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Dynamic Road-Network Hybrid Optimization for Vehicle-Based Emergency Evacuation (Case Study: Qom)

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ABSTRACT

Urban evacuation is a typical complex-system problem in which heterogeneous agents, capacity-limited shelters, and time-varying road conditions interact on a large network. This study proposes a hybrid optimization framework for vehicle-based emergency evacuation that combines an exact baseline solved by DOcplex Python with metaheuristic algorithms, namely, GWO, GA, PSO, and SA, to preserve solution quality under both static and dynamic conditions. The model instantiates a multivehicle, multidepot routing setting with two evacuee classes (injured/noninjured), multiple vehicle types (bus-ambulance, bus, minibus), and dual shelter categories (hospital/residential), embedded on a GIS-derived road graph. On a real network from District 8, Qom (Iran), the exact layer delivers the best performance in normal traffic (e.g., mean evacuation time ≈ 79.4 min vs. 85.1–93.8 min for metaheuristics), under crisis conditions involving road closures and counterflow; however, the GWO- and GA-based approaches produce the most effective routes, with evacuation times of approximately 93.4–93.6 min, without requiring full reoptimization. This two-layer design treats evacuation as control on a changing network, balancing optimality (when feasible) with adaptability (when conditions shift), and demonstrates measurable gains in clearance time and operational resilience. The results highlight how hybrid computation and network-aware dynamics can bridge the gap between theoretically optimal routing and real-time decision support in disasters.

1 | Introduction

Emergency evacuation planning is a key part of managing disasters. It helps move people safely and quickly from dangerous areas to safe locations. As disasters often happen without warning, emergency response teams must use well-organized plans that include transportation, resource management, and coordination to reduce harm and save lives [1–3].

One of the main challenges in evacuation planning is dealing with the complex and changing conditions of real emergencies. Most traditional models, like the vehicle-routing problem (VRP), are too simple. They often treat all evacuees the same and do not consider the different needs of injured people who need medical care versus healthy individuals who just need transport [4]. In addition, emergency fleets are often made up of different types of vehicles—such as buses, minibuses, and ambulance-buses—which makes route planning and resource use even more difficult.

The multivehicle multidepot routing problem (MVMDRP) provides a more realistic way to plan evacuations, but most existing models assume fixed road conditions and static travel times. This limits their usefulness during real disasters, when road accessibility may change due to blockages, infrastructure damage, or emergency traffic management measures [5]. Hospitals also play an important role during evacuations. They are not just shelters, but also centers for providing urgent care. Their performance during a crisis has a direct effect on how well the whole evacuation plan works [6]. However, many existing models still do not take into account the differences in evacuee needs or the variety of vehicles used. This leads to poor route planning and inefficient use of resources. The MVMDRP model can help solve this by including multiple depots, vehicle types, and shelter types [7], but more advanced approaches are still needed to deal with real-world problems.

This shows a clear gap in the research. Some studies use exact mathematical models, which work well for small or simple problems but are too slow for large, real-time emergencies. Others use metaheuristic algorithms, which can handle bigger problems more quickly, but do not guarantee the best solution. Since evacuation planning is an NP-hard problem, it is very hard to solve with exact methods when the scale is large and conditions are changing. Metaheuristic methods—such as genetic algorithms (GAs), particle swarm optimization (PSO), and grey wolf optimization (GWO)—are more flexible and efficient and have been used in recent years for complex routing problems [8–10]. However, these approaches alone are not enough when conditions change rapidly, like during disasters.

While exact models are ideal for small, simple problems, they are too slow for large, real-time emergencies. Conversely, metaheuristic algorithms are faster for larger problems but do not guarantee the best solution. The hybrid model combines the strengths of both, providing a solution that is both optimal under normal conditions and flexible during crises. This bridges the gap between theoretical and practical applications. To solve this problem, this study presents a hybrid optimization framework for emergency evacuation that combines the strengths of both exact and metaheuristic methods. The proposed framework adopts a two-layer optimization strategy to address both accuracy and computational efficiency in evacuation planning. In the first layer, an exact mixed-integer linear programming (MILP) model solved using the DOcplex[1] solver in Python determines optimal evacuation routes under stable network conditions, providing a benchmark optimal solution. In the second layer, four metaheuristic algorithms—GWO, GA, PSO, and simulated annealing (SA)—are implemented to rapidly generate high-quality near-optimal solutions when emergency conditions cause network instability or increased computational complexity. This hybrid structure enables the model to maintain solution optimality in normal scenarios while ensuring fast and robust decision-making during dynamic crisis situations where exact optimization alone may become computationally impractical. Modeling Real-World Needs: The model is built as an MVMDRP that includes two types of evacuees (injured and noninjured), different kinds of vehicles, multiple depots, and two types of shelters (hospitals and residential shelters). Several studies in evacuation modeling adopt within-day dynamic traffic assignment (DTA) approaches that explicitly represent network congestion and user routing behavior. For example, Marcianò et al. propose a system of models and procedures for signal-setting design in road networks under evacuation conditions, incorporating DTA and path-choice modeling to capture how signal timing affects user behavior and network performance during an evacuation scenario. Similarly, other work by the same research group presents within-day simulation procedures that estimate path flows under equilibrium constraints and endogenous signal settings, illustrating how dynamic network conditions influence evacuation performance [11]. These approaches typically involve detailed traffic assignment models where link travel times and route choices are updated in response to dynamic flow conditions. DTA models aim to capture the temporal evolution of network performance, demand, and user routing choices in a time-varying context and are frequently used to model emergency evacuations where demand peaks and network capacities change over time.

In contrast, the present study adopts a vehicle-routing perspective rather than a flow-based equilibrium assignment. Here, discrete changes in the network structure—such as road closures and counterflow activations—are incorporated via timetable-based updates, and travel times are recomputed using shortest-path algorithms at each discrete time step, without explicitly modeling traffic flow equilibrium or within-day congestion evolution. This represents a different modeling philosophy: Rather than simulating the evolution of network flows and assignment (as in DTA), we focus on the combinatorial optimization of vehicle routes under evolving structural constraints. Handling Crisis Situations: The model incorporates a discrete-time travel-time updating mechanism in which road closures and counterflow operations modify network accessibility at predefined intervals. Travel times are recalculated after each structural change, and evacuation routes are reoptimized accordingly.

Real Case Study: The model is tested using a real road network from District 8 of Qom, Iran, with data from the Osmnx library. This shows how the model can be applied in real cities and helps make the results more useful for real emergency planning.

By reducing total evacuation time and adapting to both stable and emergency conditions, this study supports more effective, fair, and fast evacuation strategies. It also helps decision-makers improve emergency response and disaster preparedness, which are important goals for building sustainable and resilient cities.

2 | Literature Review

Research on evacuation planning spans two major modeling perspectives: The first perspective is vehicle routing–based evacuation optimization, which focuses on assigning vehicles to pick-up locations, shelters, and depots; and the second is traffic assignment–based models, including DTA and within-day/day-to-day frameworks, which capture congestion propagation, path choice, and flow–supply interaction at the network level. The present study belongs to the first category and incorporates discrete, time-indexed structural network disruptions, distinguishing it from within-day congestion-flow models.

Emergency evacuation routing is a critical application of the MVMDRP, widely studied for its complexity and real-world relevance in disaster response planning. Numerous studies have investigated related topics, including ambulance dispatch, bus-based evacuation, and the use of metaheuristic algorithms to enhance routing efficiency. However, conventional VRP models often fall short in capturing key real-world challenges, such as the heterogeneity of evacuees, real-time traffic disruptions, and varying vehicle capabilities, which are essential for optimizing large-scale emergency evacuations.

Traditional VRP-based evacuation models often simplify key operational factors such as evacuee heterogeneity, road-network disruptions, and heterogeneous fleet behavior, all of which can substantially affect evacuation performance in practice. While the literature includes both exact optimization methods for small-scale scenarios and metaheuristic approaches for larger, more complex problems, few studies integrate both strategies while accounting for dynamic disaster conditions.

Moreover, few studies combine exact and heuristic optimization while explicitly modeling structural, time-indexed network disruptions that influence routing decisions during emergencies.

2.1 | Vehicle Routing–Based Evacuation Models

Azadeh et al. [12] proposed a hybrid model that combines the MVMDRP with the close-open mixed VRP (COMVRP), assuming a heterogeneous fleet of vehicles with varying characteristics and capacities. Their approach integrates a mixed-integer programming (MIP) model with a hybrid metaheuristic algorithm and the analytic hierarchy process (AHP). The performance of this method was compared against a traditional GA and a commercial MIP solver, demonstrating promising results in routing optimization [12].

Esposito Amideo et al. [13] propose SISLER, a scenario-indexed two-stage MILP that integrates the shelter location (Stage 1) with vehicle-based evacuation (Stage 2)—assigning car zones to shelters and routing buses on a disrupted road network while maintaining fixed travel-time assumptions within each scenario. The objective minimizes the (probability-weighted) maximum bus completion time, with a lexicographic tie-breaker adding total car travel time so self-evacuees are not sacrificed.

Methodologically, equity is enforced by a time-threshold and a willingness parameter for cars, restricting assignments to shelters. SISLER is solved exactly via CPLEX Branch-and-Cut, strengthened by two problem-specific valid inequalities (a bus "round-up" bound and an MCFP-based flow bound) inserted at the root node [13].

