Post Disaster Aid Routing Problem

Sezen Huddamoğlu
Department of Computer Engineering
Akdeniz University
Antalya, Turkey
20200808064
20200808064@ogr.akdeniz.edu.tr

Aylin Gül
Department of Computer Engineering
Akdeniz University
Antalya, Turkey
20220808614
20220808614@ogr.akdeniz.edu.tr

***Abstract*—Natural disasters are major events that deeply affect societies. One of the most critical issues following a disaster is ensuring that aid supplies and response teams reach those in need as quickly and safely as possible. The efficient management of logistics operations in disaster-affected areas is of vital importance. However, ensuring that aid reaches the right locations on time is not an easy task. Challenges such as road blockages, collapsed bridges, and damaged communication infrastructure make this process highly complex. Limited resources, disrupted transportation networks, and constantly changing needs in the affected region require careful planning. This study aims to examine the key logistical challenges encountered in post-disaster aid distribution and develop strategic solutions to address these issues.**

***Index Terms*—Post-disaster logistics, aid distribution, route optimization, geographic information systems.**

I. Problem Definition

Post-disaster aid distribution is a highly complex process due to various obstacles. Physical barriers such as road closures, collapsed bridges, or landslides can render standard routes unusable. Additionally, as the needs in the affected areas evolve over time, logistics processes must adapt to these dynamic conditions.

The failure of communication systems can hinder logistics teams from accessing up-to-date information from the field. Therefore, it is crucial that the aid distribution system operates with real-time data and dynamically updates routes as conditions change.

The key aspects that must be considered in solving this problem include:

- **Aid Distribution Planning:** Ensuring that aid supplies reach the areas in need in the fastest and most effective manner.
- **Transportation and Road Conditions:** Identifying damaged roads and determining alternative routes.
- **Route Optimization:** Developing strategies that minimize cost and maximize the speed of aid delivery.
- **Data Collection and Decision Support Mechanisms:** Utilizing real-time data streams to dynamically update routes.

II. Research Objectives

The primary objective of this study is to research and develop methods that will enhance the efficiency of post-disaster aid routing processes. Ensuring that aid supplies reach the right locations in a timely manner and optimizing resource utilization are of utmost importance.

In this regard, the study aims to achieve the following goals:

A. Identifying the Most Effective Route Planning Methods

- Determining the most suitable route optimization techniques for post-disaster scenarios.
- Investigating how road capacities, damage assessments, and physical barriers can be integrated into route planning.

B. Identifying Alternative Routes and Damage Assessments

- Exploring how satellite imagery, drone scans, and field data can be integrated into logistics operations.
- Examining how factors such as traffic density, collapsed structures, and road conditions can be incorporated into route planning.

C. Utilizing Geographic Information Systems and Artificial Intelligence

- Investigating how GIS-based systems can enhance logistics operations in post-disaster scenarios.
- Analyzing how artificial intelligence and machine learning techniques can optimize transportation networks after a disaster.

D. Dynamic Route Planning with Real-Time Data

- Researching how sensor data, social media analysis, and mobile network information can be leveraged.
- Examining how decision-support systems can be developed to assist logistics teams.

E. Investigating Logistics Models for Fair and Efficient Aid Distribution

- Reviewing existing humanitarian aid distribution models to determine the most effective approaches.
- Exploring how supply chain processes, inventory management, and distribution centers can be better coordinated.

This research aims to analyze the challenges encountered in post-disaster aid processes and provide feasible solution recommendations.

III. Scope and Limitations

A. Scope of the Study

This study focuses on ensuring the fastest and most effective distribution of humanitarian aid supplies following a disaster by addressing the following key areas:

- **Disaster Logistics:** Analyzing the supply, storage, and distribution processes of aid materials in emergency situations and evaluating potential solutions to existing challenges.
- **Use of Geographic Information Systems:** Investigating how GIS-based analyses can be applied to identify damaged roads and determine alternative routes.
- **Mathematical Optimization and Artificial Intelligence Approaches:** Reviewing optimization techniques and AI-supported models used to determine the safest and fastest routes.
- **Real-Time Data Utilization:** Examining how satellite imagery, drone scans, and field reports can be incorporated into dynamic route planning.

