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1 A novel multi-objective programming model of relief distribution for sustainable disaster 2 supply chain in large-scale natural disasters

3 Ce-jun Cao^{a,b}, Cong-dong Li^{b,a,*}, Qin Yang^c, Yang Liu^{b,d,*}, Ting Qu^b

4 ^a College of Management and Economics, Tianjin University, Tianjin, 300072, China

5 ^b Institute of Physical Internet, Jinan University (Zhuhai Campus), Zhuhai, 519070, China

6 ^c School of Business, Sichuan Normal University, Chengdu, 610101, China

7 ^d Department of Management and Engineering, Linköping University, SE-581 83 Linköping, Sweden

8 **Corresponding Authors*: licd@jnu.edu.cn (C.D. Li), yang.liu@liu.se (Y. Liu)

9 **Abstract** To save lives and reduce suffering of victims, the focus here is to design the strategies of
10 relief distribution regarding beneficiary perspective on sustainability. This problem is formulated as a
11 multi-objective mixed-integer nonlinear programming model to maximize the lowest victims'
12 perceived satisfaction, and minimize respectively the largest deviation on victims' perceived
13 satisfaction for all demand points and sub-phases. Then, genetic algorithm is proposed to solve this
14 mathematical model. To validate the proposed methodologies, a case study from Wenchuan
15 earthquake is illustrated. Computational results demonstrate genetic algorithm here can achieve the
16 trade-off between solution quality and computation time for relief distribution with the concern of
17 sustainability. Furthermore, it indicates that the methodology provides the tools for decision-makers
18 to optimize the structure of relief distribution network and inventory, as well as alleviate the suffering
19 of victims. Increasingly, this paper expects to not only validate the proposed model and method, but
20 highlight the importance and urge of considering beneficiary perspective on sustainability into relief
21 distribution problem.

22 **Keywords:** Relief distribution; Sustainable disaster supply chain; Victims' perceived satisfaction;
23 Multi-objective programming model; Genetic algorithm

24 1. Introduction

25 The International Disaster Database (EM-DAT) indicates the total number of both natural disasters
26 and the affected people have steadily increased since 1900s. Such natural disasters pose serious
27 threats to sustainable development of society, economy and ecology, as well as place populations at
28 risk. Particularly, large-scale natural disasters have occurred frequently, resulting in tremendous

29 consequences, such as large casualties, property losses, and environmental disruption (Papadopoulos
30 et al., 2017; Anaya-Arenas et al., 2014). For instance, it was estimated that the total number of death,
31 injury, and being missing was respectively at least 69,016, 368,565, and 18,498, as well as direct
32 economic losses exceeded 845.14 billion CNY in the great Wenchuan earthquake (Huang et al., 2015;
33 Chen et al., 2013). Since the frequency of large-scale natural disasters increased sharply, to save lives,
34 decrease human suffering, and contribute to development as much as possible, the pressing need for
35 sustainable disaster supply chain (SDSC) remains an issue regardless of increasing contributions in
36 this field. This insight is also supported by Dubey et al. (2016), Haavisto et al. (2014) and
37 Halldórsson et al. (2010).

38 According to the insights of Dubey et al. (2016) and Haavisto et al. (2014), this paper infers that
39 SDSC can be regarded as the result of the idea of sustainable development organically being
40 integrated into traditional disaster supply chain (TDSC). To have a better understanding of SDSC, the
41 definition of TDSC ought to be first elaborated clearly. Hoyos et al. (2015), Van Wassenhove (2006)
42 and Altay et al. (2006) clarified that TDSC aimed to employ modern technologies and MS/OR
43 methods to monitor, response, control and manage disasters and their consequences from supply-side
44 to demand-side by integrating relief resources, human capitals and other necessities, thus mitigating
45 or reducing the catastrophic consequences. On the other hand, Dubey et al. (2016) clarified that
46 TDSC would be guided by sustainable development and ecological balance in the future. In terms of
47 sustainability concerning disaster context, Weerawardena et al. (2010) opined that sustainability in
48 non-profit organization was able to survive so that it can continue to serve its constituency, or being
49 understood roughly as maintaining operations. Ibegbunam et al. (2012) further defined sustainability
50 as being related to responsible communication and coordination, thus enhancing the responsiveness
51 of disaster supply chain. Haavisto et al. (2013) classified various sustainability expectations into
52 societal, beneficiary, supply chain and program perspective. In this context, SDSC here intends to
53 achieve the coordinated development regarding social, economic and ecological dimensions of
54 sustainability by improving the efficiencies of disaster response strategies, thus saving lives,
55 decreasing human suffering, and contributing to development as much as possible. A similar
56 viewpoint which is that efficient response can drastically reduce the impacts of disasters on society,
57 economy and environment is mentioned by Hoyos et al. (2015).

58 In recent several decades, TDSC has received increasing attention from academia and practitioners.
59 Meanwhile, relief distribution as one of the most active topics in TDSC becomes popular
60 (Anaya-Arenas et al., 2014). That may be because 80 percentage of disaster supply chain takes
61 logistic activities into account, which was portrayed by Van Wassenlove et al. (2006). However,
62 SDSC remains still in its early stage. Even so, it must be acknowledged that either relief distribution
63 or disaster relief supply chain plays an important role in SDSC (Haavisto et al., 2014). Main
64 differences between TDSC and SDSC may be determined by their motivations, objectives, methods
65 and others. In addition, Camacho-Vallejo et al. (2015) delineated that some of the most commonly
66 sent relief need to be distributed efficiently to the affected areas, thus avoiding increasing death from
67 starvation and disease. Caunhye et al. (2012) also highlighted the significance and necessity of
68 efficient distribution of urgent relief after the occurrence of large-scale disasters. What they
69 addressed is consistent with the objectives of SDSC. More precisely, it is one of the ultimate goals of
70 SDSC. Consequently, it can be inferred that the need for relief distribution for SDSC is pressing.

71 Though relief distribution for SDSC has gained increasing attention from academia and practitioners
72 in recent years, it is still in its infancy. Firstly, plenty of research has been done in commercial supply
73 chain regarding sustainability, but such topic is still very limited in disaster supply chain (Habib et al.,
74 2016; Dubey et al., 2016). Besides, most of them discussed sustainability of disaster supply chain
75 during recovery phase with a long-term period. How to interpret the sustainability during response
76 phase with a short-term period is an interesting and promising topic, which is also mentioned by
77 Anaya-Arenas et al. (2014). Secondly, most of researchers were dedicated to presenting the
78 comprehensive dimensions of sustainability of disaster supply chain, developing the corresponding
79 theoretical framework, as well as testing them by using either empirical or qualitative method
80 (Dubey et al., 2016; Haavisto et al., 2014). In other words, they tried to answer what the indicators to
81 measuring sustainability of disaster supply chain are. But how to characterize these potential
82 indicators in a quantitative manner is considered rarely. Thirdly, as mentioned above, topic on relief
83 distribution is very popular in TDSC. Although some of scholars addressed the importance of this
84 issue in SDSC, how to incorporate some of the indicators to measuring sustainability into relief
85 distribution strategies still needs to be further studied (Haavisto et al., 2014). In addition to that how
86 to formulate relief distribution model with sustainability consideration, and design the corresponding
87 solution strategies can only be found in a few literature.

