DESIGNING A RESILIENT INFRASTRUCTURE LEARNING GAME TO EVALUATE MAINTENANCE DECISIONS

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ABSTRACT

Restoration and maintenance decisions in critical infrastructure sectors are mainly driven by individual municipalities. Numerous studies have studied optimal restoration activities to improve the overall infrastructure network performance. However, not all dynamic interactions and human factors such as managers' knowledge of interdependencies and decision-making skills can be modelled via mathematical models. Therefore, in this study, we design a simulation-based game platform that allows players to evaluate their strategies through a feedback learning environment. The agent-based simulation serves as the backbone of logical behavior among players and infrastructure networks. We implemented the proposed learning game for hypothetical water distribution and road networks. Eleven players were recruited to test the game and their restoration decisions were recorded. We analyze and compare players' decisions to optimal decisions obtained from a Travelling Salesman Problem (TSP).

Keywords: Infrastructure, Maintenance, Resilience, Game-Based Learning, Agent-Based Modeling, Emergency Response.

1 INTRODUCTION

Critical Infrastructure (CI) systems, encompassing water, transportation, and power networks, provide essential services. Rising natural calamities and cyber threats prompt efforts to enhance infrastructure resilience [1]. Such external stressors pose challenges, especially in co-located road and pipe networks with geological interdependencies. The ability of a system to quickly restore to its original operational state is referred to as resilience. The repair activities that aid in improving the resilience of the CIs are commonly carried out by each network administrator [2]. Thus, the utility managers are often left with decision-making tasks at times of failures to improve overall performance of the network [3]. Various optimization models optimize restorative actions to maximize resilience while considering other factors such as cost [4, 5], but often miss dynamic interactions, highlighting the need for simulation in restoration analysis [6]. Understanding decision-makers' actions and their collective impact on interconnected CIs is crucial, yet there's a gap in capturing individual decision-making behavior within complex CI systems [6, 7], necessitating specialized training for utility managers.

Serious games have shown their effectiveness in emergency preparedness and CI protection, facilitating managerial decision-making and highlighting the dynamic interplay between technical and human aspects [8, 9]. However, there is still a gap to illustrate the evolution of decision-making behavior dynamically.

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Training, including serious games is essential for CI protection, improving vulnerability awareness and mitigation strategies [10, 11]. Therefore, this study introduces a game to bolster technical training and assess restoration strategies. This game illustrates the progress of infrastructure networks performance through participant restoration actions. Players assume the role of utility managers and make decisions, which are compared against an optimal policy obtained from a Traveling Salesman Problem (TSP). We aim to provide a maintenance game that not only shows network evolution but also demonstrates how dynamic restoration information affects decisions and network resilience.

2 AGENT-BASED SIMULATION GAME

Our learning game models hypothetical water (67 pipes) and road networks (98 roads), each managed by distinct utilities. It features an agent-based simulation with road/pipe networks and maintenance crews as agents. Crews experience four states—*Idle*, *goToFix*, *Fixing*, *goBackHome*—with one water and two road crews. Game vehicles adjust routes based on road conditions. The interdependent road and pipe networks demonstrate how pipe failures affect adjacent roads. Infrastructure agents are either operational or non-operational after disruptions. Agents interact within the environment and with each other using Dijkstra's shortest path algorithm, along with specialized origin-destination routing for in-game vehicles.

2.1 Game Framework

While various serious game frameworks exist, such as those discussed in [12], our choice depends on specific objectives. Aligning with our goals to provide entertaining game with serious purpose, we drew inspiration from the Lu-Lu framework [13] and Cormas [14] for our agent-based simulation game, incorporating Ludic and Lusory dimensions. This synthesis aims to achieve an effective serious game design. Thus, our game (see Fig. 1) includes the entertainment aspect while educating on the serious purpose with players assuming the role of Utility Managers ordering the crew agents to restore failed components. The game features engaging elements like tutorials, in-game resource names, crew details, and simulated traffic, balancing entertainment with crucial information, such as graphically updated network resilience post-restoration epochs. This feature enables players to assess the efficiency of their network restoration efforts as the game progresses. We selected Unity 3D as our game engine for the development of a simulation-based game. To optimize computational resources, we implemented a server-based deployment for the game, allowing players to access it through a designated link.