Woo and Kang [14] formulate a city-scale, congestion-aware evacuation–relief problem that jointly selects which shelters to open, routes evacuation buses, accounts for car evacuees under user equilibrium (UE), and routes relief-supply trucks, with the goal of minimizing total cost (shelter operation + car/bus evacuation time + relief transport).

Methodologically, they use a bilevel program: The upper level is a capacitated fixed-charge shelter-location model minimizing the total system cost; the lower level is a UE traffic assignment that implements dynamic virtual links from each active shelter to a sink so that destination choice (which shelter cars select) emerges endogenously while enforcing shelter capacities under congestion [14]. Unlike vehicle-level routing approaches, their framework explicitly models flow-dependent congestion and equilibrium-based travel-time evolution. In contrast, the present study does not simulate within-day congestion dynamics but instead updates link travel times at discrete time intervals to represent structural network disruptions such as road closures and counterflow operations. In contrast, the present study does not simulate within-day congestion dynamics, but instead, updates link travel times at discrete time intervals to represent structural network disruptions such as road closures and counterflow operations.

Kulshrestha et al. [15] tackle transit-based evacuation planning under uncertain demand (unknown numbers of transit-dependent evacuees), deciding where to locate pick-up points and how to allocate buses to move people to shelters while minimizing total evacuation time. They formulate a robust mixed-integer linear program and solve it via a cutting-plane scheme so the plan performs well across demand realizations (not just a single forecast). Key modeling choices include evacuees walking to their nearest pick-up, fixed shelter locations/capacities, and buses assigned to one pick-up making multiple round trips to shelters; travel times between pick-ups and shelters are taken as given. In tests on the Sioux Falls network, the robust plan is both reliable and efficient, cutting total evacuation time by ∼9% vs. a worst-case design, whereas a nominal (deterministic) plan meets demand in only ∼2% of simulated cases—highlighting the value of robust planning under uncertainty [15].

Zheng [16] addresses bus-based mass evacuation in which buses operate continuously (demand-responsive) rather than on fixed routes, using the spatiotemporal distribution of evacuee demand to plan operations; it formulates a deterministic mixed-integer optimization model that minimizes exposed-casualty time and derives routing/operating strategies for the bus fleet under shelter-capacity and network travel-time constraints, solved via a Lagrangian relaxation–based algorithm, outperforming fixed-route baselines by reducing total exposure time [16].

However, network topology is assumed fixed during optimization. For operations, they design bus-routing rules (multitrip tours from depots to pick up points, capacity thresholds, and return-to-nearest-shelter logic tied to network travel times) and a truck-routing heuristic from the distribution center to shelters; solution quality is boosted by an evolutionary algorithm with a local-search add/drop and swap procedure that reuses previous TA results to keep computation tractable. Applied to an Ulsan (Korea) flood network, the approach outperforms nearest-shelter baselines and shows that ignoring congestion can underestimate evacuation time by ∼41% (and relief costs by ∼44%), underscoring the need for congestion-coupled, multimodal planning in vehicle-based evacuations. However, unlike congestion-flow modeling approaches, the present study focuses on discrete-time updates of link travel times to represent structural disruptions rather than modeling flow-dependent equilibrium dynamics.

Building on dynamic traffic considerations, Anuar et al. [17] introduced the MDDVRPSRC with stochastic road capacity (MDDVRPSRC), an extension of the deterministic MDVRP with road capacity constraints (D-MDVRPRC). They developed a two-stage stochastic integer linear programming (SILP) model—MDVRPSRC-2S—and validated it using small simulated instances and the CPLEX solver. To address real-time complexity, they also proposed a metaheuristic solution and employed reduced two-stage models to generate routing policies under scenario-based capacity uncertainty [17].

Uslu et al. [18] addressed postdisaster logistics through the lens of the stochastic demand multidepot VRP (SDMD_VRP), applied to a case study in Ankara, Turkey. Their model incorporated stochastic demand to reflect uncertainty in humanitarian relief efforts. By developing a mathematical model under uncertainty, the study demonstrated the practical value of VRP extensions in postdisaster scenarios [18].

Focusing on public transport during emergencies, Vitali et al. [19] explored bus-routing optimization for evacuation. Their goal was to minimize total evacuation time by identifying optimal bus routes from high-risk zones to safe shelters. Using a greedy randomized adaptive search procedure (GRASP), they showed that combining greedy and local-search strategies could generate high-quality solutions efficiently—making their approach suitable for real-world application [19].

In the context of emergency medical services, Tlili et al. [20] proposed a GA-based solution to optimize ambulance routing. Their approach, designed as an open and simplified ambulance routing problem (ARP), utilized a customized recombination agent to evolve candidate solutions iteratively. The objective was to enhance the speed and efficiency of patient transport, especially under pressure from increased EMS response times [20].

Tavakkoli-Moghaddam et al. [21] expanded on the EMS response by introducing a dual-objective optimization model that simultaneously addresses the location of temporary emergency stations and optimal ambulance routing. Their model considered key objectives such as response time, operational cost, and patient categorization. This integrated planning framework supports more effective EMS deployment in disaster scenarios [21].

In the context of wildfire emergencies, Zhang et al. [22] integrate GWO with graph neural networks and multiagent reinforcement learning to dynamically optimize evacuation routes under rapidly changing fire conditions, reducing travel time while improving safety through real-time path weight adaptation [22]. In contrast to such learning-based and continuously adaptive routing approaches, the present study adopts a deterministic framework in which link travel times are updated at discrete intervals to reflect predefined structural disruptions.

2.2 | Traffic Assignment–Based Evacuation Modeling: Dynamic, Semidynamic, and Within-Day Approaches

A parallel stream of evacuation research relies on traffic assignment models—DTA, semidynamic assignment, and within-day simulation. These approaches model time-dependent traffic flow evolution and emphasize network loading, congestion propagation, and UE relationships.

Traffic assignment models are classified into static, semi-dynamic, and dynamic categories based on temporal treatment. In DTA, route choice occurs over discrete periods, while smaller time steps handle network loading, enabling detailed modeling of temporal congestion [23, 24].

Within-day evacuation assignment has been advanced by Marcianò, Vitetta, and colleagues, who propose a signal-setting framework with equilibrium constraints. The model determines the signal parameters and simulates within-day path-choice and flow redistribution. Travel demand flows must remain consistent with travel times, ensuring flow equilibrium throughout the evacuation horizon.

Other DTA-based studies focus on calibrating link/node models using empirical evacuation data to simulate traffic-control strategies and congestion patterns.

Explicit day-to-day learning is generally absent in these evacuation studies; they instead address short-term within-event dynamics.

Although powerful for modeling aggregate flows and equilibrium effects, these models differ fundamentally from vehicle-routing approaches, which treat evacuees as discrete units. The present study follows the VRP paradigm and updates link travel times discretely to represent structural disruptions rather than modeling flow-dependent dynamics.

Despite these significant advancements, critical gaps persist. Most existing VRP-based evacuation models assume static demand, fixed vehicle assignments, and stable road networks—conditions that rarely hold true in actual disaster events. Moreover, the combined use of exact and metaheuristic methods remains underexplored, despite its potential to balance computational efficiency with solution quality.

To address these gaps, the present study introduces a hybrid framework that combines exact linear programming (via DOcplex) for optimal routing under stable conditions with metaheuristic algorithms (GWO, GA, PSO, and SA) for rapid decision-making when discrete-time structural network changes occur. Travel times are updated at predefined intervals to reflect evolving road availability—without invoking within-day flow-equilibrium modeling. Embedding this mechanism within an MVMDRP structure and applying it to a real urban network improves operational realism while maintaining computational efficiency.

2.3 | Problem Definition and Mathematical Formulation

Graph G, which shows the road network in District 8 of Qom in Iran, includes different collection points for both types of evacuees including injured (Type 0) and noninjured (Type 1). Figure 1 illustrates the collection points for both types of evacuees, along with shelters for noninjured and a hospital shelter for injured people.

The emergency evacuation of vehicles contains several components as follows.

- Evacuees: This group includes people who should be transported from the danger zone to designated shelters. Both types of evacuees are hypothesized in the problem. Furthermore, the total number of evacuees and evacuees of each group is hypothesized.

  A. Injured people (Type 0 evacuees)

  B. Noninjured people (Type 1 evacuees)

- Vehicles: Totally, two types of vehicles participate in the emergency evacuation.

  A. Type 1 vehicles: These vehicles include buses and minibuses, which transport noninjured people (Type 1 evacuees). The maximum capacity of each bus and minibus is hypothesized to be 80 and 50 people, respectively.

