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A cooperative optimization model and enhanced algorithm for guided strategies in emergency mobile facilities

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In the realm of emergency response, the swift and efficient deployment of mobile units is of paramount importance. This research introduces a strategy centered around the "proximity response" principle, aiming to strategically position emergency services nearer to areas of higher demand. This approach is designed to enhance response times while optimizing resource allocation. Through the integration of practical planning with user-friendly computational methodologies, this paper presents a novel framework for improving the allocation and reach of emergency facilities. This includes extending critical care to broader areas and minimizing operational costs. The simulations conducted demonstrate that this strategy markedly enhances crisis management effectiveness. The paper also includes a statistical analysis that provides substantial evidence of the practicality and efficiency of this approach in real-world emergency scenarios. This study contributes to the field by offering a new perspective on resource distribution and emergency response planning, potentially impacting the way these critical services are organized and deployed.

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Introduction

In recent years, public health and emergency response systems worldwide have faced unprecedented challenges from global emergencies such as the COVID-19 pandemic and the Beirut port explosion. These events have led to significant casualties and property losses, underscoring the importance of rapidly and accurately deploying emergency mobile facilities. Mobile medical clinics, distribution centers, and temporary shelters have been crucial in mitigating disasters, providing relief, and controlling epidemics (Ahmadi-Javid et al., 2017; McGowan et al., 2020). However, effectively configuring and scheduling these facilities to meet evolving emergency needs remains an urgent challenge.

One key issue in current emergency responses is information inequality, where essential facility and service information is not adequately communicated to the public. Additionally, the public's preference for conveniently located facilities (Pilkington et al., 2012; Al-Mandhari et al., 2008) exacerbates resource utilization issues, leading to some facilities being overwhelmed and others underused, thus compromising response efficiency and increasing public safety risks.

For instance, during the initial stages of China's response to the COVID-19 pandemic, there was a notable imbalance in the utilization of mobile nucleic acid testing facilities. Facilities in easily accessible locations experienced high demand, while others in remote areas were underutilized, leading to an uneven distribution of healthcare resources and reducing overall response efficacy.

To address these challenges, this paper proposes a collaborative optimization model for emergency mobile facilities, using a proximity-based guidance strategy. The model aims to efficiently allocate emergency resources and guide the public to appropriate facilities. A key aspect of this model is addressing the complexities of multi-objective optimization, crucial for balancing various objectives in emergency resource allocation. The authors introduce an enhancement to existing multi-objective optimization algorithms, focusing on improving efficiency and accuracy in scenarios involving multiple, often conflicting objectives.

In these connections, the paper's contributions and innovations include (1) a newly designed demand allocation strategy addressing uneven facility usage; (2) the introduction of humanitarian principles to meet public needs conveniently; (3) a tight integration of facility scheduling and demand allocation in a collaborative optimization model; and (4) an improved algorithm enhancing solution efficiency.

The rest of the paper is structured as follows: the section "Empirical literature" revisits and compares relevant empirical literature. Section "Modeling" details the construction of the collaborative allocation model. Section "Algorithm" describes the improved algorithm. Section "Simulation" validates the model and algorithm through an actual emergency response case. Section "Conclusion" summarizes the research findings and outlines future research directions.

Empirical literature

In recent times, there have been several global emergencies that have presented substantial obstacles in effectively managing the resource requirements of public health. These include the 2019 COVID-19 outbreak, the 2014–2016 West African Ebola epidemic, and the 2015 Nepal earthquake, among others. These occurrences have exerted tremendous pressure on meeting the escalating need for medical resources. Consequently, conventional healthcare facilities often encounter challenges in adequately addressing these demands (Anderson et al., 2020; Emanuel et al., 2020; Elston et al., 2017). Recent studies have also highlighted the non-linear relationship between pandemic uncertainty and public health spending, emphasizing the significance of response strategies and preparedness in sudden public health events (Teng et al., 2023). Especially in situations with heightened uncertainties in demand or when compounded by specific risk factors like epidemic outbreaks, the allocation of medical resources becomes particularly complex (Lei et al., 2014; 2014).

In this particular scenario, the utilization of emergency mobile facilities, including mobile medical vehicles, medical rooms, and nucleic acid sampling facilities, etc., is regarded as a versatile and expedient remedy (Bloomfield et al., 2014; Nair and Miller-Hooks, 2009; Yang et al., 2021; Çakır et al., 2022). Nevertheless, the optimal allocation and scheduling of these facilities, to ensure the utmost fulfillment of demand, remains an unresolved and arduous matter (Jenkins et al., 2020; Büsing et al., 2021).

This problem encompasses various elements, including the quantity and pathway of movement for facilities, as well as constraints related to service capacity. The presence of either an excess or a deficiency in the number of facilities, coupled with the quality of route selection and the overload or insufficiency of service capacity, can all have an impact on the efficiency of emergency response. To illustrate, having too many facilities or an excessive service capacity can result in wastage of resources, whereas a scarcity of facilities, subpar route selection, or inadequate service capacity can hamper response speed and limit the effectiveness of epidemic control (Halper et al., 2015; Raghavan et al., 2019; Lei et al., 2016; Calogiuri et al., 2021). Moreover, an unresolved issue of significance is the development of effective facility routes that can conveniently cater to the demands at hand (Halper and Raghavan, 2011; Doerner et al., 2007). For a more in-depth exploration, please refer to the source cited as (Alarcon-Gerbier and Buscher, 2022).

Resource allocation plays a crucial role in resolving this issue (Rahman and Smith, 2000). Existing studies primarily concentrate on three key areas: the distribution of resources from facilities to points of demand, the scheduling of resources between different facilities, and the collaborative optimization of both these aspects (Khayal et al., 2015; Balcik and Beamon, 2008; Vitoriano et al., 2021). Nonetheless, the presence of dynamic and uneven demand, particularly when the general public prefers to access the nearest and most convenient resources, introduces new obstacles. Consequently, it becomes imperative to guide the demand in a scientifically informed manner to ensure a balanced relationship between demand and available resources (Altay and Green III, 2006; Galindo and Batta, 2013).

Existing studies often examine the relationship between resource and demand quantities (Caunhye et al., 2012; Sharma et al., 2019; Ghaffari et al., 2020; Wang et al., 2022). Yet, this relationship has garnered limited attention in the context of facility scheduling. Research has evaluated factors like the facility's status (Calogiuri et al., 2021), quantity (Güden and Süral, 2014; 2019), available resources (Raghavan et al., 2019), and uncertainties such as demand volume (Bayraktar et al., 2022; Sharma et al., 2019; Qi et al., 2017) and response time (Li et al., 2021; Li et al., 2019), to inform facility movements. However, a frequently overlooked aspect is the practical scenarios wherein multiple facilities are required to address a single demand point. Such situations can influence facility operations, impacting their availability, the number of transfers, and periods of (in)activity, which subsequently affects demand allocation. While some studies (Rawls and Turnquist, 2010; Yücel et al., 2020; Salman et al., 2021) highlight the significant connection between facility scheduling and associated costs, there is a lack of in-depth research into collaborative decision-making concerning facility movements and emergency resource allocation. This knowledge gap

Table 1 Variable and parameter definitions.

