GIS-Based Optimization of Humanitarian Aids Logistics in Earthquake-Affected Urban Areas

Amirhossein Mahmoudnia[1], Zahra Bahramian[1*], Amir Parvini[2]

[1] School of Surveying and Geospatial Engineering, College of Engineering, University of Tehran, Tehran, Iran
[2] Dept. of Geodesy and Geomatics Engineering, K.N. Toosi University of Technology, Tehran, Iran

Keywords: Humanitarian Aids Logistics, Capacitated Multi-Depot Vehicle Routing Problem, Genetic Algorithm, Earthquake

Abstract

Earthquakes rank among the most devastating natural disasters, causing profound harm to communities and ecosystems. Their impacts extend beyond physical destruction, leading to economic losses and significant human suffering. In the aftermath, collapsed infrastructure and widespread injuries create an urgent need for medical care, food, and other essentials. Humanitarian aid logisticseffectively in such scenarios is complex, as it requires addressing the spatial distribution of affected areas, and ensuring rapid response. This study tackles these challenges by addressing the allocation and routing in humanitarian aid logistics for earthquake relief in the west of Tehran's Region 4. A depot-aware Genetic Algorithm (GA) cluster-seeded initialization is employed to solve the allocation and routing of aid as a Capacitated Multi-Depot Vehicle Routing Problem (CMDVRP), designing efficient routes for aid distribution across 649 demand points using 2 depots, with each depot deploying 6 vehicles of 12,800-unit capacity. The GA solution achieves a total distance of 297372.159 meters across 12 routes, successfully serving all customers. By focusing on spatial analysis and route efficiency, this work contributes to GIS-driven disaster response strategies.

1. Introduction

A growing majority of the global population resides in urban areas, making cities particularly megacities increasingly vulnerable to natural disasters. Among these, earthquakes stand out as especially devastating, often causing widespread destruction, fatalities, and disruption of essential infrastructure. Cities situated near tectonic fault lines, such as Tehran, are particularly susceptible to frequent and severe seismic events. Over the years, such disasters have exposed significant shortcomings in existing emergency response systems, underscoring the urgent need for efficient and coordinated humanitarian aid delivery.

Timely distribution of relief supplies such as food, water, and medical equipment is crucial in the aftermath of an earthquake. However, logistical planning in densely populated urban settings is complex and requires the integration of spatial data, and infrastructure status. Despite growing interest in optimization methods for disaster logistics, current research often focuses on simplified scenarios involving single depot, which do not accurately reflect the operational realities of megacities (Long, et al., 2023).

In addition, another critical factor in post-disaster logistics planning is the consideration of vehicle capacity constraints. In real-world scenarios, relief vehicles have limited storage space, and disregarding these limitations can result in inefficient deliveries, overloading, or the need for repeated trips, which delays aid and increases operational costs. Especially in urban environments affected by earthquakes, where infrastructure may be partially damaged and access routes restricted, optimizing vehicle loads becomes essential to ensure that the maximum amount of aid reaches those in need with the fewest possible trips. Incorporating capacity constraints into the optimization model ensures that each vehicle operates within its physical limits while contributing to an overall efficient distribution strategy. This not only improves the feasibility of the routing solution but also enhances the responsiveness and reliability of disaster relief operations.

Moreover, many existing models lack integration with Geospatial Information System (GIS), limiting their applicability in real-world settings where spatial variability and road accessibility are critical factors. Although GIS tools are increasingly used in disaster response, their combination with advanced optimization methods, such as metaheuristic algorithms, remains underutilized, especially in multi-depot settings (Lakzaei et al., 2023).

Dispatching aid from multiple depots to several demand points under capacity constraint is a Capacitated Multi-Depot Vehicle Routing Problem (CMDVRP), an extension of the classical Vehicle Routing Problem (VRP). The CMDVRP is particularly relevant in earthquake response scenarios, where resource limitations add significant complexity (Ermagun and Tajik, 2023).

Metaheuristics for VRP variants include single-trajectory schemes such as simulated annealing (SA) and tabu search (TS), adaptive large-neighbourhood search (ALNS), and population-based methods such as genetic algorithms (GAs). SA/TS have a long record of success but typically explore one incumbent solution at a time; performance can depend on neighbourhoods' design and cooling/tenure schedules, and they may struggle to escape deep local minima on large, multi-depot urban instances (Osman, 1993). In contrast, GA's which combining problem-aware encoding, diversity control, consistently report state-of-

* Corresponding author

https://doi.org/10.5194/isprs-annals-X-4-W8-2025-457-2026

the-art or near-state-of-the-art results across many VRP variants. Their population-based recombination exploits spatial structure; and their operators parallelize naturally.

In this paper, in order to tackle this problem, a Genetic Algorithm (GA) based solution is proposed to optimize the distribution of aid across from multiple depots considering vehicles' capacity as a CMDVRP. Also, it contributes a GIS-based framework for post-earthquake aid logistics in urban areas. By modelling a real-world case in the west of region 4 of Tehran, this study proposes a solution tailored to the urban disaster context.