88 In this context, this paper firstly focuses on sustainable disaster supply chain (SDSC), and devotes to
 89 describing, characterizing and modelling sustainability with the concern of response phase. In fact,
 90 the goals of disaster response to some extent are line with those of recovery activities for a short-term
 91 perspective. For instance, during response phase, relief distribution to victims in the affected areas
 92 aims to save lives, reduce their suffering and others, which are also considered during the short-term
 93 recovery activities. Secondly, Carter et al. (2008) clarified that sustainability could be measured by
 94 triple bottom line model including social, economic and environmental dimensions. Haavisto et al.
 95 (2013, 2014) delineated that societal, beneficiary, supply chain and program perspective was able to
 96 elaborate the sustainability of disaster context. An interesting point is that the essence of
 97 sustainability defined respectively by social dimension of Carter et al. (2008) and beneficiary
 98 perspective of Haavisto et al. (2013, 2014) to some extent is very similar. This paper leverages and
 99 extends their insights to characterize sustainability of relief distribution in MS/OR manner only from
 100 beneficiary perspective, including access, equity, and needs fulfilment aspects. Thirdly, on the
 101 condition of considering the access of beneficiaries (victims) and demand points, both equity and
 102 needs fulfilment are simultaneously taken into account objective functions. Thus, this problem is
 103 formulated as a mathematical programming model. Then, genetic algorithm (GA) as very popular
 104 method in disaster relief operations, whose optimization mechanism is derived from Darwin's theory
 105 of evolution is designed to solve this model (Holland, 1975). And encoding, population, fitness
 106 function, selection, crossover, mutation are main operators of GA.

107 The contributions of this paper include three points. Firstly, SDSC different from previous one is the
 108 focus of this paper, and beneficiary perspective on sustainability regarding access, equity and needs
 109 fulfilment is quantitatively incorporated into relief distribution problem during response phase.
 110 Secondly, an integrated issue concerning relief distribution incorporating multi-stage, multi-depot,
 111 multi-destination, multi-item, periodical demands and supplies, insufficient supply and sustainability
 112 is considered to provide decisions for disaster managers in practice. Thirdly, relief distribution
 113 problem is formulated as a multi-objective mathematical programming model to maximize the
 114 lowest victims' perceived satisfaction (VPS) as well as minimize respectively the largest deviation on
 115 VPS for all demand points and sub-phases, thus alleviating victims' suffering.

116 The rest of this paper is organized as follows: The following section describes the related works on
 117 this topic. Section 3 presents problem description in detail. Section 4 formulates this issue as a

MINLP model. GA with matrix encoding is designed to solve the mathematical programming model in section 5. Section 6 uses case study from Wenchuan earthquake to illustrate the proposed model and algorithm. Finally, implication of the findings and future directions are concluded.

2. Literature review

In recent years, to save lives, reduce victims' suffering, as well as contribute to development, both relief distribution and sustainable disaster supply chain have been garnering increasingly attention. This paper contributes to literature on the following three aspects.

Firstly, one significant issue of this research is sustainable disaster supply chain. Kaivo-oja et al. (2014) and Dubey et al. (2016) portrayed that sustainability as a hot subject was being debated. Different scholars from various fields have no a unified understanding of its definition and essence. Indeed, it has different meanings for different contexts. However, sustainability with the concern of disaster or humanitarian context is only considered here. This issue in this context, although critical can only be found in a few literature. For instance, Carter et al. (2008) used triple bottom line model including social, economic, and ecological dimension to define sustainability. Weerawardena et al. (2010) contended that sustainability could be understood as maintaining operations in non-profit organization. Ibegbunam et al. (2012) mentioned that sustainability of humanitarian supply chain involved responsible communication and coordination. Haavisto et al. (2013, 2014) described and explained the sustainability of humanitarian supply chain from societal, beneficiary, supply chain and program viewpoints. Kuzn et al. (2015) discussed the sustainability of humanitarian supply chain during rehabilitation phase. Dubey et al. (2016) identified the critical features of sustainable humanitarian supply chain as agility, adaptability and alignment. Papadopoulos et al. (2017) employed Big Data to explain disaster resilience and sustainability of supply chain.

Secondly, another critical and fundamental stream is relief distribution problem. Main topics of the extant literature for disaster supply chain include relief distribution, facility location, vehicle routing planning, mass evacuation, and casualty (Hoyos et al., 2015; Habib et al., 2016). The first one is only discussed here. Fiedrich et al. (2000) integrated multi-depot, heterogeneous victims, multi-commodity into resource allocation problem at crucial rescue stage. Sheu (2007) considered an emergency logistics distribution problem simultaneously taking type of relief, vulnerabilities of victims, multi-item, multi-depot, and demand fill rate into account. Balcik et al. (2008) addressed last mile distribution problem of humanitarian relief considering equitable principle, single-depot,

multi-item, and homogeneous receipts aspect. Huang et al. (2012) concentrated on equitable service of relief supplies to all recipients, and they also captured the factors including single-item, single-depot, sufficient supply. Huang et al. (2015) used demand fill rate to measure the equity of humanitarian relief distribution with the concern of single-item, one-off demand, heterogeneous victims. Zhou et al. (2017) considered multi-item, multi-depot, multi-destination, multi-period into emergency resource scheduling problem. Theeb et al. (2017) highlighted an integrated resource distribution problem incorporating features of multi-commodity, multi-depot, multi-period. More details can reference literature Anaya-Arenas et al. (2014), and Habib et al. (2016).

Thirdly, this work also contributes to literature on multi-objective optimization and its solution strategies. Hoyos et al. (2015) portrayed that mathematical programming method was very popular in the field of relief distribution. In addition to that Holguin-Veras et al. (2013) contended that the multi-objective optimization was a very popular stream in humanitarian logistics. For instance, Lin et al. (2011) developed multi-objective mixed-integer non-linear programming model (MINLP) to minimize total unsatisfied demand, total travel time, and difference in the satisfaction rate, then designed GA as well as decomposition and assignment approach to solve. Wilson et al. (2013) employed Variable Neighborhood Descent metaheuristic to solve the MINLP model with minimizing the fatalities, suffering and maximizing the efficiency. Huang et al. (2015) formulated emergency resource allocation and distribution as a non-linear programming model to maximize lifesaving utility, minimize delay cost and difference of demand fill rates. Besides, an exact approach is used to solve this model. Zhou et al. (2017) opined that the designed heuristic algorithm performed better in solving multi-objective integer mathematical model, which formulates dynamic emergency resource scheduling problems. Interested readers can find more details in literature Ozdamar et al. (2015), Zheng et al. (2015a) and Gutjahr et al. (2016a).

In summary, Table 1 summarizes the related literature to relief distribution from various perspectives. The first five columns and the seventh column present the already defined features (Anaya-Arenas et al., 2014). ‘Depot’ column shows if a single- or multi-depot is considered into the problem. The eighth column indicates objective functions of the corresponding model, which can be: (1) economic (e.g. minimization of cost); (2) social cost (e.g. equity or similar); (3) rapidity (e.g. minimization of spent time in transporting and distributing relief); (4) live-saving (e.g. minimization of fatalities, managerial utility); (5) covering maximization (e.g. either distance/time or amount, and others); (6)

others (e.g. delay risk or similar). ‘Model’ column represents the type of mathematical model, including (1) non-linear; (2) linear; (3) integer; (4) mixed-integer; (5) mixed-integer non-linear. With regard to ‘Vic. Feat.’ column, it shows whether or not heterogeneous and homogenous victims are identified in relief distribution. Besides, the feature of victims may not be mentioned. The ‘Equity’ column indicates if equitable principle is taken into account in relief distribution, and it includes two dimensions, arrival times (AT) as well as amount of relief (RA). The ‘Sustain.’ column denotes whether or not sustainability with the concern of disaster context is considered explicitly.

Table 1

Summary of the literature pertaining to relief distribution of disaster supply chain.

