International Journal for Multidisciplinary Research (IJFMR)

E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Optimizing Humanitarian Relief: A Hybrid MIP-NSGA-III Framework

Mr. Rajesh Ramesh Ubale[1], Dr. Harihar Lunge[2]

[1]Associate Professor, Management, ITM University, Raipur
[2]Associate Professor, Statistics, Shri Shivaji Science College Amravati, Maharashtra, India

Abstract

Humanitarian logistics forms the backbone of disaster response efforts, as its efficiency is a decisive factor for the survival and well-being of affected communities. However, this field faces multiple challenges, including information asymmetry, resource constraints, and coordination difficulties, particularly in volunteer scheduling and task assignment. Traditional decision-making methods often struggle to cope with the complex and dynamic relief environment. This research introduces a multi-objective optimization scheme for volunteer task allocation in humanitarian relief. Leveraging a mixed-integer programming framework and the Non-dominated Sorting Genetic Algorithm III (NSGA-III), the framework concurrently optimizes three conflicting objectives: minimizing logistics expenditure, maximizing the fulfillment of beneficiary needs, and enhancing the efficiency of personnel transfer within evacuation networks. By constructing a two-tier network model comprising suppliers, relief camps, affected areas, and evacuation camps, and incorporating uncertainty factors such as camp disruptions and route risks, this research strives to more accurately reflect the complexity of humanitarian relief operations. The performance of the proposed NSGA-III model is assessed against the Multi-objective Evolutionary Algorithm based on Decomposition (MOEA/D), a widely used multi-objective evolutionary optimization scheme. Numerical experiments confirm that NSGA-III effectively resolves this complex multi-objective problem, yielding a well-distributed and diverse set of Pareto-optimal solutions. This outcome equips decision-makers with a comprehensive variety of options for navigating trade-offs according to their priorities. In a comparative analysis, NSGA-III shows improved performance over MOEA/D with respect to diversity and convergence, especially within high-dimensional objective spaces. Its reference point-based mechanism proves more adept at preserving a spread of solutions. Consequently, this research offers a robust decision-support tool for optimizing volunteer management and resource allocation in humanitarian crises. By improving the efficacy and operational performance of relief efforts, this work contributes valuable insights to both the theoretical and practical advancement of humanitarian logistics.

Keywords: Humanitarian Logistics; Volunteer Scheduling; Multi-objective Optimization; Non-dominated Sorting Genetic Algorithm III (NSGA-III); Mixed-Integer Programming; Pareto Optimal

1. Introduction

Globally, natural disasters and human-induced conflicts have increased in both frequency and severity in recent years, resulting in immense loss of life and property and severely impacting regional and even global sustainable development. Against this backdrop, the importance of humanitarian relief operations has become increasingly prominent. The core objective of these operations is to provide essential materials and services to affected populations in the shortest possible time, thereby minimizing the impact of disasters. As a critical component of humanitarian relief, humanitarian logistics encompasses the entire process from needs assessment, material procurement, warehousing, and transportation to final distribution. Its operational efficiency directly determines the success of relief operations [1]. However, compared to commercial logistics, humanitarian logistics faces more severe and unique challenges. Kovács and Spens (2007) [2] identified the defining features of humanitarian logistics as a high degree of uncertainty, abrupt and critical demand surges, compromised infrastructure, inefficient information flow, and the complex challenge of aligning multiple stakeholders. Van Wassenhove (2006) [3] built upon this by framing the discipline as supply chain management that must function at high speed, necessitating rapid and robust decision-making under the most demanding conditions. Ratliff (2007) [4] specifically highlighted a critical shortfall in information and decision-support technologies tailored to the demands of humanitarian relief organizations. This work also identified the coordination of a large influx of spontaneous volunteers as a primary logistical challenge. These challenges collectively create a complex decision-making environment for humanitarian logistics, posing a severe test for traditional optimization methods.

Among numerous humanitarian relief activities, volunteers play an indispensable role. They are not only a crucial supplement to professional rescue forces but also a bridge for conveying humanitarian care and mobilizing social cohesion. However, effectively managing and scheduling this large, often untrained workforce to maximize its positive impact while avoiding chaos and resource waste due to poor coordination is a core task for humanitarian organizations. The volunteer task assignment problem is essentially a complex optimization problem that requires comprehensive consideration of multiple factors, such as volunteers' skills, willingness, geographical location, task urgency, required skills, and the overall objectives of the relief operation. Particularly after large-scale disasters, the number of volunteers surges, task demands are diverse and dynamically changing, making manual scheduling methods often inadequate. This can lead to uneven task distribution, coexistence of volunteer idleness and overload, and critical tasks being left unattended, severely affecting relief efficiency. Therefore, developing intelligent decision support systems to assist humanitarian organizations in making scientific and rational volunteer task assignments is critical for enhancing the speed and effectiveness of relief response.

Real-world applications frequently involve Multi-Objective Optimization Problems (MOPs), which are defined by the simultaneous optimization of several objective functions that are often in direct competition. Consequently, any enhancement in one objective is likely to result in the compromise of another. Rather than pursuing a single best solution, the aim of MOP is to discover a collection of non-dominated, or Pareto optimal, solutions. This Pareto optimal set embodies the most effective compromises possible, where no solution is best across all objectives. When visualized in the objective space, these solutions form a Pareto front. This front offers decision-makers with a spectrum of optimal choices, enabling them to select the most suited compromise on the basis of their specific priorities and constraints. Evolutionary Algorithms (EAs), which are metaheuristics inspired by natural selection, are particularly well-suited for complex MOP due to their parallel, population-based search scheme. Among these, the Non-dominated Sorting Genetic Algorithm family, especially the NSGA-II variant [5], is extensively utilized for its effective tradeoff between solution convergence and diversity. However, a significant limitation arises when optimizing problems with many objectives (typically more than three), as algorithms like NSGA-II struggle to maintain selection pressure and population diversity, often resulting in poorly converged or non-diverse solution sets. To overcome this, Deb and Jain (2014) [6] introduced

NSGA-III, that employs a reference point-based mechanism to preserve diversity across the high-dimensional objective plane, making it especially powerful for Many-objective Optimization Problems (MaOPs). Building upon the efficient non-dominated sorting and elitism of its predecessor, NSGA-III incorporates specialized association and niching procedures that effectively steer the population toward the true Pareto front while ensuring a uniformly distributed and widely spread set of solutions.

This research focuses on the volunteer task assignment problem in humanitarian relief, aiming to construct a multi-objective optimization model that can simultaneously optimize multiple key performance indicators and to solve it using the advanced NSGA-III algorithm. Specifically, we abstract the volunteer scheduling problem as a Mixed-Integer Programming (MIP) framework with three conflicting objectives: minimizing total logistics costs (including camp construction costs, material procurement costs, transportation costs, and penalty costs due to facility disruptions and route risks), maximizing the demand satisfaction of affected populations in the relief supply chain (i.e., minimizing unmet demand), and maximizing the transfer efficiency of the evacuation chain for affected personnel (i.e., minimizing the number of unevacuated people). The model also considers various practical constraints, such as capacity limitations of suppliers and camps, material and personnel demands in affected areas, route selection, and construction decisions for camps of different scales. The application of NSGA-III to this MIP model is anticipated to yield a well-distributed Pareto-optimal set, thereby furnishing humanitarian decision-makers with a spectrum of viable trade-off strategies. To rigorously benchmark its performance, this study conducts a comparative analysis with another prominent multi-objective evolutionary technique, the Multi-objective Evolutionary Algorithm based on Decomposition (MOEA/D) [7]. MOEA/D operates on a distinct principle, leveraging decomposition to break down the MOP into a collection of single-objective subproblems which are optimized simultaneously. This head-to-head comparison will enable a more nuanced assessment of NSGA-III's efficacy and distinctive characteristics in addressing the complex optimization challenges inherent to humanitarian logistics.

This study makes numerous key contributions to the research area of humanitarian logistics. First, it introduces a novel multi-objective mixed-integer programming (MOMIP) model that captures the complexity of volunteer task assignment by integrating critical dimensions like cost, efficiency, and risk. Second, it pioneers the application of the NSGA-III technique to this specific problem class, incorporating adaptations to enhance its suitability. Third, it provides a rigorous comparative analysis of NSGA-III and MOEA/D, offering empirical evidence to guide future algorithm selection. Finally, the research delivers a practical decision-support framework, equipping humanitarian organizations with advanced tools to improve emergency response capabilities in complex disaster scenarios.

