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# Robust Ambulance Dispatch Using Graph-Based Optimization Under Traffic Uncertainty: A Case Study of Prague †

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**Abstract**

Urban environments are characterized by complex traffic conditions, which can significantly affect ambulance dispatch performance. This study presents a graph-based optimization approach for ambulance dispatch, using the city of Prague as a case study. The road network is modeled as a directed weighted graph based on OpenStreetMap data and constructed using the OSMnx library, where edge weights represent travel time. Traffic uncertainty is incorporated through variable edge weights to simulate fluctuating conditions. A simulation environment generates ambulance locations and emergency incidents across the network. The proposed approach combines shortest-path routing with global assignment optimization and is evaluated against a baseline nearest-ambulance strategy. The results show a relationship between coordination mechanisms and computational behavior. The Greedy and Bidirectional strategies produced similar average response times of 6.08 min and 5.77 min, respectively. The Greedy strategy achieved a higher fairness score (Gini index of 0.383) and lower maximum response time. The Bidirectional strategy reduced assignment computation time to 0.28 s per request and decreased total computation time from 85.35 s to 11.08 s, corresponding to an 87.02% reduction. The findings support the applicability of the approach in smart city emergency response systems.

**Keywords:** ambulance dispatch; graph theory; traffic uncertainty; urban informatics; optimization; smart cities

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## 1. Introduction

Fast and reliable emergency response is a fundamental component of urban safety systems [1]. In dense urban environments such as Prague, ambulance services operate under complex and dynamic traffic conditions. Congestion, road hierarchy, signal delays and spatial demand influence travel times, which are critical for patient outcomes [2]. Even minor delays increase risk in time-sensitive situations, including cardiac arrest, traffic accidents and severe trauma [3]. Improving dispatch efficiency remains an important research direction in urban informatics and intelligent transportation systems [4].

A major challenge in ambulance routing arises from the variability of urban traffic. Travel times change due to temporal patterns, road capacity and stochastic disruptions. Many existing approaches rely on simplified assumptions, including static speeds or distance-based assignment of the nearest vehicle [5]. Such simplifications support computational efficiency, yet they limit the representation of real traffic dynamics and may lead to inefficient allocation of emergency resources. The need for models that combine spatial network structure with variable travel conditions follows from these limitations.

Graph-based representations provide a suitable foundation for modeling transportation networks [6,7]. Urban road infrastructure can be expressed as a network in which intersections correspond to nodes and road segments correspond to edges, enabling the application of shortest-path and network optimization methods. The availability of high-resolution open geographic data from OpenStreetMap, together with tools such as OSMnx, supports the construction of detailed urban graphs suitable for large-scale analysis [8]. Recent work in emergency logistics and smart city systems increasingly adopts data-driven and graph-based techniques to address routing and allocation problems under uncertainty.

The interaction between dispatch strategy and traffic variability remains insufficiently examined. Existing studies often evaluate routing efficiency or allocation mechanisms in isolation, with limited attention to how local decision rules and system-level coordination influence performance under stochastic conditions [9]. The effect of these factors on both average response time and extreme cases has not been explored in a unified framework based on real urban data.

The study introduces a graph-based approach to ambulance dispatch under variable traffic conditions. Two strategies are examined within a common simulation environment: a decentralized method based on local greedy selection and a centralized method based on multi-source shortest-path search with bi-directional expansion [10]. The comparison reflects different coordination mechanisms and enables analysis of their impact on system behavior.

Real road network data is combined with stochastic travel time estimation derived from road characteristics [11]. The simulation environment captures spatial demand and traffic variability in an urban setting. Attention is given to the relationship between coordination and performance, including average response time, worst-case behavior and spatial distribution of assignments. The obtained results illustrate how dispatch strategies operate under realistic conditions and support the design of data-driven decision mechanisms for emergency response in smart city environments.