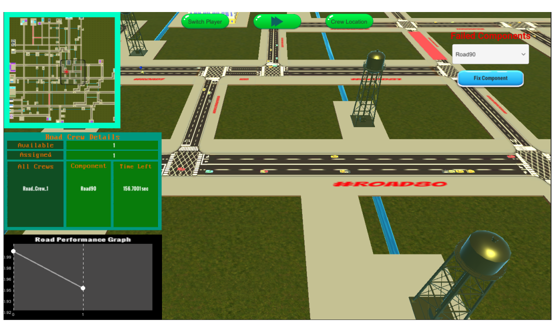

Figure 1: Game Snapshot: Game controls (top), crew availability (left-middle), performance graphs (left), miniature map (top-left) and 'Fix Component' button (top-right).

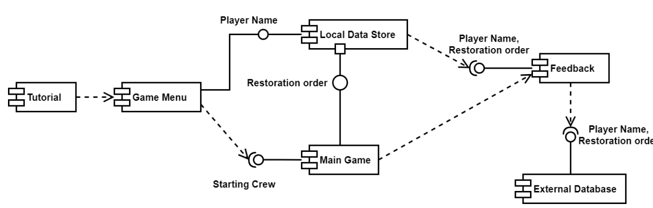

Figure 2: Architecture of the game.

2.2 Game Flow

The game encompasses multiple stages (See Fig. 2). In the initial phase, the game introduces a tutorial elucidating the gameplay mechanics with an option to skip tutorial for experienced players. In the second stage, players decide to join the road utility or the water utility. The order of restoration holds significance for calculating networks resilience. Next, players engage in the restoration of failed components, ultimately completing the game, with all player choices being recorded. The concluding stage involves a comparative analysis between the order of restoration derived from a TSP, i.e., optimal solutions, and the player's selected restoration sequence.

2.3 Data Collection

To collect data and test the game, we invited undergraduate and graduate students within the College of Engineering and Computing at George Mason University. Our focus group involved eight graduate students and three undergraduate students. Each participant played the role of both water and transportation administrators. Initially, with a five percent failure magnitude, participants encountered three pipe and five road failures After pipe restoration, their co-located road failures were transmitted. We recorded each participant's repair sequence, comparing it to the optimal sequence from the TSP model for this network.

3 RESULTS AND ANALYSIS

3.1 Network Resilience Performance Metric

Numerous studies in the literature have utilized the operational lengths of components in an infrastructure as an appropriate indicator of resilience [15]. Therefore, in this study, we defined resilience of a network n as a ratio of the operational length by the overall length of the network. Specifically, resilience of the interdependent network R^s_N (see Eq. 1) comprising of $n \in \mathscr{N}$ networks at each time step s of the game's evolution, is defined as the mean resilience of all sub-networks, given that all sub-networks contribute equally to the resilience of the overall network.

$$\mathscr{R}^s_{\mathscr{N}} = \frac{1}{N}\sum_{i=1}^{N}\mathscr{R}^s_N, \quad \forall n \in \mathscr{N}, \quad 0 \leq \mathscr{R}^s_{\mathscr{N}} \leq 1. \tag{1}$$

To evaluate the quality of decisions made by the participants, we formulated an optimization model as a special case of TSP with a distance-based objective function. The objective function is to minimize the total distance traversed by the maintenance crew to restore the components (Eq. 2). d_{ik} is the distance traveled by the maintenance crew agent k to restore the i^{th} failed component. x_{iks} are binary decision variables at time step s, and the set of constrains include resource assignments following the interdependency rules and loop eliminations in the networks.

$$\min \sum_{s=1}^{S}\sum_{i=1}^{N}\sum_{j=1}^{M} x_{iks}d_{ik} \tag{2}$$

3.2 Game Output Analysis

The network resilience evolution at every simulation epoch based on the players order of repair decisions are recorded. Table 1 displays repair choices made by 11 participants and the baseline repair sequence from the optimization model. Notably, 6 out of 11 participants opted to start with pipe repair, while others initiated restoration with roads. Although the optimal order of restoration promptly restored co-located roads after pipe repair, participants typically deferred road restoration to later stages. This tendency may stem from the limited pipe maintenance crew (1) compared to the (2) crews for roads, prolonging pipe restoration. Hence, their co-located roads were chosen during final decision epochs by the participants. Understanding interdependencies prompted 6 participants to prioritize pipe restoration. Additionally, 2 participants prioritized the closest failed components, and 4 focused on roads near buildings. Restoration times aligned with failed pipe (road) length, prompting participants to allocate crews based on the area size.

