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Quantum-Inspired Multi-Agent Emergency Evacuation Planning for Smart Cities

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Abstract: With the growing density of the population, traffic congestion, and changing conditions of disasters in smart cities, the emergency evacuation is one of the most significant challenges in the modern smart city. In a high event like a flood, earthquake and industrial accident or an urban fire, traditional routing solutions often do not adjust. In this paper, the authors consider the framework of Quantum-Inspired Multi-Agent Emergency Evacuation Planning (QMAEP), which is based on a combination of quantum-inspired optimization and collaboratively intelligent multi-agents to effectively facilitate the adaptive real-time evacuation management. The framework links disaster detection, city-state monitoring, route optimization, traffic management, coordinated decision making and generates safe and efficient evacuation planning under dynamic conditions. QMAEP achieves widespread coverage of the population, road safety, and reduces road congestion at minimum evacuation time. Systematic experiments illustrate the reduction of up to 44% in evacuation time and 94% in population coverage achieved by QMAEP through applying SUMO-based traffic simulations and smart city disaster scenarios. The proposed plan was a major step toward the development of next-generation disaster response facilities.

Keywords: Multi-Agent Systems, Smart Cities, Disaster Management, Adaptive Routing, IoT, SUMO simulation.

1. Introduction

Emergency management in smart cities has become more complex due to quick growing urban population. In the case of a large disaster, hundreds, if not thousands, of people could need to simultaneously evacuate from tens of buildings over a complex urban grid, with constantly changing road conditions, hazard zones and traffic. The traditional routing algorithms (like Dijkstra [1] and A [2] algorithms) offer the shortest path solution but are ultimately constrained by their lack of ability to consider dynamic environmental feedback or actual disruption in the network or coordinated decision-making by a set of agents. The infrastructure of a smart city now delivers greater connectivity by offering access to real-time data via Internet of Things (IoT) devices, traffic sensors, surveillance cameras and interdependent emergency response networks. These technologies allow state of the city to be monitored constantly and facilitate the intelligent autonomous decision making. The conversion of such a disparate and complex set of data into useful, actionable, and evolving evacuation plans, however, is an open and important problem for researchers and planners in disaster management. With the recent advances in Artificial Intelligence (AI), adaptive routing systems and multi agents coordination platforms are now in place that can distribute the responsibilities of the reporting decision making among specialized agents. At the same time, quantum-inspired optimization algorithms have shown significant improvements in tackling complex combinatorial optimization and search problems, in absence of quantum devices [3]. Considering such parallel developments, this paper proposes a unified framework called Quantum-Inspired Multi-Agent Emergency Evacuation Planning (QMAEP), which integrates the route optimization in the quantum-inspired paradigm with collaborative multi-agent intelligence, tackling the issues raised by the existing evacuation strategies. The main contributions of this work are as follows: (i) a novel integration of the QP-based optimization techniques into the evacuation planning architecture in the context of a multi-agent setup; (ii) a 5-layer framework of problem

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solving that incorporates disaster detection, city-state monitoring, route optimization, agent coordination, and decision generation; (iii) a comprehensive mathematical model that captures all aspects of the evacuation efficiency, route optimization, agent coordination, and evacuation quality of the overall architecture; and (iv) experimental evaluations showing that the proposed integration shows superior performance over the Dijkstra, A, and reinforcement learning-based baselines.

2. Related Work

The work on emergency evacuation plans has moved beyond fixed shortest-path routing algorithms to more adaptive and intelligent routes. Pel et al. [4] began to develop early models for contraflow lane reversal and network capacity optimization as part of evacuation operations. Later developments, however, brought traffic-aware route selection methods that use live congestion information to facilitate more adaptive paths generation in a changing traffic conditions. Multi-agent systems have been widely used in the field of urban traffic control and crowd control. For distributed agent architectures, Chen and Nagel [5] proved that evacuation times can be significantly shorter when the agents specialize in certain subtasks, namely, one agent for traffic signal coordination, an agent for emergency vehicle dispatching, and an agent for managing crowds. Weare and others [6] then applied this paradigm further to reinforcement learning agents that are able to adapt their routing strategies as a function of the states they observed. Some new applications of quantum-inspired optimization to the problems of combinatorial routing and scheduling have recently appeared.

