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Multi-Objective Optimization Model of Emergency Organization Allocation for Sustainable Disaster Supply Chain

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Abstract: To mitigate or reduce various losses and improve efficiency of disaster response, the focus of this paper is to design optimized strategies of emergency organization allocation regarding sustainability. Firstly, an integrated framework including several elements such as emergency organization, task, decision-agents, environment and their relations is developed from a systematic perspective. Then, this problem is formulated as a novel multi-objective 0–1 integer programming model to minimize total weighted completion times, total carbon emissions and total emergency costs. Next, branch and bound approach and handling strategies for multiple objectives are designed to solve this model. Finally, a case study from the Wenchuan earthquake is presented to illustrate the proposed model and solution strategies. Computational results demonstrate their significant potential advantages on allocating emergency organization from the perspectives of best practice, objective functions, preferences of decision-agents, and problem size.

Keywords: sustainable disaster supply chain; emergency organization allocation; integrated framework; carbon emissions; multi-objective programming model; branch and bound approach

1. Introduction

As a prominent component of sustainable development, how to deal with natural disasters and their consequences can benefit the maintenance of social stability, and this is an emerging topic that has garnered increasing attention from both practitioners and academics in recent years. It is reported that the total number of natural disasters and affected people shows an overall increasing tendency since 1900s (see Figure 1) according to the International Disaster Database (EM-DAT). Particularly, such natural disasters including Wenchuan earthquake, tsunami of India Ocean, typhoon Hato, pose serious threats to social development from the point of view of economic, social, and ecological dimensions of sustainability, place populations at risk, and cause large casualties, property losses as well as environmental disruptions [1,2]. For instance, the great Wenchuan earthquake in 2008 resulted in 69,277 deaths, 374,643 injuries, and 17,923 missing people based on the report of Ministry of Civil Affairs of the People's Republic of China. It also caused direct economic losses exceeding 800 billion CNY. The great earthquake that occurred in Nepal resulted in at least 8786 deaths and 22,303 injured people. Economic losses are about 113 billion CNY. Damages by Typhoon Hato in south China in 2017 reached a total of 12.5 billion CNY. Additionally, 26 people in total have been killed. Since the frequency of natural disasters increased sharply, to save lives, reduce human suffering, and contribute to development, are pressing needs for the sustainable disaster supply chain (SDSC) and this is still an issue despite of increasing contributions in this field [3,4].

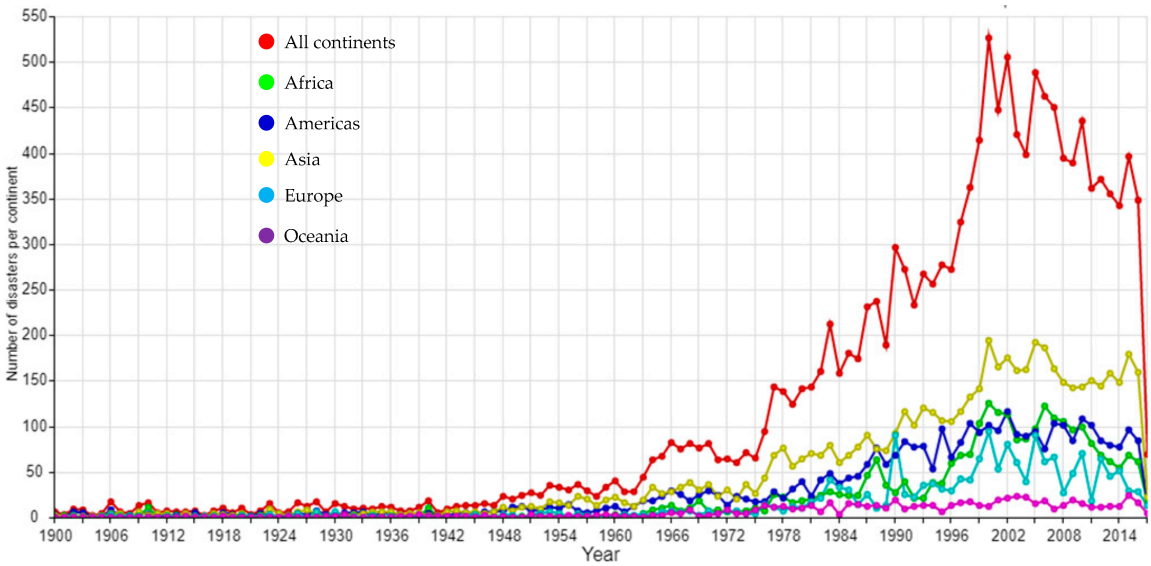

Figure 1. The number of natural disasters between 1900 and 2017 (Source: International Disaster Database).

Dubey et al. [3] and Haavisto et al. [5] pointed out that SDSC could be regarded as the result of combinations of philosophies of sustainable development and traditional disaster supply chain. Carter et al. [6] elaborated clearly that sustainability was able to be characterized by the triple bottom line model regarding social, economic, ecological dimensions. The United Nations World Commission on Environment and Development (1987) highlighted that sustainable development was to meet the needs of the present without compromising the ability of future generations to meet their own needs. On the other hand, rescue goals in practice are most often to save lives, evacuate survivors, decrease human suffering, and contribute to development. It is line with the main ideas of sustainability. In this context, this paper shows that SDSC intends to achieve the coordinated development with the concern of social, economic and ecological dimension of sustainability by optimizing disaster response strategies related to human capital (e.g., emergency organization), relief (e.g., food, water), and others [7,8]. Meanwhile, Hoyos et al. [7] portrayed a similar viewpoint, which was that efficient response can benefit reduction of impacts of disasters on society, economy and environment. Thus, they further strengthen the aforementioned ideas regarding sustainability of disaster supply chain.

Practical cases indicate that emergency organization (EO) as one of the critical elements of SDSC that is usually regarded as the link or bridge between decision- and demand-agents. Importance of EO and relevant topics in disaster operations activities are addressed by many researchers from different perspectives. For example, Lettieri et al. [9] delineated that wrong coordination among EOs would result in conflicts, resource and time wasting, as well as human and property losses. Altay et al. [1] highlighted that loose connection between amongst EOs lead to managerial confusions and ambiguity of authority. Particularly, Haavisto et al. [5] addressed that enhancing the fit between EOs and their environment could benefit the improvement of performance of SDSC. Accordingly, it can be inferred that the need for modeling EO for not only traditional disaster supply chain but also SDSC is pressing. This claim is also supported by Galindo et al. [8], Habib et al. [10], Caunhye et al. [11], Wex et al. [12].

In practice, it must be acknowledged that a set of the emergency tasks (ETs) need to be executed immediately by a variety of EOs after the occurrence of natural disasters. Nevertheless, inefficient and unreasonable/non-optimized strategies for emergency organization allocation (EOA) may result in tremendous losses involving economy, society, and ecology. Strategies here refer to the matching mechanism between EOs and ETs, and structure of ETs for each EO in disaster response decision optimization system. Consequently, how to optimize the strategies for EOA is very significant. Particularly, the motivations or goals to optimize strategies regarding EOA are to enhance utilization rate of human capital or efficiency of disaster response, improve terrible ecological environment, and reduce excessive emergency costs.

In recent years, although EOA problem has received increasing attention, it is still in its infancy. Such topics solved by the OR/MS technique have been addressed in the literature, but are very limited [5,11,12]. Firstly, most of the researchers are dedicated to traditional disaster supply chain rather than SDSC. Besides, how to measure sustainability regarding disaster context, and its combination with EOA remain problematic. Secondly, only EO as critical element in disaster response decision optimization system is considered with regard to making response strategies. But how to incorporate other key elements such as ETs and their matching relations into EOA problem is rarely concentrated on. Thirdly, they usually describe this problem as parallel machine scheduling model, and merely focus on the assignment of EOs. How to integrate assignment of EOs and structures or sequences of ETs into a more practical problem is an emerging topic. Finally, most of them merely focus on traditional rescue objectives, such as minimization of time and cost. Besides, single objective is more favored. How to formulate this problem as a multi-objective mathematical model regarding new perspectives (e.g., sustainability) is hardly considered in literature.

In this context, this paper focuses on SDSC, and is devoted to characterizing sustainability regarding EOA from the perspective of social, economic, and ecological dimension. The OR/MS method is used to formulate the integrated issue concerning sequences and urgencies of ETs, eligibility restrictions of EOs as a multi-objective mathematical programming model. Besides, decisions on the matching mechanism between EOs and ETs, as well as sequences of ETs for each EO need to be made by decision-makers in a centralized manner. Thus, the goals to enhance the utilization rate of human capital or the efficiency of disaster response, improve ecological environment, and reduce emergency costs might be achieved ultimately.

The contributions of this paper include three points. Firstly, SDSC differing from the previous one is the focus of this paper. Sustainability with the concern of EOA during response phase is simultaneously characterized from economic, social and ecological dimension. Besides, an integrated framework of tasks-oriented emergency organization allocation is proposed from a holistic thinking. Secondly, an integrated optimization problem regarding matching relations between EOs and ETs, heterogeneity and eligibility restrictions of EOs, sequences and urgencies of ETs, sustainability is considered. Thirdly, EOA problem for SDSC is formulated as a novel 0–1 integer programming model to minimize total weighted completion times, total carbon emissions and emergency costs. In other words, a method to achieve the matching or fit between disaster and sustainability objectives is outlined [5].

The rest of this paper is organized as follows: the next section describes and analyzes the extant literature which concerns EOA and SDSC. Section 3 presents problem definition in detail and designs an integrated framework regarding EOA. This problem is formulated as a 0–1 integer multi-objective programming model in Section 4. Section 5 proposes a branch and bound approach to solve this multi-objective programming model. A case study from Wenchuan earthquake is used to test feasibility and effectiveness of the proposed model and solution strategies in Section 6. Finally, managerial insights and future directions are provided.

