

Article

Strategies for Humanitarian Logistics and Supply Chain in Organizational Contexts: Pre- and Post-Disaster Management Perspectives

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Abstract: Every organization typically comprises various internal components, including regional branches, operations centers/field offices, major transportation hubs, and operational units, among others, housing a population susceptible to disaster impacts. Moreover, organizations often possess resources such as staff, various vehicles, and medical facilities, which can mitigate human casualties and address needs across affected areas. However, despite the importance of managing disasters within organizational networks, there remains a research gap in the development of mathematical models for such scenarios, specifically incorporating operations centers/field offices and external stakeholders as relief centers. Addressing this gap, this study examines an optimization model for both before and after disaster planning in a humanitarian supply chain and logistical framework within an organization. The affected areas are defined as regional branches, operational units, major transportation hubs, operations centers/field offices, external stakeholders, and medical facilities. A mixed-integer nonlinear model is formulated to minimize overall costs, considering factors such as penalty costs for untreated injuries and demand, delays in rescue and relief item distribution operations, and waiting costs for the injured in emergency medical vehicles and air ambulances. The model is implemented using GAMS software 47.1.0 for various test problems across different scales, with the Grasshopper Optimization Algorithm proposed for larger-scale scenarios. Numerical examples are provided to show the effectiveness and feasibility of the proposed model and to validate the metaheuristic approach. Sensitivity analysis is conducted to assess the model's performance under different conditions, and key managerial insights and implications are discussed.

Keywords: humanitarian logistics; supply chain; organizations; disaster management; staffs; relief items; distribution operations

1. Introduction

Throughout history, humanity has faced a multitude of natural disasters, including floods, earthquakes, hurricanes, and more, resulting in serious and often irreversible consequences despite technological advancements in recent decades [1–3]. Some of these

disasters have been so catastrophic that they have significantly impacted the fundamental structures of countries, including their economies, societies, physical infrastructure, and, most importantly, the lives of those affected in densely populated areas [4–6]. Natural disasters have been recurring events, causing numerous injuries across various regions, with the frequency of occurrences such as tsunamis and earthquakes increasing over time [7,8]. Consequently, casualties have risen significantly due to socio-economic and demographic factors such as urban development and population growth [9]. Over the last century, an immense loss of human life has been attributed to natural disasters, with over 2.4 million fatalities and more than 206 million individuals injured, displaced, or left unemployed between 1900 and 2020 [10]. Moreover, sudden disasters have impacted billions of people worldwide in the past decade [11]. For instance, devastating cyclones in Bangladesh (Cyclone Bhola, 1970), the Philippines (Typhoon Haiyan, 2013), India (Cyclone Odisha, 1999), Myanmar (Cyclone Nargis, 2008), and the United States (Hurricane Katrina, 2005) collectively led to the loss of an estimated 400,000 lives. A notable example occurred when a powerful earthquake measuring 6.6 Mw struck the Iburi Subprefecture in southern Hokkaido, Japan, causing numerous injuries and widespread damage, including the disruption of electrical services throughout Hokkaido. In response to such devastating events, it becomes imperative to provide an effective disaster response, with particular emphasis on the humanitarian logistics and supply chain aimed at minimizing casualties and damage in affected areas [12,13].

The humanitarian supply chain (HSC) encompasses various activities designed to plan, execute, and manage the efficient flow and storage of inventory to minimize damage and casualties during natural disasters [14,15]. Moreover, humanitarian logistics performs a crucial role in reducing the consequences of disasters, and encompasses pre-disaster and post-disaster actions. Pre-disaster operations, like establishing permanent warehouses and prepositioning relief items in these facilities, aim to decrease the impact of disasters and enhance the response time to demands in affected areas. Post-disaster operations involve the distribution of relief items (RIs), the evacuation of injured individuals, and the transfer of critically injured individuals to medical centers [16].

In essence, numerous large organizations encompass diverse components spanning multiple geographical areas. By harnessing the inherent resources and capabilities of these entities, they possess the capacity to mitigate crises to a significant degree, thereby minimizing both human and financial losses, especially in scenarios where external assistance to affected areas within the organization is absent or delayed. Despite the extensive literature on disaster management and humanitarian logistics and supply chain, scant attention has been devoted to examining intra-organizational disaster management practices and the utilization of existing organizational facilities in disaster preparedness and response efforts. Moreover, a notable lack of optimization models exist to analyze disaster management within organizations, considering all major internal components. Hence, there is a crucial requirement to establish a reliable and suitable framework for disaster management within organizations, encompassing various components such as regional branches, operational units, operations centers/field offices, etc. Given that each organization comprises numerous parts and centers located in different places, some of these centers may be susceptible to disasters and require immediate response, while the organization itself possesses crisis management capabilities, including helicopters, medical centers, and staff. To address this main research gap, this article develops an optimization mathematical model for planning before and after disasters in humanitarian supply chains and logistics within organizations.

This paper contributes to the existing literature in several significant ways. Firstly, it presents a novel humanitarian supply chain and logistics model tailored for disaster management within the internal network of organizations. To the best of the authors' knowledge, no prior studies have proposed a mathematical model specifically addressing the internal operations of organizations within the context of humanitarian logistics and supply chain management. Secondly, this paper emphasizes the importance of optimizing the utilization of an organization's internal capabilities for efficient disaster management.

Consequently, the model incorporates an assessment of the organization's internal resources and facilities, including operations centers or field offices, external stakeholders, and helicopters. It is evident that staff members stationed at operations centers/field offices and external stakeholders can play a crucial role in rescue operations and distributing RIs. Hence, the developed model contemplates the availability of staff within the network to facilitate rescue operations and distribute relief items effectively. Thirdly, this paper addresses critical challenges such as the waiting time for injured persons in emergency medical vehicles (EMVs) or Air Ambulances (AAs) to reach medical centers, as well as variations in the performance levels of rescue groups across various medical centers. These considerations are integrated into the proposed mathematical model to enhance its comprehensiveness and practical relevance.

This research is looking forward to answering the below questions:

- What is the best policy for managing disasters in the interior body of an organization?
- In which candidate sites, such as regional branches, operations centers/field offices, external stakeholders, major transportation hubs, and operational units, should the permanent relief centers (PRCs) be opened, and how many different RIs should be propositioned in the established PRCs?
- How many staff should be transported from operations centers/field offices and external stakeholders to affected areas for helping rescue activities and the distribution of RIs separately?
- How many ground vehicles, helicopters, AAs, and EMVs should the organization provide to effectively manage a disaster?
- How many untreated, injured, and unsatisfied demands would the organization have?

In order to answer the above questions, this paper designs an organization-based humanitarian logistics and supply chain network within the organization network to plan pre-and post-disaster operations. The affected areas within the organization, PRCs, temporary relief centers (TRCs), operations centers/field offices, external stakeholders, and medical centers are the main centers considered in the model. In addition, the affected areas can be regional branches, major transportation hubs, operational units, operations centers/field offices, external stakeholders, and medical centers in the proposed model.

The remainder of the paper is structured in the following way. A literature review is discussed in Section 2. The problem description and mathematical model are presented in Section 3. Section 4 discusses the solution methodology. Extensive numerical examples are investigated and analyzed in Section 5. We present the sensitivity analysis in Section 6. Section 7 expresses the discussions and some managerial implications. Eventually, the conclusions are given in Section 8.

2. Literature Review

In this section, we provide an overview of the research background in the realm of supply chain and humanitarian logistics in disaster management. It is noteworthy that no study has delved into this area specifically concerning organizational contexts, a gap we aim to address in the subsequent discussion. Given the surge in natural disasters over the past two decades, numerous studies have explored this subject under various circumstances. The recent literature has also undertaken reviews of papers within this domain. For example, an overview of the HSC was discussed by Kovács and Spens [17], and a summary of inventory management in HSC was conducted by Balcik et al. [18].

A significant part of the research in this area has developed the mathematical optimization model under various conditions. Yi and Özdamar [19] presented a routing-location model in the post-disaster phase that combines logistics support and the evacuation process. Berkoune et al. [20] developed a mathematical model for the delivery of relief goods to the affected areas, where the transportation time is minimized. Rawls and Turnquist [21] investigated a model for pre-disaster emergency response that considers the location of relief centers and various types of essential relief goods. A stochastic programming mathematical model in an HSC aimed at minimizing establishment, inventory, transportation,

and shortage costs was proposed by Döyen et al. [22]. The transferring of patients to the medical center, along with the distribution of relief items to the affected areas, was discussed in the article by [23]. One of their goals was to minimize the waiting time of patients from the time of the accident to the moment they are taken to the medical center. Camacho-Vallejo et al. [24] developed a humanitarian logistics model for international aid distribution, with the aim of reducing transportation costs and increasing responsiveness. Rezaei-Malek et al. [25] studied an integrated distribution and location-allocation model in the pre-disaster stage to compute the optimal order quantity for the supply of RIs in warehouses for perishable products. A humanitarian logistics network considering regional distribution centers and warehouses in the crisis was developed by Tofighi et al. [26], who examined the model in scenario-oriented terms. Another research that studied the HSC with a scenario-based approach and uncertain demand was presented by Hu et al. [27]. Noham and Tzur [28] considered a humanitarian relief supply chain that distributed one type of relief item to affected areas. Vahdani et al. [29] investigated a multi-objective, multi-product, and multi-period two-stage mathematical model for the distribution of RIs. Liu et al. [30] extended a resilience model for planning how to distribute relief items with the aim of minimizing unmet demands after a disaster occurs. This study aims to determine the location of warehouses, inventory management, and how to distribute goods in an optimal condition.

Momeni et al. [31] proposed an HSC regarding the reliability of routes, repair groups, and evaluation of routes. In the paper, demand points were prioritized based on population, ensuring that relief goods are sent to demand points with higher priority. A model for distributing and redistributing relief items in the post-disaster phase using a three-stage systematic method was investigated by Sakiani et al. [32]. Also, to minimize the costs and maximize the coverage of the damaged areas, a two-stage model was evaluated by Aghajani et al. [33]. Heydari et al. [34] introduced a framework for debris clearance aimed at reducing the time taken to reach critical sites such as medical centers, while optimizing the extent of the area serviced. Abazari et al. [35] proposed a nonlinear multi-objective model that considered relief centers, demand points, methods of distributing goods, and two types of goods: perishable and non-perishable. Abazari et al. [36] analyzed a mathematical model for designing an HSC in order to locate relief centers, distribute relief items, and provide medical treatment in affected areas. A bi-objective optimization model was developed for the first time by Hajipour et al. [37] to analyze an HSC combined with the traceability concept. A multi-objective problem with multiple products and multiple periods in an HSC considering trucks queue in the borders of the affected zones was studied by Masoumi et al. [38], in which a routing-inventory-queue model was used to respond to demand points with the aim of minimizing response time and reducing traffic and congestion.

Bakhshi et al. [39] modeled a relief supply chain problem in which non-governmental organizations assist governmental organizations in relief activities. This model was developed for location-allocation, inventory management, and distribution planning of relief goods under uncertainty for demand, budget, storage, and transportation costs. Ehsani et al. [40] designed an HSC problem for a contagious disease, such as COVID-19, utilizing the Internet of Things to identify infected individuals. Sheikholeslami and Zarrinpoor [41] focused on a humanitarian logistics network design for response and preparedness stages in times of crisis. Lohrasbpoor et al. [42] addressed a four-level humanitarian network, where the degree of compatibility and destruction of blood units in the state of an earthquake was assessed. Khalili-Fard et al. [43] presented a comprehensive model for a pre- and post-disaster humanitarian supply chain network, considering pre-positioning strategy, NGO and GO collaboration in post-disaster distribution planning. Altay et al. [44] presented a systematic literature review to specify gaps in the literature on innovation in HSCs, and developed a suitable framework for future research. The goal of [45] is to assess pivotal challenges for implementing the relief measures of humanitarian logistics in the pre- and post-disaster phase. Beiki Ashkezari et al. [46] developed a bi-objective MINLP model to consider pre-positioning and distributing relief items, which is formulated as

an integrated location-allocation-routing problem under uncertainty. Mousavi et al. [47] studied a combined mathematical and simulation model to design a hierarchical network of temporary medical facilities during a disaster.