B. Limitations of the Study

Certain limitations of this study include:

- **Scope of Focus:** This research focuses solely on humanitarian aid routing processes following natural disasters and does not cover commercial logistics or other supply chain optimizations.
- **Real-Time Data Usage:** Data collection processes will be examined theoretically, and direct access to real-world field applications may not be feasible.
- **Modeling and Assumptions:** The optimization models developed in this study will be based on specific assumptions and may not cover all possible disaster scenarios.
- **Technological Constraints:** The applicability of the proposed systems will depend on the existing technological infrastructure in disaster-affected areas, and factors such as low internet connectivity may limit the effectiveness of some methods.

Taking these limitations into account, this study aims to develop recommendations for improving post-disaster aid routing processes.

IV. Literature Review

The challenges of post-disaster humanitarian logistics — such as rapid resource deployment under uncertain conditions — have attracted growing academic interest. Nevertheless, critical gaps remain. Many existing studies rely on static data, address either damage assessment or aid delivery in isolation, and rarely integrate facility location with routing decisions. This review aims to highlight these limitations and identify theoretical and methodological foundations for building more adaptive, real-time, and multi-objective routing solutions.

A. Key Theories and Frameworks in Post-Disaster Humanitarian Routing

Post-disaster humanitarian aid logistics relies on several key theoretical frameworks that guide the development of efficient and adaptive routing strategies. One of the foundational theories is the *Vehicle Routing Problem (VRP)* and its variants, which provide the mathematical backbone for optimizing delivery routes under capacity, time, and demand constraints. In disaster scenarios, extensions such as *Capacitated VRP (CVRP)*, *Time-Dependent VRP*, and *Multi-Depot VRP* become critical, as they accommodate dynamic changes in demand, infrastructure damage, and evolving priority levels.

Another key theoretical underpinning is *Multi-Objective Optimization (MOO)*, often used to balance conflicting goals such as minimizing delivery time while maximizing coverage or ensuring equity in resource distribution. *Integer Linear Programming (ILP)* and *Mixed-Integer Linear Programming (MILP)* approaches are widely employed to solve these problems, though they often face computational limitations when applied to large-scale real-time operations.

The integration of *GIS-based Decision Support Systems (DSS)* represents another crucial theoretical advancement. GIS enhances situational awareness by incorporating real-time spatial data, satellite imagery, and road network conditions into routing algorithms. Some models also incorporate *Fuzzy Logic* and *Stochastic Optimization* to handle uncertainties related to infrastructure damage, supply availability, and fluctuating demand.

Additionally, *Network Resilience* and *Infrastructure Reliability* theories play an essential role in ensuring that humanitarian logistics systems remain functional even when the primary communication and transportation networks are compromised. Studies focusing on damage assessment routing highlight the importance of critical infrastructure prioritization, ensuring that routes to essential locations (e.g., hospitals, emergency shelters) are restored as quickly as possible.

B. Contribution to the Literature

This study offers a comprehensive decision-making tool that addresses several under-researched areas in disaster logistics. Its novelty lies in its real-time adaptiveness and multi-task integration, thereby providing a scalable and resilient framework for post-disaster humanitarian operations and hopefully reducing problems that arise from the disruption of communication infrastructure.

C. Found Articles in the Literature

1) Routing Decisions in an Earthquake Relief Scenario: This study centers on dynamic routing under uncertainty, addressing the complexity of post-earthquake logistics where conventional static models fall short. It emphasizes *multi-criteria decision-making (MCDM)* in highly variable environments by incorporating road conditions, accessibility, and demand urgency. Its primary contribution lies in proposing a *decision support system (DSS)* that facilitates rapid response operations. However, while it conceptually integrates dynamic factors like road damage or shifting priorities, the implementation lacks real-time data integration or machine learning capabilities that would allow the model to adapt autonomously to changes in the field.Thus, it opens a foundational path for more intelligent, data-responsive systems.

