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Multi-Agent and AI-Driven Optimization Techniques for Emergency Response in Urban Traffic Systems

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Abstract: Urban traffic congestion severely affects emergency vehicle response times, leading to preventable loss of life and reduced efficiency of public safety systems. Traditional traffic management relies on static signal plans and fixed routing, which cannot adapt to sudden congestion, roadblocks, or peak-hour variations. Recent research on **Multi-Agent Systems (MAS)**, **Reinforcement Learning (RL)**, and **vehicle-to-infrastructure (V2I) coordination** has shown promising results for dynamic and intelligent emergency mobility. This review analyzes ten influential studies across three domains: emergency vehicle routing algorithms, learning-based traffic signal control, and cooperative multi-agent negotiation frameworks. Prior work such as EMVLight and MARL-based traffic control demonstrates that decentralized agents can learn to reduce delays, but most systems are limited to small grids, isolated intersections, or single-agent routing. Few provide city-scale simulations integrating ambulances, fire trucks, and traffic lights within a shared communication environment. To address these gaps, this paper highlights the need for a unified, scalable simulation combining SUMO traffic modeling with SPADE-based agent communication, enabling adaptive routing, green-wave negotiation, and real-time scenario testing. The review concludes that multi-agent simulation is a practical and scalable approach for optimizing emergency response in future smart cities.

Keywords: Multi-Agent Systems, SUMO, SPADE, Reinforcement Learning, Emergency Vehicle Routing, Traffic Signal Control, Vehicle-to-Infrastructure Communication, Intelligent Transportation Systems, Q-Learning, Smart Cities

1.INTRODUCTION

Emergency response systems depend heavily on the speed and efficiency of ambulances, fire trucks, and rescue vehicles. In rapidly growing urban environments, traffic congestion remains one of the biggest barriers to timely response. Even a 2–4 minute delay can significantly increase mortality in cardiac emergencies or escalate property damage in fire incidents. Traditional traffic infrastructure is static in nature—traffic lights follow preset timing cycles, and emergency vehicles rely on predetermined routes that do not adapt to sudden congestion, accidents, or peak-hour surges.

To address this challenge, intelligent traffic management has emerged as a major research focus within **Intelligent Transportation Systems (ITS)**. Early work on emergency routing applied classical shortest-path algorithms such as Dijkstra and A*, providing efficient navigation but lacking real-time adaptability. More recent studies explore **reinforcement learning (RL)** for dynamic traffic signal control. Models such as **Deep Q-Learning** and **Multi-Agent RL (MARL)** enable signals to learn optimal timings and reduce vehicle waiting time. However, most RL-based systems focus on general traffic flow, not emergency prioritization.

A growing research trend uses **Multi-Agent Systems (MAS)**, where emergency vehicles and traffic signals behave as autonomous agents capable of communication, negotiation, and route selection. Projects such as **EMVLight**, **MARL signal control**, and **V2I priority systems** demonstrate that cooperative agents can form temporary "green corridors" to clear a path for ambulances. While promising, existing studies are mostly tested on small synthetic networks or isolated intersections. Large-scale coordination across a full city—with multiple emergency vehicles, heterogeneous agents, and real congestion patterns—remains largely unexplored.

This review analyzes ten major research papers across three research directions:

1. **Emergency vehicle routing and optimization**,
2. **Reinforcement learning for adaptive traffic signal control**, and
3. **Multi-agent negotiation and V2I communication frameworks**.

The review identifies key limitations such as lack of scalability, absence of combined routing + signal learning, and limited real-world scenario testing. The paper concludes by recommending an integrated simulation approach using

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SUMO for traffic modeling and **SPADE** for agent-based communication, enabling scalable, cooperative, and adaptive emergency mobility in smart cities.