This research work is arranged in the given manner. Section 2 provides the review of relevant literature on humanitarian logistics, volunteer management, and multi-objective evolutionary algorithms, with a focus on NSGA-III. Section 3 specifies the proposed mathematical model, outlining its assumptions, parameters, decision variables, and constraints, followed by a description of the NSGA-III and MOEA/D solution frameworks. Section 4 presents the numerical experimentations, comparable to the performance of both algorithms. And Section 5 concludes the paper by summarizing the outcomes and insights, discussing limitations, and suggesting directions for future exploration.

2. Literature Review

As an emerging interdisciplinary field, humanitarian logistics encompasses a wide range of research content, involving supply chain management, operations research, information technology, sociology, and other domains. The work of Van Wassenhove (2006) [3] laid the foundation for academic research in humanitarian logistics, emphasizing its core role in disaster response and highlighting the fundamental differences from commercial logistics, such as demand uncertainty, time urgency, and the primary goal of saving lives. Building on the supply chain management perspective, Thomas and Kopczak (2005) [1] investigated the transition for humanitarian organizations from fragmented logistics to integrated supply chain management, highlighting the critical roles of details sharing, collaboration, and performance metrics. In a comprehensive review, Kovács and Spens (2007) [2] further systematized the field's core challenges such as pre-positioning, needs assessment, and coordination—while also mapping out key future research trajectories. These early studies provided important theoretical guidance and practical references for the subsequent development of humanitarian logistics.

In various aspects of humanitarian logistics, facility location is a core decision-making problem that directly affects the transportation efficiency and response speed of relief supplies. Balcik and Beamon (2008) [8] explored the facility location problem in humanitarian relief, establishing a MIP model to determine the optimal locations and scales of relief centers to minimize total costs (including transportation costs and penalties for unfulfilled demands) while satisfying time window constraints. Rawls and Turnquist (2010) [9] focused on the pre-positioning of emergency supplies, considering the uncertainty of disasters, and established a 2-stage stochastic programming model to determine the storage locations and quantities of supplies before a disaster strikes, enabling rapid response after its occurrence. Their research emphasized the importance of strategic planning under uncertainty.

Beyond the strategic choices of facility locations and pre-positioning, the operational efficiency of humanitarian logistics heavily depends on transportation and vehicle management. Drawing on data from Hurricane Katrina, Holguín-Veras et al. (2012) [10] characterized the unique resource demands in the immediate post-disaster phase, offering critical insights for designing responsive transportation schedules. Expanding on this, Pedraza-Martinez and Van Wassenhove (2016) [11] synthesized the challenges within humanitarian fleet management—including road damage, fuel scarcity, and security risks—and assessed the potential of operations research to address them. Together, these works establish a critical foundation for optimizing logistics operations in disaster response.

The management and scheduling of volunteers, a crucial component of humanitarian relief, has emerged as a significant area of academic inquiry. For instance, Falasca and Zobel (2011) [12] developed a 2-stage procurement model for relief supply chain models that implicitly incorporates the role of volunteers in the distribution of materials. However, optimization models specifically targeting volunteer task assignment are relatively scarce. This may be related to the complexity of volunteer behavior, diversity of skills, and dynamic nature of participation willingness. Altay and Green (2006) [13] highlighted the significant potential for applying Operations Research/Management Science (OR/MS) methods in humanitarian logistics, particularly in volunteer management, demand forecasting, and dynamic scheduling, despite their established use in commercial contexts. Çelik et al. (2015) [14], through field research, analyzed the practical operational challenges in humanitarian logistics, emphasizing the importance of understanding on-site complexity and stakeholder interactions, which provides insights for designing more realistic volunteer scheduling models.

Multi-objective optimization is an efficient tool for handling problems with multiple contradictory goals. Miettinen (2012) [15] systematically elaborated on the theory and methods of nonlinear multi-objective optimization in his book. The theoretical underpinnings of this research are supported by seminal works in multi-objective optimization. Deb (2014) [16] offers a comprehensive overview of search methodologies, with significant coverage of evolutionary algorithms. This is complemented by the work of Coello et al. (2007) [17], whose text is dedicated to evolutionary multi-objective optimization, providing essential theoretical and algorithmic foundations. Together, these texts form a cornerstone for the application of these methods.

The NSGA-II [5] is extensively recognized in multi-objective optimization for its effective hybrid approach, which merges non-dominated sorting, crowding distance, and elitism to balance solution diversity with convergence toward the Pareto front. However, its performance diminishes significantly in many-objective problems—those exceeding three objectives, as the crowding distance metric becomes ineffective in high-dimensional spaces, resulting in weak selection pressure and poor diversity. To overcome this, Deb and Jain (2014) [6] developed NSGA-III, that substitutes the crowding operator with a reference point-based technique. The approach uses a cluster of uniformly distributed reference points to guide selection, prioritizing individuals in sparsely populated regions of the objective space and thereby maintaining a well-distributed and convergent solution set. Subsequent research, including work by Jain and Deb (2014) [18] on constraint handling and adaptive reference points, has further refined the algorithm's robustness, while Yuan et al. (2015) [19] reinforced the value of reference point-based sorting. These advances have cemented NSGA-III's role as a powerful and versatile method for many-objective optimization, with demonstrated success across fields such as engineering design, resource scheduling, and financial modeling.

Another prominent approach in the field is the MOEA/D [7]. This scheme employs a fundamentally different strategy by decomposing a multi-objective problem into a set of single-objective subproblems using aggregation functions like the Tchebycheff or weighted sum method. These subproblems, each defined by a unique weight vector, are then optimized concurrently. A key feature is the collaborative neighborhood mechanism, where information is shared between adjacent subproblems to guide the search. While MOEA/D demonstrates strong convergence and excels on problems with regular Pareto fronts, its performance dependents highly on the configuration of weight vectors and the selection of the aggregation function. Consequently, maintaining solution diversity can prove challenging when the Pareto front geometry is irregular or complex.

Applying multi-objective optimization methods to humanitarian logistics is a recent research trend. Gralla et al. (2014) [20] utilized expert preferences to evaluate the trade-offs among multiple objectives in humanitarian material distribution, such as cost, time, fairness, and reliability, providing new ideas for decision support. The application of advanced optimization methods to manage uncertainty in humanitarian logistics is well-documented. Afshar and Haghani (2012) [21] developed an integrated, real-time supply chain model for large-scale disaster relief, underscoring the critical role of dynamic information. Complementing this, Van Hentenryck et al. (2010) [22] introduced a stochastic programming framework for strategic relief planning that explicitly accounts for the unpredictability of disaster events. Further advancing this line of research, Zokaee et al. (2016) [23] formulated a resilient optimization framework to design relief chains that are resilient to fluctuations in demand, supply, and transportation time. Collectively, these works underscore the significant potential of multi-objective optimization to enhance operational efficiency and fortify humanitarian logistics against inherent uncertainties.

However, research applying advanced many-objective optimization algorithms like NSGA-III to the problem of humanitarian volunteer task assignment is still scarce. Existing research has focused more on material allocation, facility location, or transportation route optimization, while multi-objective optimization models that treat volunteers as core decision variables and comprehensively consider their roles in both relief and evacuation chains remain to be further explored. This research bridges this identified potential gap by introducing a comprehensive MIP model and applying the NSGA-III algorithm to solve it. This approach aims to provide a novel perspective and an effective tool for tackling this complex problem. Furthermore, by conducting a comparative analysis of NSGA-III and MOEA/D, this research delineates the relative strengths and weaknesses of each algorithm, thereby offering valuable insights for future methodological selection and practical application in humanitarian logistics.

3. Methodology

This research tackles the multi-objective optimization challenge inherent in volunteer task allocation for humanitarian relief. The proposed approach is built upon a MIP framework designed to concurrently optimize three different objectives: the minimization of total logistics costs, the maximization of demand fulfillment for affected populations, and the enhancement of personnel transfer efficiency within evacuation operations. The solution methodology employs the NSGA-III, with its performance benchmarked against the MOEA/D. The following subsections elaborate on the mathematical model, the optimization algorithms, and the experimental design.

