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Dynamic heterogeneous resource allocation in post-disaster relief operation considering fairness☆

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ABSTRACT

Efficient and fair resource allocation is essential in post-disaster relief operations to save lives and mitigate losses. However, due to the highly dynamic and uncertain relief supplies and rescue demands, as well as the complex interdependent relationships among heterogeneous relief resources, the practice of relief resource allocation frequently suffers from low efficiency or unfairness, thus delaying the response activities or even causing social tensions. To address these problems, this paper investigates the heterogeneous relief resource allocation problem and develops a dynamic solution method for efficient and fair allocations. Specifically, a heterogeneous resource allocation model is built to maximize efficiency considering the tight collaboration among resources. A Gini-based fairness evaluation metric is proposed for assessing allocation fairness, and an analysis of the balance between fairness and efficiency is conducted. Then, a dynamic resource allocation method is designed based on the rolling horizon framework, with an Adaptive Dynamic REsource Allocation Method (A-DREAM) developed to balance allocation fairness and efficiency in dynamic scenarios. The performance of the proposed method is verified through systematic experimental case studies, and potential factors affecting allocation fairness are investigated. Finally, the managerial implications for practical relief operations are also derived through sensitivity analysis.

1. Introduction

Relief operation is crucial in post-disaster response as it provides immediate necessities to those in need, restores vital services, and mitigates further risks [1,2]. Inefficient relief operations will not only delay the response activities, but also lead to many unsatisfied rescue demands, and waste of resources, which further put disaster victims at risk and worsen disaster situations [3,4]. For instance, at the onset of the COVID-19 pandemic in Wuhan, millions of different types of relief resources (e.g., defibrillators, ECG monitors, infusion pumps, and N95 masks) were donated from various places and transported to Wuhan continuously. Nevertheless, due to inefficient relief distribution, a large amount of them was stored in the central warehouse while many hospitals reported a shortage of medical supplies [5]. Similarly, earthquake survivors after the 2024 Noto earthquake had to live in extreme environments without heat or water due to the shortage of relief resources [6]. Meanwhile, fairness is also vital in relief operations that unfair operations bring contradictions or conflicts between individuals or communities, and may further lead to social instability [7]. For instance, the unfair aid distribution in the 2015 Pakistan earthquake caused a lot of accusations from survivors and a protest, further triggering social unrest [8]. Motivated by these practical problems, this work aims to investigate the method of efficient and fair relief operations for improved performance of post-disaster responses.

Currently, relief operations in post-disaster response have been widely studied from various aspects, from relief network design [9], relief location–allocation [10], to last-mile relief delivery [11,12]. Focusing on the relief receiving and distribution at distribution centers, especially during large-scale disasters, efforts have been put into the mechanisms and methods for minimizing total response time [13] to decrease the casualty rates [14], as well as improving resource utilization rate [15]. Meanwhile, there are also some works considering fairness combined with the Gini coefficient [16], deprivation cost [17], and total utility [18] in relief operations. These works provide valuable insights into the practices of post-disaster relief operations. However, considering the complexities of relief operations and the varied disaster scenarios, there are still many problems remain unsolved.

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Firstly, the dynamics and uncertainties in both the relief supply and demand sides make it challenging to allocate relief resources to corresponding demands efficiently. Responding to large-scale disasters, a large amount of relief resources are transported from various places, some are official stockpiled resources and some are donations from the public. It makes the relief supplies highly dynamic and uncertain in terms of content, quantity, and time. Meanwhile, the demands are being continuously and dynamically found driven by the search and rescue process, or the development of the disasters. It makes the matching between relief resources and demands difficult. Moreover, since most disasters are non-reproducible that are difficult to predict, it thus requires the relief resources can be dispatched dynamically based on real-time available information, which is challenging in nature and still open for discussion in literature.

Secondly, the heterogeneous relief resources involved and their complex interdependent relationships make their effective allocation challenging. In practice, different types of relief resources play different roles in post-disaster response. They are usually required to be jointly dispatched to fulfill the demand [19] due to the complex interdependent relationships among them [20]. For example, blood and tourniquets should be sent together to treat severely injured persons. The lack of one or more types of resources may lead to the delay of response activities, as well as the waiting of other arrived resources, thus affecting the utilization rate of these already insufficient relief resources. It is thus challenging to effectively coordinate different types of relief resources while efficiently dispatching them.

Thirdly, problems still exist in balancing resource dispatching efficiency and fairness in dynamic disaster scenarios. The pursuit of efficiency often leads to discrimination based on proximity, urgency, and accessibility [21]. For instance, prioritizing efficiency might involve allocating relief resources to demands that arise earlier, require fewer resources, or are easier to reach, while inadvertently neglect others, thus compromising fairness. Conversely, an excessive focus on fairness can result in limited relief resources being distributed thinly across various demands, preventing any single demand from being adequately met and thus reducing overall allocation efficiency. Besides, in dynamic scenarios where relief supply and demand information is continuously updated, the dispatching of relief resources at the current stage can affect the availability of resources for the new demands in subsequent stage, thereby affecting overall dispatching fairness. Therefore, efforts are still needed to balance efficiency and fairness, as well as dispatching resources across different stages.

Taking the above problems into consideration, this paper aims to study the dynamic heterogeneous resource allocation problem in post-disaster relief operations, with a consideration of both efficiency and fairness. The contributions of this paper can be summarized as follows:

- An innovative dynamic resource allocation model is developed that could well depict the interdependent relationships among heterogeneous relief resources.
- A Gini-based fairness evaluation method is developed that considers the coordination of heterogeneous relief resources.
- An Adaptive Dynamic REsource Allocation Method (A-DREAM) is proposed, which could automatically balance the allocation efficiency and fairness based on real-time supply and demand information.
- Extensive experiment results prove the effectiveness of the proposed method and several valuable managerial insights are derived for practical implementation.

The remainder of this paper is organized as follows. Literature review is conducted in Section 2. The model of heterogeneous resource allocation problem in post-disaster relief operations is presented in Section 3. The rolling horizon-based dynamic resource allocation framework and the A-DREAM are proposed in Section 4. Experimental case studies are carried out in Section 5. Finally, conclusions of the whole paper and discussions of future works are given in Section 6.

2. Literature review

In this section, the literature review will be conducted from three perspectives: heterogeneous resource allocation, dynamic resource allocation, and fairness.

2.1. Heterogeneous resource with tight collaboration

Many studies have been conducted on heterogeneous resource allocation problems in disasters, specifically focusing on the collaboration among heterogeneous relief resources. Rauchecker et al. [22] proposed a definition for the collaboration among heterogeneous relief resources, categorizing it into two distinct types: *loose* collaboration, where heterogeneous relief resources can operate independently, and *tight* collaboration, where heterogeneous relief resources are required to arrive simultaneously and work collaboratively.

In terms of *loose* collaboration between heterogeneous relief resources, researchers have investigated the allocation problem with resources with different capabilities in post-disaster and incident response activities [23,24]. Specifically, Altay et al. [23] considered allocating different types of relief resources for diverse post-disaster activities, and developed two models for sufficient and scarce supplies respectively. Scheryen et al. [24] studied the collaborative rescue unit assignment and scheduling problem, where heterogeneous rescue units with different capacities are considered. Additionally, researchers have investigated the different inventory levels of heterogeneous relief resources, such as basic relief and emergency relief [25], and expendable relief and non-expendable relief [26]. Specifically, Bodaghi et al. [26] formulated a multi-resource scheduling and routing problem and developed a framework for efficiently distributing them.

For *tight* collaboration between heterogeneous relief resources, Baxter et al. [19] introduced a multiple Resource multiple Demand (mRmD) problem, where multiple types of resources are requested by multiple demands simultaneously at a specified time. An integer programming model and approximation algorithms were developed for variations of the mRmD problem. Taking *tight* collaboration between heterogeneous vehicles into account, researchers studied vehicle routing and scheduling problems with synchronized visits [27,28]. Specifically, Bredstrom et al. [27] introduced temporal constraints for combined vehicle routing and scheduling problems, which imposed pairwise synchronization and temporal precedence between visits. Hashemi et al. [28] studied vehicle routing problems with synchronized visits, where a specific set of heterogeneous vehicles must be available at healthcare locations simultaneously. They also developed a two-stage stochastic integer programming model and an L-shaped algorithm to solve it.

However, most studies focused on *loose* collaboration while still few works on efficient heterogeneous resource allocation problems with *tight* collaboration, which are common in post-disaster responses. Considering the highly dynamic and uncertain environment, new models and methods are still missing for the efficient heterogeneous resource allocation methods with *tight* collaboration.

2.2. Dynamic resource allocation

Dynamic resource allocation refers to distributing resources sequentially in an ever-changing environment [29]. This challenges finding optimal solutions, as decisions must be made without accurate future information. In dynamic resource allocation problems, the primary dynamic features are mainly from demands [30] and supplies [31]. For instance, Rivera et al. [30] proposed a model for assembling relief kits that considered the dynamic demands, priorities, and capacities, and developed a heuristic-based solution algorithm with a rolling horizon framework.

