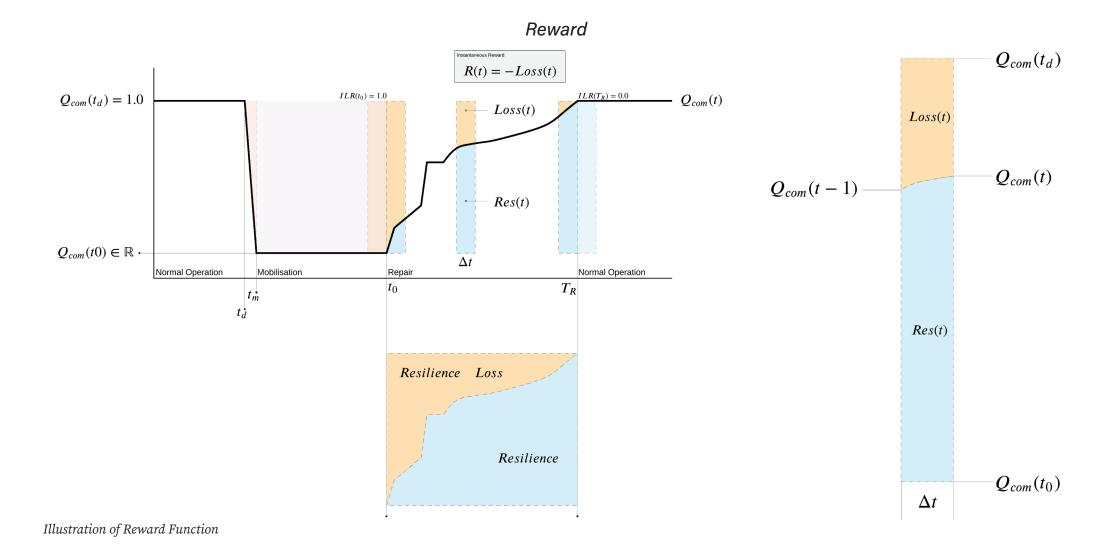


Context ____O Conclusion Fragility Recovery Resilience Traffic Reinforcement Learning Reward Experiment



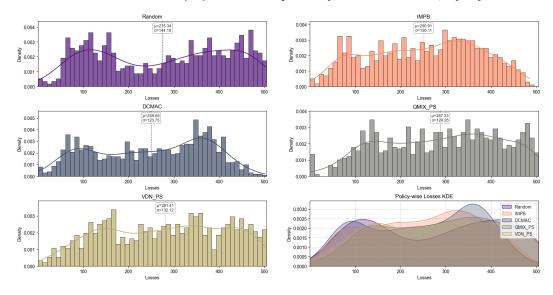




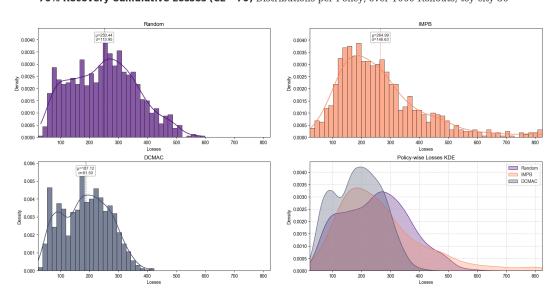


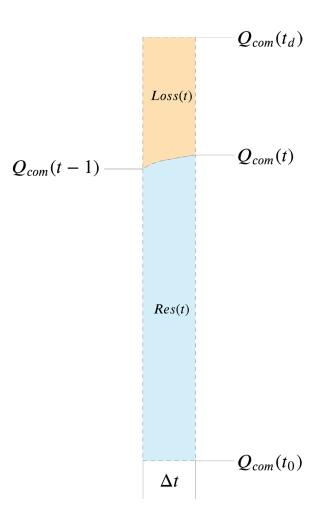
Results

Cumulative Losses (CL) Distributions per Policy, over 1000 Rollouts, toy-city-4



70% Recovery Cumulative Losses (CL - 70) Distributions per Policy, over 1000 Rollouts, toy-city-30