The contribution of this paper is to advance post-disaster logistics by: (1) Formulating and solving a large, real CMDVRP with strict capacity limits in a dense urban region; (2) Designing a depot-aware GA that combines cluster-seeded initialization (nearest-depot GIS distances), elitism, ordered crossover, swap mutation, to accelerate convergence while preserving feasibility; (3) Integrating a GIS-to-Optimization pipeline that seeds depot clusters, and compute route fitness based on OD connectivity.

Section 2 surveys the relevant literature. Section 3 details the methodology, including CMDVRP formulation, and the proposed GA. Section 4 presents the results, including visualizations of the GA's performance. Finally, Section 5 outlines conclusions and future directions.

2. Literature Review

The VRP (Ni and Tang, 2023) involves designing optimal routes for a fleet of vehicles to serve a set of customers while minimizing costs, such as distance or time, subject to constraints like vehicle capacity and depot locations. (Potvin, 2009) provides a comprehensive review of evolutionary algorithms, including GAs, for solving classical VRP and its variants, such as Capacitated VRP (CVRP) and VRP with Time Windows (VRPTW). The study highlights GAs' ability to explore large solution spaces efficiently, comparing their performance with other metaheuristics like Tabu Search (TS) and Simulated Annealing (SA) on benchmark instances. It notes that GAs excels in finding near-optimal solutions for complex VRP variants due to their population-based approach, which evolves solutions through selection, crossover, and mutation operators. This foundational work underscores the suitability of GAs for the MDVRP in the current study, where multiple depots and capacity constraints are critical.

Similarly, (Karakatič and Podgorelec, 2015) reviews GA applications in VRP, highlighting their robustness and extensibility. It discussed how GAs leverage rapid random search to optimize routes, particularly for large-scale problems, and highlight their adaptability to constraints like time windows and multi-depot settings. It noted that GAs often outperforms traditional heuristics in scenarios requiring scalability and flexibility, such as logistics in dynamic environments.

On the other hand, Disaster relief logistics introduce additional complexities to VRP, including time critical delivery, disrupted infrastructure, and dynamic demand. (Mguis et al., 2014) propose a distributed and guided GA for humanitarian relief planning, modelled as a Dynamic Vehicle Routing Problem with Time Windows (DVRPTW). Their approach uses a distributed framework to improve scalability, allowing rapid computation of routes for emergency aid delivery. Tested with theoretical data, the algorithm demonstrates high efficiency and consistency, making it suitable for disaster scenarios where quick response is paramount.

(Pu and Zhao, 2024) presented a comprehensive model for optimizing emergency logistics in post-earthquake scenarios, focusing specifically on the vehicle routing and depot location problem while accounting for real-world constraints. Their study introduced a multi-objective mixed-integer programming model that simultaneously considered route planning, facility location, and three-dimensional vehicle loading constraints—an aspect often overlooked in traditional models. The proposed solution used a hybrid metaheuristic algorithm called MOGA-ALNS (Multi-Objective Genetic Algorithm combined with Adaptive Large Neighbourhood Search and simulated annealing), which effectively addresses the complexity of the model and avoids premature convergence. The authors validate their method through computational experiments and demonstrate that it significantly outperforms standard approaches in balancing logistics cost, deprivation cost, and risk exposure in disrupted urban networks. This study is highly relevant to the present research, as it highlighted the effectiveness of GAs in solving high-constraint post-disaster distribution problems and aligns with the goal of integrating GIS-based spatial analysis with vehicle capacity considerations.

(Xu et al., 2023) further advanced the application of GAs in disaster relief by addressing the Energy Saving-Oriented Multi-Depot Vehicle Routing Problem with Time Windows (ESMD-VRPTW). The two-stage approach first used a Floyd-NL algorithm to minimize travel costs and then applies a GA with a large neighbourhood search (GA-LNS) to optimize delivery schemes for electric vehicles. The study emphasized energy efficiency and time constraints, which are critical in disaster scenarios where resources are limited.

Earthquake relief logistics presents unique challenges due to widespread infrastructure damage and urgent medical and supply needs. (Allen, 2017) modelled the operations of the Himalayan Disaster Relief Volunteer Group after the 2015 Nepal earthquake as a VRP, using Fisher and Jaikumar's two-stage method. The first stage allocated locations to vehicles via an integer program, and the second stage employed heuristics for routing. While the study did not use GAs, it provided a practical case study of VRP in earthquake relief, highlighting the computational necessity of heuristics in time-sensitive scenarios.

Despite the richness of the existing literature, key limitations persist. Many GA-based VRP models rely on synthetic or simplified datasets, limiting their applicability to real-world urban disaster contexts. Furthermore, there is a dearth of studies that combine high-resolution geospatial data with CMDVRP solutions under realistic capacity constraints and depot configurations. The present study addresses these gaps by implementing a GA to optimize post-earthquake aid delivery in Tehran's Region 4, encompassing 649 demand points, 2 depots, and 12 vehicles with specific load capacities. The proposed model not only ensures complete demand coverage, but also achieves significant route efficiency, contributing a GIS-driven and empirically validated methodology to the field of disaster logistics.

https://doi.org/10.5194/isprs-annals-X-4-W8-2025-457-2026 | © Author(s) 2026. CC BY 4.0 License.