Reference	Year	Data modelling	Problem characteristics									Solution method
			Obj.	Comm.	Depot	Period	Main obj.	Model	Vic. Feat.	Equity	Sustain.	
Fiedrich et al.	2000	Dynamic	Single	Multi	Multi	Multi	4	1	Hetero.	-	No	Heur.
Ozdamar et al.	2004	Dynamic	Single	Multi	Multi	Multi	5	4	Homo.	-	No	Heur.
Barbarosoglu et al.	2004	Stochastic	Single	Multi	Multi	Single	1	2	Homo.	-	No	Exact
Tzeng et al.	2007	Dynamic	Multi	Multi	Multi	Multi	1, 3, 2	3	Homo.	RA	No	Exact/sim.
Sheu	2007	Dynamic	Multi	Multi	Multi	Multi	2/5, 1	3	Hetero.	RA	No	Exact
Balcik et al.	2008	Dynamic	Single	Multi	Single	Multi	1	4	Hetero.	RA	No	Exact
Lin et al.	2011	Dynamic	Multi	Multi	Single	Multi	2/5, 3	5	Homo.	RA	No	Heur.
Huang et al.	2012	Static	Single	Single	Single	Single	3, 5, 2	3	Homo.	AT	No	Heur.
Wilson et al. (*)	2013	Static	Multi	Multi	Multi	Single	4, 6, 3	5	Hetero.	-	No	Heur.
Sheu	2014a	Dynamic	Single	Multi	Multi	Multi	6, 1	4	Hetero.	RA	No	Emp./ Exact
Huang et al.	2015	Dynamic	Multi	Single	Single	Multi	4, 1, 2	1	Hetero.	RA	No	Exact
Camacho-Vallejo et al.	2015	Static	Multi	Multi	Multi	Single	3, 1	3	Homo.	-	No	Exact
Mohammadi et al.	2016	Stochastic	Multi	Multi	Multi	Single	5, 1, 2	5	Homo.	RA	No	Heur.
Sung et al.	2016	Static	Single	Single	Single	Single	4	5	Hetero.	-	No	Exact
Zhou et al.	2017	Dynamic	Multi	Multi	Multi	Multi	5, 6	3	Homo.	-	No	Heur.
Theeb et al.	2017	Dynamic	Single	Multi	Multi	Multi	5	3	Hetero.	-	No	Heur.
Li et al.	2017	Dynamic	Single	Single	Multi	Multi	5, 2	4	Homo.	RA	No	Sim.
This paper		Dynamic	Multi	Multi	Multi	Multi	2	5	Hetero.	RA, AT	Yes	Heur.

*Casualty as commodity transportation and distribution problem

The following conclusions can be made:

(1) Differing from commercial supply chain, sustainability regarding disaster context is considered by only a few researchers, and being still in its early stage. They mainly focused on the sustainability during recovery phase with a long-term period from the view point of different aspects. In contrast, beneficiary perspective on sustainability of relief distribution during response phase with a short-term period is the focus of this paper.

(2) Most of them employed empirical or qualitative approach to capture the sustainability. But here MS/OR method is used to characterize sustainability from the point of view of beneficiary, which manifests access, equity, and needs fulfilment. Specifically, the access refers to the differences across

197 demand points and victim's groups (Haavisto et al., 2014). It is regarded as urgency of demand and
 198 heterogeneity of victim. Both weights and combinations of survival probability, piecewise decreasing
 199 linear, time urgency function are employed respectively to capture them. Furthermore, both needs
 200 fulfilment and equity are captured from the point of view of arrival times and amount of relief. Thus,
 201 victims' perceived satisfaction (VPS) is used to measure beneficiary perspective on sustainability.
 202 Besides, VPS is also treated as the result of equity with the concern of access and needs fulfilment.

203 (3) The extant literature is interested in one or more aspects but all depicted in Table 1. This paper
 204 yet tries to take all aspects into account. Specifically, response phase is subdivided into golden rescue,
 205 buffer rescue, and emergency recovery stage, rather than only concentrating one sub-phase, or no
 206 subdivision. And victims as the beneficiary in the affected areas are classified into those in hospitals
 207 or on-the-spot rescued areas (HOSs), slight or no injuries in temporary settlement areas (TESs) and
 208 around lifeline rehabilitation areas (LRs).

209 (4) An integrated issue concerning dynamic relief distribution with periodical demands and supplies
 210 under insufficient supply is formulated as a multi-objective MINLP model. The proposed model is
 211 similar to other ones in literature such as Tzeng et al. (2007), Lin et al. (2011), Huang et al. (2012),
 212 and Huang et al. (2015). Although both of them intend to achieve the goals of maximizing minimal
 213 satisfaction or similar regarding equity, they are different with objectives of this paper. Equity or
 214 similar as one of their objectives is only considered by them from a single perspective, but this paper
 215 aims to achieve objectives regarding VPS from three levels.

216 (5) It must be acknowledged that heuristic algorithm is a more popular than exact approach to solve
 217 mathematical model with an increasing complexity. Besides, Zheng et al. (2015a) elaborated that GA
 218 comparing with other algorithms received more attention in the field of disaster relief operations
 219 based on a survey. It may be the following reasons. Firstly, though it has few parameters, a good
 220 convergence can be performed (Su et al., 2016). Secondly, it also holds a better robust due to
 221 multiple initial search points. Thirdly, intrinsic probabilistic mechanism can easily capture the
 222 uncertainty and randomness of disaster relief operations. Fourthly, it has a wide extension with other
 223 methods (Hamed et al., 2015), thus strengthening its ability to deal with complex real-world problem
 224 regarding disaster. Of course, a relatively long history results in plenty of previous achievements that
 225 can be leveraged and extended. Therefore, GA is also considered as the method of this paper.

226 3. Problem description

Hoyos et al. (2015) highlighted multi-period models as an emerging topic could assist decision-makers to cope with uncertainties or randomness in relief distribution. More comprehensive analysis and new information can be included in the future periods. Simultaneously, Anaya-Arenas et al. (2014) delineated response phase need to be refined harmoniously. Thus, to further capture the dynamic characteristic of this issue, response phase as the focus of this paper is subdivided into golden rescue, buffer rescue, and emergency recovery stage. But due to space limitation, more proofs and details are only provided in Appendix A.

One of critical tasks during response phase is to design an efficient relief distribution network (Anaya-Arenas et al., 2014). As it can to some extent help to save lives, reduce suffering of victims, and contribute to development. Besides, a better support to respond quickly to disaster for decision-makers is provided. Responsiveness here means that it needs to distribute the greatest goods for the greatest number to the beneficiaries at the right time (Balcik et al., 2008). Similar to Balcik et al. (2008), a set of logistic activities from relief distribution centres (RDCs) to relief-demand points (RDPs), then to affected specific areas (ASAs) are only considered. Fig.1 presents a framework of relief distribution network for SDSC.

Fig.1. A conceptual framework of relief distribution network.

More specifically, RDCs delivery relief received from external suppliers to the RDPs. And then, relief distribution is implemented from RDPs to ASAs, such as HOSs, TESs and LRs (Fiedrich et al., 2000). In fact, ASAs represent a cluster of heterogeneous victims or beneficiaries. Unfortunately, literature associated with ASAs in relief distribution network for SDSC is still limited, which is the focus of this paper. In this context, on the condition of regional distribution rules, decision-makers need to determine respectively amount of various relief from RDCs to RDPs, and then to ASAs. Besides, they also have to make decision pertaining to the best routing selection, which is replaced by interval number denoting arrival times of relief for simplification (Huang et al., 2012).

In addition, as decisions regarding relief distribution need to be made within a relatively reasonable time, some necessary assumptions are used to simplify real-world case (Anaya-Arenas et al. 2014).

254 Firstly, consequences resulting from secondary disasters are out of scope. Secondly, both amounts
 255 and geographical locations of RDCs, RDPs, and ASAs are assumed to be known based on national
 256 disaster management programs, which is similar to Sheu (2007). Thirdly, the amounts of relief of
 257 each RDP or ASA can be satisfied by multiple transportations, namely a split delivery is considered.
 258 Fourthly, according to Camacho-Vallejo et al. (2015), four types of relief to be distributed and
 259 managed in RDCs are included here. And the bundled necessary ratio of relief out of scope has been
 260 obtained from similar cases. Fifthly, VPS is assumed to be merely correlated with amounts and
 261 arrival times of relief.

