GIS-BASED OPTIMIZATION OF DISASTER RELIEF LOGISTICS IN EARTHQUAKE-AFFECTED URBAN AREAS

KEY WORDS: Disaster Response, Earthquake Relief, Vehicle Routing Problem, Multi-Depot, Genetic Algorithm

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. Delivering humanitarian aid effectively in such scenarios is complex, as it requires addressing the spatial distribution of affected areas, prioritizing needs, and ensuring rapid response. This study tackles these challenges by modeling and addressing the allocation and routing of aid for earthquake relief in Tehran's Region 4. A genetic algorithm (GA) is employed to solve the Multi-Depot Vehicle Routing Problem (MDVRP), 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 740,690.97 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, with ongoing efforts to improve performance.

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. Countries situated on active tectonic fault lines, such as Iran, 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, infrastructure status, and rapidly changing conditions. Despite growing interest in optimization methods for disaster logistics, current research often focuses on simplified scenarios involving single depots or static routing frameworks, which do not accurately reflect the operational realities of megacities (Long et al. 2023)

Moreover, many existing models lack integration with 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). Recent reviews highlight that many routing models prioritize computational speed over the practical feasibility of routes, particularly in the face of infrastructure damage and uneven spatial demand in urban areas (Ni and Tang 2023).

This study addresses these gaps by focusing on the Multi-Depot Vehicle Routing Problem (MDVRP), an extension of the classical Vehicle Routing Problem (VRP), which involves dispatching aid from multiple depots to several demand points under time and capacity constraints. The MDVRP is particularly relevant in earthquake response scenarios, where infrastructure damage, time sensitivity, and resource limitations add significant complexity (Ermagun and Tajik 2023). By modeling a real-world case in Region 4 of Tehran, this study proposes a solution tailored to the urban disaster context.

To tackle the MDVRP, we apply a Genetic Algorithm (GA), a bio-inspired optimization technique known for its flexibility and robustness in solving NP-hard problems. GAs are well-suited for dynamic disaster scenarios due to their ability to handle large solution spaces and adapt to complex constraints (Maroof et al. 2024). Recent advances also show the effectiveness of hybrid GAs in improving convergence rates and solution quality by incorporating local search techniques (Shamsipoor 2024). Compared to other methods, such as Ant Colony Optimization or Particle Swarm Optimization—GAs offer a balanced trade-off between computational efficiency and solution robustness, particularly in scenarios with high constraint complexity.

The proposed GA-based solution optimizes the distribution of aid across 12 routes, achieving a total travel distance of 740,690.97 meters. By integrating GIS-driven spatial analysis, this study ensures practical route feasibility in the context of Tehran's urban landscape. The work contributes a scalable, GIS-based framework for post-earthquake aid delivery, addressing both methodological and practical gaps in disaster response logistics.

Section 2 surveys the relevant literature. Section 3 details the methodology, including MDVRP formulation, GA implementation, and data preparation. Section 5 presents the results, including visualizations of the GA's performance, and Section 6 outlines conclusions and future directions for enhancing the model's performance.

2. LITERATURE REVIEW

The VRP 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 and simulated annealing on benchmark instances. Potvin notes that GAs excel 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. The authors discuss 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. They note that GAs often outperform traditional heuristics in scenarios requiring scalability and flexibility, such as logistics in dynamic environments.

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, modeled 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.

(Xu et al. 2023) further advance the application of GAs in disaster relief by addressing the Energy Saving-Oriented Multi-Depot Vehicle Routing Problem with Time Windows (ESMD-VRPTW). Their two-stage approach first uses a Floyd-NL algorithm to minimize travel costs and then applies a GA with a large neighborhood search (GA-LNS) to optimize delivery schemes for electric vehicles. The study emphasizes energy efficiency and time constraints, whcih 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) model 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 allocates locations to vehicles via an integer program, and the second stage employs heuristics for routing. While the study does not use GAs, it provides 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 scalable MDVRP 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.