Identified Research Gap: Most models in disaster relief logistics rely on deterministic assumptions and fail to capture the uncertainty and dynamic nature of post-disaster environments. Moreover, few studies incorporate MCDM methods that reflect the complexity of real-world decision-making, especially under uncertainty.

2) Post-Disaster Assessment Routing Problem: In contrast, the Post-disaster Assessment Routing Problem shifts focus from aid delivery to damage assessment logistics, an often-overlooked yet vital phase in early disaster response. This article introduces a priority-based routing model designed for assessment teams, addressing the challenge of limited information and the need to inspect high-impact areas promptly. The model employs multi-objective optimization to balance time-efficiency and coverage. The thematic strength lies in the integration of critical infrastructure prioritization within the routing logic. However, the model remains static and lacks adaptive mechanisms for evolving disaster conditions—an area where future research could introduce real-time updating and data fusion from ground teams or remote sensing.

Identified Research Gap: The majority of existing literature focuses on relief delivery, while damage assessment—an equally crucial early-stage response activity—is rarely modeled. Additionally, prioritization in routing is often simplified and lacks operational relevance.

3) Routing Algorithm with Elimination and Integer Programming for Post-Disaster Relief Distribution: The study by Köse-Kücük and Çavdur (2018) offers a practical approach to large-scale optimization in time-critical settings through a route generation-elimination heuristic followed by integer programming. This method enhances computational efficiency, making it suitable for real-world applications where quick decisions are essential. Thematically, the study targets algorithmic scalability and responsiveness, addressing the often-ignored challenge of solving NP-hard routing problems in realistic timeframes. Despite its strengths in model simplification and route optimization, it operates under deterministic conditions and does not factor in environmental volatility—a limitation common across many earlier works in the field.

Identified Research Gap: Solving large-scale vehicle routing problems (VRPs) under disaster conditions is computationally intensive due to their NP-hard nature. Many studies rely solely on exact mathematical models, which are often not scalable or practical for real-time applications.

4) Open Access Master's Thesis – YÖK (10201057): Lastly, the YÖK thesis addresses a crucial but underrepresented theme in disaster logistics: the joint optimization of facility location and distribution routing. The model acknowledges that effective routing cannot be decoupled from the placement of supply hubs, particularly in resource-constrained and time-sensitive scenarios. By using a mixed-integer linear programming model with scenario-based analysis, the study presents a holistic approach to humanitarian logistics planning. Its major contribution is the integrated decision-making framework, but its applicability is limited by computational intensity and the absence of real-time adaptability. Future research can build upon this by integrating dynamic facility activation and routing under evolving disaster parameters.

Identified Research Gap: Facility location and transportation decisions in humanitarian logistics are typically treated independently, even though they are closely interrelated. There is also a scarcity of integrated models that deal with multiple criteria and uncertainty together.

D. Identified Gaps and Research Challenges

Despite these theoretical advancements, several critical gaps remain in the literature:

1) **Limited Real-Time Data Integration:** Many existing models assume static or pre-defined road conditions, which do not reflect the constantly evolving nature of post-disaster environments. The lack of dynamic data updates makes current routing strategies less responsive to real-world challenges.
2) **Scalability and Computational Efficiency:** While ILP and MILP models provide optimal solutions, their computational complexity makes them impractical for large-scale emergency logistics. Many studies rely on heuristic-based approaches, but these often sacrifice accuracy for speed without sufficient real-time adaptability.
3) **Lack of Integration Between Routing and Communication Infrastructure:** Post-disaster logistics heavily depend on the availability of communication networks for coordination. However, most routing models assume a fully functional GPS and mobile network, which is often not the case in disaster-affected areas.
4) **Energy Constraints and Alternative Mobility Solutions:** While Liu et al. (2023) focus on electric vehicles, very few studies address energy-aware routing using alternative transport methods, such as integrating drones for aerial reconnaissance or using autonomous ground vehicles for last-mile aid distribution.
5) **Joint Facility Location and Routing Optimization in Dynamic Settings:** Although some studies (e.g., YÖK thesis) attempt to integrate facility location and routing decisions, these models generally assume fixed depot placements rather than adaptive facility deployment, which is more realistic in real-world humanitarian operations