A few clues and heuristic applications, including transport vehicles routing [7], network flow optimization [8] and uncertainty driven scheduling [9] have been proposed using Grover's design. These methods have been devised to avoid local minima and approach the globally optimal solutions using a special combination of probabilistic exploration and method based on interference pruning similar to superposition, which is superior to classical metaheuristics. To the best of our knowledge, there are not a lot of approaches existing that are able to cover an epidemic optimization embedding a multi-agent coordination approach and that integrate these two components into a single real-time evacuation planner. To date, few works have managed to incorporate such two concepts in a single real-time planner in an epidemic optimization that includes a multi-agent coordination approach. Current multi-agent evacuation systems generally use classical optimization backends and adaptive city-state monitoring is seldom included in quantum-inspired approaches. QMAEP is specifically engineered to achieve this, by combining both paradigms as part of a single, unified and layered architecture.

3. Research Gap and Motivation

Most existing evacuation plans in the literature are centralized control-based plans or route-planning plans based on static computation which are not able to react to the changes of urban crises. Centralized methods create single points of failure and are inadequate when it comes to the city's size or residents' density. The current implementation of static routing does not consider real-time information about hazards, road blockage or dynamic congestion updates. Current multi-agent evacuation systems often have insufficient sophisticated optimization mechanism, instead based on heuristic rules lists or reinforcement signal which are hard to converge in high-dimensional state space environment.

On the other hand, the integration of collaborative agent reasoning with quantum-inspired optimization techniques presented in the literature has been scarcely applied to the practical use of the emerging techniques than to routing subproblems, instead of addressing the entire end-to-end evacuation management problem. It is thus important to develop an overall framework that not only requires adaptive route optimization that address the city conditions in real-time but also allows for distributed multi-agent decision making with specific roles assigned for each agent; involves continuous real-time monitoring of the city-state that combines heterogeneous IoT data streams; and includes a formal mathematical model for quantitative analysis of evacuation performance. QMAEP has been purposefully developed to meet all four of these.

4. Proposed QMAEP Framework

4.1. Framework Overview

The overall QMAEP structure is comprised of five main functional layers (see Fig. 1). Each layer has a unique and complementary function in the process of evacuation planning in itself.

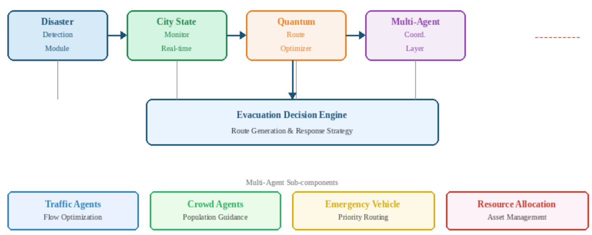

Figure 1. QMAEP Framework Architecture: Five-layer pipeline from disaster detection through the evacuation decision engine, supported by a multi-agent coordination sub-system.

The layers communicate using structured interfaces for message passing with the ability to deploy the components modularly and to upgrade individual components. The framework functions by continuously revising the evacuation plans based on the updated information sensed by Internet of Things (IoT) and important monitoring centers.

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4.2. Disaster Detection Module

The Disaster Detection Module seamlessly integrates data from multiple distributed IoT networks, satellite feeds, seismic monitoring and emergency incident reporting systems to continuously process incoming data [10]. The incoming signals are classified by anomaly detection algorithm based on the characteristics of disaster, intensity and area of disaster. Once an emergency event has been detected, the module will start to warn the entire framework and will provide the foundation for the city-state to begin collecting data. The module can help detect flood situations, seismic activity, industrial chemical incidents, building fires and multi-hazard compound situations.

