

DOI: https://doi.org/10.48009/4_iis_2026_140

Graph-based decision support system for last-mile humanitarian logistics: The case of Peru

Lucas Machuca, *Universidad del Pacífico*, lg.machucag@up.edu.pe

Marcelo Briceño-Egúsqiza, *Universidad del Pacífico*, me.bricenoe@alum.up.edu.pe

Renato Quiliche, *Pontifical Catholic University of Rio de Janeiro*, renato.quiliche.pe@gmail.com

Ana Luna, *Universidad del Pacífico*, ae.lunaa@up.edu.pe

Juan Lazo, *Unviersidad del Pacífico*, jg.lazo@up.edu.pe

Mario Chong, *Universidad del Pacífico*, m.chong@up.edu.pe

Abstract

This study demonstrates that existing social infrastructure can be strategically repurposed into safe clustering and distribution hubs during extreme crises, provided real-world complications are embedded into the planning architecture. A Mixed-Integer Goal Programming model is developed to enforce strict capacity thresholds and universal coverage across 832 vulnerable blocks under a simulated tsunami crisis in Callao, Peru. To maintain computational tractability, a neighborhood sparsification strategy is implemented and solved via an exact COIN-OR Branch-and-Cut engine. The empirical findings reveal that the network-based formulation converged to a tight 2.00% optimality gap in 320.31 seconds. Due to population constraints and physical accessibility barriers, the model opened 28 active distribution centers rather than the 14 initially targeted administrative regions. Crucially, ignoring real road topology introduces a severe 44.71% (166.23 kilometers) transportation underestimation bias that would lead to immediate fleet shortages during physical deployment. Ultimately, this framework bridges the gap between abstract optimization and urban friction, proving that incorporating physical street geometry and localized facility constraints is an operational prerequisite to generate dependable decision support systems for resilient disaster response.

Keywords: humanitarian logistics, last mile, disaster management

Introduction

Globally, urban migration continues to accelerate, with over 55% of the world population currently residing in urban areas, a figure projected to exceed 66% by 2050 (United Nations, 2018). This rapid urbanization has fueled the emergence of megacities with more than 10 million inhabitants (Fransoo, 2017), which articulate complex political, socioeconomic, and technological systems. From a supply perspective, they generate critical transportation, logistics, and pollution challenges. By 2030, high-density megacities will face extreme demographics, such as Delhi (38.93 million), Tokyo (36.57 million), Dhaka (28.07 million), Mexico City (24.11 million), São Paulo (23.82 million), and Lima (12.26 million), leading to the rise of inmegacities, dense urban clusters embedded within these larger networks (Castillo et al., 2019).

E-commerce represents a dominant operational trend in these environments, driving unprecedented volume metrics. For instance, package density reached 327.2 packages/km² in Beijing and 1,124.5 packages/km² in Shanghai (Huang et al., 2018), while China overall delivered 60 billion packages in 2019 (China Post, 2019). To navigate these hyper-dense layouts, companies deploy multi-echelon logistics systems to balance operational flows against strict routing constraints. While traditional two-echelon systems offer simplicity for low-volume distribution, their performance degrades under

extreme density thresholds (Huang et al., 2018). Consequently, commercial delivery architectures are increasingly designed around spatial cells, blocks, and workload balancing to manage massive localized flows.

Crucially, the mathematical principles governing these high-density commercial systems hold significant potential for public safety when transposed to emergency logistics. Megacities face severe vulnerability to natural disasters, which have increased in both frequency and intensity (Wei et al., 2015; Ibrión et al., 2015). In 2017 alone, worldwide natural disasters caused approximately 10,000 deaths and 400 billion dollars in economic losses (AON, 2018). Managing these crises relies heavily on humanitarian supply chains designed to distribute critical resources rapidly, thereby minimizing human suffering and mortality (Balcik et al., 2008).

Within humanitarian logistics, last-mile distribution stands as the most critical yet volatile phase (Balcik et al., 2008; Battini et al., 2014). This operation is systematically hindered by sudden demand spikes, supply uncertainty, communication breakdowns, the lack of coordination between aid entities, damaged infrastructure, and limited transportation resources (Penna et al., 2018; Balcik et al., 2008). Fleet deployment, vehicle routing, and distribution center allocation remain paramount to driving rapid response times (Vahdani et al., 2018), particularly because compromised networks can isolate affected areas (Nikoo et al., 2018). Preparedness and recovery measures constitute core disaster management (Khan et al., 2008). Immediate victim relief occurs during the response phase (Battini et al., 2014; Khan et al., 2008), where logistics operations become highly complex due to degraded operating environments, resource convergence, and incomplete information (Kunz et al., 2014; Van Wassenhove & Pedraza Martinez, 2012).

This research delivers four primary contributions to the information systems and logistics literature by bridging the gap between abstract optimization and real-world urban friction. First, it adapts high-density e-commerce concepts to humanitarian delivery within vulnerable zones. Second, it uses cell-and-block operational structures to manage volatile post-disaster requirements through localized zoning. Third, it optimizes humanitarian logistics via workload balancing, mapping population demands against facility capacities. Fourth, it proves that existing social infrastructure can be dynamically repurposed into safe distribution hubs during catastrophic events where demand uncertainty and density are simultaneously high.

Ultimately, this study optimizes last-mile routes to ensure complete node coverage and minimize arrival times, positioning physical road networks and facility capacity limits as operational prerequisites (Pérez et al., 2010; Safeer et al., 2014). The decision support system is validated by a case study simulating a seismic and tsunami crisis in Callao, Peru, a high-risk region along the Pacific Ring of Fire (INEI, 2018a). Given Peru's historical destructive earthquakes, this model provides critical predictive utility for disaster preparedness by incorporating physical urban complications into tactical response frameworks. The paper is organized as follows: Section 2 reviews the literature; Section 3 outlines the methodology; Section 4 presents the Callao case study; Section 5 displays results; Section 6 discusses managerial implications; and Section 7 concludes.

