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Smart Route Optimization for Emergency Vehicles

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Abstract- Emergency vehicle response time is one of the most decisive factors in determining survival outcomes across cardiac arrest, fire, and trauma scenarios. In India alone, an estimated 10,000 lives are lost annually due to preventable ambulance delays in urban areas. Yet despite the proliferation of GPS and connected vehicle technologies, most emergency routing systems continue to rely on static, pre-computed paths that fail entirely when confronted with real-time traffic disruption. A review of more than 20 peer-reviewed studies published between 2012 and 2025 reveals a field that has generated genuine progress across individual sub-domains — reinforcement learning-based routing, IoT signal preemption, VANET-based tracking, and GIS-driven planning — but has consistently failed to unify these capabilities into a single, coherent system. No reviewed study simultaneously addresses the full problem: every approach treats either the route or the signal or the prediction as the primary optimization target and handles the others as secondary concerns. This paper presents a structured thematic review of the existing body of knowledge, a rigorous comparative analysis of 20 studies and their limitations, and the design of the Adaptive Emergency Routing Intelligence System (AERIS) — a novel framework integrating deep reinforcement learning with a graph neural network traffic encoder, IoT-enabled multi-intersection signal coordination, and a predictive traffic modeling layer. Projected performance improvements of 25–35% over conventional routing, combined with a city-agnostic modular design, position AERIS as a meaningful step forward for emergency transportation systems.

Index Terms—Emergency Vehicle Routing, Smart Route Optimization, Deep Reinforcement Learning, IoT Signal Preemption, Intelligent Transportation Systems, Green Corridor, Graph Neural Networks, Real-Time Traffic Management, Urban Mobility, VANET

I. INTRODUCTION

1.1 BACKGROUND OF THE STUDY

Urban traffic congestion has emerged as one of the most pressing infrastructure challenges of our time, and nowhere are its consequences more immediate than in emergency medical services. When an ambulance navigates a congested arterial road during peak hours, every red light, every bottleneck, every wrong turn is measured not in minutes but in lives. A widely cited figure from emergency medicine captures this with stark precision: a single-minute delay in cardiac arrest response can increase patient mortality by approximately 10%. For building fires, that same delay translates to structural damage that grows exponentially with each passing moment.

India's urban landscape makes this problem particularly severe. Cities like Bengaluru, Mumbai, and Delhi have seen average vehicle speeds during peak hours drop from over 40 km/h to as low as 9 km/h over the past fifteen years. Ambulances in major metropolitan areas routinely take between 20 and 45 minutes to reach patients — often well beyond the critical 'Golden Hour' threshold that emergency medicine defines as the window for effective intervention. Talukdar (2024) documented IoT-enabled routing reducing response times by 15–20% in Indian smart city case studies, suggesting that even partial technology deployment yields measurable benefits, and that a fully integrated system could do considerably more.

The tools to address this problem are, in many respects, already available. GPS tracking, IoT sensor networks, AI-based traffic prediction, and connected vehicle infrastructure collectively provide the building blocks of a fundamentally better emergency routing system. What has been missing is integration: a principled, unified architecture that brings these capabilities together.

1.2 PROBLEM STATEMENT

Traditional ambulance dispatch systems assign a route at the moment of the call, typically via GPS shortest-path calculations against a static or minimally updated road graph. This approach has three fundamental weaknesses. First, it is reactive rather than predictive:

it cannot anticipate how traffic conditions will evolve over the 10 to 15 minutes of a typical urban emergency journey. Second, it operates in isolation from traffic signal infrastructure, meaning that even a well-chosen route is repeatedly interrupted by red lights at intersections. Third, existing intelligent routing solutions in the academic literature, while individually sophisticated, have been designed for specific urban contexts and resist generalization.

The compound effect of these weaknesses is that emergency response in dense urban environments remains far below its potential. As the literature reviewed in this paper demonstrates consistently, even minor improvements in routing intelligence produce meaningful results in isolation. The potential of a truly integrated, learning-based, infrastructure-aware system has not yet been realized.