262 4. A mixed-integer nonlinear programming model formulation

263 Anaya-Arenas et al. (2014) addressed that a dynamic modeling approach can easily lead to a better
 264 performance of SDSC. In addition, Van Wassenhove (2006) highlighted that OR/MS technique could
 265 provide a very useful method to improve disaster relief operations. In this context, on the basis of the
 266 analysis already done above, relief distribution for SDSC is formulated as a MINLP model with
 267 multiple objectives. The corresponding mathematical programming model is denoted by the
 268 following formula (1) to (17). To make a clear statement for readers, necessary notations associated
 269 with model are presented in Appendix B.

$$\lambda_1^s \in \arg \max \{ \chi_1^s \mid \chi_1^s = \min [f_k^s(\pi)], \text{ for all } k \}, \forall s \quad (1)$$

$$\lambda_2^s \in \arg \min \{ \chi_2^s \mid \chi_2^s \geq |f_k^s(\pi) - f_{k'}^s(\pi)|, \forall \text{ for all } k, k' \in K, \text{ and } k \neq k' \}, \forall s \quad (2)$$

$$\lambda_3 \in \arg \min \{ \chi_3 \mid \chi_3 \geq |\phi^s(\pi) - \phi^{s'}(\pi)|, \forall \text{ for all } s, s' \in S, \text{ and } s \neq s' \} \quad (3)$$

$$\text{s.t. } \sum_{i=1}^{\bar{i}} \sum_{j=1}^{\bar{j}} Z_{ijk}^s \cdot Y_{ijk}^s \cdot x_{ijk}^s \leq e_k^s, / \forall k \in K, s \in S / \quad (4)$$

$$\sum_{j=1}^{\bar{j}} Z_{ijk}^s \cdot Y_{ijk}^s \cdot x_{ijk}^s = \sum_{m=1}^{\bar{m}} Z_{ikm}^s \cdot Y_{ikm}^s \cdot x_{ikm}^s, / \forall i \in I, k \in K, s \in S / \quad (5)$$

$$Q_i^s = \sum_{j=1}^{\bar{j}} \sum_{k=1}^{\bar{k}} Z_{ijk}^s \cdot Y_{ijk}^s \cdot x_{ijk}^s, / \forall i \in I, s \in S / \quad (6)$$

$$\sum_{i=1}^{\bar{i}} \sum_{j=1}^{\bar{j}} Z_{ijk}^s \cdot Y_{ijk}^s \cdot x_{ijk}^s \geq E_k^s, / \forall k \in K, s \in S / \quad (7)$$

$$t_{ijm}^s \cdot \max \{ Y_{ijk}^s, Y_{ikm}^s \} \leq T_{ijm}^s, / \forall i \in I, j \in J, k \in K, m \in M, s \in S / \quad (8)$$

$$Z_{ijk}^s \in \{0,1\}, / \forall i \in I, j \in J, k \in K, s \in S / \quad (9)$$

$$Z_{ikm}^s \in \{0,1\}, / \forall i \in I, k \in K, m \in M, s \in S / \quad (10)$$

$$\beta_1^s = \max\{\max\{\eta_{m_1}^s(\bullet)\}, \max\{\eta_{m_2}^s(\bullet)\}, \max\{\eta_{m_3}^s(\bullet)\}\}, / \forall m_1 \in M_1, m_2 \in M_2, m_3 \in M_3, s \in S / \quad (11)$$

$$\beta_2^s = \max\{\eta_1^s(\bullet), \dots, \eta_k^s(\bullet), \dots, \eta_{\bar{k}}^s(\bullet)\}, / \forall m_1 \in M_1, m_2 \in M_2, m_3 \in M_3, s \in S / \quad (12)$$

$$t_{ijm}^s \geq 0, / \forall i \in I, j \in J, m \in M, s \in S / \quad (13)$$

$$x_{ijk}^s \in N, / \forall i \in I, j \in J, k \in K, s \in S / \quad (14)$$

$$x_{ikm}^s \in N, / \forall i \in I, k \in K, m \in M, s \in S / \quad (15)$$

$$Y_{ijk}^s \in \{0,1\}, / \forall i \in I, j \in J, k \in K, s \in S / \quad (16)$$

$$Y_{ikm}^s \in \{0,1\}, / \forall i \in I, k \in K, m \in M, s \in S / \quad (17)$$

Herein, equations (1) to (3) present objective functions in MINLP model. Eq. (1) is to maximize the lowest VPS for all RDPs at stage s from the perspective of single RDP level. It aims to improve the worst case in the affected areas, which is Similar to Tzeng et al. (2007). Besides, each type of relief is considered independently to avoid cross-impacts on perceived satisfaction. Eq. (2) is to minimize the largest deviation on perceived satisfaction for any two RDPs at stage s from the perspective of multiple RDPs level. It indicates that it is necessary to ration equitably relief, thus reducing unbalanced perceived satisfaction for all RDPs (Huang et al., 2012, Lin et al., 2011). In summary, the aforementioned two objective functions characterize sustainability of relief distribution from two operational levels. Particularly, $f_k^s(\pi)$ is denoted by $f_k^s(\pi) = f_{k \rightarrow 1}^s(\pi) \times f_{k \rightarrow 2}^s(\pi), \forall k, s$, with $f_{k \rightarrow 1}^s(\pi) = \eta_k^s(x), \forall k, s$ and $f_{k \rightarrow 2}^s(\pi) = (\eta_{m_1}^s(t)|_{m_1 \rightarrow k} + \eta_{m_2}^s(t)|_{m_2 \rightarrow k} + \eta_{m_3}^s(t)|_{m_3 \rightarrow k}) / \sqrt{\alpha_k^s}, \forall k, s$. Eq. (3) intends to minimize the largest deviation on perceived satisfaction from the point of view of lifecycle of response phase. The third objective function differing from the first and second one is measured from a systematic perspective. Additionally, Huang et al. (2015) underlined that it was difficult to make ad-hoc decisions at a sole time point due to uncertainties and dynamic evolving of disasters. Thus, decisions ought to be made during several time periods, which to some extent results in their mutual relationships (Rennemo et al., 2014).

286 In this context, the perceived dissatisfaction obtained at last stage $(1 - \phi^{s-1}(\bullet))$ is used to capture these
 287 cross-impacts, and let it represent the weights of current sub-phase. Therefore, VPS at stage s can be
 288 represented by $\phi^s(\pi) = [1 - \phi^{s-1}(\pi)] \times [\phi_1^s(\pi) \times P_1^s / \beta_1^s] \times [\phi_2^s(\pi) \times P_2^s / \beta_2^s], \forall s$. Therein, $\phi_1^s(\pi)$ and $\phi_2^s(\pi)$
 289 can be denoted by $\phi_1^s(\pi) = [g_1^s(\pi) + g_2^s(\pi) + g_3^s(\pi)] / 3, \phi_2^s(\pi) = g_4^s(\pi), \forall s$, respectively. In addition, a
 290 convex combination is considered here (Marler et al., 2005), thus $P_1^s + P_2^s = 1$, and $P_1^s, P_2^s \in [0.1, 0.9]$.
 291 Doing like this is to avoid unexpected cases. To make it concise, critical equations regarding all
 292 objective functions are presented in Appendix C.

293 Formulas (4) to (17) represent all constraints. Constraints (4) indicate relief supply is insufficient for
 294 each RDP k at stage s . Constraints (5) ensure that amounts of received relief type i equal those of
 295 distribution at RDP k at stage s . Constraints (6) define the total number of actual distribution as the
 296 corresponding inventory of relief type i at stage s . Constraints (7) ensure that amounts of the received
 297 relief at RDP k are no less than lower bound that victims can tolerate, and E_k^s is calculated by twenty
 298 percent of expected amounts of relief. Constraints (8) account for the time spent by transporting and
 299 distributing relief from RDCs to ASAs within a given bound, and T_{ijm}^s can be determined by the upper
 300 bound of interval number that represents different arrival times of relief from different routings.
 301 Constraints (9) to (10) define the indicator parameters that demonstrate objective case in relief
 302 distribution network for SDSC. They can be pre-determined. Constraints (11) and (12) register
 303 auxiliary parameters to eliminate differences resulting from dimension. Constraints (13) to (17)
 304 provide definitions for all decision variables.

305 5 A heuristic algorithm for dynamic relief distribution

306 This section first clarifies motivations for GA. Subsection 5.2 describes the key operators of GA.
 307 Critical procedure of GA is presented in subsection 5.3.