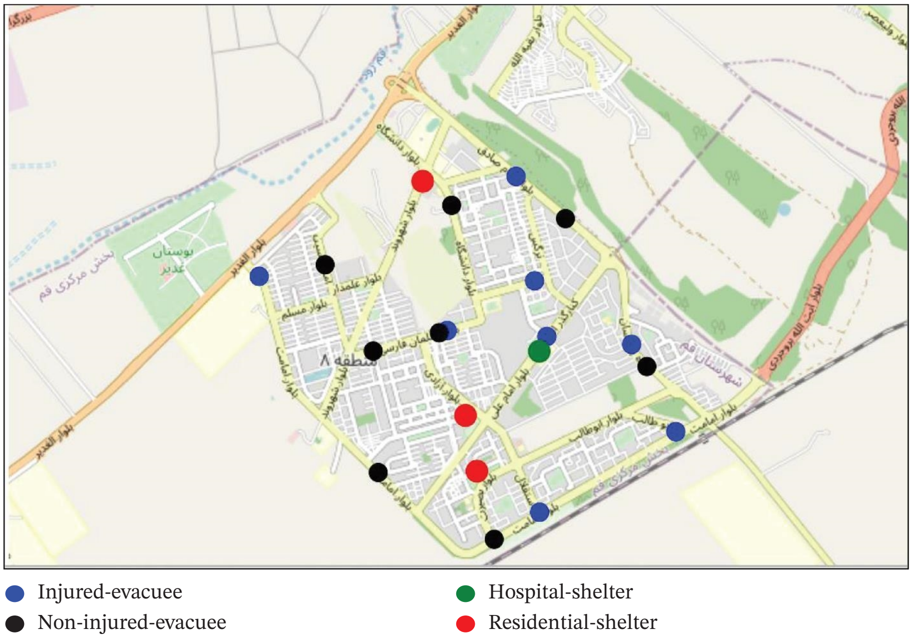

FIGURE 1 | Location of evacuee collection points, shelters for noninjured people, and hospital shelters in the study area.

   B. Type 0 vehicles: These vehicles include bus-ambulances, which transport injured people (Type 0 evacuees). The maximum capacity of each bus-ambulance is hypothesized to be 13 people.

- Shelters: Totally, two types of shelters are hypothesized in the emergency evacuation process in the problem.
   A. Residential shelter: These shelters are regarded as places in which noninjured people (Type 1 evacuees) are transported by Type 1 vehicles (buses and minibuses) from evacuee collection points to these types of shelters.
   B. Hospital: This shelter is hypothesized to be the origin and destination of bus-ambulance trips to provide services to injured people (Type 0 evacuees).
- Depot: The emergency evacuation process for noninjured people (Type 1 evacuees) starts from this point. The depot, which is among the residential shelters in the model, is demonstrated in graph G by N_0. The depot is a place in which buses and minibuses are stationed at the beginning of the emergency evacuation process.
- Evacuee collection points: These points, which are located throughout the study area, are employed by Type 1 (buses and minibuses) and Type 0 vehicles (bus-ambulances) to transport evacuees to shelters. Evacuees are allocated to shelters to minimize travel distance for each vehicle and ensure an efficient evacuation process. The emergency evacuation process for noninjured people (Type 1 evacuees) starts from the depot, which is displayed in graph G by N_0. Then, the evacuees are transferred to one of the places designated for noninjured people (Type 1 evacuees), which are called residential shelters. The abovementioned points are shown in graph G by N_2 or N_3.

The emergency evacuation process for injured people (Type 0 evacuees) starts from the hospital, which is illustrated by N_1 in graph G. The Type 0 evacuees are transferred to the hospital, meaning that the starting and ending points of the travel are the same for these types of evacuees. Figure 2 demonstrates the evacuees, evacuee collection points, residential shelter, hospital, depot, and general concept of the evacuation process.

The following hypotheses are presented as the basis for the linear evacuation planning model. These hypotheses are recognized as the basis for defining the constraints and conditions, which form the pillar of the decision-making process related to the allocation of evacuees to shelters and determination of vehicle routes.

- Based on the hypothesis, the number of evacuees and their final destination (residential shelter or hospital) are predetermined.
- Based on the hypothesis, the number of vehicles available for emergency evacuation is predetermined.
- Based on the hypothesis, each shelter can accommodate all of the people.
- Hospital is considered the starting and ending point of the travel for injured people (Type 0 evacuees).
- The starting point of the travel for noninjured people (Type 1 evacuees) starts at the depot and ends at one of the residential shelters to minimize the total travel time.

The main indices, sets, and problem parameters are summarized in Table 1.

The decision variable in the aforementioned problem is as follows:

$$x_{ij}^{u} = \begin{cases} 1, & \text{if the vehicle } u \text{ uses the arc } (i,j), \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

Minimizing the total cost (hypothesized travel time), which is regarded as a combination of travel time between nodes and

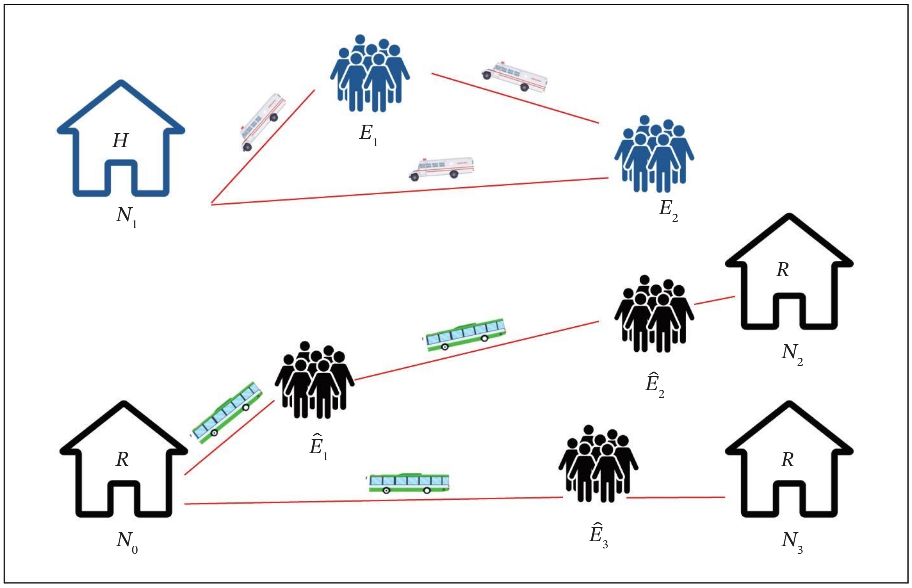

FIGURE 2 | General process of emergency evacuation for both groups of evacuees.

TABLE 1 | Index, set, and problem parameters.

	Indices and sets		
$i, j and k\widetilde{S}$			Index of a node in N set
$\overline{S}$			Shelter of Type 0 set
			shelter of Type 1 set
$\widehat{S}$	$\widehat{S} = \widetilde{S} \cup \overline{S}$		Shelter set
$\widetilde{E}$			Evacuee of Type 0 set
$\overline{E}$			Evacuee of Type 1 set
E	$E = \widetilde{E} \cup \overline{E}$		
L	$L = \overline{S} \cup \overline{E}$		Shelters and evacuee of Type 1
W	$W = \widetilde{S} \cup \widetilde{E}$		Shelters and evacuee of Type 0
N	$N = \widehat{S} \cup E$	$N = L \cup W$	Set of nodes
u_1			The first type of vehicle set (vehicle of Type 0)
u_2			The second type of vehicle set (vehicle of Type 1)
u	$u = u_1 \cup u_2$		Set of vehicles
Parameters			
τ_{ij}			Travel time from node i to node j at time interval t
μ_i			Service time for node i
S_i^u			Starting time for vehicle u at node i
C_u			Capacity of vehicle in set u
U			Size of the fleet of vehicles

binary decision variables representing the vehicle routes, is recognized as the objective function.

$$\min Z = \sum_{u=1}^{U_1} \sum_{i \in L} \sum_{j \in L} \left(\tau_{ij}(t) . x_{ij}^u\right) + \sum_{u=1}^{U_0} \sum_{i \in W} \sum_{j \in W} \left(\tau_{ij}(t) . x_{ij}^u\right). \quad (2)$$

At each discrete time interval t, travel time is denoted as $\tau_{ij}(t)$. Travel times are computed based on the shortest path between nodes i and j on the updated road-network graph G. Travel times remain constant within each time interval and are recalculated only when structural network changes occur (e.g., road closures or counterflow activation). Travel times are deterministic and are not modeled as flow-dependent functions of traffic volume. So, travel time is denoted as $\tau_{ij}(t)$ represents a deterministic shortest-path travel time on the updated network at time t, rather than a flow-dependent congestion function.

In the revised objective formulation, the first summation accounts for the total travel time of Type 1 vehicles (buses and minibuses) operating over the node set L, which includes the depot, collection points for noninjured evacuees, and residential shelters. The second summation accounts for the total travel time of Type 0 vehicles (bus-ambulances) operating over the node set W, which includes the hospital and collection points for injured evacuees.

It is worth noting that in the set L, point L_0 indicates the depot and is equivalent to point N_0, while in the set W, point W_0 represents the hospital and is equivalent to point N_1.

The evacuation process is modeled over discrete time intervals. At the beginning of each interval t, the road-network graph G is updated to reflect structural modifications such as road closures or counterflow operations. Following each update, the travel-time matrix $\tau_{\text{ij}}(t)$ is recalculated using shortest-path algorithms on the modified graph. Within each time interval, travel times are treated as constant and deterministic. The model does not incorporate within-day traffic assignment, UE modeling, or flow-dependent congestion effects. Instead, dynamic conditions are represented through time-indexed structural updates followed by route reoptimization.