Literature Review

The physical movement of products across a network represents a critical component of aggregate supply chain logistics, serving as a primary driver of operational expenditures whose optimization directly determines systemic success. According to the definition established by Chopra and Meindl (2013), a freight forwarder or shipper refers to any individual or corporate entity managing the transport of commodities between two distinct nodes within a value chain. The Vehicle Routing Problem (VRP) serves as the fundamental bedrock of logistics optimization, characterized by multi-dimensional formulations with high parameter variability designed to satisfy complex operational constraints such as vehicle capacities, fleet sizes, and localized customer demand coordinates (Balinski & Quandt, 1964;

Toth & Vigo, 2002). Researchers focus heavily on the VRP due to its analytical complexity and its utility as a paradigm of combinatorial optimization. Formally, Lenstra and Rinnooy Kan (1981) classified the VRP as an NP-complete challenge, establishing that it cannot be resolved within polynomial time using deterministic computational methods (Alfonseca Moreno, 2000). The precursor formulation within this domain was the Traveling Salesman Problem (TSP), introduced by Flood in 1956 (Applegate et al., 2011). This classical approach describes the trajectory of an agent who must visit a designated set of cities in a single closed-loop tour, starting and ending at a common origin node, to determine the optimal sequence that visits each node exactly once while minimizing the cumulative distance or spatial friction of the tour (Toth & Vigo, 2002).

Routing by phases

One-phase routing

One-phase routing generalizes the classical TSP by embedding multi-dimensional operational metrics, such as financial expenditures, strict time frames, and service quality parameters, directly into the system objective function. Methodological approaches to resolve these search spaces encompass heuristics, evolutionary genetic algorithms, multi-objective frameworks, and Large Neighborhood Search (LNS) architectures under both deterministic and stochastic demand parameters. Heuristics guide real-time decision-making layers by efficiently exploring restricted solution spaces to yield high-quality, near-optimal solutions within viable runtimes (Olivera, 2004). For instance, Huang et al. (2013) engineered a continuous approximation heuristic designed to minimize beneficiary arrival latencies during post-disaster distribution operations. Similarly, Ropke and Pisinger (2006) introduced an Adaptive Large Neighborhood Search (ALNS) heuristic applied to the Pickup and Delivery Problem with Time Windows (PDTW) to optimize cumulative fleet utilization.

Multi-objective formulations frequently target humanitarian logistics and disaster relief scenarios. Molina et al. (2018) addressed a multi-period, multi-objective VRP focused on minimizing fleet size, operational expenditures, and maximum victim arrival latency using a Multi-start with Intelligent Neighborhood Selection (MSINS) algorithm, which structurally outperformed conventional NSGA-II frameworks. Concurrently, Perez et al. (2010) integrated standard operational expenses with human deprivation costs into a multi-commodity linear network model to minimize the overall societal cost of disaster response. Regarding stochastic variables, Moghaddam et al. (2012) deployed a Particle Swarm Optimization (PSO) algorithm to resolve VRP variants with unknown customer demand distributions. To evaluate distinct optimization strategies under parameter volatility, Allahviranloo et al. (2014) presented three selective routing formulations, demonstrating that accounting for uncertainty provides superior decision-support value compared to static TSP models. Under known demand parameters, Lin et al. (2011) developed an emergency logistics model designed for rapid response and prioritized resource allocation under narrow time windows, multi-period routing, and split-delivery deployment strategies. In relation to large neighborhood frameworks, Azi et al. (2012) evaluated a dynamic routing environment where transport fleets execute delivery sequences across multiple daily paths while dynamic customer requests arrive in real time. Their methodology, built on an adaptive local search heuristic, demonstrated the operational benefits of modeling future demand trends when determining whether to accept or reject incoming real-time requests.

Two and three phases routing

To handle the compounding complexities of massive distribution scales, research has evolved toward multi-tier architectures. Huang et al. (2018) conducted a comprehensive computational study validating the operational benefits of structuring routing configurations into two distinct phases within hyper-dense metropolitan environments characterized by high order volumes. Two-phase routing structurally implies a primary distribution echelon where freight is transported from a central warehouse to intermediate distribution centers (DCs) located inside designated territorial blocks; subsequently, a secondary echelon governs last-mile distribution sequences from these DCs to individual points of distribution (PODs) at local households. Conversely, Saragih et al. (2019) developed a three-phase routing framework linking a primary supplier across three-tiered levels to distribution points, local

retailers, and final consumers, noting that the cascading scalability of this approach significantly escalates computational complexity.

Methodological variations within multi-tier routing encompass batch demand processing, structural capacity variations, neighborhood searches, facility location paradigms, and Mixed-Integer Programming (MIP) formulations. Wang et al. (2018) modeled capacity and passenger-freight flow restrictions for a last-mile transit framework, solving the architecture through exact MIP models, myopic operational strategies, and targeted Tabu Searches. Regarding green transportation fleets, Breunig et al. (2019) addressed electric vehicle routing configurations over two echelons using large neighborhood search decomposition approaches. Concurrently, Belgin et al. (2018) evaluated the Two-Echelon Vehicle Routing Problem with Simultaneous Pickup and Delivery (2E-VRPSD) to minimize total expenditures, introducing a hybrid heuristic based on variable neighborhood descent (VND) and local search (LS) capable of efficiently resolving large-scale network instances.

Furthermore, dynamic tier configurations were advanced by He and Li (2019), who introduced a two-echelon multi-trip VRP with a dynamic satellite (2E-MTVRPDS) framework to optimize vehicle waiting times and minimize fleet sizes. In the facility location domain, Pichka et al. (2018) formulated the two-echelon open location routing problem (2E-OLRP) to minimize aggregate transportation, hiring, and satellite operational costs using a hybrid simulated annealing (SA) heuristic. Hemmelmayr et al. (2012) engineered a high-performance ALNS engine capable of resolving two-echelon location-routing problems (LRP), outperforming alternative algorithms within urban logistics domains. This integration of location and layout analytics is fundamental to city logistics; specifically, Crainic et al. (2010) analyzed the two-echelon capacitated vehicle routing problem (2E-CVRP) to evaluate the spatial relationship between customer density and intermediate satellite positions, proving that multi-phase architectures structurally outperform single-phase VRP schemes in extensive metropolitan grids. Finally, to handle parameter fluctuations, Federgruen et al. (2018) optimized two-echelon distribution configurations under random demands and storage boundaries using an exact dynamic programming model driven by Lagrangian relaxations.

Humanitarian Logistics and VRP

While the discussed multi-phase frameworks provide a solid mathematical foundation for extensive commercial environments, their structural logic is increasingly being transposed to crisis contexts. While published research regarding commercial transport optimization and corporate cargo scheme routing is extensive (Bermeo Munoz, 2009; Wang, 2017), including large delivery networks handling dense consumer demand (Sacramento et al., 2019; Ropke & Pisinger, 2006; Azi et al., 2012; Belgin et al., 2018), applying these variants to humanitarian logistics remains a vital but developing domain. Recently, VRP models have been deployed to assist communities affected by catastrophic natural disasters, civil conflicts, and structural crises (Santos et al., 2012).