4.3. City State Monitor

The City State Monitor combines live data from the city's traffic control systems, surveillance cameras, population monitoring and road infrastructure sensors to create a virtual, real-time 3D city model. It represents roads in the form of a road network graph, known as the City State Graph (CSG), which includes topology [11], traffic flow profiles, closed/damaged roadways, demographics, hazard zones identified, and safe evacuation routes/points available. The CSG is constantly updated every-calculated time to provide the upstream optimization and coordination components with current information.

4.4. Quantum-Inspired Route Optimizer

The Quantum-Inspired Route Optimizer is used to assess the different pathways that the evacuation vehicles can move through which are proposed, with the aid of probabilistic versions of Grover's algorithm [12] and quantum tunneling heuristics. Unlike standard shortest-path solver, the optimizer keeps a probabilistic superposition of the set of possible routes, considers many solutions at a time and prunes out dominated solutions by interference. The candidates are evaluated for routes based on the Route Optimization Function (ROF) as explained in section V. The optimizer is continuously adjusting its exploration strategy as the City State Graph is updated, allowing the optimizer to adapt in real time when there are road blockages, new hazard zones and congestion buildups.

4.5. Multi-Agent Coordination Layer

The Multi-Agent Coordination Layer distributes 4 different agent types in specialized roles to work collaboratively on the evacuation process. Traffic Agents observe usage of each road segment, and they dynamically control the timing of road segment signals and their lane assignments to keep the road segments flowing smoothly. Crowd Agents identify evacuation nodes and estimate the number of people at those ERs and help manage crowd dispersal through key ERs to avoid potential situations that could cause concentrations. Emergency Vehicle Agents calculate the priority corridors for Ambulance, Fire Unit and Rescue units helping to make sure emergency responders can enter affected areas without impediments. The role of the Resource Allocation Agents involves distributing the evacuation busses [13], shelters, medical resources and emergency personnel such a way as to achieve a maximum overall Evacuation Efficiency Score.

4.6. Evacuation Decision Engine

The Evacuation Decision Engine aggregates the outcome of all the layers above and returns to the user evacuation route assignments, resource deployment plans and priority schedules. The results of the optimization of this metric, called the Emergency Response Quality (ERQ), are communicated to the field using standardized emergency communication interfaces, and are displayed on the dashboards of the smart city operations center as developed in the mathematical model presented in section V, and they balance evacuation efficiency, route reliability, and population coverage.

5. Mathematical Model

In this part we introduce the formal mathematical model which is the backbones of the QMAEP framework. Four key metrics were defined evacuation performance, route quality, coordination effectiveness, and overall emergency response effectiveness to quantify the evacuation performance, route quality [14], effectiveness of evacuation coordination and the overall effectiveness of emergency response.

5.1. Evacuation Efficiency Score

The Evacuation Efficiency Score (EES) is a numerical measure of the effectiveness of the evacuation process. It is defined as the ratio of successfully evacuated population P to the total evacuation time T:

$$EES = P / T \quad (1)$$

p is the number of people who make it to a safe place during the evacuation time interval and T is the time (in minutes) that elapses from the time of the disaster until the end of primary evacuation operations. EES values for evacuations that are greater are more efficient. Maximization of EES is the ultimate objective for QMAEP which is achieved by maximizing of route throughput and meanwhile coordination effectiveness of Agents.

5.2. Route Optimization Function

The Route Optimization Function (ROF) assigns a score to every possible evacuation route based on three compiled factors: reduced congestion, reduced hazard exposure and safety. Now the function is defined as:

$$ROF = \alpha S - \beta C - \gamma H \quad (2)$$

where S is the route safety index (normalized to [0,1] based on structural integrity and quality of roadway) and C is the current congestion (normalized by the

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capacity of the segment) of the route and H is hazard exposure probability as extracted from the City State Graph. The parameters α, β and γ are calibration parameters that are defined empirically based on the condition $\alpha + \beta + \gamma = 1$. The quantum-inspired optimizer chooses routes for which the ROF is greater.