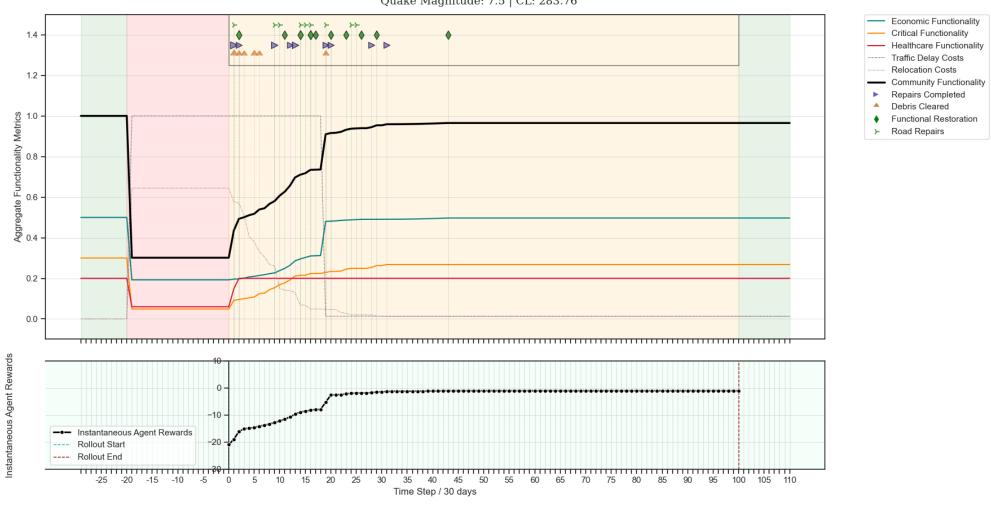




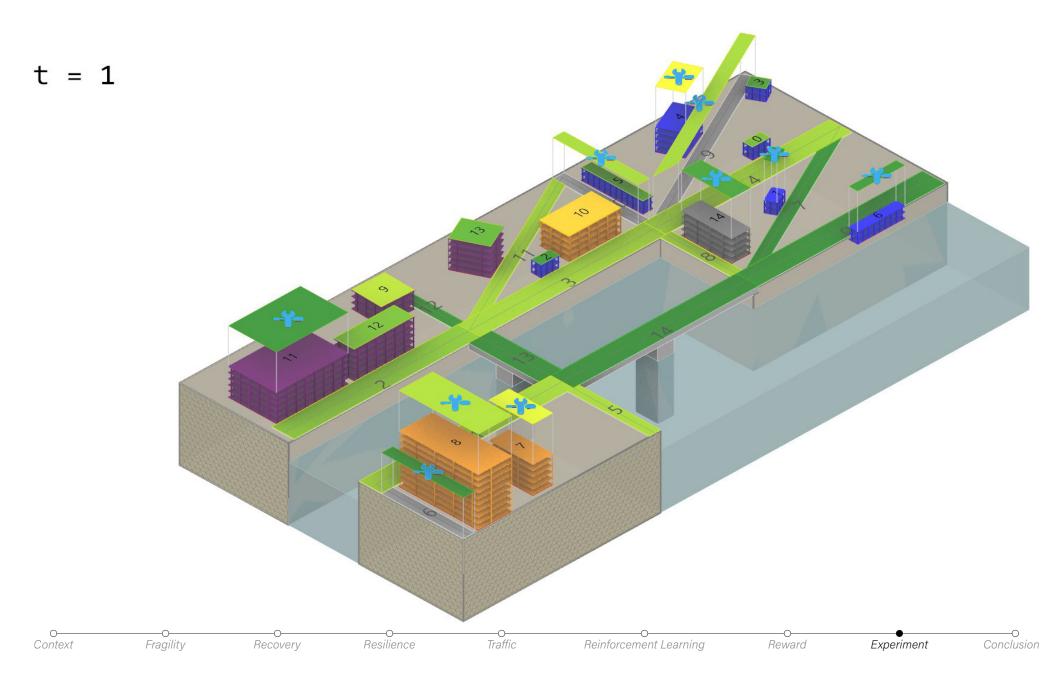
Deep Centralised Multi Agent Actor Critic (DCMAC)