According to the review of related papers and the authors' best knowledge, no study has yet proposed a mathematical model specifically addressing disaster management in a humanitarian logistics and supply chain framework with a focus on organizations and considering all main internal components. Developing a comprehensive model is crucial for organizations to successfully manage disasters within their own internal networks, leveraging their existing facilities and staff. Therefore, this study introduces an organization-centric approach to humanitarian logistics and supply chain planning, tailored for pre- and post-disaster operations. In this paper, we examine the internal components of an organization, including regional branches, operational centers/field offices, major transportation hubs, external stakeholders, medical centers, and operational units. The definition of the organization in this study is quite comprehensive and covers various essential components. The following is a breakdown of each part:

- **Regional branches:** These represent decentralized units or branches of the organization located in different regions. They can help ensure that the organization has a presence and can effectively serve its stakeholders across various geographic areas.
- **Operational units:** These are the frontline teams responsible for executing operational tasks within the organization. They encompass different departments or teams involved in core operational activities, such as production, service delivery, logistics, and customer support.
- **Major transportation hubs:** These are critical facilities or locations where transportation activities are centralized or concentrated. They play a crucial role in facilitating the movement of goods, services, and people within the organization's network.
- **Operations centers/field Offices:** These represent centralized or decentralized facilities that serve as command and control centers for monitoring, coordinating, and managing operational activities. They can include operations centers, command centers, control rooms, and field offices, depending on their specific functions and locations.
- **External stakeholders:** These are the various entities outside the organization that have a stake or interest in its activities, decisions, or outcomes. External stakeholders can include suppliers, customers, partners, regulatory agencies, government bodies, communities, and other organizations or individuals with whom the organization interacts or collaborates.
- **Medical centers:** These represent facilities or units within the organization dedicated to providing healthcare services. They can include medical centers, clinics, medical centers, and other healthcare facilities that offer medical treatment, diagnostic services, and patient care.

Overall, this definition covers a wide range of internal parts and external relationships within the organization, which provides a comprehensive understanding of its structure, operations, and interactions. Government agencies serve as prime examples of organizations, comprising various essential components such as regional or district offices, airports managed by government entities, government-owned corporations, department of health services, border security, public medical centers, or healthcare facilities operated by government entities, which correspond to the abovementioned centers for an organization. An additional illustration involves the utilization of a multinational logistics corporation's diverse infrastructure and resources, including regional branches, transportation hubs, operational units, operations centers, external stakeholders, and medical centers. These corporations often maintain regional branches across various affected regions and possess transportation centers. Additionally, they have operational units, such as warehouses and manufacturing facilities. Moreover, they have operations centers with numerous personnel to coordinate logistical activities, and industry partners, with some individuals serving as external stakeholders, and health clinics or medical facilities as part of their medical centers.

The review of the existing literature revealed a predominant focus on humanitarian logistics and supply chains at a macro level, often overlooking the specific needs and challenges encountered by individual organizations. Consequently, there exists a pressing need for research that effectively addresses this gap and offers practical insights tailored to the unique contexts of organizations. Additionally, given the magnitude of disasters and the delayed assistance from governmental and public institutions in affected regions, many organizations may experience prolonged periods without aid. Nevertheless, these organizations possess resources that, if effectively managed, can significantly mitigate the adverse effects of disasters. Consequently, the proposed topic stands apart from previous works in its comprehensive consideration of various perspectives, including applicable areas, centers, and networks. The main contributions of the research are as follows:

- Providing a pre- and post-disaster management model inside an organization using the system's internal capabilities and which is independent of other organizations.
- Presenting a mathematical model for pre-and post-disaster planning in an organization considering operations centers/field offices and external stakeholders as the relief parts.
- Taking into account the personnel stationed at operations centers/field offices, and involving external stakeholders to assist in rescue activities and the distributing relief items.
- Taking into account regional branches, major transportation hubs, operational units, operations centers/field offices, external stakeholders, and medical centers as the affected areas.
- Considering the regional branches, operations centers/field offices, external stakeholders, major transportation hubs, and operational units as candidate sites for opening PRCs.
- Considering two types of injuries in the affected areas.
- Taking the total time that injured staffs waited in EMVs or AAs to arrive medical centers into account.
- Considering different performance levels of the rescue groups of various medical centers.

3. Problem Description and Formulation

In this study, optimal strategies for humanitarian logistics and supply chain management in organizational contexts are derived. Taking into account that this model is originally designed for pre-and post-disaster planning in an organization, all internal components of the organization are considered, ensuring that it can optimally implement the required activities for response and preparedness phase. The network consists of affected areas, PRCs, TRCs, operations centers/field offices, external stakeholders, and medical centers. Also, the affected areas include regional branches, major transportation hubs, operational units, operations centers/field offices, external stakeholders, and medical centers. In the first phase, the PRCs are located and the amount of relief items is pre-positioned in each established PRC. There are some candidate sites to establish the PRCs. It is assumed that the PRCs with not-identical capacity can be opened in the regional branches, operations centers/field offices, external stakeholders, major transportation hubs, operational units in addition to some proposed sites for PRCs. Furthermore, various relief items such as water, canned food, and others are strategically positioned in advance, taking into account their volume and weight. After a disaster occurs and in the second phase, the TRCs' locations and donated RIs are specified. Donated RIs are directly sent to TRCs, and the capacity for all of them is the same. In addition, the number of transferred RIs from TRCs and PRCs to affected areas would be determined. There are some ground vehicles and helicopters to distribute RIs among the affected areas, and how many RIs with each transportation system is sent to affected areas is specified in this phase. Furthermore, there are a number of injuries in the affected areas to be treated by rescue groups transported from medical centers to these areas. Some emergency response vehicles (ERVs) and AAs are considered as transportation options for the rescue groups from medical centers. Based on the number of

available rescue groups in medical centers, ERVs, and AAs, the number of allocated rescue groups to each area and the required ERVs and AAs are determined. It is assumed that each rescue group from each medical center can treat a predetermined number of injuries that may lead to a number of untreated injurers in each affected area, considering the total rescue groups allocated to the area. Also, a percentage of injuries in each affected area need to be transported to medical centers after treatment. Consequently, some ERVs and AAs are considered which may be able to transport these injuries to medical centers. In this case, the model determines how many ERVs and AAs are needed and how many injuries from each affected area must be sent to medical centers. Due to the fact that the organization can utilize the available staff in the operations centers/field offices, and external stakeholders to help the rescue activities and distribution of RIs in accelerating the process of these operations, some staff from these centers are transported to the affected areas. It is assumed that an operations center/field office or external stakeholder does not need staff from other operations centers/field offices or external stakeholders to help rescue actions and the distribution of RIs, due to there being enough staff at these centers. Figure 1 demonstrates the overview of the entire proposed network.

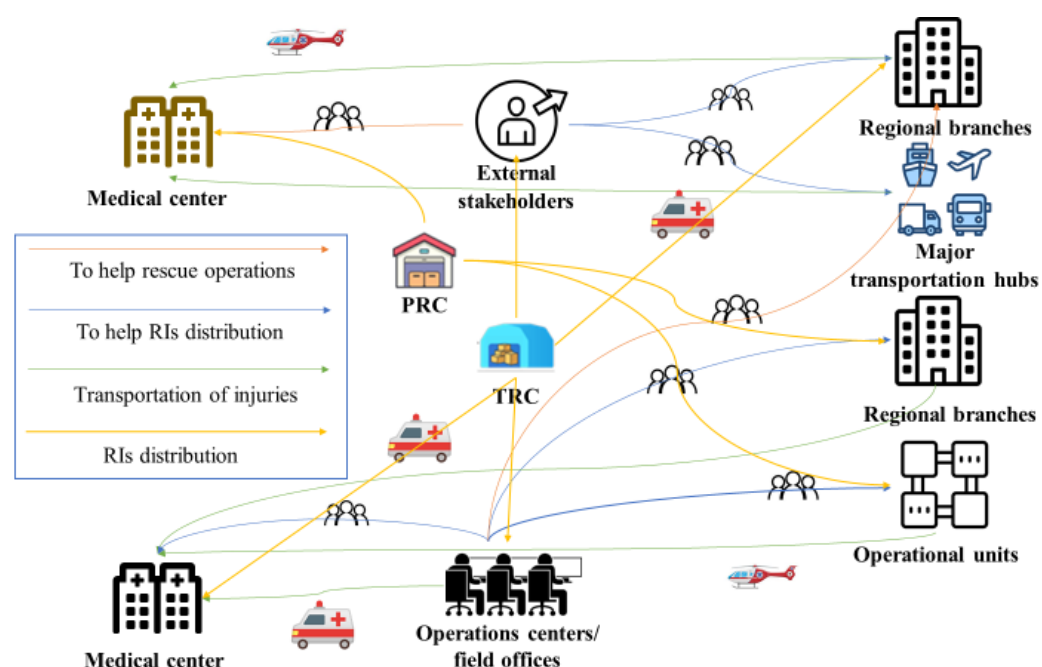


Figure 1. Schematic view of the proposed model.

A mixed integer nonlinear programming (MINLP) model is developed to optimally locate and assign PRCs and TRCs to affected areas, and specify the amount of stored RIs in TRCs and PRCs, the amount of distribution of RIs, the number of ground vehicles needed, as well as helicopters, EMVs, AAs, and ERNs, the number of injuries and rescue groups transferred among medical centers and affected areas, and the number of transported staff from operations centers/field offices and external stakeholders to other affected areas. The objective function is to minimize the total costs for pre-and post-disaster planning in addition to penalty costs for untreated injuries and demand, delayed total time of rescue and distribution of RIs operations, and waiting cost of injured persons in EMVs and AAs. In the following section, our assumptions will be mentioned.

3.1. Assumptions

- The main internal parts of the organization are considered for pre-and post-disaster planning.

- The operations centers/field offices, regional branches, external stakeholders, medical centers, major transportation hubs, and operational units are considered to be the affected areas.
- Some potential sites, operations centers/field offices, regional branches, external stakeholders, medical centers, major transportation hubs, and operational units are taken into account as the candidate sites for PRCs.
- The capacities for TRCs are the same.
- Different capacities are considered for PRCs.
- Distribution of RIs are conducted using ground vehicles and helicopters.
- The rescue groups are transferred from medical centers to affected areas using ERVs and AAs.
- The injured are transported from affected areas to medical centers using ERVs and AAs.
- The number of staff in the operations centers/field offices and external stakeholders, number of available rescue groups in medical centers, number of available all-ground vehicles, helicopters, ERVs, and AAs are known.
- The number of injuries and demands in the affected areas are known.
- Donated RIs are transported to TRC and are distributed among areas.

3.2. Notations

In this section, the notation utilized in developing the mathematical optimization model is introduced.

Sets

s	Set of external stakeholders
i	Set of operational units
a	Set of major transportation hubs
e	Set of regional branches
h	Set of medical centers
g	Set of operations centers/field offices
r	Set of RIs
p	Set of candidate sites for PRCs
$l \in \{g \cup e \cup s \cup h \cup a \cup i\}$	Set of affected areas
f	Set of capacity type for PRCs
m	Set of candidate zones for TRCs
$j \in \{p \cup g \cup e \cup s \cup h \cup a \cup i\}$	Set of candidate zones for PRCs
v	Set of AAs
z	Set of ERV
n	Set of ground vehicles
o	Set of helicopters
q	Set of EMVs

Parameters

PEN_r	Unmet demand penalty of RI r
$CAPG_n$	Capacity of ground vehicle n
$CAPH_o$	Capacity of helicopter o
$CAPE_q$	Capacity of EMV q
$CAPA_v$	Capacity of AA v
$CAPRS_z$	Capacity of ERV z
UIP	Untreated injury penalty cost
PTR	The penalty cost of each unit time the rescue operation is delayed
PTD	The penalty cost of each unit time that the distributing RIs operation is delayed
NRM_h	Number of injuries that rescue group of medical center h can treat
$SCPG_{rjln}$	Shipping cost of RI r from PRC j to the affected area l by ground vehicle n (Currency unit/(km·kg))
$SCPH_{rjlo}$	Shipping cost of RI r from PRC j to the affected area l by helicopter o (Currency unit/(km·kg))
$SCMG_{rmln}$	Shipping cost of RI r from TRC m to the affected area l with ground vehicle n (Currency unit/(km·kg))

