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Scheduling optimization for joint transport of heterogeneous injured patients by ambulances and rescue aircrafts

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A B S T R A C T

This paper studies the scheduling optimization in casualty transportation after large-scale natural disasters, with a particular focus on the impact of injury heterogeneity on dispatch decisions. By considering different deprivation cost functions, we quantify the economic value of the pain endured by casualties before receiving medical treatment. An exact mathematical programming model is developed to minimize total economic and deprivation costs and optimize transportation strategies for critically and mildly injured patients. This model incorporates a collaborative ambulance-air rescue transportation mode that prioritizes air rescue for critically injured patients under emergency medical requirements. By using the historical medical rescue data from Jianyang City in Sichuan Province of China, we verify the effectiveness of the model through a case study by CPLEX 12.8.0 solver. Sensitivity analysis further provides some theoretical foundations and practical guidance for post-disaster casualty transportation planning.

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1. Introduction

Since the 21st century, the frequent occurrence of global natural disasters, including Hurricane Katrina (2005), Wenchuan Earthquake in China (2008), Nepal Earthquake (2015) and Pakistan Floods (2022), has caused massive casualties and socioeconomic losses. The severity of large-scale disasters highlights their profound impact on human society and the urgency of enhancing disaster prevention, mitigation, and emergency preparedness. In China, in response to natural disasters, a unified, specialized, agile, and coordinated emergency management framework has been established with significant improvements in comprehensive rescue operations. From 2013 to 2021, China's annual averages for deaths/missing persons, collapsed buildings, and direct economic losses (as a percentage of GDP) due to natural disasters experienced respective reductions of 87.2%, 87.4%, and 61.7% relative to the historical averages from 2000 to 2012[1]. However, the reform of China's emergency management system remains ongoing with substantial government budgetary expenditures. According to the data from the Ministry of Emergency Management, total budget expenditures fluctuated between 2018 and 2021, reaching 5.975 billion yuan in 2020 and rebounding to 9.698 billion yuan in 2023[2]. Thus, building a cost-effective and operationally efficient rescue network is critical for emergency response. In the emergency response system, ambulances are not only widely used for transportation of medical supplies, but also convenient for rescue and escort of patients. Their operation efficiency is highly dependent on route optimization strategy. In particular, Talarico et al. (2014) developed an ambulance routing model to minimize weighted waiting times for post-disaster casualty treatment, employing a large neighborhood search algorithm to enhance solution validity and safety. Sung and Lee (2016) transformed post-disaster casualty management into an ambulance scheduling problem, maximizing expected survival rates via column generation algorithms. Repoussis et al. (2016) integrated ambulance dispatching, hospital allocation, and treatment queuing into a dynamic model to reduce total response and flow times. Shavarani and Vizvari (2018) addressed ambulance allocation and routing in densely populated disaster zones to maximize patient survival. Paul and Zhang (2019) proposed a two-stage stochastic programming model to optimize medical supply prepositioning and transportation, indirectly improving ambulance rescue efficiency during hurricanes.

Ambulances and rescue aircraft are main vehicles in emergency operations, but their applications are different due to their different operational characteristics. When dealing with complex terrain or urgent rescue missions, stand-alone ambulance resources are often difficult to meet demands. To enhance rescue efficiency and ensure timeliness and effectiveness,

1 https://www.mem.gov.cn/xw/xwfbh/2022n8y30rxwfbh/mtbd_4262/202208/t20220831_421580.shtml
2 https://x.qianzhan.com/xcharts/detail/69e178084a87f3c6.html

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establishing a cooperative mechanism between ambulances and other rescue vehicles becomes crucial. Sun et al. developed a post-earthquake secondary evacuation model considering the synergistic effects of ambulances and rescue aircraft, aiming to maximize the number of rescued casualties and minimize psychological costs. Through capacity variations of rescue vehicles and medical facilities, they derived management insights (Sun et al., 2021). Desi-Nezhad et al. (2022) constructed a two-stage stochastic programming model for post-disaster rescue network design, incorporating economic, social, and environmental sustainability. The model included budget and pollution emission constraints, utilizing ambulance-rescue helicopter collaboration to overcome terrain and road network limitations, while minimizing total transportation time for casualties to determine optimal transfer points and nodal flows. Xu et al. (2023) proposed a truck-drone cooperative response strategy considering high road density, multiple interruption points, and large-scale demand in urban emergency scenarios, establishing a mixed integer programming model for scheduling optimization with minimized response time.

Casualty scheduling is indispensable to disaster response efforts, serving as a critical bridge between frontline disaster areas and rear hospitals. Scientific scheduling planning ensures safe and efficient transportation of casualties to medical facilities, securing precious time for subsequent treatment. During major natural disasters, limited resources necessitate casualty classification. Simple Triage and Rapid Treatment (START) is a common method for casualty classification (Benson et al., 1996). As shown in Table 1, this method classifies casualties into four categories using clearly defined injury descriptions for efficient resource allocation in emergency response scenarios. The literature frequently mentions using "classification tags" to identify urgency levels and optimize evacuation processes. For instance, Na and Banerjee emphasized the importance of effective evacuation models in disaster risk management, considering different priority levels of evacuees, vehicle types, and resource categories (Na & Banerjee, 2015).

Table 1

START Triage Classification System and Criteria

Casualty Classification	Label Color	Treatment Protocol	Injury Description
Minor Injuries	Green	No transport/treatment required	Non-life-threatening conditions requiring only basic first aid.
Moderate Injuries	Yellow	Delayed transport/treatment permitted	No urgent intervention needed; stable condition within a defined timeframe.
Severe Injuries	Red	Priority transport/treatment required	Require immediate medical intervention with critical therapeutic time windows; life-threatening if delayed.
Moribund Casualties	Black	No transport/treatment required	Unstable vital signs, in extreme critical or terminal condition.

Based on these insights, this paper aims at the emergency rescue scenario after major natural disasters by constructing a hierarchical casualty transport model for coordinated scheduling of ambulances and rescue aircrafts from multiple dimensions. The main contributions are as follows:

1. Most existing studies focus on single-mode transportation and few studies on the combination of multi-vehicle cooperative scheduling and stratified casualty transportation. Different from the homogeneity treatment of injury types in existing studies, this study constructs a differentiated deprivation cost based on injury classification to depict the actual rescue effect and the feelings of injuries. Moreover, the principle of "flexible treatment" is adopted in the cooperative transport of ambulance-rescue aircraft, which allows the rescue aircraft to flexibly carry out the transport of lightly injured people according to the real-time situation on the premise of ensuring that all seriously injured people are preferentially transported by rescue aircraft.

2. Different from the existing studies to consider the single economic cost only, this study comprehensively considers the direct economic expenditure in rescue dispatch and the additional pain cost caused by the delay or improper rescue. Then, an integer linear programming model is constructed by embedding both economic and deprivation cost within the objective function.

The rest of the paper is structured as follows. Section 2 offers a comprehensive review of the existing literature related to our study. Following this, Section 3 outlines the key parameters and presents the essential schematic diagram relevant to this study. The detailed mathematical formulation of the proposed model is elaborated in Section 4. Subsequently, Section 5 demonstrates the practical application of our approach through a case study conducted in Jianyang City, China, accompanied by a thorough sensitivity analysis. Finally, in Section 6, we present some remarks and directions for future research in this topic.

2. Literature Review

In emergency response to large-scale natural disasters, rational rescue dispatch and efficient transportation systems are pivotal factors in ensuring timely medical treatment for casualties and reducing the casualty rate. With the increasing frequency of natural disasters, research on emergency response systems has been continuously deepened on a global scale, while post-disaster rescue dispatch and multi-modal emergency transportation systems as core components of emergency response have garnered extensive attention. In Section 2.1, we focus on the significance of post-disaster rescue dispatch, highlighting that rational dispatch plays a crucial role in the overall emergency management system. Subsequently, in Section 2.2, we review the research on multi-modal emergency transportation systems to elucidate that enhancing the flexibility and adaptability of transportation systems is an important research topic.