1.3 MOTIVATION

This research is motivated by three converging realities. First, the human cost: preventable emergency response delays represent a public health challenge of significant scale, particularly in rapidly urbanizing economies where infrastructure development has lagged behind population growth. Second, the technical readiness: the convergence of deep reinforcement learning, graph neural networks, 5G-enabled V2X communication, and IoT infrastructure has created a moment at which a genuinely integrated solution is achievable. Third, the academic gap: despite a rich body of literature on individual components, no published work has yet proposed or validated a framework that addresses route optimization, signal coordination, and predictive modeling as a unified, co-designed system.

1.4 OBJECTIVES OF THE STUDY

1.5 RESEARCH QUESTIONS

1.6 CONTRIBUTIONS OF THE PAPER

This paper makes four original contributions. First, it provides a thematic classification of 20 emergency vehicle routing studies spanning 2012–2025, categorized by technique, application domain, and performance outcome. Second, it produces a rigorous cross-study comparative analysis evaluating methodological soundness, real-world deployability, and scalability. Third, it identifies and articulates six primary research gaps representing the most significant open problems in the field. Fourth, it proposes the AERIS framework — a novel, integrated architecture for AIdriven emergency routing — and outlines a grounded evaluation methodology.

1.7 ORGANIZATION OF THE PAPER

Section 2 presents the thematic literature review across four technique categories. Section 3 provides the comparative analysis and research gap assessment. Section 4 describes the proposed AERIS framework. Section 5 outlines expected results and the evaluation plan. Section 6 discusses real-world applications. Section 7 concludes the paper.

II. RELATED WORK / LITERATURE REVIEW

2.1 TRADITIONAL APPROACHES

The earliest systematic work on emergency vehicle routing relied on graph-based shortest-path algorithms — Dijkstra's and A* being most prevalent. Elmandili et al. (2013) applied VANET communication with Kalman Filter tracking in a SUMO simulation, demonstrating measurable travel delay reductions. While technically sound, these approaches share a fundamental limitation: they compute routes against static or minimally updated road graphs with no mechanism for adapting to conditions that change during the journey.

Signal preemption strategies represent a parallel traditional approach. Shaaban et al. (2019) developed a joint path selection and preemption strategy tested on a real traffic network in Doha, Qatar, achieving an average 24.3% reduction in EV travel time across three peak-hour scenarios. Their work is notable for explicitly modeling the impact on general traffic — a consideration many later studies neglect. However, their approach was tested on a four-intersection corridor and acknowledged results would vary with different traffic volumes or signal configurations.

2.2 MACHINE LEARNING APPROACHES

Machine learning application to emergency routing accelerated after 2018. Khan et al. (2023) proposed a genetic algorithm-based dispatching model, demonstrating improved dispatch efficiency in simulated urban scenarios. Gamal et al. (2022) combined Dijkstra's algorithm with WSN-collected data and fuzzy logic controllers in Zagazig, Egypt, reporting a 99% reduction in EV queue time and 69% improvement in average EV speed. These results are impressive but constrained by the specific characteristics of that single deployment.

Gupta et al. (2024) applied a modified Whale Optimization Algorithm (mWOA) to ambulance allocation in Southern Delhi, outperforming genetic algorithm, PSO, and SFLA baselines and reducing average response time by 14.6%. This work stands out for grounding in real operational data — 50 ambulances across 11 stations — rather than pure simulation, though it is constrained to optimizing existing configurations rather than enabling fully dynamic routing.

2.3 DEEP LEARNING AND REINFORCEMENT LEARNING APPROACHES

Deep learning, particularly reinforcement learning, has emerged as the most promising paradigm for dynamic emergency routing. Ding et al. (2022) proposed LEVID, a cooperative vehicle-road scheduling approach using deep RL with graph attention networks, achieving EV travel time reductions of up to 74.71% over fixed-time baselines across five datasets. However, the multi-agent RL component required over 100 hours of training time on the New York dataset, raising serious questions about practical deployment.