Symbol	Meaning
Parameters	
i	Community node index, $i \in \boldsymbol{I}$;
a_i	Demand of community i, which may be affected by specific risk factors such as epidemic risk. For simplicity and comprehensibility, the demand quantity is measured by the number of community requirements in the following.
j, k, q	Facility node index, $j, k, q \in \boldsymbol{J}$;
s_j	Number of facilities at location j;
D	The maximum distance that demanders are willing to accept;
d_{ij}	Distance from community node i to facility node j;
d_{jk}	Distance from facility node j to facility node k;
c	Cost of opening a unit facility;
c_t	Cost of transferring a facility per unit distance, defined as α times the cost of opening a unit facility ($c_t = \alpha c$). Here, α is a ratio factor, and since the cost of moving facilities is usually small, the value of α will be small;
R	Service capacity of each facility;
β	percentage of demanders will reliably adhere to the guidance;
N_i	$N_i = \{j \mid d_{ij} \le D, j \in \boldsymbol{J}\}$: The set of indices j within D from i;
v_{ij}	Convenience level from demand node i to facility node j;
Variables	
x_j	Number of facilities opened at location j;
y_{ij}	Demands of community i guided to location j;
t_{jk}	Number of facilities moved from location j to k;

becomes especially evident in scenarios involving sudden public health events, where effective facility scheduling and precise demand allocation are crucial.

Hence, there is a critical need to develop a multi-objective collaborative model that incorporates both facility flow and demand allocation in order to effectively tackle these challenges. Furthermore, it is imperative for this model to consider the overall cost implications. By doing so, this model will significantly enhance resource utilization during emergency situations, optimize demand fulfillment, and ultimately bolster the efficiency and effectiveness of emergency management operations.

The Non-dominated Sorting Genetic Algorithm II (NSGAII) is recognized for its effectiveness in identifying Pareto optimal solutions within the realm of multi-objective optimization (Megiddo et al., 1983). It has been widely adopted for complex problem-solving scenarios, including resource allocation, due to its capability to balance various conflicting objectives, which is a common challenge in intricate decision-making processes such as emergency facility management and resource distribution (Deb et al., 2002; Chen Zhang and Yang, 2021).

Despite its robustness, NSGAII can be computationally intensive, leading researchers to propose two main enhancements: optimization of the search strategy through new heuristic rules or adjustments in genetic operations (Esmikhani et al., 2022; Ardali et al., 2022; Chen et al., 2019; Rabiei et al., 2023; Feng et al., 2017; Zhou et al., 2017), and development of more suitable coding methods to align with problem specifics to enhance search efficiency (Shuwen Zhang et al., 2017; Fogue et al., 2013; Abadi et al., 2021; Kaushik and Vidyarthi, 2016). These coding methods, known as vector encoding (NSGAIIV) and matrix encoding (NSGAIIM), have been tailored for multi-objective optimization problems like resource allocation.

Traditional coding methods often struggle to meet the dynamic and immediate demands of mobile facility allocation, presenting a challenge in the context of real-world emergency management. Addressing this critical gap, this study presents the NSGAIIVU

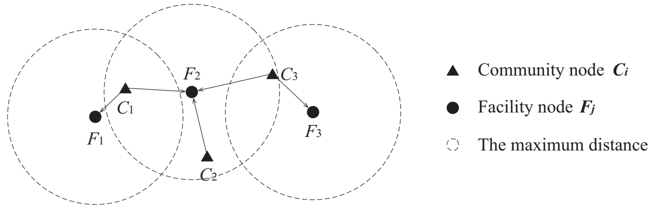

Fig. 1 Convenience level of demand satisfaction.

strategy, a significant enhancement to the NSGAII algorithm. This innovative approach adapts to the operational flux of facilities, incorporating their real-time status into the encoding process at each iteration. Distinct from the static encoding of NSGAIIV and NSGAIIM, NSGAIIVU is specifically tailored to improve search efficiency for large-scale or capacity-constrained problems. The methodology and advantages of NSGAIIVU will be elaborated in the section "Algorithm", underlining its capacity to deliver pragmatic, actionable solutions that effectively translate theoretical optimization into practical, on-the-ground applications.

Modeling

A demand-guided collaborative model is developed in this section to determine the positioning and allocation of mobile facilities. Each community's needs are taken into consideration and allocated to neighboring facility locations through resource allocation. The capacity of each facility location is constrained but can cater to several nearby communities. Hence, the objective of this model is to find the most efficient allocation scheme for community needs, while making decisions on facility locations (both open and mobile) to optimize response efficiency and minimize total costs (Table 1).

Parameters and assumptions. The authors initiate the model by establishing an initial network that comprises facility nodes and community nodes. The specific model parameters and assumptions are outlined in the following manner:

The mathematical model is based on certain assumptions:

(1) Number of facility openings at a location: The number of open facility points follows a dynamic adjustment strategy (Holguín-Veras et al., 2012), especially in the event of disasters or sudden incidents (Tzeng et al., 2007). It is assumed that the number of facilities opened at each point j, denoted as x_j, is constrained by the demand a_i of the community it serves and the number of facilities s_j at that point.

(2) Facility Resource Mobility: During emergency responses, resources are typically dynamically allocated (Sheu, 2007). The study considers the movement of facilities from one point to one or more other points. The number of facilities opened at point j, x_j, is determined by the original number of facilities at that point s_j, the number of facilities moved into that point from another point k as t_{kj}, and the number of facilities moved out to another point k as t_{jk}. Here, the number of facilities t_{jk} moving out from point j should not exceed its original number.

(3) Demand satisfaction: In disaster response, fulfilling the demand is often influenced by distance, with the nearest facilities being prioritized (Berman et al., 2003; Teixeira and Antunes, 2008). The demands of community i are mainly met by nearby facility points, and resource allocation should not exceed the facility's service capacity. As shown in Fig. 1, when demand node C_1 has a large demand, it is first responded to by the nearby facility F_1. If F_1 cannot meet the demand, the next nearest F_2 supplements the response. Node C_2 is served by facility point F_2. Additionally, the distance ratio $v_{ij} = (D - d_{ij})/D$, for all $\forall d_{ij} \le D$,

represents the convenience level from demand point i to facility point j. When d_{ij} approaches D, the level of convenience decreases, and vice versa. If $d_{ij} \geq D$, $v_{ij} = 0$. Therefore, $v_{13} = v_{21} = v_{23} = v_{31} = 0$, $0<v_{32}<v_{22}<v_{12}<v_{33}<v_{11}<1$.

(4) Demanders' behavior: The public's behavior during emergencies typically follows official guidance, with the majority complying to ensure safety. As mentioned (Drabek, 1999), warnings from authoritative sources significantly improve compliance rates. The authors assume that the vast majority of demanders will follow official guidance. Although there are exceptions, to keep the model simple and efficient, they are not elaborated upon in detail.

Collaborative optimization model. This study presents a demand-guided collaborative model, aiming to optimize the location decisions for both open and mobile facilities, the number of facilities to activate at each location, and the allocation of community needs to these facilities, in a manner that maximizes response efficiency and minimizes total costs.

$$Max\, Z_1 = \beta \sum_i \sum_j y_{ij}. \quad (1)$$

$$Max\, Z_2 = \beta \sum_i \sum_j y_{ij} v_{ij}. \quad (2)$$

$$Min\, Z_3 = c \sum_j x_j + \alpha c \sum_j \sum_k d_{jk} t_{jk}. \quad (3)$$

$$s.t.\, y_{ij} \leq x_j \cdot M; \forall i, j \in N_i. \quad (4)$$

$$\sum_k t_{jk} \leq s_j; \forall j. \quad (5)$$

$$x_j \leq s_j + \sum_k t_{kj} - \sum_k t_{jk}; \forall j. \quad (6)$$

$$\sum_i y_{ij} \leq R \bullet x_j; \forall j. \quad (7)$$

$$\beta \sum_{j \in N_i} y_{ij} \leq a_i; \forall i. \quad (8)$$

$$x_j \in N; \forall j. \quad (9)$$

$$t_{jk} \in N; \forall k, j. \quad (10)$$

$$y_{ij} \in N; \forall i, j \in N_i. \quad (11)$$

The objective function (1) aims to maximize the total guided demand being met from all communities to all facility locations. The objective function (2) aims to maximize the convenience level weighted guided demand satisfaction volume, reflecting the closer the facility is to the demand node, the greater the value of meeting this demand. Objective function (3) aims to minimize the total cost, which includes the cost of opening facilities at all locations and the cost of moving facilities from one location to another. Constraint (4) stipulates those residents of community i are guided to facilities only within distance D, where M is a sufficiently large positive number. Constraint (5) restricts the number of facilities that can move from location j, not exceeding its current quantity. Constraint (6) defines the number of facilities opened at location j, accounting for the original count and migration. Constraint (7) ensures assigned demand to each facility doesn't exceed its capacity. Constraint (8) ensures each community's assigned demand across all locations must not surpass its total demand. Equations (9) to (11) require all decision variables to be positive integers.