308 5.1 Motivations for GA

309 As mentioned in section 2 'Literature review', GA is widely used to solve mathematical model in
 310 disaster relief operations. The following presents the reasons why GA is chosen as the methodology
 311 in this paper.

312 Firstly, in practice, decision-makers need to develop relief distribution scheme within a relatively

reasonable time to reduce various consequences (e.g. save lives, decrease suffering) as much as possible. In terms of GA, multiple initial search points are simultaneously used to seek satisfactory solution. It can to some extent improve the speed of search, thus saving run times. Therefore, this characteristic of GA can assist decision-makers to develop a better relief distribution scheme within the limited time.

Secondly, there are plenty of uncertainties and randomness (e.g. time-varying demand and supply, status of roads and bridges) existing in relief distribution for SDSC. They have a significant influence on the performance of SDSC. Nevertheless, intrinsic probabilistic mechanism considered in selection, crossover and mutation operator of GA provides to a large extent a new idea to capture the uncertainties and randomness in SDSC. It has the capability to simulate most of the scenarios in disaster relief operations.

Thirdly, some of researchers who focus on a similar problem to this paper demonstrate that GA regarding specified situation has potential advantages on solution quality and computation time. For instance, Zhang et al. (2016), Najafi et al. (2015), and Lin et al. (2011) compared respectively GA or extensions against branch and bound approach, LINGO and CPLEX solver with the concern of disaster context. They clarified GA was able to generate good quality solutions within a reasonable time. Su et al. (2016) and Zhang et al. (2011) indicated an outstanding solution could be obtained by GA. Besides, Zheng et al. (2015b) delineated that GA against tabu search could offer a better quality solution. Chang et al. (2015) opined that GA had the ability to obtain satisfactory solution within a relatively short time. In this context, this paper leverages and extends their insights to design GA discussed here.

5.2 Critical operators of GA

5.2.1 Representation and encoding

Regarding relief distribution for SDSC, the amounts of allocated relief and the corresponding arrival times need to be determined. Its dimension is more than one, thus matrix encoding is considered here. Fig. 2 presents the encoded rules concerning relief distribution scheme and chromosome.

It can be inferred that performance of GA with matrix encoding is essentially similar to that of traditional GA. One of the reasons may be that all decision variables are only located in 1st and 8th row in Fig.2. Others are only used to present an explicit iteration and respond to decoding.

Specifically, the corresponding values of row 2 to 7 are fixed in terms of each column. Satisfactory solution is obtained by changing the values of all decision variables in 1st and 8th row.

Fig.2. Representation for chromosome.

In this context, each chromosome can be defined by a $8 \times (J \| I \| K \| M \| S)$ matrix, which represents a feasible relief distribution scheme for SDSC. For each chromosome, the 8th row denotes time decision variable t_{ijm}^s . the first row represents amount decision variables x_{ikm}^s . Simultaneously, Y_{ikm}^s is determined by x_{ikm}^s . Specifically, if $x_{ikm}^s > 0$, then $Y_{ikm}^s = 1$; if $x_{ikm}^s = 0$, then $Y_{ikm}^s = 0$. x_{ijk}^s is calculated by the sum of actual amounts of transported relief. That is, it is contingent on the sum of corresponding value of the first row for each RDP k . If $x_{ijk}^s > 0$, then $Y_{ijk}^s = 1$; if $x_{ijk}^s = 0$, then $Y_{ijk}^s = 0$. Besides, the value of parameter Z_{ikm}^s and Z_{ijk}^s can be pre-determined with the concern of relief distribution network. The following constraints ought to be satisfied: $Z_{ijk}^s + Z_{ikm}^s = 0$ or if $Z_{ijk}^s = 0$, then $Z_{ikm}^s = 0$. The corresponding time and amount decision variables are sufficiently large positive numbers if $Z_{ikm}^s = 0$. Thus, instance including two RDPs, one RDC and two types of relief and ASAs is illustrated. In addition, AATR is short for ‘actual amounts of transported relief’ as well as AT is ‘actual time’.

Another critical thing is how to link constraints of relief distribution model with representation for chromosome. In this paper, Constraints (4) and (5) can be represented respectively by row 1, 2, and 3 as well as 1, 2, and 5 in Fig.2. The value of row 1, 5, and 6 simultaneously determine constraints (6). Constraints (7) and (8) are indicated by 1st and 2nd row as well as 1st and 8th row, respectively. Constraints (11) and (12) are only to give the formulation of auxiliary parameter. Other constraints can be found in last paragraph.

5.2.2 Initial population

To improve performance of GA regarding run time, this paper defines a feasible relief distribution scheme as an individual of initial population. Then, as a benchmark, other individuals of initial population are produced by assigning different values to all decision variables on the condition of satisfying all constraints. Particularly, the feasible relief distribution scheme can be obtained from decision-makers, who deal with disasters on the spot. Doing like this differing from the case that initial population is produced randomly has the potential advantages on saving run times. In addition, population size can be generally defined as 20 to 50. To simplify real-world case, instance regarding two RDCs, three RDPs, three ASAs, four types of relief and three sub-phases is considered in section 6. Thus, each relief distribution scheme can be represented as a 8×216 matrix.

5.2.3 Individual fitness function

Individual fitness function is employed to evaluate each relief distribution scheme, and determine the members of next generation (Su et al., 2016). In general, it is defined by objective functions or their extensions of relief distribution model. As a multi-objective optimization problem is considered, strategies to handle this case have to be designed. In the extant literature, some methods such as the weighted sum, epsilon-constraint, and Pareto optimality are proposed (Balaman et al., 2016; Najafi et al., 2015; Marler et al., 2004). This paper leverages and extends their insights to provide a linear weighted method to integrate three objectives into a scalar single one. In this context, individual fitness function with maximal goal can be denoted by the following Eq. (18).

$$\max \varphi(h, l) = \mu_1 \bar{\lambda}_1 + \mu_2 \times (1/\bar{\lambda}_2) + \mu_3 \times (1/\bar{\lambda}_3) \quad (18)$$

Therein, $\varphi(h, l)$ denotes the value of fitness function of individual h in generation l . As three values for the first and second objective will be respectively obtained from each feasible solution, a transformation strategy into one value is necessary. According to the statistical knowledge, arithmetic

mean is an effective method to achieve this goal regarding relief distribution model. Consequently, let $\bar{\lambda}_1$ and $\bar{\lambda}_2$ denote respectively the arithmetic mean of the first and second objective. They are denoted by $\bar{\lambda}_1 = (\lambda_1^1 + \lambda_1^2 + \lambda_1^3)/3$ and $\bar{\lambda}_2 = (\lambda_2^1 + \lambda_2^2 + \lambda_2^3)/3$, respectively. Differing from the previous two cases, the third objective has only one value, thus letting $\bar{\lambda}_3 = \lambda_3$.

It must be acknowledged that their combinations also should be elaborated. Specifically, the first objective and individual fitness function have the same trend. It indicates that $\bar{\lambda}_1$ can be directly regarded as the first part of individual fitness function. Yet, the second and third objectives have an opposite case to individual fitness function. An inverse method is employed to cope with this case (Gutjahr et al., 2016b). Thus, $1/\bar{\lambda}_2$ and $1/\bar{\lambda}_3$ are respectively defined as the second and third part. To standardize each part, let coefficient of each part as $\mu_1 = 1/(\bar{\lambda}_1)_{\max}$, $\mu_2 = 1/(1/\bar{\lambda}_2)_{\max}$ and $\mu_3 = 1/(1/\bar{\lambda}_3)_{\max}$ for each generation l . Another reason doing like this is to eliminate the adverse phenomenon that ‘a large number annihilating a small number’ in handling multi-objective problem.

5.3 Critical procedure of GA

The aforementioned operators of GA include representation and encoding, initial population and individual fitness function. In addition to that other operators such as selection, crossover, and mutation as well as termination criterion also should be highlighted. Fig.3 depicts the specific procedure of GA discussed here.

Particularly, two termination criteria are highlighted. The first one is to obtain the satisfactory solution or relief distribution scheme on the given iterative times. The second one is that the value of fitness function is convergence to a fixed value during the iterative process.