2.1. Post-disaster Rescue Dispatch

Disaster emergency management is typically divided into four phases based on chronological logic: prevention/mitigation, preparedness, response, and recovery. Among these phases, the response phase is regarded as the most critical component. This phase encompasses a wide range of emergency management activities, ranging from direct rescue operations and resource allocation to medical support, as well as the distribution of emergency supplies and the establishment of temporary shelters. The efficiency of the response phase directly determines the overall effectiveness of disaster emergency management. Moreover, post-disaster rescue operations and resource scheduling represent the most fundamental and critical emergency management activities, as they significantly impact the safety of affected populations and their ability to evacuate hazardous areas and access subsequent medical assistance.

The issues of casualty dispatch and resource allocation in disaster emergency rescue have received extensive attention. Scholars have conducted research from aspects such as multi-objective optimization, dynamic decision-making, and system efficiency. In the context of disaster emergency response and humanitarian material distribution, the integration of advanced optimization algorithms and multi-objective models is employed to comprehensively consider factors such as logistics costs, deprivation costs, and rescue time, in order to achieve efficiency, equity, and minimization of social costs in rescue and material distribution (Cai et al., 2025; Wang et al., 2018). For example, Zhu et al. (2019) developed a multi-objective model integrating fairness and priority-based rescue routing, employing an ant colony algorithm and hybrid transportation strategies to balance efficiency and humanitarian goals. Liu et al. (2019) proposed a bi-objective optimization model to determine optimal locations of temporary medical facilities and allocation of medical resources by maximizing the number of expected survivors and minimizing operational costs to generate the Pareto front via the ε-constraint method to balance survivors and costs. Similarly, Tikani and Setak (2019) addressed the ambulance routing problem in mass-casualty scenarios by incorporating semi-soft time windows and heterogeneous ambulance capacities to minimize service completion time and delay penalties. In spatial resource allocation for emergency response, researchers have developed optimization models and methods to efficiently locate temporary medical centers and transport relief goods, considering factors such as triage costs, road damage probability, transportation costs, and warehouse/shelter locations to enhance resource deployment and distribution (Oksuz and Satoglu, 2020; Qezelbash-Chamak et al., 2023).

Dynamic decision-making studies emphasize real-time casualty allocation. In particular, Dean and Nair (2014) introduced a severity-adjusted victim evacuation model to optimize decision-making process of distributing victims to multiple hospitals during a mass casualty incident. This model considered the severity of injury, survival probability, hospital capacity, and ambulance availability to maximize the expected number of survivors. Jin et al. (2015) introduced a dynamic allocation model by incorporating time-decaying survival probabilities, with case studies demonstrating superiority over traditional transport-time minimization. To address the issue of how to dynamically allocate patients to medical facilities after a disaster, Mills et al. (2018) proposed two heuristic policies based on the Markov decision process formulation, which may increase the expected number of survivors under resource constraints. Moreover, Najafi et al. (2013) established a model for rescue scheduling to minimize unmet demand and rescue time based on the uncertainty of demand and supply. Rennemo et al. (2014) proposes a three-stage mixed integer stochastic programming model considering the opening of local distribution facilities, the initial distribution of materials and the last-mile distribution. Yan et al. (2023) constructed a UAV delivery scheduling model based on network flow techniques and mathematical programming methods, aiming to minimize the total operating cost. They developed a relax-and-fix heuristic algorithm to efficiently solve large-scale problems that may arise in practice. Wang et al. (2017) proposed a triage-based treatment model that categorized casualties into minor and severe injuries. Minor casualties were treated on-site to stabilize their conditions, while severe casualties were transported to hospitals for emergency care. They also introduced the Trauma Index Score to dynamically reflect the changes in the injury severity of casualties. By adopting an optimization scheme that minimizes the sum of TIS, the overall loss of the casualty group was effectively reduced, better meeting the actual needs of the casualties.
In addition, Yi and Özdamar (2007) considered the re-allocation of medical personnel among nearby hospitals, as well as the optimal distribution of medical staff between temporary and permanent emergency units. By simulating earthquake scenarios and hypothetical disaster scenarios, the behavior and solvability of the model were demonstrated, providing effective decision support for logistics coordination in disaster response. Huang et al. (2010) addressed another crucial aspect of rescue scheduling, namely facility location problems. It can be applied to determine the locations of rescue centers, temporary hospitals, and material distribution points. This model accounted for the possibility that facilities may fail to respond to local demands, thereby helping rescue schedulers more accurately address facility failures in large-scale disasters and ensuring the timely delivery of rescue resources. Ni et al. (2018) investigated how to simultaneously optimize the decisions of facility location, emergency inventory pre-positioning, and relief delivery operations within a single-commodity disaster relief network. They analyzed the performance of the robust model under different uncertainty budgets and explored how to control the model's conservativeness by adjusting the uncertainty budget.

These studies have not only optimized resource allocation and scheduling strategies, but also integrated advanced technologies and interdisciplinary collaboration to provide more precise and efficient solutions for post-disaster rescue efforts. This paper focuses on the transportation scheduling of casualties of different severity levels from disaster sites to hospitals after large-scale natural disasters, with the goal of ensuring that every casualty receives subsequent medical treatment. To achieve this

objective, the optimization of casualty scheduling through post-disaster multi-model integrated transportation is deemed essential. The following discussion reviews the relevant literature on this topic.

2.2. Multi-modal Emergency Transport Systems

This subsection delves into the critical role of post-disaster multi-modal integrated transportation in emergency rescue. The concept of multi-modal transportation involves the coordinated use of various transportation modes such as ground vehicles, helicopters, and temporary medical facilities so as to ensure timely and effective medical care for casualties of different severity levels (Ertem et al., 2017). Empirical research has demonstrated that efficient utilization of multi-modal transportation systems can significantly reduce system evacuation time. For instance, in the case study of Lower Manhattan in New York City, the evacuation time was reduced from 480,742 minutes to 298,342 minutes through optimized coordinated operation of automobiles, buses, and subways. This finding indicates that multi-modal transportation systems hold advantages not only in routine traffic management but also play a crucial role in emergency evacuations (Yang et al., 2018). Related studies in urban logistics also provide useful references for modeling integrated transportation scheduling under complex operational constraints. Fajardo-Calderin et al. (2016) developed an intelligent vehicle routing solver for last-mile logistics by jointly considering multimodal transportation, time-dependent travel conditions, driving restrictions, and multi-objective optimization.

Hu (2011) proposed an affinity model for container multimodal transportation emergency relief by simulating the structure and function of the immune system. For the cooperative trajectory planning problem of unmanned aerial vehicles and ground vehicles for post-disaster communication recovery, Zhu and Wang (2023) proposed an attention-based model based on deep reinforcement learning. Furthermore, Zhang et al. (2023) employed an integrated transportation mode of truck-aircraft-truck, combined with a four-tier service network comprising material supply points, transfer stations, distribution centers, and demand points, aiming to enhance the efficiency of emergency material transportation and rescue effectiveness. Similarly, Rahimi and Rahmani (2025) investigated the optimization of relief goods distribution routes through the coordinated transportation of trucks and drones in disaster scenarios, considering both route reliability and travel time. To address this problem, they developed a hybrid approach based on the Adaptive Large Neighborhood Search algorithm, integrating heuristic techniques and multi-objective optimization methods. Building on these cooperative transportation strategies, Shi et al. (2024) proposed a mixed-integer programming model that took into account the constraints of transportation capacity, road conditions, and the collaboration of multiple transportation modes (trucks, helicopters, and drones). For mountainous areas, Zhang et al. (2025) developed a mixed-integer programming model for truck-drone collaborative routing, integrating payload, range, and road condition constraints to minimize transportation time. Similarly, Yang et al. (2025) also studied a new type of collaborative transportation method involving unmanned aerial vehicles and trucks for post-disaster rescue.