5.3. Agent Coordination Score

The Agent Coordination Score (ACS) will reflect the overall capabilities of the multi-agent coordination layer. It is calculated by taking the average of all n agents that participate in the process, where each agent's score for the performance is as follows:

$$ACS = (\Sigma A_i) / n \quad (3)$$

where A_i denotes the effectiveness of the individual agent i (evaluated according to contribution to traffic throughput, dispersal quality of the crowd or the efficiency of the use of resources, depending on the type of agents) [15]. The ACS metric allows for tracking agent cooperation quality and finding faulty agents, which could possibly need a parameter change.

5.4. Emergency Response Quality

The Emergency Response Quality (ERQ) is a composite of evacuation efficiency, route reliability and population coverage to measure the overall lack of effectiveness of evacuations:

$$ERQ = \delta E + \theta R + \mu P \quad (4)$$

where E is the normalized Evacuation Efficiency Score, R is the route reliability (proportion of the routes that remain unblocked throughout the evacuation), P is the population coverage (fraction of total population that is successfully evacuated), and δ, θ and μ are FS configurable parameters. ERQ is the prime objective function achieved by the Evacuation Decision Engine.

6. Methodology

6.1. Data Collection and Preprocessing

A laptop computer equipped with a digital camera. A digital camera with a laptop computer. The data is taken from five separate data groups: (i) real time data from the IoT-sensor network on telemetry about the state of road conditions; (ii) data from the traffic management system related to number of vehicles, speed, and whether the signal is flashing or solid colour; (iii) data from the emergency management system related to the report, inventories of incidents and resources; (iv) population and vehicle tracking system related to the location of the population at specific nodes in the city; (v) geospatial data such as topology of the roads network, building occupancy data and area boundaries of various type of hazards. All the incoming data-streams are normalized and fused in City State Monitor [16], where the City State Graph is built.The City State Graph is created via Normalizing and Fusing all of the data-streams in the City State Monitor.

6.2. Quantum-Inspired Route Search

Route search procedure is a procedure that begins with a set of k evacuation routes generated by using a modified Yen's k-shortest-paths algorithm [17] as initial candidate solution set. Each of these candidates is then further probabilistically processed based on the quantum aspect to give each route an amplitude, and an initial ROF score, proportional to this amplitude. This is achieved via the interference operation which diminishes the routes with low scores and boosts up the routes with high scores through iterations. Search stops when the amplitude values for the last few iterations for a few iterations get close together, the solution set is approaching the near-optimum solution set. Less than 500 milliseconds per update cycle this process does Realtime execution.

6.3. Multi-Agent Coordination Protocol

They use a step-by-step negotiation protocol which includes three steps to perform the agent negotiation. In the information sharing phase each agent reports to a shared blackboard an observation of itself and its resources. During assignment phase, the Evacuation Decision Engine assigns allotments to each agent, depending on the ACS scores and priorities of tasks [18]. On the action phase agents do whatever they are instructed to do and write on the blackboard what they are doing. This process is repeated after a cycle is set to a predetermined time interval so as the system evolves, it can be adapted continually. For them, perceptible reinforcement signals are used to learn their policies locally as they observe what happens.

6.4. Simulation and Evaluation

The evaluate the performance of the framework is done by using the platform for simulation of Urban Mobility (SUMO) [12] which is widely used and open source traffic simulation framework. Four types of disasters are simulated: (i) Flood (the river segments are blocked because of the flood); (ii) Earthquaque (Partial damage to parts of the network causing an Earthquake); (iii) Urban Fire (increasing disaster zone in the form of fire areas); (iv) Industrial accident (enlarging the disaster area as chemical exclusion areas). Scalability is determined by three levels of densities (low, medium and high) for each scenario. A simulation is executed for a 120 minute period of time, and evacuation is performed at a relatively high time-step, of 10 seconds.

