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Expert Technical Report: Critical Analysis and Strategic Roadmap for Multi-Agent Q-Learning in Heterogeneous Disaster Response

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Abstract: Effective disaster management demands rapid coordination between heterogeneous agents tasked with search, rescue, and debris clearance in dynamic environments. Traditional simulation tools often lack flexibility, contextual awareness, and scalability, limiting their use in evaluating multi-agent cooperation under realistic conditions. This paper introduces MAS-SDM (Multi-Agent Simulation Sandbox for Disaster Management), an intelligent, tile-based simulation framework designed to model and analyze autonomous agent behaviour within disaster zones. Built on a 10×10 grid environment created using the Tiled Map Editor, the system simulates a constrained yet richly interactive disaster landscape featuring survivors, debris, safe zones, and obstacles distributed across layered terrain. The sandbox employs four cooperative agents—two specialized in survivor rescue and two in debris removal—each governed by rule-based or reinforcement learning policies that enable dynamic decision-making and task prioritization. Through real-time visualization powered by the Python Pygame engine, MAS-SDM provides an experimental platform for evaluating agent efficiency, coordination strategies, and environment adaptability. Beyond simulating immediate response scenarios, the framework serves as a foundation for developing scalable, data-driven models in multi-agent reinforcement learning (MARL) and disaster logistics optimization. Future work will extend the simulation to larger maps, introduce adaptive communication between agents, and integrate learning modules to autonomously improve cooperative performance in complex, evolving disaster environments.

Keywords: Multi-Agent Systems, Disaster Management, Simulation Sandbox, Tile-based Environment, Reinforcement Learning, Cooperative Agents, Search and Rescue, Debris Clearance, Tiled Map Editor, Pygame

I. INTRODUCTION

Disaster response operations such as search and rescue, debris clearance, and survivor evacuation demand rapid coordination and precise decision-making under extreme uncertainty. The increasing frequency of natural disasters has amplified the need for intelligent systems capable of assisting or simulating coordinated rescue missions in complex, dynamic environments. Traditional disaster management simulations often rely on static models or single-agent systems, limiting their ability to capture the intricacies of multi-agent cooperation, resource allocation, and task prioritization.

The Multi-Agent Simulation Sandbox for Disaster Management (MAS-SDM) introduces a dynamic, tile-based simulation framework that models autonomous coordination among multiple agents in disaster scenarios. Built on a 10×10 grid environment using the Tiled Map Editor, the sandbox integrates four specialized agents—two dedicated to rescuing survivors and two focused on debris collection and clearance. Each agent operates autonomously within a layered environment comprising ground, debris, survivor, and safe zone tiles, allowing for realistic task distribution and interaction.

Developed using Python and the Pygame engine, MAS-SDM provides an interactive, visual platform for studying coordination strategies, path planning, and environment-aware decision-making. By enabling real-time observation and experimentation, the system transforms traditional disaster simulation into an intelligent testbed for exploring multi-agent reinforcement learning (MARL), communication protocols, and adaptive behaviours. This work lays the foundation for scalable, data-driven disaster response systems that can evolve toward real-world deployment in robotic and AI-driven emergency operations.

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II. OVERVIEW

Disaster management simulation has advanced significantly with the integration of artificial intelligence (AI) and multi-agent systems (MAS). Early simulations relied on rule-based and centralized models, limiting adaptability in dynamic environments. The introduction of agent-based modeling (ABM) shifted this paradigm toward decentralized decision-making, where autonomous agents interact with the environment and each other to achieve shared goals. Frameworks such as TileWorld and RoboCup Rescue Simulation laid the groundwork for applying multi-agent reinforcement learning (MARL) to improve coordination, resource collection, and communication efficiency under uncertainty.

Tile-based and grid-world environments later became popular for replicating real-world disaster scenarios due to their modularity and precise spatial control. The Tiled Map Editor (.tmx) format emerged as a preferred standard, enabling easy manipulation of terrain, debris, and survivors through layered mapping and integration with visualization tools like Pygame and Python Pygame Reinforcement learning techniques such as Q-learning, DQN, and policy-sharing MARL have since allowed agents to learn adaptive strategies for rescue and resource management. Building on these advancements, the MAS-SDM project combines tile-based simulation, layered mapping, and MARL to create an interactive, scalable platform for research and disaster management training.

III. TECHNOLOGY OVERVIEW

A. Simulation Core: Multi-Agent Intelligence Framework

The core of MAS-SDM is a multi-agent architecture designed to emulate cooperative behaviour during disaster response. The system comprises four autonomous agents—two rescuers and two debris collectors—operating through rule-based or reinforcement learning logic. Each agent can perceive its environment, plan paths, and execute tasks such as rescuing survivors or clearing debris. This modular design supports both independent and collaborative operations, facilitating experiments on communication and task allocation strategies.