To address these dynamic features in resource allocation problems, Pillac et al. [32] suggested that it could be solved a priori or dynamically. From the a priori perspective, dynamic problems are solved statically to get robust [33], stochastic [34] optimal solutions, or predict-then-optimize method [35], which perform well in dynamic environments. Specifically, Wang et al. [33] formulated the emergency resource allocation problem as distributionally robust chance-constrained programming. Meng et al. [36] presented a two-stage chance-constrained stochastic programming model for supply distribution under dynamic uncertain scenarios. However, these methods may not well fit our problems as they need prior knowledge of the distributions of dynamic features or large quantities of possible scenarios, and the dynamic adaptation of one-shot decisions is seldom considered.

Given these challenges associated with a priori solution, researchers have studied resource allocation problems from a dynamic perspective, addressing these issues sequentially with continuous environmental inputs [37,38]. For instance, Alkaabeneh et al. [37] developed an approximate dynamic programming approach for resource allocation. Duma et al. [38] developed an online resource allocation algorithm with a process mining model. These methods may require prior knowledge or in-distribution data about the demands, which is not the case in our problem. Meanwhile, few works considered the dynamics from both the supply and demand sides. Rolling horizon approach provides another way on solving the problem without enough prior knowledge. It is widely adopted in various contexts, including last-mile relief transportation [39], relief resource allocation [40], etc., and proved to be easy to implement and could adapt to different situations [13].

2.3. Fairness

It is widely recognized that fair (or equitable) resource allocation is highly important for alleviating disaster impact in the affected areas as it reduces the probability of conflicts and social instability [41]. To address fair resource allocation, the primary goal is to clarify the understanding of fairness. From previous literature, fair resource allocation refers to allocating limited resources in a balanced manner and ensuring everyone has equal access to vital services [42]. It can be categorized into horizontal and vertical equity, where horizontal equity is where every individual or group is given the same resources, and vertical equity is to allocate resources based on the different needs of individuals equally. According to Li et al. [43], vertical equity is more appropriate for relief resource allocation as it is supposed to be more on the demands of all victims from a humanitarian operation perspective and provide relief fairly and equitably.

Recently, fairness metrics have been introduced to the resource allocation problem, with commonly adopted indicators like the satisfied resource quantity [44], demand fill rate [40,45], response time [46,47], and deprivation costs [17]. Various fairness measurements were proposed, such as the max–min method [48], deprivation cost [17], and Gini coefficient metric [16]. With the principle of avoiding poverty, the max–min method refers to maximizing the minimum utility among all individuals to increase the relief utility [44]. However, it always focuses on the worst-case performance, which is sensible to outlier individuals [49]. In view of the principle of equal opportunity, some metrics like deprivation cost, and the Gini coefficient were designed based on fill rate and response time [42]. The deprivation cost always collaborates response time and fill rate to measure the human suffering caused by the lack of access to a good or service [50], where the Gini coefficient represents the degree of unfairness based on either response time or fill rate [16]. In this work, we choose the Gini coefficient to measure the unfairness of the fill rate because (1) the Gini coefficient is independent of the units of measurement, which allows fairness comparison between various contexts; (2) By using the Lorenz curve, it is easy to interpret the meaning of the value of the Gini coefficient, where 0 stands for fairness, and 1 for unfairness.

Following these fairness metrics, researchers made great efforts to maximize fairness and efficiency simultaneously. Wang et al. [51] used a utility function to represent the total loss caused by unfair allocation and developed a multi-objective allocation model for emergency resources. Considering Pareto efficiency and fairness, Avishan et al. [52] presented an adjustable robust optimization approach for the humanitarian resource allocation problem. Other researchers have also attempted to balance fairness and efficiency across various fields [53,54]. For instance, in the context of urban logistics, Li et al. [54] innovatively integrated equity and efficiency to study assessment methods and improvement strategies for resilience under emergency lockdown scenarios. Although extensive studies have been made for fair resource allocation, there is little research considering efficiency in dynamic scenarios, where efficient resource allocation can easily cause unfair allocation for late-occurred demands with insufficient supplies.

Motivated by previous work, this paper aims to achieve efficient and fair heterogeneous resource allocation in dynamic post-disaster response, where tight collaboration between heterogeneous relief resources is considered.

2.4. Research gaps and objectives

Extensive knowledge has been accumulated in existing literature that provides strong support for this work. However, there are still some gaps which can be summarized as follows.

First, existing resource allocation models may not be suitable for heterogeneous relief resource allocation problems that require *tight* collaboration, especially when dealing with large-scale supplies and demands for interdependent heterogeneous resources. There is a need for a more complex yet easy-to-solve model to quickly provide optimal solutions in dynamic post-disaster response systems.

Second, current works on dynamic resource allocation problems mainly focus on using static methods with robust or stochastic considerations. Although these solutions perform well, they typically do not account for the dynamic adaptation of one-shot decisions, which is crucial in disaster scenarios.

Third, current research on efficient and fair resource allocation rarely addresses dynamic conditions. However, dynamically revealed supplies and demands motivate us to balance efficiency and fairness not only across dimensions of space and quantity but also time.

To address these gaps, this paper investigates the dynamic heterogeneous relief resource allocation problem with a focus on fairness for post-disaster response systems. Specifically, this work aims to build an easy-to-implement dynamic and fair resource allocation model that could well cope with the complex interdependent relationships among heterogeneous relief resources, develop an efficient method to provide decision-support for relief allocation, and discover the key factors affecting its performance.

3. Heterogeneous relief resource allocation problem

In this section, the heterogeneous relief resource allocation problem is introduced first. Then its model considering allocation efficiency is proposed. Besides, the fairness evaluation method based on the Gini coefficient is analyzed.

3.1. Problem description

After a disaster occurs, the rescue demands will emerge gradually along with the development of the disaster, both actively (reported by victims themselves) or passively (found by the search and rescue teams). At the same time, various relief resources will be transported to the disaster areas continuously, some are from official stockpiled resources stored in other places, while some are donations from the public. Since these relief supplies are from different entities voluntarily, it is always difficult to know the exact content, quantity, and arrival time of these relief resources in advance. Additionally, due to the multiple combinations of different resources, most voluntary heterogeneous relief resources are not paired into relief kits. As a result, it raises the

Table 1
Notations.

Notation	Description
Sets	
$\mathcal{D}$	set of points of distribution
$\mathcal{R}$	set of resource types
T	set of discrete time points
Variables	
w_d^t	unit reward of completely satisfying POD d at time t
h_d^t	fill rate of POD d at time t
p_d	fill rate of demand d
I_r^t	inventory of resource type r at time t
$q_{r,d}^t$	unsatisfied quantity of resource type r required in POD d at time t
Parameters	
w_d	unit reward of on-time satisfaction of POD d
$q_{r,d}$	total quantity of resource type r required in POD d
l_r^t	supplementary quantity of resource type r at time t
t_d	occurring time of POD d
Decision Variables	
$x_{r,d}^t$	an integer variable indicating the quantity of resource type r allocated to POD d at time t

difficulty level of heterogeneous relief resource allocation with tight collaboration. In large-scale disaster response, to better manage these relief resources from various places, they are always required to be sent to a central warehouse first (e.g., the airport, the warehouse of the Red Cross Society, schools, and government compound). After that, these relief resources will be allocated centrally and then dispatched to the rescue demands. This work focuses on such an allocation process, a typical dynamic heterogeneous resource allocation problem with dynamic and uncertain supplies and demands. To facilitate the description of the problem, the notations adopted are presented in Table 1.

In this work, consider a disaster area with a set of supply entities, a set of pre-positioned Points of Distribution (PODs) $\mathcal{D}$, and a Local Distribution Center (LDC), as illustrated in Fig. 1. Each supply entity dynamically provides heterogeneous relief resources with a range of types $\mathcal{R}$ (e.g., masks, protection suits, disinfectants, etc.) to the LDC. At a certain time t_d, a POD $d \in \mathcal{D}$ will be observed, and its all requirements on heterogeneous relief resources $q_{r,d}, r \in \mathcal{R}$ will be recorded in waiting list. Without loss of generality, we assume the dynamically revealed rescue demands will not change or disappear once they are recorded. The dynamic feature of this problem implies that the information, including the supplementary quantity of each resource type l_r^t and the total quantities $q_{r,d}$ of each resource type required in PODs, are dynamically revealed during the response phase. Once new information on supply and demand becomes available, the centralized decision-making agency will make new allocation decisions for the current situation. These decisions are conveyed to the LDC, which executes them and allocates the corresponding quantities of heterogeneous relief resources to PODs. In turn, the LDC conveys the execution information back to the decision-making agency for further reference and updating. Specifically, the decision-making agency is responsible for deciding the quantities and corresponding allocation times of heterogeneous resources based on current supply and demand information. Hence, the decision variable $x_{r,d}^t$ is set to determine the quantity of resource type r allocated to POD d at time t.

3.2. Resource allocation objective

The objective of managing heterogeneous resource allocation in post-disaster response is to optimize efficiency, addressing the key aspects of urgency and collaborative needs. In other words, the efficiency metric (total reward) should not only capture the amount of allocated resources, but also explicitly account for the timely satisfaction and synchronous allocation of the resources. On the one hand, timely resource allocation can significantly enhance the effectiveness of relief efforts, while delays always lead to decreased overall response efficiency and even potential negative outcomes for those in need [55]. Therefore, the reward is maximized when resources are allocated on time. Reward will decrease with the increasing of delays, as modeled by function $\gamma(\delta)$, where $\delta = t - t_d$ representing the waiting time from the desired allocation time t_d to the actual allocation time t. On the other hand, synchronized allocation of dependent resources is also essential. To capture this, a variable h_d^t, the minimum fill rate of POD d at time t, is used to ensure that the collaboration among different types of resources is taken into account.