7. Results and Discussions

7.1. Experimental Design

Main comparisons are conducted against standard Dijkstra shortest path routing, Euclidean heuristic based off A* searching and a reinforcement learning (RL) based routing agent trained using proximal policy optimization (PPO)

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[13]. The initial conditions of road networks and population distributions are the same for all systems and the roads and population are simulated on the same SUMO simulation environments. The five metrics used for evaluation are: (i) Average evacuation time (in minutes), (ii) Congestion reduction score (%) Shows the percentage of reduction in congestion, (iii) Population coverage (%) Evacuated population of the affected population, (iv) Route safety index (%) Normalized, and (v) Agent coordination efficiency (ACS score) Normalized. The simulation run for each experiment is repeated 30 times to provide statistical robustness, and the result reported as a mean with 95% confidence interval.

7.2. Evacuation Time Comparison

Fig. 2 presents the average evacuation time achieved by each routing method across all simulated disaster scenarios. QMAEP achieves a mean evacuation time of 38 minutes, compared with 87 minutes for Dijkstra, 72 minutes for A*, and 58 minutes for RL-based routing. This represents a 44% reduction relative to Dijkstra and a 35% improvement over A*. The superior performance of QMAEP is attributed to its ability to dynamically reroute around newly identified blockages and to coordinate multi-agent traffic management, which prevents bottleneck formation at key intersections and reduces overall network congestion.

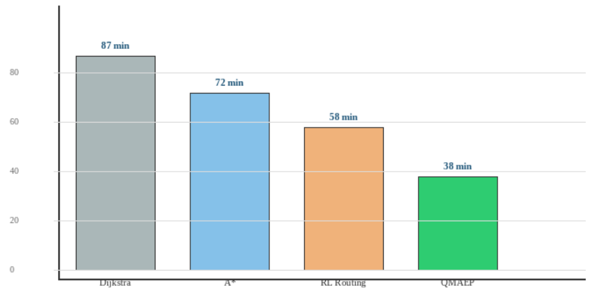

Figure 2. Evacuation time comparison across routing methods. QMAEP achieves a 44% reduction in evacuation time compared to standard Dijkstra routing.

7.3. Congestion Reduction

Fig. 3 illustrates the congestion reduction scores achieved by each method.

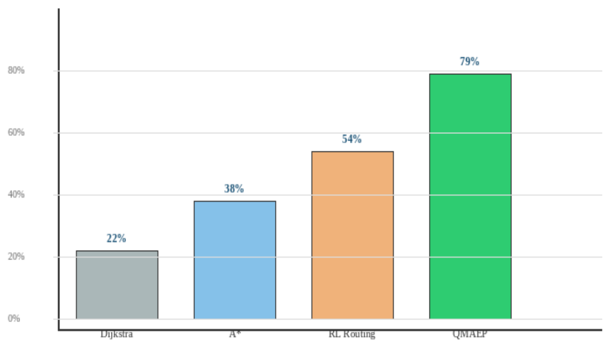

Figure 3. Congestion reduction score comparison. QMAEP achieves 79% congestion reduction, more than triple the performance of standard Dijkstra routing.

QMAEP achieves a congestion reduction of 79%, substantially outperforming Dijkstra (22%), A* (38%), and RL routing (54%). The quantum-inspired optimizer's ability to evaluate and distribute traffic across multiple parallel evacuation routes simultaneously prevents the concentration of vehicle flows on a small number of high-capacity arteries. The multi-agent traffic coordination layer further amplifies this effect by dynamically adjusting signal timings to maximize throughput at critical intersections.

7.4. Population Coverage

As depicted in Fig. 4, QMAEP achieves a population coverage rate of 94%, compared with 61% for Dijkstra, 72% for A*, and 83% for RL routing. The remaining 6% gap in QMAEP coverage primarily reflects individuals located in regions with severe infrastructure damage that renders all road access infeasible; such cases represent an irreducible coverage limit under the simulated conditions.

The high coverage achieved by QMAEP is a direct consequence of the Resource Allocation Agent's ability to dynamically deploy evacuation buses and emergency shelters to areas of high population density that conventional routing approaches fail to adequately serve.