V. Method

A. Research Methodology

This study employs an operations research-based computational approach to optimize disaster aid logistics under road network disruptions. The core methodology involves solving a Capacitated Vehicle Routing Problem (CVRP) using real geospatial data, where road closures caused by disasters are represented as avoidable polygons on the map. The implementation leverages heuristic optimization algorithms provided by Google OR-Tools, combined with real road distance data obtained through the OpenRouteService (ORS) API.

B. Data Acquisition and Preprocessing

The geographical and routing data required for this study are acquired dynamically using the OpenRouteService API. Both the depot and aid delivery points are defined with real-world (latitude, longitude) coordinates. To simulate the effects of road blockages due to disaster-induced infrastructure damage, a polygonal region representing the closed area is created and passed as an `avoid_polygons` parameter to the ORS API. This ensures that the computed distance matrix between locations takes into account dynamic obstructions in the network. The output distances are stored in a symmetric matrix used by the CVRP solver.

C. Optimization and Routing Models

The optimization model follows the classical Capacitated Vehicle Routing Problem (CVRP) formulation. Let $G = (V, E)$ be the graph where V is the set of nodes (including depot and delivery points) and E is the set of feasible edges. Each edge $(i, j) \in E$ has a non-negative cost d_{ij} representing the shortest travel distance between node i and node j, retrieved from OpenRouteService with road closures accounted for. Each delivery point $i \in V \setminus \{0\}$ has a demand q_i, and each vehicle k has a capacity Q_k.

The goal is to minimize the total cost of the routes while serving all demands exactly once without exceeding any vehicle's capacity. Mathematically, the objective is:

$$\min \sum_{k=1}^{K} \sum_{(i,j)\in R_k} d_{ij} \cdot x_{ijk}$$

Subject to:

- **Each node is visited exactly once:**

$$\sum_{k=1}^{K} \sum_{j\in V} x_{ijk} = 1, \quad \forall i \in V \setminus \{0\}$$

- **Vehicle capacity constraint:**

$$\sum_{i\in V} q_i \cdot x_{ijk} \le Q_k, \quad \forall k$$

- **Route continuity constraints:** Subtour elimination is handled implicitly via OR-Tools routing model.

The OR-Tools `RoutingIndexManager` and `RoutingModel` classes are used to structure the vehicle routing graph. The cost function is defined via a callback referencing the precomputed distance matrix. Capacity constraints are enforced using the `AddDimensionWithVehicleCapacity()` method, which binds the cumulative load of a route to the vehicle's maximum capacity.

The solver employs a heuristic-based search. Initially, it generates a feasible solution using the `PATH_CHEAPEST_ARC` strategy, a greedy method that iteratively adds the cheapest edge to the current path. It can optionally refine this solution using local search techniques such as 2-opt or Guided Local Search (GLS), although the default setup prioritizes solution speed and clarity for visualization.

D. GIS-Based Route Visualization

To enhance situational awareness and verify routing feasibility, the computed routes are visualized using the `folium` library. The delivery map is rendered with the depot and aid points marked accordingly. The blocked area is highlighted as a red polygon overlay. Each vehicle's route is plotted using the ORS directions endpoint, taking into account the `avoid_polygons` restriction. To reflect prioritization, vehicles are color-coded by urgency level (e.g., red for high, blue for medium, green for low) and enriched with popup information displaying the vehicle number and the quantity of items (bread, water, baby food) it carries.