2. Literature Review

In recent years, EOA as one of critical issues in disaster supply chain has garnered increasing attention. This paper contributes to literature on SDSC, EOA and multi-objective optimization problem.

Firstly, a significant issue of this research is SDSC. Sustainability of disaster supply chain is an emerging topic in recent years. Although this issue is significantly critical, it is still in its early stage. In terms of the concept of sustainability, different scholars hold different opinions, thus having no unified definition. However, as a common cognition, the main ideas in nature of sustainability are to reduce, reuse, recovery and recycle. And its measurement dimensions include society, economy and ecology [6]. In the context of disaster, Ibegbunam et al. [13] delineated that sustainability was related to responsible communication and coordination, thus improving the responsiveness of disaster supply chain. Weerawardena et al. [14] elaborated that sustainability in the non-profit organization was defined roughly as maintaining operations. In other words, it is able to survive, thus continuing to serve its constituency. Haavisto et al. [15] opined that sustainability was related to the embeddedness of humanitarian supply chain in society and nature. Particularly, they pointed out that long-term effects of rescue on local economies, society and environment ought to be considered. Haavisto et al. [5] further showed that sustainability could be understood from the point of view of societal, beneficiary, supply chain and program. They also proposed a conceptual framework based on contingency theory, and tested it. With regard to the SDSC, Papadopoulos et al. [2] proposed and tested a theoretical framework to explain resilience and sustainability of disaster supply chain networks via responses of emergency managers participating in relief activities of the Nepal earthquake. Dubey et al. [3] identified the critical characteristics of sustainable humanitarian supply chain as agility, adaptability and alignment, and tested theses constructs using empirical studies. Kuzn et al. [16] clarified that the local environment should be considered into disaster rehabilitation during recovery phase, and proposed a framework regarding sustainability. Habib et al. [17] developed an integrated location-allocation model for sustainable disaster debris management during response phase, and sustainability was reflected by the term 'reuse' and 'recycle'.

Secondly, EOA problem is another important stream in this paper. Caunhye et al. [11] highlighted that centralized methods might be better to drastically improve the coordination between the multiple parties involved. Mathematical programming is one of the most popular methods to characterize the coordination or horizontal intergovernmental relations among emergency organizations in a centralized manner. For example, Yan et al. [18] used a time–space network approach to model work team scheduling problem after a major disaster. Chen et al. [19] took into account optimal team deployment problem regarding selection of sites and order of visits in urban search and rescue. Maya-Duque et al. [20] contended that the state of post-disaster road network was the main factor to influence relief distribution. They concentrated on scheduling and route planning of a single repair crew from a single depot. Ren et al. [21] considered priority disaster areas and limited amounts into rescue team scheduling problem with regard to forest fires. Su et al. [22] considered matching problem between multiple rescue teams and concurrent incidents, thus obtaining the optimal scheme concerning rescue teams. To restore the critical components of multiple interdependent lifeline infrastructure systems, Zhang et al. [23] focused on homogeneous rescue team allocation problem with the concern of a precedence relation constraint so as to reduce the total losses and improve the efficiency of disaster response. Only assignment of EO is considered in the aforementioned literature. A more complex, but interesting, issue regarding matching relations between EOs and ETs, and structure of ETs for each EO requires a lot of attention. For instance, Wex et al. [12] applied a single-objective programming model to capture assignment of rescue units and their matching mechanism with incidents in natural disaster management. Zheng et al. [24,25] took into consideration both assignment of multiple rescue teams and the corresponding structure of emergency tasks. Rolland et al. [26] concentrated on assignment of heterogeneous response teams, and their matching relationships with emergency tasks.

Thirdly, this paper also contributes to literature on multi-objective optimization model. Holguin-Veras et al. [27] elaborated that multi-objective optimization was a very popular stream in humanitarian logistics, even disaster supply chain. In terms of relief scheduling problem, Zhou et al. [28] proposed a multi-objective programming model to minimize the sum of quantity of all types of unsatisfied resources as well as risks for dynamic emergency resource scheduling problem. Tzeng et al. [29] formulated relief distribution problem as a multi-objective programming model to minimize total costs and travel time, as well as maximize satisfaction. Sheu et al. [30] considered a composite weighted multi-objective optimization model to maximize time-varying relief demand fill rate and minimize time-varying distribution costs. Huang et al. [31] highlighted the trade-off of multiple objectives regarding lifesaving utility, delay cost and fairness. With respect to

EOA problem, Su et al. [22] formulated rescue teams allocation as an integer programming model to minimize the weighted travel time and total emergency costs. Zhang et al. [23] developed a two-stage stochastic mixed-integer programming model for rescue team allocation with the minimization of total losses or costs and the latest completion time of tasks (namely, makespan). Zheng et al. [25] focused on matching problem between rescue teams and tasks, aiming to minimize the weighted completion time and total operation risk.

In summary, the aforementioned literature discussed either EOA problem or SDSC from different perspectives. Table 1 presents the summary of related literature regarding EOA problem. The first four rows respectively present the already defined features, including literature, main elements of disaster response decision optimization system, research question, and integrated framework regarding EOA problem. 'Problem characteristics' row describes if heterogeneity, workloads, eligibility restrictions of EO, and urgency as well as setup times of ET is considered. 'Model characteristics' row consists of 'Obj.', 'Main Obj.', and 'Categ.'. Specifically, 'Obj.' row indicates the model is either single or multiple objectives. But 'Main Obj.' row focuses on the factors (e.g., time, cost, carbon emissions, or others) considered in mathematical model. 'Categ.' row demonstrates that the type of model can be integer, 0–1 integer, mixed-integer programming, and others. 'Sustainability' row depicts whether or not sustainability regarding disaster context is considered clearly. The last row represents the solution method is either exact or heuristic.

Table 1. Summary of the literature related to emergency organization allocation (EOA) of the disaster supply chain.

Reference			[12]	[18]	[19]	[20]	[21]	[22]	[24]	[26]	[23]	[25]	This paper
System Elements		**EOs**	√	√	√	√	√	√	√	√	√	√	√
		ETs	√					√	√	√		√	√
		Fit	√						√	√		√	√
Research Question		**Asign.**	√	√	√	√	√	√	√	√	√	√	√
		Stru.	√						√	√		√	√
Integrated Framework		**Yes**											√
		No	√	√	√	√	√	√	√	√	√	√	
Problem Characteristics	**Categ.**	**Homo.**		√	√	√	√	√	√		√	√	
		Hetero.	√							√			√
	Urgen.	**Yes**	√						√			√	√
		No		√	√	√	√	√		√	√		
	Worklo.	**Yes**				√	√			√			√
		No	√	√	√			√	√		√	√	
	Eligib.	**Yes**	√								√		√
		No		√	√	√	√	√	√	√		√	
	Set. Tim.	**Yes**	√						√			√	√
		No		√	√	√	√	√		√	√		
	Othe.			√	√			√					
Model Characteristics	**Obj.**	**Sing.**	√	√	√	√	√			√			
		Multi.						√	√		√	√	√
	Main Obj.	**Time**	√	√		√	√	√	√				√
		Cost						√		√	√		√
		Carbon											√
		Othe.			√				√		√		
	Categ.	**Integ.**						√					
		0–1 Integ.	√				√			√			√
		Mixed Integ.		√							√		
		Othe.			√	√			√			√	
Sustainability		**Yes**											√
		No	√	√	√	√	√	√	√	√	√	√	
Solution Methods		**Exac.**		√	√	√					√		√
		Heur.	√	√			√	√	√	√	√	√	

The following conclusions can be summarized:

(1) The majority of the extant literature defines sustainability and SDSC from a long-term perspective. Besides, reduce, reuse, recovery and recycle are identified as main ideas of SDSC. They mainly focus on the term 'reuse', 'recycle' and 'recovery' during recovery phase. However, the term 'reduce' during response phase from the point of view of short-term perspective is the focus of this paper by comparing with Papadopoulos et al. [2], Kunz et al. [16], and Habib et al. [17].

(2) An empirical or qualitative approach to investigate sustainability or relevant is popular in the existing literature. In addition, Carter et al. [6] clarified that social, economic and ecological dimension could be used to measure sustainability. In this paper, OR/MS method is yet considered to quantitatively characterize sustainability regarding disaster context from these dimensions, which is different from Dubey et al. [3], Haavisto et al. [5,15], and Carter et al. [6]. Meanwhile, an integrated framework with the concern of tasks-oriented EOA is also proposed to elaborate optimized mechanism.

(3) Most of them are only dedicated to assignment of EO except for Wex et al. [12], Zheng et al. [24,25], Rolland et al. [26] and Zhang et al. [18]. At the same time, they merely take into account one or more aspects but not all depicted in Table 1. In contrast, combined issue regarding assignment of EOs, sequences of ETs and their matching relations is concentrated on here. Besides, heterogeneity and eligibility restrictions of EOs, sequences and urgencies of ETs, as well as sustainability are all considered by comparing with all literature presented in Table 1.

(4) Single objective model for EOA is favored in literature except for Su et al. [22], Zhang et al. [23], Zheng et al. [24,25]. Moreover, time or similar is the most popular objective, and cost is the secondary, carbon emissions are rare. Their insights are leveraged and extended here to develop a multi-objective 0–1 integer programming model for EOA regarding sustainability, attempting to minimize total weighted completion times, total carbon emissions, and total emergency costs.

3. Problem Definition

On the one hand, as mentioned above, SDSC can be regarded as organic combinations between sustainable development and traditional disaster supply chain. It attempts ultimately to enhance efficiency of disaster response, reduce emergency costs, and mitigate environmental disruptions. On the other hand, response strategies regarding goals of SDSC are usually made in disaster response decision optimization system, which can be understood as integration of decision-agent, EO, survivors, ET, relief, environment and their interactive relations [12,32].