3. Methodology

3.1 Problem Formulation

This study optimizes allocation and routing in aid delivery logistics after earthquake as a Capacitated Multi-Depot Vehicle Routing Problem (CMDVRP), an extension of the classic VRP. It aims to determine efficient routes for a fleet of vehicles to serve a set of demand points from one or more depots, minimizing total travel distance while adhering to operational constraints such as vehicle capacity and route continuity. It adapts this framework to multiple depots, reflecting the complexity of disaster relief in an urban setting. This subsection formalizes the proposed CMDVRP for the given context, defining the mathematical model, decision variables, objective function, and constraints that ensure feasibility in a post-disaster environment.

Problem Definition. Consider a set of depots $K = \{1, 2, . . ., n_{depot}\}$, and a set of demand points $P = \{1, 2, . . ., n_{demand}\}$, where n_{depot} and n_{demand} are number of depots and demand points, respectively. Each depot $k \in K$ is equipped with a fleet of n_v vehicles, each with a capacity $Q_v=Q$ units. The demand for demand points $i \in P$ is denoted d_i. Also, consider a graph $G(V,E)$ where a set of nodes $V = \{1, 2, . . ., n_{depot} + n_{deman}\}$, where nodes $\{1,2,\ldots,n_{depot}\}$ represent the depots, and nodes $\{ n_{depot}+1, . . . , n_{depot} + n_{demand}\}$ denote the demand locations. A distance matrix $D = [d_{ij}]$ also known as OD matrix, provides the travel distance between nodes i and $j \in V$.

Decision Variables. The proposed CMDVRP model uses the following decision variables to define allocation and routing decisions and ensure constraint satisfaction:

- x_{ijk}: Binary variable, equal to 1 if a vehicle from depot k travels from node i to node j, and 0 otherwise ($i, j \in V$, $k \in K$).
- u_{ik}: Auxiliary variable representing the load of the vehicle from depot k after visiting node i, used to eliminate sub-tours ($i \in N$, $k \in K$).

Objective Function. The objective is to minimize the total travel distance across all routes, ensuring efficient use of resources in the disaster response operation:

$$Minimize Z = \sum_{k\in K}\sum_{i\in V}\sum_{j\in V} d_{ij}, x_{ijk} \tag{1}$$

Constraints. The following constraints ensure the feasibility of the solution in the context of post-earthquake logistics:

- **Each Demand Point Served Exactly Once**: Ensures every demand point is visited by exactly one vehicle from any depot, guaranteeing full coverage of demand points.

$$\sum_{k\in K}\sum_{i\in V} x_{ijk} = 1, \forall j \in P \tag{2}$$

- **Vehicle Departure and Return to Depot**: Guarantees that each of the n_v vehicles per depot starts from and returns to its respective depot, maintaining operational consistency.

$$\sum_{j\in V} x_{ojk} = m_k, \forall k \in K \tag{3}$$

$$\sum_{i\in V} x_{ijk} = m_k, \forall k \in K \tag{4}$$

- **Flow Conservation**: Ensures continuity of routes, where the number of vehicles entering a node equals those leaving, except for depots, preventing disconnected routes.

$$\sum_{i\in V} x_{ijk} = \sum_{i\in V} x_{ik}, \forall j \in V, k \in K \tag{5}$$

- **Capacity Constraint**: Limits the vehicle load to Q units, accounting for cumulative demand and preventing overloading using the Miller-Tucker-Zemlin (MTZ) (Miller et al., 1960) sub-tour elimination approach.

$$u_{ik} \leq Q \;\; \forall i \in P, k \in K \tag{6}$$

$$u_{ik} \geq d_i \;\; \forall i \in P, k \in K \tag{7}$$

$$u_{ik} - u_{jk} + d_j \leq Q(1 - x_{ijk}) \;\; \forall i, j \in P, k \in K \tag{8}$$

- **Sub-tour Elimination**: Prevents disconnected routes by enforcing a logical sequence of visits, ensuring that vehicles follow a continuous path.

$$u_{ik} - u_{jk} + Q\cdot x_{ijk} \leq Q - d_j \quad \forall i, j \in P, k \in K \tag{9}$$

- **Binary and Non-negativity Constraints**: Defines the binary nature of routing decisions and ensures non-negative loads for feasibility.

$$x_{ijk} \in \{0, 1\} \; \forall i, j \in V, k \in K \tag{10}$$

$$u_{ik} \geq 0 \; \forall i \in P, k \in K \tag{11}$$

This formulation captures the CMDVRP's complexity, tailored to the post-earthquake relief needs, where spatial distribution, and vehicle constraints are critical factors. Also, isolated nodes or undefined distances (e.g., NaN values in the matrix) are ignored. The proposed GA, detailed in the next subsection, provides a metaheuristic solution to this NP-hard problem in designing practical allocation and route for disaster response.