2.LITERATURE SURVEY

EMVLight: Multi-Agent Reinforcement Learning for Emergency Vehicle Control (Li et al., 2022). Li and colleagues proposed EMVLight, a multi-agent reinforcement learning system designed to improve the movement of emergency vehicles through congested intersections. In this approach, both the emergency vehicle and the traffic lights are treated as intelligent agents capable of learning and coordination. When an ambulance approaches, nearby traffic signals cooperate to form a temporary green corridor, reducing waiting time and improving clearance speed. Their experimental results demonstrated that reinforcement learning can significantly minimize delays during emergency movements. However, the simulation was tested only on a small grid network, and the model did not include large city maps, fire truck movement, or multiple emergency cases. As a result, the scalability and real-world applicability of EMVLight remain limited.

Reinforcement Learning for Adaptive Traffic Signal Control (Wei et al., 2018). Wei et al. developed a Deep Q-Learning based adaptive traffic signal control system that adjusts light timings according to real-time vehicle flow. The model learns optimal signal phases by continuously observing queue length, waiting time, and traffic density at each intersection. Their results showed a noticeable improvement in overall traffic movement and reduced congestion compared to traditional fixed-timing signals. The system proved effective in multi-intersection environments and demonstrated the potential of reinforcement learning in urban traffic management. However, this work focused only on general vehicles and did not prioritize emergency services such as ambulances or fire trucks. Additionally, no communication or negotiation was included between vehicles and traffic lights, which limits its use in critical emergency scenarios.

Multi-Agent Deep Reinforcement Learning for Large-Scale Traffic Signal Control (Chu et al., 2019) Chu et al. introduced a large-scale traffic signal control system based on Multi-Agent Deep Reinforcement Learning (MARL). In their approach, each traffic signal operates as an independent learning agent that observes local traffic and coordinates with neighboring intersections to improve overall flow. The model successfully reduced congestion and improved vehicle throughput across multiple junctions. Their study demonstrated that decentralized learning can outperform centralized signal control, especially in dense urban roads. However, the system was designed only for general traffic and did not include any mechanism for handling emergency vehicle priority or real-time communication with ambulances. As a result, even though congestion was reduced, emergency response improvement was not addressed in their work.

A Review on Emergency Medical Vehicle Routing Using Artificial Intelligence (Zhang et al., 2021). Zhang and colleagues presented a detailed review of artificial intelligence techniques used for routing emergency medical vehicles. Their study focused on classical algorithms such as A*, Dijkstra, and heuristic search methods, explaining how these techniques help ambulances find the shortest or fastest routes on road networks. The review concluded that intelligent routing can reduce travel distance, but its effectiveness decreases when road congestion is unpredictable or signals remain fixed. The authors highlighted that most existing routing systems do not communicate with traffic lights or adapt to dynamic traffic flow. As a limitation, the study emphasized that routing alone cannot guarantee fast emergency response unless combined with real-time traffic control and infrastructure coordination.

Emergency Response Arrival Time Modeling Using SUMO (Singh & Reddy, 2023). Singh and Reddy used the SUMO traffic simulator to analyze ambulance arrival times under different congestion levels. Their study simulated multiple traffic densities and road conditions to estimate how delays occur during real emergencies. The results showed that SUMO can accurately predict arrival times and provide insights into where bottlenecks are likely to form. The work demonstrated the usefulness of simulation for urban planning and emergency dispatch strategies. However, this research focused only on measuring delays and did not propose any optimization method to reduce them. There was no coordination between traffic lights and emergency vehicles, meaning the simulation remained descriptive rather than solution-oriented.

Q-Learning Based Urban Traffic Signal Optimization (Tan et al., 2020). Tan et al. proposed a Q-Learning based model for optimizing traffic signal timings in busy urban intersections. The system allows traffic lights to learn from real-time road conditions, such as queue length and vehicle density, and adjust signal phases accordingly. Their results showed a noticeable reduction in waiting time and congestion during peak hours compared to fixed-time control. The study demonstrated that reinforcement learning can improve traffic flow without manual tuning or predefined schedules. However, the model focused only on general traffic efficiency and did not include any provision for emergency vehicle priority. Since ambulances and fire trucks were not part of the learning process, the system could not guarantee fast clearance during emergencies.