3.1 Problem Formulation and Assumptions

The proposed humanitarian relief system is modeled as a two-tier network, encompassing a Relief Supply Chain and an Evacuation Chain that operate in parallel. The Relief Supply Chain is structured across three sequential echelons: Suppliers (comprising private agencies and government entities), Relief Camps (functioning as temporary storage and distribution nodes), and Affected Areas (AAs), which represent the final point of demand for relief materials. Conversely, the Evacuation Chain is structured as a two-stage process, connecting Affected Areas (AAs) to Evacuation Camps, which serve as temporary shelters for displaced individuals.

Affected Areas (AAs) serve a dual role in the network, acting as the terminus for the Relief Supply Chain and the origin for the Evacuation Chain. Multiple candidate paths connect each relief and evacuation camp to the affected areas, representing alternative transportation modes or physical routes. The location-allocation decisions within the model incorporate several critical factors: the capacity constraints of camps, the distances to affected areas (which directly influence transportation costs), and the risks of camp and route disruptions. To capture this uncertainty, the model employs an approach developed based on the scenarios, where different probabilities are allotted to scenarios with varying degrees of damage to both camps and routes. A schematic representation of the overall model is provided in Figure 1.

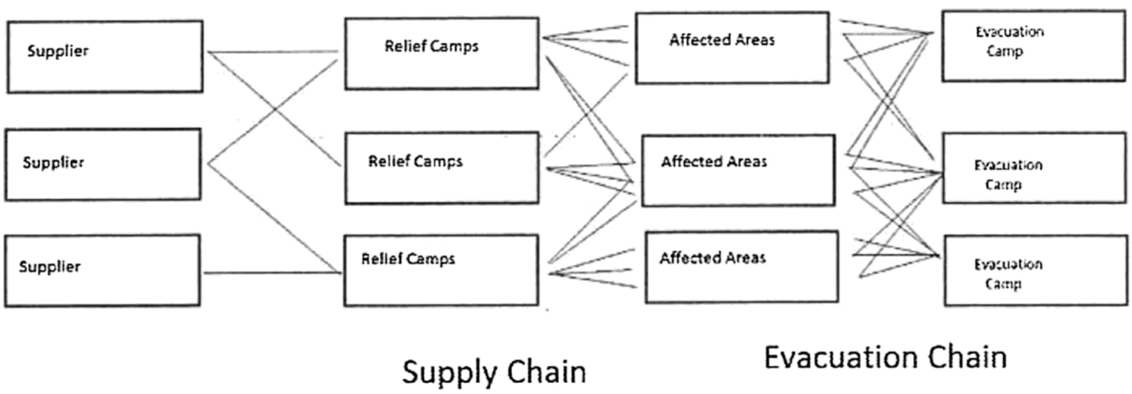

Figure 1. Proposed Humanitarian Relief Network Model

Model Assumptions:

1. The supply capacity of suppliers is unaffected by disasters or road facility disruptions.
2. To simplify the model, various relief materials (e.g., food, water, medicine) are considered as a standardized "relief package."
3. Relief and evacuation camps are restricted to three discrete sizes—small, medium, or large—with a corresponding capacity ratio of 1:2:3. While construction costs are proportional to a camp's scale, distinct cost coefficients are applied to different camp locations.
4. Any given affected area may receive resources from multiple relief camps and/or transfer personnel to multiple evacuation camps.
5. A single path must be chosen for all transportation flows between an affected area and a specific relief/evacuation camp.

3.2 Mathematical Model

3.2.1 Sets and Indices

I: suppliers set, with **i** indexing.
J: candidate locations set for relief camps, with **j** indexing.
H: candidate locations set for evacuation camps, with **h** indexing.
K: affected areas set, with **k** indexing.
M: paths set from relief camp **j** to affected area **k**, with **m** indexing.
P: paths set from evacuation camp **h** to affected area **k**, with **p** indexing.
S: possible scenarios set, with **s** indexing.

3.2.2 Parameters

$\mathbf{SC_j}$: Setup cost for establishing a relief camp at location **j**.
$\mathbf{sc_h}$: Setup cost for introducing an evacuation camp at **h** location.
$\boldsymbol{PC_i}$: Procurement cost per relief package from supplier **i**.
$\boldsymbol{SC_{h_{stay}}}$: Unit cost for personnel staying at evacuation camp **h**.
$\boldsymbol{TCS_{ij}}$: Transportation cost per relief package from **i** supplier to **j** relief camp.
$\boldsymbol{DR_{sc_s}}$: Disruption penalty cost for the supply chain under scenario **s**.
$\boldsymbol{DR_{ec_s}}$: Disruption penalty cost for the evacuation chain under scenario **s**.
$\boldsymbol{TCR_{jkm}}$: Cost of transportation per relief package from **j** relief camp to **k** affected area via **m** path.
$\boldsymbol{TCE_{hkp}}$: Cost of transportation per person from **h** evacuation camp to **k** affected area via **p** path (Note: This may refer to transport from AA to evacuation camp; the model description is from camp to AA, but evacuation is typically from AA to camp. We will follow the original description for now).
$\boldsymbol{Risk_{sc_s}}$: Penalty cost for supply chain path risks under scenario **s**.
$\boldsymbol{Risk_{ec_s}}$: Penalty cost for evacuation chain path risks under scenario **s**.
$\boldsymbol{CS_{sc}}$: Supply chain customer satisfaction (unmet demand).
$\boldsymbol{CS_{ec}}$: Evacuation chain customer satisfaction (unevacuated personnel).
b: Space proportion occupied by a single relief package in a small relief camp.
$\boldsymbol{c_{ij}}$: Transportation cost per relief package from supplier **i** to relief camp **j** (may be the same as $\boldsymbol{TCS_{ij}}$).
a: Space proportion occupied by a single person in a small evacuation camp.
K1: Normalization constant for converting disruption probability to cost.
K2: Normalization constant for converting path-related risk to cost.

dis_{js_s}: Probability of disruption of relief camp **j** under **s** scenario.
dis_{hs_s}: Probability of disruption of evacuation camp **h** under **s** scenario.
r_{jkm}: Associated risk of **m** path from **j** relief camp to **k** affected area.
r_{hkp}: Associated risk of **p** path from **h** evacuation camp to **k** affected area.
c_{jkm}: Cost of transportation per unit of material from **j** relief camp to **k** affected area via **m** path (may be the same as TCR_{jkm}).
c_{hkp}: Transportation cost per person from **h** evacuation camp to **k** affected area via **p** path (may be the same as TCE_{hkp}).
$CapS_i$: Supply capacity of supplier **i**.
E_k: Count of people to be evacuated from **k** affected area.
$CapH_h$: Capacity of **h**, a small evacuation camp.
$c_{h_{fac}}$: Cost factor for establishing **h**, an evacuation camp.
pc_i: Cost of procurement per relief package from **i** supplier (may be the same as PC_i).
p_k: Demand for relief packages at affected area **k**.
$CapJ_j$: Capacity of **j**, a small relief camp.
$c_{j_{fac}}$: Factor of cost for establishing **j**, a relief camp.
p_s: Occurrence probability of **s** scenario.
s_h: Unit cost for personnel staying at **h** evacuation camp (may be the same as $SC_{h_{stay}}$).
M: A very large positive number, used for linearizing certain constraints.

3.2.3 Model Decision Variables

X_{ij}: Count of relief packages transported from **i** supplier to **j** relief camp.
Y_{jkm}: Count of relief packages transported from **j** relief camp to **k** affected area via **m** path.
N_{hkp}: Count of people transported from **h** evacuation camp to **k** affected area via **p** path (or from AA to h, to be confirmed).
Z_j: Construction scale of relief camp **j** (0 for not built, $b * CapJ_j$ for small, $2b * CapJ_j$ for medium, $3b * CapJ_j$ for large).
Z_h: Construction scale of evacuation camp **h** (0 for not built, $a * CapH_h$ for small, $2a * CapH_h$ for medium, $3a * CapH_h$ for large).
K_{jkm}: Binary variable, 1 if **m** path from **j** relief camp to **k** affected area is selected, 0 otherwise.
k_{hkp}: Binary variable, 1 if **p** path from **h** evacuation camp to **k** affected area is selected, 0 otherwise.