3 | Methodology and Solution Approach

An outline of the steps to implement the code in Python is as follows:

- Class definitions: The first step in implementing the model in Python involves defining three classes of evacuee, shelter, and vehicle. These types of data classification represent the entities involved in the problem, namely, evacuees, shelters, and vehicles. Each class has characteristics that represent information about the entities in the form of a group.
- Model decision variables: These variables include m.x_var to determine the arc through which the vehicle in question traverses.
- Discrete-time network updating mechanism: This part includes a predefined timetable in which structural network modifications such as road closures and counterflow operations are specified. At the beginning of each time interval t, the road-network graph is updated and the travel-time matrix τij(t) is recalculated using Dijkstra's algorithm. Travel times remain constant within each interval and are updated only when network state changes occur. Accordingly, τij(t) represents a deterministic shortest-path travel time on the updated network at time t, rather than a flow-dependent congestion function. The model does not incorporate flow-dependent congestion or within-day traffic assignment.
- Within this framework, the study adopts a pretrip optimization perspective with discrete network updates. At each iteration of the optimization process, vehicle routes are recalculated based on the current structural state of the network defined in the scenario, such as road closures or counterflow implementation. Travel times are computed according to the updated network structure; however, they are not dynamically adjusted based on traffic flow evolution or congestion propagation. Vehicles do not receive continuous real-time en-route guidance, and route selection is reoptimized only when predefined structural network changes occur according to the timetable. The exact solution of the problem is modeled under stable network conditions, while structural disruptions are activated according to the timetable.
- The optimization algorithms GWO, SA, PSO, and GA are employed to minimize total travel time by encoding vehicle routes as candidate solutions. Each algorithm is executed under both stable and disrupted network conditions. Parameter settings are defined explicitly (population size, iteration number, crossover and mutation rates for GA; swarm size and coefficients for PSO; population size for GWO; initial temperature; and cooling rate for SA) to ensure the reproducibility of results.

The specific parameter settings used for each metaheuristic algorithm are summarized in Table 2.

The parameter values were selected to ensure a fair comparison across algorithms while preserving algorithmic efficiency and manageable runtime. A fixed iteration number (10) was adopted to evaluate algorithm performance under identical computational budgets. The swarm and population sizes were chosen to balance exploration capability and runtime efficiency. For PSO, the cognitive and social coefficients were set equally (0.5) to provide balanced individual and collective learning. In SA, the initial temperature (1000) and cooling rate (0.95) were selected to allow sufficient early exploration while ensuring gradual convergence. These settings were validated through preliminary testing to ensure stable algorithm behavior.

Due to the moderate size of the case-study network and to maintain comparability between static and disruption scenarios (5 normal + 5 crisis iterations), a fixed iteration limit of 10 was adopted.

The parameter values were selected following preliminary sensitivity experiments conducted on the case-study network. The objective was to ensure a balance between exploration capability and computational efficiency.

Given the moderate size of the network and demand set, relatively small population sizes (10–30) and iteration limits (10) were adopted to maintain comparable computational effort across metaheuristics. This ensures that differences in performance reflect algorithmic characteristics rather than computational budget.

For SA, the initial temperature (1000) was chosen sufficiently high to allow exploration in early iterations, while the cooling rate (0.95) ensures gradual convergence without premature stagnation.

In the GWO algorithm, a slightly larger population (30) was adopted to enhance leader-based exploration mechanisms.

The penalty value used in the MILP formulation (200,000) was selected to strongly discourage leaving evacuees unassigned while still allowing feasibility in extreme network conditions.

- Objective function: The objective function in this model is defined to minimize the total travel time of vehicles. The objective function is formulated as the summation of time-

TABLE 2 | Parameter settings of metaheuristic algorithms.

Method	Key parameters	Values used in this study	Notes for reproducibility
Exact MILP (DOcplex)	Unassigned-evacuee penalty	200,000	Implemented via binary variables in the objective.
	Unreachable links	$\tau_{ij} = \infty$ (No-path)	Computed from OSMnx shortest paths; infeasible pairs are marked as infinity in the travel-time matrix.
GA	Population size	10	population_size = 10
	Generations	10	generations = 10
	Mutation rate	0.1	mutation_rate = 0.1
	Selection	Top 50%	population = population [: population_size//2]
	Crossover	Uniform per vehicle	Each vehicle route copied from parent1 or parent2 with prob. 0.5
PSO	Number of particles	10	num_particles = 10
	Max iterations	10	max_iterations = 10
	Velocity update	Scalar placeholder	Uses cost differences to update a scalar "velocity" (per your script).
	Position update	Neighbor move (swap)	Particle updated by route-swap neighbor operator.
GWO	Population size	30	population_size = 30
	Max iterations	10	max_iterations = 10
	Leaders	(α, β, γ)	Best three solutions after sorting by cost each iteration.
	Movement operator	Partial route adoption	Wolf partially adopts target route with randomness (as in move_towards).
SA	Max iterations	10	max_iterations = 10
	Initial temperature	1000	initial_temp = 1000
	Cooling rate	0.95	cooling_rate = 0.95
	Acceptance rule	Metropolis	Accept if ($\Delta < 0$) or ($r < \exp(-\Delta/T)$).

indexed travel times $\tau ij(t)$ over all selected arcs, weighted by the binary routing decision variables.

- Problem solving: The model is solved by minimizing the objective function, the output of which includes the optimal routes and corresponding travel time.

In the model under discussion, Dijkstra algorithm, implemented through the nx.shortest_path_length package from the networkx library, is applied to calculate the shortest distance between two given nodes in a graph. The nx. Shortest_path_length function calculates the shortest path length by selecting the travel time as the weight parameter for computing the shortest distance between two nodes in a given graph, considering the weights assigned to its edges or arcs. The abovementioned algorithm determines the shortest path and provides its length as output. In the graph, the real coordinates of the points including the latitude and longitude of each node are employed to calculate the shortest path. To this aim, a Python package called Osmnx is used to retrieve the real information in the road network under study [25]. Algorithm 1 presents the structured pseudocode of the main optimization procedure to ensure the clarity and reproducibility of the implementation. Finding the most optimal paths with minimum total travel time for the emergency evacuation process in District 8 of Qom is considered the solution sought in the problem. District 8 contains a depot, two residential shelters, and a hospital. Furthermore, 16 evacuee collection points including eight ones for injured people (Type 0 evacuees) and eight others for noninjured people (Type 1 evacuees) are hypothesized in this area, along with a fleet containing five Type 0 vehicles (bus-ambulance) and four Type 1 ones (three buses and one minibus) to optimize the vehicle routing for minimizing the total travel time while satisfying the demand and service constraints for each location.

A timetable is utilized to change the road situations and implement structural disruption scenarios during crisis conditions. The following definitions are activated in this set for some roads in some iteration.

- Closure: All of the edges (roads) corresponding to road names are found and their weight (travel time) changes to infinity, representing inaccessibility of the road.
- Counterflow: The travel time is multiplied by 1.5 for the corresponding edges to simulate the effect of changing the direction of traffic flow.
- Then, the travel-time matrix is recalculated to reflect the new changes.

The first five iterations are executed under stable network conditions, and the subsequent five iterations activate the disruption timetable to evaluate model performance under structurally modified network states. Table 3 presents the locations of evacuee collection points and shelters, while Table 4 indicates the characteristics of emergency vehicles.

Algorithm 1 presents the structured pseudocode of the exact MILP formulation implemented in Python via the DOcplex modeling framework and solved using the CPLEX optimization engine under fixed travel times within each time interval.

In Algorithm 1, the evacuation-routing problem is solved exactly under fixed travel times corresponding to a given time interval. The model enforces routing feasibility, vehicle capacity, and shelter

TABLE 3 | Characteristics of evacuee collection points and shelters.

Point	Index	Type	Latitude	Longitude	Demand
Depot	0	1	34.57051	50.80683	0
Shelter	1	0	34.55379	50.82096	0
Shelter	2	1	34.542	50.81341	0
Shelter	3	1	34.54748	50.81203	0
Evacuee	4	1	34.56683	50.82414	24
Evacuee	5	1	34.55382	50.80084	68
Evacuee	6	1	34.56814	50.81035	24
Evacuee	7	1	34.55562	50.80883	24
Evacuee	8	1	34.5353	50.8155	18
Evacuee	9	1	34.54187	50.80145	12
Evacuee	10	1	34.5523	50.834	57
Evacuee	11	1	34.5623	50.79501	20
Evacuee	12	0	34.53796	50.821	6
Evacuee	13	0	34.5589	50.83751	5
Evacuee	14	0	34.55448	50.83215	8
Evacuee	15	0	34.55542	50.82188	7
Evacuee	16	0	34.56073	50.8204	9
Evacuee	17	0	34.57099	50.81815	7
Evacuee	18	0	34.55583	50.80981	7
Evacuee	19	0	34.56116	50.78701	3

TABLE 4 | Characteristics of emergency vehicles.

Fleet	Index	Type	Capacity
Bus-ambulance	0	0	13
Bus-ambulance	1	0	13
Bus-ambulance	2	0	13
Bus-ambulance	3	0	13
Bus-ambulance	4	0	13
Bus	5	1	80
Bus	6	1	80
Bus	7	1	80
Minibus	8	1	50

assignment constraints within a MILP framework. For each time interval, the travel-time matrix is treated constant, and the solver computes the optimal routing plan accordingly. This exact solution serves as a benchmark under stable network conditions and provides a reference for evaluating the performance of the metaheuristic approaches under timetable-based structural changes.