Algorithm

Encoding design. In an effort to address large-scale or capacity-limited challenges, this paper has developed a novel encoding update strategy. At the heart of this strategy is the continuous integration of the real-time status of the facilities with every iterative cycle. This ensures that the encoding remains tightly aligned with the genuine intricacies of the problem at hand. As a result, this study not only simplifies the encoding length but also significantly enhances search efficiency. When compared to traditional methods, this paper provides a more nuanced understanding of the complexity of the problem, opening up new possibilities for the application of NSGAII. Subsequent sections will provide a deeper exploration of the strategy's operational mechanics and its associated benefits.

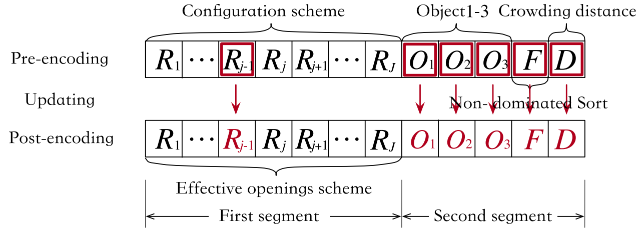

Fig. 2 Chromosome encoding design. R_j Quantity of facilities at site j, O objective values, F crowding distance, D non-dominated sorting.

The main focus of this study is to determine the optimal number of facility openings based on a predetermined configuration scheme, S_J. In this context, facilities can predominantly exist in one of four states: crowded, fully utilized, partially idle, or completely idle. What distinguishes this paper from conventional strategies is its focus on the interaction between the predetermined number of facilities and the actual number of operational facilities. These states not only shed light on the dynamics of facility operations but also form the cornerstone for encoding updates using chromosome gene strings. Such an approach fosters a more adaptive encoding framework, ensuring it remains responsive to evolving challenges in the problem space.

Figure 2 depicts both the chromosome vector encoding and the method used for updating the chromosome encoding. In this representation, the authors employ chromosomes of length $|J| + 5$ to indicate various potential solutions. These chromosomes are bifurcated into two sections. The first segment, spanning a length of $|J|$, represents the configuration plan of the facility. Subsequent to this, there is a gene segment of length 5, encapsulating three objective values, crowding distance, and non-dominated sorting.

The main emphasis during the updating procedure is the adjustment of facilities not in full utilization. Specifically, the first gene segment, $S_J = (R_1, \cdots, R_j, \cdots, R_J)$, gives insights into the configuration quantity of facilities at each site, denoted as $R_j = s_j (s_j \geq 0)$. Facilities that are only partially idle will have their numbers tweaked based on their actual operational status to align with the desired quantity "x_j". If a facility remains not utilized, its corresponding gene locus will be assigned a value of "0". Once these modifications are complete, the chromosome's second segment is updated in tandem to maintain up-to-date information.

Algorithm steps

Initialization. Randomly generate an initial population of a specified size. Calculate the objective values, perform non-dominated sorting, and determine the crowding distance for all chromosomes.

Selection. Using the tournament method, select parent chromosomes P_1 and P_2.

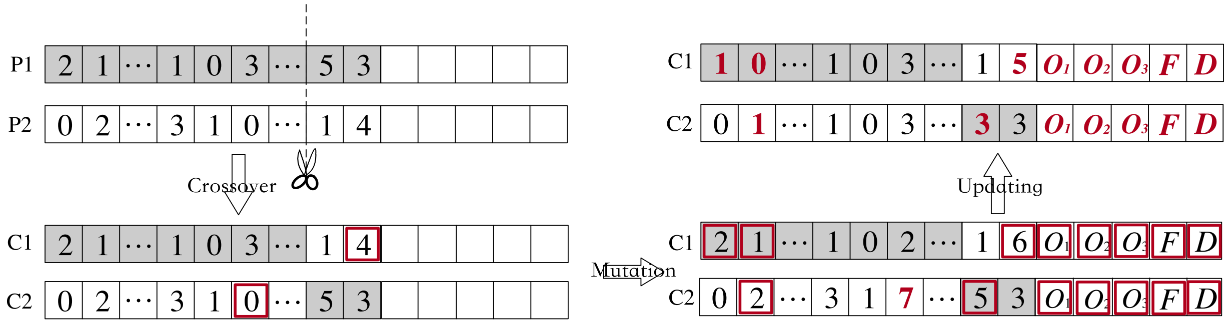

Fig. 3 Genetic operation. O objective values, F crowding distance, D non-dominated sorting.

Crossover. Refer to Fig. 3 for the genetic operation. Determine a crossover position k at random. Generate two offspring chromosomes, C_1 and C_2. The first k genes of C_1 are inherited from P_1, while the subsequent $|J| - k$ genes come from P_2. Conversely, the initial k genes of C_2 are derived from P_2, and the remaining genes from P_1.

Mutation. Choose a gene locus in the chromosome at random and mutate it. Ensure that its value doesn't surpass the maximum feasible number of facilities, $\sum_j s_j - \sum_j x_j$, to maintain the solution's feasibility.

Encoding update. In accordance with the guidelines mentioned in the section "Encoding design", modify the gene loci of chromosomes to transition from the configuration scheme to the opening scheme.

Population integration. Through non-dominated sorting and crowding distance assessments, choose the top N individuals. These should exhibit superior performance in both multi-objective tasks and spatial density from the combined population, forming the new population.

Iteration. Persistently repeat the steps above until reaching the predefined count of genetic iterations.

Simulation

In this section, the authors evaluated the proposed model and algorithm using nucleic acid sampling facilities for COVID-19 prevention and control as a backdrop. Under the simplified scenario where $\beta = 1$, implying all demanders act according to the guidance, 100 iteration tests were conducted for varying key parameters J, R, and α to gauge the algorithm's efficiency and precision. The other parameters include a mutation probability of 0.9, a crossover probability of 0.4, and a population size of 100. All experiments were performed on a computer equipped with an M1 chip using Matlab2021a.

Case description. The simulation in this study utilizes the nucleic acid sampling facilities located in Shuangta Street, Suzhou City, China. This location was selected due to its high population density and its representation of an urban environment. With 115 facilities spread over 52 locations serving 97,923 residents in 21 communities, it offers a microcosm of broader urban emergency response scenarios (refer to Fig. 4 and Table 2 for detailed visuals). Data collection for this study involved conducting structured telephone interviews to gather information on facility locations and community demographics. To ensure the accuracy and reliability of the data, these interviews were cross-verified with public records and local health department reports. This comprehensive approach provides a solid empirical foundation for the simulation and enhances the practical applicability of the study's findings.

The shortage of efficient resource scheduling methods in practical operations can lead to overcrowded or underused facilities, as depicted in Fig. 4. As a consequence, there is an irrational utilization of resources and a decline in detection efficiency. The primary reason behind this is that the public tends to select nearby facilities for sampling randomly, which leads to excessive usage of some facilities while leaving others idle. This presents a significant challenge for epidemic prevention and control.

