Proceedings of the 2024 Winter Simulation Conference
H. Lam, E. Azar, D. Batur, S. Gao, W. Xie, S. R. Hunter, and M. D. Rossetti, eds.

RESILIENT INFRASTRUCTURE NETWORK SCHEDULING: A HYBRID SIMULATION AND REINFORCEMENT LEARNING APPROACH

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ABSTRACT

Critical infrastructure systems exhibit complex interdependencies across multiple levels, with their collective resilience affected by various factors. Traditional centralized resource allocation models often fall short in addressing the decentralized nature of these network-of-networks structures, where individual entities manage distinct components. This study presents a hybrid simulation approach that integrates top-down and bottom-up modeling to capture the dynamic and stochastic decision-making processes in infrastructure management. Integrating system dynamics for organizational-level budgetary decisions with agent-based modeling of maintenance activities and network evolution, this approach provides a holistic framework for analyzing interdependent infrastructures. Additionally, it leverages deep reinforcement learning to determine optimal restoration strategies for each network, accounting for financial constraints. Applied to the water distribution and mobility networks in Tampa, FL, this methodology effectively enhances the resilience of decentralized, interdependent infrastructure systems.

1 INTRODUCTION

Critical infrastructure (CI) systems exhibit complex interdependencies that can lead to cascading failures. With increasing climate-related risks, enhancing CI resilience is crucial. While mathematical modeling and machine learning have been applied to restoration problems (Baidya and Sun 2017), they often struggle to capture the dynamic nature of interdependencies in complex systems. Simulating complex infrastructure networks presents challenges, particularly with cross-layered interactions that require different simulation methods. Integrating System Dynamics (SD) and Agent-Based Modeling (ABM) enables a comprehensive representation of CI systems.

2 HYBRID SIMULATION MODEL

A novel hybrid simulation model integrates SD and ABM to simulate restoration crew scheduling across i interdependent networks. The SD component employs a layered approach: the financial layer manages maintenance funding with stock variables (*Overall Financial Budget*, *Financial Resource for Water/Mobility Maintenance*) and flow variables (*Road/Pipe Restoration*), while the physical layer represents components in *Good/Poor Condition*, with transitions managed by failure magnitude variables. The ABM simulates interactions of 197 pipe and 249 road segments as agents that can fail randomly or under defined conditions, allowing failure propagation between co-located components. Crew agents repair failures using Dijkstra's algorithm, and traffic flow is simulated with origin-destination routing. Integration of SD and ABM enhances the representation of interdependent networks, with SD variables incorporated into the ABM and ABM outputs updating the SD model for realistic daily repair constraints based on financial resources. Most scheduling problems are NP-hard, and reinforcement learning serves as an alternative to centralized approaches for complex scheduling in CIs (Dehghani et al. 2021). The integrated hybrid simulation-reinforcement learning approach (Figure 1) combines SD, ABM, and DRL to optimize financially constrained restoration schedules, incorporating co-location and financial interdependencies.

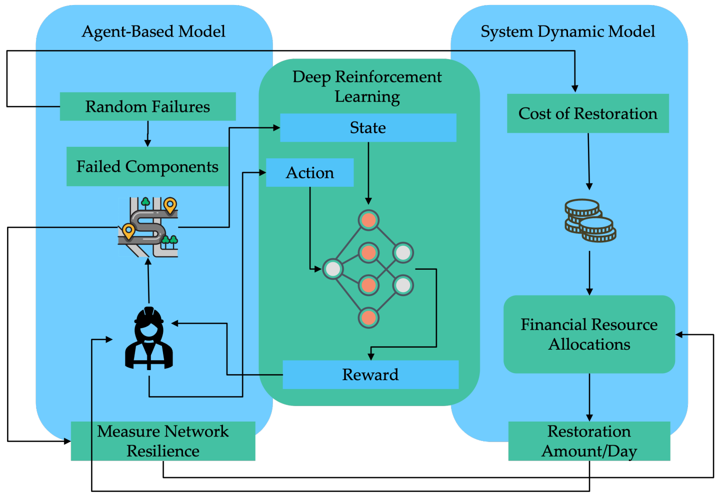

Figure 1: Hybrid Simulation and Restoration Scheduling via Deep Reinforcement Learning.

3 RESTORATION SCHEDULING - DEEP REINFORCEMENT LEARNING

The restoration problem is formulated as a Decentralized Markov Decision Process (Dec-MDP) with:

- State space: $\mathscr{S} = \{f_t^1, \ldots, f_t^i\}$, where f_t^i is the list of failed components in network i at time t.
- Action space: $\mathscr{A}(S_t) = \{a_t^1, \ldots, a_t^i\}$, repair order actions for each network.
- Reward: $r_t^i = \sum_{i \in f^i} w^n (q_t^n)^i$, where $(q_t^n)^i$ is component size and w^n is position-based weight.

Each agent aims to maximize expected cumulative rewards using a state-action value function approximated by Deep Q-Networks. Separate networks were trained for each utility type, enabling decentralized optimal repair sequence identification. Simulations determined optimal financial allocation ratios between Water and Mobility departments (27:73 for 5% and 23:77 for 10% failure rates), constraining daily restoration efforts. Comparative analysis showed the DRL-optimized strategy outperformed a First-In-First-Out (FIFO) approach. In a scenario with 5% failures in both networks, DRL achieved full restoration in 30 days, compared to 36 days under FIFO.

4 CONCLUSIONS

The developed hybrid simulation model, integrating system dynamics, agent-based modeling, and deep reinforcement learning, effectively optimizes restoration strategies for interdependent infrastructure networks. Results demonstrate significant improvements in network restoration time and resilience, underscoring the approach's potential for enhancing critical infrastructure management. While scalability challenges persist for larger networks, the research establishes a foundation for future advancements in complex infrastructure system optimization and decision-making.

ACKNOWLEDGMENTS

This work was partially supported by the US National Science Foundation under Grant Number 1638301.

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