Therefore, the objective function is formulated as:

$$\max \quad W = \sum_{d\in D}\sum_{t\in T} w_d^t \cdot h_d^t. \tag{1}$$

Here, w_d^t denotes the unit reward of allocating resource type r to POD d at time t, which is calculated by $w_d \cdot \gamma(t - t_d)$.

To be more specific, the concept of the minimum fill rate h_d^t emphasizes the collective fulfillment of resources needs over consequent allocations. For instance, in Fig. 2, a POD requires 4 units of resource A and 2 units of resource B. A and B have a tight collaboration with each other. At time t, 2 units of A and 2 units of B are allocated. However, since the demand for both resources must be met simultaneously due to their tight collaboration, only the resources that can be used together count for satisfaction. Thus, 2 units of A and 1 unit of B can be effectively utilized, leading to a satisfaction level of 0.5 for the POD at time t. The remaining unit of B cannot contribute to satisfaction as there are not enough units of A to pair with it. At time $t+1$, an additional 2 units of resource A are allocated. Now, the previously unpaired unit of B from time t can be effectively used alongside the new units of A, illustrating the carry-over effect in collaborative resource allocation.

Therefore, h_d^t can be calculated as follows:

$$h_d^t = \min_{r\in\mathcal{R}}\left\{\frac{\sum_{\tau\le t} x_{r,d}^\tau}{q_{r,d}}\right\} - \min_{r\in\mathcal{R}}\left\{\frac{\sum_{\tau\le t-1} x_{r,d}^\tau}{q_{r,d}}\right\}, \forall d \in \mathcal{D}, \forall t \in T. \tag{2}$$

Here, the first part of the right-hand side is the total demand satisfaction in time t, and the second is the total demand satisfaction at $t-1$.

3.3. Heterogeneous resource allocation model

Given the supply and demand information within a certain time range T, the heterogeneous resource allocation problem can be addressed by solving the following Integer Programming (IP) model:

$$\max \sum_{d\in D}\sum_{t\in T} w_d^t \cdot h_d^t \tag{3}$$

s.t.

$$\sum_{d\in D} x_{r,d}^t \le I_r^t, \forall r \in \mathcal{R}, \forall t \in T, \tag{4}$$

$$x_{r,d}^t \le q_{r,d}^t, \forall r \in \mathcal{R}, \forall d \in \mathcal{D}, \forall t \in T, \tag{5}$$

$$h_d^t = \min_{r\in\mathcal{R}}\left\{\frac{\sum_{\tau\le t} x_{r,d}^\tau}{q_{r,d}}\right\} - \min_{r\in\mathcal{R}}\left\{\frac{\sum_{\tau\le t-1} x_{r,d}^\tau}{q_{r,d}}\right\}, \forall d \in \mathcal{D}, \forall t \in T, \tag{6}$$

$$I_r^{t+1} = I_r^0 + \sum_{\tau\le t} l_r^\tau - \sum_{\tau\le t}\sum_{d\in D} x_{r,d}^\tau, \forall r \in \mathcal{R}, \forall t \in T, \tag{7}$$

$$q_{r,d}^{t+1} = q_{r,d} - \sum_{\tau\le t} x_{r,d}^\tau, \forall r \in \mathcal{R}, \forall d \in \mathcal{D}, \forall t \in T, \tag{8}$$

$$x_{r,d}^t \in \mathbb{Z}^+, \forall r \in \mathcal{R}, \forall d \in \mathcal{D}, \forall t \in T. \tag{9}$$

Constraint (4) guarantees that the total quantity of allocated resource type r should not exceed its total quantity stored in the LDC. Constraint (5) imposes that the allocated resource type r to POD d cannot exceed the required quantity of resource type r of POD d. Constraint (6) calculates the minimum fill rate of POD d at time t. Constraint (7) calculates the inventory quantity of resource type r at time $t+1$. Constraint (8) calculates the remaining required quantity of resource type r in POD d at time $t+1$. Constraint (9) denotes the value range of decision variables $x_{r,d}^t$.

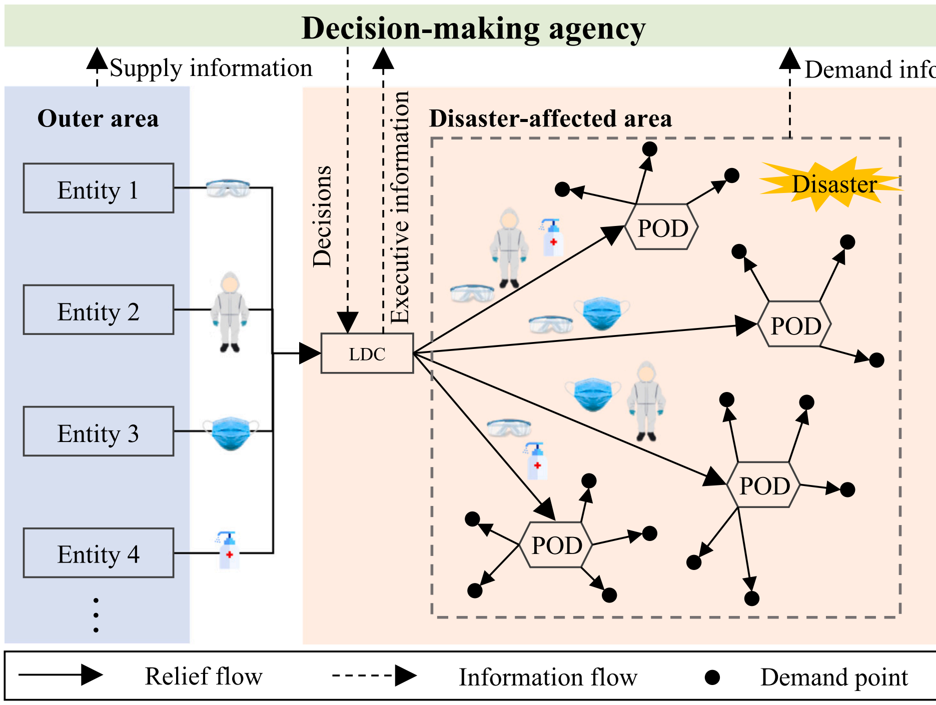


Fig. 1. An example of the decision-making scenarios in a disaster-affected area.

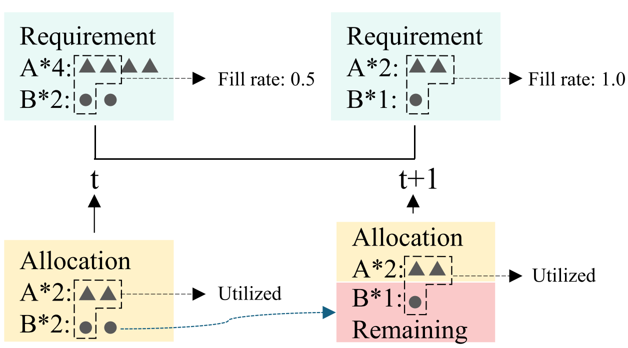


Fig. 2. An example to illustrate the minimum fill rate.

3.4. Fairness analysis

The trade-off between efficiency and fairness has long been discussed in literature [42]. In general, there are three widely used methods for balancing efficiency and fairness: (1) An integrated objective with efficiency; (2) Setting a constraint for fairness; (3) Setting fairness as a performance criterion. The former two approaches integrate fairness into the model, where one changes the single-objective programming to multi-objective programming, and another adds a hard constraint to the model. For the performance criterion, fairness is only a measurement of allocation performance, where the model itself does not involve any element of fairness. In this work, the third one, that is setting fairness as a performance criterion, is selected because: (1) It avoids the complexity of handling multi-objective programming by selecting specific weights of efficiency and fairness, which are difficult to find a suitable value and can vary significantly across different contexts; (2) Setting fairness as a constraint can lead to infeasible solutions if the parameters are not appropriately selected, which can be mitigated by using it as a performance criterion; (3) It does not integrate fairness into the decision-making model and allows for the use of various fairness measurement methods, which enables more flexibility and adaptability in dynamic decision-making and evaluation processes.

As illustrated in Section 2.3, with good interpretability and scale-invariance, the Gini coefficient is adopted based on the fill rate to evaluate allocation fairness at each decision round. The Gini coefficient of a specific indicator a_i among n individuals is calculated as follows:

$$G = \frac{1}{2n^2\eta} \cdot \sum_{i=1}^{n}\sum_{j=1}^{n}|a_i - a_j|. \tag{10}$$

Here, a_i and a_j are chosen indicators of individual i and j, respectively; η is the indicator's average; $G \in [0,1]$, where the smallest G represents best fairness.