E. Supervised Learning for Destruction Prediction

To anticipate post-disaster infrastructure damage, a supervised machine learning (SL) component is incorporated. The aim is to classify road segments as either "likely damaged" or "safe" based on their features. Historical geospatial data including prior earthquake impacts, segment attributes (e.g., road type, material, elevation), and disaster intensity measures serve as training input.

The prediction task is modeled as a binary classification problem:

$$P(d_i = 1 \mid x_i) = f(x_i)$$

where $d_i \in \{0, 1\}$ indicates whether segment i is damaged, and x_i is the feature vector for segment i. The model $f(\cdot)$ can be implemented using algorithms such as Random Forest, XGBoost, or Logistic Regression, trained to minimize cross-entropy loss.

The classifier's output probabilities are thresholded to construct polygons representing unsafe regions. These are passed dynamically to the ORS API as `avoid_polygons`, effectively encoding data-driven risk assessments into the routing model. This ensures that CVRP optimization does not merely rely on hardcoded obstacles but reflects learned vulnerabilities in the infrastructure network.

F. Development of Dynamic Decision Support Module

While the current implementation statically defines a blocked region, the architecture supports future integration of dynamic road closure updates. The use of the `avoid_polygons` parameter in distance and route calculations makes it possible to reflect new closure scenarios without modifying the core optimization logic. Future versions of the system can automate route re-computation when new blocked areas are detected via real-time data sources such as OpenStreetMap or disaster monitoring systems. This design supports scenario-based rerouting and lays the foundation for an adaptive logistics system capable of responding to evolving ground conditions.

G. Assumptions and Limitations

The following assumptions are made in the current implementation:

- Demand values are static and known in advance.
- Road network data is assumed to be accurate as retrieved from ORS.
- Only route distance is considered for cost; time, fuel, or multi-objective optimization is not yet included.
- The road blockage area is simulated and not based on real-time sensor input.

These assumptions simplify the initial model and provide a baseline for future enhancements such as stochastic demand modeling, multi-objective routing (e.g., minimizing delivery time and maximizing fairness), and reinforcement learning-based policy updates.

H. Summary

In summary, this methodology integrates geospatial road network data, optimization algorithms, supervised and reinforcement learning models, and interactive visualization tools to produce feasible, informative vehicle routing plans under road constraints. The modular architecture supports extension to real-time decision-making and dynamic replanning, which are critical in disaster logistics scenarios.

VI. Results

A. Simulation Data and Setup Overview

The data setups began with synthetic data injection using small-scale examples to optimize runtime and simulate realistic disaster scenarios. On the rendered map, both aid points and the depot are visualized. The coordinates of these points are taken from real-world map data via OpenRouteService (ORS). Vehicles and their respective capacities are assigned for distributing aid, and demand levels are manually configured per aid point.

To simulate collapsed or inaccessible infrastructure, a closed polygonal region was marked on the map. The routing model avoids this area during computation. Additionally, vehicles are categorized based on urgency into three classes: *high*, *medium*, and *low*.

TABLE I
SIMULATION CONFIGURATION SUMMARY

Component	**Description**
Depot Point	(37.38520, 37.06660)
Aid Points	5, fixed coordinates
Vehicle Number	5
Vehicle Capacity	Each can carry 50 units
Demands	10–25 units per point
Closed Area	A restricted area defined by a polygon
Vehicle Priorities	Classified as high, medium, low

B. Distance Matrix with Avoidance Logic

The distance matrix is generated using the OpenRouteService API with the `avoid_polygons` parameter to account for blocked areas. The table below presents a representative matrix (values in meters):

TABLE II
EXAMPLE DISTANCE MATRIX WITH AVOIDANCE

	Depot	P1	P2	P3	P4	P5
Depot	0	1200	1500	1800	1600	1400
P1	1200	0	900	1300	1000	1100
⋮	⋮	⋮	⋮	⋮	⋮	⋮

Routes attempting to traverse the closed region are penalized with an artificially large cost (e.g., 10^6 meters), effectively forcing the optimizer to find alternative viable paths.