Vehicle-to-Infrastructure Priority System for Emergency Vehicles (Priya et al., 2022). Priya and colleagues developed a vehicle-to-infrastructure (V2I) communication system that allows ambulances to request signal priority while approaching an intersection. When the request is received, the traffic light switches to green, providing a clear

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passage for the emergency vehicle. Their results showed a reduction in intersection delay without requiring major changes to the traffic network. This method is simple, cost-effective, and practical for real deployment. However, the system uses predefined rules and does not include learning or negotiation. If multiple emergency vehicles request priority simultaneously, the system may not respond efficiently. The approach also lacks city-wide coordination and works only at isolated intersections.

Multi-Agent Negotiation for Urban Emergency Response (Kumar & Patel, 2024). Kumar and Patel presented a lightweight multi-agent negotiation framework for handling emergency vehicle movement in urban traffic. In their system, traffic signals behave as autonomous agents that can decide whether to grant priority based on local traffic density and the urgency of an incoming request. This method reduced delays at individual intersections and required less computational power compared to deep learning approaches. However, the framework relies on static routing for emergency vehicles and does not use reinforcement learning to improve decisions over time. The system was also tested on a small simulated network, limiting its scalability for large cities or multiple simultaneous emergencies.

Agent-Based Fire Truck Coordination Simulation (Hassan et al., 2023). Hassan and colleagues developed an agent-based simulation system for coordinating fire trucks and traffic lights during emergency responses. Their model used Unity ML-Agents to simulate realistic vehicle behavior and traffic movement. The system allowed signals to detect approaching fire trucks and adjust timings to reduce delay. The study demonstrated improved response time and showed how agent interaction can be beneficial in emergency cases. However, Unity-based simulations require high computational resources and are difficult to scale for large city networks. The approach is limited to small test environments and does not support multiple emergency vehicle types or complex routing strategies.

Survey of Multi-Agent Models for Intelligent Transportation Systems (Moradi & Chen, 2020). Moradi and Chen conducted a detailed survey on the use of multi-agent models in intelligent transportation systems. Their review covered traffic coordination, communication among agents, and decentralized decision-making in smart cities. The study concluded that multi-agent systems are effective for self-organizing traffic and can reduce dependency on centralized control. They also highlighted that real-time communication, adaptive learning, and large-scale deployment are essential for practical implementation. However, the survey noted that most existing systems are limited to small simulations, lack reinforcement learning, and do not integrate routing with signal coordination for emergency vehicles.

3.RESEARCH GAP

Although previous studies have introduced routing algorithms, reinforcement learning for traffic signals, and basic vehicle-to-infrastructure communication, several important limitations remain. Most routing-based systems still assume fixed traffic signals and do not communicate with the traffic network, which reduces their effectiveness during heavy congestion. Reinforcement learning models improve traffic flow, but they are designed for normal vehicles and rarely prioritize emergencies. Multi-agent negotiation systems show faster clearance at intersections, yet they are tested only on small maps and do not scale to real city conditions. Across all reviewed papers, there is no unified framework where emergency vehicles and traffic lights operate as intelligent agents that can learn, communicate, and negotiate in real time. Additionally, very few studies use large, realistic road networks or simulate multiple congestion scenarios such as rush hour, night traffic, rain, or sudden accidents. These gaps indicate a need for a city-level, cooperative multi-agent system that combines routing, learning, and signal coordination within a single simulation environment.