The most effective approach should consider the arrangement of facilities while addressing the requirements of residents, aiming to prioritize meeting demand and minimizing financial costs. However, accomplishing this is particularly difficult during an emergency pandemic situation. Consequently, the authors anticipate that this developed model can enhance the allocation of facility resources, guide demand, guarantee high-quality service provision, and ensure the reasonable utilization of resources. Ultimately, this will lead to the greatest societal benefit.

Collaborative scheme. This section delves into the guiding strategies essential for effective facility relocation decisions, a departure from conventional approaches. These strategies, as explored in Table 3 and Fig. 5, are instrumental in balanced facility utilization during emergency responses. Traditional emergency response methods typically prioritize the effectiveness of actions. However, the simulations conducted in this paper demonstrate that this model effectively balances the satisfaction of demand with cost considerations.

Figure 5 presents the collaborative approach to resource scheduling, illustrating various Pareto optimal solutions. Figure 5 depicts the strategic facility transfers, where the size of a node corresponds to the facility count. For instance, "6(2) → 15" signifies relocating two facilities from "6. Shipaotou Small Park" to "15. Wanshou Palace Gate" to optimize their use. Figure 5 further illuminates the demand guidance integral to this strategy, where opening 109 facilities across 44 locations meets the needs of 97923 individuals.

Table 3 contrasts scenarios with and without guiding strategies and inter-facility transfers. The data suggest that guiding strategies prevent the uneven utilization of facilities, and permitting transfers enhances both demand satisfaction and proximity-based service convenience. Planners typically focus on sites that can meet more or nearer demands within a service range. Although transfers entail additional logistics costs, these can be offset by strategic facility openings, potentially lowering overall costs. This evidence accentuates the significance of strategic transfers within a guiding framework for operational management across different sites.

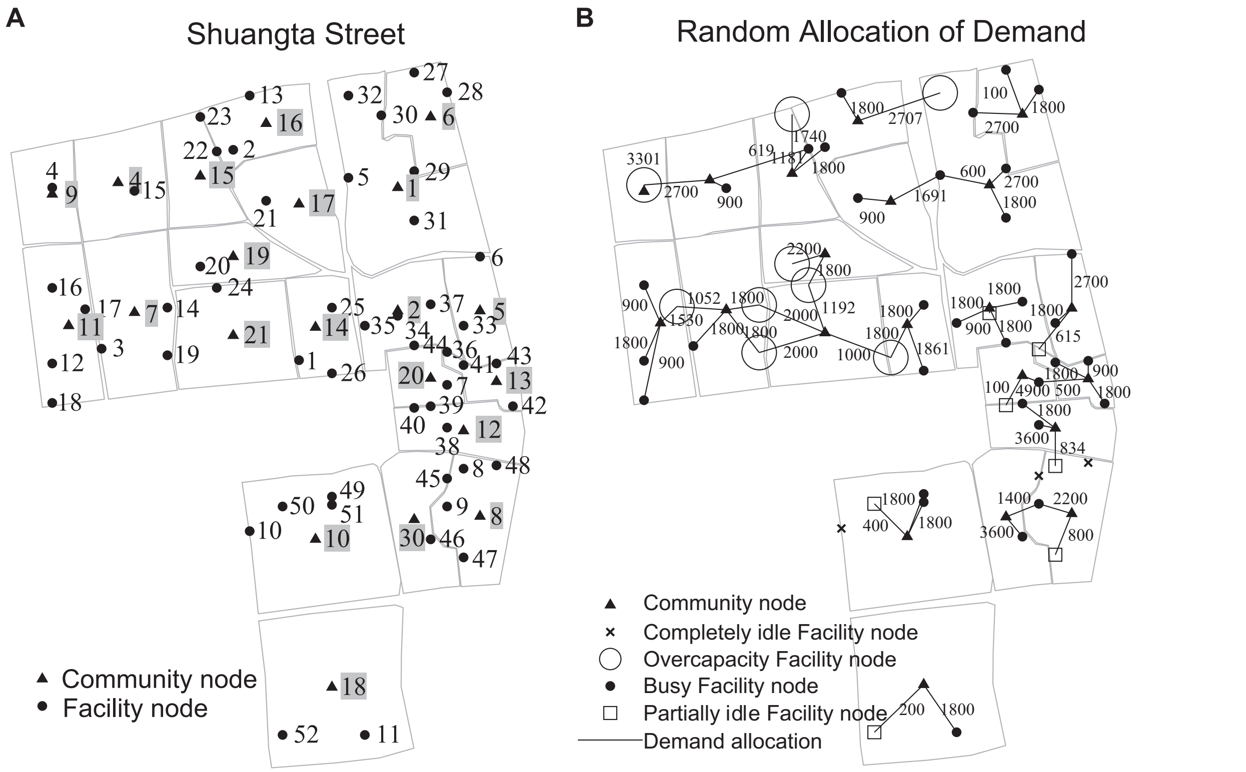

Fig. 4 Problem instance. A The spatial location of facilities and communities. **B** A potential random allocation of demand.

Table 2 Detailed information.

Facility				**Community**	
***j*. Location**	s_j	***j*. Location**	s_j	***i*. Location**	a_i
1. Xiangwang Road Park	2	27. Changyihuayuan Complex's West No.2 Gate	1	1. Fengxi	5100
2. Zhonglou New Village Complex's West Gate	2	28. Changjin Alley	2	2. Changdao	6300
3. Wuque Bridge	2	29. Hongfeng Complex's Gate	3	3. Xingxiu	5000
4. Wusan Road Stadium	3	30. Qinghuali Complex's West Square	3	4. Big Park	4219
5. Moye Road Parking Lot	3	31. Cansangdi Complex	2	5. Heng Street	5115
6. Shipaotou Park	3	32. Lvjunhuayuan Complex's East Gate	2	6. Hongfeng	4600
7. Magnolia Plaza	6	33. Yangzhiercun Park	2	7. Gunxiufang	6452
8. Beichengwan Street Parking Lot	2	34. Changdao Garden Complex's East Gate	2	8. CityBay	3000
9. Guannanyuan Plaza	4	35.19 West Street Complex	2	9. Jinfan	3301
10. Cuiyuanercun Complex's East Gate	2	36. Yangzhiyicun Complex's South Gate	2	10. Cuiyuan	4000
11. Jinqiujiayuan Complex's West Gate	2	37. No.4 Gate of Oil Field	2	11. Canglang Pavilion	5130
12. Canglangting Street	2	38. Lihexincun Park	4	12. Midu	6234
13. Hanlinhuayuan Complex's Gate	2	39. Lihe 2nd Complex's Northwest Gate	2	13. Yangzhi	5000
14. Shiquan Building's Gate	2	40. Miduli Complex's North Gate	2	14. Erlang Alley	5461
15. Wanshou Palace	1	41. Lihexincun Complex's North Side	2	15. Dinghuisi Alley	4721
16. Changzhou Road No.41 Complex	1	42. Yangzhi Building 84's West Side	2	16. Tangjia Alley	4507
17. Yanjia Alley No.18	2	43. Yangzhi Building 55's West Side	1	17. Bell Tower	2591
18. Entrance of Jinyi Cinema	1	44. Lihexincun Complex's North Square	2	18. Lianqing	2000
19. Muxingxincun Complex's Entrance	2	45. Park next to Building 85 of Juyuan Complex	4	19. Hundred Steps Street	4000
20. Old Site of Weaving Office	2	46. Modern Garden Square	4	20. Lihe	5000
21. Entrance of Bell Tower Community	1	47. Modern Garden Complex's Plum Garden	2	21. Wangshi Alley	6192
22. Tangsong Heritage Square	2	48. Jinzhiyuan Complex's Gate	2		
23. Shijiang Alley No.2 Plaza	1	49. Miducuiting Square	2		
24. Entrance of Wangshi Alley	2	50. Cuiyuanyicun Park	2		
25. Erlang Alley Community's Playground	2	51. Luochakeji Parking Lot	2		
26. Zhuyuan Complex's Gate	3	52. Suyuanercun Complex's Platform	2		

Table 3 Comparison of collaborative results.