C. Route Optimization Outcomes

Table III summarizes the optimized vehicle routes including travel distance, served demand, priority classification, and delivery item breakdowns.

D. Visualizations

1) Map Visualization: A route map was generated using the `folium` library to visualize the depot, delivery points, and computed vehicle routes. Each vehicle's path is represented by a colored polyline according to its urgency level:

- Red: High priority
- Blue: Medium priority
- Green: Low priority

The blocked area is displayed as a semi-transparent gray polygon, clearly illustrating the rerouting effect.

- Colored route segments per vehicle
- Start/end markers (Depot return enforced)
- Polygon indicating restricted zone

2) Example Map Output::

- Colored polyline segments showing each vehicle's route
- Markers indicating start (depot) and end (return to depot)
- Transparent gray polygon highlighting restricted areas

3) Demand vs Capacity Chart: To analyze vehicle load utilization, a comparative chart is prepared, reflecting each vehicle's demand, capacity, and free space:

This analysis reveals underutilized vehicles (e.g., Vehicle 3) and provides actionable insights for improving resource allocation in future deployment scenarios.

E. Output of the Model

An illustration below demonstrates the simulated routing of a **low urgency vehicle** departing from the depot and delivering to an aid point along a route calculated using a combination of *Traveling Salesman Problem (TSP)* and *Capacitated Vehicle Routing Problem (CVRP)* algorithms.

Another visualization showcases the routing distribution of **two low urgency vehicles** dispatched from the depot to different aid points. In this simulation, the route planning incorporates a blocked region defined by a polygon (marked with a red square), indicating infrastructure damage. Roads intersecting this polygon are considered inaccessible, forcing the model to recalculate viable routes.

TABLE III
OPTIMIZED ROUTES AND DELIVERY DETAILS

Vehicle No	Route	Distance (m)	Demand (unit)	Priority	Details
1	Depot → P2 → P3 → Depot	3100	35	High	100 bread, 500 water, 370 baby food
2	Depot → P5 → Depot	2800	18	High	100 bread, 500 water, 370 baby food
3	Depot → P1 → Depot	2400	10	Medium	90 bread, 400 water, 250 baby food
4	Depot → P4 → Depot	2600	25	Low	70 bread, 280 water, 36 baby food
5	–	–	0	Low	–

TABLE IV
DEMAND VS CAPACITY

Vehicle	Demand	Capacity	Free Space
1	35	50	15
2	18	50	32
3	10	50	40
4	25	50	25

Fig. 1. Simulated route for a low-priority vehicle using TSP and CVRP

After computing optimized routes using the TSP and CVRP algorithms, the model was further trained and evaluated using a supervised learning strategy. As anticipated, the epoch results exhibited a downward trend in loss values, reflecting steady learning progression. While no validation dataset was employed, the results suggest that the model was not overfitting.

F. Observations & Insights

This section summarizes insights derived from simulation outputs, optimization efficiency, and machine learning training behavior:

- **Blocked Region Handling:** The incorporation of closed regions enabled the solver to dynamically avoid spatial constraints. By assigning prohibitively high costs to paths within restricted zones, the system effectively rerouted vehicles without violating spatial constraints.