## 2. Materials and Methods

This section presents the framework for modeling and evaluating ambulance dispatch strategies using graph-based optimization under traffic uncertainty. The methodology integrates real-world spatial data, stochastic travel time modeling and algorithmic comparison within a unified simulation environment.

### *2.1. Study Area and Graph Construction*

The study is conducted in Prague, the capital of the Czech Republic, characterized by a dense and diverse urban road network. The city includes historical streets, arterial roads, bridges and modern infrastructure, which makes it suitable for analyzing emergency response under complex traffic conditions.

The transportation network includes multiple road classes, ranging from motorways to local residential streets. This diversity influences travel speeds, congestion patterns and

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accessibility, all of which are critical factors in ambulance routing and dispatch performance. The road network is represented as a directed graph $G$

$$G = (V, E) \tag{1}$$

where $V$ is the set of nodes corresponding to road intersections and endpoints, $E$ is the set of edges corresponding to road segments connecting nodes [12].

The network data is obtained from OpenStreetMap [13], an open-source geographic database that provides detailed and up-to-date information on road infrastructure. The graph is constructed using OSMnx, which enables automated extraction, simplification and conversion of spatial data into a NetworkX-compatible graph structure.

Each edge in the graph is associated with attributes such as length, road type (motorway, primary, residential) and direction. These attributes are subsequently used to estimate travel times and represent traffic conditions.

### *2.2. Travel Time Modeling and Simulation Setup*

The traffic emulation layer implements empirical urban velocity profiles derived from real traffic conditions. Edge travel times are modeled stochastically using the Zenodo Prague speed profiles dataset [14]. The dataset contains historical time-dependent speed intervals for individual road segments and introduces realistic traffic variability, congestion effects, and urban bottlenecks into the OpenStreetMap graph network.

The travel time for each edge is computed as:

$$t_e = \frac{l_e}{v_e} \tag{2}$$

where $l_e$ is the length of the edge, $v_e$ is the assigned speed.

This approach results in a weighted graph where edge weights represent estimated travel times under variable conditions, enabling more realistic routing compared to static models.

Emergency scenarios are simulated by generating ambulance locations and incident points across the network. Both are distributed over graph nodes using probabilistic sampling based on road importance. Nodes connected to higher-class roads are assigned greater probability, reflecting higher traffic density and increased likelihood of incidents.

Let $A \subset V$ denote the set of ambulance locations and $I \subset V$ denote the set of incident locations.

The number of ambulances and incidents is predefined, with the number of incidents exceeding available ambulances in order to simulate resource constraints. Hospitals, medical centers and clinics are extracted from OpenStreetMap and mapped to the nearest graph nodes. These locations serve as final destinations for completed routes.

### *2.3. Dispatch Strategies and Route Construction*

Two dispatch strategies are implemented and compared, representing decentralized and centralized decision-making. In the local greedy approach, each ambulance independently selects the nearest incident based on estimated travel time. Once an incident is assigned, it is removed from the available pool, and the process continues sequentially for all ambulances.

This method is computationally simple, but it does not guarantee global optimality, as ambulances do not coordinate their choices. In the centralized approach, all ambulance locations are treated as simultaneous sources. Using Dijkstra's algorithm, the graph is explored to determine the closest incident reachable from any ambulance [15].

At each step, the globally optimal ambulance–incident pair is selected, and both are removed from further consideration. The process continues until no further assignments are possible. For each assigned ambulance–incident pair, routing is performed in two stages. The first stage connects the ambulance location to the incident, and the second stage connects the incident to the nearest hospital.

Shortest paths are computed using travel-time-weighted edges. The nearest hospital is determined by minimizing travel time from the incident location to all candidate hospital nodes.

### *2.4. Evaluation Metrics and Implementation*

Performance is assessed through routing computation time, defined as the time required to assign ambulances and compute the corresponding routes. Aggregate indicators include average computation time and maximum computation time across all assignments. The performance of dispatch is also measured by average ambulance response time, maximum ambulance response time, fairness (Gini index) and robustness (p95 index), which denotes the time required to serve 95% of all incidents. The number of served incidents is recorded to reflect system utilization.