3. METHODOLOGY

3.1 VRP Formulation and Constraints

This study addresses the Multi-Depot Vehicle Routing Problem (MDVRP), an extension of the classic Vehicle Routing Problem (VRP), designed to optimize aid delivery routes in post-earthquake scenarios. The VRP aims to determine efficient routes for a fleet of vehicles to serve a set of customers from one or more depots, minimizing total travel distance while adhering to operational constraints such as vehicle capacity and route continuity. The MDVRP adapts this framework to multiple depots, reflecting the complexity of disaster relief in an urban setting like Tehran's Region 4. This subsection formalises the MDVRP 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 nodes $N = \{0, 1, \ldots, n\}$, where nodes $\{0, 1\}$ represent the depots, and nodes $\{2, \ldots, n\}$ denote the customer locations. Each depot $k \in K = \{0, 1\}$ is equipped with a fleet of vehicles, each with a capacity Q units. The demand for customer $i \in N \setminus K$ is denoted d_i. A distance matrix $D = [d_{ij}]$ provides the travel distance between nodes i and j.

Decision Variables. The MDVRP model uses the following decision variables to define 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 ($i, j \in N$, $k \in K$).
- u_{ik}: Auxiliary variable representing the load of the vehicle from depot k after visiting node i, used to eliminate subtours ($i \in N \setminus K$, $k \in K$).

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

$$\text{Minimise } Z = \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} d_{ij} \cdot x_{ijk} \tag{1}$$

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

1. **Each Customer Served Exactly Once**: Ensures every customer is visited by exactly one vehicle from any depot, guaranteeing full coverage of demand points.

$$\sum_{k \in K} \sum_{i \in N} x_{ijk} = 1 \quad \forall j \in N \setminus K \tag{2}$$

2. **Vehicle Departure and Return to Depot**: Guarantees that each of the 6 vehicles per depot starts from and returns to its respective depot, maintaining operational consistency.

$$\sum_{j \in N} x_{0jk} = m_k \quad \forall k \in K \tag{3}$$

$$\sum_{i \in N} x_{i1k} = m_k \quad \forall k \in K \tag{4}$$

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

$$\sum_{i \in N} x_{ijk} = \sum_{i \in N} x_{jik} \quad \forall j \in N, k \in K \tag{5}$$

4. **Capacity Constraint**: Limits the vehicle load to 12,800 units, accounting for cumulative demand and preventing overloading using the Miller-Tucker-Zemlin (MTZ) subtour elimination approach.

$$u_{ik} \leq Q \quad \forall i \in N \setminus K, k \in K \tag{6}$$

$$u_{ik} \geq d_i \quad \forall i \in N \setminus K, k \in K \tag{7}$$

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

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

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

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

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

$$u_{ik} \geq 0 \quad \forall i \in N \setminus K, k \in K \tag{11}$$

This formulation captures the MDVRP's complexity, tailored to the post-earthquake relief needs of Tehran's Region 4, where spatial distribution, vehicle constraints, and infrastructure damage are critical factors. The genetic algorithm, detailed in the next subsection, provides a heuristic solution to this NP-hard problem, balancing computational feasibility with practical route design for disaster response.

3.1.1 Genetic Algorithm A Genetic Algorithm (GA) is a population-based metaheuristic inspired by natural selection, evolution, and genetics. Unlike deterministic methods, GAs operate by evolving a pool of candidate solutions via reproduction, mutation, and recombination, guided by a fitness function that evaluates route efficiency (Ochelska-Mierzejewska et al. 2021). In each iteration (a "generation"), superior individuals are probabilistically selected to breed offspring, ensuring that beneficial solution substructures—known as "building blocks"—are preserved and propagated.

The MDVRP is an NP-hard problem, exacerbated by the large number of demand points and multi-depot constraints. GAs efficiently navigate large solution spaces, providing near-optimal solutions where exact methods are computationally infeasible (Potvin 2009). Unlike traditional heuristics, such as nearest-neighbor approaches, GAs maintain solution diversity, reducing the risk of suboptimal solutions (Sulianta n.d.). (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. GAs, with their population-based approach and flexible operator design, are better suited for the complex, constraint-heavy MDVRP in this study. In conclusion, the GA's attributes—large-scale optimization, constraint adaptability, and robustness—make it an ideal choice for solving the MDVRP

Figure 1 illustrates the GA process, which is detailed in the following.