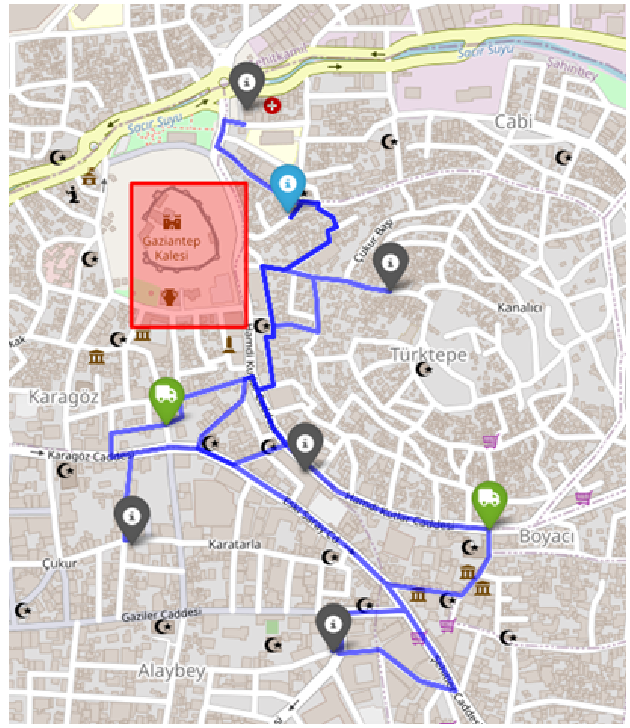

Fig. 2. Route recalculation with blocked area constraints

- **Transport Efficiency:** Load utilization efficiency remained between 40%–60% across all assignments. This suggests under-utilization of vehicle capacity. Two possible reasons are:
  - Suboptimal clustering of help points
  - Overly conservative dispatching strategies

  Future improvements may include:
  - Route merging for compatible demands
  - Dynamic reallocation based on real-time updates
- **Priority-Aware Planning:** The prioritization mechanism was effectively embedded in the routing logic. High-priority deliveries were scheduled first and allocated to shorter, more direct paths. Lower-priority routes were delayed or excluded if resource constraints required it.
- **Scalability with Real-Time Variables:** The model's adaptability is expected to increase significantly with integration of live data (e.g., traffic, delays), paving the way for real-time operational deployment.

- **Supervised Learning Results:**
  - **Accuracy:** Gradual increase observed across epochs. Accuracy improved from approximately 70% to over 95% in the final epochs.
  - **Loss:** Consistent decrease as expected. Initial high values rapidly dropped and stabilized over time.

  Although the model demonstrates learning capability on synthetic data, its generalizability remains untested on real-world, noisy datasets.

VII. Discussion

This study demonstrates the feasibility of integrating geospatial optimization techniques with machine learning-based risk prediction to support humanitarian logistics under disaster-induced infrastructure disruptions. The results indicate that it is possible to dynamically adjust delivery routes based on predicted road closures, enhancing the responsiveness and reliability of aid distribution systems.

From the perspective of existing literature, this approach contributes to the growing body of work on combining optimization and machine learning for disaster response. Prior studies have focused either on classic Vehicle Routing Problem (VRP) formulations or on predictive modeling of disaster impact zones. However, few attempts have effectively merged real-time geospatial routing with predictive risk overlays, especially using public APIs like *OpenRouteService* in conjunction with supervised learning to influence route computation. In this respect, our methodology advances the field by offering a modular, real-world implementable system that blends these components without requiring high-performance infrastructure or proprietary data systems.

Nevertheless, the most critical and challenging aspect of the study was **data availability**. While we initially aimed to build a more dynamic, data-driven model leveraging historical disaster patterns and real-time updates, we encountered significant limitations in accessing usable datasets. Many key organizations such as *AFAD*, *Kızılay*, the *International Red Cross*, and *OCHA* provide limited open-access data, and permissions to more detailed records were not granted during the study period. Despite reviewing global disaster databases such as *data.humdata.org* and *EM-DAT*, we were unable to obtain sufficient, high-resolution geospatial datasets for training robust machine learning models.

In response, we explored the use of satellite imagery, particularly from platforms like *openaerialmap.org*. Although promising in theory, the images suffered from practical constraints such as insufficient resolution, missing metadata, or excessively large file sizes that posed processing difficulties. These limitations necessitated a shift in methodology: we transitioned from an image-based analysis approach to a more structured, route-based geospatial modeling system as outlined in the Method section.