$SCMH_{rml}$	Shipping cost of RI r from TRC m to the affected area l with helicopter o (Currency unit/(km·kg))
$SCHE_{hlz}$	Shipping cost of a rescue group from the medical center h to affected area l (Currency unit/km) by ERV z
$SCHA_{hlv}$	Shipping cost of a rescue group from the medical center h to affected area l (Currency unit/km) by AA v
$SCSO_{gl}$	Shipping cost of staff from the operations center/field office g to the affected area l (Currency unit/km)
$SCSE_{sl}$	Shipping cost of staff from the external stakeholder s to the affected area l (Currency unit/km)
CRM_h	Operational cost of every rescue group from the medical center h
FEC_{jf}	Establishing cost of PRC j with capacity f
PEC_r	The buying cost of RI r
HEC_{rj}	Holding cost of RI r in PRC j
FCM_m	Fixed cost of opening TRC m
NI_l	The number of injuries in affected area l
$NSRO_l$	The number of staff needed to help rescue operations in the affected area l
$NSDO_l$	The number of staff needed to help distributing RIs in the affected area l
$TSRO_l$	The time span that the rescue activity is delayed because of a lack of staff in the affected area l
$TSRD_l$	The time span that the distribution of RIs' operation is delayed because of a lack of staff in the affected area l
DD_{rl}	RI r demand in the affected area l
NDD_r	The number of donated RI r
NAO_g	Number of accessible staff in the operations center/field office g
NAE_s	Number of accessible staff in the external stakeholder s
NAG_n	Number of accessible ground vehicles n
NAH_o	Number of accessible helicopters o
NAA_q	Number of accessible EMVs q
$NAMMH_v$	Number of accessible AAs v
NRE_z	Number of accessible ERVs z
$ENPRT$	The number of staff in every rescue group
$DAPG_{lj}$	Distance between the affected area l and the PRC j by ground vehicle
$DAPH_{lj}$	Distance between the affected area l and the PRC j by helicopter
$DATG_{lm}$	Distance between the affected area l and the TRC m by ground vehicle
$DATH_{lm}$	Distance between the affected area l and the TRC m by helicopter
$DAME_{lh}$	Distance between the affected area l and the medical center h by ERVs or EMV
$DAMH_{lh}$	Distance between the affected area l and the medical center h by helicopter
DAO_{lg}	Distance between the affected area l and the operations center/field office g
DAE_{ls}	Distance between the affected area l and the external stakeholders s
$NRTM_h$	Number of rescue groups in the medical center h
CMI_h	The capacity of the medical center h to receive injuries from the affected areas
VU_r	Volume unit of RI r
WU_r	Weight unit of RI r
VC_f	Volume capacity of a PRC with capacity type f
VOT	TRC volume capacity
P_l	The percentage of injuries in the affected area l should be transported to the medical center after treating
WC	Waiting cost an injured person spent in EMVs or AAs to arrive at the medical center per unit time
MSE_q	Mean speed of the EMV q
MSA_v	Mean speed of the AA v
MB_1	Budget organization before disaster
MB_2	Budget organization after disaster
MP	Maximum number of PRCs that can be opened
M	A big number
Decision variables	
$NSOR_{gl}$	The number of staff transferred from the operations center/field office g to the affected area l to help rescue operations
$NSOD_{gl}$	The number of staff transferred from the operations center/field office g to the affected area l to help the distribution of RIs within the area

$NSER_{sl}$	The number of staff transferred from external stakeholders s to the affected area l to help rescue operations
$NSED_{sl}$	The number of staff transferred from external stakeholders s to the affected area l to help the distribution of RIs within the area
UD_{rl}	The number of unmet demands for RI r in the affected area l
NNG_n	The number of ground vehicles needed n
NNH_o	The number of helicopters needed o
NNE_q	The number of EMVs q
NNA_v	The number of AAs v
NNV_z	The number of ERV z
$NRMAR_{hlz}$	Number of rescue groups from the medical center h transferred to the affected area l for treating injuries using an ERV z
$NRMAH_{hlv}$	Number of rescue groups from the medical center h transferred to the affected area l for treating injuries using an AA v
NUI_l	Number of untreated injuries in the affected area l
X_{jf}	1, if PRC is established in the selected site j with capacity f ; 0, O.W.
Y_m	1, if TRC is established in the selected site m ; 0, O.W.
$NIAM_{lhv}$	Number of injuries transferred from the affected area l to the medical center h with an AA v
$NIDM_{lhq}$	Number of injuries transferred from the affected area l to the medical center h with an EMV q
SSR_l	Staff shortage in the affected area l to help rescue operations
SSD_l	Staff shortage in the affected area l to help in the distribution of RIs
QOP_{rj}	Quantity of prepositioned RI r at PRC j
QOD_{rm}	Quantity of donated RI r stored at TRC m
$QTPG_{rjln}$	Transported quantity of RI r from PRC j to the affected area l with a ground vehicle n
$QTPH_{rjlo}$	Transported quantity of RI r from PRC j to the affected area l with a helicopter o
$QTTG_{rmln}$	Transported quantity of RI r from TRC m to the affected area l with a ground vehicle n
$QTTH_{rml o}$	Transported quantity of RI r from TRC m to the affected area l with a helicopter o
$TTIP$	Entire time that patients with injuries waited in EMVs or AAs to arrive at medical centers

3.3. Mathematical Model

Here, an MINLP model is derived. The goal of the model is to minimize the total cost of the proposed model. The model is given as follows:

$$\begin{aligned}
 \text{Min } Z = & PTR \sum_l SSR_l TSO_l + PTD \sum_l SSD_l TSD_l + UIP \sum_l NUI_l \\
 & + \sum_r \sum_l PEN_r UD_{rl} + \sum_r \sum_j QOP_{rj} (PEC_r + HEC_{rj}) \\
 & + \sum_j \sum_f FEC_{jf} X_{jf} + WC TTIP \\
 & + \sum_h \sum_l CRM_h \left(\sum_z NRMAR_{hlz} + \sum_v NRMAH_{hlv} \right) \\
 & + \sum_h \sum_l \sum_z SCHE_{hlz} DAME_{lh} NRMAR_{hlz} \\
 & + \sum_h \sum_l \sum_v SCHA_{hlv} DAMH_{lh} NRMAH_{hlv} \\
 & + \sum_r \sum_j \sum_l \sum_n SCPG_{rjln} QTPG_{rjln} WU_r DAPG_{lj} \\
 & + \sum_r \sum_j \sum_l \sum_o SCPH_{rjlo} QTPH_{rjlo} WU_r DAPH_{lj} \\
 & + \sum_r \sum_m \sum_l \sum_n SCMG_{rmln} QTTG_{rmln} WU_r DATG_{lm} \\
 & + \sum_r \sum_m \sum_l \sum_o SCMH_{rml o} QTTH_{rml o} WU_r DATH_{lm} \\
 & + \sum_g \sum_{l \in \{g \cup s\}} SCSO_{gl} (NSOR_{gl} + NSOD_{gl}) DAO_{lg} \\
 & + \sum_s \sum_{l \in \{g \cup s\}} SCSE_{sl} (NSER_{sl} + NSED_{sl}) DAE_{ls} + \sum_m FCM_m Y_m
 \end{aligned} \tag{1}$$

The cost function Z intends to minimize the total cost of the considered model that includes the penalty cost of the delayed total time of rescue and distribution of RI operations, the untreated injuries penalty cost, the unsatisfied demands penalty cost, the buying cost of

RIs and hold cost of them at PRCs, the establishing cost of PRCs, the waiting cost of injured persons in EMVs and AAs, the transportation and operation costs of rescue groups, the RI transportation costs, and the transportation costs of staff from operations centers/field offices and external stakeholders to affected areas.

S.t.

$$TTIP = \sum_l \sum_h \sum_q NIDM_{lhq} \left(\frac{DAME_{lh}}{MSE_q} \right) + \sum_l \sum_h \sum_v NIAM_{lhv} \left(\frac{DAMH_{lh}}{MSA_v} \right) \quad (2)$$

Constraint (2) calculates the total time of injured persons spend in EMVs or AAs to arrive in medical centers.

$$SSR_l = NSRO_l - \sum_g NSOR_{gl} - \sum_s NSER_{sl} \quad \forall l - \{g \cup s\} \quad (3)$$

Constraint (3) computes staff shortages in the affected area l to help rescue operations.

$$SSD_l = NSDO_l - \sum_g NSOD_{gl} - \sum_s NSED_{sl} \quad \forall l - \{g \cup s\} \quad (4)$$

Constraint (4) computes staff shortages in the affected area l to help in the distribution of RIs.

$$\sum_h \sum_q NIDM_{lhq} + \sum_h \sum_v NIAM_{lhv} = P_l \sum_h NRM_h \left(\sum_z NRMAR_{hlz} + \sum_v NRMAH_{hlv} \right) \quad \forall l \quad (5)$$

Constraint (5) derives the number of injuries transferred from the affected area l to medical centers with EMVs and AAs.

$$\sum_l \sum_v NIAM_{lhv} + \sum_l \sum_q NIDM_{lhq} \leq CMI_h \quad \forall h \quad (6)$$

Constraint (6) guarantees that transferred injuries from the affected areas to every medical center is lower than the capacity of each medical center.

$$\sum_l \sum_n QTPG_{rjln} + \sum_l \sum_o QTPH_{rjlo} \leq QOP_{rj} \quad \forall r, j \quad (7)$$

Constraint (7) represents the number of transported RIs from every PRC that is not higher than the stored RIs.

$$\sum_l \sum_n QTTG_{rmln} + \sum_l \sum_o QTTH_{rml o} \leq QOD_{rm} \quad \forall r, m \quad (8)$$

The above constraint ensures that the amount of transported RIs from every TRC is not higher than stored RIs.

$$DD_{rl} - \sum_j \sum_n QTPG_{rjln} - \sum_j \sum_o QTPH_{rjlo} - \sum_m \sum_n QTTG_{rmln} - \sum_m \sum_o QTTH_{rml o} = UD_{rl} \quad \forall r, l \quad (9)$$

This constraint (9) obtains the unmet demands for RI r in the area l .

$$NUI_l = NI_l - \sum_h NRM_h \left(\sum_z NRMAR_{hlz} + \sum_v NRMAH_{hlv} \right) \quad \forall l \quad (10)$$

Constraint (10) calculates the number of untreated injuries in the area l .

$$\sum_j X_{jf} \leq 1 \quad \forall j \quad (11)$$

Inequality (11) stipulates that only one PRC with a specified capacity could be established at most on every potential site.

$$\sum_j \sum_f X_{jf} \leq MP \quad (12)$$

The aforementioned constraint guarantees the upper limit on the number of PRCs that can be established.

$$\sum_{l \in \{g \cup s\}} NSOR_{gl} + \sum_{l \in \{g \cup s\}} NSOD_{gl} \leq NAO_g \quad \forall g \quad (13)$$

$$\sum_{l \in \{g \cup s\}} NSER_{sl} + \sum_{l \in \{g \cup s\}} NSED_{sl} \leq NAE_s \quad \forall s \quad (14)$$

Constraints (13) and (14) guarantee that transported staffs from operations centers/field offices and external stakeholders are less than the total accessible staff.

$$\sum_m QOD_{rm} \leq NDD_r \quad \forall r \quad (15)$$

Constraint (15) ensures that the quantity of each relief item stored in TRCs is lower than the total amount of donated RIs.

$$\sum_r \sum_j QOP_{rj} (PEC_r + HEC_{rj}) + \sum_j \sum_f FEC_{jf} X_{jf} \leq MB_1 \quad (16)$$

$$\begin{aligned} \sum_h \sum_l CRM_h \bigg(& \sum_z NRMAR_{hlz} + \sum_v NRMAH_{hlv} \bigg) \\ & + \sum_h \sum_l \sum_z SCHE_{hlz} DAME_{lh} NRMAR_{hlz} \\ & + \sum_h \sum_l \sum_v SCH_{hlv} DAMH_{lh} NRMAH_{hlv} \\ & + \sum_r \sum_j \sum_l \sum_n SCPG_{rjln} QTPG_{rjln} WU_r DAPG_{lj} \\ & + \sum_r \sum_j \sum_l \sum_o SCPH_{rjlo} QTPH_{rjlo} WU_r DAPH_{lj} \\ & + \sum_r \sum_m \sum_l \sum_n SCMG_{rmln} QTTG_{rmln} WU_r DATG_{lm} \\ & + \sum_r \sum_m \sum_l \sum_o SCMH_{rml o} QTTH_{rml o} WU_r DATH_{lm} \\ & + \sum_g \sum_{l \in \{g \cup s\}} SCSO_{gl} (NSOR_{gl} + NSOD_{gl}) DAO_{lg} \\ & + \sum_b \sum_{l \in \{g \cup s\}} SCSE_{sl} (NSER_{sl} + NSED_{sl}) DAE_{ls} + \sum_m FCM_m Y_m \leq MB_2 \end{aligned} \quad (17)$$