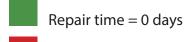
Earthquake Repair Scheduling Rollout

toy-city-30 Policy: DCMAC Quake Magnitude: 7.5 | CL: 283.76

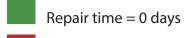






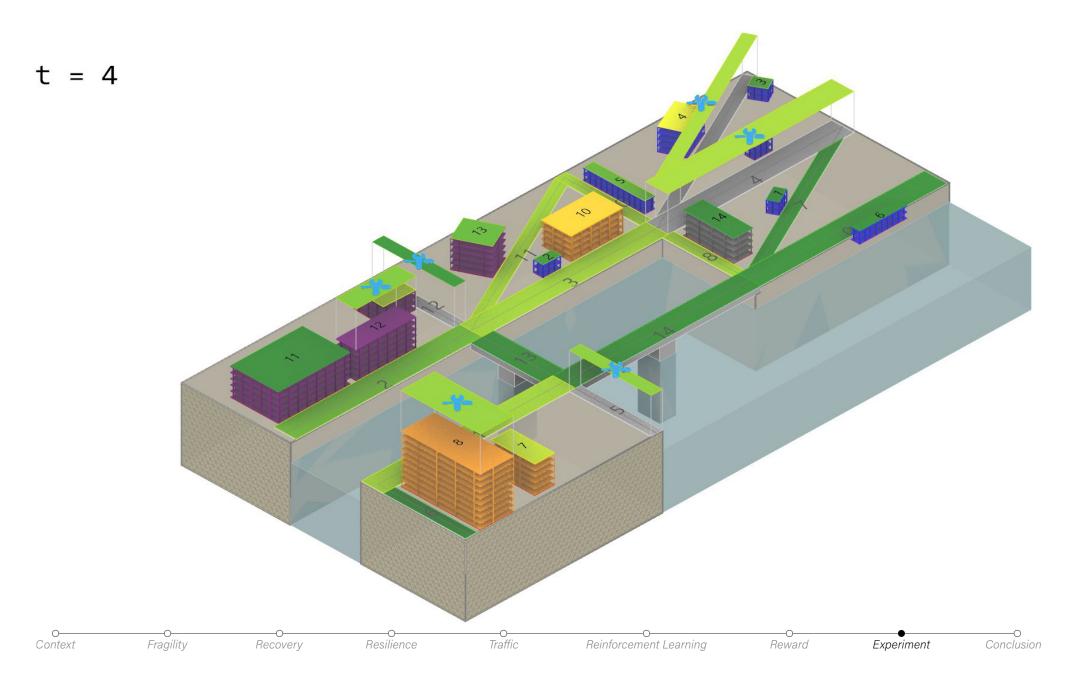




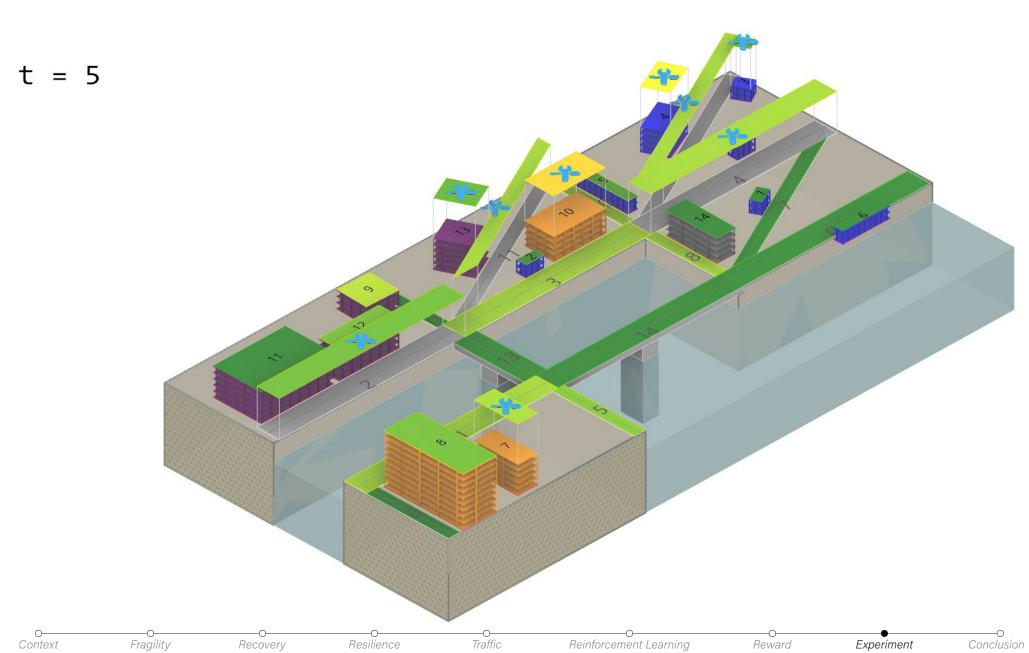








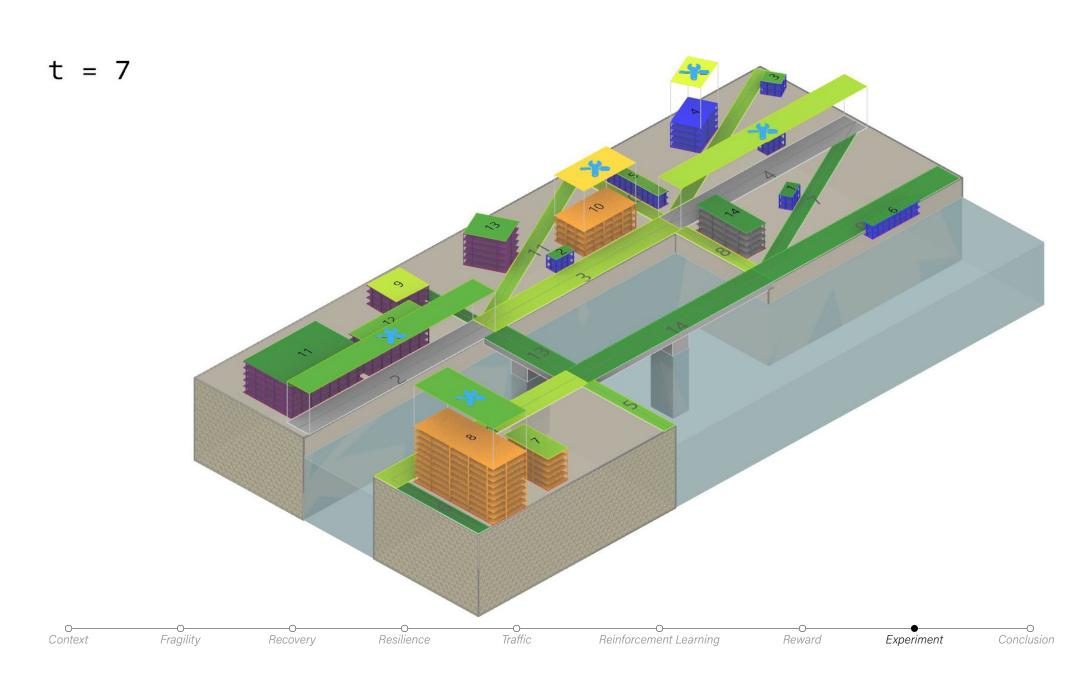


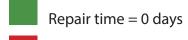










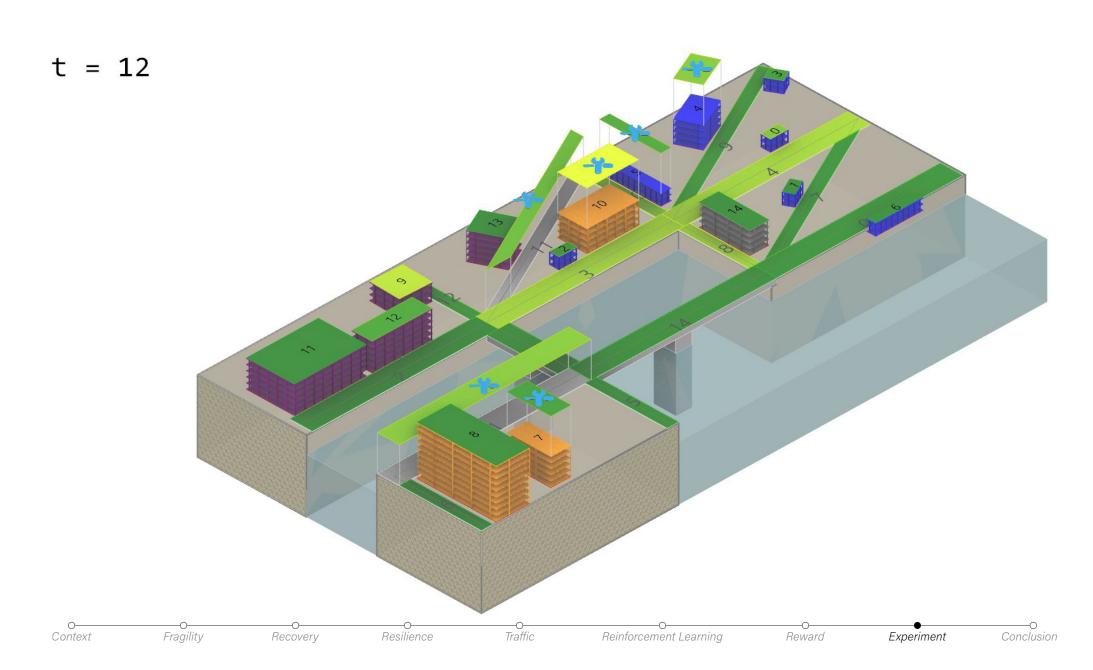