This paper only involves several critical elements including decision-agent, EO, ET and their matching relations. That is, only response strategies regarding EOA are considered here. Specifically, EO represents a cluster of personnel with technical skills [12,19]. Chen et al. [19] clarified that each EO could be composed of specially trained fire and rescue personnel, physicians, paramedics, structural engineers, canine handlers, crane operators, and others. They also delineated that members of each EO was able to be over 100 personnel. This claim is supported by Virginia Task Force consisting of 131 members as one of the FEMA task forces in response to Haiti earthquake. Besides, according to Wang et al. [32] and Xie et al. [33], it can be inferred that each ET is composed of a series of sub-tasks. For instance, ET regarding relief distribution encompasses multiple sub-tasks with the concern of identification of demand- and supply-point, development of dispatching plan, coordination of transportation resource, and others. In addition to that, matching relations refer to how to assign EOs to accomplish all of ETs in an efficient manner, so as to achieve ultimate goals of SDSC. In summary, both EO and ET discussed in this paper are identified from a coarse-grained perspective. Thus, these critical elements and their relations compose an integrated framework regarding tasks-oriented EOA for SDSC. It is depicted in Figure 2.

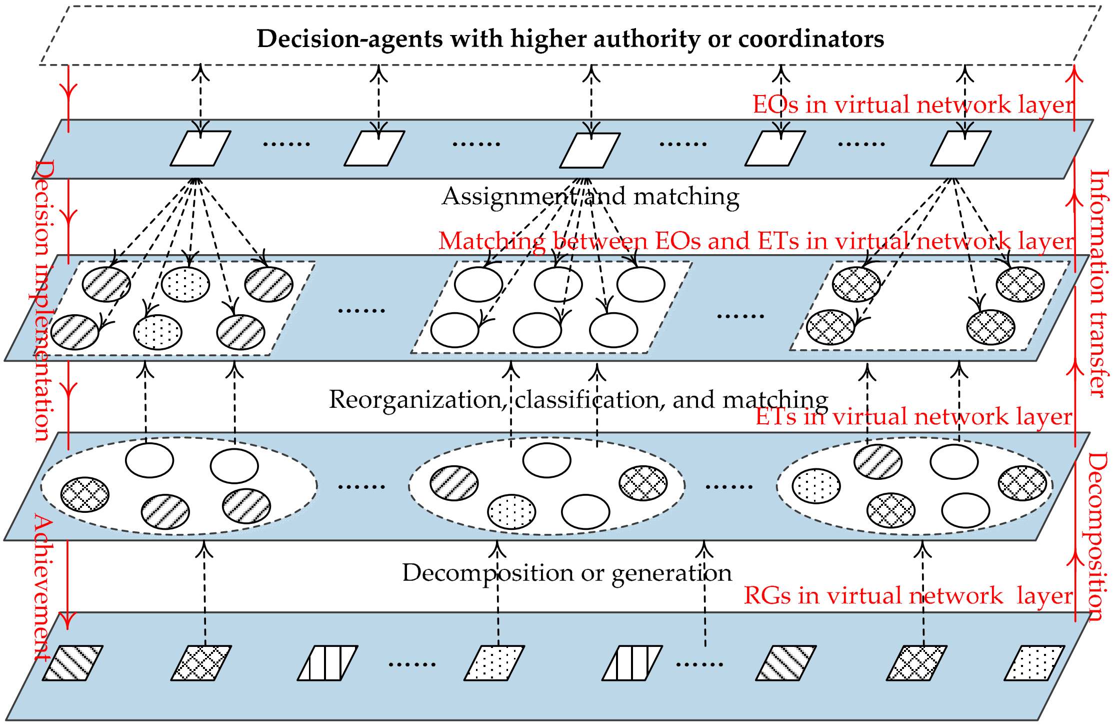

Figure 2. Integrated framework regarding tasks-oriented EOA.

Following Figure 2, it can be concluded that a set of the scattered EOs with different capabilities are identified and virtualized, which results in the corresponding virtual network layer. On the other hand, after the occurrence of natural disasters, rescue goals (RGs) in physical layer are identified, and then mapped into virtual network layer by decision-agents as soon as possible. In practice, RGs will be decomposed into different ETs, thus identifying a series of ETs. In other words, all ETs are generated based on the RGs [32]. Then, these ETs are reorganized and classified, thus constituting ETs in virtual network layer. Thus, coordinators or decision-agents with higher authority would determine the matching relations between EOs and ETs in virtual network layer. In other words, EOs with different capabilities would be assigned to accomplish these ETs in an optimized way.

In this context, the critical issue of this paper is to design an optimized allocation mechanism of EO with the concern of heterogeneity, workloads, and eligibility restrictions, urgency of non-split ETs, and setup times, as well as sustainability. Besides, the term 'reduce' is different from other literature and that is the main focus here. Its essence in nature aims to eliminate redundancies or improve utilization rate of emergency resources, decrease emergency costs, and reduce carbon emissions via the optimized mechanism, thus achieving sustainability of disaster supply chain. More specifically, decision-agents with higher authority need to determine whether or not ETs are assigned to the corresponding EOs, and determine the structure of ETs for each EO. It is obvious that both of them are regarded as decision variables of EOA optimization problem. Meanwhile, decision-agents concentrate on how to achieve the sustainability of disaster supply chain from the perspective of social, economic and ecological dimension.

In detail, with regard to social dimension of sustainability, total weighted completion times are used to characterize it. The reason for doing this includes the following points. On the one hand, it is in accordance with the goal to improve efficiency of disaster response, which is as one of several aspects regarding victims' satisfaction or similar. On the other hand, victims' satisfaction reflected their suffering can to some extent manifest social sustainability [5]. In terms of economic dimension of sustainability, it is measured by total costs spent in accomplishing all ETs [26]. In addition to that ecological dimension of sustainability is captured by carbon emissions produced by all activities involved. It intends to provide a new perspective for decision-agents to make response strategies regarding EOA. Nevertheless, this paper attempts to reduce carbon emissions only via an optimized mechanism of EOA, which indicates that specific methods to measure carbon emissions are out of the scope. In other words, excessive carbon emissions are only produced by wrong matching or fit between EOs and ETs rather than others. To simply real-world cases, average carbon emissions per unit time produced by the activity that ETs processed on EOs are assumed to be given but different.

The reason for doing this includes the following points. Firstly, completion of ETs here needs to rely on transportation tools, professional equipment, or others. It can be inferred that all activities of accomplishing these ETs are energy-consuming (e.g., gasoline, electric energy), thus producing carbon emissions. Secondly, in general, since most of measurements of carbon emissions derived from different types of energy or fields is commonly known [34], carbon emissions produced by unit energy-consumed to accomplish each ET can be naturally obtained. Thirdly, energy-consumed in unit is always directly or indirectly related to distance, time and others [35]. To a large extent, other dimensions are able to be replaced by time through some transformations [36,37]. Fourthly, as ETs that represents a set of sub-tasks are identified from a coarse-grained viewpoint, an average value could be used here. In this context, the assumption that average carbon emissions per unit time spent in accomplishing ETs on EOs seems reasonable. Furthermore, both processing and setup time for any ET processed on EO is known. Consequently, different matching relations between EOs and ETs would result in different total carbon emissions. In this context, change of total carbon emissions would be influenced by processing and setup times of ET.

4. A Multi-Objective Programming Model Formulation

4.1. Explanations of Parameters and Variables

K	Set of m EOs, indexed by $k(\forall k \in K)$
J	Set of n ETs, indexed by $j(\forall j \in J)$
L	Set of n sequences or orders of ETs executed by EOs, indexed by $l(\forall l \in L)$
M_j	Eligibility restrictions of EO k with the concern of ET j
C_j^k	Completion time of ET j on EO k
w_j^k	Weights of ET j executed on EO k
cap_j^k	Whether or not EO k has the capability of executing ET j, namely not every EO is able to execute each ET, and if $k \in M_j$, then $cap_j^k = 1$, otherwise, $cap_j^k = 0$
p_j^k	Non-negative duration or processing time of ET j on EO k
$s_{j,l}^k$	Average setup times of executing ET j with order l on EO k, and it is non-negative
$A_{j,l}^k$	Carbon emissions produced per setup times of executing ET j with order l on EO k
B_j^k	Carbon emissions produced per processing time of ET j on EO k
D_j^k	Carbon emissions produced by other activities of accomplishing ET j on EO k
$a_{j,l}^k$	Cost per setup times of executing ET j with order l on EO k
b_j^k	Cost per processing time of ET j on EO k
h	Average workloads (average amounts of assigned tasks) of each EO
x_j^k	Whether or not EO k is assigned to execute ET j, if yes, then $x_j^k = 1$; otherwise, $x_j^k = 0$
$y_{j,l}^k$	Whether or not sequence of ET j on EO k is l, if yes, then $y_{j,l}^k = 1$; otherwise, $y_{j,l}^k = 0$

4.2. Assumptions

To simplify real-world cases in a reasonable manner and develop a mathematical model, the following necessary assumptions should be clarified.