Constraints (16) and (17) indicate the budget limitation in the pre-and post-disaster phase, where the former includes the buying and inventory cost in addition to the establishment cost, and the latter includes the cost of allocating rescue groups and transferring them to affected zones that could not cost more than the available budget.

$$NNG_n \geq \frac{1}{CAPG_n} \left(\sum_r \sum_j \sum_l VU_r QTPG_{rjln} + \sum_r \sum_m \sum_l VU_r QTTG_{rmln} \right) \quad \forall n \quad (18)$$

$$NNH_o \geq \frac{1}{CAPG_o} \left(\sum_r \sum_j \sum_l VU_r QTPH_{rjlo} + \sum_r \sum_m \sum_l VU_r QTTH_{rml o} \right) \quad \forall o \quad (19)$$

$$NNE_q \geq \frac{1}{CAPE_q} \sum_l \sum_h NIDM_{lhq} \quad \forall q \quad (20)$$

$$NNA_v \geq \frac{1}{CAPA_v} \left(ENPRT \sum_h \sum_l NRMAR_{hlv} + \sum_l \sum_h NIAM_{l hv} \right) \quad \forall v \quad (21)$$

$$NNV_z \geq \frac{ENPRT}{CAPRS_z} \sum_h \sum_l NRMAR_{hlz} \quad \forall z \quad (22)$$

The constraints (18)–(22) compute the total number of ground vehicles needed, helicopters, EMVs, AAs, and ERVs.

$$NNG_n \leq NAG_n \quad \forall n \quad (23)$$

$$NNH_o \leq NAH_o \quad \forall o \quad (24)$$

$$NNE_q \leq NAA_q \quad \forall q \quad (25)$$

$$NNA_v \leq NAMMH_v \quad \forall v \quad (26)$$

$$NNV_z \leq NRE_z \quad \forall z \quad (27)$$

Constraints (23)–(27) guarantee that the ground vehicles and helicopters needed cannot be more than the total accessible ground vehicles and helicopters.

$$\sum_l \sum_z NRMAR_{hlz} + \sum_l \sum_v NRMAR_{hlv} \leq NRTM_h \quad \forall h \quad (28)$$

Constraint (28) guarantees that the transported rescue groups is lower than total accessible rescue group in every medical center.

$$\sum_r QOP_{rj} VU_r \leq \sum_f VC_f X_{jf} \quad \forall j \quad (29)$$

Inequality (29) specifies that the quantity of pre-positioned relief items in each designated PRC must not exceed its capacity, and if a PRC is established, it is capable of storing RIs.

$$\sum_r QOD_{rm} VU_r \leq VOTY_m \quad \forall m \quad (30)$$

Inequality (30) indicates that the quantity of pre-positioned relief items in each designated TRC must not exceed its capacity, and if a TRC is established, it has the capability to store relief items.

4. Solution Approach

Metaheuristic algorithms have gained significant traction across various domains due to their ability to provide robust and near-optimal solutions for complex optimization problems [48–52]. Their advantages include flexibility, simplicity, and the capacity to handle large-scale and nonlinear problems effectively [53–59]. These algorithms have demonstrated success in various fields such as engineering, logistics, and artificial intelligence [60–66]. Among these, the Grasshopper Optimization Algorithm (GOA) stands out for its efficiency and effectiveness in solving intricate optimization challenges. In this paper, we explore the application of GOA to solve a developed model, showcasing its potential to deliver high-quality solutions in a timely manner. This approach is particularly beneficial for medium- to large-scale problems, where traditional methods may prove to be time-consuming and economically unfeasible.

Grasshopper Optimization Algorithm

GOA, introduced by Saremi et al. [67], is a variant of evolutionary algorithms derived from the Genetic Algorithm, and is inspired by the foraging behavior of grasshoppers in nature. GOA operates as a population-based algorithm with the primary objective of seeking optimal solutions. Its approach aligns with the natural behavior of grasshoppers, where

the search space is logically divided into exploration and exploitation phases, mirroring the soft and continuous movement of nymph grasshoppers for exploitation and the abrupt movement of adult grasshoppers for exploration [67].

GOA has several advantages for solving single-objective problems. By exploring a larger portion of the search space, it increases the likelihood of discovering global optimal compared to single-solution algorithms. Furthermore, the exchange of information within the search space among multiple solutions facilitates rapid progress towards optimal objectives [68]. Additionally, due to the high rates of repulsion and attraction among grasshoppers, GOA exhibits remarkable capabilities in both exploitation and exploration. Consequently, considering its documented benefits and performance in various studies [69,70], it can be asserted that GOA is effective in addressing real-world problems characterized by unknown search spaces [71,72]. According to [67,73], the steps of the GOA are presented in the following equations:

$$X_i = S_i + G_i + A_i \quad (31)$$

In Equation (31), X_i is the situation of the i^{th} grasshopper, S_i denotes the social interaction, G_i indicates the gravity force on the i^{th} grasshopper, and A_i denotes the wind advection. The social interaction's component as the main search mechanism is derived as the following:

$$S_i = \sum_{j=1, j \neq i}^N s(d_{ij}) \hat{d}_{ij} \quad (32)$$

In Equation (32), d_{ij} presents the distance between the i^{th} and the j^{th} grasshopper using the equation $d_{ij} = |x_j - x_i|$. Also, s is a function to specify the strength of social forces and $\hat{d}_{ij} = x_j - x_i / d_{ij}$. Function s is the main part of the social interaction function, which denotes the direction of movement of the grasshopper in the group (social force) as follows:

$$s(r) = f e^{\frac{-r}{l}} - e^{-r} \quad (33)$$

In Equation (33), the intensity of attraction with parameter f and the attractive length scale with parameter l have been demonstrated. $s(r)$ leads to the creation of repulsion and attraction forces between the grasshoppers, so changing its parameters has a remarkable effect on the swarm behaviors. As a result, Saremi, Mirjalili, and Lewis [67] developed the following model to plan an optimization algorithm:

$$X_i^d = c \left(\sum_{j=1, j \neq i}^N c \frac{ub_d - lb_d}{s} s \left(|x_j^d - x_i^d| \right) \frac{x_j - x_i}{d_{ij}} \right) + \hat{T}_d \quad (34)$$

ub_d and lb_d are the upper and lower bounds of the d^{th} dimension. The parameters $\hat{T}_d$ and c are used as controller parameters to achieve the target (best solution found so far). The grasshoppers' interactions and target pursuit lead to updating the best solution, and parameter c is the main controller parameter, which is computed by Equation (35):

$$c = cmax - l \frac{cmax - cmin}{L} \quad (35)$$

in which $cmax$ and $cmin$ are regarded as the maximum and minimum values of c , respectively. The value of $cmax$ is 1, and $cmin$ is 0.00001. L and l denote the maximum number of iterations and the current iteration, in order.

5. Computation Study

5.1. Numerical Experiments

To validate the model developed in this study, a series of small and medium-scale problems are solved. The mathematical model, formulated as the MINLP model, is solved

using the BARON solver within GAMS version 25.1.2. The computations were executed on a computer system equipped with an AMD Ryzen 5 3500U processor clocked at 2.10 GHz and 8 GB of RAM. However, the utilization of the exact method for solving problems, especially those of a large-scale nature, can be time-consuming and cost-ineffective. To address this challenge, metaheuristic approaches are commonly employed. Therefore, in this study, GOA are proposed as a solution method for these conditions. Furthermore, the efficiency of the proposed metaheuristic algorithm is evaluated by comparing the results obtained from solving some sample problems of small and medium sizes using GOA with those obtained from the GAMS solver.

Tables 1 and 2 show the scale of all sample problems and some parameter ranges utilized in the test problems, respectively. It is important to note that the medium- and large-sized problems are considered by expanding the number of several sets such as RIs, operations centers/field offices, regional branches, external stakeholders, etc., rather than small-size tests.

Table 1. Assumed sets in sample problems.

Problem Scale	Sample Problems	r	g	e	b	h	a	i	p	f	m	n	o	q	v	z
Small	1	2	2	1	1	2	1	1	2	2	2	1	2	1	1	2
	2	2	3	2	2	3	2	2	2	2	2	2	3	2	2	2
	3	3	3	3	2	4	3	2	3	2	3	3	4	2	2	3
Medium	4	4	3	4	4	5	4	4	4	4	4	4	5	4	4	4
	5	5	4	5	4	6	4	4	5	4	5	4	6	4	4	4
	6	5	5	5	4	7	5	5	5	5	6	5	6	5	5	5
Large	7	8	10	7	6	10	7	6	8	5	10	8	8	7	6	7
	8	10	15	12	8	12	8	8	10	7	12	10	10	10	12	8

Table 2. The boundaries of several parameters utilized in the assumed examples.

Parameters	Values	Parameters	Values
WU_r (kg)	U(0.5, 3)	NI_l	U(30, 150)
NDD_r (Unit)	U(300, 1500)	$TSRO_l$ (h)	U(0.05, 0.2)
HEC_{rj} (IRR)	U(5, 30)	$MSE_q \left(\frac{km}{h} \right)$	U(60, 100)
$SCPG_{rjln}$ (IRR)	U(1, 3)	$MSA_v \left(\frac{km}{h} \right)$	U(220, 250)
$SCPH_{rjlo}$ (IRR)	U(3, 6)	P_l	U(0.05, 0.3)
$SCMG_{rmln}$ (IRR)	U(1, 3)	$SCSO_{gl}$ (IRR)	U(5, 15)
$SCMH_{rmllo}$ (IRR)	U(4, 8)	$SCSE_{sl}$ (IRR)	U(5, 15)
$SCHE_{hlz}$ (IRR)	U(40, 60)	$SCHA_{hlv}$ (IRR)	U(80, 120)

5.2. Results and Model Validation

In this section, the optimal results of first and fourth sample problems are presented as a small and medium size of the developed model, respectively. Table 3 shows some optimal decision variables for sample problem 2. Also, Figure 2 demonstrates the optimal allocation of operations centers/field offices to affected areas to help rescue operations. The number of staff transported through these areas have also been presented in Table 3 ($NSOR_{gl}$). The objective function value for this sample problem is 27,140,952,496 IRR. As can be seen in Table 3, the NUI_l values are high for regional branches, but the range of this variable is low for the other sites, and values for operations centers/field offices 1 and 2, the medical center, and major transportation hub 1 are zero. Moreover, the medical center 1 and major transportation hub 2 are selected to establish PRCs. Based on Table 3, it is observed that the number of staff transferred from the operations center/field office $g3$ to the affected area $e1$, and operations center/field office $g3$ to affected area $h2$, to assist the distribution of RIs within the area are 35 and 28, respectively ($NSOD_{g3e1} = 35$, $NSOD_{g3h2} = 28$). Another example from this table indicates that the quantity of donated RI $r3$ stored at TRC $m1$ would be 334 ($QOD_{r3m1} = 334$).

Table 3. Optimal outcomes of sample problem 2.