In the heterogeneous relief resource allocation problem, the fill rate p_d of each demand at the end of the considered time can be used to calculate the Gini coefficient. The detailed formula is as follows:

$$G = \frac{1}{2|\mathcal{D}|^2 \cdot \overline{p_d}} \cdot \sum_{i\in D}\sum_{j\in D}|p_i - p_j|. \tag{11}$$

Here, due to the tight collaboration between heterogeneous resources, the ultimate fill rate p_d should be calculated with previous decisions and current information of supplies and demands:

$$p_d = \min_{r\in R}\{\frac{\sum_{\tau\le t_{end}} x_{r,d}^{\tau}}{q_{r,d}}\}. \tag{12}$$

It is important to note that the Gini-based metric can only evaluate allocation fairness after each decision round, which is independent of the optimization process. In the following section, a dynamic resource allocation method will be developed to balance efficiency and fairness by minimizing the Gini coefficient while maximizing the reward.

4. Dynamic resource allocation method considering fairness

To address the dynamic heterogeneous resource allocation problem quickly and efficiently, a rolling horizon-based dynamic resource allocation framework combined with the proposed heterogeneous resource allocation model is developed first. Within the decision of each period in the rolling-horizon-based framework, an adaptive dynamic resource allocation method is introduced to balance allocation efficiency and fairness.

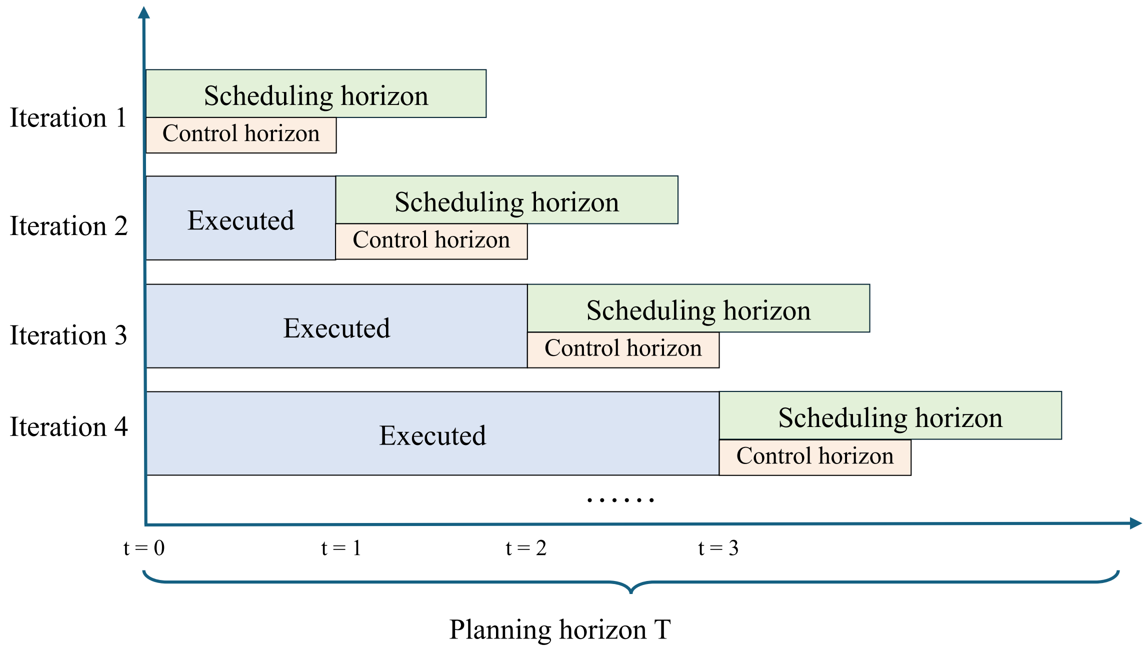


Fig. 3. Rolling horizon-based planning procedure.

4.1. Rolling horizon-based dynamic resource allocation framework

In the rolling horizon-based dynamic resource allocation framework (as shown in Fig. 3), the decisions are made sequentially following a predefined pace, which is called control horizon (CH) in this work. For each decision, the decision-making agency will consider the available relief supplies and rescue demands in the next t_{sh} periods, called scheduling horizon (SH). After the decisions are made, they will be executed for t_{ch} periods, and then start another round of decisions based on updated information. In the following periods, the decision and execution will roll forward until all periods turn to be executed.

4.2. Adaptive dynamic resource allocation method

Although the dynamic resource allocation framework is flexible to adjust decisions based on streaming supply and demand information, the decision is still myopic because future demands of potential PODs are not considered in each decision process. This may lead to using up all available relief resources to maximize efficiency at each decision stage, while late-occurring demands are possible to encounter a curse of no response. In this circumstance, the fairness among all PODs cannot be guaranteed. To address this issue, this paper develops an A-DREAM to balance global efficiency and fairness within the planning horizon.

The idea of the A-DREAM is that the fill rate cannot exceed a threshold k_t at any time until all the demand and supply information is revealed. As time progresses, the threshold k_t should be updated based on current observations of demand and supply. Once all information is known, the allocation model will not follow this method but will allocate all remaining relief resources to all PODs efficiently. This method mainly contains two parts: a threshold constraint and an adaptive threshold updating mechanism.

4.2.1. Adaptive threshold constraint

To ensure the fill rate does not exceed the threshold at any period, a threshold constraint is added to the original model:

$$\frac{\sum_{t\in T'} x^t_{r,d}}{q^t_{r,d}} \leq k_t, \forall t \in T', \forall r \in \mathcal{R}, \forall d \in \mathcal{D}', \tag{13}$$

where k_t is the fill rate threshold at time t, which will be discussed in the following section. k_0 is assigned a predicted initial supply–demand ratio.

Constraint (13) means that the total fill rate of resource type r in POD d during period T' should not be larger than the threshold k_t. With this constraint, relief resources will not be allocated completely at the beginning of disasters, but leave some of them for future possible demands, thus providing a guarantee that subsequent demands can still be satisfied to some extent. This would help improve the resource allocation fairness of current demands with future demands.

4.2.2. Adaptive threshold updating mechanism

Since the information on demands and supplies is revealed dynamically in post-disaster responses with different features or trends, the allocation cannot be efficient and fair enough if the fill rate threshold remains constant based on the original demand-supply information at the very beginning. Therefore, the fill rate threshold should be updated based on observations (allocation scheme, inventory, and remaining requirements) along the allocation processes. To address this, an adaptive threshold updating mechanism is proposed, which could "learn" and "predict" the trend of relief supply and rescue demand based on its observations of the environments, and dynamically update the threshold accordingly. The adaptive updating equation is given as follows:

$$k_{t+1} = \beta k_t + (1-\beta) \cdot \hat{k}_t, \tag{14}$$

where β implies the acceptance degree to which the previous threshold k_t is accepted, while $(1-\beta)$ refers to the degree to which the estimated fill rate $\hat{k}_t$ is accepted.

In this equation, the estimated fill rate $\hat{k}_t$ is denoted as the minimum supply–demand ratio among different relief resources at time t:

$$\hat{k}_t = \min_{r\in\mathcal{R}} \frac{I^0_r + \sum_{\tau\leq t+t_{sh}} l^\tau_r}{\sum_{d\in\{\mathcal{D}|t_d\leq t+t_{sh}\}} q_{r,d}}. \tag{15}$$

Here, the numerator part is the total emerging supply quantity of resource type r, and the denominator part is the total emerging requirement quantity of resource type r.

Algorithm 1 Pseudo-code of the dynamic resource allocation method considering fairness

Input: $|\mathcal{D}|, |T|, \mathcal{R}, t_p, I_r, k_0$.
1: $t_0 \leftarrow 0, queue \leftarrow \emptyset, \mathbf{X} \leftarrow \emptyset$
2: **while** $t_0 \leq |T|$ **do**
3: $t_{end} \leftarrow \min\{t_0 + t_p, |T|\}$.
4: $T' \leftarrow \{t_0, t_0 + 1, ..., t_{end}\}, queue \leftarrow \{d \in \mathcal{D} | t_d \leq t_0, p_d < k_0\}$.
5: Get $l_r^t, q_{r,d}, \forall r \in \mathcal{R}, \forall t \in SH, \forall d \in queue$ from the environment.
6: Update the fill rate threshold with updating Eq. (15) (see Section 4.2.2).
7: Solve the heterogeneous resource allocation model with constraint (13) (see Section 4.2.1).
8: $\mathbf{X} \leftarrow \mathbf{X} \cup \{x_{r,d}^{t_0}, ..., x_{r,d}^{t_0+t_{ch}}, \forall r \in \mathcal{R}, \forall d \in queue\}$.
9: $t_0 \leftarrow t_0 + t_{ch}$.
10: **end while**
Output: The optimal allocation scheme $\mathbf{X}$ and its objective value.

4.2.3. Overall framework of dynamic resource allocation method considering fairness

Combined with the rolling horizon-based resource allocation framework and the proposed A-DREAM, the overall framework of the dynamic resource allocation method considering fairness is shown in Algorithm 1.