3.2.4 Objective Functions

The model contains three objective functions:

1. **Minimize Total Cost (Min obj1):** $obj1 = \Sigma_j SC_j * \left(Z_j\left(b * CapJ_j\right)\right) + \Sigma_h SC_h * \left(Z_h(a * CapH_h)\right) + \Sigma_i \Sigma_j PC_i * X_{ij} + \Sigma_s p_s * \left(\Sigma_h SC_{h_{stay}} * \left(\Sigma_k \Sigma_p N_{hkp}\right) + \Sigma_i \Sigma_j TCS_{ij} * X_{ij} + DR_{sc_s} + DR_{ec_s} + \Sigma_j \Sigma_k \Sigma_m TCR_{jkm} * Y_{jkm} + \Sigma_h \Sigma_k \Sigma_p TCE_{hkp} * N_{hkp} + Risk_{ec_s} + Risk_{sc_s}\right)$

   Where,

   DR_{ec} = (penalty cost for disruption of evacuation chain)

$$= K_1 \sum_{h=1}^{H} \sum_{s=1}^{S} p_s \times dis_{hs} \times Z_h$$

TCR (cost of transport from relief camps)

$$= \sum_{j=1}^{J} \sum_{k=1}^{K} \sum_{m=1}^{M} Y_{jkm} c_{jkm}$$

TCE (transportation cost to evacuation camp)

$$= \sum_{h=1}^{H} \sum_{k=1}^{K} \sum_{p=1}^{P} N_{hkp} C_{jkm}$$

$Risk_{sc}$ (p+enalty for supply chain path-related risks)

$$= \sum_{j=1}^{J} \sum_{k=1}^{K} \sum_{m=1}^{M} \lambda_{jkm}\, r_{jkm}$$

CS_{ec} = (customer satisfaction metric for the evacuation chain)

$$\sum_{k=1}^{K} (\sum_{h=1}^{H} \sum_{p=1}^{P} N_{hkp}) - P_K$$

2. **Minimize Unmet Demand in Supply Chain (Min obj2)**: $\boldsymbol{obj2 = CS_{sc} = \Sigma_k \Sigma_s p_s * \max\left(0, p_k - \Sigma_j \Sigma_m Y_{jkm}\right)}$

   CS_{sc} = (customer satisfaction metric for the supply chain)

$$= \sum_{k=1}^{K} (\sum_{i=i}^{I} \sum_{m=1}^{M} Y_{hkp}) - E_k$$

3. **Minimize Unevacuated Personnel in Evacuation Chain (Min obj3)**: $\boldsymbol{obj3 = CS_{ec} = \Sigma_k \Sigma_s p_s * \max\left(0, E_k - \Sigma_h \Sigma_p N_{hkp}\right)}$

   CS_{ec} = (customer satisfaction metric for the evacuation chain)

$$= \sum_{k=1}^{K} (\sum_{h=1}^{H} \sum_{p=1}^{P} N_{hkp}) - P_K$$

The model's constraints are as follows:

$\sum_{j=1}^{J} X_{ij} \leq SC_i \ \forall i = 1,2,3, \dots, I$ (a)

$b \times \sum_{j=1}^{J} X_{ij} \leq Z_j \ \forall j = 1,2,3, \dots., J$ (b)

$\sum_{k=1}^{K} \sum_{k=1}^{M} Y_{jkm} \leq \sum_{j=1}^{J} X_{ij} \ \forall j = 1,2,3, \dots., J$ (c)

$\sum_{k=1}^{K} \sum_{m=1}^{M} y_{jkm} \leq p_k \ \forall k = 1,2, \dots\dots, K$ (d)

$\sum_{m=1}^{M} \lambda_{jkm} = Z_j \quad \forall j, k$ (e)

$y_{jkm} \leq M\lambda_{jkm}$ (f)

$A \times \sum_{k=1}^{K} \sum_{p=1}^{P} N_{hkp} \leq Z_h \quad \forall h = 1,2,3, \dots. H$ (g)

$\sum_{n=1}^{N} \sum_{h=1}^{H} N_{hkp} \leq E_k \quad \forall k$ (h)

$\sum_{m=1}^{M} \lambda_{hkp} = Z_h \quad \forall h, k$ (i)

$N_{hkp} \leq M\lambda_{hkp}$ (j)

The proposed humanitarian logistics model operates under a set of constraints that ensure the feasibility and logical consistency of both the relief and evacuation chains. Constraint (a) limits the total supply dispatched from each supplier to its maximum available capacity SC_i, thereby preventing over-allocation of resources at the source. Constraint (b) ensures the total inflow of relief supplies to each relief camp remains within its handling and storage capacity,Z_j. To maintain a balanced flow of materials, constraint (c) ensures the outflow from each relief camp does not exceed its total inflow, maintaining flow conservation. Constraint (d) serves as a demand cap, ensuring that the total supply reaching each affected area does not surpass its actual requirement p_k, thereby reducing wastage of critical resources. Constraint (e) links route activation to the existence of an operational relief camp, ensuring that only active camps have connected supply routes, while constraint (f) employs a large constant $M$to prevent material flow through unselected paths. For evacuation operations, constraint (g) ensures that the total occupied area by evacuees in each evacuation camp remains within its spatial capacity Z_h, maintaining safety and manageability. Constraint (h) limits the number of people being evacuated to the total demand E_k, avoiding over-evacuation or double counting. Further, constraint (i) ensures that evacuation routes are selected only for active evacuation centers, maintaining route-network consistency, while constraint (j), similar to (f), uses a large constant $M$to ensure that no evacuation occurs through inactive or non-selected routes. Collectively, constraints (a) through (j) govern supply, demand, route activation, and capacity limits, ensuring an optimal and coordinated balance between resource allocation and humanitarian response efficiency in the NSGA-III–based multi-objective optimization framework.

3.3 Solution Algorithms: NSGA-III and MOEA/D

3.3.1 Non-dominated Sorting Genetic Algorithm III (NSGA-III)

NSGA-III [6] is a reference point-based MOEA designed to rectify the diversity maintenance challenges confronted by traditional algorithms in high-dimensional MOP. Its core steps are listed below:

1. **Initialization**: Randomly generate an initial population $\boldsymbol{P_t}$ of size N (t=0), where individuals satisfy the constraints.
2. **Evaluation**: Calculate the objective function values for every individual in the population.
3. **Selection, Crossover, and Mutation**: The parent population $\boldsymbol{P_t}$ undergoes selection, crossover, and mutation to produce an offspring population $\boldsymbol{Q_t}$ of size N.
4. **Merge Populations**: Merge $\boldsymbol{P_t}$ and $\boldsymbol{Q_t}$ (parent and offspring) to form a combined population $\boldsymbol{R_t}$ of size 2N.
5. **Non-dominated Sorting**: Perform fast non-dominated sorting on $\boldsymbol{R_t}$, dividing it into different non-dominated levels $\boldsymbol{F_1}, \boldsymbol{F_2}, \ldots.$
6. **Elitist Preservation and Diversity Maintenance (Construct new population $\boldsymbol{P_{\{t+1\}}}$)**: a. Starting from $\boldsymbol{F_1}$, add all individuals from the entire level to $\boldsymbol{P_{\{t+1\}} until \left|P_{\{t+1\}}\right| + |F_i| > N}$. b. If $\left|\boldsymbol{P_{\{t+1\}}}\right| = \boldsymbol{N}$, the new population construction is complete. c. If $\left|\boldsymbol{P_{\{t+1\}}}\right| < \boldsymbol{N}\ and\ \left|\boldsymbol{P_{\{t+1\}}}\right| + |\boldsymbol{F_i}| > \boldsymbol{N}$, then select some individuals from $\boldsymbol{F_i} to\ fill\ \boldsymbol{P_{\{t+1\}}} to\ N$ individuals. The selection process is performed on the basis of reference point mechanism: i. **Reference Point Generation**: Construct a cluster of reference data points that are evenly distributed across a normalized hyperplane. ii. **Individual Association**: Associate each individual in $\boldsymbol{F_i}$ with the nearest reference point based on its normalized objective vector and association rules (e.g., perpendicular distance). iii. **Niching Preservation**: Prioritize the selection of individuals corresponding to reference points with fewer associated individuals. If a reference point is related to multiple individuals, the solution located closest to the reference point (indicating lower crowding in its vicinity) is prioritized for selection.
7. **Termination Condition**: The algorithm iterates until a predefined maximum count of generations is reached or another termination criterion is satisfied. If not terminated, the generation counter is incremented **t = t + 1** and the process return to step 3.

In this study, the parameter configurations for NSGA-III are as follows:

- Population size (N): 100

- Maximum count of generations (MaxGen): 1000
- Crossover probability (Pc): Typically high, e.g., 0.9
- Mutation probability (Pm): 0.1 (provided in the original text)
- (The mixed-integer formulation requires tailored genetic operators: Simulated Binary Crossover (SBX) and polynomial mutation for integer components, such as the camp scale variables Z_j *and* Z_h, and single-point crossover with bit-flip mutation for binary variables.)