NUI _l										
g3 31	e1 95	e2 99	b1 6	b2 12	h2 1	h3 8	a2 9	i1 3	i2 6	
QOP _{rj}			X _{jf}		NSER _{sl}			NSED _{sl}		
r1.a2		5205	h1.f1	1	b1.a1		15	b1.a1	15	
r2.h1		4213	a2.f2	1	b2.h3		15	b2.h3	12	
NSOR _{gl}										
g1.h2 12	g1.a1 10	g1.i1 20	g1.i2 10	g3.e1 35	g3.e2 45	g3.h1 25	g3.h2 28	g3.a2 10	g3.e1 35	
NSOD _{gl}					NNG _n			NNE _q		
g1.h2 10	g1.i1 11	g1.i2 12	g3.e1 20	g3.e2 15	g3.h1 8	g3.a2 14	n1 20	n2 25	q1 3	q2 3
NNH _o		NNA _v			NNV _z		QOD _{rm}	Y _m	TTIP 4.58	
o1 15	o2 10	o3 10	v1 4	v2 7	z1 15	z2 18	r3.m1 334	m1 1		

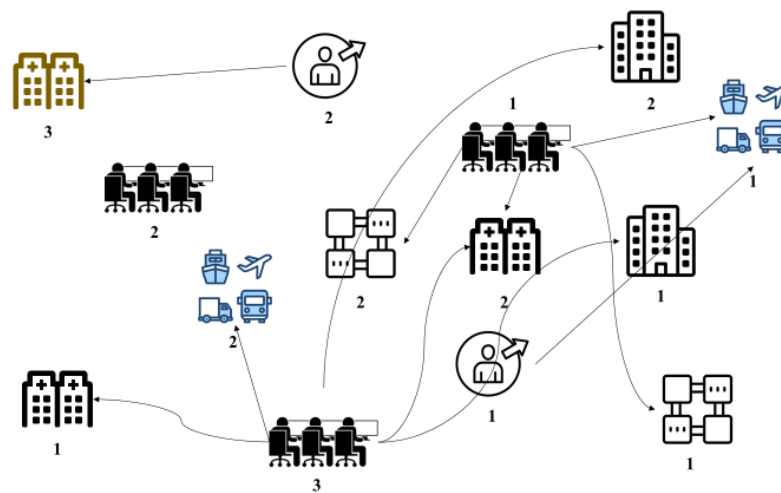


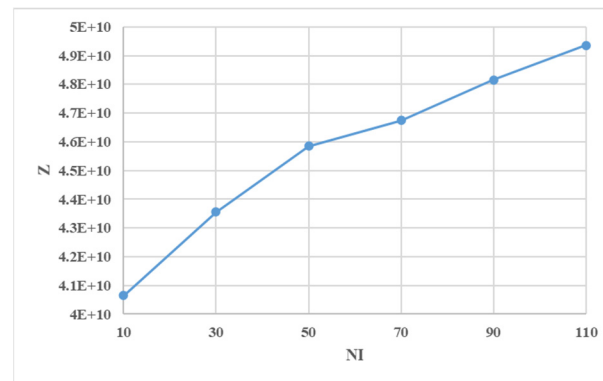
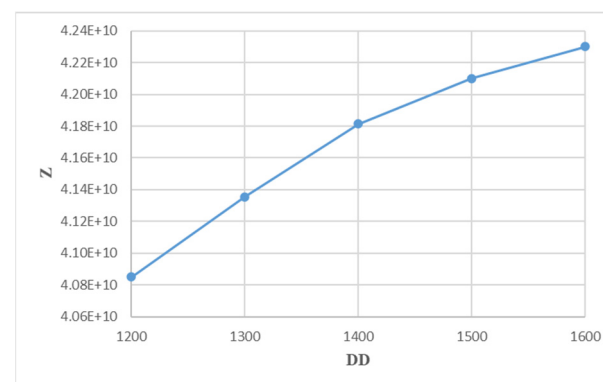
Figure 2. The optimal allocation of operations centers/field offices to affected areas to help rescue operations (sample problem 2).

As the proposed model comprises 17 sets, increasing each set by just one unit significantly elevates the model's complexity. Consequently, the number of parameters, variables, and constraints remarkably increase. As a result, and based on Table 1, the forth sample problem is more complicated than the second one, and is identified to be a medium-scale problem. Some results of this problem have been presented in Table 4. It is observed that a lack of staff in affected areas to help rescue operations (SSR_l) is not zero in the medium-scale problem, dissimilar to the previous sample problem. In addition, the number of opened PRCs increased, and one site from four proposed sites for PRCs was opened. For more clarification in this table, quantity of donated RI $r2$ stored at TRC $m1$, and RI $r4$ stored at TRC $m3$ are 154 and 87, respectively ($QOD_{r2m1} = 154$, $QOD_{r4m3} = 87$). As another example, a PRC should be established in major transportation hubs $a4$ with capacity type $f4$ ($X_{a4f4} = 1$).

Table 4. Some results of sample problem 4.

SSR _l											
<i>e1</i>	<i>e2</i>	<i>e3</i>	<i>e4</i>	<i>h1</i>	<i>h2</i>	<i>h3</i>	<i>h4</i>	<i>h5</i>	<i>i1</i>	<i>i3</i>	
55	65	42	52	35	40	25	20	30	50	25	
QOD _{rm}				X _{jf}				Y _m			
<i>r2.m1</i>	154	<i>r4.m1</i>	180	<i>e3.f4</i>	1	<i>a4.f4</i>	1	<i>p2.f2</i>	1	<i>m1</i>	1
<i>r2.m3</i>	247	<i>r4.m3</i>	87	<i>b4.f4</i>	1	<i>i1.f2</i>	1			<i>m3</i>	1

Furthermore, the effect of parameters NI_l and DD_{rl} on objective function is investigated in Figures 3 and 4 to verify the performance of the proposed model. As expected, when the number of injuries or demand of RIs in affected areas increases, total cost also increases. Observing that the results of these test problems are predictable and reasonable demonstrates that the model is working correctly and is verified to be implemented in various size of the model.

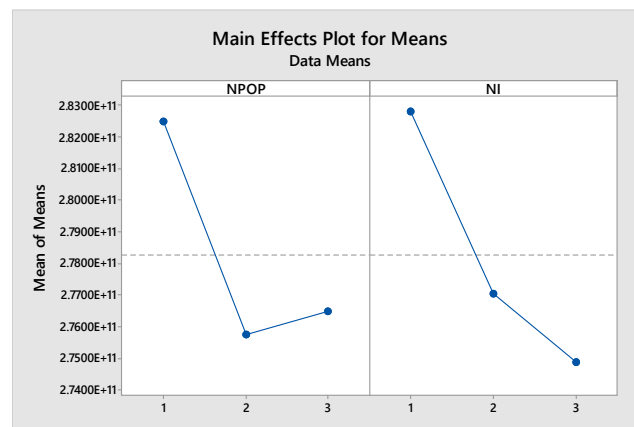
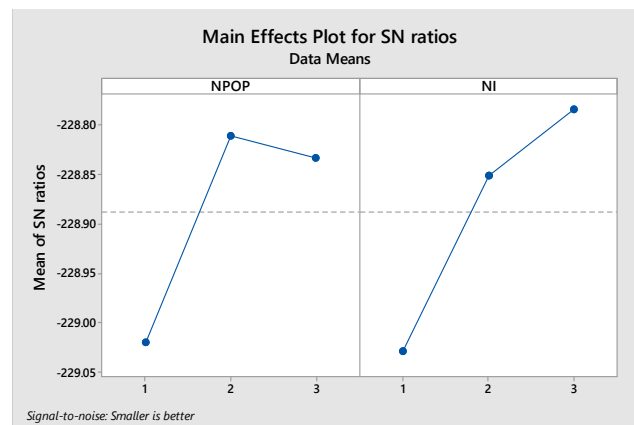
**Figure 3.** Objective function vs. NI_l .**Figure 4.** Objective function vs. DD_{rl} .

5.3. GOA Parameters Tuning

In order to use meta-heuristic algorithms, it is essential to modify their parameters for obtaining acceptable solutions. In this section, GOA parameters such as grasshopper's population scale (NPOP) and iterations number (NI) are determined using the Taguchi method by MINITAB. These parameters and their different level are demonstrated in Table 5. The L27(32) experiment was applied to adjust the parameters of GOA. After conducting experiments in MINITAB, corresponded mean and signal-to-noise ratio (SNR) graphs were obtained, as shown in Figures 5 and 6, respectively.

Table 5. The level of GOA parameters.

Level	Factors	
	NPOP	NI
1	60	80
2	80	100
3	100	120

**Figure 5.** Mean graph of Taguchi experiment.**Figure 6.** SNR graph of Taguchi experiment.

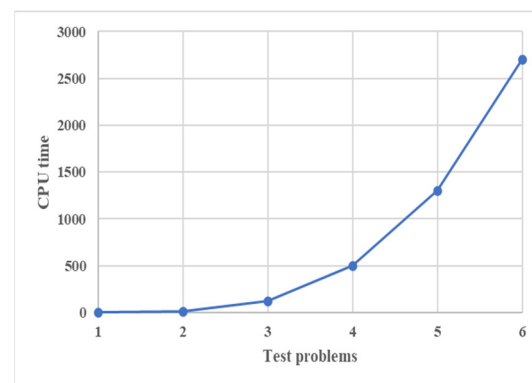
According to the mean graphs (Figure 5), the minimum mean was at the second level for NPOP and the third level for NI. In the SNR graph (Figure 6), the maximum signal-to-noise was at the second and third level for the parameters, respectively. Consequently, the optimal values for NPOP and NI were 80 and 120, respectively.

5.4. Comparative Experiments

Table 6 represents a comparative analysis for six sample tests presented in Table 1 between GAMS and GOA. Including numerous sets in the proposed model substantially increases computational time when solving problems with exact methods, particularly as the indices rise. Therefore, employing an exact approach for large-scale problems is neither rational nor economical. In such scenarios, resorting to a metaheuristic algorithm presents a more suitable solution for tackling the model efficiently. Figure 7 shows how solution time exponentially rises as the scale of problem rises.

Table 6. Solutions obtained using GOA and GAMS for sample problems.

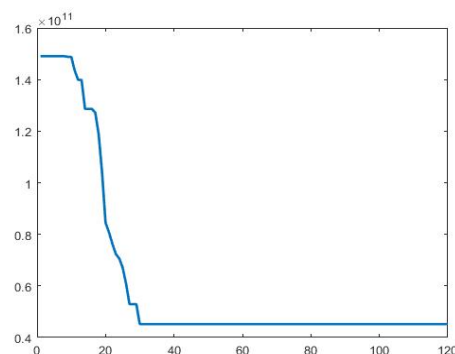
Sample Problems	Value of Objective Functions		CPU Engagement Time		Gap%
	GAMS	GOA	GAMS	GOA	
1	5,035,880,177	5,036,745,935	4.1''	40.2''	0.01
2	27,140,952,496	27,283,427,521	12.5''	46.7''	0.52
3	32,750,214,458	33,028,439,877	120.2''	50.3''	0.84
4	43,948,560,292	44,513,486,111	500.1''	70.5''	1.28
5	49,799,224,339	50,780,269,058	1300.3''	77.4''	1.96
6	58,218,472,604	59,621,537,793	2700.9''	84.9''	2.40
7	-	101,342,146,208	-	115.3''	-
8	-	141,075,529,112	-	149.4''	-

**Figure 7.** CPU time for proposed sample problems.

To demonstrate the efficiency of the proposed meta-heuristic algorithm, the gap rate between GAMS and GOA is derived using Equation (36) as follows:

$$\text{Gap rate} = \frac{100 * (Z_{GOA} - Z_{GAMS})}{Z_{GAMS}} \quad (36)$$

in which Z_{GAMS} and Z_{GOA} are the optimal cost of GAMS and GOA, respectively. According to the obtained gaps in Table 6, There is negligible gap observed between the two solvers in terms of the cost function value. Also, Table 6 shows that the computational time of GOA is remarkably lower than exact approach as the scale of problems increases. Therefore, it can be concluded that the GOA is reliable and qualified, and can be applied to large-scale problems. Figure 8 depicts the convergence graph for sample problem 4. Finally, the results of sample problems 7 and 8 as two large-scale problems are presented in Table 6. As observed, the GOA can solve the large-scale problems in an acceptable and economical time.

**Figure 8.** Convergence of GOA to the optimal solution for sample problem 4.

6. Sensitivity Analysis

Conducting sensitivity analysis helps to identify the primary influential parameters and elucidate their impact on optimal solutions and the objective function. This analysis facilitates a comprehensive comprehension of the model's behavior. The results of the sensitivity analysis are derived in Figures 9–18. Figures 9 and 10 show the impact of the available budget before disaster (MB_1) on objective function and total unsatisfied demands of affected areas, respectively. As can be seen in Figure 9, when the budget before disaster decreases by 10% and 20%, the total cost increases about 0.5% and 2.5%, respectively, and as seen in Figure 10, the unsatisfied demands also increases. This is because either some PRCs have been closed, or PRCs with lower capacities have been opened. On the opposite side, when MB_1 increases by 10%, unsatisfied demands considerably decrease and total cost increases due to the opening new PRCs and increasing distribution of RIs costs after disaster. Moreover, as MB_1 increases by 20%, unsatisfied demands and the total cost decrease. This may be because increasing the capacity of PRCs can be less costly than the penalty for unsatisfied demands, which has decreased once again. Figures 11 and 12 show the impact of the available budget after disaster (MB_2) on objective function and total unsatisfied demands of affected areas, respectively. It is observed that when the MB_2 increases, total cost and unsatisfied demands are reduced. Considering this point that the fixed cost for opening TRCs is significantly lower than PRCs, increasing the budget after disaster has more impact on total cost rather than budget before disaster. Another reason is that costs associated after disaster include many components such as the cost of distribution of RIs, the transportation of rescue groups, staff., etc., all of which are influenced by MB_2 .