Guided or not	Transfer or not	Usage	Satisfaction	Convenience	Cost		
					Open	Transfer	Total
N	Y	Uneven	87,549	59,877.7	100	0	100
Y	Y	Even	**97,923**	76,755.685	109	0.2384	**109.2384**
	N	Even	**97,923**	41,189	110	—	**110**

Bold values facilitate easier comparison between different data points.

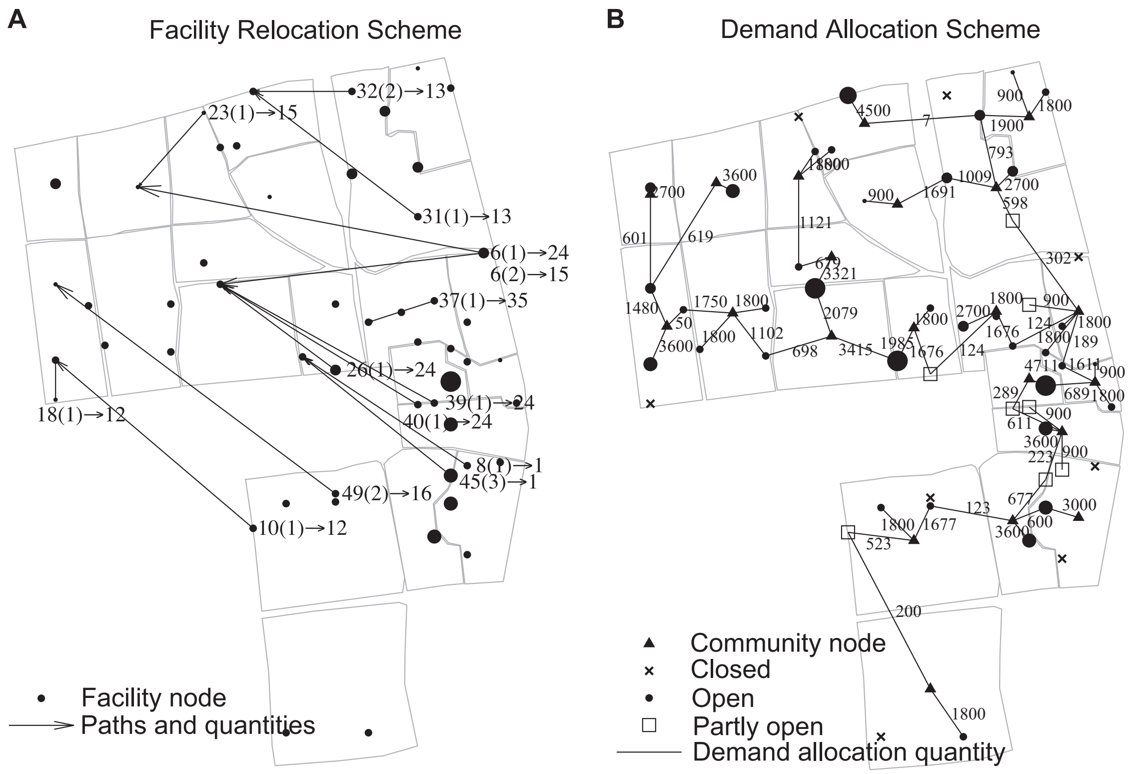

Fig. 5 Operational schemes for facility and demand management. A Facility relocation scheme, showing relocation paths and quantities between nodes. **B** Demand allocation scheme, depicting demand distribution to community nodes marked as open, closed, and partly open nodes.

In summary, the model in this paper exhibits a high proficiency in resource allocation and meeting demand, bolstering its practical utility. The model's ability to facilitate facility transfers significantly augments demand responsiveness and service accessibility while managing costs effectively. As such, this study introduces novel perspectives and robust decision support tools to enhance operational efficiency in emergency management.

Sensitivity analysis. This section focuses on analyzing how changes in the two key factors, facility service capacity (R) and transfer cost (represented by factor α), affect the stability of the solution in designing and planning emergency facility networks using a collaborative approach.

Service capacity. The impact of increasing the facility service capacity R from 200 to 1200 demand/day on the solution is illustrated in Fig. 6. While other parameters remain unchanged, the two-dimensional projection of the Pareto optimal solution was analyzed. The analysis revealed that as the service capability improves and overall satisfaction increases, there is a certain point where the growth of nearby satisfaction slows down, while the total cost continues to rise. This suggests that under specific conditions, moderately improving service capacity can enhance overall satisfaction and proximity satisfaction without significantly increasing total costs. Furthermore, it also demonstrates the changes in the trade-off relationship among different goals as service capabilities grow, highlighting the interconnectedness of solutions.

This analysis highlights the significance of considering facility service capacity in collaborative planning decisions. It particularly becomes crucial when resources are limited, as determining how to distribute and adapt facility service capacity to meet demand becomes a key concern. Furthermore, this analysis also offers a technique to assess the most suitable planning strategies based on various service capacities, offering valuable support for practical decision-making.

Transfer cost. The authors examine the effects of gradually increasing the unit mobility cost (controlled by the scaling factor α) from 1e-5 to 6e-5 on the solution in Fig. 7. The findings suggest that variations in transfer costs within the tested range