Assumption 1. *Since each EO and ET that respectively represents a set of personnel and sub-tasks is identified from a coarse-grained perspective, and available computing power is insufficient, small and moderate scale natural disasters are only considered here. Besides, a subset of a large-scale one is also suitable. More details are presented in Section 6.*

Assumption 2. *ETs are non-split and their execution is non-preemptive, and each ET can only be executed once by one of EOs.*

Assumption 3. *All ETs involved here need to be accomplished by professional equipment, transportation tools, and others. In other words, execution of these ETs is energy-consuming (e.g., gasoline, electric energy), thus producing carbon emissions.*

Assumption 4. *EOs are heterogenous, being classified into general and professional type.*

Assumption 5. *Eligibility restrictions of EOs are considered since not every EO has the capability of processing each ET. That is, the capability of each EO of executing ET may be different.*

Assumption 6. *EOs have different processing speeds, thus resulting in different processing times even thought with regard to the same ET.*

Assumption 7. *Processing time, sequences dependent average setup times, costs per processing time and average setup times, carbon emissions produced per processing time and average setup times, and carbon emissions produced by other activities obey uniform distribution.*

4.3. A 0–1 Integer Programming Model for EOA

In this context, EOA taking into account the urgency of tasks, heterogeneity, workloads, eligibility restrictions, setup times dependent on sequences as well as sustainability is formulated as a multi-objective 0–1 integer linear programming model. It is defined as Formulas (1)–(18).

Minimize

$$\sum_{k\in K}\sum_{j\in J} w_j^k C_j^k \tag{1}$$

$$\sum_{k\in K}\sum_{j\in J} w_j^k \left(B_j^k p_j^k + C_j^k\right) x_j^k + \sum_{k\in K}\sum_{j\in J}\sum_{l\in L} w_j^k A_{j,l}^k s_{j,l}^k y_{j,l}^k \tag{2}$$

$$\sum_{k\in K}\sum_{j\in J}\sum_{l\in L} \left(s_{j,l}^k a_{j,l}^k + p_j^k b_j^k\right) y_{j,l}^k \tag{3}$$

Subjective to

$$C_j^k = \sum_{l\in L} \left(s_{j,l}^k + p_j^k\right) y_{j,l}^k \tag{4}$$

$$\sum_{j\in J} x_j^k \geq h / \forall k \in K / \tag{5}$$

$$x_j^k \leq cap_j^k / \forall j \in J, k \in K / \tag{6}$$

$$\sum_{j\in J} x_j^k \leq n / \forall k \in K / \tag{7}$$

$$\sum_{k\in K} x_j^k = 1 / \forall j \in J / \tag{8}$$

$$\sum_{k\in K}\sum_{j\in J} x_j^k = n \tag{9}$$

$$\sum_{l\in L} y_{j,l}^k = x_j^k / \forall j \in J, k \in K / \tag{10}$$

$$\sum_{j\in J}\sum_{l\in L} y_{j,l}^k = \sum_{j\in J} x_j^k / \forall k \in K / \tag{11}$$

$$\sum_{k\in K}\sum_{j\in J}\sum_{l\in L} y_{j,l}^k = \sum_{k\in K}\sum_{j\in J} x_j^k \tag{12}$$

$$\sum_{k\in K}\sum_{l\in L} y_{j,l}^k = 1/\forall j \in J/ \tag{13}$$

$$\sum_{j\in J} y_{j,l}^k \leq 1/\forall l \in L, k \in K/ \tag{14}$$

$$y_{j,l}^k \leq x_j^k/\forall l \in L, j \in J, k \in K/ \tag{15}$$

$$\sum_{j\in J} y_{j,r}^k \geq \sum_{j\in J} y_{j,l}^k/\forall r < l \in L, k \in K/ \tag{16}$$

$$x_j^k = \{0,1\}/\forall j \in J, k \in K/ \tag{17}$$

$$y_{j,l}^k = \{0,1\}/\forall l \in L, j \in J, k \in K/ \tag{18}$$

In the model, Formulas (1)–(3) are objective functions of mathematical programming model. Specifically, Formula (1) is to minimize total weighted completion times as one of the most important focus in traditional disaster supply chain [38–40]. Completion time of ET j is determined by setup times dependent on sequences and processing time. Formula (2) represents the second objective function is to minimize total carbon emissions produced by waiting, processing and other activities, and weights are the relatively urgency of ET j. Formula (3) denotes the third objective function is the minimization of total emergency costs including waiting and executing cost.

Constraint (4) defines completion time of ET j on EO k. Constraint (5) ensures that the number of the assigned ETs for each EO is no less than a fixed or given amount. Constraint (6) gives eligibility restrictions of EO k. Constraint (7) limits the number of the assigned ETs for each EO. Constraint (8) denotes any ET j can only be executed by EO k. Constraint (9) denotes all ETs are executed for SDSC. Constraint (10) indicates ET will be distributed with an order as long as it is assigned to any EO. Constraints (11) and (12) measure balance of the assigned tasks with regard to EO k and disaster response decision optimization system for SDSC, respectively. Constraint (13) demonstrates each ET can only be executed once. Constraint (14) represents the number of the assigned tasks may be different. Constraint (15) shows that sequences of only the assigned tasks on EO k need to be determined, and some sequences of EO k may be idle. Constraint (16) delineates that EO k is allocated in order. Constraints (17) and (18) register 0–1 decision variables.

5. Solution Strategies for Multi-Objective Integer Programming Model

5.1. Reformulations or Transformations of Mathematical Programming Model

5.1.1. Equivalent Mathematical Programming Model

To decrease complexity of the proposed model, some necessary constraints should be checked again. With regard to multi-objective 0–1 integer programming model defined by Formulas (1)–(18), Constraints (8) and (9) are equivalent. Proofs are given as follows.

According to Constraint (8), the following conclusion can be made $\sum_{k\in K} x_j^k = 1/\forall j \in J/$. Then, calculate the sum of two sides of equation with the concern of ETs. Thus, Equation (19) is gained.

$$\underbrace{\sum_{k\in K} x_1^k + \sum_{k\in K} x_2^k + \cdots \sum_{k\in K} x_n^k}_{n} = \underbrace{1 + 1 + \cdots + 1}_{n} = n \tag{19}$$

Consequently, it is able to the aforementioned conclusion. In addition, based on Constraint (10), it can be concluded that $\sum_{l\in L} y_{j,l}^k = x_j^k/\forall j \in J, k \in K/$. And then, compute the sum of two sides of Equation regarding ETs for each EO. Thus, the following equation can be achieved.

$$\underbrace{\sum_{l\in L} y^k_{1,l} + \sum_{l\in L} y^k_{2,l} + \cdots + \sum_{l\in L} y^k_{n,l}}_{n} = \underbrace{x^k_1 + x^k_2 + \cdots + x^k_n}_{n} \Leftrightarrow \sum_{j\in J}\sum_{l\in L} y^k_{j,l} = \sum_{j\in J} x^k_j / \forall k \in K / \tag{20}$$

Therefore, Constraints (10) and (11) play the same role in solving this mathematical model regarding EOA. Furthermore, for SDSC, Equation (21) is obtained after summing two sides of Equation (20) taking into account all EOs.

$$\underbrace{\sum_{j\in J}\sum_{l\in L} y^1_{j,l} + \cdots + \sum_{j\in J}\sum_{l\in L} y^m_{j,l}}_{m} = \underbrace{\sum_{j\in J} x^1_j + \cdots + \sum_{j\in J} x^m_j}_{m} \Leftrightarrow \sum_{k\in K}\sum_{j\in J}\sum_{l\in L} y^k_{j,l} = \sum_{k\in K}\sum_{j\in J} x^k_j \tag{21}$$

Thus, it must be acknowledged that Constraint (11) is equivalent to Constraint (12). In addition to that, the following Equation can be otained acocording to Equation (10).

$$\underbrace{\sum_{l\in L} y^1_{j,l} + \cdots + \sum_{l\in L} y^m_{j,l}}_{m} = \underbrace{x^1_j + x^2_j + \cdots + x^m_j}_{m} \Leftrightarrow \sum_{k\in K}\sum_{l\in L} y^k_{j,l} = \sum_{k\in K} x^k_j = 1/\forall j \in J/ \tag{22}$$

It can be inferred that Constraints (10) and (13) are equivalent. In summary, Constraints (8) and (9) has the same influence on the computational results. Constraints (10)–(12) as well as (13) are all equivalent. In this context, Constraints (8) and (10) are only considered or retained in solving original model. The equivalent integer programming model is defined by Formulas (1)–(8), (10), and (14)–(18).

5.1.2. Handling Strategies for Multiple Objectives

As mentioned above, EOA problem is formulated as a multi-objective integer programming model. In general, handling strategies designed to cope with multiple objectives are very critical, and they ought to be clarified clearly so as to solve the proposed mathematical model. According to the previous works in literature, it can be concluded that the methods to solve multi-objective optimization problem include the weighted sum, epsilon-constraints, and other relevant [30,41,42]. In this paper, their insights are leveraged and extended to develop a linear weighted method to integrate two objective functions into a single one. Consequently, the objective functions can be replaced by the following Formula (23).

$$F(f_1, f_2, f_3) = \beta_1 f_1 + \beta_2 f_2 + \beta_3 f_3 \tag{23}$$

where in f_1 denoted by Formula (1) is the first objective function, f_2 represented by Formula (2) is the second one, and f_3 is the third one. In addition to that β_1, β_2 and β_3 are the weights and preferences of decision-agents on completion times, carbon emissions and emergency costs in making the optimized strategies regarding EOA for SDSC, and $\beta_1 + \beta_2 + \beta_3 = 1$.

5.2. Motivations for Branch and Bound Approach

In this paper, as mentioned above, EOA taking into account sustainability of disaster supply chain and structure of ETs is formulated as a multi-objective 0–1 integer programming model. Besides it is obvious that the proposed multi-objective mathematical model is linear and discrete. That is, it is convex programming, and a unique optimal solution can be garnered. Thus, an exact approach can be considered to solve it. On the other hand, methods to solve such model generally include exhaustion, implicit enumeration, and branch and bound algorithm as well as others. Particularly, EOA problem discussed here is the extension of traditional assignment problem. Branch and bound approach proposed by Richard M. Karp in 1960s is a common way to solve integer programming model. The idea in nature of this method is to search all feasible solution spaces for original optimization problem, thus ultimately obtaining optimal solution. In recent years, branch and bound approach is widely used in the field of disaster supply chain. For instance, Zhan et al. [43] used branch and bound and Bayesian methods to solve single-objective programming model regarding relief allocation. Goerigk et al. [44] developed branch and bound algorithms to solve vehicle routing problem that is formulated as a single-objective mathematical model. In this context, branch and bound approach is leveraged to solve multi-objective 0–1 integer programming model that capture EOA.