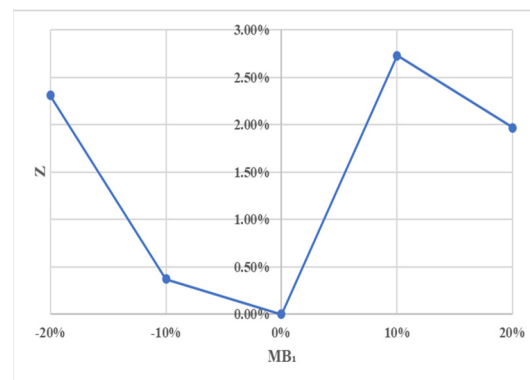


Figure 9. Objective function vs. MB_1 .

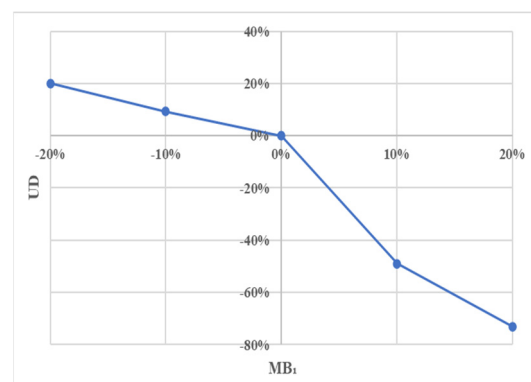


Figure 10. Unsatisfied demands (UD_{rl}) vs. MB_1 .

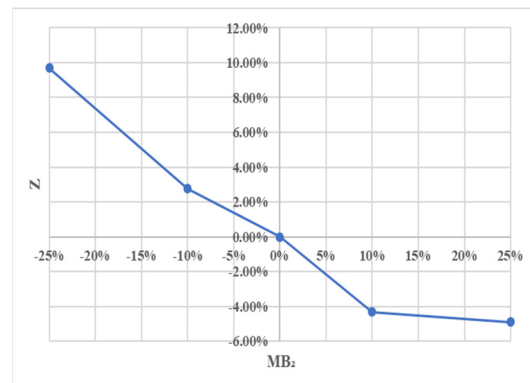


Figure 11. Objective function vs. MB_2 .

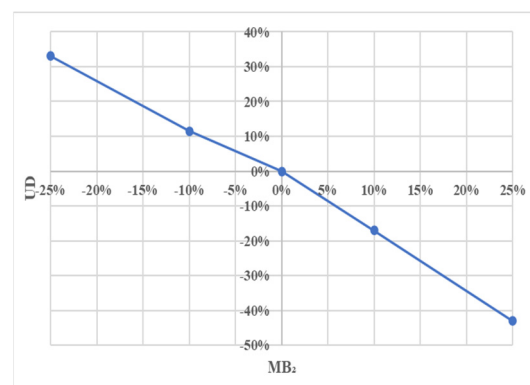


Figure 12. Unsatisfied demands (UD_{rl}) vs. MB_2 .

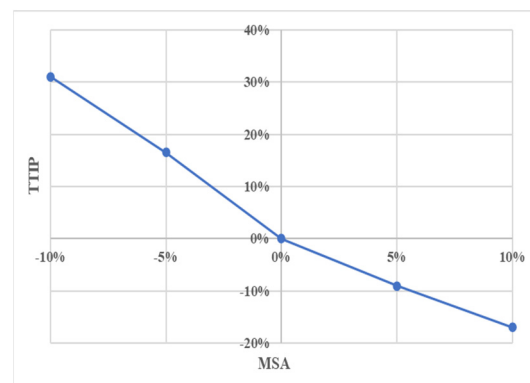


Figure 13. TTIP vs. MSA_p .

Figures 13 and 14 show the impact of mean speed of AA on the entire time that patients with injuries spend in EMVs or AAs to arrive medical centers ($TTIP$) and objective functions. As observed, providing that the speed of AAs increase, $TTIP$ can considerably decrease, which resulted in saving the lives of patients with injuries. Therefore, even a five percent increase in speed has a significant impact on the efficiency of the system. Also, the total cost is affected by changing speed. Using the newest and advanced AAs in the organization can avoid losing the lives of the injured

Figures 15 and 16 indicate the impact of the number of available EMVs (NAA_q) on $TTIP$, objective function, and NUI_l . As can be seen, when NAA_q increases, $TTIP$ increases, but the total costs and number of untreated injured decreases. It is because the number of injuries transported from the affected areas to medical centers with EMVs and AAs increases and decreases, respectively, by increasing NAA_q . Hence, when more AAs are used to transport rescue groups from medical centers to affected areas, the number

of untreated injured decreases, as shown in Figure 16. The impact of the number of available AAs ($NAMMH_v$) on $TTIP$, objective function, and NUI_l is evaluated through Figures 17 and 18. As observed, by increasing total available AAs, $TTIP$ decreases, and the total costs and number of untreated injured decrease. This is because the number of injuries transported from affected areas to medical centers decreases with EMVs and increases with AAs, resulting in a decrease in $TTIP$. Also, the total number of untreated injured decreases, and hence, total cost decreases.

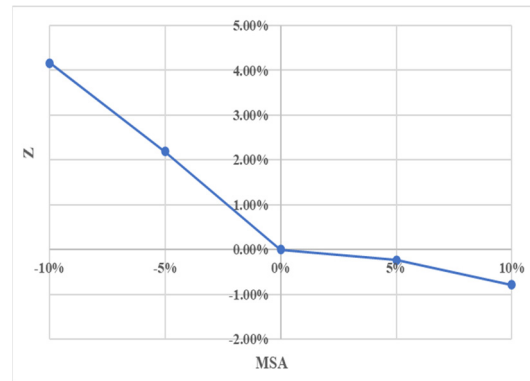


Figure 14. Objective function vs. MSA_v .

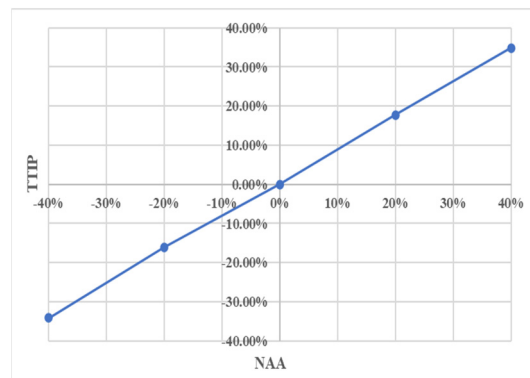


Figure 15. $TTIP$ vs. NAA_q .

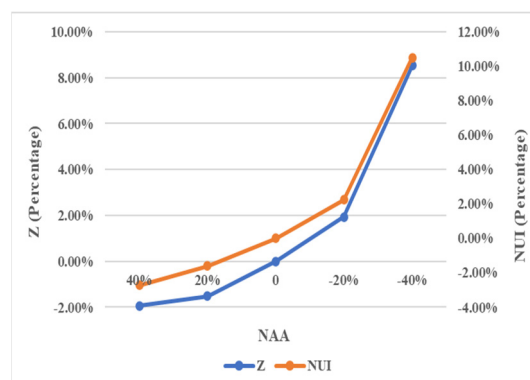


Figure 16. Objective function and NUI_l vs. NAA_q .

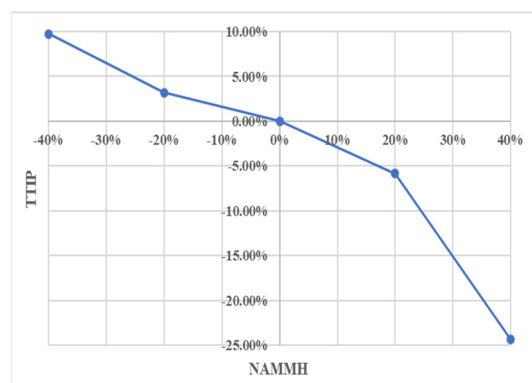


Figure 17. TTIP vs. $NAMMH_v$.

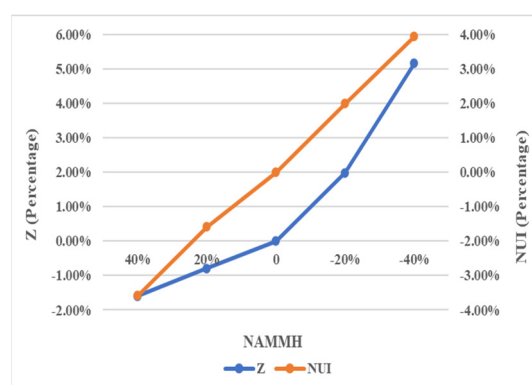


Figure 18. Objective function and NUI_l vs. $NAMMH_v$.

7. Discussions and Managerial Implications

This study pioneers the development of a mathematical optimization model tailored specifically for an organization-based humanitarian logistics and supply chain network, encompassing pre- and post-disaster planning, a novel endeavor not previously explored. In contrast to prior research focusing on humanitarian relief operations, this study represents a groundbreaking approach by uniquely integrating all facets of an organization, including operations centers/field offices, external stakeholders, medical centers, regional branches, major transportation hubs, and operational units. In other words, the literature review reveals that most existing research in this field have studied humanitarian logistics and supply chains outside the confines of a single organization. These studies typically involve non-governmental organizations (NGOs), governmental organizations (GOs), the Red Cross, and other relevant entities conducting humanitarian activities to manage disasters in broader regions, cities, or areas. To our knowledge, no prior study has presented a comprehensive mathematical optimization model for disaster management within an organization that concurrently addresses all aspects, including the distribution of RIs, the transfer of rescue groups from medical centers to affected areas, the transportation of emergency injuries to medical centers, the mobilization of staff from operations centers/field offices and external stakeholders to affected areas for distribution of RIs and rescue activities support, and the utilization of all transportation vehicles available within the organization. Moreover, the core of this study is a novel approach to humanitarian logistics and supply chain management, focusing on managing disasters within an organization without external assistance, an area that has not been previously explored. By utilizing the proposed model, an organization can effectively and independently manage disasters within its internal operations.

Specifically, a notable distinction in the proposed model is the inclusion of the waiting time for injured individuals in EMVs or AAs until they reach medical centers—a factor

overlooked in prior research. This waiting time is incorporated as a critical criterion within the objective function of this study. The reason is that it is vital for an organization to quickly attend to its human resources after a disaster occurs. Another significant departure in the theoretical framework of this research, as opposed to previous studies, is the acknowledgment of two vital organizational components as relief centers. These centers, namely operations centers/field offices and external stakeholders, are recognized as integral relief hubs within the organization. This recognition marks a departure from prior works, which typically focused on external entities for relief efforts. For example, operations centers/field offices are considered to be relief centers within an organization because they typically have their own resources and personnel to support their functions and operations. They include staff such as operations managers, field workers, coordinators, and support teams who collaborate to ensure the smooth operation of the organization's activities. Additionally, they often have access to local resources and partnerships, which enable them to effectively address local needs and facilitate their activities.

Regarding the general applicability of the proposed model to different organizations, it is important to note that the components were selected based on their broad relevance and critical roles in humanitarian logistics and supply chain management within organizations. The following are the reasons why these components are broadly applicable:

- **Regional Branches:** These act as localized hubs that can quickly respond to regional needs. Most organizations, regardless of their industry, have a decentralized structure with regional branches to ensure efficient operations and responsiveness. That is why these centers can be considered to be candidate zones for PRCs.
- **Operational Units:** These units are the backbone of an organization's response mechanism, handling everything from logistics to administration. Their presence is universal across organizations to ensure operational continuity and efficiency. That is why these centers can be considered as candidate zones for PRCs.
- **Major Transportation Hubs:** Effective disaster management and humanitarian logistics depend on the ability to quickly move resources. Major transportation hubs are crucial for facilitating the rapid distribution of supplies and personnel, making them a vital component in any organization's logistics network.
- **Operational Centers/Field Offices:** These centers are pivotal for coordinating on-ground activities and managing logistics. Almost all organizations have some form of operational centers or field offices to oversee their day-to-day activities and emergency responses. This clarification confirms why these centers can be considered to be relief centers.
- **External Stakeholders:** Collaborations with external stakeholders, such as suppliers, local authorities, and NGOs, are essential for extending an organization's reach and resources during disasters. This interconnectivity is a common feature in organizational logistics, ensuring that no entity operates in isolation. This clarification confirms why these centers can be considered to be relief centers.
- **Medical Centers:** Health and safety is paramount during disaster management. Incorporating medical centers ensures that immediate medical needs are met, a necessity for all organizations involved in humanitarian efforts.

By including these components, the proposed model ensures a comprehensive and versatile framework that can be adapted to various types of organizations and their specific needs. This generalizability is intended to provide a robust foundation that can be tailored to the unique contexts of different organizations, enhancing their capacity to manage disasters effectively.