The solution procedure based on the GA is summarized in Algorithm 2, which incorporates discrete-time road-network updating through timetable-based closures and counterflow adjustments.

In Algorithm 2, an initial population of feasible evacuation-routing plans is generated and evaluated based on total travel time. At each iteration, the road network is updated according to the predefined timetable, and the travel-time matrix is

ALGORITHM 1 | Exact MILP solution for the evacuation-routing problem.

Input:

Node sets (L, W), vehicle sets (U1, U0),

demands q_i, capacities Q_u,

travel-time matrix $\tau_{ij}(t)$ (fixed within time interval t)

Output:

Optimal routes and objective value $Z\ (t)$

1. Build MILP model M
2. Define binary routing variables x_{ij}^{u}
3. Define objective function Z(t): minimize total travel time

$$Z(t) = \sum_{u=1}^{U_1} \sum_{i \in L} \sum_{j \in L} (\tau_{ij}(t) x_{ij}^{u}) + \sum_{u=1}^{U_0} \sum_{i \in W} \sum_{j \in W} (\tau_{ij}(t) x_{ij}^{u})$$

4. Add routing and feasibility constraints:
   - Flow conservation
   - Depot/hospital start and end conditions
   - Each evacuee served exactly once
   - Vehicle capacity limits
   - Subtour elimination
5. Solve model using CPLEX
6. Extract routes from x_{ij}^{u}
7. Return optimal routes and $Z\ (t)$

recalculated before fitness evaluation. Selection, crossover, and mutation operators are then applied to evolve candidate solutions while preserving feasibility constraints related to vehicle capacity and shelter assignment. This evolutionary process enables adaptive improvement of routing plans under time-indexed structural network changes.

ALGORITHM 2 | Genetic algorithm with discrete-time road-network updating.

Input: Road graph G; shelters; evacuees; vehicles; population size P; generations T; mutation rate μ

Output: Best solution S^*

1. Compute initial distance matrix from G
2. Generate initial feasible population
3. for generation = 1 to T do
4. Update Road conditions according to timetable
5. Recompute distance matrix
6. Evaluate population (total route distance)
7. Select top P/2 solutions
8. Generate offspring via crossover
9. Apply mutation with probability μ
10. Form new population
11. Update best solution
12. end for
13. Return S^*

In this implementation, each particle is a routing solution object, and the "position update" is realized by a neighbor operator (swap between two vehicles). Road-network changes are applied in discrete time steps, and the distance matrix is recalculated after each update. (see Algorithm 3).

To enhance routing performance under time-indexed network disruptions, a GWO metaheuristic is employed. The procedure model's candidate evacuation plans as wolves and iteratively updates them toward the three leading solutions (alpha, beta, and delta). The complete framework is summarized in Algorithm 4.

In Algorithm 4, an initial population of evacuation plans is generated and evaluated based on total travel time and feasibility constraints. At each time step, the road network is updated according to the predefined timetable, and the travel-time matrix is recalculated before re-evaluating all solutions. The three best solutions (alpha, beta, and delta) guide the remaining wolves through adaptive route modifications. This mechanism allows the algorithm to balance exploration and exploitation while responding to structural network disruptions.

ALGORITHM 3 | Particle swarm optimization with discrete-time road-network updating.

Input: road graph G; node set N = nodes (shelters and evacuee points); timetable T; swarm size P; max iterations I

Output: best routing plan and its objective value

1. Compute initial distance matrix using shortest paths on G
2. Construct an initial feasible routing plan
3. Initialize swarm with P particles as neighbors of the initial plan
4. Set each particle's personal best to its current solution
5. Set global best as the best particle in the swarm
6. for t = 1 to I do
7. Update road conditions using timetable T at time step t (closure/counterflow)
8. Recompute distance matrix
9. for each particle do
10. Update routing plan (assign evacuees and shelters)
11. Evaluate total travel cost
12. Update personal best if improved
13. Update global best if improved
14. Update particle position (swap evacuees between vehicles)
15. end for
16. end for

return global best solution

ALGORITHM 4 | GWO for evacuation routing with discrete-time travel-time updating.

Input: road graph G; shelters; evacuee points; vehicles (Type 0/1, capacities); timetable T; population size P; iterations I

Output: best feasible routing plan (Alpha) and its objective values (total cost, evacuation time)

1. Build initial road graph G and compute baseline travel-time matrix

T $\longleftarrow$ ShortestPathTimeMatrix (G, nodes)

2. Construct an initial feasible plan (initialize vehicle start/end shelters; assign evacuees to vehicles)
3. Initialize population:

Create P solutions by making an identical copy of the initial plan and applying small random route perturbations (shuffle/swap/move)

4. Evaluate each solution's fitness (total route travel time + penalties for infeasibility/unreachable links)
5. Set Alpha, Beta, Delta as the 3 best solutions in the population
6. Set current time $t \longleftarrow t_0$
7. for iteration = 1 to I do
8.   Update road conditions using timetable T at time t (closure/counterflow)
9.   Recompute travel-time matrix T←ShortestPathTimeMatrix (G, nodes)
10.   for each wolf (solution) in population do
11.   Update its travel-time matrix T
12.   Reassign evacuees to vehicles (type + capacity + reachability checks)
13.   Compute fitness (route time + penalties); compute evacuation time (sum of vehicle route times)
14.   end for
15.   Sort population by fitness; update Alpha, Beta, Delta
16.   for each non-Alpha wolf do
17.   Move wolf toward Alpha, Beta, Delta (partially adopt their route segments if feasible)
18.   Recompute wolf fitness
19.   end for
20.   t $\longleftarrow t + 1\,\text{min}$
21. end for
22. return Alpha (best plan)

The proposed SA-based evacuation-routing procedure, incorporating discrete-time travel-time updates, is detailed in Algorithm 5.

In Algorithm 5, the initial routing plan is iteratively improved through neighborhood perturbations (e.g., evacuee swaps between vehicles). At each time step, the road network is updated according to the predefined timetable, and travel times are recalculated before evaluating candidate solutions. The acceptance mechanism allows occasional uphill moves based on temperature, enabling the method to escape local minima. The cooling schedule gradually reduces exploration and promotes convergence toward a high-quality evacuation plan.

4 | Results and Discussion

This section examines the effectiveness of the proposed model in solving the real-world emergency evacuation problem, its performance under normal traffic flow and crisis conditions, and model results.

4.1 | Performance Under Normal Traffic Flow Conditions

Tables 5 and 6 show the model outputs under normal traffic flow conditions. As represented, the final value of the objective function (cost) under normal traffic flow conditions in GWO, SA, PSO, and GA equals 5107.18, 5267.64, 5268.36, and 5199.24, respectively. This value equals 4765.1 for the proposed exact solution algorithm, which is regarded as the same in all of the iterations. Thus, the best performance under normal traffic conditions is related to the proposed exact solution algorithm, followed by the GWO and GA, which provide the optimal results of the routing model under emergency conditions.

Table 6 indicates the evacuation time (minutes) presented for each algorithm under normal traffic flow conditions. As shown, the average evacuation time for all of the evacuees under normal conditions applying the GWO, SA, PSO, GA, and proposed exact solution algorithm equals 85.116, 88.618, 93.806, 86.654, and

ALGORITHM 5 | Simulated annealing for evacuation planning.

Input:

Road graph G; shelters; vehicles; evacuees; timetable T;

initial temperature; cooling rate; maximum iterations I

Output:

Best feasible routing plan and its objective value

```
1.  Initialize road network graph with shelters and evacuee nodes
2.  Compute initial travel time matrix using G
3.  Construct an initial routing solution (vehicle assignment + shelter assignment)
4.  current_solution ⟵ initial solution
5.  best_solution ⟵ current_solution
6.  temperature ⟵ initial temperature
7.  for t = 1 to I do
8.      Update G using timetable T at time step t (closure/counterflow)
9.      Recompute travel time matrix using updated G
10.     Generate candidate_solution as a neighbor of current_solution
(e.g., swap evacuees between vehicles)
11.     Assign routes and shelters using updated travel times
12.     Evaluate total travel time of candidate_solution
13.     Compute cost difference Δ
14.     if Δ < 0 then
15.        current_solution ⟵ candidate_solution
16.     else if random () < exp (−Δ/temperature) then
17.        current_solution ⟵ candidate_solution
18.     end if
19.     if current_solution is better than best_solution then
20.        best_solution ⟵ current_solution
21.     end if
22.     temperature ⟵ temperature × cooling_rate
23. end for
24. return best_solution
```

TABLE 5 | Model output cost under normal traffic conditions.

	GWO	SA	PSO	GA	Exact solution utilizing DOcplex
Iteration 1	5177.00	5133.60	5579.40	5048.40	4765.10
Iteration 2	4971.20	5579.40	5561.40	5241.00	
Iteration 3	5331.90	5586.00	5685.00	5264.40	
Iteration 4	5023.30	5068.20	5570.40	5213.40	
Iteration 5	5032.50	4971.00	5745.60	5229.00	
Mean	5107.18	5267.64	5628.36	5199.24	

TABLE 6 | Model output evacuation time (minutes) under normal traffic conditions.