In addition, Abdelgawad et al. (2010) studied the multi-objective optimization problems in emergency evacuation, including minimizing en-route travel time, waiting time, and overall network clearance time. They proposed the optimal spatiotemporal evacuation model and the multiple depot, time-constrained pickup and delivery vehicle routing problem to optimize traffic demand management and the scheduling of public transit vehicles during the evacuation process. Manopiniwes and Irohara (2021) proposed a mathematical model based on a multi-period and multi-modal approach to optimize the location of temporary depots in flood disaster response. The model integrates mixed integer linear programming and dynamic demand processing, considering the transfer between different transportation modes (such as trucks and boats). In a related vein, Ramadhan et al. (2025) focused on flood disaster scenarios, studying the distribution of humanitarian relief items using trucks, drones, and inflatable boats. They proposed the traveling salesman problem with drones and boats, aiming to minimize the completion time. Their study effectively demonstrated that combining multiple transportation modes can significantly enhance rescue efficiency in disaster relief operations. Beyond disaster-specific studies, broader transportation research also provides useful references for emergency transport scheduling. Nuzzolo et al. (2009) proposed an aggregate demand modelling system for international road freight transport, covering freight generation, attraction, distribution, and vehicle loading processes. From an equity perspective, Feng et al. (2025) systematically reviewed transport accessibility during COVID-19 and emphasized the importance of targeted emergency response plans for disadvantaged populations.

The integration of multi-modal transportation systems in emergency medical services represents a significant advancement in disaster response strategies. By leveraging the unique advantages of each transportation mode, such as the speed of helicopters and the accessibility of ground vehicles, these systems can effectively reduce response times and improve the likelihood of positive patient outcomes. The use of mathematical models and optimization techniques, as demonstrated by the aforementioned studies, provides a robust framework for decision-makers to evaluate and implement efficient transportation networks. These models not only account for the dynamic nature of disaster scenarios, but also offer flexibility in adapting to changing conditions and priorities.

3. Model Description

3.1. Problem Statement and Model Assumptions

Large-scale natural disasters often lead to a large number of casualties, posing a severe challenge to the emergency medical

response system. After a disaster, how to efficiently transfer the injured to appropriate medical institutions within a limited time window and optimize their treatment sequence is a key to reducing mortality rate and long-term sequelae. This study focuses on the collaborative rescue problem between post-disaster multi-disaster sites (i.e., multiple casualty aggregation points) and multiple hospitals, and proposes an integrated optimization method for casualty allocation and scheduling based on a hybrid transportation mode. Suppose that there are two types of heterogeneous transportation tools, namely ambulances and rescue aircraft. Due to practical constraints such as road damage and airport capacity, a spatio-temporal network model is constructed to achieve joint decision-making on casualty transfer and medical resource allocation.

To improve the operational efficiency, we adopt the classification criteria in Table 1 and divide the casualties into two levels: severe injury and minor injury. Specifically, based on Table 1, we consider to transport rescuable casualties, not including the black-tagged (moribund) casualties. The yellow-tagged (moderate) and green-tagged (minor) casualties in Table 1 are combined into minor injury category and the red-tagged (severe) casualties are classified as severe injury category, in contrast with minor injury category. Corresponding deprivation cost functions are established for each level respectively to quantify the economic value of the suffering endured by the wounded during the waiting for treatment.

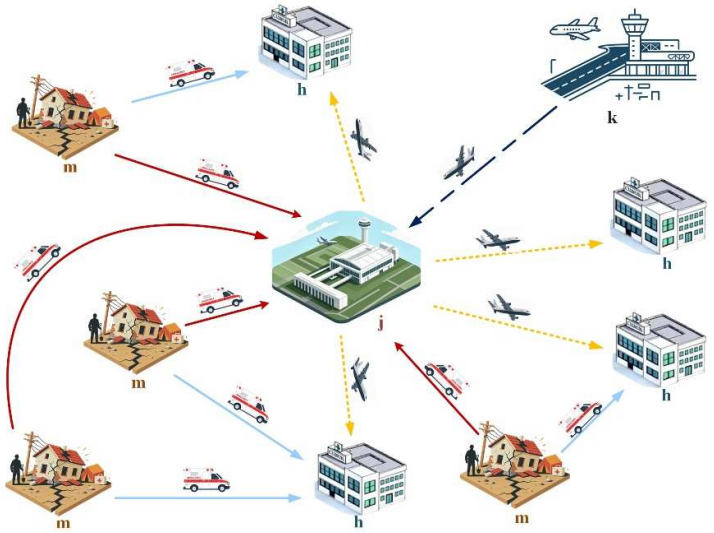


Fig. 1. Schematic diagram of collaborative transportation for casualties

Consider a rescue dispatching network, as illustrated in Fig. 1, which comprises three members: disaster sites, a designated large transfer point, and hospitals. In this network, the following two modes of casualty transportation are considered:

Mode 1: Ambulances stationed at disaster site directly transport local casualties to target hospital (represented by solid blue lines).

Mode 2: Ambulance-rescue aircraft collaborative transportation: rescue aircraft depart from the airport to a designated large transfer point (indicated by dark blue dashed-dotted lines). Simultaneously, ambulances travel from the disaster site to the transfer point (marked by red lines). After casualties and rescue aircraft arrive at the transfer point , casualties are transferred to the aircraft for final delivery to the target hospital (shown as yellow dotted lines).

Based on the above description, we make the following assumptions:

a) Road driving conditions and aerial operation conditions are subject to post-disaster uncertainty. In this study, the corresponding transportation times are approximated by their mean values for tractability.
b) Ambulances and rescue aircraft are available to meet all casualty transportation demands.
c) Casualties are triaged into severe (red-tagged) and minor (yellow/green-tagged) categories, with only transportable casualties considered.
d) All ambulances and rescue aircraft exhibit identical operational efficiency and technical specifications.
e) Waiting time at disaster sites and transfer time at the transfer point are assumed to be negligible compared with the main transportation time.

3.2. Notations

Based on the problem description, the parameters and variables are defined in Table 2.

Table 2
Parameters and Variables

Sets	Definitions
M	Set of disaster sites m , $m \in M$
H	Set of hospitals h , $h \in H$
Parameters	**Definitions**
Q_m	Total quantity of casualties at disaster area m
Z_m	Quantity of severe casualties at disaster area m
T_{mh}	Transportation time from disaster area m to hospital h (Mode 1)
T_{mjh}	Transportation time from disaster area m to hospital h via transfer point j (Mode 2), where $T_{mih} = \max\{t_{mi}, t_{kj}\} + t_{ih}$
t_{mi}	Ambulance transportation time from disaster area m to transfer point j
t_{kj}	Rescue aircraft transportation time from airport k to transfer point j
t_{ih}	Rescue aircraft transportation time from transfer point j to hospital h
C_{mh}	Unit transportation cost from disaster area m to hospital h (Mode 1)
C_{mi}	Unit transportation cost from disaster area m to transfer point j (Mode 2- ambulance part)
C_{kj}	Unit transportation cost from airport k to transfer point j (Mode 2- aircraft part)
C_{ih}	Unit transportation cost from transfer point j to hospital h (Mode 2- aircraft part)
Γ^{I}	Deprivation cost function for minor casualties
Γ^{II}	Deprivation cost function for severe casualties
Γ^{I}_{mh}	Unit deprivation cost for minor casualties transported via Mode 1($m \to h$)
$\Gamma^{\mathrm{I}}_{mjh}$	Unit deprivation cost for minor casualties transported via Mode 2($m \to j \to h$)
$\Gamma^{\mathrm{II}}_{mih}$	Unit deprivation cost for severe casualties transported via Mode 2($m \to j \to h$)
A_h	Capacity limit of hospital h
B_j	Capacity limit of transfer point j
E_h	Maximum rescue aircraft capacity allocated to hospital h
Decision Variables	**Definitions**
y_{mih}	Quantity of severe casualties evacuated from m to hospital h via transfer point j (Mode 2)
x_{mh}	Quantity of minor casualties evacuated from m to hospital h (Mode 1)
x_{mjh}	Quantity of minor casualties evacuated from m to hospital h via transfer point j (Mode 2)