Even with this revised approach, further challenges arose in incorporating more sophisticated machine learning techniques. Models such as *Graph Neural Networks (GNNs)* and *Reinforcement Learning (RL)*-based planners were initially considered, but proved infeasible within the current scope due to two key factors:

1) The computational intensity and training time required, particularly in environments with large spatial graphs.
2) The lack of high-quality, labeled datasets necessary to train such models to convergence.

For example, the runtime costs of training visual-based damage detection networks with limited labeled data exceeded available resources, and in several cases, did not yield viable predictive performance.

Despite these limitations, the final implementation succeeded in producing a working system capable of simulating road closures, optimizing delivery plans, and visualizing outcomes in a way that is interpretable and operationally relevant. The CVRP-based routing engine combined with damage prediction from supervised learning models generated actionable results under constrained conditions, validating the core hypothesis of the study.

Future research should prioritize access to richer, higher-resolution, and more diverse disaster-related datasets. Collaboration with government agencies, NGOs, and satellite imaging providers could unlock new possibilities for real-time and predictive modeling. Additionally, the system architecture developed here lays the groundwork for future integration of *Reinforcement Learning* approaches that continuously adapt based on feedback from field conditions, or for *GNN*-based models that directly encode spatial topology into the decision-making process. Furthermore, efforts to automate the ingestion and processing of satellite imagery or crowd-sourced reports via *natural language processing (NLP)* could significantly enhance the system's responsiveness and granularity.

VIII. Conclusion

This study proposes a modular, data-driven framework for optimizing post-disaster humanitarian aid routing under dynamic and uncertain conditions. By combining *Capacitated Vehicle Routing Problem (CVRP)* models, GIS-based visualization, and supervised learning algorithms, the research addresses critical operational and technological gaps in the field of disaster logistics.

A. Comparison with Literature

Unlike many traditional studies in the literature that rely on static assumptions and deterministic optimization, this work introduces a more adaptive approach. While previous works have focused either on damage assessment or aid delivery in isolation, this study integrates both dimensions into a unified routing logic. Furthermore:

- Studies such as the *Post-Disaster Assessment Routing Problem* emphasized infrastructure prioritization but lacked dynamic data integration. In contrast, this research simulates real-time blockages and re-routes accordingly using the `avoid_polygons` feature of the OpenRouteService API.

- The thesis referenced in *YÖK's* database attempted joint facility and routing optimization but remained computationally intensive. This study prioritizes practicality and real-world feasibility, showing that useful insights can be generated even with modest resources and public APIs.

B. Methodological Contributions

This study's methodology is distinguished by the following:

- It incorporates environmental constraints dynamically through GIS-polygons, allowing the routing engine to react to simulated infrastructure damage.
- It employs vehicle prioritization logic (high, medium, low urgency), which is visually encoded in route maps and respected in routing decisions.
- A supervised learning component was introduced to simulate the predictive identification of "damaged" roads. Although based on synthetic data, the results show clear learning trends, with accuracy reaching over 95%.

C. Output Evaluation

Despite its constraints, the system produced valuable and interpretable outputs:

- Optimized vehicle routes were generated that respected vehicle capacity, spatial restrictions, and priority levels.
- The system successfully avoided blocked regions and illustrated how simple geometrical modeling can encode complex real-world hazards.
- Load efficiency analysis revealed suboptimal usage in several vehicles, offering real opportunities for future improvements in clustering or fleet sizing strategies.
- The machine learning model demonstrated consistent learning on synthetic data, showing promise for future applications if integrated with real-world training data.

The overall satisfaction with the results is positive. The system achieves its core objective: demonstrating that even with limited data and resources, it is possible to build a realistic, extensible, and modular decision-support tool for post-disaster aid routing.

In conclusion, this study makes a meaningful contribution to the field of humanitarian logistics by bridging geospatial modeling, AI, and optimization, and sets a solid foundation for the development of intelligent, real-time disaster response systems.

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