3.2. The Proposed Genetic Algorithm

This paper proposes a GA to optimize humanitarian aid logistics as a CMDVRP. The CMDVRP is an NP-hard problem, exacerbated by the large number of demand points and multi-depot constraints. GA, a bio-inspired optimization technique known for its flexibility and robustness in solving NP-hard problems. GAs is well-suited for dynamic disaster scenarios due to their ability to handle large solution spaces and adapt to constraints (Maroof et al., 2024). Compared to other methods, such as Ant Colony Optimization or Particle Swarm Optimization—GAs offers a balanced trade-off between computational efficiency and solution robustness, particularly in scenarios with high constraint complexity. In addition, (Vonolfen et al., 2011) demonstrates that appropriately designed GAs can deliver strong performance on VRP instances of up to 1,000 customers without instance-specific tuning, underscoring their robustness for large-scale problems. Also, population-based recombination (ordered crossover) creates route segments that reflect spatial contiguity, which yields faster convergence than single-trajectory SA/TS for our scale and constraints. GAs, with their population-based approach and flexible operator design, are better suited for the complex, constraint-heavy CMDVRP. In conclusion, the GA's attributes large scale optimization, constraint adaptability, and robustness make it an ideal choice for "generation", superior individuals are probabilistically selected to breed offspring, ensuring that beneficial solving the CMDVRP. Figure 1 illustrates the steps of proposed GA, which is detailed in the following.

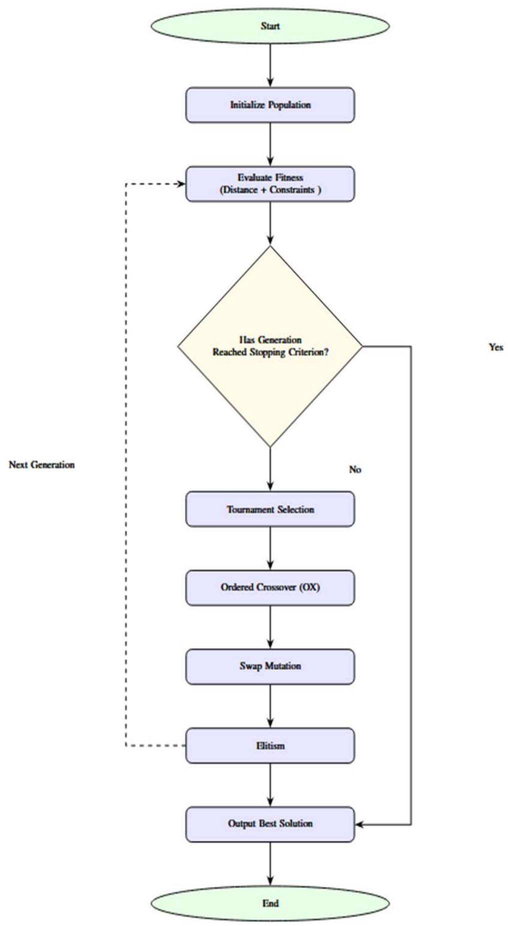

Figure 1. The Proposed GA to allocate humanitarian aid

Chromosome Representation

Chromosome Representation defines how candidate solutions are encoded. In the proposed method, each chromosome represents a complete solution to the aid distribution problem, indicating both the allocation of demand points to vehicles and the visiting sequence of each vehicle. The chromosome is encoded in such a way that the routes of different vehicles are distinguishable, while vehicle capacity constraints are respected. This representation allows the algorithm to simultaneously handle demand point assignment, route construction, and feasibility checking. This encoding allows for efficient evaluation of solution quality, particularly with respect to vehicle capacity constraints and route optimization. Also, there are n_{pop} chromosomes in the population of each generation.

Initial Population

In the proposed method, the initial population provides the starting solutions for the evolutionary process. For this purpose, demand points are assigned to depots based on proximity to ensure efficient and localized vehicle routing. To achieve this, a clustering step is proposed using a distance-based grouping function. Customers are clustered using a cluster-first, route-second procedure grounded in the road network. The function iterates through all demand points and, for each, calculates its distance to all available depots using OD matrix. Each demand point is then assigned to the nearest depot—ignoring any isolated nodes or undefined distances (e.g., NaN values in the matrix). The result is a set of clusters where each depot is associated with a subset of demand points for which it is the closest depot. This method ensures that demand points are grouped logically, reducing overall travel cost and simplifying the problem. Then, each chromosome in the population represents a candidate solution to the problem and is initialized by randomly shuffling the list of demand points assigned to each vehicle of depot. In this study, chromosomes are represented as a dictionary where depot keys are associated with randomly ordered demand points lists. This randomized yet depot-aware construction introduces diversity into the population, which is essential for effective exploration in subsequent generations.

Fitness Function Calculation

The fitness function evaluates the quality of each chromosome based on the objective of the problem. In this study, the fitness value is directly derived from the total travel distance, which is to be minimized. This distance is computed by summing the travel costs between consecutive nodes in each vehicle route across all depots. The objective function defined earlier serves as the fitness function without modification, meaning chromosomes with shorter total distances are assigned better fitness values. This approach effectively guides the GA toward more be routing configurations in subsequent generations.