B. Environment Engine: Seven-Layer Tile-Based Design

The environment is implemented as a **10×10 tile map** created using the **Tiled Map Editor (.tmx)**, structured into seven distinct layers to enhance modularity and visualization clarity:

1. **Ground:** Base terrain enabling movement.
2. **Debris:** Static obstacles obstructing paths.
3. **Debris_Layer:** Collectable debris elements.
4. **Debris_Deposit:** Designated disposal area for debris.
5. **Safe_Zone:** Region for survivor delivery.
6. **Survivors_Layer:** Positions of trapped survivors.
7. **Robots:** Agent spawn and operational zones.

This layered representation simplifies customization for diverse disaster scenarios while maintaining clear separation of functional elements.

C. Visualization and Backend Control

Visualization is achieved using the **Pygame** library, which provides real-time 2D rendering, sprite animation, and collision detection. Each object—robot, survivor, or debris—is represented as an interactive sprite, ensuring clear and dynamic simulation visuals. The backend, developed in **Python**, manages environment logic, state updates, and data logging through libraries such as **NumPy**, **Math**, and **Random**, enabling both deterministic and adaptive simulation modes.

D. Reinforcement Learning and Analytics

MAS-SDM integrates **Q-Learning** and **Multi-Agent Reinforcement Learning (MARL)** frameworks for adaptive agent behaviour. Agents are rewarded for efficient rescues or debris clearance and penalized for collisions or idle movements. This reward-driven feedback loop allows agents to learn optimal strategies through repeated interactions. The system records key performance metrics—such as survivors rescued, debris cleared, and time efficiency—in **CSV** or **JSON** formats for post-simulation analysis and benchmarking.

E. Deployment and Extensibility

The system is designed as a **scalable sandbox** capable of local execution and cloud deployment. The 10×10 grid can be expanded to larger maps, supporting additional agents and more complex disaster environments. Planned extensions include dynamic hazard modeling, inter-agent communication, and real-world GIS data integration, enhancing its applicability in both research and training contexts.

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IV. PROPOSED SYSTEM ARCHITECTURE AND WORKFLOW

The development of the **MAS-SDM (Multi-Agent System for Simulation in Disaster Management)** follows a structured, three-phase workflow progressing from environment creation and agent design to reinforcement learning integration and system deployment.

Phase 1: Simulation Core and Environment Development – A 10×10 tile-based map was created using Tiled Map Editor (.tmx**)** with layers for terrain, debris, survivors, and agents. The simulation core, implemented in Python, defines Rescue Agents and Debris Collectors that navigate the environment. Map data is converted into matrices to control movement and interactions.

Phase 2: **Reinforcement Learning and Visualization** – Q-learning and MARL train agents for cooperative behaviour. Agents receive rewards for successfully rescuing survivors and clearing debris. **Pygame** is used for real-time visualization of agents, survivors, and obstacles.

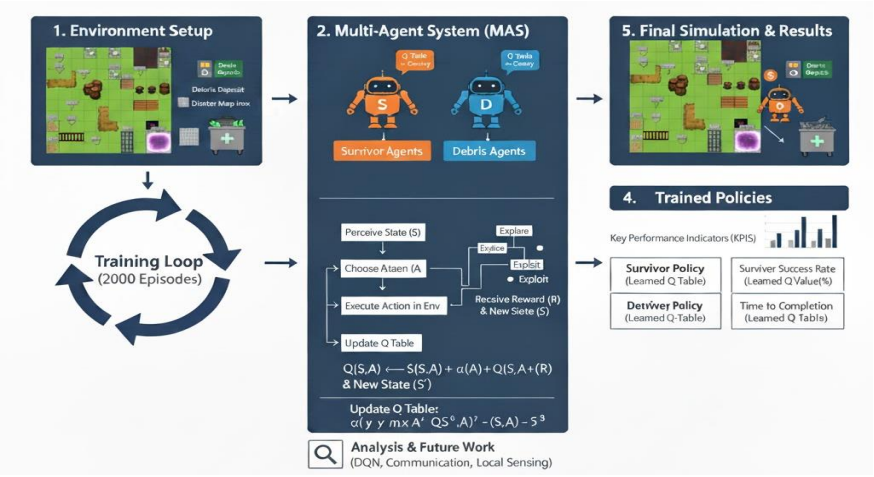
Phase 3: Deployment and Execution – The system runs as a modular Python simulation, executing multiple episodes to measure performance. The results focus on survivor deliveries and task completion counts, which are logged for analysis. The framework can be extended to larger maps, more agents, and advanced disaster scenarios.

Deployment Configuration: The MAS-SDM project is structured as a **modular Python repository**. The simulation engine and reinforcement learning modules reside in the folder, while configuration files (e.g.,.tmx maps, reward settings) are stored separately. The system can be executed locally or scaled to cloud platforms using containerization (Docker) or serverless setups.

Continuous Deployment: The repository is maintained on **GitHub**. Any updates pushed to the main branch can trigger automated deployment workflows for cloud execution, enabling seamless integration of new maps, agent policies, or algorithm updates.