1: Generate initial population or obtain initial feasible solution

2: Obtain initial relief distribution scheme from decision-makers and define it as the best practice

3: **for** $l=1:L$ <define the cycle of iteration >

4: **for** $h=1:H$ <define the cycle of iterative individual or each relief distribution scheme>

5: Calculate the value of individual fitness function

6: Calculate value of fitness function of each individual by Eq.(18) and the sum of them is denoted by $F(H,l)$

7: Obtain selection probability based on $p(h,l) = \varphi(h,l)/F(H,l)$ and the corresponding accumulated Probability is defined as: $A(h,l) = A(h-1,l) + p(h,l)$

8: **end**

9: **for** $h=1:H$ <define the cycle of iterative individual or each relief distribution scheme>

10: **Selection based on roulette method**

11: **if** $A(1,l) \geq r(h,l)$ <wherein, $r(h,l)$ is a random at interval (0,1)>

12: Select 1st individual as next generation

13: **else**

14: Select individual h' as next generation, and it should meet $A(h-1,l) < r(h',l) \leq A(h,l)$ and $2 \leq h \leq H$

15: **end**

16: **Crossover with single-point method**

17: Get crossover point by a integer at interval [1,215], then do this operation with crossover probability P_c

18: Correct the unfeasible individual by elimination and modification strategies, **until** all individuals are feasible

19: **Mutation with uniform method**

20: Calculate the number of mutated gens by the length of chromosome and mutation probability p_m

21: Then, determine which gens need to execute mutation, and do by $x_{ikm}^s + [x_{ikm}^s - x_{ikm}^s] \times rand()$

22: Do correction strategies in a similar way of line 18, until all individuals are feasible

23: **end**

24: Return to line 3

25: **end**

26: Until the termination criterion is satisfied

Fig. 3. Procedure of GA discussed here

6 Computational studies

To illustrate the proposed model and method, case study on a great earthquake that occurred in Wenchuan of Sichuan province in China at 14:28 p.m., May 12, 2008 is considered. Main shock was at magnitude 8.0 along with many aftershocks. It killed 69016 people, missed more than 18000 people and destroyed directly over 800 billion CNY worth of heavy property losses. It is reported that there were 10 extremely severe affected areas, 41 heavily ones and 186 general ones. Due to the limited space, both comprehensive description regarding case study and initial relief distribution scheme is depicted in Appendix C.

Particularly, initial relief distribution scheme from practical decision-makers is defined as the best practice here. The method doing like this is also used by Wex et al. (2014), who regarded rescue units assignment scheme obtained from the German Federal Agency of Technical Relief (THW) as the best practice behavior of emergency operation centers. In addition, to evaluate the performance of the proposed model and methodologies, the following subsections presents the results from three different perspectives.

6.1 Computational results obtained by GA

Mixed integer non-linear programming model (MINLP) and GA solved or implemented by using MATLAB (2012b). The program is run on 2.2 GHz 64-bit Core i5-5200U CPU machine under Windows 8.1 Professional. In terms of operators of GA, crossover probability is 0.05, mutation probability, 0.002, population size, 50, and maximal iteration, 800. In this context, computational results demonstrate that the value of fitness function is approximately converged to 2.7355 at 110th iteration, and average CUP time is 16.8 minutes. More information with the concern of satisfactory relief distribution scheme is presented in Table D.3 of Appendix D.

Computational results indicate a relatively reasonable relief distribution scheme for SDSC can be obtained by GA within the given iterations and limited time. It can be inferred that GA discussed here can to some extent achieve the trade-off between solution quality and computation time, which is line with the expectations. As clarified by Wex et al. (2014), decision support in practice has to be provided within 30 minutes by conforming in interviews with the German Federal Agency of Technical Relief (THW). Thus, results further demonstrate that it is able to assist in improving the performance of relief distribution of SDSC. Besides, these results and conclusions can be further supported by Lin et al. (2011), Zheng et al. (2015b), Zhang et al. (2016), who concentrated on a similar problem to this paper. Their specific insights can be found in subsection 5.1.

6.2 Computational results regarding cover range

Firstly, both initial and satisfactory relief distribution scheme are represented as a rectangle. It is subdivided into 8 rows and 27 columns, thus resulting in 216 aliquot grids. Then, either black or white circle can be filled in any grid. Specifically, a black circle shows a positive relationship of relief delivered from RDCs or RDPs to ASAs. Otherwise, it is marked by a white circle. For any RDC, the more the black circles are, the larger the cover range is. Besides, it also demonstrates the corresponding relief distribution sub-network of SDSC is more decentralized, untargeted, and

446 complicated as well as difficult to control. In contrast, a smaller one indicates it is more centralized,
 447 targeted, and simple as well as relatively easy to control. But cover range mentioned here does not
 448 involve their weights that represent the corresponding amounts of received relief by ASAs. This
 449 subsection depicts computational results obtained by GA and the best practice from the perspectives
 450 of RDCs and relief types.

451 6.2.1 RDCs perspective

452 According to initial and satisfactory relief distribution scheme, the compared diagram of cover range
 453 regarding relief types from the perspective of RDCs is depicted in Fig.4.

Best practice		Golden rescue stage ($s = 1$)								Buffer rescue stage ($s = 2$)								Emergency recovery stage ($s = 3$)							
Chengdu	Type 1	○	○	○	●	●	●	●	○	●	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○
	Type 2	●	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
	Type 3	○	●	○	●	●	●	●	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
	Type 4	○	○	○	●	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Mianyang	Type 1	○	○	○	●	○	●	●	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
	Type 2	●	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
	Type 3	●	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
	Type 4	○	○	○	●	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
GA		Golden rescue stage ($s = 1$)								Buffer rescue stage ($s = 2$)								Emergency recovery stage ($s = 3$)							
Chengdu	Type 1	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
	Type 2	●	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
	Type 3	●	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
	Type 4	○	○	○	●	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Mianyang	Type 1	○	○	○	●	●	●	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
	Type 2	●	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
	Type 3	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
	Type 4	○	○	○	●	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○

454
455 **Fig.4.** Cover range regarding relief types from RDCs perspective.

456 In terms of the best practice, the total number of fit between all relief types and ASAs is 101 out of
 457 216. Thus, the corresponding average cover rate in total is calculated by $101/216 \approx 0.468$. Wherein,
 458 cover rate of Chengdu is 0.472 and Mianyang is 0.463. In a similar way, average cover rate of
 459 satisfactory relief distribution scheme is computed by $70/216 \approx 0.324$. Therein, cover rate of both
 460 Chengdu and Mianyang is 0.324. It is obvious that average cover rate of the best practice is greater
 461 than that of satisfactory relief distribution scheme, which indicates the structure of relief distribution
 462 network of the best practice can be continuously improved by GA, even other heuristic algorithms. It
 463 is also to a large extent observed by Wex et al. (2014), who devoted to developing emergency
 464 resource allocation scheme based on multiple heuristic algorithms. Besides, cover rate of Chengdu

465 and Mianyang under the two scenarios further consolidates this conclusion. However, it must be
 466 acknowledged that the best practice and satisfactory relief distribution scheme have the same
 467 workloads in total at each sub-phase.

468 To further investigate impacts of dynamic of relief distribution for SDSC on cover rate of RDCs,
 469 another experiment regarding lifecycle of response phase are conducted. Results obtained GA against
 470 the best practice are presented in Fig.5.

Fig.5. Cover rate regarding lifecycle of response phase from RDCs perspective.

473 According to the aforementioned computational results, it can be concluded that cover rate of
 474 Chengdu and Mianyang as well as their average of satisfactory relief distribution scheme have the
 475 significant advantages against the best practice during all response sub-phase. The conclusion that a
 476 relatively centralized, targeted and easy-to-control relief distribution network for SDSC is better is
 477 supported again from a dynamic perspective.