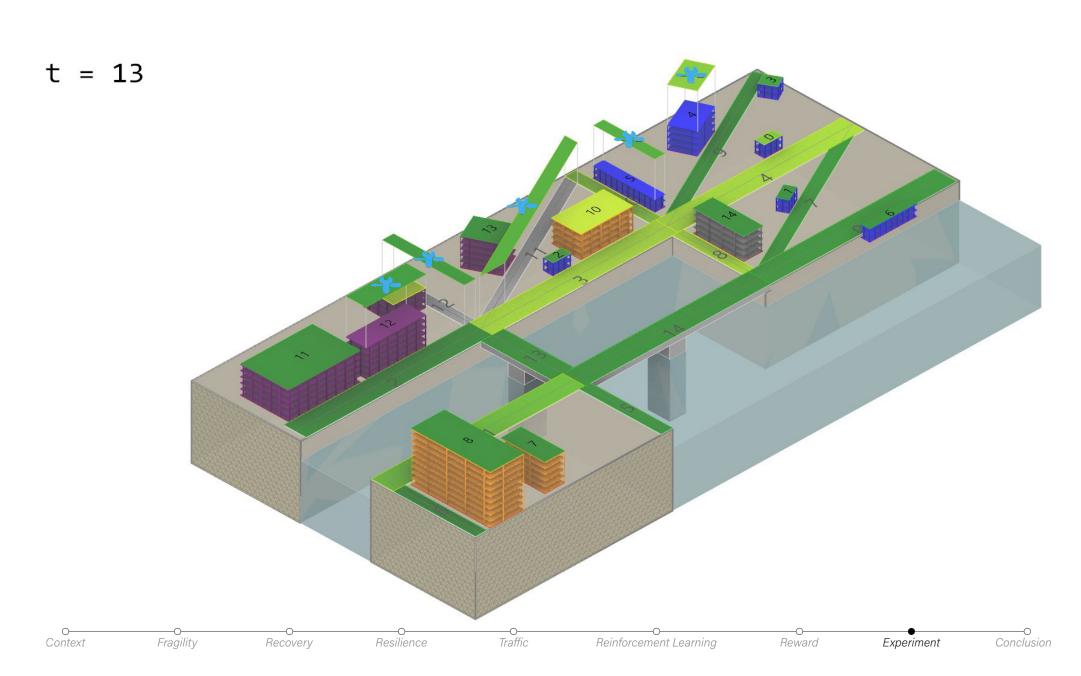




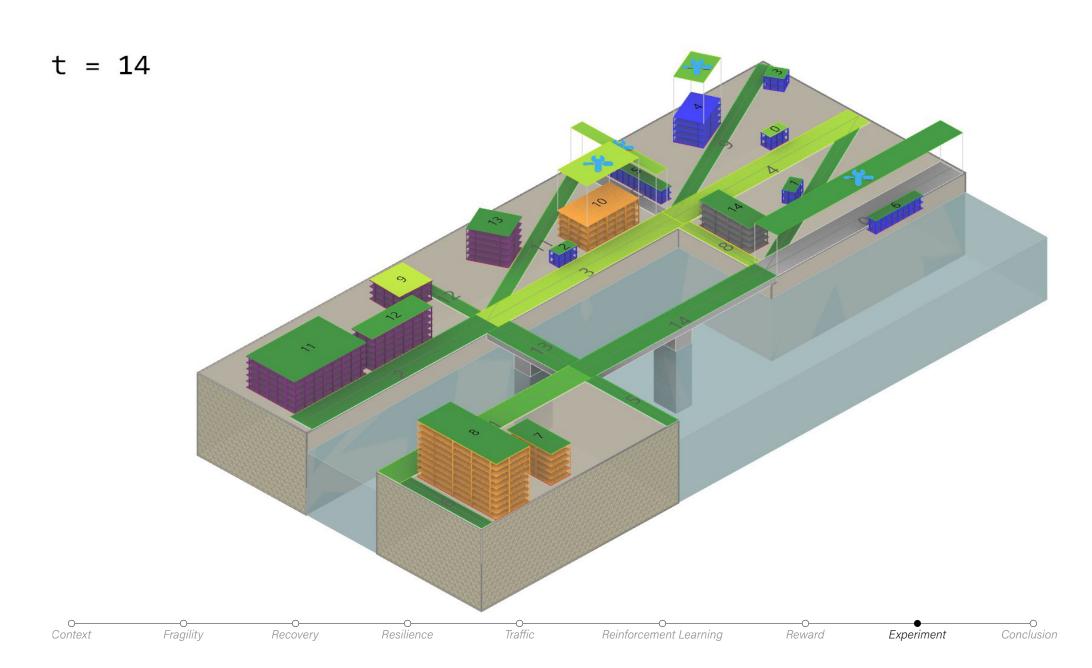


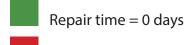










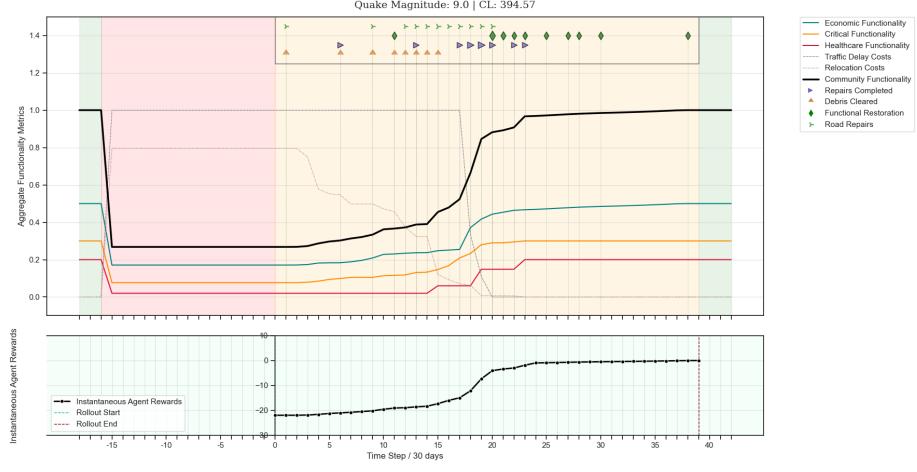