In this method, the overall decision procedure follows the rolling horizon framework, in which the planning interval T' is moved forward after each solution step (lines 2–10). In each step, the planning interval T' and the potential demand set *queue* are updated based on the information of the scheduling horizon $SH = [t_0, t_0 + t_{sh}]$ (lines 3–4). After obtaining the additional supply l_r^t and demand $q_{r,d}$ during period SH from the environment (line 5), the fill rate threshold will be adaptively updated (line 6). Then, the heterogeneous resource allocation model with constraint (13) (see Section 4.2.1) is solved by the Gurobi optimizer (line 7). With the optimal solution, the decision for the period $CH = [t_0, t_0 + t_{ch}]$ will be stored and executed (line 8). After all periods are covered, the optimal allocation scheme and corresponding objective value will be generated.

From a practical view, the effectiveness of this method can be illustrated in the following two cases.

(1) $\hat{k}_t \leq k_t$. In this case, the threshold $k_{t+1} < k_t$, which means that the supply is not enough for the demands. Then the PODs whose fill rate is k_t and occurring before time t will not be considered in the allocation queue in time $t+1$. The remaining relief resources will be allocated to demands emerging at time $t+1$. In other words, if the decision agency observes that previous decisions are over-optimistic about the supply level, it will lower the fill rate threshold, temporarily lay the previous PODs aside, and leave the current supply to PODs in the next decision period. Consequently, relief resources will not be allocated to those whose fill rate exceeds the fill rate threshold and supplies can focus on those with low fill rates. So the fill rate difference between previous PODs and future PODs can be narrowed and the Gini coefficient can be decreased, thus promoting allocation fairness.

(2) $\hat{k}_t \geq k_t$. In this case, the threshold $k_{t+1} > k_t$, that is, supply exceeds demand. So all demands will be considered in the allocation queue in time $t+1$, thus all demands can be further treated without distinction to reach the same fill rate threshold in resource allocation. As a result, the difference in fill rate between different PODs will also decrease, causing the Gini coefficient to decrease, which demonstrates that allocation fairness will be improved.

5. Experimental case study

In this section, systematic experimental case studies will be presented to verify the performance of the proposed methods, including both the rolling horizon-based dynamic resource allocation framework and the proposed A-DREAM, on balancing the efficiency and fairness in post-disaster relief operations. A sensitivity analysis is also conducted to explore the potential factors (e.g., the initial fill rate threshold k_0, the acceptance degree β, the number of resource types $|\mathcal{R}|$, and the ratio of initial inventory V) affecting allocation performance. All computational experiments were run under a Python 3.9 environment in a 64-bit Linux operating system with a 2.1 GHz CPU and 64 GB RAM. Besides, all results denote an average value of ten instances with the same parameters.

5.1. Generating instances

To the best of our knowledge, there are no existing test datasets available for the dynamic heterogeneous resource allocation problem. Therefore, we utilize experimental datasets created by [19], modifying them accordingly to generate our problem instances. Specifically, we have referred to the number of resource types $|\mathcal{R}| \in [2, 7]$, the number of PODs $|\mathcal{D}| \in \{100, 200, \ldots, 800\}$, and the unit reward of on-time satisfaction of each demand w_d from the previous datasets. Furthermore, the service starting time from the previous datasets has been mapped to the demand occurrence time t_d. From our investigation, most relief resource allocation operations have happened within 1 week, so we set the number of considered periods $|T| = 7$. Based on the parameters outlined above, we randomly generate the values for the quantity of demand and supply. Similar to [25], we independently and uniformly draw the demand quantity $q_{r,d}$ of resource type r at POD d and the supply quantity $l_{r,t}$ of resource type r at time t from the range $[20, 100]$. To simulate scenarios with limited inventory at the onset of a disaster, we define a ratio of initial inventory to total demand V on the set of $\{0.1, 0.2, \ldots, 0.9\}$, which applies uniformly to heterogeneous relief resources.

5.2. Validation

In this section, we validate the performance of the proposed A-DREAM by comparing it with three benchmarks:

- **Resource allocation without consideration of fairness (*Baseline*):** This benchmark uses rolling horizon-based dynamic resource allocation framework illustrated in Section 4.1, which greedily pursues high rewards during resource allocation. This method provides an upper bound of total reward, which indicates the maximum achievable performance under dynamic conditions without any fairness constraints. By comparing with this method, we can quantify the trade-offs between efficiency and fairness. Additionally, it helps to identify the potential inefficiencies introduced by fairness considerations and serves as an evaluation method to evaluate the effectiveness of various fairness improvement methods.
- **Resource allocation with Gini constraint (*Gini-C*):** This is the most straightforward and easy-to-implement method to ensure a certain level of fairness when maximizing allocation efficiency [56]. It integrates the heterogeneous relief resource allocation model (presented in Section 3.3), the Gini-based evaluation method (Formulas (11)–(12)), and a Gini-based constraint $G \leq \overline{G}$.

Here, $\overline{G}$ denotes the upper bound of the Gini coefficient that is pre-determined at the beginning and keeps constant across the entire process. During each iteration of the rolling horizon process, the current Gini coefficient is obtained by ultimate fill rate p_d, which incorporates both past decisions and up-to-date information at hand. Then the integrated model is adjusted accordingly in each step to ensure the decision adheres to the predefined Gini coefficient threshold. Decisions that have a Gini coefficient exceeding this threshold are discarded to satisfy the Gini constraint. By comparing with this method, we can assess how well the proposed method balances between efficiency and fairness.

- **Resource allocation with urgency concern (*Urgency*):** Many researchers emphasized that fair allocation should consider the urgency of different requirements [38,57], so it is necessary to examine the effectiveness of the urgency-based method on balancing efficiency and fairness. In our settings, the most urgent demand is who has been waiting for the longest time with the lowest fill rate. Therefore, the urgency u_d of a POD d can be calculated by $u_d = (t - t_d)/T - p_d$, where $u_d \in [-1, 1]$. $u_d = -1$ shows that the POD is completely satisfied once it is revealed, so k_d will be set as 0. On the contrary, $u_d = 1$ shows the POD has been waiting for a complete planning horizon without any response, whose $k_d = 1$. If $u_d \in (-1, 1)$, k_d will be set by an urgency-related no-increasing function. By considering urgency, this method ensures that resources are allocated not only based on the potential rewards but also on the critical needs of different PODs. It helps address the most urgent demands first, thereby improving the overall fairness of the allocation process. The comparison with this method provides insights on the effectiveness of urgency-aware allocation strategies in achieving a balanced and fair resource allocation, thus further verifying the superiority of the proposed method.

With these benchmarks, we first analyze the objectives, and fairness achieved by *Baseline* with varying scheduling horizons t_{sh} to demonstrate the effectiveness of the proposed method. Subsequently, we verify the effectiveness of the proposed A-DREAM by comparing the efficiency and fairness of the dynamic resource allocation method with the above three benchmarks. These experiments are conducted under the conditions of $|T| = 7$, $|\mathcal{D}| \in \{100, 200, 300, \dots, 800\}$, $|\mathcal{R}| = 2$, $V = 0.4$, $k_0 = 0.6$, and $\beta = 0.8$. The running time of Gurobi is limited to 300 s.

5.2.1. Effectiveness of the proposed model

In this part, we analyze the results from the benchmark resource allocation without consideration of fairness. On one hand, the effectiveness of the model and the rolling horizon-based framework can be verified. On the other hand, it can be used as a benchmark in the following validation.

The key performance metrics, such as total reward w, the Gini coefficient, and total CPU time of different t_{sh} and $|\mathcal{D}|$ are listed in Table 2. In each instance scale, the total reward W increases as the scheduling horizon t_{sh} increases, which is consistent with results in earlier literature [58]. Additionally, the Gini coefficient exhibits increased volatility, ranging from 0.49 to 0.60, as the scheduling horizon t_{sh} increases. In terms of computational performance, the total CPU time increases as the problem instance scale increases, but remains within reasonable limits for practical application.

In general, the proposed IP model is available for heterogeneous dynamic relief resource allocation, and the rolling horizon-based resource dynamic framework can be easily applied to post-disaster dynamic resource allocation with acceptable decision time. However, the best Gini coefficient of 0.494 indicates a significant disparity in resource allocation, suggesting that fairness should be explicitly considered in the decision process.

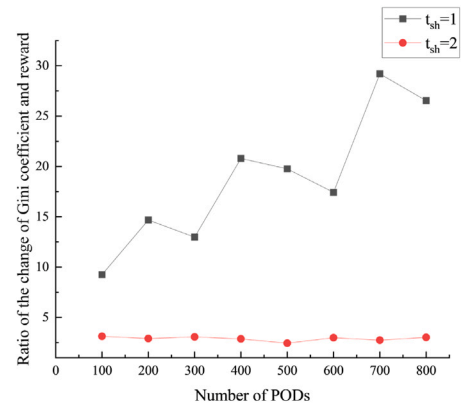


Fig. 4. Results of $\Delta G/\Delta W$ in different length of scheduling horizon t_{sh}.

5.2.2. Performance of the proposed A-DREAM

This part verifies the performance of the proposed A-DREAM by comparing the reward, fairness, and CPU time obtained by the A-DREAM and the above three benchmarks in different instance scales and scheduling horizons.