Resolving vehicle routing disruptions within humanitarian contexts requires evaluating specialized heuristic algorithms, known demands, stochastic variables, multi-criteria targets, and optimal facility allocation. Al Theeb & Murray (2017) and Lolli et al. (2015) designed multi-objective frameworks solved via iterative 4-phase and constructive heuristics to optimize post-disaster relief agency coordination and municipal fire station response patterns. Similarly, Bruni et al. (2018) developed a rapid heuristic routing engine to address the critical urgency of vehicle arrival speeds at disaster sites, while Döyen et al. (2012) formulated a two-echelon stochastic facility location model solved via Lagrangian relaxation and local search to optimize total cost mitigation and pre-disaster warehouse pre-positioning.

Under epistemic uncertainty, Tofighi et al. (2016) engineered a resilient humanitarian logistics network leveraging a two-phase possibilist-stochastic programming approach that incorporates multi-objective optimization within its secondary tier to manage central and local distribution centers. A highly integrated multi-stage approach was developed by Jha et al. (2017), who modeled a dual emergency network coupling a three-phase humanitarian supply chain with a two-phase disaster evacuation chain,

resolving the mathematical structure via multi-objective evolutionary algorithms (NSGA-III). LNS methods have also been specialized for resource allocation; Eisenhandler and Tzur (2019) proposed an exact solution mechanism driven by a large neighborhood search heuristic to optimize collection site sequences and enforce equitable resource allocations under strict supply limits (Pisinger & Ropke, 2010).

Ultimately, evolutionary computation represents a robust tool for mapping high-complexity emergency distribution routes due to its adaptive search capabilities (Gaspar Cunha et al., 2012). In last-mile humanitarian operations, Zhu et al. (2018) engineered a specialized methodology where the tolerable suffering duration of injured victims is modeled as a temporal restriction window to mathematically dictate rescue sequence priorities. Finally, comprehensive frameworks like the one designed by Tavana et al. (2018) structure pre- and post-disaster earthquake response through integrated location-inventory-routing networks. Their approach resolves the primary facility tier via Mixed-Integer Linear Programming (MILP) and the secondary deployment layer via advanced evolutionary sorting algorithms, such as NSGA-II and RPBNSGA-II, demonstrating the utility of multi-objective metaheuristics in high-dimensional emergency logistics.

Methodology

Problem and model description

The two-echelon logistic system model has its fundamental basis in the routing model used to delivery fleet proposed by Huang and Rafiei (2019) and the pre-positioning of emergency warehouses using deterministic demand of relief supplies (de Brito et al., 2014), considering the population density level of Callao, Peru. The block is an arbitrary division of a continuous territory that groups the needs of the population inside. Furthermore, the blocks are contiguous and grouped into regions, one of the blocks contains a distribution center (DC) to supply the region.

From the main warehouse (W) located in Lima, the relief supplies would be transported to the distribution centers in Callao (DC, first echelon) and from there to the points of distribution (POD, second echelon), where the beneficiaries receive the products. Heavy vehicles (HV) are used for the transportation of relief supplies from the W to the DC, and light vehicles (LV) from the DC to the POD. Each POD will supply a block inside the region, that is served by a single driver, who receives a vehicle flow to select which route to take. Figure 1 shows the model hierarchy.

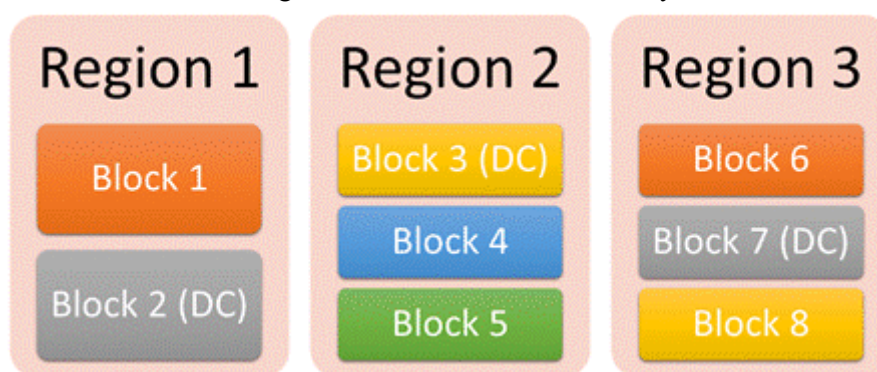


Figure 1: Example of model hierarchy

A goal-based programming model has been proposed in order to design the block supply network of humanitarian aid kits during the disaster, considering deterministic demand related to the needs in each specific block, as well as the goals of this model: the number of regions and distance travelled by the victims.

The constraints are the attention capacity per region, the demand, the block geolocation, and additional elements, which allow a better approach to a real crisis event in a densely populated urban area. We consider the problem of determining the grouping of the blocks that constitute a region, select the block that will serve as a DC and calculate how many blocks are served by the DC. In addition, the model proposes the flow of the vehicle (LV) with supply from the distribution center to the blocks.

Data pre-processing and spatial filtering

To ensure data fidelity within the DSS, geo-referential information was synthesized from the Information System of the National Center for Estimation, Prevention and Reduction of Disaster Risk in Peru (SINIGRD) and the Regional Government of Callao. Critical spatial filtering constraints were applied via relational database queries to identify viable infrastructure capable of safe operation during a tsunami crisis:

- Safety elevation: Candidate locations were restricted to an altitude of more than 10 meters above sea level to ensure complete inundation safety.
- Institutional utility: Locations were restricted to resilient public and civilian zones, including parks, stadiums, schools, complexes, and emergency service stations.

An initial geospatial audit identified 842 potential points of interest (POIs) across the target area. A data-cleaning process identified and removed 10 records exhibiting critical georeferencing anomalies (missing latitude and longitude fields), resulting in a finalized operational set of 832 georeferenced Points of Distribution (PODs).