Variability is introduced through stochastic travel speeds and probabilistic spatial distribution. Multiple simulation runs are performed in order to capture this variability and to obtain stable comparative results.

The implementation is carried out in Python 3.12.12, using OSMnx 2.1.1 for network extraction, NetworkX 3.6.1 for graph operations and shortest-path computation, and Matplotlib 3.10.0 for visualization. All experiments are executed on a standard desktop system, without reliance on specialized computational resources.

Open data and widely accessible tools support reproducibility. Randomness can be controlled through fixed seeds, and aggregation across runs reduces sensitivity to individual realizations.

## 3. Results

### *3.1. Quantitative Results*

The performance of the two dispatch algorithms is evaluated using routing computation time and the number of served incidents. After 30 program runs, the results are presented in Table 1.

**Table 1.** Routing computation time for the decentralized greedy algorithm.

| Metric | Greedy Algorithm | Bi-Directional Algorithm |
|---|---|---|
| Avg Response Time | 6.08 min | 5.77 min |
| Max Response Time | 19.43 min | 23.31 min |
| Fairness (Gini Index) | 0.383 | 0.456 |
| Robustness (p95) | 14.13 min | 15.37 min |
| Avg Calc Time per Assignment | 2.1374 s | 0.2779 s |
| Max Calc Time per Assignment | 3.4949 s | 0.4789 s |
| Total Computational Time | 85.35 s | 11.08 s |

The simulation is conducted with 40 ambulances and 52 incidents. The number of incidents exceeds the number of available ambulances, which creates a constrained scenario where not all incidents can be immediately served. In all runs, 40 incidents are successfully assigned. When the number of incidents is less than the number of ambulances (<40), the simulation assigns all incidents to available ambulances, leaving some ambulances idle. In

cases when the number of incidents is equal to the number of ambulances (40), the program assigns all incidents to all ambulances.

For the greedy algorithm, average computation time ranges from 1.6 s to 2.7 s, and maximum computation time per assignment from 2.8 s to 4.05 s, total computation time ranges from 65.96 s to 99 s, average response time ranges from 4.34 min to 10.96 min, maximum response time ranges from 13.72 min to 37.02 min, robustness p95 index ranges from 10.06 min to 21.3 min, fairness Gini index ranges from 0.232 to 0.707.

For the bi-directional algorithm, average computation time per assignment ranges from 0.21 s to 0.41 s, and maximum computation time per assignment from 0.02 s to 0.5 s, total computation time ranges from 7.55 s to 15.17 s, average response time ranges from 2.98 min to 7.65 min, maximum response time ranges from 16.23 min to 27 min, robustness p95 index ranges from 13.46 min to 18.38 min, fairness Gini index ranges from 0.274 to 0.468.

All assignments are completed in both algorithms, and differences are observed in routing computation time. Figure 1 shows that the average calculation time per assignment and maximum calculation time are significantly higher for the greedy algorithm than for the bi-directional algorithm. This indicates that the bi-directional algorithm performs faster on average.