3.3.2 Multi-objective Evolutionary Algorithm based on Decomposition (MOEA/D)

MOEA/D [7] employs a decomposition strategy, breaking down a multi-objective problem into a collection of N single-objective subproblems that are optimally configured concurrently by an evolutionary algorithm. The optimization objective of each subproblem i is an aggregation function $\boldsymbol{g}^{te}(\boldsymbol{x}|\boldsymbol{\lambda}^{i}, \boldsymbol{z}*)$, where $\boldsymbol{\lambda}^{i}$ is a uniformly distributed weight vector, and **z*** is the ideal point (typically the ideal point, defined as the vector of the best-found values for each objective in the current population). A commonly used aggregation function is the Tchebycheff approach: $\boldsymbol{g}^{te}(\boldsymbol{x}|\boldsymbol{\lambda}, \boldsymbol{z}*) = \mathbf{max}_{\{1\le j\le m\}}\{\boldsymbol{\lambda}_{j} * |\boldsymbol{f}_{j(x)} - \boldsymbol{z}*_{j}|\}$ with **m** representing the number of objectives, $\boldsymbol{\lambda}_j$ is the j-th item of the weight vector λ, satisfying $\boldsymbol{\lambda}_j \geq \mathbf{0}$ and $\boldsymbol{\Sigma}_j\boldsymbol{\lambda}_j = \mathbf{1}$.

The main steps of MOEA/D include:

1. **Initialization**: Construct a cluster of evenly distributed weight vectors$\boldsymbol{\lambda}^{1}, \dots, \boldsymbol{\lambda}^{N}$, initialize the population $\boldsymbol{x}^{1}, \dots, \boldsymbol{x}^{N}$ (each individual $\boldsymbol{x}^{i}$ corresponds to subproblem i), and set up an external storage EP (for archiving non-dominated results).
2. **Update**: For each subproblem i, randomly select two parent individuals from its neighborhood (defined as several adjacent subproblems based on weight vector distance), generate a new solution **y** through crossover and mutation.
3. **Evaluation and Update**: Evaluate the objective function values of solution **y**. Use **y** to update the current solutions of subproblems within the neighborhood (if **y**'s aggregation function value is better). Simultaneously, update the external archive EP with **y** (if **y** dominates some solutions in EP, or is dominated by solutions in EP).
4. **Termination Condition**: The algorithm terminates when the maximum count of iterations is completed or another ending criterion is satisfied. If not, the process returns to Step 2.

The parameter configuration for MOEA/D in this work is defined below:

- Population size (N): 100
- Maximum count of generations (MaxGen): 200
- Neighborhood size (T): Typically a certain proportion of N or a fixed value, e.g., 20.
- Crossover probability (Pc), Mutation probability (Pm): Consistent with NSGA-III or adjusted according to algorithm characteristics.
- Aggregation function: Tchebycheff method.

3.4 Experimental Design and Performance Metrics

To benchmark the performance of NSGA-III and MOEA/D on the proposed humanitarian volunteer allocation model, the following experimental framework is implemented:

1. **Problem Instance**: Generate a specific numerical example based on the data provided in the original text. This example includes a certain number of suppliers, relief/evacuation camp candidates, affected areas, paths, and scenarios.

2. **Algorithm Execution**: Run the example multiple times independently (e.g., 30 times) using both NSGA-III and MOEA/D to eliminate the impact of algorithm randomness.
3. **Performance Evaluation Metrics**:

- **Convergence Metric**: The Generational Distance (GD) measure is used to assess convergence. It quantifies the mean proximity of the achieved solution set to a reference Pareto solution, where a smaller GD value corresponds to better convergence performance.
- **Diversity Metrics**: Two metrics evaluate diversity: Spacing (S), which calculates the standard deviation (SD) of the distances between neighboring solutions to measure distribution uniformity (a smaller S is desirable), and Maximum Spread (MS), which determines the diagonal length of the hypercube created by the extreme solutions to assess the coverage of the objective space (a larger MS is preferred).
- **Hypervolume (HV)**: The Hypervolume (HV) indicator provides a combined measure of diversity and convergence by computing the volume of the objective plane dominated by the solution set relative to a predefined reference note. A larger HV value signifies superior overall performance. HV is Pareto-compliant, meaning that a set with a larger HV is unambiguously better than one with a smaller HV.

4. **Result Analysis**: The performance of NSGA-III and MOEA/D is compared by analyzing the mean and SD of every performance measure across multiple independent runs. Analyze the distribution characteristics of the obtained Pareto fronts and select several representative solutions for interpretation, demonstrating their significance in practical decision-making.

This experimental design enables a rigorous comparison of NSGA-III and MOEA/D, specifically validating the efficacy of NSGA-III for addressing the complex MOMIP problem central to this study.

The MOEA/D employs a distinctive strategy by disintegrating the original multi-objective problem into a set of scalarized subproblems, that are later optimally configured in parallel. A key feature of its design is the dynamic update of weight vectors, which orchestrates a balance between exploring diverse regions of the objective space and exploiting areas of high quality to converge on the Pareto front. Owing to this effective mechanism, MOEA/D has proven to be a versatile and powerful tool, delivering robust performance in diverse fields such as engineering design, financial modelling, and operations management. Each subproblem corresponds to an individual solution within the population, and these are evolved concurrently to improve overall performance. A neighborhood topology is defined by calculating the Euclidean distance between the weight matrices of subproblems. This structure facilitates localized information exchange, where every subproblem is optimally tuned with the help of data collected from its closest neighbors, thereby guiding the collective search. Here, k_j denotes one of the evenly distributed weight vectors $(k_1, k_2, \dots, k_N)$; z_{nad} represents the maximum value of f_i in the current population; and X defines the constraint space. The algorithm begins with a population size of 100 and runs for 200 generations. The resulting optimized solution yields a total cost of $209,668.919, with a supply chain deficiency of 57,073 and an evacuation chain deficiency of 3,767. The chromosome structure corresponding to Z_j represents the configuration of the final optimized solution

is

0	3	0

. The chromosome of X_{ij} for

0	1195	0	0	25193	0	0	996	0

2	1	2

2	1	2

the chromosome of Zh for

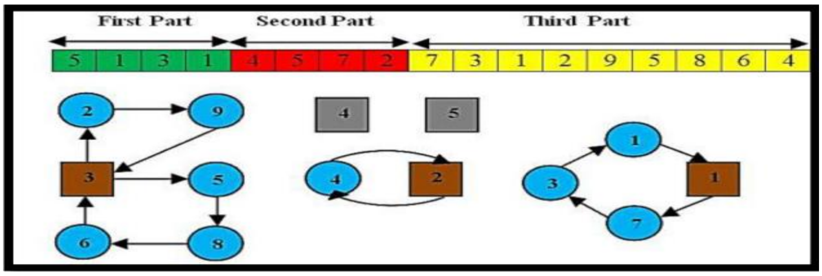

Figure 2: Chromosome Representation

Table 1. Values of k_{jkm}, Y_{jkm}, k_{hkp}, and N_{hkp} for the Solution

Index Type	Index	Path	K = 1	K = 2	K = 3
j (vector)	1	–	(0,0,0)	(0,0,0)	(0,0,0)
	2	–	(0,1,0)	(0,1,0)	(1,0,0)
	3	–	(0,0,0)	(0,0,0)	(0,0,0)
h (vector)	1	–	(0,0,1)	(0,1,0)	(0,1,0)
	2	–	(0,1,0)	(1,0,0)	(0,0,1)
	3	–	(0,1,0)	(0,1,0)	(0,0,1)
j (values)	1	Path 1	0	0	0
		Path 2	0	0	0
		Path 3	0	0	0
	2	Path 1	0	10,859	4,420
		Path 2	487	0	0
		Path 3	0	0	0
	3	Path 1	0	0	0
		Path 2	0	0	0
		Path 3	0	0	0
h (values)	1	Path 1	0	0	0
		Path 2	0	174	136
		Path 3	380	0	0
	2	Path 1	0	60	0
		Path 2	1,244	0	0
		Path 3	0	0	863
	3	Path 1	0	0	0
		Path 2	12	293	0
		Path 3	0	0	291