To model the vehicle routes over the 832 blocks (B), the system connects all points using real street distances instead of a simple map of adjacent streets. Restricting the vehicles only to adjacent streets would limit routing options for a large network of 832 nodes. Instead, the pre-processing pipeline calculates the shortest path between every single pair of points using the real OpenStreetMap grid. This step generates a distance matrix with all $C(832,2) = 345,696$ unique route combinations. Therefore, the network edge set (E) represents a complete graph where every block connects to every other block ($E = B \times B$). This allows the exact solver to directly read the exact street distance between any distribution center and delivery point during the optimization process

Demographic demand parameters were obtained from the census block microdata provided by the National Institute of Statistics and Informatics (INEI). Population counts were aggregated by computing geometric centroids for each block area, mathematically ensuring a zero-duplication rate across the final set of 832 operational points.

Mathematical Formulation

The structural configuration of the multi-echelon network is modeled using Mixed-Integer Goal Programming (MIGP). This paradigm is selected because humanitarian relief operations must simultaneously balance conflicting societal metrics which cannot be adequately resolved by single-objective distance minimization.

Sets, parameters, and decision variables

The Mixed-Integer Goal Programming (MIGP) formulation is built upon a structured set of mathematical components that define the spatial and operational boundaries of the disaster zone. The system architecture defines the territory through primary sets, including B for the total territorial blocks requiring humanitarian relief, R for the operational regions partitioning the area, and E for the complete network of directed transport arcs connecting all operational blocks ($E = B \times B$), matching the dense shortest-path distance matrix pre-computed via the street graph pipeline. Within these boundaries, the model evaluates deterministic parameters that constrain the system, specifically the inhabitant count (Population_i) for each block $i \in B$, the maximum service volume of a localized facility (Capacity_b) for each potential distribution center $b \in B$, and the real network distance between connected blocks (distance_{jk}) for each arc $(j,k) \in E$, alongside predefined milestone targets for the ideal number of operational regions ($\text{lim}_{\text{region}}$) and the maximum collective fleet distance ($\text{lim}_{\text{distance}}$).

To optimize the network configuration, the model utilizes a combination of decision and deviation variables that govern assignment, facility location, and target tracking performance. Binary decision variables include X_{ib} , which determines the formal allocation of a specific block of victims i to an operational region anchored by block b , and Y_b , which establishes whether block b is selected to host a regional distribution center. The physical sequence and continuous flow of emergency supplies through the approved network arcs are managed by the unified multicommodity routing variable F_{ibjk} , which represents the continuous flow of humanitarian aid dedicated to satisfying the demand of victim block i , dispatched from the distribution center at block b , and physically traversing the directed road segment $(j, k) \in E$. Finally, continuous deviation variables (D_{region} , E_{region} , $D_{distance}$, $E_{distance}$) are integrated into the goal programming structure to mathematically measure the under-achievement or over-achievement of the system relative to its established regional and distance milestones.

Objective function

The goal targets are structurally embedded into the optimization model through achievement balance functions. The first goal models structural capacity targets:

$$\sum_{b \in B} Y_b + D_{region} - E_{region} = \lim_{region}$$

The second goal evaluates the aggregate spatial friction over the calculated routing components:

$$\sum_{(i,j,k,l) \in B \times B \times B \times B} distance_{jk} * F_{ibjk} + D_{distance} - E_{distance} = \lim_{distance}$$

The multi-criteria objective function (Z) aims to minimize undesirable deviations, which are normalized by their respective target limits to account for scale differences:

$$\min Z = \frac{E_{region}}{\lim_{region}} + \frac{E_{distance}}{\lim_{distance}}$$

The objective function Z utilizes a one-sided penalization structure, omitting under-achievement variables (D_{region} , $D_{distance}$) because opening fewer distribution hubs or decreasing cumulative transit distances inherently represents an operationally superior state in humanitarian relief. To reconcile the disparate units and magnitudes of administrative counts and physical meters, each over-achievement variable is normalized by its respective target limit ($\lim_{region}$ and $\lim_{distance}$). This mathematical transformation converts absolute values into dimensionless, commensurate ratios that reflect relative percentages of target violations, bringing both metrics onto an identical relative scale to prevent numerical dominance during the multi-criteria optimization process.

Operational Constraints

1. Regional capacity: Ensures that the cumulative population assigned to any given region does not exceed the physical processing capability of its designated central DC:

$$\left(\sum_{i \in B} Population_i * X_{ib} \leq Capacity * Y_b \right) \forall b \in B$$

2. Universal coverage mandate: Enforces strict partitioning, requiring that every single territorial block containing vulnerable populations is allocated to exactly one operational region, preventing any single victim from being marginalized:

$$\left(\sum_{b \in B} X_{ib} = 1 \right) \forall i \in B$$

3. Logical consistency of facilities: Dictates that a region b can only exist and manage surrounding nodes if block b itself is physically designated as an active operational DC:

$$(Y_b = X_{bb}) \forall b \in B$$

4. Network Flow Conservation: Guarantees sequence continuity, ensuring that all emergency supplies entering an intermediate routing node must exit it, preventing physical delivery drop-offs outside authorized POD zones:

$$\begin{aligned} (\sum_{(j,k) \in E} F_{ibjk} - \sum_{(j,k) \in E} F_{ibkj} &= 0) \forall (i, b) \in B \times B; i \neq b; \forall j \in B; j \neq i \wedge j \neq b \\ (\sum_{(j,k) \in E} F_{ibjk} - \sum_{(j,k) \in E} F_{ibkj} &= X_{ib}) \forall (i, b) \in B \times B; i \neq b; \forall j \in B; j = b \\ (\sum_{(j,k) \in E} F_{ibjk} - \sum_{(j,k) \in E} F_{ibkj} &= -X_{ib}) \forall (i, b) \in B \times B; i \neq b; \forall j \in B; j = i \end{aligned}$$

5. Flow boundary: Ensures that transport flow can only traverse directed arc (j, k) if the origin, destination, and the physical road segment itself reside entirely within the verified boundary of the assigned operational cluster:

$$\begin{aligned} F_{ibjk} &\leq X_{ib} \forall (i, b) \in B \times B / i \neq b \wedge (j, k) \in E \\ F_{ibjk} &\leq X_{jb} \forall (i, b) \in B \times B / i \neq b \wedge (j, k) \in E \\ F_{ibjk} &\leq X_{kb} \forall (i, b) \in B \times B / i \neq b \wedge (j, k) \in E \end{aligned}$$

Algorithmic solution architecture

Because resolving multi-echelon network flows over large-scale real-world infrastructure constitutes a highly complex optimization challenge (NP-complete), balancing exact mathematical convergence against strict computational time limits is paramount for strategic disaster preparedness. To achieve this, the proposed Decision Support System (DSS) couples the Mixed-Integer Goal Programming (MIGP) formulation with an exact commercial optimization engine.