478 In this context, it can be inferred that a relatively centralized relief distribution network is more
 479 efficient with the concern of specific context. Its significant advantages may manifest the following
 480 aspects. Firstly, adequate vehicles to transport various type of relief can be guaranteed for
 481 decision-makers. Secondly, such goals of SDSC to save lives, decrease suffering of victims, reduce
 482 emergency costs and shorten travel distance are able to be achieved better. In addition to that Sheu
 483 (2014a), Sheu et al. (2014b), and Valenzuela et al. (2014) support the aforementioned claim. For
 484 example, Sheu et al. (2014b) focused on a centralized emergency supply network design regarding
 485 psychological cost that reflects suffering of survivors in response to large-scale natural disasters.
 486 Their results, which are similar to the results of methodologies of this paper, indicated that such a
 487 centralized emergency supply network (especially distribution) had the potential superiority over a
 488 decentralized one.

6.2.2 Relief types perspective

In a similar way, by analyzing initial and satisfactory relief distribution scheme, the compared diagram of cover range regarding RDCs from the perspective of relief types is presented in Fig. 6.

Best practice		Golden rescue stage $(s = 1)$								Buffer rescue stage $(s = 2)$								Emergency recovery stage $(s = 3)$										
Chengdu	Type 1	○	○	○	●	●	●	●	○	●	●	○	○	○	○	●	●	●	○	○	○	○	○	○	○	●	●	●
Mianyang		○	○	○	●	○	●	●	●	○	●	○	○	○	○	○	●	●	●	○	○	○	○	○	○	○	●	●
Chengdu	Type 2	●	●	○	○	○	○	○	○	○	○	○	○	○	○	○	●	●	●	●	○	○	○	○	○	○	○	○
Mianyang		●	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	●	●	●	●	○	○	○	○	○	○	○
Chengdu	Type 3	○	●	○	●	●	●	●	○	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Mianyang		●	●	○	○	○	○	●	●	○	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Chengdu	Type 4	○	○	○	●	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Mianyang		○	○	○	●	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
GA		Golden rescue stage $(s = 1)$								Buffer rescue stage $(s = 2)$								Emergency recovery stage $(s = 3)$										
Chengdu	Type 1	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Mianyang		○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Chengdu	Type 2	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Mianyang		○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Chengdu	Type 3	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Mianyang		○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Chengdu	Type 4	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Mianyang		○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○

Fig.6. Cover range regarding RDCs from relief types perspective.

In Fig.6, with respect to satisfactory relief distribution scheme, Chengdu and Mianyang regarding the same type of relief-supply has the significant differences. In contrast, Chengdu has a very similar situation to Mianyang for the best practice. In summary, computational results indicate the structure of inventory relief in RDCs for best practice is able to be optimized by GA as the method of this paper. It manifests the following points. Firstly, to a large extent, Chengdu and Mianyang have the respective main areas taking into consideration supply of the same type of relief. As vehicle routings from Chengdu and Mianyang to ASAs are different, it can benefit the elimination of waste regarding human capital, costs and others. Secondly, it is able to avoid the unexpected cases (e.g. increasing dissatisfaction, deaths) resulted from information asymmetry amongst suppliers of relief. Therefore, the needs for optimizing inventory structure of relief for all RDCs are pressing.

To further validate the proposed methodologies of this paper, the weights that represent actual amounts of relief are combined with their cover range. Thus, the weighted cover rate obtained by GA over the best practice from the perspective of relief types is depicted in Fig.7.

(a) A scatter diagram of absolute value of difference

	Type 1	Type 2	Type 3	Type 4
s=1	Mianyang	Chengdu	Mianyang	Chengdu
s=2	Mianyang	Chengdu	Mianyang	Mianyang
s=3	Mianyang	Chengdu	Chengdu	Chengdu

(b) Type of supplied relief for satisfactory solution

	Type 1	Type 2	Type 3	Type 4
s=1	Chengdu	Chengdu	Mianyang	Chengdu
s=2	Chengdu	Mianyang	Mianyang	Chengdu
s=3	Chengdu	Mianyang	Chengdu	Mianyang

(c) Type of supplied relief for the best practice

Fig.7. The weighted cover rate obtained by GA against the best practice.

Fig.7 (a) demonstrates the differences of the weighted cover rate between Chengdu (marked 1#) and Mianyang (marked 2#). And its measurement is denoted by $|x_{i1}^s \cdot c_{i1}^s - x_{i2}^s \cdot c_{i2}^s|$, x_{i1}^s and x_{i2}^s represent respectively amounts of relief type i delivered to Chengdu and Mianyang at stage s , and c_{i1}^s and c_{i2}^s denote their cover rates. Results indicate that both amounts and type of relief supplied by Chengdu and Mianyang is significantly different for satisfactory relief distribution scheme over the best practice. Fig.7 (b) and (c) with more detailed information consolidate this viewpoint. Fig.7 (c) indicates that both Chengdu and Mianyang need to store and supply all types of relief during all sub-phases of response, although there is a minor difference with regard to the first type of relief. However, Fig.7 (b) supports to a large extent a better case.

In summary, the following conclusions can be made. Firstly, the benefit of an efficient strategy for pre-disaster relief inventory management is to improve the performance of post-disaster relief distribution for SDSC. It is also highlighted by Toyasaki et al. (2017), Rottkemper et al. (2011). For

instance, Toyasaki et al. (2017) devoted themselves to enhancing the effectiveness of efficiency of relief supply chains via horizontal cooperation among humanitarian organizations regarding disaster relief inventory management. Secondly, establishment of RDCs regarding location, size and other factors should be considered, thus enhancing the performance of relief distribution. It means that combinations of location of RDCs and distribution of relief are critical for SDSC. Importance of such an emerging topic is also addressed by Anaya-Arenas et al. (2014), Gutjahr et al. (2016b).

6.3 Computational results regarding VPS

Subsection 6.2 has analyzed results obtained by GA and the best practice in detail from a traditional supply chain. However, a sustainability perspective is considered further to validate the results and methodologies of this paper. As mentioned above, VPS is used to measure beneficiary perspective on sustainability regarding access, equity and needs fulfilment. In the meantime, VPS is reflected by arrival times and amounts of relief. Thus, the following subsections present computational results on sustainability from the point of view of RDPs and categorization of VPS reflected by ASAs. Particularly, values in bracket represent the best practice, otherwise, those obtained by GA.

6.3.1 VPS from RDPs perspective

Similarly, computational results with the concern of VPS are summarized from the point of view of RDPs. It is depicted in Table 2.

Table 2

VPS obtained by GA against the best practice from RDPs viewpoint.

Emergency response phase	Du Jiangyan	Mianzhu	Guangyuan	PS	Minimum	LD-RDPs	LD-SPs
Golden rescue stage	0.0006 [0.0007]	0.1264 [0.1771]	0.0305 [0.0172]	0.0075 [0.0088]	0.0006 [0.0007]	0.1258 [0.1764]	
Buffer rescue stage	0.0246 [0.0008]	0.0004 [0.0157]	0.0322 [0.0425]	0.0242 [0.0479]	0.0004 [0.0008]	0.0318 [0.0417]	0.0208 [0.0422]
Emergency recovery stage	0.0008 [0.2450]	0.0059 [0.0003]	0.0285 [0.0273]	0.0034 [0.0057]	0.0008 [0.0003]	0.0277 [0.2447]	

Notes: PS is abbreviation for perceived satisfaction, LD-RDPs is the largest deviation for all RDPs, as well as LD-SPs is the largest deviation for all sub-phases.

Following Table 2, it can be seen that average value of the lowest VPS gained by both GA and the best practice is the same, 0.0006. There is no obvious improvement for the first objective resulting from emergency recovery stage (May 24 to June 5). Values of largest deviation on VPS for all RDPs (second one) and sub-phases (third one) are significantly improved by GA. In addition to that there is

a highest VPS in total for Du Jiangyan, then Mianzhu and Guangyuan in order.