Chromosome Representation

Chromosome Representation defines how candidate solutions are encoded. Each chromosome represents a complete routing plan, often as a sequence or structured assignment of customers to vehicles and depots. In our implementation, a chromosome is represented as a dictionary structure specifically designed. Each chromosome encodes a complete solution by mapping each depot to a sequence of customers assigned to it. Depot identifiers serve as keys, and their corresponding values are lists of customer nodes associated with those depots. During the initialization process, customer lists are randomly shuffled to promote genetic diversity in the population. In addition, customers who are marked isolated, due to factors such as disconnected network links or missing data, are excluded from the chromosome.

Initial Population

In the genetic algorithm, the initial population provides the starting solutions for the evolutionary process. Each chromosome in the population represents a candidate solution to the Vehicle Routing Problem and is initialized by randomly shuffling the list of customers assigned to each depot. In our implementation, chromosomes are represented as a dictionary where depot keys are associated with randomly ordered customer lists. Isolated or invalid nodes are excluded during initialization to ensure feasibility. This randomized yet depot-aware construction introduces diversity into the population, which is essential for effective exploration in subsequent generations.

Fitness Function

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 genetic algorithm toward more optimal routing configurations in subsequent generations.

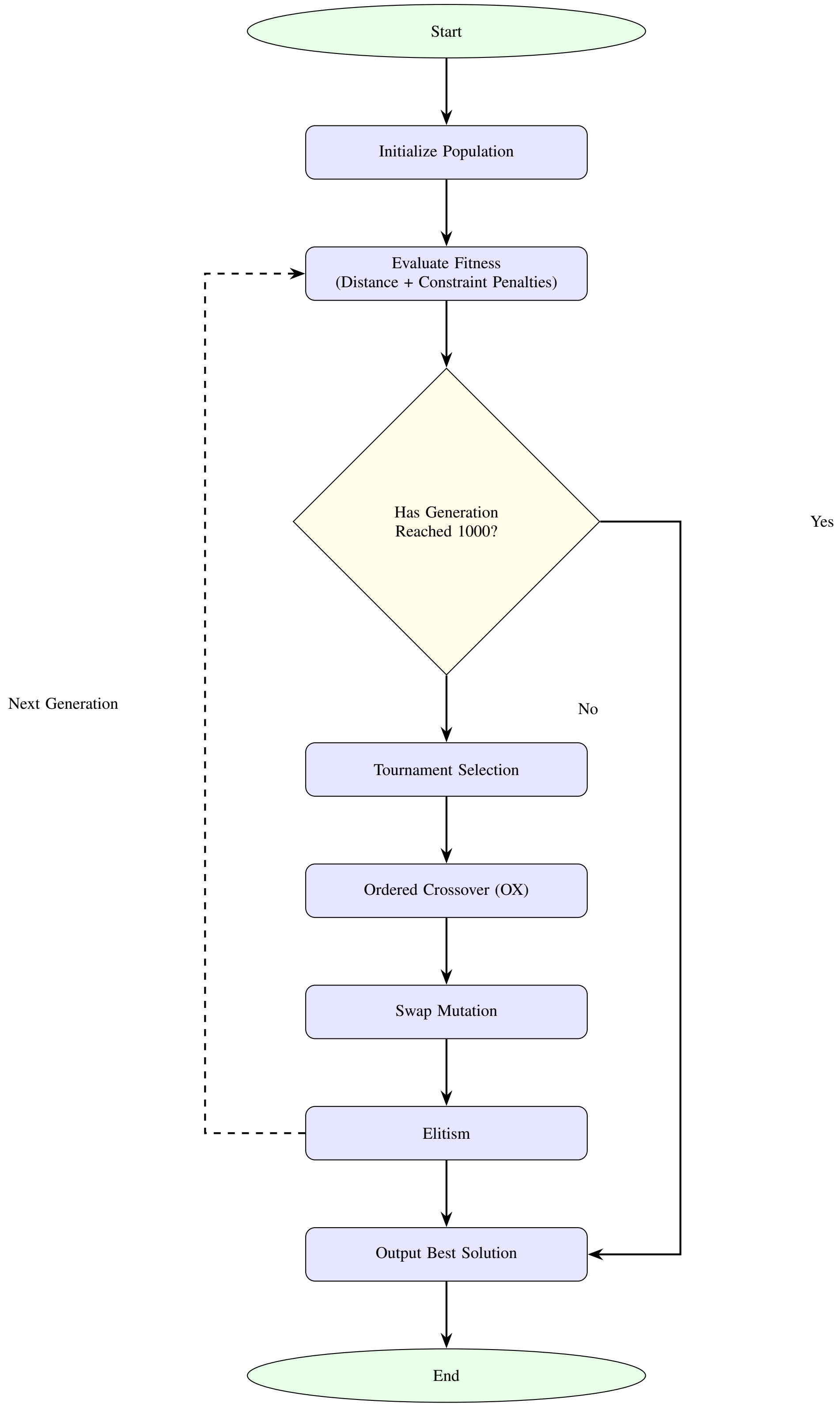

Figure 1. Flowchart of the Genetic Algorithm process used for solving the Multi-Depot Vehicle Routing Problem (MDVRP).

Selection

The selection process in the genetic algorithm is responsible for choosing parent chromosomes from the current population to participate in the generation of offspring. Tournament selection is used to choose parents for reproduction, balancing selection pressure and population diversity. In each tournament, a subset of 5 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 less fit solutions a chance to contribute,

Crossover