4. Mathematical Model

4.1. Deprivation Cost Functions

The deprivation cost refers to the economic assessment of human suffering inflicted on individuals by unmet needs for goods and services. This concept is especially important in humanitarian logistics and emergency relief as it measures the economic suffering of victims or beneficiaries due to untimely allocation of supplies. Deprivation cost is often used in medical supply allocation research, but less in casualty scheduling. Pérez-Rodríguez and Holguín-Veras (2016) utilize the deprivation cost functions for high-priority and low-priority medical supplies and adjusts with an exponential function of a certain base to describe the degree of pain of light casualties during transportation. Specifically, the same deprivation cost function is used for the same type of patients, but different scheduling modes and routes lead to different scheduling times, which become the only factor causing different deprivation costs for the same type of patients. The deprivation cost functions for transporting different patients in different ways are as follows.

The deprivation cost associated with evacuating minor casualties through Mode 1 is set as

$$\Gamma^{\mathrm{I}}_{mh} = e^{(\beta_1 + \alpha_1 T_{mh})} - e^{\beta_1}.$$

The deprivation cost associated with evacuating minor casualties through Mode 2 is set as

$$\Gamma^{\mathrm{I}}_{mjh} = e^{(\beta_1 + \alpha_1 T_{mjh})} - e^{\beta_1}.$$

The deprivation cost associated with evacuating severe casualties through Mode 2 is set as

$$\Gamma^{\mathrm{II}}_{mjh} = e^{(\beta_2 + \alpha_2 T_{mjh})} - e^{\beta_2}.$$

Here, we assume that $\alpha_1 < \alpha_2$ and $\beta_1 < \beta_2$, which means that, during the same period, the deprivation cost borne by those with minor casualties is generally lower than that of those with severe casualties and the growth rate of the deprivation cost of the former is smaller than that of the latter.

4.2. Objective Measures

The total costs of the system include the ambulance operation cost, the rescue aircraft operating cost, and the deprivation cost borne by the wounded before they are delivered to the hospitals.

(1) Ambulance Operation Cost:

The ambulance operation cost includes two parts: the operation cost of full-journey transportation in Mode 1 and the operation cost of evacuating casualties from disaster sites to the transfer point in Mode 2. Its expression is given as

$$\sum_{m\in M}\sum_{h\in H} C_{mh}x_{mh} + \sum_{m\in M}[C_{mj}\sum_{h\in H}(x_{mjh}+y_{mjh})].$$

(2) Rescue Aircraft Operation Cost:

The rescue aircraft operation cost includes two parts: the operation cost of rescue aircrafts traveling from their initial station to the transfer point and the operation cost of traveling from the transfer point to the hospitals. Its expression is given as

$$\sum_{h\in H}[(C_{kj}+C_{jh})\sum_{m\in M}(x_{mjh}+y_{mjh})].$$

(3) Deprivation Cost:

We adopt distinct deprivation cost function for severe and minor casualties. The overall deprivation costs comprise three parts: the minor casualties transported by Mode 1, the minor casualties transported by Mode 2, and the severe casualties transported by Mode 2. The expression is given as

$$\sum_{m\in M}\sum_{h\in H}\Gamma^{\mathrm{I}}_{mh}x_{mh} + \sum_{m\in M}\sum_{h\in H}\Gamma^{\mathrm{I}}_{mjh}x_{mjh} + \sum_{m\in M}\sum_{h\in H}\Gamma^{\mathrm{II}}_{mjh}y_{mjh}.$$

4.3. Mathematical Model

From the above description, the mathematical model for the system can be formulated as

$$\begin{aligned}\min\ & \sum_{m\in M}\sum_{h\in H} C_{mh}x_{mh} + \sum_{m\in M}[C_{mj}\sum_{h\in H}(x_{mjh}+y_{mjh})] + \sum_{h\in H}[(C_{kj}+C_{jh})\sum_{m\in M}(x_{mjh}+y_{mjh})] \\ & + \sum_{m\in M}\sum_{h\in H}\Gamma^{I}_{mh}x_{mh} + \sum_{m\in M}\sum_{h\in H}\Gamma^{I}_{mjh}x_{mjh} + \sum_{m\in M}\sum_{h\in H}\Gamma^{I}_{mjh}y_{mjh}\end{aligned} \tag{1}$$

subject to

$$\sum_{h\in H} x_{mh} + \sum_{h\in H} x_{mjh} + \sum_{h\in H} y_{mjh} = Q_m, \forall m\in M, \tag{2}$$

$$\sum_{h\in H} y_{mjh} = Z_m, \forall m\in M, \tag{3}$$

$$\sum_{m\in M} x_{mh} + \sum_{m\in M} x_{mjh} + \sum_{m\in M} y_{mjh} \le A_h, \forall h\in H, \tag{4}$$

$$\sum_{m\in M} x_{mjh} + \sum_{m\in M} y_{mjh} \le E_h, \forall h\in H, \tag{5}$$

$$\sum_{m\in M}\sum_{h\in H}(x_{mjh}+y_{mjh}) \le B_j, \tag{6}$$

$$x_{mh}\in Z_+, y_{mjh}\in Z_+, x_{mjh}\in Z_+, \forall m\in M, \forall h\in H. \tag{7}$$

The objective function (1) encompasses the economic costs of transporting two categories of casualties and the deprivation costs they endure prior to medical treatment. Constraint (2) guarantees all injured individuals being transported to the hospitals. Constraint (3) specifies that severe casualties must be transported via Mode 2. Constraint (4) restricts each hospital's casualty intake to its capacity. Constraint (5) represents each rescue aircraft capacity for each targeted hospital. Constraint (6) means that the transfer point can accommodate minor and severe casualties transported via Mode 2. Constraint (7) represents non-negative integer variables. This mathematical model is an integer linear program that can be readily optimized using standard commercial solvers. We will use CPLEX to solve this model in the following case study.

5. Case Study

5.1. Dataset

This section utilizes medical rescue data from Jianyang City in Sichuan Province of China. We demarcated the disaster sites at the township level and selected 12 out of the 16 streets and 21 towns in Jianyang City as our research subjects. Within the city, the primary medical facilities are the People's Hospital and the Traditional Chinese Medicine Hospital, covering 47 grassroots healthcare institutions. We selected 8 hospitals as our subjects, as depicted in Fig. 2. Moreover, Chengdu Tianfu International Airport was chosen as the transfer point due to its spacious terminal area of 710,000 square meters, which can adequately meet the capacity requirements for casualty scheduling and evacuation in this case study. Additionally, Chengdu Shuangliu International Airport, located at 30.560°N, 103.951°E, was designated as the starting point for rescue aircrafts. This

site can continuously dispatch rescue aircrafts to Chengdu Tianfu International Airport to support Mode 2. The satellite illustration of the case is shown in Fig. 2. The 12 disaster points in this case are marked with “yellow house” symbols and the 8 medical hospitals in this case are indicated with “red cross” symbols. Meanwhile, both Chengdu Shuangliu International Airport and Chengdu Tianfu International Airport are also labeled on the figure.