4.PROBLEM STATEMENT

In large urban cities, emergency vehicles such as ambulances and fire trucks face significant delays due to unpredictable traffic congestion, fixed signal timings, and lack of real-time coordination with road infrastructure. Existing routing systems find shortest paths, but they cannot adapt dynamically when traffic density changes or roads become blocked. Similarly, reinforcement learning–based traffic signal models improve general traffic flow but do not prioritize emergency vehicles. Current multi-agent or V2I-based systems are limited to small maps and isolated intersections, making them unsuitable for full city environments. As a result, emergency response times remain high, leading to delayed medical treatment, increased mortality, and higher property loss. Therefore, there is a need for a scalable, intelligent system where emergency vehicles and traffic lights can communicate, learn, and negotiate in real time to create faster, congestion-free passage across a full city network.

5.OBJECTIVES OF THE STUDY

1. **To develop a city-scale simulation framework** that models real urban traffic using SUMO and supports interaction between emergency vehicles and traffic signals.
2. **To implement intelligent agents**—such as ambulances, fire trucks, and traffic lights—that can communicate and make autonomous decisions using SPADE.

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3. **To apply A*** for routing and **Q-Learning** for adaptive decision-making so that emergency vehicles can re-route dynamically under different congestion conditions.
4. **To simulate multiple real-world traffic scenarios**, including rush hour, night traffic, rain, festivals, and accident-based congestion, in a 5×5 km Pune city map.
5. **To measure system performance** using key indicators such as emergency response time, waiting time at intersections, queue length, and successful green-wave formation.
6. **To analyze whether cooperative multi-agent negotiation** between emergency vehicles and traffic lights can reduce delays and improve emergency response efficiency compared to traditional static systems.

6.PROPOSED METHODOLOGY

The proposed solution is a city-scale, multi-agent emergency response simulation that combines traffic modeling in SUMO with autonomous agent communication through SPADE. The system is designed to allow ambulances, fire trucks, and traffic signals to cooperate in real time and reduce delays caused by unpredictable congestion.

6.1 Simulation Environment

A 5×5 km road network of Pune city is extracted from OpenStreetMap and converted into a SUMO-compatible format using NETCONVERT. Traffic flow and vehicle density are calibrated using publicly available datasets from the Pune Municipal Corporation. Multiple realistic scenarios such as rush hour, night traffic, rain, festival congestion, and road-block accidents are simulated to evaluate system behavior under diverse conditions.

6.2 Agent Architecture

Five types of intelligent agents are created using the SPADE framework:

- **AmbulanceAgent** – detects current traffic density, requests priority, and performs real-time route planning.
- **FireTruckAgent** – follows similar behavior, with different dispatch and routing rules.
- **TrafficLightAgent** – controls signal phases, receives emergency requests, and grants green-wave priority when suitable.
- **IncidentAgent** – generates emergency events at random locations.
- **CoordinatorAgent** – monitors global performance and records KPIs.

All agents communicate using FIPA-ACL messaging over XMPP, enabling asynchronous negotiation without centralized control.

6.3 Routing and Learning

Emergency vehicles first compute a shortest path using the A* algorithm. During simulation, if congestion increases or a better route becomes available, the agent applies **Q-Learning** to update decisions. TrafficLightAgents also learn when to switch signals to minimize delays for both emergency and normal vehicles. This combination allows adaptive decision-making rather than fixed rules.

6.4 Cooperative Negotiation

When an emergency vehicle approaches an intersection, it sends a priority request to the nearest TrafficLightAgent. The signal decides whether to grant priority based on current queue length, phase time remaining, and other nearby emergencies. If approved, a temporary green wave is formed. This distributed negotiation removes the need for centralized control.

6.5 Performance Evaluation

For each scenario, SUMO logs are analyzed to compute:

- Emergency response time
- Waiting time at intersections
- Queue length
- Number of successful green-wave formations
- Impact on normal traffic

These metrics indicate whether intelligent coordination improves emergency mobility compared to static traffic systems.

7.MATHEMATICAL MODEL

1. Road Network Representation

- Let the city road network be a directed graph:
    - G = (V, E)
    - V = set of intersections (nodes)
    - E = set of roads (edges)

2. Cost of Each Road Segment

For every edge e in E:

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- Cost(e) = distance + waiting delay
- Cost(e) = d(e) + w(e)

3. A Route Cost Function

A* selects a route with minimum total cost.