	GWO	SA	PSO	GA	Exact solution utilizing CPLEX
Iteration 1	86.28	92.99	92.99	84.14	
Iteration 2	82.85	93.1	92.69	87.35	
Iteration 3	88.86	84.47	94.75	87.74	79.42
Iteration 4	83.72	82.85	92.84	86.89	
Iteration 5	83.87	89.68	95.76	87.15	
Mean	85.12	88.62	93.81	86.65	

79.42 min, respectively. Therefore, the best performance under normal traffic conditions is related to the proposed exact solution algorithm, followed by the GWO and GA, which provide optimal evacuation time results in the routing model under emergency conditions.

4.2 | Performance Under Crisis (Dynamic) Traffic Conditions

Exact solution is employed for small and simple problems due to its potential in investigating all of the cases and obtaining an optimal solution. For more complex problems where the search space is considered large and travel times are updated at discrete time intervals to reflect predefined structural network disruptions (e.g., closures and counterflow), also metaheuristic algorithms are used due to their flexibility and ability to achieve optimal solutions in a short time. Thus, the exact solution model presented here was not studied in crisis conditions due to its inflexibility with these situations.

The constraints of crisis conditions including closure or counterflow in some roads were modeled in the metaheuristic algorithms utilized here (Tables 7 and 8).

As represented in Table 6, the cost value based on the GWO, SA, PSO, and GA in crisis conditions equals 5618.36, 6032.76, 6118.38, and 5602.92, which are higher than the normal traffic flow conditions. The most optimal value of the emergency routing objective function is observed in the GWO with a slight difference from GA. In other words, these algorithms can be applied in emergency vehicle routing in crisis conditions.

Table 8 presents the evacuation time of evacuees in minutes. Based on the GA, all of the studied evacuees were evacuated in 93.57 min. This value is 100.55, 103.14, and 93.38 min in the SA, PSO, and GA, respectively. Therefore, the GA and GWO can provide the most optimal routing in emergency and crisis conditions.

Figures 3, 4, 5, and 6 display the routes of emergency vehicles in each iteration in metaheuristic algorithms GWO, PSO, SA, and GA to compare routing in solving the emergency evacuation problem in crisis situations (the last ten iterations in each algorithm). Specifically, Figure 3 shows the GWO-based route optimization, Figure 4 presents the PSO-based results, Figure 5 displays the SA-based outcomes, and Figure 6 demonstrates the GA-based route optimization, each comparing normal and crisis scenarios for emergency evacuation.

As shown, different routes are proposed in each of the algorithms due to changing route conditions including the occurrence of closure and activation of counterflow.

TABLE 7 | Value of the model output cost in crisis (dynamic) conditions.

	GWO	SA	PSO	GA
Iteration 6	5646.60	5977.80	5778.00	5390.40
Iteration 7	5474.00	5945.4	6316.2	5453.40
Iteration 8	5501.00	5762.40	6381.60	5576.40
Iteration 9	5662.80	6292.20	6027.60	5760.00
Iteration 10	5807.40	6186.00	6438.00	5834.40
Mean	5618.36	6032.76	6188.28	5602.92

TABLE 8 | Evacuation time (minutes) in crisis (dynamic) conditions.

	GWO	SA	PSO	GA
Iteration 6	94.11	99.63	96.30	89.84
Iteration 7	91.23	99.09	105.27	90.89
Iteration 8	91.68	96.04	106.36	92.94
Iteration 9	94.05	104.87	100.46	96.00
Iteration 10	96.8	103.1	107.3	97.24
Mean	93.57	100.55	103.14	93.38

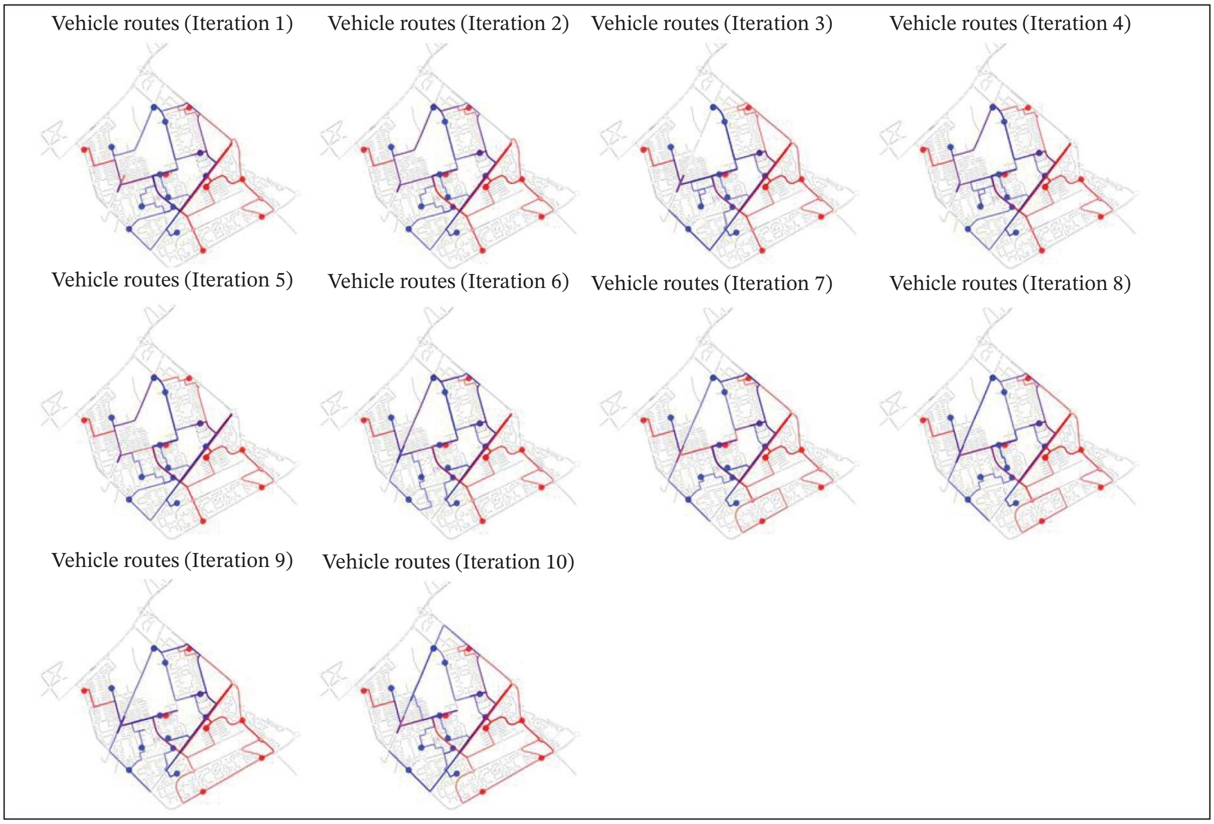

FIGURE 3 | GWO-based route optimization for emergency evacuation: A comparison of normal and crisis scenarios.

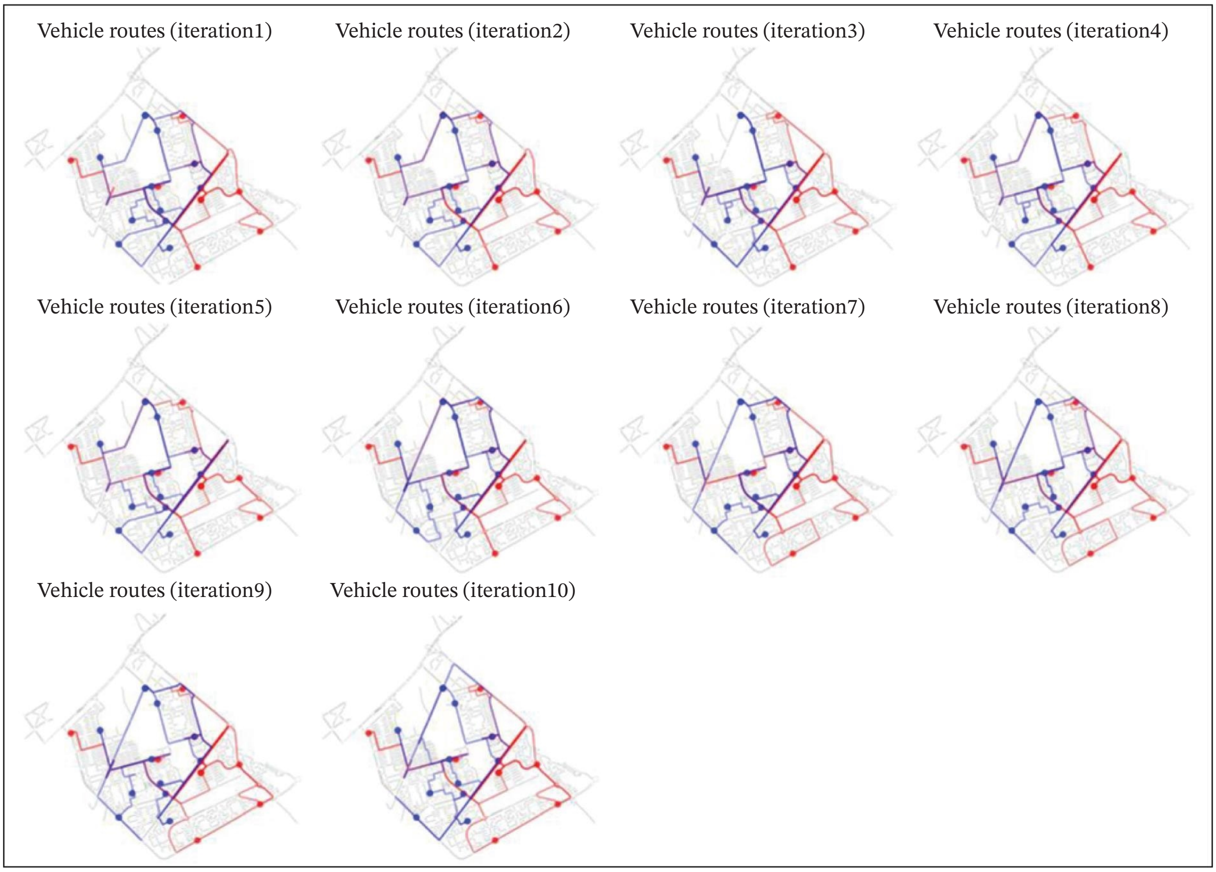

FIGURE 4 | PSO-based route optimization for emergency evacuation: A comparison of normal and crisis scenarios.

