Risk-Aware Multi-Agent Approach for Energy-Efficient Emergency Traffic Management

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Abstract: In this study, we propose a novel Risk-Aware Hierarchical Energy-Managed Twin (RA-HEMT++) framework to address these problems by leveraging coordinated UAV-UGV collaboration and deep reinforcement learning to form traffic corridors in emergency scenarios. The proposed framework combines hierarchical multi-agent reinforcement learning, spatiotemporal traffic-state fusion, digital twin simulation, and energy-aware optimization, enabling adaptive, real-time traffic management. Various datasets are used, including SUMO traffic simulations, UAV traffic observations, NGSIM vehicle trajectories, and OpenStreetMap road networks, to build a realistic and scalable urban traffic environment. The framework uses a hierarchical decision-making approach with strategic corridor planning, cooperative task allocation, and low-level motion control, while also reducing the delay time of emergency vehicles, the severity of congestion, and system energy usage. Experimental results show the superiority of the proposed RA-HEMT++ framework over traditional traffic control, RL-based optimization, federated DRL, and hierarchical RL methods. The proposed model can achieve 75 secs of corridor formation time, 55 secs of emergency vehicle delay time, a 60% reduction in congestion, and 3.0 kWh of energy consumption. The results demonstrate that RA-HEMT++ is a robust, scalable, and energy-efficient solution for next-generation emergency traffic management in smart cities.

Keywords: UAV–UGV Collaboration; Deep Reinforcement Learning(DRL) ; Multi-Agent Systems; Traffic Signal Control; Digital Twin;

Introduction

Urban traffic congestion is one of the most prominent challenges in intelligent transportation systems (ITS), resulting from rapid urbanisation, the growing number of vehicles, and a complex traffic environment [1], [2]. Multi-agent reinforcement learning (MARL) systems have been proposed to manage traffic signals across multiple intersections, enabling decentralized decision-making and improving overall network performance [3, 4]. Multi-agent models with decentralization promote the scalability and resilience of large traffic systems [5], [6]. These models can help coordinate global and local traffic control policies, thereby improving scalability and convergence in large-scale scenarios [7]. Additionally, multi-agent intelligent systems are effective in managing mixed traffic flows and optimizing global objectives in smart cities through inter-agent communication and the optimization of global objectives [8], [9]. Multi-objective reinforcement learning (MORL) has been introduced to jointly optimize performance metrics in traffic, such as delay, energy consumption, and environmental impact

[10], [11]. At the same time, with the recent advances in large-scale traffic control, mixture-of-experts reinforcement learning models have been developed, generalizing and scaling better by learning from multiple specialized models under different traffic situations [12], [13]. The insights gained from this work are important and valuable for the development of intelligent transportation systems (ITS) for emergency traffic management in cities, as shown in Figure 1.

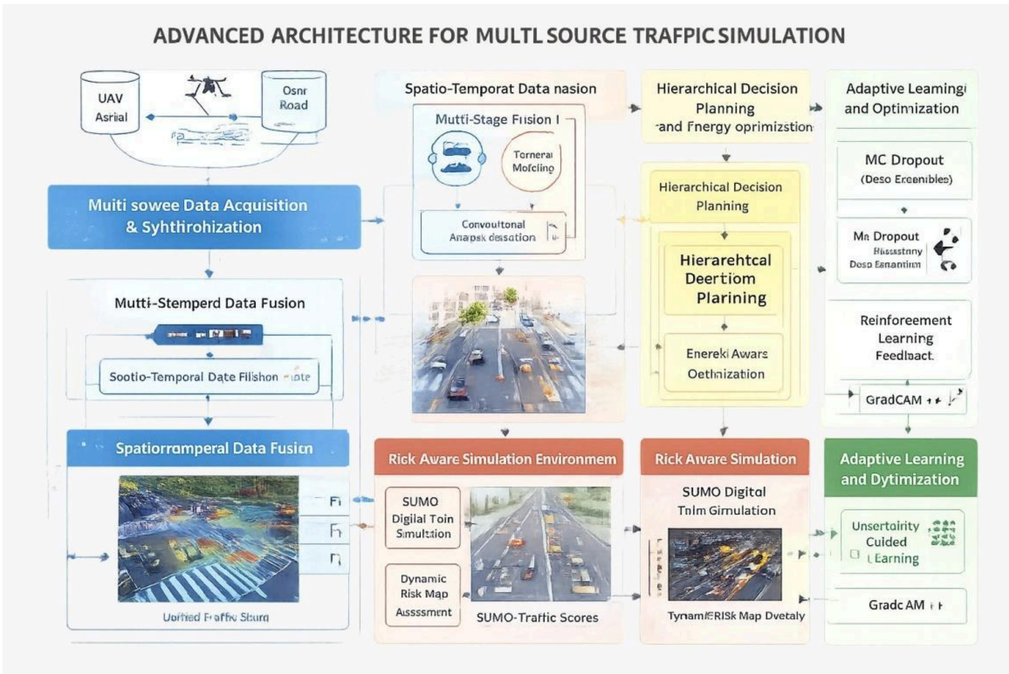


Fig 1: Workflow for Multi-Source Traffic Simulation

Research Gaps

1. Current traffic signal control systems are not sufficiently effective at prioritizing emergency vehicle use, resulting in delayed corridor formation and longer emergency response times.
2. Coordination across multiple intersections is not effective for most current reinforcement learning-based methods, rendering them unable to scale up in large urban traffic networks.