Selection

The selection process in GA is responsible for choosing parent chromosomes from the current population to participate in the generation of offspring. In the proposed method, tournament selection (Goldberg and Deb, 1991) is used to choose parents for reproduction, balancing selection pressure and population diversity. In each tournament, a subset of $n_{tournamen}$ chromosomes is randomly sampled from the population, and the chromosome with the lowest fitness (shortest distance) is selected as a parent. This process is repeated to select pairs of parents for crossover. Tournament selection ensures that better solutions are favored while allowing fewer fit solutions a chance to contribute.

Crossover

The crossover operator is applied to use selected parent chromosomes and generate new offspring by combining segments of their genetic material. In this study, ordered crossover (OX) (Davis, 1985) is applied to combine parent chromosomes while preserving the permutation structure of the demand point sequence. Two crossover points are randomly selected. The segment between these points is copied from the first parent to the child, and the remaining positions are filled with nodes from the second parent in their relative order, avoiding duplicates. For example, if the segment between positions 200 and 400 is copied from Parent 1, the child inherits this segment directly, and the remaining positions are filled by traversing Parent 2's sequence, skipping nodes already present in the child. This ensures that the child remains a valid permutation of customer indices, maintaining feasibility while introducing new route combinations.

Mutation

The mutation operator introduces random variations into chromosomes to preserve genetic diversity and prevent premature convergence. In the proposed method, swap mutation (Syswerda, 1991) is employed to introduce diversity and prevent the GA from getting trapped in local optima. Two positions in the chromosome are randomly selected and swapped (e.g., 300 and 500). Swap mutation is simple yet effective for permutation-based representations, as it directly alters the visit order, allowing the GA to explore alternative route configurations that might reduce the total distance.

Elitism

Elitism is employed to ensure that the so far best-performing solutions are preserved across generations. In each iteration of the GA, a fixed percent of top-ranked chromosomes, $r_{Elitism}$ based on their fitness values, are directly carried over to the next generation without undergoing crossover or mutation. This strategy guarantees that the quality of solutions does not degrade and accelerates convergence by retaining the most promising individuals. By integrating elitism, the algorithm maintains a balance between exploration and exploitation, ensuring steady progress toward optimal or near-optimal solutions. To preserve the best solutions across generations, elitism retains the top $r_{Elitism}$% of the population with the lowest fitness values in each generation. Elitism helps maintain solution quality, especially in later generations when genetic operators might otherwise disrupt high-quality solutions.

Stopping Criterion

The GA runs for n_{itr} generations to balance computational feasibility with solution quality in the context of this large-scale problem. At each generation, the best fitness is recorded to monitor convergence and progress.

The proposed GA solves CMDVRP and produces feasible allocation and routes that serve all demand points while minimizing distance.

4. Implementation and Results

Study Area and Used Data

The proposed method is implemented in west of Tehran's Region 4, around the intersection of Hemmat Expressway and Sayyad Shirazi Expressway, as is displayed in Figure 2 in UTM, Zone 39N projected system. It is a densely populated urban area with significant seismic risk, making it a critical case for post-earthquake aid delivery optimization. This area spans approximately 15 km² and includes diverse neighborhoods with varying infrastructure quality, ranging from modern high-rises to older, seismically vulnerable structures. Its proximity to the North Tehran Fault and high population density amplifies the need for efficient disaster response logistics.

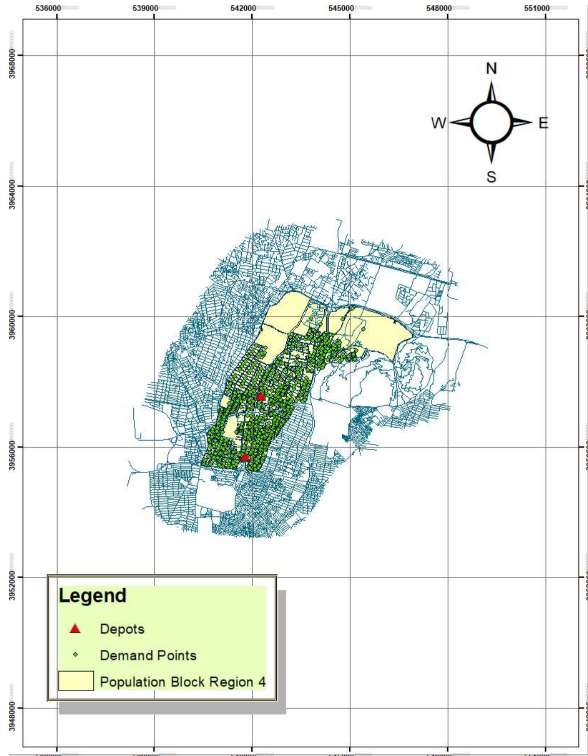

Figure 2. Case area with depots and demand points.