5.3. Procedure of Branch and Bound Approach

This subsection presents the procedure of branch and bound approach embedded in EOA problem for SDSC according to Zhan et al. [43] and Goerigk et al. [44]. It is depicted in Figure 3. The following clarifies specific steps.

Step 1: Original and relaxed problem regarding EOA for SDSC is defined as IP and LP, respectively. Relax all binary decision variables (x_j^k and $y_{j,l}^k$) regarding IP as real ones (Z_i), thus LP is obtained.

Step 2: Solve LP, initial upper and lower bound of optimal value of objective function (F^*) are denoted by $\underline{F}$ and $\overline{F}$. Optimal solution of LP (Z_i) is gained.

Step 3: judge whether or not Z_i is integer. If yes, output this solution which is also optimal with respect to original problem (IP); otherwise, turn to next step.

Step 4: Subdivide LP into two sub-problems by adding two constraints related to Z_i, and find their corresponding optimal solutions as well as optimal values.

Step 5: Compare optimal values of objective function for all sub-problems, and then modify the upper and lower bound of optimal value of objective function (F^*).

Step 6: Judge whether or not upper bound equals lower bound of optimal value of objective function. If yes, output this solution (Z^*) and optimal value (F^*); otherwise, turn back to Step 4.

Step 7: Repeat operations pertaining to branch and bound, until optimal solution (Z^*) and value (F^*) of IP is achieved.

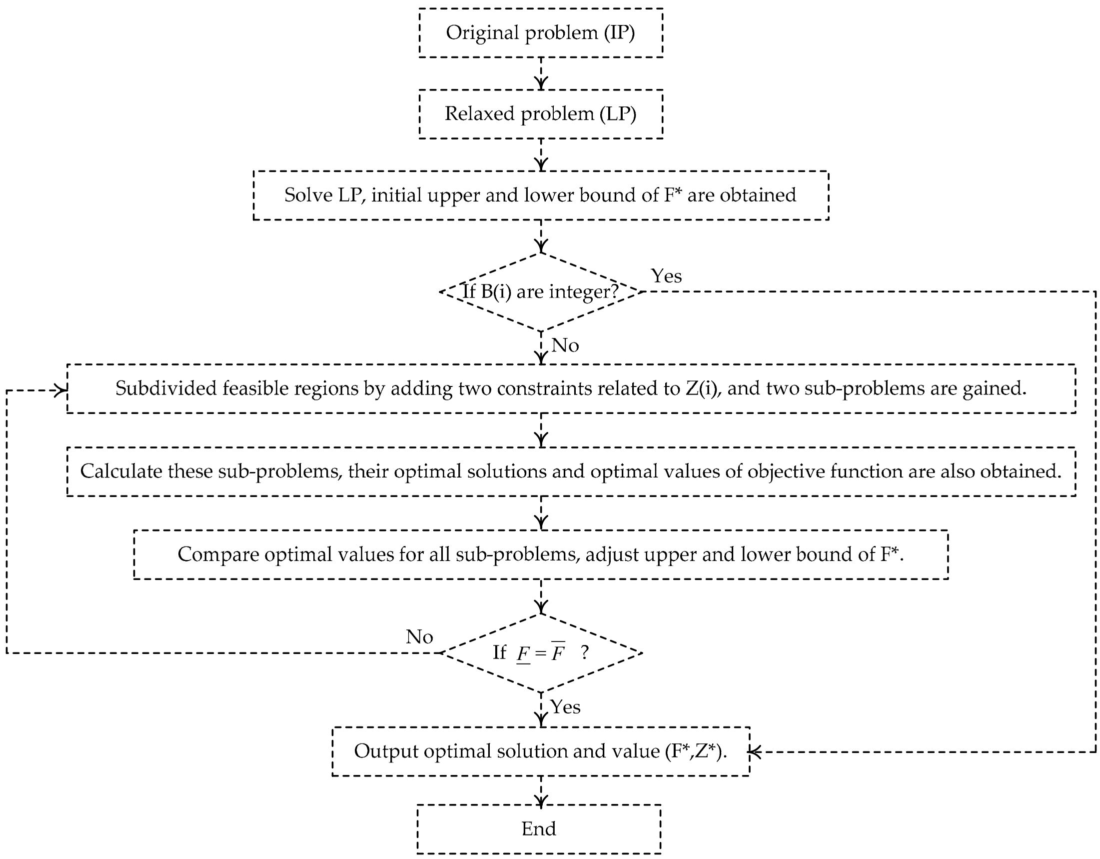

Figure 3. Flowchart of branch and bound regarding EOA for sustainable disaster supply chain (SDSC).

6. Computational Studies

6.1. A Case Study from Wenchuan Earthquake

According to International Disaster Database, Wenchuan earthquake occurred in 2008 resulting in large casualties, property losses, and environmental disruptions. During the whole response phase, more than 300 in total EOs participated in disaster operations [45]. Besides, plenty of ETs need to be executed immediately [32]. For example, evacuating victims in the affected area, distributing relief to beneficiaries, and rescuing, treating as well as transferring the wounded survivors are all critical and urgent tasks.

However, this paper firstly only makes decisions concerning EOA in Wenchuan County within 24 h of the earthquake. This is, only a subset of Wenchuan earthquake is used to validate the proposed model and method. It must be acknowledged that it is very difficult for EOs to enter Wenchuan County during the first day of the earthquake. Critical resources such as professional equipment, medical relief are extremely limited. Thus, there are only a few EOs to execute the urgent tasks. Particularly, as mentioned in Section 3, each EO can consist of more than 100 personnel [19], and each ET is a set of sub-tasks [32,33]. In this context, according to the report of Ministry of Civil Affairs of the People's Republic of China, it can be assumed that there are 3 EOs available over the decision horizon (the first day). As well as 8 ETs need to be processed immediately. Change of the number of EOs and ETs (problem size) from the second day of the earthquake might be increasing until rescue activities are accomplished. In addition to that the first EO belonging general type can process all of ETs, the second and third as professional type is able to respectively execute task 1 to 5, and task 4 to 8. That is, all of EOs have eligibility restrictions. Other necessary parameter settings are presented in Table 2. But there may have different settings with regard to different problem sizes in Section 6.5. Particularly, time, carbon emissions, and emergency cost in unit are hour, kilogram (kg), and ten-thousand CNY, respectively.

Table 2. Parameter settings.

Parameters	The Corresponding Description in Detail
cap_j^k	$cap_j^1 = 1/\forall j/; cap_j^2 = 1/\forall j = 1,2,3,4,5/, cap_j^2 = 0/\forall j = 6,7,8/;$ $cap_j^3 = 1/\forall j = 4,5,6,7,8/, cap_j^3 = 0/\forall j = 1,2,3/$
$p_j^k, s_{j,l}^k$	$p_j^1 \sim U(1,6);\ p_j^2 \sim U(1,3);\ p_j^3 \sim U(2,5);\ s_{j,l}^k \sim U(1,2)$
$A_{j,l}^k, B_j^k, C_j^k$	$A_{j,l}^k \sim U(0,1);\ B_j^k \sim U(1,3);\ C_j^k \sim U(1,1)$
$a_{j,l}^k, b_j^k$	$a_{j,l}^k \sim U(0,1);\ b_j^1 \sim U(0,1);\ b_j^2, b_j^3 \sim U(0,1)$
$\beta_1, \beta_2, \beta_3; w_j^k$	$\beta_1, \beta_2, \beta_3 \in [0,1]; w_j^k \in (0,1]/\forall j/$, and $\sum_{j \in J} w_j^k = 1/\forall k = 1,2,3/$

In this context, according to these input parameters mentioned above, the proposed multi-objective 0–1 integer programming model in Sections 4.3 and 5.1.1 can be rewritten. In other words, all parameters except for decision variables are given by a specific number. Thus, the number of all objective functions, their coefficient, constraints, and decision variables is naturally known. At the same time, branch and bound approach as one of optimization algorithms is applied to solve this model [46–49]. Specifically, the objectives and constraints are mapped into the corresponding elements involved in branch and bound approach. Thus, the proposed model and designed approach are embedded and coded by Matlab (2016b). Finally, all results can be obtained. Furthermore, all experiments are implemented by Matlab (2016b) and run on a computer with a dual-core processor, core i5-5200U under Windows 8.1 Professional.

6.2. Comparision of Optimal Assignments Obtained by Branch and Bound Approach against Best Practice

A deterministic case is considered in this subsection. A fixed value of each parameter can be given by computers. The combinations of these fixed values are regarded as a deterministic instance with 8 ETs and 3 EOs. In this context, one of the feasible assignment schemes regarding EOs from practical decision-agents is defined as the best practice for SDSC. It is depicted in Figure 4a, thus acting as a suitable benchmark. The method doing like this is also considered by Wex et al. [12]. They opined that rescue units assignment scheme obtained from the German Federal Agency of Technical Relief (THW) were treated as the best practice behavior of emergency operation centers. On the other hand, this paper uses branch and bound approach to improve the best practice, thus gaining optimal allocation scheme of EOs presented in Figure 4b.