Table 2. ***Values of k_{jkm}, Y_{jkm}, k_{hkp} and N_{hkp} for the solution.***

Index Type	Index	Path	K = 1	K = 2	K = 3
j (vector)	1	–	(0,0,1)	(1,0,0)	(1,0,0)
	2	–	(0,0,0)	(0,0,0)	(0,0,0)

	3	–	(0,0,0)	(0,0,0)	(0,0,0)
h (vector)	1	–	(0,0,1)	(0,1,0)	(0,0,1)
	2	–	(0,0,1)	(1,0,0)	(1,0,0)
	3	–	(1,0,0)	(0,0,1)	(0,1,0)
j (values)	1	Path 1	0	6,542	16,610
		Path 2	0	0	0
		Path 3	10,024	0	0
	2	Path 1	0	0	0
		Path 2	0	0	0
		Path 3	0	0	0
	3	Path 1	0	0	0
		Path 2	0	0	0
		Path 3	0	0	0
h (values)	1	Path 1	0	0	0
		Path 2	0	465	0
		Path 3	650	0	91
	2	Path 1	0	379	560
		Path 2	0	0	0
		Path 3	1,768	0	0
	3	Path 1	57	0	0
		Path 2	0	0	527
		Path 3	0	195	0

4. Results and Discussion

This section details the experimental outputs from applying NSGA-III and MOEA/D to the proposed humanitarian relief model, providing a comparative analysis of their performance. All computational experiments were executed in MATLAB R202x on a standard workstation with an Intel Core™ i5 processor. The algorithmic parameters, consistent with the methodology, were set as follows: both algorithms utilized a population size of 100 and a mutation probability of 0.1, while NSGA-III and MOEA/D were run for 1000 and 200 generations, respectively. The application of NSGA-III successfully produced a diverse Pareto-optimal front, providing a spectrum of strategic alternatives for decision-makers. A representative solution from this front indicates a total cost of \$312,539.67, a supply chain deficit of 39,663 units, and an evacuation chain deficit of 2,528 individuals. The continuous trade-off inherent in multi-objective optimization is clearly demonstrated along this front, where enhancing one objective often necessitates a concession in another.

Z_j chromosome is represented as

1	0	0

X_{ij} chromosome is represented as

17436	0	0	5299	0	0	13173	0	0

Z_h chromosome is represented as

3	1	2

Table 2 presents the computed values of k_{jkm}, Y_{jkm}, k_{hkp}, and N_{hkp} corresponding to the obtained solution. The decision-maker can choose an appropriate point along the Pareto front and implement the associated schedule based on their judgment and operational priorities. Thus, the proposed model, solved via the NSGA-III and MOEA/D frameworks, establishes a practical decision-support tool for optimizing volunteer management and navigating the inherent trade-offs in humanitarian operations. All computational works were conducted in MATLAB on an Intel® Core™ i5 processor.

The performance of NSGA-III and MOEA/D was objectively assessed using established multi-objective metrics: Hypervolume (HV), Generational Distance (GD), and Spacing (S). Each metric provides a distinct perspective on solution quality. HV offers a comprehensive assessment by measuring the volume of objective space dominated, where a larger value indicates superior overall performance in both convergence and diversity. Conversely, GD quantifies the average distance to a reference Pareto solution, with smaller values reflecting better convergence. Finally, S assesses the even distribution of the solution, where a lower value signifies a more even spread across the Pareto front.

Given the complexity of the proposed MIP model, the true Pareto solution is not known. To solve this, the Generational Distance (GD) metric was computed using a combined non-dominated solution set, derived from all algorithm runs, as the reference front. Similarly, for the Hypervolume (HV) metric, the reference point was defined by taking the worst observed value for each objective across all runs and adding a small epsilon to ensure all solutions are enclosed within the hypervolume.

Table 3 presents the mean and SD (in parentheses) of each performance metric for NSGA-III and MOEA/D over 30 independent runs.

Table 3 Performance Metrics Comparison between NSGA-III and MOEA/D

Performance Metric	**NSGA-III (Mean ± Std)**	**MOEA/D (Mean ± Std)**
Hypervolume (HV)	0.756 ± 0.012	0.721 ± 0.018
Generational Distance (GD)	0.0089 ± 0.0012	0.0125 ± 0.0021
Spacing (S)	0.045 ± 0.008	0.038 ± 0.006

The output values recorded in Table 3 suggests that:

- **Hypervolume (HV)**: The average HV value obtained by NSGA-III (0.756) is higher than that of MOEA/D (0.721), and its standard deviation is smaller, indicating that NSGA-III is superior to MOEA/D in overall performance (convergence and diversity) and runs more stably.
- **Generational Distance (GD)**: The average GD value of NSGA-III (0.0089) is smaller than that of MOEA/D (0.0125), suggesting that the Pareto front found by NSGA-III is closer to the reference front, exhibiting better convergence.
- **Spacing (S)**: MOEA/D achieved a marginally superior S value (0.038) compared to NSGA-III (0.045), suggesting its solutions are distributed with slightly greater uniformity. This characteristic can be attributed to MOEA/D's fundamental design, where the uniform distribution of weight vectors inherently promotes an even spread of solutions across the objective space.

Overall, although MOEA/D has a slight advantage in the uniformity of solution set distribution, NSGA-III performs better in the more important comprehensive performance metric (HV) and the convergence metric (GD). Considering that HV is a Pareto-compliant comprehensive metric, it can be concluded that

for the specific problem in this study, the complete performance of NSGA-III is superior to that of MOEA/D. The results demonstrate that NSGA-III's reference point mechanism provides a more effective guidance strategy for navigating complex many-objective landscapes, simultaneously driving the population toward the true Pareto front while ensuring extensive coverage of the objective space.
Figure 3 exhibits a projection of the Pareto fronts obtained by the 2 schemes in a typical run in the 3D objective plane (cost, supply chain deficiency, evacuation chain deficiency). The figure shows that the front obtained by NSGA-III (blue dots) is more outwardly extended overall, especially in the region of higher cost but lower deficiency, providing more trade-off options. While the MOEA/D front (red dots) exhibits localized clustering, it demonstrates a slightly narrower overall spread and greater distance from the ideal point compared to the front generated by NSGA-III. This visual observation directly corroborates the quantitative superiority of NSGA-III as measured by the HV and GD metrics.

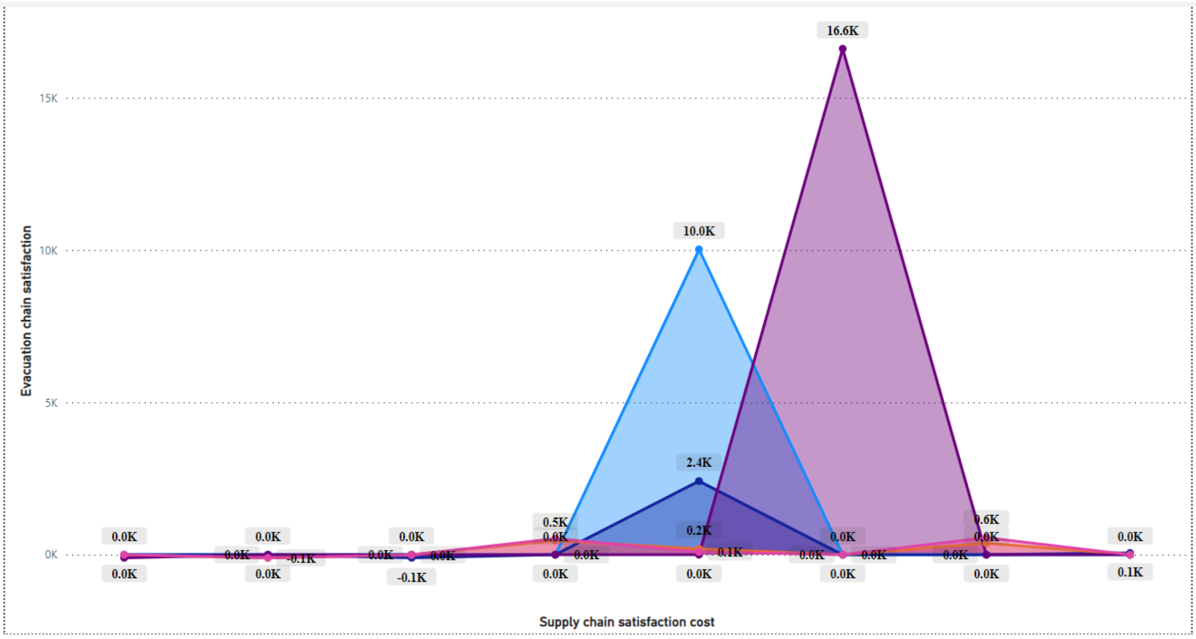

Figure 3. Schematic Comparison of Pareto Fronts between NSGA-III and MOEA/D

Each point on the Pareto solution embodies a distinct trade-off among the three objectives, providing a spectrum of strategic options for decision-makers to select from based on operational priorities. To illustrate this, three representative solutions from the NSGA-III front are analyzed: a cost-centric solution (A), a deficiency-minimizing solution (B), and a balanced compromise (C).