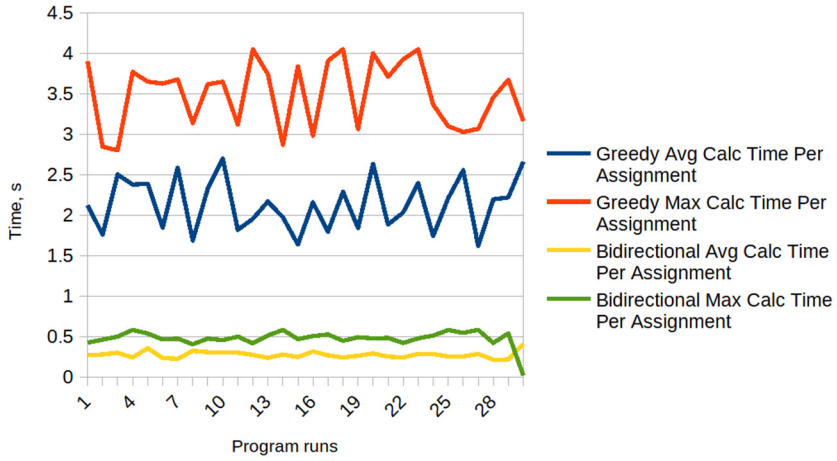



**Figure 1.** Average and maximum algorithm calculation time.

Figure 2 shows that the greedy algorithm has lower maximum computation time compared to the bi-directional algorithm. This suggests that, in terms of maximum waiting time, the local greedy algorithm performs more efficiently.

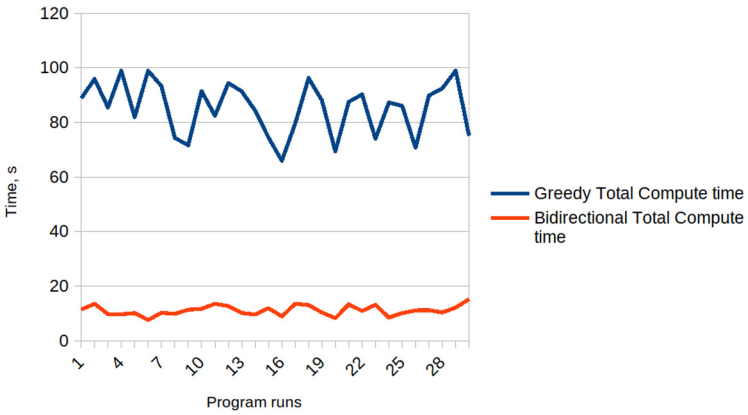



**Figure 2.** Total algorithm calculation time.

Figure 3 presents the average response time, maximum response time, and p95 robustness index for the greedy and bi-directional algorithms. The bi-directional algorithm achieved a slightly lower average response time. The greedy algorithm produced lower maximum response times and a higher p95 robustness index, indicating faster response performance for 95% of simulated incidents.

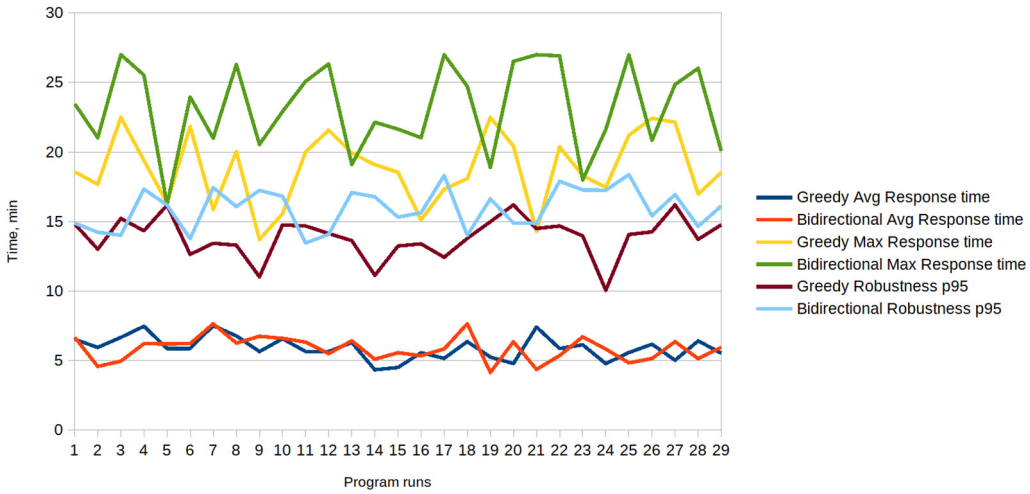



**Figure 3.** Maximum algorithm calculation time.

Figure 4 shows fairness Gini indices for the greedy algorithm and the bi-directional algorithm, where the greedy algorithm has higher fairness scores on average than the bi-directional algorithm.