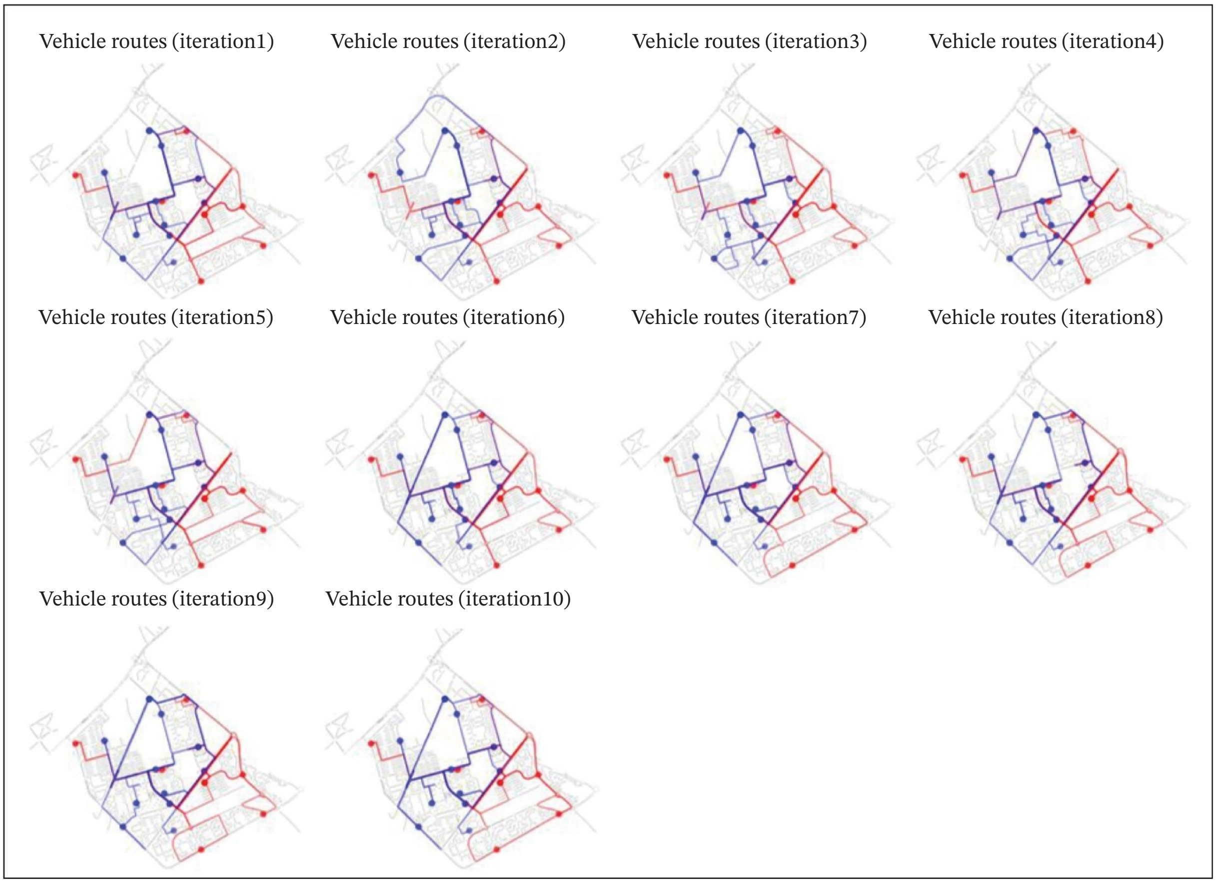

FIGURE 5 | SA-based route optimization for emergency evacuation: A comparison of normal and crisis scenarios.

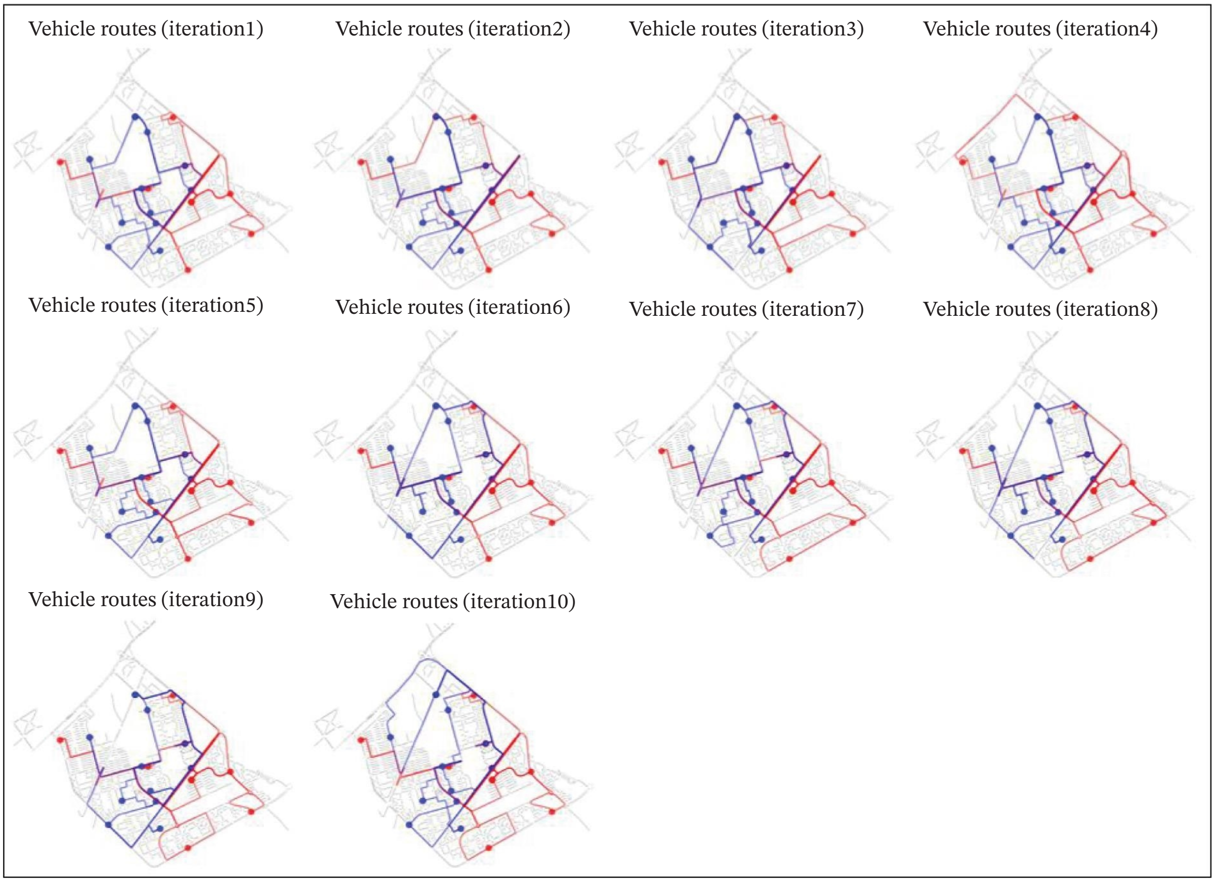

FIGURE 6 | GA-based route optimization for emergency evacuation: A comparison of normal and crisis scenarios.

TABLE 9 | Statistical performance over 10 independent runs (cost in seconds).

Algorithm	Mean	Std dev	Best	Worst
GA	5401.08	260.47	5048.40	5834.40
PSO	5908.92	351.92	5561.40	6438,00
SA	5674.52	460.32	4971,00	6292.20
GWO	5362.77	297.13	4971.20	5807.40

4.3 | Route Adjustments in Crisis Conditions

Figures 3–6 illustrate how different optimization algorithms adjusted emergency vehicle routes in response to road closures and counterflow activations. As observed, each algorithm proposed different evacuation routes, with GWO and GA consistently selecting the shortest and most effective paths under crisis conditions.