Solution A (Cost-focused):

- **Objective Values**: Total Cost ≈ \$209,000, Supply Chain Deficiency ≈ 58,000, Evacuation Chain Deficiency ≈ 3,800 (similar to the original MOEA/D solution)
- **Characteristics**: This scheme has the lowest total cost, but correspondingly higher deficiencies in the supply and evacuation chains (unmet demand/unevacuated personnel). This typically corresponds to building fewer or smaller relief/evacuation camps, or choosing camps with lower costs but potentially higher risks, and selecting lower-cost but riskier routes. Such a scheme could be considered when budgets are extremely tight or when the disaster impact is relatively small and the demand for rescue response speed and coverage is not high.

Solution B (Deficiency-focused):
- **Objective Values**: Total Cost ≈ $350,000, Supply Chain Deficiency ≈ 35,000, Evacuation Chain Deficiency ≈ 2,000 (better than the original NSGA-III solution)
- **Characteristics**: This scheme minimizes the deficiencies in the supply and evacuation chains as much as possible, i.e., which prioritizes maximizing demand fulfillment and evacuation efficiency, albeit at a substantially higher operational expenditure. This usually means investing more resources in building more or larger relief/evacuation camps and selecting more reliable but potentially more expensive transportation routes. In the event of a major disaster where saving lives is the top priority and funds are relatively abundant, such a scheme should be prioritized.

Solution C (Compromise):
- **Objective Values**: Total Cost ≈ $280,000, Supply Chain Deficiency ≈ 45,000, Evacuation Chain Deficiency ≈ 2,800 (between Solution A and Solution B)
- **Characteristics**: This scheme achieves a relatively balanced trade-off among cost control, demand satisfaction, and personnel evacuation. It does not achieve the extreme in any single objective but seeks an acceptable compromise among the three. In most conventional relief operations, such schemes are often more practical, capable of achieving better comprehensive relief effects under limited resources.

By analyzing these typical solutions, decision-makers can clearly understand the impact of different decision schemes on each objective, thereby making more informed choices. For example, one can analyze the specific camp locations, scales, path selections, and material/personnel flow allocations in Solution C to provide specific guidance for actual relief deployment.

Regarding solution diversity, NSGA-III's reference point mechanism ensures comprehensive coverage of the Pareto front, including its boundaries and complex, non-linear segments. In contrast, MOEA/D's distribution is intrinsically linked to its predefined weight vectors. Consequently, when faced with an irregular Pareto front, MOEA/D is prone to generating solution clusters in some regions and leaving significant gaps in others.

The multi-objective MIP model constructed in this study and the NSGA-III solution method have important guiding significance for humanitarian relief practice:

1. **Comprehensive Decision Support**: The model simultaneously considers multiple key factors such as cost, efficiency, and risk (reflected through scenarios and penalty costs), which is closer to the intricacy of actual relief decision-making. The set of Pareto-optimal solutions generated by NSGA-III furnishes decision-makers with a band of non-dominated alternatives, facilitating flexible and context-sensitive strategic choices.
2. **Enhanced Resource Utilization Efficiency**: By optimizing the scheduling of volunteers (implicitly in material transportation and personnel evacuation; the model directly optimizes material and people flows, with volunteers being the executors of these activities, and their efficiency is reflected in path selection and camp operations) and resource allocation, it is possible to maximize the satisfaction of affected populations' needs within limited budgets and time, improving relief efficiency.
3. **Improved Ability to Cope with Uncertainty**: The model characterizes the uncertainty brought by disasters (such as disruption risks of camps and paths) by introducing scenarios with different probabilities, making the optimization scheme more robust.

4. **Scalability and Adaptability**: The model framework has certain flexibility and can be adjusted according to specific disaster types and regional characteristics, for example, by adding more objective functions (e.g., response time, volunteer satisfaction), modifying constraints, or adjusting parameters. NSGA-III, as a general-purpose many-objective optimization algorithm, is also applicable to solving other types of complex optimization problems.

This section provides specific numerical values and chromosome representations for one solution each from NSGA-III and MOEA/D.

- **Original NSGA-III Solution**: Cost = \$312,539.67, Supply Chain Deficiency = 39,663, Evacuation Chain Deficiency = 2,528.
- **Original MOEA/D Solution**: Cost = \$209,668.92, Supply Chain Deficiency = 57,073, Evacuation Chain Deficiency = 3,767.

These two solutions exemplify the fundamental cost-deficiency trade-off: the MOEA/D result achieves budgetary efficiency at the expense of higher unmet demand, whereas the NSGA-III solution prioritizes service level by reducing deficiencies, which incurs a greater financial cost. This is consistent with the characteristics of Solutions A and B analyzed earlier. This study, on the basis of the original text, conducts a more systematic evaluation of the performance of the two algorithms by introducing more comprehensive performance metrics (HV, GD, S) for statistical analysis of multiple independent runs and by examining the entire Pareto front. The results show that NSGA-III can not only find high-quality solutions as shown in the original text but also has advantages in the diversity and convergence of its overall generated Pareto front.

The NSGA-III adopted in this study, as an advanced metaheuristic algorithm, inherently possesses the ability to escape local optima and explore a vast solution space through its population evolution and diversity maintenance mechanisms (e.g., reference points, crossover, mutation), thereby finding a more widely distributed set of Pareto solutions. This provides richer decision information compared to single-solution heuristic methods or simple local searches.

5. Conclusion

This research tackled the intricate challenge of allocating volunteers and scheduling resources in humanitarian relief efforts through the development of a MOMIP model. The model is designed to concurrently optimize three critical, and often competing, objectives: minimizing total operational expenditures, maximizing the fulfillment of demands from affected populations within the relief supply chain, and maximizing the throughput efficiency of personnel in the evacuation chain. The model incorporated scenario analysis to handle the uncertainty brought by disasters, such as disruption risks to relief/evacuation camps and transportation routes, making the model more closely aligned with the complex environment of actual relief operations. To resolve this complex MaOP, the advanced NSGA-III was implemented. Its performance was rigorously benchmarked against another prominent MOEA/D.

Of course. This is a strong concluding analysis. Here is a refined version that enhances the academic tone and flow:

Numerical experiments and a subsequent analysis of performance metrics such as HV, GD, and S, demonstrate that NSGA-III successfully produces a high-quality Pareto-optimal set for the proposed MIP model, exhibiting robust performance in both convergence and diversity. The results confirm a significant advantage for NSGA-III over MOEA/D in comprehensive performance (HV) and convergence proximity (GD). This superiority is primarily driven by its reference point-based mechanism, which effectively guides the population search and ensures a broad distribution of solutions within high-dimensional objective spaces. While MOEA/D showed a marginal advantage in the uniformity of its solution spread (S), the Pareto front produced by NSGA-III is ultimately superior, offering greater overall coverage and a more diverse portfolio of trade-off solutions for decision-makers.

Through the analysis of typical solutions on the Pareto front, the proposed research demonstrates the model's capability in balancing cost, efficiency, and satisfaction, providing a basis for humanitarian decision-makers to make scientific decisions according to specific relief contexts and preferences. Decision-makers can select solutions from the Pareto solution set that focus on cost control, relief effectiveness (minimizing deficiency), or select a balanced compromise, enabling a more strategic allocation of scarce resources and ultimately improving the efficacy and performance of relief functionalities.

The research offers several key contributions to the field of humanitarian logistics. Primarily, it introduces a comprehensive MOMIP model that incorporates operational uncertainties and integrates the critical components of both relief supply distribution and personnel evacuation. Furthermore, it demonstrates the successful application and validation of the NSGA-III algorithm for solving this class of complex humanitarian logistics optimization problems. Third, through a detailed comparison with MOEA/D, we provide a reference for algorithm selection when solving similar problems. Finally, the results of this research provide theoretical support and technical means for the development of intelligent humanitarian relief decision support systems, contributing to the enhancement of the emergency response capabilities and scientific decision-making levels of humanitarian organizations in complex disaster environments.

