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Emergency Route Optimization During Disasters Using AI And Iot: A Comprehensive Review of Sensing Approaches, Routing Algorithms, Reported Evidence, and Deployment Challenges

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Abstract. Disasters such as floods, earthquakes and cyclones damage roads and delay ambulances, fire brigades and rescue teams, while conventional navigation relies on static maps that ignore flooding, blockages and congestion. This paper presents a focused narrative review that synthesises five studies on AI-based emergency and evacuation routing: a decentralized reinforcement-learning framework that couples Dijkstra-style routing with traffic-signal control; a machine-learning recommendation system that predicts congestion for ambulances; a flood-sensor system that converts water-level readings into dynamic edge weights for evacuation routing; a graph-based method that reconfigures road directions in real time; and a hybrid quantum machine-learning approach to escape routing. The review examines three connected themes: sensing approaches and routing models, the strength and comparability of the reported evidence, and the conditions that matter when routing is extended into a full IoT-to-dashboard pipeline. All five studies were assessed from their published abstracts and available excerpts, not read in full; the one headline figure found is a 74% improvement in evacuation efficiency, and it cannot be ranked against the other results, which are mostly qualitative. Only one study links physical sensor readings to routing. The review contributes a comparative table, a conceptual architecture for the proposed system, which is not experimentally validated, and a prioritised agenda of research gaps.

Keywords: Emergency route optimization, disaster management, Internet of Things, machine learning, reinforcement learning, Dijkstra, evacuation routing.

I. Introduction

Disasters such as floods, earthquakes, cyclones and landslides regularly damage infrastructure and block roads, making it hard for emergency vehicles to reach affected people, and every minute of delay matters. Traditional navigation systems use static maps and do not consider real-time road damage, flooding or traffic conditions. Su et al. note that emergency response time is a key indicator of a city's emergency management capability [1], and Behrooz and Ilbeigi describe evacuation routing as a critical component of disaster management that ensures safe and timely relocation of people from hazardous areas [4].
The project behind this review is an emergency route optimization system for disasters using AI and IoT. According to the seminar synopsis, IoT sensors collect vehicle location, water level, weather and traffic data, which are sent over Wi-Fi, LoRa or GSM to a cloud or edge server; the road network is represented as a weighted graph whose edge weights are updated dynamically; ML models predict congestion and blockage risk; Dijkstra, A* or reinforcement learning find the best route; and the result reaches the driver through a mobile app and the control room through a dashboard. Its stated objectives are to reduce

response time, avoid flooded and blocked roads, improve coordination and support smart-city disaster management. Any technology proposed for this setting must do two jobs: sense the changing road conditions, and turn them into a route an emergency crew can follow.

This paper reviews five studies that together cover decentralized RL routing [1], ML congestion prediction for ambulances [2], flood-sensor-driven evacuation routing [3], adaptive graph reconfiguration [4] and hybrid quantum ML for escape routing [5]. Three questions guide the review. RQ1: Which sensing approaches and routing models are used? RQ2: What performance and trade-offs do the studies report, and how reliable is the evidence? RQ3: What do the studies imply for an IoT-to-route pipeline? The paper ends with a comparative table, a conceptual architecture and a list of research gaps.

II. Review Methodology

This is a narrative review of five papers selected for the study, not a systematic database search, so no claim of exhaustive coverage is made. The papers are one AAAI conference paper [1], one journal article from the International Journal of Advanced Computer Science and Applications [2], one conference-hosted article [3], one conference paper from Stevens Institute of Technology [4] and one arXiv preprint [5]. For each paper the aim, method, data, reported results and stated limitations were extracted and compared. Depth of access is stated so that no claim is overstated. All five papers were assessed only from their published abstracts, search excerpts and bibliographic records; none was read in full. Items such as dataset size, hyperparameters, numerical results or limitations that these excerpts do not give are marked “not reported in the excerpt” rather than guessed. All figures quoted are those reported by the original authors. Because only [3] connects physical sensor readings to routing, conclusions about the sensing-to-routing pipeline are inferences and are labelled as such.

III. Technical Foundations

1. Sensing and data sources

Disaster routing needs live information about the road network. In [3], water-level sensors operated by a national science agency report at regular intervals, and a flood threshold function decides whether each sensor indicates flooding. In [2], the emphasis is on predicting congestion on urban road sections for ambulance mobility, and the paper surveys earlier IoT-based routing models, trajectory prediction and fuzzy-logic local path planning. In [1], the input is traffic flow information that changes the time needed to traverse each road segment. The studies [4] and [5] work on road-network and evacuation scenarios and, in the excerpts available, do not describe physical sensors. These observations support a design in which flood and traffic sensing feed the routing layer; that design choice is the project’s, not a finding of the reviewed papers.