4.4 | Comparison With Previous Studies

The findings align with prior research on metaheuristic algorithms for emergency evacuation, confirming that GWO and GA provide robust solutions for dynamic crisis scenarios [11, 16]. Unlike conventional VRP studies that assume static evacuee demand and fixed road conditions, this study incorporates real-time crisis scenarios, making it more applicable to real-world disaster management. By integrating road-network disruptions (closures, counterflow) and evaluating algorithm performance under both normal and crisis conditions, this study bridges the gap between static evacuation models and real-time adaptive routing approaches. The results highlight the practical advantages of hybrid metaheuristic solutions, particularly GWO and GA, in handling large-scale and time-sensitive evacuations.

4.5 | Statistical Validation of Results

To account for stochastic variability, each metaheuristic algorithm was executed independently 10 times using different random seeds. The mean, standard deviation, best, and worst objective values are reported in Table 9.

To strengthen the comparison, a one-way ANOVA ($\alpha = 0.05$) was applied to test whether differences in mean performance among the four algorithms were statistically significant. The results confirmed that the algorithms do not belong to the same statistical population, indicating significant performance differences. Post hoc Tukey tests showed that GWO performed significantly better than PSO and SA, while its difference with GA was smaller but still statistically meaningful. As a complementary robustness measure, 95% confidence intervals were also computed for the mean objective values, showing that GWO had the narrowest interval, confirming its stability.

The descriptive results also support these findings. GWO achieved the lowest mean objective value (5362.77 seconds) with relatively low variability, demonstrating high reliability. GA provided competitive performance with moderate variance, while SA achieved the best single solution but exhibited the highest inconsistency across runs. PSO showed both the highest mean evacuation time and the largest spread, indicating poorer robustness. Overall, GWO offered the best balance between solution quality and stability.

5 | Conclusion

This research presents a comprehensive emergency evacuation-routing model that balances operational efficiency with sustainability goals. To this aim, two types of vehicles (bus and minibus for noninjured evacuees and bus-ambulance for injured ones), along with different collection points and shelters, were hypothesized within the area. The presented model aimed to minimize the total travel time for the emergency evacuation process while ensuring efficient allocation of evacuees to shelters and determining optimal routes for all of the emergency vehicles involved in the emergency evacuation process.

The problem was formulated in the form of a linear mathematical model, and an algorithm was presented to find the optimal routes and corresponding travel time. This model included decision variables which indicate the routes traveled by the emergency vehicles. The applied restrictions bound the model to the specific conditions of the problem. Here, Dijkstra algorithm was employed to calculate the shortest distance between nodes in the graph related to Qom.

The exact model was solved under normal traffic conditions using a static CPLEX-based implementation, and its reliability was assessed by comparing its results with those obtained from four metaheuristic algorithms (GWO, SA, PSO, and GA). The proposed algorithm was implemented statically in CPLEX Python under normal traffic conditions, and its reliability was evaluated by comparing its results with those of four metaheuristic algorithms (GWO, SA, PSO, and GA). The optimal routes in each algorithm were calculated by solving the model to minimize the total travel time. In the next step, the results were presented. The final value of the objective function (cost) in normal traffic flow conditions in the GWO, SA, PSO, and GA equaled 5107.18, 5267.64, 5268.36, and 5199.24, respectively. This value equaled 4765.1 for the proposed exact solution algorithm, which was regarded as the same in all of the iterations. On average, the evacuation time for all of the evacuees under normal conditions equaled 85.116, 88.618, 93.806, 86.654, and 79.42 min using the GWO, SA, PSO, and GA and proposed exact solution algorithm, respectively. The results represented the superiority of the exact solution model under normal traffic conditions. In addition, the validity of the model was confirmed based on the values obtained from the metaheuristic models. The GWO algorithm performed best after the proposed exact solution model under normal traffic flow conditions.

In emergency (crisis) conditions, the proposed exact solution model was not reviewed due to its inflexibility with dynamic conditions, as well as limitations in search space and analysis time. In these conditions, the final value of the objective function (cost) in the case of routing or utilizing the GWO, SA, PSO, and GA equaled 5618.36, 6032.76, 6118.28, and 5602.92, which are higher than the normal traffic flow conditions. The evacuation time for all of the evacuees in the case of routing or applying the GWO, SA, PSO, and GA was 93.57, 100.55, 103.14, and 93.38 min, respectively. The GA and GWO algorithms performed the best and provided optimal routes in emergency or crisis conditions.

Overall, the proposed exact solution model produced optimal routing results under normal traffic conditions, whereas GA and GWO were more suitable for crisis situations where the network structure and travel times evolve through discrete update steps.

5.1 | Limitations of the Study

Despite the effectiveness of the proposed model in optimizing emergency evacuation routing, several limitations exist. The model assumes a static evacuee demand, meaning the number and destination of evacuees are predetermined and do not change dynamically over time. Additionally, the model does not account for real-world constraints such as vehicle breakdowns, fuel limitations, or varying shelter capacities, which may impact evacuation efficiency. Furthermore, while the exact solution model performs optimally under normal traffic conditions, it lacks flexibility in crisis situations, as it cannot efficiently handle dynamic changes in road conditions such as closures or counterflow activations. Another limitation is the single-objective focus on minimizing total travel time, whereas other important factors such as vehicle usage minimization or equitable evacuee distribution are not considered. Lastly, the model does not incorporate human behavioral factors, such as delayed evacuations or noncompliance with designated routes, which could influence the evacuation process.

5.2 | Future Suggestion

To enhance the effectiveness and practicality of emergency evacuation routing, several directions for future research can be explored. One key improvement is introducing a dynamic evacuee demand model, where evacuee numbers and destinations update in real-time based on the evolving crisis situation. Additionally, a multiobjective optimization approach could be implemented to balance travel time with other factors, such as minimizing operational costs, reducing fuel consumption, and evenly distributing evacuees across vehicles. Robustness analysis should also be conducted by simulating various disaster scenarios, including sudden road blockages and fluctuations in vehicle availability, to assess the model's adaptability under uncertainty. Furthermore, real-time traffic data integration through GIS and IoT-based sensors could improve route optimization by continuously updating road conditions. Lastly, incorporating human behavioral simulations into the model would provide a more realistic evacuation strategy by accounting for panic-driven movements and deviations from planned routes.

5.3 | Novelty of the Study

This study introduces several novel contributions to the field of emergency evacuation vehicle routing compared to traditional VRP models. Unlike most VRP-based evacuation models that assume homogeneous evacuees, the proposed framework explicitly models two evacuee classes (injured and noninjured) and incorporates vehicle–shelter compatibility, ensuring that each evacuee type is assigned to appropriate vehicles and shelter categories (hospital vs. residential). The evacuation problem is formulated as a MVMDRP that jointly integrates multiple depots, multiple capacity-limited shelters, and a heterogeneous fleet (bus-ambulance, bus, minibus), a configuration rarely addressed in prior evacuation-routing studies. A key contribution is the hybrid optimization architecture, in which an exact CPLEX MILP provides optimal routing under stable network conditions, while metaheuristic algorithms (GWO, GA, PSO, SA) rapidly generate effective solutions when disruptions occur. This stability–adaptability balance is largely missing in previous studies that rely solely on either exact or heuristic methods. The model incorporates discrete-time structural network disruptions—such as road closures and counterflow operations—by updating link travel times at predefined intervals. This mechanism captures evolving network availability without requiring flow-equilibrium or within-day congestion modeling, which differentiates it from traffic assignment–based evacuation studies. Finally, applying the model to a GIS-derived road network of District 8 in Qom provides operational validation and demonstrates that the proposed approach improves clearance time and resilience in realistic emergency settings.

Nomenclature

VRP	Vehicle-routing problem
MVMDRP	Multivehicle multidepot routing problem
GWO	Grey wolf optimizer
GA	Genetic algorithm
PSO	Particle swarm optimization
SA	Simulated annealing

Author Contributions

Conceptualization: Shahriar Afandizadeh and Mohammad Ebrahimian; methodology: Mohammad Ebrahimian and Shahriar Afandizadeh; software: Mohammad Ebrahimian and Ali Naderan; validation: Mohammad Ebrahimian and Ali Naderan; formal analysis: Mohammad Ebrahimian; investigation: Mohammad Ebrahimian and Ali Naderan; data curation: Ali Naderan; visualization: Ali Naderan; writing–original draft: Mohammad Ebrahimian; writing–review and editing: Shahriar Afandizadeh and Ali Naderan; supervision: Shahriar Afandizadeh; project administration: Shahriar Afandizadeh.

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Disclosure

No generative AI software was used for data collection, analysis, writing, or editing of this article. All computations were performed with standard scientific software (Python 3.x, IBM CPLEX/Docplex, NetworkX, and OSMnx), and all text was written and edited by the authors.

Disclosure

All authors have read and approved the final manuscript and agree to be accountable for all aspects of the work.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The full source code used for implementing the MILP model, metaheuristic algorithms, and experimental workflow is publicly available at https://github.com/ebrahimiansme1-cell/evacuation-hybrid-routing.

The evacuee and shelter inputs (indices, types, WGS84 coordinates, and demands) are reported in Table 3, and the vehicle fleet is reported in Table 4 of the manuscript. The underlying road network was obtained from OpenStreetMap via OSMnx (© OpenStreetMap contributors; ODbL). Derived matrices/routes are available on request.

Endnotes

[1]Decision optimization CPLEX modeling for Python.

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