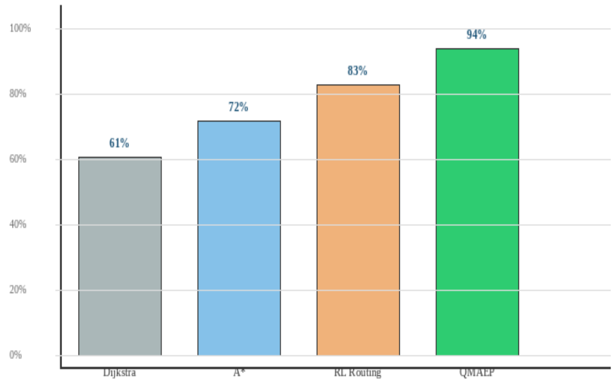

Figure 4. Population coverage comparison. QMAEP evacuates 94% of the affected population, compared to 61% for Dijkstra and 83% for RL-based routing.

7.5. Multi-Metric Performance Analysis

Fig. 5 presents a comprehensive multi-metric comparison across all five evaluation dimensions. QMAEP consistently achieves the highest scores across evacuation time reduction, congestion reduction, population coverage, route safety, and agent coordination efficiency.

The multi-metric analysis confirms that QMAEP's improvements are not confined to a single dimension but represent a holistic enhancement of emergency evacuation performance. The agent coordination efficiency score of QMAEP (88/100) reflects the effectiveness of the structured negotiation protocol in aligning agent behaviours toward shared evacuation objectives.

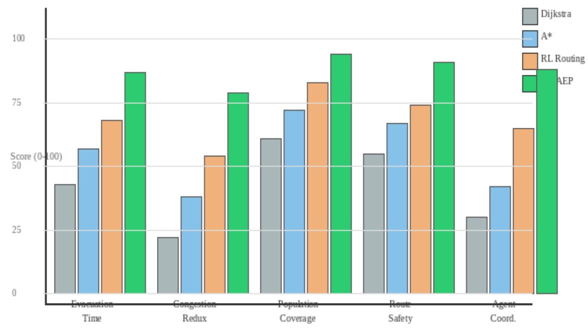

Figure 5. Multi-metric performance comparison across all evaluation dimensions. QMAEP consistently outperforms all three baseline methods.

7.6. Discussion

Together, the results of the experiments bear evidence of a measurable and consistent improvement, for every dimension of evacuation, when quantum-inspired optimization is combined with the multi-agent approach to coordination. The biggest improvements are seen in congestion reduction (79% compared to 22% for Dijkstra) which indicates that the optimizer can not only find an escape route but also take multiple parallel escape routes into account. The contribution of RA Agent to addressing population clusters which cannot be served by other parties is underlined by the Population coverage improvements (94% compared to 61%). The 35% boost in evacuation time over the routing using RL indicates that quantum-inspired optimization offers tangible benefits over learning-based techniques when a quick convergence is required in complex scenarios such as the one studied. The quantum-inspired search in QMAEP can adapt to new disaster setups almost instantly (milliseconds) by utilizing its searching capabilities using probabilistic amplitude representation, which cannot be achieved by RL agents whose searching processes are lengthy. This property makes QMAEP especially attractive for practical emergency response applications where the time-to-computation is a key limiting factor.