Table 2, Table 3, Table 4, and Table 5 show the results of the aforementioned three benchmarks and the proposed A-DREAM. By comparing with the results in Tables 2 and 5, the A-DREAM can sacrifice some reward to achieve improvements in the Gini coefficient. For instance, when $|\mathcal{D}| = 100, t_{sh} = 1$, the total reward decreases from 3104.01 to 2794.71, while the Gini coefficient decreases from 0.521 to 0.257. In other words, the A-DREAM can decrease the Gini coefficient by 102.38% while the drop in the reward is only 11.07%. Fig. 4 shows the improvement more intuitively, where the y-axis represents the ratio of the increase in the Gini coefficient to the increase in reward (denoted as $\Delta G/\Delta W$). The results show that the A-DREAM has excellent performance for $t_{sh} = 1, 2$. Surprisingly, $\Delta G/\Delta W$ can reach nearly 30 with $t_{sh} = 1$ in large-scale instances.

In summary, the performance evaluation demonstrates the effectiveness of the proposed A-DREAM approach in balancing the trade-off between reward maximization and fair resource allocation, with significant improvements in fairness metrics at the cost of only a small decrease in overall reward.

Regarding the results of the Gini-C benchmark (see Table 3), we found that it performs worse than any other benchmark in reward and the Gini coefficient. In most instances, the Gini-C benchmark cannot find a feasible solution within the specified CPU time limit, which is unacceptable in post-disaster relief resource allocation operations.

In terms of urgency-based benchmark performance (see Table 4), it can also improve allocation fairness by sacrificing some of the rewards. However, this method sacrifices too much reward for a small improvement in fairness. On the contrary, our proposed A-DREAM outperforms both in terms of reward and the Gini coefficient. The reason is that the urgency-based benchmark focuses more on maximizing the minimum fill rate of individual POD, rather than optimizing the overall performance in both reward and fairness. By taking a more balanced approach, the A-DREAM method is able to achieve superior results in both efficiency and fairness.

Overall, the proposed A-DREAM can improve allocation fairness by sacrificing some efficiency effectively, achieving the $\Delta G/\Delta W$ up to 30. It performs better than other benchmarks like Gini-C and urgency-based benchmarks in terms of both efficiency and fairness. Besides, the A-DREAM also reduces the computational complexity compared to the Gini-C benchmark, which is crucial for practical applications in time-sensitive post-disaster scenarios.

Table 2
Performance of the IP model and the rolling horizon-based framework.

	$\lvert\mathcal{D}\rvert = 100$			$\lvert\mathcal{D}\rvert = 200$			$\lvert\mathcal{D}\rvert = 300$			$\lvert\mathcal{D}\rvert = 400$		
	W	Gini	CPU time	W	Gini	CPU time	W	Gini	CPU time	W	Gini	CPU time
$t_{sh} = 1$	3104.01	0.521	0.93	5557.73	0.564	2.74	8045.13	0.570	4.87	10 455.93	0.578	9.75
$t_{sh} = 2$	3462.67	0.511	1.62	6500.78	0.549	3.59	9511.88	0.551	6.40	12 612.01	0.559	10.04
$t_{sh} = 3$	3680.44	0.516	2.37	7029.23	0.543	4.18	10 416.16	0.546	7.55	13 859.03	0.550	11.74
$t_{sh} = 4$	3810.90	0.518	2.63	7376.18	0.539	5.77	11 035.28	0.537	9.10	14 654.86	0.545	13.71
$t_{sh} = 5$	3816.44	0.524	3.10	7493.60	0.542	6.44	11 221.98	0.539	10.92	14 893.92	0.545	15.18
$t_{sh} = 6$	3802.91	0.531	3.13	7499.12	0.544	5.92	11 233.62	0.540	11.97	14 962.22	0.544	18.81
$t_{sh} = 7$	4013.19	0.494	2.35	7710.05	0.525	4.81	11 439.18	0.529	9.67	15 191.52	0.536	18.62
	$\lvert\mathcal{D}\rvert = 500$			$\lvert\mathcal{D}\rvert = 600$			$\lvert\mathcal{D}\rvert = 700$			$\lvert\mathcal{D}\rvert = 800$		
	W	Gini	CPU time	W	Gini	CPU time	W	Gini	CPU time	W	Gini	CPU time
$t_{sh} = 1$	12 764.93	0.579	14.00	15 438.74	0.583	20.02	17 893.17	0.585	28.91	20 360.19	0.586	37.29
$t_{sh} = 2$	15 629.25	0.560	14.44	18 669.43	0.567	22.98	22 036.35	0.566	32.76	24 937.39	0.567	39.88
$t_{sh} = 3$	17 165.45	0.551	16.71	20 840.24	0.555	22.72	24 466.53	0.555	28.94	27 694.87	0.557	40.52
$t_{sh} = 4$	18 125.69	0.546	20.22	21 895.52	0.550	26.80	25 893.60	0.546	38.44	29 252.26	0.551	53.26
$t_{sh} = 5$	18 389.50	0.546	23.16	22 201.13	0.548	35.15	26 346.96	0.544	46.42	29 834.31	0.550	70.62
$t_{sh} = 6$	18 452.80	0.546	29.26	22 286.87	0.547	57.05	26 481.13	0.544	116.39	29 969.42	0.549	234.18
$t_{sh} = 7$	18 675.35	0.539	38.46	22 499.26	0.541	110.80	26 714.34	0.538	156.49	30 228.33	0.544	204.14

Table 3
Results of Gini-C.

	$\lvert\mathcal{D}\rvert = 100$			$\lvert\mathcal{D}\rvert = 200$		
	W	Gini	CPU time	W	Gini	CPU time
$t_{sh} = 1$	2445.47	0.572	462.20	3358.05	0.697	1170.47
$t_{sh} = 2$	2670.62	0.628	621.90	3560.66	0.796	1202.83
$t_{sh} = 3$	2712.02	0.669	416.93	3953.02	0.782	901.32
$t_{sh} = 4$	3502.48	0.562	85.21	6012.92	0.629	474.93
$t_{sh} = 5$	3827.34	0.524	29.42	7016.47	0.573	430.18
$t_{sh} = 6$	3813.35	0.532	35.90	4139.73	0.750	477.53$^{(1)}$
$t_{sh} = 7$	4020.47	0.494	22.93	7974.76	0.523	282.61$^{(8)}$

	$\lvert\mathcal{D}\rvert = 300$			$\lvert\mathcal{D}\rvert = 400$		
	W	Gini	CPU time	W	Gini	CPU time
$t_{sh} = 1$	4287.93	0.718	1300.45	5789.00	0.712	1274.32
$t_{sh} = 2$	4282.04	0.804	1526.40	5040.91	0.830	1778.53
$t_{sh} = 3$	3479.31	0.836	1428.72$^{(2)}$	3220.72	0.863	1616.94$^{(5)}$
	$\lvert\mathcal{D}\rvert = 500$			$\lvert\mathcal{D}\rvert = 600$		
$t_{sh} = 1$	6748.09	0.727	1292.88	8798.46	0.707	1309.70
	$\lvert\mathcal{D}\rvert = 700$			$\lvert\mathcal{D}\rvert = 800$		
$t_{sh} = 1$	10 118.15	0.717	1337.17	11 453.43	0.714	1430.43

1 The number in the form of $a^{(b)}$ means there are b instances with no solution in the specified time. The instances with feasible solutions calculate the average W, Gini, and CPU time in the corresponding settings.
2 The data not provided demonstrates that there is no feasible solution in any of the instances. For example, when $\lvert\mathcal{D}\rvert = 300, 400$, no feasible solution found in $t_{sh} = 4, 5, 6, 7$. When $\lvert\mathcal{D}\rvert \geq 500$, no feasible solution found in $t_{sh} \geq 2$.

Table 4
Results of Urgency-based benchmarks.

	$\lvert\mathcal{D}\rvert = 100$			$\lvert\mathcal{D}\rvert = 200$			$\lvert\mathcal{D}\rvert = 300$			$\lvert\mathcal{D}\rvert = 400$		
	W	Gini	CPU time	W	Gini	CPU time	W	Gini	CPU time	W	Gini	CPU time
$t_{sh} = 1$	2439.67	0.347	0.70	4481.53	0.386	1.48	6515.14	0.379	3.05	8624.94	0.388	5.04
$t_{sh} = 2$	2678.08	0.358	1.18	5057.19	0.396	2.50	7477.51	0.388	4.63	9831.68	0.398	7.03
$t_{sh} = 3$	2890.82	0.420	1.67	5583.78	0.452	3.75	8249.46	0.450	7.52	10 770.55	0.451	11.47
$t_{sh} = 4$	2692.54	0.522	2.03	3839.67	0.616	5.12	3443.50	0.687	7.99	6630.53	0.638	14.93
$t_{sh} = 5$	2896.08	0.550	2.61	5208.20	0.583	6.20	10 192.20	0.523	15.59	12 506.43	0.545	27.71
$t_{sh} = 6$	3646.82	0.529	3.03	7199.78	0.541	6.97	10 835.73	0.539	14.25	14 388.01	0.541	23.68
$t_{sh} = 7$	4013.19	0.494	1.72	7710.05	0.525	3.44	11 439.18	0.529	6.69	15 191.52	0.536	12.31
	$\lvert\mathcal{D}\rvert = 500$			$\lvert\mathcal{D}\rvert = 600$			$\lvert\mathcal{D}\rvert = 700$			$\lvert\mathcal{D}\rvert = 800$		
	W	Gini	CPU time	W	Gini	CPU time	W	Gini	CPU time	W	Gini	CPU time
$t_{sh} = 1$	10 559.25	0.390	8.47	12 726.83	0.387	11.98	14 835.70	0.395	18.38	16 882.95	0.391	25.22
$t_{sh} = 2$	12 172.03	0.400	10.68	14 388.76	0.398	15.63	17 170.86	0.403	21.45	19 024.42	0.401	38.18
$t_{sh} = 3$	13 407.41	0.457	18.31	15 343.58	0.449	28.58	19 013.30	0.457	45.13	18 052.39	0.450	98.10
$t_{sh} = 4$	4715.95	0.703	25.82	8498.50	0.643	27.51	6420.20	0.713	42.12	5475.12	0.733	55.50
$t_{sh} = 5$	14 104.69	0.572	43.44	16 893.30	0.566	66.92	18 261.27	0.588	114.58	18 631.00	0.609	201.89
$t_{sh} = 6$	17 777.42	0.545	40.27	17 603.25	0.607	69.47	23 236.44	0.574	131.68	26 157.83	0.577	236.18
$t_{sh} = 7$	18 675.35	0.539	25.22	22 499.26	0.541	66.85	26 714.34	0.538	123.24	30 228.33	0.544	189.33