- For every node n:
  - f(n) = g(n) + h(n)
  - g(n) = cost so far
  - h(n) = estimated distance to destination

Optimal route:

- P* = the path with the minimum total cost across all edges.

4. Reinforcement Learning Model

Each intelligent agent uses a Markov Decision Process:

- S = set of possible states (traffic density, queue length, signal status)
- A = set of actions (change signal, reroute, grant priority)
- R = reward for each action
- T = state transition based on action taken

5. Q-Learning Update Rule (Plain Text)

$Q(s, a) \leftarrow Q(s, a) + \alpha\, [r + \gamma \max\_a' Q(s', a') - Q(s, a)]$

Where:

- Q(s, a) = quality value of taking action a in state s
- reward = change in response time or traffic flow
- discount_factor = importance of future decisions
- learning_rate = how fast learning happens

6. Reward Function

For emergency vehicles:

- Reward = negative of (travel delay + waiting time)
- Reward = – (delay + wait_time)

So less delay → higher reward.

For traffic lights:

- Reward = negative of queue length
- Reward = – (queue_length)

So shorter queue → better reward.

7. Signal Priority Condition

A traffic light grants green priority to an emergency vehicle if:

- Distance of vehicle from signal < threshold AND queue length is manageable

Or in plain condition:

- IF vehicle_distance < threshold AND queue_length < limit → grant priority

8. Objective of the System

Minimize total emergency response time:

- Response Time = travel time + waiting time
- Goal: Minimize Response Time

8.EXPECTED OUTCOMES

The proposed multi-agent simulation is expected to demonstrate that cooperative communication between emergency vehicles and traffic lights can significantly improve response efficiency in congested urban environments. By integrating adaptive routing with real-time signal negotiation, emergency vehicles should require fewer stops, experience shorter waiting times at intersections, and reach incident locations faster than in traditional fixed-signal systems. The use of Q-Learning allows both vehicles and traffic lights to adjust behavior dynamically as traffic conditions change, making the system more robust than static or rule-based approaches.

The simulation is also expected to show that forming temporary green corridors can reduce queue length without causing major disruption to normal traffic. Since all agents operate in a decentralized manner, the system should remain functional even in high congestion or during multiple simultaneous emergencies. Performance improvements will be reflected in key indicators such as reduced response time, reduced intersection delay, and higher success rate of priority clearance.

Overall, the expected outcome is a scalable and practical framework that demonstrates how multi-agent intelligence can enhance emergency response in future smart cities. The results will provide a foundation for real-world deployment, hardware integration, and further research in intelligent transportation systems.

9.CONCLUSION AND FUTURE SCOPE

Conclusion: Urban emergency vehicles continue to face delays due to congestion and fixed signal timing systems. The literature shows that routing algorithms, reinforcement learning, and multi-agent negotiation each improve different parts of the problem, but no existing system integrates all of them into a coordinated, city-scale solution. The proposed SUMO–SPADE framework provides a unified simulation environment where ambulances, fire trucks, and traffic lights behave as autonomous agents that can communicate, negotiate priority, and learn from traffic conditions. By combining A* routing, Q-Learning, and signal preemption, the system has the potential to reduce waiting time, create temporary green corridors, and improve emergency mobility in a realistic urban network. The study contributes toward building smarter and faster emergency response strategies for future smart cities.

Future Scope: This work can be extended by integrating real GPS feeds, IoT sensors, and live traffic camera data to achieve real-time deployment. More advanced learning algorithms like MARL (Multi-Agent Reinforcement Learning), DQN, or PPO can allow signals to learn coordinated behavior across a full city. The simulation can be expanded to include police operations, disaster evacuation, ambulance–hospital assignment, and drone-based first aid delivery. Eventually, the system can be implemented in real traffic control cabinets through V2I communication modules, enabling field trials in smart city environments.

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