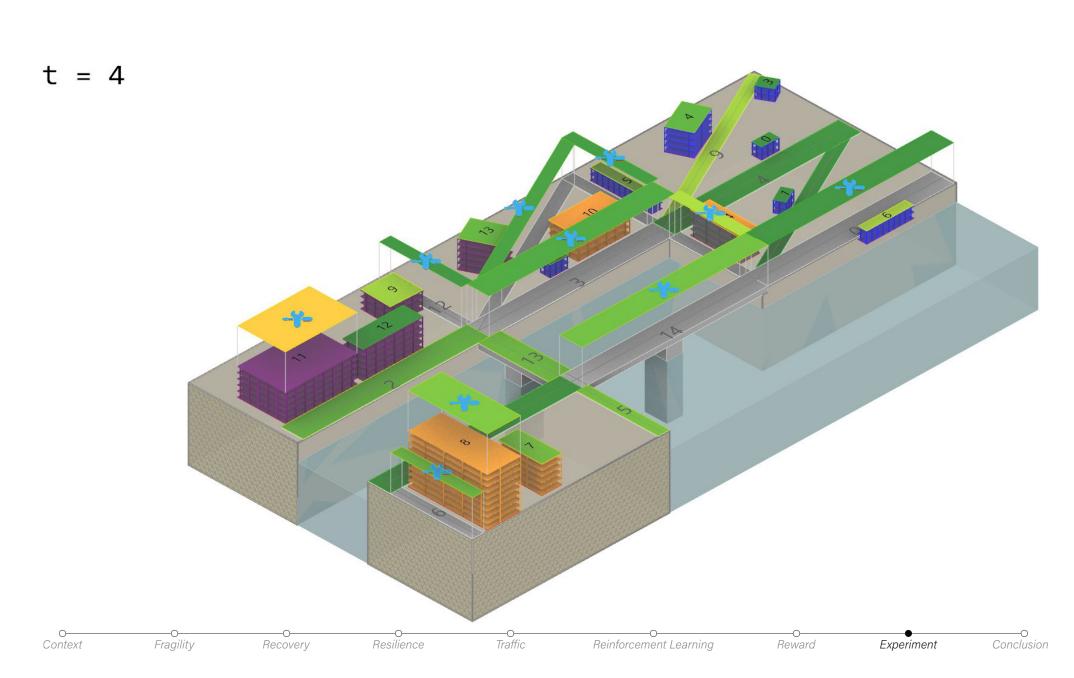
Importance Based (IMPB)

Earthquake Repair Scheduling Rollout

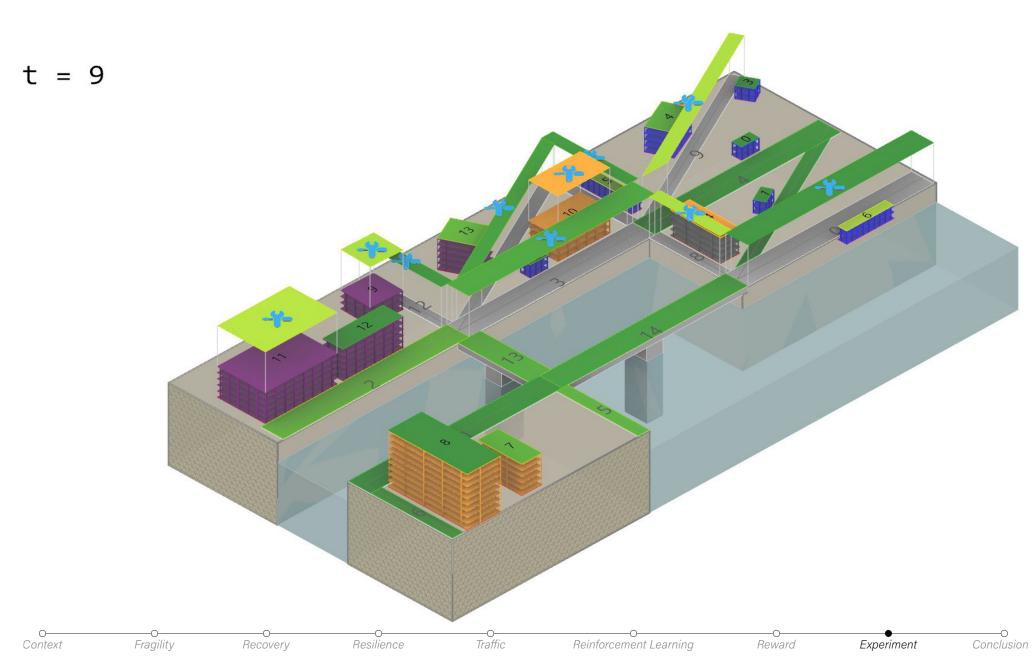
toy-city-30
Policy: importance_based
Quake Magnitude: 9.0 | CL: 394.57