With regards to Figure 4, the assigned tasks for each EO and their sequences are presented. In addition to that task number, urgencies of ETs, processing time as well as average setup times are presented respectively. Following Figure 4, several conclusions can be made. Firstly, there are significant differences between the best practice and optimal allocation scheme of EOs. In terms of the latter, task 2, 3, 4, 5, 6 and 8 are assigned to the first EO, task 1 is executed by EO 2#, and the third EO is matched with task 7. However, with regard to the former, the first EO processes four tasks in total, and two tasks are respectively assigned to the second as well as third one. Secondly, with respect to optimal allocation scheme regarding EOs obtained by branch and bound approach, total weighted completion times are 3.67 h, total carbon emissions are 5.467 kg, and total emergency costs 185 thousand CNY, as well as run time is 5.18 s. But, in terms of the best practice, they are 5.63 h, 9.72 kg, 351 thousand CNY and 35.27 s, respectively. Thirdly, the make-span of the best practice is 22 h, and that of optimal allocation scheme is 21 h. It indicates that 8 ETs can be finished within 21 h of the earthquake. They have a similar make-span different from total weighted completion times.

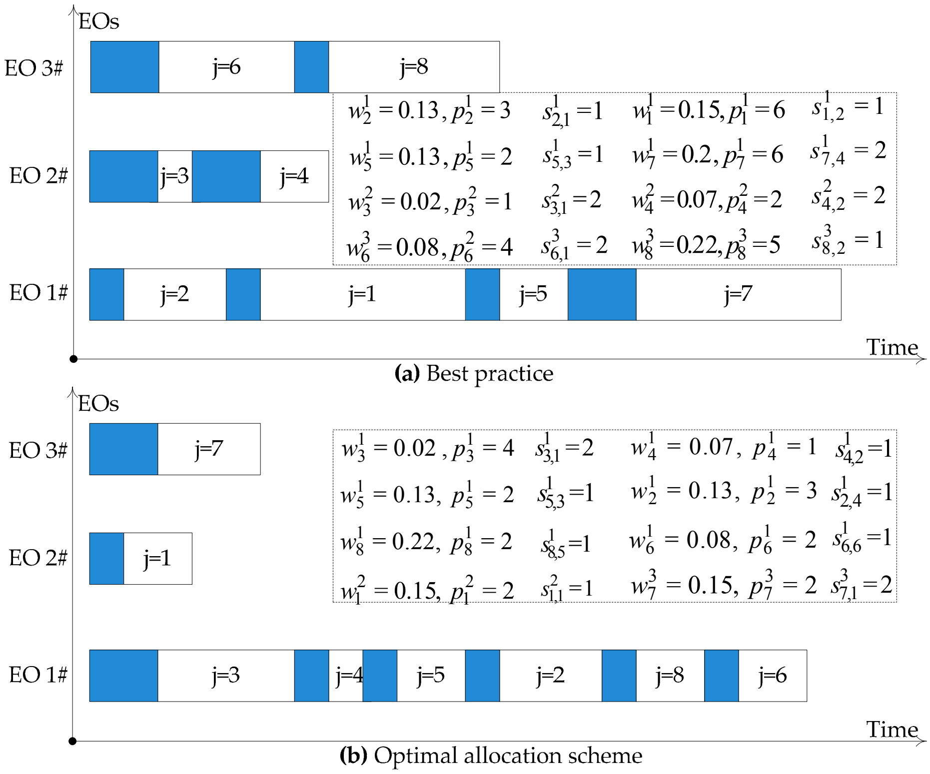

Figure 4. Assignment schemes with 3 emergency organizations (EOs) and 8 emergency tasks (ETs) under deterministic context. (**a**) Best practice obtained from decision-makers; (**b**) Optimal allocation scheme gained by branch and bound approach.

In summary, results indicate that the best practice pertaining to EOA for SDSC can be improved continuously by employing branch and bound approach. Simultaneously, they also demonstrate the proposed model and solution strategies have the potential advantages on solution quality and computation time. It is consistent with the insights provided by Wex et al. [12]. Furthermore, it might be able to enhance the cognition of decision-agents on most of activities with the concern of EOA. Nevertheless, what should be elaborated is that all approaches only intend to help managers to make decisions rather than completely substitute the practitioners.

6.3. Comparisons of Computational Results under Different Scenarios

As mentioned above, most of the parameters, such as processing time, sequence dependent average setup times, cost per processing time and average setup times, carbon emissions produced per processing time and average setup times, as well as carbon emissions produced by other activities obey uniform distribution. That is, the corresponding values of parameters are stochastic or non-deterministic at certain interval. In this subsection, the impacts of non-deterministic parameters on the three objective functions are mainly highlighted. Besides, to demonstrate the potential advantages of EOA model with multiple objectives for SDSC, different scenarios are considered. Specific meanings of different scenarios are clarified in detail in Table 3.

Table 3. Meanings of different scenarios.

Scenario	S1	S2	S3	S4	S5	S6	S7 (This paper)
Objectives	f_1	f_2	f_3	f_1+f_2	f_1+f_3	f_2+f_3	$f_1+f_2+f_3$
Coefficient	$\beta_1=1$	$\beta_2=1$	$\beta_3=1$	$\beta_1=0.5/\beta_2=0.5$	$\beta_1=0.5/\beta_3=0.5$	$\beta_2=0.5/\beta_3=0.5$	$\beta_1=1/3/\beta_2=1/3/\beta_3=1/3$

It is obvious that seven scenarios are simultaneously addressed. Particularly, the unmentioned coefficients for each scenario equal zero. In this subsection, ten experiments and their average are independently conducted for each scenario so as to present a general conclusion. Computational results obtained by branch and bound approach under different scenarios are given as the following Table 4.

Table 4. Computational results under different scenarios.

Obj.		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Ave.**
S1	f_1	3.95	3.07	3.8	3.25	2.95	3.17	3.41	3.24	3.65	4.37	3.486
	f_2	5.53	6.03	5.1	6.15	5.08	6.08	6.61	5.07	6.94	7.54	6.013
	f_3	214	253	268	275	321	315	311	292	255	328	283.2
S2	f_1	4.49	3.22	2.74	3.43	3.03	3.28	4.44	3.9	3.17	3.75	3.545
	f_2	5.48	4.65	4.31	5.85	4.5	3.67	5.43	4.16	4.89	8.75	5.169
	f_3	372	243	233	341	182	190	436	320	196	249	276.2
S3	f_1	4.17	4.28	4.16	3.79	3.55	3.63	4.29	3.96	3.91	3.51	3.925
	f_2	9.55	5.9	6.47	7.06	7.35	6.33	5.31	6.95	6.74	5.93	6.759
	f_3	167	182	181	152	189	133	161	127	142	139	157.3
S4	f_1	3.39	3.09	2.62	3.51	3.62	2.96	2.71	4.29	3.71	3.75	3.365
	f_2	5.06	4.5	3.01	5.01	4.64	3.54	4.59	5.95	6.19	8.75	5.124
	f_3	260	246	265	236	259	283	185	289	299	249	257.1
S5	f_1	4.26	5	3.66	5.09	4.59	3.81	4	3.97	4.91	4.46	4.375
	f_2	7.79	7.38	8.54	6.33	7.14	6.47	6.87	7.39	9.61	8.67	7.619
	f_3	177	176	186	158	162	170	190	226	145	142	173.2
S6	f_1	4.7	4.09	3.32	2.77	4.19	3.54	3.28	5.28	4.21	3.54	3.892
	f_2	6.92	6.45	5.47	4.79	9.41	4.79	4.15	9.98	6.84	5.26	6.406
	f_3	181	256	180	172	186	128	164	196	159	143	176.5
S7	f_1	4.28	3.09	3.37	3.77	3.92	3.42	2.78	3.78	4.24	4.41	3.706
	f_2	7.09	4.95	4.61	5.75	5.54	6.8	5.19	6.95	7.92	6.4	6.12
	f_3	136	209	109	141	215	127	152	188	178	182	163.7

According to computational results depicted in Table 4, several critical issues can be concluded. Firstly, average value of total weighted completion times is 3.706 h, that of total carbon emissions is 6.12 kg, and average emergency costs are 163.7 CNY. Thus, it can be seen that average weighted completion times spent in executing 8 ETs by 3 EOs are 3.706 h, which differs from their make-span. It produces averagely carbon emissions with 6.12 kg, and spends averagely emergency costs with 163.7 thousand CNY. Secondly, the advantage of the proposed model on total weighted completion times is supported by the results under scenario 1, 4, 5 and 7. Results obtained under scenario 2, 4, 6 and 7 demonstrate that the objectives to reduce carbon emissions and others can be achieved with a median value. Comparisons of results garnered under scenario 3, 5, 6 and 7 indicate that it has the advantages on emergency costs. Overall, although the optimal value of each objective function under different scenarios is not found by the proposed model and method, it gets a better trade-off value among all objectives from a global perspective. In this context, computational results, to a large extent, provide sufficient proofs to test potential advantages of the model with the concern of response time, carbon emissions and emergency costs.

6.4. *Sensitivity Analysis of Preferences of Decision-Agents under Non-Deterministic Context*

To verify the impacts of preferences of decision-agents or coefficients of objective functions on results, ten experiments as well as stochastic parameters which are similar to the case discussed in Section 6.3 are simultaneously considered. Due to the limited space, only computational results of sensitivity analysis of decision-agents' preference on total weighted completion times are presented in Table 5.

Table 5. Sensitivity analysis of preferences of decision-agents on weighted completion time.