The proposed method is implemented on a dataset consisting of spatial and population data of 649 population blocks as demand points across a defined study area. Also, spatial data of depots and their number of vehicle and their capacity data, and street network are used. The demand points are assigned to n_{depot}=2 depots, each equipped with $n_v = 6$ vehicles. All vehicles have a uniform capacity constraint of $Q = 12800$ units. The total demand across all demand points sums to 153,479 units, requiring efficient allocation and routing to satisfy capacity and coverage constraints. Also, we construct the OD matrix in ArcGIS Network Analyst using the Region 4 road network. The street data are cleaned for connectivity, projected to WGS 84 / UTM Zone 39N (EPSG:32639), and compiled into a network dataset with standard restrictions. The Impedance is set to Meters (distance as cost). An OD Cost Matrix layer is created with origins destinations.

Parameter Tuning and Sensitivity Analysis

The proposed GA is applied to solve earthquake relief problem as a CMDVRP in case area, optimizing routes for 649 demand points across 2 depots, each with 6 vehicles (12,800-unit capacity). Each chromosome in the algorithm represents a set of routes for the vehicles at each depot, and the objective is to minimize the total travel distance while respecting vehicle capacity limitations.

The performance of a Genetic Algorithm is influenced by the choice of its control parameters, such as population size, crossover rate, mutation rate, and elitism rate. To ensure the robustness of our result and to justify the parameter values used in the final simulation, a sensitivity analysis is conducted.

We evaluate the algorithm's performance across a range of parameter values, with the total travel distance after 200 generations as the primary metric. The base configuration is set as follows: population size = 50, crossover rate = 0.8, mutation rate = 0.2, and elitism rate = 0.05 (5%). Each parameter is varied individually while keeping the others at their base value. The results of this analysis are summarized in Table 1.

Parameter	Tested Values	Impact on Final Total Distance
Population Size	30 **50** 70	~302,500, ~297,372, ~297,800
Crossover Rate	0.6 **0.8**	~299,100, ~297,372,
Mutation Rate	0.1 **0.2** 0.3	~298,900, ~297,372, ~299,500
Elitism Rate	0.0 **0.05** 0.10	~298,200, ~297,372, ~298,000

Table 1. Sensitivity analysis of GA parameters.

As Table 2 shows, a smaller population (30) leads to premature convergence and a higher final distance due to insufficient genetic diversity. A larger population (70) provides better exploration but at a significantly increased computational cost without a commensurate improvement in solution quality. The population size of 50 is selected as it offered a good balance between efficiency and effectiveness. In addition, the combination of a high crossover rate (0.8) and a moderate mutation rate (0.2) proves most effective. A lower crossover rate (0.6) slows convergence by reducing the exchange of high-quality genetic material, while a higher mutation rate (0.3) introduces excessive randomness, disrupting good solutions and preventing stable convergence. This confirms that crossover is the primary driver for solution improvement in this problem, while mutation serves to maintain diversity. On the other hand, the analysis validates the choice of a 5% elitism rate. Without elitism (0%), the best solution is occasionally lost between generations, leading to unstable convergence. A higher elitism rate (10%) overly reduces the population diversity available for crossover, stifling exploration and resulting in a slightly inferior final solution.

Based on this systematic analysis, the parameter set of {population size: 50, crossover rate: 0.8, mutation rate: 0.2, elitism rate: 0.05} is identified as the most effective for our specific CMDVRP instance and is used to generate the results.

Results

The GA run for 200 generations with a population of 50 chromosomes, achieving a solution with a total travel distance of 297372.159 meters across 12 routes, serving all demand points. The GA uses tournament selection with a tournament size ($n_{tournament}$) of 3 to select 20 parents from a population of 50, balancing selection pressure and diversity. An OX crossover operator is applied to preserve gene order critical for routing problems. Mutation is performed using swap mutation within routes to maintain diversity without disrupting good solutions. Elitism is implemented to retain the best solutions across generations, improving convergence speed. The choice of 5% elitism is determined through experimentation, balancing the preservation of good solutions with the need for population diversity. The parameter values used in this final run, including the crossover rate of 0.8 and mutation rate of 0.2, were selected based on a systematic sensitivity analysis.

The proposed solution generated by the proposed method is visualized in Figures 3. The solution clearly demonstrates the spatial division of service areas between the two depots. Depot 1 (shown in red) serves demand points located primarily in the southern region of the network, while Depot 2 (shown in blue) covers the northern and eastern zones. Each route begins and ends at its corresponding depot, adhering to the capacity constraint of 12,800 units per vehicle and the maximum fleet size of six vehicles per depot.

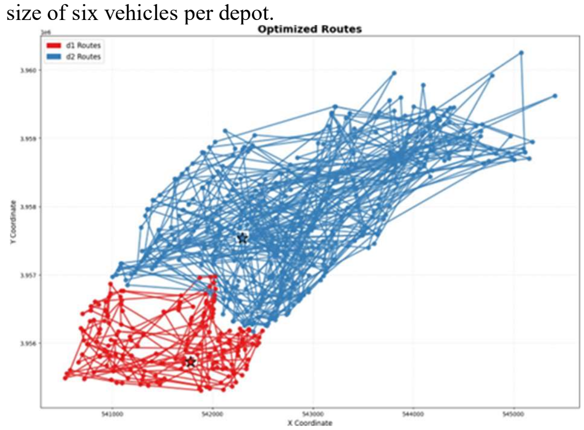

Figure 3. Proposed vehicle allocation for two depots. Routes originating from Depot 1 (d1) are shown in red, and routes from Depot 2 (d2) are shown in blue. Star markers indicate depot locations.