5.3. Sensitivity analysis

This section aims to present sensitivity analyses of parameters related to the parameter of the A-DREAM (the initial fill rate threshold k_0 and acceptance degree β) and scenario-related information (the number of resource types $\lvert\mathcal{R}\rvert$, and the ratio of initial inventory V). To examine the relationship between those parameters and the performance of dynamic resource allocation, we mainly analyze the performance for small t_{sh}.

5.3.1. Initial fill rate threshold

Since the initial fill rate threshold k_0 directly determines the maximum fill rate at the first period and further affects allocation schemes, we explore the influence of the initial fill rate threshold on allocation performance in this section. The experiments are conducted with different initial fill rate thresholds ($k_0 \in \{0.1, 0.2, \dots, 0.9, 1.0\}$). Besides, other parameters $\lvert\mathcal{D}\rvert = 400, \lvert\mathcal{R}\rvert = 2, \lvert T\rvert = 7, V = 0.4, \beta = 0.8$.

Fig. 5 provides details on the reward and fairness trend for $t_{sh} = 1$ and $t_{sh} = 2$. For $t_{sh} = 1$, when $k_0 = 0.6$, the solution gets good fairness with a high reward. While k_0 increases, the fairness worsens with a

Table 5
Results of A-DREAM.

	$\lvert\mathcal{D}\rvert = 100$			$\lvert\mathcal{D}\rvert = 200$			$\lvert\mathcal{D}\rvert = 300$			$\lvert\mathcal{D}\rvert = 400$		
	W	Gini	CPU time	W	Gini	CPU time	W	Gini	CPU time	W	Gini	CPU time
$t_{sh} = 1$	2794.71	0.257	0.56	5233.08	0.295	1.50	7497.22	0.293	3.09	9979.95	0.290	5.14
$t_{sh} = 2$	2966.67	0.335	1.00	5592.35	0.372	2.38	8227.04	0.373	4.35	10 802.96	0.378	7.11
$t_{sh} = 3$	3092.35	0.411	1.84	5986.28	0.446	3.71	8836.72	0.443	6.95	11 595.76	0.444	11.33
$t_{sh} = 4$	3248.68	0.470	2.37	6335.93	0.488	7.08	8884.02	0.505	13.69	12 501.76	0.495	21.88
$t_{sh} = 5$	3443.03	0.509	2.68	6826.84	0.523	8.89	10 121.72	0.525	17.72	13 471.21	0.528	30.05
$t_{sh} = 6$	3649.09	0.529	2.93	7202.16	0.541	7.39	10 820.71	0.539	13.80	14 372.65	0.542	27.09
$t_{sh} = 7$	4013.19	0.494	1.66	7710.05	0.525	3.51	11 439.18	0.529	6.76	15 191.52	0.536	12.59
	$\lvert\mathcal{D}\rvert = 500$			$\lvert\mathcal{D}\rvert = 600$			$\lvert\mathcal{D}\rvert = 700$			$\lvert\mathcal{D}\rvert = 800$		
	W	Gini	CPU time	W	Gini	CPU time	W	Gini	CPU time	W	Gini	CPU time
$t_{sh} = 1$	12 221.72	0.309	8.85	14 589.08	0.289	12.69	17 320.02	0.298	18.75	19 612.24	0.291	22.54
$t_{sh} = 2$	13 287.64	0.391	10.40	15 885.28	0.372	15.58	18 882.93	0.388	21.63	21 384.65	0.378	24.41
$t_{sh} = 3$	13 352.60	0.483	18.29	15 839.79	0.470	28.53	19 432.51	0.460	31.12	22 898.27	0.445	36.67
$t_{sh} = 4$	15 488.08	0.499	37.62	17 306.37	0.510	51.13	20 559.41	0.515	78.62	21 044.81	0.542	100.34
$t_{sh} = 5$	16 686.35	0.533	54.55	19 946.10	0.532	97.62	22 047.88	0.549	134.96	26 901.60	0.535	171.44
$t_{sh} = 6$	17 758.50	0.545	48.34	21 457.42	0.545	100.60	23 221.26	0.571	138.85	26 304.15	0.578	186.91
$t_{sh} = 7$	18 675.35	0.539	30.09	22 499.26	0.541	88.93	26 714.34	0.538	113.86	30 228.33	0.544	125.14

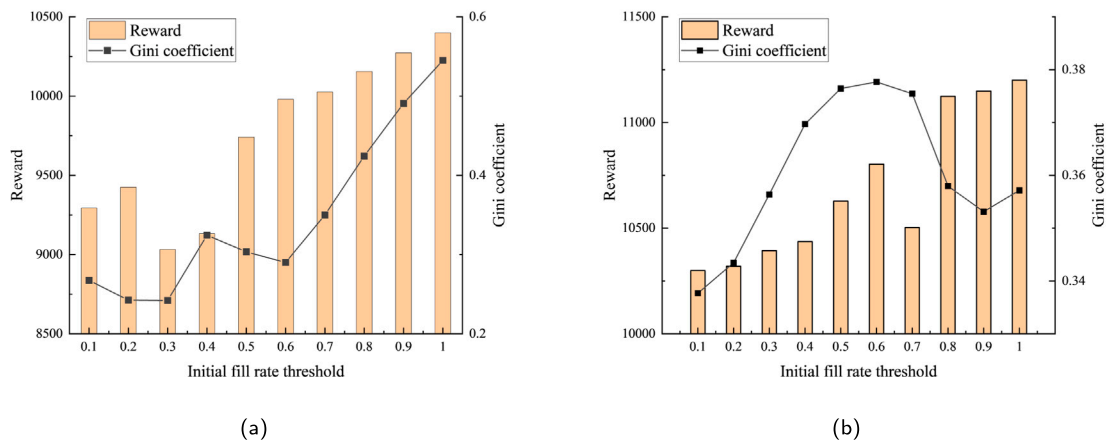


Fig. 5. Results for sensitivity analysis on initial fill rate threshold k_0. (a) length of scheduling horizon $t_{sh} = 1$. (b) length of scheduling horizon $t_{sh} = 2$.

small reward improvement. Besides, the results in Fig. 5(b) illustrate that as the initial fill rate threshold increases between $[0.1, 0.6]$, the optimal decision sacrifices a portion of the fairness, thereby increasing reward and further advancing the objectives. While k_0 increases to 0.7, the optimal solution loses many rewards to achieve a little fairness improvement. As k_0 increases to $[0.8, 1.0]$, the optimal solution can get a higher reward with smaller G. This is because, as the initial fill rate threshold increases, the resource allocation scheme will be more optimistic about the future supply and allocate more relief resources at the beginning of the response, thus achieving higher rewards. Nevertheless, allocation fairness cannot be guaranteed in this manner, leading to worse fairness outcomes. As the initial fill rate threshold continuously increases, a greedier solution can even get a more efficient and fairer allocation.

In short, we recommend the decision-making agency take a relatively optimistic view of future supply with little information, thereby achieving both fairer and more efficient resource allocation.

5.3.2. Acceptance degree β

The value of β denotes the acceptance degree of previous decisions, which also affects the efficiency and fairness of dynamic allocation. In this part, we conduct experiments with different $\beta \in [0, 0.9]$ to explore the correlations between β and the allocation performance. Other parameters are set as $|\mathcal{D}| = 400$, $|T| = 7$, $k_0 = 0.6$, $t_{sh} = 1, 2$.

As Fig. 6 shows, as β increases, the total reward increases, while the Gini coefficient decreases first and then increases dramatically. The results indicate that if the main objective is to maximize allocation efficiency, a higher β should be used. The major cause of this observation is that a large β allows the A-DREAM to rely more on the previous allocation while ignoring the potential impact of future supply information. This can lead to a more optimistic and greedy allocation strategy, resulting in higher rewards. On the contrary, if the main objective is to maximize allocation fairness, a suitable β such as 0.5,0.6,0.7 should be selected. This balances the exploitation of previous thresholds with the exploration of new information, helping to maintain a reasonable level of fairness in resource allocation.