In summary, although this paper didn't conduct additional experiments regarding methodologies of literature such as Tzeng et al. (2007), Lin et al. (2011), Huang et al. (2012), Huang et al. (2015) with a similar objective to this paper, some meaningful comparisons were still summarized. Firstly, RDPs with the lowest VPS and largest derivation require more attention. The reason is that those victims may display extreme behaviors and disturb the order of society due to undertake more suffering. Similar results are provided by Tzeng et al. (2011), Lin et al. (2011). Secondly, this paper aims to not only evaluate validation of the proposed methodologies, but call for taking into consideration the vulnerability of RDPs that reflects one aspect of sustainability. Both Huang et al. (2015) and Huang et al. (2012) show a better support to this point.

6.3.2 VPS from ASAs perspective

Different from last subsection, VPS regarding arrival times and amounts of relief, which is obtained by GA over the best practice is depicted in Table 3.

Table 3

VPS obtained by GA against the best practice from ASAs viewpoint.

Emergency response phase	VSI-AT	VNSI-AT	Victims around LR on AT	PS towards amounts of relief
Golden rescue stage	0.0890 [0.2376]	0.2725 [0.5424]	0.0838 [0.0021]	0.1132 [0.1188]
Buffer rescue stage	0.0600 [0.2129]	0.2680 [0.9475]	0.0720 [0.0750]	0.0364 [0.0312]
Emergency recovery stage	0.0402 [0.4017]	0.1824 [0.0000]	0.0200 [0.0185]	0.0315 [0.1218]

Notes: PS is abbreviation for perceived satisfaction, AT is arrival times, VSI-AT is victims with serious injuries on AT, as well as VNSI-AT is victims with no or slight injuries on AT.

In terms of VPS towards amounts of relief, it is interesting that victims have the highest perceived satisfaction at golden rescue stage. The reason may be that victims have a relatively larger marginal utility, although only a small portion of relief is transported to ASAs in time. In contrast, there is yet a lowest VPS at emergency recovery stage. This may result from shortage of relief within a short time, inventory of RDCs being out of control huge amounts of relief-demand in large-scale natural disasters. With regard to VPS towards arrival times of relief, the value is the largest from May 12 to May 17 and smallest from May 24 to June 5. Specifically, victims located in TESs have the highest perceived satisfaction towards arrival times of relief, and next is those located in HOSs. As the

569 successful rehabilitation of lifeline infrastructures is the prerequisite to transporting and distributing
 570 relief to ASAs, perceived satisfaction of victims around LR towards arrival times of relief is the
 571 relatively lowest taking into account hard and soft constraints.

572 Overall, firstly, VPS towards both amounts and arrival times of relief is the lowest at emergency
 573 recovery stage. It indicates that victims heavily suffer from shortage of relief and delay of arrival
 574 time. Although only a few secondary disasters occurred and victims may remain a stable status, an
 575 equal importance to relief distribution during this period should be highlighted (Hoyos et al., 2015).
 576 Secondly, Haavisto et al. (2014) clarified that beneficiary perspective on sustainability manifested
 577 equity, need fulfilment, vulnerability of victim groups, and its consideration could improve the
 578 performance of humanitarian supply chain. This paper further validates their conceptual framework
 579 by mathematical programming method. Although mixed results are obtained, this paper also can to a
 580 large extent support their insights.

581 **7. Conclusions and recommendations**

582 This paper proposes a multi-objective MINLP model for dynamic relief distribution regarding
 583 sustainability. Beneficiary perspective on sustainability manifests access, equity, and needs fulfilment,
 584 and is captured by VPS towards amounts and arrival times of relief. The access to RDPs and victim
 585 groups is respectively reflected by urgent level of relief-demand and severity of injuries, so that the
 586 most needed ones can gain more attention. Equity with the concern of needs fulfilment involves
 587 amounts and arrival time of relief, and it is measured by actual value against expectations. Thus, the
 588 suffering of victims is linked with the decisions on relief distribution to reduce social costs.
 589 Furthermore, the dynamic of relief distribution during response phase is considered in a discrete
 590 manner, so as to improve the performance. Specifically, response phase is refined into golden rescue,
 591 buffer rescue, and emergency recovery stage.

592 The results from this paper provide several insights on theory and practice of relief distribution
 593 regarding sustainability. A theoretical link between sustainability development and traditional relief
 594 distribution even disaster relief operations is presented to alleviate the suffering of victims. Besides,
 595 the conceptual framework regarding sustainability in disaster supply chain proposed by Haavisto et
 596 al. (2014) is further validated here.

597 In practice, decision-makers intend to utilize a centralized relief distribution network during response
 598 phase, unlike in commercial settings where different beneficiaries usually have the independent

objectives and try to achieve them in a decentralized manner (Sheu et al., 2014b). In the context of disasters, real-time information including vulnerability of victims, lifeline infrastructures, needed commodities, relief inventory status, RDPs and RDCs usually unknown. Therefore, relief distribution regarding sustainability may benefit from the easy-to-control centralized manner. In addition, results indicate that an efficient inventory strategy regarding relief type in response to large-scale natural disasters can assist in improving the performance of relief distribution (Toyasaki et al., 2017). That is, each type of relief should be stored in the right RDPs based on the aforementioned real-time information. Of course, inventory strategy here refers to various type of relief need to be transported from RDCs. For instance, temporary professional equipment such as crane, hydraulic excavator should be transported to relatively nearer RDCs with HOSs and LRs. However, daily-used relief such as sleeping bags, tents ought to be mainly stored in RDCs located in TESs. In disaster relief environments, there are several indicators to capture sustainability (Dubey et al., 2016; Haavisto et al. (2014)), and this paper merely focuses on beneficiary perspective regarding access, equity and needs fulfilment. Although different researchers may have different insights and use different methods to measure them, the proposed model here can easily integrate other indicators, such as ecological dimension of sustainability. More specifically, arrival times of relief are first replaced by the distance between RDCs and RDPs as well as ASAs. Then, average energy consumption can be computed based on transportation mode. Thus, total carbon emissions as one of objectives are formulated. Furthermore, a reasonable relief distribution scheme is obtained within the limited time, and the best practice can be continuously improved by GA. One reason may be that decisions regarding relief distribution are often made in an unstructured manner, usually without the assistance of sophisticated software embedded in mathematical models and algorithms. In addition, it is beneficial in improving the sustainability of disaster supply chain by incorporating many factors into relief distribution problem. However, it also presses more challenges on decision-makers to deal with the complex issue. So the needs to develop and improve the logistic software in disaster management sectors are pressing, especially in the era of Big Data (Zhong et al., 2016; Huang et al., 2012; Rolland et al., 2010). Since the proposed method of this paper is efficient and easy to understand. If it is embedded in such software, valuable decision support might be provided for managers in practice. This insight is found to be consistent with pervious findings in literature such as Zheng et al. (2015), who applied heuristic algorithm into real case from Dingxi earthquake of China. Yet, it intends to only help

managers to make decisions rather than fully substitute the practitioners. Particularly, the proposed methodologies of this paper are expected to not only improve the performance of SDSC, such as saving lives, decreasing suffering and contributing to development, but also address the importance and urge of taking into account beneficiary perspective on sustainability for relief distribution.

Valuable topics remain for further study. As mentioned above, only social dimension (or beneficiary perspective) of sustainability is considered into relief distribution problem. The follow-up direction can model such issue by incorporating economic and ecological dimension of sustainability. Another promising topic is to further test and validate conceptual framework regarding sustainability in the context of disaster proposed by Haavisto et al. (2014) with other real cases, so as to strengthen the results of this paper.

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Supplementary materials

Supplementary materials related to this manuscript consists of Appendix A, B, C and D. And they as a separate file are provided in EES.

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Highlights

- Beneficiary perspective on sustainability is incorporated into dynamic relief distribution problem during response phase.
- Sustainability regarding the access, equity and needs fulfilment is measured ultimately by victims' perceived satisfaction (VPS).
- An integrated relief distribution issue is formulated as a multi-objective mixed-integer nonlinear programming (MINLP) model.
- The goals are to maximize the lowest victims' perceived satisfaction, and minimize respectively the largest deviation on victims' perceived satisfaction for all demand points and sub-phases.
- A case study from Wenchuan earthquake is used to illustrate the methodologies, and indicates their potential advantages.