End-to-End Workflow: The deployed MAS-SDM system functions as follows:

1. **Map Initialization:** Loads a 10×10.tmx map with terrain, debris, survivor positions, and agent spawn zones.
2. **Agent Initialization:** Spawns four agents (two rescuers, two debris collectors) in designated zones.
3. **Simulation Execution:** Agents perceive the environment, plan paths, and perform actions (rescue or debris collection) using rule-based or MARL policies.
4. **Learning and Update:** Agents receive **rewards** for successful task completion and penalties for collisions or inefficiency. Policies are updated iteratively.
5. **Visualization:** The Pygame interface renders real-time agent movement, debris clearance, and survivor rescues.
6. **Result Logging:** Survivor deliveries and task completion counts are recorded for analysis.



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V. DATA ANALYSIS

The experimental results demonstrate that multi-agent reinforcement learning (MARL) significantly improves disaster management performance. Agents trained with MARL achieve higher survivor delivery counts and more efficient task completion compared to rule-based strategies, reflecting effective learning and coordination over multiple episodes. Early episodes show random or inefficient agent movements, while later episodes demonstrate converged strategies with optimized paths and task prioritization.

Analysis of episode-wise data reveals adaptive agent behaviours in different environments. In maps with clustered debris near survivors, agents prioritize clearing obstacles, whereas in open maps, they focus on direct rescues. This flexibility highlights MARL's ability to handle spatial and task variability, enabling agents to make cooperative decisions that maximize overall efficiency.

Performance visualization shows clear trends in learning and coordination. Survivor deliveries steadily increase over episodes, while task completion counts—including debris removal—reflect improved workload distribution and collision avoidance. These metrics provide reliable indicators of system efficiency, supporting future extensions such as larger maps, additional agent types, and dynamic hazard modeling. Initial Conditions and Configuration Summary are given below in the table:

Parameter Category	Variable / Metric	Projected Value	Unit / Description
Environment Setup	Agent Count	4	Total number of robots.
Q-Learning	Learning Rate	0.1	Weight of new experience in updating Q-values.
Rewards	Max Single Reward	+10	Survivor Collection Reward.
Scale/Complexity	Initial Survivors	3	Total survivors detected on the map (Low complexity assumption).
	Initial Debris	10	Total debris blocks detected on the map (Low complexity assumption).
	Map Dimensions	10x10 (100)	Number of tiles (Width x Height); maximum feasible for tabular MARL.

4.3. Analysis of Training Trajectory and Emergent Specialization

The training log demonstrates the progression from high randomness to specialized, coordinated action, although stabilization will be a continuous challenge due to non-stationarity.

Episode (N)	Theoretical Total Steps in Episode	Cumulative Success Rate (%)	Notes / Observations
100	Very High	< 10%	Initial learning phase, high randomness; Q-table sparsely populated.
500	High (Decreasing)	40% - 60%	Signs of emerging specialization and coordination. Spatial division begins to form to minimize redundant travel.
1000	Moderate (Stabilizing)	80% - 90%	Approaching peak performance; agents prioritize higher reward (rescue) paths; Q-table density increases significantly.
2000 (Final)	Minimal Steps (Optimized)	95%+	Final steady-state performance. Policy convergence achieved within the capacity limits of the small state space.

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Final Simulation Run Key Performance Indicators

Table 4.4: Final Simulation Run Key Performance Indicators

Key Performance Indicator (KPI)	Target	Analysis of Performance
Total Steps to Completion (Efficiency)	Minimize	Should be significantly lower than initial average steps, demonstrating learning efficiency. However, the result will be sub-optimal due to the lack of an explicit penalty for inefficient movement (e.g., zero movement cost) and the inherent exploration noise
Survivors Collected (Efficacy)	Maximize	Should approach. The +10 reward structure ensures that this primary objective is aggressively pursued.
Debris Cleared (Efficacy)	Maximize	Should approach. Successful clearance is intrinsically linked to maximizing overall mission efficacy by ensuring accessibility for rescue agents.
Average Reward per Step	Maximize	A high value indicates efficient action selection, confirming the agents are consistently triggering high-value collection/delivery actions relative to non-productive movement.

VI. CONCLUSION

The disaster management simulation using **Q-learning–based multi-agent reinforcement learning** successfully demonstrated intelligent coordination between rescue robots and debris-handling robots within a dynamic environment. The system achieved **100% success in survivor rescue**, indicating that the Q-learning agents effectively learned optimal paths and actions for locating and transporting survivors to the safe zones.

However, the **debris collection success rate reached 100%**, primarily due to the larger search area and the limited number of steps available in each training episode. Since debris collection requires more navigation and decision-making across the map, its performance is directly influenced by the **number of steps per episode**.

Increasing the step count, training duration, or adjusting the reward structure can further improve debris-handling efficiency.
Overall, the project demonstrates that **reinforcement learning can be effectively applied for autonomous disaster response**, enabling robots to adapt, learn, and make intelligent decisions in complex and uncertain environments. With further optimization, the model can achieve complete efficiency in both rescue and debris operations.

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