Preferences	Objectives	①	②	③	④	⑤	⑥	⑦	⑧	⑨	⑩	Ave.
$\beta_1 = 0, \beta_2 = \beta_3 = 0.5$	f_1	4.28	3.40	3.77	3.77	3.92	3.48	2.78	3.78	4.24	4.41	3.783
	f_2	7.09	5.22	4.92	5.75	5.54	7.08	5.19	6.95	7.92	6.40	6.206
	f_3	136	205	103	141	215	124	152	188	178	183	162.5
$\beta_1 = 0.1, \beta_2 = \beta_3 = 0.45$	f_1	4.29	3.83	5.61	4.59	3.06	4.00	4.01	5.01	4.71	4.70	4.381
	f_2	6.35	7.70	6.20	7.14	4.38	6.87	7.25	9.56	8.46	6.92	7.083
	f_3	186	194	156	162	185	190	227	145	140	181	176.6
$\beta_1 = 0.2, \beta_2 = \beta_3 = 0.4$	f_1	4.09	3.32	2.75	3.67	3.54	3.08	5.28	4.21	3.54	4.74	3.822
	f_2	6.45	5.47	4.79	7.08	4.79	3.89	9.98	6.84	5.26	10.36	6.491
	f_3	256	180	172	211	128	167	196	159	143	142	175.4
$\beta_1 = 0.3, \beta_2 = \beta_3 = 0.35$	f_1	3.70	3.97	3.43	3.79	3.33	3.63	3.91	3.59	3.42	3.11	3.588
	f_2	7.05	5.24	6.23	7.06	6.54	6.33	5.16	6.01	5.18	5.32	6.012
	f_3	184	183	185	152	196	133	162	135	150	143	162.3
$\beta_1 = 0.4, \beta_2 = \beta_3 = 0.3$	f_1	4.33	3.87	2.87	4.22	3.53	3.19	3.14	3.77	3.59	4.03	3.654
	f_2	6.16	7.38	4.98	6.88	6.74	4.37	6.52	5.91	5.93	6.13	6.100
	f_3	190	150	189	173	134	181	148	158	144	173	164.0
$\beta_1 = 0.5, \beta_2 = \beta_3 = 0.25$	f_1	3.29	5.84	4.04	3.70	3.78	3.80	2.81	3.43	3.94	3.21	3.784
	f_2	5.77	8.55	7.25	6.59	5.57	5.19	4.34	6.37	6.70	6.36	6.269
	f_3	130	205	190	162	186	172	136	160	158	133	163.2
$\beta_1 = 0.6, \beta_2 = \beta_3 = 0.2$	f_1	3.63	3.53	2.72	3.13	3.92	3.24	2.60	3.49	3.19	3.31	3.276
	f_2	7.59	4.96	5.02	5.94	6.03	6.27	3.49	6.48	6.14	5.89	5.781
	f_3	96	161	148	223	154	178	170	166	157	253	170.6
$\beta_1 = 0.7, \beta_2 = \beta_3 = 0.15$	f_1	3.32	3.57	3.57	3.47	3.67	2.80	3.50	3.29	4.84	4.92	3.695
	f_2	5.37	6.97	6.38	4.93	6.84	4.49	6.61	4.42	9.39	7.64	6.304
	f_3	202	193	225	245	193	141	162	179	238	148	192.6
$\beta_1 = 0.8, \beta_2 = \beta_3 = 0.1$	f_1	3.05	3.19	3.66	3.68	3.36	2.97	3.60	3.42	2.49	3.44	3.286
	f_2	5.48	5.71	7.00	6.61	5.58	5.31	5.07	6.65	4.42	6.83	5.866
	f_3	179	169	193	181	237	180	177	177	146	204	184.3
$\beta_1 = 0.9, \beta_2 = \beta_3 = 0.05$	f_1	2.65	3.63	3.48	4.22	3.17	3.58	2.59	3.44	4.10	3.61	3.447
	f_2	5.36	6.51	4.87	7.28	5.75	6.80	4.32	5.14	5.97	6.57	5.857
	f_3	172	283	270	245	126	305	224	281	162	163	223.1
$\beta_1 = 1, \beta_2 = \beta_3 = 0$	f_1	3.05	2.82	3.07	3.77	3.44	3.12	3.23	3.54	3.54	2.86	3.244
	f_2	4.28	4.13	7.32	6.31	5.12	7.58	5.21	4.74	6.72	5.19	5.660
	f_3	302	260	265	276	213	219	298	261	321	186	260.1

The following conclusions can be inferred based on the results in Table 5. Firstly, with an increasing preference of decision-agents (β_1), average value of total weighted completion times and that of total carbon emissions show a smooth and decreasing trend at certain interval. In contrast, total emergency costs demonstrate an increasing and relatively sharp tendency. Besides, it has a larger fluctuation at interval [162, 261]. Secondly, it is reported that minimums or optimal values of total weighted completion times and total carbon emissions are located in $\beta_1 = 1$. Unexpectedly, their maximum are simultaneously achieved while $\beta_1 = 0.1$ rather than $\beta_1 = 0$. In addition, minimal emergency costs obtained in $\beta_1 = 0$ are 162.5 thousand CNY. And its maximum is 260.1 thousand CNY, which can be found in $\beta_1 = 1$. To present a more general conclusion, sensitivity analysis of preferences of decision-agents on all or three objective functions (β_1, β_2, β_3) is conducted. All results are depicted in Figure 5.

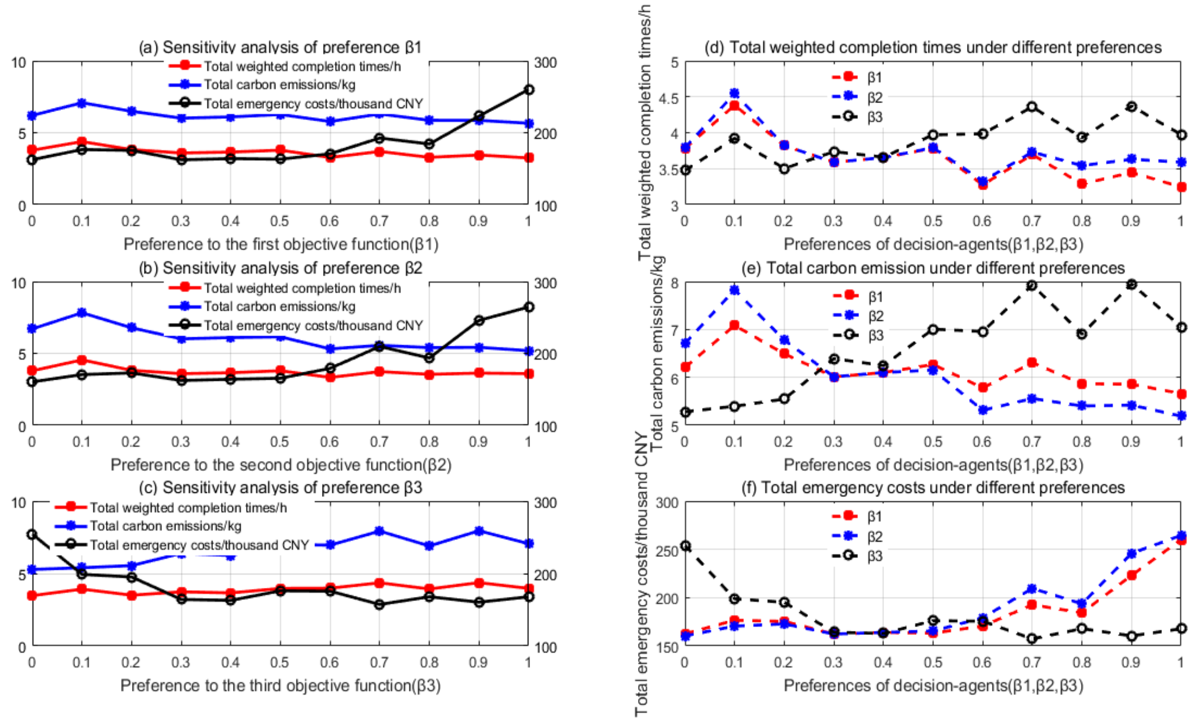

Figure 5. Sensitivity analysis of decision-agents' preferences to three objective functions. (**a**) Sensitivity analysis of preference β_1; (**b**) Sensitivity analysis of preference β_2; (**c**) Sensitivity analysis of preference β_3; (**d**) Change of total weighted completion times under different preferences; (**e**) Change of total carbon emissions under different preferences; (**f**) Change of total emergency costs under different preferences.

Particularly, Figure 5a–c respectively depicts the results regarding each kind of preference of decision-agents on three objective functions. Figure 5d–f presents the change of total weighted completion times, total carbon emissions, and total emergency costs under different preferences of decision-agents, respectively. According to Figure 5, some key points are able to be summarized. Firstly, with the increasing values of preferences, change trend of both total weighted completion times and total carbon emissions is always opposite to that of total emergency costs. Besides, the change trend of the former two is smoother than that of the third objective function. In other words, the value of total emergency costs has a larger fluctuation. Secondly, Figure 5d indicates that total weighted completion times under different preferences at interval [0.3, 0.4] are similar approximately. Besides, it can be also supported by the case of total carbon emissions based on Figure 5e. Differing from the former two objective functions, Figure 5f demonstrates that total emergency costs have no obvious change at interval [0.3, 0.6]. Thirdly, total weighted completion times as well as total carbon emissions with the concern of varying preference of decision-agents to the third objective function (β_3) are the best at interval [0, 0.3]. Yet optimal total emergency costs located at this interval are garnered according to varying β_2. Fourthly, at interval [0.4, 1], optimal values of the former two objective functions are obtained under the varying β_1 and β_2, respectively. And total emergency costs located at interval $\beta_3 \in [0.6, 1]$ are the best.

In summary, the computational results provide useful proofs and insights to the practice of emergency organization allocation (EOA) with the concern of sustainability. More specifically, preferences of decision-agents have more significant impacts on emergency costs than both total weighted completion times and total carbon emissions. Therefore, it can be inferred that a sufficient financial support plan in practice plays a significant role in developing the targeted allocation scheme regarding EOs for SDSC. In the extant literature, Su et al. [22], Zheng et al. [23], and Rolland et al. [26] also addressed the importance of financial support in the context of disaster. Besides, on the condition that keep total completion times and total carbon emissions in a reasonable range, it is necessary for beneficiaries to minimize total emergency costs as much as possible. Overall, preferences of different decision-agents ought to be considered into rescue activities with the concern of EOA for SDSC. Similar conclusions in the field of emergency logistics were provided by Sheu et al. [50].