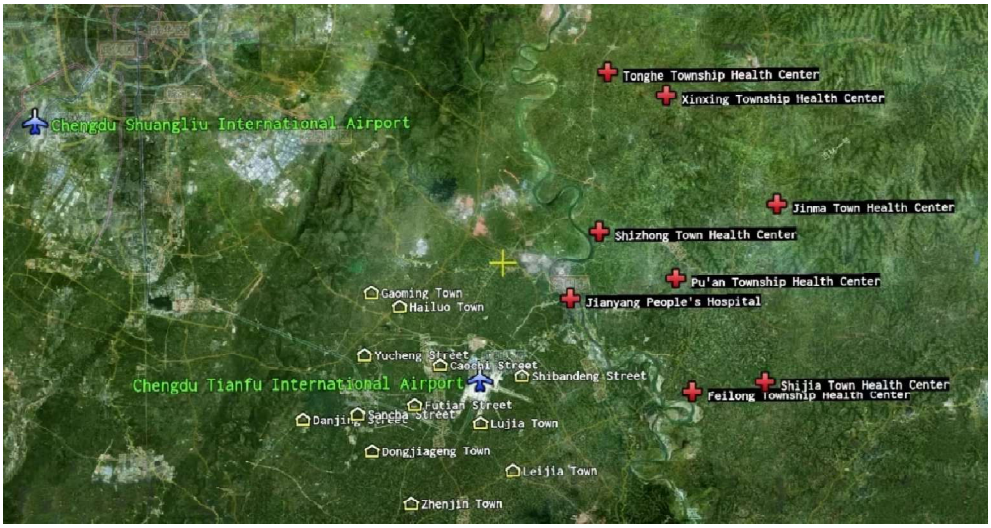


Fig. 2. Satellite Illustration

Assume that an earthquake occurred and rescue operations are conducted for casualties at the 12 disaster sites, with all casualties ultimately allocated to 8 hospitals. Table 3 details the specific casualty counts across all disaster sites. Given the need for high-precision transportation distance data in emergency rescue situations, the Vincenty distances from each disaster site to each hospital are determined through programming code in this study, as presented in Table 4, while the accommodation capacities of the 8 hospitals and the upper limits of rescue aircraft transportation capacity for each hospital are shown in Table 5. Unit transportation costs and times from different disaster sites to different hospitals under two modes are presented in Tables 6 and 7. As shown in Table 3, we conducted a population count of the permanent residents at each location and assumed that 10% of the population became casualties. We further assumed that 9% of the casualties were severe casualties, with the remainder being minor casualties. Then, we can count the numbers of casualties with varying injury severity.

Table 3
Numbers of People at Each Disaster Site

Serial Number	Disaster Site	Permanently Resident Population	Severe Casualties	Minor Casualties
1	Lujia Town	27511	248	2503
2	Shibandeng Street	24064	217	2189
3	Caochi Street	33701	303	3067
4	Futian Street	11697	105	1065
5	Yucheng Street	19421	175	1767
6	Sancha Street	40936	368	3726
7	Dongjiageng Town	18022	162	1640
8	Leijia Town	18049	162	1643
9	Gaoming Town	14585	131	1328
10	Zhenjin Town	22766	205	2072
11	Hailuo Town	17475	157	1591
12	Danjing Street	11189	101	1018

Table 4
Distances from Disaster Sites to Hospitals (Unit: Kilometers)

Disaster Sites	Hospital Numbers							
	1	2	3	4	5	6	7	8
1	18.64	11.72	24.97	24.76	15.81	26.35	35.48	37.6
2	13.58	6.36	19.66	19.41	10.48	21.12	30.25	32.24
3	22.49	16.33	29.27	29.54	20.27	31.34	40.46	42.34
4	25.81	19.57	32.57	32.76	23.55	34.46	43.59	45.57
5	31.37	25.65	38.36	38.86	29.5	40.7	49.82	51.64
6	32.67	26.7	39.58	39.89	30.63	41.61	50.74	52.7
7	31.29	25.09	38.1	38.25	29.08	39.88	49.01	51.07
8	16.14	8.57	21.85	21.1	12.7	22.44	31.56	33.91
9	30.11	24.69	37.19	37.9	28.45	39.86	48.96	50.62
10	27.33	20.65	33.87	33.67	24.73	35.13	44.26	46.51
11	26.73	21.14	33.74	34.35	24.93	36.3	45.4	47.1
12	39.29	33.48	46.27	46.69	37.38	48.42	57.55	59.49

To enhance the accuracy of the case data, we employed the algorithm for calculating the precise distance between two points along the ellipsoidal surface of the Earth, namely the Vincenty distance. We obtained the latitude and longitude information of each target location using the Ovito map software and then substituted these coordinates into the Vincenty formula to derive the distance matrix from each disaster point to each hospital, as shown in Table 4. To ensure the integrity and reliability of the case data, a comprehensive approach was adopted, incorporating both qualitative analysis and specific assumptions where necessary. In particular, the hospital capacity upper limit was carefully estimated through an in-depth examination of the relationship between the hospital's land area and its maximum capacity. This estimation involved analyzing historical data, consulting with experts in hospital planning and operations, and applying established principles of facility management to arrive at a realistic upper limit for the hospital's capacity. Additionally, the transportation times and costs under two different transportation modes were meticulously determined by considering specific assumptions regarding speed and cost per unit. For each transportation mode, the average speed was estimated based on factors such as traffic conditions, route characteristics, and vehicle types. The cost per unit was calculated by taking into account fuel consumption, labor costs, maintenance expenses, and other relevant factors. These assumptions were validated through comparison with industry standards and real-world data to ensure their accuracy and applicability to the case at hand.

Table 5
Casualty Capacity Limits of Each Hospital (Unit: Persons)

Serial Numbers	Hospitals	Capacity Limits(A_h)	Transportation Capacity Limits(E_h)
1	Tonghe Township Health Center	2500	825
2	Jianyang People's Hospital	7000	722
3	Xinxing Township Health Center	1000	1011
4	Pu'an Township Health Center	3500	351
5	Shizhong Town Health Center	2200	583
6	Feilong Township Health Center	2300	1228
7	Shijia Town Health Center	3500	541
8	Jinma Town Health Center	4000	541

Table 6
Unit Transportation Costs from Disaster Site to Hospital under Two Modes (Unit: Yuan)

Disaster Site Number	Hospital Number			
	1	2	3	4
1	(33.55, 184.48)	(21.1, 167.82)	(44.95, 200.71)	(44.57, 200.69)
2	(24.45, 189.74)	(11.45, 173.09)	(35.38, 205.97)	(34.94, 205.96)
3	(40.49, 189.44)	(29.4, 172.78)	(52.69, 205.67)	(53.17, 205.65)
4	(46.45, 193.34)	(35.23, 176.69)	(58.63, 209.57)	(58.96, 209.56)
5	(56.47, 201.13)	(46.16, 184.48)	(69.05, 217.36)	(69.96, 217.35)
6	(58.81, 202.28)	(48.05, 185.63)	(71.24, 218.51)	(71.81, 218.5)
7	(56.33, 200.2)	(45.16, 183.55)	(68.58, 216.44)	(68.85, 216.42)
8	(29.06, 188.98)	(15.43, 172.32)	(39.33, 205.21)	(37.99, 205.19)
9	(54.21, 200.23)	(44.44, 183.58)	(66.94, 216.46)	(68.21, 216.45)
10	(49.19, 194.72)	(37.18, 178.07)	(60.96, 210.95)	(60.61, 210.94)
11	(48.11, 195.79)	(38.05, 179.14)	(60.73, 212.02)	(61.84, 212.01)
12	(70.72, 210.79)	(60.26, 194.13)	(83.29, 227.02)	(84.04, 227.01)
Disaster Site Number	Hospital Number			
	5	6	7	8
1	(28.47, 177.92)	(47.43, 204.99)	(63.87, 227.8)	(67.67, 232.75)
2	(18.86, 183.18)	(38.02, 210.25)	(54.44, 233.07)	(58.04, 238.02)
3	(36.49, 182.88)	(56.4, 209.95)	(72.82, 232.77)	(76.21, 237.71)
4	(42.39, 186.78)	(62.03, 213.86)	(78.46, 236.67)	(82.03, 241.62)
5	(53.11, 194.57)	(73.26, 221.65)	(89.68, 244.46)	(92.95, 249.41)
6	(55.13, 195.72)	(74.9, 222.79)	(91.34, 245.61)	(94.87, 250.56)
7	(52.34, 193.65)	(71.78, 220.72)	(88.22, 243.53)	(91.93, 248.48)
8	(22.86, 182.42)	(40.39, 209.49)	(56.81, 232.3)	(61.03, 237.25)
9	(51.21, 193.67)	(71.75, 220.74)	(88.13, 243.56)	(91.12, 248.51)
10	(44.52, 188.16)	(63.24, 215.23)	(79.66, 238.05)	(83.71, 243)
11	(44.88, 189.23)	(65.34, 216.3)	(81.72, 239.12)	(84.77, 244.07)
12	(67.29, 204.23)	(87.15, 231.3)	(103.59, 254.12)	(107.08, 259.06)