In summary, the choice of β should be carefully balanced based on the specific objectives and priorities of the resource allocation problem. A moderate β value can help achieve a better trade-off between efficiency and fairness, while a higher β may be preferred if the focus is mainly on maximizing the total reward.

5.3.3. Number of resource types

In this part, the effect of the number of resource types is evaluated. Since the total reward naturally varies depending on the number of different resource types, our experiments cannot directly compare the reward values. Instead, we focus on examining the impact of the number of resource types on allocation fairness. Several experiments are carried out with different numbers of resource types ($|\mathcal{R}| \in [2, 7]$). All experiments are conducted with parameters $|\mathcal{D}| = 400$, $|T| = 7$, $k_0 = 0.6$, $\beta = 0.8$, $t_{sh} = 1, 2$.

The numerical results are presented in Fig. 7. It shows that as $|\mathcal{R}|$ increases, the value of the Gini coefficient rises from 0.29 to 0.34 for $t_{sh} = 1$ and from 0.38 to 0.42 for $t_{sh} = 2$. This indicates that with a greater diversity of heterogeneous relief resources, the allocation fairness, as measured by the Gini coefficient, tends to decrease. However,

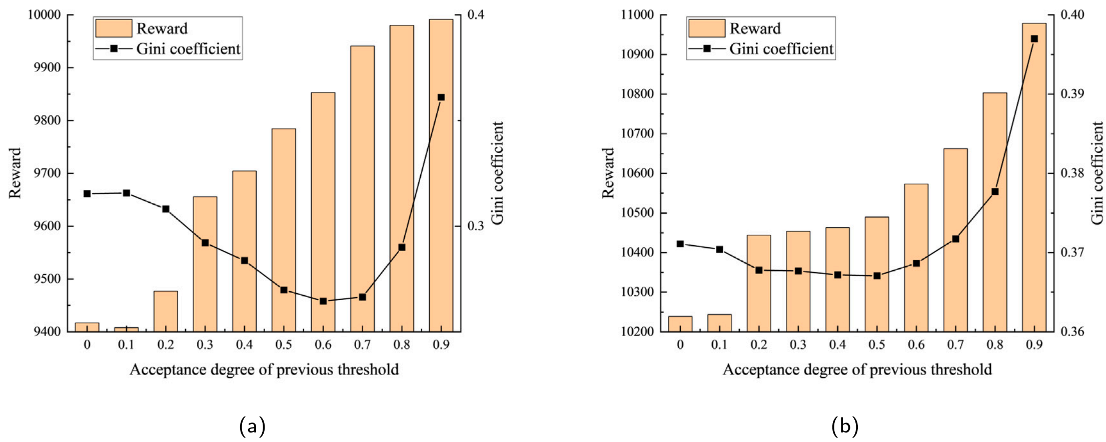


Fig. 6. Results of sensitivity analysis on acceptance degree of the previous threshold β. (a) length of scheduling horizon $t_{sh} = 1$. (b) length of scheduling horizon $t_{sh} = 2$.

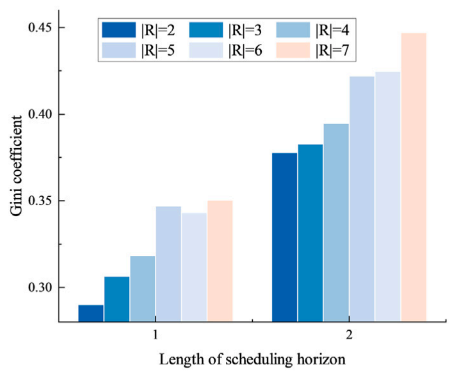


Fig. 7. Results of sensitivity analysis on number of resource type $|\mathcal{R}|$.

even as the number of resource types increases, the Gini coefficient remains around 0.4, suggesting that the allocation is still reasonably fair. Moreover, the Gini coefficient increases dramatically when $|\mathcal{R}|$ increases from 4 to 5, indicating a more significant deterioration in allocation fairness.

In summary, it is recommended that, for the heterogeneous resource allocation problem, the optimal number of resource types is ideally 2, as this can help maintain a higher level of fairness in the allocation. However, in practice, it may be difficult to assemble so many heterogeneous relief resources with close dependencies into only two categories. Therefore, we suggest the local distribution center try to divide those heterogeneous resources into fewer categories, preferably no more than four. This approach can help balance the trade-off between resource diversity and allocation fairness, which is crucial for effective post-disaster relief operations.

5.3.4. Ratio of initial inventory

To examine the effect of the ratio of initial inventory on allocation performance, several experiments are carried out with different ratios of initial inventory ($V \in \{0.1, 0.2, 0.3, \dots, 1.0\}$). Other parameters are set as $|\mathcal{D}| = 400$, $|T| = 7$, $k_0 = 0.6$, $\beta = 0.8$.

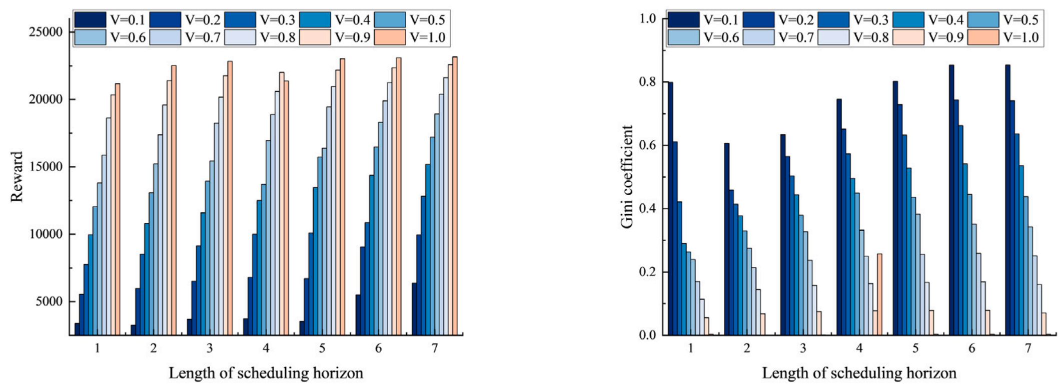
Fig. 8 shows that the values of total reward increase linearly, while the Gini coefficient decreases, as the ratio of initial inventory increases from 0.1 to 1.0 with a step size of 0.1. Besides, When $V \in [0.1, 0.5]$, the improvement of reward and the Gini coefficient obtained by increasing 0.1 unit of V is more obvious than that in $[0.5, 1.0]$. It indicates that the effects of the ratio of inventory V on the allocation performance becomes less pronounced in post-disaster response with relatively sufficient relief resources. Additionally, if $V \geq 0.5$, the Gini coefficient is below 0.4 for any value of t_{sh}, representing a fair allocation in dynamic post-disaster scenarios. Therefore, in this experimental setting, the most cost-efficient initial inventory ratio is 0.5.

In general, the results showed that the initial inventory has a marked positive impact on allocation performance, which means that a larger initial inventory leads to better resource allocation. However, a larger initial inventory also leads to higher emergency preparation costs. Therefore, suitable pre-prepared inventories of heterogeneous relief resources facilitate resource allocation. To achieve a quick response to disasters, state governments are highly recommended to predict the demands for heterogeneous relief resources based on historical disaster data and population knowledge. Based on the predicted information of demands, the initial inventory of the distribution center can be determined considering the trade-off between allocation performance and economic burden, thus realizing an economically reasonable and sufficient inventory to meet the requirement of allocation fairness.

6. Conclusions

This paper proposed a dynamic heterogeneous resource allocation method to achieve efficient and fair resource allocation for post-disaster response. Specifically, taking tight collaboration of heterogeneous relief resources into account, a heterogeneous resource allocation model is presented to maximize allocation efficiency. Additionally, a Gini-based metric is proposed to evaluate fairness and is used as a performance criterion when balancing efficiency and fairness. Given that supply and demand information can only be known up to a certain period in advance, a dynamic resource allocation method incorporating a rolling horizon framework and an Adaptive Dynamic REsource Allocation Method (A-DREAM) is designed to settle the dynamic resource allocation problem both fairly and efficiently. Furthermore, the performance of the proposed integer programming model, rolling horizon-based framework, and A-DREAM is verified through extensive experiments. Finally, sensitivity analysis is carried out to examine the factors influencing allocation fairness and provide some managerial insights for practical post-disaster response.

In the future, this work can be extended from the following perspectives. First, the post-disaster response not only involves resource allocation, but also relief transportation problems, so the integrated resource allocation and relief transportation problem can be studied considering dynamic road conditions in the future. Second, we assume the information of supply and demand can be known in advance and will not be changed once the information is revealed. This will further influence the mathematical model during the decision process. Thus, future research can focus on stochastic heterogeneous resource allocation problems. Third, as a typical dynamic decision-making process, online optimization-based methods can be investigated to tackle this problem.



(a) (b)

Fig. 8. Results of sensitivity analysis on ratio of initial inventory V. (a) Effect on total reward. (b) Effect on the Gini coefficient.

CRediT authorship contribution statement

Yuying Long: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Conceptualization. **Peng Sun:** Writing – review & editing, Resources, Methodology. **Gangyan Xu:** Writing – review & editing, Project administration, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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