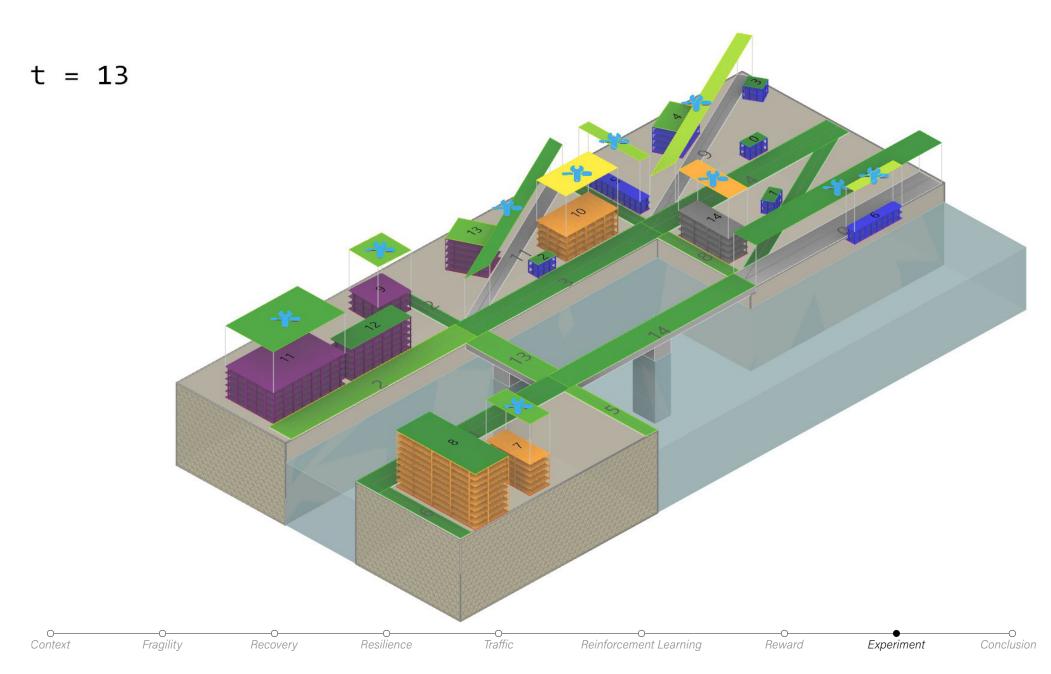


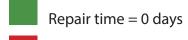


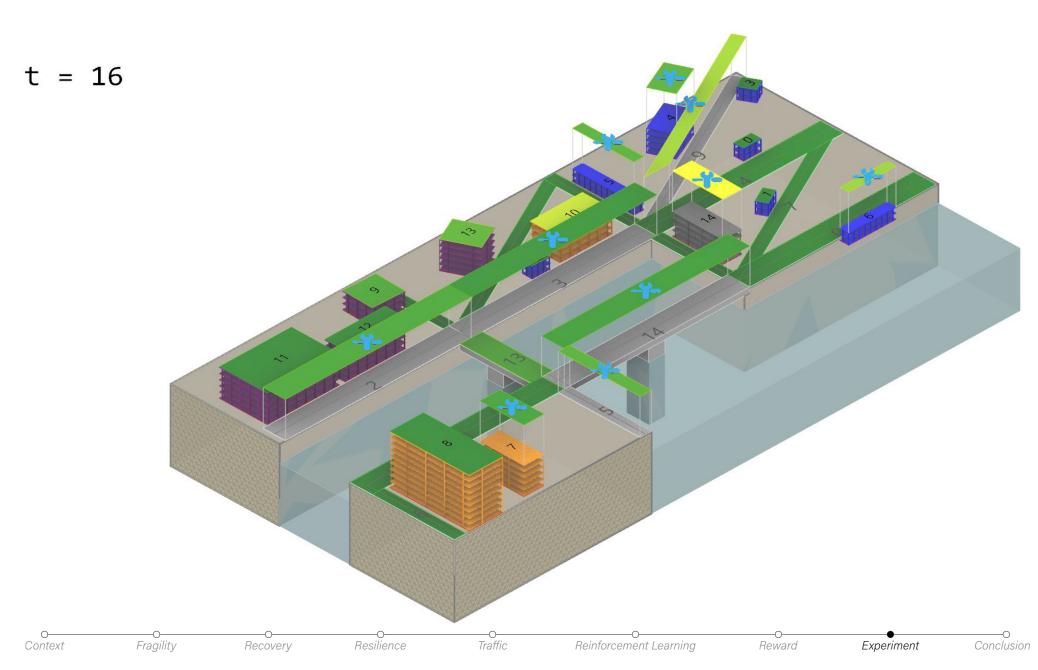












Conclusions

Context Fragility Recovery Resilience Traffic Reinforcement Learning Reward Experiment Conclusion