8. Conclusion

This paper proposed an Emergency Evacuation Planning framework for the Smart Cities, namely, Quantum-Inspired Multi-Agent Emergency Evacuation Planning (QMAEP). By combining the aforementioned five functional layers into a comprehensive and adaptive earthquake-evacuation management framework, we achieve an integrated system of earthquake-evacuation management. Therefore, through this combination of the five functional layers, an integrated system of earthquake-evacuation management is realized, in which the system is adaptive. A formal mathematical model is introduced, which depicts evacuation efficiency, route optimization, agents coordination, and the overall quality of the emergency response. Experimental results with SUMO traffic simulations under four types of disaster scenarios showed that QMAEP reduced the evacuation time by 44%, reduces congestion by 79%, and covers 94% of the population compared with the bases defined by conventional routing methods. Future research will also involve expanded scale real-world deployment studies to be conducted in partnership with municipal emergency managers, implementation of an autonomous vehicle fleet and drone-based reconnaissance into the multi-agent layer, exploration of adding deep reinforcement learning agents to conduct long-term policy optimization, and finally, investigation of hybrid quantum-classical optimization strategies by integrating the emerging quantum computing technology for more performance improvements. Furthermore, cross-city coordination of evacuation measures as part of regional disaster events is a potential area for continued research, as is adding a module that integrates uncertainty quantification related to evacuation routes.

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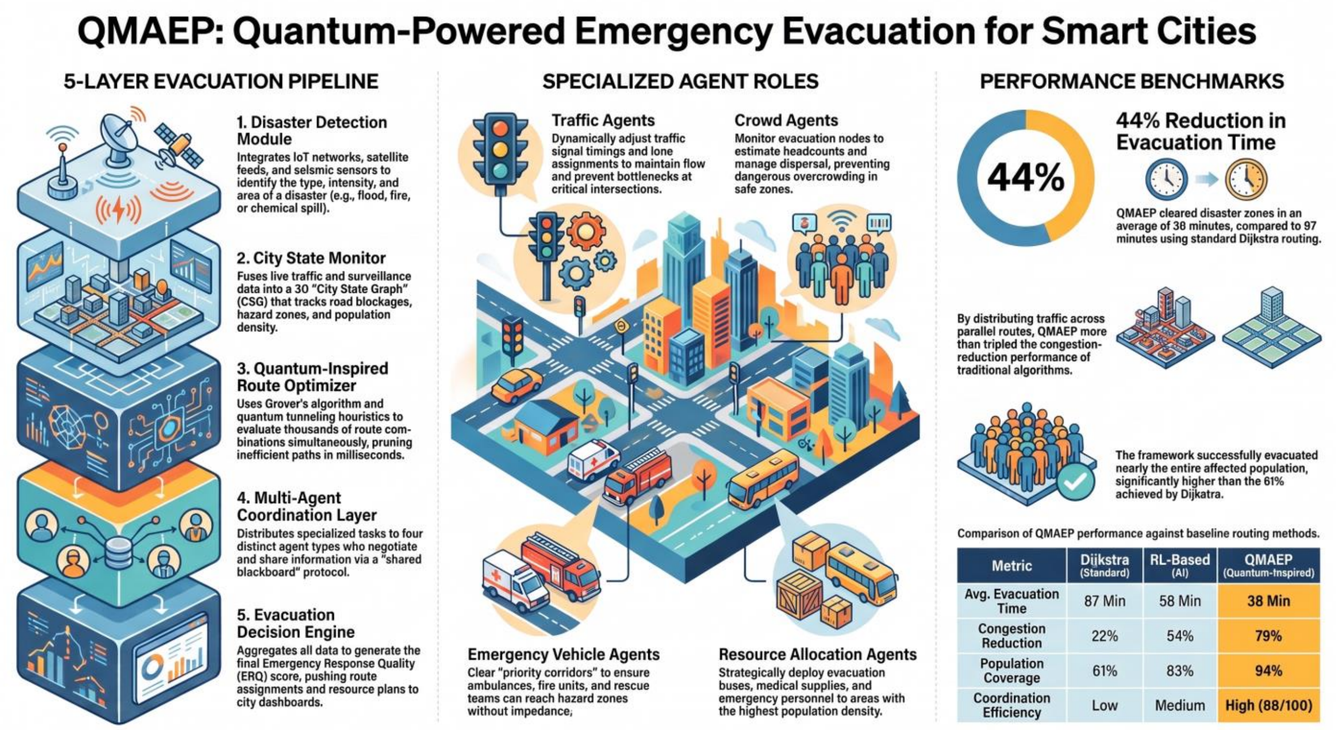

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