Objectives

1. To establish a hierarchical multi-agent framework that is risk-conscious to allow coordinated operation between UAVs and UGVs to form emergency traffic corridors speedily in the dynamic urban setting.
2. To develop a simulation and learning environment based on a digital twin to simulate the use of SUMO to test and continuously enhance the performance of the proposed framework in different traffic and incidence conditions.

Methodology

Risk-Aware Hierarchical Energy-Managed Twin (RA-HEMT++) Model

The system can be designed as an organized pipeline integrating traffic simulation, data processing, machine learning, and multi-agent control to implement the proposed (RA-HEMT++) model for the formation of emergency traffic corridors. The first step is data preparation, during which the datasets of interest (such as SUMO traffic simulation data, aerial traffic observations, vehicle trajectory data, and road network data) are collected and processed. The traffic scenario is simulated using the Simulation of

Urban Mobility (SUMO) platform, and the resulting vehicle trajectories, congestion levels, queue lengths, and traffic signal states are used to train and evaluate the model, as shown in Figure 2.

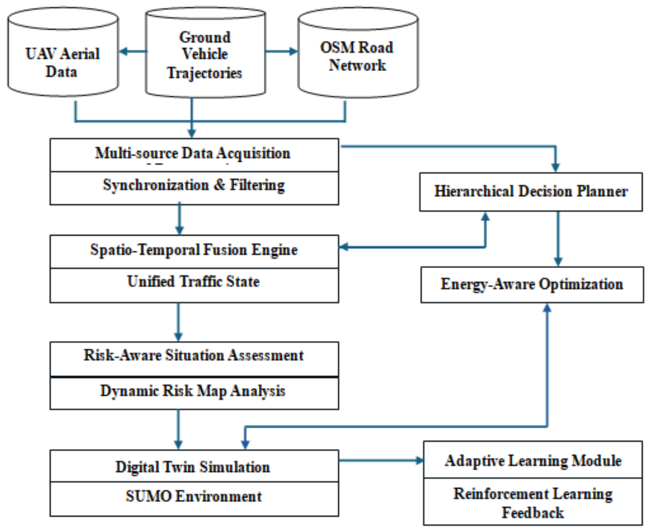


Fig 2: Work Flow of the Proposed Model

After data preparation, the spatio-temporal fusion module is run, which is based on an integrated representation St of the traffic state that combines aerial surveillance with vehicle tracks and road topology. These movements are optimized using an energy-sensitive module that minimizes a cost function that accounts for energy consumption, emergency delay, and traffic congestion.

Algorithm 1: RA-HEMT++ for Energy-Aware Emergency Traffic Corridor Formation

Input: Multi-source datasets D, road network graph G, UAV–UGV fleet configuration F

Output: Optimal coordinated policy π^* and actions A_t

Step 1:	Initialize model parameters θ
Step 2:	Initialize hierarchical policies π_H(high-level), π_M(mid-level), π_L(low-level)
Step 3:	Initialize digital twin environment T
Step 4:	Initialize energy states E_0 for all UAVs and UGVs
Step 5:	**for** each time step $t = 1 \rightarrow T$ **do**
Step 6:	Collect heterogeneous traffic data D_t from UAV, UGV, and infrastructure, preprocess, synchronize, and clean D_t
Step 7:	Compute the fused traffic state $S_t \leftarrow FusionEngine(D_t, G)$
Step 8:	Estimate the dynamic risk map $R_t \leftarrow RiskEstimator(S_t)$
Step 9:	High-level planning: $G_t \leftarrow \pi_H(S_t, R_t)$
	Mid-level planning: $P_t \leftarrow \pi_M(G_t, E_t)$
	Low-level control: $A_t \leftarrow \pi_L(P_t)$
Step 10:	Refine actions under energy constraints $A_t \leftarrow EnergyOptimizer(A_t, E_t)$
Step 11:	Simulate joint actions in a twin environment $(r_t, S_{t+1}) \leftarrow T(A_t)$
Step 12:	Update model parameters using reinforcement signal $\theta \leftarrow \theta + \nabla J(r_t)$
	Update agent energy states E_{t+1}
Step 13:	Deploy optimized actions A_t to UAV–UGV fleet
Step 14:	**end for**
Step 15:	Return optimal policy π^*