Work Presented

Two environments are modelled (4 components, 30 components) Stochastic earthquake scenario set Stochastic fragility and vulnerability functions Importance based repair scheduling is compared to DRL

Policy Performance Comparison Across Environments Policy Random QMIX-PS DCMAC 4 Components 30 Components 350 500 420.4 287.3 281.4 275.3 300 I 250.9 249.7 359.6 CL Mean C250 200 400 I 311.9 300 150 200 100 100 50 300 197.3 265.0 250.4 200 169.2 169.7 168.4 CL-70 Mean 250 I 152.6 187.1 200 150 100 50 50

Traffic

Reinforcement Learning

Reward

Experiment

Conclusion

Resilience

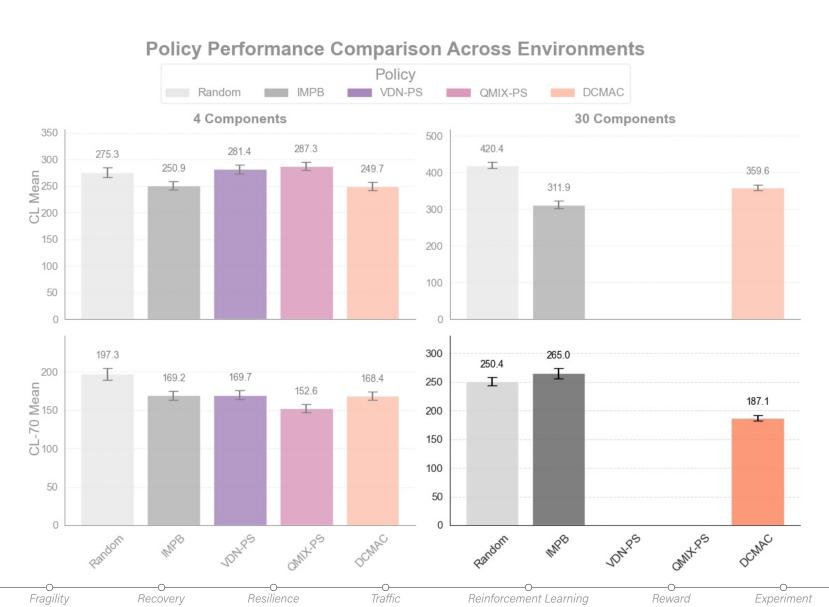
Fragility

Context

Recovery

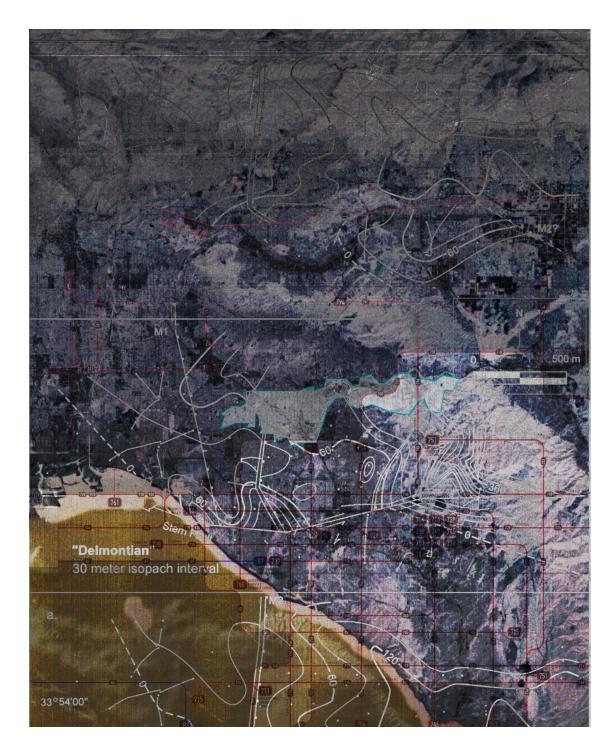
Key Takeaways

DRL performs better in the early recovery phase (effective early prioritisation) IMPB performs better in full recovery (poor early prioritisation) DRL is resource-hungry, requiring approx. 40 hrs of training DRL performs better for environments with more, complex interdependencies



Context

Conclusion



Q-RES MARL

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