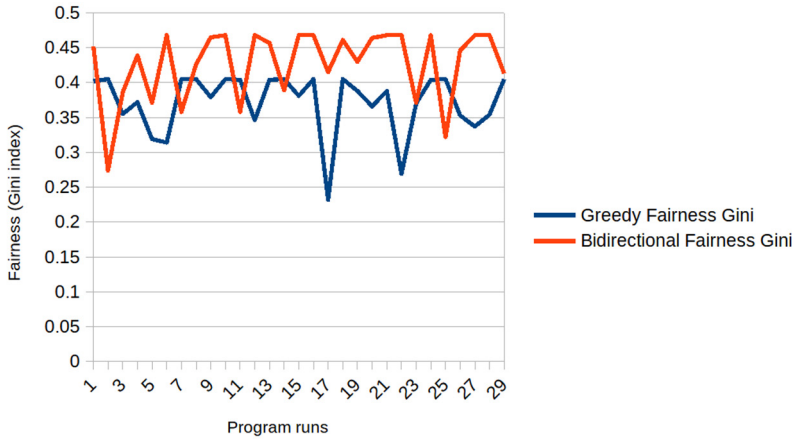



**Figure 4.** Algorithm fairness Gini index.

For each assignment, routing is performed in two stages:

- Stage 1—From the ambulance location to the incident.
- Stage 2—From the incident to the nearest hospital.

### *3.2. Visualization of Dispatch Behavior*

The spatial distribution of dispatch operations is illustrated using the road network of Prague. The visualization includes the road network graph as a base layer, ambulance starting locations, incident locations (served and unserved), and hospitals and clinics.

Routes from ambulances to incidents and from incidents to the nearest hospitals are also displayed. The visualization reflects the two-stage routing process and shows how assignments are distributed across the network. The map highlights how different dispatch

strategies influence routing patterns and spatial coverage. The centralized approach tends to produce more balanced and efficient route distributions. The greedy method is associated with localized clustering and longer individual routes.

Figure 5 presents the overall outcomes of the algorithm. The spatial distribution of incidents and ambulance locations is shown in Figure 6, illustrating the randomized setup of the simulation. Additional system output, including the extracted list of hospitals, is provided in Figure 7a, and a detailed view of computed routes is shown in Figure 7b.