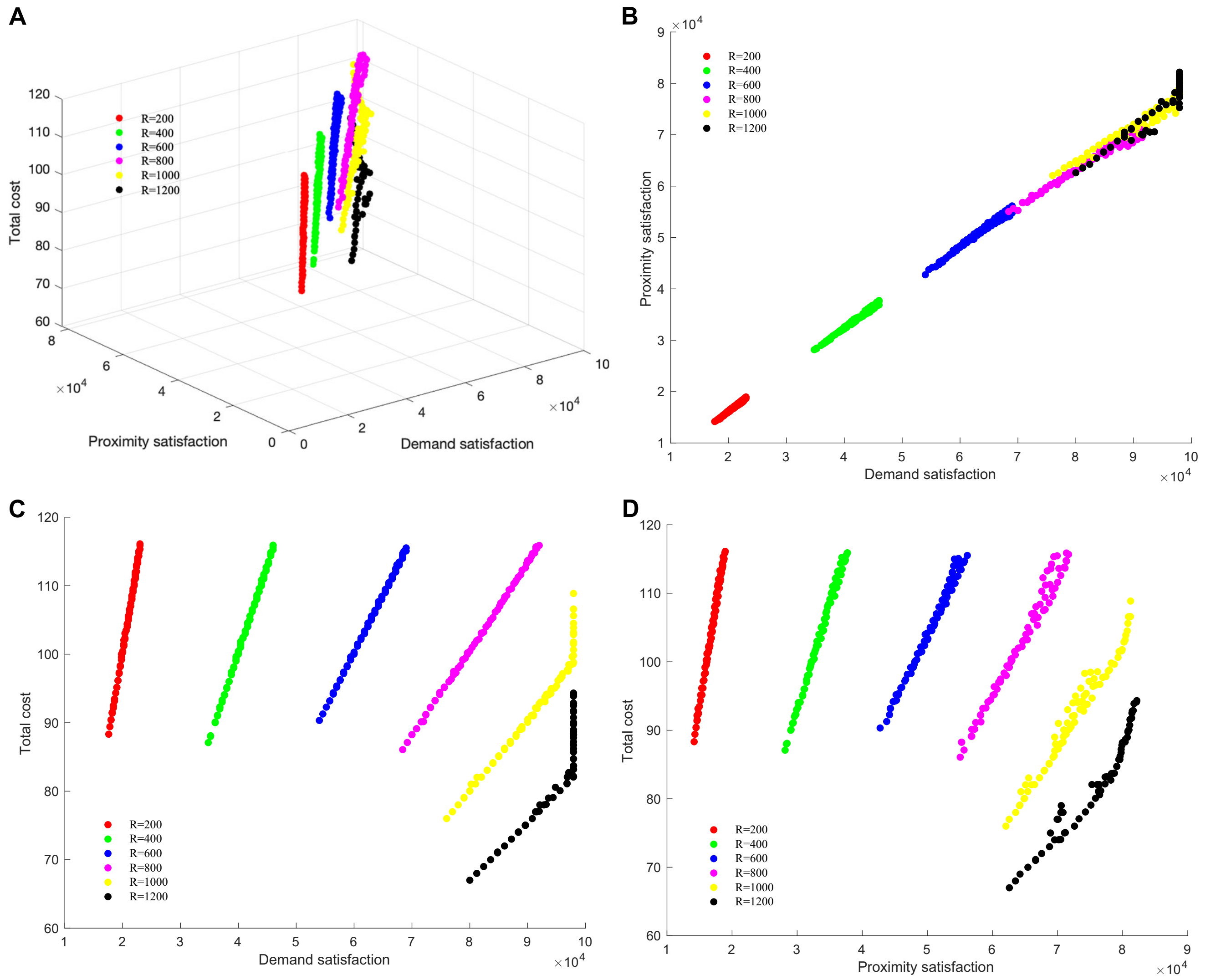

Fig. 6 Sensitivity analysis of service capacity. A 3D plot of cost against satisfaction metrics. **B** 2D plot correlating proximity and demand satisfaction. **C** 2D plot of cost versus demand satisfaction. **D** 2D plot showing cost against proximity satisfaction.

are unlikely to have a substantial impact on the quality or preference of optimization results. This implies that the model remains robust even when the transfer costs undergo such changes.

The significance of service capability and transfer costs in the design and collaborative planning decisions of emergency facility networks with limited resources is highlighted by both analysis results. In order to successfully fulfill the highest demand, it is crucial to thoroughly comprehend and make necessary adaptations to these two factors. This understanding and adjustment of service capability and transfer costs can lead to effective strategies.

Statistical tests. In Table 4, a comparison was made between three methods: the traditional matrix encoding algorithm (NSGAIIM), the vector encoding algorithm (NSGAIIV), and the vector encoding algorithm with update strategy (NSGAIIVU). The time required for processing (columns 4, 7, and 10) indicates that NSGAIIM has the longest processing time for handling multi-objective problems. In contrast, NSGAIIV and NSGAIIVU demonstrate higher processing efficiency. Particularly, as the number of facility points increases and reaches 200, the processing time of NSGAIIM exceeds 800 seconds, whereas NSGAIIVU only takes less than 500 seconds. However, the table does not display this information due to space limitations.

The comparison of values representing the proportion of solutions dominated by different algorithms, specifically C (M, V), C (M, VU), C (V, M), C (V, VU), C (VU, M), and C (VU, V), reveals that as the number of facility points increases, NSGAIIVU generates more solutions that can dominate the solution sets produced by NSGAIIM and NSGAIIV. This indicates that NSGAIIVU has a significant advantage in solution quality.

To measure the stability of the algorithm, the *P*-value (columns 11–13) is utilized. When the *P*-value is below 0.01, it signifies a statistically significant difference between the two algorithms. In this case, the *P*-value of the MVU column is less than 0.01, highlighting a significant performance difference between NSGAIIM and NSGAIIVU. Moreover, as the number of facility locations increases, the *P*-value of the VVU column decreases, while the *P*-value of the MV column gradually increases. This indicates that the performance difference between NSGAIIV and NSGAIIVU intensifies with the problem size growth, whereas the performance difference between NSGAIIM and NSGAIIV diminishes.

These findings suggest that vector encoding algorithms with update strategies enhance processing efficiency and solution

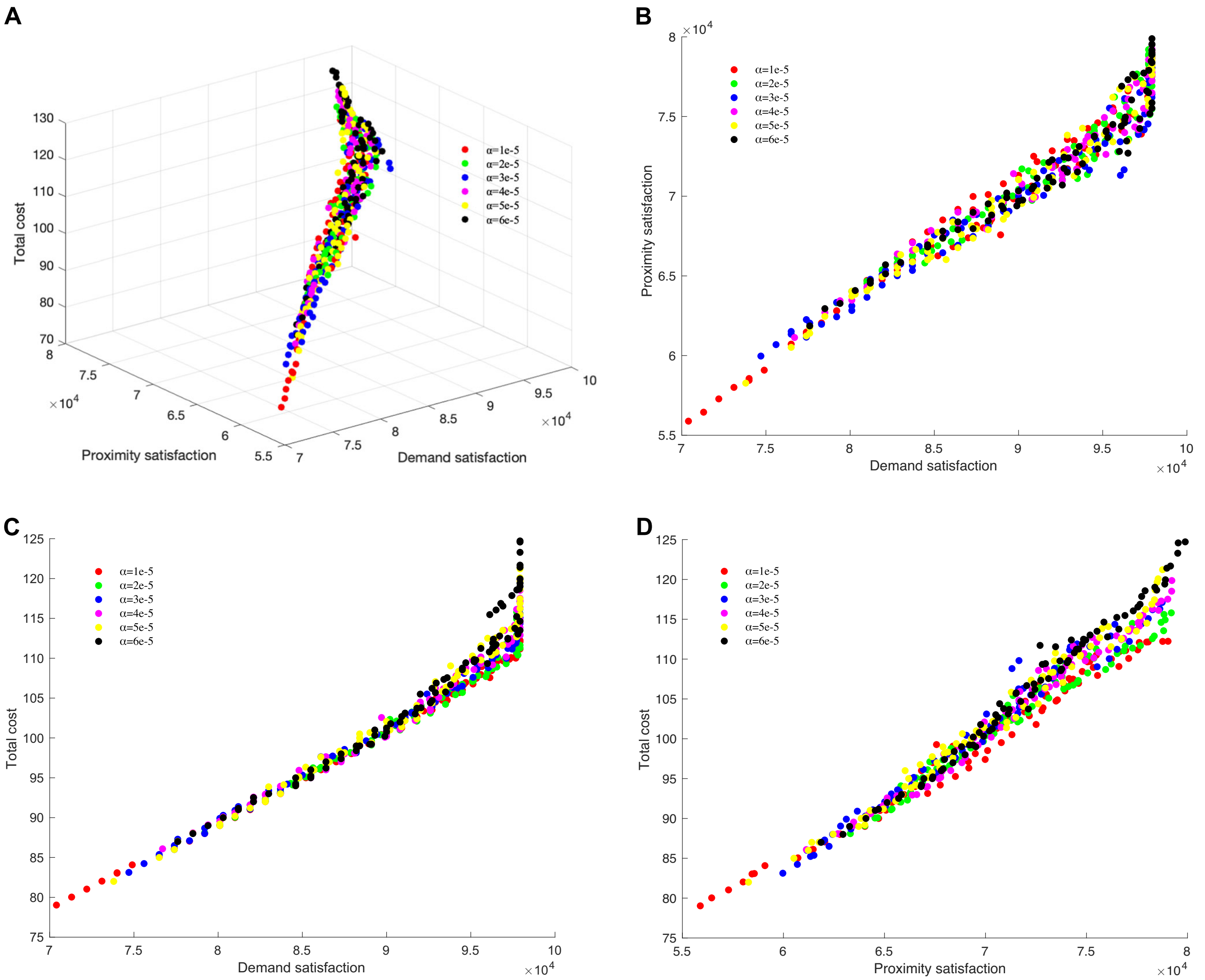

Fig. 7 Sensitivity analysis of transfer cost. A 3D plot showing total cost against proximity satisfaction and demand satisfaction. **B** 2D plot of demand satisfaction against proximity satisfaction. **C** 2D plot of total cost versus demand satisfaction. **D** 2D plot of total cost against proximity satisfaction.