Table 7
Transportation Time from Disaster Site to Hospital under Two Modes (Unit: Hours)

Disaster Site Number	Hospital Number			
	1	2	3	4
1	(0.47, 0.09)	(0.29, 0.08)	(0.62, 0.1)	(0.62, 0.1)
2	(0.34, 0.15)	(0.16, 0.15)	(0.49, 0.16)	(0.49, 0.16)
3	(0.56, 0.15)	(0.41, 0.14)	(0.73, 0.16)	(0.74, 0.16)
4	(0.65, 0.23)	(0.49, 0.22)	(0.81, 0.23)	(0.82, 0.23)
5	(0.78, 0.38)	(0.64, 0.37)	(0.96, 0.39)	(0.97, 0.39)
6	(0.82, 0.4)	(0.67, 0.4)	(0.99, 0.41)	(1, 0.41)
7	(0.78, 0.36)	(0.63, 0.35)	(0.95, 0.37)	(0.96, 0.37)
8	(0.4, 0.14)	(0.21, 0.13)	(0.55, 0.15)	(0.53, 0.15)
9	(0.75, 0.36)	(0.62, 0.36)	(0.93, 0.37)	(0.95, 0.37)
10	(0.68, 0.25)	(0.52, 0.25)	(0.85, 0.26)	(0.84, 0.26)
11	(0.67, 0.27)	(0.53, 0.27)	(0.84, 0.28)	(0.86, 0.28)
12	(0.98, 0.57)	(0.84, 0.57)	(1.16, 0.58)	(1.17, 0.58)
Disaster Site Number	Hospital Number			
	5	6	7	8
1	(0.4, 0.09)	(0.66, 0.1)	(0.89, 0.11)	(0.94, 0.12)
2	(0.26, 0.15)	(0.53, 0.16)	(0.76, 0.18)	(0.81, 0.18)
3	(0.51, 0.14)	(0.78, 0.16)	(1.01, 0.17)	(1.06, 0.17)
4	(0.59, 0.22)	(0.86, 0.24)	(1.09, 0.25)	(1.14, 0.25)
5	(0.74, 0.38)	(1.02, 0.39)	(1.25, 0.4)	(1.29, 0.41)
6	(0.77, 0.4)	(1.04, 0.41)	(1.27, 0.43)	(1.32, 0.43)
7	(0.73, 0.36)	(1, 0.37)	(1.23, 0.38)	(1.28, 0.39)
8	(0.32, 0.14)	(0.56, 0.15)	(0.79, 0.16)	(0.85, 0.16)
9	(0.71, 0.36)	(1, 0.37)	(1.22, 0.39)	(1.27, 0.39)
10	(44.52, 188.16)	(63.24, 215.23)	(79.66, 238.05)	(83.71, 243)
11	(44.88, 189.23)	(65.34, 216.3)	(81.72, 239.12)	(84.77, 244.07)
12	(67.29, 204.23)	(87.15, 231.3)	(103.59, 254.12)	(107.08, 259.06)

5.2. Solution Results

Based on the provided data, we solved the model present in the last section by using MATLAB R2018a and the CPLEX solver on a laptop configured with an Intel Core i5-9300H processor (2.40 GHz) and 8 GB of memory. The obtained results are shown by three matrices to represent the allocation relationships between disaster sites and hospitals, as well as the numbers of casualties transported by each mode of transportation, as shown in Fig. 3. In the figure, the two coordinate axes on the same horizontal plane correspond to the indices of disaster sites and hospitals respectively, while the axis perpendicular to this plane represents the numbers of people. Each bar represents the allocation relationship from a specific disaster site to a particular hospital, with its height indicating the number of casualties transported. Specific values are marked near the top of each bar.

The results indicate that all 12 disaster sites' casualties are allocated, achieving a one-to-one disaster site-hospital match. The 8 hospitals are fully utilized, with a total system cost of 5,540,949.45. Notably, minor casualties from the sites 6 and 12 are transported via Mode 2. Those from the site 6 are sent to the hospitals 3, 7, and 8, while those from the site 12 are concentrated in the hospital 6 for treatment.

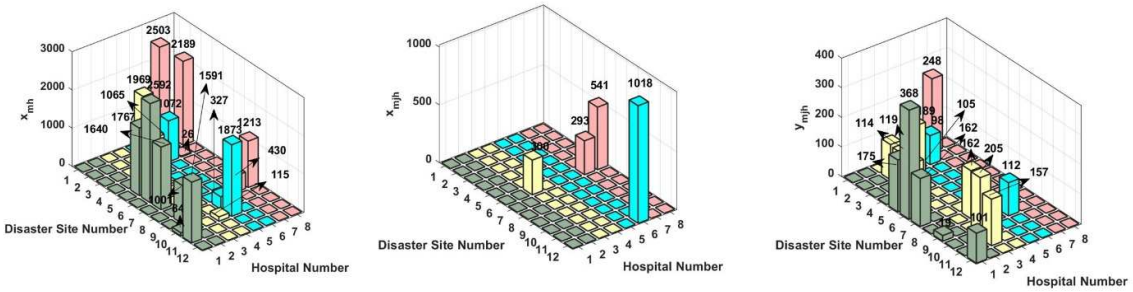


Fig. 3. 3D Bar Chart of Solution Results

5.3. Sensitivity Analysis

On the basis of the preceding subsection, this subsection conducts a sensitivity analysis by focusing on three parameters, the rescue aircraft transport capacity upper limit E_h, the casualty severity distribution, and the hospital capacity upper limit A_h, so as to get some management insights.

5.3.1. Rescue Aircraft Transport Capacity Upper Limit E_h

We adjusted the rescue aircraft transport capacity upper limit for each hospital to explore its impact on the results. Starting from the base case, we increased this capacity by 1.2, 1.4, 1.6, 1.8, and 2.0 to create six scenarios in total (including the base

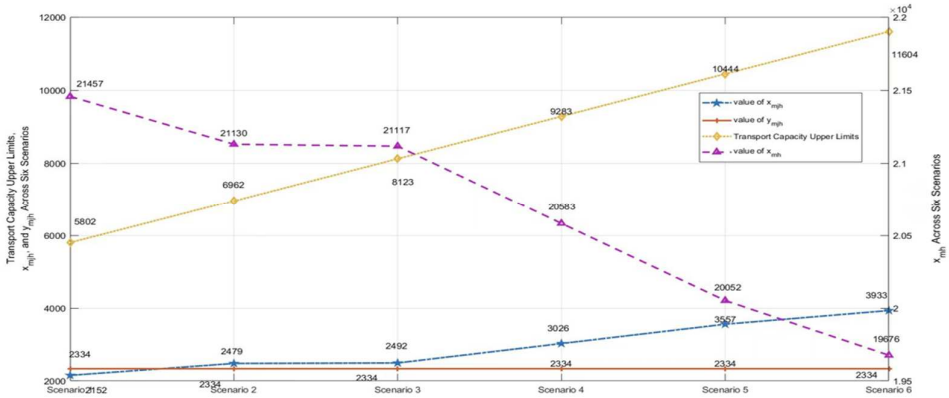
case). These scenarios are defined as shown in Table 8.