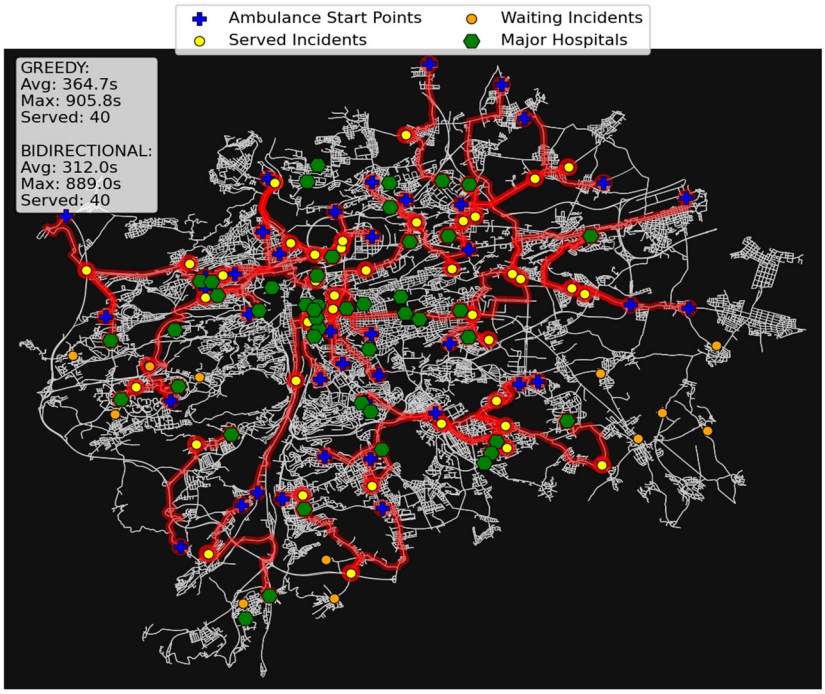



**Figure 5.** Visualized outcomes of the algorithm.

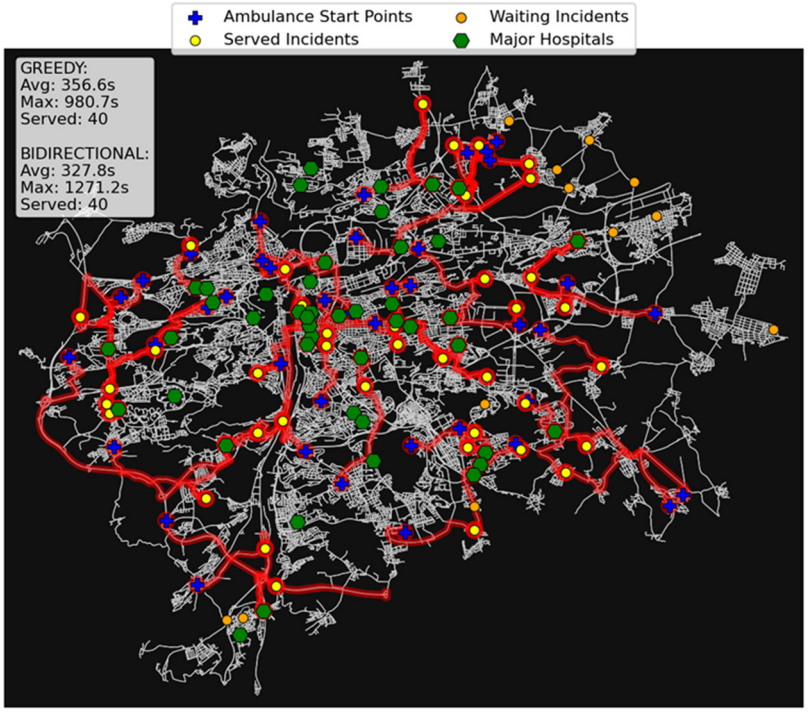



**Figure 6.** Randomized incidents and ambulances scattered on the map of Prague. Outcomes of the algorithm.

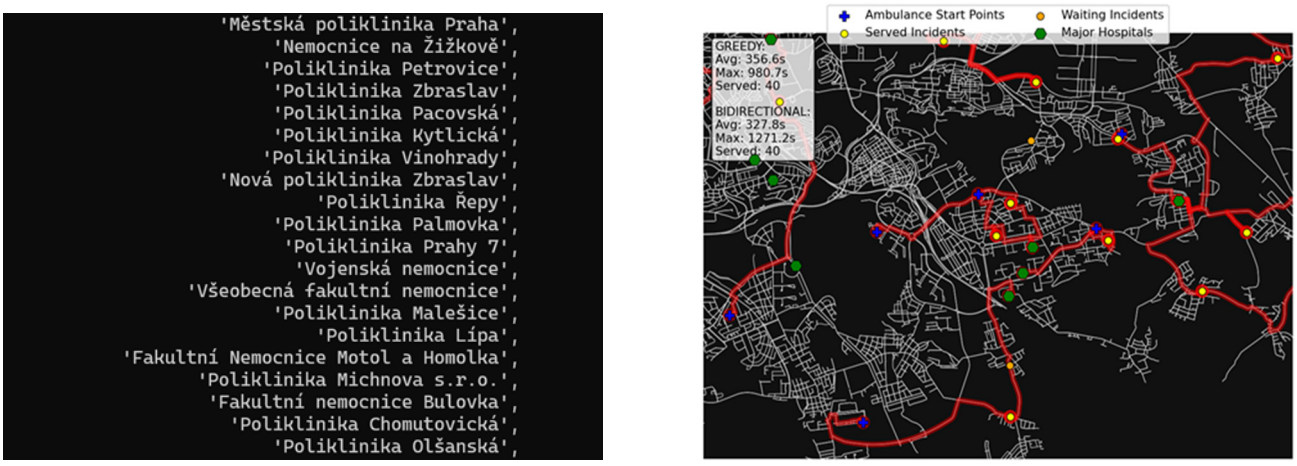



**Figure 7.** (**a**) Output of list of hospitals in terminal; (**b**) close-up view of the ambulance route.

### *3.3. Spatial Reliability and Threshold Coverage Analysis*

Figure 8 shows the distribution function F(t) of the random response time of an ambulance: F(t) = P(T < t), where T is the random value of the response time obtained as a result of the simulation, and t is the current value of the response time. This mathematical formulation outlines the exact probability curve of achieving response targets across the urban network. Evaluating the system under a strict 10 min intervention ceiling shows a coverage baseline of (P = 0.42), which scales non-linearly to a nearly absolute safety profile of (P = 0.998) as the mission target expands to 20 min. Compiling this curve confirms that a larger Monte Carlo methodology resolution (N = 30) effectively minimizes local stochastic noise relative to exploratory iterations (t_8 = 17.2 min vs. t_30 = 16.8 min).