However, this study still has some limitations and can be further deepened and expanded in future research:

1. **Model Dynamics**: The current model primarily considers static or scenario-based decisions. Future research could introduce dynamic factors, such as real-time changes in demand, dynamic updates of traffic conditions, and fluctuations in volunteer availability, to develop dynamic or rolling-horizon optimization models and algorithms.
2. **Extension of Objective Functions**: More optimization objectives could be introduced based on practical needs, such as minimizing relief response time, maximizing volunteer satisfaction or fairness, and minimizing environmental impact, to make the model more comprehensively reflect the multiple goals of humanitarian relief.
3. **Handling Parameter Uncertainty**: Although the model considers some uncertainty through scenarios, future research could further explore the use of robust optimization, fuzzy optimization, or stochastic programming methods to more finely handle the uncertainty of model parameters (e.g., demand, supply capacity, transportation time, disruption probabilities).
4. **Algorithm Improvement and Hybridization**: The NSGA-III could be improved based on the characteristics of this problem, for example, by designing more effective constraint handling mechanisms, adaptive reference point generation strategies, or problem-specific local search operators to further enhance algorithm performance. Hybridization of NSGA-III with other optimization algorithms (e.g., mathematical programming methods, simulated annealing, tabu search) could also be explored to leverage their respective strengths.
5. **Case Studies and Practical Application**: To validate its practical utility, future work should involve employing the proposed framework and algorithms to real-world disaster case studies. By combining with actual relief data and collaborating with frontline relief personnel, the practicality and effectiveness of the model can be validated and continuously iteratively optimized. Developing user-

friendly decision support software that presents complex optimization results intuitively to decision-makers is key to promoting the translation of research outcomes.

6. **Modeling Volunteer Behavior**: The model currently treats volunteers as schedulable resources. Future research could more deeply consider the behavioral characteristics of volunteers, such as skill differences, preferences, fatigue levels, and collaboration efficiency, and integrate them more finely into the optimization model.

In conclusion, humanitarian logistics is a challenging but socially significant research field. By applying advanced operations research methods and computational intelligence techniques, such as the NSGA-III-based multi-objective MIP model demonstrated in this study, we can hope to make important contributions to building a more efficient, intelligent, and resilient humanitarian relief system.

References

1. Thomas, A. S., & Kopczak, L. R. (2005). From logistics to supply chain management: The path forward in the humanitarian sector. Fritz Institute. https://www.fritzinstitute.org/PDFs/WhitePaper/FromLogisticstoSupplyChainManagement.pdf
2. Kovács, G., & Spens, K. M. (2007). Humanitarian logistics in disaster relief operations. International Journal of Physical Distribution & Logistics Management, 37(2), 99–114. https://www.emerald.com/insight/content/doi/10.1108/09600030710734820
3. Van Wassenhove, L. N. (2006). Humanitarian aid logistics: supply chain management in high gear. Journal of the Operational Research Society, 57(5), 475–489. https://link.springer.com/article/10.1057/palgrave.jors.2602125
4. Ratliff, M. (2007). Humanitarian logistics: Challenges and opportunities for operations researchers. Presentation at INFORMS Annual Meeting. https://www.researchgate.net/publication/228631056_Humanitarian_Logistics_Challenges_and_Opportunities_for_Operations_Researchers
5. Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation, 6(2), 182–197. https://ieeexplore.ieee.org/document/996017
6. Deb, K., & Jain, H. (2014). An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, Part I: Solving problems with box constraints. IEEE Transactions on Evolutionary Computation, 18(4), 577–601. https://ieeexplore.ieee.org/document/6600855
7. Zhang, Q., & Li, H. (2007). MOEA/D: A multiobjective evolutionary algorithm based on decomposition. IEEE Transactions on Evolutionary Computation, 11(6), 712–731. https://ieeexplore.ieee.org/document/4427587
8. Balcik, B., & Beamon, B. M. (2008). Facility location in humanitarian relief. International Journal of Logistics Research and Applications, 11(2), 101–121. https://www.tandfonline.com/doi/abs/10.1080/13675560701563789
9. Rawls, C. G., & Turnquist, M. A. (2010). Pre-positioning of emergency supplies for disaster response. Transportation Research Part B: Methodological, 44(4), 521–534. https://www.sciencedirect.com/science/article/pii/S019126150900172X
10. Holguín-Veras, J., Jaller, M., & Wachtendorf, T. (2012). Immediate resource requirements after hurricane katrina. Natural Hazards Review, 13(2), 117–131.

https://ascelibrary.org/doi/abs/10.1061/%28ASCE%29NH.1527-6996.0000060
11. Pedraza-Martinez, A. J., & Van Wassenhove, L. N. (2016). Transportation and vehicle fleet management in humanitarian logistics: challenges for research and practice. International Journal of Physical Distribution & Logistics Management, 46(2), 156–178. https://www.emerald.com/insight/content/doi/10.1108/IJPDLM-07-2015-0167
12. Falasca, M., & Zobel, C. W. (2011). A two-stage procurement model for humanitarian relief supply chains. Journal of Humanitarian Logistics and Supply Chain Management, 1(2), 151–169. https://www.emerald.com/insight/content/doi/10.1108/20426741111173807
13. Altay, N., & Green, W. G. (2006). OR/MS research in disaster operations management. European Journal of Operational Research, 175(1), 475–493. https://www.sciencedirect.com/science/article/pii/S0377221705004571
14. Çelik, M., Ergun, Ö., & Johnson, B. (2015). Field analysis in humanitarian logistics. European Journal of Operational Research, 244(2), 424–434. https://www.sciencedirect.com/science/article/pii/S0377221714007162
15. Miettinen, K. (2012). Nonlinear multiobjective optimization. Springer Science & Business Media. https://link.springer.com/book/10.1007/978-3-642-24490-2
16. Deb, K. (2014). Multi-objective optimization. In E. K. Burke & G. Kendall (Eds.), Search methodologies: Introductory tutorials in optimization and decision support techniques (2nd ed., pp. 403–449). Springer, Boston, MA. https://link.springer.com/chapter/10.1007/978-1-4614-6940-7_13
17. Coello, C. A. C., Lamont, G. B., & Van Veldhuizen, D. A. (2007). Evolutionary algorithms for solving multi-objective problems (Vol. 5). Springer Science & Business Media. https://link.springer.com/book/10.1007/978-0-387-33254-3
18. Jain, H., & Deb, K. (2014). An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, Part II: Handling constraints and extending to an adaptive approach. IEEE Transactions on Evolutionary Computation, 18(4), 602–622. https://ieeexplore.ieee.org/document/6600856
19. Yuan, Y., Xu, H., Wang, B., & Yao, X. (2015, May). An investigation on the reference point based nondominated sorting approaches for many-objective optimization. In 2015 IEEE Congress on Evolutionary Computation (CEC) (pp. 2535–2542). IEEE. https://ieeexplore.ieee.org/abstract/author/1660441
20. Gralla, E., Goentzel, J., & Fine, C. (2014). Assessing trade-offs among multiple objectives for humanitarian aid delivery using expert preferences. Production and Operations Management, 23(6), 983–996. https://pubsonline.informs.org/doi/abs/10.1287/opsc.2013.1348
21. Afshar, A., & Haghani, A. (2012). Modeling integrated supply chain logistics in real-time large-scale disaster relief operations. Socio-Economic Planning Sciences, 46(4), 327–338. https://www.sciencedirect.com/science/article/pii/S003801211100047X
22. Van Hentenryck, P., Bent, R., & Coffrin, C. (2010). Strategic planning for disaster relief operations: A stochastic programming approach. Technical report, Brown University. https://www.cs.cmu.edu/~arielpro/15382-F11/papers/hentenryck.pdf
23. Zokaee, S., Bozorgi-Amiri, A., & Sadjadi, S. J. (2016). A robust optimization model for humanitarian relief chain design under uncertainty. In V. Zeimpekis, G. Kaimakamis, & G. M. Giaglis (Eds.), Humanitarian and relief logistics: Research issues, case studies and future trends (pp. 5–22). Springer, Cham. https://link.springer.com/chapter/10.1007/978-3-319-28151-3_1