In the preceding sections, we conducted several numerical examples and extensive sensitivity analysis to enhance our comprehension of the proposed model's behavior. This endeavor yielded significant economic and managerial implications, which are summarized as follows:

- (1) According to Figures 9–12, managers in the organization are advised that if they encounter budget limitations, they should ensure that the budget before a disaster is

maintained at an acceptable level to sufficiently open PRCs. They can then increase the budget after the disaster occurs. The proposed model can determine the acceptable level for both budgets.

- (2) Based on Figures 13 and 14, the organization managers should use the advanced AAs and EMVs to transport the injuries from affected areas to medical centers as soon as possible. Additionally, effective maintenance of AAs and EMVs is crucial, as it can significantly impact the health and reliability of these transportation systems. Figure 13 clearly shows how the speed of the vehicle can affect injured transfer time. Furthermore, there are various types of AAs available, and the organization can opt for types with shorter setup times and higher speeds.
- (3) Based on Figure 14, total cost can be reduced when the speed increases. Hence, the organization should consider this saving and invest in renewing the transportation system. It should be noted the value of this saving can be obtained through the proposed model.
- (4) Considering that weight and wind significantly affect helicopter performance, and given the importance of helicopter speed in the proposed model, organizations should assess wind speeds before employing AAs to transfer injured individuals and rescue groups. Based on this assessment, the allocation of AAs can be determined. Also, the weight of AAs should be considered before the rescue operation after disaster.
- (5) Based on Figures 15 and 16, the decision-makers in organizations should increase EMVs when the number of AAs are limited, which resulted in decreasing number of untreated injured and total cost. In this case, they can allocate more AAs to transport rescue group of medical centers to affected areas.
- (6) When more AAs are allocated to transport rescue groups, assuming that EMVs increase, managers should implement transportation planning and routing solutions. This involves selecting the best and least congested roads for EMVs to enhance their expected speed and reduce the time that injured individuals spend in EMVs.
- (7) Based on Figure 17, the organizations can considerably reduce the total time that injured individuals spend on roads to arrive medical centers, total cost, and the total number of untreated injured individuals decreases by increasing the number of AAs.
- (8) By comparing Figures 15 and 17, it is concluded that if the number of AAs remain unchanged, the increasing number of EMVs leads to an increase in the total time that injured individuals spend on roads to arrive medical centers. Therefore, organization managers should consistently allocate funds for acquiring AAs to expedite the transportation of injured individuals to medical centers. Increasing just EMVs is not a good strategy to transport patients to medical centers.
- (9) Organization managers are advised to increase EMVs or allocate more budget to them when the number of AAs is at a sufficient level, which can be determined by the proposed model. In other words, as long as the number of AAs is not enough for transferring rescue groups to affected areas, an increase in EMVs leads to an increase in the time that injured individuals spend in roads to arrive medical centers.
- (10) According to the results, it is suggested that the organization transfer some staff from operations centers/field offices and external stakeholders to affected areas for the distribution of RIs and helping in rescue operations. The proposed model can be used to obtain the optimal number of transferred staff.

8. Conclusions and Future Directions

This study introduces an organization-centered humanitarian logistics and supply chain network for both pre- and post-disaster planning. For the first time, the proposed model considered the internal components of the organization, and was developed based on the main components of the organization, i.e., regional branches, major transportation hubs, operational units, operations centers/field offices, external stakeholders, and medical centers as the affected areas. Also, the affected areas, PRCs, TRCs, operations centers/field offices, external stakeholders, and medical centers are the main centers that were considered

in the model. Moreover, the operations centers/field offices and external stakeholders were considered to be the relief parts. This paper develops a MINLP model to minimize the total costs associated with pre- and post-disasters. Some new cost factors, such as delayed total time of rescue and distribution of RIs operations, and waiting cost of injured persons in EMVs and AAs, have been taken into account. The proposed model was solved using GAMS software in small and medium scales. Because of the complexity of the model, the GOA was proposed as a metaheuristic method for large size problems. The results showed that the GOA has an acceptable performance for solving large-scale problems. Extensive numerical examples and selectivity analysis were conducted to show the applicability and behavior of the model. Some important managerial insights for the manager in organizations were presented. Furthermore, the results indicate that the organization should use advanced AAs and EMVs for transferring injuries, and implement an effective maintenance on these transportation systems. Moreover, simply increasing EMVs is not an appropriate policy for transporting patients to medical centers. Managers should prioritize investing more in providing AAs.

Although this model has been presented for the first time in an organization, and tried to consider all aspects, there are some limitations to this study. Several parameters, like the number of staff required to help with the rescue operations and in distributing RIs, the time span for the rescue operation or distributing RIs being delayed due to the absence of staff, the number of available staff in operations centers/field offices and external stakeholders, etc., were assumed to be deterministic, while considering them to be uncertain parameters may be more realistic and is recommended in future studies. It has been assumed that injuries are just transported to medical centers, while in some conditions where there are a lack of internal medical centers, they can be transported to external clinics and medical centers, which can be an interesting topic for future directions. Although this paper considered two types of injuries in the affected area, considering damage severity could be another research topic in the future. Finally, considering interactions among organizations to provide a quick response for affected areas is recommended for future research.

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References

1. Wang, J.; Ng, Y.Y.E. Post-earthquake housing recovery with traditional construction: A preliminary review. *Prog. Disaster Sci.* **2023**, *18*, 100283. [\[CrossRef\]](#)
2. Kotani, H.; Okai, H.; Tamura, M. Activities and roles of mosques in Japan after the recent major earthquakes: A comprehensive study. *Prog. Disaster Sci.* **2023**, *20*, 100297. [\[CrossRef\]](#)
3. Kodag, S.; Mani, S.K.; Balamurugan, G.; Bera, S. Earthquake and flood resilience through spatial Planning in the complex urban system. *Prog. Disaster Sci.* **2022**, *14*, 100219. [\[CrossRef\]](#)
4. Mukherjee, M.; Abhinay, K.; Rahman, M.M.; Yangdhen, S.; Sen, S.; Adhikari, B.R.; Nianthi, R.; Sachdev, S.; Shaw, R. Extent and evaluation of critical infrastructure, the status of resilience and its future dimensions in South Asia. *Prog. Disaster Sci.* **2023**, *17*, 100275. [\[CrossRef\]](#)
5. Jihad, A.; Muksin, U.; Syamsidik; Ramli, M.; Banyunegoro, V.H.; Simanjuntak, A.V.H.; Rusdin, A.A. Tsunami evacuation sites in the northern Sumatra (Indonesia) determined based on the updated tsunami numerical simulations. *Prog. Disaster Sci.* **2023**, *18*, 100286. [\[CrossRef\]](#)
6. Marome, W.; Rodkul, P.; Mitra, B.K.; Dasgupta, R.; Kataoka, Y. Towards a more sustainable and resilient future: Applying the Regional Circulating and Ecological Sphere (R-CES) concept to Udon Thani City Region, Thailand. *Prog. Disaster Sci.* **2022**, *14*, 100225. [\[CrossRef\]](#)

7. Gray, J.; Lloyd, S.; Healey, S.; Opdyke, A. Urban and rural patterns of typhoon mortality in the Philippines. *Prog. Disaster Sci.* **2022**, *14*, 100234. [\[CrossRef\]](#)
8. Ginige, K.; Mendis, K.; Thayaparan, M. An assessment of structural measures for risk reduction of hydrometeorological disasters in Sri Lanka. *Prog. Disaster Sci.* **2022**, *14*, 100232. [\[CrossRef\]](#)
9. Hoeppe, P. Trends in weather related disasters—Consequences for insurers and society. *Weather Clim. Extrem.* **2016**, *11*, 70–79. [\[CrossRef\]](#)
10. Chaudhary, M.T.; Piracha, A. Natural disasters—Origins, impacts, management. *Encyclopedia* **2021**, *1*, 1101–1131. [\[CrossRef\]](#)
11. Hwang, K.-E.; Kim, I. Post-COVID-19 modular building review on problem-seeking framework: Function, form, economy, and time. *J. Comput. Des. Eng.* **2022**, *9*, 1369–1387. [\[CrossRef\]](#)
12. Farazmehr, S.; Wu, Y. Locating and deploying essential goods and equipment in disasters using AI-enabled approaches: A systematic literature review. *Prog. Disaster Sci.* **2023**, *19*, 100292. [\[CrossRef\]](#)
13. Bodin, Ö.; Nohrstedt, D.; Orach, K. A diagnostic for evaluating collaborative responses to compound emergencies. *Prog. Disaster Sci.* **2022**, *16*, 100251. [\[CrossRef\]](#)
14. Daneshvar, M.; Jena, S.D.; Rei, W. A two-stage stochastic post-disaster humanitarian supply chain network design problem. *Comput. Ind. Eng.* **2023**, *183*, 109459. [\[CrossRef\]](#)
15. Anjomshoe, A.; Banomyong, R.; Mohammed, F.; Kunz, N. A systematic review of humanitarian supply chains performance measurement literature from 2007 to 2021. *Int. J. Disaster Risk Reduct.* **2022**, *72*, 102852. [\[CrossRef\]](#)
16. McLoughlin, D. A framework for integrated emergency management. *Public Adm. Rev.* **1985**, *45*, 165–172. [\[CrossRef\]](#)
17. Kovács, G.; Spens, K.M. Humanitarian logistics in disaster relief operations. *Int. J. Phys. Distrib. Logist. Manag.* **2007**, *37*, 99–114. [\[CrossRef\]](#)
18. Balcik, B.; Bozkir, C.D.C.; Kundakcioglu, O.E. A literature review on inventory management in humanitarian supply chains. *Surv. Oper. Res. Manag. Sci.* **2016**, *21*, 101–116. [\[CrossRef\]](#)
19. Yi, W.; Özdamar, L. A dynamic logistics coordination model for evacuation and support in disaster response activities. *Eur. J. Oper. Res.* **2007**, *179*, 1177–1193. [\[CrossRef\]](#)
20. Berkoune, D.; Renaud, J.; Rekik, M.; Ruiz, A. Transportation in disaster response operations. *Socio-Econ. Plan. Sci.* **2012**, *46*, 23–32. [\[CrossRef\]](#)
21. Rawls, C.G.; Turnquist, M.A. Pre-positioning of emergency supplies for disaster response. *Transp. Res. Part B Methodol.* **2010**, *44*, 521–534. [\[CrossRef\]](#)
22. Döyen, A.; Aras, N.; Barbarosoğlu, G. A two-echelon stochastic facility location model for humanitarian relief logistics. *Optim. Lett.* **2012**, *6*, 1123–1145. [\[CrossRef\]](#)
23. Najafi, M.; Eshghi, K.; de Leeuw, S. A dynamic dispatching and routing model to plan/re-plan logistics activities in response to an earthquake. *OR Spectr.* **2014**, *36*, 323–356. [\[CrossRef\]](#)
24. Camacho-Vallejo, J.-F.; González-Rodríguez, E.; Almaguer, F.-J.; González-Ramírez, R.G. A bi-level optimization model for aid distribution after the occurrence of a disaster. *J. Clean. Prod.* **2015**, *105*, 134–145. [\[CrossRef\]](#)
25. Rezaei-Malek, M.; Tavakkoli-Moghaddam, R.; Zahiri, B.; Bozorgi-Amiri, A. An interactive approach for designing a robust disaster relief logistics network with perishable commodities. *Comput. Ind. Eng.* **2016**, *94*, 201–215. [\[CrossRef\]](#)
26. Tofighi, S.; Torabi, S.A.; Mansouri, S.A. Humanitarian logistics network design under mixed uncertainty. *Eur. J. Oper. Res.* **2016**, *250*, 239–250. [\[CrossRef\]](#)
27. Hu, S.-L.; Han, C.-F.; Meng, L.-P. Stochastic optimization for joint decision making of inventory and procurement in humanitarian relief. *Comput. Ind. Eng.* **2017**, *111*, 39–49. [\[CrossRef\]](#)
28. Noham, R.; Tzur, M. Designing humanitarian supply chains by incorporating actual post-disaster decisions. *Eur. J. Oper. Res.* **2018**, *265*, 1064–1077. [\[CrossRef\]](#)
29. Vahdani, B.; Veysmoradi, D.; Noori, F.; Mansour, F. Two-stage multi-objective location-routing-inventory model for humanitarian logistics network design under uncertainty. *Int. J. Disaster Risk Reduct.* **2018**, *27*, 290–306. [\[CrossRef\]](#)
30. Liu, Y.; Lei, H.; Wu, Z.; Zhang, D. A robust model predictive control approach for post-disaster relief distribution. *Comput. Ind. Eng.* **2019**, *135*, 1253–1270. [\[CrossRef\]](#)
31. Momeni, B.; Aghsami, A.; Rabbani, M. Designing humanitarian relief supply chains by considering the reliability of route, repair groups and monitoring route. *Adv. Ind. Eng.* **2019**, *53*, 93–126.
32. Sakiani, R.; Seifi, A.; Khorshiddoust, R.R. Inventory routing and dynamic redistribution of relief goods in post-disaster operations. *Comput. Ind. Eng.* **2020**, *140*, 106219. [\[CrossRef\]](#)
33. Aghajani, M.; Torabi, S.A.; Heydari, J. A novel option contract integrated with supplier selection and inventory prepositioning for humanitarian relief supply chains. *Socio-Econ. Plan. Sci.* **2020**, *71*, 100780. [\[CrossRef\]](#)
34. Heydari, H.; Aghsami, A.; Rabani, M. A mathematical model to optimize debris clearance problem in the disaster response Phase: A case study. *J. Ind. Syst. Eng.* **2021**, *14*, 1–34.
35. Abazari, S.R.; Aghsami, A.; Rabbani, M. Prepositioning and distributing relief items in humanitarian logistics with uncertain parameters. *Socio-Econ. Plan. Sci.* **2021**, *74*, 100933. [\[CrossRef\]](#)
36. Abazari, S.R.; Jolai, F.; Aghsami, A. Designing a humanitarian relief network considering governmental and non-governmental operations under uncertainty. *Int. J. Syst. Assur. Eng. Manag.* **2021**, *13*, 1430–1452. [\[CrossRef\]](#)