Figures 4 presents the convergence trend of the proposed GA over the course of 200 generations. Starting from an initial population with a best fitness value of 308521.481, the algorithm steadily improved the solutions through genetic operators such as selection, crossover, and mutation. A significant reduction in total travel distance occurred during the first few generations, followed by slower, more gradual improvements. The optimization process ultimately converges to a solution with a cost of 297372.159 units. This result demonstrates the algorithm's efficiency in effectively exploring the solution space and identifying a near-optimal routing configuration.

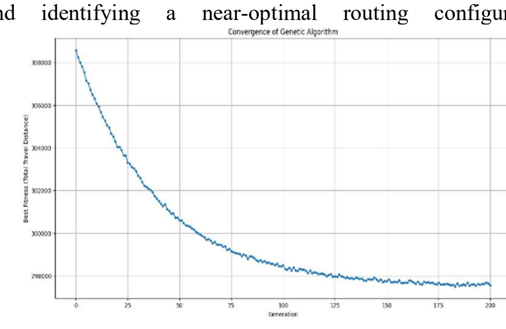

Figure 4. Convergence of the proposed GA over 200 generations

Route statistics provide further insight into the solutions. For the GA, the average route distance is 53093.95 meters, with the longest route at 16007.71 meters, reflecting variability due to the spatial distribution of demand points and depot assignments. Table 2 summarizes these metrics, confirming that the GA satisfies all CMDVRP constraints (e.g., vehicle capacity, customer coverage).

Metric	GA Solution
Total distance (meters)	297372.159
Number of routes	12
Customers served	649
Average route length (meters)	53093.95
Longest route (meters)	16007.71

Table 2. Performance of the proposed GA.

5. Discussion

The purpose of this study was to develop a GIS-integrated optimization framework for post-earthquake humanitarian aid logistics in a dense urban environment. The results demonstrate that the proposed GA successfully solves a large-scale CMDVRP, generating a feasible solution that serves all 649 demand points from two depots with a total travel distance of 297,372.159 meters across 12 routes. The algorithm efficiently managed vehicle capacity constraints and produced a convergent solution, highlighting its applicability to complex disaster relief scenarios.

These findings are consistent with a growing body of literature that applies metaheuristics to complex vehicle routing problems in disaster contexts. For instance, (Pu and Zhao 2024) also reported significant success using a hybrid Multi-Objective Genetic Algorithm combined with Adaptive Large Neighbourhood Search (MOGA-ALNS) for post-earthquake logistics, emphasizing that GAs is highly effective at handling the multiple constraints inherent in such environments. Similarly, (Maroof, Ayvaz et al. 2024) found that hybrid GAs provided robust solutions for the Vehicle Routing Problem with Time Windows (VRPTW), underscoring the algorithm's flexibility and robustness in large-scale, constrained optimization, which aligns with our experience of achieving full demand coverage under strict capacity limits.

The most compelling explanation for the strong performance of our GA is the integration of a problem-aware design within a GIS framework. The cluster-seeded initialization, which assigned demand points to their nearest depot using real road network distances, inherently respected the spatial structure of the problem, reducing the solution space the algorithm needed to explore. This contextual grounding, combined with ordered crossover that preserved route segments, allowed the GA to efficiently exploit spatial contiguity. The results imply that for large-scale, multi-depot routing in a disrupted but static urban network, a well-designed GA can produce highly efficient and practical distribution plans.

Despite these promising results, certain limitations must be acknowledged. A primary limitation is the static nature of the model; it does not account for dynamic post-disaster factors such as changing road accessibility, fluctuating demand, or the arrival of new information. The model's performance is tied to the specific road network structure, population density, and depot configuration of this urban seismic case. Disaster scenarios with different spatial characteristics, such as widespread flooding that disrupts an entirely different set of routes, might yield different results and necessitate model adaptations.

These findings have direct practical implications for disaster preparedness planning. The proposed GIS-to-optimization pipeline provides a replicable methodology for urban authorities to pre-plan relief distribution routes, potentially saving crucial time and resources in the immediate aftermath of an earthquake. By minimizing total travel distance, the model directly contributes to reducing operational costs, including fuel consumption and vehicle wear-and-tear, which is critical for resource-constrained humanitarian organizations. Theoretically, this study contributes to the field by demonstrating the efficacy of embedding spatial intelligence directly into the metaheuristic's initialization process, a strategy that could benefit other spatial optimization problems.

Future research should focus on addressing the identified limitations. A critical next step is to extend the model into a dynamic framework that can incorporate real-time data on road blockages and emerging demand points. To assess generalizability, it is essential to test the proposed methodology in diverse urban and rural settings and adapt it to other disaster scenarios, such as floods or hurricanes, which present unique challenges like different patterns of infrastructure damage and population displacement.