Table 4 Comparison of three encoding methods.

J	NSGAIIM			NSGAIIV			NSGAIIVU			*P*-value		
	C(M,V)	C(M,VU)	Time	C(V,M)	C(V,VU)	Time	C(VU,M)	C(VU,V)	Time	VVU	MVU	MV
40	0.14	0.14	70.0	0	0.46	64.5	0.01	0.22	64.3	>0.05	<0.01	<0.01
41	0.29	0.29	72.2	0.01	0.47	65.5	0.01	0.11	65.1	>0.05	<0.01	<0.01
42	0.14	0.14	72.7	0	0.42	66.5	0.01	0.14	66.7	>0.05	<0.01	<0.01
43	0.25	0.25	76.6	0	0.34	67.7	0.01	0.34	67.6	>0.05	<0.01	<0.01
44	0.22	0.22	74.9	0	0.38	68.8	0	0.19	68.6	>0.05	<0.01	<0.01
45	0.17	0.17	77	0.03	0.41	70	0	0.21	70.1	>0.05	<0.01	<0.01
46	0.66	0.77	79.2	0	0.35	73	0	0.23	72.6	>0.05	<0.01	<0.01
47	0.78	0.87	79.6	0	0.66	73.6	0	0.01	73.1	>0.05	<0.01	<0.01
48	0.85	0.76	80.4	0	0.61	73.7	0	0.08	73.7	>0.05	<0.01	$0.01 < P < 0.05$
49	0.33	0.93	81.1	0.03	0.86	75.3	0	0	77.6	$0.01 < P < 0.05$	<0.01	>0.05
50	0.46	0.65	81.1	0.01	0.62	75.4	0	0.05	73.9	<0.01	<0.01	>0.05
51	0.7	0.96	83.7	0.01	0.24	76.9	0	0.14	76.0	<0.01	<0.01	$0.01 < P < 0.05$
52	0.28	0.96	85.5	0	0.59	76.6	0	0	76.8	<0.01	<0.01	>0.05

quality. Consequently, they have the potential to replace NSGAIIM and NSGAIIV. It is hoped that these discoveries will inspire future research to further explore and uncover the potential and advantages of heuristic algorithms.

Conclusion

In conclusion, this study represents a significant milestone in emergency management as it introduces an innovative approach to deploying and coordinating mobile emergency facilities. By embracing the principle of "proximity response", this approach revolutionizes traditional methods and strikes a delicate balance between response effectiveness and cost efficiency.

A key contribution of this research is the development of strategic strategies to address the unequal utilization of emergency facilities. These strategies not only ensure a more equitable distribution of services but also greatly enhance demand satisfaction and service convenience, particularly through strategic facility transfers. Additionally, this study demonstrates the effectiveness of managing operational costs, with the NSGAII(VU) showcasing remarkable improvements in processing efficiency and solution quality in large-scale emergency scenarios.

For policymakers and emergency management practitioners, this study offers practical and actionable insights. The authors strongly recommend integrating the model and algorithm presented in this paper into existing urban planning and crisis management frameworks. Such integration promises more informed and expeditious decision-making, leading to more cost-effective and efficient post-disaster recovery. Strategic facility transfers and guiding strategies, as exemplified by this research, play a vital role in optimizing resource allocation and minimizing operational costs.

Looking ahead, the authors aim to refine the model to better accommodate the dynamic nature of demand fluctuations over time, further enhancing its practicality and effectiveness. They plan to explore advanced predictive analytics and scenario planning techniques to ensure that the model remains robust and adaptable to the evolving needs of disaster-affected communities.

Data availability

All data generated or analyzed during this study are included in this article.

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References

Abadi MQH, Rahmati S, Sharifi A, Ahmadi M (2021) HSSAGA: designation and scheduling of nurses for taking care of COVID-19 patients using novel method of hybrid salp swarm algorithm and genetic algorithm. Appl Soft Comput 108:107449

Ahmadi-Javid A, Seyedi P, Syam SS (2017) A survey of healthcare facility location. Comput Oper Res 79:223–263

Al-Mandhari A, Al-Adawi S, Al-Zakwani I, Al-Shafaee M, Eloul L (2008) Impact of geographical proximity on health care seeking behaviour in Northern Oman. Sultan Qaboos Univ Med J 8:310

Alarcon-Gerbier E, Buscher U (2022) Modular and mobile facility location problems: a systematic review. Comput Ind Eng 173:108734

Altay N, Green III WG (2006) OR/MS research in disaster operations management. Eur J Oper Res 175:475–493

Anderson RM, Heesterbeek H, Klinkenberg D, Hollingsworth TD (2020) How will country-based mitigation measures influence the course of the COVID-19 epidemic? Lancet 395:931–934

Ardali NR, Zarghami R, Gharebagh RS, Mostoufi N (2022) A data-driven fault detection and diagnosis by NSGAII-t-SNE and clustering methods in the chemical process industry. Computer aided chemical engineering 49:1447–1452

Balcik B, Beamon BM (2008) Facility location in humanitarian relief. Int J Logist 11:101–121

Bayraktar OB, Günneç D, Salman FS, Yücel E (2022) Relief aid provision to en route refugees: Multi-period mobile facility location with mobile demand. Eur J Oper Res 301:708–725

Berman O, Krass D, Drezner Z (2003) The gradual covering decay location problem on a network. Eur J Oper Res 151:474–480

Bloomfield GS, Vedanthan R, Vasudevan L, Kithei A, Were M, Velazquez EJ (2014) Mobile health for non-communicable diseases in Sub-Saharan Africa: a systematic review of the literature and strategic framework for research. Glob Health 10:1–9

Büsing C, Comis M, Schmidt E, Streicher M (2021) Robust strategic planning for mobile medical units with steerable and unsteerable demands. Eur J Oper Res 295:34–50

Çakır E, Taş MA, Ulukan Z (2022) Spherical bipolar fuzzy weighted multi-facility location modeling for mobile COVID-19 vaccination clinics. J Intell Fuzzy Syst 42:237–250

Calogiuri T, Ghiani G, Guerriero E, Manni E (2021) The multi-period p-center problem with time-dependent travel times. Comput Oper Res 136:105487

Caunhye AM, Nie X, Pokharel S (2012) Optimization models in emergency logistics: a literature review. Socio-Econ Plan Sci 46:4–13

Chen X, Liu Y, Li X, Wang Z, Wang S, Gao C (2019) A new evolutionary multiobjective model for traveling salesman problem. IEEE Access 7:66964–66979

Deb K, Pratap A, Agarwal S, Meyarivan T (2002) A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans Evolut Comput 6:182–197

Doerner K, Focke A, Gutjahr WJ (2007) Multicriteria tour planning for mobile healthcare facilities in a developing country. Eur J Oper Res 179:1078–1096

Drabek TE (1999) Understanding disaster warning responses. Soc Sci J 36:515–523

Elston JW, Cartwright C, Ndumbi P, Wright J (2017) The health impact of the 2014–15 Ebola outbreak. Public Health 143:60–70