The computational pipeline is structured in two primary phases. First, a high-performance Python preprocessing layout leveraging the OSMnx and NetworkX libraries is deployed. This pipeline extracts the real urban road graph of Callao directly from OpenStreetMap and executes an all-pairs shortest-path search based on physical street constraints and topography. Second, the resulting high-fidelity distance matrix is dynamically integrated into a mathematical environment developed in Python using a direct programming interface with the commercial Gurobi Optimizer API. The exact Branch-and-Bound algorithm executes under a strict 3% Mixed-Integer Programming (MIP) optimality tolerance gap, utilizing multi-core parallel processing to guarantee deterministic convergence within realistic operational windows.

Results

The proposed optimization framework was evaluated using a validated empirical instance comprising 832 georeferenced social infrastructure assets, after eliminating ten incomplete records from the initial database. The experiment evaluated these assets, which include public schools, stadiums, municipal offices, clinics, and hospitals, under two distinct spatial representations: a linear geometric formulation based on Euclidean distances and a graph-based formulation that incorporates road accessibility.

To maintain computational feasibility while preserving realistic spatial relationships, the network formulation implemented a neighborhood sparsification strategy based on the 50 closest candidate social infrastructure hubs for each affected block. This restriction was introduced because a fully connected directed graph among the 832 operational nodes would generate 692,224 possible origin-destination relationships, considerably increase the number of binary assignment variables and complicating the branch-and-bound exploration. By limiting candidate connections to the closest 50 nodes, the model preserves local accessibility patterns while reducing unnecessary long-distance links that would rarely represent viable emergency allocation decisions under real post-disaster conditions.

Table 1: Computational Performance and Algorithmic Workload Metrics

Algorithmic Parameter	Linear Geometric Model	Graph-Based Network Model
<i>Optimization Solver Engine</i>	PuLP / CBC	PuLP / CBC
<i>Neighborhood Sparsification</i>	50 Closest Centroids	50 Closest Centroids
<i>Estimated Active Binary Variables</i>	25,000 Variables	42,436 Variables
<i>Algorithmic Execution Status</i>	Stopped on Time Limit	Converged to Global Optimum
<i>Total Processing Runtime</i>	1,800.79 seconds	320.31 seconds
<i>Simplex Iterations Executed</i>	364,848 Iterations	91,018 Iterations
<i>Final Optimality Gap</i>	4.00%	2.00%

Table 1 summarizes the computational workload and convergence performance of both spatial formulations. The results demonstrate that incorporating real road distances does not necessarily increase computational difficulty when combined with an adequate reduction of the search space. Although the network-based model required a larger number of active binary variables (42,436 compared with 25,000), it reached a tighter optimality gap of 2.00% within 320.31 seconds, whereas the Euclidean formulation terminated at the maximum computational limit with a remaining 4.00% gap.

The difference in convergence behavior indicates that the neighborhood restriction significantly improved the efficiency of the exact optimization procedure. Instead of exploring an excessively large combination of potential humanitarian allocations, the solver concentrated on spatially meaningful alternatives, allowing the CBC branch-and-cut framework to identify high-quality solutions with fewer explored nodes.

The computational differences were accompanied by important changes in the resulting territorial configuration. While Euclidean formulations assume unrestricted movement across a planar space, emergency distribution systems operate under physical accessibility constraints imposed by the urban road structure.

Table 2: Goal Attainment and Mathematical Deviation Matrix

Goal Programming Component	Linear Geometric Model	Graph-Based Network Model
<i>Realized Distribution Centers</i>	24 Centers Opened	28 Centers Opened
<i>Under-achievement Deviation</i>	0 Regions	0 Regions
<i>Over-achievement Deviation</i>	10 Regions	14 Regions
<i>Total distance</i>	371,802.79 Meters	538,035.42 Meters
<i>Under-achievement Deviation</i>	0.00 Meters	0.00 Meters
<i>Over-achievement Deviation</i>	221,802.79 Meters	388,035.42 Meters
<i>Final Objective Function Value</i>	2.192971	3.586903

As presented in Table 2, the network-based model estimated an aggregate distribution distance of 538,035.42 meters, compared with 371,802.79 meters obtained by the geometric formulation. This difference of 166,232.63 meters represents a 44.71% underestimation of transportation requirements when road topography is ignored. Such distortion proves that abstract planning models introduce a critical information deficit, leading to inaccurate estimations of vehicle fleet requirements and delivery times during emergency response planning.

The effect of realistic accessibility conditions was also reflected in facility deployment. The network-based formulation required the activation of 28 strategic social infrastructure hubs, whereas the Euclidean model activated only 24 facilities. This increase results from the need to compensate for accessibility barriers and maintain population coverage under the established capacity threshold of 90,000 inhabitants per hub. Therefore, the use of road network distances modifies not only travel estimation but also the strategic location and required number of emergency distribution facilities, demonstrating that real-world friction dictates the physical viability of the response