The crossover operator is applied to selected parent chromosomes to generate new offspring by combining segments of their genetic material. Ordered crossover (OX) is applied to combine parent chromosomes while preserving the permutation structure of the customer 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. Swap mutation 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., customer 300 and customer 500). The decaying mutation rate ensures higher exploration in early generations and more exploitation as the algorithm converges. 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 best-performing solutions are preserved across generations. In each iteration of the genetic algorithm, a fixed number of top-ranked chromosomes, 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 5% (5 chromosomes) 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. The choice of 5% elitism was determined through experimentation, balancing the preservation of good solutions with the need for population diversity.

Stopping Criterion

The GA runs for 1000 generations, a value chosen 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.

This GA implementation effectively navigates the MDVRP's complexity, producing feasible routes that serve all customers while minimizing distance.

4. IMPLEMENTATION

The proposed genetic algorithm was implemented on a dataset consisting of 649 demand points distributed across a defined service area. These points are assigned to two depots, each equipped with $m_k = 6$ vehicles. All vehicles have a uniform capacity constraint of $Q = 12800$ units. The total demand across all customers sums to 153,479 units, requiring efficient allocation and routing to satisfy capacity and coverage constraints. 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.

Study Area

The study focuses on Tehran's Region 4, a densely populated urban area with significant seismic risk, making it a critical case for post-earthquake aid delivery optimisation. Region 4 spans approximately 15 km^2 and includes diverse neighbourhoods 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 (over 53,000 residents per km^2) amplify the need for efficient disaster response logistics. (Figure 2) showcase our study area.

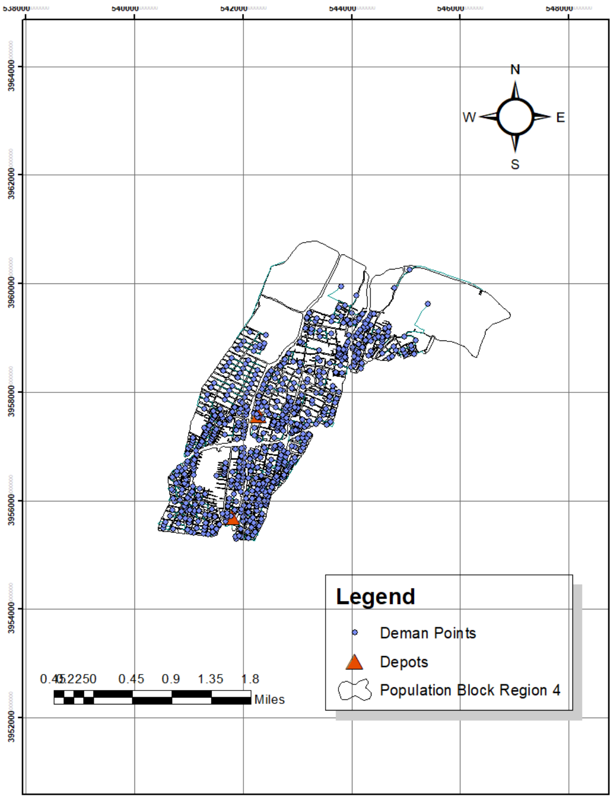

Figure 2. Map of Region 4 of Tehran with Depots and Demand points.