In conclusion, the present research contributes to a growing body of evidence suggesting that genetic algorithms, when thoughtfully integrated with geospatial data and problem-specific knowledge, are a powerful tool for solving complex humanitarian logistics problems. Despite its limitations, this study provides a validated, efficient, and practical framework for optimizing aid distribution, offering a significant step toward more resilient and responsive disaster management systems. The demonstrated reduction in total distance has clear implications for lowering operational costs and improving logistical efficiency, a crucial consideration for all disaster response operations.

6. Conclusion

This study applies a GA to solve the optimize of humanitarian aid logistics as a CMDVRP for earthquake relief in west of Tehran’s Region 4, generating routes for 649 demand points using 2 depots. The GA produces a feasible solution with a total distance of 297372.159 meters across 12 routes, successfully serving all demand points while adhering to vehicle capacity (12,800 units) and depot constraints (6 vehicles each).

The optimized routes ensure demand fulfillment while minimizing travel distance and respecting vehicle capacity constraints. These results highlight the potential of GA as a powerful and flexible algorithm for solving complex logistics challenges, particularly in time-sensitive and resource constrained humanitarian contexts. The results highlight the GA’s ability to produce feasible routes in a complex urban disaster scenario. Also, the integration of GIS tools, such as generating the OD matrix, underscores the importance of spatial analysis in disaster response planning, providing a realistic model of post-earthquake road network.

While the current study demonstrates the effectiveness of a GA in solving post-earthquake aid delivery as a CMDVRP, several avenues remain for further enhancement. One critical area of future research involves the integration of hybrid approaches. By combining the GA with local search techniques; such as SA or TS—the algorithm can exploit both global exploration and fine-grained local exploitation. Also, future models could utilize real-time data on road accessibility and infrastructure damage following earthquakes to enable dynamic and adaptive routing. Finally, expanding the optimization model into a multi-objective framework such as Pareto-based GAs or epsilon-constraint methods, include objectives such as minimizing response time, maximizing population coverage, or balancing supply equity across regions, would allow for a more holistic evaluation of disaster relief effectiveness.

References

Allen, S., 2017: "A two stage vehicle routing algorithm applied to disaster relief logistics after the 2015 nepal earthquake." arXiv preprint arXiv:1709.00162.

Davis, L., 1985: Applying adaptive algorithms to epistatic domains. IJCAI.

Ermagun, A. and N. Tajik, 2023: "Multiple-drones-multiple-trucks routing problem for disruption assessment." Transportation Research Record 2677(2): 725-740.

Goldberg, D. E. and K. Deb, 1991: A comparative analysis of selection schemes used in genetic algorithms. Foundations of genetic algorithms, Elsevier. 1: 69-93.

Karakatič, S. and V. Podgorelec, 2015: "A survey of genetic algorithms for solving multi depot vehicle routing problem." Applied Soft Computing 27: 519-532.

Lakzaei, S., et al., 2023: "Integrated optimal scheduling and routing of repair crew and relief vehicles after disaster: a novel hybrid solution approach." Annals of Operations Research 328(2): 1495-1522.

Long, S., et al., 2023: "Two-stage multi-objective stochastic model on patient transfer and relief distribution in lockdown area of COVID-19." International Journal of Environmental Research and Public Health 20(3): 1765.

Maroof, A., et al., 2024: "Logistics optimization using hybrid genetic algorithm (hga): a solution to the vehicle routing problem with time windows (vrptw)." IEEE Access 12: 36974-36989.

Mguis, F., et al., 2014: Distributed and guided genetic algorithm for humanitarian relief planning in disaster case. Distributed Computing and Artificial Intelligence, 11th International Conference, Springer.

Miller, C. E., et al., 1960: "Integer programming formulation of traveling salesman problems." Journal of the ACM (JACM) 7(4): 326-329.

Ni, Q. and Y. Tang, 2023: "A bibliometric visualized analysis and classification of vehicle routing problem research." Sustainability 15(9): 7394.

Osman, I. H., 1993: "Metastrategy simulated annealing and tabu search algorithms for the vehicle routing problem." Annals of Operations Research 41(4): 421-451.

Potvin, J.-Y., 2009: "State-of-the art review—Evolutionary algorithms for vehicle routing." INFORMS Journal on computing 21(4): 518-548.

Pu, X. and X. Zhao, 2024: "Post-Earthquake emergency logistics location-routing optimization considering vehicle three-dimensional loading constraints." Symmetry 16(8): 1080.

Syswerda, G., 1991: "Schedule optimization using genetic algorithms." Handbook of genetic algorithms.

Vonolfen, S., et al., 2011: Solving large-scale vehicle routing problem instances using an island-model offspring selection genetic algorithm. 3rd IEEE International Symposium on Logistics and Industrial Informatics, IEEE.

Xu, P., et al., 2023: "Energy saving-oriented multi-depot vehicle routing problem with time windows in disaster relief." Energies 16(4): 1992.

This contribution has been peer-reviewed. The double-blind peer-review was conducted on the basis of the full paper.
https://doi.org/10.5194/isprs-annals-X-4-W8-2025-457-2026