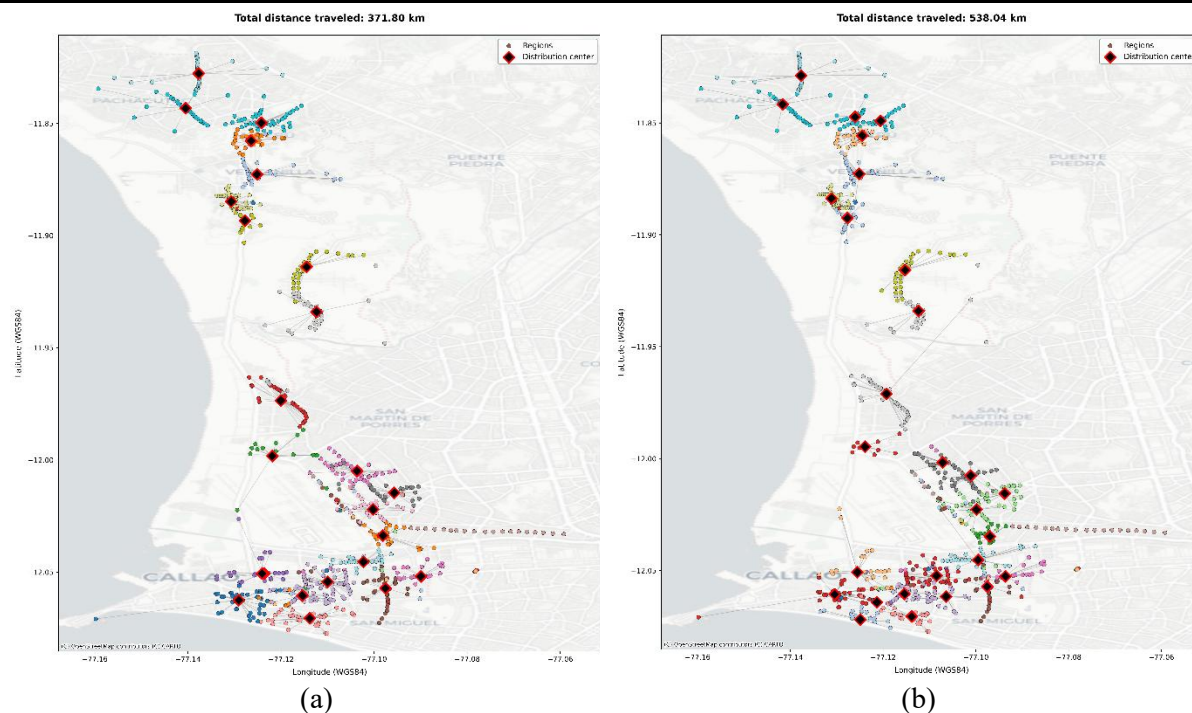


Figure 2: Linear distances graph (a) and real distances graph (b)

The resulting territorial configurations are illustrated in Figure 2. The allocation maps show the assignment of vulnerable blocks to their corresponding distribution hubs under both spatial representations.

Discussion and Implications

The empirical findings of this research confirm the computational challenges associated with combinatorial optimization in large-scale emergency management. Resolving a network containing 832 operational nodes shifts the routing and facility positioning problem into a high-complexity domain, directly aligning with the classification of multi-echelon vehicle routing problems and location-routing problems as NP-hard challenges. Transitioning from approximate metaheuristics to an exact Mixed-Integer Goal Programming formulation driven by the COIN-OR Branch-and-Cut solver allows the framework to guarantee deterministic convergence and bounded solution quality within critical tactical planning windows. This methodological shift aligns with the theoretical foundations established by Payne and Dror (2017), who constructed topographical networks where each arc carries localized structural friction. Embedding this topological reality positions the decision support system within information systems research by proving that high-fidelity street networks are essential to align abstract algorithmic optimization with physical post-disaster execution.

The structural variance observed between the unconstrained geometric linear model and the proposed street-graph formulation underscores a fundamental divergence from traditional transportation assumptions. By reporting the actual goal programming achievement metrics, this study closes the empirical loop demanded by multi-criteria frameworks. While the administrative milestone targeted 14 ideal regions, the strict localized population demands and the facility capacity ceiling of 90,000 inhabitants forced an over-achievement deviation of 14 extra zones in the network model and 10 extra zones in the linear model, resulting in 28 and 24 active distribution centers respectively. Furthermore, omitting real road structures underestimates the absolute spatial transportation workload by 44.71%. This distortion validates the use of a one-sided penalized objective function Z , where focusing

exclusively on over-achievement deviations balances conflicting societal metrics to prioritize equitable distribution and resource survivability rather than commercial cost minimization.

From a managerial and system implications view, relying on linear distance approximations introduces an information deficit that misleads emergency coordinators, directly amplifying human deprivation and suffering costs during immediate post-disaster response phases. Consequently, integrating high-fidelity street graph analytics directly into the information layer of the decision support system is an operational mandate to generate physically viable distribution plans. To bypass the quadratic computational overhead of processing 345,696 unique shortest-path combinations for the 832 nodes, civil defense authorities must transition toward pre-computed hybrid information systems. The state information infrastructure should maintain statically indexed, georeferenced real-world distance matrices of vulnerable urban zones. This data pre-positioning allows the exact optimization engine to focus its computational cores entirely on the branch-and-bound tree, achieving high-quality tactical routing layouts within bounded planning horizons.

Additionally, the autonomous cell-zoning partition framework managed by the variable Xib transforms its primary focus from commercial optimization to the mitigation of supply chain chaos and the absorption of highly variable beneficiary requirements. This configuration ensures that if a specific street sector or terminal node collapses physically due to the tsunami's impact, the data disruption remains isolated within that specific cell cluster. This containment architecture prevents cascading systemic failures across the broader response network, allowing emergency managers to preserve operational visibility and dynamically distribute humanitarian aid kits through the secure, uncompromised sectors of the territory.

Limitations and Future Directions

Regarding study limitations, the current formulation operates under static post-disaster road conditions and assumes a completely homogeneous vehicle fleet for last-mile distribution activities. Future research should expand operational resilience by evaluating multi-period scheduling with dynamic routing network state updates and incorporating heterogeneous fleet capacities. Furthermore, future extensions should simulate extreme disaster environments by dynamically removing edges from the pre-computed topograph to model physical road damage and structural debris blocking, establishing the humanitarian counterpart to this deterministic baseline.

Conclusions

In conclusion, this research successfully shifts the tactical focus of emergency management by demonstrating that existing social infrastructure can be strategically repurposed into safe clustering and distribution zones during catastrophic events. By validating this framework on an 832-node instance in Callao, Peru, the study proves that utilizing civilian infrastructure, such as public schools and parks, is highly viable if selection criteria incorporate strict elevation safety thresholds and institutional utility. However, the central insight of this work underscores that activating these clustering networks cannot rely on idealized geometric models, as ignoring actual road-network topology introduces a severe 44.71% transport underestimation bias that would cause immediate vehicle fleet shortages and critical supply chain delays during physical execution. Therefore, embedding real-world structural complications into the system layer is an operational mandate to translate abstract optimization into a physically viable and dependable emergency response.

Furthermore, the successful implementation of the multi-criteria Mixed-Integer Goal Programming model proves that exact mathematical programming remains computationally efficient and actionable within critical planning windows. By deploying a neighborhood sparsification strategy, the exact solver bypassed combinatorial complexity to reach a tight 2.00% optimality gap in 320.31 seconds, closing the empirical loop by balancing strict capacity thresholds of 90,000 inhabitants per hub against real

localized workloads. This localized pressure forced an over-achievement deviation that activated 28 active distribution centers rather than the 14 initially targeted administrative regions, illustrating how physical constraints reshape optimal facility layouts. Ultimately, this modular, cell-based architecture provides civil defense authorities with a fault-tolerant framework that isolates localized network failures, paving the way for future extensions to integrate real-time traffic telemetry and simulate dynamic road damage to maintain universal coverage under highly volatile post-disaster conditions.