Table 8
Six Scenarios Based on Changes in Rescue Aircraft Transport Capacity Upper Limit

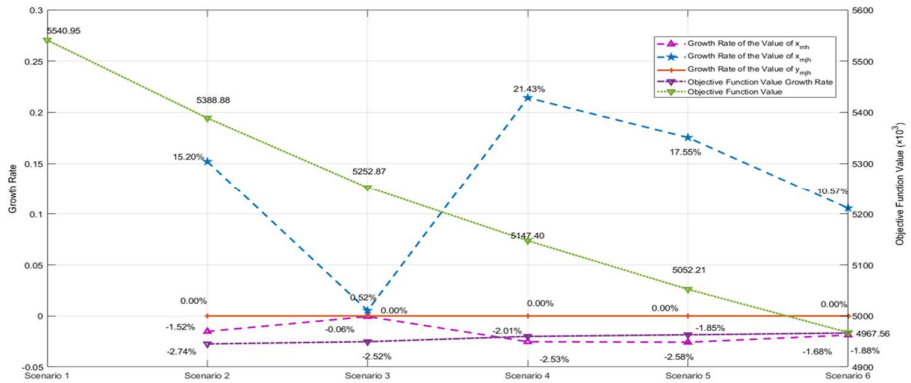
Scenario Number	Transport Capacity Upper Limit	x_{mh}	x_{mjh}	y_{mjh}	Objective Function Value
1	5802	21457	2000	2334	5540949.45
2	6962	21130	2479	2334	5388881.35
3	8123	21117	2492	2334	5252868.56
4	9283	20583	3026	2334	5147395.70
5	10444	20052	3557	2334	5052209.80
6	11604	19676	3933	2334	4967563.65

In addition, the transport capacity upper limits of rescue aircrafts and the trends in the numbers of x_{mjh} and y_{mjh} vary across six scenarios, as shown in Fig. 4. From Fig. 4(a), as the upper limit of rescue aircraft transport capacity E_h increases proportionally, the value of x_{mjh} rises. However, since the number of casualties is fixed, the value of y_{mjh} remains unchanged. From Fig. 4(b), with the increase of E_h, the objective function value decreases at a rate of 2.74% initially and hence the rate slows down. The value of x_{mh} decreases, while y_{mjh} stays constant. The growth rate of x_{mjh} fluctuates but remains positive.

Based on the analysis of the rescue aircraft transport capacity upper limit E_h, we may draw the following insights: (1) As rescue aircraft transport capacity increases, the number of minor casualties scheduled for transport via Mode 2 shows an upward trend. However, due to the high economic cost of Mode 2 compared to Mode 1 and the unchanged accommodation levels of hospitals, the growth rate is relatively slow. (2) With increased rescue aircraft transport capacity, there may be more flexibility in casualty allocation. The increase in x_{mjh} and the optimization of disaster site-hospital matching for three types of x_{mh}, x_{mjh} and y_{mjh} may reduce system costs.



(a) Numbers of Different Types of Casualties Transported under Various Transport Capacity Upper Limits



(b) Objective Function Values under Different Transport Capacity Upper Limits

Fig. 4. Analysis of Rescue Aircraft Transport Capacity Upper Limits

5.3.2. Casualty Severity

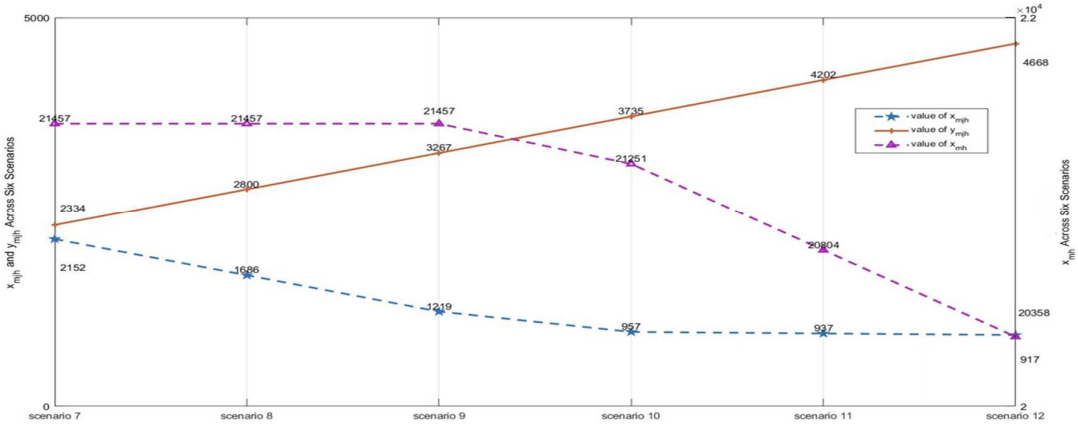
We also adjusted the casualty severity ratio to analyze its impact on the results. Using the base case severity ratios from each disaster site Z_m as a benchmark, we increased them proportionally to obtain five new sets of Z_m values. As shown in Table 9, we derived six scenarios with distinct severity proportions while keeping Q_m fixed.

As shown in Fig. 5, the six scenarios exhibit variations in x_{mh}, x_{mjh}, y_{mjh} and the objective function values. From Fig. 5(a), as the number of severe casualties rise, y_{mjh} absorbs all severe casualties, which means that the severe casualty graph and y_{mjh}'s trend line coincide. In the scenarios Nos.7-9, x_{mh} stays constant and x_{mjh} decreases. In the scenarios Nos.10-12, both x_{mh} and x_{mjh} decrease, while x_{mjh} remains almost unchanged and x_{mh} drops significantly. From Fig. 5(b), in the scenarios Nos. 8-9, as y_{mjh} increases, x_{mjh} decreases by 22% and 28% respectively with x_{mh} unchanged. In the scenarios Nos. 10-12, x_{mh} decreases by 1%, 2%, 2%, while x_{mjh} decreases by 21%, 2%, 2%. In particular, the objective function value increases by 3% across six scenarios.