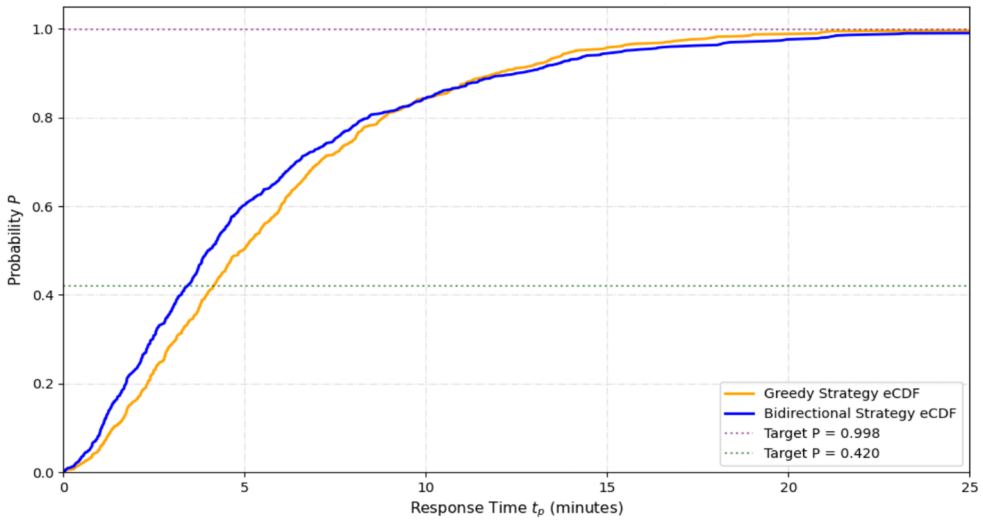



**Figure 8.** Empirical Cumulative Distribution Function (eCDF) comparing system-wide patient waiting times (t) between the Greedy Strategy and the Robust Bidirectional Strategy across all simulation loops.

The empirical Cumulative Distribution Function (eCDF) profiles F(t) = P(T < t) reveal distinct structural behaviors across operational response thresholds (Figure 8). At short-range operations under 7.5 min, the centralized Bidirectional algorithm (blue curve) consistently outperforms the Greedy mechanism (yellow curve), yielding up to a 10% higher probability of rapid intervention due to its unified global matching logic. Near the

8.5 min mark, both architectures achieve structural parity. Evaluating the network under a standard 10 min intervention ceiling shows an excellent coverage baseline of approximately 83% for both strategies, which scales non-linearly to an absolute safety profile exceeding 99% as the mission target expands to 20 min. Crucially, as the response scope extends toward long-range bounds, the system curves converge, with both models capturing nearly identical spatial coverage probabilities for any target exceeding 12 min.