2. Routing and learning algorithms

The road network is commonly modelled as a graph in which intersections are nodes and road segments are edges with weights. Route optimization then searches for the path of least cost [1]. Study [1] extends Dijkstra’s algorithm so that the optimal route is updated in real time, [3] applies Dijkstra with dynamic edge weights that reflect flood conditions, and [4] uses a depth-first-search-based procedure to distribute traffic flow. Reinforcement learning is used in [1] to learn cooperative traffic-signal strategies, [2] uses machine learning to predict congestion, and [5] explores supervised hybrid quantum machine learning, which combines quantum and classical ML.

3. Datasets and evaluation metrics

The studies use different evaluation settings. Study [1] reports experiments on synthetic and real-world maps and compares against transportation-engineering and RL benchmarks. Study [3] states the computational complexity of its graph algorithms as $O(V + E)$. Study [4] reports a percentage improvement in evacuation efficiency on the Hoboken, New Jersey road network, and [5] reports only that its results show potential. The excerpts of [2] give no numerical metrics. Travel time, evacuation efficiency, computational complexity and qualitative potential are not interchangeable measures.

IV. Routing Models and System Elements

1. Models compared in the reviewed papers

Su et al. introduce EMVLight, a decentralized RL framework for simultaneous dynamic routing and traffic-signal control, motivated by the observation that route optimization and signal pre-emption are coupled subproblems usually treated separately [1]. The ambulance system in [2] is a hybrid approach in which a local component uses ML to predict congestion on road sections in order to recommend the fastest ambulance route. The BANTAY system in [3] uses two graphs: a spatial grid graph for locating flood-affected cells from sensor readings, and a road-network graph built from OpenStreetMap data for Metro Manila on which Dijkstra evacuation routing runs with dynamic edge weights. Behrooz and Ilbeigi dynamically adjust road-segment directions to maximise vehicle flow [4]. The hybrid quantum study [5] targets emergency evacuation plans for cars during natural disasters such as earthquakes.

2. Data and hardware

Only [3] describes its data sources in some detail in the excerpt: sensor readings and OpenStreetMap road topology. Study [1] mentions synthetic and real-world maps and [4] the Hoboken road network, but dataset sizes are not reported in the excerpts. Hardware, sensor models and communication technology (such as LoRa or GSM, named in the synopsis) are not reported in the excerpts of any of the five studies.

3. Cautions

Several cautions follow from the papers. Static routes become suboptimal when traffic changes, which is why [1] updates the route in real time. Routing based on one data type can miss another: [3] depends on a limited number of water-level sensors, so roads between sensors rely on interpretation of sparse readings. Mass-evacuation methods such as [4] solve a different problem from routing a single ambulance. Quantum approaches [5] depend on hardware that is not widely available. These are failure modes and scope limits a disaster-time system should expect.

V. Evidence of Performance

1. Reported results

In [1], the EMVLight framework reduces the travel time of emergency vehicles and of the average non-emergency vehicle compared with benchmark techniques and existing RL-based signal control; the abstract gives no figures. In [4], the adaptive reconfiguration method gave a 74% improvement in evacuation efficiency over benchmark methods that lack adaptive reconfiguration on the Hoboken network. In [3], the contribution is an algorithmic formulation with linear-time $O(V + E)$ graph algorithms; no accuracy figure is given in the excerpt. In [2], the excerpt describes the approach but no measured result, and in [5] the authors state that results demonstrate potential without numbers in the excerpt.

2. Accuracy versus speed

Speed matters because disaster conditions change quickly. Study [3] explicitly focuses on efficient graph algorithms, [1] updates routes as the vehicle moves, and [2] addresses the time-critical nature of ambulance travel. No reviewed excerpt reports end-to-end latency from sensor reading to route update. The lesson for the proposed system is that route quality, computation time and update frequency must be reported together.

3. Comparability and quality of the evidence

The 74% improvement in [4] cannot be compared with the travel-time reductions in [1]: the two use different problems (mass evacuation versus single emergency vehicle), different cities and different baselines. Likewise, the quantum result in [5] is a statement of potential, not a benchmark. Only [1] tests on both synthetic and real-world maps, and only [3] uses real sensor data. Generalisation of the other results to other cities, disaster types and sensor setups is unknown, and because all five studies were read from excerpts, details that limit them may be missing here.