Table 1: Order of Repair - Optimal vs Chosen by Participants 1 to 11 (O - Order, F - Failed Component, R - Resilience, *r* - Road, *p* - Pipe).

O	Optimal		**1**		**2**		**3**		**4**		**5**	
	F	*R*	*F*	*R*	*F*	*R*	*F*	*R*	*F*	*R*	*F*	*R*
1	*r* 133	0.876	*p* 23	0.876	*r* 139	0.876	*r* 177	0.876	*p* 186	0.876	*r* 138	0.876
2	*p* 25	0.896	*r* 139	0.895	*r* 136	0.887	*r* 136	0.879	*r* 139	0.889	*r* 139	0.889
3	*p* 23	0.899	*r* 136	0.907	*p* 186	0.905	*p* 186	0.897	*r* 136	0.902	*p* 186	0.902
4	*p* 186	0.913	*p* 186	0.920	*r* 32	0.918	*p* 25	0.910	*p* 23	0.920	*r* 133	0.920
5	*r* 135	0.931	*r* 155	0.925	*r* 133	0.931	*r* 138	0.923	*r* 177	0.925	*r* 136	0.925
6	*r* 32	0.933	*r* 133	0.955	*r* 177	0.933	*r* 133	0.933	*r* 133	0.927	*p* 23	0.927
7	*r* 136	0.946	*p* 25	0.958	*p* 23	0.947	*r* 139	0.953	*r* 138	0.941	*r* 177	0.941
8	*r* 139	0.957	*r* 177	0.971	*r* 138	0.95	*r* 32	0.958	*r* 155	0.952	*r* 32	0.952
9	*r* 177	0.970	*r* 138	0.972	*p* 25	0.965	*p* 23	0.971	*p* 25	0.965	*p* 25	0.965
10	*r* 155	0.982	*r* 32	0.987	*r* 135	0.985	*r* 135	0.972	*r* 32	0.985	*r* 155	0.985
11	*r* 138	1.000	*r* 135	1.000	*r* 155	1.000	*r* 155	1.000	*r* 135	1.000	*r* 135	1.000

O	**6**		**7**		**8**		**9**		**10**		**11**	
	F	*R*	*F*	*R*	*F*	*R*	*F*	*R*	*F*	*R*	*F*	*R*
1	*p* 186	0.876	*p* 25	0.876	*p* 186	0.876	*r* 177	0.876	*r* 177	0.876	*p* 186	0.876
2	*r* 177	0.889	*r* 133	0.889	*r* 133	0.889	*p* 186	0.889	*r* 139	0.887	*r* 136	0.895
3	*r* 136	0.902	*r* 177	0.902	*r* 177	0.902	*r* 139	0.899	*p* 186	0.899	*r* 177	0.908
4	*r* 133	0.920	*r* 136	0.920	*p* 25	0.920	*r* 138	0.917	*r* 138	0.917	*r* 133	0.923
5	*r* 138	0.925	*r* 138	0.925	*p* 23	0.925	*p* 23	0.922	*r* 136	0.931	*r* 138	0.933
6	*p* 23	0.927	*p* 23	0.927	*r* 135	0.927	*r* 32	0.936	*p* 23	0.948	*r* 139	0.946
7	*r* 139	0.941	*r* 139	0.941	*r* 138	0.941	*p* 25	0.950	*r* 32	0.963	*r* 32	0.951
8	*r* 155	0.952	*p* 186	0.952	*r* 32	0.952	*r* 136	0.963	*r* 133	0.965	*p* 25	0.971
9	*p* 25	0.965	*r* 155	0.965	*r* 139	0.965	*r* 155	0.982	*r* 155	0.978	*p* 23	0.985
10	*r* 32	0.985	*r* 135	0.985	*r* 155	0.985	*r* 133	0.985	*p* 25	0.998	*r* 135	0.987
11	*r* 135	1.000	*r* 138	1.000	*r* 136	1.000	*r* 135	1.000	*r* 135	1.000	*r* 155	1.000