## 4. Discussion

The observed differences between the two strategies are related to the way assignment decisions are constructed and evaluated during execution. The decentralized approach relies on independent local selections, which reduces coordination overhead and leads to more stable execution times across runs. This behavior is reflected in the lower maximum computation times, where extreme values remain within a narrower range.

The centralized strategy introduces a global search process that evaluates multiple candidate assignments simultaneously. This increases computational effort per iteration, as the algorithm explores a larger portion of the graph to identify optimal matches. Execution time becomes more sensitive to network structure and stochastic variation in edge weights, which explains the higher variability in maximum values.

The centralized method consistently achieves lower average computation times. This reduction is associated with more efficient assignment ordering, which decreases the number of redundant or suboptimal routing calculations. By selecting globally favorable ambulance–incident pairs at each step, repeated evaluations are avoided. In practice, this trade-off suggests that the centralized strategy is better suited for high-frequency dispatch environments where average performance is critical, whereas environments with strict requirements on worst-case response times—such as under-resourced or geographically constrained settings—may benefit from the predictability of the decentralized approach.

From an implementation perspective, the choice between the two strategies depends on system requirements. Environments with strict constraints on execution stability may benefit from decentralized selection, whereas systems that prioritize overall computational efficiency may favor centralized coordination. The observed differences suggest that hybrid approaches could combine these characteristics by adjusting the level of coordination during execution.

The framework highlights the role of open geographic data and graph-based modeling in decision-support for urban systems. The integration of real network structure with stochastic parameters enables evaluation under conditions that approximate real-world variability.

For live smart city integration, algorithmic scalability is an absolute prerequisite. The 87.02% compression in execution overhead demonstrated by the multi-source Bidirectional approach (11.08 s vs. 85.35 s total compute) proves its readiness for high-frequency, city-wide deployment. Moving from a closed simulation to an operational dispatch environment would require transitioning the Python graph environment into an asynchronous microservice architecture. This service must ingest live GPS feeds from active emergency vehicles and real-time traffic updates via floating car data (FCD) to continually recalculate dynamic edge weights.

The study extends the analysis beyond average response-time metrics through a spatial reliability framework based on empirical cumulative distribution functions ($F(t) = P(T < t)$). The resulting distribution profiles show differences between the evaluated coordination strategies. The global coordination strategy reduced backend computation time and improved early-stage response performance. The decentralized approach produced more uniform spatial response behavior across the simulated urban area and reduced long-

tail delays affecting isolated incidents. The framework was evaluated through a Monte Carlo simulation executed across 30 independent iterations. Repeated simulation runs reduced localized stochastic variation and stabilized the average system response variance. ($t_8$ = 17.2 min, $t_{30}$ = 16.8 min)The resulting architecture supports scalable simulation of emergency-response deployment scenarios in smart-city environments.

## 5. Conclusions

The study examines two dispatch strategies within a graph-based simulation framework that incorporates stochastic travel time estimation and real urban network data. The comparison highlights differences in computational behavior associated with decentralized and centralized decision-making. Lower average response times and faster computation times are observed for the centralized strategy, indicating more efficient assignment ordering. The decentralized approach shows more stable maximum computation times, higher robustness and fairness and reduced variability under local decision rules. These results indicate a dependency between coordination mechanisms and execution performance in graph-based dispatch systems.

Open geographic data and stochastic modeling support the evaluation of algorithmic behavior under variable conditions. The framework enables controlled experimentation and preserves key structural properties of urban networks. This supports the design of data-driven decision processes.

Further development may include the incorporation of real-time data sources and adaptive coordination mechanisms. Extensions in this direction would support more flexible dispatch strategies and improve responsiveness in dynamic environments.

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**Conflicts of Interest:** The authors declare no conflicts of interest.

## Abbreviations

The following abbreviations are used in this manuscript:

| | |
|---|---|
| OSM | OpenStreetMap |
| OSMnx | Python library for OpenStreetMap network analysis |

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