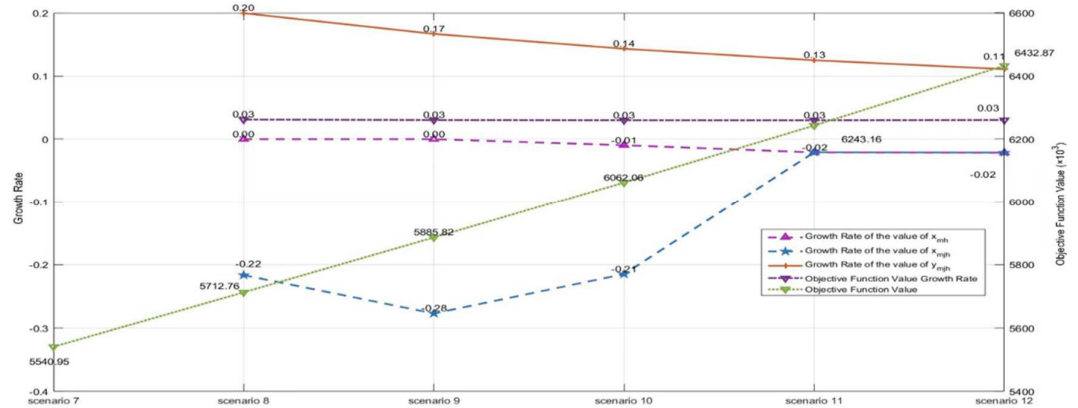
Table 9

Six Scenarios Based on Changes in Injury Severity

Scenario Number	Number of Severe Casualties (Percentage)	Number of Minor Casualties (Percentage)	Transport Capacity Upper Limit	Objective Function Value
7	2334 (9%)	23609 (91%)	5802	5540949.45
8	2801 (11%)	23142 (89%)	5802	5712762.71
9	3268 (13%)	22675 (87%)	5802	5885820.18
10	3734 (14%)	22209 (86%)	5802	6062061.69
11	4201 (16%)	21742 (84%)	5802	6243159.37
12	4668 (18%)	21275 (82%)	5802	6432865.07



(a) Numbers of Different Types of Patients Transported under Various Injury Severity Ratios



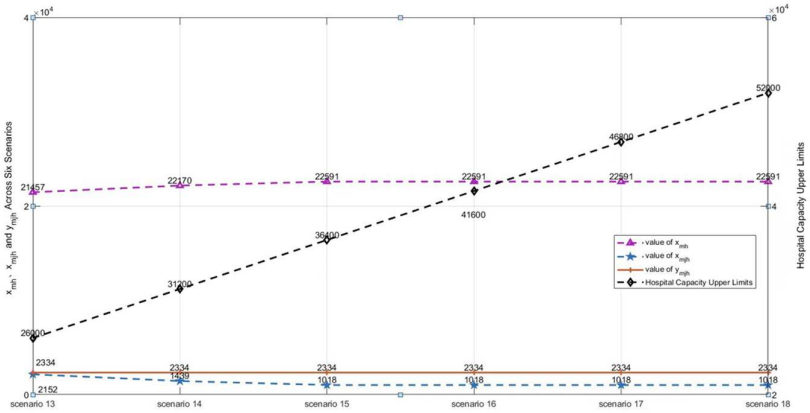
(b) Growth Rates of Casualty Numbers and Objective Function Values under Different Injury Severity Ratios

Fig. 5. Analysis of Casualty Severity Ratios

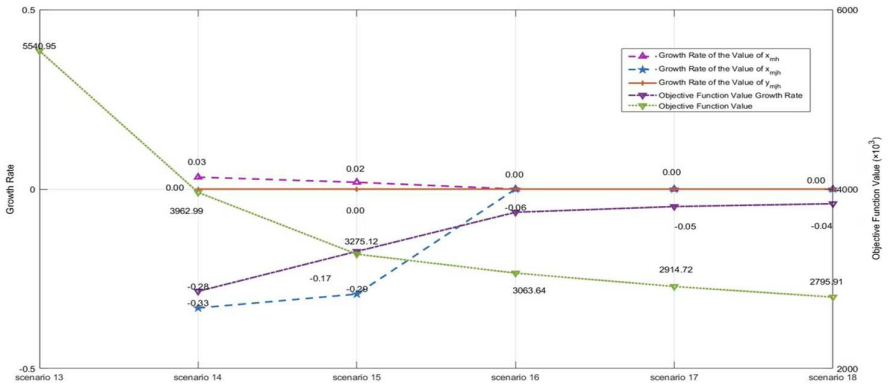
Based on the above analysis of casualty severity ratios, we deduce the subsequent insights: (1) When the count of severe casualties grows and other conditions remain unchanged, the number of minor casualties transported via Mode 2 decreases, while the number transported via Mode 1 stays constant within a certain range (severe casualty ratio ≤ 13%). When the severe casualty ratio exceeds 13%, Mode 1's numbers also decrease, while the proportion of minor casualties transported via Mode 2 increases due to more and more severe casualties are occupying the capacities of more desirable (relatively nearer) hospitals for minor casualties. (2) An increase in severe casualties may lead to more individuals within this group needing to be scheduled via Mode 2, raising both economic and deprivation costs and thus raising the objective function value. This indicates that high proportion of severe casualties may increase system costs and social losses.

5.3.3. Hospital Capacity Upper Limit A_h

We adjusted the hospital capacity upper limit to obtain six scenarios (Nos.13-18), as shown in Table 10. The analysis results are presented in Fig. 6.



(a) Numbers of Different Types of Patients Transported under Different Hospital Capacity Upper Limits



(b) Growth Rates of Casualty Numbers and Objective Function Values under Different Hospital Capacity Upper Limits

Fig. 6. Analysis Figure for Different Hospital Capacity Upper Limits

Table 10
Six Scenarios Based on Changes in Hospital Capacity Upper Limit

Scenario Number	Hospital Capacity Upper Limit	x_{mh}	x_{mjh}	y_{mjh}	Objective Function Value
13	26000	21457	2152	2334	5540949.45
14	31200	22170	1439	2334	3962994.42
15	36400	22591	1018	2334	3275123.07
16	41600	22591	1018	2334	3063639.29
17	46800	22591	1018	2334	2914715.55
18	52000	22591	1018	2334	2795908.25

From Fig. 6(a), in the scenarios Nos.13-15, as hospital capacity upper limit rises, x_{mh} increases while x_{mjh} decreases with y_{mjh} unchanged. In the scenarios Nos.16-18, all three values keep stable. From Fig. 6(b), the objective function value decreases with high hospital capacity upper limit, dropping by 28% and 17% in the scenarios Nos.14-15 respectively and then stabilizing

around 4%. In the first three scenarios, x_{mh} rises and x_{mjh} drops sharply (33% and 28%). In the last three scenarios, all values remain stable. Drawing from the aforementioned analysis, we have the following insights: (1) Within a certain range, as hospital capacity upper limit increases, few minor casualties are transported via Mode 2 and more via Mode 1, which indicates that high capacity levels may allow more direct ambulance transport. In the scenarios Nos.15-18, the numbers for all three casualty groups remain stable. (2) Increasing hospital capacity upper limit may effectively reduce the objective function value. In the scenarios Nos.13-15, more minor casualties are transported via Mode 1 to near hospitals, reducing Mode 2 transports and decreasing the objective function value significantly. In the scenarios Nos.15-18, although the casualty group numbers stabilize, the objective function value still decreases slightly, likely due to ongoing optimization of casualty-hospital matching such as transporting more casualties to near hospitals.

6. Conclusions

This study focuses on optimizing the scheduling of casualties with different injury severities after a major natural disaster. Severe casualties are prioritized for transport to hospitals via rescue aircrafts after being transported to transfer points, while minor casualties can be transported directly to hospitals by ambulance or rescue aircrafts if rescue aircraft capacity permits. We have developed an integer linear programming model to minimize both economic and deprivation costs. We have further presented a case study about Jianyang City in Sichuan Province of China and conducted sensitivity analysis on three factors: the rescue aircraft transport capacity, the ratio of casualty severity, and the hospital capacity. Main findings are as follows: (1) Increasing the ratio of casualty severity, enhancing the rescue aircraft transport capacity, and enlarging the hospital capacity may all reduce system costs and improve rescue outcomes. (2) When the ratio of casualty severity is high, increasing rescue aircraft transport capacity may allow more casualties to be scheduled via Mode 2. (3) High hospital capacity may significantly boost emergency rescue effectiveness and hence decision-makers should ensure adequate hospital capacity in real-world rescue operations. (4) Economic and deprivation costs are conflicting objectives and decision-makers need to balance them for optimal casualty scheduling. As a future research, we will incorporate uncertainties such as random casualty demands and resource environments into the model for further practical management insights.

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