Figure 3 shows the resilience evolution for the infrastructure networks, illustrating the impact of failures and subsequent recovery through player decisions, as detailed in the Table 1. Comparing the optimal repair sequences with those made by players helps to understand decision-making dynamics. We analyzed the percentage of resilience improvement resulting from players' choices by comparing the average performance of players against resilience obtained from optimal solutions (see Table 2). Results indicate that at certain decision steps, players outperformed the optimal solutions. While optimization models can generate optimal policies, human decisions occasionally exceeded the optimized ones. This suggests that learning games can effectively train utility managers for informed decision-making.

4 CONCLUSIONS

Game-based learning, an effective tool for training decision-makers, addresses the growing interconnectivity of infrastructures and the critical role of cyber-physical interdependencies. Our game aimed to illuminate the effects of restoration decisions on network resilience by integrating agent-based simulation for sequential decision-making, enabling players to assume the role of utility managers. Engaging 11 students, we

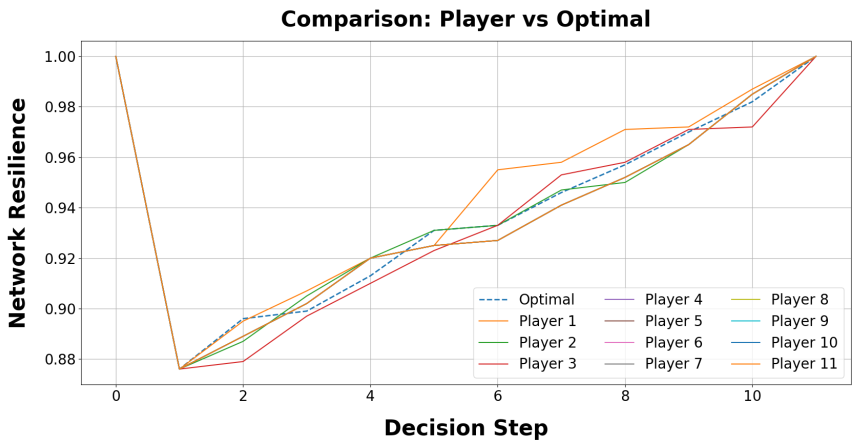

Figure 3: Resilience Curve - comparison between game participants' choices & optimal order of repairs.

Table 2: Comparison of Resilience (Player 10 (P10), Player 3 (P3) and Mean of All Players (All P) vs. Optimal).

Decision Step	P10	P3	Mean (All P)	Optimal	(%) ↑ Mean (All P)	(%) ↑ P10	(%) ↑ P3
1	0.876	0.876	0.876	0.876	0.0	0.0	0.0
2	0.887	0.879	0.889	0.896	-0.78	-1.00	-1.90
3	0.899	0.897	0.902	0.899	0.33	0.0	-0.22
4	0.917	0.910	0.919	0.913	0.66	0.44	-0.33
5	0.931	0.923	0.926	0.931	-0.54	0.0	-0.86
6	0.948	0.933	0.935	0.933	0.21	1.61	0.0
7	0.963	0.953	0.948	0.946	0.21	1.80	0.74
8	0.965	0.958	0.958	0.957	0.10	0.84	0.10
9	0.978	0.971	0.971	0.970	0.10	0.82	0.10
10	0.998	0.972	0.985	0.982	0.31	1.63	-1.02
11	1.000	1.000	1.000	1.000	0.0	0.0	0.0

analyzed their repair strategies against optimal TSP-derived solutions. Feedback indicated the 'Go-Repair' game effectively enhanced awareness of network resilience evolution amidst disruptions. While our findings shed light on the potential of the game to educate players about maintaining infrastructure networks, we recognize that involving actual utility professionals in the game would have enriched the evaluation of the game. Future work may include variable maintenance crew functionality and player communication, emphasizing communication's role in restoration.

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