Trehan and Sharma (2026) combined YOLO-based vehicle detection with RL signal control, reducing EV response time by 40% versus fixed-time control (190 seconds vs. 320 seconds) while simultaneously reducing average delay for non-emergency traffic. Jadhav and Saraf (2025) combined real-time path optimization algorithms with an adaptive green corridor system, evaluated on 125 real emergency response trips. The RL algorithm achieved the lowest travel time (13.7 minutes) and delay per intersection (15.2 seconds), with SLA compliance improving from 57.6% to 83.2%.

2.4 IOT AND CONNECTED INFRASTRUCTURE APPROACHES

A major strand of research has focused on IoT-enabled infrastructure. Rajeshwari et al. (2021) implemented RFID and IoT sensor-based signal automation, demonstrating measurable intersection waiting time reductions. Rosayyan et al. (2023) conducted one of the few genuine real-world deployments, implementing a GPS IoT sensor system with edge computing on an actual road in Thiruvananthapuram, reducing normal vehicle waiting time by 73.23% and demonstrating communication latency below 100 milliseconds.

Bhardwaj (2025) designed a GIS-driven smart emergency framework for Indian cities using K-means clustering for accident hotspot identification and modified Dijkstra/A* algorithms for dynamic routing, achieving simulated response time reductions of 35% for Bangalore. Nirmalkar et al. (2025) integrated GPS tracking, automated signal control, Google API-based route optimization, and V2X communication in a preliminary evaluation, reporting a 30% reduction in ambulance travel time.

2.5 SURVEY AND REVIEW STUDIES

Several significant survey papers have shaped the conceptual landscape of the field. Humagain et al. (2019) reviewed 72 articles and concluded that the field urgently needed more dynamic approaches and real-world validation. Yu et al. (2022) reviewed 81 articles in IEEE Access, observing that the field had evolved from single-objective traditional optimization to multi-objective machine-learning methods, though hybrid strategies remained undervalidated in real-world settings. Kamble and Kounte (2022) surveyed 56 EV preemption studies, finding that the vast majority addressed single-vehicle scenarios and lacked capability to handle multiple simultaneous emergency vehicles.

2.6 COMPARATIVE ANALYSIS OF EXISTING METHODS

The following table provides a consolidated comparison of all 20 primary studies reviewed, synthesizing methods, key findings, and limitations.

2.7 CRITICAL REVIEW

Reading across the literature as a whole, several patterns emerge with clarity. First, there is a persistent tendency toward simulation-only evaluation: of the 20 studies reviewed, only three (Rosayyan et al., Jadhav and Saraf, Gupta et al.) include realworld empirical data, and only one (Rosayyan et al.) involves a live road deployment. This creates a significant validity gap between reported performance figures and what systems can plausibly achieve under real urban conditions.

Second, the field's most technically sophisticated contributions require computational resources and training data volumes unavailable in most operational contexts. The gap between academic innovation and deployable engineering solutions remains wide. Third, and most fundamentally: no reviewed study simultaneously addresses the full problem. Every approach treats either the route or the signal or the prediction as the primary target and handles the others as secondary or not at all. This fragmentation is the structural weakness that a genuinely integrated framework must resolve.

III. IDENTIFIED RESEARCH GAPS

Drawing from the comparative analysis and critical review, the following six gaps represent the most significant open problems in the field. These gaps directly motivate the framework design proposed in Section 4.

The most critical gap — and the one most directly addressed by AERIS — is the absence of an integrated, real-time system combining adaptive routing, predictive traffic modeling, and multi-intersection signal coordination in a single, co-designed architecture. As the literature demonstrates, each capability individually produces meaningful improvements. The theoretical and empirical basis for expecting greater improvements from their combination is strong, yet this combination has not been attempted in the reviewed literature.

IV. PROPOSED METHODOLOGY: THE AERIS FRAMEWORK

4.1 SYSTEM OVERVIEW

The Adaptive Emergency Routing Intelligence System (AERIS) is designed around three foundational principles: realtime adaptability, in which every routing decision is based on current information re-evaluable at 10–30 second intervals; predictive awareness, meaning the system models how conditions will likely evolve over the duration of the emergency journey rather than merely reacting to current states; and infrastructure integration, where routing decisions are coupled in real-time with signal control commands, creating a dynamic green corridor that adapts as the optimal route adapts.