37. Hajipour, V.; Niaki, S.T.A.; Akhgar, M.; Ansari, M. The healthcare supply chain network design with traceability: A novel algorithm. *Comput. Ind. Eng.* **2021**, *161*, 107661. [\[CrossRef\]](#)
38. Masoumi, M.; Aghsami, A.; Alipour-Vaezi, M.; Jolai, F.; Esmailifar, B. An M/M/C/K queueing system in an inventory routing problem considering congestion and response time for post-disaster humanitarian relief: A case study. *J. Humanit. Logist. Supply Chain Manag.* **2022**, *12*, 182–219. [\[CrossRef\]](#)
39. Bakhshi, A.; Aghsami, A.; Rabbani, M. A scenario-based collaborative problem for a relief supply chain during post-disaster under uncertain parameters: A real case study in Dorud. *J. Model. Manag.* **2022**, *18*, 906–941. [\[CrossRef\]](#)
40. Ehsani, B.; Karimi, H.; Bakhshi, A.; Aghsami, A.; Rabbani, M. Designing humanitarian logistics network for managing epidemic outbreaks in disasters using Internet-of-Things. A case study: An earthquake in Salas-e-Babajani city. *Comput. Ind. Eng.* **2023**, *175*, 108821. [\[CrossRef\]](#)
41. Sheikholeslami, M.; Zarrinpoor, N. Designing an integrated humanitarian logistics network for the preparedness and response phases under uncertainty. *Socio-Econ. Plan. Sci.* **2023**, *86*, 101496. [\[CrossRef\]](#)
42. Lohrasbpour, M.; Arshadi Khamseh, A.; Nemati-Lafmejani, R.; Naderi, B. Four Echelons Humanitarian Network Design Considering Capacitated/Lateral Transshipment with a Destruction Radius and ABO Compatibility: Tehran Earthquake. *Int. J. Supply Oper. Manag.* **2023**, *10*, 1–22.
43. Khalili-Fard, A.; Hashemi, M.; Bakhshi, A.; Yazdani, M.; Jolai, F.; Aghsami, A. Integrated relief pre-positioning and procurement planning considering non-governmental organizations support and perishable relief items in a humanitarian supply chain network. *Omega* **2024**, *127*, 103111. [\[CrossRef\]](#)
44. Altay, N.; Heaslip, G.; Kovács, G.; Spens, K.; Tatham, P.; Vaillancourt, A. Innovation in humanitarian logistics and supply chain management: A systematic review. *Ann. Oper. Res.* **2024**, *335*, 965–987. [\[CrossRef\]](#) [\[PubMed\]](#)
45. Tarefi, P.K.; Gumte, K.M.; Patnaik, J.; Oktari, R.S. Analysing barriers to humanitarian logistics for distributing relief aid in pre-and post-disaster situations. *Int. J. Disaster Risk Reduct.* **2024**, *104*, 104388. [\[CrossRef\]](#)
46. Beiki Ashkezari, A.; Zokaee, M.; Rabbani, E.; Rabbani, M.; Aghsami, A. A scenario-based game theory integrating with a location-allocation-routing problem in a pre-and post-disaster humanitarian logistics network under uncertainty. *J. Model. Manag.* **2024**. [\[CrossRef\]](#)
47. Mousavi, S.; Sajadi, S.M.; AlemTabriz, A.; Najafi, S.E. Hybrid mathematical and simulation model for designing a hierarchical network of temporary medical centers in a disaster. *J. Simul.* **2024**, *18*, 119–135. [\[CrossRef\]](#)
48. Liu, B.; Zhou, Y.; Luo, Q.; Huang, H. Quantum-inspired African vultures optimization algorithm with elite mutation strategy for production scheduling problems. *J. Comput. Des. Eng.* **2023**, *10*, 1767–1789. [\[CrossRef\]](#)
49. Ma, B.; Hu, Y.; Lu, P.; Liu, Y. Running city game optimizer: A game-based metaheuristic optimization algorithm for global optimization. *J. Comput. Des. Eng.* **2023**, *10*, 65–107. [\[CrossRef\]](#)
50. Chen, S.; Zheng, J. Sand cat arithmetic optimization algorithm for global optimization engineering design problems. *J. Comput. Des. Eng.* **2023**, *10*, 2122–2146. [\[CrossRef\]](#)
51. Goodarzimehr, V.; Talatahari, S.; Shojaee, S.; Hamzehei-Javaran, S.; Sareh, P. Structural design with dynamic constraints using weighted chaos game optimization. *J. Comput. Des. Eng.* **2022**, *9*, 2271–2296. [\[CrossRef\]](#)
52. Xing, J.; Zhao, Q.; Chen, H.; Zhang, Y.; Zhou, F.; Zhao, H. Utilizing bee foraging behavior in mutational salp swarm for feature selection: A study on return-intentions of overseas Chinese after COVID-19. *J. Comput. Des. Eng.* **2023**, *10*, 2094–2121. [\[CrossRef\]](#)
53. Jia, H.; Wen, Q.; Wu, D.; Wang, Z.; Wang, Y.; Wen, C.; Abualigah, L. Modified beluga whale optimization with multi-strategies for solving engineering problems. *J. Comput. Des. Eng.* **2023**, *10*, 2065–2093. [\[CrossRef\]](#)
54. Eslami, N.; Yazdani, S.; Mirzaei, M.; Hadavandi, E. A modified binary version of aphid-ant mutualism for feature selection: A COVID-19 case study. *J. Comput. Des. Eng.* **2023**, *10*, 549–577. [\[CrossRef\]](#)
55. Wang, S.; Hussien, A.G.; Kumar, S.; AlShourbaji, I.; Hashim, F.A. A modified smell agent optimization for global optimization and industrial engineering design problems. *J. Comput. Des. Eng.* **2023**, *10*, 2147–2176. [\[CrossRef\]](#)
56. Premkumar, M.; Jangir, P.; Sowmya, R.; Alhelou, H.H.; Mirjalili, S.; Kumar, B.S. Multi-objective equilibrium optimizer: Framework and development for solving multi-objective optimization problems. *J. Comput. Des. Eng.* **2022**, *9*, 24–50. [\[CrossRef\]](#)
57. Zheng, R.; Hussien, A.G.; Qaddoura, R.; Jia, H.; Abualigah, L.; Wang, S.; Saber, A. A multi-strategy enhanced African vultures optimization algorithm for global optimization problems. *J. Comput. Des. Eng.* **2023**, *10*, 329–356. [\[CrossRef\]](#)
58. Jia, H.; Li, Y.; Wu, D.; Rao, H.; Wen, C.; Abualigah, L. Multi-strategy Remora Optimization Algorithm for solving multi-extremum problems. *J. Comput. Des. Eng.* **2023**, *10*, 1315–1349. [\[CrossRef\]](#)
59. Yildiz, B.S.; Mehta, P.; Panagant, N.; Mirjalili, S.; Yildiz, A.R. A novel chaotic Runge Kutta optimization algorithm for solving constrained engineering problems. *J. Comput. Des. Eng.* **2022**, *9*, 2452–2465. [\[CrossRef\]](#)
60. Gorji, S.A. Challenges and opportunities in green hydrogen supply chain through metaheuristic optimization. *J. Comput. Des. Eng.* **2023**, *10*, 1143–1157. [\[CrossRef\]](#)
61. Mousapour Mamoudan, M.; Ostadi, A.; Pourkhodabakhsh, N.; Fathollahi-Fard, A.M.; Soleimani, F. Hybrid neural network-based metaheuristics for prediction of financial markets: A case study on global gold market. *J. Comput. Des. Eng.* **2023**, *10*, 1110–1125. [\[CrossRef\]](#)
62. Jia, H.; You, F.; Wu, D.; Rao, H.; Wu, H.; Abualigah, L. Improved snow ablation optimizer with heat transfer and condensation strategy for global optimization problem. *J. Comput. Des. Eng.* **2023**, *10*, 2177–2199. [\[CrossRef\]](#)

63. Qiao, S.; Yu, H.; Heidari, A.A.; El-Saleh, A.A.; Cai, Z.; Xu, X.; Mafarja, M.; Chen, H. Individual disturbance and neighborhood mutation search enhanced whale optimization: Performance design for engineering problems. *J. Comput. Des. Eng.* **2022**, *9*, 1817–1851. [[CrossRef](#)]
64. Chen, Y.; Lu, C.; Yan, J.; Feng, J.; Sareh, P. Intelligent computational design of scalene-faceted flat-foldable tessellations. *J. Comput. Des. Eng.* **2022**, *9*, 1765–1774. [[CrossRef](#)]
65. Sogandi, F.; Shiri, M. Metaheuristic algorithms for a sustainable saffron supply chain network considering government policies and product quality under uncertainty. *J. Comput. Des. Eng.* **2023**, *10*, 1892–1929. [[CrossRef](#)]
66. Cho, Y.I.; Nam, S.H.; Cho, K.Y.; Yoon, H.C.; Woo, J.H. Minimize makespan of permutation flowshop using pointer network. *J. Comput. Des. Eng.* **2022**, *9*, 51–67. [[CrossRef](#)]
67. Saremi, S.; Mirjalili, S.; Lewis, A. Grasshopper optimisation algorithm: Theory and application. *Adv. Eng. Softw.* **2017**, *105*, 30–47. [[CrossRef](#)]
68. Gouran-Orimi, S.; Ghasemi-Marzbali, A. Load Frequency Control of multi-area multi-source system with nonlinear structures using modified Grasshopper Optimization Algorithm. *Appl. Soft Comput.* **2023**, *137*, 110135. [[CrossRef](#)]
69. Alrashidi, M.; Alrashidi, M.; Rahman, S. Global solar radiation prediction: Application of novel hybrid data-driven model. *Appl. Soft Comput.* **2021**, *112*, 107768. [[CrossRef](#)]
70. Ingle, K.K.; Jatoth, R.K. Non-linear Channel Equalization using Modified Grasshopper Optimization Algorithm. *Appl. Soft Comput.* **2024**, *153*, 110091. [[CrossRef](#)]
71. Hirbod, F.; Eshghali, M.; Sheikhasadi, M.; Jolai, F.; Aghsami, A. A state-dependent M/M/1 queueing location-allocation model for vaccine distribution using metaheuristic algorithms. *J. Comput. Des. Eng.* **2023**, *10*, 1507–1530. [[CrossRef](#)]
72. Abbaspour, S.; Aghsami, A.; Jolai, F.; Yazdani, M. An integrated queueing-inventory-routing problem in a green dual-channel supply chain considering pricing and delivery period: A case study of construction material supplier. *J. Comput. Des. Eng.* **2022**, *9*, 1917–1951. [[CrossRef](#)]
73. Luo, J.; Chen, H.; Xu, Y.; Huang, H.; Zhao, X. An improved grasshopper optimization algorithm with application to financial stress prediction. *Appl. Math. Model.* **2018**, *64*, 654–668. [[CrossRef](#)]

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