References

- Al Theeb, N., & Murray, C. (2017). Vehicle routing and resource distribution in postdisaster humanitarian relief operations. *International Transactions in Operational Research*, 24(6), 1253-1284.
- Allahviranloo, M., Chow, J. Y., & Recker, W. W. (2014). Selective vehicle routing problems under uncertainty without recourse. *Transportation Research Part E: Logistics and Transportation Review*, 62, 68-88.
- Alfonseca Moreno, M. (2000). La máquina de Turing. *Números*, (43), 165–168.
- AON. (2018). *Weather, climate & catastrophe insight: 2017 annual report*. AON Benfield Analytics.
- Applegate, D. L., Bixby, R. E., Chvátal, V., & Cook, W. J. (2011). *The traveling salesman problem: A computational study*. Princeton University Press.
- Azi, N., Gendreau, M., & Potvin, J. Y. (2012). A dynamic vehicle routing problem with multiple delivery routes. *Annals of Operations Research*, 199(1), 103-112. <https://doi.org/10.1007/s10479-011-0991-0>
- Balinski, M. L., & Quandt, R. E. (1964). On an integer program for a delivery problem. *Operations Research*, 12(2), 300-304.
- Balcik, B., Beamon, B. M., & Smilowitz, K. (2008). Last mile distribution in humanitarian relief. *Journal of Intelligent Transportation Systems*, 12(2), 51-63.
- Battini, D., Peretti, U., Persona, A., & Sgarbossa, F. (2014). Application of humanitarian last mile distribution model. *Journal Of Humanitarian Logistics And Supply Chain Management*, 4(1), 131-148. <https://doi.org/10.1108/jhlscm-01-2013-0001>
- Belgin, O., Karaoglan, I., & Altiparmak, F. (2018). Two-echelon vehicle routing problem with simultaneous pickup and delivery: Mathematical model and heuristic approach. *Computers & Industrial Engineering*, 115, 1-16.
- Bermeo Munoz, E. (2009). Diseño de un modelo de optimización de rutas de transporte. *El Hombre y La Máquina*, (32), 52.
- Fransoo, J. (2017). *Reaching 50 million nanostores: Retail Distribution in Emerging Megacities (Colored Version)*.
- Breunig, U., Baldacci, R., Hartl, R. F., & Vidal, T. (2019). The electric two-echelon vehicle routing problem. *Computers & Operations Research*, 103, 198-210.

- Bruni, M. E., Beraldi, P., & Khodaparasti, S. (2018). A fast heuristic for routing in post-disaster humanitarian relief logistics. *Transportation Research Procedia*, 30, 304-313.
- Castillo, M., Goicochea, J., Chong, M., & Rodriguez, J. (2019). Inmegacity characterization: Trends and realities. *Management Research: Journal of the Iberoamerican Academy of Management*, 17(2), 187-204.
- China Post. (2019). *Annual report on the development of China's express delivery industry*. State Post Bureau of the People's Republic of China.
- Chopra, S., & Meindl, P. (2013). *Supply chain management: Strategy, planning, and operation* (5th ed.). Pearson Education.
- Crainic, T. G., Perboli, G., Mancini, S., & Tadei, R. (2010). Two-echelon vehicle routing problem: A satellite location analysis. *Procedia - Social and Behavioral Sciences*, 2(3), 5944-5955.
- de Brito, I., Jr., Yoshizaki, H. T. Y., & Carmo, B. B. T. (2014). Pre-positioning of emergency supplies under deterministic and uncertain demand conditions. *Conference paper*.
- Döyen, A., Aras, N., & Barbarosoğlu, G. (2012). A two-echelon stochastic facility location model for humanitarian relief logistics. *Optimization Letters*, 6(6), 1123-1145.
- Eisenhandler, O., & Tzur, M. (2019). The humanitarian pickup and distribution problem. *Operations Research*, 67(1), 10-32.
- Federgruen, A., Guetta, C. D., & Iyengar, G. (2018). Two-echelon distribution systems with random demands and storage constraints. *Naval Research Logistics (NRL)*, 65(8), 594-618.
- Gaspar Cunha, A., Takahashi, R., Henggeler Antunes, C., & Pereira, F. J. B. (2012). Algoritmos genéticos. In *Manual de computação evolutiva e metaheurística* (pp. 25-47). Imprensa da Universidade de Coimbra.
- He, P., & Li, J. (2019). The two-echelon multi-trip vehicle routing problem with dynamic satellites for crop harvesting and transportation. *Applied Soft Computing*, 77, 387-398.
- Hemmelmayr, V. C., Cordeau, J. F., & Crainic, T. G. (2012). An adaptive large neighborhood search heuristic for two-echelon vehicle routing problems arising in city logistics. *Computers & Operations Research*, 39(12), 3215-3228.
- Hillier, F. S., & Lieberman, G. J. (2010). *Introduction to operations research* (9th ed.). McGraw-Hill Higher Education.
- Huang, Y., Savelsbergh, M., & Zhao, L. (2018). Designing logistics systems for home delivery in densely populated urban areas. *Transportation Research Part B: Methodological*, 115, 95-125. <https://doi.org/10.1016/j.trb.2018.07.006>
- Huang, K., & Rafiei, R. (2019). Equitable last mile distribution in emergency response. *Computers & Industrial Engineering*, 127, 887-900.
- Huang, M., Smilowitz, K. R., & Balcik, B. (2013). A continuous approximation approach for assessment routing in disaster relief. *Transportation Research Part B: Methodological*, 50, 20-41.