AERIS consists of four tightly integrated modules: the Data Ingestion Module, the Traffic State Encoder, the Route Decision Agent, and the Signal Coordination Module. Together, these form a closed feedback loop that continuously updates both the route and the signal environment in response to evolving urban traffic conditions.

4.2 ARCHITECTURE AND DATA FLOW

The Data Ingestion Module aggregates real-time inputs from multiple heterogeneous sources: GPS telemetry from the emergency vehicle, sensor feeds from roadside IoT units, historical traffic pattern databases, and incident data from the city emergency management system. This heterogeneous data is preprocessed and normalized before being passed to the Traffic State Encoder.

The Traffic State Encoder applies a graph neural network (GNN) to represent the current road network as a dynamic weighted graph, where node weights reflect real-time traffic density at intersections and edge weights reflect current travel times on road segments. The GNN's key advantage is its ability to model not just local conditions at individual nodes but the propagating effects of congestion across the broader network — capturing, for example, how an accident two kilometres from the current route may create bottlenecks on the ambulance's likely path in the next five minutes.

The Route Decision Agent is the deep reinforcement learning core of AERIS. Pre-trained using a reward function that penalizes total travel time, signal stops, and route deviation while rewarding steady progress toward the destination, the agent receives the encoded traffic state and outputs a routing action at each decision interval. The Signal Coordination Module translates route decisions into infrastructure commands, issuing preemption instructions to IoT-capable signals along the planned route 60–90 seconds in advance of the vehicle's projected arrival. When the route changes, preemption commands update automatically.

4.3 WORKFLOW DESCRIPTION

At dispatch, AERIS initializes with the vehicle's starting position, destination coordinates, and the current encoded traffic state graph. The Route Decision Agent computes an initial route, and the Signal Coordination Module begins issuing preemption commands. As the vehicle moves, new sensor data flows continuously into the system, updating the traffic state graph every 10–30 seconds. If the updated graph indicates a material change in conditions — sudden congestion, a newly reported incident, signal timing changes — the Route Decision Agent re-evaluates and may output a new route, which the Signal Coordination Module immediately reflects in its command stream.

This feedback loop operates throughout the entire journey. The system is designed to degrade gracefully with sensor dropout: the Traffic State Encoder includes a predictive fallback module estimating traffic conditions from historical patterns when live data is unavailable, allowing AERIS to maintain near-optimal performance even with 20–30% IoT sensor outage rates.

4.4 DATASET DESCRIPTION

AERIS will be trained using the SUMO (Simulation of Urban Mobility) simulator configured across three representative urban configurations: a regular grid network (typical of planned cities like Chandigarh), an irregular historical network (representative of older city cores in Bengaluru and Mumbai), and a mixed arterial network (representative of rapidly urbanizing peri-urban areas). For validation, real-world road network data will be sourced from OpenStreetMap and ITMS archives for Bengaluru and Pune, providing empirical grounding for the simulationtrained model.

V. EXPECTED RESULTS AND DISCUSSION

5.1 EXPECTED OUTCOMES

Based on benchmarks established by the literature and the architectural advantages of the integrated AERIS design, several key outcomes are anticipated. In terms of travel time reduction, AERIS is expected to achieve 25–35% improvement over conventional GPS-based routing — in line with best-in-class singlecomponent systems, but achieved through a different mechanism: not by pushing any one module to its limits, but by eliminating the coordination losses that exist between separate routing and signal systems that do not share state.

AERIS is expected to outperform standalone RL routing systems (without signal coordination) by 8–12 percentage points in high-congestion scenarios, and to outperform IoT-only signal preemption systems (without adaptive routing) by a similar margin in mid-journey disruption scenarios. SLA compliance is projected to reach approximately 85%, representing a 25–28 percentage point improvement over baseline conventional dispatch.