6.5. Comparisons of Computational Results under Different Problem Sizes

This subsection validates the proposed model and solution strategies from the perspective of problem size. Both the number of EOs and that of ETs are limited to a maximum of 30, which seems realistic [12]. Their matching relations in detail are presented in Table 6. The motivations doing like this include the following several points. Firstly, as elaborated in Section 3, a single EO discussed in this paper may be composed of multiple personnel, and each ET represents a set of multiple sub-tasks. Besides, Chen et al. [19] delineated that this claim could be also supported by practice of disaster management. Secondly, it is obvious that the proposed model or this issue here is static. Nevertheless, decisions regarding EOA in practice should be dynamic. Decision support system updates optimal allocation scheme of EO over time. To simplify this model, a discrete manner rather than continuous one is considered [19]. Thirdly, if decision-agents determine to update the current allocation scheme of EOs, a new instance is created. Since some EOs have been already assigned to conducted tasks, and some of known ETs either have already been or are being executed, it is assumed that new instance satisfies these limits. Fourthly, with regard to the implausible case or instance that includes more than 30 EOs and ETs, optimal solution cannot be obtained within a reasonable time. That is, available computing power is insufficient. Fifthly, it may exceed the maximal dimensions of matrix defined in Matlab (2016b), and notation '-' in Table 6 represents this case. In this context, computational results regarding different problem sizes are presented in Table 6. In addition, each case is implemented for five times, and their average is computed.

Following Table 6, it is reported that for a set of given ETs excluding size 20, total weighted completion times, total carbon emissions, total emergency costs, and combined results show mostly the decreasing tendency with an increasing number of EOs. Particularly, in terms of 20 ETs, the four indicators mentioned above are firstly decreasing, and then have a slightly increasing trend. Secondly, for the given EOs, computational results are mixed together with increasing number of ETs. Specifically, total completion times and total carbon emissions suggest a decreasing trend, and total emergency costs show an uptrend after decreasing for 10 and 20 ETs. Yet most of results with the concern of instances including 3 ETs do not show the expectations. As a consequence, results are better only in some cases. Thirdly, with increasing problem sizes, computational results indicate that run time of programs is always increasing, which is consistent with real case. However, it is unexpected that the time spent in obtaining optimal solution of the largest instance consisting of 20 EOs and 30 ETs is more than half an hour. As decisions in the context of disaster should be made within 30 min [12], this situation requires a lot of attention in practical rescue activities after the occurrence of natural disasters. Overall, the advantages of the proposed model and solution strategies to a large extend are provided from the point of view of problem size.

Table 6. Computational results for different problem sizes.

|J|		8	10		15		20			25			30			
|K|		**3**	**3**	**10**	**3**	**10**	**3**	**10**	**20**	**3**	**10**	**20**	**3**	**10**	**20**	**30**
f	1	9.42	11.30	6.70	11.13	5.93	13.67	6.04	6.77	17.05	6.13	5.96	16.48	6.51	5.78	-
	2	9.25	10.15	6.37	11.86	5.86	11.90	6.54	7.21	18.96	6.69	6.10	19.50	6.82	6.13	-
	3	7.21	10.83	7.92	12.62	5.97	16.02	5.87	7.52	16.47	6.03	6.71	20.34	6.34	5.18	-
	4	7.54	10.68	6.15	12.58	6.44	14.61	6.59	6.92	17.49	6.64	5.82	19.66	5.40	5.80	-
	5	9.97	9.55	7.37	10.61	6.38	15.47	5.44	6.08	22.44	6.42	6.39	20.33	5.68	6.40	-
	Ave.	8.68	10.50	6.90	11.76	6.12	14.33	6.10	6.90	18.48	6.38	6.20	19.26	6.15	5.86	-
f_1	1	3.88	4.36	3.98	4.05	3.61	4.33	3.47	3.63	3.75	3.78	3.10	4.41	3.34	3.50	-
	2	4.43	4.30	4.31	3.67	3.77	4.33	4.06	4.35	3.83	3.37	3.34	4.15	3.40	3.71	-
	3	2.76	4.06	4.68	3.37	3.04	4.15	3.22	4.17	4.25	4.23	3.89	4.16	3.75	3.40	-
	4	3.36	4.79	3.37	3.50	3.84	4.34	3.68	4.23	3.73	3.67	3.69	4.29	3.76	3.33	-
	5	3.93	4.25	3.85	3.80	3.78	3.59	3.44	3.64	3.79	3.84	3.69	4.56	3.60	3.26	-
	Ave.	3.67	4.35	4.04	3.68	3.61	4.15	3.57	4.00	3.87	3.78	3.54	4.31	3.57	3.44	-
f_2	1	6.47	7.74	5.91	7.05	6.77	7.19	5.35	6.56	6.02	5.81	4.98	7.43	5.00	5.74	-
	2	7.93	8.85	6.59	6.50	5.92	6.55	5.64	5.99	6.85	5.50	5.05	8.15	5.07	5.69	-
	3	3.96	6.91	7.98	5.80	5.26	7.29	5.28	6.50	7.47	6.56	6.55	6.56	5.57	5.34	-
	4	5.07	6.54	5.58	6.34	6.77	7.49	6.29	5.83	6.85	5.85	5.27	7.89	5.33	5.16	-
	5	7.79	9.11	6.97	5.82	6.07	6.70	5.66	5.49	6.42	6.02	5.68	8.62	5.64	5.64	-
	Ave.	6.24	7.83	6.61	6.30	6.16	7.04	5.64	6.07	6.72	5.95	5.51	7.73	5.32	5.51	-
f_3	1	179	218	102	223	74	295	93	101	414	88	98	376	112	810	-
	2	154	173	82	254	79	248	99	113	462	112	99	462	120	90	-
	3	149	215	111	287	96	366	91	119	377	73	97	503	97	68	-
	4	142	207	95	279	87	320	98	107	419	104	85	468	710	890	-
	5	182	153	113	222	93	361	72	91	571	94	98	478	780	103	-
	Ave.	161	193	100	253	86	318	91	106	449	94	95	457	364	392	-
R.	1	1.1	0.4	1.0	0.9	2.2	0.9	8.9	78.1	2.8	9.6	184	1.9	136	3561	-
	2	0.1	0.2	0.2	0.4	2.4	0.5	45.0	92.7	2.4	143	1165	1.5	39.2	4189	-
	3	0.1	0.2	0.3	0.3	1.3	0.8	8.2	75.3	4.9	18.7	1021	24.2	446	663	-
	4	0.1	0.3	0.4	0.3	1.6	1.2	6.1	51.1	1.2	22.0	666	4.0	35.4	997	-
	5	0.1	0.4	0.2	0.4	1.9	0.8	4.0	62.8	3.3	66.9	1667	8.8	204	3621	-
	Ave.	0.3	0.3	0.42	0.5	1.9	0.8	14.4	72.0	2.9	52.0	941	8.1	172	2606	-

Notes: R. is short for run time of programs.

7. Conclusions

This paper formulates the EOA problem regarding sustainability of disaster supply chain and sequences of tasks as a novel multi-objective 0–1 integer programming model. Sustainability in the disaster context is measured by social, economic and ecological dimensions. Additionally, total weighted completion times, total carbon emissions and total emergency costs are respectively used to characterize social, ecological and economic dimension of sustainability. In addition to that EOs have different capabilities of processing ETs in disaster response decision optimization system. ETs are non-split and non-preemptive. In this context, an integrated framework with the concern of tasks-oriented EOA is proposed.

Computational results provide several insights on theory and practice of EOA with the concern of sustainability of disaster supply chain. Firstly, a theoretical link between sustainable development and traditional disaster supply chain is considered to improve the coordination between EOs to accomplish

ETs [51]. Secondly, it attempts to provide a new perspective for decision-agents to integrate carbon emissions produced by mismatching between EOs and ETs into making decisions on EOA problem.

In practice, firstly, the combined results indicate mathematical programming method is suitable for modeling EOA problem. It can benefit the improvement of ecological environment and efficiency of disaster response, as well as reduction of emergency costs. Thus, the cognition of decision-agents on all activities regarding EOA for SDSC can be enhanced. Secondly, best practice of EOA for SDSC can be improved continuously by employing branch and bound approach, which yet cannot fully substitute practitioners. This point is also highlighted by Wex et al. [12]. Thirdly, a single objective is hard to capture and characterize uncertainties of natural disasters. Thus, multiple objectives in accordance with real-world case should be considered to cope with these complexities of rescue activities. Fourthly, preferences of decision-agents have significant influences on total emergency costs. It can be inferred that sufficient financial support plan is necessary and critical in developing EOA scheme [22,23,26]. Fifthly, instance with a larger size from real-world case is able to be subdivided into several groups with a relatively small size so as to save times or garner optimal solution within a reasonable time. Particularly, this paper aims to not only evaluate and validate the proposed model and method, but highlight the importance and urgency of EOA problem with the concern of sustainability.

Valuable topics remain for further study. Firstly, a bi-level programming model to characterize vertical intergovernmental relations among beneficiaries in decentralized context is the follow-up research. Secondly, psychological perception of EOs can be considered into the design of allocation mechanism for SDSC in the future. Thirdly, as mentioned above, large instance consisting of more than 30 EOs and ETs is hard to find solution. A heuristic algorithm (such as genetic algorithm, plant growth simulation algorithm) with high performance will be designed to solve this class of model in next work [52].

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