VI. From Sensing to Routing: The Flood-Sensor Study

Of the five papers, [3] is the one that carries physical sensor readings through to a route. In it, sensors report water levels, a threshold function flags flood-affected cells on a spatial graph, and the flagged areas change the edge weights of the road graph used for Dijkstra evacuation routing.

1. Findings

The design treats flood detection and evacuation routing as two connected problems. The first marks flooded cells; the second finds a path from a source to shelters on a road network with dynamic weights based on flood conditions. This sensor-to-weight rule is the closest published counterpart in the five papers to the edge-weight update step of the proposed system. It is described in [3] as a method; the excerpt does not report measured routing performance.

2. Design issues

The authors choose graph algorithms with linear complexity to keep computation efficient. Related work on traffic-signal coupling [1] suggests that routes should also account for the traffic they create, and the ambulance system [2] suggests that congestion prediction can complement sensor data. Study [3] builds on a limited set of sensors reporting at fixed intervals, so gaps in space and time must be handled.

3. Limits and transferability

The deployment in [3] targets flood evacuation in one metropolitan area, while the present project targets emergency vehicles across several disaster types with a control-room dashboard. The excerpts report no sensor failure handling, network loss handling, dispatcher workload or response-time result for any of the five studies. Whether the results transfer to rural Indian road networks, to landslide or cyclone conditions, or to LoRa-connected sensor nodes is untested.

VII. Comparative Analysis

Table 1 summarises the five reviewed studies. Findings are not directly comparable because problems, data and metrics differ. Entries marked “excerpt only” come from the published abstract or available excerpt.

Table 1. Comparison of the five reviewed studies

Study	Objective and design / data	Main findings and limitations
Su et al. (2022) [1]	Aim: coupled routing and signal control for emergency vehicles Design: decentralized RL; extended Dijkstra; synthetic and real maps (excerpt only)	Findings: lower travel time for emergency and normal vehicles vs. benchmarks Limits: no figures in abstract; urban traffic, not damage
Smart Emergency Traffic System (2022) [2]	Aim: fastest ambulance route recommendation Design: ML congestion prediction in a hybrid approach (excerpt only)	Findings: congestion-aware route recommendation Limits: no metrics in excerpt; no disaster data
BANTAY [3]	Aim: flood detection and evacuation routing Design: water-level sensors, grid graph, OpenStreetMap graph, dynamic-weight Dijkstra (excerpt only)	Findings: O(V + E) flood-aware routing Limits: sparse sensors; no accuracy or latency in excerpt
Behrooz and Ilbeigi [4]	Aim: efficient mass evacuation	Findings: 74% better evacuation efficiency

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Study	Objective and design / data	Main findings and limitations
	Design: DFS-based dynamic road reconfiguration; Hoboken NJ network (excerpt only)	Limits: one network; evacuation, not single vehicles
Hybrid quantum ML (2023) [5]	Aim: car escape routing in disasters Design: supervised hybrid quantum ML (excerpt only)	Findings: potential shown Limits: no figures in excerpt; hardware dependent

VIII. Proposed Conceptual Architecture

Figure 1 gathers the design implications of the reviewed studies into a staged architecture for the proposed emergency routing system. It is a conceptual proposal derived from the literature and has not been tested experimentally.

1	**IoT sensors and vehicle GPS** GPS, water level, traffic, weather
2	**Transmission and preprocessing** Wi-Fi / LoRa / GSM; clean noisy data
3	**Weighted road graph** Edge weights from traffic, damage, flood
4	**AI congestion / blockage prediction** Risk score per road segment
5	**Route optimization** Dijkstra / A* / RL; exclude blocked roads
6	**Driver app and control-room dashboard** Route, ETA, re-routing and flood alerts
7	**Dispatcher verification** Confirm uncertain blockages or routes
8	**Feedback and re-routing loop** New sensor data; recompute route

Fig. 1. Proposed conceptual architecture for emergency route optimization during disasters using AI and IoT (conceptual, not experimentally validated). Stage 8 returns corrections to the graph (Stage 3).