5.2 COMPARATIVE EVALUATION PLAN

AERIS will be evaluated against four baseline systems: a static Dijkstra's shortest-path router (conventional GPS routing), a genetic algorithm-based dynamic router (best traditional ML approach), an LSTM-based predictive router without signal coordination (current DL state-of-the-art), and a standard RL routing agent without the GNN encoder or signal coordination (closest prior RL approach). All systems will be tested across three traffic density scenarios and three urban configurations, generating 36 experimental conditions per system.

5.3 DISCUSSION

The expected results speak to a broader architectural insight: the value of integration is not merely additive. When routing and signal coordination are designed as separate systems, each must operate under uncertainty about what the other will do — the router cannot fully exploit the green corridor because it does not know which signals will be preempted, and the signal controller cannot fully optimize because it does not know what route the vehicle will take. AERIS resolves this uncertainty by design: routing decisions and signal coordination commands are generated by the same system, from the same information state, at the same decision interval. This tight coupling is the source of performance advantages that individual components cannot achieve alone.

VI. APPLICATIONS AND USE CASES

6.1 EMERGENCY MEDICAL SERVICES

The most direct application is urban ambulance services. Cardiac arrest survival rates decline by approximately 10% per minute of delay in defibrillation; a 25–35% reduction in ambulance travel time represents a clinically significant intervention. For stroke and trauma patients, faster delivery to appropriate facilities similarly improves outcomes across severity levels. The work of Almalki et al. (2025) underscores an important additional dimension: optimizing not just the route to the nearest facility, but to the most appropriate one given real-time resource availability — a capability that AERIS's data integration layer can readily incorporate.

6.2 FIRE AND POLICE SERVICES

AERIS is architecturally agnostic to vehicle type; the routing and signal coordination logic applies equally to fire engines and police vehicles. For fire departments, faster response reduces structural damage and the risk of fire spread. A planned extension of the framework to multi-vehicle coordination would enable simultaneous dispatch of multiple agencies with coordinated routing, addressing one of the most significant gaps identified in the literature.

6.3 SMART CITY INFRASTRUCTURE PLANNING

Cities considering investments in IoT traffic infrastructure face significant uncertainty about the return on those investments. AERIS provides a quantitative modeling framework for evaluating the marginal benefit of expanded IoT signal coverage, enabling planners to prioritize infrastructure investment in corridors where emergency response frequency is highest and current signal coordination is weakest. This application gives AERIS direct relevance to municipal policy and infrastructure planning beyond its primary emergency response purpose.

6.4 BROADER TRANSPORTATION APPLICATIONS

The core AERIS architecture — a GNN traffic encoder feeding an RL routing agent with real-time signal coordination — is not inherently specific to emergency vehicles. With appropriate retraining and a different reward function, the same architecture could be applied to public transit bus priority systems, time-sensitive logistics delivery routing, or autonomous vehicle navigation in complex urban environments.

VII. CONCLUSION

This paper has presented a comprehensive review of emergency vehicle route optimization literature, a systematic analysis of its limitations, and the design of AERIS — an integrated framework intended to address those limitations at their structural root.

The review of 20 studies spanning 2012–2025 reveals a field that has generated meaningful technical progress across individual sub-domains, but has consistently failed to integrate routing intelligence, signal coordination, and predictive traffic modeling into a unified system. The dominant approach has been to optimize one element at a time. Performance figures in the literature — ranging from 14.6% to 74.71% travel time reduction depending on the approach and baseline — reflect what isolated interventions can achieve. The theoretical basis for expecting significantly stronger results from a properly integrated system is clear, and the gap in the literature for such a system is well-established.

AERIS addresses this gap through four tightly coupled modules: a data ingestion layer, a GNN-based traffic state encoder, a deep RL routing agent, and an IoT-enabled signal coordination module. The tight coupling between the routing agent and the signal controller — generating decisions and preemption commands from the same information state, at the same decision interval — is the core architectural innovation and the primary source of AERIS's projected advantages over existing systems.

Future work will focus on full-scale implementation and empirical validation in a live urban environment, extension of the framework to multi-vehicle coordination, and development of privacy-preserving mechanisms for the real-time data pipelines on which AERIS depends. The authors believe that AERIS represents both a practical step forward for emergency transportation systems and a replicable template for integrated, learning-based urban mobility management.

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