Results and Discussions

DATASETS and their Description

1. In the SUMO Traffic Simulation dataset [14], there is no fixed number of records or features because SUMO is a traffic generator rather than a static dataset.
2. The UAV Aerial Traffic Dataset (UAVDT) [15] is a large-scale benchmark for vehicle detection and tracking by low-altitude uncrewed aerial vehicles.
3. NGSIM (Next Generation Simulation) [16] is a dataset containing trajectories of a large number of vehicles in a real-world scenario.
4. An international community of volunteers maintains the OpenStreetMap dataset [17], which contains structured map information.

The impact of the metrics on their performance at work.

a. **Corridor Formation Time (sec):** Time needed to clear the way to the emergency vehicle [18].

$$T_{corridor} = T_{clear} - T_{request}$$

$T_{request}$: Emergency request time and T_{clear}: The period when the density of traffic in the chosen route is below a certain limit.

b. **Emergency Vehicle Delay (sec):** The additional time an emergency vehicle will spend in comparison to free flow [19].

$$D_{emg} = T_{actual} - T_{freeflow}$$

$where$ T_{actual}: Travel time in current traffic and $T_{freeflow}$: Current traffic travel time.

c. **Traffic Congestion Reduction (%):** Percentage of traffic flow improvement once your model has been applied [20].

$$CR = \frac{C_{before} - C_{after}}{C_{before}} \times 100$$

$where$ C_{before}: Mean congestion (control) and C_{after}: Congestion following the application of RA-HEMT++.

d. **Energy Consumption (kWh):** Total power used by UAVs and UGVs in operation [21].

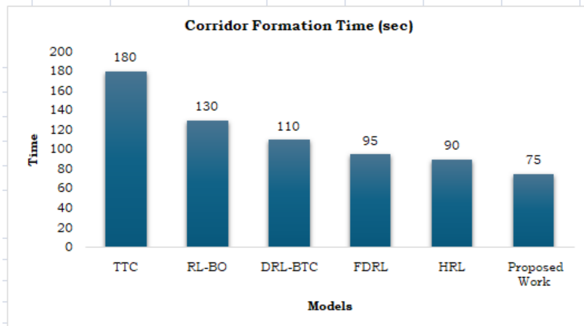
$$E_{total} = \sum_{i=1}^{N} (E_i^{UAV} + E_i^{UGV}) \quad \text{Where:} \quad E = P \times t \quad P\text{: power consumption, } t\text{: operation time}$$

Table 1: Results obtained for the various Metrics

Model	Corridor Formation Time (sec)	Emergency Vehicle Delay (sec)	Traffic Congestion Reduction (%)	Energy Consumption (kWh)
Traditional Traffic Control [22]	180	145	10%	5.2
RL-Based Optimization [23]	130	100	28%	4.5
DRL-Based Traffic Control [24]	110	85	35%	4.2
Federated DRL [25]	95	75	42%	3.8

Proposed RA-HEMT++ Framework	75	55	60%	3.0

The findings of Table 1 show the relative performance of the proposed RA-HEMT++ framework. Figure 3 compares the times to form corridors using different methods. The comparison of emergency vehicle delays is shown in Figure 4.



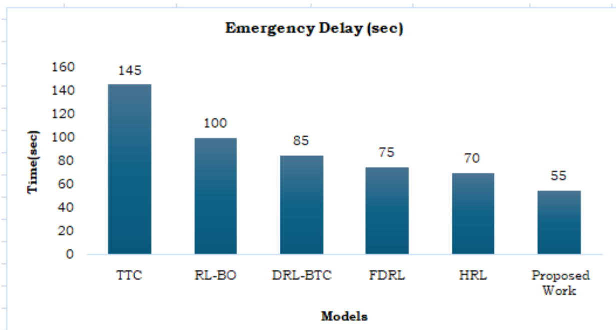


Fig 3: Graph for the Corridor Formation Time (sec) Fig 4: Graph for the Emergency Delay (sec)

Conclusion

The main contributions of this study are the RA-HEMT++ framework to form efficient emergency traffic corridors, which combines hierarchical deep reinforcement learning, UAV-UGV coordination, and digital twin technology. With adaptive and risk-aware traffic management, the framework effectively minimizes energy consumption, formation time in the corridor, traffic jams, and unnecessary delays of emergency vehicles. The addition of multi-agent coordination and real-time learning enhances scalability and decision-making capabilities.

Future efforts will involve deployment in the real world, using edge-optimized optimization techniques, and incorporating additional connected autonomous vehicle integration to optimize the system's performance and robustness further.

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