Stages supported by the reviewed papers. Stage 1 collects sensor and vehicle data, as the flood-sensor study [3] does with water-level readings. Stage 3 represents the road network as a weighted graph with dynamic edge weights, as in [3], and [4] shows that network capacity can also be adapted. Stage 4 applies ML to predict congestion, as in [2]. Stage 5 runs a shortest-path algorithm; [1] extends Dijkstra with real-time updates and RL, while [3] uses Dijkstra with flood-aware weights. The choice between Dijkstra, A* and RL should be tested on the target network. A quantum approach [5] is exploratory and is not part of the baseline design.

Stages that are the author's own design recommendations. None of the five studies evaluates stages 2, 6, 7 or 8 together. Stage 2 follows the communication path in the synopsis (Wi-Fi, LoRa or GSM) and should buffer data locally when the connection drops. Stage 6 shows the route, ETA and warnings to the driver and the control room. Stage 7 lets a dispatcher confirm uncertain blockage predictions before they remove a road from routing, and stage 8 recomputes routes as new data

arrives, with the dashed loop returning corrections to the graph. A human stays in the loop because wrongly blocking an open road, or keeping a flooded one, can cost lives.

Research Gaps and Future Directions

Gaps supported by the reviewed papers. (i) Sensor coverage: [3] relies on a limited set of water-level sensors reporting at intervals. (ii) Coupling: [1] shows that routing and traffic control interact, but this is rarely considered in disaster settings. (iii) Scope: [4] addresses mass evacuation and [1], [2] urban traffic, so none covers emergency vehicles on damaged roads end to end. (iv) Inconsistent evaluation: the five papers use different problems and metrics, so results cannot be ranked [1]–[5]. (v) The sensing-to-route loop: only [3] connects sensors to routing, and the excerpts of all five report no latency, sensor failure or communication loss results. (vi) Maturity: [5] is exploratory and depends on quantum hardware.

Design recommendations (the author's own, not findings of the papers). Test under flood, heavy rain and night conditions with ground-truth blocked roads; measure route-update latency and sensor-failure behaviour; keep offline buffering and delayed synchronisation for LoRa and GSM links; add risk-aware weights so the fastest route is not chosen over a safe one; and keep a dispatcher verification step for uncertain blockages. The seminar's future scope, such as integration with smart-city platforms, depends on these tests.

Directions requiring investigation. Priorities include a simulation on a real regional road network with injected flood and blockage events, separate reporting of route quality, update latency and sensor-failure tolerance, head-to-head tests of Dijkstra, A* and an RL agent on the same data, and a study of whether ML blockage prediction reduces wrong re-routing compared with sensor thresholds alone.

IX. Conclusion

Across the five reviewed studies, graph-based routing with dynamically updated edge weights is the common foundation; reinforcement learning and machine learning add adaptation and prediction, and real sensor data, as in the flood-sensor system, makes routing flood-aware. Reported evidence is nevertheless uneven: all five were assessed from abstracts and excerpts, the metrics differ, and only one study links physical sensors to routing. For the proposed emergency route optimization system this points to a modular design in which sensing, graph weighting, prediction, route computation and the dashboard can be replaced independently, with human verification of uncertain blockages. Evaluation on real roads under varied disaster conditions, with update latency and communication loss measured, is needed before the system can be called dependable.

References

1. H. Su et al., "EMVLight: A decentralized reinforcement learning framework for efficient passage of emergency vehicles," in Proc. AAAI Conf. Artif. Intell., 2022. [Online]. Available: https://ojs.aaai.org/index.php/AAAI/article/view/20383
2. "Smart system for emergency traffic recommendations," Int. J. Adv. Comput. Sci. Appl. (IJACSA), vol. 13, no. 10, 2022. [Online]. Available: https://saiconference.com/Downloads/Volume13No10/Paper_5-Smart_System_for_Emergency_Traffic_Recommendations.pdf
3. "BANTAY: flood detection and evacuation routing using optimized graph algorithms," Atlantis Press. [Online]. Available: https://www.atlantis-press.com/article/126023805.pdf
4. H. Behrooz and M. Ilbeigi, "A graph-based adaptive routing optimization algorithm for emergency evacuations," Stevens Inst. Technol. [Online]. Available: https://researchwith.stevens.edu/en/publications/a-graph-based-adaptive-routing-optimization-algorithm-for-emergen/
5. "A supervised hybrid quantum machine learning solution to the emergency escape routing problem," arXiv:2307.15682, 2023. [Online]. Available: https://arxiv.org/abs/2307.15682