- Ibrion, M., Parsizadeh, F., Naeini, M. S., Mokhtari, M., & Nadim, F. (2015). Handling of dead people after two large earthquake disasters in Iran: Tabas 1978 and Bam 2003 – Survivors' perspectives, beliefs, funerary rituals, resilience and risk. *International Journal of Disaster Risk Reduction*, 11, 60-70.
- INEI. (2018a). *Provincia Constitucional del Callao: Compendio estadístico 2018*. Instituto Nacional de Estadística e Informática.
- Jha, A., Acharya, D., & Tiwari, M. K. (2017). Humanitarian relief supply chain: A multi-objective model and solution. *Sādhanā*, 42(7), 1167-1174.
- Khan, H., Vasilescu, L. G., & Khan, A. (2008). Disaster management cycle: A theoretical approach. *Journal of Management and Marketing*, 6(1), 43-50.
- Kunz, N., Reiner, G., & Gold, S. (2014). Investing in disaster management capabilities versus pre-positioning inventory: A new approach to disaster preparedness. *International Journal Of Production Economics*, 157, 261-272. <https://doi.org/10.1016/j.ijpe.2013.11.002>
- Lenstra, J. K. and Rinnooy Kan, A. H. G. (1981). Complexity of vehicle routing and scheduling problems. *Networks*, 11(2), 221–227. <https://doi.org/10.1002/net.3230110211>
- Lin, Y. H., Batta, R., Rogerson, P. A., Blatt, A., & Flanigan, M. (2011). A logistics model for emergency supply of critical items in the aftermath of a disaster. *Socio-Economic Planning Sciences*, 45(4), 132-145.
- Lolli, F., Pergreffi, A., Gamberini, R., Rimini, B., & Regattieri, A. (2015). A bi-objective heuristic for supporting fire stations to respond quickly and efficiently in case of micro calamities. *International Journal of Operations and Quantitative Management*, 21(2), 97-114.
- Moghaddam, B. F., Ruiz, R., & Sadjadi, S. J. (2012). Vehicle routing problem with uncertain demands: An advanced particle swarm algorithm. *Computers & Industrial Engineering*, 62(1), 306-317. <https://doi.org/10.1016/j.cie.2011.10.002>
- Molina, J., López-Sánchez, A. D., Hernández-Díaz, A. G., & Martínez-Salazar, I. (2018). A Multi-start Algorithm with Intelligent Neighborhood Selection for solving multi-objective humanitarian vehicle routing problems. *Journal of Heuristics*, 24(2), 111-133.
- Nikoo, N., Babaei, M., & Mohaymany, A. S. (2018). Emergency transportation network design problem: Identification and evaluation of disaster response routes. *International Journal Of Disaster Risk Reduction*, 27, 7-20. <https://doi.org/10.1016/j.ijdr.2017.07.003>
- Olivera, A. (2004). *Heurísticas para problemas de ruteo de vehículos*. Instituto de Computación – Facultad de Ingeniería, Universidad de la República.
- Penna, P. H. V., Santos, A. C., & Prins, C. (2018). Vehicle routing problems for last mile distribution after major disaster. *Journal of the Operational Research Society*, 69(8), 1254-1268.
- Perez, N., Holguín-Veras, J., Mitchell, J. E., & Sharkey, T. C. (2010). Integrated vehicle routing problem with explicit consideration of social costs in humanitarian logistics. *Proceedings of the 9th International Conference on Humanitarian Logistics*.

- Pichka, K., Bajgiran, A. H., Petering, M. E., Jang, J., & Yue, X. (2018). The two echelon open location routing problem: Mathematical model and hybrid heuristic. *Computers & Industrial Engineering*, 121, 97-112.
- Pisinger, D., & Ropke, S. (2010). Large neighborhood search. In *Handbook of Metaheuristics* (pp. 399–419). Springer.
- Ropke, S., & Pisinger, D. (2006). An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows. *Transportation Science*, 40(4), 455-472.
- Sacramento, D., Pisinger, D., & Ropke, S. (2019). An adaptive large neighborhood search metaheuristic for the vehicle routing problem with drones. *Transportation Research Part C: Emerging Technologies*, 102, 289-315.
- Safeer, M., Anbuudayasankar, S., Balkumar, K., & Ganesh, K. (2014). Analyzing Transportation and Distribution in Emergency Humanitarian Logistics. *Procedia Engineering*, 97, 2248-2258. <https://doi.org/10.1016/j.proeng.2014.12.469>
- Santos, E. A., Villar, C. B., & Burgarelli, E. (2012). Logística humanitária: Conceitos, relacionamentos e oportunidade. In *SIMPOI* (pp. 1–16).
- Saragih, N. I., Bahagia, N., & Syabri, I. (2019). A heuristic method for location-inventory-routing problem in a three-echelon supply chain system. *Computers & Industrial Engineering*, 127, 875-886.
- Tavana, M., Abtahi, A. R., Di Caprio, D., Hashemi, R., & Yousefi-Zenouz, R. (2018). An integrated location-inventory-routing humanitarian supply chain network with pre-and post-disaster management considerations. *Socio-Economic Planning Sciences*, 64, 21-37.
- Tofighi, S., Torabi, S. A., & Mansouri, S. A. (2016). Humanitarian logistics network design under mixed uncertainty. *European Journal of Operational Research*, 250(1), 239-250.
- Toth, P., & Vigo, D. (2002). *The vehicle routing problem*. Society of Industrial and Applied Mathematics (SIAM).
- United Nations. (2018). *World urbanization prospects: The 2018 revision*. Department of Economic and Social Affairs, Population Division.
- Vahdani, B., Veysmoradi, D., Noori, F., & Mansour, F. (2018). Two-stage multi-objective location-routing-inventory model for humanitarian logistics network design under uncertainty. *International Journal Of Disaster Risk Reduction*, 27, 290-306. <https://doi.org/10.1016/j.ijdr.2017.10.015>
- Van Wassenhove, L. N., & Pedraza Martinez, A. J. (2012). Transportation and vehicle fleet management in humanitarian logistics: Challenges for future research. *EURO Journal on Transportation and Logistics*, 1, 185-196.
- Wang, H. (2017). Optimization of last-mile transportation systems. *Transportation Science*, 51(3), 1012-1028.
- Wang, Y., Peng, S., Xu, C., Assogba, K., Wang, H., Xu, M., & Wang, Y. (2018). Two-echelon logistics delivery and pickup network optimization based on integrated cooperation and transportation fleet sharing. *Expert Systems with Applications*, 113, 44-65.

- Wei, Y., Huang, M., Lam, J. S. L., & Yuan, Y. (2015). Sustainable urban development: A review on urban carrying capacity assessment. *Habitat International*, 46, 64-71.
- Zhu, L., Gong, Y., Xu, Y., & Gu, J. (2018). Emergency relief routing models for injured victims considering equity and priority. *Annals of Operations Research*, 263(1), 1-34.