Data Collection and Preparation

Data for this study were sourced from two primary files: Real Data file which contains spatial and demand information for the nodes in the study area, reflecting the post-earthquake scenario and OD matrix, which provide the necessary inputs for the MDVRP formulation and GA implementation, capturing the spatial and logistical characteristics of the region.

Origin-Destination Matrix: The OD matrix file provides the distance matrix D, capturing travel distances between all pairs of nodes in the network. This matrix was generated using ArcMap, a GIS software tool, where spatial data from a shapefile was utilised to digitise Region 4's road network.

Preprocessing. Data preprocessing was conducted to ensure compatibility with the MDVRP model and to reflect the post-disaster environment accurately:

1. **Node Indexing**: Nodes were re-indexed to align with the problem definition, with depots at indices 0 and 1, and customers from 2 to 650, simplifying the implementation of the GA and mathematical model.

2. **Isolated Node Removal**: Nodes with no feasible connections (infinite distances to all other nodes due to complete road destruction) were identified and excluded during preprocessing, resulting in a final set of 649 customers.

3. **Clustering** : Before route optimization begins, demand points must be assigned to depots based on proximity to ensure efficient and localized vehicle routing. To achieve this, a clustering step was implemented using a distance-based grouping function. The function iterates through all customer nodes and, for each, calculates its distance to all available depots using a precomputed distance matrix. Each customer 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 customers for which it is the closest service center. This method ensures that customers are grouped logically, reducing overall travel cost and simplifying the route planning problem.

4. **Distance Matrix Adjustment**: The distance matrix was converted into a square matrix D of size 651×651, with diagonal entries set to 0 (no self-loops) and infinite distances preserved for infeasible routes, ensuring the model accounts for realistic travel constraints.

Additional preprocessing steps included normalising the demand values to ensure consistency with vehicle capacity units and verifying the spatial coordinates for accuracy using ArcMap's georeferencing tools. This dataset provides a realistic representation of the post-earthquake logistics challenge in Tehran's Region 4, enabling the GA to optimise routes while accounting for spatial distribution, demand variability, and infrastructure constraints.

5. RESULTS

The genetic algorithm (GA) was applied to the Multi-Depot Vehicle Routing Problem (MDVRP) for earthquake relief in Tehran's Region 4, optimizing routes for 649 demand points across 2 depots, each with 6 vehicles (12,800-unit capacity). The GA ran for 1000 generations with a population of 50 chromosomes, achieving a solution with a total travel distance of 740,690.97 metres across 12 routes, serving all customers.

Route statistics provide further insight into the solutions. For the GA, the average route distance was 53093.95 metres, with the longest route at 16007.71 metres, reflecting variability due to the spatial distribution of demand points and depot assignments. Table 1 summarizes these metrics, confirming that the GA satisfies all MDVRP constraints (e.g., vehicle capacity, customer coverage).

Metric	GA Solution
Total distance (metres)	740,690.97
Number of routes	12
Customers served	649
Avg. route length (metres)	53093.95
Longest route (metres)	16007.71

Table 1. Performance of the Genetic Algorithm.

The optimized routing solution generated by the proposed genetic algorithm is visualized in Figures 3. The optimized routing solution generated by the proposed genetic algorithm is visualized in Figure X. The solution clearly demonstrates the spatial division of service areas between the two depots. Depot 1 (shown in red) serves customers 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.

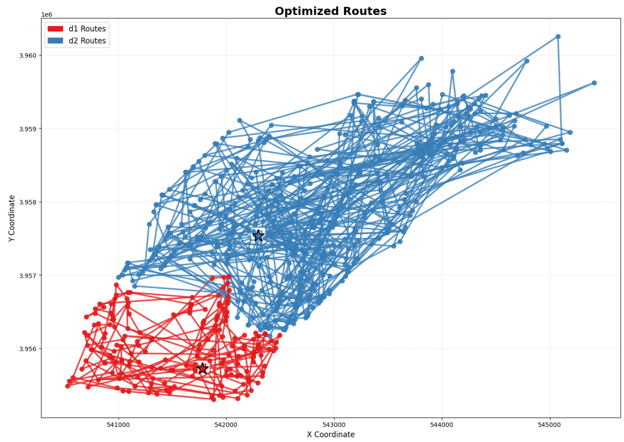

Figure 3. Optimized vehicle routes for two depots. Routes originating from Depot 1 (d1) are shown in red, and routes from Depot 2 (d2) are shown in blue. Star markers indicate depot locations.