Emanuel EJ, Persad G, Upshur R, Thome B, Parker M, Glickman A, Zhang C, Boyle C, Smith M, Phillips JP (2020) Fair allocation of scarce medical resources in the time of Covid-19. N Engl J Med 382:2049–2055

Esmikhani S, Kazemipoor H, Sobhani FM, Molana SMH (2022) Solving fuzzy robust facility layout problem equipped with cranes using MPS algorithm and modified NSGA-II. Expert Syst Appl 210:118402

Feng Y-Y, Wu I-C, Chen T-L (2017) Stochastic resource allocation in emergency departments with a multi-objective simulation optimization algorithm. Health Care Manag Sci 20:55–75

Fogue M, Garrido P, Martinez FJ, Cano J-C, Calafate CT, Manzoni P (2013) A novel approach for traffic accidents sanitary resource allocation based on multi-objective genetic algorithms. Expert Syst Appl 40:323–336

Galindo G, Batta R (2013) Review of recent developments in OR/MS research in disaster operations management. Eur J Oper Res 230:201–211

Ghaffari Z, Nasiri MM, Bozorgi-Amiri A, Rahbari A (2020) Emergency supply chain scheduling problem with multiple resources in disaster relief operations. Transp A: Transp Sci 16:930–956

Güden H, Süral H (2014) Locating mobile facilities in railway construction management. Omega 45:71–79

Güden H, Süral H (2019) The dynamic p-median problem with mobile facilities. Comput Ind Eng 135:615–627

Halper R, Raghavan S (2011) The mobile facility routing problem. Transp Sci 45:413–434

Halper R, Raghavan S, Sahin M (2015) Local search heuristics for the mobile facility location problem. Comput Oper Res 62:210–223

Holguín-Veras J, Jaller M, Van Wassenhove LN, Pérez N, Wachtendorf T (2012) On the unique features of post-disaster humanitarian logistics. J Oper Manag 30:494–506

Jenkins PR, Lunday BJ, Robbins MJ (2020) Robust, multi-objective optimization for the military medical evacuation location-allocation problem. Omega 97:102088

Kaushik A, Vidyarthi DP (2016) A green energy model for resource allocation in computational grid using dynamic threshold and GA. Sustain Comput: Inform Syst 9:42–56

Khayal D, Pradhananga R, Pokharel S, Mutlu F (2015) A model for planning locations of temporary distribution facilities for emergency response. Socio-Econ Plan Sci 52:22–30

Lei C, Lin W-H, Miao L (2014) A multicut L-shaped based algorithm to solve a stochastic programming model for the mobile facility routing and scheduling problem. Eur J Oper Res 238:699–710

Lei C, Lin W-H, Miao L (2014) A stochastic emergency vehicle redeployment model for an effective response to traffic incidents. IEEE Trans Intell Transp Syst 16:898–909

Lei C, Lin W-H, Miao L (2016) A two-stage robust optimization approach for the mobile facility fleet sizing and routing problem under uncertainty. Comput Oper Res 67:75–89

Li J, Lai KK, Fu Y, Shen H (2021) Robust optimization approach to emergency mobile facility routing. Sci Prog 104:0036850420982685

Li J, Lai KK, Lin Q (2019) Robust optimization solution to emergency mobile facility fleet size and location. Math Probl Eng 2019:1–11

McGowan CR, Baxter L, Deola C, Gayford M, Marston C, Cummings R, Checchi F (2020) Mobile clinics in humanitarian emergencies: a systematic review. Confl Health 14:1–10

Megiddo N, Zemel E, Hakimi SL (1983) The maximum coverage location problem. SIAM J Algebraic Discret Methods 4:253–261
Nair R, Miller-Hooks E (2009) Evaluation of relocation strategies for emergency medical service vehicles. Transp Res Rec 2137:63–73
Pilkington H, Blondel B, Drewniak N, Zeitlin J (2012) Choice in maternity care: associations with unit supply, geographic accessibility and user characteristics. Int J Health Geogr 11:1–13
Qi M, Cheng C, Wang X, Rao W. (2017) Mobile facility routing problem with service-time-related demand. 2017 International Conference on Service Systems and Service Management. IEEE, pp. 1–6
Rabiei P, Arias-Aranda D, Stantchev V (2023) Introducing a novel multi-objective optimization model for Volunteer assignment in the post-disaster phase: Combining fuzzy inference systems with NSGA-II and NRGA. Expert Syst Appl 226:120142
Raghavan S, Sahin M, Salman FS (2019) The capacitated mobile facility location problem. Eur J Oper Res 277:507–520
Rahman S-u, Smith DK (2000) Use of location-allocation models in health service development planning in developing nations. Eur J Oper Res 123:437-452
Rawls CG, Turnquist MA (2010) Pre-positioning of emergency supplies for disaster response. Transp Res Part B: Methodol 44:521–534
Salman FS, Yücel E, Kayı İ, Turper-Alışık S, Coşkun A (2021) Modeling mobile health service delivery to Syrian migrant farm workers using call record data. Socio-Econ Plan Sci 77:101005
Sharma B, Ramkumar M, Subramanian N, Malhotra B (2019) Dynamic temporary blood facility location-allocation during and post-disaster periods. Ann Oper Res 283:705–736
Sheu J-B (2007) An emergency logistics distribution approach for quick response to urgent relief demand in disasters. Transp Res Part E: Logist Transp Rev 43:687–709
Teixeira JC, Antunes AP (2008) A hierarchical location model for public facility planning. Eur J Oper Res 185:92–104
Teng C, Zhu X, Nazar R, Kanwal T (2023) Asymmetric nexus between pandemic uncertainty and public health spendings: evidence from quantile estimation. Risk Anal 1–16. https://doi.org/10.1111/risa.14226
Tzeng G-H, Cheng H-J, Huang TD (2007) Multi-objective optimal planning for designing relief delivery systems. Transp Res Part E: Logist Transp Rev 43:673–686
Vitoriano B, Ortuño M, Tirado Domínguez G, Montero J (2021) A multi-criteria optimization model for humanitarian aid distribution. J Glob Optim 51:189–208
Wang Q, Liu Z, Jiang P, Luo L (2022) A stochastic programming model for emergency supplies pre-positioning, transshipment and procurement in a regional healthcare coalition. Socio-Econ Plan Sci 82:101279
Yang L, Yu X, Wu X, Wang J, Yan X, Jiang S, Chen Z (2021) Emergency response to the explosive growth of health care wastes during COVID-19 pandemic in Wuhan, China. Resour Conserv Recycl 164:105074
Yücel E, Salman FS, Bozkaya B, Gökalp C (2020) A data-driven optimization framework for routing mobile medical facilities. Ann Oper Res 291:1077–1102
Zhang C, Yang T (2021) Optimal maintenance planning and resource allocation for wind farms based on non-dominated sorting genetic algorithm-II. Renew Energy 164:1540–1549
Zhang S, Guo H, Zhu K, Yu S, Li J (2017) Multistage assignment optimization for emergency rescue teams in the disaster chain. Knowl-Based Syst 137:123–137
Zhou Y, Liu J, Zhang Y, Gan X (2017) A multi-objective evolutionary algorithm for multi-period dynamic emergency resource scheduling problems. Trans Res Part E: Logist Trans Rev 99:77–95

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Author contributions
CT designed the research and wrote the initial draft of this article. PY provided many suggestions for the revised manuscript. LL made many constructive comments on the earlier versions. All authors contributed to the article.

Competing interests
The authors declare no competing interests.

Ethical approval
Ethical approval was not required as the study did not involve human participants.

Informed consent
This article does not contain any studies with human participants performed by any of the authors.

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