Figures 4 presents the convergence trend of the genetic algorithm over the course of 1000 generations. Starting from an initial population with a best fitness value of 1,263,074.13, 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 hundred generations, followed by slower, more gradual improvements. The optimization process ultimately converged to a best solution with a cost of 740,690.97 units, representing a 41.4% reduction from the initial solution. This result demonstrates the algorithm's efficiency in effectively exploring the solution space and identifying a near-optimal routing configuration.

These findings highlight the GA's ability to produce feasible routes in a complex urban disaster scenario but underscore the

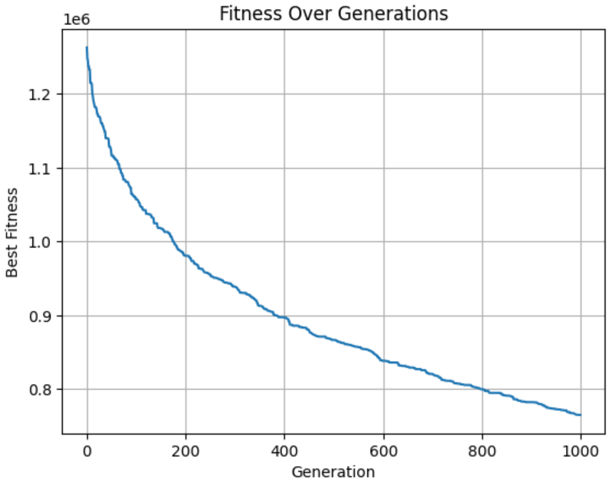

Figure 4. Convergence of the Genetic Algorithm over 1000 generations.

need for further optimization to reduce travel distances. Potential improvements, such as hybridizing the GA with local search heuristics or adjusting its parameters, are discussed in the conclusions.

6. CONCLUSIONS

This study applied a genetic algorithm (GA) to solve the Multi-Depot Vehicle Routing Problem (MDVRP) for earthquake relief in Tehran's Region 4, generating routes for 649 demand points using 2 depots. The GA produced a feasible solution with a total distance of 740,690.97 metres across 12 routes, successfully serving all customers 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 genetic algorithms as a powerful and flexible tool for solving complex logistics challenges, particularly in time-sensitive and resource-constrained humanitarian contexts.

The integration of GIS tools, such as ArcMap for generating the distance matrix, underscores the importance of spatial analysis in disaster response planning, providing a realistic model of Tehran's post-earthquake road network.

Future Research Directions

While the current study demonstrates the effectiveness of a Genetic Algorithm (GA) in solving the Multi-Depot Vehicle Routing Problem (MDVRP) for post-earthquake aid delivery, several avenues remain for further enhancement. One critical area of future research involves parameter optimization within the GA framework. Fine-tuning parameters such as increasing the population size (e.g., to 200 individuals) or implementing a decay schedule for the mutation rate could yield more refined solutions. These adjustments are expected to enhance convergence stability and improve the overall quality of the routing plans, particularly in large-scale scenarios.

Another promising direction is the integration of hybrid approaches. By combining the GA with local search techniques—such as simulated annealing or Tabu Search—the algorithm can exploit both global exploration and fine-grained local exploitation. This hybridization would allow for more precise minimization of route distances and better handling of local optima, potentially leading to significant improvements in route efficiency and computational time.

Incorporating dynamic constraints represents a third key development. Future models could utilize real-time data on road accessibility and infrastructure damage following earthquakes to enable adaptive routing. Integrating such data would make the system responsive to changing ground conditions, thereby increasing its operational relevance and reliability in real-world humanitarian missions.

Finally, expanding the optimization model into a multi-objective framework would allow for a more holistic evaluation of disaster relief effectiveness. Beyond minimizing total travel distance, future iterations of the model could include objectives such as minimizing response time, maximizing population coverage, or balancing supply equity across regions. This can be achieved using advanced multi-objective optimization techniques, including Pareto-based GAs or epsilon-constraint methods, providing a richer decision-making toolkit for emergency planners and logistics coordinators.

Together, these enhancements aim to evolve the current GA-based model into a more robust, adaptive, and operationally realistic tool for disaster relief logistics.

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